Impact of electricity market feedback on investments in solar photovoltaic and battery systems in Swedish single-family dwellings

Citation for the original published paper (version of record):
Goop, J., Nyholm, E., Odenberger, M. et al (2021)
Impact of electricity market feedback on investments in solar photovoltaic and battery systems in Swedish single-family dwellings
Renewable Energy, 163: 1078-1091
http://dx.doi.org/10.1016/j.renene.2020.06.153

Renewable Energy 163 (2021) 1078–1091

Contents lists available at ScienceDirect

Renewable Energy

journal homepage: www.elsevier.com/locate/renene

Impact of electricity market feedback on investments in solar photovoltaic and battery systems in Swedish single-family dwellings

Joel Goop *, Emil Nyholm , Mikael Odenberger , Filip Johnsson

Department of Energy and Environment Chalmers, University of Technology, SE-412 96, Göteborg, Sweden

ARTICLE INFO

Article history:
Received 15 July 2019
Received in revised form
16 May 2020
Accepted 30 June 2020

Keywords:
Solar power
Batteries
Energy systems modelling

ABSTRACT

The profitability of investments in photovoltaics (PVs) and batteries in private households depends on the market price of electricity, which in turn is affected by the investments made in and the usage of PVs and batteries. This creates a feedback mechanism between the centralised electricity generation system, and household investments in PVs and batteries. To investigate this feedback effect, we connect a local optimisation model for household investments with a European power generation dispatch model. The local optimisation is based on the consumption profiles measured for 2104 Swedish households. The modelling compares three different scenarios for the centralised electricity supply system in Year 2032, as well as several sensitivity cases. Our results show total investment levels of 5–20 GW_p of PV and 0.01–10 GWh of battery storage capacity in Swedish households in the investigated cases. These levels are up to 33% lower than before market feedback is taken into account. The profitability of PV investments is affected most by the price of electricity and the assumptions made regarding grid tariffs and taxes. The value of investments in batteries depends on both the benefits of increased self-consumption of PV electricity and market arbitrage.

1. Introduction

Distributed generation in the form of solar photovoltaics (PVs) in combination with battery storage has the potential to be an important part of a future sustainable electricity system. The global installed capacity of PVs has increased dramatically over the last 10 years, concomitant with drastic reductions in production costs [1]. Given the grid parity effect, PVs may become competitive sooner at the residential level than at utility scale. Batteries have also decreased substantially in cost in recent years [2] and are becoming an increasingly attractive option to increase self-consumption of the electricity produced by PVs. Although high usage of PVs and batteries at the residential level could be crucial for the transition to a sustainable electricity system, it could also have a disruptive effect on the functioning of the electricity system and the market through, e.g., an increased need for fast-ramping generation capacity and restructuring of distribution grid tariffs [3,4]. Therefore, it is an important topic for research.

The sizing and economic viability of combined PV and battery systems for households, have been studied extensively. Hoppmann et al. [5], having reviewed the literature, have reported a lack of studies that optimise in economic terms investments in the combination of PVs and batteries. They have also performed a modelling analysis to identify the cost-optimal combination of investments in PV and batteries, using one standardised household load profile that was retrieved from a utility and an electricity tariff that is constant across each year, but changes from year to year over the life-time of the investments. Hoppmann et al. [5] found that investments in battery storage are already economically viable for small residential PV systems given 2013 costs. For future PV and battery investment costs they concluded that there is considerable potentials for investments in both PV and batteries for all analyzed future electricity price scenarios. Mulder et al. [6] have modelled the dimensioning of combined PV and battery systems using 65 household demand profiles and a fixed electricity purchase tariff that includes a self-consumption bonus, where the electricity price also changes over the life-time of the investments. In addition, they have examined the tariff systems used in many European countries and have concluded that several countries are moving towards hourly pricing and that studies that target years after Year 2020 should be based on dynamic pricing. Mulder et al. [6] concluded that in order to make PV-battery system investments economically

* Corresponding author.
E-mail address: joel.goop@chalmers.se (J. Goop).

https://doi.org/10.1016/j.renene.2020.06.153

viable without subsidies both an annual electricity price increase of 4–6% and reduced PV and battery costs compared to their base year of 2012 are required. Cucchiella et al. [7] have investigated the sizing of residential PV and battery systems while assuming a predetermined self-consumption share that is dependent upon the ratio of PV array size to battery size based on information from the literature. They have assumed a fixed electricity tariff per year. They conclude that the level of self-consumption is important for the profitability of a PV system in cases without subsides for PV. However, batteries are found to be unprofitable in the scenarios investigated.

Ren et al. [8] have investigated the energy consumption and bill savings from PV battery systems in Australian houses under several different tariff structures, PV sizes, and battery sizes. They found that with a PV-panel alone a flat rate retail energy price resulted in the greatest bill savings. With the inclusion of a battery in conjunction with a PV-panel critical peak pricing showed the greatest savings, i.e., a more dynamic electricity price was beneficial for battery investments. Khalilpour and Vassallo [9] conducted a techno-economic parametric analysis of PV-battery systems in Australian households, examining, e.g., tariff levels, PV/battery costs, and household load profiles. For the various scenarios investigated, their results showed that battery costs below $750 per kWh were required for a positive impact on net present value. Furthermore, they found that the magnitude of the households' electricity purchase price and the selling price of excess generation from the PV system had a major impact on the value of a battery, with a smaller magnitude being detrimental to battery investments. Talent and Du [10] optimised the economic sizing of PV and batteries for one residential and one commercial consumer in Australia. Two different tariff structures were investigated, one time-of-use structure and one demand tariff structure, with a power tariff included in the demand tariff. The electricity prices reflected current (2017) prices. They found that large PV investments and no battery investments are the cost optimal solution for the investigated cases. Although battery investments are not cost optimal, PV-battery systems can still be economically preferable to purchasing all electricity from the grid. Koskela et al. [11] investigate the economic incentives for investing in PV-battery systems for both apartment buildings and detached houses in Finland given different PV costs, battery costs and electricity tariff structures. They use an hourly market-price-based tariff based on day-ahead area prices for Finland in the Nordic electricity market and different tariffs for the distribution grid costs, but do not account for any feedback between decisions of households and the market. They conclude that PV battery installations can be profitable in Finish conditions, however, this profitability is highly dependent on the structure of the electricity and distribution grid tariffs.

There are several other studies which investigate households economic incentives for investing in PV-battery systems [12–18]. The conclusions reached differ depending on local conditions, e.g., annual solar PV electricity generation, electricity price structures, and assumed PV and battery prices. However, none of the papers account for the interaction between the large-scale household investments in PV and batteries and the surrounding electricity system.

Other studies have taken a different approach and investigated the attractiveness of solar PVs and storage from the systems perspective. Pietzcker et al. [19] have used the REMIND model to propose that solar power might dominate the global electricity mix by Year 2100. Mileva et al. [20] have also demonstrated, using the SWITCH model, that solar power can cost-effectively cover over a third of the electricity demand in the Western US electricity system by Year 2050, assuming that the US Department of Energy's cost target of $1 per W_p for solar PVs is reached. However, these studies do not take into account the household perspective, which could significantly affect the diffusion of PV technologies.

Some previous studies have implemented iterative approaches so as to couple the household level to the system level centralised dispatch. For example, Tapia-Ahumada et al. [21] have investigated the system effects of large-scale penetration of micro-combined heat and power (micro-CHP) at the household level by iterating between a unit commitment model and a local household model, thereby optimising the operation of the micro-CHP based on electricity prices derived from the unit commitment model. Patteeuw et al. [22] have compared different approaches to modelling the demand response of electric heating loads, performing iterations between a unit commitment and dispatch model, so as to represent the supply-side effects and a local demand-side model taking into account the electricity prices from the supply-side model. While these iterative methods can account for the feedback effects between the demand and supply sides in the electricity system, they have not been applied to the modelling of investments in household-level PV/battery systems.

The previous studies have focused either on sizing PV and battery systems using fixed electricity tariffs or investigating the role of PVs in least-cost scenarios for the future electricity system. However, large-scale investments in PV and batteries in households could have a significant impact on the electricity market which in turn might affect the profitability of those household investments. We identified a need for a modelling analysis of this feed-back interaction. Therefore, we apply an iterative approach that combines a cost-minimising investment model for households with an electricity dispatch model to model the impact of household PV investments on the electricity price. The household model is applied to Sweden using measured hourly electricity consumption profiles from 2104 households and is iteratively coupled to the Electric POwer Dispatch (EPOD) model, which encompasses northern Europe. The modelling is performed for Year 2032 and the capacity mix used in the dispatch model is derived using the ELectricity INvestment (ELIN) model.

Using this approach, we study how the profitability of PV and battery investments in households is affected by the feed-back mechanism in conjunction with the electricity market, and how household PV and battery systems will affect the dispatch of centralised power plants and the marginal cost of electricity. In contrast to most of the previous PV and battery dimensioning studies, we apply an hourly pricing regime which is important for future studies as more and more countries are moving towards hourly tariff systems [6]. Furthermore, we use a large number of measured household electricity consumption profiles with hourly resolution.

2. Methodology

We apply an iterative approach to investigate the feedback effects between the power system dispatch and investment and operation of PVs and batteries in households. The iterative procedure involves three modelling tools: the ELIN model; the EPOD model; and a household-level PV and battery investment model for southern Sweden.

The geographical areas covered by each of the three modelling tools are distinct. The ELIN model, which generates the capacity mix for the centralised electricity system as well as investments in transmission capacity between neighbouring regions, and is run only once per scenario, includes all the regions of the EU-27,[1] Norway, and Switzerland. By including the full geographical area in the ELIN model, the generation as well as transmission capacity investments take into account trade patterns throughout the entire

[1] Excluding the electrically isolated islands of Malta and Cyprus.

area.

For the EPOD model, which is run once per iteration, a subset of regions comprising the Nordic countries and neighbouring countries is selected[2] so as to shorten the computational times. Neighbouring countries are included to account for their effect on the marginal cost of electricity in Sweden, which is used as an input to the household investment model. As the household investment model only contains data from households in Swedish regions SE1 and SE2, it is only run for those particular regions. The geographical scopes of the three modelling tools are shown in Fig. 1.

The iterative modelling procedure, which is illustrated in Fig. 2, involves the following steps:

1. The ELIN model generates a development path for the electricity generation system in the EU-27, Norway, and Switzerland up to Year 2050 under different scenario-related assumptions. Installed capacities for Year 2032 in the model regions are then extracted from the ELIN results for each scenario and fed into the EPOD model.
2. EPOD calculates the least-cost hourly dispatch over 1 year as well as the marginal cost of electricity in each region of the Nordic countries and neighbouring countries (see Fig. 1).
3. The hourly marginal costs of electricity are used as price curves and transferred to the household investment model, which determines the optimal investment in PV and battery capacity, as well as the battery charge and discharge patterns for each of the 2104 individual sample households in Swedish regions SE1 and SE2 (see Fig. 1).
4. The new household net loads (i.e., load plus battery charge minus the PV electricity produced and battery discharge) are scaled up to represent all single-family dwellings in SE1 and SE2, i.e., all represented households in these two regions are assumed to participate and make investments that minimise their own electricity costs.
5. The EPOD load curves for regions SE1 and SE2 are adjusted according to the new household load.
6. Steps 2 to 2 are repeated until there is convergence or the maximum number of iterations is reached.

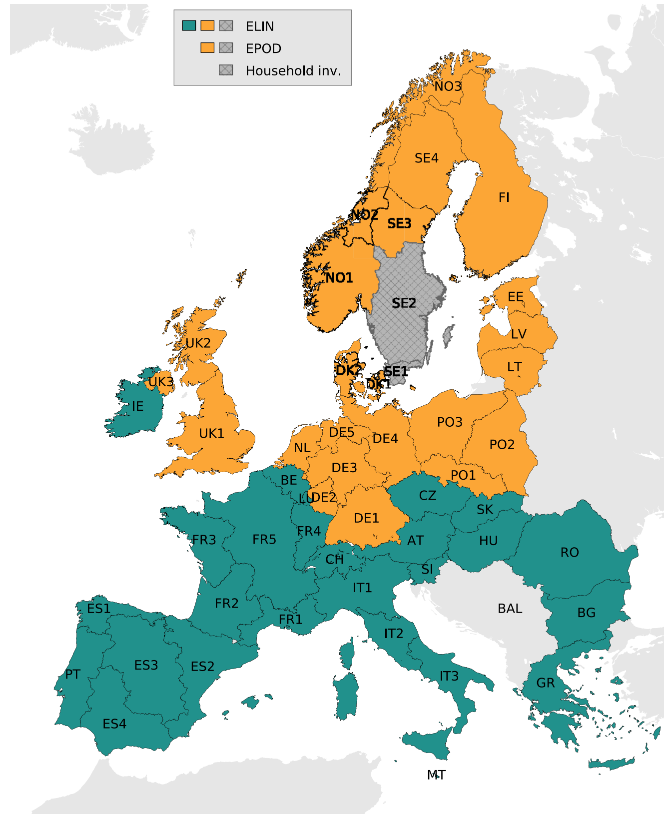

Fig. 1. Geographical scope chosen for the three modelling tools: the ELIN model; the EPOD model; and the household-level PV and battery investment model.

2.1. The ELIN model

To generate the mix of generation capacity in the European electricity system in Year 2032, we use the ELIN model, which was originally created by Odenberger et al. [23], and further developed by Göransson et al. [24]. The ELIN model identifies the cost-minimal development of investments and production for centralised power plants as well as investments in inter-regional transmission lines in the European electricity supply system up to Year 2050, given a description of the current power system in Europe and assumptions regarding the development of demand, CO_2 emissions reduction targets and climate and renewable policies up to Year 2050. The current power system capacity mix is taken from the Chalmers Power Plant Database [25], and existing transmission line capacity from the ENTSO-E [26–28]. The ELIN model covers the EU-27 (excluding Malta and Cyprus), Norway, and Switzerland, divided into a total of 50 regions based primarily on transmission grid bottlenecks reported by the ENTSO-E [29] (see Fig. 1).

The ELIN model is run for the following three scenarios: Green Policy; Regional Policy; and Climate Market. The scenarios differ with respect to CO_2 emission targets and policies for CO_2 abatement and renewable energy beyond Year 2020, as well as in relation to the assumed development of the electricity demand in each country up to Year 2050 (a summary of the differences in assumptions between the scenarios can be found in Table A1). Implicit to the scenarios is decarbonisation of the European electricity supply, which entails decreasing CO_2 emissions by 95% compared to Year 1990 for the Green Policy and Climate Market scenarios, and 99% for the Regional Policy scenario. Furthermore, all the EU member states are assumed to reach the targets for renewable electricity generation in Year 2020 stated in the National Renewable Energy Action Plans [30]. The scenarios are documented in greater detail by Unger et al. [31].

2.2. The EPOD model

Once the capacity mix is extracted from the ELIN model, the linear cost-minimising EPOD model is used to obtain the marginal electricity generation costs fed to the household model as price curves. The EPOD model was first presented by Unger and Odenberger [32] and developed and refined by Göransson et al. [24] and Goop et al. [33]. In general, the EPOD model uses the same regional subdivision of Europe as is used by the ELIN model. However, to reduce the computational time required for the iterative procedure in the present work, the EPOD model is run over a subset of regions consisting of the Nordic countries and neighbouring countries (see Fig. 1). Electricity trading across the boundaries of the modelled area is set as fixed (for each hour) to the result obtained from one initial EPOD model run that spans all of the regions included in the ELIN runs (see Fig. 1).

[2] Specifically, all regions that belong to Sweden, Norway, Finland, Denmark, Germany, Poland, Estonia, Latvia, Lithuania, the Netherlands, and the United Kingdom.

Nomenclature

Sets	
I	Model regions
P_i	Plants (aggregates) in region $i \in I$
T	Time steps
N	Subset of regions (i.e., $N \subset I$) that contain household load profiles
H_i	Households in region $i \in N$
Variables, EPOD	
c_{tot}	Total running cost [M€]
$c_{p,t}^{\text{cycl}}$	Start-up and part-load costs in plant $p \in P$, $i \in I$ at time $t \in T$ [M€]
$g_{p,t}$	Power generated in plant $p \in P_i$, $i \in I$ at time $t \in T$ [GWh]
$q_{i,j,t}^{\text{trade}}$	Electricity exported from region $i \in I$ and $j \in I$ (negative in case of import from j to i) at time $t \in T$ [GWh]
Parameters, EPOD	
$C_{p,t}^{\text{run}}$	Specific fuel and O&M costs in plant $p \in P$, $i \in I$ at time $t \in T$ [€/MWh]
$D_{i,t}$	Demand in region $i \in I$ at time $t \in T$ [GWh]
Variables, household model	
$e_{h,t}^{\text{bought}}$	Electricity bought by household $h \in H_i$, $i \in N$ at time $t \in T$ [kWh]
$e_{h,t}^{\text{sold}}$	Electricity sold by household $h \in H_i$, $i \in N$ at time $t \in T$ [kWh]
b_h	Battery investment in household h [kWh]
f_h	PV investment in household h [kW_p]
u_h	Inverter investment in household h [kW_p]
$s_{h,t}^{\text{add}}$	Energy added to the battery in household $h \in H_i$, $i \in N$ at time $t \in T$ [kWh]
$s_{h,t}^{\text{rem}}$	Energy discharged from the battery in household $h \in H_i$, $i \in N$ at time $t \in T$ [kWh]
$v_{h,t}$	Electricity generated by PV-panel in household $h \in H_i$, $i \in N$ at time $t \in T$ [kWh]
$l_{h,t}$	Storage level of battery in household $h \in H_i$, $i \in N$ at time $t \in T$ [kWh]
Parameters, household model	
$P_{i,t}^{\text{buy}}$	Purchase price for electricity for region $i \in N$ at time $t \in T$ [€/MWh]
$P_{i,t}^{\text{sell}}$	Selling price for electricity for region $i \in N$ at time $t \in T$ [€/MWh]
K^{bat}	Battery cost [€/kWh]
K^{PV}	PV cost [€/kW_p]
K^{inv}	Inverter cost [€/kW_p]
A^{bat}	Annuity factor, battery
A^{PV}	Annuity factor, PVs
A^{inv}	Annuity factor, inverter
$D_{h,t}$	Demand for electricity in household $h \in H_i$, $i \in N$ at time $t \in T$ [kWh]
r	Interest rate
n	Investment life-time
η^{bat}	Battery discharge efficiency

The EPOD model minimises the total running cost as follows:

$$c_{\text{tot}} = \sum_{i \in I} \sum_{p \in P_i} \sum_{t \in T} \left(C_{p,t}^{\text{run}} g_{p,t} + c_{p,t}^{\text{cycl}} \right), \tag{1}$$

where I is the set of all modelled regions, P_i is the set of plants (aggregates) in region i, and T is the set of all time-steps. Furthermore, $g_{p,t}$ is the power generated in plant p at time t, $c_{p,t}^{\text{run}}$ is the running cost (fuel costs plus variable operation and maintenance costs), and $c_{p,t}^{\text{cycl}}$ is the sum of the start-up and part-load costs for plant p at time t.

To ensure that the demand is met in all the regions at all time-steps, the optimisation is subject to the following:

$$D_{i,t} < \sum_{p \in P_i} g_{p,t} + \sum_{\substack{j \in I \\ j \neq i}} q_{i,j,t}^{\text{trade}} \quad \forall i \in I,\ t \in T, \tag{2}$$

where $D_{i,t}$ is the electricity demanded in region i at time t after adjustment for electricity production and battery usage pattern in households, and $q_{i,j,t}^{\text{trade}}$ is the quantity of electricity (positive or negative) traded between region i and j at time-step t. The marginal cost of generating electricity, which is assumed to represent the market price, is extracted as the shadow price on the demand constraint (2). The shadow price is the change in the objective function per unit change in the constraint constant (in this case the demand) and is obtained directly from the solver as the optimal value of the dual variable corresponding to the constraint in question.

2.3. Household investment model

Given the electricity price that emanates from the EPOD model, each of the 2104 households (see Section 2.4) in the household investment model can invest in a PV-panel and make decisions regarding the size of the battery and the battery dispatch, thereby creating a new net load profile for each household. The profiles are then scaled up to represent the entire stock of single-family dwellings in each represented region and fed to the EPOD model. The household investment model minimises the total electricity cost for all households, as follows:

$$K_{\text{tot}} = \sum_{i \in N} \sum_{h \in H_i} \sum_{t \in T} \Big(P_{i,t}^{\text{buy}} \cdot e_{h,t}^{\text{bought}} - P_{i,t}^{\text{sell}} \cdot e_{h,t}^{\text{sold}} + b_h \cdot K^{\text{bat}} \cdot A^{\text{bat}} + f_h \cdot K^{\text{PV}} \cdot A^{\text{PV}} + u_h \cdot K^{\text{inv}} \cdot A^{\text{inv}} \Big), \tag{3}$$

where $N \subset I$ represents the regions that contain household load profiles and H_i is the set of households in region i. The term $P_{i,t}^{\text{buy}}$ is the price for buying electricity from the grid (including the electricity price from the EPOD model, VAT, energy tax, and variable

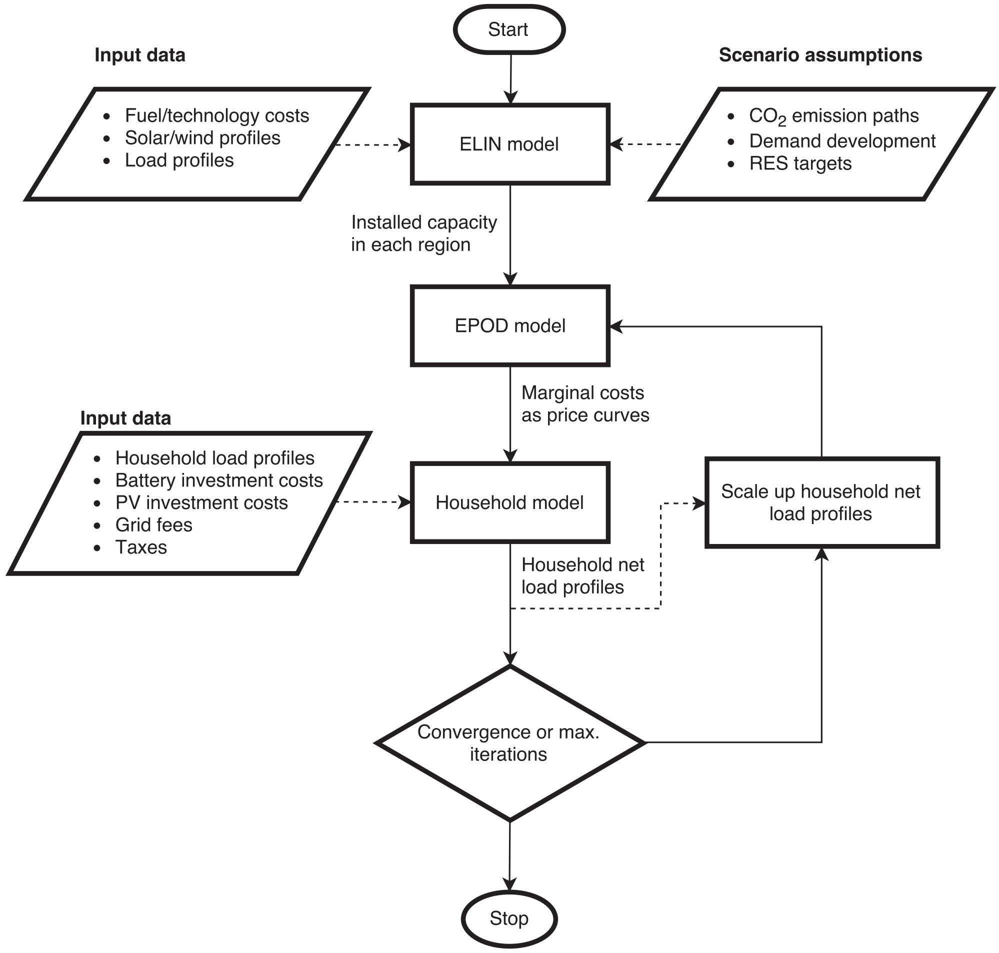

Fig. 2. Flow chart illustrating the iterative procedure and the roles of the ELIN, EPOD, and household investment models. Solid lines represent the procedural flow and dashed lines represent data transfer.

distribution grid fees), and $P^{sell}_{i,t}$ is the price for selling electricity to the grid (comprising the electricity price from the EPOD model and reimbursement from the distribution grid owner) in region i at time t. The variable $e^{bought}_{h,t}$ is the amount of electricity bought from the grid, and $e^{sold}_{h,t}$ is the amount of electricity sold to the grid by household h at time t. For the investments, b_h is the size of the battery investment, f_h is the size of the PV-panel investment, and u_h is the size of the inverter investment made by household h. Note that the same inverter is assumed to be used by both the PV and the battery. Furthermore, K^{bat} is the cost of the battery, K^{PV} is the cost of the PV-panel, K^{inv} is the cost of the inverter, and A^{bat}, A^{PV} and A^{inv} represent the annuity factors for the battery, PV-panel and inverter, respectively. The annuity factor is defined as:

$$a = \frac{r}{1-(1+r)^{-n}}, \tag{4}$$

where r is the interest rate and n is the life-time of the investment.

Since the electricity demand for each household needs to be fulfilled, the optimisation is subject to:

$$D_{h,t} + e^{sold}_{h,t} + s^{add}_{h,t} = e^{bought}_{h,t} + v_{h,t} + s^{rem}_{h,t} \cdot \eta^{bat} \quad \forall\ h \in H_i,\ i \in N,\ t \in T, \tag{5}$$

where $D_{h,t}$ is the electricity demand from household h at time t. The variable $s^{add}_{h,t}$ is the energy added to the battery and $s^{rem}_{h,t}$ is the energy discharged from the battery for household h at time t. The energy discharged is multiplied by the battery discharge efficiency, η^{bat}, so as to capture energy losses resulting from operating the battery. Furthermore, $v_{h,t}$ is the electricity generated by a PV-panel belonging to household h at time t.

The charging and discharging of the battery are subject to:

$$l_{h,t} = l_{h,t-1} - s^{rem}_{h,t} + s^{add}_{h,t} \cdot \eta^{bat} \quad \forall\ h \in H_i,\ i \in N,\ t \in T, \tag{6}$$

where $l_{h,t}$ is the storage level of a battery belonging to household h at time t. The invested storage size limits the amount of energy that can be stored, as follows:

$$l_{h,t} \le b_h \quad \forall\ i \in N,\ h \in H_i,\ t \in T. \tag{7}$$

The power capacity (kW) of the battery is assumed to be equal to the battery size (kWh), i.e., the battery can be fully charged from an empty state in 1 h. The maximum size of the invested PV-panel in each household is limited to the size which generates the same amount of annual electricity as the households annual electricity consumption, as Swedish regulations do not allow households to become annual net electricity producers. It should also be noted that simultaneous optimisation of all households is equivalent to optimising one household at a time, as there is no interdependency of the households.

Estimates and projections of PV investment costs differ widely

Table 1
Key assumptions regarding investment options in the household model.

Technology	Inv. Cost	Life-time [years]
Battery	150 €kWh	12.5
PV	900 €/kW$_p$	30
Inverter	100 €/kW$_p$	15

between sources [34–37]. The IEA project the investment cost for building-mounted PV systems in Europe for Year 2030 as being approximately 970 €/kW$_p$ [36], whereas the Danish Energy Agency project 830 €/kW$_p$ [34] for the same year. Tsiropoulos et al. [37] summarised literature for 2030 cost projections for residential battery solutions as being in the 100–650 €/kWh range. Based on these sources, we have assumed the investment costs and life-times listed in Table 1. For batteries, we assume that the calendar life-time rather than the cycle life-time will be the limiting factor, i.e., that no cost is incurred by cycling the battery.

To summarize the drivers for households to invest in PVs and batteries, the incentives for households to invest in PVs are strongest when the electricity can be consumed in-house, since the value of the PV electricity is then the sum of the electricity spot price, taxes, and grid fees. For surplus PV production, that must be sold to the grid, the value is only the spot price. For investments in batteries, the incentives are firstly, in combination with PVs, to increase the amount of in-house consumption of PV electricity, where the value of each additional unit of electricity consumed in-house is the sum of the taxes and grid fees. Secondly, if there is sufficient variations in the electricity spot price, the battery can be used for arbitrage, i.e., to buy at low prices and sell at high prices, where the value is the difference in price between the bought and the sold electricity.

2.4. Household load data

The household load profiles in the model are derived from 2104 measured hourly load profiles for Swedish single-family dwellings.[3] The measured load profiles are all located in modelling regions SE1 and SE2, so they only represent the households in these regions. Nevertheless, 81% of the total Swedish electricity demand and 89% of the Swedish single-family dwellings are located in these regions. To represent the total single-family dwelling load in the two EPOD regions the 2104 measured profiles are scaled up to represent the 1.7 million single-family dwellings that are present in the two regions.

The scale-up of the 2104 households is carried out by assigning a scale factor to each of the households in the dataset, i.e., a value that indicates the weight of the households with regards to the overall building stock. The scale factor for each household profile is based on information collected about each household's heating equipment and the total number of households that contain that specific heating equipment in the two EPOD model regions, according to statistical data provided by the Swedish Energy Agency [39]. In the collected data, each household has selected from 11 different choices for the type of heating system used. The statistics (see Ref. [39]) also classify the heating equipment into 11 categories, although these do not correspond directly to the categories in the collected data. Thus, the categories are aggregated into six different heating equipment categories used for the scale-up exercise. Table 2 shows the classification of the collected and statistical data into the six categories used for the scale-up exercise. The statistical data are for Year 2010, whereas the measurements were conducted during Year 2012. To compensate for this discrepancy, all the statistical values are increased by 2.2%, which corresponds to the increase in the number of single-family dwellings observed between the two years. The scale factor for each scale-up heating equipment category is calculated by dividing the number of households from the statistical data by the number of households from the collected data for each EPOD model region. Table 3 shows the resulting scale factors for each scale-up heating equipment category. The actual number of buildings represented is approximately 800 times larger than the sample size of the collected data. This means that a scale factor >800 indicates that the category is under-represented in the collected data; conversely, a scale factor <800 indicates an over-representation of the category in question. From Table 3 it is clear that households with electric heating are over-represented in the measured data, especially in region SE1. All the heating categories, with the exception of “Others”, are more strongly represented in households in region SE1 than in region SE2 (indicated by a higher scale factor for SE1).

The scale-up is validated by comparing the total up-scaled annual electricity consumption for heating with the corresponding values from the statistics dataset. The yearly electricity consumption levels that result from the scale-up for the SE1 and SE2 regions are 3.78 TWh and 17.80 TWh, respectively. For Year 2012, the statistics for the two regions show electricity consumption levels of 3.79 TWh and 18.40 TWh for SE1 and SE2, respectively [40]. In the statistics dataset, data are missing for some municipalities. For these municipalities, data from Year 2009 is used. The Year 2009 data are corrected for inter-annual variations by assuming the same change in electricity demand as that of the average municipality between Year 2009 and Year 2012. Overall, the scale-up procedure is found to work well, although the scaled-up annual electricity consumption level is 0.3% lower than the value obtained from the statistics for region SE1 and 3.3% lower than that obtained for region SE2. In addition to the replacement of missing data, an error may arise in that the household profiles were measured from February to February while the statistics are presented by calendar year, i.e., the electricity consumption levels in January might differ between the two datasets.

2.5. Investigated scenarios and cases

The analysis described above (cf. Fig. 2) is performed for each of the three different scenarios for the centralised electricity generation system described above: the Green Policy scenario; the Regional Policy scenario; and the Climate Market scenario. In addition, we also investigate a case that is based on the Green Policy scenario, but in which all the grid fees for households are assumed to be fixed, i.e., variable grid fees are zero for all households. This weakens the incentive for self-consumption of electricity, although the households still pay taxes for electricity bought from the grid. We denote this as the “Fixed Grid” case. To identify the factors that are significant for the results, the following sensitivity cases are also analyzed: a case with higher battery investment costs (300 €/kWh); a case with lower battery investment cost (90 €/kWh); and a case with higher solar PV investment costs (1200 €/kW$_p$).

3. Results and discussion

The total annual electricity generation between Year 2010 and Year 2050, as obtained from the ELIN model is shown in Fig. 3 for each scenario. The Green Policy scenario (Fig. 3a), in which we assume a moderate growth in demand, is predominated by wind power, with some solar power investments after Year 2035 and some coal and gas power being used as bridging technologies. Note that the solar power shown in the ELIN model results is only utility-

[3] The measurements where conducted by E.ON during the period from February 2012 to February 2013. For further information, see Ref. [38].

Table 2
The different heat equipment categories used in the scale-up exercise and the classification of the heat equipment data from collected data and statistics into the scale-up categories.

Scale up	Collected data	Statistics[39]
Electric heating	Direct electric Electric furnace Heat pumps	Direct electric Hydronic electric
Ground source heat pumps	Ground source heat pump type 1 Ground source heat pump type 2	Ground source heat pump Ground source heat pump + electricity Ground source heat pump + biofuels
Biofuels	Pellet fuels Firewood	Biofuels Biofuels + electricity
District heating	District heating	District heating
Oil	Oil	Oil Oil + electricity
Others	Gas Passive houses	Others

Table 3
Number of buildings in the measured data and the statistical data, and the calculated scale factor for each combination of heating category and region. Statistical data are retrieved from the Swedish Energy Agency [39].

	Number of buildings			
Heating category	Model region	Collected data	Statistical data	Scale factor
Electric heating	SE2	620	384,807	620.7
	SE1	837	110,038	131.5
Ground source heat pumps	SE2	290	265,066	914.0
	SE1	132	36,616	277.4
Biofuels	SE2	60	433,616	7226.9
	SE1	55	70,810	1287.5
District heating	SE2	36	163,923	4553.4
	SE1	39	37,311	956.7
Oil	SE2	0	17,814	–
	SE1	1	4681	4681.0
Others	SE2	30	127,531	4251.0
	SE1	4	32,127	8031.8

scale and that the ELIN model makes no investments in distributed generation, i.e., household investments are added on top of the capacity from the ELIN model. Existing nuclear power is assumed to be phased out after a life-time of 45 years and no re-investments are made by the model. In the Regional Policy scenario (Fig. 3b), growth in demand is assumed to be weak over the entire period. Furthermore, nuclear power plants remain operational for a longer time (a life-time of 60 years is assumed in the Regional Policy scenario) and some re-investments are made after Year 2040. After Year 2040, the model also invests in carbon capture and storage (CCS) technologies, although renewable generation (and wind power in particular) dominates the mix in Year 2050. The Climate Market scenario (Fig. 3c) exhibits a more diversified generation mix with significant amounts of variable renewables as well as large re-investments in nuclear power and investments in CCS, both starting as early as Year 2025.

Moving now to the results from the iterative analysis, it is evident that the marginal costs of electricity in Sweden from the EPOD model show significant differences between the three modelled scenarios. Marginal cost duration curves for all three scenarios for region SE1 from the first iteration, i.e., before any household investments, are shown in Fig. 4. The Green Policy scenario, which has high levels of wind power in the generation mix, demonstrates the most volatile marginal costs of the three scenarios. The presence of hydropower with reservoir storage in the Nordic system can smoothen out marginal costs over extended periods of time, which still gives a stable marginal cost during a substantial part of the year. In both the Regional Policy and Climate Market scenarios, the hydropower capacity is sufficient to maintain the marginal costs at a stable level for almost all of the year. However, this level is significantly higher in the Climate Market scenario, mainly due to the higher price of CO_2 emissions allowances.

In all the cases we investigate, there are significant investments in household PVs in the selected Swedish regions of SE1 and SE2. Fig. 5 shows the total investments in PVs and batteries in all households (i.e., in SE1 and SE2 combined) as a function of iteration number for each scenario as well as the Fixed Grid case, in which variable grid fees are assumed to be zero for all the households. The simulation is run for 10 iterations for all cases, except the Green Policy scenario, where it is run for 15 iterations to ensure that results remain stable. Note that all household investments in solar PVs are added on top of the capacity mix obtained from the ELIN model.

Owing to the differences in the marginal cost of electricity, the levels of household investments in PVs and batteries differ significantly between the three scenarios. The only difference between the scenarios seen by the household investment model is the different marginal cost of electricity (treated as an electricity price in the household model). The largest investments in batteries, approximately 10 GWh in total after the iterations, occur in the Green Policy and Climate Market scenarios. However, the installed level of PV capacity differs considerably between the two scenarios, with 13 GW_p and 20 GW_p installed respectively. The considerably

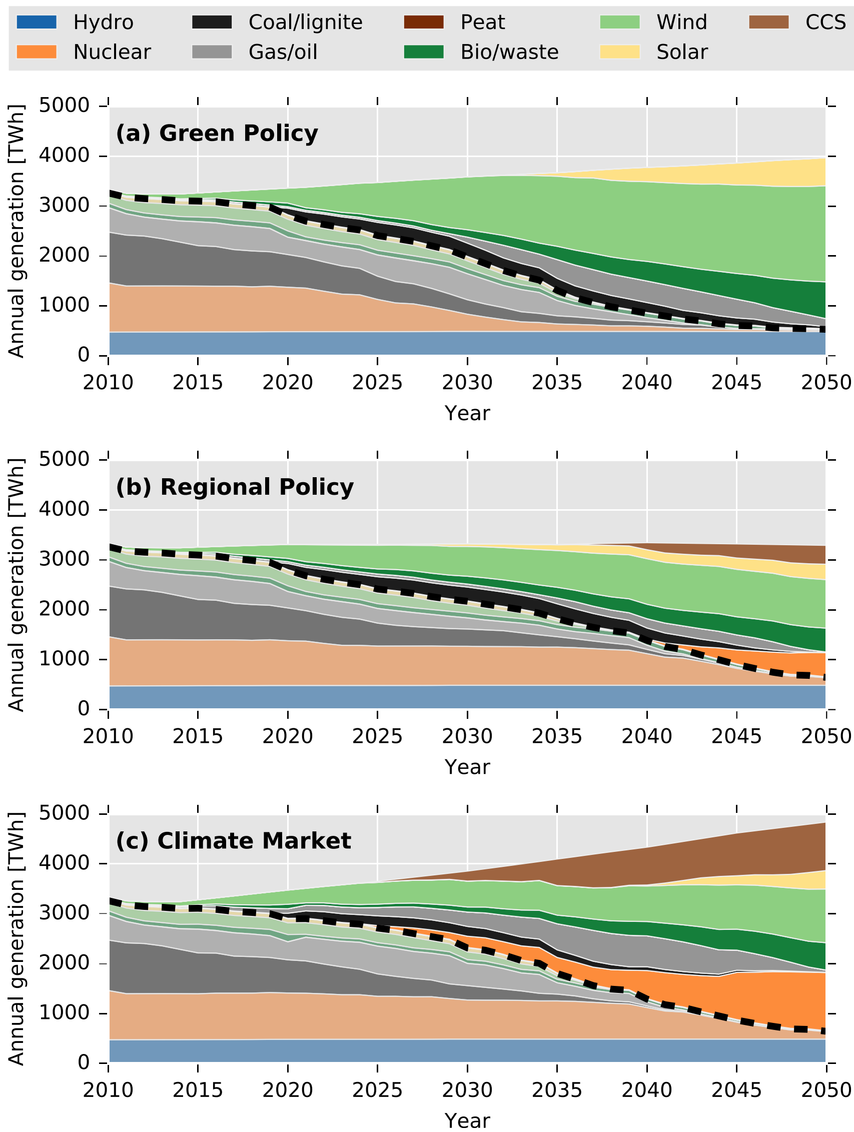

Fig. 3. Evolution of the European electricity generation mix, as obtained from the ELIN model, for the three scenarios: (a) Green Policy; (b) Regional Policy; and (c) Climate Market. The areas below the dashed line represent currently existing capacity and the areas above the line represents new investments made by the ELIN model.

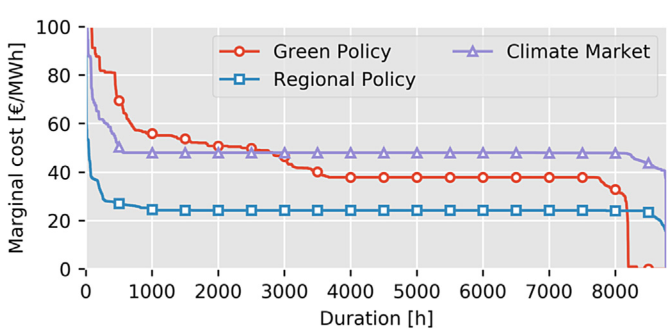

Fig. 4. Duration curves for the marginal cost of electricity in region SE1 from the first iteration, i.e., before any household investments, for the three scenarios: Green Policy; Regional Policy; and Climate Market.

higher volatility in marginal cost seen in the Green Policy scenario, as compared to the stable and on average somewhat higher marginal cost in the Climate Market scenario, can thus drive large battery investments with considerably smaller PV investments. This shows that profitability of investment in batteries can be driven by both the potential for increased self-consumption of PV electricity and market arbitrage.

However, we can also state that, in the Fixed Grid case, where the system composition in the EPOD model is identical to that in the Green Policy scenario (and which therefore has an identical marginal cost in the first iteration), the removal of the variable grid fee strongly decreases the profitability of investments in PVs and also affects the profitability of investments batteries. This indicates that both the self-consumption of PV electricity and price arbitrage are drivers of household investments in battery capacity. The lowest investment levels, 5 GW_p of PVs and 0.5 GWh of battery capacity, are noted for the Regional Policy scenario, where the marginal cost of electricity is comparatively low and stable.

Taking feedback into account, i.e., looking at the effect of the iterations, we find that in the cases with a significant volatility in the marginal cost of electricity, market feedback has a strong dampening effect on the levels of investment. In the Green Policy scenario, the capacities of both the batteries and PVs decrease by about a third after the iterations. However, in the Regional Policy scenario, in

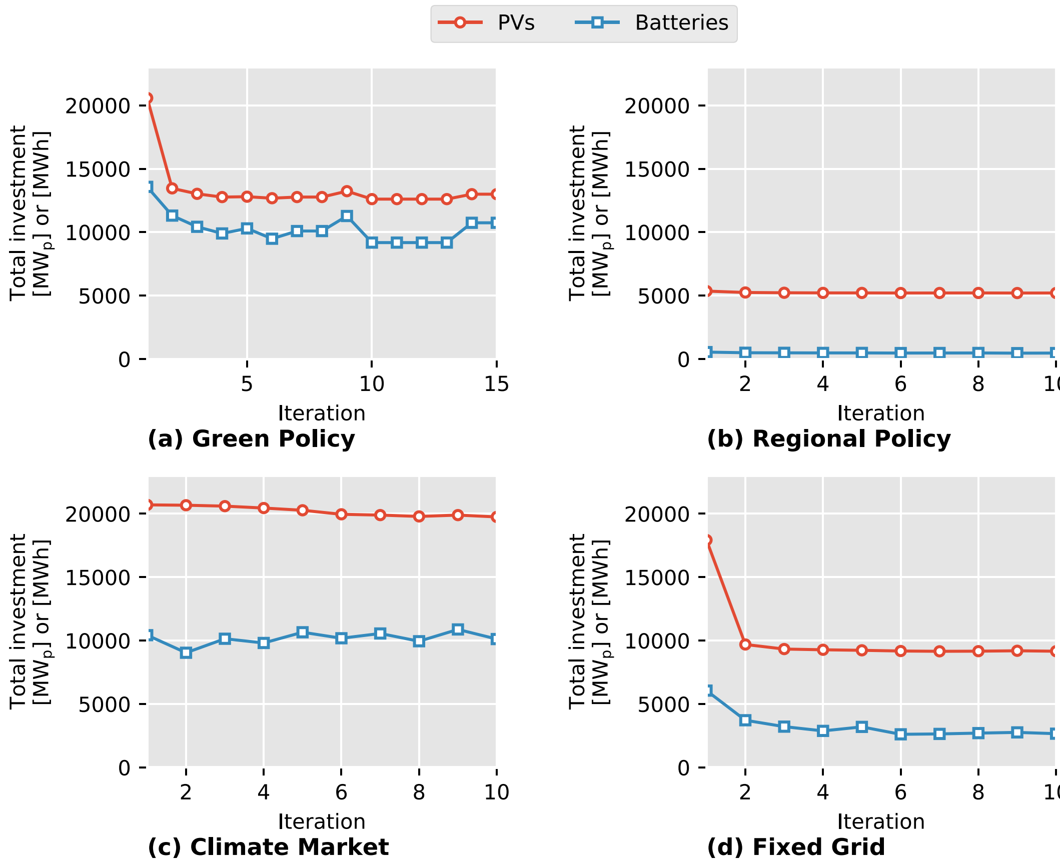

Fig. 5. Total household investments in PVs and batteries in MW_p and MWh respectively for: (a) the Green Policy scenario; (b) the Regional Policy scenario; (c) the Climate Market scenario; and (d) the Fixed Grid case, the latter of which is identical to the Green Policy scenario except that the variable grid fees are assumed to be zero for all the households.

which there are very low investments in batteries and where the PV investment is small compared with the other cases, the iterations have no significant effect, indicating that investments at these levels have little impact on marginal price formation. The Climate Market scenario shows only a minor change between iterations. This could in part be due to that a large segment of the households have reached their maximum allowed solar PV size (due to the net consumer regulations), i.e., the first iterations might have resulted in larger investments if this limit was not present. It should be noted that the effects on the dispatch and market prices from changes in the household load profiles in Sweden are dampened by the availability of flexible hydropower. In a system that has a less flexible capacity mix in the centralised generation system, the feedback effects are likely to be significantly stronger.

Compared to the results presented in Ref. [5,6] the installed PV and battery capacities per household are in general lower in our results. However, the relative size between the PV panel and battery, i.e., the RBC, is of similar magnitude. In Mulder et al. the installed capacity ranges between ALR 2–13 and RBC 0-1 for PVs and batteries, respectively. The results from Ref. [5] corresponds to the ranges ALR 4.5–31 and RBC 0.6–1.4. The lower values shown in our study are most likely due to several different factors. The market feedback, lower average electricity prices, and different tariff structure applied in our work will have a dampening effect on the installation levels. The generally lower annual PV electricity generation and more seasonally skewed generation profile for Swedish conditions, as well as the limitation that households cannot be annual net producers, also lower investment incentives.

The levels of household investments in PVs and batteries (around 13–20 GW_p in all of Sweden) found in the Green Policy and Climate Market scenarios have a significant impact on the market price of electricity. Fig. 6 shows the duration curves for the difference in the marginal cost of electricity between iteration 1 and iteration 10 for each of the four cases. In the Green Policy scenario, the average marginal cost of electricity is 3.1 €/MWh lower after household investments in PVs and batteries. The large investments in battery capacity made in the Green Policy scenario, combined with the volatile marginal costs, enable the number of high-price hours to be reduced. In the Climate Market scenario, the solar PVs and batteries mainly cause a decrease in the stable base level of the marginal cost set by the so-called “water value”, which is the marginal value of hydropower energy. The substantial PV investments also result in an increased number of hours with marginal costs of electricity close to 0. Fig. 6 also shows that the marginal cost of electricity increases during some

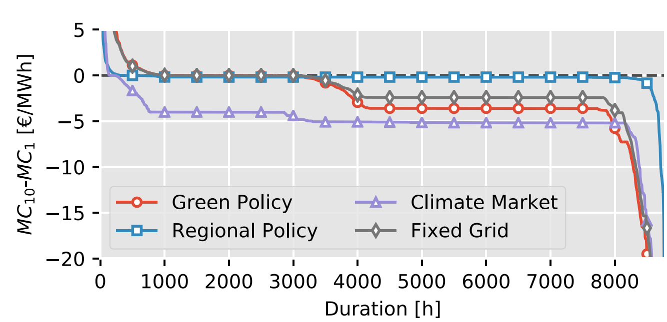

Fig. 6. Duration curves for the difference in the marginal cost of electricity between iteration 1 (before any household investments) and iteration 10 for region SE1 for: the Green Policy scenario; the Regional Policy scenario; the Climate Market scenario; and the Fixed Grid case, the latter of which is identical to the Green Policy scenario except that the variable grid fees are assumed to be zero for all the households.

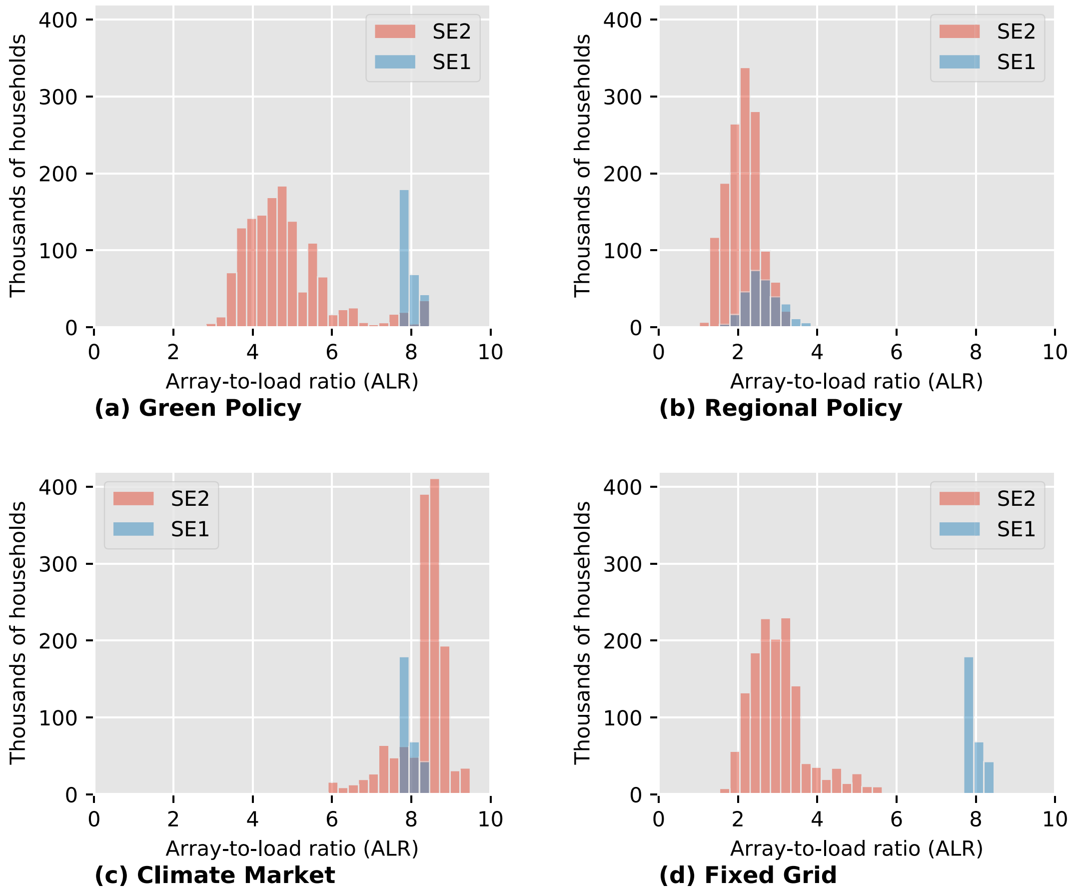

Fig. 7. Distributions of array-to-load ratio (ALR, the installed PV capacity in W_p divided by the average hourly load in W) after iteration 10 for households in regions SE1 and SE2 for (a) the Green Policy scenario; (b) the Regional Policy scenario; (c) the Climate Market scenario; (d) and the Fixed Grid case, the latter of which is identical to the Green Policy scenario except that the variable grid fees are assumed to be zero for all the households. The distributions are scaled up to represent all the households in the two regions. The darker colour indicates the overlap between the two distributions.

hours, especially in the Green Policy scenario, which means that some price spikes cannot be avoided completely but instead can only be shifted in time using the available battery capacity. Note that this effect may reflect that the households only react to the price from the last iteration. If the dispatch of the battery storage is optimised together with the dispatch of the centralised power plants it may be possible to reduce the number of price spikes even further.

The investments in PVs also has a significant impact on the electricity costs for individual households. The weighted average decrease in annual electricity costs after iterations range from 6% in the Regional Policy scenario to 18% in the Climate Market scenario. The cost for each household is calculated as the net electricity cost including taxes and grid fees plus the annualised investment cost for PV and battery investments.

The sizing of the PV array in relation to the household electricity consumption differs between the SE1 and SE2 regions. The distributions of the array-to-load ratios[4] (ALRs) are shown in Fig. 7, where they have been scaled up in line with the data presented in Table 3 to represent all the households. The households in region SE1, which is the south-most region in Sweden, on average have a higher ALR than the households in SE2. The difference in the marginal cost of electricity between the two regions is small, ranging from, on average before iterations, 0.1 €/MWh higher in region SE1 in the Climate Market scenario to 2.7 €/MWh in the Green Policy scenario. However, the superior solar irradiation conditions and differences in electricity consumption for heating, attributed to a warmer climate, could contribute to different prerequisites for the two regions in terms of investments in solar PVs and batteries. It should be noted that most households in region SE1 reach their maximum PV installation sizes in the Green Policy and Climate Market scenarios, as do many households in region SE2 in the Climate Market scenario.

The storage capacities of the batteries, in relation to the amount of installed PV capacity, differ significantly between the investigated cases. In Fig. 8, the distributions of relative battery capacity[5] (RBC) are shown for each of the investigated cases for households in region SE1 and region SE2. The RBC shows similar distributions for the households in the two regions, except in the Fixed Grid scenario, where the households in region SE1 (the southern-most Swedish region) install significantly larger batteries in relation to their PV array sizes than the households in region SE2. The ALR values (the sizing of the PV array in relation to the average load) show clear differences between the two regions, whereas the RBC is generally similar between the regions, which indicates that the sizing of the battery depends mostly on PV capacity.

The ways in which the households utilise their battery storage, differ over the seasons of the year, depending on how much electricity the PV is producing. Fig. 9 shows how the battery storage is utilised in

[4] Defined as the PV capacity in W_p divided by the average hourly load in W, see Ref. [38].

[5] Defined as the battery energy capacity in Wh times 1000 divided by the annual PV production in a household, see Ref. [38].

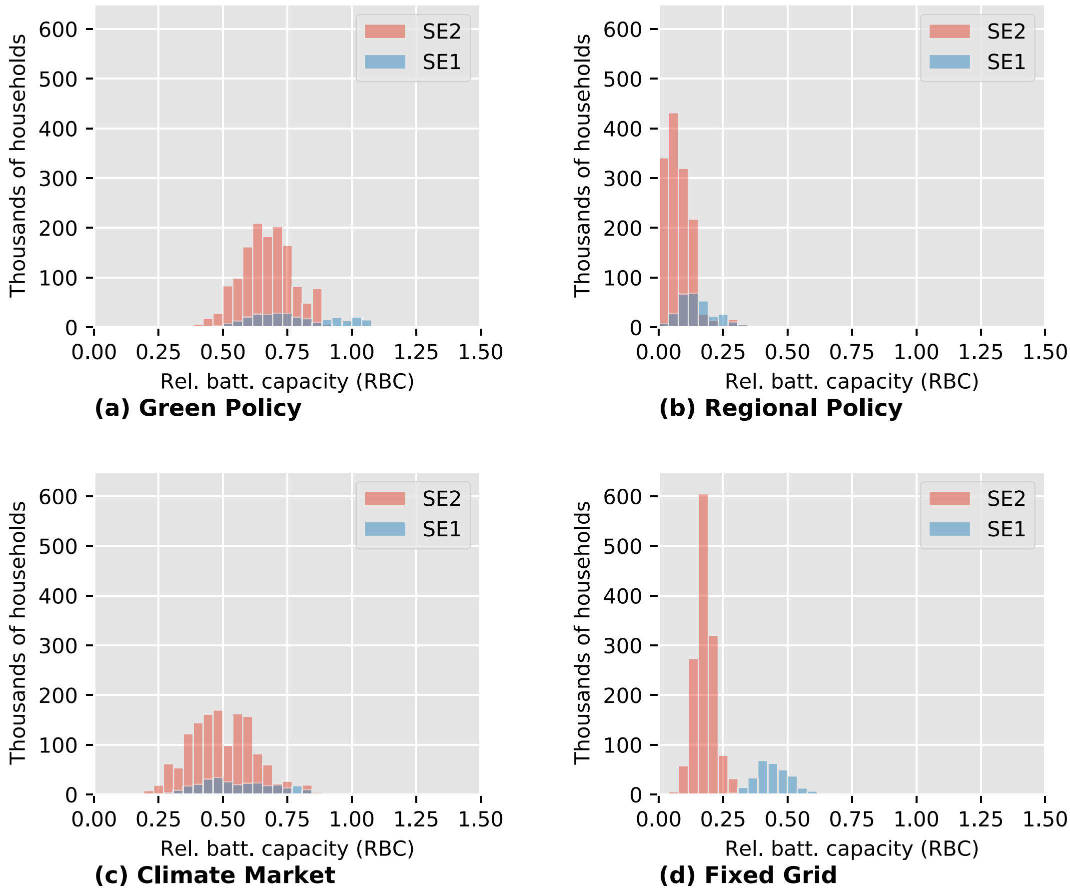

Fig. 8. Distributions of relative battery capacity (RBC, battery energy capacity in Wh × 1000 divided by the annual PV production) after iteration 10 for households in the SE1 and SE2 regions for: (a) the Green Policy scenario; (b) the Regional Policy scenario; (c) the Climate Market scenario; (d) and the Fixed Grid case, the latter of which is identical to the Green Policy scenario except that the variable grid fees are assumed to be zero for all the households. The distributions are scaled up to represent all the households in the two regions. The darker colour indicates the overlap between the two distributions.

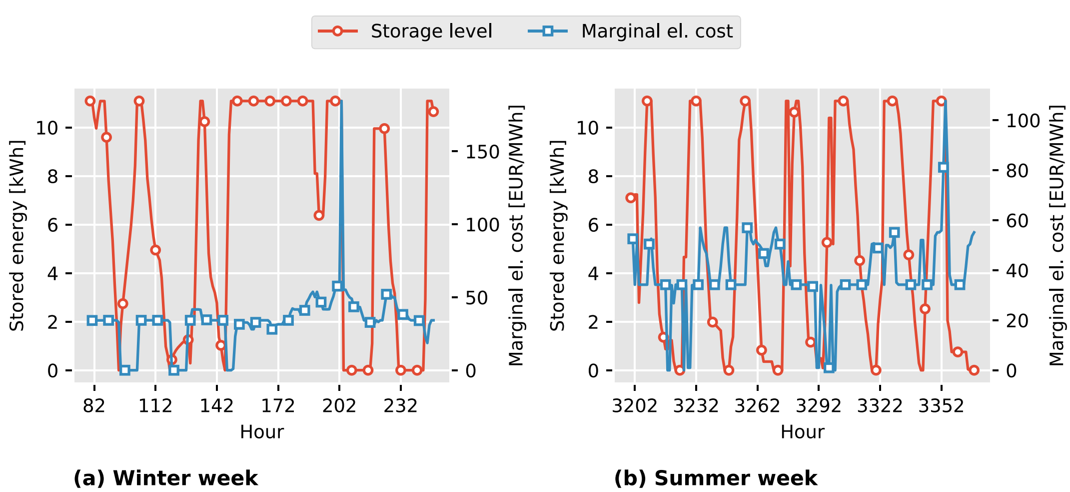

Fig. 9. Amount of energy stored in the battery for an example household and the marginal cost of electricity for: (a) a winter week and (b) a summer week in the Green Policy scenario after iteration 10.

an example household during a winter week and a summer week. During the winter week, the behaviour of the household is clearly governed by the marginal cost of electricity, i.e., the electricity price seen by the household, discharging whenever there is a peak in the price and charging during local price troughs. The marginal cost also affects the charge and discharge patterns during the summer week, although a marked diurnal pattern is observed, which indicates that the battery is being used to self-consume electricity generated in-house by PVs. This behaviour can be attributed to the fact that the benefits accrued from avoiding taxes and grid fees through the self-consumption of PV electricity outweigh the diurnal variations in the market price of electricity that constitute the benefits of market arbitrage, i.e., buying at a low price and selling at a high price. The benefits of using the battery for market arbitrage could be overestimated due to the perfect foresight nature of the household model. The electricity price curve for the entire year, the level of solar production, and the load are all known in advance, and the usage of the battery can be optimised accordingly.

3.1. Sensitivity analysis

To investigate the importance of the battery investment cost a sensitivity case based on the Green Policy scenario, but with an investment cost of 90 €/kWh is modelled. With the lower investment cost, total battery investments initially increase to 51 GWh and stabilise at 25 GWh after iterations, an increase of 150% compared with the original Green Policy scenario. As a consequence the PV investments increase by 28% to 17 GW_p. At this cost, in the Green Policy scenario, with a relatively volatile marginal cost of electricity, it is profitable to use the batteries for market arbitrage, which is the main driver of the increased battery investments. As a side-effect, the increased battery capacity enables an increased self-consumption of PV electricity, which results in the increased PV investments. The substantial decrease of battery investments after iterations, shows that market feedback effects are highly important when it comes to determining the profitability of using batteries for market arbitrage. It is likely, however, that at a battery investment cost this low, there would also be investments in centralised battery storage facilities, which is not accounted for here. The presence of additional centralised storage in the system would stabilise the electricity prices, thus weakening incentives to invest in residential battery storage.

A case with a higher investment cost for solar PVs is also modelled to investigate how strongly the investments in batteries are dependent upon the investments in solar PVs. An assumed investment cost of 1200 €/kW_p yields a total investment in solar PVs of 8 GW, corresponding to a decrease of 38% compared with the original Green Policy results. As a consequence, the battery investments also drop by 20% to 8 GWh. This shows that if it is to be profitable for households, the level of investment in batteries is significantly dependent upon the presence of solar PVs.

An additional model run was performed, in which a doubling of the battery investment cost to 300 €/kWh was assumed, in combination with the higher PV cost of 1200 €/kW_p. With these changes, battery investments decreased to 0.35 GWh after the iterations, which is approximately 97% lower than the level in the Green Policy scenario with the original investment costs. PV investments are still significant, around 6.5 GW_p in total, i.e., there is a decrease in PV investment of approximately 18% compared to when the same PV investment cost is combined with a lower battery cost. This shows that a large proportion of the PV investments can be profitable at a relatively high investment cost despite the absence of battery storage systems.

4. Conclusions

We present an iterative approach to modelling investments in PVs and batteries in Swedish single-family dwellings, which involves coupling the cost-minimising dispatch model EPOD to a household investment model using 2104 measured load profiles for Swedish single-family dwellings.

The modelling results show that, given the assumptions made, the electricity prices in the modelled system for Year 2032 provide significant incentives for investments in PVs and batteries in Swedish households, yielding up to 20 GW_p of PV capacity and 10 GWh of battery storage capacity. However, the investment levels are heavily dependent upon the characteristics of the wholesale price of electricity, as well as upon additional fees that incentivise the self-consumption of PV electricity. For the three investigated scenarios for the capacity mix of the centralised electricity generation system, the results show investment levels as low as 5 GW_p and 0.5 GWh for the PVs and batteries, respectively.

We show that investments in batteries are driven by the benefits of both increased self-consumption of PV electricity and market arbitrage. The relatively high and stable marginal cost of electricity in the Climate Market scenario and the more volatile marginal cost in the Green Policy scenario both create strong incentives for household investments in PVs and batteries, although the investments in PVs are approximately twice as high in the Climate Market scenario. The difference is that the stable and slightly higher marginal cost in the Climate Market scenario, which is not dominated to the same extent by variable renewable sources, results in a larger incentive for self-consumption and thus larger solar PV installations.

When considering market feedback, i.e., after iteration between the dispatch and the household investment model, the investment levels decrease significantly, especially when the initial investments in batteries are high and there is high volatility in the marginal cost of electricity. This shows that, with hourly pricing, and if household investments in PVs and batteries have a high penetration level, it is necessary to take market feedback effects into account, i.e., that household investments in PVs and batteries can have a significant impact on the market price of electricity and therefore affect the profitability of such investments.

Our sensitivity analysis shows that a significant fraction of PV investments in households can be profitable even in the absence of low-cost battery storage. However, the profitability of battery investments, depends both on the use of such investments for increasing self-consumption of PV-generated electricity as well as the potential for using batteries for market arbitrage.

The generalizability of the results for other countries depends on the geographical location of the country and its electricity system composition. The trends presented should be applicable to countries with electricity consumption and solar irradiation profiles similar to Sweden. At latitudes where the solar PV generation is more uniformly distributed over the year the value of batteries can be expected to be higher. The large share if hydropower in the Swedish electricity system diminishes the marginal value of storage and thereby the possibilities for arbitrage. In countries with less flexible generation capacity, variations in electricity price could intensify both in terms of frequency and magnitude, increasing the potential for arbitrage.

CRediT authorship contribution statement

Joel Goop: Conceptualization, Methodology, Software, Visualization, Writing - original draft. **Emil Nyholm:** Conceptualization, Methodology, Software, Writing - review & editing. **Mikael Odenberger:** Conceptualization, Methodology, Supervision, Writing - review & editing. **Filip Johnsson:** Conceptualization, Methodology, Supervision, Writing - review & editing.

Declaration of competing interest

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

Acknowledgements

This work is co-funded by the Chalmers–E.ON Initiative, the Pathways to Sustainable European Energy Systems research programme, and the Chalmers Energy Initiative.

Appendix A. Scenarios

Table A 1
Summary of the main differences in assumptions between the scenarios used. More details on the scenarios can be found in Ref. [31].

	Green Policy	Regional Policy	Climate Market
Demand growth	Moderate	Low	High
Drivers/policies	Common European goals on RES-levels corresponding to 95% RES by Year 2050 CO_2 target	National goals on RES-levels based on NREAPs (corresponding to a total European level of 70% RES by Year 2050), European efficiency target affect the demand for electricity	A pure CO_2 target between the years 2020 and 2050 implemented as a continuation of the ETS scheme
Nuclear	Phase out in Germany, Belgium, and Sweden. Re-investments allowed in others. Lifetime 45 yr	Phase out in Germany, Belgium, and Sweden. Re-investments allowed in others. Lifetime 60 yr	Expansion allowed
CCS	After Year 2025	After Year 2030	After Year 2025
CO_2 target 2050	93%(1)	99%(1)	93%(1)

[1] Compared with the emission levels in Year 1990.

References

[1] International Energy Agency, A snapshot of global pv (1992–2014), URL: http://www:iea-pvps:org/fileadmin/dam/public/report/technical/PVPS_report_-_A_Snapshot_of_Global_PV_-_1992-2014:pdf, , 2014.
[2] B. Nykvist, M.n. Nilsson, Rapidly falling costs of battery packs for electric vehicles, Nat. Clim. Change 5 (2015) 100–103.
[3] M. Schwarz, J. Ossenbrink, C. Knoeri, V.H. Ho_mann, Addressing integration challenges of high shares of residential solar photovoltaics with battery storage and smart policy designs, Environ. Res. Lett. 14 (2019), https://doi.org/10.1088/1748-9326/aaf934.
[4] S.A. Janko, M.R. Arnold, N.G. Johnson, Implications of high-penetration renewables for ratepayers and utilities in the residential solar photovoltaic (pv) market, Appl. Energy 180 (2016) 37–51, https://doi.org/10.1016/j.apenergy.2016.07.041.
[5] J. Hoppmann, J. Volland, T.S. Schmidt, V.H. Homann, The economic viability of battery storage for residential solar photovoltaic systems – a review and a simulation model, Renew. Sustain. Energy Rev. 39 (2014) 1101–1118.
[6] G. Mulder, D. Six, B. Claessens, T. Broes, N. Omar, J.V. Mierlo, The dimensioning of PV-battery systems depending on the incentive and selling price conditions, Appl. Energy 111 (2013) 1126–1135.
[7] F. Cucchiella, I. D'Adamo, M. Gastaldi, Photovoltaic energy systems with battery storage for residential areas: an economic analysis, J. Clean. Prod. 131 (2016) 460–474.
[8] Z. Ren, G. Grozev, A. Higgins, Modelling impact of PV battery systems on energy consumption and bill savings of Australian houses under alternative tariff structures, Renew. Energy 89 (2016) 317–330, https://doi.org/10.1016/j.renene.2015.12.021.
[9] K.R. Khalilpour, A. Vassallo, Technoeconomic parametric analysis of PV-battery systems, Renew. Energy 97 (2016) 757–768.
[10] O. Talent, H. Du, Optimal sizing and energy scheduling of photovoltaic-battery systems under different tariff structures, Renew. Energy 129 (2018) 513–526, https://doi.org/10.1016/j.renene.2018.06.016.
[11] J. Koskela, A. Rautiainen, P. Järventausta, Using electrical energy storage in residential buildings – sizing of battery and photovoltaic panels based on electricity cost optimization, Appl. Energy 239 (2019) 1175–1189, https://doi.org/10.1016/j.apenergy.2019.02.021.
[12] K. Uddin, R. Gough, J. Radcliffe, J. Marco, P. Jennings, Techno-economic analysis of the viability of residential photovoltaic systems using lithium-ion batteries for energy storage in the United Kingdom, Appl. Energy 206 (2017) 12–21, https://doi.org/10.1016/j.apenergy.2017.08.170.
[13] C.O. Okoye, O. Solyalı, Optimal sizing of stand-alone photovoltaic systems in residential buildings, Energy 126 (2017) 573–584, https://doi.org/10.1016/j.energy.2017.03.032.
[14] C. Goebel, V. Cheng, H.-A. Jacobsen, Profitability of residential battery energy storage combined with solar photovoltaics, Energies 10 (7) (2011), https://doi.org/10.3390/en10070976.
[15] M. Kharseh, H. Wallbaum, How adding a battery to a grid-connected photovoltaic system can increase its economic performance: a comparison of different scenarios, Energies 12 (1) (2018), https://doi.org/10.3390/en12010030.
[16] S. Schopfer, V. Tiefenbeck, T. Staake, Economic assessment of photovoltaic battery systems based on household load profiles, Appl. Energy 223 (2018) 229–248, https://doi.org/10.1016/j.apenergy.2018.03.185.
[17] E. O'Shaughnessy, D. Cutler, K. Ardani, R. Margolis, Solar plus: optimization of distributed solar PV through battery storage and dispatchable load in residential buildings, Appl. Energy 213 (2018) 11–21, https://doi.org/10.1016/j.apenergy.2017.12.118.
[18] J. Li, Optimal sizing of grid-connected photovoltaic battery systems for residential houses in Australia, Renew. Energy 136 (2019) 1245–1254, https://doi.org/10.1016/j.renene.2018.09.099.
[19] R.C. Pietzcker, D. Stetter, S. Manger, G. Luderer, Using the sun to decarbonize the power sector: the economic potential of photovoltaics and concentrating solar power, Appl. Energy 135 (2014) 704–720.
[20] A. Mileva, J.H. Nelson, J. Johnston, D.M. Kammen, Sunshot solar power reduces costs and uncertainty in future low-carbon electricity systems, Environ. Sci. Technol. 47 (16) (2013) 9053–9060.
[21] K. Tapia-Ahumada, I. Pérez-Arriaga, E. Moniz, A methodology for understanding the impacts of large-scale penetration of micro-combined heat and power, Energy Pol. 61 (2013) 496–512.
[22] D. Patteeuw, K. Bruninx, A. Arteconi, E. Delarue, W. D'haeseleer, L. Helsen, Integrated modeling of active demand response with electric heating systems coupled to thermal energy storage systems, Appl. Energy 151 (2015) 306–319.
[23] M. Odenberger, T. Unger, F. Johnsson, Pathways for the North European electricity supply, Energy Pol. 37 (5) (2009) 1660–1677.
[24] L. Göransson, J. Goop, T. Unger, M. Odenberger, F. Johnsson, Linkages between demand-side management and congestion in the European electricity transmission system, Energy 69 (2014) 860–872.
[25] J. Kjärstad, F. Johnsson, The European power plant infrastructure––Presentation of the Chalmers energy infrastructure database with applications, Energy Pol. 35 (7) (2007) 3643–3664, the database used is updated to the Year 2016 version.
[26] ENTSO-E, Interconnected network of continental Europe, URL, https://www.entsoe.eu/Documents/Publications/maps/2019/Map_Continental-Europe-2.500.000.pdf, 2019. (Accessed 13 May 2020).
[27] ENTSO-E, Interconnected network of northern Europe, URL, https://www.entsoe.eu/Documents/Publications/maps/2019/Map_Northern-Europe-3.000.000.pdf, 2019. (Accessed 13 May 2020).
[28] ENTSO-E, Power flows from country to country 2015–2019. https://eepublicdownloads.blob.core.windows.net/public-cdn-container/clean-documents/Publications/Statistics/PEPF_data-2015-2019.xlsx, 2020. (Accessed 13 May 2020).
[29] ENTSO-E, Ten-year network development plan 2010–2020. https://www.entsoe.eu/fileadmin/user_upload/_library/SDC/TYNDP/TYNDP-final_document.pdf, 2010. (Accessed 3 September 2015).
[30] European Commission, National action plans. https://ec.europa.eu/energy/en/topics/renewable-energy/national-action-plans, 2015. (Accessed 10 September 2015).
[31] T. Unger, M. Odenberger, F. Johnsson, Four scenarios for the European electricity generation, in: F. Johnsson, T. Unger, E. Axelsson, U. Claeson Colpier (Eds.), European Energy Pathways – towards a Sustainable European Electricity System, Energy Technology, Energy and Environment, Chalmers University of Technology, Göteborg, 2014, pp. 131–142, 978-91-978585-6-4.
[32] T. Unger, M. Odenberger, Dispatch modelling of the European electricity supply: the EPOD model, in: F. Johnsson (Ed.), Methods and Models Used in the Project Pathways to Sustainable European Energy Systems, 97–101, 2011. Mölndal.
[33] J. Goop, M. Odenberger, F. Johnsson, The effect of high levels of solar generation on congestion in the European electricity transmission grid, Appl. Energy 205 (2017) 1128–1140, https://doi.org/10.1016/j.apenergy.2017.08.143.
[34] Danish Energy Agency and Energinet, Technology data - energy plants for electricity and district heating generation, first published, https://ens.dk/sites/ens.dk/files/Statistik/technology_data_catalogue_for_el_and_dh_-_0009.pdf, 2016. (Accessed 13 May 2020), 2020.
[35] Danish Energy Agency and Energinet, Technology data - energy storage, first

published, https://ens.dk/sites/ens.dk/files/Analyser/technology_data_catalogue_for_energy_storage.pdf, 2018. (Accessed 13 May 2020), 2020.
[36] International Energy Agency, World energy outlook, URL, https://www.iea.org/reports/world-energy-outlook-2016, 2016, 2016.
[37] I. Tsiropoulos, D. Tarvydas, N. Lebedeva, Li-ion Batteries for Mobility and Stationary Storage Applications; Scenarios for Costs and Market Growth - Study, Joint Research Centre (European Commission), 2018, https://doi.org/10.2760/87175. EUR KJ-NA-29440-EN-N.
[38] E. Nyholm, J. Goop, M. Odenberger, F. Johnsson, Solar photovoltaic-battery systems in Swedish households – self-consumption and self-sufficiency, Appl. Energy 183 (2016) 148–159.
[39] Swedish Energy Agency, Energy statistics for one- and two-dwelling buildings 2010, Statistical report ES 2011:10 (2011). URL, https://energimyndigheten.a-w2m.se/FolderContents.mvc/Download?ResourceId=2582.
[40] Statistics Sweden, Slutanvändning (MWh), efter län och kommun, förbrukarkategori samt bränsletyp. År 2009–2014, URL, http://www.statistikdatabasen.scb.se/pxweb/sv/ssd/START__EN__EN0203/SlutAnvSektor/?rxid=a3198f8f-6428-4de1-a844-8fac9aefed50, 2016.