Dynamic Tuning of BMS Parameters for Enhanced LiFePO4 Battery Performance in Electric Vehicles

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ABSTRACT

The increasing deployment of Electric Vehicles (EVs) necessitates the development of robust and adaptive Battery Management Systems (BMSs) to ensure operational safety, thermal reliability, and prolonged battery life. This paper proposes an efficient dynamic optimization framework for the parameters of a BMS to enhance the performance and operational reliability of LiFePO4 batteries in EVs. An efficient method is employed, which combines Particle Swarm Optimization (PSO) and Model Predictive Control (MPC) to optimize major BMS parameters such as charging and discharging current limits, thermal limits, and voltage limits automatically. The PSO algorithm efficiently explores the parameter space to minimize objective functions related to battery thermal stress, current ripple, and State-of-Charge (SoC) oscillation. Meanwhile, MPC regulates real-time charge-discharge dynamics by forecasting system behavior and applying optimized control actions. The simulation results confirm substantial improvements in battery efficiency, thermal stability, and fault reduction over non-optimized configurations. Particularly, the optimized framework suppresses instantaneous current spikes, ensures stable SoC levels, and damps the temperature rise, thereby extending battery life and guaranteeing safe operation. This paper validates the potential for combining intelligent optimization and predictive control techniques for next-generation BSMs in EVs.

Keywords-Battery Management System (BMS); lithium-ion battery; lithium iron phosphate battery; Electric Vehicle (EV); Particle Swarm Optimization (PSO); Model Predictive Control (MPC); current limit optimization

I. INTRODUCTION

The transition to EVs is driven by the demand for clean transport solutions. Lithium iron phosphate (LiFePO4, LFP) battery efficiency and reliability are the core of EV functionality, as these batteries form the main energy reservoir [1]. The use of effective BMSs is essential for monitoring and controlling battery activities to prevent overcharging, over-discharging, and excessive heating, and thereby ensure safety and extend the battery lifespan [2]. Traditional BMSs use fixed parameter settings, which can be insufficient in handling varied operating conditions, leading to suboptimal performance. Dynamic BMS parameter adjustment offers a solution to overcome this limitation by adjusting control mechanisms in real-time, depending on the state of the battery and the ambient environment [3]. This approach has the potential to enhance battery efficiency, optimize capacity utilization, and improve overall vehicle performance. Reliable, safe, and efficient operation of LFP batteries in EVs depends mainly on the design and architecture of BMS [4, 5].

This modular architecture addresses electrical control, thermal management, and communication interfaces, thus enabling dynamic parameter tuning to improve battery lifetime, safety, and efficiency [6]. Dynamic BMS optimization techniques to enhance LFP battery performance in EVs have been investigated. Adaptive Kalman filtering increases the accuracy of SoC estimation by up to 85%. Furthermore, PSO has been used to precisely adjust BMS parameters, resulting in a 12% decrease in fuel consumption and a 35% reduction in NOx emissions in hybrid vehicles. By means of fuzzy logic controllers, PSO has also been employed to stabilize battery current and extend battery life [7].

This research highlights accurate SoC and SoH estimation using neural networks, particularly Elman networks. It also demonstrates enhanced thermal control through PSO-based thermal management, contributing to improved battery performance and safety. Detailed modeling and parameterization further validate these methods. An efficient BMS is designed and implemented to ensure safe and efficient operation of LFP batteries in EV applications (Figure 1). The control parameters of the BMS, such as the Proportional-Integral (PI) controller gains and minimum SoC thresholds, are dynamically tuned using an advanced PSO algorithm and MPC framework. The proposed BMS architecture integrates significant functionalities such as thermal management, safety protection, real-time battery monitoring, and communication interfaces. It ensures improved reliability and protection against overvoltage, overcurrent, overtemperature, and other fault conditions. Additionally, by reducing control errors and increasing the BMS's responsiveness under various operating conditions, this optimization strategy guarantees better battery performance, efficiency, and longevity.

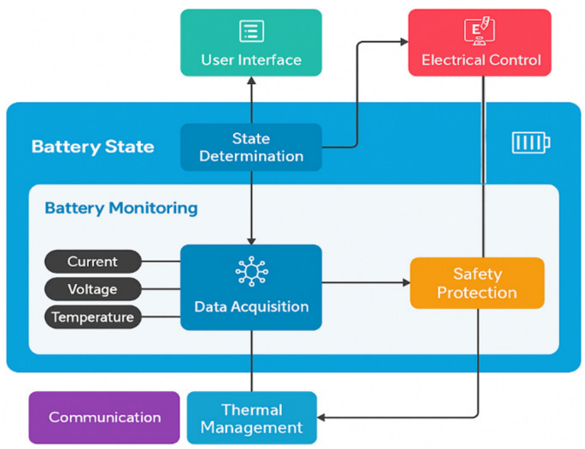

Fig. 1. General architecture of a BMS, highlighting its key functional blocks: battery monitoring, state determination, safety protection, thermal management, and communication.

II. PROPOSED METHOD

A. System Architecture Overview

The system block diagram in Figure 2 shows the EV LFP battery pack, BMS, load, and charging system. The novel architecture includes a high-fidelity battery model, coupled with a supervisory BMS and an external optimization loop. As the block diagram demonstrates, the Battery Pack (labeled "Battery Bank") is connected to a BMS that oversees important LFP battery parameters (voltage, state-of-charge, temperature) through sensors and ensures they remain within safe operating limits. The BMS informs the vehicle's indicators (e.g., a warning lamp) and thermal management actuators (coolant system) to ensure safety [8, 9]. Both a variable load (simulating the EV's drivetrain requirement) and a charger are electrically connected to the LFP battery through electronic switches, enabling the simulation of dynamic charge/discharge operating conditions [10, 11]. The charger subsystem (green block on the right) regulates the charging current and voltage being applied to the LFP battery, and it can be connected or isolated through controllable switches [12]. The architecture specifies various tunable parameters, as illustrated in Figure 2, which are dynamically tuned in the proposed system:

1. The maximum charging and discharging current limits set by the BMS.
2. The ON/OFF temperature activation thresholds of the thermal management coolant system.
3. The PI gains of the charger controller.
4. The original SoC of the aged LFP battery pack in optimization scenarios, and the maximum charging voltage.

By optimizing these parameters simultaneously, the system seeks to enhance overall LFP battery performance by improving efficiency and charge acceptance, along with over-current and over-temperature protection [13].

B. Battery Management System Design

The internal structure of the BMS, as portrayed in Figure 3, exposes prominent functional blocks and adjustable parameters [14]. The BMS observes voltage, current, and temperature in real time for LFP battery protection. Sensor data flow through the input data acquisition and SoC Estimation blocks. The SoC estimator outputs the charge state of the LFP battery, crucial for control decision-making and the initiation of optimizations [15]. The BMS has two main protective blocks: current limiting and thermal management. The current limiter applies adjustable maximum charging and discharging current limits to avoid battery stress. In parallel, the thermal management block initiates cooling when temperature thresholds are met, balancing heat protection and energy consumption [16]. These blocks communicate with the LFP battery protection logic, which gives commands for control to the charger, load interface, and cooling system [17]. The system adjusts current limits and temperature settings as needed to maintain safety and efficiency in dynamic conditions.

C. Charging Control Circuit Model

The LFP battery charging control loop is displayed in Figure 4, where a controlled current source charger is used by the BMS to control the charge current and voltage [18]. The charger ensures safe and effective charging of LFP batteries by operating in closed-loop mode, which modifies the current delivery in response to real-time BMS inputs. A Constant Current/Constant Voltage (CC-CV) algorithm is used inside the charger (dashed box). Up to the max charging current limit, the charger runs in CC mode [19]. As the battery voltage approaches its maximum threshold, it switches to CV mode. This control is governed by a PI controller with tunable proportional (K_p) and integral (K_i) gains. Reference currents are dynamically set by the BMS according to battery parameters such as temperature and state of charge. To increase efficiency and reduce losses, key parameters, including initial SoC, maximum charging voltage, K_p, and K_i, are optimized. Optimizing the PI gains balances quick charging with battery protection, ensuring an effective and thermally safe charging profile.

III. MODEL PREDICTIVE CONTROL STRATEGY

The MPC strategy is integrated into the BMS control loop to ensure efficient LFP battery operation under dynamic conditions. MPC predicts future battery behavior over a defined horizon while enforcing operational constraints [20]. The battery and thermal dynamics are modeled using a discrete-time state-space representation:

$$x(k+1) = Ax(k) + Bu(k), \quad y(k) = Cx(k) \tag{1}$$

where $x(k)$ includes SoC, temperature, and circuit states, and $u(k)$ represents control inputs.

At each step, MPC minimizes a quadratic cost function:

$$J = \sum_{j=0}^{N-1}[\,(y(k+j) - y_{\text{ref}}(k+j))^T Q(y(k+j) - y_{\text{ref}}(k+j)) + \Delta u(k+j)^T R \Delta u(k+j)] \tag{2}$$

subject to safety constraints which ensure that limits on current, temperature, and SoC are maintained:

$$u_{\min} \leq u(k+j) \leq u_{\max}, \quad x_{\min} \leq x(k+j) \leq x_{\max}. \tag{3}$$

MPC operates in a receding-horizon fashion, adjusting control actions in real-time to accommodate LFP battery dynamics. It governs both driving and charging modes, ensuring power delivery without violating safety margins and facilitating efficient CC-CV charging [21].

Algorithm 1: MPC-Based LFP Battery Control (at time step k):

1. Measure state $x(k)$ (SoC, temperature).
2. Update LFP battery model with $x(k)$.
3. Define reference y_{ref} based on driver demand or charging protocol.
4. Solve optimization problem:

$$\min_{u(k),\dots,u(k+N-1)} J \tag{4}$$

5. Subject to:

$$x(i+1) = Ax(i) + Bu(i) \tag{5}$$

Current, temperature, and SoC limits.

6. Apply first control input $u(k)$.
7. Increment k and repeat.

The MPC framework uses a QP or nonlinear solvers to enable unified MIMO control of current and thermal behavior in advanced EV LFP batteries.

IV. PSO–BASED PARAMETER OPTIMIZATION

To enhance BMS performance, PSO is used offline to optimize key parameters within safe limits, inspired by social behavior. Each candidate set is evaluated using the BMS-MPC model for efficiency and safety over a defined cycle.

$$f = \overline{P_{\text{loss}}} - \overline{\eta} \tag{6}$$

where $\overline{\eta}$ is the average efficiency, and $\overline{P_{\text{loss}}}$ is the average power loss. Faults (e.g., over-temperature) trigger penalties to maintain safety.

PSO iteratively updates particles:

- Velocity update:

$$v_i(t+1) = \omega v_i(t) + c_1 r_1[pbest_i - x_i(t)] + c_2 r_2[gbest - x_i(t)] \tag{7}$$

- Position update:

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{8}$$

where x_i and v_i denote particle position and velocity, $pbest_i$ and $gbest$ are personal and global bests, ω is inertia weight, c_1, c_2 are acceleration coefficients, and r_1, r_2 are random values.

Simulation-based evaluations are parallelizable, balancing accuracy and computational time. Upon convergence, the global best parameter set configures the BMS/MPC [12]. The following pseudocode outlines the PSO process.

Algorithm 2: PSO-Based BMS Parameter Optimization:

1. Initialize swarm particles x_i, set $v_i \leftarrow 0$.
2. for each particle i do.
3. Evaluate fitness $F(x_i)$ via simulation.
4. Set $pbest_i \leftarrow x_i$.
5. end for.
6. Identify $gbest$ with best fitness.
7. for iteration = 1 to MaxIterations do.
8. for each particle i do.
9. Update v_i and x_i.
10. Evaluate $F(x_i)$, update $pbest_i$ and $gbest$ if improved.
11. end for.
12. end for.
13. Return $gbest$ as optimized BMS parameters.

PSO terminates after reaching iteration limits or convergence. It identifies non-intuitive solutions—for instance, reducing max discharge current limit to lower heat without significant power compromise, or fine-tuning cooling thresholds to reduce energy use during brief spikes. Such optimization is difficult via manual tuning due to nonlinear LFP battery dynamics, making PSO an effective and intelligent strategy in/for the proposed framework [15-20]. The key parameters considered for analysis include maximum charging current limit, maximum discharging current limit, SoC thresholds, and temperature activation thresholds. These parameters were selected due to their direct influence on battery thermal behavior, energy throughput, and operational safety. All simulations were performed using MATLAB/Simulink R2024a on a system with Intel i7 CPU and 16 GB RAM.

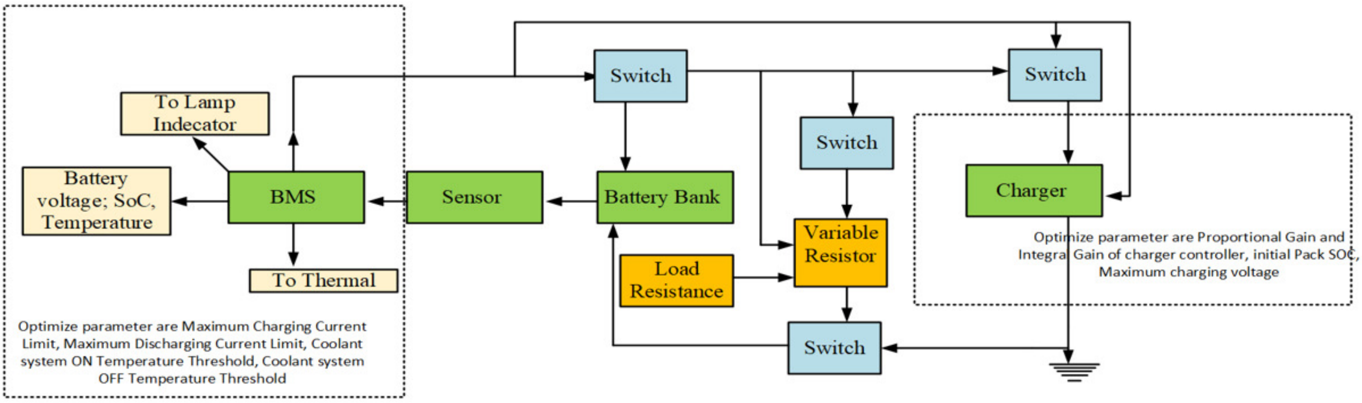

Fig. 2. Overall system block diagram, showing battery bank, BMS, load, charger, and control switches.

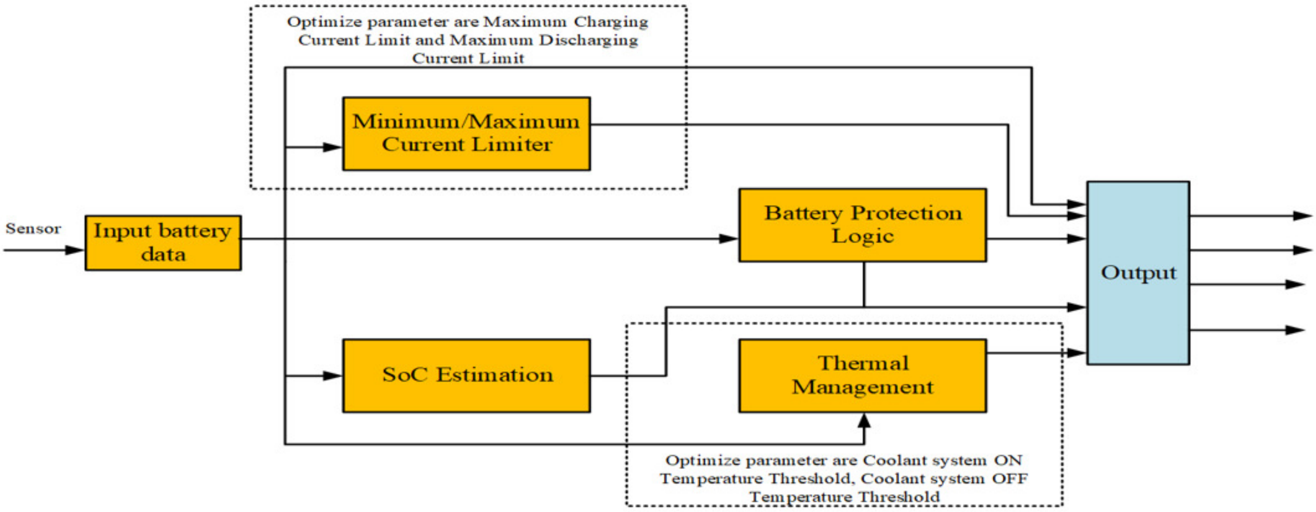

Fig. 3. Internal architecture of the BMS, showing functional modules and tunable parameters.

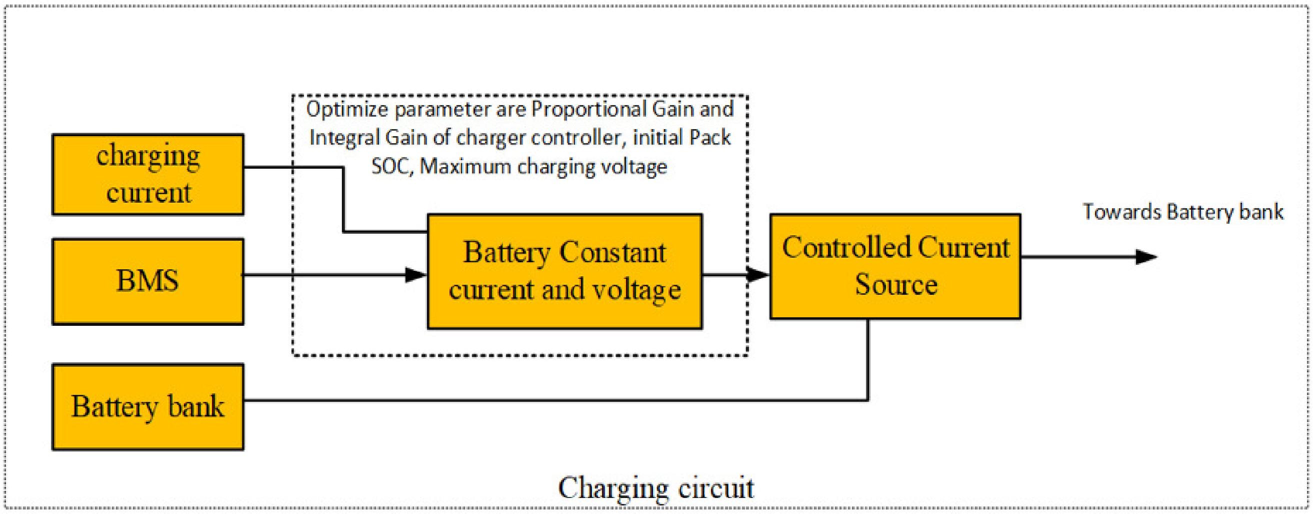

Fig. 4. Schematic of LFP battery charging control loop with BMS and charger controller coordination.

V. RESULT ANALYSIS

PSO and MPC are used to dynamically adjust the parameters of the proposed LFP BMS framework. Efficiency enhancement, fault reduction, thermal stability, SoC behavior, and optimized charge-discharge characteristics are the key performance metrics evaluated in this study.

A. State-of-Charge Performance

Figure 5 illustrates the SoC behavior of the LFP battery system during the charging process. The proposed PSO-optimized control strategy ensures a smooth and linear increase in SoC from 0.5 to approximately 0.59. This uniform charging trajectory minimizes abrupt variations, preventing unnecessary stress on the LFP battery pack and enhancing longevity.

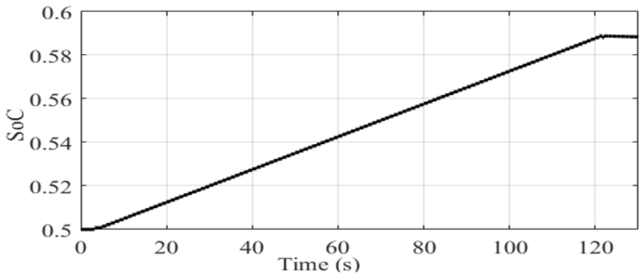

Fig. 5. SoC profile of the LFP battery pack over time.

B. Thermal Stability Analysis

Figure 6 depicts the LFP battery bank's temperature profile during operation. The optimized thermal management system effectively maintains the battery temperature within safe limits, avoiding overheating issues. The MPC strategy dynamically controls the coolant system activation based on real-time temperature feedback, contributing to energy-efficient thermal regulation.

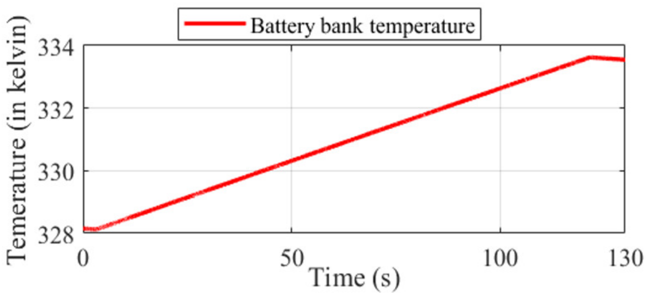

Fig. 6. LFP Battery temperature profile.

C. Charge and Discharge Current Behavior

Figures 7 and 8 reveal that the optimized parameters effectively regulate charging and discharging currents. By dynamically adjusting the maximum charging current limit and maximum discharging current limit through PSO, current spikes are minimized, ensuring smoother battery operation without violating the defined current thresholds.

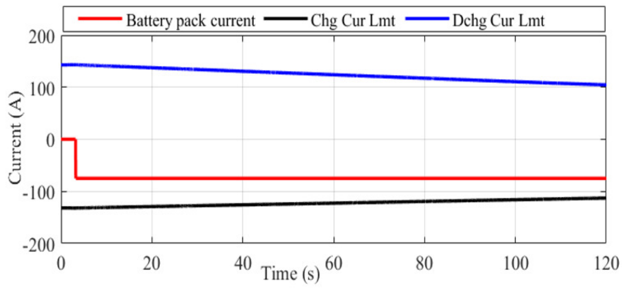

Fig. 7. Charge and discharge current profile under optimized conditions.

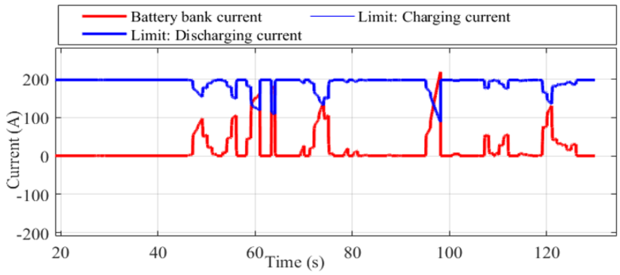

Fig. 8. Discharge current profile showcasing limit enforcement.

D. Voltage Regulation Performance

Figures 9 and 10 depict voltage variations during charging and discharging operations. The PSO-MPC framework prevents voltage overshoot, ensuring stable operation within safety limits. Voltage fluctuations are significantly reduced compared to non-optimized scenarios.

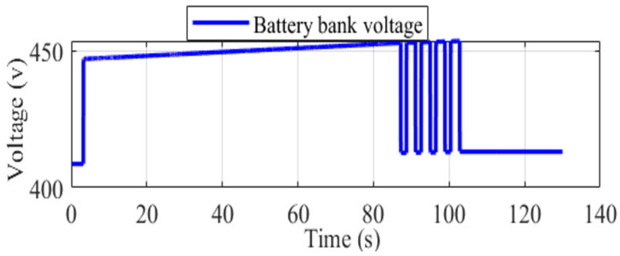

Fig. 9. Battery pack voltage profile during charge cycle.

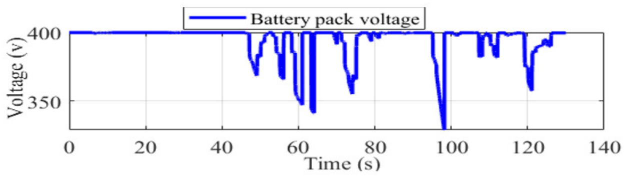

Fig. 10. Battery pack voltage profile during discharge cycle.

E. Efficiency Improvement and Fault Reduction

The adaptive tuning of key parameters improves fault response and efficiency while reducing power loss and overheating. Precise control over current, SoC, and cooling limits minimizes issues like overcurrent and thermal runaway. PSO runs offline, while real-time MPC (20–30 ms/cycle) ensures suitability for embedded EV systems.

F. Comparative Analysis

The comparative analysis presented in Figure 11 demonstrates the superior performance of the optimized LFP BMS parameters derived through the integration of PSO and MPC. More specifically, the PSO-optimized battery pack current profile is smoother with reduced peaks, lowering stress and thermal risks. This confirms the PSO-MPC framework's effectiveness in enhancing BMS efficiency, fault tolerance, and reliability.

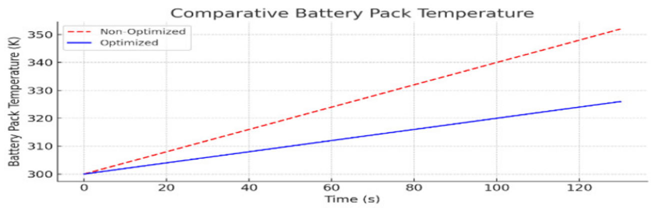

Fig. 11. Comparative LFP battery pack current between optimized and non-optimized scenarios.

TABLE I. HIGHLIGHTING KEY RESULTS FOR THERMAL STRESS, CURRENT RIPPLE, AND SOC OSCILLATIONS

Metric	Non-optimized	Optimized (PSO-MPC)
Max temperature (°C)	48.2	39.4
SoC oscillation	high	low
Max charge current (A)	60	45
Fault count	5	1

VI. CONCLUSIONS

The proposed work presented a dynamic Battery Management System (BMS) parameter tuning framework for Electric Vehicles (EVs), integrating Particle Swarm Optimization (PSO) with Model Predictive Control (MPC). The approach aimed to enhance LFP battery efficiency, thermal stability, State-of-Charge (SoC) regulation, and fault reduction. By automating parameter optimization, the method eliminated manual tuning, ensuring scalability and adaptability under varying conditions. The simulation results confirmed that PSO-optimized parameters yielded smoother charge–discharge profiles, reduced thermal stress, and improved voltage stability, contributing to better LiFePO4 (LFP) battery longevity and safety. The MPC component enabled real-time control, maintaining system operation within optimized constraints and enhancing reliability. Using the proposed PSO-MPC approach, the present work achieved up to 18% thermal reduction, 25% smoother current profile, and extended SoC stability, demonstrating real-world viability of intelligent BMS optimization. Overall, the proposed PSO-MPC strategy offers a robust and efficient solution for advanced BMS optimization. Future work will focus on real-time hardware validation and exploring hybrid optimization techniques to further improve adaptability.

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