Optimizing the lead time of operational flexibility trading from distributed industrial energy systems in future energy and flexibility markets

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Abstract

To meet the challenges of increasing volatile and distributed renewable energy generation in the electric grid, local flexibility and energy markets are currently investigated. These markets aim to encourage prosumers to trade their available flexible power locally, to be used if a grid congestion is being predicted. The markets are emerging, but the characterizing parameter are still heterogeneous. Especially the lead time between accepting offered flexibility power and the delivery varies significantly. Since this signal lead time is critical to the availability and the costs of the flexibility power from the prosumers, we investigate the effect of changing signal lead times on flexibility provision. In this context, we conduct a simulation of a 48 h moving horizon MPC for multiple distributed energy systems participating on a market platform, delivering flexibility power under different lead times. The deliverings are further investigated with changing demand durations, electricity tariffs, daytimes and seasons. The results indicate that with a signal lead time of 3 hours, the costs of providing flexibility with current combined heat and power systems are minimized. However, the transition towards modern heat pump, photovoltaic and battery storage designs shows a considerable increase in optimized signal lead time, reaching around 16 hours.

Keywords: energy flexibility, signal lead time, energy market, flexibility market, distributed energy system optimization

1. Introduction

With the rising global attention regarding climate change and the therefore increasing efforts in reducing greenhouse gas emissions, the share of renewable energy generation sources is increasing steadily [1]. However, this shift from centrally installed conventional energy generation to distributed renewable energy generation is leading to a growing number of grid problems such as, e.g., grid congestions, since renewable energy sources are mostly weather-dependable and therefore highly fluctuating [2]. To meet this challenge of the changing production, energy flexibility services such as demand response or demand side management have become critical for the stability of the grid [3, 4]. These services use disconnectable loads or parts of the rising amount of distributed energy resources (DER) from the industry or privates homes, to stabilize the grid by controlling their energy demand or production according to the desired load profile [5].

1.1. Local market platforms

A currently further discussed way of using DER flexibility of companies and private homes has been found in local market platforms [6]. These markets aim to encourage small- and medium- sized prosumers

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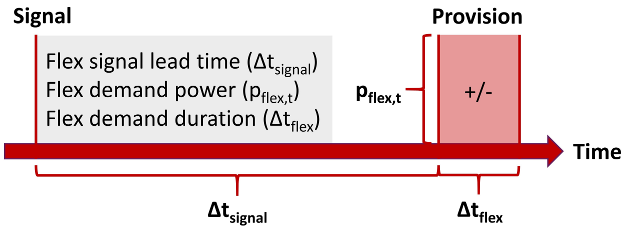

Fig. 1 Lead time $\Delta t_{\mathrm{signal}}$ between notification and delivery of required flex power $p_{\mathrm{flex},t}$ with duration Δt_{flex}.

to trade their available flexibility power locally, which can then be used if a grid congestion is being predicted by the distribution system operator (DSO), or to share it with other local market participants [7]. Since the platforms are still in a testing phase and because of the high variety of platforms, a short overview of recent market platforms is given in Tab. 1. The overview thereby focuses on the mainly discussed *flexibility markets* and *energy markets* [7]. While in *flexibility markets*, the DSO is the only consumer of flexibility power, in *energy markets* prosumers can also trade their flexibility locally among each other, providing an additional sales opportunity. Further reviews can be found in [8, 6, 9, 10] and [11].

Independent from the platform and its market or technical design, the traded flexibility power is mainly described by 6 parameters. They are [20, 21]: the offered flexibility power, its direction (up, down), the rate of change, the signal lead time (or the starting time of the flexibility demand), the duration and the location. However, as can be seen in Tab. 1, the market and technical design highly varies between the platforms and mainly depends on the target audience and main goal of the platform. Also the time frame between accepting an offered flexibility power and the delivery varies between the platform designs. Mostly this time frame lies between 24 h and a few minutes, since this time frame also matches the forecast cycle of many energy system devices, e.g., battery storage units for photovoltaic systems [22] as well as the time frame of existing energy markets, e.g., the day ahead market [23]. However, an investigation of the cost and the availability of flexibility (flex) power $p_{\mathrm{flex},t}$ depending on the signal lead time $\Delta t_{\mathrm{signal}}$ with duration Δt_{flex} as shown in Fig. 1 has, to the best knowledge of the authors, not been carried out so far.

1.2. Related work

To gain an overview of the different market designs, Jin et al. present an extensive investigation on concepts, models and clearing methods of local flexibility markets, demonstrating the need for further comparison and investigation of each design choices [7]. Similar to this, Dronne et al. grouped the proposed designs of different European flexibility markets, outlining that the market designs highly depend on the local needs, which can be, among other things, distinguished between short-term designs, e.g., day-ahead trading and long-term designs, e.g., year-wise contracting [24]. Minniti et al. analyzed key enablers for local flexibility markets, identifying the uncertainty in forecasting the variability of renewable energy sources as one of the obstacles in handling grid congestions. The work concludes that short term changes need to be considered in the planning of flexibility market designs, to be able to request DERs accordingly [25]. To meet forecast uncertainties, Esmat et al. and Torbaghan et al. propose a two-piece market design, which uses a day-ahead market for trading the predicted next days flexibility need and an intra-day market for adjusting the predicted day-ahead needs with the latest congestion calculations [26, 27]. Correa-Florez et al. and Olivella-Rosell et al. introduce the use of an aggregator, to minimize forecast uncertainties of single DERs and to streamline the trading process for prosumers by directly controlling their DERs along with other local DERs [28, 29]. However, as presented in the investigation from Bouloumpasis et al., the signal lead time which effects forecast uncertainties is still controversial among the platform designs [6].

To be able to place flex power offers on market platforms, prosumers or aggregators need to know their DER operation and the available flex power with the corresponding costs in advance. This forecast in DER operation and flexibility can be done by, e.g., a model predictive control (MPC) application as introduced in Bürger et al. and Fischer et al., which continuously optimizes the operation of the corresponding DER according to the predicted demands and other influencing factors [30, 31]. The MPC applications can then

Platform		Platform design		Market design				Technical design
Projekt/ Platform Name	Ref.	Flexibility market	Energy market	Trading method	Clearing mechanism	Bidding period	Trading intervals	Signal lead time
EMPOWER	[12]		X	Auction	Pay-as-bid	11:00 pm day ahead	15 minutes	11:00 pm day ahead
Enera	[13]	X		Open order book	Pay-as-bid	Day ahead to 5 minutes before delivery	15 minutes	Day ahead to 5 minutes before delivery
ENKO	[14]	X		Auction	Pay-as-bid	1:00 pm to 2:00 pm day ahead	minutes	1:00 pm to 2:00 pm day ahead
ETPA	[15]		X	Open order book	Pay-as-bid	Day ahead to minutes before delivery	15 minutes	Day ahead to minutes before delivery
iPower	[16, 17]	X		Open order book, auction	Pay-as-clear	Hours before delivery	Hourly	Hours to minutes before delivery
Nodes	[18]	X		Auction	Pay-as-bid	Days to minutes before delivery	Depending on case	Days to minutes before delivery
Piclo	[19]		X	Auction	Pay-as-bid	Months before delivery	minutes	30 minutes or less before delivery

Tab. 1 Grouping of flexibility markets and energy markets.

Nomenclature

Abbreviations

BES	Battery energy storage
CHP	Combined heat and power
COP	Coefficient of performance
DER	Distributed energy resources
DSO	Distribution system operator
HP	Heat pump
HS	Heat storage
MILP	Mixed Integer Linear Program
MPC	Model predictive control
OCP	Optimal control problem
PV	Photovoltaik

Parameters

Δt_{tech}	Temperature delta HP (K)
η_b	Thermal efficiency boiler
$\eta_{c,\text{el}}$	Electric efficiency CHP
$\eta_{c,\text{th}}$	Thermal efficiency CHP
η_h	Thermal efficiency HP
$\eta_{p,\text{cycle}}$	Charging/discharging efficiency BES
$\eta_{p,\text{time}}$	Storage efficiency per hour BES (1/h)
$\eta_{s,\text{cycle}}$	Charging/discharging efficiency HS
$\eta_{s,\text{time}}$	Storage efficiency per hour HS (1/h)
$\lambda_{b,\text{part}}$	Minimum part load boiler
$\lambda_{c,\text{part}}$	Minimum part load CHP
$\lambda_{h,\text{part}}$	Minimum part load HP
$c_{\text{el,buy},t}$	Cost of electricity (€/kWh)
$c_{\text{el,sell},t}$	Earnings from electricity sales (€/kWh)
$c_{\text{gas,var}}$	Cost of gas (€/kWh)
$c_{p,\text{wear}}$	Cost of BES wear (€/kWh)
$\text{cop}_{h,t}$	COP HP
$e_{p,\text{max}}$	Maximum storage capacity BES (kWh)
$p_{c,\text{max}}$	Maximum electric power CHP (kW)
$p_{\text{cons},t,\text{new}}$	New electricity consumption grid (kW)
$p_{\text{dem},t}$	Electricity demand company (kW)
$p_{\text{feed},t,\text{new}}$	New electricity feed in grid (kW)
$p_{\text{flex},t}$	Requested flex power (kW)
$p_{p,\text{max}}$	Maximum power BES (kW)
$p_{v,\text{cap}}$	Installed capacity PV (kW_p)
$p_{v,\text{profile},t}$	Electricity profile PV ($\text{kW}/\text{kW}_\text{p}$)
$\dot{q}_{b,\text{max}}$	Maximum thermal power boiler (kW)
$\dot{q}_{\text{dem},t}$	Thermal demand copmany (kW)
$\dot{q}_{h,\text{max}}$	Maximum thermal power HP (kW)
$\dot{q}_{s,\text{max}}$	Maximum power HS (kW)
$q_{s,\text{max}}$	Maximum storage capacity HS (kWh)
$t_{h,\text{source},t}$	Source temperature HP (°C)
$t_{h,\text{target}}$	Target temperature HP (°C)

Subscripts

b	Index of boiler
c	Index of CHP
h	Index of HP
i	Iteration step model predictive control
p	Index of BES
s	Index of HS
t	Timestep optimization
v	Index of PV

Variables

C_{flex}	Flexibility costs (€)
C_{ref}	Reference costs (€)
$C_{\text{tot},t}$	Total costs at time step t (€)
C_{tot}	Total costs (€)
$E_{p,t}$	Charging level BES (kWh)
$\dot{F}_{b,t}$	Gas demand boiler (kW)
$\dot{F}_{c,t}$	Gas demand CHP (kW)
$\dot{F}_{\text{cons},t}$	Total gas consumed (kW)
$P_{c,t}$	Produced electricity CHP (kW)
$P_{\text{cons},t}$	Electricity consumed from grid (kW)
$P_{\text{feed},t}$	Electricity feed in grid (kW)
$P_{h,t}$	Electricity demand HP (kW)
$P_{p,\text{in},t}$	Charging power BES (kW)
$P_{p,\text{out},t}$	Discharging power BES (kW)
$P_{v,t}$	Produced electricity PV (kW)
$\dot{Q}_{b,t}$	Produced heat boiler (kW)
$\dot{Q}_{c,t}$	Produced heat CHP (kW)
$\dot{Q}_{h,t}$	Produced heat HP (kW)
$\dot{Q}_{s,\text{in},t}$	Charging power HS (kW)
$\dot{Q}_{s,\text{out},t}$	Discharging power HS (kW)
$Q_{s,t}$	Charging level HS (kWh)
$Y_{b,t}$	Boolean for minimum part load boiler
$Y_{c,t}$	Boolean for minimum part load CHP
$Y_{h,t}$	Boolean for minimum part load HP
$Y_{p,\text{in},t}$	Decision variable charging BES
$Y_{p,\text{out},t}$	Decision variable discharging BES
$Y_{s,\text{in},t}$	Decision variable charging HS
$Y_{s,\text{out},t}$	Decision variable discharging HS

be extended by, e.g., the methodology introduced by De Coninck et al., which determines the price for DER flexibility by calculating the cost difference between the originally planned DER operation and the recalculated operation with requested flex power [32]. The recalculation of the DER operation according to the requested flexibility leads to increased costs in the form of power dependent cost curves, which can then be used as a basis for flexibility pricing at a market [33].

Multiple studies in the literature explore the available flexibility and maximize the revenue of flexibility delivery by using DER optimization. Harder et al. investigated the available flex power and its corresponding costs of multiple household designs during the day with different load profiles and electricity tariffs [34]. Nalini et al. introduced the open source model OpenTUMFlex, to quantify and price prosumer flexibility to optimize its operation schedule as well as its bidding table on flexibility markets [35]. Fleschutz et al. proposed a demand response analysis framework to quantify the energy flexibility of DER and to optimize the design of the energy systems depending on costs and emissions [36]. Bohlayer et. all quantified the potential of an industrial company participating in sequential electricity and balancing markets [37]. To quantify the cost-optimal integration of flexible buildings into a congested distribution grid, Hanif et al. present and evaluate two benchmark pricing methods, which aim to solve grid congestions [38]. Zaidi et al. investigated combinatorial double auctions, showing that the optimization of each individual energy system operation increases the overall social welfare on the markets [39].

1.3. Contribution of this work

Despite the variety of different DER flexibility investigations, the literature so far lacks a quantitative analysis of the economic effects of different signal lead times on common current and future DER systems. Therefore, this work presents the results of a 48 h moving horizon MPC simulation for different typcial distributed energy systems participating on a market platform, which are evaluated regarding the availability and the costs of flex power under different signal lead times. Moreover, several signal lead time influencing factors, including different daytimes, times of the year, electricity tariffs and demand durations are examined. The electric and thermal demands as well as the original energy system design are based on a company in the south of Germany. The system design is further adapted to two heat pump designs, using a design optimization as presented in [40]. To provide a comprehensive overview of the findings, a newly developed flexibility heatmap is introduced, showing the flexibility costs dependent on the lead time and the flex power. The results aim to offer an extensive quantitative overview of the minimum signal lead time required for cost-optimized provision of flex power, as well as an assessment of the impact of the ongoing electrification of the heat supply from current boiler + combined heat and power (CHP) designs to heat pump + photovoltaic + battery designs on the signal lead time.

1.4. Outline

The remainder of the paper is structured as follows: In Section 2, the implementation of the adaptable energy system model, its 48 h moving horizon MPC, and the flexibility requests are introduced. Section 3 presents the results of the signal lead time investigation case study and introduces a new flexibility heatmap. Finally, Section 4 concludes.

2. Method

The methodology consists of a case-specific adaptable energy system model of industrial energy systems components controlled by a MPC, which we assume to be connected to a market platform. At first (Subsection 2.1), the formulation of the energy system model and its optimal control problem (OCP) is presented. Afterwards, the MPC implementation is introduced in Subsection 2.2. Then, the calculation of a flexibility request and its corresponding costs are presented in Subsection 2.3. After that, the case study as well as the computation and implementation details are specified in Subsection 2.4.

2.1. Energy system model

The energy system model includes commonly used industrial energy system components such as CHPs, boilers, heat pumps (HP), photovoltaic (PV) fields, heat storage units (HS), and battery energy storage units (BES), as illustrated in Fig. 2 in the *Energy system components* section. The components are connected to each other through a thermal, an electric and a fuel balance, which are represented by the red, green and brown lines. The thermal and electric demand in the *Demands* section are modeled as time-varying profiles, representing the time-dependent electric demand of machine tools and other technical equipment as well as

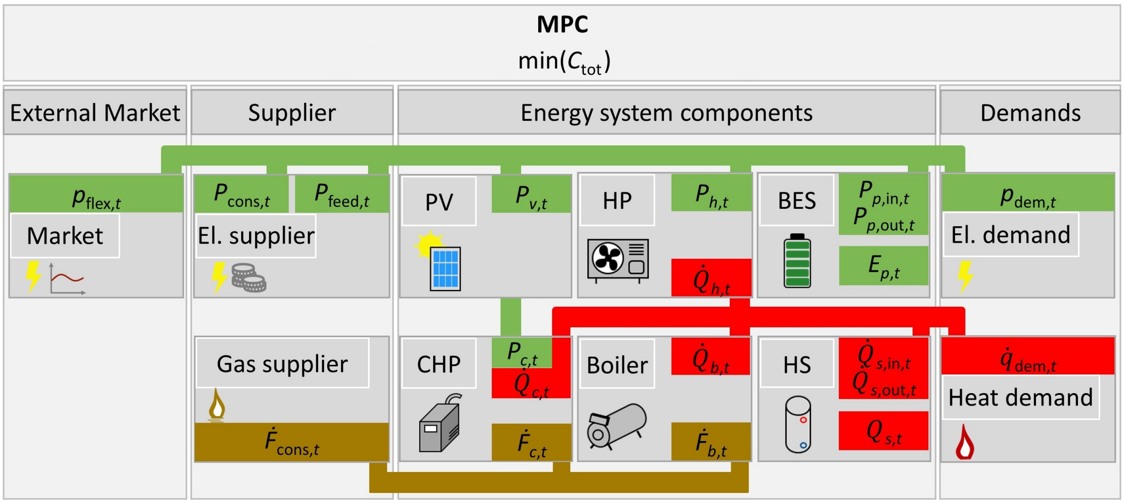

Fig. 2 Design of the energy system model, the MPC, and the flexibility market.

the thermal demand of production processes, offices and production halls. In this investigation the demands can not be shifted, as the shifting of industrial processes is very company specific, making the comparison between different energy system layouts difficult. The price for the needed electricity from the grid and the gas supply in section *Supplier* are also modeled as fixed time-varying profiles, depending on the investigated tariff. On the far left in section *External Market*, a flexibility market is attached to the electricity balance, requesting flex power from the energy system model. All forecast are assumed to be known under perfect foresight.

A detailed description of the energy system components is given in the following. Parameters are written in lowercase letters, while optimization variables are written in uppercase letter. All variables are positive continuous, except of C_{tot} and $C_{\text{tot},t}$, which can also be negative. Operation variables Y represent binaries.

The boilers are described by their gas consumption $\dot{F}_{b,t}$ and thermal production $\dot{Q}_{b,t}$ at time t as well as their thermal efficiency factor η_b, maximum power $\dot{q}_{b,\max}$ and minimum part load $\lambda_{b,\text{part}}$.

$$\dot{Q}_{b,t} = \eta_b \; \dot{F}_{b,t} \tag{1}$$
$$\dot{Q}_{b,t} \leq \dot{q}_{b,\max} \; Y_{b,t} \tag{2}$$
$$\dot{Q}_{b,t} \geq \dot{q}_{b,\max} \; Y_{b,t} \; \lambda_{b,\text{part}} \tag{3}$$

Similar, the CHPs are described by their gas consumption $\dot{F}_{c,t}$, thermal efficiency factor $\eta_{c,\text{th}}$, thermal production $\dot{Q}_{c,t}$ and the minimum part load $\lambda_{c,\text{part}}$. In addition, their electric efficiency factor $\eta_{c,\text{el}}$ is used to describe the produced electricity $P_{c,t}$.

$$P_{c,t} = \eta_{c,\text{el}} \; \dot{F}_{c,t} \tag{4}$$
$$\dot{Q}_{c,t} = \eta_{c,\text{th}} \; \dot{F}_{c,t} \tag{5}$$
$$P_{c,t} \leq p_{c,\max} \; Y_{c,t} \tag{6}$$
$$P_{c,t} \geq p_{c,\max} \; Y_{c,t} \; \lambda_{c,\text{part}} \tag{7}$$

The heat pumps are described by the coefficient of performance (COP) and the thermal efficiency η_h. The COP is calculated using the current outside temperature $T_{h,\text{source},t}$ and the target temperature $T_{h,\text{target}}$ of the system. The additional temperature spread ΔT_{tech} represents the heat transfer delta inside the heat pump [41].

$$\dot{Q}_{h,t} = \mathrm{cop}_{h,t}\ \eta_h\ P_{h,t} \tag{8}$$

$$\dot{Q}_{h,t} \leq \dot{q}_{h,\max}\ Y_{h,t} \tag{9}$$

$$\dot{Q}_{h,t} \geq \dot{q}_{h,\max}\ Y_{h,t}\ \lambda_{h,\mathrm{part}} \tag{10}$$

$$\mathrm{cop}_{h,t} = \frac{t_{h,\mathrm{target}} + \Delta t_{\mathrm{tech}}}{t_{h,\mathrm{target}} - t_{h,\mathrm{source},t} + 2\Delta t_{\mathrm{tech}}} \tag{11}$$

The produced electricity $P_{v,t}$ of a PV field is calculated by an electricity profile $p_{v,\mathrm{profile},t}$ per installed peak power ($\mathrm{kW_p}$) and the actual installed peak power $p_{v,\mathrm{cap}}$. The profile includes a weather profile of a reference year, as well as an efficiency factor of a state of the art PV panel.

$$P_{v,t} = p_{v,\mathrm{profile},t}\ p_{v,\mathrm{cap}} \tag{12}$$

The current charging levels of the heat storage units are described by the variable $Q_{s,t}$. Charging and discharging powers are described by the variables $\dot{Q}_{s,\mathrm{in},t}$ and $\dot{Q}_{s,\mathrm{out},t}$. The charging and discharging processes are provided with the efficiency factor $\eta_{s,\mathrm{cycle}}$. A storage efficiency $\eta_{s,\mathrm{time}}$ represents the cooling process of the storage units over time. To prohibit an energy dissipation by utilizing the charging and discharging efficiencies, the two mutually exclusive binary decision variables $Y_{s,\mathrm{in},t}$ and $Y_{s,\mathrm{out},t}$ are introduced, together with the maximum power $\dot{q}_{s,\max}$.

$$\begin{aligned} Q_{s,t+1} = {} & Q_{s,t}\ \eta_{s,\mathrm{time}} \\ & + \left(\dot{Q}_{s,\mathrm{in},t}\ \eta_{s,\mathrm{cycle}} - \frac{\dot{Q}_{s,\mathrm{out},t}}{\eta_{s,\mathrm{cycle}}} \right)\ \Delta t \end{aligned} \tag{13}$$

$$\dot{Q}_{s,\mathrm{in},t} \leq \dot{q}_{s,\max}\ Y_{s,\mathrm{in},t} \tag{14}$$

$$\dot{Q}_{s,\mathrm{out},t} \leq \dot{q}_{s,\max}\ Y_{s,\mathrm{out},t} \tag{15}$$

$$Q_{s,t} \leq q_{s,\max} \tag{16}$$

$$1 \geq Y_{s,\mathrm{in},t} + Y_{s,\mathrm{out},t} \tag{17}$$

The BES are formulated analogous to the heat storage units. Instead of heat, the electricity $E_{p,t}$ is stored.

$$\begin{aligned} E_{p,t+1} = {} & E_{p,t}\ \eta_{p,\mathrm{time}} \\ & + \left(P_{p,\mathrm{in},t}\ \eta_{p,\mathrm{cycle}} - \frac{P_{p,\mathrm{out},t}}{\eta_{p,\mathrm{cycle}}} \right)\ \Delta t \end{aligned} \tag{18}$$

$$P_{p,\mathrm{in},t} \leq p_{p,\max}\ Y_{p,\mathrm{in},t} \tag{19}$$

$$P_{p,\mathrm{out},t} \leq p_{p,\max}\ Y_{p,\mathrm{out},t} \tag{20}$$

$$E_{p,t} \leq e_{p,\max} \tag{21}$$

$$1 \geq Y_{p,\mathrm{in},t} + Y_{p,\mathrm{out},t} \tag{22}$$

The electricity balance contains the sum of all electricity produced and consumed in the energy system. It is used to calculate the amount that needs to be covered from the electric grid $P_{\mathrm{cons},t}$ as well as the feed into the grid $P_{\mathrm{feed},t}$. The demand $p_{\mathrm{dem},t}$ is the electricity demand of the company.

$$\begin{aligned} p_{\mathrm{dem},t} = {} & P_{\mathrm{cons},t} - P_{\mathrm{feed},t} \\ & - \sum_{h \in H} P_{h,t} + \sum_{v \in V} P_{v,t} + \sum_{c \in C} P_{c,t} \\ & - \sum_{p \in P} \left(P_{p,\mathrm{in},t} - P_{p,\mathrm{out},t} \right) \end{aligned} \tag{23}$$

Analogous, the thermal balance contains all thermal producers, consumers and the storage units of the energy system.

$$\begin{aligned}\dot{q}_{\text{dem},t} = & \sum_{b \in B} \dot{Q}_{b,t} + \sum_{c \in C} \dot{Q}_{c,t} + \sum_{h \in H} \dot{Q}_{h,t} \\ & + \sum_{s \in S} \left(\dot{Q}_{s,\text{out},t} - \dot{Q}_{s,\text{in},t} \right)\end{aligned} \tag{24}$$

The fuel balance contains the overall gas consumption $\dot{F}_{\text{cons},t}$ of the energy system components.

$$\dot{F}_{\text{cons},t} = \sum_{b \in B} \dot{F}_{b,t} + \sum_{c \in C} \dot{F}_{c,t} \tag{25}$$

To minimize the total costs of the energy system operation while meeting the demands of the industry company, an OCP is formulated. The objective of the OCP contains the total costs C_{tot} of the energy system, consisting of fuel costs, electricity procurement costs, electricity feed-in payments as well as wear costs of the battery within the selected forecast time frame T. The previous introduced energy system component Equations (1)-(25) are included as constraints.

$$\text{minimize} \quad C_{\text{tot}} \tag{26}$$

$$\text{subect to} \quad (1) - (25) \tag{27}$$

$$C_{\text{tot}} = \sum_{t \in T} C_{\text{tot,t}} \tag{28}$$

$$\begin{aligned}C_{\text{tot,t}} = & \ \dot{F}_{\text{cons},t} \ c_{\text{gas,var}} \\ & + P_{\text{cons},t} \ c_{\text{el,buy},t} \\ & - P_{\text{feed},t} \ c_{\text{el,sell},t} \\ & + \sum_{p \in P} \left(P_{p,\text{in},t} \ c_{p,\text{wear}} \right)\end{aligned} \tag{29}$$

2.2. Model predictive control

To simulate a MPC-control of the energy system, the introduced OCP is solved in iterations $i \in I$ at a step size of $\Delta i_{\text{stepsize}}$. This leads to a closed loop MPC simulation as shown in Fig. 3. In this case, the rolling horizon step size matches the step size $\Delta t_{\text{stepsize}}$ of the OCP, wherefore the charging levels of the storage units in, e.g., optimization step $i = 0$ at time $t = 1$ are used as starting conditions $t = 0$ in the next optimization step $i = 1$ and so forth. The control signals from every step i at time $t = 0$ and the charging levels at $t = 1$ then add up to the resulting control schedule and the corresponding costs as formulated in Eq. (30).

$$C_{\text{ref}} = \sum_{i \in I} C_{\text{tot},0} \tag{30}$$

2.3. Flexibility request

Flexibility requests are assumed to be published by either the DSO or market participants, asking for a change in the planned electricity consumption from the grid or feed in into the grid. To calculate the change in electricity consumption by the energy system, the following methodology is used:

If a flexibility request for positive or negative power at a certain point in time is received, the current control schedule of the energy system is recalculated together with the additional requested flex demand $p_{\text{flex},t}$. To do so, the current planned optimal electricity consumption $P_{\text{cons},t}$ and feed into the grid $P_{\text{feed},t}$ is used as reference and depending on the flex demand added or subtracted by the flex amount $p_{\text{flex},t}$ as in Eq. (31)-(32). A positive flex demand is represented as a reduction in consumption or an increase in feeding

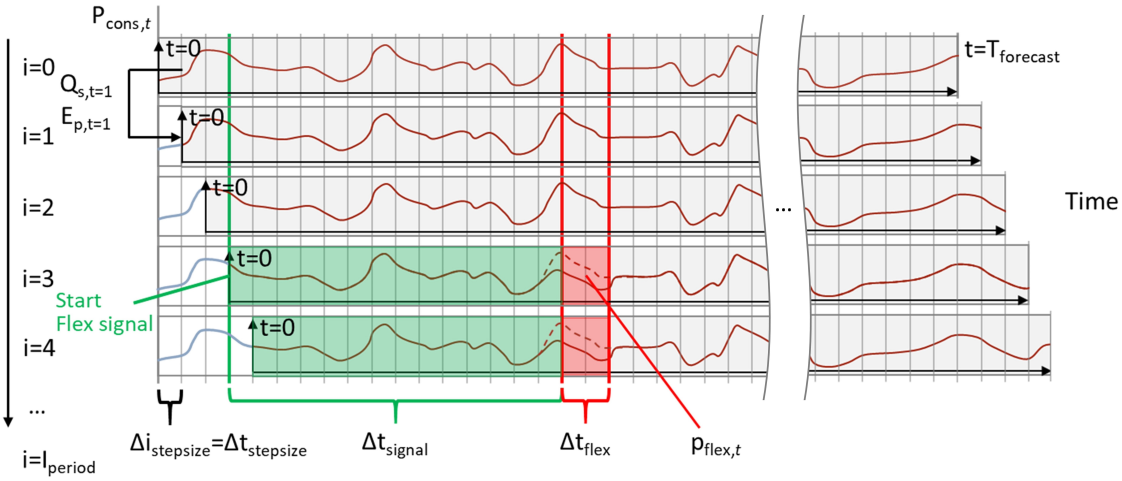

Fig. 3 Rescheduling of the electricity consumption from the grid due to a flexibility request.

into the electric grid, while a negative demand is represented by an increase in consumption or a reduction of feeding into the electric grid.

$$\begin{aligned}
&\text{if } P_{\text{feed},t} - P_{\text{cons},t} + p_{\text{flex},t} \geq 0 : \\
&\qquad p_{\text{feed},t,\text{new}} = P_{\text{feed},t} - P_{\text{cons},t} + p_{\text{flex},t} \qquad (31)\\
&\qquad p_{\text{cons},t,\text{new}} = 0 \\
&\text{else if } P_{\text{feed},t} - P_{\text{cons},t} + p_{\text{flex},t} < 0 : \\
&\qquad p_{\text{feed},t,\text{new}} = 0 \qquad (32)\\
&\qquad p_{\text{cons},t,\text{new}} = P_{\text{cons},t} - P_{\text{feed},t} - p_{\text{flex},t}
\end{aligned}$$

The calculated new grid feed $p_{\text{feed},t,\text{new}}$ and consumption $p_{\text{cons},t,\text{new}}$ is then set as two additional constraints in the energy system OCP, depending on the direction of the requested power $p_{\text{flex,t}}$ as in Eq. (33)-(36). The equations force the energy system to either consume more or less power from the grid, or feed in more or less power into the grid, respectively. Since the equations only consist of greater-equal or less-equal constraints, the energy system is also free to provide more than just the minimum requested power-change. This exceeding in delivery is tolerated, to enable energy system components with e.g. a minimum part load to deliver flex power.

$$\text{if } \; p_{\text{flex,t}} > 0 :$$

$$P_{\text{cons},t} \leq p_{\text{cons},t,\text{new}} \tag{33}$$

$$P_{\text{feed},t} \geq p_{\text{feed},t,\text{new}} \tag{34}$$

$$\text{else if } \; p_{\text{flex,t}} < 0 :$$

$$P_{\text{cons},t} \geq p_{\text{cons},t,\text{new}} \tag{35}$$

$$P_{\text{feed},t} \leq p_{\text{feed},t,\text{new}} \tag{36}$$

Depending on the signal lead time Δt_{signal}, the recalculation of the new electricity consumption/feeds is conducted at different iteration steps i before the flex delivery. Fig. 3 shows the concrete example of a negative flex demand $p_{\text{flex},t}$, with a signal lead time Δt_{signal} of 14 hours and a flex demand duration Δt_{flex} of 2 hours.

Since the delivering flex power shifts the energy system operation from its previous planned optimum conditions, the operational costs increase [32]. This increased in operational costs are the minimum that must be charged at a market, to compensate for the additional expenses. To calculate these additional cost, a reference run without a flex request as in Eq. (30) is carried out first. After that, a run with a specific flex demand $p_{\text{flex},t}$, signal lead time Δt_{signal} and duration Δt_{flex} is conducted. The costs are then subtracted from the reference run, to obtain the additional costs of the provided flex demand.

$$\begin{aligned} &C_{\text{flex}}(\Delta t_{\text{signal}}, \Delta t_{\text{flex},}, p_{\text{flex},t}, I) = \\ &C_{\text{tot}}(\Delta t_{\text{signal}}, \Delta t_{\text{flex},}, p_{\text{flex},t}, I) \; - C_{\text{ref}} \end{aligned} \tag{37}$$

Before, during, and after a flexibility delivery, the charging levels of the storage units $\sum_{s \in S} Q_{s,t}$ and $\sum_{e \in E} E_{p,t}$ deviate from the original optimized fill level schedule. This leads to a different optimal operation of the energy system, which is widely known as prebound and rebound effect. Therefore, to catch all long-term operational changes, the investigated time period I must be chosen long enough, to include both time frames $\Delta t_{\text{prebound}}$ and $\Delta t_{\text{rebound}}$ as shown in Fig. 4.

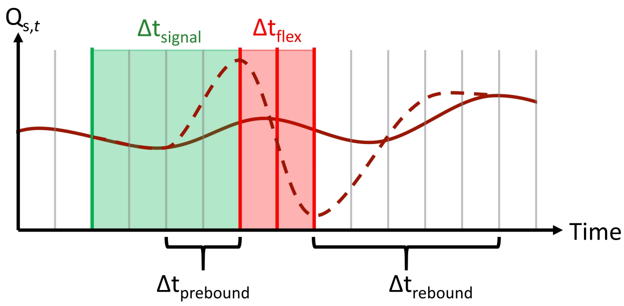

Fig. 4 Prebound $\Delta t_{\text{prebound}}$ and rebound $\Delta t_{\text{rebound}}$ time of the energy system storage.

2.4. Case study

The sample energy system structure as well as the load profiles stem from a company in the south of Germany. The company has an annual electrical demand of about 8 GWh and a thermal demand of around 7.5 GWh. The electric demand stems mostly from machine tools, computers and lighting. The thermal demand is mainly used to heat the office buildings and the production halls. The energy system consists of three boilers, a CHP, and a thermal storage. The model parameters can be found in the following Tab. 2. While the price of gas is fixed, the electricity price depends on the selected scenario. The scenarios are: a flat tariff with 14 ct/kWh as well as a time of use tariff with hourly prices from the pre-COVID-19 pandemic electricity spot market of Germany in 2019. The used spot market data stem from the Bundesnetzagentur/SMARD [42].

The MPC of the energy system is assumed to have a 48 hours forecast horizon $T \in \{0, .., 47\}$, which is updated on an hourly basis. To catch all long-term cost effects of the flex signal on the system operation (Fig. 4), a time period of three days $I \in \{0, .., 71\}$ is used. All demand forecasts as well as the charging level of the thermal storage are assumed to be known under perfect foresight.

The energy system formulation is written in Python 3.8 using the commercial Gurobipy interface. To solve the OCP, the solver Gurobi on version 9.1.1 is used [43]. On average, a calculation of one example day with the forecast horizon of 48 hours, 25 different signal lead times, 24 flex powers and 5 demand durations took about 12 hours on a 3.2 GHz quad core CPU.

Parameter	**Symbol**	**Value**	**Unit**
	General		
Gas price	$c_{\text{gas,var}}$	0.019	€/kWh
	Boiler		
Nominal thermal power	$\sum_{b\in B}\dot{q}_{b,\max}$	6200	kW
Average efficiency	η_b	0.935	
Minimum part load	$\lambda_{b,\text{part}}$	0.1	
	CHP		
Nominal electric power	$\sum_{c\in C}p_{c,\max}$	240	kW
Electric efficiency	$\eta_{c,\text{el}}$	0.359	
Thermal efficiency	$\eta_{c,\text{th}}$	0.559	
Minimum part load	$\lambda_{c,\text{part}}$	0.5	
	Thermal storage		
Storage capacity	$\sum_{s\in S}q_{s,\max}$	300	kWh
Charge/discharge power	$\dot{q}_{s,\max}$	300	kW
Charge/discharge eff.	$\eta_{s,\text{cycle}}$	0.998	
Storage efficiency	$\eta_{s,\text{time}}$	0.998	1/h

Tab. 2 Parameters of the sample energy system.

3. Results

First, the energy system operation and the flex power depending operation cost curves similar to [32] are presented in Subsection 3.1. Then, a new developed flexibility heatmap showing an extensive view of the flexibility costs depending on flex power and signal lead time is introduced in Subsection 3.2. Afterwards, to investigate the flexibility performance of the energy system under different conditions, multiple influencing factors are varied and evaluated in the Subsections 3.3 to 3.5. Finally, to quantify the impact of the ongoing electrification of the heat supply on the lead time, the energy system design is changed to two modern HP designs and evaluated in the same fashion as the CHP design in Subsection 3.6.

3.1. Energy system operation and cost curves

At first, the flex power on a typical spring evening with low thermal loads and high outside temperatures as usually recorded during this season is investigated. For this, multiple flex signal requests with a lead time between 0 and 24 hours are sent to the energy system. The requested flex power varies in 20 kW steps between -240 kW and 240 kW, which matches the maximum output power change of the CHP. The duration of the requested flex powers ranges from one to four hours.

As a result of the requested flex power, we receive the cost curves of a 2 hour flexibility demand as shown in Fig. 5. The plot resembles the flexibility cost curves known from other investigations like De Coninck et al., where increasing flex power leads to increasing flexibility costs per kWh [33, 32]. However, unlike the investigations in the literature, the presented cost curves do not increase steadily due to minimum part loads of the energy system components. This can be seen at the rapid rising costs of flex power around -40 kW, where the boilers are activated with a minimum part load of 10%. The end of each cost curve (e.g. -120 kW) represents the maximum available flex power of the energy system.

Looking at the price differences between the signal lead time of 1 hour (blue) and 3 hours (orange) in Fig. 5, it is noticeable that the costs of providing flex power are significantly higher if the signal lead time is shorter. Particularly in the case of positive power, providing flex power with only 1 hour of lead time costs three times more than providing it with 3 hours of lead time. The reason for the much higher costs can be found in Fig. 6. The figure shows the control strategy and storage charging levels of the energy system with the signal lead time of 1 and 3 hours, at a flex power of 60 kW and -60 kW. Looking at the flex power case of 60 kW, it can be seen how the MPC tries to reduce the charging level of the thermal storage units at the beginning of time step 8, so that the excessive thermal production of the CHP in time step 8 and 9 can be

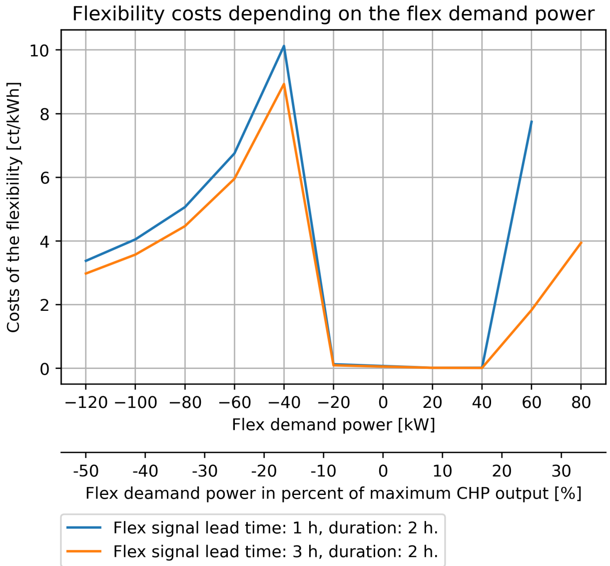

Fig. 5 Flexibility costs of the sample energy system depending on the flex demand power and the signal lead time for a 2 hour flex demand duration on a spring evening.

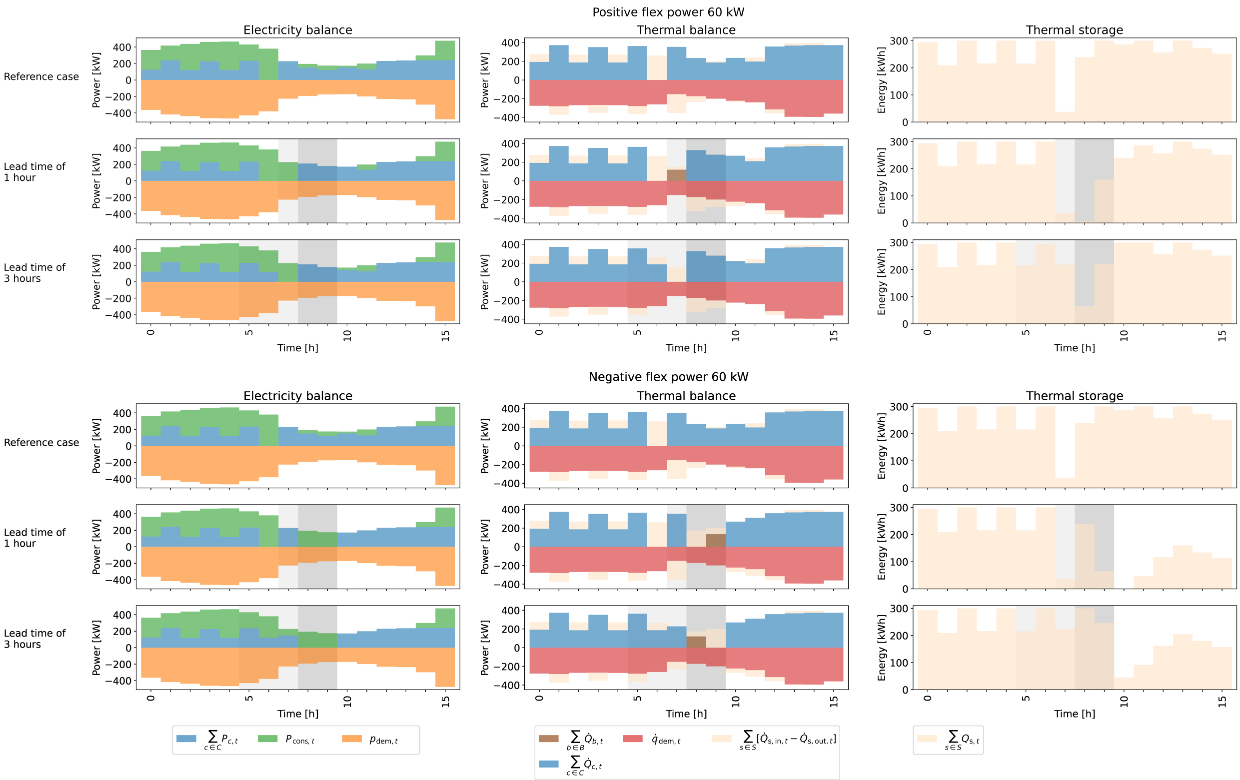

Fig. 6 Control strategy of the sample energy system on a spring evening. The light gray marked boxes represent the time frame of the signal lead time, the dark gray boxes represent the time of the flex power delivery.

captured. To reach that goal, the CHP, which is the most economical option for providing electricity and thermal power, must run at a lower power level in the preceding hours. However, with a lead time of 1 hour the CHP can only be turned off since it has a minimum part load of 50 %, leading to an activation of the boilers. Meanwhile with a lead time of 3 hours, the CHP can run at low power in advance, enabling the system to adapt the storage without the use of the boilers. For the same reason, only with a signal lead time of 3 hours a flex power of 80 kW can be offered, to have enough time to sufficiently discharge the thermal storage units.

Conversely in the negative flexibility case, the CHP is running at a higher power level in advance to the requested negative flex power, to charge the storage as much as possible. This can be seen at the storage differences in time step 8, where the storage is fully loaded in the 3 hour lead time case, while in the 1 hour lead time case it did not have enough time to charge the storage completely. On the cost side (Fig. 5), the maximum utilization of the storage due to the higher lead time is reached at -40 kW, as can be seen as the cost curves start proceeding parallel.

3.2. Flexibility heatmap

To gain more detailed information of the development of the flex power cost depending on the signal lead time, a new flexibility heatmap (Fig. 7) is introduced. As shown in Fig. 5, the cost development of rising flexibility demand can be found by reading the heatmap vertically. The prices are therefore represented by a color scale from yellow (lower costs per kWh) to red (higher costs per kWh). Looking at the heatmap horizontally, the cost effects of the signal lead time can be investigated. Grey checked boxes show the limits of the available flex power.

Reading the flexibility heatmap horizontally from left to right, it is noticeable how the flex power price ceases to change beyond a certain lead time. In the present case of a typical spring evening and a common CHP + boiler energy system with a flat electricity tariff, this stop in change occurs at a signal lead time of 3 hours. With this lead time the thermal storage units of the energy system are optimally prepared for all possible flex demands, resulting in the lowest possible flex costs and the shortest optimal lead time for this specific case. The availability of negative flexibility is independent of the lead time, as the boilers can replace the thermal production of the CHP. However, positive flex power requires lead time to discharge the storage units in order to capture the excessive thermal power of the CHP.

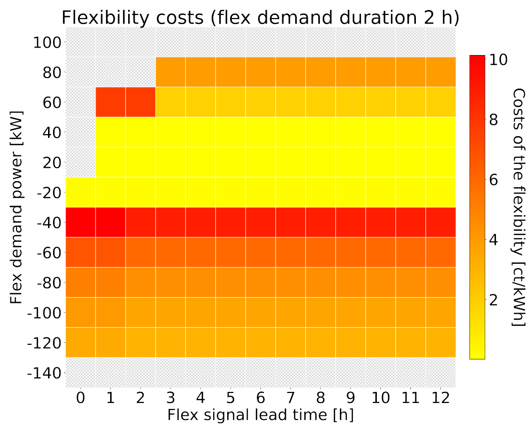

Fig. 7 Flexibility heatmap showing flexibility costs of the sample energy system depending on requested flex power and signal lead time on a spring evening.

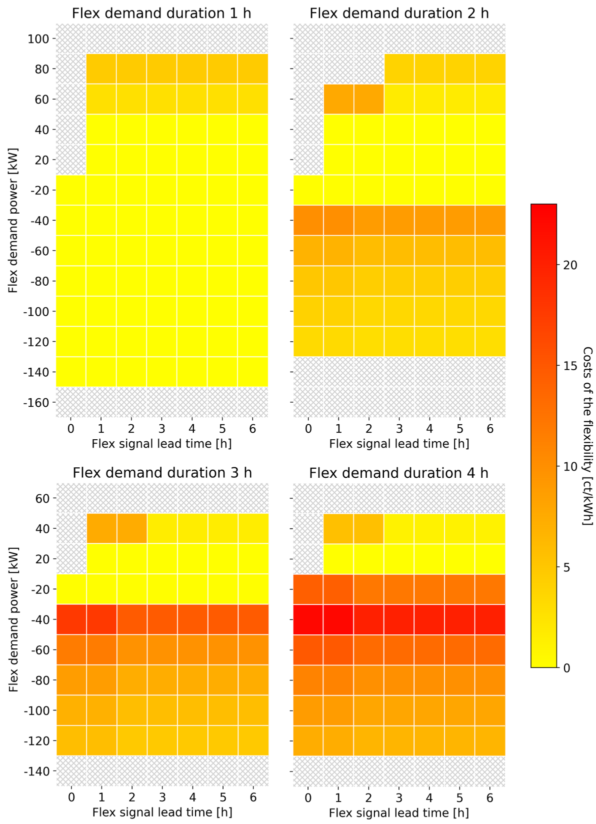

Fig. 8 Flexibility costs of the sample energy system depending on the flex demand duration on a spring evening.

3.3. The influence of the flex demand duration

Fig. 8 shows the flexibility heatmaps of 4 flex demand durations between 1 to 4 hours. Similar to rising flex power, the respective costs per kWh as well as the benefits of higher signal lead times increase with rising flex duration. Even smaller flex powers like, e.g., -40 kW which only cost a fraction of a cent per kWh during a duration of 1 hour, cost 10 cents per kWh in the case of a duration of 2 hours and 25 cents per kWh in the case of 3 or more hours. Furthermore, the required lead time for a positive flex power of 80 kW increases from 1 to 3 hours, if the duration changes from 1 to 2 hours. Additionally, a rising flex demand duration decreases the available flex power in general, since the requested flex power of the CHP accumulates over time and therefore empties/overcharges the storage units at already lower power levels.

3.4. The influence of the daytime and the time of the year

The previous introduced signal lead time evaluation only focuses on one specific point in time. To get a better overview of the system behavior, 3 additional points in time are investigated in the following, differing in both daytime and the time of the year. Please note, that in Fig. 9 all 3 plots are in different scales, to improve readability.

3.4.1. Summer day

Fig. 9 a) shows the flexibility heatmap for a typical warm summer day, which is characterized by a low thermal demand and a high electricity demand of the company. Accordingly, the CHP is operating on a part-load level, whereby positive as well as negative flex power can be delivered. The negative flex power can be provided at all lead times, but the price drops significantly with a signal lead time of 1 hour or more. This is due to the time required to charge the thermal storage units with the cheaper heat from the CHP

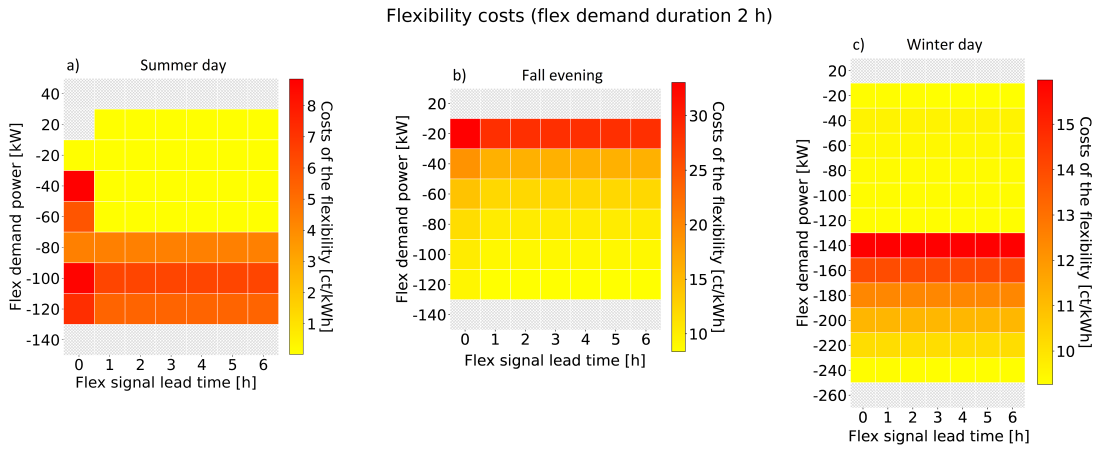

Fig. 9 Flexibility costs of the sample energy system depending on the daytime and time of the year.

instead of the boilers, as can be seen in Appendix A1. Furthermore, the positive flex power can only be provided if known 1 hour ahead, which is again due to the longer operation of the CHP and the therefore required extra free thermal capacity in the thermal storage units.

3.4.2. Fall evening

Fig. 9 b) shows the flexibility heatmap for a typical fall evening scenario. Due to the colder weather and the therefore moderate thermal demand, the CHP is mostly in full operation, preventing a further increase in power for providing positive flexibility. Furthermore, the costs of little negative flex power are high due to the minimum part load of the boilers, which instantly need to be turned on if less thermal power is provided by the CHP. Despite the high costs in general, the costs for negative flex power still shows slight changes if known 1 hour ahead, which is due to minimal optimized storage charging levels by the CHP.

3.4.3. Winter day

Fig. 9 c) shows the flexibility heatmap for a typical winter case scenario during the day. Due to the usually low ambient temperatures and the therefore high thermal demand, the CHP is constantly running at full power, being unable to offer any positive flex power or achieving (cost) advantages of signal lead times. For the same reason, even smallest amounts of negative flex power result in high costs, since the reduced thermal power of the CHP needs to be instantly compensated by a boiler. At -140 kW a second boiler needs to be turned on, which can be seen by the rapidly rising costs of flexibility.

Comparing the four different times of the year, it is noticeable how mostly in spring and summer a signal lead time between 1 and 3 hours is optimal for providing flexibility. This is due to the fact, that most of the today installed CHPs have been designed for an economic base load operation with little thermal storage units, which therefore lead to only little flexibility. Nevertheless, even for this energy system which was not designed for energy flexibility, a signal lead time of 3 hours decreases the cost in spring by up to 8 cents per kWh.

3.5. The influence of the electricity tariffs

The influence of the electricity tariff on cost and optimal signal lead time can be seen in Fig. 10, where a typical warm spring evening is being analyzed with (a) a fixed and (b) a variable electricity tariff. The signal lead time increases from 1 hour on the fixed electricity tariff to 2 hours on the variable tariff. Additionally, the price of flexibility rises up to 15 ct/kWh on the variable electricity tariff, since the energy system is already using its storage flexibility on the variable electricity tariff and therefore has to run on less profitable hours, if flex power is requested. Comparing the available flex power from a preparation time of 2 hours and more, both electricity tariffs offer the same flex power band width again. In this case the flex power band width of the variable electricity tariff is shifted by -40 kW, which is caused by the deviant price condition.

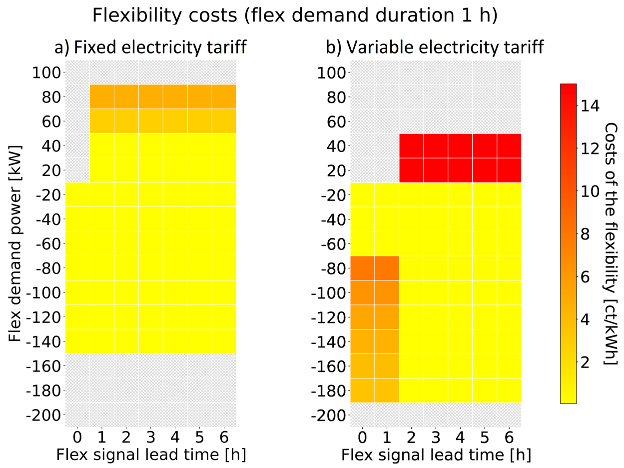

Fig. 10 Flexibility costs of the sample energy system depending on the electricity tariff on a spring evening.

3.6. *The influence of the changing energy system designs*

Due to the plan of the EU to gain carbon neutrality by 2050 and the discussions regarding new laws to shift the heat supply to renewable sources through the implementation of heat pumps, the energy systems designs are currently rapidly changing [44, 45]. Therefore, to consider future changes in energy system designs and to examine their availability of flex power, the two high temperature heat pump systems: HP + HS and HP + HS + PV + BES are introduced (see Fig. 11) and investigated in the same fashion as the CHP system. The energy system designs have been designed by a Mixed Integer Linear Program (MILP) similar to Bohlayer et al. [40] and adapted to the electricity and thermal demand of the presented company. The resulting parameters of the models can be found in Tab. 3 and 4. The source temperature $T_{h,\text{source},t}$ of the heat pumps are the ambient temperature of the closest weather station of the Deutsche Wetterdienst [46].

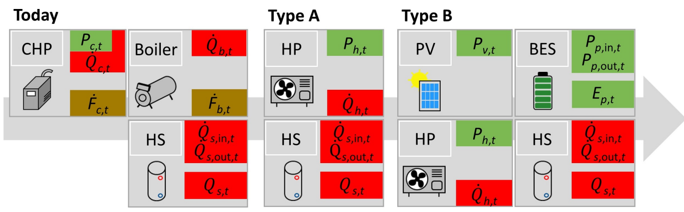

Fig. 11 Design change of future energy systems.

3.6.1. *Type A - HP and HS*

Fig. 12 shows the flexibility costs of the HP + HS energy system on (a) the summer day and (b) the winter day introduced in Subsection 3.4.1 and 3.4.3 in combination with a fixed electricity tariff. As can be seen, different from the CHP design considered in the previous sections, the HP system design increases the available energy flexibility significantly due to the large dimensioning of the HP and HS.

Looking at the summer day, the HP is shut down due to the little thermal demand of the company and can therefore only offer negative flex power. Furthermore, due to the fixed electricity tariff and only little changes in the ambient temperature, the availability and costs of negative flex power do not depend on the signal lead time. Only the losses of the thermal storage which occur by shifting the thermal production of the HP to different times determine the flexibility costs. This can be seen by the rising flexibility costs with rising flex power and by comparing the low thermal demand summer day with the high thermal demand

Parameter	Symbol	Value	Unit
	HP		
Nominal thermal power	$\sum_{h\in H} \dot{q}_{h,\max}$	4800	kW
Target temperature	$t_{h,\text{target}}$	75	°C
Temperature delta	Δt_{tech}	5	K
Minimum part load	$\lambda_{h,\text{part}}$	0.1	
Thermal efficiency	η_h	0.6	
	Thermal storage		
Storage capacity	$\sum_{s\in S} q_{s,\max}$	5800	kWh
Charge/discharge power	$\dot{q}_{s,\max}$	2900	kW
Charge/discharge eff.	$\eta_{s,\text{cycle}}$	0.998	
Storage efficiency	$\eta_{s,\text{time}}$	0.998	1/h

Tab. 3 Parameters energy system Type A and B.

Parameter	Symbol	Value	Unit
	PV		
Installed capacity	$p_{v,\text{cap}}$	400	kW_p
	BES		
Storage capacity	$\sum_{p\in P} e_{p,\max}$	1000	kWh
Charge/discharge power	$p_{p,\max}$	700	kW
Charge/discharge eff.	$\eta_{p,\text{cycle}}$	0.98	
Storage efficiency	$\eta_{p,\text{time}}$	0.999	1/h

Tab. 4 PV and BES parameters energy system Type B.

winter day. Nevertheless, both cases result in a cheap way of shifting the energy consumption for flex power delivery, compared to the much higher costs of up to 16 ct/kWh in the CHP design.

On the winter day, negative as well as positive flex power can be provided. However, the positive flexibility can only be achieved through lead time, because the reduced energy consumption from the grid can only be provided by producing the future thermal demand in advance and storing it in the heat storage. In this specific case, a lead time of 2 hours for positive flex power is leading to an optimal flexibility provision.

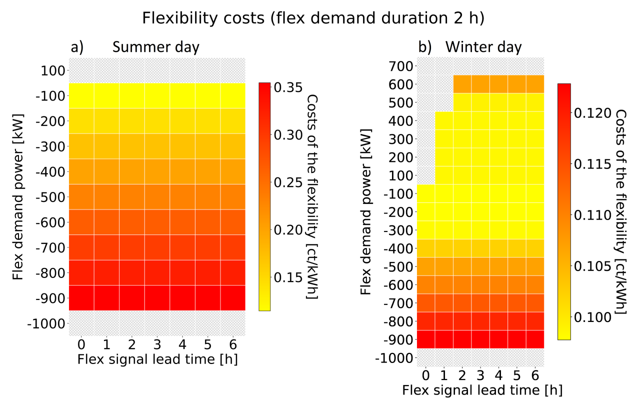

Fig. 12 Flexibility costs of energy system Type A on a summer and winter day.

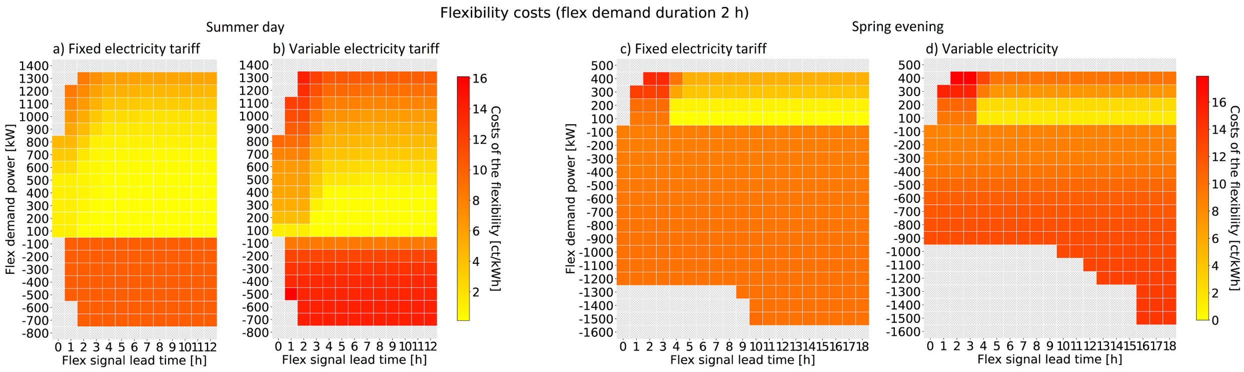

Fig. 13 Flexibility costs of energy system Type B on a summer day and a spring evening.

3.6.2. *Type B - HP, HS, PV, and BES*

Fig. 13 shows the flexibility costs of system Type B on a spring evening and a summer day, both for a fixed and a variable electricity tariff. As can be seen, the additional PV and BES increase flex power availability, but also raise flexibility costs.

In the case of a typical summer day, the price of flex power varies between 0.1 and 16 ct/kWh. While the price of negative flex power is constant, the price of positive flex power decreases gradually with increasing lead time. The reason for the degrading costs can be found in Fig. A2, which shows the operation schedule of a positive power request of 500 kW with 1 and 6 hours lead time at a variable electricity tariff. As can be seen at a signal lead time of 1 hour, the power flexibility is mostly provided by the changing charging operation of the battery. However, with a signal lead time of 6 hours, the thermal storage in combination with the HP is used. This change from the relative expensive battery to the cheaper heat storage occurs gradually with increasing lead time, which leads to the presented costs profile.

Looking at a request of positive 200 kW flex power in the spring evening, it is noticeable how the price rapidly changes from around 12 cent per kWh to nearly 0 cent per kWh. The reason for that can be found in Fig. A3, which shows a delayed and therefore advantageous charge/discharge behavior of the battery, if the requested flex power is known at least 4 hours ahead. The negative case of more than -1300 kW in the spring evening represents the same pattern as the positive case of the CHP, where an additional operation time of the HP can only be achieved if the storage is empty enough to store the additional amount of thermal energy. In this specific case a lead time of 16 hours is required.

In summary, the optimal lead time increases from 3 hours with the CHP design to 16 hours in the variable electricity tariff case of system Type B. However, the available flex power is increasing enormously and the price of the delivered flex power is less than with the CHP design. The results show the importance of including the ongoing electrification of the heat supply in flexibility markets, since the shift to energy systems with HPs provide large and cheap flexibility potentials if sufficient lead time is given.

4. Conclusion

This paper presented the effects of signal lead time on the availability and cost of industrial flex power on energy markets. For this, an energy system design of a company in the south of Germany has been used to simulate a 48 h rolling horizon MPC of an example CHP system, which is assumed to be connected to an energy market asking for different flex powers with different signal lead times. To evaluate the results, a new flexibility heatmap has been introduced, which shows an extensive overview of the amounts and the corresponding costs of flex power depending on the signal lead time. To investigate various flexibility performances of the energy system, influencing factors such as the requested flex power, the flex demand duration, the electricity tariff and time of the year have been varied and evaluated. Moreover, by using a MILP design optimization considering the demand of the current energy system, two possible future energy system designs for the company have been determined and analyzed in the same fashion as the CHP system.

The results indicate the need of carefully choosing the right signal lead time on market platforms, as energy systems often require at least a 1 hour notice to offer cheap flexibility. The shortest lead time to provide flex power at minimum costs with the present CHP design has been found at 3 hours. Variations of lead time influencing factors show, that an increase in flex power and flex demand duration as well as a change to a variable electricity tariff leads to an increase in optimal signal lead time. Varying the time of the year, it can be summarized that the signal lead time heavily depends on the thermal load of the energy system and the energy system design itself.

Changing the energy system designs towards new HP designs, the results show a great increase in energy system flexibility due to the larger storage capacities. However, to provide the flexibility in a cheap way, signal lead times need to be several hours, to allow a preparation of the cheap thermal storage units. Otherwise the much more expensive BES system is being used or a more expensive operation schedule needs to be realized. Especially in the case of a highly fluctuating electricity tariff, a signal lead time of 16 hours has been found as optimum in this research.

Future work could include a simultaneous use of multiple energy systems with different system designs, in order to test the flexibility availability on a market scale. Furthermore, an all year comparison between the different energy systems and their benefit on a market platform could be investigated.

Declaration of Competing Interest

The authors declare that they have no known competing interests that could have appeared to influence the work presented in this paper.

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Appendix

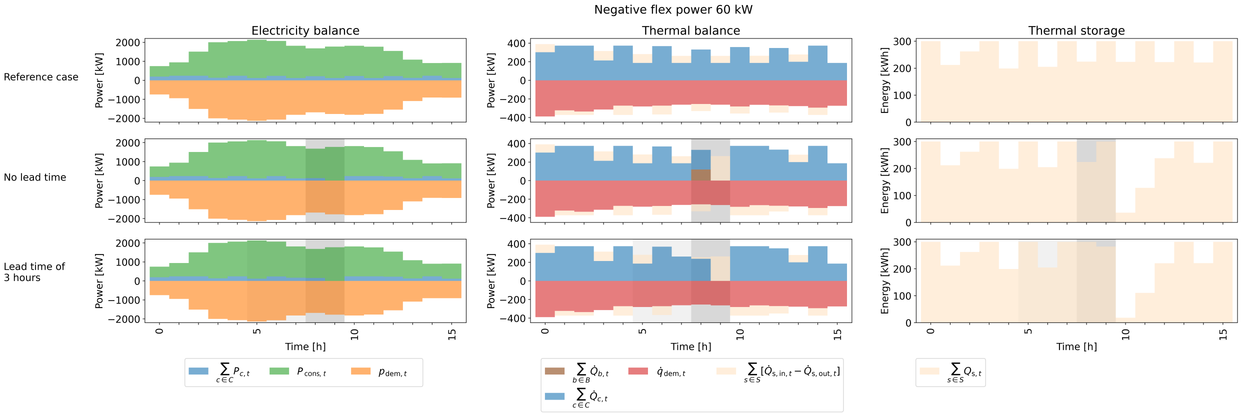

Fig. A1 Control strategy of the sample energy system on a summer day.

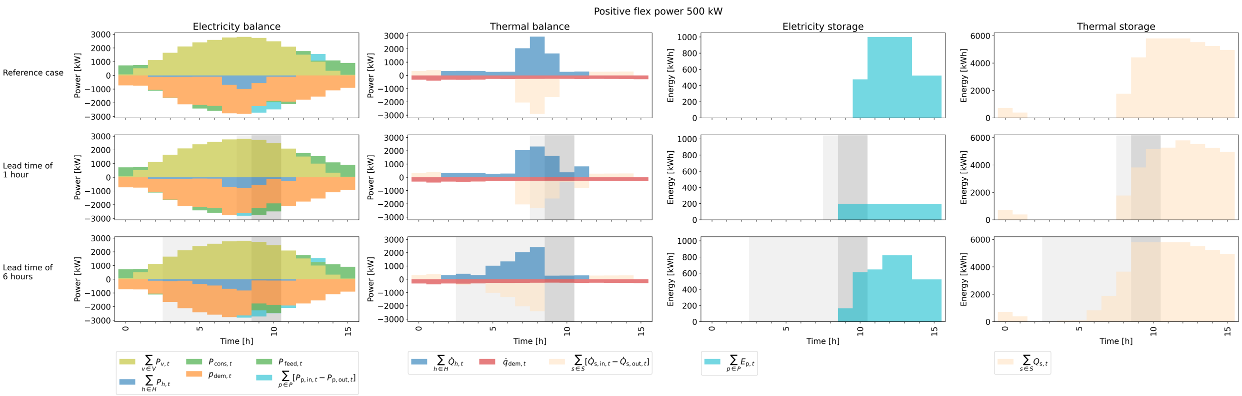

Fig. A2 Control strategy of energy system Type B on a summer day.

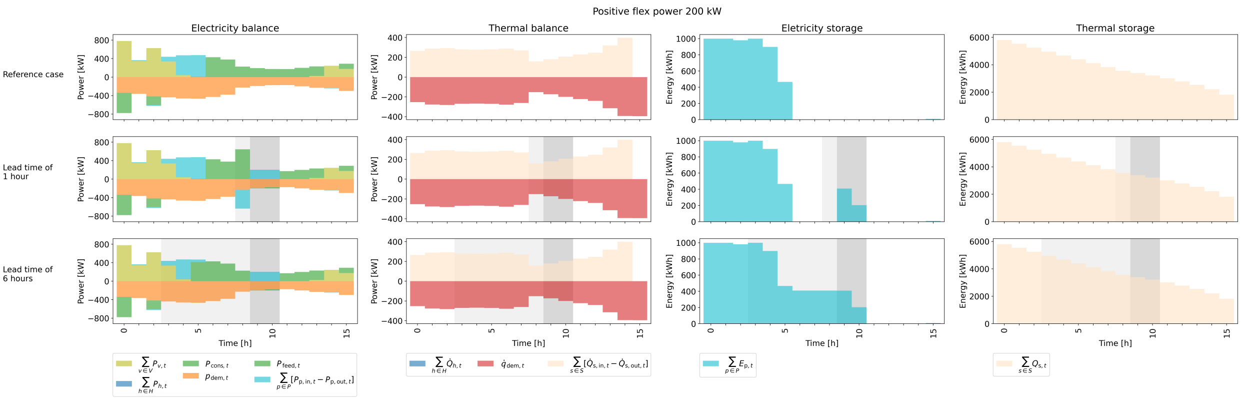

Fig. A3 Control strategy of energy system Type B on a spring evening.