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Research paper

Improving energy system design with optimization models by quantifying the economic granularity gap: The case of prosumer self-consumption in Germany

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ABSTRACT

Energy system models are widely used to inform the political decisions required to successfully mitigate climate change in the energy sector. The energy system optimization models (ESOMs) used to identify cost-minimal transformation pathways assume the perfect behavior of market participants from a central planner's perspective. Neglecting the decision-making under uncertainties or biased perceptions and attitudes leads to inaccurate assumptions regarding the requirements of a successful energy transition. In particular, ESOMs underestimate the required capacities for power generation, storage, and transmission compared with real-world energy systems, a phenomenon known as the "economic granularity gap". Agent-based models (ABMs) are helpful tools for capturing the behavior of market actors. Hence, attempts have been made to identify and alleviate this phenomenon through the coupling of ESOMs and ABMs. In this paper, we propose an automated workflow for such model coupling and quantify the economic granularity gap for the case of photovoltaic-prosumer self-consumption. Our results show that the current business models and regulatory frameworks affecting prosumer self-consumption patterns require the adaptation of cost-minimal energy system designs. However, if correctly implemented, instruments such as dynamic tariffs could narrow the economic granularity gap, shifting real-world energy systems closer to their ideal counterparts.

1. Introduction

1.1. Background

To successfully mitigate climate change, it is important for the energy sector to understand how future energy supplies can be realized in a secure, affordable, and sustainable manner. In this sense, a multitude of aspects need to be considered, such as the electrification of energy demand sectors (IPCC, 2022), security of supply even in time periods that lack renewable power generation (Lund et al., 2015), and a highly diverse, economically feasible mix of technologies. Hence, identifying suitable policy measures to incentivize the transformation of the energy supply system is a complex task. Models are often applied to gain insights into possible future scenarios for the energy system (e.g., to serve as decision support in energy policy and industry Pfenninger et al., 2014). To investigate the uptake of renewable power generation and the deregulation of power markets from a macro-perspective, a broad variety of so-called energy system models has evolved, each having different strengths for addressing the abovementioned aspects (Ringkjøb et al., 2018; Horschig and Thrän, 2017). One prominent category is energy system optimization models (ESOMs) (Hawker and Bell, 2020), which are applied to observe the possible operation of power plants and technologies for balancing the intermittent power supply of renewable energy sources. Due to the clear specification of an objective function and constraints, they provide an easy-to-use framework for modeling decision processes and simulating investment decisions when multiple solutions are conceivable (i.e., different technologies for load-balancing). Moreover, they are used to design future energy systems subject to the relevant political targets (e.g., greenhouse gas (GHG) mitigation targets) (Sasanpour et al., 2021). The purpose of drafting such ideal system designs is to provide templates for navigating the transformation of the system, e.g., by setting incentives. However, at this point, obvious discrepancies between the ideal scenario

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and the real world occur. We refer to these discrepancies as the granularity gaps that are revealed across several dimensions of a model. For example, Prina et al. (2020) identified four dimensions of interest in this regard, which they refer to as resolution in time, in space, in techno-economic detail, and in sector-coupling. Similarly, we have defined four model dimensions where granularity gaps occur (Cao et al., 2021), but propose, in addition to the distinction of the temporal, spatial, technological scale, the consideration of an economic scale.

1.2. Economic granularity gap

The economic granularity gap comprises different aspects. In general, similar to the well-studied granularity gaps in the spatial, temporal, and technological dimensions (Fleischer, 2020; Poncelet et al., 2016), it includes the error made by abstracting processes and phenomena of the real world in a model (abstraction bias). This may relate to the assumption of perfect and equal information of market participants, thus neglecting decision-making under uncertainty or ignoring distortions due to regulatory framework conditions. The obvious solution for bridging the economic granularity gap in this regard relates to the calibration of a model. This calibration may be based on observations of the real world or, if this is not possible, with models that simulate the real world with greater accuracy. A more specific aspect concerning the economic granularity gap reflects the differences between a hypothetical macroeconomic optimum and the entirety of decisions of heterogeneous actors in the real world. This is particularly important in liberalized energy markets under the absence of large integrated energy utilities (Hawker and Bell, 2020), where a multitude of stakeholders and decision-makers, each having diverging levels of knowledge or economic rationale, may lead to significant economic efficiency losses compared with the desired system optimum (aggregation bias).

The aggregation bias is a notable weakness of the above-mentioned ESOMs. Other modeling approaches are more accurate in this regard, but have drawbacks elsewhere. Consequently, model-coupling frameworks are popular for compensating the weaknesses of different modeling approaches. In this context, it becomes obvious that granularity gaps also exist between modeling approaches, so we can study different gaps depending on our reference point. Maintaining the perspective of a partial-equilibrium model, such as an ESOM, an economic granularity gap exists when compared with a macroeconometric model, which describes the entire economy. Studying this "upper economic granularity gap" is a typical research subject in energy economics. For example, this relates to so-called hybrid modeling (Catenazzi, 2009) (realized by coupling bottom-up and top-down models). In this paper, we focus on the less-studied "lower economic granularity gap", which concerns discrepancies between a central, technology-rich planning approach and the microeconomic decision-making of individuals.

1.3. Research questions

Given the existence of the lower economic granularity gap in the context of transforming the energy system, several questions arise. They concern, for instance, the technological composition of desired energy systems (e.g., in terms of the required expansion of energy storage, power grids, or other so-called flexibility services). As shown by Neumann and Brown, diverse system compositions exist near the macroeconomic optimum (Neumann and Brown, 2021). Accordingly, the two research questions to be answered in this study are as follows:

1. Does the economic granularity gap significantly affect system designs that result from an ESOM?
2. If this is the case, how can the economic granularity gap be bridged?

Answering these questions is relevant because, from a central planner's perspective, it would help improve the quality of an ESOM in terms of the plausibility of ideal system designs. From a policy-making perspective, the answers would offer opportunities for evaluating the system-friendliness of regulatory frameworks or incentives. However, both questions come down to one key requirement: the capability to quantify effects that can be summarized as the lower economic granularity gap.

1.4. How to quantify the economic granularity gap?

To quantify the lower economic granularity gap in the context of energy system design, we seek approaches that extend or complement the capabilities of central planning by modeling real-world processes at greater detail in terms of decision-making in liberalized markets. This includes the possibility to influence these processes by the application of policy measures. Data-driven approaches allow such models to be calibrated according to empirical data (e.g., by comparing investment decisions from before and after the liberalization of power markets). Against the background of fundamental changes in the existing energy system (which are poorly reflected by empirical data), we consider data-driven approaches to be insufficient. In other words, they are limited to effects that are assumed to be crucial in energy futures with unprecedented power generation from renewable energy sources. A large spectrum of different model types can simulate liberalized markets with asymmetric behavior, each having strengths and weaknesses. In the field of decentralized electricity markets, several simulation approaches have been established. For instance, System Dynamics is a suitable approach because it enables the modeling of imperfections and allows the dynamic influencing of individuals' decision-making (Teufel et al., 2013). From a technological bottom-up perspective, agent-based models (ABMs) are similar (Macal, 2010). Accordingly, they are useful when considering the bounded rationality of actors and understanding the impact of self-organized actions on the overall energy system (Deissenroth et al., 2017). In contrast to ESOMs, ABMs have no superior, centrally specified objective function and each actor is modeled as a self-interested agent with the aim of maximizing their own utility. This property enables the evolution of the energy system to be simulated, in which agents act autonomously based on their microeconomic interests, but are affected by external factors such as regulatory frameworks. Compared with ESOMs, simulation approaches have several drawbacks. From a microeconomic perspective, estimating the feedback of the overall system to the multitude of individual decisions and anticipating the behavior of other actors becomes very complex. This requires more profound knowledge about actors on the micro-level, and thus, more data. Accordingly, modeling anticipations across a large diversity of actor groups, and particularly decision-making on investments into competing flexibility options, becomes as challenging as stand-alone microeconomic simulation models. The substantial data demand also complicates the development of energy simulation models with broad system boundaries (i.e., for sector-coupling in an international context) needed to draft comprehensive energy system designs.

To conclude, simulation approaches are a valuable building block for quantifying the lower economic granularity gap. However, simulating aspects that are easily modeled in ESOMs (e.g., investments into competing technologies) is somewhat difficult. Therefore, instead of extending existing models to integrate the strengths of other model types, the coupling of both macroeconomic system optimization and microeconomic simulation provides an alternative means of studying the lower economic granularity gap within broad system boundaries. In the literature, such model setups have been applied by Torralba-Diaz et al. (2020), who coupled the ESOM E2M2 with the ABM AMIRIS to investigate the effect of increasing the share of renewable energy sources on the lower economic granularity gap. They demonstrated the suitability of this methodological approach for the analysis of energy policy instruments, and revealed the importance of a harmonized model-coupling setup. Additionally, Torralba-Díaz and her co-authors recommend bidirectional model couplings for studying the impact of policy measures on the granularity gap. Few studies have examined a combination of macroeconomic system optimization and microeconomic simulation to investigate the effects of different policy measures. One example is the study of Fraunholz et al. who used the ESOM ELMOD for multi-regional dispatch optimization and the ABM PowerACE to analyze the long-term effects of splitting the German electricity market into two zones (Fraunholz et al., 2021). Their key result was the negative welfare effect of splitting into northern and southern price zones from benchmarking against a single price zone. Hence, in a very simplified way, this means that market splitting under the assumptions used by Fraunholz et al. contributes to an increase in the lower economic granularity gap.

1.5. Scope and contribution

Granularity gaps in energy system designs are known. However, in the domain of energy system analysis, they are mainly studied with regard to spatial and temporal model dimensions. The economic dimension has been the focus of economic research, where the granularity gap between macroeconometric and partial-equilibrium models is investigated. However, there are few model-coupling frameworks that quantify the biases between central planning and decentralized decision-making in liberalized energy markets using only bottom-up models. Accordingly, this study considers the question of how to implement an optimal overall energy system in an environment with a multitude of decentralized decision-makers. For this purpose, we set up a modeling framework that combines two bottom-up energy system models: (1) a partial-equilibrium model, represented by an ESOM, for designing future energy systems and (2) an ABM for simulating the individual decision-making behavior of market participants. In this way, we combine the strengths of both modeling approaches: the capability of determining the globally required investment decisions across a broad set of technological options ensures mitigation of GHG emissions for a future target year, while the influence of specific policy measures on decision-makers in a market and the impact on optimal energy system design can be investigated. The framework retains a holistic perspective by ensuring a broad technological and spatial scope. Therefore, our analysis focuses on Germany, which is embedded in the European power system, while pan-European power exchange and hourly operation planning of competing load-balancing technologies are optimized, and further energy demand sectors are interfaced. As an example for a specific policy instrument, we investigate dynamic tariffs for photovoltaic (PV)-prosumers.

To summarize, our contributions are as follows:

1. We present a modeling framework based on the coupling of an ESOM and an ABM implemented via automatized and reproducible workflows. This allows the market alignment (Klein et al., 2019) of defined technologies in interaction with a transforming European energy system to be studied.
2. We quantify the lower economic granularity gap in energy system design in terms of changes in system costs and underlying model-endogenous investment decisions induced by the different modeling perspectives. This answers research question 1.
3. We demonstrate and assess the different effects that cause model-specific deviations in system costs starting from a fully harmonized modeling framework.
4. For an exemplary real-world application, we examine how the implementation of frequently discussed instruments (e.g., real-time pricing) influences the economic granularity gap. This answers research question 2.

We do not claim to study all aspects of the economic granularity gap in detail (i.e., uncertainty or distortions due to changing framework conditions).

The remainder of this paper is structured as follows. Section 2 describes how we quantify the economic granularity gap, and briefly introduces the specific energy system models used. Next, we detail the crucial aspects of how to establish and calibrate a stable model-coupling system and introduce our case-study and the underlying assumptions and data, before presenting our results on the influence of actor behavior and, thus, the operation strategy of PV-prosumers on the economic granularity gap. The corresponding evaluations are presented in Section 3 and critically discussed in Section 4. Section 5 concludes this paper. A list of acronyms and abbreviations used in this paper is presented in Appendix A.

2. Methodology

2.1. Overall workflow

The core of our methodology is the coupling of two existing energy system models, i.e., REMix, an ESOM with a geographical focus on Europe and Maghreb (EUMA), and AMIRIS, an ABM of the German electricity market. These models are introduced in Section 2.2. We perform our analysis in four phases. Fig. 1 schematically illustrates these phases and the proposed model-coupling workflow. We prepare the model-coupling setup in phases A and B of the overall workflow. The complete model-coupling workflow is then applied in phases C and D to investigate the case of PV-prosumers. In the following, we give an overview of the proposed workflows, followed by a more in-depth description in Sections 2.3 and 2.4.

In general, our analysis relies on the definition of an observable deviation Δ that allows us to measure a quantity we refer to as the economic granularity gap Δ^{econ}. In Section 2.4, we propose an indicator for quantifying these deviations (i.e., to calculate Δ). The overall workflow begins with the harmonization of both models. In phase A, we configure the models with a set of equal values for parameters that describe the same quantities in order to produce identical results. This means that if AMIRIS is configured with a macroeconomic ideal energy system expansion and system-cost-minimizing storage dispatch (resulting from REMix), the power system operation of both models will be congruent (no deviation, i.e., $\Delta = 0$). Therefore, the techno-economic input data are unified, and the power generation capacities, cross-border power exchange, and dispatch of all storage technologies are fed from REMix into AMIRIS. To select and process the input parameters for AMIRIS, we use iog2x[2] (see Section 2.4.1 for a detailed explanation of the harmonization phase). In contrast to the harmonization phase, where the operation of all storage

[2] iog2x is a Python-based software tool that uses the open-source workflow manager ioproc (Fuchs et al., 2020).

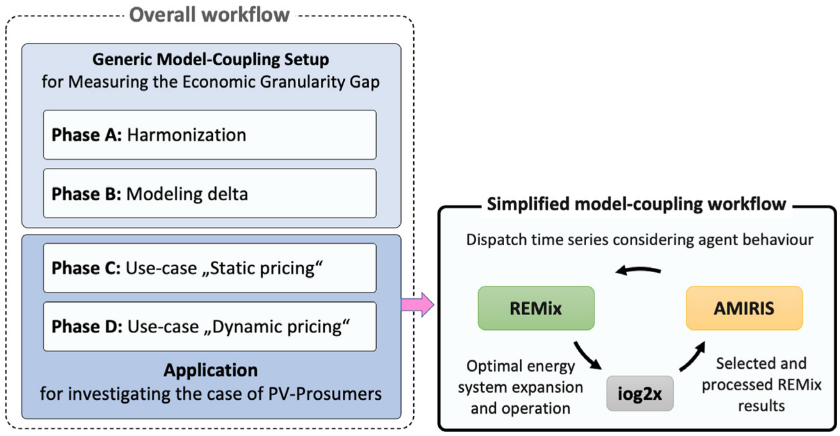

Fig. 1. Schematic overview of the overall and model-coupling workflow. In phase A, both models are harmonized. In phase B, the modeling delta between REMix and AMIRIS is measured. In phases C and D, stakeholder behavior is enabled and different tariffs for prosumers are compared. In the proposed model-coupling workflow (applied in phases C and D), data are exchanged between REMix and AMIRIS through a Python tool called iog2x.

technologies is determined in REMix, phase B optimizes the dispatch of the selected storage technology in AMIRIS. While the storage systems in both models are optimized to minimize the system costs, the resulting deviation is caused by different model implementations of the storage operation in REMix and AMIRIS. In our analysis, we call this deviation the modeling delta Δ^{model}. If Δ^{model} is sufficiently small, we conclude that the Δ observed for the following application of the model-coupling setup mainly represents the economic granularity gap, rather than deviations caused by different real-world abstractions of energy storage ($\Delta^{\text{model}} \ll \Delta^{\text{econ}}$). The derivation of Δ^{model} is further detailed in Section 2.4.2. In phase C, stakeholder behavior is enabled in AMIRIS. For the specific use-case investigated in Section 2.5, this means that instead of minimizing total system costs, storage units mimic actor behavior under current market and regulatory conditions. In particular, AMIRIS simulates PV-battery storage systems in households (PV-prosumers) in Germany. Next, we run REMix for the second time, while constraining the dispatch of the PV-storage system according to the PV-prosumer behavior given by AMIRIS. This allows us to assess the impact of PV-prosumer self-consumption patterns on the optimal system design (i.e., system expansion), and thus on the economic granularity gap ($\Delta \approx \Delta^{\text{econ}}$). How this gap can be influenced is finally demonstrated by exposing the PV-prosumers to different market implementations of dynamic tariffs (phase D). To integrate the required data processing into an automated, executable workflow, the Remote Component Environment (RCE) software is used (Seider et al., 2012).

2.2. Models

This section describes the energy system models used in this study. Table 1 provides an overview of the model scopes and features that are relevant to our methodological approach. Note that the model characteristics listed in Table 1 are limited to their application in this paper.

2.2.1. REMix

REMix is a modeling framework used for setting up ESOMs that optimize the capacity and hourly dispatch of technologies under perfect foresight for one target year by minimizing total system costs. The total system costs are represented by investment (i.e., costs for new renewable power generators, grid and storage technologies) and operational expenditure (e.g., fuel costs). Accordingly, power plants are only built and dispatched if this contributes to a least-cost solution within the operation horizon of one year. The modeled power sector is represented by various power plant technologies, energy storage facilities, and power transmission capacities, and includes the electricity demand for conventional consumers, heat pumps, heat boilers, and electric vehicles. Typical applications of REMix are scenario studies for interconnected countries (Gils et al., 2017). The model input includes techno-economic parameters for each technology, feed-in time series, and potential data for renewable power generation, such as from wind and solar radiation. Besides prescribed and maximal capacities for power generation, storage, and transmission, the costs for CO_2 certificates are part of the scenario dataset (see Section 2.5.2).

2.2.2. AMIRIS

AMIRIS is an ABM that simulates the operational behavior of the actors in the energy-only market with an hourly resolution and uses a merit order model to calculate the electricity prices.[3] In AMIRIS, the power plants offer their generated electricity based on their marginal costs, which are calculated based on power plant-specific techno-economic parameters (such as efficiency and variable costs) as well as fuel and CO_2 prices. Depending on the implemented policy regimes, renewable power generators may be entitled to receive financial support.

Based on information from fossil-fired and renewable power plants, the forecaster agent in AMIRIS provides a prediction of electricity prices for a certain period in the future (e.g., the next 24 h). In the following analysis, we assume that forecasts do not contain any errors. This forecast can then be used by storage operators to optimize the bidding strategy and maximize their utility function. The model setup allows the implementation and strategic optimization of one storage entity. In other words, in our case study (see Section 2.5), one flexibility option is operated according to stakeholder behavior: PV-prosumers (remaining flexibility options mimic the macroeconomic optimal dispatch in REMix). For the purpose of this study, two new agents are modeled and introduced to AMIRIS: prosumers and aggregator agents. The role and functionality of these agents are described in Section 2.5. The structure of AMIRIS and the interactions among agents are schematically illustrated in Appendix B.

[3] A basic version of AMIRIS is open-source. The model developments made in this study are not part of the open-source model at the time of publication. See also Appendix B.

Table 1
Model comparison between REMix and AMIRIS based on the model setups used in this study.

	REMix	AMIRIS
Primary purpose	Planning of large-scale energy systems	Simulation of actors' behavior with limited information
Model type	Linear optimization	Agent-based simulation
Economic scope	System perspective: Central planner minimizes total system cost	Actor perspective: Each actor minimizes its own costs
Temporal scope	One year with hourly resolution	One year with hourly resolution
Spatial scope	Country-specific	Country-specific
Geographical focus	Europe and Maghreb	Germany
Specific features	Investment planning, cross-border power exchange, power sector coupling to heat and transport sector	Actor behavior under different policy regimes

2.3. Model coupling

To perform our analysis, multiple datasets need to be processed and exchanged between REMix and AMIRIS. Depending on the individual phase of our overall workflow, this is done in a unidirectional or bidirectional manner. In the following, we describe the four steps required for bidirectional data exchange in phases C and D of the overall workflow. The unidirectional data exchange in phases A and B require only steps 1–3 of the model-coupling workflow. Note that this model-coupling methodology is independent of the specific use-case analyzed in this paper and can therefore be used to investigate a large variety of policy regimes. Fig. 2 provides a more detailed overview of the corresponding model-coupling workflow implemented in RCE. The advantage of this workflow implementation is that all data processing steps can be executed without specialist knowledge of the models or data processing tools involved.

The model-coupling workflow consists of four data processing steps:

1. The reference energy system (REF) is determined. Therefore, energy system optimization is executed in REMix to provide the optimal expansion and dispatch of power plants, storage technologies, and the electricity grid for a GHG mitigation scenario on the European level. After optimization of REMix, the outputs and input parameters, such as CO_2 and fuel prices, are passed on to iog2x.
2. The iog2x module filters and processes the REMix outputs into AMIRIS inputs. This includes unit conversions, changing data formats, and data aggregation, such as balancing power demand and power exchange time series. We describe the data aggregation process in Section 2.4.1. Appendix C provides a more detailed overview of all technology-specific modifications of the REMix outputs.
   The processed data representing the cost-optimal energy system design are then sent to AMIRIS over a peer-to-peer network connection using RCE.
3. The processed data together with additional parameters that describe the regulatory framework and business model, are used to simulate the electricity market for one year in AMIRIS. In the harmonization phase, the storage agent imitates the determined optimal storage dispatch in REMix. To determine the modeling delta in phase B, the storage agent in AMIRIS minimizes the system costs. In our case study, the AMIRIS market simulation includes PV-storage optimization that minimizes the PV-prosumers' costs.
4. In the last step, we pass the time-series back to REMix. The energy system is then optimized for a second time, with the dispatch of selected technologies constrained according to the AMIRIS results. Regarding the specific case study of this paper (see Section 2.5), we fix the charging and discharging profiles[4] of the batteries that belong to German prosumers with the PV-storage dispatch obtained by AMIRIS. In doing so, we ensure that the corresponding storage technology in REMix reflects the PV-prosumer stakeholder behavior derived from AMIRIS. Concerning generation and storage expansion, the capacity values are directly prescribed according to REF for all regions except that for which dispatch is constrained.

2.4. Setup for measuring the granularity gap

In this section, we describe the measures necessary to achieve a modeling setup that can quantify the economic granularity gap. In particular, we perform model harmonization and measure what we refer to as the modeling delta.

2.4.1. Harmonization

Harmonization requires that, for a certain set of identical input parameters, both involved models produce identical results. However, this is only possible in the absence of model-specific features. Accordingly, in phase A of the overall workflow, the power plants in AMIRIS bid at their marginal costs, and the dispatch of storage systems resembles that from REMix. Furthermore, influences that stem from unequal technological and geographical scopes need to be treated. In particular, this translates into balancing the hourly demand time-series that is input to AMIRIS to consider technologies that are not simulated there. Based on the REMix outputs for Germany, D_t^{total} is calculated as follows:

$$D_t^{total} = D_t^{conv} + D_t^{hp} + D_t^{eBoiler} + D_t^{eCars} + E_t^{export} - E_t^{import} + Z_t^{C,stor} - Z_t^{D,stor} + L_t^{trans}, \forall t, \quad (1)$$

where D_t^{conv} represents the electricity demand of conventional consumers and D_t^{hp}, $D_t^{eBoiler}$, and D_t^{eCars} represent the power consumption of heat pumps, electric boilers, and electric vehicles, respectively. Moreover, electricity imports to Germany E_t^{import}, and the discharging of storage technologies, $Z_t^{D,stor}$, are deducted, whereas electricity export from Germany, E_t^{export}, charging of storage technologies, $Z_t^{C,stor}$, and power transmission losses, L_t^{trans}, are added to the total hourly electricity demand of Germany. Due to the different representations of storage self-discharge in AMIRIS and REMix, this feature is deactivated in both models, i.e., we neglect self-discharge in all storage technologies. Due to the very low self-discharge rate and short charge cycle (less than one day) of the PV-storage systems, this assumption does not significantly impact the results.

To achieve successful harmonization, two indicators that can be directly obtained from the model outputs are useful: electricity prices and costs. The former is the more intuitive choice, but different mechanisms for determining wholesale market electricity prices with REMix and AMIRIS render a direct comparison difficult.[5] Although an appropriate model configuration would allow

[4] In other words, we set the lower and upper bounds of the storage optimization variables, i.e., hourly amounts of charged and discharged electricity, equal to a fixed value.

[5] To derive the electricity prices in REMix, the dual variables of the power-balance constraint (so-called shadow prices) are used. However, this common

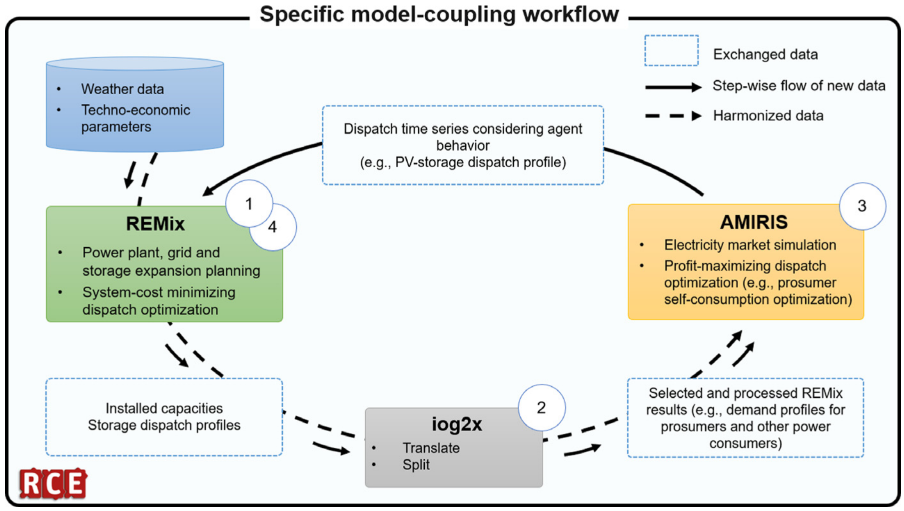

Fig. 2. Data exchange during model-coupling of REMix and AMIRIS. Step 1: Energy system optimization in REMix to determine the REF. Step 2: Filtering and processing the REMix outputs for AMIRIS simulation. Step 3: Electricity market simulation in AMIRIS based on the REF energy system design. Step 4: Second round of energy system optimization in REMix while constraining the dispatch of the selected technologies according to AMIRIS results.

the model harmonization to be assessed, numerical issues still complicate a meaningful comparison. In particular, these issues can be traced back to the non-differentiability of the merit-order curve. Considering a vertical demand curve, the price cannot be precisely determined for supply amounts that lie at the transition between two price levels. At this point, minor numerical differences in demand can cause significant differences in the resulting electricity prices. Unlike the prices, the value of the operational system costs, represented by the area under the price curve, is insensitive to these complications. For this reason, we evaluate the operational system costs of our models instead.[6]

2.4.2. Modeling delta

In phase B of the overall workflow, we determine the modeling delta Δ^{model}. In general, we define the modeling delta as the deviation between results from REMix and AMIRIS that cannot be treated by harmonization. In other words, it is the difference between operational system costs if the dispatch of energy storage is modeled individually in both REMix and AMIRIS (even if storage agents still aim to minimize system costs in AMIRIS).[7] In this phase of the overall workflow, our target is to keep Δ^{model} as small as possible, which calls for additional adjustments of our model-coupling setup. This relates to the reference quantity of a storage component's capacity.[8] To resolve the corresponding discrepancies, the REMix source code adapts the constraints for the capacity cap and storage-balancing so that the converter and storage capacities in REMix represent chemical or potential values, similar to AMIRIS. Additionally, the storage level in REMix is fixed to zero for the last time step of the operational time horizon. This is to replicate the behavior of the storage in AMIRIS, which sees no economic advantage in stored energy at the end of the operation period.

When it comes to modeling energy storage technologies, a further aspect is crucial: the storage operators in AMIRIS use a forecast of the upcoming market prices to optimize the storage dispatch. However, in this model, the competition among storage systems is neglected, meaning that one operator does not anticipate the strategy of other operators. Thus, exposing more than one flexibility option to the same electricity market forecast leads to an overreaction of the storage entities. This model artifact, which is referred to as the avalanche effect in the literature (Ensslen et al., 2018), results in extreme price peaks. Hence, we optimize the operation of only one storage system in AMIRIS and fix the dispatch of all other storage technologies according to the results of REMix.

Nevertheless, the operational system costs vary between the models. The final modeling delta comprises several effects: REMix operates storage technologies with variable costs and has perfect foresight over the whole modeled year, whereas AMIRIS does not consider variable costs for a storage agent's business model. In contrast to REMix, the operation foresight horizon is limited to 48 h, and (dis-)charging is modeled for discrete storage levels.

2.4.3. Granularity gap indicator

As mentioned before, we measure the economic granularity gap in terms of total system costs. The total system costs consist of all expenses for electricity supply in one year of a future scenario, which includes both operational costs (C_k^{OPEX}) and amortization charges (C_k^{CAPEX}) for investments in new infrastructure. Accordingly, we measure Δ^{model} and Δ^{econ} by comparing the total system costs for REF in REMix C_1 (step 1 of the model-coupling workflow, see Fig. 2), with C_4, which is observable after constraining REMix according to the results from AMIRIS in step 4 of the model-coupling workflow:

$$\Delta = C_4 - C_1. \tag{2}$$

The total system costs C_k in step k of the model-coupling workflow are composed of

$$C_k = \underbrace{C_k^{fuels} + C_k^{\mathrm{O\&M}} + C_k^{\mathrm{CO_2}}}_{=C_k^{OPEX}} + C_k^{CAPEX}, \quad \forall k \in \{1, 4\}. \tag{3}$$

interpretation of shadow prices is distorted if the costs for storage operations or capacity expansion are considered in the energy system optimization. A consequence of this circumstance would be additional price levels in the resulting merit-order, which do not formally occur in the real market. In contrast, AMIRIS correctly models the price-building procedure, and thus the merit-order based on individual bids in the day-ahead market.

6 Note that the compared operational system costs for the harmonization of the models are only one part of the total system costs. As we will explain in Section 2.4.3, we use the total system costs as an indicator for quantifying the economic granularity gap.

7 Hence, in phase B, $Z_t^{D,stor}$ and $Z_t^{C,stor}$ are no longer considered in Eq. (1) for the storage technology modeled in AMIRIS.

8 Initially, the capacities of both power converters (e.g., pumps and turbines) and storage (e.g. a water basin) are provided in terms of electricity in REMix. This is not the case for AMIRIS, where converter and storage capacities refer to their chemical or potential values. As the charging and discharging capacities are identical in both models, they cannot be harmonized if one model considers electrical and the other chemical/potential values.

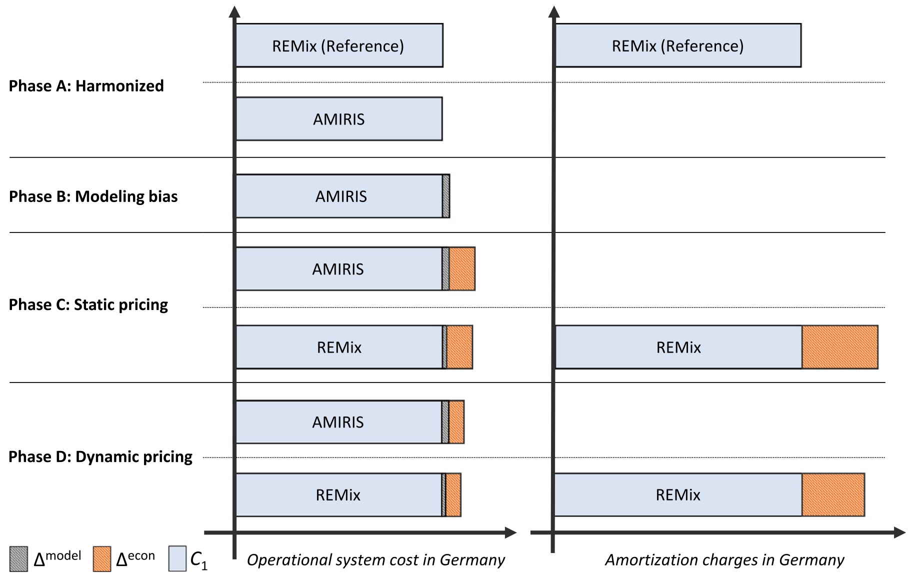

Fig. 3. Schematic overview of qualitative system cost relations: System costs of the reference energy system (C_1, blue bars), the modeling delta (Δ^{model}, gray bars), and the economic granularity gap (Δ^{econ}, orange bars) in the different phases of the overall workflow. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The operational system costs, C_k^{OPEX}, comprise the costs for fuel C_k^{fuels}, operation and maintenance (O&M) costs of the power system components $C_k^{O\&M}$, and costs for emission allowances $C_k^{CO_2}$. Fig. 3 illustrates the different cost components for each phase of our overall workflow. While the operational system costs in AMIRIS and REMix are equal in the harmonization step, a modeling delta (Δ^{model}, shown in gray) can be observed in phase B. The prosumer operation strategy in phases C and D of the overall workflow increases the operational system costs and amortization charges in Germany, resulting in the economic granularity gap (Δ^{econ}, shown in orange).[9]

2.5. Case study

The model-coupling setup is now ready to be applied. Therefore, we consider the battery storage used to moderate the intermittency of the power supply from rooftop PV as the technology to be investigated. In other words, given the successful completion of phases A and B in the overall workflow, we are ready to quantify the impact of stakeholder behavior on energy system design for one particular technology.

2.5.1. PV-prosumers in Germany

The levelized cost of electricity from PV systems has fallen below the retail electricity price in many countries worldwide, a development that has incentivized investment in PV rooftop systems for many households (Lang et al., 2016; Bazilian et al., 2013). Similar to PV systems, battery storage has experienced a significant reduction in system prices. Several studies indicate that this trend will continue in the next few years (Agnew and Dargusch, 2015). As a result, storage systems for rooftop PV (PV-prosumers) have become economically viable for households under certain support schemes and generation potentials (Hoppmann et al., 2014; Bertsch et al., 2017). The available storage capacity gives PV-prosumers the flexibility to store electricity at specific times (e.g., when self-generated PV electricity exceeds the electricity demand or when grid electricity is cheap) and discharge it at later times (e.g., to cover the electricity demand or sell to the grid) (Sarfarazi et al., 2023).

From an overall systems perspective, self-consumption with PV-storage systems is neither desirable nor detrimental (Günther et al., 2021). While the flexibility of PV-prosumers can contribute to the integration of renewable energies, current business models and regulatory frameworks are unable to incentivize a system-beneficial dispatch of PV-prosumers (Sarfarazi et al., 2020; Klein et al., 2019). Moreover, to untap the potential of the residential demand-side flexibility, an entity should undertake the aggregation of the small prosumer capacities (Plaum et al., 2022). Therefore, we investigate how the operation of aggregated PV-prosumers leads to an economic granularity gap under the current regulatory framework and business models in Germany, and how it could be decreased. Accordingly, assessing alternative policy instruments is part of our analysis.

Next, we introduce the energy scenarios and input data used in our case study (Section 2.5.2). In Section 2.5.3, we describe the investigated business models and regulatory framework for two different use-cases: static pricing (phase C of the overall workflow) and several implementations of dynamic pricing (phase D). How PV-prosumers are modeled in AMIRIS is discussed in Section 2.5.4.

2.5.2. Scenarios, input data, and modeling assumptions

The starting point for our analysis is a dataset of the European power system from the year 2020 and the aim for GHG mitigation of 55% compared with 1990. The REMix inputs are based on a previous study by Cao et al. (2020), where the corresponding scenario is referred to as "55% Base: Trend". However, instead of a CO_2 cap, we apply penalties to achieve the emissions reduction target. Therefore, a price of 50 euros per ton of CO_2 is assumed.[10] While the energy system optimization is conducted for EUMA on a national level, the electricity market simulation and the model coupling are carried out for Germany only. According to this scenario, system planning comprises the capacity expansion of wind turbines, PV, pumped-hydro storage, lithium-ion batteries

[9] Note that, for a simple illustration, the operational system cost differences caused by the modeling delta and the economic granularity gap are stacked in this figure. This might not be the case in reality.

[10] In our scenarios, the focus is on the power sector. The study by Cao et al. (2020) shows that, within this model setup, a CO_2 price of 50 euros per ton can achieve GHG mitigation of 55% in the power sector.

and power transmission lines. In addition, the current model setup considers a technology split for both lithium-ion batteries and PV to distinguish rooftop PV with and without storage, utility PV, and stand-alone stationary battery storage, each of which has individual techno-economic parameters. For Germany, this means that the scenario's minimal total generation capacity of PV (46.8 GW) comprises 34.9 GW rooftop PV, which is equally split and assigned to systems with and without storage. In the following, we refer to former as "PV-prosumers". In considering their capacity expansion in REMix, we assume a fixed capacity ratio between PV generators and battery power (factor 2), and for the energy-to-power-ratio of the battery (factor 3).[11] Furthermore, the electricity demand is split to distinguish between PV-prosumers and other power consumers:

- **Aggregated prosumers** (AP) consist of virtually aggregated PV-prosumer households whose hourly power consumption is calculated using typical household demand profiles. These are scaled by the annual electricity demand of PV-prosumers. The former come from a dataset containing measured load profiles of 74 different German households (Tjaden et al., 2015). The annual electricity demand D_t^{AP} is estimated by assuming that a household with an annual demand of 750 kWh installs 1 kW of PV rooftop capacity. Accordingly, the total value for Germany depends on the resulting capacity expansion of rooftop PV systems in step 1 of the model-coupling workflow.
- **Other power consumers** (OPC) represent all electricity demand except that of AP. This includes PV-rooftop systems without integrated battery systems. Accordingly, we calculate the electricity demand by subtracting the electricity demand of the prosumers D_t^{AP} from the total electricity demand of Germany D_t^{total}:

$$D_t^{OPC} = D_t^{total} - D_t^{AP}, \forall t. \tag{4}$$

In other words, in contrast to model harmonization (phase A of the overall workflow), data for the prosumer systems are treated separately in AMIRIS.

Moreover, we assume that conventional and renewable power plants always bid with their marginal costs, i.e., no mark-ups or mark-downs for conventional power plants and no feed-in incentives for renewable power plants, except for PV-prosumers. Moreover, as mentioned above, large-scale storage systems (e.g., pump storage systems) have the system-optimal dispatch calculated in REMix. Regarding prosumer self-consumption, we consider complete relief from regulatory-induced charges for behind-the-meter use of self-generated electricity.

2.5.3. Use-cases under investigation

In this section, we define the use-cases for phases C and D of our overall workflow. In phase C, the electricity retail price (p_t^s) and the price of purchasing electricity from prosumers (p_t^p) are fixed over a year. In this case, p_t^p adopts the value of the feed-in remuneration (FiT). Taxes and levies, which make up over 70% of the retail electricity price in Germany, are fixed over a year and do not include any time-varying component. This static pricing approach is referred to as the business-as-usual (BAU) use-case. Accordingly, the retail electricity price can be written as

$$p_t^s = (p_t^{elec} + r + p^{tax} + p^{nc} + p^{lev} + p_t^{eeg}) \cdot (1 + VAT), \tag{5}$$

where p_t^{elec} is the cost of acquiring electricity, r is the aggregator's profit margin, p^{tax} are the associated taxes, p^{nc} are the volumetric network charges. p_t^{eeg} and p^{lev} are respectively levies to support the renewable energy feed-in (according to the German renewable energy act, EEG[12]) and other mechanisms. VAT is the value-added tax.

Table 2
Regulatory framework and business model parameters.

Parameter	Symbol	Value	Source
Taxes [¢/kWh]	p^{tax}	2.05	BDEW (2022)
Network charges [¢/kWh]	p^{nc}	7.65	BDEW (2022)
EEG levies [¢/kWh]	p_t^{eeg}	3.72	BDEW (2022)
Other support levies [¢/kWh]	p^{lev}	4.1	BDEW (2022)
Value added tax [%]	VAT	19	BDEW (2022)
Feed-in remuneration [¢/kWh]	FiT	7.69	BSW (2021)
Market price upper cap [¢/kWh]	$\overline{p^m}$	30	o.a.[a]
Aggregator's profit margin [¢/kWh]	r	2	o.a.
Scaling factor in RTP tariff [−]	κ	0.88	o.c.[b]
Scaling factor for $vFiT$ [−]	θ	1.28	o.c.
Scaling factor for dEEG [−]	ι	0.53	o.c.

[a]Own assumption.
[b]Own calculation (see Appendix D).

In phase D of the overall workflow, we study different levels of dynamism in the retail and purchase electricity prices via real-time pricing. The basic idea behind this is that p_t^p or certain components of p_t^s follow the fluctuating market prices and therefore, the demand and supply in the market to better align the distributed decisions made by PV-prosumers. Based on suggestions discussed in the literature, the following instruments are considered:

1. Real-time pricing (RTP) (Hogan, 2014). The resulting dynamic prices include variable procurement costs (p_t^{elec}), which are proportional[13] to the electricity wholesale prices.
2. Variable feed-in tariff (vFiT) (Ossenbrink, 2017; Klein et al., 2019). This instrument denotes remuneration for PV electricity feed-in proportional to the wholesale prices.
3. Dynamic EEG levy (dEEG) (Economics and BET, 2016; Freier et al., 2019). The EEG levy (p_t^{eeg}) in this instrument varies hourly according to the market prices.[14]

For these dynamic instruments, the values of p_t^{elec}, p_t^p, and p_t^{eeg} are determined such that their cumulative monetary effect over the course of a year compared with the static equivalent for a benchmark user is zero (i.e., the instruments do not affect the annual cost or revenue of a benchmark user). The choice of benchmark users and the calculation of the used scaling factors for this calibration, κ (for RTP), θ (for vFiT), and ι (for dEEG), are explained in Appendix D. The assumed values for the parameterization of the electricity tariffs are given in Table 2.

Considering the introduced instruments and their combinations, in addition to BAU, we build three use-cases with the naming conventions given in Table 3. For example, the instrument mix of RTP and vFiT would be called "RTP + vFiT".

2.5.4. PV-prosumer modeling in AMIRIS

As explained in Section 2.5.2, we assume that all PV-prosumers in AMIRIS are virtually aggregated to a single agent. An aggregator is responsible for managing the electricity load and feed-in of PV-prosumers. The aggregation of prosumers without PV-storage

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11 This means, for instance, that a PV-prosumer with a 10 kWp PV system is equipped with 5 kW battery power and 15 kWh battery storage.

12 Based on the German government' decision, the EEG levy was eliminated recently to lower the cost burden of power consumers.

13 Read as: wholesale market price times a constant.

14 Despite the omission of the EEG levy, this instrument is still relevant as it can be applied to other regulated elements of the retail electricity price.

Table 3
Naming convention of the use-cases under investigation.

Use-case	RTP	vFiT	dEEG
BAU	–	–	–
RTP	✓	–	–
RTP + vFiT	✓	✓	–
RTP + vFiT + dEEG	✓	✓	✓

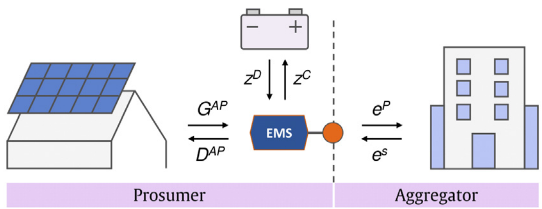

Fig. 4. Schematic overview of the prosumer's model.

systems and using community energy storage systems instead has already been investigated with AMIRIS (Safarazi et al., 2020). For the current analysis, we further develop the aggregator and prosumer agents as follows:

Aggregator: The aggregator agent receives a forecast of the upcoming market prices and related policy-related information, such as electricity price elements induced by the government. Based on the chosen instrument, the aggregator agent creates and sends two sets of prices, i.e., retail and purchase prices (p^s and p^p), to the prosumers. Note that the market price forecasts are generated based on the electricity demand and generation of all market actors except the prosumers.

Prosumer: This prototype agent represents an aggregated PV-prosumer entity[15] with a conventional household load, generation from a PV rooftop system, and battery storage system. In reaction to the aggregator price signals, the PV-prosumer uses a dynamic programming approach to optimize the dispatch of the PV-storage system. Fig. 4 schematically illustrates the virtual power flows in the PV-prosumer model and between the PV-prosumer and aggregator. The prosumer's electricity load and generation are managed by an energy management system (EMS), which determines the amount of battery charge (z^C) or discharge (z^D) as well as grid usage (e^s) and grid feed-in (e^p) on an hourly basis according to the prosumer's generation (G^{AP}) and demand (D^{AP}). In Appendix E, we provide a more detailed explanation of the mathematical model employed for prosumer storage optimization.

3. Results

3.1. Model harmonization and modeling delta

In phase A of the overall workflow, AMIRIS does not operate any PV-storage and adopts the optimized dispatch of its counterparts in REMix. The hourly sum of all discrepancies in operational system costs between REMix and AMIRIS is 26 800 € for Germany, which (considering overall German operational system costs of around 5.96 B€) corresponds to a relative deviation of 0.00045%. The root-mean-square error is 1900 €. With this marginal difference, we consider the models to be harmonized and phase A to be complete.

[15] The model can also be parameterized for individual prosumers. Due to computational impracticality and lack of data, we consider an aggregated prosumer entity.

Table 4
Cost components of the EUMA and GER in the Reference energy system.

Cost component	Cost–EUMA [B€]	Cost–GER [B€]
CAPEX	114.73	3.07
O&M cost	27.86	0.55
Fuel cost	18.94	2.57
CO_2 cost	8.19	2.85

To calculate Δ^{model}, PV-prosumers operate such that operational system costs are minimized by AMIRIS (phase B).[16] The annual sum of the hourly differences between the operational costs of the first and third steps of the model-coupling workflow is $\Delta^{\text{model}} = 899\,300$ €. The corresponding root-mean-square error is 13 500 €. In other words, due to the modeling delta, our indicator for measuring the granularity gap increases by 0.015% compared with the reference energy system[17] (see Fig. 3). This indicates that the modeling delta is negligibly small.

3.2. Economic granularity gap

In this section, the economic granularity gap is quantified for the case of PV-prosumers in the German electricity market. The indicator used is the difference in total system costs (see Section 2.4.3). We distinguish the system costs for two spatial scopes: (i) EUMA and (ii) Germany (GER). Therefore, based on Eq. (2), the economic granularity gap to be observed in this case-study is

$$\begin{aligned} &\Delta^{\text{econ}}_{\text{c,s}} = C_{\text{c,s}} - C_{\text{REF,s}}, \\ &\forall c \in \{\text{BAU, RTP, RTP+vFiT, RTP+vFiT+dEEG}\}, \\ &\forall s \in \{\text{EUMA, GER}\}, \end{aligned} \tag{6}$$

where c is the set of studied use-cases and s is the spatial scope. $C_{c,s}$ represents the total system costs considering the stakeholder behavior of PV-prosumers and $C_{REF,s}$ is the total system costs for the cost-minimal reference energy system design (REF) (step 1 of the model-coupling workflow, see Fig. 2). By considering EUMA as well as GER, we can differentiate between the impacts of the instruments on the overall and German energy systems. The tariffs are only applied in Germany. However, by modeling the whole EUMA region, we can consider the electricity grid and observe changes in imports and exports. This allows us to analyze the German energy system in a more dynamic setup.

In general, high retail electricity prices in comparison to feed-in remunerations make self-consumption of electricity profitable. However, in the BAU use-case, this self-consumption is scheduled independently from market signals. Therefore, it is likely that the system operation deviates from the macroscopic cost minimum of REF, which may also affect the optimal energy system design. In contrast, introducing instruments such as RTP, vFiT, and dEEG increases the alignment of the operations of PV-prosumers, and should thus decrease the economic granularity gap.

Table 4 lists the cost components on the EUMA level and in Germany for REF. The macroeconomic optimum is at 169.71 B€ of total system costs in REF. For Germany, system costs comprise 0.55 B€ for O&M of the power system, with 2.57 B€ and 2.85 B€ of fuel and CO_2 costs, respectively. Amortization charges (CAPEX) for additional power system components are 3.07 B€.

[16] Note that the modeling delta is determined between REMix (REF) and AMIRIS, but it finally affects the economic granularity gap measured against a second energy system optimization with REMix. Therefore, we estimate an upper bound for the modeling delta because, even if constrained to the AMIRIS output, the operational system costs observed in step 4 of the model-coupling workflow can be further minimized in REMix, e.g., by re-dispatching storage technologies other than PV-prosumers.

[17] If the optimized PV-prosumer dispatch from AMIRIS is implemented in REMix, CAPEX increases by 128 000 €, corresponding to an increase of 0.0042%, and OPEX increases by 54 000 €, an increase of 0.00091%.

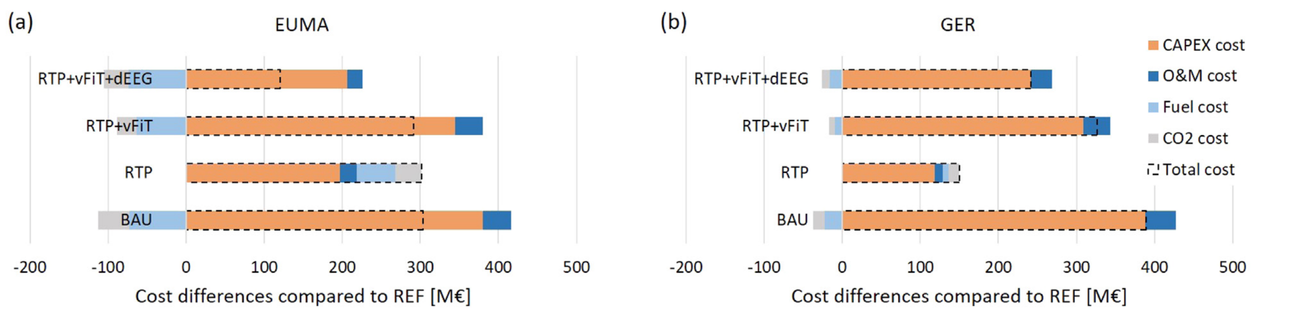

Fig. 5. Differences in the cost components of EUMA and GER compared with REF for different tariff options. In the BAU scenario, the cost increase in Germany is the highest at almost 400 M€. With the RTP tariff, the additional investment cost decreases in Germany by around two-thirds, shifting costs abroad. With a more flexible vFiT the additional costs in Germany increase, while the overall system costs decrease.

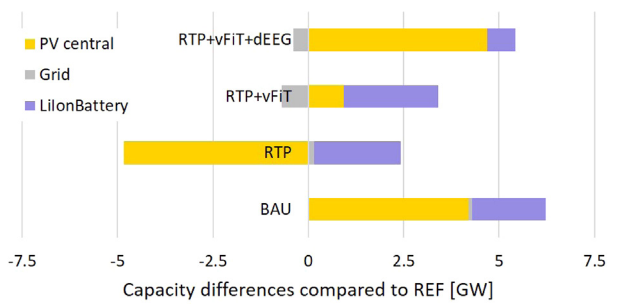

Fig. 6. Capacity differences in GER compared with REF for different tariff options. The BAU scenario leads to the highest additional capacities in GER. In the RTP scenario, the capacity of central PV decreases significantly. With an additional vFiT, the capacity of the grid decreases. The additional flexibility of the EEG results in comparably low additional lithium-ion battery capacities.

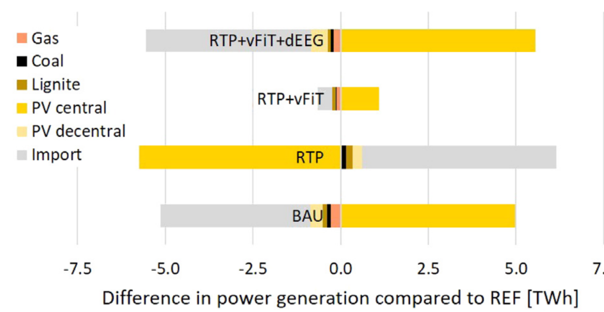

Fig. 7. Differences in power generation in GER compared with REF for different tariff options. In the BAU and RTP+vFiT+dEEG scenarios, the power generation of central PV increases significantly, leading to less power generation and imports from abroad. In the RTP+vFiT scenario, the power generation shifts slightly to Germany. With the RTP tariff, the central PV power generation decreases significantly in Germany, resulting in additional imports from abroad.

Fig. 5(a) shows the economic granularity gaps for the EUMA scope, and thus, the cost components and total system costs in the overall energy system compared with REF. As the power generation and storage capacities are similar to REF in all countries but Germany (see Section 2.3), the relative changes in total system costs on the EUMA level are rather low. However, differences can be observed depending on the tariff implemented for PV-prosumers: higher flexibility of the prosumer tariff produces a smaller economic granularity gap on the EUMA level. For BAU and RTP, similar additional system costs can be observed, while introducing a variable feed-in-tariff leads to a marginal improvement in RTP+vFiT. The additional implementation of dynamic EEG has a rather strong influence on the economic granularity gap. RTP+vFiT+dEEG reduces the deviation of system costs significantly.

For a better understanding of the impact of PV-prosumer behavior on energy system design in Germany, Fig. 5(b) illustrates economic granularity gaps for the German scope and thus, the cost components in Germany compared with the least-cost REF. In all use-cases, the energy system design changes in a way that increases investment costs, which dominates the effect on the total system costs. As expected, this is striking in BAU, where additional investment costs are at 428 M€. In particular, Fig. 6 shows that the economic granularity gap is mainly visible in the form of an additional need for stationary lithium-ion battery capacity in Germany and, for all use-cases but RTP, utility PV. The installed capacities in Germany in the REF are listed in Table F.1.

In general, the above results indicate that, in the case of PV-prosumers, the economic granularity gap is mainly driven by the nonaligned, and thus, inflexible operation of the associated PV-storage systems. They do not fully exploit their capability to balance power supply and demand. This is underestimated in the optimal energy system design of REF, which ignores PV-prosumer behavior. Therefore, the resulting inflexibility needs to be balanced by further installations of technologies having the same capabilities. However, with a sufficiently dynamic electricity retail tariff and feed-in remuneration, and with additional energy storage capacity, the granularity gap in Germany can be reduced, e.g., down to 242 M€ in the RTP+vFiT+dEEG case. If the share of dynamic price components in the prosumer tariff becomes larger, such as in RTP+vFiT+dEEG, the need for temporal energy balancing in the form of lithium-ion batteries is minimized (+0.7 GW compared with REF) and the need for spatial energy balancing is reduced. This is even more significant for RTP+vFit, where the grid transfer capacity between Germany and its neighbors is reduced by 0.7 GW compared with REF.

As shown in Fig. 5(b), RTP gives the smallest economic granularity gap for Germany due to considerably lower investments in additional power generation and storage capacity. Fig. 6 illustrates that considering RTP[18] causes a displacement of 4.9 GW of utility PV compared with REF. However, carbon emission costs decrease across all use-cases except RTP. The reason is that, in the RTP use-case, the cost savings observed for Germany are compensated by shifting power generation to other countries. Although the additional costs in Germany decrease with the RTP tariff compared with the BAU tariff, the additional costs in EUMA are almost the same, indicating higher additional costs abroad. This becomes evident when looking at Fig. 7, which shows the changes in power generation in GER compared with REF. The power generation in REF is listed in Table F.2. Given the significant additional imports of about 5.5 TWh for RTP, it becomes clear that the missing

[18] According to our methodology, only in the German electricity market.

solar power is mainly compensated by both greater renewable and fossil-fired power generation outside Germany. This leads to the most extensive GHG emissions across the analyzed use-cases, even at the EUMA scope, with 33 M€ for additional CO_2 emission allowances compared with REF. At the same time, while the additional costs of the German energy system decrease with the RTP tariff, Germany's import dependency increases.

Furthermore, Fig. 7 shows that BAU and RTP+vFiT+dEEG are very similar in terms of power generation: the power generation from utility PV increases significantly, while imports from abroad decrease and less fossil-fired power plants are operated, both in Germany and abroad, leading to lower fuel and CO_2 costs, as indicated in Fig. 5. However, due to the more efficient usage of PV-storage systems in the RTP+vFiT+dEEG use-case, a decrease in imports to Germany can be achieved with less infrastructure in the form of additional lithium-ion battery capacity.

4. Discussion

4.1. Results summary

Our case-study has quantified the economic granularity gap that arises, from a central planner's perspective, when stakeholder behavior is considered in the optimization of large-scale energy systems. In particular, we studied the case of PV-prosumers aiming to optimize the dispatch of PV-storage systems at the household level in Germany. Under the actual pricing regime, which we refer to as BAU, we observed an economic granularity gap in Germany represented by an increase of 389 M€. To put this into context, designing future energy systems with an optimization model implies an underestimation of costs, whereas the absolute value of 389 M€ is rather interesting from a technical point of view. However, the novelty of our study is that we were able to quantify these costs, which are usually hidden if stakeholder behavior is ignored. In addition, we studied the influence of different prosumer tariffs, which are supposed to increase the alignment of PV-prosumer dispatch decisions according to price signals from the electricity market. We showed that a larger share of dynamic components in electricity retail prices and feed-in remunerations results in lower additional total system costs at the overall system level. Accordingly, the economic granularity gap could be reduced. In the case of variable procurement prices (RTP use-case), the additional cost in Germany decreases to 150 M€, but at the cost of increasing GHG emissions and additional power generation outside Germany, resulting in a higher import dependency.[19] In contrast, for a prosumer tariff that additionally considers variable feed-in-tariffs and a dynamic EEG levy (RTP+vFiT+dEEG use-case), we observed a very similar annual electricity mix as in BAU. However, this could be realized with less investment, and thus at lower total system costs, while also decreasing GHG emissions.

In summary, replacing the static components of the prosumer electricity prices with time-varying elements that contain signals from the wholesale market reduces the total system costs at the overall system level. Looking at Germany, considering only system costs may provide an incomplete picture. Therefore, additional factors such as power exchange with neighboring countries need to be considered when quantifying the economic granularity gap.

[19] In this particular case, a greater utilization of fossil-fired power plants and purchasing emission allowances at 50 €/t turned out to be more cost-efficient than greater investment in new PV plants.

4.2. Limitations

One limitation of our modeling setup is the isolated consideration of stakeholder behavior for a single electricity market (Germany) and solely for one technology. This limits the scope for studying the economic granularity gap from an overall system perspective and causes inaccuracies. In particular, when evaluating system costs in Germany, the profits and expenses of power exchange are not considered because they cannot be directly derived from REMix, which calculates the total system costs across Europe and Maghreb. Additionally, it is clear from the relative cost deviations that the granularity gaps are rather low compared with the absolute total system costs. This effect is a consequence of our methodology, where expenses for power plants and storage outside Germany cannot be changed after determining the reference energy system. In this way, we consider policy instruments to be solely implemented for individual countries. This severe limitation of the solution space fosters more significant changes in the German energy system caused by stakeholder behavior. In our study, this refers to investments in technologies, which are directly affected by the dispatch decisions of PV-prosumers' lithium-ion batteries. Accordingly, further improvements in the context of quantifying the economic granularity gap require the consideration of stakeholder behavior for more than one decentralized actor, necessitating more technologies in the market. This includes the optimization of diverse storage technologies, each of which is suitable for a specific system need.

4.3. Policy implications of the case-study

The implementation of retail prices with dynamic components based on perfect forecasts of wholesale market prices is still largely hypothetical. Despite the associated simplifications, the results of our case-study provide valuable insights into the system impacts of different implementation levels of dynamic pricing instruments for prosumers. In this context, we conclude that dynamic electricity tariffs and remuneration schemes are not a "system-friendly" policy instrument by default. Against our expectations, the total system costs in Germany did not alter consistently with the increasing market alignment of PV-prosumers. Whether dynamic pricing mechanisms are beneficial depends on the specific implementation (i.e., which price components are dynamic) and also where it is introduced. Therefore, we can confirm that the desired effects are possible in terms of both reducing GHG emissions and the need for energy infrastructure. Concerning the observed additional GHG emissions in one of our use-cases, we recommend further research to cross-check our findings with sensitivity analysis of CO_2 costs.

In this context, our results show that replacing more than one component of the electricity retail price with time-varying elements significantly increases the effectiveness of the instrument. However, the remaining distortions caused by other static taxes and levies prevent complete alignment of the prosumer operation with the electricity market, and so complete elimination of the economic granularity gap is not achieved (these findings are similar to the results of Klein et al. (2019) and Sarfarazi et al. (2020)). The implementation of other instruments, such as fixed network charges (Borenstein, 2016), that reduce the share of fixed volumetric components of the electricity retail price may further improve the system impacts of prosumer operations. Moreover, for the "system-friendly" operation of prosumers, besides fluctuations in wholesale market prices, the condition of the physical infrastructure, e.g., congestion in the distribution grid, should also be signaled to the prosumers.

5. Conclusion and outlook

How can a climate neutral overall energy system be implemented in a society with a multitude of decentralized decision-makers? This was the overall research question that motivated the study described in this paper. As an extension to existing research in energy system analysis, we have introduced different economic perspectives with regard to the transformation of large-scale energy systems that affect the potential gains from model-based analyses on energy system design. In particular, we applied the energy system optimization model REMix and the agent-based electricity market model AMIRIS to explore different economic perspectives. We described the economic granularity gap as a metric for bringing these two perspectives closer together. In general, this approach was useful in identifying effective policy measures in terms of system-friendliness. From a technical point of view, we set up an automated and reproducible modeling workflow by coupling the energy system models in a bidirectional manner. This technical implementation is an essential novelty compared with the state-of-the-art. We demonstrated the usefulness of this formulation in a case-study for PV-prosumers, providing an example of how unaligned stakeholder behavior affects energy system designs provided by ESOMs.

In the case-study, we analyzed a set of different policy measures that affect the deviation of simulated operation decisions of PV-prosumers in the German power market and compared them with optimal decisions from the overall system perspective. We found that the developed modeling workflow was capable of investigating the influence of different policy instruments for bridging the economic granularity gap, and was thus able to reduce costs, which are usually underestimated when designing energy systems. From a practical point of view, the strength of the established modeling workflow is its adaptability to a large spectrum of further research questions that go beyond our particular case-study. Therefore, an intuitive next step would be a roll-out to further stakeholder groups, such as operators of other storage technologies. It is expected that, when a large variety of stakeholders are covered, the economic granularity gap will increase. Thus, research on effective policy measures for bridging this gap becomes even more important. Accordingly, examples for further research are analyses of the market premium (Frey et al., 2020), the interaction of markets due to increasing coupling of energy demand sectors, or the impact of the strategic behavior of stakeholders on the economic granularity gap. In this context, an important topic for future research is modeling policy measures that directly influence investment decisions.

CRediT authorship contribution statement

Seyedfarzad Sarfarazi: Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Shima Sasanpour:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Visualization. **Karl-Kiên Cao:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Seyedfarzad Sarfarazi reports financial support was provided by the German Federal Ministry for Economy and Energy.

Data availability

The authors do not have permission to share data.

Table A.1
List of abbreviations and acronyms.

Shortened form	Description
ABM	Agent-based model
AP	Aggregated prosumers
BAU	Business-as-usual
CAPEX	Capital expenditure
EEG	Renewable energy act (Erneuerbare-Energien-Gesetz)
EMS	Energy management system
ESOM	Energy system optimization model
EUMA	Europe and Maghreb
dEEG	Dynamic EEG levy
GER	Germany
GHG	Greenhouse gas
O&M	Operation and maintenance
OPC	Other power consumers
OPEX	Operational expenditure
PV	Photovoltaic
REF	Reference energy system
RTP	Real-time pricing
VAT	Value-added tax
vFiT	Variable feed-in tariff

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Appendix A. Abbreviations

Table A.1 presents a list of the acronyms and abbreviations used in this paper.

Appendix B. Structure of AMIRIS

The structure of the ABM AMIRIS and the financial, information, and power flows among the enabled agents in this study are illustrated in Fig. B.1. A more detailed description of AMIRIS can be found in Deissenroth et al. (2017). AMIRIS has already been used in several electricity market studies (Torralba-Diaz et al., 2020; Frey et al., 2020; Nitsch et al., 2021; Safarazi et al., 2020).

For the assessment of PV-prosumer stakeholder behavior, we have further developed the model and added two new agents, i.e., prosumer and aggregator agents. The aggregator agent provides electricity tariffs for the prosumers and trades according to their electricity excess or deficit in the wholesale market. The prosumer agent reacts to the electricity prices and optimizes the operation of the storage system to minimize their costs. Note that, at the time of publishing this paper, the developed aggregator and prosumer models for this analysis are not part of the open-source model.

Appendix C. Data exchange details

As shown in Fig. 2, the data from REMix are processed within iog2x before being sent to AMIRIS. Table C.1 lists the data types and units that REMix and AMIRIS require and how they are translated by iog2x.

Appendix D. Calculation of market constants

The instruments under investigation are determined in such a way that their implementation disadvantages a benchmark user. In the case of RTP and dEEG, the benchmark user is assumed to be a household with no storage and generation potential. For the calibration of the vFiT instrument, we consider a stand-alone PV

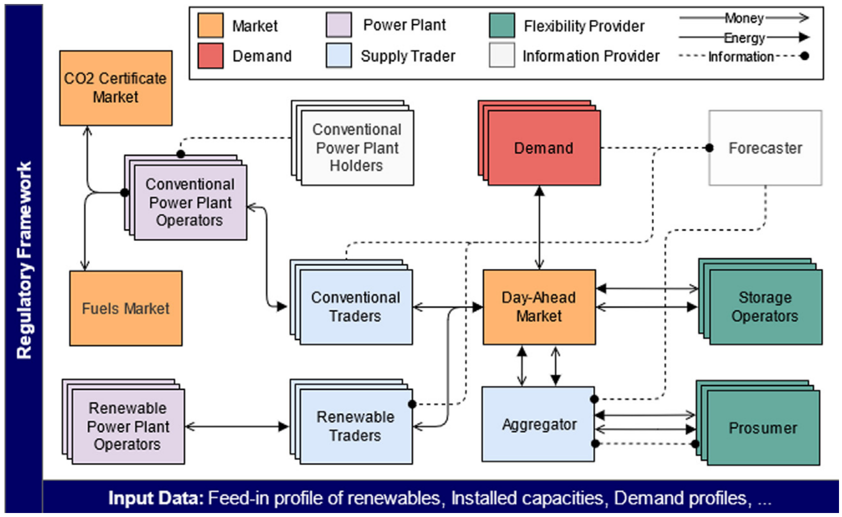

Fig. B.1. Schematic structure of AMIRIS in this study.

Table C.1
Data exchange from REMix to AMIRIS within iog2x.

	Parameter	REMix	Transformation	AMIRIS
Global	CO_2 price	Scalar [k€/t]	Scalar to time series	Time series [k€/t]
	Fuel price	Scalar [k€/MWh$_{th}$]	Scalar to time series	Time series [k€/MWh$_{th}$]
	Specific CO_2 emissions per fuel	Scalar [t/MWh$_{th}$]	–	Scalar [t/MWh$_{th}$]
Demand	Demand Germany (D_t^{total})	Time series [GWh]	$(D_t^{conv} + D_t^{hp} + D_t^{eBoiler} + D_t^{eCars} + E_t^{export} - E_t^{import} + Z_t^{C,stor} - Z_t^{D,stor} + L_t^{trans}) * 10^3$	Time series [MWh]
	Demand Prosumer (D_t^{AP})	Time series [GWh]	$* \ 10^3$	Time series [MWh]
	Demand OPC (D_t^{OPC})	–	$D_t^{total} - D_t^{AP}$	Time series [MWh]
Storages	Storage converter capacity	Scalar [GW]	($* \ 10^3$) to time series	Time series [MW]
	Energy-to-power-ratio	Scalar [TWh]	$* \ 10^6$/storage converter capacity [MW]	Scalar [h]
	Charge efficiency	Scalar [–]	–	Scalar [–]
	Discharge efficiency	Scalar [–]	–	Scalar [–]
Power plants	Installed power	Scalar [GW]	($* \ 10^3$) to time series	Time series [MW]
	RE yield profile	Time series [GWh]	(power generation + curtailment) $* \ 10^3$/installed power [MW]	Time series [–]
	Variable O&M cost	Scalar [k€/MWh]	$* \ 10^3$	Scalar [€/MWh]
	Availability factor	Scalar [–]	Scalar to time series	Time series [–]
	Minimum efficiency	Scalar [–]	Scalar to time series	Time series [–]
	Maximum efficiency	Scalar [–]	Scalar to time series	Time series [–]

system as the benchmark user. We derive the scaling factor χ of the instruments in its general form as follows:

$$p_t^x = \chi p_t^{mc}, \tag{D.1a}$$

$$\chi = \frac{p_{avg}^{mc} \sum_{t=1}^{Z} m_t^{AP}}{\sum_{t=1}^{Z} p_t^{mc} m_t^{AP}}. \tag{D.1b}$$

The scaling factor χ and the price p_t^x respectively represent κ, ι, θ, and p_t^{elec}, p_t^{eeg}, p_t^p for the RTP, dEEG, and vFiT instruments. p_{avg}^{mc} is the average market price and p_t^{mc} is the capped market price with lower and upper bounds (zero and $\overline{p^m}$). m_t^{AP} is the normalized electricity demand of the prosumers (d_t^{AP}) in the RTP and dEEG calculations and the normalized generation profile (g_t^{AP}) in the vFit calibration. We carry out the calculation with an hourly resolution and for a simulation time of one year ($Z = 8760$ h).

Appendix E. Prosumer optimization model

Eqs. (E.1a)–(E.1f) describe the EMS logic, i.e., the cost function and the optimization constraints of the prosumer.

$$\underset{\xi}{\text{Minimize}}\ C = \sum_{t=1}^{T} (p_t^s e_t^s - p_t^p e_t^p) \tag{E.1a}$$

$$\text{subject to: } a_t = a_{t-1} + E^C z_t^C - \frac{z_t^D}{E^D}, \forall t \neq 0, \tag{E.1b}$$

$$0 \leq a_t \leq \varphi \varsigma, \forall t \neq 0, \tag{E.1c}$$

$$a_t = A_0, t = 0, \tag{E.1d}$$

$$G_t^{AP} - D_t^{AP} = e_t^s - e_t^p - z_t^C + z_t^D, \forall t \neq 0, \tag{E.1e}$$

$$G_t^{AP} = \gamma^{AP} g_t^{AP}, \forall t \neq 0, \tag{E.1f}$$

$$0 \leq z_t^C \leq \frac{\varphi}{E^C}, \forall t \neq 0, \tag{E.1g}$$

$$0 \leq z_t^D \leq \varphi E^D, \forall t \neq 0. \tag{E.1h}$$

ξ in Eq. (E.1a) is the set of prosumer decision variables $\xi = \{e_t^s, e_t^p, a_t, z_t^C, z_t^D\}$. C is the cost of the prosumer agent during one optimization period (T), calculated based on the grid usage (e_t^s) and grid feed-in (e_t^p) of the prosumer. Note that the investment, operation, and maintenance costs of PV-storage systems are not considered in the cost function. In Eq. (E.1b), which represents the storage state of the charge constraint to the prosumer's optimization problem, a_t is the energy content of the battery in time step t. The storage technical parameters E^C and E^D are the battery's charging and discharging efficiency, respectively. Constraint (E.1c) ensures that the energy content of the battery remains between the minimum (zero) and maximum allowed

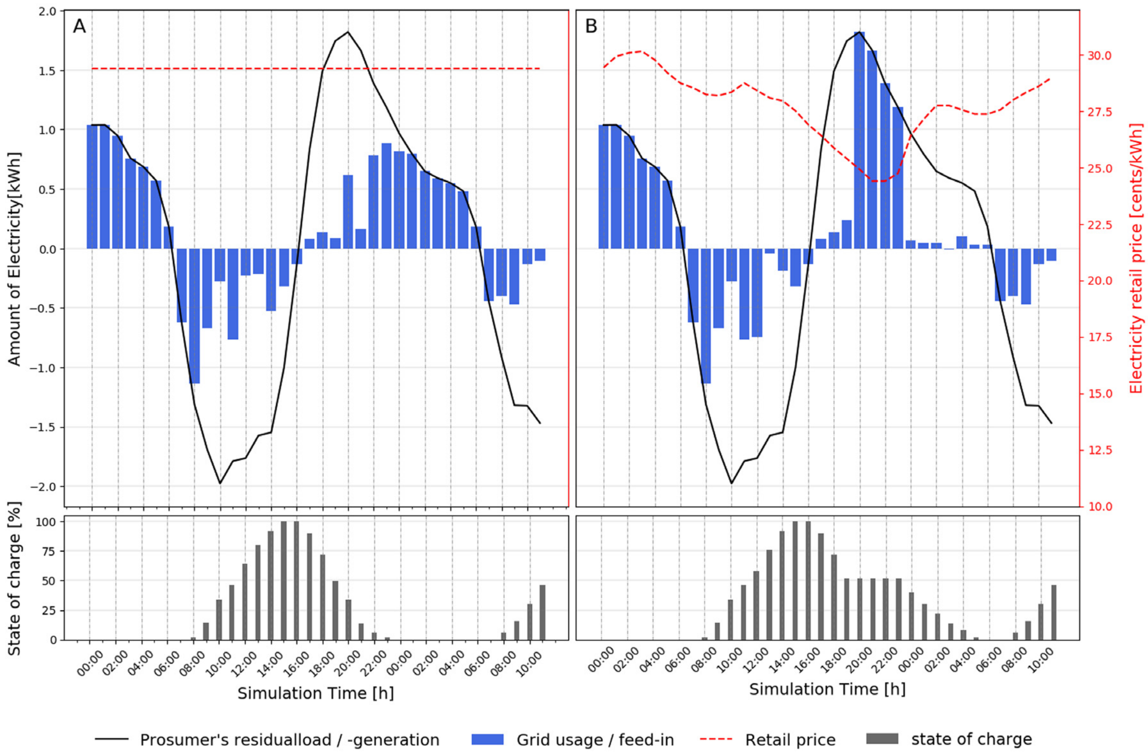

Fig. E.1. Prosumer dispatch for an exemplary 36 h simulation time for the BAU (A) and RTP (B) use-cases. Positive electricity amounts correspond to residual load and grid usage, negative amounts are residual generation and grid feed-in.

limits, i.e., maximum battery capacity, which is represented by the battery's installed power (φ) multiplied by its energy to power ratio (ς). Moreover, Eq. (E.1d) updates the initial battery energy content (A_0) in every optimization period. Note that the value of A_0 depends on the previous optimization result and therefore, needs to be updated before every optimization. The constraint formulated as Eq. (E.1e) balances the hourly power flows managed by the EMS. Based on this equation, we assume that the prosumer primarily utilize the electricity generation to cover the electricity demand. We make this assumption due to the near-zero marginal costs of produced solar energy and the exemption of the self-consumed electricity from the regulatory-induced charges. Electricity generated by prosumer is calculated according to Eq. (E.1f) from the average PV generation profile (g_t^{AP}) and installed PV rooftop capacity (γ^{AP}). Finally, the electricity charged (z_t^C) or discharged (z_t^D) from the battery in each time step is limited in Eqs. (E.1g) and (E.1h). Note that in our modeling, we neglect the grid restrictions and losses.

Fig. E.1 shows the dispatch of PV-storage systems in the BAU (A) and RTP (B) use-cases in AMIRIS. As can be seen, the introduction of a dynamic electricity tariff scheme influences the self-consumption pattern of prosumers. The most prominent change in the usage of battery storage happens from 20:00 to 22:00. In the case of an RTP tariff, the prosumer takes advantage of low retail prices in these hours and covers the electricity demand from the grid. The battery discharges later, from 00:00 to 04:00, to cover the electricity demand. In BAU, in contrast, the battery discharges as soon as the electricity demand exceeds the generation.

Appendix F. Reference energy system in Germany

Table F.1 presents the installed capacities in Germany in REF as a reference for the capacity differences shown in Fig. 6.

Table F.1
Installed capacities in GER in REF.

Technology	Capacity [GW]
Gas	11.14
Coal	8.36
Lignite	9.71
Oil	0.37
Hydro run-of-river	4.38
PV central	23.23
PV decentral	34.94
Wind onshore	49.64
Wind offshore	6.42
Grid	118.69
Lithium-ion battery	8.74
Pumped hydro-storage	6.49

Table F.2
Annual power generation in GER in REF.

Technology	Power generation [TWh]
Gas	22.64
Coal	19.78
Lignite	39.00
Oil	0.05
Hydro run-of-river	21.80
PV central	27.54
PV decentral	25.39
Wind onshore	97.50
Wind offshore	18.96
Import	306.82

Table F.2 presents the power generation and imports in Germany in REF as reference for the deviations in the use-cases in Fig. 7.

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