Time-based economic hierarchical model predictive control of all-electric energy systems in non-residential buildings

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Abstract
Battery energy storage systems (BESSs) in buildings provide flexibility and can lead to reduced operating costs. In this context, different sources of revenue exist. These require the consideration of different timescales making hierarchical model predictive control (HMPC) promising. Here, typical prediction horizons of the upper layer are 1 month, although peak charges are usually based on annual loads. Additionally, the benefit of HMPC compared to 1-layer MPC and rule-based control (RBC) approaches is seldom quantified. We therefore present an HMPC approach with consideration of a BESS’s annual performance and benchmark it to a monthly HMPC, a 1-layer MPC and a RBC approach. The results indicate that the annual HMPC outperforms the others when considering operating costs, computational effort and battery residual lifetime simultaneously.

Key Innovations
• 3-layer HMPC with annual prediction horizon
• Holistic comparison of a HMPC, 1-layer MPC and a RBC approach for a multi-use BESS

Practical implications
For the successful implementation of HMPC, one should carefully select the exchanged variables between the layers. Avoid declaring them as hard constraints since lower layers may need to exceed them. If prediction horizons are similar and computational efforts low, aggregate multiple layers into one.

Introduction
MPC is a well-known approach to optimize building energy systems’ operation. In case of large systems, boundary conditions of different timescales often have to be incorporated into one optimization problem resulting in bloated models and thus high computational effort. This challenge is met by the concept of HMPC. HMPC separates the control problem into different layers, which can be either time- and/or state-based. In this work, we focus on a time-based approach in order to incorporate different prediction horizons. For time-based HMPC, the overall optimization problem is split into subproblems, which depend on different timescales and can thus be solved consecutively. Time-based HMPC is promising as model complexity can be adapted to each layer’s optimization aim and constraints, hence facilitating the integration of different prediction horizons. Thus, a more flexible MPC structure is realized. In this regard, BESSs with multiple sources of revenue can be taken as an example. They contribute to higher flexibility and thus support the attenuation of fluctuations which are caused e.g. by increasing feed-in of renewable energy sources (RESs). These developments make BESSs a crucial part of the future energy system. As a part of a building energy system, they can be operated exploiting different sources of revenue. Among these are e.g. peak-shaving, maximizing local RES integration and providing frequency containment reserve (FCR). As the above mentioned purposes are based on different timescales, they require different prediction horizons. Therefore, HMPC is a promising approach to operate multi-use BESSs. Most studies focusing on HMPC for BESS with peak-shaving use monthly prediction horizons (s. Section Related work: HMPC for BESS). Yet, peak pricing is often determined based on maximum annual and not monthly loads in Europe and network planning also depends on maximum annual loads. Therefore, we develop an annual optimization of the peak load and compare it with the monthly one. In addition, to the best knowledge of the authors none of the studies dealing with BESS quantify the advantages of a HMPC compared to a 1-layer MPC as well as a RBC approach holistically. For this reason, we contribute to research by benchmarking the developed HMPC model to a 1-layer MPC and a RBC approach with regard to computational effort and performance. In this context, we evaluate the performance from an economic point of view in the form of annual operating costs and the estimated BESS’s end of life.

State of the art
For BESSs in practice, different sources of revenue exist. Kain et al. (2018) categorize them according to the beneficiary into customer-, grid- or market-oriented applications (see Table 1). For some purposes the installation of a photovoltaic plant (PV) is required. We focus on the highlighted usages.
Related work: HMPC for BESS

The concept of HMPC has been discussed in literature in a few studies for residential and commercial buildings. Most studies dealing with HMPC for BESSs only incorporate 2 different applications. While Wang et al. (2012) focus on maximizing RES self-consumption and peak-shaving, Kumar et al. (2018) consider FCR supply and peak-shaving. All of the researched studies realize the integration of 2 sources of revenue adopting a 2-layer approach. In our study, however, we simultaneously consider 3 sources of revenue, whose time horizons differ. Plus, we want to keep the lowest layer as lean as possible to enable real-time application. Therefore, we assess the potential of a 3-layer HMPC approach.

Apart from that, the maximum prediction horizon differs greatly among the researched HMPC studies. While the majority of the studies dealing with peak-shaving incorporates a maximum prediction horizon of 1 month (e.g. Vatanparvar and Sharma (2018) or Wang et al. (2012)), others choose 24 h or even smaller prediction horizons (e.g. Ma et al. (2012)).

For our use case, however, we want to assess the suitability of an annual prediction horizon as top layer as both network planning and peak pricing are mainly based on annual maximum grid loads. In addition, the question arising for model developers is, whether a multi-layer HMPC is advantageous compared to 1-layer MPC or conventional RBC approaches. Yet, most studies only choose one benchmark model for the developed HMPC. While e.g. Kumar et al. (2018) and Abreu et al. (2018) choose a 1-layer MPC model as benchmark, other studies like Ma et al. (2012) use a traditional RBC based on expert knowledge. In this paper, we compare our developed HMPC approach with both a conventional RBC and a 1-layer MPC approach.

Method

Use case: All-electric building

We apply the method to a non-residential building called FUBIC. It is an old military hospital, which is being transformed into an all-electric innovation center. The building will offer both office and laboratory spaces. In order to increase the share of RESs, a PV plant is installed and a central BESS will support the energy management of FUBIC’s electrical loads. In this study, we estimate FUBIC’s electrical load by applying Modelica-based reduced-order building performance simulations and use it as a boundary condition and forecast for the operation optimization of the BESS. Thus, the interaction of the actual building energy system and the BESS is simplified (see Figure 1).

(H)MPC approach

The (H)MPC framework is implemented in Python and realized as a conventional closed control loop as shown in Figure 2. Key components are the optimization problem, forecasts and the simulation model. We use Pyomo (Python Optimization Modeling Objects), an open-source software package, for formulating the optimization problem. Due to short computing times, we use the optimization solver gurobi. Besides, we include predictions assuming perfect forecast and other forecasting scenarios, which are presented at the end of this Section. A dynamic simulation model of our use case is realized using the object-oriented modeling language Modelica and included as functional mock-up unit (FMU).

fmpy transfers control variables for charging and discharging ($P_{Bat,c}^k, P_{Bat,d}^k, FCR$) resulting from the optimization, to the simulation model for the next control step $k \in K$, which is set to 1 hour. In practice, the control horizon should be smaller as grid-related applications often require shorter response times as in the case of FCR. Here, a maximum response time of 30 seconds is mandatory in Germany (TransnetBW GmbH, 2020). For each loop and control variable, the optimization transmits 4 values corresponding to a 15 min control sequence. After the simulation of the control horizon, the current state of charge (SoC) of the BESS $SoC_{Bat}^{k+1}$ serves as initialization value for the optimization model for the next iteration step.

To face the mentioned challenge of different timescales when combining multiple applications, we divide the MPC model into different optimization layers. The resulting hierarchical structure composes of 3 layers with different prediction horizons and model configurations (Figure 3). This is crucial as the model

<table>
<thead>
<tr>
<th>Customer</th>
<th>Grid</th>
<th>Market</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximizing RES self-consumption (i.e. FCR)</td>
<td>Balancing power</td>
<td>Arbitrage</td>
</tr>
<tr>
<td>Peak-shaving</td>
<td>Voltage control</td>
<td>Real time pricing</td>
</tr>
<tr>
<td>Time-of-use tariffs</td>
<td>Black start</td>
<td>Pricing</td>
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<tr>
<td>Emergency power</td>
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Table 1: Overview over possible BESSs’ purposes following Engels (2020)

![Figure 1: Basic structure of use case FUBIC](https://example.com/figure1.jpg)

![Figure 2: MPC framework](https://example.com/figure2.jpg)
complexity increases significantly with the number of variables and/or time steps. Therefore, reasonable computing times over long horizons are achievable with low model accuracy (top layer). Further, this structure enables shorter horizons for reduced computation times, where real-time capability and higher modeling complexity and more exact forecasts are required (lower layer).

We introduce the upper layer for peak-shaving. The corresponding forecasting horizon can be set to 1 month or 1 year, depending on the chosen billing model. In this layer we determine the optimal grid limit and subsequently set it as upper limit of the lower layers for the residual year/month. The middle layer decides whether to do or not to provide FCR. Since July 2020, tenders for FCR in the German market have taken place daily at 8 am containing six 4 h-product periods for the following day. This corresponds to a necessary prediction horizon of at least 40 h. In this study, we use 48 h to avoid decisions assuming the end of operation for the BESS in the relevant time horizon. The middle layer communicates the result in form of fixed binary set points to the lowest layer, which stay constant for the duration of closed tenders. In order to find an ideal control sequence, researched studies choose a prediction horizon of 24 h to capture daily dynamics (Weitzel and Glock, 2018; Engels, 2020). Here, we set it to 16 hours to only consider periods, in which FCR tenders are closed and therefore participation in the FCR market is certain for the whole prediction horizon of the lowest layer. Consequently, the middle layer is only carried out every 24 h and thus less frequently than the lowest layer, which is looped every hour.

**MILP**

We formulate the optimization problem as a mixed-integer linear program (MILP), which is a common modeling approach for optimization-based energy management of BESSs (Weitzel and Glock, 2018; Aragon et al., 2018). The objective function (OF) (1) forms the basis of the control strategy. Besides costs terms $c_t$ for energy and peak power, it contains revenues $r_t$ gained through feed-in and FCR. Additionally, penalties $p_t$ capture battery degradation and violations of soft constraints.

$$
\min_{t=0}^{T-1} \sum_{t=0}^{T-1} c_t - r_t + p_t
$$

Apart from that, the system’s power balances (2)-(4) detect the power flows across system boundaries, which are fundamental for pricing. We split both battery and grid power into two variables. Thus, we can include the battery efficiency for charging $P_{t}^{\text{Bat,c}}$ and discharging $P_{t}^{\text{Bat,d}}$ and apply different rules for grid demand $P_{t}^{\text{Grid,dem}}$ and feed-in $P_{t}^{\text{Grid,feed}}$:

$$
P_{t}^{\text{Grid,dem}} = P_{t}^{\text{PV}} - P_{t}^{\text{Load}} + P_{t}^{\text{Bat,c}}
$$

$$
P_{t}^{\text{Bat}} = P_{t}^{\text{Bat,d}} - P_{t}^{\text{Bat,c}}
$$

$$
P_{t}^{\text{Grid,feed}} = P_{t}^{\text{Grid,dem}} - P_{t}^{\text{Bat,c}}
$$

The top layer’s cost term includes both energy ($\text{€}/\text{kWh}$) and peak charge ($\text{€}/\text{kW}$) for the respective billing horizon. Therefore, we determine the maximum grid power $P_{\text{Grid,dem}}^{\text{max}}$ with the help of (5) and set it as optimal grid limit $P_{\text{Grid,dem}}^{\text{Limit}}$ to the lower layers. Here, a soft constraint limits operation through (6). This ensures that the limit can be exceeded by $P_{\text{Grid,dem}}^{\text{max}}$, when lower layers consider more accurate predictions. In addition, soft constraints prevent the problem from being infeasible in case of model inaccuracies (Kumar et al., 2018). The lower layer’s highest violation $P_{\text{add,max}}^{\text{Grid,dem}}$ of the set limit within the prediction horizon is then priced based on the peak charge and determined similar to (5).

$$
P_{t}^{\text{Grid,dem}} \leq P_{\text{add,max}}^{\text{Grid,dem}}
$$

$$
P_{t}^{\text{Grid,dem}} \leq P_{\text{Limit}}^{\text{Grid,dem}} + P_{\text{add,max}}^{\text{Grid,dem}}
$$

Further, we include constraints for the system’s technical restrictions. Here, we prevent simultaneous charging and discharging and limit the battery power to the technical maximum. Also, a system of equations avoids simultaneous grid demand and feed-in. Furthermore, we limit the BESS’s SoC to protect the BESS from deep discharging and overloading and exclude SoC areas where aging is exponential (Xu et al. (2018); Koller et al. (2013)). Formulating this as a soft constraint enables a controlled violation, which makes the problem feasible in case of inaccuracies. To predict the SoC, we include a BESS model in the optimization framework as formulated in (7). In literature, this approach is widely used with a constant efficiency for BESS charging $\eta^{\text{c}}$ and discharging $\eta^{\text{d}}$, including all power electronics (i.e. converter, inverter) (Weitzel and Glock, 2018). While we adopt this simplified approach for the top layer, the modeling in the lower layer is more accurate. Here, we implement a piece-wise linearized function (PWLF) of a power-dependent efficiency for the power electronics instead of integrating them into the battery efficiency. For
further information, we refer to publications of Magnor and Sauer (2016) and Driesse et al. (2008).

\[ \text{SoC}_t^{\text{Bat}} = \text{SoC}_{t-1}^{\text{Bat}} + (P_t^{\text{Bat,c}} \cdot \eta_t - P_t^{\text{Bat,d}}) \cdot \Delta t / C_{\text{Bat}} \]  

In addition to an inefficient operation, the incorrect use of BESSs can also have a considerable influence on its residual lifetime and thus its profitability (Vatnaparvar and Sharma, 2018). Therefore, we include penalty costs for calendrical and cyclic aging of the battery. For calendrical aging we adapt the modeling approach of Magnor and Sauer (2016). They use experimental assessments to determine a reference lifetime of a lithium-ion BESS under specific temperature and voltage levels, which have the main impact on calendrical aging. In order to determine the aging in case of deviations from the reference conditions, they apply typical approaches from literature (i.e. Arrhenius-Law and Tafel-Equation) (Koller et al., 2013; Xu et al., 2018). To simplify the highly nonlinear approach for the MILP, we neglect the temperature dependency, assuming an efficient air-conditioning system for the BESS (Koller et al., 2013). Due to the correlation of voltage and SoC (Han et al., 2013), we then model calendrical aging as a PWLF dependent on the SoC only.

We derive cyclic aging from so-called S-N or Wöhler curves, usually used in material science, which show the total number of achievable cycles over cycle depths. The resulting cycles are commonly counted using the rainflow counting algorithm (Magnor and Sauer, 2016) and we follow an approximated approach suitable for optimizations proposed by Xu et al. (2018). Further, we penalize aging mechanisms according to the theoretical replacement costs. Due to high computational effort, we include the aging models only in the lower layers.

The model presented so far enables an efficient and BESS-preserving optimised self-consumption and peak-shaving operation strategy. As a third application, we investigate the participation in the FCR market. This is realized in the middle layer. The decision variable in the middle layer is a binary variable \( x_t^{\text{FCR}} \), which indicates whether the operator should participate in the tenders or not. If accepted, the operator is obliged to deliver the requested power \( P_t^{\text{FCR,req}} \). This is proportional to the current frequency deviation \( \Delta f_t \) from the nominal frequency \( f_{\text{nominal}} \) (8) and results in (9). In this context, \( \Delta f_{\text{max}} \) represents the frequency deviation at which the total provided control power \( P_t^{\text{FCR,prov}} \) is called. For \( P_t^{\text{FCR,prov}} \), we choose the minimum permitted bidding value of 1 MW, referring to German regulations (TransnetBW GmbH, 2020).

\[ \Delta f_t = f_t - f_{\text{nominal}} \]  
\[ P_t^{\text{FCR,req}} = \Delta f_t / \Delta f_{\text{max}} \cdot P_t^{\text{FCR,prov}} \cdot x_t^{\text{FCR}} \]  

As the BESS is an energy-constrained unit, we need to apply an appropriate recharging strategy to ensure availability of the storage while offering FCR at any time. In order to obtain a control variable \( P_t^{\text{Bat,control}} \) that is independent of the requested FCR \( P_t^{\text{FCR,req}} \), we divide the BESS power \( P_t^{\text{Bat}} \) according to (10). By allowing negative values for all three powers, we realize a recharging strategy that represents a shift of the operation point of the storage. If, for example, \( \Delta f_t \) is positive, the BESS is supposed to consume power. However, if the opposite occurs, the discharge power is only reduced by \( P_t^{\text{FCR,req}} \). A reversal of the sign is also possible, which is why we do not consider charging and discharging separately. Still, (11) provides individual charging and discharging power as control variables and (12) supplies the corresponding power for the battery model. The model assigns positive values to the charging and negative values to the discharging power.

\[ P_t^{\text{Bat,control}} = P_t^{\text{Bat,control,c}} - P_t^{\text{Bat,control,d}} \]  

Further, (13) and (14) ensure that \( P_t^{\text{FCR,prov}} \) is available at any time. Also, regulations limit the SoC level while offering FCR, which we realize in (15) and (16). These two equations are soft constraints, so that the BESS can leave the SoC boundaries if necessary.

\[ P_t^{\text{Bat,control,c}} \leq P_{\text{max}}^{\text{Bat,c}} - P_t^{\text{FCR,prov}} \cdot x_t^{\text{FCR}} \]  

\[ P_t^{\text{Bat,control,d}} \geq -P_{\text{max}}^{\text{Bat,d}} + P_t^{\text{FCR,prov}} \cdot x_t^{\text{FCR}} \]  

\[ \text{SoC}_t^{\text{Bat}} \leq \text{SoC}_{\text{min}}^{\text{Bat}} \]  

\[ \text{SoC}_t^{\text{Bat}} \geq \text{SoC}_{\text{min}}^{\text{Bat}} + P_t^{\text{FCR,prov}} / (C_{\text{Bat}} \cdot 4) \cdot 100 \cdot x_t^{\text{FCR}} \]  

Besides that, an additional constraint adds revenues from the FCR products to the OF. So far, \( x_t^{\text{FCR}} \) represents a variable, but this is only partially true. The middle layer needs to decide at 8 am whether to offer FCR for the following day or not. However, between 8 am and 24 pm \( x_t^{\text{FCR}} \) is not allowed to change due to closed tenders and therefore we include it as parameter for this period. The middle layer transmits its decision to the lower layer as a parameter, too.

**Benchmark models**

We introduce 3 benchmark models for the HMPC:

- HMPC with monthly peak optimization (HMPC-M)
- 1-layer MPC
- Conventional RBC

The HMPC-M is the same as the introduced HMPC except for the fact that the upper layer’s prediction horizon is 1 month instead of 1 year and the pricing scheme is adapted accordingly. We therefore refer to the HMPC with a 1 year prediction horizon as HMPC-A. Apart from that, the 1-layer MPC is based on the same model configuration as the middle and
lower layer of the HMPC approach. Since it consists of only 1 layer, we set the prediction horizon to 48 h to be able to participate in the tenders for FCR. Consequently, the optimization model determines the start value for peak-shaving on basis of the first two days. In the case of the RBC predefined expert rules are the basis of the choice for the source of revenue instead of optimizations. The resulting control strategy is shown in Table 2. In order to increase self-consumption, energy from the PV power plant is stored directly when generation exceeds current demand. To enable peak shaving RBC keeps the BESS at a high SoC to be prepared to discharge the storage if the building’s load surpasses a specified grid limit. According to Leadbetter and Swan (2012) the highest 1 to 2% of peak loads have the greatest impact on grid charges. In order to smooth the most expensive peaks, while mitigating the risk of exceeding the predefined level, we use 1% as grid limit in this study. In addition, a simple rule-based recharging strategy maintains the SoC between two predefined levels while offering FCR.

Table 2: Time and month-based choice of source of revenue for the RBC approach.

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<tbody>
<tr>
<td>day-time</td>
<td>(4 am-8 pm)</td>
<td>night-time</td>
</tr>
<tr>
<td>peak-shaving</td>
<td>FCR</td>
<td>self consumption</td>
</tr>
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KPIs for a holistic assessment

In this study, we quantify the value added by a 3-layer HMPC approach compared to the benchmark models. For the given use case, the operating costs are part of the OF and thus the annual operating costs serve as our 1st KPI. In addition, the lifetime of BESSs strongly depends on the amounts of cycles and the SoC and hence the control strategy. As a 2nd KPI, we therefore introduce the resulting lifetime. Finally, a major advantage of HMPC is reduced computational effort. Hence, the average computational effort of each control loop is the 3rd KPI.

Model inputs and forecasting scenarios

The HMPC and the benchmark models use PV power generation, weather data, FUBIC’s electrical load and FCR tender data as inputs. The PV power generation as well as FUBIC’s electrical load are results of a Modelica building performance simulation model. Most models are part of the open-source library AixLib (Müller et al., 2016), except for the BESS model, which is adopted from investigations by Magnor and Sauer (2016). All model parameters are based on data from the current building planning process. The building model is developed using TEASER (Remmen et al., 2018). Standardized weather data, so-called test reference years, provided by Germany’s National Meteorological Service, as well as typical user behaviour profiles serve as further model inputs (Germany’s National Meteorological Service, 2017; Sandels et al., 2016). Plus, we estimate the requested FCR using historic data provided by a major German grid operator (TransnetBW GmbH, 2020). To evaluate the influence of different forecasting scenarios in our framework, we also analyze the effect of divergent load forecasts on the (H)MPC as well as the RBC approaches. To derive different scenarios, we apply Design of Experiments using Central Composite Design and change both weather and usage conditions for our building energy system. For the former, 3 different weather scenarios (a warm, a cold and an average scenario) are applied (Germany’s National Meteorological Service, 2017). For the latter, we adapt the internal loads intensity of the server and laboratory zone by up to 50%. For the server room, we also change usage pattern (constant vs. dynamic load). The building performance simulation results serve as forecast of the HMPC’s top layer. Thus, the annual and weekly loads for the perfect forecast scenario. A typical week in winter (middle) and summer (bottom) are shown.

Figure 4: Simulated thermal and electrical demands for the perfect forecast scenario. A typical week in winter (middle) and summer (bottom) are shown.

Results

In the following, we compare the HMPC-A model with the benchmark models. The resulting annual operating costs and the estimated end of life for the perfect forecast scenario are compared in Figure 5.
The operating costs are normalized based on the RBC approach. All in all, each of the developed (H)MPC models leads to decreased operating costs and a higher end of life than the RBC approach. The HMPC-A approach performs best regarding operating costs, leading to a cost reduction of 13%. Yet, taking the estimated end of life into account, the 1-layer MPC model slightly dominates the others. Apart from that, Figure 5 shows that the HMPC-A surpasses the HMPC-M for both KPIs. One reason for this is illustrated in Figure 6. The upper plot illustrates the grid load while at the bottom, the model’s decision to offer FCR is depicted. As a reference, the resulting grid power without a BESS is illustrated. It becomes obvious, that the HMPC approaches limit the grid load to different peaks. With an annual prediction horizon, the HMPC-A optimizes the grid limit for the whole year, resulting in a higher peak. The HMPC-M on the other hand, cuts peaks as in the exemplary week of February to a limit, which is not necessary from an annual point of view. However, considering the peak pricing scheme which is based on each month’s maximum load, this is the optimal operation. This leads to fewer opportunities of providing FCR and thus decreased revenues. Additionally, stronger peak-shaving leads to a reduced lifetime due to a higher number of cycles.

In order to visualize, why the (H)MPC models surpass the RBC approach, Figure 7 depicts an exemplary week in winter comparing the HMPC-A and the RBC. The following effects are also applicable for the HMPC-M and the 1-layer MPC. Besides the grid load and the decision concerning FCR, the middle plot depicts the BESS’s SoC for a better understanding of the charging strategies. Even though the upper limit for the RBC is set based on expert knowledge to 828 kW, it overshoots it resulting in a peak load of 935 kW. On the other hand, the HMPC-A sets the maximum grid load based on top layer optimization results to 798 kW. Consequently, the HMPC-A leads to reduced peak power charging. In addition, the HMPC-A is able to offer FCR at 98% of the bidding periods, while the RBC only provides FCR in 33% of the periods. This is due to the fact, that the BESS operated based on RBC cannot prioritize the selected applications using predictions. Therefore, the HMPC-A raises revenues through FCR supply by more than 200%.

Besides the significant decrease in operating costs, all (H)MPC approaches strongly increase the estimated residual lifetime after one year of operation (see Figure 5). This improvement results from different effects. The estimated BESS’s end of life depends on both calendrical and cyclic aging. Calendrical aging accelerates, when SoC is kept at high levels. In Figure 7, a comparison of the battery’s SoC for both the HMPC-A and the RBC highlights that the RBC encourages calendrical aging due to higher SoCs. In winter, RBC keeps the SoC at around 90% in order to shave sudden peaks while the HMPC-A only charges the BESS if necessary. This leads to higher calendrical aging and thus a lower lifetime estimation for the RBC. Another reason for the lower end of life of the RBC is the higher number of cycles. This results from adjusting the SoC levels depending on the requirements of the different applications, which are continuously switching for RBC.

In Figure 5, we demonstrate that the HMPC-A approach outperforms the 1-layer MPC regarding operating costs but not concerning estimated end of life. However, the 1-layer MPC results highly depend on the grid load of the first two days as the peak is optimized based on the first prediction horizon. Therefore, the MPC’s performance highly depends on the load of the first loop. So far, we only analyzed the perfect forecast scenario of the top layer. As the top layer is the one with highest uncertainty, we also assess the effect of divergent forecasting for a lower and higher peak case. The results are shown in Figure 8. It becomes obvious that the RBC control results are only marginally influenced by the different forecasts. While the RBC perfect forecast scenario leads to a predefined peak of 828 kW, the lower peak and higher peak scenario result in a heuristically determined peak of 671 kW and 840 kW, respectively. Yet, the RBC is not able to comply with these aims and reaches a peak of 935 kW in all scenarios. Hence, the forecasting scenarios do not influence the presented results for the RBC. For the HMPC-A and the HMPC-M, on the other hand, we determine a diver-
Discussion

A comparison of the HMPCs with a 1-layer MPC and a RBC approach proves that the HMPC-A model outperforms the others when all defined KPIs are considered. Yet, both the HMPC and the 1-layer MPC result in similar operating costs and estimated end of life. However, the results of the latter are sensitive regarding the load of the first 48h. In addition, the computational effort of the 1-layer MPC approach is much higher, making model development less flexible and impeding real time grid-related application. This is where the advantage of the HMPC approach comes into play: each layer’s model complexity can be adapted more independently. Apart from that, we detect that an annual HMPC is advantageous compared to the monthly approach for our use case (see Figure 6). This is partially due to different schemes for monthly and annual peaks and the fact that for multi-use BESSs the storage is less occupied with peak shaving when only annual peaks are considered leading to more capacity for other applications.

In addition, the integration of different forecasting scenarios using a reduced-order building performance simulation proves that HMPC remains its good performance despite faulty forecasts (see Figure 8). However, we only evaluated forecasting methods for the top layer as it has the highest uncertainty due to long prediction horizons. The forecasts of the middle and bottom layer show lower uncertainty due to shorter prediction horizons, but they will likely influence the presented results. Apart from that, we strongly recommend to couple the presented framework with MPC of the building’s HVAC. The top layer could either incorporate a simulation-based approach coupled with a heuristic optimization to optimize e.g. plant operation or a deterministic approach. For the former, we propose heuristic optimization methods, resulting in a realistic building behavior estimation but eventually only local optimums. It could be integrated prior to the presented framework, leading to a sequential process neglecting interactions and thus synergy effects of the thermal and electrical system for peak cutting. The latter approach, on the other hand, could lead to inaccuracies due to model simplifications. As an advantage, it should directly be integrated in the presented MILP approach. Here, in the top layer additional synergy effects could be realized by optimizing the grid limit based on battery and building operation simultaneously. Subsequently, the middle and bottom layer could incorporate HVAC plants and realize the optimized limit (see Figure 3).

Conclusion

In this study, we develop a 3-layer HMPC model with annual prediction horizon, benchmark it to a HMPC with a monthly one, a 1-layer MPC and a RBC approach and apply it to a building energy system with
a BESS and PV. The results indicate that all MPC approaches lead to significant cost reductions and increased estimated BESS’s end of life when compared to the RBC. The 1-layer MPC, however, leads to a less flexible framework for developers and is less suitable for grid-related real-time applications such as FCR. In addition, the HMPC-A outperforms the HMPC-M as unnecessary peak-shaving is prevented. We also investigated different forecasting scenarios for the top layer as it has the highest uncertainty. Future research should also develop forecasting models for the lower layers and assess their influence on the results. In addition, we chose operating costs and the BESS’s residual lifetime as separate KPIs and results indicate that a trade-off between them exists. For future studies we propose system’s annuity as KPI to assess both simultaneously and include HVAC MPC.

Acknowledgment

We gratefully acknowledge the financial support by Federal Ministry for Economic Affairs and Energy (BMWi), promotional reference 03ET1619B.

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