Optimal Real-Time Control of Multiple Battery Sets for Power System Applications

Philipp Fortenbacher
Göran Andersson
ETH Zurich, Switzerland
{fortenbacher,andersson}@eeh.ee.ethz.ch

Johanna L. Mathieu
University of Michigan, USA
jlmath@umich.edu

Abstract—Due to high power in-feed from photovoltaics, it is expected that more battery systems will be installed in the distribution grid in near future. In this paper, we present a method to optimally control multiple battery sets in real-time to collectively provide services to power systems. The method is based on a Model Predictive Control (MPC) framework that tries to track an aggregated signal, while minimizing i) operation in high/low state of charge regimes, which would lead to battery degradation; ii) overall power losses including battery system, and iii) network losses, and considering network constraints. The performance of our approach is demonstrated for an application that coordinates several battery sets operating within a network containing photovoltaics and loads. Since our MPC controller can deal with non-convex piece-wise linear functions, the system losses can be modeled in more detail than in convex formulations. We show that the total battery system losses can be reduced by 35% with our approach as compared to approaches that operate all batteries in the same way.

Index Terms—battery management systems, optimal control, power systems, predictive control

I. INTRODUCTION

The need of energy storage in power systems has increased with higher penetrations of intermittent renewable energy sources [1]. In particular, battery systems can be used to balance short-term power fluctuations and improve power quality. In the next years, it is expected that many battery systems will be installed in the distribution grid to cope with high in-feed from photovoltaics (PV) [2] and other fluctuating energy sources connected to the distribution grid. To enhance profitability, battery systems could be coordinated to provide system-wide ancillary services in addition to their local services. A battery coordinator would solve optimization problems to optimally allocate portions of each battery to different services for given periods of time. For complexity reasons, such planning algorithms often use simple representations of batteries [3]. Those methods also often use low resolution, aggregated forecast profiles of loads and PV generation. This means that such allocation strategies are not able to consider (1) battery wear (i.e., capacity degradation), (2) power losses (from the battery and the inverter), (3) short-timescale battery dynamics, and (4) real-time fluctuations of dispersed intermittent renewable sources and loads. Consideration of these factors within real-time battery control algorithms will enhance the economic viability of batteries and improve power quality.

Some recent papers propose methods to include battery degradation costs in economic cost functions [4], [5], [6]; however, these methods do not consider a detailed model for battery and network losses. In addition, most work uses simple battery models that do not capture the short timescale dynamics that are present when batteries are operated in high/low state of charge regimes. Specifically, in these regimes the full charge capacity is only accessible at lower charging/discharging powers. To exploit the full battery capacity potential, it is necessary to consider this dynamic behavior when designing control strategies. In sum, the main challenge is to develop real-time control methods that are able to tackle all these challenges with reasonable computational complexity so that they can be deployed in computationally limited controllers.

The main contribution of this paper is a control method that controls multiple battery sets to track an aggregated set-point trajectory while minimizing battery degradation, battery system and network losses, and considering short timescale battery dynamics and distribution network constraints. In contrast to rule-based control methods [7], we present a method that optimally controls the individual battery power set points using Model Predictive Control (MPC), while considering real-time measurements of loads and PV generators. The MPC controller requires reasonable real-time computation and can handle non-convex cost functions allowing us to consider a more detailed power loss model. Within the controller, we use a battery model that captures the rate capacity effect [8], which allows us to effectively operate the batteries at high/low state of charge. A further contribution of this work is that the approach can be used to coordinate battery systems of different energy/power capacities and technologies.

This paper is organized as follows. Section II presents a detailed battery system model. Section III provides an approximation method to linearly represent the grid constraints for radial networks. Section IV introduces the MPC formulation and the general structure of the cost functions. Section V shows a case study for an application that coordinates the battery storages within a local group of PV generators and loads. Section VI provides the conclusion.

This work is supported by the Swiss Commission for Technology and Innovation (project no. 14478).
II. DETAILED BATTERY SYSTEM MODEL

A. Short Timescale Dynamics
To capture the short timescale battery dynamics, we use the battery model from [6]:

\[
\begin{bmatrix}
x_1' \\
x_2'
\end{bmatrix} = 
\begin{bmatrix}
\frac{c_r}{C_r} & \frac{c_r}{C_W} \\
\frac{c_r}{C_W} & -\frac{c_r}{C_W}
\end{bmatrix}
\begin{bmatrix}
x_1 \\
x_2
\end{bmatrix} + 
\begin{bmatrix}
C_{bat}^{-1} \\
0
\end{bmatrix}
P_{bat},
\]

\[
SOC = \begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix},
\]

(1)

where \(A_{bat}\) defines the battery dynamics. The parameters \(c_r\) and \(c_w\) model the rate capacity effect [8]. The states \(x_1, x_2\) model the amount of charge that is deposited in two virtual wells that are interconnected with a valve. Charge can only be withdrawn from the well corresponding to \(x_1\). Variable \(P_{bat}\) is the battery power, \(C_{bat}\) is the battery capacity, and the state of charge (SOC) is the sum of the charges in both wells.

B. Model of Multiple Battery Sets
To control \(n\) battery sets and to incorporate them in our controller we formulate the following dynamic model

\[
\dot{X} = AX + Bu^P_{bat},
\]

\[
SOC = CX,
\]

(2)

where \(X = [x_{bat1}, \ldots, x_{batn}]^T\), \(u^P_{bat} = [P_{bat1}, \ldots, P_{batn}]^T\), \(A = \text{diag}\{A_{bat1}, \ldots, A_{batn}\}\), \(B = \text{diag}\{b_{bat1}, \ldots, b_{batn}\}\), \(C = \text{diag}\{c_{bat1}, \ldots, c_{batn}\}\), and \(SOC = [SOC_1, \ldots, SOC_n]^T\). The aggregated SOC of \(n\) battery sets is

\[
x_{agg} = (1^T C_{bat})^{-1} C_{bat} CX,
\]

(3)

where \(C_{bat} = [C_{bat1}, \ldots, C_{batn}]^T\).

C. Efficiency
In order to assess a cost optimal operation of multiple battery sets, we first need an accurate model that describes the total efficiency of an individual battery set. The crucial parameter that influences the battery efficiency \(\eta_{bat}\) is the battery’s internal resistance \(R\). By using a Thevenin circuit equivalent the battery power \(P_{bat}\) is

\[
P_{bat} = V_{oc}I_{bat} - RI_{bat}^2,
\]

(4)

where \(V_{oc}\) is the open circuit voltage (OCV), which depends on the SOC. The battery efficiency for discharging currents \(I_{bat} > 0\) is given by

\[
\eta_{bat} = \frac{P_{bat}}{P_{cell}} = \frac{V_{oc}I_{bat} - RI_{bat}^2}{V_{oc}I_{bat}} = 1 - \frac{RI_{bat}}{V_{oc}},
\]

(5)

where the internal cell power \(P_{cell}\) is referred to as the power input. For charging currents \(I_{bat} < 0\), we have to reference the battery power \(P_{bat}\) to the power input:

\[
\eta_{bat} = \frac{P_{cell}}{P_{bat}} = 1 + \frac{RI_{bat}}{V_{oc} - RI_{bat}}.
\]

(6)

For \(V_{oc} >> RI_{bat}\), we can approximate (6) to

\[
\eta_{bat} \approx \eta_{bat}^{dis} = 1 - \frac{RI_{bat}}{V_{oc}}.
\]

(7)

The battery efficiency can be expressed as a function of the applied battery power \(P_{bat}\) by solving (4) for \(I_{bat}\) and putting this expression into (7)

\[
\eta_{bat} = 1 - \frac{V_{oc} - \sqrt{V_{oc}^2 - 4RI_{bat}^2}}{2V_{oc}}.
\]

(8)

In order to obtain the total losses of an individual battery set, we have to consider the inverter efficiency \(\eta_{inv}\). The total losses are

\[
P_{loss} = (1 - \eta_{bat}(SOC, P_{bat}, \eta_{inv}(P_{bat})) | P_{bat}|,
\]

(9)

where the multiplication of \(\eta_{bat}\) and \(\eta_{inv}\) leads to a non-convex function in battery power that can be approximated with following non-convex piece-wise linear function

\[
P_{loss}(P_{bat}) \approx \sum_{k=1}^{l} \lambda_k (1 - \eta_{bat} \eta_{inv} | P_{bat}^k |),
\]

(10)

where \(P_{bat} = \sum_{k=1}^{l} \lambda_k P_{bat}^k\) and \(\sum_{k=1}^{l} \lambda_k = 1\) define \(l\) piece-wise linear segments and the \(\lambda_k\) represent a Special Ordered Set (SOS) of type 2 [9].

III. GRID MODELING

We aim to control batteries in ways that do not lead to violations of distribution network voltage and line constraints. Most Low Voltage (LV) networks are radial, so that we focus on radial network configurations. The AC power flow equations are non-linear and induce complexity to our control problem. Therefore, based on a forward/backward sweep load flow method [10], we adopt linear approximations of the line and voltage constraints, so that we can use them in our linear control framework.

First, the complex nodal phase current injection vector \(I\) for the buses \(1 \ldots n\) can be expressed by

\[
I = \frac{1}{3} \text{diag}\{1/V_1, \ldots, 1/V_n\}^* | P + jQ |^*,
\]

(11)

where \(P\) and \(Q\) are the balanced three-phase real and reactive power injections at each bus \(n\). The variables \(V_1, \ldots, V_n\) are the complex nodal line to neutral voltages. According to [10] we can define a matrix \(M\) that maps the nodal current injection vector \(I\) to the branch current vector \(I_b\), with

\[
I_b = M I.
\]

(12)

The matrix \(M \in \mathbb{R}^{m \times n}\) is also called bus-injection to branch-current (BIBC) matrix. Since we want to minimize the real power loss \(P_{loss}\) with our controller, we can write

\[
P_{loss} = 3 \sum |R_d| \text{Re}(Z_d) I_b^*,
\]

(13)

where \(Z_d = R_d + jX_d = \text{diag}\{R_1 + jX_1, \ldots, R_m + jX_m\}\) represents the complex line impedances of the network. By
Inserting (11) and (12) into (13) the network losses can be expressed as

\[
P_{\text{loss}} = [P^T Q^T] \begin{bmatrix} W(|V|) & 0 \end{bmatrix} \begin{bmatrix} P \\ Q \end{bmatrix},
\]

(14)

where \(W(|V|) = |V_d| M^T R_d M |V_d|\). By using Ohm’s law the voltage deviations at the \(m\) buses with respect to the feeder voltage \(V_0\) can be exactly expressed by

\[
\Delta V = M^T Z_d l_b = \frac{1}{3} M^T [R_d + j X_d] M V_0^n [P + j Q]^*.
\]

(15)

However, (16) is complex, such that we can not find a linear and real approximation for our controller. If we assume that the nodal voltage angles are small (\(\approx 0\)) and the \(R/X\) ratio is high (> 3), which is usually the case for LV networks, we can approximate the voltage deviations by

\[
\Delta V \approx \Re\{\Delta V\} = L(|V|) \begin{bmatrix} P \\ Q \end{bmatrix},
\]

(17)

with 

\[
L(|V|) = \frac{1}{3} [M^T R_d M |V_d|, M^T X_d M |V_d|].
\]

Also the branch currents can be exactly expressed by using Ohm’s law as

\[
l_b = \frac{1}{3} [R_d + j X_d]^{-1} [R_d + j X_d] M V_0^n [P + j Q]^*.
\]

(16)

If we consider the aforementioned assumptions on the voltage angles and the \(R/X\) ratios, the branch currents can be linearly approximated by

\[
l_b \approx \Re\{l_b\} = B_i(|V|) \begin{bmatrix} P \\ Q \end{bmatrix},
\]

(19)

with

\[
B_i(|V|) = \frac{1}{3} [M |V_d|, X_d R_d^{-1} M |V_d|].
\]

IV. MODEL PREDICTIVE CONTROL DESIGN

To demonstrate our proposed controller, we consider an application that coordinates a local group of batteries, loads and PV over a one day horizon. As shown in Fig. 1 based on the solar and load forecast, the scheduler block calculates an aggregated SOC trajectory \(x_{\text{set}}\) that tries to maximize the self-consumption of the local group. As depicted in Fig. 2 we use an MPC to track the aggregated SOC \(x_{\text{set}}\) by solving for the optimal vectors containing the real and reactive power consumption/ production of each battery \(u_{\text{bat}}^P, u_{\text{bat}}^Q \in \mathbb{R}^n\) subject to an economic objective, which includes battery degradation costs as in [6]. We assume we can not predict the PV and load power in real-time, and therefore use MPC primarily to manage constraints, and so choose an MPC horizon of 1 step. We take real-time measurements of PV generation \(P_{\text{PV}}, Q_{\text{PV}} \in \mathbb{R}^n\) and loads \(P_l, Q_l \in \mathbb{R}^n\) into account via the disturbance vector \(u_{\Delta} = [P_l - P_{\text{PV}} \ Q_l - Q_{\text{PV}}]^T\). Note that in this formulation each node has a battery set, a PV generator, and a load connected to it. If, at some nodes, all three are not present, we can constrain the corresponding variables to zero.

We implemented a Luenberger observer to estimate the internal states \(x_{\text{bat}}\) of each individual battery set, since battery management systems typically provide only the SOC. Since the system (1) is detectable [11] we can design following Luenberger observer

\[
\dot{x}_{\text{bat}} = (A_{\text{bat}} - l e_{\text{bat}}^T) x_{\text{bat}} + |b | l [P_{\text{bat}} SOC],
\]

(20)

where \(l\) has to be chosen such that the dynamic matrix \((A_{\text{bat}} - l e_{\text{bat}}^T)\) is stable. For our simulations we apply the control inputs to battery sets modeled with the linear extended model from [6].

A. Problem Formulation

The optimization problem, which determines the optimal control vector \(u_0 = [u_{\text{bat}}^P, u_{\text{bat}}^Q]^T\) for one time step ahead, is

\[
\min_{u_0} T_{\text{s}c} c_{\text{net}}(u_0 - u_{\Delta}^T W(|V|))^{(u_0 - u_{\Delta})}
\]

network losses

\[
+ T_{\text{s}c} c_{\text{loss}} \sum_{i=1}^n P_{\text{loss}}(P_{\text{bat}}) + a |x_{\text{agg}}(X_1) - x_{\text{set}}|
\]

trajectory deviation

\[
+ T_{\text{s}c}(C X_1 - x_{\text{bat}})^T \hat{W} \{q_1, . . . , q_n\}(C X_1 - x_{\text{bat}})
\]

battery degradation

\[
+ b (u_{\text{bat}} - u_{\text{gen}})^T J (u_{\text{bat}} - u_{\text{gen}})
\]

ramp rates

s.t. (a) \(X_1 = \Phi X_0 + H u_{\text{bat}}^P\)

(b) \(SOC_{\text{min}} \leq CX_1 \leq SOC_{\text{max}}\)

(c) \(0 \leq X_1 \leq \frac{1}{\Phi} \begin{bmatrix} c_{w,1} \\ 1 - c_{w,1} \\ : \\ 1 - c_{w,n} \\ c_{w,n} \end{bmatrix}\)

(d) \(- \Delta V_{\text{max}} \leq L(|V|) (u_0 - u_{\Delta}) \leq \Delta V_{\text{max}}\)

(e) \(- I_{\text{max}} \leq B_i(|V|) (u_0 - u_{\Delta}) \leq I_{\text{max}}\)

(f) \(u_{\text{bat}}^P \leq S_{\text{max}} - A_{\text{bat}} u_{\text{bat}}^P\)

(g) \(u_{\text{bat}}^Q \leq S_{\text{max}} + A_{\text{bat}} u_{\text{bat}}^Q\)

(h) \(u_{\text{bat}}^\Delta \geq - S_{\text{max}} - A_{\text{bat}} u_{\text{bat}}^\Delta\)

(i) \(u_{\text{bat}}^\Delta \leq - S_{\text{max}} + A_{\text{bat}} u_{\text{bat}}^\Delta\)

(j) \(- B_g S_{\text{max}} \leq u_{\text{bat}}^Q \leq B_g S_{\text{max}}\)

(21)

where the objective operates in one economic cost domain. The network losses and battery losses are weighted with the cost factor \(c_{\text{net}}\) reflecting the costs for the lost energy. Our controller uses the non-convex piece-wise linear cost function (10) to model the total battery losses. This non-convexity results in a Mixed Integer Quadratic Programming (MIQP)
Algorithm 1, which iteratively combines the optimization constraints (21d) and (21e). To reduce this error, we developed

have to estimate them, which results in some error in the magnitudes more detail, where the gray region Figure 3 shows this relationship for one battery system in order cone formulation that leads to a highly-complex problem.

The constraint (21a) is the discretized version of (2). Specifically, X1 is the battery system state, after one time step; \( \Phi \) is the battery system dynamics matrix, and \( H \) is the control input matrix. The sample time is \( T_n \). Constraint (21b) specifies the minimum and maximum \((SOC_{min}, SOC_{max})\) bounds for the battery’s individual SOCs. Constraint (21c) avoids an overspill of the capacity wells. This constraint enables us to operate the maximum allowable voltage deviations with respect to the voltage at the slack bus. Constraint (21e) enables us to consider branch flow limits indicated with the vector \( I_{\Delta} \).

As we set the active and reactive power \((P, Q)\) of the battery systems, we had to include a second order cone constraint that defines the operating area for \((P, Q)\) by a circle around the maximum apparent power \( S_{max} \) with \( P^2 + Q^2 \leq S_{max}^2 \). To avoid a second order cone formulation that leads to a highly-complex problem to solve, we approximate this operating area with a polygon. Figure 3 shows this relationship for one battery system in more detail, where the gray region I can be described with the inequalities in the right corner. The \( \cos \phi \) is the power factor that defines the shape of the polygon. The constraints (21f)-(21j) describe the regions \( I - IV \) for \( n \) battery systems, where \( A_q = \text{diag} \{ a_1, \ldots, a_{qn} \} \) and \( B_q = \text{diag} \{ b_1, \ldots, b_{qn} \} \).

B. Algorithm

The matrices \( L \) and \( B_i \) depend on the nodal voltage magnitudes \( |V| \). Since we do not control the bus voltages, we have to estimate them, which results in some error in the constraints (21d) and (21e). To reduce this error, we developed Algorithm 1, which iteratively combines the optimization problem in (21) with the forward/backward sweep load flow method from [10]. In step 1 we initialize the start voltages with the slack bus voltages. After solving the problem (step 3) in stage \( k \), we calculate in the forward stage the currents (step 4). Then, the voltages are updated in the backward stage at step 5. These steps are iteratively repeated until the mean absolute error is below a threshold \( \epsilon \) (step 7). Since forward/backward sweep methods have a high convergence rate, typically \( k \) is small \((k \leq 4)\) [10].

Algorithm 1 Iterative algorithm to determine optimal battery control input.

1. \( Y^0 = V_b, k = 0 \)
2. \( \textbf{do} \)
3. \( [u^P_{bat} \ u^Q_{bat}] = \text{min} \ J((V^k)) \)
4. \( I^k = \frac{1}{2} \text{diag} \{V^k \}^{-1} |(u^P_{bat} - u^P_\Delta) + j(u^Q_{bat} - u^Q_\Delta)|^2 \)
5. \( V^k = V_b + M^T Z M L^k \)
6. \( k = k + 1 \)
7. \( \textbf{while} \ \text{mean}(|V^{k-1} - V^k|) > \epsilon \)

V. CASE STUDY

A. Definition

In our case study, we use three Li-ion battery sets with energy capacities 10 kWh, 15 kWh, and 20 kWh (see Table V-A). We calculate the non-convex cost functions using (10) with 10 regions and show them for each battery on Fig. 4. The inverter efficiency \( \eta_{in} \) was taken from [12]. The batteries are installed at different households that have loads and PV generators. We assume that we have real-time measurements of real and reactive power injections at each node, and so we have full knowledge of the grid state. For our simulations, we use generated load profiles from [13] and historic PV profiles. The households are connected to a radial network as depicted in Fig. 5. The impedances are chosen to represent a rural radial network with long lines. Table II lists the scenario parameters.

B. Simulation Environment

We implemented our controller in MATLAB using YALMIP [14] on an Intel Core i7 CPU at 2.9GHz and used CPLEX.
specified battery sets.

configuration is reasonable for a real controller in practice. To solve the MPC problem, we assume that this hardware formulation that minimizes deviations from the optimal state considering radial network constraints. We proposed an MPC controller operates in real-time and coordinates several multiple battery sets subject to an economic objective, while efficiencies in the lower power range. The battery with the highest capacity (20 kWh) is only used when power demand is high, since at high powers it has the best efficiency. As a result, the controller reduces losses by up to 35% as compared to when each battery follows the aggregated set point trajectory, referred to as “balanced” operation (see Table III). Figure 6 e) shows the curves for the network and battery losses. According to Table III, we can see that the network losses are dominant due to high PV in-feed to the grid. Since the storage capacities are too small to store more PV energy, our controller has a limited ability to reduce network losses.

Figures 6 b) d) and f) give more insights on shorter timescales. On the top figure, we see that battery 3 has to be charged in constant voltage mode, since its high SOC does not allow it to charge at higher power. Figures 6 d) and f) show the handling of the grid constraints. We can see that before the active power of battery 3 is used to decrease the voltage, inductive reactive power is consumed to lower the voltage at node 3. If there are no grid constraints violations, the controller tries to compensate for the inductive reactive power that is consumed by the loads. To demonstrate deviations in voltage estimates, we use one iteration step and obtain some error in the voltage drop. This relationship is also depicted on Fig. 7, where we have calculated the voltage mean absolute error (MAE) as a function of the iteration k including all nodes. For this specific case, we only have to iterate three times to achieve a voltage error of around 10^-2%. Additionally, we measured the execution times for solving the optimization problem for differently-sized battery sets. As shown in Fig. 8, we still get low execution times (≈ 40 msec) when we consider 10 battery sets, and so we believe that this approach can be implemented for real applications.

C. Results

The control results are shown in Fig. 6. On Fig. 6 a) the aggregated power of the loads, batteries and PV generators are displayed over 1 sunny day. Figure 6 c) displays the battery SOC curves. As shown, the controller switches between different battery sets. For lower power demands, the batteries with lower capacities are used at first, since they have higher efficiencies in the lower power range. The battery with the highest capacity (20 kWh) is only used when power demand is high, since at high powers it has the best efficiency. As a result, the controller reduces losses by up to 35% as compared to when each battery follows the aggregated set point trajectory, referred to as “balanced” operation (see Table III). Figure 6 e) shows the curves for the network and battery losses. According to Table III, we can see that the network losses are dominant due to high PV in-feed to the grid. Since the storage capacities are too small to store more PV energy, our controller has a limited ability to reduce network losses.

VI. Conclusion

We have presented an approach that optimally controls multiple battery sets subject to an economic objective, while considering radial network constraints. We proposed an MPC formulation that minimizes deviations from the optimal state of charge as well as battery and network power losses. Our MPC controller operates in real-time and coordinates several battery sets to follow an aggregated SOC trajectory. The execution times are reasonable, and so we believe that our controller can be implemented in practice. Our MPC controller is able

<table>
<thead>
<tr>
<th>Table I</th>
<th>PARAMETERS OF BATTERY SETS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Battery set</td>
<td>bat1</td>
</tr>
<tr>
<td>Capacity $C_{bat}$ (kWh)</td>
<td>10</td>
</tr>
<tr>
<td>Power $P_{max}$ (kW)</td>
<td>10</td>
</tr>
<tr>
<td>Charge well factor $c_w$</td>
<td>0.1</td>
</tr>
<tr>
<td>Recovery factor $c_t$ (sec^-1)</td>
<td>1e-3</td>
</tr>
<tr>
<td>Resistance $R$ (mΩ)</td>
<td>10.7</td>
</tr>
<tr>
<td>OCV $V_{bat}$</td>
<td>48</td>
</tr>
<tr>
<td>SOC target $x_s$</td>
<td>0.37</td>
</tr>
<tr>
<td>SOC cost $q$ (€/h)</td>
<td>4.2</td>
</tr>
</tbody>
</table>

1 Note that different values for $c_t$ and $c_w$ were reported in [6], but those were found to be inaccurate. The values reported above are the values for a typical Li-Ion battery.

2 Averaged open circuit voltage.

<table>
<thead>
<tr>
<th>Table II</th>
<th>SCENARIO PARAMETERS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample time $T_s$</td>
<td>10 sec</td>
</tr>
<tr>
<td>Line resistance $R_1$</td>
<td>82.4e-3 Ω</td>
</tr>
<tr>
<td>Line reactance $X_1$</td>
<td>32e-3 V/A</td>
</tr>
<tr>
<td>Slack voltage $V_0$</td>
<td>220V</td>
</tr>
<tr>
<td>Voltage limit $\Delta V_{max}$</td>
<td>22V</td>
</tr>
<tr>
<td>Current limit $I_{max}$</td>
<td>300A</td>
</tr>
<tr>
<td>Load max $P_{L1}, Q_{L1}$</td>
<td>5kW/50kW/cos $\phi$ = 0.9</td>
</tr>
<tr>
<td>PV max $P_{PV1}, Q_{PV1}$</td>
<td>40kW/40kW/cos $\phi$ = 1</td>
</tr>
<tr>
<td>Polygon variables $u_{bat}$, $b_{bat}$</td>
<td>0.22 for $\cos \phi$ = 0.9</td>
</tr>
<tr>
<td>Penalization factors $a$, $b$</td>
<td>1e3, 1e-5</td>
</tr>
<tr>
<td>Observer gain $l$</td>
<td>[1e-3 2.7e-4]^T</td>
</tr>
</tbody>
</table>

to solve the MPC problem. We assume that this hardware configuration is reasonable for a real controller in practice. For validation of the voltage and power flow constraints we use MATPOWER [15].
to reduce battery losses by 35% as compared to a balanced battery operation. Further research includes consideration of larger and weakly-meshed networks.

REFERENCES


