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Incentivizing system friendliness of decentralized resources in sustainable energy systems

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HIGHLIGHTS

- Extension of system friendliness framework to reflect multi-node systems.
- We show the inherent trade-off between storage and grid capacities.
- We optimize the incentives for a system-friendly behaviour of decentralized storage.
- Pareto-optimal price signals decrease storage and grid requirements simultaneously.
- Residential self-sufficiency maximization has no measurable system-friendly impact.

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ABSTRACT

To address the challenge of weather-dependent energy generation, synchronization tasks are shifted to the system and demand levels. The behaviour of decentralized actors, known as “system friendliness”, reduces the burden on central energy systems. This behaviour can be incentivized through financial mechanisms such as electricity prices and feed-in tariffs. However, designing pricing mechanisms specifically for system friendliness in sustainable energy systems remains unclear. In this work, we extend the methodology for assessing system friendliness to multi-node energy systems, developing indicators to capture the impact of decentralized actors on storage and grid requirements. Our approach allows for evaluating system friendliness at every node and connection using only residual load data and grid structure information. Through extensive hyper-parameter optimization of the information weightings in price signals in a future German energy system, we explore optimal incentivization mechanisms. We demonstrate the trade-off between storage and grid capacities, requiring price signals to consider both global energy balance and local grid usage. Our results produce Pareto-optimal price signals, balancing local and global information. We find that in wind-dominated regions, dynamic grid usage information is crucial for system-friendly incentives, while PV-dominated regions benefit from price signals focused on system-wide energy balance. Despite regional differences, we show that price mechanisms that incentivize system-friendly behaviour in both regions simultaneously exist.

1. Introduction

The global energy transition is driving the transformation of energy systems towards highly distributed energy generation, primarily based on weather-dependent sources such as wind and photovoltaics (PV) [1,2]. As a result, large controllable power plants that can synchronize demand and supply are becoming increasingly scarce [3,4]. The task of synchronization has to be covered by the system and demand levels, elevating the importance of decentralized actors in particular. However, to date, many decentralized actors are operating inflexibly oftentimes due to the lack of smart metering [5] which enables demand response [6,7]. In contrast, a system-friendly behaviour refers to operational strategies that benefit the surrounding energy system [8]. The development of

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system-friendly operational strategies is crucial for harnessing the potential of decentralized resources from a system-wide perspective. If decentralized actors actively optimize their operation they mostly do it based on electricity prices [9]. Thus, the question arises how can these market-oriented operational strategies also be system-friendly at the same time?

Research has already yielded numerous approaches and strategies aimed at integrating decentralized resources into the system. Examples include a bidirectional charging strategy with vehicle-to-grid (V2G) technologies [10], the respective charging infrastructure [11,12], controllable heat pumps that can function as flexible demands [13,14], and residential storage systems that serve as sources of flexibility [15]. The specific goals, incentives and indicators however differ vastly and depend on the regulatory environment, technology or market mechanisms. It is crucial to develop methods to make these studies comparable by shared common indicators to quantify system friendliness. Additionally, system friendliness has to be differentiated from grid ancillary services. Grid ancillary services are well-defined and address bigger actors who oftentimes are able to build business models on the respective service and optimize themselves with respect to market forecasts (e.g. day-ahead electricity prices). The concept of system friendliness addresses otherwise inflexible or “egoistic” actors by incentivizing them [8]. The incentivization can be carried out by e.g., financial mechanisms like electricity prices.

What is system-friendly behaviour?

In order to be able to incentivize system-friendly behaviour, a clear definition of it including respective indicators to measure the success of the respective incentivization mechanisms is crucial. Until recently, the term system friendliness was not well defined in literature and was used in many different ways and through many different methods to quantify it. In Section 2, we outline the current research on system friendliness indicators in detail. Due to the unclear definition and taxonomy, we developed the burden formulation in our previous work [8] and defined the concept as: *System friendliness is a reduction of the burden on an energy system, which is the hypothetically needed minimal infrastructure to ensure stable operation of said system.* The burden formulation neglects the operation of the energy system and solely looks at a technical infrastructure minimum as limiting case. The framework from our previous work looked at sustainable energy systems with one node only. While this “copperplate assumption” is often used in research [16] and even in complex market models [17], it neglects grid capacities which play a major role in the burden formulation. One goal of this paper is therefore to include grid capacities, i.e. multinode reference systems in the existing methodology of system friendliness assessments. This opens a variety of different possibilities for system friendliness analyses such as locally resolved indicators for spatial impact analyses, examination of avalanche effects or testing of locally resolved price signals.

How can system-friendly behaviour be incentivized?

Currently, local imbalances between demand and generation are usually equalized by redispatch which can be inefficient and slow [18]. Therefore, it is technically infeasible to address the increasing number of very small actors such as electric vehicles, heat pumps and storage units through redispatch. Another approach to make use of decentralized resources is to incentivize specific behaviours through financial mechanisms such as electricity prices [19,20]. In Section 2.2, we provide an overview of existing mechanisms for electricity price formation and other incentives, along with their implications for decentralized actors’ system friendliness. We refer to these incentives as *steering signals* throughout this work. Steering signals are all kinds of tools, signals or levers that incentivize a certain behaviour or operation of decentralized actors. For instance, electricity prices and grid fees are part of the broader set of steering signals. Despite various market models and incentives, it remains unclear how to design steering signals for system friendliness specifically. This is also driven by differing understandings of system friendliness itself among researchers, policymakers, and industry stakeholders. Our previous work [8] contributes to this debate by formulating a technical definition of system friendliness and identifying multiple assessment indicators. However, developing effective steering signals is a complex task due to the strong dependence of system-friendly behaviour on the overall system’s characteristics, as well as the actor’s location and time within the energy system. System-friendly operation can vary significantly across different locations within the same energy system, owing to local constraints or concentrated energy generation and demand.

Research contributions As outlined above, there are two major research gaps we want to contribute to with this work: Firstly, while there is a framework to assess system friendliness from our previous work [8], it currently only reflects one-node systems. This copperplate assumption is a major simplification which completely neglects limited grid capacities and the respective constraints. Thus, there are currently no indicators to measure the system friendliness impact on the grid within the respective framework. We have also already outlined the importance of incentivizing system friendliness through financial mechanisms especially in sustainable energy systems. However to date, it is still very unclear how these mechanisms have to be designed in order to incentivize a system-friendly behaviour of a decentralized actor optimizing himself with respect to this incentive.

In order to address these two issues, we make the following contributions to the field:

- We extend the existing system friendliness framework from [8] to examine the effects of decentralized actors in multi-node systems and develop respective system friendliness indicators that account for electricity grid constraints.
- For the first time, we optimize steering signals to incentivize system friendliness specifically. We do this in two distinct scenario-based energy systems simultaneously, demonstrating which weighted combinations of local and global information yield Pareto-optimal operational strategies with respect to system friendliness indicators subject to storage and grid capacities.
- In order to demonstrate the robustness and transferability of the framework, we additionally examine exemplary steering signals in a second energy system representing the grid of an isolated onshore-wind dominated county. The results indicate and underline the importance of local information in steering signals of decentralized players.

The developed framework can assess the technical system friendliness of decentralized actors of any technology and size, independent of market mechanisms and regulatory environments. This makes it applicable to energy systems with unique characteristics while still ensuring comparability. As system friendliness indicators can be computed for every node and connection in the energy system, the methodology enables locally resolved system friendliness assessments. However, considering multi-node systems introduces a trade-off between transferring and storing energy, which affects grid and storage capacities. We show how to address this trade-off in our developed framework. Note, that even though the indicators assess changes in hypothetical storage and grid capacities, the developed framework is not meant to be used for extensive grid or storage planning. It rather denotes changes in an infrastructural limiting case which is suitable to evaluate if an actor is behaving system-friendly or not with minimal required data and information about the system. In a case study on decentralized storage, we apply the method to two regions of Germany: the wind energy-dominated north and the PV-dominated south. We examine the impact of different steering signals on the system friendliness of a decentralized actor (a residential energy storage) in both systems simultaneously. Our findings indicate that decentralized storage can reduce central storage needs and grid capacities concurrently. Nevertheless, due to the inherent trade-off between grid and storage capacities, these indicators compete with each other. Through an extensive hyper-parameter optimization, we calculate Pareto-optimal price building mechanisms. Our results suggest that central storage requirements are minimized when steering signals are based

Table 1
Exemplary overview of typical indicators to assess the impact of actors on energy systems related to "system friendliness", "system support", "system services" or "grid impact".

Indicator	References	Advantages	Disadvantages
Technical			
Self-sufficiency	[21,22]	easy to evaluate	not necessarily a measure of system friendliness
Peak power	[21–23]	easy to evaluate	not necessarily a measure of system friendliness
Energy consumption	[13,22,23]	easy to evaluate	not necessarily a measure of system friendliness
Curtailment	[24–26]	assesses integration of renewables in to the system	not necessarily a measure of system friendliness
Voltage levels	[27–29]	quantifies direct impact on the grid	extensive grid modelling required
Line or transformer loading	[30,31]	quantifies direct impact on the grid	extensive grid modelling required
Economical			
LCOE	[27]	good comparability	requires many assumptions
Total electricity costs	[27]	good comparability	requires many assumptions
Grid reinforcements costs	[32]	measures direct grid impact	requires many assumptions and grid structure information
Market alignment indicator	[16]	measures sychronization with market (system)	not independent of input price signal
Environmental			
Emissions (CO2, NOX, SO2)	[21,23,33]	good comparability, meaningful indicator for energy transition and climate impact	requires many assumptions and information, highly dependent on infrastructure out of the control of the decentral actor
Social			
Social acceptance	[34]	important to assess for expected success	comparability limited, no clear definition, not adequate for measuring system friendliness
Social or societal welfare	[18,35,36]	assesses impact on the whole system	comparability limited, complex to assess

primarily on global information about the energy balance. In contrast, grid capacities can be minimized by incorporating higher weightings of local grid utilization information in the steering or price signal. Optimal weightings in the price signal depend on the surrounding grid's characteristics; however, we demonstrate that average solutions can be found to incentivize system-friendly behaviour in both regions simultaneously.

This paper is structured as follows. Firstly, we outline the existing research and relevant literature on system friendliness assessments and indicators as well as respective incentives and the implications of different electricity price building mechanisms on system friendliness in Section 2. This is followed by explaining the methodology for system friendliness evaluation in one-node systems based on [8] in Section 3.1 and our model extensions and newly developed indicators in Section 3.2. Section 4 covers the theory behind our understanding of steering signals and what information they comprise. Our case study simulation setup, including the modelling of the respective reference systems and decentralized actors is described in Section 5. The results of that experiment are presented in Section 6 and discussed in Section 7. We conclude with a summary and an outlook on possible future work in Section 8.

2. Current state of research

We divide our overview of related work into two parts: First, we give a brief overview of methodologies for assessing system friendliness in Section 2.1. Secondly, different measures and levers for incentivizing certain kinds of behaviours in decentralized actors are outlined in Section 2.2.

2.1. Review of existing indicators for measuring system friendliness

Generally, indicators aimed at measuring system friendliness can be categorized into technical, economic, environmental and social indicators. Note, that many related works do not refer to the term "system friendliness" directly but call it "system support", "system serving" or assess the "grid impact". In Table 1, we provide an exemplary overview of typical indicators that are assessed when examining the impact of measures, operational strategies, investments or regulatory changes on energy systems in current literature. Most of these indicators come with disadvantages. They either require extensive amounts of data, assumptions or grid models which makes them hard to apply in situations where information about the energy system is limited, e.g. in scenario-based analyses. Alternatively, the indicators are strongly dependent on the regulatory environment or price signals which makes it hard or impossible to examine the effect of e.g. changes in the electricity market or legislation on energy systems. Lastly, most of them are not directly linked to system-friendly behaviour. For instance, a higher peak power is often considered system-friendly. However, when realized at times of peak generation, a higher peak demand could even be system-friendly as long as it complies with grid capacities. This is why we developed the purely technical definition of system friendliness in our previous work in [8] and also developed respective indicators that overcome these disadvantages. In Section 3.1, we recap on the developed methodology. This work focuses on extending that methodology of the system friendliness assessment framework and applying it to the research question of optimal incentives for decentralized actors in sustainable energy systems.

Other studies focusing on the development of dedicated indicators for system friendliness are presented and compared in our previous open access work [8].

2.2. Review on incentives for actors in sustainable energy systems

As stated above, system friendliness in sustainable energy system is highly dependent on the *local* availability of energy and the *local* grid utilization. However, local and global interests in an energy system could differ or even be contrary to each other [37]. In order to optimally incentivize system-friendly behaviour, measures should therefore take into account the local conditions such as the local energy mix and grid constraints as well as global or system-wide information [32]. Generally, there are many possible levers and tools to incentivize a certain behaviour of decentralized actors. The most common and effective known levers are: electricity prices, feed-in tariffs, grid fees, levies or taxes and other subsidies e.g., investment support [38]. In the following we discuss existing measures or different approaches for each of the above mentioned possibilities to incentivize system friendliness.

Electricity prices: We divide the electricity prices into three categories: Constant prices, local (nodal) and global (zonal) dynamic pricing. Constant electricity retail prices mostly lead to self-sufficiency and energy efficiency maximization. Self-sufficiency maximization has been proven suboptimal in many studies and can lead to negative implications for the system. In [8], we showed that PV-storage-systems operated under constant prices have no positive impact on system-friendliness indicators independent of the storage size. Self-sufficiency maximization in the residential sector can even lead to higher energy consumption and higher emissions [21]. Supporting this, the authors in [39] show the importance of different pricing schemes taking into account grid costs, variable energy generation costs and the current demand for mitigating the so-called utility "death-spiral" where infrastructure requirements peak.

In order to overcome these shortcomings of constant electricity prices, dynamic retail prices are extensively examined in research and already well-established in many countries. They support the integration of renewable energies and load management by specifically increasing electricity consumption during times of high renewable feed-in and decreasing it during times of low availability on a global scale with respect to the energy system. Dynamic retail prices can be exploited by decentralized actors if they optimize their behaviour with respect to it as [32] show. The authors show, that the median household savings are up to 30 % when equipped with a heat pump, electric vehicle and PV battery storage. Despite the advantages of dynamic electricity prices over constant prices, it comes with flaws if bidding zones are very large and unable to take into account local conditions. This is why splitting markets into a given number of price zones is heavily discussed as in [18,40]. Especially in Europe and Germany in particular a price zone splitting is under examination due to the local differences regarding energy generation and demand [41]. The discussion even gained momentum with the recently published bidding zone review of the European Network of Transmission System Operators for Electricity (ENTSO-E) [42]. Other countries like Sweden already had a market splitting reform with impacts e.g., on investments into wind power [43]. Besides the discussed zonal pricing with bidding zones of various size, nodal pricing is an approach to make electricity prices as local as possible and to incentivize actors to act according to the local conditions. Nodal pricing aims for maximizing social welfare and enhance congestion management [44]. In [45], the authors find that nodal pricing led to the lowest overall costs in a German case study. Nodal pricing is able to decrease grid congestion significantly as [46] show in their study on wind power expansion under different pricing models. As a famous example, Texas has already implemented nodal pricing in 2010 with significant changes in the behaviour of coal and natural gas units [47]. The authors in [48] study how demand response is able to enhance grid reliability in nodal pricing systems like Texas. However, nodal pricing also comes with a risk of highly volatile local prices due to the non-linearity of grid congestion.

Feed-in tariffs: Feed-in tariffs are one of the most favoured policies to incentivize the deployment of renewable energy since they are a strong incentive for investments in renewables, especially solar PV [49,50]. Even small changes in feed-in tariffs can lead to a significant impact on behaviour and investments in renewables [51]. The importance of the right choice of feed-in tariffs is also shown in [52] where the authors model the interaction between the electricity demand and the feed-in tariff. They find increasing demand if the feed-in tariff exceeds the electricity price. Especially dynamic feed-in tariffs seem to be a promising approach to incorporate renewables into the system in a system-friendly manner [53]. In [54], the authors show that a wind-dependent feed-in tariff is more cost-effective than a uniform tariff.

Grid fees: Grid restrictions have hardly been taken into account so far in price signals. Large-scale grid bottlenecks caused by market-based operation are usually subsequently compensated for by measures such as redispatch. This is why (dynamic) grid charges are currently under discussion in many countries and extensively researched. In [37], the authors find that three-level grid fees together with day-ahead prices is not enough to reliably limit the grid load and avoid avalanche effects due to herding effects based on simultaneous behaviour when optimizing for a global price signal. Riedel et al. examine the effect of dynamic grid fees as incentives for building energy management systems in [55] and show that grid bottlenecks caused by herding effects are difficult to avoid if the grid fee overrides the residual-load oriented dynamic price. In a recent study on different regions of Germany, the authors found that grid tariffs with power fees show a higher potential for the reduction of peak demand and feed-in than energy fee-based tariffs [56]. Naturally, there is an interplay between different grid fees and the dynamic retail electricity price. The authors in [32] find that with a grid charge design with capacity subscription, the share of households opting for a dynamic electricity retail tariff can be increased.

Other fees, levies and taxes: Besides electricity prices, feed-in tariffs and grid charges, other fees or taxes can also serve as incentives for certain kinds of behaviours. The authors in [57] examine how pricing schemes could be optimized for electric vehicles (EVs) to contribute to peak shaving, valley filling and flattening the load curve of the grid. They show, that EVs can generate profits only if the system-serving electricity quantities are billed without levies, taxes, and fees. This underlines the importance to also consider constant per-unit fees when examining how to incentivize decentralized actors to operate system-friendly.

Other subsidies: Subsidies for e.g., investments can also act as incentives for certain kinds of infrastructure to be built which can be operated in a system-friendly way. This is why we also consider them here as one measure to incentivize system friendliness. However, research on subsidies and their implications for system friendliness of decentralized actors is limited compared to the other levers described above. In [58], the authors examine the effect of per-unit subsidies for participants who pay fixed retail prices to incentivize demand reduction during times of high wholesale prices. The authors of [38] emphasize the importance of the regulatory environment for e.g., tax credits, grants, and subsidies that reduce the initial capital costs for renewable energy projects. Consequently, inefficient subsidies for fossil fuel can act as a major stumbling block to the development of renewable energy sources [59].

3. System friendliness framework

In this section, the methodology to assess the system friendliness of decentralized actors in energy systems is outlined. Generally, system friendliness is the reduction of the burden on an energy system which itself can be described in four dimensions representing the minimal infrastructure required to ensure stable operation [8]. Note, that the framework assesses this theoretical limiting case of the energy system to just being able to secure stability of supply. Therefore, the framework does not take into account additional safety concerns or backup capacities and is no substitute for e.g., grid extension simulation or storage planning tools. The main purpose of the framework is the evaluation of different operational strategies of decentralized actors and their comparison while taking into account the prescinded system's characteristics. A system friendliness result of e.g., a storage capacity reduction of x kWh does imply that this amount can be realistically decreased. But, looking at the theoretical point of minimal infrastructure ensures comparability of results and indicates if the operational strategy of a decentralized actor is beneficial to the system by decreasing the minimal amount of infrastructure.

The burden consists of the following four dimensions:

1. Inflexible (renewable) energy generation capacity,
2. Grid capacity,
3. Energy storage capacity, and
4. Controllable (conventional) energy generation capacity.

The burden dimensions referring to energy generation capacities are divided into controllable and inflexible generation. Most controllable energy generation relies on fossil fuels with exceptions being e.g., hydropower or biomass. Most inflexible energy generation on the other hand relies on the weather like PV or wind power. Indicators measure system friendliness subject to one burden dimension at a time and assess changes in respective properties caused by a decentralized actor.

System friendliness is highly dependent on the characteristics of the respective systems. Therefore, an assessment always has to be carried out with respect to the systems time series for demand and inflexible generation and existing infrastructure. The characteristics of the reference system can be summarized by its residual load which is defined as:

$$R(t) = G(t) - D(t) \tag{1}$$

with $G(t)$ being the inflexible energy generation and $D(t)$ the system's energy demand for the given time interval $t \in \{0, 1, \ldots, T\}$. The ratio of generation to demand is defined by:

$$\lambda = \frac{\sum_t G(t)}{\sum_t D(t)}. \tag{2}$$

In order to guarantee security of supply in sustainable energy systems without flexible energy generation, $\lambda \geq 1$ must hold true. If $\lambda > 1$, curtailment has to be included in the considerations. In our first study [8], we simplified the energy system such that only energy storage requirements remained for measuring system friendliness. This work aims for extending the methodology and take into account the grid capacities in the assessment as well. In this section we therefore begin by reiterating the existing methodology for strongly simplified renewable energy systems in Section 3.1. This is followed by Section 3.2 in which we explain the extensions to the framework. We outline the remaining simplifications in Section 3.4 and end with a step-by-step instruction how to apply the developed methodology.

3.1. One node systems - copperplate

Fig. 1 depicts the system friendliness framework for fully renewable and thus inflexible one-node systems. The actor to be evaluated is called "point-of-interest" (POI). The POI is connected to the surrounding energy system which is referred to as the "reference system" in the following. The POI is mathematically described by its residual load $r(t)$ with $r(t)$ being negative during times of energy consumption and positive when the POI is feeding energy into the system. The energy feed-in and consumption is typically incentivized by so-called steering signals like an electricity price or feed-in tariff.

The reference system itself is strongly simplified and consists of the following information or data:

- The time series for the inflexible residual load $R(t)$ has to be provided. Only surplus of energy can be curtailed.
- All mismatches between demand and generation are balanced out by a hypothetical energy storage with time series $S(t)$ which is typically optimized.
- The POI affects the residual load of the overall system and therefore can also influence the hypothetical system storage and accordingly changes $S(t)$ to $\hat{S}(t)$ which is also optimized.

All indicators measuring system friendliness in the one-node system take into account the changes between $S(t)$ and $\hat{S}(t)$. Here, only one node describes the energy system such that grid capacities are neglected which is often called "copperplate" assumption. However, limited grid capacities and respective grid congestions are often a crucial obstacle in the energy transition with more volatile energy generation based on wind and solar. Since grid extensions are of particular importance in most energy systems, this simplification is particularly limiting since it prevents indicators directing to the grid itself. Additionally, the required grid capacities are one of four burden dimensions as introduced at the beginning of this section. This is why we present a model extension in the next chapter outlining how to incorporate multi-node reference systems into the framework.

3.2. Model extension: system friendliness in multinode systems

The presented framework from [8] is only capable of measuring system friendliness in one-node systems by evaluating storage indicators under a copperplate assumption. When only taking into account global data, this approach is sufficient. However, if locally resolved generation and demand data is available, assessing the system friendliness of a POI with respect to the location in the reference system becomes first of all possible but is also highly relevant.

In the multi-node system, the POI is described by one time series: Its residual load $r(t)$, analogously to the one-node system. $r(t)$ has to be

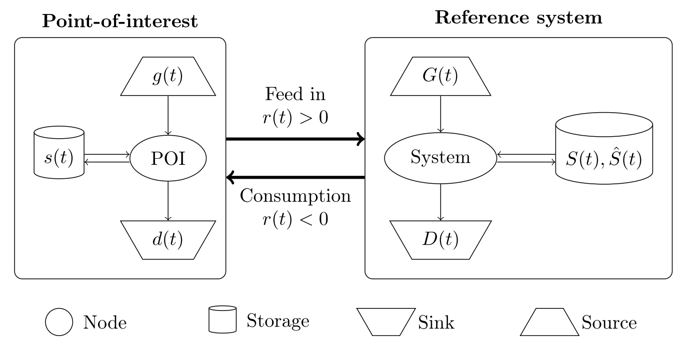

Fig. 1. Simplified relationship between the point-of-interest (POI) and the reference system for indicator evaluation in the one-node-system as in [8].

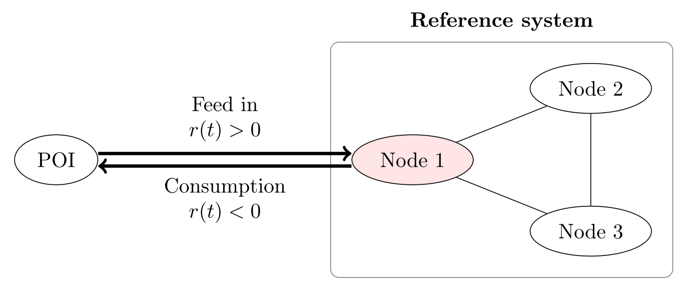

Fig. 2. Relationship between the point-of-interest (POI) and the reference system for indicator evaluation in the multinode-system. One source, sink and storage are connected to each bus respectively but not shown in this figure due to visibility reasons. The node in the reference system to which the POI is connected to is called connection node. The POI is feeding in and consuming energy from the system via the connection node. The respective connection can be limited in its power capacity. In the assessment, the time series of the connection node and the POI are aggregated.

given beforehand for the system friendliness assessment e.g., by measurement or simulation. This implies that there are no real-time feedback loops between the reference system and the POI just like in the one-node framework. In the multi-node system, the POI is no longer connected to the system as a whole but to one specific "connection node" as depicted in Fig. 2 for an exemplary 3-node system. The connection node is coloured, respectively. Every system node gets assigned an individual storage, a local energy generation and demand which is not shown in Fig. 2 due to visibility reasons.

The following information and data describe the multi-node reference system:

- Required input: The local fixed energy generation and demand has to be provided for every node in the reference system. They are summarized by the local residual load $R_\mathrm{i}(t) = G_\mathrm{i}(t) - D_\mathrm{i}(t)$.
- Optional input: The matrix J indicates if system nodes can be connected to each other. Elements of J can either be binary values with $J \in \{0, 1\}^{i \times i}$ if J only contains information if two nodes are possible to connect or not. Or $J \in \mathbb{R}^{i \times i}_{>0}$ when information about already existing line capacities are available. If there is no information about the grid structure available at all, one can also assume a fully connected grid for the assessment only. This is not realistic for a real-world grid. However, it is still possible to assess the impact on this hypothetical grid by a POI and with that evaluate its system friendliness with respect to the burden dimension of grid capacities.
- Optional input: Analogously, the spatial distances between grid nodes can be passed as an optional input. Spatial distances between nodes represent the length of the respective cable and can be represented by the distance matrix $B \in \mathbb{R}^{i \times i}_{>0}$. Longer distances between nodes impact the parametrization of the reference system: The cost of

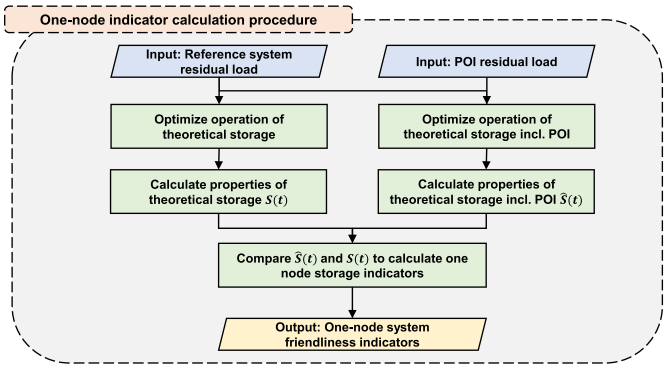

Fig. 3. Step-by-step procedure of the system friendliness assessment in one-node systems.

adding capacities to a certain power line in the model is proportional to the distance between the two respective nodes. If there is no information on the distance of nodes in the reference system available at all one could assume equal lengths of all connections for the assessment only. This means that grid expansion costs are independent of the distance between nodes. In a real-world system equidistant nodes are not realistic but a system friendliness assessment can still be carried out for this theoretical grid structure providing valuable information on the impact of a POI on the grid.

- Optimized: The storage time series at a node i is referred to as $S_i(t)$. A POI changes each $S_\mathrm{i}(t)$ to $\hat{S}_\mathrm{i}(t)$. $S_\mathrm{i}(t)$ and $\hat{S}_\mathrm{i}(t)$ are optimized e.g., by linear optimization based on the given inputs.
- Optimized: Flows between two nodes i and j are called $F_\mathrm{ij}(t)$. A POI changes each $F_{ij}(t)$ to $\hat{F}_\mathrm{ij}(t)$. $F_\mathrm{ij}(t)$ and $\hat{F}_\mathrm{ij}(t)$ are optimized e.g., by linear optimization based on the given inputs.

All indicators in the multi-node system are calculated by comparing $S_\mathrm{i}(t)$ with $\hat{S}_\mathrm{i}(t)$ and $F_\mathrm{ij}(t)$ with $\hat{F}_\mathrm{ij}(t)$. $S_\mathrm{i}(t)$, $\hat{S}_\mathrm{i}(t)$, $F_\mathrm{ij}(t)$ and $\hat{F}_{ij}(t)$ are all optimized based on the given inputs $R_\mathrm{i}(t)$ and $r(t)$ and optionally J and B. The optimization determines the transfer of energy between nodes, the curtailment and the amount and point in time of energy storage or withdrawal from the local energy storage while minimizing storage and grid capacities. This optimization is carried out two times: Without the POI as a reference case and afterwards including the POI which changes the time series of the connection node. This procedure is conceptually depicted in Fig. 5. Linear optimization can be used for the calculations. In this work we use the framework `oemof` [60] which is based on `pyomo` [61,62]. The exact procedure is explained in Section 5.2. The corresponding code to recreate the results is published on Zenodo with details in the appendix of this work.

Storage indicators in the multi-node system are calculated for every node while grid indicators can be assessed for every connection. However, they can also be aggregated for easier interpretation and visualization. Generally, a POI can have a positive impact in one area but a negative impact in another. In the following section, we outline the developed system friendliness indicators in the multi-node system. Fig. 3 shows the procedure to evaluate the system friendliness indicators of a given POI in a one-node-reference system.

3.3. System friendliness indicators in the multi-node system

For the indicator development in the multi-node system, we want to assess the impact of a POI on two burden dimensions: Grid and storage capacities. But storage and grid are intertwined as soon as there is an excess amount of energy in the overall system at a specific point in time. This is due to the surplus enabling a decision whether excess energy is transferred to a node with energy scarcity or stored locally for later times or even curtailed. A minimum amount of storage capacity C is needed, if there is a point in time where the system as a whole either

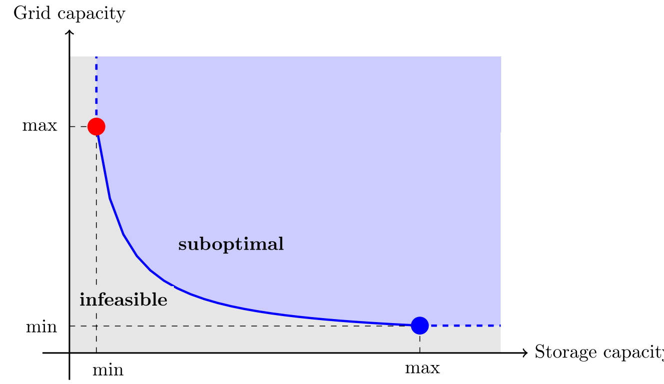

Fig. 4. Theoretical visualization of the trade-off between grid and storage capacities in multi-node systems. The blue line represents a Pareto-front with every solution beneath being infeasible for securing stable operation. Solutions above the Pareto-front are considered suboptimal since they provide excess infrastructure. The marked red dot indicates the position on the Pareto-front for system friendliness assessments.

has a surplus or a lack of energy that cannot be resolved by transferring energy between nodes:

$$\exists t : \sum_i D_i(t) \neq \sum_i G_i(t) \rightarrow C > 0 \tag{3}$$

A minimum amount of grid capacity Y is required if there is at least one node in the system that is not self-sufficient over the period of time and needs energy to be transferred to it to fulfill the demand:

$$\exists i : \sum_t D_i(t) \geq \sum_t G_i(t) \rightarrow Y > 0 \tag{4}$$

The dependency between storage and grid is reciprocal: The more energy is stored locally with larger storage capacities, the less energy transfer and therefore grid capacity is required. This trade-off between storage and grid capacities is conceptually depicted in Fig. 4 by showing the Pareto-optimal solutions as a blue line.

The Pareto-front of Fig. 4 can be computed using linear optimization. For that, two parameters are defined: The investment costs assigned to one unit of storage capacity c_S and grid capacity c_G. Then, the following steps are carried out:

1. First, the smallest possible storage size under a copperplate assumption is determined by setting $c_S = 1$ and $c_G = 0$. The optimizer builds as much grid as needed to minimize the storage size down to the capacity needed with an infinite grid. This first step yields the very left point of the Pareto-front. Note, that bigger grid sizes would not further decrease the storage size at this point. This point is highlighted in red in Fig. 4.
2. Secondly, the very right point of the Pareto-front highlighted in blue in Fig. 4 is determined analogously by setting $c_S = 0$ and $c_G = 1$. Therefore, the optimizer builds as much storage as required to minimize the grid capacities to the absolute possible minimum. Note, that analogously to the first step, bigger storage sizes would not further decrease grid capacities here.
3. Lastly, since the constraints are known, either the storage size or the grid size can be iterated to yield the full Pareto-front. If the storage size is iterated, it is given as input and no further investment is possible into storage capacity. By setting $c_G > 0$, the optimizer afterwards minimizes the respective grid size. The step-width of the iteration can be chosen with respect to accuracy and runtime. Note, that as soon as the constraints are calculated as outlined in the first two steps, all other optimizations can be parallelized to speed up the calculation.

A POI could affect the whole curve by e.g., bending or shifting it. However, assessing this whole Pareto-front is computationally costly since storage sizes or grid capacities have to be iterated. Thus, we only evaluate one point of this whole curve for the system friendliness assessment which we choose to be the point of the smallest possible grid with minimal storage capacities highlighted in red.

This is due to storing energy being more expensive than transferring it to other nodes in a strongly connected energy grid. In some energy systems, this might be different, especially in very rural or other sparsely connected regions. In that case, one could opt for another point on the curve or include constraints for the grid capacities into the considerations. For instance, the blue point which denotes the point of smallest possible storage capacity at minimal grid.

A system-friendly POI would impact the system so that the red point moves down and left towards smaller minimal storage and grid capacities. Assessing this point of minimal storage, a system friendliness analysis of multi-node systems yields the same but locally resolved storage indicators as in Section 3.1. They comprise: Storage capacity, maximum charging power, maximum discharging power, mean state of charge, total stored energy, length-of-stay.

Out of the storage indicators the storage capacity indicator is the most important one since it is a direct burden driver. The procedure to derive the storage indicators is described in detail in [8]. With multi-node systems indicators referring to the grid itself become possible. Note that the grid indicators can be evaluated for every power line in the grid. Nevertheless, aggregated indicators for the whole grid are possible by taking the sum or mean values of certain properties. The most important grid indicator of all which directly corresponds to the burden is the grid capacity which we consider to be a primary system friendliness indicator. If a POI decreases the needed overall grid capacity it is considered system-friendly and vice versa.

The line capacity of a single power line connecting node i and node j is denoted by $\hat{a}_{ij}$ if a POI is included and a_{ij} without taking the effect of a POI into account. $\hat{a}_{ij}$ and a_{ij} are the entries of the optimized capacity adjacency matrices A and $\hat{A}$ based on the given inputs. y_{ij} is the product of the lines capacity and its length b_{ij} taken from the distance matrix B which is fixed:

$$y_{ij} = a_{ij} \cdot b_{ij} \tag{5}$$

We define the local grid indicator for the power line between node i and node j to be:

$$\mathrm{y}_{ij} = \hat{y}_{ij} - y_{ij} = b_{ij} \cdot (\hat{a}_{ij} - a_{ij}) \tag{6}$$

A POI can change the required grid capacities, thus $\hat{A}$ represents the grid capacity matrix including the POI and A without the POI's influence. B represents the distance matrix between nodes which does not change by adding a POI to the system. Therefore, a_{ij} and $\hat{a}_{ij}$ in Eq. (6) denote the entries of A and represent the power line capacity between node i and node j without and with the POI's impact on the system. y can be aggregated by taking the sum over all connections according to the capacity adjacency matrix A:

$$\mathcal{Y} = \hat{Y} - Y = \sum_i \sum_{j<i} \hat{a}_{ij} \cdot b_{ij} - \sum_i \sum_{j<i} a_{ij} \cdot b_{ij} \tag{7}$$

Here, A is symmetric since the AC power lines do not have a direction but one could also assume directed DC power lines and an asymmetric adjacency matrix accordingly. With A being symmetric we only calculate the sum over the upper diagonal of A in Eq. (7). Note, that we multiply the maximum line capacity with the line's length which yields $W \cdot m$ as unit for the indicator.

Besides $\mathcal{Y}$, there are other descriptive properties of power lines that can be assessed. We refer to them as "secondary indicators" since they quantify the utilization and operation of the grid and therefore only indirectly indicate the required grid capacities. Note, that each of the

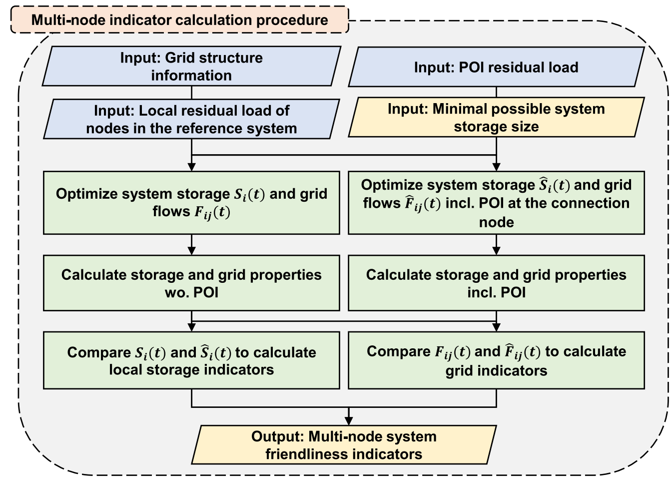

Fig. 5. Step-by-step procedure of the system friendliness assessment in multi-node systems.

secondary indicators can be evaluated for each power line. They comprise: Frequency of maximum utilization, frequency of utilization above 80 % of the nominal line capacity, variability of the power flow, mean utilization.

Fig. 5 shows the procedure to determine system friendliness indicators of a given POI in a multi-node reference system. An energy flow optimization is performed for the system with and without POI which yields the flows between nodes $\hat{F}_{ij}(t)$ and $F_{ij}(t)$ and the local SOC curves $\hat{S}_i(t)$ and $S_i(t)$. The indicators are evaluated by comparing the system properties with and without POI. Note, that one of the inputs (marked in yellow) is the minimal possible storage size of the system which is derived based on the assumption of an infinite grid. This input allows us to assess the indicators for the upper left point of the grid-vs-storage Pareto front shown in Fig. 12. Hence, this is a direct outcome of the one-node indicator assessment. The procedure of the multi-node assessment would therefore include a one-node assessment by neglecting the grid capacities in the first place. By using the one-node storage capacity from that assessment, the multi-node assessment can be carried out afterwards.

3.4. Remaining simplifications

This system friendliness framework is able to assess the impact of a POI or even multiple POIs on the hypothetical grid and storage capacities of a given reference system and with that measures changes in its burden. The reference system comprises fixed demand and generation time series and does not include flexible loads or other controllable generation itself. Every mismatch between demand and generation is equalized either by energy transfer, curtailment or storage. With this assumption, controllable conventional generation like coal or gas power plants or controllable renewable generation like pumped hydro or biomass is not included as an optimizable entity into the framework. However, they can be part of the fixed time series for the system's energy generation but are no source of the system's flexibility. Thus, the burden dimension of conventional generation capacity is still neglected here but is subject of future work since it would enable the assessment of system friendliness in energy systems of shared energy generation of renewable and fossil i.e., controllable and inflexible energy generation. Nevertheless, a controllable power plant could be serving as POI for an otherwise inflexible energy system. The POI's time series has to be given beforehand in order to be evaluated. This neglects a real-time reaction on the surrounding systems behaviour. Thus, if a POI is too big in comparison to the reference system, so called "avalanche" effects can occur. We consider the threshold of an avalanche effect to be defined by the size of the POI where the system friendliness impact starts to decrease for the same operational strategy. The storage indicator can be used to assess the avalanche threshold since there is a well-defined upper limit for the system friendliness potential: A decentralized storage of size e.g., 1 MWh can at maximum decrease the hypothetical storage by 1 MWh at optimal operation. This would be considered 100 % system friendly. The threshold can be determined by systematically increasing the POI's size and calculating the relative system friendliness. As soon as the system friendliness drops below 100 %, the negligibility assumption is clearly no longer valid. Avalanche effects for the grid indicator can be calculated analogously by considering a system-friendly operation of a POI with respect to the grid indicator and systematically increase its size. As soon as the grid reduction slows down or grid requirement even increase, the avalanche threshold is reached.

The analysis is carried out ex-post which excludes real-time feedback loops between the system and the POI and assumes a fixed system. In order to take into account feedback loops, the POIs operation would have to be carried out based on forecasts and including uncertainty likely with an iterative procedure. This would also include a sensitivity analysis of how responsive POIs are with respect to steering signals and how the system's behaviour would change respectively. This could be done by incorporating the indicators into market models like AMIRIS [17] who are already able to reflect this uncertainty and feedback loops. This can be part of future work since it requires extensive adaptions of the methodology.

The minimal grid and storage capacities are connected to each other and are underlying a trade-off as shown in the Pareto-front in Fig. 4. We only consider one specific point on that Pareto-front for the system friendliness assessment due to computational cost but theoretically every other point or even multiple points are possible as well. Note, that if another point on the Pareto-front is chosen, results are only comparable if the same point on the grid-vs-storage Pareto-front is considered for the assessment.

Note, that the framework enables the evaluation of multiple POIs. As long as the sum of all POIs is negligible compared to the system any number of POIs can be examined. However, the analysis framework presented in this work is always an ex-post evaluation of operational strategies of decentralized actors. This holds true when considering one POI but also multiple POIs at the same time, even if they interact. In our framework, this POI interaction would therefore be evaluated *after* it took place, e.g., with measured operational time series from real-world systems. Since the indicators are derived for the overall system they would reflect the aggregated or combined impact of all POIs. Eventhough the storage indicators can be evaluated for every node and the grid indicators for every line, it would not be possible to trace back a change in one line or node to a specific POI.

4. Incentives in the multi-node system: optimal steering signals

In this work, we examine the effect of different steering signals on the system friendliness of a decentralized actor representing a residential district energy storage which optimizes its behaviour based on the steering signals. We look at the steering signals from a purely technical perspective and examine how they have to be designed in order to incentivize system-friendly behaviour. Note, that steering signals are not electricity prices directly since we do not model a respective market. They are technical signals that can be used as objective functions for e.g., energy management systems. However, our findings can serve as input for more economically focused research to derive specific price building mechanisms based on them. There are two different steering signals to be communicated to a POI:

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.

Given $p(t)$ and $f(t)$, the aggregated costs of a POI over the considered period of time can be defined as:

$$c = \sum_{\substack{t \text{ s.t.} \\ r(t)<0}} r(t)p(t) + \sum_{\substack{t \text{ s.t.} \\ r(t)>0}} r(t)f(t)\,. \tag{8}$$

A decentralized actor optimizes its behaviour, thus its residual load in a way that minimizes the aggregated costs c which can be mathematically written as

$$r(t) = \underset{r(t)}{\operatorname{argmin}} \sum_{\substack{t \text{ s.t.} \\ r(t)<0}} r(t)p(t) + \sum_{\substack{t \text{ s.t.} \\ r(t)>0}} r(t)f(t) \tag{9}$$

In a previous work, we already showed that symmetric steering signals based on the global residual load are able to harness the full system friendliness potential of decentralized energy storage in the one-node system [8]. This is why we also only consider symmetric steering signals here, thus:

$$f(t) = -p(t) \tag{10}$$

Asymmetric steering signals could however be examined in future work. As outlined in Section 3.2, in multi-node systems there is a trade-off between grid and storage capacities. This implies challenges for deriving steering signals for the incentivization of decentralized actors when not assuming an infinite grid like in most market focused studies. A sub-optimal steering signal could incentivize system-friendly behaviour with respect to the storage indicator but at the same time lead to an increase of required grid capacities. For instance, a price signal based on global information could decrease central storage capacities as shown in [8] but lead to local challenges like local grid congestions or imbalances. From a technical perspective, it is still unclear how to define optimal steering signals for incentivizing system-friendly behaviour in multi-node systems. Additionally, due to the inherent trade-off between grid and storage, one is only able to find Pareto-optimal solutions. In the best case, a steering signal is able to incentivize a behaviour of decentralized actors which simultaneously decreases local *and* global infrastructure needs. However, after deriving the Pareto-optimal steering signals, a prioritization of burden dimensions still has to be made which of the Pareto-optimal solutions to choose. The priorities depend on the situation in the reference system and external factors like energy storage costs or grid extension costs.

Generally, we consider four contributions to the steering signals:

1. Constant μ: Represents arbitrary levies and taxes.
2. Local information $F_1(t)$: Grid utilization information of power lines directly connected to the connection node, also called flows of first order.
3. Regional information $F_2(t)$: Grid utilization information of power lines connected to the connection node via one neighboring node, also called flows of second order.
4. Global information $R(t)$: The global residual load as information about the current global energy balance.

With that, $p(t)$ can be defined as:

$$p(t) = \mu + x \cdot F_1(t) + y \cdot F_2(t) - z \cdot R(t) \tag{11}$$

with x, y and z being the respective weightings to the individual summands. Since a constant factor does not change the operational strategy in an optimization as in Eq. (9), this is equivalent to:

$$\begin{aligned} p(t) &= 1 + x/\mu \cdot F_1(t) + y/\mu \cdot F_2(t) - z/\mu \cdot R(t) \\ R(t) &= 1 + \alpha \cdot F_1(t) + \beta \cdot F_2(t) - \gamma \cdot R(t) \end{aligned} \tag{12}$$

The variables α, β and γ are hyperparameters which can be optimized. Every combination of hyperparameters leads to a different

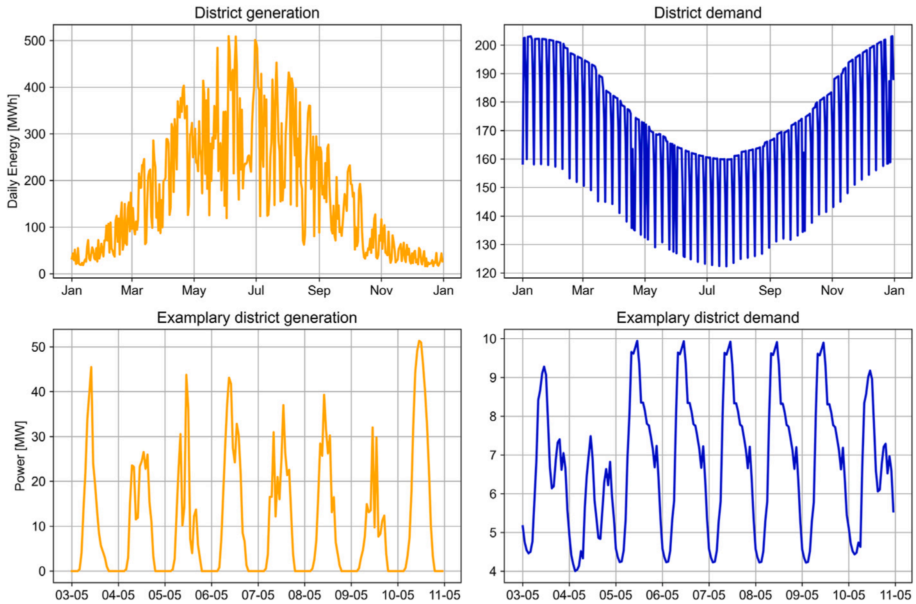

Fig. 6. District data: PV generation on the left and demand on the right. The upper graphs show the aggregated daily energy, the bottom shows the respective power of one exemplary week in May.

steering signal, which leads to a different behaviour of the POI leading to a different impact on the system friendliness indicators. Generally, the optimization problem can therefore be formulated as:

Minimize C and $\mathcal{Y}$ with respect to α, β and γ

One possible procedure to optimize the steering signals for system friendliness incentivization is outlined in Section 5.3. Note, that $F_2(t)$ denotes grid utilization information of power lines of second order meaning connections of direct neighbours of the POI to other nodes. Theoretically, these flows to other nodes also include flows *between* neighbouring flows which we call diagonal flows. Here, we exclude these diagonal flows from the considerations since their direction cannot be clearly defined. $F_2(t)$ therefore only includes flows of neighbour nodes of the connection node to or from *other* nodes, that are not neighbour nodes of the POI itself.

5. Simulation setup

In a case study, we aim to demonstrate our methodology for system friendliness analysis in multi-node energy systems. Similarly to our previous work in [8], we examine decentralized district energy storage in a future German energy system. While the case study of the previous publication focused on a proof of concept of the storage indicators, our main focus in this case study is the optimization of steering signals in multi-node systems for the maximum incentivization of system friendliness. We model a system similarly to Fig. 2 with the POI being a district energy storage. In Section 5.1, we describe the simulation and underlying data of the district storage while Section 5.2 covers the modelling and data of the multi-node reference system. The optimization of the hyperparameters in the steering signals as theoretically outlined in Section 4 is described in Section 5.3. All simulations are carried out for a period of one year with an hourly data resolution.

5.1. Modeling the decentralized storage

The POI under examination is simulated analogously to [8]. It represents a city district of 10,000 living units including an energy storage with a capacity of 1000 MWh operated under different steering signals. The respective time series for the demand is provided by [63] where the authors simulated the demand and generation of a large residential district for one year for the location Oldenburg, Germany using the tool FlexiGIS [64]. Since we consider a future German scenario, we scale the demand data to 6.25 MWh per residential unit per year analogously to [8] which also includes electrified heating and electric vehicles. The city district also includes PV generation which is provided by [63] as well. The PV data is based on the weather of the year 2015 and is simulated for the same location in Oldenburg, Germany. The energy system of the POI can be represented by the left side of Fig. 1. The effect of the flexibility provided by the decentralized storage is isolated for the system friendliness assessment of the decentralized storage. This is done by comparing the indicators of the inflexible district i.e., without energy storage, to the district including the energy storage. The city district includes PV energy generation. Demand $d(t)$ and district generation $g(t)$ over the simulation time period of one year are depicted in Fig. 6. The district is nominally self-sufficient with:

$$\sum_t g(t) = \sum_t d(t) \tag{13}$$

The POI's residual load is input for the system friendliness assessment as depicted in Figs. 5 and 2. Here, we use the energy system modeling framework `oemof.solph` [60] which is based on `pyomo` [61,62] to simulate the operation of the district. Since demand and generation are fixed, only the storage operation can be optimized with linear optimization to solve the optimization problem from Eq. (9). We simplify the decentralized district storage to be loss-free. The data is provided in hourly resolution. Table 2 shows important data features of the modelled district.

We conduct an analysis to determine if the negligibility assumption between system and POI holds true with the presented data. For that, we choose an operation of the decentralized storage which is known to be 100 % system-friendly with respect to the storage indicator for small POIs. The POI's size is systematically increased and the relative system friendliness is shown in Fig. 7. Here, the avalanche threshold is at approximately 1.5 % for the POI size compared to the system size. The original POI size is approximately 0.01 % as can be seen in Table 2, thus far away from a possible avalanche effect.

5.2. Modelling the reference system

As a reference system in this study, we assume a scenario-based fully sustainable energy system of Germany. This corresponds to the national

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

	Reference system	District (% of system)
Maximum generation power	382.74 GW	54.72 MW (0.014 %)
Minimum generation power	4.16 GW	0.00 MW (0.000 %)
Maximum demand	84.87 GW	11.22 MW (0.013 %)
Maximum residual load (before curtailment)	323.17 GW	45.68 MW (0.014 %)
Minimum residual load	−77.43 GW	−11.21 MW (0.014 %)
Maximum energy generation in one day	4.84 TWh	510.04 MWh (0.011 %)
Minimum energy demand in one day	1.02 TWh	122.34 MWh (0.012 %)
Maximum energy demand in one day	1.84 TWh	203.15 MWh (0.011 %)
Mean energy demand in one day	1.46 TWh	171.21 MWh (0.012 %)
Total demand	534.00 TWh	62.50 GWh (0.012 %)
Total generation	965.65 TWh	62.50 GWh (0.006 %)

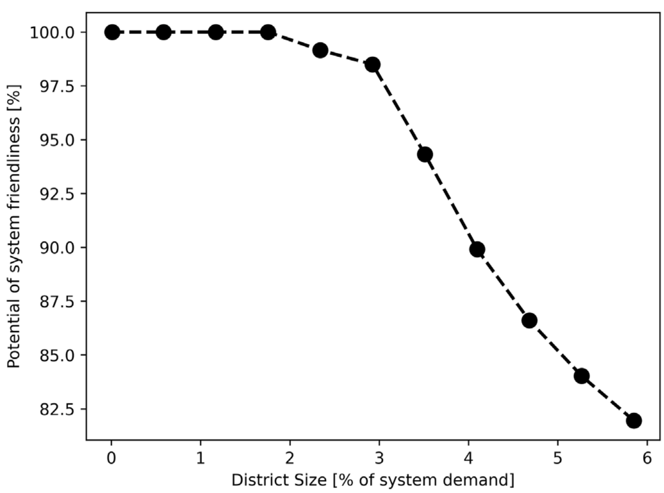

Fig. 7. Sensitivity analysis of the negligibility assumption of the POI size compared to the system's size. The negligibily assumption is no longer valid for POI sizes greater than 1.5 % of the system size indicated by the dashed line. The storage indicator is used to determine the potential system friendliness.

energy transition plans of the year 2050 [65–67]. As shown in Figs. 1 and 2, we model the reference system with the energy modelling framework `oemof` [60] in the version 0.5.5. `oemof` creates a set of linear equations for the energy system optimization which is then solved with an external solver, here `cbc` [68]. Nodes in the reference system are defined as `Buses` each with generation as `Source`, demand as a `Sink` and a `Storage` object. Generation and demand data are passed as fixed input at each node. Curtailment is possible by setting the `max` parameter in oemof instead of the `fix` parameter of the corresponding input of the respective source. Power lines between nodes are modelled as `Flows` between buses including an investment variable into the capacity of the line. The investment costs for each power line are set with the `ep_costs` parameter of oemof and are equal to the distance between the two respective nodes. This ensures that capacity expansion for longer power lines to be more expensive than for shorter lines. The energy transfer itself is loss free and has no variable costs assigned to it. Each grid node also gets assigned a loss free storage of variable capacity. A constraint is added using the pyomo `constraint` functionality [61,62] ensuring that the total storage capacity at all nodes does not exceed the minimal viable storage size determined under the copperplate assumption. This procedure determines the indicators for the marked red point on the Pareto-front between grid and storage according to Fig. 4. The minimal viable storage size is determined in a calculation procedure according to Fig. 3 and [8] where a one-node system is assumed by aggregating the data over all nodes. This yields the storage size assuming an infinite grid which is passed as input to the multi-node system as shown in Fig. 5.

In order to get data for a fully sustainable German energy system serving as a reference system, we use the tool REMix. REMix is an open-source framework for energy system optimization modelling, designed to facilitate the development of comprehensive models for optimizing energy system expansion and dispatch [69]. By employing linear programming approaches, REMix aims to minimize total system costs, thereby maximizing overall efficiency and sustainability. The framework enables consideration of various sectors, including power, heat, and transport, as well as distinct technology groups, such as conventional and renewable converters, storage and transport technologies. The input requirements for REMix include weather and demand profiles based on historical data, as well as techno-economic parameters such as technology-specific investment costs, operational expenses, and efficiencies. By integrating these factors into a cohesive model, researchers and practitioners can gain valuable insights into the performance and optimization of energy systems. The REMix model employed in this study is based on the high-resolution REMix power system model for Germany [70]. To enable the meaningful application of the methodology developed in this work, two key modifications were implemented:

1. All dispatchable (i.e., flexible) power generation capacities were removed.
2. The upper bound for offshore wind capacity expansion was doubled.

Following these adjustments, the model includes only the following technologies: Onshore wind, offshore wind, photovoltaic (PV) and lithium-ion battery storage. These technologies are subject to endogenous capacity expansion within the optimization. Additionally, the model includes run-of-river hydropower and pumped-storage hydropower. For both hydro technologies, the realistic assumption for Germany is, that these are fixed and non-expandable. The model power grid is an aggregated representation of the German transmission grid, with its transmission capacities also being optimized by the REMix model.

As a result, we obtain time series for electricity generation, demand, and storage, as well as the expanded capacities of power plants, storage systems, and transmission infrastructure. As input for the system friendliness assessment, we use the time series for demand and generation as well as the information if two nodes in the system are connected to each other. We do not include the exact REMix line capacities for the transmission infrastructure but only the information if two nodes are connected to each other. One could implement existing power lines into the assessment framework by e.g. setting the "existing" parameter in the oemof investment object. The REMix model based on [70] includes 10 nodes for cross border energy trade to other countries close to Germany. In this work, we only look at the national scale energy system and assume a closed system for Germany which results in 50 grid nodes total. Therefore, we neglect these cross border nodes as a simplification. The system's demand $D(t)$ and generation without curtailment $G(t)$ aggregated over all system nodes is depicted in Fig. 8. The seasonal dependence of the PV generation is clearly visible. The overall energy balance of the system is $\lambda_S = 1.8$. Table 2 shows important data features of the modelled reference system. Note, that it represents the data aggregated over all nodes. Due to visibility reasons, we do not show node-granular data. In the simulation of the reference system, we use the "raw" generation without curtailment as input since the oemof model optimizes the curtailment itself.

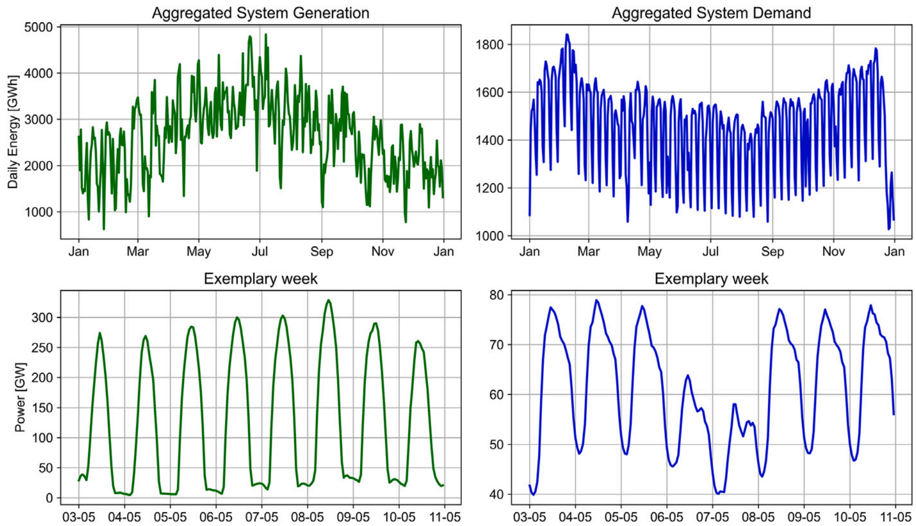

Fig. 8. Reference system data aggregated over all nodes with raw generation without curtailment (left) and demand (right) being depicted. The graphs on the top show the aggregated daily energy and the bottom graphs show the power of an exemplary week in October.

Optimal steering signals can differ regionally depending on the local energy demand and supply imbalances and, e.g., energy generation technologies. This is why we exemplarily consider two sub-systems within the national German energy system model: The wind generation dominated north-west and the industry and PV dominated south-west. We optimize steering signals for both simultaneously. The procedure to do so is outlined in Section 5.3. Fig. 9 represents the spatial structure of the grid models. On the left hand side, the full complexity grid model including 50 nodes is depicted while the maps in the middle and on the right hand side of Fig. 9 show the two considered sub-systems. Grid nodes derived from REMix are represented as blue markers, power lines are shown in green. The line thickness indicates the power capacity of the respective power line. In the two sub-systems, the remaining national grid is aggregated by an arbitrary node depicted as red marker shown in the middle of all aggregated nodes. The length of power lines connecting grid nodes is encoded in the distance matrix B_{ij} while the optimized capacity of these lines is represented by A_{ij}. The sub-systems contain subsets of B_{ij} and A_{ij} which are denoted by $B^{\mathrm{s}}_{\mathrm{ij}}$, $B^{\mathrm{n}}_{\mathrm{ij}}$ and $A^{\mathrm{s}}_{\mathrm{ij}}$, $A^{\mathrm{n}}_{\mathrm{ij}}$ respectively. They also comprise one arbitrary node for the aggregated remainder of the grid model. The distance to this arbitrary node is equal to the smallest distance of the respective node within the sub-system to the closest node outside of the sub-system.

The two sub-system differ vastly in their characteristics which is represented by their respective residual load excluding the red node from Fig. 9 as shown in Fig. 10. The south is dominated by PV generation in the summer and higher demand which often results in negative residual loads. On the other hand, the north sub-system mainly comprises a lot of the German national wind generation which results in a large energy surplus and fewer points in time with negative residual loads. However, due to adding the remaining system via the red node $\lambda_{\mathrm{S}} = 1.8$ holds true for both sub-systems in total to make results comparable.

The POI is connected to one specific grid node within each subsystem which is highlighted in orange in Fig. 9.

5.3. Hyperparameter optimization for deriving optimal steering signals

As described in Section 4 and Eq. (12), α, β and γ are hyperparameters of the steering signal $p(t)$ which have to be optimized for $p(t)$ being able to incentive system-friendly behaviour of the POI. They define the weightings of the three summands $R(t)$, $F_1(t)$ and $F_2(t)$ in $p(t)$ with

$$F_1(t) \in [-0.2, 0.2]$$

$$F_2(t) \in [-0.2, 0.2]$$

$$R(t) \in [-0.2, 0.2]$$

$F_1(t)$ and $F_2(t)$ comprise multiple flows in different directions. In order to equally take their information into account independent of the power line capacity all of these flows have to be normalized individually. Afterwards the normalized individual flows are aggregated and finally normalized to the interval $[-0.2, 0.2]$. Therefore, the following procedure applies:

- Firstly, the flows without the POI have to be determined. Therefore, the reference system is optimized without the POI according to the left side of Fig. 5 and the flows between nodes $F_{ij}(t)$ are calculated.
- The corresponding flows between the connection node and first order neighbours are normalized individually to a maximum of 1.
- The flows between first and second order neighbours to the connection node are determined and normalized individually. Note, that flows *between* first order neighbours – called diagonal flows – are excluded from the consideration.
- The mean of all flows of first order is calculated and normalized again to the interval $[-0.2, 0.2]$ to determine $F_1(t)$.
- The mean of all flows of second order is calculated and normalized again to the interval $[-0.2, 0.2]$ to determine $F_2(t)$.

The parameter space for α, β and γ is set to:

$$\alpha \in [-3, 3]$$

$$\beta \in [-3, 3]$$

$$\gamma \in [0, 3]$$

Negative values for γ are excluded since $p(t)$ should be proportional to the *availability* of electricity, not the opposite. For optimizing the hyperparameters, we use the optimization framework `pygmo` and a metaheuristic optimization approach [71]. We calculate Pareto-optimal solutions of the steering signal with regard to the two primary system friendliness indicators, namely storage capacity C and grid capacity $\mathcal{Y}$. The weightings α, β and γ are dependent on the characteristics of the surrounding reference system. This is why we consider two different subsystems as described in Section 5.2 at the same time. This makes the hyperparameter optimization problem four-dimensional since we optimize α, β and γ with respect to C^{n}, C^{s}, $\mathcal{Y}^{\mathrm{s}}$ and $\mathcal{Y}^{\mathrm{n}}$. Doing that

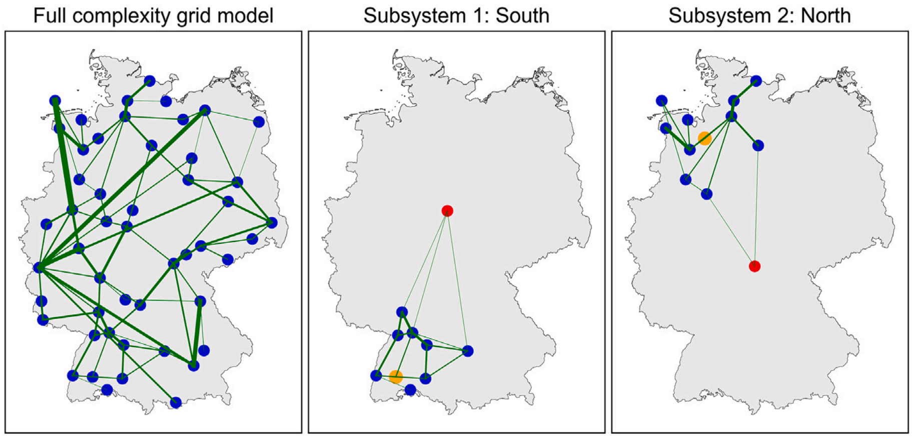

Fig. 9. Representation of three grid models: On the left, the full German 50-nodes ReMix model (excluding foreign nodes), in the middle a subsystem with nine nodes in the south-west of Germany and on the right a subsystem with 11 nodes in the north-west. Blue markers represent grid connection points. The orange node shows the connection node of the POI in our simulations and the red marker represents the geographical average of the remaining and aggregated energy system nodes. Note, that in the model, the distance to the red node is equal to the shortest distance of the blue node to a system node outside the sub-system.

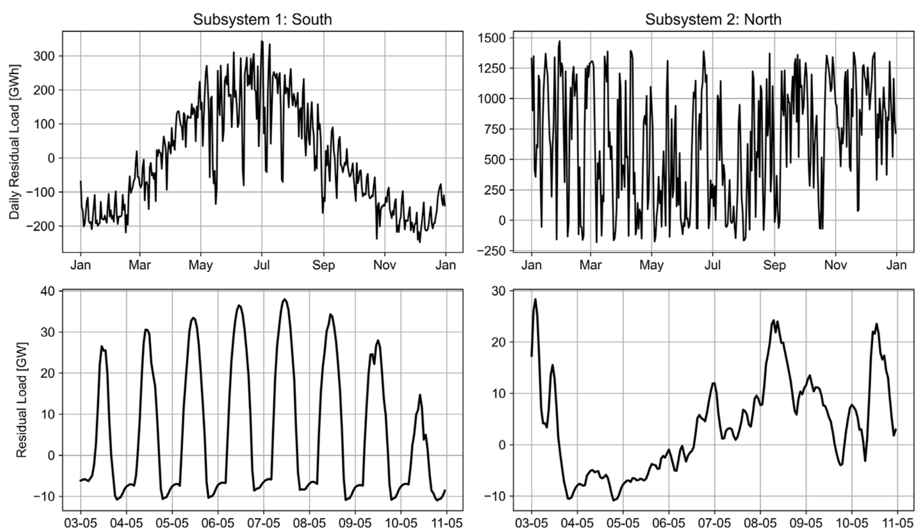

Fig. 10. Residual load of the two sub-systems from Fig. 9 without the remaining aggregated node (shown in red in Fig. 9). The graphs on the top show the aggregated daily residual energy while the graphs on the bottom depict the residual load of an exemplary week in October.

for northern Germany and southern Germany at the same time reflects the location-dependent optimum and can find a compromise of hyperparameters which leads to system-friendly behaviour *on average*.

In this work, we use the "Non-dominated Sorting Genetic Algorithm" (NSGA2) [72] provided by `pygmo` with 100 evolutions and 64 individuals per population. NSGA2 is a multi-objective evolutionary algorithm which also allows multiple input parameters chosen from a continuous parameter space. The algorithm generates offspring with crossover and mutation by selecting the next generation according to non-dominated sorting including crowding distance comparison [72]. We parallelize the calculation of the fitness of individuals within one population by using the batch fitness evaluator functionality of `pygmo`. All other learning parameters are kept at the default values set by `pygmo`. Note, each individual in each generation calculates C^{n}, C^{s}, $\mathcal{Y}^{\mathrm{s}}$ and $\mathcal{Y}^{\mathrm{n}}$ based on one combination of α, β and γ.

5.4. Additional county grid simulation: wesermarsch

In order to demonstrate the robustness and transferability of our proposed system friendliness framework we apply it to a second reference system. The second system represents a county grid which is located in northern Germany and dominated by onshore wind. Fig. 11 shows the 9-node grid model including the node names representing municipalities in the respective county called "Wesermarsch". Here too, REMix is used to simulate the data in a similar way as for the national energy system. The underlying weather year of the simulation is 2019. The renewable self-sufficiency factor of the county grid is $\lambda = 1.05$ which indicates much less energy surplus compared to the national energy system. The POI analysed in this reference system is the same as before: A residential district including an energy storage. Note, that the district in this county grid comprises only 1000 living units and the storage has a 100 MWh capacity in order to not violate the negligibility assumption of the POI with respect to the system. We do not perform an extensive hyper-parameter optimization of steering signals in the county grid since the national scale energy system is more relevant for this research question. Instead, we show the results of exemplary steering signals in this small energy system particularly for demonstrating the transferability capabilities of the framework and examine the effects of system friendliness in much smaller energy systems.

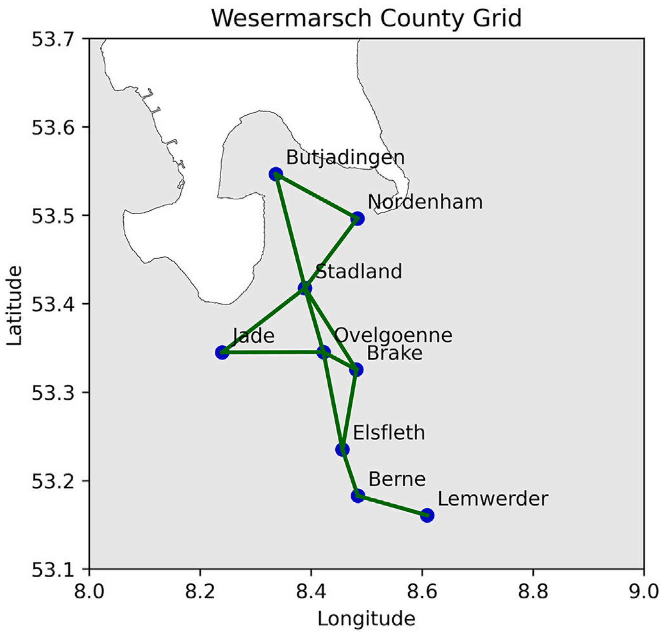

Fig. 11. Grid model of the examined county grid representing the municipality "Wesermarsch" in northern Germany. Nodes are named according to the cities or villages they represent. The POI is connected to Butjadingen and for one experiment to Ovelgoenne.

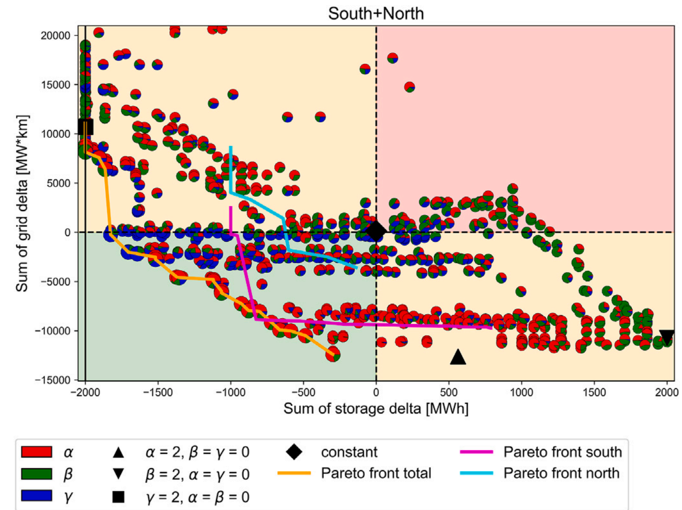

Fig. 12. Results of the system friendliness assessment of decentral storage under different steering signals. Depicted indicators are the sum of indicators for the two subsystems in the north and south of Germany. The weightings of local grid utilization (α), regional grid utilization (β) and residual load (γ) are shown as individual pie markers. The green area indicates both indicators decreasing the burden, yellow areas decrease only one of the two indicators while the red area indicates system unfriendly behaviour in both burden dimensions. Steering signals that are not Pareto-optimal are depicted with smaller pie markers.

6. Results: case study on incentives for system-friendly decentralized energy storage

In this section, we present the results of our case study on system friendliness incentives for a future German energy system. In our experiment we optimize the steering signals $p(t)$ and $f(t)$ which are the objective functions for the POIs operation with respect to the system friendliness indicator of said POI. In doing so, we simultaneously consider two different locations of the POI in two subsystems (north and south) with vastly varying characteristics. Therefore, the results for the steering signals look at Pareto-optimal parameter combinations of α, β and γ in four dimensions, namely the grid and storage indicator for the northern and southern subsystem.

Fig. 12 shows the results of overall the hyper-parameter optimization including all individuals of the optimization, not only the Pareto-optimal ones. Every marker represents a pie chart denoting the absolute values of α, β and γ.

The four coloured quadrants of Fig. 12 denote how system-friendly or unfriendly the specific quadrant is. The red quadrant shows the area where both burden dimensions are being increased due to the decentral storage which is considered system-unfriendly. Yellow areas mean a decrease in one burden dimension but an increase in the other. The green quadrant denotes the area where a steering signal is able to lead to an operation where the POI decreases central storage needs and grid capacities at the same time. This quadrant is considered system-friendly. Three Pareto-fronts are shown in Fig. 12 with the orange one being the overall Pareto-front considering $\mathcal{C}^{\text{tot}} = \mathcal{C}^{\text{s}} + \mathcal{C}^{\text{n}}$ and $\mathcal{Y}^{\text{tot}} = \mathcal{Y}^{\text{s}} + \mathcal{Y}^{\text{n}}$. The two other dashed lines represent the individual Pareto-fronts of the north and the south sub-system. This is why they only reach -1000 MWh storage reduction maximum because they subject to $\mathcal{C}^{\text{s}}$ and $\mathcal{C}^{\text{n}}$ only. Since we look at two residential storage units simultaneously, the hypothetical maximum storage reduction is $\mathcal{C}^{\text{max}} = -2000$ MWh which is shown as solid black line in Fig. 12. It is visible, that multiple steering signals are able to lead to an operation of the storage that maximizes the storage reduction. However, all of these steering signals lead to an increase in grid requirements in the energy system. Generally, steering signals with high weightings of local grid utilization information (higher α) tend to decrease grid requirements the most while higher values for β which weighs the regional grid utilization information mostly do not lead to Pareto-optimal solutions since they increase the storage needs. The very left of the Pareto front is reached by steering signals with a combination of a negative value for β combined with moderate weightings of the global residual load γ. However, these solutions increase the grid requirements drastically.

Additionally, the results of benchmark steering signal are shown in Fig. 12 by black markers. These benchmarks are a constant steering signal with $p(t) = 0.3$ and $f(t) = -0.1$ and three limiting steering signals where only one of the hyper-parameters is set to a value of 2 and the others are set to zero. The γ-only case therefore only takes into account the residual load and decreases storage requirements up to the hypothetical maximum. The β-only and α-only steering signals only contain grid utilization information, respectively. Both therefore increase storage needs drastically but strongly decrease grid requirements. The constant steering leads to an operation, that maximizes self-sufficiency. Notably, self-sufficiency maximization does not have a positive effect on the energy system in terms of system friendliness. Despite building two 1000 MWh storage units, neither system wide grid nor storage capacities are reduced.

The individual results of the subsystems are shown in Fig. 13. Note, that differing from Fig. 12 we only show the Pareto-optimal points here. For all Pareto-optimal points of one subsystem, we also depict the indicator values of the respective other sub-system in the same graph but with different colours of the pie markers, respectively. Especially in the southern subsystem, the grid indicator can be decreased by up to 10,000 MW*km while still decreasing storage requirements significantly at the same time. This can be realized with high values of γ which is the weight for the residual load in $p(t)$ and $f(t)$. High weightings of the residual load γ also decrease the storage requirements in the northern sub-system but lead to an increase in required grid capacities. In the northern subsystem, only steering signals which have high values for α and β are able to reach the green quadrant. The values of the benchmark steering signals are shown for each sub-system individually as well in Fig. 13. The γ-only case even is left to the Pareto-front of the southern system which might be surprising. But note, that the optimizer optimizes

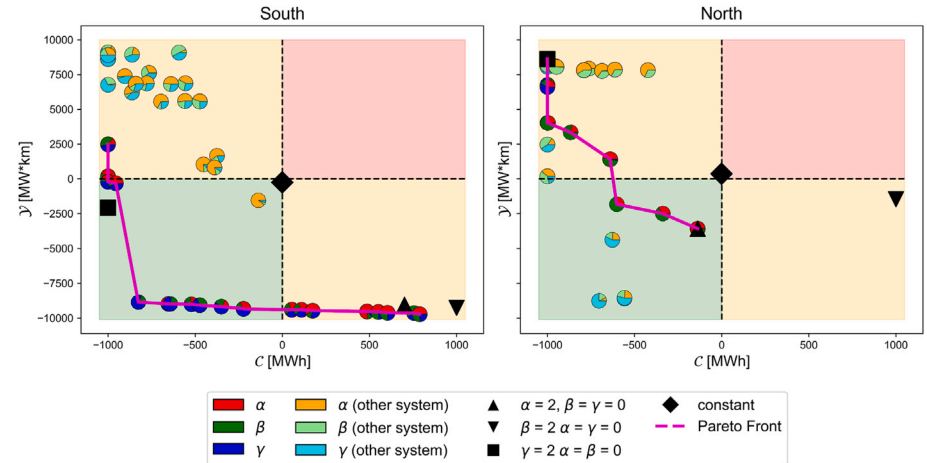

Fig. 13. Results of the system friendliness assessment of decentral storage under different steering signals analogously to Fig. 12 but for the two sub-systems individually.

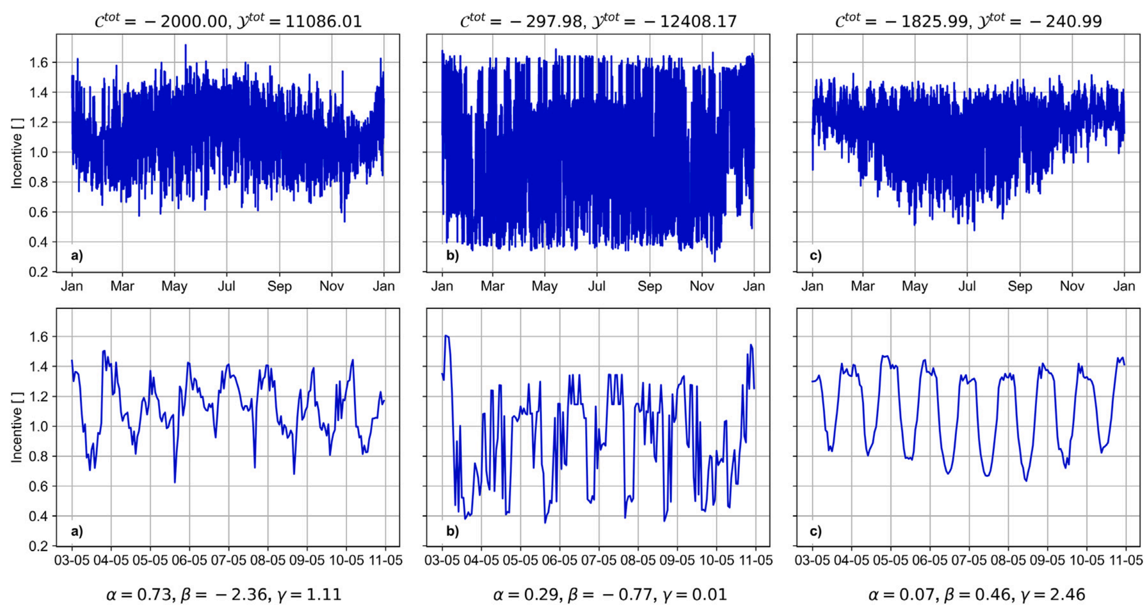

Fig. 14. Three exemplary Pareto-optimal steering signals (BS1: left, BS2: middle, BS3: right) incl. the weights α, β and γ shown in the respective text boxes below. Steering signals are calculated for the connection node in the southern subsystem. The two primary system friendliness indicators $\mathcal{C}^{\text{tot}}$ and $\mathcal{Y}^{\text{tot}}$ are shown in the title of the respective subplot. The top graphs show the whole simulation time period of one year while the graphs on the bottom show an exemplary week in May.

the hyper-parameters with respect to the four system friendliness indicators at the same time and not for each sub-system individually. Fig. 12 shows, that the γ-only case is on the *overall* Pareto-front but not left of it.

For a more specific depiction of Pareto-optimal steering signals, Fig. 14 shows three steering signals, which are all on the overall Pareto-front but realize very different values of the respective system friendliness indicators. The steering signal **(a)** optimizes the overall storage indicator and reaches the maximum storage reduction on the very left of the Pareto-front in Fig. 12 but increases grid requirements drastically. Note, that steering signal **(a)** chooses a big but negative value for β. That means that the negative grid utilization of flows of second order plays a major role in this steering signal. The steering signals in the middle graph **(b)** in Fig. 14 are on the very right of the Pareto-front reducing grid capacities drastically by almost setting the weight of the residual load γ to zero and only taking into account grid utilization information. Note that also here $\beta < 0$. The last exemplary steering signal **(c)** reduces both central storage and grid needs with a very big γ and both α and β being positive. Here, the seasonal impact of the PV generation is very pronounced while the spread of the steering signal is smaller compared to **(a)** and **(b)**. All steering signals shown in Fig. 14 are Pareto-optimal with respect to $\mathcal{C}^{\text{tot}}$ and $\mathcal{Y}^{\text{tot}}$, however look very different from each other.

Fig. 15 depicts the development of the four considered system friendliness indicators over the 100 evolutions of the hyper-parameter optimization of α, β and γ. Each point represents the mean value of the respective indicator over the whole population of individuals. The red line represents a rolling average with a window size of five evolutions. Note, that the optimization of steering signal weights is performed with respect to all four indicators simultaneously with the optimizer trying to find Pareto-optimal solutions. Clearly visible is a convergence of the indicators for the subsystem representing the north of Germany. The indicators for the southern subsystem are more scattered and show less convergence. The clearest convergence is visible for the grid indicator

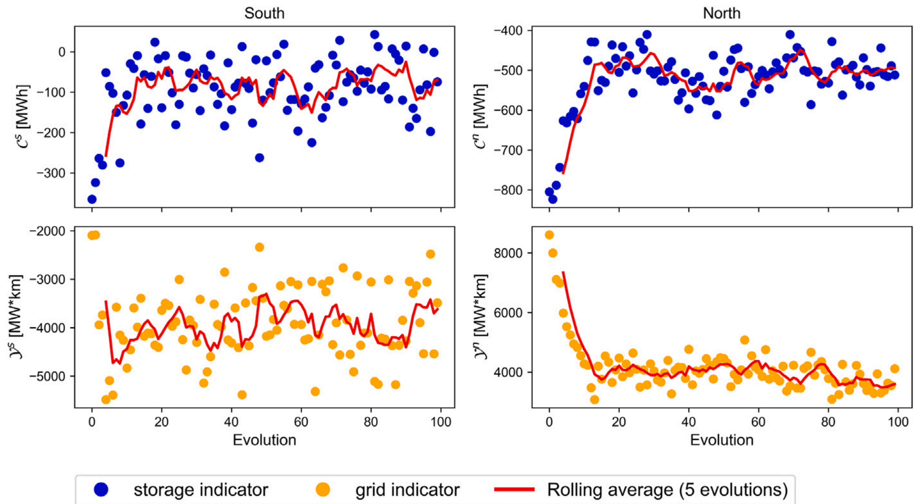

Fig. 15. Development of the four system friendliness indicators C^n, C^s, $\mathcal{Y}^n$ and $\mathcal{Y}^s$ for 100 evolutions of the hyper-parameter optimization of α, β and γ. Shown is the mean value of the whole population. The red line indicates the rolling average over five evolutions.

in the northern subsystem. However, even at the last evolutions, the mean value of all individuals is still positive indicating a grid requirement increase. On the other hand, all data points for the southern grid indicator have negative values meaning a grid requirement decrease on average. It becomes clear, that the two indicators subjecting to the storage and to the grid compete with each other. Less storage reduction leads to a higher grid reduction and vice versa. The optimizer aims for an optimization of said trade-off between grid and storage needs which is why storage reduction is being compromised for grid capacity reduction.

As a deeper insight into the operational strategies, Fig. 16 shows four different operational management strategies for an exemplary week. Positive values represent a feed-in of energy while negative value represent a energy consumption from the reference system. The respective steering signals are the same as in Fig. 14 and the constant steering case in black. The four operational strategies are shown for the district connected to the southern and the northern sub-system individually. Note, that the constant steering signal leads to a location independent operation of self-sufficiency maximization which is why the operation is the same in both sub-systems. Even though the weights of the three other steering signals are the same in both sub-systems, they take into account local information and therefore lead to location-dependent operations of the decentralized storage. All of them lead to a maximum utilization of the line capacity between district and grid which is 130 MW. The differences between the operational strategies under the three steering signals are greater in the southern sub-system compared to the northern one. Depending on the steering signal, the operation can be completely contrary to each other at some points in time with one steering signal leading to a maximum feed-in while another one leads to a maximum demand at the same time.

In Fig. 17, we show the results of exemplary steering signals in an additional small county grid in order to demonstrate the robustness of the method. The indicators are carried out with respect to this new and much smaller energy system. First, we examine the same benchmark signals as for the national-scale energy system with similar results. A constant steering signal has no measurable impact on the system friendliness of a decentralized storage in the county grid. A steering signal only including the residual load of the system leads to 100 % system friendliness regarding the storage indicator but has no impact on the grid indicator here. Including grid utilization only in the steering signals with the parameters α and β leads to an increase of storage requirements in the county grid and also does not significantly reduce grid

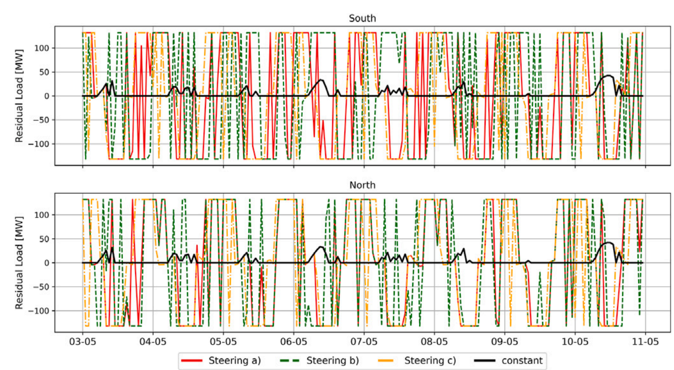

Fig. 16. Residual load of the modelled residential district under the three Pareto-optimal steering signals from Fig. 14 and the constant benchmark steering signal in black. The upper graph shows the residual load of the district in the southern sub-system and the lower graph for the northern subsystem, respectively. An exemplary week in May is shown. Since the constant steering signal includes no local information, the operational management of the district is equal for north and south.

requirements. The "β-only" signal including only grid utilization of flows of second order even increases the grid requirements. Eventhough the extensive optimization was carried out with a completely different data basis, the resulting steering signal weightings BS1, BS2, BS3 lead to system-friendly operations of the decentralized storage also in this isolated subgrid which shows that they are relatively robust with respect to the considered energy system characteristics. However, in this isolated subgrid, the γ-parameter represents the residual load of the small region and is no longer a good representative of the overall energy balance and wholesale price as for the national energy system. The underlying weather year of the Wesermarsch county grid data set is 2019 which is why we are able to analyse another steering signal: The realized German electricity prices from 2019 provided by the SMARD platform [73]. When positioned at the Butjadingen-node, the real electricity prices lead to a reduction of local storage needs by almost 40 % of the theoretical maximum but significantly increase the needed grid infrastructure. When positioned in the middle of the county grid, in Ovelgoenne, the storage operation puts much less stress on the grid requirements under the same price signal.

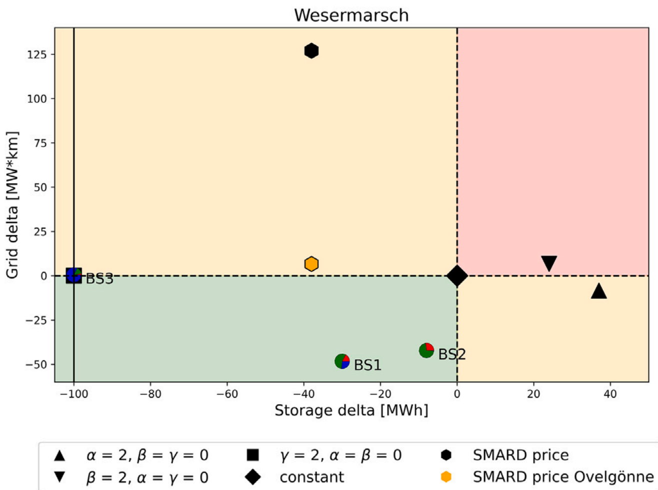

Fig. 17. System friendliness indicators for exemplary steering signals of the same but smaller POI in the Wesermarsch county grid as presented in Fig. 11. The steering signals BS1, BS2 and BS3 refer to the three exemplary pareto-optimal steering signal weightings as shown in Fig. 14 (BS1: left, BS2: middle, BS3: right).

7. Discussion

This work makes two major contributions to the research field of system friendliness of decentralized resources in sustainable energy systems. First, we extend the existing methodology to be able to assess multi-node systems which is discussed in Section 7.1. Secondly, we apply the new methodology to derive Pareto-optimal steering signals to optimally incentivize decentralized storage in a scenario-based German energy system which we discuss in Section 7.2.

7.1. Discussion of the methodology extension

Our model extension makes it possible to assess system friendliness of decentralized actors in a multi-node system on an aggregated level but also locally. Thus, the respective storage indicators can be evaluated for each grid node and the grid indicators for each connection between nodes. The methodology is flexible with regard to the inputs. The minimum information required is the residual load for every considered grid node. The grid structure can optionally be passed as input as adjacency matrix J either with already existing or built grid capacities or only containing boolean values. The latter only provides the information if two grid nodes are connected to each other or not. The distance of grid nodes can also be passed as distance matrix B. If this is not given, equidistant nodes can be assumed. A POI can be connected to any of the grid nodes. Theoretically, also multiple POIs can be evaluated at the same time at different locations in the energy system. Currently, we only consider electricity as energy carrier and neglect e.g., the gas grid. However, one could theoretically transfer the approach also to other energy carriers or grids. With sector integration by e.g., electrolysers, an effect of other energy carriers could be taken into account into the framework as well. The extension of the system friendliness framework from [8] to reflect grid capacities and complex multinode systems led to a trade-off between grid capacities and storage capacities. Both are major burden drivers. To face and counter this trade-off, we proposed a concept that decouples calculation procedure of the grid and the storage indicators. The decoupling first solves the one-node system to derive the aggregated storage indicators. The aggregated storage capacity serves as boundary condition for the multi-node system. This procedure implies the assumption that storage capacities are the more scarce resource in sustainable energy systems compared to grid capacities. In other energy systems e.g. regions with a lot of natural water reservoirs and hydropower plants, this might not be true. In that case one could switch the procedure around by first calculating the minimum grid capacities and afterwards deriving the required storage capacities to not exceed the grid capacities. Our system friendliness framework should not replace infrastructure planning or system optimization. The infrastructural burden dimensions rather represent the flexibility requirements of the system with respect to time and space: The hypothetical storage size represents temporal flexibility needs while the hypothetical grid requirements represent spatial flexibility needs. Of course, the hypothetical infrastructure can be translated into real-world infrastructure by taking into account respective regulations and reliability concerns, e.g., N-1 criteria or reserve margins. However, we consider this to be part of future work.

One simplification remains: The reference system is considered to be an inflexible input. That means demand and generation at each node are fixed with only curtailment of energy generation surpluses being possible. This currently neglects the burden dimension of controllable energy generation capacity. This is why controllable energy generation will be implemented into the framework as part of future work. Doing so, a third trade-off is created: At times of local energy scarcity, electricity could be *either* transferred via an electricity grid *or* taken from an energy storage *or* produced by a controllable power plant. The respective system friendliness indicators and the calculation procedure would have to reflect this additional trade-off e.g., by fixing one or more burden dimensions and iterating through them. For now however, the impact of flexible energy generation or demand could be examined as a POI itself.

As in [8], the POI is also an inflexible input with the time series being simulated or measured beforehand. The current framework therefore represents an ex-post evaluation. This implies one important assumption, namely the independence of the POI and the reference system. That means, the POI has to be small enough with $G(t) \gg g(t)$ and $D(t) \gg d(t)$ to not cause so-called avalanche effects in the energy system which would significantly change the overall situation. A systematic examination of the boundaries of that assumption could be carried out in future work. This would also have implications for the required “resolution” of steering signals and objective functions and could answer the questions regarding how big pricing zones should have to be in order to avoid said avalanche effects.

In this work, we considered only one POI in our experiment but multiple POIs are possible as well. A possible interplay of multiple POIs could be part of future work.

For this work, we implemented the assessment framework and our case study in `oemof.solph` which is an optimization framework using linear optimization [60]. The respective code is publicly available with respective details in the appendix of this work. Note, that the methodology is not bound to `oemof.solph`. Other simulation tools like PowerFactory can be used as well to determine the flows between nodes and the storage usage. If more technical detail or specifications are included in these tools, comparability of results however might be limited. Using linear optimization in this work, the computational runtime especially of larger multi-node system or very long time series can be a bottleneck. As shown in Fig. 5, the system friendliness assessment requires the optimization of the whole system with and without POI which can take a long time. As a reference, on a EPYC 7542 core with 3.4 GHz, the system friendliness assessment according to Fig. 2 takes approximately 40 min for a whole year in hourly resolution. If multiple POIs are assessed, the reference system without them can be solved only once and be reused for the indicator calculation.

7.2. Discussion of steering signals for incentivizing system friendliness in energy systems

In this work, we call the incentives for system friendliness of decentralized actors “steering signals”. We propose a hypothetical steering signal combination $p(t)$ and $f(t)$ which can be interpreted as abstract price and feed-in signals. Besides a constant factor which could represent taxes or levies, we include three sources of information into the steering signals: The global residual load, local and regional grid utilization information with different weightings. The global residual load can be seen as proxy for the zonal electricity wholesale prices. The grid utilization information however could represent a variable grid fee as it is currently heavily discussed in Germany [32,37]. In future work, other kinds of information could also be taken into account like the SOC of the local hypothetical storage. Despite the ongoing discussion of redesigning price building mechanisms for electricity prices, it is not clear how these different contributions should be weighted against each other. This is why we perform the extensive hyper-parameter optimization of these weights which yields Pareto-optimal solutions with respect to system friendliness of decentralized actors. With our case study, we are fully independent of current regulatory conditions or assumptions for the electricity market but present a purely technical approach. By taking into account the grid utilization directly at the connection node but also one grid node neighbour further away, we examine the importance of regional data. In some tests, we saw that including even further distant flow information is not beneficial in our case study due to the limited considered grid size. But with bigger reference systems, it would be possible to systematically increase the radius of information that are taken into account. Due to the inherent trade-off between grid and storage requirements there is not only one best steering signal. An external prioritization of the importance of both burden dimensions still needs to be done which reflects the current infrastructural needs of the given energy system.

Generally, the derived steering signals – even when using the same weights α, β and γ – are calculated for each node which corresponds to the economic concept of nodal prices where individual prices for every connection point to the transmission grid are derived [45]. However, we consider a combination of global and local information. Thus, the same results could be achieved by combining global wholesale prices with local dynamic grid fees. The effect of zonal pricing or price zone splitting could also be examined using the proposed system friendliness framework e.g., by giving multiple connection points the same steering signals. In this work, we assume $f(t)$ to be symmetric to $p(t)$ by taking just the corresponding negative value. This is due to the findings in [8], where only symmetric and variable steering signals were able to harness the full system friendliness potential. However, asymmetric steering signals for buying and selling electricity could be examined in future work.

Our case study looks at two sub-systems of the national energy system of Germany simultaneously. That makes the optimization problem four-dimensional due to four primary indicators being relevant, namely changes in hypothetical storage capacities C^{n} and C^{s} and changes in hypothetical grid capacities $\mathcal{Y}^{\mathrm{n}}$ and $\mathcal{Y}^{\mathrm{s}}$. Also other publications work on optimizing incentives. For example, the authors in [74] use a game-theoretic approach to optimize electricity prices for systems with high PV penetration with the aim of stabilizing the grid. However, they evaluate their findings on economic indicators only and without taking into account specific grid information which we do here. Fig. 12 shows the overall results while Fig. 13 shows the results for the two sub-systems individually. It gets visible, that optimal steering signal weights are very different in the north and the south of Germany. This is due to locally vastly different generation and demand patterns. The north of Germany is dominated by wind energy with frequent grid congestions and as a consequence a lot of curtailment [75]. Consequently, the α and β weightings are more important for the steering signals to reduce grid requirements which can be seen on the right side of Fig. 13. The south on the other hand is dominated by larger consumers due to industry and the seasonality of the PV generation concentrated there. This puts an emphasis on γ which weighs the residual load which can be expected and also seen on the left side of Fig. 13. Here, many steering signals reach the green quadrant and are able to reduce grid and storage requirements simultaneously. We allow negative values for α and β in the hyper-parameter optimization. While all Pareto-optimal steering signals have positive values for α, β is often negative. That means, taking into account the negative grid utilization of neighboring nodes of second order yields system-friendly incentivizing steering signals. This can be due to the higher number of second order neighbors compared to first order neighbors and locally concentrated energy generation causing opposing flows or residual loads. Note, that the values of the indicators are based on a hypothetical storage and grid and do not reflect real-world capacity reduction. But they indicate the system friendliness potential of different operational strategies and make them comparable without requiring extensive regulatory or economic assumptions.

Although the local characteristics are very different from one subsystem to the other, there are steering signals that yield system-friendly operational strategies in total as can be seen in the green quadrant in Fig. 12. However, it could be part of further discussion if different weightings of the parts that make up the price signals in different regions could be possible in real energy systems. This discussion however, has to take into account many political and regulatory considerations to ensure fairness between different regions. Fig. 15 shows the convergence of the four considered indicators which becomes visible. However, more evolutions for the NSGA2 algorithm could be beneficial but are limited due to computational time. Nevertheless, with our hyper-parameter optimization we show, that the optimal weights in steering signals are system and location dependent but that there exist also Pareto-optimal solutions that yield system-friendly behaviour *in total*.

7.3. Transferability and robustness of the system friendliness framework

In order to demonstrate the flexibility of the framework, we analyse system friendliness indicators in a second energy system with very different characteristics. The second system represents a small isolated subgrid of 9 nodes in a very wind-dominated county of northern Germany and a much smaller energy surplus compared to the national-scale energy system. We show, that the approach works just the same for this system. Note, that the resulting indicators only reflect the burden of the considered county grid and not the burden for the surrounding larger energy system. The results emphasize a couple of aspects. Firstly, the exact same steering signal and thus same operational strategy can have a different impact at different locations of the energy systems, even when considering smaller grids. This holds particularly true for the grid indicator since this is determined by only a few time steps in the year where the grid is used to its full capacity. This is why the grid indicator is much more sensitive to the local conditions and positioning. Especially when positioned at the border or in sparsely connected regions in the energy system, the POI can easily cause grid extension when operated under suboptimal incentives. This emphasizes the locational aspect of system friendliness and the importance of local information in steering signals. Secondly, even at the more favourable position in Overgoenne, 60 % of the installed local storage capacity is not contributing to the subgrid's burden when applying global electricity prices as steering signal. This shows that suboptimal steering signals can lead to significant regional inefficiencies in using decentralized resources and infrastructure in a system-beneficial way. Thirdly, also in this very different setting, a constant steering signal which leads to self-sufficiency maximization of the POI has no positive impact on the system's burden. As for the national-scale energy system, additional decentralized storage does not decrease system wide storage needs if it is operated this way. Lastly, the exemplary Pareto-optimal steering signal weights lead to system-friendly behaviour also in this very different energy system which underlines their robustness and transfer capabilities.

7.4. Connection to existing market designs and pathways for real-world implementation

The design of the steering signals in this work generally correspond to a combination of zonal electricity prices and a local dynamic grid fee. In contrast, nodal pricing like it is implemented in Texas, provides a local dynamic electricity price for each grid connection point to the high voltage grid which is a completely different market design. Nodal pricing has a couple of advantages over zonal pricing like the stronger local investment incentives and an incentives based congestion management [47]. However, drawbacks can be price hot spots, low price credibility and frequent local scarcity. In Germany specifically, there is a strong political will arguing for a uniform bidding zone instead of a price zone splitting or even nodal pricing. This has also been officially agreed on in the coalition agreement from 2025 [76]. However, our current work already shows the importance of a combination of global and local information in the price signal to yield Pareto-optimal incentives. The system friendliness potential of decentralized actors under nodal pricing specifically could be examined in future work.

In 2025, the ENTSO-E published their bidding zone review suggesting a price zone splitting for Germany with highest economic efficiency for a split into five bidding zones [42]. As mentioned above, political decision makers in Germany favour a uniform bidding zone implying negative consequences for the economic and technical efficiency of the German energy system. This is why other locational incentives are heavily discussed currently with local dynamic grid fees being one of the most popular levers [77]. This is why we focused on the interplay of global prices and local grid fees in this work. However, similar as for nodal pricing, an examination of the system friendliness effect of a price zone splitting would be possible with the presented framework and highly interesting. This could be carried out in future work.

In this work we show the importance to include local grid utilization information in price signals. However, in real-world systems with a high proportion of variable, weather-dependent electricity generation, it is not possible to formulate long-term stable temporal patterns of grid utilization [78]. Thus, it only makes sense to set a dynamic price signal on a short-term basis. This creates a dilemma: Grid utilization to determine the dynamic grid fees is a result of the market. However, grid fees could have an impact on the market themselves due to market participants locally reacting to them which creates a recursive decision problem. Therefore, it is crucial to work on sufficiently good forecasts of grid utilization and sensitivity analyses taking into account the reaction of the system to the dynamic grid fee. The forecasts should be available before the fee is actually determined [77]. A 24 h-day-ahead forecast horizon could be a compromise between planability and accuracy. While dynamic grid fees are already well-established in many countries also in Europe, implementing them in Germany specifically would require regulatory adjustments, especially in §14 a EnWG and §19 StromNEV [79].

8. Conclusion and outlook

In this work, we introduced an extension to the existing system friendliness evaluation framework of [8] by the option to take into account multi-node reference systems. With that, we introduced a second burden dimension – grid capacities – into the system friendliness assessment with the new indicator $\mathcal{Y}$. $\mathcal{Y}$ evaluates the impact of a given POI on the grid capacity of the reference system by taking into account the maximum power but also the length of the respective grid. We show how to deal with the inherent trade-off between grid and storage capacities arising from the option of either transferring energy or storing it.

In order to apply this new methodology, we extensively examine different steering signals for decentralized actors in a case study on a sustainable German electricity grid. We show, that in order to be able to incentivize system friendliness in decentralized actors, steering signals have to take into account global and local information with different weightings. These comprise the global residual load, local and regional grid utilization information. An extensive hyper-parameter optimization for the respective weights yields Pareto-optimal steering signals for two sub-systems at the same time. Even though system friendliness differs locally and different weights are optimal for different regions within the system, certain combinations of weights are able to incentivize system friendliness in two very different sub-systems at the same time. With a storage-focused Pareto-optimal steering signal, decentralized energy storage of 2 GWh capacity can reach 100 % of the maximum possible storage reduction but increase grid requirements by 11.1 GW·km. On the other hand, a grid-focused Pareto-optimal steering signal leads to operational strategies that reach only 14.9 % of the possible storage reduction but reduce grid requirements by 12.4 GW·km. It depends on external priorities and factors like storage and grid extension costs, which steering signal to choose out of the set of Pareto-optimal signals.

Future work could extend the methodology even further by taking into account flexible and controllable energy generation into the reference system or to be able to reflect other energy carriers than electricity. The system friendliness assessment framework theoretically allows multiple POIs to be added to the reference system at the same time, which could be systematically applied in future studies. Regarding optimal steering signals, many future possible experiments are possible. Firstly, additional information sources could be possibly included and their effect examined. Secondly, more energy systems with other characteristics could be considered and steering signals could be optimized for them. Lastly, asymmetric steering signals are very common in reality, i.e., decoupled prices and feed-in tariffs which has not been considered in this work since we assume the feed-in steering signal to be the negative price signal.

With our case study, we are able to derive technically Pareto-optimal steering signals to incentivize system friendliness of decentralized actors for a future German energy system. A specific analysis on how to design real price building mechanisms out of these technically optimal steering signals should be conducted with first pathways being outlined in the discussion section. This would be extremly relevant for decision makers and politics to develop the respective regulatory environment to be able to harness the decentralized resources in a sense of system friendliness for the overall energy system.

CRediT authorship contribution statement

Karoline Brucke: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Sunke Schlüters:** Writing – original draft, Supervision, Methodology, Funding acquisition, Conceptualization. **Jan Buschmann:** Writing – original draft, Resources, Data curation. **Benedikt Hanke:** Writing – original draft, Supervision, Conceptualization. **Carsten Agert:** Supervision, Resources, Conceptualization. **Karsten von Maydell:** Supervision, Funding acquisition.

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.

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Data availability

The code to recreate the figures as well as the results of the `pygmo` optimization are published on Zenodo under the following link: https://doi.org/10.5281/zenodo.15772275. The data of the reference system and the district cannot be published due to confidentiality reasons.

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