Achieving the Dispatchability of Distribution Feeders through Prosumers Data Driven Forecasting and Model Predictive Control of Electrochemical Storage

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Abstract—We propose and experimentally validate a control strategy to dispatch the operation of a distribution feeder interfacing heterogeneous prosumers by using a grid-connected battery energy storage system (BESS) as a controllable element coupled with a minimally invasive monitoring infrastructure. It consists in a two-stage procedure: day-ahead dispatch planning, where the feeder 5-minute average power consumption trajectory for the next day of operation (called dispatch plan) is determined, and intra-day/real-time operation, where the mismatch with respect to the dispatch plan is corrected by applying receding horizon model predictive control (MPC) to decide the BESS charging/discharging profile while accounting for operational constraints. The consumption forecast necessary to compute the dispatch plan and the battery model for the MPC algorithm are built by applying adaptive data driven methodologies. The discussed control framework currently operates on a daily basis to dispatch the operation of a 20 kV feeder of the EPFL university campus using a 750 kW/500 kWh lithium titanate BESS.

Index Terms—Battery storage plants, Optimal control, Modeling.

I. INTRODUCTION

The progressive displacement of conventional generation in favor of renewables requires to restore an adequate capacity of regulating power to assure reliable power system operation. An emerging concept to tackle this problem consists in achieving the controllability of portions of distribution networks by exploiting controllable distributed energy resources (DERs), such as flexible loads and battery energy storage systems (BESSs), and dispatching local generation. This paradigm can be traced in a number of frameworks, such as virtual power plants (VPPs) and microgrids which, in broad terms, consist in operating aggregates of heterogeneous DERs to provide ancillary services to an upper grid later, e.g. dispatchable power for primary/secondary frequency/voltage support and energy management (e.g. [1]–[3]). In general, solutions based on aggregating the capability of DERs require an extended ICT infrastructure and an efficient control policy to harvest flexibility until LV distribution level [4]–[6]. As a matter of fact, these solutions are of difficult integration in the existing grid because: (i) they might not offer the same reliability level as conventional generation, (ii) they are not always compatible with current regulation schemes, and (iii) their technical requirements are not met. An essential aspect to enable the transition towards a smarter grid is the availability of plug-and-play solutions, namely solutions that can provide ancillary services to the grid in the current operational and regulatory framework with a reduced set of technical requirements with minimal complexity level. In this paper, we propose and experimentally validate a control framework that achieves to dispatch the operation of a medium voltage (20 kV) distribution feeder by using a BESS. It is implemented as a two-stage procedure: day-ahead scheduling, where the feeder dispatch plan is determined, and an intra-day stage where the mismatch is tracked to zero by adjusting the BESS power injections by using model predictive control (MPC). In comparison to conventional closed loop controllers, integrating the BESS models into the MPC framework improves the awareness of the control action thanks to an efficient handling of the BESS constraints and the possibility of integrating predictions at different time scale. Both battery and consumption forecasting models (the latter is used during day-ahead operation) are identified and estimated from measurements (data-driven) and relies on a minimally invasive monitoring infrastructure.

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Fig. 1. The experimental setup: a MV distribution feeder of the EPFL campus equipped with an utility-scale BESS. The only requirement for dispatching the feeder is knowing the power flow at the GCP and the BESS power injection. Measurements are provided by a PMU placed at the beginning of the feeder and the battery management system (BMS). The feeder consumption \( L \) is estimated from the other two measurements.
The experimental validation is performed on a distribution feeder supplying five buildings with photovoltaic generation (300 kWp), using a grid connected 750 kW/500 kWh lithium titanate BESS. The paper is organized as follows: Section II states the problem, III presents the two-stage control strategy, IV discusses the models that were identified and their integration in the MPC strategy, V summarizes the experimental setup, VI presents the experimental results and VII draws the conclusions.

II. PROBLEM STATEMENT

We consider a distribution network populated by an unknown mix of electric loads, possibly distributed generation too, and equipped with a BESS. The power transit at the grid connection point (GCP) and BESS power injection are known from measurements, which are respectively provided by a remote terminal unit (RTU) or a phasor measurement unit (PMU) installed at the root of the feeder and the battery management system (BMS). An example of the setup is given by our experimental configuration, depicted in Fig. 1. Fig. 1 also introduces the notation for the power flows: $P$ is the aggregated consumption as seen at the GCP, $B$ is the BESS injection (positive when discharging and vice versa) and $L$ is the feeder consumption, that, by ignoring transmission losses between the BESS and GCP, is estimated as $L = P - B$. The problem is given by dispatching the feeder according to a 5-minute average power consumption profile, called feeder dispatch plan, that is determined the day before operation. Similarly to the conventional power system operational paradigm based on day-ahead scheduling and intra-day balancing, the control strategy consists in a two-stage structure (see Fig. 2).

- Day-before operation: the feeder dispatch plan is determined based on consumption forecasts and used to dispatch the operation of the feeder;
- Intra-day/real-time operation: the BESS power injection is controlled in order to compensate from any deviations from the dispatch plan (that are likely to occur due to prediction errors) using a MPC action to account for BESS operation constraints.

The choice of the 5 minute dispatch interval is according to the envisaged trend for real-time electricity markets. Although not specifically discussed in this work, this formulation potentially allows for day-ahead scheduling considering also dynamic electricity prices, in a similar way as done in [7]–[9].

There are two motivations underlying the willingness of dispatching the feeder:

1) it is a bottom-up solution to decrease the amount of regulating power capacity required to operate the grid, a well known issue related to operating the grid at a large proportion of production from intermittent renewable generation. The amount of regulating power, that could be potentially saved on a large scale might be indeed used to schedule additional renewable generation too.

2) the feeder dispatch plan is built in order to respect the power flow constraints at the GCP, therefore implicitly accomplishing congestion management in this point allowing the integration of non-dispatchable generation.

The control strategy is passive, in the sense that its objective is strictly local and does not require exchange of information with other parts of the grid. Moreover, the fact of relying on a minimally invasive monitoring infrastructure (only the power transit at the GCP is required) makes this strategy an eligible solution for DSOs who might install utility scale BESSs in primary substations to provide ancillary services to the grid and manage local congestions.

III. METHODS

A. Day-ahead scheduling

The objective is to determine the feeder dispatch plan, namely the average power consumption profile on a 5-minute basis that the feeder should follow the day-after. We denote the feeder dispatch plan as the sequence $\hat{P}_0, \hat{P}_1, \ldots, \hat{P}_{N-1}$ of $N = 288$ (number of 5-minute intervals in 24 hours) average power consumption values. The feeder dispatch plan is as:

$$\hat{P}_t = \hat{L}_t - \hat{B}^o_t, \quad t = 0, \ldots, N - 1,$$

namely, the difference between the predicted power consumption profile $\hat{L}$ and the BESS demand $\hat{B}^o$ necessary to bring the battery state-of-charge (SOC) to a predefined target value, denoted as SOC*. The reason of the latter contribute is promptly explained: at the end of the day of operation, the BESS SOC is likely different than e.g. 50%, that is the optimal level to compensate for unbiased (i.e. with nonzero mean error) consumption forecast. Indeed, including in the dispatch plan the battery charge/discharge demand to restore and adequate charge level for the coming day of operation naturally allows to ensure continuity of operation and optimal feeder dispatchability. A similar solution is also envisaged in [10], whereas it is normally disregarded in dispatch strategies for PV installations, which normally assume that the battery can be charged during overnight [11]–[13].

1) Computation of $\hat{L}$ (day-ahead consumption forecasting):

The feeder consumption is only known in terms of aggregated power consumption (type and consumption and individual loads are unknown). Therefore, we approach the forecasting problem applying a simple black-box, data driven method based on vector autoregression (VAR). The forecasting procedure is as follows. First, the vectors are obtained by splitting the time series of the historical power consumption measurements with 5 minutes resolution in 1-day long sequences (in our study, 1.5 year of data were considered). Vectors are
grouped into two sets, according to if they refer to national holidays or not. The consumption forecast for a given day is determined by selecting the right set of vectors (holiday or non-holiday) and then averaging the \( p \) most recent vectors that refer to the same day of week (Monday, Tuesday, \ldots), where \( p \) is a design parameter (in our case is empirically chosen as 3). It is noteworthy that the formulation of the proposed control strategy is independent of the forecasting tool used at this stage.

2) Computation of \( \hat{B}^o \) (BESS demand): The BESS demand profile is with the objective of achieving the target BESS SOC\(^*\). Additionally, it should be such to peak shave the aggregated power consumption to respect power flow constraints at the GCP. These requirements are modelled by the following convex optimization problem:

\[
\hat{B}_0^o, \ldots, \hat{B}_{N-1}^o = \arg\min_{\hat{B}_0^o, \ldots, \hat{B}_{N-1}^o} \sum_{t=0}^{N-1} (\text{SOC}^* - \text{SOC}_t)^2
\]

subject to:

\[
\begin{align*}
\text{SOC}_{t+1} &= \text{SOC}_t + \eta \frac{\hat{B}_t}{\text{E}_{\text{nom}}} \cdot \frac{60 \cdot 5}{3600}, \quad t = 0, \ldots, 1 - 2 \quad (3) \\
0 &\leq \text{SOC}_t \leq 1, \quad t = 0, \ldots, N - 1 \quad (4) \\
|\hat{B}_t| &\leq B_{\text{nom}}, \quad t = 0, \ldots, N - 1 \quad (5) \\
\hat{P}_t &= \hat{L}_t + \hat{B}_t, \quad t = 0, \ldots, N - 1 \quad (6) \\
|\hat{P}_t| &\leq S_{\text{nom}} \cdot \text{PF}, \quad t = 0, \ldots, N - 1 \quad (7)
\end{align*}
\]

where \( E_{\text{nom}} \) is the BESS nominal energy capacity in kWh, \( \eta \) and \( B_{\text{nom}} \) the efficiency and nominal power of the BESS converter, \( S_{\text{nom}} \) the nominal apparent flow of the substation, and PF the power factor of the substation power transit. Although the BESS converter is four-quadrant and the reactive power can be easily included as control objective in the proposed formulation, at this stage we only focus on the active power (we assume PF=1). Since day-ahead procedure is performed one hour before operation, SO\(C_0 \) (the initial BESS SOC) is still unknown and, therefore, needs to be estimated. In this case we use a simply persistent predictor, namely SO\(C_0 \) as the current SOC. If available, one might consider to use short-term consumption forecast (e.g. one-hour-ahead) to improve the SO\(C_0 \) estimate.

B. Intra-day/real-time operation

At the beginning of the day of operation, the feeder is dispatched according to the dispatch plan. During operation, the consumption will likely differ from it because forecasting errors: the objective of intra-day operation is to control the BESS power injection in order to compensate for deviations with respect to the dispatch plan. The decision process is implemented using MPC, that is applied in a receding horizon fashion once each 15 seconds with updated measurements. Before proceeding further with the formulation, we introduce the following notation (that is also exemplified in Fig. 3):

- double index subscripting, like \((t, k)\), denotes quantities with 15 seconds resolution: indexes respectively refers to the 5 minutes interval and 15 seconds subinterval. E.g. \( L_{t0} \) is the measured power consumption of the feeder, averaged over the first 15 seconds of the 5-minute interval with index \( t \).
- \( L_{tk} \) denote power consumption measurements, that progressively become available in real-time. \( B^o_{tk} \) is the BESS power injection set-point on the AC side calculated by the MPC strategy (superscript \( o \) stands for “optimal”).

In the following, we will introduce two MPC formulation in increasing order of complexity.

1) MPC: Formulation A (MPC-A): Say being at time \((t, k)\), the dispatch plan error is defined as:

\[
e_{tk} = \begin{cases} 
0, & k = 0 \\
\hat{P}_t - \frac{1}{k} \sum_{j=0}^{k-1} (L_{tj} + B_{tj}), & k > 0
\end{cases}
\]

where \( e_{tk} \) is the sum of known terms \( e_{t2} = \hat{P}_t - (L_{t0} + B_{t0} + L_{t1} + B_{t1})/2 \) and \( e_{t3} = 0 \), we have that

\[
\hat{P}_t = (L_{t0} + B_{t0} + L_{t1} + B_{t1})/2
\]

e.g. at \((t, 2)\) as in Fig. 3, it is the sum of known terms \( e_{t2} = \hat{P}_t - (L_{t0} + B_{t0} + L_{t1} + B_{t1})/2 \).

The dispatch plan error (8) corrected accounting for the current control action \( B_{tk} \) is:

\[
\hat{P}_t - \frac{1}{k} \left( \sum_{j=0}^{k-1} (L_{tj} + B_{tj}) + B_{tk} \right) = e_{tk} - \frac{1}{k} B_{tk}
\]

We seek for the control action \( B^o_{tk} \) that minimizes the squared value of (11) while respecting BESS constraints, formally:

\[
B^o_{tk} = \arg\min_{B_{tk} \in \mathbb{R}} (e_{tk} - 1/k B_{tk})^2
\]

subject to:

\[
\begin{align*}
B_{\text{min}} &\leq B_{tk} \leq B_{\text{max}} \quad (13) \\
v_{\text{max}} &\leq v_{tk+1} \leq v_{\text{max}} \quad (14) \\
0 &\leq \text{SOC}_{tk+1} \leq 1 \quad (15) \\
v_{tk+1} &= f(B_{tk}, \text{SOC}_{tk}) \quad (16) \\
\text{SOC}_{tk+1} &= g(B_{tk}, \text{SOC}_{tk}) \quad (17)
\end{align*}
\]
The constraints (13)-(15) are to respect BESS converter nominal power, battery DC nominal voltage and SOC limits. Not respecting those might result in anomalous BESS conditions, which are eventually conducive to disruptive general system failures, like converter tripping. Clearly, system failures are highly undesirable because they imply the complete loss of controllability. In this respect, MPC allows to handle system constraints more efficiently than conventional close-loop control strategies. Expressions (16)-(17) specify that voltage and constraints more efficiently than conventional close-loop control strategies. In this respect, MPC allows to handle system failures, like converter tripping. Clearly, system failures are highly undesirable because they imply the complete loss of controllability.

2) MPC: Formulation B (MPC-B): It can be noted from Fig. 3 that at time $t(t+1,0)$ it not possible to compensate for the events at the previous subinterval $(L_{t19})$ because they refer to two different dispatching periods. In order to compensate in advance for the next power consumption realization, we introduce the concept of short-term consumption forecast. Being at time $(t,k)$, the predicted dispatch plan error is as:

$$\hat{e}_{tk+1} = \hat{P}_t - \frac{1}{k+1} \left( \sum_{j=0}^{k-1} (L_{tj} + B_{tj}) + \hat{L}_{tk} + B_{tk} \right)$$

(18)

where $\hat{L}_{tk}$ denotes the power consumption for the incoming subinterval period, that is calculated as the average of the previous three power consumption realizations (with respect to the persistent predictor, normally used for short-term consumption prediction at high level of disaggregation e.g. [14], this allows a smoothing effect). We reformulate (18) as:

$$\hat{e}_{tk+1}^- = \hat{P}_t - \frac{1}{k+1} B_{tk},$$

(19)

$$\hat{e}_{tk+1}^+ = \hat{P}_t - \frac{1}{k+1} \sum_{j=0}^{k-1} (L_{tj} + B_{tj}) + \hat{L}_{tk}.$$  

(20)

The objective of this MPC is to find the value of $B_{tk}$ that minimizes the squared value of (19). Formally, it is as:

$$B_{tk}^o = \arg \min_{B_{tk} \in \mathbb{R}} \left( \hat{e}_{tk+1}^- - \frac{1}{k+1} B_{tk} \right)^2$$

(21)

subject to the same constraints (13)-(17) as the previous MPC formulation.

IV. PREDICTION MODELS FOR BESS AND THEIR INTEGRATION INTO MPC

A. Grey-box dynamic voltage models

Battery models for control applications are normally to the purpose of predicting the terminal voltage as a function of the charge/discharge current or power and trade detailed modelling of electrochemical reactions for an increased level of tractability, as e.g. in [15]–[17]. In this work, the purpose of this section is to formalize the constraints (13)-(17). System identification of voltage dynamics is carried out by applying grey-box modelling, a framework that allows to identify a validated model incorporating available physical knowledge together with measurements from a real device [18], [19]. In our specific case, it consisted in: (1) model formulation, (2) estimation of model parameters from experimental measurements (BESS voltage and charge/discharge current) using maximum likelihood estimation (MLE) and (3) model validation through checking for residual correlations in the one-step-ahead prediction errors (residual analysis). If the residual analysis is satisfactory the model is retained (4), otherwise a new model is formulated (adding for example a state) and the procedure above is repeated. In order to achieve an efficient identification of the system dynamics out of the BESS voltage measurements, we performed a specific experimental session where we controlled the BESS charge/discharge power according to a nearly pseudo-random-binary-signal (PRBS), a signal with two states ($\pm 200$ kW), constant period and random, uniformly distributed duty cycles. The general model structure is from existing literature and consists in a voltage generator with a series resistance and multiple RC-branches, until accomplishing the criteria (4) specified above. To capture the dependency of the model parameters with respect to the BESS SOC, we estimated five sets of parameters by feeding MLE with the identification signal performed at five different level of BESS SOC (10, 30, 50, 70 and 90%): during operation, the right set of parameters is selected according to the current BESS SOC (model scheduling). Models are formulated using continuous-time, stochastic state-space representation:

$$dx = A_c(\theta)x_{tk} + B_c(\theta)u_{tk} + \kappa_c(\theta)dw$$

(22)

$$v_{tk} = C^Tx_{tk} + D^T(\theta)u_{tk} + q_{tk}$$

(23)

where $x \in \mathbb{R}^n$ is the system state vector, $A \in \mathbb{R}^{n \times n}, B \in \mathbb{R}^{n \times 2}, C, D \in \mathbb{R}^n$ are the state-space matrices, $\omega$ is a standard $n$-dimension Wiener process, $\theta$ a vector of $p$ parameters to estimate and $q_{tk}$ a white noise process with variance $q^2$.

1) Model Selection and Formulation: It was found that the third order model shown in Fig. 4 was able to satisfy the residual analysis for all the SOC ranges. The model is formalized as in (22)-(23) with the following state-space matrices, state vector and inputs:

$$A_c = \begin{bmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & -1 \end{bmatrix}$$

$$B_c = \begin{bmatrix} 1/C_1 \\ 1/C_2 \\ 1/C_3 \end{bmatrix}$$

(24)

$$\kappa_c = \text{diag}(k_1, k_2, k_3), C = [1 \quad 1]^T, D = [R_s \quad E]^T$$

(25)

$$x = \begin{bmatrix} v_{C_1} \\ v_{C_2} \\ v_{C_3} \end{bmatrix}, u_{tk} = \begin{bmatrix} \hat{e}_{tk} \\ 1 \end{bmatrix}$$

(26)

where the estimated model parameters are shown in Table I. The residual analysis of the selected model in the case of

\footnote{It is known from the literature that parameters of equivalent circuit models also depend on temperature and C-rate [15]: at the current stage, these dependencys are not included in the models and will be the focus of future investigations.}
Combining this with (23), yields:
\[ v_{t+1} = CAx_{t} + CBu_{t} + Du_{t} \]  
(28)

By partitioning the input vector and matrices as
\[ B = \begin{bmatrix} B_0 & B_1 \end{bmatrix}, \quad D = \begin{bmatrix} D_0 & D_1 \end{bmatrix}, \]  
(29)
the expression (28) can be written as:
\[ v_{t+1} = \alpha + \beta i_{t}, \]
\[ \alpha = CAx_{t} + CB1 + D1, \quad \beta = CB0 + D0. \]  
(30)

The average BESS power injection during the time interval \((t, k)\) to \((t, k+1)\) is approximated by the product between the DC current, average DC voltage and converter efficiency \(\eta\):
\[ B_{t,k} = i_{t,k} \cdot (v_{t+1} + v_{t})/2 \]  
(31)

Multiplying both sides of (30) by \(\eta(v_{t+1} + v_{t})/2\) and using the expression above for \(B_{t,k}\) leads to:
\[ v_{t+1}^{2} + \frac{v_{t}}{2} - \alpha v_{t} v_{t+1} - \frac{\alpha v_{t} + 2/\eta \beta B_{t,k}}{\eta} \cdot^{1/2}. \]  
(33)
The function \(h(B_{t,k})\) above is the BESS voltage evolution as a function of the AC injected power. The linearization with respect to \(B_{t,k}\) is given by its first order Taylor approximation:
\[ v_{t+1} \approx h(B_{x}) + \frac{dh}{dB_{t,k}} \bigg|_{B_{t,k}=B_{x}} (B_{t,k} - B_{x}), \]  
(34)
where \(B_{x}\) is the linearization point. Our choice for \(B_{x}\) is zero. In (34), the first derivative of \(h\) with respect to \(B_{t,k}\) is:
\[ \frac{dh}{dB_{t,k}} = \frac{\beta}{\eta} \left( \frac{v_{t} - \alpha}{4} + \alpha v_{t} + 2/\eta \beta B_{t,k} \right)^{-1/2}. \]  
(35)

Summarizing, the linear relationship between the BESS voltage and power is
\[ v_{t+1} \approx f(B_{t,k}) = h(0) + dh/dB_{t,k} \bigg|_{B_{t,k}=0} B_{t,k}. \]  
(36)

3) State estimation: In state-space battery voltage models, the full information on the state vector \(x\) (necessary in (30) to compute the system evolution) is not available because individual state components are a modelling abstraction and do not correspond to measurable quantities. Rather, their contributions are lumped into the measurement of the battery terminal voltage \(v\), normally available from the BMS. Since the residual analysis of the previous section indicated overall satisfactory performance, state estimation is performed with Kalman filtering (KF, [20]) that is known to provide best estimates in hypothesis of i.i.d. system and measurement noise. KF consists in a two-stage procedure, repeated at each discrete time interval: a prediction step to determine the system

50% SOC is shown Fig. 5: vertical lines denotes the auto-correlation function of the model one-step-ahead prediction errors (using the training data set), while the horizontal lines are the limits of the autocorrelation function (ACF) of white noise (uncorrelated by definition) at 95% confidence level. The last should be considered as the thresholds above/below which the model residuals are correlated in time. Fig. 5 denotes that the model structure together with the identified parameters was able to capture all the dynamics contained in the measurements data set. This condition was also satisfied for the other combinations of parameters of Table I. Models are characterized by a fast time constant (few seconds) and two slower (minutes). Since the MPC is applied once every 30 and that the fastest dynamic of the system correspond to a real eigenvalue, it is computationally convenient to drop it and replace it with an algebraic relationship.

**TABLE I**
**Experimentally Estimated Model Parameters According to the BESS State-of-Charge**

<table>
<thead>
<tr>
<th>SOC</th>
<th>0.1</th>
<th>0.3</th>
<th>0.5</th>
<th>0.7</th>
<th>0.9</th>
</tr>
</thead>
<tbody>
<tr>
<td>(E)</td>
<td>592.2</td>
<td>625.0</td>
<td>652.9</td>
<td>680.2</td>
<td>733.2</td>
</tr>
<tr>
<td>(R_a)</td>
<td>0.029</td>
<td>0.021</td>
<td>0.015</td>
<td>0.014</td>
<td>0.013</td>
</tr>
<tr>
<td>(R_i)</td>
<td>0.095</td>
<td>0.075</td>
<td>0.090</td>
<td>0.079</td>
<td>0.199</td>
</tr>
<tr>
<td>(C_1)</td>
<td>8930</td>
<td>9809</td>
<td>13996</td>
<td>9499</td>
<td>11234</td>
</tr>
<tr>
<td>(R_2)</td>
<td>0.04</td>
<td>0.009</td>
<td>0.009</td>
<td>0.009</td>
<td>0.010</td>
</tr>
<tr>
<td>(C_2)</td>
<td>909</td>
<td>2139</td>
<td>2482</td>
<td>2190</td>
<td>2505</td>
</tr>
<tr>
<td>(R_3)</td>
<td>2.5e-3</td>
<td>4.9e-5</td>
<td>2.4e-4</td>
<td>6.8e-4</td>
<td>6.0e-4</td>
</tr>
<tr>
<td>(C_3)</td>
<td>544.2</td>
<td>789.0</td>
<td>2959.7</td>
<td>100.2</td>
<td>6177.3</td>
</tr>
<tr>
<td>(k_1)</td>
<td>0.639</td>
<td>0.677</td>
<td>0.617</td>
<td>0.547</td>
<td>0.795</td>
</tr>
<tr>
<td>(k_2)</td>
<td>-5.31</td>
<td>-0.22</td>
<td>-0.36</td>
<td>-0.28</td>
<td>0.077</td>
</tr>
<tr>
<td>(k_3)</td>
<td>5.41</td>
<td>40</td>
<td>0.40</td>
<td>2.83</td>
<td>-0.24</td>
</tr>
</tbody>
</table>

Fig. 4. Equivalent circuit of the BESS voltage model. The quantities \(v\) and \(i\) are respectively the BESS terminal voltage and DC current, while \(v_{C_1}, v_{C_2}, v_{C_3}\) denote the states of the state-space model.

Fig. 5. ACF of model residuals (full line) and white noise (horizontal lines) at 95% confidence level.

2) Implementation of voltage models in the MPC: The objective is to determine the voltage evolution as a linear function \(f\) of the BESS power injection \(B_{t,k}\). We denote the discretized voltage models as:
\[ x_{t+1} = A x_{t} + B u_{t} + K \omega. \]  
(27)
Combining this with (23), yields:
\[ v_{t+1} = CAx_{t} + CBu_{t} + Du_{t} \]  
(28)
evolution (state expected value and covariance matrix $P$) solely on the basis of the knowledge on the system

$$x_{k|k-1} = Ax_{k-1|k-1} + Bu_{k-1}$$

$$P_{k|k-1} = AP_{k-1|k-1}AT + KKK^T,$$

and an update stage, where the predicted state is corrected accounting for the last measurement $y_k$

$$x_{k} = x_{k|k-1} + G(y_k - Cx_{k|k-1})$$

$$P_{k} = \left(P_{k|k-1} + CTC - 1 \right),$$

where $G$ is the Kalman gain:

$$G = P_{k|k-1}CT \left( CP_{k|k-1}CT + v^2 \right)^{-1},$$

where $v$ is the measurement noise (also known from the parameters estimation). KF requires full system observability, that in our case is enforced by construction since the model is estimated from measurements. It is noteworthy that when computing (37), there are two possible choices for the input signal $u$: the battery power, known since it is the control setpoint, or the average DC current, that is normally known from the BMS at the next discrete time interval. We use the latter because it allows to retain a linear formulation of the problem (the former would require extended KF).

B. State of charge model

1) Model Formulation: The one-step-ahead prediction of the BESS SOC is as:

$$SOC_{tk+1} = SOC_{tk} + \gamma t_{tk}$$

where the coefficient $\gamma = T_s/C_{nom}$ is the ratio between the subinterval duration and the BESS nominal capacity $C_{nom}$, and $SOC_{tk}$ is known from the BMS.

2) Linearization of SOC constraints: The objective is to determine the evolution of the BESS SOC as a function $g$ linear in the BESS power injection $B_{tk}$. Multiplying both sides of (42) by $\eta(v_{tk+1} + v_{tk})$ and rearranging yields:

$$(SOC_{tk+1} - SOC_{tk}) \eta(v_{tk+1} + v_{tk}) = 2\gamma B_{tk},$$

that by using (36) to approximate $v_{tk+1}$ and reorganizing is:

$$SOC_{tk+1} \approx l(B_{tk}) = SOC_{tk} + \frac{2\gamma}{\eta} B_{tk}.$$ As for the voltage, the linearization of the BESS SOC with respect to $B_{tk}$ is obtained by a first order Taylor approximation around $B_{tk} = 0$:

$$SOC_{tk+1} \approx g(B_{tk}) = l(0) + dl/dB_{tk}|_{B_{tk}=0} B_{tk}$$

where

$$dl/dB_{tk} = (b + v_{tk})/(m B_{tk} + b + v_{tk})^2.$$
exemplify the operation of the control strategy and the second is a quantitative assessment of the performance of the two MPC controllers.

A. Experimental operation of the control strategy

Fig. 8 shows the operation of MPC-A during the experimental day scenario 0. Fig. 8a shows the elaboration performed in the day-ahead stage: the dispatch plan $\hat{P}$ (denoted by the yellow dashed profile) is computed according to Eq. (1) as the difference between the consumption forecast $\hat{L}$ (blue) and the BESS demand $\hat{B}^o$ (orange). Recalling from III-A, the dispatch plan includes the BESS demand in order to bring the BESS SOC to 50%, namely with at the largest capacity to compensate for unbiased electricity consumption forecast. The effect of incorporating the BESS demand into the dispatch plan is well visible if observing the first hours of intra-day/real-time operation. In particular from Fig. 8c, it can be seen that the BESS is close to be fully charged at the beginning of the day of operation: a positive $\hat{B}^o$ causes the dispatch plan to underestimate the real consumption (Fig. 8b). This requires the BESS to inject power in order to compensate for it, finally inducing its SOC to decrease close to its target level at around five in the morning (57% vs 50%, Fig. 8c). There are two sources of uncertainty in the dispatch plan that prevent the BESS SOC to exactly reach the half level: first, $\hat{B}^o$ is determined without knowing the real BESS SOC at the beginning of the day of operation (as discussed in III-A2); second, an unforeseen BESS activity in the time frame from midnight to five in the morning due to imprecise consumption forecast $\hat{L}$ included in the dispatch plan.

Similar considerations apply to day scenario 1 in Fig. 9, unless that, in this case, the BESS needs to be charged at the beginning of the day of operation.

B. Performance assessment of the MPC controllers

To evaluate the ability of the MPC strategies to track the dispatch plan, we introduce the relative error sequence

$$e = \left\{ (\hat{P}_t - P_t)/\hat{P}_t, \ t = 0, \ldots, N - 1 \right\}$$  \hspace{1cm} (47)

that is determined for each day of operation and used to compute the statistics shown in Table II. The data in Table II refer to two experimental day scenarios and are to compare the effect of applying MPC with respect to respective base-case (as if the BESS injection was 0). The former is obtained by calculating the relative error (47) using the actual power transit at the GCP, whereas, in the latter, the BESS contribute (that is known from the BMS) is subtracted from the the actual consumption; moreover, in the base-case, also the battery charging demand $\hat{B}_t$ is ignored (in other words, $\hat{P}_t = L_t$ and $P_t = L_t$, $t = 0, \ldots, N - 1$). Numerical results in Table II show that both MPC-A and MPC-B accomplishes a fairly accurate tracking of the feeder dispatch plan,
with the RMS and mean metrics that are well below 1% and substantially lower than their respective base-case. Although MPC-B achieves better performance (lower RMS, lower median, reduced skewness, lower extreme values), it is noteworthy that, at this stage, it is not possible to operate a fair comparison since the base-cases are different. This is because they refer to two different experimental day-scenarios, and clearly the stochasticity inherent the real consumption profile cannot be replicated from one day to another. In this respect, a quantitative assessment of the different performances of the two MPC controllers should be performed using a larger dataset covering different seasons corresponding to different prosumers behaviours (i.e., loads and PV production).

### TABLE II

<table>
<thead>
<tr>
<th>Metric (%)</th>
<th>Day Scenario 0</th>
<th>Day Scenario 1</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Base-case (no MPC)</td>
<td>MPC-A</td>
</tr>
<tr>
<td>RMS(e)</td>
<td>11.44</td>
<td>0.46</td>
</tr>
<tr>
<td>mean(e)</td>
<td>0.1</td>
<td>-0.07</td>
</tr>
<tr>
<td>median(e)</td>
<td>-3.97</td>
<td>-0.1</td>
</tr>
<tr>
<td>max(e)</td>
<td>39.85</td>
<td>1.01</td>
</tr>
<tr>
<td>min(e)</td>
<td>-21.68</td>
<td>-2.08</td>
</tr>
</tbody>
</table>

VII. CONCLUSIONS AND PERSPECTIVES

Motivated by the objective of reducing the amount of regulating power required to operate the grid to achieve a larger proportion of production from renewables, we have proposed and experimentally validated on a realistic scale a control framework that achieves to dispatch the operation of a grid-connected BESS. The proposed approach relies on a minimally invasive monitoring infrastructure and is suggested as a potential solution for DSO to deploy utility-scale BESS. The control strategy consisted in following a consumption profile with 5 minute resolution (called dispatch plan and determined the day before operation) by adjusting the BESS charging/discharging set-points. The real-time tracking problem was accomplished by applying receding horizon model predictive control (MPC), that was formulated as a convex optimization problem. The models implemented in the MPC were estimated from measurements applying the greybox modelling methodology, allowing for robust BESS operation thanks to implementing predictive voltage and SOC constraints. The experimental validation consisted in dispatching the operation of a 20 kV distribution feeder of the EPFL university campus by using a 750 kW/500 kWh lithium titanate BESS. Experimental results show that the proposed control framework is able to track the dispatch plan precisely, with a RMS error below 0.5%.

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REFERENCES


