Data-informed control of Hybrid Energy Storage Systems in LVDC microgrids

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***Abstract*—Multiple energy storage technologies may be combined into a Hybrid Energy Storage System (HESS) to maximize the benefit from differing underlying technologies. In this paper we examine the control of a HESS in an LVDC microgrid. HESS control is complex due to balancing objectives of both storage technologies, and even more so when the goal is provide network services (e.g. voltage regulation) as well. In this paper, we utilize data-based control methods applied to the control of a Li-ion and supercapacitor (SC) HESS system connected to a LVDC microgrid scenario. To accomplish this, we use hybrid data-enabled predictive control (HDeePC), allowing incorporation of known (and relatively well understood) dynamics of the underlying storage mediums, while retaining a model-free control approach to the network (the LVDC microgrid) for which it may be difficult in practice to determine an accurate model for. We demonstrate the proposed controller in a LVDC microgrid example, and perform comparisons to pure data-driven predictive control (DeePC) and model predictive control (MPC).**

***Index Terms*—Data driven control, Data-enabled predictive control (DeePC), Hybrid Energy Storage Systems (HESS), Battery Energy Storage System (BESS), Supercapacitors**

I. Introduction

Energy storage (ES) devices [1] are crucial to the integration of intermittent renewable energy. Common energy storage devices include chemical, mechanical and thermal batteries. There are many competing technologies, including lithium ion (Li-ion), flow batteries (e.g. vanadium redox) and supercapacitors (SC). These may be grouped by their specific power density, energy density, ramp rate, lifespan and cost.

For example, supercapacitors possess greater power density and a fast ramp rate, making them suitable for fast response and large cycle counts. Comparatively, Li-ion batteries have greater energy density, but a lower ramp rate and greater cycling degradation. It is advantageous to combine ES technologies to provide benefit of multiple technologies, known as a hybrid energy storage system (HESS). A common combination is the SC and Li-ion, e.g. [2]. This combination allows high ramp-rate and power density, while still providing large energy storage capabilities. Additionally, high cycle counts can be achieved (through the SC) with minimal degradation to the Li-ion battery.

The control of such HESS is a complex and non-trivial endeavor. This control system must cope with the difference in time-constants between the mediums, providing the optimal charging and discharging methodology to minimize costs (including battery degradation) while meeting energy demands and regulating the microgrid. Design of these control systems generally requires accurate modeling of the underlying dynamics of each storage medium and the networks which they are connected to, which can be increasingly complex.

Literature Review: Research has focused on a single HESS within a variety of scenarios, including applying them to DC microgrids and fluctuation of wind generation [3]. Existing control methods can be broadly grouped into the following: a) PI control; b) Model-based Predictive Control (MPC); c) Rule-based or fuzzy logic; d) Data-driven control (e.g. DeePC). Traditional PI control was applied in [4] and [5]. Drawbacks to these include the need for accurate transfer functions of the BESS and SC to tune PI parameters. Additionally, constraints (such as SOC limits) are difficult to include.

Model-Predictive Control (MPC) is a type of optimal control methodology that solves an input-output optimization problem over a finite control horizon. A variety of MPC schemes have been applied to HESS including traditional MPC [6], two-stage MPC [3], current control [7] and multi-mode MPC [8]. The premise of these methods involves an accurate model of the underlying energy storage medium, allowing the prediction of the system's response to different inputs. Cost functions include state-of-charge (SOC) terms for both BESS (SOC_B) and SC (SOC_{SC}) and directly take into account system constraints (such as maximum ramp rate). Again, these methods require a highly accurate system model, which is often derived from a set operating point.

Rule-based and fuzzy logic controllers have been applied to HESS control in [9]–[11] in which a range of heuristic and rule-based approaches provide both stability to the grid and SOC balance. These approaches inherently handle nonlinearities and constraints. However, they are mostly a trial-and-error approach, and changing conditions and battery technologies may require different heuristics.

Data-driven approaches attempt to skip the need for system identification. DeePC [12] is one of the most important frameworks based on the Fundamental Lemma of behavioral systems theory [13]. Through collection of input-output data of an LTI system the system can be represented directly by data. A hierarchical fuzzy neural network with DeePC was applied to HESSs within EV drive trains [14].

Contribution: Although the previous literature has demonstrated success in controlling various HESS configurations, they generally rely on having a complete and accurate model of the HESS and network. This may not always be the case in practice, with HESS often connected to complex networks.

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This motivates the use of data-based methods; however purely data-driven methods can struggle with differing time-scales. Additionally, the incorporation of partial model dynamics may reduce computational expense and increase accuracy [15]. This paper uses a hybrid data-enabled predictive control (HDeePC [15]) to control a battery/SC HESS within a LVDC microgrid, incorporating the known model dynamics of the BESS and SC, while retaining data-driven control of the LVDC microgrid voltage dynamics. The main contributions of this paper are:

1) Application-specific design of a hybrid data-enabled predictive control scheme for HESSs, incorporating the known physical dynamics of the storage technologies.
2) Simulation and comparison of the scheme to conventional MPC and DeePC methods, focusing on key metrics: computation time, storage degradation and constraint violations.

This paper is organized as follows: section II outlines preliminaries on system modeling and DeePC/HDeePC. Section III then presents the proposed controller design, while section IV outlines the case study and results, including a comparison to DeePC and MPC. Section V concludes the paper.

II. Preliminaries

A. System Modeling

A general DC microgrid is considered, where each bus is numbered and connected through RL branches R_i, L_i. Lumped bus capacitance are given by C_i and their voltages by v_i. The voltage dynamics are:

$$C_i \frac{dv_i}{dt} = -\sum_{j \in \mathcal{N}_i} i_{ij} \ + \ i_{\text{bess},i} + i_{\text{sc},i} \ + \ i_{\text{load},i}, \tag{1}$$

where i_{ij} are the currents flowing into the bus i and C_i is the lumped capacitance model of bus B_i. Current flow on each RL branch is modeled by (2):

$$L_{ij} \frac{di_{ij}}{dt} = v_i - v_j - R_{ij} i_{ij} \tag{2}$$

We consider four elements that may be connected to each node: (1) BESS, (2) SC-ESS, (3) stochastic gen/load and (4) an external grid connection. The states of the system are $x = [\mathbf{v}_{dc}^T, \ \mathbf{i}_L^T, SOC_b, \ V_{SC}]^T$ as in Table I.

Table I
System States of the DC Microgrid

State Variable	Description
$\mathbf{v}_{dc} \in \mathbb{R}^{n \times 1}$	Bus voltages
$\mathbf{i}_L \in \mathbb{R}^{(n-1) \times 1}$	Inductor (line) currents on RL branches
$SOC_b \in \mathbb{R}$	State of charge of the BESS
$V_{SC} \in \mathbb{R}$	Voltage of the super-capacitor

1) BESS Modeling: The BESS is modeled as a controllable constant current source. Internal current regulation is assumed to be handled by a form of current mode control (CMC), which regulates the internal bi-directional PWM power converter to supply a fixed current source. The SOC dynamics are modeled using a standard coulomb counting method and is given by (3), where i_{bess} is defined to be charging when negative. (3):

$$\frac{dSOC_{\text{bess}}}{dt} = \frac{i_{\text{bess}}}{Q_{\text{bess}}} \tag{3}$$

And $i_{\text{bess}}, SOC_{\text{bess}}$ are constrained by operational limits:

$$\begin{aligned} i_{\text{bess,min}} \le i_{\text{bess}}(t) \le i_{\text{bess,max}}, \\ SOC_{\min} \le SOC(t) \le SOC_{\max}. \end{aligned} \tag{4}$$

2) SC-ESS Modeling: The SC-ESS is modeled as an ideal capacitor connected through an ideal bi-directional PWM converter to the DC bus which boosts the 10V SC to the nominal bus voltage, appearing as a controllable current source. The capacitor terminal voltage changes according to:

$$C_{sc} \frac{dV_{sc}}{dt} = i_{sc} \tag{5}$$

where the energy stored within the capacitor is given by:

$$E_{\text{sc}} = \tfrac{1}{2} C_{\text{sc}} v_{\text{sc}}^2. \tag{6}$$

and limits are imposed:

$$\begin{aligned} & v_{\text{sc,min}} \le v_{\text{sc}}(t) \le v_{\text{sc,max}}, \\ & |i_{\text{sc}}(t)| \le i_{\text{sc,max}}. \end{aligned} \tag{7}$$

3) Load and Grid Modeling: The total load, i_{load}, is given by the sum of a base load and a load fluctuation modeled by an Ornstein-Uhlenbeck process. It is described by (8):

$$\begin{aligned} \dot{\tilde{i}}_{\text{load}}(t) = -\lambda \, \tilde{i}_{\text{load}}(t) + \sigma \, w(t), \\ i_{\text{load}}(t) = i_{\text{base}}(t) + \tilde{i}_{\text{load}}(t). \end{aligned} \tag{8}$$

where $\tilde{i}_{\text{load}}(t)$ denotes the fluctuation of the load around the baseline, which is influenced by the mean-reversion rate λ, noise intensity σ and the white noise process $w(t)$. The load is represented by an ideal current source.

B. Data Enabled Predictive Control

We consider an unknown discrete-time linear system of the form:

$$\begin{cases} x(t+1) = Ax(t) + Bu(t), \\ y(t) = Cx(t) + Du(t). \end{cases} \tag{9}$$

where $A \in \mathbb{R}^{n \times n}$, $B \in \mathbb{R}^{n \times m}$, $C \in \mathbb{R}^{p \times n}$ and $D \in \mathbb{R}^{p \times m}$. Additionally, $x(t) \in \mathbb{R}^n$, $u(t) \in \mathbb{R}^m$ and $y(t) \in \mathbb{R}^p$ (i.e. the system has m inputs, p outputs and n state variables). Input and output trajectories are denoted $u = \text{col}(u_1, u_2, ...)$ and $y = \text{col}(y_1, y_2, ...)$, respectively. Rather than using an intermediate system identification stage, Hankel matrices are constructed which contain consecutive (input/output) data and are used directly within the optimization problem. The (input) Hankel matrix of order $L \le T$ is expressed:

$$\mathcal{H}_L(u) := \begin{bmatrix} u_1 & u_2 & \cdots & u_{T-L+1} \\ u_2 & u_3 & \cdots & u_{T-L+2} \\ \vdots & \vdots & \ddots & \vdots \\ u_L & u_{L+1} & \cdots & u_T \end{bmatrix} \tag{10}$$

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An important aspect of DeePC is ensuring that the data is of sufficient length and quality, allowing the linear system dynamics to be fully represented via the Fundamental Lemma [16]. Such data is said to be *persistently exciting* [12, Def. 4.4]. The DeePC optimization problem [12, Eq. 6] is the basis of the hybrid DeePC algorithm we now discuss.

C. Hybrid Data Enabled Predictive Control

HDeePC incorporates known model dynamics into the DeePC formulation, allowing two distinct advantages: a) the known model dynamics are impervious to noise; b) numerical issues regarding known dynamics of extremely lengthy time constants are avoided. The second point is of particular importance to the presented HESS application. As with DeePC, the unknown (linear) part of the dynamics are represented through the input/output Hankel matrices [15, Equation (7)] while the known part of the plant dynamics are represented by their model: $A_\kappa, B_\kappa, C_\kappa, D_\kappa$. The reduction of Hankel matrices achieved through partial model knowledge typically reduces the computational burden of the unknown dynamics [15].

III. Controller Formulation

Using the aforementioned HDeePC formulation, the energy storage systems (BESS and SC) are the known plant dynamics, modeled through (3) and (5), respectively. The voltage dynamics of the microgrid, $\mathbf{v}_{dc}$, are chosen to be the unknown, data-driven dynamics. The input is given by $u(k) = \begin{bmatrix} i_{\text{load}}(k) & i_b(k) & i_{sc}(k) \end{bmatrix}^T$ and the output is given by $y(k) = \begin{bmatrix} v_{\text{bus}}(k) & SOC_b(k) & v_{\text{sc}}(k) \end{bmatrix}^T$. The known states are given by $x_\kappa = [SOC_b,\ V_{SC}]^T$. This leads to the following optimization problem which minimizes the cost over the controller horizon N:

$$
\begin{aligned}
&\min_{g,\ u,\ y,\ y_u,\ SOC_b,\ V_{SC}} \\
&\sum_{k=0}^{N-1} \Big(\|v_{\text{bus}}(k) - v^\star\|^2_{Q_v} + \|SOC_b(k) - SOC^{ref}\|^2_{Q_{\text{SOC}}} \\
&\quad + \|V_{sc}(k) - V_{sc}^{ref}\|^2_{Q_{\text{sc}}} \\
&\quad + \|u(k)\|^2_R \Big) + \lambda \|g\|^2 \\
\text{s.t.}\quad & \begin{bmatrix} U_P \\ Y_{U,P} \\ U_F \\ Y_{U,F} \end{bmatrix} g = \begin{bmatrix} u_{\text{ini}} \\ y_{u,\text{ini}} \\ u \\ y_u \end{bmatrix} \\
& x_\kappa(0) = \hat{x}_\kappa(t), \\
& SOC_b(k{+}1) = SOC_b(k) \ - \ \frac{i_b(k) T_s}{\tau_q} \\
& V_{\text{sc}}(k{+}1) = v_{\text{sc}}(k) \ + \ \frac{T_s}{C_{\text{sc}}}\, i_{sc}(k), \\
& i_{sc,\min} \le i_{sc}(k) \le i_{sc,\max}, \\
& i_{bess,\min} \le i_b(k) \le i_{bess,\max}, \\
& v_{\min} \le v_{\text{bus}}(k) \le v_{\max}, \\
& SOC_{\min} \le SOC_b(k) \le SOC_{\max}, \\
& v_{\text{sc},\min} \le v_{\text{sc}}(k) \le v_{\text{sc},\max}, \quad \forall k \in \{0, \dots, N{-}1\}.
\end{aligned} \tag{11}
$$

where the input U consists of the random load variable, i_{load}, and controllable inputs for each storage medium (and grid tie converter). Significant terminal costs placed on the model-based ESS control are critical to allowing prediction of SOC and V_{SC} dynamics over a short time frame. It should also be noted that there are no coupling terms present between the known dynamics (as SOC and V_{SC} depend only on the requested currents from each storage medium) and thus the lack of couplings trivially permit HDeePC to be applied to this problem (see [15] for more detail).

An inherent problem, as mentioned in the introduction, is the coordination of multiple 'SOC' references (BESS SOC or super-capacitor voltages). The optimization problem aims to appropriately 'trade off' these goals and thus minimize the cost. Intuitively (and based on power-systems experience), the SC should be more responsive to high-frequency deviations of voltage, while the BESS should supply larger quantities of power over a longer period to satisfy lower frequency demands. To accomplish this, cross-coupling of the SOC and V_{SC} terms is implemented through the cost matrix Q. The cross-coupling term γ penalizes the BESS SOC and V_{SC} from moving together, effectively staggering the response and allowing (through manipulation of cost weightings) the SC to respond quicker to transients while the BESS SOC takes longer to respond. This coupled cost matrix term is:

$$
Q_{\text{coupled}} = \begin{bmatrix} Q_{\text{SOC}} & \gamma I \\ \gamma I & Q_{\text{sc}} \end{bmatrix}, \tag{12}
$$

where: $0 < \gamma < \sqrt{\lambda_{\min}\big(Q_{\text{SOC}}\big)\, \lambda_{\min}\big(Q_{\text{sc}}\big)}$ to ensure the weighting matrix $Q \ge 0$.

The optimal control problem is solved according to Algorithm 1 at each time step. Regularization terms λ are added to the cost function to aid in robustness against noise.

Algorithm 1 HDeePC Controller

Require: Initialized input/output Hankel matrices, $\mathcal{H}_L(u)$ and $\mathcal{H}_L(y)$. Known system dynamics of the BESS, $SOC(t, i_b)$, and SC, $v_{sc}(t, i_{sc})$. Horizon N, weights Q_v, Q_{SOC}, R.

1: **for** each time step t **do**
2: Get current $SOC_b(t)$ and $v_{sc}(t)$
3: Solve (11) for g^*, u^*, x^*, y^*
4: Apply u^* at the next input timestep
5: **end for**

IV. Case Study and Results

A single HESS connected to a fixed 400 V_{DC} grid through an RL line is simulated via a custom Python program. A BESS/SC HESS, along with fluctuating load ($\mathcal{N}(0,1)A$) are connected to the single bus-bar. The state model is discretized using the Forward Euler Discretization method as in (13), with system parameters given in Table II. The HDeePC controller parameters are contained in Table III. Measurement noise of $\mathcal{N}(0, 10^{-3})$ is added to the simulation.

$$[A \mid B] = \left[\begin{array}{cccc|ccc} 0.98 & 1.0 & 0 & 0 & 1 & 1 & 1 \\ -0.2 & 0.6 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & -10^{-4} & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & -0.01 \end{array}\right],$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad D = \mathbf{0}_{3\times 3}. \tag{13}$$

Table II
SYSTEM AND DISCRETIZATION PARAMETERS

Parameter	Symbol	Value
Sampling time	T_s	1×10^{-3} s
Load resistance	R_{load}	50 Ω
DC-link capacitance	C_{dc}	1 mF
Line inductance	L_{line}	5 mH
Line resistance	R_{line}	2 Ω
BESS time constant	τ_q	10 s [1]
Supercapacitor capacitance	C_{sc}	0.1 F

Table III
HDEEPC CONTROLLER PARAMETERS

Parameter	Symbol	Value
Prediction horizon	N (N)	10
Data length (for Hankel matrices)	T (T)	200
Past window length	T_{ini} (Tini)	20
Simulation length (steps)	lengthSim	1000
BESS current limit	$I_{\max}^{\text{bess}}$	5.0
SC current limit	$I_{\max}^{\text{sc}}$	5.0
Voltage deviation soft bound	$\Delta V_{\max}$	20.0
SC voltage reference	$V_{\text{sc}}^{\text{ref}}$	10.0
State-of-charge reference	SOC^{ref}	0.5
Weight on V_{dc} deviation	Q_v	1.0×10^{-6}
Weight on SOC deviation	Q_{SOC}	1.0×10^{4}
Weight on V_{sc} deviation	Q_{sc}	1.0×10^{2}
Control move weight (all inputs)	R	1.0×10^{-4}
Derivative weight on y	$w_{\dot{y}}$ (wy_dot)	1.0×10^{-1}
Derivative weight on SOC	$w_{\dot{\text{SOC}}}$ (wsoc_dot)	1.0×10^{8}
Derivative weight on V_{sc}	$w_{\dot{v}_{\text{sc}}}$ (wvsc_dot)	1.0×10^{1}
Derivative weight on u	$w_{\dot{u}}$ (wu_dot)	1.0×10^{-1}
Regularization on g	λ_g (lg)	1.0
Noise (L1) regularization	λ_y (ly)	1.0×10^{5}

Figure 1 shows that V_{SC} rapidly meets the target reference, while the BESS SOC follows a smoother trajectory. Additionally, once the references are met, i_{SC} fluctuates more significantly than i_b. This is a result of penalty being applied to the change in i_{SC} combined with the coupling method previously described. Additionally, the proposed HDeePC controller was compared to a traditional DeePC (zero model knowledge) and MPC (full model knowledge) controller. In contrast, the proposed controller has knowledge of the dynamics of two states (SOC and V_{SC}). A numerical summary of results are presented in Table IV.

[1]In order to be able to simulate significant SOC changes over the short simulation time-frame an artificially small time constant is chosen, which is still hundreds of times slower than the supercapacitor or LVDC dynamics.

Table IV
PERFORMANCE COMPARISON OF CONTROLLERS

Controller	RMSE$_v$	TV$_u$	SOC Error	Solve Time (p95, ms)
HDeePC	3.07	4000.91	0.0119	0.455
DeePC	2.70	4027.10	0.0254	0.453
MPC	6.25	3613.25	1.53×10^{-5}	0.0295

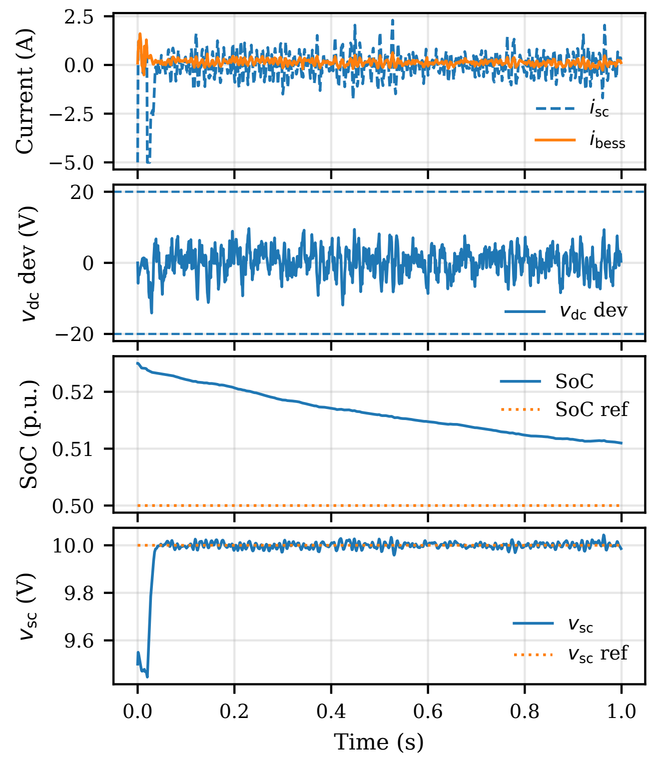

Figure 1. BESS/SC currents, bus voltage deviation, SOC, and SC voltage over time (Proposed HDeePC controller).

It can be seen from the results that partial state knowledge of SOC and V_{SC} dynamics reduces the SOC tracking error, although computation time was largely unaffected and DeePC was slightly more successful in tracking the desired voltage reference. Compared to MPC, both data-enabled control methods provide a reduction in voltage tracking error, but a substantial increase especially for DeePC) in SOC tracking error. This is due to the fact that in the presence of noise DeePC struggles to "learn" the behaviour of the very slow SOC dynamics.

Nevertheless, HDeePC significantly improves the ability of the proposed control method to track the desired V_{SC} and SOC where DeePC struggles. Figs. 2 and 3 illustrate our results.

In terms of battery degradation, a rough estimate is given by:

$$\mathcal{D}_{\text{BESS}} = \frac{1}{T_s} \sum_{k=0}^{T-2} \left(\Delta i_{\text{bess}}[k]\right)^2. \tag{14}$$

Figure 4 shows that HDeePC provides a lower degradation than DeePC, even with the latter being unable to sufficiently

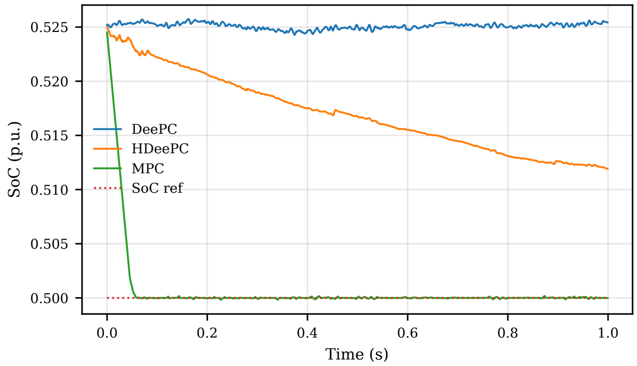

Figure 2. SOC comparison of DeePC, HDeePC and MPC controllers

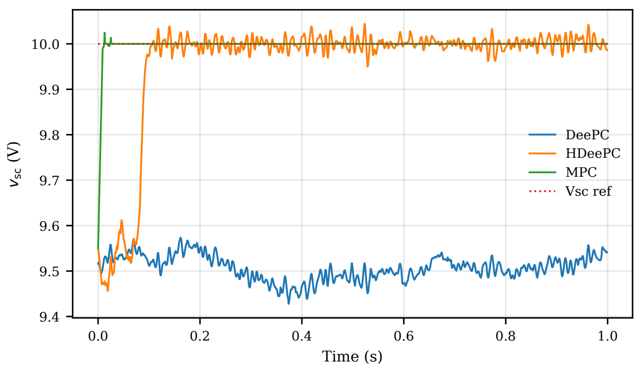

Figure 3. V_{SC} comparison of DeePC, HDeePC and MPC controllers

track the reference.

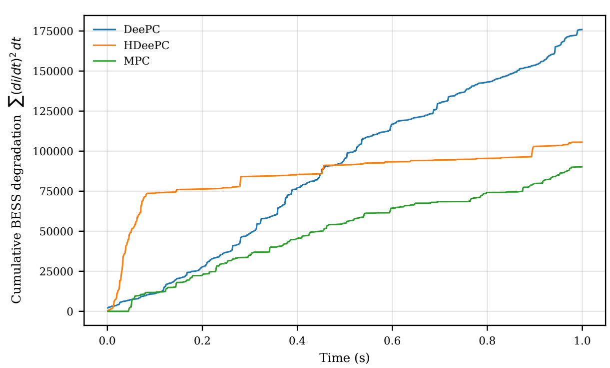

Figure 4. Battery degradation comparison of DeePC, HDeePC and MPC controllers

V. Conclusion

This paper presented the use of hybrid data enabled predictive control (HDeePC) to control HESSs within a LVDC microgrid scenario. The proposed controller has been applied to a BESS and super-capacitor HESS, incorporating known model dynamics of the energy storage mediums into the control problem. The proposed controller framework was shown to appropriately control the unknown bus voltage dynamics while managing BESS and supercapacitor SOC. In comparison, pure DeePC was unable to accurately track these dynamics due to the short prediction horizon compared to the slow SOC dynamics. Overall, the results demonstrate that incorporating known HESS dynamics into a data-driven predictive controller can improve the tracking of SOC metrics while reducing BESS degradation. Future work should explore more complex microgrid scenarios, including additional nodes and more complex HESS configurations.

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