Real-Time Implementation of Consensus Tracking Control for Battery Energy Management and SoC Balancing

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***Abstract*—This paper presents the real-time implementation of a consensus-based tracking control technique for battery energy management systems (BEMS) and state of charge (SoC) balancing. The consensus tracking controller is designed by applying linear quadratic regulator (LQR) control on the battery linearized model in MATLAB, where the state variables are the battery's output power and energy. The LQR weighting matrices are selected to give reasonable overshoot, consensus mismatch, and consensus convergence time. A three-battery model is used from the hardware-in-the-loop laboratory testbed and open platform (HILLTOP) to integrate the consensus tracker and its related communication parameters. One battery uses a hardware vendor controller, while the other two are controlled via Typhoon HIL software controllers. The hardware-in-the-loop (HIL) controller for battery 1 acts as the leader, with batteries 2 and 3 functioning as followers in the consensus control process. The results demonstrate that the output powers of all batteries reach consensus, aligning with the dynamic power setpoint, and maintain balanced SoC levels, effectively preventing over-charging or over-discharging.**

***Index Terms*—BESS, consensus tracking control, energy management, real-time simulation, SoC balancing.**

I. Introduction

The battery energy storage system (BESS) plays a pivotal role in modern energy systems by storing surplus energy during periods of low demand and discharging it during peak demand, thereby enhancing grid stability and sustainability. By strategically utilizing stored energy, BESS contributes to cost reduction and overall energy efficiency improvement [1]–[3].

To maintain long-term efficiency, precise control of BESS is necessary to mitigate battery degradation under diverse operational conditions. Key parameters, such as state of charge (SoC) and state of health, are fundamental in ensuring optimal BESS performance. Variations in initial SoC, capacity, and voltage across multiple BESS units can lead to operational imbalances and potential safety concerns [4]. Therefore, achieving SoC equilibrium is critical for prolonging battery lifespan and optimizing system performance. Maintaining SoC within an optimal range is recommended to ensure operational stability [5]. Effective power management strategies must be integrated into the BESS control framework to maintain this balance.

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Battery energy management system (BEMS) is essential for efficiently regulating energy production, distribution, and consumption while minimizing operational costs. Within microgrids, BEMS plays a key role in optimizing battery charging and discharging cycles to ensure safe and effective operation [6]–[9]. This study focuses on developing a BEMS-based real-time control strategy for efficient BESS management.

Various control strategies have been proposed for BEMS in recent research. Hierarchical control methods address multiple operational levels, including primary, secondary, and tertiary layers, to enhance energy stabilization and distribution [10], [11]. While centralized control relies on a single controller, making it susceptible to failures, decentralized and distributed control methods enhance system resilience. Among these, consensus-based distributed control has been widely adopted for coordinated power sharing and SoC balancing [9], [12]–[14].

Consensus-based control techniques facilitate SoC alignment while maintaining operational constraints [15], [16]. The average consensus approach harmonizes battery SoC values, whereas delay-resilient multi-agent control has been explored for SoC regulation [5], [17]. However, the complexity of certain models can hinder their practical implementation. Distributed consensus methods further improve active/reactive power sharing and system synchronization [18]–[20]. Despite these advancements, real-time consensus tracking for BEMS charging/discharging remains an unexplored area, which this research aims to address through hardware-in-the-loop laboratory testbed and open platform (HILLTOP) [21] and Typhoon HIL real-time simulations.

The real-time implementation of BEMS for energy management has gained attention due to its potential to enhance grid stability, optimize renewable energy utilization, and improve cost efficiency. Several studies have explored different control strategies and optimization methods to enhance the real-time operation of BESS [22]–[27]. For instance, [23] investigated a nonlinear model predictive control algorithm to manage hybrid BESS, while [24] proposed a deep reinforcement learning approach to manage real-time energy dispatch effectively. Furthermore, [25] developed a hybrid energy management system integrating fuzzy logic and model predictive control methods to ensure efficient real-time operation. In addition, [26] presented an adaptive control strategy for a grid-connected BESS enhancing both grid stability and energy efficiency by addressing system nonlinearities and uncertainties. Finally, a real-time energy management scheme that considers the involvement of prosumers to support net-zero power systems was introduced by [27], demonstrating the capability of real-time balancing energy fluctuations. These studies collectively highlight the advancements in real-time BESS implementation and underscore the need for continued research to refine supervisory control strategies and improve integration with renewable energy sources. To the best of our knowledge, consensus tracking control methods have yet to be extensively applied in real-time simulation environments for managing the battery charging process.

This study explores the implementation of a consensus tracking control method in HILLTOP, leveraging developed Typhoon HIL and HILLTOP simulation files and codes in [28], [29] for this purpose. A state feedback linear quadratic regulator (LQR) is employed to optimize feedback gains for individual batteries, with control inputs derived through a consensus process incorporating LQR gains. The proposed approach aims to enhance real-time battery charging operations and improve BESS efficiency.

The structure of this paper proceeds as follows: Section II details the formulation of the control problem and design of the consensus tracking controller. The HILLTOP/Typhoon HIL model, along with simulation results, is discussed in Section III. Section IV provides the concluding remarks.

II. Consensus Tracking Control Design

A. Battery Model

The general linear model that describes the battery system dynamics is [30]:

$$\dot{x_i} = Ax_i + Bu_i,\ i = 1, 2, \ldots, n, \tag{1}$$

where $x_i \in \mathbb{R}^n$ and $u_i \in \mathbb{R}^h$ are the state and consensus tracking control input signal of the battery i, respectively. $A \in \mathbb{R}^{n\times n}$ and $B \in \mathbb{R}^{n\times h}$ are the state and input matrices, respectively.

For a real battery, the state-space model is represented as [9]

$$\dot{E}_i(t) = \frac{-1}{3600}\ P_i(t), \tag{2}$$

$$\dot{P}_i(t) = u_i(t), \tag{3}$$

where the state variables $E_i(t)$ and $P_i(t)$ are the battery energy and power, respectively.

A virtual battery state-space model defines the target command as follows [9]:

$$\dot{x}_T = Ax_T + Bu_i, \tag{4}$$

where $x_T \in \mathbb{R}^n$ is the target's state variable. In terms of the battery state variables, the target state space model is represented as

$$\dot{E}_T(t) = \frac{-1}{3600}\ P_T(t). \tag{5}$$

The reference set value of each battery is calculated as

$$P_{ref_i}(t) = P_{0_i} + u_i(t), \tag{6}$$

where P_{0_i} is the initial set/reference value for the battery's current control loop.

The linearized battery model fits well with the energy management system because the BEMS acts as a supplementary controller, and the time frame spans from minutes to hours.

B. Design of LQR Control Gains

Using the LQR method [31], we design the feedback gain matrices $K_1 = [k_1\ k_2]$ for the real battery and $K_2 = [k_3\ k_4]$ for the target virtual battery. The gain vector K_1 is designed by selecting Q_1 and R_1 matrices and solving the ARE to get a positive definite matrix H_1 as follows:

$$A^T H_1 + H_1 A + Q_1 - H_1 B B^T H_1 = 0, \tag{7}$$

$$K_1 = R_1^{-1} B^T H_1. \tag{8}$$

Likewise, the target gain, K_2, is determined by selecting Q_2 and R_2 matrices and solving the ARE to get H_2 as follows:

$$A^T H_2 + H_2 A + Q_2 - H_2 B B^T H_2 = 0, \tag{9}$$

$$K_2 = R_2^{-1} B^T H_2. \tag{10}$$

The Q matrix is a diagonal weight matrix related to the states of the battery (power and energy/SoC), and the R matrix is associated with the control input u_i.

C. Q and R Matrices Selection

The selection of the Q and R matrices is based on various factors of battery performance. These factors are:

1) To prevent efficiency losses and battery degradation from circulating currents, all batteries are constrained to operate concurrently in either charging or discharging mode.
2) The control law ensures power closely tracks the consensus reference in all operating conditions.
3) Improving the convergence between the batteries with low power mismatch when consensus/agreement is achieved.
4) Decreasing the consensus time taking to balance power and energy/SoC.

Figure 1 shows a flowchart that summarizes the process of Q and R selection.

D. Consensus Tracking Control Input Signals

To synchronize the power management between BESS, the developed controller is fed into each battery unit. Considering battery 1 is a leader and batteries 2 and 3 are followers, the control inputs for consensus tracking among the three batteries are [9]:

$$\begin{aligned}
u_1(t) &= -k_1(m_{11}E_1 - m_{12}E_2 - m_{13}E_3) - k_2(m_{11}P_1 - m_{12}P_2 - m_{13}P_3) \\
&\quad - k_3(zE_1 - zE_T) - k_4(zP_1 - zP_T), \\
u_2(t) &= -k_1(m_{22}E_2 - m_{21}E_1 - m_{23}E_3) - k_2(m_{22}P_2 - m_{21}P_1 - m_{23}P_3), \\
u_3(t) &= -k_1(m_{33}E_3 - m_{31}E_1 - m_{32}E_2) - k_2(m_{33}P_3 - m_{31}P_1 - m_{32}P_2),
\end{aligned} \tag{11}$$

where the E_i is calculated using the measured values of SoC_i. The elements m and z [9] are determined based on the topology shown in Fig. 2. Based on this topology, the architecture of the consensus tracking input signals is presented in Fig. 3. This architecture shows the implementation of the three-battery consensus tracking control in both the HILLTOP and Typhoon HIL environments. The integrated system provides a clear picture of how the proposed consensus tracking technique can track the desired power so that the SoC levels of BESS are kept away from over-charging and over-discharging.

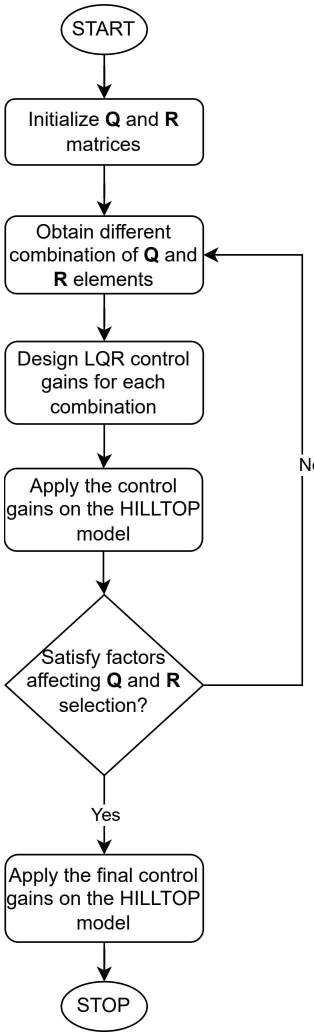

Fig. 1: Flow chart describing the exact steps of selecting Q and R matrices

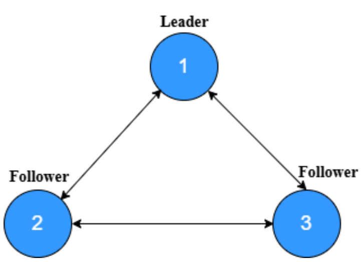

Fig. 2: The three-battery model's data sharing. Battery 1 is assigned target power and is considered a leader, while batteries 2 and 3 are followers

III. System Model, Simulation Results and Analysis

A. BEMS Model

The three batteries shown in Fig. 3 are considered a case study of BEMS. Every battery charger model includes both a battery and a three-phase switching converter, which functions as a two-level voltage source inverter, and is simulated in the Typhoon HIL real-time simulator [32]. Battery 1 utilizes the real-time electric power hardware controller (EPC power inverter controller), which was originally utilized within the HILLTOP simulation platform for either PV or BESS inverter control [33]. EPC is a high-performance embedded hardware controller with response times ranging from microseconds to milliseconds. EPC communicates with the battery 1 converter via Modbus TCP/IP, facilitating real-time data exchange for real-time control in BEMS [33], [29]. The proposed consensus tracking control (explained in Sections II for the battery 1 controller) is implemented in the real-time automation controller (RTAC) device [34], which was originally programmed for a PV-BESS community microgrid within the HILLTOP simulation platform [33]. Batteries 2 and 3 utilize the Typhoon HIL software switching battery inverter model with primary current control loop [32] and remote charge/discharge setpoint dispatch capability [28]. Shared values (in (11) and Fig. 3) are handled using Modbus TCP/IP. The parameters of the converters and batteries used in the model are listed in Tables I and II, respectively.

TABLE I: Battery converter parameters in Typhoon HIL schematic editor

Parameter	Value
Converter input bus voltage	$V_{ac} = 480$ V
Inner current control I_d gains	$K_{Pd} =$ 0.347, $K_{Id} = 347.22$,
Inner current control I_q gains	$K_{Pq} =$ 0.347, $K_{Iq} = 347.22$
Switching frequency	$f_{sw} = 10000$ Hz
Battery side capacitor	$C_B = 0.02\mu$F, $R_{CB} = 50e-9\Omega$
Converter rating	$S_n = 1.6$ MVA

TABLE II: Technical specifications of batteries

Parameter	Battery 1	Battery 2	Battery 3
Battery capacity (kWh)	250	250	250
Battery voltage (V)	1000	1000	1000
Battery capacity (Ah)	250	250	250
Battery resistance ($m\Omega$)	100	100	100
SoC range (%)	10-90	10-90	10-90
SoC initial (%)	30	32	34

B. LQR Control Gains Design and Topology Parameters

To select Q and R matrices, the procedure in section II-C is applied. First, we chose the initial elements of Q and R based on a similar case study in reference [9]. Then, we changed the elements of Q and R matrices to get reasonable overshoot, mismatch, and consensus convergence time. Numerically, we selected: for real batteries: $Q_1 = diag([500,10])$, $R_1 = 1000$ and for the target: $Q_2 = diag([1,90000])$, $R_2 = 100$. Hence, the designed LQR controller gains (used and to be as input in the following Typhoon HIL and HILLTOP models) are as below by solving the *MATLAB LQR problem m-file* with the aforementioned inputs: For real batteries: $k_1 = -0.7070$, $k_2 = 0.1019$ and for target: $k_3 = -0.1000$, $k_4 = 30.0000$. Based on the topology diagram in Fig. 2, the topology matrix is $M = [2\ 1\ 1; 1\ 1\ 1; 1\ 1\ 1]$ and the target topology $z = 1$. The topology elements and the designed control gains are applied to (11) in the framework of Fig. 3. Stability of the designed consensus technique and the LQR controller is discussed in [9].

C. Real-Time Application and Performance Analysis of Consensus Tracking Controller

Consider the initial set/reference value for the battery's control as -33, -20, and -13 *kW* for P_{0_1}, P_{0_2}, and P_{0_3}, respectively. The consensus tracking controller is applied to the HILLTOP/Typhoon HIL model (shown in Fig. 3) using variable target power (shown in Fig. 4), which is assigned for battery 1 as a leader controller.

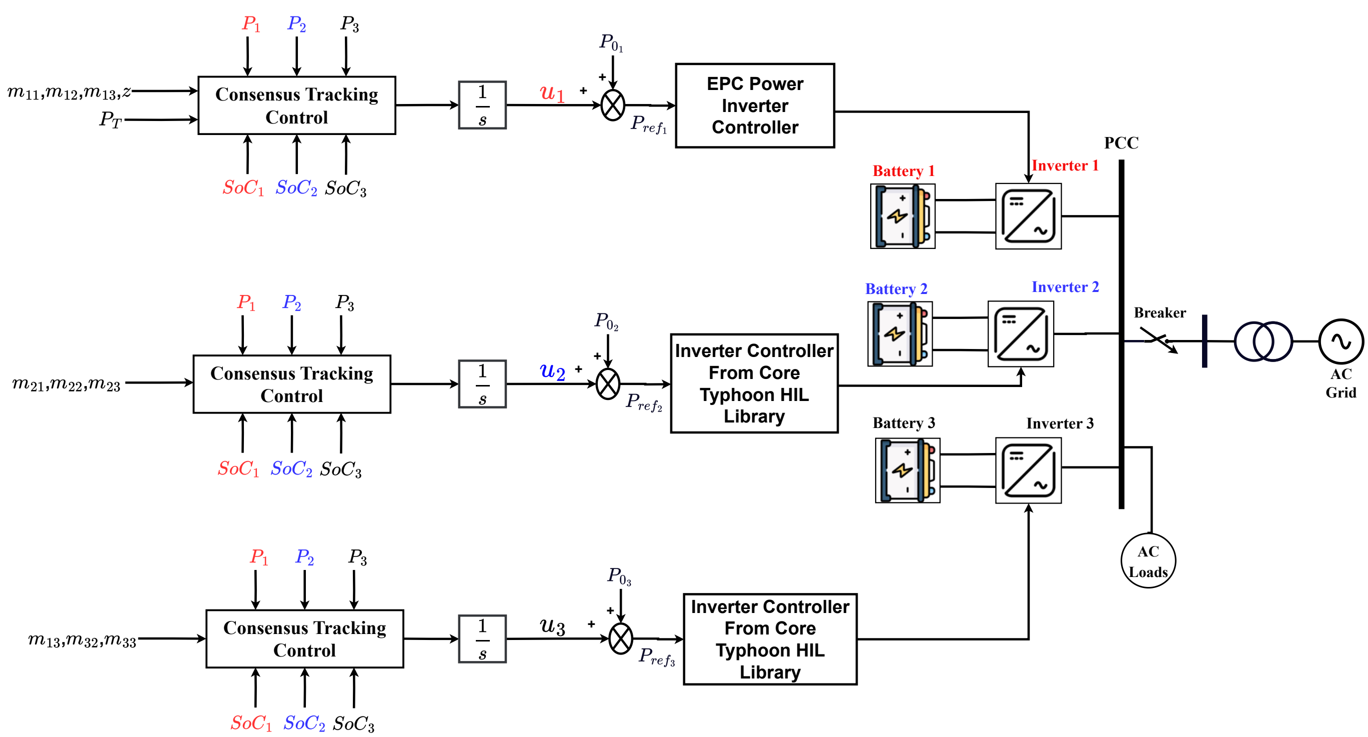

Fig. 3: Architecture for consensus-based tracking control of three batteries utilized within the HILLTOP environment

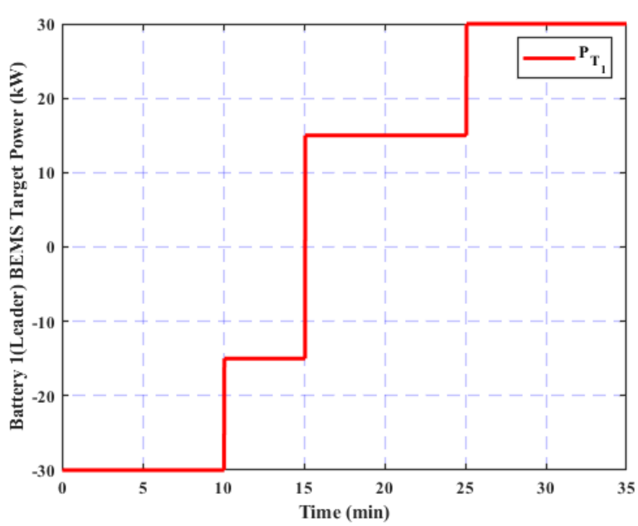

Fig. 4: Variable target power assigned for battery 1 as a leader controller

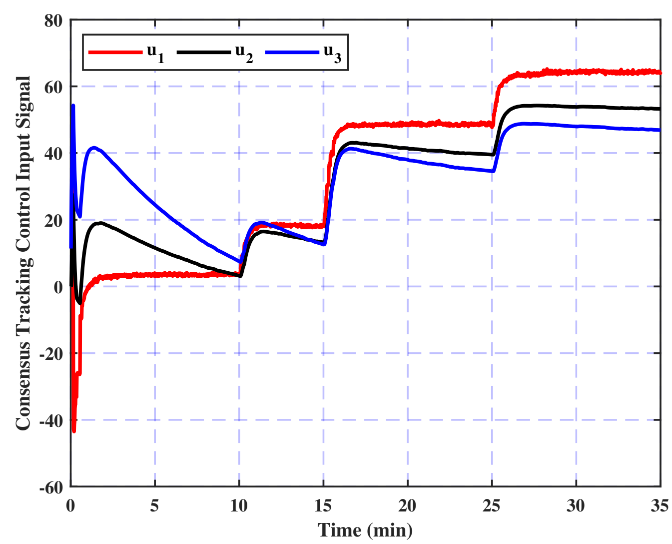

Fig. 5: Batteries' consensus tracking control input signals, u_i

The target power can be determined based on power dispatch (from the system operator to the EMS of the BESS plant). It represents the batteries' charging commands (happening from 0 to 15 minutes) and discharging commands (happening from 15 to 35 minutes). From 0 to 10 minutes, the grid load is decreased (based on the accepted value by the system operator) to 30kW. From 10 to 15 minutes, the grid load is decreased to 15kW. From 15 to 25 minutes, the grid load is increased to 15kW. From 25 to 35 minutes, the grid load is increased to 30kW. The resulting consensus tracking control signals are shown in Fig. 5.

By applying the control signals, the proposed consensus tracking controller demonstrates several advantages in real-time operation. As shown in Fig. 6, the followers (Batteries 2 and 3) successfully track the leader's (Battery 1) power setpoint, which itself follows the dynamic target command. The controller achieves reasonable consensus performance with a steady-state power mismatch of less than 0.5kW, despite operating in a mixed hardware-software environment with inherent communication latencies. This demonstrates the robustness of the proposed approach in practical implementation scenarios.

The LQR-based consensus controller provides rapid convergence towards new operating points, with a settling time of approximately 45 seconds after each step change in the target power. This fast response capability makes the system well-suited for real-time energy dispatch applications where quick adjustments to grid commands are essential.

The selected LQR weights ensure a stable transient response with minimal overshoot (less than 8% maximum), preventing large power oscillations that could stress battery systems or destabilize the grid. The smooth power transitions observable in Fig. 6 highlight the controller's ability to maintain system stability during mode transitions.

The consensus-based power management directly enables effective SoC balancing, as shown in Figs. 7 and 8. The controller actively reduces the initial SoC spread of 4% (30%, 32%, 34%) throughout the operational cycle. This autonomous balancing capability can be crucial for maximizing battery lifespan and ensuring uniform aging across all units. By maintaining balanced SoC levels, the controller ensures all batteries operate within their safe limits (10-90%), effectively preventing over-charging or over-discharging of any individual battery. The SoC trajectories in Fig. 8 show how the consensus tracking controller synchronizes the energy levels while respecting operational constraints.

The time-domain performance metrics of the proposed consensus tracking controller are quantitatively summarized in Table III, providing a clear overview of its effectiveness in real-time battery energy management. The consensus tracking controller real-time implementation indicates that the proposed LQR-based consensus tracker provides a potential alternative solution for BEMS, in providing coordinated power dispatch according to system operator commands, autonomous SoC balancing for enhanced battery health, and safe operation within specified constraints. The controller's performance in this mixed hardware-software environment shows its potential applicability for real-world BESS plant applications.

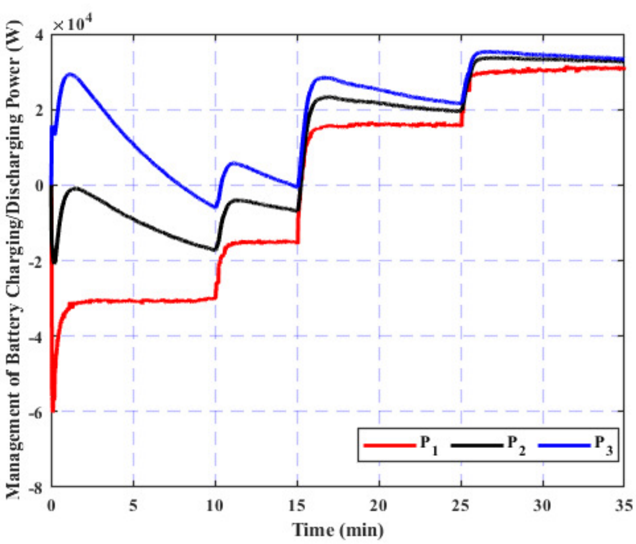

Fig. 6: Batteries' powers demonstrating effective consensus tracking. Battery 1 (leader) follows the dynamic target, while Batteries 2 and 3 (followers) converge to the leader's power with minimal steady-state error

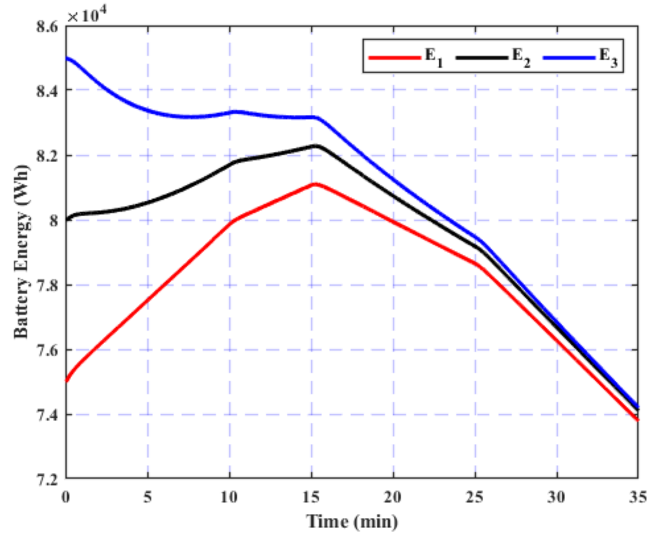

Fig. 7: Total batteries' energies. The coordinated slopes of the energy curves correspond to the consensus power tracking in Fig. 6, demonstrating synchronized charging and discharging operations across all battery units

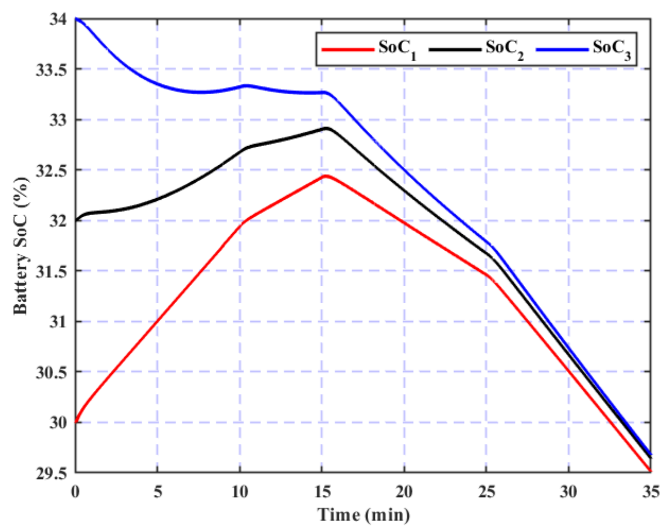

Fig. 8: Batteries' state of charge. The proposed controller successfully balances the SoCs, reducing the initial 4% spread and maintaining all units within a safe operating range while preventing over-charging and over-discharging

TABLE III: Performance summary of consensus tracking controller

Performance Metric	Value
Steady-state power consensus mismatch	< 0.5kW
Maximum power overshoot	< 8%
Consensus towards settling time	≈ 45 seconds
Initial SoC spread	4%
Maximum SoC deviation during operation	< 4%
SoC operating range maintained	10% - 90%
Communication topology	Leader-follower
Controller environment	Mixed hardware-software

IV. CONCLUSIONS

This study implements a consensus tracking control approach for a real-time battery energy management application, with a focus on power tracking and SoC balancing. A linearized battery model, with output power and energy as state variables, was used alongside the LQR to design the consensus tracking controller. The LQR weighting matrices were systematically selected to achieve a balanced performance, limiting the maximum power overshoot to less than 8%, reducing the steady-state power consensus mismatch to under 0.5kW, and achieving consensus convergence within approximately 45 seconds of a setpoint change. The control strategy was tested in the HIL environment with a three-battery system. In this environment, Battery 1 operated under a hardware vendor controller (leader), while Typhoon HIL software controllers managed Batteries 2 and 3 (followers). The results demonstrated that all batteries' output powers effectively reached consensus, tracking a dynamic power setpoint with the performance metrics mentioned above. Consequently, the SoC levels were maintained within a tight band, with the maximum deviation between any two batteries kept below 4%, thereby successfully preventing over-charging and over-discharging and extending battery lifespan.

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