Harnessing Heterogeneity
Understanding Urban Demand to Support the Energy Transition

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Nina Voulis

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Dissertation

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by

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Dissertation
Harnessing Heterogeneity – Understanding Urban Demand to Support the Energy Transition

Systems Engineering Group
Faculty of Technology, Policy and Management
Delft University of Technology
The Netherlands

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Бабушке Лене,
она мне с детства говорила,
что я тоже везде побываю.

Πάντα ῥεῖ.

Ἡράκλειτος

Acknowledgements

Le 22 mai 2014, à 6 heures 58 minutes et 11 secondes, une mouche bleue de la famille des Calliphoridae capable de produire 14 670 battements d'ailes à la minute se posait rue Seneca, à Ithaca. A la même seconde à la terrasse d'un restaurant à cent mètres de la Gorge de Cascadilla, le vent s'engouffrait comme par magie sous une nappe faisant danser les verres sans que personne ne s'en aperçoive. Toujours à la même seconde un message provenant de Martijn Warnier et Frances Brazier est apparu dans ma boîte mail. Quatre mois plus tard je commençais mon doctorat.

– Après Jean-Pierre Jeunet et Guillaume Laurant

I was jumping up and down an old couch in my living room. It would become a beautiful spring day, but most of all – I had been accepted for a PhD position in the Systems Engineering group at Delft University of Technology. I could not have been happier then, and I could not be happier now, looking back at the journey. I am very grateful to all of you who have supported me in these last few years.

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This thesis is a stepping stone, I sincerely hope for many more than just for me. Our world is changing, continuously and in many ways, but now, in particular, in an alarming direction. Climate change is a reality that will alter many aspects of our and our children's lives. Πάντα ῥεῖ – everything is changing – but we do not have to be passive spectators, we still can steer the changes into a more favourable direction.

Nina Voulis,
January 2019

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1 Introduction

Dit is het land waar grote mensen wonen.

– Annie M. G. Schmidt

The summer of 2018 was marked by a record-breaking heatwave on four continents [1]. This was, however, not a stand-alone event. The preceding four years, 2014 to 2017, were worldwide the hottest ever measured [2]. Such extreme weather conditions will become more frequent and more severe due to rising anthropogenic greenhouse gas emissions [3, 4]. The 2018 heatwave in particular was likely exacerbated by climate change [5].

The consequences of unabated climate change have a wide range of dramatic effects on the Earth's ecosystem and on humankind as a whole [3, 6]. Heatwaves are predicted to increase heat-related mortality rates worldwide, up to 2 000%, if no adaptation measures are taken [7]. Increasing frequency and severity of extreme weather events in general are expected to exacerbate existing conflicts, disrupting local societies and economies [8, 9]. Sea-level rise caused by climate change is shown to increase the vulnerability of coastal regions and islands, potentially making them eventually uninhabitable [6, 10, 11]. Increasing floods and droughts all over the world, and specifically in tropical and subtropical regions, are also expected to disrupt the livelihoods of hundreds of millions of people [6]. Such dramatic environmental changes are predicted to displace people from their homes, thus creating flows of tens to hundreds of millions of so-called climate refugees around the globe [12].

To avoid the worst of these disastrous consequences, 194 states and the European Union (EU) have signed the Paris Agreement that was adopted at the 2015 United Nations Climate Change Conference [13]. The signatories agree to "hold the increase in the global average temperature to well below 2°C above pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5°C above pre-industrial levels, recognising that this would significantly reduce the risks and impacts of climate change" [13]. While the Paris Agreement of 2015 has reinvigorated climate change as a high-priority political topic, the 2018 heatwave has shaken up the public opinion, raising awareness that climate change is happening now and not in a distant future [14].

Mitigating the effects of climate change requires far-reaching efforts across all economic sectors [6]. The energy sector is of particular importance as fossil fuel demand for electricity generation, heating, transportation, and industry contributes to two-thirds of anthropogenic greenhouse gas emissions globally and to 78% in the European Union [15]. The EU is currently on track to meet its 20-20-20 targets[1]. However, to achieve the EU's mid-term and long-term greenhouse gas reduction goals, respectively 40% emission cuts by 2030, and 80% to 95% by 2050, considerable additional efforts are required [16].

Ambitious targets such as set by the EU for 2030 and 2050 can only be achieved through a so-called **energy transition**: a complete switch from fossil fuels to renewable resources. The energy transition requires profound changes across the technical, economic, and governance layer of the energy sector [17]. According to the European Environment Agency, the primary challenges include (1) regulatory continuity, necessary to safeguard investors' confidence in renewables, (2) reconsideration of the gas and electricity markets, currently preventing active market participation of small residential and service sector consumers, and (3) adaptation of the power system infrastructure and operation to support a high penetration of renewables [16].

The latter two challenges – active consumer participation and renewable resource integration in the power system – emphasise the increasing importance of **decentralisation**. With respect to renewable resources, decentralisation means that power is increasingly produced by small generators in distribution grids, rather than by conventional large power plants connected to the transmission grid. With respect to consumer participation, decentralisation entails that decisions are made by a multitude of small, independent actors (such as households and companies), instead of by a few large players, such as large power plant operators [18]. In both cases, decentralisation implies profound changes to the design, management, operation and governance of power systems, and an increasing role of actions at the local scale to tackle climate change, pointedly summarised by the adage "Think Globally, Act Locally" [19–22].

Cities, communities, and concerned citizens worldwide are taking initiatives to reduce the emissions of their local energy systems. Transitioning to renewable energy generation is part of such transformations, along with electrification of the heating and the transportation sector [23–27]. These transformations pose numerous new challenges. Resolving them requires a deep understanding of system behaviour at the local level. This understanding is currently incomplete, largely because the local level was not of significant importance to traditional, centralised, fossil fuel-based power systems [28–31]. For decentralised power systems based on renewable resources this understanding is, however, essential: renewable resources are smaller than conventional power plants and are located closer to demand. The understanding of local interactions between generation and demand are thus of key importance for the integration and utilisation of renewables [31]. While the characteristics of renewable resources are widely researched, local characteristics of urban energy *demand* are less often addressed and are often simplified to household demand only. However, urban areas are heterogeneous, they consist not only of households, but also of offices, schools, shops, *etc*. These different consumers use different amounts of energy at different times of the day. Moreover, they are not evenly distributed across cities, some urban areas are

[1] The 20-20-20 targets are a package adopted by the EU in December 2008 consisting of three goals to be achieved by 2020: (1) 20% reduction in greenhouse gas emissions, compared to the level in 1990, (2) generation 20% of the energy consumed in the European Union from renewables, and (3) increase in energy efficiency to reduce energy consumption by 20% [16].

residential, others business-oriented, yet others are mixed. This variation in timing and location of demand leads to **spatio-temporal demand heterogeneity**. Currently, demand heterogeneity is not well characterised in literature. Neither is its impact on local renewable resource utilisation.

This thesis addresses this knowledge gap: it characterises urban spatio-temporal demand heterogeneity, and shows its effects on local utilisation of renewable resources in urban areas. The primary focus of this thesis is energy demand for *electricity*. However, as the heating sector is electrifying, heating demand is also partially covered. Transportation and industry are left out of the scope.

The following sections describe the research objective, approach, scope, terminology, and, finally, the outline of this thesis.

1.1 Research Objective

A large and continuously growing body of literature exists on energy transition in urban areas [19, 22, 32, 33]. The vast majority of current research focuses on the development of new technologies capable of generating power from renewable resources, and on the changes required to the existing technical, economic, and governance layer of the power system to facilitate the integration and utilisation of these renewables. While these efforts are indispensable for the success of the energy transition, they leave out some important factors. One of them pertains to the geographic scale studied. The majority of existing research focuses either on the scale of single components, appliances, consumers or buildings, or on the national or supranational scale. The intermediate scale that spans neighbourhoods, districts, and municipalities, also called the **urban scale**, has received less attention [34]. Although in recent years both researchers and practitioners have begun to tackle this issue [20, 34–37], many knowledge gaps still remain. This thesis addresses the following research question:

How can local renewable resource utilisation be facilitated in urban areas?

Answering this research question requires an understanding of the interplay between generation and demand sides in urban areas. The large body of research on new technologies that generate power from renewable resources provides a solid basis for an understanding of the generation side in urban areas. The demand side has received considerably less attention. Most literature simplifies local demand to household demand only, overlooking the fact that urban areas consist of a mix of households, services, and industry. Systematic knowledge of local demand characteristics and their impact on local renewable resource utilisation is currently lacking in literature. However, understanding the *existing* system is a prerequisite to build visions and pathways towards *future* systems. Without this understanding, future scenarios are without solid foundations. To answer the main research question, this thesis therefore addresses the knowledge gap of urban demand heterogeneity and its impact on local renewable resource utilisation. It adopts a step-by-step approach, and answers the following three partial research questions.

RQ1 ***How can local demand be characterised in urban areas?***

- **RQ1a** How can temporal heterogeneity of urban demand profiles be characterised?
- **RQ1b** How can spatial heterogeneity of urban demand profiles be characterised?

RQ2 ***How does spatio-temporal demand heterogeneity influence local renewable resource utilisation, and the interventions aimed to facilitate it?***

- **RQ2a** What is the impact of spatio-temporal demand heterogeneity on local renewable resource utilisation?
- **RQ2b** What is the impact of spatio-temporal demand heterogeneity on interventions aimed to facilitate local renewable resource utilisation?

RQ3 ***How can local renewable resource utilisation be facilitated through policies?***

- **RQ3a** How can demand response of heterogeneous energy consumers be stimulated through energy taxation?

The three partial research questions are addressed in three subsequent parts of this thesis. Each of the subquestions is answered in a separate chapter.

1.2 Research Approach

Answering the research questions outlined above entails the creation of new knowledge. A systematic approach to knowledge creation requires an overarching understanding of how new knowledge can be obtained, what determines knowledge validity, and thus what can be known and by whom [38]. This understanding follows from a research philosophy, which determines what constitutes acceptable knowledge. Given a research philosophy, research questions can be approached from different perspectives and using different methods. This section describes the research philosophy, perspective, and methods chosen to tackle the research questions in this thesis.

1.2.1 Research Philosophy

The author adheres a **post-positivist** view of research. Post-positivism is a research philosophy developed in the second half of the twentieth century as a critique on *positivism*. Positivism has been the traditional philosophy underpinning the classic view of the scientific process as uncovering the *objective truth* [39]. It has its origins in the 19th century, following the Age of Enlightenment in the Western philosophy [39, 40]. Etymologically, positivism is derived from the Latin *positum*, a verbal noun of *poner* meaning “to put down, set, place, or lay” [40]. The “something” that has been “put down” is the objective truth that exists in reality and which can be discovered by a researcher through empirical observation, measurements, and data collection. The methodology is repeatable as the researcher is independent from its subject [40–42].

This view is criticised by post-positivism. The critique is primarily rooted in the inseparability of the researcher and the subject of study [39, 40]. The motivation and commitment of researchers to their endeavour are considered to be crucial to its process [43]. Post-positivists acknowledge that researchers are biased by their background and prior experiences [39]. As such, post-positivism does not reject the concept of an objective truth, but acknowledges that observations and measurements are fallible and pursues objectivity by recognising the possible effects of biases [40, 44]. The search for the objective truth is thus approached from different angles (*e.g.,* by different researchers and/or using different techniques). The observations and measurements made are considered to be instances of larger, underlying patterns or structures [40, 44]. Moreover, while positivists emphasise the need to reduce problems to their simplest possible elements, post-positivists recognise problems within their context, thus embracing complexity [39]. One of the consequences thereof is the assertion that both quantitative and qualitative methods are valid. This contrasts with the positivist view that recognises only the validity of quantitative methods [39, 40, 43]. Finally, post-positivists accept that research can have an open-ended and thus exploratory character [43].

Investigation of a researcher's own biases, background, knowledge, and values, and their effects on the research conducted is an essential part of the post-positivist approach [43]. This thesis is rooted in the author's concerns for the disastrous effects of unabated climate change, and the resulting motivation to create necessary insights and means to avert its worst impact. These insights and means are considered as inseparable from a larger context. This inseparability mandates an all-encompassing perspective on the research at hand, which is discussed next.

1.2.2 Research Perspective

This thesis positions itself within the field of **energy systems** and requires a systems approach to elucidate the *interaction* between different system components and the behaviour of these components as a whole [45, 46]. The systems approach or *systems engineering* approach originates in the 1940s and 1950s as the complexity of predominantly engineering disciplines such as communication and control increased following post-war technological developments [45]. The biologist von Bertalanffy underscored the applicability of the concepts of the systems approach beyond the engineering disciplines, to science in general [46]. The systems approach is a prime example of the application of the post-positivist philosophy. The fundamental principle of the systems approach asserts that all system components should be considered jointly to create a better understanding of the behaviour of the system as a whole [47].

The study of energy systems is inherently multidisciplinary, involving engineering, social, economic, geographical, behavioural, policy, political, planning, and other disciplines [48]. Energy systems can thus be seen as examples of socio-technical systems, and of complex systems. **Socio-technical systems** emphasise both social (*e.g.,* human, organisational) and technical factors in the study, design, and operation of systems [49]. **Complex systems** are defined as "systems that do not have a centralising authority and are not designed from a known specification, but instead involve disparate stakeholders creating systems that are functional for other purposes and are only brought together in the complex system because the individual 'agents' of the system see such cooperation as being beneficial for them" [50]. The decentralisation of energy systems makes them complex systems as the number of *active* agents increases [20].

The complex, socio-technical systems perspective on the research objective at hand drives the methods chosen to answer the formulated questions. This thesis primarily uses quantitative methods. However, also qualitative deductions are made based on the obtained results.

1.2.3 Research Methods

The main research methods used in this thesis are modelling and simulation, and data and statistical analysis, augmented with scenario analysis, case studies, and literature review. **Data and statistical analysis** is a systematic way to gain insights in large datasets. Scenario analysis and case studies serve the complementary purposes of respectively gaining exploratory insights within a larger realm of possibilities, and building an understanding of the details of a phenomenon under study in specific, realistic conditions. Literature review provides the means to establish the state-of-the-art in the field of study and related fields.

Modelling and simulation is a key research method in this thesis. This method allows for the description of a system under study in abstract and appropriately simplified terms that aid its understanding [51]. It thus creates a structured way of thinking about the effects of changes to a system, and provides the means to formalise otherwise dispersed knowledge about complex interactions between system components [52].

Models are often contrasted with physical experiments. Models are *virtual representations* of a system under study, and experiments are *material arrangements* aimed to study an effect or component of a system in isolation. Mäki [53] argues that "models are experiments, and experiments are models", pointing out that "theoretical models are ('thought') experiments", and "experiments are ('material') models". He states that the main difference between experiments and models is their control possibilities, with the former relying on "material manipulations", and the latter on assumptions [53]. Both models and experiments are inherently abstractions or simplifications of reality. In particular, components represented in a model are idealised, that is, reduced to the characteristics a modeller considers to be most important [51]. According to Hazelrigg, "engineers are often somewhat aware of the things that they represent to construct a model. They never know entirely what they leave behind" [54]. Most existing urban energy system models assume only residential demand. One of the central themes of this thesis is the omission of the service sector in such models, and the effects this omission has on their results in terms of their assessment of local renewable energy utilisation.

1.3 Research Scope

This thesis embraces the complexity of energy systems, as underscored by the post-positivist research philosophy and complex socio-technical systems perspective adopted. Yet, the complexity and size of these systems entail that they cannot be modelled in their entirety within one thesis. Limiting the research scope is thus inevitable to resolve the research questions at hand.

Positioned in the realm of energy systems, this thesis focuses primarily on renewable energy resources for electricity generation, and thus on **power systems**. Heating demand is included in some case studies, reflecting the ongoing electrification of heating systems [55].

Both transportation and industry are left out of the scope, as both are addressed by dedicated research branches. Power systems can be considered to consist of three interconnected layers: technical, economic, and governance. The **technical layer** is the primary focus of this thesis. This layer in itself has many facets. The thesis concentrates on the **spatio-temporal demand characteristics**, leaving other aspects, including the physical grid, out of the scope. Spatio-temporal characteristics can be studied on many scales. The scale considered in this thesis is the intermediate scale. In spatial terms, this scale comprises neighbourhoods, districts, and municipalities, which are collectively called the **urban scale**. In temporal terms, the scale considered spans hours to a single year. This thesis considers developed countries, with the Netherlands used as a case study.

Many aspects that are left out of the scope in this thesis, are addressed in other existing literature. Others are open questions, subject for future research. The seeming contradiction between the theoretical assertion of complexity and the practical considerations dictating model simplifications can, and should, be reconciliated by considering the findings of this thesis in concert with those of other researchers.

1.4 Research Terminology

The perspective and scope of this thesis place it on the intersection of multiple disciplines, including power systems and electrical engineering, urban planning, and energy policy. This multidisciplinarity gives rise to some terminology challenges. Key terms used in this thesis are defined in the Glossary (page 243). The most important terms are highlighted here:

- ***Households* and *Residential Sector*.** The term *households* is used to refer to dwellings, their occupants and their electricity use. The term *residential sector* describes the collection of households.
- ***Services* and *Service Sector*.** The terms *services* and *service sector* are used in parallel to *households* and *residential sector*. The *service sector* is defined as the collection of non-manufacturing commercial and governmental activities, excluding agriculture, transportation, power sector, street lighting, and waterworks. The term *services* refers to buildings where these activities take place, and the electricity use arising from these activities.
- ***Energy* versus *Power***. Both *energy* and *power* are well defined in physics. *Energy* is the capacity to do work. *Power* is energy per unit of time.
- **Energy *System* versus Power *System*.** The differences between energy and power are more subtle when concerning energy and power *systems*. An *energy system* is the combined processes of acquiring and using energy in a given society or economy [56, 57]. A *power system* is an instance of an energy system, defined by its energy carrier electricity [58]. Literature that is rooted in power systems engineering, uses the term *power system*, while modelling approaches typically refer to *energy system* models, doing so for historical reasons. In this thesis, the term *power system* is used preferentially. *Energy system* is adopted as a *totum pro parte*, respecting the terminological tradition of energy system modelling.

- ***Load* versus *Demand***. The term *load* describes a device in which power is dissipated. The term is also used in a more aggregated way, referring to individual consumers, or a set of consumers. *Demand* refers to the amount of electrical energy used within a given time window by a single consumer, or a set of consumers. The term *demand* thus emphasises the energy used, while *load* the device using it [58]. However, both terms are often used synonymously, including in this thesis.
- **Electricity *Generator* versus Electricity *Producer***. A *generator* is a device that converts movement into electricity, thus *producing* a voltage drop and causing current to flow [58]. The terms electricity *generation* and *production* are therefore used interchangeably. Moreover, the term *generator* is also often used as a *pars pro toto* for the person or company who owns and/or operates this device. The term *producer* is used as a synonym.
- **Energy *Use* versus Energy *Consumption*.** *Energy use* and *energy consumption* are closely related to the terms *load* and *demand*. From the perspective of physics, *energy consumption* is incorrect as energy cannot be consumed according to the first law of thermodynamics. However, from an economics perspective, energy can be consumed when it creates economic value [56]. In the disciplines of power and energy systems both *energy use* and *energy consumption* are often adopted as interchangeable, and also used as such in this thesis.
- ***Energy Consumers***. Households, services, and industry are defined as *energy consumers*.

1.5 Thesis Outline

This thesis consists of ten chapters, organised in five parts, as depicted in Figure 1.1. The text is based on four journal papers [59–62] and five conference papers [63–67].

Part I positions the thesis in the existing body of literature. **Chapter 2** introduces the literature and societal context, specifically the energy transition, urbanisation, and digitalisation, and their impact on the power system. **Chapter 3** discusses the state-of-the-art of energy systems modelling, concluding with the knowledge gap addressed in this thesis.

Part II lays the foundations of this research by developing an understanding of the spatio-temporal heterogeneity of urban demand. This part addresses **RQ1**. **Chapter 4** focuses on the temporal dimension (**RQ1a**), **Chapter 5** on the spatial dimension (**RQ1b**).

Part III combines the understanding of spatio-temporal urban demand heterogeneity with scenarios of renewable energy resource penetration (**RQ2**), addressing its direct utilisation in **Chapter 6** (**RQ2a**), and the impact of interventions in **Chapter** 7 (**RQ2b**).

Part IV, **Chapter 8**, extends the technical analysis of the previous parts with a governance dimension for a case study on the influence of energy taxation on demand response participation by residential and service sector consumers. This part thus addresses **RQ3** in its concrete formulation as **RQ3a**.

Part V reflects on the obtained results and summarises them. **Chapter 9** discusses the findings in a broader context, and **Chapter 10** revisits the research questions, draws final conclusions, and provides an outlook for future research.

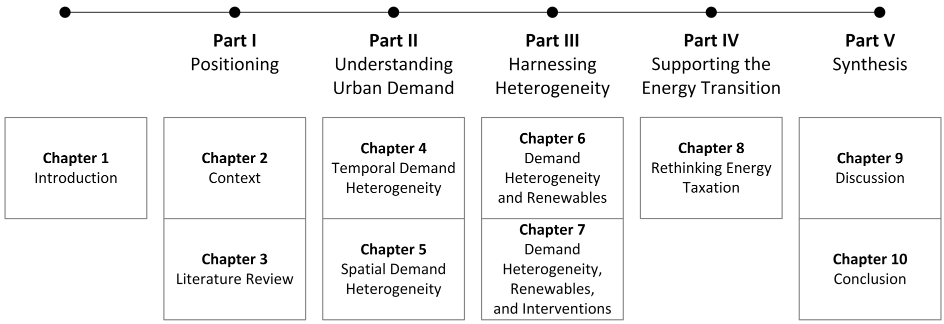


Figure 1.1 Thesis outline.

Part I

Positioning

EMBRACING the multidisciplinarity of the chosen research domain and the complexity of the system under study, Part I provides the societal and literature context of this thesis. It consists of two chapters.

Chapter 2 describes the context of the societal and technological developments in which this thesis is rooted. The main socio-technical development addressed in this thesis is the *energy transition*. However, this transition does not happen in isolation. Two other important contemporary socio-technical developments are highlighted: *urbanisation* and *digitalisation*. Urbanisation drives the demand for energy in urban areas. Digitalisation is seen as an enabler of technological advancements that make the energy transition possible. Jointly, the energy transition, urbanisation, and digitalisation have profound effects on the power system that has until recently remained largely unchanged throughout its one hundred year history. These changes form the setting in which this thesis is written, and are therefore briefly described in the next chapter.

The subject of energy transition and the chosen methods of modelling and simulation place this thesis in the tradition of *energy systems modelling*. **Chapter 3** first outlines the established fields of national-scale energy system models, building-scale energy use models, and power system models. The main focus is on the emerging field of *urban energy system modelling*, that is described in the second part of Chapter 3. As this is a considerably younger field, important knowledge gaps remain. The chapter concludes by highlighting the gap addressed in this thesis: the limited understanding of local spatio-temporal characteristics of urban demand and their impact on local renewable resource utilisation.

2 The Power System – A Socio-Technical Energy System in Transition

> *Timeo hominem unius libri.*
>
> – Thomas Aquinas

THE power system is a complex, socio-technical system, embedded in the society it serves. Socio-technical developments can therefore have far-reaching consequences for its design and operation. This is in particular so in the case of the energy transition, which is the primary focus of this thesis. The energy transition is driven by growing political and societal concerns for climate change, and embodies the switch from traditional, fossil fuel-based, centralised power plants to emerging, renewable, decentralised generation [13, 68–70]. This development coincides in time with ongoing urbanisation and increasing digitalisation [71]. Urbanisation entails that energy demand is more and more concentrated in cities, making urban areas particularly relevant to study in the context of the energy transition. Digitalisation underlies the development of so-called *smart grids* and *smart appliances*. It is seen as both a challenge in itself and an enabling factor for the energy transition, and is considered in the latter capacity in this thesis.

This chapter first introduces the energy transition as a central theme to the remainder of the thesis. Next, urbanisation and digitalisation are discussed in the context of the energy transition. The final part of this chapter describes the traditional power system and the changes it faces.

2.1 Energy Transition – Towards Renewable Generation

Following political and societal concerns for the effects of climate change, recent years have witnessed a rapid growth in renewable energy resources [13, 68–70]. In particular, wind turbines and solar photovoltaics (PVs) are currently the most rapidly growing generation technologies. Worldwide, the average annual growth rate of solar PVs between 1990 and 2015 was 45.5%, that of wind turbines 24% [72]. The costs of wind turbines and solar PVs have fallen dramatically in the last decade: by 25% for the former, and by 70% for the latter [73]. According to the International Energy Agency, 22.8% of electricity worldwide is currently generated from renewables, equalling the amount generated by gas. In OECD[1] countries, the most common renewable energy source is hydropower (12.9%), followed by wind (5.5%), biofuels (2.8%), and solar (2.0%). Another 0.5% is generated from solar thermal, geothermal and tidal sources [73].

Despite relatively modest contribution of solar and wind generation technologies to the energy mix today, these resources are expected to become the main generation technologies of the future [74, 75]. Although hydropower is currently the main source of renewable energy, these power plants are dependent on favourable geographic topology. Most suitable sites around the world are already developed, thus limiting the growth of hydropower in the future [76]. Biofuels that exist today are thwarted by environmental concerns such as deforestation, and destruction of wildlife habitats, and by the fear for the so-called *food versus fuel dilemma*, the competition between crops for food production and for energy generation [47]. Given the limitations of hydropower and biofuels, and the expected main role of solar and wind in the future, this thesis considers the latter resources only.

To limit the increase in global average temperature to 1.5°C to 2°C above pre-industrial levels, as set out in the Paris Agreement [13] (see Chapter 1), solar and wind energy generation need to grow by as much as a factor 30 to 50 by 2050 as compared to 2013 (from 3 EJ to 58-155 EJ) [77]. The primary challenges for the integration of large amounts of solar and wind are their intermittent and decentralised character. The existing power grid is technically and economically not equipped to accommodate more than 10% to 20% energy generation from intermittent resources [78–81]. The main reason is that the balancing mechanisms used today rely on dispatchable, centralised fossil fuel plants such as fast-ramping gas power plants [81]. This approach to maintaining the continuous balance between supply and demand is unsuitable for power systems with a high (above 20%) penetration of renewable resources. Thus, new approaches are needed as energy generation becomes non-dispatchable and more decentralised.

The remainder of this section describes solar photovoltaics and wind turbines as renewable energy resources, first in their own right, then in the light of the challenges both technologies pose to the existing power system. The power system adaptation is addressed further in Section 2.4.

2.1.1 Solar Energy Generation

Solar energy is ubiquitously available. The power contained in sunlight that strikes the earth at any time (173 000 TW) exceeds the world's energy consumption (14 TW) by four orders of magnitude [82]. Solar energy can be used both for heat and electricity generation. Technologies that allow to harvest solar energy efficiently are becoming available and affordable. The focus in this thesis is on electricity generation.

2.1.1.1 State of Affairs

In OECD countries, the share of solar PVs in renewable electricity production increased from almost nil to 8.4% between 1990 and 2016 [72]. Currently, Europe has an installed PV

[1] Organisation for Economic Co-operation and Development

capacity of 104 GW. Most additions are taking place in Germany and the United Kingdom. Globally, Asia has the largest installed capacity (159 GW), and is growing faster than other regions with an expansion of 50 GW in 2016 (of which 34 GW in China alone) [83].

2.1.1.2 Generation Technology

Sunlight can be converted into electricity using either PV cells or concentrated solar power (CSP) systems. PV technology harvests solar light using semiconductor cells thereby relying on the so-called *photoelectric effect*. When sunlight (*i.e.*, photons) strikes the semiconductor material, it releases electrons, thus directly producing current (*i.e.*, moving electrons). CSP relies on mirrors (so-called *heliostats*) that concentrate solar light onto a receiver, heating a fluid within the receiver. This heat in turn can be used to produce steam and drive a turbine, that is similar to the ones used in conventional systems [84, 85].

Although PV and CSP systems rely on the same primary energy source, they are (to a certain extent) complementary technologies. CSP systems primarily use direct, perpendicular and unscattered sunlight (experienced as "sun rays") that is mostly available in subtropical latitudes (15° to 40° north or south). CSP is thus less suitable for most European countries as they are located too far north [86]. In contrast, PV can use both direct sunlight and diffuse radiation (experienced as "daylight"). The latter is available even on cloudy days. The sum of diffuse and direct sunlight is called *global solar radiation*. As PV can use both direct sunlight and diffuse radiation, it has gained momentum even in relatively northern countries such as Germany [87]. Moreover, currently PV arrays are cheaper to produce than CSP [84], and their costs are rapidly decreasing. CSP costs are also decreasing, albeit slower [86]. The total global installed PV capacity (300 GW in 2016 [88]) therefore by far outweighs that of CSP systems (4.8 GW in 2016 [88]).

This thesis further considers only solar PV for two reasons. First, it focuses on the Netherlands as the geographical region under study. PVs fit better with the environmental conditions in the Netherlands than CSP. Second, PVs are considered to be particularly suitable for the urban context, which is the primary subject of this thesis. PVs do not rely on any moving parts and are thus completely silent in operation, a desirable property in dense urban areas [85, 89].

2.1.2 Wind Energy Generation

The use of wind as an energy resource has a history of over five thousand years. The first wind turbines for electricity generation were installed in the United States (U.S.) in the late 19th century. Development of wind power technologies accelerated after the 1973 oil crisis due to strong U.S. government incentives. Since the 1990s however, Europe has been the frontrunner in wind power production, spurred by a demand for more renewable generation [90].

2.1.2.1 State of Affairs

Among OECD regions, Europe had the highest share (51.4%) of the total wind energy production in 2016. Most of the growth in installed wind capacity has also been in Europe, with generation increases of 25.9% per year. The United States, Germany, and Spain are the largest OECD producers of electricity from wind, with respectively 229.3 TWh, 77.4 TWh, and 48.9 TWh generated in 2016 [72]. However, non-OECD countries, in particular China, are taking the lead in wind energy generation. In 2016, China installed more capacity (19 GW) than the following three countries – the United States (9 GW), Germany (5 GW), and India (4 GW) – combined [83].

2.1.2.2 Generation Technology

Wind power can be harnessed both offshore and onshore. Offshore wind power production is currently more expensive due to high investment and maintenance costs. However it has two main advantages: (1) lower turbulence than onshore locations, and (2) fewer regulations and placement restrictions than on land. The latter allows for the construction of taller towers with larger blades for a single machine, and for the combination of turbines into large wind parks [91]. Yet, in 2014, only 8 GW, or 6%, of European wind power capacity was installed offshore, but this figure is expected to increase in the coming years [92].

Onshore wind turbines can be further classified according to their capacity: *utility-size* (over 0.5 MW), *community-size* (100 kW to 0.5 MW) and *small-scale* (less than 100 kW). Utility-scale wind turbines are often used in wind farms with tens to hundreds of turbines connected to the grid. Community-scale and small-scale turbines can power a few houses, farms or enterprises and can be connected to the grid or used off-grid [91]. Small-scale turbines can be used as a local source of electricity, particularly in an urban context where larger scale turbines are undesirable due to visual and noise disturbance. These turbines are commercially available today and can be as small as a 1.5 kW rooftop turbine (*e.g.*, [93]). However placement of turbines in aerodynamically rough urban areas, and the restrictions on their size are limiting the power output of these turbines. Today the market share of small-scale turbines is well below 1%. Also in the future, small turbines are expected to contribute only marginally to electricity production [91, 94].

In general, the output of a wind turbine depends on two factors: wind speed and rotor area. The power produced by a turbine is proportional to the cube of **wind speed** [85]. Turbulent air is less favourable for power production. Turbulence can be avoided by choosing for *aerodynamically smooth* areas, *i.e.*, areas with few structures such as vegetation or buildings [91]. Furthermore, the output of a wind turbine is approximately linearly dependent on the **rotor area** [85]. As wind generation technology matures, the turbines increase in size. Increasing the height of wind turbines decreases the effect of surface-related turbulence, and thus improves their output. As the hight of the turbine increases, so does the rotor area. Currently rotors with blade diameter up to 130 m are being placed. Typical power output values of existing wind turbines are around 2 to 3 MW per turbine, and up to 7 MW for the largest commercial machines installed [90, 91].

This thesis focuses on the urban context, which is in general more suitable for solar PVs than for wind turbines [85, 89]. Therefore, the primary source of renewable energy generation in urban areas is assumed to be solar PVs. However, as wind turbines can be placed in less dense urban areas and in their vicinity, onshore community-size wind turbines are included in the scenario analysis in Chapter 6.

2.1.3 Solar and Wind – The Intermittency Challenge

One of the biggest challenges of renewables such as solar and wind is their intermittency: the output of these resources is variable, to some degree uncertain, and non-dispatchable. Solar and wind power are generated whenever the sun shines and the wind blows, which does not necessarily coincide with times of high demand. Variability patterns differ between these two resources. Sunlight has a predictable seasonal and daily variability component and an unpredictable weather (cloud) dependent component. Wind has less well-defined daily patterns.

The mismatch between high solar and wind generation and high demand results in relative low *capacity factors*. A *capacity factor* of a power plant, a wind turbine or solar PV in particular, is defined as "the ratio of the average annual power output to the rated, or so-called *nameplate*, capacity" [90]. Capacity factors depend on several parameters, but are typically lower for renewables (33% for wind and 26% for solar [55]) than for conventional power plants (from 52% for gas to 92% for nuclear [55]). More efficient utilisation of renewable energy requires a redesign of power system operation. Of particular importance hereby are new sources of flexibility that can improve the matching of electricity demand and non-dispatchable renewable generation. The existing flexibility, the so-called *reserve capacity*, has been designed to balance peak demands and plant outages. The margin of this reserve capacity is approximately 20% [95]. This amount is insufficient to accommodate the variability and forecast errors of increasing shares of renewable energy resources [81]. Power system operation and balancing will thus need to shift to other parts of the power system, such as demand response [96–98], storage [99–101], and grid interconnection [102]. These flexibility options are described in more detail in Section 2.4.

2.1.4 Solar and Wind – The Decentralisation Challenge

Solar and wind power generation resources are more geographically spread and smaller in size than traditional thermal and nuclear power plants [68, 103]. This is referred to as the *decentralisation* of power generation. Decentralisation of generation has both positive and negative effects on the power system. Among the positive effects are reduction of greenhouse gas emissions, decreased losses, and thus increased efficiency, as well as decreased vulnerability to the loss of any individual generator. On the other hand, decentralisation of energy generation brings about drastic changes in the design, operation, management, and governance of traditionally centralised and hierarchically structured power systems. In a centralised power system, large power plants are the driving force safeguarding the balance between power demand and generation. As generation decentralises and becomes intermittent (see above), the responsibility to maintain the power balance shifts to other parties, leading to both local empowerment of consumers and decentralisation of control [58, 69, 71, 104, 105]. This decentralisation of power systems brought about by increasing penetration of renewables is further addressed in Section 2.4.

2.2 Urbanisation – Growing Energy Demand

Since 2005 more than half of the world population lives in urban areas. This figure is expected to rise to two-thirds by 2050 [32, 106]. In Europe, today, almost 75% of the population is urban [107]. Cities attract growing numbers of inhabitants due to the economic and social opportunities they offer, such as employment, education and community [108].

Spurred by ongoing urbanisation, energy demand is increasingly tied to urban areas. Cities use between 60% and 80%[2] of the energy worldwide, emitting about 70% of the total greenhouse gases [108]. Accounting for their large share in global energy demand and associated emissions, as well as for their role as centres of power, cities are expected to play a cornerstone role in achieving national and realising global greenhouse gas emission reduction plans [33, 109]. Both the European Union [110–112] and the International Panel on Climate Change [113] champion the efforts of local authorities and communities for this purpose, at least in theory. In practice, the role of cities and regions is not clearly reflected in existing energy transition roadmaps, that typically focus on countries in their entirety [16, 74, 114]. For instance, in the European Roadmap 2050, the European Commission states that "the role of local organisations and cities will be much greater in the energy systems of the future" [114], however, it does not provide any further details on the specifics of this role.

Without top-down guidance, cities are defining their own role in the energy transition through initiatives such as Covenant of Mayors, C40 Cities, and Energy Cities [23–25]. Thus, although climate change and the energy transition required to mitigate it are global issues, there is an increasing interest to address these challenges at the local level, summarised by the motto "Think Globally, Act Locally" [19–22]. This thesis taps into this need by explicitly focussing on the urban scale.

2.2.1 Defining Urban Areas

Urban areas are often associated with *mega*cities, cities with a population of more than 10 million inhabitants [32]. However, most urban dwellers live in small cities (37% in cities smaller than 100 000 inhabitants, and 63% in cities smaller than one million). Currently there is no globally applicable definition of urban areas. According to the United Nations, the definition is country-specific [115]. This thesis adheres to a broad view on *urban areas* and uses the United Nations definition which states that urban areas in the Netherlands are "settlements of more than 2 000 inhabitants" [115].

2.2.2 Delineating Urban Energy Demand – Highlighting the Service Sector

Urban energy demand is usually divided into four sectors: residential, service, industrial, and transportation [47, 116]. In the European Union, the largest share of the *total energy demand* (*i.e.*, *electricity* and *heating*) is used by the transportation sector (34%), followed by industry

[2]Answering the seemingly simple question "How much energy do cities use?" is surprisingly hard. First, comprehensive energy statistics such as available on the national scale, do not exist for the urban scale. Second, calculating such statistics from other data is subject to different system boundaries, which results in differences in estimations [106].

(27%), households (25%), and services (14%) [117]. The picture is different for *electricity* demand only. Transportation accounts for only a minor share (less than 3%), industry uses 37%, services 30%, and households another 30%. Between 2000 and 2014, both residential and service sector electricity demand increased, by respectively 12% (from 718 TWh per year to 807 TWh per year) and 24% (from 633 TWh per year to 785 TWh per year). In the same period, industrial demand decreased by 6% [117].

Despite the substantial share of electricity use that can be attributed to the service sector, this sector is omitted in most of the existing energy-related literature [118–121]. The lack of a common definition of the service sector further complicates the matter. The service sector, also termed the commercial, business, or tertiary sector, is comprised of a highly heterogeneous group of energy consumers. Although the many definitions of the sector differ, most include non-manufacturing commercial activities and exclude agriculture and transportation [120, 122]. This thesis defines the service sector as the collection of non-manufacturing commercial and governmental activities, excluding agriculture, transportation, power sector, street lighting, and waterworks.

The omission of the service sector in research is further illustrated by a literature review that evaluates energy demand studies in urban areas in the United Kingdom (U.K.) for the period between 2008 and 2015. The review reports on the number of times different sectors are mentioned in the literature analysed. The transportation sector is mentioned most often, followed by the residential and the industrial sector. The service sector is mentioned least often [48]. Omission of the service sector is not limited to the U.K., as shown by other researchers [118–121] and the literature review in Chapter 3.

Prompted by the contradiction between the importance of the service sector, and its omission in most of the existing energy-related literature, this thesis focuses on the role of the service sector in the energy transition in urban areas. As services and households are often collocated[3] in urban areas, the residential sector is also taken into account. The transportation sector is left out of the scope given the large and growing body of literature dedicated to the this sector (*e.g.*, [126–129]). The industrial sector is also left out of the scope. This sector is primarily comprised of large energy consumers. On an urban scale, their size is considerably larger than that of residential and service sector consumers. For cities, districts and neighbourhoods, industrial consumers therefore require a case-by-case approach, while residential and service sector consumers can be characterised through data-based statistical approaches. In addition, the electricity demand characteristics of industrial consumers are well understood. They have been participating in electricity markets and power balancing activities for decades [130].

2.2.3 Urban Energy Planning – A Wicked Problem

To drastically reduce fossil fuel consumption and associated emissions, cities need to integrate energy-related issues with the existing practices of urban planning [20, 131]. The

[3] Currently urban planners consider so-called *mixed-use* urban areas as the most desirable type of land use. In these areas, different types of activities, such as housing and services, are collocated [123]. Such mixed-use urban areas are shown to have benefits in terms of accessibility of services and facilities [124], as well as a higher quality of civic life and health [125].

Table 2.1 Characteristics of wicked problems (from [132]).

Characteristics of Wicked Problems
1. There is no definitive formulation of a wicked problem.
2. Wicked problems have no stopping rule.
3. Solutions to wicked problems are not true-or-false, but good-or-bad.
4. There is no immediate and no ultimate test of a solution to a wicked problem.
5. Every solution to a wicked problem is a "one-shot operation"; because there is no opportunity to learn by trial-and-error, every attempt counts significantly.
6. Wicked problems do not have an enumerable (or an exhaustively describable) set of potential solutions, nor is there a well-described set of permissible operations that may be incorporated into the plan.
7. Every wicked problem is essentially unique.
8. Every wicked problem can be considered to be a symptom of another problem.
9. The existence of a discrepancy representing a wicked problem can be explained in numerous ways. The choice of explanation determines the nature of the problem's resolution.

resulting approach is termed *urban energy planning*. Traditionally, *urban planning* encompasses the "intentional interventions in the urban development process, usually by a local government" that are meant to improve both infrastructure and civic life [131].

Research that informs and supports urban planning is pre-eminently multidisciplinary, and includes contributions from a broad range of disciplines, such as urban planning *sensu stricto*, urban ecology, architecture, engineering, economics, environmental science, political science, and sociology [133]. Although these disciplines generally agree on the need to incorporate energy-related issues with other urban planning practices [22, 134], no consensus exists on *how* this should be achieved, or even how the task should be *defined* [134].

Complex problems that lack a common understanding of the definition are referred to as *wicked problems*, a term coined by Rittel and Webber in 1973 [132]. The main characteristics of wicked problems are summarised in Table 2.1 (from [132]). Different societal and environmental problems have been (re)defined as wicked problems (*e.g.*, [135–137]). Planning problems are "inherently wicked problems," according to Rittel and Webber [132]. The addition of the energy dimension to urban energy planning only increases the "wickedness" of the problem at hand [20].

Addressing urban energy planning challenges is far from trivial. According to Cajot *et al.*, part of the solution can be achieved by supranational, top-down (*e.g.*, European) harmonisation of sustainable urban energy planning practices [20]. Currently, such harmonisation at the European level is absent. The lack of top-down guidance for cities is highlighted above. Another part of the solution, is bottom-up collaboration, which requires a shared understanding that urban planning challenges are inherently interconnected, and solutions that embrace this interconnectedness [20]. Thus, cities face the daunting task of enabling the energy transition, while lacking top-down guidance, and tackling conflicting views that arise from bottom-up collaborative processes. In a similar context, Barnett observed almost 40 years ago that "Part of the problem, as always, lies in the lack of a strong political will to achieve planning objectives. But part of the problem is technical; if planners could provide policy makers with better alternatives, they could get better results" [138]. This thesis contributes to the latter aspect – the understanding and provision of alternatives.

2.3 Digitalisation – The Smart Grid

The integration of information and communication technology (ICT) in a growing range of processes and activities enables the digital collection of data, control, and management of these processes and activities. This trend is called *digitalisation* [139]. Digitalisation is ongoing throughout all societal sectors. The focus of this thesis is on its role in the power system. Digitalisation of the power system drives the transformation of the existing grid into a so-called *smart grid* [96, 140–143]. It is widely assumed that the roll-out of the smart grid and its components (such as *smart meters* and *smart appliances*) is an indispensable enabling factor for the transition to decentralised renewable resources, and for supporting interventions such as demand response, flexibility, and power grid balancing [141].

The term *smart grid* is ubiquitous, yet no consensus on the definition exists in the literature [140, 141, 144, 145]. The European Commission uses the definition of the European Regulators Group for Electricity and Gas: "A Smart Grid is an electricity network that can cost efficiently integrate the behaviour and actions of all users connected to it – generators, consumers, and those that do both – in order to ensure economic efficiency, sustainable power system with low losses and high levels of quality and security of supply and safety" [145]. Furthermore, the European Commission stresses that the "smart grid of the future" features "intelligent monitoring, control, communication, and self-healing technologies" and is "able to handle more complexity than today's grid" [146].

As information and communication technologies, in particular sensors and supporting software, are widely available and increasingly affordable [147], the smart grid of the future is taking shape already today with numerous demonstration projects around the world [141]. However, transforming the existing grid into a smart grid is not without challenges, ranging from the development of standards over costs to cyber security issues [141, 148, 149]. These challenges are out of the scope of this thesis.

In this thesis, digitalisation of the power system is considered in its capacity as an enabler for the transformation of the power system, in particular for the integration of renewable resources. For instance, digitalisation can facilitate the harnessing of demand-side flexibility (*i.e.*, demand response). It also underlies the emergence of new market parties, such as prosumers and aggregators [141] (see next section).

2.4 The Power System – History and Transition

The power system has the primary purpose to provide electricity to consumers, and to do so in a reliable manner. When operating as intended, the power system is nearly invisible to electricity consumers, a flip of a switch is effortless and seamlessly provides the required light, sound, or any other service. Over the course of the last century the power system has been perfected to reliably supply electricity [58]. The upcoming energy transition requires considerable changes to this well-established system. One of the key characteristics of the existing power system is its centralised, hierarchical organisation. Many challenges related to the energy transition arise from the incompatibility of decentralised resources – such as small-scale renewables and storage devices – with this traditional centralised organisation [47, 58]. Understanding the transition challenges therefore requires insights in the traditional organisation of the power system.

2.4.1 The Traditional Power System

This section briefly describes the power system as it has existed for approximately one hundred years, largely coinciding with the twentieth century. This traditional power system can be seen as consisting of three layers [55, 149]. The first layer is the *technical layer*, the power system as a physical grid. The second layer is the *economic layer*, which includes the power markets in which electricity and associated services are traded. The third layer is the *governance layer*, which determine the rules, agreements, and arrangements in which the other two layers operate [149].

2.4.1.1 Technical Layer

The technical layer of the traditional power system consists of four distinct segments: generation, transmission, distribution, and load. *Generation* refers to power plants and generators that provide electricity to the system. The *transmission* grid transports electricity under high voltage over long distances, while the *distribution* grid serves as the low-voltage end-branches that provide power to individual consumers. Finally, *load* refers to individual devices in which power is dissipated, or to an aggregated collection of such devices [58].

Conventional **generators** in use today are based on combustion of fossil fuels – coal, oil, and gas – or nuclear fission. In Europe, 48% of power production originates from combustion of fossil fuels, and 26% from nuclear fission [150]. Fossil fuel combustion leads to emission of greenhouse gasses, in particular CO_2. The operation of conventional power plants is based on steam turbine technology developed in the 19^{th} century. Combustion of fossil fuels or nuclear fission generates heat, which is used to convert water into steam. This high pressure steam is then fed into a turbine causing rotary movement of its blades. The kinetic energy of this so-called rotor is in turn converted into electrical energy by a generator: a rotating magnet creates a changing magnetic field which induces a current in the surrounding windings of a stator [58].

The current and voltage produced by a rotor-based generator are alternating, with a nominal frequency of 50 Hz in Europe. A typical power grid consists of numerous generators, that can only be connected within one system if operated *synchronously*. This means that all units must be in phase with each other, *i.e.*, have the same rotational frequency and a coinciding timing of the alternating voltage and current [58].

Within such a synchronous system, electric power is transported over large distances in a **transmission grid**. Transmission occurs at high voltage (typically a few hundred kV) to reduce losses and thus increase efficiency of the system [58]. The largest connected transmission grid in the world is the European continental synchronous zone serving 500 million people in 24 countries and having a production capacity of 640 GW [151]. Asynchronous regions (*i.e.*, areas that operate at different frequencies) are connected by so-called *interconnectors*, high voltage transmission lines through which power flows as direct current (DC), that is converted on both sides from and to appropriate alternating current (AC) frequencies [58].

Only a few large (industrial) consumers are directly connected to the transmission network. Most medium and small consumers draw power from the **distribution grid**. Unlike the meshed network of the transmission grid, the distribution network mostly has a radial layout, and is thus hierarchical. The lines closest to the transmission grid are operated at voltages around a few tens of kV (referred to as the *primary distribution grid* or *medium voltage grid*). The *secondary distribution grid* (or *low voltage grid*) consists of lines terminating at the end consumers and transferring power at the nominal supply voltage of 220 to 240 V [58].

Load has been traditionally seen by power systems engineers as an uncontrollable, given variable that must be met by the generators at all times. This philosophy is deeply ingrained in the physical system and operation practices of the power grid. Only recently, after liberalisation of the electricity markets, and even more with the advance of renewables, this view is slowly changing to one where load becomes more flexible, *i.e.*, consumers vary their demand if provided with price or information signals [58].

The single most important technical characteristic of power systems is the **maintained balance between generation and demand** [58]. At each instant in time, the exact amount of electricity consumed by the aggregate of loads must be generated by the collection of generators, nothing more, nothing less. Minimal deviations from the balance cause the frequency to increase above 50 Hz (generation exceeds consumption) or to decrease below 50 Hz (generation falls behind on consumption) and are tolerated by the system only to a very limited extent. As larger deviations (called *imbalances*) can cause costly black-outs, the precise balance between generation and demand within the power system needs to be guaranteed at all times. This has traditionally been achieved by adjusting the output of generators. Such adjustments are called *dispatching* [152]. As wind turbines and solar panels are *non-dispatchable* generators, the existing approach to maintain the balance between supply and demand is unsuitable for a power system with a high penetration of renewables. New approaches are necessary, these are discussed in Section 2.4.2.

2.4.1.2 Economic Layer

The economic layer finances the operation of the power system. Historically, financing of power plants has been determined by a so-called *merit order*: *baseload* power plants for (nearly) continuous operation, *intermediate* power plants for operation during periods of at least several hours at a time, and *peaking* power plants to cope with spikes in demand [152]. During baseload hours, (wholesale) electricity prices are low, during peak hours they are high. As each power plants is designed and operated to meet its dedicated segment of the time-dependent load, financing its construction and operation relies on an expectation of operation during a certain number of hours per year, and on the revenue corresponding to operation in these hours [55].

Until the end of the twentieth century, large-scale utilities owned and operated generators as well as transmission and distribution grids. Utilities that own all these segments are referred to as *vertically integrated*. Such vertically integrated utilities are often government-owned. In that case, utilities are monopolistic and they finance their operation from public funds. The *market reforms* of the 1990s (see next paragraph) lead to the *unbundling* of such utilities and the creation of *power markets*. These are virtual market places where electricity producers trade with electricity consumers or their representatives [149, 153].

The following parties are key players in today's power markets [153]. Vertically integrated utilities are split up in (commercial) producers and (regulated, monopolistic) transmission and distribution system operators. **Producers** are commercial companies that own and operate power plants. These are often also referred to as (unbundled) *utilities*, or *generators*[4]. As long as renewable generation has a small contribution to the total installed generation capacity, generators finance power plants following the merit order logic as described above. **Transmission system operators** (TSOs) are regulated monopolists who own and operate a transmission grid. TSOs are often also the end-responsible for the overall system balance in their country or region of operation. **Distribution system operators** (DSOs) are also regulated monopolists, who own and operate a distribution grid. Within the responsibility area of one TSO often multiple DSOs are active. The tariffs from which TSOs and DSOs finance their operation are regulated. The **regulator** is a state-controlled legal entity responsible for the enforcement of the legislative framework within which producers, TSOs and DSOs operate [58, 152].

Since the market reforms, power markets are responsible for maintaining the balance of supply and demand. Balancing of supply and demand occurs both ahead of time and in real time. Most of the electricity consumed (85% in the Netherlands [153]) is traded in long-term bilateral agreements, whereby consumption and the corresponding supply are planned well in advance. The remainder of the electricity is sold on day-ahead *spot markets*. Consumers, producers or their representatives submit *energy plans* for each time slot (typically one hour) of the following day. Each party that submits such a plan is called a *balance responsible party* (BRP). In current systems, load is assumed to be passive and thus mostly inalterable. Therefore generation is required to adopt a load-following role. The energy plans submitted by consumers' representatives are used by the TSO to establish the power volumes to be supplied in each time slot. Subsequently, producers can bid to provide portions of the required electricity supply. In theory, producers bid according to the marginal operation costs of their power plants. They are willing to provide power as long as the price is higher than their operation costs (which is lowest for baseload power plants and highest for peaking power plants, see above) [152, 154].

As actual generation and demand deviate from the energy plans submitted, real-time accommodation of the resulting *imbalances* is required. This is taken care of by *operational reserves* and settled in the *balancing market*. Parties that offer such balancing services – a subset of producers and large industrial consumers – are called *balancing service providers* (BSPs). Depending on the reaction times of the operational reserves, they are subdivided in three categories. The *primary reserve* is activated automatically and immediately by frequency deviations from the nominal value (50 Hz in Europe). This first-line reserve is replaced

[4]Note that in the technical layer, *devices* that produce electricity are referred to as *generators*. In the economic layer, the term *generator* is used as a *pars pro toto* for the *company* that owns and operates these devices. Both meanings are common in the literature.

within minutes by the *secondary reserve*. The secondary reserve can start up within minutes and can operate for up to a few hours. On a longer term, the *tertiary reserve* takes over the balancing duties and operates on a time scale of multiple hours [152, 154].

Renewable resources do not fit well in the existing power markets. First, renewables do not require fuel and can thus run at near-zero marginal cost. This means that they are willing to sell power as long as the market price is non-negative, but to do so, they are dependent on weather conditions. Their zero marginal cost places renewable resources first in the merit order of power plants. As a result of increasing renewable resource penetration, conventional power plants are required to operate with greater flexibility, and for a reduced number of hours, resulting in lower profitability [55, 155]. Moreover, renewables are non-dispatchable, and have therefore limited to no ability to provide balancing services. On the contrary, renewables are variable, and thus create additional fluctuations in power output. Balancing these additional fluctuations requires new market models [156–158].

2.4.1.3 Governance Layer

The governance layer is comprised of "the myriad of processes through which a group of people set and enforce the rules needed to enable that group to achieve desired outcomes" [109, 159]. As a result of these processes, a framework of arrangements is put in place, that confers rights and obligations to the different parties active within a system, in this case the power system [160].

The governance layer thus determines the rules to be followed by parties active in the power system. The so-called *energy market reforms* illustrate the importance of the governance layer on the operation of the power system. These reforms originated in the 1970s with the passage of the Public Utilities Regulatory Policies Act (PURPA) in the United States, and came into being with the introduction of deregulated electricity markets in Chile in 1990. Other countries, including the United States and European Member States followed later in the 1990s [161, 162].

The energy market reforms included the *unbundling* of vertically integrated utilities, *deregulation* and *liberalisation*. A vertically integrated utility refers to the ownership of the different technical layer power system parts – generators, transmission grid, and distribution grids – by a single party (see above). Unbundling means that a vertically integrated utility is divided into competitive and monopolistic activities. Energy generation is considered a competitive activity, while transmission and distribution are monopolistic activities. The competitive activities are *deregulated, i.e.,* regulations by the government are removed. The corresponding companies – producers – can operate in liberalised markets (described above). A *liberalised market* is a market opened to commercial companies. Monopolistic parties remain regulated [58, 161].

The ongoing changes in legislation and regulation of energy use, generation, and greenhouse gas emissions are also prominent examples of the role which the governance layer plays in the design, operation, and management of power systems. Some examples are given in Section 2.4.2.5. The changes to the power system as a whole are addressed in the next section.

2.4.2 The Power System in Transition

To enable the energy transition, the power system needs to adapt to accommodate increasing amounts of renewable energy resources that are intermittent and decentralised. *Intermittency* requires new forms of flexibility. Interconnection, demand response, and storage are the ones most commonly proposed [96–102]. *Decentralisation* of energy generation requires a new power system planning and management paradigm [163]. Both flexibility and decentralisation lead to a more important role of the distribution grid (in the physical layer), new roles and market parties (in the economic layer), and requires new forms of regulation and legislation (governance layer). In addition, other systems, in particular the heating and the transportation system, are electrifying, *i.e.*, substituting fossil fuel energy carriers (respectively gas and liquid fuels) by electricity. Each of these changes is briefly addressed in the following paragraphs.

2.4.2.1 Interconnection: From Micro- to Megagrids

Integration of a higher share of intermittent, non-dispatchable renewable resources in the electricity grid requires new power system planning and management paradigms. Two mutually non-exclusive options are currently proposed in the literature: microgrids and megagrids.

Microgrids are geographically small, potentially independent parts of the distribution grid. They typically contain both loads and generation, and often also storage. Key features of microgrids are (1) local control of its components, and (2) the option to operate either in grid connected or in islanded mode [164]. The first feature – local control – enables microgrids to facilitate management of large numbers of dispatchable devices and decentralised generation in the power system of the future. The second feature – islanding option – helps mitigate grid disturbances and can serve as resource for faster system response and recovery, thus strengthening grid resilience [165].

On the other side of the geographic spectrum are so-called **megagrids**, large-scale transmission networks that permit the trade of large volumes of electricity over long distances. The current pan-European synchronous grid can be considered to be a precursor of a megagrid. Its further expansion (both in terms of geographical coverage and capacity of links between countries) is expected to bring considerable benefits to the integration of renewable resources. For instance, a strong European megagrid can link load both to solar generation in the south of Europe, and wind generation in the north, thus balancing local and regional weather-dependent fluctuations in renewable energy generation [165].

The research in this thesis focuses on the local – urban – scale, and thus fits better within the microgrid framework. As microgrids and megagrids are, in principle, mutually compatible, the research presented in this thesis can compliment the megagrid framework.

2.4.2.2 Storage

A wide range of storage technologies exists. Each technology features its own particular benefits and disadvantages with respect to efficiency, energy capacity, energy density, maturity, investment costs, lifetime, *etc*. In general, four technology categories can be distinguished, depending on the form in which energy is stored: mechanical, electrical, thermal, and chemical [166]. **Mechanical energy storage** technologies allow energy to be stored as potential or kinetic energy. The two most common technologies are *pumped hydro energy storage* (PHS) and *compressed air energy storage* (CAES). **Electrical energy storage** technologies store energy using only an electric field, or the interaction between a magnetic and an electric field. **Thermal energy storage** technologies use heat or cold to store energy. Finally, **chemical energy storage** systems are based on reversible chemical or electrochemical reactions to store and retrieve energy [99, 101, 166] (see these references for more in-depth information on these technologies).

Chemical energy storage technologies are best suited for local storage, in particular in urban areas [166]. Two types can be distinguished: (1) batteries and (2) fuel cells [99, 101, 166, 167]. **Conventional batteries** consist of an anode and a cathode immersed in an electrolyte and connected by a conductor. A number of different conventional batteries exist. They differ primarily in the type of electrode and electrolyte used. Amongst the most promising for power system storage applications are *lithium-ion* batteries, used in electric vehicles [166]. **Flow batteries** rely on two external electrolytes which contact each other in an electrochemical cell, converting chemical energy directly into electricity or vice versa. *Zinc-bromine* and *vanadium redox* batteries are the most common examples of flow batteries. The use of external electrolytes make flow batteries suitable for long-term, seasonal energy storage. Finally, **fuel cells** convert chemical energy contained in a fuel (in this case hydrogen) into electricity in a reaction with oxygen [166]. Given the current prevalence of batteries over fuel cells [167], this thesis only considers batteries as storage technology used in urban areas. Specifically, in Chapter 7 the use of conventional lithium-ion batteries is assumed.

2.4.2.3 Demand Response

Demand response is the active participation of consumers in power system operation. This thesis adheres to the following definition of demand response: "Changes in electricity use by demand-side resources from their normal consumption patterns in response to changes in the price of electricity, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardised" [97, 130]. Historically, demand response programmes were limited to a few large-scale industrial consumers [95, 97, 168]. Digitalisation opens possibilities for demand response participation by small residential and service sector consumers [141, 169]. Their participation is termed "mass market demand response" [96].

Both monetary and non-monetary incentives for demand response participation are considered in the literature [170]. The former are considerably more common and fit best with the definition of demand response adopted in this thesis. Two types of finacial demand response incentives can be distinguished [130, 171, 172]: *incentive-based* (or *direct load control*) and *price-based* (or *indirect load control*) programmes. *Incentive-based programmes* are further subdivided in *classic programmes* and *market-based programmes*. In **classic programmes**, consumers receive a remuneration fee or a bill reduction for their participation. These programmes include direct load control (DLC) *sensu stricto* and interruptible/curtailable load programmes. In **market-based programmes**, consumers are remunerated based on their performance, *i.e.*, participation in the programme. Market-based programmes include emergency demand response, demand bidding, capacity market, and reserve services market. Incentive-based programmes, in particular market-based programmes, are primarily geared towards larger, industrial consumers. *Price-based programmes* provide dynamic tariffs to consumers, aiming to shape their demand curve. **Price-based programmes** include time of use (TOU), critical peak pricing (CPP), extreme day pricing (EDP), and real time pricing (RTP) programmes [130, 171, 172]. This thesis only considers price-based programmes, in particular RTP, as this type of dynamic pricing of retail electricity is advocated in the Proposal for a new Directive on the Internal Electricity Market of the European Union [173] (see Chapters 7 and 8).

Demand response is considered to be a key component of future high-renewables power systems [96, 156, 168, 174–176]. However, it requires considerable effort from consumers. Sufficient consumer engagement is currently one of the main challenges for demand response [168].

2.4.2.4 New Roles and Market Players

As the power system decentralises, new, mostly local parties emerge. The most important among them are prosumers, aggregators, and energy communities. As these parties are currently just emerging, their roles and definitions are not entirely consolidated.

Prosumers are small or medium-sized consumers that have their own generation (PVs and/or small wind turbines) and/or storage. These technologies enable them to generate their own energy and to provide excess energy to the power system (usually only part of the time). Unlike consumers in the traditional power system, prosumers are *active* participants in the power system [149, 161, 177]. Prosumers are modelled in Chapters 6, 7, and 8.

Aggregators are mediators between consumers and parties such as utilities and system operators [178]. They enable small consumers to participate in wholesale electricity markets [168]. Aggregators can thus resolve a number of challenges existing market parties face. First, aggregators can balance the negotiation power of small consumers with those of large incumbents by representing them as one entity. Second, aggregators can solve scalability challenges for system operators by decreasing the number of parties offering demand response services. Third, aggregators can provide the knowledge and expertise in designing and deploying demand response programmes: know-how the incumbents often lack [178]. Fourth, aggregators can engage otherwise unengaged consumers and navigate power market complexities on their behalf [179].

Energy communities are less well-defined than the other parties. In essence, energy communities are groups of, most often, collocated individual consumers and prosumers who undertake local energy initiatives, fostering the transition to renewable energy. Worldwide a large and growing number of such initiatives exists, widely varying in size, used technologies, internal and external organisation, *etc*. [26, 27].

As both aggregators and energy communities are not consolidated concepts yet, the difference between the two is not always clear. Some consider aggregators to be commercial parties. This is increasingly the case in the U.S. [179]. Others see aggregators as enablers and representatives of energy communities [180]. As both enable load aggregation and joint demand response service provision, this thesis considers aggregators in both capacities and explicitly specifies whether they are assumed to have commercial interests or not. Energy communities and aggregators are addressed in Chapters 7 and 8.

2.4.2.5 New Legislation and Regulation

Worldwide, legislation and regulation concerning a range of topics related to energy use and greenhouse gas emissions is increasingly tightening [181]. This evolution is spurred both by international impetuses, such as the Paris Agreement [13], and local pressure, such as the Klimaatzaak or Climate Case[5] in the Netherlands [182]. This section focuses on the European Union. The EU has committed to drastically reduce greenhouse gas emissions by increasing reliance on renewable resources [114].

European legislation covers a wide range of energy-related topics. One of the most important ones for the power system is the so-called Winter Package, published on 30 November 2016. The package contains eight proposals to reform the design and operation of the European power market [183]. It covers six key areas, including the power system, but also the heating and transportation systems, empowerment of consumers, biofuels, and emission targets. Other existing EU legislation covers both similar and other topics that range from empowering every European consumer to request a smart meter and a dynamic price contract [173], to increasingly stringent requirements on building efficiency and energy consumption (*e.g.*, Energy Performance of Buildings Directive [184] and Energy Efficiency Directive [185]). The future direction of the European Union in terms of sustainable energy provision is defined in its 2030 [110] and 2050 [114] European targets.

2.4.2.6 Electrification of Transportation and Heating Systems

The energy transition extends beyond the power system. For other systems, including transportation and heating, the energy transition entails the switch from fossil fuels (such as liquid fuel and gas) to renewably generated *electricity* [55]. This *electrification* of other systems is expected to have large effects on the power system, and is therefore briefly introduced below.

Electrification of the heating system primarily refers to the transition to heat pumps which replace existing systems that burn fossil fuels (*e.g.*, gas and fuel oil) [186]. Heat pumps are devices that move heat from a cooler space (*e.g.*, the outdoor) to a warmer space (*e.g.*, the indoor), using electricity in the process. The principle of their operation is similar to that of a refrigerator[6]. Electrification of the heating system is expected to considerably increase electricity demand, posing a major challenge for the power system as it needs to expand accordingly. At the same time, electrification of heating systems can increase the potential for demand response. Heat pumps store energy in the form of temperature gradients and,

[5] The Klimaatzaak was a legal case against the Dutch government in which citizens held the government responsible to mitigate climate change and its effects. The case was ruled in favour of the citizens on 24 June 2015, and again, in appeal, on 9 October 2018.

[6] A detailed description of heat pump operation can be found in [187].

thanks to thermal inertia, their demand can be shifted in time without major loss of comfort [168, 188, 189]. Demand response using heat pumps is considered in Chapters 7 and 8.

Electrification of the transportation system entails the transition to electric vehicles. The two types of electric vehicles currently on the market are *battery electric vehicles*, which run entirely on batteries charged from the grid, and *plug-in hybrid electric vehicles*, which can run on batteries charged from the grid alone, liquid fuel (petrol), or a combination of both. Widespread adoption of these vehicles is expected worldwide [128]. The electrification of the transportation system is left out of the scope in this thesis.

2.5 Summary

Today's power system is, for the most part, similar to the one that existed a century ago. It is said that "if Alexander Graham Bell were somehow transported to the 21st century, he would not begin to recognise the components of modern telephony – cell phones, texting, cell towers, *etc*. – while Thomas Edison, one of the grid's key early architects, would be totally familiar with the grid" [190].

The energy transition is a major challenge for the existing power system. Driven by political and societal concerns for climate change, energy generation is transitioning from fossil fuel-based power plants to renewable energy resources. These renewable resources have markedly different characteristics from traditional power plants. In particular, they are non-dispatchable and more decentralised. The existing power system operates according to a centralised paradigm, where large-scale, dispatchable power plants are responsible for its reliable operation. As this paradigm is not suitable for a system with a large share of renewables, a new, decentralised paradigm is required to embrace and enable the energy transition. Given the combination of power system decentralisation and increasing concentration of energy demand in urban areas (a consequence of ongoing urbanisation), cities are expected to play a key role in the energy transition. Digitalisation is seen as an important enabling development that can facilitate the decentralisation of the power system and support the integration of renewable resources. This chapter summarises the challenges of the energy transition in their own respect, and links them to urbanisation and digitalisation. It provides insights in the history and traditional structure of the power system, as well as in its ongoing transformation as an increasing share of generation becomes renewable.

Currently, considerable uncertainty exists with respect to the energy transition and its impact on the power system. The power system is a complex, socio-technical system, and, given its size and complexity, in-field experiments are often infeasible to alleviate this uncertainty. Therefore, *modelling* is relied upon to improve the understanding and insights needed to support the transition to renewable resources. The state of the art in this field is presented in the next chapter.

3 Energy System Modelling – A Multidisciplinary Literature Review

> *When we try to pick out anything by itself,*
> *we find it hitched to everything else in the Universe.*
>
> – John Muir

Power systems are part of larger energy systems. They are defined by their energy carrier – electricity [56, 58]. Although the focus of this thesis is on *power systems*, the literature review in this chapter addresses *modelling* of *energy systems* for two reasons. The first reason is historical: established modelling approaches for purposes ranging from national energy planning to single-building energy use simulation often consider different energy carriers (*e.g.*, electricity and gas) within the same model [48, 52]. The second reason is future-oriented: increasing shares of the gas-based heating sector and the liquid fuel-based transportation sector are expected to switch to electricity, thus blurring the boundaries between services formerly linked to distinct energy carriers [191, 192].

Understanding *how* energy systems, and power systems as part thereof, can transition to a sustainable[1] energy supply in the future is a growing concern for energy system stakeholders, policy makers and researchers (see Chapter 1). *Energy system models* are important tools to provide insights in the present and future of energy supply and demand [52]. The ability of these models to deliver insights and analyses that go beyond mere numbers has been reiterated since their inception in the middle of the twentieth century [194]. The kind of insights sought from energy system models however evolved over time. Today, in the face of climate change, the emphasis is on pathways to achieve significant reductions in greenhouse gas emissions [48, 52].

Four fields of energy system models *sensu lato* (*s.s.*) are distinguished: (1) energy system models *sensu stricto* (*s.l.*) developed for energy planning and policy advice, (2) single-building energy use models, (3) power flow models, and (4) urban energy system models. The first three fields of energy system models have a history going back to the middle of the twentieth century, while the last one – urban energy system models – is an emerging field linked to the three established fields [37]. The rising interest in urban energy systems reflects the growing role of cities in the energy transition (see Chapter 2).

[1] This thesis adheres to an environmental perspective on sustainability and uses the Bruntland definition: “sustainable development is development that meets the needs of the present without compromising the ability of future generations to meet their own needs” [193].

This thesis is positioned within the *urban energy system modelling* field. As this field is historically and methodologically linked to the other energy system modelling fields, the following literature review starts with an overview of the three established fields. Next, the focus moves to the emerging urban energy system modelling field. This field addresses the intermediate spatial scale – the urban scale – not covered by the established energy system models. The final part of this literature review is dedicated to *input data*. More specifically, it focuses on *energy demand data* that are required in urban energy system models to assess the local impact of renewable energy resources, and supporting interventions and policies. Renewable resources are non-dispatchable and decentralised (see Chapter 2). The degree of *simultaneity* between power generated by these non-dispatchable resources and local demand determines to what extent renewable energy is directly usable, and to what extent additional interventions are needed [195]. Simultaneity is calculated by combining the time- and space-dependent variations of renewable energy generation with those of demand. Thus, urban energy system models require input data with sufficiently high spatio-temporal resolution of both demand and generation. The latter are readily available, for instance, from meteorological sources. High-resolution demand data are considerably more scarce. This data scarcity is at the heart of the knowledge gap identified in the closing part of this literature review. This knowledge gap is addressed in this thesis.

3.1 Energy System Models – Established Fields

The field of energy system modelling covers a vast breadth of topics, on scales ranging from sub-second power flow simulations to decades-long energy planning scenarios. The field is therefore considered to be inherently multidisciplinary [48]. However, each individual model typically relates to only a subset of disciplines. Energy system models *s.s.* originate in Energy Planning, Policy, and Economics disciplines. Single-building energy use models are primarily developed and used by building designers, and heating, ventilation, and air conditioning (HVAC) engineers. Power flow models belong to the disciplines of electrical and control engineering. The disciplines of model users and developers determine, to a large degree, the goals, assumptions, methodological approaches, and terminology of each model.

Given the variety of disciplines, goals, assumptions, and approaches, no single classification scheme exists for energy system models [48]. Instead, energy system models can be classified based on a wide range of characteristics such as model purpose, mathematical approach, geographical coverage, time horizon, and time step [47, 48, 52, 196]. Broadly speaking, energy system models can be linked to the three layers of the power system introduced in Chapter 2: technical, economic, and governance. Following this classification, Pfenninger *et al.* distinguish two trends in terms of spatio-temporal *detail* and *uncertainty* in models: technical-layer models (single-building energy use and power flow models) have a high degree of spatio-temporal detail and are low in uncertainty, while governance-layer models (energy system models *s.s.*) have low spatio-temporal detail and are high in uncertainty [52].

The remainder of this section provides a bird's-eye view of established energy system models, highlighting the spatio-temporal scales covered, as the gap in intermediate spatial scales left unaddressed by these models necessitates the development of urban energy system models. These are described in Section 3.2.

3.1.1 Energy System Models *Sensu Stricto*

Energy system models *s.s.* have the primary purpose of providing insights on energy markets, strategic energy system planning and design, and implications of energy policies to governments, energy companies, policy makers, and researchers [52, 197]. The field originated in the second half of the twentieth century, following the oil crisis of the 1970s, and had the objective of safeguarding national energy security [48, 52]. The oil crises also marked the nascence of Energy Policy as a field, as industry and policy makers realised the importance of long-term strategic energy planning [198]. Scenario analysis, an important part of energy system modelling today, dates back even earlier, to the 1940s, and was developed at the RAND[2] Corporation as the "future-now thinking" [199]. Since the electricity market liberalisation, energy market design has become an important part of energy system models *s.s.* [200, 201].

The twentieth-century roots of energy system modelling are not necessarily applicable for twenty-first-century challenges. Adaptation of existing, often already bulky, models to new technologies such as intermittent renewable resources, interventions (*e.g.*, storage and demand response), and energy system decentralisation is not always straightforward [48, 52]. Ongoing efforts result in varying degrees of usability and transparency [48, 197].

Given the long history of the energy system modelling field *s.s.*, numerous different models currently exist [52]. One of the of the most popular classifications of energy system models is the *top-down* versus *bottom-up* distinction [48, 196]. **Top-down** models adhere to a macroeconomic worldview, and relate energy demand and supply to macroeconomic variables over long time horizons (*e.g.*, decades) and large spatial areas (*e.g.*, nations). **Bottom-up** models, on the other hand, heavily rely on a detailed physical, technological, and engineering-based representation of an energy system. In addition to these two approaches, a third, hybrid approach is gaining popularity [48, 196]. Comprehensive energy system model reviews and classifications can be found in [47, 48, 52, 196, 202, 203]. Two models are highlighted below: the MARKAL/TIMES[3] family, as it is widely used, and OSeMOSYS[4], its open source alternative.

The family of MARKAL/TIMES models is currently reported to be used in 70 countries by 250 institutions [204]. MARKAL is the original model, developed from 1980 onwards [205], while TIMES is its successor since 2000 [204, 206]. Both MARKAL and TIMES are technology-explicit, linear programming-based models of energy markets. The models are mostly used for studies on policy impact on renewable resource utilisation, climate

[2] Research ANd Development
[3] MARKAL stands for "MARKet ALlocation" and TIMES for "The Integrated MARKAL-EFOM (Energy Flow Optimisation Model) System".
[4] OSeMOSYS stands for "Open Source energy Modelling System"

change mitigation, energy efficiency improvement, and future prospects of specific energy generation and storage technologies [204, 206].

OSeMOSYS is seen by some as an open source alternative for MARKAL/TIMES [48, 52, 202, 207, 208]. OSeMOSYS is also a linear programming-based model aimed at long-term optimisation of energy systems. Its source-code is available online [209], similarly to that of MARKAL/TIMES [204]. However, unlike MARKAL/TIMES, OSeMOSYS does not require the purchase of commercial software, solver, or interface [202, 207, 209], and is thus truly open source.

Knowledge Gap. As energy system models are developed for long-term energy market and policy analysis, they have typical time horizons of 20 to 100 years and spatial reach of nations, supra-national regions or even the entire world. Therefore, these energy system models do not provide insights at the more detailed time and spacial scales relevant for urban areas [19].

3.1.2 Single-Building Energy Use Models

Single-building energy use models are used to demonstrate compliance with building energy codes, define and implement building energy rating programs, and design efficient building envelopes and HVAC systems [210, 211]. Single-building energy use modelling software dates back to the 1960s, when manual rule-of-thumb procedures to compute energy consumption by HVAC and lighting systems were replaced by computing tools [210, 212]. The oil crisis of the 1970s was an important impetus for the pursuit of higher energy efficiency in buildings, pushing towards increased use of single-building energy use models [213]. Over the last decade, interest in single-building energy use modelling has grown to follow increasingly strict governmental requirements on energy use intensity [210, 214–216]. Current challenges in modelling of single-building energy use include (1) understanding the gap between expected and actual building performance, (2) supporting the design and operation of zero-energy-use buildings, and (3) informing policy-making on building energy use codes and regulations [210].

A broad range of single-building energy use simulation tools and software packages currently exists. A comprehensive list can be found in the Building Energy Software Tools Directory [217]. Single-building energy use models can be classified according to various parameters, similarly to energy system models *s.s.* In particular, the top-down versus bottom-up classification introduced for energy system models *s.s.* is also applicable to single-building energy use models [216, 218]. **Top-down** models in this case attribute building energy use to sector statistics, while **bottom-up** models calculate them based on engineering and physical data [216, 218]. Alternative classifications, reviews, and comparisons of single-building energy use models can be found in [215, 216, 219–222]. One software package, EnergyPlus, is highlighted below, as it is widely used by researchers and practitioners [221, 223, 224], including in this thesis (see Chapter 4).

EnergyPlus is an open-source bottom-up physical simulation tool that calculates detailed energy demand of buildings based on data that include environmental conditions, construction details, operation schedules, and HVAC design information [223, 225]. It has been under development since 1996 by the United States Department of Energy (U.S. DOE) [211, 223]. EnergyPlus is a *text-based* simulation tool, *i.e.*, it stores all data in a text-based file [221]. The high level of detail and flexibility of EnergyPlus are considered to be its main advantages [211, 224].

Knowledge Gap. The temporal resolution of single-building energy use models ranges from hours to a single year (when average annual data are used). The spatial dimension of these models is, in essence, collapsed to a single building. Single-building energy use models can provide valuable building-block data, insights and approaches for urban-scale energy demand modelling. Typical single-building energy use models are limited to one building, but are increasingly used as input for urban energy planning and assessment studies, as discussed in Section 3.2.1.

3.1.3 Power System Analysis Models

Power system analysis deals solely with the electricity-related part of energy systems. It is used to support power system operations and to plan expansions of grid and generation facilities [226, 227]. Power system analysis originated in the beginning of the twentieth century, as AC grids grew increasingly large. Real-world AC power systems are too complex for analytical solutions to exist. Power flow analysis is therefore performed numerically through iteration [58, 227]. Until the 1950s, no sufficiently powerful computational tools existed for such analysis, therefore power system analysis was carried out using miniature analogue DC models of AC power systems [58, 228, 229]. Currently a broad range of digital power system analysis models and software tools exist. Reviews are available in, for instance, [230, 231].

The classification of power system analysis approaches is usually based on the type of problem solved and the mathematical algorithms used. Three classic types of problems are distinguished: *power flow* (also termed *load flow*), *unit commitment*, and *optimal power flow* [228]. **Power flow** models describe how power moves in a meshed grid [58]. Power flow calculations result in mathematically, but not necessarily physically, feasible or optimal solutions [228]. Power flow analysis has been traditionally used for transmission grids and less for distribution grids given their radial, *i.e.*, uni-directional topology [232, 233]. **Unit commitment** solves the problem of selecting generating units (traditionally baseload, intermediate, and peaking power plants, see Chapter 2) to be operated and determining the duration of operation within a given scheduling period. The selected ("committed") units must meet demand requirements while minimising operation costs, given a range of constraints, although power flow constraints are usually simplified or omitted [228, 234]. In a world of vertically integrated utility companies, unit commitment problems are solved by economic dispatch algorithms. In a liberalised world, unit commitment is determined through bilateral contracts and electricity markets [58]. Finally, **optimal power flow** models find an optimal solution for a given set of systems conditions. These conditions are formalised as objective function (*e.g.*, cost minimisation, losses minimisation, *etc.*) and a range of constraints [162, 228, 235].

Knowledge Gap. Given the growing penetration of intermittent renewable energy resources, power system analysis is increasingly performed on smaller power system scale, such as (meshed) urban distribution grids. It is used to analyse the impact of renewables on network performance and operation, including voltage regulation and loss minimisation [236–238]. However, traditional power system analysis assumes static, steady-state conditions [227], and has therefore essentially no temporal dimension. As such, these models are not suitable to generate insights in the time-dependent interactions between demand and non-dispatchable renewable generation. Although recently extensions such as the quasi-static time series approach have been introduced for this purpose [239, 240], these approaches assume demand is known, and thus do not focus on modelling urban-scale demand, which remains unaddressed.

3.1.4 Summary

Established energy system models have roots in the twentieth century, where primarily two spatial scales were important – national scale and single building scale. Energy system models *s.s.* and power flow models cover the national scale, and have been designed to inform high level, centralised authorities, such as governments and transmission system operators [22, 241]. Single-building energy use models have been developed either for individual building designers, owners, and managers, or, recently more often, for policy makers [242, 243]. Although these models increasingly incorporate decentralised, intermittent renewable energy resources, they do not natively support decision-making at the intermediate scale, in particular, the urban scale [22, 31, 244, 245]. Recently, a novel field of *urban* energy system models has emerged to address challenges at this intermediate scale. These models are reviewed next.

3.2 Urban Energy System Models – An Emerging Field

Urban energy system modelling is an emerging field [20], the number of publications with the topic or title `(urban OR city) energy model` has surged only since the onset of the twenty-first century [37]. Established large-scale energy system models and single building-scale energy system models are merging into *hybrid* approaches aimed to analyse energy systems at the *urban scale* [246]. However, truly hybrid models remain rare. Rather, established models are being sourced and adapted for the urban scale [37].

The following review provides a general overview of the field. More in-depth reviews can be found in [37, 242]. The aim of the following review is the demonstration of a knowledge gap in the existing literature: **the limited understanding of local spatio-temporal characteristics of urban demand and their impact on local renewable resource utilisation** (see also the research objective in Section 1.1).

Each of the following sections highlights how established energy system models *s.s.*, single-building energy use models, and power system analysis models are sourced and adapted for the urban scale, and why these approaches do not resolve the highlighted knowledge gap.

The review starts with models rooted in single-building energy use, as these are adapted most frequently, followed by approaches inspired by energy system models *s.s.* and power system analysis models [247, 248]. The last part of this section highlights studies featuring truly hybrid and multidisciplinary approaches to urban energy system modelling, showing that also these approaches do not resolve the existing knowledge gap.

3.2.1 Bottom-Up – Building-Based Approaches

An important segment of urban energy system models is emerging by extending single-building energy use models to several hundreds or thousands of buildings. However, practical considerations of time, cost, and information availability prevent a simple scaling up of current approaches used for a single building to hundreds or thousands of buildings [246, 249]. Thus, new approaches are being developed to scale up building-based urban energy system models[5]. A distinction can be made between demand- and generation-oriented approaches. **Demand-oriented approaches** include (1) models that are based on *building archetypes*, and (2) models that are based on *statistical analyses*, both aimed at characterising the existing building stock and its energy demand. **Generation-oriented approaches** focus on estimating renewable energy *generation potential*. For both demand- and generation-oriented approaches, models are increasingly integrated with geographical information systems (GIS).

3.2.1.1 Defining Building Archetypes to Characterise the Building Stock and its Energy Demand

Established single-building energy use models provide a detailed representation of energy use in a given building based on the description of its construction details, operation schedules, HVAC design, *etc*. (see Section 3.1.2). However, on a scale of a neighbourhood or a municipality, with several hundreds to thousands of buildings, obtaining such detailed data and using them for each individual building is not practically feasible [246, 249]. Therefore, a widely used urban-scale bottom-up approach is based on so-called *building archetypes*, *i.e.*, models or data of buildings that are deemed to be representative for the general building stock. Statistical methods are used to classify existing or future building stock according to these archetypes [248].

Determining such archetypes and linking them to real building stocks is, however, not straightforward due to the large diversity in buildings and lack of reliable statistical data [250–252]. Brøgger and Wittchen remark that few studies actually address the question of *what* makes a building representative [249]. Instead, different authors propose different building characteristics to create building archetypes. The most common characteristics are building age (*e.g.*, [252–257]), type (*e.g.*, [252, 253, 255, 258]), and function (*e.g.*, [254, 255, 257]). Different authors have applied this approach to buildings in different countries, including Switzerland [253, 257], Italy [252, 256, 258], Greece [254], and France, Germany, Spain and the United Kingdom [255]. The characterisation serves the main purpose of increasing understanding of energy use in buildings within a given urban area and informing stakeholders and policy makers on the energy saving potential.

[5] Building-based urban energy system models are also known as *urban building energy models* [246, 249].

Although most authors state that the proposed approaches are applicable to both residential and non-residential buildings, the majority of the reviewed studies focus on residential buildings only [252, 254–256]. Kavggic *et al.* provide a review of bottom-up building stock models, focusing specifically on the residential sector [259]. However, a few authors do explicitly include non-residential buildings in their work, in particular [253, 255, 257].

Knowledge Gap. Most literature on building archetypes considers average annual demand, and focuses on subdividing demand by end-use categories such as lighting, ventilation, and cooking [255, 257], or even a higher degree of end-use detail, up to appliance level [252]. Although approaches based on average annual demand data are well-suited for energy efficiency and energy saving potential studies, they do not have sufficient *temporal* detail to assess the simultaneity between demand and time-dependent renewable generation.

3.2.1.2 Using Statistical Approaches to Characterise the Building or Urban Scale Energy Demand

Statistical approaches are typically used to bridge gaps between the available and the desired spatial resolution, if additional data are available. Such approaches are used both to downscale demand data available at higher spatial scales to single buildings, and to aggregate demand data from single buildings to urban areas.

Both Howard *et al.* [245] and Mastrucci *et al.* [260] apply statistical approaches to **downscale** aggregated energy demand data to single buildings, and subsequently use the obtained results to predict demand in other urban areas. Howard *et al.* [245] use multiple linear regression to obtain electricity, gas, steam, and fuel oil demand intensities of individual residential and non-residential buildings. Energy carrier demand is subsequently allocated to different end-uses. The results are used to model energy demand buildings across 859 134 tax lots in New York City [245]. Mastrucci *et al.* [260] downscale annual energy (gas and electricity) consumption information from post-code level to single dwelling level, also using multiple linear regression. The resulting regression coefficients are used to predict energy consumption of 300 000 dwellings in Rotterdam from characteristics such as dwelling type, floor area, and number of occupants [260]. Both Howard *et al.* [245] and Mastrucci *et al.* [260] consider only average annual demand.

A number of authors use statistical approaches to **aggregate** building scale energy demand to urban scales. The two main purposes of these statistical approaches are (1) providing the right weight to different building types when aggregating them, and (2) appropriately matching them with spatial data. For instance, Mikkola and Lund propose a statistical aggregation method that can be applied to areas with known spatial distribution of buildings, as well as to areas with unknown spatial distribution, in that case using general city density statistical representation [31]. Best *et al.* use a similar approach, based on known spatial distribution of buildings, to model urban-scale energy demand and optimise the local mix of energy generation technologies [261]. Andersen *et al.* apply a statistical demand aggregation approach to characterise current urban-scale demand and forecast future demand [262–264].

Knowledge Gap. As shown by the examples above, statistical approaches can be a powerful tool to bridge gaps between available and desired spatial resolution, using additional data. The temporal resolution of the resulting dataset remains in these cases the same as that of the original dataset. Existing statistical approaches that characterise building or urban-scale energy demand therefore do not resolve the lack of detail in the temporal demand data.

3.2.1.3 Estimating Urban Renewable Energy Generation Potential

Urban renewable energy generation potential studies primarily focus on solar energy as primary source [265], although others, such as wind [91, 94] and biomass [266] also exist. However, wind is less suitable for urban areas due to inefficiencies created by aerodynamic roughness of buildings [91, 94] (see Section 2.1.2.2). The availability of biomass in urban areas is limited to waste streams [266]. Therefore this literature review focuses solely on solar energy generation potential studies.

In an urban area, solar power is decentralised, *i.e.*, generated by a large number of small PV arrays [267]. For each array, the amount of solar power generated within a period of time depends on the angle and the shading of the solar PV panels. Accurately estimating the total solar power generation potential of a given area therefore requires modelling of the exposed surfaces of a large group of buildings, based on their morphology and orientation. A large collection of solar potential simulation tools is currently available, including GOSOL (one of the first simulation tools available) [268], SolarAnalyst [269], SORAM [270], Solar Envelopes [271], r.sun [272], and PVGIS (web-based) [273]. A comprehensive review and comparison of urban scale solar energy potential models, ranging from simple 2D to more sophisticated 3D approaches, is provided by Freitas *et al.* [267].

Solar potential calculations have been carried out for a large number of cities and areas, for instance for all municipalities in Germany (with a focus on residential buildings) by Mainzer *et al.* [274], for a single municipality in Germany by Ramirez Camargo *et al.* [275], for a small city in Slovakia by Hofierka and Kaňuk [276], for Mumbai in India by Singh and Banerjee [277], and for Geneva (Switzerland) by Mohajeri *et al.* [278].

Knowledge Gap. Given the wide availability of detailed spatio-temporal meteorological data, used as input to calculate solar power generation, and the increasing availability of spatial urban GIS data (see next paragraph), solar energy potential models can currently achieve a high degree of spatio-temporal solar generation resolution. These models address the generation-side in detail, but leave out the demand-side.

3.2.1.4 Integrating Building Energy Use Data and Local Renewable Energy Generation Data with Geographical Data

Established single-building energy use models do not need spatial information as they focus on individual buildings. To enrich building-based *urban* energy system models with data on spatial distribution of (archetype) buildings, models are increasingly often integrated with spatial information from geographical information systems (GIS). Such databases have proliferated over the past years and have become more and more accessible to the general public [246], for instance through the open standardised data model and exchange format called *CityGML* [244, 246, 279]. In general, GIS databases can provide a wealth of information ranging from geometric building data and cartographic information to energy certificates [255].

GIS databases are used across all building-based urban energy system models, both for demand and generation sides. The following examples illustrate the use of GIS-integration with demand-side modelling. Aksoezen *et al.* derive a large portion of their data for archetype-based building demand modelling and building stock classification from a GIS database of the City of Basel (Switzerland) [253]. Dall'O' *et al.* and Caputo *et al.* use a GIS database as a platform to manage collected demand data [256, 258]. Mastrucci *et al.* use the municipal GIS database of the City of Rotterdam (the Netherlands) as a basis for their statistical building stock energy demand model [260]. Chow *et al.* use spatial data to forecast the growth of energy demand in urban areas [280]. For the generation side, all tools and papers reviewed above are integrated with GIS [268, 270–272, 274, 276–278, 281]. A systematic review of GIS-integrated urban energy system models is carried out by Alhamwi *et al.* [28]. The authors distinguish between urban energy demand, urban energy generation potential, environmental assessment, and decision support papers.

Knowledge Gap. GIS databases primarily increase spatial detail in urban energy system models, not affecting temporal detail of generation or demand. The lack of detailed temporal demand data thus remains unresolved.

3.2.2 Top-Down – Energy Systems Approaches

Although national-scale energy system models are well developed and widely used, there are relatively few urban-scale counterparts or adaptations [282]. A few notable examples are reviewed here. The examples are divided into (1) adapted national-scale models, and (2) optimisation models.

3.2.2.1 Adapted National Scale Models

Despite the popularity of the MARKAL/TIMES model family on the national and supranational scales, these models have not been widely adopted for the urban context. Lind and Espegren [282] are a notable exception for their work on an adaptation of the TIMES model for the City of Oslo (Norway). The new model is called TIMES-Oslo. As electricity in Norway is nearly entirely generated by hydropower plants, and is thus renewable, the model addresses the problem of fossil fuel use and greenhouse gas emissions in the transportation sector. The energy use by the residential and the service sector is exogenously provided based on [283]. The TIMES-Oslo model considers Oslo as a single geographical area and has a time horizon between 2010 and 2050, with 260 time slices per year. The model compares three scenarios of transportation fuel use, and formulates recommendations based on the obtained results [282]. Although the focus on the transportation sector is out of the scope of this thesis, the work by Lind and Espegren is included as it is a rare illustration of the use of TIMES on the urban scale.

Another example of adaptation of a national-scale model to the urban scale is the work of Dagoumas [284]. He applies the national MDM-E3 model[6] to the City of London (U.K.) to study long-term (100 years) changes in energy demand, climate impact, and greenhouse gas emissions. The model includes aggregate demand equations based on annual data, as well as data on the labour market. Dagoumas compares three economic growth scenarios and analyses their impact on employment in various sectors, and on the related energy demand and emissions, seeking to inform policy makers on the interactions between economics and sustainability on the urban scale [284].

Knowledge Gap. Urban-scale energy system models, like their national-scale counterparts, are primarily aimed to inform long-term decision making and have, in general, relatively low resolution in both space and time. Although the TIMES model can provide finer temporal detail through time slicing, the resolution depends on the input data (see Section 3.3).

3.2.2.2 Optimisation Models

A small, but growing number of optimisation models on the urban scale has been proposed in the literature. For instance, Xydis [285] describes a linear programming method to optimise renewable energy supply mix for the City of Athens (Greece), basing the results on annual input data. Xydis analyses the obtained results in terms of economic optimality for society as a whole, and in terms of profitability for the investors [285]. Morlet and Keirstead [109] propose an optimisation model to assess the lowest-cost pathways to achieve emission reduction targets. Input data are expressed as averages per capita. Results show an interaction between governance of urban energy systems and costs for achieving the envisioned targets [109]. Samsatli and Samsatli [286] present a general purpose mixed-integer linear programming model for simultaneous design and operation of urban energy systems. The model is intended to represent all energy carriers, and energy conversion and storage technologies, and can be applied at different spatial and temporal scales. The model is illustrated for an eco-town in the U.K.: the town is divided into nine spatial zones and the modelled year is represented by three typical days with multi-hour temporal resolution [286].

Knowledge Gap. Optimisation models are in the first place designed to address long-term energy policy questions, similarly to national-scale and urban-scale energy system models. Although optimisation models can handle spatial and temporal data of different resolutions, in practice such high spatio-temporal detail is rarely required and thus rarely implemented given the purpose of these optimisation models.

3.2.3 Power System Analysis Approaches

The power system analysis approach to urban energy systems is primarily concerned with the impact of the increasing penetration of small-scale, intermittent renewable energy resources on the distribution grid [287]. Renewable energy resources connected to the distribution grid can have both positive and negative impacts. Potential positive impacts on grid operation include reduced power flows and thus reduced losses and voltage drops.

[6] MDM-E3 stands for Multisectoral Dynamic Model that considers Energy, Environment, and Economy [284].

Potential negative impacts include power quality issues[7] [104, 105]. Comprehensive reviews of possible issues and impacts are provided in [104, 105].

Several authors have analysed the effects of increasing penetration of solar PVs in distribution grids (essentially the power system view on urban areas). Different power quality issues are addressed separately or jointly, such as prevention of overvoltages[8] [289–291], reactive power[9] control [291–293], and abatement of harmonic distortion[10] [291, 294]. The aim of these and similar studies is to propose (usually technical) solutions to prevent power quality issues. Solutions include reactive power control [287, 289, 290, 292, 293], active power curtailment [287, 289, 290], energy storage [287], distribution grid reconfiguration (assuming meshed topologies of urban areas) [295], and the use of on-load tap changers[11] [287, 296]. A side-by-side comparison of these solutions is given in [287].

Knowledge Gap. Power system analysis studies have different representations of time dependencies. Some studies are based on static calculations [288, 293], while others include temporal variations in solar PV generation and demand, and the resulting voltage profile variations [290–292, 294, 295]. Detailed characteristics of urban demand are usually not addressed. Note further that real distribution grid topologies are rarely available for research. Most studies are therefore based on IEEE test feeders [297].

3.2.4 Hybrid and Multidisciplinary Approaches

The discipline-related modelling approaches described above can be combined into hybrid and multidisciplinary approaches. The definition of a hybrid or multidisciplinary approach vis-à-vis urban energy system modelling is not yet consolidated. In this thesis, a hybrid and multidisciplinary approach is defined as an approach that combines elements from established energy system models *s.l.* described above. Three illustrative examples are highlighted next.

In the first example, methods from power systems analysis and building-based solar energy potential estimations are combined. The study is conducted by Freitas *et al.* [35]. The authors investigate how power balances at the transformer level depend on the method used to assess solar PV potential, comparing a simple peak power method with a more detailed irradiance method. For the second method, the authors use hourly generation and demand data, but assume only residential demand. The Alvalade neighbourhood in Lisbon (Portugal) is taken as a case study. The authors conclude that the irradiance method should be used

[7] Electricity supplied by the power grid has to fulfil a range of requirements, defined by standards. These requirements are called *power quality requirements* and include limitations on admissible voltage fluctuations, overvoltages, power fluctuations, and fault currents [58, 104].

[8] Distribution grids were historically designed solely to provide power to loads, not for the connection of small-scale generators such as solar PVs. For this historical reason, distribution lines (called *feeders*) typically have (set) higher voltages at the transformer and lower voltages at the end of the feeder. If solar PVs are connected within the feeder, the local voltage increases. Increases above allowed limits are called *overvoltage* [288].

[9] Reactive power is the component of power that is exchanged between the electric and magnetic fields. Reactive power does not lead to net transfer of energy to loads. It is therefore desirable to limit reactive power flows in the system. The ratio of active power (power component that does transfer energy to loads) to reactive power is called the *power factor* [58].

[10] Harmonic distortions are distortions of the waveform of the voltage [58, 104].

[11] On-load tap changers operate by changing the number of turns in one of the two windings of a transformer to keep the transformer output voltage within admissible limits [296].

with very high penetrations of solar PVs (*e.g.*, PVs installed on building façades in addition to building roofs) as this method provides a more accurate representation of temporal interactions between local demand and generation, and the corresponding power flows through transformers [35].

The second example presents a similar combination of methods as the first, but with the addition of single-building energy use calculation. The combined model is called IDEAS (Integrated District Energy Assessment by Simulation) and has been developed by Baetens *et al.* [298]. The model is used to describe a residential neighbourhood of 33 buildings representative for the Belgian residential building stock. The dwellings are assumed to have building-integrated PV systems (the PV generation model uses the web-based PV model PVGIS [273]). The paper assesses how zero-energy buildings influence power quality at the feeder level. PV generation losses and possible overloads of the transformer are identified as the main issues. This result emphasises the importance of modelling at the neighbourhood level to detect such issues [298]. Protopapadaki and Saelens [36] continue on the work of Baetens *et al.* using the IDEAS model to assess the impact of solar PVs and heat pumps on low-voltage distribution grids. The authors also focus on residential demand only, analysing a wide range of neighbourhood scenarios with different numbers of dwellings, renovation parameters, cable types, *etc*. Based on the obtained results, the authors conclude that heat pumps have a larger impact on the studied feeders than PV panels [36].

In the third example, elements from all three established energy system modelling approaches are combined: a building-based energy use demand model, a top-down optimisation for the design and operation of a decentralised power system and district heating network, and power flow calculations for the local distribution grid. Morvaj *et al.* [19] propose this hybrid and multidisciplinary model to optimise the design and operation of the energy system in an urban district in Zürich (Switzerland) under different scenarios of renewable energy penetration. Based on this detailed representation of the various energy system parts, in particular hourly matching between renewable generation and local energy demand, the authors assess the energy transition impacts on local carbon emissions, system operation and upgrading, and building design [19].

Knowledge Gap. The examples of hybrid and multidisciplinary models indicate that such models can provide holistic insights in the impact of energy transition at urban scales. The high degree of spatio-temporal detail incorporated in these models enhances their applicability to real urban areas. The main drawback of the studies reviewed is their focus on residential energy demand only. These examples do not provide solutions to the general lack of detailed spatio-temporal demand data for non-residential consumers.

3.2.5 Summary

As their name suggests, urban energy system models are explicitly developed for the urban scale, as this scale is not covered by the established energy system models that focus on single-building or national scales. The increasing availability and high level of detail of GIS databases provides the spatial information required by urban scale energy models. The temporal scale resolution is less consistent among urban energy system models. The degree of temporal detail depends on the model aim, and on the available data. Whenever data are the limiting factor, the lack of temporal detail is to be attributed to the demand side, as renewable generation can be modelled based on widely available meteorological data that have a high degree of temporal detail. Examples of power system analysis models, and hybrid and multidisciplinary models applied to the urban scale provide insights in the importance of temporal detail to assess the simultaneity between renewable generation and demand, and its effects on the design and operation of future sustainable power systems in urban areas. The next section addresses the availability of urban energy demand data.

3.3 Urban Energy Demand Data

Data are both an input for and an output of models [191]. The adagio "garbage in, garbage out" pointedly underscores the importance of good data for the quality of results generated by models [37, 210, 299]. Demand profiles are key input data for energy system models as they describe the time-dependent fluctuations of demand in the area of interest. The prerequisites for demand data to be considered qualitatively "good" depend on the modeller's perspective and aim. The first set of prerequisites concerns the question of *getting data*, *i.e.*, before all else, data should be *available* [37, 251, 283, 300]. An important issue related to data availability and accessibility, is the kind of licence under which they are distributed, as licences determine the legal usage and sharing rights of data [191, 251, 301]. The second set of prerequisites is related to *handling* data once they are available, and includes requirements of machine-readability, availability of metadata (descriptions of assumptions and conditions under which the data were collected), completeness, level of noise, and occurrence of outliers [37, 301, 302]. The primary consideration in this thesis is data availability, as this is the *conditio sine qua non* for using data in models.

3.3.1 Data Availability Challenge

Availability of measured energy demand data is a known bottleneck in single-building energy use and urban energy system modelling [251, 303]. The lack of publicly available data in the energy field, and the contrast to other research fields such as health and climate sciences has been pointed out by Summerfield and Lowe [251], and by Pfenninger [300]. The largest shortage pertains to data with a high degree of *temporal detail* (*i.e.*, with a resolution less than a year) [251]. In the context of the energy transition, the time resolution is an important attribute of energy demand data. As shown by Voskamp *et al.*, interventions supporting the integration of renewable resources in urban areas require detailed spatio-temporal data, with temporal resolution ranging from *seconds* to *days* [195].

Such detailed demand data are not always registered. However, with the advance of smart meters, more and more consumer energy demand data is collected throughout Europe [304]. Privacy concerns are one of the major obstacles to the public availability of such data [141]. Energy demand data contain sensitive information, and can, for instance, reveal building occupants habits (*i.e.*, privacy-sensitive information) or underperformance of equipment (as compared to manufacturer specifications). Stakeholders are well aware of the sensitivity of energy demand data and are thus not inclined to share this information out of fear of compromising their personal or commercial interests [220, 251, 300]. However, the energy field is not the only field handling sensitive data. Summerfield and Lowe [251] call attention to the data collection, management, and sharing practices in health sciences, where privacy concerns are also of utmost importance. The authors stress that the energy field can benefit tremendously if data protocols and sharing practices similar to those used in health sciences are implemented for energy demand data [251]. Finally, even when datasets are publicly available, Babaei *et al.* [220] point out that "owing to the lack of a standard nomenclature and structure for reporting the collected data, as well as the lack of benchmark data sets, it is a challenging task to find, collect, understand, and compare different energy consumption data sets" [220]. Thus, getting "good" energy demand data is challenging, and, once obtained, handling these data is often not straightforward.

3.3.2 Current Use of Energy Demand Data in Models

Notwithstanding the difficulties in obtaining and handling demand data, existing models do use energy demand data as input. Use of realistic demand data can make urban energy system models more representative and thus better applicable to real-world challenges. Urban energy demand varies both in time and space. The review below shows how this spatio-temporal heterogeneity is currently reflected in the datasets used in urban energy system models.

3.3.2.1 Temporal Demand Heterogeneity

Residential and service sector consumers use electricity at different times of the day [119, 122]. This variation of demand over time is called the *demand profile*. Both residential and service sector consumers contribute to a considerable part of the total urban demand in developed countries (see Section 2.2.2). However, a large portion of existing studies is limited to residential demand only. Of the papers reviewed above, this is the case for the following studies: [19, 35, 36, 249, 252, 254, 256, 259, 260, 274, 298]. Among these authors, Freitas *et al.* [35] explicitly state that their model considers residential demand only due to lack of availability of non-residential demand data [35]. A similar picture emerges from the review of energy consumption data for single buildings carried out by Babaei *et al.* [220]. The authors show that of the 19 reviewed papers that are based on measured datasets, 14 report on residential data, two on office buildings, one on a university building, and two on not further specified buildings [220].

Not all studies are limited to residential demand. Of the papers reviewed above, ten [31, 253, 257, 261, 263, 277, 282, 290, 292, 295] include both residential and non-residential demand data. However, four papers [253, 257, 282, 290] are based on proprietary data sources (such as energy providers) that are thus not available for other researchers. The data sources of another five authors [31, 263, 277, 292, 295] cannot be verified, as either the reference provided is no longer valid [31, 263, 277, 295] or is not clearly referenced at all [292]. Only the data source of Best *et al.* [261] – the Commercial Reference Buildings database of the U.S. DOE [305] – is publicly accessible. This database is discussed in the next paragraph and is used as one of the foundations for this thesis.

Other authors of papers reviewed above who have included both residential and non-residential buildings, base their work on data with annual time resolution [245, 255, 258, 280, 284] or do not consider demand at all [275, 276].

Knowledge Gap. The examples given are far from exhaustive, yet they are illustrative of the current representation of urban demand: either as solely residential, or as mixed demand, in which case it is mostly based on data sources inaccessible to other researchers. Thus, although energy demand data availability is a general barrier in energy research, the problem is particularly acute for the availability of non-residential and urban-scale demand data. Mata *et al.* attribute the second fiddle position of non-residential sector to the greater political attention generally given to the residential sector [255].

3.3.2.2 Spatial Demand Heterogeneity

Consumers with different temporal demand profiles are not evenly distributed across urban areas. This leads to a spatial heterogeneity in demand at urban scales – neighbourhoods, districts and municipalities. However, this spatial demand heterogeneity has not been traditionally taken into account, as established energy system models *s.l.* focus on either the national or the single-building scale (see above). For these scales, the most relevant fluctuations of demand are those over time [22, 241–243]. As the intermediate (urban) scale becomes more important in energy system modelling for the energy transition, demand fluctuations over both space and time become relevant [31, 244, 245]. To underscore the importance of both dimensions, such demand profiles are explicitly called *spatio-temporal demand profiles*.

Currently two types of demand profiles are made available by utilities and TSOs: *standard load profiles* for specific connection types (*e.g.*, [306] for the Netherlands), and *country-level load profiles* (*e.g.*, [307] for Europe). Standard load profiles lack essential metadata which thwarts their use for the estimation of demand in real urban areas. Country-level load profiles do not give sufficient insights at urban scales. Realistically representing spatio-temporal variations in demand is therefore challenging, and requires data analysis and combination techniques of energy-related data at other (national or building) scales, and non-energy related data. Bottom-up approaches based on building-scale data are the preferred option as they results in detailed descriptions of spatio-temporal variations of urban demand [241, 257, 260].

In general, four different approaches to representation of spatio-temporal demand variations can be distinguished in the existing literature:

- The first approach leaves **demand data out of the scope**, focusing instead on model development, *e.g.*, [275, 276].
- The second approach accounts for **temporal demand variations**, often assuming household demand only, and leaving spatial demand variations out of the scope. A considerable part of energy system modelling studies follows this approach, see above.
- The third approach addresses **spatial demand variations**, while using cumulative annual data and thus not taking the temporal demand variations into account. For instance, Yamaguchi *et al.* classify urban districts according to building type to gain

a better understanding of spatial variations in energy use and CO_2-emissions [308]. Howard *et al.* have built a model that estimates spatial heating and cooling end-use intensity [245]. Chow *et al.* have proposed a method for spatial demand forecasting [280]. Alhamwi *et al.* have developed an open-source GIS-based platform for spatial demand modelling, leaving the temporal component for future research [28].

- The fourth approach develops and uses **spatio-temporal demand profiles**, striving to represent both spatial and temporal variations in urban demand in detail. The models using these spatio-temporal demand profiles are developed for different purposes. For instance, Mikkola and Lund, Fonseca *et al.* and Best *et al.* characterise local energy consumption [31, 257, 261]. Pitt and Kirschen, and Gerbec *et al.* aim to devise better tariff plans for utilities [309, 310]. Andersen *et al.* have published several papers describing forecasting of future demand [262–264]. Davila *et al.* have developed targeted emission reductions plans for cities [244].

Knowledge Gap. When the spatial dimension is added to the temporal, the lack of non-residential demand profiles is compounded by the lack of detailed data on spatial distribution of consumers [31, 37, 262, 263]. Urban-scale demand profiles, *i.e.*, demand profiles of urban areas such as neighbourhoods are an alternative. However, such profiles are, to the best of the author's knowledge, not publicly available. Systematic characterisation of spatio-temporal urban energy demand therefore remains an important open question [20, 219, 242, 300].

3.3.3 Publicly Available Energy Demand Datasets

The challenge of obtaining energy demand data is reflected in the number of publicly available datasets. In recent years, efforts have been increasing to create open energy models, a trend that also strengthens the interest in open energy data. Recently, existing open energy projects, *i.e.*, both open models and data, have been reviewed by Pfenninger *et al.* [191] and by Morrison [301]. These reviews show that while open modelling efforts are gaining momentum, the open energy data are lagging behind: only 2 out of 17 projects reviewed by Pfenninger *et al.* [191], and only 7 out of 36 projects reviewed by Morrison are open databases [301].

Table 3.1 combines, refines, and extends the work of Pfenninger *et al.* and Morrison [191, 301] by providing an overview of publicly available energy *demand* databases. Databases are included in the overview if two conditions are met: (1) the temporal resolution is less than one year and (2) the database contains non-residential consumers.

The references in Table 3.1 show that the Commercial Reference Buildings database provided by the U.S. DOE has the highest spatio-temporal resolution combined with detailed metadata. However, data in this database are only available at building scale, not at urban scales, and are calibrated and validated for the U.S. Detailed spatio-temporal energy demand data for urban scales and for other countries than the U.S. are currently not publicly available. Part II of this thesis describes methods that allow for the use of the available U.S. DOE Commercial Reference Buildings data, in combination with other, non-energy related datasets, in other countries and at urban scales. The methods are implemented for the Netherlands.

Table 3.1 Overview of publicly available energy demand databases. Databases are included in the overview if two conditions are met: (1) the temporal resolution is less than one year and (2) the database contains non-residential consumers.

Database Name	Content	Comments	Ref.
Demand data with high spatial resolution			
Irish Social Science Data Archive	Half-hourly resolution, building scale (residential and service sector consumers)	Data available upon request. Limited metadata on consumer type	[311]
Commercial Reference Buildings	Hourly resolution, building scale (16 types of residential and service sector buildings)	Most detailed database available to the best of the author's knowledge	[305]
OpenEI	Hourly resolution, building scale. Datasets based on [305]	Generation, renewables, environmental, standards data also available	[312]
Demand data with low spatial resolution			
Energy Research Data Portal for South Africa	Hourly and annual resolution, sector scale, limited metadata	Environmental impact data also available	[313]
Open Power System Data	Hourly and annual resolution, country scale	Renewable generation data also available	[314]

3.4 Detailed Spatio-Temporal Urban Demand Profiles – A Knowledge Gap

Energy system models that have been developed since the middle of the twentieth century, *i.e.*, models for (1) energy systems *s.s.*, (2) single-building energy use, and (3) power system analysis, are not well suited to support and inform the energy transition at the urban scale. The models are *spatially* either too coarse, or too fine for the urban scale. This gap is addressed by the emerging field of *urban* energy system models, that has been growing since the turn of the twenty-first century. The new models explicitly focus on the intermediate scale, describing energy demand and supply in areas containing hundreds to thousands of buildings.

However, the *temporal* dimension in the existing urban energy system models remains relatively coarse. Most models use average annual data. While generation data can be obtained at higher temporal resolutions, more detailed demand data are scarce, in particular for non-residential energy consumers. This issue has been solved on a case-by-case basis by a number of researchers by using proprietary datasets. Other researchers omitted the non-residential demand in their models. Neither approach is sustainable, as neither addresses the core of the issue: devising systematic and generalisable approaches to model urban-scale energy demand, in which non-residential demand is anything but negligible.

This lack of detailed spatio-temporal urban demand profiles is a clear knowledge gap in itself. Moreover, it subsequently leads to the lack of realistic assessment of (1) the impact of renewable resources on urban energy systems, (2) the efficacy of interventions taken to support the local integration of renewable resources, and (3) the adequacy of policy and regulatory decisions.

This thesis addresses this knowledge gap by (1) proposing a systematic approach to scale the service sector energy demand data from the U.S. to other countries (the Netherlands in the case of this thesis), combining the results with residential data and aggregating them to urban scales, (2) quantitatively showing the impact of omitting the service sector on renewable resource utilisation metrics and effects of interventions, and (3) showing how the obtained technical insights can be linked to advice for policy-makers. The following Parts II, III, and IV address each of these points respectively.

Part II

Understanding Urban Demand

A detailed understanding of the spatio-temporal characteristics of urban demand is currently lacking in literature. This knowledge gap poses a considerable barrier for the development of urban energy system models that can inform and support the energy transition in urban areas. Yet, urban areas are expected to become a key stage for the energy transition. Demand is progressively concentrated in urban areas, as more and more people live in cities (see Chapter 2). Renewable energy resources are smaller than conventional power plants, and thus located closer to demand. Understanding the local interaction between demand and generation requires detailed spatio-temporal profiles for both sides. Considerable amount of research focuses on the generation side. Much less attention has been dedicated to the demand side. Part II addresses this knowledge gap. It answers **RQ1 – How can local demand be characterised in urban areas?**

This question is tackled in two steps. **Chapter 4** focuses on the *temporal* dimension of urban demand, addressing **RQ1a** – ***How can temporal heterogeneity of urban demand profiles be characterised?*** Urban areas consist of a mix of households and services, such as offices, shops, and schools. Yet, most energy transition studies simplify local demand to household demand only (see Chapter 3). One of the main reasons for this simplification is the lack of detailed demand data for the service sector. **RQ1a** is answered by proposing and implementing *building equivalents* as a means to estimate detailed service sector demand profiles for an area of interest based on demand profiles from a reference area.

Chapter 5 focuses on the *spatial* heterogeneity of urban demand. The chapter addresses **RQ1b** – ***How can spatial heterogeneity of urban demand profiles be characterised?*** To answer this question, the demand profiles of 14 698 urban areas in the Netherlands are modelled and classified. The modelling step is based on *scaling factors*, which are, to some extent, an alternative approach to building equivalents. The scaling factors-approach emphasises spatial heterogeneity, while the building equivalents-approach focuses on the temporal heterogeneity. The spatial demand characterisation results demonstrate that in all analysed urban areas – neighbourhoods, districts, and municipalities – three types of areas can be distinguished, which are termed *residential*, *business*, and *mixed*. These areas are pairwise statistically different in their demand profile and their composition. Residential-type areas, used in most energy system models, are shown to represent only a minority of urban demand.

4 Temporal Heterogeneity

> *Want tussen droom en daad*
> *staan wetten in de weg*
> *en praktische bezwaren.*
>
> – Willem Elsschot

ELECTRICITY demand of urban areas is comprised of the demand of various consumers, including both households and services. The demand of these different consumers is heterogeneous in time, as periods of activity differ between them. For instance, offices and shops primarily use electricity during the working day, while household demand peaks in the evening after working hours.

Although real urban demand is heterogeneous, most urban energy system models only consider household demand, omitting the service sector. This leads to an unrealistic representation of urban energy demand, yet occurs because detailed demand profiles are far more often available for households than for the service sector (see Chapter 3). To resolve this situation, this chapter proposes and implements a method to estimate service sector demand profiles for any area of interest (the Netherlands, in this thesis) based on U.S. DOE Commercial Reference Buildings database [305], which is, to the best of the author's knowledge, the most detailed service sector energy demand database currently openly available. The method is based on so-called *building equivalents*: representation of energy demand of local buildings based on the U.S. DOE Commercial Reference Building database.

The result obtained at the end of this chapter is a collection of building equivalents and corresponding demand profiles of 13 service sector consumer types. The dataset containing this data is published online [315]. In the remainder of this thesis, both the residential and the service sector are taken into account as households and services are often collocated (see Section 2.2.2). The building equivalents and corresponding demand profiles obtained for the service sector are therefore combined with an already available average household demand profile [306] that is representative of the residential sector in the Netherlands. Together, these 14 consumer types represent a considerable part of the Dutch services and households. The building equivalents and demand profiles are the basis for the remainder of this thesis. The emphasis in this chapter lies on the service sector, as this sector has been thus far largely omitted.

This chapter is based on a previous publication [59].

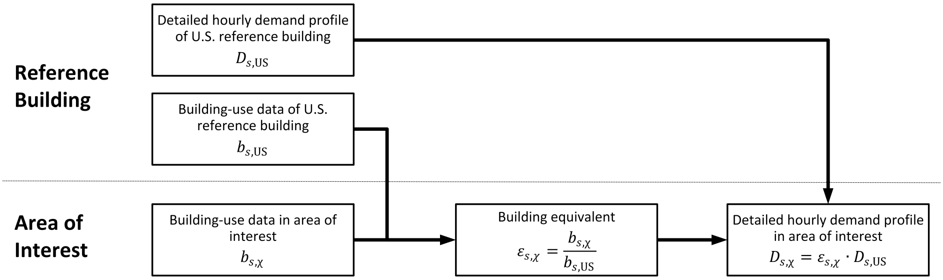


Figure 4.1 Method for calculation of building equivalents. Building equivalents are used to devise demand profiles of the service sector in an area of interest (the Netherlands, in this thesis).

4.1 Method to Devise Local Demand Profiles

The method developed in this thesis proposes the use of *building equivalents* as a means to use U.S. reference buildings and their demand profiles to represent service sector demand in an area of interest (the Netherlands, in this thesis). A *building equivalent* is defined as a U.S. reference building that represents the demand of similar Dutch service sector buildings in a given area. Building equivalents are calculated based on the comparison of building-use data (*e.g.*, occupancy and floor area) from the area of interest and the corresponding U.S. reference building from the U.S. DOE Commercial Reference Buildings database [225]. Once the number of building equivalents representing a service subsector (*e.g.*, food retail) for an area of interest is calculated, its demand profile is determined as equal to the combined demand profile of the corresponding number of U.S. building equivalents, *i.e.*, U.S. reference buildings.

4.1.1 Building Equivalents

The proposed method is depicted in Figure 4.1 and can be summarised as follows. Let χ be the area of interest. Let $C_{s,\mathrm{US}}$ be the set of U.S. DOE Commercial Reference Buildings and $|C_{s,\mathrm{US}}|$ the number of service sector consumers in this set. The number of building equivalents is found by comparing non-energy use data of U.S. reference buildings, and buildings in the area of interest. Formally, let $b_{s,\chi}$ denote the building-use data for service sector consumer c_s for the area of interest χ, and $b_{s,\mathrm{US}}$ the building-use data for the U.S. reference building (note that shorthand subscript s is used instead of c_s). The building equivalent for service sector consumer c_s is then calculated as follows:

$$\epsilon_{s,\chi} = \frac{b_{s,\chi}}{b_{s,\mathrm{US}}} \tag{4.1}$$

This method is applied to the U.S. DOE Commercial Reference Building dataset [225] and an area represented by 100 000 Dutch households.

The U.S. DOE publishes reference building data for 16 types of commercial buildings, of which 13 types, relevant for the Netherlands, are used in this thesis (thus, $|C_{s,\mathrm{US}}| = 13$). These 13 service sector consumer types are listed in the first column of Table 4.1. The building equivalent for each service sector consumer type is based on the comparison of

Table 4.1 Calculation of building equivalents based on U.S. Department of Energy Commercial Reference Buildings. The lasts column lists the Dutch references used to calculate building equivalents. On the U.S. side, the scaling is based on [225].

Service Sector Consumer Type	Building Equivalents per 100 000 households	Type of Building-Use Data Used	References for Dutch Data
Hospital	3	Patient Beds	[319, 320]
Large Hotel	1	Rooms	[321, 322]
Small Hotel	16	Rooms	[321, 322]
Large Office	9	Floor area	[323, 324]
Medium Office	47	Floor area	[323, 324]
Small Office	6	Floor area	[323, 324]
Primary School	32	Students	[325, 326]
Secondary School	9	Students	[325, 327]
Stand Alone Retail	177	Floor area	[328]
Supermarket	12	Floor area	[316–318]
Restaurant	170	Restaurants	[329]
Quick Service Restaurant	189	Restaurants	[329]
Warehouse	163	Employees	[122, 330]

building-use data between the corresponding U.S. reference building and Dutch buildings. For instance, the building equivalent for supermarkets is calculated based on floor area. The floor area of U.S. reference building "Supermarket" is 4 181 m^2 (thus, $b_{c_s,\mathrm{US}} = 4\,181$) [225]. The total supermarket area in the Netherlands is 3 781 699 m^2 [316] (cross-referenced with [317, 318]). Combined, these supermarkets serve 7.59 million households (data from reference year 2014). An urban environment of 100 000 households (the area of interest χ) is thus serviced by 3 781 699/75.9 = 49 825 m^2 supermarket floor space. This supermarket floor space and the energy demand of these supermarkets can jointly be represented by 49 825/4 181 = 12 building equivalents of the type "Supermarket" obtained from the U.S. DOE Commercial Reference Buildings database.

Similar calculations are carried out for all service sector consumer types. Details of these calculations, and of the U.S. and Dutch data sources used for these calculations are given in Appendix A. The results are summarised in Table 4.1. These results are also accessible online [315].

4.1.2 Service Sector Demand Profiles

Service sector demand profiles are obtained using the U.S. DOE EnergyPlus modelling software [223]. This software is a bottom-up open-source physical simulation tool (see Section 3.1.2) that builds demand profiles based on technical building data and environmental data. The output of EnergyPlus are demand profiles. Each demand profile is a vector with

8 760 elements, where each element corresponds to the energy demand of the given hour of the year.

The following assumptions are made with respect to building age, climate data, and building location. The simulations assume the latest building standards. Therefore, post-2004 building standard is used. To create profiles representative for the Netherlands, Amsterdam climate data are used [331]. Finally, the location match in terms of climate zone is based on both the ASHRAE climate classification [332] and the available U.S. locations for the reference buildings, yielding Seattle as the closest match for Amsterdam. This location match ensures adequate heating and cooling requirements. All data used are from the reference year 2014.

Demand profiles for the area of interest are based on building equivalents calculated. Let $D_{s,\chi}(t)$ denote the demand profile of service sector consumer s in the area of interest χ over time t, and let $D_{s,\mathrm{US}}(t)$ be the demand profile of the corresponding U.S. DOE Commercial Reference Building. Then,

$$D_{s,\chi}(t) = \epsilon_{s,\chi} \cdot D_{s,\mathrm{US}}(t) \tag{4.2}$$

Using Eq. 4.2, the demand profiles of all 13 service sector consumer types are modelled for an area represented by 100 000 Dutch households.

4.1.3 Household Demand Profile

Household demand data are obtained from [306]. This source describes electricity demand as a fraction of the annual demand, which is assumed to be 3 500 kWh based on data from [333]. The single household profile describes an *average* Dutch household [306].

4.2 Results – Heterogeneous Demand Profiles

The result of the proposed method is a collection of demand profiles of 13 service sector consumers. This collection is combined with the average Dutch household demand profile from [306]. All demand profiles have an hourly granularity and span an entire year. These profiles are available in an online dataset [315]. The following sections describe the resulting demand profiles in terms of their temporal heterogeneity.

4.2.1 Annual Demand Profiles

Figure 4.2 shows the annual demand profiles for 13 services and a single average Dutch households. Two types of temporal heterogeneity can be seen in the annual demand profiles: (1) seasonal heterogeneity for a single consumer, and (2) demand heterogeneity between consumers.

The most apparent seasonal demand heterogeneity is the difference between summer and winter months (respectively the middle and the edges of each panel). The transition between summer and winter months is sharper for some consumers (such as the Primary School) and more gradual for others (such as the Medium Office), while almost non-existent for a third category (*e.g.*, Warehouse). The differences between summer and winter months can be

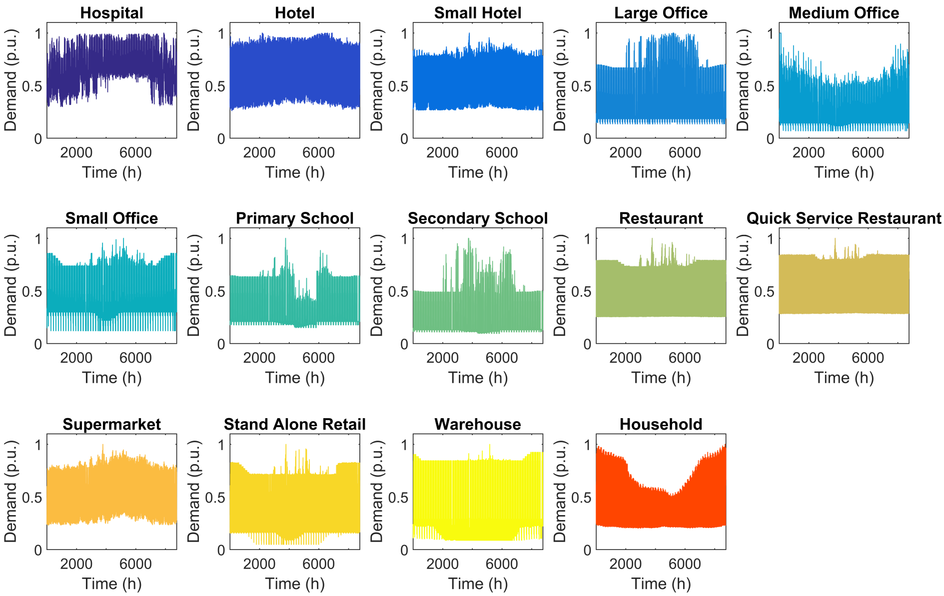


Figure 4.2 Annual profiles for 13 service sector and a single average household consumer. The time is expressed in hours, with hour 1 being 00:00-01:00 on the 1st of January 2014.

attributed to different factors, such as differences in energy services required, and differences in time spent inside. These factors differ between consumers due to their particular demand characteristics. The first factor, differences in required energy services, is most clear in the Large Office, where demand increases during the summer months due to increased demand for air conditioning[1]. Note that the Medium and Small Offices have a smaller or no summer peak, as air conditioning is more common in larger office buildings. Similarly, the Supermarket demand increases during the summer time due to higher demand for cooling (as the outside temperature is higher during this time of the year). The second factor, time spent inside, is visible in the profiles of the Primary School and the Household. Summer is a typical period for holidays, leading to decreased demand in both cases. Note that the Secondary School has an increase in demand during the summer, which can be attributed to the continued use of these buildings during the summer holidays, and the assumption of presence of air conditioning, the latter likely being an artefact of using U.S. buildings in a Dutch context. Finally, note that some consumers do not have pronounced differences in seasonal demand, including hotels and restaurants. This is noteworthy, as seasonal tourism can markedly increase the hotel and restaurant occupation and thus result in demand peaks. Unfortunately, such local phenomena cannot be captured based on the proposed approach, as they require more detailed, local data.

4.2.2 Average Daily Demand Profiles

Figure 4.2 shows the average weekday demand profiles for the same 13 service sector consumers and a single average Dutch household as described in the previous paragraph.

[1] Note that most of the heating is provided by gas in the Netherlands [334], which is reflected in the settings of the reference building models.

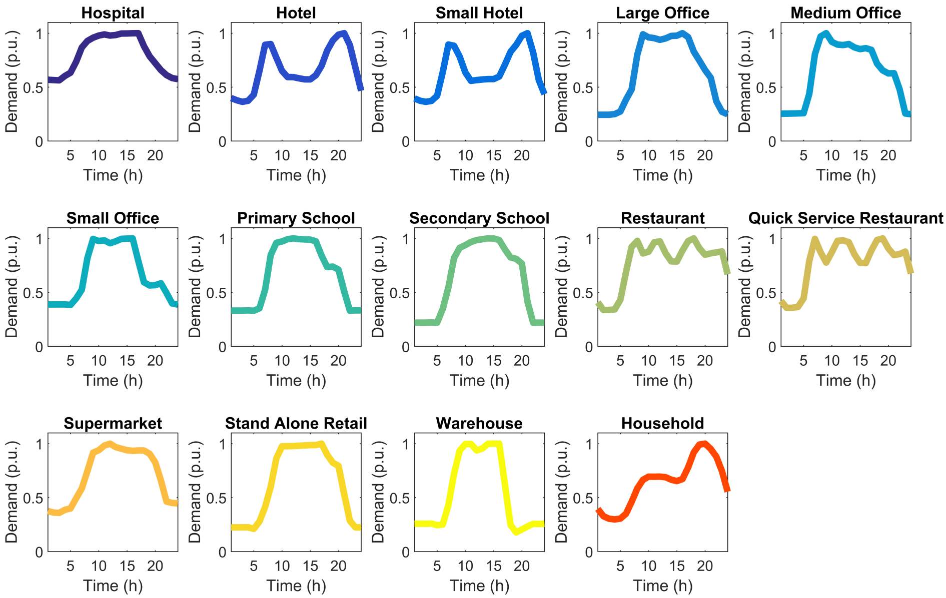


Figure 4.3 Average weekday profiles for 13 service sector and a single average household consumer.

On a daily basis, the same two types of temporal heterogeneity can be distinguished: (1) daily heterogeneity for a single consumer, and (2) demand heterogeneity between consumers.

Based on daily demand patterns, four groups of consumers can de differentiated. The first group is the group with a demand peak during the working hours. This group includes the Hospital, Offices, Schools, Shops, and Warehouses. The second group is comprised of Hotels and has a morning and an evening peak, as most guests spend their time outside the hotel during the day. The third group represents the Restaurants, with three peaks corresponding to the three main meal times. Note that the evening peak for this group has a longer tail than the two other peaks. The final group is the Household, with the typical evening peak.

4.3 Method Validation

The demand profiles from the previous section show that all services have a markedly different profile than the average household. This strengthens the intuition that using household demand profiles as a proxy for entire urban areas is not realistic. Moreover, the results also show that different types of service sector consumers should be taken into account, as demand profiles differ between the various services.

The main challenge of the proposed method is related to data. Although the method resolves the lack of local service sector demand profiles, to do so, it depends on non-energy related building-use data. Obtaining open building-use data which are comparable and reliable for both the Netherlands and the U.S. is not straightforward. This challenge is resolved in this thesis by using independent national databases whenever possible, consulting a large number of data sources, and cross-validating them if multiple sources are available (see references in Table 4.1 and in Appendix A). However, as discussed in Section 3.2.1.1, the use of archetype – or reference – buildings within a single country is challenging given the large diversity in buildings and lack of reliable statistical data [250–252]. This uncertainty is exacerbated when data from one country are used in the context of another.

The main issue with the proposed approach and the ensuing results is thus the question how accurately the building equivalents based on U.S. DOE Commercial Reference Buildings represent the service sector demand in the Netherlands. The best validation is arguably the comparison of the resulting synthetic profiles with statistically representative, real, measured profiles. However, such profiles are currently not publicly available. That is the very issue this thesis is seeking to overcome by estimating service sector profiles and showing the importance of the sector for renewable resource integration. Given the lack of measured data, the validation thus has to rely on a different approach. This approach has both a quantitative and a qualitative component as detailed below.

4.3.1 Quantitative Validation

The obtained results are compared with *cumulative* annual Dutch service sector demand data, which are openly available but do not suffice to assess the impact of the service sector on renewable resource integration. The Netherlands Environmental Assessment Agency attributes 43.8 TWh of the Dutch annual electricity consumption to the service sector, waste and wastewater treatment, and agriculture and fisheries combined [335]. Solely the service sector consumes 77% of this value [336], *i.e.*, 33.6 TWh. Statistics Netherlands reports service sector consumption of 30.6 TWh [337]. The service sector consumption in this chapter amounts to 26.9 TWh for the entire Netherlands, *i.e.*, 80% to 88% of the demand published by respectively the Netherlands Environmental Assessment Agency and Statistics Netherlands. The discrepancies in published data likely arise from the lack of unified definitions, an issue also raised by other researchers [119, 120, 220, 338] (see also Section 3.3.1).

This quantitative validation indicates that the service sector profile estimation approach used in this thesis can account for a substantial part of the Dutch service sector power demand. The remainder includes unaccounted for subsectors (*e.g.*, leisure), inaccuracies in subsector share estimations, and demand profile deviations.

4.3.2 Qualitative Validation

It remains an open question whether the use of U.S. buildings in the Dutch context causes deviations from real Dutch demand profiles. Perez-Lombard *et al.* [338] compare office energy end-use between U.S., Spain, and the U.K. End-use differences exist between the three countries. The differences between U.S. and the two European countries are however not larger than between the two European countries themselves. A similar qualitative conclusion can be drawn across the entire service sector by comparing the service sector end-use electricity consumption in the U.S. [339] and 29 European countries [121]. This suggests that using U.S. data for the Netherlands does not lead to larger errors than using data from another European country. Although undesirable, the practice of using data from other countries is currently common due to limited service sector data availability in the area of interest [31, 119].

Across countries, the *shape* of the aggregated service sector demand profile, with a peak during the day, is similar [119, 225, 338, 340]. Moreover, it markedly differs from the shape of household demand profiles, which typically peak in the evening [306, 341]. This observation qualitatively validates the use of U.S. profiles for the Dutch environment.

4.4 Conclusion

Urban areas consist of a mix of households and services, such as offices, shops, and schools. However, most urban energy models only consider household demand profiles, omitting the service sector. This is unrealistic, yet follows from the lack of detailed local service sector demand profiles. To the best of the author's knowledge, the most detailed, publicly available resource for service sector demand is the U.S. Department of Energy Commercial Reference Buildings database [225]. This database is used in combination with a large number of U.S. and Dutch non-energy related datasources to calculate *building equivalents*, *i.e.*, the number of U.S. buildings that is representative for corresponding Dutch buildings. Subsequently, building equivalents are used to estimate the demand profiles of Dutch service sector consumers. This chapter describes and implements the proposed method for an area represented by 100 000 Dutch households. The result is a collection of building equivalents for 13 service sector consumers and corresponding demand profiles, which are combined with a single average household demand profile (that is obtained without further conversion from [306]). This collection of demand profiles is available online [315]. All demand profiles have an hourly resolution and span an entire year. Although the lack of measured representative local demand profiles prevents an ideal validation of the building equivalents method, alternative validation approaches are satisfactorily carried out. The resulting building equivalents and demand profiles are used in Chapters 6, 7, and 8 to improve the understanding of the impact of the energy transition in urban areas. The following chapter describes an alternative approach to scale demand profiles, based on *scaling factors*. This approach allows for a more detailed representation of spatial demand heterogeneity, but, given the data available, results in a coarser representation of temporal heterogeneity. The choice between the two approaches depends on the application, as illustrated in Chapters 6 to 8.

5 Spatial Heterogeneity

> *I think it's very important that historic cities are allowed to reinvent their future.*
>
> – Zaha Hadid

Households and services are not evenly distributed across urban areas. Although some areas are characterised primarily by residential use, others feature a concentration of office buildings, yet others are shopping destinations. The different local composition of consumers leads to a spatial heterogeneity in electricity demand. The collective demand profiles of consumers within an area determine to a considerable extent how much renewable energy can directly be used locally, and how the local grid is impacted by renewable energy resources. Unfortunately, currently a systematic understanding of the demand profiles of urban areas is lacking in literature.

This chapter addresses this knowledge gap through modelling and classification of electricity demand of urban areas, taking into account both households and services. Urban energy demand is modelled bottom-up, based on the premise that the demand profile of an area equals the sum of the demand profiles of the energy consumers in that area [262, 263]. The temporal demand profiles of 14 types of consumers, developed in the previous chapter, are combined with data on the local distribution of these consumers, to construct spatio-temporal *urban* demand profiles. While the previous chapter is concerned with the temporal aspect of demand heterogeneity, this chapter focuses on the spatial dimension of spatio-temporal urban demand. The chapter consists of two parts. The first part, Section 5.1, describes a linear regression method for urban energy demand modelling. The second part, Section 5.2, details the classification of the resulting urban demand profiles. Figure 5.1 provides an overview of both modelling and classification parts.

5.1 Modelling of Urban Demand Profiles

The lack of detailed demand data is one of the main challenges in urban energy system modelling (see Chapter 3). Modelling electricity demand in urban areas therefore has to rely on a combination of the few datasets that are available. These datasets come from different sources, and their combination requires the application of data science techniques. The approach proposed and implemented in this chapter is a two-step method based on linear regression. The first block in Figure 5.1 shows these two steps. In the first step, the available datasets are made compatible with each other using linear regression. In the second step,

This chapter is based on previous publications [60] and [65].

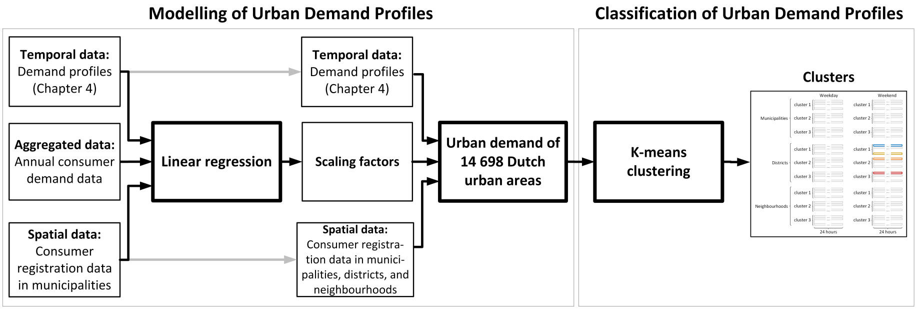


Figure 5.1 Flow diagram of modelling and classification of urban demand profiles. Modelling of urban demand profiles consists of a two-step approach. The first step is based on linear regression, which yields scaling factors used in the second step to model electricity demand in an urban area of interest. This step is applied to 14 698 urban areas in the Netherlands. The resulting urban demand profiles are classified using k-means clustering. The clusters are shown in more detail in Figure 5.4.

the regression coefficients (termed *scaling factors*) are used to model electricity demand of urban areas of interest. This step is applied to all 403 municipalities, 2 725 districts, and 11 570 neighbourhoods in the Netherlands (14 698 areas in total), and the resulting demand profiles are classified and analysed as described in Section 5.2.

5.1.1 Data

The two steps of urban demand modelling are based on similar datasets: (1) temporal demand profiles of individual consumers (from Chapter 4), and (2) spatial data that describe the local number of different consumers. In addition, the linear regression step requires a third dataset to calculate the regression coefficients: (3) aggregated annual demand data. All data used are from the reference year 2014.

5.1.1.1 Temporal Dimension Data

The temporal dimension is described by hourly household and service sector demand profiles from Chapter 4. These demand profiles are shown in Figures 4.2 and 4.3.

5.1.1.2 Spatial Dimension Data

To determine spatial consumer distribution, local registration data of households and services are used. These data are obtained from Statistics Netherlands [342, 343]. The data for the municipality scale are publicly available [343]. The datasets for district and neighbourhood scales are protected by privacy laws and are not publicly available [342], but could be accessed through a research agreement.

Solely the municipality-scale data are used in the linear regression step because aggregated annual demand data are only available at this urban scale (see further). The complete spatial dataset – neighbourhoods, districts and municipalities – is used to model the spatial heterogeneity of Dutch urban demand. The data cover 14 698 areas in the Netherlands: 11 570 neighbourhoods, 2 725 districts, and 403 municipalities.

Table 5.1 Summary of urban scale sizes in the Netherlands in terms of land area and annual (modelled) electricity demand.

	Municipality	**District**	**Neighbourhood**
Mean Area (*ha*)	8 680	1 097	255
Median Area (*ha*)	6 613	635	64
Maximum Area (*ha*)	46 005	24 748	12 821
Mean Demand (*GWh/y*)	102	15	3.5
Median Demand (*GWh/y*)	57	7.2	1.6
Maximum Demand (*GWh/y*)	1 972	428	97

The urban scales are defined as follows. **Municipalities** are the largest scale, and are defined by Dutch law. A municipality is the third level of government in the Netherlands, after the central and provincial government [344]. **Districts** are subdivisions of municipalities and are typically defined by a single prevailing land use. A district consists of one or multiple neighbourhoods. A **neighbourhood** is defined either based on socio-economic or historical resemblance, *i.e.*, a neighbourhood has a strong socio-economic coherence, or has been developed as a single area. Districts pertain to a single municipality, and neighbourhoods to a single district[1]. Both districts and neighbourhoods are defined by the municipal authorities. The defining factors can therefore differ between municipalities. The size of urban scales in terms of area and annual (modelled) electricity demand is given in Table 5.1.

5.1.1.3 Aggregated Demand Data

Aggregated demand data describe the real, *annual* demand of consumers [346]. These data are used to appropriately scale the temporal demand profiles, while respecting the spatial distribution of consumers. The temporal dimension data describe the demand profiles of physical buildings, *i.e.*, the demand profile of the 14 consumer types obtained in Chapter 4. The spatial dimension data describe the local number of consumers. The annual sum of the demand profiles of each consumer type, multiplied by the corresponding number of consumers needs to match the real, aggregated, annual demand data. Linear regression (see below) is used to guarantee this match.

5.1.1.4 Compatibility of Data

The datasets used to construct urban demand profiles come from different sources. Two issues need to be solved to make them mutually compatible.

Service sector subdivisions. No standardised classification of service sector consumers exists: data included and subdivisions considered differ between datasets. First, some datasets include certain subsectors, while others do not. For instance, the subsectors “Prison” and “Sports Facility” are included in the spatial dataset, but corresponding temporal demand data are lacking. These subsectors are therefore not considered in this thesis. Second, the

[1] Although municipalities, districts, and neighbourhoods are relatively stable, combinations or divisions occasionally occur [345]. As the reference year in this chapter is 2014, the areas as existed in 2014 are used.

Table 5.2 Comparison of 14 consumer types (Chapter 4), and six and seven consumer classes. The six consumer classes are based on the combination of temporal, spatial, and aggregated demand data. The seven consumer classes are based on temporal and spatial data. The number of consumer types and classes is determined by the combined datasets. Note that consumer types are referred to in the singular, and consumer classes in the plural.

14 Consumer Types (C)	Six Consumer Classes ($\dot{C}$)	Seven Consumer Classes ($\ddot{C}$)
Hospital	Hospitals	(–)*
Large Hotel	Cafés, Restaurants, and Hotels	Hotels
Small Hotel		
Restaurant		Cafés and Restaurants
Quick Service Restaurant		
Large Office	Offices	Offices
Medium Office		
Small Office		
Primary School	Schools	Schools
Secondary School		
Stand Alone Retail	Retail, Supermarkets, and Warehouses	Retail and Supermarkets
Supermarket		
Warehouse		Warehouses
Household	Households	Households

**Hospitals are omitted in the urban demand classification due to low R^2-value of the corresponding scaling factor obtained in the linear regression step (see Section 5.1.2.2).*

service sector subdivisions differ between datasets. The degree of correspondence between the subdivisions of different datasets determines the number of consumer classes that can be distinguished when datasets are combined. Table 5.2 provides an overview of the correspondence between the 14 consumer types from Chapter 4, the six consumer classes that can be distinguished based on the combination of temporal, spatial, and aggregated demand data, and the seven consumer classes that can be distinguished based on temporal and spatial data. Tables B.1 and B.2 provide more detail.

The demand profiles of the seven consumer classes $\ddot{C}$ are calculated based on the demand profiles of the 14 consumer types C. Let C'' be the set of consumer types c corresponding to consumer class $\ddot{c}$. The demand profile $D_{\ddot{c}}(t)$ of consumer class $\ddot{c}$ is then given by:

$$D_{\ddot{c}}(t) = \sum_{c \in C''} \omega_c \cdot D_c(t) \tag{5.1}$$

with ω_c the weighting factors based on the relative occurrence of the building equivalents, as shown in Table 4.1. For instance, the demand profile of consumer class "Offices" is calculated based on the demand profiles of consumer types "Large Office", "Medium Office", and "Small Office", which are weighted by respectively 0.097, 0.758, and 0.145.

Differences in dataset domains. Different datasets refer to different *domains*: physical buildings, administrative entities, and subsectors. The temporal demand profiles pertain to *physical buildings* (data expressed in kWh/h per building) [225, 306]. The spatial consumer composition data pertain to *administrative entities*: households and services (data expressed in number of administrative entities in a given area) [342, 343]. The aggregated annual consumer demand describes electricity demand of *subsectors* (*e.g.*, healthcare) (data expressed in MWh/year per subsector) [346]. Linear regression is used to relate data from these different domains to each other. Note that linear regression also takes into account the difference in building sizes between the U.S. and the Netherlands. Linear regression is thus an alternative approach to the building equivalents from Chapter 4. The main difference between the two approaches is the data used to determine the scaling. Linear regression relies on electricity demand data. The building equivalents approach is based on building use data. Moreover, linear regression results in a higher spatial granularity (municipality-scale instead of average national scale), but has a lower degree of temporal heterogeneity detail (seven consumer classes instead of 14 consumer types).

5.1.2 Linear Regression

Linear regression is used to combine datasets with different domains. Specifically, it makes sure that the annual sum of the temporal demand profiles of different consumers (physical buildings) multiplied by the respective number of consumers (administrative entities) equals the real measured demand of the corresponding subsector. Linear regression coefficients – scaling factors – are calculated to this purpose. These scaling factors are determined for each of the seven consumer classes in Table 5.2.

Formally, let $D_{\ddot{c}}(t)$ be the temporal demand profile of consumer class $\ddot{c}$. Let $n_{\ddot{c},\mu}$ be the number of consumers of class $\ddot{c}$ in municipality $\mu \in M$. Note that both datasets are available for seven consumer classes. Let $\bar{D}_{\dot{c},\mu}$ be the aggregated annual demand of consumer class $\dot{c}$. These data are available for six consumer classes. Linear regression allows for the calculation of multiple regression coefficients within a single consumer class $\dot{c}$. Thus, for the set of consumers $\ddot{C}'$ that corresponds to consumer class $\dot{c}$, the scaling factors $\beta_{\ddot{c}}$ are obtained through linear regression as follows:

$$\bar{D}_{\dot{c},\mu} = \sum_{\ddot{c} \in \ddot{C}'} \left(\beta_{\ddot{c}} \cdot n_{\ddot{c},\mu} \cdot \sum_{t=1}^{8760} D_{\ddot{c}}(t) \right) \tag{5.2}$$

For example, separate scaling factors are calculated for consumer class “Hotels” and for consumer class “Cafés and Restaurants”, although annual measured demand data are only available for the combined class “Cafés, Restaurants, and Hotels” (see Tables 5.2 and 5.3).

5.1.2.1 Calibration and Validation

The linear regression model is calibrated and validated using data for 383 municipalities. These are the municipalities for which both local consumer composition and cumulative annual consumer demand data are available. Municipalities are randomly assigned to a training and a test dataset, such that the training dataset contains 268 (70%), and the test dataset 115 (30%) municipalities. The coefficients $\beta_{\ddot{c}}$ are estimated based on the training dataset, their predictive power is validated using the test dataset using R^2 as fitness metric.

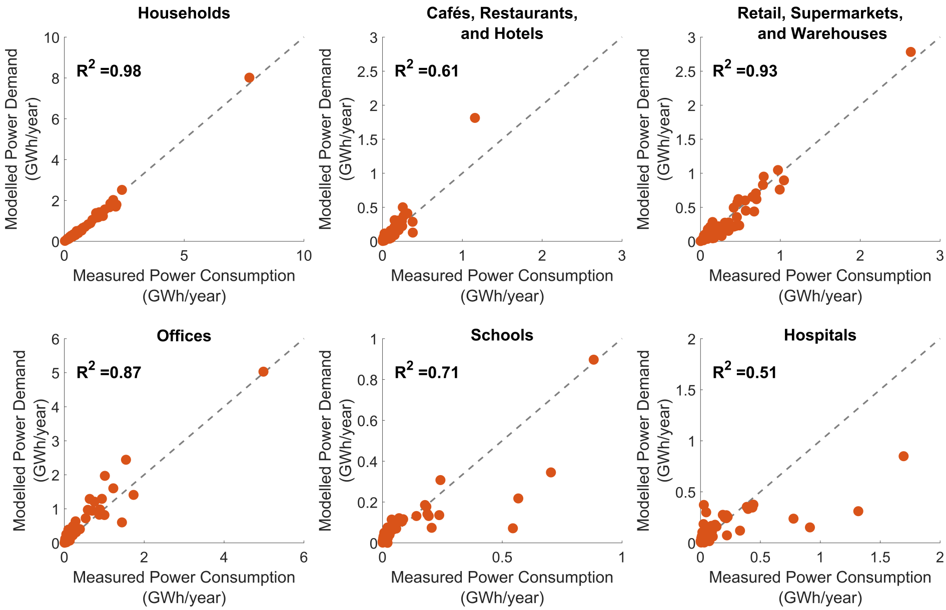


Figure 5.2 Scatter plots for six consumer classes for 115 Dutch municipalities (test dataset). Each plot shows how well the modelled annual electricity demand matches the measured electricity demand. R^2 is used as fitness metric, and reported for each consumer class. Copyright © 2018 IEEE.

5.1.2.2 Scaling Factors

Figure 5.2 shows scatter plots of modelled versus measured annual demand for six consumer classes for 115 municipalities from the test dataset. Modelled annual demand is the right-hand side of Eq. 5.2, and measured annual demand the left-hand side. The resulting scaling factors $\beta_{\ddot{c}}$ are summarised in Table 5.3, alongside with R^2-values, for both the training and test datasets. The scaling factors are part of the dataset that accompanies this thesis [315].

Table 5.3 Scaling factors and R^2-values for seven consumer classes. Copyright © 2018 IEEE.

Consumer Class	Scaling Factor	R^2 Training	R^2 Test
Households	0.74	0.97	0.98
Cafés & Restaurants / Hotels	0.25 / 0.002	0.81	0.61
Retail & Supermarkets / Warehouses	0.06 / 0.05	0.87	0.93
Offices	0.10	0.91	0.87
Schools	0.12	0.76	0.71
Hospitals*	0.01	0.43	0.51
Total	(-)	0.97	0.99

**Hospitals are omitted in the remainder of this chapter due to low R^2-values of the corresponding scaling factor.*

The scaling factors in Table 5.3 are all less than 1 due to domain differences between the datasets. The following examples provide intuition. First, a single service sector building can house multiple administrative units, for instance, a single office building can house 10 different companies, yielding a scaling factor of 0.1. Second, a relatively large reference building can be used to simulate electricity demand of smaller administrative units. For instance, the electricity consumer class "hotels" includes small lodging rooms and bed-and-breakfasts, yielding a very low scaling factor. Third, for households a conceptual difference exists between the temporal dataset that describes physical demand profiles, and the spatial that contains administrative data. From a physical perspective, a "household" is determined by a unit with a single electricity meter. From the administrative perspective, a "household" is one or multiple people living at the same address. Some residential buildings in the Netherlands do not have individual meters for each apartment, thus, although multiple administrative households live in that building, it is characterised as a single physical household. The calculated scaling factors overcome these domain differences.

Moreover, note that the scaling factors further incorporate the difference between U.S. and Dutch building sizes, and thus can be used as an alternative for the building equivalents calculated in Chapter 4. The building equivalents can be calculated for all 13 different service sector consumer types separately, while, based on the available data, scaling factors can be determined only for six service sector consumer classes (excluding hospitals). The choice between the two approaches thus depends on the application, in particular whether the focus is on temporal or spatial demand heterogeneity. The application of both building equivalents and scaling factors is illustrated in Chapters 6 to 8.

R^2-values (Figure 5.2 and Table 5.3) represent the share of variability explained by the regression model. Most of the obtained R^2-values vary between 61% and 98%, with lower-end values for broader and more diverse classes (*e.g.*, cafés, restaurants, and hotels). Hospitals have a relatively low R^2-value of 51% (for the test set). Hospital electricity demand is known to be challenging to model [347]. Obtained R^2-values are compared to values in literature. Fonseca and Schlueter [257] report building-level electricity model errors of 4% to 66%, and area-level electricity model errors of 1% to 19% [257]. Mastrucci *et al.* [260] use linear regression to downscale electricity demand from postcode-level to building-level, obtaining an R^2-value of 81.7% [260]. The method proposed in this chapter thus yields a regression model with a predicted variability similar to, or higher than, that of comparable models.

5.1.3 Urban Demand Simulation

The scaling factors obtained through linear regression are used to model electricity demand in areas of interest. In this chapter, areas of interest are 14 698 Dutch neighbourhoods, districts, and municipalities.

Formally, let $D_\gamma(t)$ be the demand profile for urban area γ, modelled over time t. This profile is calculated as follows:

$$D_\gamma(t) = \sum_{\ddot{c} \in \ddot{C}} \beta_{\ddot{c}} \cdot n_{\ddot{c},\gamma} \cdot D_{\ddot{c}}(t) \tag{5.3}$$

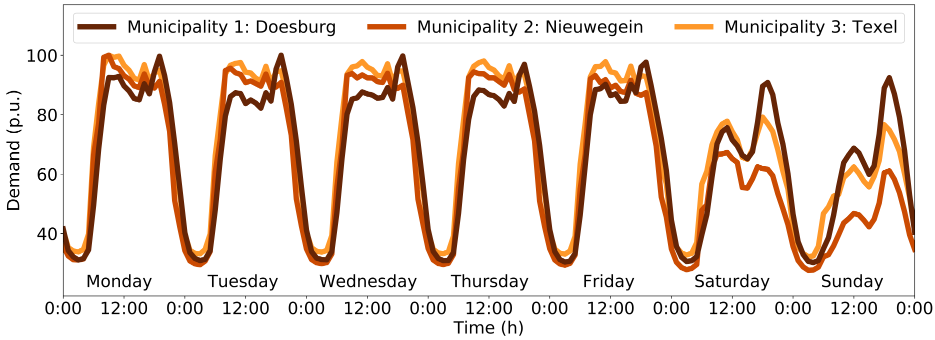


Figure 5.3 Modelled electricity demand profiles for three Dutch municipalities from the test dataset for one week (24th February until 2nd March 2014). Copyright © 2018 IEEE.

Note that $\ddot{C}$ is the set of the *seven* consumer classes obtained from the combination of the temporal and spatial datasets (see Table 5.2, and Table B.2 for more details). The result of urban demand simulation is illustrated in Figure 5.3 for three municipalities (Doesburg, Nieuwegein, and Texel) for one week (February 24th until March 2nd, 2014). Note that Figure 5.3 shows *per-unit* (p.u.) demand profiles, *i.e.*, demand profiles scaled to their peak. Such demand profiles are calculated for all 403 Dutch municipalities, their constituting 2 725 districts and 11 570 neighbourhoods. The demand profiles of all these urban areas are classified and analysed as described in the next section.

5.2 Classification of Urban Demand Profiles

The classification analysis covers a large dataset of thousands of Dutch urban areas: hundreds of municipalities, and thousands of districts and neighbourhoods within those municipalities. The scale of the dataset and the goal of the analysis – classification of urban demand profiles into *archetypes* and their subsequent comparison – mandates the use of data analysis techniques. *Clustering* is an established approach for this type of problems: it is a collective term for a range of unsupervised algorithms that classify patterns into groups (clusters) [348]. Here, patterns are spatio-temporal demand profiles at different urban scales, and groups are archetypes of similar urban spatio-temporal demand profiles.

5.2.1 Clustering Techniques for Urban Demand Modelling

Clustering is a technique that has been frequently used for classification of electricity demand profiles. It has been mostly applied to gain insights in large databases of *individual* consumer demand profiles for the purpose of improving utilities' understanding of their consumers demand and for subsequent adjustment of billing tariffs.

A number of authors [309, 310, 349, 350] have proposed and implemented different clustering algorithms. Gerbec *et al.* [310] use fuzzy c-means clustering algorithm to allocate consumers demand profiles to service sector consumers with specific economic activities [310]. Pitt and Kirschen choose a combination of four algorithms: one-pass clustering, binary splitting algorithm, iterative join-two algorithm, and exhaustive binary search for database knowledge discovery purposes [309]. Figueiredo *et al.* apply solely C5.0 clustering algorithm for the same purposes [349]. Räsänen *et al.* use k-means clustering for load forecasting [350]. Lamedica *et al.* have developed a tool based on clustering techniques for the identification of outliers in demand profiles at the high to medium voltage substation level. The tool offers both traditional and hierarchical algorithms [351].

In contrast to the authors above, Yamaguchi *et al.* apply clustering to *districts*, with Osaka, Japan, as a case study. However, the authors base their clusters on commercial floor space instead of on demand profiles. In their paper, the authors compare clustering based on single buildings and on districts as clustering units [308]. Finally, Chicco provides a comprehensive review of clustering techniques used for electrical load pattern grouping, comparing the most commonly used clustering techniques and cluster validity indicators [352]. The following section follows the general methodology described by Chicco, delineating the details of the clustering technique and data used in this section.

5.2.2 Methods

The approach used for urban areas follows existing procedures for classification and analysis of individual consumers demand profiles [352]. This approach consists of four phases: (1) data gathering and processing, (2) pre-clustering, (3) clustering, and (4) post-clustering. The novel aspect of this thesis is the application of this approach to demand profiles of *urban areas* instead of individual consumers.

5.2.2.1 Data Gathering and Processing

The data gathering and processing phase corresponds to the modelling of urban demand profiles based on the two-step method described above. One additional processing step is taken: the single-year temporal demand profiles of urban areas are divided into working days (Monday to Friday) and weekends (Saturday, Sunday, and holidays)[2]. This conversion is similar to [264, 310, 352, 353] and serves here the purpose of reducing the problem size and thus solution time for the subsequent clustering phase [349, 350].

5.2.2.2 Pre-clustering Phase

In the pre-clustering phase, the datasets are prepared to be used as input for the clustering algorithm. The clustering algorithm classifies so-called *patterns*. Thus, the available data need to be defined in terms of such patterns. For the purpose of clustering, each pattern is typically described by a so-called *feature vector*. The individual scalar components of the feature vector are called *features* [348].

The feature vector is the demand profile of a single area (a neighbourhood, district, or municipality) for one of the two day types (weekday or weekend). Let $\Gamma = M \cup Z \cup V$ be the set of urban areas at three urban scales, with M the set of municipalities, Z the set of districts, and V the set of neighbourhoods. Let T be the set of the two day types

[2] Seasonal demand variation is not taken into account for the following reason. The average deviation between seasonal and annual demand profiles for both weekdays and weekends is limited to 10% to 20%. Splitting the dataset in different seasons decreases the number of data points available in each data subset, thus decreasing the power of subsequent statistical tests and increasing the likelihood of finding false positives.

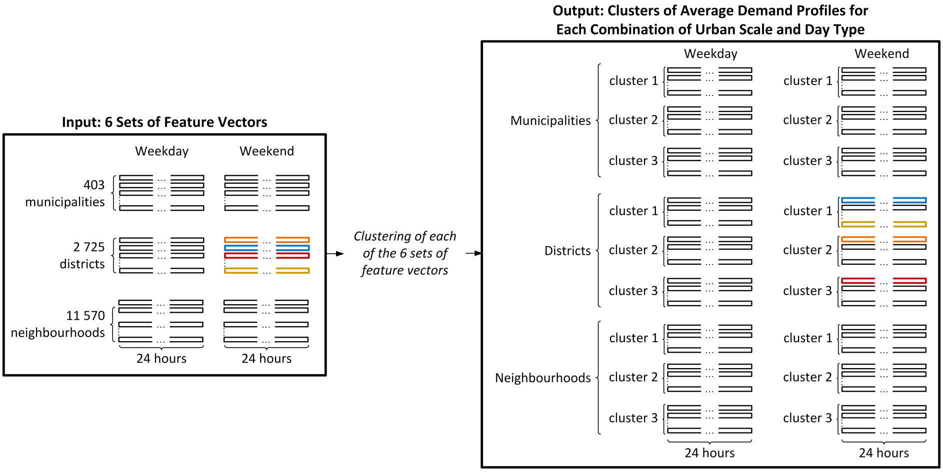


Figure 5.4 Flow diagram of the clustering phase. Clustering is carried out six times, once for each combination of day type (weekday and weekend) and urban scale (municipality, district, and neighbourhood). At each urban scale, and for each day type, three clusters of 24-hour demand profiles can be distinguished. These clusters are analysed in the post-clustering phase. The analysis results are shown in Figures 5.4 to 5.12.

$\tau \in \{\texttt{weekday, weekend}\}$. For each of the six combinations of urban scale and day type (γ, τ), the 24-hour spatio-temporal demand profile of area γ is described by the feature vector $D_{\gamma,\tau} = \{d^1_{\gamma,\tau}, \ldots, d^h_{\gamma,\tau}, \ldots, d^{24}_{\gamma,\tau}\}$ with $d^h_{\gamma,\tau}$ the individual features. The feature vector $D_{\gamma,\tau}$ is the demand profile of urban area γ for day type τ. This formulation is an extension of the approach in [349].

The feature vector $D_{\gamma,\tau}$ is calculated as follows. Let $D_{\ddot{c},\tau}$ be the 24-hour demand profile of consumer class $\ddot{c}$ on day type τ. Let $n_{\ddot{c},\gamma}$ be the number of consumers of class $\ddot{c}$ in urban area γ. This area-specific demand profile equals the sum of the demand profiles of the different consumer classes multiplied by the respective scaling factor, and by the respective number of consumers in the area in question:

$$D_{\gamma,\tau} = \sum_{\ddot{c} \in \ddot{C}} \beta_{\ddot{c}} \cdot n_{\ddot{c},\gamma} \cdot D_{\ddot{c},\tau} \tag{5.4}$$

The aim of clustering is classification of spatio-temporal demand profiles in terms of their shape. For this purpose, profiles need to be normalised using a suitable normalising factor. The maximal electricity demand of the spatio-temporal demand profiles $D_{\gamma,\tau}$ is used as the normalising factor (similarly to [310, 349, 352]), yielding per-unit profiles $\tilde{D}_{\gamma,\tau}$, which are called *representative load patterns* (RLPs):

$$\tilde{D}_{\gamma,\tau} = \frac{D_{\gamma,\tau}}{\max(D_{\gamma,\tau})} \tag{5.5}$$

In this thesis, RLPs are used as clustering feature vectors.

Algorithm 5.1: K-means clustering

Choose k cluster centres: The centres are k feature vectors randomly chosen from the set of feature vectors

while *feature vectors are reassigned to new cluster centres, or squared error is larger than a pre-set value* **do**

  Assign each feature vector to the closest cluster centre

  Recompute the cluster centres using the new cluster memberships

end

5.2.2.3 Clustering Phase

Clustering is an established unsupervised data analysis technique used for classification of patterns (in this case, spatio-temporal demand profiles) into groups called *clusters* [348]. The input and output datasets of the clustering phase are shown in Figure 5.4. Several clustering algorithms exist. This thesis uses the k-means algorithm. This choice is based on the comparison of clustering algorithms by Chicco [352], which shows that k-means clustering yields clusters populated in a relatively uniform way, contrary to other methods such as hierarchical clustering, that tend to isolate outliers and group the remaining patterns in a single large group. The choice for k-means clustering is in line with the purpose of this thesis to find areas with similar demand profiles and within the same order of magnitude. Moreover, k-means clustering is often computationally faster than other algorithms [352]. Thus, k-means clustering is chosen for the type of clusters it yields and its computational speed. The implemented k-means clustering algorithm is described by Algorithm 5.1 [348].

The k-means clustering algorithm requires an *a priori* choice of the number of clusters k. To determine the optimal number of clusters, a so-called *cluster validity index* (CVI) is calculated for a range of cluster numbers. The CVI used in this thesis is the Davies-Bouldin index (*DBI*) [354], chosen because it provides a good balance between cluster compactness and separation [350, 355]. The Davies-Bouldin index for k cluster centres is defined as follows:

$$DBI(k) = \frac{1}{k}\sum_{i=1}^{k} \max_{i \neq j} \left\{ \frac{l_i + l_j}{g_{i,j}} \right\}, \quad \text{for } i, j = \{1, \dots, k\} \tag{5.6}$$

where l_i is the within-cluster distance of cluster i, and $g_{i,j}$ the between-cluster distance for clusters i and j. The distances are defined as:

$$l_i = \frac{1}{|i|} \sum_{q_i \in i} ||q_i - m_i|| \tag{5.7}$$

$$g_{i,j} = ||m_i - m_j|| \tag{5.8}$$

where q_i is a feature vector[3] in cluster i, m_i is the centre of the cluster i, and $|i|$ is the number of elements in cluster i. The notation $||q_i - m_i||$ represents the Euclidean distance between vectors q_i and m_i [348, 354].

[3] Note that q_i in Eq. 5.7 and $\tilde{D}_{\gamma,\tau}$ in Eq. 5.5 refer to the same feature vectors, but emphasise different aspects. The notation q_i indicates the cluster membership and thus the result of clustering, while the notation $\tilde{D}_{\gamma,\tau}$ expresses the feature vector construction from the available data, and thus the input for clustering.

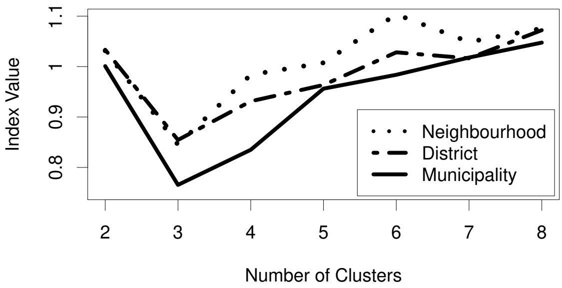


Figure 5.5 Davies-Bouldin indices for three urban scales (neighbourhood, district, and municipality) for day type weekday. The optimal number of clusters is determined by the lowest index value, which is 3 for all the urban scales.

Davies-Bouldin indices are calculated for all combinations of urban scale and day type. The result for day type weekday is shown in Figure 5.5. The optimal number of clusters is 3 for all urban scales. This is also the optimal number of clusters for day type weekend for neighbourhoods and districts. The optimal number of clusters for municipalities on weekends is 2, however, for consistency and to ease comparison, the number of clusters is chosen to be 3 for all combinations of urban scale and day type.

5.2.2.4 Post-clustering Phase

The post-clustering phase covers the analysis of the spatio-temporal demand profile classification obtained through clustering. It consists of characterisation and statistical analysis of the clusters obtained at all urban scales.

Characterisation. Each combination of urban scale and day type is characterised in terms of (1) its daily demand profile, and (2) the annual demand of the seven consumer classes analysed.

Statistical analysis. Overall and pairwise statistical comparisons of the demand profiles and annual consumer demand compositions are carried out. As the distributions are non-normal, parametric statistical tests are used. The Kruskal-Wallis test is used for the overall comparison, followed by the Mann-Wilcoxon-Whitney test for the pairwise comparison [356]. To avoid increasing the likelihood of Type I errors (*i.e.*, finding false positives), all tests are subject to a Bonferroni correction [356]. The family-wise error rate is kept at 5% by correcting for 288 comparisons for demand profiles and for 84 comparisons for consumer annual demand composition.

5.2.2.5 Logistic Regression

The clustering analysis as described above is based on detailed local households and services registration data. Such data are often not available to other researchers (for this thesis, the data could be accessed by the author through a research agreement with Statistics Netherlands). To facilitate the application of the results and insights obtained through clustering by other researchers, a logistic regression model has been developed. This model is available as a spreadsheet tool and can be found online, in the addendum of the publication upon which this chapter is based [60], and in the dataset accompanying this thesis [315].

The logistic regression model in the spreadsheet tool determines the probabilities that an urban area of interest belongs to each of the three clusters, based solely on relative annual demand data of different consumer classes. Such annual demand data are more frequently publicly available than detailed local households and services registration data. Relative annual demand data reflect local consumer composition. This thesis shows that this consumer composition differs significantly between each two pairs of clusters, for each combination of urban scale and day type (see below).

The logistic regression model is built for each of the six combinations of day type (weekday and weekend) and urban scale (municipality, district and neighbourhood), mirroring the clustering analysis. For each combination, 70% of the data points are used for logistic regression model calibration, and 30% for its validation. The model correctly classifies over 98% of the areas from the validation dataset. Formally, the logistic regression model determines the probability **P** that an urban area χ at urban scale γ on day type τ belongs to each of clusters {`residential, business, mixed`}:

$$\mathbf{P}(\chi \in \texttt{residendial}) = 1 \cdot (1 + \exp v_{\gamma,\tau} + \exp w_{\gamma,\tau})^{-1} \tag{5.9}$$

$$\mathbf{P}(\chi \in \texttt{business}) = \exp v_{\gamma,\tau} \cdot (1 + \exp v_{\gamma,\tau} + \exp w_{\gamma,\tau})^{-1} \tag{5.10}$$

$$\mathbf{P}(\chi \in \texttt{mixed}) = \exp w_{\gamma,\tau} \cdot (1 + \exp v_{\gamma,\tau} + \exp w_{\gamma,\tau})^{-1} \tag{5.11}$$

where $v_{\gamma,\tau}$ and $w_{\gamma,\tau}$ are given by:

$$v_{\gamma,\tau} = \log\left(\frac{\mathbf{P}(\chi \in \texttt{business})}{\mathbf{P}(\chi \in \texttt{residential})}\right) = \kappa_{0,\gamma,\tau} + \sum_{\ddot{c}} \kappa_{\ddot{c},\gamma,\tau} \cdot \bar{X}_{\ddot{c},\gamma} \tag{5.12}$$

$$w_{\gamma,\tau} = \log\left(\frac{\mathbf{P}(\chi \in \texttt{mixed})}{\mathbf{P}(\chi \in \texttt{residential})}\right) = \lambda_{0,\gamma,\tau} + \sum_{\ddot{c}} \lambda_{\ddot{c},\gamma,\tau} \cdot \bar{X}_{\ddot{c},\gamma} \tag{5.13}$$

with $\kappa_{0,\gamma,\tau}$, $\kappa_{\ddot{c},\gamma,\tau}$, $\lambda_{0,\gamma,\tau}$, and $\lambda_{\ddot{c},\gamma,\tau}$ regression coefficients calculated from Dutch neighbourhoods, districts and municipalities data; and $\bar{X}_{\ddot{c},\gamma}$ the relative annual consumer demand for consumer class $\ddot{c}$ in the urban area γ, to be provided by the user of the spreadsheet tool.

The model can be used to determine the type of area (residential, business, or mixed) and its average weekday and weekend demand profile for an urban area based solely on the relative annual demand of the different consumer classes in that area.

5.2.3 Results

Overall, the results show that three types of clusters can be distinguished for all three urban scales, to which this thesis refers as *residential*, *business*, and *mixed* clusters. The cluster names are based on the most prevalent consumer classes in each of the clusters: households in the residential cluster, offices in the business cluster, and mixed consumers in the mixed cluster. The following paragraphs describe the results in more detail in terms of demand profiles, consumer composition (expressed as relative annual demand), and the relative importance of clusters at the different urban scales. The results are published in the accompanying dataset [315].

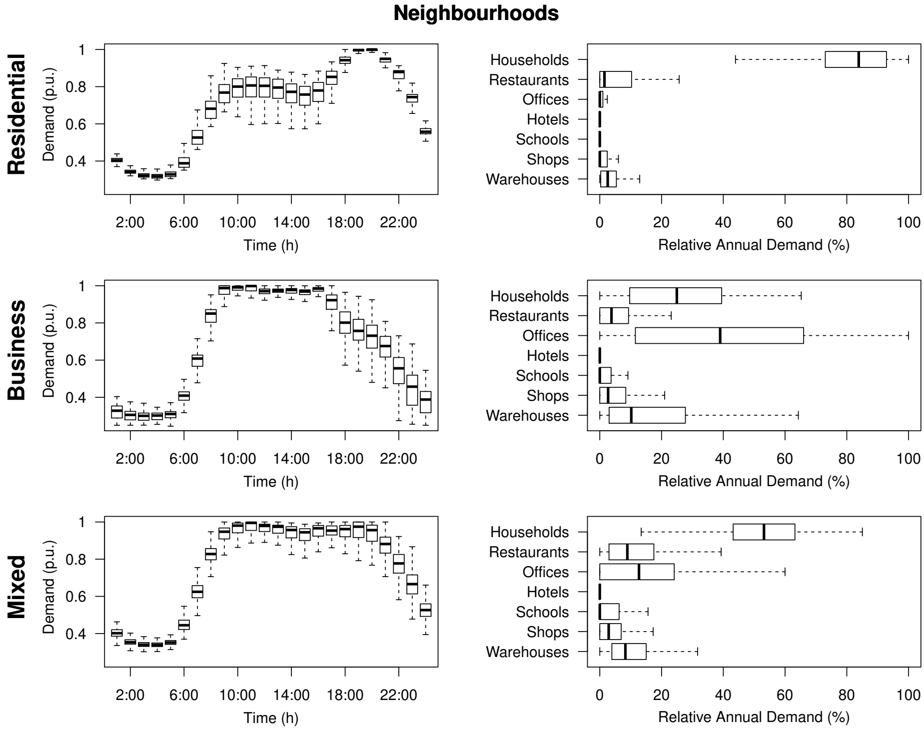


Figure 5.6 Characterisation of clusters at the neighbourhood scale. Left panels show the per unit (p.u.) demand profiles, right panels the consumer composition in terms of relative annual demand. The three rows represent the three clusters. Clusters are formed based on similarity of weekday spatio-temporal demand profiles. Both profiles and consumer compositions are shown as boxplots, with the middle line representing the median, the boxplot edges the 25% and 75% percentiles, and the whiskers the minima and maxima. Due to privacy rules of Statistics Netherlands [342], outliers are not shown.

5.2.3.1 Cluster Demand Profiles and Composition

Figures 5.6 to 5.8 show the demand profiles and consumer composition of different clusters at three urban scales for weekdays. Weekend results are shown only for neighbourhoods in Figure 5.9, as the trends for districts and municipalities are similar (see below). The following paragraphs first describe the results within one urban scale, then provide the results of the statistical analysis, and finally compare the three urban scales and the two day types.

Single Urban Scale Profile and Composition. Within one urban scale, three clusters are distinguished: residential, business and mixed. Both on weekdays (Figures 5.4 - 5.8) and on weekends (Figure 5.9), the *residential cluster* (upper row on all figures) has a demand profile similar to that of an average household, *i.e.*, with a peak in the evening hours. The residential cluster contains areas in which the largest part of the annual electricity demand is consumed by households (*e.g.*, a median of 84% at the neighbourhood scale on weekdays, see Figure 5.4, right upper panel).

The *business cluster* has a demand profile with a plateau between 9:00 and 16:00 on weekdays, with decreasing demand in the evening hours. On weekends, demand starts decreasing

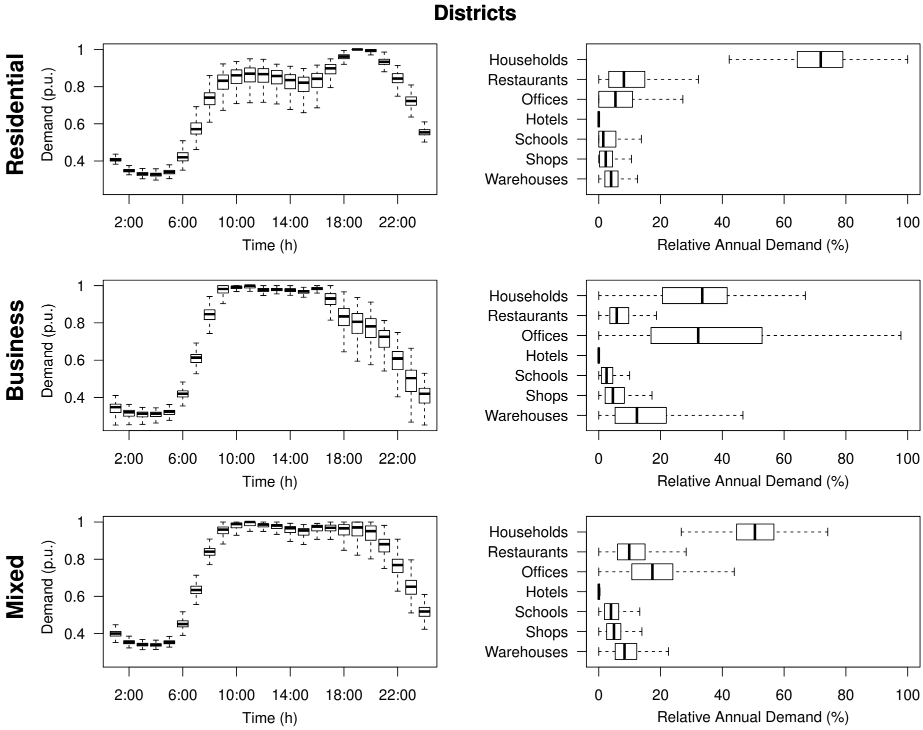


Figure 5.7 Characterisation of clusters at the district scale. Left panels show the per unit (p.u.) demand profiles, right panels the consumer composition in terms of relative annual demand. The three rows represent the three clusters. Clusters are formed based on similarity of weekday spatio-temporal demand profiles. Both profiles and consumer compositions are shown as boxplots, with the middle line representing the median, the boxplot edges the 25% and 75% percentiles, and the whiskers the minima and maxima. Due to privacy rules of Statistics Netherlands [342], outliers are not shown.

earlier, from 14:00. The business cluster contains areas in which the largest part of the annual electricity demand is consumed by offices (*e.g.*, a median of 39% at the neighbourhood scale on weekdays, see Figure 5.4, right middle panel).

Finally, the *mixed cluster* has a demand profile with a double-peak between 9:00 and 20:00. The peaks are more pronounced on weekends than on weekdays. The mixed cluster contains areas in which the largest part of the annual electricity demand is consumed by households (*e.g.*, a median of 53% at the neighbourhood scale on weekdays, see Figure 5.4, right bottom panel). However, the relative share of the annual demand of households is considerably smaller than in the residential cluster, with a higher share of demand attributed to all other consumer classes, in particular restaurants, offices, and warehouses.

Statistical Analysis. Statistical analysis of **demand profiles** at each urban scale shows that the differences are significant between nearly all pairs of clusters, both on weekdays and on weekends. At the *neighbourhood scale*, on weekdays, p-values of all pair-wise profile comparison tests are smaller than the family-wise cut-off p-value of 5.21×10^{-4}. At the *district scale* on weekdays, all pairs of clusters are statistically different (p-value less than

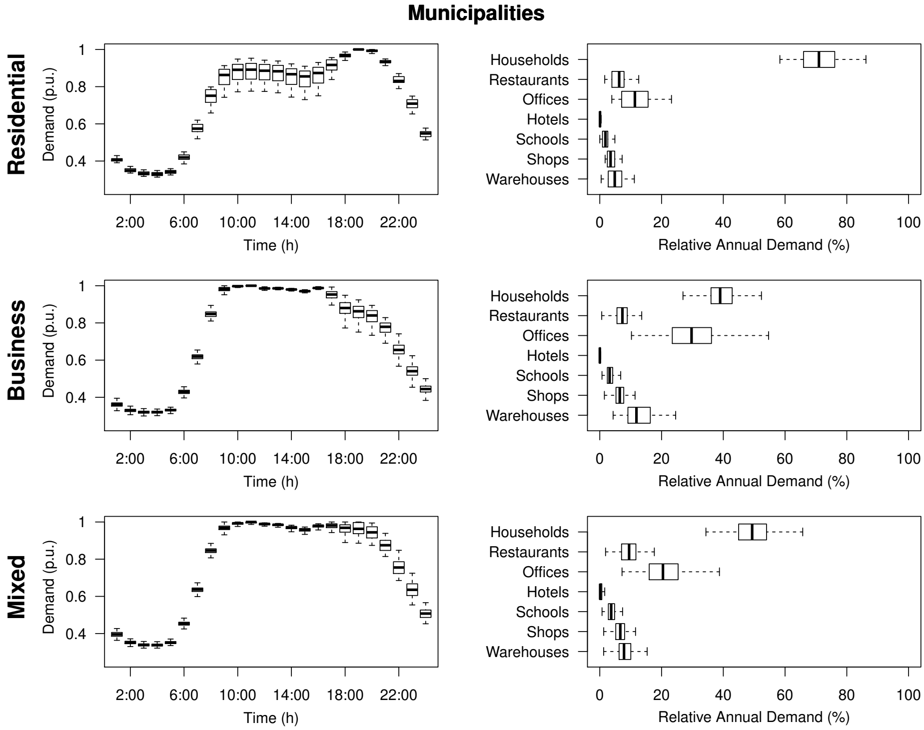


Figure 5.8 Characterisation of clusters at the municipality scale. Left panels show the per unit (p.u.) demand profiles, right panels the consumer composition in terms of relative annual demand. The three rows represent the three clusters. Clusters are formed based on similarity of weekday spatio-temporal demand profiles. Both profiles and consumer compositions are shown as boxplots, with the middle line representing the median, the boxplot edges the 25% and 75% percentiles, and the whiskers the minima and maxima. Due to privacy rules of Statistics Netherlands [342], outliers are not shown.

5.21×10^{-4}), except the residential and business clusters at 6:00, the business and mixed clusters at 11:00 and 14:00, and the residential and mixed clusters at 18:00. At the *municipality scale* on weekdays, clusters are pairwise statistically different (p-value less than 5.21×10^{-4}), with a few exceptions, namely mixed and residential clusters at 2:00 and 18:00, and business and mixed clusters at 8:00 and 13:00. On weekends, pairwise statistical difference in profiles is similarly found for nearly all hours and all cluster pairs.

Statistical analysis of **consumer composition** shows that most clusters are pairwise statistically different on all urban scales and for both day types. At the *neighbourhood scale* on weekdays, statistically significant distinction can be made between all cluster pairs for all consumer classes in terms of their annual demand (family-wise cut-off p-value of 1.78×10^{-3}). On weekends, annual energy demand by different user types is significantly different, except for that of hotels in the residential and business clusters. At the *district scale*, both on weekdays and on weekends, all clusters are pairwise statistically different (family-wise cut-off p-value of 1.78×10^{-3}), except for the annual demand of hotels in residential and business clusters, and the annual demand of shops in business and mixed clusters. At the *municipality scale* on weekdays and weekends, most clusters are statistically

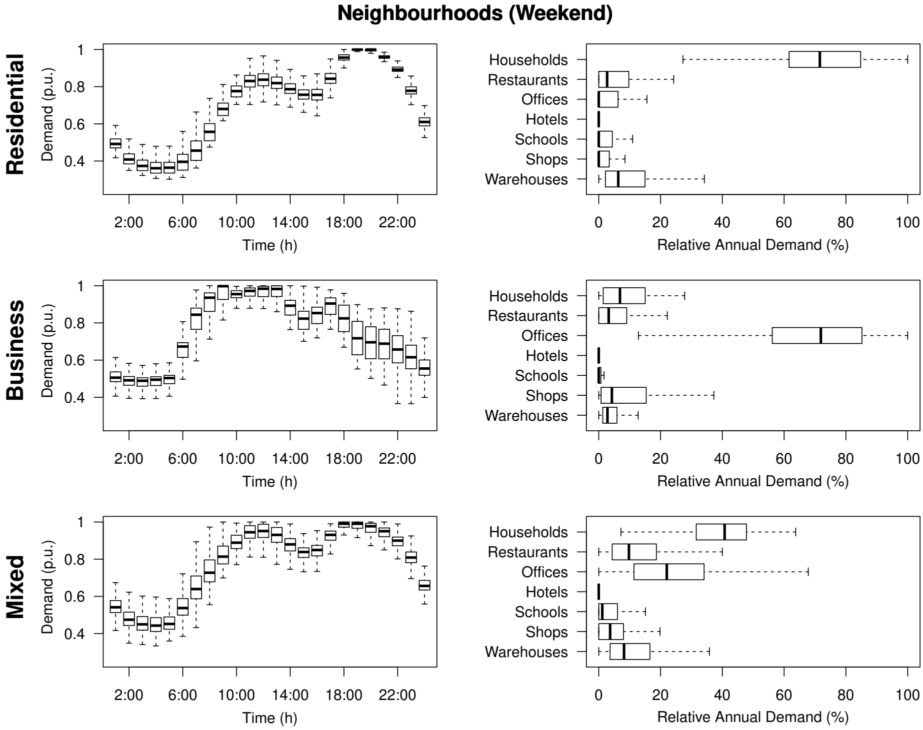


Figure 5.9 Characterisation of clusters at the neighbourhood scale for weekend days. Left panels show the per unit (p.u.) demand profiles, right panels the consumer composition in terms of relative annual demand. The three rows represent the three clusters. Clusters are formed based on weekend spatio-temporal demand profiles. Both profiles and consumer composition are shown as boxplots, with the middle line representing the median, the boxplot edges the 25% and 75% percentiles, and the whiskers the minima and maxima. Due to privacy rules of Statistics Netherlands [342], outliers are not shown.

different (family-wise cut-off p-value of 1.78×10^{-3}), with a few exceptions: on weekdays, the annual demand of restaurants and hotels in residential and business clusters, that of schools and shops in business and mixed clusters, and that of hotels in the residential and mixed clusters is not statistically different; on weekends, no statistical distinction can be made in annual demand of restaurants in residential and business clusters, that of hotels in residential and mixed clusters, and that of schools, shops and warehouses in mixed and business clusters.

In summary, despite the conservative Bonferroni correction, the statistical analysis shows that, with a few exceptions, significant differences exist in demand profiles and in consumer composition between all cluster pairs, on all urban scales, both for weekends and weekdays and for most hours and consumer classes.

5.2.3.2 Comparison across Urban Scales and Day Types

Both the profiles and the consumer composition of same-type clusters across urban scales are similar. However, the variation in both the profiles and the consumer composition

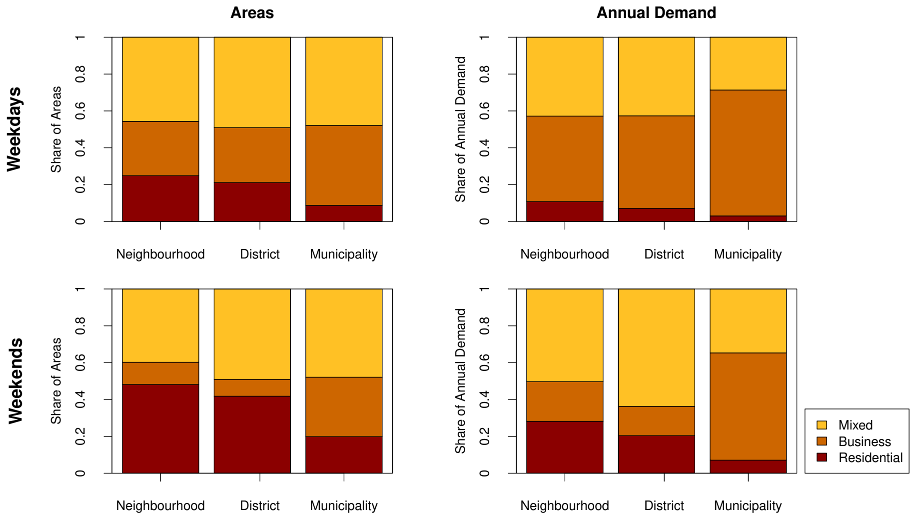


Figure 5.10 Relative importance of clusters at three urban scales in terms of the number of areas (left panels) and annual demand (right panels) covered by each cluster. Top row shows clusters based on weekday profiles, bottom row shows those based on weekend profiles. The absolute number of areas is 11 570 at the neighbourhood scale, 2 725 at the district scale and 403 at the municipality scale. The total annual demand is 41 TWh/year at all scales.

decreases with increasing urban scale. The three clusters – residential, business, and mixed – as described above exist for all three urban scales. There is less variation in both the profiles and the consumer composition at the municipality scale (Figure 5.8) than at the district scale (Figure 5.7), and at the neighbourhood scale (Figure 5.4). This is the case both on weekdays (Figures 5.4 - 5.8) and on weekends. On weekends, only the results for neighbourhoods are shown (Figure 5.9). The results for higher urban scales are similar in terms of demand profile and consumer composition, but with smaller variations (and are therefore not shown).

Relative Cluster Importance. Figure 5.10 shows the relative importance of the three clusters (residential, business, and mixed) for the three urban scales, both on weekdays and on weekends. Two metrics are used: relative share of areas, and relative share of annual demand. **On weekdays** (upper row), the residential cluster contains the least number of areas (25% of the neighbourhoods to 8.6% of the municipalities), covering an even smaller part of the annual demand (10% at the neighbourhood scale to 3% at the municipality scale). For all three urban scales, the mixed-type cluster contains the most areas (46% to 49%), while the business-type cluster covers the largest part of the annual demand (46% to 68%). **On weekends** (lower row), more areas are classified as residential, and less as business. Approximately the same number of areas remains classified as mixed-type, however these areas cover more demand than during weekdays.

Interaction between Urban Scales. Figure 5.11 shows the distribution of lower-scale clusters across higher-scale clusters on weekdays. The distribution is similar on weekends, accounting for the higher share of residential-type clusters, and the lower share of business-type clusters. The interpretation of Figure 5.11 is described for the left panel (neigh-

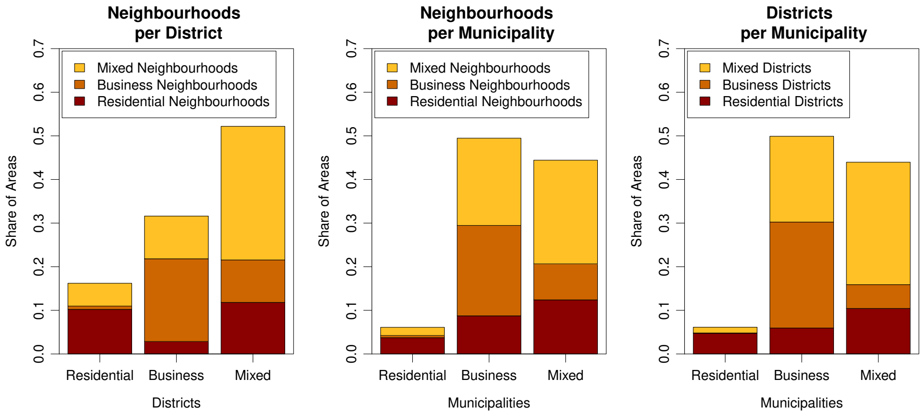


Figure 5.11 Distribution of lower-scale clusters across higher-scale clusters on weekdays. In each panel, the sum of all neighbourhoods or districts is 1, the sum of same-type areas (*e.g.*, residential-type) equals the share of that area type in Figure 5.10. For instance, the left panel shows the distribution of the 11 570 neighbourhoods across districts: 2 876 of these neighbourhoods are residential (25%, see also left upper panel in Figure 5.10). Of these residential neighbourhoods, 1 181 are classified in residential districts (10%), 329 in business districts (3%), and 1 366 in mixed districts (12%). The distribution of neighbourhoods and districts on the other panels should be interpreted similarly.

bourhoods per district). The panel shows how the 11 570 *neighbourhoods* are distributed across *districts*.

The residential **neighbourhoods**, 2 876 in total, or 25% of all neighbourhoods (see also left upper panel in Figure 5.10) are classified across all three district types: 1 181 (10%) are classified in residential districts, 329 (3%) in business districts, and 1 366 (12%) in mixed districts. The residential **districts** consist of 1 875 neighbourhoods (16% of all neighbourhoods), the mixed districts consist of 6 038 neighbourhoods (52% of all neighbourhoods). Thus, although the absolute number of residential neighbourhoods in both residential and mixed districts is approximately the same, 62% of residential districts consists of residential neighbourhoods, while only 23% of mixed districts consists of residential neighbourhoods. The distribution of business and mixed neighbourhoods across respectively business and mixed districts is similar, 60% of business districts consists of business neighbourhoods, and 59% of mixed districts consists of mixed neighbourhoods.

These results show a correlation between clusters at lower-level and at higher-level urban scales, although clustering is carried out independently at each scale. Note that on the middle and right panels of Figure 5.11 there are more business municipalities than mixed municipalities, while on the left upper panel in Figure 5.10 there are more mixed-type municipalities than business-type. This is seemingly contradictory, but can be explained as follows: Figure 5.11 shows the relative number of *neighbourhoods* (middle panel) and *districts* (right panel) classified across municipalities, while the right bar on the left panel in Figure 5.10 shows the relative number of *municipalities* themselves. Thus, although fewer municipalities are classified as business-type than as mixed-type, the business municipalities contain a higher number of districts and neighbourhoods than the mixed municipalities.

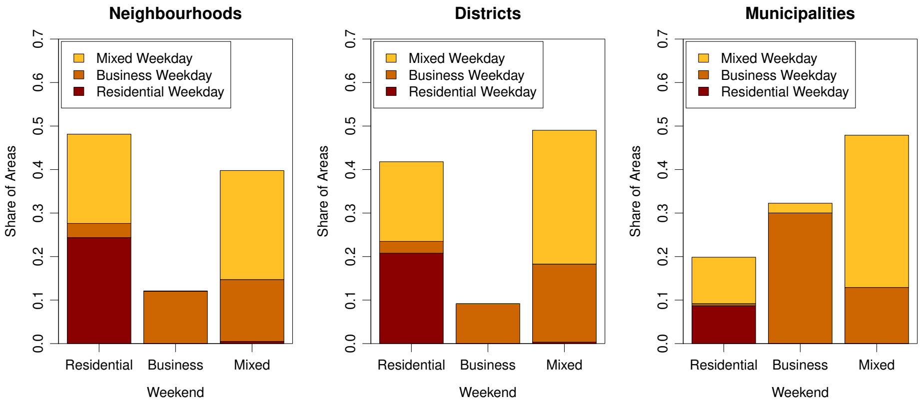


Figure 5.12 Distribution of weekend clusters across weekday clusters at different urban scales. In each panel, the sum of all areas is 1. This sum represents 11 570 neighbourhoods (left panel), 2 725 districts (middle panel), and 403 municipalities (right panel).

Interaction between Day Types. Figure 5.12 shows how clusters formed based on weekend profiles relate to clusters formed based on weekday profiles at each urban scale. In general, Figure 5.12 shows that the areas that are classified as residential on weekends, are also classified as such on weekdays. However, on weekends, more areas are classified as residential. Primarily areas that are classified as mixed on weekdays are reclassified as residential on weekends. A similar pattern can be distinguished for business areas. Areas that are classified as business on weekends, are also classified as such on weekdays. However, on weekdays, more areas are classified as business, these areas are classified predominantly as mixed on weekends. In both reclassification cases, mixed to residential and business to mixed, this reclassification occurs due to smaller demand of non-household consumers on weekends than on weekdays.

5.2.4 Discussion

The results presented in this chapter provide insights in the demand profiles and consumer composition at three urban scales. These insights can improve existing and future energy system models, used to assess and support the transition to renewable generation and electrification of transportation and heating. Most existing energy models assume that the local demand in the area of study is solely residential.

The results in this thesis show that three types of areas can be distinguished: residential, business, and mixed. Statistical analysis demonstrates that these area types are significantly different, both in terms of their daily demand profiles and their consumers composition. Moreover, this thesis shows that the residential-type demand assumed by many existing energy models is representative only of a minority of areas, and accounts only for a small share of the total urban demand.

The following paragraphs validate the approach used, and discuss the importance of the obtained results for urban energy systems modelling.

5.2.4.1 Approach Validation

In this chapter, a bottom-up approach is used to model urban scale spatio-temporal demand profiles. In urban energy systems literature, this approach is preferred over the alternative top-down approach as it yields more detailed demand profiles [241, 257, 260]. A drawback of this bottom-up approach is the need for a large number of data sources. In particular, as detailed spatial-temporal energy data are not publicly available, data sources from other fields need to be combined [28, 31, 280, 308]. The best validation for this bottom-up approach is arguably the comparison of the resulting demand profiles with measured profiles of statistically representative urban areas, along with metadata of these areas, such as the local consumer composition. However, such data are currently not publicly available. This is the very issue highlighted by this thesis. The validation therefore has to rely on the comparison of the results with available data, and prior studies. The validation consists of two parts: (1) comparison of the total annual modelled demand to published annual demand data, and (2) comparison of the results to those published by other authors.

Annual Demand Validation. The obtained results are compared with the total annual electricity demand of Dutch residential and service sector consumers, an approach similar to the one used in Chapter 4. The total annual residential electricity demand is 26.3 TWh [333]. The total annual service sector demand lies between 30.6 TWh [337] and 33.6 TWh [335, 336] (see Section 4.3.1). Healthcare uses 3.4 TWh [346]. As healthcare cannot be modelled based on the available data, its demand is subtracted from the total annual service sector demand, yielding a demand between 27.2 TWh and 30.2 TWh. This chapter models 19 TWh consumed by households, and 22 TWh consumed by the service sector. This means that the modelled demand covers 84% of the residential demand, and 73% to 81% of the service sector demand. These percentages are slightly lower than the ones obtained using the building equivalent method (Chapter 4), although they are comparable. The difference of 1.5 TWh between Chapters 4 and 5 arises from differences in conversions and definitions. Overall, this validation indicates that the scaling factors method presented in this chapter also yields values which are in line with the measured Dutch household and service sector demand data. Further research and, in particular, more detailed data are necessary to explain the differences between the building equivalents and the scaling factors methods in detail, and account for the remaining demand unaccounted for by both methods.

Literature-Based Validation. Several studies [31, 262, 263, 308, 357] are used to validate four subsequent parts of this chapter: (1) data combination, (2) bottom-up demand modelling based on linear regression, (3) clustering of areas instead of individual consumers, and (4) obtained results.

- **Data Combination.** The data used in this chapter are a combination of individual building demand profiles for the temporal dimension, and administrative registration data for the spatial dimension. A similar data combination has been used by Brownsword *et al.* [357].
- **Bottom-up Demand Modelling.** The bottom-up demand modelling approach in this chapter is based on the premise that the demand profile of an area is the sum of the demand profiles of the consumers in that area. The same premise is assumed in

the work of Andersen *et al.* [262, 263]. These authors determine the local consumer composition based on a combination of transformer-level demand profiles, reference Danish demand profiles, and Nord Pool market data [262, 263]. They similarly choose for linear regression as the methodological approach, and use it to estimate the *weight* of the demand of an *consumer class* in a given area [262, 263]. Note that this is a similar, but data-wise reversed approach to the one developed in this chapter, where the weight of the consumer class is known from annual energy demand data, and linear regression is used to appropriately *scale* reference building *demand profiles*.

- **Area-Scale Clustering.** Clustering is used in this chapter to classify areas instead of individual consumers, the latter being more common in literature (*e.g.*, [309, 310, 349, 350]). Yamaguchi *et al.* [308] also describe clustering of areas, in particular of districts in Osaka, Japan. The authors use floor space of commercial buildings as clustering features. Their analysis results in six clusters: residential, mixed-use commercial, concentrated commercial, urban core, low-rise office, and high-rise office. The clustering approach in this thesis is based on 24-hour demand profiles. The difference in clustering features explains the lower number of clusters in this thesis as compared to the results of Yamaguchi *et al.* [308]. Low-rise and high-rise office buildings are likely to have similar, business-type shapes of electricity demand. Similarly, mixed-use commercial, concentrated commercial, and urban core areas are likely to correspond to mixed-type demand profile areas. The work of Yamaguchi *et al.* [308] shows that clustering is a valid methodology to classify urban areas.

- **Results: Three Cluster Types.** The results in this chapter show the existence of three clusters on all urban scales, each cluster with a distinct demand profile. Similar results are found by Mikkola and Lund, who have developed a spatio-temporal energy demand model and applied it to 136 neighbourhoods in the city of Helsinki, Finland [31]. Based on their results, the authors distinguish three neighbourhoods with the same classification as in this thesis, and provide examples of each: residential area (Puistola), office buildings area (Kluuvi), and mixed area (Punavuori). The authors also discuss the shape of the demand profiles in each area: the profile peaks during the morning and evening for Puistola, during the day for Kluuvi, and Punavuori is a mix of the two types [31]. Both the classification, and the demand profile shapes are similar to the results found in this thesis. Although the results of Mikkola and Lund cover a hundredfold smaller number of areas, they thus validate the findings of this thesis.

5.2.4.2 Implications for Urban Energy System Models

The primary purpose of the classification of areas presented in this thesis is to increase understanding of the heterogeneity of urban scale demand profiles. The results emphasise the importance of using local demand profiles in individual areas simulated in urban energy system models.

Importance of Demand Profile Types. Many studies assume residential-type demand when assessing the impact of renewable energy resources on local energy systems (*e.g.*, [128, 275, 358]). The results in this chapter show that this assumption is incorrect for the majority of real urban areas. The results show that the majority of areas has a business-type or a mixed-type profile, *i.e.*, a profile with demand having a plateau during the day, or a double-peak during the day and the evening. Such profiles can be expected to interact differently than residential-type profile (with the demand peaking during the evening) with time-dependent renewables, such as solar PVs. Moreover, similar considerations can be made for interactions with new loads, such as electric vehicles (EVs). Robinson *et al.* show that EV charging peaks during the morning in workplaces, during the day in public charging points and during the evening at home [127]. Thus, the mismatches between PV generation and local demand can be expected to be smaller in business and mixed areas than in residential areas. The effect of EV charging depends on both the type of EV charging points and the area they are located in, and thus require an assessment tailored to the area under study.

Importance of Scale and Day Type. Two main conclusions can be drawn from the comparisons of urban scales and day types. First, the scale at which the impact of a new technology is assessed is important. As shown in Figure 5.11, lower-scale demand types overlap with higher-scale demand types in only approximately half of the cases (55% on average). Thus, although data from a higher-scale area (such as a municipality) might be more readily available, they can only be expected to correctly predict the demand profile of lower-scale areas in approximately half of the cases. Appropriate scale data should therefore be used in energy system models. Second, for individual areas, both weekday and weekend profiles should be taken into account when assessing the local impact of new technologies. In this chapter, same-scale areas are classified independently for weekdays and weekends. Results show that most areas, *i.e.*, 61% of the neighbourhoods and districts and 74% of municipalities are classified in the same clusters both on weekdays and on weekends. The remainder is reclassified to a cluster with a higher weight attributed to household demand due to a decreased business activity on weekends (Figure 5.12). In reality, the difference in demand profiles of weekdays and weekends in a specific areas should be taken into account when assessing the local impact of new technologies.

5.2.4.3 Improving Models despite Lacking Data

Determining the local profile of a particular area requires local data, which at present are often lacking. This issue has been raised in literature (*e.g.*, [28, 31, 261, 300]), and remains largely unresolved. In absence of detailed hourly demand data, urban energy system models can be improved by using approximations. The logistic regression model, that is calibrated and validated based on the same data as used to cluster areas, is provided as a spreadsheet tool to give other researchers and stakeholders the opportunity to gain more insights in their areas of interest based on limited local data. It can be found online, in an addendum to [60] and in [315]. This model can be used to determine the type of demand profile in an urban area of interest based solely on the relative annual demand of different consumers in that area. This type of cumulative data is more often available than detailed profiles, although, if available, the superiority of local demand profiles remains undisputed and should be used whenever possible.

5.3 Conclusion

This chapter describes the development and implementation of an approach for modelling and classification of urban electricity demand profiles. Modelling demand at urban scales is challenging due to limited availability of sufficiently detailed data. In this chapter, this challenge is overcome by using a two-step method based on linear regression that makes it possible to combine the few datasets that are publicly available. This method is applied to all 403 municipalities, 2 725 districts and 11 750 neighbourhoods in the Netherlands. The obtained demand profiles are subsequently classified and analysed. Such systematic spatio-temporal demand profile characterisation has thus far been lacking in literature. To help other researchers and practitioners overcome this issue, the results are published in the accompanying dataset [315]. The obtained results demonstrate that at all urban scales (neighbourhood, district, and municipality), three types of area demand profiles can be distinguished, which are termed *residential*, *business*, and *mixed* in this thesis, based on the most prevalent consumer class in each of them. Statistical analysis shows that at all urban scales, these areas are pairwise significantly different from each other, both in terms of their demand profiles and their consumer composition. Moreover, this chapter establishes that residential-type demand profiles, used in many energy system models, are found only in a minority of areas, and account for only a small share of the total demand. As a consequence, case studies of local impact of renewables, electric vehicles, *etc*. that assume solely household demand are representative for only a small share of urban areas and cannot be generalised without errors. Existing and future urban energy system models should therefore be expanded with more realistic and detailed spatio-temporal local demand profiles that account for both household and non-household consumers.

The following chapters use the spatio-temporal demand profiles developed in this chapter and in the previous chapter to study the impact of renewable resource integration in urban areas, in their own respect, and in combination with interventions that are aimed to facilitate this integration.

Part III

Harnessing Heterogeneity

Local interactions between electricity demand and generation are of increasing importance in urban energy systems as they transition to renewable energy resources. Unlike conventional power plants, these resources are non-dispatchable and decentralised. Both characteristics have profound consequences for the operation of power systems, whose cornerstone is the sustained balance between power demand and generation. For power systems with a high share of renewables, new balancing approaches are required, such as demand response and storage (see Chapter 2). As renewable generation resources are smaller and thus more decentralised than conventional power plants, the choice of balancing approaches for a certain area depends on the *local* interplay between demand and renewable generation. Moreover, ultimately, the need for balancing approaches is determined by the degree of renewable resource utilisation *prior* to any intervention. Part II builds on the insights of demand heterogeneity gained in Part I, moving from understanding to employing – or harnessing – it. It addresses **RQ2 – How does spatio-temporal demand heterogeneity influence local renewable resource utilisation, and the interventions aimed to facilitate it?**

Chapter 6 focuses on the degree of renewable resource utilisation prior to any interventions. It thus answers **RQ2a** – ***What is the impact of spatio-temporal demand heterogeneity on local renewable resource utilisation?*** This question is addressed for a range of solar and wind penetration scenarios, for different time and weather conditions, and for various mixes of residential and service sector consumers (for the latter building further on the spatio-temporal demand profiles obtained in Chapters 4 and 5). The results show that mixed areas have a higher renewable resource utilisation than areas with only households. This implies that if the service sector is omitted in urban energy system models, the assessment of renewable resource utilisation underestimates its true value in the majority of urban areas.

Chapter 7 considers two case studies of interventions aimed to facilitate local integration of renewable energy resources: storage and demand response. The chapter thus addresses **RQ2b** – ***What is the impact of spatio-temporal demand heterogeneity on interventions aimed to facilitate local renewable resource utilisation?*** The first case study focuses on the use of individually-owned storage and its applicability to mitigate the effects of non-dispatchability of renewable generation. The second case study explores the potential of demand response to offset both non-dispatchability and uncertainty of solar energy generation. Overall, both case studies show that detailed knowledge of local demand characteristics is indispensable for an adequate understanding of both technical and governance implications of the considered interventions.

6 Impact of Demand Heterogeneity on Renewable Resource Integration

> *You don't have to sort of enhance reality. There is nothing stranger than truth.*
>
> – Annie Leibovitz

The previous chapters develop an understanding of the spatio-temporal heterogeneity of urban demand. This chapter explores how much impact this demand heterogeneity has on local renewable resource integration. Answering this question provides theoretical insights in the local interplay between demand and renewable generation, and has practical implications for urban energy system modelling. Detailed urban demand profiles are challenging to obtain and time consuming to construct (see Chapters 4 and 5), while residential demand profiles are more readily available, making them an attractive proxy for urban areas as a whole. However, residential and service sector demand profiles differ considerably, raising the question whether the approximation of urban demand by residential demand only to assess local renewable resource utilisation can be justified. This chapter shows that the differences in demand between the residential and service sectors have a statistically significant impact on local renewable resource integration metrics, and that substitution of real urban demand profiles by residential profiles is misleading.

This chapter describes three modelling experiments, each of which sheds light on a different aspect of the interaction between heterogeneous urban demand and renewable resource integration. The first experiment analyses a wide range of solar and wind generation scenarios. The second experiment zooms in on different time and weather conditions (*e.g.*, sunny windless weekend days, or cloudy windy weekday nights) within a single (optimised) scenario of solar and wind generation. These two experiments compare two demand cases: residential-only consumers and a realistic mix of residential and service sector consumers (based on the demand modelling approach described in Chapter 4). The third experiment considers the three archetype neighbourhood demand profiles found in Chapter 5, and compares their interaction with renewable generation in different time and weather conditions for three solar and wind generation scenarios.

This chapter is based on a previous publication [59].

6.1 Metrics

Local renewable resource integration is assessed based on four metrics: positive mismatch, negative mismatch, renewable energy utilisation, and self-consumption. These metrics reflect different aspects of the design and operation of power systems with a high share of renewable resources: the first two metrics reflect the need for controlled operation of the power system, the latter two represent the requirement of effective use of renewable energy. Mismatch between generation and demand (first two metrics) is unacceptable in real power systems, and in practice has to be resolved through additional measures (such as curtailment, demand response, and dispatching of other power plants), such that generation and demand remain in perfect balance for the proper operation of the power system. Quantifying the extent of both the positive and negative mismatch (respectively generation excess and shortage) is important to assess the need for such additional measures.
While mismatches are undesirable, a high degree of renewable energy utilisation and self-consumption (last two metrics) is desirable. A high degree of renewable energy utilisation entails an effective use of renewable energy whenever it is available, and thus a reduction in the reliance on fossil fuels. A high degree of self-consumption means that renewable energy generated can be used locally immediately, and thus does not require additional interventions, such as grid interconnection, or storage.

The metrics considered in this chapter are summarised and formalised as follows.

Positive Mismatch. Positive mismatch accounts for generation excess.

$$MM^{+}(t) = \begin{cases} G(t) - D(t) & \text{if } G(t) > D(t) \\ 0 & \text{if } G(t) \leq D(t) \end{cases} \tag{6.1}$$

with $G(t)$ renewable generation, and $D(t)$ demand at time t.

Negative Mismatch. Negative mismatch accounts for generation shortage. Note that negative mismatch is always a negative value.

$$MM^{-}(t) = \begin{cases} 0 & \text{if } G(t) \geq D(t) \\ G(t) - D(t) & \text{if } G(t) < D(t) \end{cases} \tag{6.2}$$

Mismatch. Difference between generation and demand.

$$MM(t) = MM^{+}(t) + MM^{-}(t) = G(t) - D(t) \tag{6.3}$$

Renewable Energy Utilisation. Renewable energy utilisation is the amount of renewable energy that can be used by the coinciding demand, assuming that whenever renewable energy is available, it is utilised first. Only if no renewable energy is available, are conventional resources (not modelled) used.

$$RU(t) = \begin{cases} D(t) & \text{if } G(t) > D(t) \\ G(t) & \text{if } G(t) \leq D(t) \end{cases} \tag{6.4}$$

Self-Consumption. Self-consumption is the ratio of renewable energy utilised by the coinciding demand and the total renewable energy generated.

$$SC(t) = \frac{RU(t)}{G(t)} \tag{6.5}$$

Mismatch and renewable energy utilisation metrics can also be expressed in relative terms:

$$\widehat{MM}^{+}(t) = \frac{MM^{+}(t)}{D(t)} \tag{6.6}$$

$$\widehat{MM}^{-}(t) = \frac{MM^{-}(t)}{D(t)} \tag{6.7}$$

$$SS(t) = \frac{RU(t)}{D(t)} \tag{6.8}$$

Note that the relative version of renewable energy utilisation is called self-sufficiency SS. Absolute metrics (Eq. 6.1 to 6.4) and self-consumption (Eq. 6.5) are used in the first two experiments, relative metrics (Eq. 6.5 to 6.8) are used in the last experiment as the archetype neighbourhoods demand profiles considered are expressed in per-unit terms (see Chapter 5).

6.2 Rationale

Households and services use electricity during different times of the day – households primarily in the evening and services primarily during the day (see Chapter 4). This chapter hypothesises that the temporal differences in demand lead to significant differences in renewable resources integration metrics. This hypothesis entails that the demand of the service sector has to be accounted for explicitly, and cannot be substituted by residential demand. The hypothesis is tested through comparison of renewable resource integration metrics for different demand cases. Experiments 1 and 2 focus on residential-only consumers versus an average mix of residential and service sector consumers (as determined in Chapter 4). Experiment 3 considers the three neighbourhood archetypes from Chapter 5, which are all mixes of residential and service sector consumers.

Below, a theoretical rationale is developed that provides intuition why temporal differences in demand lead to significant differences in renewable resources integration metrics. For clarity, the rationale focuses on residential-only consumers versus an average mix of residential and service sector consumers. Figure 6.1 shows the demand profiles of both residential-only consumers, and mixed residential and service sector consumers for an average weekday.

The demand of the two consumer cases is formally denoted as follows: $D_{HHH}(t)$ for residential-only consumers and $D_{H\&S}(t)$ for mixed residential and service sector consumers.

Let $D_H(t)$ represent the demand of 100 000 households, and $D_S(t)$ the demand of the corresponding mix of services (see Table 4.1). Then,

$$D_{HHH}(t) = \xi \cdot D_H(t) \tag{6.9}$$

$$D_{H\&S}(t) = D_H(t) + D_S(t) \tag{6.10}$$

D_H is scaled by a factor ξ to ensure that $\sum_{t=1}^{8760} D_{HHH} = \sum_{t=1}^{8760} D_{H\&S}$ for hourly steps of t (accounting for 8 760 hours in a year). In this thesis, $\xi = 2.03005$.

Mismatch. Assuming that these two groups of consumers have the same local generation $G(t)$, the *difference* in their mismatch *MM* is:

$$\begin{aligned}
\Delta MM(t) &= MM_{HHH}(t) - MM_{H\&S}(t) \\
&= G(t) - D_{HHH}(t) - (G(t) - D_{H\&S}(t)) \\
&= -\xi \cdot D_H(t) + D_H(t) + D_S(t) \\
&= (1 - \xi) \cdot D_H(t) + D_S(t)
\end{aligned} \tag{6.11}$$

From Eq. 6.11 follows that the difference in mismatch $\Delta MM(t)$ only depends on the demand $D_H(t)$ and $D_S(t)$, $\Delta MM(t)$ does not depend on the generation $G(t)$. Fig. 6.1 shows that $\Delta MM(t) > 0$ during the day and $\Delta MM(t) < 0$ in the evening. This suggests that in urban areas with a mixed demand, power imbalance calculations based on residential-only consumers lead to underestimations of the mismatch between supply and demand during the day and overestimations of this mismatch during the evening. Numerical values and statistical significance of these errors are shown in the following experimental sections.

Renewable Energy Utilisation. A similar analysis can be carried out for renewable energy utilisation. Given a generation $G(t)$, the *difference* in renewable energy utilisation between residential-only consumers and mixed consumers is:

$$\Delta RU(t) = RU_{HHH}(t) - RU_{H\&S}(t) \tag{6.12}$$

Expanding Eq. 6.12 yields $\Delta RU(t)$ as a function of both renewable generation and demand. Note that a similar dependency exists for self-consumption, as it is derived from renewable energy utilisation (see Section 6.1).

As both generation and demand are dependent on time and weather, assessment of renewable energy utilisation and self-consumption requires an analysis of time and weather interactions, in addition to correct demand profile estimation. A novel time and weather classification system is developed for this purpose, it is presented in Section 6.3.4.

Overall, the theoretical rationale shows that differences in demand between consumers lead to differences in all renewable resource integration metrics. These differences are quantified in modelling experiments. The following sections describe the methods used and the results obtained.

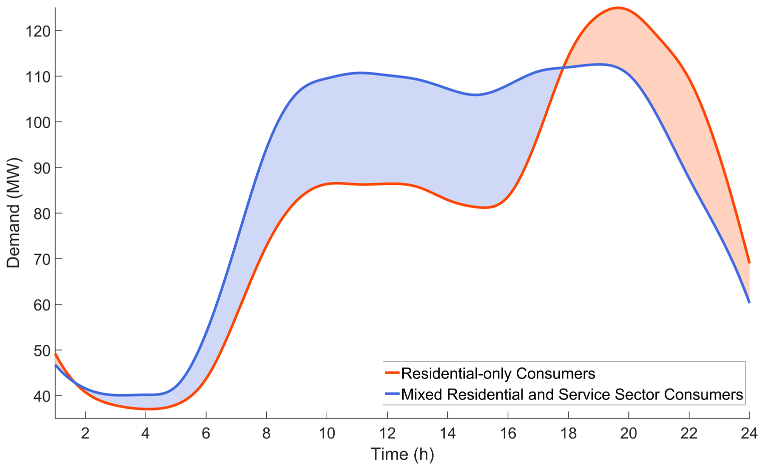


Figure 6.1 Comparison of demand profiles of residential-only consumers (orange) and mixed residential and service sector consumers (blue) on an average weekday. The shaded area represents the cumulative demand difference. The blue shaded area shows energy consumption underestimation by residential-only consumers as compared to mixed consumers. The orange shaded area represents the opposite case. Note that for the mixed consumers, the proportions of residential and service sector are representative for the Netherlands (as determined in Chapter 4).

6.3 Methods

The impact of demand heterogeneity on renewable resource integration is quantified in three modelling experiments. The first two experiments compare renewable resource integration metrics for two demand cases: residential-only consumers, and a realistic mix of residential and service sector consumers. The total annual demand in both cases is equal, the two cases essentially differ only in the timing of demand peaks and lows. The first experiment considers 121 scenarios of solar and wind generation. The second experiment zooms in on combinations of time and weather conditions (*e.g.*, sunny windless weekend day) for one (optimised) scenario of solar and wind generation. The third considers the demand profiles of the three neighbourhood archetypes found in Chapter 5. This experiment studies the differences between these demand profiles in different time and weather conditions (similarly to experiment 2), doing so for three scenarios of solar and wind generation. An overview of the three experiments is given in Table 6.1.

6.3.1 Data

The modelling experiments take both demand and generation into account. Demand is modelled based on the profiles from Chapters 4 and 5. Generation is modelled based on weather data obtained from the Royal Netherlands Meteorological Institute [359] assuming state-of-the-art technologies as described in Chapter 2. The network is assumed to be a "copper plate". All resulting profiles have an hourly granularity and span a single year. To ensure spatial and temporal consistency, all calculations are done for the same area (the Netherlands) and the same period (2014), taking into account official Dutch holidays and daylight saving times.

Table 6.1 Overview of three modelling experiments on the impact of demand heterogeneity on renewable resource integration.

	Experiment 1	**Experiment 2**	**Experiment 3**
Demand	Residential-only vs. mixed consumers	Residential-only vs. mixed consumers	Three archetype neighbourhoods
Generation	Solar and wind (0% – 300%)[a]	Solar and wind (245%)[a]	Solar and wind (20% – 300%)[b]
Granularity	Annual average	Hourly	Hourly
Methods	•Scenario analysis (121 scenarios)	•Optimisation (area constrained)	•Scenario analysis (3 scenarios)
		•Time and weather classification	•Time and weather classification
	•Statistical analysis	•Statistical analysis	•Statistical analysis

[a] *Generation expressed as share of peak demand, assuming households only.*
[b] *Generation expressed as share of cumulative annual demand.*

6.3.1.1 Demand

All three experiments compare renewable resource integration metrics for different demand cases. In **experiments 1 and 2**, two demand cases are defined: (1) residential-only consumers and (2) mixed residential and service sector consumers. For both consumer cases, residential demand is represented by a single average Dutch household profile[1]. For the mixed consumers, the service sector demand is calculated as a weighted sum of thirteen reference building demand profiles obtained in Chapter 2. To ensure that the two consumer cases are comparable, an equal annual cumulative consumption (710 GWh/year) is used for both consumer cases. To achieve this, the residential consumers are weighted by a factor ξ (see Eq. 6.9; $\xi = 2.030$, the ratio between the total mixed consumption of 7.104 GWh and the household consumption for 100 000 households, 3.500 GWh).
For **experiment 3**, the demand profiles of the three archetype neighbourhoods[2] – residential, business, and mixed – from Chapter 5 are used. These profiles are available only as single-day profiles, one for weekdays and one for weekends, while whole-year profiles are available for wind and solar generation. To match the two, an annual demand profile is constructed for each neighbourhood through replication of the weekday and weekend profiles.

6.3.1.2 Generation

All three experiments consider both solar and wind generation. They differ only in the assumed installed capacity. Experiments 1 and 3 take multiple scenarios of installed renewable generation capacity into account (see Section 6.3.2). Experiment 2 considers a single scenario with an optimal mix of solar PVs and wind turbines, which is constrained by

[1] The use of a single average household profile is assumed to be representative at the scale used in the simulations in this thesis (100 000 or 203 005 households, depending on the consumer case) since the combined profile of such a large number of similar consumers is expected to regress to the mean profile [360].
[2] Only neighbourhood scale demand profiles are considered because district and municipality scale profiles are very similar in shape (see Figures 5.6 to 5.8).

available area (see Section 6.3.3). This experiment focuses on metric differences in a range of time and weather conditions (see Section 6.3.4).

Solar power generation is modelled using a MATLAB model developed by Walker [361]. The technical specifications are based on Solarex MSX-60 PV panels [362]. Solar PV panels are assumed to be placed on roofs of residential and service sector buildings. The roof area constrains the number of solar panels that can be used. For the service sector, the maximal available roof area is calculated as the ratio between the total floor area and the number of storeys [225]. For households, an average roof area of 33 m^2 is used [363]. All roofs are assumed to allow for optimal positioning of solar panels[3].

Wind power generation is modelled following standard methods [85], for community-size wind turbines of the type 500 kW EWT DIRECTWIND 52/54-500 kW [366]. These turbines are 50 m high, have a 54 m rotor diameter and a nominal capacity of 500 kW. The cut-in and cut-out windspeeds of respectively 2.5 m/s and 25 m/s are included in the model. Wind power output is calculated using the following equation [85]:

$$G_{turbine}(t) = \frac{1}{2} * \rho_{air} * a_{rotor} * v_{wind}^3 * \psi_{turbine} \tag{6.13}$$

where:

$G_{turbine}(t)$: wind power generation

ρ_{air}: air density, calculated using temperature and pressure data [359]

a_{rotor}: rotor area, 2290 m^2 for modelled turbine

v_{wind}: wind speed [359], corrected for the height of the modelled turbine (50 m)

$\psi_{turbine}$: power coefficient, 0.35 for the modelled turbine

6.3.2 Scenario Analysis

Experiments 1 and 3 consider a range of solar and wind generation scenarios. In **experiment 1**, both solar and wind generation capacity is varied between 0 MW and 525 MW with steps of 52.5 MW (121 scenarios in total). Note that for the residential-only case, 525 MW represents 300% of peak demand (175 MW). For the mixed consumers case, 525 MW is 367% of peak demand (143 MW), as mixed consumers has a flatter profile (see Fig. 6.1). These capacities are comparable to [367], where renewable resource capacity of up to 341% of peak demand is considered for 2050.

Experiment 3 considers only three scenarios: installed solar and wind generation capacity equal to 20%, 100%, and 300% of *cumulative annual demand*. Note the difference in reference demand with experiment 1 (where peak demand is used). This difference arises from the *demand* profiles used in both experiments. For experiment 3, only average weekday and weekend demand profiles are available, not an annual time series as for experiment 1. Peak demand can therefore not be estimated accurately and is thus not used as reference.

[3]The resulting overestimation of solar generation is offset by an underestimation of solar PV efficiency, which is rising by 1.0 to 1.2% per year [87]. These two factors are expected to balance out between 2030 and 2050, both recurring horizons in literature for scenarios assuming high renewables penetration (*e.g.*, [364, 365]).

6.3.3 Area-Constrained Optimisation

Experiment 2 zooms in on a single scenario of solar and wind generation. This scenario minimises both positive and negative mismatch, maximises renewable energy utilisation, and takes the available area into account as a constraint. The optimisation problem is formulated as a constrained multi-objective non-linear problem with design variables x the number of solar PV panels and wind turbines: $x = [x_{PV}, x_{turbine}]$:

$$\begin{aligned} \underset{x}{\text{minimize}} \quad & f(x) = \omega_{MM+} \cdot MM^{+}(x) + \omega_{MM-} \cdot |MM^{-}(x)| + \omega_{RU} \cdot RU(x) \\ \text{subject to} \quad & 0 \leq x_{PV} \leq \alpha \cdot a_{roof} \\ & 0 \leq x_{turbine} \leq (\alpha - 1) \cdot a_{roof} \\ & x_{PV} + x_{turbine} \leq \alpha \cdot a_{roof} \end{aligned} \tag{6.14}$$

where:

ω_{MM+}: weighting factor of positive mismatch ($p_{MM+} > 0$, here $p_{MM+} = 1$)

ω_{MM-}: weighting factor of negative mismatch ($p_{MM-} > 0$, here $p_{MM-} = 1$)

ω_{RU}: weighting factor of renewable energy utilisation ($p_{RU} < 0$, here $p_{RU} = -5$)

a_{roof}: roof area available

α: factor accounting for additional area available ($\alpha \geq 1$, here $\alpha = 3$)

The total annual positive mismatch $MM^{+}(x)$ is calculated as follows:

$$MM^{+}(x) = \sum_{t=1}^{8760} MM^{+}(x,t) \tag{6.15}$$

$$MM^{+}(x,t) = \begin{cases} G(x,t) - D_{H\&S}(t) & \text{if } G(x,t) > D_{H\&S}(t) \\ 0 & \text{if } G(x,t) \leq D_{H\&S}(t) \end{cases} \tag{6.16}$$

where $G(x,t) = x_{PV} \cdot G_{PV}(t) + x_{turbine} \cdot G_{turbine}(t)$, with $G_{PV}(t)$ and $G_{turbine}(t)$ respectively the generation profiles of 1 m^2 solar PVs and one 500 kW wind turbine. The total annual negative mismatch $MM^{-}(x)$ and total annual renewable energy utilisation $RU(x)$ are calculated in an analogous way, based on Eq. 6.2 and 6.4.

The total area available for renewable power generation is assumed to be three times the size of the cumulative roof area of all the buildings considered ($\alpha = 3$). This value represents 0.4% of Dutch land area, similar to the value estimated for the U.S. in [368]. The roof area itself is only available for solar power generation, while at most twice the roof area is available for wind power generation ($\alpha - 1$ in Eq. 6.14). The footprint of a wind turbine is assumed to be 0.345 km^2/MW [369].

Eq. 6.14 is a constrained multi-objective non-linear optimisation problem, which is solved using the genetic algorithm in MATLAB [370]. This algorithm relies on a population of possible individual solutions, which evolve to an optimal solution over a number of iterations. In each iteration, the best solutions are used to create solutions for the next iterations which are more likely to be close to the optimal solution. The algorithm terminates when the improvement in solutions falls below a threshold.

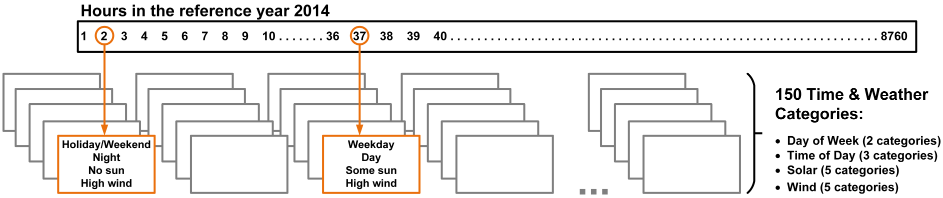


Figure 6.2 Classification of hours using the proposed time and weather classification system. The year 2014 is used as reference year. Two examples are given. The 2nd hour of 2014 (*i.e.*, 01:00 - 02:00 on January 1st, 2014) is classified as a holiday/weekend hour during the night with no sun and high wind. The 37th hour of 2014 (*i.e.*, 12:00 - 13:00 on January 2nd, 2014) is classified as a weekday hour during the day with some sun and high wind.

6.3.4 Time and Weather Classification

Experiments 2 and 3 explore the interaction between demand heterogeneity and renewable generation in different time and weather conditions. Examples of such time and weather conditions are "sunny, windless weekend days", "cloudy, windy weekday nights", *etc*. Each of these examples gives an indication of four parameters – two describing weather (amount of sun and wind) and two describing time (weekday or weekend, and time of day). In traditional power systems, only time is considered as a parameter since in such systems only demand is assumed to be non-dispatchable, and demand primarily varies with time (*e.g.*, services work during the day, whether it is sunny, cloudy, windy, or windless). In a power system with a high penetration of renewables, *residual* demand[4] determines the system state. Thus, weather conditions are expected to play a considerably larger role, in addition to time. To account for the future system dependency on both time and weather, this chapter introduces a novel time and weather classification system. In this system, each hour of the year is classified according to four parameters: (1) day of the week, (2) time of day, (3) solar power generation, and (4) wind power generation. Two categories are distinguished for the day of the week: weekday and weekend. Three categories are distinguished for the time of the day: night (00:00 - 08:00), day (08:00 - 16:00), and evening (16:00 - 00:00). Five categories are distinguished for both solar and wind power generation. The cut-off points of these categories are determined as quantiles. For solar generation, only daylight hours are used to determine the quantiles. In total, 150 time- and weather-dependent categories are defined. The classification of hours for the reference year 2014 according to this time and weather classification system is shown in Figure 6.2. The number of hours classified in each category is shown in Table 6.2.

6.3.5 Statistical Analysis

Metric differences between residential-only consumers and mixed consumers are analysed for statistical significance using the two-sample t-test [356]. As multiple scenarios or categories are compared at once, the significance level is corrected using Holm-Bonferroni correction to control family-wise error rate at 5% [371]. The number of comparisons for experiments 1, 2, and 3 is respectively 121, 150, and 4 050.

[4] Residual demand is the net result of the difference between demand and must-take renewable generation.

Table 6.2 Hours in 2014 classified using the proposed time and weather classification system. Values represent the number of hours in each category. Time dependency is expressed as time of day (3 categories), weather dependency as solar and wind (5 categories each). The 5 solar and wind categories are based on quantiles. For the sake of conciseness, no distinction is made between weekdays and weekends. These can be inferred statically: 5/7 of all hours fall on weekdays and 2/7 on weekends. The table should be read as follows: the value 627 in the first row, first column, represents the number of night hours (*i.e.*, hours between 00:00 and 08:00) in 2014 with low wind (between 0% and 5% of maximum) and low solar generation (between 0% and 3% of maximum). The corresponding results are indicated in Figures 6.4 - 6.9 with a red arrow.

		Wind (Share of Max.)					
Time of Day	**Solar (Share of Max.)**	**0-5%**	**5-13%**	**13-26%**	**26-71%**	**71-100%**	**Total Hours**
	0-3%	627	419	426	409	414	2295
	3-9%	92	53	40	29	29	243
Night	**9-21%**	73	59	36	25	17	210
	21-40%	35	48	37	13	9	142
	40-100%	8	12	4	5	1	30
	0-3%	31	26	48	68	99	272
	3-9%	31	58	93	128	198	508
Day	**9-21%**	50	78	106	157	173	564
	21-40%	90	120	128	166	186	690
	40-100%	132	226	177	196	155	886
	0-3%	540	526	532	450	419	2467
	3-9%	21	58	45	39	18	181
Evening	**9-21%**	15	42	47	31	23	158
	21-40%	7	24	28	30	10	99
	40-100%	0	3	5	6	1	15
Total Hours		1752	1752	1752	1752	1752	8760

6.4 Results

This section presents the results of three modelling experiments. Each experiment highlights different aspects of the interaction between demand heterogeneity and renewable generation. **Experiment 1** shows that the difference between residential demand only and mixed demand persists across a broad range of solar and wind generation scenarios. **Experiment 2** zooms in on the effects of time and weather conditions on the differences between the two demand cases. **Experiment 3** extends this analysis to the three archetype neighbourhood profiles, showing that the difference in renewable resource integration metrics is largest between the residential and the business neighbourhoods, with the mixed neighbourhood positioned in between.

6.4.1 Experiment 1 – Solar and Wind Generation Scenarios

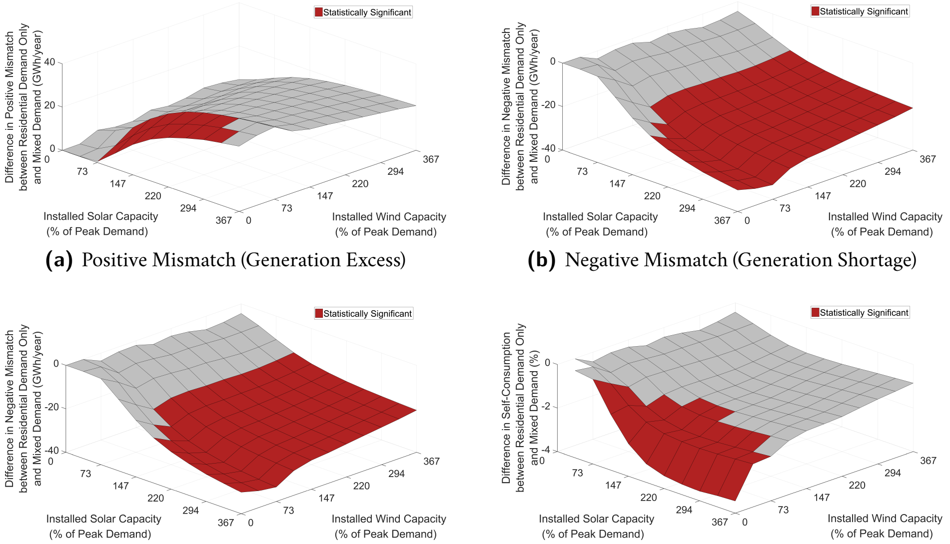
Figure 6.3 shows annual average *differences* between (1) residential-only consumers, and (2) mixed residential and service sector consumers for four renewable resource integration metrics across a broad range of renewable resource penetration scenarios. Scenarios with solar and wind generation capacity between 0 MW and 525 MW are considered, *i.e.*, 300% of peak demand for residential-only consumers and 367% of peak demand for the mixed consumers (mixed consumers have a flatter profile, see Figure 6.1).

6.4.1.1 Mismatch

Figures 6.3a and 6.3b show respectively the annual average positive and negative mismatch *differences* between residential-only consumers and mixed consumers (Eq. 6.11).

Positive mismatch represents renewable generation excess, *i.e.*, renewable energy that cannot be used by local demand (Eq. 6.1). Positive mismatch *differences* indicate to what extent renewable generation excess is overestimated if residential-only consumers are used instead of mixed consumers. The positive mismatch difference is zero when solar and wind penetration equals zero, since no renewable power is generated. For all other penetration scenarios, differences increase with increasing solar penetration, while the variation as a function of wind is limited. Overall, Figure 6.3a shows that substituting mixed consumers by residential-only consumers leads to overestimation of generation excess. Results are statistically significant for solar penetration levels above 73% of peak demand, and for wind penetration scenarios below 73% of peak demand. Note that these cut-off values are based on the scenario step granularity of 36.5% of peak demand.

Negative mismatch represents generation shortage, *i.e.*, additional energy to be supplied by non-renewable resources (Eq. 6.2). Negative mismatch *differences* indicate to what extent generation shortage is overestimated if residential-only consumers are used instead of mixed consumers. Negative mismatch difference is zero when solar and wind penetration equal zero as no renewable generation is available for either consumer case. Negative mismatch is larger in case of residential-only consumers than in case of mixed consumers, leading to negative mismatch differences below zero across all remaining scenarios. Overall, Figure 6.3b shows that substituting mixed consumers by residential-only consumers leads to overestimation of generation shortages. Results are statistically significant for scenarios



(a) Positive Mismatch (Generation Excess) **(b)** Negative Mismatch (Generation Shortage)

(c) Renewable Energy Utilisation **(d)** Self-Consumption

Figure 6.3 Annual average metric *differences* between residential-only consumers and mixed consumers. The XY plane represents scenarios of wind and solar penetration (expressed as percentage of peak demand of mixed consumers). Statistically significant differences are shown as red areas.

with solar penetration above 110% of peak demand (except for scenarios with very low installed wind capacity).

6.4.1.2 Renewable Energy Utilisation

Figure 6.3c shows renewable energy utilisation *differences* between residential-only consumers and mixed consumers (Eq. 6.12). Renewable energy utilisation is the amount of renewable energy that is used by the coinciding demand (Eq. 6.4). Renewable energy utilisation *differences* indicate to what extent the renewable energy utilisation is underestimated if residential-only consumers are used instead of mixed consumers. Renewable energy utilisation differences follow the same pattern as negative mismatch differences. For all scenarios, renewable energy utilisation is higher for the mixed consumers than for the residential-only consumers, thus the renewable energy utilisation difference is negative. Overall, Figure 6.3c shows that substituting mixed consumers by residential-only consumers leads to underestimation of renewable energy utilisation. Results are statistically significant for scenarios with solar capacity at or exceeding 147% of peak demand, at any wind penetration.

6.4.1.3 Self-Consumption

Figure 6.3d shows self-consumption *differences* between residential-only consumers and mixed consumers ($SC_{HHH}(t) - SC_{H\&S}(t)$). Self-consumption is the ratio of renewable energy utilised by the coinciding demand and the total renewable energy generated (Eq. 6.5). Self-consumption *differences* indicate the extent to which the amount of generated renewable energy that can be used by the coinciding demand is underestimated if residential-only consumers are considered instead of mixed consumers. Self-consumption is highest when the penetration of renewable generation is low, it is undefined for zero penetration. If only a small amount of renewable power is generated, any type of coinciding demand is sufficiently high to use it entirely. Self-consumption differences have a similar pattern as renewable energy utilisation differences, although differences at low wind penetration scenarios are more pronounced. Overall, Figure 6.3d shows that substituting mixed consumers by residential-only consumers leads to underestimation of self-consumption. Results are statistically significant for solar capacity scenarios above 73% of peak demand and for wind penetration of at most 147% of peak demand.

6.4.1.4 Summary

Differences in renewable resource integration metrics between residential-only and mixed consumers are found across a broad range of solar and wind generation scenarios. Considering all metrics together, statistically significant results are found in all scenarios except low solar. Note that non-significant results in low solar, low wind scenarios (left corner in Figures 6.3a-6.3d) occur because all metrics depend on the presence of renewable generation, which is small in these scenarios. Overall, this experiment shows significant misestimations of annual average metrics if residential-only consumers substitute mixed consumers. The relative magnitude of these average annual differences is small, up to approximately 5% of the total annual demand. However, the differences between the metrics for residential-only consumers and mixed consumers vary throughout the year, depending on both time and weather conditions. These variations are assessed in the next experiment.

6.4.2 Experiment 2 – Time and Weather Dependency

Results of experiment 2 are shown in Figures 6.4, 6.5, and 6.6. In each figure, the upper row represents weekdays, the lower row weekends. The columns represent three different times of the day: night, day, and evening. Within each panel, 25 weather-dependent categories are shown. The three figures show the same metrics as considered for the renewable energy penetration scenarios, with positive and negative mismatches shown in one figure.

The results shown are obtained assuming the mix of solar PVs and wind turbines as determined by the area-constrained optimisation (see Section 6.3.3). This generation mix is optimal for *mixed* consumers: 399 MW solar PVs and 30 MW wind turbines (*i.e.*, total renewable capacity amounting to 245% of peak demand in case of residential-only consumers and 300% of peak demand in case of mixed consumers).

6.4.2.1 Mismatch

Figure 6.4 shows mismatch dependency on time and weather, comparing residential-only and mixed consumers. Positive mismatch indicates renewable generation excess. Negative mismatch indicates renewable generation shortage.

During weekdays and on weekend nights (Figure 6.4a-d), the mismatch is more positive for residential-only consumers than for mixed consumers. In the weekends, during the day and in the evening (Figure 6.4e-f), the mismatch is more positive for mixed consumers,

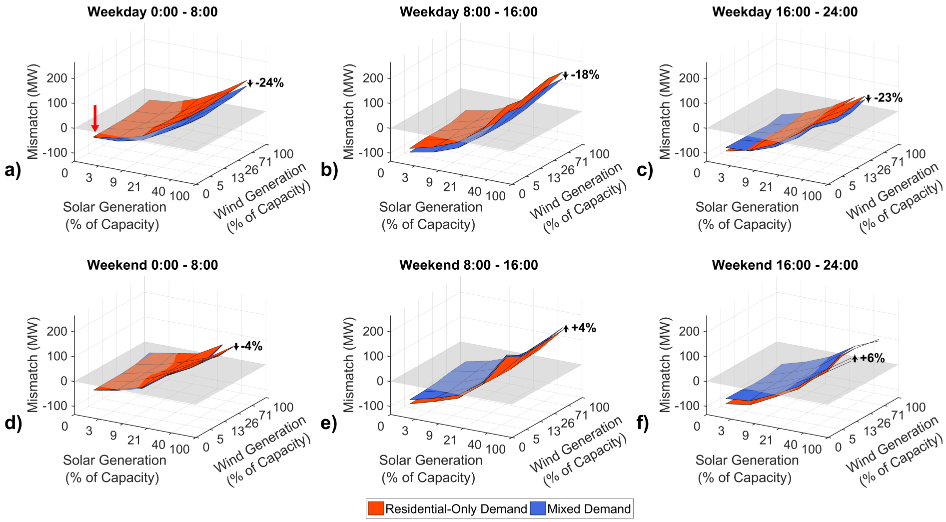


Figure 6.4 Dependency of mismatch on time and weather: comparison between residential-only consumers and mixed consumers. The surface plots depict the average mismatches per time and weather category. The six panels represent different days of the week and times of the day. Within each panel, 25 weather-dependent categories are shown. Each category has four parameters: day of the week, time of the day, solar generation, and wind generation. For example, the category indicated by the red arrow represents all weekday night hours (0:00 - 8:00) of 2014 with solar generation between 0% and 3% of installed capacity and wind generation between 0% and 5% of installed capacity. The average mismatch in these hours is -41 MW for both consumer cases. The black arrows in each panel show the maximal relative changes in mismatch when mixed consumers, instead of residential-only consumers are taken into account (the values shown are for the most sunny hours). The values on the x- and y-axes are quantiles. Note that some high solar categories are missing because they do not occur in the modelled reference year. The results shown assume 399 MW solar PVs and 30 MW wind turbines as installed capacity.

although the differences are relatively small compared to the weekday categories. The largest differences occur on sunny weekdays (Figure 6.4a-c), and amount to up to 24% lower mismatch between demand and supply in case of mixed consumers than in case of residential-only consumers.

The results obtained through the time and weather classification system can be used to identify critical combinations of time and weather. For instance, 62% of positive mismatches occur during weekdays at daytime when solar generation exceeds 40% of installed capacity, which corresponds to 7% of the time. Most negative mismatches (46%) occur during weekdays in the evening with solar generation below 3% of installed capacity, which corresponds to 20% of the time.

Statistical significance is not shown in the graph, yet is calculated as described in Section 6.3.5. Significant differences between mismatch results for the two consumer cases are found for all data points on weekdays during the day (Figure 6.4b), as well as weekday and weekend evenings (Figure 6.4c and f) for low solar (generation below 3% of installed capacity). In other periods, statistically significant differences occur for some categories. The disparity in

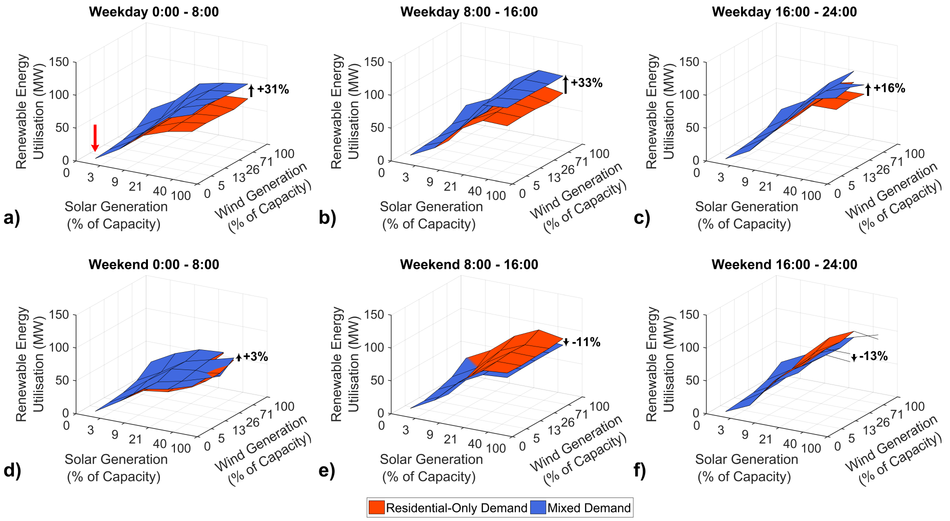


Figure 6.5 Dependency of renewable energy utilisation on time and weather: comparison between residential-only consumers and mixed consumers. Surface plots depict the average renewable energy utilisation per time and weather category. The six panels represent different days of the week and times of the day. Within each panel, 25 weather-dependent categories are shown. The black arrows in each panel show the maximal relative changes in renewable energy utilisation when mixed consumers, instead of residential-only consumers, are taken into account (the values shown are for the most sunny hours). The values on the x- and y-axes are quantiles. The red arrow indicates the example category introduced in Figure 6.4.

statistical significance between periods can be attributed to two factors: the number of data points and the relative difference between residential-only consumers and mixed consumers for a given period. First, as weather patterns are not dependent on the day of the week, weekdays have on average 2.5 times more data points per weather category than weekends. Second, during weekends and during night periods, the difference between residential-only consumers and mixed consumers is smaller than during other periods as most service sector activities are shut down.

6.4.2.2 Renewable Energy Utilisation

Figure 6.5 shows the dependency of renewable energy utilisation on time and weather and compares residential-only consumers and mixed consumers. Renewable energy utilisation is the amount of generated renewable energy that can be used by the coinciding demand.

The differences in renewable energy utilisation between residential-only consumers and mixed consumers are most pronounced if solar generation is high, both on weekdays and in weekends, and during all times of the day. Wind generation has limited effects as it represents only a small portion of the total renewable generation due to area constraints (see optimisation problem definition in Section 6.3.3). At higher solar generation levels, renewable energy utilisation is higher for mixed consumers than for residential-only consumers. The service sector consumption profile is better aligned with the solar power generation profile as both peak during the day. In the weekend, during the day and the evening hours (Figure 6.5e-f),

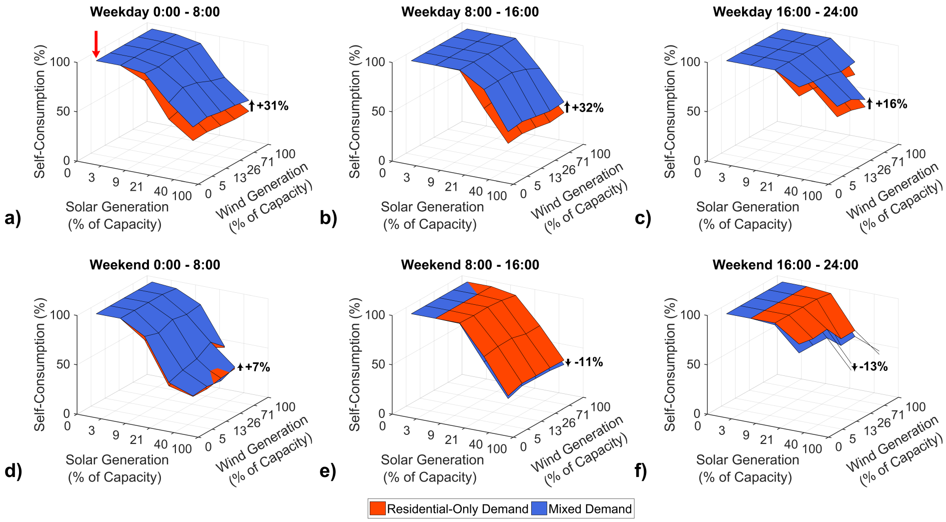


Figure 6.6 Dependency of self-consumption on time and weather: comparison between residential-only consumers and mixed consumers. Surface plots depict the average self-consumption per time and weather category. The six panels represent different days of the week and times of the day. Within each panel, 25 weather-dependent categories are shown. The black arrows in each panel show the maximal relative changes in self-consumption when mixed consumers, instead of residential-only consumers, are taken into account (the values shown are for the most sunny hours). The values on the x- and y-axes are quantiles. The red arrow indicates the example category introduced in Figure 6.4.

renewable energy utilisation at high solar insolation levels is higher for residential-only consumers. This can be explained by limited operation (and thus demand) of service sector consumers. The largest differences between the two demand cases occur on sunny weekdays (Figure 6.5a-c), and amount to up to 33% more renewable energy used directly by mixed consumers than by residential-only consumers.

Statistically significant differences are found during weekdays at high solar generation levels for all periods (Figure 6.5a-c). Most renewable energy utilisation (26%) occurs during weekdays at daytime with high solar generation levels (above 40% of installed capacity), these categories correspond to 7% of the time. Further, 7% of the renewable energy is consumed during night and evening periods with lowest sun and highest wind (occurring 10% of the time).

6.4.2.3 Self-Consumption

Figure 6.6 shows the dependency of self-consumption on time and weather and compares residential-only consumers and mixed consumers. Self-consumption is the amount of renewable energy utilised relative to the amount generated.

During weekdays (all periods) and on weekend nights, self-consumption of mixed consumers is higher than that of residential-only consumers (Figure 6.6a-d). This result is similar to the results obtained for mismatch and renewable energy utilisation metrics. During weekend days and evenings the opposite is the case, although differences are small (Figure 6.6e-f). The largest differences are found on sunny weekdays (Figure 6.6a-c): mixed consumers have a self-consumption of up to 32% higher than residential-only consumers.

Statistically significant differences occur for similar categories as for mismatch. At low solar generation levels and at all wind generation levels, self-consumption is 100%, meaning that all renewable power generated can be used by the modelled demand. As solar generation increases, self-consumption decreases. During weekdays the differences between the two consumer cases are largest (Figure 6.6b). In these periods self-consumption decreases faster for residential-only than for mixed consumers. This result illustrates that modelling only households underestimates the self-consumption of realistic mixed urban areas.

6.4.2.4 Result Dependency on Load Assumptions in the Optimisation Step

The results presented above rely on a renewable resource generation mix obtained by solving an optimisation problem assuming mixed consumers. The optimisation is constrained by area (see Section 6.3.3). This is the binding constraint for the number of wind turbines, regardless of the consumer case assumed. However, the optimal solar generation capacity depends on the consumer case considered. It is 15% lower if residential-only consumers instead of mixed consumers are assumed. The general trends for time and weather dependency as shown in Figures 6.4 - 6.6 remain similar if residential-only consumers instead of mixed consumers are assumed. However, overall mismatches become more negative, renewable energy utilisation decreases, and self-consumption increases.

6.4.2.5 Summary

Renewable power integration metrics vary as a function of both time and weather. The results shown rely on the proposed time and weather classification system. Pronounced solar generation dependency is found for all metrics due to the high share of solar PVs in the generation mix. Relative metric performance of residential-only consumers and mixed consumers differs per period. Overall, on weekdays (panels a-c on Figures 6.4, 6.5, and 6.6) mixed consumers lead to lower mismatches and higher renewable energy utilisation. During weekends (panels d-f on Figures 6.4, 6.5, and 6.6) the opposite is the case. This difference can be attributed to service sector operation hours. Statistically significant differences between residential-only consumers and mixed consumers are primarily found on weekdays due to a larger number of data points per category and a larger difference between the two consumer case profiles. Overall, results show considerable differences (of up to 33%) between metrics calculated assuming residential-only consumers and those assuming mixed consumers.

6.4.3 Experiment 3 – Neighbourhoods

In experiment 3, demand profiles of three archetype neighbourhoods from Chapter 5 substitute the two demand cases (residential-only and mixed consumers) used above. This experiment combines the scenario analysis of experiment 1 and the time and weather dependency analysis of experiment 2. Instead of 121 scenarios, only three are considered here: installed solar and wind capacities of respectively 20%, 100%, and 300% of the cumulative annual demand each. Figures 6.7 through 6.9 show the mismatch, self-sufficiency, and self-consumption metrics. In each figure, the upper row shows results for 20% solar and wind penetration scenario, middle row for 100% penetration scenario, and bottom row for 300% penetration scenario. The columns represent three different times of the day: night, day and evening. Within each panel, 25 weather-dependent categories are shown. Note that only weekday results are included as the distinction between weekday and weekend results is small. This is the case because demand profiles of weekday and weekend neighbourhoods (see Figures 5.6 and 5.9) differ less between themselves than weekday and weekend demand profiles of the average Dutch mix of residential and service sector consumers. The difference is smaller because clusters are formed differently on weekends and weekdays (see Figure 5.12), while the average mix remains unchanged.

6.4.3.1 Mismatch

Figure 6.7 shows the mismatch between demand and generation for the three archetype neighbourhoods (residential in orange, mixed in purple, and business in blue). Three scenarios of installed solar and wind generation capacity are shown: 20% of cumulative annual demand, 100% of cumulative annual demand, and 300% of cumulative annual demand. Overall, the higher the renewable resource penetration, the more frequent and the higher the positive mismatches become, and the less frequent and the lower the negative mismatches. This is the case for all neighbourhoods, and all time and weather conditions. The largest positive mismatches are 40% of the demand with 20% renewable resource penetration, rising to 600% of the demand at 100% renewable resource penetration and nearly twentyfold the demand at 300% renewable resource penetration. Yet, negative mismatches, *i.e.*, generation shortages, persist even at very high renewable resource penetration levels.

Within each scenario, mismatches are overall more positive in the residential neighbourhood than in the mixed neighbourhood, and more positive in the mixed neighbourhood than in the business neighbourhood during night and day hours. The opposite trend can be observed in the evening hours. The largest differences between neighbourhoods occur during night hours (00:00 - 08:00) and day hours (08:00 - 16:00), while only small differences can be observed in the evenings (16:00 - 24:00). The pairwise differences between the residential and the other two neighbourhoods are statistically significant for weekday and weekend day hours and for evening hours with low solar generation, for all three renewable penetration scenarios. The differences between the neighbourhoods increase with increasing renewable resource penetration. The largest difference between the residential and the mixed neighbourhoods is 14% of the average demand at 20% renewable resource penetration, 71% at 100% renewable resource penetration, and 214% at 300% renewable resource penetration. The differences between the residential and the business neighbourhoods are respectively 24%, 124%, and 371%.

These results are largely in line with the mismatch observed in experiments 1 and 2. The main difference is that in experiment 3, the trends are similar for weekdays and weekends, while in experiment 2, the mismatches are more negative for the residential demand case for weekend days and evenings. This can be attributed to the fact that real residential neighbourhoods, such as the archetype modelled here, also include some services, in contrast to the residential demand only case modelled in experiments 1 and 2, which consists solely of households.

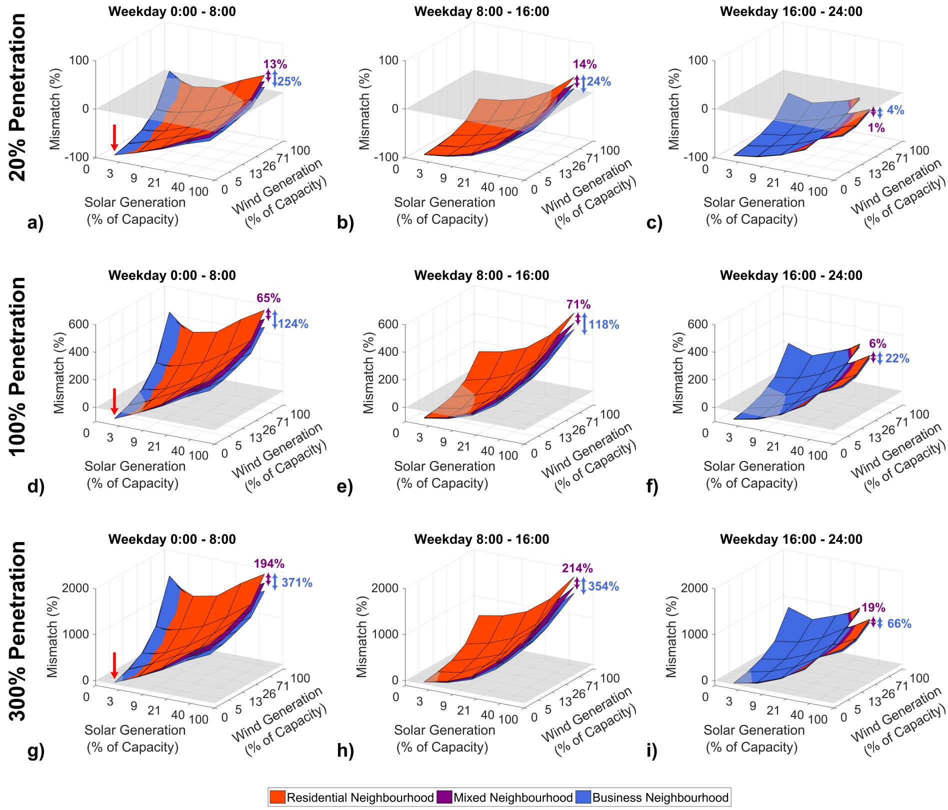


Figure 6.7 Mismatch in the three archetype neighbourhoods: residential (orange), mixed (purple), and business (blue). Three scenarios of installed solar and wind generation capacity are shown: 20%, 100%, and 300% of cumulative annual demand. The panels in each row represent weekday nights, days, and evenings. Within each panel, 25 weather-dependent categories are shown. The purple and blue arrows in each panel show the maximal relative differences in mismatch for respectively mixed and business neighbourhoods, in both cases with respect to the residential neighbourhood. The values on the x- and y-axes are quantiles. The red arrow indicates the example category introduced in Figure 6.4.

6.4.3.2 Self-Sufficiency

Figure 6.8 shows the self-sufficiency of the three archetype neighbourhoods (residential in orange, mixed in purple and business in blue). Self-sufficiency is the ratio between renewable energy utilisation and coinciding demand (Eq. 6.8). Three scenarios of installed solar and wind generation capacity are shown: 20% of cumulative annual demand, 100% of cumulative annual demand, and 300% of cumulative annual demand. Overall, the higher the renewable resource penetration, the more often (in more time and weather conditions) 100% self-sufficiency is achieved. In the 20%-scenario, full self-sufficiency is achieved only during night and day hours, and only with the maximal solar and wind generation. In the 100%-scenario, full self-sufficiency is achieved for all hours of the day, with medium-high solar and wind generation. In the 300%-scenario, full self-sufficiency is achieved even at

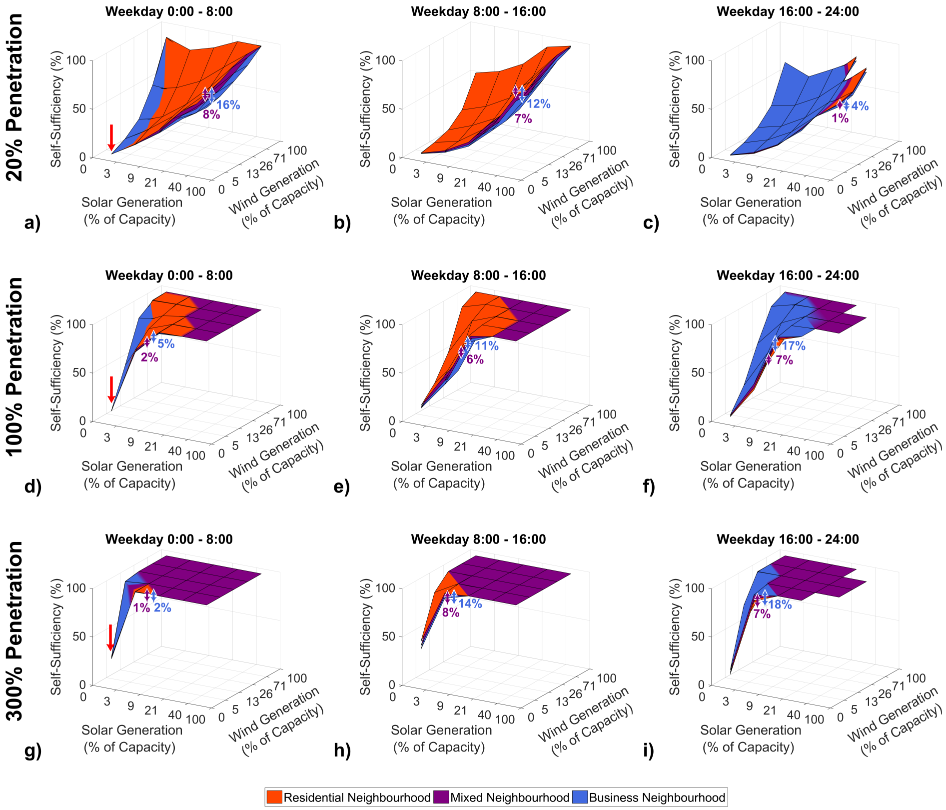


Figure 6.8 Self-sufficiency of the three archetype neighbourhoods: residential (orange), mixed (purple) and business (blue). Three scenarios of installed solar and wind generation capacity are shown: 20%, 100%, and 300% of cumulative annual demand. The panels in each row represent weekday nights, days, and evenings. Within each panel, 25 weather-dependent categories are shown. The purple and blue arrows in each panel show the maximal relative differences in mismatch for respectively mixed and business neighbourhoods, with respect to the residential neighbourhood. The values on the x- and y-axes are quantiles. The red arrow indicates the example category introduced in Figure 6.4.

medium solar and wind generation. These trends are consistent with positive mismatch trends (*i.e.*, generation excess) shown in Figure 6.7.

Within each scenario, self-sufficiency is higher for the residential neighbourhood than for the mixed neighbourhood, and higher for the mixed neighbourhood than for the business neighbourhood during night and day hours. The opposite trend is observed during evening hours. The differences between the neighbourhoods shift in time (from night, over day to evening hours) with increasing renewable resource penetration. The largest difference between the residential and the mixed neighbourhoods is 8% (night time) in the scenario with 20% renewable resource penetration, 6% to 7% in the 100% renewables scenario (respectively day and evening hours), and 7% to 8% in the 300% renewables scenario (also day and evening hours). The differences between the residential and the business neighbourhoods are 7% to 8% (respectively day and night hours) in the 20% renewables scenario, 17% (evening hours)

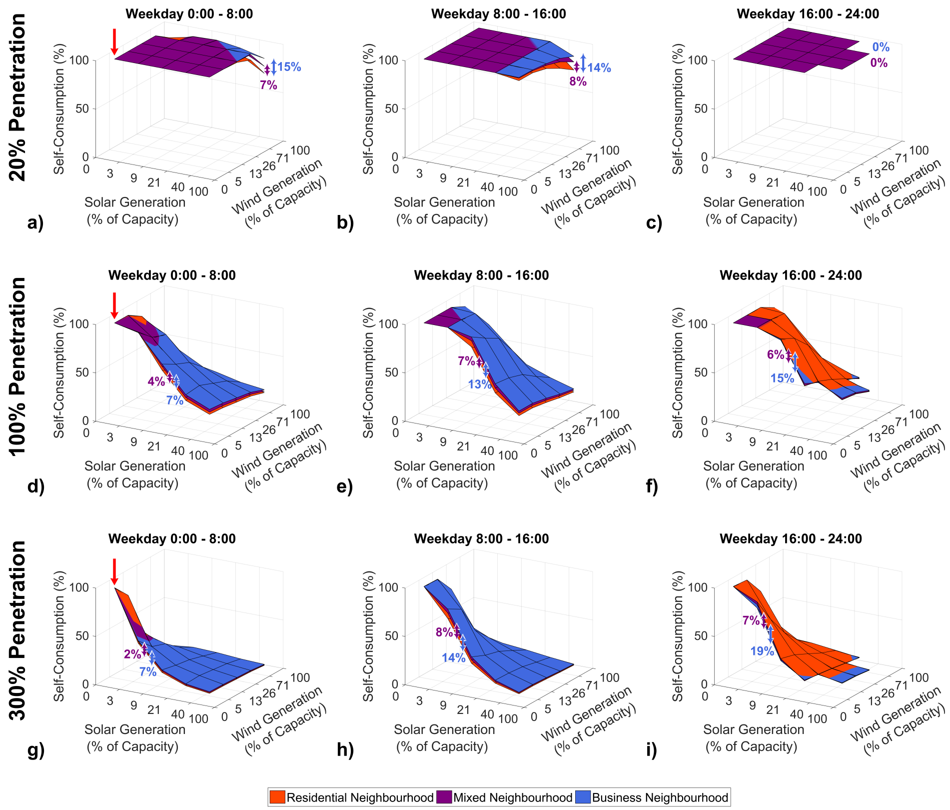


Figure 6.9 Self-consumption in the three archetype neighbourhoods: residential (orange), mixed (purple) and business (blue). Three scenarios of installed solar and wind generation capacity are shown: 20%, 100%, and 300% of cumulative annual demand. The panels in each row represent weekday nights, days, and evenings. Within each panel, 25 weather-dependent categories are shown. The purple and blue arrows in each panel show the maximal relative differences in mismatch for respectively mixed and business neighbourhoods, with respect to the residential neighbourhood. The values on the x- and y-axes are quantiles. The red arrow indicates the example category introduced in Figure 6.4.

in the 100% renewables scenario, and 18% in the 300% renewables scenario (also evening hours).

Pairwise statistical difference between neighbourhoods is found during day hours in the 20% renewables scenario, during times with low solar generation in the 100% renewables scenario, and during nights and evenings in the 300% renewables scenario.

6.4.3.3 Self-Consumption

Figure 6.9 depicts the self-consumption in the three archetype neighbourhoods (residential in orange, mixed in purple and business in blue). Three scenarios of installed solar and wind generation capacity are shown: 20% of cumulative annual demand, 100% of cumulative annual demand, and 300% of cumulative annual demand. Overall, self-consumption decreases with increasing renewable resource penetration. Self-consumption is high (72% - 100%) in all time and weather categories at 20% renewable resource penetration. At higher renewable resource penetration scenarios (100% and 300%), all renewable energy is consumed locally only if solar and wind generation are very low. In very high solar and wind generation conditions, self-consumption decreases to 16% (in the 100% renewables scenario) and 8% (in the 300% renewables scenario). These trends are consistent with both increasing self-sufficiency, and increasing positive mismatch trends shown in Figures 6.7 and 6.8.

Within each scenario, self-consumption is highest in the business neighbourhood, followed by the mixed and the residential neighbourhoods during the night and day hours. The opposite is the case during the evening hours. The differences between the neighbourhoods shift in time (from night, over day to evening hours) with increasing renewable resource penetration, similarly to the differences in self-sufficiency (see Figure 6.8). The largest difference between the residential and the mixed neighbourhoods is 8% (day time) in the scenario with 20% renewable resource penetration, 13% to 15% in the 100% renewables scenario (respectively day and evening hours), and 14% to 19% in the 300% renewables scenario (also day and evening hours). The differences between the residential and the business neighbourhoods are 14% to 15% (respectively day and night hours) in the 20% renewables scenario, 6% to 7% (day and evening hours) in the 100% renewables scenario, and 7% to 8% in the 300% renewables scenario (respectively evening and day hours).

Pairwise statistical difference between the neighbourhoods is found primarily during the daytime hours in the scenarios with higher renewable resource penetration (in the 20%-scenario, self-consumption is very high and nearly equal in all neighbourhoods).

6.4.3.4 Summary

Differences in renewable resource integration metrics are found between the three archetype neighbourhoods across three renewables penetration scenarios, and in various time and weather conditions. The largest differences exist between the residential and the business neighbourhoods. The mixed neighbourhood is positioned in between, as intuitively expected. The trends found in experiment 3 largely follow the trends of the other two experiments. The results for the residential neighbourhood are close to those obtained for the residential-only consumers demand case. Yet it should be noted that all three neighbourhoods are mixes of households and services, with the business and the mixed neighbourhood leaning closest to the mixed demand case of experiments 1 and 2. Overall, this experiment confirms that on small urban scale the demand heterogeneity cannot be neglected when estimating renewable resource integration metrics.

6.5 Discussion

Integration of renewable energy resources in urban energy systems mandates a detailed understanding of the existing potential for renewable energy utilisation. In real urban areas, demand consists of a mix of residential and service sector consumers. Existing urban energy system models primarily consider residential demand profiles. As shown by the obtained results, omitting the service sector leads to misestimations of renewable energy integration metrics in realistic urban areas. These misestimations are shown to be statistically significant for a broad range of situations – solar and wind penetration scenarios, and time and weather conditions. This is the case both for an average mix of residential and service sector demand, and for three demand profile archetypes that are found to be representative of urban areas in the Netherlands. The following paragraphs discuss the obtained results in the light of renewable resource integration in real urban areas.

6.5.1 Experiment 1 – Solar and Wind Generation Scenarios

Results obtained in experiment 1 show that service sector consumers have a significant impact on local renewable resource integration metrics. This is the case across a broad range of renewable resource penetration scenarios. Statistically significant differences between renewable resource integration metrics for residential-only consumers and mixed consumers are found for all renewable resource penetration scenarios, except in those with high installed wind turbine capacity and low installed solar PV capacity, and those with few renewable resources (Figure 6.3).

From experiment 1 can be concluded that within a large range of scenarios, mixed consumers lead to significantly less renewable energy excess, significantly less energy requirements from other non-renewable resources, and thus to a significantly higher renewable energy utilisation and significantly higher self-consumption. Although the future renewable energy generation mix is not known, these results show that service sector consumers should be taken into account in a broad range of plausible renewable resource integration scenarios.

6.5.2 Experiment 2 – Time and Weather Dependency

Experiment 2 shows that renewable resource integration metrics differ between demand cases across a wide range of time and weather conditions. The most and largest differences (of up to 33%) are found on weekdays, in particular during sunny periods. Such conditions occur in over 1300 hours per year. These results demonstrate that using residential demand profiles to model mixed urban areas results in statistically significant metric misestimations.

The reported numerical results are based on an analysis of a single scenario. The following considerations indicate that the trends are generalisable. First, significant annual differences in metrics are found across a broad range of scenarios (experiment 1). Second, the match of solar power generation with service sector power demand is better than with residential demand. Third, the mixed demand profile is more constant than the residential profile, making it more likely that wind power generated at a random moment in time is used by mixed consumers than by residential-only consumers. Therefore, from the results obtained in experiment 2 can be generally concluded that during periods of high renewable power generation, the differences in metrics between residential-only consumers and mixed consumers are sufficiently large to necessitate the dedicated and detailed consideration of the service sector. This is further substantiated by the results of experiment 3.

The results of experiment 2 are obtained based on a **novel time and weather dependency classification system** introduced in this chapter. This classification system is flexible and can be readily applied to a wide range of data series. For the dataset used in this chapter, time and weather categories are based on time intervals of one hour, full-year data, and five solar and wind energy generation categories (yielding 150 time- and weather-dependent categories). For other purposes, time interval, data series size and number of categories can be varied. For instance, the time and weather dependency classification system can be used with statistical data from multiple years to identify critical combinations of time and weather, to plan and manage distribution grid operations accordingly. In Section 6.4.2 such critical combinations are reported for the reference year 2014. The ability to identify such critical values as a function of time and weather, and to assess their likelihood of occurrence is important for the design and management of power systems with a high share of renewable resources.

6.5.3 Experiment 3 – Neighbourhoods

The results of experiments 1 and 2 underscore the overall importance of including the service sector in urban energy system models. Yet, as shown in Chapter 5, urban areas differ in consumer composition. Experiment 3 accounts for this spatial heterogeneity. Three archetype demand profiles, that are found to be representative for Dutch urban areas[5], are used in this experiment. Overall, the results show similar trends to those found in the first two experiments. Unsurprisingly, renewable resource integration metrics of residential areas are closest to those found in the residential demand only case assumed in experiments 1 and 2. As shown in Chapter 5, only a minority of urban areas can be classified as residential.

The reported results are based on average weekday and weekend profiles, and not on an annual demand profile, as is the case in experiments 1 and 2. The main drawback of this approach is loss of seasonal variability. However, as indicated in Chapter 5, this variability is relatively small. Of much larger importance is the seasonal variability in renewable generation, which has been taken into account based on a full-year hourly generation profiles. As statistically significant effects are found even with average weekday and weekend demand profiles, the lack of full-year data is considered not to be limiting for the purpose of experiment 3. If seasonal variability is taken into account, metric differences between different time and weather categories can be expected to increase as seasons are unevenly divided between these categories.

Overall, experiment 3 shows that differences in renewable resource integration metrics between the three archetype neighbourhoods are statistically significant for all three renewable resource penetration scenarios tested, and across a variety of time and weather conditions. In general, largest differences are found between residential and business areas, as the main consumer types in these areas, respectively households and offices, have distinct demand profiles (see Figure 4.3). Note that, although mixed areas have a considerable share of residential consumers, the corresponding renewable resource integration metrics differ significantly from those in residential areas. Thus can be concluded that the presence of the service sector has an important impact on the local utilisation of renewable resources in

[5] Experiment 3 is based on neighbourhood-scale demand profiles. Neighbourhoods, districts, and municipalities are found to have the same three demand profile archetypes (residential, business, and mixed), albeit with larger variations at the neighbourhood scale. The results found for neighbourhoods are thus applicable to other urban scales.

the vast majority of urban areas in the Netherlands. The service sector can therefore not be omitted at any urban scale.

6.5.4 Geographical Generalisation

This thesis considers the Netherlands as a case study. It is an open question to what extent the results can be generalised *quantitatively* to other countries. The service sector composition and its share in the total national demand differ between countries [120–122]. This is not an issue in itself. The biggest challenge in comparing different regions arises due to inconsistencies in service sector definitions, as also underlined by other authors [119, 120, 338]. Even within a country, different sources provide different values for service sector power consumption (see Section 4.3). To improve service sector modelling, at least three issues need to be addressed: (1) inconsistent service sector definitions, (2) lack of openly available service sector data in general, and (3) lack of detailed (*e.g.*, hourly) service sector and local (*e.g.*, city or neighbourhood) demand profiles in particular.

Qualitatively, the obtained results can be generalised to other developed countries because the *shape* of the service sector demand profile, with a peak during the day, is similar across developed countries [119, 225, 338, 340]. Based on the results, can be expected that the more important solar generation is in a country's renewable resource mix, the greater the impact of service sector consumers will be. Since solar power generation peaks during the day, it matches better with the service sector demand peak than with the household demand peak.

6.6 Conclusion

This chapter shows that the service sector in urban areas has a significant impact on local renewable resource integration metrics. Mixed areas can use significantly more renewable energy locally than can be expected from estimation of urban demand profiles based on household demand only. The obtained results and insights can be valuable for researchers, practitioners, and decision-makers. More realistic urban demand profiles, based on both households and the service sector, can be used to extend urban energy system models (see Chapter 3). Decision-makers and practitioners can apply the reported results to improve grid planning, operation, and management, for instance to guide interventions such as storage location, demand response programmes, and grid reinforcement. The appropriate choice of such interventions depends on the timing and the extent of the mismatches between renewable generation and demand. Intervention choices based on misrepresented urban demand profiles (*e.g.*, profiles only accounting for residential consumers in mixed urban areas), can lead to outcomes suboptimal for the real system. Case studies of the effect of demand response and storage interventions in urban areas are presented in the next chapter.

7 Harnessing Flexibility of Heterogeneous Demand: Two Case Studies

> *Ceterum censeo Carthaginem esse delendam.*
>
> – Cato Maior

The transition to renewable generation requires new sources of flexibility to maintain the balance between demand and generation, as the latter becomes more variable and less dispatchable. Different possibilities are proposed to safeguard this balance, the most common are interconnection, storage, and demand response (see Chapter 2). This chapter describes two case studies that focus on storage and demand response respectively. The aim of this chapter is to illustrate how datasets and insights developed in the previous chapters can be used to more realistically assess the effect of interventions aimed at improving local renewable resource integration.

The main conclusion from the previous chapters can be summarised as follows. Urban demand is heterogeneous: variations in local consumer composition lead to considerable temporal and spatial differences in urban energy demand (Chapters 4 and 5). These differences have a significant impact on the amount and the timing of renewable energy that can be directly utilised locally (Chapter 6). Hence, interventions that aim to improve local renewable energy utilisation need to be tailored to specific local conditions. The following two case studies illustrate this.

The first case study addresses the challenge of non-dispatchability of renewable generation by using **individually-owned storage** units to increase the utilisation of solar energy. Three real neighbourhoods in the city of Amsterdam, the Netherlands, are modelled. The results show that storage improves local renewable integration metrics in the three neighbourhoods considered, regardless of their consumer composition. This result is in line with the general understanding in literature that renewable resource utilisation increases with higher penetration of storage [71, 100, 372]. The novel insights from this case study are more subtle. Taking into account the real – heterogeneous – consumer composition improves both technical design and operation of the intervention, as well as its governance, by making the main local stakeholders explicit.

The second case study explores the potential of **demand response** as a source of flexibility that can offset both non-dispatchability and uncertainty of solar energy generation. The

This chapter is based on previous publications [62–64, 67].
Section 7.1.2.1, based on [63], copyright © 2011 IEEE.

potential for demand response is closely tied to the timing and the type of the demand itself. The case study therefore starts with a characterisation of demand flexibility in residential and service sector, revealing important differences between the two. Results of the case study show that the effects of demand response on both non-dispatchability and uncertainty of renewable generation are limited by the maximal shifting time of the considered loads. This finding underscores the importance of the availability of demand profiles with sufficient temporal and spatial detail for an accurate assessment of interventions, such as demand response.

This chapter is structured as follows. The two case studies, on storage and demand response, are described in Sections 7.1 and 7.2 respectively. The final section presents an overarching conclusion on the interplay between urban demand heterogeneity and the impact of interventions aimed to increase local renewable resource utilisation.

7.1 Storage – The Case for Local Coordination

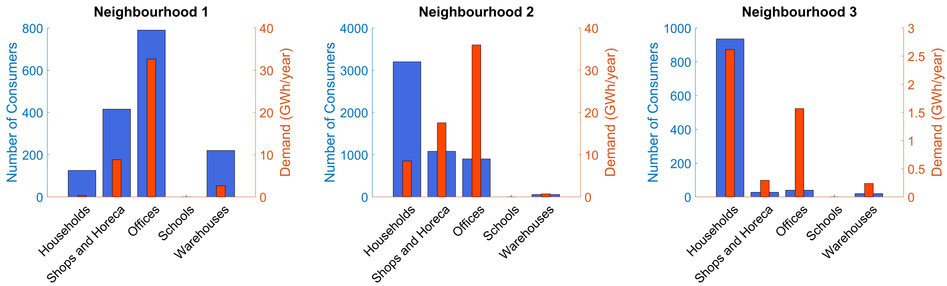
Matching non-dispatchable renewable generation with local demand is expected to become one of the main challenges as the penetration of renewable energy resources increases in urban power systems [69, 71]. Storage is seen by many as a means to resolve this challenge [99–101]. This case study addresses the effects of coordination and peak-shaving operation of individually-owned storage units.

Although a considerable amount of literature on storage coordination and operation currently exists, very few studies focus on the context of real urban areas. This hiatus is related to the limited consideration of local spatio-temporal interaction between urban demand and renewable generation in general (see Sections 1.1 and 3.2). A storage-specific three-tiered knowledge gap is identified. First, existing literature addresses either individual storage systems (component scale) [340, 373], or storage adoption scenario analyses (national-scale) [374]). Second, most studies adhere to a simplified view of consumers who own or use storage. Models are often limited to households only (*e.g.*, [375–377]), although a few consider service sector consumers (*e.g.*, [378]). Third, the primary aim of existing modelling studies is specific technical and economic storage applications, such as voltage management (*e.g.*, [372, 375, 378, 379]) and local energy cost minimisation (*e.g.*, [376, 377]), not storage integration in urban environments. Only a few authors study the coordination of individual storage systems, thereby considering solely residential demand (*e.g.*, [375, 377]). This case study addresses this knowledge gap by (1) focussing on the scale of neighbourhoods, (2) modelling both residential and service sector, and (3) addressing the question how coordination and peak-shaving operation of individually-owned storage units influences local renewable energy utilisation.

7.1.1 Methods

The impact of storage is studied for three representative neighbourhoods in Amsterdam, the Netherlands (see Figure 7.1). Their relative annual electricity demand is summarised in Table 7.1. Using the logistic regression tool presented in Section 5.2.2.5, these neighbourhoods are each classified as one of the three urban area archetypes. Neighbourhood 1 is classified

(a) Location



(b) Consumer Composition and Demand

Figure 7.1 Three modelled neighbourhoods in Amsterdam, the Netherlands. Upper panel (a) shows the location of the neighbourhoods. Lower panels (b) depict local consumer composition (blue) and modelled annual demand per consumer type (orange).

as business area, and both Neighbourhoods 2 and 3 as mixed areas. The classification of Neighbourhood 3 as mixed area once again illustrates the importance of the service sector even in a neighbourhood with a relatively high share of households.

Table 7.1 Share of demand by different consumer types in three case study neighbourhoods in Amsterdam, the Netherlands. Based on this cumulative demand, the neighbourhoods are classified using the logistic regression tool presented in Section 5.2.2.5.

	Neighbourhood 1	**Neighbourhood 2**	**Neighbourhood 3**
Households	1%	13%	53%
Shops, Hotels & Restaurants	20%	28%	7%
Offices	74%	58%	35%
Schools	0%	0%	0%
Warehouses	6%	1%	5%
Classification	*Business*	*Mixed*	*Mixed*

Two complementary aspects of local storage are addressed. First, a **greedy** and a **peak-shaving algorithm** used by the storage units are compared in terms of *peakiness* of the resulting power exchanged between a neighbourhood and the main grid. Maxima in power exchange are used as a metric to study this interaction. Second, **individual** and **coordinated** use of individually-owned storage units is examined using renewable resource integration metrics introduced in Section 6.1. For the latter analysis, storage penetration is varied between 0% and 100%. Only solar PV panels are included as renewable energy resources in the case study. PV penetration is assumed to be 50%. The case study models battery-type storage, found in electrical vehicles or small stand-alone units. Batteries are particularly suited for local energy matching [166] (see also Chapter 2). However, results are expected to be applicable to small-scale storage in general, as assumptions are limited to capacity and efficiency.

7.1.1.1 Greedy versus Peak-Shaving Algorithms

The behaviour of a neighbourhood towards the main grid is compared for two storage algorithms: a *greedy* and a *peak-shaving* algorithm. Both schedule charging and discharging in discrete timesteps (here: one hour).

Algorithm 7.1 describes the **greedy** algorithm. The operation of the greedy algorithm is solely based on the mismatch $MM(t)$ between renewable generation and demand in each timestep t. If any *generation excess* occurs ($MM(t) > 0$), it is stored to the degree that free storage capacity (*FreeS*) is available. Free storage capacity is calculated as the difference between the maximal storage capacity of the battery (*CapS*), and its state of charge ($SoC(t)$) at the beginning of timestep t. The remaining mismatch at timestep t is sent to the grid ($GridExchange(t)$). If *generation shortage* occurs, demand is met entirely, or until all stored energy is used. In that case, the flow of energy is opposite, but the principle of the algorithm is similar and therefore not shown.

Algorithm 7.2 describes the **peak-shaving** algorithm. The operation of the peak-shaving algorithm is based on the mismatches that are forecast to occur in the foreseeable future ($MM([t, \ldots, t+\eta])$), which is determined by the forecast time horizon η. If *generation excess* occurs at timestep t ($MM(t) > 0$), the peak-shaving algorithm considers the predicted mismatch $\widetilde{MM}([t, \ldots, t+\eta])$ between renewable generation and demand for all timesteps from t up to $t+\eta$. The first u consecutive, positive elements of this forecast ($\widetilde{MM}([t, \ldots, t+\eta])$) are stored in descending order in $\overrightarrow{MM}([1, \ldots, u])$. Next, the differences $\Delta\overrightarrow{MM}([1, \ldots, u])$ between the subsequent elements of $\overrightarrow{MM}([1, \ldots, u])$ are calculated. This step ranks the peaks within the forecast period from large to small and reserves storage capacity $ResS(\iota)$ to decrease the largest peaks first, moving on to smaller peaks. This procedure is repeated until storage capacity is reserved for all differences (and thus all mismatches), or until no remaining storage capacity is available. Once the reservation step is completed, the algorithm stores the energy reserved in timestep t only. If any excess energy remains at timestep t, it is sent to the grid ($GridExchange(t)$). A similar procedure (not shown) is followed when *demand exceeds generation*.

Algorithm 7.1: Greedy Storage Algorithm

Input : $MM([1,\ldots,8760])$; $SoC(1) = 0$

Output: $SoC([1,\ldots,8760])$; $GridExchange([1,\ldots,8760])$

for $t \leftarrow 1$ **to** 8760 **do**

  if $MM(t) > 0$ **then**

    $FreeS \leftarrow CapS - SoC(t)$

    $ToS(t) \leftarrow \min(FreeS, MM(t))$

    $SoC(t+1) \leftarrow SoC(t) + ToS(t)$

    $GridExchange(t) \leftarrow MM(t) - ToS(t)$

  end

end

Algorithm 7.2: Peak-Shaving Storage Algorithm

Input : $MM([1,\ldots,8760])$; η; $SoC(1) = 0$

Output: $SoC([1,\ldots,8760])$; $GridExchange([1,\ldots,8760])$

for $t \leftarrow 1$ **to** 8760 **do**

  if $MM(t) > 0$ **then**

    $\widetilde{MM}([t,\ldots,t+\eta]) \leftarrow$ forecast based on $MM([t,\ldots,t+\eta])$

    $\overrightarrow{MM}([1,\ldots,u]) \leftarrow$ first u consecutive, positive elements of $\widetilde{MM}([t,\ldots,t+\eta])$ sorted in descending order

    $\Delta\overrightarrow{MM}([1,\ldots,u]) \leftarrow$ differences between subsequent elements of $\overrightarrow{MM}([1,\ldots,u])$ with $\Delta\overrightarrow{MM}(u) = \overrightarrow{MM}(u)$

    $FreeS \leftarrow CapS - SoC(t)$

    for $\iota \leftarrow 1$ **to** u **do**

      $ResS(\iota) \leftarrow \min\left(FreeS, \iota \cdot \Delta\overrightarrow{MM}(\iota)\right)/\iota$

      $FreeS \leftarrow FreeS - \iota \cdot ResS(\iota)$

    end

    $ToS(t) \leftarrow \sum_{\iota=\iota_t}^{u} ResS(\iota)$ with ι_t the position of t in $\overrightarrow{MM}([1,\ldots,u])$

    $SoC(t+1) \leftarrow SoC(t) + ToS(t)$

    $GridExchange(t) \leftarrow MM(t) - ToS(t)$

  end

end

Consider Figure 7.2 as an example with $\eta = 5$, $SoC(t) = 2$, and $CapS = 6$. The available storage capacity $FreeS$ is $6 - 2 = 4$. Using the *greedy algorithm*, the mismatch in the first three timesteps $[t, t+1, t+2]$ is stored, and the remaining mismatch is exchanged with the grid, leading to a peak at timestep $t+3$. Using the *peak-shaving algorithm*, first storage capacity is reserved for all (forecast) mismatch peaks. Since no storage capacity is left after peak shaving, the remaining mismatch is exchanged with the grid, one unit at each timestep in $[t, t+\eta]$.

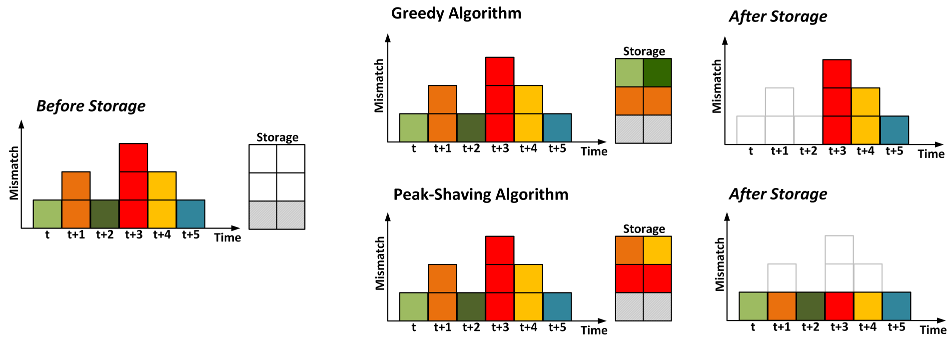


Figure 7.2 Illustration of storage operation with the greedy and the peak-shaving algorithm in case of energy excess. Both algorithms store the same amount of energy, however, the greedy algorithm (upper row) stores energy as soon as energy excess occurs. The peak-shaving algorithm (bottom row) uses demand and generation forecasts to reserve storage capacity for excess peaks, thus flattening the profile of power exchanged with the main grid.

The use of the peak-shaving algorithm enables the adaptation of charging and discharging schedules to forecast demand, generation, and state-of-charge of a battery such that, given enough storage capacity is available, all foreseeable excess is stored or demand is met, while peaks in generation and load excess power flows are limited. The algorithm assumes increasing forecast uncertainty, starting at 5% for the current timestep t.

7.1.1.2 Individual versus Coordinated Operation

Renewable resource integration metrics are studied for individual and coordinated use of individually-owned batteries and PV units. In the case of **individual** operation, owners of PVs and/or storage use only the individual capacity of their own installation. Excess or shortage of power is exchanged with the main grid. In the **coordinated** case, all PV and storage capacities of the neighbourhood are pooled together and used jointly. Residual power excesses or shortages are exchanged with the main grid.

7.1.1.3 Data and Assumptions

The three modelled neighbourhoods are taken from the pool of 11 570 neighbourhoods modelled in Chapter 5. The **demand** of these neighbourhoods is simulated as described in Section 5.1. Renewable solar power **generation** is modelled using weather data [359], which are converted into power generation data using the model developed by Walker [361] and technical specifications of Solarex MSX-60 panels [362]. **Storage** is modelled as lithium-ion batteries with battery-to-grid and grid-to-battery efficiencies of each 90%, thus a round-trip efficiency of 81%.

The model assumes that 50% of consumers have PVs. The penetration of storage is varied between 0% and 100%. Both PV and storage unit capacity are proportional to the owners' annual power demand (PV size of 1 kW_{peak} per MWh annual demand and battery size of 1 kWh per MWh [340, 373]). PVs and storage owners do not necessarily overlap. The model errs on the conservative side by assuming that PVs owners have a higher probability of owning storage units. PV and storage units are assigned at random, this assignment is repeated 30 times. Note that since PV and storage capacity depend on the consumer's annual demand, their random assignment changes the total capacity of storage and PVs in each run. This approach represents the real uncertainty aggregators or distribution system operations face, as consumer decisions to install, for instance, PVs is beyond their control. Results from the 30 simulation runs are analysed using non-parametric statistical tests [356] (underlying values are found not to be normally distributed).

7.1.2 Results

The following paragraphs describe the results of this case study. First, results on the influence of the charging/discharging algorithm employed by the storage units are shown. As the obtained results indicate an advantage of the peak-shaving algorithm over the greedy algorithm, further analysis on the influence of storage coordination and its increasing penetration is limited to the peak-shaving algorithm only.

7.1.2.1 Greedy versus Peak-Shaving Algorithm

The first aspect of the research gap concerns the influence of the charging/discharging algorithm on the peakiness of power exchanged between a neighbourhood and the remainder of the grid. Figure 7.3 shows the mismatch (*i.e.*, power exchanges with the grid) and renewable energy utilisation for a period of seven days (3 – 9 June 2012) for Neighbourhood 2. The results shown assume 50% storage penetration. Left panels represent results obtained with the greedy algorithm and right panels those obtained with the peak-shaving algorithm. Both are applied to individual as well as to coordinated storage operation. For reference, original mismatch (*i.e.*, without storage) is also shown on the upper panels. Note that each upward peak corresponds to day times, while the valleys in between are night times.

On the 8$^{\text{th}}$ of June at 10:00 the largest power peak (22 MW) of the modelled year occurs. With the greedy algorithm, either with individual or coordinated storage operation, the reduction of the peak is minimal (respectively 2% and 9%). With the peak-shaving algorithm, the height of the peak decreases to 13 MW with individual storage operation, and to 9 MW with coordinated storage operation. Note that with the greedy algorithm, mismatch is zero for the three hours preceding the onset of this peak. At that point, all available storage capacity is used and excess renewable energy is transferred to the main grid (*i.e.*, residual mismatch equals original mismatch). With the peak-shaving algorithm, storage is not used at the onset of the peak, thus initially mismatch equals original mismatch, leaving storage capacity available to store energy during the highest generation hours. Note further that, for the same period, the increase in renewable energy utilisation is less steep for the peak-shaving algorithm than for the greedy algorithm. Renewable energy utilisation at timestep t is defined here as the sum of direct utilisation and energy stored during that timestep. Since demand is independent of the charging/discharging algorithm, the difference in renewable energy utilisation can be attributed to the different use of storage by the two algorithms. The total renewable energy utilisation over the course of the entire year is equal for both algorithms, as the peak-shaving only affects the timing of power exchanged with the main grid.

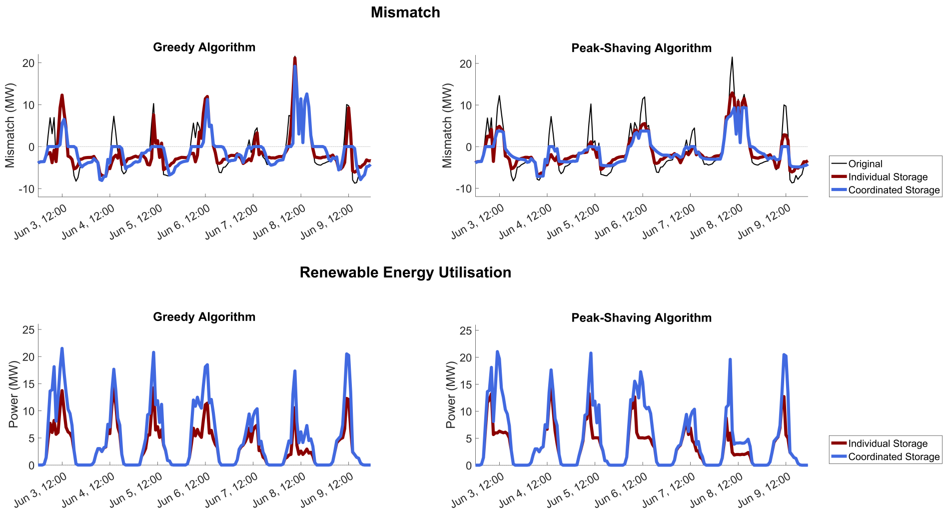


Figure 7.3 Comparison of mismatch (*i.e.*, power exchanged with the grid) and renewable energy utilisation metrics for the greedy (left panels) and the peak-shaving (right panels) algorithm. In both cases, individual and coordinated storage operation are compared. Additionally, original mismatch (*i.e.*, mismatch without storage) is shown on the top panels. The period shown is 3 – 9 June 2012.

The use of the peak-shaving algorithm does not always result in a decrease of *demand* peaks (*e.g.*, peak in negative mismatch on the 4^{th} of June at 7:00). The largest demand peak of the year is 16 MW, irrespective of storage operation or algorithm. This peak occurs on the 6^{th} of January 2013 (not shown in Figure 7.3). This winter demand peak is approximately 73% of the size of the highest generation peak in the modelled system (22 MW). The inability of the peak-shaving algorithm to reduce demand peaks can be attributed to the insufficient local generation capacity to meet all local demand (annually only 28% to 41% of the demand in the neighbourhood is supplied by local generation). This is in particular the case in periods of low solar power generation (such as, for instance, in the early hours of the 4^{th} of June on Figure 7.3).

To test the statistical significance of the differences in mismatch between the greedy and the peak-shaving algorithm, Wilcoxon signed-rank test [356] is used for both individual and coordinated storage operation. For each hour of the year, the mismatch values obtained after application of the greedy algorithm in 30 simulation runs are compared to the corresponding values obtained with the peak-shaving algorithm. Statistically significant differences in mismatch between the two algorithms are found for both individual and coordinated storage operation. For example, the p-values for the difference between the two algorithms for both individual and coordinated storage operation are $1.23 \cdot 10^{-5}$ on both the 4^{th} of June at 7:00, and the 8^{th} of June at 10:00. Thus, the peak-shaving algorithm significantly outperforms the greedy algorithm, irrespective of storage coordination.

7.1.2.2 Individual versus Coordinated Operation

Figure 7.4 shows the impact of increasing storage penetration and of storage coordination for the three neighbourhoods in Amsterdam using four renewable resource integration

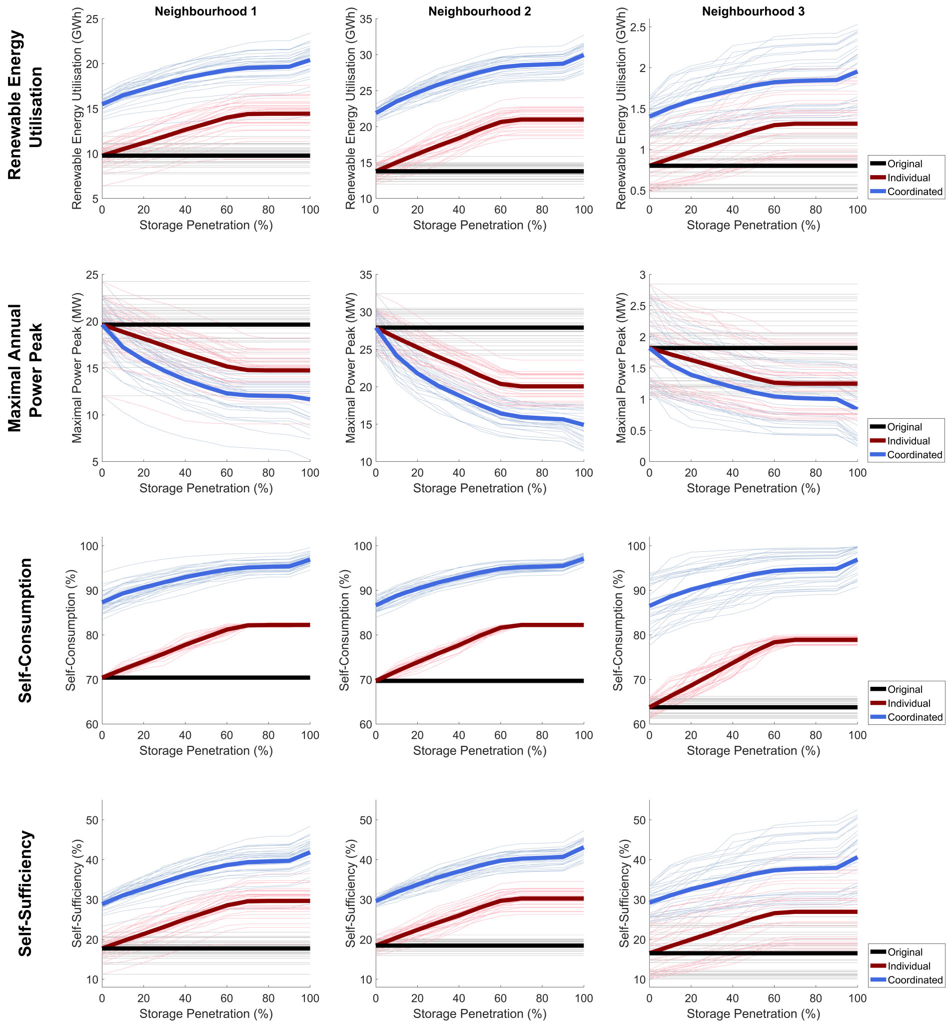


Figure 7.4 Impact of increasing storage penetration and of storage coordination in three neighbourhoods in Amsterdam, the Netherlands. Each panel shows the impact of increasing storage penetration (between 0% and 100% of consumers have their own storage units) for three scenarios: *original* (without storage, and with individual PVs), *individual* use of storage and PVs, and *coordinated* use of storage and PVs. For all plots and scenarios, the PV penetration is kept constant at 50%. The thin lines represent 30 individual simulation runs, the thick lines the averages. Noise is attributed to variations in PV and storage sizes, which result from the random assignment and corresponding sizing of PV and storage systems. Note that in each simulation, the original, individual, and coordinated scenarios are calculated for the same set of PV and storage capacity.

metrics: renewable energy utilisation, maximal annual power peak, self-consumption, and self-sufficiency (see also Section 6.1). The four metrics are shown in subsequent rows on Figure 7.4. In each panel, thin lines represent individual simulation runs, and thick lines the averages. Note that relative standard deviations between the simulation runs are largest for Neighbourhood 3 (14% to 24% for the four metrics), and smallest for Neighbourhood 1 (1% to 10%). This variability is found across all storage penetration scenarios.

Increasing penetration of storage leads to higher **renewable energy utilisation**. This effect is strengthened by coordinated use of storage, as compared to individual use. For individual operation of storage, the steepest gain in local renewable energy use is found for storage penetration of up to 60% to 70%, depending on the neighbourhood. This implies that incentivising storage penetration beyond a capacity of 0.6 to 0.7 kWh per MWh annual demand is likely to be ineffective, especially without additional interventions (*e.g.*, demand response or generation diversification). The exact value of the turning point depends on the share of consumers with both storage and PVs, as storage ownership without access to PVs does not yield benefits in the case of individual unit operation. Local renewable energy utilisation further improves significantly if storage and PVs are used in a coordinated fashion. The benefits of coordination are already apparent at 0% storage penetration. Coordination then pertains to the use of PV systems only. This increases local renewable energy utilisation by up to 78%, as compared to individual PV utilisation. Storage further improves this value. At 60% storage penetration, renewable energy utilisation nearly doubles as compared to no storage scenario. The benefits of increasing storage penetration taper off in the coordinated scenario, similarly to the results of the individual-use scenario.

The **maximal annual power flow peak** is a key metric for sizing of physical components in the distribution grid. Decreasing this peak can result in considerable cost savings for a distribution grid operator. Figure 7.4 shows that no reduction in maximal peak is obtained without storage (no difference between scenarios in second row of Figure 7.4 at 0% storage penetration). Both with individual and coordinated use of storage and PVs, largest peak reductions are reached at storage penetrations around 60%. With individual storage operation, the maximal annual power peak is reduced by up to 25%. With coordinated storage, the reductions of maximal power peaks are up to 40%.

Self-consumption is relatively high without storage in all three neighbourhoods, although notably lower (64%) in Neighbourhood 3 than in the other two neighbourhoods (70%). This difference can be attributed to the relatively high share of households in Neighbourhood 3. The demand profile of households has a poorer match with solar generation profile than the demand profile of services. A higher share of households thus leads to a lower self-consumption if no storage is available. Storage improves self-consumption in all neighbourhoods. At a penetration of 60%, self-consumption increases to 80% with individual use, and to 95% with coordinated use of storage capacity.

Contrary to self-consumption, **self-sufficiency** is low (17% - 18%) without storage. Storage improves this metric. At 60% penetration, self-sufficiency is around 30% if storage and PVs are used individually, and around 40% if they are used in a coordinated fashion. The values are approximately 3% lower in Neighbourhood 3 than in the other two neighbourhoods. The combination of a high self-consumption (close to 100% at high coordinated storage penetration) and corresponding low self-sufficiency indicates that overall, a total area solar panel capacity of 0.5 kW_{peak} per MWh annual demand is insufficient to supply the power needs of the modelled neighbourhoods. If further increase in self-sufficiency is desired, additional local generation is required.

7.1.3 Discussion

The results show benefits of peak-shaving operation and coordination of individually-owned storage units in urban neighbourhoods with a high penetration of renewables. Implementation of a peak-shaving algorithm is of particular importance to distribution system operators as it reduces the occurrence of peak power flows, which determines grid operation and investment costs. Storage coordination improves local energy autonomy and renewable energy utilisation, and is thus advantageous for local consumers. The following paragraphs discuss the technical and governance implications of the obtained results.

7.1.3.1 Technical Implications

Peak-shaving operation of storage units flattens the profile of the power exchanged between a neighbourhood and the main grid. This reduces the strain on assets of distribution system operators, while maintaining the same level of charging/discharging services for consumers. The main technical implications related to peak-shaving arise from the need to have sufficiently precise generation and load forecasting models that can be accessed and used by individual storage units. The development of such models at small scale is an active field of research [380, 381].

Coordination of storage units improves all studied metrics for the three neighbourhoods. However, the extent of the gains varies. Highest average gains in renewable resource integration metrics are observed for the mixed Neighbourhoods 2 and 3, while lowest benefits are obtained in the business Neighbourhood 1. This can be attributed to demand profile differences. Business demand peaks during the day, *i.e.*, simultaneously with the peak in solar power generation, while residential demand peaks in the evening. Thus, the baseline for the business area is relatively higher, and therefore the gains achieved due to increasing storage penetration are smaller. However, mixed Neighbourhoods 2 and 3 show more variability between the 30 simulation runs than business Neighbourhood 1. This variability arises from variations in the size and thus the output of PV arrays. Note that in real power systems, PV system size is typically outside of the control of distribution system operators who manage the local grid. The obtained results indicate that the uncertainty in the business neighbourhood is considerably smaller than in the mixed neighbourhoods. Thus, similar measures (*e.g.*, the installation of x kWh storage capacity per MWh annual demand) in a mixed neighbourhood on average leads to the highest metric gains. However, the actual outcome is more uncertain in a mixed or residential than in a business neighbourhood.

7.1.3.2 Governance Implications

Implementation of **peak-shaving operation** of individually-owned units requires adequate remuneration from the distribution grid operation or another grid responsible third party. The algorithm used by storage units primarily influences the timing of power exchanges with the grid, and thus the occurrence of peak power flows. Therefore, the use of the peak-shaving algorithm is of particular importance to the grid operator. Reducing peak power flows can, for instance, lead to deferral or avoidance of grid reinforcement investments. The remuneration mechanism for peak-shaving is therefore expected to be based on the grid operator's payments to storage owners. A similar topic is addressed by Sugihara *et al.* [378], who propose an initial subsidy for individual storage purchase paid by the grid operator to (commercial) consumers in exchange for partial control of their storage units.

Coordination of individually-owned storage units is an important advantage for local energy autonomy. From a technical perspective, coordinated operation can be achieved both through centralised and decentralised control, assuming bidirectional communication channels, *i.e.*, smart grids, are in place. However, in addition to the technical ability to coordinate individually-owned storage units, also incentive mechanisms inciting owners to allow coordination and resource sharing are needed. This requires adequate incentive schemes. For instance, as batteries only have a limited number of charge cycles [379], community use of individually-owned units is only economically viable if lifetime reduction due to community use is offset by financial compensation to the storage owner. Thus, successful deployment of storage coordination requires both the right control as well as the right incentive scheme. A good understanding of the main stakeholders in a neighbourhood is of particular importance, as households might need different incentives and a different approach than office managers, restaurant holders, *etc*. Joint neighbourhood ownership of storage units can be considered as an alternative to community use of individually-owned storage units. Also in this case, tailored incentive schemes for co-ownership and use of storage are needed to ensure its economic viability.

The technical and the governance implications demonstrate that detailed knowledge of both local generation and demand sides is needed to design and operate storage appropriately for different urban neighbourhoods. Detailed knowledge of local demand in particular implies thorough understanding of local stakeholders.

7.2 Demand Response – Addressing Non-Dispatchability and Uncertainty

Demand response is considered to be a promising source of flexibility that can support the integration of renewable resources in future power systems [96, 156, 168, 174–176]. Specifically, demand response can provide flexibility to offset the variability inherent to solar and wind generation. The output of solar PVs and wind turbines has annual, seasonal, daily, and hourly variations, none of which are fully predictable. According to some researchers, demand response is best suited to resolve inter-day and intraday variations in renewable generation [96]. This second case study focuses on two challenges related to this short-term variability of renewable resources: non-dispatchability and uncertainty. **Non-dispatchability** entails that solar and wind generation cannot be controlled to increase generation in times of more demand. Instead, demand response can be used to shift demand to times of high generation [163]. **Uncertainty** is the direct consequence of the limited predictability of renewable generation. The expected output of solar and wind generators is based on weather forecasts, that improve closer to real-time, but remain imperfect [381, 382].

Mass market demand response – demand response by large number of small residential and service sector consumers (see Chapter 2) – is expected to gain importance in the future [96, 304]. Participation of consumers is the *conditio sine qua non* for its success. Among the most important issues determining consumer participation is the degree of discomfort arising from demand response. Discomfort is closely linked to the types of loads that are targeted for demand response [383]. Detailed understanding of demand characteristics of both residential and service sector consumers can therefore help designing and implementing programmes that limit the degree of discomfort. In literature, three types of loads are distinguished: non-flexible, semi-flexible, and flexible [188, 189]. **Non-flexible loads** (*e.g.*, lighting and computers) cannot be shifted without loss of comfort. **Semi-flexible loads** can be shifted only if notice is given in due time. Washing machines and dishwashers are semi-flexible loads as their operation (for instance loading and unloading) requires active participation of consumers. **Flexible loads** are typically so-called *thermostatically controlled loads* (TCLs) that store energy in the form of temperature gradients, such as refrigerators and heat pumps [188, 189]. Due to thermal inertia, the demand of TCLs can be shifted in real-time without major loss of comfort [168].

Figure 7.5 shows the annual and daily average variability of residential and service sector demand. The values are based on measured residential demand profiles (data courtesy of Alliander, a Dutch DSO) and synthetic service sector profiles (see Chapter 4), assuming that 50% of heating demand is satisfied by heat pumps[1]. The three load flexibility categories, as introduced above, are shown separately. Loads belonging to each of the categories are summarised in Table 7.2. This subdivision is based on [341] for the residential sector and on [225] for the service sector. Figure 7.5 illustrates the differences between the residential and the service sector. First, **annual demand variability** is larger in the residential than in the service sector (left panels in Figure 7.5). The main variation in residential demand arises from higher heating and lighting demand in winter. In the service sector, heating demand is also high in winter, but is substituted by more cooling demand in summer. Additionally, lighting in the service sector is used more persistently, regardless of the outdoor lighting conditions, leading to more similar demand in summer and winter. Moreover, heating and lighting represent a smaller share of the demand in the service sector than in the residential sector. Second, **daily demand variability** differs between the residential and the service sector: demand of the residential sector peaks in the evening, while that of the service sector peaks around midday (see also Chapter 4). Third, the **ratio of flexible to non-flexible loads** is different between the two sectors. In the residential sector, 48% of the average annual load is flexible, 8% semi-flexible, and 44% non-flexible. In the service sector, 25% is flexible and 75% is non-flexible. No semi-flexible loads are defined in the service sector based on [189, 225]. Note that a high share of flexible demand can be attributed to the assumption of high penetration of heat pumps: 52% of flexible residential demand and 37% of flexible service sector demand (under the same assumption of 50% heat pump penetration in both sectors).

Overall, this analysis demonstrates that both residential and service sectors can provide demand flexibility. However the timing and magnitude differ considerably between the two sectors. This result is in line with the insights obtained in the previous chapters.

[1] This assumption is made following the decision of the Dutch government to phase out gas by 2050 [384]. Gas is currently the main fuel used to satisfy heating demand in the Netherlands.

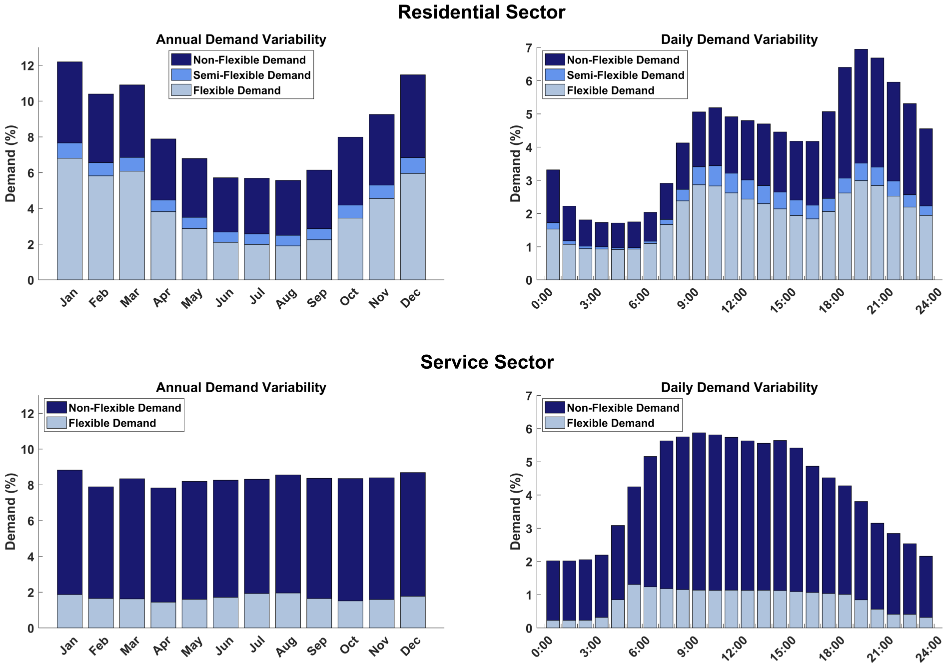


Figure 7.5 Annual and daily variability of residential and service sector demand. Three demand types are distinguished: non-flexible, semi-flexible, and flexible. Left panels show annual demand, with monthly demand expressed as a percentage of total annual demand. Right panels show average daily demand, with hourly demand expressed as a percentage of the total daily demand (data from [225, 341] and Alliander, a Dutch DSO).

The following case study explores to what extent demand flexibility of both sectors can be used to address the challenges of non-dispatchability and uncertainty of renewable generation. The case study focuses on solar generation. Individually, residential and service sector consumers are not allowed to participate in the existing electricity markets. Therefore, an aggregator is assumed to connect consumers and incumbents, interacting with the former in the retail market and with the latter in the wholesale market [168, 178] (see Chapter 2).

Table 7.2 Overview of residential and service sector loads in three load flexibility categories. Data based on [341] for households, and on [225] for the service sector.

	Residential Sector	**Service Sector**
Non-flexible	Audiovisual, computing, cooking, lighting, other	Lighting, equipment, other
Semi-flexible	Washing, drying	(-)
Flexible	Cold appliances, heating, water heating	Fans, cooling, heating

7.2.1 Methods

To address the challenges of non-dispatchability and uncertainty of solar generation, this case study takes a two-step approach. In the first step, non-dispatchability is considered. Both semi-flexible and flexible loads are used to improve the match between demand and non-dispatchable solar generation. In the second step, the focus is on reducing imbalances between day-ahead and latest intraday forecasts. Only flexible loads are assumed to be suitable to participate in intraday demand response. Semi-flexible loads are considered to remain available to address non-dispatchability of solar generation. In both steps, demand response is limited to demand shifting only, no demand curtailment is carried out. The maximum time period a load can be shifted prior to or later than its original time of demand, is assumed to be two hours, based on [189]. Furthermore, also for both steps, the aggregator is assumed to have suitable agreements with the consumers on load control, and perfect information of the consumers' loads.

The case study makes a distinction between residential and service sector consumers (*cf.* D_{HHH} and $D_{H\&S}$ respectively in Chapter 6). In both cases the consumers are assumed to be pooled together by an aggregator into respectively a residential and a service sector *aggregate*. The residential aggregate has an annual demand of 322 MWh/year and the service sector aggregate of 252 MWh/year. This equals the demand of 63 households[2] and an average mix of services for those 63 households (as determined in Chapter 4) respectively. Both consumer aggregates are assumed to generate 207 MWh of solar energy annually.

The potential of demand response to balance non-dispatchable and uncertain solar generation is studied using a simulation and optimisation modelling approach. The models are developed as a collaborative effort, with the mathematical formulation of the optimisation problems out of the scope of this thesis. These can be found in [67] and [62]. The focus in this thesis is on the analysis of the potential of mass market demand response to resolve the challenges of non-dispatchability and uncertainty of solar generation.

7.2.1.1 Addressing Non-Dispatchability

In the first step, demand response is used to improve the matching between non-dispatchable solar generation and demand, or, more formally, to maximise the utilisation of renewable generation by local demand [67]. In line with the results of the storage case study, maximisation of local renewable energy utilisation is assumed to be performed in a coordinated fashion by the entire consumer aggregate rather than individually by each of the consumers. Both semi-flexible and flexible loads are used for the maximisation of renewable energy utilisation. The optimisation[3] performed is formulated as mixed integer linear programming and described in [67].

[2] Measured data of 63 households have been made available by Alliander, a Dutch DSO.

[3] The paper [67] describes two optimisation scenarios: aggregator-optimised and consumer-optimised scenario. The results presented in this thesis pertain to the consumer-optimised scenario. In the paper, the consumers' objective function is formulated as cost-minimisation, with the assumption of constant retail and solar power feed-in prices. The feed-in price is at all times lower that the retail price, therefore cost-minimisation is equivalent to maximisation of renewable energy utilisation by the consumers.

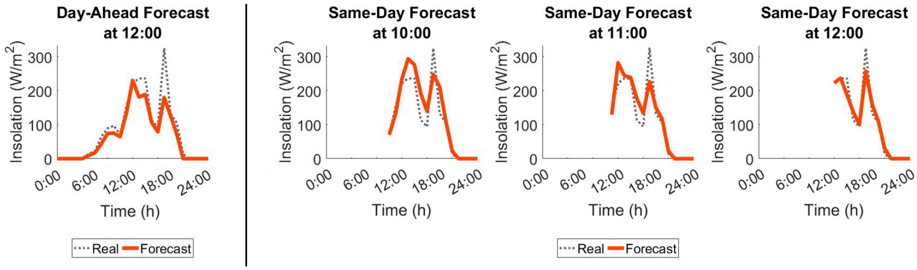


Figure 7.6 Simulated consecutive day-ahead and same-day insolation forecasts for the 3rd of June 2012. Forecasts are modelled as described in Appendix C. From these forecasts, solar power generation is predicted.

7.2.1.2 Addressing Uncertainty

In the second step, demand flexibility is used to mitigate the effects of uncertainty of renewable generation using flexible loads. Semi-flexible loads of households are assumed to remain available to be scheduled day-ahead to improve matching between generation and demand. The focus in this step is on the scheduling of flexible loads to reduce *imbalances* that arise from imperfect forecasts of solar generation. Imbalances are formally defined as the differences between the forecast available day-ahead and the last forecast available before real-time.

When the aggregator, acting on behalf of residential or service sector consumers, buys (or sells) electricity on the day-ahead market, the amount of traded electricity is based on the solar generation forecast available at that time. As the day-ahead market closes at noon on the day before delivery [154], the last forecast available pertains to a time window of 12 to 36 hours in the future. This forecast is not perfect [381, 385], thus without further actions, the aggregator can be expected to face imbalances between the generation predicted day ahead, and the actual generation. If such imbalances are not addressed by the aggregator, they have to be resolved in the balancing market against potentially high costs. However, as time progresses, increasingly more accurate forecasts become available. This case study assumes that the aggregator has access to hourly forecast updates. Figure 7.6 illustrates such improving insolation forecasts for the 3rd of June 2012. Solar power generation is calculated based on these forecasts. The figure is made using a solar forecasting simulation model, described in Appendix C.

This case study explores to what extent the aggregator can use load flexibility to reduce imbalances between the last forecast available before real-time, and the generation forecast at day-ahead market closure. This process is called *internal balancing* and is defined as "the real-time adjustment of generation and consumption within the portfolio of a balance responsible party" [386]. In this case study, the balance responsible party is the aggregator and the real-time adjustment is limited to flexible loads only. The aggregator is assumed to use an optimisation algorithm based on model predictive control (MPC) for demand response load management. The MPC algorithm is carried out iteratively each 15 minutes[4], starting at

[4]In the Dutch balancing market, transactions are determined within a time window of 15 minutes, which is called the *programme time unit* (PTU).

midnight. In each iteration, the algorithm finds the optimal scheduling of the flexible loads for the remainder of the day, given the latest forecasts for solar power generation. Once the MPC algorithm has determined the optimal scheduling of the loads for the remainder of the day, the schedule is implemented for the first quarter hour. The next quarter hour, the optimal scheduling procedure is repeated. The mathematical formulation of this algorithm is described in [62].

7.2.1.3 Data

The case study takes into account local demand and generation. In addition, a dataset of historical electricity prices is used to evaluate existing financial incentives for demand response participation. An entire year is modelled, starting on the 1st of June 2012 and ending on the 31st of May 2013. This reference year is used because measured household demand data for that period have been made available by Alliander, a Dutch DSO.

Demand is modelled separately for two consumer aggregates, one consisting of 63 households, and the other one of a corresponding average mix of services, as determined in Chapter 4. Household demand is modelled based on measured data of 63 households in the Netherlands. Service sector demand is represented by the weighted sum of the service sector demand profiles from Chapter 4, scaled to 63 households. Both the households and the service sector are assumed to use heat pumps to cover 50% of their heating demand. This assumption is made following the decision of the Dutch government to phase out gas consumption in the Netherlands by 2050 [384]. Heating demand is modelled in a similar fashion as electricity demand, using building equivalents (Chapter 4). However, as existing heating demand is met by burning gas, a number of conversion steps are required to translate gas-based heating demand into heat pump-based heating demand. These conversion steps are described in Appendix D.

Solar power generation is modelled based on an algorithm developed by Walker [361]. The technical specifications are based on Solarex MSX-60 PV panels [362]. The case study assumes that 50% of the households own solar PV panels, and that the service sector produces an equal amount of solar energy (207 MWh/year). The first step of the case study is based on the assumption of perfect knowledge of future solar generation. In the second step, uncertainty in solar power generation is taken into account. Day-ahead and hourly intraday forecasts are modelled based on historical data as described in Appendix C. Two **solar forecast scenarios** are modelled, with respectively high and low forecast errors. For high forecast errors, the relative root mean squared error (see Appendix C) is assumed to range from 25% for the next hour, to 42% for 36 hours ahead of time (see Figure C.1). For low forecast errors scenario, the magnitude of the errors is assumed to be five times lower, ranging from 5% for the next hour to 8.4% for 36 hours ahead of time. The magnitude of the error depends on the quality of the forecasting model and on the capacity of the power plant, with the high errors representative of solar power plants with a capacity below 1 MW, and the low errors representative of solar power plants with a capacity between 100 MW and

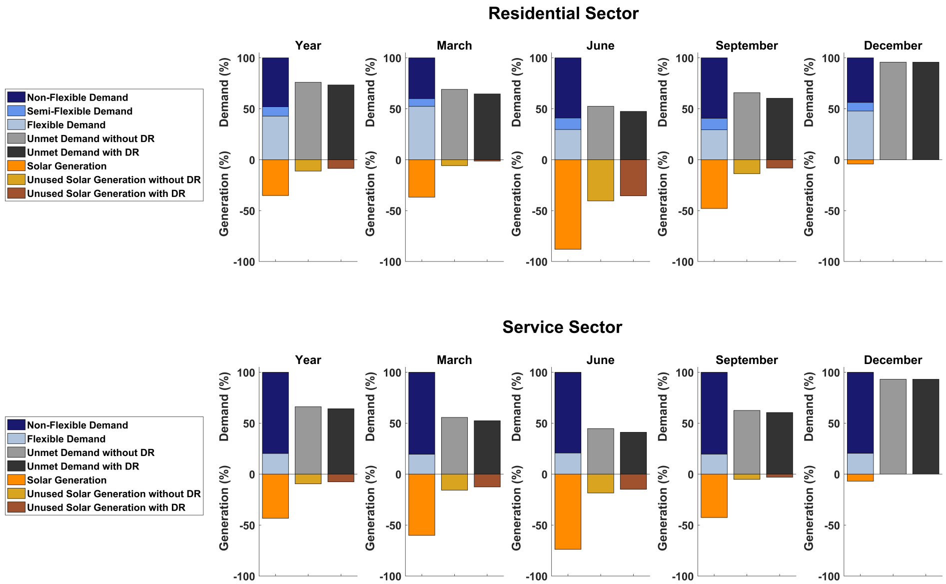


Figure 7.7 Demand, solar power generation, and mismatch (unmet demand and unused solar generation) before and after demand response. The upper panels show values for the residential sector, the lower panels for the service sector. The left panels represent the yearly average, the other four panels in each row show values for selected months. All values are represented as percentage of the total demand (which is thus 100% in each panel).

1 000 MW [381]. The total capacity of the modelled solar panels in each aggregate is 0.1 MW, the two scenarios can thus respectively be considered as "realistic" and "optimistic"[5].

Historical prices are used to analyse financial incentives provided by the existing markets to participate in demand response. In the first step, three prices are taken into account: wholesale, retail, and feed-in prices. Real historical wholesale prices for the period between June 2012 and May 2013 are used. The retail price is assumed to be 0.1822 €/kWh, which is the average from the period 2012 – 2016 [387]. Currently, the same retail price is used when consumers sell electricity, however, this practice is expected to be abandoned in 2020, although the feed-in prices are not known yet [388]. Therefore, the feed-in price assumed in the analysis, 0.06 €/kWh, is based on the German feed-in price [389], scaled to the (lower) Dutch retail price. In the second step, only wholesale prices are taken into account, as intraday load scheduling is assumed to be managed by the aggregator, whose financial incentives depend on the imbalance cost paid or avoided in the imbalance wholesale market.

[5]Note that the uncertainty of the optimistic low error scenario here is equal to the uncertainty assumed in the first case study. However, the scale of this case study is approximately three orders of magnitude smaller than the first one. Thus, while this uncertainty is optimistic for the scale modelled here, it is a realistic assumption for the previous case study, given its larger scale.

7.2.2 Results

The following paragraphs present the results of the two case study steps assessing the potential of demand response to address respectively non-dispatchability and uncertainty of solar power generation.

7.2.2.1 Addressing Non-Dispatchability

Figure 7.7 shows demand and solar power generation, as well as mismatch (unmet demand and unused solar generation) before and after demand response. The upper panels show values for households, the lower panels for the service sector. The left panels represent the yearly average, the other four panels in each row show the values for selected months. All values are represented as percentage of the total demand (which is thus 100% in each panel). Overall can be concluded that demand response reduces only a small part of the mismatch between demand and solar generation. The largest reduction in mismatch is achieved in March by the households aggregate, with a reduction of 75% of unused solar power generation and a corresponding reduction of 6% of previously unmet demand. The reason why the largest effect of demand response is observed in March and in the households aggregate can be explained as follows. A relatively large share of household demand is flexible in March (see Figure 7.5), as a result of (1) high heating demand (which is flexible), and (2) insolation approximately equal to the yearly average. Demand of the service sector is on average less flexible throughout the year, in particular in the winter months (see also Figure 7.5).

The effect of demand response on solar power utilisation is overall small. In other words, non-dispatchability of solar power generation can be only marginally remediated by load shifting. The reason is that, although demand is flexible, shifting time is limited to at most two hours [189]. This flexibility is insufficient to bridge the daily differences in solar generation and demand. Moreover, seasonal variations in demand and generation are also mismatched. The largest amount of flexibility is available in winter, when the least solar power is generated and all the generated power is utilised even without demand response. These results indicate that the potential of demand response to address non-dispatchability of solar power is limited, both for the residential and the service sector.

The results further confirm that with or without demand response, the service sector has a better match with solar power generation than households, with a relatively higher share of solar power generation used, and a higher share of demand met without demand response.

7.2.2.2 Addressing Uncertainty

Demand response can be used to reduce part of the imbalances resulting from forecast errors. The type of forecast error determines whether or not demand response leads to a decrease in imbalances. Two error types can be distinguished: *systematic errors* and *alternating errors*. Figure 7.8 illustrates the the two error types. **Systematic errors** are illustrated by the forecasts for 11 June. The day-ahead forecast is higher than the last intraday forecast throughout the day (Figure 7.8, first row, third panel), resulting in systematic negative errors (Figure 7.8, second row, third panel). **Alternating errors** occur on the other days shown,

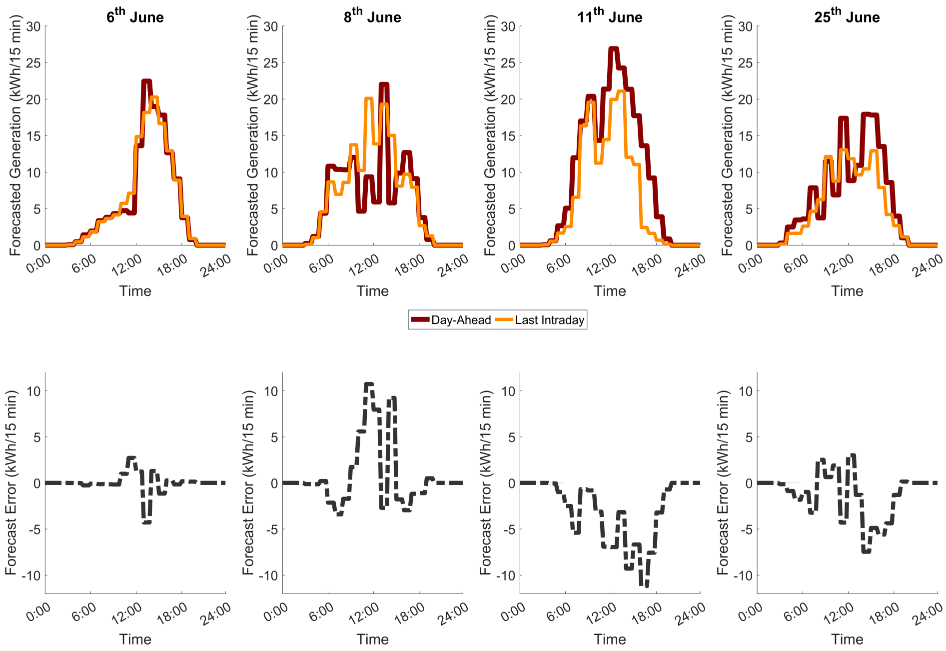


Figure 7.8 Illustration of two forecast error types: systematic and alternating errors. On 11 June, the day-ahead forecast is higher than the last intraday forecast during the entire day, resulting in *systematic* (negative) errors throughout the day. On the other days, the day-ahead forecast is alternately higher and lower than the last intraday forecast, yielding *alternating* positive and negative errors. Values are modelled assuming high forecast errors.

6th, 8th, and 25th of June. On these days, the day-ahead forecasts are in some hours higher than the intraday forecasts, and in other hours lower, creating alternating positive and negative errors. Demand response can resolve alternating errors, as load can be shifted from hours with underestimation of generation to hours with overestimation of generation. However, systematic errors cannot be resolved by load shifting, given the maximal shifting time of two hours [189].

Demand response in both the residential and the service sector can be used to balance alternating solar generation forecast errors. The extent to which imbalances can be reduced depends on both the errors and the sector providing demand response. The larger and the more systematic the errors, the less they can be resolved through demand response. The closer the match between a peak in (flexible) demand and the overestimation of solar power generation, the better imbalances can be resolved. For instance, Figure 7.9 shows that no reduction in imbalances can be achieved by either sector on the 11th of June, given that only systematic forecast errors occur on this day. On the other days, demand response by both the residential and the service sector can reduce imbalance. The extent of the reduction depends on the error magnitude, on their timing, and on the sector. For instance, the second panel in the upper row of Figure 7.9 shows that on the 8th of June between 14:00 and 14:30, demand response by the service sector leads to a larger reduction of imbalances than demand response by the residential sector. This difference can be attributed to the higher availability

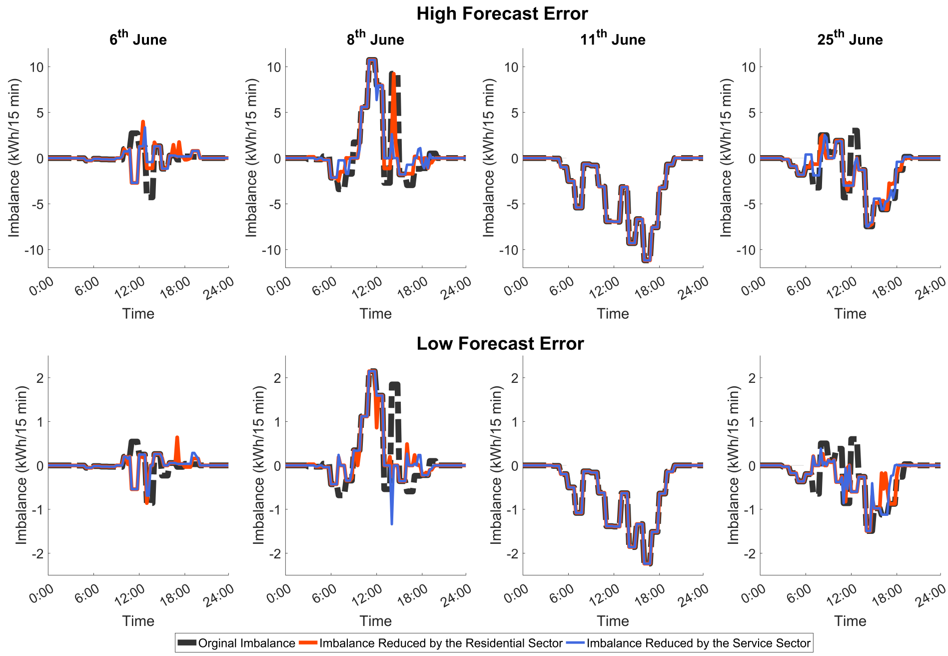


Figure 7.9 Reduction of imbalances through demand response on four days in June 2012. Upper row represents imbalances occurring under the assumption of high forecast errors, lower row under the assumption of low forecast errors (note the difference in y-axis scales). On 11 June no imbalance reduction can be achieved, as only systematic forecast errors occur on this day (see also Figure 7.8).

of flexible loads in the middle of the day on a weekday in June in the service sector than in the residential sector. Overall, throughout the year, the flexibility of service sector loads is used to a higher degree than that of residential loads.

Note that the shape of the imbalances after demand response in Figure 7.9 results from minimisation of *total* imbalances within a day. Single peaks can occur locally, such as the imbalance peak after demand response by the service sector on 8th of June at 14:30 in the low forecast error scenario (Figure 7.9, lower row, second panel). This peak occurs because no peak-shaving condition has been implemented in the demand response algorithm, which is thus comparable to the greedy storage algorithm discussed in Section 7.1. Future work should address additional requirements of peak-shaving.

Table 7.3 shows the highest achieved decrease in imbalances in four months, one for each of the four seasons. Note that the lowest achieved decrease in imbalances is 0% for all months, as systematic errors such as on the 11th June occur throughout the year. The table summarises results for both residential and service sector, and for high and low forecast error scenarios. Comparison between the two sectors and the two scenarios shows that the final result depends on more than the combination of sector and error scenario alone. First, whether demand response by the residential or by the service sector can reduce more imbalances depends on the timing and the size of the imbalances, as illustrated by the examples of selected days in June (Figure 7.9). Second, not all imbalances can be resolved

Table 7.3 Maximal imbalance reduction through demand response by the residential and the service sector. Results are shown for four months, representing different seasons. Values are based on forecasts with high errors (upper rows) and low errors (lower rows).

	March	June	September	December
High forecast error				
Residential Sector	45%	30%	53%	74%
Service Sector	45%	40%	49%	74%
Low forecast error				
Residential Sector	36%	37%	55%	75%
Service Sector	37%	33%	52%	75%

even in the low forecast error scenario, even though the absolute amount of imbalances is lower in the low forecast error scenario than in the high forecast scenario, and the total amount of flexible load remains the same in both scenarios. The reason for this is again the time limitation on load shifting: load is assumed to be only shiftable within a window between two hours before and two hours after the original timing of demand, based on [189]. Thus, even in the low forecast errors scenario, some imbalances cannot be resolved, either because the error is systematic, or because all available load flexibility in the two hours preceding and following the imbalance is used. Remaining imbalances in both sectors in the low forecast error scenario (Figure 7.9, lower row) illustrate these limitations. Finally, note that of the four months shown in Table 7.3, the highest relative imbalance reductions occur in December, as the amount of demand flexibility is highest in winter due to increased use of heating (see Figure 7.5), while the absolute insolation and the corresponding absolute forecast errors are low. The lowest imbalance reductions are achieved in June, as both insolation and the corresponding absolute forecast errors are high. The results for March and September fall in between these two extremes.

7.2.3 Discussion

This case study explores to what extent mass market demand response can be used to address short-term challenges of solar power generation, in particular non-dispatchability and uncertainty. The case study takes a two-step approach. In the first step, all available flexibility, from flexible and semi-flexible loads, is assumed to be available to improve the temporal matching between solar power generation and demand. The results show that the efficacy of demand response in resolving this challenge is limited. The main limitation is the time window in which loads can be shifted without resulting in discomfort to consumers [189]. In the second step, flexible loads are used to reduce the mismatch that arises from imperfect solar generation forecasts. From the results can be concluded that imbalances that occur as a result of alternating errors can be resolved through demand response. Load is then shifted from periods with overestimation of generation to periods with underestimation of generation. Also in this case, the load shifting time window limits the amount of imbalances that can be reduced. The following paragraphs address the technical and governance implications of these results, in a similar manner as the previous case study.

7.2.3.1 Technical Implications

The results of this case study show that the maximal shifting time of two hours limits the potential of demand response to address the challenges of non-dispatchability and uncertainty of renewable generation. The shifting time is limited to safeguard consumers' comfort [189, 383]. Improved insulation of appliances and buildings can increase their thermal inertia, and thus increase the maximal load shifting times without reduction in comfort. The design of appliances and buildings with additional requirements that enable demand response necessitates multidisciplinary collaboration between manufacturers of appliances and architects on the one hand, and power system operators and demand response programme managers (such as aggregators) on the other hand.

Another time-related aspect of demand response is the limit to the *frequency* of demand response, *i.e.*, the frequency of on and off switching of loads participating in demand response. In this case study, the aggregator makes decisions every hour. However, from the perspective of the grid, loads can be used for more frequent response, up to nearly instantaneous frequency control [96]. Similar to the design of appliances and buildings for maximisation of shifting time, maximisation of response frequency needs to be determined and designed in a collaboration between appliance manufacturers and power system engineers.

Moreover, the frequency of weather forecast updates determines how often an aggregator can make internal balancing decisions. An understanding between the interplay of the technicalities of forecasts, their inherent errors, and the implications for the power system, is an important topic for further research. This case study shows that load shifting cannot resolve systematic errors in weather forecasts. Currently, to the best of the author's knowledge, the literature relating weather forecasts to demand response potential is limited to non-existent. Availability of not only historical real weather data, but also the preceding forecasts is necessary to improve the understanding of the interplay between weather forecasts and operation of power systems with a high share of renewables. This topic also requires both further research and a multidisciplinary approach.

7.2.3.2 Governance Implications

Governance implications discussed here are limited to financial incentives for demand response participation. The second case study shows that demand response can be suitable for both improving the matching between demand and generation, and reducing imbalances that arise from imperfect weather forecasts. Arbitrage between the two demand response applications modelled here can be expected to depend on both the technical possibilities, as discussed above, and on financial incentives provided for either application.

The results presented in both case study steps are based on minimisation of mismatch or imbalance. This is a grid operator's perspective. However, existing price patterns in electricity markets currently do not provide financial incentives for demand response participation. Individual consumers pay a constant retail price, and, at least until 2020, receive the same price for the power they sell as for the power they buy [388]. This price scheme does not incentivise any demand response. Aggregators react to prices on wholesale markets. The case study is based on historical wholesale prices, which show that the incentives provided by existing day-ahead and imbalance price patterns financially *discourage* local utilisation of renewable resources. Prices are low during the day, and high in the evening, therefore price-optimised demand response minimises self-consumption of solar energy, creating local generation peaks during the day and local demand peaks during the night (see [67] for more details). Current price patterns on wholesale markets arise from a system dominated by fossil-fuel power plants. It remains an open question how price patterns will change when more renewables enter the power system.

7.3 Conclusion

The two case studies presented in this chapter illustrate that interventions designed to improve renewable resource integration in urban areas depend on local generation and demand conditions. In particular, results show that detailed knowledge of local demand characteristics is indispensable for an adequate understanding of both technical and governance implications of the considered interventions.

The first case study demonstrates that, although storage has a positive impact on all urban areas considered, its effects in a particular neighbourhood depend on the local conditions. This is highlighted by the relatively high variation in results between simulation runs. The differences in local consumer composition imply that each neighbourhood has different stakeholders. This indicates that different stakeholder groups should be addressed and incentivised in different neighbourhoods. Both researchers and practitioners should therefore be mindful of the local consumer heterogeneity when designing interventions such as local storage.

The second case study underscores the importance of the availability of demand profiles with sufficient temporal detail. If such detailed profiles are not available, the potential of demand response can only be assessed based on aggregated data. These data provide information on (at best) the total amount of flexible demand available, not its temporal, or spatial, distribution. The results of the second case study indicate that aggregated flexibility data are likely to lead to overestimations of the extent to which demand response can address non-dispatchability and uncertainty of renewable generation.

Finally, both case studies demonstrate that interventions in power systems require a multidisciplinary approach that crosses all three layers of the power system. The focus of both case studies in this chapter is on technical questions. However, the assumptions made about the economic and the governance layer play an important role in the obtained results and their interpretation. In reality, all of these layers interplay. The next chapter shows a particular example of the interplay between the three levels, addressing the effects of taxes on consumers' financial incentives for demand response participation. In Chapter 9 the need for integration, open models and data, and standardisation is discussed further.

Part IV

Supporting the Energy Transition

The power system is a socio-technical system. It can be considered as consisting of three layers: the technical, economic, and governance layer. The existing mechanisms of operation across the three layers have been designed and implemented for a centralised and fossil fuel-based system. Transitioning to renewable generation requires a more decentralised system with new sources of flexibility to maintain the balance between demand and intermittent solar and wind power generation. As the three system layers are closely interconnected, changes to one of them – the technical layer in the case of the energy transition – requires corresponding adaptations of the other two. Parts II and III focus on the role of demand heterogeneity within the technical layer. Part IV makes a connection with the other two layers. It addresses **RQ3 – How can local renewable resource utilisation be facilitated through policies?**

Redesigning the mechanisms of operation across the three power system layers is an enormous endeavour, one that requires many years of multidisciplinary research. This part consists of a single chapter, and is limited to a single illustration of how insights in the technical power system layer can be used to advise and support changes in the other layers. The primary focus of Chapter 8 is the governance layer. It addresses a specific instance of the broader **RQ3**: **RQ3a** – ***How can demand response of heterogeneous energy consumers be stimulated through energy taxation?*** This chapter analyses to what extent energy taxes can provide incentives to heterogeneous residential and service sector consumers to incite them to participate in demand response. The importance of demand response is widely supported in existing literature [96, 156, 176, 304, 390] as it is considered a promising approach to decrease mismatches between demand and supply, and increase local renewable resource utilisation and self-consumption (see Chapters 6 and 7). Demand response is infeasible without participation of consumers. Providing them with the right incentives is thus paramount. Chapter 8 shows that existing energy taxes not only fail to provide incentives, but disincentivise demand response participation. Based on an analysis of the interaction between demand and renewable generation on the one hand, and financial incentives that can steer demand to provide increased flexibility on the other hand, an alternative energy tax paradigm is proposed.

8 Rethinking Energy Taxation

— Потому, — ответил иностранец [...], — что Аннушка уже купила подсолнечное масло, и не только купила, но даже и разлила. Так что заседание не состоится.

– Михаил Афанасьевич Булгаков

Demand response is considered by more and more researchers, policy makers, and stakeholders to be pivotal for the power system as it transitions to intermittent renewable resources [96, 156, 176, 304, 390]. Within the European Union, the importance of demand response for the power system is set out in various Directives, including the Third Energy Package [391], and the Energy Efficiency Directive [392]. These Directives detail the role of demand response as an instrument to achieve climate and energy goals.

Demand response is defined in Section 2.4.2.3 as the "changes in electricity use by demand-side resources from their normal consumption patterns in response to changes in the price of electricity, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardised" [97, 130]. Thus, providing consumers with financial incentives is key to achieve a so-called *demand follows supply* power system paradigm [163]. This is a power system where demand is, to some degree, flexible and can use variable renewable generation when it is available. The European Parliament and Council [173] recognise that currently consumers do not receive price signals that incentivise such demand flexibility. The Proposal for a new Directive on the Internal Electricity Market focuses on real-time retail prices as a means to provide these price signals [173]. This chapter argues that in addition to these real-time retail prices, the European energy tax legislation needs to be rethought to provide consumers financial incentives for demand response participation.

In the European Union, energy tax constitutes a considerable part of the final consumer electricity bill. The European average is 26%, the range spanning from 4.8% in Malta, to 68% in Denmark [393, 394]. The framework for European energy taxes is set out by Directive 2003/96/EC on Energy Taxation [395]. This Directive is solely geared towards incentivising energy efficiency and energy conservation. It does not give any financial incentives for shifting demand in time, and thus providing demand flexibility. In its current form, it is thus inconsistent with the European Energy Vision, that requires both energy efficiency and demand flexibility.

This chapter is based on a previous publication [61].

European Member States can set their own energy taxes within the boundaries determined by the Energy Taxation Directive. In almost all European countries, electricity consumption is taxed with a so-called *per-unit* tax, *i.e.*, a fixed amount of tax per kWh electricity consumed [393, 394] (*e.g.*, 0.12 € per kWh in the Netherlands [387]). Spain is a noteworthy exception with a tax rate which is an *ad valorem*[1] tax, *i.e.*, a percentage (5.1113%) of the generation price paid by the consumer instead of a fixed amount of tax per kWh [396]. A side-effect of implementation of energy tax as *per-unit* tax is the lack of financial incentives for demand flexibility.

This chapter argues that if the European Union implements real-time retail prices to encourage demand response, the clarity of price signals for consumers will be dampened by a *per-unit* energy tax, currently used in the vast majority of European Member States. The dampening effect is larger if the share of the energy tax in the final electricity bill is higher, as a smaller portion of the bill is effectively affected by the generation price fluctuations. On the other hand, if an *ad valorem* energy tax is implemented, real-time price fluctuations affect both the generation cost and the tax portions of the electricity bill, providing a stronger financial incentive for demand flexibility.

Thus far, relatively little attention has been paid to the effect of consumer energy tax on demand response incentives. The issue is briefly mentioned by a few authors [175, 397], who merely note that given the existing consumer electricity bill structure, energy tax negatively affects price clarity. The lack of attention for the issue can be explained by focus limitations of different fields addressing energy taxes and demand response. This chapter (1) provides a review of the literature of energy taxes and demand response across different research fields (Section 8.1), and (2) shows in a simulation case study how tax impacts consumers' financial incentives for demand response participation (Sections 8.2 to 8.4). The case study compares financial incentives of *per-unit* and *ad valorem* tax for demand response with heat pumps in the Netherlands. The results of the case study show that an *ad valorem* tax provides a much stronger financial incentive for demand response participation than a *per-unit* tax. This insight calls for an open discussion on the role of energy tax with respect to financial incentives for consumer demand flexibility.

8.1 Literature Review

Both energy taxation and demand response are currently receiving increased interest among researchers, policy makers, and stakeholders as a result of societal and political concerns regarding climate change [96, 156, 176, 304, 390, 398, 399]. A considerable and growing body of literature is available on both topics. Literature on energy taxes primarily addresses how they can be used to internalise the negative environmental costs of energy use. Literature on demand response analyses the extent of the technical potential of demand response in future power systems and how consumers can be incentivised to offer demand flexibility. The following literature review provides an overview of the (disconnected) research fields of energy taxes and demand response.

[1] An *ad valorem* tax is a tax based on the *value* of the product.

8.1.1 Energy Taxes

Energy taxes, environmental taxes, and carbon taxes are often named in one breath, or even as synonyms [398, 400]. They all serve the purpose of internalising negative external environmental costs, but have different scopes and bases. The OECD defines an *environmental tax* as "a tax whose tax base is a physical unit (or a proxy of it) that has a proven specific negative impact on the environment" [401]. It distinguishes four types of environmental taxes: energy taxes, transport taxes, pollution taxes, and resource taxes [401]. Energy taxes are taxes that are levied based on energy use (*e.g.*, fuel or electricity), while carbon taxes (a type of pollution taxes) are expressed per unit emitted CO_2 [402]. This chapter focuses on energy taxes for electricity use.

Energy taxes are an example of excise taxes: they discourage the consumption of electricity based on the negative environmental impacts that arise from power generation from fossil fuels [398, 399, 403]. Excise taxation is indeed the guiding principle behind the existing EU Energy Taxation Directive, which stipulates that EU Member States are required to levy a minimum energy tax for electricity consumption (0.5 €/MWh for businesses and 1 €/MWh for non-business users) [395].

Current literature on energy taxes specifically, and environmental taxes in general, addresses the question *how to set such tax rates correctly*, *i.e.*, what should be taxed and by how much [398, 399]. The choice of tax base and level are classically addressed by Pigouvian Theory [404], that states that energy taxes, being a type of excise taxes, should equal the marginal cost of the damages caused. The taxes should be levied directly on the source of emission [404]. The OECD adheres to the Pigouvian Theory [399].

The existing Pigouvian excise taxes approach for energy taxation implicitly assumes that the use of electricity is equally damaging for the environment regardless of the timing of electricity consumption. This is true for electricity generated from fossil fuels. The picture is more complex for power systems with a high share of renewable resources. Energy generated from renewable resources is considerably less damaging for the environment than that generated from fossil fuels. Renewable resources such as solar and wind are abundantly available. However, materials and area to capture and transform them to electricity are limited [102, 364]. Thus, energy conservation is expected to remain important in power systems with high shares of renewable generation [364, 392]. However, the degree of energy conservation necessary varies on very short time scales in such power systems. Since renewable resources such as wind and solar are intermittent, the *timing* of energy use, and thus demand flexibility, becomes key [243]. Electricity demand at times of high solar or wind generation leads to direct consumption of renewably generated electricity, and thus low environmental impact. Demand at times of low solar or wind power generation requires storage or long-distance transportation of renewably generated electricity, or generation from non-renewable resources, and has thus a higher environmental impact [102, 364, 405]. To the best of the author's knowledge, taxes which are explicitly time-dependent currently do not exist.

The question thus arises what the role of energy taxes will be as power systems transition to increasing shares of renewable generation. The following two arguments can be used in favour of diminishing or abolishing energy taxes for electricity generated from renewable resources. First, as energy taxes are excise taxes, they are designed to internalise negative environmental costs associated with electricity generation. As these costs are considerably lower in case of renewables than in case of fossil fuels, consumption of electricity generated from renewables can be partially or fully exempt from energy taxes. This provision currently exists in the Energy Taxation Directive [395]. Second, the European Union seeks to move to real-time retail pricing [173]. Such pricing schemes are considered to be optimal as they have the theoretical potential to perfectly convey the real cost of electricity to consumers. Taxation of such optimal pricing schemes is therefore said to induce economic inefficiencies [406]. Thus, the low environmental impact of renewables and the optimality of real-time retail pricing can be used as arguments to discontinue energy taxation in power systems with high shares of renewables.

However, in practice it is unlikely that governments would (soon) entirely forego current income from energy taxes. In 2016, the European Member States collected 275 billion euro from energy taxes [407]. These energy taxes are typically not earmarked for specific use, and thus seen as a part of governmental income [408]. Recent literature addresses which role environmental taxes can play for general government spending purposes such as deficit reduction and infrastructure financing [409, 410]. Moreover, a number of authors argue that high environmental taxes and low labour taxes can be used to transition to a "green" or "circular" economy, with low resource utilisation and high employment rates [408, 411, 412]. Thus, assuming continued existence of energy taxes in power systems with high shares of renewables, their impact on financial incentives for demand response requires further study. Providing such financial incentives for demand response through taxes can result in either a decrease in governmental energy tax income, or increased taxation of consumers who do not participate in demand response, depending on the energy tax design.

8.1.2 Demand Response

Demand response is widely considered to be an important part of high-renewables power systems [96, 156, 176, 304, 390]. This source of flexibility has been briefly introduced in Section 2.4.2.3. The following review is limited to literature which deals with financial incentives for demand response participation, and participation barriers, as these topics provide the closest links with energy taxation literature, although the fields, thus far, remain disconnected.

The existing literature on financial incentives for demand response usually pertains only to the energy generation component of the consumers' electricity bill because this is currently the only component subject to market competition[2] [130, 413]. Two types of incentives or so-called *remuneration programmes* are typically distinguished [130, 171, 172]: *price-based* (or *indirect load control*) programmes, and *incentive-based* (or *direct load control*) programmes. **Price-based programmes** provide dynamic tariffs to customers. Price-based programmes include real time pricing (RTP), time of use (TOU), critical peak pricing (CPP), and extreme

[2] Currently, interest in dynamic tariffs for regulated network charges is also increasing. Analyses and position points from different parties can be found in [177, 413–415]. Network charges are left out of the scope in this chapter.

day pricing (EDP) programmes. **Incentive-based programmes** provide consumers with a remuneration fee for their participation in demand response. Such programmes are primarily geared towards large, industrial consumers. Detailed reviews of remuneration programmes can be found in [130, 171, 172].

Most of the literature concerned with different price-based programmes or *pricing schemes* either analyses the benefits and challenges of roll-out of large-scale demand response programmes in the power system [97, 130, 175, 416, 417], or describes the results of specific pilot projects (*e.g.*, [383, 418] for residential consumers and [419] for service sector consumers). Literature on the roll-out of large-scale demand response programmes includes studies that address consumer price elasticities, *i.e.*, the changes in electricity use due to changes in electricity prices [416, 417]. To the best of the author's knowledge, none of the existing studies explicitly discusses the fact that a *per-unit* tax superimposed on a dynamic electricity price negatively affect the clarity of price signals, and thus consumer response.

The European Commission recognises that "the potential for optimal demand response remains untapped" and acknowledges that the current regulatory framework "does not provide the consumers with signals and value for participation in the market" [420]. Academic literature seeks to give insights in barriers for consumer demand response participation. Bergaentzlé *et al.* show that the existence of fixed, regulated prices, that prevent new market parties from providing consumers with real price signals, are a barrier to demand response success [176]. This issue is addressed by the European Proposal for a new Directive on the Internal Electricity Market which offers consumers the choice for real-time retail prices, aiming to provide price signals incentivising demand flexibility [173]. Several authors identify additional barriers for demand response which arise from various issues related to smart meters. Bergaentzlé *et al.* consider the lagging roll-out of smart meters as a main obstacle to large-scale demand response [176]. Lamprinos *et al.* argue that norms and regulations governing smart meters and smart devices are inadequate both to protect the privacy of consumers and to incentivise market parties to invest in these devices [172]. Vallés *et al.* similarly identify the ambiguity in roles and responsibilities of smart meter and data management as a main barrier [421]. Some of these authors further name broader demand response recognition and regulatory issues. Lamprinos *et al.* show that incumbent parties, such as transmission system operators, do not always recognise demand response as a systems resource, limiting its uptake possibilities [172]. Vallés *et al.* underscore the regulatory uncertainties in remuneration of distribution system operators, feasibility of cost-reflective network tariffs, and lack of regulation of suppliers and aggregators in their role as demand response providers [421].

Energy taxes are not identified as a barrier in these analyses. Only a few authors – O'Connell *et al.* [175] and Eid *et al.* [397] – briefly mention the obscuring effects of existing tax tariffs on final price signal clarity for consumers, and thus on financial incentives for demand response participation. However, these authors do not provide further analysis on the interaction between demand response and energy taxes.

8.1.3 Synthesis – Knowledge Gap

Neither the existing academic literature on energy taxation and demand response, nor European regulations and proposals provide insights on the impact of energy taxes on financial incentives for consumers' demand response participation. Energy taxation literature focuses on setting energy taxes correctly, implicitly assuming time-independence of environmental impacts of energy consumption. Demand response literature is limited to the generation component of the consumers' electricity bills, as this is the only component subject to market competition. Existing studies do not address how market signals sent through dynamic pricing are affected by *per-unit* energy taxes used in the vast majority of European Member States.

Reconsideration of energy taxation can provide an important opportunity for policy makers to financially stimulate demand response. A future energy tax design can be consistent with both energy efficiency targets, and renewable resource integration targets, *i.e.*, demand flexibility. This chapter highlights the potential of energy taxation to achieve both goals and thus align energy taxation regulations with the European Energy Vision.

The remainder of this chapter illustrates how financial incentives for demand response participation for small residential and service sector consumers differ between the *per-unit* and *ad valorem* tax. The latter is chosen as an alternative to *per-unit* tax for two reasons. First, an *ad valorem* tax passes on electricity price signals to consumers, thus supporting demand response and integration of renewables, while retaining (part of) the current government revenue from energy taxes. Second, although the Spanish *ad valorem* energy taxation law was signed in 1992, and thus pre-dates the public and political interest in demand response, its implementation shows that this type of energy taxation is compatible even with the current EU regulatory taxation framework. The following case study explores and compares the effects of *per-unit* and *ad valorem* energy tax on financial incentives for demand response participation.

8.2 Case Study Motivation

The case study is motivated by the need for clear financial incentives for demand response programmes. Currently, price signals that can be provided to residential and service sector consumers by commercial parties are dampened by existing *per-unit* energy tax. Dampened price signals negatively affect the operation of such commercial parties as consumers receive lower financial incentives for demand response participation. Thus, the clarity of price signals is relevant for both the consumers and the parties managing the programme. Aggregators are expected to take on the role of new commercial parties enabling and managing demand response in future power systems [178] (see also Section 2.4.2.4). This case study simulates a demand response programme managed by an aggregator and shows the impact of *per-unit* and *ad valorem* tax on the clarity of price signals.

The case study considers flexibility from heat pumps due to (1) their increasing popularity as colder-climate countries move away from fossil-fuelled space heating systems [186], and (2) their large flexibility potential (see further, Section 8.3). This chapter thus assumes

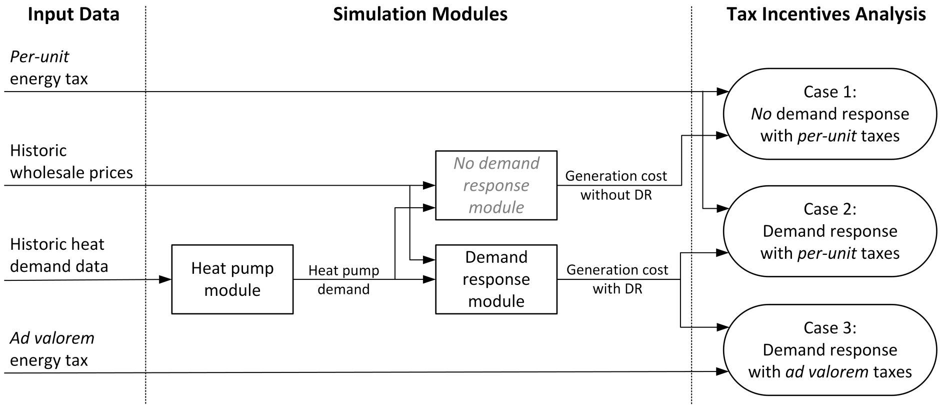


Figure 8.1 Flow chart of heat pump demand response case study. Heat pump electricity demand is modelled based on historical space heating demand data, represented here by the "Heat pump module" (for technical details, see Appendix D). The case study compares three cases: (1) no demand response (reference), (2) demand response with *per-unit* tax, and (3) demand response with *ad valorem* tax. For the reference case, heat pump demand profiles are combined with historical wholesale prices, yielding electricity cost without demand response (DR). For the other two cases, heat pump demand profiles are modified through demand response, represented here by the "Demand response module" (for technical details, see Appendix E), and also combined with wholesale prices, yielding the electricity cost with DR. This approach is carried out for three consumer groups separately: residential, office, and city centre consumers (not shown).

electrification of heating systems and builds further on the demand heterogeneity insights obtained in the previous chapters. Individually, consumers' heat pumps (or other appliances) are too small for grid-scale purposes. Therefore, an aggregator or other intermediary party is required to offer their joint demand flexibility in bulk to large incumbent parties [422, 423]. The case study assumes real-time pricing of electricity, for the following two reasons. Real-time pricing is considered optimal to signal the real cost of electricity [130, 171, 172], and the European Parliament and Council propose to mandate electricity retailers to offer this type of pricing to consumers in the future [173].

Today, however, real-time retail pricing is far from being a reality for most residential and service sector consumers [397]. Moreover, field experimentation with different energy taxes requires considerable resources. Thus, a simulation approach is best suited to provide insights in the financial incentives given by real-time pricing of electricity generation, with either *per-unit* or *ad valorem* taxes. The following section details the modelling approach and assumptions.

8.3 Case Study Methods

This simulation case study quantitatively illustrates how financial incentives for demand response participation for residential and service sector consumers differ between *per-unit* energy tax and *ad valorem* energy tax. Heat pumps for space heating are chosen as the illustrative source of demand flexibility.

Table 8.1 Three consumer groups considered in this case study: residential, office, and city centre. The table summarises the breakdown of the consumer groups in their respective consumer types.

Consumer	Composition
Residential	100% households[a]
Office	52% large offices, 47% medium offices, 1% small offices
City Centre	2% hotels, 33% restaurants, 14% cafés, 10% shops, 41% supermarkets

[a] Percentages shown with each consumer type indicate the share of annual demand this consumer type represents within the given consumer group. The electricity demand shares within each consumer group are representative for the Netherlands [59]. For comparison purposes, the three consumer groups are scaled to have equal annual heat pump electricity demand of 98 MWh.

The modelling approach is schematically shown in Figure 8.1. The model is based on the same demand data as used for the case studies in Chapter 7. The same time period, from 1 June 2012 until 31 May 2013, is considered. The model is implemented in Matlab [370].

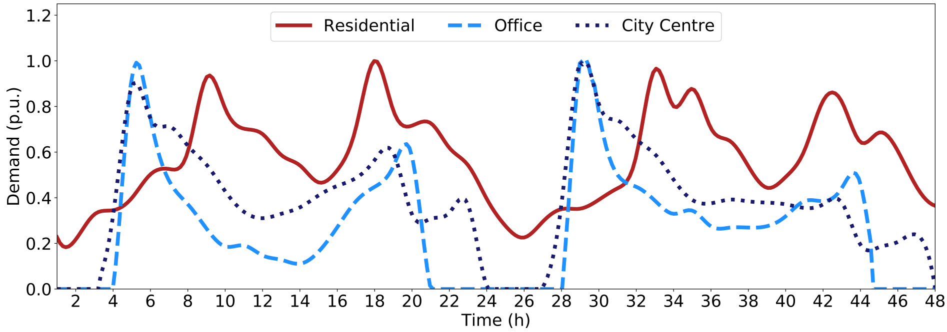
8.3.1 Consumer Types

The case study takes demand heterogeneity into account by considering three different types of consumers: (1) residential consumers (households), (2) office consumers (offices), and (3) city centre consumers (shops, restaurants, and hotels). These consumer groups can be considered to be simplified versions of the three archetype urban areas, respectively residential, business, and mixed areas (see Chapter 5). Table 8.1 summarises the composition of each consumer group in terms of annual heat pump electricity demand.

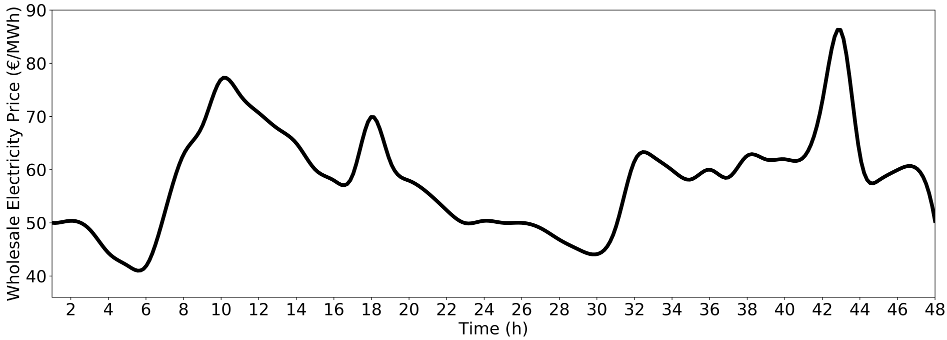
The key difference between the three consumer groups lies in the *timing* of their demand. This is the case for heating demand in the same fashion as for other appliances (see Chapter 3). Figure 8.2a illustrates heating demand profiles for each of the three consumer groups. Residential heating demand peaks around 10 a.m. and 8 p.m., and is overall relatively high during the day, and relatively low at night (data courtesy of Dutch DSO Alliander). Office and city centre demand peaks around 6 a.m., just before office hours (data based on [225, 331]). Office consumer demand has a second smaller peak at 8 p.m. City centre consumer demand has a second peak just before midnight. During the course of the day, city centre consumer demand is higher than that of offices. These differences in timing of demand are important for the technical potential to shift demand from more expensive hours to cheaper hours. Figure 8.2b illustrates price fluctuations for the same two days as shown in Figure 8.2a (data courtesy of Alliander, a Dutch DSO). A consumer's heat demand profile determines how much demand can be technically shifted and at which time (see also Section 7.2).

8.3.2 Heat Pump Demand

The case study focuses on heat pumps as flexible appliances used for demand response. The choice of heat pumps for demand response is motivated by two reasons. First, heat pumps are expected to gain popularity as colder-climate countries move away from fossil-fuelled space heating systems [186]. The Dutch government in particular plans to phase out gas



(a) Heating demand profiles



(b) Wholesale electricity prices

Figure 8.2 Heating demand profiles and wholesale electricity prices for two illustrative days (Wednesday 16th of January and Thursday 17th of January 2013). Upper panel (a) shows heating demand profiles of residential, office, and city centre consumers. Bottom panel (b) shows historical EPEX wholesale market electricity prices. Residential heating demand data and wholesale price data courtesy of Alliander, a Dutch DSO. Office and city centre demand data are based on [225].

consumption by 2050 [384]. Second, heat pumps are so-called thermostatically controlled loads (TCLs). TCLs in general are considered particularly suitable for demand response because (1) they store energy in the form of temperature gradients, and (2) their demand can be shifted without major loss of comfort [168]. Heat pumps are thus an upcoming class of large consumer-scale TCLs that have a considerable demand flexibility potential.

The model is based on measured data (for residential consumers) and realistic simulated data (for service sector consumers). In both cases, historical space heating demand is converted into corresponding heat pump electricity demand for space heating. Technical details of this conversion are described in Appendix D. Heat pumps for all consumer groups are modelled in the same manner (Figure 8.1). For the purpose of this chapter, heat pumps are assumed to be fully available for demand response within technical and consumer-defined comfort limits. Identical limits are assumed across all three consumer groups. Moreover, for comparison purposes, the three consumer groups are scaled to have an equal annual heat pump electricity demand of 98 MWh (equalling the residential demand, which is based on historical data). Thus, the difference in demand response between the consumer groups arises solely from timing differences in their heat demand profiles (Figure 8.2a).

8.3.3 Demand Response Programme

The demand response programme modelled in this case study is run by an aggregator. The aggregator represents consumers of each of the three consumer groups separately, offering the heat pump flexibility of the consumers of each group in bulk to other power market parties. Individual consumers are assumed to have agreements with the aggregator that allow the aggregator to manage their heat pump electricity use on their behalf based on market price signals (consistent with EU Proposal [173]), while respecting the technical limits and consumer-set preferences.

The demand response model seeks to realistically represent the operation of an aggregator. Therefore, the modelled aggregator is assumed to use two commercial software packages, PowerMatcher [424] and Realtime Energy eXchange (R.E.X.) [425], to manage heat pump demand. These two software packages in practice enable an aggregator to communicate with the heat pumps (which thus become "smart" devices). This detailed modelling approach is chosen because it captures the interactions in time-dependent fluctuations in wholesale electricity price, heat demand, and heat pump flexibility (the latter varies with temperature). The advantage of using detailed demand data (see previous paragraph) and a detailed demand response model is a more realistic representation of the effects of energy tax on financial incentives for demand response participation.

In the model, the aggregator operates both on the day-ahead and the balancing market. Day-ahead the aggregator receives information about the status of the consumers' heat pumps, and their historical consumption on similar days (that determines the flexibility potential of the heat pumps). After day-ahead market closure, the aggregator receives day-ahead market price information. This price information is passed on to the heat pumps, and used to automatically adjust heat pump demand if necessary (*e.g.*, if the price is high, and technical and user-set preferences allow for a demand shift to a cheaper timeslot). In real-time, if imbalances occur, they are settled on the imbalance market. Thus, consumers are subject to real-time pricing, in line with the EU Proposal on the Internal Electricity Market [173].

In this case study, historical day-ahead and imbalance market wholesale price data are used to account for fluctuating electricity cost, see Figure 8.2b. Further technical modelling details of the demand response programme are given in Appendix E. For clarity of subsequent analysis, the aggregator is assumed to have no commercial interests, thus entirely passing on wholesale prices to the consumers, not retaining any financial gains obtained from demand response.

8.3.4 Electricity Bill Components

In the Netherlands, the electricity bill of consumers, like that of many of their European counterparts, currently consists of the following components (ranges over the period 2012 – 2017): (1) electricity supply cost ranging between 0.065 and 0.079 €/kWh [387], (2) energy tax ranging between 0.1063 and 0.1232 €/kWh [426], (3) 21% value added tax (VAT) on the sum of electricity generation and energy tax components [426], and (4) network charges ranging around 200 euro per year for an average household, the exact amount depends on the DSO and the connection type [387]. This case study considers only the electricity generation, energy tax[3], and VAT. Fixed costs (network charges) and tax rebates are excluded. Network charges are excluded because they are paid cumulatively for a consumer's entire electricity connection, which is used only partially by the modelled heat pumps. A tax rebate is provided to households by the Dutch government, and amounts to 309 to 319 euro per electricity connection [426]. This tax rebate is excluded for the following two reasons: (1) it pertains to the entire electricity connection, and (2) a tax rebate does not provide any demand flexibility incentives.

In summary, the total electricity bill considered in this case study consists of three price components: (1) wholesale prices passed on perfectly to the consumers, representing real-time retail prices, (2) energy tax, and (3) 21% value added tax (VAT) on the sum of electricity generation and energy tax cost. Two energy tax designs are considered. First, *per-unit* energy tax at a rate of 0.1165 €/kWh (average energy tax over the period 2012 - 2017). Second, an *ad valorem* tax, which is a percentage of the electricity generation cost. Energy taxation is described further in the next paragraph.

8.3.5 Energy Taxation

The case study analyses the effect of an energy tax on financial incentives to participate in demand response. Two tax designs are compared: *per-unit* energy tax, and *ad valorem* energy tax in the following three demand response cases:

- **Case 1: No demand response.** Consumers do not participate in demand response. They pay real-time electricity prices, plus 0.1165 €/kWh *per-unit* energy tax, plus 21% VAT over generation and tax components.
- **Case 2: Demand response with *per-unit* tax.** Consumers participate in the demand response programme offered by the aggregator for heat pump space heating. They pay real-time electricity prices, plus 0.1165 €/kWh *per-unit* energy tax, plus 21% VAT over generation and tax components.
- **Case 3: Demand response with *ad valorem* tax.** Consumers participate in the demand response programme offered by the aggregator for heat pump space heating. They also pay real-time electricity prices, however, in this case they pay an *ad valorem* energy tax, plus 21% VAT over generation and tax components.

This chapter proposes to design the *ad valorem* tax in such a way that the government does not forgo any tax revenues if consumers do not participate in demand response. Thus, if consumers do not shift demand, they pay as much tax with the *ad valorem* tax as they would with the *per-unit* tax. This also means that, although *per-unit* tax is modelled in case 1 (no demand response), the same results would be obtained if *ad valorem* tax was assumed for the

[3] This chapter considers the total energy tax, which in the Netherlands is the sum of electricity tax and energy storage tax components. The tax range provided is valid for consumers with an annual consumption of up to 10 MWh. The modelled individual residential and service sector consumers are assumed to fall in this range based on the calculations in Chapter 4.

Table 8.2 *Ad valorem* tax rates for different consumer groups.

	Residential	Office	City Centre
Average annual electricity cost (€/kWh)	0.04711	0.04385	0.04337
Proportional tax rate (share of generation cost)	247%	266%	269%

reference case. The *ad valorem* tax rate $\tilde{\theta}_i$ for each consumer group $\ddot{c}$ can be found from the *per-unit* tax rate θ (0.1165 €/kWh) and the customer's average annual electricity cost $K_{\ddot{c}}$:

$$\tilde{\theta}_{\ddot{c}} = \frac{\theta}{K_{\ddot{c}}}, \qquad \forall \ddot{c} \in \ddot{C} = \{\texttt{residential, office, city centre}\} \tag{8.1}$$

The *ad valorem* tax rates for each of the three consumer groups are summarised in Table 8.2, alongside the average annual electricity cost. The average annual electricity cost differs between consumers because of the differences in demand profiles (see Figure 8.2a). These differences result in differences in *ad valorem* tax rates. The effects and desirability of such differences are discussed in Section 8.5.

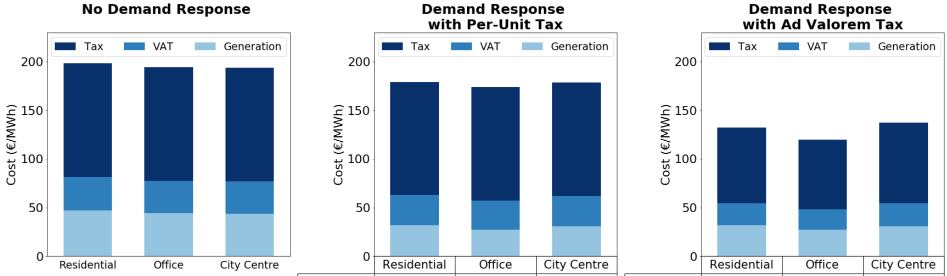
8.3.6 Synthesis – Tax Incentive Comparison

The aim of this case study is to illustrate differences in financial incentives that small residential and service sector consumers receive for participation in a demand response programme with different tax designs. Heat pumps for space heating are used as an illustrative example of flexible loads. Total electricity costs, as billed to the consumers, of three cases are compared: no demand response, demand response with *per-unit* tax (current tax design), and demand response with *ad valorem* tax (alternative tax design). Total electricity cost for heat pump operation without demand response is used as a reference for the two cases with demand response. Formally, the metric used to quantify financial incentives (ϕ) is the normalised difference between the electricity cost K_{ref} without demand response (reference), and electricity cost with demand response K_{DR}:

$$\phi = \frac{K_{ref} - K_{DR}}{K_{ref}} \tag{8.2}$$

8.4 Case Study Results

This section shows the simulation results of different consumers' financial incentives to participate in a demand response programme. Heat pump electricity demand for space heating is used as an example of flexible load. Electricity cost for heat pump operation is broken down into electricity generation, tax and, VAT components and are compared for three cases defined in Section 8.3.5. Results are shown for three different consumer groups: residential, office, and city centre consumers. Financial incentives (as defined in Eq. 8.2) for



	Residential	Office	City Centre
Tax	-0%	-0%	-0%
VAT	-10%	-10%	-8%
Generation	-33%	-38%	-29%
Total	-10%	-10%	-8%

	Residential	Office	City Centre
Tax	-33%	-38%	-29%
VAT	-33%	-38%	-29%
Generation	-33%	-38%	-29%
Total	-33%	-38%	-29%

Figure 8.3 Overview of consumer generation, VAT, and tax cost per unit demand for three cases (no demand response, demand response with *per-unit* tax, and demand response with *ad valorem* tax), and for three consumer groups (residential, office, and city centre). The tables below the cases with demand response show the changes in cost as compared to the reference case without demand response.

demand response participation are expressed in three ways: (1) per unit total demand, (2) per unit shifted demand, and (3) for a representative consumer of each consumer group.

8.4.1 Financial Incentives per Unit Total Demand

Figure 8.3 depicts consumers' generation, VAT, and tax cost per unit total demand for the three different consumer groups (residential, office, and city centre, see Table 8.1), and for three cases: (1) no demand response, (2) demand response with *per-unit* tax, and (3) demand response with *ad valorem* tax. The tables below the cases with demand response show the changes in cost as compared to the case without demand response, *i.e.*, the financial incentive as defined in Eq. 8.2.

No demand response. If consumers do not participate in demand response, the cost of heat pump operation lies around 195 €/MWh. Cost differences between the three consumer groups are small (around 2 €/MWh). The cost per MWh is an annual average value as hourly fluctuating wholesale electricity prices are assumed to be passed on to the consumers. This assumption follows the European Parliament and Council Proposal [173] that states that every customer will have access to a dynamic price contract that reflects wholesale electricity price fluctuations.

Demand response with *per-unit* tax. If consumers do participate in demand response, they can save between 29% and 38% on their electricity generation cost, depending on the consumer group. These savings come solely from accepting a shift in heat pump demand to hours with cheaper wholesale prices (demand shifting occurs only within technical constraints and consumer-defined preferences). The model assumes that the total heat pump electricity consumption is equal with and without demand response. Given the *per-unit* tax design, consumers do not pay less tax by participating in demand response. As VAT is levied both on generation cost and on tax, VAT cost decreases only partly (*i.e.*, 8% to 10%). The total savings amount to 8% to 10% (*i.e.*, 15 to 20 €/MWh). Final electricity cost with demand response with *per-unit* tax lies between 174 €/MWh (office consumers) and 179 €/MWh

Table 8.3 Comparison of savings per unit shifted demand. Given the same demand response programme, residential consumers shift 31% of their heat pump demand, offices 20%, and city centre consumers 17%.

		Residential	Office	City Centre
Demand response with *per-unit* tax	Generation Savings (€/MWh)	50	86	74
	VAT Savings (€/MWh)	11	18	16
	Tax Savings (€/MWh)	0	0	0
	Total Savings (€/MWh)	61	104	90
Demand response with *ad valorem* tax	Generation Savings (€/MWh)	50	86	74
	VAT Savings (€/MWh)	37	66	57
	Tax Savings (€/MWh)	124	223	199
	Total Savings (€/MWh)	211	379	330

(residential consumers). Differences in cost arise due to differences in demand profiles, and thus differences in the amount of demand which can be shifted to hours with cheaper wholesale prices.

Demand response with *ad valorem* tax. If an *ad valorem* tax design is implemented, consumers can save the same relative amount on their tax, and thus on the VAT component, as on the generation component, *i.e.*, between 29% and 38% depending on the consumer group. The total savings in this case are between 56 €/MWh (city centre consumers) and 74 €/MWh (office consumers). The total cost lies between 120 €/MWh (office consumers) and 137 €/MWh (city centre consumers).

8.4.2 Financial Incentives per Unit Shifted Demand

Due to differences in demand profiles, both the amount of annual shifted demand and the financial incentives per unit shifted demand differ considerably between different consumer groups. Assuming the same demand response conditions, residential consumers shift 31% of their heat pump demand, offices 20%, and city centre consumers 17%.

Table 8.3 shows cost savings per unit shifted demand. Although office consumers shift less demand than residential consumers, per unit shifted demand they obtain the highest savings (86 €/MWh shifted demand). Residential consumers obtain the least savings (50 €/MWh shifted demand). For **demand response with *per-unit* tax**, generation savings do not yield any tax savings, and thus only partial VAT savings. Office consumers save 104 €/MWh shifted demand, city centre consumers 90 €/MWh shifted demand, and residential consumers 61 €/MWh shifted demand. For **demand response with *ad valorem* tax**, generation savings lead to proportional savings on the tax and VAT components. Office consumers save 379 €/MWh shifted demand, city centre consumers 330 €/MWh shifted demand, and residential consumers 211 €/MWh shifted demand.

Table 8.4 Comparison of electricity cost of representative individual consumers. An average household, office building and shop are used to illustrate costs for respectively residential, office, and city centre consumers. Annual heat pump electricity demand of an average Dutch household is calculated to be 1.6 MWh, an average office (7 649 m^2 floor space) 18.3 MWh, and an average shop (284 m^2 floor space) 6.6 MWh. The annual cost for each of the customers is shown for three cases: no demand response (DR), DR with *per-unit* tax (current situation), and DR with *ad valorem* tax.

		Household	**Office (7 649 m²)**	**Shop (284 m²)**
No demand response	Generation (€/year)	74	803	284
	VAT (€/year)	54	617	220
	Tax (€/year)	182	2 134	764
	Total (€/year)	309	3 554	1 268
Demand response with *per-unit* tax	Generation (€/year)	49	496	201
	VAT (€/year)	49	552	203
	Tax (€/year)	182	2 134	763
	Total (€/year)	280	3 182	1 167
Demand response with *ad valorem* tax	Generation (€/year)	49	496	201
	VAT (€/year)	36	381	156
	Tax (€/year)	122	1 318	541
	Total (€/year)	207	2 195	898

8.4.3 Financial Incentives per Consumer

Table 8.4 shows electricity costs of representative individual consumers. An average single household, an average Dutch office (with an area of 7 649 m^2), and an average shop (with an area of 284 m^2) are considered to be representative of respectively residential, office, and city centre consumer groups. Annual heat pump electricity demand for the household is calculated to be 1.6 MWh, for the office building 18.3 MWh, and for the shop 6.6 MWh.

In case of **no demand response**, the household pays 309 €/year for heat pump electricity costs, the office building 3 554 €/year, and the shop 1 268 €/year. The breakdown of the cost across the generation, VAT, and tax components is shown in Table 8.4. For **demand response with *per-unit* tax**, the total cost decreases to respectively 280 €/year for the household, 3 182 €/year for the office building, and 1 167 €/year for the shop. This is a decrease of 8% to 10%, as also shown in Figure 8.3. For **demand response with *ad valorem* tax**, the total cost decreases to respectively 207 €/year for the household, 2 195 €/year for the office building, and 898 €/year for the shop. This is a decrease of 29% to 38% (equal to the relative savings shown in Figure 8.3).

8.5 Discussion

The results of the case study on financial incentives for residential and service sector demand response show that the *ad valorem* energy tax provides considerably stronger financial incentive for demand response participation than the *per-unit* tax. The results of the case study are analysed first, followed by a more general analysis of the *ad valorem* energy tax.

8.5.1 Case Study Analysis

The results of the case study are first analysed in terms of a comparison of the *per-unit* and *ad valorem* energy tax. Next, differences between the different consumer groups are addressed. The analysis ends with a discussion of the case study limitations and possible generalisation of the results.

8.5.1.1 Per-Unit Tax versus *Ad Valorem* Tax

The case study shows that heat pump electricity cost savings are approximately 3.5 times higher with *ad valorem* tax than with *per-unit* tax. For the modelled year, this is, for instance, a difference between savings of 29 €/year and 102 €/year for an average household (Table 8.4).

Further, case study results show that for demand response with *per-unit* energy tax, the tax becomes a relatively larger portion of the total electricity price (rising from around 60% of the total cost to around 66%). This is not the case with demand response with *ad valorem* energy tax, since that tax is defined as a percentage of electricity generation cost, and thus has a constant (approximately 60%) share in the total electricity bill. Thus, the *ad valorem* tax tariff has two main benefits compared to the *per-unit* tax. First, the *ad valorem* tax does not dampen the wholesale price differences. This means that the *ad valorem* tax provides consumers with signals and value for participation in the market, a requirement explicitly named by the European Commission [420]. Second, the *ad valorem* tax maintains the relative tax burden for demand response participants equal to that of non-participants, *i.e.*, both consumer groups pay equal amount of tax relative to the electricity generation cost. Demand response is a power system and societal service [96, 176, 304, 390], and should not be subject to higher relative taxation.

The *ad valorem* energy tax can have additional effects, compared to the *per-unit* tax. First, switching between electricity retailers can become more attractive as electricity generation price differences between retailers are extended to the energy tax portion of the bill, and thus magnified. This effect is a benefit of the *ad valorem* tax in the context of the Third Energy Package [391] as it improves competition in the retail market. Second, as the *ad valorem* tax is defined as a percentage of the electricity generation price, electricity retailers have an influence on the governmental revenue from energy tax, as they can set the retail prices. This effect is similar to the effect of prices of general goods and services on governmental income from VAT, which is also an *ad valorem* tax. This effect can further be addressed as the European Union determines the rules on real-time electricity retail pricing, continuing on the work of the current Proposal [173].

8.5.1.2 Influence of Consumer Type

The effect of consumer group on the total cost of electricity (including energy tax and VAT) and on the savings through demand response depends on the specific demand response case. In the reference case with **no demand response**, the consumer group has little influence on the average unit electricity price that consumers pay (Figure 8.3). For the three consumer groups analysed, the original average electricity price difference is approximately 2.5%. For **demand response with *per-unit* tax**, total price differences between consumer groups remain small (2.75%), despite the increased differences in electricity price component (14%). For **demand response with *ad valorem* tax**, differences between consumer groups become more explicit in the final price. The differences in the amount different consumer groups pay for their generation component (14%) are passed on to the total unit price. The final price difference between different consumer groups thus rises to 14%. This price difference is the result of differences in demand shifting potential between the three consumer groups, which is in turn due to the differences in heating demand profiles (Figure 8.2a).

The differences between consumer groups are larger when the financial incentives per unit *shifted* demand are analysed (Table 8.3). All three consumer groups shift only a part of their heat pump demand. However, the shifted share varies considerably between consumer groups. In this case study, residential consumers shift 31% of their heat pump demand, office consumers 20%, and city centre consumers 17%. This difference arises from the differences in heat demand profiles (see Figure 8.2a), as all other factors (indoor and outdoor temperatures, technical heat pump specifications, consumer-defined preferences, *etc*.) are kept equal in the model across consumer groups. Differences in heat demand profiles lead both to (1) different amounts of shifted demand, and (2) different financial incentives per unit shifted demand (see Table 8.3).

8.5.1.3 Case Study Generalisation

The case study illustrates the energy tax financial incentives for demand response participation for a single set of assumptions. The numerical results are limited to a single year (1st of June 2012 until 31st of May 2013), a single country (the Netherlands), a single type of flexible appliance (heat pump), a single retail pricing scheme (real-time pricing), and three consumer groups (residential, office, and city centre) with a single set of preferences (temperature comfort limits acceptable for 90% of consumers, as shown in [427]), assuming consumers as price takers. The limitations of this approach and possible generalisations are addressed next.

Single year limitation and generalisation. The main limitation of the single-year dataset is its inability to capture variations in electricity prices and weather-dependent heat demand between years. Therefore, the absolute values of the costs and savings as reported in the result section are valid only for the modelled year. However, the comparison between *per-unit* and *ad valorem* tax, for instance, the 3.5-fold *difference* in savings, does not depend on the electricity price or the heat demand, because they are expressed as *relative* values. This comparison is the main goal of the case study, and is generalisable.

Single country limitation and generalisation. The main limitation of the assumption of a single country is the use of the local ratio between electricity generation, energy tax, and VAT shares of the final electricity bill. The influence of tax on the price signal clarity increases as the relative share of energy tax to electricity generation cost increases (as also briefly mentioned in [175, 397]). The Netherlands has a relatively high share of consumer energy tax compared to the electricity generation cost [393, 394] and can therefore serve as a clear example for the difference in financial incentives between the *per-unit* and *ad valorem* tax. The relevance of the results for other countries depends on the local ratio of energy tax to electricity generation cost, and is of particular interest for countries with high ratios, such as Germany and Denmark [393, 394].

Single type of flexible appliance limitation and generalisation. The main differences between heat pumps and other flexible loads with respect to their demand response potential is the timing of their demand, their size, and their flexibility limits. Thermally controlled loads (such as fridges, freezers, and heat pumps) and electrical vehicles are generally considered to be the most viable options for residential and service sector consumer demand response [161, 428, 429]. Differences in demand profiles between these appliances are expected to have a similar impact on the demand response potential as the differences between consumer groups as presented in the case study. The absolute values of financial incentives are expected to be (partially) determined by the appliance. However, the relative difference between *per-unit* and *ad valorem* tax is expected to differ only to a limited extent between appliances.

Single retail pricing scheme limitation and generalisation. The difference in dynamic retail pricing schemes (RTP, TOU, CPP, EDP, see Section 8.1) lies primarily in the frequency of price changes [130, 171, 172]. With RTP these changes occur continuously, with EDP they occur only on some extreme days. The difference in financial incentives between *per-unit* and *ad valorem* energy tax is independent of the frequency of the price signal. It only depends on the amplitude of the price signal: the larger the difference between the cheaper and more expensive prices within a pricing scheme, the larger the difference between *per-unit* and *ad valorem* tax financial incentive. The comparison between the two tax designs from this case study is thus equally applicable to other dynamic retail pricing schemes.

Single set of consumer preferences limitation and generalisation. The chosen consumer preferences for comfort level is assumed to be acceptable for 90% of the consumers. This is the most conservative level in the study of Van der Linden *et al.* [427]. Less conservative preferences lead to marginally larger savings, as shown in [430]. The relative effect of the *per-unit* and *ad valorem* energy tax does not depend on the consumer preferences.

Consumers as price takers limitation and generalisation. The case study assumes that consumers are price takers, *i.e.*, that demand response does not influence wholesale electricity market prices. If demand response becomes widespread, wholesale prices can become dependent on consumers' demand response participation, resulting in changed price dynamics, such as smaller price differences. This can lead to smaller absolute demand response savings. However, the relative differences between the *per-unit* and *ad valorem* tax remain as long as *any* price differences exist.

In general, it can be concluded that the limitations of the case study pertain to the absolute result values. The relative values, *i.e.*, the comparison between *per-unit* and *ad valorem* energy tax are generalisable. This comparison is the primary aim of the case study.

8.5.2 *Ad Valorem* Energy Tax Analysis

Within the European Union, an *ad valorem* energy tax currently exists only in Spain. However, the Spanish energy taxation law dates back to 1992, *i.e.*, before interest in demand response became wide spread [396]. Spanish energy taxation rules can therefore not be simply copied to other countries, as they were not made for demand response *per se*. In fact, demand response in Spain is currently limited to an interruptible load programme for large industrial customers due to other regulatory barriers, such as prohibition of aggregation [304]. The existence of the Spanish *ad valorem* energy tax primarily shows that alternative energy taxation that provides incentives for both energy efficiency and demand flexibility is possible even within the current EU regulatory framework [395]. However, a dedicated update of the European Energy Taxation Directive, as a part of the electricity market redesign, is required to remove current inconsistencies with the European Energy Vision.

8.5.2.1 *Ad Valorem* Energy Tax as Part of Electricity Market Redesign

Recent studies [156, 157, 177, 431–434] show that the current European electricity markets are not well equipped to accommodate large amounts of decentralised variable renewable generation, neither to harness demand flexibility. These studies reveal the existence of multiple barriers, resolving which requires a market overhaul and a design of novel "second generation" high-renewables electricity markets, according to many authors [156, 157, 177, 431–434].

The market redesign recommendations from recent literature can be broken down in different categories: (1) efficient signals for investment in (renewable) generation (*e.g.*, [431, 432]), (2) efficient signals for network investments (*e.g.*, [177]), (3) cross-border market variation and congestion management rules (*e.g.*, [157, 433], (4) market settlement resolution rules (*e.g.*, [156]), and (5) pricing rules for consumers (*e.g.*, [434]). To the best of the author's knowledge, none of these papers address energy taxation in Europe. Energy taxation as a financial policy instrument used to incentivise demand response can be positioned within the latter category of market design research, *i.e.*, electricity pricing policies for consumers.

Insights gained from the case study support the use of *ad valorem* energy tax design to provide clear consumer signals for electricity market participation, as required by the European Commission [420]. Further research is necessary to provide more detailed recommendations on the design of energy taxes within a "second generation" high-renewables electricity market with respect to parameters such as tax base, tax level, governmental use of tax revenue, and interaction with other taxes and electricity market components.

The results in this chapter are limited to the difference in financial incentives between energy taxes for two tax bases, unit electricity demand (*per-unit* tax), and value of electricity (*ad valorem* tax). The choice of tax level is qualitatively addressed in the next section, setting out the need for further quantitative research. Governmental use of tax revenue and the position of energy taxes within a larger "second generation" high-renewables electricity market are topics for future research.

8.5.3 Setting an *Ad Valorem* Tax Level

In the case study, the *ad valorem* tax level is determined as described in Section 8.3. The aim of the used method is to ensure that if consumers do not participate in demand response, the government does not forgo any tax income. However, the method used in Section 8.3 uses information which is in reality available only *ex-post*. In reality, the average unit electricity price paid by consumers is not known, and needs to be estimated. Thus, *ad valorem* tax tariff results in extra uncertainty on tax income by governments. The extent of this uncertainty depends on the annual fluctuations in retail prices, and thus (partially) on the future consumer retail price scheme. Policy makers should weigh the disadvantage of increased uncertainty in governmental tax income against the advantages of increased financial incentives for demand response participation for consumers, which in turn leads to advantages for power system sustainability.

The tax level chosen in the case study equals the current tax level if consumers do not participate in demand response. The goal of the *ad valorem* energy tax is to incentivise consumers to do so. If consumers participate in demand response, they save money, both on the electricity generation cost and on energy tax with the *ad valorem* tax design. The latter entails that the government tax revenue decreases as more consumers participate in demand response. The decrease in government tax revenue equals the relative average consumer savings multiplied by the share of consumers who participate in demand response.

The question who pays for the decrease in government revenue is both a political and a policy question. A government can consider the decrease in tax revenue as a subsidy for demand flexibility, and carry the difference itself. Alternatively, an estimation can be made of the share of consumers who are expected to participate in demand response programmes, and of their expected savings. A government can then increase the *ad valorem* tax rate, such that it does not forgo any tax income. However, in this case, consumers without demand response capabilities bear a relatively higher electricity cost burden. It is again a policy question whether that is a desirable situation if, for instance, a disproportional share of poorer consumers do not have access to smart appliances and thus to demand response programmes.

This chapter takes only the first step towards energy taxation design which takes into account its financial impact on demand response participation. Further research is necessary to support policy makers in choosing the best energy tax design, and determining appropriate tax levels.

8.6 Conclusion and Policy Implications

Demand response is widely deemed to be an important enabler for high-renewables power systems. This chapter shows that the EU Energy Taxation Directive and the *per-unit* energy tax implemented in most European Member States do not provide consumers with financial incentives for demand response participation. The impact of energy taxes on demand response participation has thus far not been comprehensively addressed in the literature. This chapter quantifies the financial incentives for demand response participation in a case study on demand response with heat pumps in the Netherlands. Results of the case study show that the financial incentive for demand response participation is 3.5 times higher with an *ad valorem* than with a *per-unit* energy tax. Based on these results, the following recommendations for policy makers are given.

First, both European and Member States' policy makers should consider energy taxes as policy instruments to encourage both energy conservation and demand flexibility, *i.e.*, demand response participation. In contrast to the European strategy to support demand response, existing European legislation on energy taxation (Directive 2003/96/EC [395]) and its implementation by European Member States do not include incentives for demand response participation. The Directive does, however, not *per se* impede the development of tax tariffs that pass on electricity price signals, as shown by the existence of the Spanish *ad valorem* energy tax. Thus, alternative tax tariffs that incentivise demand response participation can be designed within the existing European Energy Tax Framework, and be a key design parameter for its update.

Second, energy tax levels that pass on electricity market signals to consumers should be carefully designed with respect to costs and benefits for all market parties involved (consumers who can and those who cannot participate in demand response programmes, aggregators, retailers, DSOs, TSOs, *etc*.). This is particularly important to prevent system gaming and abuses, as these risks increase with increasing financial benefits associated with demand response participation. Furthermore, when deciding upon the level of energy taxes, and thus considering government revenue, it is key that policy makers weight this revenue against financial implications for various market parties who can benefit from widespread demand response, and against environmental benefits of renewable integration supported through demand response.

Third, energy tax design incentivising demand response participation should be considered as one of the puzzle pieces in a new approach to market and incentive design for a modern power system. Other barriers preventing demand response participation, and barriers preventing other types of grid modernisation should be taken into account, both in their own right, and with respect to each other.

Further research is necessary to offer policy makers the knowledge needed to design energy taxes in such a way that they do provide financial incentives for demand response participation. Further research should also consider social justice effects, distributive effects, and socio-economic cost-benefits analysis of current and alternative tax designs. The research presented in this chapter should be integrated with ongoing efforts to develop novel, second generation electricity markets that are well equipped to accommodate large amounts of decentralised, variable, renewable generation and flexible demand.

Part V

Synthesis

The previous chapters build an understanding of urban demand heterogeneity to support the energy transition. The need for this energy transition is spurred by political and societal concerns for the consequences of climate change. The transition to renewable generation resources, however, poses many challenges. It requires considerable efforts across societal borders, as well as across disciplines within the research domain. The previous chapters describe modelling and simulation work situated on the intersection of power systems engineering, urban planning, and energy policy. This final Part V synthesises the presented research.

Chapter 9 discusses the obtained results from a broader perspective. It describes the lessons learned that are relevant for the different disciplines concerned, and reflects on the upcoming urban energy system modelling field, focusing on the need for and the challenges of open data and models.

Chapter 10 concludes this thesis. It revisits the research questions as formulated in Chapter 1 and addressed in Chapters 4 to 8. Based on the results and insights obtained in these chapters, Chapter 10 finishes with an outlook for future research.

9 Discussion

> *This world has seen a great many civilisations. And many of them have survived for longer periods than ours up to the present. They were all as sure as we are today of having founded the first eternal civilisation. We today differ from them in having our western civilisation spread to embrace the entire planet, leaving no room on any continent for any other culture to take over if we fail.*
>
> – Thor Heyerdahl

THIS thesis is motivated by concerns for the consequences of unabated climate change, and the drive to create insights and means necessary to avert its worst consequences. As fossil fuel consumption for energy generation is a major cause of climate change, the transition to renewable resources is chosen as the topic of study (Chapter 1). The energy transition is considered in concert with other contemporary societal developments, in particular urbanisation and digitalisation. Urbanisation underscores the need to study the energy transition in the context of urban areas, while digitalisation is seen as an enabler for the integration of novel technologies in existing and future power systems (Chapter 2).

In this context, Chapters 4 to 8 present modelling, simulation, and analysis aimed to improve the understanding of local renewable resource utilisation in urban areas. This chapter takes a broader perspective on the presented research. First, it reflects on the lessons learned for both researchers and practitioners across different disciplines. Second, it discusses the role of open models and data in energy systems research.

9.1 Lessons Learned – A Multidisciplinary Perspective

The subject of this thesis is positioned at the intersection of multiple disciplines, including power systems and electrical engineering, urban planning, and energy policy. Lessons can be drawn for each of these disciplines separately, as well as for all of them jointly. Although this thesis embraces multidisciplinarity, in general, the vast majority of issues and challenges in literature are addressed within the boundaries of established disciplines. The lessons learned are therefore subdivided along traditional lines of such disciplines. Yet, it is important to note that the themes central to this thesis – energy transition, urbanisation, demand heterogeneity, and spatio-temporal scale – are recurring for all of the disciplines discussed.

9.1.1 Power Systems and Electrical Engineering

One of the main insights of this thesis is the role of the demand side and its heterogeneity for the energy transition in urban areas. Traditionally, the demand side has received little attention from the disciplines of power systems and electrical engineering. These disciplines primarily focus on the other three segments of the technical layer of the power system: generation, transmission, and distribution (see Chapter 2). Typical tasks of power systems engineers, and electrical engineers in related disciplines such as control and electronics include the design and management of power system generation and transmission components, calculation of power flows through the power system, and development of control algorithms. Demand – or load – is considered primarily from the point of view of standardisation, aiming to warrant safety and reliability. Otherwise, the demand side is seen as unchangeable and hence treated as a given – thus upholding the *supply follows demand* paradigm [58].

This mode of operation reflects the traditional top-down, centralised view on the power system, a view well-suited for a system dominated by large, possibly vertically-integrated utilities. Since the market reforms that started in the 1990s, the process of unbundling is dissolving such vertically-integrated utilities (see Chapter 2). These ongoing reforms, the rise of smart grids, and the energy transition drive the decentralisation of power systems. Market reforms and smart grids are expected to empower small consumers to participate in the electricity markets [173], while the energy transition has spurred to development of small-scale generation technologies [68, 103]. Decentralisation requires a paradigm shift in the way the power system is designed and operated, towards a system where *demand follows supply*.

Such a paradigm shift drives numerous changes. The one highlighted in this thesis is the view on the *demand side*. As demand is traditionally considered uncontrollable, power systems engineers typically describe it using only a few metrics, in particular its maximum, yearly total, and the load coincidence factor[1] [435, 436]. More detailed, temporal demand profiles do exist, but they either describe an entire country, a region serviced by a single utility company, or the demand of individual consumers with certain technical connection characteristics (see Chapter 4). As the power system becomes decentralised and consumers take on an active role, this simplified view of the demand side no longer suffices.

A more sophisticated view of the demand side is thus necessary. This thesis, in particular Chapters 5, 6, and 7, shows that urban demand is heterogeneous, and that this spatio-temporal heterogeneity has a significant impact on both direct local renewable resource utilisation and on the effect of interventions aimed to increase it. Demand should therefore be described in terms of detailed spatio-temporal demand profiles. To this end, reference profiles, such as currently exist for households and connection types, should be extended to profiles for different types of consumers. Classification of consumers along connection types does not provide the insights needed to empower and engage consumers in active participation in the power system as connection types do not shed light on the stakeholders

[1] The coincidence factor is defined as "the percentage of the simultaneous maximum demand of a group of consumers to the sum of their individual maximum demands" [435].

behind them, their interests, needs, action potential, and motivation. Application of ongoing work on consumer clustering [309, 310, 349, 350] (see Chapter 5) can help to develop a new understanding of consumers if the scope of this work is broadened to consumer market and demand response participation interests, needs, action potential, and motivation.

The service sector deserves particular attention. The share of service sector demand in the total national demand is large in developed countries [367, 437, 438], and is expected to grow in the coming decades, overtaking the industrial sector by 2050 [367, 439, 440]. In developing countries, such as China and India, the economy is also becoming more service-oriented, similarly leading to an increasing share of the electricity demand used by the service sector [73].

Summarising, the energy transition, the rise of smart grids, and the market reforms are predicted to bring a paradigm shift to the design and operation of power systems. The future system is expected to be more decentralised, with more active participation by consumers. Accommodating these changes requires a different approach to the demand side from power systems and electrical engineers: a better and more detailed understanding of its heterogeneity, especially at the urban scale, and a continued shift of perspective from meters or connections to stakeholders.

9.1.2 Urban Planning

Cities are expected to play a major role in the energy transition [33] (see also Chapter 2). Although urban areas cover only 2% of the Earth's surface, they represent an estimated 75% of the total energy demand [106, 116]. Thus, urban areas are major contributors to climate change. At the same time, cities are particularly vulnerable to its consequences [21]. For instance, urban areas heat up more than their surroundings – a phenomenon known as the *urban heat island* [106] – making the urban population more susceptible to heat-related deaths [441]. Finally, given the concentration of economic activities, political power, and human resources in urban areas, cities are well positioned to take actions in climate change abatement, mitigation, and energy transition in particular [21, 116].

According to Grubler *et al.* [106], local governments have the largest leverage and potential if they focus on the demand side of the energy transition. Specifically, city administrations can determine standards and requirements for buildings and urban form[2] [106]. This thesis underwrites this view, emphasising the importance of urban form, in particular land use, on local renewable energy utilisation. Results from Chapter 6 show that mixed urban areas (also called *mixed-use* urban areas) use significantly more renewable energy than single-use, residential areas. Such mixed urban areas are currently seen as the most desirable urban form[3] [123], and are shown to have benefits such as increased accessibility of services and facilities [124], and higher quality of civic life and health [125]. Remarkably, local renewable

[2] *Urban form* is the physical expression of land use in a city. *Land use* is determined by the type of activities (*e.g.*, housing, production, services) that predominantly take place in an area [241, 442].

[3] Historically, urban areas have been mixed, with functions such as housing, production, and services intermingled. This changed in the 19th century as the industrial revolution replaced small artisanal shops by large factories. Dedicated residential areas were developed as peasants turned labourers requiring cities to provide housing. Moreover, pollution instigated the creation of zoning rules that institutionalised separated land use. Today's compartmentalisation of land use in cities is thus a legacy of the 19th century [123].

energy utilisation is rarely considered as a factor influenced by land use. This thesis shows that land use has an important effect on the degree of autonomy of local energy systems, and should be taken into account as such by local governments and urban planners.

Urban areas considered in this thesis are limited to developed countries, with the Netherlands as a case study. However, globally, most urbanisation takes place in the developing world, in Asia and especially in Africa. Urban growth is primarily concentrated in small and medium-sized cities, which house today 60% of the world's urban population [108]. Such cities often lack the financial, political, and policy instruments and capabilities to develop comprehensive urban planning programmes [108, 113]. Therefore, while all local governments worldwide require support in their transition to climate-resilient and sustainable urban systems, small and medium-sized cities in developing countries need particular attention. Lack of data on local demand is a challenge for cities in the developed world, as underscored in this thesis. Such data are not published at city scale [106] (see also Chapter 2), or are not openly available (see Chapter 3). However, this problem is even more acute for small and medium-sized cities in the developing world, as local urban demand data mostly do not exist at all, creating barriers both for dedicated research and for data-informed actions by local governments. This thesis therefore endorses the call by Grubler *et al.* for "serious efforts in capacity building, novel applications of remote sensing, information, and decision support techniques, and new institutional partnerships" in small and medium-sized cities in developing countries [106].

Summarising, cities are pivotal in the abatement of climate change. Local initiatives already exist, for instance, the Convenant of Mayors [23], Energy Cities [25], and C40 Cities [24]. However, many issues remain unresolved. The issue highlighted in this thesis is the lack of appropriate knowledge of and insights in urban demand. Many local governments do not have comprehensive statistics on energy use at the urban scale, as such information is only available at the national scale [106], or is not openly available at all (see Chapters 2 and 3). This is in particular the case in small and medium-sized cities in the developing world [108, 113]. The lack of data and insights in urban demand is problematic as the demand-side is the part of the energy system that can be most influenced by local governments through policies and regulations [106]. Existing approaches linking urban planning and energy transition emphasise energy efficiency of buildings. This thesis shows that in addition, land use and its relationship with local renewable resource utilisation should receive more attention.

9.1.3 Energy Policy

Climate change is a "super" [135] wicked problem[4]. Addressing wicked problems is by definition extremely complex. Among the main characteristics of wicked problems are the lack of a common view or formulation of the problem among the different parties involved and the impossibility of a trial-and-error approach as every wicked problem is unique and requires a "one-shot" solution [132] (see Table 2.1). Climate change is thus a preeminent example of a wicked problem. Its global character, amongst others, entails that it needs to be tackled at the supranational level, where binding agreements are few and far between. Although the Paris Agreement [13] embodies an important step forward, it is based on

[4]See also Chapter 2, where wicked problems are introduced in the context of urban energy systems.

voluntarily commitments of signatories, which moreover need to be further translated to actionable policies.

The European Union and countries worldwide are taking steps to formulate such actionable policies. While such policies target specific consequences, they can also have unintended side-effects [135]. Chapter 8 illustrates such unintended consequences, showing that existing European *per-unit* energy taxes disincentivise demand response participation by residential and service sector consumers. This side-effect has arguably not been intended when energy taxes were conceived, in particular because mass market demand response or the necessity thereof did not yet exist.

Avoiding unintended consequences is key to achieve effective policy that abate climate change and promote the energy transition. As in-field trials of policies are often undesirable, modelling and simulation (see also Chapter 1) can provide insights in both the intended and the unintended effects of policies. For this purpose, models need to be both detailed enough and have an explorative character. The first requirement is intended to ensure that modelling results are realistic within the scope of their purpose. The second requirement creates the conditions to bring unintended consequences to light. The case study in Chapter 8 not only illustrates unintended consequences, but also their discovery through an explorative effort, as, ironically, it is in itself a side-effect of another research pursuit [430].

Summarising, while policy making cannot get around the wickedness of climate change, concrete policies taken to abate it should be checked for unintended or perverse effects. Modelling and simulation can provide the tools to bring such consequences to light. For this purpose, models should be realistic (see also further, Section 9.2) and to some degree exploratory. Researchers – and funding agencies – should keep an open mind to detect and describe unintended or perverse side effects, even in cases when that is not the original goal of the research effort. Policy makers should be aware of unintended consequences of policies and be open to adapt policies when such consequences are signalled.

9.1.4 Crossing Disciplinary Borders

The energy transition is a preeminently multidisciplinary endeavour. Addressing it requires collaboration between disciplines – and mutual understanding. However, bridging the barriers between disciplines is difficult in practice. Despite the growing recognition for the need of multidisciplinary research, remaining within the own discipline is attractive because of its familiarity. Disciplines are frames of reference, providing well-defined sets of methodological approaches, theoretical canons, and shared concepts and language [443]. Cross-disciplinary collaboration obligates scientists to leave the familiar grounds of their own disciplines and is thus often challenging, yet it is very much needed to tackle the wicked problems of climate change and energy transition.

9.2 Towards Realistic and Open Energy System Models

Many of the challenges posed by climate change raise questions which in practice can be answered only through modelling, as in-field experimentation is impossible given the scale of the system under study. The literature review in Chapter 3 describes the existing energy system models and datasets, focusing on the spatio-temporal scales which they cover. Across all scales, energy system models can be classified according to various parameters, including model purpose, mathematical approach, assumptions, and use of data [47, 48, 52, 196]. The discussion below focuses on the latter two: assumptions and data, making the following two arguments. First, more energy demand data are needed to make energy system models more realistic. Second, assumptions across energy system models should be standardised and current efforts to develop open energy system models can facilitate this process.

9.2.1 The Importance of Data for Realistic Models

This thesis shows that the lack of detailed service sector and urban-scale electricity demand data results in less realistic assessments of local renewable energy utilisation in urban areas. The degree of realism "required" in a model is a philosophical question [53]. Models are inherently abstractions and simplifications of reality. In particular, models represent only a few aspects of the real world. Which aspects are included, depends on the specific research purposes a model is developed for [444]. This discussion stresses the other side, the pitfalls of unawareness of what is *left out* in a model and its consequences [54].

The present discussion is not concerned with philosophical considerations that assert model realism. Instead, it underwrites the widely employed heuristic that judges the validity of a model by whether it produces results that look similar to reality [445, 446]. Chapters 6 and 7 show that this is not the case for existing urban energy system models that are based on residential-only demand data. However, validation of these results remains the Achilles' heel of the argument. Very few data sources are publicly available [303]. First, most bottom-up urban energy system models, including the ones in this thesis, are based on data generated by building energy use models, often the ASHRAE Standards, and the EnergyPlus model (see Chapter 3). Despite the extensive efforts to make the ASHRAE Standards [447] and the reference buildings in EnergyPlus [331] representative of the U.S. building stock, discrepancies with measured values from real buildings and with other simulation models exist. Yet, it remains unclear which assumptions and modelling details cause these deviations [211]. Second, the quality and reliability of other sources is uncertain, and/or explicit licences for data use are lacking [191, 301]. Third, combinations between datasets are not straightforward, mostly due to inconsistencies in metadata [191, 253] and definitions (see Chapter 5). Finally, the combination of the issues above entails that translating U.S. reference building models to other countries, as done in this thesis (Chapter 4), can compound the uncertainties of each of these issues, although to what extent remains unclear. Resolving these problems and thus decreasing the uncertainty of the validity of energy use datasets and the results of models using them requires more open energy data worldwide.

Yet obtaining these data is a chicken-or-the-egg problem. Personal discussions with members of academia and industry indicate a mixed interest in the issue. Recognition of the problem is limited, as most researchers and practitioners do not have experience with the service sector, perceive it as unimportant and/or too heterogeneous to deal with. Moreover, while there is increasing research on the behaviour of individual consumers in the context of energy demand and energy transition, very little research exists on decision-making by companies in general, and in particular with respect to energy. At the same time, informal discussions with the industry and local authorities indicate that detailed *proprietary* data do exist, in particular data collected by growing numbers of smart meters, installed both in residential and service sector buildings. Privacy issues are named as the main reason why these data cannot be shared with researchers. This thesis asserts that privacy is key and needs to be warranted whenever data is shared, in particular in the case of energy demand data as they can reveal substantial private information. However, methods and approaches (*e.g.*, aggregation and anonymisation) exist that can prevent leaking of private information. These approaches can be applied to create datasets that can be made public without revealing personal or commercial details of individual consumers, but that can provide considerable spatial and temporal detail of urban demand, for instance by publishing detailed data of reference buildings or consumer types. The existence of connection-type demand profiles within the energy field, and the anonymised health data in the medical sciences [300] illustrate that public availability of such datasets is possible. The lack of service sector and urban-scale demand profiles can thus be attributed to inertia of institutions publishing demand profiles and the lack of interest among researchers, practitioners, and (local) governments to use such data.

In summary, this thesis seeks to raise awareness of the pitfalls and drawback caused by the lack of detailed demand data in urban energy system models. Whether a *particular* model and its results are *realistic* depends on the model and its purpose. However, researchers, practitioners, and (local) governments should be aware that neglecting the importance of input data in models *in general* can prompt practices described as "garbage in – garbage out". This risk is highly undesirable if real-world decisions are based on insufficiently realistic models. Therefore, efforts should be made by industry and authorities to create publicly available, detailed, and representative spatio-temporal energy demand data while respecting the privacy of individual energy consumers.

9.2.2 Standardisation Supported by Open Models

Historically, research institutions, government agencies, and vertically-integrated utilities have developed mostly closed and proprietary energy system models. In the traditional, centralised power system paradigm this did not pose significant problems: institutions, agencies, and utilities were all large and thus had the capacity to develop and maintain their own models. Pfenninger *et al.* argue that this practice is unacceptable in a decentralising power system as the number of parties increases and the requirements on the power system are changing [191]. Pfenninger *et al.* are members of the Open Energy Modelling Initiative (OpenMod), a collective of modellers from various universities and research institutes who promote open models and open data to advance knowledge and support energy policies.

They emphasise three benefits of open energy system models: (1) reduction of parallel efforts and work duplication, (2) consolidation of efforts through common datasets and standards, and (3) changing institutional and academic incentives to create broader support for open models [300]. The author of this thesis supports the views of OpenMod. The following discussion illustrates the need for and the practical difficulties of standardisation of assumptions aiming to avoid unnecessary work repetition and improve the quality, comparability, and interoperability of energy system models.

As all models, energy system models cover only a part of reality, specifically, of the energy system under study [196]. Other parts of that system can however have influence on the part modelled. This influence is typically addressed through assumptions. Two particular examples of exogenous influences are encountered in this thesis: (1) future wholesale market energy prices, and (2) forecast uncertainties for renewable energy generation. Wholesale market prices and generation uncertainties influence the results of the case studies described in Chapters 7 and 8. However, models or predictions for both are scarce to non-existent. In this thesis, this issue is solved by (1) assuming historical wholesale market prices based on proprietary data, and (2) creating an own model of solar generation forecasts (see Appendix C). The approach in both cases is not ideal. Proprietary data cannot be shared with other researchers. Development of an own model without training in user-oriented model development, documentation, and maintenance makes the model likely unusable for other researchers. The first issue should be solved by closer collaborations between academia and industry that emphasise the need for open data for research. The second issue should be solved by dedicated training of researchers that strives for more standardisation of modelling assumptions and approaches, as well as for user-oriented model development. Such efforts can lead to the creation of modules within a larger framework that can be integrated with other models, avoiding repetition of work, and increasing comparability of results.

Although this thesis supports the views of the OpenMod, the presented models are built predominantly in MATLAB [370], a proprietary software. The reasons for this arise from educational limitations: MATLAB is emphasised as the scientific programming language in engineering education, prompting its use in later research careers. Educational background is in particular the reason behind programming language choice for this thesis. The majority of the work on this thesis predates the main publications of OpenMod of 2017 [300] and 2018 [191]. Although R [448] and Python [449] are used in the later stages of this thesis, migrating the MATLAB models to an open language has been considered too time consuming, and has therefore not been pursued. The lesson learned is the importance of education and training. If open energy system models are to become the standard practice, open languages such as Python [449] and Julia[5] [452] should be taught to students to avoid future lock-in in proprietary languages.

Summarising, the current energy systems modelling field is fragmented, with the majority of models being developed in independence of each other, limiting interoperability, comparability and leading to unnecessary work repetition. Moreover, many models are developed as proprietary or are based on proprietary languages, limiting their use by a broad community.

[5] Currently, ongoing efforts take place to develop modular energy system models in, for instance, open source programming languages Python [450] and Julia [451].

However, the challenges of the energy transition mandate more openness of models and datasets. The earliest efforts to create open energy system models date back to the creation of the Balmorel model in 2001 [191, 453]. The Open Energy Modelling Initiative that currently drives open energy system models in Europe (in Germany in particular) was established in 2014. Overall, open modelling practices should be promoted more broadly, as they support collaboration, and bolster multidisciplinarity, efficiency, and effectiveness of energy systems research. Training and education play key roles, the former to help current generation of researchers and professionals to transition to open languages, and the latter to promote their use amongst future generations.

9.3 Closing Remarks

The discussion above reflects on research practices in the field of energy systems in the context of the energy transition. In summary, it emphasises collaboration and information sharing: between disciplines to tackle multidisciplinary challenges, between universities to create and use open models, and between the industry, government, and research communities to exchange data that can make research more realistic and thus better applicable. Communication challenges are key barriers to achieve far-reaching collaboration. Increasing mutual understanding is thus necessary to improve and facilitate communication between industry, government, and research communities. The need for collaboration cannot be overstated. Tackling climate change – one of the major problems of the twenty-first century – mandates joint efforts across societal boundaries.

Conclusion

10

> *Je n'ai fait celle-ci plus longue que parce que je n'ai pas eu le loisir de la faire plus courte.*
>
> – Blaise Pascal

This thesis has the objective to improve the understanding of local renewable resource utilisation in urban areas, aiming to facilitate it. The presented research is positioned at the intersection of multiple disciplines, including power systems and electrical engineering, urban planning, and energy policy. Moreover, this thesis is rooted in ongoing societal developments: energy transition, urbanisation, and digitalisation. Energy transition is its primary focus, as it embodies the switch in energy generation from fossil fuels to energy generation from renewable resources. Next, this thesis explicitly addresses urban areas. Urbanisation leads to the concentration of energy demand in cities. Yet, the urban scale has been largely neglected in existing energy systems research. Finally, digitalisation is taken into account in its capacity of enabler of the energy transition: it is the driving force behind the rise of so-called smart appliances and smart grids.

This thesis adopts a multidisciplinary, complex, socio-technical systems perspective. Acknowledging the existence and importance of different layers of the power system – technical, economic, and governance – it primarily focuses on the former. The main method of research is modelling and simulation, placing the presented work in the emerging field of urban energy system models.

The following sections evaluate in how far the objective of this thesis is achieved by revisiting the research questions addressed, and by summarising the main contributions of the thesis. The chapter concludes with an outlook for future research, and development of the field.

10.1 Research Questions Revisited

The main research question of this thesis reads: "**How can local renewable resource utilisation be facilitated in urban areas?**" Renewable resource utilisation is considered to emerge from the *temporal* interplay between demand and (renewable) generation. In the case of urban areas, *local* renewable energy utilisation is additionally determined by the *spatial* distribution of demand and generation. A large body of literature currently exists on renewable generation. Considerably less work is done on understanding the characteristics of urban *demand*, and its influence on local renewable energy utilisation. This thesis therefore focuses on the demand side to answer the main research question.

The main research question is addressed in a step-by-step approach. Part II of this thesis addresses **RQ1**, focussing on urban **demand** by itself. It builds an understanding of spatio-temporal demand heterogeneity, and results in detailed spatio-temporal demand profiles. This part is the foundation of the thesis. Part III, which addresses **RQ2**, is the core of the thesis as it quantifies **renewable energy utilisation** by combining the detailed spatio-temporal demand profiles with renewable generation profiles in the first stage, and with renewable generation profiles and interventions (storage and demand response) in the second stage. Part IV (**RQ3**) connects the technical layer with the governance layer by focusing on **policies** that can facilitate local renewable energy utilisation.

Research Question 1

Demand is addressed from the perspective of its spatio-temporal characteristics as its timing and location are considered to be the primary determinants for the extent of energy utilisation from non-dispatchable renewable resources (*e.g.*, wind and solar) in urban areas. **RQ1** reads "**How can local demand be characterised in urban areas?**" This question is broken down into two subquestions: subquestion **a** addresses the temporal dimension, subquestion **b** the spatial dimension.

RQ1a ***How can temporal heterogeneity of urban demand profiles be characterised?***

Urban areas typically consist of a mix of households and services. The demand of these different consumers is heterogeneous in time, as periods of activity differ between the different consumers. Yet, most existing urban energy system models consider only household demand, omitting the service sector. This is caused by a widespread lack of detailed data on service sector demand. **RQ1a** is therefore answered by devising and implementing a method to calculate detailed service sector demand profiles for an area of interest (the Netherlands) based on reference demand profiles of the Unites States Department of Energy (U.S. DOE). The U.S. DOE Commercial Reference Buildings database [225] is, to the best of the author's knowledge, the most detailed data source publicly available today. The developed method proposes *building equivalents* as a means to use reference buildings from the reference area to model the demand in the area of interest. The calculation of building equivalents is based on the comparison of building use data from both areas. The method yields a collection of hourly demand profiles for 13 service sector consumer types. Together with already available residential demand profiles, this collection represents the characterisation of temporal heterogeneity of urban demand. It is available online in the dataset that accompanies this thesis [315].

RQ1b ***How can spatial heterogeneity of urban demand profiles be characterised?***

The shares of households and different services vary from one urban area to another, some are more residential, others commercial, yet others mixed. The different local compositions of consumers lead to a spatial heterogeneity in electricity demand as individual demand profiles of consumers within an area determine the collective demand profile of that area. This spatial heterogeneity has not been quantified in literature at urban scales – neighbourhoods, districts, and municipalities. Therefore, to answer **RQ1b**, demand profiles of 14 698 urban areas in the Netherlands are modelled based on the demand profiles of the consumers within those areas. The developed model is based on *scaling factors* (derived through linear regression), which provide an alternative method to scale U.S. DOE reference building profiles to urban areas. The resulting demand profiles are classified using k-means clustering. The results demonstrate that at the urban scales analysed (neighbourhood, district, and municipality), three types of area demand profiles can be distinguished, termed *residential*, *business*, and *mixed*, based on the most prevalent consumer types. The residential-type urban demand profile, used in many existing energy system models, is found only in a minority of areas, that account for only a small share of the total demand. Statistical analysis shows that at each scale, the three archetypes are pairwise significantly different from each other, both in terms of their demand profiles and their consumer composition. These three statistically different archetype demand profiles represent the spatial heterogeneity of urban demand.

RQ1 How can local demand be characterised in urban areas?

Local demand in urban areas can be characterised based on the composition of consumers and their demand profiles. Variations in consumer composition represent the spatial heterogeneity in urban demand, differences between their demand profiles the temporal heterogeneity. By taking both into account, detailed spatio-temporal demand profiles are constructed. The degree of detail depends on the available data. In this thesis, the temporal granularity is one hour, the spatial granularity varies depending on the urban scale considered, with the smallest urban scale – neighbourhood – having a mean granularity of 2.5 km^2. The resulting demand profiles are published in an online database [315]. They are used as the foundation to answer the remaining research questions.

Research Question 2

Renewable resource utilisation is determined based on spatio-temporal simultaneity between demand and non-dispatchable renewable generation. Corresponding **RQ2** reads "**How does spatio-temporal demand heterogeneity influence local renewable resource utilisation, and the interventions aimed to facilitate it?**" This question is broken down into two subquestions: subquestion **a** addresses renewable resource utilisation without interventions, subquestion **b** with interventions.

RQ2a ***What is the impact of spatio-temporal demand heterogeneity on local renewable resource utilisation?***

This research question is answered quantitatively based on three modelling experiments. Each of these experiments sheds light on a different aspect of the interactions between demand and generation. The first experiment analyses a wide range of solar and wind penetration scenarios. The second experiment zooms in on different time and weather conditions (*e.g.*, sunny windless weekend days, or cloudy windy weekday nights) within a single (optimised) scenario of solar and wind generation. These two experiments compare two demand cases: residential-only demand, and a mix of residential and service sector demand representative for the Netherlands. The third experiment considers the three archetype urban demand profiles, and compares their interactions with renewable generation in different time and weather conditions for three solar and wind generation scenarios. The results of these experiments show that mixed areas have a higher renewable resource utilisation than areas with only households. This implies that if the service sector is omitted in urban energy system models, the assessment of renewable resource utilisation underestimates its true value. As only a minority of urban areas is found to have a residential-type demand profile, this underestimation can have considerable consequences for city-wide estimations of renewable resource utilisation, and the decisions made based on such results.

RQ2b ***What is the impact of spatio-temporal demand heterogeneity on interventions aimed to facilitate local renewable resource utilisation?***

This research question is addressed based on two case studies, that aim to illustrate some effects of spatio-temporal demand heterogeneity and how the detailed spatio-temporal demand dataset [315] can be used by other researchers to more realistically assess the effect of such interventions in different conditions. The first case study focuses on the use of individually-owned storage units and their applicability to mitigate the effects of non-dispatchability of renewable generation. The second case study explores the potential of demand response as a source of flexibility to offset both non-dispatchability and uncertainty of solar energy generation. Overall, both case studies show that detailed knowledge of local demand characteristics is indispensable for the understanding of both technical and governance implications of the considered interventions. In the case of individually-owned storage, the importance of *governance* dominates. The case study shows that local coordination of individually-owned units increases local renewable energy utilisation more than their individual use. Achieving such coordination requires insights in stakeholder composition, their interests, and potential. The second case study underscores the *technical* importance of the availability of demand profiles with sufficient temporal detail. If such detailed profiles are not available, the potential of demand response can only be assessed based on aggregated data. Such data are shown to likely overestimate the potential of demand response to address the challenges of non-dispatchability and uncertainty of renewable generation. The answer to **RQ2b** is thus nuanced. The impact of spatio-temporal demand heterogeneity on the effects of an intervention is likely to depend on the details of said intervention, and can have technical or governance implications, or both.

RQ2 How does spatio-temporal demand heterogeneity influence local renewable resource utilisation, and the interventions aimed to facilitate it?

The influence of spatio-temporal demand heterogeneity on local renewable resource utilisation and the interventions aimed to facilitate it has several dimensions. First, mixed urban areas – this is the majority of urban areas – are shown to have a higher local renewable resource utilisation than areas with only households, or if only households are modelled in real (mixed) areas. This is caused by the higher likelihood of simultaneity between the timing of renewable generation and the timing of demand in a more heterogeneous set of consumers. Second, the effects of spatio-temporal demand heterogeneity on interventions that are aimed to increase local renewable resource utilisation depend on the intervention. Such effects can have both technical and governance aspects, and should be considered case-by-case using realistic representations of demand, generation, and the intervention.

Research Question 3

Policies can have key effects on the energy transition. Acknowledging this, **RQ3** reads "**How can local renewable resource utilisation be facilitated through policies?**" The effects of policies on renewable resource utilisation can be both intended and unintended, and both should be assessed to achieve the intended effects and avoid the unintended ones. As in-field testing of policies is generally undesirable or infeasible, modelling is the primary tool to study their effects. Thus, models should be as realistic as possible for their intended purpose. In the case of this thesis, the developed detailed spatio-temporal demand profiles increase model realism for policy analysis. As the main focus of this thesis concerns demand heterogeneity, the broad **RQ3** is narrowed down to a formulation limited to demand response of heterogeneous consumers. The policy addressed is European energy taxation.

RQ3a ***How can demand response of heterogeneous energy consumers be stimulated through energy taxation?***

Mass market demand response by small residential and service sector consumers is widely deemed to be an important enabler for a power system with a large share of renewables. To incentivise demand response participation, the European Union plans to implement real-time retail prices. However, existing energy taxation legislation in the European Union does not provide financial incentives for demand response participation. The existing *per-unit* taxes, implemented in almost all European Member States, dampen the clarity of the real-time price signal. The impact of energy taxes on demand response participation has thus far not been comprehensively addressed in the literature. In this thesis, financial incentives received by consumers participating in demand response are modelled using the developed detailed demand profiles. Two cases are compared: the existing *per-unit* tax and an alternative *ad valorem* tax. Results show that the financial incentives provided by the latter are considerably larger than those provided by the former. Thus, policy makers are advised to stimulate demand response by implementing an energy tax which does not dampen the clarity of a real-time retail price signal.

RQ3 How can local renewable resource utilisation be facilitated through policies?

This broad research question is answered in this thesis for a case study on the effect of energy taxation on demand response, as demand response is considered a promising tool to support renewable resource utilisation. The results of the case study show that the degree to which financial incentives can be increased depends on the consumer type and demand profile. From a broader perspective on **RQ3**, the results obtained for **RQ3a** illustrate the importance of detailed demand profiles in modelling studies for policy analysis. Including such detailed demand profiles in future policy analyses can thus make the assessment of their effects more realistic, providing better insights in their ability to improve renewable resource utilisation.

Main Research Question

Having answered the three partial research questions, the main research question is revisited. It is answered based on the combined insights obtained.

How can local renewable resource utilisation be facilitated in urban areas?

Based on the partial research questions, the main research question is answered as follows. Local renewable resource utilisation in urban areas can be facilitated by improving the understanding of spatio-temporal characteristics of local demand, and tailoring interventions and policies to it. The complexity and socio-technical character of the power system should be considered when doing so. From a technical and modelling perspective, "tailoring" implies that more detailed representations of urban demand should be taken into account when designing interventions. From a social perspective, "tailoring" entails recognising and addressing the heterogeneity in stakeholders, their incentives, and action potential.

The ongoing energy transition and urbanisation can be expected to increase the need for such tailored approaches. The energy transition drives decentralisation of the power system and necessitates a reconsideration of its design and operation. Thus, the local scale can be expected to gain importance. Urbanisation increases the share of energy used in cities, making urban areas particularly important targets for the energy transition. Digitalisation is considered to be an enabling factor that can aid the creation of such tailored approaches. Overall, facilitating renewable resource utilisation in urban areas requires a paradigm shift from the historically centralised view on power systems to involvement and empowerment of small and large players across the system, in particular, consumers.

10.2 Research Contributions

This thesis contributes to the understanding of the interplay between renewable generation and demand in urban areas. It develops insights needed to support governments, communities, and companies in their endeavours to make local energy systems sustainable and free of fossil fuels. The contributions of this thesis are both theoretical and practical. From a theoretical perspective, this thesis shows that more realistic urban energy system models, in particular with respect to demand-side data and modelling, are needed to support the energy transition. From a practical perspective, it provides an accompanying dataset [315] that can be used to extend existing and future models to this purpose.

In summary, the contributions of this thesis are:

- Extension of state-of-the-art urban energy system models with novel insights of the importance of the *demand side* and its *heterogeneity* in urban areas (Chapters 4 and 5).
    - Novel approach to *model service sector demand* despite current scarcity of publicly available demand profiles for this sector. The approach is based on a combination of non-energy-related data and demand profiles provided by the United States Department of Energy, that is currently the only sufficiently detailed database that is publicly available, to the best of the author's knowledge. The proposed approach is applied to the Netherlands. It yields 13 service sector demand profiles that are made available online [315].
    - Data-driven *characterisation and classification* of *spatio-temporal heterogeneity of urban demand*. Three archetype urban areas – residential, business, and mixed – are distinguished. These archetype urban areas are statistically significantly dif-

ferent from each other, both in terms of their demand profiles and consumer composition. Moreover, residential-type urban areas, that are often used in urban energy system models, are shown to represent only a minority of urban areas, and account for only a small share of the total demand. The corresponding urban-scale demand profiles and classification of urban areas is available in the dataset that accompanies this thesis [315].

- Impact of spatio-temporal demand heterogeneity on *local renewable resource utilisation* in urban areas is quantified (Chapters 6 and 7).
  - Differences in renewable energy utilisation between areas with mixed residential and service sector consumers, and areas with residential-only consumers (or if only residential demand is assumed) are shown to be *statistically significant*. Mixed urban areas use significantly more renewable energy locally. This result is persistent across a wide range of renewable resource penetration scenarios, and time and weather conditions.
  - Detailed understanding of local demand-side characteristics is shown to be of key importance for the design and assessment of *interventions* such as storage and demand response.
- Formulation of *advice for policy makers* based on technical insights in spatio-temporal demand heterogeneity and its role in the energy transition (Chapter 8).
  - The impact of *energy tax* on financial incentives for demand response participation of heterogeneous consumers is quantified. Existing European *per-unit* energy tax is shown to dampen financial incentives for demand response participation. An *ad valorem* energy tax is proposed as an alternative to resolve this issue.

This thesis bridges multiple disciplines, in particular power systems and electrical engineering, urban planning, and energy policy. Its contributions can be relevant for researchers from these and other disciplines, as well as for governments, communities, and companies.

10.3 Outlook

Informing and supporting the energy transition is an enormous endeavour. Although a growing body of literature exists, to which this thesis contributes, numerous issues remain unresolved. Based on the insights from this thesis, the following issues are highlighted as important topics for future research.

Expanding Demand Heterogeneity to Industry, Transportation, and Heating. Traditionally, the demand side has received little attention in energy and power systems research. Addressing this hiatus, this thesis focuses on the role of the service sector in urban energy systems. Future work should expand this focus by integrating the obtained insights and results with ongoing and future research of other sectors, in particular industry, transportation, and heating. Industry is an important contributor to energy demand in urban areas. However, it is unevenly distributed (*e.g.*, not every city has a steel production plant). The assessment of the role of industrial consumers in the energy transition in specific urban areas thus requires a case-by-case approach. This can be realised by creating an open library of industrial subsectors that can be used by urban energy system models. Both the transportation and heating sector are expected to undergo dramatic changes as a result of electrification. The role of these sectors and their impact on local urban demand require further study. Although these sectors are more ubiquitous in urban areas, a similar, modular, open-library approach can also be adopted for transportation and heating.

Detailed Demand Data. One of the main research challenges highlighted in this thesis is the current lack of detailed and publicly available urban energy demand data. This issue needs to be resolved through closer collaboration between academia, industry, and governments. As smart meters become increasingly common, more and more detailed demand data are collected. These data are, however, currently not accessible for research. Dedicated efforts are required to make these data available while safeguarding the privacy of energy consumers. In the context of this thesis, measured detailed data could alleviate two main limitations encountered – validation and geographical generalisation. Particular attention should be paid to collecting and publishing data from developing countries, as small and medium-sized cities in these countries are predicted to have the largest urbanisation rates and thus the highest contribution to future urban energy demand.

Scenario Development and Standardisation. The results presented in this thesis should be extended with projections and scenarios of the evolution of future demand. This thesis develops a thus far non-existent baseline scenario. It illustrates the effects of improved understanding of the current demand. This is a first step. The next step should address the effects of demand changes. However, without understanding of the current situation, future scenarios and projections do not have the necessary foundations.

Open Data and Models. Urban energy system modelling can be considerably improved through a transition to open models and databases. They can be the basis for standardisation of assumptions and scenarios, thus avoiding unnecessary work duplication and improving comparability and interoperability of models. Training and education are to play a key role in the transition from proprietary to open energy system models and databases.

Cross-Disciplinary Research. The power system is a socio-technical system. This thesis focuses on its technical layer. The obtained results should be seen as one component of a larger whole. Future research should integrate the obtained technical insights with social aspects. A particular knowledge gap to be addressed in this respect is the energy-related decision-making of companies and organisations. This topic has remained largely unaddressed thus far.

The energy transition is a multidisciplinary endeavour. Closer collaboration between various disciplines is necessary to successfully tackle it. Awareness of the differences in frames of reference, methodological approaches, theoretical canons, terminologies, *etc*. is indispensable to overcome the barriers posed by these differences. This is even more the case for collaborations across other societal division lines. Both education and open-mindedness are much needed to overcome such barriers and foster joint efforts to tackle one of the major problems of the twenty-first century.

Epilogue

> *La machine à malaxer la guimauve malaxe la guimauve.*
>
> – Jean-Pierre Jeunet et Guillaume Laurant

LIMITING global warming to 1.5°C requires unprecedented efforts across all societal sectors [6]. Transforming the energy sector is of particular importance to ensure that reliable energy provision continues to drive global economies, while causing no or very limited greenhouse gas emissions. Bringing such unparalleled changes into being hinges on a profound – heartfelt – understanding of their necessity. In other words, they require *sustainability* to be embraced as a *core value* in the energy sector.

A core value of a sector is a core value of its community. The community of the energy sector is undeniably diverse. However engineers, in particular power systems, electrical, and electronics engineers, are a key group in this community. The IEEE – Institute of Electrical and Electronics Engineers – is a global professional organisation that represents this group. According to its Code of Ethics, "the members of the IEEE [...] strive to comply with [...] sustainable development practices, and to disclose promptly factors that might endanger [...] the environment" [454]. Sustainability is thus explicitly named as a core value, however its application in practice remains inadequate. For instance, sustainability is not part of IEEE's own Strategic Plan 2015 – 2020, while, according to the IEEE, this plan "should provide a clear picture of [...] the goals our community is pursuing" [455].

Furthermore, despite the urgent need for profound energy sector transformations, sustainability is not a core value in the education of *future* power systems and electrical engineers across the world [456–459]. Although increasing numbers of universities worldwide offer sustainability-related programmes and courses in their energy and power system curricula, especially in Graduate or Master of Science programmes, these remain elective and are thus not part of the default curriculum (*e.g.*, [460, 461]). As a result, engineers who have barely or never encountered sustainability throughout their education are expected to play key roles in the energy transition [462].

According to a world-wide survey of engineering students in 2005, they generally consider sustainability to be an important issue, but often do not know how to link it to engineering practice [462]. This hiatus still persists across many universities worldwide now, more than a decade later [463–465]. This underscores the discrepancy between the societal need for an unprecedented energy transition, and the background, education, and mindset of engineers who are expected to play a pivotal role in realising this transition.

Sustainability is a core value of environmental engineering [466]. This discipline is one of the younger branches of engineering. Environmental engineering was originally a subdiscipline within civil engineering, and became independent in the 1980s and 1990s [466, 467]. Most of the existing curricula and professional work in environmental engineering focus on water and wastewater management and sanitation, air quality monitoring, solid and hazardous waste management, noise and light pollution, environmental microbiology and chemistry, *etc*. [460, 466, 468–470]. These topics are primarily centred on the *treatment* of negative by-products of human activities reaching the environment, also called *end-of-pipe* solutions. In the context of energy, environmental engineering primarily focuses on reducing emissions, not on reducing demand driving those emissions [471]. This is a narrow interpretation of the discipline's core commitment to sustainability. A broader interpretation includes the development of solutions that *prevent* such negative by-products, in particular greenhouse gases in the case of energy use.

As a discipline, environmental engineering has worked towards the recognition of its independence and relevance for the last 30 to 40 years [466, 467]. Climate change and, in particular, energy transition challenges vividly underscore the latter, putting environmental engineering in a prime position for partnerships with other engineering disciplines, in particular power systems, electrical, and electronics engineering to develop solutions that *prevent* greenhouse gas emissions. Currently, such partnerships are rare to non-existent [464]. Despite their broad curriculum, environmental engineers lack knowledge of power systems, electrical, and electronics engineering basics. On the other hand, as illustrated earlier, power systems, electrical, and electronics engineers consider sustainability at best a secondary concern. Education and training should be directed at remediating this lack of cross-pollination.

In conclusion, there is a disconnect between the societal needs for *sustainable* energy systems and the *values* currently embraced by many power systems, electrical, and electronics engineers working on these systems [468]. It is noteworthy that environmental engineers do strongly emphasise sustainability, yet, their involvement in the energy transition is limited, and mostly concerns biofuels only. Both disparities need to be resolved. Sustainability should be universally taught as one of the core values for all engineering disciplines – in particular those tightly involved with the energy transition. A basic understanding of power systems, electrical, and electronics engineering should be added to the environmental engineering curricula and training. Cross-disciplinary collaboration and education are much needed to train well-prepared generations of engineers who can tackle current challenges, and realise the energy transition, engineers who deeply understand the necessity of this transition, and who know how to turn this understanding into practice.

Appendices

A Calculation of Service Sector Building Equivalents

United States Department of Energy (U.S. DOE) Commercial Reference Building data [225] are used to model service sector electricity demand in the Netherlands. A U.S. reference building is used as a *building equivalent* to represent the energy demand of corresponding Dutch buildings. Building equivalents are calculated based on Dutch national data, or data obtained from subsector-related organisations (see further). The calculations are described below per U.S. reference building or building group. If available, data for the reference year 2014 are used to ensure the best correspondence with other data used in this thesis. Otherwise, the latest available data are used.

A reference urban environment of $100\,000$ households is assumed. To obtain the number of reference buildings representative for this urban environment, the number of reference buildings calculated for the Netherlands as a whole is divided by 75.9, as the total number of households in the Netherlands is 7.59 million [472]. The final result is rounded to the nearest integer.

A.1 Hospitals

The building equivalent for U.S. reference building "Hospital" is calculated based on the number of patient beds. The average number of beds in hospitals in the U.S. is 161 [319]. The average number of beds in hospitals in the Netherlands is 316 [320]. The "Hospital" building equivalent thus equals $316/161 = 1.96$. There are 134 hospitals in the Netherlands [320], which can be represented by $134 \cdot 1.96 = 263$ U.S. reference buildings of the type "Hospital". In an urban environment of $100\,000$ households, Dutch hospitals can be represented by $263/75.9 = 3$ U.S. reference buildings of the type "Hospital".

A.2 Hotels

The building equivalents for U.S. reference buildings "Large Hotel" and "Small Hotel" are calculated based on the number of hotel rooms. The number of rooms in the "Large Hotel" U.S. reference building is 300 [225]. The number of rooms in the "Small Hotel" U.S. reference building is 77 [225]. There are 3 185 hotels in the Netherlands with a total of 112 565 rooms [321]. In the Netherlands, 2.6% of the hotels (83 hotels) have more than 200 rooms per hotel [322]. These hotels are represented by the "Large Hotel" reference building. Hotels with less than 200 rooms are represented by the "Small Hotel" reference building. Large Dutch hotels are assumed to have an average of 250 rooms per hotel, and can thus be represented by $83 \cdot 250/300 = 69$ U.S. reference buildings of the type "Large Hotel". The remaining

Table A.1 Floor area distribution of offices in the Netherlands [323]. The average area is obtained from the minimum and maximum areas. The number of offices is the solution of a set of equations which satisfy both the third column and the total (used) office floor area in the Netherlands, which equals 49.55 million m^2 [324]. The last column illustrates this.

Input Data [323]			Calculated Values		
Min. Area (m^2)	Max. Area (m^2)	Share (%)	Average Area (m^2)	Number of Offices (-)	Total Area (m^2)
500	1 000	5	750	326	244 249
1 000	2 500	19	1 750	1 238	2 165 675
2 500	5 000	23	3 750	1 498	5 617 729
5 000	1 0000	21	7 500	1 368	10 258 462
10 000	(-)	32	15 000	2 048	31 263 884

91 865 rooms can be represented by 1 193 U.S. reference buildings of the type "Small Hotel". In an urban environment of 100 000 households, Dutch hotels can be represented by $83/75.9 = 1$ U.S. reference buildings of the type "Large Hotel" and $1\,193/75.9 = 16$ U.S. reference buildings of the type "Small Hotel".

A.3 Offices

The building equivalents for U.S. reference buildings "Large Office", "Medium Office", and "Small Office" are calculated based on office floor area. The floor area of the "Large Office" U.S. reference building is 46 320 m^2 [225]. The floor area of the "Medium Office" U.S. reference building is 4 982 m^2 [225]. The floor area of the "Small Office" U.S. reference building is 511 m^2 [225]. Office floor area distribution for the Netherlands is shown in Table A.1 [323]. The total (used) office floor area in the Netherlands is 49.55 million m^2 [324].

Dutch offices with an area larger than 10 000 m^2 are represented by $31\,263\,884/46\,320 = 675$ "Large Office" U.S. reference buildings. Dutch offices with an area between 1 000 and 10 000 m^2 are represented by $(2\,165\,675 + 5\,617\,729 + 10\,258\,462)/4\,982 = 3\,569$ "Medium Office" U.S. reference buildings. Dutch offices with an area between 500 and 1 000 m^2 are represented by $244\,249/511 = 478$ "Small Office" U.S. reference buildings.

In an urban environment of 100 000 households, Dutch offices can be represented by $675/75.9 = 9$ U.S. reference buildings of the type "Large Office", $3\,569/75.9 = 47$ U.S. reference buildings of the type "Medium Office" and $478/75.9 = 6$ U.S. reference buildings of the type "Small Office".

A.4 Schools

The building equivalent for U.S. reference buildings "Primary School" and "Secondary School" are calculated based on student numbers. The number of students in the "Primary School" U.S. reference building is 650 [225, 325]. The number of students in the "Secondary School" U.S. reference building is 1 200 [225, 325]. The number of primary schools in the Netherlands is 7 155, with an average of 219 students per school [326]. These schools can be represented by $7\,155 \cdot 219/650 = 2\,411$ U.S. reference buildings of the type "Primary School". The number of secondary schools in the Netherlands is 642 with an average of 1 295 students per school [327]. These schools can be represented by $642 \cdot 1\,295/1\,200 = 693$ U.S. reference buildings of the type "Secondary School". In an urban environment of 100 000 households, Dutch schools can be represented by $2\,411/75.9 = 32$ U.S. reference buildings of the type "Primary School" and $693/75.9 = 9$ U.S. reference buildings of the type "Secondary School".

A.5 Retail

The building equivalent for U.S. reference building "Stand Alone Retail" is calculated based on floor area. The floor area of "Stand Alone Retail" U.S. reference building is 2 294 m^2 [225]. The total (used) retail area in the Netherlands is 30 775 168 m^2 [328]. Thus, retail in the Netherlands can be represented by $30\,775\,168/2\,294 = 13\,416$ U.S. reference buildings of the type "Stand Alone Retail". In an urban environment of 100 000 households, Dutch retail can be represented by $13\,416/75.9 = 177$ U.S. reference buildings of the type "Stand Alone Retail".

A.6 Supermarkets

The building equivalent for U.S. reference building "Supermarket" is calculated based on floor area. The floor area of "Supermarket" U.S. reference building is 4 181 m^2 [225]. The total supermarket area in the Netherlands is 3 781 699 m^2[316] (cross-referenced with [317, 318]). Thus, supermarkets in the Netherlands can be represented by $3\,781\,699/4\,181 = 904$ U.S. reference buildings of the type "Supermarket". In an urban environment of 100 000 households, Dutch supermarkets can be represented by $904/75.9 = 12$ U.S. reference buildings of the type "Supermarket".

A.7 Restaurants

The building equivalent for U.S. reference buildings "Full Service Restaurant" and "Quick Service Restaurant" are calculated based on the number of restaurants in the Netherlands. The number of restaurants of different types are obtained from [329] and are summarised in Table A.2. The table indicates which restaurants are considered to be equivalent with "Full Service Restaurant" and which with "Quick Service Restaurant". The distinction is made based on the expected time customers spend in a restaurant. The total number of restaurants in the Netherlands that can be represented by U.S. reference building of the type "Full

Table A.2 Number of restaurants of different types in the Netherlands [329].

Restaurant Type (Dutch Name)	Restaurant Type (English Translation)	Number	U.S. Restaurant Equivalent
Lunchroom/Tearoom	Lunchroom/Tearoom	1 929	Full
Selfservice restaurant	Self-service Restaurant	162	Quick
Broodjeszaak/Croissanterie	Sandwichbar/Eat-in Bakery	937	Quick
Internationale fastfoodketen	International Fast Food Chain	325	Quick
Cafetaria/Snackbar	Cafeteria/Snack Bar	5 888	Quick
Shoarma/Grillroom/ Kebab	Shoarma/Grillroom/ Kebab	1 926	Quick
IJssalon	Ice Cream Parlor	876	Quick
Restaurant (buitenlandse keuken)	Restaurant (International Cuisine)	5 667	Full
Restaurant (nationale keuken)	Restaurant (National Cuisine)	4 663	Full
Pizzeria	Pizzeria	644	Full
Eetcafe	Pub	3 318	Quick
Creperie/Pannenkoeken	Creperie/Pancakes	429	Quick
Recreatiemeer- /Strandpaviljoen	Recreation Park/Beach Pavilion	511	Quick

Service Restaurant" is 12 903. The total number of restaurants in the Netherlands that can be represented by U.S. reference building of the type "Quick Service Restaurant" is 14 372. In an urban environment of 100 000 households, Dutch restaurants can be represented by $12\,903/75.9 = 170$ U.S. reference buildings of the type "Full Service Restaurant" and $14\,372/75.9 = 190$ U.S. reference buildings of the type "Quick Service Restaurant".

A.8 Warehouses

The building equivalent for U.S. reference building "Warehouse" is calculated based on the power consumption and the number of employees in warehousing in the Netherlands and the U.K. The latter is used due to lack of suitable Dutch data. The annual electricity consumption of U.S. reference building "Warehouse" is 239 MWh per year [225]. The total warehousing electricity consumption in the U.K. is 12 TWh per year [122]. The total number of employees in warehousing in the U.K. is 334 100. The total number of employees in warehousing in the Netherlands is 82 600 [330]. Warehouses in the Netherlands are therefore estimated to be represented by $12\,000/0.239 \cdot 826\,000/3\,341\,000 = 12\,397$ U.S. reference buildings of the type "Warehouse". In an urban environment of 100 000 households, Dutch warehouses can be represented by $12\,397/75.9 = 164$ U.S. reference buildings of the type "Warehouse".

B Classification of Service Sector Consumers

No standardised classification of service sector consumers exists. Datasets from different sources therefore have different subdivisions. In this thesis, different datasets are combined. Chapter 5 describes the modelling and classification of urban-scale demand profiles. The modelling step requires the combination of three datasets, while the classification step relies on two different datasets. These differences in underlying datasets result in somewhat different end-classifications of service sector consumers. Tables B.1 and B.2 provide an overview of the consumer classes that can be distinguished based on the combination of respectively three and two datasets. The combination of three datasets (Table B.1) results in 6 joint consumer classes, while the combination of two datasets (Table B.2) results in 7 joint consumer classes. Differences lie with the following consumer types: (1) whether *hotels* are included with cafés and restaurants, or represent a separate consumer type, (2) whether *warehouses* are included with retail and supermarkets, or represent a separate consumer type, and (3) whether *hospitals* are included.

Modelling and **linear regression** of urban-scale energy demand is based on the following three datasets: (1) *temporal data*: consumer energy demand profiles (based on U.S. DOE Commercial Reference Buildings database for service sector consumers [225] and on standard Dutch demand profiles for households [306]), (2) *spatial data*: local consumer composition dataset at municipality scale from Statistics Netherlands [343], and (3) *aggregated demand data*: annual local power demand dataset from the Dutch Directorate-General for Public Works and Water Management [346].

Classification of urban-scale energy demand profiles is based on the following two datasets: (1) *temporal data*: consumer energy demand profiles (based on U.S. DOE Commercial Reference Buildings database for service sector consumers [225] and on standard Dutch demand profiles for households [306]), and (2) *spatial data*: local consumer composition dataset at municipality, district, and neighbourhoods scales from Statistics Netherlands [342, 343].

Table B.1 Consumer classes distinguished based on the combination of three datasets.

Temporal Data (14 Subsectors)	**Spatial Data (11 Subsectors)**	**Aggregated Demand Data[1] (6 Subsectors)**	**Joint Data (6 Subsectors)**
Household	Wonen (*Housing*)	Woningen (*Houses*)	Households
Small Hotel	Logies (*Lodging*)	I	Cafés, Restaurants, and Hotels
Hotel			
Restaurant	Bijeenkomst (*Gathering*)		
Quick Service Restaurant			
Small Office	Kantoor (*Office*)	J, K, L, M, N, O	Offices
Medium Office			
Large Office			
Primary School	Onderwijs (*Education*)	P	Schools
Secondary School			
Stand Alone Retail	Winkel (*Shop*)	G	Retail, Supermarkets, and Warehouses
Supermarket			
Warehouse	Overig (*Other*)		
Hospital	Gezondheidszorg (*Healthcare*)	Q	Hospitals

[1] **Key:** G: Groot- en detailhandel (*Wholesale & Retail*)
I: Logies, maaltijd- en drankverstrekking (*Lodging, food, and drinks distribution*)
J: Informatie & Communicatie (*Information & Communication*)
K: Financiële activiteiten & verzekeringen (*Finance & Insurance*)
L: Exploitatie van en handel in onroerend goed (*Real Estate Management & Trade*)
M: Vrije beroepen en wetenschappelijke en technische activiteiten (*Independent Professionals, Scientific & Technical Activities*)
N: Administratieve en ondersteunende dienstverlening (*Administrative Services*)
O: Openbaar bestuur en defensie; verplichte sociale verzekeringen (*Governmental Agencies & Social Insurances*)
P: Onderwijs (*Education*)
Q: Gezondheids- en welzijnszorg (*Healthcare*)

Table B.2 Consumer classes distinguished based on the combination of two datasets.

Temporal Data (14 Subsectors)	**Spatial Data (11 Subsectors)**	**Joint Data (7 Subsectors)**
Household	Wonen (*Housing*)	Households
Small Hotel Hotel	Logies (*Lodging*)	Hotels
Restaurant Quick Service Restaurant	Bijeenkomst (*Gathering*)	Restaurants
Small Office Medium Office Large Office	Kantoor (*Office*)	Offices
Primary School Secondary School	Onderwijs (*Education*)	Schools
Stand Alone Retail Supermarket	Winkel (*Shop*)	Shops
Warehouse	Overig (*Other*)	Warehouses
Hospital	Gezondheidszorg (*Healthcare*[1])	*(not used in this thesis)*
(no equivalent)	Cel (*Prison*)	*(not used in this thesis)*
(no equivalent)	Industrie (*Industry*[2])	*(not used in this thesis)*
(no equivalent)	Sport (*Sports Facility*)	*(not used in this thesis)*

[1] *Healthcare could not be satisfactorily modelled based on the available datasets due to low R^2-value of the corresponding scaling factor (see Section 5.1.2.2).*
[2] *Industry is left out of the scope of this thesis.*

C Simulating Solar Forecasting for Energy Market Decision Models

Today's energy markets are increasingly challenged by the uncertainty of supply inherently associated with weather-dependent energy resources [473]. Market participants' behaviour depends on available forecasts. Current models of market participants' behaviour are based either on perfect foresight assumptions, or on a single forecast, usually 24 hours ahead of time. In reality, consecutive, increasingly more reliable forecasts become available closer to real time. These improvements affect consecutive decisions of market participants. For energy market modelling, usually only historical data, not the preceding forecast are available. Limited amount of work currently exists on simulating consecutive, increasingly more reliable forecasts from the available historical data. The following method is proposed to model solar forecasting based on historical data, for multiple forecasts, up to several days in advance.

C.1 Method

The proposed method extends existing Gaussian noise addition methods available in literature [474]. The method relies on error addition to measured historical data. The magnitude of the error increases with increasing forecast horizon. Formally, the insolation forecast $\hat{y}(t_f, t_c)$ for a future timestep t_f at timestep t_c is calculated using the measured insolation value $y(t_f)$ for that timestep and a relative error e_η with η the forecast time horizon, *i.e.*, the difference between the current timestep t_c and the future timestep t_f. The errors are normally distributed with a mean 0 and a variance σ_η^2 which increases as the forecast time horizon η increases:

$$\hat{y}(t_f, t_c) = y(t_f) \cdot (1 + e_\eta) \quad \text{with } (t_f, t_c) \text{ such that } t_f - t_c = \eta \tag{C.1}$$

$$e_\eta \sim \mathcal{N}(0, \sigma_\eta^2) \tag{C.2}$$

One of the main challenges of this approach is the estimation of time horizon-dependent variances σ_η^2. The proposed method shows that the root mean square error (*RMSE*) metric, often used to assess the quality of real forecasts, can be used to estimate the σ_η^2-values. RSME-values (and derived *relative RSME*, or *rRMSE*-values) are available from literature describing meteorological forecasting models (*e.g.*, [385]). The proposed model uses *rRMSE*$_\eta$ for each time horizon η. The value of *rRMSE*$_\eta$ is calculated based on N observations of

This appendix is based on a previous publication [66].

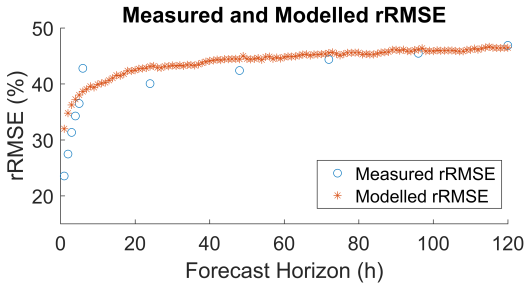


Figure C.1 Comparison of measured rRMSE and modelled rRMSE. Measured rRMSE are calculated from [385].

measured values $y_i(t_f)$ for timestep t_f, and the corresponding forecast values $\hat{y}_i(t_f, t_c)$ for timestep t_f made at timestep t_c:

$$rRMSE_\eta = \sqrt{\frac{\sum_{i=1}^{N}\left(\frac{\hat{y}(t_f,t_c)-y_i(t_f)}{y_i(t_f)}\right)^2}{N}} \qquad \text{with } (t_f, t_c) \text{ such that } t_f - t_c = \eta \tag{C.3}$$

The standard deviation of a normal distribution is defined as:

$$\sigma = \sqrt{\frac{\sum_{j=1}^{M}(\hat{z}_j - \bar{z})^2}{M-1}} \tag{C.4}$$

Equations C.3 and C.4 are equivalent if (1) the insolation predictions $\hat{y}_i(t_f, t_c)$ are unbiased around the real value $y_i(t_f)$, then $y_i(t_f) = \bar{\hat{y}}(t_f, t_c)$, and (2) with the approximation $M - 1 \approx N$. Then, $\hat{z} = \hat{y}_i(t_f, t_c)/y_i(t_f)$ and $\bar{z} = 1$. The $rRMSE_\eta$-value then approximates σ_η.

The resulting model is a purely statistical one, it therefore cannot entirely capture the behaviour of real meteorological forecasting methods. Two main issues need to be corrected: (1) **unrealistic values**, and (2) **independence artefacts in subsequent forecasts**.

Unrealistic values, such as negative insolation and too high values for the time of the day and year, should be corrected:

Correction rule 1: Negative insolation value = 20% of time-appropriate clear sky value (equals cloudy sky)

Correction rule 2: Value higher than time-appropriate clear sky value = time-appropriate clear sky value

Independence artefacts in subsequent forecasts arise because forecasts made in subsequent timesteps $t_{c,j-1}$ and $t_{c,j}$ (*i.e.*, as the present timestep t_c moves forward) are independent from each other: the errors e_η are drawn independently at each timestep t_c. This can lead to considerably different forecasts $\hat{y}(t_f, t_{c,j-1})$ and $\hat{y}(t_f, t_{c,j})$ for the same timestep t_f drawn at subsequent timesteps $t_{c,j-1}$ and $t_{c,j}$. This can be corrected by making subsequent forecasts interdependent. The following empirically found correction is implemented. If two subsequent forecasts $\hat{y}(t_f, t_{c,j-1})$ and $\hat{y}(t_f, t_{c,j})$ differ by more than 10%, the final forecast $\hat{y}_{final}(t_f, t_{c,j})$ is the average of: the original forecast $\hat{y}_{orig}(t_f, t_{c,j})$, a new forecast $\hat{y}_{new}(t_f, t_{c,j})$,

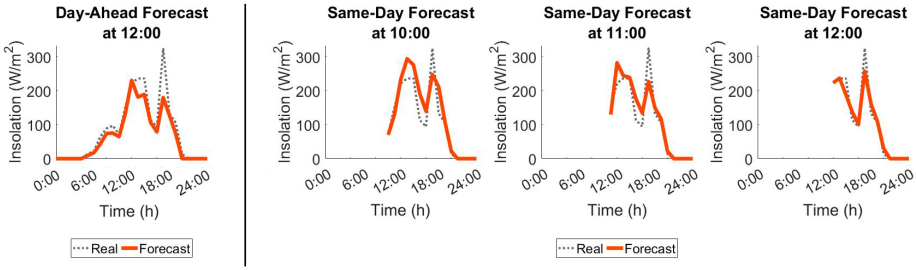


Figure C.2 Simulated consecutive day-ahead and same-day forecasts for the 3rd of June 2012.

the forecasts of the previous timesteps $t_{c,j-1}$ and $t_{c,j-2}$, and the real value of the previous hour $y(t_f - 1)$:

$$\hat{y}_{final}(t_f, t_{c,j}) = \text{mean}[\hat{y}_{orig}(t_f, t_{c,j}), \hat{y}_{new}(t_f, t_{c,j}), \hat{y}(t_f, t_{c,j-1}), \hat{y}(t_f, t_{c,j-2}), y(t_f - 1))] \quad \text{(C.5)}$$

The parameters of this empirical correction can be adapted to the context in which this forecasting simulation is used. The method is validated through comparison of modelled *rRMSE* values with measured *rRMSE* values from [385] (see Figure C.1). The modelled *rRMSE* values are slightly higher than measured values for small forecast horizons, yet overall, closely simulate the real *rRMSE* trends of meteorological forecasting models. This shows the validity of the method.

C.2 Results

The method is applied to a solar insolation dataset from the Netherlands. Figure C.2 shows an example of simulated day-ahead and same-day forecasts for the 3rd of June 2012. The day-ahead forecast simulation somewhat misestimates insolation throughout the entire day (as can be expected from a real forecast). However, the model returns no unrealistic (negative or very high) values. The same-day forecast at 10:00 shows errors for the later afternoon hours, but is close to real values for the morning hours. As the day progresses, the forecasts for the later hours become closer to reality. This closely resembles the behaviour of real meteorological forecasting methods.

These forecasts can be used to realistically simulate market participant behaviour, for instance that of an aggregator with renewables in her portfolio, who bases her decisions on forecasts. This aggregator bids in the day-ahead market based on the day-ahead forecast from Figure C.1. Same-day forecasts are then used to model intraday behaviour such as intraday bidding or rescheduling of flexible loads (demand response) or dispatchable generation. In this thesis, this model is applied in Chapter 7 to study how demand response can be used to address imbalances that occur as a result of uncertainty in solar generation.

D Modelling Heat Pump Demand

Electrification of the heating sector is part of the energy transition (Chapter 2). In the Netherlands, the government has decided to phase out gas by 2050 [384]. In this thesis, electrification of the heating sector is taken into account by modelling heat pumps in the case studies in Chapters 7 and 8.

Heat pump demand is modelled in a similar way as electricity demand of other appliances (as described in Chapter 4). Residential heat pump demand is based on measured household gas demand data (courtesy of Alliander, a Dutch DSO). Service sector heat pump demand is based on U.S. DOE Commercial Reference Buildings database [225]. However, unlike electricity demand for other appliances, heat pump demand requires additional conversion steps: (1) conversion of energy carrier consumption data into thermal heat demand profiles, (2) scaling of the thermal heat demand to account for the decrease in energy consumption due to improved insulation required for switching to heat pumps-based heating systems, and (3) conversion of thermal heat demand profiles into electrical demand profiles of heat pumps.

D.1 Conversion of Gas Consumption to Heat Demand

The conversion of energy carrier consumption data into thermal heat demand profiles is somewhat different for residential and service sector consumers due to differences in data availability.

For **residential consumers**, available historical data are measured gas demand profiles of 63 Dutch households (data courtesy of Dutch DSO Alliander). These data concern the total gas demand profiles, which includes space heating, hot water, and cooking. Space heating gas demand is derived from these total profiles using additional data sources. The study of Menkveld shows that on average space heating represents 73% of the total gas demand in Dutch households [475]. Thus, residential gas demand profiles are scaled by a factor 0.73. However, this factor varies by the hour of the day. Therefore, daily fluctuations of this average are taken into account based on [476]. The resulting gas demand profile for space heating is converted into thermal demand profiles assuming the heating value of Dutch Groningen gas (31.65 MJ/m^3 [477]) and the conversion efficiency of a high-efficiency boiler (107% [478]).

For **service sector consumers**, modelled historical demand profiles are used due to the lack of measured service sector demand data. These modelled profiles are derived from commercial buildings reference models of the United States Department of Energy (U.S.

DOE) [225], and scaled to the Dutch context using the approach described in Chapter 4. The U.S. DOE reference models provide separate space heating demand profiles, which do not need to be scaled further. The models assume both gas and electricity consumption, depending on the building type. Gas demand is converted to thermal heat demand using an efficiency factor of 80% [331] and the heating value of Dutch Groningen gas [477]. Electricity demand is converted to thermal demand using an efficiency factor of 100% [331].

D.2 Scaling of Heat Demand to Higher Insulation

Heat pump-based heating systems operate at a lower temperature than conventional heating systems. Therefore a high degree of insulation is required when switching from conventional to heat pump-based heating systems. The improvements in insulation decrease the total heat demand. In this thesis, heat demand for heat pumps is assumed to be 55% of the original heat demand for space heating, based on data from [479, 480].

D.3 Conversion of Thermal to Electrical Heat Demand

For both the residential and the service sector consumers, the thermal heat demand profiles are converted into electrical heat demand profiles using the technical heat pump specifications and so-called *COP*-values [481]. COP stands for *coefficient of performance* and equals the ratio between energy supplied to the heated room and electrical energy used. This ratio is temperature-dependent. A heat pump supplies the required heat through a cycle of steps. First, heat is extracted from a low temperature source (such as air, water, or ground) and transferred to a fluid termed "refrigerant". Second, the refrigerant is compressed (this step requires electrical energy) into a hot, high pressure gas. Third, the heat from the hot, pressurised gas is transferred to the building heating system. Finally, the pressure of the gas is lowered (*e.g.*, through an expansion valve), making the refrigerant ready to resume the cycle. The COP of the heat pump depends on the heat source and on its temperature. In this case study, air is assumed to be the heat source. The outdoor temperature is taken from measured values as reported by the Royal Netherlands Meteorological Institute [359].

E

Modelling Heat Pump Demand Response

This appendix provides technical modelling details of heat pump demand response simulation used to illustrate the effect of energy tax in Chapter 8.

The demand response model minimises the operation cost of heat pumps by shifting their demand. Note that in the model, the aggregator simultaneously represents only one of the three consumer groups. Thus, the simulation is run three times, once for each consumer group. The demand response model uses Dutch day-ahead EPEX wholesale prices as price signal (data courtesy of Alliander, a Dutch DSO). The aggregator is assumed to have no commercial interest, and therefore passes on wholesale prices as real-time retail prices. In other words, heat pump electricity demand (calculated as described in Appendix D) is shifted from hours with high wholesale prices to hours with lower wholesale prices. Demand shifting is restricted by both technical constraints and consumer-defined preferences. Technical constraints are based on heat pump specifications in [481]. Consumer-defined preferences are modelled by assuming thermal comfort limits that are acceptable for 90% of consumers, based on [427].

Demand response is assumed to be managed by an aggregator. For this purpose, the modelled aggregator uses two commercially available software packages: PowerMatcher and Realtime Energy eXchange (R.E.X.). This approach simulates the operation of a real aggregator. PowerMatcher is a communication platform and protocol for decentralised control of devices [424]. It is extended with R.E.X. software developed by Energy eXchange Enablers (a member of the Dutch DSO Alliander) [425] which links PowerMatcher to the Dutch EPEX wholesale market. PowerMatcher makes heat pumps *smart*, the software provides them with a certain degree of local intelligence, and communication possibilities with the aggregator. The joint behaviour of these two software packages, as used by the aggregator and by the heat pumps, is simulated in the demand response model. The overall logic goes as follows.

The aggregator operates both on the day-ahead and the balancing markets. Day-ahead, the aggregator needs to determine the amount of electricity to buy for each hour of the next day to satisfy the heat demand of the consumers she represents. The aggregator minimises the consumers' electricity cost if space heating demand is satisfied at a minimum price. Heat pump demand is determined as described in Appendix D, whereby minimum and maximum electricity consumption limits of consumers are calculated for each hour, based on the outdoor temperature and on consumer-defined preferences. The outdoor temperature determines how fast a building cools down. Consumer-defined preferences determine the range of indoor temperatures to be maintained. The same preferences are used for all three consumer groups, namely indoor temperature settings that are acceptable for 90% of the consumers, these settings are described in [427]. Thermal inertia of buildings enables thermal energy storage, which leads to flexibility in the operation of heat pumps. This flexibility is harnessed for demand response. Thus, for each hour of the next day, for each heat pump in the aggregator's portfolio the range of electricity demand is determined. Each heat pump communicates this range in the form of a *bid*. A bid is a demand function that represents the electricity demand of a heat pump given a certain electricity price (for instance, "electricity demand of 2 kWh in the sixth hour of the next day at a price below 30 €/MWh and 1 kWh at a price of 30 €/MWh or higher"). To comply with consumer-defined preferences, the minimum electricity demand is satisfied at any electricity price and the maximum electricity demand is satisfied if the electricity price is lower than or equal to zero. The aggregator combines the bids of all heat pumps, and communicates the joint bid for each hour of the following day to the market operator (*e.g.*, a TSO). The market operator clears the day-ahead market, thus returning an equilibrium price for each hour of the next day. This price determines the amount of electricity the aggregator buys for each hour of the following day, and thus the amount of electricity consumed by each heat pump in each hour of the following day. This demand satisfies space heating demand at a minimum day-ahead electricity price. On the day of operation itself, *i.e.*, in real-time, if imbalances occur, they are settled by the aggregator on the imbalance market on behalf of the consumers.

The combination of PowerMatcher and R.E.X. provides the software environment to realise the procedure described above. The behaviour of these two software packages is simulated in MATLAB [370]. Further details on the implementation are described in [430]. PowerMatcher is described in detail in [424]. Further information about R.E.X. can be found in [425].

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- **N. Voulis**, M. J. J. van Etten, É. J. L. Chappin, M. Warnier, and F. M. T. Brazier. Rethinking European Energy Taxation to Incentivise Consumer Demand Response Participation. *Energy Policy*, **124**: 156-168, 2019.
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- **N. Voulis**, M. Warnier, and F. M. T. Brazier. Statistical Data-Driven Regression Method for Urban Electricity Demand Modelling. In: *IEEE International Conference on Environment and Electrical Engineering and IEEE Industrial and Commercial Power Systems Europe*. 2018.
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Acronyms

AC alternating current

ASHRAE American Society of Heating, Refrigerating, and Air-Conditioning Engineers

BRP balance responsible party

BSP balancing service provider

COP coefficient of performance

CPP critical peak pricing

CVI cluster validity index

DBI Davies-Bouldin index

DC direct current

DLC direct load control

DOE Department of Energy (of the United States of America)

DR demand response

DSO distribution system operator

EDP extreme day pricing

EU European Union

EV electric vehicle

GIS geographical information system

HVAC heating, ventilation, and air conditioning

IAEE International Association for Energy Economics

ICT information and communication technology

IEEE Institute of Electrical and Electronics Engineers

MPC model predictive control

OECD Organisation for Economic Co-operation and Development

PTU programme time unit

p.u. per unit, *i.e.*, scaled to the maximum value

PV photovoltaic

RLP representative load pattern

RMSE root mean square error

rRMSE relative root mean square error

RTP real time pricing

s.l. *sensu lato,* broad sense

s.s. *sensu stricto,* narrow sense

TCL thermostatically controlled load

TOU time of use

TSO transmission system operator

U.K. United Kingdom

U.S. United States of America

Glossary

***ad valorem* tax** tax based on the value of a product

aggregator mediator between consumers and large-scale incumbents such as utilities and system operators [178]

balancing ~ *supply and demand*, reducing the real-time difference between electricity generation and demand, *i.e.*, reducing imbalance [482]

complex system system that does not have a centralising authority and is not designed from a known specification, but instead involves disparate stakeholders creating their own systems that are functional for other purposes and are only brought together in the complex system because the individual stakeholders of the system see such cooperation as being beneficial for them [50]

consumer energy user; households, services, and industry are considered to be consumers

demand amount of electrical energy used within a given time window by a single consumer, or a set of consumers [58]

demand response changes in electricity use by demand-side resources from their normal consumption patterns in response to changes in the price of electricity, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardised [97, 130]

demand profile variation of demand over time, formally a vector describing this variation

dispatchable ~ *resources*, electricity generation resources that can be turned on or off on demand following system needs

end-use *electricity* ~, purpose for which electricity is used by a consumer, such as cooking, ventilation, and lighting

energy capacity to do work

energy system combined processes of acquiring and using energy in a given society or economy [57]

energy tax tax that is levied based on energy use [402]

energy transition a shift in energy generation from fossil fuels to energy generation from renewable resources

flexibility ability to adapt to dynamic and changing conditions, in particular for the purpose of balancing or matching supply and demand

generation extraction of energy from primary sources

generator a device that converts movement into electricity, also often used as a *pars pro toto* for the person or company who owns and/or operates this device [58]

household a dwelling, its occupants, and their electricity use

imbalance real-time difference between electricity generation and demand [482]

internal balancing real-time adjustment of generation and demand within the portfolio of a balance responsible party [386]

intervention addition of new components to the power system for the purpose of balancing or matching supply and demand

land use ∼ *in an urban area*, type of activities such as housing, production, and services that takes place in that area

load any device in which power is dissipated, or the collection of such devices [58]

matching ∼ *supply and demand*, reducing the predicted difference between electricity generation and demand, *i.e.*, reducing mismatch [482]

mismatch predicted difference between electricity generation and demand [482]

non-dispatchable ∼ *resources*, electricity generation resources that cannot be turned on or off on demand following system needs as their power output depends on factors that cannot be controlled, for instance, on weather

per-unit tax tax based on the amount of a product

power energy per unit of time

power system type of energy system, defined by its energy carrier electricity [56, 58]

producer ∼ *of electricity*, person or company who owns and/or operates a device that converts movement into electricity (see **generator**)

prosumer consumer who has their own generation (PVs or small wind turbines) and/or storage on-site

renewable energy resources also **renewable resources** or **renewables** sources of energy that are naturally replenished at short time scales, including solar energy, wind energy, hydro energy, and biomass

residential sector collection of households

service building where non-manufacturing commercial or governmental activities take place and the electricity use arising from these activities (excluding agriculture, transportation, power sector, street lighting, and waterworks)

service sector collection of non-manufacturing commercial and governmental activities, excluding agriculture, transportation, power sector, street lighting, and waterworks [120, 122]

smart $\sim$ *grid*, $\sim$ *appliance*, having the ability for two-way communication, enabling intelligent monitoring, control, communication, and self-healing technologies [146]

socio-technical system system that involves complex interactions between humans and technology [49]

storage any device that can store electrical energy for future use, including mechanical, electrical, thermal, and chemical technologies [166]

sustainable, sustainability sustainable development is development that meets the needs of the present without compromising the ability of future generations to meet their own needs [193]

urban area settlement of more than 2 000 inhabitants (number specific for the Netherlands) [107]

urban energy system the combined processes of acquiring and using energy to satisfy the energy service demands of a given urban area [37].

urban planning intentional interventions in the urban development process, usually by the local government, including through regulation, collective choice, organisational design, market correction, citizen participation, and public sector action [20, 131]

urban scale spatial scale relevant for urban areas, three urban scales are distinguished in this thesis: neighbourhood, district, and municipality

Symbols

Latin Symbols

a_{roof}	roof area available for solar PVs (area-constrained optimisation)
$b_{s,\mathrm{US}}$	building-use data for service sector consumer s for the corresponding U.S. Commercial Reference Building
$b_{s,\chi}$	building-use data for service sector consumer s in area of interest χ
C	set of consumers (with **13** types[1] of service sector consumers), with $c \in C$, and $C = C_H \cup C_S$
$\lvert C \rvert$	number of consumer types in C
$\dot{C}$	set of consumer classes (with **five** service sector consumer classes[1]), $\dot{C} = C_H \cup \dot{C}_S$
$\ddot{C}$	set of consumer classes (with **six** service sector consumer classes[1]), $\ddot{C} = C_H \cup \ddot{C}_S$
$\dddot{C}$	set of consumer groups[2], $\dddot{C}$ = {`residential, office, city centre`}
C''	set of consumer types c that corresponds to consumer class $\ddot{c}$
$\ddot{C}'$	set of consumer classes $\ddot{c}$ that corresponds to consumer class $\dot{c}$
C_H	set of household consumers, with $c_h \in C_H$, and $C_H =$ {`household`}
C_S	set of **13**[1] service sector consumer types, with $c_s \in C_S$, and $C_S =$ {`hospital, large hotel, small hotel, large office, medium office, small office, primary school, secondary school, stand alone retail, supermarket, restaurant, quick service restaurant, warehouse`}
$\dot{C}_S$	set of **five**[1] service sector consumer classes, with $\dot{c}_s \in \dot{C}_S$, and $\dot{C}_S =$ {`hospitals; cafés, restaurants, and hotels; offices; schools; retail, supermarkets, and warehouses`}
$\ddot{C}_S$	set of **six**[1] service sector consumer classes, with $\ddot{c}_s \in \ddot{C}_S$, and $\ddot{C}_S =$ {`hotels; offices; schools; restaurants; shops; warehouses`}
CapS	maximal storage capacity of a battery

[1] The relationship between the original 13 service sector consumer types, and the five and the six service sector consumer classes is shown in Tables B.1 and B.2.
[2] Consumer groups are defined in Table 8.1.

$D(t)$	demand profile, *i.e.*, vector where each element equals the energy demand at time t
$D_H(t)$	demand profile of the residential sector, with H shorthand for C_H, and t time
$D_S(t)$	demand profile of the service sector, with S shorthand for C_S, and t time
$D_{s,\mathrm{US}}(t)$	demand profile over time t of a U.S. DOE Commercial Reference Building representing service sector consumer s
$D_{s,\chi}(t)$	demand profile over time t of service sector consumer s in area of interest χ
$D_{\ddot{c}}(t)$	demand profile of consumer class $\ddot{c}$ over time t
$\bar{D}_{\dot{c},\mu}$	cumulative annual demand of consumer class $\dot{c}$ in municipality μ
$D_\gamma(t)$	demand profile for urban area γ
$D_{\gamma,\tau}(t)$	demand profile of urban area γ for day type τ; also called "feature vector"
$d^h_{\gamma,\tau}$	individual feature (*i.e.*, element) of a 24-hour demand profile $D_{\gamma,\tau}$
$\tilde{D}_{\gamma,\tau}(t)$	normalised demand profile over time t of area γ for day type τ
$DBI(k)$	Davies-Bouldin index for k cluster centres (k-means clustering)
e_η	relative error with η the forecast time horizon (solar forecasting simulation model)
FreeS	free storage capacity of a battery
$g_{i,j}$	distance between the centres of clusters i and j (k-means clustering)
$G(t)$	renewable power generation at time t
$G_{PV}(t)$	renewable power generation at time t of 1 m^2 PVs (area-constrained optimisation)
$G_{turbine}(t)$	renewable power generation at time t of one 500 kW wind turbine (area-constrained optimisation)
$GridExchange(t)$	energy exchanged with the grid at time t
h	shorthand notation for household consumer $c_h \in C_H$
HHH	used as subscript, denotes residential-only demand of 203 005 households
H&S	used as subscript, denotes an average mix of residential and service sector demand of 100 000 households and corresponding services
i	cluster index (k-means clustering)
	index over observations (solar forecasting simulation model)
j	cluster index (k-means clustering)
	index over observations (solar forecasting simulation model)
k	number of cluster centres (k-means clustering)
K_{ref}	electricity cost without demand response (reference)
K_{DR}	electricity cost with demand response
l_i	within-cluster distance of cluster i (k-means clustering)
m_i	centre of cluster i (k-means clustering)
M	number of observations (solar forecasting simulation model)

$MM(t)$	mismatch at time t
$MM^{+}(t)$	positive mismatch at time t
$\widehat{MM}^{+}(t)$	relative positive mismatch at time t
$MM^{-}(t)$	negative mismatch at time t
$\widehat{MM}^{-}(t)$	relative negative mismatch at time t
$\widetilde{MM}([t,\ldots,t+\eta])$	predicted mismatch for all timesteps from t up to $t+\eta$
$\overrightarrow{MM}([t,\ldots,t+u])$	first u consecutive, positive elements of $\widetilde{MM}([t,\ldots,t+\eta])$ sorted in descending order
N	number of observations (solar forecasting simulation model)
$\mathcal{N}$	normal distribution (solar forecasting simulation model)
$n_{\ddot{c},\gamma}$	number of consumers of class $\ddot{c}$ in area γ
P	probability
q_i	feature vector of cluster i (k-means clustering)
$ResS(\iota)$	reserved storage capacity at step ι
$rRMSE_{\eta}$	relative root mean square error for time horizon η (solar forecasting simulation model)
$RU(t)$	renewable energy utilisation at time t
s	shorthand notation for service sector consumer $c_s \in C_S$
$SC(t)$	self-consumption at time t
$SoC(t)$	state of charge of a battery at time t
$SC(t)$	self-sufficiency at time t
t	time
t_c	current timestep (solar forecasting simulation model)
t_f	future timestep (solar forecasting simulation model)
$ToS(t)$	energy stored in a battery at time t
u	number of subsequent mismatches with the same sign
v_{wind}	wind speed
x	design variables, $x = [x_{PV}, x_{turbine}]$, with x_{PV} the number of 1 m^2 PV panels, and $x_{turbine}$ the number of 500 kW wind turbines (area-constrained optimisation)
$\bar{X}_{\ddot{c},\gamma}$	relative annual consumer demand for consumer class $\ddot{c}$ in urban area γ, to be provided by the user (logistic regression model)
$y(t_f)$	measured insolation value for timestep t_f (solar forecasting simulation model)
$\hat{y}(t_f, t_c)$	insolation forecast for a future timestep t_f at timestep t_c (solar forecasting simulation model)
$\hat{z}_j$	observation with index j (solar forecasting simulation model)
$\bar{z}$	average over all observations $\hat{z}_j$ (solar forecasting simulation model)

Greek Symbols

α	factor accounting for the area available for renewable energy generation
$\beta_{\ddot{c}}$	scaling factor for consumer class $\ddot{c}$
Γ	set of urban areas, with $\gamma \in \Gamma$, and $\Gamma = M \cup Z \cup V$
$\Delta MM(t)$	difference in mismatch at time t between $MM_{HHH}(t)$ and $MM_{H\&S}(t)$
$\Delta\overrightarrow{MM}([1,\ldots,u])$	difference between subsequent elements of $\overrightarrow{MM}([1,\ldots,u])$, with $\Delta\overrightarrow{MM}(u) = \overrightarrow{MM}(u)$
$\Delta RU(t)$	difference in renewable energy utilisation at time t between $RU_{HHH}(t)$ and $RU_{H\&S}(t)$
$\epsilon_{s,\chi}$	building equivalent for service sector consumer s in area of interest χ
Z	set of districts, with $\zeta \in Z$
η	forecast horizon
$\theta_{\ddot{c}}$	*per-unit* tax rate for each consumer group $\ddot{c}$
$\tilde{\theta}_{\ddot{c}}$	*ad valorem* tax rate for each consumer group $\ddot{c}$
ι	index over the differences in mismatch $\Delta\overrightarrow{MM}([1,\ldots,u])$
ι_t	position of t in $\overrightarrow{MM}([1,\ldots,u])$
$\kappa_{0,\gamma,\tau}$	regression coefficient (logistic regression model)
$\kappa_{\ddot{c},\gamma,\tau}$	regression coefficient for consumer class $\ddot{c}$ (logistic regression model)
$\lambda_{0,\gamma,\tau}$	regression coefficient (logistic regression model)
$\lambda_{\ddot{c},\gamma,\tau}$	regression coefficient for consumer class $\ddot{c}$ (logistic regression model)
M	set of municipalities, with $\mu \in M$
V	set of neighbourhoods, with $\nu \in V$
ξ	factor that ensures that $\sum_{t=1}^{8760} D_{HHH}(t) = \sum_{t=1}^{8760} D_{H\&S}(t)$
ρ_{air}	air density
σ	standard deviation
σ_η^2	variance dependent on time horizon η
T	set of day types, with $\tau \in T$, and $T = \{\texttt{weekday, weekend}\}$
ϕ	normalised difference between electricity cost without demand response and electricity cost with demand response
χ	urban area of interest
$\psi_{turbine}$	power coefficient of a wind turbine
ω_c	weighting factor for the demand profile of consumer type c
ω_{MM+}	weighting factor of positive mismatch (area-constrained optimisation)
ω_{MM-}	weighting factor of negative mismatch (area-constrained optimisation)
ω_{RU}	weighting factor of renewable energy utilisation (area-constrained optimisation)

Translations

Original	Translation	Chapter
Бабушке Лене, она мне с детства говорила, что я тоже везде побываю.	To my grandmother, Lena, who told me from young age that I would go everywhere as well.	Preface
Πάντα ῥεῖ. Ἡράκλειτος	Everything flows. Heracleitos	Preface
Le 22 mai 2014, à 6 heures 58 minutes et 11 secondes, une mouche bleue de la famille des *Calliphoridae* capable de produire 14 670 battements d'ailes à la minute se posait rue Seneca, à Ithaca. A la même seconde à la terrasse d'un restaurant à cent mètres de la Gorge de Cascadilla, le vent s'engouffrait comme par magie sous une nappe faisant danser les verres sans que personne ne s'en aperçoive. Toujours à la même seconde un message provenant de Martijn Warnier et Frances Brazier est apparu dans ma boîte mail. Quatre mois plus tard je commençais mon doctorat. Après Jean-Pierre Jeunet et Guillaume Laurant	On the 22nd of May 2014 at 6 o'clock, 58 minutes and 11 seconds, a bluebottle fly belonging to the family *Calliphoridae*, whose wings can beat at a rate of 14 670 times per minute, landed on Seneca Street in Ithaca. At the exact same second, on a terrace of a restaurant about one hundred metres from Cascadilla gorge, the wind was sweeping in under a tablecloth, causing the glasses to dance without anybody noticing it. Still at the same second, an e-mail from Martijn Warnier and Frances Brazier landed in my mailbox. Four months later I would start my PhD. After Jean-Pierre Jeunet and Guillaume Laurant	Acknowledgements
Dit is het land waar grote mensen wonen.	This is the land where grown-ups live. Annie M. G. Schmidt	1
Timeo hominem unius libri.	I fear the man of a single book. Thomas Aquinas	2

Want tussen droom en daad staan wetten in de weg en praktische bezwaren.	For between dream and deed are laws that bar the way, and practical objections. Willem Elsschot Translation after Tanis Guest	4
Ceterum censeo Carthaginem esse delendam. Cato Maior	Moreover, I am of the opinion that Carthage must be destroyed. Cato the Great	7
Потому, — ответил иностранец [...], — что Аннушка уже купила подсолнечное масло, и не только купила, но даже и разлила. Так что заседание не состоится. Михаил Афанасьевич Булгаков	Because, the foreigner replied [...], Annushka has already bought the sunflower oil, and has not only bought it, but has already spilled it. So the meeting will not take place. Mikhail Afanasyevich Bulgakov Translation by Richard Pevear and Larissa Volokhonsky	8
Je n'ai fait celle-ci plus longue que parce que je n'ai pas eu le loisir de la faire plus courte.	I made this longer only because I did not have the leisure to make it shorter. Blaise Pascal	10
La machine à malaxer la guimauve malaxe la guimauve. Jean-Pierre Jeunet et Guillaume Laurant	The marshmallow-mixing machine mixes marshmallow. Jean-Pierre Jeunet and Guillaume Laurant	Epilogue

Samenvatting

Klimaatverandering is een van de grootste uitdagingen van de eenentwintigste eeuw. Ze is een rechtstreeks gevolg van de wereldwijde afhankelijkheid van fossiele brandstoffen voor de energieopwekking. De overstap naar hernieuwbare energiebronnen is dus onontbeerlijk om de hoeveelheid uitgestoten broeikasgassen op een acceptabel niveau te houden. De vraag naar energie is steeds meer geconcentreerd in steden. De energietransitie in steden bewerkstelligen is daarom van bijzonder belang. Dit proefschrift biedt nieuwe inzichten die de integratie van hernieuwbare energiebronnen in de gebouwde omgeving kunnen ondersteunen. Het brengt de *heterogeniteit* van de *stedelijke energievraag* in kaart, en haar rol in de *lokale integratie* van *hernieuwbare energiebronnen*.

Hernieuwbare energiebronnen integreren in bestaande elektriciteitssystemen is geen sinecure. De functionele eigenschappen van deze energiebronnen verschillen sterk van die van traditionele, op fossiele brandstof werkende elektriciteitscentrales. Hernieuwbare energiebronnen zijn variabel, kunnen beperkt gestuurd worden en zijn kleiner dan conventionele elektriciteitscentrales. Bestaande elektriciteitssystemen zijn ontworpen om elektriciteit te leveren van een klein aantal grote elektriciteitscentrales die gecentraliseerd gestuurd kunnen worden. In deze vorm zijn bestaande elektriciteitssystemen dus niet geschikt om gebruik te maken van grote aantallen variabele, niet-stuurbare en gedecentraliseerde hernieuwbare energiebronnen. Overstappen op hernieuwbare opwek vraagt daarom aanzienlijke technische, economische en bestuurlijke aanpassingen van bestaande elektriciteitssystemen.

Om de elektriciteitssystemen van de toekomst te ontwerpen zijn nieuwe en gedetailleerde inzichten nodig in de interacties tussen hernieuwbare opwek en energievraag. Vooral inzichten op *lokale schaal* ontbreken momenteel. Deze schaal is van bijzonder belang omdat hernieuwbare energiebronnen gedecentraliseerd zijn en dichter bij vraaglocaties liggen. Dit is vooral het geval in stedelijke gebieden. Om historische redenen, die gelinkt zijn aan de manier waarop elektriciteitssystemen traditioneel ontworpen en gebruikt werden, focust de bestaande literatuur vooral op de kleine schaal (afzonderlijke componenten, toestellen, consumenten of gebouwen) en op de grote (nationale of supranationale) schaal. De intermediaire – stedelijke – schaal heeft weinig aandacht gekregen. Dit proefschrift vult dit hiaat in en richt zich expliciet op de stedelijke schaal. Het beantwoordt de volgende onderzoeksvraag: ***'Hoe kan het lokaal gebruik van hernieuwbare energiebronnen gefaciliteerd worden in stedelijke gebieden?'***

Om deze onderzoeksvraag te beantwoorden is gedetailleerde kennis vereist over de wisselwerking tussen energieopwekking en -vraag in de gebouwde omgeving. De bestaande literatuur over hernieuwbare energiebronnen biedt een solide basis om de opwekzijde te begrijpen. De *vraagzijde* heeft aanzienlijk minder aandacht gekregen. De meeste literatuur vereenvoudigt de lokale vraag tot uitsluitend huishoudelijke vraag. In werkelijkheid bestaan steden uit een mix van huishoudens, diensten (zoals scholen, kantoren en winkels) en industrie. De focus in dit proefschrift ligt op de dienstensector, omdat deze sector tot dusver weinig aandacht heeft gekregen in de literatuur. Huishoudens worden ook meegenomen in de analyses, omdat huishoudens en diensten in steden vaak dicht bij elkaar liggen. Industrie wordt buiten beschouwing gelaten. Ze ligt meestal aan de rand van stedelijke gebieden en wordt bovendien elders in de literatuur behandeld. De inzichten in de eigenschappen van de elektriciteitsvraag van diensten worden gecombineerd met bestaande kennis over de huishoudelijke elektriciteitsvraag en vervolgens gebruikt om de elektriciteitsvraag op stedelijk niveau te modelleren en beter te begrijpen.

Een van de belangrijkste uitdagingen bij het modelleren van de energievraag van zowel diensten als stedelijke gebieden is het gebrek aan gedetailleerde, publiek beschikbare *data*. Een belangrijk type data zijn zogenaamde *vraagprofielen*. Deze profielen beschrijven de variaties van de energievraag als functie van tijd. Verschillende consumenten gebruiken energie gedurende verschillende tijden van de dag: huishoudelijke vraag piekt 's avonds, terwijl diensten vooral tijdens werkuren elektriciteit gebruiken. Deze verschillen leiden tot *temporele* verschillen in vraagprofielen. Bovendien zijn huishoudens en diensten niet evenredig verspreid over stedelijke gebieden: sommige gebieden hebben een woonfunctie, andere een commerciële of een gemengde functie. Deze verschillen – of *heterogeniteit* – in de samenstelling van energieconsumenten leiden tot *ruimtelijke* verschillen in vraagprofielen van stedelijke gebieden. Gecombineerd kunnen variaties in stedelijke energievraag dus beschreven worden door *ruimtelijk-temporele vraagprofielen*. Momenteel zijn zulke profielen niet publiek beschikbaar. Ook vraagprofielen van de dienstensector, die gebruikt zouden kunnen worden om stedelijke energieprofielen te maken, zijn schaars. Daarom is een aanzienlijk deel van dit proefschrift gewijd aan datacombinatie en -analyse. Het doel is om vraagprofielen van diensten en stedelijke gebieden te construeren, gebruikmakend van de weinige bronnen die wel publiek beschikbaar zijn. Zowel de ontwikkelde methodes als de resulterende vraagprofielen van diensten en stedelijke gebieden zijn een eerste belangrijke bijdrage van dit proefschrift.

De resulterende ruimtelijk-temporele stedelijke vraagprofielen worden verder geanalyseerd. *Drie archetypes* stedelijke vraagprofielen kunnen onderscheiden worden in zowel buurten, wijken als gemeentes. Deze archetypes worden *huishoudelijk*, *zakelijk* en *gemengd* genoemd, gebaseerd op de meest voorkomende types consumenten. Analyse van 14 698 stedelijke gebieden in Nederland toont aan dat vraagprofielen van het huishoudelijke type, die gebruikt worden in de meeste energiesysteemmodellen, slechts een minderheid van stedelijke gebieden representeren en slechts een klein deel van de totale stedelijke energievraag vertegenwoordigen. Deze analyse toont aan dat de dienstensector niet buiten beschouwing kan worden gelaten bij het modelleren van de stedelijke energievraag.

Om inzichten te ontwikkelen die de energietransitie kunnen ondersteunen, worden de verkregen ruimtelijk-temporele vraagprofielen gecombineerd met productieprofielen van zonne- en windenergie. De simulaties in dit proefschrift zijn gebaseerd op een groot aantal scenario's van de penetratie van hernieuwbare energiebronnen, en houden rekening met verschillende tijds- en weersomstandigheden. De resultaten tonen aan dat de *heterogeniteit* van de stedelijke energievraag een *statistisch significant* effect heeft op het gebruik van *lokaal geproduceerde hernieuwbare energie*. Specifiek betekent dit dat gemengde gebieden significant meer hernieuwbare energie lokaal gebruiken dan geschat kan worden op basis van alleen huishoudelijke vraagprofielen. Deze bevinding heeft aanzienlijke gevolgen voor *interventies* die bedoeld zijn om het lokaal gebruik van hernieuwbare energiebronnen te stimuleren. Resultaten van twee casussen, één over energieopslag en één over vraagsturing, tonen aan dat de effecten van dergelijke interventies afhangen van de lokale eigenschappen van zowel energieopwekking als energievraag. Gedetailleerde kennis van dergelijke lokale eigenschappen is dus onontbeerlijk voor een adequaat begrip van zowel technische als bestuurlijke aspecten van mogelijke interventies. De verworven inzichten in de lokale interacties tussen een realistische, heterogene stedelijke energievraag, lokale energieopwek (bijvoorbeeld door zonnepanelen en windturbines) en interventies (zoals opslag en vraagsturing) zijn een tweede belangrijke bijdrage van dit proefschrift.

Tenslotte worden de technische inzichten in de heterogeniteit van de stedelijke energievraag gebruikt om te tonen hoe deze kennis kan toegepast worden om *advies voor beleidsmakers* te formuleren. Hiervoor wordt een casus beschouwd die focust op het effect van *energiebelastingen* op financiële prikkels voor de deelname van huishoudens en diensten aan vraagsturingsprogramma's. De casus toont aan dat de bestaande zogenaamde *eenheidsgebaseerde* energiebelasting de financiële prikkels die ontstaan door dynamische energiebeprijzing dempt. Om deze demping te voorkomen, wordt een alternatieve, *waardegebaseerde* belasting voorgesteld. De combinatie van technische inzichten met kennis van economische en bestuurlijke aspecten van elektriciteitssystemen, en het advies voor beleidsmakers dat daaruit voortvloeit zijn een derde belangrijke bijdrage van dit proefschrift.

Samenvattend toont dit proefschrift aan dat heterogene ruimtelijk-temporele vraagprofielen noodzakelijk zijn om stedelijke energiesystemen realistisch weer te geven. Dit is nodig om hen voor te bereiden op de energietransitie. Daarom moeten bestaande en toekomstige energiesysteemmodellen uitgebreid worden met ruimtelijk-temporele data die de lokale energievraag in detail weergeven, rekening houdend met zowel huishoudelijke als niet-huishoudelijke consumenten, in het bijzonder met de dienstensector. Dit proefschrift beschrijft methodes die dergelijke gedetailleerde weergave van stedelijke energievraag mogelijk maken, uitgaand van de weinige databronnen die momenteel publiek beschikbaar zijn. Gebruikmakend van de verkregen gedetailleerde ruimtelijk-temporele vraagprofielen biedt dit proefschrift nieuwe inzichten voor de integratie en het gebruik van hernieuwbare energiebronnen in stedelijke energiesystemen. De resultaten en inzichten kunnen overheden, burgers en bedrijven ondersteunen in hun streven naar een succesvolle energietransitie.

Summary

Climate change is one of the major challenges of the twenty-first century. It is caused by the world's reliance on fossil fuels for energy generation. Transitioning to renewable energy resources is thus key to halt the amount of emitted greenhouse gasses at an acceptable level. Demand for energy is more and more concentrated in cities. Addressing energy transition in urban areas is therefore of particular importance. This thesis contributes to the understanding of renewable energy resource integration in urban areas. It characterises *urban demand heterogeneity* and its role in *local renewable energy resource integration*.

Integrating renewable energy resources in existing power systems is not straightforward. These resources have markedly different operational characteristics from traditional fossil-fuel power plants. Renewable energy resources are variable, can be controlled only to a limited extent, and are much smaller than conventional power plants. The existing power systems were designed to deliver power from a few large power plants to passive consumers. They have remained almost unchanged since their conception a century ago. The existing design and operation of power systems rely on centralised control of a small number of large, conventional, and controllable (dispatchable) power plants. In their current form, power systems cannot accommodate and rely on large numbers of small, variable, non-dispatchable, and decentralised renewable resources. Transitioning to renewable energy generation therefore requires considerable adaptations across the technical, economic, and governance layers of power systems.

To design the power systems of the future, new and detailed insights in the interactions between renewable energy resources and demand are necessary. Insights at the *local scale* are of particular importance given the decentralised character of renewable resources and their close proximity to demand, especially in urban areas. However, for historical reasons, that are tied to the way power systems have traditionally been designed and operated, most existing research concentrates either on the small scale (single components, appliances, consumers or buildings), or on the large (national or supranational) scale. The intermediate – urban – scale has received little attention thus far. This thesis addresses this hiatus, focussing on the urban scale. It answers the question ***"How can local renewable resource utilisation be facilitated in urban areas?"***

Answering this research question requires detailed knowledge of the interplay between generation and demand in urban areas. The existing body of literature on renewable energy resources provides a solid basis for the understanding of the generation side. The *demand side*

has received considerably less attention. Most literature simplifies local demand to household demand only. However, real urban areas consist of a mix of households, services (such as schools, offices, and shops), and industry. This thesis focuses on the service sector because this sector has been largely omitted in the literature. It also takes households into account as households and services are often collocated in urban areas. Industry is left out of the scope as it is typically located at the periphery of urban areas. Moreover, industrial energy demand is addressed by dedicated literature. The insights in electricity demand characteristics of the service sector, and existing knowledge of electricity demand of households are used to model and understand demand at urban scales.

One of the main challenges in modelling of service sector and urban-scale demand is the lack of detailed, publicly available *data*. A key type of data are so-called *demand profiles*. These profiles describe the variations of demand over time. Different consumers use energy during different times of the day: household demand peaks in the evening, while services primarily use electricity during working hours. These differences result in *temporal* differences in demand profiles. In addition, households and services are not evenly distributed in urban areas. Some areas are residential, others commercial, yet others mixed. These variations – or *heterogeneity* – in consumer composition result in *spatial* differences in the demand profiles of urban areas. Combined, variations in urban demand can be described by *spatio-temporal demand profiles*. Currently, such urban demand profiles are not publicly available. Moreover, service sector demand profiles, that could be used to construct urban-scale demand profiles, are scarce. Therefore, a considerable part of this thesis focuses on data combination and analysis to construct service sector and urban-scale demand profiles using the few data sources that are publicly available. Both the developed methods, and the resulting service sector and urban-scale demand profiles are the first key contribution of this thesis.

The constructed spatio-temporal urban demand profiles are further analysed. *Three archetypes* of urban demand profiles are distinguished at each of the studied urban scales: neighbourhood, district, and municipality. These archetypes are called *residential*, *business*, and *mixed*, based on the most prevalent consumer types in these areas. Analysis of 14 698 urban areas in the Netherlands shows that residential-type demand profiles, used in many existing energy system models, represent only a minority of urban areas, and account for only a small share of the total urban demand. This analysis shows that the service sector cannot be ignored when modelling demand at urban scales.

Aiming to develop insights that can support the energy transition at urban scales, the constructed spatio-temporal demand profiles are combined with solar and wind generation profiles. This is done for a broad range of renewable resource penetration scenarios, and time and weather conditions. The obtained results demonstrate that urban demand *heterogeneity* has a *statistically significant* impact on *local renewable resource utilisation* in urban areas. Specifically, areas with mixed household and service sector consumers are shown to use significantly more renewable energy locally than can be expected from estimation of urban demand profiles based on household demand profiles only. This finding has profound consequences for *interventions* aimed to improve local renewable resource utilisation in urban areas. Results of two case studies, one on storage and one on demand response, show that the effects of these interventions depend on local generation and demand conditions.

Detailed knowledge of such local characteristics is thus indispensable for an adequate understanding of both technical and governance implications of the considered interventions. These insights in the local interactions between realistic, heterogeneous urban demand, local renewable resources (such as solar panels and wind turbines), and interventions (such as storage and demand response) are the second key contribution of this thesis.

Finally, the technical insights in urban demand heterogeneity are used to demonstrate how this knowledge can be applied to develop *advice for policy-makers*, ultimately to prepare power systems for the energy transition. For this purpose, a case study on the impact of *energy tax* on financial incentives for demand response participation by small household and service sector consumers is presented. The case study shows that the existing so-called *per-unit* energy tax dampens financial incentives given through dynamic prices. To avoid this dampening, an alternative, *ad valorem* tax is proposed. The combination of technical knowledge with insights in the economic and the governance layers of power systems, and the resulting advice for policy-makers are the third key contribution of this thesis.

Overall, this thesis demonstrates that heterogeneous spatio-temporal demand profiles are required for a realistic representation of urban energy systems. This is needed to prepare them for the energy transition. Therefore, existing and future urban energy system models should be expanded with more detailed spatio-temporal local demand data that account for both household and non-household consumers, in particular for the thus far omitted service sector consumers. This thesis describes methods and approaches that allow for such detailed modelling of urban demand profiles based on the few publicly available data sources. Using the developed detailed spatio-temporal demand profiles, this thesis provides new insights in the impact of renewable energy resources in realistic, heterogeneous urban areas. The presented results can support governments, communities, and companies in their endeavours to bring the energy transition to fruition.

About the Author

Nina Voulis is an environmental and complex systems engineer. She is interested in sustainability, renewable energy, and urban development. Nina leverages her multidisciplinary background to work on energy systems and their transition to renewable energy resources.

Nina has co-authored multiple articles in top scientific journals and has presented her work at several international conferences. The topics addressed in her work include urban energy systems, demand modelling, energy policy, renewable resource integration, third-generation biofuels, and resource recovery. Besides her scientific presentations, Nina has held talks for various companies, aiming to disseminate her results to a broader audience, and to bridge the gap between academia and industry.

Nina has obtained a Master of Science degree in Environmental Engineering from Ghent University in Belgium. She graduated *summa cum laude*. Soon after completing her studies, Nina moved to the United States, where she was invited to strengthen a multidisciplinary research team at Cornell University to develop a novel photobioreactor for algal biofuel production. Having successfully completed the project, Nina decided to broaden her knowledge of renewable energy technologies to solar and wind-based power generation, and their integration in power systems. She joined a collaborative project between Cornell University, ThinkEco, and Con Edison, and helped develop and deploy a demand response programme for household consumers in New York City. The project is part of the award-winning coolNYC programme.

Further motivated by the persisting need for sustainable energy alternatives, and impressed by the many challenges posed by their integration in existing power systems, Nina decided to pursue a PhD to deepen her expertise in this domain. This thesis is the result thereof.

For the future, Nina seeks to use her expertise in energy systems, environmental issues, and sustainability to address real-world challenges. Currently, Nina works as an advisor for CE Delft, an independent not-for-profit research and consultancy organisation specialised in developing innovative solutions to environmental problems and energy challenges.