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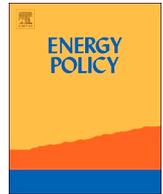
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Aligning prosumers with the electricity wholesale market – The impact of time-varying price signals and fixed network charges on solar self-consumption

Martin Klein^{a,*}, Ahmad Ziade^{a,1}, Laurens de Vries^b

^a German Aerospace Center (DLR), Institute of Engineering Thermodynamics, Department Energy Systems Analysis, Pfaffenwaldring 38-40, 70569, Stuttgart, Germany

^b Delft University of Technology, Faculty of Policy, Technology and Management, Energy & Industry Section, P.O. Box 5015, 2600 GA, Delft, the Netherlands

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ABSTRACT

PV-battery systems are currently not operated in an energy system optimal way as their operation heuristic (maximization of self-consumption) is generally unaffected by competitive market signals. To evaluate potential regulatory intervention, we propose a market alignment indicator which measures the relative economic efficiency of a prosumer battery compared to a benchmark system that is completely responsive to wholesale market prices. Investigating the case of PV-battery systems in Germany, we find that scarcity signals transmitted to prosumers improve the market alignment of PV-battery systems while retaining similar levels of self-consumption and autarky rates. Both dynamic prices for generation (time-varying feed-in remuneration) and consumption (real-time electricity prices) can improve welfare, that is lowering consumer expenditures for electricity at the wholesale market. The effectiveness of the respective instrument mix depends on the relative levels of the feed-in tariff, the grid consumption to be saved and the solar generation costs. Accordingly, increasing fixed network charges can have a significant positive impact on the market alignment of prosumer batteries if combined with dynamic prices, as they change the relative composition of retail prices.

1. Introduction

The levelized cost of electricity (LCOE) of solar photovoltaics (PV) has fallen rapidly in recent years, a development that is transforming energy markets worldwide (Agnew and Dargusch, 2015; Bazilian et al., 2013; Breyer et al., 2017; Farmer and Lafond, 2016; Green, 2016). In many countries around the world, the LCOE of solar PV is now below the household retail electricity price (Lang et al., 2016). From the consumer's point of view, there is thus an incentive to produce and consume solar electricity directly on-site, as this saves the difference between the household electricity price and the generation costs (Schill et al., 2017). In Germany, for example, household consumers are subject to average retail electricity prices of around 0.29 Euro/kWh (BDEW, 2017), while solar electricity can be produced for 0.12 Euro/kWh or less under ideal conditions.

Like photovoltaics, battery storage has observed a significant drop in system prices in recent years, indicating a similar transformation ahead (Agnew and Dargusch, 2015). To moderate the intermittency of solar and increase self-consumption, solar systems including batteries

are now becoming economically viable for end-consumers under certain support schemes and local generation potentials (Hoppmann et al., 2014; Quoilin et al., 2016; Weniger et al., 2014).

Such PV-battery systems can be scaled as required and can be used decentrally in residential and commercial applications where demand occurs, providing renewable electricity without transmission losses. These systems establish a direct link between producers and consumers and generate a new class of electricity market players – so-called prosumers, who operate partially independently from the rest of the electricity system (Schleicher Tappeser, 2012). Solar home systems can facilitate the overall shift of the electricity system towards more sustainable generation, as they allow for decentralized investments in solar energy and are able to actualize the site potential of roof surfaces (Mainzer et al., 2014; Schill et al., 2017).

These systems are not free of concerns, however, both technically and economically. From a consumer perspective, the economic attractiveness of PV-battery systems depends largely on the avoided costs of retail electricity, circumventing payments for grid services and other surcharges. Retailers and system operators will have to recuperate this

* Corresponding author.

E-mail address: martinklein@posteo.de (M. Klein).

¹ Now: Uniper SE, Holzstraße 6, 40221 Düsseldorf.

missing money by increasing charges for the remaining consumers, while the cost induced by a prosumer to the grid are essentially similar to the standard case of not having a PV-battery system. For example, the contribution to peak grid consumption does not change substantially in most cases, and prosumers still subscribe to the “service of security of supply”. In the worst case, this decoupling can lead to a parasitic effect on the system at large (Khalilpour and Vassallo, 2015; Laws et al., 2017; Parag and Sovacool, 2016).

Moreover, PV-battery systems are in many cases not operated in an energy system optimal way because the market's scarcity signals (expressed by the wholesale prices for electricity, assuming a frictionless, optimized power system) do not reach the consumer, as they are always exposed to the same retail price; the operation optimization is carried out locally under the premise of maximizing self-consumption. This situation thus incurs additional costs and introduces economic inefficiencies (Schill et al., 2017; Rubino, 2018).

How can one incentivize prosumers to align their battery operation to the scarcity signals from the wholesale market? For example, how would one incentivize that prosumers feed electricity into the system when electricity is scarce, or that storages are charged if electricity is abundant energy-system wide? To the authors' knowledge, an operationalization on how to measure “market alignment” of prosumers with different system configurations is so far lacking, with the result that the questions above cannot be answered conclusively yet.

To overcome these shortcomings, this article provides two contributions to the current body of knowledge. Firstly, we offer a proposal for quantifying and comparing the market alignment of different PV-battery systems. For this purpose, we define a so-called *market alignment indicator (MAI)*, which measures the relative economic efficiency of a prosumer battery operation compared to an idealized benchmark case that is completely aligned to wholesale market price signals. In contrast to a welfare analysis in absolute numbers, the indicator *MAI* has the advantage that different relative system sizes can be compared.

Secondly, we provide an evaluation of possible regulatory interventions to improve prosumer market alignment for a real-world case study from Germany. We are examining three policy instruments whose goal is to make self-consumption more “system-friendly” by providing more efficient incentives for consumers and aligning them more closely to the wholesale market. The policy instruments under consideration are real-time retail electricity prices, time-varying feed-in remuneration and an increase of fixed network charges. The policy instruments are examined individually and in combination, i.e. form $2^3 = 8$ possible “instrument mixes” (Rogge and Reichardt, 2016). As such, we show that the indicator is useful for comparing the effectiveness of different instrument mixes. The situation is analyzed from the perspective of the system (via the indicator *MAI*) and the prosumers themselves via several economic indicators.

As a case study, we look at Germany. Here, the spread between the solar LCOE and household electricity prices is high. Residential consumers in Germany are not exposed to wholesale market prices. Instead, the energy suppliers buy energy from the wholesale electricity market and guarantee energy delivery to consumers at a fixed price. The wholesale price of electricity acquisition makes a fraction of the consumer electricity bill (19%), while the remaining constitutes network charges (26%), the renewable energy feed-in (EEG) and other support mechanism levies (23%), and sales, taxes and other charges (32%) (BDEW, 2017). Apart from some (small) monthly fixed charges, the bill components are all volume-based and can be in principle avoided by self-generation. There is no net-metering of the generation fed into the grid. Instead, PV-battery systems are subsidized – PV via feed-in remunerations, battery systems via a loan subsidization.² It was estimated that more than 80,000 PV-battery systems have been installed in Germany up until late 2017 (Figgener et al., 2018). This indicates that

these systems are becoming increasingly relevant to the electricity system as a whole, and the adverse effects described above might make regulatory intervention necessary earlier than in other countries.

The remainder of the paper is structured as follows. Section 2 presents the methodology, i.e. the definition of the *market alignment indicator (MAI)*, the techno-economic modeling of PV-battery systems and the approach to determine their optimal charging pattern. We present modeling assumptions and the data of the used case study. Section 3 presents how the *MAI* performs for different instrument mixes and system configurations and why it takes certain values and distributions. Additionally, we elaborate how the economic prospect of a single prosumer would change per instrument mix. Possible shortcomings and extensions of the study are discussed in section 4. Section 5 concludes with policy recommendations.

2. Methodology

2.1. Market alignment indicator (MAI)

As described above, PV-battery systems do not necessarily operate in the most system-friendly way, mainly due to the fact that the market's scarcity signals do not reach the prosumers, as they are exposed to a fixed retail electricity price in many countries. In order to find a proxy for the “system-friendliness” of different system configurations, we here develop a *market alignment indicator (MAI)*.

We define the *MAI* via the contribution to welfare W of the prosumer battery, i.e. by the ratio of the welfare effect of the actual operation of the prosumer battery over the welfare effect of a benchmark system of the same size:

$$MAI = \frac{W_{Actual}}{W_{Benchmark}} \quad (1)$$

In other words, a completely market aligned benchmark case is defined and then compared to the actual state, i.e. the prosumer feed-in and storage usage depending on the actual instrument mix.

The short-term welfare effect of consumption and generation for a given instrument mix j is obtained by the delta of electricity fed into ($E_{\rightarrow G,j}$) or withdrawn from the grid ($E_{G \rightarrow j}$), multiplied by the wholesale market price $P_{wholesale}$ in that hour:

$$W_j(t) = (E_{\rightarrow G,j}(t) - E_{G \rightarrow j}(t)) \cdot P_{wholesale}(t) \quad (2)$$

Assuming a frictionless power system with no network constraints, the wholesale market price for electricity is a perfect scarcity signal, and a completely efficient, market aligned storage system would act as arbitrage storage: Buying electricity at comparatively low prices to store it, and selling at high prices, discharging accordingly. Thus, the benchmark case is an arbitrage battery directly connected to the grid, being able to follow market price signals without distortions.

In comparison, the prosumer battery has a different dispatch profile because its incentive structure is different. To isolate the effect of the battery of the self-consumption system, we consider two self-consumption systems, one PV-battery system and one PV system without battery, with the same load and same rated solar power. We further assume that the battery has the same size as the benchmark battery. The additional welfare provided by the prosumer battery $W_{Prosumer Battery}$ is then given by:

$$W_{Actual} = W_{Prosumer Battery} = W_{PV+Battery System} - W_{PV System} \quad (3)$$

A *MAI* of +1 indicates a dispatch that is completely aligned to market signals, i.e. efficient operation according to wholesale market prices – the charging state of the actual case always corresponds to the charging state of the benchmark case, which means it is charged when electricity is comparatively highly available and discharged when electricity is comparatively scarce. The indicator cannot be higher than 1, as this would mean the actual system would generate more welfare than the benchmark case, which is impossible as the benchmark is by

² This support scheme is currently being phased out.

definition already perfectly efficient and completely aligned to market signals. A market alignment indicator of 0 denotes that the operation of the prosumer battery neither increases nor decreases overall welfare. Negative values indicate battery dispatch patterns that are not aligned to market signals and that decrease overall welfare. For example, a value of -1 indicates that for every Euro that could be saved with the benchmark battery, one additional Euro would have to be expended under the actual instrument mix. Negative values are possible as there is no limit to inefficiency; the indicator can attain large negative values. In real cases under investigation here, negative values do occur but never exhibit values < -0.5 .

The *MAI* can be evaluated for time durations of arbitrary length. In this evaluation, welfare values are evaluated on an hourly basis and are aggregated over all time steps $W = \sum_{t=1}^T W(t)$ with T as the total evaluated duration.

This approach neglects additional possible sources of welfare that battery systems can provide. These include, but are not limited to, the provision of ancillary services, distribution grid relief and increased resilience of the system in times of unforeseen events like disasters or blackouts. These potential benefits are notoriously hard to monetize and are therefore not part of the operationalization of the *MAI*. Conversely, we use market-alignment only as a proxy indicator for the “system-friendliness” of solar self-consumption at large.

2.2. Other indicators

Additionally, an evaluation of individual merits from the perspective of the single prosumer per instrument mix is performed. As an indicator of economic attractiveness, we perform an internal rate of return (*IRR*) evaluation of each PV-battery system and instrument mix in question. The formulation can be found in the annex in subsection [Appendix B.1](#). As [Engelken et al. \(2018\)](#) have shown, independence from the grid is a decisive factor for the perceived utility of PV-battery systems for many prosumers. Therefore, the autarky (the share of self-consumed electricity relative to the total consumption) and self-consumption rates (the share of consumed electricity relative to the total PV generation) per instrument mix are considered. Formulas are found in the annex in subsection [Appendix B.2](#).

2.3. Investigated instrument mixes

Ideally, electricity prices would better align the distributed decisions made by individuals with the efficient operation and planning of the power system ([Pérez-Arriaga et al., 2017](#)). Three policy instruments that aim to improve the current electricity market design are investigated, individually and in combination, making up for $2^3 = 8$ different instrument mixes. The policy instruments under consideration are:

- *Real-time vs. fixed retail electricity prices*: Real-time electricity prices represent cases where the household consumer is exposed to time-varying retail prices proportional³ or parallel⁴ to the electricity wholesale market price. These schemes have been considered to be most representative of efficient energy prices and most reflective to actual systems costs ([Hogan, 2014](#)), and should therefore incentivize the efficient operation of prosumer storages, as they would reveal to consumers how scarce electricity is at the moment.
- *Time-varying vs. fixed feed-in remuneration*: Time-varying feed-in remuneration denotes remuneration for generators proportional or parallel to the wholesale market price. For example, [Ossenbrink \(2017\)](#) evaluated the effects of feed-in remuneration designs on the economics of PV-systems in several countries and suggests that

exposing PV prosumers to market price signals through feed-in remuneration would allow for a smoothed integration of distributed solar into new electricity market designs.

- *Fixed vs. volumetric network charges*: Fixed network charges represent cases where consumers pay a fixed (comparatively high) amount of network charges, which is not proportional to their energy consumption, but to their peak usage of the grid or simply fixed per connection ([Borenstein, 2016](#)). The main purpose is to reflect fair cost allocation and provide security to network cost recovery ([Rubino, 2018](#)). An increased fixed network charge component comparatively lowers the attractiveness of solar self-consumption, as the difference between a marginal unit of retail electricity and the LCOE of PV would decrease. The network charge investigated here is fixed in a sense that it would not take into account the consumer's peak capacity requirement, but rather that all investigated consumers pay the same charge.

For the instrument mix naming convention, refer to [Table D1](#). For example, the instrument mix which would exhibit real-time pricing (RTP), time-varying feed-in remuneration (VFFIT) and volumetric network charges (the business-as-usual case) would be called ‘RTP + VFFIT’.

The cases are designed so that their cumulative monetary effect over the course of a year is zero, meaning that a non-PV owner would be paying the same amount of money for electricity per year. This has been done by adding a constant per kWh to the wholesale electricity prices in the real-time pricing scheme, and by multiplying proportionality factors to the wholesale market prices for time-varying remuneration schemes. The details of this parametrization are shown in section [Appendix C](#) in the annex.

2.4. Technical modeling and dispatch optimization

2.4.1. Overview

In order to assess the effect of different policy instruments on market alignment for many possible situations, the optimal operation of PV-battery systems from the perspective of the prosumer is simulated. The optimization of the battery dispatch is formulated as a mixed integer linear programming (MILP) problem. The most important technical parameters defining the PV-battery system are the charging and discharging efficiency of the battery, the self-discharge and the maximum charge and discharge capacity of the battery (defined by the energy to power (E/P) ratio). Further inputs in the form of time-series are the solar feed-in, the household load and the electricity wholesale prices.

The next subsections will present how the dispatch optimization is carried out. The dispatch algorithm has an optimization interval of $N = 24$ hours and ensures that the net prosumer cash flow from electricity sales and expenditures on electricity purchases is maximized. The result is the dispatch of the battery, the state of charge of the battery, and the flows of electricity to and from the grid.

2.4.2. Dispatch optimization of the benchmark case

As mentioned before, the benchmark case is designed to resemble a battery operation pattern that is completely aligned to wholesale market signals. The battery is connected directly to the grid, see [Fig. 1](#). This pure arbitrage mode of operation serves as an *idealized* reference for the other cases.⁵ The optimization criterion is the maximization of the income from trading per time slot T , i.e. that the battery is charged at times of comparatively low prices and discharged at times of comparatively high prices.

On these grounds, the dispatch is obtained by maximizing the

³ Read as: Wholesale market price times a constant.

⁴ Read as: Wholesale market price plus a constant.

⁵ Batteries are not operated with this pattern under current market conditions, as other components of real-world electricity prices (taxes, levies, etc.) would have to be factored in.

Table 1
Naming convention of the instrument mixes under investigation

Instrument mix	Fixed network charges	Real-time electricity prices	Time-varying feed-in remuneration
BAU	×	×	×
F	✓	×	×
RTP	×	✓	×
RTP + F	✓	✓	×
VFIT	×	×	✓
VFIT + F	✓	×	✓
RTP + VFIT	×	✓	✓
RTP + VFIT + F	✓	✓	✓

where N is the optimization interval, t is a single time step and z is an element of the total amount of optimization periods Z , where Z is:

$$Z = \frac{T}{N} = \frac{8760}{24} = 365 \quad (5)$$

$P_{wholesale}(t)$ is the price of the electricity at time t on the wholesale market, $E_{B \rightarrow G}(t)$ is the energy from the battery into the grid at time t and $E_{G \rightarrow B}(t)$ is the energy from the grid to the battery at time t . T is, in hours, the total evaluated duration. Consequently, the total revenue R for each year is:

$$R = \sum_{z=1}^Z r_z \quad (6)$$

To summarize the objectives of the arbitrage dispatch pattern:

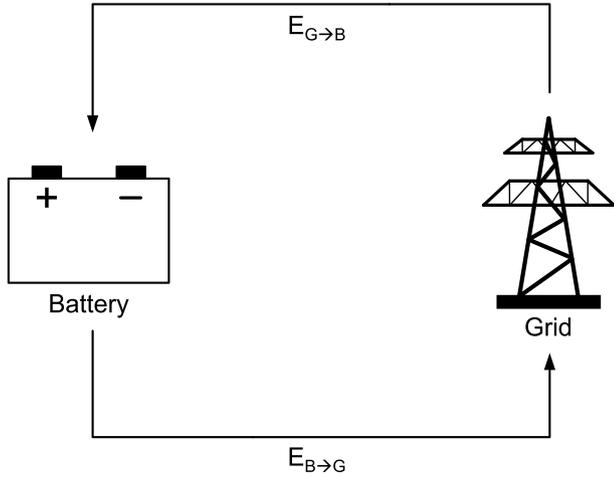
1. Technology: Battery storage only.
2. Focal economic parameters:
 - Charging cost: wholesale market price.
 - Discharging revenues: wholesale market price.
3. Storage application: Arbitrage dispatch.

The constraints of the formulation can be found in the annex [Appendix A.1](#).

2.4.3. Dispatch optimization of the business as usual instrument mix

In the business as usual (BAU) case, a PV-system is connected to a battery. For a schematic depiction of the technical layout, see [Fig. 2](#). The electricity consumer can obtain electricity from the grid and, depending on generation and state of charge, from the PV system and the battery. Conversely, the generation from the solar system can be consumed directly, stored in the battery or fed into the grid. Solar power fed directly into the grid is compensated via a feed-in remuneration. Electricity purchased from the grid must be paid at the household electricity price. For the sake of completeness, the battery may also be charged and discharged directly via the grid. Electricity fed into the grid from the battery is compensated with the wholesale price. For this reason, feeding-in from the battery to the grid is unattractive under current circumstances, since the wholesale price is usually lower than the feed-in remuneration for solar energy. However, this could change in principle if solar module prices and hence feed-in remunerations continue to fall.

Fig. 1. Schematic sketch of the benchmark case (arbitrage battery directly connected to the grid).



revenue for each optimization interval:

maximize r_z

r_z is the revenue at the z^{th} period:

$$r_z = \sum_{t=z \cdot N+1}^{(z+1) \cdot N} P_{wholesale}(t) \cdot (E_{B \rightarrow G}(t) - E_{G \rightarrow B}(t)) \quad (4)$$

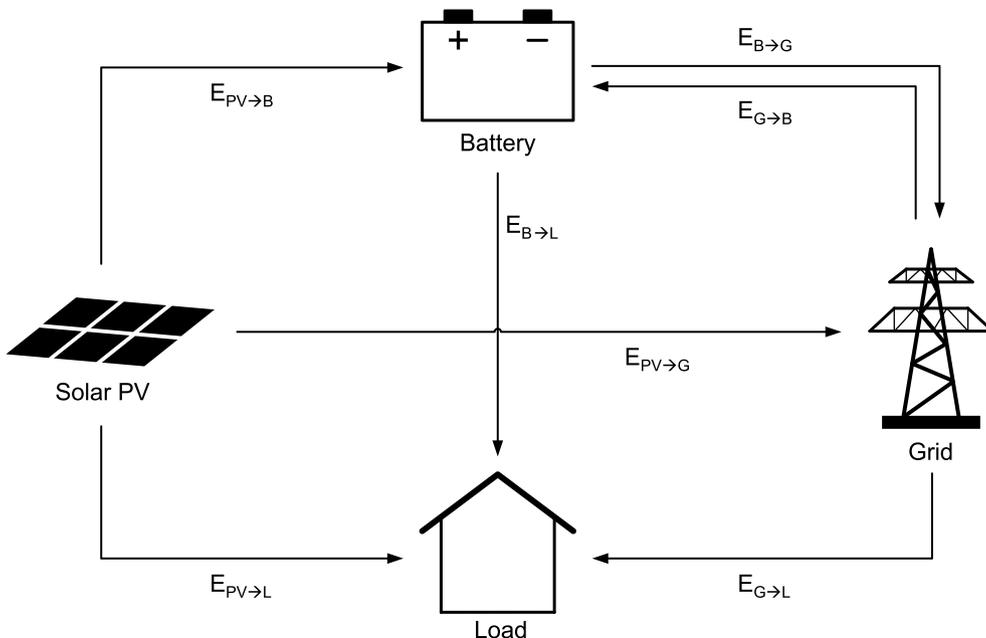


Fig. 2. Schematic sketch of the PV-battery system responding to dynamic prices.

In the BAU case, the dispatch optimization can be formalized in a straightforward way. Since the household electricity price is assumed to be constant and there are no other charging or load flow restrictions,⁶ and the wholesale electricity price is always lower than the retail electricity price, and the retail prices always exceed the level of feed-in remuneration, the following simple dispatch pattern corresponds to the optimum: If there is excess power (i.e. solar generation > consumption), energy is stored in the battery as long as the battery is not yet fully charged. As soon as the battery is fully charged, the generation surpluses are fed into the grid. Conversely, if generation is low (i.e. solar generation < consumption), the battery is discharged until empty, then electricity is drawn from the grid.

To summarize:

1. Technology: PV-battery system.
2. Focal economic parameters:
 - Charging cost: 0 (from PV).
 - Discharging revenues: Avoided retail electricity price.
3. Storage application: Minimization of expenditures for electricity, i.e. maximization of self-consumption.

The constraints of the optimization, which is a special case of the following setting, can be found in the annex [Appendix A.2](#).

2.4.4. Dispatch optimization for alternative instrument mixes

For the alternative cases, the battery is also connected to a PV system, the same technical layout as before applies (see [Fig. 2](#)). Depending on the instrument mix, the prices for generation and/or consumption now vary per hour, so the simplifications from the previous case do not hold true at all time steps. Net cash flows stem from electricity sales via the feed-in remuneration in the case of feed-in of solar electricity or via the wholesale market price in the case of feed-in of electricity from the battery, and from expenditures on retail electricity purchases. The dispatch algorithm chooses the best option of the trade-off between feeding in electricity and thus generating income from sales, and storing or using electricity directly to cover the local load, thus minimizing the expenditures to be paid for grid electricity. For each optimization interval, the wholesale market prices, generated solar power and the household consumption are known with perfect foresight. The revenue maximizing objective function for each optimization period z is:

maximize r_z

with r_z as the revenue over an interval N per optimization period z :

$$r_z = \sum_{n=z \cdot N+1}^{(z+1) \cdot N} (FIT(t) \cdot E_{PV \rightarrow G}(t) + P_{wholesale}(t) \cdot E_{B \rightarrow G}(t) - P_{retail}(t) \cdot E_{G \rightarrow L}(t) - P_{retail}(t) \cdot E_{G \rightarrow B}(t)) \quad (7)$$

To summarize:

1. Technology: PV-battery system.
2. Focal economic parameters:
 - Charging cost: 0 (from PV), retail electricity price (from grid).
 - Discharging revenues: Avoided retail electricity price (from PV), wholesale market price (from grid).
3. Storage application: Minimization of expenditures for electricity, i.e. optimization of battery dispatch to maximize avoided retail electricity (primary) and wholesale market revenues (secondary).

⁶ If a subsidized loan for solar battery storage is used, the output of the PV-battery system is restricted to 50% of the nominal power of the PV panels ([Figgenger et al., 2018](#)). This restriction is neglected here, since it only occurs in the special case if the support scheme is used. The support scheme is phased out, and only about 20% of new installations have made use of the scheme and are therefore subject to the restriction ([Figgenger et al., 2018](#)).

Table 2

Mean values for self-consumption and autarky rate and avoided network charges for all considered cases (74 households)

Instrument mix	Self-Consumption Rate	Autarky Rate	Avoided Network Charges in Euro/a
BAU	0.501	0.711	189.49
F	0.501	0.711	0.00
RTP	0.442	0.636	149.99
RTP + F	0.440	0.631	0.00
VFIT	0.445	0.640	149.99
VFIT + F	0.436	0.629	0.00
RTP + VFIT	0.446	0.628	144.70
RTP + VFIT + F	0.442	0.619	0.00

The constraints of the formulation can be found in the annex [Appendix A.3](#).

2.5. System sizing

Investment and system sizing decisions are to a large degree dependent on the instrument mix consumers are governed by ([Ossenbrink, 2017](#)). However, a dynamic adjustment of the system size according to the instrument mix is not considered in this analysis; the size of the battery or the PV modules is not determined within the MILP economic optimization, but instead set heuristically. Numerous drivers determine when households invest in PV and/or battery systems ([Klingler, 2017](#); [Frey et al., 2019](#)), so system size optimization according to mere economic indicators would neglect other important investment and sizing variables. For example, prosumers also strive to increase autarky and self-consumption rates, among others ([Engelken et al., 2018](#)). As a complete investment model for PV-battery systems was outside the scope of the analysis, we take current literature values for the relative size of the battery and PV modules compared to the household load and leave these relative sizes constant per instrument mix.

The size of the battery s^B in kWh is chosen relatively to the yearly load Λ in MWh of each household:

$$\hat{s}^B = s^B / \Lambda \quad (8)$$

with \hat{s}^B as the relative battery size. We define the relative size of the PV modules as $\hat{s}^{PV} = s^{PV} \cdot h / \Lambda$ in the same way with s^{PV} in kW and h as a unit of time so that \hat{s}^{PV} is dimensionless. Additionally, one can determine the PV size in comparison to the size of the battery as $\kappa = s^{PV} \cdot h / s^B$.

2.6. Data and input parameters

Concerning these sizing parameters, [Figgenger et al. \(2018\)](#) report a value of $\hat{s}^B = 1.6$ for 2017, so a household with a load of 5 MWh = 5000 kWh would install a battery of $5 \cdot 1.6 = 8$ kWh in this analysis. κ is found to be 1 ([Figgenger et al., 2018](#)), i.e. \hat{s}^{PV} is also 1.6.

Load time series with a high temporal resolution are necessary in order to depict the variance of self-consumption. [Beck et al. \(2016\)](#), among others, have shown that the shape of the household load profile has a higher impact on attainable self-consumption and autarky rates than the generation profile. Here, 74 profiles by [Tjaden et al. \(2015\)](#) in hourly resolution are considered.⁷ On aggregate, these profiles yield roughly the shape of the standard load profile, i.e. the load profile of an average household ([Tjaden et al., 2015](#)). The mean yearly load is 4685 kWh (see [Table 5](#)), so the mean size of the analyzed PV modules

⁷ For higher modeling accuracy, a sub-hourly time resolution of generation and load is preferable in sole PV self-consumption systems ([Beck et al., 2016](#)). Modeling in hourly resolution yields satisfactory accuracy if a battery is used (like in our case), as [Quoilin et al. \(2016\)](#) and others have shown.

Table 3
Parameters and Assumptions

Input Parameter	Symbol	Unit	Value	Derived From
Project Lifetime	Y	Years	20	Model Assumption
PV Specific Investment	I_0^{PV}	Euro/kW _p	1280	PV Magazine (2019)
PV Cost Scaling Factor	γ	–	–0.063	Feldman et al. (2012)
PV Operation & Maintenance	$C_{o\&m}^{PV}$	%	1	Model Assumption
Relative PV size	\tilde{s}^{PV}	–	1.6	Figgenger et al. (2018)
Relative battery size	\tilde{s}^B	–	1.6	Figgenger et al. (2018)
Battery Specific Investment	I_0^B	Euro/kWh	1300	Figgenger et al. (2018)
Battery Cost Scaling Factor	ν	–	–0.154	Figgenger et al. (2017)
Battery Operation & Maintenance	$C_{o\&m}^B$	%	1	Model Assumption
Battery Lifetime	L	Number of Cycles	8000	Model Assumption
Discharge Efficiency	η_d	%	95	Model Assumption
Charge Efficiency	η_c	%	95	Model Assumption
Self-discharge	η_s	%/h	0.2	Model Assumption
Optimization Interval	N	h	24	Model Assumption
Total Evaluated Duration	T	h	8760	Model Assumption
Energy to power ratio	E/P	–	2	Model Assumption
Value added tax	VAT	%	19	–
Feed-in Remuneration	FIT	cent/kWh	12.3	Bundesverband Solarwirtschaft eV (2017)
Mean Cost of Acquiring Electricity	$P_{electricityAcq}$	cent/kWh	5.63	BDEW (2017)
EEG and other support levies	P_{levies}	cent/kWh	7.68	BDEW (2017)
Taxes	P_{taxes}	cent/kWh	3.71	BDEW (2017)
Volumetric Network Charge	P_{volNC}	cent/kWh	5.69	BDEW (2017)
Fixed network charge (baseline)	$P_{fixedNC}$	Euro/a	66	BDEW (2017)
Fixed network charge (policy instrument €)	$P_{fixedNC}$	Euro/a	204	Model Assumption

Table 4
Intermediate factors derived from model calculations

Input Parameter	Symbol	Unit	Value
Optimization Periods	Z	–	365
Account Balancing Constant	c	cent/kWh	2.59
Scaling Factor for Time Varying Levy	α	–	1.36
Scaling Factor for Time Varying Feed-in Remuneration	β	–	2.32

Table 5
Descriptive statistics of main time series

Descriptor	Spot prices $P_{wholesale}$ [EUR/MWh]	Yearly Household Load Λ [kWh]
Mean	28.95	4685.0
Median	28.21	4561.9
Min	– 130.09	1398.9
Max	104.96	8635.0
SD	12.49	1414.3

and batteries are $s^{PV} = 7.5$ kW and $s^B = 7.5$ kWh, respectively.

The feed-in time series is based on the average solar generation in Germany of the year 2016, data is taken from (Open Power System Data, 2017; Wiese et al., 2019). The data source also includes the day ahead wholesale electricity market prices of 2016 for Germany (see Table 5 for descriptive statistics). Further techno-economic parameters and their sources are listed in Table 3.

3. Results

3.1. Market alignment for different instrument mixes

As described above, the market alignment indicator MAI is measured by comparing the short-term welfare effect of a prosumer battery with an optimal benchmark case. In the following, we present how well

this operationalization is able to assess the market alignment of PV-battery systems for different instrument mixes.

Fig. 3 shows the distribution of the MAI for each instrument mix under investigation. The variation among each individual instrument mix stems from the variance of the 74 household load profiles. The business-as-usual (BAU) case and its fixed network charge counterpart case (€) exhibit the lowest MAI values, in fact slightly negative ones.⁸

The closer the price signals for the PV-battery system match those of the wholesale market, the closer the dispatch profiles should be to the theoretical benchmark. The highest MAI values are therefore attained by the two cases which combine real-time prices and a time-varying feed-in remuneration ($RTP + VFIT$ and $RTP + VFIT + F$), with mean values of 0.25 and maximum values of 0.4. As an example, see the two dispatch examples for a sunny and cloudy day (Fig. 4 and 5). These cases transmit both signals for consumption (real-time retail electricity prices) and generation (a time-varying feed-in remuneration). As more scarcity information is revealed to the prosumer, there is a higher incentive and flexibility to shift the charging of the battery. As outlined in the figure captions, the charging of the battery is shifted to the afternoon in the sunny example (Fig. 4) when retail prices are lower. In the cloudy example (Fig. 5), the battery is not used at all in the BAU case, whereas deltas in retail prices are utilized to charge and discharge the battery in the $RTP + VFIT + F$ case.

In the middle of the MAI spectrum are the instrument mixes with sole time-varying feed-in tariffs or real-time pricing schemes (Fig. 3), realizing mean MAI values of ca. 0.1–0.2. With the RTP instrument present, the instrument mixes with fixed network charges exhibit significantly higher values of market alignment, as the overall retail price signal shape and therefore the incentive structure is different. With less constant “offset” by volumetric network charges, the wholesale market signals can be transmitted more directly.⁹ Hence the fixed network component has an effect on market alignment.

⁸ The bau and f case exhibit the same dispatch pattern, as the optimization logic of the business as usual case described above also applies to f.

⁹ As an example, see Figs E4 and E.5 where the mean retail price level is lower in $RTP + VFIT + F$ compared to bau as the network charges are already paid for.

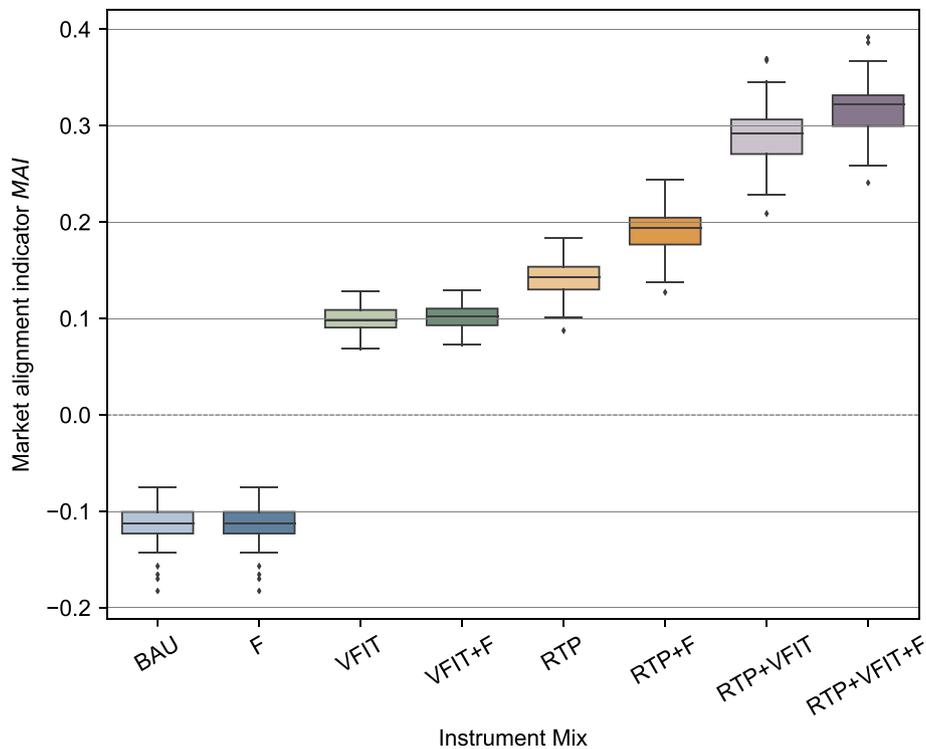


Fig. 3. Distribution of the market alignment indicator (MAI) for different instrument mixes. The uncertainty in the values per instrument mix stems from a variation of the household load profiles.

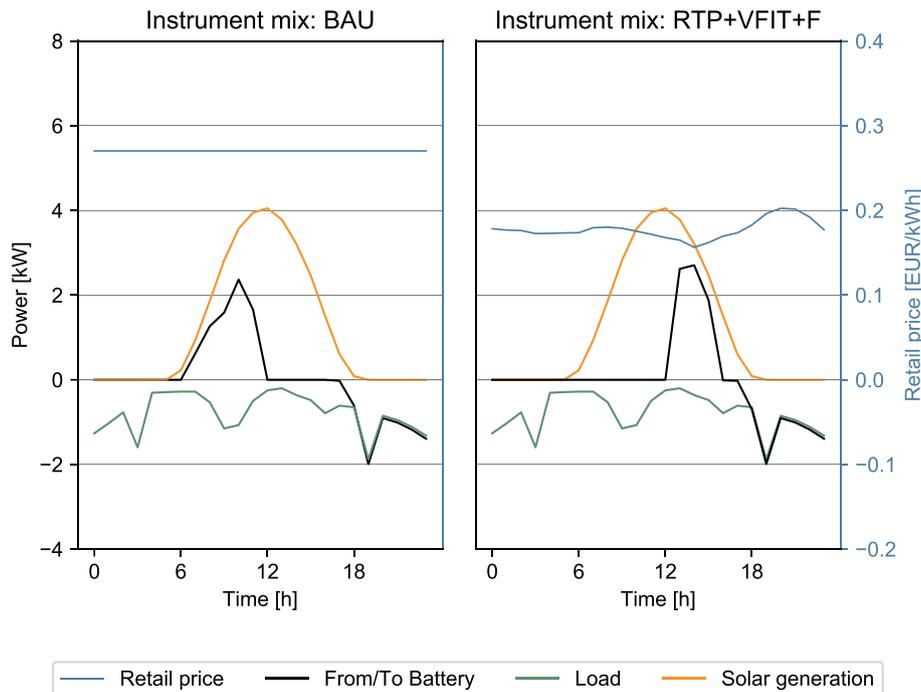


Fig. 4. Dispatch example for a sunny day for the instrument mixes BAU and RTP + VFIT + F. In the latter, the retail price (blue curve, right axis of both plots) is not fixed, incentivizing to shift battery charging to the afternoon. In the BAU case, there is no such incentive and the battery is charged as soon as a local surplus is generated.

3.2. Market alignment for different relative system sizes

The relative sizing of the PV-battery system plays an important role for the MAI. Fig. 6 depicts the MAI for a relative battery of size of 1.6 (mean absolute size: 7.5 kWh) and different PV sizes.

For small PV sizes, RTP attains comparatively higher values and vice versa for VFIT schemes. RTP + VFIT performs the best for all combinations;

BAU always exhibits the lowest MAI values (ca. -0.1).

RTP shows higher MAI values for smaller PV sizes, as such a system is more grid-consumption driven, because the amount of self-produced energy is comparatively small. Hence RTP can regulate the system more, as this is a consumption price signal. Conversely, a large PV-system has many hours of high generation, and a time-varying generation signal will reveal scarcity signals on that side of the chain, leading to a

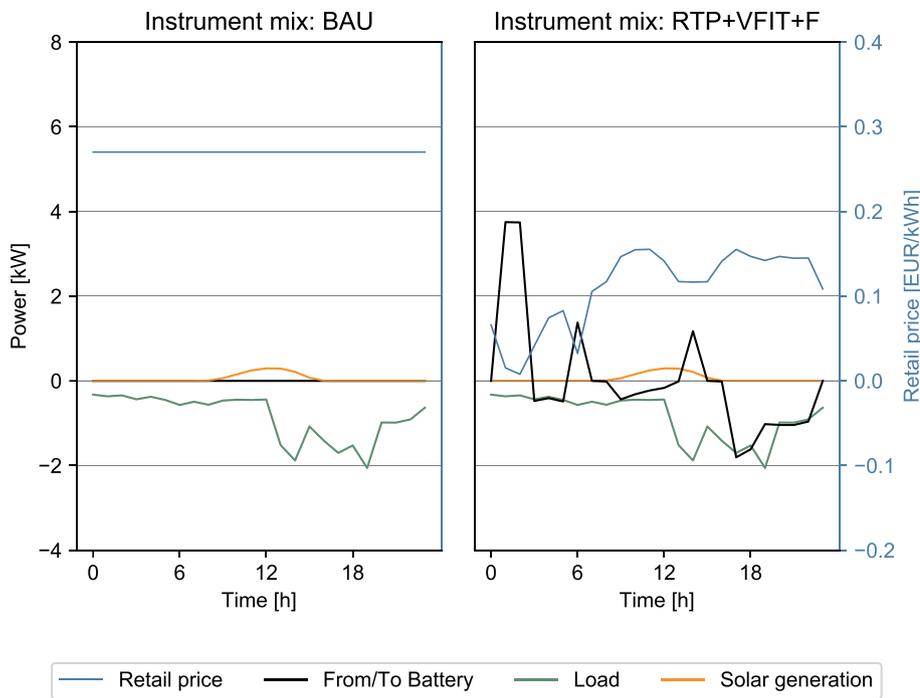


Fig. 5. Dispatch example for a cloudy day for the instrument mixes BAU and RTP + VFIT + F. The local generation cannot cover the load. In the BAU case, the battery is not used at all. For the RTP + VFIT + F instrument mix, the battery is charged in low demand hours at night and discharged when electricity is comparatively scarce system-wide (in the evening). Moreover, the battery uses retail price dips during the day to recharge. For this particular case, the RTP + VFIT + F instrument mix reduces the yearly self-consumption rate to 0.44 compared to 0.50 in the BAU case, reduces the autarky rate from 0.68 to 0.58, but raises MAI from -0.12 to 0.33.

changed battery usage and thus a higher comparative MAI for VFIT for larger PV-systems. The RTP + VFIT instrument mix is able to exploit both signals, in the figure RTP + VFIT is the superposition of the shape of the two MAI curves of RTP and VFIT.

The relative size of the battery has an equally important impact on the market alignment: Fig. 7 depicts the MAI for a fixed relative PV size of 1.6 (mean size: 7.5 kW) and varying relative battery sizes. Again, the BAU case always exhibits lowest MAI values, less than -0.1 for larger batteries sizes. As opposed to the PV size variation, the MAI monotonically decreases for all instrument mixes (but the BAU case) for increasing system sizes. A larger battery gives the prosumer more scope of

action for the optimization exercise. It thus becomes possible to exploit asymmetries in incentives over longer time-scales. This is true for all instrument mixes under investigation as all of the proposed ones cannot reduce distortions completely (and hence do not attain MAI values close to 1, as seen in Fig. 3).

The BAU case is comparatively good for relatively small PV-systems (or comparatively larger batteries) by mere ‘coincidence’. For small PV systems, not much solar generation is fed into the grid; the battery undergoes one cycle per day, loading in the morning and the afternoon, discharging in the evening, roughly matching the arbitrage case. This cannot be guaranteed for larger PV systems (or smaller batteries),

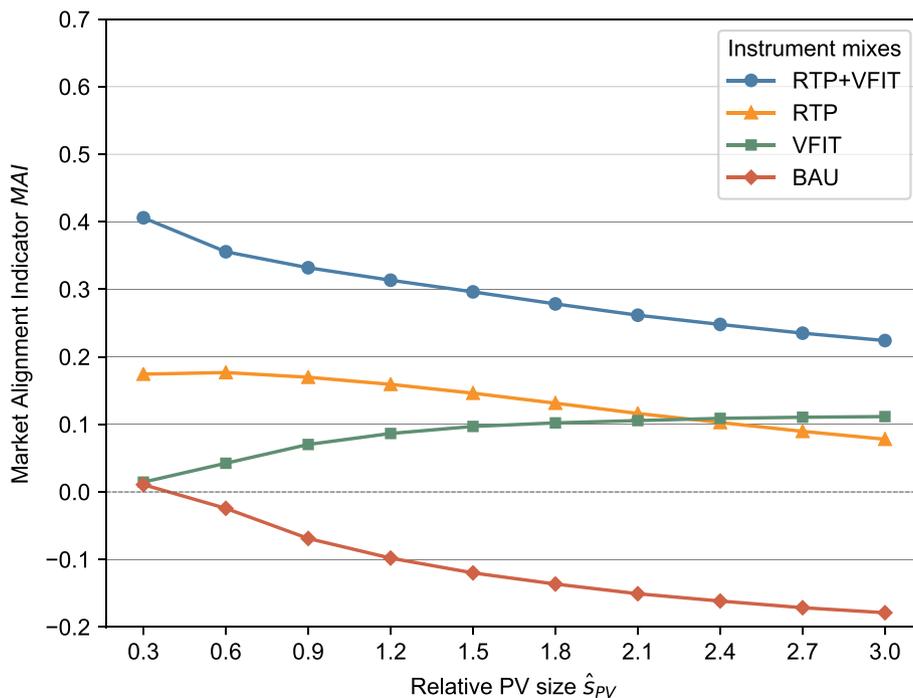


Fig. 6. Mean market alignment indicator MAI for different PV sizes and various instrument mixes for a mean battery size of 7.5 kWh.

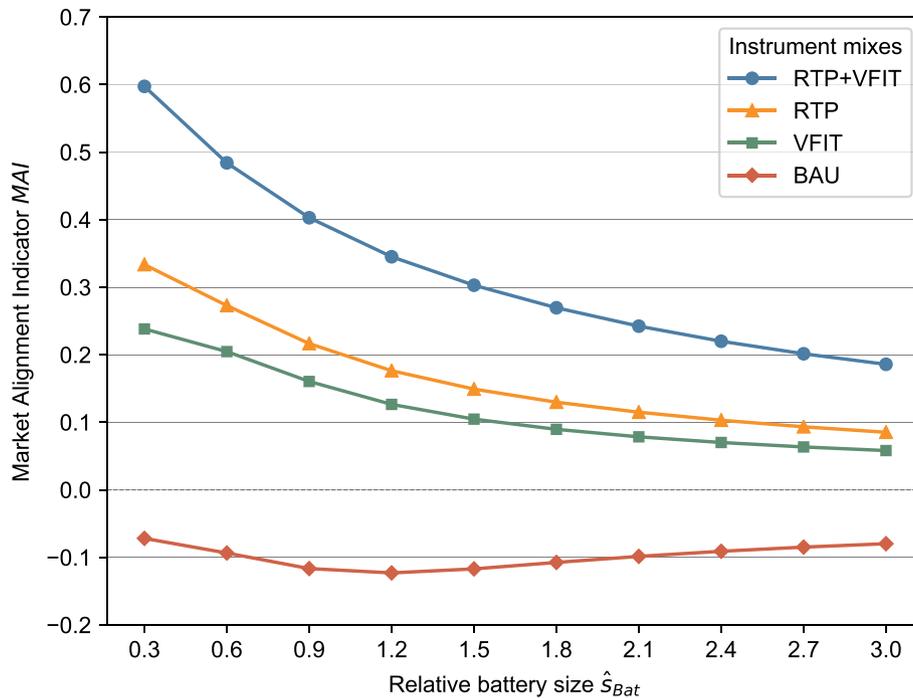


Fig. 7. Mean market alignment indicator MAI for different battery sizes and various instrument mixes for a mean PV system size of 7.5 kW_p .

which tend to feed-in their surplus electricity during peak times at noon, when prices are low, lowering their MAI considerably.

As outlined above, the instrument mixes including fixed network charges exhibit higher MAI values if combined with real-time prices. However, the general shape of the sizing curve in Fig. 6 and 7 would look the same. For visual clarity, we therefore neglected them in both examples.

3.3. MAI - A useful operationalization?

The previous two subsections revealed that one can evaluate the market alignment of PV-battery systems by merely looking at the storage component and not at the solar feed-in profile. This is possible as the two are interrelated via the household load. Hypothetically, if there would be no distinction between ‘before the meter’ and ‘behind the meter’, i.e. if generation/consumption would be remunerated/billed with the same time-varying price, the economic signal should be symmetrical, and the market alignment indicator MAI should converge to 1. This is indeed true: if the PV generation gets remunerated with the wholesale price, and the retail electricity price seen by the prosumer is also the wholesale price without any extras, MAI takes a value of exactly 1. In such an ideal system, it would not matter if the PV modules or battery were located before or behind the meter. In reality, we just showed that market distortions like levies (such as the renewable energy support levy) and taxes (tax on electricity and value-added tax) will prevent the indicator from becoming close to 1.

The MAI formulation has the advantage that it is relatively parsimonious and can be normalized in a simple way. It thus conveniently summarizes an important dimension of the integration challenge of distributed energy sources. A MAI of 1 means that in all cases, the charging states point in the same direction, and vice versa a MAI of low to negative values that the operation of the battery is inefficient in terms of alignment to wholesale market signals. With this simple normalization, different systems at different sizes can be compared.

3.4. Other indicators

How would the proposed instrument mixes affect the individual

prosumer? Fig. 8 shows the mean IRR for all households per instrument mix. The rates do not change considerably between BAU and RTP, VFIT and RTP + VFIT, because the proportionality factors of the consumption and generation real-time signals were set to resemble current consumer price levels on average. For the fixed network charge cases, considerably lower IRR (ca. 2% lower) are attained, as a significant share of the retail price cannot be circumvented with self-generation anymore.

The calculated IRR are considerably lower than in other similar studies like that of Bertsch et al. (2017). These differences are mostly attributable to other capital expenditure assumptions. What if batteries were cheaper? To test this sensitivity, Fig. 9 shows the mean IRR for different specific battery costs in the RTP case. Positive returns can be achieved for all system configurations under consideration at specific battery prices of 500 Euro/kWh, (compared to around 1300 Euro/kWh as of 2017, but falling rapidly (Figgner et al., 2018)). We did not test for a PV cost sensitivity, as the feed-in remuneration is dynamically adjusted to account for changes in the LCOE of solar in Germany, hence similar levels of profitability should be attained in a feed-in tariff scheme like the one at hand.

Autarky and self-consumption rates are slightly lower for all alternative cases. The avoided network charges are by definition 0 for the fixed network charge cases, as they are covered as a lump-sum per accounting period. See Table 2 for a summary. The other alternative instrument mixes (RTP, VFIT, RTP + VFIT) exhibit slightly lower avoided network charges, but are for themselves likely not sufficient to compensate fully for the network charge attribution problem outlined in the introduction.

4. Discussion

4.1. External validity: transferability to other (real-world) cases

Our evaluation did not assess the practical implementation of the possible instrument mixes in detail. The following aspects are pointers to further necessary research.

Concerning the technical implementation, an agency question arises about who would execute the optimization of the prosumer system, i.e. who would forecast, optimize and take dispatch decisions. It could well

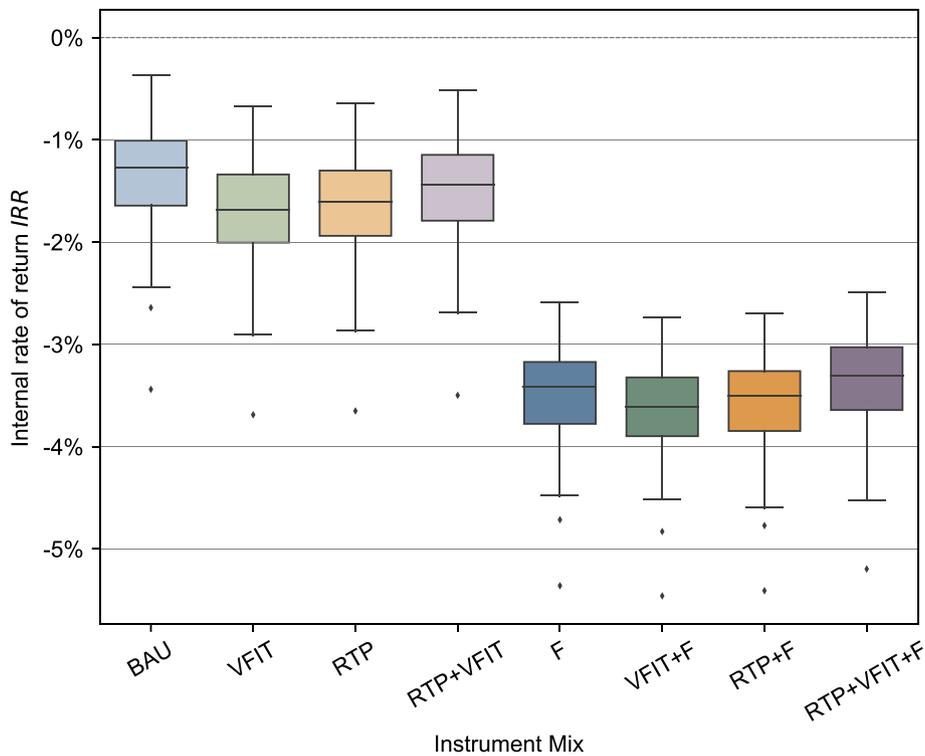


Fig. 8. Distribution of the internal rate of return (IRR) for different instrument mixes. The uncertainty in the values per instrument mix stems from variation of the household load profiles.

be that optimization algorithms such as the ones described here would be automated and act rather autonomously. Another possibility is that aggregators would pool the flexibility of the prosumer systems and control and market them in lieu of their costumers. In any case, depending on the local level of sophistication, the measuring and calculation equipment would come at a cost (which is not considered in this

evaluation). Further research should elaborate on how economic and technical scarcity signals could be transmitted efficiently and securely to the relevant stakeholders. If the exponential price decline of computation, communication and storage devices continues (Kurzweil, 2005), at least the cost aspect might not be a significant obstacle.

The evaluation has shown that technical parameters like the system

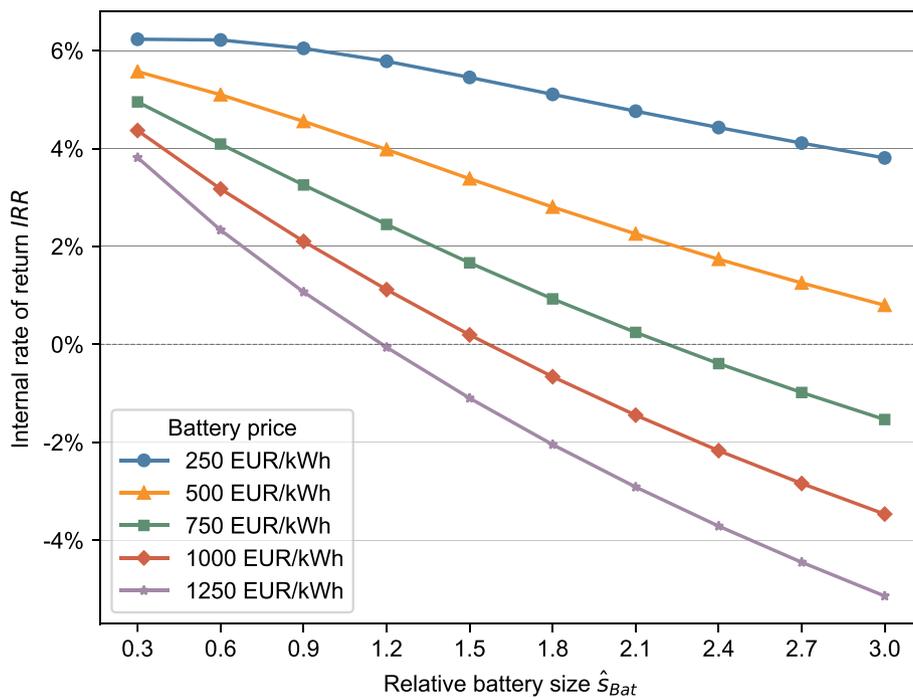


Fig. 9. IRR variation for different battery sizes and prices for the RTP instrument mix and a mean PV system size of 7.5 kW_p. The current (2018) value is around 1250 Euro/kWh.

size have a significant impact on the level of market alignment. The current approach only evaluates “statically” the optimal dispatch of already built systems. If an instrument mix favors a particular sizing (for example: comparatively larger batteries), this could have a substantial effect on the market alignment, as relative size plays an important role (see Fig. 6 and 7). In order to model this “dynamic” market alignment, investment models for PV-battery systems are needed to depict the sizing dependence of the particular instrument mix.

The higher the relative market value of solar energy, the more important a well-aligned battery dispatch to wholesale market signals would become. High market values for solar, e.g. during noon hours due to high system-wide demand of air-conditioning, could render it important that solar energy is available for all consumers and not stored locally at those times. General conclusions about the instrument mixes outside the German case study should be made with caution. Nevertheless, the study is transferable to other cases insofar as the general approach – comparing an ideal benchmark to a proposed policy instrument – can be applied to any instrument mix, any technology and any local setting.

Implications on internal validity are listed in the online model documentation.¹⁰

4.2. Market alignment indicator revisited

One important constraint of the current approach is the fact that we neglect a price influence of the prosumers on the system at large. Currently, the market alignment indicator is only properly defined if the aggregated dispatch of PV-battery systems does not have a significant impact on the wholesale market price.

All cases are simulated using perfect foresight of demand, PV generation and wholesale market prices. While this is a reasonable assumption for the wholesale market prices (in real world cases, day-ahead wholesale price information would be available; this is the reason why an optimization interval of 24 h was chosen), the other two components are to be predicted. The simulated values for the MAI and the other economic indicators therefore correspond to a best case estimate that is likely not attainable in reality. The effect of uncertainty on the market alignment indicator could be random in nature, but we expect that it would systematically shift the indicator downwards (it would be an unlikely coincidence if the dispatch would align systematically better to the benchmark, to the contrary, it would likely be worse aligned to market signals especially when the perfect-foresight market alignment was very high in the first place). Follow-up studies should look at the effect of uncertainty on the market alignment indicator.

The definition of the MAI used here is limited insofar as no consideration about the grid, especially the distribution grid, is made. As Moshövel et al. (2015) have shown, the usage of PV-battery systems can help to alleviate stress from distribution networks under the right conditions. This cannot be captured with the current approach and is not part of the market alignment definition here. Furthermore, note that storage can provide many other system services (ancillary services, etc.). Therefore, the market alignment is only a proxy about how “system-friendly” prosumer storages are towards the electricity system at large. If market signals would reflect the constraints of the additional components that allow for the system’s functioning, the market alignment would correspond to overall system-friendliness. Future work could, for example, study other forms of capacity or fixed tariffs which take into account the contribution of grid-usage at peak times.

¹⁰ The open-source model and its documentation can be found at <https://gitlab.com/energy-systems-analysis/prosumerpolicy/>.

4.3. Policy interpretation

The assessment in this paper shows that the current retail electricity price and solar remuneration structures in Germany provide inefficient incentives for household PV-battery system operation. This fact is represented by a MAI that is less than zero, which means that the operation of these plants is misaligned to market signals and induces on average additional costs. For example, prosumer storages can be idle even if there would be system-wide storage demand, or they can store energy while electricity is relatively scarce.

This inefficiency can be alleviated by transmitting scarcity signals to prosumers. Both time-varying prices for generation (time-varying feed-in remuneration) and consumption (real-time electricity prices) can improve the market alignment. The introduction of real-time electricity prices is the biggest individual lever to align distributed energy to the wholesale market.

The parameters of real-time electricity prices and feed-in tariffs can be chosen so that other indicators such as profitability and self-consumption rates are left virtually untouched. Conversely, this means that these measures can be implemented without affecting individual investment incentives. The situation is different for fixed network charges, which do affect the business case of self-consumption, as it is no longer possible to circumvent network charges (the main motivation to implement them in the first place).

The effectiveness of the particular instrument mix depends on the relative levels of the feed-in tariff, the grid consumption to be saved and the solar LCOE. For example, increasing fixed network charges have a positive impact on the MAI if combined with RTP, as the missing network charges alter the overall retail price signal shape. With less constant offset, the wholesale market signals can be transmitted “more directly” and can sometimes be even be lower than the feed-in remuneration. Hence, fixed network charges send scarcity signals and have an effect on market alignment under such circumstances. In contrast the VFIT + F case: Here, fixed network charges have no influence on the MAI. This is specific to the German case, where retail electricity prices are comparatively high. Even if the network charge is not part of the retail price, the price is still higher than the time-varying feed-in tariff, transmitting no different signal to prosumers as in the VFIT case (Fig. 3).

The economic analysis revealed that a larger number of PV-battery system configurations will become attractive if batteries become cheaper (Fig. 9). If current PV and battery price trends continue, more systems will probably be built in the future. Novel business models such as leasing, new forms of trading platforms or community energy storage could further increase profitability. If many households invest in PV-batter systems under the assumption that the current retail price and remuneration scheme will remain as it is, future revenue expectations are created. It could thus become politically more and more difficult to change the retail price structure. In order not to delay investments in distributed energy systems or to jeopardize refinancing of already built systems, it seems advisable to implement regulatory changes as soon as possible to avoid such situations.

This paper has shown that an improved regulatory framework concerning the market alignment of distributed energy sources offers enormous potential for value creation and the measures to be taken appear relatively straightforward. Other trends in the energy system such as the introduction of heat pumps and electric cars are likely to point in a similar direction: If many consumers are to participate actively and efficiently in the energy system, scarcity signals or other incentives must be given, or else the flexibility potential of these technologies will remain untapped.

5. Conclusion and policy implications

Many operation modes of distributed energy sources are currently not optimal from an overall electricity system perspective because its

scarcity signals do not reach the end consumer. For example, solar self-consumption and battery operation in Germany is currently optimized locally under the premise of maximizing self-consumption, as prosumers are generally exposed to fixed retail prices and feed-in tariffs. The article has therefore argued that robust indicators of what constitutes “system-friendly” operating patterns of distributed prosumer storages of different configurations are needed to assess potential alternative market designs that could better align the distributed actors with the operation of the electricity system at large. We presented a so-called market alignment indicator (*MAI*) that measures how close the dispatch of a prosumer storage resembles that of a battery which acts solely on market scarcity signals. By comparing the relative economic efficiency of a prosumer battery to such a benchmark case that is completely responsive to wholesale market signals, the indicator *MAI* has the advantage that different system sizes and different policy instrument mixes can be conveniently compared.

While the perceived fairness of dynamic prices is debatable (Neuteleers et al., 2017), we find for the German case that such pricing schemes can have a significant impact on the dispatch of PV-battery systems. Remaining distortions like levies and taxes will prevent a complete alignment with wholesale market prices – our study has shown that the dispatch of prosumer batteries never reaches the ideal benchmark even if all alternative policy instruments under investigation were regarded in combination. However, we showed that the parameters of retail electricity prices can be tweaked in such a way that the operation patterns of distributed energy sources are better aligned to the scarcity signals of the wholesale market. With the right parametrization of proportionality factors, both real-time prices and time-

varying feed-in remuneration do not significantly influence the economic indicators (internal rate of return, self-consumption and autarky rates) of the PV-battery systems, meaning that they are neutral for the single prosumer concerning investment incentives compared to the business-as-usual case. Moreover, the paper has argued that incentive asymmetries should be alleviated before a large number of systems requiring the current electricity rate scheme to refinance have been built.

The proposed indicator can assess the effectiveness of such adjustments. More and more actors are already participating as active consumers and producers in the electricity system with devices and measures such as heat pumps, electric vehicle charging, demand response and community and prosumer storages. Given any instrument mix, any technology or any local setting, the presented market alignment indicator approach can be used to analyze situations where the synchronization of many distributed actors with the overall system is in question.

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Appendix A. Dispatch Optimization

The following section describes the constraints of the dispatch optimization in subsection 2.4.

Appendix A.1. Constraints of benchmark case

For the benchmark case, the objective function is subject to the following energy constraints:

$$E_{\text{storage}}(t) = \begin{cases} E_{\text{initial}} & \text{if } t = 0 \\ E_{\text{storage}}(t-1) \cdot \zeta_s \\ + E_{G \rightarrow B}(t) \cdot \eta_c - \frac{E_{B \rightarrow G}(t)}{\eta_d} & \text{otherwise} \end{cases} \quad (\text{A.1})$$

where $E_{\text{storage}}(t)$ is the energy in the storage at time t (also know as state of charge (SoC)) and E_{initial} is the initial energy present in the battery. Battery losses are taken into account by a discharge and charge efficiency, η_d and η_c , respectively, and an hourly battery self discharge ζ_s . The upper and lower bounds of the optimization variables are:

$$0 \leq E_{G \rightarrow B}(t) \leq \frac{K_{\text{Max}}}{\eta_{\text{charge}}} \quad (\text{A.2})$$

$$0 \leq E_{B \rightarrow G}(t) \leq K_{\text{Max}} \eta_{\text{discharge}} \quad (\text{A.3})$$

$$0 \leq E_{\text{Storage}}(t) \leq E_{\text{MaxCapacity}} \quad (\text{A.4})$$

where K_{Max} represents the maximum battery charge and discharge capacity¹¹, and $E_{\text{MaxCapacity}}$ is the maximum storage capacity.

Appendix A.2. Constraints of business as usual case

The dispatch optimization for the BAU case is subject to the following energy constraints:

$$E_{\text{load}}(t) = E_{PV \rightarrow L}(t) + E_{B \rightarrow L}(t) + E_{G \rightarrow L}(t) \quad (\text{A.5})$$

$$E_{\text{Storage}}(t) = \begin{cases} E_{\text{initial}} & \text{at } t = 0 \\ E_{\text{Storage}}(t-1) \cdot \zeta_s \\ + E_{PV \rightarrow B}(t) \cdot \eta_c - \frac{E_{B \rightarrow L}(t)}{\eta_d} & \text{otherwise} \end{cases} \quad (\text{A.6})$$

¹¹ In this work, the terms charge capacity and battery capacity refer to the energy capacity and not the power capacity.

Appendix A.3. Constraints of dispatch optimization responding to dynamic prices

The dispatch optimization for the time-varying cases is subject to the following energy constraints:

$$E_{Storage}(t) = \begin{cases} E_{initial} & \text{at } t = 0 \\ E_{Storage}(t-1) \cdot \zeta_s + E_{PV \rightarrow B}(t) \cdot \eta_c + E_{G \rightarrow B}(t) \cdot \eta_c & \text{otherwise} \\ -E_{B \rightarrow G}(t) / \eta_d - E_{B \rightarrow L}(t) / \eta_d & \end{cases} \quad (\text{A.7})$$

$$E_{PV}(t) = E_{PV \rightarrow L}(t) + E_{PV \rightarrow B}(t) + E_{PV \rightarrow G}(t) \quad (\text{A.8})$$

$$E_{Load}(t) = E_{G \rightarrow L}(t) + E_{B \rightarrow L}(t) + E_{PV \rightarrow L}(t) \quad (\text{A.9})$$

$$E_{B \rightarrow G} \leq \delta \cdot K_{max} \cdot \eta_{discharge} \quad (\text{A.10})$$

$$E_{G \rightarrow B} \leq (1 - \delta) \cdot \frac{K_{max}}{\eta_{charge}} \quad (\text{A.11})$$

$$E_{PV \rightarrow L}(t), E_{PV \rightarrow G}(t), E_{G \rightarrow L}(t) \geq 0 \quad (\text{A.12})$$

$$0 \leq E_{Storage}(t) \leq E_{MaxCapacity} \quad (\text{A.13})$$

Equations A.7, A.8 and A.9 represent the energy balance for the storage, the solar generation and the household load, respectively. Equations A.10 and A.11 represent the upper bound of the variables $E_{B \rightarrow G}$ and $E_{G \rightarrow B}$. In these equations, δ is a binary variable that can be either 1 or 0. By introducing this variable, $E_{B \rightarrow G}$ and $E_{G \rightarrow B}$ can not co-exist and the battery is prevented from withdrawing and feeding into the grid at the same time step t .

Appendix B. Other indicators

In this section, the formulation of all other indicators besides the *MAI* are presented.

Appendix B.1. . NPV and IRR

The *NPV* is calculated as

$$NPV(r) = -C_0 + \sum_{y=1}^Y \frac{C_{act}(y) - C_{baseline}(y)}{(1+r)^y} \quad (\text{B.1})$$

where C_0 , C_{act} , $C_{baseline}$ denote initial investment and actual and baseline case cash flows, respectively, in the y^{th} year. r is the discount rate, Y the project lifetime. The baseline is that no PV-battery system is built, i.e. the consumer only obtains electricity from the grid and must therefore pay the household electricity price for all consumption.

The initial investment in the net present value calculation is defined as:

$$C_0 = (s^{PV} \cdot I^{PV} + s^B \cdot I^B) \cdot (1 + VAT) \quad (\text{B.2})$$

where s^{PV} denotes the PV size in kW_p, I^{PV} the PV cost per kW_p, s^B the battery system size in kWh and I^B the specific initial investment cost of a battery system per kWh and *VAT* the purchase tax.

Initial PV specific investment is:

$$I^{PV} = I_0^{PV} \cdot \left(\frac{s^{PV}}{10 \text{ kW}_p} \right)^\gamma \quad (\text{B.3})$$

where I_0^{PV} is the specific investment cost of PV and γ is a scaling parameter that accounts for the higher specific costs of smaller PV-systems. Similarly, the initial battery specific investment cost is:

$$I^B(y) = I_0^B(y) \cdot \left(\frac{s^B}{10 \text{ kWh}} \right)^\nu \quad (\text{B.4})$$

where ν is similarly a scaling parameter and $I_0^B(y)$ is the specific investment cost of the battery at year y .

The yearly actual cost $C_{act}(y)$ is:

$$C_{act}(y) = R(y) - s^{PV} \cdot C_{o\&m}^{PV} - s^B \cdot C_{o\&m}^B - C_{repl}^B(y) \quad (\text{B.5})$$

$R(y)$ represents the total revenue R per year y defined as:

$$R(y) = \sum_{z=1}^Z r_z - P_{fixedNC} \cdot (1 + VAT) \quad (\text{B.6})$$

where z is the total number of optimization intervals.

$C_{o\&m}^{PV}$ and $C_{o\&m}^B$ are the yearly maintenance cost of PV and battery respectively and $C_{repl}^B(y)$ is the cost of replacing a battery defined as follows:

$$C_{repl}^B(y) = \begin{cases} 0 & \text{if } \sum_{x=1}^y i_x < L \\ s^B \cdot I^B(y) & \text{if } \sum_{x=1}^y i_x \geq L \end{cases}$$

L is the battery cycle lifetime. When the added yearly cycle counts i exceed the lifetime, at the given year y the battery is replaced to a cost dependent on the year y . On the other hand, $C_{baseline}(y)$, the baseline case at each year y , is considered to be that of a normal consumer without a PV or a storage system. This implies that the consumer will satisfy all her load λ from the grid as follows:

$$C_{baseline}(y) = \sum_{t=1}^T P_{retail}(t) \cdot \lambda(t) \quad (B.7)$$

The internal rate of return (IRR) is defined by the discount rate r for which the NPV becomes exactly 0:

$$-C_0 + \sum_{y=1}^Y \frac{C_{act}(y) - C_{baseline}(y)}{(1 + IRR)^y} = 0 \quad (B.8)$$

Appendix B.2. Self-consumption and autarky rate

The self-consumption rate SC is defined as the share of consumed electricity relative to the total PV generation (Luthander et al., 2016). Consequently, SC is found:

$$SC = \frac{\text{self} - \text{Consumed PV}}{\text{Total PV generated}} = 1 - \frac{\text{Fed} - \text{In}}{\text{Total PV generated}} \quad (B.9)$$

where Fed-In is the total energy fed into the grid. The autarky rate A is given via:

$$A = \frac{\text{self} - \text{Consumed PV}}{\text{Total Consumption}} \quad (B.10)$$

In order to assess the influence on the distribution of network charges and the distribution of costs and thus the ‘death spiral’ problem of the investigated instrument mixes, the lost or avoided network charges are accounted for. Depending on the instrument mix, the network charge prosumers avoid NC_{avoid} can vary. The NC_{avoid} is:

$$NC_{avoid} = \text{self} - \text{Consumed PV-volumetric Network Charges} / \text{kWh} \quad (B.11)$$

Appendix C. Market Constants

The following section will present the determination of certain constants that will allow to parametrize the individual instrument mixes in such a way that their cumulative monetary effect over the course of a year is, by design, zero, meaning that a consumer without PV system would pay same amount of money for electricity per year for each instrument mix.

The retail electricity price the prosumer pays at time t for each kWh consumed from the grid is made up of the following components:

$$P_{retail} = (P_{electricity} + P_{volNC} + P_{levies} + P_{axes}) \cdot (1 + VAT) \quad (C.1)$$

where $P_{electricity}$ is the cost of acquiring electricity, P_{volNC} is the volumetric network charge, P_{levies} is the renewable energy feed-in (EEG) and other support mechanism levies, P_{axes} are associated taxes and VAT is the sales tax. Consequently, what a customer pays to the utility each year is:

$$P_{year} = \sum_{t=1}^T (P_{retail} \cdot E_{G \rightarrow L}(t)) + P_{fixedNC} \cdot (1 + VAT) \quad (C.2)$$

which is the sum of the product of the retail price and the total energy consumption from the grid, plus and additional $P_{fixedNC}$ that represents a fixed network charge along with a VAT tax.

Appendix C.0.1. Real-time electricity pricing

In cases involving real pricing schemes, the $P_{electricity}$ at each time t is:

$$P_{electricity}(t) = P_{wholesale}(t) + c \quad (C.3)$$

where $P_{wholesale}(t)$ is the spot market price and c is a constant that accounts for the additional administrative and service fees associated with acquiring electricity. The constant c can be calculated through the following equation:

$$c = \frac{P_{electricityAcq} \cdot \sum_{t=1}^T \lambda(t) - P_{wholesale}(t) \cdot \lambda(t)}{\sum_{t=1}^T \lambda(t)} \quad (C.4)$$

where $P_{electricityAcq}$ is the component of the electricity bill allocated for electricity acquisition and λ is the hourly load. By adding the constant c , the average consumer without a PV system will pay the same amount of money for electricity, see Table 4 for numerical values.

Appendix C.0.2. Feed-in Remuneration

Feed-in remuneration can be either fixed or time varying. In case of fixed feed-in remuneration, the prosumer receives a constant level of remuneration fit regardless of the time of the feed-in. The retail electricity bill, as shown in equation (C.1), has a levy component that is directly related to the feed-in remuneration FIT . Consequently, in cases of a fixed feed-in remuneration, the levy will also be a constant as shown in the following equations:

$$FIT(t) = fit$$

$$P_{levies}(t) = eeg$$

On the other hand, in cases of time-varying FIT , prosumer will receive a variable remuneration depending on the time of feeding in. The value of the FIT is:

$$FIT(t) = \beta \cdot P_{electricity}(t) \quad (C.5)$$

$$\beta = \frac{fit \cdot \sum_{t=1}^T E_{PV \rightarrow G}(t)}{P_{electricity}(t) \cdot E_{PV \rightarrow G}(t)} \quad (C.6)$$

where fit is the fixed feed-in remuneration and β represents the scaling factor to ensure a conservation of the total payments of the FIT between the instrument mixes. In cases where the retail electricity prices are also varying, the levy component in equation (C.1) will also be time-varying and can similarly be found:

$$P_{levies}(t) = \alpha \cdot P_{electricity}(t) \quad (C.7)$$

$$\alpha = \frac{eeg \cdot \sum_{t=1}^T \lambda(t)}{P_{electricity}(t) \cdot \lambda(t)} \quad (C.8)$$

where eeg is the constant levy, λ is the hourly load and α is the scaling factor that ensures the conservation of paid levies across the various evaluated instrument mixes.

Appendix D. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.enpol.2019.110901>.

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