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Causevic, S.

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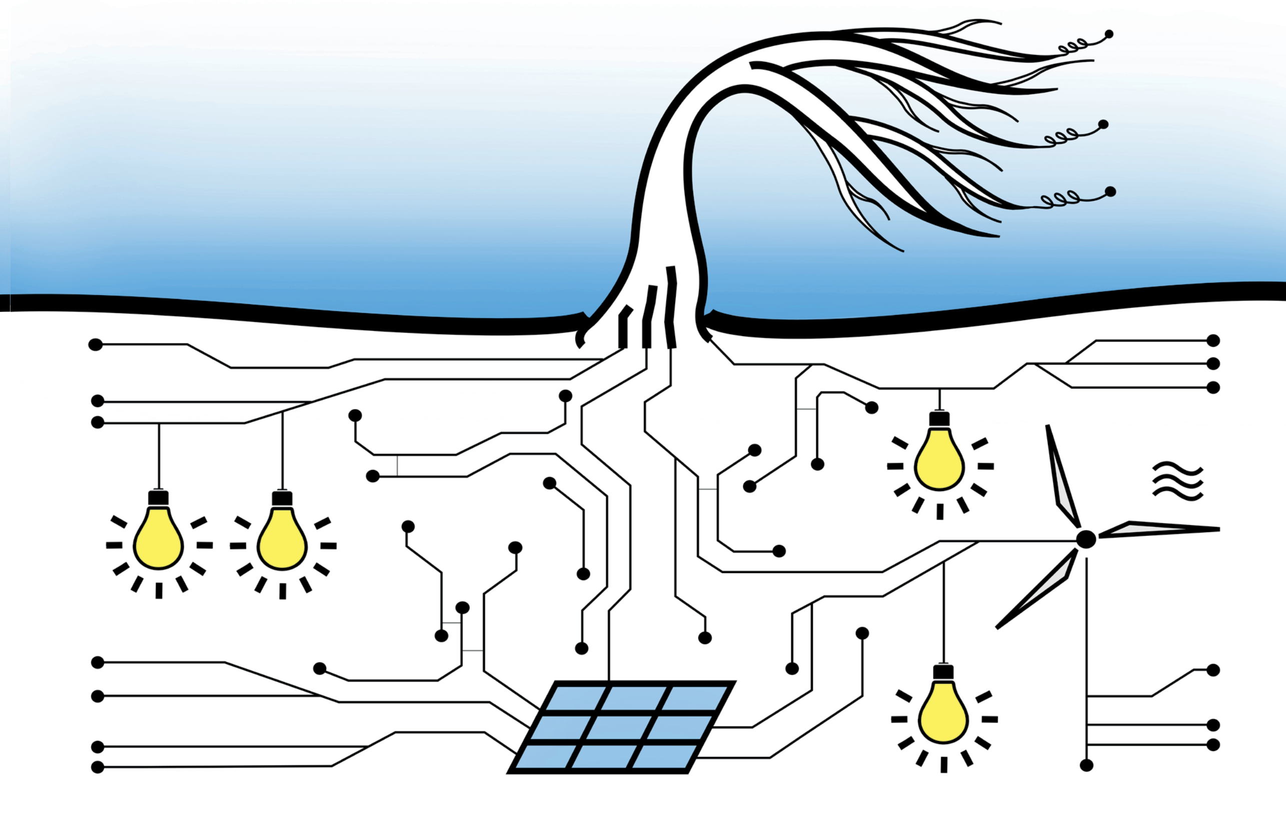
# ENERGY RESILIENCE THROUGH SELF-ORGANIZATION

SELMA ČAUŠEVIĆ



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## Proefschrift

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**Selma ČAUŠEVIĆ**

Master of Science in Computer Science,
Sarajevo School of Science and Technology, Bosnia and Herzegovina,
geboren te Bihać, Bosnië en Herzegovina.

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| | |
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*To my parents.*

# Contents

# Summary

Power systems are large-scale, complex socio-technical systems that provide modern society with one of its most indispensible assets: electricity. Electricity supply is not only an irreplaceable asset in daily activities, it is also vital for operation of other critical infrastructures of the technological age. Crucial socio-economic systems depend on electricity supply to support infrastructures such as telecommunications, transportation, water and natural gas supply, as well as financial and healthcare services. Therefore, ensuring secure and reliable operation of power systems as an enabling infrastructure is crucial.

Traditionally built as centralized systems, and organized around fossil fuel-based power plants, modern power systems are shifting towards decentralized, renewables-based systems. Driven by the societal and political concerns regarding climate change, as well as a number of geo-political factors, the energy transition is set as a pathway to transform energy systems into more sustainable, zero-carbon systems, that rely on decentralized renewable generation and storage. The change in the energy system landscape is also reflected in the digital transformation of power systems, supported by advancements in and the incorporation of (smart) information and communication technologies (ICT) in energy systems. This results in so-called smart grids, that combine physical devices and ICT to perform advanced monitoring, control, and data communication. This is seen as an enabling factor in the transition towards a more renewable, decentralized system, as it can be used to perform demand response, peak load reduction, energy curtailment, and energy balancing.

Power systems are faced with many uncertainties that can severely impact their operation. Caused by a number of internal and external factors such as demand increase, increased penetration of renewable energy resources, over-aging infrastructure, but also increase in extreme weather events caused by climate change, these uncertainties indicate that power systems could face more frequent interruptions. As these interruptions are likely to (more frequently) happen, there is an emphasis on making power systems more resilient, so that they are prepared for and can cope with these interruptions, minimizing their impact. To do so, power systems should be more loosely-coupled, with less interdependence and more potential for flexibility and adaptability in cases of distrubances.

To mitigate the negative impact of interruptions, the potential of distributed renewable energy resources combined with consumer engagement and ICT can be harnessed to improve energy resilience, especially on the local level. To understand how and if this is feasible, this thesis proposes a set of interventions based on the principles of self-organization that bridge together physical, ICT and social elements of power systems. The designed interventions and their results can be used not only to improve resilience of power systems, but also to support decentralization of power systems on its different levels in its transition towards a more sustainable energy system.

This thesis is motivated both by the increasing need for improving resilience of power systems faced with a number of challenges, as well as the decentralization of power sys-

tems in aspects of generation, ICT infrastructure, but also decision-making processes.

Power systems consist of three layers, namely: physical, ICT and social layer. Each of these layers is incorporated in the designed interventions that aim to enhance power system resilience: (1) an ICT intervention for decentralized energy sharing, (2) an ICT-social intervention for self-determined distribution of energy resources, an (3) ICT-physical intervention for energy sharing accross multiple distribution grids, and (4) an ICT intervention with implicit social and physical elements for flexibility prediction in decentralized grids. These interventions are based on the principles of self-organization and can be used to enhance the behaviour of power systems when faced with interruptions. The following paragraphs describe each of these in more detail.

The developed ICT intervention enables local energy resource sharing in a fully decentralized, adaptive way. Self-organization is achieved using the concept of autonomous agents, distributed across the network. Each agent is a software component that has access to local information of, for example, a consumer, and is hosted on a local device. These agents represent individual energy consumers, prosumers and producers that share local information on their supply and/or demand and perform balancing. This information-sharing is continuous, ensuring minimum energy imbalance. Using this mechanism, consumers, prosumers and producers organize themselves into virtual energy groups. The groups can reconfigure based on the fluctuations in local supply and demand. The results show that large-scale centralized systems can operate in a decentralized fashion when only local information is available. The more frequent reconfiguration (adaptation to supply/demand fluctuations) yields virtual energy groups with less energy imbalance.

The ICT intervention demostrates that supply and demand can be matched in a decentralized way. However, imbalances still occur and the system can rely on the backbone grid to meet the unmet demand or import excess supply. When the backbone grid is unavailable, these imbalances have to be dealt with in an alternative way. Due to scarcity of available local resources, a decision on how to distribute them has to be made. In contrast to existing outage management techniques where loads are prioritized before an outage occurs by a central authority, this thesis brings in the community perspective by letting members of communities prioritize consumers and prosumers themselves and, using that prioritization, distribute local resources in a fully decentralized manner.

The ICT-social intervention extends the ICT intervention with a social component enabling consumers, prosumers and producers to determine for themselves (*self-determine*) how local energy resources are distributed. They do so by differentiating between consumers and prosumers in the area, and assigning priorities. For example, a community can decide that schools should have electricity during an outage, making the school a primary destination for locally produced electricity. Or a community can decide to allocate local energy resources to a sports field if an outage occurs during a match. In both cases, social arguments are the basis for such decisions. In practical terms, agents have access not only to information about local supply and/or demand, but also to priorities assigned. The results show that by empowering members of communities to decide for themselves how local resources are distributed during an outage, the duration of power supply can be prolonged for specific members of affected communities.

Power systems interruptions can lead to widespread outages that affect multiple distribution systems. During large-scale blackouts, parts of different distribution grids can become unavailable, and consumers and prosumers in impacted areas have to rely on local resources and coordination schemes to function during disturbances. Decentralization mechanisms can be used to let not only consumers, prosumers and producers take independent decisions, but also the grid itself.

The ICT-physical intervention brings together the physical and the ICT layer of power systems in a self-organizing approach for decentralized coordination of local energy resources in changing distribution system topologies, with the aim of improving power system resilience. The ICT mechanism is extended by adding the physical component where autonomous agents perform distribution system reconfiguration to change grid topologies, called self-organizing grids. Self-organizing energy groups form by locally matching their supply and demand and sharing local resources, while components in self-organizing distribution networks reconfigure themselves. This way, local energy resources from different distribution systems can be shared, given that physical components to allow such reconfiguration are in place. The approach is generic and can be used in different settings where the backbone grid is not available. As it uses both distribution system reconfiguration and local energy group formation, it is scalable and can be applied to both localized and widespread damages which affect multiple distribution systems.

The ICT intervention (with implicit social and physical elements) explores the potential of using and learning from decentralized data in power systems. The three interventions described above rely on perfect knowledge of supply and demand to perform balancing, and on the willingness of data owners to share this data with others. However, this is not always the case, since such data might be unavailable or data owners might not be willing to share it due to privacy concerns. A potential way of addressing this challenge is to use a decentralized machine learning technique, Federated Learning (FL), that uses the notion of local and global models to ensure privacy-preservation. Using FL, raw local data stays on consumer devices, while the global knowledge can be built from shared data. This approach be used to forecast supply and demand of different consumers, prosumers and producers, or their available flexibility. This can be used to plan in advance for interruptions by pre-forming virutal energy groups, but also to learn about the state of the grid and plan for congestion management. In terms of the proposed ICT mechanism for energy sharing, local FL models can be integrated with autonomous agents to perform forecasting, matching and differentiation.

This dissertation shows that, given a supporting ICT and physical infrastructure, decentralized, adaptive energy resource sharing is feasible and can be a means to enhance system resilience during interruptions. Combined with traditional control operations, novel ICT technologies and DERs open up new possibilities to make power systems more resilient. Locally owned DERs have the potential to mitigate the effects of small- and large-scale outages by providing electricity to affected consumers and prosumers. Further analysis shows that decentralized coordination through self-organization is a promising approach to improve resilience of power systems, as it possesses the integral resilience properties. To improve resilience, self-organization has to be considered and implemented on different levels: physical, ICT and social. Self-organized energy groups can operate in a loosely-coupled way even with the backbone grid available. This pre-formation increases responsiveness to disasters and rapidity in terms of restoring normal operation of a system, and can guarantee resilience.

Finally, this research shows that decision making between individual consumers and prosumers can benefit the affected communities by sharing available locally produced energy as well as data, given appropriate mechanisms. In case of scheduled outages, the mechanism can be used by decision makers and planners beforehand as a tool to gain an insight how different community perspectives on energy priorities can influence supply reliability in affected communities. Based on the results, backup plans for alternative power sources can be made.

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I do not like leaving things unfinished. After almost eight years since I started my PhD journey, numerous paper rejections and revisions, life's ups and downs, becoming a mom, getting a new job, taking up on new hobbies, and trying to balance all these together, I finally sat down to write the acknowledgements. It is coming to an end.

During my PhD journey I grew both in a personal and a professional way, met many people, got to know and experience different cultures, travelled... *No woman is an island*, and none of this would have been possible without wonderful people that accompanied me on this journey.

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*Selma*
*Rijswijk, May 2023*

# 1

# Introduction

In July 2012 India was affected by the most severe power outage in history. The outage left more than 600 million people without electricity and caused failures of all major infrastructures. Trains failed, traffic lights stopped working, surgical operations were cancelled, there was no air conditioning in India's most humid and warm season, and miners were trapped in mines in West Bengal. Government officials blamed the Indian states for drawing more electricity from the grid than they are allotted and causing the major outage. This overdrawing was due to the high demand and insufficient supply [1]. India's power sector relies mostly on centralized, coal-powered power plants. This, in combination with poor infrastructure, supply and demand mismatch and power theft is the reason behind frequent scheduled and unscheduled outages throughout India [2, 3].

India's 2012 outage, but also other major blackouts [4, 5], show the dependence of modern society on electricity and our vulnerability when faced with the lack thereof. Existing power systems are designed to ensure supply reliability during normal operating conditions as well as foreseeable and low impact interruptions. However, additional challenge arises when faced with unexpected events they are not designed to handle [6]. Uncertainties power systems face due to both external and internal factors, challenge the operation of power systems and can increase the frequency and impact of outages. Demand increase, aging infrastructure, introduction of (typically locally-owned) distributed energy resources (DERs) into power systems, increase the complexity of an already highly complex system. This, in turn, makes the centralized governance of power systems an even more challenging task, and amplifies the need to make power systems more resilient [7–10]. To address this challenge, it is imperative to improve the resilience of power systems. Even though the definitions of resilience are many, it is generally accepted that a resilient system is able to anticipate a disruption, absorb it and adapt to new circumstances so that it provides a (sufficient) level of operation, and rapidly recover from it [11–16].

Power systems are large-scale, complex socio-technical systems on which our modern-day society highly depends. It consists of heterogeneous, interconnected resources, and multiple stakeholders that use and depend on them to achieve their (often competing) goals. Socio-technical means that power systems are embedded in the society they serve, with societal changes driving technological advancements [17, 18].

Power systems have a multi-layer architecture, consisting of a physicial, an ICT and a social layer. The physical layer consists of underlying physical infrastructure assets such as lines, transformers, substations, smart meters and other assets. The ICT layer integrates information processing, computing and communication technologies into the operation of power systems. The ICT layer receives data from the physical layer on power flows and state of devices for balancing and grid control. With the trend of digitalization and smartification of power systems, the ICT layer encompasses a wide range of operations. On top of these two layers is the social layer. This layer represents all the human factors in the system, from grid operators to consumers and prosumers, policy- and decision-makers, markets and their interactions. With an uptake of renewables, the roles and interactions within the socio-economic layer are expanding and changing the landscape of power systems.

Power systems are also systems in transition, more specifically in the energy transition. Traditionally built as centralized systems, and organized around fossil fuel-based power plants, modern power systems are shifting towards decentralized, renewable-based systems. Driven by the societal and political concerns regarding climate change, as well as a number of geo-political factors, energy transition is set as a pathway to transform energy systems into more sustainable, zero-carbon systems, that rely on decentralized renewable generation and storage. This change of the energy landscape is partly driven by increased consumer awareness of the effects of fossil fuel-based generation, but also societal and economic effects leading to consumer empowerment [19, 20]. Energy consumers are becoming prosmers, taking an active role in the system through more localized decision-making process and control, forming energy communities, but also participating in energy markets through demand-response and flexibility services. This socio-economic reform, combined with the technological advancements is further leading decentralization of power systems.

This accelarated transition towards more sustainable energy-neutral systems, supported by rapidly increasing penetration of distributed renewable energy resources (DERs), brings its own challenges for grid operators. High uptake of DERs, as well as other factors such as adoption of electric vehicles (EVs) and increased electricity demand (due to, for example, heat demand electrification), introduce more strain on the power grid, potentially leading to interruptions. Current transmission and distribution grids were not built to support such high penetration of non-dispatchable DERs. This can lead to power outages due to grid's physical constraints. This is a growing concern for network operators. In the Netherlands, for example, this challenge is prominent; the electricity grid cannot keep up with the transition to sustainable energy and rapid electrification of other sectors, leading to businesses not being supplied with sufficient electricity [21, 22]. This growing challenge affects the residential sector as well: projects for newly built houses that are supplied using heat pumps are delayed due to infrastructure constraints. Network operators are now looking for ways to deal with energy scarcity through load prioritization.

The change of energy system landscape is also reflected in the digital transformation of power systems, supported by advancements in and the incorporation of (smart) information and communication technologies (ICT) in energy systems. This results in so-called smart grids, that combine smart devices (smart meters, smart appliances, sensors) with smart ICT to perform advanced monitoring, control, and data communication [23]. This digital transformation is an enabling factor in the transition towards a more renewable, decentralized system, making it possible to perform decentralized demand response, peak load reduction, energy curtailment, and energy balancing. These measures can improve system resilience, facilitating integration of renewables and mitigating the effects of their intermittency. Digitalization of the energy sector relies on availability of different types of data. At the same time, digital transformation brings its own challenges as well: for example, risk from cyber attacks increases, making the grid more vulnerable and susceptible to failure.

Together, digital transformation, energy transition and consumer engagement bring both challenges and opportunities. To mitigate the negative impact of outages, the potential of distributed renewable energy resources combined with consumer engagement and ICT can be used to improve energy resilience, especially on the local level. This thesis recognizes the potential of harnessing distributed energy resources through physical, ICT and social interventions in power systems. Power systems are observed from the perspective of their three layers, bridging them together in interventions that harness the potential of distributed energy resources for energy resilience.

This thesis is motivated by, on the one hand, the increasing need for improving resilience of power systems faced with a number of challenges, and, on the other hand, the decentralization of power systems in aspects of generation, ICT infrastructure, but also decision-making process. To this end, this thesis explores how local energy resources can enhance power system resilience through self-organization and local decision-making. The designed interventions and their results can be used not only to improve resilience of power systems, but to support decentralization of power systems on its different levels in the transition towards a more sustainable energy system.

## 1.1 Research overview

This section gives an overview of the research in this thesis. The research objectives outline the main goals of the thesis, the research questions address the specific knowledge needed to achieve the pursued objectives, and the research approach explains the scientific means and tools for conducting the research. Finally, this section concludes by highlighting the main contributions of this thesis.

### 1.1.1 Research objectives

The main objective of this thesis is to show how the potential of local energy resources can be harnessed to improve power system resilience through the principles of self-organization and (local) decentralized control. In the context of the conducted research, self-organization is explored on different levels: social (local energy resource owners determine for themselves how the resources are distributed), ICT (mechanism for fully-decentralized supply and demand matching), and physical (self-reconfiguration of the physical network(s)).

The main research question this thesis aims to answer is the following:

**RQ** Can energy resilience be enhanced through self-organization using a decentralized approach to energy resource coordination?

To answer this question, a set of sub-research questions are addressed:

**SRQ1** What are requirements for a resilient power system? (Chapter 2)

**SRQ2** Can an intervention be designed that enables fully decentralized, adaptive energy supply and demand matching through self-organization and how? (Chapter 3)

**SRQ3** Can this mechanism be used to facilitate self-determined energy sharing for energy provisioning of differentiated consumers during outages and how? (Chapter 4)

**SRQ4** Can self-organization on both the ICT and physical layer improve resilience during widespread outages and how? (Chapter 5)

**SRQ5** Can local information from distributed energy assets be used to gain knowledge of a global system and how? Chapter 6

In the remainder of this thesis, each of the chapters addresses one of the sub-research questions. Chapter 2 addresses SRQ1, Chapter 3 answers SRQ2, Chapter 4 answers SRQ3, while Chapter 5 and Chapter 6 focus on SRQ4 and SRQ5, respectively.

### 1.1.2 Research approach

The *research philosophy* this thesis follows is that of post-positivism [24]. Post-positivism is a school of thought that builds on the foundations of positivism. Positivism adheres to the view that trustworthy knowledge is gained only through empirical observations and measurements. Consequently, this entails that there is an objective truth independent of the observer/researcher and the human factor is not taken into account. The role of the researcher in positivist studies is data gathering and processing using objective approaches [25]. Post-positivism builds on the positivist principles of scientific inquiry, but acknowledges that the human factor can influence the objectivity of truth by recognizing it. [24].

This thesis considers large-scale socio-technical systems. Socio-technical systems are complex, adaptive systems that consist of both technical components and social entities [26]. Thus, the social factor plays a key role in such systems. As this thesis explores the effects of local decision-making for energy resource sharing and its effect on resilience of power systems, the social aspect is a given. Therefore, this thesis follows the post-positivist school of thought.

In terms of the *research strategy*, this thesis follows the principles of *research through design*. In this strategy, researchers aim to decompose a system and develop artifacts (e.g. models) of its components to help them gain a better understanding of the system [27]. The results of this thesis are concepts, mechanisms, models and measures regarding the resilience of power systems through self-organization.

The *research instruments* used in this thesis include *literature review, artifact development, experimentation, case study*, and *evaluation*. Literature review gives deeper knowledge and the state-of-the-art of the research domains [28]. Experimentation assesses the performance of the research through a series of experiments, using different metrics. A case study gives insight into the applied context of the research [29]. Finally, evaluation enables researchers to assess the final outcomes of their research. This thesis performs literature review to gain more insight into the concept of resilience in terms of power systems and uses this to assess how current local energy resource sharing interventions can improve power system resilience. Artifacts are developed and their outcomes assessed through a series of experiments. The developed artifacts are implemented and evaluated through a number of case studies, and conclusions are drawn.

## 1.2 Research contributions

This thesis investigates how local control of energy resources, information, and decision-making can be used to enhance power system resilience through self-organization.

The main contributions of this thesis are as follows:

**C** Bringing together self-organized local energy sharing on different layers of a power system in a system-perspective approach, and demonstrating its effect on energy resilience (Overall contribution of this thesis).

**C1** Exploring how current local energy interventions (that address different power system layers) translate to, and can be used for, energy resilience with respect to their properties and resilience characteristics (See Chapter 2, SRQ1).

**C2** Developing an ICT intervention for a fully-decentralized local energy resource sharing (coordination). The developed intervention is assessed using a number of metrics, and its adaptivity component is analyzed for varying time-scales (See Chapter 3, SRQ2).

**C3** Introducing the concept of self-determined distribution of energy resources, whereby electricity provisioning is maximized for differentiated consumers at the local level. This principle is used together with the proposed ICT intervention to maximize self-sufficiency at the local level (See Chapter 4, SRQ3).

**C4** Exploring how self-organization and decentralized control can be expanded from the local to the level of multiple grids, and how this impacts resilience of power systems during widespread outages (See Chapter 5, SRQ4).

**C5** Investigating how local information from distributed flexible energy assets can be used to gain knowledge of a global system in a privacy-preserving way, using a decentralized machine-learning technique (See Chapter 6, SRQ5).

## 1.3 Thesis outline

This thesis consists of 7 chapters. Figure 1.1 shows the structure of the thesis, how the chapters relate to each other, and how they fit in the different power systems layers, depending on the intervention (elements) designed. Each of the core chapters targets different layers of power systems (physical, ICT, social) with an objective to address one or more resileince characteristics.

Chapter 2 introduces the concept of resilience in the context of power systems (specifically the smart grid), gives an overview of different local energy resource sharing interven-

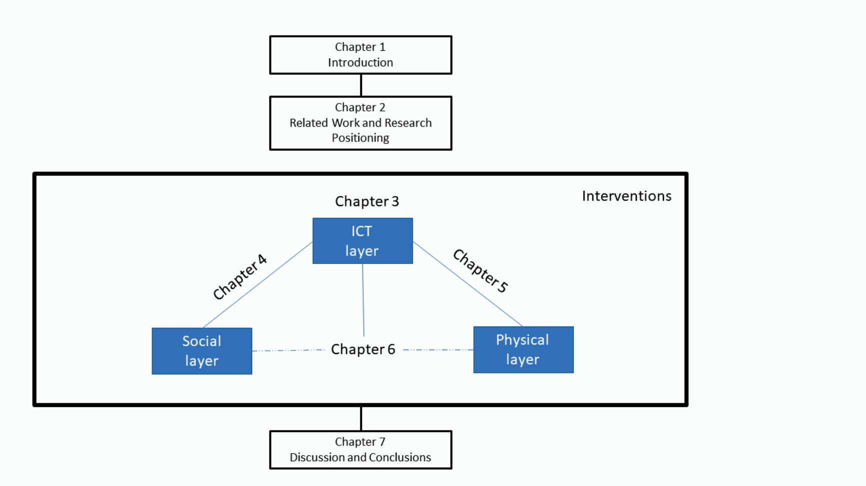



Figure 1.1: The outline of this thesis

tions that have a potential to ensure/improve resilience of power systems, and positions the research of this thesis.

Chapter 3 presents a decentralized coordination mechanism for adaptive energy supply and demand matching, based on self-organization. This mechanism is the core ICT intervention of the thesis. The mechanism is used in the remaining chapters to explore different scenarios regarding resilience of power systems. Chapter 3 is published in the proceedings of *IEEE International Conference on Networking, Sensing and Control* [30].

Chapter 4 introduces a social aspect to the developed ICT intervention. The concept of consumer differentiation based on community preferences is introduced, and the mechanism is used to explore self-sufficiency of groups of differentiated consumers. Chapter 4 is published in *Energy Informatics* journal [31].

Chapter 5 introduces a physical component to the ICT intervention by introducing the concept of self-organizing grids, where distribution system reconfiguration is performed in a decentralized, autonomous way. Chapter 5 is published in *Sustainable and Resilient Infrastructure* journal [32].

Chapter 6 takes a different look at the use of decentralized energy resources for resilience enhancement. This chapter explores how Federated Learning, a decentralized machine learning technique, can be used to gain insight into aggregated load flexibility, based on local data, without disclosing sensitive consumer data, and what the implications for different stakeholders thereof are. In itself an ICT intervention, it also brings both a physical component (e.g. using flexiblity to anticipate the state of the grid, based on local information) and a social component (using local energy data in a privacy-preserving way). Chapter 6 is published in the proceedings of *CIRED 2021 - The 26th International Conference and Exhibition on Electricity Distribution* [33].

Finally, Chapter 7 discusses the results and concludes this thesis with an outlook on future work.

# 2 Background and Research Positioning

This thesis investigates the potential of using local renewable energy resources for improving power system resilience. It takes a systems approach to designing and implementing interventions that address different aspects of resilience. Recognizing the importance of all the layers of power systems (physical, ICT and social) in local energy resource sharing, this thesis incorporates all three layers in the designed interventions. Contrary to most of the current resilience improvement measures [14, 34] that are context-specific and usually target a specific system element/layer, interventions designed in this thesis can be applied to a variety of different contexts. To understand what the requirements for such interventions are, this chapter first investigates the concept of resilience and the characteristics that define a resilient system, and maps them into the context of power systems. As this thesis focuses on the potential of local distributed energy resources to improve resilience from a multi-layer perspective, this chapter analyzes how existing interventions for local energy sharing address different resilience characteristics, and identifies a knowledge gap. As these interventions differ based on the context/layer, an analysis is done for three types of interventions: physical, ICT and social. In this context, interventions refer to resilience-improvement measures on the physical grid (such as hardening, but also things such as microgrids and virtual power plants - VPPs), technologies that can be used to support energy-sharing in a decentralized system (ICT perspective), and social intiatives that facilitate local energy-sharing such as energy communities.

This thesis brings together the concept of self-organization, the notion of energy resilience, and distributed energy resources (see Figure 2.1). In the context of this thesis, the concept of self-organization is instrumental in designing and implementing interventions that harness the potenitial of DERs for improving energy resilience, by facilitating local energy sharing.


Figure 2.1: Positioning of this thesis (the shaded area) in the related areas

## 2.1 Resilience of power systems: Definition and context

The concept and the study of power system resilience started to develop along that of other critical infrastructures [14]. Two reviews on power grid resilience [11, 14] provide an overview of different generic definitions and properties of a resilient system. Following these overviews, a generally accepted characterization of a resilient system is of that which is able to anticipate, absorb, adapt to and (rapidly) recover from a disruption [13–16]. These four fundamental characteristics can be used to understand and assess power system resilience [35].

**Anticipation** is the ability of a system to foresee possible damage caused by a disturbance [14]. For this purpose, smart ICT technologies with forecasting capabilities can be used to better prepare a system for an event: to estimate the level of damage and to take precautionary measures to minimize damage. In the context of power systems, anticipation of a disturbance can be both in the form of event forecasting (e.g. time of occurrence, duration, location, impact, probability etc.), and load forecasting (e.g. short-term hourly load forecasting during a disturbance). Estimation of disturbance parameters can instigate preventive measures such as network reconfiguration in a state that helps system operators deal effectively with the upcoming disturbance, or positioning resources possibly required after an event, e.g., repair and recovery crews, mobile generators, etc [34]. Following the specification of anticipation in terms of power systems, systems that have built-in smart ICT technologies with forecasting capabilities, such as machine learning

(ML) techniques, are a form of resilience enhancement.

**Absorption** is the ability of a system to withstand the impacts of a disturbance and to minimize damages caused [14]. Thus, a system that has this property is able to stay within an acceptable range of functionality, with no or small fluctuations in its performance (i.e. able to withstand/resist a disturbance) [13, 36, 37]. In the context of power systems, performance can be measured in terms of the demand met or the loss of load, the generation capacity available, the number of people with or without power, and reliability indices such as the System Average Interruption Duration Index (SAIDI) [11]. Absorption can also be defined in terms of the physical system, to include hardening (adding additional lines, moving cables underground and upgrading or installing new physical components) or (defensive) islanding and grid isolation, all of which are current resilience enhancement strategies [34]. Operational resilience enhancement strategies use smart ICT technologies and decentralized generation to improve the operational resilience of power systems by maximizing customer supply availability during a disturbance, providing operational flexibility and rapid recovery time [14].



Following the specification of absorption in terms of power systems, properties such as self-sufficiency and self-healing are form of resilience enhancement.

**Adaptability** in the context of resilience is the ability of a system to adjust to new circumstances by undergoing changes (e.g. introducing or removing components [38, 39]) to maintain an operational level during a disturbance [15]. In the context of power systems, it can include changes in/reconfiguration of topology, dynamic supply and demand balancing, demand response, and local generation and storage utilization during a disturbance in order to maximize power system performance indicators (namely, demand met, consumers served, available generation capacity etc.). Appropriate anticipation techniques (e.g. forecasting and uncertainty) can be used to enhance a power system's response to changes by being more prepared for future disruptions [15], thereby improving system adaptability. Following the specification of adaptability, self-organization, dynamic reconfiguration (both on the physical and ICT level), load prioritization are form of resilience enhancement.

Finally, **recovery** is the ability of a system to restore its operation to a functioning level following a disruption [13–15, 36]. The recovery capacity of a resilient system is often characterized by rapidity of return to normal operations/reliable and sustainable performance [15], being able 'to meet priorities and achieve goals in a timely manner in order to contain losses and avoid future disruption' [37]. In the context of power systems, a system that fully recovers from a disturbance is able to meet all the demand need of all of its consumers, and to restore the full physical grid operation. To reach full recovery, a resilient power system should 'first restore the disconnected customers (i.e., operational resilience) and then restore the collapsed infrastructure (i.e., infrastructure resilience). Several actions should take place in this phase, such as reenergizing transmission and distribution lines, restoration of damaged components, unit restarting, resynchronization of areas, load restoration, etc.' [34]. Other recovery measures include physical infrastructure repair actions, but also switching to local energy generation and storage to meet some consumer demand (given that the physical infrastructure for local energy sharing is not damaged). For this, different stakeholder engagement is crucial [15], as consumers and prosumers play a significant role in terms of local generation utilization and load prioritization (on the local level). Therefore, some characteristics (e.g. load prioritization, local resource distribution) are overarching for both adaptability and recovery.

Following the specifications of the four resilience characteristics, a resilient power system needs "structural flexibility, modularity and distributed decision-making integrated with intelligent control and communication capabilities", together with detailed knowledge of the system's behavior in three time scales: historical, real-time, and forecasting/-future [16].

The potential of using distributed energy resources, especially on the local level, is studied as a promising measure to improve power system resilience [6, 34, 40–42]. Generating, storing and managing energy locally enables faster response time, maximizes locally met demand, and adds flexibility and adaptability during widespread outages [14, 34]. Combined with the smart ICT technologies as a part of the smart grid, and resulting socio-economic changes, different local energy resource sharing interventions in power systems have emerged that harness the potential of distributed energy resources. Some of these interventions, such as microgrids, have already proven to enable local energy resilience during disturbances [6], while others possess some of the resilience characteristics, but are not primarily used for this purpose. This thesis recognizes this potential and analyzes how they can be used for local energy resilience, with respect to the four resilience properties.

## 2.2 DER interventions for energy resilience: An overview

The increase in penetration of distributed renewable resources has brought significant changes to power systems operation in physical, ICT, and social aspects.

On the physical level, distributed energy resources are installed both on the dispersed (e.g. solar and wind farms) and the local level (rooftop solar panels, community storage, community wind turbines). This decentralization of generation introduces changes in the design, operation and management of the physical grid, particularly the distribution grid. Some of the most prominent interventions for integration and management of DERs on the physical level referred to in the literature are microgrids, rural electrification projects, and isolated grids, but also privately owned DERs [6, 42–46].

On the ICT level, the integration of smart digital technology has brought about changes in smart coordination, sensing and monitoring, data collection, processing, management and exchange, as well as integrated forecasting and uncertainty methods [47–49]. With the shift towards decentralized generation, the role of prosumers changes, leading to development of dedicated technologies and platforms for electricity supply and demand matching, energy trading and smart contracts, coordination and allocation mechanisms, necessary to facilitate the new decentralized paradigms [49]. Some of the most prominent paradigms to facilitate this are multi-agent systems (MAS), blockchain, and other peer-to-peer (P2P) technologies/platforms. These platforms increase consumer engagement, enable real-time, decentralized supply and demand matching, and facilitate energy trading. Furthermore, as described in the anticipation characteristic of resilience, machine learning techniques can play an important role in current power system management. Estimation of the potential of consumer flexibility for demand response or anticipating load patterns can help grid operators better plan for DER integration and managing fluctuations.

Increase in DER penetration shifts not only generation but also operational management to a local decentralized level, brining societal changes. These societal changes are reflected through actions and engagement of different stakeholders (actors) within power systems, such as government, policy makers, energy utility companies, distribution and transmission system operators, aggregators, and energy producers and consumers. These different stakeholders play active roles in the operation and coordination of DERs, and drive technological advancements that support power system transformation [17, 18]. This ongoing transformation is partly steered by and asks for higher consumer engagement, leading to consumer empowerment (as more consumers become prosumers) and emergence of local energy communities, and enables the move towards self-sufficiency at a local level [44, 48–50]. Power system transformation requires active participation from governments and policy-makers to regulate the transformed system and its energy markets. This aspect of stakeholder engagement is outside the scope of this thesis.

The following subsections describe these types of interventions and technologies in more detail, and explore how they can be used for local energy resilience.

### 2.2.1 Physical infrastructure interventions

On the physical level, DERs are integrated at different scales: remotely in forms of solar and land and offshore wind parks, and locally in forms of individual installations such as, for example, rooftop PV and household storage [50, 51]. Some of the most prominent interventions that integrate DERs to operate independently are microgrids, and off-the-grid projects [42, 43, 52]. These interventions are already partially used for resilience enhancement, but still lack some of the main resilience characteristics, such as adaptability, as they are geographically-bound and have a dedicated, fixed amount of energy production. Furthermore, the use of privately-owned DERs is explored in the context of household resilience, where households both currently with and without continuous access to electricity have to adapt to uncertainties in power supply [45].

The use of microgrids has become one of the most common resilience enhancement strategies that include integration of DERs. Microgrids are subsets of existing power systems that can operate both in parallel with the existing backbone grid, and independently, in an islanded mode [42]. During disruptions, microgrids can disconnect from the main grid, and operate autonomously (and, in some cases, self-sufficiently) [43]. This autonomous operation enables them to efficiently absorb a disturbance. Microgrids can shed and schedule their loads, and local renewable resources can feed the critical loads during the disturbance period. This ensures local resilience for microgrid members, and enables faster system response and recovery, strengthening grid resilience [6]. In some cases, geographically co-located microgrids can be coupled to supply the loads of other microgrids by forming networked microgrids [53, 54]. Both standalone and networked microgrids are bound by a dedicated infrastructure, thus still lacking the adaptability property of resilience. To account for this, dynamic microgrids are researched, where microgrids could potentially use smart ICT tools to dynamically change their configuration [6]. The contribution of microgrids for energy resilience of areas frequently affected by disruptions caused by extreme weather event has been demonstrated in several real cases [42, 55, 56]. A detailed review on microgrids as a resilience enhancement strategy is published in [6].

The integration of DERs is prominent in facilitating off-the-grid (OTG) electricity to areas with no access to a central grid, supporting electrification of rural areas, and making remote areas self-sufficient in the form of isolated grids [52, 57, 58]. The term *mini-grid* is often used for these systems, interchangeably with microgrids [46, 52, 59]. As they operate autonomously, and are potentially self-sufficient, they have the ability to absorb a disturbance and supply their loads independent of the main grid. Furthermore, as rural electrification microgrids aim to provide access to areas with no or limited access to the main grid, they increase the overall system resilience.

### 2.2.2 ICT interventions

The transition to decentralized, smart power systems requires mechanisms and algorithms to share and communicate information on, and support coordination of, heterogeneous resources within those systems, and to solve challenges involving heterogeneous actors (stakeholders) each with their own (often competing) objectives, operating within a certain level of uncertainties and dynamism [60, 61]. These mechanisms are facilitated by different ICT technologies which include concepts such as multi-agent systems, peer-to-peer technologies (P2P), control algorithms, Internet of Things (IoT), blockchain and different machine learning tools for load and production forecasting, grid-state estimation and smart operation [62]. These technologies are used to integrate DERs into smart grids and support grids' operation by, for example, performing active demand-side management, load forecasting, EV and storage charging and discharging, and help actors such as Distribution System Operators (DSOs) to better plan for congestion management, prevent grid overloading or come up with alternative measures to match supply and demand [60]. DER integration into smart grids goes beyond grid operation. ICT technologies are also used to provide decentralized energy trading platforms and to support operation of energy markets [63, 64]. When integrated in a socio-technical power system, these ICT technologies can enable modularity, adaptivity and support faster recovery, improving power system resilience.

One of the most promising ICT paradigms for facilitating smart grids is that of multi-agent systems (MAS), and their application in the domain of DER management is well-established [43, 61, 65–71]. MAS are autonomous, scalable and highly adaptable [67, 72, 73], and have a wide range of possible applications. In terms of power systems, MAS has been applied for problems such as management of customer-owned distributed resources [73, 74], supply and demand matching [67], as well as the control of distributed energy resources [75, 76]. Agents are installed on physical devices, and can perform control and monitoring, and complex decision-making. Thus, agents can perform autonomous decisions both on the physical grid level, as well as that of consumers and prosumers. In [65], a set of design principles for resilient control using MAS is presented, indicating both the changes in system structure and dynamics it has to support. To ensure resilience, future power systems will have to be in a regular state of change, "allowing generators, loads and even whole microgrids to connect and disconnect as is necessary in an interoperable fashion. Similarly, the dynamics of the physical power grid and its associated enterprise control will also change [65]". MAS agents can be modeled to perform real-time autonomous task execution in a flexible and scalable way [77]. Therefore, MAS can facilitate resilience of future power systems by being adaptable, and by supporting the decentralized control of devices and decision-making of resource owners, enhancing absorption and faster recovery. Even though MAS itself is not used for forecasting, forecasting methods can be incorporated in agent operations (e.g. agents can forecast their supply and/or demand), improving anticipation.

It is important to note that, while ICT interventions do not directly ensure resilience of power systems, they offer necessary ICT tools for the physical interventions to facilitate power system resilience. Furthermore, as a communication infrastructure, these technologies are highly adaptable and, due to their distributed architecture, they can recover quickly in case of communication infrastructure failures, as they eliminate a central point-of-failure.



### 2.2.3 Social interventions

The increase in penetration of DER has brought significant changes on the social level of power systems and for all the actors in the power system. Through increased consumer awareness and empowerment, local energy communities and initiatives have significantly risen in number; motivations are many: self-sufficiency and sustainability (communities that aim to be carbon-neutral) at the local level, novel business opportunities (selling the overproduction to the grid or trading electricity with other consumers and prosumers) [78], self-governance and increased control of own resources [79], local community benefits/strengthening social cohesion (e.g. community storage) [44] etc. Decentralized local coordination and decision-making are emerging phenomena of such interventions. This self-governance of energy resources enables local energy communities to collectively manage their resources and potentially develop consumer/prosumer-side response strategies for disturbance periods such as, for example, load prioritization and excess generation distribution. During disturbances, load prioritization is routinely performed by the utilities to supply loads based on their importance to public health and safety. By letting communities prioritize and supply their loads, utilities can focus on other critical loads that cannot sustain themselves [41]. Therefore, local energy communities can facilitate faster recovery for the grid. If completely self-sufficient, local energy communities can operate in a fully autonomous way (as a part of a community micro-grid or using the backbone grid), thereby ensuring absorption of a disturbance at the local level. Local decision-making and flexibility the local level (e.g. load prioritization, DER distribution and coordination, demand response etc.) enables energy communities to quickly adapt to new circumstances and undergo changes. Therefore, given the appropriate communication and physical infrastructure, energy communities can ensure resilience at the local level, and help improve it on the grid level.

Other types of socio-economic interventions for DER integration include ”virtual power plants, energy hubs, community micro-grids, prosumers community groups, community energy systems and integrated community energy systems” [78]. However, as they differ only in objectives, but not the properties, they are excluded from this review. A summary of each of these interventions can be found in [78].

## 2.3 Self-organization

This thesis uses the concept and principles of self-organization to represent and orchestrate the interaction between different system elements. To better understand how self-organization can be used in interventions that tackle the challenge of energy resilience, this section first gives a definition of self-organization and describes its principles in a broader sense. According to [80], self-organization is defined as a mechanism that enables a system (of systems) to adapt to changes in its goals and environment by changing its internal organization, without explicit external control. From this definition it follows that a system (of systems) is self-organizing if it has the following properties [80]:

- *Decentralized control*: There is no central authority or centralized information flow. Instead, system components interact locally with each other, exchanging local information.
- *Dynamic operation*: A system can change its behaviour when needed and to the context that is relevant. Since no external control exists (see the next property), this change in behavior (adaptation) is continuous.
- *Absence of explicit external control*: The system is autonomous, changing its organization and behavior solely based on internal decisions (the self- part of the self-organization definition).

In the context of Computer Science, the concept and principles of self-organization relate to that of *autonomic computing*, where computer systems are able to manage themselves (self-manage), following the so-called MAPE-K framework [81], as shown in Figure 2.2. In this framework for adaptive systems, system components *Monitor* the system, *Analyze* its behavior, *Plan* the following steps for new system state, and *Execute* actions to reach the new state. All the components have access to a common knowledge base, containing information about the system and its environment.

Inherent to this framework are *self-** properties, such as *self-awareness*, *self-configuration*, *self-optimization*, *self-healing* and *self-protection* [81–84]. Some of the properties of self-managed systems directly map to those of resilient systems, while others can be seen as instrumental to desiging resilient systems or enabling mechanisms. In the context of power systems, the term *self-healing systems* has widely been used to refer to power systems that are able to localize and analyze faults, and take appropriate actions to mitigate the effects thereof [85–90]. For this purpose, a combination of (smart) sensing, control and communication technologies and re-configurable network topologies can be used [91]. Autonomous networked microgrids are researched in literature as a means to support self-healing grids by communicating and sharing resources with physically connected microgrids during outage periods [53, 87, 92–94]. To facilitate self-healing in power systems, agent-based solutions have been proposed in literature, where autonomous agents communicate and cooperate to provide adaptive restorative protection [95]. With decentralization of power systems in generation distribution as well as decision making, self-organization characteristics and enabling technologies should also be harnessed on other layers as well (e.g. ICT, social). Integrating these layers by combining real-time monitoring, distributed adaptive energy management system and control, information and communication networks, and flexible power grid structure capable of reconfiguration could enhance power system resilience by harnessing the potential of self-organization [60, 91] to its fullest. The social aspect of self-organization can be seen in local energy communities (LEIs), where self-organization plays a role not only in the formation of initiatives themselves, but in

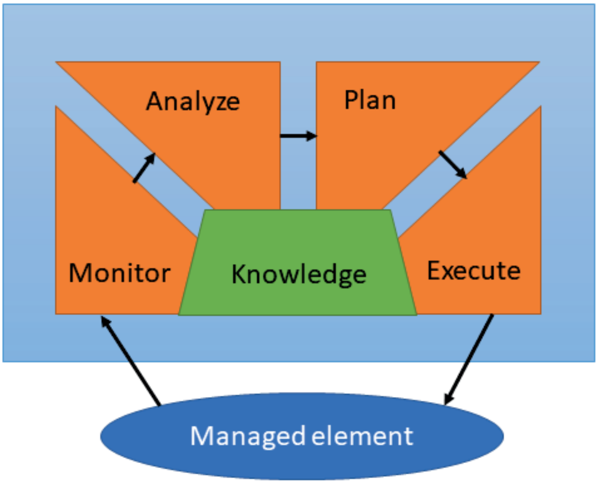



Figure 2.2: MAPE-K framework for autonomic computing adapted from [81]

their interplay with various other stakeholders as well, giving more sense of ownership to the members [96].

One of the prominent technologies that follows the concept of self-organization and exhibit properties of autonomic computing is that of multi-agent systems. In MAS, agents share a common goal and to achieve that goal, they may continually communicate (local information) and coordinate with each other in a decentralized fashion, therefore self-organizing [87, 97–100]. Given these properties, their application in the energy domain and their ability to integrate social and physical elements of the system, MAS are chosen as the implementation technology in this thesis.

## 2.4 Research positioning

This thesis observes resilience from a holistic perspective and proposes (a set of) interventions that incorporate each of the resilience characteristics by design and brings together different concepts from existing DER interventions on each of the system layers. This subchapter positions each of the core chapters of the thesis with respect to: 1) the type of intervention designed, and 2) the resilience characteristics/properties the intervention possesses/has. The intervention types correspond to three different power system layers. An overview of this positioning can be seen in Figures 2.3 and 2.4. Note that the orange-colored boxes indicate that interventions in the chapters do not directly ensure recovery, but can be a means to achieve it (i.e. recovery is not the key concept for those interventions).

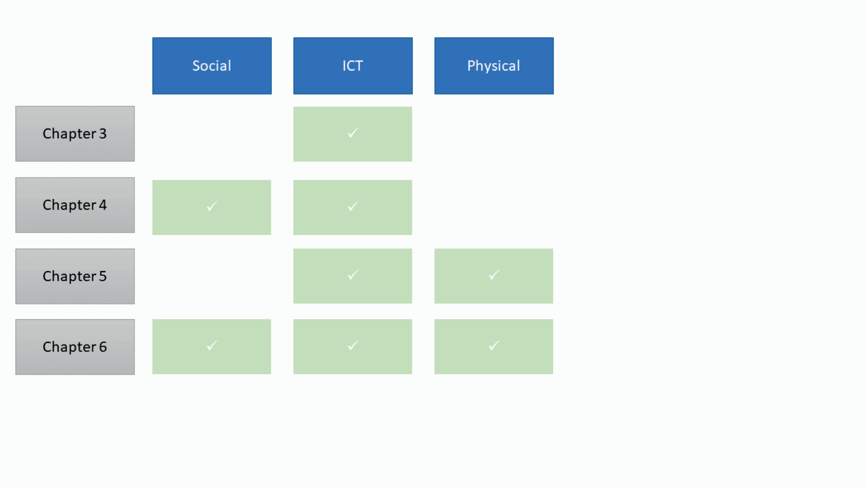



Figure 2.3: Chapter positioning in terms of designed intervention types

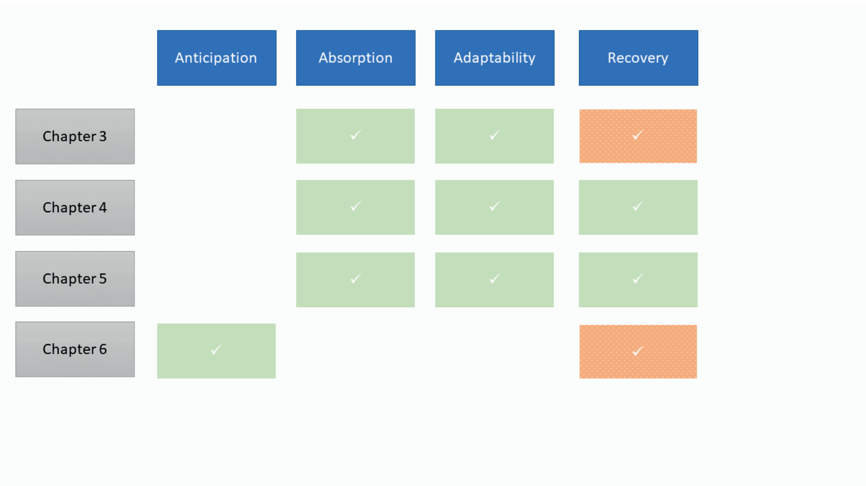



Figure 2.4: Chapter positioning in the context of resilience characteristics

Chapter 3[1] presents an ICT intervention for decentralized supply and demand matching, based on the principles of self-organization. The intervention supports local energy management, without the need of a central data repository. It considers the physical grid as a copperplate, and does not take into account physical grid constraints, nor the social

[1]For the publication, see [30]

aspect of consumers and prosumers engagement (e.g. preferences) in energy resource sharing. Therefore, with respect to the three power system layers, this intervention falls only in the ICT layer type.

The intervention uses local information on supply and/or demand of individual consumers, prosumers and producers to create virtual groups (clusters) that locally balance their supply and demand, minimizing the group's mismatch, and maximizing the demand met. With respect to resilience characteristics, this demonstrates the ability of the designed intervention to absorb an interruption by staying within a pre-determined range of functionality in terms of the demand met. The intervention can be used to maximize the number of consumers whose demand is met, or met within an acceptable range.

At the core of the intervention is the concept of self-organization, which uses the notion of autonomous agents. For that purpose, the concept of multi-agent systems (MAS) is used, where each consumer, prosumer and producer is represented by an autonomous agent that has information on local supply and/or demand. A decentralized information-sharing algorithm (gossiping) is used to find neighboring agents, with which local information is shared. Using MAS, the intervention is designed and implemented so that it enables dynamic reconfiguration of formed virtual groups to respond and adapt to (sudden) changes in the environment such as, supply and demand fluctuations, interruptions, external changes to the system. This is the adaptability characteristic of resilience, as the intervention enables the system to adjust to new circumstances by undergoing changes in cluster formation.

In summary, Chapter 3 presents an ICT intervention with adaptability and absorption characteristics that can be used towards improving energy resilience both on the local and overall level (see Figure 2.5).

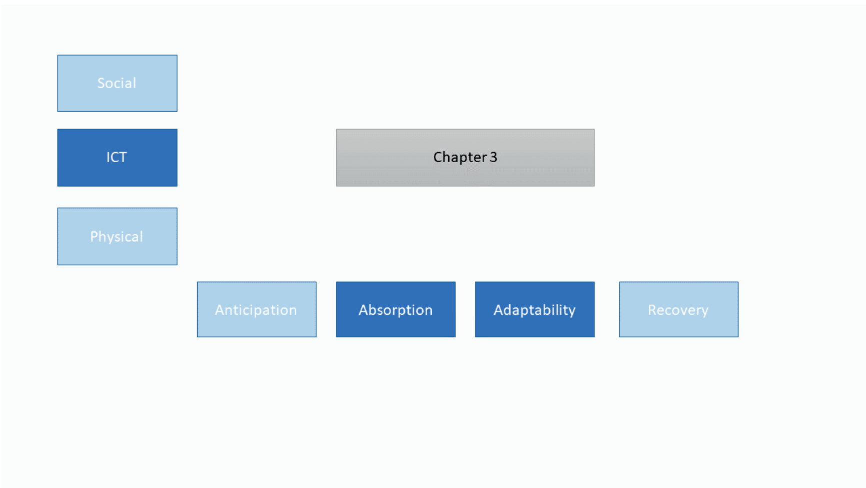



Figure 2.5: Chapter 3 positioning in the context of intervention types and resilience characteristics

Chapter 4[2] builds on the intervention for supply and demand matching from Chapter 3 by introducing the social element through the concept of consumer differentiation. In the context of this thesis, the notion of consumer differentiation entails that local energy consumers and/or prosumers in an area can decide for themselves who gets priority for energy provisioning when limited energy resources are available, with an aim to maximize met demand of prioritized consumers. To include consumer differentiation, the intervention presented in Chapter 3 is extended to include priorities in local information repository available to agents. Therefore, agents now have knowledge on their supply and/or demand profiles and their priorities. This extends the previously ICT-only intervention to an intevention that includes the social aspect as well, as seen in Figure 2.6. With respect to resilience characteristics, this intervention is adaptable, as the formed energy groups can dynamically reconfigure to respond to changes in the environment. The reconfiguration of energy groups can also happen due to changes in priorities, as they can also be dynamically adjusted. Furthermore, as is the case with the ICT intervention in Chapter 3, this intervention also demonstrates the absorption ability, as it ensures that the number of prioritized consumers whose demand is met is maximized. Furthermore, this intervention can be instrumental to enabling faster system recovery, as local energy groups that maximize self-sufficiency can operate independently, while restoration of other parts of the system is performed. Ensuring that the prioritized consumers are supplied first is one of the properties of resilient recovery.

In summary, Chapter 4 presents an ICT intervention with social elements, that possesses adaptability, absorption and recovery characteristics, which can improve energy resilience both on the local and overall level (see Figure 2.6).

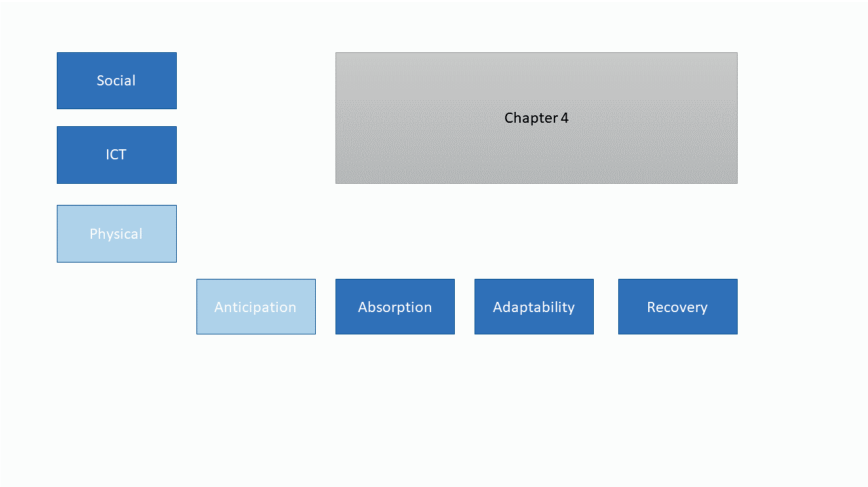



Figure 2.6: Chapter 4 positioning in the context of intervention types and resilience characteristics

Chapter 5[3] adds a physical layer component to the ICT intervention from Chapter 3 by

[2]For the publication, see [31]
[3]For the publication, see [32]

introducing the concept of self-organizing grids. In self-organizing grids, grids themselves perform traditional operational measures such as network reconfiguration in a decentralized fashion by means of MAS. Distribution system reconfiguration (DSR) can be used as a resilience measure to provide the emergency restorative supply to unment demand until the fault is repaired [101]. DSR alters the topology of power systems (e.g. multiple distribution systems) by opening and closing the switches that connect different distribution systems.

2

In this intervention, agents that represent physical grid components such as buses are added, that perform power flow calculations and system reconfiguration. These agents communicate with consumer and prosumer agents to obtain information about their supply and demand, and gather information of distribution system parameters such as losses, switch status, and energy utilization. Within the new topology, virtual energy groups are formed that maximize their self-sufficiency. This intervention can be used during widespread outages to facilitate energy sharing accross multiple networks, while respecting the physical grid constraints. With respect to resilience characteristics, this intervention's adaptability property is reflected not only through reconfiguration of local energy groups, but through the autonomous and dynamic reconfiguration of grids themselves. This improves the system's ability to absorb an interruption, by maximizing met demand accross multiple grids. Finally, this intervention can improve system's recovery.

In summary, Chapter 5 presents an ICT intervention with physical elements, that possesses adaptability, absorption and recovery characteristics, which can improve energy resilience both on the local and multi-grid level (see Figure 2.7).

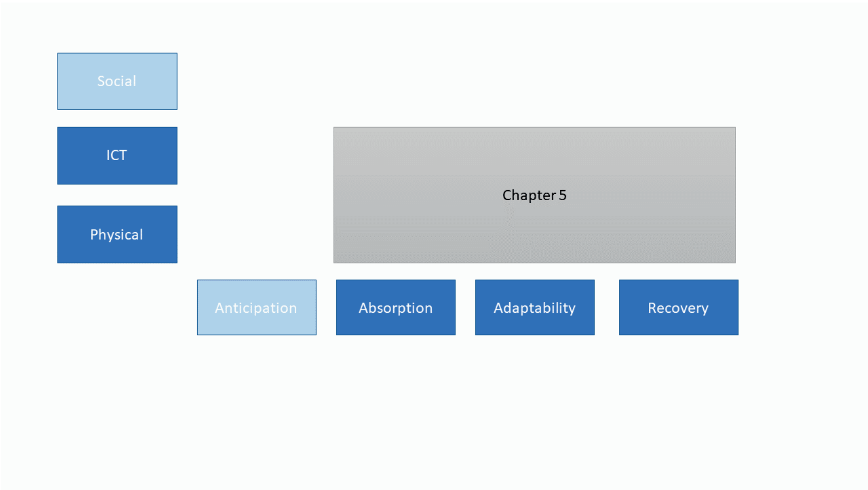



Figure 2.7: Chapter 5 positioning in the context of intervention types and resilience characteristics

The interventions discussed so far rely on perfect knowledge of consumers' and prosumers' supply and demand to perform energy sharing and local supply and demand matching, which can often be challenging due to different system uncertainties.

The final chapter, Chapter 6[4], presents an ICT intervention that uses a decentralized machine learning technique, Federated Learning (FL), to anticipate the flexibility potential of decentralized energy assets in areas with low information availability, while taking into account consumers' privacy concerns. It investigates the potential of this approach for various actors in a power system, by performing a multi-sakeholder analysis.

Chapter 6 explores how FL can be used to support decentralization of power systems and addresses some of the challenges it brings, and what that means for different stakeholders in a system. Using FL, local information from flexible assets can be used to gain insight into aggregated load flexibility, without disclosing sensitive consumer data, a concern empowered energy consumers have [102]. This information can then be used by distribution system operators to learn more about the probability of line or transformer overloading, improving resilience of power systems by anticipating the state of the grid. While in itself an ICT intervention, at its core are physical grid elements, as well as social tat concern consumer privacy.

In summary, Chapter 6 presents an ICT intervention with inherent physical and social elements that possesses can be used to anticipate the state of the grid, improving energy resilience (see Figure 2.8).

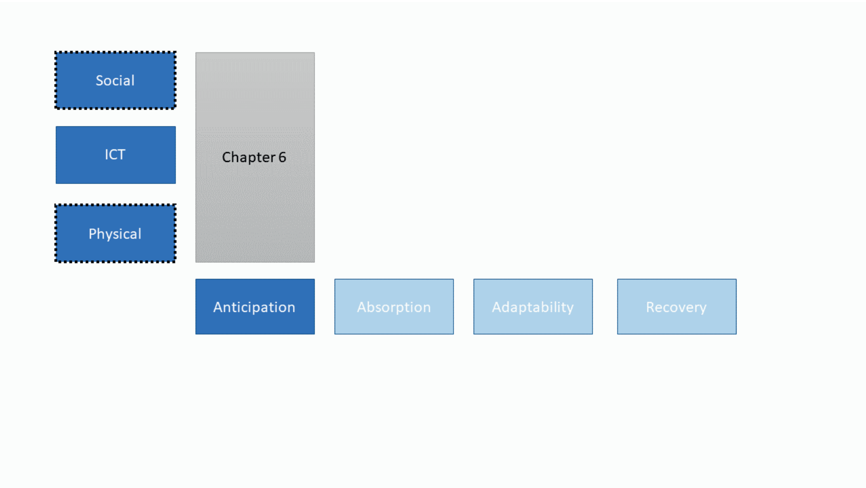



Figure 2.8: Chapter 6 positioning in the context of intervention types and resilience characteristics

## 2.5 Defining the knowledge gap

Improving power system resilience is necessary given the challenges they face. Current approaches for improving power system resilience are often context-specific and targeted at a single power system layer [14, 34, 91]. These approaches often involve using DERs and local control, given their widespread use, but do not fully harness their potential. Furthermore, these approaches do not address all the characteristics of resilience in an

[4]For the publication, see [33]

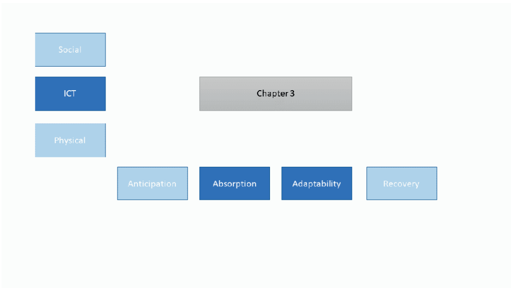
over-arching approach. For example, interventions such as microgrids that extensively use DERs, as well as supporting ICT infrastructure to manage them are seen as a promising approach to improving resilience [91, 91, 94, 103]. However, as physical, geographically-bound interventions, they are not able to dynamically adapt to (sudden) changes in their environment. Other interventions such as, for example, energy trading platforms, focus more on the ICT aspect of energy sharing and do not target resilience at all. Another drawback of some of these interventions is that they rely on centralized data availability which could not be possible in cases of interruptions, or when social factor of data privacy is concerned. Therefore, a decentralized approach to resource sharing is required. To be able to share local energy resources, both physical and social aspects, supported by ICT, have to be taken into account. This means hat the system should be in balance and that resource owners have to be willing to share their resources, information and make local decision, while their privacy concerns are addressed. Current solutions for DER sharing do not bring all of these aspects together.

This thesis addresses this gap by proposing a set of interventions that bring together different power systems layers, and incorporate all resilience characteristics in a systemic solution based on the principles of self-organization.

# 3



# Dynamic, self-organized clusters as a means to supply and demand matching in large-scale energy systems




*Centralized management of power systems is becoming more challenging due to the increased introduction of distributed renewable energy resources, along with demand increase and aging infrastructures. To address these challenges, this chapter proposes new mechanisms for decentralized energy management. Based on* self-organization *of consumers, prosumers and producers into virtual groups, called* clusters, *supply and demand of electricity is locally matched. Distributed multi-agent systems are used as a way to represent virtual cluster members. The mechanisms are illustrated, and static and dynamic virtual clusters are compared.*

Chapter 3 is published in the proceedings of *IEEE International Conference on Networking, Sensing and Control* [30].

*Dynamic reconfiguration is achieved by varying the time periods for which clustering is performed. The proposed clustering mechanisms demonstrate that large-scale centralized energy systems can operate in a decentralized fashion when only local information is available.*

## 3.1 Introduction

Power systems are large scale, complex socio-technical systems that provide society with one of its most valuable assets: electricity. Electricity is not only an irreplaceable asset in households, but is also vital for day-to-day operations of today's critical infrastructures. The main objective of power systems [104] is to constantly ensure that there is enough electricity supply to meet the demand of consumers. This is also known as supply and demand matching or balancing. In a traditional power system, this matching is centrally controlled, with big power plants with centralized generation still as the main electricity suppliers [67]. As power systems increase in size and complexity, centralized control becomes more challenging [104]. This is particularly the case due to the increased introduction of distributed renewable energy resources (DER) [69]. As a consequence of increased flexibility of the demand-side for choosing supply sources, traditional, centrally controlled nature of energy systems management is changing to coordination among a large number of supply sources and responsive loads [67]. Thus, the complexity of an already highly complex system is increasing.

To handle this complexity, different types of decentralized organization of power systems that enhance local control with respect to energy supply and demand [7–9] have been proposed. Methods for minimizing centralized control are proposed in [7, 9, 69]. These methods use complex adaptive systems to represent power systems, and intelligent agents as their components. The potential of a multi-agent approach to manage distributed energy resources is assessed in [66–68], where residential combined heat and power units are represented by individual groups acting as a type of a virtual power plant. While these papers envision power systems as decentralized, they do not propose mechanisms for enabling this decentralization.

Key concepts such as microgrids and virtual power plants (VPPs) have been introduced in the past to facilitate decentralized power system organization, and to support the increased introduction of distributed renewable energy resources into power systems [105, 106]. Microgrids are subsets of existing power systems that can operate together with the main power system, or run independently in an *islanded* mode. The latter is considered one of the main beneficial characteristics of microgrids. However, microgrids require sophisticated physical infrastructure for their operation and are tied to specific geographic regions, making them static (non-reconfigurable) [106, 107]. Future microgrids are envisioned as being able to dynamically meet changing objectives in real-time. This requires the change in power systems management, as well as the change in system infrastructure. One of the main motives for enabling real-time, dynamic reconfiguration is to improve system resilience and quality of service for consumers [43].

Unlike microgrids, virtual power plants do not require a dedicated infrastructure. Their main aim is to group several types of power sources, and allow them access to the energy market as a group for economic and other reasons [106]. VPPs are typically organized as fixed groups. As such, the composition of a VPP does not change over time. In contrast with microgrids, VPPs are not designed for islanding during outage periods, thus they are always grid-tied. However, an advantage of VPPs is that they are not geographically limited and do not require new, sophisticated infrastructures [106].

Both microgrids and VPPs are promising developments in the move towards a more decentralized power system. However, both typically assume prior full knowledge of a power system, focus on long term relationships with their members and lack the flexibility required for near real-time dynamic supply and demand matching in changing group compositions, see e.g. [108].

The rest of the chapter is organized as follows: Section 3.2 gives an overview of clustering and explains the concept in context of this chapter, Section 3.3 explains the proposed decentralized clustering mechanism in detail, Section 3.4 describes the conducted experiments, and Section 3.5 discusses the obtained results. Finally, Section 3.6 summarizes the main conclusions and gives suggestions for future work.



## 3.2 Clustering as the enabling mechanism of decentralization

In this chapter, the concepts of microgrids and VPPs are further extended with clustering techniques for enabling the formation of dynamic, virtual groups in power systems. These virtual groups locally perform electricity provisioning and are able to adapt to changes in supply and demand.

Clustering is a technique used to organize objects into groups according to a specified criteria [109, 110]. Depending on its operation, clustering can be distributed or centralized. In centralized clustering methods, such as K-means, a central repository contains the information about the entire system and performs clustering. In contrast, in a distributed approach, nodes have only local information and obtain aggregate information about other nodes by communicating [111–113]. Depending on the changes in their composition, clustering can be static or dynamic. In dynamic clustering, clusters adapt to changes in the environment by changing their composition, whereas in static clustering, clusters are initially formed and do not change during their lifetime [114].

In this chapter, consumers, prosumers and producers organize themselves into local communities [7–9], which are referred to as *virtual clusters*. Geographical distance, and load and production profiles are the main clustering criteria, whereas the main objective is to locally, i.e. within a cluster, minimize supply and demand mismatch. Autonomous organization into clusters based on local information is referred to as *self-organization*. Self-organized clusters enable more flexibility in matching local demand and supply [71]. Clusters reconfigure to adapt to changes in the dynamic environment. This chapter proposes mechanisms that do not assume full knowledge of a power system and rely only on local information of every system member.

The main objective of developing the mechanism for dynamic self-organization is twofold, namely (i) to demonstrate that large-scale centralized systems can operate in a decentralized fashion when only local information is available, and (ii) to study the effects of changing the time period for which clusters stay the same, thus, to observe the differences in outcomes of static and dynamic clustering.

3

## 3.3 Clustering algorithm for decentralized supply and demand balancing

The proposed mechanisms abstract from the physical layer of power systems. Clustering is performed on the virtual level, relying on external communication, e.g., using telecommunication networks, to create the grouping.

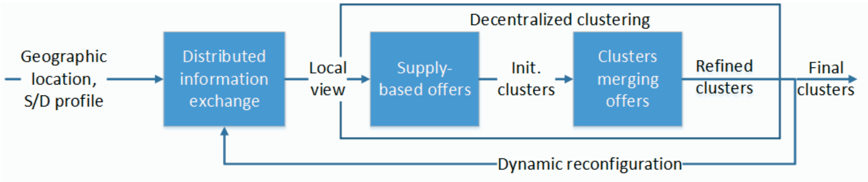



Figure 3.1: The proposed clustering mechanism

Cluster members are represented by autonomous agents with a local view of the system that exchange information with other agents. This chapter assumes that every consumer, prosumer and producer in a power system has a computational device on which an autonomous agent (a software component) is installed that acts on their behalf. Thus, a consumer is represented by a *consumer agent (CA)*, a prosumer by a *prosumer agent (PSA)*, and a producer by a *producer agent (PDA)*. Devices which agents are installed on are distributed across the network and can communicate with each other, regardless of the geographical distance. Every agent contains information such as its own geographic location, load and production profile for a period of time (usually a daily profile), energy type produced, and the cluster which it belongs to. Load and production profiles of every agent are sampled every hour, and these sampled profiles are then used to match supply and demand with other agents or clusters. Agents are reconfigurable, enabling individuals they represent to change their settings at any time. They negotiate membership in clusters, and can send and receive membership offers. Each agent can belong to only one cluster and each cluster has a coordinator which monitors it, and manages and facilitates the negotiation. Agents can accept or reject cluster membership offers. Negotiation results in a formed service level agreement (SLA), that specifies the terms and conditions of electricity service provisioning [83]. Negotiation can be performed using one of the standard negotiation protocols for SLAs, such as Web Services Agreement [115, 116]. In this chapter, SLAs contain information about the membership offer, and are as such used as a means to fix cluster boundaries.

As seen on Fig. 3.1, the process starts by building a local view containing the geographically closest neighboring agents of every agent. In this work, geographic proximity is taken as the distance measure, more advanced distance measures are left for future research. To build this local view, a distributed information exchange algorithm (gossiping) is used. This algorithm assumes that every agent is reachable by any other agent in the system, either directly or through alternative paths (via other nodes) [117, 118]. After building the local view, the distributed clustering phase begins. Each agent has a local objective function, which differs based on the agent's type. For *PSA*s and *PDA*s, the initial objective is to provision electricity to those *CA*s whose demand is the highest. *PSA*s and

*PDA*s ask *CA*s which match their objective function to join their clusters. This step results in membership offers sent to *CA*s. *CA*s assess every offer received, and choose the best one. In this case, the best offer is the one which minimizes *CA*'s mismatch. The process is repeated until all the *CA*s are clustered. This phase results in initial clusters, formed by local objectives of its members. Cluster coordinators of the generated clusters are the *PSA* or the *PDA* that initially sent the offers.

The next phase refines the clusters by letting the coordinators communicate and send offers to merge clusters. In this stage, the objective of every cluster is to minimize its supply and demand mismatch. Coordinators (*PSA*s or *PDA*s) send offers for merging to neighboring (geographically closest) clusters (see Algorithm 1). Offers are sent only to those clusters whose mismatch, when combined with that of the cluster sending the offer, is closest to zero. The number of offers sent is parametrized. Clusters that receive an offer can either accept or reject it, depending on how good it is. In this case, a good offer means that the mismatch will be decreased. The output of this phase are the final clusters. The number of rounds for which this process is repeated is controlled by parameters such as maximum cluster size, and maximum number of iterations. Clustering is performed for different time periods, observing the changes in cluster numbers, sizes and composition in dynamic environments.

The main objective is to minimize the supply and demand mismatch on the local level (i.e. on the cluster level). The mismatch of an agent $a$ at time $t$ is calculated using Equation 3.1. Accordingly, the mismatch of a cluster $c$ (containing $N$ agents) at time $t$ is calculated using Equation 3.2. In this chapter, a positive mismatch denotes overproduction (surplus), while a negative mismatch represents underproduction (shortage of supply). Zero mismatch means that the cluster is in perfect balance. Surplus of electricity in a cluster is fed into the backbone grid, while lack of supply is covered by drawing the electricity from the main grid. Clusters can reconfigure based on changes in supply and demand, e.g. cluster composition can change every hour or every day, depending on the determined time period for which it is performed. Thus, the generated clusters are virtual groups of consumers, prosumers and producers, which are able to dynamically change their group composition according to changes in the (external) environment or their (internal) preferences.

$$agent\ mismatch = Supply_{(t)} - Demand_{(t)} \tag{3.1}$$

$$cluster\ mismatch(t) = \sum_{n=1}^{N} Supply_{(n,t)} - Demand_{(n,t)} \tag{3.2}$$

To join another cluster, the absolute mismatch between an agent and members of a cluster is calculated using Equation 3.3. For every sample at time $t$, supply and demand mismatch of all $N$ agents is calculated. Then, the absolute values of all the mismatches are summed to obtain the total absolute mismatch between $N$ agents. Absolute values are used so that the amount of overproduction or underproduction per hour is preserved. The agents join clusters that are closest to their profiles, i.e., with the minimum $absolute$ and $cluster\ mismatch$. This approach ensures that agents join the cluster that most closely matches their profiles.

**Algorithm 1** Decentralized supply and demand matching

```
procedure Refine clusters
    for all Clusters do
        C_N ← N best neighboring clusters
        for all C_N do
            Send membership offer O_n
        end for
        for all Clusters do
            if received offers ≥ 0 then
                O_b ← best offer
                if O_b mismatch < cluster mismatch then
                    Accept O_b
                end if
                Reject pending offers
                Send Accept/Reject to clusters
            end if
        end for
        for all Clusters do
            if accepted offers ≥ 0 then
                O_b ← best accepted offer
                Add the agent A(O_b) to the cluster
                Recalculate cluster mismatch
            end if
        end for
    end for
end procedure
```

$$absolute\ mismatch = \sum_{t=0}^{T} \left| \sum_{n=1}^{N} (Supply_{(n,t)} - Demand_{(n,t)}) \right| \tag{3.3}$$

This mechanism can be used to encourage demand to follow supply, since consumers can shift their load to join a cluster which meets their objective at a given time period. This is more realistic in a more dynamic scenario, where clustering is performed every 8 hours or on hourly basis.

Clustering in this way gives local empowerment to every agent, and allows flexibility in adapting to changes in supply and demand, without rerunning the process for the entire system. Thus, nodes entering or leaving the system can use the local view of the neighborhood to decide which cluster to join.

Currently, the same simple, local objective functions (per agent type) are used to form initial clusters. However, due to its configurability, different (individual) objective functions can be used per agent, allowing the objectives to include preferred type of electricity supply, cost functions, duration of service provisioning, or priority level as clustering criteria.

## 3.4 Experiments

This section studies the outputs of the proposed clustering mechanism by assessing supply and demand mismatches of generated clusters, as well as the number of clusters obtained. To demonstrate the ability of generated clusters to reconfigure based on changes in the environment (changes in supply and demand), time periods for which clustering is performed are varied, and static and dynamic clusters are compared.

### 3.4.1 Experiments assumptions

The daily load profile data used for the experiments is obtained from NEDU [119], the Dutch energy data exchange, and represents an average load profile of a Dutch household consumer. To diversify household profiles, the load profile data is varied for a sampling period applying a normal distribution, generating variations of maximum $\pm$20%. Prosumers with solar production are modeled. Solar power production of prosumers is calculated as in [120], using the Dutch solar irradiance data [121]. The data from July 1, 2015 is used in the experiments. To ensure that there is enough supply to meet the demand for a period of a day, diesel generators with capacities of 10 kW which run constantly for the period of a day, are modeled as production units. Clustering is performed for a maximum period of a day (24 hours). This work assumes that every agent has perfect information of their own demand and/or supply for the clustering period. Future work will explore how forecasting mechanisms can be used to deal with partial information about both energy demand and supply.

### 3.4.2 Key performance indicators (KPIs)

As the main objective of power systems is to match supply and demand of electricity [104], supply and demand mismatch is taken as the main clustering criteria, with the main objective being to minimize the mismatch within clusters.

The key performance indicators (KPIs) used for evaluation of obtained clusters are the following:

1. **Supply and demand mismatch of a cluster**: Total supply and demand mismatch of cluster members is calculated by summing up all the members' mismatches.

2. **Average supply and demand mismatch of all the clusters for a given period**: Supply and demand mismatches of all the clusters are summed at every hour, and an average is taken.

3. **Average negative supply and demand mismatch of all the clusters for a given period**: Supply and demand mismatches of all the clusters with negative mismatches are summed at every hour, and an average is taken.

### 3.4.3 Experimental setup

The experiments are run with 500 agents, each with full knowledge of its own production, consumption, and geographic location.

To ensure that there is enough total supply to meet the demand for a period of a day, experiments varying the percentage of consumer, prosumer, and producer agents are conducted. The system configuration which gives the average mismatch closest to zero is chosen.

The experiments use three case studies to assess the outcomes of the proposed clustering mechanism, namely: (i) daily clustering (static), (ii) clustering every 8 hours (dynamic), and (iii) hourly clustering (dynamic). In this work, dynamism refers to how frequently clusters reconfigure within the longest time period for which clustering is performed.

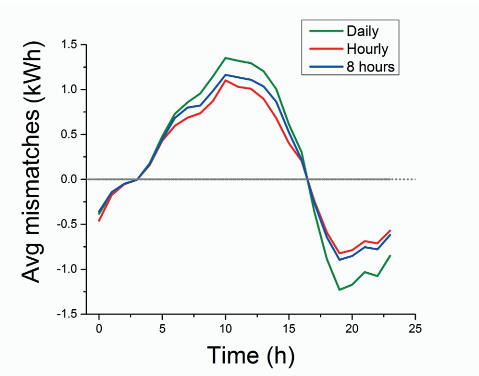
The first set of experiments observes the behavior of static clusters with the chosen system configuration in terms of mismatches and number of clusters obtained. Clustering is performed for a full-day period, where supply and demand of each agent for a period of 24 hours is aggregated. The percentage of prosumers is varied from 10% to 90%, while the percentage of producers (diesel generators) is varied from 0% to 4%.

The next set of experiments aims at observing the reconfiguration of clusters when adapting to changes in supply and demand. For this purpose, the original clustering timespan (full day) is divided into two sets of experiments, namely (i) 8 hours, where clusters are reconfigured every third of the day (8 hour period is chosen to reflect a typical household load profile), and (ii) 24 hours, where clusters are reconfigured every hour.

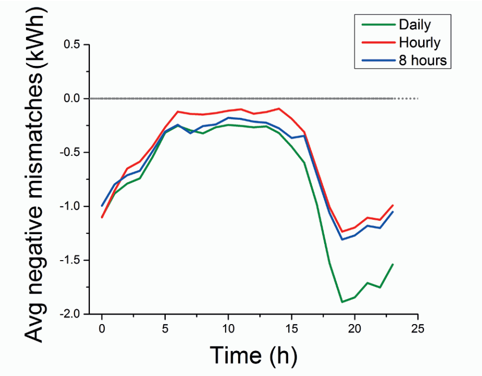
The comparison in outcomes of static (daily) and two types of dynamic clustering (8 hours and hourly) is made in terms of average mismatches, average negative mismatches, and number of clusters. Average negative mismatches served as the main means of comparison, as these indicate in which cases there is underproduction of electricity.

## 3.5 Results and discussion

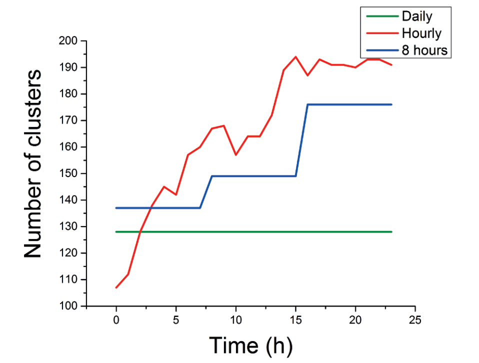
The obtained results indicate that self-organization based only on local information is feasible, and that using the proposed mechanisms, supply and demand can be to an extent locally satisfied. In terms of dynamism, static and dynamic clustering follow similar trends in terms of average mismatches (Fig. 3.2a), but differ significantly in terms of number of clusters generated (Fig. 3.2c). As seen in Fig. 3.2b, hourly clustering generates the overall



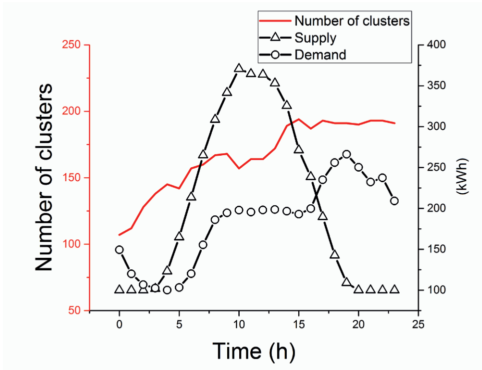

(a) Average mismatches




(b) Average negative mismatches




(c) Number of clusters




(d) Hourly clustering

Figure 3.2: A comparison of static (daily) and dynamic (every 8 hours and hourly) clustering (based on 100 algorithm runs)

lowest underproduction compared to both daily and clustering every 8 hours. This is due to the ability of clusters to rapidly adapt to sudden changes. Consequently, hourly clustering results in the highest level of fluctuations in terms of number and sizes of clusters. Thus, more dynamic clustering results in overall lower mismatches, but requires more frequent changes in number and sizes of clusters.

The results in Tables 3.1 and 3.2, as well as the figures Fig. 3.2a–d, are based on 100 algorithm runs. Tables 3.1 and 3.2 show the obtained clusters' parameters for static (daily) and dynamic (8 hours) clustering. As shown, static clusters generate an overall low average mismatch. Clustering every 8 hours shows average mismatches that follow the standard load and (solar) production profiles. In the first part of the day, there is enough supply to meet the low demand, while in the second part there is a high level of overproduction due to relatively low demand compared to high solar irradiation. However, in the last part of the day, when the demand increases, there is not enough supply to meet the demand, indicated by the negative average mismatch.

Fig. 3.2a compares average mismatches for three types of clustering, namely (i) daily,

| Time period | Average mismatch (kWh) | Number of clusters | Average cluster size | Smallest cluster size | Largest cluster size |
|---|---|---|---|---|---|
| 0-24 | 4.25 | 128 | 3 | 2 | 56 |

Table 3.1: Static daily clustering (based on 100 algorithm runs)

| Time period | Average mismatch (kWh) | Number of clusters | Average cluster size | Smallest cluster size | Largest cluster size |
|---|---|---|---|---|---|
| 0-8 | 1.54 | 137 | 3 | 2 | 35 |
| 8-16 | 7.64 | 149 | 3 | 2 | 33 |
| 16-24 | -4.58 | 176 | 2 | 2 | 34 |

Table 3.2: Dynamic clustering every 8 hours (based on 100 algorithm runs)

(ii) hourly, and (iii) every 8 hours, while Fig. 3.2b compares average underproduction at every hour. Both figures indicate that static clustering generates clusters with overall highest mismatches and most underproduction at every hour of the day, compared to those in dynamic clustering. This is due to more flexibility to adapt to sudden changes in supply and demand. Even though both types of dynamic follow similar trends, hourly clustering generates overall less underproduction. Fig. 3.2c shows how the number of clusters changes rapidly when the granularity of the period for which the clustering is performed is increased. As indicated by the graphs, the more dynamic clustering mechanism, the higher the number of clusters and its variation.

Fig. 3.2d shows the relation between total supply, total demand, and generated number of clusters for hourly clustering. When both supply and demand are low, the number of clusters is relatively low. As the demand increases, the number of clusters increases. This is the most evident when the supply starts decreasing in the last part of the day, indicating that the agents organize in smaller groups to try to compensate for the lack of supply. Since the prosumers do not generate enough electricity in this period, there are fewer rounds of cluster merging.

## 3.6 Conclusions

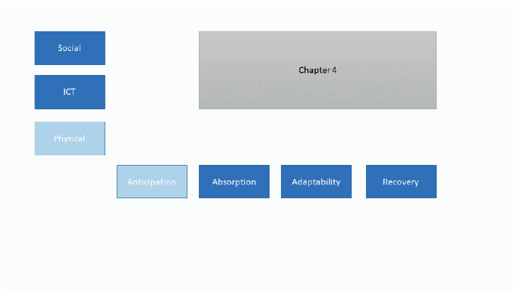
This chapter proposes mechanisms for decentralization of supply and demand matching by letting consumers, prosumers and producers organize themselves into clusters that locally match electricity. The main motivation is twofold, namely (i) to demonstrate that supply and demand matching can be decentralized when only local information is available, and (ii) to assess the outcomes of static and dynamic clustering. The results show that the techniques developed can provide mechanisms for enabling self-organization based on local information. In terms of dynamism, the results show that the more dynamic clustering methods produce overall better clusters with lower negative mismatches. However, more dynamism means more communication, frequent reconfiguration and changes in cluster sizes and numbers. Thus, there is a tradeoff between overall reduction of mismatches and the burden on the infrastructure itself. The developed mechanisms can be used to decide where to place alternative sources of power generation, storage units, or to decide when to turn the generators on.

Besides the aforementioned extension of the model with supply and demand forecasting techniques, other extensions left for future work are to explore the effect of storage on the formation of clusters and to explore the potential of the proposed mechanisms as a means of achieving a more reliable energy supply and a more resilient power system. The main idea here is to let consumers, prosumers and producers in an area affected by a power outage, temporarily organize themselves in (dynamic) clusters that distribute available supply to preferred consumers.

# 4

# Self-determined distribution of local energy resources for ensuring power supply during outages






*Ensuring access to reliable and sustainable electrical power supply is becoming more and more challenging due to a combination of factors such as more frequent power grid outages caused by extreme weather events, the large-scale introduction of renewable energy resources that increases the complexity of the power system, but also aging infrastructure, supply and demand imbalance and power theft in some areas. Combined, all these factors can cause outages and together they can make electricity supply unreliable. The implications of this are many, ranging from minor inconveniences to major failures of critical infrastructures. A potential solution to ensure electricity supply during outages is to use local generation in the form of renewable resources to supply energy. This chapter proposes a community-based mechanism that demonstrates that when community members can determine for themselves how excess energy generation is distributed, the electricity supply of specific members can be ensured.*

Chapter 4 is published in *Energy Informatics* journal [31].

*Self-determination is achieved by prioritizing and differentiating between community members as well as automatically and continuously redistributing energy, thereby adapting to sudden changes in supply and demand. Simulation results show that the proposed mechanism can be used to empower local communities to decide for themselves how local resources are distributed during events such as outages, ensuring prolonged electricity supply for differentiated members of affected communities. Harnessing the potential of renewable resources and smart technologies for intelligent coordination through empowerment of consumers to become pro-active participants is a promising solution for the future power systems.*

## 4.1 Introduction

4

Power outages present a challenge for current and future power systems. Such outages can be caused by a number of factors including the increasing frequency and severity of extreme weather events due to climate change, infrastructure failures and aging power plants that require frequent maintenance, but also supply and demand imbalance. Power outages adversely impact people and other infrastructures that rely on electricity. The negative social impact of outages can be very severe, ranging from inconveniences to normal daily operations to failures of critical infrastructures such as drinking water and communication systems [42]. This challenge is further amplified by the rapid introduction of renewable energy resources. As these renewables are volatile & non-dispatchable, they add uncertainty to and increase the complexity of an already highly complex power system.

At the same time, renewable resources owned by local communities provide a potential to ensure reliable electricity supply when the backbone grid is unavailable [122, 123]. Decentralization of energy systems through such smaller-scale initiatives that rely on local resources is a promising approach for the future of smart grids [107, 124]. Existing solutions that deal with decentralization of power systems are associated with concepts such as microgrids and virtual power plants (VPPs), that aim to enable easier integration of distributed renewable resources and to empower consumers and prosumers [105, 106]. VPPs are typically virtual groups of several types of energy resources for which the main motivation for grouping is usually shared access to an energy market for economic reasons [106]. As such, their purpose is not to operate independently during outages. In contrast, microgrids are subsets of power systems that are planned to operate both in parallel with the main grid and independent of it in an *islanded* mode when needed. To enable this type of independent operation, they require sophisticated physical infrastructure and are as such tied to specific geographic locations [106, 107]. During outages a microgrid can be decoupled from the main grid and run in a stand-alone islanded mode which ensures continuous electricity supply within the microgrid. In principal, the rest of the power grid does not benefit from this behavior. The members of a microgrid agree to the terms and conditions of membership, and together form the ownership structure of a microgrid. Real-time adaptation of a membership is not common, if not impossible. This poses a constraint in case of unexpected events such as outages, where changes in supply and demand can vary in near real-time and mechanisms for dynamic supply and demand matching in changing groups of consumers and prosumers might be required [43]. During outages, multiple isolated microgrids can be connected to form a networked microgrid cluster and gain additional flexibility in outage response [53]. To harness the potential of multiple microgrids while still preserving their autonomy, a hierarchical outage management scheme (OMS) is proposed in [54] to enhance resilience of distribution systems during outages.

Community microgrids such as those in Japan [55], supported by Japan's "National Resilience Program", and Brooklyn [125], are a move towards more self-reliant, resilient power systems that ensure long-term, locally generated electricity supply within a community. To fully use the potential of these microgrids, active participation of all stakeholders from local communities is needed [42, 126].

Even though microgrids can deal with uncontrollable disturbances in an islanded mode, they can collapse under extreme, high impact events, such as floods, earthquakes etc. To be able to account for this type of events, a reliability and resilience framework can be applied, so that a microgrid can withstand social, technical, economic, or natural hazards without losing its functionality. A potential solution to quickly recover is by prioritizing which loads to connect if full recovery is not possible due to infrastructure damage [42]. Increasing self-sustainability of microgrids through load prioritization is considered in [127], where multi-agent systems (MAS) are used to represent members of a microgrid as intelligent agents that operate autonomously to achieve local goals. In this chapter, prioritization is performed on the level of consumers that prioritize their own controllable loads by applying shedding and re-scheduling procedures [127]. Consumer prioritization with the purpose of consumer-centric energy management is proposed in [128].



Load prioritization is routinely used for load shedding, curtailment, system restoration and microgrid management [103, 129, 130]. Different types of loads are considered, such as critical and controllable loads [131]. With respect to outage management, when restoring loads, utilities currently prioritize them based on their importance for general concepts such as public safety and health. However, this process is static and does not take into account neither real-time conditions of an outage, nor the specifics of a community an outage occurs in [41]. To bring in the societal perspective with respect to load prioritization during outages, systems such as Styrel in Sweden have been introduced, where consumers are categorized into pre-defined categories and assigned classes and points, based on which electricity distribution is performed during a power shortage [132, 133]. However, this type of prioritization still does not include active participation of communities affected by outages that can be empowered to make local decisions regarding their energy resources. Thus, different prioritization schemes are needed to reflect local needs of an affected community and real-time conditions of a specific outage [41].

Methodologies for active engagement of communities in the introduction and management of local energy resources facilitate sustainable resource management in future power systems [134–140]. Energy communities can potentially play an important role in facilitating energy interventions, because they enhance trust relationships, support behavioral changes and encourage other local benefits, such as lower energy bills, new local jobs, increase in the sense of ownership, but also reduction of carbon emissions [44, 141]. As traditional, centralized power systems transform into more decentralized, prosumers and consumers acquire a more active role in decision making on the local level [127, 142]. Such active engagement of local communities increases social acceptance [42] and can significantly enhance the reliability of electricity supply [128].

To address the challenges related to intelligent coordination of an increased number of local renewable resources and empower consumers to become pro-active participants of the future energy systems, new paradigms for power system coordination and planning will be needed [122, 123]. A potential solution that ensures (partial) continuation of electricity supply during outages for communities in frequently affected areas, is to rely on locally generated supply in the form of renewables. To this purpose communities need to agree to share energy, as an energy community. As such, they can use local resources to their full capacity, and collectively decide how to distribute energy locally.

This chapter bridges the concepts of local engagement from energy communities with features such as islanding from existing decentralization mechanisms (microgrids), and builds upon them to ensure prolonged electricity supply in areas frequently affected by outages. The concepts are further extended by allowing communities to dynamically adapt to changes in their environment. This chapter assumes that although a limited number of local renewable resources is available, they will not always be sufficient to meet the demand of all community members affected by an outage. Due to scarcity of available resources, a decision on how to distribute these resources has to be made. In contrast to existing outage management techniques where loads are prioritized before an outage occurs by a central authority, this chapter brings in the community perspective by letting members of communities prioritize consumers and prosumers themselves and, using that prioritization, distribute local resources in a fully decentralized manner. For this purpose, this chapter proposes a mechanism that supports communities affected by an outage to determine for themselves (*self-determine*) how local energy resources are distributed. It does so by differentiating between consumers and prosumers in the area. For example, a community can decide that schools should have electricity during an outage, making the school a primary destination for locally produced electricity. Or a community can decide to allocate local energy resources to a sports field if an outage occurs during a match. In both cases social arguments are the basis for such decisions.

The main contribution of this chapter is twofold. One, it demonstrates that by empowering members of communities to decide for themselves how local resources are distributed during an outage, the duration of electricity supply can be prolonged for specific members of affected communities; and two, it proposes and develops a fully decentralized mechanism serving as an ICT platform for energy sharing in communities frequently affected by outages.

The rest of the chapter is organized as follows: Section 4.2 describes the concepts of the proposed mechanism, Section 4.2.3 describes the system, assumptions and the mechanism's algorithm in detail, and Section 4.3 describes the experiments conducted, as well as the key performance indicators used to assess the mechanism outputs and the experimental setup used. Section 4.4 presents the results, while Section 4.5 discusses potential applications, as well as the limitations of the proposed mechanism with respect to the assumptions made. Finally, Section 4.6 concludes the chapter.

## 4.2 Self-determined distribution of local resources

This section describes the main concepts of the proposed mechanism for self-determined distribution of local energy resources during outages, based on differentiation. As stated in Section 4.1, the main objective of this chapter is to demonstrate that by letting communities decide for themselves how local resources are distributed during an outage, the duration of electricity supply can be prolonged for specific members of affected communities.

This objective is achieved by first demonstrating that supply and demand can be matched based on locally available information only, using a *dynamic clustering* sub-mechanism, and then by including *prioritization* as a means to differentiate between different consumers and prosumers. These two sub-mechanisms are used to form self-organized local energy communities that are self-sustainable during outages. Subsections 4.2.1 and 4.2.2 explain the two sub-mechanisms in detail, respectively.

### 4.2.1 Dynamic clustering

This chapter builds upon the mechanism proposed in [30] that enables decentralized supply and demand balancing in energy systems. Consumers, prosumers and producers of electricity rely on local knowledge of their production and/or demand to organize themselves (*self-organize*) into small-scale local energy communities (*clusters*) that locally match supply and demand [7–9, 69]. The main objective of clusters is to minimize the supply and demand mismatch within the cluster. Clusters act as autonomous groups that enable energy sharing of local resources. They can dynamically reconfigure by changing their composition to adapt to changes in the (external) environment or their (internal) preferences [30]. This subsection briefly describes the previously proposed mechanism.

4

Distributed multi-agent systems (MAS) are used to represent cluster members (e.g. households, schools and supermarkets) as intelligent agents. A dedicated simulation tool developed in the Java programming language is used to setup multi-agents and conduct experiments. The tool implements basic agent behavior and enables asynchronous message exchange and processing. The agents have perfect knowledge of their supply and/or demand, and can communicate with each other, exchanging information about their location, and load and production profiles. Using a distributed information exchange algorithm (gossiping), agents build their own local view of the neighborhood. A distributed approach reduces the risk of single point failure in the network, and can be applied to a variety of scenarios where full knowledge of the system is unavailable. After building their own local views, agents send cluster membership offers to neighboring agents that *best* match their load and/or production profile. As the main objective of power systems is to match supply and demand of electricity [104], the best match is that which minimizes the mismatch. The mismatch between an agent and a cluster at time $t$ is calculated using Equation 4.1 for the entire period for which clustering is performed. Contrary to the previously published work in [30], the optimization function for calculating the mismatch is adapted in this chapter. The best match is found using Equation 4.2. For the clustering period, the number of hours with zero mismatch ($Z_h$), negative mismatch/underproduction ($UP_h$), and positive mismatch/overproduction ($OP_h$) is counted, and the total amount of underproduction ($UP_{amt}$) and overproduction ($OP_{amt}$) is calculated. Weights are assigned to every parameter ($\omega_{zh}$, $\omega_{UPh}$, $\omega_{UPamt}$, $\omega_{OPh}$, and $\omega_{OPamt}$).

$$mismatch(a,c)_t = Supply(a,c)_t - Demand(a,c)_t \tag{4.1}$$

$$\begin{aligned} min\frac{1}{\omega_{zh}\,Z_h}(&\omega_{UPh} * UP_h + \omega_{UPamt} * UP_{amt} + \\ &\omega_{OPh} * OP_h + \omega_{OPamt} * OP_{amt}) \end{aligned} \tag{4.2}$$

where,

$$\omega_{zh} \gg \omega_{UPh} \gg \omega_{UPamt} \gg \omega_{OPh} \gg \omega_{OPamt} \tag{4.3}$$

To join a cluster, agents negotiate cluster membership, and this negotiation results in service level agreements (SLAs). SLAs are used as a means of fixing cluster composition, specifying the terms of electricity provisioning [83, 143] and committing agents to those terms. Clusters are either fixed for a relatively long period of time, or dynamically reconfigure to respond to changes in supply and demand of the agents.

### 4.2.2 Prioritization



This chapter introduces the concept of consumer and prosumer differentiation based on community preferences. To enable differentiation of consumers and prosumers, local communities agree on the levels of supply priority (*high*, *medium*, or *low*) and pre-assign them to consumers and prosumers, before an outage occurs. These priorities indicate, for example, the social importance of a consumer or prosumer. Some priorities may be fixed, such as, for example, high priority for a school or a supermarket, while other priorities can change depending on the specific situation. The mechanism through which this differentiation is performed is referred to as prioritization. Prioritization aims to ensure that electricity is supplied to the highest priority consumers and prosumers first, if there is enough supply to meet their demand. The remaining electricity is then distributed to those with lower priority.

The prioritization mechanism is used to allow local communities to assign levels of supply priority to individual consumers and prosumers, and to decide for themselves how locally available renewable resources are distributed, so that prolonged electricity supply during outages is ensured. In the rest of this chapter, prolonged electricity supply during outages is referred to as *reliable electricity supply*.

Supply reliability depends on the amount of *leftover supply* in the system. Leftover supply is energy supply that is left after all of the prosumers have consumed the energy they have produced to meet their own demand. It also includes any other renewable production that is not generated by prosumers, such as independent wind turbine generation. Thus, leftover supply depends on the type of renewable resources in the system (e.g., if only solar is available, there is no production during the evening, or during cloudy periods). Each level of priority requires to be supplied for a *minimum number of hours of leftover supply*. For example, if the system total leftover supply is 10 hours, the highest priorities can be supplied for a minimum of e.g. 7 hours. This parameter is reconfigurable and can be changed at any time. It can be different for every priority (e.g. higher priorities can require more hours of supply, while the lower ones can settle for fewer), or even different for every agent. The required minimum number of hours of leftover supply is crucial for assessing supply reliability for every priority. If an agent is supplied for a minimum number of hours required by its priority, the agent is said to have reliable supply during the outage period.

### 4.2.3 System setup

This section describes the system used for implementation of the proposed mechanism, including the main assumptions on which it is based. Furthermore, a detailed algorithmic

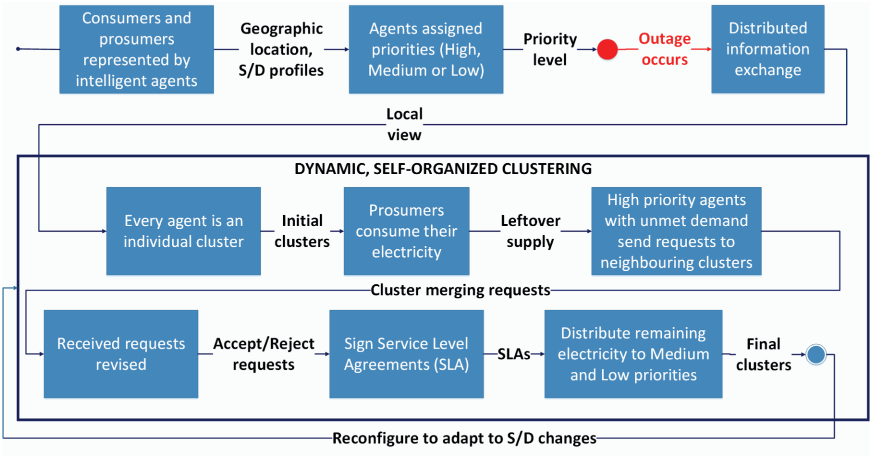



Figure 4.1: Dynamic, priority-based clustering mechanism

description of the mechanism is given.

### 4.2.4 System assumptions

This chapter considers areas that are frequently affected by planned and unplanned outages, and have high, but limited penetration of distributed renewable resources, locally owned by members of affected communities. It is assumed that no non-renewable production such as that of diesel generators is available. In terms of sustainability, two types of community members are distinguished: *self-sufficient* and *non-self-sufficient* members. Self-sufficient members are those who can sustain themselves with their own resources for at least an hour during an outage. Consequently, non-self-sufficient members are those who do not have any production of their own, or not enough to meet their own demand. During an outage, prosumers first meet their own demand using their own generated supply. Then, supply that is left is distributed to the highest priorities first using the proposed mechanism. The term "priorities" in this context refers to all the consumers and prosumers of the same priority. This resource distribution approach results in formation of clusters, that dynamically reconfigure to adapt to changes in their environment and have as a purpose reliable supply provisioning and maximization of self-sufficiency.

This chapter assumes that communities themselves pre-determine the priorities. Negotiation mechanisms for assigning priorities are outside the scope of this chapter. Assuming that there are fewer consumers and prosumers who should have the highest priority, compared to the medium and low priorities, priorities are assigned randomly in such a way that there is a higher probability that an agent is low or medium priority, compared to the high priority.

The proposed clustering mechanism abstracts from the physical layer of power systems. This chapter assumes that there is a physical infrastructure that connects all consumers, prosumers and resources in an area affected by an outage, so that electricity can be distributed from any one point to another. Additionally, this chapter assumes that the infrastructure enables "closing" and "opening" of connections between consumers, prosumers and available resources, so that electricity can be distributed to selected consumers and prosumers. Clustering creates clusters for which the topology is not fixed nor restricted by geographic location, and relies on existing communication infrastructure to exchange information between agents to create the grouping. This chapter assumes that agents have perfect knowledge of their supply and/or demand profiles for the duration of clustering period.

Finally, this chapter assumes that the area for which clustering is performed is part of a single distribution system that is affected by a planned or an unplanned outage. Consequently, there is no electricity supply from the backbone grid.

### 4.2.5 Algorithm details



As shown in Fig. 4.1, at the beginning, every consumer, prosumer and producer (e.g. a wind turbine) is represented by an intelligent agent (a piece of software) that has perfect knowledge of its load and/or production profile and geographic information. Thus, a consumer is represented by a consumer agent *(CA)*, a prosumer by a prosumer agent *(PSA)*, and a producer by a *producer agent (PDA)*. Additionally, CAs and PSAs are assigned a supply priority level, based on which, the decision of electricity distribution is made. PDAs do not have a priority level, as they only supply electricity. When an outage occurs, agents exchange information on their geographic location to build a local view of the neighborhood. Information exchange is performed using a distributed information exchange algorithm (gossiping), where every agent in the system is connected to every other agent, directly or via other agents [117, 118]. After building the local view of a neighborhood (which depends on the neighborhood size), the dynamic clustering phase begins. This phase is executed for every time period for which clustering is performed (e.g. every hour or every day). Initially, each agent is a cluster on its own.

During an outage, each PSA first meets its own demand with the generated supply from, for example, solar panels. PSAs that have supply left after meeting their own demand can now distribute it to selected CAs and PSAs in their neighborhood whose supply is not met. Next, the dynamic distribution of resources begins. All agents with high priority whose supply is not met send requests to neighboring clusters that best match their profile. Recall from Subsection 4.2.1 that the best match is the one that generates the minimum mismatch, and is found using Equation 4.2. After all requests are sent, clusters that have received membership requests revise them. If a cluster contains any agents with high priority, it accepts the request only if accepting it does not result in underproduction. If all agents are of lower priorities, a request with the best match is accepted. After acceptance, agents sign SLAs with clusters. SLAs contain information about a cluster membership request, and information about a cluster topology including: a list of cluster members, their load and production profiles, levels of supply priority and the minimum number of hours for which they would like to be supplied. Thus, SLAs are used as a means to fix cluster boundaries and ensure supply reliability. If at the end of this stage there is still supply left, the same procedure is repeated for medium and then low priorities. In the end, final clusters are formed and fixed for the clustering period. During the next clustering period, clusters dynamically reconfigure to adapt to changes in the environment (changes in supply and demand or in priorities).

## 4.3 Experiments

This section describes the experiments conducted to study the output of the proposed clustering mechanism. To achieve the main objective of this chapter, the two sub-mechanisms described in Subsections 4.2.1 and 4.2.2 are used, and experiments are conducted accordingly (1) to explore if supply and demand can be matched in a decentralized way by studying supply and demand mismatch in the system and observing the effects of static vs. dynamic clustering, and (2) to explore how prioritization can be used to ensure prolonged electricity supply during outages. Subsection 4.3.1 describes the experimental setup, while Subsections 4.3.2 and 4.3.3 describe both experiments, respectively.

Note that the aim of the experiments is not to do an exhaustive investigation of the feasibility of the proposed mechanism under various circumstances. The large uncertainty in, for example, power generation, energy demand, seasonal variations or the frequency of outages, prohibits this. It would be possible to do such an analysis for a specific location and time frame, provided that both generation and demand profiles are available, however this is outside the scope of the current chapter. The main motivation for the experiments conducted here is to demonstrate that, under specific conditions, given adequate resources in an affected community, there is a working mechanism that can be used by the communities to ensure supply reliability by deciding how to share available resources.



### 4.3.1 Experimental setup

The experiments are run with 500 agents, and consider two different renewable resources: rooftop solar and wind production. The neighborhood size for the distributed information exchange algorithm is set to 40%, meaning that every agent can form clusters with maximum 40% of the agents in the system. Out of 500 agents, 2.8% are high, 33.8% are medium, and 63.4% are low priority.

For illustration purposes and due to data availability, the data from the Netherlands is used to model load and production profiles. The daily load profile data is obtained from NEDU [119], the Dutch Energy Data Exchange, and represents an average load profile of a household consumer. To add diversity in household profiles, the load profile data from [119] is varied by maximum ±20% for every consumer modeled. The data from July 1, 2015 is used in the experiments, as a representative day with high solar production to demonstrate the potential of the mechanism, given enough resources [30]. It should be noted that the mechanism would not work on a cloudy, windless day, provided only solar and wind generation is available.

Experiments are first run with rooftop solar production only, where 40% of agents are prosumers with solar panels and 60% are consumers. Solar production is chosen as the only resource in this setup to demonstrate the output of the clustering mechanism in a dynamic environment, where electricity is not available during the night. Residential solar panels with standard dimensions of 1.651 $m$ x 0.99 $m$ [144] (total area of 1.63 $m^2$) are modeled. According to [145], average rooftop area available for installing solar panels per Dutch household is ≈33 $m^2$, which amounts to maximum 20 residential solar panels for 100% rooftop usage. However, to account for different orientation of rooftops, only 30%-60% rooftop area is used. This means that prosumers are modeled with a minimum of 6 and a maximum of 12 solar panels per household.

Solar production is calculated as in [120], using the Dutch solar irradiance data [121].

The load and production profiles for this setup are shown in Fig. 4.2. The ratio between self-sufficient and non-self-sufficient agents is shown in Fig. 4.3. The Fig. 4.3a shows the ratio in percentages, while Fig. 4.3b show the absolute values.

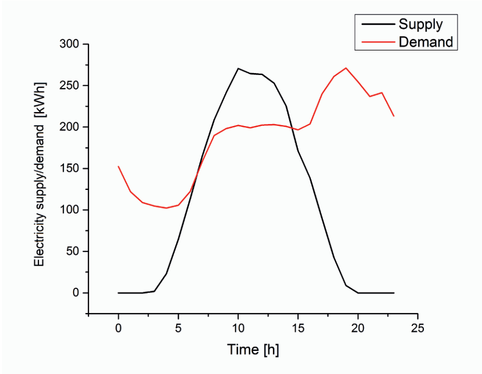



Figure 4.2: Aggregate load and production profiles - rooftop solar production only

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To diversify the available resources, wind production is added, where a community- or intermediate-size 500 kW turbine is modeled [146]. 500 agents are modeled, of which 40% are prosumers with solar panels, 0.2% wind turbines (thus, 1 wind turbine), and 59.8% consumers. In the rest of this chapter, the wind turbine is referred to as a *producer*. Wind production is calculated as in [120], using Dutch wind speed, temperature, and air pressure data [121]. The load and production profiles for this setup are shown in Fig. 4.4.

It is important to note that all parameters set for the experiments are the best estimate for a given case scenario, as no data on a real case scenario is available. The proposed mechanism, as well as the experimental parameters observed, can serve as a starting point to address future challenges in such areas. However, thorough analysis of potential parameter settings in an area observed should be performed, and decisions should be made accordingly.

### 4.3.2 Experiment set 1: Static vs. dynamic clustering

To explore if supply and demand can be matched in a decentralized way with the same level of performance (minimum supply/demand mismatches) of a centralized system, and to observe the effects of changing the frequency of clustering reconfiguration, three clustering scenarios are used, namely: (a) daily clustering (static), (b) clustering every 8 hours (dynamic), and (c) hourly clustering (dynamic). In (a), clusters are formed and fixed for a period of 24 hours, based on 24-hour perfect forecast of agents' load and production profiles. In (b), clusters reconfigure every 8 hours, reflecting changes in the standard load profile of households. The most dynamic reconfiguration scenario is (c), where clusters reconfigure every hour to respond to changes in the environment. All three cases are compared to the centralized case, where no decentralized matching is performed and all agents are part of one big cluster. The centralized case is taken as the theoretical (and currently practical) best solution in terms of supply and demand balancing. Thus, the motivation is

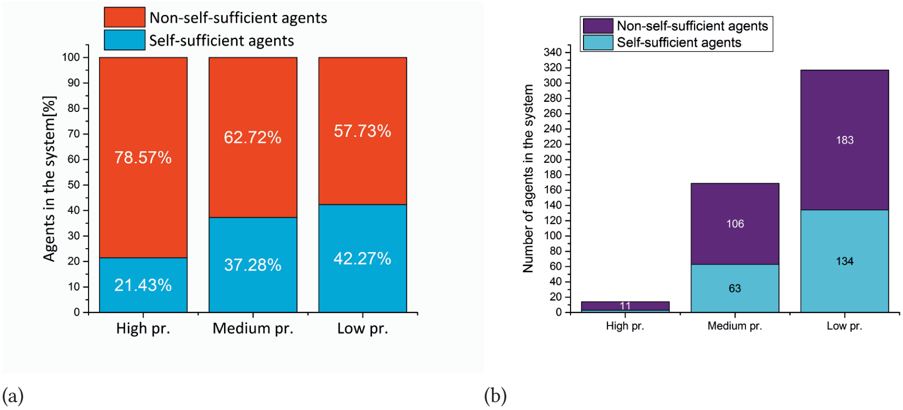



Figure 4.3: Self-sufficient and non-self-sufficient agents in the system in (a) percentages and (b) absolute numbers

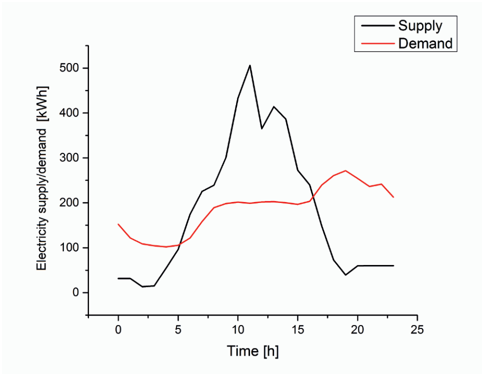



Figure 4.4: Aggregate load and production profiles - wind and rooftop solar production

not to perform better than the centralized system, but to have a decentralized system that can operate almost as well as the centralized, giving control to individual agents.

For the purpose of these experiments, all agents are assumed to be part of a single distribution system. In this case, the distribution system considered is not affected by an outage. Consequently, there is no differentiation between consumers and prosumers. In these experiments, only rooftop solar production is considered as a locally available renewable resource. When there is surplus of electricity, it is fed into the backbone grid, while lack of supply is met by drawing electricity from the main grid.

The experiments are assessed using the following key performance indicators (KPIs):

1. Total overproduction (TOP) - this KPI looks at clusters that have more supply than needed, and calculates how much overproduction they generate in total (per hour)

2. Total underproduction (TUP) - this KPI looks at clusters that do not have enough supply, and calculates how much underproduction they generate in total (per hour)

| Experiment set | Purpose | Experiment case study | Input | Output | Local renewable production | KPI | Objective |
|---|---|---|---|---|---|---|---|
| | | Daily | 24-hour load and production profiles | | | | |
| Static vs. dynamic | Match supply and demand in a decentralized way | 8 hours | 8-hour load and production profiles | Clusters' mismatch | Rooftop solar | Total overproduction (TOP), Total underproduction (TUP), TOP DEV, TUP DEV | Minimize TOP, TUP, TOP DEV and TUP DEV |
| | | Hourly | Hourly load and production profiles | | | | |



Table 4.1: Overview of static vs. dynamic experiments

3. TOP deviation from centralized system (TOP DEV) - this KPI calculates how much the proposed clustering mechanism deviates from the centralized system in terms of total overproduction

4. TUP deviation from centralized system (TUP DEV) - this KPI calculates how much the proposed clustering mechanism deviates from the centralized system in terms of total underproduction

The main motivation is to minimize these KPIs for each clustering type (daily, 8 hours and hourly). Table 4.1 gives an overview of all of the experiments conducted for dynamic vs. static clustering, as well as their setup.

### 4.3.3 Experiment set 2: Prioritization and reliability assessment

To explore how differentiation of consumers and prosumers using prioritization can ensure supply reliability for communities in areas affected by outages, priorities are assigned, and clustering is performed using the best-performing clustering scenario from Subsection 4.3.2. In this experiment, the distribution system is considered to be affected by an outage, thus, there is no supply from the backbone grid.

Supply reliability is assessed with respect to the minimum required number of hours of supply. Three different case scenarios are considered:

1. In the first scenario, the priority level does not matter for the assessment of reliability. In this case, all agents with high, medium and low priorities need to be supplied during all, i.e. 100%, of the hours with leftover supply in the system. This is an extreme case when no importance is given to the level of priority in terms of choosing reliability parameters, and no pre-assessment on leftover supply and the demand of agents is made. It can be seen as greediness of agents that are not willing to compromise and adjust to an outage situation.

2. In the second scenario, the priority level still does not matter for the assessment of reliability, but the minimum required hours of supply is set to a lower number.

<table>
<tr><th>Experiment set</th><th>Purpose</th><th>Experiment case study</th><th>Input</th><th>Output</th><th>Local renewable production</th><th>KPI</th><th>Objective</th></tr>
<tr><td rowspan="3">Prioritization and reliability assessment</td><td rowspan="3">Explore how prioritization can ensure supply reliability for selected consumers and prosumers during outages</td><td>All priorities require 100% of hours of available supply</td><td rowspan="3">Hourly load and production profiles, Priority level, Minimum number of hours of supply required</td><td rowspan="3">Clusters with 100% self-sufficiency (hourly)</td><td>Rooftop solar</td><td rowspan="3">Required supply reliability (RSR), Self-sufficiency of clusters (SSC)</td><td rowspan="3">Maximize RSR and SSC</td></tr>
<tr><td>All priorities require 90% of hours of available supply</td><td>Rooftop solar</td></tr>
<tr><td>High priorities require 90%, medium require 50%, and low require 30% of hours of available supply</td><td>Rooftop solar, Wind and rooftop solar</td></tr>
</table>

Table 4.2: Overview of prioritization and reliability assessment experiments

Now, all priorities need to be supplied during 90% of the hours with leftover supply. This minimum is set by the high priority agents, but since no difference is made between priorities in terms of parameter settings, other priorities require the same. In contrast with the previous case scenario, high priorities are willing to compromise and lower their requirement, since there might not be enough leftover supply for them all.

3. In the last scenario, a difference in terms of required number of hours of supply is made based on priority levels. Each level of priority needs to be supplied for a different minimum percentage of hours of leftover supply, with minimum set to: 90% for high, 50% for medium, and 30% for low priorities. These numbers are chosen as the best estimate for different levels of supply priority and the system considered. The values can be set according to leftover supply in the system for every hour, and the demand of each of the priority level at those hours.

The three case scenarios are firstly run with only solar rooftop production as a locally available renewable resource. To diversify local production, and explore the effects of different renewable resources in the area, the third case scenario (with a difference between supply priority levels in terms of reliability requirement) is then run with both local solar and wind generation.

All the experiments are assessed using the following KPIs:

1. Required supply reliability (RSR) - For each priority, the percentage of agents that meet the minimum required number of hours of supply. Agents do not require con-

tinuous supply, so the number of hours supplied is counted over the entire outage period, with or without hourly interruptions. This number denotes the *number of hours supplied during an outage*. It is compared to the minimum required by the level or priority, and the percentage of agents that met this minimum is calculated.

2. Self-sufficiency of clusters (SSC) - For each priority, the percentage of agents that are in 100% *self-sufficient* clusters. Self-sufficient clusters are those that have enough local resources to meet the demand of its members.

The main objective is to maximize these KPIs, in particular for high priority agents. Table 4.2 gives an overview of all of the experiments conducted for prioritization and reliability assessment, as well as their setup.

4

## 4.4 Results

This section presents the results obtained in the two main sets of experiments. First, a comparison is made between static and two types of dynamic clustering with the centralized approach in terms of total underproduction and overproduction. Then, the mechanism that performs the closest to the centralized approach is taken as the best-performing, and is used in further experiments with prioritization to assess supply reliability during an outage. The following two Subsections discuss the results in detail.

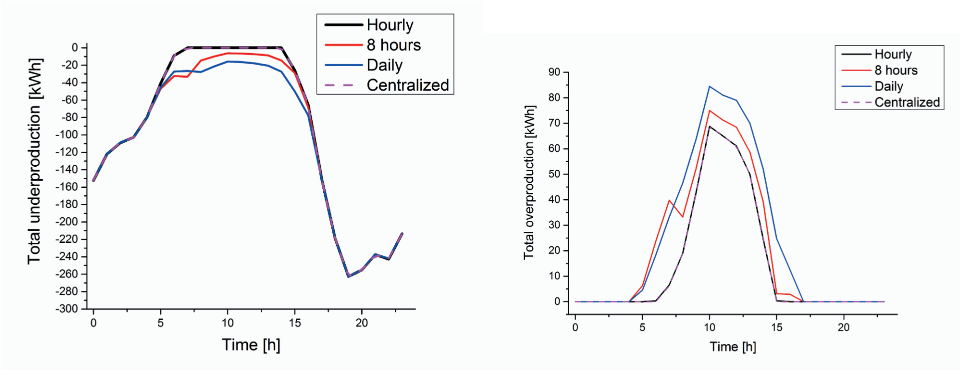
### 4.4.1 Experiment set 1: Static vs. dynamic clustering

| Clustering type | Underproduction deviation from centralized | Overproduction deviation from centralized |
|---|---|---|
| Hourly | 0.06% | 0.29% |
| 8 hours | 5.97% | 40.45% |
| Daily | 10.19% | 68.95% |

Table 4.3: Clustering type deviation from centralized system

The results in this section present the ability of agents to match their supply and demand in a decentralized fashion based on local information only. Each of the case scenarios for static vs. dynamic clustering (see Subsection 4.3.2) is considered in terms of total overproduction and total underproduction.

As shown in Fig. 4.5a and 4.5b, clustering every hour generates clusters that have overall lowest total underproduction and overproduction, and the system operates almost the same as the centralized system. Daily clustering and clustering every 8 hours both follow a similar trend, but with more overproduction and underproduction compared to hourly clustering. Table 4.3 shows deviations of each of the clustering types from the centralized system. The results show that the more dynamic adaptation scenarios perform better in terms of supply and demand matching, but require more frequent reconfiguration and changes in cluster topology. Thus, for the purpose of further experiments, hourly clustering type is used.




(a) (b)



Figure 4.5: Comparison of clustering mechanisms in terms of (a) total underproduction and (b) total overproduction

### 4.4.2 Experiment set 2: Prioritization and reliability assessment

The results in this section present reliability assessment of non-self-sufficient agents only, i.e. those agents that do not have any or enough production of their own to meet their demand (see Subsection 4.2.2). The reason for this is that the self-sufficient agents already have enough electricity available to meet their demand, and the proposed mechanism does not impact their supply reliability.

Fig. 4.6 shows the difference between the total supply in the system (indicated by the dashed line) and the supply that is left for other consumers and prosumers, once the self-sufficient prosumers meet their own demand (indicated by the gray line). These results include rooftop solar production from prosumers only. The leftover supply is distributed to non-self-sufficient consumers and prosumers that are in the local neighborhood view of self-sufficient prosumers. This means that even after the distribution of resources, there might still be agents with unmet demand and those with (over)supply. However, their supply and demand cannot be matched because they are not in the local neighborhood of each other (i.e. they do not see each other). As can be seen, supply from self-sufficient agents is available in the system from hours 5 to 17 (inclusive), meaning that non-self-sufficient agents can receive electricity for 13 hours. However, there might not be enough electricity for all of the agents that need it, or electricity that is available might not be enough to meet the demand of any of the non-self-sufficient agents.

As stated in Subsection 4.3.3, three separate case scenarios are run to observe the effect of changing the minimum required number of hours of supply on reliability assessment. The results obtained in each of the scenarios are presented in the rest of the section.

In the first case scenario, all priorities are required to be supplied during all, i.e. 100% of the hours of leftover supply. In terms of required supply reliability (RSR), results show that when all priorities require to be supplied during the entire period with supply left in the system (see Fig. 4.7a), only 7.69% of high priority agents meet this requirement (see Table 4.4). At the same time, none of the medium and low priorities meet the requirement. The reason for the low percentage of high priorities that meet their requirement is that at hour 17, there is not enough available supply in the system to meet the demand of all the high priority agents. This is both due to high demand at that hour and only rooftop solar

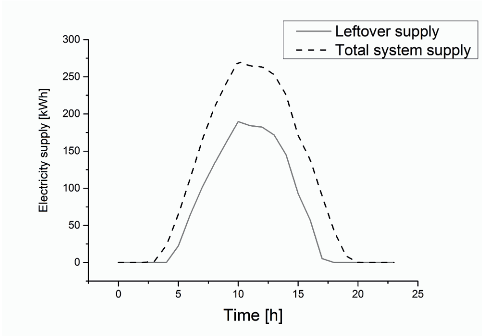



Figure 4.6: Total supply in the system and leftover supply (after self-consumption by prosumers) - Solar rooftop production only



as the supply resource (for load and production profiles, see Fig. 4.2).

| Priority level | Agents supplied as demanded | Minimum required number of hours of supply | Number of hours with leftover supply |
|---|---|---|---|
| High | 7.69% | 13 | 13 |
| Medium | 0% | 13 | 13 |
| Low | 0% | 13 | 13 |

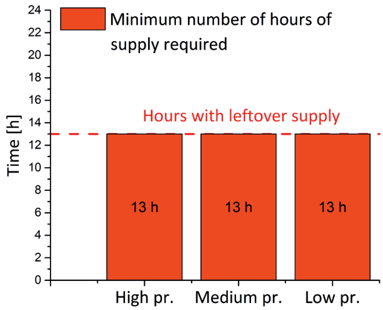
Table 4.4: Required supply reliability assessment of non-self-sufficient agents - all agents need to be supplied during all the hours with leftover supply

In the second case scenario, all priorities are required to be supplied during minimum 90% of hours of leftover supply (i.e. 12 out of 13 hours, as shown in Fig. 4.7b). The second set of results shows that reliability assessment is significantly impacted by adjusting the minimum required number of hours of supply. As shown in Table 4.5, 83.33% of high priority agents meet the requirement, as during 12 hours there is enough leftover supply for the majority of high priorities to be supplied. Still, however, there is not enough supply left during those hours for medium and low priorities to be supplied. Thus, the percentage of these priorities that meet their minimum requirement is 0%. According to these results, 83.33% of high priority non-self-sufficient agents have reliable electricity supply during minimum 12 hours of a 24-hour outage.

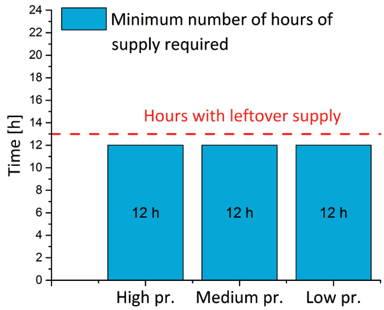
| Priority level | Agents supplied as demanded | Minimum required number of hours of supply | Number of hours with leftover supply |
|---|---|---|---|
| High | 83.33% | 12 | 13 |
| Medium | 0% | 12 | 13 |
| Low | 0% | 12 | 13 |

Table 4.5: Required supply reliability assessment of non-self-sufficient agents - all agents require to be supplied for 90% of the hours with leftover supply

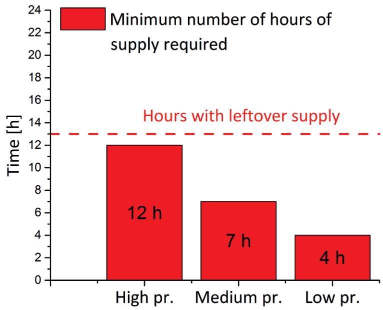
In the last case scenario, different priorities require supply for different minimum num-



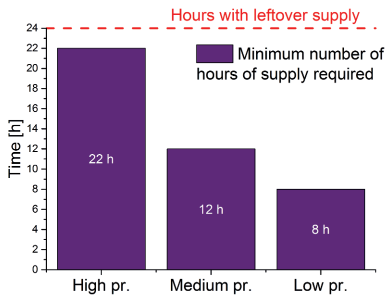

(a) Minimum required number of hours of supply - all priorities require 13 hours of supply




(b) Minimum required number of hours of supply - all priorities require 12 hours of supply




(c) Minimum required number of hours of supply - all priorities require a different number of hours of supply




(d) Minimum required number of hours of supply - all priorities require a different number of hours of supply - Wind and solar production

Figure 4.7: Minimum required number of hours of supply

ber of hours of leftover supply. As shown in Fig. 4.7c, high priorities require a minimum of 12 (90%) hours of leftover supply, medium priorities require a minimum of 7 (50%) hours of leftover supply, and low priorities require a minimum of 4 (30%) hours of leftover supply. The highest priorities require reliable electricity supply during the longest period of time, while the lower priorities can only be supplied with electricity that is left after supplying high priorities. Table 4.6 shows that 83.33% high priorities meet the 12 hours minimum required for reliable supply, while 100% medium priorities meet their minimum of 7 hours, and, finally, 100% of low priorities meet the 4 hours minimum. This means that 100% of both medium and low priorities are supplied during the period when there is supply left after the demand of high priorities is met. Looking back, Fig. 4.6 shows that during the day there is a solar production peak, and that peak lasts for several hours that are enough to meet the requirement of 7 hours minimum of medium and 4 hours minimum supply of low priorities.



| Priority level | Agents supplied as demanded | Minimum required number of hours of supply | Number of hours with leftover supply |
|---|---|---|---|
| High | 83.33% | 12 | 13 |
| Medium | 100% | 7 | 13 |
| Low | 100% | 4 | 13 |

Table 4.6: Required supply reliability assessment of non-self-sufficient agents - all agents require to be supplied for a different number of hours with leftover supply

Fig. 4.8 shows the percentage of non-self-sufficient agents for each of the priorities that are in 100% self-sufficient clusters, for every hour. Self-sufficient clusters are those that rely only on their own production resources to meet the demand of all of their member agents. The clusters can have members with different priorities. As can be seen, 100% of high priorities are in 100% self-sufficient clusters during the daylight period when there is a lot of leftover supply, while there is a somewhat lower percentage during hours 4 and 17, when supply starts rising and declining, respectively, and demand fluctuates significantly. Medium priorities are all supplied during the hours with high leftover supply, while the low priorities are, overall, supplied the least. Recall that the highest number of agents have low priority, followed by medium and then high priority agents. This ratio affects the percentage of low priorities in 100% self-sufficient clusters.

To add more local generation diversity, the last case scenario (when each priority requires a different minimum number of hours of supply) is run by adding wind production to the system. As stated in Subsection 4.3.1, one intermediate-size 500 kW wind turbine is modeled as an additional power source in the community. Note that, due to distributed information exchange that builds of the local geographic view, the wind turbine is not in the vicinity of all of the agents. Thus, for some, solar production is still the only resource available. Fig. 4.9 shows the difference between the total and leftover electricity supply in the system. Fig. 4.7d shows that, due to wind production, leftover supply is now available for 24 hours. The same scenario setup is used, with the minimum required percentage of hours of leftover supply set to 90% for high, 50% for medium, and 30% for low priorities. Thus, now, high priorities require to be supplied for minimum 22 hours, medium priori-

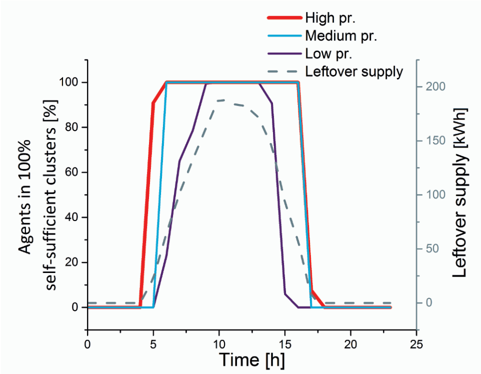



Figure 4.8: Percentage of non-self-sufficient agents of each priority that are in 100% self-sufficient clusters

4

ties require minimum 12 hours, while low priorities require minimum 8 hours of leftover supply. Table 4.7 shows that now, 85.71% of high priority, non-self-sufficient agents are supplied by electricity during at least 22 hours of the day, 100% of medium priorities are supplied during at least 12 hours of the day, while 91.76% of low priorities are supplied during at least 8 hours of the day. This difference between medium and low priorities is due to fluctuations in wind generation available during the day. At intervals when there is no solar production, all consumers and prosumers are non-self-sufficient. Thus, available wind generation is distributed to all of the high priorities that have the wind turbine in their local view, and the rest is distributed to medium and low priorities. Fig. 4.10 shows that now, a high percentage of high priorities is in 100% self-sufficient clusters during the entire duration of the outage. The percentage of both medium and low priorities in 100% self-sufficient clusters fluctuates more significantly. However, due to wind production, this percentage is overall increased, compared to the case where rooftop solar production was the only available resource in the system.

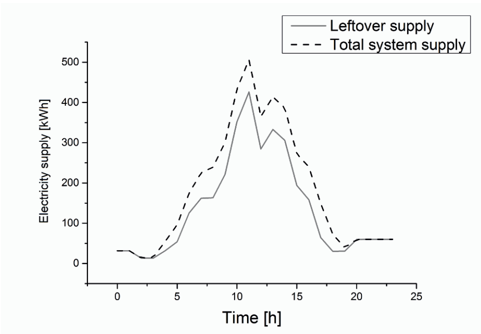



Figure 4.9: Total supply in the system and leftover supply (after self-consumption by prosumers) - Wind and solar production

As expected, the results from reliability assessment (see Subsection 4.3.3) show that supply reliability primarily depends on the type of resources available, but also on the ratio between high, medium and low priorities in the system. If solar production is the

| Priority level | Agents supplied as demanded | Minimum required number of hours of supply | Number of hours with leftover supply |
|---|---|---|---|
| High | 85.71% | 22 | 24 |
| Medium | 100% | 12 | 24 |
| Low | 91.76% | 8 | 24 |

Table 4.7: Required supply reliability assessment of non-self-sufficient - all agents require to be supplied for a different number of hours with leftover supply - Wind and solar production)

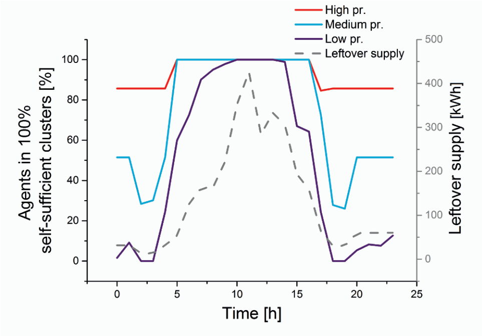



Figure 4.10: Percentage of non-self-sufficient agents of each priority that are in 100% self-sufficient clusters - Wind and solar production

only resource available, leftover supply is available during the sunny period of the day. However, if wind generation is also present in the system, there is more flexibility, and overall more supply is available in the system. Thus, the performance of the proposed mechanism in terms of reliability improvement is fully-dependent on the type of local resources available in an impacted area. Given only solar and wind generation are available, the results would significantly differ on a windless, cloudy day. As an alternative, other types of resources (e.g. storage) can be used for different periods.

The reliability assessment itself depends on several parameters, including setting of the minimum required number of hours of leftover supply for every priority, as well as the ratio between high, medium and low priorities in the system. The required minimum number of hours of leftover supply depends on the supply availability, types of resources in the system and the knowledge of agents. In practice, a more extensive study would be needed to set parameters appropriately for specific situations.

## 4.5 Discussion

The results discussed in the previous section show that the mechanism proposed in this chapter can be used as an ICT platform that enables decentralized supply and demand matching in changing environments. Decentralized supply and demand matching can be valuable if and when there is no central information on total and individual supply and demand in the system, and the backbone grid is unavailable. By facilitating local energy sharing, prolonged electricity supply is ensured for members of communities affected by an outage. Thus, a functioning mechanism is developed that improves supply reliability by maximizing local resource utilization.

Besides providing a functioning platform for local energy exchange during outages, the possible applications of the mechanism are many. As a tool, it can be used by decision and policy makers to run extensive scenarios for specific communities, demonstrating what impact community's decisions regarding consumer prioritization have on the level of its supply reliability. These case scenarios can help explain different implications of, for example, varying the percentage of high, medium and low priorities, or fixing the priorities for selected consumers. This, in turn, can be used to make decisions on additional resources needed to achieve reliability goals of specific communities. This can include installing generators, additional solar panels or (community) energy storage. As the mechanism is highly adaptable, it provides potential for resilient energy communities that dynamically adapt to changes to respond to rapid onset events [41, 42, 147, 148].



More responsible resource planning by, for example, avoiding curtailing of overproduction by sharing energy or installing community-owned storage based on the specific community's needs, promotes more sustainable use of resources, especially when resources are scarce. Ultimately, relying on local production only can lead to less dependence on the main grid, even when the backbone grid is available, increasing self-sufficiency of local (energy) communities.

The application of the proposed mechanism can potentially have wider implications in terms of social interaction and cohesion in impacted communities. Instrumental to the mechanism is the consumer differentiation as a means to determine how to distribute electricity according to a community's preferences. Here, the basis for differentiation, i.e. priorities, are determined by the community members themselves, based on their perceived social values. In this chapter, the differentiation process is not automated; the power of deciding on priorities is given to the community members, which means that they have to come together and reach a mutual agreement on consumer priorities. By giving them a common goal, such as increasing supply reliability during outages, the mechanism enforces social interaction of different stakeholders, which can ultimately lead to social cohesion [44, 52, 134, 139]. Thus, community members are empowered to make decisions that directly benefit community members. Even though social cohesion is one of the possible outcomes, depending on the community, if misused such a system could also possibly have negative implications towards more vulnerable groups. More research is needed to determine this. However, the study of these implications is outside the scope of this chapter.

Alternatively, assigning priorities can also be done by institutions (e.g. distribution system operators), in cooperation with the local communities, depending on the specific situation or a type of consumer or prosumer. The process of assigning priorities can also differ based on the type of outage, e.g. whether it is planned or unplanned. Finally, priorities can be static (fixed) or dynamic, adapting to changing circumstances and specific community's preferences, depending on the time of the outage for example.

## 4.6 Conclusions

This chapter proposes a mechanism that enables decentralized supply and demand matching, based only on locally available information and self-organization of consumers and prosumers. The proposed mechanism empowers local communities to decide for themselves how local resources are distributed during events such as outages, ensuring prolonged electricity supply for differentiated members of affected communities. In addition the chapter shows that more frequent reconfiguration scenarios generate the overall lowest total overproduction and underproduction, and deviate the least from the centralized approach.

On a higher level, this chapter shows that decision making between individual consumers and prosumers can benefit the affected communities by sharing available locally produced energy, given appropriate mechanisms. In case of scheduled outages, the mechanism can be used by decision makers and planners beforehand as a tool to gain an insight how different community perspectives on energy priorities can influence supply reliability in affected communities. Eventually, based on the results, backup plans for alternative power sources can be made.



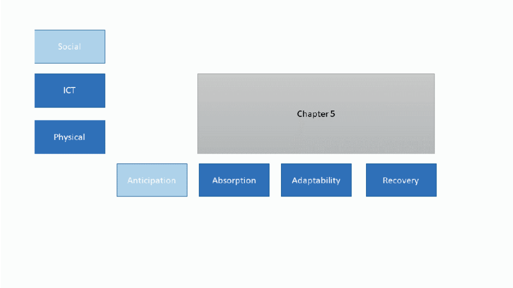
Negotiation mechanisms for agreeing upon resource sharing between different consumers and prosumers will be explored in detail in the future work. Current work uses the mechanism proposed in this chapter in combination with distribution system reconfiguration to assess if power systems can be made more resilient in case of large-scale outage caused by a rapid onset event.

The future brings challenges. To face these challenges, power systems will need new paradigms for coordination and planing. Harnessing the potential of renewable resources and smart technologies for intelligent coordination through empowerment of consumers to become pro-active participants is a promising solution for the future power systems.

# 5

# Energy resilience through self-organization during widespread power outages






*Resilience of power systems is highly impacted by factors such as increasing severity and frequency of weather events, but also smart grid advances that introduce major operational changes in power systems. Rapidly adapting to these changing circumstances and harnessing the potential of technological advances is the key to ensuring that power systems stay operational during disturbances, thereby improving resilience. This chapter addresses this challenge by presenting an approach for improving resilience through local energy resource sharing across multiple distribution systems. The approach brings together the physical and the ICT layer of power systems through a self-organization approach that automatically alters the physical grid topology and forms local energy groups in order to mitigate the effects of widespread outages. Thereby, supply and demand are locally matched, and demand met*

Chapter 5 is published in *Sustainable and Resilient Infrastructure* journal [32].

*is maximized during an outage. The results demonstrate that using the proposed approach, operational resilience of impacted distribution systems is improved.*

## 5.1 Introduction

Power systems are faced with many uncertainties that can severely impact their operation. These uncertainties are caused by factors such as increased penetration of renewable resources that require more complex measures such as load shifting, load and generation forecasting and dynamic pricing, but also by an increase in extreme weather events caused by climate change, as well as challenges due to the increased complexity of power systems [149]. Combined, these factors can severely impact power systems on various levels [150]. Failure of and damage to these critical infrastructures has a negative impact on society, especially in cases of widespread outages. Widespread outages negatively impact everyday lives of people and infrastructures relying on electricity, potentially causing more than just an inconvenience in today's electricity-driven world.

As other critical infrastructures (communication, transportation, health services etc) on which modern society relies, depend on the availability of the electrical grid, the impact of blackouts extends beyond the power system itself. Due to this interdependence between infrastructural systems, it is crucial to make infrastructures not only more robust, but also more resilient [41]. Even though the definitions of resilience are many, it is generally accepted that a resilient system is able to quickly recover from an external shock, adapting to new circumstances so that it provides a (sufficient) level of operation [11, 12]. Furthermore, a resilient system should quickly bounce back to its normal operating state and adapt to be better prepared to future catastrophic events [16, 151]. The Multidisciplinary Center for Earthquake Engineering Research extends this definition to include the role of social units in mitigating disasters by carrying out activities that minimize the impact of disruptions [37]. Boosting the resilience of critical infrastructure depends on the type of infrastructure itself, available resources, but also social components of a system (e.g. resource owners).

Another challenge that amplifies system vulnerability arises due to technological advancements and rapidly-changing roles of end-consumers of these systems. In the case of power systems, this is reflected through an increase in distributed energy resources (DER) (solar panels, storage, wind turbines), typically locally owned by end-consumers. Due to the volatile nature of renewables, power systems could face even more disturbances at different scales. With the complexity of these systems increased, as well as potential infrastructure failures and information unavailability during widespread outages, centralized coordination of power systems (including generation, dispatch and control) becomes challenging which has led to the exploration of new decentralized approaches to power system analysis and control [10].

A potential solution to achieve an improved level of operation during disturbances is to harness the power of smart ICT technologies and locally-owned resources, and shift the coordination from a central unit to distributed units within power systems [107]. Decentralization mechanisms can be used to let not only consumers, prosumers and producers take independent decisions, but also the grid itself. This chapter addresses this challenge from both perspectives by bringing together the physical and the ICT layer of power systems in a self-organizing approach for decentralized coordination of local energy resources in changing distribution system topologies with the aim of improving power system resilience.

By sharing resources during disturbances, normal operation can be (to an extent) restored in an impacted area. For this purpose, both social and technological components are crucial; (1) resource owners have to be willing to share their resources, and (2) mechanisms that facilitate resource sharing have to be installed. The potential impact of emergent local energy groups is explored in this chapter, in combination with a self-organizing grid on improving resilience of areas affected by rapid-onset events.

The remainder of this chapter is organized as follows: Section 5.2 further explains the concept of resilience w.r.t. power systems, while Section 5.3 presents the proposed approach for ensuring resilience based on self-organization. Section 5.4 demonstrates the application of the proposed approach through a case study w.r.t. resilience assessment. Section 5.5 discusses the results and potential applications of the mechanisms, and Section 5.6 concludes the chapter.

## 5.2 Resilience of power systems



As discussed previously, many critical infrastructures on which modern society relies, depend on reliable electricity supply and predictable operation of power systems. As they can be severely impacted by uncertainties that cause outages of different scales, it is crucial to make them more resilient. Technological advances such as novel ICT infrastructures integrated within power systems, smart meters, social and operational changes related to an increased penetration of renewables etc pose new challenges for power system operation, but also open new possibilities to deal with uncertainties and improve the resilience of these systems. Power systems are vulnerable to these uncertainties and will require a shift in their operation to deal with them [11].

Traditional approaches to make power systems more resilient include hardening solutions that boost the infrastructure resilience (e.g. adding new lines, moving the cables underground etc), but also smart operational solutions such as defensive islanding, that provide preventive and corrective operational flexibility in dealing with disruptions [34]. Hardening enhances the physical resilience of infrastructure against an external shock, and aims to reduce the physical impact on the grid [34]. Operational measures aim at enhancing operational resilience, making use of the flexibility of available technologies in power systems to effectively deal with a disturbance. The potential of DERs can be used to enhance system resilience. Using these resources, energy can be supplied locally, without relying on a backbone grid that can be affected by a disruption for a longer period of time [34]. The potential of DERs is exploited through installation of microgrids, that can island and operate independently during periods of disruptions. Multiple islanded microgrids that are in geographic vicinity of each other can merge to form a microgrid cluster and gain additional flexibility for resilient operations [53, 152, 153]. Another concept related to the integration of DERs are virtual power plants (VPPs) that aggregate multiple types of generation resources to jointly participate on the electricity market [106]. As VPPs rely on collaboration of different stakeholders, they inherently incorporate the ability to dynamically adapt to different circumstances (e.g. various stakeholder goals). Their potential to dynamically re-organize can be used to build resilient collaborative VPP architectures [137].

Concepts such as microgrids have a fixed geographic location and cannot adapt to changing circumstances in real-time. Thus, a mechanism that allows more flexibility to respond to changes is needed. Furthermore, to mitigate the potential effects of central coordination during outages (such as single point of failure that can propagate widespread outages), decentralized coordination during disturbances can improve system resilience.

The combination of traditional control operations with novel ICT technologies and DERs opens up new possibilities to make power systems more resilient in case of widespread blackouts. Locally owned DERs have the potential to mitigate the effects of small- and large-scale outages by providing electricity to affected consumers and prosumers. It is estimated that 90% of consumer outages are related to distribution systems (DSs), the most vulnerable parts of the network [16, 154]. These outages can affect a single DS, or spread to multiple DSs. When multiple distribution systems are affected, a control operation called distribution system reconfiguration (DSR) can be used to alter the topology of power systems by opening and closing the switches that connect different DSs. Under normal operating conditions (i.e. no outages), DSR is performed periodically to achieve objectives such as minimum loss, voltage control, etc [155]. During outages, however, reconfiguration is an event-based activity and is invoked to provide the emergency restorative supply to the unserved demand until the fault is repaired [101].



In general, reconfiguration is performed by the central grid operator. However, in a widespread outage, the reach of the central grid operator is limited. This can be because of physical component failure or loss of ICT which may cause islanded grid operations. Thus, there is a need for decentralized reconfiguration that can withstand multiple failures and still perform reliable operation under outage conditions. DSR plays an important role in maximizing system resilience as it supports load restoration in an event of a widespread outage and optimizes local energy sharing between load and generation.

Most approaches from literature that focus on the resilience of power systems consider the power system itself as given. The resilience of a power system is consequently assessed under various circumstances, for example by changing loads, thereby 'stress testing' the power system. In contrast, in this chapter, the power system is not assumed as given, but rather aims to improve the resilience of power systems by proposing an intervention in a form of a decentralized coordination mechanism based on self-organization.

## 5.3 Energy resilience through self-organization

An agent-based mechanism is proposed that brings together the physical layer and the ICT layer of power systems in an approach for decentralized coordination based on self-organization. The approach automatically directs both the physical topology of the grid and changes in supply and demand of individual consumers and prosumers. At the physical layer, the topology of affected DSs is changed by performing distribution system reconfiguration. Given the changed topology, supply and demand are matched at the ICT layer to form local, self-sufficient energy groups. As centralized coordination is challenging during outages, both operations are performed in a decentralized way. In that way, multi-level self-organization is achieved (both at the grid level and the level of consumers and prosumers).

Decentralized coordination on both of the layers is achieved using different types of autonomous agents. Here, an agent is a piece of software that has local information and is able to share this information with other agents on different layers and perform autonomous actions based on their own and aggregated information. The presented approach does not use traditional optimization methods to perform either the group formation or the distribution system reconfiguration, but relies on self-organization using an agent-based approach based on decentralized message exchanges.

At the ICT layer consumer and prosumer agents (C/PAs) are installed at consumers' or prosumers' ends and have information about their demand and/or supply profile. C/PAs are assumed to have perfect information about production and demand. In practice, this can be approximated for the near future using forecasting techniques [156, 157]. C/PAs share this information with agents on the physical layer (to alter the topology) and with each other (to locally match supply and demand). By doing so, they organize themselves (*self-organize*) into energy groups that locally minimize S/D mismatch and maximize demand met. The groups have to abide the laws of the physical grid, which is ensured by bi-directional communication with agents from the physical grid.

At the physical layer, two types of agents are distinguished: a bus agent (BA) and a coordinator agent (CA). These agents are located beside physical grid components, and perform power flow calculations and system reconfiguration. BAs represent network buses and gather information about net supply and demand of consumers and prosumers connected to their representative bus. They obtain this information by communicating with C/PAs located on those buses. CAs coordinate with BAs to gather information of distribution system parameters such as losses, switch status, energy utilization, etc and initiate the process of DS reconfiguration. This way, centralized coordination is eliminated and the grid is able to reconfigure itself (*self-organize*).



Figure 5.1 illustrates the proposed approach: once an outage that affects multiple distribution systems occurs, the C/PAs from the ICT layer start sharing the information about supply and demand profiles with BAs on the physical layer. BAs aggregate this information to compute the net generation/demand of the bus.

Using this information, BAs exchange messages with connected neighboring BAs to compute partial power flow solution. The CA collects the information on loss and utilization from power flow solution of all scenarios that reflect different topologies of grid connection and determines the optimal solution to the reconfiguration. CA issues signal to all BAs to enact the optimal topology. The concerned BAs initiate signals to the switches if their status has to be changed (open or close) as per CA's optimal scenario, and the topologies are changed.

Once the agents on the physical layer change the topologies of DSs, C/PAs find other C/PAs connected on the physical layer and share supply/demand profiles with them. Agents with the best matching profiles (minimum S/D mismatch) form local energy groups that ensure energy resilience for their members. These groups are virtual and not necessarily geographically co-located. However they do use the existing physical infrastructure to perform energy sharing, and thus need to be part of the same distribution system or connected to other distribution systems via the grid. As the proposed approach is used to ensure resilience, the entire process is dynamic, so that both the grid and the formed groups can dynamically reconfigure to be able to quickly respond and adapt to changes in the environment. In such a way, if supply and demand fluctuate, DS topologies can change and new energy groups are formed to minimize the mismatch. Finally, once an outage terminates and the backbone grid is restored, affected distribution systems return to their normal operating state, with original topologies, and the formed energy groups cease to exist.

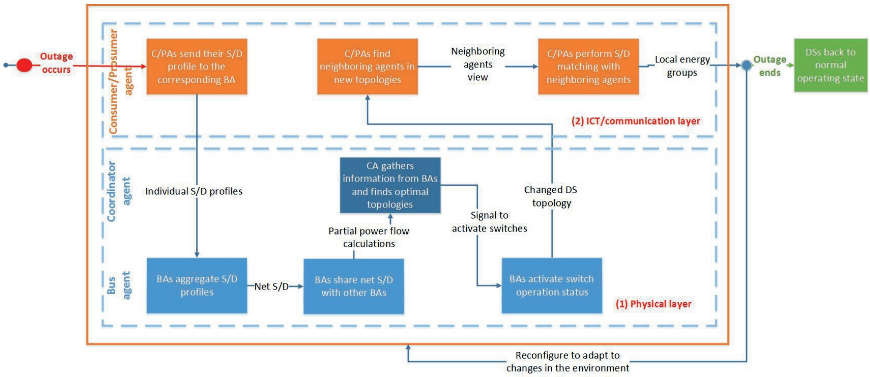



Figure 5.1: An approach for ensuring energy resilience

5

Subsections 5.3.1 and 5.3.2 explain both the decentralized DSR and supply and demand matching process in more detail. Subsection 5.3.3 describes the metrics used to assess the achieved resilience.

## 5.3.1 Self-organizing grid (Physical layer)

As distribution systems are changing due to technological and social changes introduced with smart grids, the conventional way of DS operation and analysis is challenged [10, 158]. To support these changes from the grid perspective, the grid itself can be given a means to perform traditional operational measures such as network reconfiguration in a decentralized fashion, eliminating the single point of failure. A fault tolerant decentralized reconfiguration mechanism proposed in [159, 160] is extended to provide the means for self-organization with minimum loss and maximum utilization of local resources given power flow considerations.

Two agents are distinguished, i.e. a Bus Agent (BA) and a Coordinator Agent (CA). A CA coordinates with the substation buses' BAs to gather information of individual DS's parameters such as losses, switch status, energy utilization, etc. In addition, the BA continuously monitors its representative bus and stores all associated parametric attributes. Parameters $P$ and $Q$ (active and reactive power) are collected from the consumer and prosumer agents located at $i^{th}$ bus. Figure 5.2 shows a diagram of the decentralized distribution system reconfiguration process. Once an outage occurs, BAs collect supply and demand profiles from C/PAs representing consumers and prosumers connected to their representative buses and compute the net S/D at the bus. This information, along with other network parameters is aggregated by the CA, which uses this information to formulate different topology scenarios. For each considered scenario, the CA directs the substations BAs to compute distributed power flow and losses of their respective DS. BAs compute the distribute power flow using forward backward sweep behavior [161].

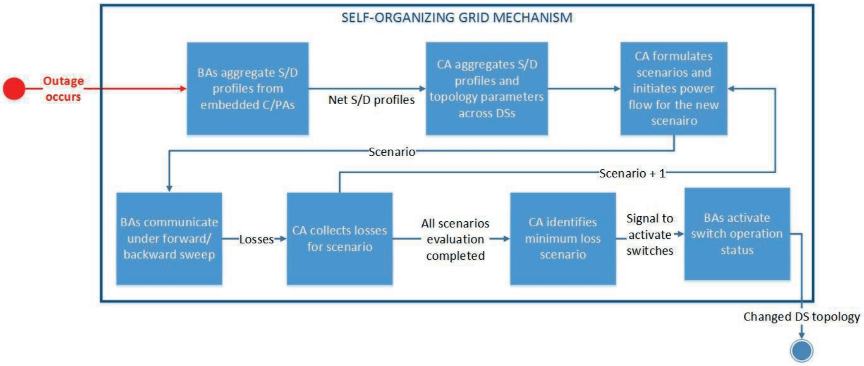



Figure 5.2: Decentralized DS reconfiguration algorithm



$$I_{inj,BA_i} = \frac{P_{BA_i} - jQ_{BA_i}}{V^*_{BA_i}} \tag{5.1}$$

$$V_{BA_i} = V_{BA_{i+1}} + I_{BA_{i+1}} * Z_{BA_{i+1}} \tag{5.2}$$

$$I_{BA_i} = I_{inj,BA_i} + I_{BA_{i+1}} \tag{5.3}$$

$$loss_{BA_i} = I^2_{BAi} * R_{BA_{i+1}} \tag{5.4}$$

$$Demand_{BA_i} = Util_{BA_{i-1}} + x_{i,3} \tag{5.5}$$

Here, $V$ and $I$ are voltage and current to be computed where give $Z$ is the impedance, $R$ is resistance, and $x_{i,3}$ is the active power demand. Each $BA_i$ computes the bus voltage $V_{BAi}$, partial system losses $loss_{BAi}$ and partial demand $Demand_{BAi}$ using (1)-(5). At substation BA, power flow convergence is checked using (5.6). If the power flow does not converge, a forward sweep is initiated and proportional voltages are computed using (7). If the power converges, then the computed losses and net demand by DS is sent to CA.

$$\gamma = \frac{V_S}{V_1} \tag{5.6}$$

$$V_{BAi} = \gamma * V_{BAi} \tag{5.7}$$

A CA coordinates with all the substation BAs to gather information of system losses and energy withdrawn by substation under all considered scenarios. From the pool of possible reconfiguration scenarios, the CA selects the one with the minimum loss and maximum utilization of resources as the optimal scenario. Then, messages are issued to the respective BAs to operate the switches. The advantage of self-organizing, decentralized DSR is that the neighboring agents can automatically provide the functionality of the failed agent without central coordination, as discussed in [159]. The implementation of an optimization method for distributed DS reconfiguration is considered to be out of scope of this chapter and is researched in [162, 163].

### 5.3.2 Self-organized energy-sharing (ICT layer)

The self-organizing energy approach extends the principles of decentralized supply and demand matching proposed earlier in [31] to steer the actions of C/P agents on the ICT layer. As opposed to the original work, the proposed mechanism is used without consumer prioritization. The mechanism is dynamic, adapting to the changes in the environment (e.g. hourly fluctuations in supply and demand) by reconfiguring groups to better match changing energy demands. Groups reconfigure hourly, based on their own supply and/or demand and obtained information on local supply and demand in the system.

During an outage, prosumers first meet their own demand, and then distribute the leftover supply to other affected members. Instrumental to the mechanism is that local resource owners in impacted distribution systems are willing to share their resources. It is assumed that once an outage occurs, resource sharing is instantaneous. Thus, there is no time delay that affects resilience of the system.

Figure 5.3 shows a diagram of the supply and demand matching mechanism performed at the ICT layer. The system is designed in such a way that each consumer and prosumer has a device on which a stand-alone piece of software is installed. The software is an intelligent agent that has local information about its owner's geographic location and its supply and demand (e.g. daily load and production profile or their forecasts), and can exchange that information with other agents in the system. During an outage, agents use a distributed information exchange algorithm (e.g. gossiping) to find other neighboring agents in the same DS. In the next step, agents exchange information about their supply and demand with their neighbors. Information is exchanged in the form of messages that contain each agent's S/D profile and the mismatch calculation between the sending and receiving agent. Mismatches are calculated as in [31], including the amount and the number of hours of overproduction and underproduction. Agents then send requests to join the agents whose profiles best match theirs in terms of minimum mismatch. As each agent has a list of calculated mismatches, and all the exchange is performed in a decentralized manner, no traditional optimization methods are necessary to perform the selection. Once the requests are sent, the receiving agents accept the best-matching requests (using the same minimization approach, and with respect to the amount of their overproduction), and the groups are formed. The groups merge so that the demand is best met. As the system is dynamic, the groups reconfigure if there are changes in supply and demand to adapt to the new environment. Group reconfiguration is performed on an hourly basis, as the load and production profiles are hourly.

### 5.3.3 Resilience metrics

Measuring the improvement of power system resilience requires metrics designed to this purpose. Most studies on resilience use the so-called *resilience triangle* [147] as the main measure of resilience. This triangle depicts the loss of functionality of a component or a system from and during a damage. Figure 5.4 depicts a typical resilience triangle, where a fully-functioning system fails to operate at time $t_{oe}$ (e.g. due to a weather event), and continues to recover throughout the event, regaining is full functionality at the end of disruption ($t_{ee}$). The area of the created triangle indicates the resilience of an impacted system. The smaller the area, the more resilient a system is. Thus, resilience-boosting measures aim at reducing the area of the triangle. Variations of the resilience triangle

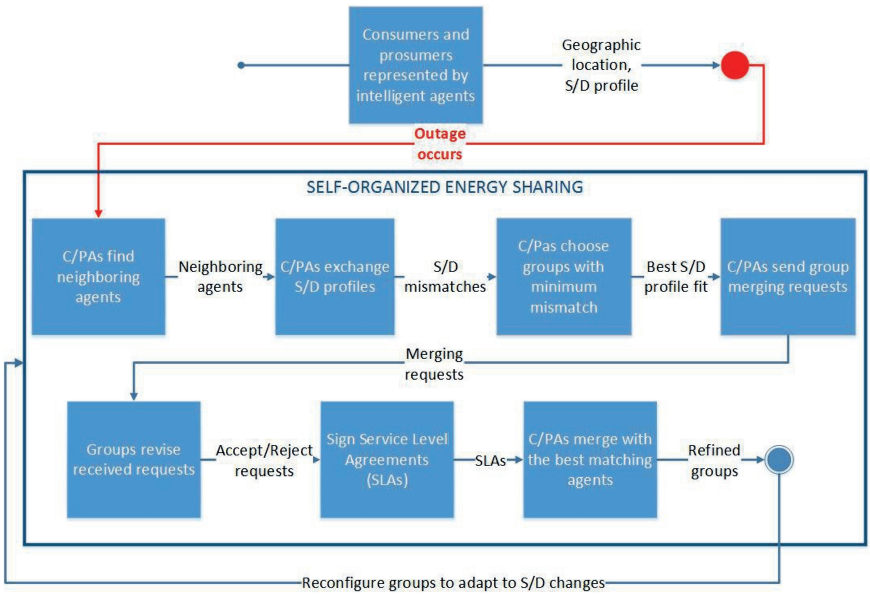



Figure 5.3: Distributed energy-sharing algorithm (adapted from [31] under the Creative Commons Attribution 4.0 International License (http://creativecommons.org/licenses/by/4.0/))

are used, one of them being the *resilience trapezoid*, proposed in [164], that gives more insight into rapidity of component failure and recovery. Two main concepts are assessed: operational and infrastructure resilience [164]. The operational resilience metric assesses operational performance of a system under disturbance through parameters such as the amount of generation capacity available during a disturbance.

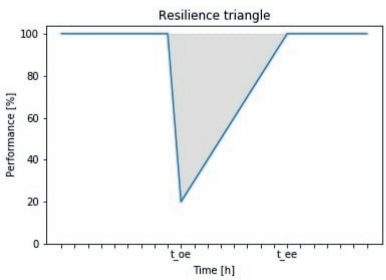



Figure 5.4: Resilience triangle (adapted from [151]) under IEEE license number 4673051363436

With more consumers becoming prosumers that have more local control, local resource owners become directly involved in a system's operational resilience. The concept of operational resilience is used to capture the effect of a disturbance on impacted consumers and prosumers. Here, the operational resilience is captured using three metrics:

1. Demand met (DM) - This metric assesses how much demand is met during the distur-

bance, given that resource owners share available energy resources. The aggregate demand met for all the consumers and prosumers is calculated, per hour of an outage. An aggregate of the demand met for the duration of the event is calculated (DM$_{agg}$).

2. Consumers served (CS) - This metric assesses the percentage of consumers and prosumers whose demand is fully met during the disturbance period, per hour of the outage.

3. Resilience area (RA) - This metric calculates the area of the resilience triangle [147], an indicator commonly used to measure resilience. The resilience area is expressed as the integral of the area between resilience curves for the duration of the event, and the main objective is to minimize it. This metric demonstrates (1) the loss of performance of the systems in terms of each of the above metrics, and (2) the improvement of resilience compared to a situation where no energy resources are shared during a disturbance. For this purpose, two resilience area indicators are distinguished, respectively, namely, resilience loss (RL) and resilience improvement (RI). Resilience area is an aggregate metric over the whole duration of the disturbance.



Demand met and consumers served are the two main metrics used to specify operational resilience of a power system. The resilience area indicates the overall improvement in resilience when prosumers share local resources during a disturbance.

## 5.4 Assessing energy resilience: A case study

To illustrate the effect of sharing local resources in self-organized energy groups affected by outages, a case study is conducted that considers a large-scale outage that affects three distribution systems. The damage is assumed to be upstream, making the backbone grid unavailable to the three DSs. Note that this does not affect the ability to locally open and close switches that connect the DSs. Thus, reconfiguring the topologies of the three DSs is still possible. To assess the achieved energy resilience using the proposed approach, a best-case and a worst-case scenario are used. A fully-operational grid during no outage scenario is taken as the best-case (all demand is met), whereas a grid with no resource sharing during an outage is taken as the worst-case scenario. To be able to share local resources, this case study assumes that the local infrastructure that enables energy sharing is not physically impacted. It is assumed that once an outage happens, both reconfiguration and energy sharing instantaneously take place. Thus, there is no time delay before recovery commences.

In the present context, immediate energy sharing is on the pretext of grid interconnection. If the sources and the loads are connected, energy transfer is instantaneous. Upon a sudden loss of network resources, the energy sharing could take a while which depends on the restoration time. Grid restoration is performed by opening or closing of switches at different grid sections, that allows instantaneous energy transfer with the restored grid section. However, the time lapse in decision making and actual switch operation induces delay in the energy resource sharing. The problem is different from the typical everyday reconfiguration as it is primarily operated under distributed paradigm where there is no centralized data and the grid periodically examines itself and takes corrective action for reconfiguration. The proposed approach does not include repair actions, but it provides temporary relief to the grid by changing the grid topology so that the maximum available load can be restored under an contingency event. The aim here is to reconfigure the system as fast as possible, such that the system does not lose stability. Typically, reconfiguration occurs within milliseconds. The damage repair is subject to physical repairs somewhere upstream in the grid, if any. Once the fault is restored, the system base configuration can be restored.

### 5.4.1 System setup

For illustration purposes, a modified IEEE 16-bus system [165] divided into three separate distribution systems is considered. Figure 5.5 shows the topologies of each of the DSs and the total supply and demand profiles of the three distribution systems over a period of 24 hours. As seen in the figures, distribution systems 1 and 3 have overproduction during the day, whereas the demand of the distribution system 2 is always higher than its supply. Thus, without the backbone grid, the demand of DS 2 is not met at any hour of the day. Each DS consists of multiple buses spread throughout the network, and has a limited number of local renewable resources (in this case, solar panels). Each of the buses has a number of consumers ($C$) and/or prosumers ($P$). The number next to the abbreviation denotes the number of consumers and prosumers on a specific bus. Figure 5.6 shows the distribution of consumers and prosumers on each of the buses of separate DSs. The DSs are connected with switches (SW1, SW2 and SW3) that can be open and closed when DS reconfiguration is performed (see Subsection 5.3.1).

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Following [31], daily hourly load profile data is obtained from NEDU [119], the Dutch energy data exchange, and represents an average load profile of a Dutch household consumer. The load profile is varied to add some variation in consumer loads. As solar panels are considered as the type of locally owned energy resources, Dutch solar irradiance data [121] is used to calculate the production of solar panels as in [120]. In the case of The Netherlands, an average rooftop area on which solar panels can be installed is ≈33 $m^2$ [145]. To account for rooftop orientation, and w.r.t. the standard residential solar panels of an area of 1.63 $m^2$ [144], prosumers are modeled with a minimum of 6 and a maximum of 12 solar panels per household (randomly determined per prosumer).

The main objective of this case study is to demonstrate how operational resilience of multiple distribution systems during a widespread outage can be improved using a multi-layered self-organized approach to local energy resource sharing across impacted DSs.

For the purpose of the case study, all three distribution systems depicted in Figure 5.5 are assumed to be affected by the outage. Thus, consumers and prosumers from all three DSs rely only on locally available resources. When no local resources are shared, prosumers meet their own demand, while other consumers are not supplied with electricity. When local energy resources are shared, prosumers share excess generation (i.e. after meeting their own demand) with others that are physically connected to them.

The outage is simulated over a 24-hour period, with results for different outage durations and time occurrences presented. A 24-hour outage is simulated to demonstrate the performance of the mechanism over a longer period of time and the potential to improve the system's resilience in such a setting. Subsection 5.4.2 presents the experiments and the results in detail. Note that the objective of the experiments is not to perform an in-depth

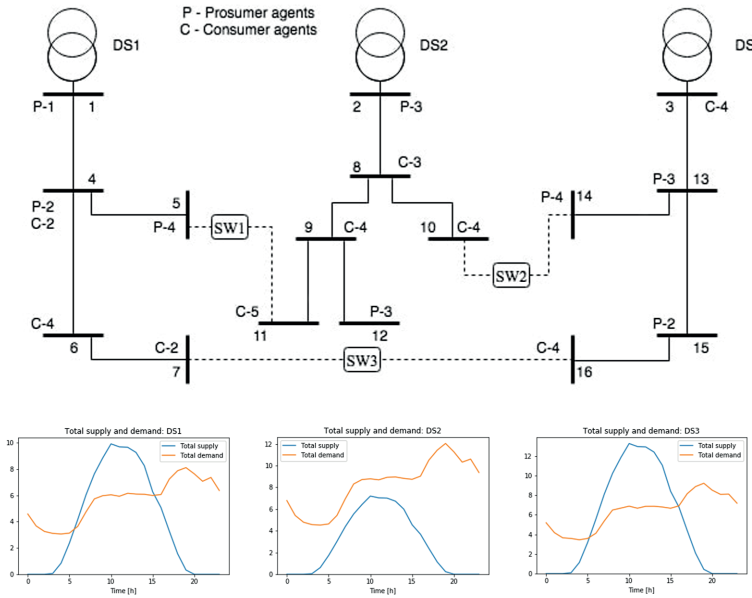


Figure 5.5: Topologies and aggregate supply and demand profiles of the three distribution systems

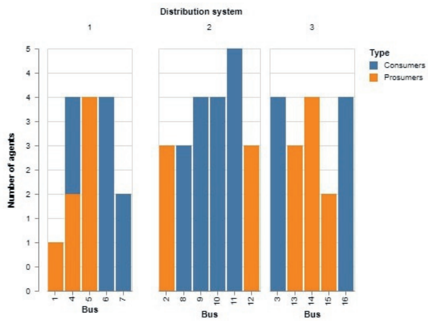


Figure 5.6: Number of consumers and prosumers per distribution system (per bus)

study of the efficiency of the proposed approach over a long period. Factors such as physical grid infrastructure and topology, types of available local resources, as well as weather conditions and seasonal variations highly impact the performance of the approach and limit its applicability to specific scenarios.

### 5.4.2 Case study simulation

The case study simulates a large-scale outage when the backbone grid is no longer available. The results are presented in two sets: (1) DSR results show the optimal topology configurations for every hour over 24-hour period, and (2) energy resource sharing results show the effect of local energy group formation with respect to demand met and overall resilience improvement across DSs, and compares the generated results to no resource sharing scenario. It should be noted that, even though the results are presented separately, the simulations are run iteratively for every hour, performing first DSR and then energy sharing.

The first set of results is presented in Table 5.1 and shows the optimal hourly reconfiguration topologies over a period of 24 hours. At the beginning, all DSs operate independently. The DSR objective is to maximize local resource utilization and minimize system losses. In early hours, demand is greater than supply for all DSs, thus all switches are open, as there is not enough supply to meet the demand in any of the DSs (see Figure 5.7 (a)). At hours 6 and 15, when supply and demand in all three DSs start to rise, the three DSs are connected together, and both DS1 and DS3 supply some demand for DS2 (see Figure 5.7 (b)). In mid-day, depending on the amount of overproduction in DS1 and DS3, the two are interchangeably connected to DS2 to meet its demand (see Figure 5.7 (c) and (d)). In the later part of the day, demand again increases and the system reverts to the early hour configurations. This case assumes that the production is non-dispatchable and the demand not served must be shedded.

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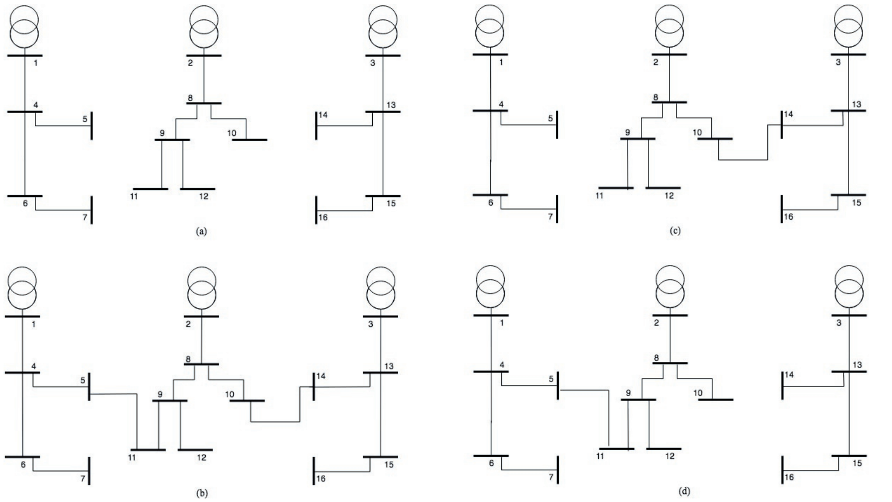


Figure 5.7: IEEE 16 Bus distribution system

The second set of results demonstrates the effect of energy resource sharing across DSs. The effect of local supply and demand matching is compared to both the fully operational grid with no outage when all demand is met via a backbone grid (best-case) and the grid with no resource sharing during an outage (worst-case).

With respect to DS reconfiguration results from Table 5.1, hourly simulations are run, and individual and aggregate demand met of DSs is observed. Using the configurations from Table 5.1, Figure 5.8 shows the hourly results of the simulations in terms of the demand met (in kWh). As indicated by the blue line, at times of the day when there is solar production, the demand met is very high, compared to the system when no local resources are shared.

| Hour | SW1 | SW2 | SW3 | DS configuration | Remarks |
|---|---|---|---|---|---|
| 0-5 | Open | Open | Open | DS1, DS2, DS3 separate | Figure 5.7 (a) |
| 6 | Close | Close | Open | DS1, DS2 and DS3 connected | Figure 5.7 (b) |
| 7-8 | Open | Close | Open | DS1 separate, DS2 and DS3 connected | Figure 5.7 (c) |
| 9-14 | Close | Open | Open | DS1 and DS2 connected, DS3 separate | Figure 5.7 (d) |
| 15 | Close | Close | Open | DS1, DS2 and DS3 connected | Figure 5.7 (b) |
| 16-23 | Open | Open | Open | DS1, DS2, DS3 separate | Figure 5.7 (a) |

Table 5.1: Reconfiguration results for large scale outage

Figure 5.9 compares the aggregate demand met for all three impacted DSs using the presented approach with the worst-case scenario, when no resources are shared.

To illustrate the impact on resilience, two simulations are run with different outage time and duration. The outage happens at time $t_{oe}$ and ends at time $t_{ee}$. Figure 5.10 and Table 5.2 show the results of the simulations in terms of operational resilience metrics (see Subsection 5.3.3). During a 24-hour long outage, compared to the worst-case scenario (no energy resource sharing), resilience is improved by 24.70% in terms of demand met, and by 25.12% in terms of consumers served. In the case of a shorter outage during the time when supply is high, e.g. from 7AM to 15PM, the achieved resilience in terms of demand met is improved by 58.62%, and by 58.71% in terms of consumers served. The results demonstrate the full potential of the proposed approach for achieving a high level of operational resilience. The simulation also shows that the resilience depends on the type and number of resources available (e.g. the resilience of the system is low when there is no solar production, if only solar is available). However, the proposed system can deal with outages of any duration, provided there is some local generation, lasting from minutes to hours or days.

| $t_{oe}$-$t_{ee}$ [h] | $DM_{agg}$ [%] | $RL_{NOES}$ DM [%] | $RL_{ES}$ DM [%] | $RI_{ES}$ DM [%] | $RL_{NOES}$ CS [%] | $RL_{ES}$ CS [%] | $RI_{ES}$ CS [%] |
|---|---|---|---|---|---|---|---|
| 00-24 | 47.45 | 75.11 | 50.41 | 24.70 | 77.94 | 52.82 | 25.12 |
| 07-15 | 98.99 | 59.15 | 0.53 | 58.62 | 59.26 | 0.55 | 58.71 |

Table 5.2: Aggregate resilience assessment for Distribution Systems 1, 2 and 3

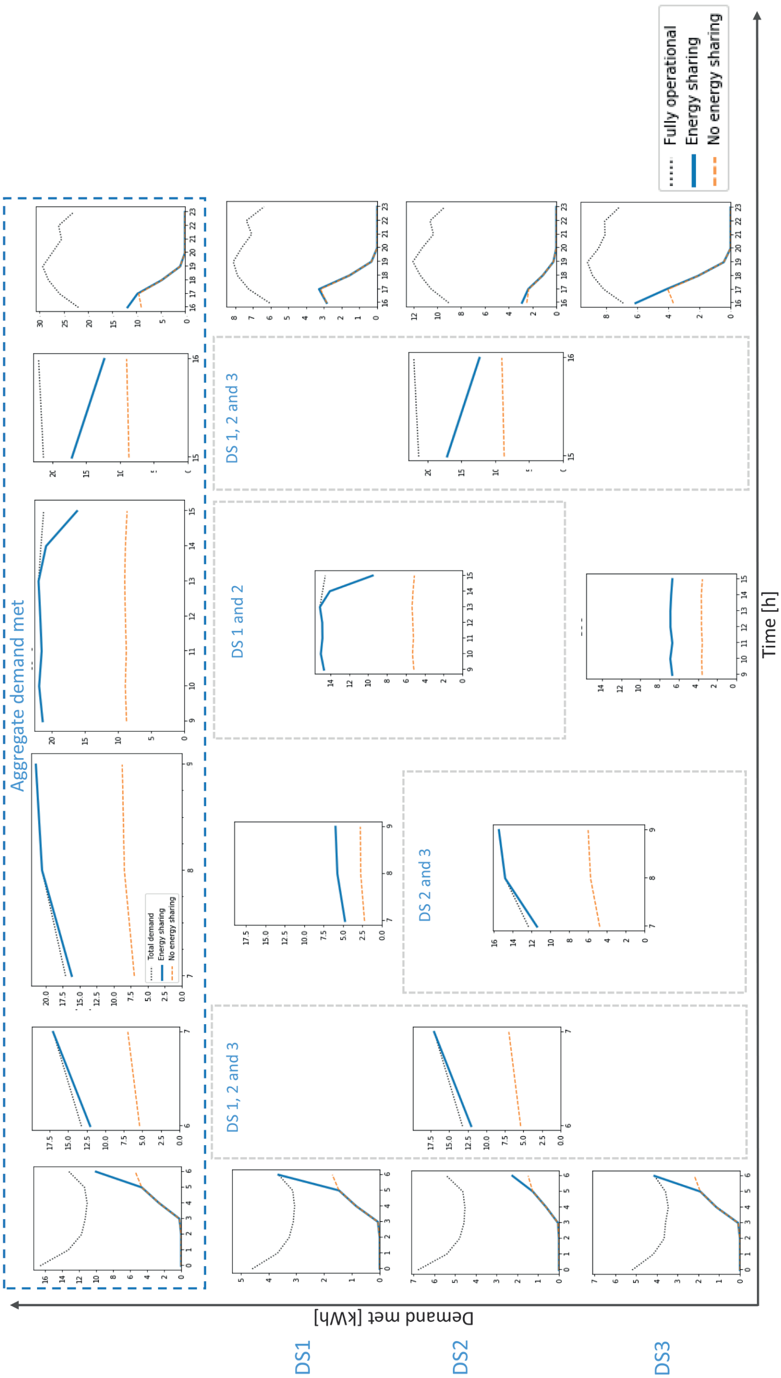


Figure 5.8: Hourly demand met assessment: DS reconfiguration with energy sharing

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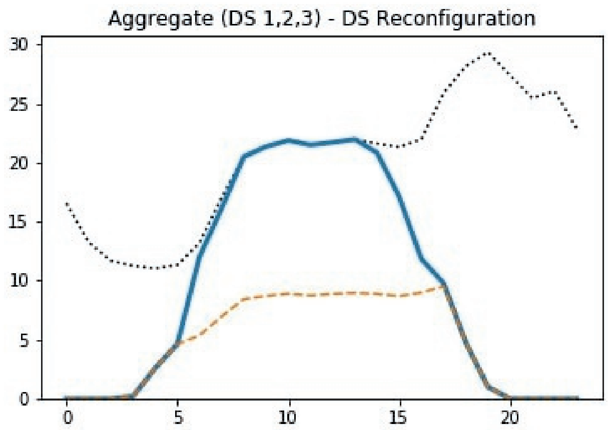
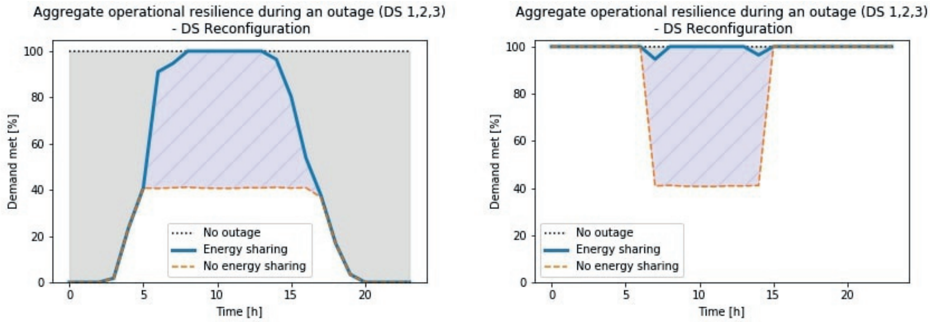



Figure 5.9: Demand met - A comparison between no resource sharing and the presented approach






(a) (b)

Figure 5.10: Demand met during an outage: A comparison between no resource sharing and the presented approach

## 5.5 Discussion

As discussed in Section 5.3, the presented approach requires that local resource owners agree to share excess electricity supply during outage periods with other consumers and prosumers, and form local energy groups during outage periods. These groups are highly adaptable by being able to reconfigure to respond to changes in the environment. Group members are chosen by local resource owners based on the best profile match that minimizes supply and demand mismatch. To account for other factors that can be incorporated in choosing members (e.g. energy resource type, consumers type, price, etc), negotiation mechanisms such as WS-agreement [115] or automated negotiation [83] can be used. However, those are outside the scope of this chapter. Groups are assumed to be formed and reconfigured hourly. However, as frequency of cluster reconfiguration depends on availability of (fine-grained) data, forecasts or other external and internal inputs, this parameter can be altered. Note that depending on the size of the system and communication infrastructure, this can potentially create a delay in cluster formation. To avoid the delay, negotiation can be performed in advance, prior to an outage, based on local knowledge of supply and demand (or their forecasts), so that default groups are already formed. When an outage occurs, the group formation part based on S/D mismatch calculation can be skipped, and the default groups can instantaneously function autonomously, adapting to changes as needed. As such, they can operate as in a loosely-coupled way even with the backbone grid available. This pre-formation increases responsiveness to disasters and rapidity in terms of restoring normal operation of the system, and can guarantee resilience.

The role of local energy groups in power systems can be further emphasized by not only asking permission from resource owners to distribute their excess production, but to also give them power to decide how and to whom to distribute it. A set of policies/institutional regulations should be developed with other types of resilience measures and metrics. Future work will assess resilience of different types of members of local energy groups (e.g. schools, supermarkets, hospitals, offices, households) with respect to their social importance.

Achieved resilience depends upon several factors, such as the type of local resources available, the amount of generated electricity by the resources, the number and load demand of consumers, time of occurrence and duration of disturbance etc. In the case study discussed in this chapter only solar production is modeled as a local resource. The results show that depending on the time of occurrence and duration of disturbance, the performance of a system might still be sub-optimal (depending on outside circumstances such as renewable generation). This indicates that the resilience of the system can be further improved. This *resilience gap* can be overcome by using different types of renewable energy sources, such as wind turbines or energy storage devices (e.g. batteries, electric vehicles).

However, using only renewables that are volatile, the load cannot be constantly fully matched and at times it might not be met at all. To bridge this gap, diesel generators (DGs) or dispatchable technologies (such as battery power, biogas) can be installed in a system to provide energy support to residual load and system losses. Where a DG or dispatchable technologies are placed depends on the location itself, see for example [166] for methodologies currently deployed.

From the case study experimentation, DS2 is a suitable candidate for DG placement due to lesser generation availability in DS2 sub system. In a contingency scenario, DG placed on DS2 can also supply energy to nearby DSs and enhance system resiliency ans stability with minimum efforts. The corresponding reconfiguration results are also reported in Table 5.3 for all hours. These results correspond to the fact that all shedded loads in the previous case are now supplied by the newly installed DG located in DS2.

| Hour | SW1 | SW2 | SW3 | Remarks |
|---|---|---|---|---|
| 0-23 | Close | Close | Open | Figure 5.7 (b) |

Table 5.3: Reconfiguration under DG placement at DS2

Although the proposed approach provided a vision for the future, a promising step towards such systems can be seen in several projects based on peer-to-peer technologies, such as Piclo, SonnenCommunity, Smart Watts, TransActive Grid, and several others [64].

However, these projects are primarily developed and implemented to be used as energy trading platforms and do not take the physical elements of the power grid into account. The main challenge of applying the proposed system in real-life lies in laying the cyber-physical infrastructure that could operate in real-time for a large-scale complex power system. Although not a difficult task, the integration of intelligent electronic devices at each node and mapping of the underlying circuit, would require a major upgrade of existing power systems. Initiatives with smart meters follow similar strategy, where our proposed approach can complement existing infrastructures to provide system resilience. In terms of the ICT infrastructure, the application of such a system would require installation of software (an agent) at appropriate nodes, either on existing or new devices, and configuring them to perform the assigned tasks. Another key challenge is the social component, as prosumers have to be willing to share their excess production. The existance of local energy initiatives and communities is a promising indication of the feasibility of such an approach.



## 5.6 Conclusions

During large-scale blackouts caused by severe weather events, the traditional centralized coordination of power systems becomes challenging, and consumers and prosumers in impacted areas have to rely on local resources and coordination schemes to function during disturbances. Global information on supply and demand might not be available, making traditional supply-demand balancing impossible.
This chapter presents an approach for improving resilience of power systems based on decentralized coordination of (1) local resources and (2) the grid itself. Self-organizing energy groups form by locally matching their supply and demand and sharing local resources, while components in self-organizing distribution networks reconfigure themselves. As the approach is fully decentralized, the need for a central unit of coordination and a joint information repository is eliminated.
Consequently, there is no single point of failure, which means that even if a part of the system is unavailable, the rest of the system is unaffected and can still perform supply and demand balancing. In such a loosely-coupled, self-organizing system, consumers and prosumers are less dependent on others. Both network and energy group reconfiguration are automatic, making the system more resilient and responding faster to new circumstances. The results demonstrate that by using these two mechanisms combined, resilience of impacted distribution systems in terms of demand met and consumers served is improved.

The approach is generic and can be used in different settings where the backbone grid is not available. As it uses both distribution system reconfiguration and local energy group formation, it is scalable and can be applied to both localized and widespread damages which affect multiple distribution systems.

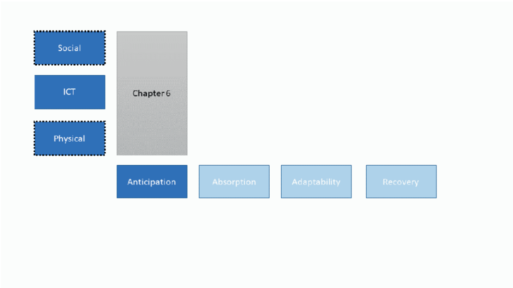
An ICT-enabled platform of this type can provide the functionality required to mitigate power outages, providing a more resilient power system. Integrated with traditional, but modernized operational measures for distribution system reconfiguration, decentralized energy resource sharing shows a promising potential for facing future challenges of power systems in face of uncertainties, given that local resource owners are willing to share excess generation.

In the future work, mechanisms for negotiating membership in these groups, supported by operational adaptive distributed system reconfiguration, are to be explored. Different types of service level agreements will be used to ensure supply reliability for the members of the groups.

# 6

# Flexibility prediction in Smart Grids: Making a case for Federated Learning






*High penetration of renewable energy sources brings both opportunities and challenges for Smart Grid operation. Due to their high contribution to energy consumption, aggregated load flexibility of small residential and service sector consumers has a potential to address the intermittency challenge of distributed generation. Predicting aggregated load flexibility of this consumer sector involves access to sensitive smart meter data, raising data collection and sharing concerns. Federated Learning, a decentralized machine learning technique that uses data distributed on user devices to construct an aggregated, global model, offers potential solutions to tackling this challenge. This chapter explores the potential of using Federated Learning for flexibility prediction in Smart Grids through an analysis of its opportunities and*

Chapter 6 is published in the proceedings of *CIRED 2021 - The 26th International Conference and Exhibition on Electricity Distribution* [33].

*implications for different stakeholders involved, as well as the challenges faced. The analysis shows that Federated Learning is a promising approach for building privacy-preserving energy portfolios of aggregated demand data.*

## 6.1 Introduction

Power systems are large-scale, complex socio-technical systems that are continually in transition. Traditionally built as centralized systems, societal and technological changes drive modern power systems to become more decentralized. This transition is further supported by advancements in, and the incorporation of smart Information and Communication Technologies (ICT), resulting in Smart Grids. Such a decentralized energy system requires novel intelligent energy management techniques.

In an energy system with volatile, non-dispatchable production, these techniques rely on flexibility of energy consumers and prosumers to perform demand response (DR) and load shifting [167]. Flexibility refers to the extent to which these stakeholders can adapt their energy demand in response to changes. Reynders et al. [168] outline and discuss various definitions and quantification methods for flexible energy.

Advancements in smart home technologies empower small consumers and prosumers to become proactive members of the system and trade their flexibility in energy markets, which can render financial benefits [169]. Participation in demand response services and forming energy communities bring residential and service sector consumers at the core of the energy transition. Currently, DR programs are mainly focused on energy-intensive industrial and commercial consumers, as typical residential and service sector consumers are too small to individually participate in these programs [170]. However, due to their high contribution to electricity consumption, there is a large potential when considering their aggregated load flexibility [171]. Load flexibility aggregation for residential and service sector consumers comes with challenges regarding data collection and privacy preservation, as it involves collecting sensitive consumer data conform national and international directives on data collection and processing such as GDPR [172].

Another challenge lies in understanding demand heterogeneity of small residential and service sector consumers, as most existing models are based solely on residential load and do not include the service sector [173]. Therefore, service sector consumers' flexibility is not properly reflected in current models. To address these challenges, methods to predict aggregated load flexibility, while attaining data integrity and privacy in a decentralized energy system should be considered.

Federated Learning (FL), a decentralized Machine Learning (ML) technique [174], offers a solution to tackle these challenges. FL can enable different stakeholders to create global representative models without sharing raw data, addressing the challenges of data privacy [175]. In Smart Grids, FL can be used to create local energy flexibility models of different consumer and prosumer categories and to aggregate these into global models, without exchanging local data.

The main objective of this chapter is to further explore the application of FL for load flexibility prediction (more specifically, demand response) of small-sized consumers in Smart Grids through an analysis of its opportunities, challenges and implications for different stakeholders.

## 6.2 Load flexibility prediction using Federated Learning: A stakeholder analysis

This section gives an overview of FL and analyses the potential of using this technique for addressing the challenges faced by stakeholders involved in aggregating load flexibility of small residential and service sector consumers and prosumers.

### 6.2.1 An overview of Federated Learning

Capable of discovering complex patterns from raw data, ML techniques are used for load flexibility prediction in Smart Grids. However, due to privacy concerns and data ownership, collecting all required data becomes challenging [176]. Federated Learning, a class of ML, capable of learning a single model across distributed devices, offers a solution to this. In FL none of the original data samples needs to be shared among different devices, thus offering potential benefits in lowering bandwidth requirements, data ownership and preserving privacy of its users.

The term and general concept of FL has originally been introduced in 2016 by McMahan et. al. [174] in order to learn keyboard suggestions on mobile phones [177]. Since then, it has been applied in many other domains. For Deep Learning [178], Federated Stochastic Gradient Descent (FedSGD) [179] and Federated Averaging (FedAVG) [174] are well-known variants for FL. FL can also be used for other types of machine learning models, such as Support Vector Machines [180].

FL aims to provide a solution to the problem of learning a global model from distributed data sets that should remain local, on nodes (data owners) with sufficient computation power to fit local models. In the context of this chapter, the nodes are consumers and prosumers. For these data owners, the main opportunity therefore lies in maintaining data privacy whilst enabling local contributions to a shared model. This means all individual nodes can reap the benefits of each others contributions to the global model and at the same time keep their personal data private. From a model owner perspective (e.g. an energy aggregator), computation is now partially offloaded to local nodes, which opens up opportunities for cost reduction.

Despite the applicability of FL in the energy domain, current research on this topic is limited [102, 181].

The following subsections discuss the potential implications of using FL by different stakeholders that participate in aggregated small residential and service sector demand response.

### 6.2.2 Consumers and prosumers

Aggregating load flexibility can enable small residential and service sector consumers and prosumers to jointly participate in energy markets through DR programs, which can bring them financial benefits. As the main concern lies in data privacy (as some consumers are reluctant to share private information with centralized ML models used by aggregators) [182], FL offers a potential solution to this, as private consumer and prosumer data can stay on their devices, without the need to be shared with other stakeholders. Therefore, using FL could potentially increase the willingness of small consumers and prosumers to participate in aggregated DR.

### 6.2.3 Aggregators

This aggregated flexibility can be used by aggregators to create energy portfolios, and trade them in energy markets [183, 184]. Depending on their business model, aggregators with different roles face a number of challenges. Information exchange is identified as one of these challenges, as different stakeholders need access to aggregator's data to enable accurate load forecasting [185]. The privacy-preserving property of FL offers a potential opportunity to address this challenge, as stakeholders involved do not have to share data with each other. Another challenge lies in data availability, as aggregators' access to data generated by smart energy devices is not guaranteed and can be incomplete, questioning data integrity [183]. To tackle this challenge, aggregators can use global flexibility models (potentially hosted on their own devices) generated for specific consumer and prosumer categories to get an estimation of offered flexibility.

### 6.2.4 Distribution System Operators

High penetration of renewable energy sources (RES) brings both opportunities and challenges for Distribution System Operators (DSOs) when it comes to grid planning and operation. Load flexibility prediction of small residential and service sector consumers' demand reponse is a promising approach to deal with variability and uncertainty of RES. To have an impact on network planning and RES integration, small consumer flexibility should be considered on an aggregated level [186]. From the perspective of DSOs, FL can offer a number of opportnunities to integrate small residental and service sector DR into grid operation planning, and better respond to uncertainties and non-dispatchability of RES. Global FL models that aggregate a large number of small residential and service sector consumers on geographically distant locations, can be used by DSOs to better understand the DR of this sector. This knowledge can be used to gain insight into local flexibility, when data is unavailable or insufficient, and help make better plans for future grid investments and planning.

### 6.2.5 Policy and decision makers

As mentioned before, another challenge lies in the lack of representative service sector models, which can lead to significant misestimations for RES integration [173]. FL can be used to construct global models of different consumer categories (e.g. residential, service sector) and subcategories (e.g. offices, supermarkets, schools) to better use their potential in demand response and RES integration. These models can support policy and decision makers to get better insight into future energy transition scenarios.

In this section, the potential of using FL for aggregated load flexibility prediction is discussed with respect to the stakeholders involved. However, despite its promising benefits, FL comes with challenges that need to be addressed. The next section outlines these challenges and gives guidelines and recommendations to address them.

## 6.3 Addressing the challenges of Federated Learning: Guideliness and recommendations

Fig. 6.1 provides an abstract example application of using FL within the energy domain and illustrates some of the challenges as discussed further in the following subsections.

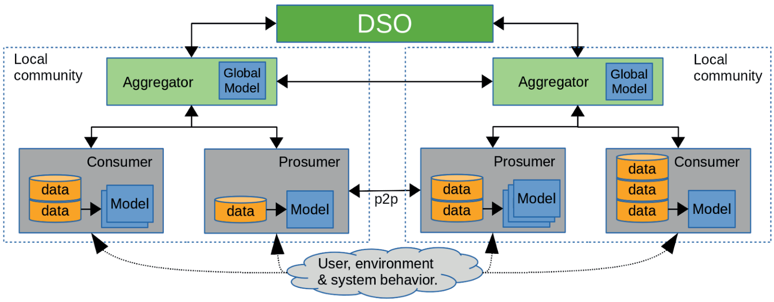



Figure 6.1: An example application of using Federated Learning within a Smart Grid. A local community (e.g. an energy neutral village) typically consists of multiple consumers, producers and prosumers, which in turn consists of multiple devices that may require a different type of model. Data is typically distributed unevenly over multiple devices and influenced by different user behavior, system behavior and other environmental influences.

Most variants use a single central server to aggregate all changes to the global model from multiple clients. However, as the ecosystem grows in complexity and local communities become more independent, it is likely to assume that multiple of these central servers (or model aggregators) may exist for the purpose of improving scalability or to abstract the global model at a certain level. This might especially be relevant in the energy domain which consists of multiple (competing) stakeholders and communities that may heaviliy rely on self-organization.

6

### 6.3.1 Data Distribution

Many ML techniques often have the underlying assumption that training data is sampled Independent, and is Identically Distributed (IID) in order to obtain an unbiased estimate of the gradient that is being approximated [187, 188]. A major challenge in FL, therefore, is the use of non-IID, statistically heterogeneous, and vertically distributed data.

Solutions have been proposed such as, item reparametrization of existing models to help them converge in the heterogeneous scenario [189], sharing a small IID subset of the data globally, or using proxy data [187].

### 6.3.2 Communication Efficiency

Communication is a primary bottleneck of distributed computation, especially the case of FL that often requires many rounds of sharing updates from resource-constrained nodes. It is therefore key to balance the size of model updates, communication frequency, sparsity and model performance, which remains an open problem [188].

### 6.3.3 Privacy and Security

Providing that none of the data samples are shared among the devices, it seems intuitive to assume that this protects the privacy of the user. However, sensitive information can still become compromised during the updates of the model. For instance, in the work of [190], a Generative Adversarial Network (GAN) is trained to generate the original samples as used to train the model of other users. Alternatively, the (aggregated) gradients, that are shared from users to a central server (and other users through updates of the global model), may compromise sensitive information about the private training data being used [191].

Apart from the original input, aggregated gradients can also be used to classify the presence of specific properties (not present in the input features) using a separate trained classifier [192]. Potential solutions to these attacks include the Double Blind Collaborative Learning algorithm [193], which uses random matrix sketching for the parameters on the central server side to obscure the information between model updates.

### 6.3.4 Model Bias, Fairness and Personalization

FL also poses challenges in reducing unwanted bias and increasing fairness in the model [194]. Global models might be biased towards specific users and may achieve poor accuracy on an individual level. For instance, devices with poor connectivity in rural areas might not be able to participate in the federated learning scheme as often. This increases the risk of biasing the global model towards devices within an urban area which may have a very different energy profile.

Potential solutions to these problems include Model Agnostic Meta Learning [195] or Agnostic Federated Learning [196]. The latter uses a mixture of client distributions to optimize the central model for any target distribution. An alternative is to use clustering in order to match the best global model to specific users, which is similar to what is done for energy demand prediction for electric vehicle networks [102].

The key challenge is to find a way to use generic information from the global model (e.g., by learning typical usage profiles over time) while adapting it to a particular situation (e.g., by including personal preferences and local differences in the environment). For this purpose, one could also consider using methods similar to Meta-Learning [197, 198] or Transfer Learning [199, 200] to adapt pretrained models to a particular situation. Or using local and global representations to account for the heterogeneity in the data [201].

## 6.4 Conclusion

Due to their high contribution to energy consumption, aggregating load flexibility of small residential and service sector consumers has a potential to address the intermittency challenge of distributed generation. However, predicting aggregated load flexibility of this consumer sector involves access to sensitive smart meter data, raising data collection and sharing concerns. With its privacy-preserving properties for data aggregation, FL offers a potential solution to tackle this challenge. The analysis discussed potential benefits for stakeholders involved, potentially resulting in higher consumer participation in demand response programs, and getting a better insight in residential and service sector flexibility. This chapter shows that, given the need for privacy preservation, increased scalability and the shift towards decentralization, FL is a promising approach to support privacy-preserving data aggregation.

Using FL comes with challenges that need to be addressed. As using such models can potentially incentivise consumers to share their data, aggregators should start investigating methods to model the value of those contributions to a global model, and define billing and pricing models on top of that. Furthermore, as more consumers participate, security measures have to be researched, as there is a possibility for influx of potentially harmful data. Finally, as decentralized approaches for flexibility prediction become more prominent, the future work should also focus on how to share different models and adapt them for various applications.

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# 7

# Discussion and conclusions

Power systems face challenges that arise due to a number of factors such as extreme weather events caused by climate change, aging infrastructure and power grid assets, demand increase, as well as the changes brought by energy transition and digital transformation. To face these challenges, power systems need new paradigms for coordination and planning to make them more resilient not if, but when, disturbances occur. Harnessing the potential of renewable resources and smart technologies for smart coordination through empowerment of consumers to become pro-active participants supported by technologyis a promising solution for the future power systems. To this end, this thesis explores how local energy resources can enhance power system resilience through self-organization and local decision-making. The designed interventions and their results can be used not only to improve resilience of power systems, but to support decentralization of power systems on its different levels in the transition towards a more sustainable energy system. This thesis shows that designing solutions that improve resilience of power systems first and foremost requires understanding the concept of resilience and including all its properties in the design of the solution that tackles it. Furthermore, it shows that when designing and developing interventions that aim to solve challenges of complex systems, it is important to consider and include different aspects/layers of it. In the context of this thesis, to improve resilience of power systems, not only the physical elements (layer) should be considered, but the ICT an social layer as well. Doing this creates a less-biased solution that is able to take into consideration different aspects of the system.



Decentralized coordination through self-organization is a promising approach to improve resilience of power systems. To improve resilience, self-organization has to be considered and implemented on different levels: physical, ICT and social. Self-organized energy groups can operate in a loosely-coupled way even with the backbone grid available. This pre-formation increases responsiveness to disasters and rapidity in terms of restoring normal operation of the system, and can guarantee resilience.

Furthermore, this research shows that decision making between individual consumers and prosumers can benefit the affected communities by sharing available locally produced energy as well as data, given appropriate mechanisms. In case of scheduled outages, the mechanisms can be used by decision makers and planners beforehand as a tool to gain insight on how different community perspectives on energy priorities can influence supply reliability in affected communities. Eventually, based on the results, backup plans for alternative power sources can be made.

## 7.1 Research questions revisited

This section revisits the main and the sub-research questions posed in Chapter 1 and answers them with the insight gained through this research.

The main research question of this thesis is:
**RQ** Can energy resilience be enhanced through self-organization using a decentralized approach to energy resource coordination?

Resilience of power systems is impacted by various internal and external elements. Enhancing this resilience first requires a good understanding of its characteristics. Variety of characteristics and the complexity of the targeted system implies that a systemic approach that integrates different system aspects has to be taken. In the case of power systems, this entails carefully addressing its physical, ICT and social elements. This thesis demonstrates the importance of such a systemic approach to designing solutions that aim to complex system features such as resilience.

Conducted research shows that energy resilience can be enhanced when principles of self-organization are used to design interventions that facilitate sharing local energy resources in a decentralized way. A loosely-coupled, bottom-up solution eliminates the central point of failure and ensures that the system can operate during interruptions by dynamically adapting to its environment even when partial information is available. This adaptability is the key to enhancing system resilience. The potential of a solution based on self-organization is demonstrated not only for the ICT layer, but also for the physical and social layers. In cases of widespread outages, grids have to be able to reconfigure themselves, enabling energy resource sharing accross multiple networks. When resources are scarce, decisions on energy provisioning have to be made. Local energy resource owners can play a pivotal role in ensuring energy is supplied to differentiated consumers. This thesis also shows that a systemic apporach comes with tradeoffs (e.g. not all differentiated consumers get power supply and may need to agree on an acceptable level of service during an interruption), and system/intervention designers have to make descisions on how to deal with those tradeoffs.

**SRQ1** What are requirements for a resilient power system?

To ensure resilience of an energy system, a set of characteristics that it requires has to be well-defined. This thesis investigates the state-of-the-art literature to outline the main characteristics of a resilient power system, and to explore the potential of current local energy sharing interventions for resilience in terms of these characteristics. According to the literature, a resilient system has to possess the following characteristics: anticipation, absorption, adaptability and recovery. In the context of power systems, anticipation of a disturbance can be both in the form of event forecasting (e.g. time of occurrence, duration, location, impact, probability etc.), and load forecasting (e.g. short-term hourly load forecasting during a disturbance). Absorption is the ability of a power system to withstand the impacts of a disturbance by maximizing the demand met, the number of customers served and the generation capacity availability during a disturbance. Adaptability is the ability of a power system to adjust to new circumstances by undergoing changes to maintain an operational level during a disturbance, including changes in topology, dynamic supply and demand balancing, demand response, and local generation and storage utilization during a disturbance in order to maximize power system performance indicators. Finally, recovery is the ability of a power system to restore its full physical grid operation and to be able to meet all the demand of all of its consumers. This question is answered in Chapter 2.

**SRQ2** Can an intervention be designed that enables fully decentralized, adaptive energy supply and demand matching through self-organization and how?

In the current trend of power systems decentralization, there is a need for a fully decentralized coordination of local energy resources. On an ICT level, such coordination can be facilitated using technologies such as multi-agent systems that enable local decision-making and information sharing between different agents in a system. This thesis designs and develops a fully decentralized energy resource coordination intervention based on principles of self-organization, locally balancing supply and demand of consumers and prosumers. During normal operation, centralized coordination of power systems keeps supply and demand of electricity matched. The thesis demonstrates that a decentralized approach to energy supply and demand matching can be achieved, given that local information is available and can be shared. This question is answered in Chapter 3.



**SRQ3** Can this mechanism be used to facilitate self-determined energy sharing for energy provisioning of differentiated consumers during outages and how?

This thesis introduces the concept of self-determined distribution of local energy resources, where electricity provisioning is performed to meet the demand of differentiated consumers and prosumers during an outage. This differentiation is performed by consumers and prosumers themselves, and can also change dynamically, depending on local preferences and supply availability. The mechanism for self-organized coordination of energy resources is extended to enable differentiation in energy provisioning. This approach empowers local communities to decide for themselves how local resources are distributed during events such as outages, ensuring prolonged power supply for differentiated members of affected communities, especially when local resources are limited. This question is answered in Chapter 4.

**SRQ4** Can self-organization on both the ICT and physical layer improve resilience during widespread outages and how?

With an increase in extreme weather events, widespread outages that affect multiple power systems will become more frequent, and consumers and prosumers in affected areas have to rely on local resources to meet their demand. An approach for improving resilience of power systems based on decentralized coordination of (1) local resources and (2) the grid itself is developed. Self-organizing energy groups form by locally matching their supply and demand and sharing local resources, while components in self-organizing distribution networks reconfigure themselves to dynamically change topologies. As the approach is fully decentralized, the need for a central unit of coordination and a joint information repository is eliminated. Such an approach can improve power supply availability across different distribution system networks, sharing resources while abiding to the physical grid properties. This question is answered in Chapter 5.

**SRQ5** Can local information from distributed energy assets be used to gain knowledge of a global system and how?
To address the challenges brought by demand and generation increase, transmission and distribution system operators need insights into the state of the grid to plan for congestion management and respond to production peaks. Demand response using flexibile assets is a promising approach to address this. However, system operators do not have a good insight into available flexibility at a larger scale. Driven by the digitalization of power systems in terms of (smart) ICT as well as physical devices such as smart meters, data from local assets can be used to gain information about available flexibility. However, this data is often sensitive and its owners might not want to share it, as it can reveal personal information (e.g. behavior patterns). This thesis shows that by using a decentralized machine learning technique such as Federated Learning, stakeholders can share their local data, without revealing private information. This local data can then be aggregated to give insigts into the global state of the grid (or the area where data is located in). Having this aggregated infromation, along with the area topology can be used by different stakeholders to learn about the available flexibility in a privacy-preserving way. This question is answered in Chapter 6.



## 7.2 Future work

During the research for this thesis, several courses for future work are recognized:

**FW1 Membership SLAs**
To be able to match supply and demand, consumers and prosumers have to negotiate membership in an energy group. To that end, different negotiation mechanisms for ensuring the membership in a group can be explored as a future course of research, answering the question how, and for how long, this membership can last, and under what terms. In Chapter 3 and 4, service-level-agreements (SLAs) are mentioned as a way to fix the group boundaries, but are not explored in detail. Future research should explore how these SLAs are signed, what they contain and how the content of SLAs can affect the supply and demand matching process. Furthermore, research around SLAs can explore how commitment to energy provisioning and consumption can be ensured (e.g. introducing penalties), and what effect this could have on energy resilience study.

**FW2 Institutional framework for consumer differentiation**
The concept of self-determined distribution of local energy resources is used to explore how differentiating consumers and prosumers, and dynamically distributing locally available renewable resources to those consumers and prosumers, can ensure supply reliability during an outage. Future research should explore the institutional framework necessary to enable this self-determined differentiation. The framework could explore some of the

following things: different approaches to differentiate between consumers, focusing on local decision-making within an energy group, the duration of differentiation assignment (e.g. only temporary or fixed) etc. Additionally, more thorough research on differentiation could be made in terms of its societal and economic benefits. An agent-based model can be designed to explore the effects of different institutions on supply reliability during outages. Two case scenarios can be observed, namely static vs. dynamic priority assignment, where a comparison is made between pre-assigned, fixed priorities, and those dynamically (ad-hoc) assigned when an outage occurs.

An ICT-enabled platform based on self-organization that harnesses the potential of local generation can provide the functionality required to mitigate power outages, providing a more resilient power system. Integrated with traditional, but modernized operational measures for distribution system reconfiguration, decentralized energy resource sharing shows a promising potential for facing future challenges of power systems in face of uncertainties, given that local resource owners are willing to share excess generation and that the enabling physical and communication infrastructure exists. The challenge lies in developing such an infrastructure, as well as in establishing institutional and policy regulations that could enable it.

To be ready for the future is to be ready to adapt to challenges it brings. Like many other critial infrastructures, power systems are traditionally built as rigid, centralized systems. To enhance their resilience and ensure their operability in the future, these infrastructures have to be able to bend with the changes and adapt to their environment in a proactive, not a reactive way, embracing the different transitions they undergo.

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# Curriculum Vitæ

## Selma Čaušević

Selma Čaušević was born on March 28, 1989 in Bihać, Bosnia and Herzegovina. She spent most of her life in Sarajevo, where she completed her Bachelor (2011) and Master (2014) studies in Computer Science, at Sarajevo School of Science and Technology. In the period of 2011-2015, she worked as a Software Developer in a local telecommunications company. She moved to the Netherlands in 2015 to pursue her Ph.D. degree at Delft University of Technology (TUD) in Systems Engineering Group at the Faculty of Technology, Policy, and Management.

Since the beginning of 2020, she has been working as a Scientist Integrator in Advanced Computing Engineering (ACE) department at the Netherlands Organisation for Applied Scientific Research (TNO). Both her Ph.D. researh and her current work focus on the application of Computer Science in (smart) energy domain. She is passionate about researching, designing and developing smart ICT solutions that facilitate energy transition.

# List of Publications

Included in this thesis:


1. Selma Čaušević, Ron Snijders, Geert Pingen, Paolo Pileggi, Mathilde Theelen, Martijn Warnier, Frances M.T. Brazier, Koen Kok: Flexibility prediction in Smart Grids: Making a case for Federated Learning. In CIRED 2021 - The 26th International Conference and Exhibition on Electricity Distribution, volume 2021, pages 1983–1987, 2021.

2. *Selma Čaušević, Kritika Saxena, Martijn Warnier, Abhijit Abhyankar R, Frances M.T. Brazier*: Energy resilience through self-organization during widespread power outages. Sustainable and Resilient Infrastructure, 6(5):300–314, 2021.

3. *Selma Čaušević, Martijn Warnier, Frances M.T. Brazier*: Self-determined distribution of local energy resources for ensuring power supply during outages. Energy Informatics, 2(1), 2019.

4. *Selma Čaušević, Martijn Warnier, Frances M.T. Brazier*: Dynamic, self-organized clusters as a means to supply and demand matching in large-scale energysystems. In 2017 IEEE 14th International Conference on Networking, Sensing and Control (ICNSC), pages 568–573, 2017.


Not included in this thesis:


1. *Selma Čaušević, Shreshtha Sharma, Syrine Ben Aziza, Aliene van der Veen, Elena Lazovik*: LV Grid state estimation using local flexible assets: A Federated Learning approach. To appear in the 27th CIRED International Conference & Exhibition on Electricity Distribution, Rome, Italy, 2023.

2. *Selma Čaušević, George B. Huitema, Arun Subramanian, Coen van Leeuwen, Mente Konsman*: Towards positive energy districts in smart cities: A data-driven approach using aggregation and disaggregation of energy balance calculations. In Environmental Sciences Proceedings, 11(1), 2021.

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**2015-07**. *Maria-Hendrike Peetz(UvA)* . Time-Aware Online Reputation Analysis.

**2015-08**. *Jie Jiang (TUD)*. Organizational Compliance: An agent-based model for designing and evaluating organizational interactions .

**2015-09**. *Randy Klaassen(UT)* . HCI Perspectives on Behavior Change Support Systems.

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