On Decisive Storage Parameters for Minimizing Energy Supply Costs in Multicarrier Energy Systems

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Abstract—Energy storage is one possibility to cope with increasing fluctuating renewable generation in power systems. Especially when considering a number of different energy carriers, synergies enable a reduction in energy supply costs and an increase in operational flexibility. However, the devices have to be selected carefully since installation and operation are generally costly. This paper examines the influence of storage capacity and prediction horizon on the cost optimal multienergy supply of a single-family house and a network of three interconnected houses. Similarities and differences of the two cases are assessed. The energy hub concept is chosen to model the conversion and storage of the energy carriers electricity, gas, and heat. Then, model predictive control is applied to determine the cost optimal control strategy of the available conversion and storage technologies. The results show that storage capacity and the selection of the prediction horizon strongly depend on each other, both in the case of private customers and interconnected houses. Thereby, the prediction horizon is more crucial as it determines the amount of available information to operate the storage devices optimally.

Index Terms—Energy hub, energy storage, model predictive control, multicarrier energy systems, prediction horizon, storage capacity.

I. INTRODUCTION

TODAY’s electricity supply infrastructure is undergoing a number of changes. The existing grid is hierarchically structured due to the centralized production scheme of the last century. However, recently, more and more diverse distributed generation units have been built, resulting in new challenges and opportunities both for large and small plant operators.

The increasing decentralization allows the coupling of different energy carriers and load demands, e.g., via co- and trigeneration plants [1], [2], and enables consumers and providers to be more flexible in their energy purchasing.

However, demand for different energy carriers, e.g., heat and electricity at a cogeneration plant, may not coincide perfectly. Also, load demand and renewable generation often mismatch. Energy storage is one possibility to balance the discrepancy in different load demands and generation [3], and can be applied in a wide range, from private customers to industries and utilities. Nevertheless, the resulting benefits have to pay off the investment costs [4]. But what are the decisive parameters for a beneficial operation of an energy storage device? Are these parameters the same for both utilities and customers, or do they differ? This is important to know to build a prospective energy supply infrastructure that is advantageous for both consumers and suppliers.

The aim of the research presented in this paper is to evaluate the influence of energy storage parameters on the cost optimal multienergy supply. Thereby, two points of view are taken into account to assess similarities and differences: the one of a private household and the one of a utility.

Various research has been carried out with respect to the application of energy storage on utility and private household scale. In [5], an electric thermal storage is used to shift electricity consumption from higher to lower price periods. The results show that the costs can be reduced with increasing storage size if real time pricing applies. For the time of use tariff nearly no influence of the storage size could be observed. The financial attractiveness of energy storage in a private household is examined in [6]. The analysis shows that storage is best applied for a reduction of grid infeed, as the savings on the yearly electricity bill are around two to three times higher than for load shift. Reference [7] investigates the impacts of fixed-size electricity and hot water storage devices on the yearly energy costs of a household, and [8] presents a control algorithm to minimize the electricity and heat costs of a single household, using a heat buffer and a battery energy storage. The combination of energy storage and local renewable energy sources (RES) are widely treated in the literature. In [9], a hydrogen energy storage is combined with a wind turbine to supply a university’s energy demand. The optimum capacity is determined by the wind generation and the load curve. In [10], a phase change material heat storage is used to provide summer solar energy during winter time.

Also, current research effort is addressing the integrated control of combined electricity and natural gas systems [11]–[16]. It is expected that the integrated control of several of such systems yields improved performance. The various energy carriers available and the conversion possible between them significantly affect both the technical and the economical operation of energy systems. In particular, consumers get flexibility in supply and could, therefore, decide in favor of, e.g., cost, system emissions, availability, or a combination.

The research presented in this paper examines the parameters storage capacity and prediction horizon and their effects on energy supply costs. The work is a continuation of [14], where
the couplings between the electricity and gas systems are modeled using the concept of energy hubs. By means of the energy hub modeling framework, distributed generation, storage devices and renewable energy sources can be taken into account. For showing the benefits of coupling several energy carrier systems, a single-family house is considered which uses electricity and natural gas for supplying electric and thermal loads. Also, a three-hub network interconnected by an electricity and gas network is used for demonstration. In both cases, the operation of a micro combined heat and power plant (μCHP) is coupled with an energy storage device, electric or thermal. By optimally using the storage device, it can decouple electric and thermal load supply of the μCHP and thus benefit from price variations in electricity and gas prices. Thereby, the issues of proper prediction and proper storage capacity play an important role when considering optimal operation strategies and minimum operation costs [15], [16]. To assess the point of view of private customers, an optimization problem for determining the optimal power supply of the single-family house is solved. From a network point of view, an optimal power flow (OPF) problem is solved which determines the optimal operation of the three-hub system. In both cases, an optimization over multiple time steps is required as storage devices with dynamic behavior are present.

We choose model predictive control (MPC) [17] as the control algorithm, wherewith system dynamics, forecasts, and operational constraints can be taken into account explicitly. MPC uses an internal model to determine those actions that yield the best predicted system behavior over a certain prediction horizon of length $N$. MPC operates in a receding horizon fashion, i.e., at each time step new system measurements and new predictions into the future are made.

This paper is organized as follows. In Section II, the modeling and optimization frameworks of the energy hub, the single-family house and the three-hub network are presented. The following Section III contains the results of the case studies. Section IV concludes the study and the paper.

II. MODELING AND OPTIMIZATION

A. Energy Hub

An energy hub [14] (Fig. 1) coordinates all conversion and storage technologies available to fulfill a given multienergy load demand. The hub processes a number of different input energy carriers $\mathbf{P}$ to supply the multienergy load $\mathbf{L}$.

Here, load demand $\mathbf{L}$ consists of electricity and heat

$$\mathbf{L}(t) = \begin{bmatrix} L_{el}(t) \\ L_{th}(t) \end{bmatrix}$$

where $t$ denotes the time. By analogy to $\mathbf{L}$, the input vector $\mathbf{P}$ comprises electricity and gas

$$\mathbf{P}(t) = \begin{bmatrix} P_{el}(t) \\ P_{gas}(t) \end{bmatrix}.$$  

The input vector $P_{el}$ comprises conventional and renewable energy, e.g., grid and local photovoltaic (PV) electricity, and $P_{gas}$ is only conventional. Note that $P_{el}$ can also be fed back to the grid.

Input $\mathbf{P}$ and output $\mathbf{L}$ are connected via the efficiencies $\eta$ of the conversion plants

$$L_{el}(t) = \eta_{el,el} \cdot P_{el}(t) + \eta_{el,th} \cdot P_{el}(t)$$

$$L_{th}(t) = \eta_{th,el} \cdot P_{el}(t) + \eta_{th,th} \cdot P_{gas}(t).$$

The parameter $\eta_{el,el}$ denotes the efficiency of the electric transformer, $\eta_{gas,el}$ and $\eta_{gas,th}$ the gas-electric and gas-thermal efficiencies of the combined heat and power plant (CHP), and $\eta_{th,th}$ the efficiency of the furnace. Additionally, a dispatch factor $\nu(t)$ ($0 \leq \nu(t) \leq 1$) has to be introduced as gas is consumed by both the CHP and the furnace

$$P_{gas}(t) = P_{gas}(t) + (1 - \nu(t)) \cdot P_{gas}(t).$$

Consequently, $\nu(t) \cdot P_{gas}(t)$ of the consumed gas is converted to electricity and heat via the CHP at time instant $t$, whereas the furnace converts $(1 - \nu(t)) \cdot P_{gas}(t)$ to heat only. Efficiency $\eta$ and dispatch factor $\nu(t)$ together determine the coupling factor $c_{ij}(t)$ between output carrier $L_i(t)$ and input carrier $P_j(t)$. The conversion matrix $\mathbf{C}$ contains the coupling factors of all input and output carriers resulting in the equation for energy conversion

$$\mathbf{L}(t) = \mathbf{C}(t) \cdot \mathbf{P}(t).$$

The power balance (6) has to hold true for every instant of time while keeping the technological limits of the system.

An energy storage device, in this study hot water or battery, exchanges the power $M(t)$ with the system at time $t$ [18]. The energy flow into the storage is defined to be positive. The power $M(t)$ charged to or discharged from the storage device depends on the change in the state of charge, $E(t) - E(t - 1)$, within the time period $\Delta t$ according to

$$M(t) = s \cdot \Delta t \cdot \left( E(t) - E(t - 1) \right) + E_{th}$$

with $s = \frac{1}{\eta_{th}}$ if $\Delta t > 0$

$$s = \frac{1}{\eta_{th}} \cdot \Delta t$$

with $\eta_{th}$ being the charge and discharge efficiencies, respectively, and $E_{th}$ the standby losses. The maximum nominal storage capacity $E_{nom, max}$ is defined by the minimum and maximum value of the admissible state of charge, $E_{min}$ and $E_{max}$, respectively

$$E_{nom, max} = E_{max} - E_{min}.$$
Applying (7), (6) can be extended to
\[ \mathbf{L}(t) = \mathbf{C}(t) \cdot \mathbf{P}(t) - \mathbf{M}(t). \] (9)

Again, the technological limits of all devices have to be kept for all time instants.

The hub model is applicable to systems with arbitrary numbers of input and output carriers and storage devices.

**B. Single-Family House**

1) **System Setup:** Two single-family houses are considered, one in the moderate climate of Switzerland, and one in the hot climate of southern Spain.

The evolution of the inner room temperature defines the necessary heating or cooling power to keep the house at a comfortable temperature level. The electricity and thermal load supply technologies are represented by an energy hub.

2) **Modeling:** A detached house with length \( l \), width \( w \), and height \( h \) has to be conditioned to the nominal temperature \( \vartheta_{\text{nom}} \) with a maximum deviation of \( +\Delta \vartheta_{\text{nom}} \). A more detailed description can be found in [19].

At time \( t \), the heat flow \( \dot{Q}_t(t) \) is exchanged via walls and windows between the interior and the ambient due to temperature differences [20]
\[ \dot{Q}_t(t) = U_{\text{wall}} \cdot (A_{\text{wall}} + A_{\text{roof}}) \cdot (\vartheta_{\text{in}}(t) - \vartheta_{\text{out}}(t)) + U_{\text{window}} \cdot (\vartheta_{\text{in}}(t) - \vartheta_{\text{out}}(t)) \] (10)

where \( \vartheta_{\text{in}}(t) \) and \( \vartheta_{\text{out}}(t) \) denote the ambient and inside temperature at time \( t \), respectively, \( U \) the heat transfer coefficient, and \( A \) the surface.

Each \( n_{\text{air}} \) hours, artificial ventilation completely replaces the air within the house by ambient air. The ambient air has to be adjusted to the inner temperature requiring the power \( \dot{Q}_{\text{air}}(t) \)
\[ \dot{Q}_{\text{air}}(t) = (1 - \eta_{\text{recov}}) \cdot \frac{1}{n_{\text{air}}} \cdot V_{\text{DH}} \cdot \rho_{\text{air}} \cdot c_{\text{air}} \cdot (\vartheta_{\text{out}}(t) - \vartheta_{\text{in}}(t)) \] (11)

with \( V_{\text{DH}} = l \cdot w \cdot h \) being the volume of the detached house, \( \rho_{\text{air}} \) the density, and \( c_{\text{air}} \) the heat capacity of air. The percentage of heat recovered within the ventilation system is denoted by \( \eta_{\text{recov}} \).

Solar irradiation is estimated using the global irradiation \( G \), the energy transmission value \( g \) of the windows, and the conversion factor \( \alpha \) for determining the global irradiance on a vertical surface from the horizontal value
\[ \dot{Q}_{\text{sol}}(t) = \alpha \cdot g \cdot G(t) \cdot A_{\text{window}}. \] (12)

Consequently, the heat flow \( \dot{Q}_{\text{res}}(t) \) between the house and the ambient at time instant \( t \) results in
\[ \dot{Q}_{\text{res}}(t) = \dot{Q}_{\text{sol}}(t) + \dot{Q}_{\text{air}}(t) + \dot{Q}_t(t) \] (13)
causing a temperature change \( \Delta \vartheta_{\text{house}}(t) \) within the house
\[ \Delta \vartheta_{\text{house}}(t) = \frac{\dot{Q}_{\text{res}}(t) \cdot \Delta t}{m \cdot c} \] (14)
where \( \Delta t \) is the time interval, \( m \) the heat storing mass of the house, and \( c \) the heat capacity of the wall material, respectively.

The parameters \( m \) and \( c \) depend on the building characteristics and are selected according to [21]. Space heating or cooling have to ensure that the inner temperature \( \vartheta_{\text{in}} \) stays within the admissible temperature range \( \vartheta_{\text{nom}} - \Delta \vartheta_{\text{nom}} \)
\[ \vartheta_{\text{nom}} - \Delta \vartheta_{\text{nom}} \leq \vartheta_{\text{in}}(t) + \Delta \vartheta_{\text{house}}(t) + \frac{\dot{Q}(t) \cdot \Delta t}{m \cdot c} \leq \vartheta_{\text{nom}} + \Delta \vartheta_{\text{nom}} \] (15)
with \( \dot{Q}(t) \) being the furnace or cooling power released in time interval \( t, t + 1 \), and \( \Delta t \) being the length of the considered time interval. In the Swiss case, only space heating is available, whereas in Spain, only cooling is applied. Consequently, the upper or lower boundary in (15), respectively, cannot be kept if the external conditions (13) cause a temperature change (14) that cannot be compensated.

The resulting space conditioning demand curve is given by \( Q(t) \) with (mod) for moderate and (hot) for hot climate (\( \dot{Q}_{\text{furr}} = Q \geq 0 \), \( \dot{Q}_{\text{ac}} = Q \leq 0 \))
\[ I_{\text{el}}^{\text{[mod]}}(t) = I_{\text{el}}(t), \quad I_{\text{th}}^{\text{[mod]}}(t) = I_{\text{th}}^{\text{[w]}}(t) + \dot{Q}_{\text{furr}}(t) \] (16)
\[ L_{\text{el}}^{\text{[hot]}}(t) = I_{\text{el}}(t) - \dot{Q}_{\text{ac}}(t), \quad L_{\text{th}}^{\text{[hot]}}(t) = I_{\text{th}}^{\text{[w]}}(t) - I_{\text{th}}^{\text{[w]}}(t) \] (17)
where \( I_{\text{th}}^{\text{[w]}}(t) \) is the warm water demand and \( I_{\text{ac}}(t) \) the standard electricity demand. The house in the moderate climate is equipped with a grid connection, a gas-fueled \( \mu \text{CHP} \), and a gas-driven furnace to supply thermal and electric load demand. The house in the hot climate has a grid connection, an electrically driven air conditioning and a gas-fueled furnace for warm water demand. Both houses have a PV plant of variable size, whose generation curves are modeled with available data of real plants. Also, an electric battery storage device is available. Its nominal maximum capacity \( E_{\text{nom}, \text{max}} \) is varied. It can be charged with up to \( M_{\text{max}} = 0.8 \text{kW} \) and discharged with up to \( M_{\text{min}} = -0.5 \text{kW} \), the cycle efficiency is \( \eta_{\text{cycle}} = 0.81 \), and the standby losses are \( E_{\text{stab}} = 4 \cdot 10^{-5} \%/\text{h} \). The electricity consumption is modeled with a standardized load profile in hourly resolution.

3) **Formulation of the Optimization Problem:** The house model and the multienergy hub are combined to determine the optimal power supply strategy for the single-family house. The household tries to supply its load demand with the least fuel costs possible. Consequently, the objective function \( \mathcal{F}_{\text{h}} \) for time interval \( t = 1 \ldots N \) is defined as
\[ \mathcal{F}_{\text{h}} = \sum_{t=1}^{N} \Pi_{P}(t) \cdot \mathbf{P}(t) \] (18)
where \( \Pi_{P}(t) \) denotes the cost matrix containing the electricity costs \( \pi_{\text{el}}(t) \) and the gas costs \( \pi_{\text{gas}}(t) \) of the input carriers; \( N \) defines the prediction horizon.

The control variables include the storage charge and discharge power, the electricity and gas inputs into the hub, and the dispatch factor of gas
\[ \mathbf{u} = [\mathbf{M} \quad \mathbf{P}_{\text{el}}^T(t) \quad \mathbf{P}_{\text{gas}}^T(t) \quad \mathbf{\nu}(t)]^T. \] (19)
TABLE I

<table>
<thead>
<tr>
<th>#</th>
<th>π_{el} [kWh]</th>
<th>π_{gas} [kWh]</th>
<th>category</th>
<th>line style</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8/17</td>
<td>8</td>
<td>LT/HT - const.</td>
<td>solid</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>6/12.75</td>
<td>const. - LT/HT</td>
<td>dash-dotted</td>
</tr>
<tr>
<td>3</td>
<td>8/12/19</td>
<td>6/12.75</td>
<td>LT/MT/HT/HT</td>
<td>diamonds</td>
</tr>
</tbody>
</table>

Three different price constellations with constant and/or variable gas and electricity prices are considered (Table I).

The price levels vary across the day according to:
1) Low/high-tariff (LT/HT): HT Monday–Friday 8–19 h, Saturday 8–12 h.
2) Low/medium/high-tariff (LT/MT/HT):
   a) LT 22–5 h;
   b) MT 6–8 h and 14–17 h.

The solution defines the optimal power supply strategy for the system. It results from the optimization stated in (20).

The values and define the lower and upper boundaries of the respective value. For solar irradiation and load demand, perfect forecasts are assumed. The simulation horizon is selected to be N_{sim} = 1000 h, and two scenarios are considered: winter with hours 1 to 1000 of the year, and summer with hours 4001 to 5000 of the year. The MPC prediction horizon is N = 12 h. The optimization is repeated every 4 hours, each time implementing the optimal solution for the next 4 hours. It is assumed that private customers do not reconsider the usage of electric devices every hour. Then, the optimization continues until reaching N_{sim}.

\[
\min \mathcal{F}_{\text{sth}} \\
\text{s.t.} \\
L(t) + M(t) - C \cdot P(t) = 0, \quad \forall t \\
P_{\text{min}} \leq P(t) \leq P_{\text{max}}, \quad \forall t \\
0 \leq \nu(t) \leq 1, \quad \forall t \\
E_{\text{min}} \leq E(t) \leq E_{\text{max}}, \quad \forall t \\
M_{\text{min}} \leq M(t) \leq M_{\text{max}}, \quad \forall t \\
\vartheta_{\text{nom}} - \Delta \vartheta_{\text{nom}} \leq \vartheta_{\text{in}}(t) \leq \vartheta_{\text{nom}} + \Delta \vartheta_{\text{nom}}, \quad \forall t. \quad (20)
\]

The household’s fuel costs for its energy supply are

\[
\pi(\text{run}) = \sum_{t=1}^{N_{\text{sim}}} \Pi^n_{\text{th}}(t) \cdot P^*(t) \quad (21)
\]

where \( P^* \) defines the optimal electricity and gas inputs in \( u^* \).

C. Three-Hub Network

1) System Setup: Fig. 2 presents a three-hub network, where the energy hubs are interconnected by an ac electricity and a natural gas network. Each hub represents a general consumer, e.g., a household, that uses both electricity and natural gas. Active power is provided by three generators \( G_1, G_2, G_3 \), and natural gas supply is carried out by accessing two adjacent natural gas networks \( N_1 \) and \( N_2 \), where \( N_2 \) represents a small gas tank with limited flow capacity. The hubs contain a \( \mu \)CHP device and a furnace. All hubs are equipped with hot water storage devices (Fig. 2). No battery storage devices are considered in the three-hub network. Compressors are present in the pipeline network to enable a gas flow from the large gas network \( N_1 \) to the surrounding gas sinks.

2) Modeling: For each hub \( i \), the electrical \( L_{\text{el},i}(t) \) and thermal output \( L_{\text{th},i}(t) \) are related at every time step \( t \) to the electricity \( P_{\text{el},i}(t) \) and natural gas hub input \( P_{\text{gas},i}(t) \) as shown in (22), at the bottom of the page, where \( \eta_{\text{gas,el}}(t) \) and \( \eta_{\text{gas,th}}(t) \) denote the gas-electric and gas-heat efficiencies of the \( \mu \)CHP device, respectively; \( \eta_{\text{furn}}(t) \) is the efficiency of the furnace. As mentioned above, the dispatch factor \( \nu(t) \) defines how the gas is divided between \( \mu \)CHP and the furnace. The heat storage devices are modeled as ideal storage units in combination with storage interfaces, according to (7).

The ac electricity network is modeled by means of nodal power balances of complex power, according to [15] and [22]. The pipeline network is modeled based on nodal volume flow balances, where the model of a gas pipeline is composed of a compressor and a pipeline element [15].

3) Formulation of Optimization Problem: The MPC approach is implemented for the three-hub network. Actions are determined for each individual energy hub, such that energy usage can be adapted to fluctuations of energy prices, load profiles and renewable input profiles. In this study, perfect forecasts are assumed. The optimization is run for \( N_{\text{sim}} = 24 \) hours, each time optimizing for the MPC prediction horizon \( N = 3 \) h.

The objective is the minimization of energy costs

\[
\mathcal{F}_{\text{3H}} = \sum_{l=1}^{N} \sum_{i \in \Omega} \left[ a_{\text{el}}(t) + b_{\text{el}}(t) P_{\text{el},i}(t) + c_{\text{el}}(t) P_{\text{gas},i}(t) \right]^2 \\
+ a_{\text{th}}(t) + b_{\text{th}}(t) P_{\text{gas},i}(t) + c_{\text{th}}(t) P_{\text{gas},i}(t) \quad (23)
\]

Set \( \Omega \) includes all generation units \( i \), i.e., all generators \( P_{\text{el},i}^{\text{CHP}} \) and natural gas imports \( P_{\text{gas},i}^{\text{CHP}} \) of the system. Costs for active power generation and natural gas consumption are modeled as quadratic functions of the corresponding powers. The factors

\[
\begin{bmatrix}
L_{\text{el},i}(t) \\
L_{\text{th},i}(t) + M_{\text{th},i}(t)
\end{bmatrix} = \begin{bmatrix}
1, \\
0, \nu(t)\eta_{\text{gas,el}}(t)\nu(t)^{(\text{CHP})} + (1 - \nu(t))\eta_{\text{furn}}(t)
\end{bmatrix} \begin{bmatrix}
P_{\text{el},i}(t) \\
P_{\text{gas},i}(t)
\end{bmatrix} \quad (22)
\]
Fig. 2. System setup of three interconnected energy hubs. Active power is provided by generators $G_1$, $G_2$, and $G_3$. Hubs $H_1$ and $H_2$ have access to adjacent natural gas networks $X_1$, $X_2$. Central controller measures all system variables (dashed arrows).

<table>
<thead>
<tr>
<th>symbol</th>
<th>$a$ [m.u.], $b$ [m.u./p.u.], $c$ [m.u./p.u.$^2$]</th>
</tr>
</thead>
<tbody>
<tr>
<td>$G_1$</td>
<td>$a_{G_1} = 0$, $b_{G_1} = 12$, $c_{G_1} = 1.2$</td>
</tr>
<tr>
<td>$G_2$</td>
<td>$a_{G_2} = 0$, $b_{G_2} = 15$, $c_{G_2} = 1.5$</td>
</tr>
<tr>
<td>$G_3$</td>
<td>$a_{G_3} = 0$, $b_{G_3} = 15$, $c_{G_3} = 1.5$</td>
</tr>
<tr>
<td>$N_{1,2}$</td>
<td>$a_{N_{1,2}} = 0$, $b_{N_{1,2}} = 6$, $c_{N_{1,2}} = 0.6$</td>
</tr>
</tbody>
</table>

TABLE II

The variables $\theta$ and $V$ denote the voltage angles and magnitudes, $p$ the pressures of all buses, and $p_{\text{in},i}$ the amplification of the compressors. Index $i \in H$ denotes the index for each hub, $n \in \{N_e, N_{\text{gas}}\}$ describes all nodes of the electricity and gas system, $\alpha \in E$ the different energy carriers, i.e., electricity and natural gas, $i_G \in \Omega_G$ all generation units (electricity generators and natural gas imports), $i_C$ the compressors, $i_k \in \Omega_k$ all thermal storage devices, and $t$ the iteration step, respectively. All power flow equations of the electricity and natural gas network are collected in $G_n$, (25b).

## III. RESULTS OF THE CASE STUDIES

The MPC problem is solved for the single-family house (Section III-A) and for the three-hub network (Section III-B), considering different storage scenarios. Especially, the storage capacity and the prediction horizon for the approach are examined.

### A. Single-Family House

1) Impact of Storage Capacity: For the single-family house, only electricity storage is considered due to the presence of renewable solar electricity generation. First, the maximum nominal storage capacity $E_{\text{nom}, \text{max}}$ (8) is increased from 1 kWh to 14 kWh for a house in moderate climate.

Fig. 3 shows the energy costs of the household in moderate climate in winter and summer depending on the maximum storage capacity $E_{\text{nom}, \text{max}}$ and the different price constellations listed in Table I. The renewable PV generation amounts to 3500 kWh/a. In price constellation #1 (solid curve) and #3 (solid with diamonds), the costs are in summer mainly decreased for an increase of $E_{\text{nom}, \text{max}}$ from 1 kWh to 14 kWh. For higher capacities, the costs saturate. This is also the case in winter, but with a smaller impact and a saturation a bit later. Generally, in winter the influence of the storage device is much lower due to a dominance of thermal load demand over electricity demand.

In constellation #2 (dashed–dotted curve), the storage is nearly not used due to the constant electricity price. In price constellation #2, the storage device is only used if PV generation exceeds load demand and excess renewable electricity can be stored.

With excess renewable electricity to be stored, the cost savings that can be achieved with a storage device increase significantly; e.g., with a yearly PV generation of 4500 kWh/a, costs can be decreased by around 25%–30% compared to 6%–8% for 500-kWh/a PV electricity, depending on the available storage capacity. In hot climate, the results are similar. The increase of the available storage capacity from $E_{\text{nom}, \text{max}} = 1$ kWh to around 3 kWh or 4 kWh allows a cost decrease between 5% and 9% for 500-kWh/a PV electricity (Fig. 4) (except for price constellation #2), and between 5% and 18% for 4500 kWh/a.
Storage capacities larger than \( \approx 4 \text{ kWh} \) have only little additional benefit on the costs. Contrary to the case in moderate climate, the savings potential is larger in winter although the electric load demand is smaller there:

a) For small amounts of renewable electricity, almost only price variations can be exploited due to missing renewable excess electricity. In summer, more energy is charged into the storage as load demand is higher. But due to the limited prediction and optimization horizon, the amount of energy to be stored expediently is reached rapidly, not exploiting the full storage capacity (saturation for \( E_{\text{nom, max}} \geq 4 \text{ kWh} \)). As the overall load and hence the costs are smaller in winter, the price reductions from the capacity increase are more distinct than in summer.

b) For large amounts of renewable generation, the mismatch between renewable generation and electric load is (much) larger in winter than in summer. The amount of electricity that can be bought in low-tariff and consumed in high-tariff times is larger in summer, but the exploitation of excess renewable electricity saves more money. Consequently, the savings potential is higher in winter.

2) Impact of Prediction Horizon: As mentioned, the prediction horizon influences the operation of the storage device and consequently affects the overall energy costs. Table III shows the energy costs of the house in moderate climate in summer for price configuration #1, depending on the storage capacity and the prediction horizon length. The values are related to

\[
E_{\text{nom, max}} = 1 \text{ kWh} \quad \text{and a prediction horizon of 2 hours. The renewable generation amounts to 4500 kWh/a.}
\]

Increasing the prediction horizon from 2 to 12 hours, the same storage capacity can save up to 42% of the energy costs, when \( E_{\text{nom, max}} \geq 5 \text{ kWh} \). Consequently, the prediction horizon is crucial for the cost optimal operation of the storage device. The larger the horizon, the more savings are possible under otherwise similar conditions. However, the point where an increase of the prediction horizon \( N \) does not significantly effect the energy costs any more strongly depends on the available storage capacity. Table III also shows that the prediction horizon increase is more important for cost savings than the storage capacity, as the results for \( E_{\text{nom, max}} = 5 \text{ kWh} \) and \( E_{\text{nom, max}} = 14 \text{ kWh} \) are quite similar.

B. Three-Hub Network

1) Impact of Prediction Horizon: For showing the impact of prediction, the control scheme is operated with different prediction horizon lengths \( N \) between \( N = 1 \), i.e., no prediction (optimization just for the actual time step), and \( N = 24 \), i.e., predicting for all 24 time steps at once. Fig. 5, upper plot, shows the total operation costs as defined in (23) for different lengths of the prediction horizon \( N \). Generally, operation costs decrease with increasing prediction horizon. As can be seen, a fast decay of the operation costs occurs within prediction horizon lengths \( N = 1, \ldots, 6 \). For longer prediction horizons, no essential reduction in operation costs is gained. Besides that, computational effort increases with increasing prediction horizon length. Fig. 5, lower plot, shows the computation time for different prediction horizon lengths. Computational effort increases quadratically with increasing prediction horizon length.

In Fig. 6, the evolution of storage contents for different lengths of the prediction horizon are presented. The horizontal lines indicate the storage limits \( 0.5 \text{ p.u.} \leq E_{\text{smax}}(t) \leq 3 \text{ p.u.} \). It can be seen that with increasing prediction horizon length, storage devices are actively filled up before heat load peaks. The further ahead the controller is aware of the heat load peaks, the earlier the storage devices are filled up.

Summarizing, operation costs decrease but accordingly computational effort increases with increasing prediction horizon length. A tradeoff between control performance and computational effort has to be made. Moreover, characteristics such as obtainable forecasts and size of possible disturbances influence the choice of an adequate prediction horizon.

2) Impact of Storage Capacity: In general, storage devices enable us to store energy at most beneficial time instants
Fig. 5. Total operation costs (upper plot) and computation time (lower plot) for different lengths of the prediction horizon $N$.

**Fig. 6.** Evolution of storage contents: comparison of different lengths of the prediction horizon: (dotted), (dashed–dotted), (dashed), (solid).

and to release it at instants of optimal usage. For this, the possibility to predict prices and loads sufficiently far and a sufficiently high storage capacity are necessary. Operation costs for different storage capacities and for different prediction horizon lengths $N$ are presented in Fig. 7. The line marked by diamonds delineates the costs with basic storage sizes, $E = [E_{\text{min}}, E_{\text{max}}] = [0.5, 3]$, as they are used for the previous simulations (Figs. 5 and 6). This curve corresponds to the one depicted in Fig. 5, upper plot. Considering the evolution of operation costs ($E = [E_{\text{min}}, E_{\text{max}}] = [0.5, 3]$, diamond curve), increasing the prediction horizon length above $N = 6$ does not yield essential advantages, since storage capacities are too small. The other curves in Fig. 7 describe operation costs for increased storage capacities. As can be seen, when storage capacities are increased, lower operation costs are obtained and increasing the prediction horizon length enables costs reductions. When operating the system with storage sizes of $E = [E_{\text{min}}, E_{\text{max}}] = [0.5, 8]$, a stagnation of operation costs only appears at a prediction horizon length of $N = 13$. Hence, when storage capacities are high enough, high prediction horizon lengths are advantageous and enable reductions in operation costs. However, when deciding about an appropriate storage capacity, one has to make a compromise between control performance and costs for additional storage capacity.

**IV. CONCLUSION**

This paper has presented a modeling approach for multicareer energy systems in a single-family house and a network of three interconnected energy hubs. Thermal and electric load were supplied by various conversion and storage technologies. The impact of the prediction horizon length $N$ and the storage capacity $E_{\text{min}, \text{max}}$ of electric and thermal energy storage devices were examined.

The results clearly show that both for the house with electric storage device and for the three-hub network with thermal storage devices the storage capacity and the prediction horizon of the MPC approach play an important role for cost savings within the system. However, the prediction horizon $N$ is more crucial than the capacity (see Table III and Fig. 7), as $N$ determines the amount of energy that is stored for usage at a later instant of time instead of being fed to the grid immediately. The further the prediction horizon length is increased, the less energy is exported during low demand times but rather stored. The higher the prediction horizon length, the more cost-efficiently the storage devices can be operated, reducing operation costs. However, cost savings have to be traded against increasing computation times, reduced quality of forecasts, and lower ability to react on disturbances.

Beyond that, the storage capacity $E_{\text{min}, \text{max}}$ has to be carefully adapted to the situation, e.g., renewable generation, and the reliably available prediction horizon $N$. In the considered scenarios, in private households, a storage capacity at around 5 kWh is sufficient to exploit local renewable electricity and price variations. Larger capacities only have small additional benefits. Similar results apply for the three-hub network. Nevertheless, these results may change with increased $N$: increased
prediction horizon lengths are only effective when storage capacities are high enough. Consequently, the interaction between storage capacities and prediction horizon have to be taken carefully into account when dimensioning a storage device for application either within a single-family house or a network of several interconnected houses. The parameters are crucial for the cost optimal application of storage devices.

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REFERENCES


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