A Comparative Study of Optimization- and Rule-Based Control for Microgrid Operation

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***Abstract*—As local renewable energy based generation units are being deployed worldwide, distribution grids are facing integration challenges. Here, microgrids provide a solution, by allowing intentional islanding and connection to the public distribution grid depending upon its current state. Microgrids may consist of loads, generation units and storages which can be operated as a single controllable entity. This paper investigates two control approaches for cost-efficient operation of grid-connected microgrids: optimization- and rule-based control. For optimization-based control, a model predictive control algorithm with mixed integer linear programming formulation is used. A case study for a microgrid in an office building consisting of distributed generation units and different storage units is presented to assess the performance of the two control approaches. The simulation results show the effectiveness of the optimization-based approach and a potential for lower microgrid operating costs compared to the rule-based approach.**

Keywords*—Microgrids, grid-connected, energy management system (EMS), mixed integer linear programming (MILP), moving horizon control, model predictive control (MPC), energy storage

I. Introduction

Renewable energy sources (RES) are experiencing high growth rates worldwide due to rising interest in green energy and a decline in investment costs. Especially, photovoltaic (PV) systems are getting rapidly deployed on lower voltages levels in the distribution grid leading to grid integration challenges [1]. These challenges can be addressed by exploiting active and reactive power control capabilities of local generation and storage units [2], [3]. Yet, control approaches which only take into account generation based control are unable to fulfil the supply stability requirements of the owners of such distributed generation (DG) units. Hence, microgrid concepts are becoming more popular as they allow intentional switching between island and grid-connected operational mode depending on the current state of the public distribution grid. A typical electrical microgrid is a cluster of loads, DGs and energy storage systems (ESS) which are connected to the distribution grid at the point of common coupling and respond to the grid as a single controllable entity. Microgrids provide a solution for large-scale grid integration of DGs and can be exploited as building blocks for the realization of smart grids [4], [5]. Another appealing aspect of microgrid operation is its ability to lower local electricity costs. Here, its control approach and its energy management system (EMS) provide the key to ensure reliable, economic and secure operation [4], [5], [6].

In this paper, two different control approaches for microgrid operation are investigated: optimization- and rule-based control. While a rule-based approach allows for a simple, lean implementation of a given control objective [7], it is limited as it is less flexible, acts only based on current measurements and does not necessarily lead to an optimal operation schedule of the controllable devices. Modern control approaches such as model predictive control (MPC) allow to exploit optimization-based techniques and enable meeting multiple control objectives simultaneously [5]. A comparison of a similar heuristic algorithm and an MPC based EMS has been performed in [8], where the authors compare the total costs of an experimental microgrid in Athens, Greece. In this paper, we are benchmarking these two approaches for active power control for cost-efficient operation of a grid-connected microgrid consisting of ESSs and RESs installed at a Chinese office building. The control approaches are assessed regarding their capability to reduce operating costs while increasing local usage of local generation and minimizing storage losses. Further, the impact of load forecast errors and of the length of prediction horizon are investigated.

II. Literature review on control approaches for microgrid operation

Energy management strategies can be implemented as rule-based control strategies for microgrid operation, similar to [7]. Modern control approaches use optimization-based algorithms to ensure efficient operation while meeting several different control objectives simultaneously. For example, [9] proposes a multi-objective optimization for minimizing operating costs and emissions of a microgrid at each iteration. Yet, it does not ensure optimal operation over a span of multiple time steps. Offline calculations for optimal scheduling over a time horizon are also common [10]. The performance of such systems depends strongly on the quality of load and RE production forecasts. In this context, online model predictive control (MPC) approaches are appealing, in which a rolling window is used for performing optimization routine periodically, hence, enabling adaptation to changing operating conditions [5]. For example, in [11], MPC has been used for economic coordination of a power plant portfolio while performing reference tracking and disturbance rejection.

An operation schedule for storage systems in a microgrid can be solved using a mixed integer linear programming (MILP) approach. In [8], the authors use an MPC based EMS to achieve economic operation of a microgrid consisting of ESSs, generators, and controllable and critical loads. Unit commitment, storage dynamics, and load curtailment constraints have been formulated using MILP. Reference [12]

TABLE I. NOMENCLATURE

$\Delta T, N_p$	EMS sample time [h], time steps in prediction horizon
n	number of storage units
$S_{k,i}$	state of charge (SOC) [%] of storage unit k at time i
$P^c_{k,i}, P^d_{k,i}$	charging, discharging power [kW] for storage unit k at time i. $P \in \mathbb{R}^+$
$\eta^{sd}_k, \eta^c_k, \eta^d_k$	self-discharge (sd) coefficient, charging (c) and discharging (d) efficiencies for storage k. $\eta \in (0, 1]$
C_k	energy capacity [kWh] of storage k
$S_{k,max}, S_{k,min}$	maximum, minimum SOC [%] allowed for storage k
$P^c_{k,max}, P^d_{k,max}$	maximum charging, discharging power [kW] allowed for storage k. $P \in \mathbb{R}^+$
b_i	charging/discharging (0/1) mode for all storages at time i
$\Delta P_{k,max}$	maximum rate of discharge / charge [kW] allowed in time ΔT for storage unit k. $P \in \mathbb{R}^+$
P^p_i, P^s_i	purchased, sold power [kW] to utility grid at time i. $P \in \mathbb{R}^+$
P^{rl}_i	residual load demand [kW] at time i. $P \in \mathbb{R}$
$P^l_i, P^{reav}_i, P^{reu}_i$	load demand [kW], RES available power [kW], RES used power [kW] at time i. $P \in \mathbb{R}^+$
$S_{k,terminal}$	minimum SOC [%] at end of prediction horizon for storage k. $P \in \mathbb{R}^+$
c^p_i, c^s_i	electricity price for purchased and sold energy [RMB/kWh] at time i. $c \in \mathbb{R}^+$
c_k	specific operating cost [RMB/kWh] of storage unit k. $c \in \mathbb{R}^+$

presents an adaptive EMS for multiple features like battery signal shaping and grid signal flattening along with economic operation using MILP optimization. The authors also introduce a robust optimization approach which considers the presence of uncertainties in the predictions. In [13], the authors use a MILP MPC based approach for analyzing the optimal storage capacity for a high RES penetration autonomous microgrid based on the type and the installed capacity of RES. Optimization-based control provides a flexible and versatile solution suitable for EMS applications in microgrids.

III. OPTIMIZATION-BASED CONTROL APPROACH

As discussed in the previous section, optimization-based control offers several advantages. This section introduces the MPC approach and the MILP optimization problem formulation used in the later presented microgrid case study. Here, the objective function is introduced, followed by the storage model, power balance constraints, and other related constraints.

Table I describes the notation used in this section.

A. Model Predictive Control Approach

The MPC approach uses a load and generation forecast over a prediction horizon of N_p time steps. At each time step, a MILP optimization problem is solved to obtain an optimal sequence of storage power set-points for the entire prediction horizon. Only the first sample of the output sequence is used for microgrid operation, the MILP problem is solved again with updated data in the next time step. The advantage of using MPC is that it receives updated information from the real system at every time step which handles uncertainties in forecasts, system disturbances, time-varying energy prices and inaccuracies due to simplification of storage models.

For MPC implementation the algorithm is as follows:

Step 1: Read input system data, price data, measured values of current load, generation and SOC for storages.
Step 2: Obtain forecast profiles for load, RES generation for upcoming $Np - 1$ time steps.
Step 3: Solve the following MILP problem:
minimize: operating costs J from (1).
subject to: constraints (2) to (9)
for decision variables: $P^c_{k,i}, P^d_{k,i}, b_i, P^p_i, P^s_i, P^{reu}_i$, $k \in \{1 \dots n\}, i \in \{1 \dots N_p\}$
Step 4: Implement output sequence for $i = 1$, and repeat from Step 1 for next time step.

B. Objective function

The overall objective is cost-efficient microgrid operation. While RE production is cost-free, costs are attached to electricity purchases. Furthermore, weighting factors in form of costs are implemented for the different storage units to allow prioritizing their operation and cope with the different conditions of the storage units. Hence, optimal storage unit scheduling is required to minimize operation costs over the prediction horizon:

$$J = \sum_{i=1}^{N_p} \left(c^p_i . P^p_i - c^s_i . P^s_i + \sum_{k=1}^{n} c_k . \left(P^c_{k,i} + P^d_{k,i} \right) \right). \quad (1)$$

Here, power exchanged with the public distribution grid is modeled as separate variables for purchase P^p_i and sale of electricity, P^s_i at time step i, while c^p_i and c^s_i are corresponding grid prices in RMB/kWh. The term $c^s_i \cdot P^s_i$ is subtracted from J to represent earning for the microgrid for sale of electricity. Since $c^s_i < c^p_i$ is always true for the considered case, the microgrid cannot purchase and sell electricity at the same time. We consider n storage units and power through storage k at time i is represented by charging, $P^c_{k,i}$, and discharging terms, $P^d_{k,i}$. A weight parameter c_k is considered for charging and discharging processes. This parameter can be related to specific storage operating and maintenance costs (see [8]), [12]). It is used in the optimization to penalize frequent cycling.

C. Constraints

1) Prediction model for storage state of charge: A portfolio of n storages is considered, where the state of charge (SOC) level of a storage for the entire prediction horizon can be represented as:

$$S_{k,i} = (\eta^{sd}_k)^i S_{k,0} + \sum_{j=1}^{i} (\eta^{sd}_k)^{i-j} \left(\eta^c_k K_k P^c_{k,j} - \frac{K_k}{\eta^d_k} P^d_{k,j} \right), \quad (2)$$

with $K_k = \frac{\Delta T \times 100}{C_k}$ and $i = 1, 2, \dots, N_p$.

Here, $S_{k,0}$ and $S_{k,i}$ are the initial SOC and SOC level at time i for storage k, respectively. SOC level is given by the energy level available in the storage, taken as percent of its total energy capacity, C_k. The constants $\eta^{sd}_k, \eta^c_k, \eta^d_k \in (0, 1]$ are self-discharge coefficient, charging and discharging efficiencies of storage k, respectively. The term $\eta^{sd}_k \cdot S_{k,i-1}$ gives the energy available after self-discharge losses.

The SOC of storage k is limited by its storage capacity. However, to minimize storage degradation due to ageing, additional limits are imposed:

$$S_{k,min} \le S_{k,i} \le S_{k,max}. \quad (3)$$

To avoid storage depletion at the end of the prediction horizon, an additional constraint is implemented:

$$S_{k,N_p} \geq S_{k,terminal}. \tag{4}$$

However, since we are employing MPC, the negative effect of removing constraint (4) can be negligible.

2) Power balance constraint: The balance between electricity produced and consumed must be maintained at each time step:

$$P_i^l - P_i^{reu} + \sum_{k=1}^{n} \left(P_{k,i}^c - P_{k,i}^d\right) = P_i^p - P_i^s, \tag{5}$$

where $P_i^p, P_i^s \geq 0$. P_i^l and P_i^{reu} are load forecast and RES used power at time step i.

The maximum RES used power at each time step is limited by the RES available power,

$$P_i^{reu} \leq P_i^{reav}. \tag{6}$$

3) Power and Power Rate Constraints: Storage charging and discharging powers are limited by the respective maximum allowed power limits, $P_{k,max}^c$ and $P_{k,max}^d$.

$$0 \leq P_{k,i}^d \leq P_{k,max}^d b_i, \tag{7}$$

$$0 \leq P_{k,i}^c \leq P_{k,max}^c \left(1 - b_i\right), \tag{8}$$

where b_i is a binary decision variable for time step i such that $b_i = 0$ indicates charging and $b_i = 1$ indicates discharging, ensuring mutual exclusivity of both processes. For every time step, the same binary variable is used for all n storages to avoid power exchange among different storage units.

Additionally, the following constraints are imposed to limit the maximum rate of change of storage power to limit harmful effects of transients on storage [12]:

$$-\Delta P_{k,max} \leq \left(P_{k,i}^c - P_{k,i}^d\right) - \left(P_{k,i-1}^c - P_{k,i-1}^d\right) \leq \Delta P_{k,max}. \tag{9}$$

IV. Rule-based Control Approach

The optimization-based strategy is compared to a rule-based strategy which does not require a forecast and only uses real-time measurements and prices to derive the operation schedule for the storage systems. The control strategy is designed for this specific case study. The power set-points for microgrid components are calculated at each time step according to the rule-based algorithm shown in Fig. 1 using only the knowledge of current SOC, load, RES generation and grid price.

Some key points of this algorithm are:

- RE production is utilized in priority order:
  load > storage > sale to public distribution grid.
- Load is supplied with priority order:
  RE > storages > purchase from public distribution grid.
- Storages are charged during off-peak hours and discharged to feed the load during peak hours.
- Storages are used in priority order according to their operating costs (cheapest one first).

Read current load P_i^l, RES generation P_i^{reav}
Residual load, $P_i^{rl} := P_i^l - P_i^{reav}$
Arrange storages in order of increasing operating costs
if $P_i^{rl} \leq 0$ or c_i^p = valley price **then**
  for storage k =1 to n **do**
    if $S_{k,i-1} < S_{k,max}$ **then**
      $P := \dfrac{S_{k,max} - \eta_k^{sd} S_{k,i-1}}{\eta_k^c \times \Delta T \times 100} \cdot C_k$
      charge at $P_{k,i}^c = \min\{|P_i^{rl}|, P, P_{k,max}^c\}$
      update residual $P_i^{rl} \leftarrow P_i^{rl} + P_{k,i}^c$
  if $P_i^{rl} \leq 0$ **then**
    sell residual to grid, $P_i^s = |P_i^{rl}|$
  else
    buy residual from grid, $P_i^p = P_i^{rl}$
else if $P_i^{rl} \geq 0$ and c_i^p = peak price **then**
  for storage k =1 to n **do**
    if $S_{k,i-1} > S_{k,min}$ **then**
      $P := \dfrac{\eta_k^{sd} S_{k,i-1} - S_{k,min}}{\Delta T \times 100} \cdot \eta_k^d \cdot C_k$
      discharge at $P_{k,i}^d = \min\{P_i^{rl}, P, P_{k,max}^d\}$
      update residual $P_i^{rl} \leftarrow P_i^{rl} - P_{k,i}^d$
  buy residual from grid, $P_i^p = P_i^{rl}$
else
  buy complete residual from grid, $P_i^p = P_i^{rl}$

Figure. 1. Rule-based algorithm for energy management

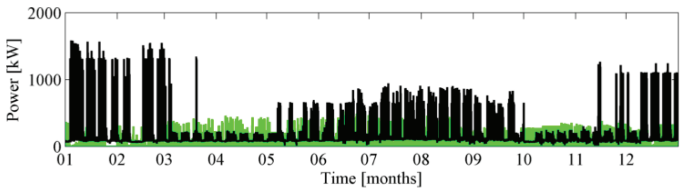

Figure. 2. Load (black) and RE generation (green) profile for 2013.

- Power is only sold to the distribution grid in case of excess RE production and charged storages. This relates to the considered pricing system, as it is not economic to discharge storages just for sale during peak hours.

V. Simulation Setup and Performance Indicators

This section describes data and parameters used in our simulation. The microgrid is operated in grid-connected mode. It can purchase or sell energy to the public distribution grid. The simulations are carried out using MATLAB.

A. Load and generation profiles

PV, wind and load data is based on measured data for year 2013 for an office building in China in a 10 minute time resolution. For missing data points, interpolation is employed. Fig. 2 shows the load and RE generation profile used for simulation based on a installed PV capacity of 500 kWp and 10 kW installed wind power. Maximum RE power is 496.5 kW. The load is highly dependent on the season with maximum and minimum of 1582.9 kW and 16.0 kW for year 2013. For the year 2013, total load demand is 1985 MWh and total RE production is 517 MWh.

TABLE II. PARAMETERS FOR STORAGE SYSTEMS

Unit	C	P^c_{max}	P^d_{max}	ΔP_{max}	η^{sd}	η^c	η^d	c
1	30	20	20	30	99.9	90.0	92.0	.08
2	150	100	100	150	99.9	90.0	92.0	.11
3	150	100	100	150	99.9	90.0	92.0	.06

TABLE III. TIME-OF-USE TARIFF FOR PURCHASED ELECTRICITY

Jan 01 to Jun 30 and Oct 01 to Nov 30				
Time	05:00-17:00 Flat hours	17:00-23:00 Peak hours		23:00-05:00 Valley hours
Price (RMB/kWh)	0.8014	1.04182		0.56098
Jul 01 to Sep 30 and Dec 01 to Dec 31				
Time	05:00-17:00 Flat hours	17:00-19:00, 21:00-23:00 Mid-peak hours	19:00-21:00 Peak hours	23:00-05:00 Valley hours
Price (RMB/kWh)	0.8014	1.2021	1.44252	0.447

B. Parametrization of storage systems

The microgrid has three Li-ion batteries which are parametrized according to Table II. For all storages, the maximum, minimum and terminal SOC limits are kept at 90 %, 10 %, and 11 %, respectively.

C. Grid electricity prices

A time-of-use (TOU) tariff system is used for electricity procured from the grid as shown in Table III. Sale prices are assumed to be one-third of the corresponding purchase prices following the assumption that prices for procured electricity include grid fees and taxes [14].

D. EMS assumptions

The EMS provides power set-points to the storage systems. An intermediate local control acts as a fast controller to ensure stability of the microgrid. Real-time measurements of load, RES generation, electricity price information and SOC of storage units are available to the EMS. Electricity prices are known *a priori* in case of TOU pricing. Both control approaches use an EMS sample time of 10 minutes ($\Delta T = 1/6[h]$). The prediction horizon is set to 15 hours for MPC approach. For the purpose of this simulation, we assume perfect forecasts for RE generation and load at first.

To get an indication of long-term performance of the MPC strategy with an imperfect forecast, a simple load forecasting algorithm is integrated. The used forecasting algorithm is based on a polynomial regression model which uses a gradient descent method for parameter fitting. The model calculates forecasts based on characteristics such as time of the day, season, temperature data and collected load data [15].

E. Performance Parameters

To benchmark the two strategies, several performance indicators are used similar to [16].

1) Operating costs: Operating costs in [RMB] are calculated for the different control strategies over the simulation period of one year according to (1).

2) RE self-consumption: RE self-consumption, in [%], represents the percentage of total RE production in one year which is consumed directly, either instantaneously by the load or through storage systems [17]. Higher RE self-consumption indicates a better local utilization of the installed PV capacity.

$$r = \frac{P^{re}_l}{\sum_i P^{reav}_i} \times 100, \tag{10}$$

where $P^{re}_l = \sum_i P^{re}_{i,dl} + \sum_i P^{re}_{i,cl}$. Term P^{re}_l is the load fed by RE production over the year, given by the sum of:

- $\sum P^{re}_{i,dl}$, RE production fed to microgrid load directly, and
- $\sum_i P^{re}_{i,cl}$, RE production used to charge storage systems which are later used to feed load.

3) Self-sufficiency: Self-sufficiency parameter in [%], describes the percentage of local load which is supplied directly by RE or through RE based storage discharging:

$$s = \frac{P^{re}_l}{\sum_i P^l_i} \times 100. \tag{11}$$

Since it is not possible to explicitly calculate the term $\sum_i P^{re}_{i,cl}$, we consider the best possible scenario to get an indication of the possible values of this performance parameter.

4) Losses in storages: Storage losses in [kWh] for charging, discharging and self-discharge are also analyzed by calculating the difference in net energy input and output over the year.

5) Total electricity exchange with the distribution grid: The energy exchange with the distribution grid is calculated as an additional performance indicator. Here, total purchased energy and total sold energy are obtained from $P^p_i, P^s_i \in \mathbb{R}^+$ and converted to [MWh].

VI. RESULTS AND DISCUSSION

To assess the performance of the two control approaches, this section is split into four subsections. First, differences between the two control strategies are explained by evaluating storage operation over example days. Afterwards, an overall assessment is presented according to the performance indicators described above. A sensitivity analysis regarding the impact of the chosen optimization horizon is presented. Finally, the results are discussed.

A. Operation analysis of MPC and rule-based approaches

Fig. 3 shows the performance of the two control strategies for three working days i.e. July 2 to 4, 2013. Next to the load demand and the RE production, the storage operation schedule is shown and visualized via its SOC and charging and discharging powers. Furthermore, the power exchange with the distribution grid is displayed. The load demand shows two characteristic peaks daily; one is during daytime working hours and the second one is air conditioning load which is operated during off-peak hours.

Compared to the rule-based strategy, MPC based operation improves the price-oriented and production-oriented storage operation. Especially, during off-peak price periods the difference between the two control approaches can be noticed.

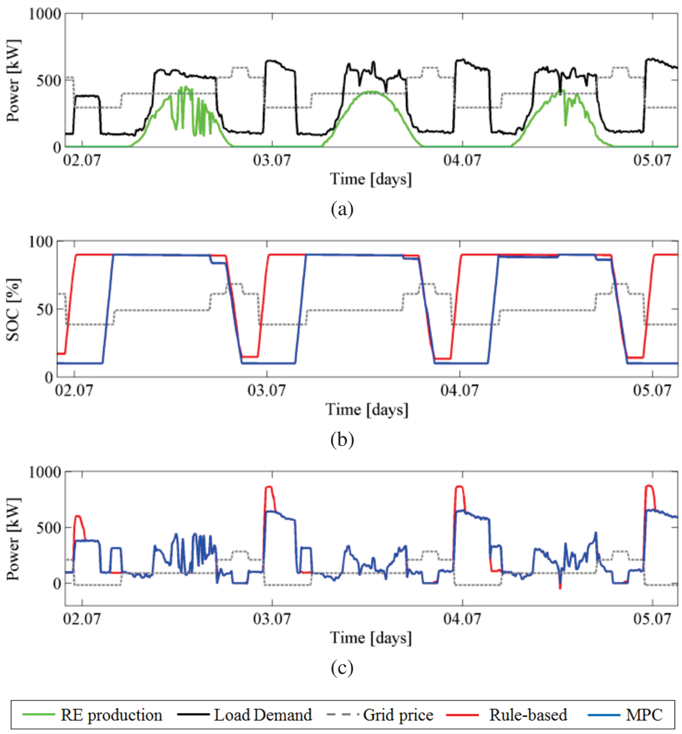

Figure. 3. Comparison of MPC and rule-based microgrid operation for three days in July: (a) load, RE generation and grid price profile, (b) Average SOC for three storages units, (c) Power exchanged with distribution grid: positive and negative values represent purchase and sale, respectively.

While the rule-based strategy leads to storage charging at the beginning of such a period, the optimization based strategy delays the charging to avoid unnecessary self-discharge losses. As a result, additional load peaks due to storage charging are experienced with the rule-based strategy.

B. *Overall assessment of control approaches*

This section evaluates overall strategies performance according to the predefined indicators. A reference case for microgrid operation without any storage is also considered. In this case, the local RE production is directly consumed and the surplus/deficit is balanced by the public distribution grid. From Fig. 3 (a) it is appreciated that the load has two peak periods in a day, one during working hours and the second during valley hours, which corresponds to the activation of the air conditioning unit. It means that the normal operation of the microgrid without storages already benefits from the TOU pricing. As the optimization-based algorithms rely on the quality of the used forecasts, the performance of MPC approach is evaluated by comparing a perfect and an imperfect load forecast. Table IV presents the summary of the different performance indicators for the two control approaches.

The MPC control approach results in 5.38 % and 1.85 % lower operating costs than the reference case and the rule-based case, respectively. Higher savings are not accomplished as the rule-based strategy is also able to benefit from the TOU price differences. RE self-consumption and self-sufficiency experience a moderate increase by approximately 10 %-points and 2.5 %-points, respectively. Even though self-consumption is not defined explicitly in MPC's objective function, the

TABLE IV. EVALUATION OF PERFORMANCE INDICATORS FOR CONTROL APPROACHES

Performance Parameter	Without Storages	Rule-based	MPC Perfect	MPC Imperfect
Operating costs [RMB $\times 10^3$]	1,101.4	1,061.7	1,042.1	1,047.4
Storage operating costs [RMB $\times 10^3$]	-	2.6	2.9	2.7
RE self-consumption [%]	76.7	76.8	86.9	85.4
Self-sufficiency [%]	19.9	20.0	22.6	22.2
Losses in storage [MWh]	-	21.0	20.4	19.3
Purchased energy [MWh]	1589.4	1610.0	1557.2	1561.4
Sold energy [MWh]	120.5	119.9	67.7	75.4

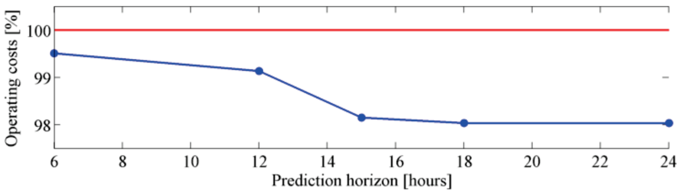

Figure. 4. Variation in one-year operating costs of microgrid with increasing prediction horizon for MPC EMS (blue). Rule-based EMS (red) is also plotted as a reference. Prediction horizons of 6 h, 12 h, 15 h, 18 h and 24 h are considered.

improvement on self-consumption, when compared to rule-based, occurs because of the following reason: when MPC predicts a surplus of RES production, it tries to empty the units so the predicted energy surplus can be stored and used later for local demand, instead of purchasing from the grid. The overall energy exchanged with distribution grid is lowered by 85-105 MWh. This reduces operating costs as expensive electricity purchases are avoided. There is also a slight reduction in storage losses.

The implemented load forecast has an overall mean average percentage error of 24.7 % over one year. Yet, through the feedback loop and the continuous optimization, the control approach is able to reduce the impact of such an error as annual savings only decrease by 5,000 RMB compared to the perfect forecast, which still corresponds to savings of 4.90 % over the reference case. After introduction of an imperfect forecast, RE self-consumption and self-sufficiency remain at a similar level. Storage losses slightly decrease with an imperfect forecast which indicates that less energy is stored overall. The exchanged grid energy is marginally higher compared to the perfect forecast.

C. *Sensitivity analysis of prediction horizon*

To evaluate the impact of the optimization horizon on the performance of the MPC strategy, the length of the optimization window is varied from 6 h to 24 h. Fig. 4 shows the resulting one-year operating costs.

There is a noticeable decrease in operating costs as the prediction horizon changes from 12 h to 15 h. This indicates that up to 12 h, the EMS is unable to forecast off-peak and peak hours within one optimization period. The differences between off-peak and flat hour prices as well as flat and peak hour prices are not sufficient to operate the storage system in a cost-decreasing way. This results in lower usage of storage units and the EMS is unable to take advantage of differences between peak and off-peak prices. A further increase in prediction horizon leads to only a marginal improvement in savings, with maximum of 2% with 24 h horizon. Hence, a 15 h prediction is chosen for the simulation as it provides a good compromise between a reduction in operation cost and an increase in calculation time.

D. Discussion of results

In general, the MPC approach leads to a more efficient microgrid operation as it is able to exploit price differences more effectively than a rule-based strategy. The achieved improvement is not extremely high compared to the rule-based strategy, which is a result of the chosen TOU pricing system and the installed sizes of the microgrid components. Note that the performance of the rule-based strategy is limited to the considered case and any changes may require redefining the control strategy. With MPC, the same EMS offers a sustainable optimal performance irrespective of considered pricing systems, major changes in load/generation profiles and components in microgrid. Additionally, MPC effectively minimizes the impact of the forecast quality as the key performance indicators such as operating costs do not decrease much with an imperfect load forecast. Yet, an RE production forecast is not implemented which might affect MPC performance slightly.

VII. Conclusion

As large-scale integration of local generation units poses increasing challenges to distribution grids, microgrids receive increased attention. Especially cost-efficient microgrid operation while satisfying local load demand and system constraints is of high interest. This paper analyzes and assesses two control approaches for grid-connected microgrids: rule- and optimization-based control. For the former, a specialized heuristic algorithm is used while for the latter, a model predictive control algorithm with mixed integer linear programming implementation is chosen. Both approaches are simulated for an office building microgrid in China.

Simulation results show that the optimization-based approach leads to a more cost-efficient microgrid operation while increasing local utilization of RE production. Savings of up to 5 % compared to operation without storages and 2 % compared to the rule-based approach are observed in considered case study. Furthermore, MPC is also able to minimize the impact of load forecast errors. Finally, a careful selection of the prediction horizon is necessary to be able to achieve a good trade-off between performance and computational complexity.

Nevertheless, the results are limited to the used data. Since, only operation-related costs are included in current study, additional costs, e.g. system fixed costs and investment costs can be added in the future. Some other interesting points for further work are the extension of the model with additional microgrid components, other operational objectives, other pricing systems and performance with more sophisticated forecasting algorithms.

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