

Towards Stakeholder-Aware Demand-Side management assessment in heterogeneous residential Microgrids: A Multi-Agent approach[☆]

Kevin Henne^{*}, Henning Rahlf, Marius Naumann^{id}, Henning Meschede

Department of Energy System Technologies, Paderborn University, Paderborn, Germany

ARTICLE INFO

Keywords:

Microgrid
Decentralised Energy Systems
Multi-Agent System
Residential Demand-Side Management
Optimisation

ABSTRACT

Expanding renewable energy sources is essential for a sustainable energy supply but challenges grid stability, as the volatility of solar and wind causes periods of over- and undersupply. Private households are central to this transition, combining dynamic consumption with decentralised generation.

This paper presents a multi-agent microgrid simulation built on the Mesa framework, focusing on the heterogeneous objectives and technological capabilities of residential participants. Households are modelled as autonomous agents with individual strategies, while a dedicated “grid agent” represents the distribution system operator and regulates the microgrid in a grid-supportive manner. The emission factor serves as the key indicator for grid-friendly behaviour.

Results show that in summer, unmanaged PV feed-in from heterogeneous households causes substantial grid stress and balancing effort for the distribution system operator. Dynamic electricity prices can incentivise grid-friendly dispatch, but their effectiveness depends on the correlation between price signals and renewable availability and cannot guarantee grid-supportive behaviour alone. The grid agent reliably improves the grid-supportive coefficient, yet its operating strategy, for instance additional peak-reduction objectives, can interfere with price-based incentives. Effective demand-side management therefore requires careful analysis of stakeholder interactions.

Building on this insight, the paper provides a basic framework for the design, implementation, and assessment of both integrated and individual energy management strategies within a microgrid environment. By simulating the dynamic interactions among system participants and strategies, it enables comprehensive evaluation of their collective impact on the grid, supporting the development of robust solutions for future electricity networks.

1. Introduction

The increasing integration of renewable energy sources (RES) into the power grid presents significant challenges for grid stability. Unlike traditional power generation, which is predictable and centrally controlled, RES such as solar and wind power fluctuate depending on weather conditions. At the same time, the rising use of electrification in various sectors and other high-consumption technologies further intensifies the need for reliable grid availability [1]. This is particularly evident for distribution grids in the residential sector, where decentralised energy generation and consumption involves many heterogeneous participants. Fischer et al. [2] state that the uncertain behaviour of residents in conjunction with the current development of emerging technologies leads to a significant change in future load profiles of

households. This requires a detailed modelling of individual residential grid participants, taking into account the uncertainty of demands, technological components and individual behaviour to derive aggregated load profiles for residential areas to evaluate their impact on the electricity grid. Reimuth et al. [3] analyse the impact of varying penetration of decentralised photovoltaic (PV) system in residential areas on the energy balance. It was found that increasing self-sufficiency rates, by utilising e.g. battery storage systems (BSS), can have a positive impact on the overall grid. However, high penetrations of decentralised RES can also lead to excessive surplus energy, especially in the summertime with high solar irradiance, causing high stress in the electricity grid. This results in an increased load balancing demand as also analysed in [4].

Considering the development of decentralised RES in residential areas in conjunction with the high uncertainty and variability of individual household configuration and behaviour, regulation strategies

[☆] This article is part of a special issue entitled: ‘SDEWES 2025 - ECMX’ published in Energy Conversion and Management: X.

^{*} Corresponding author.

E-mail address: kevin.henne@upb.de (K. Henne).

Nomenclature			
<i>Latin letters</i>		mod	Module
A_{PV}	Area of the PV modules	O&M	Operation and maintenance
C	Total costs	P	Prosumer
DOD	Depth of discharge	PV	Photovoltaics
E	Energy	S	Supply
e	Total emissions	STC	Standard test conditions
f^{cost}	Value of the cost function	w	Wind
GSC	Grid support coefficient	<i>Abbreviations</i>	
K	Electricity price	AI	Artificial intelligence
$LCOE$	Levelised cost of electricity	BSS	Battery storage system
n_p	Number of prosumer agents	COP	Coefficient of performance
P	Power	CO ₂	Carbon dioxide
$\dot{Q}$	Heating power	CO ₂ e	Carbon dioxide equivalents
SOC	State of charge	DOD	Depth of discharge
T	Temperature, Prediction horizon	DSM	Demand side management
t	Time	DSO	Distribution system operator
U	Thermal loss factor	EMS	Energy management system
v_w	Wind speed	ESS	Energy storage system
<i>Greek letters</i>		GSC	Grid support coefficient
α	Ramping penalty factor	HP	Heat pump
ϵ	Emissions factor	LCOE	Levelised cost of electricity
γ	Temperature coefficient	LV	Low voltage
η	Efficiency coefficient	MAS	Multi-agent system
<i>Sub- and Superscripts</i>		OB	Optimisation-based
bat	Battery	OBPro	Optimisation-based prosumption (scenario)
C	Consumption	MV	Medium voltage
conv	Convection	O&M	Operation and maintenance
costs	Cost	PV	Photovoltaics
d	Demand	RB	Rule-based
elec	Electricity	RBPro	Rule-based prosumption (scenario)
G	Grid	RES	Renewable energy sources
heat	Heat	SOC	State of charge
i	i-th (prosumer) agent	UnCon	Unmanaged consumption (scenario)
		UnPro	Unmanaged prosumption (scenario)
		RMSD	Root mean squared deviation

become significantly more complex due to a growing number of actors.

To address these challenges, smart microgrids offer a promising approach by locally balancing energy generation and consumption [5]. These decentralised energy networks integrate RES, energy storage, and advanced control systems to enhance grid resilience and efficiency. By operating either independently or connected to the supply grid, smart microgrids optimise energy distribution, reduce load or supply peaks, and improve overall stability within the local neighbourhood grid and in the higher-level distribution grid [6].

Microgrids and energy management systems (EMS) in smart grid applications have been extensively studied in the literature [7], however further research is required especially in the efficient integration of RES and the development of control strategies for a stable and resilient operation [8]. Most studies focus on reducing energy costs within the microgrid, employing various techniques such as multi-objective optimisation or multi-agent simulations [9]. In general, two main approaches can be distinguished: either the microgrid is treated as a single system with a centralised EMS, or as a network of multiple independent participants working towards specific objectives. An example of a centralised EMS is the real-time system developed by Elsied et al. [10], which aims to minimise energy costs by considering the operational expenses of RES and enabling energy trading with the external grid while utilising energy storage systems (ESS). A related concept, where households share a common ESS to optimise energy usage, is explored by Hosseini et al. [11]. Another approach is presented by Arcos-

Aviles et al. [12], who propose a fuzzy logic-based EMS for grid-connected residential microgrids with centralised RES and ESS. Beyond system operation, research also addresses the optimal sizing of RES and ESS within microgrids. Atia et al. [13] analyse sizing strategies to achieve minimal energy costs, ensuring an efficient balance between generation and storage capacity. Meanwhile, Nasr et al. [14] take a different perspective by developing a predictive optimisation based EMS, with a primary focus on system stability. Their approach aims to reduce peak loads and promote a more balanced grid power usage.

A fundamental challenge in these approaches is that the microgrid is often treated as a single, unified actor. However, in the residential sector, multiple participants with divergent interests coexist, and their behaviour often deviates from the idealised assumptions in the centralised EMS models. Additionally, a single EMS may not necessarily have access to all resources within the grid, which can limit its effectiveness in optimising energy distribution and consumption.

To tackle these challenges, multi-agent systems (MAS) have emerged as a promising approach for analysing the behaviour of individual grid participants within a microgrid. Anvari-Moghaddam et al. [15] developed a collaborative multi-agent-based EMS, where individual houses, a central ESS, and distributed RES act as independent agents, ensuring stable and cost-optimised microgrid operation. Similarly, Radhakrishnan et al. [16] defined different agent types, such as load, supply, and storage agents, which work together to maintain power balance and grid stability. Another approach by Jun et al. [17] introduced a three-layer

communication model to coordinate interactions between agents. Khan et al. [18] explored different control strategies, including swarm optimisation, to optimise microgrid operations. While MASs provide a suitable framework for simulating individual grid participants in the residential sector, most existing studies assume a fully cooperative interplay between agents without conflicting objectives.

Karavas et al. [19] proposed a decentralised EMS based on game theory, analysing the impact of cooperative versus competitive agent behaviour within an internal energy market. Similarly, Cui et al. [20] developed an energy management strategy where retailers and prosumers trade energy within the microgrid to minimise energy costs. The work of El-Affifi et al. [21] utilises a game theory design to develop a new electricity pricing scheme to set incentives for load shifting. Akter et al. [22] introduced a hierarchical EMS tailored to residential microgrids, where houses contribute to both energy supply and storage. Their approach implements an internal energy market to reduce overall costs and minimise reliance on external grid supply.

In this context, flexible electricity pricing can serve as an effective mechanism to influence agent behaviour in a way to achieve decreased peak loads [23]. However, approaches exclusively relying on flexible pricing are not sufficient to guarantee grid stable operation as shown by Yan et al. [24] and Roozbehani et al. [25]. Therefore, additional effort is required, a responsibility that falls within the remit of the Distribution System Operator (DSO). According to the considered literature, this aspect remains insufficiently addressed. Table 1 provides an overview of the reviewed studies and their core concepts, illustrating that existing approaches either rely on centralised EMS under the assumption of cooperative behaviour among all grid participants, thereby neglecting individual interests and decisions, or focus on the interplay of individual households optimising their own objectives.

Since flexible pricing schemes alone cannot ensure grid-stable operation, active involvement of the DSO through dedicated control mechanisms becomes indispensable. To adequately reflect the resulting complexity and the diversity of interacting stakeholders, dedicated frameworks are required that capture the interplay between grid participants and grid operators within a unified modelling environment. Such frameworks form a crucial prerequisite for transferring theoretical concepts into practice, as they enable the systematic evaluation of regulatory strategies under realistic conditions and provide a basis for assessing their feasibility prior to real-world deployment.

The developed MAS establishes an innovative framework for future development and assessment of regulatory strategies that combine two prominent approaches to achieve grid supportive behaviour within microgrids and towards the external electricity grid: (1) dynamic electricity pricing to incentivise resident prosumer households, as demonstrated in Arunkumar et al. [9], Cui et al. [20] or Stute et al. [23]; and (2) centralised control units focussing on grid stability, as analysed in Radhakrishnan et al. [16] and Jun et al. [17]. Further, it allows the

evaluation of different distributions of EMS and flexibility options across different households and their impact on the microgrid.

This approach builds the foundation to assess various regulatory strategies, considering both the grid stability concerns of distribution system operators, in terms of load shifting and demand response of the microgrid, and the cost-minimisation objectives of individual households. In the model, individual households are represented as prosumers, each optimising energy costs with their own components, such as PV or BSS. Additionally, a central agent, representing the DSO, is incorporated focussing on load shifting and energy balancing. Centralised agents are designed to mitigate destabilising decisions made by the prosumers to achieve a stable operation within the microgrid. In this paper, it is assumed that the microgrid is connected to a broader electricity grid, which allows the grid agent to additionally provide load balancing capabilities to the external grid.

This paper constitutes an initial step towards a comprehensive framework by empirically exploring a foundational concept for analysing the interplay of multiple stakeholders within a microgrid, each pursuing heterogeneous interests and decision strategies. It investigates how these strategic interactions affect the microgrid's overall energy balance and the microgrid's propensity to operate in a grid-supportive manner with respect to the external electricity system. Thus, the study establishes both the methodological basis and an application-oriented implementation that can be systematically extended in subsequent work into a more generalised framework and a robust test environment for the comparative evaluation of diverse demand-side management approaches.

2. Methodology

In this section the topology of the considered smart grid and its participants is explained. The general layout of the system is shown in Fig. 1.

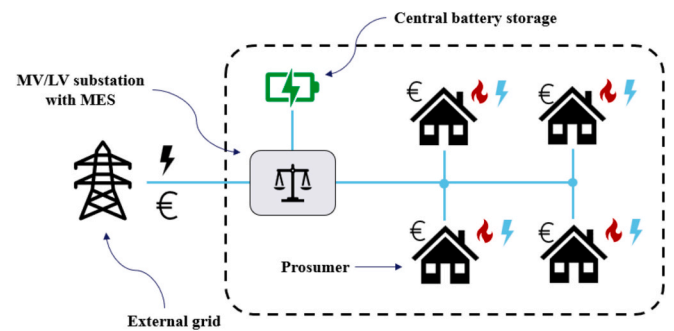


Fig. 1. General layout of the smart grid including prosumers and centralised MES.

Table 1
Literature overview.

Reference	MAS	Individual EMS	CentralEMS	CompetitiveBehaviour	Optimisation goals: Energy cost	Grid friendliness
Elsied et al. [10]			x		x	x
Hosseini et al. [11]			x		x	x
Arcos-Aviles et al. [12]			x			x
Atia et al. [13]			x			x
Nasr et al. [14]			x		x	
Moghaddam et al. [15]	x		x		x	
Radhakrishnan et al. [16]	x	x				x
Jun et al. [17]	x		x		x	x
Karavas et al. [19]	x	x		x	x	
Cui et al. [20]	x	x		x	x	
El-Affifi et al. [21]	x	x		x	x	x
Akter et al. [22]	x	x		x	x	x
This study	x	x	x	x	x	x

The smart grid consists of a defined number of prosumer agents representing individual households, which are connected to the electricity grid. At the medium-/low-voltage (MV/LV) substation, an EMS is implemented in the form of a grid agent. This grid agent is equipped with a large-scale ESS, providing balancing capacity both within the grid and for external grid stabilisation measures.

2.1. Prosumer agent

In the residential smart grid under consideration, individual households are modelled as prosumer agents. Each household has both electricity demand $P_{d,elec}$ and heat demand $P_{d,heat}$ that must always be met. Electricity can be supplied either from the supply grid or through the household's individual PV system. To meet the heat demand, it is assumed that the considered households within the microgrid are equipped with an air-source heat pump (HP), resulting in an extra electricity demand $P_{HP}(P_{d,heat})$. The modelling of the PV power output as well as the efficiency of the used HPs relies on environmental circumstances such as solar irradiation or outside air temperature. Additionally, a portion of the households is equipped with an ESS, which is used in conjunction with cost-optimisation to minimise overall energy costs. The modelling of each component is presented in the following.

Load profiles: Describing the demand in the residential sector is challenging due to the heterogeneous structures of households and the individual preferences and needs of occupants. Thus, analysing individual EMS and their impacts on the broader electricity grid requires the individual modelling of each household's demand profile. In this study, electricity loads are generated using the "LoadProfileGenerator" [26]. The "LoadProfileGenerator" allows for an action-based creation of individual electricity profiles for residential households [27]. Therefore, individual profiles with individual characteristics for each prosumer agent can be derived. This is important, as stylised standard load profiles across multiple agents will lead to the exact same behaviour across different agents and does not reflect the heterogeneity in individual actions and habits.

For space heating demand, randomised standard load profiles [28] are applied, assuming an average space heating demand of 13,400kWh per year and household, which reflects an average annual demand for a German residential building [29]. Hence, for this work, prosumer agents are assumed to only utilise BSS as an (electrical) flexibility option, thermal flexibility, such as heat storage or strategic operation of the HP, is not considered in this work. Consequently, the thermal domain is only considered on a marginal level, and the modelling of the heat demands is simplified, including the omission of domestic hot water and relying on thermal standard load profiles.

Both profiles are sampled at a $\Delta t = 15\text{min}$ resolution. Fig. 2 presents

the resulting daily electricity and heating demand for the individual households throughout different seasons of the year. The solid line depicts the mean demand across all profiles, while the coloured areas indicate the minimum and maximum values observed at each time step throughout the sample. It can be observed that there is particularly high variance in electricity demand, resulting in distinct load profiles. This enables the modelling approach to reflect the diversity of individual behaviours and the heterogeneity of households.

Heat Pump: HPs are highly efficient systems for heating and cooling buildings. They upgrade low-temperature heat, e.g. outside ambient air, to higher temperatures using electrical driven compression. This makes them a sustainable alternative to conventional heating systems which convert other energy carriers into heat like natural gas boilers. For heat pumps, the heating power $\dot{Q}$ is linked to the electrical power consumption P_{HP} via the coefficient of performance (COP).

$$\dot{Q} = COP(\Delta T) \cdot P_{HP} \quad (1)$$

The COP depends on the temperature difference ΔT between the inside T_{inside} and outside ambient temperature $T_{ambient}$, as well as the system efficiency ratio of the HP η_{HP} , which describes technical losses of the system components. The COP can then be expressed as [30]

$$COP(\Delta T) = \eta_{HP} \cdot \frac{T_{inside}}{T_{inside} - T_{ambient}(t)} \quad (2)$$

The inside temperature of the individual houses is assumed to be constant at $T_{inside} = 20^\circ\text{C}$ [31] while the outside temperature relies on given weather data based on the open-meteo database [32]. If the outside temperature exceeds 20°C the required electricity demand is set to $P_{HP} = 0\text{kW}$. The efficiency ratio is set to $\eta_{HP} = 60\%$ [33].

PV plant: Individual PV systems will play a crucial role in the future transition to a more sustainable energy system. For households, they also offer an effective way to lower electricity costs. The power output generated by the PV system is influenced by several factors, including local solar irradiation $I(t)$, the surface area of the installed panels A_{PV} , the efficiency of the modules η_{PV} , as well as the module temperature $T_{module}(t)$, that decreases the cell efficiency. The power output can be calculated according to [34] as

$$P_{PV} = \eta_{PV} \cdot A_{PV} \cdot I(t) \cdot (1 - \gamma_{PV}(T_{module}(t) - T_{STC})), \quad (3)$$

with the efficiency of the modules $\eta_{PV} = 18\%$ [35], the temperature coefficient $\gamma_{PV} = 0.4\%/K$. For this study an installed peak power of $P_{PV,peak} = 9\text{kW}$ is assumed, as it reflects an average size for private PV systems in Germany, which corresponds to a surface area of $A_{PV} = 44\text{m}^2$ [36]. The module temperature, which influences the efficiency of the PV system, can be described as

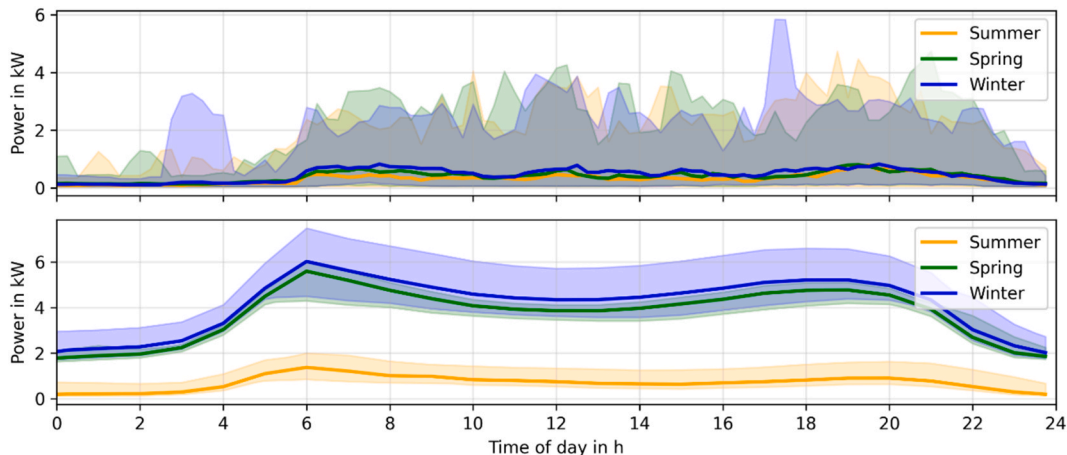


Fig. 2. Electricity (top) and heating (bottom) demand of individual households in different seasons.

$$T_{\text{module}} = T_{\text{ambient}} + \frac{I(t)}{U_{\text{conv}} + U_w \cdot v_w(t)}, \quad (4)$$

where $U_{\text{conv}} = 20\text{W}/(\text{mK})$ represents the thermal loss factor for natural convection,

$U_w = 1.2\text{Ws}/\text{K}$ the thermal loss factor due to forced convection and the wind speed $v_w(t)$ [37]. The variable $T_{\text{STC}} = 25^\circ\text{C}$ describes the reference cell temperature under standard test conditions, which are used to specify and compare the rated performance of PV modules [38].

Battery storage system: BSS are essential for enhancing the efficiency and reliability of PV systems in residential applications. By storing excess solar energy generated during peak sunlight hours, these systems enable households to optimise self-consumption, reduce dependence on the electrical grid, and mitigate fluctuations in energy supply. In this study BSS in individual households is used to achieve minimal electricity costs or increase self-sufficiency of private households. Kairies et al. [39] analysed the development of PV storage systems in Germany and identified typical BSS capacities between 4 kWh and 11 kWh. However, due to the development of market prices and technological improvement of BSS [23], typical BSS capacities will most likely increase in the future, so that battery sizes of up to 15 kWh are considered [40]. The corresponding maximum charge/discharge power is derived assuming a typical C-rate of 0.5 for private BSS [40]. For this study a set of different storage capacities $E_{\text{P,bat,cap}}$ are randomly spread across the households. The different BSS are displayed in Table 2.

For each case a maximum depth of discharge (DOD) of $\text{DOD} = 95\%$ [41] is assumed, which results in a reduced effective capacity of

$$E_{\text{P,bat,max}} = \text{DOD} \cdot E_{\text{P,bat,cap}} \quad (5)$$

Further, system efficiencies for charging and discharging are considered as of $\eta_{\text{charge}} = 91\%$ and $\eta_{\text{discharge}} = 92\%$ [41]. Due to the short simulation horizon, battery degradation and self-discharge are neglected in this study, as their impact on the state of health becomes relevant only over substantially longer time scales [42].

Besides the individual components themselves, such as PV systems or BSS, appropriate control of these elements is essential to ensure their effective utilisation and to realise potential benefits. The literature presents a wide range of EMS, including optimisation and predictive optimisation based approaches [43–45], rule-based strategies [46,47], as well as methods based on AI and reinforcement learning [48–50]. In this study, two types of EMS are implemented for use within the prosumer agents. These approaches are introduced in the following sections.

Rule-based EMS: The first EMS is a simple rule-based approach, representing households with a focus on self-consumption and self-sufficiency, by utilising surplus energy from the PV system to cover the electricity demand. The general structure of the rule-based EMS is shown in Fig. 3.

In each timestep t the PV output is compared to the current electricity demand. Surplus energy will be used to.

charge the battery, if the SOC is smaller than 100%. Otherwise, it will be sold to the external grid if the battery is fully charged. In case the PV output is not sufficient to meet the electricity demand first the BSS is discharged before energy is drawn from the grid. Due to its simplicity and low computational [51] and informational requirements, such as interoperability with external participants and data connections [52], the rule-based EMS provides an easily accessible option for many

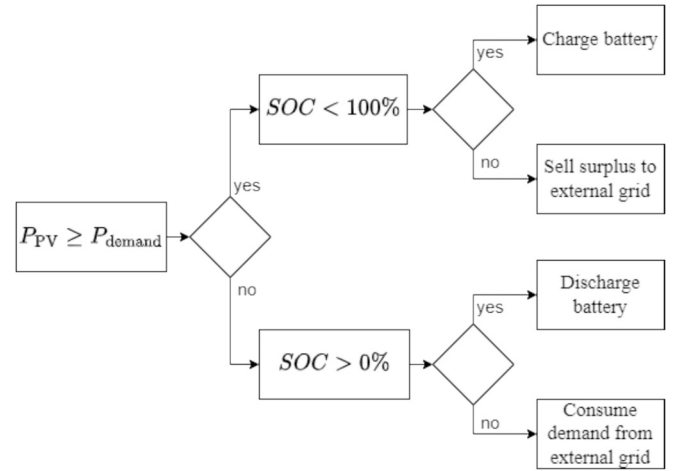


Fig. 3. Decision tree of the rule-based EMS.

households. Therefore, it can be assumed that, due to high user acceptance, simple EMS will likely be adopted in the future if the penetration of individual PV systems and ESS increases in the residential sector [51].

Predictive optimisation-based EMS: A major concern of residents in individual households is to reduce energy costs. Therefore, households with PV and an ESS can be equipped with a second EMS using model predictive optimisation to find an optimal charging/discharging strategy over a given time horizon $T = 24\text{h}$ for achieving minimal energy costs. The objective function can be expressed as shown below:

$$\min^{cost} = \sum_{\tilde{t} \in T} (P_{\text{grid,buy}}(\tilde{t}) - P_{\text{grid,sell}}(\tilde{t})) \cdot K(\tilde{t}) \quad (6)$$

$P_{\text{grid,buy}}(\tilde{t})$ and $P_{\text{grid,sell}}(\tilde{t})$ describe a constant power in each optimisation time step $\tilde{t}$ over a sample interval of $\Delta\tilde{t} = 15\text{min}$. The electricity price $K(t)$ results from historical data of the day-ahead electricity prices for Germany, referenced to an equivalent power consumption for the sample interval [53].

As a constraint, the electricity demand for the household must be fulfilled for each time step:

$$P_{\text{PV}}(\tilde{t}) + P_{\text{grid,buy}}(\tilde{t}) + P_{\text{bat,discharge}}(\tilde{t}) = P_d(\tilde{t}) + P_{\text{bat,charge}}(\tilde{t}) + P_{\text{grid,sell}}(\tilde{t}), \forall \tilde{t} \in T \quad (7)$$

Where $P_d(\tilde{t}) = P_{\text{d,elec}}(\tilde{t}) + P_{\text{HP}}(\tilde{t})$ represents the total electricity demand including the HP power to cover the heat demand.

To ensure a correct charging/discharging of the BSS, additional constraints are required to describe the battery dynamics:

$$E_{\text{bat}}(\tilde{t}) = E_{\text{bat}}(\tilde{t}-1) + \left(\eta_{\text{charge}} \cdot P_{\text{bat,charge}}(\tilde{t}) - \frac{P_{\text{bat,discharge}}(\tilde{t})}{\eta_{\text{discharge}}} \right) \cdot \Delta\tilde{t}, \forall \tilde{t} \in T \quad (8)$$

$$0 \leq E_{\text{bat}}(\tilde{t}) \leq E_{\text{P,bat,max}} \quad (9)$$

$$0 \leq P_{\text{bat,charge}}(\tilde{t}) \leq P_{\text{bat,max}} \quad (10)$$

$$0 \leq P_{\text{bat,discharge}}(\tilde{t}) \leq P_{\text{bat,max}} \quad (11)$$

The corresponding parameters thereby reflect the battery characteristics of the assigned BSS for each specific household, which are described above, with $\eta_{\text{charge}} = 91\%$ and $\eta_{\text{discharge}} = 92\%$, and the corresponding capacities and charge/discharge power from Table 2.

After finding an optimal strategy, the first step of this strategy is then implemented. In the next time step $t+1$, the optimisation horizon is

Table 2
Capacities of BSS in residential households.

$E_{\text{P,bat,cap}}$ in kWh	$P_{\text{P,bat,max}}$ in kW
4	2
8	4
11	5.5
15	7.5

shifted forward, and the optimisation problem is solved again. This iterative process continues in a rolling manner, ensuring that the strategy is continuously updated based on the latest information.

2.2. Grid agent

Beside the target of cost optimisation for individual households, distribution system operators need to ensure a safe and stable grid operation. To this end, load shifting plays a significant role [54]. For this simulation, a grid agent at the MV/LV-substation is introduced, utilising a larger scale ESS to achieve a grid-friendly behaviour of the microgrid to the outer electricity grid.

A crucial aspect of maintaining grid stability with the increasing integration of RES is adjusting demand to periods of high renewable electricity generation. Studies indicate that the share of renewables in the current electricity grid correlates with the associated CO₂e emissions [55]. By shifting the electricity demand into times of low CO₂e emissions in the electricity mix, a reduction of the residual load can be achieved and therefore aligns demand and RES availability. Therefore, the emission factor of the electricity mix can serve as an indicator for identifying favourable times to draw power from the grid or to provide electricity, thereby promoting the efficient utilisation of RES.

To achieve this behaviour, the grid agent uses its ESS capabilities to minimise the total CO₂e emissions caused by energy obtained from the public grid.

As shown in Fig. 4 the total CO₂e emissions (e) caused by the microgrid can be expressed as the total power from the grid $P_G(t)$ and the emission factor $\epsilon(t)$:

$$e(t) = \epsilon(t) \cdot P_G(t) = \epsilon(t) \cdot (P_{G,bat}(t, \epsilon(t)) + P_P(t)) \quad (12)$$

$P_{G,bat}(t, \epsilon(t))$ represents the charging/discharging power of the BSS in the grid agent, while

$$P_P(t) = \sum_i P_{P,i}(t) \quad (13)$$

describes the total power consumed from all prosumers.

The optimal charging strategy for the grid agent is derived by solving an optimisation problem for each time step t over a given time horizon T by minimising the following objective function:

$$\min f^{\text{emissions}} = \sum_{t \in T} \epsilon(t) \cdot P_G(t) = \sum_{t \in T} \epsilon(t) \cdot (P_{G,bat}(t, \epsilon(t)) + P_P(t)) \quad (14)$$

In addition to the task of load shifting, which aims to reduce CO₂e emissions $e(t)$, highly volatile interactions with the broader electricity grid, characterised by steep power gradients, can induce frequency deviations, particularly when the grid is unable to respond sufficiently fast to rapid changes in power demand [56]. Therefore, high peaks in the net load profile can have a negative impact on grid stability. To consider this, the objective function of the grid agent is extended by an additional term penalising high gradients in the resulting grid interaction $P_G(t)$. Therefore, the objective function results to

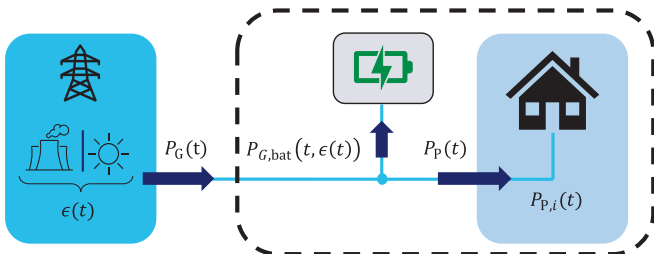


Fig. 4. Grid agent for emission reduction.

$$\min f^{\text{grid}} = \sum_{t \in T} \epsilon(t) \cdot P_G(t) + \alpha (P_G(t) - P_G(t-1))^2. \quad (15)$$

The parameter α serves as a design parameter that allows balancing the two competing objectives of minimising emissions and reducing intense ramping. The appropriate choice of α depends on the specific structure and

characteristics of the external grid and can therefore not be specified in a generalised manner within the scope of this study. For this reason, $\alpha = 0$ is assumed by default, placing the focus on load shifting. Nevertheless, a dedicated analysis is conducted to evaluate the influence of α on the resulting net load profile.

The optimisation is constrained by the same battery dynamic rules as presented in the optimisation problem for the cost optimisation for the prosumer. As for the prosumer agent, this optimisation follows the same rolling procedure as described earlier, with the horizon being shifted forward at each time step and the problem being re-optimised iteratively. The battery capacity for the grid agent is assumed to be $E_{G,bat,max} = 1\text{MWh}$ and a maximum charging/discharging power of $P_{G,bat,max} = 300\text{kW}$. The size of the battery is oriented at Elkazaz et al. [57], which considered a similar size of a microgrid (approximately 100 households) for a centralised optimisation of energy costs and peak shaving applications. However, different battery sizes, ranging from 300 kWh to 4 MWh will be considered in form of a sensitivity analysis to evaluate the impact of BSS sizing on the overall results.

2.3. Assessment of grid-supportive load flexibility

To assess grid friendly behaviour for different combinations of prosumer and grid agents, key performance indicators are required to quantify the impact of various scenarios. These indicators should capture how different microgrid configurations influence overall emissions and, consequently, the grid-friendly and grid supportive behaviour of the system in relation to the external power grid.

The Grid Support Coefficient (GSC) proposed by Klein et al. [58] is used as an indicator to quantify grid-friendly behaviour of a consumer by weighting a time-resolved electricity consumption $P(t)$ with a time-resolved reference quantity $G(t)$, reflecting the current grid state, and compare it to the average of the referencing quantity over the considered evaluation interval.

$$GSC = \frac{\int P(t) \cdot G(t) dt}{\int P(t) dt \cdot \bar{G}} \quad (16)$$

As the CO₂e emissions in the electricity grid correlate well with the availability of RES, the emission factor of the electricity mix reflects the residual load, representing the share of electricity demand that cannot be covered by renewable energy sources and must therefore be met by conventional, fossil-fuel-based power plants. Using the emission factor as the reference quantity the expression can be reformulated as

$$GSC = \frac{\int P_G(t) \cdot \epsilon(t) dt}{\int P_G(t) dt \cdot \bar{\epsilon}} \quad (17)$$

If the microgrid consumes power mainly in times of low carbon emissions, this will cause the GSC to be smaller than one. This implies that the electricity consumption is aligned to RE availability. Conversely, values greater than one suggest high consumption during periods of elevated CO₂e emissions, leading to an increased residual load.

The applicability of the GSC to advanced energy management concepts has been demonstrated by Rahlf et al. [59], who employed the metric to evaluate bidirectional charging strategies in industrial DC grids.

While this metric provides a simple method for evaluating grid-friendliness, it is limited in scope, as it pertains solely to electrical loads but not to supply. To address this issue, separate GSC values for

consumption and supply are derived.

For the consumption case the GSC is now labelled as

$$GSC_C = \frac{\int P_G(t) \cdot \epsilon(t) dt}{\int P_G(t) dt \cdot \epsilon(t)}, \forall P_G(t) \geq 0 \text{ kW}, \quad (18)$$

and can be interpreted as shown above.

However, for the supply case the formulation of the GSC needs to be separated and adjusted due to the following two reasons.

First, supplying to the grid results in a negative value for the power consumption $P_G(t)$, but due to the fraction the sign will cancel out. Therefore, the direction of the energy flow is lost during the evaluation.

Second, when supplying electricity to the grid, times of a high emission factor are desired, hence supplying from RES will reduce the residual load. In contrast supplying to the grid in times of (already) low emission factors may introduce additional stress in the grid, due to an overproduction from RES and is therefore not favourable. Therefore, grid friendly behaviour for the supply case is reflected by a GSC larger than one, because we want large RES supply in times of high emission factors. On the other hand, a GSC smaller one would indicate, that the electricity supply occurs mainly in times of a high share of RES in the electricity mix and therefore might cause stress in the grid due to overproduction.

Comparing the supply and the consumption case, it can be seen, that the interpretation of the GSC value is opposite, while simultaneously losing the information of the direction of the energy flow. To compensate for this the GSC for the supply case is inverted as shown in equation (19).

$$GSC_S = \left(\frac{\int P_G(t) \cdot \epsilon(t) dt}{\int P_G(t) dt \cdot \epsilon(t)} \right)^{-1}, \forall P_G(t) < 0 \text{ kW} \quad (19)$$

To keep the direction of the power flow and obtain a total GSC for a given period T_{total} , the load profile is dissected into individual sections $n \in N$ of consumption or supply. The total GSC can then be expressed as:

$$GSC = \sum_n \frac{T_s}{T_{\text{total}}} \begin{cases} GSC_C, n : \text{consumption state} \\ GSC_S, n : \text{supply state} \end{cases}, \forall n \in N \quad (20)$$

2.4. Economic assessment

In addition to technical considerations, the economic perspective plays a crucial role in the investment and efficient operation of RES and ESS. Particularly for cost-oriented prosumers, the decision to deploy individual PV systems or ESS is largely determined by their economic viability and overall cost-effectiveness. Therefore, the energy costs of both the prosumers and the grid agent are evaluated.

The agent's energy costs can be calculated as the sum of the electric energy costs and additional costs for operation and maintenance (O&M) for the utilised technology:

$$C_i(t) = E_i(t) \cdot K(t) + C_{O\&M,P} \quad (21)$$

$C_i(t)$ describes the overall costs in timestep t , while $K(t)$ refers to the electricity price. $E_i(t)$ represents the total electric energy consumed, which results from the mean power consumption $P_i(t)$ multiplied by the sample interval $\Delta t = 15 \text{ min}$. For prosumer agents the costs for operation and maintenance $C_{O\&M,P}$ can be expressed as

$$C_{O\&M,P}(t) = LCOE \cdot P_{PV}(t) \quad (22)$$

where $LCOE$ describes the levelized costs of electricity, representing the mean production costs of electricity for the prosumer, depending on their individual technology used. For PV and additional individual BSS the levelized costs of electricity are assumed to be

$LCOE = 16 \text{ ct/kWh}$ [60]. The costs for individual PV without individual BSS are set to

$$LCOE = 10 \text{ ct/kWh}$$

For the grid agent the investment and operation costs for the large-scale BSS are taken into account by a CAPEX of 600€/kWh and OPEX equal to 2% of CAPEX per year [60].

Considering a battery lifetime of $T_{G, \text{bat}} = 20 \text{ a}$ [57] the O&M- costs for the BSS result in

$$C_{O\&M,G} = CAPEX \cdot E_{G, \text{bat}, \text{max}} \cdot \left(\frac{1}{T_{G, \text{bat}}} + 2 \frac{\%}{a} \right) = 1.20 \frac{\text{€}}{\Delta t} \quad (23)$$

The total costs per timestep can then be expressed as:

$$C_G(t) = P_G(t) \cdot K(t) + C_{O\&M,G} \quad (24)$$

3. Case study

As a case study, a microgrid consisting of $n_p = 100$ households is analysed under various assumptions regarding the degree of household demand flexibility and seasonal variations in electricity and heating needs. Four distinct scenarios are examined, each evaluated over three representative weeks throughout the year.

For the weather information relevant to energy conversion (PV, HP), such as solar irradiance and temperature, historical data for the location of Paderborn was used [32]. The electricity price $K(t)$ results from the day-ahead-price from 2023 [61]. Further, an artificial offset of 25ct/kWh is applied to the market price to incorporate aspects such as taxes, marketing expenses, or distribution fees, so that the resulting average annual electricity price for private households reflects a realistic level. For the grid agent the emission factor $\epsilon(t)$ of the German electricity mix from 2023 is used [61].

Prosumer types: To simulate different levels of household flexibility options, four distinct types of prosumer agents are defined. The first type is a basic consumer with no access to PV or BSS. However, it is equipped with a heat pump, so that its heating needs are met through electricity usage. This type of grid participant is labelled as an “unmanaged consumer”. The second type of household features a rooftop PV system as described previously but lacks a BSS. Consequently, any discrepancy between PV output and electricity demand will be instantaneously met by either drawing from or feeding into the grid, as there is no capacity for shifting loads. In the following, this type of prosumer will be referred to as an “unmanaged prosumer.” In contrast to these unmanaged households, the third and fourth type of prosumer feature a BSS and an EMS to strategically utilise their BSS capacity. Thereby, the EMS can either be the aforementioned rule-based strategy (RB-prosumer) or utilise the predictive optimisation-based approach (OB-prosumer) as described above, either focussing on a high self-sufficiency or minimal energy costs.

Scenarios: To investigate the impact of varying levels of intelligence, objectives and energy flexibility options of the prosumer agents on the overall energy demand four scenarios are analysed. For each scenario, different distributions of prosumer types are examined. The shares of the individual prosumer types are shown in Table 3.

The first scenario (UnCon) represents a traditional grid layout with individual households acting as consumers and a small proportion of individual PV systems, where most households lack substantial automation options. In the second scenario (UnPro), a higher share of

Table 3
Shares of prosumer types in different scenarios.

	Unmanaged consumer	Unmanaged prosumer	RB-prosumer	OB-prosumer
UnCon	70%	20%	10%	0%
UnPro	20%	70%	10%	0%
RBPro	10%	10%	70%	10%
OBPro	5%	5%	20%	70%

unmanaged prosumers is assumed, illustrating the effects of uncontrolled decentralised electricity production within the microgrid. The third scenario (RBPro) features a larger proportion of managed, rule-based prosumer households. Here, there is a greater emphasis on self-consumption and the use of flexibility options, but without the need for advanced infrastructure or high implementation and data requirements. The fourth scenario (OBPro) focuses on minimising energy costs, utilising advanced EMS and strategies, even with higher implementation effort.

To explore how the agents behave in various environmental scenarios, three distinct weeks spread over the year are analysed as shown in Fig. 5.

The first week, set in summer, is characterised by high and consistent solar radiation during the days, as well as

distinct periodic patterns in both electricity prices and emissions. The second analysed week, taking place in March, represents an intermediate scenario with less regular patterns. Notably, the second half of this week experiences lower solar irradiance. In the third week, which falls in the winter season, there is almost no solar irradiance, meaning that most of the energy demand must be covered by consumption from the external grid.

For each scenario, the GSC is calculated to assess grid friendly behaviour of the microgrid against the broader electricity grid with and without the grid agent, showcasing the impact of centralised ESS on overall load management.

Additionally, the overall energy costs of each agent type are evaluated, to examine the profitability of each agent configuration under the assumption of dynamic electricity prices.

The results are presented in the following chapter. To further substantiate the results, an additional simulation was conducted, using different weeks from the respective season. The results can be found in the [appendix](#).

4. Results and evaluation

This chapter presents key simulation results and analyses the system's operational behaviour under varying prosumer configurations and seasonal conditions.

4.1. Agent behaviour

Initially, the energy exchange of the prosumer agents is examined, focusing on the impact of the different EMS and strategies in response to the system states.

Fig. 6 displays the overall electricity demand for different household's agent types for the summer season.

The unmanaged consumer has neither an individual PV system nor a BSS. Therefore, this agent is forced to cover its electricity demand $P_{demand,i}(t)$ by consuming from the external grid for a given price $K(t)$ over the time t . The resulting power consumption is labelled $P_{p_i}(t)$. The unmanaged prosumer utilises an (unmanaged) PV system. The PV output power $P_{PV}(t)$ is given by the blue line. It can be seen, that especially in the summer season, $P_{PV}(t)$ is much higher than the electricity demand $P_{demand,i}(t)$, resulting in a significant over production throughout the day. However, due to missing storage capabilities external electricity needs to be consumed during nighttime, when the

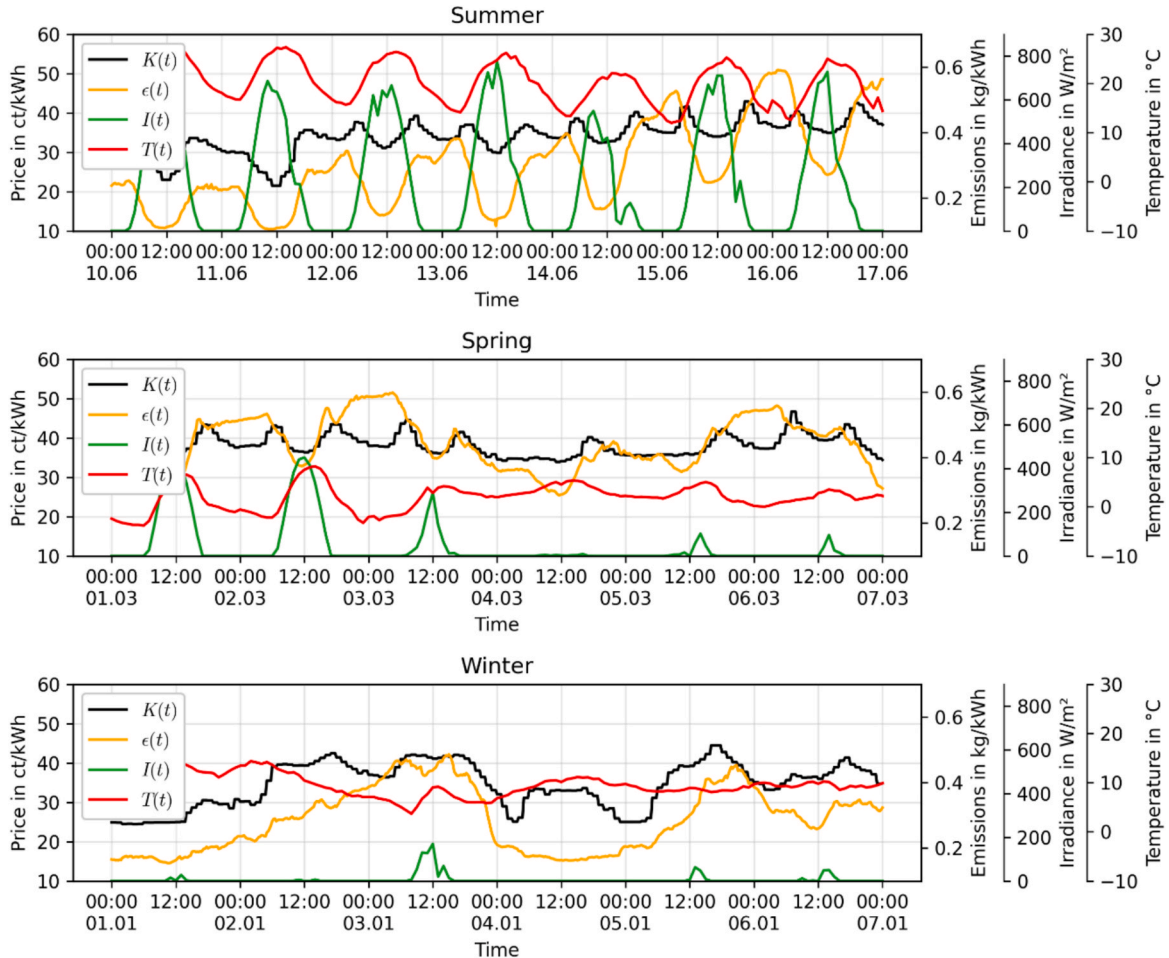


Fig. 5. Solar irradiance, emission factor of the electricity mix and electricity price for three seasons.

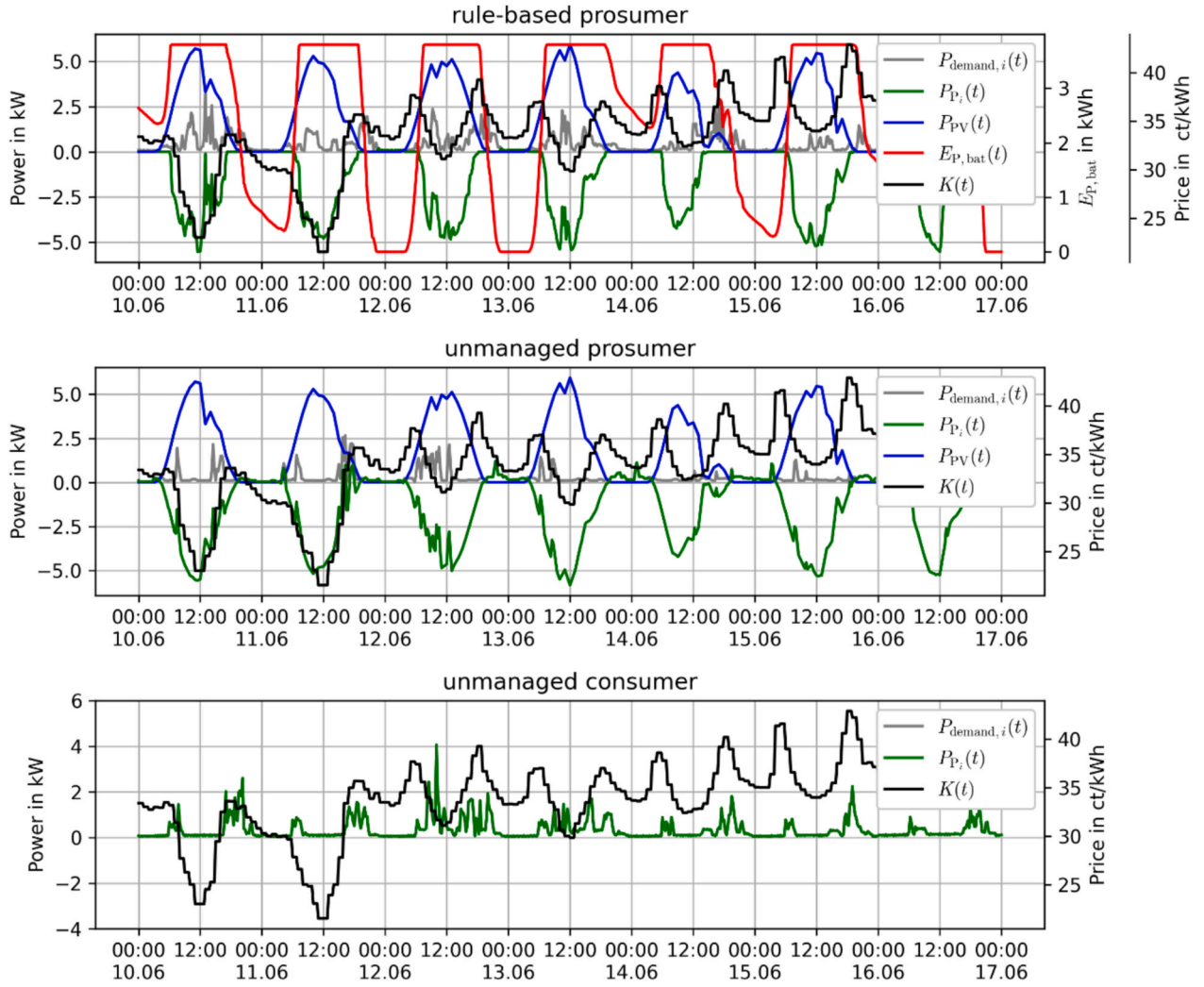


Fig. 6. Electricity exchange of the unmanaged consumer, unmanaged prosumer and rule-based prosumer during the summer season.

electricity price is generally higher compared to midday.

For the rule-based prosumer agent, utilising a BSS, the power exchange with the electricity grid is similar to the unmanaged prosumer. This is because in the summertime, which is characterised by high solar irradiation, the battery remains fully charged throughout most of the day. This forces the agent to sell surplus electricity as soon as the SOC reaches 100%.

However, the electricity demand during the night and in the evening can be supplied by the battery, resulting in no electricity consumption from the grid throughout the week. In the morning, the battery is

recharged, resulting in a delayed electricity supply to the grid compared to the unmanaged prosumer. Nevertheless, this behaviour is strongly dependent on the PV output. Especially in times of less solar irradiance over a longer period, this approach becomes more effective to reduce the overall grid interaction and reduce energy costs.

To illustrate the behaviour of the optimisation-based EMS, Fig. 7 presents the charging strategy of a randomly selected optimisation-based prosumer agent. The dashed lines indicate the charging strategy resulting from the agent's cost optimisation over a one-day prediction horizon. As expected, it can be observed that the prosumer charges its

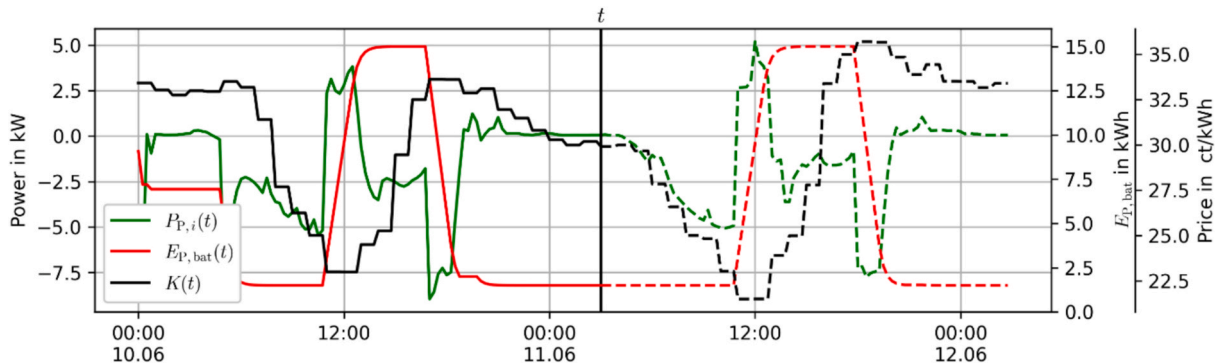


Fig. 7. Charging strategy of the optimisation-based prosumer agent.

battery when electricity prices are low and sells electricity back to the grid during periods of high electricity costs. This approach results in minimal electricity costs. However, it comes with the disadvantage of high peaks in the electricity exchange during favourable electricity prices and a more volatile and dynamic behaviour.

Fig. 8 depicts the charging strategy of the grid agent. In contrast to the prosumer agents, the grid agent determines its optimal strategy based on the emission factor $\epsilon(t)$. The evolution of the battery's SOC demonstrates that the grid agent's actions are consistent with the objective of emission reduction. Notably, the aggregated power demand of the prosumer agents $P_P(t)$, resulting from individual cost-optimised strategies, exhibits a temporal profile that closely resembles the charging behaviour of the grid agent. This observation indicates a high correlation between the electricity price and the emission factor in the presented week, as both optimisation approaches lead to similar operational patterns, particularly around midday.

4.2. Scenario evaluation

To illustrate the impact of the different scenarios on the overall demand profiles of the microgrid, Fig. 9 shows the effective power consumption from the grid.

In scenario UnCon, the microgrid primarily consists of consumer agents. As a result, the power exchanged with the grid is largely influenced by the grid agent, which generally charges the battery during midday and discharges it at night. The contribution of the consumer households to the overall demand profile is relatively small.

The scenario UnPro describes a microgrid predominantly including unmanaged prosumer agents, utilising PV plants. In this scenario a high surplus during midday can be obtained resulting in large negative values for $P_{P,i}(t)$. The grid agent works against this trend, compensating for the overproduction of the prosumer agents in times of already low emissions.

The third scenario RBPro showcases a higher focus on rule-based EMS. The difference between scenarios UnPro and RBPro is comparatively small, as rule-based and unmanaged prosumers exhibit similar behaviour in summer (see Fig. 6).

The fourth scenario OBPro shows the most volatile demand profile, hence the large amount of cost-driven optimisation-based prosumer agents show a strong reaction to the electricity price. Depending on the correlation between the price and the carbon emissions in the electricity mix, the grid agent either works against or emphasises the behaviour of the prosumer agents. The effect is especially visible during midday, when the grid agent as well as the prosumer agents charge their batteries.

4.3. Impact of environmental conditions

Apart from the level of intelligence in the microgrid, environmental conditions significantly influence the demand profile. To assess the impact of seasonal variations and weather conditions, Fig. 10 illustrates

the resulting demand profiles for a typical week in summer, spring, and winter for scenario OBPro.

In the summer months, a strongly periodic pattern can be observed in the carbon emissions. Additionally, significant fluctuations in the electricity price occur. This behaviour leads to a correspondingly volatile load profile, as both the grid agent and the prosumers react to these fluctuations. In contrast, during the spring week, a significantly less pronounced control behaviour of the prosumer agents can be observed. While the electricity price and emission factor still exhibit periodic fluctuations, these are less pronounced and generally persist at a higher level. The reduced reactivity of the prosumers can be attributed to the smaller changes in electricity prices, which make the use of the battery uneconomical due to charging and discharging losses. Only in the second half of the week the prosumers begin to charge their batteries in anticipation of a price peak at the end of the week. In the winter months, no periodic pattern can be observed in the emissions, indicating a low share of PV energy in the electricity mix. However, given that the emission factor is lower compared to spring, it can be assumed that a high share of wind energy is available. At the same time, the electricity price exhibits a less dynamic pattern. Due to the less dynamic and aperiodic emissions and cost profiles, reactions from the prosumers and the grid agent are infrequent, mainly reacting to very few extensive peaks in emissions and electricity price. This can also be seen in the absolute electricity exchange of the agents with the external grid, as shown in Fig. 11.

The overall interaction with the external grid varies intensely on the season. During the summer each prosumer agent's energy balance is characterised by a high amount of surplus energy, that is supplied to the grid. This behaviour can cause high stress in the grid due to the extensive power to be transferred [62]. As observed for the grid agent, electricity exchange with the broader grid mainly comprises surplus electricity from prosumer agents, temporarily stored in the grid agents BSS for load shifting. In contrast, the winter period is mainly characterised by consumption, both for the grid agent and the prosumers. In this case, the grid agent primarily imports electricity from the broader electricity grid during periods of low emissions to supply the prosumer agents within the microgrid.

Beside the season, the prosumer type results in significant differences in the grid interaction. For the optimisation-based prosumer the highest amount of electricity is exchanged with the grid, due to the price sensitive charging and discharging. With an unmanaged prosumer, lower values can be obtained. The rule-based prosumer generally shows the lowest grid interaction. However, in summer, a significant surplus is supplied to the grid due to the high PV generation and limited BSS capacity. Nevertheless, in the spring and winter season, the rule-based EMS allows for a reduced grid interaction compared to all other prosumer agents, due to its focus on self-sufficiency.

The overall electricity exchange can impact grid stability due to line capacities and overall overproduction and undersupply cases, especially in systems with a high share of RES. Therefore, not just the absolute exchange is important, but the time, when energy is consumed or

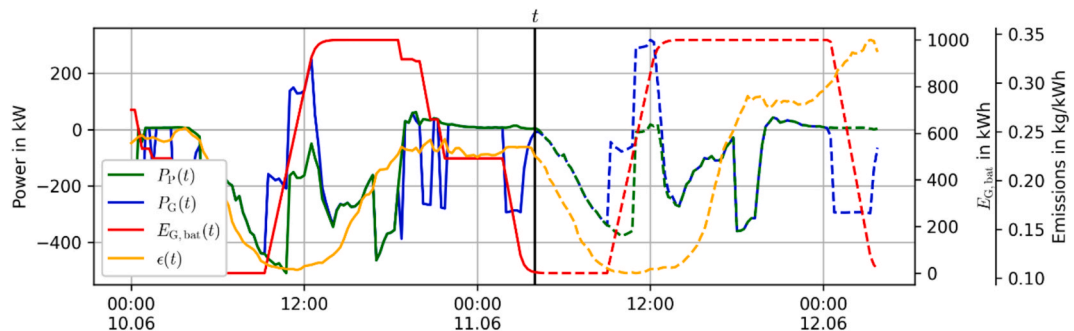


Fig. 8. Charging strategy of the grid agent.

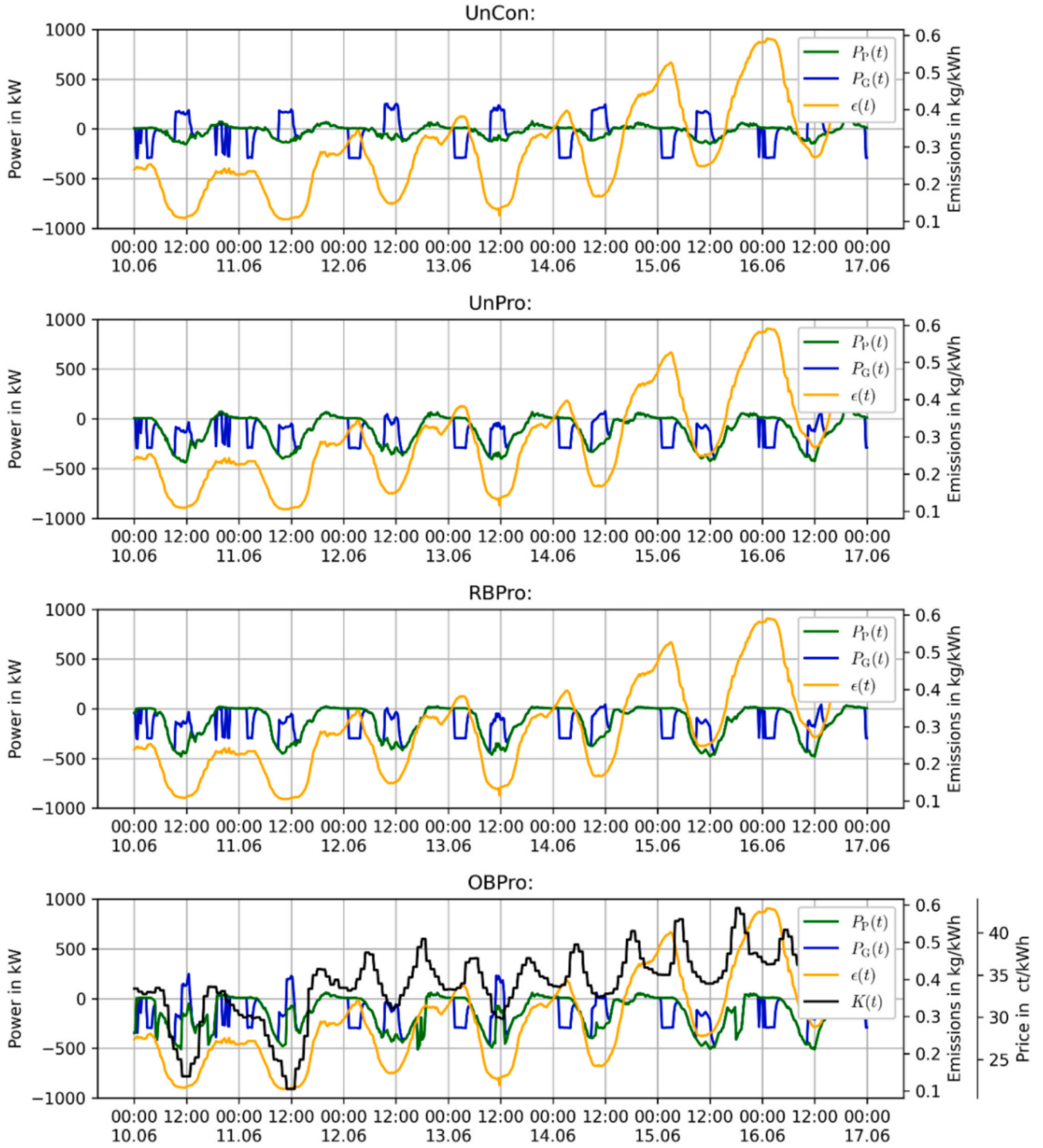


Fig. 9. Demand profile and power consumption from microgrid in different scenarios for summer.

supplied to achieve a grid friendly behaviour. To gain some insights into the overall grid friendliness of the microgrid against the broader electricity grid, each simulation is analysed and evaluated using the GSC as introduced in Equation (20). Furthermore, the impact of the grid agent is assessed by calculating the metric both with and without the stabilising grid agent. The results are presented in Table 4, which shows two GSCs for each combination of scenario and season.

It can be observed that in all configurations, the integration of a centralised grid agent contributes to a more grid supportive operation of the microgrid. However, the extent of this impact varies depending on the scenario and season. In summer, when low emissions are largely

driven by photovoltaic generation, the grid agent and the level of prosumer agent intelligence significantly influence overall grid supportiveness. In contrast, simulations without the grid agent exhibit behaviour that is strongly non-compliant with grid supportive behaviour. In spring and winter, the effect of the grid agent is less pronounced, resulting in relatively similar performance across all four scenarios. This indicates that high solar irradiance in conjunction with a high penetration of decentralised PV systems result in a non-grid supportive behaviour, even with a grid agent striving to compensate for the surplus electricity. This is why the summer months are of particular interest for the evaluation.

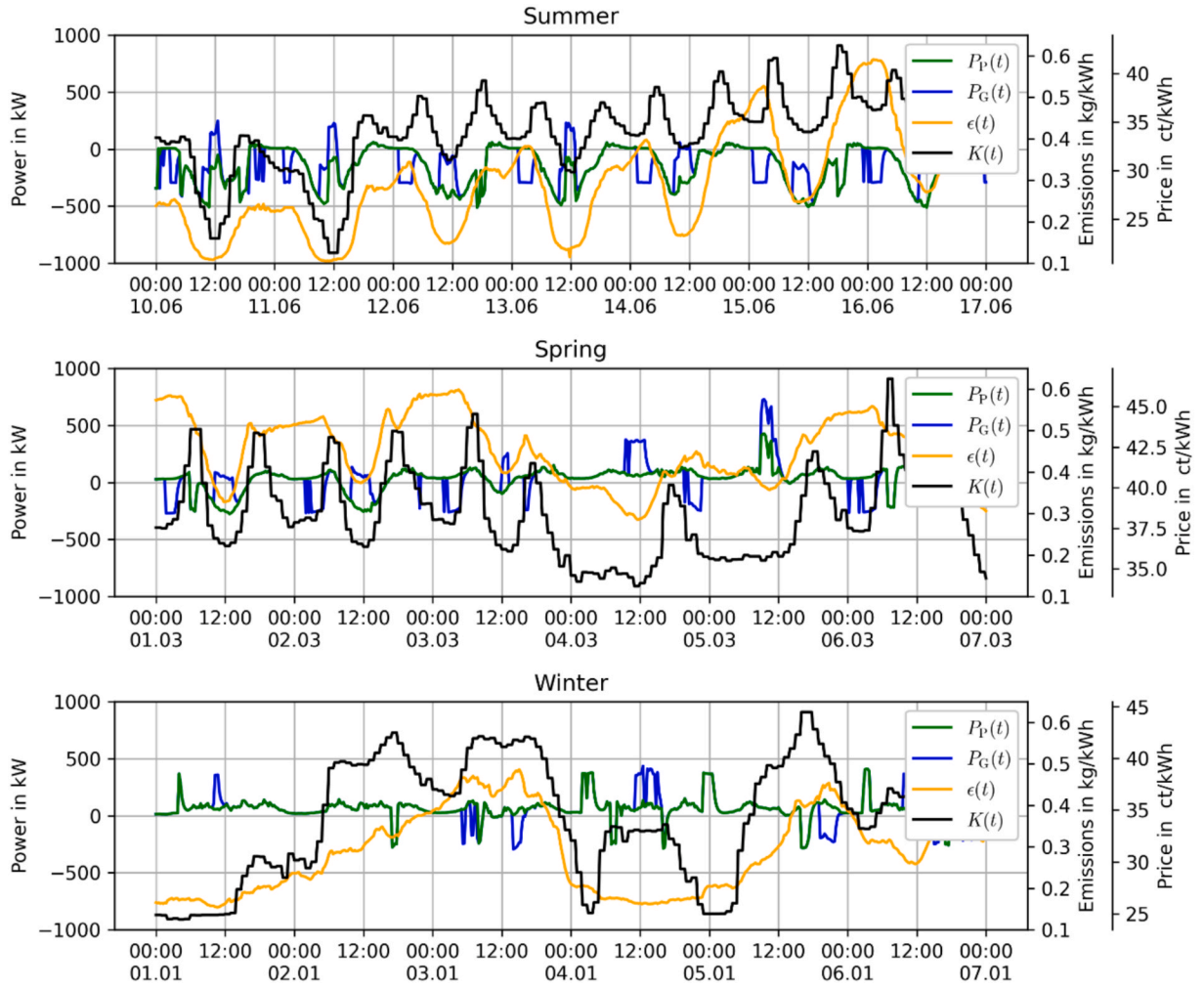


Fig. 10. Impact of environmental conditions on the behaviour of the grid and prosumer agents.

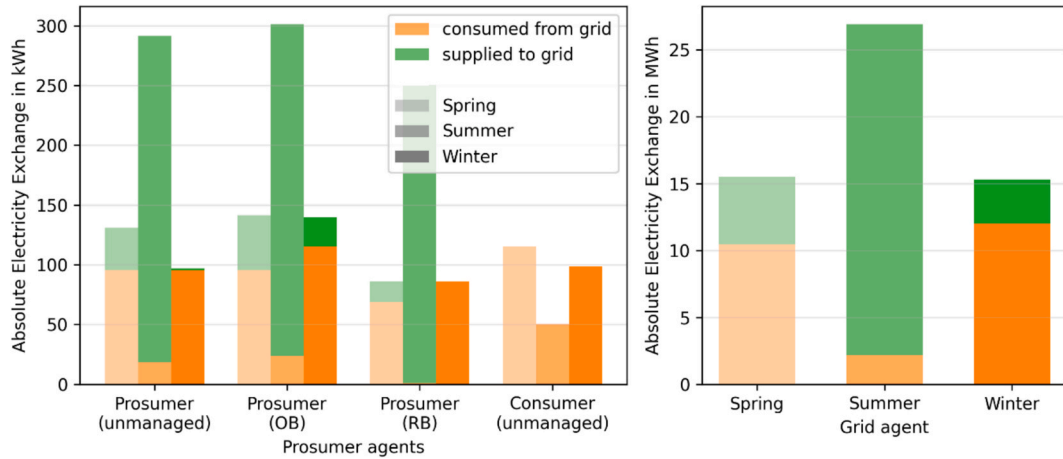


Fig. 11. Absolute electricity exchange of each agent type in different seasons.

When considering the UnCon scenario, adding the grid agent shows the biggest impact, reaching $GSC = 0.831$. One possible explanation is the relatively small grid interaction of consumer households compared to prosumer agents with substantial surplus electricity. As a result, the actions of the grid agent primarily contribute to load shifting with respect to the external electricity grid, rather than balancing energy flows within the microgrid itself or compensating for the surplus of the

prosumer agents. However, when comparing scenarios in summer, optimisation-based prosumers (scenario OBPro) exhibit a lower GSC and more grid-supportive behaviour than unmanaged or rule-based prosumer agents. This shows that strategic price driven EMS can help to achieve grid supportive behaviour. To confirm and further substantiate the statements made, the same analysis was repeated using three alternative weeks in each season. The resulting GSCs with and without a grid

Table 4
Grid Support Coefficient for load shifting assessment in different scenarios.

	Summer (1 week)		Spring (1 week)		Winter (1 week)	
	incl.grid agent	nogrid agent	incl.grid agent	nogrid agent	incl.grid agent	nogrid agent
UnCon	0.831	1.405	0.91	1.02	0.912	1.03
UnPro	1.145	1.411	0.92	1.03	0.9	1.013
RBPro	1.103	1.428	0.89	1.0	0.9	1.015
OBPro	1.03	1.34	0.9	1.01	0.86	0.96

Table 5
GSC for alternative weeks in summer, spring and winter.

	Summer (1 week)		Spring (1 week)		Winter (1 week)	
	incl.grid agent	nogrid agent	incl.grid agent	nogrid agent	incl.grid agent	nogrid agent
UnCon	0.711	1.222	0.846	1.058	0.972	0.994
UnPro	0.803	1.306	0.894	1.130	0.972	0.994
RBPro	0.749	1.185	0.863	1.120	0.971	0.994
OBPro	0.758	0.932	0.881	1.035	0.970	0.992

agent are shown in Table 5. Additional evaluations can be found in the appendix.

It can be seen, that for the alternative weeks generally lower GSC values in all scenarios and seasons can be obtained compared to Table 4. This can be explained by a lower solar irradiance as shown in B 1 in the appendix. Nevertheless, Table 4 and Table 5 show similarities. In both cases the grid agent has the highest impact in the summer season, while the differences become less significant in spring or winter. Further, the UnPro scenario again shows the most non-grid supportive behaviour, which underlines the importance of a controlled energy production. In this summer week, however, the RBPro scenario shows a lower GSC value than the UnCon or UnPro scenario, which indicates that the rule-based agents can achieve a better utilisation of their BSS compared to the initial case study. The OBPro scenario shows a grid supportive behaviour even without a grid agent. When considering the electricity price and the emissions in the electricity mix from B 1, it can be seen that in this week both price and emissions often have their minima and maxima at the same time. Therefore, cost driven prosumer agents assist the grid agent in achieving grid supportive behaviour while optimising their battery management for low electricity costs.

4.4. Economic evaluation

An economic evaluation was conducted to assess the profitability of different EMS and household configurations by analysing the energy costs of grid participants as shown in Table 6 for the described case study.

For each agent type the mean overall costs are calculated with and without additional O&M-costs. It shows that prosumer agents can gain significant profit in the summer, due to the surplus of their PV system. However, in spring and winter positive energy costs are obtained, due to the reduced solar irradiance. Nevertheless, the integration of individual PV systems still results in lower energy costs for individual households.

Table 6
Total energy costs for different agent types and scenarios. The table shows the mean values over all agent of each type.

	Summer (1 week)		Spring (1 week)		Winter (1 week)	
	incl.O&M	noO&M	incl.O&M	noO&M	incl.O&M	noO&M
OB-prosumer	-62.55 €	-111.74 €	33.93 €	24.58 €	39.12 €	37.84 €
RB-prosumer	-56.50 €	-105.57 €	34.98 €	25.71 €	41.66 €	40.44 €
unmanaged prosumer	-77.46 €	-108.18 €	36.57 €	30.78 €	44.12 €	43.37 €
unmanaged consumer	22.82 €	22.82 €	57.5 €	57.5 €	45.9 €	45.9 €
Grid Agent	791 €	215.69 €	384 €	-109 €	193 €	-300 €

The addition of an EMS and a BSS shows some slight improvements on the overall costs compared to unmanaged prosumers. However, the impact is rather low, especially if additional O&M-costs are considered. Even though managed prosumers using an optimisation-based EMS adjust their charging patterns to increase profit, in the summer unmanaged prosumers reach even higher profits due to lower Levelised cost of electricity (LCOE). However, this effect is primarily seen in the summer months. In spring, the results between optimisation-based and unmanaged prosumers only differ slightly, while in winter the managed prosumer benefits from its strategic charging compared to the unmanaged prosumer. This shows that, in situations with a lower PV output, a more strategic approach to charging and discharging the battery can lead to lower total costs, even if the LCOE are higher. For rule-based agents, self-sufficiency also leads to lower energy costs; however, the impact is less pronounced than for optimisation-based agents. Moreover, the additional O&M costs for PV and BSS result in only minor advantages compared to unmanaged prosumer agents.

The grid agent shows a different behaviour. While in the summer month the operation of the grid agent causes high costs, the costs are highly reduced in the spring and winter week. When not considering O&M costs even profit can be obtained, indicating, that electricity price and emission factor show a high correlation in these specific weeks, aligning economic concerns and grid friendly behaviour. This matches the observations from Table 5, where even without a grid agent GSC values smaller one can be obtained.

4.5. Sizing and operation of the grid agent

The introduction of a dedicated grid agent reduces the GSC value in all examined cases and thereby promotes more grid-friendly behaviour at the microgrid level. The sizing of the grid agent's BSS plays a decisive role in this context: larger BSS capacities are expected to further improve the aggregated net load profile, but at the expense of increased investment as well as O&M costs. To evaluate this trade-off, a sensitivity analysis has been conducted, examining the influence of varying grid agent battery capacities on both the GSC and the overall costs for the grid agent. The OBPro scenario in the summer week was selected as the baseline for this evaluation, as it captures the interplay of diverging interests of the prosumers and the grid agent. Based on this scenario different battery sizes for the grid agent were considered ranging from $E_{G,bat,max} = 300\text{kWh}$ to $E_{G,bat,max} = 4\text{MWh}$. The results are shown in Fig. 12.

the resulting trade-off between grid support and load profile smoothness (right).

It can be observed that increasing the grid agent's battery capacity leads to more pronounced peaks in the microgrid's net load profile $P_G(t)$, since a larger storage capacity enables the grid agent to shift greater amounts of energy into periods of high RES-availability. This behaviour is also reflected in the resulting GSC: higher battery capacities yield a lower GSC and thus a more grid-friendly operation of the microgrid towards the broader electricity grid. At the same time, however, larger battery capacities result in higher total costs for the grid agent, driven both by increased O&M costs and by the additional energy traded on the

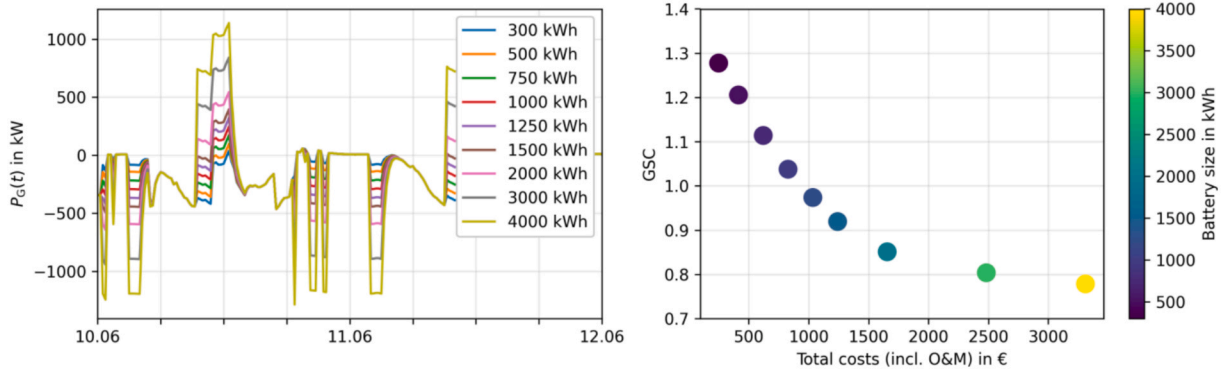


Fig. 12. Influence of the grid agent's battery storage capacity on the microgrid's net load profile (left) and on the resulting GSC and total costs of the grid agent (right)..

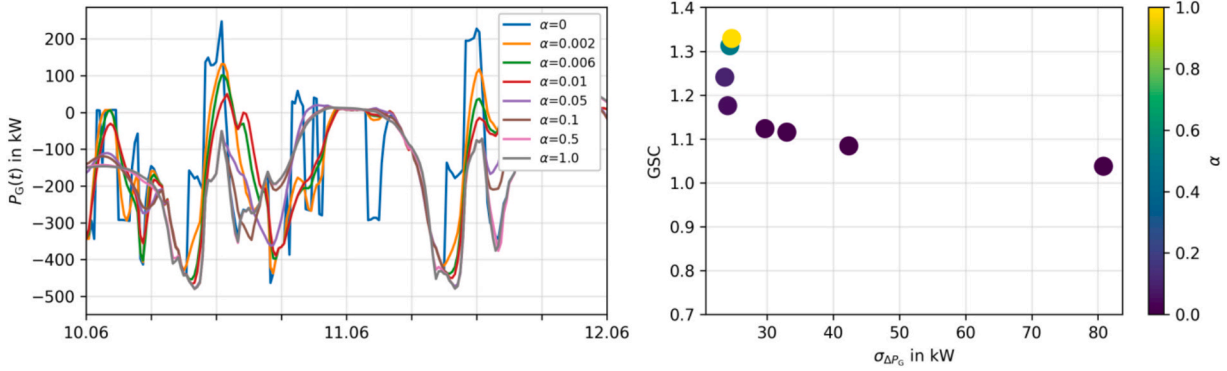


Fig. 13. Effect of the ramping penalty weight α on the microgrid net-load profile (left) and.

market. From these results, it follows that larger battery capacities are generally preferable regarding grid-friendly behaviour. However, the pronounced peaks occurring at high capacities can pose a challenge for the external grid, as such load spikes complicate grid balancing and may impair overall system stability [56]. To avoid high ramping, the objective function of the grid agent can penalise high gradients in the net load profile, dependent on the design parameter α as described in equation (15). The impact of different α on the microgrids load for a battery size of 1 MWh is displayed in Fig. 13.

The left plot illustrates the microgrid's net-load profile for varying ramping penalty weights α in the grid agent's objective function. As α increases, the volatility of the interaction with the upstream electricity grid decreases noticeably, and pronounced peaks in both load and feed-in are smoothed out. While this qualitative behaviour is directly visible in the time series, a quantitative assessment of the overall profile

volatility requires an aggregated metric. For this purpose, the root mean squared deviation (RMSD) of the net-load ramp

$$\sigma_{\Delta P_G} = \sqrt{\frac{1}{T} \sum_{t=0}^T (P_G(t) - P_G(t-1))^2} \quad (25)$$

is evaluated, capturing the typical magnitude of fluctuations between consecutive time steps.

The right plot in Fig. 13 displays the impact of different α -values on $\sigma_{\Delta P_G}$ and the GSC. It can be observed, that the GSC increases substantially with rising α . This behaviour can be explained by the strong correlation between electricity prices and emissions around midday, which incentivises the prosumer agents to charge their batteries during this period. However, the grid consumption of the prosumer agents is

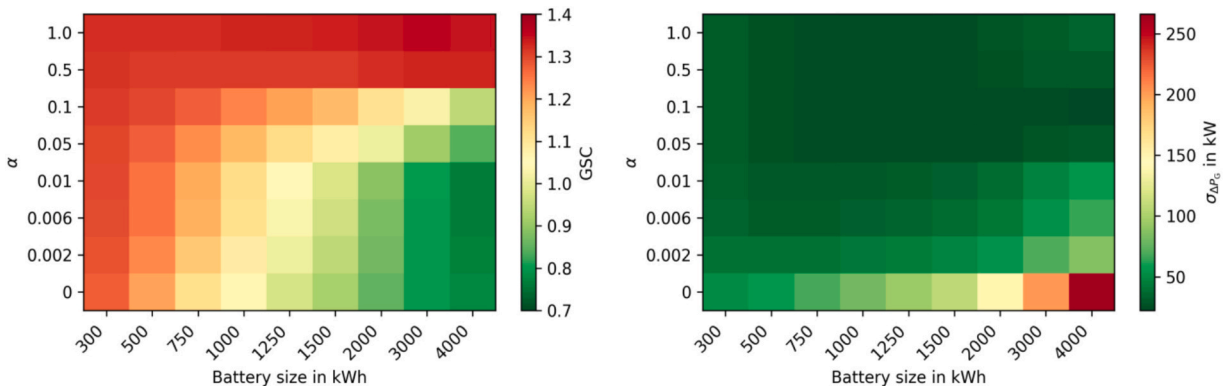


Fig. 14. Impact of varying BSS sizes and ramp penalties on the GSC (left) and the RMSD (right).

constrained by the ramping penalty, so that their batteries are predominantly charged from the grid agent's battery storage rather than directly from the grid. Consequently, the grid-supportive effect of a high correlation between electricity price and emission factor is partially counteracted, resulting in a deterioration of the GSC. This effect is further substantiated by Fig. 14, in which different combinations of α and battery capacity are evaluated jointly.

Both parameters have a pronounced impact on the load-shifting capabilities of the microgrid. While a large battery capacity in conjunction with a low α generally facilitates effective load shifting, this configuration simultaneously gives rise to comparatively high values of $\sigma_{\Delta P_G}$. The opposite parameter combination, a higher α paired with a smaller battery capacity, improves $\sigma_{\Delta P_G}$ but at the expense of reduced shifting flexibility. The sizing and operation of stabilising units therefore necessitate a careful balance between these competing objectives, particularly because the dispatch decisions of the individual prosumer agents directly shape the operating regime of the grid agent. This finding emphasises that the interplay between the heterogeneous grid participants and their respective objectives can only be addressed adequately through a detailed analysis of the underlying dependencies, which constitutes a prerequisite for deriving practically applicable strategies for microgrid operation.

5. Discussion and future research

The presented study investigates diverging interests between individual households and distribution system operators in microgrids by simulating the interaction between price-driven households and a central grid agent responsible for achieving grid supportive behaviour under the assumption of different EMS and flexibility options of individual prosumer agents. However, various assumptions were made, that heavily influence the overall results and need to be discussed in the following.

In this study, historical day-ahead market data were used to describe the electricity price profile for the households; however, these data were found to only partially promote grid-friendly behaviour among individual prosumer agents as needs to be seen as a placeholder for dynamic pricing concepts, that incentivise grid friendly behaviour. Especially the second simulation (cf. Table 5) indicate, that dynamic pricing mechanism can support grid supportive behaviour of cost driven prosumer agents. Therefore, future research will focus the establishment of microgrid-internal electricity markets and the evaluation of price driven concepts for grid stable operation. Beyond the isolated consideration of pricing mechanisms, future research should investigate the strategic interaction between the control strategy of the centralised grid agent and the effects of dynamic pricing schemes. A coordinated design, in which market signals and the dispatch strategy of the grid agent operate in a complementary manner, can compensate for the inherently unpredictable behaviour of residential participants, as also demonstrated by Yan et al. [24], and thereby enhance the resilience and grid stability of the microgrid in a more systematic way than either mechanism could achieve in isolation. Combining these approaches may allow a reduction of the required capacity, thereby lowering costs for distribution system operators. However, the results reveal a substantial discrepancy between the different seasons, indicating that a more detailed temporal analysis is required to holistically assess the overall impact of the grid agent on the electricity grid and profitability of the different technologies used by individual households under varying environmental and economic conditions. Especially in the case of grid operators, whose main task is to maintain grid stability, an economic assessment must take into account the entire system as well as alternative stabilisation measures that may be required in order to make a statement about profitability and suitability of the grid agent.

In this study the GSC is used to evaluate load shifting capabilities and to assess grid supportive behaviour. The definition of the metric as provided by Klein et al. [58] was further extended to be applicable not

just to electric loads, but to allow the assessment of both, electricity consumption and supply. However, load shifting only reflects one aspect of technical system stability. By varying the optimisation strategy of the grid agent, the trade-off between peak load reduction and load shifting was evaluated. However, important technical factors such as frequency regulation, line capacities and voltage stability are not yet included in this framework and would need to be incorporated for a more comprehensive assessment of grid stability. Therefore, in future work, this concept will be further developed including the integration of distribution grid topologies and more advanced technical simulation based on the pandapower framework [63]. Additionally, the emission factor employed in this study represents the national German electricity mix, so that the influence of a single microgrid on this aggregated signal is negligible. However, the national emission factor provides only limited information on the local emission factor and, consequently, on the grid-friendliness of the resulting operation with respect to the local distribution network. Moreover, as the concept is scaled up to multiple microgrids, their collective operation would increasingly affect the local emission factor, further weakening the validity of treating the external grid as independent.

Moreover, prosumer agents need to be modelled with greater detail by incorporating more realistic demand profiles, based on different building types and demographic characteristics to appropriately reflect the heterogeneity and uncertainty in resident's electricity and heating demands. As this work relies on synthetic load profiles, real-world demands will deviate due to occupant-specific behaviour and stochastic fluctuations not captured by synthetic data. The findings should therefore be read as a relative comparison between scenarios rather than as absolute predictions.

This also applies to the agent's energy assets. The modelling of PV systems can be extended to include varying system sizes and orientations, resulting in individualised PV profiles for each household. Furthermore, degradation effects and battery ageing, as described, for example, by Wamalwa et al. [64], should be incorporated into the BSS model. Since this study evaluates only three representative weeks, the impact of battery degradation is assumed to be negligible. However, for longer simulation periods, these effects become significant due to their influence on the reduced flexibility of both prosumers and grid agent. In addition to the energy assets themselves, a broader range of EMS must be considered to enable more realistic and diverse simulations of residential areas. The choice of different EMS strategies substantially affects the overall load profiles of prosumer households and should therefore be systematically analysed in future investigations. In this study, heat demands were modelled in a simplified manner, as only electrical flexibility options (BSS) were available. Once thermal flexibilities and more advanced EMS are integrated, heat demands will need to be modelled in greater detail, particularly with regard to their heterogeneity across households. Furthermore, the assumption that heat pumps will be used to meet the heat demand of households and the resulting impact on the electric load profile may be mitigated by alternative heating concepts such as district heating, which also provide a promising approach for a sustainable heat supply in residential areas, as demonstrated by Divkovic et al. [65]. Another critical aspect is the integration of electric vehicles, which are anticipated to significantly shape household electricity consumption patterns in the future and simultaneously offer greater flexibility to the prosumer agents by utilising smart charging strategies.

An important aspect in the evaluation and analysis of different DSM concepts is the reliability of the derived findings. Since decisions of the prosumer agents are mainly influenced by the highly uncertain behaviour of residents, the underlying electrical and thermal load profiles reflect only one possible behaviour of a prosumer agent. However, in reality, the resulting load profile will vary and impact the results as stated by Fischer et al. [2]. Therefore, sensitivity analyses (e.g. Monte Carlo methods) need to be carried out to robustly substantiate the results by accounting for uncertainties in load profiles, weather conditions,

disruptive events or external influences from the broader electricity grid. Further, the results need to be validated against real-world data of existing microgrids in future research to confirm that the proposed modelling approach yields trustworthy representations of individual grid participants' behaviour and the resulting system-level implications.

6. Conclusion

The proposed MAS provides a framework for evaluating demand-side flexibility in a microgrid by simulating the interactions between heterogeneous participants, namely economically motivated prosumer households and a grid agent tasked with coordinating load shifting at the system level. Its primary purpose is to establish a foundational basis for the joint evaluation of different DSM approaches, such as dynamic electricity pricing in combination with centralised, grid-stabilising assets, while accounting for the perspectives of residents and distribution system operators.

The investigations reveal that the heterogeneity of the individual households, together with varying distributions of energy assets such as PV systems and BSS, substantially influences the energy exchange between the microgrid and the external grid. This effect is most pronounced in summer, when the unmanaged feed-in of decentralised PV systems causes a non-grid-supportive behaviour of the microgrid. For cost-driven prosumer agents, a strong correlation between electricity prices and emission factors can mitigate this effect by incentivising grid-friendly dispatch at the household level. The benefit, however, varies considerably across seasons and depends on the individual EMS configuration, which limits the reliability of price-based mechanisms as a stand-alone instrument.

The introduction of a dedicated grid agent addresses this limitation by actively balancing the aggregated load profile of the microgrid. In most cases, its presence results in a grid-supportive behaviour with a GSC below one. During summer periods with high PV penetration, however, the surplus electricity exceeds the compensation capability of the grid agent (cf. Table 4). Increasing the battery capacity of the grid agent generally enhances its load-shifting capabilities yet entails additional investment and operational costs for the DSO. The concrete operating strategy is equally relevant: incorporating additional objectives such as peak reduction reduces the influence of the grid agent on the GSC and was further found to counteract the positive effect of incentivising grid-friendly behaviour at the household level, as the grid agent limits the energy exchange with the external grid. Consequently, for the development of suitable operating strategies for microgrids, these interdependencies must be thoroughly analysed and accounted for. If these interactions are appropriately considered, however, a combined deployment of both approaches appears promising: dynamic pricing

steers the dispatch decisions of the prosumer agents towards grid-friendly operation, while the grid agent compensates for residual imbalances that cannot be resolved through price signals alone. This allows reducing the energy costs of individual households, while simultaneously reducing the technical effort for DSOs to balance and stabilise the electricity grid.

The present work establishes the methodological basis for systematically investigating these interdependencies and provides a foundation for future studies on the coordinated design of market mechanisms and centralised grid-stabilising assets, ultimately supporting the development of resilient and efficient microgrid management concepts.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the author(s) used DeepL for grammar and spelling checks and ChatGPT to assist with the formulation and translation of individual sentences. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

CRediT authorship contribution statement

Kevin Henne: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. **Henning Rahlf:** Writing – review & editing, Methodology, Formal analysis. **Marius Naumann:** Writing – review & editing, Methodology. **Henning Meschede:** Writing – review & editing.

Funding

Kevin Henne acknowledge support for the publication cost by the Open Access Publication Fund of Paderborn University. Henning Rahlf acknowledges financial support within the project “FlexLabQuartier: Climate-neutral transformation of urban districts”. The project FlexLabQuartier received funding under the joint programming initiative EFRE/JFT-Program NRW and the Ministry of Economic Affairs, Industry, Climate Action and Energy of the State of North Rhine-Westphalia (Grant No. 34.EFRE-20300085). The remaining authors received no specific funding for this work.

Declaration of competing interest

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

Appendix A

The simulation parameters and assumptions are listed in the following table:

Parameter	Value	Source/Assumption
$P_{d,elec}$	Timeseries	[26,27]
Average annual heating demand of a German household	13,400kWh	[29]
$P_{d,heat}$	Timeseries	[28]
η_{HP}	60%	[33]
T_{inside}	20°	[31]
$T_{ambient}$	Timeseries	[32]
η_{PV}	18%	[35]
γ_{PV}	0.4%/K	[34]
U_{conv}	20W/mK	[37]
U_w	1.2Ws/K	[37]
T_{STC}	25° C	[38]
A_{PV}	44m ²	[36]

(continued on next page)

(continued)

Parameter	Value	Source/Assumption
$E_{p,bat,cat}$	[4, 8, 11, 15]kWh	[39,40]
C-Rate	0.5	[40]
DOD	95%	[41]
η_{charge}	91%	[41]
$\eta_{discharge}$	92%	[41]
$E_{G,Bat}$	1MWh	[57]
$P_{G,bat,max}$	300kW	[57]
LCOE	[10, 16]ct/kWh	[60]
CAPEX	600€/kWh	[60]
OPEX	2%ofCAPEX/a	[60]
$T_{lifetime}$	20 years	[57]
$I(t)$	Timeseries	[32]
$K(t)$	Timeseries	[53]
$\epsilon(t)$	Timeseries	[53]

Appendix B

The following figures show the second simulation with different weeks, that was carried out to verify the results from the initial case study described in the paper. The nomenclature and labelling of the scenarios were kept:

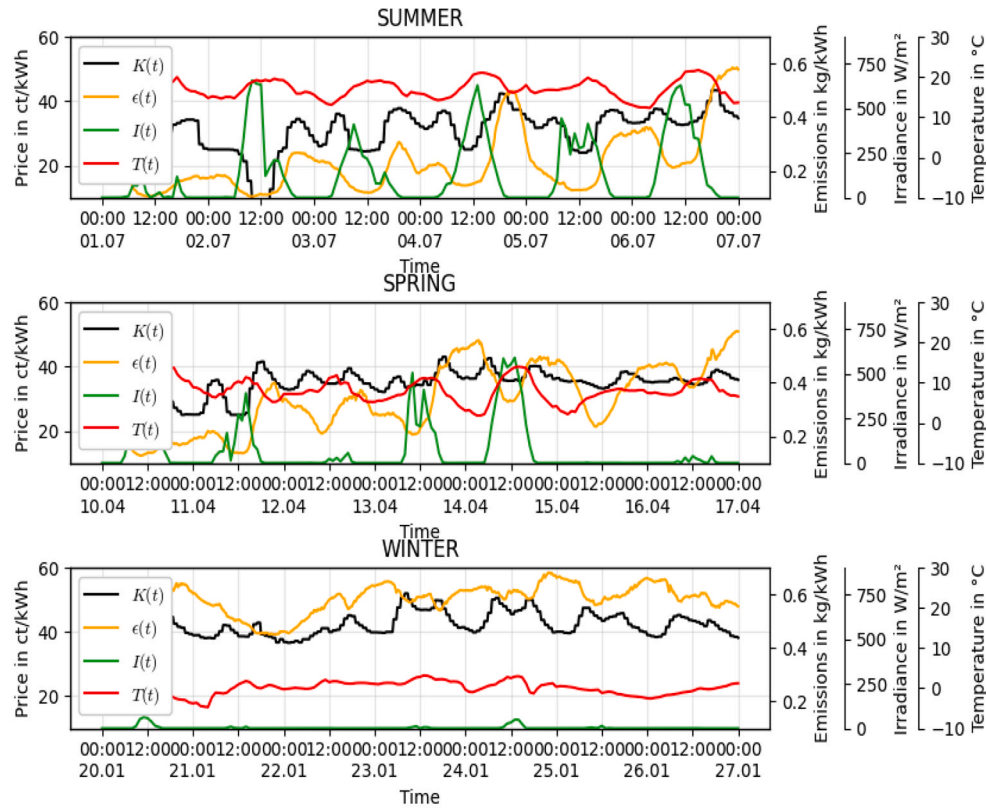


Fig. B1. Alternative weeks. Electricity price, emission factor irradiance and ambient temperature for each week.

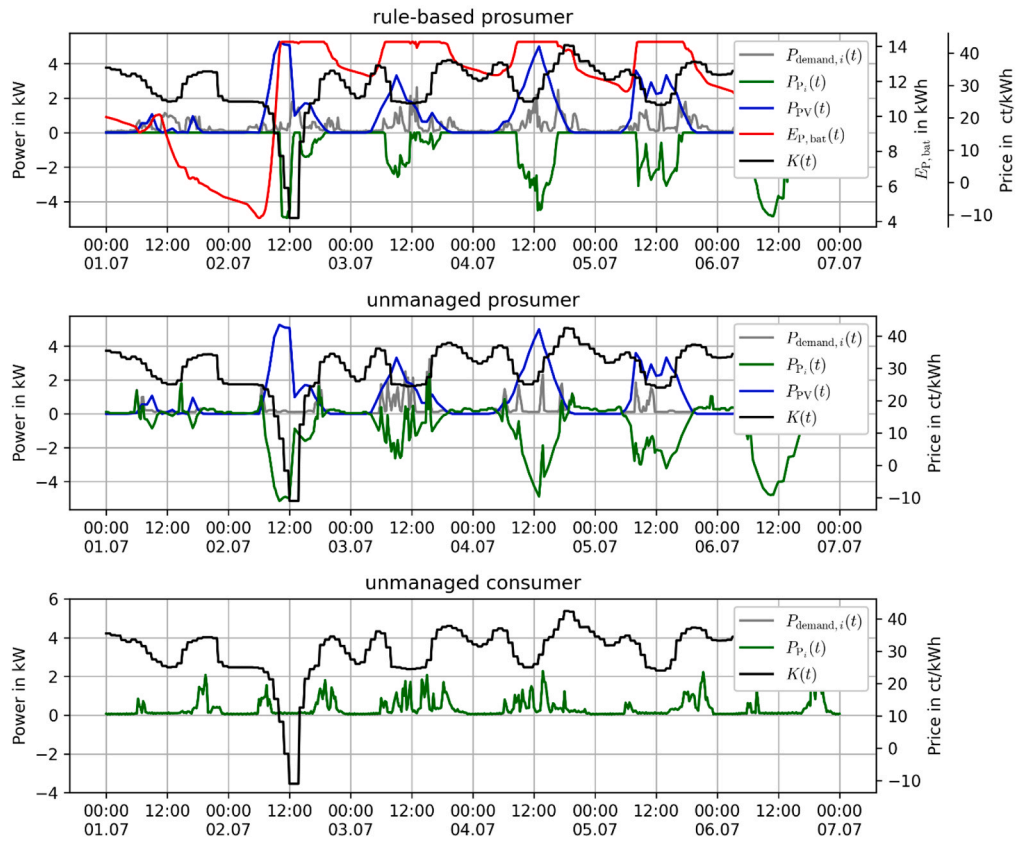


Fig. B2. Alternative weeks. Electricity exchange of the unmanaged consumer, unmanaged prosumer and rule-based prosumer during the summer season.

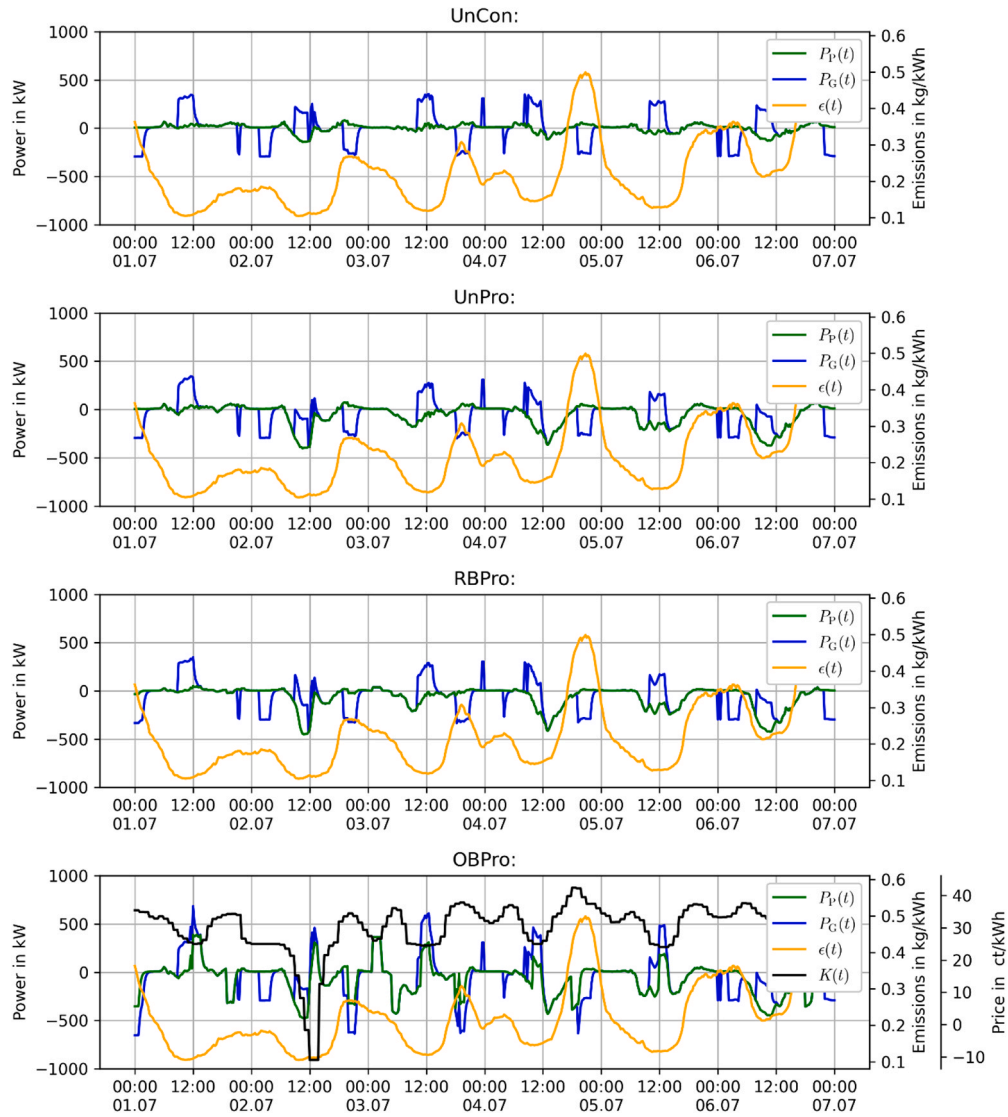


Fig. B3. Alternative weeks. Demand profile and power consumption from microgrid in different scenarios

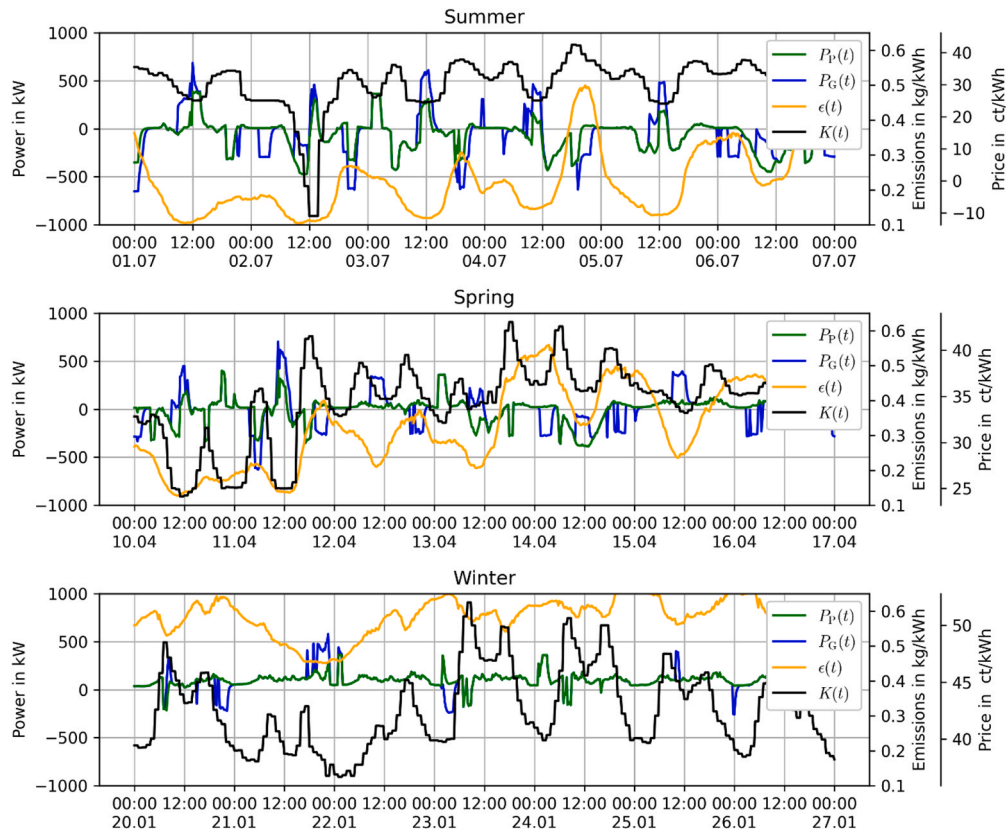


Fig. B4. Alternative weeks. Impact of environmental conditions on the behaviour of the grid and prosumer agents

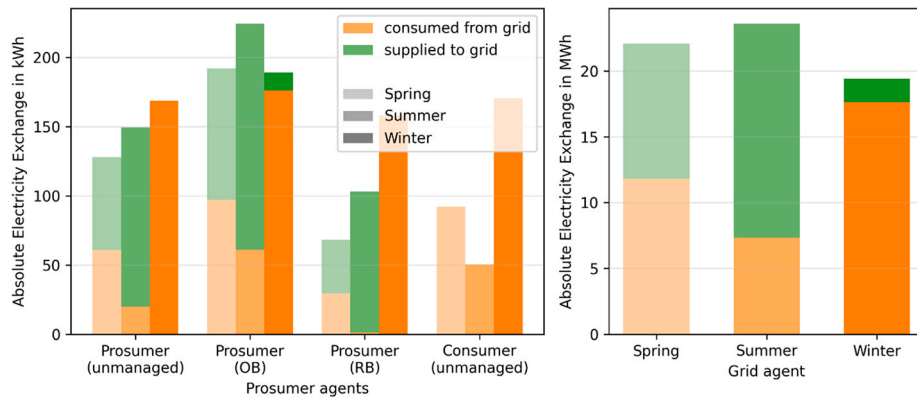


Fig. B5. Alternative weeks. Absolute electricity exchange of each agent type in different seasons.

Table B6

Total energy costs for different agent types and scenarios. The table shows the mean values over all agents of each type.

	Summer (1 week)		Spring (1 week)		Winter (1 week)	
	incl.O&M	noO&M	incl.O&M	noO&M	incl.O&M	noO&M
OB-prosumer	-21.95 €	-47.31 €	14.66 €	-3.90 €	86.84 €	86.06 €
RB-prosumer	-11.80 €	-36.73 €	12.30 €	-0.81 €	86.35 €	85.66 €
unmanaged prosumer	-23.22 €	-39.01 €	8.67 €	-0.89 €	91.78 €	91.35 €
unmanaged consumer	21.45 €	21.45 €	41.95 €	41.95 €	92.4 €	92.4 €
Grid Agent	-2.28 €	-495 €	787 €	211 €	377 €	-198 €

Data availability

Data will be made available on request.

References

- [1] Bakare MS, Abdulkarim A, Zeeshan M, Shuaibu AN. A comprehensive overview on demand side energy management towards smart grids: challenges, solutions, and future direction. *Energy*. Inform 2023;6(1). <https://doi.org/10.1186/s42162-023-00262-7>.
- [2] Fischer D, Surmann A, Lindberg KB. Impact of emerging technologies on the electricity load profile of residential areas. *Energy Buildings* 2020;208:109614. <https://doi.org/10.1016/j.enbuild.2019.109614>.
- [3] Reimuth A, Locher V, Danner M, Mauser W. How does the Rate of Photovoltaic Installations and coupled Batteries Affect Regional Energy Balancing and Self-Consumption of Residential buildings? *Energies* 2020;13(11):2738. <https://doi.org/10.3390/en13112738>.
- [4] Spiegel T. J. sustain. dev. energy water environ. syst. Impact of Renewable Energy Expansion to the Balancing Energy Demand of Differential Balancing Groups 2018; 6(4):784–99. <https://doi.org/10.13044/j.sdwes.6.0215>.
- [5] Meliani M, Barkany AE, Abbassi IE, Darcherif AM, Mahmoudi M. Energy management in the smart grid: State-of-the-art and future trends. *International Journal of Engineering Business Management* 2021;13. <https://doi.org/10.1177/184797902111032920>.
- [6] Kazmi SAA, Shahzad MK, Khan AZ, Shin DR. Smart distribution Networks: a Review of Modern distribution Concepts from a Planning Perspective. *Energies* 2017;10(4):501. <https://doi.org/10.3390/en10040501>.
- [7] Battula AR, Vuddanti S, Salkuti SR. Review of Energy Management System Approaches in Microgrids. *Energies* 2021;14(17):5459. <https://doi.org/10.3390/en14175459>.
- [8] Quizhpe K, Arévalo P, Ochoa-Correa D, Villa-Ávila E. Optimizing Microgrid Planning for Renewable Integration in Power Systems: a Comprehensive Review. *Electronics* 2024;13(18):3620. <https://doi.org/10.3390/electronics13183620>.
- [9] Arunkumar AP, Kuppusamy S, Muthusamy S, Pandiyan S, Panchal H, Nagaiyan P. An extensive review on energy management system for microgrids. *Energy Sources Part A* 2022;44(2):4203–28. <https://doi.org/10.1080/15567036.2022.2075059>.
- [10] Elsieid M, Oukaour A, Youssef T, Gualous H, Mohammed O. An advanced real time energy management system for microgrids. *Energy* 2016;114:742–52. <https://doi.org/10.1016/j.energy.2016.08.048>.
- [11] Hosseini SM, Carli R, Dotoli M. Robust Optimal Energy Management of a Residential Microgrid under Uncertainties on demand and Renewable Power Generation. *IEEE Trans Automat Sci Eng* 2021;18(2):618–37. <https://doi.org/10.1109/TASE.2020.2986269>.
- [12] Arcos-Aviles D, Pascual J, Marroyo L, Sanchis P, Guinjoan F. Fuzzy Logic-based Energy Management System Design for Residential Grid-Connected Microgrids. *IEEE Trans Smart Grid* 2018;9(2):530–43. <https://doi.org/10.1109/TSG.2016.2555245>.
- [13] Atia R, Yamada N. Sizing and Analysis of Renewable Energy and Battery Systems in Residential Microgrids. *IEEE Trans Smart Grid* 2016;7(3):1204–13. <https://doi.org/10.1109/TSG.2016.2519541>.
- [14] Nasr M-A, Rabiee A, Kamwa I. MPC and robustness optimisation-based EMS for microgrids with high penetration of intermittent renewable energy. *IET Generation Trans & Dist* 2020;14(22):5239–48. <https://doi.org/10.1049/iet-gtd.2020.0460>.
- [15] Anvari-Moghaddam A, Rahimi-Kian A, Mirian MS, Guerrero JM. A multi-agent based energy management solution for integrated buildings and microgrid system. *Appl Energy* 2017;203:41–56. <https://doi.org/10.1016/j.apenergy.2017.06.007>.
- [16] Radhakrishnan BM, Srinivasan D. A multi-agent based distributed energy management scheme for smart grid applications. *Energy* 2016;103:192–204. <https://doi.org/10.1016/j.energy.2016.02.117>.
- [17] Jun Z, Junfeng L, Jie W, Ngan HW. A multi-agent solution to energy management in hybrid renewable energy generation system. *Renew Energy* 2011;36(5):1352–63. <https://doi.org/10.1016/j.renene.2010.11.032>.
- [18] Khan MW, Wang J, Ma M, Xiong L, Li P, Wu F. Optimal energy management and control aspects of distributed microgrid using multi-agent systems. *Sustain Cities Soc* 2019;44:855–70. <https://doi.org/10.1016/j.scs.2018.11.009>.
- [19] Karavas C-S, Arvanitis K, Papadakis G. A Game Theory Approach to Multi-Agent Decentralized Energy Management of Autonomous Polygeneration Microgrids. *Energies* 2017;10(11):1756. <https://doi.org/10.3390/en10111756>.
- [20] Cui S, Wang Y-W, Xiao J-W, Liu N. A Two-Stage Robust Energy Sharing Management for Prosumer Microgrid. *IEEE Trans Ind Inf* 2019;15(5):2741–52. <https://doi.org/10.1109/TII.2018.2867878>.
- [21] El-Affifi MI, Sedhom BE, Eladl AA, Sanjeevikumar P, Fawzy S. Leveraging Game Theory to Design Incentive-Compatible Time-Varying electricity pricing with Demand-Side management. *Energy Convers Manage: X* 2024;24:100815. <https://doi.org/10.1016/j.ecmx.2024.100815>.
- [22] Akter M, Mahmud M, Oo A. A Hierarchical Transactive Energy Management System for Energy Sharing in Residential Microgrids. *Energies* 2017;10(12):2098. <https://doi.org/10.3390/en10122098>.
- [23] Stute J, Kühnrich M. Dynamic pricing and the flexible consumer – investigating grid and financial implications: a case study for Germany. *Energy Strat Rev* 2023;45:100987. <https://doi.org/10.1016/j.esr.2022.100987>.
- [24] Yan X, Ozturk Y, Hu Z, Song Y. A review on price-driven residential demand response. *Renew Sustain Energy Rev* 2018;96:411–9. <https://doi.org/10.1016/j.rser.2018.08.003>.
- [25] Roozbehani M, Dahleh MA, Mitter SK. Volatility of Power Grids under Real-Time pricing. *IEEE Trans Power Syst* 2012;27(4):1926–40. <https://doi.org/10.1109/TPWRS.2012.2195037>.
- [26] Pflugrad N, Stenzel P, Kotzur L, LoadProfileGenerator SD. An Agent-based Behavior simulation for Generating Residential load Profiles. *JOSS* 2022;7(71):3574. <https://doi.org/10.21105/joss.03574>.
- [27] Pflughardt ND. Modellierung von Wasserund Energieverbräuchen in Haushalten [Dissertation]. Chemnitz: Technische Universität Chemnitz; 2016.
- [28] Overview — demandlib 0.2.2a1 documentation. [March 25, 2025]; Available from: <https://demandlib.readthedocs.io/en/latest/>.
- [29] German Federal Statistical Office. Electricity consumption of private households by household size classes. [January 05, 2026]; Available from: https://www.destatis.de/EN/Themes/Society-Environment/Environment/Environmental-Economic-Accounting/private-households/_node.html.
- [30] Sarbu I, Sebarchievici C. General review of ground-source heat pump systems for heating and cooling of buildings. *Energy Buildings* 2014;70:441–54. <https://doi.org/10.1016/j.enbuild.2013.11.068>.
- [31] German Environment Agency. Correct heating protects the climate and your wallet. [May 05, 2026]; Available from: <https://www.umweltbundesamt.de/umwelttipps-fuer-den-alltag/richtiges-heizen-schuetzt-das-klima-dengeldbeutel#so-erreichen-sie-das-ideale-raumklima-in-ihrem-heim>.
- [32] Zippenfenig P. Open-Meteo.com Weather API; 2023.
- [33] Meggers F, Ritter V, Goffin P, Baetschmann M, Leibundgut H. Low exergy building systems implementation. *Energy* 2012;41(1):48–55. <https://doi.org/10.1016/j.energy.2011.07.031>.
- [34] Charles Lawrence Kamuyu W, Lim J, Won C, Ahn H. Prediction Model of Photovoltaic Module Temperature for Power Performance of floating PVs. *Energies* 2018;11(2):447. <https://doi.org/10.3390/en11020447>.
- [35] Dallaev R, Pisarenko T, Papež N, Holcman V. Overview of the Current State of Flexible Solar Panels and Photovoltaic Materials. *Materials (basel)* 2023;16(17). <https://doi.org/10.3390/ma16175839>.
- [36] Killinger S, Lingfors D, Saint-Drenan Y-M, Moraitis P, van Sark W, Taylor J, et al. On the search for representative characteristics of PV systems: Data collection and analysis of PV system azimuth, tilt, capacity, yield and shading. *Sol Energy* 2018;173:1087–106. <https://doi.org/10.1016/j.solener.2018.08.051>.
- [37] Kaldellis JK, Kapsali M, Kavadias KA. Temperature and wind speed impact on the efficiency of PV installations. Experience obtained from outdoor measurements in Greece. *Renew Energy* 2014;66:612–24. <https://doi.org/10.1016/j.renene.2013.12.041>.
- [38] Amran NFQ, Zulkifli WNAW, Jaalam N, Arith F, Shah ASM. Investigation of Standard Test Condition Requirement in establishing Alternative Measurement Platform for Photovoltaic Cell. *J Phys Conf Ser* 2024;2928(1):12003. <https://doi.org/10.1088/1742-6596/2928/1/012003>.
- [39] Kairies K-P, Figgenger J, Haberschus D, Wessels O, Tepe B, Sauer DU. Market and technology development of PV home storage systems in Germany. *J Storage Mater* 2019;23:416–24. <https://doi.org/10.1016/j.est.2019.02.023>.
- [40] Figgenger J, Hecht C, Bors J, Spreuer K, Kairies K-P, Stenzel P et al. The development of battery storage systems in Germany: A market review (status 2023). <https://doi.org/10.48550/arXiv.2203.06762>.
- [41] Orth N, Munzke N, Weniger J, Messner C, Schreier R, Mast M, et al. Efficiency characterization of 26 residential photovoltaic battery storage systems. *J Storage Mater* 2023;65:107299. <https://doi.org/10.1016/j.est.2023.107299>.
- [42] Figgenger J, van Ouwerkerk J, Haberschus D, Bors J, Woerner P, Menekes M, et al. Multi-year field measurements of home storage systems and their use in capacity estimation. *Nat Energy* 2024;9(11):1438–47. <https://doi.org/10.1038/s41560-024-01620-9>.
- [43] Leonori S, Rocca R, Ricci M, Frattale Mascioli FM. Smart home energy flow optimization, a practical case study. *Energy Convers Manage: X* 2025;28:101340. <https://doi.org/10.1016/j.ecmx.2025.101340>.
- [44] Angenendt G, Zurmühlen S, Rücker F, Axelsen H, Sauer DU. Optimization and operation of integrated homes with photovoltaic battery energy storage systems and power-to-heat coupling. *Energy Convers Manage: X* 2019;1:100005. <https://doi.org/10.1016/j.ecmx.2019.100005>.
- [45] Pajares A, Vivas FJ, Blasco X, Herrero JM, Segura F, Andújar JM. A novel energy management system based on move-blocking based predictive control for use in microgrid control. *Energy Convers Manage* 2025;345:120400. <https://doi.org/10.1016/j.enconman.2025.120400>.
- [46] Camblong H, Zapiain I, Curea O, Ugartemendia J, Boussaada Z, Zamora R. Rule-based Energy Management System to Enhance PV Self-Consumption in a Building: a Real Case. *Energies* 2024;17(23):6099. <https://doi.org/10.3390/en17236099>.
- [47] Jafari M, Malekjamshidi Z, Zhu J, Khooban M-H. A Novel Predictive Fuzzy Logic-based Energy Management System for Grid-Connected and Off-Grid operation of Residential Smart Microgrids. *IEEE J Emerg Sel Topics Power Electron* 2020;8(2):1391–404. <https://doi.org/10.1109/JESTPE.2018.2882509>.
- [48] Judge MA, Franzitta V, Curto D, Guercio A, Ciriuncione G, Khattak HA. A comprehensive review of artificial intelligence approaches for smart grid integration and optimization. *Energy Convers Manage: X* 2024;24:100724. <https://doi.org/10.1016/j.ecmx.2024.100724>.
- [49] Asghar E, Sengor I, Hill M, Lynch C. Deep Q-Network for intelligent energy management system in an energy community. *Energy Strat Rev* 2025;62:101991. <https://doi.org/10.1016/j.esr.2025.101991>.
- [50] Salehpour MJ, Hossain MJ, Shafie-khah M. Resilient coordination of energy storage and renewable generation in residential systems using deep reinforcement learning considering extreme weather conditions. *J Storage Mater* 2026;146:119868. <https://doi.org/10.1016/j.est.2025.119868>.

- [51] Azuatalam D, Paridari K, Ma Y, Förstl M, Chapman AC, Verbić G. Energy management of small-scale PV-battery systems: a systematic review considering practical implementation, computational requirements, quality of input data and battery degradation. *Renew Sustain Energy Rev* 2019;112:555–70. <https://doi.org/10.1016/j.rser.2019.06.007>.
- [52] Haupt T, Jungwirth J, Hofmann G, Vaidya H. Home Energy Management Systems (HEMS): 2nd Market Overview for Germany (2025). *PV-Symposium Proc* 2025;2. <https://doi.org/10.52825/pv-symposium.v2i.2641>.
- [53] entsoe. Transparency Platform. [April 25, 2025]; Available from: <https://newtransparency.entsoe.eu/market/energyPrices>.
- [54] Kamakshi Prashadini S, Mala D. *Analysis of Effectiveness of flexible load Shifting Order on Optimum DSM*. IEEE 2017.
- [55] Krauter S, Zhang L. Correlation of grid-frequency, electricity prices, share of renewable, and CO₂—contents in the German electricity grid to enable inexpensive triggering of Demand—Side—Management. In: 2020 47th IEEE Photovoltaic Specialists Conference (PVSC). IEEE; 2024, p. 1672–1674.
- [56] Gumilar L, Islamey IS. Frequency Stability Analysis in IEEE 30 Bus Power System Due to Large Load Addition. In: 2024 International Seminar on Application for Technology of Information and Communication (iSemantic). IEEE; 2024, p. 575–580.
- [57] Elkazaz M, Sumner M, Naghiyev E, Hua Z, Thomas DW. Techno-Economic Sizing of a community battery to provide community energy billing and additional ancillary services. *Sustainable Energy Grids Networks* 2021;26:100439. <https://doi.org/10.1016/j.segan.2021.100439>.
- [58] Klein K, Langner R, Kalz D, Herkel S, Henning H-M. Grid support coefficients for electricity-based heating and cooling and field data analysis of present-day installations in Germany. *Appl Energy* 2016;162:853–67. <https://doi.org/10.1016/j.apenergy.2015.10.107>.
- [59] Rahlf H, Knorr L, Althoff S, Meschede H. Analysis of bidirectional EV charging infrastructures within industrial DC grids. *Smart Energy* 2026:100227. <https://doi.org/10.1016/j.segy.2026.100227>.
- [60] Dr Christoph Kost. *Fraunhofer ISE. Study: Levelized Cost of Electricity- Renewable Energy Technologies*; 2024.
- [61] ENTSO-E. Transparency Platform.
- [62] Smith O, Cattell O, Farcot E, O'Dea RD, Hopcraft KI. The effect of renewable energy incorporation on power grid stability and resilience. *Sci Adv* 2022;8(9):eabj6734. <https://doi.org/10.1126/sciadv.abj6734>.
- [63] Thurner L, Scheidler A, Schafer F, Menke J-H, Dollichon J, Meier F, et al. Pandapower—An Open-Source Python Tool for Convenient Modeling, Analysis, and Optimization of Electric Power Systems. *IEEE Trans Power Syst* 2018;33(6): 6510–21. <https://doi.org/10.1109/TPWRS.2018.2829021>.
- [64] Wamalwa F, Ishimwe A. Optimal energy management in a grid-tied solar PV-battery microgrid for a public building under demand response. *Energy Rep* 2024; 12:3718–31. <https://doi.org/10.1016/j.egy.2024.09.054>.
- [65] Divkovic D, Knorr L, Meschede H. Design approach to extend and decarbonise existing district heating systems - case study for German cities. *IJSEPM* 2023;38: 141–56. <https://doi.org/10.54337/ijsepm.7655>.