When are battery electric vehicles economically convenient? A sensitivity analysis based on multi-carrier residential energy system renovation modelling

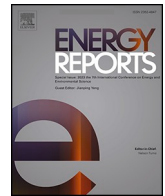Rinaldi, Lorenzo; Golinucci, Nicolò; Guerrieri, Giulia; Sanvito, Francesco Davide; Rocco, Matteo Vincenzo; Colombo, Emanuela

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Research paper

When are battery electric vehicles economically convenient? A sensitivity analysis based on multi-carrier residential energy system renovation modelling

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ABSTRACT

Investing in low-carbon technologies, including light-duty vehicles, is a strategy to decarbonize the residential sector and private mobility. This work aims to assess the parameters driving the economic convenience of battery electric vehicles (BEVs) for a household, and what are the economic implications of BEV adoption on the total cost of the residential energy system in case of house renovation. An archetypal household energy system has been modelled for the Italian context, where strong residential energy efficiency incentives have been put in place in recent years. Adopting a least-cost-oriented energy system optimization model, 33'600 residential energy system configurations have been analysed through an extensive sensitivity analysis carried out focusing on crucial input parameters, classified as behavioural (annual travelled distance, expected ownership time of the car), energy-related (electricity and heating demand, house location, PV installed capacity), and economic (grid electricity price, gasoline prices and incentives on BEV purchase). Results show that integration with PV installation is the parameter most strongly correlated with BEV adoption, followed by annual travelled distance and ownership time. Moreover, results suggest that an increase in electricity prices has a lower impact on disincentivizing BEVs adoption compared to how much an equivalent increase in gasoline prices disincentivizes ICEVs adoption. Valuable insights reveal that, within the range of the Italian average gasoline price, BEV-based energy systems remain competitive. This holds even with a high electricity price, provided a minimum of 3 kW photovoltaic capacity is installed. In light of the ongoing energy crisis in Europe, these findings are promising for BEV adoption, particularly if accompanied by BEV incentive policies.

1. Introduction

1.1. Background and objectives

The shift towards low-carbon technology is becoming increasingly important due to the need to limit global temperature rise. While previous energy transitions have been characterised by technological innovations and market dynamics which led naturally to improved living standards and economic margins for companies, the one we are currently facing needs to be accelerated and supported by governmental action. According to the IPCC, it is paramount to commit to achieve a 45 % reduction in carbon dioxide emissions by 2030 compared to 2010 levels (IPCC, 2022a). In light of this objective, actions and efforts shall be directed to sectors with the greatest impact, such as transport.

According to the European Environment Agency, European road transport and residential sectors accounted respectively for 13 % and 6 % of CO_2 emissions in 2020 (European Environment Agency, 2023). Considering the transport sector, 57 % of its CO_2 emissions come from light-duty vehicles. These data highlight that individual responsibility in choosing the means of transport could play a significant role in the decarbonization of this sector, which is worth to be analysed. Considering the absence of tailpipe emissions, Battery Electric Vehicles (BEVs) are a promising solution to be deployed at large scale for decarbonizing private passenger mobility (IPCC, 2022b; Hoekstra, 2019). In its Global EV Outlook (IEA, 2023a), the IEA reports that the global electric cars stock tripled during the last three years, reaching 16.5 million units in 2021: specifically, 55 % and 27 % of the global fleet of passenger BEVs

Nomenclature

BEV	Battery Electric Vehicle
ICEV	Internal Combustion Engine Vehicle
IEA	International Energy Agency
HBS	Home Battery System
HP	Heat pump
GB	Gas boiler
GS	Gas Stove
IS	Induction stove
LP	Linear Programming
MILP	Mixed-Integer Linear Programming
NG	National Grid
NPC	Net Present Cost
PV	Photovoltaic panels
RES	Reference Energy System
sp	Sensitivity parameters
SM	Supplementary Material
STP	Solar Thermal Panel
TI	Thermal Insulation
V0–6	Sensitivity values

circulate in China and Europe respectively. However, BEVs still represent only 2.3 % of European passenger cars stock and to support the households towards the purchase of an electric vehicle, in the last years an average of 5 to 6 thousand USD have been invested by the government for each vehicle as public expense (IEA, 2023a).

Although public subsidies represented a substantial enabler towards BEVs adoption at a mass scale, it is also relevant to investigate the influence of other possible drivers which are widely discussed in literature: this paper aims to provide a quantitative assessment of the impact of a set of parameters over the economic sustainability of a BEV to be purchased in residential context concerning an Internal Combustion Engine Vehicle (ICEV) of the same segment.

1.2. Literature review

Among the factors driving the economic viability of BEVs, it is worth mentioning Ling et al (Ling et al., 2021). and Brückmann et al (Brückmann et al., 2021)., which already focused on assessing how social and behavioral factors, together with vehicle performances and political frameworks, may influence on BEV adoption; however, they overlooked on exploring how potential synergies among the vehicle and other energy technologies may correlate with the vehicle purchase in residential contexts.

With this in mind, a critical literature analysis was performed on 37 articles published from 2015 to 2023, which are presented in Table 1 and clustered according to their methodology and whether they apply such methodology to a single household unit or a district/community. Regarding the methodologies, four main approaches are identified, namely agent-based and system-dynamics models, demand simulation models, energy system optimization models and predictive control models.

Schwarz et al (Schwarz et al., 2020). adopt an agent-based model to investigate how BEV owners' charging habits are influenced by varying the electricity price in case of high renewables penetration. Golinucci et al (Golinucci et al., 2023)., instead, propose a consumer-oriented emission reduction mechanism developing a system-dynamic model in which the main drivers behind the purchase of a BEV compared to an equivalent ICEV are modelled. Regarding studies adopting demand simulation models, the article from Muratori (Muratori, 2018) stems out as one of the first-of-its-kind case studies building on the modelling of both electricity and transport demands of households to determine how

the electricity grid is impacted by uncoordinated plug-in electric vehicles charging. Gottwalt et al (Gottwalt et al., 2017)., instead, analyse the possible strategies of demand-side management practices to increase the stability of district microgrids with a high share of renewable generation: by simulating both electricity and transport demand with a simulation model they conclude BEVs are among the most promising residential technologies for this purpose. A third approach identified in the literature, which allows to modelling integrated power and transport residential needs, is the model predictive control: Yousefi et al (Yousefi et al., 2021)., Mirakhorli and Dong (Mirakhorli and Dong, 2017) and Guo et al (Guo et al., 2019). adopt model predictive control algorithms to minimize the electricity costs in residential and district applications while optimizing the provision of electricity and transport services.

While all the previously cited works focus on integrating BEVs as a synergic technology within the residential or community energy system framework, adopting different methodologies, the most adopted approach in the analysed literature is represented by the energy system optimization models. Such models are usually mathematically formulated as linear systems of equations including an objective function (usually the minimization of the total cost of the system) and other constraints. Among the many applications found, it is worth mentioning: Brahman et al (Brahman et al., 2015)., who model a residential energy system optimizing electricity, thermal and transport dispatch and technology sizing both using single- and multi-objective models oriented to least-cost and least emissions criteria; the application of Sun et al (Sun et al., 2019)., where a least-cost oriented energy system optimization model is set up to analyse the benefits of vehicle-to-grid power exchange in different feed-in tariffs scenarios; the analysis conducted by Kwon et al (Kwon et al., 2020). assesses the impact of different electricity tariffs on behaviour change by BEV owners in residential context regarding charging strategies.

The findings coming from the scientific literature drove the motivation for selecting an energy system optimization model as the best-fitting methodology for the present work. Although such approach is demonstrated to be commonly used to mathematically describe integration between transport and other (i.e. power, heat) demands, it seems none of the reviewed studies aim at assessing which the parameters that mostly affect the choice of purchasing a BEV or an ICEV are, except for some contributions that analyse the impact of lower or higher grid electricity prices. Other tools are found in scientific and grey literature which are considered close to the scope of this study. The Climobil application (Gibon and Chion, 2019) allows to compare two models of BEV and ICEV in terms of environmental performance, giving the possibility to change parameters such as lifetime, mileage and electricity mix. While the focus of Climobil is on the emission side only, the Carboncounter tool (Miotti and Trancik, 2021), compares both costs and lifecycle greenhouse gas emissions of different models of electric and internal combustion engine vehicles. It also allows the user to change the price of fuels or the level of taxes and/or subsidies (for the USA only). However, these tools do not explore the parametric viability of BEVs under other external conditions which include the integration of the vehicles within a residential energy system.

The lack of studies addressing both the integration of transport technologies within residential energy systems and the quantitative assessment of the influence of different parameters on BEVs economic convenience represents a gap in the literature that the present study aims to bridge.

1.3. Research contributions and outline

Drawing from the considerations coming from the literature review, this paper is innovative because of two reasons: (i) it adopts an intrinsic model-based instead of survey-based methodological approach; (ii) it extends the scope of the analysis to the integration between BEV and other technologies which may be installed within the domestic energy system. While this is not the first study addressing reason (i) or (ii), it can

Table 1

Relevant studies on energy-transport comprehensive systems, classified by methodology and application focus.

Year	Authors	Ref	Methodology				Application focus	
			Agent-based and System dynamics models	Demand simulation models	Energy system optimization models	Model predictive control	Household energy system	District-scale or community energy system
2015	Brahman F. et al.	(Brahman et al., 2015)			x		x	
	van der Kam M. et al.	(van der Kam and van Sark, 2015)			x			x
	Zhang Y. et al.	(Zhang et al., 2015)			x			x
	Yousefi M. et al.	(Yousefi et al., 2021)				x	x	
	Atia R., Yamada N.	(Atia and Yamada, 2015)			x			x
2016	Coelho V.N. et al.	(Coelho et al., 2016)			x			x
2017	Gottwalt S. et al.	(Gottwalt et al., 2017)		x			x	
	Melhem F.Y. et al.	(Melhem et al., 2017)			x		x	
	Li G. et al.	(Li et al., 2017)			x			x
	Calvillo C.F. et al.	(Calvillo et al., 2017)			x			x
	Mirakhorli A., Dong B.	(Mirakhorli and Dong, 2017)				x		x
2018	Muratori M.	(Muratori, 2018)		x			x	
	Sedighizadeh M. et al.	(Sedighizadeh et al., 2018)			x			x
	Mohammadkhani N. et al.	(Mohammadkhani et al., 2018)			x			x
	Akram U. et al.	(Akram et al., 2018)			x			x
	Kamal T. et al.	(Kamal et al., 2018)			x			x
	Calvillo C.F. et al.	(Calvillo et al., 2018)			x			x
2019	Mazzeo D.	(Mazzeo, 2019)			x		x	
	Sun Y. et al.	(Sun et al., 2019)			x		x	
	de Souza Dutra M.D. et al.	(de Souza Dutra et al., 2019)			x		x	
	Aoun A. et al.	(Aoun et al., 2019)			x			x
	Guo X. et al.	(Guo et al., 2019)				x		x
2020	Farrokhifar M. et al.	(Farrokhifar et al., 2020)			x			x
	Khemakhem S. et al.	(Khemakhem et al., 2020)			x			x
	Foroozandeh Z. et al.	(Foroozandeh et al., 2021)			x			x
	Foroozandeh Z. et al.	(Foroozandeh et al., 2020)			x			x
	Schwarz M. et al.	(Schwarz et al., 2020)	x				x	
	Kwon Y. et al.	(Kwon et al., 2020)			x		x	
2021	Liu J. et al.	(Liu et al., 2021)			x			x
	Zeynali S. et al.	(Zeynali et al., 2021)			x			x
	Wang N. et al.	(Wang et al., 2021)			x			x
	Momen H. et al.	(Momen et al., 2021)			x			x
	Gil G.O. et al.	(Gil et al., 2021)			x			x
	Higashitani T. et al.	(Higashitani et al., 2021)			x		x	
	Muthiah-Nakarajan V. et al.	(Muthiah-Nakarajan et al., 2021)			x		x	
2022	Wei H. et al.	(Wei et al., 2022)			x		x	
2023	Golinucci et al.	(Golinucci et al., 2023)	x				x	

be counted among the first to explore both.

For this purpose, this study couples the adoption of energy systems optimization modelling with an extensive sensitivity analysis ranging over a set of multi-dimensional parameters, classified as follows:

- *behavioural*, such as the annual travelled distance or the expected ownership time (e.g. how many years the user is expected to possess the vehicle);
- *energy-related:* different house size archetypes have been classified according to their energy demands, with a particular focus on electricity and heat. Moreover, the influence of the presence of other domestic energy technologies (PV and heat pumps) and the solar radiation profiles are investigated;
- *economic-related*, the national grid electricity and gasoline prices, the presence of national subsidies for the purchase of a BEV. Such parameters may be interpreted as externalities since they are not typically under the control of the household.

The paper comes with a supplementary material document containing additional information on input data preparation and complementary results. Such supplementary material is henceforth indicated as "SM" and is available on GitHub (Rinaldi et al., 2022).

2. Methods and materials

2.1. Energy system optimization model

This paragraph provides an overview of the optimization model adopted for this study. The source code of the model is available on Github (Golinucci et al., 2022).

An archetypal household reference energy system has been modelled, considering a set of multiple technologies, including storage technologies, supplying a number of energy commodities. Such commodities can be consumed by technologies themselves (intermediate demand) and by the household (final demand). Multiple commodities

may compete with one another for the fulfilment of the same energy need. The demand of energy needs is modelled as a time-dependent variable: in this application, a multi-year hourly resolution has been considered.

The model is based on a mixed-integer linear programming (MILP) algorithm. The choice of the optimization algorithm was based on two aspects: (i) linear programming (LP) algorithms are a standard for energy system models, as reported by many reviews such as those by Prina et al (Prina et al., 2020). and by Dominković et al (Dominković et al., 2022).; (ii) focusing of a household energy system application, a MILP algorithm was preferred to standard LP, since the model must provide discrete outputs in terms of resulting technological capacities. The objective is to minimize the total discounted cost (net present cost, *NPC*) of the energy system over a period of y years. The objective function of the model is reported in Eq. 1, where the total investment cost of the capacity deployed is represented by the term $k_t \mathbf{D}_t$; particularly k_t represents a vector of specific investment costs per unit of installed capacity of technology *t*. The specific operation costs of activities $\mathbf{o}_a$ are multiplied by the related hourly production $\mathbf{X}_h$, then summed over the hourly time-steps h and annualized according to discount rate *r*.

$$NPC = \min \sum_t \left[k_t \mathbf{D}_t + \sum_y \frac{\sum_h \mathbf{o}_a \mathbf{X}_h}{(1+r)^y} \right] \tag{1}$$

The optimization algorithm operates in perfect foresight mode, therefore all the demand profiles throughout the time horizon are known from the start of the model's run period.

The model is then subject to a constraint over the energy need supply (**R**) and demand ($\mathbf{S}_n$) balance, as described by Eq. 2. The two supply and demand terms are respectively defined as follows in Eq. 3 and Eq. 4. The energy balance is complemented by two additional terms:

$$\mathbf{R} = \mathbf{S}_n \tag{2}$$

$$\mathbf{R} = \mathbf{Y} + \mathbf{I} \bullet [\mathbf{u} \bullet (\mathbf{s} \bullet \mathbf{X})] \tag{3}$$

$$\mathbf{S}_n = \mathbf{I} \bullet \mathbf{X}_n \tag{4}$$

The total demand **R**, in turn, is equal to the summation of the final demand of needs **Y** and of the intermediate demand. The latter

represents the energy needed by each technology to operate and is built upon the specific intermediate demand matrix **u**, which is multiplied by the production matrix $\mathbf{X}_n$.

To manage the state of charge of the storage technologies, two different constraints are set. The first one, Eq. 5, avoids overcharging beyond the nominal capacity $\widehat{\mathbf{D}_s}$ C_s, the second instead, Eq. 6, fixes a minimum state of charge (depth of discharge, *DoD*) in order not to overexploit the capacity. The nominal capacity of each storage technology is indicated henceforth as C_s. It is worth noting that all storage technologies are able to perform two activities: to charge and to discharge. In the next two Equations, the subscripts *ch* and *dis* identify these two activities.

$$\mathbf{X}_{s,ch} - \mathbf{X}_{s,dis} \leq \widehat{\mathbf{D}_s} \quad C_s \tag{5}$$

$$\mathbf{X}_{s,ch} - \mathbf{X}_{s,dis} \geq \widehat{\mathbf{D}_s} \quad C_s \quad DoD \tag{6}$$

Being the BEV modelled as a storage technology, these last two constraints are also adopted to describe the charge and discharge dynamic of the vehicle battery. The household reference energy system (RES) considered for the present work includes multiple energy needs and technologies. A schematic representation is proposed in Fig. 1.

In particular, the electricity, heating, cooling, domestic hot water (DHW) and cooking energy needs were considered. The demand time series have been calculated considering seasonality and hourly time resolution.

– *Electricity* can be satisfied alternatively by different technologies, respectively: the national grid (NG), domestic solar photovoltaic (PV) modules of 1 kW capacity and a home battery storage system (HBS) of 7 kW; PV is modelled to sell the extra-production to the national grid.

   The electricity demand has been obtained by adopting RAMP, an open-source model useful to generate stochastic electricity demand profiles (Prina et al., 2020). Further information about the electricity demand model is provided in Section 2.1.1 of the SM.

– *Heating* need is satisfied by heat pumps (HPs) or gas boilers (GBs), while heat pumps are the only technology serving the *Cooling* need. A thermal insulation (TI) technology has been also modelled which, if

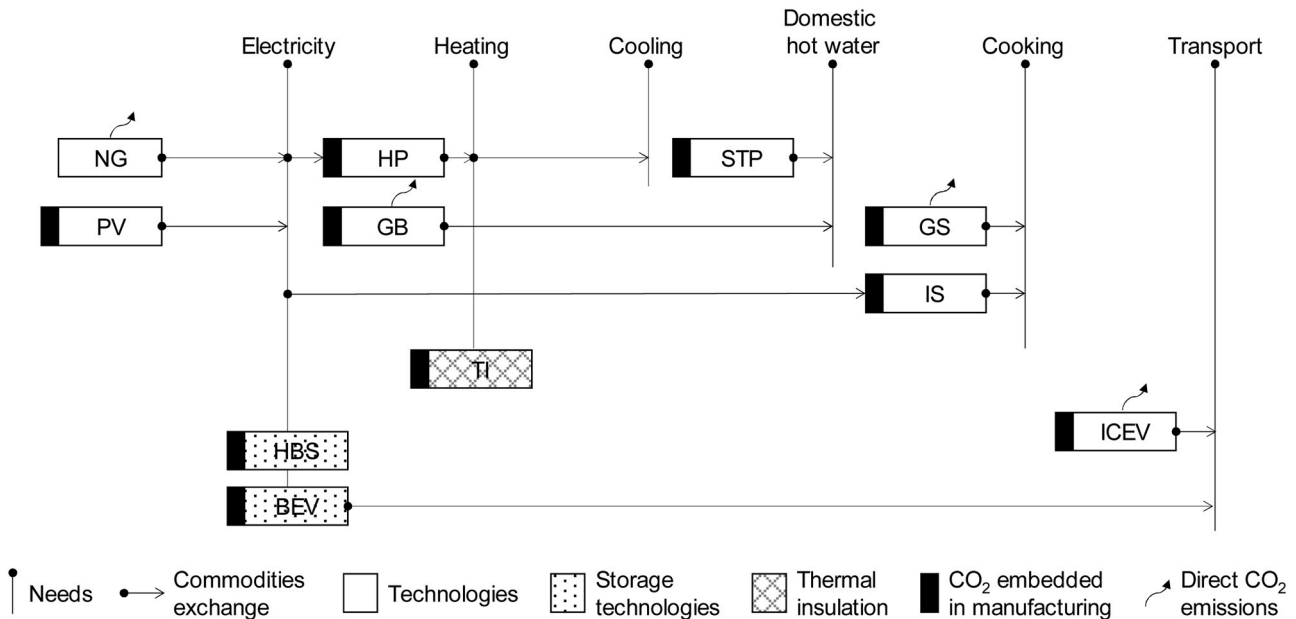**Fig. 1.** Schematic representation of the household reference energy system (RES) considered. Legend of acronyms, from top left to bottom right – NG: national grid, PV: photovoltaic panels; HP: heat pump; GB: gas boiler; HBS: home battery system; BEV: battery electric vehicle; TI: thermal insulation; STP: solar thermal panel; GS: gas stove; IS: induction stove; ICEV: internal combustion engine vehicle.

installed, causes a reduction of heating demand or an increase in cooling demand. Regarding the demand profiles, heating demand has been calculated in line with the climatic zone and governmental regulation. Further information about the heating demand model is provided in Section 2.1.2 of the SM.

– For the *transport* need, the study compares a 37 kWh BEV with a full starting price of 27'300 € to an ICEV with a price of 17'000 €. The hourly transport demand was built based on typical driving behaviours, using statistical data. Different profiles have been generated for different yearly driven distances.
– *Domestic hot water* could be supplied by both gas boilers and by solar thermal panels (STP).
– In the end, both gas stoves (GS) and induction stoves (IS) could be adopted for cooking.

The carbon footprint of each technology installed is determined by its CO_2 emissions factor. The emissions related to the operation of each technology are calculated by multiplying its direct emissions factor by its activity production. Each technology also has an investment cost specific to its installed capacity, and a production-specific operation cost is associated with each activity. The operation cost is time-dependent and expressed on an hourly basis, while the investment cost is not time-dependent and is assumed to occur in the first year of the time horizon. Further details about the technical and economic parameters used in the study can be found in Section 2.2 of the SM.

2.2. Sensitivity analysis

An extensive sensitivity analysis was performed, following a similar approach as Jing et al (Jing et al., 2022)., to assess the influence of crucial parameters on BEV preferability (p_{BEV}) together with other second-order economic implications. p_{BEV} is defined as the ratio between the number of cases in which the BEV is selected as the preferred transport technology within the household energy system (n_{BEV}), and the total number of cases (n). p_{BEV} has been expressed as a function of each sensitivity parameter (sp) and its general definition is given by Eq. 7.

$$p_{BEV_{sp}} = \frac{n_{BEV_{sp}}}{n_{sp}} \tag{7}$$

The investigation around the BEV preferability indicator is further complemented by analysing the impact of specific couples of sensitivity parameters on the Net Present Cost (NPC) of the residential energy system, deepened in the next paragraphs.

A schematic overview of the workflow of the analysis is represented in Fig. 2. In particular, Fig. 2a shows each of the m sensitivity parameters (sp) can range among n sensitivity values (V), generating k possible combinations of input data feeding the core model runs. The geographical scope of the analysis was set in the Italian context.

Therefore, the input data and sensitivity values of some parameters were targeted accordingly. Given recent Italian policies on energy efficiency in buildings mentioned in Section 1, it is important to note that the technological configurations proposed by the model are not intended as an addition or partial replacement to the baseline residential energy system. Instead, the model accounts for a complete renovation of the household energy system: in more technical terms, the model works with a green- and not with a brown-field assumption. The full list of the parameters subject to sensitivity analysis and their associated values are reported in Table 2: henceforth, the least and the most favourable conditions for BEV selection will be indicated by referring to V0 and V6 respectively. It is worth noting that this analysis is limited to the values within its boundaries, therefore the concepts of "least" and "most favourable conditions" are to be intended in relative and not absolute terms. The energy system optimization model is solved for each of the k combinations of inputs (Fig. 2b): a total number of 33'600 sets of final results (Fr, Fig. 2c) are discussed in Section 4.

2.2.1. Behavioural parameters

Behavioural parameters considered in the analysis include the *annual travelled distance* and the *expected ownership time*.

– According to data from the Italian National Statistics Office (ISTAT, 2019), the annual travelled distance of Italians ranges from 5'000-25'000 km per year. Larger distances are typical of company car drivers (ISTAT, 2022).
– The average expected ownership time of a private Italian passenger car is 11.8 years, as reported by ACEA (ACEA); this sensitivity analysis considers more conservative ownership times of 3, 5, 7, and 10 years.

It is important to clarify other widely discussed behavioural aspects, such as range anxiety, are considered out of the scope of the methodology selected for this work.

2.2.2. Energy-related parameters

The sensitivity analysis encompasses the variation of electricity and heating demand profiles based on house size archetypes of 60, 120, 180, and 240 m². Different electricity and heating demand profiles are modelled for each house size, taking into account different electric appliances and wall surfaces for thermal exchange. Three cities in different geographical locations (Milan in the north, Rome in the centre, and Syracuse in the south) are selected to model heating demand. The yearly values of electricity and heating demands adopted are provided in Table 3. The study also focuses on the impacts of other energy-system-related parameters on the BEVs preferability, including the integration with PV panels. The geographical location of the house affects solar radiation availability, which is generated using the Renewable Ninja application (Staffell and Pfenninger, 2016; Pfenninger and Staffell,
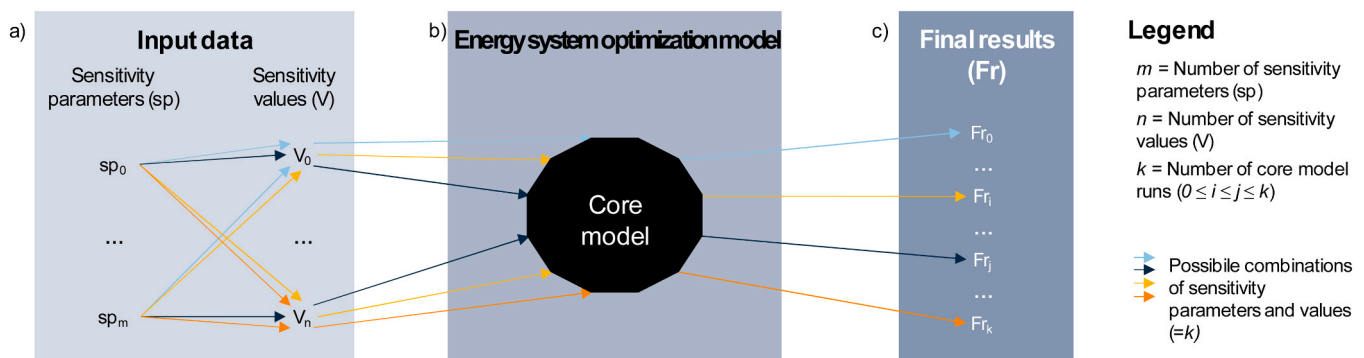

Fig. 2. Schematic overview of the workflow of the analysis. a) Input data are provided as m sensitivity parameters to which n values are assigned in each model run. b) Each of the k resulting combinations of inputs feeds the core of the energy system model. c) Finally, each of the k model runs provides a set of final results.

Table 2

List of sensitivity parameters along with category, unit of measures and list of sensitivity values assumed along the sensitivity analysis.

Sensitivity parameters	Category	Unit	Sensitivity values						
			V0	V1	V2	V3	V4	V5	V6
sp_0: Annual trav. Distance	Behavioural	km/y	5'000		10'000		2'0000		25'000
sp_1: Ownership time	Behavioural	y	3		5		7		10
sp_2: House size*	Energy-rel	m^2	60		120		180		240
sp_3: Solar radiation	Energy-rel	kW	0.12			0.14			0.16
sp_4: National grid electricity price	Economic	€/kW	0.45	0.4	0.35	0.3	0.25	0.2	0.15
sp_5: National gasoline price	Economic	€/litre	1.4		1.6	1.8	2		2.2
sp_6: BEV purchase subsidies	Economic	k€	1		2	3	4		5

Table 3

Yearly electricity and heating demand by house size archetypes and geographical location.

House size (m^2)	Yearly electricity demand [kWh/y]	Yearly heating demand [kWh/y]		
		North	Centre	South
60	2856	540	435	153
120	3782	1200	968	340
180	3866	1919	1548	544
240	4172	2559	2064	726

2016). The average daily radiation peak, from the northern to southern region, is respectively equal to 0.12 kW/m^2, 0.14 kW/m^2 and 0.16 kW/m^2.

2.2.3. Economic parameters

This category includes parameters outside of household control, specifically:

– the national grid electricity price, which has been volatile in recent years due to the COVID-19 pandemic and Russia-Ukraine conflict, ranging from 0.15 €/kWh to 0.45 €/kWh on the Italian market (Gestore Mercati Energetici, 2022; Pfenninger and Staffell, 2016): extreme values and intermediate values stepped by 0.05 €/kWh have been considered;
– the national gasoline price, whose trends have also been fluctuating, with extreme values ranging from 1.504 €/litre to 2.154 €/litre (MInistero della Transizione Ecologica, 2022): values of 1.4, 1.6, 1.8, 2.0, and 2.2 €/litre have been accounted for;

– the presence of subsidies for BEV purchase, which in the Italian context amounted to 650 million euros starting from May 2022 (Ministero dello Sviluppo Economico, 2022): in case of BEV purchase, the final consumer is subsidized up to 5'000 €. This work considers an interval between 1'000 € and 5'000 € with a 1'000 € step.

3. Results discussion

3.1. Drivers of BEV preferability

Among the 33'600 set of results obtained, BEV has been selected as the preferred passenger transport technology in 30.1 % of the cases. Fig. 3 highlights the trends of BEV preferability driven by each of the sensitivity parameters.

Starting from the less impactful parameters, it seems the influence of *solar radiation* and *house size* (used as a proxy of electricity and heating demand) is negligible. While the former may be more impactful where solar availability fluctuates more than in Italy, it is relevant to consider how the BEV selection is strongly independent of the energy consumption patterns associated with each house size, despite the significant variation (46 %) yearly electricity demand experiences between V0 and V6.

Grid electricity price is among the least affecting drivers: BEV preferability varies between 27 % and 36 % within the sensitivity range of this parameter which, in turn, shifts from 0.45 €/kWh (V0) to one-third of this value (0.15 €/kWh, V6). On the contrary, a variation of 57 % in *gasoline price* (ranging from 1.4 to 2.2 €/litre) affects BEV preferability much more: in the least favourable condition V0 (gasoline price set at 1.4 €/litre), BEV preferability corresponds to 17 %, while V6 (2.2
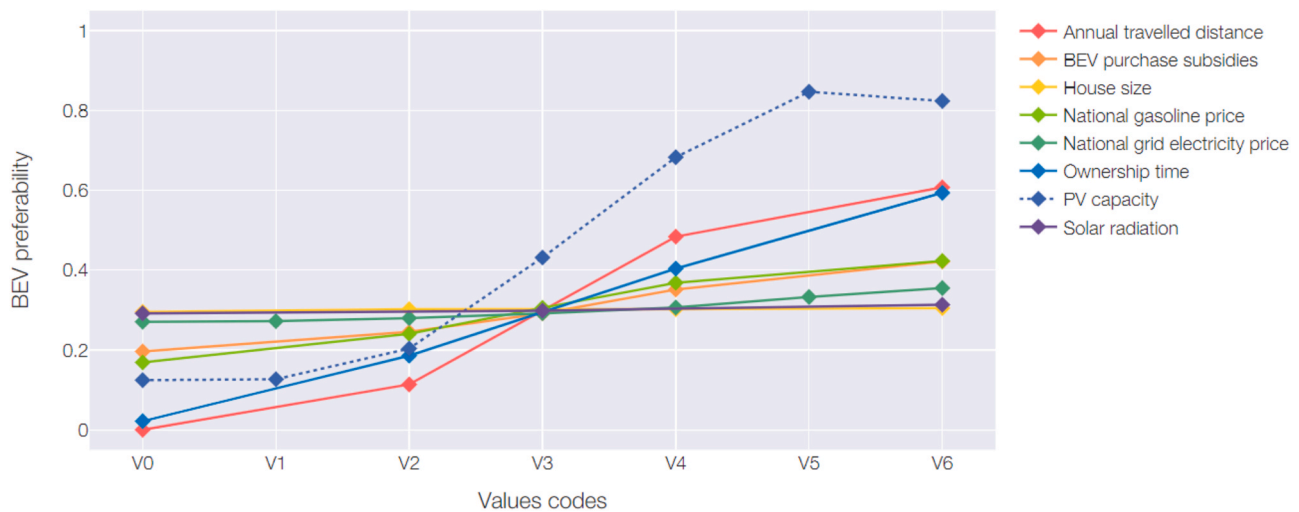
Fig. 3. BEV preferability (y-axis %) with respect to alternative same-segment ICEV: sensitivity around different parameters. Values codes for each parameter (from V0 to V6, x-axis, described in Table 2) are sorted from least to most favourable towards BEV adoption. PV capacity is indicated with a dotted line being an endogenous parameter of the model, unlike all the other exogenous ones represented with solid lines.

€/litre) leads to a BEV preferability of 42 %.

The presence of different levels of subsidies for BEV (*BEV incentives*) has almost the same impact as the variation of gasoline price, leading to almost the same value in the most favourable conditions (42 % in V6). It is relevant to remind that the V6 value (5'000 €) is assumed according to the current state of policies, while higher values are expected to impact more significantly.

As foreseeable, the household driving attitude resulted in strongly influencing the selection of the transport technology: BEV preferability range is among the highest concerning the variation of both *ownership time* and *annual travelled distance*: in case of a very short expected ownership time horizon (3 years, V0) or a very low yearly travelled distance (5'000 km/y, V0), ICEV is the preferred technology in almost the totality of the cases. Moving towards V6, these BEV preferability reaches 59 % for the ownership time and 61 % for the annual travelled distance.

The most impactful parameter is, in the end, *PV capacity*, both in terms of maximum value of BEV preferability and in BEV preferability range between V0 and V6. In fact, solutions without PV installed (V0) include BEV just in 12 % of the cases, while it is included in 92 % of the cases when PV capacity is at least 6 kW (V6).

By analysing the outcomes of other studies, some similarities can be identified: for instance, the IEA estimates a payback period for BEVs 6.1 and 12 years assuming an annual mileage between 10'000 and 17'000 km/year (between the V2 and V4 values considered in these paper), also highlighting a strong influence of petrol price (IEA, 2023b). Moreover, the synergy between BEVs and PV installation emerges from many of the works analysed in Table 1 such as those of Schwarz et al (Schwarz et al., 2020). and Kwon et al (Kwon et al., 2020). While it

seems the findings of this and other studies are overall aligned, it is also true, however, that the different underlying methodologies, assumptions, and scope of application may make them difficult to compare. However. the main contribution of this paper is not only to qualitatively highlight which parameters drive BEVs economic convenience but also to quantitatively assess how this latter is affected by a variation of each parameter, which is the aim of the next section.

3.2. Economics insights of BEV adoption in light of sensitivity parameters

Annual travelled distance and ownership time of the vehicle have been highlighted as two of the most impactful parameters on BEV adoption in our sensitivity. Fig. 4 shows the distribution of the NPC for all the cases represented by each couple of these two parameters, distinguishing into two different violin plots for cases in which a BEV (yellow) or an ICEV (blue) is adopted.

As anticipated, the NPC strongly increases from shorter to longer ownership time horizons as well as from smallest to largest travelled distances due to the higher costs to be sustained to operate the whole residential energy system. It is interesting to notice BEVs are never preferred to ICEVs when the expected travelled distance is 5'000 km/y. This holds also in the case of very short time of ownership, up to 5 years.

However, for all the other combinations of annual travelled distance and ownership time, the mean and median NPC of the cases where BEV is preferred is always lower with respect to the corresponding ICEVs counterparts. In particular, considering average values, the solution adopting a BEV can be from 2.19 % to 12.2 % cheaper than the one adopting an ICEV. Furthermore, in the case of 10 years of ownership time and 25'000 travelled km/y, BEV preferability is 100 %.

Fig. 4. NPC of the residential energy system in cases where ICEVs (blue) and BEVs (yellow) are the preferred transport technology, broken down by different values of annual travelled distance (x-axis) and years of ownership of the vehicle (subplots). The violins' shape represents the kernel density while the horizontal line within each violin represents the mean value of NPC of the cases represented.

Limiting to the cases with long ownership times (at least 7 years) and with many travelled km per year (at least 20'000 km/y), it is also interesting to highlight the influence that fuel prices (both electricity for BEVs, and other energy services which may be electrified, and gasoline for ICEVs) have on the NPC of the household energy system. Fig. 5a shows low gasoline prices lead to lower NPCs for ICEV-based energy systems: this holds for all the cases ranging from 1.4 to 1.6 €/litre gasoline price, even though the difference between the mean NPC of the BEV- and ICEV-based configurations reduces when electricity price decreases. When gasoline price increases above 1.6 €/litre, the NPCs become more and more similar, until the point where only BEV is selected as a transport technology.

A focus box has been provided in Fig. 5b on the most representative match for the Italian situation, namely 0.3 €/kWh for electricity price (Gestore Mercati Energetici, 2022; Pfenninger and Staffell, 2016) and 1.8 €/litre for gasoline price (MInistero della Transizione Ecologica, 2022). It is interesting to note that the integration with PV plays a significant role also in this case since BEV is preferred only in case the capacity of PV installed in the household energy system is at least 3 kW. Under these conditions, the mean NPC of BEV-based systems is lower than the one of ICEV-based. The distribution of NPCs of the latter is indeed limited within a much smaller range, however, the very high NPC of BEV-based solutions are related to solutions with very high installed capacity of PV.

4. Conclusions

This work underscores the relevance of synergies among technologies within the residential energy system on BEV adoption: indeed, the results of this study show that the strongest positive correlation with BEV preferability is PV capacity installation. Additionally, PV and BEV joint installation lead generally to lower costs than ICEV-based systems, emphasizing the importance of comprehensive and integrated modelling for residential applications.

The results also highlight the limited impact of grid electricity prices on the preference towards BEVs, whereas a limited rise in gasoline prices impedes the adoption of ICEVs. The research provides valuable insights, indicating that, within the range of Italian average gasoline prices (1.4 to 1.6 €/litre), the net present cost of BEV-based energy systems remains competitive, even with a high electricity price (0.3 €/kWh) if a minimum photovoltaic capacity of 3 kW is installed.

Given the high cost of fossil fuels resulting from the ongoing energy crisis in Europe, these outcomes are particularly encouraging for BEV adoption. This is especially true if the socio-economic context is supplemented with more robust policies on BEV incentives.

Beyond price considerations, the decision to electrify the transport demand is driven by the opportunity to reduce costs and leverage self-generated solar power. Notably, factors such as fuel prices and photovoltaic integration significantly influence the net present cost of household energy systems, with electric vehicle configurations

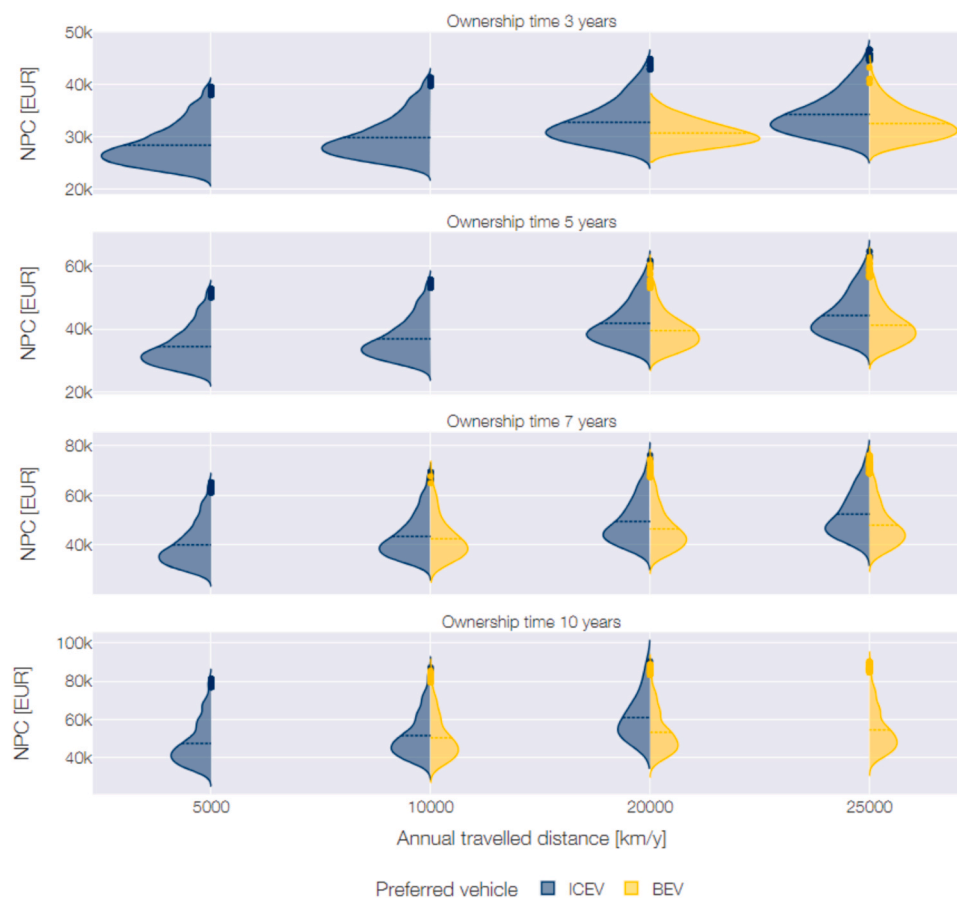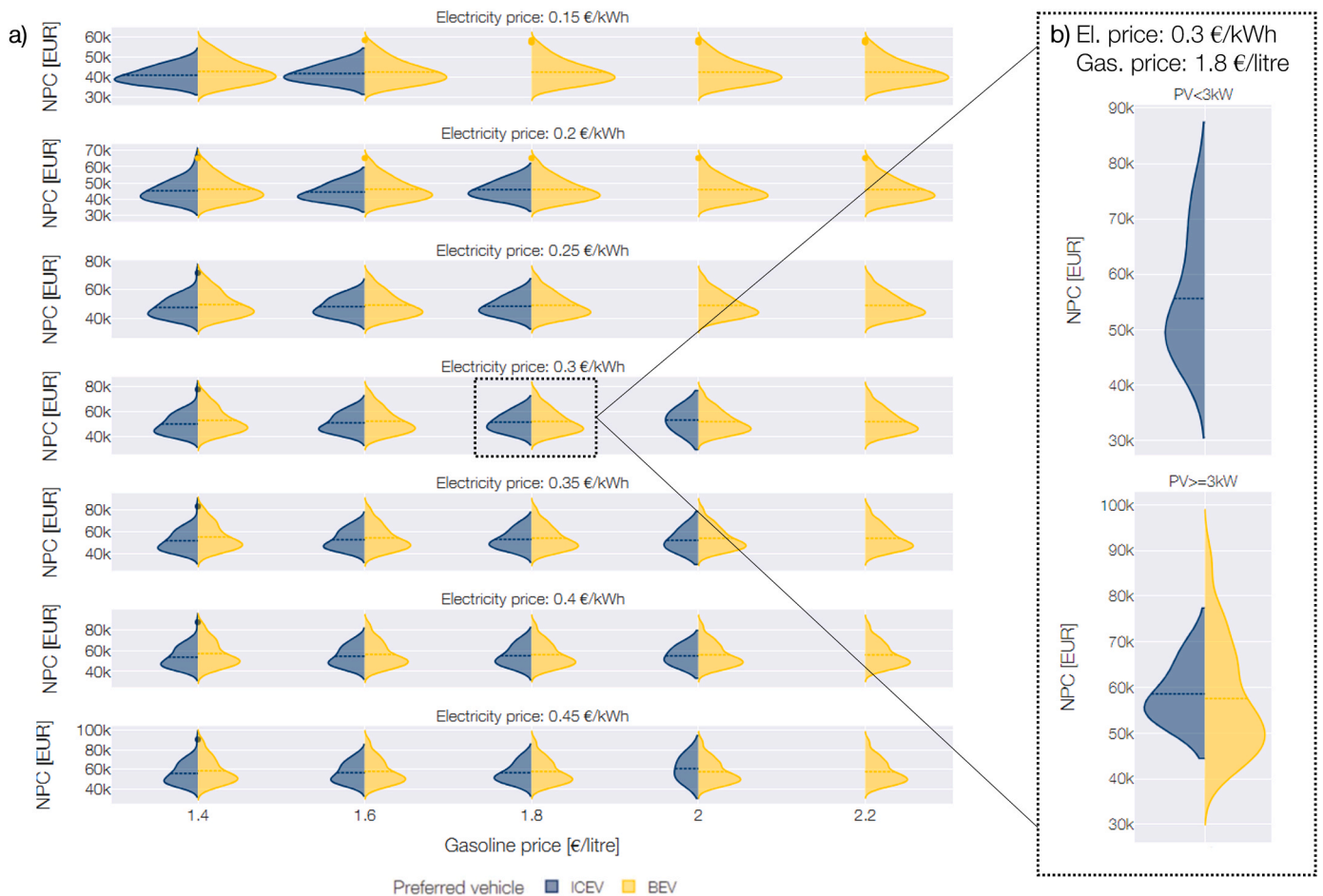**Fig. 5.** a) NPC of the residential energy system in cases where ICEVs (blue) and BEVs (yellow) are the preferred transport technology, broken down by different values of gasoline price (x-axis) and grid electricity price (subplots). All the represented NPCs are referred to cases where vehicle ownership time is at least 7 years and annual travelled distance is at least 20'000 km. b) Zoom on the most representative combination of electricity and gasoline prices for the Italian case (respectively 0.3€/kWh and 1.8€/litre), broken down by installed PV capacity lower or larger than 3 kW. The violins' shape represents the kernel density while the horizontal line within each violin represents the mean value of NPC of the cases represented.

becoming more favourable as gasoline prices rise and photovoltaic capacity increases.

It is worth noticing one of the assumptions of the study is that only green field cases are considered in the analysis: moving to practical terms, this means that all the considerations drawn from this work are valid mostly in case of new constructions or renovations, when the domestic energy system needs to be designed from scratch. It is in the authors' belief the green field assumption allows for a neutral starting point, therefore it is necessary to lead to a fair comparison in the selection of an ICEV or BEV vehicle. Also, even for short time horizons, no residual value of the vehicle has been considered, which is actually a conservative assumption since BEVs generally suffer less from depreciation over time with respect to ICEVs. As a final note, despite focusing on the Italian context, the adopted methodology is context-agnostic since it can be applied to different contexts by updating the input data.

Further developments of this work may broaden the scope in terms of BEV models to be accounted for, since in this case just one model for ICEV and BEV have been considered and the possibility of charging from third-party charging stations and not only at home.

CRediT authorship contribution statement

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The adopted data, code, results along with interactive figures shown in this article are available in the Github repository associated to the study available at www.github.com/eNextHub/MARIOU-RESBEV.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.egyr.2024.01.025.

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