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Research article

Energy management system using load following- terminal slide mode control strategy in DC microgrid with hybrid energy storage system

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Abstract: An Energy Management System (EMS) in a direct-current (DC) microgrid system is essential to manage renewable energy sources (RES), stored energy units, and demand load. However, the conventional load-following (LF)-based EMS strategy presents several issues due to its integration with proportional-integral (PI) controllers. These controllers have weak performance under sudden irradiation or demand load changes, which result in high overshoot, low convergence speed, and unwanted energy losses in DC microgrid responses. Therefore, this article introduces an improved LF strategy using the terminal-slide mode control (TSMC) method. Moreover, the studied power system consists of a photovoltaic (PV) system, a hybrid energy storage system (HESS) using lithium-ion batteries, and supercapacitors (SCs). The suggested EMS strategy aims to reduce the fluctuation of the grid voltage and enhance the reliability of the system under different irradiance and demand variations. It employs voltage regulation for the DC bus using a robust TSMC instead of using the classical PI controllers. The simulation was conducted using MATLAB/Simulink software. The obtained results indicate that the proposed LF-TSMC strategy can cancel the voltage overshoot, offer better settling time, and provide higher efficiency. Finally, the presented EMS introduces superior dynamics with a settling time of $(< 0.1\ s)$ and overshoot percentage of (1%), compared with a settling time of $(0.45\ s)$ and overshoot percentage of (2.5%) for the classical LF-PI method.

Keywords: Photovoltaic; energy management; lithium batteries; supercapacitors; DC microgrid; load following; terminal slide mode control; PI control

1. Introduction

1.1. Background and motivation

There is an increasing reliance on renewable energy (RE) sources. Therefore, microgrids (MG) enhance the effective incorporation of RE sources, such as solar and wind energy. They locally store and transmit renewable energy, therefore diminishing reliance on fossil fuels and decreasing carbon emissions [1,2]. In the last few years, the direct-current (DC) MG has been a trending topic in power systems and MG applications due to its simplicity and more effective power control. Moreover, the strategy ensures a reliable operation by aligning the power supply from renewable energy sources, such as photovoltaic (PV) systems and energy storage systems (ESS), with demand, thereby maintaining a supply-and-demand scenario [3,4]. The management of DCMG can boost the dependability and consistency of the system by guaranteeing power shifts and resilience to faults. Additionally, it extends the lifespan of the ESS, including the battery, by preventing overcharging and deep discharge and by monitoring the state of charge (SoC) through algorithms [5–7].

However, an energy management system (EMS) can help cut down on energy expenses by giving preference to power when it is available and utilizing the battery during peak times to save on electricity consumption and distribution in the MG system [8,9]. It assists in incorporating energy by managing fluctuations in energy production caused by factors such as clouds or shadows. This boosts the use of energy and decreases dependence on non-renewable resources within the MG. Therefore, using an efficient EMS can minimize the system's impact by maximizing the utilization of eco-energy sources, such as solar power, to meet sustainability objectives and comply with environmental regulations. By either supplying surplus electricity to the grid or obtaining power during deficits, enhanced energy management techniques also enable enhanced grid connectivity and self-sufficiency. This result is achieved by managing hybrid RE with a battery energy storage system (BESS) in a DC MG system. However, DC microgrids are rapidly gaining traction when it comes to integrating RE resources. While they are compatible with renewable technologies, one of the major reasons for their increased popularity is their simpler utilization [10,11]. DC microgrids also perform better, offering higher efficiency while reducing conversion losses as well as eliminating reactive power concerns. More simplicity in components and load characteristics also means that development for microgrids is less time-consuming and more efficient. More renewable resources or storage systems can be simply added to achieve a scaled power system for both small- and large-scale projects. They have better control and reliability with the availability of centralized and distributed control architectures and can work in island mode or easily connect with the larger power grid. With less installation and operating costs, they require a lesser number of cables and lower maintenance requirements, along with faster setup [12,13]. The most used DCMG configurations include a DC load, PV system, wind energy, fuel cell, and BESS, such as a lithium-ion battery or supercapacitor (SC), as applied in previous works [14,15]. This configuration of the MG requires a robust EMS to optimize the power sharing between the load and sources.

However, extensive research in the field of energy management strategies for DC microgrids has omitted some critical challenges. The conventional rule-based, droop-based, and optimization-driven EMS methods that are usually mentioned in literature have issues like slow dynamic response, sensitivity to system uncertainties, and limited robustness in hybrid energy storage systems coordination under changing load and source conditions. Most of the presented control schemes are geared toward steady-state power allocation; thus, they hardly acknowledge the significance of fast load-following capability and tracking time convergence, which are vital to maintaining DC-bus stability and increasing the lifetime of energy storage devices. Based on these drawbacks, this work presents a load-following terminal sliding mode control-based energy management system for a DC microgrid with a hybrid energy storage system. The battery and supercapacitor units should be able to track the load accurately, the DC-bus voltage should be regulated robustly, and power sharing should be carried out effectively even under load disturbances and system uncertainties, as per the proposed method. The proposed EMS achieves fast time convergence, better robustness, and improved dynamic performance as compared to the state-of-the-art methods.

1.2. Literature review

In the last few years, several studies have been conducted to improve the performance of DC microgrids or hybrid power systems (HPS), considering different RES and energy storage technologies. The authors in [16,17] presented an efficient flatness theory-based EMS to control the DC-bus voltage under different load conditions. Using flatness control improved the performance of the DCMG under different loads or fast changes in irradiance. The presented strategy was compared with load-following and proportional-integral (PI) methods under different circumstances. The authors in [18] proposed a fuzzy logic (FL)-based EMS strategy to enhance the PV/BESS system. The study introduced a novel energy management method for MG that improves the efficacy of power distribution, frequency, voltage, and load management by utilizing a real-time monitoring platform and an FL controller. The authors in [19] proposed an artificial neural network (ANN). The MG comprised variable loads, an ESS system, and distributed generation. The ANN utilized power data from variable DGs and loads to ascertain the appropriate operational mode and power reference. In [20], an innovative EMS using an adaptive neural fuzzy inference system (ANFIS) for a hybrid microgrid augmented by a predictor using an echo state network (ESN) was proposed. The training algorithm was explicitly formulated to optimize earnings from energy transactions with the grid, taking into account a time-of-use (TOU) pricing strategy. The main aim of this research was to assess the influence of the prediction system on the performance of the EMS. In addition, the authors in [21] presented a robust EMS using ANFIS for vehicle-to-grid-based MG applications. Solar PV and wind turbine RE sources with BESS for EVs were considered. By determining the EV power demand, the studied EMS can control the motor generator (MG). The presented method was compared with the FL method in terms of solving demand power issues. The results achieved demonstrate that this method is highly efficient in optimally determining the power allocation for vehicle-to-grid (V2G) systems.

A centralized EMS for a hybrid DC MG system consisting of solar photovoltaic, fuel cell, and battery energy storage was proposed in [22], indicating a novel approach, in which a controller manages a hydrogen fuel cell (FC)-battery system that incorporates a BESS. Additionally, the authors stated that the use of PV modules would improve BESS performance. This, in turn, would enable BESS to avoid recharging in extreme conditions when the demand is minimal. The latter not only improves hydrogen fuel economy but also helps to further reduce the battery discharge depth during high demand. The gathered information regarding load power, battery SOC, and each source power is passed onto the centralized EMS. Such complex systems as hybrid energy storage systems (HESS) have mostly nonlinear characteristics; hence, there is a huge complexity in controlling such a system. Therefore, the research in [23] addressed a hierarchical EMS with a fractional order-based slide mode control (FOSMC) structure that is utilized to circumvent some of these complexities. When the energy in SCs needs to be maximized, a typical governing layer divides the control strategies into two operational methods. The suggested method is a more efficient solution than fuzzy logic, which is widely employed in the control layer, as it analyzes the system performance and stability in the control process using the Lyapunov stability criterion. In [24], an islanded microgrid with PV and ESS was simulated with an EMS to enhance efficiency and reliability. This work focused on increasing efficiency in energy management with switching-model predictive control to minimize depletion and instability of the energy systems. The dynamical characteristics of the battery were considered, and the method of iterative reasoning was used in solving the non-affine function of the constraints. In this context, the proposed concept allows minimizing energy loss while meeting the energy storage system state of charge requirements, which is applicable without performing a prediction of future external conditions.

Montano et al. [25] developed the concept of EMS, combining the use of multi-objective optimization algorithms to effectively manage the energy of standalone and grid-connected DC microgrids. The study aimed to minimize the operating cost of the system, thus maintaining the power balance, as well as ensuring the safety of the power system by means of optimally scheduling the battery energy-storage operation together with power exchange with the grid. This particular work considered the technical constraints (power flow, battery cycling limits) with various economic factors such as electricity price and battery life cost. As a result, it set the bar for the improvement of cost-effectiveness and energy efficiency of a system as compared with the single-objective EMS approaches by a significant amount. The limitation of that approach is that it depends on offline or quasi-static optimization and is devoid of a fast real-time control layer. Consequently, rapid changes in irradiance, errors in forecasting, and unforeseen load fluctuations become only partial solutions. The authors in [26] presented a deep reinforcement method that powers the energy storage system of a heterogeneous medium-voltage microgrid without any external connection. They wanted to link temporal forecasting using long short-term memory neural networks (LSTM-NN) with smooth control for the efficient dispatch of energy, as well as for the stabilization of voltage supply amid fast renewable variations. Compared with traditional rule-based EMS, the simulated results provided better prediction accuracy and less energy loss. The main issue of the EMS is that it needs a very large amount of high-quality training data and long training periods, which can be difficult to attain if there is little or no historical data.

Satyanarayana and Maurya [27] introduced a combined control strategy for a high-gain DC/DC converter, which is part of a photovoltaic-battery hybrid system that is suitable for both standalone and DC microgrid applications. The objectives of the suggested method were to raise the DC voltage gain and guarantee easy energy exchange between the PV array and battery, ensuring a stable DC bus. Their control plan managed to perform both tasks effectively (voltage regulation and efficient energy flow), and the achieved results indicated better steady-state performance than the traditional converter controls. However, there was very little testing of the hardware to validate the dynamic performance in cases of harsh partial shading, sudden load changes, or faults. Without a comprehensive EMS layer and a rigorous hardware testing program, the proposed method might struggle to be successful in large, real-world DC microgrids with varying operating conditions. The research study in [28] proposed an efficient AI-based EMS strategy aiming at managing and stabilizing an islanded MG system. The applied EMS confirms the improvement of power tracking and the regulation of the DC bus to be more stable compared to the use of conventional control methods. However, there are still some drawbacks to be considered in the applied method, namely, the difficulty of ANN datasets. The training of the ANN relies heavily on the availability of abundant historical data and well-defined patterns, which may limit the ability to extend to new operating conditions that include sudden faults or unusual weather patterns. The article mainly concentrates on power-quality improvements and does not fully integrate techno-economic optimization or cost-based scheduling.

The authors in [29] introduced a power management method combined with a DC-bus voltage regulation for a hybrid PV-BESS power system. The main objective of this study was to stabilize the DC-bus voltage and ensure a reliable power system when the weather conditions change rapidly. The applied method involved the use of coordinated control of DC-DC converters and battery charge/discharge operations, and the results showed successful voltage regulation and power quality improvement. Nevertheless, the technique was still rule-based with limited capabilities for predictive or adaptive optimization over stochastic renewable fluctuations. Economic objectives, like the life-cycle cost or the best battery sizing, are not explicitly indicated. The study work in [30] proposed a Lyapunov-based sliding-mode control (SMC) as a method to solve the problem of stability of the PV-wind hybrid DC microgrid with a HESS system. The research goal was to ensure not only the global voltage stability but also the optimal power to be shared between the renewable sources and the storage devices during large and rapid disturbances. The nonlinear control in question made use of Lyapunov stability theory to guarantee the achievement of the desired performance in a finite time and the effectiveness of strong robustness against parameter variations. However, the studied method presented disadvantages, such as its computational complexity and tuning effort, which can restrict easy implementation on cost-sensitive embedded controllers. Moreover, the issue of economic dispatch, along with the long-term battery aging effects, was not considered in the model, and thus, the problem of scalability for multi-bus or large DC grids was only partially resolved. The researchers in [31] introduced a scheme that distributes power and assesses the performance of a wind energy–fed DC microgrid integrated with hybrid energy storage. Their focus was on ensuring the flow of power with balance and high reliability, while at the same time aiming to reduce the effect of wind generation that changes frequently. The implementation of the strategy with coordinated converter control and real-time monitoring resulted in the achievement of a more stable DC-bus voltage and better supply continuity. This study offered key sizing and operational efficiency insights into hybrid storage. Nevertheless, the approach was mainly based on deterministic control logic and did not incorporate sophisticated optimization or machine learning techniques that would be able to handle unpredictable wind variations and load spikes. Montano et al. [32] conducted a comparative study focusing specifically on several optimization techniques aimed at improving energy-storage systems of the standalone and grid-connected DC microgrids. The main objective was to find out the best metaheuristic method that can provide the best balance between computational efficiency and solution quality for the optimal charge–discharge scheduling. This was an important benchmark work under the same test conditions, measuring the speed of convergence, precision, and economic savings of various algorithms. However, the study was purely analytical and based on simulations; it was not an integration of a complete EMS architecture for real-time control or fault management. Besides, uncertainties in renewable forecasting have been only partially accounted for in the microgrid. Meng et al. [33] introduced the conceptualization and optimization of a framework for the off-grid solar PV system at a residential scale, integrating adaptive storage control. The key goal of the study was to lower the life cycle cost and raise the operational reliability of batteries and inverters. The system, through the mixed-integer optimization method, empowered with the adaptive charge–discharge control, selects the optimum capacities of PV and battery and a storage allocation, which is a function of the real-time demand and irradiance, thereby significantly reducing the cost of energy and extension of battery lifetime compared with the static scheduling method.

The study in [34] proposed a rule-based energy management system to function as an automatic voltage stabilizer in a standalone DC microgrid. The used method employed decision rules to coordinate PV generation, battery charge/discharge, and DC/DC converters, which do not require heavy computation or extensive communication. Moreover, the rule-based EMS, despite its simplicity and robustness, had several shortcomings. Namely, it does not have predictive capability or adaptive optimization; hence, it becomes less effective when renewables and load profiles differ from the pre-established rules. On the other hand, economic aspects such as the life cycle cost and the best storage size for the battery were only very slightly considered. The authors in [35] proposed a control method and dynamic energy-supply strategy that was very simple but effective in managing a solar PV system. The goals of the designed method were to ensure a smooth change of the modes, maintain the power balance, and extend the power supply through emergency batteries. In the controller, simple switching logic and PI regulation for flow management were employed, which was done by a power trip between the PV array, battery, and local loads. The implemented system showed stable performance with minimal voltage variation and rapid changeover between modes. Yao et al. [36] focused on designing a model-based reinforcement learning (RL) control structure that combined the knowledge of the physical system with the learning mechanisms to improve control accuracy, robustness, and stability of electrohydraulic position servo systems under nonlinearities and uncertainties. The integration of system models into the reinforcement learning process was intended to boost learning efficiency and guarantee fast and reliable performance in safety-critical applications. On the other hand, Yao et al. [37] went for a completely data-driven reinforcement learning control method for hydraulic manipulators, aiming at achieving adaptive and ultra-precise control without the need for explicit mathematical models. The primary idea of this work was to overcome the problem of strong nonlinear coupling and uncertain dynamics by interaction-based learning, thus making a model-free intelligent control approach feasible for complex nonlinear systems.

A robust FL-EMS method was proposed in [38] to control the microgrid under different weather or load conditions. The fuzzy inference rules allow on-the-spot decision-making that does not need an exact mathematical model, thus providing flexibility to the uncertainties of renewables and loads of the microgrid (MG). However, the method is still very reliant on the way the rules are written and the knowledge of the experts, which can somewhat restrict the range of application and its efficiency when the system is in a situation that is outside the predefined rule base. Hu et al. [39] suggested a power system control for the battery/supercapacitor hybrid energy storage unit in a solar DC microgrid. The algorithm, which was based on historical and real-time data of the system, dynamically shares the power between the battery (for energy) and the supercapacitor (for quick changes) to achieve a stable DC-link voltage and enhance the system's overall performance. On the other hand, the performance of this method depends heavily on how well the training data covers the possible situation, which might lower the method's robustness for unknown environmental or load conditions. Besides, only a few economic aspects, such as the optimal dispatch of costs and the degradation of long-term storage, are considered. Gajjar and colleagues [40] presented an efficient HESS control for DC microgrids, which is fundamentally based on state-of-charge (SoC) management. Their goal was to properly mix energy between batteries and supercapacitors to improve its quality during quick changes of load and generation, as well as to extend the lifetime of the battery. Their method takes the SoC limits as decision criteria of charge or discharge orders for the real-time operation, which, as a result, leads to a more stable DC-bus voltage and higher system reliability than when using traditional droop or PI-based controls.

The literature review is summarized in Table 1. As observed in this table, the main attraction of the rule-based and droop-based EMS methods lies in their simplicity and low computational load; however, they are generally less flexible, and their performances tend to deteriorate under quickly changing load and source conditions. Methods based on AI, such as fuzzy logic, ANN, and ANFIS architectures, enhance the system's nonlinear decision-making and forecasting abilities but are highly dependent on the availability of large training datasets, have difficulties in tuning, and cause reliability and interpretability issues in real time. While optimization-based and MPC-driven EMS strategies open the door to systematic and multi-objective control, they are, in most cases, accompanied by heavy computational work and a limited capability to interact with swiftly changing dynamics in practical DC microgrids. On the other hand, nonlinear control-based EMS schemes, especially those implementing SMC, extend their capabilities to include a high degree of robustness to disturbances and modeling inaccuracies. However, the majority of current SMC-based methods are only able to demonstrate asymptotic convergence and do not explicitly consider load-following or coordinated power sharing in hybrid energy storage systems. This research therefore presents a load-following terminal sliding mode control–based EMS that guarantees finite-time convergence, rapid dynamic response, and robust DC-bus voltage regulation, along with battery–supercapacitor power sharing coordination as a solution to the issues raised in this paper.

Table 1. Some studied EMS strategies in the DC microgrid.

Reference	EMS strategy	Complexity	Microgrid configuration	Contributions and limitations
[18]	Fuzzy logic	Moderate	PV-battery	-Adaptive EMS. - The strategy can deal with uncertainty and has straightforward implementation
[19]	ANN	High	PV-WT-battery	- Improved management strategy but requires a larger training dataset.
[20]	ANFIS	High	PV-WT-battery	- Presents predictive energy scheduling, but the method takes more computational time.
[21]	ANFIS	High	EV-battery	- Enhances the V2G operation with bidirectional power flow.
[22]	Rule-based EMS	Low	PV-FC-battery	- It is a simple and highly efficient EMS.
[23]	Hierarchical EMS with SMC	Very high	Battery-SC	- An improved EMS with high performance under different load conditions is presented. - The transient of the system is improved.
[24]	MPC	High	RES with battery	- High efficiency and less power oscillation. - The computational cost is high.
[25]	Optimization-based EMS	Very high	Battery	- Techno-economic approach is studied for BESS in a grid-connected microgrid.
[26]	LSTM-NN	High	HESS	- Smart power management. - Self-learning advantage. - Needs a heavy dataset for NN.
[28]	ANN	High	HESS	- Improved EMS coordination. - Very high dynamic response.
[29]	Classical EMS	Very low	PV-battery	- Used to regulate the DC-bus regulation. - Simple and very effective.
[30]	SMC	Moderate	PV-WT-HESS	- The MG stability is enhanced. - Very effective EMS under step load changes.
[31]	Coordinated	High	WT-HESS	- The MG reliability is enhanced.

	control EMS			- Load following analysis is not considered.
[35]	Simple EMS	Very low	PV-battery	- Simple hardware implementation. - Moderate dynamic response.
Proposed	**LF-TSMC**	**Moderate**	**PV-SC-Battery**	**- Mitigating power fluctuations and enhancing DC-bus voltage stability.**

1.3. Article contributions

In this paper, an improved EMS based on the load following strategy (LF) is proposed. The new method combines LF with terminal slide mode (TSMC) control to enhance the microgrid response and minimize voltage overshoot. The LF-TSMC strategy can improve the performance of the DC MG by stabilizing the DC-bus voltage regulation without any overshoot and with a fast response to variations in the load and the solar irradiance. The main contributions are:

i. The implementation of a load-following (LF) strategy with nonlinear TSMC control can balance the RES generation, storage, and load demand.
ii. The new EMS is capable of mitigating power fluctuations, enhancing DC-bus voltage stability, and lowering energy losses in comparison with those based on the conventional PI-controlled methods.
iii. A comprehensive PV-battery-supercapacitor power system has been implemented in MATLAB/Simulink to capture the dynamics of the system under load and irradiance variation.
iv. The numerous case studies in irradiance conditions are tested, and the reduction of overshoot and settling time shows that efficiency and battery lifetime are enhanced.
v. This method can provide a solution for real-world DC microgrid systems utilized in homes, commercial buildings, or areas without a power supply.

1.4. Organization of the article

The rest of the article is organized as follows: Section 2 presents the description of the studied microgrid. Section 3 introduces the design of the applied EMS strategy. Section 4 presents the simulation results and discussion. Finally, section 5 addresses the conclusion of the article.

2. Microgrid configuration

The configuration of the proposed MG system is shown in Figure 1. This section describes the structure, components, and basic operational principles of the proposed DC microgrid system, as well as its significance within modern energy systems. Particularly, PV systems, SCs, and batteries that operate on DC are compatible with DC microgrids. This part explores the design and functional elements of power conversion units, as shown in the next sub-sections.

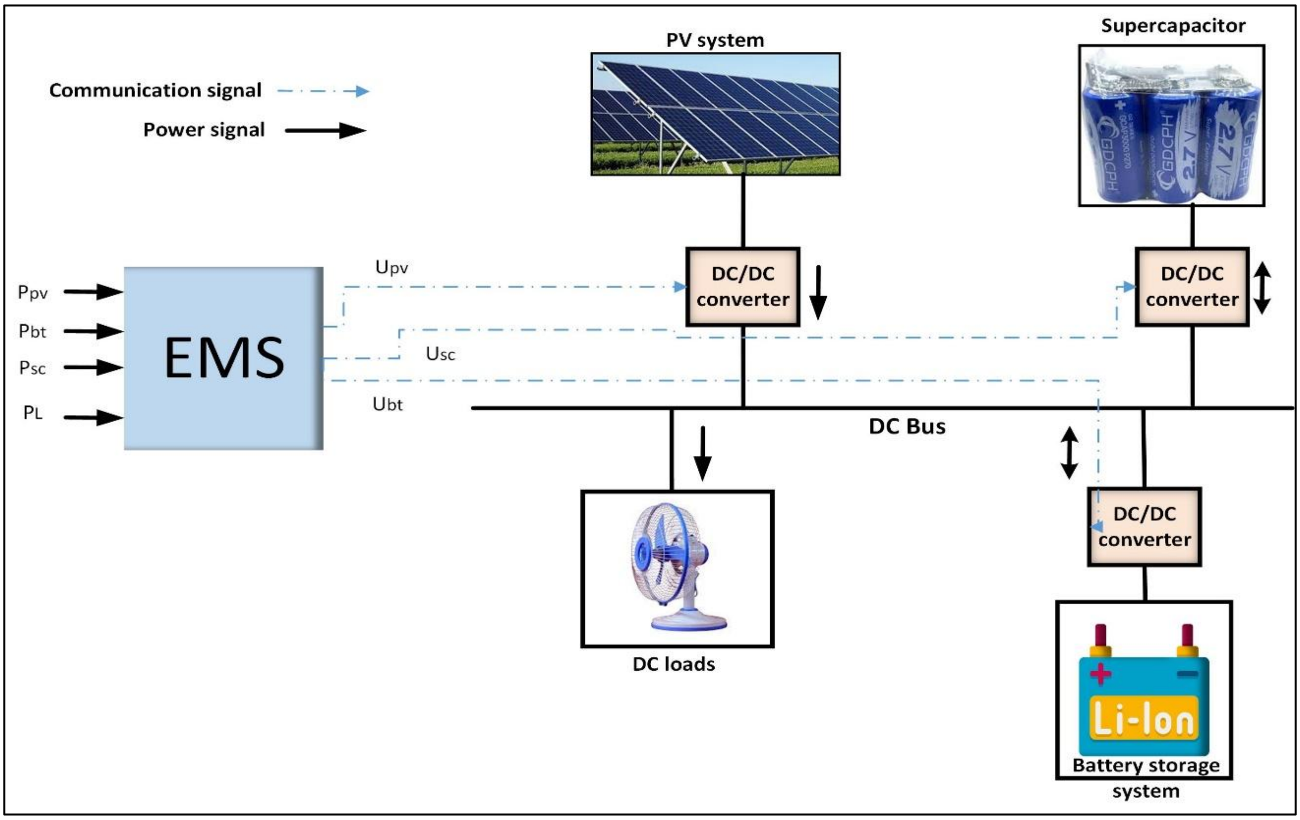

Figure 1. Proposed MG configuration.

2.1. Solar PV modeling

The solar PV cell or array was modeled using a single diode, as displayed in Figure 2. This mode is the most popular because it balances accuracy and mathematical effort. It captures the essential electrical behavior of a solar cell [41,42]. The single diode model simplifies the complex internal physics of a PV cell into an equivalent electrical circuit, consisting of a current source, a diode, a series resistor, and a parallel resistor. The main equations of the PV module are written as follows [41]:

$$I_{pv} = I_{PH} - I_S\left(exp\left[\frac{(V_{pv} + I_{pv}R_S)}{\delta V_{th}}\right] - 1\right) - I_{sh} \tag{1}$$

$$I_{PH} = (I_{SC} - K_I\,(T - T_n))\frac{G}{G_n} \tag{2}$$

$$I_{sh} = \frac{(V_{pv} + I_{pv}R_S)}{R_{SH}} \tag{3}$$

The following is a definition of each symbol used in the aforementioned equations:

- ✓ I_{pv} represent the solar cell current.
- ✓ V_{pv} denotes the PV's voltage.
- ✓ I_{PH} denotes the current of the sunlight.
- ✓ I_S denotes the current of the diode.
- ✓ R_S denotes the series resistance.
- ✓ R_{SH} represents the shunt resistance.
- ✓ δ represents the constant of the diode.

- ✓ I_{SC} represents the short-circuit current.
- ✓ V_{OC} is the terminal voltage without load.
- ✓ G and T are the solar irradiance and temperature.
- ✓ $T_n = 25$ ℃ denotes the temperature at STC.
- ✓ $G_n = 1000\ W/m\text{^}2$ denotes the irradiation at STC.
- ✓ K_V denotes the voltage-temperature coefficient.
- ✓ K_I denotes the current-temperature coefficient.
- ✓ V_{th} denotes the voltage of the diode at STC.

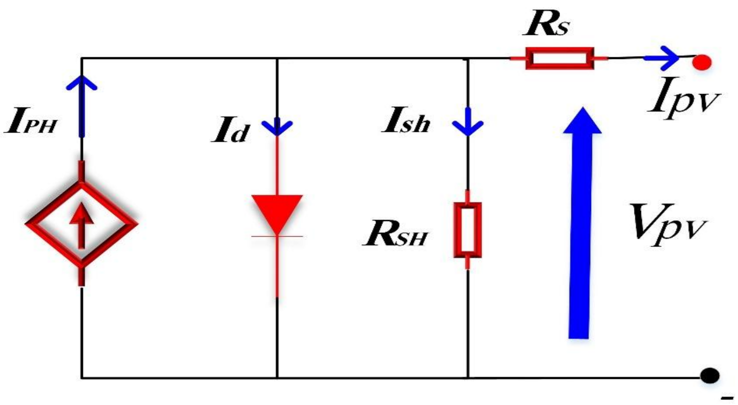

Figure 2. Single-diode PV cell model.

To realize the MPPT algorithm, the DC/DC converter is employed. PV array energy is maximized in this work through the improved incremental conductance (InC) based MPPT method [43]. The entire PV system is displayed in Figure 3. In this study, the maximum power of the PV generator is extracted via 15 PV modules with a capacity of 4.4 kW. Data of the used PV module are listed in Table 2. The extracted PV and I-V curve of the array are shown in Figure 4.

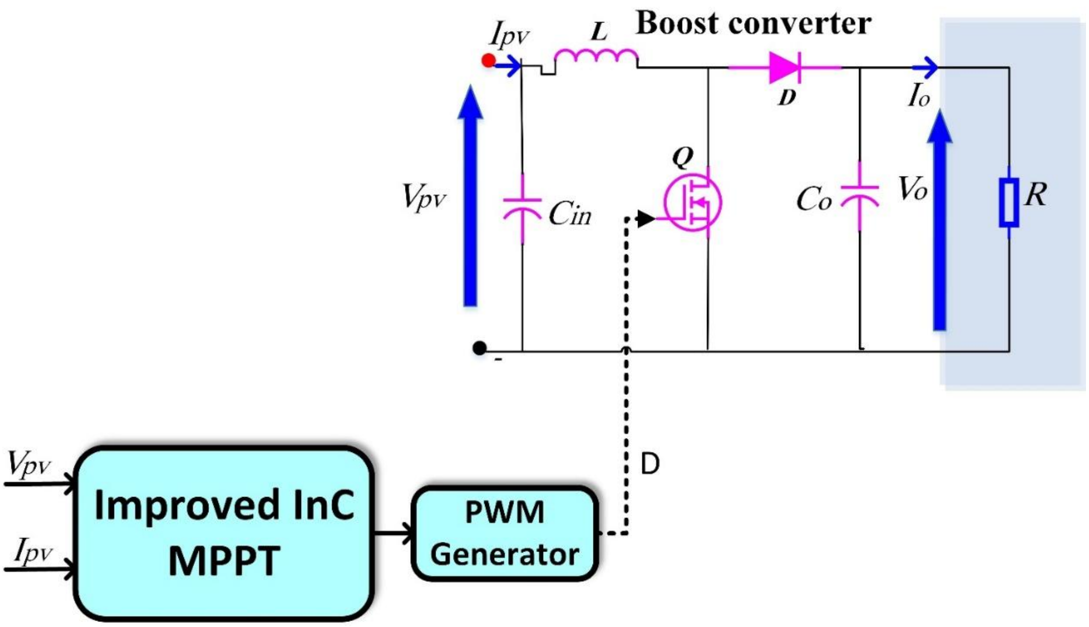

Figure 3. Improved InC-based MPPT configuration.

Furthermore, the boost converter circuit is represented by input capacitance C_{in}, an inductor L, and output capacitance C_o. The input and output capacitances are used to decrease the ripple of the voltages. The pure resistive load is represented by R. The obtained voltage and current are represented using Eqs. (4–5). The mentioned parameters are determined using Eqs. (6–8).

$$V_o = \frac{V_{pv}}{1-D} \tag{4}$$

$$I_o = I_{pv} \times (1-D) \tag{5}$$

$$C_o = \frac{D}{8 \times f \times L \times 0.01} \tag{6}$$

$$L = \frac{D \times (1-D)^2 \times r}{2 \times f} \tag{7}$$

$$C_{in} = \frac{D}{0.02 \times f \times r} \tag{8}$$

where D is the duty cycle, f is the switching frequency, and r is the ripple value in the inductor current, assumed as 0.25. The main parameters are listed in Table 2.

Table 2. Parameters of the studied system.

Item	Parameters	Value
PV array	V_{mpp}	$36.8\ V$
	I_{mpp}	$8.02\ A$
	P_{mpp}	$295.1\ W$
	I_{SC}	$8.53\ A$
	V_{OC}	$44.9\ V$
	K_I	$0.08\%/℃$
	K_V	$-0.427\%/℃$
	N_p	3
	N_s	5
Boost converter	L	$2\ mH$
	C_{in}	$200\ \mu F$
	C_o	$2000\ \mu F$
	f	$5 kHz$
	$duty$	$0.1 < duty < 0.95$

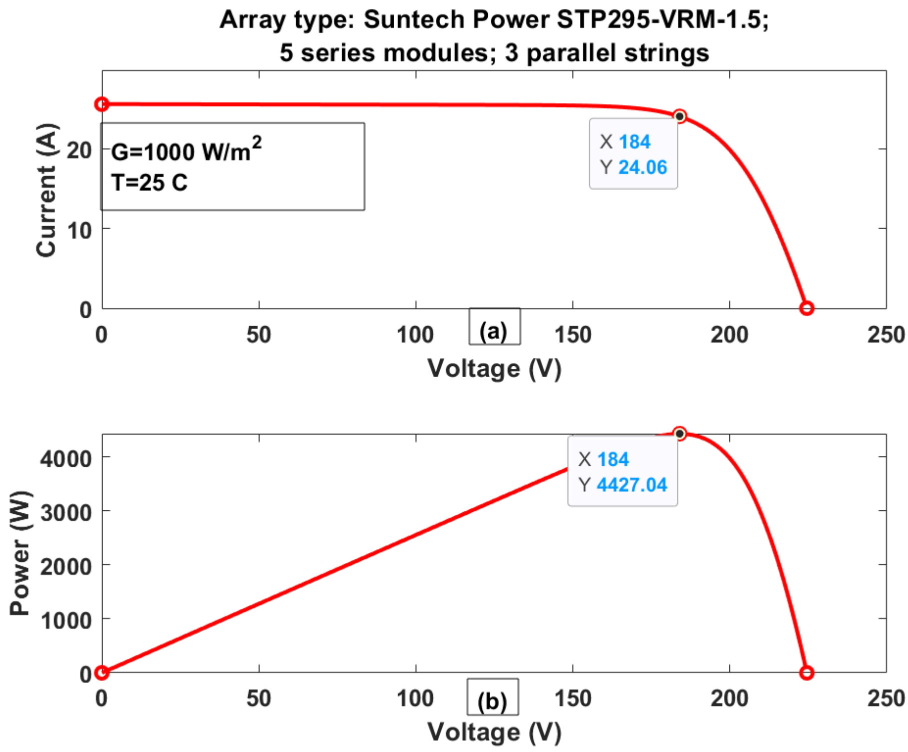

Figure 4. (a) I-V characteristics of PV array. (b) P-V characteristics of used PV array.

2.2. Battery modeling

The suggested HESS diagram of this study is shown in Figure 5. In the suggested DC microgrid, both HESS are interfaced with the DC-bus link via DC/DC bidirectional converters for assistance in charging and discharging the SC and battery. The EMS controls the power switches (S1–S4) to control the energy sharing between the load and sources. Each converter has an inductor L, a capacitor C, and two active switches (S1–S2) for the battery side and two (S3–S4) for the SC side. This bidirectional topology allows both buck and boost operations, thus controlling charging and discharging as per the system requirements can be obtained. Corresponding to these signals, the EMS acts as follows:

- The SC transfers the high-frequency power fluctuations of short duration so that the battery is protected from rapid cycling.
- With the help of a battery, it sets up a long-term energy demand route so that the system has a high energy density.
- The HESS helps in the stability of the DC-bus voltage and makes sure that power flow is bidirectional when the MG regenerates or discharges.

This method effectively separates the power- and energy-oriented functions of the storage system. The SC gives or takes the sudden transient, while the battery provides the energy that can be sustained. Therefore, battery lifetime is extended, thermal stress is reduced, and system dynamic response is improved. Table 3 shows the battery parameters used in this work. The characteristics of the used battery module are shown in Figure 6. The rated voltage of the battery is expressed using Eq. (9), and the required SOC of the battery is written using Eq. (10) [44,45].

$$V_b = V_n - K\,\frac{Q}{Q - i_t}\left(\int i_b\,dt\right) + A.\,e^{-B\int i_b\,dt} \tag{9}$$

$$SOC = 100\left(1 + \frac{\int i_b dt}{Q}\right) \tag{10}$$

where V_b represents the battery voltage, V_n is the battery's nominal voltage, Q is the battery's capacity, i_b is the battery current, and the amplitude (A) of the exponential region and the polarization constant is denoted by K. The parameters of the bidirectional converters are $C = 10\ \mu F$ and $L = 2\ mH$.

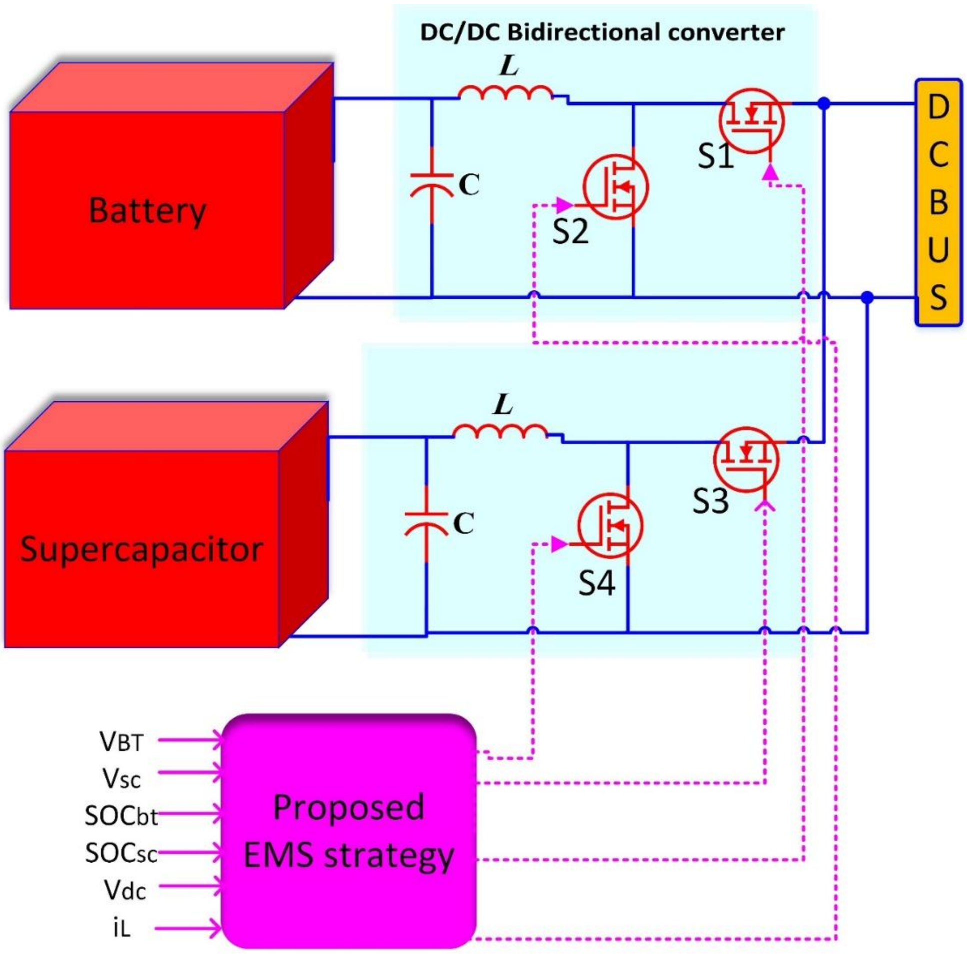

Figure 5. Diagram of the HESS.

Table 3. Battery parameters.

Parameter	Value
Rated voltage	$200\ V$
Capacity	$500\ Ah$
Initial SOC	80%
Maximum energy	$10\ kWh$

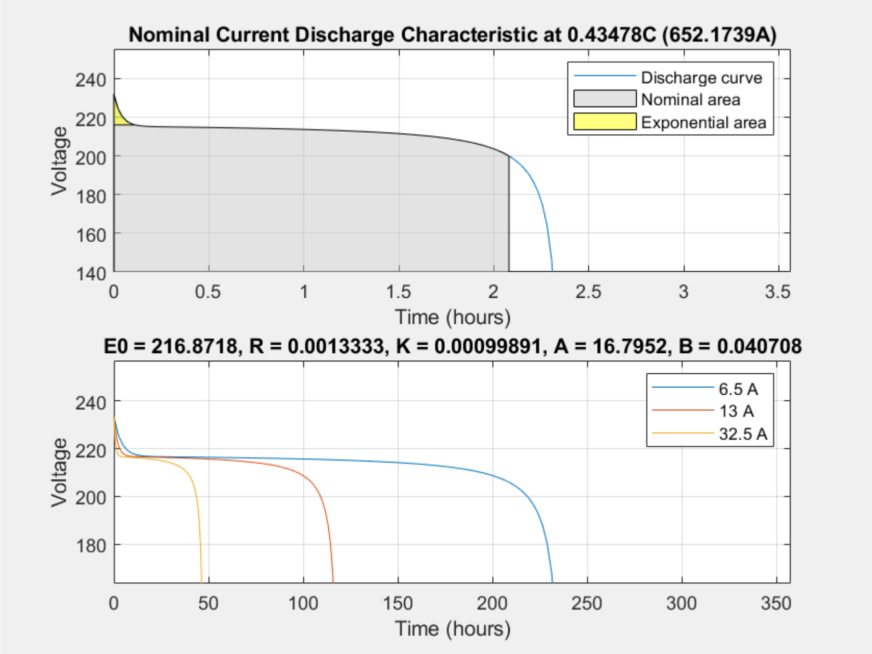

Figure 6. Simulation battery characteristics.

2.3. Supercapacitor modeling

Supercapacitors (SCs) are being increasingly used in DC microgrid systems due to their ability to meet high power requirements and deliver quick energy dispatch. SCs can absorb or supply energy during quick changes in power generation (e.g., variation of solar irradiance) or load demand [46]. Peak power requirements can occur for a short period; SCs discharge their energy rapidly and can serve such peak power requirements, such as those needed at the startup time of devices. In addition, SCs are able to deliver and absorb high power at millisecond timescales and are therefore useful in applications that require rapid charge and non-charge or discharge cycles. Furthermore, the SC module is connected to the DC microgrid via a bidirectional converter, as presented in Figure 5. The total voltage (V_{SC}) of the SC unit is expressed using Eq. (11) [46].

$$V_{SC} = N_{S,SC} \times v_{SC} = N_{S,SC} \times (v_1 + R_1 \times i_{SC}) \quad (11)$$

where $N_{S,SC}$ is the number of SC cells, v_{SC} and i_{SC} are the voltage and current of the SC module, R_1 represents the equivalent resistance of the SC circuit, and the voltage of the SC circuit is represented by v_1. The SC parameters are listed in Table 4, and the SC voltage characteristics are shown in Figure 7.

Table 4. Supercapacitor parameters.

Parameter	Value
Rated voltage	200 V
Rated capacitance	200 F
Initial SOC	90%
Equivalent DC series resistance	6.3 e^{-3} Ω
Operating temperature	25 °C
Number of series capacitors	18

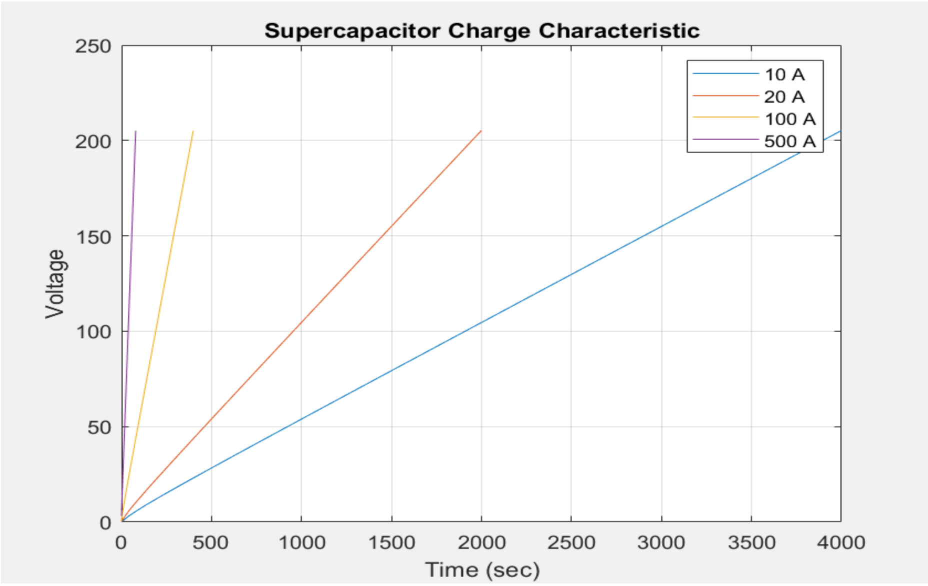

Figure 7. SC characteristics.

3. Proposed EMS of microgrid

3.1. Load following–based EMS

EMS improves the performance and reliability of DCMG systems, especially in the integration of variable renewable energy and dynamic load conditions. The load following (LF)-based EMS allows the management and balancing of the power supply and demand dynamically by ensuring that the generation or storage units follow the load [48,49]. In this case, the generation of electricity complies almost in real-time with the consumption of electricity within the microgrid, which can be all dispersed energy resources available at that moment, including renewable sources and batteries. The EMS assesses the real-time load power consumption and alters the power output of power generation units or energy storage units correspondingly. Sudden spikes in load demand or a lack of generation force the system to react, safeguarding voltage levels from overloading. LF-EMS charges during low-demand times and discharges during high usage times to optimize energy storage systems.

3.2. Proposed LF-TSMC design

The LF strategy controls the energy output of electric generation units and the charge-discharge rates of energy storage systems using control algorithms, including PI controllers [49]. It dynamically controls battery operation with load demand, thereby preventing overcharging and deep discharging. From a cost-saving perspective, it optimizes energy storage and reduces the need for expensive backup power systems. Applying LF strategies with robust or adaptive controllers in the DCMG can improve the efficiency, stability, and reliability of the microgrid. This enhancement makes it a perfect solution for addressing the effective management of renewable energy system integration and contemporary dynamic load demands.

In this paper, an improved LF-based slide mode (SMC) controller is proposed, as shown in Figure 8. The proposed LF-SMC has better performance than the LF-PI in terms of response, overshoot, and stability of the DC MG. The objective of the proposed EMS is to keep the DC-bus voltage of the DC

MG within its reference voltage (400 V). The lower-level and upper-level controllers are the two main components of the LF-SMC system. The upper-level controller provides a power reference for all sources (PV, BT, and SC), while the lower-level controller provides the fluctuations of the DC-bus current. The expression for the bus energy ($\dot{y_{bus}}$) is given using Eq. (12) [50]:

$$\dot{y_{bus}} = P_{PV} + P_{BT} + P_{SC} - P_{load} \tag{12}$$

where P_{PV} is the PV power, P_{BT} is the battery power, P_{SC} represents the SC's output power, and the load demand power is denoted by P_{load}. Based on this expression, the reference power of the SC is determined using Eq. (13):

$$P_{SC,ref} = \dot{y_{bus}} - P_{PV} - P_{BT} + P_{load} \tag{13}$$

Based on Eq. (13), PI or fractional PI controllers have been used to provide the necessary power reference to control the DC-bus voltage and improve the system performance. In this work, the SMC controller is used instead of classical PI controllers. In addition, the reference power of the battery is obtained by the following equation:

$$P_{BT,ref} = P_{SC,dem} - P_{PV} + P_{load} \tag{14}$$

where $P_{SC,dem}$ is the demand reference power of the SC, which is estimated based on the SMC controller of SC voltages.

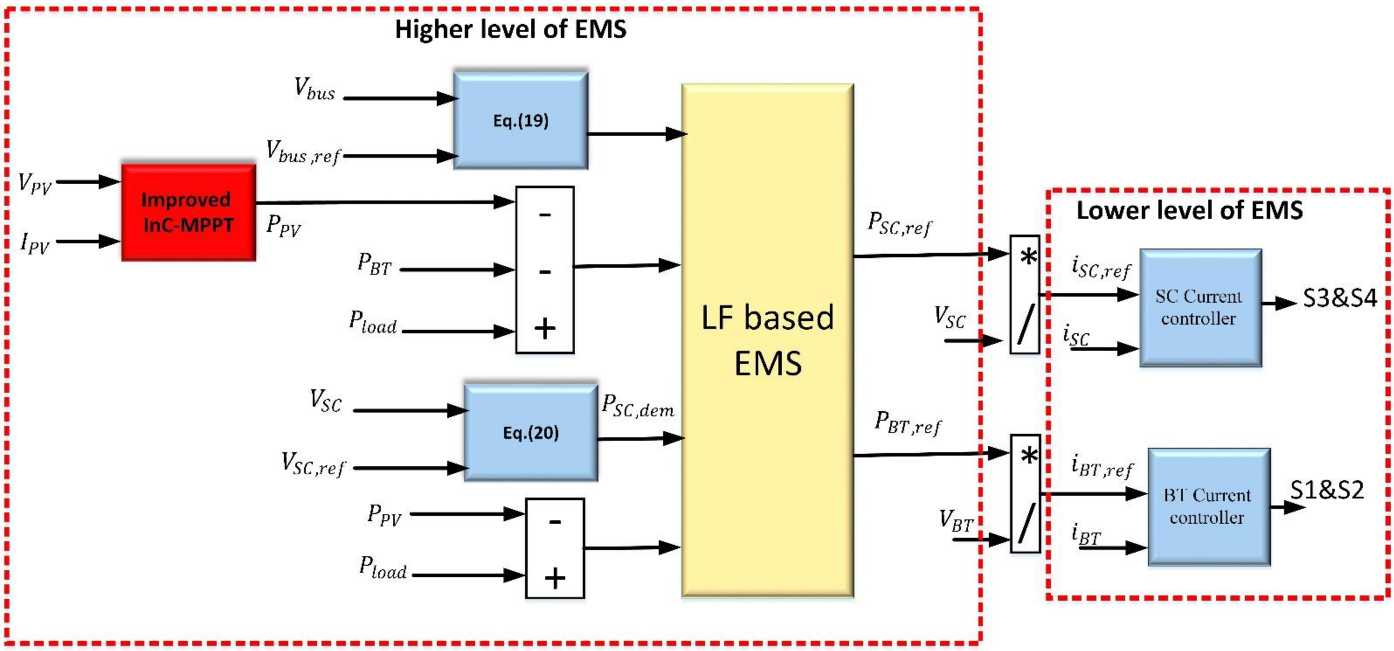

Figure 8. Proposed LF-SMC-based EMS method.

However, in the SMC approach, the selection of an appropriate "sliding surface" should be based on achieving the dynamic characteristics of the system while it slides on that surface. Once this composite constraint is reached, the selected sliding surface will ensure appropriate behavior by maintaining continuous reference trajectories for the system states, which will be both stable and robust, while also achieving the desired performance. This requirement includes the specifications of the design, the internal dynamics of the system that is used, and the control targets, as well as the desired performances in a transient period and in a steady-state region. Other physical considerations, such as sensitivity and chattering, should also be viewed as limitations during the design stage, making the sliding surface vital to achieving effective control. The classical SMC surface is written as follows [51]:

$$S = e_1 + k_1 e_2 \tag{15}$$

where e_1 is the error, e_2 is the derivative of the e_1, and the constant of e_1 is denoted by k_1. The formula $e_2 = \dot{e_1}$ can be considered in this design.

In this work, the error includes the voltage of the battery and the voltage of the SC; this error can be written as follows:

$$e_{11} = V_{bus,ref} - V_{bus} \quad \text{and} \quad e_{12} = V_{SC,ref} - V_{SC} \tag{16}$$

Furthermore, the other sliding surface, called terminal SMC, can be modified as follows [51]:

$$S_t = e_1 + k_1 {e_2}^n \tag{17}$$

where S_t is the terminal slide surface, n is lower than one, and k_1 is always positive. As shown, the relationship between the parameters in Eq. (17) is nonlinear. The structure of the terminal sliding surface makes TSMC more appropriate compared to the classical SMC. TSMC guarantees convergence in a finite time, greater accuracy around an equilibrium point, enhanced performance in the presence of nonlinearities, reduced chattering, and better control over higher-order and complex systems. Depending on the error signal magnitude, the steady-state errors can be minimized via its unique structure, which permits dynamic adjustment to the error magnitude. In this paper, the enhanced TSMC surface is introduced as follows:

$$S_{it} = e_2 + k_1 e_1 + k_2 |e_2|^n \, sign(e_2) \tag{18}$$

where k_2 is the constant of e_2. Based on the law of the improved TSMC, the proposed SC control law of the system is written as follows:

$$S_{it1} = \left(V_{bus\dot{,}ref} - \dot{V_{bus}}\right) + k_1\left(V_{bus,ref} - V_{bus}\right) + k_2\left|V_{bus,ref} - V_{bus}\right|^n sign(V_{bus,ref} - V_{bus}) \tag{19}$$

The control law of the battery is derived as follows:

$$S_{it2} = \left(V_{SC\dot{,}ref} - \dot{V_{SC}}\right) + k_1\left(V_{SC,ref} - V_{SC}\right) + k_2\left|V_{SC,ref} - V_{SC}\right|^n sign(V_{SC,ref} - V_{SC}) \tag{20}$$

where $k_1 = k_2 = 200$ and $n = 0.8$.

The objective is to establish the voltage error at zero, i.e., $V_{bus,ref} - V_{bus} = 0$ and $V_{SC,ref} - V_{SC} = 0$. The presence of the nonlinear absolute relation term $\left(\left|V_{bus,ref} - V_{bus}\right|^n\right)$ and $\left(\left|V_{SC,ref} - V_{SC}\right|^n\right)$ in the sliding surface equation ensures full convergence to the sliding surface. The coefficients of the TSMC (k_1 *and* k_2) are selected using the trial and error method.

Furthermore, based on Eqs. 19 and 20, the suggested TSMC controllers are used instead of the classical PI controllers. Therefore, the energy sharing between the battery and the SC follows their complementary dynamic characteristics. The SC is employed to absorb high-frequency transient power components due to sudden load changes, while the battery is used to deliver the average and slowly varying power demand. In this way, the lifecycle of the battery is prolonged, and the occurrence of high-frequency current is avoided.

4. Results and discussion

The simulation results depict the performance of the designed DC microgrid under different load and irradiance conditions. To determine the effectiveness of the optimal LF-EMS, metrics such as power sharing, voltage regulation, and power balance were examined. The obtained results verify that the implemented TSMC control concept enables the system to remain stable whilst efficiently managing the energy distribution flow. The MATLAB/Simulink diagram of the proposed LF-based EMS is presented in Figure 9. In this section, the results are discussed in two different scenarios, namely under constant and variable irradiance conditions.

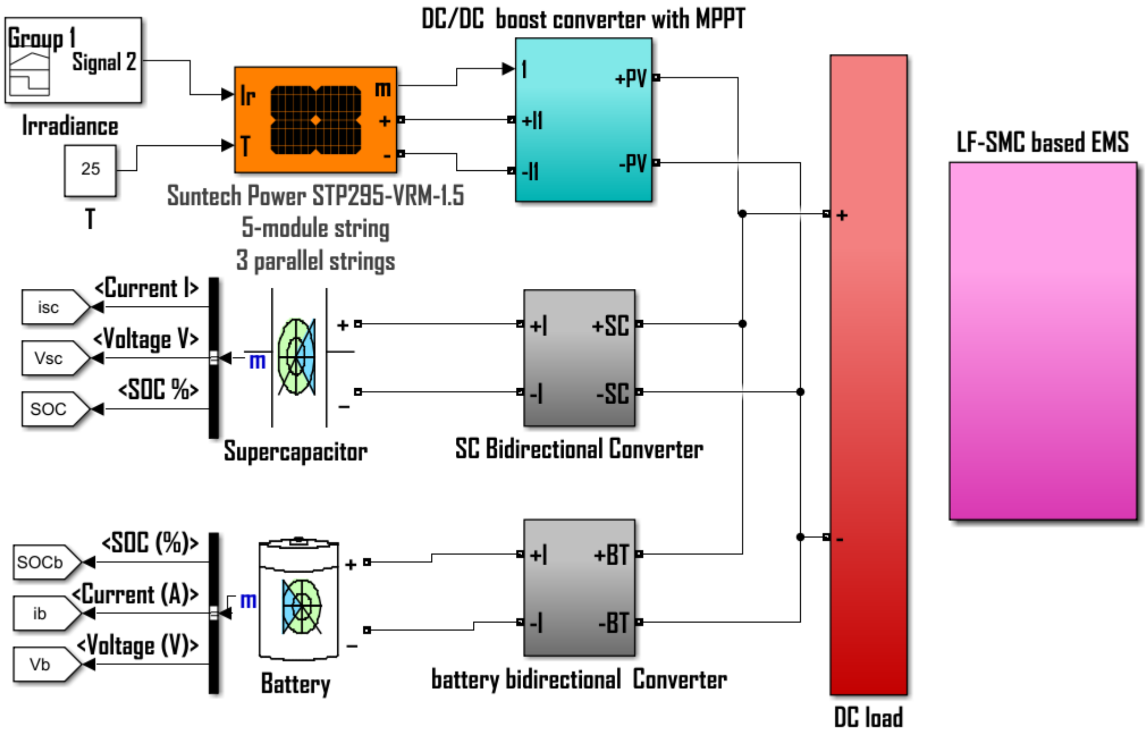

Figure 9. MATLAB/Simulink diagram.

4.1. Testing performance under constant irradiance conditions

In this scenario, the solar irradiance and ambient temperature are kept constant ($1000\ W/m\char`^2$ and 25 °C). The profiles of the weather conditions are shown in Figure 10. The output DC load current in this scenario is shown in Figure 11. As observed, the demand load varied three times over a period of 5 s, decreasing from 10 to 5 A, and then increasing to 15 A. This demand represents the load of a commercial building. This variation of the load was tracked via SC and battery. The PV generator provides the DC bus with constant power because irradiance is fixed.

The output curves of the HESS and the PV system are shown in Figure 12. The demand load varies according to the load current profile. During the time interval $(0-1\ s)$, the PV power value $(4\ kW)$ is less than the demand load $(4.4\ kW)$; therefore, the SC quickly damps the short transient while the battery charges with about $-0.8\ kW$. When the simulation time reaches $2\ s$, the demand load reduces to $2\ kW$, and the battery goes to the charging state according to the SOC limits due to the PV generation being high. At time $(2-3\ s)$, the load power jumps to a high value (about $6\ kW$), while the PV generation is constant (4 kW). The SC instantly supplies the required load by 3.5 kW for a very short duration to regulate the bus voltage. During this interval, the required load is supplied by the battery storage system. The optimum power sharing is reached by stabilizing the DC link voltage and computing the absorbing or injection power into the bus. The proposed strategy was able to rely considerably on backup generation, which would have a reasonable operational expense. The results show that 90% of the load demand was satisfied directly from the PV system, while the rest was from the battery and SC during high solar irradiance. This shows that the EMS, as proposed, manages the combined energy storage system in an efficient way; thus, the SC can manage the sudden power changes while the battery can provide continuous energy. As such, the stability of the DC bus is maintained, and the battery use is reduced, which is particularly important for DC microgrids with high reliability. This maintains an equilibrium of DC-bus energy.

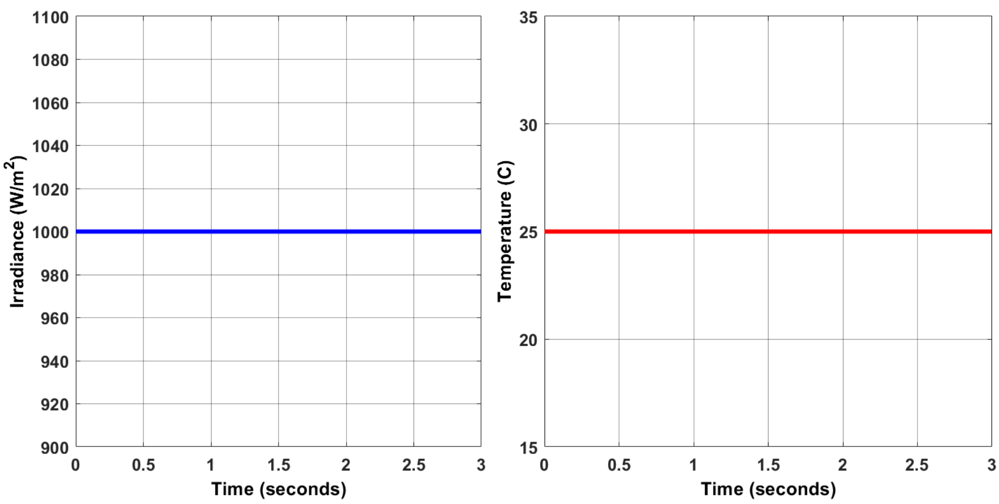

Figure 10. Irradiance and temperature profiles.

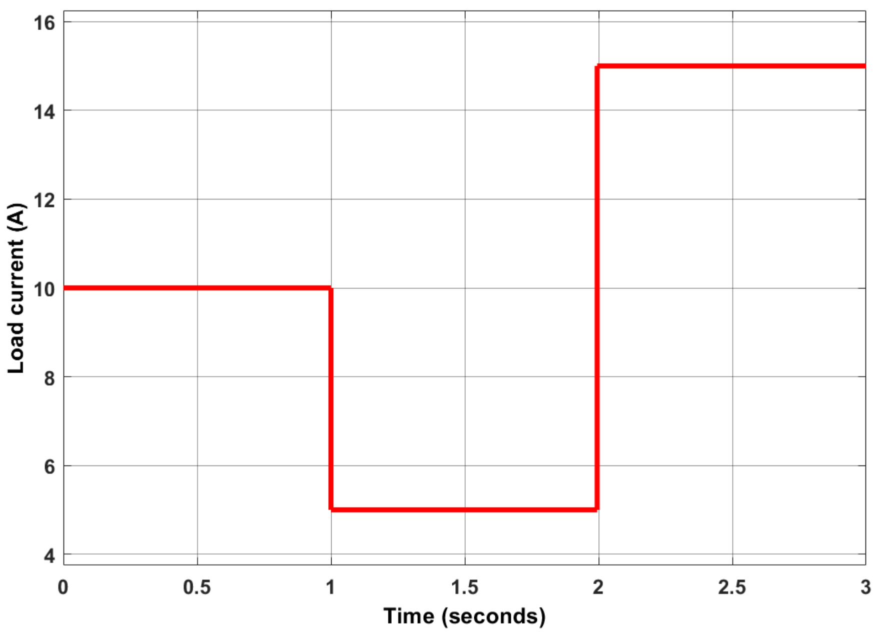

Figure 11. Demand load current.

Figure 13 shows the SOC of the battery and SC curves. In case of step load changes, SC is able to quickly provide or absorb power in order to ensure that the DC-bus voltage does not fall below critical limits. These elements are used for short-term bursts of power, thereby relieving the burden on batteries and other generating units. Due to their nearly instant reaction to load change, SC assists in voltage neutrality across the microgrid. The SOC shows a good charge/discharge strategy, and this can enhance reliability. As shown in this figure, the SOC of the battery is increased when the generation is over the load. The SOC of the SC depends on the transient in the load; when it is increased, the SC is discharged. The proposed EMS ensured that unused portions of the battery were minimally used by favoring PV sources, thereby extending its life.

However, to clarify the novelty of the proposed LF-SMC, a comparison with the classical LF-PI strategy is conducted, as shown in Figure 14. As observed, the DC-bus voltage stayed fixed at 400 V, and fluctuations were within less than 1.5% boundary limits during load variations. The comparison showed that the proposed EMS makes the SC deploy to discharge and supply the energy shortage before slower-acting devices, such as batteries or PV systems. If the load changes downward, the suggested EMS takes this excess energy to smooth out voltage spikes. The proposed method presents low overshoot and less ripple in the DC-bus voltage. The stable voltage of the DCMG guarantees system stability and operates with high reliability when load variations occur. Otherwise, the presented EMS outperforms the conventional target PI to reduce energy losses by 10% and is able to control the system to a relatively faster response during load changes by 20% control improvement.

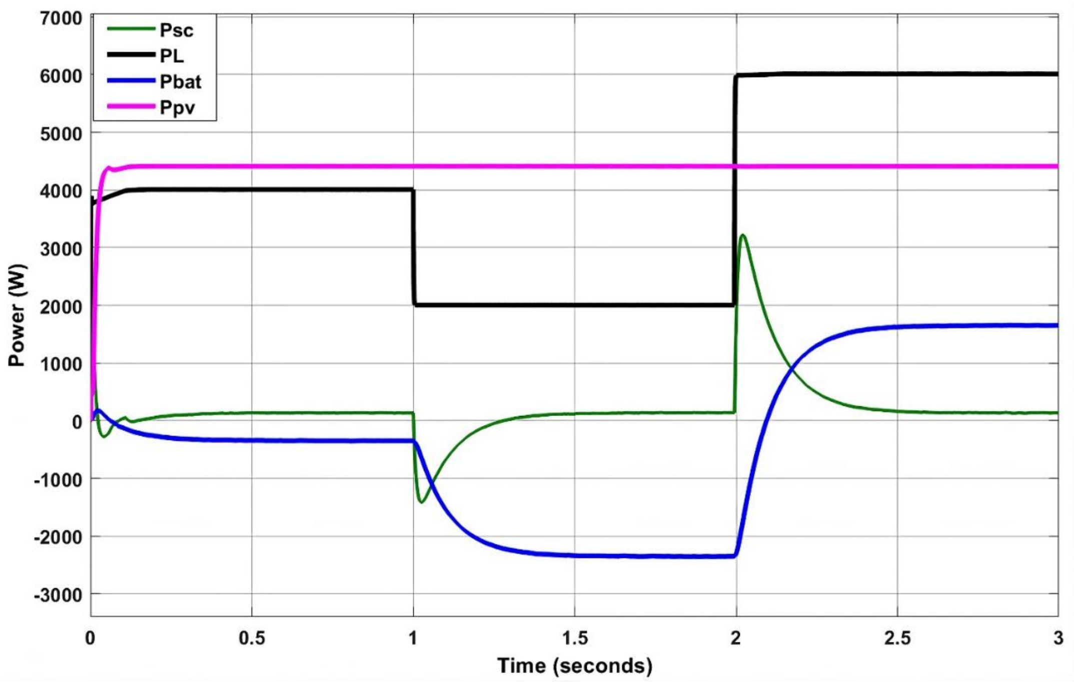

Figure 12. Power curves of the DC MG.

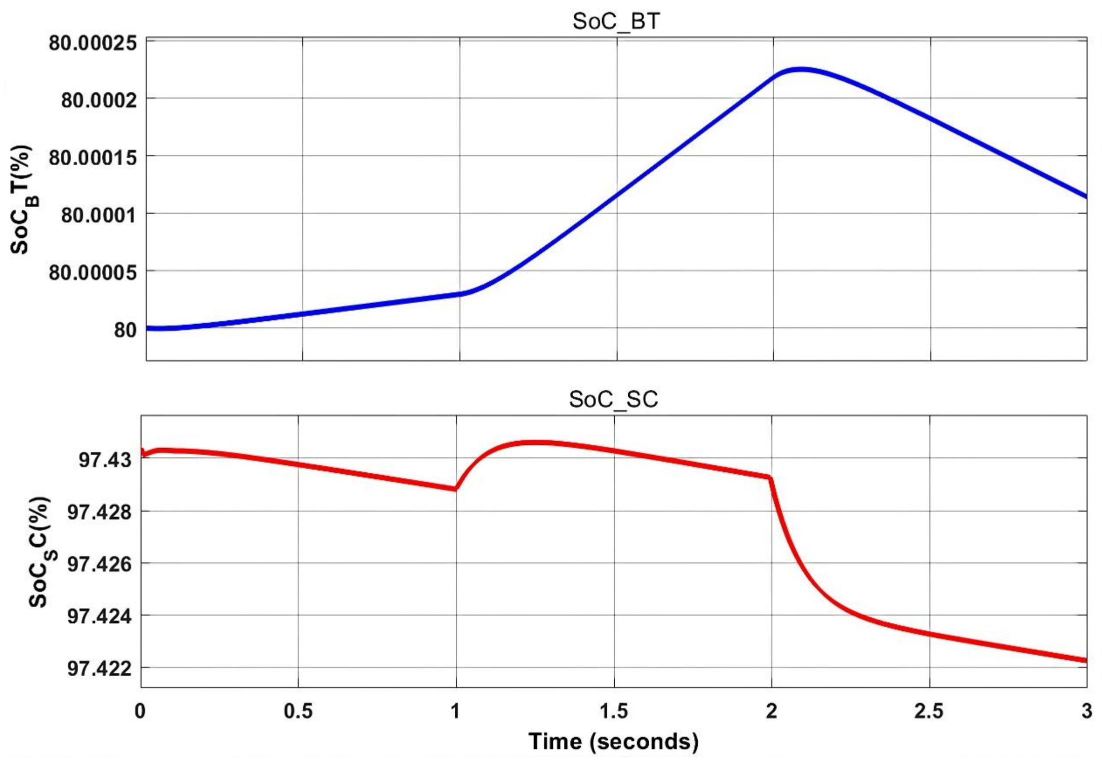

Figure 13. SOCs of the battery and SC.

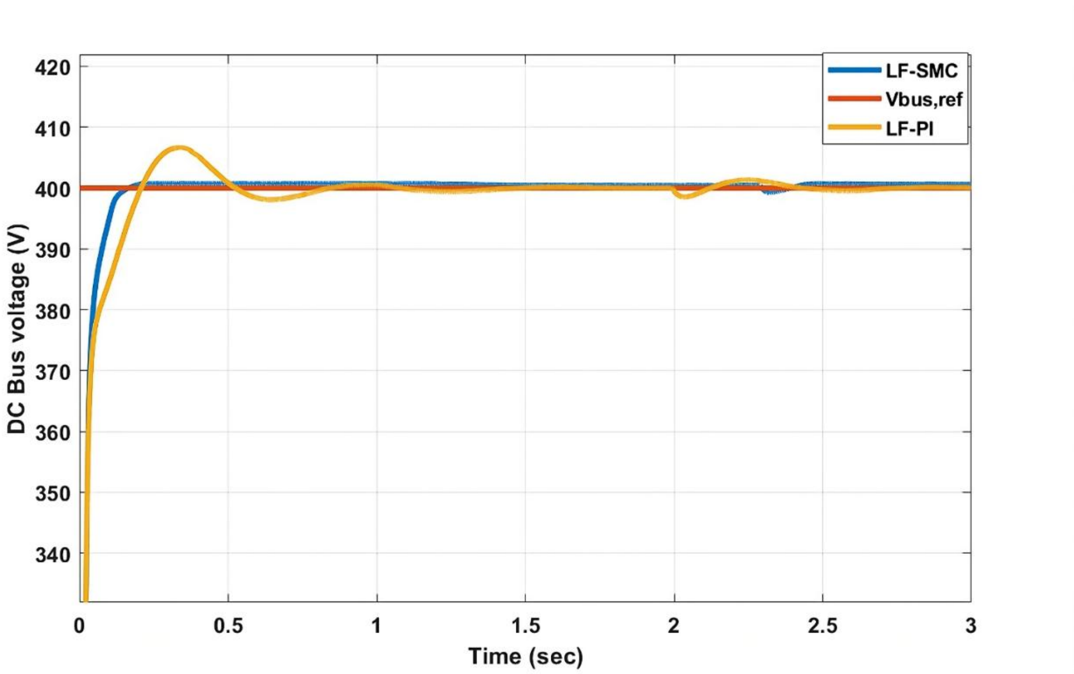

Figure 14. DC-bus voltage response.

4.2. Testing the performance under variable irradiance conditions

In this section, changes in both load and irradiance are applied. The solar irradiance and temperature profiles during this section are illustrated in Figure 15. As observed, the solar irradiance is reduced from 1000 to 500 W/m ^{2}at 1.5 s of the simulation and then increased from 500 to 800 W/m ^{2}

The load current profile of this scenario is shown in Figure 16. The load profile is similar to the working of the EV load, where the current after 2 s is changed from positive to negative. Moreover, the battery power is consumed when the EV increases its speed or keeps it constant in order to move the motor. The motor drawing the current is positive, which means that energy is being drawn off from the battery or SC to the drivetrain. However, negative load represents the regenerative braking of the EV. In this case, the motor of the EV acts as a generator, converting kinetic energy back into electrical energy when the EV slows or brakes.

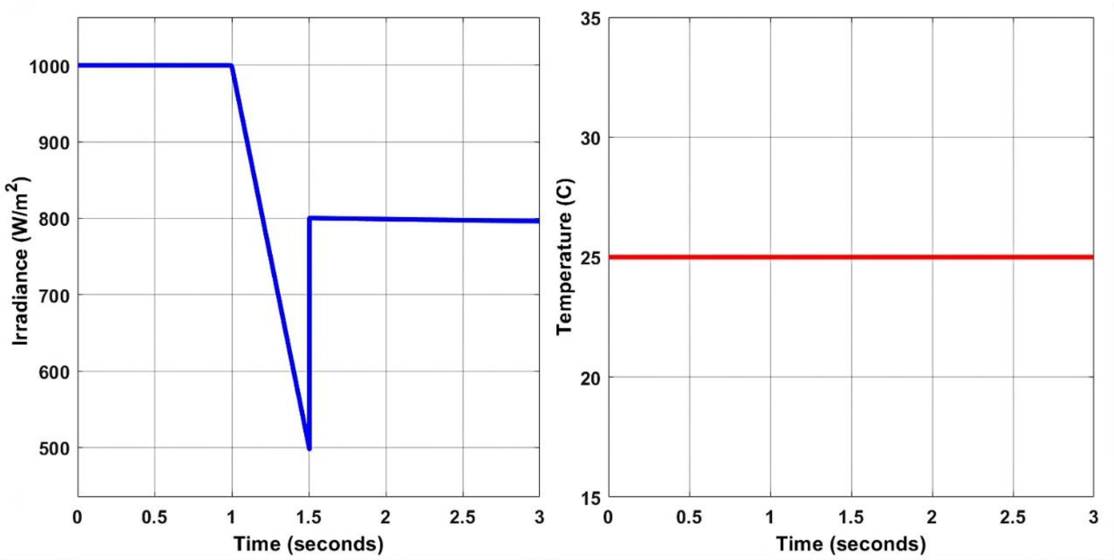

Figure 15. Irradiance and temperature profiles.

Figure 17 shows the power curves of the DCMG under scenario 2. As observed, the load demand as well as the solar irradiance have changed, and the operation of the scenario can be summarized as follows:

- $(0 - 1\ s)$: The solar generation is higher due to the high solar irradiance. At this interval, the SOC of the battery increases due to the battery staying in the charging state while SC absorbs the excess energy from the PV system to stabilize the voltage.
- $(1 - 2\ s)$: When the load demand is increased while the irradiance is lowered, the PV output is reduced. When solar light intensity is reduced due to shading or any other reason, this influences the generation of PV panels. SC maintains these oscillations, which provide a continuous power supply to the DC load. The SC, helping the DC-bus voltage remain in range and avoiding interruptions to any sensitive loads, will always compensate for the short depression that occurs. The battery switches from a charging to a discharging state to supply the load due to a reduction in generation.
- $(2 - 3\ s)$: The load demand is converted to the negative (regenerative braking), where the solar generation is increased via increasing solar irradiation. In this moment, the impact of a reduction in load may cause high transients on the DC bus. The proposed EMS makes the system stable without overshooting the voltage due to the SC, which absorbs the excess energy. In addition, the battery switches to a charging mode operation.

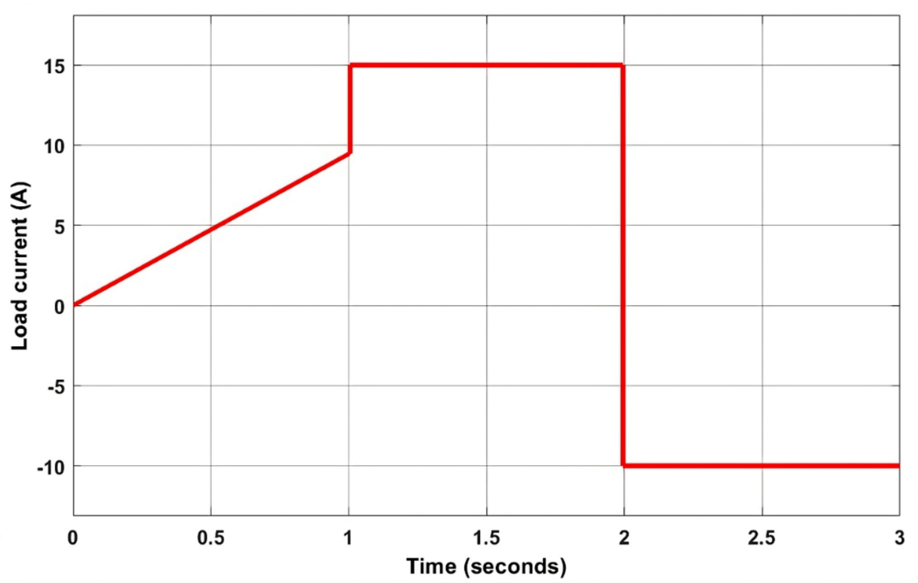

Figure 16. Load profile of scenario 2.

The SOC of the battery and SC are displayed in Figure 18. The DC-bus voltage under scenario 2 is shown in Figure 19. The comparison is conducted with the PI method in terms of settling time, rise time, and overshoot. As observed, the proposed EMS presents high efficiency and less overshoot in the voltage. Against this, the classical LF-PI strategy shows a huge ripple in the DC-bus voltage because of the variation in irradiance. The reference voltage is maintained at 400 V. The proposed strategy reaches to this value within $0.2\,V$, with negligible oscillation less than $1.5\,W$, whereas the conventional strategy shows an unwanted overshoot in the voltage of $6\,V$, and it requires to reach the optimum response time about 0.35 seconds. The LF-TSMC strategy quickly returns the bus voltage to its optimum value. The dynamic response of the LF-PI is very slow requiring about 10 s to reach the steady-state value. Against this, the suggested method minimizes the overshoot, which makes the system smoothly approach the reference voltage.

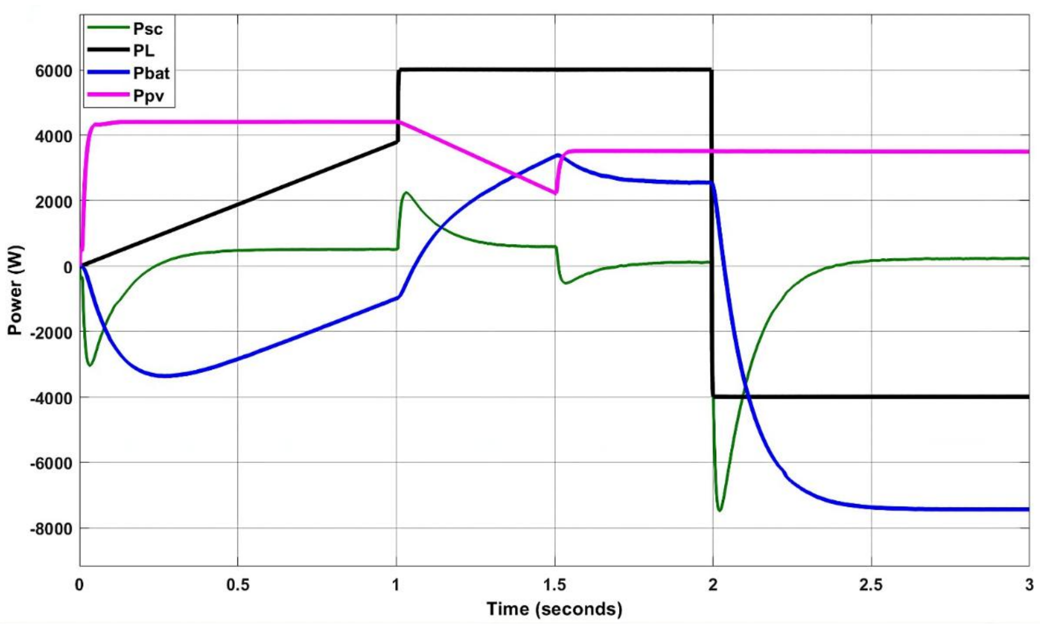

Figure 17. PV power, SC power, load power, and battery power curves under scenario 2.

The inherent nonlinearity of the proposed LF-TSMC ensures that the control law of the SC and battery adapts to changes quickly, preventing large deviations from the reference trajectory. Figure 20 displays the comparison between the LF-PI and proposed LF-TSMC strategies in terms of settling time, rise time, and overshoot percentages in the DC-bus voltage. The comparison shows that the proposed method is faster than the conventional strategy, and it reaches the steady-state condition with minimal time. The energy loss in the new EMS is low, and the convergence speed is very high.

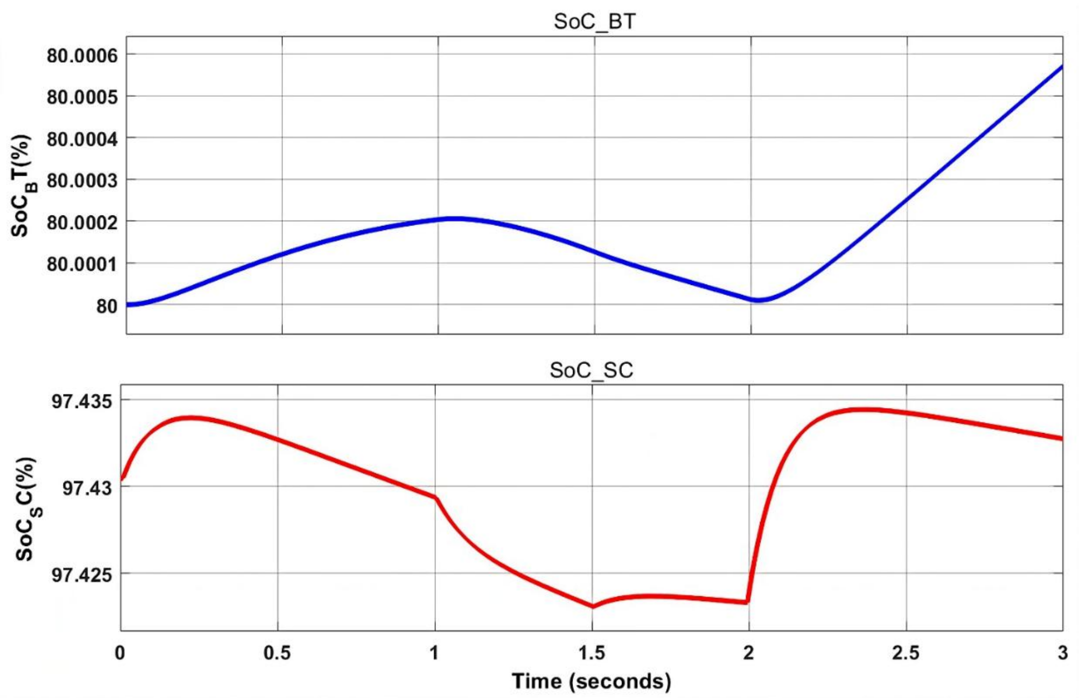

Figure 18. SOC responses for the battery and SC units.

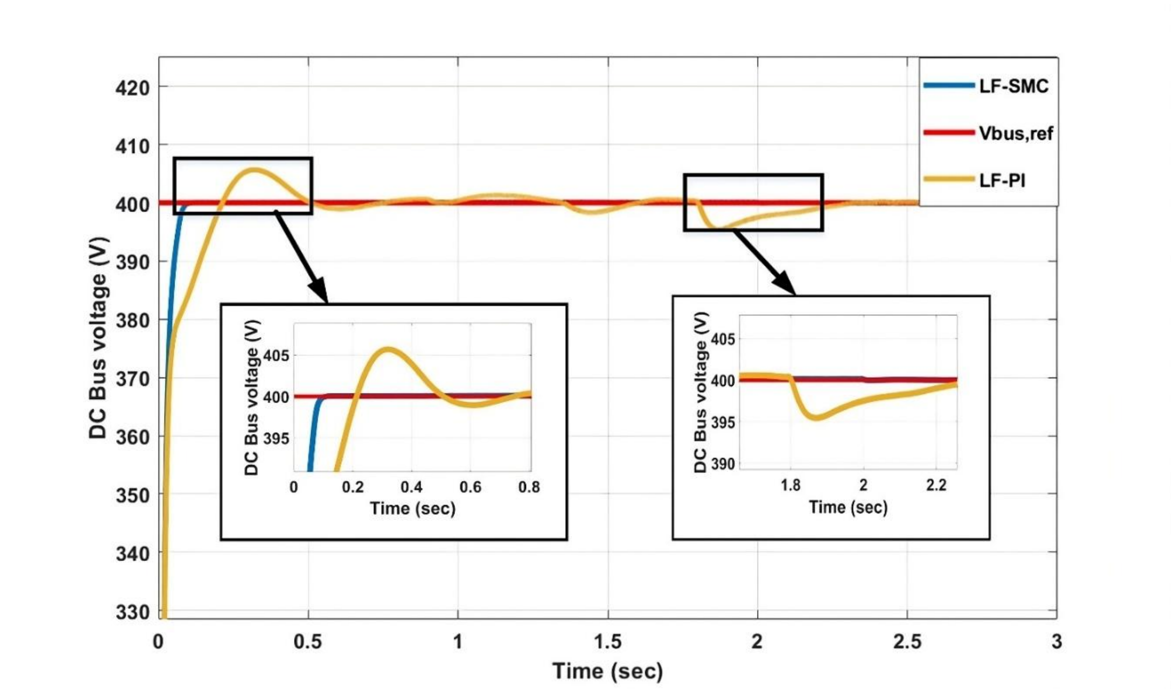

Figure 19. DC-bus voltage response under scenario 2.

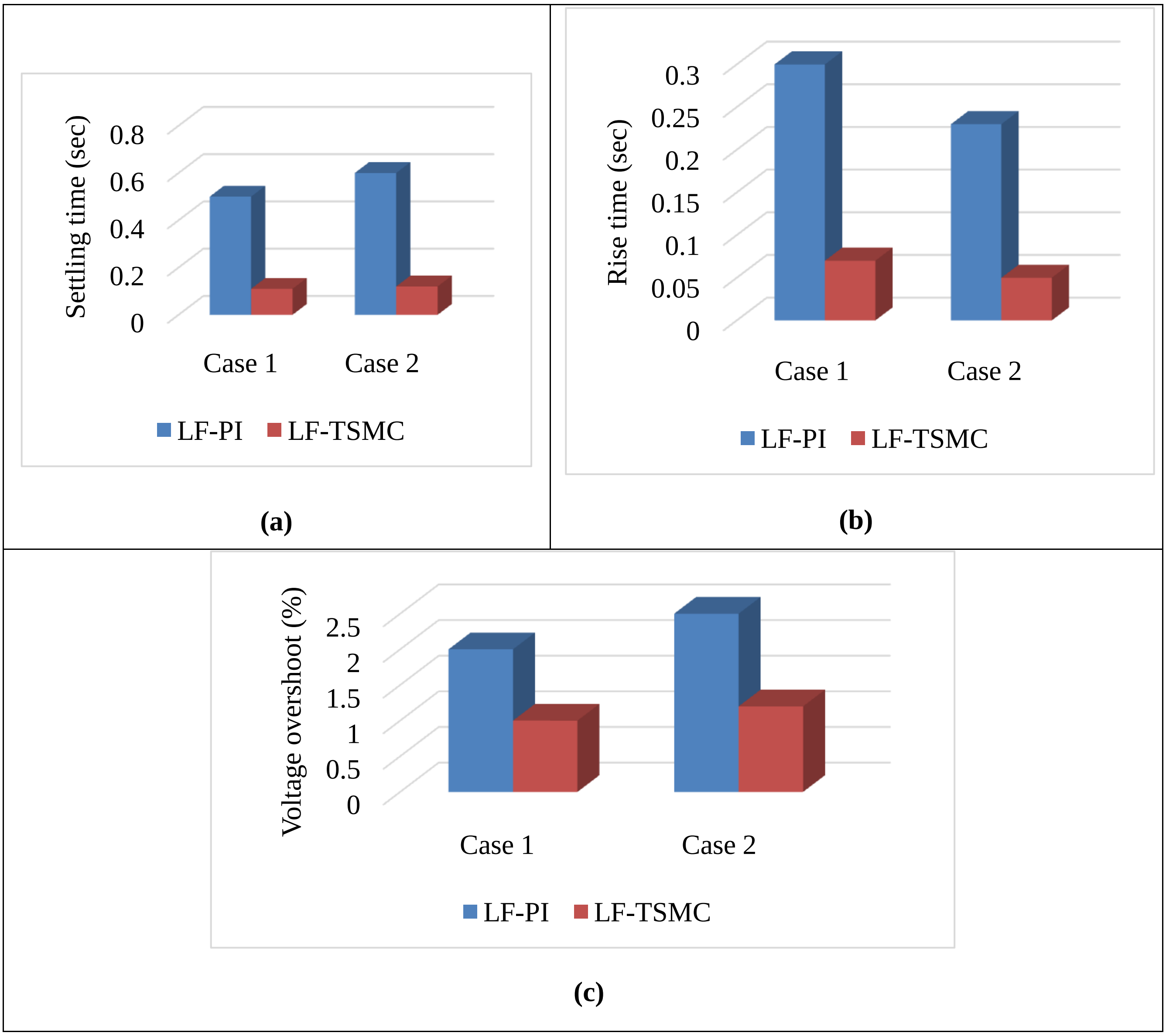

Figure 20. Comparison results regarding (a) settling time, (b) rise time, and (c) voltage overshoot percentage.

Table 5. Comparative results between the proposed EMS and PI method.

Time interval	**Case study**	**RMS voltage deviation**	**Tracking time**	**Power loss**	**RMS voltage deviation**	**Tracking time**	**Power loss**
		PI			LF-TSMC		
$(0\ s-1\ s)$	Case 1	$6\ V$	0.35	$10\ W$	$0.2\ V$	0.1	$2\ W$
$(1s-2)s$		$6.8\ V$	0.32	$9.6\ W$	$0.22\ V$	0.12	$1.5\ W$
$(2s-3)s$		$8\ V$	0.37	$13\ W$	$0.4\ V$	0.16	$1.7\ W$
$(0\ s-1\ s)$	Case 2	$6.2\ V$	0.343	$8\ W$	$0.1\ V$	0.09	$2.4\ W$
$(1s-1.5)s$		$13\ V$	0.374	$12\ W$	$0.25\ V$	0.102	$3\ W$
$(1.5s-2)s$		$9\ V$	0.317	$11\ W$	$0.19\ V$	0.1	$2.7\ W$
$(2s-3)s$		$10.5\ V$	0.32	$12.4\ W$	$0.2\ V$	0.12	$3.1\ W$

5. Limitations of the EMS strategy

The simulation results show excellent dynamic performance and robustness under different changes in the irradiance and demand load. However, real-world implementation issues, such as sensor noise, communication delays, quantization effects, and hardware constraints, have not been tested experimentally. Still, due to its minimized calculation load and non-iterative configuration, the LF-TSMC-based EMS can be tested in a real-time implementation. The TSMC control law of the system does not require any complicated operations; it just needs simple arithmetic operations and nonlinear sliding surface evaluations. Hence, the algorithm has constant-time computational complexity and does not need online optimization or any training processes. Regarding scalability, the EMS is a modular and decentralized design, where each energy storage unit has a local controller that operates according to the same control principles. As a result, the framework can be scaled up to larger DC microgrids or more distributed energy resources without a substantial change or increase in computational complexity. Thus, the proposed EMS can be effectively used in embedded controllers of real DC microgrids, which is an excellent equilibrium between control performance, robustness, and ease of implementation.

6. Conclusions

In conclusion, an advanced energy management strategy (EMS) for hybrid power systems composed of PV panels, supercapacitors (SC), and Li-ion battery has been proposed in this paper using load following (LF) controlled by terminal sliding mode control (TSMC). Using HESS by incorporating an SC into the microgrid improved power flow by allowing the management of transient loads, reducing demand on the Li-ion battery, and improving the system's power efficiency. The proposed EMS was developed with the aim of improving stability, efficiency, and strength of the DC microgrid during dynamic operation conditions. The system model was simulated in MATLAB/SIMULINK to obtain the performance of the operation system, comparing TSMC and PI-type controllers. The achieved results show that the LF-TSMC strategy works better than the LF-PI method in terms of settling time and rise time. Because of the controller's ability to regulate the system's nonlinearities, satisfactory tracking of the desired reference voltage is ensured, and efficient energy sharing between the SC and the battery is guaranteed. On the other hand, the LF-PI strategy responds slowly to irradiance disturbances within a settling time of $0.45\ s$. Finally, the designed LF-TSMC has a fast response and is strong under various operating conditions with a settling time of $0.1\ s$. In addition to transient and sudden load disturbances, the suggested EMS is more reliable when compared with the conventional LF-PI method.

Future studies will focus on experimental validation and hardware-in-the-loop testing to assess real-time performance under practical constraints. Other research directions include adaptive or self-tuning control gains to improve system robustness under varying operating conditions, as well as the integration of intelligent supervisory frameworks that combine metaheuristic optimization or learning-based decision making with the proposed model-based robust control strategy. These developments will further strengthen the feasibility of the proposed EMS for real-world DC microgrid implementation.

Author contributions

Writing-original draft, Methodology, software, validation: Wisam Raheem Resen; investigation, data curation, and review and editing: Sarah Sabeeh; Review and editing, project administration, and acquisition: Salam J. Yaqoob.

Use AI tools declaration

The authors declare they have not used artificial intelligence (AI) tools in the creation of this article.

Conflict of interest

All authors declare that there are no competing interests.

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