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Make or buy: IT-based decision support for grid imbalance settlement in smarter electricity networks

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Abstract

Decision (support) systems are a particularly important type of information system to energy informatics. A key challenge in energy informatics is that electricity supply must be in balance with demand at all times. More volatile renewable energy sources increase the relevance of electricity network balancing, i.e., imbalance settlement. Typically, electricity distribution network operators bought balancing power from external service providers (Buy option). Interestingly, however, more local energy resources help smarter electricity networks develop a Make option, as in our real-world evaluation. Choosing the better decision alternative within the relevant timeframes challenges human decision-making capabilities. Therefore, this research proposes a model-based decision system to improve the operators' decisions concerning Make or Buy under various levels of data quality represented by availability, granularity, and timeliness. The study reports savings up to 40% of costs for imbalance settlement supporting ambitious development efforts by the municipality we study in our real-world evaluation.

Keywords: Decision system, Model-based decision support system, Distribution network, Data quality, Grid imbalance

Introduction

Reducing carbon emissions in the electricity sector means initiating a transition towards renewable energies (RES), mostly intermittent wind power and photovoltaics (Grubler 2012). Despite RES' intermittency, supply must be in balance with demand at all times. RES are often integrated close to the consumer as so-called distributed energy resources (DER), e.g., rooftop photovoltaics. Especially distribution networks (DN) are challenged to deal with this transition (Ipakchi and Albuyeh 2009). Consequently, assuring grid stability continues to be a major activity for electricity distribution network operators (DNO) (Bayod-Rújula 2009). According to Mukherjee (2020), this will remain "significant for the years to come".

To follow up on this activity, DNO generally have two options: As a first option, they can offset imbalances by sourcing balancing power (BP) from higher grid levels (*Buy*), e.g., transmission networks (TN). This is because TN typically operate markets for flexibility or have easier access to them (Consentec 2014). This is assumingly the predominant option up to date. However, BP prices can diverge greatly and, in Germany for example, have risen to more than € 77,000[1] per megawatt-hour (MWh) (Bundestag 2019) in comparison to average spot market prices of € 30 to € 50 MWh during the same period of time (EPEX SPOT SE 2022). As a second option, the latent potential for limiting a DN's inner power imbalances is largely available locally (Stadler 2008; Clement-Nyns et al. 2010; Lu 2012) and is an effective measure to counter price volatility (Manfren et al. 2011). Combined heat and power (CHP), heating, ventilating, air-conditioning, and prosumer appliances (electric vehicles, batteries, etc.) are well-suited resources for doing so. Thus, balancing on the DN level is a second option that is—apart perhaps from regulatory constraints—available as a potential to DNO (*Make*).

As DNO are business organizations, decisions regarding network operations should reflect economic rationale (Simon 1979). To improve decision-making concerning *Make* or *Buy*, the current state of the respective DN, the corresponding TN, netted imbalances, and (historic) market prices for BP all have to be considered. In addition, a decision-maker must take into account the availability, granularity, and timeliness of such information. To that end, the agenda setting research paper by Watson et al. (2010) on *Energy Informatics* (EI) formulated the following key research question (as one of nine), at which we target here:

> *"What information, and at what level of granularity, is required to optimize a given type of flow network?".*

In this study, we specifically analyze DN as the respective flow network and study the availability, granularity, and timeliness of imbalance-related information on a DNO's business outcome. To do so, we design a model-based Decision Support System (DSS) that conducts informed decisions concerning *Make* or *Buy* as an agent to a DNO.

To address the research question, we structure the paper as follows: In the next section, we reference the literature this research builds upon and position our approach among the existing body of EI research. At the same time, we establish the theoretical background for the DSS design. The following "Decision support system requirements for grid imbalance settlement" section describes the problem statement. Subsequently, in the "Decision support system design" section, we develop the model the DSS is based on. We then devote the "Decision support system evaluation" section to evaluating the model. In the "Discussion" section, we discuss the studies' findings, before we conclude our study and highlight directions for further research in the"Conclusion and outlook" section.

Background and related work

In this section, we motivate the role of designing DSS within EI and introduce the technical concepts pertinent to this study. Moreover, we argue our design-oriented research approach and put this piece of research in the context of the closely related EI research at the intersection of DSS design and grid imbalance settlement. We do so by scoping the research space according to five criteria. That as a basis, we classify the identified

[1] The BP price rose to € 77,778 per MWh on the 17th October 2017.

related research regarding the qualified criteria. Thereby, we highlight the research gaps in which we position this study.

Generally, EI research strives to deploy information and communication technology to accelerate the transition to sustainable economies (Goebel et al. 2014) by collecting and analyzing energy datasets to support the optimization of energy distribution and consumption networks (Watson et al. 2010). The resultant breadth and depth of analysis and optimization activities in EI give the design of DSS an especially prominent role. We thus identify the availability of a DSS artifact as a criterion on which we compare related literature (criterion 1).

Consequently, we choose a design-oriented research approach as it allows the evaluation of the DSS artifact and its expected impacts before it is eventually implemented infield. In addition, Gregor and Hevner (2013) state that also design science research (DSR) as a particular form (Hevner and Park 2004) "involves the construction of a wide range of socio-technical artifacts, such as decision support systems [...]". In fact, DSR has been applied many times in numerous EI publications to date (cf. Gust et al. 2016; Fridgen et al. 2015a; Stein and Flath 2016; Brandt et al. 2014). To that end, Klör (2016) presents findings based on a structured literature review which highlight that DSR and DSS in the energy domain are a very well-established research approach, especially within business contexts.

However, in order to follow up on calls for more solution-oriented (Sarkis et al. 2013) and more impactful research in the energy domain (Gholami et al. 2016), it is important to acknowledge that "EI research can only inform the design of these [decision support] systems in a satisfactory way if economic considerations are part of their evaluation and if the proposed solutions take existing institutional frameworks, e.g., current electricity market designs, into account" (Goebel et al. 2014). For that reason, we pay close attention to applying and evaluating our DSS regarding the German institutional framework using real-world data. We expect related literature to align with economic objectives (criterion 2) and institutional frameworks as well (criterion 5).

To that end and within EI research, Feuerriegel et al. (2012), Bodenbrenner et al. (2013), and Fridgen et al. (2014) analyze how DSS can improve demand response systems to better align demand and supply while quantifying their economic potential. Similarly, Brandt et al. (2014) and Fridgen et al. (2015b) propose DSS designs to improve operations and respective investment decisions regarding microgrids, which are considered a future more cellular architecture of power systems (German Association of Energy and Water Industries, Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) GmbH, PricewaterhouseCoopers AG WPG 2015). Microgrids (Lasseter et al. 2003) in turn may be construed similar to active distribution networks (ADN) as we introduce them in the following:

"Distribution networks were formerly designed for a predominantly passive operation because their task was mainly to distribute electricity with unidirectional power flow from the transmission level down to the consumer. In future, the distribution system should be controllable more actively to utilize both the network and the DER/RES units more efficiently" (Braun and Strauss 2008). ADN consist of "Controllable Distributed Energy (CDE) units [which] are sources or sinks of electric power that can be connected to the public DNs, and are able to control [...] power" (Braun and Strauss 2008). They provide electricity services like satisfying bilateral or exchange-traded power contracts and/or fulfill ancillary services (AS) including frequency control, voltage control, reduction of power losses, improvement of power quality, and reliability. Typically, CDE are aggregated and controlled as if they were a single entity because of lower transaction costs (Bakos and Brynjolfsson 2001). For that purpose, operators deploy “an information and communication system that aggregates [CDE units] by direct centralised control” (Braun and Strauss 2008). An ADN thus is a (public) distribution network, in which CDE units can also provide AS for network operation. The operation of an ADN can either aim at optimizing cost-efficiency or security of supply. In this study, we focus on cost-efficiency through coordinating demand and supply (criterion 3).

As criterion 4, we expect DSS to support in guiding physical balancing activities to address grid imbalance management. In this vein, Köpp et al. (2013) present a prototypical implementation of a DSS for Load Management in power grids. With a similar goal in mind, Guo et al. (2014) minimize imbalance cost through a stochastic program while Wirtz and Monti (2018) determine a theoretical optimum for cost reduction, which a DSS could potentially deliver to a DN.

After having introduced the criteria for comparing related literature, we next classify the identified literature according to the criteria in a structured approach. We summarize the literature and its gaps by Table 1.

Among the relevant design-oriented and EI-related DSS, Fridgen et al. (2015b) and Gust et al. (2016) present DSS designs for DN that include economic considerations in their objectives. However, their DSS provide decision support during the planning phase rather than the operational phase of a DN. Stein and Flath (2016) and Feuerriegel et al. (2012) present respective DSS designs for the operational phase in order to support matching demand and supply. However, as their DSS target at energy retailers in liberalized power markets, physical balancing actions are not considered.

Brandt et al. (2014) present a DSS following economic rationale that sets out to coordinate supply and demand by physical balancing activities. However, their research setting involves a private microgrid, where institutional frameworks for public DN do not apply. Consequently, imbalance settlement concepts are not adequately reflected in their work.

Köpp et al. (2013) develop a DSS for compensating imbalances from planned generation and consumption in a DN. But, its models for the pricing, payment, and information structure of the German balancing power system for imbalance settlement divert largely from the institutional frameworks in place. Instead, it assumes a known kilowatthour-price for each time interval on which the DSS acts upon. As a result, the *Make* or *Buy* decision pertinent to this study does not exist in their setting. As a result, their approach generally puts local options for balancing first instead of applying an economic rationale to distinguish when to better rely on BP from a higher-grid level as in our research. In addition, while the study targets an economic optimization, it does not present a thorough quantitative analysis in the artifact’s evaluation.

Guo et al. (2014) present relevant models and algorithms being part of a model-based DSS. While their focus rests on the stochastic optimization algorithm, actors and information flows remain abstract for a DSS design. Targeting at the minimization of imbalance cost through shifting loads in time, Guo et al. (2014) demonstrate a DSS that supports DNO with physical balancing decisions to optimize for economic benefit. The

Table 1 Classification of related literature in the field of EI-based DSS design

Study/Criterion	**Fridgen et al. (2015b)**	**Gust et al. (2016)**	**Stein and Flath (2016)**	**Feuerriegel et al. (2012)**	**Fridgen et al. (2015b)**	**Brandt et al. (2014)**	**Köpp et al. (2013)**	**Guo et al. (2014)**	**Wirtz and Monti (2018)**	**This work**
DSS artifact (1)	X	X	X	X	X	X	X	(X)	(X)	X
Economic optimization (2)	(X)	X	X	X	X	X	(X)	X	X	X
Supply/Demand Coordination (3)	N/A	N/A	X	X	X	X	X	X	X	X
Physical balancing (4)	N/A	N/A	–	–	–	X	X	X	X	X
Institutional framework (5)	N/A	N/A	X	X	X	(X)	–	–	(X)	X

N/A Not applicable, – criterion not fulfilled, (X) criterion not completely fulfilled, *X* criterion fulfilled study places their work in the institutional framework prevalent in the New York independent system operator region. However, the imbalance price is modeled as a function of the day-ahead price. This, in addition, implies the availability of real-time information at all the times. A DSS, however, should conform to relevant market designs, if it intends to represent impactful research (Watson et al. 2010). That modeling assumption, however, makes their program hard to apply to market designs, where imbalance prices are posted with delay (which includes the New York system).

Lastly, Wirtz and Monti (2018), similarly to Guo et al. (2014), present relevant models and algorithms as part of a DSS design. However, from an EI perspective, relevant DSS design elements are not fully elaborated on. Wirtz and Monti (2018) target an economic objective while matching supply and demand through physical balancing actions in line with this work. Since their goal is to determine a theoretical optimum for cost reduction, they, however, assume perfectly accurate forecasts on balancing energy and its price. This renders their approach impractical for real-world applications as their approach remains incompatible with existing institutional frameworks.

This work, in contrast, presents a DSS design with an economic target that supports DNO in their task of coordinating supply and demand by introducing an active role in physical balancing adhering to the institutional framework. In addition and despite acknowledging its significance for decision-making, none of the identified related works studies the influence of information granularity, e.g., with regard to the number of sensor readings within an interval. Therefore, in this study, we design and evaluate a DSS based on thoroughly derived requirements. We introduce the requirements for DSS design supporting grid imbalance settlement in ADN in the "Decision support system requirements for grid imbalance settlement" section. Thereby, we introduce the novel traits of this work. Eventually, we summarize the positioning our work among the previously introduced related literature in Table 1.

Decision support system requirements for grid imbalance settlement

Historically, power grids have evolved as top-down structures, i.e., high-/middle/low-voltage networks (Kok et al. 2005), with mostly unidirectional power, information, and cash flows (Farhangi 2010). This was due to economies of scale and technically simpler marketability of electricity (Kok et al. 2005). However, RES with near to no variable cost (Hach and Spinler 2013) and advanced marketing approaches cause these advantages to diminish. Since RES are often DER, power grids increasingly transform towards bottom-up structures (Farhangi 2010). This transformation is a continuous process and creates hybrid structures, i.e., an integration of conventional power plants applying conventional marketing and RES applying novel marketing approaches. In this vein, DSS that intelligently utilize these hybrid structures might improve the delivery of electricity services including AS—the latter especially for purposes of imbalance settlement. The objective of this research, thus, is to design a DSS that will improve imbalance settlement in an ADN to further the integration of DER. To do so, it is crucial to outline the setting in which DN operate.

We focus on the typical case where a DNO manages a single coherent DN and where it is the only party involved in coordinating interactions with the TNO. This implies

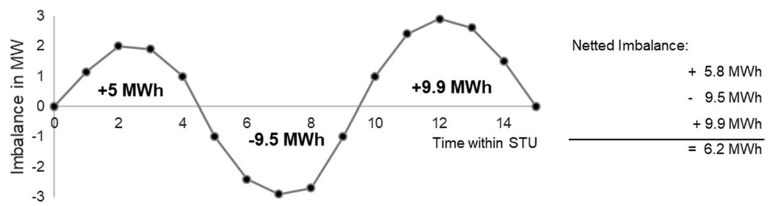


Fig. 1 A stylized example of the netted imbalance calculation within an STU in discrete time steps

that the DNO is obliged to manage the DN on multiple levels: physical power quality management, physical energy flows, and grid accounting. In this study, we present an approach for more economical management of a DN regarding its physical energy flows. The management particularly concerns the interface of the DN and the TN.

In DNs, like in power grids[2] in general, generation and consumption must be in balance at all times. In case of an imbalance, the DN generally receives AS in the form of BP by a higher grid level, which usually and in also this study is the TN. These imbalances happen due to stochastic deviations as they occur from imperfect forecasting and planning actions (Chaves-Ávila et al. 2013). The DNO will then have to reimburse the TNO for the cost of acquiring and deploying BP in the form of imbalance charges (i.e., the product of the imbalance price per MWh and the quantity deployed) (Koliou et al. 2014). The TNO determines imbalance prices by public procedures (cf. Regelleistung.net (2020) for Germany). TNO measure imbalances in all subordinated DN for each so-called settlement time unit (STU) in real-time and coordinate the deployment of BP, if necessary. Regulatory authorities define the length of the STU. For each DN, the net energy accrued at the end of one STU is termed the netted imbalance. In its calculation, positive and negative imbalances offset each other, as depicted in Fig. 1. Thus, even despite (large) momentary imbalances, the netted imbalance may be close to zero. Note that we refer to '*current* netted imbalance' when the netted imbalance within an STU is relevant (in contrast to the end of an STU). By charging each DN for its netted imbalance, the TNO recovers the cost for contracting and deploying BP (Chaves-Ávila et al. 2013; Koliou et al. 2014; Veen et al. 2012).

The TNO determines an imbalance price for each STU based on the cost incurred for procuring and deploying BP. The imbalance charges which a DNO faces depend on the sign of the netted imbalance (positive/negative) present in its DN, while the imbalance price is equal in all DNs and for all DNO, respectively. If a DN has a surplus of energy at the end of one STU (i.e., a positive netted imbalance), it is considered long, if it has a shortage, it is considered short (Chaves-Ávila et al. 2013). Accordingly, there are two imbalance prices: a long and a short imbalance price. The long imbalance price applies to DNO per MWh of surplus and the short imbalance price applies to DNO per MWh of shortage. Imbalance pricing usually results in long imbalance prices below and short imbalance prices above-market prices for energy (e.g., day-ahead spot prices). This is caused by the fact that in long situations, electricity must be removed from the grid, which consumers of any kind will only do for electricity

[2] Note that the term grid is often used synonymously to network. Hence, we continue to use 'grid', too, where it is a fixed phrase.

prices at or below the market level. In short situations, additional electricity must be provided to the network, which will usually be sold at or above market prices due to the extreme flexibility requirements. Consequently, in long situations, the DNO effectively sells energy to the higher grid-level below-market prices, and in short situations, the DNO buys energy above-market prices. Thereby, DNO are incentivized to minimize imbalances. The method of calculating these prices differs depending on national regulation: Van der Veen et al. (2012) describe five different imbalance pricing settings, with more being conceivable. What is common to all settings is its intended incentivizing effect on DNO: from their perspective, they buy or sell energy almost exclusively at a worse price than the market price. Thereby, even when a DNO is long and receives a cash inflow, this is less than what would have possible with better planning and selling the surplus energy on a spot market. The DNO thus suffers imputed costs from imbalances (cost of opportunity), regardless of its long or short position. In conclusion, the DNO must bear the cost of balancing while remaining passive in the cost-generating process of its usage.

In this study, we propose that a DNO should adopt an active role in the process of balancing by performing internal balancing. This means influencing one's netted imbalance by adjusting generation and/or consumption by oneself, as opposed to being supplied with BP by the TNO (Van der Veen et al. 2012). To this end, the availability, granularity, and timeliness of two sets of information are relevant: (a) the DN's imbalance and (b) imbalance prices.

(a) Without the DN's balance, it is impossible to determine the necessary extent of internal balancing appropriately. There are two dimensions to information availability: Information timeliness and granularity. Information timeliness relates to "the availability of the output information at a time suitable for its use" (Bailey and Pearson 1983). Information granularity refers to the number of data records within a time period. Regarding information timeliness, IS can provide imbalance information to the DNO immediately after recording. The point of time of recording, however, is a question of granularity: recording may occur anywhere from once per STU to very high frequencies resembling the continuous nature of electricity (e.g., every nanosecond). In conclusion, information on the DN's imbalance is available at a certain level of granularity and with no delay after its recording. Information about the TN's imbalance, however, is not available to the DNO, which represents the current practice in major regulatory environments.

(b) The second set of information relevant for internal balancing decisions is the imbalance prices the DNO faces when internal balancing is not performed. Possessing such information in real-time would simplify the economic trade-off between the cost of BP provided by the TN and the cost of internal balancing, which the DNO is empowered and capable to assess. Importantly however, information on imbalance prices cannot be easily determined at every moment (in real-time) as the TNO cannot assess the cost of BP employed during an STU before it has ended. While the cost of internal balancing can be expected to be available without delay and to be constant for each STU, imbalance prices are not available to the DNO. Figure 2 summarizes the research setting regarding the availability, granularity, and timeliness of

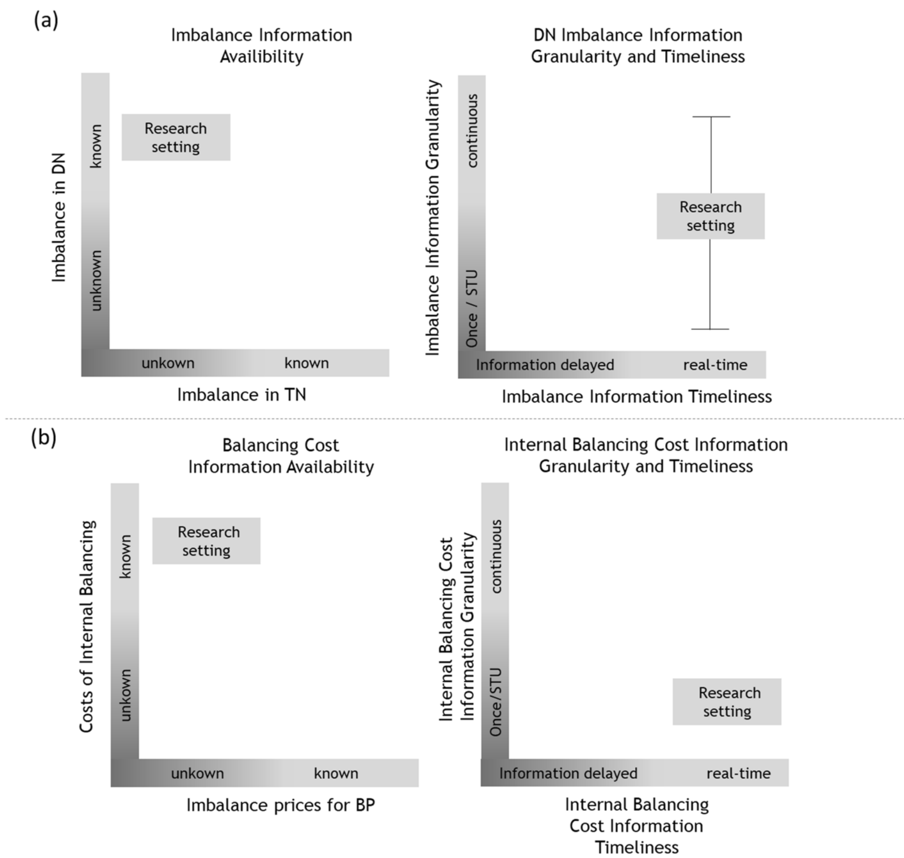


Figure 2 Research setting: Information sets (imbalance informtion (a), balancing cost (b)) at the time of decision-making

information in line with settings as characterized by Van der Veen et al. (2012). We present the research setting along the two sets of information (a) and (b).

Even without the availability of imbalance prices, the incentives they provide against DN imbalances support implicitly solving the trade-off between costs of internal balancing and external BP provision, as we will describe in the "Decision support system design" section. To that end, we summarize the requirements a DSS needs to fulfill before we continue with the design of the DSS in the next section. In "Decision support system evaluation" section, we evaluate the DSS and test if the initial requirements are satisfied.

We refer to the DSS development framework by Sprague (1980) to come up with a rigorous definition of DSS requirements. These strongly relate to the concept of performance objectives DSS stakeholders will impose. In this study, DNO and governments including regulation bodies are the main stakeholders. We summarize the three key requirements as follows:

> **Requirement 1:** *Cope with different levels of information granularity.* While immediate availability is already the status quo, levels of information granularity might increase when relevant technologies become more affordable. Therefore, the DSS

must be capable of coping with various levels of information granularity. Also, it must be capable of supporting decisions without the availability of the momentary imbalance price to apply to a broad class of market designs as described by (Van der Veen et al. 2012).

Requirement 2: *Test of applicability via statistical methods*. Make or buy decisions by the DSS are necessarily subject to stochastic modeling. In all cases and times, it must be possible to determine via statistical methods, if underlying stochastic modeling assumptions hold. In unforeseen cases, i.e., if the DSS' applicability cannot be validated, the DSS must involve the human decision-maker and report that it is in such a state.

Requirement 3: *Increase Eco-efficiency.* DNO as users of the DSS are highly regulated because their business represents a natural monopoly (Prez-Arriaga 2017). Prices for DNO services may oftentimes be subject to a cap or benchmark (Saumweber et al. 2021). However, DNO seek to improve efficiency in core business processes based on economic rationale. Besides, sometimes voluntarily but more often also for economic reasons, DNO strive to perform actions to maintain grid stability in increasingly eco-aware manners, i.e., they target emissions reductions. We subsume this requirement as eco-efficiency because "[it] is essentially an economic pressure, as organizations will seek this goal in their quest for greater profits" (Watson et al. 2010). Thus, we further specify this requirement by the following statement: While maintaining grid stability and at least not increasing emissions, the DSS must be able to improve the cost-efficiency of delivering AS. This they do through the provision control signals for CDEs regarding *Make* or *Buy*.

In the following section, we will describe the design of the DSS with these requirements in mind.

Decision support system design

In the following section "Decision support system environment and setup", we describe the environment and setup of the DSS for *Make* and *Buy* decisions in an ADN, operated by a DNO. Then, in the "Decision model of the DSS" section, we develop the decision model of the DSS adhering to Requirements 1–3.

Decision support system environment and setup

The model-based DSS consists of a training module and a decision module. The training module serves to calibrate heuristic decision rules based on historical data. These decision rules determine whether to activate or not activate CDE for internal balancing. For that reason, we feed the training module of the DSS with historical data from sources containing information at potentially different levels of granularity (Requirement 1) regarding internal balancing cost, power exchange prices, imbalance prices, and imbalance data itself. The DSS is part of an ADN that features multiple CDE, which the DNO can aggregate on a technical level (cf. section "Background and related work") and deploy for internal balancing (*Make).* These CDE can be, e.g., lithium-ion batteries, CHP, or biomass power plants, etc. The ADN is connected to a TN from which it usually would receive BP (*Buy).* A grid coupling point connects the ADN and the TN

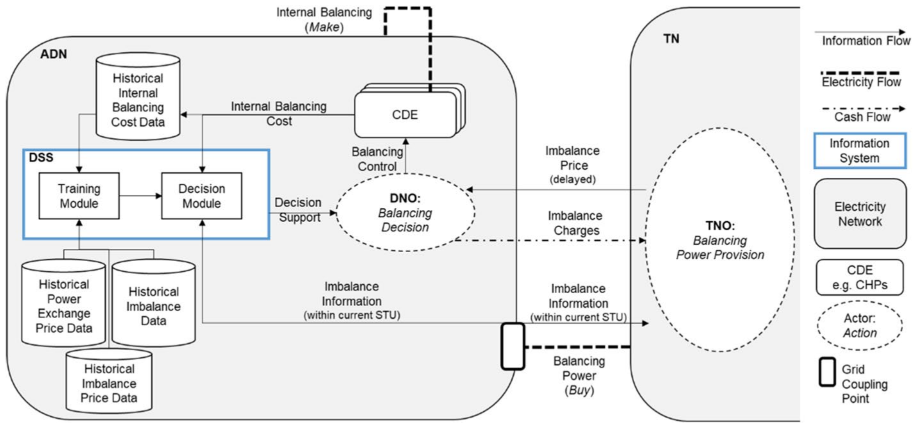


Fig. 3 Research setting: ADN with internal balancing controlled by a DSS

allowing to measure imbalances. The granularity of measurement may vary as described in the "Decision support system requirements for grid imbalance settlement" section. The momentary imbalance information, i.e., imbalances within an STU, is available to both the DSS and the TNO. We present the DSS setup and its environment in Fig. 3.

Decision model of the DSS

As mentioned before, the training module calibrates decision rules on historical data. These decision rules then serve as a heuristic in the decision module, which actually performs the *Make* or *Buy* decisions on current data, i.e., in live situations. Therefore, in this subsection, we introduce what the decision rules are and how the training module calibrates the decision rules for use in the decision module.

To derive decision rules, we first present an intuition based on an example before we then formalize the decision rules: when there is only one measurement of imbalance at the end of an STU, there is no other way but to receive BP from the TNO. However, if there is more than one measurement of imbalance, the DNO has an opportunity to undertake internal balancing actions. For simplicity's sake (and for this consideration only), assume that there is exactly one additional measurement in the middle of the STU. Then, the DNO will have to weigh the options between *Make* and *Buy* at that time. In case the measurement finds the ADN to be long, chances are high that consuming additional electricity to settle the current netted imbalance is economically viable, if the DNO knew that the current netted imbalance would otherwise pertain. However, imbalances are stochastic and thus there are chances that the settlement of the imbalance would occur without active involvement by the DNO. Then, internally balancing would not only be less cost-efficient but also counterproductive as the DN would swing from a long to a short situation. This consideration thus suggests that there should be thresholds for imbalances ("imbalance barriers"), only beyond which it is on average more cost-efficient to perform internal balancing actions. Since costs for internal balancing are asymmetric, there likely will be also asymmetric barriers. This is because consuming additional electricity is cheaper than generating additional electricity. While for high granularity measurements the decision rule might seem to be "wait until the second last imbalance measurement and then decide on *Make* or *Buy*", CDE characteristics such as system inertia (e.g., ramp-up times and rates) demand for a more continual approach. To do so, we first develop a simple stochastic time series model for the imbalance based on testable properties (cf. Requirement 2) and then exemplarily demonstrate a time-adaptive decision rule.

Firstly, on average there should not be DN imbalances, i.e., their mean is zero. This is because the DN operation would be systematically erroneous otherwise, and systematic errors incur costs to the DNO. As described, a DNO would rather sell a surplus or buy contracts to compensate for a deficit via power exchanges. Also, regulators in many geographies give penalties to DNOs with systematic errors, making it economically irrational to pertain systematic imbalances. For this reason, our first testable hypothesis for modeling imbalances is that the time series model of imbalances should have a zero mean.

Secondly, as points of measurement are discrete in time, it is well conceivable that the next measurement of the current netted imbalance depends on the current observation (or the last few), in addition to some degree of randomness. The DSS' decision model uses an autoregressive (AR) time series model to describe these properties. In an AR(p) time series model, each value is predicted by the previous p-many values including summands for randomness. Randomness results from effects outside the control of the DNO such as weather conditions influencing the productivity of RES, power-intensive industries uncoordinatedly changing production plans or unexpected patterns in private consumption, etc. For this reason, our second testable hypothesis is that the momentary imbalances exhibit significant autoregressive property.

Thirdly, when such external shocks occur, we do not consider them to propagate eternally into the future in the form of the imbalance time series centering on a new mean. Instead, the decision model considers the current netted imbalance to revert to its original zero mean for the reasons given above. Thus, it should be reasonable to assume that any level of imbalance returns to its mean over time until another external shock occurs. As it is unclear whether any future shock will be in the positive or negative direction, it is also unpredictable whether it will add up to the current netted imbalance or instead (partly) remove it. In our research setting, the DNO possesses the imbalance information within an STU and is, therefore, able to calculate the current netted imbalance and to counteract (too) large values with internal balancing. The decision model thus needs to determine when a current netted imbalance is too large. Speaking qualitatively, internal balancing via CDE is required, if an STU is likely to close with a large netted imbalance. In contrast, it is potentially counterproductive to do so if it is likely that the STU will end with a netted imbalance close to zero. For this reason, our third testable hypothesis is the existence of the mean reversion property.

Summing up the three properties, in this study, we consider a stochastic mean-reverting AR(p) time series model of DN imbalances subject to hypothesis testing. From this model, it follows that the probability of a given netted imbalance to be lowered or even removed by opposite-sign shocks constantly diminishes as the time during an STU passes on. Therefore, we need to refine our concept of imbalance barriers described above with a temporal component. We determine initial (positive and negative) barrier levels for the (current) netted imbalance for all STU, from which the barrier levels converge towards zero during the STU. The simplest converging imbalance barrier is one

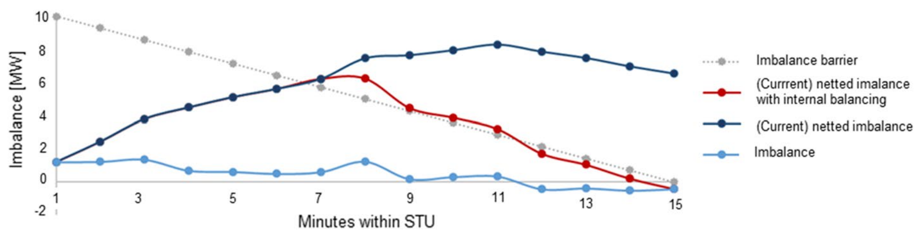


Fig. 4 Illustrative example of the application of the decision model on real-data world imbalance data

decreasing linearly in time. We formalize this after the example. Note that we also tested non-linear models of mean-reversion in the process of developing the DSS. The results, however, did only very marginally improve, whereas the decision rule and its underlying model became drastically more intricate. Therefore, we present the simpler decision rule for providing control signals to the CDE. The training module, thus, identifies initial values for the linearly decreasing pairs of imbalance barriers (for long and short situations) calibrated on historical data.

The decision module, then, uses these barriers in the sense of a decision rule to check if the current netted imbalance remains within the barriers. Whenever the current netted imbalance exceeds the barriers, it controls the aggregated CDE to actively remove the surplus (or the deficit) of the current netted imbalance that cannot be expected to be offset naturally (i.e., the difference to the current imbalance barrier). We exemplify the decision-making procedure in Fig. 4. It displays real-world imbalance data from our case study, on which we thoroughly elaborate in the "Decision support system evaluation" section. We use a sample of 15 imbalance measurements to illustrate the decision-making within a 15-min STU. The imbalance (light blue), is positive until minute 11 of the STU. Therefore, a positive (current) netted imbalance (dark blue) accrues until then. For this example, the start value for the imbalance barrier is set at 10 MWmin (10MWmin = 0.1667 MWh). The imbalance barrier (dotted, grey) falls from this value to a value of zero at the end of the STU. A similar barrier exists for negative netted imbalances but it is irrelevant in the DN's long situation and therefore not depicted. When the current netted imbalance exceeds the imbalance barrier in minute 7 the DSS starts performing negative internal balancing actions via the CDE. In the following minutes, the current netted imbalance after internal balancing (red), closely follows the imbalance barrier until minute 12, where a change of sign of the imbalance by itself begins to lower the current netted imbalance, offsetting it almost completely. As a result, no further internal balancing is advisable. From a network stability viewpoint, this outcome is favorable compared to a netted imbalance without internal balancing of approximately 6.2 MWmin at the end of the STU. If internal balancing costs are lower than the imbalance charges for a netted imbalance of 6.2 MWmin, internal balancing according to our model is economically beneficial for the DNO.

Based on the previous description of what the decision rule and its intuition are, we next formulate the decision model in continuous time as for readability's sake. The DSS implementation is based on a straight discretization of the model. As part of the DSS' training module, the identification of the cost-optimal pair of imbalance barriers rests at the core of the decision model. As described, we determine the optimal initial barrier levels and therefore have the barriers' start values as decision variables ($start^{pos} \in \mathbb{R}_{\leq 0}, start^{neg} \in \mathbb{R}_{\geq 0}$). In specific, the decision model aims at minimizing the total imputed costs $cost^{total}$ over a period of time represented by the sequence of STUs $\in \{1; \ldots ; S\}$. The DNO's total imputed costs in each STU s result from the sum of internal balancing ($cost_s^{make}$) and the costs for any netted imbalance potentially remaining at the end of s ($cost_s^{buy}$). We thus define the total imputed costs $cost^{total}$ by Eq. (1):

$$cost^{total} = \sum_{s=1}^{S} (cost_s^{make} + cost_s^{buy}) \tag{1}$$

Firstly, turning to the cost of internal balancing, it is important to distinguish whether the CDE react to a short or a long situation by either decreasing supply by the amount $amt_s^{bal\_neg} \in \mathbb{R}_{\leq 0}$ or by increasing supply by $amt_s^{bal\_pos} \in \mathbb{R}_{\geq 0}$, as the cost for either may differ. Accordingly, $cost_s^{bal\_pos}$ denotes the cost of supplying one unit of energy (MWh), whereas $cost_s^{bal\_neg}$ refers to the cost incurred from reducing supply by one unit. Note that as part of the training module, we refer to historical cost data for both types of cost. We thus define *Make* costs per STU s as the sum of the cost for positive and negative balancing. Both positive and negative balancing actions may even be necessary within the same STU since one STU can theoretically last several hours. Formally, we calculate the cost for *Make* during an STU as described by Eq. (2):

$$cost_s^{make} = amt_s^{bal\_pos} \cdot cost_s^{bal_{pos}} + |amt_s^{bal\_neg}| \cdot cost_s^{bal\_neg} \tag{2}$$

In this continuous model formulation, each STU s comprises an infinite amount of points in time, which we denote as $t \in s$. With $t = 0$ representing the start of s and $t = T^s$ its end, we define the amounts of internal balancing in s as by the Eqs. (3) and (4), respectively:

$$amt_s^{bal\_pos} = \int_{t=0}^{T^s} power_t^{bal\_pos} \tag{3}$$

$$amt_s^{bal\_neg} = \int_{t=0}^{T^s} power_t^{bal\_neg} \tag{4}$$

The terms $power_t^{bal\_pos}$ ($power_t^{bal\_neg}$) represent the positive (negative) balancing action as electric power measured in megawatts (MW). As positive balancing is denoted as positive energy and negative balancing as negative energy, $amt_s^{bal\_pos}$ is always greater than or equal to zero, and $amt_s^{bal\_neg}$ less than or equal to zero. Negative balancing at a time t ($power_t^{bal\_neg}$) takes place if and only if the current netted imbalance at time t exceeds the negative barrier ($barrier_t^{neg}$), meaning there is a too large positive current netted imbalance. The current netted imbalance at time t might, however, have already been influenced by previous internal balancing actions within the same STU. Thus, to determine the current netted imbalance, all these balancing actions are added to the current netted imbalance without internal balancing (which is calculated as $\int_{u=0}^{t} (power_u^{imbal})$) The difference between the negative barrier and the current netted imbalance provides for a negative balancing action at time t if the result is negative. Note that $power_t^{bal\_neg}$ is defined by Eq. (5) such that it is negative or zero:

$$power_t^{bal\_neg} = \min\left\{barrier_t^{neg} - \int_{u=0}^{t}\left(power_u^{imbal} + power_u^{bal\_pos} + power_u^{bal\_neg}\right); 0\right\} \tag{5}$$

Analogously, when the current netted imbalance in t falls below $barrier_t^{pos}$, i.e., it becomes more negative, the result ($power_t^{bal\_pos}$) is a positive real value representing positive internal balancing, or else there is no internal balancing as described analogously by Eq. (6):

$$power_t^{bal\_pos} = \max\left\{barrier_t^{pos} - \int_{u=0}^{t}\left(power_u^{imbal} + power_u^{bal\_pos} + power_u^{bal\_neg}\right); 0\right\} \tag{6}$$

As mentioned, the decision model determines the start values of the imbalance barriers as decision variables, while the model generally defines the barrier levels within an STU as a function of time within the STU and the respective start value of the barrier. Specifically, we suggest a model formulation with a simple linear function of time. Consequently, for every point of time t, we determine the positive and negative barriers levels as described by Eq. (7) and (8), respectively:

$$barrier_t^{pos} = \left(1 - \frac{t}{T^s}\right) * start^{pos} \tag{7}$$

$$barrier_t^{neg} = \left(1 - \frac{t}{T^s}\right) * start^{neg} \tag{8}$$

Secondly, turning to external balancing costs, the remaining netted imbalance must be settled through the *Buy* option. The netted imbalance remaining after internal balancing, i.e. $\left(amt_s^{net\_imbal} + amt_s^{bal\_pos} + amt_s^{bal\_neg}\right)$, is then valued at the difference between the STU's imbalance price ($price_s^{imbal}$) and a spot market price ($price_s^{market}$), e.g., observed at a power exchange (cf. section "Decision support system requirements for grid imbalance settlement"). The training module uses historical data for imbalance prices and power exchange prices. We compute the costs for the remaining netted imbalance at the end of an STU settled by the TNO (*Buy*) as defined by Eq. (9):

$$cost_s^{buy} = \left(amt_s^{net\_imbal} + amt_s^{bal\_pos} + amt_s^{bal\_neg}\right) \cdot \left(price_s^{imbal} - price_s^{market}\right) \tag{9}$$

Analogously to Eqs. (3) and (4), we define the netted imbalance without internal balancing as by Eq. (10):

$$amt_s^{net\_imbal} = \int_{t=0}^{T^s} power_t^{imbal} \tag{10}$$

The momentary imbalance $power_t^{imbal}$ can be positive, negative, or equal to zero, according to the nature of imbalances. This incorporates the offsetting effect involved with the definition of the netted imbalance. Finally, we then determine the total imputed costs ($cost^{total}$) by summing up the costs from external balancing ($cost_s^{buy}$) and internal balancing ($cost_s^{make}$).

To identify optimal pairs of start values for the barriers given the decision objective (cf. Eq. (1)), various methods are conceivable. To that end, it is, however, relevant to recall that the evaluation of the objective is rather computationally expensive. This is because it requires the simulation of the application of the decision rule for all S-many STU. From a theoretical point of view, it was feasible to formulate the decision model in a way so that a mixed-integer-linear-program could solve it. However, we deliberately choose to conduct a structured variation analysis. This is because it helps display the sensitivity of the objective concerning variations in the start values of the barriers and at the same time identify barriers that are robust over time. By doing so, we keep the DSS' decision model simple and identify good instead of optimal pairs. This procedure prescribes to evaluate the decision objective for pairs of barriers in their relevant ranges in equidistant steps. This procedure works regardless of the granularity of the information underlying the calculation. In this section, we have provided guidance on how to identify start values of these barriers in line with Requirement 1, i.e., being able to cope with different levels of information granularity. Given Requirement 2, the DSS provides testable criteria to check if the DSS is applicable. Lastly, DNO can deploy the designed DSS in their grid stability efforts. The DSS' design targets improving cost-efficiency by its decision models' objective. Through the increased cost-efficiency the DNO gains several options to decrease directly or indirectly its emissions for balancing power. First, it can use batteries for internal balancing charged with RES. Second, it can use CHP to deliver thermal energy to buildings that otherwise use fossil fuels. In that case, additionally, many CHP types can be fueled with emission-neutral gases – so-called green gases. Thirdly, a DNO can also invest the monetary savings from deploying the DSS to purchase additional emission certificates. We, therefore conclude that the DSS is designed to meet the Requirements 1 to 3.

Decision support system evaluation

To evaluate the artifact, we carry out a case study in line with Goebel et al. (2014) using real-world data from a German DNO responsible for a DN serving a mid-sized German city with about 300,000 citizens and a respective number of businesses and industry. This real-world case study evaluates how well our design proposal of the DSS adheres to the requirements.

Evaluation setting

We process four sets of information: DN imbalance data obtained from the DNO, data on the cost of operating the aggregated CDE for internal balancing purposes, the imbalance prices with which German DN are charged by their respective TNO, and market prices at which electricity could alternatively be bought or sold. In the following, we give an in-depth description of each set of information.

Firstly, the German DNO has provided a dataset containing DN imbalance data spanning the years 2013 to 2015. The data represents the average imbalance in the DN in each STU (15 min by German regulation). This data thus represents the most granular data available in the real-world setting in Germany. Since we want to study the effect of more granular data on the eco-efficiency, we decouple from the German 15-min STUs. Instead, we treat each average imbalance (German STU) as one data point within a longer fictitious STU, which encompasses several of these data points. We set aggregation levels denoted by numbers, where the number represents the number of data points aggregated into one fictitious STU. In this evaluation, we present the following aggregation levels: 1, 2, 3, 4, 5, 6, 8, 12, 16, 24, 32, 48, 96. An aggregate level of 4 corresponds to an STU duration of 1 h and four measurements. An aggregate of 96 corresponds to an STU duration of one day with 96 measurements every 15 min. The data set contains 3 years or 1095 days, or 105,120 15-min STU, respectively. The decision model in the "Decision support system design" section considers an AR(p) time series model with mean reversion for the DN imbalance. Based on the imbalance data provided by the German DNO it is thus mandatory to validate the underlying stochastic properties on the empirical observations in line with Requirement 2: autoregressive property and mean-reversion. To do so, we follow the approach by Maddala and Lahiri (2009) and first fit an AR(p) model to the data with the optimal p being determined using the Akaike Information Criterion (AIC) as a measure of goodness-of-fit. We then obtain an optimal model with $p = 1350$, validating the existence of autocorrelation. Next, we test that shocks are non-permanent via the Augmented Dickey-Fuller (ADF) unit root test as described by Maddala and Lahiri (2009). If a unit root is present, shocks are permanent. Without a unit root, a time series gradually returns to its mean. The ADF test considers the null hypothesis that a unit root exists. The authors further describe that researchers should carry out an ADF test with a time lag chosen through the AIC, or generally move from high to low time lags when testing. In ADF tests on our data, the null hypothesis can be rejected on all tested time lags (k) with its probability value $\mathrm{p} < 0.01$ for $\mathrm{k} \leq 1242$; $\mathrm{p} < 0.05$ for $1243 \leq \mathrm{k} \leq 1350$. In conclusion, network imbalance displays autoregressive behavior and random shocks are non-permanent, supporting the model defined in the "Decision support system design" section . By this, we can—and in this case successfully did—statistically test the applicability of the proposed decision model. Consequently, we positively confirm Requirement 2 by testing the decision models applicability, i.e., its assumptions, by statistical methods.

Secondly, it is important to recall that the decision model (see section "Decision support system design") works in a setting, where information on *Make* prices is available. The decision model considers these prices to be given as input parameters, i.e., *Make* prices are model-exogenous. Determining *Make* prices will differ from case to case. When the CDE are lithium-ion batteries then there is a different method for the calculation as there is for CHP, or biomass, etc. Various methods for assessing these prices are available (Ueckerdt et al. 2013; Zakeri and Syri 2015). In our case study, the DNO operates 17 CDE, which are CHP units that can be technically aggregated as described in the "Decision support system requirements for grid imbalance settlement" section. For the study, we assume that the DNO carries out active balancing using these aggregated CDE. Thus, it is necessary to calculate the operating costs of the aggregated CHPs for positive or negative balancing purposes, respectively, to evaluate the DSS. We obtain these costs via straightforward calculations, which consider the European Gas Index (EGIX) gas prices and calculating the cost of electricity production under fixed electrical and heat levels of efficiency. These levels vary depending on the size of the CHP and its load factor. From the range of available CHP, we have chosen a 19 kW CHP, which is similar in size to those used in the DNO's network. We model a CHP that has a thermal efficiency of 64.3% and an electric efficiency of 33.9% (Bosch 2016). For DN balancing, only the electricity production of the CHP is of relevance. Simply calculating the cost of the natural gas used to provide the required balancing power, however, neglects the economic value of the simultaneously produced heat, as the CHPs possess a thermal storage for later heat usage. Therefore, this heat is valued with the alternatively occurring costs for its production with a gas burner. We consider an average a real-world gas burner with 10 kW at an efficiency of 75% (Junkers 2015). Similarly, DN perform negative balancing by explicit non-production of electricity from the aggregated CDE, the result would be a shortage of heat production. Hence, heat is taken from the thermal storage. In this setting, we consider a 60% efficiency level of the storage unit. In conclusion, in the case of positive balancing, the DNO faces the cost of the required gas for the CHP less the theoretical amount of gas required to produce the respective amount of heat with a gas burner. In the case of negative balancing, the DNO saves the cost of the gas otherwise necessary to produce the amount of electricity in question. At the same time, the DNO has to bear the cost, i.e., the economic value, of the heat taken from the thermal storage (again quantified as the value of natural gas necessary to (re-)produce this amount of heat energy).

Thirdly, data on the German imbalance prices with which DN are charged are made publicly available online by the TNO after settlement has occurred (Regelleistung.net 2019). In the German market setting, there are four TNO, each operating a part of the German transmission network. Nevertheless, there is a common measurement of network state (i.e., long or short) over all four TNO' combined networks referred to as the "Netzregelverbund" (NRV), and all four TNO charge the same imbalance price, called "regelzonenübergreifender einheitlicher Bilanzausgleichsenergiepreis" (reBAP). We use historical reBAP data as imbalance prices in this case study.

Lastly, to account for the described incentivizing effect that in long positions the DNO could have sold surplus energy on the electricity market at higher prices and in short positions the DNO could have bought electricity at lower prices on the exchange, we additionally obtain the European Power Exchange (EPEX) day-ahead spot prices as market prices. As described, netted imbalances remaining after an STU are valued with the reBAP price minus the market price, thus including imputed costs for not buying/selling on the market. As an additional effect, the German imbalance pricing mechanism is set up so that the reBAP will usually be larger than market prices if the TN (more precisely, the NRV) is short and below-market prices in long situations. It is, therefore, possible that DN will receive financial rewards if they are beneficial to a TN's stability, as described in Table 2. Again, this financial benefit is not as large as it would have been if they had settled imbalances in advance through spot market exchanges. Koch and Maskos (2020) give first empirical evidence that German market participants appear to react on the latest published system (im-)balances, since much of the trading shortly before market closure is caused by market participants trying to avoid these imputed costs.

Table 2 Costs/rewards from imbalance charges under German regulation depending on the ADN/network state

		ADN short: Imbalance < 0	ADN long: Imbalance > 0
Overall network short	reBAP > EPEX	*(reBAP – EPEX) * imbalance* (positive) * negative negative => TN destabilization by ADN leads to cost	*(reBAP – EPEX) * imbalance* (positive) * positive positive => TN stabilization by ADN leads to reward
Overall network long	reBAP < EPEX	*(reBAP – EPEX) * imbalance* (negative) * negative positive => TN stabilization by ADN leads to reward	*(reBAP – EPEX) * imbalance* (negative) * positive negative => TN destabilization by ADN leads to cost

Using the four datasets in combination, we determine the DNO's imputed costs when using our DSS during the period available. We use data from 2013–2014 within the training module and apply the decision rules on data from 2015 (*Model* case). To assess improvements from the use of our model, we also determine the costs when our model is not applied and thus where the TNO settles all imbalances alone (*Base* case). Besides, we calculate a theoretical case in which the DNO has access to imbalance information in real-time (*Real-time* case) to observe the effects of improved information timeliness, i.e., that information is available not only immediately after the STU but already meanwhile. Finally, as an upper bound for improvements, we calculate a case under the assumption that imbalance prices and netted imbalance are known at the beginning of each STU. As the *Model* case is designed to beat the *Base* case on average over all STU, it does not necessarily beat it in every single STU. Having both types of information in advance, however, allows for a separate decision for each STU to apply either *Model* or *Base* (*Perfect information* case). While future electricity networks may be able to better predict netted imbalances, predicting imbalance prices is impossible in the current regulatory framework (for details, see "Decision support system requirements for grid imbalance settlement"). This case should, therefore, be observed as a theoretical upper bound.

In combination, the four cases depicted in Table 3 allow an evaluation of the improvements regarding eco-efficiency that our DSS provides over the currently practiced *Base* model and the potential for further optimization using more intricate models. We additionally perform all calculations for all time aggregation levels. The aggregation levels correspond to the numbers of data records within a time period or more specifically, how many measurement points are there within an STU. With this imbalance information, we can observe the effects of various levels of information granularity.

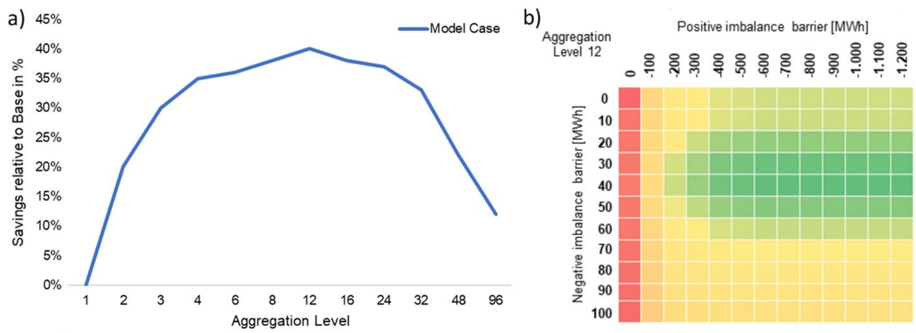
Evaluation results

Our DSS identifies the cost-optimal pair of the imbalance barriers' start values (from here on only "barriers"). We will, therefore, present the following results: first, the sensitivity of *Model* cost savings to the choice of aggregation level and barrier, second, the costs produced by the *Model*, *Base*, *Real-time,* and *Perfect Information* cases in comparison, and third, the effects on the required use of BP.

First, considering time aggregation levels, we find that higher levels enhance the performance of both *Base* and *Model*, translating to lower costs except for very high levels (for all results, see Table 3). As becomes obvious from Fig. 5a, *Model* profits much stronger from

Table 3 Overview on simulation results regarding total costs, cost savings, and barriers for all three cases

Aggregation level		1	2	3	4	6	8	12	16	24	32	48	96
Base case	Cost [k€]	466	465	470	470	466	458	462	444	437	421	404	415
Model case	Cost [k€]	466	370	331	308	299	286	278	277	274	281	315	365
	Savings [k€]	0	95	139	162	167	172	184	167	163	140	88	50
	Savings [%]	0	20	30	35	36	38	40	38	37	33	22	12
	Neg. barrier	0	0	40	0	10	10	40	50	100	100	100	100
	Pos. barrier	0	− 100	− 100	− 200	− 300	− 600	− 1100	− 1200	− 1200	− 1200	− 1200	− 1200
Real−time case	Cost [k€]	272	266	265	261	268	261	266	269	269	278	316	365
	Savings [k€]	193	199	205	209	198	198	196	175	168	143	88	50
	Savings [%]	42	43	44	44	42	43	42	39	38	34	22	12
	Neg. barrier	0	0	0	0	10	20	40	50	100	100	100	100
	Pos. barrier	− 100	− 100	− 100	− 200	− 300	− 700	− 1200	− 1200	− 1200	− 1200	− 1200	− 1200
Perfect Inf. case	Cost [k€]	466	− 445	− 650	− 734	− 446	− 558	− 412	− 435	− 394	− 414	− 362	− 284



Legend **Legend**

Figure 5 Model savings (**a**) and savings sensitivity to barriers for aggregation level 12 (**b**). Blue line: Model savings relative to *Base* case and sensitivity to aggregation level. Savings sensitivity to the barrier setting for the aggregation level 12 = 3 hours (*Base* case vs. *Model* case). Green low deviation, yellow medium deviation, red high deviation from optimum

low to medium aggregation levels and can outperform *Base* by up to 40% (aggregation level 12: STU duration = 3 h). This translates to cost improvements of up to € 184,000. Focusing on aggregation level 12, which provides the largest cost improvement relative to *Base*, as an example, Fig. 5b depicts a heat map of cost sensitivity to the choice of barriers. There is a visible optimal range for the negative barrier around 40 MWh, while for the positive barrier, the optimal costs can be obtained for all values below -600 MWh. As a general trend, lower aggregation levels lead to lower (absolute) barrier pairs and higher ones to higher barriers. This is coherent considering that over a longer time span (a longer STU), more extreme netted imbalance values can occur. Conversely, a longer STU requires more extreme netted imbalances to justify internal balancing, as a longer STU of course provides more time for external shocks to offset on their own. In similar heat maps, a shift of the optimal green region to the top left (for lower levels) or bottom right (for higher levels) would indicate this.

Second, Table 3 summarizes costs, absolute, and relative savings for all time aggregation settings. For *Model* and *Real-time*, we provide the optimal set of barriers. *Base*, representing the current state of not performing internal balancing, obviously has no such barriers. For *Perfect Information*, we do not represent them either, as it may switch between *Base* and *Model* for each STUs. For *Model* and *Real-time*, optimal barriers are very similar. Yet, on low aggregation levels, cost improvements are strikingly higher for *Real-time*. For high aggregation levels, however, the results converge. The results for *Perfect Information* show that with such information, one would be able to create significant financial benefits from imbalance “charges”, as they result from situations where the DN is beneficial to TN stability. As discussed, these calculations indicate a theoretical upper bound and are not realistic to achieve. Note that Model is equal to Base for aggregation level 1 since only one data point is available for the STU. When it becomes available (i.e., immediately after recording, which is after the STU), the STU is already over, thus no action can be taken.

Discussion

In this section, we compare the results of our study with those from the related literature section, discuss the techno-economic implications of our work, and follow-up with suggestions for EI.

The evaluation gives evidence to the fact that it is highly appropriate to consider the *Make* option. This might be surprising because markets for BP seek efficiency by competitive auctioning and pooling of energy resources from all parts of the power system. Nonetheless, pulling the *Make* option leads to improved cost-efficiency across all aggregation levels. The improvements reach 40% based on our relatively simple decision model. Comparing these results and findings with similar studies from the related literature section like Guo et al. (2014), Köpp et al. (2013), Wirtz and Monti (2018) can be useful as to put the results into context. However, at the same time it is important to be specific in how far the results can be compared based on the different studies' settings and approaches.

First, while Köpp et al. (2013) place their research within the German institutional framework, they provide a description of their technical prototype instead of reporting on the economic benefits of their DSS. Second, Guo et al. (2014), in contrast, report on savings of up to 95% against the benchmark in extreme scenarios (cf. Figure 1a in Guo et al. (2014)). However, it is important to mention that this is only possible under real-time information. We thus should compare the results to the *Real-time* case within this study rather than the *Model* case. In addition, it is worth mentioning that their results require shifting demand which is assumed to be cost-neutral and available through direct control. In our study, in contrast, there is a producer-side CHP, which comes at a cost when being active. This clearly reduces the economic benefit compared to the study by Guo et al. (2014). However, we thereby have fairly modeled the CHP's available capacity and cost of opportunity. This is in favor of a more realistic application. Eventually, also, Guo et al. (2014) place their study in the New York system region, where a very different institutional framework is applicable than in Germany. This and model abstractions in Guo et al. (2014) can make findings difficult to compare. Lastly, Wirtz and Monti (2018) look at a theoretical optimum (corresponding to our *perfect information* case) and do not adhere to the identified three requirements outlined above. As a result, it will be difficult compare the reported theoretical savings per week for an unknown system size in the optimum case. In addition, their model can speculate on the markets, i.e., the model can bet on opposite sign imbalances as to cash in the imbalance price. It is noteworthy that systematically not covering imbalances is legally disallowed in Germany where their study takes place. That is why it is fairer to compare our results against their more realistic imbalance minimization case. In that case, their study reports approx. € 30,000 savings with 150 batteries deployed during the evaluation of one week. However, even their base case has yielded a benefit of approx. € 20,000 without batteries during that period. This thus results in 50% additional savings (i.e., € 10,000 per week or a linearly extrapolated € 520,000 per year), which is in the range of what is possible indicated by our study, as well. However, in our *Model* case, the 40% savings stem from CHP also serving the loads the system was designed for, i.e., our DSS uses latent potential. In contrast, Wirtz and Monti (2018) consider deploying batteries dedicated to imbalance management. This comes with high capital cost and should be considered when performing a return-on-investment study. More recently, though, big battery-based systems appear with large charging hubs to support electric mobility (Haupt et al. 2020; Halbrügge et al. 2020). It thus would be interesting to see their approach being extended in a way that it allows batteries to serve the consumer loads while being deployed to manage imbalances. In the same vein, our DSS can easily be equipped with batteries instead of CHP allowing for a direct comparison of both approaches.

Looking at our findings from an energy policy perspective, then, the large improvements of up to 40% indicate considerable amounts of untapped flexibility at the DN level. From a societal welfare perspective, the untapped flexibility at the DN level points toward economic inefficiencies, i.e., DN participants pay more than necessary.

However, there exist barriers to market flexibility. First, there are relatively strict prequalification criteria for offering BP (Regelleistung.net 2022). Second, there are regulatory difficulties regarding aggregation approaches to provide services outside the DN (Eid et al. 2015). Third, insufficient data regarding a DN' s structure and state may also pose limiting factors as well (Roberts et al. 2016). It is worth highlighting that under current regulatory setups, imbalance prices are higher than spot market prices to avert speculation on the BP market. With our study, we underline that this is not only a precondition to the relevance of this paper's DSS, but also to the functioning of power markets. Therefore, IS overseeing this is of high practical relevance. Also, there are local synergies between energy sectors, e.g., power and heat. Whereas it is often economically feasible to transfer power over long distances, it is hardly possible to do so for thermal energy. Given that CHP likely exist in practically all DN allows us to conclude that there is a broad field of application for the proposed DSS.

Conclusion and outlook

Electricity is the basis of modern life and is pivotal to societies' prosperity. Simultaneously, today's electricity sector is a major contributor to human-made climate change. There is a broad consensus that energy systems must transform to become ecologically (more) sustainable. However, changing the system at the expense of stability and economic feasibility might result in a deterioration of today's standard of living and society. EI with its information-centered Weltanschauung is taking a new perspective on power systems. It might help to improve sustainability without burdening stability and economic feasibility, or vice versa.

With this paper, we strive to contribute to that field with a DSS conducting informed decisions regarding *Make* or *Buy* of BP based on a rigorous stochastic decision model taking information availability, granularity, and timeliness into account. We demonstrated the utility of the DSS via a real-world case study in a German city with 300,000 inhabitants. We found that the DSS delivers valuable results for the EI research domain as well as practice whilst adhering to the design requirements. Setting up and operating a DSS for active network management might generate a viable business case. This might be so because of fewer regulatory constraints and latent untapped potential for balancing on a local level as well as reaping local synergies between energy sectors, e.g., from CHP. This improvement has generated cost-savings of up to 40% in our case study despite the partly coarse information granularity. Besides, the application resulted in a lower demand for BP. Since it is fossil-fueled power plants that typically provide BP, it is fair to assume that the DSS contributes largely to eco-efficiency. If prices for reserve and BP rise significantly in the future as suggested by research (Kladnik et al. 2012; Madrigal and Porter 2013) the application of the DSS could be financially even more rewarding. The same holds for increased volatility of imbalance prices.

For future work, it is relevant to consider extending this work concerning four aspects. First, we are convinced that it is necessary to quantify the saved emissions rigorously to better understand, if, when, and how the transformation towards DER can and should be encouraged from an eco-efficiency perspective. For that purpose, we suggest providing a generic emissions quantification method for *Make* or *Buy* decisions. Second, our *perfect information* case shows further savings potential. While we applied a simple AR model, we suggest that it might be relevant to apply more advanced methods to this context. To that end, a comprehensive analysis of alternative conceptualizations of information granularity can be advantageous to theory and research. Third, we believe it is very important to model the potential impact on imbalance prices when DNO are assumed to adopt our DSS. Finally, while in this work we have fixed the barriers, we may assess in future work when it is best to reset the barriers.

Eventually, shifting toward more active management of DN allows reaping latent potential. However, more information and higher quality of information will be a requirement for the DSS and EI in general to fully capture the potential.

Abbreviations

ADF	Augmented-Dickey-Fuller
ADN	Active distribution network
AIC	Akaike information criterion
AR	Autoregressive
BP	Balancing power
CDE	Controllable distributed energy
CHP	Combined heat and power
DER	Distributed energy resources
DN	Distribution network
DNO	Distribution network operator
DSR	Design science research
DSS	Decision support system
EGIX	European gas index
EI	Energy informatics
EPEX	European power exchange
MWh	Megawatthour
NRV	Netzregelverbund
IS	Information System
reBAP	Regelzonenübergreifender einheitlicher Bilanzausgleichsenergiepreis
STU	Settlement time unit
TN	Transmission network
TNO	Transmission network operator

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Author contributions
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Availability of data and materials
The datasets generated and analyzed during the current study are not publicly available due contractual requirements.

Declarations

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Not applicable.

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The authors declare that they have no competing interests.

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