Applied Energy 377 (2025) 124607

Contents lists available at ScienceDirect

Applied Energy

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

System friendliness of distributed resources in sustainable energy systems

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ARTICLE INFO

Dataset link: https://zenodo.org/records/11044874

Keywords:
System friendliness
Energy system burden
Sustainable energy systems
Steering signals
Incentivization mechanisms

ABSTRACT

The increasing share of volatile renewable energy generation in current and future energy systems which does not follow the demand, makes it necessary to shift the synchronization tasks to the system and demand level. The intended demand side consumption management is usually incentivized via financial mechanisms. However, the optimum design of related incentives is still unclear. It is usually discussed under the term "system friendliness" which in turn still lacks a broadly accepted definition. In this article we introduce a new technical definition of "system friendliness" and develop comprehensive and holistic related indicators. For that, we introduce the burden concept for energy systems which represents the amount of technical infrastructure required for stable operation. We use the concept of a hypothetical system energy storage to derive indicators that are capable of quantifying the system friendliness of a given point-of-interest. The developed indicators are independent of regulations or market environments which enables comparability of results between studies and different systems. In a case study we demonstrate our newly developed methodology and exemplary examine decentral district energy storages. Our findings demonstrate that today's regulatory environments that usually support residential self-consumption maximization are counterproductive. Instead, we show that dynamic end-user prices coupled with dynamic feed in tariffs are able to incentivize an almost 100% system friendly behavior of distributed prosumers.

1. Introduction

In conventional energy systems, the synchronization of power generation and consumption is largely handled by centralized and controllable thermal power plants. This holds no longer true in increasingly sustainable energy systems [1,2] where the synchronization of demand and generation is shifted to the demand side and lower system levels. Thus, a coordinated operational strategy of the decentralized resources which supports the energy system stability is needed [3]. The kind of behavior which is supportive and beneficial to the overall energy system stability is often called *"system friendly"* behavior. In mostly conventional energy systems, system friendly behavior corresponds to a demand that is as constant as possible without high load peaks. In sustainable energy systems with fluctuating generation, the concept of "system friendliness" is more complex and is still not quantitatively defined which makes its measurement and evaluation unclear.

For a better understanding of system friendliness in sustainable energy systems, we define it qualitatively in the first place. This enables a later quantitative formulation of it. System friendly behavior in sustainable energy systems should aim for …

1. …synchronizing demand and (renewable) energy generation.
2. …not exceeding the available grid capacities.
3. …maximizing the plannability of energy consumption and in-feed.
4. …providing flexibility to the overall energy system.

In order to avoid peaking system costs in (future) sustainable energy systems [4], the potential of available distributed energy resources (DER) needs to be harnessed [5–7] in a system friendly way. DER can contribute mainly via two ways [8]: Firstly, system operators could operate these resources directly [9] e.g., in a way of virtual power plants [10] to provide ancillary services [11]. Infrastructure requirements [12] and associated costs [13] will increase substantially while the acceptance of direct control differs vastly across societal groups [14] and is questionable due to the loss of perceived control [15]. Secondly, active players like energy management systems (EMS) could be addressed by incentivizing them to operate in a system friendly way without directly controlling them [8,16]. Incentivizing EMS the right way with e.g. financial mechanisms will play a key role in energy systems [17–19]. Doing so with respect to the specific location in the energy system is important to avoid avalanche effects [20, 21], i.e. an "overreaction of demand response" [22] which can cause e.g. sudden load increases when demand is collectively allocated in a price-sensitive way [23]. We call incentivizing factors of EMS "steering

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https://doi.org/10.1016/j.apenergy.2024.124607
Received 15 May 2024; Received in revised form 17 July 2024; Accepted 27 September 2024

List of Abbreviations and Symbols

DER	Distributed energy resources
POI	Point-of-interest
EMS	Energy management system
SOC	State-of-charge
LCA	Life-cycle-analysis
LCOE	Levelized costs of electricity
ENTSO-E	European Network of Transmission System Operators for Electricity
$\mathcal{C}, \tilde{\mathcal{C}}$	Storage capacity indicator without and including losses
$\mathcal{P}^+, \mathcal{P}^-$	Charging and discharging power maximum indicator
$\mathcal{F}$	Stored energy indicator
$\mathcal{E}$	Mean state-of-charge indicator
$\mathcal{L}$	Mean length of stay indicator
I	Number of nodes in an energy system
$D(t)$, $d(t)$	Electricity demand in reference system or POI
$G(t)$, $g(t)$	Electricity generation in reference system or POI
$R(t)$, $r(t)$	Residual load in reference system or POI
$S(t)$, $s(t)$	Storage charging time series in reference system or POI
$E(t)$	State-of-charge of storage
$B(t)$	Curtailment
C	Storage capacity
c	Cost function of the POI
$p(t)$, $f(t)$	Steering signals for buying and selling energy
c_{invest}	Investment costs
L	Length of stay
F	Total amount of stored energy
P^+, P^-	Storage charging and discharging power maximum
$g_{\text{d,max}}$	Maximum daily energy generation in the POI
E_{init}	Initial state-of-charge
λ	Generation to demand ratio
$\mathcal{S}$	Hypothetical system energy storage

signals". Currently, most EMS maximize self-consumption [24] with questionable positive implications for energy systems [25]. At high shares of prosumers it is even debated if a so-called "death-spiral" could be enabled where energy consumption at the bulk electricity market gets very low but infrastructure requirements peak [26]. Installing decentralized resources which worsen the overall situation in the energy system would be technically and economically counterproductive.

The system friendly operation of technologies like energy storage [27,28], electric vehicles [29], heat pumps [30] or wind turbines [31] is broadly studied. However, the assessment of the respective system friendliness and its general understanding varies significantly. Section 1.1 gives a brief overview of the literature on existing methods to quantify system friendliness to date and which indicators are actually applied in recent studies.

1.1. Current state of research on system friendliness

We distinguish between two different kinds of publications which are relevant for this work. Firstly, we consider related work that is *using* existing system friendliness indicators for the analysis of their results. This gives a brief overview of what methodology on system friendliness analysis is currently being applied in research. We additionally explain the limitations of the most used indicators. Secondly, we analyze the publications whose core is to *extend or develop methodology* i.e., indicators for system friendliness evaluation in more detail. For the latter, we include a tabular summary of existing methods in Table 1.

Note, that the term "system friendliness" is also often called "grid friendliness" in literature. Other related works quantify and refer to the "grid impact" of decentral players. All of these terms are closely related, however not well defined yet.

Existing indicators which are used for system friendliness assessments can be categorized into technical, economic and environmental indicators. As technical indicators, most studies assess the overall consumption, peak power and self-consumption of the evaluated player [30,32–34]. However, due to the scarcity of controllable energy generation in sustainable energy systems, the demand itself should be synchronous to the energy generation. This might even include peak demands at times of high local energy generation. The above mentioned indicators are therefore not describing system friendliness in a sufficient way. Other technical indicators are highly specific to the study design and mostly include detailed local grid information or simulation. They commonly comprise e.g., curtailment of renewable energy generation [8,35,36], voltage levels [37–39] or line and transformer loading [40,41]. Due to the limited data and grid simulation availability these indicators lack completeness and comprehensiveness.

Economic indicators comprise mainly (annual) electricity costs, levelized costs of electricity (LCOE) [37] or grid reinforcement costs [42]. While they are important to assess for the economic viability of approaches, economic indicators are highly dependent on the present market mechanisms and regulatory environment. This makes studies between e.g., different countries hardly comparable.

This limitation is overcome by the environmental indicators which mainly include CO2, SO2 or NOX emissions and are evaluated in [32,34,43] for assessing the system friendliness of players. However, emissions are complicated to quantify and can sometimes even include a full life-cycle-analysis (LCA) of technologies. LCAs can get very complex and are highly dependent on the made assumptions which strongly limits the applicability and comparability [44].

Besides the above mentioned indicators for system friendliness, only very few publications worked on developing new concepts and definitions for system friendliness in the past. A tabular overview of these publications is given in Table 1. Regarding the evaluated player, the main limitations of the approaches is the dependency on a specific level in the energy system or the limitation to one specific kind of player, e.g. buildings. On the other hand, with respect to the system's point of view, the developed approaches are either dependent on extensive grid information or the specific regulatory environment like [45]. Both limit the fields of application of the respective methods or the comparability of results. Only very few publications take the actual grid situation into account for the system friendliness analysis. However, this is crucial since the kind of behavior which is considered system friendly strongly depends on the characteristics of the surrounding system. The biggest gap in current research is the missing general and quantitative definition of the term "system friendliness" while it is for that matter required to develop the respective assessment methodologies and indicators.

1.2. Contribution of this study

The core of this work is the introduction of a new technical and holistic definition of system friendliness which is based on the concept of the "technical burden" on energy systems. We apply the burden concept to a simplified sustainable energy system and derive four primary and three secondary system friendliness indicators. They are all based solely on residual load data and are independent of technology, level in the energy system and regulatory environment. This enables system friendliness assessment independent of strong assumptions which is a mayor contribution to make studies in the field comparable and help with decision making processes on e.g., regulations or market

Table 1
Overview of system friendliness assessment methodology publications.

Publication	Contribution	Limitations
Bianco et. al., 2021 [34]	Technical and environmental KPIs for energy communities.	Indicators for the electrical performance only consider the energy efficiency and electrical self-production.
Yue et. al., 2024 [46]	Building–grid interaction evaluation covering planning and operational stages to guide grid-friendly interactions	Limited to buildings.
Verbruggen & Driesen, 2015 [47]	Grid impact indicators, evaluates the performance of local control mechanisms, affecting the impact of a net-zero energy building on the electricity grid	Limited to buildings.
Roselli et. al., 2019 [43]	Energy index to assess the impact of renewables in electricity sector, evaluates bidirectional energy flows on the external power grid.	Limited to buildings, index only looks at the overall energy export/import ratio with respect to the demand.
Yue et. al., 2024 [48]	Methodology to estimate the grid friendliness influence of buildings on the grid based on planned capacity by referring to Hooke's law.	Limited to buildings, does not consider operational data.
Klein et. al., 2019 [45]	Market alignment indicator, measures the relative economic efficiency of a prosumer battery compared to a benchmark system. Benchmark system is fully responsive to wholesale market prices.	Strong dependence on market assumptions and the regulatory environment, limited applicability to other technologies other than PV-battery systems.

mechanisms and incentives. However, the methodology focuses on future energy systems and is therefore currently limited to fully sustainable one-node energy systems which neglects grid capacities and conventional generation. The simplifications will be described in detail in Section 2. In a case study we demonstrate the application of our newly developed methodology. For that, we exemplary evaluate the system friendliness of a residential district in a fully renewable scenario of Germany 2050, whose behavior is incentivized by three different steering signals. However, the presented methodology is not bound to the district level or a specific technology and could later be used for all kinds of DER and different levels of data granularity.

We find, that especially a self-consumption maximization strategy of the district proves to be unfavorable while variable steering signals for consumption and feed-in lead to the DER reach their maximum system friendliness potential.

This paper is structured as follows: Firstly, we define technical system friendliness in Section 2 where we also introduce the burden concept. Secondly, the developed methodology of how to measure system friendliness and the derivation of respective indicators are described in Section 3. This is followed by an explanation of the simulation setup of our case study on residential districts in Section 4 and a description of respective data in Section 5. The results of our case study are presented in Section 6 and we finish with a discussion in Section 7 and a conclusion and outlook in Section 8.

2. Defining technical system friendliness

In the following we introduce the general "burden" concept as the basis for the evaluation of system friendliness of DER. In this work we introduce simplifications regarding the reference system which will lead to a reduced burden formulation. These assumptions are described in Section 2.2. Future work will focus on more complex systems to include more burden dimensions.

2.1. General burden concept

Consider a self-sufficient energy system of I arbitrary nodes representing producers, consumers or prosumers of energy. Connections between the nodes represent transformers or power lines. To ensure stable operation of the energy system, demand and supply have to match at all times. Since curtailment of energy generation is possible, stable operation is also given if the generation is bigger compared to the demand. Renewable energy generation is considered first for meeting the given demand.

Depending on the characteristics of the energy system, the technical effort to ensure stable operation can vary significantly. We therefore define five limiting extreme cases from minimum to high technical effort , where $D_i(t)$ and $G_i(t)$ denote demand and renewable generation at node i and time t, respectively. Every node i in the energy system can be described by the respective time series for renewable and conventional generation as well as demand and energy storage. Note, that any of the assigned time series can also be zero.

Minimum effort. In a hypothetical optimal scenario, the renewable generation and the demand match at each node at all points in time. This would require the minimum possible technical effort.

$$\forall t, i\,:\, D_i(t) \leq G_i(t) \tag{1}$$

No storage required. If

$$\forall t\,:\, \sum_i D_i(t) \leq \sum_i G_i(t) \tag{2}$$

holds true, storage is not needed but energy transfer is necessary which causes a certain grid capacity to be obligatory.

Self sufficient nodes. Theoretically, no grid but only storage capacity is required when

$$\forall i\,:\, \sum_t D_i(t) \leq \sum_t G_i(t) \tag{3}$$

holds true.

Storage and grid inevitable. The energy system is self-sufficient with renewable energy but needs energy storage as well as a grid to ensure stable operation.

$$\sum_t \sum_i D_i(t) \leq \sum_t \sum_i G_i(t) \tag{4}$$

Storage, grid and conventional generation required. The system is only able to ensure stable operation if additional controllable generation, e.g. conventional energy generation, is present, i.e.

$$\sum_t \sum_i D_i(t) > \sum_t \sum_i G_i(t) \tag{5}$$

Based on the five limiting cases with varying required technical effort, we introduce the burden on an energy system. The system friendliness definition builds on the burden definition, respectively.

Definition 1. The burden on an energy system is the amount of technical infrastructure required to ensure stable operation of the energy system.

The burden can be described in four dimensions

1. **Renewable energy generation capacity,**
2. **Grid capacity,**
3. **Energy storage capacity,** and
4. **Conventional energy generation capacity.**

The four burden dimensions are intertwined, e.g. an excess amount of renewable energy generation could decrease needed storage or grid capacities. The newly introduced burden concept can be used to evaluate the system friendliness impact of any player on an energy system. If a player in the energy system reduces the overall burden it acts system friendly and vice versa. This leads to the following definition:

Definition 2. Technical system friendliness is a reduction of the technical burden on an energy system.

Assessing changes in the burden on an energy system in full, i.e. including all four burden dimensions requires extensive system information which is not always available. This is why we introduce three simplifications in Section 2.2 to reduce the burden complexity to storage requirements only.

2.2. Assumptions of this study

In this study, we apply three assumptions which lead to a significant simplification of the burden and system friendliness assessment accordingly. This approach limits the complexity of the respective energy systems.

1. Firstly, we assume the energy system to be given with known fixed demand and renewable generation $D(t)$ and $G(t)$. This means, we do not consider expansion of renewable generation capacity for the burden assessment.
2. Secondly, we focus on fully renewable energy systems where no conventional generation is present. However, we allow curtailment. With that follows that the burden due to conventional energy generation capacity is not considered in this study.
3. Lastly, we assume a one-node-system, i.e. $I = 1$, with one aggregated time series for demand and generation. This simplification is often called "copper plate" assumptions since it neglects the limitations due to a finite grid capacity. Accordingly, the burden due to grid capacities is not considered here.

Summarizing the simplifications, the burden dimensions renewable energy generation capacity, grid capacity and conventional energy generation can be neglected. It will be part of future studies to develop respective indicators taking into account these burden dimensions. The reduced burden formulation comprises only storage.

In the following, the assessment is therefore carried out by solely taking into account storage requirements resulting from the mismatch of generation and demand. Indicators measuring system friendliness subject to these storage requirements.

3. Measuring technical system friendliness

We refer to the considered player for system friendliness evaluation as "point-of-interest" (POI). The energy system for which system friendliness is evaluated is called the "reference system". The relationship between the POI and the reference system is expressed according to Fig. 1. A POI can be a subset of a bigger energy system (e.g. a whole medium-voltage grid or district) but also a single device (e.g. a battery storage). Typically, the operation is optimizing towards a given objective function which is commonly a financial steering signal like an electricity price or a feed-in tariff. System friendliness is typically no direct goal of a POI but can be achieved indirectly when the given price signals are chosen and designed accordingly.

In our presented framework, the POI is prescinded by a single node with time series for generation and demand and storage operation, denoted by $g(t), d(t)$ and $s(t)$, respectively. It is able to feed into or consume energy from the reference system which results in the respective residual load $r(t)$ with positive part $r^+(t)$ and negative part $r^-(t)$. The reference system is described by one node with a demand and a renewable generation time series, denoted by $D(t)$ and $G(t)$, respectively. By $R(t) = G(t) - D(t)$ we denote the residual load. We introduce a hypothetical and idealized energy storage $\mathcal{S}$ that equals out mismatches between $G(t)$ and $D(t)$. $\mathcal{S}$ does not subject to any restrictions or parametrizations and is not of any specific technology but a purely hypothetical construct. If $\sum_t G(t) > \sum_t D(t)$, not all energy surpluses have to be stored in $\mathcal{S}$. Otherwise, the required storage capacity would be overestimated. Therefore we introduce $B(t) > 0$ as the curtailment of the excess energy. Its charging and discharging time series is then described by:

$$S(t) = -\big(R(t) - B(t)\big) \tag{6}$$

A POI changes the residual load in the reference system from $R(t)$ to

$$\hat{R}(t) = R(t) + r(t), \tag{7}$$

which subsequently changes the storage time series $S(t)$ to

$$\hat{S}(t) = -\big(\hat{R}(t) - \hat{B}(t)\big) \tag{8}$$

This implies a change of characteristics of the hypothetical energy storage $\mathcal{S}$. All indicators are evaluated by comparing $S(t)$ and $\hat{S}(t)$. Therefore, only the residual load of the reference system and the POI is needed for the evaluation of the proposed indicators.

As long as $D(t) \gg d(t)$ and $G(t) \gg g(t)$ hold true, the size and grid level of the POI and of the reference system can be chosen freely. All indicators are technology agnostic and work for variable data granularities. However, for small datasets the indicators might not be meaningful anymore. The system friendliness assessment is performed ex-post for a specific operation of the POI and a specific reference system.

3.1. Primary indicators system friendliness indicators

The four proposed primary system friendliness indicators measure changes of properties of the hypothetical system storage. They subject indirectly to storage investment costs and are direct burden drivers. A description of the calculation procedure of all indicators is described in Section 3.3. The primary system friendliness indicators comprise

1. Storage capacity $\mathcal{C}$,
2. Storage capacity including loss $\tilde{\mathcal{C}}$,
3. Maximum charging power $\mathcal{P}^+$, and
4. Maximum discharging power $\mathcal{P}^-$.

$\mathcal{C}$ describes the changes of required system storage capacity and indirectly measures the synchronicity of demand and generation. If $\mathcal{C} > 0$, the POI increases the hypothetically needed storage capacity which is not system friendly. Vice versa, $\mathcal{C} < 0$ corresponds to system friendly behavior since it means a storage capacity reduction. $\tilde{\mathcal{C}}$ is evaluated if losses are considered for POI which would otherwise falsify the loss-free indicator $\mathcal{C}$. $\mathcal{P}^+$ and $\mathcal{P}^-$ represent the changes in maximum charging and discharging powers. If the POI results in negative $\mathcal{P}^+$ and positive $\mathcal{P}^-$, it reduces the peak load and generation of the whole system and is therefore system friendly. Limited connection capacity between the POI and the reference system also limit $\mathcal{P}^+$ and $\mathcal{P}^-$.

3.2. Secondary system friendliness indicators

The proposed secondary system friendliness indicators measure properties of the hypothetical system storage $\mathcal{S}$ that are not direct cost or burden drivers but provide insights about its characteristics and usage. They comprise

1. Stored energy $\mathcal{F}$,
2. Mean state-of-charge $\mathcal{E}$, and
3. Length-of-stay $\mathcal{L}$.

$\mathcal{F}$ assesses changes in the total amount of stored energy in the hypothetical storage and provides insights about the synchronicity of demand and generation on shorter timescales compared to the capacity indicator $\mathcal{C}$. Positive $\mathcal{F}$ mean an increase of stored energy and vice versa for negative $\mathcal{F}$. $\mathcal{E}$ denotes changes in the mean state-of-charge of the hypothetical system storage which provides insights about possible storage technologies in a real-world setting. If the POI results in positive

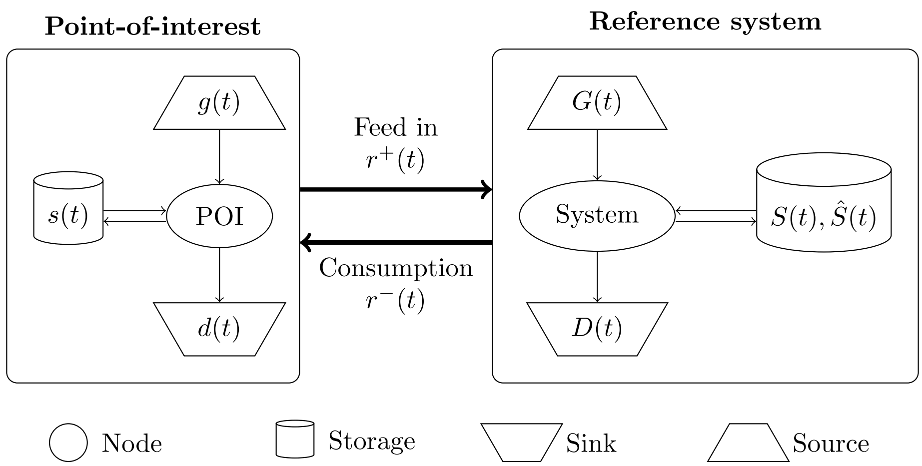

Fig. 1. Simplified relationship between the point-of-interest (POI) and the reference system for indicator evaluation.

$\mathcal{E}$, it increases the mean filling of the storage and vice versa for negative $\mathcal{E}$. $\mathcal{L}$ denotes changes in the mean length-of-stay of energy in the hypothetical system storage. If $\mathcal{L} > 0$, the POI shifts the system's mean length-of-stay towards longer time periods and vice versa. If the POI additionally decreases the system storage capacity, $\mathcal{L}$ assesses if long-term or short-term storage is replaced.

3.3. Indicator calculation methodology

As prerequisite for the indicator calculation method, we introduce the "degree of renewable self-sufficiency" λ which represents the fraction of the sum of the renewable generation G over the sum of the demand D at all nodes i over all times t:

$$\lambda = \frac{G}{D} = \frac{\sum_i \sum_t G_i(t)}{\sum_i \sum_t D_i(t)} \tag{9}$$

All indicators denote a change in relevant system parameters subjecting to the hypothetical reference system storage. Therefore, the respective system parameters are determined without the POI based on $S(t)$ and including the POI whose impact changes $S(t)$ to $\hat{S}(t)$. Afterwards, the difference is calculated which serves as respective indicator. If $\lambda = 1$ for the considered energy system, $S(t)$ results directly from Eq. (6). If $\lambda > 1$ on the other hand, $S(t)$ and $\hat{S}(t)$ have to include possible curtailment for indicator evaluation. To determine $S(t)$, $\hat{S}(t)$ and possible curtailment linear optimization is used. For that purpose, the open energy modeling framework `oemof.solph` is available in this work [49]. Fig. 3 visualizes the system to be optimized. The time series for demand and generation are fixed inputs. The curtailment as well as the system storage operation $S(t)$ are subject to optimization. The state-of-charge (SOC) of the hypothetical system storage is denoted by $E(t)$ and can easily be calculated using solely $S(t)$ as in Eq. (10).

$$E(\tau) = \int_0^{\tau} S(t)dt + E_{\text{init}} \tag{10}$$

with E_{init} denoting the initial SOC at time step $t = 0$ which ensures positive SOCs at all time steps

$$E_{\text{init}} = -\min\left(\int_0^T S(t)dt\right) \tag{11}$$

The system storage is set to be balanced, thus the initial and the final SOC have to be equal. This ensures no energy losses by emptying the storage from the beginning to end of the time period. Constant investment costs for every unit of storage capacity are assigned to the system storage in Fig. 3 to ensure the optimization resulting in minimal possible storage capacities. Other than that, no costs are assigned to the reference system. $\hat{S}(t)$, $\hat{E}(t)$ and $\hat{E}_{\text{init}}$ are determined analogously but with changed inputs for the generation and demand time series of the reference system. The generation $G(t)$ and demand $D(t)$ are changed to $\hat{G}(t) = G(t)+r^+(t)$ and $\hat{D}(t) = D(t)+r^-(t)$ by the POI. In the following, the procedure to calculate all system friendliness indicators is presented. Note, that $S(t)$ derived by linear optimization is only used for that purpose as long as systems with $\lambda > 1$ are considered. All indicators can be calculated including losses in the district and system storage or without taking losses into account. The procedure is explained in detail for the capacity indicator $\mathcal{C}$ but for all other indicators this works analogously. Indicators including losses are denoted by their respective symbol including a tilde.

Hypothetical storage size indicators $\mathcal{C}$ and $\tilde{\mathcal{C}}$:. Given $E(t)$ derived from linear optimization and Eq. (10), the maximum capacity of the storage is

$$C \stackrel{\text{def}}{=} \max_t(E(t)) \tag{12}$$

$\hat{C}$ is determined accordingly taking the POI into account. The first and one of the most important indicators is the impact of the POI on the hypothetical storage capacity:

$$\mathcal{C} \stackrel{\text{def}}{=} \hat{C} - C \tag{13}$$

Note, according to the above described procedure the hypothetical storage capacity C is derived from an idealized time series without storage losses. This could falsify results if losses are considered in the POI. If so, the system storage $\mathcal{S}$ can be parameterized reflecting the same losses as the POI. This can also be done using the linear optimization tool `oemof.solph` with two parameters. Firstly, a conversion loss can be applied as a relative loss on charged and discharged energy. Secondly, a loss rate can be applied in every time step which relatively decreases the amount of energy stored. This way, the outputs of the optimization change to $\tilde{S}(t)$, $\tilde{E}(t)$ and $\tilde{E}_{\text{init}}$ and include losses. $\tilde{C}$ and $\hat{\tilde{C}}$ are determined analogously. The respective indicator equals to:

$$\tilde{\mathcal{C}} \stackrel{\text{def}}{=} \hat{\tilde{C}} - \tilde{C} \tag{14}$$

Note, that when losses apply for the hypothetical system storage, the total energy system is not self sufficient anymore at $\lambda = 1$. This effect is most significant in energy systems with very seasonal energy generation like in PV dominant generation mixes.

Hypothetical storage power indicators $\mathcal{P}^+$ and $\mathcal{P}^-$:. $S(t)$ denotes the charging and discharging time series of the hypothetical system storage $\mathcal{S}$ after curtailment. Thus, the maximum charging and discharging power are defined by:

$$P_+ \stackrel{\text{def}}{=} \max_t(S(t)) \tag{15}$$

and

$$P_- \stackrel{\text{def}}{=} \min_t(S(t)) \tag{16}$$

$\hat{P}_+$ and $\hat{P}_-$ are determined accordingly taking the POI into account. Therefore, we define the next two indicators as:

$$\mathcal{P}^+ \stackrel{\text{def}}{=} \hat{P}_+ - P_+ \tag{17}$$

$$\mathcal{P}^- \stackrel{\text{def}}{=} \hat{P}_- - P_- \tag{18}$$

$\mathcal{P}^+$ and $\mathcal{P}^-$ are limited by the power capacity of the respective connection between the POI and the reference system.

Amount of stored energy indicator $\mathcal{F}$:. In order to assess the usage of the hypothetical system storage, the respective total amount of stored energy is calculated

$$F \stackrel{\text{def}}{=} \sum_t S^+(t) \tag{19}$$

where $S^+(t)$ are the positive elements of $S(t)$. $\hat{F}$ is determined accordingly taking the POI into account. The according indicator is defined by:

$$\mathcal{F} \stackrel{\text{def}}{=} \hat{F} - F \tag{20}$$

Mean SOC of the hypothetical storage indicator $\mathcal{E}$:. Additionally, the mean SOC of the hypothetical storage $\mathcal{S}$ can be calculated easily with Eq. (21). The hypothetical storage is of no specific technology but the theoretical mean state of charge can give insights about its characteristics and kind of use.

$$\bar{E} \stackrel{\text{def}}{=} \frac{1}{T} \sum_t E(t) \tag{21}$$

Note, the mean state of charge $\bar{E}$ can also be evaluated in percentage values by dividing by the maximum storage capacity. $\hat{\bar{E}}$ is determined accordingly taking the POI into account. The according indicator is defined by:

$$\mathcal{E} \stackrel{\text{def}}{=} \hat{\bar{E}} - \bar{E} \tag{22}$$

Length-of-stay indicator $\mathcal{L}$:. The mean length-of-stay L of energy in the storage can be derived based on [50]. Given $S(t) = S^+(t) - S^-(t)$ with $S^+(t), S^-(t) \geq 0$ for all t, we define the positive and negative SOC curve $E^+(t)$ and $E^-(t)$ as

$$E^+(\tau) \stackrel{\text{def}}{=} \int_0^\tau S^+(t)dt \tag{23}$$

$$E^-(\tau) \stackrel{\text{def}}{=} \int_0^\tau S^-(t)dt \tag{24}$$

With that, the length of stay L is defined as

$$L \stackrel{\text{def}}{=} \frac{V(t_a, t_b)}{\sum_t S^+(t)} \tag{25}$$

with

$$V(t_a, t_b) = \int_{t_a}^{t_b} E^+(t)dt - \int_{t_a}^{t_b} E^-(t)dt\,, \tag{26}$$

where the integral's borders t_a and t_b are chosen, such that V being a renewable inventory mass which is closed on both sides, i.e. $E^-(t_a) = E^+(t_a)$ and $E^-(t_b) = E^+(t_b)$. $V(t_a, t_b)$ is the area between the two curves $E^+(t)$ and $E^-(t)$. Fig. 2 visualizes $V(t_a, t_b)$. Thus, t_a and t_b are the points of time, where the SOC of $\mathcal{S}$ reaches its minimum. If the minimum is only reached one time in the period of time under consideration, t_b is defined to be the closest earlier point in time which corresponds to t_{a-1}. If the minimum SOC is taken on more than two times, L is calculated for every time period between the respective points in time. Afterwards, the mean of all lengths of stay is calculated. The indicator is defined as follows:

$$\mathcal{L} \stackrel{\text{def}}{=} \hat{L} - L \tag{27}$$

4. System friendliness case study simulation setup

The presented system friendliness indicators shall be demonstrated in a case study which simulates the impact of energy storage in residential districts on the fully renewable German energy system of 2050. The code to recreate the results of this study including all assumptions and parameters is publicly available [51]. Doing so, the energy system modeling framework `oemof.solph` [49] is used for optimization of the district's operation and the indicator evaluation as described above in Section 3.3. Fig. 3 shows the simulation setup conceptually.

The district comprises a PV system with a fixed generation time series $g(t)$, a fixed demand $d(t)$ and a storage system of varying capacities C_D with the storage time series $s(t)$. Therefore, the residual load of the district solely depends on the optimized storage operation $s(t)$ and equals to

$$r(t) = g(t) - d(t) + s(t) \tag{28}$$

As explained in Section 3.3, the required data for indicator assessment comprise $S(t)$ and $\hat{S}(t)$ which denote the time series of the hypothetical system storage without and including the effect of a POI. Here, the POI is a residential district. However, we want to isolate the effect of one device in the district, namely a residential storage unit. In the following, the procedure to determine $S(t)$ and $\hat{S}(t)$ is described.

1. The optimization of the reference system including the fixed district generation $g(t)$ and demand $d(t)$ but without a district storage is carried out to determine $S(t)$. $S(t)$ represents the storage time series of the hypothetical system storage
2. The optimization of the district storage operation $s(t)$ is carried out which determines $r(t)$.
3. The adjusted time series for the generation and demand of the reference system are calculated which are referred to as $\hat{G}(t)$ and $\hat{D}(t)$, respectively. The time series are determined based on

   $$\hat{G}(t) = G(t) + r^+(t)$$

   and

   $$\hat{D}(t) = D(t) + r^-(t)$$

   where $r^+(t)$ and $r^-(t)$ denote the positive and negative elements of the POI's residual load.
4. With $\hat{G}(t)$ and $\hat{D}(t)$, the reference system's optimization is carried out again to determine the adjusted storage time series $\hat{S}(t)$ taking into account the district.

With $S(t)$ and $\hat{S}(t)$ being determined, the indicators for the given district storage operation can be evaluated.

4.1. Steering signals to incentivize the POI

To get to a certain operational strategy, a POI typically optimizes itself with respect to minimizing its energy costs or maximize revenue based on a given price signal. In our case study on districts, we examine three different "steering cases" which comprise different steering signals for the district's storage optimization. One steering case consists of two steering signals $p(t)$ and $f(t)$:

1. $p(t)$ for buying electricity from the reference system, which can be seen as an arbitrary electricity price and
2. $f(t)$ for selling electricity to the reference system, which can be seen as an arbitrary feed-in tariff.

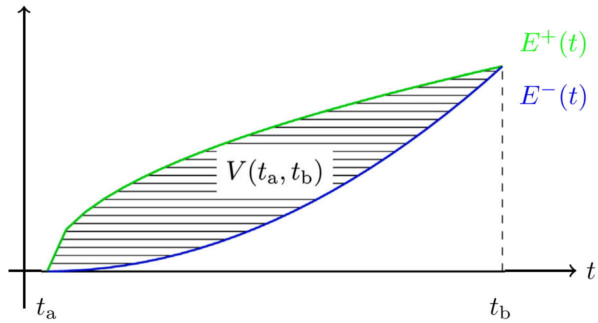

Fig. 2. Visualization of the length-of-stay indicator calculation procedure. $V(t_a, t_b)$ denotes the area between $E^+(t)$ (green) and $E^-(t)$ (blue).

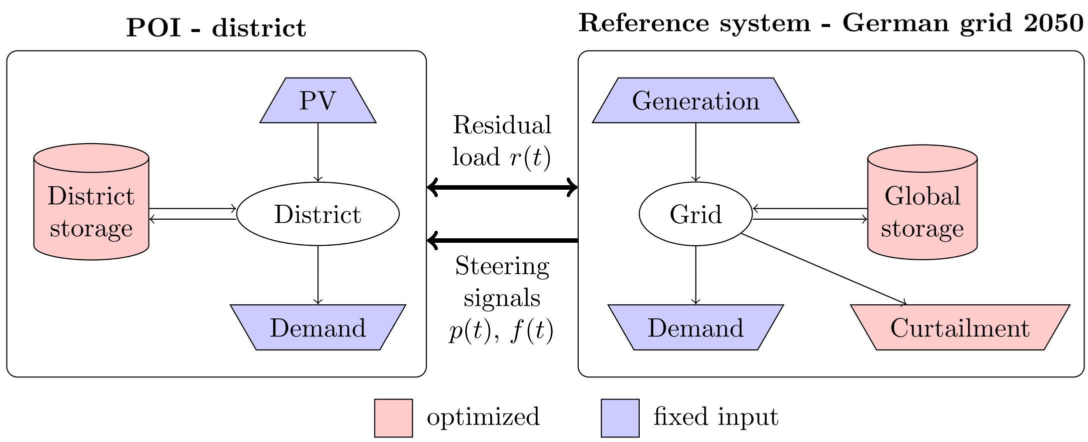

Fig. 3. Conceptual visualization of the case study simulation setup. A time series can be assigned to each object. The model of the point-of-interest (POI) and the reference system are optimized individually.

The aggregated cost function which the district is subjecting to for its optimization can be written as:

$$c = \sum_t r^-(t) \cdot p(t) + r^+(t) \cdot f(t)\,. \tag{29}$$

The steering signals $p(t)$ and $f(t)$ are the only sources of costs for the simulated district. Thus, the district's operation is optimized with respect to minimizing c. Since the district storage is the only device to be optimized in the district, a minimization of c directly yields the district storage time series $s(t)$. All other mathematical constraints and equations of the linear optimization problem are described in detail in [49]. The three steering cases are referred to as:

1. pCon-fCon: Constant price $p(t)$ and constant feed-in tariff $f(t)$
2. pVar-fCon: Variable price $p(t)$ and constant feed-in tariff $f(t)$
3. pVar-fVar: Variable price $p(t)$ and variable feed-in tariff $f(t)$

Steering cases pVar-fCon and pVar-fVar are based on the scaled residual load of the reference system. The scaling procedures for pVar-fCon and pVar-fVar is conducted using the `MinMaxScaler` of `sklearn` [52]. The steering signals in all steering cases can be described quantitatively:

Steering case pCon-fCon:. Steering case pCon-fCon is a default scenario with $p(t) = \text{const} > 0$ and $f(t) = \text{const} < 0$ and $|p(t)| > |f(t)|$. Therefore, self-consumption is maximized.

$$p(t) = 0.3 \quad \text{and} \quad f(t) = -0.1 \tag{30}$$

Steering case pVar-fCon:. Steering case pVar-fCon combines a variable $p(t)$ with a constant $f(t) = \text{const} < 0$ which is also typical in the residential sector. Negative prices are possible but $p(t) \geq f(t)$ still holds true.

$$p(t) = -R^*(t) \in [-0.1, 0.3] \quad \text{and} \quad f(t) = -0.1 \tag{31}$$

Steering case pVar-fVar:. In steering case pVar-fVar $p(t) > 0$ and $f(t) > 0$ are variable and symmetric $f(t) = -p(t)$ and follow the residual load of the reference system.

$$p(t) = -R^\dagger(t) \in [0, 1] \quad \text{and} \quad f(t) = R^\dagger(t) \in [-1, 0] \tag{32}$$

For each steering case, the whole simulation time period along with two days from summer and from fall are presented in Fig. 4. During the summer days, the classical daily PV generation cycle is more pronounced compared to the fall days. This results in generally more volatile steering signals during summer. The lowest price $p(t)$ for the cases pVar-fCon and pVar-fVar is reached in May. The highest price occurs in December which is both due to the dependency of prices on the volatile renewable energy generation.

4.2. Optimizing the district operation

The operation of the district serving as POI in this case study is being optimized using the linear optimization tool `oemof` [49]. As can be seen in Fig. 3, the district comprises a PV generation, an electricity demand and a district energy storage. Since demand and PV generation of the district are fixed, the district optimization problem reduces to solely optimizing the storage operation $s(t)$. The storage time series $s(t)$ is optimized in a way such that the residual load $r(t)$ minimizes the following minimization problem with respect to the steering signal

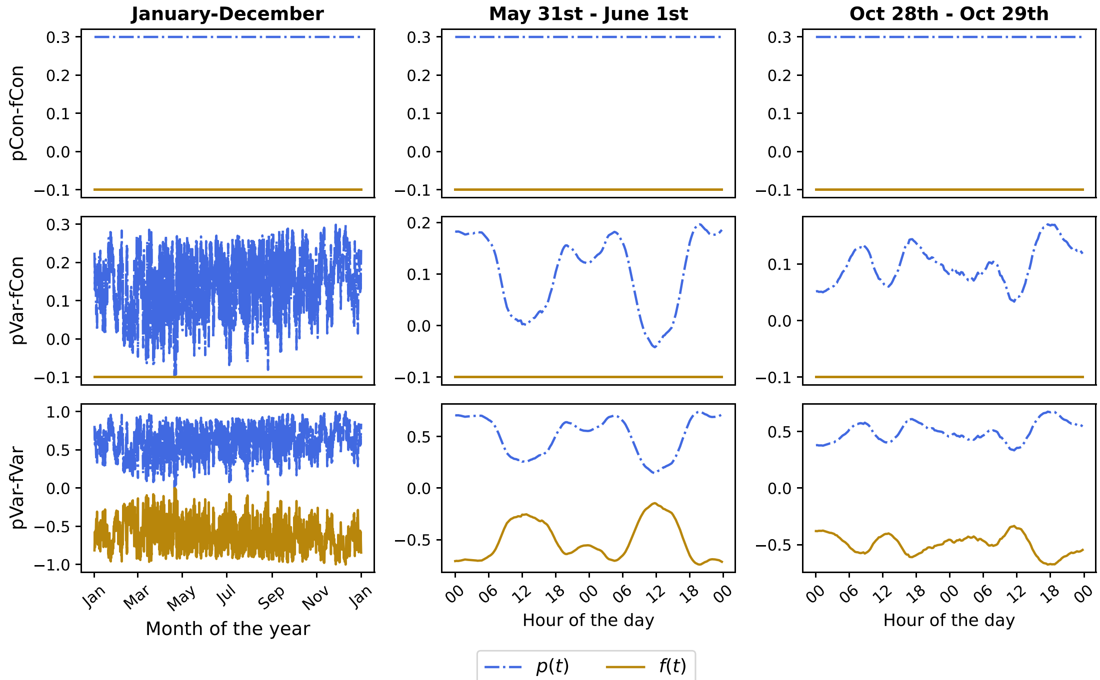

Fig. 4. Steering signal cases "pCon-fCon", "pVar-fCon" and "pVar-fVar" for the whole simulation time period on the left hand side and for 2 selected days (May 31st and June 1st) in the middle and (October 28th–October 29th) on the right hand side.

for buying energy $p(t)$ and the respective steering signal $f(t)$ for selling energy to the reference system:

$$r(t) = \underset{r(t)}{\operatorname{argmin}} \sum_{\substack{t \text{ s.t.} \\ r(t)<0}} r(t)p(t) + \sum_{\substack{t \text{ s.t.} \\ r(t)>0}} r(t)f(t) \tag{33}$$

At the district's site, different storage capacities are simulated. For every storage capacity and every steering signal a loss-free case and a loss-including case is simulated. Losses take into account a loss rate of $o_r = 0.01\%$ per time step and a conversion loss of $o_c = 1\%$ of charged and discharged energy. All simulations are carried out for one year of data at a granularity of 15 min which corresponds to 35 040 points in time under perfect foresight conditions. The capacity of the power lines connecting the district to the reference system l limits $r(t)$ and is determined with

$$l = 2 \cdot \max(d(t)) + 2 \cdot \max(g(t)), \tag{34}$$

i.e. l equals two times the maximum generation plus two times the maximum demand of the district. Further details regarding the data input of the district are described in Section 5.2.

4.3. Optimizing the reference system operation

The reference system comprises a fixed demand, a fixed generation and an energy storage whose time series $S(t)$ is subject to optimization (see Fig. 3). Since $\lambda > 1$ of the reference system holds true in our case study, a curtailment $B(t)$ also applies which is optimized using `oemof` [49] as well. No costs per time step apply for the reference system simulation model. Instead, investment costs into the storage capacity c_{invest} are assumed. This means, for every unit, here for every kWh of storage needed, constant investment costs of $c_{\text{invest}} = 10$ apply. Therefore, the system storage time series $S(t)$ and the curtailment time series $B(t)$ are optimized with regards to minimizing the storage capacity. The storage is set to be balanced i.e., the SOCs at the start and the finish of the simulation time period are equal:

$$E(0) = E(T) \tag{35}$$

Losses can be taken into account for the system storage as well which is particularly important if losses apply in the district. In our case study, we assume the same loss parameters for the hypothetical system storage as for the district storage for highest interpretability of results. However, this is not obligatory. Here, λ of the reference system is high enough to ensure self-sufficiency even with the assumed storage losses. Further details regarding the data input of the reference system are described in Section 5.1. The simulation of the reference system is carried out two times for every indicator assessment: Firstly, without taking into account the district storage and secondly including the effects of the changed district's residual load due to the district storage.

5. Data

In the following, the data for simulation is described. This comprises the data of the reference system in Section 5.1 and of the residential district in Section 5.2.

5.1. Reference system

The reference system represents the German electricity grid in 2050 with fully renewable generation. For this, the measured German generation $G(t)$ and demand data $D(t)$ of the "European Network of Transmission System Operators for Electricity" (ENTSO-E) [53] from 2020 provided by the German "SMARD"-platform [54] is used. For that purpose, the demand time series $D(t)$ from 2020 is scaled to be 1000 TWh in total for 2050. The generation $G(t)$ comprises PV, wind onshore, wind offshore, hydro and biomass. The generation time series are scaled according to the generation mix from [55] for a 100% renewable scenario of Germany 2050. The generation mix comprises 27% energy generation from photovoltaic, 45% from wind onshore, 22% from wind offshore, 2% from hydro power and 4% from biomass. The minor remaining conventional generation in the scenario of [55] accounts for less than 0.5% of the total generation and is neglected here. Afterwards, a degree of self sufficiency for the reference system of $\lambda_S = 1.5$ is assumed to avoid peaking storage requirements [56]. Additionally, the system is still self-sufficient at this demand to generation ratio even if theoretical storage losses are present. Since $\lambda_S > 1$,

Table 2
Selected data features of the reference system and the modeled district. Note, that negative residual load means a lack of generation while positive residual load means a surplus of generated energy.

	Reference system	District
Maximum generation power	490.98 GW	547.23 kW
Minimum generation power	10.98 GW	0.00 kW
Maximum residual load (before curtailment)	360.91 GW	456.80 kW
Minimum residual load	−128.58 GW	−112.66 kW
Maximum energy generation in one day	8262.41 GWh	5100.41 kWh
Minimum energy demand in one day	2035.83 GWh	1224.95 kWh
Maximum energy demand in one day	3401.25 GWh	2031.47 kWh
Mean energy demand in one day	2739.73 GWh	1712.33 kWh
Total demand	1000.00 TWh	625.00 MWh
Total generation	1500.00 TWh	625.00 MWh

curtailment takes place, but we do not associate costs to it. For the assumed surplus of energy, only PV, wind onshore and offshore are taken into account since biomass and hydropower technologies are assumed to not be easily expandable. Selected data features of the reference system are presented in Table 2. Since the data from 2020 is taken it comprises the leap day 29th of February, which is deleted for the simulation. The data granularity is 15 min.

For more insight, the data for simulation is depicted in Fig. 5 with the reference system generation and demand on the left hand side. It is visible that demand is lowest during summer and over the public Christmas and New Year holidays end of December and beginning of January. The renewable generation shows a high variability and reaches maximum power values in summer. Nevertheless, the seasonality of the generation is not very pronounced due to the rather small share of PV energy. Instead it is dominated by the volatility of wind power generation.

5.2. Residential district

The demand data of the district is taken from [57] where the authors simulated the demand and generation of a big residential district for one year for the location Oldenburg, Germany using their own tool FlexiGIS [58]. For this work, the demand data gets scaled to be 625 MWh in total per year to represent 100 residential units in 2050. In order to model the generation time series of the district the respective simulated PV data based on 2015 weather from [57] is taken. Selected data features of the district are presented in Table 2. Demand and PV generation are scaled in a way that the district itself has a degree of self-sufficiency of $\lambda_{\mathrm{D}} = 1$. That results in approximately 5.5 kWp of installed PV power per residential unit at the given weather conditions. The condition $D(t) \gg d(t)$ and $G(t) \gg g(t)$ for indicator evaluation is met. Fig. 5 shows the district data for demand and PV generation on the right hand side. The clear seasonality of PV generation and demand gets visible. While demand is highest during winter times likely due to electrified heating systems in the district, generation is naturally highest during the summer months.

6. Case study results

In order to examine the effect of different energy storage systems within the simulated district, the district storage size C_{D} is varied and given in multiples of the maximum daily district energy generation $g_{\mathrm{d,max}} = 5100.41\,\mathrm{kWh}$. For every district storage size C_{D} and every steering case (pCon-fCon, pVar-fCon and pVar-fVar), the operation of the district is optimized as described in Section 4. This leads to one district SOC time series $s(t)$ for every simulation. Depending on the given steering signal, the SOC time series vary significantly. Fig. 6 exemplary shows *one* SOC curve per steering case for a district storage capacity of $3.9 \cdot g_{\mathrm{d,max}}$. Under the constant price and feed-in tariff (case pCon-fCon) the storage gets hardly used until August since it only equals out the daily mismatch of PV generation and demand within the district. Afterwards, it is only reaching 100 % SOC once in September of the simulated year. The storage operation differs already significantly when variable prices apply in the steering case pVar-fCon. The district exploits the price fluctuations in a way to minimize its costs which leads to a higher utilization of the storage system compared to case pCon-fCon. When additionally variable feed-in tariffs apply, the storage operation changes completely as can be seen for steering case pVar-fVar on the right of Fig. 6. The district storage is cycled many times throughout the year and used during summer as much as during winter periods. The district's SOC curve is used for the system friendliness analysis of the district.

For every simulated SOC curve of the district, the district's residual load $r(t)$ is calculated according to Eq. (28) and evaluated for its system friendliness using the presented methodology. A differentiation between loss-free and loss-including district storage is made. The indicator assessment is presented in Figs. 7 and 8 and explained in Sections 6.1 and 6.2 respectively. Significant differences between the three steering cases become clear.

6.1. Primary system friendliness indicator evaluation

Fig. 7 shows that steering case pVar-fVar leads to an almost 100% system friendly operation of the district storage considering $\mathcal{C}$ and $\tilde{\mathcal{C}}$. Despite increasing storage capacities in the district, no system storage reduction can be measured for the self-consumption maximization strategy from steering case pCon-fCon. Steering case pVar-fCon leads to a maximum system friendly behavior for small storage capacities considering $\mathcal{C}$. For $\tilde{\mathcal{C}}$, the impact of storages from steering case pVar-fCon is even higher compared to steering case pVar-fVar. But for bigger residential storage they fall short of their potential.

Fluctuations of the power indicators in Fig. 7 are due to rounding errors during the simulations and limited data granularity. Residential storage operated in steering case pVar-fCon and pCon-fCon is not leading to any measurable reduction of peak charging and discharging powers. In steering case pVar-fVar already small residential storage capacities of $12.75\,\mathrm{kWh}$ per residential unit without losses or $16.32\,\mathrm{kWh}$ including losses are able to perform maximum peak power reduction in the reference system.

6.2. Secondary system friendliness indicator evaluation

All secondary system friendliness indicators are shown in Fig. 8. Additionally, the mean length of stay in the district storage L_{D} is depicted. District storages in steering case pCon-fCon and steering case pVar-fCon show only minor impact on the secondary indicators. But storage in steering case pVar-fVar decreases the mean SOC and the total amount of stored energy significantly.

Assessing $\mathcal{L}$ for steering case pVar-fVar shows that mostly short term system storage is replaced by the decentral storage. Steering cases pCon-fCon and pVar-fCon lead to a more long-term use of the decentral storage as can be seen in Fig. 8 (g). Generally, the presence of losses seem to not have a significant impact on the secondary system friendliness indicators. However, L_{D} changes for steering case pVar-fCon when losses are present as it is used more as short-term storage then.

7. Discussion

With the presented methods an assessment of system friendliness in different regulatory environments or market designs is possible. This can enable further research about what financial mechanisms are optimal to incentivize system friendliness of DER. This includes the evaluation of different price building mechanisms for electricity

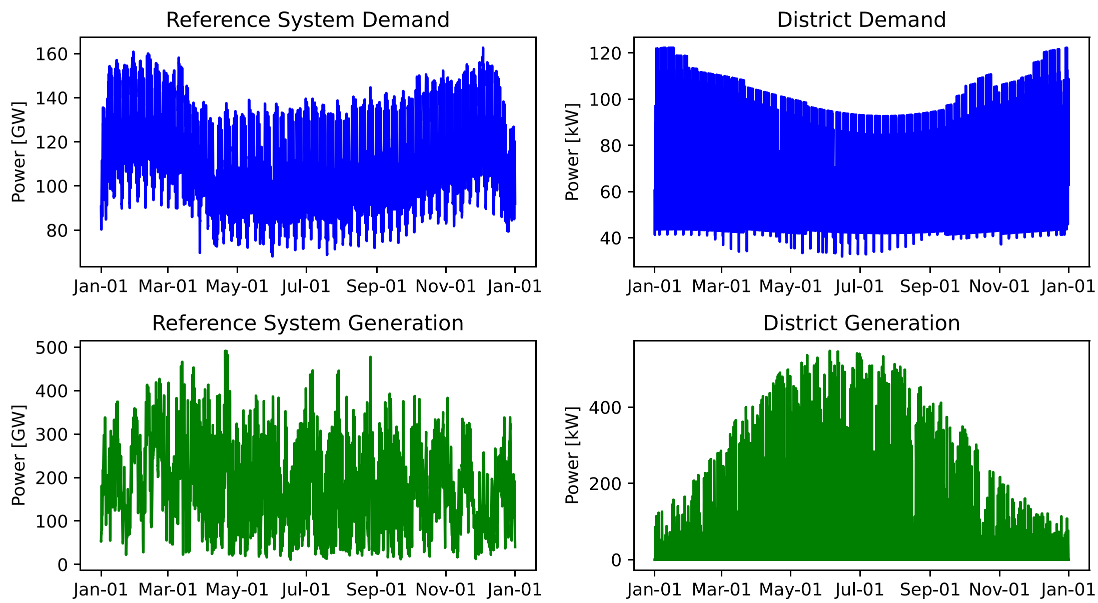

Fig. 5. Demand and generation data for the simulated reference systems (left) as well as the district (right) for one year. While the reference system generation mix comprises PV, offshore and onshore wind, hydro and biomass the district on the other hand is solely PV energy.

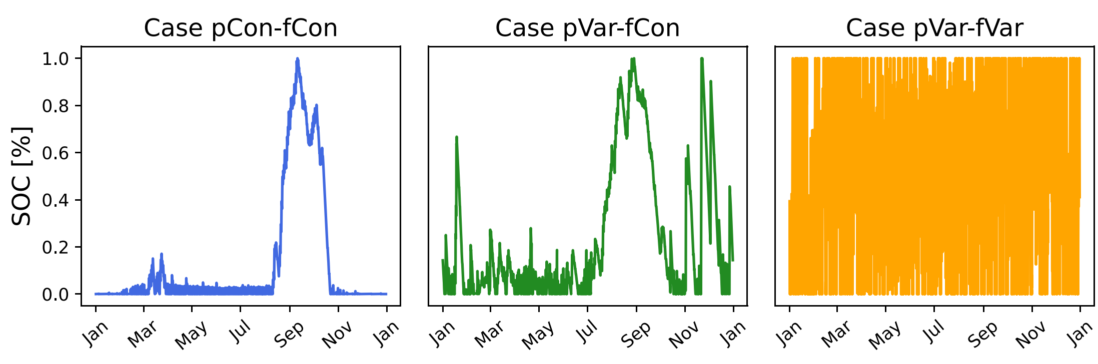

Fig. 6. SOC curves of three district energy storage systems under different steering cases. Storage size $C_D = 20$ MWh which equals $3.9 \cdot g_{\mathrm{d,max}}$.

prices or the effect of network charges, taxes or levies on the system friendliness of DER as long as a residual load time series for the respective points-of-interest is available. These analyses can support decision making processes on national levels but also grid planning more locally. The presented indicators all subject to the concept of a hypothetical system storage but consider different respective properties. Hence, a prioritization or a specific system friendliness service could be possible to target certain indicators with the respective operational strategy.

In this work, we consider a given one-node sustainable energy system which is an idealization and the case study is therefore based on scenario assumptions regarding the electricity generation and demand. Thus, future research will focus on extending the presented concepts to be able to take into account local constraints, especially grid capacities, and conventional generation. This would allow assessments in status-quo energy systems. However, this procedure will require more information about the reference system which is not always available. Here, we show a case study of residential energy storage in Germany 2050 but a broad application of the presented methods could be carried out in the future. This includes the examination of other points-of-interest or different reference systems based on scenarios with different characteristics or technologies. System friendliness assessments of other points-of-interest could include different technologies such as electric vehicles, electrolyzers, heat pumps also in combination with heat storage or decentralized renewable power plants. Other scenarios and reference systems could include other countries or smaller sub-regions in national energy systems as well as a different electricity mix or other general characteristics of the reference system.

Analyzing the results of the case study, we find that a residential self-consumption maximization strategy in steering case pCon-fCon has no measurable positive effect on the total system due to the “egoistic” use of the storage in the district. Neither system storage capacities nor maximum system storage powers are reduced due to missing incentives to do so. Nevertheless, residential self-consumption is currently incentivized by the constant pricing in most regulatory environments but many publications already heavily doubt its positive contribution in sustainable energy systems [25,26]. Our findings are also in line with a recent study on storage in Germany, where the authors find highest energy generation costs when assets are solely used for PV self-consumption [41].

A constant feed-in tariff combined with a variable electricity price is leading to system friendly behavior at small storage capacities in the district considering the effects on system storage capacities. However, with bigger storage capacities, the grid friendliness in steering case pVar-fCon stagnates and no further capacity reduction in the reference system can be observed. We do not observe a significant positive impact on the other system friendliness indicators for steering case pVar-fCon.

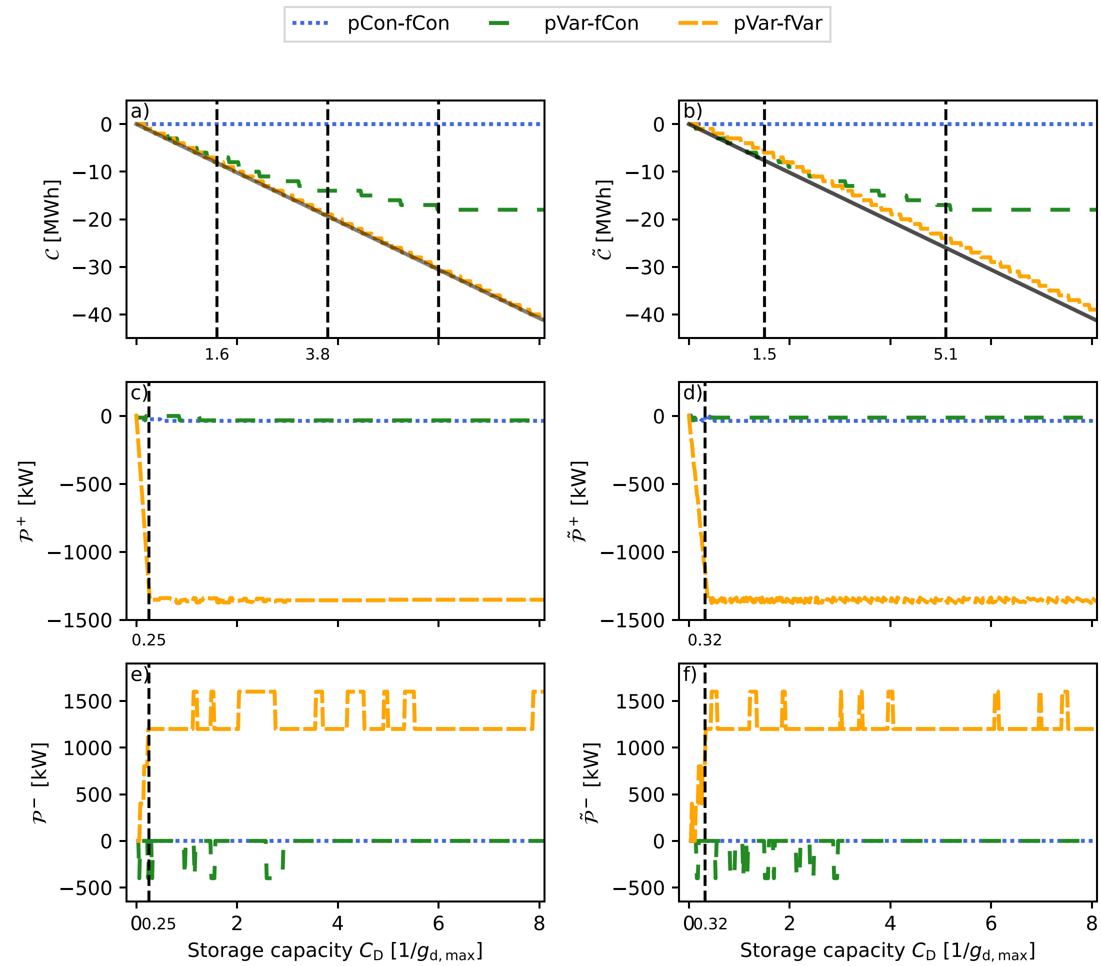

Fig. 7. Primary system friendliness indicators evaluated for the simulated residential district and three steering cases. On the left without losses. On the right including losses. **(a) and (b)** Changes in capacity of the hypothetical system storage. The solid black line denotes the maximum storage capacity reduction potential. **(c) and (d)** Changes in maximum charging power of the hypothetical system storage. **(e) and (f)** Changes in maximum discharging power of the hypothetical system storage. $g_{d,\max}$ represents the maximum energy generated in one day in the district.

Lastly, steering case pVar-fVar shows that a system friendly use of DER is possible at the right incentives as storage and power reduction all approximately reach their maximum potential values. pVar-fVar combines symmetric variable steering signals for buying and selling energy to the reference system. The district storage in steering case pVar-fVar is predominantly operated as short-term storage with a high number of charging cycles but we do not consider aging effects of the residential storage. Variable feed-in tariffs should be broadly examined in the future to understand their potential for the system friendliness of DER and to provide information for the decision making for future energy market mechanisms and regulations.

8. Conclusion and outlook

System friendliness of distributed energy resources can be seen as a kind of behavior which is beneficial and supportive to the overall system stability. However, until now it was not technically and quantitatively defined and therefore could not be measured and evaluated. In this work we therefore introduced a purely technical definition of system friendliness for energy systems. The definition is based on a newly developed concept which we call the “burden” on energy systems. The burden represents the amount of technical infrastructure required to ensure stable operation of the energy system and accordingly we defined system friendliness as a reduction of the respective burden. In order to make system friendliness measurable in sustainable energy systems, we introduced a central hypothetical system energy storage to equal out all mismatches between demand and generation. Indicators measuring system friendliness are all referring to properties of this hypothetical energy storage. Doing so, the indicators are independent of technology, data granularity or level in the energy system and can be evaluated for different market or regulatory environments. This makes them an important method to help with decision making for future energy systems. In a case study, we demonstrated the application of the indicators and examine residential districts in a German energy system of 2050. We found self-sufficiency maximization to be counterproductive from the system’s perspective but variable electricity prices coupled with variable feed-in tariffs are able to incentivize an almost 100% system friendly behavior of the district’s resources. In this work, we applied simplifications which limit the application of the indicators to fully sustainable one-node energy systems. Future work will therefore focus on an extension of the presented methods to be able to assess system friendliness in more complex energy systems. This will include conventional energy generation and taking into account limited grid capacities. Additionally, extensive system friendliness assessments for a variety of technologies, electricity prices and regulations can be carried out in the future. This might help with current discussions on electricity market design for future sustainable energy systems.

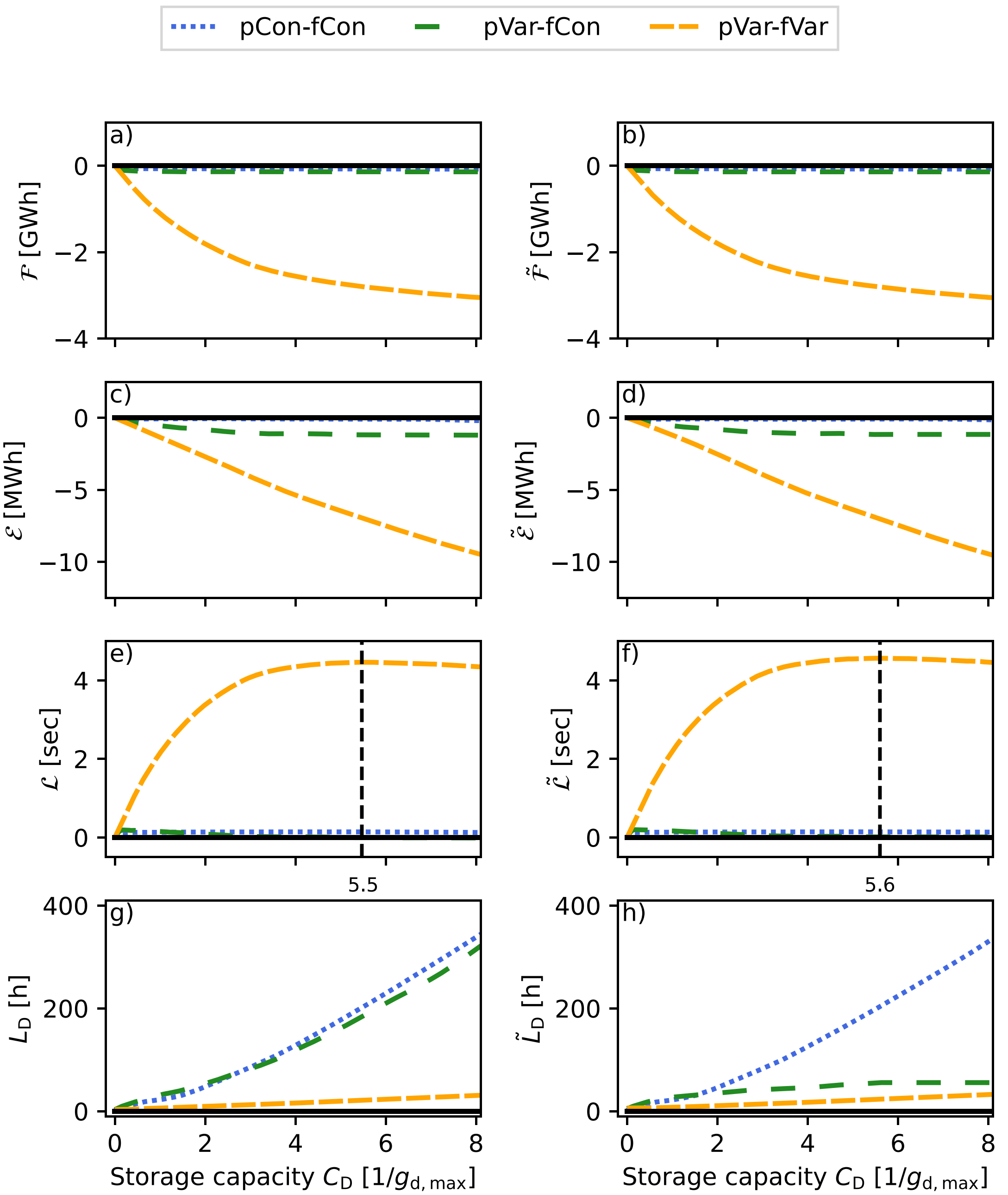

Fig. 8. Secondary system friendliness indicators evaluated for the simulated residential district and three steering cases. On the left without losses. On the right including losses. **(a) and (b)** Changes in total amount of stored energy in the hypothetical system storage. **(c) and (d)** Changes in mean SOC of the hypothetical system storage. **(e) and (f)** Changes in mean length-of-stay of energy in the hypothetical system storage. **(g) and (h)** Mean length of stay of energy in the district storage. $g_{d,max}$ represents the maximum energy generated in one day in the district.

CRediT authorship contribution statement

Karoline Brucke: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Sunke Schlüters:** Writing – original draft, Methodology, Formal analysis, Conceptualization. **Benedikt Hanke:** Supervision, Conceptualization. **Carsten Agert:** Writing – original draft, Supervision. **Karsten von Maydell:** Supervision.

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.

Data availability

Data to recreate the results is partly publicly available and partly cannot be shared due to confidentiality reasons. The code of this study is publicly available under https://zenodo.org/records/11044874.

Acknowledgments

We thank our colleagues Alaa Alhamwi, Wided Medjroubi and Tobias Naegler for their help regarding the provision of required data and resources for this work. We thank our colleague Johannes Seesing for his contributions to the literature research of this study.

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