An Optimization-Based Hybrid Energy Storage Management System for DC Microgrids

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Received: 11 February 2026 | Revised: 17 March 2026 and 28 March 2026 | Accepted: 1 April 2026

DOI: https://doi.org/10.48084/etasr.18108

ABSTRACT

Standalone DC microgrids with renewable energy sources are usually designed to include Energy Storage Systems (ESSs) comprising batteries and supercapacitors to ensure reliable operation and extended ESS lifetime. However, conventional power management strategies often subject the batteries to rapid current fluctuations, deep cycling, and thermal stress, which accelerate degradation. This study proposes an optimization-based energy management strategy for a Hybrid Energy Storage System (HESS) consisting of a battery and supercapacitor integrated with Photovoltaic (PV) and fuel cell sources in a standalone DC microgrid. The proposed controller determines the optimal battery current reference through a constrained weighted-sum optimization of power balance during excess and deficit power. The optimization framework generates the optimal battery current while enforcing operational constraints, including State-of-Charge (SoC) limits, temperature thresholds, current bounds, and ramp-rate limits. The optimized battery current is adaptively blended with a voltage-regulation component. The supercapacitor operates in voltage control mode to handle transient power fluctuations, thereby relieving the battery from high-frequency stress. MATLAB simulations conducted in this study demonstrated the effective microgrid bus voltage regulation under varying solar irradiance and load conditions, while reducing the battery current oscillations by about 40%, maintaining the battery SoC within 20-90%, and temperature limits of 35 °C. The proposed strategy enhances battery operational reliability and provides an effective framework for life-aware energy storage management in standalone DC microgrids.

Keywords-battery life optimization; DC microgrid; hybrid energy storage system; real-time control

I. INTRODUCTION

The rapid growth of renewable energy sources has transformed modern power systems, driving the development of microgrid technology. Compared with an AC microgrid configuration, DC microgrids are more efficient and cost-effective for the integration of DC sources, such as solar PV and batteries, which require fewer conversions of power [1]. DC microgrids can be categorized into isolated and grid-connected systems. Since isolated DC microgrids rely heavily on renewable energy sources with intermittent characteristics, energy storage devices are required to compensate for these fluctuations and ensure steady power operation [2]. Energy storage technologies can be classified into mechanical, electrochemical, thermal, and electrical storage, each possessing distinct operational characteristics. Battery Energy Storage Systems (BESS) are widely known for their high energy density, making them suitable for long-duration energy supply and backup applications. In contrast, supercapacitor storage exhibits very high-power density, long cycle life, and excellent capability to handle short-term and high-frequency power fluctuations due to its fast dynamic response. Integration of these storage technologies can effectively balance energy and power requirements. However, to fully utilize the benefits of each storage component, efficient management and coordinated control are necessary [3]. Energy management strategies can be classified into optimized and non-optimized control methods. Optimized control is a dynamic and adaptive management strategy in which decisions are made based on real-time system data and algorithm-based optimization techniques to maximize the operational benefits. In contrast, non-optimized control methods follow predetermined rule sets without adapting to changing system conditions. Optimization-based control strategies can significantly enhance the life of Energy Storage Systems (ESSs) by minimizing operational stress and ensuring efficient system operations.

In a microgrid, BESS are exposed to many stress factors that influence their degradation, including the number of charge-discharge cycles, depth of discharge, extreme operating temperatures, charge/discharge rates, prolonged operation at very high or very low State-of-Charge (SoC) levels, voltage and current constraints, and environmental conditions such as humidity and vibration. Consequently, effective energy management strategies are essential for improving battery reliability and extending its operational lifetime.

Several studies have investigated the coordinated control of distributed energy resources [3] and data-driven model control for voltage stability [4]. However, battery aging effects have not been explicitly addressed. Fuel cell-assisted rule-based controllers have been introduced that primarily focused on system reliability [5-7], but the reduction of battery stress has received limited attention. In [8-10], an optimal PI-controller-based energy storage management approach was proposed to improve transient performance, although thermal constraints were not considered. A multi-objective optimization strategy incorporating thermal effects and real-time load current estimation was presented in [11, 12], demonstrating improvements in battery lifespan. However, in this approach, the battery is operated in the current control mode. It followed an optimized current reference, which may limit its ability to regulate the DC bus voltage in microgrid applications owing to its computational complexity. In [13, 14], advanced and adaptive PI-based management was implemented, with a focus only on SoC-based optimization. In [15], genetic algorithm optimization was proposed; however, Hybrid Energy Storage System (HESS) and battery life optimization were not considered.

The main contributions of this study are: The proposed method focuses on battery life optimization through an adaptive multi-objective cost function that simultaneously considers SoC protection, thermal limitations, and smooth current transitions. A weighted-sum optimization method is adopted, with a higher priority assigned to the SoC constraint to ensure battery safety and longevity. Additionally, a cost-aware fuel cell utilization strategy is proposed. This adaptive control framework, combined with cost-aware energy storage management, distinguishes the proposed strategy from conventional rule-based and single-objective approaches. This study presents an optimization-based energy management strategy to determine the optimal battery current reference in a standalone DC microgrid.

II. SYSTEM DESCRIPTION

Figure 1 shows the layout of the DC microgrid, which consists of a solar PV array, proton exchange membrane fuel cell, BESS, supercapacitor module, and variable DC load. Each unit is interfaced to the bus via a dedicated power electronic converter. This enables power exchange in a controlled manner, stable voltage regulation, and protection during dynamic operating conditions. The solar PV array functions as the primary renewable source of the microgrid and is interfaced through a boost converter operating under a Maximum Power Point Tracking (MPPT) algorithm to extract maximum power.

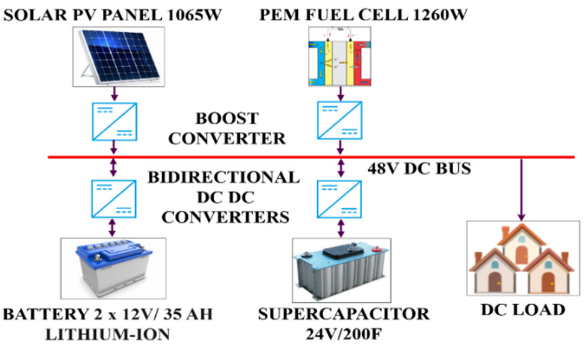

Fig. 1. The proposed DC microgrid topology.

The fuel cell is considered a secondary or emergency source, as it is costly, and its dynamic performance is relatively slow. The fuel cell converter is controlled in voltage control mode when the PV and batteries are both unable to maintain the bus voltage. Lead-acid batteries are considered the primary energy storage units and are interfaced through a bidirectional converter that operates in the buck mode during charging and boost mode during discharging to maintain the DC bus voltage. The supercapacitor control is designed in voltage mode control to pump the transient part of the current during sudden load or source transients; thus, the battery gets relieved from supplying the transient current. The behavior of the supercapacitor helps to extend the battery life. A variable DC load was included to represent the consumer's load demand and test the dynamic performance of the system. The control diagram of all components is shown in Figure 2. The parameters used for the simulation are listed in Table I. The Proportional–Integral (PI) controllers used in the voltage and current control loops were tuned using a trial-and-error approach to achieve stable system dynamics and a satisfactory transient response under varying solar irradiance and load conditions.

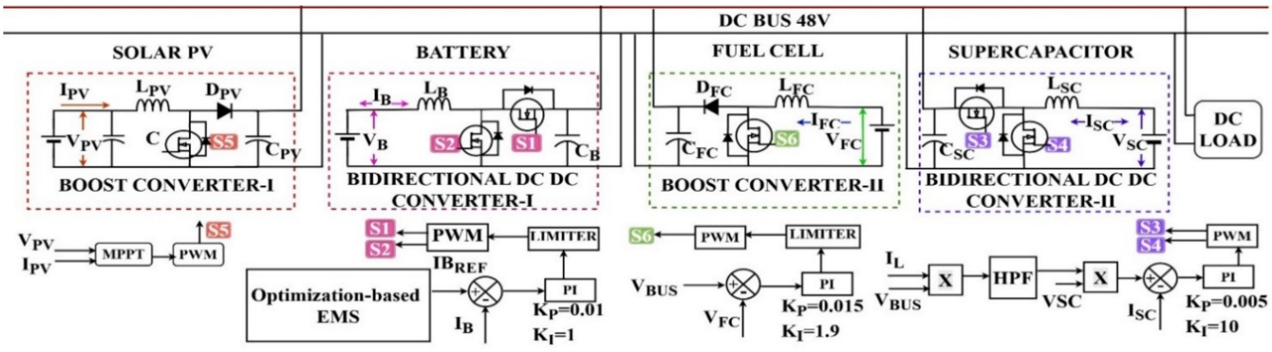

Fig. 2. Simulink model of the proposed DC microgrid with converter circuit and control architecture.

TABLE I. MICROGRID CONVERTER SPECIFICATION

Converter	Inductor (mH)	Capacitor (μF)
Solar PV converter	$L_{PV} = 5$	$C_{PV} = 330$
Bidirectional converter of battery	$L_B = 0.5$	$C_B = 3300$
Bidirectional converter of supercapacitor	$L_{SC} = 10$	$C_{SC} = 470$
Converter of a fuel cell	$L_{FC} = 500$	$C_{FC} = 900$

The inductor and capacitor values were designed based on the converter rating with the input and output voltage requirements. In the simulation, the battery SoC was allowed to vary within the range of 10–95% to evaluate its performance. The supercapacitor SoC was maintained at 75% at the beginning of each simulation to ensure sufficient capacity for handling the transient power.

III. ENERGY STORAGE MANAGEMENT

The simulation subsystem of the real-time multi-objective optimization-based energy storage management system was implemented using a MATLAB function block, as shown in Figure 3. The system attempts to enhance the battery lifespan using the following strategy. First, the optimized battery current reference is created using real-time measurements of the DC bus voltage, solar generation, load current, battery SoC, and battery temperature. The multi-objective optimization algorithm balances the voltage regulation, current fluctuation reduction, and thermal management of the battery. Simultaneously, the supercapacitor voltage control loop operates in parallel and handles rapid transients that occur owing to variations in the load or generation.

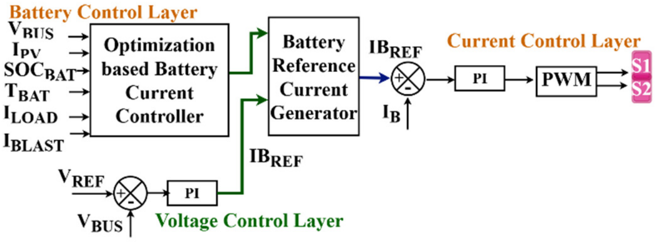

Fig. 3. Simulink subsystem of the multi-objective optimization-based EMS.

A battery current optimization algorithm calculates an optimized battery current reference, which is denoted by ib_b^{ref}. First, the battery current reference is obtained from the power gap between the available generation and load requirements. The current is then enforced by the constraints. Therefore, charging is stopped when the SoC of the battery exceeds a maximum threshold and stops discharging below a minimum SoC limit. In addition, the algorithm protects the battery from thermal stress by reducing the current magnitude when the battery temperature exceeds a predefined safe limit of 45 °C. Additionally, it considers a smoothing function to limit abrupt changes in the battery current. It avoids rapid fluctuation, which damages the battery's health. Finally, a weighted sum method combines all these factors, balancing the constraints of thermal, SoC, and smoothing to generate a safe and efficient battery current reference for the DC microgrid. This ensures that the battery operates within safe electrical and thermal boundaries and maintains system stability and voltage regulation. The system finds the mismatch in power by subtracting the load consumption from the total generated power:

$$P_{excess} = P_{PV} - P_{load} \tag{1}$$

A positive excess power indicates that the generated power is greater than the load value, and the surplus energy is used to increase the SoC of the battery. Conversely, a negative value indicates that the battery should discharge to supply the load. The ideal battery current reference is calculated by:

$$i_b^{target} = P_{excess}/V_{bus} \tag{2}$$

A positive i_b^{target} indicates charging, and a negative value indicates discharging.

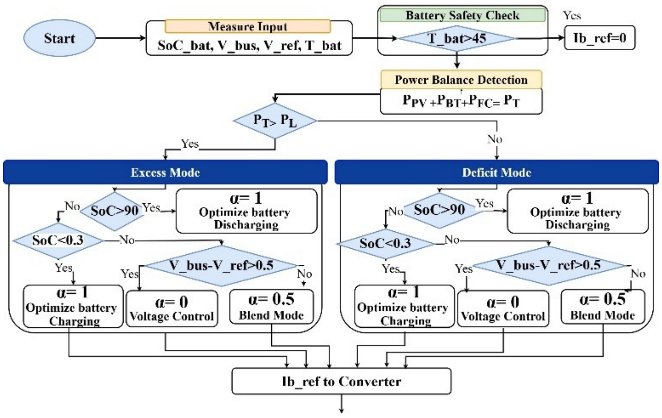

Fig. 4. Flow chart of optimization-based battery current reference.

In a DC microgrid, the battery is the primary energy storage element. The battery is responsible for maintaining the DC bus voltage under varying loads and generation. Therefore, the battery must charge and discharge rapidly to balance the power imbalance. However, this type of battery response leads to frequent and large current fluctuations, deep cycles, and temperature rise. This reduces the battery life. However, by limiting the current magnitude, reducing the cycling depth, and controlling the charging rates, the battery life can be improved, but at the cost of poorer voltage regulation. Under such conditions, the power quality decreases. Therefore, a trade-off is used between the voltage regulation and battery health management objectives. This control strategy blends these objectives by dynamically weighting the importance based on real-time system conditions. When the bus deviation is high, the priority is set to the voltage regulation. When the battery operates near its temperature and SoC limits, priority is given to the battery health. This method finds the battery current reference using a blended approach that integrates battery life optimization with voltage control. The flowchart of the proposed method is displayed in Figure 4. The blended current reference is expressed in (3), where the weighting factor α is adjusted based on the battery state SoC and the DC bus voltage deviation:

$$ib_b^{ref} = (a)ib_b^{opt} + (1-a)ib_b^{voltage} \tag{3}$$

When the SoC is very low or very high, then $\alpha = 1$, and battery protection is prioritized through optimization. When the DC bus voltage deviation is large, then α is set to zero, which gives priority to voltage recovery. For other conditions, α is set to 0.5, which balances both objectives. The sampling interval and capacity factor are given by:

$$\gamma = \frac{\Delta t}{3600C_{bat}} \tag{4}$$

Battery SoC prediction is given by:

$$SoC_{(k+1)} = SoC_{(k)} - \gamma I_b \tag{5}$$

Temperature scaling is given in (6), which is only active if T_{bat} is greater than T_{safe}:

$$P_{temp}(T_{bat}) = \begin{cases} (\frac{T_{bat}-T_{safe}}{T_{max}-T_{safe}})^2, T_{bat} > T_{safe} \\ 0, otherwise \end{cases} \tag{6}$$

The optimization component selects the battery current I_b that minimizes a multi-objective cost function, $J(I_b)$:

$$J(I_b) = w_1(I_b - I_{b,last})^2 + w_2(SoC - \gamma - SoC_{target})^2 + w_3 \cdot P_{temp}(T_{bat}, I_b^2) \tag{7}$$

There are three cost functions in (7). The first term is used to allot penalties for rapid current transitions. This contributes to smooth operation and reduces the current ripple. The second term is a penalty for deviations from the SoC from safe operational limits. The third term is the thermal stress penalty, which is a function of the battery temperature and current. w_1, w_2, and w_3 are the coefficients of giving weights to determine the importance of the cost function, current smoothness, SoC regulation, and thermal management, respectively. For optimization, the following constraints were considered to ensure safety and feasibility, as expressed in (8)-(16). Some constraints are always present, while others are only active under certain conditions.

$$g_1(i_b) = I_b - I_{b,max} \leq 0 \tag{8}$$

$$g_2(i_b) = -I_b - I_{b,max} \leq 0 \tag{9}$$

SoC safety constraints are for $SoC_{(k+1)} \leq SoC_{max}$ and $SoC_{(k+1)} \geq SoC_{max}$, respectively.

$$g_3(i_b) = -\gamma I_b - (SoC_{max} - SoC) \leq 0 \tag{10}$$

$$g_4(i_b) = -\gamma I_b + (SoC_{min} - SoC) \leq 0 \tag{11}$$

Mode-based constraints with inequality depending on the mode of operation are given in (12) and (13) for the excess and deficit modes, respectively:

$$g_5(i_b) = I_b \leq 0 \tag{12}$$

$$g_6(i_b) = -I_b \leq 0 \tag{13}$$

Also, soft SoC tapering near the boundaries was applied. It limits the current when the SoC is below 20% or above 90%:

$$g_7(i_b) = I_b - I_{charge,min} \leq 0 \tag{14}$$

A hard thermal cutoff is included as:

$$T_{bat} \geq 45°\text{C} \rightarrow I_b = 0 \tag{15}$$

$$h_1(i_b) = I_b = 0 \tag{16}$$

when the battery temperature exceeds the safe limit.

This strategy ensures that the battery operates safely and maintains stable DC bus voltage under varying operating conditions, ultimately prolonging its lifetime.

The Lagrangian equation is:

$$\mathcal{L}(i_{b,}\lambda, \mu) = J(i_b) + \lambda_1(i_b - I_{b,max}) + \lambda_2(-i_b - I_{b,max}) + \lambda_3(-\gamma i_b - (SoC_{max} - SoC)) + \lambda_4(\gamma i_b + (SoC_{min} - SoC)) + \lambda_5 g_5(i_b) + \lambda_6 g_6(i_b) + \lambda_7(i_b - I_{charge,min}) + \mu h_1(i_b) \tag{17}$$

Here, the constraints relevant under the current operating condition have nonzero multipliers; others will be equal to zero due to complementary slackness. Differentiating (17) with respect to i_b and equating it to zero yields:

$$\frac{dJ}{di_b} = 2w_1\left(I_b - I_{b,last}\right) - 2w_2\left(SoC - i_b\gamma - SoC_{target}\right) + 2w_3 \,.\, P_{temp} i_b + \lambda_1 - \lambda_2 - \gamma\lambda_3 + \gamma\lambda_4 + \lambda_5 - \lambda_6 + \lambda_7 + \mu \tag{18}$$

Equation (19) shows the Karush–Kuhn–Tucker stationarity equation. At first $\lambda_i = \mu = 0$, then the above equation is reduced to:

$$i_b^{opt} = \frac{2w_1(I_{b,last}) + w_2\gamma(SoC - SoC_{target})}{w_1 + w_2\gamma^2 + w_3 P_{temp}} \tag{19}$$

Now, constraint activity is checked.

If $-I_{b,max} \leq i_b^{opt} \leq I_{b,max}$ Case 1: Inside bounds give an optimal solution $i_b^* = i_b^{opt}$ and Case 2: Outside bounds lead to constraint activation.

If $i_b^{opt} > i_{b,max}$ then $i_b^* = I_{b,max}$, $\lambda_1 > 0$.

If $i_b^{opt} < -i_{b,max}$ then $i_b^* = -i_{b,max}$, $\lambda_2 > 0$.

The constrained solution is obtained using projection:

$$i_b^* = \Pi\Omega(i_b^{opt}) \tag{20}$$

where $\Pi\Omega$ is a projection onto the feasible set defined by the current limits, SoC, ramp rate, and mode constraints. This weighted sum multi- objective method gives a computationally efficient way to balance conflicting objectives of battery safety, thermal management, and operational smoothness without resorting to complex optimization solvers.

IV. SIMULATION RESULTS

In the simulation model, all system components, such as PV, battery, supercapacitor, fuel cell, their converters, and DC load, are Simulink blocks. The proposed EMS was implemented using a MATLAB function block embedded within Simulink. The system performance was evaluated under varying load and source conditions using a signal builder block at battery SoC levels of 18%, 50%, and 94%. These scenarios were used to assess the effectiveness of the proposed control strategy in maintaining stable DC bus voltage and proper power sharing under dynamic operating conditions. In both the optimized and non-optimized cases, the DC bus voltage was successfully regulated to approximately 48 V. The results were recorded in four subplots of the battery: SoC, current, temperature, and DC bus voltage.

A. Operating Case at 18% Battery SoC with Variable Load

In this case, initially, the battery was at 25 °C, and the battery SoC was 18%. For the variable load scenario, the 600 W load was initially applied and then varied at 0.5 s, 0.8 s, and 1.2 s to 744 W, 840 W, and 937 W, respectively, to analyze the dynamic response. The optimized system forces the battery to charge more to raise the SoC, whereas without optimization, the battery discharges below 18% SoC, as illustrated in Figure 5. As the battery SoC is 18%, it will not take part in maintaining the bus voltage. Therefore, the fuel cell operates in a voltage-controlled mode to maintain the bus voltage.

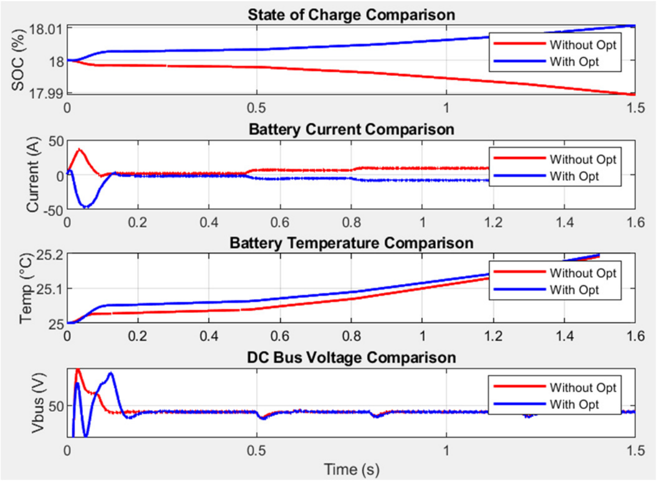

Fig. 5. Impact of optimization on DC microgrid at SoC of 18%.

B. Operating Case at a Temperature of 50 °C with Variable Load

In this operating case, the solar power generation and load demand were the same as mentioned above, and the battery was in discharging mode, as there was a deficit in power. However, the battery temperature is 50 °C, which is beyond the safe operating threshold. To protect the battery from thermal stress, the controller immediately gives the battery a current reference of zero. Therefore, the battery stops further charging or discharging for this condition. The battery is incapable of absorbing or releasing the extra power, and it also maintains the bus voltage by controlling the voltage mode. Another source is required as an emergency or auxiliary source to maintain the bus voltage at 48 V. Therefore, a fuel cell can be used to maintain the bus voltage in the voltage control mode until the temperature decreases. In addition, excess solar power can be curtailed as per the requirement, or it can be used to charge the other energy storage device if its SoC is less than the maximum SoC limit. The results show that the temperature protection mechanism is in action, as exhibited in Figure 6. The optimized controller prioritizes battery health while simultaneously managing other sources to regulate the bus voltage in the absence of the battery.

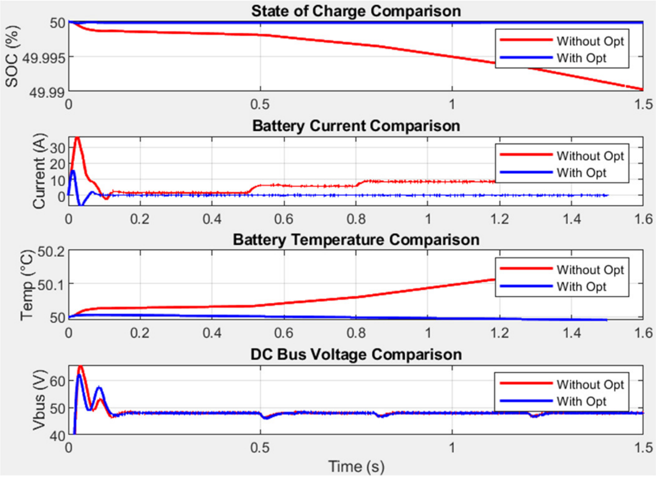

Fig. 6. Impact of optimization at battery temperature reaching 50 °C.

C. Operating Case at 94% Battery SoC with Variable Load

The case shown in Figure 7 involves the battery to be at 94% SoC. Further charging forces lead to the generation of gas and heat. This causes degradation, oxidation, and decomposition of electrodes. This further affects battery life. Therefore, when the battery SoC reaches 94%, the controller enforces relief discharging of the battery to prevent further overcharging. The optimization logic sets priority for controlled discharging from normal charging. The battery life is ensured by discharging a small current and balancing the SoC closer to the target range. Optimizer ensured that the battery did not remain at a critically high SoC level for an extended period. This demonstrates that the controller actively manages the excess energy by following SoC-based constraints and protects the battery from thermal damage. Ultimately, this contributes to extended battery life by maintaining safe operating conditions.

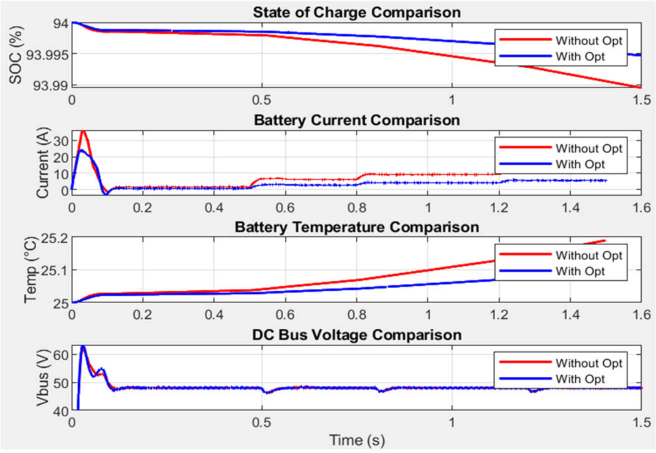

Fig. 7. Impact of optimization on DC microgrid at SoC of 94%.

D. Operation Case at Variable Source

The system was tested under variable solar PV conditions, where the irradiance changes at 0.6 s and 1.2 s, 800W/m^2 and 1000W/m^2, respectively. The load was varied in this case. As depicted in Figure 8, the battery SoC decreased at a slower rate with the optimization strategy than without optimization. This behavior in battery current is due to the optimization strategy, which smooths out large current fluctuations and limits peak discharging currents. The optimizer ensures that the battery current supplies energy in a controlled manner rather than aggressively responding to the transients and load variations. Therefore, the effective discharge current over time is reduced, resulting in a slower decrease in the SoC of the battery.

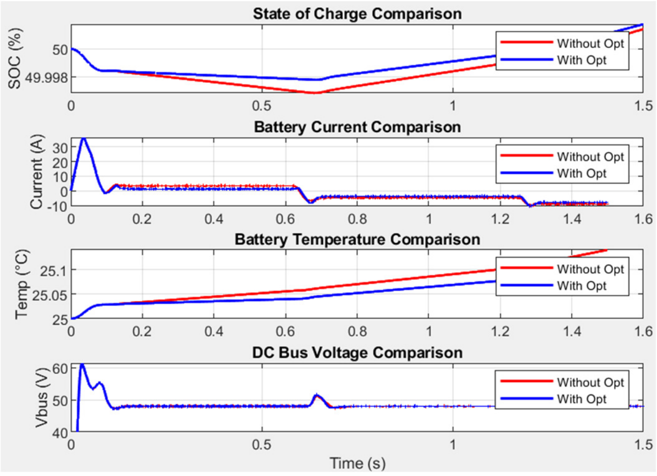

Fig. 8. Impact of optimization on DC microgrid at variable PV source.

E. Analytical Comparison with Existing EMS

Many existing studies have mainly focused on power sharing and voltage regulation in HESS-based DC microgrids using multi-objective optimization [8], data-driven control [4], and genetic-algorithm-based strategies [15]. A direct numerical comparison is challenging as these studies are developed based on different configurations and control objectives. Through these methods, the overall system performance improves, but limited attention has been paid to reducing battery stress and extending the lifetime. The proposed optimization-based EMS is aligned with existing approaches. However, the proposed approach advances these techniques by explicitly incorporating the battery degradation factor.

V. CONCLUSIONS

This study proposed a battery life-aware energy storage management strategy for a standalone DC microgrid. The proposed strategy determines the optimal battery current reference using a constrained, multi-objective optimization approach. This framework considers the state-of-charge regulation, current ripple minimization, and thermal stress mitigation. The optimization framework generates the optimal battery current under excess and deficit power conditions. To ensure DC bus voltage regulation, the optimized battery current was adaptively blended with a voltage control component, whereas the supercapacitor absorbed transient power, which extended the battery life.

Under varying solar irradiance and load conditions, MATLAB simulation results were analyzed. Through the proposed strategy, the microgrid bus voltage was close to the nominal 48 V, while a significant reduction of battery current oscillations was demonstrated through the results. Quantitative comparison indicates that the proposed method reduces the battery current ripple by approximately 40–60% and limits the DC bus voltage deviation within ±1 V, surpassing conventional strategies reported in the literature. The supercapacitor handles transient power support and steady-state energy balancing to the battery; the proposed control framework effectively alleviates electrochemical stress and improves battery operational safety. The results validate that the proposed optimization-based energy management strategy provides an effective solution for enhancing reliability and extending battery service life in standalone renewable-based DC microgrids.

Future work will focus on the experimental validation of the proposed control strategy using a real-time DSP-controlled DC microgrid platform. Further investigations will explore adaptive weight tuning within the optimization framework, incorporating detailed battery degradation models and predictive energy management techniques. This represents a promising direction for future research.

DECLARATION OF COMPETING INTERESTS

The authors declare that there are no conflicts of interest regarding the publication of this paper.

ACKNOWLEDGMENT

No funding was received for this study. This work was based on MATLAB/Simulink simulations.

DATA AVAILABILITY

Not applicable to this work.

REFERENCES

[1] R. Bhosale and V. Agarwal, "A Novel Control Strategy to Share Power among Dispatchable Battery Sources and Achieve SOC Balancing without a Droop Control in a DC MicroGrid," in *2019 IEEE Industry Applications Society Annual Meeting*, Sept. 2019, pp. 1–6, https://doi.org/10.1109/IAS.2019.8912464.

[2] H. Zhou, T. Bhattacharya, D. Tran, T. S. T. Siew, and A. M. Khambadkone, "Composite Energy Storage System Involving Battery and Ultracapacitor With Dynamic Energy Management in Microgrid Applications," *IEEE Transactions on Power Electronics*, vol. 26, no. 3, pp. 923–930, Mar. 2011, https://doi.org/10.1109/TPEL.2010.2095040.

[3] S. Muchande and S. Thale, "Hierarchical Control of a Low Voltage DC Microgrid with Coordinated Power Management Strategies," *Engineering, Technology & Applied Science Research*, vol. 12, no. 1, pp. 8045–8052, Feb. 2022, https://doi.org/10.48084/etasr.4625.

[4] Q. Hu, S. Xie, and J. Zhang, "Data-based power management control for battery supercapacitor hybrid energy storage system in solar DC-microgrid," *Scientific Reports*, vol. 14, Oct. 2024, Art. no. 26164, https://doi.org/10.1038/s41598-024-76830-y.

[5] I. Ameur and A. Benalia, "PMP Based Optimal Power Management of a PV-Fuel-Cell-Battery Hybrid Power Source," in *2019 International Conference on Advanced Electrical Engineering (ICAEE)*, Nov. 2019, pp. 1–6, https://doi.org/10.1109/ICAEE47123.2019.9015184.

[6] E. Farrokhi, H. Ghoreishy, and R. Ahmadiahangar, "Real-time optimal power management for a hybrid energy storage system with battery thermal consideration and DC microgrid current estimation capability," *Electrical Engineering*, vol. 106, no. 4, pp. 4705–4718, Aug. 2024, https://doi.org/10.1007/s00202-024-02243-9.

[7] J. Shen and A. Khaligh, "Design and Real-Time Controller Implementation for a Battery-Ultracapacitor Hybrid Energy Storage System," *IEEE Transactions on Industrial Informatics*, vol. 12, no. 5, pp. 1910–1918, Oct. 2016, https://doi.org/10.1109/TII.2016.2575798.

[8] R. J. J. Molu, S. Raoul Dzonde Naoussi, P. Wira, W. F. Mbasso, S. T. Kenfack, and S. Kamel, "Optimization-based energy management system for grid-connected photovoltaic/battery microgrids under uncertainty," *Case Studies in Chemical and Environmental Engineering*, vol. 8, Dec. 2023, Art. no. 100464, https://doi.org/10.1016/j.cscee.2023.100464.

[9] M. Vijayan *et al.*, "Optimal PI-Controller-Based Hybrid Energy Storage System in DC Microgrid," *Sustainability*, vol. 14, no. 22, Nov. 2022, Art. no. 14666, https://doi.org/10.3390/su142214666.

[10] S. Punna, S. Banka, and S. R. Salkuti, "Optimal Energy Management Scheme of Battery Supercapacitor-Based Bidirectional Converter for DC Microgrid Applications," *Information*, vol. 13, no. 7, July 2022, Art. no. 350, https://doi.org/10.3390/info13070350.

[11] S. K. Bhoi, K. Kasturi, and M. R. Nayak, "Optimisation of the operation of a microgrid with renewable energy sources and battery storage," *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 4, June 2023, Art. no. 100159, https://doi.org/10.1016/j.prime.2023.100159.

[12] M. C. Pham, Q. T. Tran, H. D. Nguyen, and L. C. Nguyen, "Hybrid Energy Storage System in an Off-grid Microgrid," in *2025 Asia Meeting on Environment and Electrical Engineering (EEE-AM)*, Hanoi, Vietnam, Aug. 2025, pp. 1–5, https://doi.org/10.1109/EEE-AM66675.2025.11473373.

[13] S. Patel, A. Ghosh, and P. K. Ray, "Efficient power management and control of DC microgrid with supercapacitor-battery storage systems," *Journal of Energy Storage*, vol. 73, Part C, Dec. 2023, Art. no. 109082, https://doi.org/10.1016/j.est.2023.109082.

[14] J. I. Shuvo, Md. Badoruzzaman, S. T. I. Anik, S. Ahmad, T. Ahmed, and M. Karimi, "Hybrid energy storage power management system harnessing battery-supercapacitor synergy for grid-isolated DC microgrid," *Journal of Energy Storage*, vol. 119, May 2025, Art. no. 116170, https://doi.org/10.1016/j.est.2025.116170.

[15] M. A. Majeed, S. Phichaisawat, F. Asghar, and U. Hussan, "Optimal Energy Management System for Grid-Tied Microgrid: An Improved Adaptive Genetic Algorithm," *IEEE Access*, vol. 11, pp. 117351–117361, 2023, https://doi.org/10.1109/ACCESS.2023.3326505.