Department of Mechanical Engineering
Energy Systems Integration & Modeling Group

Energy Systems Integration & Modeling Group Working Paper Series
No. ESIM2020-22

Influence of distribution tariff structures and peer effects on the adoption of distributed energy resources

Jorge Andrés Moncada, Zhenmin Tao, Pieter Valkering, Frank Meinke-Hubeny, Erik Delarue

Last update: 04-06-2021

Influence of distribution tariff structures and peer effects on the adoption of distributed energy resources

J. A. Moncada[1, 2], Z. Tao[1, 2], P. Valkering[2, 3], F. Meinke-Hubeny[2, 3], E. Delarue[1, 2]

1. Energy Institute. Division Applied Mechanics and Energy Conversion. Department of Mechanical Engineering. KU Leuven. Celestijnenlaan 300A box 2421, 3001 Leuven, Belgium
2. EnergyVille, Thor Park 8310, 3600 Genk, Belgium
3. VITO, Boeretang 200, BE-2400 MOL, Belgium

Abstract

The emergence of prosumers calls for a revision of distribution network tariff design to ensure efficient network utilization and optimal customer response. This article aims to investigate the influence of different distribution tariff structures and peer effects on both residential consumers' distributed energy resources adoption and the allocation of electricity distribution costs. We developed an agent-based model to analyze the interaction between distribution tariffs and the adoption of distributed energy resources. The model takes into account the influence of both economic (e.g., payback period and income level) and non-economic (e.g., peer effects) factors on technology adoption. The model endogenously considers the interplay between the technology adoption and the evolution of distribution tariffs and takes into account the interaction among consumers by incorporating peer effects. We found that under our test case assumptions, the presence of non-economic factors in the decision making, such as peer effects, is the rate-limiting step of the adoption process in the short-term. Hence, creating mechanisms that encourage interpersonal communication among residential consumers may help more risk-averse consumers redefine their attitudes about the benefits and costs of adopting distributed energy resources. We also found that a utility death spiral is more likely to occur with an annual net-volumetric distribution tariff. The increase in distribution cost was ten percentage points higher than that obtained with an annual maximum offtake capacity tariff. Given the complexities of an electricity system where the consumer is at the center, we recommend that regulators and distribution system operators adopt a whole system approach to managing the electricity system.

Keywords: distribution tariffs, distributed energy resources adoption, theory of planned behavior, agent-based modeling.

List of abbreviations and symbols

Abbreviations

BI: hourly bidirectional volumetric distribution tariff

CAP: annual maximum offtake capacity tariff

CAPBI: annual maximum bidirectional capacity tariff

DERs: Distributed Energy Resources

DSO: Distribution System Operator

ICT: Information and Communication Technology

NET: annual net-volumetric distribution tariff

NPV: Net Present Value

ODD: Overview, Design concepts, and Details

PBC: Perceived Behavioral Control

POS: hourly offtake volumetric distribution tariff

Symbols

Variables

ch_t: Power drawn from the grid to charge battery in hour *t*, [kW]

d: Total annual electricity demand, [kWh]

d_t: Residential consumer demand in hour t, [kW]

dc_t: Power provided to the grid from battery in hour *t*, [kW]

d_{max}: Annual peak demand, [kW]

$\mathrm{D_{cons,t}}$: total consumers demand at the time step *t*, [kWh, kW]

$\mathrm{D_{pros,t}}$: Total prosumers demand at the time step *t*, [kWh, kW]

$\mathrm{D_{res}}$: Total residual demand, [kWh, kW]

$dist_{bi,t}$: Distribution tariff on net hourly bidirectional energy flow, [€/kWh]

$dist_{cap}$: Offtake capacity distribution tariff, [€/kW]

$dist_{cabi}$: Bidirectional capacity distribution tariff, [€/kW]

$dist_{net}$: Net volumetric distribution tariff, [€/kWh]

$dist_{pos,t}$: Distribution tariff on hourly offtake energy, [€/kWh]

$\mathrm{dist_{cost}}$: Total distribution cost, [€]

$\mathrm{dist_{j,t+1}}$: distribution tariff *j* at every time step *t+1*, [€/kWh, €/kW]

e_{BAT_t}: Battery energy content in hour *t*, [kWh]

$n_{pro,i}$: Number of prosumers that a residential consumer *i* observe in his social network, [-]

pp: Payback period, [yr]

pv_t: Power production by PV panels in hour *t*, [kW]

$q_{bi,t}$: Absolute value of the hourly net demand, [kWh]

q_{cap}: Annual maximum offtake capacity, [kW]

q_{cabi}: Annual maximum injection/offtake capacity, [kW]

q_{net}: Annual net-volumetric consumption, [kWh]

$q_{pos,t}$: Hourly net-volumetric consumption in hour *t*, [kWh]

q_t: Resulting net demand in hour t, [kW]

R: Cash flow, [€]

Re: Revenues of the DSO at the first time step, [€]

S: Savings, [€]

S_d: Savings generated by reducing the distribution cost, [€]

S_e: Savings generated by reducing the energy cost, [€]

u_i: Total utility of the residential consumer *i*, [-]

$u_{pp,i}$: Payback period utility of the residential consumer *i*, [-]

$u_{pe,i}$: Peer effect utility of the residential consumer *i*, [-]

$w_{pe,i}$: Weight allocated to the payback period utility of the residential consumer *i*, [-]

$w_{pp,i}$: Weight allocated to the peer effect utility of the residential consumer *i*, [-]

Parameters

CR: C-rate of the battery, [-]

d_{hi}: Annual electricity consumption of a high-income residential consumer, [kWh]

d_{mi}: Annual electricity consumption of a middle-income residential consumer, [kWh]

d_{li}: Annual electricity consumption of a low-income residential consumer, [kWh]

E_{BAT}^{max}: Maximum energy content of the battery, [kWh]

E_{BAT}^{min}: Minimum energy content of the battery, [kWh]

i: Interest rate, [%]

I_0: Initial investment costs, [€/kW, €/kWh]

LF_{pvt}: Load factor of PV as a function of time of the day and year, [-]

N: Number or households

N_n: Number of neighbors, [-]

p_e: Initial electricity price (wholesale price), [€/kWh]

p_t: wholesale price in hour t, [€/kWh]

P_o: Proportion of owner-occupied houses, [%]

P_{ohi}: Probability that the owner of a property is a high-income residential consumer, [%]

P_{omi}: Probability that the owner of a property is a middle-income residential consumer, [%]

P_{rhi}: Probability that the renter of a property is a high-income residential consumer, [%]

P_{rmi}: Probability that the renter of a property is a middle-income residential consumer, [%]

P_{BAT}^{ch}: Maximum battery charging power, [kW]

P_{BAT}^{dc}: Maximum battery discharging power, [kW]

ty: Number of time periods used in the calculation of the NPV, [yr]

ΔP: Annual linear increase of the electricity price, [%]

η_{ch}: Battery charging efficiency, [-]

η_{dc}: Battery discharging efficiency, [-]

1. Introduction

Advances in electricity generation and storage technology, as well as in Information and Communication Technology (ICT), have led to a rapid increase of Distributed Energy Resources (DERs) owners connected to low- and medium voltage networks also known as prosumers. In 2019, rooftop solar photovoltaic (PV) installations represented somewhat more than one third of all PV installations worldwide [1]. This increase of prosumers is redefining market relationships between traditional sellers and buyers as well as the market structure. Prosumers have become key players in the way electricity is generated, distributed, and consumed [2].

Nevertheless, the emergence of prosumers also raises a series of challenges that cut across technical [3], social [4], and institutional dimensions [5], [6]. In the institutional realm, for instance, the use of distribution tariff structures such as net-metering can cause unintended effects such as cross-subsidization amongst electricity consumers [7]–[9]. Several authors have argued that net-metering over-incentivizes PV adoption and forces passive consumers (without PV panels) to pay the distribution costs that prosumers manage to offset. In turn, the increase of the distribution costs may incentivize passive consumers to adopt PV, creating a positive feedback loop known as the utility death spiral [5], [7]. In the social realm, the emergence of prosumers is placing the consumer at the center of the energy system. To manage this consumer-centric energy system, it is necessary to better understand how behavioral factors, such as peer effects[1], the desire for independence from the electricity grid, and environmental concerns, shape residential consumers' energy consumption and decision-making. Therefore, the emergence of prosumers calls for an assessment of distribution tariffs that takes into account consumers' behavioral factors to address network utilization and anticipate customer response.

This article aims to investigate the influence of different distribution tariff structures and peer effects on both residential consumers' DERs adoption and the utility death spiral. Reimbursement schemes such as feed-in tariffs and feed-in premium are out of the scope of this study. There are several factors that influence the design of distribution grid tariffs (e.g., cost-reflectivity and fairness). Nevertheless, this paper focuses on assessing the impact of possible tariff structures on DERs adoption and the utility death spiral, rather than analyzing how an optimal tariff should look like. Understanding the co-evolution of households' DERs

[1] Peer effect *"refers to when the attitudes, values or behaviors of an individual are influenced by the behaviors of members within a peer group"* [28]. Peer effects can occur through active or passive processes. An active peer effect occurs when a person adopts a technology after actively talking to existing adopters. A passive peer effect occurs when a person passively observes existing adopters using the technology. In this study, we focus on passive peer effects.

adoption and network charges may provide key insights into the implications of distribution tariffs on the evolution and operation of an energy system wherein the consumer is at the center.

1.1. Literature review

Different modeling approaches have been used to study the diffusion of DERs, in particular to study the diffusion of solar PV panels. Equation-based models have been used to study the interaction between PV adoption, electricity rates, and public opinion. Cai *et al.* studied the impact of the feedback between PV adoption and electricity rates on future PV penetration and net-metering costs. The authors found that under a net-metering scheme, PV adoption leads to a rapid increase in both distribution costs and the fraction of these costs borne by lower-tier customers [10]. Patra and Carvalho developed a mathematical model to analyze the interaction between PV market evolution and rate structures under regulated tariffs. The authors found that gradual transitions to higher fixed Network Access charges do not discourage PV deployment [11].

Candas *et al.* investigated the dynamics of PV adoption and the evolution of public opinion in Germany and Italy. By using an equation-based approach underpinned by the sociodynamics framework [12], the authors found that the elimination of the feed-in tariff regulation in the near future is possible without crippling PV expansion, but only if higher levels of self-consumption are promoted and the public is aware of its economic potential [13].

Agent-based models are increasingly being used to model and analyze the complex phenomenon of diffusion of technologies in different domains [14]. In the energy domain, agent-based modeling has been extensively used to analyze the effectiveness of investment tax credits, rebate levels, and feed-in tariffs on the PV adoption [15]–[19].

Agent-based modeling has been also used to analyze the importance of economic, social and attitudinal components in PV adoption. Murakami developed an agent-based model coupled to a power flow model to study the influence of social policy and communication among residential consumers on the adoption of photovoltaic systems. The author found that strong government intervention in the areas near the main high-voltage power distribution transformer drove the increased adoption of PV [20].

Robinson & Rai found that models that only account for economic factors in the agents' PV adoption decision-making satisfactorily replicate the rate of adoption and the cumulative adoption curve, but perform badly in replicating spatial and demographic patterns of adoption. Models taking into account attitudinal aspects and social interactions satisfactorily replicate the spatial pattern of PV deployment [21].

Ramshani *et al*. investigated the diffusion rate of PV panels and green roofs under uncertainties caused by climate change, adopters characteristics and their interactions. The authors developed an integrated framework combining an optimization model with an agent-based model to conduct the analysis. The authors found that an increase in the level of agent interaction leads to a higher adoption rate [22].

Other studies have focused on the analysis of the influence of tariff structures on the adoption of DERs and on the study of the utility death spiral. Stavrakas *et al.* developed an agent-based model to study the influence of both a net-metering scheme and a proposed self-consumption scheme subsidizing residential storage by 25% on small-scale PV investments in Greece over the period 2018-2025. The authors found that a net-metering scheme is more effective than a self-consumption scheme. The authors also found that storage investment costs need to follow a steep learning curve of a least a 10% annual reduction until 2025 to make self-consumption attractive to consumers in Greece [23].

Darghouth *et al.* investigated the impacts of two feedback loops: fixed cost recovery feedback and time-varying rate feedback on PV deployment. The former feedback loop describes an increase in the network charge to ensure fixed-cost recovery driven by PV adoption. The latter feedback loop describes a shift in the temporal profile of wholesale electricity prices driven by high PV penetration. The authors found that the effect of PV deployment on the utility death spiral is modest because the feedback loops operate in opposing directions [24].

Muaafa *et al*. developed an agent-based model to study to what extent the PV adoption will trigger an utility death spiral. The authors found that PV adoption is unlikely to disrupt the Distribution System Operator's (DSO) business model [25]. de Villena *et al.* developed an agent-based model to assess the interplay between DERs deployment and the evolution of the distribution tariff under different regulatory frameworks. The authors found that using net-metering leads to a spiral of the distribution tariff and observed a tradeoff between the spiral of electricity prices and the desired PV and battery deployment [26].

Previous studies either focus on the analysis of the upward spiral of the distribution tariff or on residential consumers' DERs adoption, but neglect the interplay between these two processes. To the best of our knowledge, only Darghouth *et al.* [24] and de Villena *et al.* [26] take into account this interplay, but they make normative assumptions about residential consumers' investment decisions in DERs and neglect the influence of behavioral and social components on those decisions. Nevertheless, it has been shown that consumers' investment decisions are also driven by non-economic concepts such as independence and autonomy [27] as well as peer effects [28].

1.2. Contribution

In this study, we extend the work of Darghouth *et al.* [24] and de Villena *et al.* [26] by incorporating the effect of social and attitudinal components into the DERs adoption decision-making and by providing a path dependency analysis. In particular, we aim to answer the following research questions:

- *What is the influence of both peer effects and distribution tariff structures on the adoption of integrated photovoltaic and battery energy storage systems as well as on the utility death spiral?*

- *What is the effect of a change in the distribution tariff structure, at specific periods of time, on the adoption of integrated photovoltaic and battery energy storage systems?*

To answer these research questions, we developed an agent-based model to analyze the interaction between distribution tariffs and DERs adoption. The model takes into account the influence of both economic (e.g., payback period and income level) and non-economic (e.g., peer pressure) factors on the DERs adoption. The model also takes into account the interaction among consumers by incorporating peer effects and for the diversity among actors. This diversity is modeled by specifying the social class and their willingness to adopt new technologies. Finally, the model endogenously considers the interplay between the DERs adoption and the network tariff evolution.

In summary, the main contributions of this article include:

- Novel agent-based modeling framework that incorporates the effect of social and attitudinal components into residential consumers' decision-making on DERs adoption. Furthermore, this modeling framework endogenously considers the interplay between the DERs adoption and the distribution tariff evolution, as well as the interplay between residential consumers and prosumers. Thus, key concepts such as grid defection, residential consumer/prosumer behavior, and the transition from consumers to prosumers are included in the modeling framework.
- Detailed insights into how different distribution tariff structures influence DER's adoption and the utility death spiral.
- Path dependency analysis providing insights into how the timing of a change in the distribution tariff structure affects DERs adoption.

The article is organized as follows: section 2 describes both the concepts underpinning the model structure and the agent-based model developed in this study. The results are presented in section 3 and discussed in section 4. Finally, conclusions are drawn in section 5.

2. Theory and methods

This section describes the concepts and modeling considerations required to describe both the DERs adoption and the evolution of network charges. In the first subsection, we describe how the system is conceptualized and what theories underpin this conceptualization. In the second subsection, we describe how the conceptual model is formalized into an agent-based model.

2.1. Model conceptualization

The conceptualization of the energy system at the neighborhood level as a socio-technical system is presented in **Figure 1**. It was assumed that this system comprises social network(s), physical network(s), and the Distributor System Operator (DSO). The social network consists of residential end-users. These actors were classified based on Rogers' typology of adopters (i.e., innovators, early adopters, early majority, late majority, and laggards) [29], income class (high, middle, and low), and tenure status (owner and renter). We focused on the strategic behavior of end-users concerning investment decisions and their interaction with the DSO. The physical network consists of technical elements such as the distribution grid, electric loads, solar panels, and batteries. Actors interact through the social and physical networks, which are governed by intentional relationships (e.g., legislation, property rights, codes of conduct) and by causal relationships (e.g., Kirchhoff's law), respectively. The physical networks mediate the interaction between residential consumers and the DSO. The latter will respond to the net consumption pattern of residential consumers by adjusting the distribution tariff to recover the operational costs and maintenance of the grid[2]. Each household operates as a relatively autonomous unit connected to the distribution grid. Nevertheless, social interaction occurs through peer effects among neighborhood residents. It was also assumed that the behavior of the system is driven by external factors, including battery and solar panel costs, wholesale electricity prices, electric loads, and residual demand[3]. Finally, it was assumed that a household's electricity cost amounts to the sum of both energy cost and distribution cost. The former links to the wholesale electricity price, whereas the latter is impacted by the distribution tariff structure.

[2] In this paper, we assume no grid reinforcement is needed.
[3] Residual demand refers to those residential consumers of the distribution network who cannot adopt DERs because of technical or economic constraints.

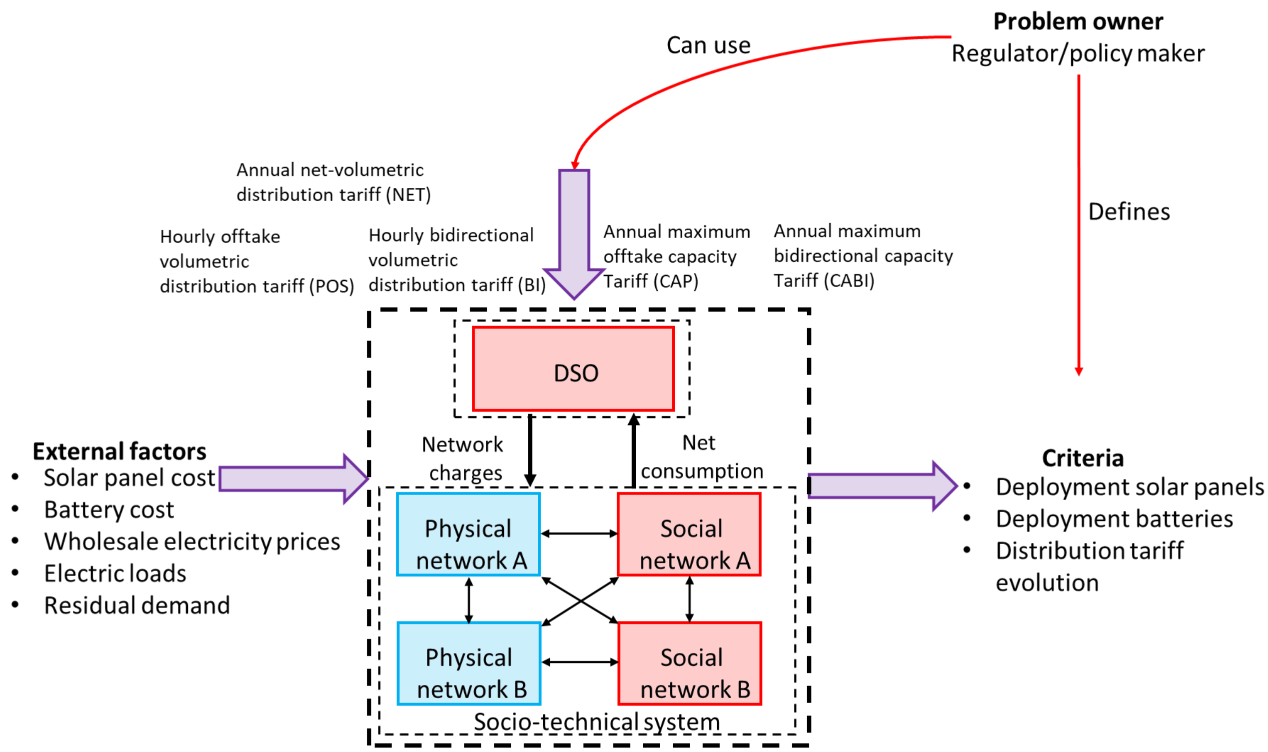

Figure 1. Conceptual model

The system was analyzed from the perspective of a regulator/policy maker. It is assumed that these actors aim to assess the influence of different distribution tariff structures on both the adoption of renewable energy technologies and the spiral of end-use electricity prices. In this study, we analyze the following distribution tariffs structures: an annual net-volumetric distribution tariff (NET), an hourly offtake volumetric distribution tariff (POS), an hourly bidirectional volumetric distribution tariff (BI), an annual maximum offtake capacity tariff (CAP), and an annual maximum bidirectional capacity tariff (CABI).

An annual net-volumetric distribution tariff charges a tariff per kWh of annual net consumption. An hourly offtake volumetric distribution tariff charges an hourly tariff per kWh of net consumption for each hour of the year. An hourly bidirectional volumetric distribution tariff charges an hourly tariff per kWh of either net offtake or net injection. An annual maximum offtake capacity tariff charges a tariff per kW of maximum net consumption capacity throughout the year. Finally, an annual maximum bidirectional capacity tariff charges a tariff per kW of either maximum net offtake or net injection capacity throughout the year.

2.2. Model formalization

The conceptual model was formalized into an agent-based model to analyze the influence of different distribution tariff structures and peer effects on both the utility death spiral and households' DERs adoption.

We used agent-based modeling because of its ability to represent individual's actions, decisions and bounded rationality, as well as peer effects. Agent-based models are uniquely positioned to describe the evolving nature of residential consumer behavior and its impact on energy systems. The following description of the agent-based model is based on the ODD (Overview, Design concepts, and Details) protocol[4] [30]. The model was implemented in Julia 1.3.1 and Gurobi 8.1.0 was used as optimization solver. The simulations were run 10 times for each distribution tariff structure to capture different representations of consumers. Properties such as adopter type, tenure status, and income level assigned to consumers differ in each run. These simulations were completed in a period of approximately 20 min. The simulations were performed on a personal computer with an Intel Core i7-8650U processor and 16 GB of RAM.

2.2.1. Purpose

The purpose of this model is to study the interaction between households' DERs adoption and the utility death spiral under different distribution tariff structures.

2.2.2. Entities, state variables, and scales

This agent-based model consists of 50 residential consumers agents and one DSO agent. These agents are assumed to be myopic. That is, they are unable to predict potential developments for both solar PV panels and batteries cost. Residential consumers can perform either the role of electricity consumers or electricity prosumers. Each residential consumer/prosumer was characterized by the adopter type, income class, electricity demand, number of neighbors, and PV/battery size installed. Each residential consumer/prosumer was also categorized as being either a house-owner or a renter. The DSO is responsible for operating and maintaining the electricity grid. The main DSO's state variables are the revenues and the network charges.

It was assumed that residential consumers interact through a social network. This network was created based on the income level. That is, it was assumed that residential consumers with similar income level live close to each other. The temporal extent of the model is twenty years and the time step is one year with hourly resolution. The global environment consists of the independent variables (i.e., distribution tariff structures) and the exogenous factors such as: solar panels costs, electricity prices, electric loads, and residual demand.

[4] The Overview, Design concepts, and Details (ODD) protocol is a method used to describe agent-based models. This protocol was developed by Grimm *et al.* [30].

2.2.3. Process overview and scheduling

The scheduling is formed by a sequence of events that take place in discrete periods over the course of a year (see **Figure 2**). In each time-step, each residential consumer agent decides between either buying electricity from the utility or adopt DERs. This decision is driven by the information received from the utility company (wholesale electricity prices) and DERs installers (PV and battery costs); residential consumer's attitude to DERs adoption (i.e., adopter type) and socio-economic attributes such as income level and tenure status (owning or renting a property), as well as the influence of other agents in the residential consumer's social network (peer effects). Furthermore, in each time step, the residential prosumer agent operates his DERs to minimize cost, whereas the DSO calculates either the total electricity flows or the peak demand capacity in the grid and updates the distribution tariff to ensure that his revenues remain constant.

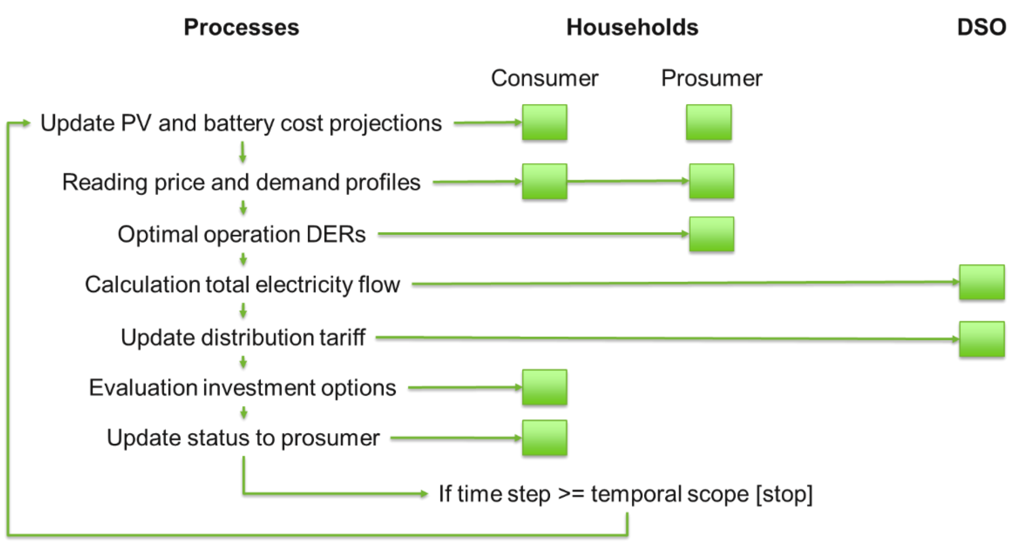

Figure 2. Model narrative. The horizontal arrows indicate the agents to which each process is attributed.

2.2.4. Design concepts

a. Basic principles: The basic principles that underpin the model structure are: the theory of planned behavior and the diffusion of innovations theory [29], [31]. The diffusion of innovation theory was used to classify the residential consumers/prosumers in five groups: innovators, early adopters, early majority, late majority, and laggards. The theory of planned behavior was used to model the investment decision-making in DERs. This theory suggests that human behavior is driven by attitudes, peer pressure, and beliefs about facilitating or impeding factors (see **Figure 3**). In this study, we assumed that payback period, the numbers of neighbors adopting DERs, and the tenure status can be used as a proxy for the attitude towards the behavior, peer pressure or subjective norm, and the perceived behavioral control, respectively.

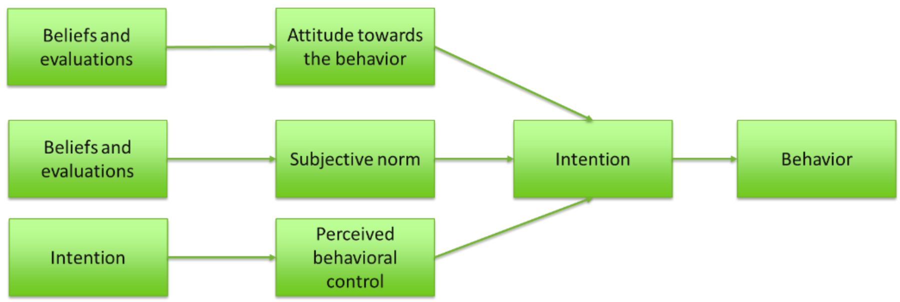

Figure 3. Theory of planned behavior [31].

b. Emergence: Emergent system dynamics includes the diffusion of DERs adoption and the evolution of network charges.

c. Adaptation: residential consumers/prosumers and the DSO are the entities that exhibit adaptive behavior in the model. Residential consumers adapt their position on adopting a DERs as electricity prices, PV installation cost, network charges, and number of neighbors adopting DERs change over time. Residential prosumers optimize the operation of their DERs as a function of electricity prices and network charges. DSO adapts his distribution tariff as a response to residential consumers DERs adoption.

d. Objectives: each residential consumer/prosumer aims to minimize his energy bills by adopting DERs. The DSO aims to keep his revenues constant over time.

e. Learning/prediction: agents lack any learning mechanisms and they are unable to predict future solar PV panel costs. Residential consumers, however, are allowed to know the value of the battery cost in 10 years. By doing so, we can take into account a replacement of the battery system for a new one in a NPV calculation.

f. Sensing: residential consumers/prosumers are assumed to know, without uncertainty, the present electricity wholesale market prices, the load factors, and the DERs capital investment cost.

g. Interaction: Residential consumers indirectly interact with each other within their social network through observation. That is, residential consumers are observing whether their neighbors are adopting DERs or not. The number of neighbors adopting DERs influences the investment decisions of a residential consumer. The greater the number of neighbors who are prosumers, the greater the probability that a residential consumer in the social network will adopt DERs. The DSO and the residential consumers/prosumers directly interact through the electricity consumption and the update of the distribution tariff.

h. Stochasticity: the model was stochastically initialized. Residential consumers were assigned an adopter type by using the distribution of adopter categories proposed by Rogers [29]. Properties such as tenure status and income level were randomly assigned to residential consumers to capture a more diversified and plausible representation of consumers. These properties remain unchanged during the course of the simulation.

i. Collectives: the model neglects the formation of aggregation among individuals.

j. Observation: the deployments of solar PV and batteries as well as the evolution of the network charges are the main key performance indicators.

2.2.5. Initialization and input data

A test case has been set-up, consisting of fifty residential consumers and one DSO, initialized for the year 2017. At the beginning of the simulation, the income class and adopter type were allocated to the residential consumers. The income class was assigned to households by using tenure status data (see **Table 1**). The adopter type was assigned to households by using the distribution provided by the diffusion of innovation theory [29]. The income class was used to create the social networks. It was assumed that each residential consumer is part of a social network wherein he can have up to seven neighbors. The initial electricity cost was set to 0.05 €/kWh. This cost was assumed to increase linearly by 2% annually. Moreover, it was assumed that the electricity demand of the households that are unable to adopt DERs is five times the initial demand of the households that are able to adopt DERs. This assumption was made to account for the limited number of rooftops for PV and for the lower electricity yield for less suitable sites [32]. For the group of households that are able to adopt DERs, it was assumed that the proportion of owner-occupied houses was 80%. Finally, the annual electricity consumption was set to 1200, 3500, and 3900 kWh for low income, middle income, and high-income residential consumers, respectively (see **Table 1**). The values used for the cost of solar photovoltaic panels and energy storage systems, as well as for load profiles, are presented in **Appendix A**.

2.2.6. Submodels

In this subsection, we described two of the most important submodels incorporated into the agent-based model. These submodels are the *decision-making model for the adoption of distributed energy resources* and the *distribution cost update*.

Table 1. Parameters used in the model initialization

Parameter	Value	Units	Description
N	50	[-]	Number of households
N_n[a]	7	[-]	Number of neighbors
p_e[b]	0.05	[€/kWh]	Initial electricity price (wholesale price).
RD	5	[-]	Residual demand factor, used to calculate the residual demand. This demand is calculated as the product of the total initial demand of households that can adopt DERs and the residual demand factor
P_o[c]	80	[%]	Proportion of owner-occupied houses
P_{ohi}[d]	30	[%]	Probability that the owner of a property is a high-income residential consumer
P_{omi}[d]	60	[%]	Probability that the owner of a property is a middle-income residential consumer
P_{rhi}[d]	10	[%]	Probability that the renter of a property is a high-income residential consumer
P_{rmi}[d]	20	[%]	Probability that the renter of a property is a middle-income residential consumer
ΔP[a]	2	[%]	Annual linear increase of the electricity price
i[e]	U(5,10)	[%]	Interest rate
d_{hi}[f]	3900	kWh	Annual electricity consumption of a high-income residential consumer
d_{mi}[f]	3500	kWh	Annual electricity consumption of a middle-income residential consumer
d_{li}[f]	1200	kWh	Annual electricity consumption of a low-income residential consumer
η_{ch}	0.95	[-]	Battery charging efficiency
η_{dc}	0.95	[-]	Battery discharging efficiency
CR[g]	0.33	[-]	C-rate of the battery

[a] This value was estimated based on that reported by [16]
[b] Value estimated based on the 2018 Belpex prices [33]
[c] This value was retrieved from [34]
[d] Values were estimated based on those reported by [35]
[e] This value was based on that reported by [36]
[f] Values were estimated based on those reported in [37]
[g] Value retrieved from [38]

Decision-making model for the adoption of distributed energy resources

At the core of this agent-based model is the evaluation of the different investment options. This investment decision-making process was modeled by formalizing the theory of planned behavior (see **Figure 4**). Only residential consumers who own the house will engage in the investment decision-making process[5]. A property-owner will decide whether to invest in DER(s) or not based on the value of the total utility. If this value is greater than the property-owner's adoption threshold, the property owner will adopt DER(s). The total utility u_i takes into account both economic and non-economic effects (the latter driven by peer-effects), which are represented by a payback period utility $u_{pp,i}$ and a peer effect utility $u_{pe,i}$, respectively (see **Equation 1**).

$$u_i = w_{pe,i} \cdot u_{pe,i} + w_{pp,i} \cdot u_{pp,i} \tag{1}$$

$$w_{pe,i} + w_{pp,i} = 1 \tag{2}$$

Where $w_{pe,i}$ and $w_{pp,i}$ refer to weight allocated to peer-effects and payback period on the investment decision-making, respectively. As mentioned above, the adopter type will determine the values given to adoption threshold and to the weight given to economic performance in the utility function (see **Table 2**).

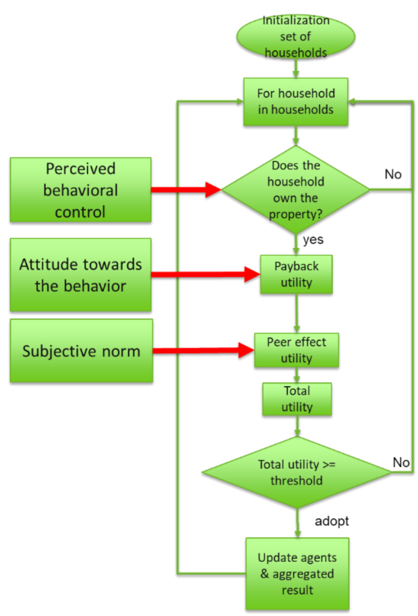

Figure 4. Formalization of the theory of planned behavior

[5] Although income level is a relevant additional factor for the Perceived Behavioral Control (PBC) as it could take into account the "Mathew effect" [55], we neglected its influence on the PBC because a high income residential consumer is unlikely to invest in DERs if he is not a homeowner.

Table 2. Residential consumers' attitude towards DERs adoption and value given to economic performance according to the adopter type

Adopter	Adoption threshold [-]	weight payback utility[a] [-]
Innovator	0.4	U(0.9, 1)
Early adopters	0.5	U(0.8, 0.9)
Early majority	0.6	U(0.6, 0.7)
Late majority	0.7	U(0.6, 0.7)
Laggards	0.8	U(0.6, 0.7)

[a] Uniform distribution(X, Y).

The values in **Table 2** were estimated based on [29]. That is, it was assumed that adoption occurs through several stages. As in the initial stage innovators are the only ones willing to adopt the new technology, they were assigned the lowest value for the adoption threshold and the highest value for the weight assigned to payback period. Innovators are followed by early adopters. These adopters are characterized as being more likely to see the benefits of new technology and less reliant on the opinion of others. Thus, they were assigned the second lowest value for the adoption threshold and the value of the weight assigned to payback period was set at a slightly lower value than that of innovators. By contrast, consumers that adopt later in the diffusion process such as: early majority, late majority, and laggards are more risk-averse and more likely to seek the opinions of others when considering the adoption of a new technology. As early majority are followed by late majority, and these in turn, are followed by laggards we used different values for the adoption threshold. We assumed that these adopters have a similar value for the weight allocated to the payback period in the utility function. In reality, however, the values for these weights may differ for different types of adopters. The weight allocated to peer effects in the utility function is calculated by using **Equation 2**. To add heterogeneity to the residential consumers belonging to the same adopter type, we used an uniform distribution to give a value to the weight assigned to the payback period utility.

The peer effect utility $u_{pe,i}$ of a residential consumer *i* was calculated based on both the number of prosumers that a residential consumer *i* observe in his social network $\mathrm{n_{pro,i}}$ and the total number of neighbors $\mathrm{N_{n,i}}$ in that network (see **Equation 3**). For the sake of simplicity, we assumed that the peer effect utility is nonnegative. In reality, however, a negative value for the peer effect utility is possible, which would reflect negative experiences from early adopters.

$$u_{pe,i} = \frac{n_{pro,i}}{N_{n,i}} \tag{3}$$

The payback period utility $u_{pp,i}$ of the residential consumer i was calculated based on the payback period pp and by assuming that the expected useful life of the DERs system is 20 years (see **Equation 4**):

$$u_{pp,i} = \frac{20-pp}{20} \tag{4}$$

The payback period was calculated based on the net present value calculation (NPV). That is, the payback period is the year in which the NPV of the DER(s) system turns from negative to positive. The NPV is defined as the sum of the discounted cash flows of the DER(s) system R, given the initial investment costs I_0, and the interest rate i (see **Equation 5**).

$$NPV = -I_0 + \sum_{t=1}^{20} \frac{R}{(1+i)^{ty}} \tag{5}$$

The initial investment costs were calculated based on the data reported in **Appendix A** (**Table A4**). The cash flow was calculated based on the savings that are generated by using the produced electricity instead of buying it from or selling it to the grid. That is, $R = S$. Savings S were calculated by taking into account both the savings generated by reducing the energy cost and the savings generated by reducing the distribution cost (see **Equation 6**). We assumed that the energy price is constant to ensure that changes in the model outcomes are only due to changes in either independent variables (i.e., distribution tariff structures) or exogenous factors of the model (e.g., solar panel costs).

$$S = S_e + S_d \tag{6}$$

The savings generated by reducing the energy cost were calculated with the following equation:

$$S_e = \sum_{t=1}^{8760} (d_t - q_t) \cdot \mathrm{p_t} \tag{7}$$

Where d_t is the residential consumer demand in hour *t*, q_t is the resulting net demand in hour *t*, which can have a negative value if the household is exporting electricity to the grid, and $\mathrm{p_t}$ is the wholesale price in hour *t*[6]. The savings generated by the reduction in the use of the grid were calculated based on the distribution tariff structure:

[6] Note that in this study it was assumed that the wholesale price is fixed. Thus, $\mathrm{p_t} = p$ in equation 7

- For an annual net-volumetric distribution tariff the savings in distribution cost were calculated as a function of the total annual electricity demand d, the annual net-volumetric consumption q_{net}, and the net volumetric distribution tariff $dist_{net}$ (see **Equation 8**).

$$S_d = (d - q_{net}) \cdot dist_{net} \tag{8}$$

$$d = \sum_{t=1}^{8760} d_t \tag{9}$$

- For the hourly offtake volumetric distribution tariff the savings in distribution cost were calculated as a function of the hourly electricity demand d_t, the hourly net-volumetric consumption $q_{pos,t}$, and the distribution tariff on hourly offtake energy $dist_{pos,t}$ (see **Equation 10**).

$$S_d = \sum_{t=1}^{8760} \left(d_t - q_{pos,t}\right) \cdot dist_{pos,t} \tag{10}$$

- For the hourly bidirectional volumetric distribution tariff the savings in distribution cost were calculated as a function of the hourly electricity demand d_t, the absolute value of the hourly net demand $q_{bi,t}$, and the distribution tariff on net hourly bidirectional energy flow $dist_{bi,t}$ (see **Equation 11**).

$$S_d = \sum_{t=1}^{8760} \left(d_t - q_{bi,t}\right) \cdot dist_{bi,t} \tag{11}$$

- For the annual maximum offtake capacity tariff the savings in distribution cost were calculated as a function of the annual peak demand d_{max}, the annual maximum offtake capacity q_{cap}, and the offtake capacity distribution tariff $dist_{cap}$ (see **Equation 12**):

$$S_d = \left(d_{max} - q_{cap}\right) \cdot dist_{cap} \tag{12}$$

- For the annual maximum bidirectional capacity tariff the savings in distribution cost were calculated as a function of the annual peak demand d_{max}, the annual maximum injection/offtake capacity q_{cabi}, and the bidirectional capacity distribution tariff $dist_{cabi}$ (see **Equation 13**):

$$S_d = (d_{max} - q_{cabi}) \cdot dist_{cabi} \tag{13}$$

The parameters q_t, q_{net}, $q_{pos,t}$, $q_{bi,t}$, q_{cap}, and q_{cabi} were calculated in an optimization problem aiming to minimize the operation cost of the DERs system configurations. This optimization problem is described in detail in **Appendix B**. Below, we focus on the description of the distribution costs component of the objective function (see **Equation 14**), which varies according to the distribution tariff structure.

$$min_{\Xi}\left(\sum_{t=1}^{8760}(p_t \cdot q_t) + dist_{cost}\right) \tag{14}$$

The decision variables Ξ are: the resulting net demand q_t in hour *t*, the power production by PV panels pv_t in hour *t*, the power drawn from the grid to charge battery ch_t in hour *t*, the power provided to the grid from battery dc_t in hour *t*, the battery energy content e_{BAT_t} in hour *t* and the distribution tariff structure parameters q_{net} , $q_{pos,t}$, $q_{bi,t}$, q_{cap}, and q_{cabi}. These parameters are used to calculate $\mathrm{dist}_{\mathrm{cost}}$ in **Equation 14** according to the distribution tariff as shown below:

- For an annual net-volumetric distribution tariff the distribution cost was calculated as:

$$dist_{cost} = dist_{net} \cdot q_{net} \tag{15}$$

Subject to:

$$q_{net} \geq \sum_t \mathrm{q_t} \tag{16}$$

$$q_{net} \geq 0 \tag{17}$$

- For the hourly offtake volumetric distribution tariff the distribution cost was calculated as:

$$dist_{cost} = \sum_t dist_{pos,t} \cdot q_{pos,t} \tag{18}$$

Subject to:

$$\forall t\colon q_{pos,t} \geq q_t \tag{19}$$

$$\forall t\colon q_{pos,t} \geq 0 \tag{20}$$

- For the hourly bidirectional volumetric distribution tariff the distribution cost was calculated as:

$$dist_{cost} = \sum_t dist_{bi,t} \cdot q_{bi,t} \tag{21}$$

Subject to:

$$\forall t\colon q_{bi,t} \geq q_t \tag{22}$$

$$\forall t: q_{bi,t} \geq -q_t \quad (23)$$

- For the annual maximum offtake capacity tariff the distribution cost was calculated as:

$$dist_{cost} = \sum_t dist_{cap} \cdot q_{cap} \quad (24)$$

$$\forall t: q_{cap} \geq q_t \quad (25)$$

$$q_{cap} \geq 0 \quad (26)$$

- For the annual maximum bidirectional capacity tariff the distribution cost was calculated as:

$$dist_{cost} = \sum_t dist_{cabi} \cdot q_{cabi} \quad (27)$$

Subject to:

$$\forall t: q_{cabi} \geq q_t \quad (28)$$

$$\forall t: q_{cabi} \geq -q_t \quad (29)$$

distribution tariff update

The DSO will update the distribution tariff at every time-step according to the following equation:

$$dist_{j,t+1} = \frac{Re}{D_{res} + D_{pros,t} + D_{cons,t}} \quad (30)$$

Where $dist_{j,t+1}$ is the value of the distribution tariff *j* at the time step *t+1*, Re are the revenues of the DSO at the first time step. This value is held constant through the temporal scope of the simulation. D_{res}, $D_{pros,t}$, and $D_{cons,t}$ are the total residual demand, the total prosumers' demand, and the total consumers' demand at the time step *t*.

We conclude this section by enumerating the main critical assumptions underpinning the model structure.

- Besides the energy and distribution component, no other parts of the electricity cost (e.g., taxes and levies) are considered.
- Note that when distribution tariffs like the annual net-volumetric tariff are in place, no excess electricity (on annual basis) can be sold to the grid, as q_{net} cannot be negative. In other tariffs, like the annual maximum offtake capacity tariff, excess electricity (on annual basis) can be sold.

- All households have the same number of members. It follows from this assumption that the electricity consumption of high-income households is higher than that of middle-income households, and that the consumption of middle-income households is higher than of low-income households as high-income households tend to have more appliances.
- We used a set of 12 representative days to represent both the annual load factors and the annual load profiles [39]. Each representative day has a one-hour resolution (see **Appendix A**).
- The load factor, electricity demand, weights of representative days, house-ownership status remains constant throughout the simulation.
- Peer effects are only exerted through observational learning.
- Residential consumers are myopic to cost developments for solar PV panels and battery energy storage systems.
- The interaction between the households and the DSO is direct. That is, there is no intermediary, such as an aggregator or flexibility provider.
- No upgrades or extensions of the solar PV panels adopted are possible as the temporal scope is 20 years. For adopted battery storage systems, it was assumed that these storage systems will be replaced by another one of the same size when they reach the end of life. This assumption is made to be able to carry out the calculation of the net present value over a period of 20 years with the same integrated PV-battery system. Note that the decision making process of the residential consumers is not affected by the temporal scope of the simulation (which is 20 years). Thus, they will assess the investment in a time frame of 20 years even if they are reaching the end of the simulation.
- The lifetime of a solar PV panel is 20 years. The lifetime of a battery is 10 years.
- The residual demand is inelastic. That is, the electricity demand in these households is unresponsive to increasing in network charges and electricity cost.
- Grid capacity is assumed sufficient to accommodate PV and battery uptake. No grid reinforcement is needed.
- Transactive energy systems[7] are neglected.
- Finally, we limited the set of integrated photovoltaic and battery energy storage systems options for residential consumers to those reported in **Table 3.**

[7] Transactive energy systems is an approach to designing and operating an electrification system. For a comprehensive overview of transactive energy systems, the reader is referred to [56]

Table 3. Overview of PV-battery configurations

Option	PV capacity [kWp]	Battery capacity [kWh]
1	2	0
2	2	2
3	4	0
4	4	2
5	4	3
6	4	4
7	6	0
8	6	2
9	6	3
10	6	4

3. Results

This section is divided in two subsections. The first subsection discusses the influence of both distribution tariff structures and peer effects on the adoption of DERs and the utility death spiral, whereas the second subsection discusses how the timing of a change in the distribution tariff structure affects DERs adoption. That is, this subsection presents a path dependency analysis. In the analysis of the influence of peer effects on DERs adoption, we focus on three relevant aspects: the evolution of installed PV and battery capacity, the percentage of residential consumers adopting a specific PV-battery configuration, and the distribution tariffs evolution. In the path dependency analysis, we focus on the evolution of installed PV and battery capacity.

3.1. Effect of peer effects on the DERs adoption and utility death spiral under different distribution tariff structures

To analyze the influence of peer-effects on both DERs adoption and utility death spiral, we compare the DERs adoption patterns obtained with an investment decision-making model that takes into account both economic factors and peer effects (i.e., $\mathrm{w}_{pe,i} > 0$ and $\mathrm{w}_{pp,i} > 0$ in **Equation 1**) with the adoption patterns obtained with a decision-making model that only takes into account economic factors ($\mathrm{w}_{pe,i} = 0$, $\mathrm{w}_{pp,i} = 1$ in **Equation 1**). The former illustrates a decision making model departing from an economic rational behavior, whereas the latter illustrates a decision-making model adopting an economic rational behavior.

Henceforth, we use *case 1* and *case 2* to refer to the decision-making model departing from rational economic behavior and the one adopting an economic rational behavior, respectively.

3.1.1. Evolution of installed PV and battery capacity under different distribution tariffs structure.

Figure 5 shows that, for all different distribution tariff structures, the use of a rational decision-making model led to a rapid solar PV adoption, under all cost and model assumptions taken. The adoption process in case 2 was saturated 2.8, 2.6, 2, 2, and 2 times faster than that in case 1 for a NET, POS, BI, CAP, and, CAPBI, respectively. This is because the adopter's total utility hinges only on the payback period of the investment. In contrast, when a decision-making model taking into account the influence of peer effects on the adoption process is used, risk-averse adopters are more likely to observe whether their neighbors are adopting DERs, and only if positive engage. If the number of neighbors adopting DERs is small, as is the case early in the adoption process, the contribution of the peer effect to the adopter's total utility is insufficient to incentivize DERs adoption.

Furthermore, as can be seen in the case of volumetric-based tariff structures, the use of a rational decision-making model neglecting the influence of peer effects on the adoption process led to lower solar PV adoption in the long-term. In case 2, the median of the final cumulative installed solar PV panels was 25%, 35%, and 6% lower than that obtained in case 1 for a NET, POS, and BI, respectively. This lower PV adoption is due to the relatively high PV costs at the early stages of the adoption process and the assumption that residential consumers are myopic about future costs for solar PV panels and increasing electricity prices. The combination of these two factors lead to the installation of small PV systems. In the case of capacity-based tariff structures, however, the use of a pure rational decision-making model led to higher PV adoption at the end of the considered horizon, as case 1 has not converged yet over the considered period.

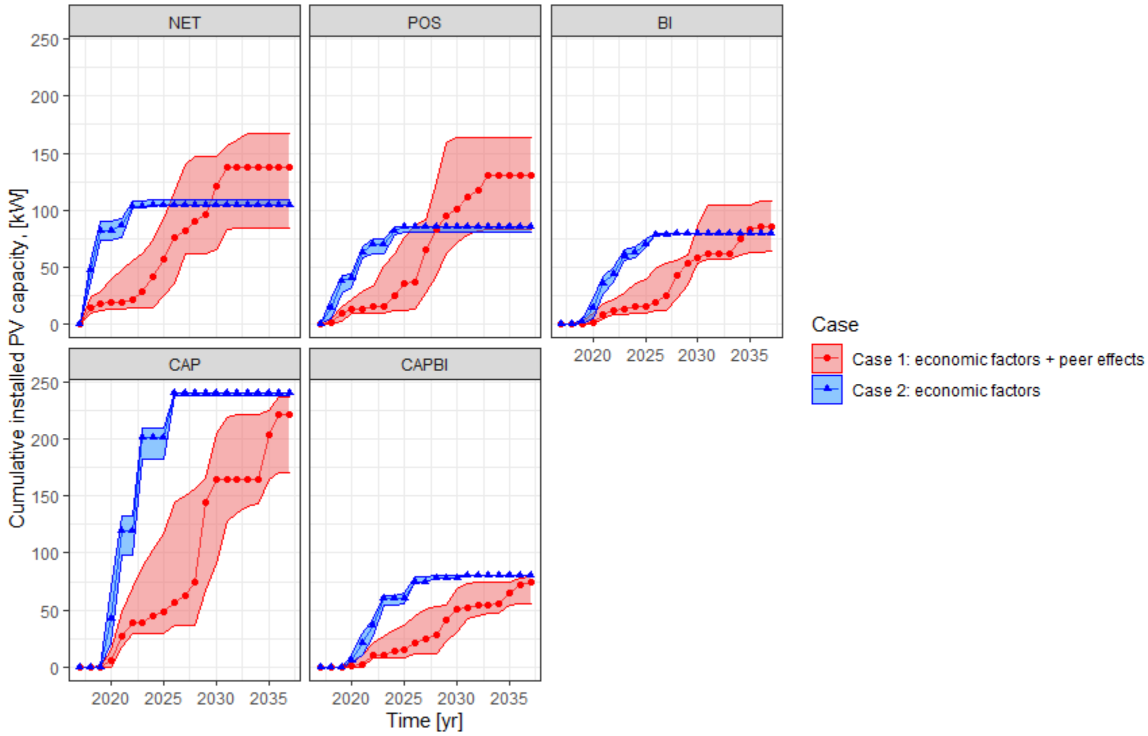

Figure 5. Evolution of the PV installed capacity under different distribution tariff structures. NET: annual net-volumetric distribution tariff; POS: hourly offtake volumetric distribution tariff; BI: hourly bidirectional volumetric distribution tariff; CAP: annual maximum offtake capacity tariff; CABI: annual maximum bidirectional capacity tariff. Solid lines represent median values, the shaded areas represent the 90 confidence interval by colors.

It is also observed that PV adoption patterns vary depending on the distribution tariff structure. In case 1, the median of the final cumulative installed solar PV panels under a CAP was 61%, 69%, 161%, and 200% higher than that under a NET, POS, BI, and CAPBI, respectively. This is because under a CAP, the conflation of a further assumed drop in the solar panel cost and increase in electricity price, as well as the absence of either injection charges or injection constraints lead residential consumers to adopt larger solar PV systems (see also **Figure 7**), which is not the case under a BI and a CAPBI, where there is a charge for injecting electricity into the grid, nor under NET, where excess electricity cannot be sold.

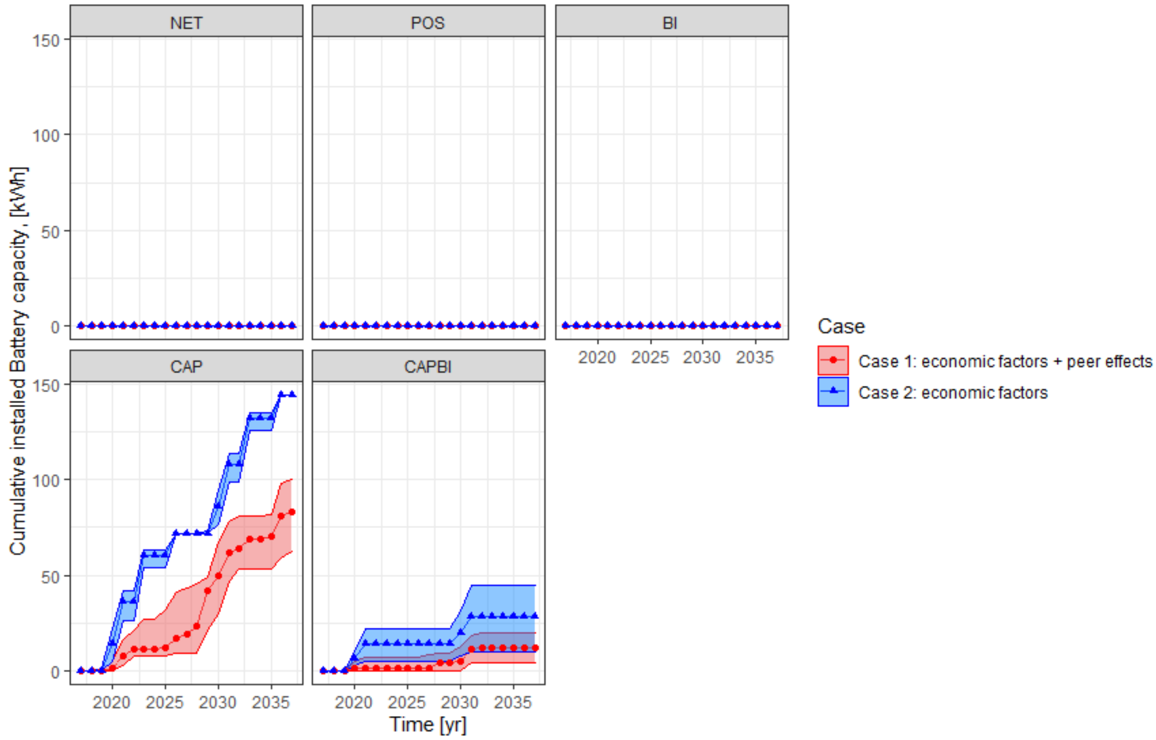

Figure 6. Evolution of the battery installed capacity under different distribution tariff structures. NET: annual net-volumetric distribution tariff; POS: hourly offtake volumetric distribution tariff; BI: hourly bidirectional volumetric distribution tariff; CAP: annual maximum offtake capacity tariff; CABI: annual maximum bidirectional capacity tariff. Solid lines represent median values, the shaded areas represent the 90 confidence interval by colors.

Battery adoption only takes place under the capacity-based tariff structures (see **Figure 6**). Even though volumetric tariffs such as POS and BI can potentially incentivize the adoption of energy storage systems, the cost of these systems do not offset the savings generated by their use. Similarly to solar PV adoption, the use of a rational decision-making model neglecting the influence of peer effects on the adoption process led to both a rapid and higher battery adoption. If it is assumed that only economic factors dominate the adoption of battery storage systems, the median of the final cumulative installed battery capacity was 73% and 133% higher than that adopted if peer effects are taken into account in the investment decision-making for a CAP and a CAPBI, respectively. This adoption pattern is due to that, in the short term, peer effects are not strong enough to encourage the most risk-averse residential consumers to adopt DERs and to the assumption that batteries will be replaced with similar ones at the end of their lifetime (i.e., 10 years). Battery adoption was higher under CAP because the potential revenues generated by grid injection (i.e., export) improves the economic outlook of adopting an integrated photovoltaic and battery energy storage system, which is not the case of BICAP where grid injection entails a distribution cost or the size of the installed PV is small, or both. In case 1, the final cumulative installed battery capacity under a cap was 7 times higher than that installed under a BICAP.

3.1.2. Installed PV and battery size distribution under different distribution tariff structures

Figure 7 shows that tariff structures and peer effects led to different patterns in solar PV panels and battery adoption. Except for a CAP, the use of a rational decision-making model led to the adoption of small PV sizes (2 kW) because of both rapid solar PV adoption and solar PV costs at early stages of the adoption process, whereas the use of a decision-making model taking into account the influence of peer effects on the adoption process led to a more diverse DERs adoption. For instance, under a NET and a POS, residential consumers adopted solar PV systems of 2, 4, and 6 kW. Under a NET, 35% and 17% of the residential consumers, who belong to the middle class, installed solar PV panels of 2 kW and 4 kW, respectively. Under a POS, however, 29% and 27% of the residential consumers, who belong to the middle class, installed solar panels of 2kW and 6 kW, respectively. As expected, residential consumers adopted small PV systems (2 kW) under a BI and adopted small integrated photovoltaic (2 kW) and battery energy storage systems (2 kWh) under a CAPBI. 80% of the residential consumers adopted 2 kW solar PV systems under a BI.

Larger solar PV systems (6 kW) and small battery energy storage systems (2 kWh) were adopted under a CAP. 75% of the residential consumers adopted an integrated PV-storage system of 6 kW and 2kWh. The adoption of large PV solar systems was caused by the substantial economic benefits that grid injection can bring to the residential consumer. Small battery energy storage systems were adopted because this battery size is enough to reduce the peak demand.

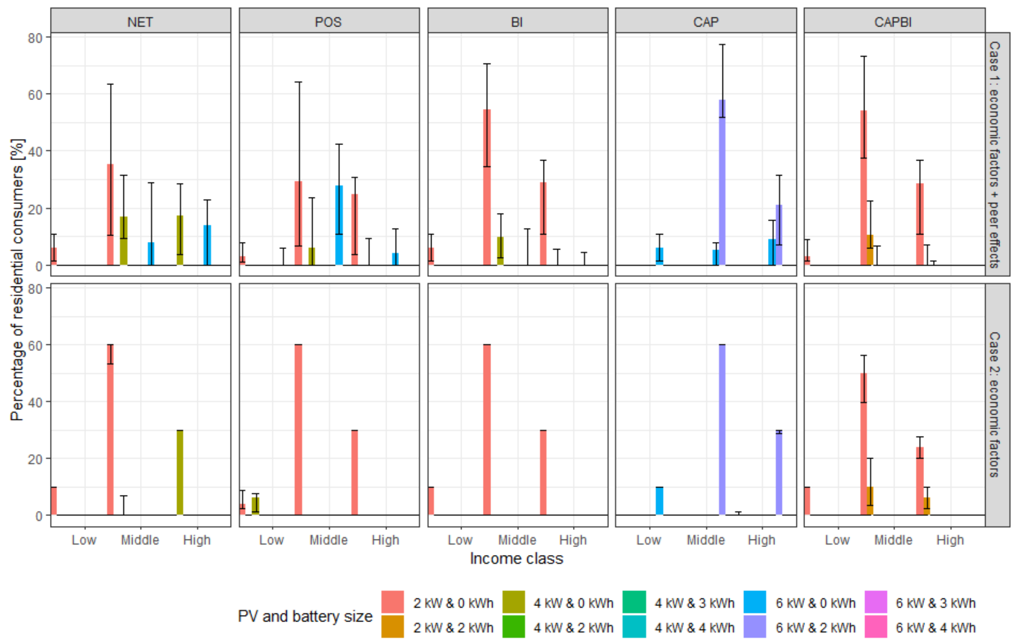

Figure 7. Percentage of residential consumers adopting a specific PV-battery configuration at the end of the simulation as a function of different distribution tariff structures. NET: annual net-volumetric distribution tariff; POS: hourly offtake volumetric distribution tariff; BI: hourly bidirectional volumetric distribution tariff; CAP: annual maximum offtake capacity tariff; CABI: annual maximum bidirectional capacity tariff. The bars represent median values, the error bars represent the 90 confidence interval.

3.1.3. Evolution of distribution tariffs.

The distribution tariff ratio is defined as the distribution tariff at the time *t* divided by the initial distribution tariff. This ratio increases quickly when a rational decision-making model was used, given the faster uptake of PV (see **Figure 8**). Interestingly, under a POS, the final value of the distribution ratio obtained in case 2 is similar to that obtained in case 1, even though, for the latter, the cumulative PV adoption is higher (see **Figure 5**). Under a POS, residential consumers are encouraged to self-consume and to inject the surplus of the electricity to the grid. Nevertheless, only households' self-consumption patterns influence the distribution cost. Thus, installing larger PV systems does not affect distribution costs more than smaller PV systems do, provided that a household with one of these PV systems engages in the same self-consumption behavior. Similarly, the final value of distribution ratio in case 1 converges to a value similar to that in case 2 under a BI and CAPBI. This is because under these distribution tariff structures, residential consumers are incentivized to inject electricity into the grid when the wholesale price offset the distribution cost. The interplay between self-consumption and retrieving or injecting electricity renders a low distribution ratio. Network charges considerably increased under NET regardless the influence of peer effects on the adoption process. In case 1, the median of the distribution tariff increased by 14% in the case of NET, 6% in the case of POS, and 5% in the case of CAP. The distribution tariff remains approximately constant under the BI and CAPBI.

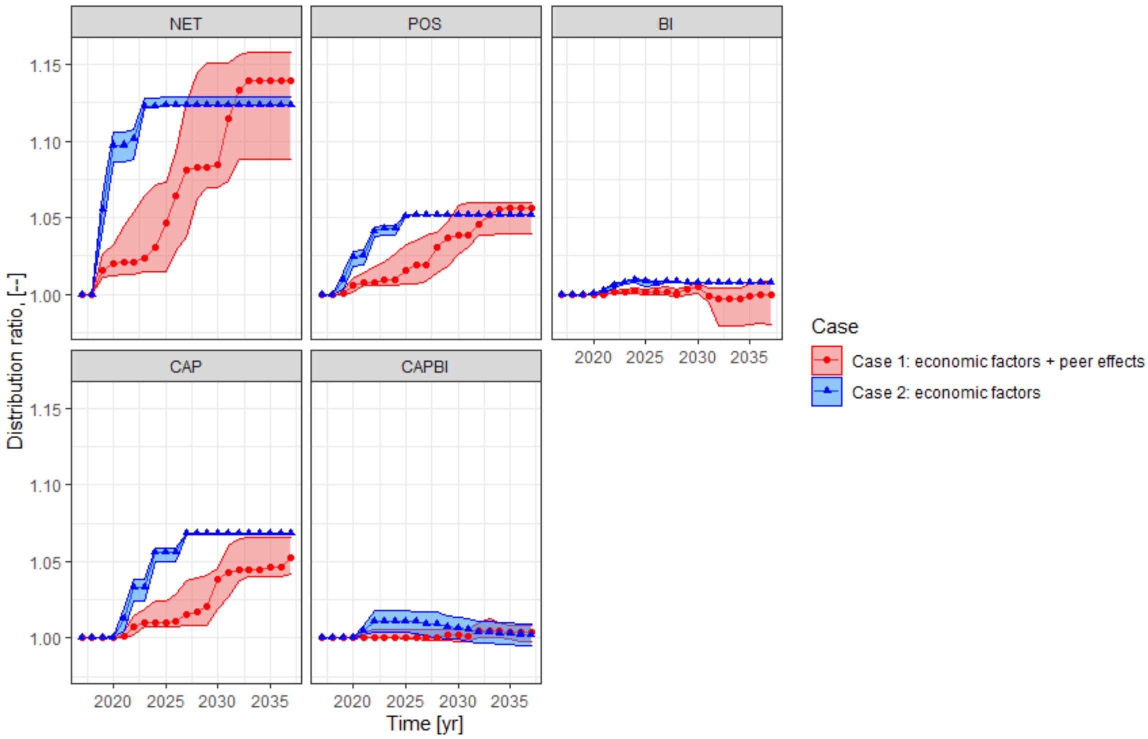

Figure 8. Evolution of the distribution tariff ratio. NET: annual net-volumetric distribution tariff; POS: hourly offtake volumetric distribution tariff; BI: hourly bidirectional volumetric distribution tariff; CAP: annual maximum offtake capacity tariff; CABI: annual maximum bidirectional capacity tariff. Solid lines represent median values, the shaded areas represent the 90 confidence interval by colors.

3.2. Path dependency analysis

We designed an experiment to study the influence of the timing of introducing an annual maximum offtake capacity tariff (CAP) in the system on the adoption of DERs. The experiment used as a baseline the results obtained from simulations run under an annual net-volumetric tariff (NET). The independent variables used are the years wherein a CAP is introduced. We assumed that a CAP can be introduced 5, 10, 15 years after a NET was enacted in 2017. That is, the independent variables are the introduction of a CAP in 2022, 2027, and 2032. The variables to be measured are the deployment of solar PV panels and batteries.

Figure 9 and **Figure 10** show the evolution of solar PV panels and battery adoption, respectively, as a function of different years of introducing a CAP when the initial tariff structure was a NET. As can be seen, the timing of introduction of a CAP into the system produces different adoption patterns for both solar PV panels and energy storage systems. Higher adoption of integrated solar PV panels and energy storage systems was observed when the capacity tariff was introduced early on. If a CAP was introduced in 2022, the solar PV adoption increased by 35%, 29%, and 35% compared to cases when no CAP was introduced, a CAP was introduced in 2027, and a CAP was introduced in 2032, respectively. Furthermore, battery adoption was 13 times higher than that adopted when a CAP was introduced in 2027. If a CAP is introduced in 2032, it was observed little adoption of energy storage systems. These adoption patterns are due to two factors: first, an early introduction of a CAP discourages the adoption of solar panels and battery energy storage systems in the short-term because both PV and battery costs are still high; Second, if a CAP is introduced late, it is very likely that most residential consumers have already adopted solar PV panels without an energy storage system under a NET, leaving little room for further adoption of DERs under a CAP[8].

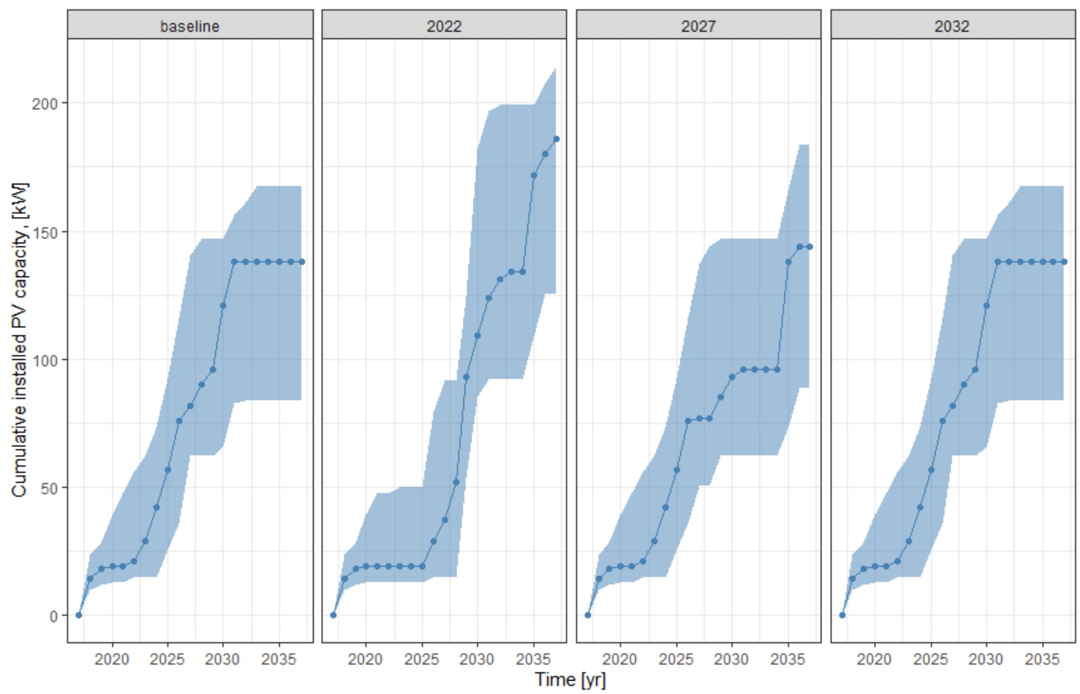

Figure 9. Evolution of the PV installed capacity as a function of the year of introduction of a CAP. The initial tariff structure is a NET. Solid lines represent median values, the shaded areas represent the 90 confidence interval.

[8] An important assumption is that all investment needs to take place at once, so prosumers with PV cannot at a later stage invest in batteries.

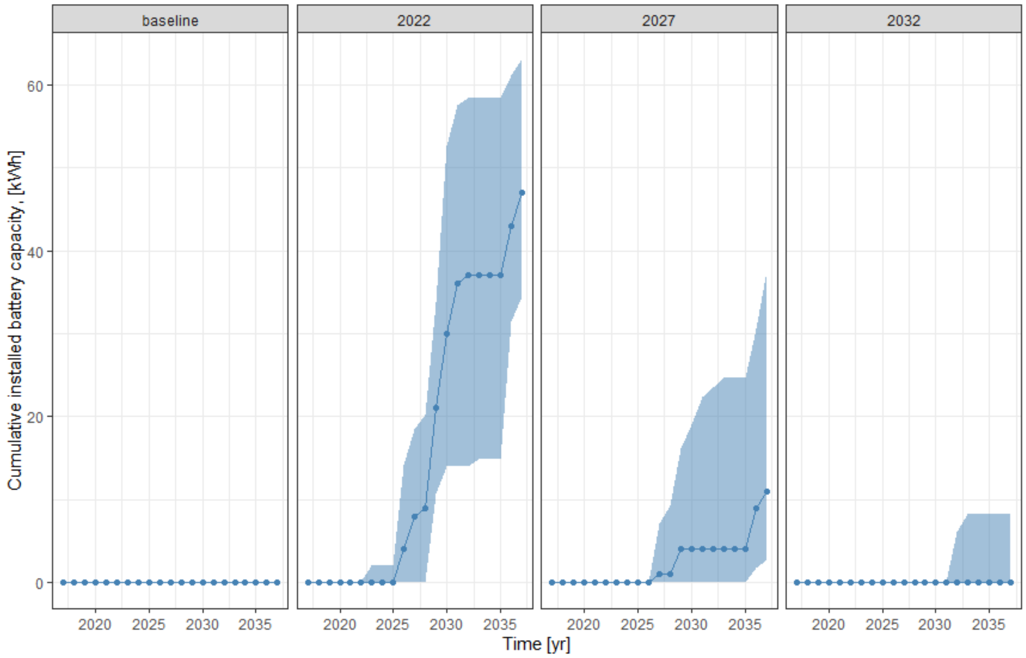

Figure 10. Evolution of the battery installed capacity as a function of the year of introduction of a CAP. The initial tariff structure is a NET. Solid lines represent median values, the shaded areas represent the 90 confidence interval by colors.

4. Discussion

The first question in this study sought to provide insights into the influence of both peer effects and distribution tariff structures on the adoption of integrated photovoltaic and battery energy storage systems, as well as on the utility death spiral. Our results show that, under the assumptions of our test case, moving away from a decision making based solely on economic factors, has a significant influence on DERs adoption patterns. When residential consumers' decision-making regarding DERs adoption was modeled taking into account economic factors and the influence of peer effects, the rate of adoption was slower than that obtained when only economic factors are taking into account in the adoption decision-making model. These results suggest that the presence of non-economic factors in the decision making process, such as peer effects, is the rate-limiting step in the early stages of the adoption process. Thus, the creation of mechanisms enhancing the influence of peer effects on the adoption process may accelerate this process, especially in the short-term. One potential mechanism is word-of-mouth communication, which can occur through different communication channels such as face-to-face conversations, organization of group meetings, and online discussion platforms. Although this finding follows directly from how adoption decisions were modeled for residential consumers (see **Equation 1**), this finding is in line with empirical evidence that suggests that peer to peer communications reduce barriers to PV adoption [40]. Another important finding was that tariff structures and peer effects lead to different patterns in the adoption of integrated photovoltaic and battery energy storage systems. This finding is in line with that of Borenstein who found that the residential tariff design can influence households' solar PV adoption [41]. This finding is also consistent with Gautier and Jacqmin who found that higher tariffs under NET do not lead to investments in larger solar PV panels [42].

Regardless of the influence of peer effects on the investment decision-making, we found that under a CAP, the adoption of DERs is higher in the long-term than that obtained under the other distribution tariffs, despite weakening residential consumers' incentive to adopt DERs in the short-term. Nevertheless, it is worth noting that this insight is contingent on the cost structure used in the distribution tariff structures, for instance, allowing residential consumers to sell excess electricity under a NET may increase the adoption of PV under this distribution tariff structure. Also important here is the assumed evolution of PV cost and the single electricity prices (that applies both for buying from and selling to the grid).

We also found that, under the assumptions of our test case, a NET may lead to a spiral of the distribution tariff because of the increase of the distribution tariff over time. If the increase in the distribution tariff is borne by the households that do not install solar panels, then a NET may also lead to substantial distributional concerns. This finding is consistent with that of de Villena *et al.* and Lu and Waddams who observed a tradeoff between the distribution price spiral and the desired PV and battery adoption for a volumetric-based tariff [26], [43]. By contrast, a tradeoff between the distribution price spiral and the deployment of solar PV panels and battery in the long-term was not found for a CAP. Finally, we found that peer effects have no significant effect on the utility death spiral.

The second question in this study sought to provide insights into the influence of the change in distribution tariff structure, from volumetric-based to capacity-based, over specific time periods on the adoption of integrated photovoltaic and battery energy storage systems. With respect to this research question, we found the formation of a lock-in effect. That is, a late introduction of a CAP has no significant effect on the adoption patterns of DERs as most residential consumers have already adopted solar PV panels without an energy storage system under a NET.

Admittedly, this study has several limitations. First, residential customers were assumed to be myopic. That is, these actors were unaware of potential developments of electricity prices when assessing the economic viability of adopting DERs. Taking into account these developments and their inherent uncertainty is an important issue that will be addressed in future research by using prospect theory [44], [45]. Second, since the aim of this study is to investigate the influence of peer effects on the adoption of DERs, the analysis of the impact of interest rate on DERs adoption was left aside. Nevertheless, several techno-economic studies stress the importance of interest rates on the long-term capital cost of energy systems [46]. Therefore, it is of interest to study the impact of intertemporal choice on DERs adoption under different distribution tariff structures. Third, this study neglects the feedback loop describing a shift in wholesale electricity prices driven by high PV penetration, and assumes buying from and selling electricity to the grid can happen at a same single price, which increases over time. To develop a full picture of the distribution tariff spiral, additional studies are needed that take into account this feedback loop and provide a more realistic description of households' investment decision making. Fourth, this study also neglects transactive energy systems enabling both network operators to control and manage the rate of consumption/generation of residential consumers, and consumers to bid and offer for transacting energy in a P2P market [47], [48]. These systems might influence adoption patterns to some extent. Thus, future work should study the effect of transactive energy systems on the adoption of distributed energy resources. Fifth, the formation of social networks is based on the income level and not on spatial proximity. Nevertheless, solid empirical evidence demonstrate that peer effects are stronger the closer solar PV panels are to each other in space [49], [50]. Sixth, some model parameters, such as electricity demand and PV load factors, are context-specific[9]. Thus, future work should examine and apply this model to other contexts to see if patterns found in this study, both for DERs adoption and for the upward spiral of distribution prices, are still observable. Finally, the results obtained in this study suggest that much of the uncertainty stems from the incorporation of peer effects into the decision-making model. Therefore, a further study with more focus on the understanding of the formation of social networks at the neighborhood level is suggested.

Yet, this study provides new insights into role of both peer effects and distribution tariff structures on the residential consumers' DERs adoption. These insights can assist policymakers in designing distribution tariff structures by shedding light on the trade-off between DERs adoption and utility death spiral, as well as how this trade-off is shaped by residential consumers' behavioral factors.

5. Conclusions

An agent-based model has been developed to analyze the influence of peer effects and distribution tariff structures on both the adoption of Distributed Energy Resources (DERs) at the household level and the utility death spiral. The results highlight the importance of considering the interaction of institutional, economic, and social factors in the analysis of the technological adoption phenomenon. The main insights are summarized as follows:

[9] Context specific refers to the immediate physical and social environment wherein people live and the technologies are designed, adopted, and operated

The creation of channels of communication enhancing the influence of peer effects on the adoption process may significantly accelerate DERs adoption in the short-term. Our results show that the presence of non-economic factors in decision making, such as peer effects, is the rate-limiting step in the adoption process in the short-term. This can be explained as follows: if there a few adopters in the system, as is the case in the early stages of the adoption process, risk-averse adopters are unlikely to adopt DERs, as they base their adoption decision not only on economic parameters, but also largely on observations on the adoption behavior of their neighbors. Hence, creating mechanisms that encourage interpersonal communication among residential consumers may help more risk-averse consumers redefine their attitudes about the benefits and costs of adopting DERs. Such interpersonal communication may be particularly important in accelerating the adoption of DERs in the short-term.

Distribution tariff structures and their timing of introduction into the system can influence DERs adoption patterns and the utility death spiral. Our results show that different patterns of DERs adoption are obtained under different distribution tariffs and under a different timing of their introduction into the system. Differences in adoption patterns are due to the underlying cost structures of distribution tariffs. For instance, distribution tariff structures allowing net excess electricity to be sold, such as the annual maximum offtake capacity tariff (CAP), encourage the adoption of large PV sizes used in this study, given the assumed PV cost and electricity price. Our results also show that a utility death spiral is more likely to occur with an annual net-volumetric distribution tariff (NET). For instance, the increase in distribution cost with a NET was ten percentage points higher than that obtained with a CAP.

From a methodological viewpoint, our study applies a number of key enhancements to prior studies. First, it endogenously considers the interplay between the DERs adoption and distribution tariff evolution, as well as the interplay between residential consumers and prosumers. Second, it incorporates the effect of social and attitudinal components into residential consumers' decision-making on DERs adoption. Previous studies only focus on one of these elements. Furthermore, this study provides evidence of how a system thinking approach in combination with agent-based modeling provide further insights into the households DERs adoption, which are inaccessible by using other modeling techniques such as optimization and equilibrium modeling (e.g., path dependency analysis). Given the complexities of an electricity system where the consumer is at the center, we recommend that regulators and distribution system operators adopt a whole system approach to managing the electricity system.

Finally, a further step in this research would be the incorporation of elements of risk and loss aversion in investment decision making, as well as the analysis of intertemporal choice. Particularly, it is of interest to extend the model developed in this study by including elements of prospect theory.

Acknowledgements

The authors would like to thank Niels Govaerts and Michiel Avau for helpful comments and suggestions. This work is supported by the Research Foundation – Flanders (FWO) under the SBO project ELDEST (Energy PoLicy DEcision Support Toolbox) with project number S006718N.

Appendix A: Techno-economic data

This appendix describes the techno-economic data used in the simulations. **Table A.1** presents the representative days and their weights used in this study. These representative days were calculated by using the method developed by Poncelet *et al.* [39]. **Table A2.** presents the load factor[10] for each representative day. **Table A3.** presents the synthetic load profile used in this study. Consumers' hourly demand was calculated by multiplying the synthetic load profile with the annual electricity consumption. Finally, **Table A.4.** presents the cost projections for solar PV panels and battery storage systems used in this study.

Table A1. Representative days weights

Periods	Weights
p033	44.96
p065	45.04
p094	33.31
p121	27.30
p179	32.71
p236	39.17
p245	34.28
p263	38.68
p294	12.68
p303	23.44
p358	12.27
p365	21.18

[10] The load factor represents the percentage of the installed solar PV system capacity that is available for production at hour *t*

Table A2. Load factor

Hour	Load factor[a]											
	p033	p065	p094	p121	p179	p236	p245	p263	p294	p303	p358	p365
1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	0.00	0.00	0.00	0.01	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00
7	0.00	0.00	0.00	0.07	0.12	0.01	0.03	0.01	0.00	0.00	0.00	0.00
8	0.00	0.01	0.03	0.17	0.27	0.10	0.14	0.08	0.01	0.00	0.00	0.00
9	0.00	0.05	0.13	0.31	0.43	0.26	0.31	0.22	0.10	0.02	0.00	0.00
10	0.03	0.12	0.23	0.41	0.57	0.40	0.47	0.33	0.24	0.04	0.01	0.01
11	0.04	0.24	0.21	0.50	0.67	0.50	0.59	0.39	0.34	0.06	0.04	0.04
12	0.05	0.34	0.23	0.58	0.72	0.54	0.65	0.46	0.37	0.06	0.08	0.05
13	0.12	0.37	0.28	0.60	0.71	0.51	0.64	0.55	0.41	0.06	0.12	0.09
14	0.16	0.32	0.28	0.61	0.67	0.44	0.63	0.57	0.41	0.05	0.12	0.09
15	0.14	0.25	0.24	0.56	0.62	0.39	0.57	0.48	0.33	0.04	0.09	0.06
16	0.12	0.17	0.28	0.42	0.53	0.32	0.45	0.35	0.22	0.02	0.04	0.03
17	0.05	0.11	0.06	0.32	0.42	0.24	0.32	0.19	0.08	0.00	0.00	0.00
18	0.00	0.04	0.13	0.19	0.30	0.15	0.17	0.07	0.01	0.00	0.00	0.00
19	0.00	0.00	0.04	0.08	0.16	0.07	0.05	0.01	0.00	0.00	0.00	0.00
20	0.00	0.00	0.00	0.02	0.06	0.01	0.00	0.00	0.00	0.00	0.00	0.00
21	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
22	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
23	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
24	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

[a] Values were obtained from Elia [51]

Table A3. Synthetic load profile

Hour	Synthetic load profile * 1e5[a]											
	p033	p065	p094	p121	p179	p236	p245	p263	p294	p303	p358	p365
1	9.22	8.90	7.39	7.65	7.31	7.51	7.75	7.25	7.87	8.40	9.64	9.62
2	7.88	7.61	6.78	6.94	6.80	7.06	7.14	6.74	7.15	7.23	8.11	8.18
3	7.26	7.01	6.35	6.39	6.45	6.68	6.62	6.34	6.53	6.71	7.39	7.31
4	6.73	6.54	6.31	6.12	6.20	6.37	6.20	6.16	6.22	6.27	6.77	6.74
5	6.81	6.57	6.82	6.27	6.63	6.62	6.22	6.60	6.21	6.22	6.77	6.64
6	7.35	7.11	8.80	6.89	7.87	7.38	6.57	8.14	6.72	6.72	6.82	6.67
7	9.87	9.45	11.21	8.03	9.56	8.61	7.86	10.30	8.40	8.76	7.80	7.38
8	13.26	12.23	12.06	10.12	10.07	9.80	10.21	10.86	11.38	11.33	10.12	9.31
9	14.18	13.07	11.92	11.80	9.98	10.13	11.82	10.68	13.49	12.07	14.20	13.53
10	13.94	12.91	11.84	12.71	10.10	10.31	13.01	10.64	14.72	11.97	16.31	15.86
11	13.65	12.76	12.83	14.01	11.00	11.16	14.41	11.44	16.28	11.86	16.74	16.43
12	14.41	13.65	12.56	13.87	10.72	11.00	14.43	11.03	16.28	12.67	17.62	17.54
13	13.99	13.06	11.58	12.64	10.08	10.50	13.20	10.28	14.82	12.09	17.76	17.42
14	12.95	12.00	11.00	11.60	9.47	9.99	12.14	9.70	13.65	11.12	17.22	16.69
15	12.53	11.55	11.08	11.23	9.30	9.96	11.42	9.66	13.01	10.67	17.27	17.00
16	12.84	11.79	11.91	11.41	10.02	10.43	11.22	10.54	12.86	10.84	18.47	17.66
17	14.09	13.08	13.76	12.60	11.81	11.53	12.22	12.34	13.82	12.01	20.50	19.12
18	17.08	15.32	15.12	13.70	13.02	12.30	13.35	13.63	15.95	16.09	23.24	22.31
19	19.88	18.03	14.92	13.73	13.20	12.20	13.73	14.19	17.69	18.34	22.45	22.59
20	19.06	19.06	15.70	13.31	12.81	12.18	14.50	15.02	16.71	17.99	20.27	19.63
21	17.62	17.59	15.20	13.98	12.54	12.65	14.21	14.01	15.22	16.54	19.10	18.21
22	16.17	16.06	13.64	12.70	12.28	11.87	12.20	12.65	13.05	15.13	17.83	16.93
23	14.78	14.42	10.94	10.29	10.24	10.43	9.86	10.37	10.25	13.51	16.49	15.57
24	12.12	11.42	8.72	8.46	8.45	8.99	8.11	8.43	8.18	10.69	14.46	13.91

[a] Values were obtained from [52]

Table A4. Solar PV panels and battery costs

Year	Solar panel investment cost[a] [€/kW]	Battery Investment cost[b] [€/kWh]
2018	1 033	322.03
2019	1 016	300.85
2020	1 000	279.66
2021	980	265.25
2022	960	251.69
2023	940	237.29
2024	920	223.73
2025	900	210.17
2026	880	203.39
2027	860	196.61
2028	840	189.83
2029	820	182.20
2030	800	175.42
2031	800	173.73
2032	800	171.19
2033	800	169.49
2034	800	166.95
2035	800	164.41
2036	800	162.71
2037	800	160.17
2038	800	158.47
2039	800	155.93
2040	800	154.24
2041	800	151.69
2042	800	149.15
2043	800	147.46
2044	800	144.92
2045	800	143.22
2046	800	140.68
2047	800	138.14
2048	800	136.44
2049	800	133.90
2050	800	133.90

[a] These values were estimated based on that reported by [53] by using linear interpolation.
[b] These values were retrieved from [54]. An exchange rate of 1.18 was used to convert from euro to dollars.

Appendix B. Operational optimization of an integrated photovoltaic and battery energy storage system

This optimization problem is described in detail below:

$$min_{\Xi}\ (\sum_{t=1}^{8760}(p_t \cdot q_t) + dist_{cost}) \quad \text{(B.1)}$$

Subject to:

$$\forall t: q_t = ch_t - dc_t - pv_t + d_t \quad \text{(B.1a)}$$

$$\forall t: pv_t \leq PV_t \quad \text{(B.1b)}$$

$$\forall t: e_{BAT_t} \geq E_{BAT}^{min} \quad \text{(B.1c)}$$

$$\forall t: e_{BAT_t} \leq E_{BAT}^{max} \quad \text{(B.1d)}$$

$$t = 1{:}23{:}\ e_{BAT_{t+1}} = e_{BAT_t} + ch_t \cdot \eta_{ch} - dc_t \cdot \frac{1}{\eta_{dc}} \quad \text{(B.1e)}$$

$$t = 24{:}\ e_{BAT_1} = e_{BAT_t} + ch_t \cdot \eta_{ch} - dc_t \cdot \frac{1}{\eta_{dc}} \quad \text{(B.1f)}$$

$$\forall t: ch_t \cdot \eta_{ch} \leq P_{BAT}^{ch} \quad \text{(B.1g)}$$

$$\forall t: dc_t \cdot \frac{1}{\eta_{dc}} \leq P_{BAT}^{dc} \quad \text{(B.1h)}$$

$$\forall t: ch_t \geq 0 \quad \text{(B.1i)}$$

$$\forall t: dc_t \geq 0 \quad \text{(B.1j)}$$

$$\forall t: pv_t \geq 0 \quad \text{(B.1k)}$$

The decision variables Ξ are: the resulting net demand q_t, the power production by PV panels pv_t, the power drawn from grid to charge battery ch_t, the power provided to the grid from battery dc_t, the battery energy content e_{BAT_t} and the distribution tariff structure parameters q_{net} , $q_{pos,t}$, $q_{bi,t}$, q_{cap}, and q_{cabi}. The other parameters are defined as follows: d_t is the residential consumer demand, $\mathrm{p_t}$ is the wholesale price, PV_t is the maximum power production of PV panels; E_{BAT}^{min} and E_{BAT}^{max} are the minimum and maximum energy content of the battery, respectively; η_{ch} and η_{dc} are the battery charging and discharging efficiency, respectively; $\mathrm{P}_{BAT}^{\mathrm{ch}}$ and $\mathrm{P}_{BAT}^{\mathrm{dc}}$ are the maximum battery charging and discharging power, respectively. The subscript *t* represents the hour t.

The optimization problem is subject to constraints describing the operating limits of the DERs. Equation **B.1a** guarantees an energy balance. Constraint **B.1b** limits the PV production to the time-dependent maximum available PV power. Constraint **B.1c** and Constraint **B.1d** limit the energy content of the battery to a min and a max value, respectively. Constraint **B.1e** describes the evolution of the battery energy content during the day. **Constraint B.1f** imposes cyclical boundary conditions for the battery. That is, the battery energy content at the start of the day must be equal to the one at the end of the same day. These boundary conditions facilitates the use of representative days. Constraint **B.1g** and Constraint **B1.h** limit the battery charging and discharging power, respectively. Finally, Constraints **B1.i-B1.k** enforce the nonnegativity of ch_t, dc_t, and pv_t. Note that in this linear optimization problem, we use battery charge and discharge efficiency values of less than one to ensure that battery charge and discharge do not occur at the same time. Under these conditions, charging and discharging the battery at the same time is not cost-effective as it produces more losses (see constraint **B.1e** and **B.1f**). Thus, the cost-minimization problem either charges or discharges the battery at a given time. Nevertheless, if curtailment of PV generation comes at a cost, which is not the case in this study, the charging and discharging of the battery can occur at the same time. In this case, the linear optimization problem must be formulated as a MILP to ensure that battery charging and discharging do not occur simultaneously[11].

The available PV power is calculated as the product of the installed capacity PV and the load factor LF_{pvt}

$$PV_t = PV \cdot LF_{pvt} \tag{B.2}$$

The charging and discharging limits of the battery as calculated as follows:

$$\mathrm{P}_{BAT}^{\mathrm{ch}} = \mathrm{P}_{BAT}^{\mathrm{dc}} = CR \cdot \left(E_{BAT}^{max} - E_{BAT}^{min}\right) \tag{B.3}$$

[11] A future version of the model will use a Mixed Integer Linear Programming problem formulation to ensure that battery charging and discharging do not occur at the same time under any circumstance.

The distribution tariff structure parameters are used to calculate $\mathrm{dist}_{\mathrm{cost}}$ in Equation **B.1** according to the distribution tariff as shown below:

- For an annual net-volumetric distribution tariff the distribution cost is calculated as:

$$dist_{cost} = dist_{net} \cdot q_{net} \tag{B.4}$$

Subject to:

$$q_{net} \geq \sum_t \mathrm{q}_\mathrm{t} \tag{B.4a}$$

$$q_{net} \geq 0 \tag{B.4b}$$

- For the hourly offtake volumetric distribution tariff the distribution cost is calculated as:

$$dist_{cost} = \sum_t dist_{pos,t} \cdot q_{pos,t} \tag{B.5}$$

Subject to:

$$\forall t\colon q_{pos,t} \geq q_t \tag{B.5a}$$

$$\forall t\colon q_{pos,t} \geq 0 \tag{B.5b}$$

- For the hourly bidirectional volumetric distribution tariff the distribution cost is calculated as:

$$dist_{cost} = \sum_t dist_{bi,t} \cdot q_{bi,t} \tag{B.6}$$

Subject to:

$$\forall t\colon q_{bi,t} \geq q_t \tag{B.6a}$$

$$\forall t\colon q_{bi,t} \geq -q_t \tag{B.6b}$$

- For the annual maximum offtake capacity tariff the distribution cost is calculated as:

$$dist_{cost} = \sum_t dist_{cap} \cdot q_{cap} \tag{B.7}$$

$$\forall t: q_{cap} \geq q_t \tag{B.7a}$$

$$q_{cap} \geq 0 \tag{B.7b}$$

- For the annual maximum bidirectional capacity tariff the distribution cost is calculated as:

$$dist_{cost} = \sum_t dist_{cabi} \cdot q_{cabi} \tag{B.8}$$

Subject to:

$$\forall t: q_{cabi} \geq q_t \tag{B.8a}$$

$$\forall t: q_{cabi} \geq -q_t \tag{B.8b}$$

Where $dist_{net}$, $dist_{pos,t}$, $dist_{bi,t}$, $dist_{cap}$, and $dist_{cabi}$ are the net volumetric distribution tariff, the distribution tariff on hourly offtake energy, the distribution tariff on net hourly bidirectional energy flow, the offtake capacity distribution tariff, and the bidirectional capacity distribution tariff, respectively.

References

[1] IEA PVPS, "Trends 2019 in Photovoltaic applications," 2019.

[2] Y. Parag and B. K. Sovacool, "Electricity market design for the prosumer era," *Nat. Energy*, vol. 1, no. 4, p. 16032, Apr. 2016.

[3] J. A. P. Lopes, N. Hatziargyriou, J. Mutale, P. Djapic, and N. Jenkins, "Integrating distributed generation into electric power systems: A review of drivers, challenges and opportunities," *Electr. Power Syst. Res.*, vol. 77, no. 9, pp. 1189–1203, Jul. 2007.

[4] L. Bach, D. Hopkins, and J. Stephenson, "Solar electricity cultures: Household adoption dynamics and energy policy in Switzerland," *Energy Res. Soc. Sci.*, vol. 63, p. 101395, May 2020.

[5] C. Eid, J. Reneses Guillén, P. Frías Marín, and R. Hakvoort, "The economic effect of electricity net-metering with solar PV: Consequences for network cost recovery, cross subsidies and policy objectives," *Energy Policy*, vol. 75, pp. 244–254, Dec. 2014.

[6] N. Govaerts, K. Bruninx, H. Le Cadre, L. Meeus, and E. Delarue, "Spillover effects of distribution grid tariffs in the internal electricity market: An argument for harmonization?," *Energy Econ.*, vol. 84, p. 104459, Oct. 2019.

[7] N. D. Laws, B. P. Epps, S. O. Peterson, M. S. Laser, and G. K. Wanjiru, "On the utility death spiral and the impact of utility rate structures on the adoption of residential solar photovoltaics and energy storage," *Appl. Energy*, vol. 185, pp. 627–641, Jan. 2017.

[8] G. Christoforidis *et al.*, "A Model for the Assessment of Different Net-Metering Policies," *Energies*, vol. 9, no. 4, p. 262, Apr. 2016.

[9] N. R. Darghouth, G. Barbose, and R. H. Wiser, "Customer-economics of residential photovoltaic systems (Part 1): The impact of high renewable energy penetrations on electricity bill savings with net metering," *Energy Policy*, vol. 67, pp. 290–300, Apr. 2014.

[10] D. W. H. Cai, S. Adlakha, S. H. Low, P. De Martini, and K. Mani Chandy, "Impact of residential PV adoption on Retail Electricity Rates," *Energy Policy*, vol. 62, pp. 830–843, Nov. 2013.

[11] R. Prata and P. M. S. Carvalho, "Self-supply and regulated tariffs: Dynamic equilibria between photovoltaic market evolution and rate structures to ensure network sustainability," *Util. Policy*, vol. 50, pp. 111–123, Feb. 2018.

[12] W. Weidlich, "Sociodynamics - A systematic approach to mathematical modelling in the social

sciences," in *Chaos, Solitons and Fractals*, 2003, vol. 18, no. 3, pp. 431–437.

[13] S. Candas, K. Siala, and T. Hamacher, "Sociodynamic modeling of small-scale PV adoption and insights on future expansion without feed-in tariffs," *Energy Policy*, vol. 125, pp. 521–536, Feb. 2019.

[14] N. Schwarz and A. Ernst, "Agent-based modeling of the diffusion of environmental innovations — An empirical approach," *Technol. Forecast. Soc. Change*, vol. 76, no. 4, pp. 497–511, May 2009.

[15] J. Zhao, E. Mazhari, N. Celik, and Y.-J. Son, "Hybrid agent-based simulation for policy evaluation of solar power generation systems," *Simul. Model. Pract. Theory*, vol. 19, no. 10, pp. 2189–2205, Nov. 2011.

[16] J. Palmer, G. Sorda, and R. Madlener, "Modeling the diffusion of residential photovoltaic systems in Italy: An agent-based simulation," *Technol. Forecast. Soc. Change*, vol. 99, pp. 106–131, Oct. 2015.

[17] V. Rai and S. A. Robinson, "Agent-based modeling of energy technology adoption: Empirical integration of social, behavioral, economic, and environmental factors," *Environ. Model. Softw.*, vol. 70, pp. 163–177, Aug. 2015.

[18] P. Pearce and R. Slade, "Feed-in tariffs for solar microgeneration: Policy evaluation and capacity projections using a realistic agent-based model," *Energy Policy*, vol. 116, pp. 95–111, May 2018.

[19] A. Nuñez-Jimenez, C. Knoeri, J. Hoppmann, and V. H. Hoffmann, "Can designs inspired by control theory keep deployment policies effective and cost-efficient as technology prices fall?," *Environ. Res. Lett*, vol. 15, no. 044002, 2020.

[20] T. Murakami, "Agent-based simulations of the influence of social policy and neighboring communication on the adoption of grid-connected photovoltaics," *Energy Convers. Manag.*, vol. 80, pp. 158–164, Apr. 2014.

[21] S. A. Robinson and V. Rai, "Determinants of spatio-temporal patterns of energy technology adoption: An agent-based modeling approach," *Appl. Energy*, vol. 151, pp. 273–284, Aug. 2015.

[22] M. Ramshani, X. Li, A. Khojandi, and O. Omitaomu, "An agent-based approach to study the diffusion rate and the effect of policies on joint placement of photovoltaic panels and green roof under climate change uncertainty," *Appl. Energy*, vol. 261, p. 114402, Mar. 2020.

[23] V. Stavrakas, S. Papadelis, and A. Flamos, “An agent-based model to simulate technology adoption quantifying behavioural uncertainty of consumers,” *Appl. Energy*, vol. 255, p. 113795, Dec. 2019.

[24] N. R. Darghouth, R. H. Wiser, G. Barbose, and A. D. Mills, “Net metering and market feedback loops: Exploring the impact of retail rate design on distributed PV deployment,” *Appl. Energy*, vol. 162, pp. 713–722, Jan. 2016.

[25] M. Muaafa, I. Adjali, P. Bean, R. Fuentes, S. O. Kimbrough, and F. H. Murphy, “Can adoption of rooftop solar panels trigger a utility death spiral? A tale of two U.S. cities,” *Energy Res. Soc. Sci.*, vol. 34, pp. 154–162, Dec. 2017.

[26] M. M. de Villena, R. Fonteneau, A. Gautier, and D. Ernst, “Evaluating the Evolution of Distribution Networks under Different Regulatory Frameworks with Multi-Agent Modelling,” *Energies*, vol. 12, no. 7, pp. 1–15, 2019.

[27] P. Valkering, E. Laes, K. Kessels, M. Uyterlinde, and K. Straver, “How to engage end-users in smart energy behaviour?,” *EPJ Web Conf.*, vol. 79, p. 04003, Dec. 2014.

[28] K. S. Wolske, K. T. Gillingham, and P. W. Schultz, “Peer influence on household energy behaviours,” *Nature Energy*. Nature Research, pp. 1–11, 27-Jan-2020.

[29] E. M. Rogers, *Diffusion of Innovations*, 5th ed. Simon and Schuster, 2003.

[30] V. Grimm *et al.*, “A standard protocol for describing individual-based and agent-based models,” *Ecol. Modell.*, vol. 198, no. 1–2, pp. 115–126, Sep. 2006.

[31] I. Ajzen, “The theory of planned behavior,” *Organ. Behav. Hum. Decis. Process.*, vol. 50, no. 2, pp. 179–211, 1991.

[32] C. Brandstätt and G. Brunekreeft, “Evolution of self-supply with different network-charging schemes,” in *IAEE International conference*, 2018.

[33] Elexys, “Market Information: Spot Belpex,” 2020. [Online]. Available: https:%0A//my.elexys.be/MarketInformation/SpotBelpex.aspx. [Accessed: 23-Apr-2020].

[34] O. De Groote, G. Pepermans, and F. Verboven, “Heterogeneity in the adoption of photovoltaic systems in Flanders,” *Energy Econ.*, vol. 59, pp. 45–57, Sep. 2016.

[35] OECD, “Under Pressure: The Squeezed Middle Class,” Paris, 2019.

[36] O. De Groote and F. Verboven, “Subsidies and Time Discounting in New Technology Adoption:

Evidence from Solar Photovoltaic Systems," *Am. Econ. Rev.*, vol. 109, no. 6, pp. 2137–2172, 2019.

[37] Energuide.be, "What is the average electrical power and gas consumption in the Brussels region?," 2020. [Online]. Available: https://www.energuide.be/en/questions-answers/what-is-the-average-electrical-power-and-gas-consumption-in-the-brussels-region/273/.

[38] N. Govaerts, K. Bruninx, and E. Delarue, "Impact of Distribution Tariff Design on the Profitability of Aggregators of Distributed Energy Storage Systems," in *2018 15th International Conference on the European Energy Market (EEM)*, 2018, pp. 1–5.

[39] K. Poncelet, H. Hoschle, E. Delarue, A. Virag, and W. Drhaeseleer, "Selecting Representative Days for Capturing the Implications of Integrating Intermittent Renewables in Generation Expansion Planning Problems," *IEEE Trans. Power Syst.*, vol. 32, no. 3, pp. 1936–1948, May 2017.

[40] V. Rai and S. A. Robinson, "Effective information channels for reducing costs of environmentally-friendly technologies: Evidence from residential PV markets," *Environ. Res. Lett.*, vol. 8, no. 1, 2013.

[41] S. Borenstein, "Private Net Benefits of Residential Solar PV: The Role of Electricity Tariffs, Tax Incentives, and Rebates," *J. Assoc. Environ. Resour. Econ.*, vol. 4, no. S1, pp. S85–S122, Sep. 2017.

[42] A. Gautier and J. Jacqmin, "PV adoption: the role of distribution tariffs under net metering," *J. Regul. Econ.*, vol. 57, no. 1, pp. 53–73, Feb. 2020.

[43] L. Lu and C. Waddams Price, "Designing distribution network tariffs that are fair for different consumer groups," 2018.

[44] D. Kahneman and A. Tversky, "Prospect Theory: An Analysis of Decision under Risk," *Econometrica*, vol. 47, no. 2, pp. 263–292, 1979.

[45] A. Tversky and D. Kahneman, "Advances in prospect theory: Cumulative representation of uncertainty," *J. Risk Uncertain.*, vol. 5, no. 4, pp. 297–323, Oct. 1992.

[46] C. S. Lai and G. Locatelli, "Economic and financial appraisal of novel large-scale energy storage technologies," *Energy*, vol. 214, p. 118954, Jan. 2021.

[47] C. S. Lai, Y. Jia, L. L. Lai, Z. Xu, M. D. McCulloch, and K. P. Wong, "A comprehensive review

on large-scale photovoltaic system with applications of electrical energy storage," *Renewable and Sustainable Energy Reviews*, vol. 78. Elsevier Ltd, pp. 439–451, 01-Oct-2017.

[48] Z. Zhao, J. Guo, C. S. Lai, H. Xiao, K. Zhou, and L. L. Lai, "Distributed Model Predictive Control Strategy for Islands Multi-Microgrids Based on Non-Cooperative Game," *IEEE Trans. Ind. Informatics*, pp. 1–1, Jul. 2020.

[49] S. Müller and J. Rode, "The adoption of photovoltaic systems in Wiesbaden, Germany," *Econ. Innov. New Technol.*, vol. 22, no. 5, pp. 519–535, Jul. 2013.

[50] M. Graziano and K. Gillingham, "Spatial patterns of solar photovoltaic system adoption: The influence of neighbors and the built environment," *J. Econ. Geogr.*, vol. 15, no. 4, pp. 815–839, Jul. 2015.

[51] Elia, "Solar power generation data," 2019. [Online]. Available: http://www.elia.be/nl/%0Agrid-data/productie/Solar-power-generation-data/Graph,. [Accessed: 23-Apr-2020].

[52] Synergrid, "Synthetic Load Profiles," 2019. .

[53] Joint Research Centre of the European Commission, "ETRI 2014: Energy Technology Reference Indicator projections for 2010-2050," Luxembourg, 2014.

[54] W. Cole and A. W. Frazier, "Cost projections for utility-scale battery storage," 2019.

[55] T. L. P. Tang, "Pay differentials as a function of rater's sex, money ethic, and job incumbent's sex: A test of the Matthew Effect," *J. Econ. Psychol.*, vol. 17, no. 1, pp. 127–144, Feb. 1996.

[56] O. Abrishambaf, F. Lezama, P. Faria, and Z. Vale, "Towards transactive energy systems: An analysis on current trends," *Energy Strateg. Rev.*, vol. 26, p. 100418, Nov. 2019.

KU LEUVEN

Department of Mechanical Engineering
Energy Systems Integration & Modeling Group

On the authors:

Jorge Andrés Moncada (jorgeandres.moncadaescudero@kuleuven.be)

Zhenmin Tao (zhenmin.tao@kuleuven.be)

Pieter Valkering (pieter.valkering@energyville.be)

Frank Meinke-Hubeny (frank.meinke-hubeny@vito.be)

Erik Delarue (erik.delarue@kuleuven.be)

On the research group:

The **Energy Systems Integration & Modeling Group** is part of the division of Applied Mechanics and Energy Conversion (TME) of the Department of Mechanical Engineering of KU Leuven in Belgium. E. Delarue and W. D'haeseleer lead this research group, currently about 15 PhD students and post-doctoral research fellows, dedicated to the modeling of integrated energy systems and markets. This young research group has already gained significant expertise and international recognition in the field. A major strength of this group is its interdisciplinary focus (techno-economic models, link to energy policies and markets). The group is further strongly embedded in EnergyVille, an association of the Flemish research institutes KU Leuven, VITO, imec and UHasselt in the field of sustainable energy and intelligent energy systems. EnergyVille brings research, development, training and industrial innovation together under one name, in close cooperation with local, regional and international partners.