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Renewable Energy-Based DC Microgrid with Hybrid Energy Management System Supporting Electric Vehicle Charging System

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Abstract: Growing Electric vehicle (EV) ownership leads to an increase in charging stations, which raises load demand and causes grid outages during peak hours. Microgrids can significantly resolve these issues in the electrical distribution system by implementing an effective energy management approach. The suggested hybrid optimization approach aims to provide constant power regardless of the generation discrepancy and should prevent the early deterioration of the storage devices. This study suggests using a dynamic control system based on the Fuzzy-Sparrow Search Algorithm (SSA) to provide a reliable power balance for microgrid (MG) operation. The proposed DC microgrid integrating renewable energy sources (RES) and battery storage system (BSS) as sources are designed and evaluated, and the findings are further validated using MATLAB Simulink simulation. In comparing the hybrid SSA strategy with the most widely used Particle Swarm Optimization (PSO)-based power management, it was observed that the hybrid SSA approach was superior in terms of convergence speed and stability. The effectiveness of the given energy management system is evaluated using two distinct modes, the variation of solar irradiation and the variation of battery state of charge, ensuring the microgrid's cost-effective operation. The enhanced response characteristics indicate that the Fuzzy-SSA can optimise power management of the DC microgrid, making better use of energy resources. These results show the relevance of algorithm configuration for cost-effective power management in DC microgrids, as it saves approximately 7.776% in electricity expenses over a year compared to PSO.

Keywords: microgrid; energy management; fuzzy logic; sparrow search algorithm

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1. Introduction

Based on sales, innovation, and environmentally friendly transportation, battery-powered vehicles began to dominate the automotive industry at the beginning of this decade. To reduce their carbon footprint and move toward a green economy, nations worldwide support clean, sustainable transportation. Governments are encouraging the use of electric vehicles as a step toward a green economy by subsidizing consumer taxes. The market for electric vehicles is expanding as a result of the significant companies in the automotive industry concentrating their investments in this sector. Due to the many factors that encourage EV use, recent business models aim to increase personal mobility, driverless mobility, vehicle sharing, public transportation, and logistics [1]. Due to the accelerating environmental impacts and carbon dioxide emissions, several countries have decided to downsize internal combustion engines and incorporate electric vehicles within a specific time period in the coming decade. Lack of charging infrastructure, range anxiety, variances in load, battery cost, non-standardization of charging, and a shortage of public charging stations are the challenges limiting the market growth of EVs. Harmonizing electric vehicle charging stations is hampered by using several connections at charging stations [2,3].

Electric utility providers should be prepared to meet the rising demand from EV consumers by installing charging infrastructure and increasing energy production. Power demand will rise during peak hours due to the expansion in EV charging, hence a dynamic energy management strategy is required to address this issue [4]. A utility's primary priorities are to lower operating costs and maintain the stability of the system while it is in operation. Integrating renewable energy resources into the grid is essential to meeting energy demand, reducing emissions, and ensuring smooth operations [5]. Microgrids are being promoted as a solution for energy and environmental disparities. Depending on the application case, the microgrids can be installed in either grid-tied or islanded mode [6].

Renewable energy sources are unreliable, and the number of EVs that need charging might change, making energy supply and demand challenging to estimate. Hence, energy waste or shortages could reduce microgrid reliability. Another problem is making power management operate well and economically. The power management approach should consider energy storage, EV charging station energy demands, and renewable energy production. The strategy for managing power must consider how much energy the EV charging stations need, how much energy can be stored, and how much renewable energy can be made. To optimize energy efficiency, sophisticated control systems and algorithms are required. Researchers have come up with several studies to deal with these problems, including power management that balances supply and demand and minimizes energy expenses. This can be implemented with intelligent control systems and predictive models. Decentralized energy management solutions enhance local energy management. The central energy management system can adjust its energy management based on energy demand and supply with real-time feedback from these systems. DC microgrids that use renewable energy to power EV charging stations and are managed by hybrid energy management systems might be a sustainable approach to providing energy. Still, modern control systems and decentralized energy management systems are needed to deal with the problems and challenges of controlling energy supply and demand and ensuring that the power management strategy is the best. DC microgrids fuelled by renewable energy can be efficient and cost-effective through the above objectives.

2. Literature Review

The MG system is an integrated system that combines energy management, efficiency, reliability, and stability with an autonomous and dynamic communications network [7]. Due to the self-healing capabilities of the microgrid, all of the energy sources will continue to operate in resilience and coordination despite changes in load demand and sources [8]. One of the benefits of islanded microgrids is that they can be placed in isolated areas where it is difficult to connect with the utility. Islands are delicate areas; thus, installing an isolated renewable-based microgrid has significant advantages. It is more environmentally friendly than fossil fuel-powered cars and energy generation [9]. The microgrids are divided into AC and DC microgrids based on their operational configuration. Concerning efficiency, system size, operational control, and cost, a DC microgrid is superior to an AC microgrid. The overall efficiency rises when fewer power electronic converters are used. Since a transformer is not necessary with AC/DC converters, the size of the microgrid is drastically reduced.

In this scenario, microgrids offer a reliable infrastructure for the controlled exchange of electricity and safe data transfer between the sources and utilities [10–12]. The DC-operated microgrid has numerous benefits, including delivering high-power energy without needing reactive power adjustment, no requirement of phase control, lower conversion losses, and effective control of imbalance conditions [13]. Microgrid energy production may change due to climatic variations [14]. The energy produced by a PV-integrated microgrid fluctuates according to variations in the amount of sunlight hitting the photovoltaic panels. Researchers worldwide have developed several control methodologies to ensure an uninterrupted power supply and improve microgrid performance [15]. Various control strategies for microgrid control are currently being studied. The hierarchical, secondary, and droop controls are the most widely used among them. Artificial intelligence techniques are the main focus of recent microgrid research.

Swarm intelligence optimizations are frequently utilized in solving complicated engineering problems due to their high flexibility and efficiency. Swarm intelligence optimization aims to identify the optimum solutions to global optimization situations [16]. The ant colony algorithm and particle swarm optimization, introduced in 1992 and 1996, respectively, are the most popular swarm intelligence-based algorithms among researchers worldwide due to their powerful global searching capabilities [17]. Recent years have seen the introduction of numerous novel algorithms inspired by the behaviour of birds, insects, and fish. The Sparrow Search Algorithm is a novel, nature-inspired algorithm developed by Xue et al. in 2020 to address ongoing optimization issues using the behaviour of sparrows as an inspiration [18]. The SSA has more stability and higher convergence accuracy compared to other swarm intelligence algorithms [19].

The future power grid scenario relies on electric vehicles. Power quality, voltage profile, frequency synchronization, and other operational issues are some of the difficulties associated with EV integration in microgrid systems. The efficient integration of EVs with microgrids will improve power system flexibility while lowering electricity costs. An intelligent microgrid energy management system incorporating EV charging will flatten the load profile, reduce peaks, and increase the use of DERs [20–23]. The authors of [24] proposed an AC microgrid with load demand-based control and onboard charging with diesel generators, but conversion and emissions are more significant. Smart charging and flexible EV charging have been applied with power control in [25,26], where the difficulties are the conversion phases and overloading. Optimal charging with variable PV power has been studied in [27]. An energy management system for the home that uses distributed energy resources and enables battery-powered electric vehicle charging and discharging was proposed by Anawach Sangswang et al. [28]. The authors of [29] introduce dynamic simulation optimization of size and achieved suitable system performance based on PV and Wind Battery as the sources. The authors of [30] introduced a data-driven model and discussed a grid-connected power management strategy. The authors of [31] have presented a microgrid topology using PV as the source and built an MPPT and PI-based charging control. The authors of [32] describe a microgrid with high penetration of renewable energy sources and management employing hybrid invasive weed optimization for the most cost-effective charging. The authors of [33] proposed a DC microgrid with EV charging by coordinating the power flow using fuzzy logic, with PV Battery and Grid as energy sources. Power management in the variation of solar power and pricing are discussed. A novel hourly energy supervisory control was analysed in [34] where wind, PV, and hydrogen energy were considered uncertainties in the solar irradiance. The authors of [35] proposed an intelligent optimization-based EMS for an islanded DC microgrid. The authors presented an energy management strategy with hourly variations in wind and solar irradiance [36]. Most research has focused on AC microgrid integration rather than DC microgrids with high renewable energy source penetration. The presence of EVs may affect the management and distribution of energy in the DC microgrid, and the effect of EVs on hybrid optimization-based EMS has been less investigated. The majority of research has focused on the efficiency of a specific DC microgrid application and size. The DC microgrid's scalability for varied uses and sizes has to be investigated.

A PSO-based fuzzy PI controller, which yields better results compared with a standalone control approach, was implemented [37,38]. Ahmed Fathy et al. validated that the Sparrow Search Algorithm outperforms the ant lion optimization, the fuzzy-self adaptive particle swarm optimization, and a few other recent swarm intelligence optimization algorithms, when tested in the microgrid with constant load using the Battery, Microturbine, and PV as sources [39]. This research aims to develop a control that combines the advantages of SSA and fuzzy logic to manage the DC microgrid, facilitate sustainable transportation, and use renewable energy sources for EV charging.

The significant contributions of the paper on the mentioned scenario include:

- Integrating renewable energy systems with electric vehicles can lower harmful emissions and increase resource efficiency by providing energy storage.
- The development of a DC microgrid driven by non-polluting energy sources that are capable of efficiently and effectively balancing power to satisfy load demand and charging electric vehicles.
- Combining the advantages of fuzzy logic control with the sparrow search algorithm to determine the optimal microgrid regulation parameters for different environmental scenarios.
- Utilizing intelligent hybrid energy management control effectively to address fluctuations in a microgrid and enable EV charging.
- Power management in the DC bus, irrespective of the variations in the irradiance and the load uncertainties using hybrid SSA and Fuzzy controller.

The paper is structured as follows; Section 3 depicts the system architecture and Section 4 discusses the control strategy involved. The simulation is conducted in MATLAB/Simulink, and the results are verified and evaluated in Section 5, which also describes future scopes.

3. System Architecture

A Photovoltaic solar system, a fuel cell energy system, a battery storage system, and an electric vehicle charger make up the proposed DC microgrid system under research, as shown in Figure 1. The solar PV system is a significant contributor to reducing greenhouse gas emissions and the cost of electricity. PV is the best option when it comes to running a self-sufficient grid. PV systems' energy depends on voltage, irradiance, and temperature [40]. PV cells are electrical devices that use semiconducting components to convert solar radiation into electricity [41]. A boost converter connects the PV array to the DC bus. The peak point of the photovoltaic curve can be used to power a PV system using a boost converter and a maximum power point tracking algorithm. Researchers employ a variety of MPPT algorithms to get the most power possible out of photovoltaic systems [42]. This paper employs Maximum PowerPoint Tracking with an incremental conductance technique to extract the most power from the specified PV system [43]. The P-V and I-V characteristics of solar cells for a range of irradiances at T = 25 °C are shown in Figure 2. The DC link voltage stability is the primary goal of the battery storage system.

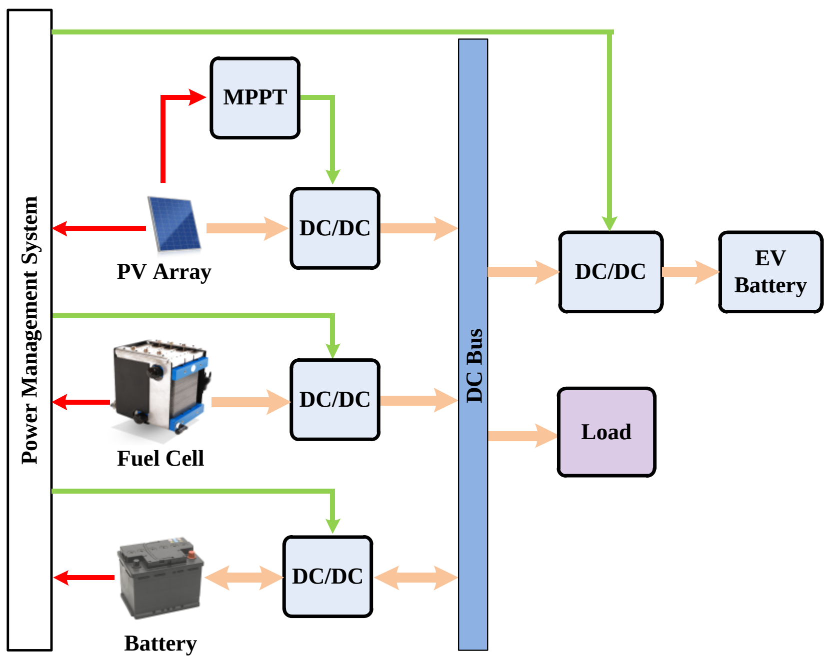

Figure 1. Schematic diagram of a Sustainable energy-based microgrid.

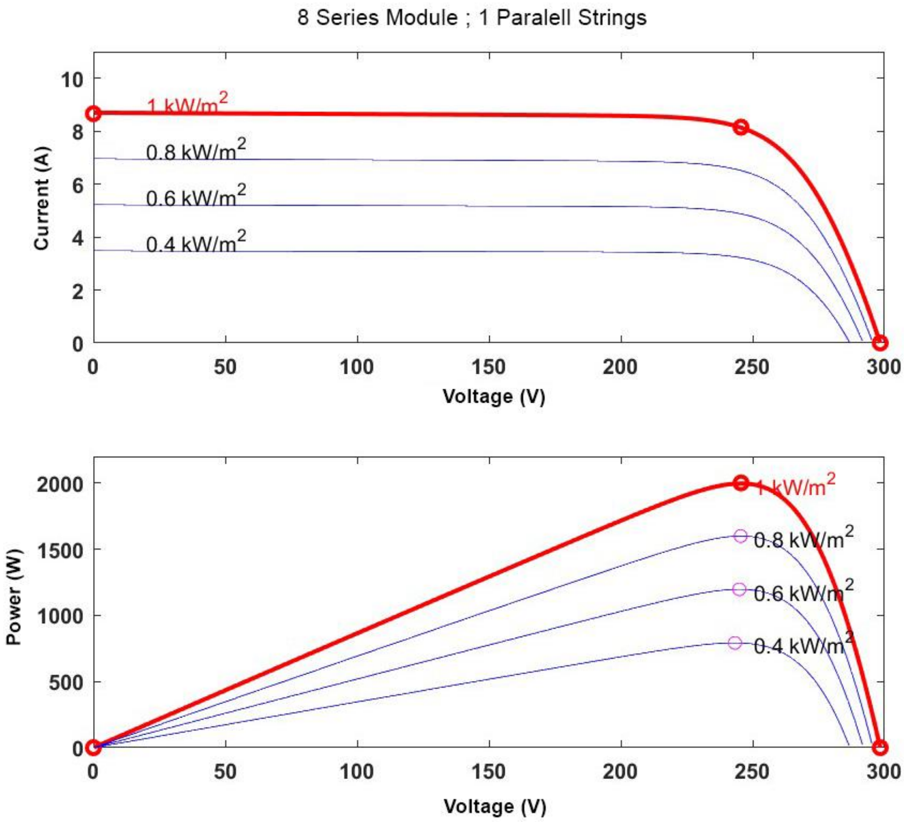

Figure 2. PV and IV characteristics of the solar cell with a constant temperature at 25 °C.

Additionally, it maintains the power balance of the microgrid by storing or releasing surplus or deficit electricity [44]. The battery storage system is powered by a bidirectional converter, allowing for both charging and discharging, as depicted in Figure 1. The Fuel Cell (FC) has attracted the interest of industries and academic institutions as a reliable source of energy since the beginning of this century. FC is gaining popularity across various industries due to recent technological developments and as a clean energy source. The advantages of a fuel cell-based energy system are to improve microgrid performance and encourage hydrogen energy utilization. The fuel cell is an electrochemical cell that uses hydrogen as fuel and oxygen as an oxidant to produce energy through chemical reactions, with only water and heat as by-products. The advantage of FC is that it does not require any moving parts to function. In microgrid operations, FC can substitute for fossil fuel-based power units. A boost converter connects the fuel cell to the grid [45–47].

4. Control Strategy

The control strategy for the DC microgrid under study is illustrated in Figure 3. The PV system is considered the primary source and is connected to the DC bus through a Boost converter [48]. The maximum power is extracted from the solar using the MPPT based on the incremental conductance algorithm [49]. The Voltage (V_{pv}) and current (I_{pv}) parameters of the PV are taken into consideration, the duty cycle is calculated and fed for pulse width modulation (PWM) generation, and control signals for the boost converter are generated [50]. The advantage of the incremental conductance method is that it can trace the peak power under rapidly changing environmental conditions [51]. The bidirectional converter and the boost converter that connects the battery and fuel cell are controlled by a PI-based controller [52]. The system is kept more stable while utilizing the PI control technique since the error derivative is not used in the event of data noise. It results from the derivative behaviour in the PI's input being less sensitive to real and relatively quick changes in the system's state without derivative intervention [53]. The different sources are operated in a balanced mode during the variations in solar irradiance.

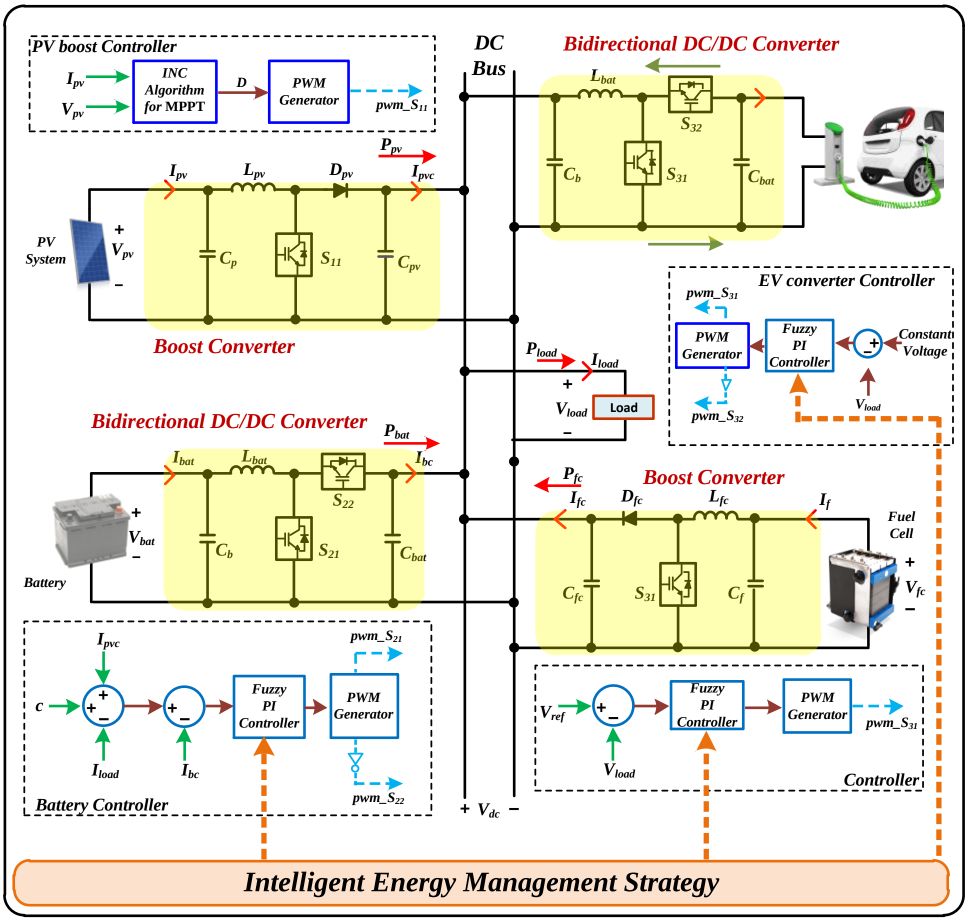

Figure 3. Control Strategy for the proposed isolated microgrid.

The fuel cell is connected to the load via a boost converter. The switching signals for the fuel cell's DC–DC boost converter are produced by the PWM generator, whose duty ratio is determined by the PI controller [54]. The reference voltage and load voltage differences are used in the PI controller feedback loop to calculate the error signal [55]. A DC–DC bidirectional converter should be used to connect the battery source to the microgrid because they charge and discharge during operation. In order to produce a switching pulse for the bidirectional converter, the PI controller compares many factors, such as the current value from the PV boost converter, FC boost converter, and load, to produce an error signal [56]. The difference in battery current and error signal from the earlier comparison is fed to the PI controller, which generates the duty ratio and passes it to the PWM generator to produce the switching signal for the DC–DC bidirectional converter [57]. The Proportional gain (k_p) and Integral gain (k_i) values for the PI controller have been determined using artificial intelligence techniques like fuzzy logic and the Sparrow search algorithm. Based on the operating conditions, the control logic determines the direction of energy flow between these components. The global optimality of the fuzzy controller's solutions could not be ensured. Fuzzy rules are therefore optimized using SSA to increase their effectiveness and precision [58]. The optimum solutions are calculated based on the Hybrid Sparrow search algorithm and are utilized to create the control signal for the converters [59]. The controller combines the advantages of fuzzy control and SSA. The schematic representation of the control is shown in Figure 4.

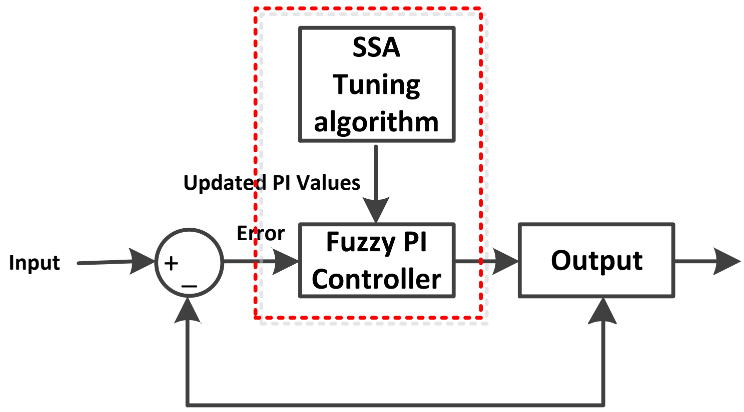

Figure 4. Schematic representation of the proposed hybrid SSA control.

Proposed Intelligent Hybrid Control with Fuzzy and Sparrow Search Algorithm

The fuzzy logic controller's rule base is designed to meet a timely and stable state response. The fuzzy controller's output has less fluctuation for slight changes in either input, which results in more precise control. The four fundamental components of a fuzzy logic controller are fuzzification, fuzzy interface, rule basis, and defuzzification. When designing the fuzzy control, the control variables must be carefully chosen. The error and its derivative are considered inputs for fuzzy logic control. The input and output rules are defined using the membership functions, although there is no set procedure to be followed. Table 1 displays the design of a 7 × 7 rule base. The primary control factors are used to identify the variables and their ranges. The fuzzy logic controller is created with the help of these control variables. An FLC controller and an FLC rule viewer with membership functions are shown in Figures 5 and 6, respectively.

Table 1. Rule base for fuzzy logic control.

Error	Change in Error						
	EL	**EM**	**ES**	**Z**	**OS**	**OM**	**OL**
Z	OL	OM	OS	OS	ZO	OS	ZO
O1	OS	OS	OM	OS	LN	EM	EM
O2	OL	OM	OM	OM	ZO	ES	ES
O3	LN	EM	ES	ZO	ES	OM	OL
O4	OM	OS	OS	ZO	OS	OS	OS
O5	OS	OS	OM	OM	ZO	ES	LN
O6	ZO	OS	OM	ZO	ES	EM	LN

O—Positive, E—negative, Z—zero, S—small, M—medium, L—large.

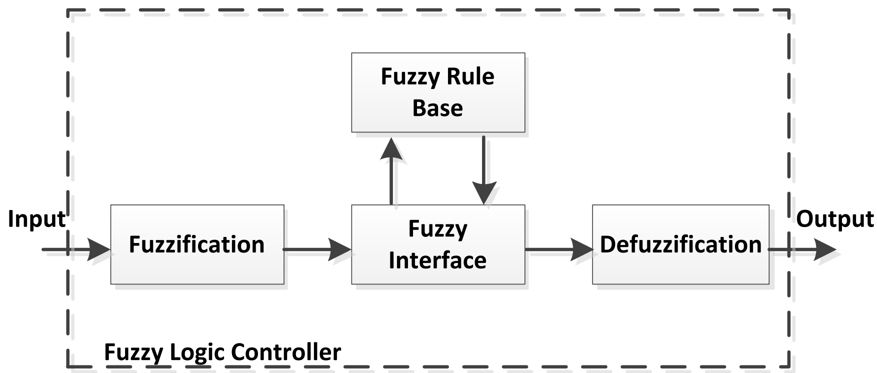

Figure 5. Structure of the Fuzzy logic Control.

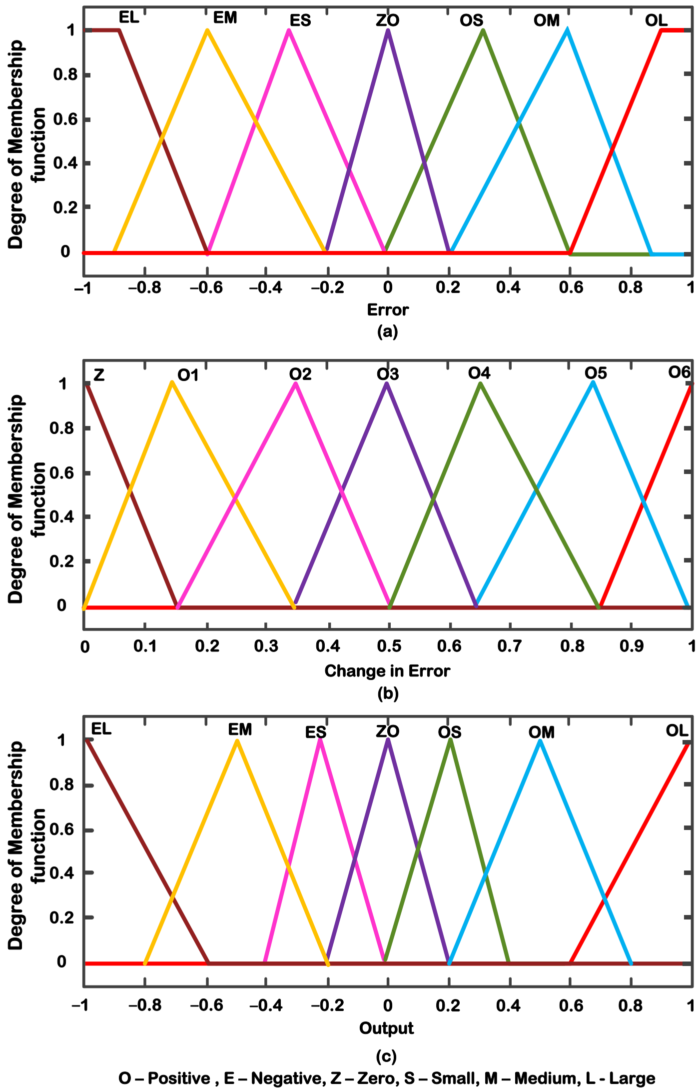

Figure 6. Membership functions for the (**a**) error, (**b**) change in error, and (**c**) output.

Xue et al. recently developed the Sparrow Search Algorithm, a unique swarm-based optimization algorithm, to resolve ongoing optimization issues. The feeding and anti-predation behaviours of the sparrow population are the basis for SSA optimization. The foraging role of the sparrow population is used to divide the sparrows into two groups. Producers (those who gather food from various sources) make up around 75% of the population, while scroungers (people who obtain food that producers uncover) make up the remaining 25%. The population of sparrows makes up the SSA's mathematical model.

$$A = \begin{bmatrix} a_{11}a_{12}\dots\dots a_{1d} \\ a_{21}a_{22}\dots\dots a_{2d} \\ \dots\dots\dots\dots\dots\dots \\ . \\ . \\ a_{n1}a_{n2}\dots\dots a_{nd} \end{bmatrix} \tag{1}$$

The fitness of the population of sparrows can be calculated as follows:

$$T(S) = \begin{bmatrix} t(s_{11}s_{12}\ldots\ldots s_{1d}) \\ t(s_{21}s_{22}\ldots\ldots s_{2d}) \\ \ldots\ldots\ldots\ldots\ldots\ldots \\ . \\ . \\ t(s_{n1}s_{n2}\ldots\ldots s_{nd}) \end{bmatrix} \quad (2)$$

The following steps are involved in the estimation of the SSA parameters.

1. Step 1

Set the settings for the sparrow population, including the number of sparrows, the maximum number of iterations, the total number of producers, the alarm value, and the safety threshold, at random. The ideal answer ought to be shown in the output. In SSA, randomization is used to initialize the population.

$$Position_{ij} = Lower\ Bound_j + \left(Upperbound_j - Lowerbound_j\right) * random(i, dimension)$$

where i is the number of individuals/sparrows in the population, j is the dimension (1,2,3,4 . . . .), and $Position_{ij}$ is the position of the ith sparrow in the jth position.

2. Step 2

In this phase, check if the current iteration (t < MaxT) is less than the maximum iteration. If the condition is true, the sparrows will be ranked based on their fitness values. The current best and worst sparrows will then be identified. The sparrow with the lowest fitness value is considered the best, while the sparrow with the highest fitness value is considered the worst, as this is an optimization procedure.

3. Step 3

In this step, the location of the scrounger and the producer are updated in the search space. The new position of the producer is mathematically given in (3), where A_2 is the alarm value and SF is the safety threshold. The sparrow foraging technique is as follows: when the sparrow sees a predator, one or more individuals will chirp, and the entire group will fly away when the chirp value exceeds the threshold value. The producer's location is updated in the search space by following the conditions below [60]:

$$P_{ij}^{t+1} = \begin{cases} P_{i,j}^{t} * exp\frac{-i}{a * MaxT}, if(A_2 < SF) \\ P_{i,j}^{t} + V * L, \quad if(A_2 \geq SF) \end{cases} \quad (3)$$

If ($A_2 > SF$), there is no predator, and the producer is looking for food. After hearing the chirp alarm, the population flies to a secure zone when another sparrow spots some predators [61]. The scrounger's location is given mathematically in the search area (4).

$$P_{ij}^{t+1} = \begin{cases} V * exp\frac{x_{worst}^{t} - x_{i,j}^{t}}{i^2}, if\left(i > \frac{n}{2}\right) \\ p_p^{t+1} + \left|p_{i,j}^{t} - p_p^{t+1}\right| * E * M, otherwise \end{cases} \quad (4)$$

The scroungers' energy level is assessed. The energy level influences the foraging method. If ($i > n/2$) the scroungers leave the area and search for food elsewhere. Otherwise, scroungers go to the producers and fight for the food.

4. Step 4

The location is updated in the search space, which is also updated. Using the equation below, we update the position of the sparrow. The following condition is validated and the search space's location is updated [62]. We update the sparrow's location using the calculation below.

$$P_{i,j}^{t+1} = \begin{cases} P_{best}^{t} + \beta \cdot \left| P_{i,j}^{t} - P_{best}^{t} \right|, \ if\ q_i > q_g \\ P_{best}^{t} + T \cdot \left(\frac{\left| P_{i,j}^{t} - P_{worst}^{t} \right|}{(f_i - f_w) + \epsilon} \right), if\ q_i > q_g \end{cases} \tag{5}$$

The following condition is checked. $Fitness_{(present)} > Fitness_{g(global\ best)}$, represents the sparrow at the edge of the group. Here, X_{best} indicates the location of the population and T indicates the sparrow's travel direction. The fundamental steps of the SSA are simplified in the flowchart presented in Figure 7.

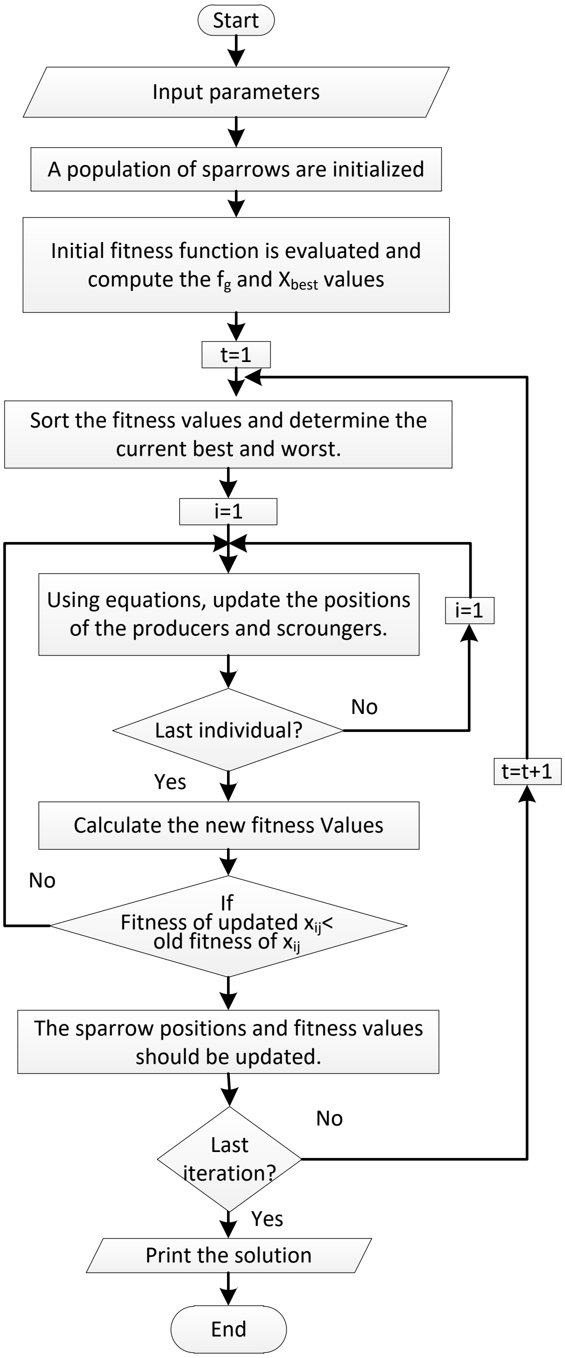

Figure 7. Flow chart of the sparrow search algorithm.

5. Results and Simulation

In a microgrid system of solar panels, fuel cells, and batteries, energy was managed using a hybrid SSA-based control. The suggested control was examined in both of the microgrid's operational modes. The two operating circumstances were evaluated. Finding the optimum solution will require going through several rounds because the process is both fuzzy- and metaheuristic-based. MATLAB/Simulink was used to develop the DC microgrid model. The energy sources and power converters were developed using Simscape in Simulink. Simscape is the physical modelling component in the Simulink environment, whereas Simulink is a graphical programming environment for modelling, testing, and evaluating system behaviour. The MATLAB code for SSA was developed, where the optimal solutions for the k_p & k_i values of PI controllers were generated and fed into the Fuzzy logic control. Variations in solar irradiance values and battery SoC values were used to operate the microgrid in various modes while maintaining the load on a DC microgrid for EV charging. Results and analysis of hybrid SSA controllers in different cases are discussed in this section. The parameters of the DC microgrid model developed are tabulated in Table 2.

Table 2. Simulation Parameters.

Component	Parameters	Value
Fuel Cell	Number of Cells	65
	Nominal Stack Efficiency	55%
	Operating Temperature	65 Celsius
	Nominal Air Flow Rate	300 Ipm
	Nominal Supply Pressure	1.5 bar
	Nominal Composition (H_2, O_2, H_2O)	(99, 21, 1)
	Fuel Cell Resistance	2.3677 ohms
	Nerst Voltage of one Cell	1.2101 V
	Stack Power (Maximal)	7000 W
Solar PV	Temperature	25 °C
	Irradiance	1000
	Series Connected Modules Per	8
	Power	2000 W
	Parallel Strings	1
	Open Circuit Voltage	37.3 V
	Short Circuit Current	8.15 V
	Number of Cells	60
Solar PV Boost Converter	Input Resistance Inductor	12
	Input Capacitor	0.48 µF
	Input Inductance	1.2 mH
Fuel Cell Boost Converter	Input Resistance	2.36 Ω
	Input Capacitor	0.13 µF
	Output Capacitor	0.16 µF
	Input Inductance	3.6 mH
Bidirectional Converter	Inductance	1.4 µF
	Input Capacitor	1.16 mH
Li-ion battery	Capacity	48 Ah
	Terminal Voltage	250 V

Case (i). The effect of the system under solar PV irradiance variation is explained.

Solar irradiation affects PV power. The variation in the output voltage, current, and power of the sources and the DC bus are shown in Figures 8–10. The solar PV irradiances are 100 W/m^2, 800 W/m^2, 600 W/m^2, and 400 W/m^2. The simulation results of the four states of irradiance variation during system operation are shown in this section. The battery's negative power represents charging activity, while its positive power denotes discharging activity. The SSA-Fuzzy hybrid control produces the best values for the proportional gain and integral gain, and the duty cycle is produced by feeding the value to the PI controller. The combined controller maintains the DC Bus voltage at 400 V during the irradiance change. In Figure 8, the irradiance value is varied at T = 1 s to 800 W/m^2.

The fuel cell starts supplying power to the grid, and the battery discharges. At T = 2, the irradiance value drops to 600 W/m^2, the PV power drops to 1000 W, and the fuel cell and battery power increase, depicting the battery discharging profile. Similarly, the irradiance values are reduced at T = 3 and T = 4 s. The load power remains constant while the solar irradiation is changed, as depicted in Figure 10. The gradual increase in the fuel cell and battery power supply can be seen in maintaining the bus power at 4000 W, keeping the bus voltage at 400 V and bus current at 10 A. Electric vehicle lithium-ion batteries are charged using a constant current or constant voltage approach. The battery charger delivers a constant amount of current to the battery being charged in constant current mode, regardless of the battery's voltage level. When a battery is first charged, this mode is typically used as its voltage gradually rises and its internal resistance falls.

The charger will operate in constant current (CC) mode until the battery voltage reaches a specific pre-set level. The charger will then enter constant voltage (CV) mode. The battery receives a constant voltage from the CV mode, which is maintained until the battery's current flow reaches a predetermined level, signalling that the battery is fully charged. The charging current in the CC mode remains constant until the voltage hits a cut-off voltage. In the CV mode, the voltage remains constant as the current falls. This procedure is designed to be controlled by a battery management system integrated into the vehicle battery system. The initial voltage is low when the EV battery starts to charge. If the charging current is not constant, both the battery and charger lifecycle will be shortened. The battery charging is unaffected by the change in irradiance at periods 1, 2, 3, and 4. The battery's SoC was set to 9, and as shown in Figure 11, the voltage and current profile of the battery indicates that it is charging as the irradiance changes.

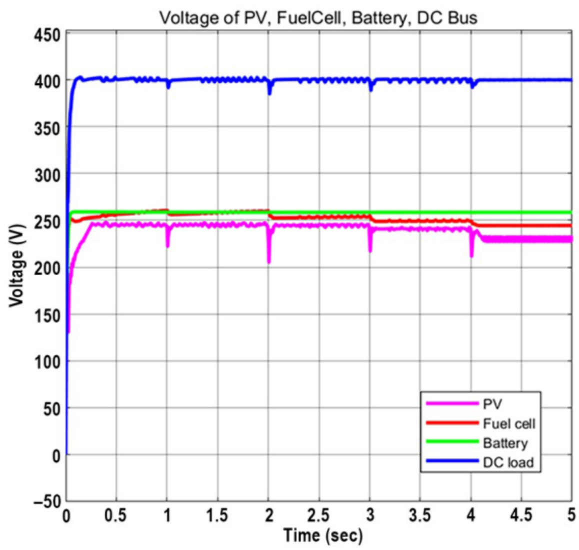

Figure 8. The output voltage of the PV, FC, Battery, and Load.

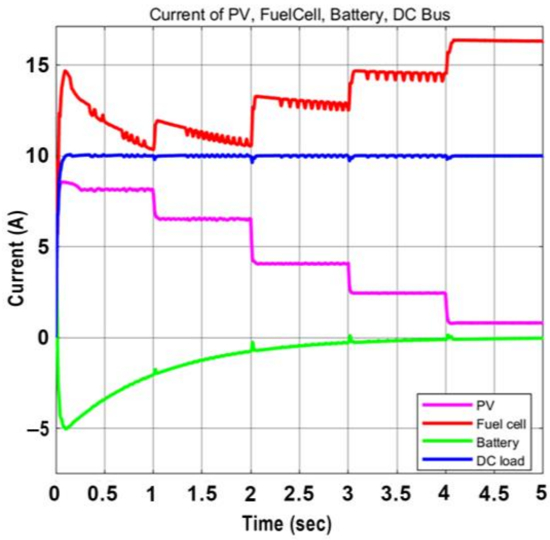

Figure 9. The output current of the PV, FC, Battery, and Load.

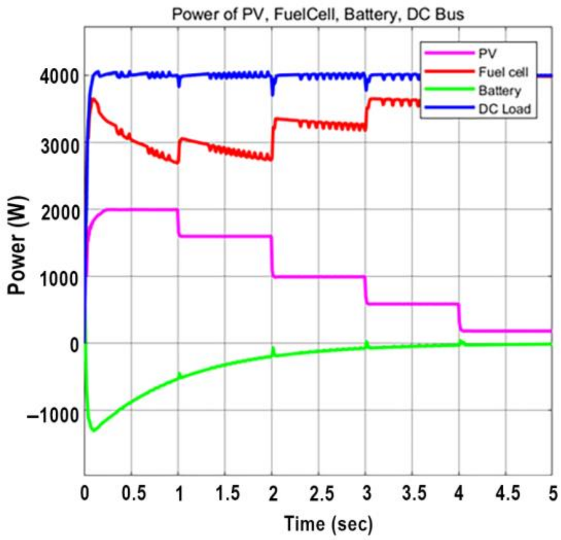

Figure 10. The output power of the PV, FC, Battery, and Load.

Case (ii). Stable charging of the EV with variations in the SoC of the storage battery.

The outcomes of testing the DC microgrid's performance for differences in the battery's SoC are shown in Figure 12. Power is absorbed when the reading is positive, whereas power is exuded when the reading is negative. This simulation demonstrates how the proposed energy management system influences the behaviour of the DC microgrid when solar energy is kept constant while the battery soc values are altered. As shown in Figure 13, the load power is balanced at the required value during variations in the battery SoC at time period T = 2 s and T = 4 s. The DC bus voltage is regulated at 400 V and the load draws a current of 10 A. Throughout the irradiance change, the control algorithm keeps the DC connection voltage at 400 V. In Figure 12, at T = 2 s, the SoC value changes; the fuel cell begins feeding power to the grid, the battery begins to discharge, and the voltage drops. At T = 4, when the SoC value reduces further and the battery voltage drops, the fuel cell's power output and the battery's discharge curve increase. While a charger is connected to the microgrid, the proposed controller's hybrid energy management strategy helps maintain the bus power, voltage, and current at constant values. According to Figure 14, the EV battery is charged without causing any changes in load demand. To assess the effectiveness of the suggested fuzzy-SSA energy management technique, PSO-based optimisation is used. Particle velocities are controlled when individual evolutionary positions are replaced in PSO, in contrast to conventional evolutionary computation methodologies. It is known from earlier studies that the PSO, with its coordination of renewable energy sources and storage devices, is well suited for the real-time operations of microgrids. When it comes to battery sources, the PSO assists in creating the best charging and discharging schedules, depending on cost and availability factors. Another virtue is its adaptability and scalability. Figure 15 shows a comparison of the output response with PSO-based regulation at the load side. It is evident from the outcome that the hybrid SSA-based optimal solutions are effective at generating the necessary output in the islanded DC mode. Compared to the PSO-based EMS, the proposed system's response exhibits greater steady-state performance in less operating time with a reduced drop in power.

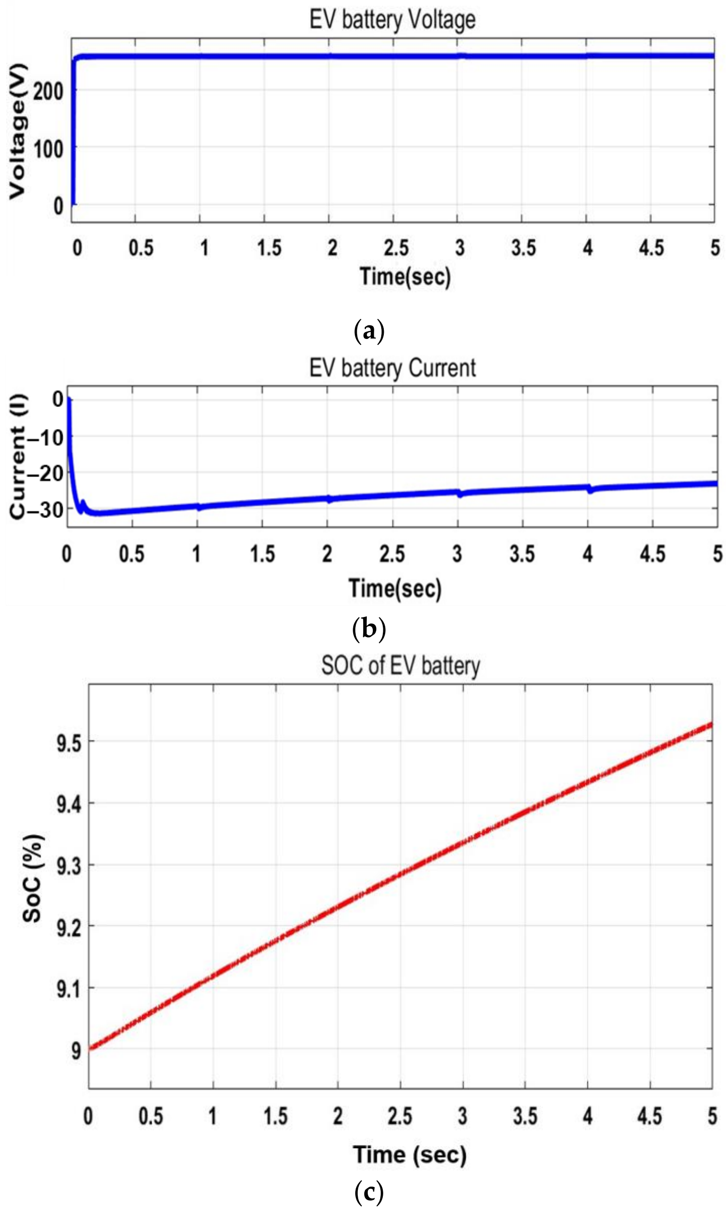

Figure 11. (**a**) EV battery Voltage (**b**) EV battery Current (**c**) EV Battery SoC during the irradiance variation.

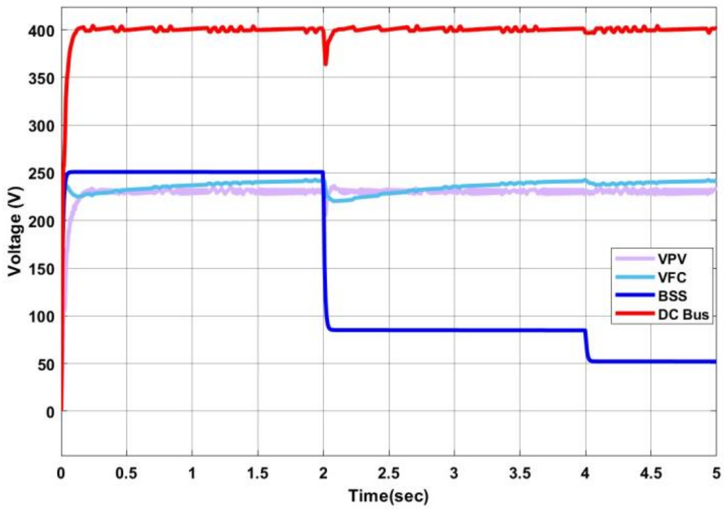

Figure 12. Voltages of PV, FC, storage battery, and DC bus during SoC variation.

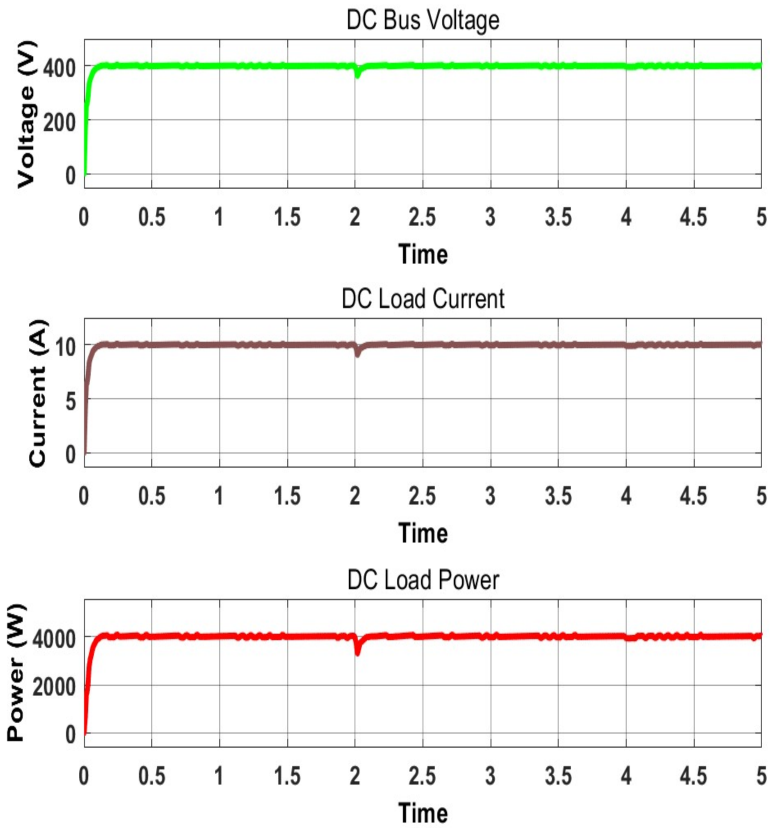

Figure 13. DC bus voltage, current, and power during the variation in SoC.

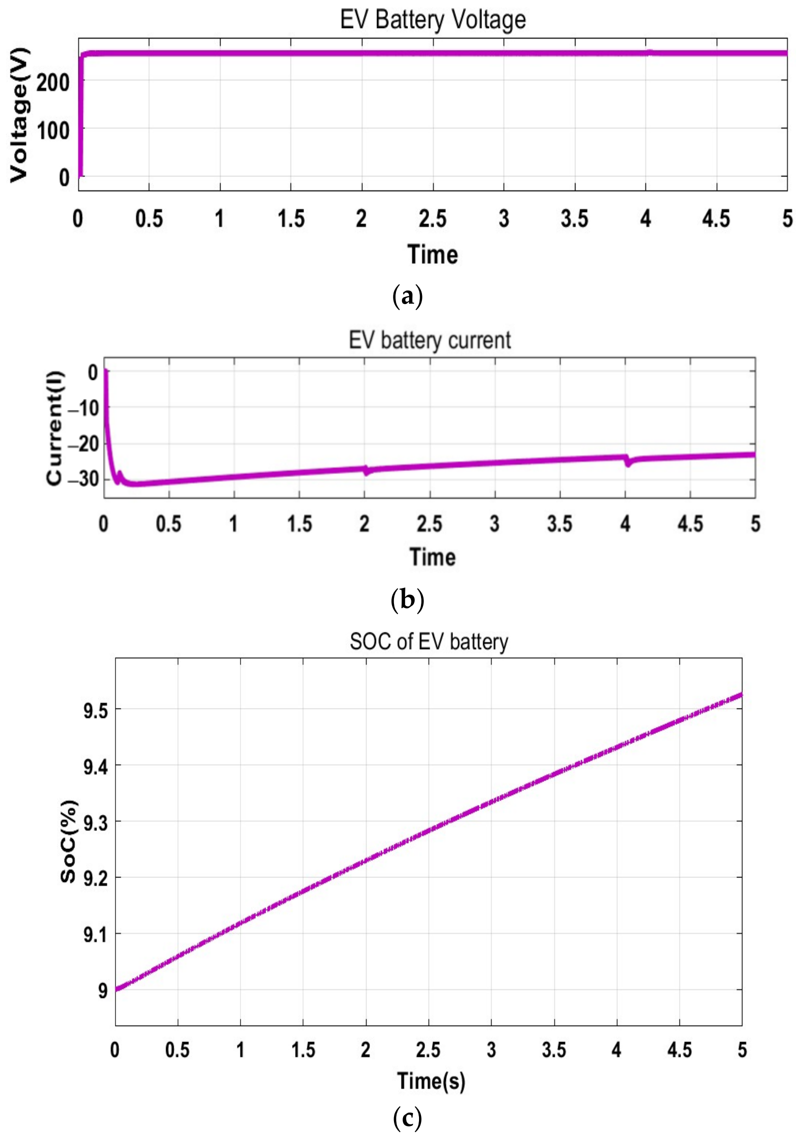

Figure 14. (**a**) EV Battery SoC, (**b**) EV battery Current with variation in battery SoC, and (**c**) SoC battery variation.

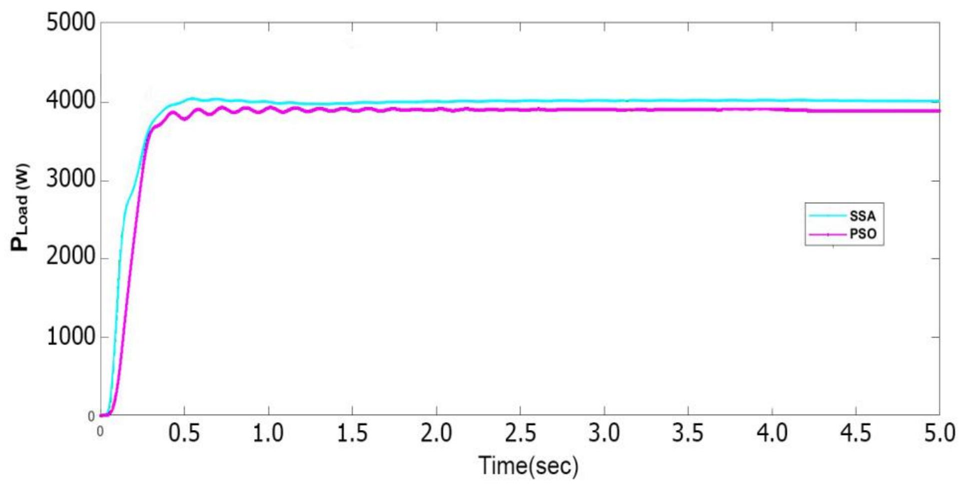

Figure 15. Response of the proposed DC MG system with SSA- and PSO-based control.

Discussion and Implications

In both operating conditions at t = 0–1 s, the total power of the PV system can supply power to the load as it generates the required amount. The moment t = 1 s in the varying irradiance condition, the generated PV power is reduced and the Battery and fuel cell compensates for the required power at the load side. The charging of the EV load is not interrupted during this variation. In varying SoC condition, the battery power is reduced at t = 2 s and the FC and PV delivers the required amount of power to the load side. The voltage is regulated without varying the EV charging while addressing the uncertainties on the generation side. The load responses of the proposed hybrid SSA and PSO-based system are compared in Table 3. The maximum output power is harnessed in the hybrid SSA method compared to PSO. The oscillations are less in hybrid SSA.

Table 3. Load response of the hybrid SSA and PSO.

Optimization Technique	Time Period	Power (W)
Hybrid SSA	0.4	3900
	0.5	3980
PSO	0.4	3800
	0.5	3900

Fuzzy logic control with sparrow search algorithms can optimise microgrid control. However, real-time implementation raises challenges. Real-time data collection and processing are difficult. Load demand and renewable energy data generation might be complicated and time-sensitive in a dynamic microgrid. Real-time data capture systems are needed to acquire inputs effortlessly and precisely. Responsiveness without accuracy loss requires accurate real-time data. Validation of data and processing can be used to find and eliminate inconsistent data. To deal with data variability, pre-processing techniques like interpolation and data smoothing can also be used. The accuracy of input variables can be improved by incorporating redundant sensors or data sources, which can also increase data reliability. The impact of inaccurate or missing data can be reduced using methods like sensor fusion, which merges data from various sources. Supervisory learning techniques can be utilized to improve the data captured. Future research should focus on establishing stable and efficient real-time data collection systems, optimising the algorithm's computational efficiency, and overcoming practical implementation hurdles. Only by overcoming these challenges can the Fuzzy-SSA algorithm be implemented in real-time microgrid control settings and realise its potential benefits.

The future scope of the proposed microgrid can include improved decision-making, car charging, and system efficiency using supervisory learning techniques. Power capacity, charging infrastructure, and vehicle requirements determine a microgrid's maximum charging capacity. Supervisory learning algorithms can analyse power capacity data, estimate power availability, and efficiently allocate resources. Predictive analytics change charge rates and schedules based on real-time data to optimise microgrid utilisation without overwhelming it. The advanced learning-driven demand response programmes motivate vehicle owners to change their charging patterns to maximise vehicle charging. Machine learning optimises charging schedules and vehicle-to-grid energy flow using real-time data.

6. Conclusions

Future-oriented sustainable development in the energy sector primarily focuses on establishing renewable-based microgrid networks with EV connectivity to enable smart grid environments. This article considered integrating solar PV systems, fuel cells, and battery energy sources to create an isolated DC microgrid that delivers power to the consumer load and EV charging. A comprehensive energy management system was developed to address the challenges of dynamic and unpredictable events. The developed microgrid system was analysed at various stages of two scenarios using the proposed hybrid intelligent algorithm. The suggested hybrid EMS maintains the necessary power balance between the sources and the storage system for supplying continuous power in light of the experimental data. The balance of the terminal power of the power components under consideration and the quick regulation of the DC bus voltage during fluctuations were also tackled. The resulting findings are examined and validated by comparing them with the PSO-based energy management strategy.

Further examination demonstrated that the hybrid SSA-based response is effective and efficient based on a comparison of the results of the hybrid SSA-based control with the PSO-based control. With fewer voltage drops and transients, the power flow is kept at its rated value. Further studies should concentrate on determining the fast response characteristics of the hybrid algorithm for application in AC microgrids and hybrid microgrids and examining the effect of rapid battery charging and discharging.

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Nomenclature

e	Dimension of the problem
n	Number of sparrows
T	Travel direction of sparrows in range [−1,1]
SF	Safety threshold
M	Dimension of the matrix in 1 × e
$P_{ij}(t)$	Position of the ith sparrow in jth position.
A_2	Alarm range [0,1]
V	Random value in normal distribution
a	Random value range [0,1]
E	Matrix of 1 × e with random elements
q_i	Sparrow fitness value
q_g	Best fitness value

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