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Towards Sustainable Energy Management: Enhancing PV Performance in DC Microgrids with the Aquila Approach

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Abstract: The emergence of DC microgrids has heightened interest in optimizing photovoltaic (PV) panels and storage systems to enhance energy management, minimize power losses, and bolster system stability. This study addresses a critical gap in current methodologies by proposing the Aquila algorithm, an optimization technique specifically designed for the unique characteristics of DC power distribution systems. Unlike traditional optimization methods that primarily cater to AC microgrids, the Aquila algorithm uniquely focuses on the intricate dynamics of DC microgrids, enabling it to determine optimal locations and sizes for PV panels and battery storage systems effectively. The efficiency of the proposed PV system optimization was validated using a MATLAB/Simulink model, with simulations executed under controlled settings to ensure accurate results. Notably, the system achieved a rapid settling time of just 0.2 seconds during load fluctuations, with the Aquila algorithm mitigating temporary imbalances and deviations in key parameters like grid power, battery power, and load power. Simulation results revealed that the PV system operated under a solar irradiance level of 700 W/m², generating a controlled power output of 10 kW with a corresponding PV output of 8 kW. The algorithm demonstrated a significant reduction in system oscillations and fluctuations, ensuring consistent performance even when sudden load changes occurred. At a critical moment (t = 0.025 s), the Aquila algorithm-maintained system stability despite a drop in solar generation, thus emphasizing its reliability in adapting to varying solar conditions. Overall, the findings indicate that the Aquila algorithm significantly enhances energy management within PV-connected DC microgrids, optimizing battery performance and improving overall system reliability and efficiency. This research presents a promising approach for optimizing battery-connected PV systems, ultimately contributing to the advancement of sustainable energy solutions within DC microgrid frameworks.

Keywords: Multi-objective optimization, Decision-making, Power demands, DC microgrid, BESS.

1. Introduction

The use of renewable energy sources (RESs) has grown recently in response to the depletion of traditional energy supplies and the detrimental impact of emissions of greenhouse gases on the environment. In the medium run, conventional generation systems powered by fossil fuels respond more slowly to control frequency deviation [1]. These issues and the risk to the stability of the electricity system have gotten worse as the number and overall capacity of RES installations have increased. This issue might be solved by deploying larger RES systems [2]. But the expense of the investment is substantial as a result. BESS, or battery energy storage systems, appear to be a useful remedy for this issue [3]. When compared to other forms of energy storage systems or conventional generators, a BESS's quick dynamic reaction qualities can help maintain the right equilibrium between supply and demand [4].

The introduction of microgrids has emerged as an efficient solution for integrating diverse renewable energy sources and supplying power to remote areas [5]. Microgrid represent a collective system that integrates various distributed generators (DGs). Historically, the utility electrical grid has predominantly relied on alternating current (AC) systems, leading to substantial research focus on AC microgrids. However, renewable energy resources, as well as certain loads like photovoltaic (PV) systems and energy storage systems, inherently operate on direct current (DC). The integration of such DC sources and loads into AC microgrids has often resulted in inefficiencies related to power conversion and system cost. Consequently, there has been a growing interest in DC microgrids. Fig. 1 illustrates a typical DC microgrid, where a common DC bus connects all of the DGs and loads. This transition to DC microgrids marks a pivotal shift in energy distribution and management, allowing for a more seamless and efficient incorporation of DC-coupled renewable energy sources and loads. The growing demand for energy has driven the widespread deployment of Renewable Energy Sources (RESs), which can be seamlessly integrated into both standalone power systems and traditional non-renewable energy grids. This integration helps enhance the overall reliability and sustainability of energy supply while reducing dependency on conventional energy sources. Among RESs, PV technology stands out as an attractive solution. However, environmental factors like temperature and solar radiation have a significant impact on solar energy generation [6]. Integrating energy storage systems (ESSs), such as super capacitors, batteries, flywheels, and hydrogen storage devices, has become crucial in addressing the intermittent nature of solar energy [7]. To ensure a stable energy supply, the integration of ESSs with renewable energy sources (RESs), particularly in standalone applications, has been explored [8]. Additionally, DC microgrids are reported to have higher efficiency compared to AC microgrids [9].

In many different applications, including telecommunications, smart structures, and electric automobiles, PV/battery systems are the fundamental building blocks of a DC microgrid. Integration of various RESs to create a microgrid has become much easier with the ongoing development of power converters. There are several alternative configurations when it comes to the variety of power converters used in a PV/battery system. In an ideal setup, a DC-DC power converter is utilized to link the PV module to a shared DC bus, and an alternate DC-DC power converter is employed to link the battery. Using or ignoring a surplus DC-DC power converter, DC loads can be connected directly to the DC bus. This diverse range of configurations offers flexibility and adaptability in designing DC microgrids to suit specific applications and requirements, enhancing the efficiency and reliability of energy distribution in modern power systems.

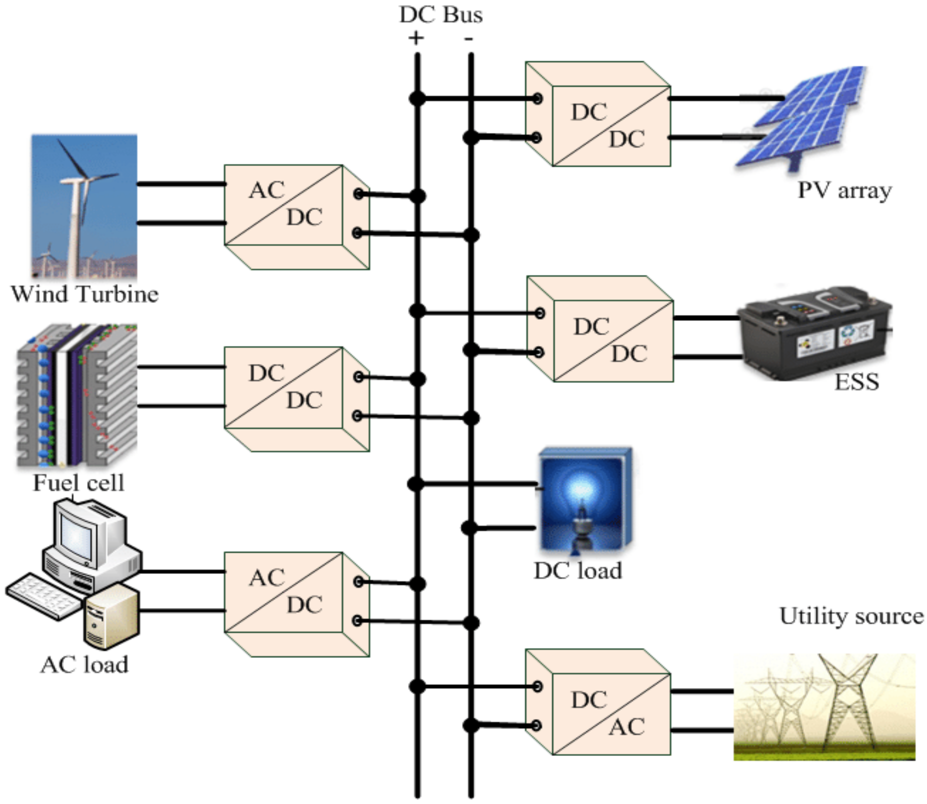

Figure. 1 DC Microgrid configuration

The proposed study presents a novel approach to optimizing PV energy utilization in DC microgrids (MG) with integrated battery systems. It revolves around harnessing the potential of solar energy captured by PV panels and efficiently managing the energy stored in the battery. This tailored energy management strategy (EMS) significantly contributes to improving the efficiency, reliability, and sustainability of DC microgrid systems. The Aquila algorithm introduces new features that enhance the performance of PV systems by determining optimal panel placements and sizes, thereby addressing specific characteristics of DC power distribution that traditional methods may overlook. Among its main advantages, the algorithm effectively reduces power losses, mitigates frequency deviations, and ensures alignment of power demands within the microgrid. By maintaining system stability during load fluctuations and adapting to varying solar conditions, the Aquila algorithm represents a significant advancement over existing methodologies, particularly those designed for AC microgrids. This research not only optimizes the deployment of PV panels but also enhances overall energy management in battery-connected PV systems, thereby promoting the sustainable use of solar resources. The main contribution of the proposed research work are as follows:

- The study optimizes the utilization of PV panels, ensuring efficient harnessing of solar energy in DC microgrids.
- The proposed Aquila Algorithm enhances energy management in DC microgrids, leading to better power distribution.
- By maximizing the use of renewable energy sources like PV panels, the study contributes to the sustainability of energy systems and enhances the reliability of DC microgrids.

The paper proceeds as follows: Section 2 reviews existing methods relevant to the current study. The proposed approach is presented in Section 3. Section 4 showcases the experimental findings and subsequent discussion. Finally, Section 5 outlines the conclusions drawn from the study.

2. Literature review

Grisales-Noreña et al. [10] addressed the challenge of optimizing battery performance in both standalone and grid-connected DC microgrids equipped with photovoltaic (PV) generators operating at their maximum power point (MPP). They developed a comprehensive mathematical framework that focused on three primary objectives: minimizing operational costs, reducing energy losses associated with DC microgrid energy distribution, and minimizing emissions from conventional generators. To tackle this complex issue, the study utilized three parallel optimization methodologies: the Parallel Ant Lion Optimizer (PALO), the Parallel Vortex Search Algorithm (PVSA), and the Parallel Particle Swarm Optimization (PPSO). The hourly power flow was optimized using these methods, taking into account various constraints and relying on successive approximations. The efficacy of these solution techniques was rigorously validated through simulations conducted on two distinct test systems in Colombia. The results demonstrated the superiority of PVSA for standalone grids and PALO for grid-connected networks, with significant average reductions in CO_2 emissions, energy losses, and both fixed and variable costs. However, a limitation of the study was that the economic indicators indicated that variable costs were not adequately accounted for in the operational analysis, suggesting that a more comprehensive evaluation of variable costs is necessary for optimizing energy management systems.

Nasr et al. [11] conducted a study aimed at enhancing the performance of PV energy systems by employing various metaheuristic optimization algorithms for MPP tracking under partially shaded conditions. They identified that common MPP tracking techniques, including perturb and observe (P&O), parasitic capacitance, hill climbing, incremental conductance, and constant voltage methods, often produced oscillatory results, which diminished accuracy, especially in scenarios involving partial shading. The authors compared the performance of several algorithms, including whale optimization algorithm (WOA), particle swarm optimization (PSO), grey wolf optimization (GWO), and cuckoo search algorithm (CSA), utilizing MATLAB SIMULINK for simulations. Their findings revealed that PSO and CSA exhibited lower tracking efficiency, whereas WOA and GWO demonstrated the highest efficiency in tracking the MPP. Notably, the conventional incremental conductance method struggled to effectively track the MPP under partial shading conditions. To address the issues of premature convergence, the study introduced a nanoparticle WOA algorithm, which proved to be superior in tracking local peaks within PV systems. WOA outperformed the other methods, achieving a tracking time of only 0.15 seconds, highlighting its improved convergence speed and ease of implementation compared to traditional techniques. However, a limitation of this study was that it did not explore the performance of the proposed algorithm under a wider range of shading patterns and environmental conditions, which could further validate its robustness and applicability in real-world scenarios.

Senthil Kumar et al. [12] addressed a critical issue within the power system network, highlighting the importance of power quality in preventing disruptions and financial challenges for consumers. Their study examined electricity quality in a PV-linked power system and introduced a novel optimization technique for day-ahead trading and control within DC microgrid power management. The researchers employed a multi-objective optimization dispatch (MOOD) approach aimed at minimizing operational costs, power losses, and emissions of pollutants such as nitrogen oxides, sulfur dioxide, and CO_2. They simplified the multi-objective problem using a weighted sum approach, determining weight coefficients through the analytical hierarchy process (AHP). Their research comprehensively considered power balancing, renewable energy integration, battery scheduling, load control, and system constraints in both grid-connected and standalone approaches. The application of the ant lion optimizer (ALO) demonstrated the effectiveness of their proposed method, revealing substantial cost savings of approximately 4.70% in the grid-connected mode. Additionally, the authors introduced a two-layer energy management system (EMS) that integrated various distributed energy sources and controllers, employing ALO for multi-objective optimization alongside fuzzy logic to minimize power losses, operational expenses, and pollution emissions. However, a limitation of their study was the reliance on a weighted sum approach, which may not adequately represent the complex trade-offs inherent in multi-objective optimization, potentially leading to suboptimal solutions in certain scenarios.

Alam et al. [13] introduced an energy management model for home microgrids that featured BESS and RES. Their approach combined deep learning-based predictive modeling, utilizing bidirectional long short-term memory (Bi-LSTM), with optimization algorithms to minimize daily electricity costs, taking into account time-of-use pricing and peak demand penalties. The research demonstrated robust performance in forecasting load and PV generation, achieving a significant reduction in daily electricity costs by up to 38.77% under specific conditions, while also optimizing the utilization of BESS energy. However, one notable limitation was the insufficient discussion on the practical challenges of implementing deep learning models in real-world residential settings, including issues related to data availability, training, and model interpretability, which are crucial for broader application and acceptance of the proposed model.

Liu et al. [14] presented an enhanced method employing Improved Particle Swarm Optimization (IPSO) to optimize the sizing and configuration of standalone PV systems and battery energy storage for a remote area in Iran. Their primary goal was to minimize the Total Net Annual Cost (TNAC) while maintaining high levels of reliability. The results indicated that IPSO achieved significant cost savings, approximately 22.9% compared to Simulated Annealing (SA) and 0.35% compared to traditional PSO across various reliability indexes (1%, 3%, and 5%). Additionally, increasing the reliability index from 1% to 5% resulted in a 38% reduction in TNAC, along with decreased energy storage requirements for the battery bank and lower power generation needs for the PV panels. However, a limitation of this study was its insufficient consideration of critical factors such as component degradation, system maintenance, and environmental variability, which could adversely affect the long-term economic and operational performance of the PV system.

Aziz et al. [15] conducted a study to determine the optimal design and control strategy for a grid-connected PV and battery hybrid energy system (HES) serving a residential residence in Iraq. They developed a new dispatch strategy using the MATLAB Link Module in HOMER software and compared it to the default methods of load following (LF) and cycle charging (CC). The modified strategy demonstrated enhanced techno-economic and environmental performance, resulting in a 16.3% reduction in Net Present Cost (NPC), a decrease in unmet load by 39.5 kWh/year compared to LF and by 31 kWh/year compared to CC, and a reduction in CO_2 emissions by 14% relative to LF and by 50.1% compared to CC. Furthermore, a sensitivity analysis revealed that factors such as the cost of grid power, PV capital expenses, solar radiation, frequency of grid outages, temperature, and project duration significantly influenced the efficacy of the HES. However, one limitation of the study was its focus on a specific geographical region, which may affect the generalizability of the findings to other locations with different environmental conditions or energy needs.

Garip et al. [16] presented a method for determining the optimal sizing of a PV system and BESS within a grid-connected MG. Their primary objective was to minimize energy costs, and they achieved this by combining an EMS with a PSO algorithm. The grid-connected MG was designed to prioritize the use of renewable energy resources while allowing for energy procurement from the grid under specific constraints and penalties when necessary. The study introduced a self-contained MG structure, incorporating an energy management algorithm for controlling grid energy and utilizing the PSO algorithm as part of the EMS. The results indicated that the proposed approach effectively identified the optimal sizes for both the PV system and BESS at the lowest cost, even in scenarios where the microgrid needed to draw energy from the grid. Furthermore, the technique demonstrated superior performance compared to the Genetic Algorithm (GA) in optimizing the sizes of PV and BESS under defined energy cost constraints. However, a limitation of the study was that it did not extensively explore the impact of varying load profiles on the optimization results, potentially affecting the robustness of the findings in real-world applications.

Alidrissi et al. [17] presented an EMS for DC microgrids, highlighting the increasing preference for DC over AC microgrids due to the rise of DC power sources, DC loads, and energy storage systems. The proposed system integrated a PV module as the primary power source, alongside an ESS and essential DC loads. Their design incorporated DC-DC boost and bidirectional converters, facilitating efficient energy flow control. A key feature of this strategy was its consideration of battery lifespan, which involved implementing constraints on charging and discharging to ensure longevity. Unlike other methods, this approach avoided complex algorithms for energy management or MPPT, making it straightforward and effective in supplying DC loads. The simulation results indicated impressive performance and stability, consistently meeting load demands. However, a limitation of this study was the lack of extensive real-world testing, which could have validated the system's performance and reliability under varied operating conditions.

Mah et al. [18] presented a multi-period P-graph optimization approach for PV-based microgrids that incorporated battery-hydrogen energy storage, effectively addressing the intermittent nature of RESs. The methodology utilized an embedded accelerated branch-and-bound algorithm to accurately determine optimal solutions for energy management. Their case studies demonstrated the cost-effectiveness of the hybrid energy storage system; however, they highlighted the requirement of a carbon price of $1000 USD/t or higher for economic viability when compared to conventional electricity use. When hydrogen storage was eliminated and grid electricity was employed to compensate for energy shortages, the overall costs were significantly reduced. Nevertheless, this approach exhibited limitations concerning its scalability and practical application, as it was confined to specific scenarios.

Murty et al. [19] discussed the advantages of microgrids powered by hybrid renewable energy sources, emphasizing their significance in scenarios where traditional grid expansion was impractical or economically unfeasible. The authors formulated the energy management of microgrids as a mixed-integer linear programming (MILP) problem and proposed a multi-objective solution that incorporated considerations for cost, emissions, and demand response. By employing fuzzy logic for energy storage scheduling, their simulation results demonstrated a notable reduction in CO_2 emissions, achieving a 51.60% decrease in standalone hybrid microgrids compared to grid-only systems. The research compared their approach against various evolutionary algorithms, confirming its effectiveness. Moreover, the integration of demand response programs resulted in decreased operating costs, lower emissions penalties, and reduced power losses. While the study provided valuable insights for microgrid operators and informed planning for rural electrification and hybrid microgrid design, a limitation was noted in the potential complexity and computational intensity of the MILP formulation.

Singh et al. [20] introduced a pioneering power management strategy (PMS) based on a Hybrid Bat Search and Artificial Neural Network (HBSANN) for the efficient control of DC MG equipped with hybrid energy storage systems (HESS). The primary goal of their strategy was to optimize power distribution among batteries and supercapacitors within the microgrid, thereby mitigating discrepancies between demand and generation while regulating the state-of-charge (SOC) within predetermined limits and controlling the DC bus voltage. Their research focused on a low-voltage DC (LVDC) MG configuration that included PV panels, a HESS comprising both batteries and supercapacitors, as well as DC and AC loads. The outcomes of this novel approach led to an extended battery lifespan due to the effective transfer of high-frequency components of unwarranted battery currents to the supercapacitor. Additionally, the study examined the Total Harmonic Distortion (THD) of the AC output voltage. Experimental validation conducted on an FPGA-based real-time simulator, using a hardware-in-loop (HIL) setup, confirmed the effectiveness of the proposed approach, which not only enhanced power-sharing between HESS components but also demonstrated rapid control of the DC bus voltage. However, a limitation of this study was that it did not address the scalability of the HBSANN strategy for larger, more complex DC microgrid systems, potentially restricting its applicability in diverse operational environments.

Energy yield was significantly influenced by the sun's varying irradiance throughout the year and across different geographical locations. To address this challenge, Ananthu et al. [21] investigated various forecasting strategies aimed at improving solar PV power prediction. Their recent analysis provided a critical overview of existing models, highlighting the advantages and disadvantages of data-driven processes in solar PV power forecasting. This clarity contributed to the understanding necessary for developing more accurate future models and applications. In the context of microgrids, EMS were identified as essential for optimizing power distribution. A comprehensive review conducted by Sriram et al. [22] explored decision-making approaches and solution techniques for microgrid EMS. The study discussed uncertainty quantification techniques to manage the unpredictability of renewable energy resources and load demand, emphasizing the importance of effective load shedding and power quality maintenance. However, a limitation of this research was its reliance on historical data, which may not adequately capture the dynamic nature of renewable energy resources and their impact on forecasting accuracy.

Bandyopadhyay et al. [23] proposed a hybrid microgeneration system that combined hydropower and solar PV power, designed to provide continuous electricity by utilizing solar energy during the day and stored water energy from a small reservoir at night. This system was particularly well-suited for off-grid applications, demonstrating its feasibility in scenarios where grid connectivity was unavailable. However, a limitation of the proposed system was its reliance on specific geographic conditions that might restrict the availability of sufficient water resources for hydropower generation, potentially affecting its overall effectiveness in various locations.

Madathil et al. [24] investigated active and passive strategies aimed at enhancing the energy efficiency of buildings. The study emphasized the importance of integrating automated management systems with energy storage solutions and renewable energy sources to achieve net-zero energy buildings. Additionally, the research considered various aspects such as user comfort, energy policy, data privacy, and security, providing valuable insights for sustainable development. However, a limitation of the study was its reliance on theoretical models, which may not fully capture the complexities and variability of real-world building environments and user behaviors.

Tooryan et al. [25] presented an innovative optimization approach aimed at reducing operational costs in a hybrid residential microgrid, which incorporated a wind turbine, diesel generator, PV array, and a BESS. Traditionally, residential microgrids primarily relied on diesel generators; however, the integration of renewable energy sources and BESS yielded substantial benefits, such as reduced generation costs, lower environmental emissions, and improved generation efficiency. The authors employed a PSO algorithm to address the optimization problem, focusing on three primary objectives: minimizing the total costs of DERs, decreasing environmental emissions within the microgrid, and increasing the penetration of RES. The numerical results demonstrated the effectiveness of their approach, revealing a significant 35% reduction in CO_2 emissions compared to scenarios relying solely on diesel generators to meet microgrid demands. However, a limitation of the study was its reliance on historical data for load growth projections, which may not account for unexpected fluctuations in demand or changes in user behavior over time, potentially affecting the long-term viability of the proposed optimization strategy.

Despite the advancements made in optimizing hybrid residential microgrids through methodologies like PSO and other traditional approaches, significant research gaps remain. Most existing methodologies primarily focus on cost reduction and emissions minimization but often overlook the dynamic interplay between RES, BESS, and the associated demand response strategies that are crucial for enhancing system resilience and operational efficiency. Additionally, many studies rely heavily on static models that do not adequately account for real-time variations in load profiles, solar irradiance, and wind speeds, leading to suboptimal performance under fluctuating environmental conditions. Furthermore, existing optimization techniques frequently fail to integrate advanced predictive analytics or machine learning algorithms, which could provide more accurate forecasts of energy generation and consumption patterns. This gap underscores the need for innovative frameworks that incorporate real-time data analytics and adaptive control mechanisms to dynamically optimize energy management in hybrid microgrids, ensuring enhanced reliability, stability, and sustainability of the overall system.

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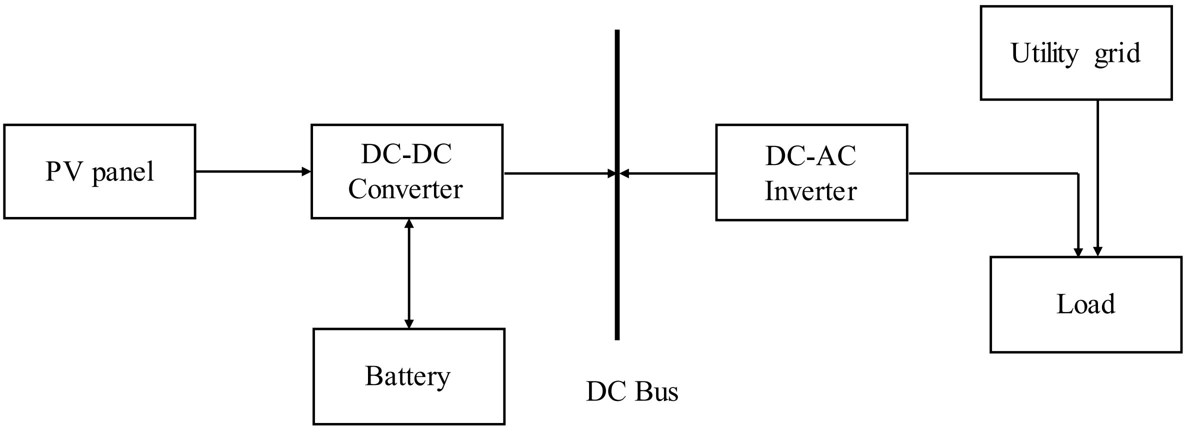

Figure. 2 Proposed Architecture

3. Proposed methodology

The microgrid illustrated in Fig. 2 serves as the foundation for the development of the suggested EMS-based approach in this research. This DC microgrid comprises several crucial components, including DC loads, a BESS, and a solar PV array. With the help of a DC–DC converter, these components are effectively integrated via a shared DC-bus. Within this MG set up, the primary power source is the solar PV array, responsible for delivering electricity to the loads. The control strategy assumes the use of an incremental conductance approach to acquire the maximum power output from the PV array efficiently.

An intelligent energy system is a multifaceted framework comprised of three primary subsystems: production, storage, and load. The configuration and scale of these components can vary considerably based on certain elements, including the accessibility of sustainable resources, the intended functions to be provided, and the distinctive energy usage patterns associated with the system's target applications. This adaptability allows intelligent energy systems to be tailored to meet diverse requirements, making them a versatile and responsive solution for modern energy needs.

The successful design and optimization of the entire system hinge primarily on a set of crucial variables. These variables encompass a vast range of factors, involving the selection and integration of various power sources, as well as the utilization of high-quality components. The choice of power sources, their efficient integration, and the quality of components collectively play a pivotal role in assessing the system's overall effectiveness and its expected lifespan. As such, these considerations are paramount in ensuring the success and longevity of the system's performance.

3.1 The PV modeling

The solar cells are equipped with a PN junction, a critical component that facilitates the solar energy conversion to DC power. The power generated by PV systems is significantly influenced by various factors, including solar irradiance, temperature, production characteristics, and geographic location. Furthermore, a PV system's voltage and capacity can be tailored to meet specific requirements by configuring PV panels in either parallel or series arrangements [26]. In an effort to increase PV systems' efficiency and ensure they operate at their maximum potential; the usage of Maximum Power Point Tracking (MPPT) technologies is popular. These techniques enable the solar panel to continuously track and operate at the MPP, optimizing energy production [27]. An incremental conductance (IC)-based MPPT algorithm is utilized to optimize the solar PV system's performance in extracting maximum power.

The output power of a solar PV array is intimately linked to the voltage and current it generates, and this connection is crucial in understanding its performance. These voltage and current parameters are not static but vary depending on several factors, such as solar irradiance, temperature, and the specific characteristics of the PV panels employed. To capture this relationship more comprehensively, it is common practice to model the current (I) as a function of voltage (V). This modeling approach often involves the use of the diode equation or the single diode model, which considers various intricacies of the PV cell's behavior. These intricacies may encompass elements such as the number of cells within the array, prevailing solar irradiance levels, and ambient temperature. The utilization of such models enables a more precise and detailed representation of the current-voltage dynamics of the PV array, facilitating a deeper understanding of its performance and aiding in effective energy management and optimization within a DC microgrid.

$$I = I_{ph} - I_0(e^{\frac{qv}{nkT}} - 1) \quad (1)$$

I represents the current produced by the PV array, I_{ph} stands for the photo-generated current, I_0 indicates the diode's reverse saturation current; q symbolizes the elementary charge, V corresponds to the voltage across the PV array, n represents the ideality factor, k is the Boltzmann constant, and T denotes the temperature in Kelvin.

The variables R_s and R_{sh} correspond to the series and shunt resistances in the system, respectively. V_{th} designates the thermal voltage as shown in Fig. 3. Applying Kirchhoff's laws to this circuit, the generated current can be stated as a function of its generated voltage in the following manner.

$$I_{pv} = I_{ph} - I_0(\exp\left(\frac{V_{pv}+R_s I_{pv}}{n\,V_{th}}\right) - 1)\frac{V_{pv}+R_s I_{pv}}{R_{sh}} \quad (2)$$

The characteristics of a PV cell, commonly depicted in its voltage-current (V-I) curve, provide valuable insights into its behavior and efficiency. Fig. 4 illustrates these V-I characteristics, helping to visualize the relationship between voltage and current in a PV cell.

Table 1 depicts the specifications of the PV panel employed in the proposed research.

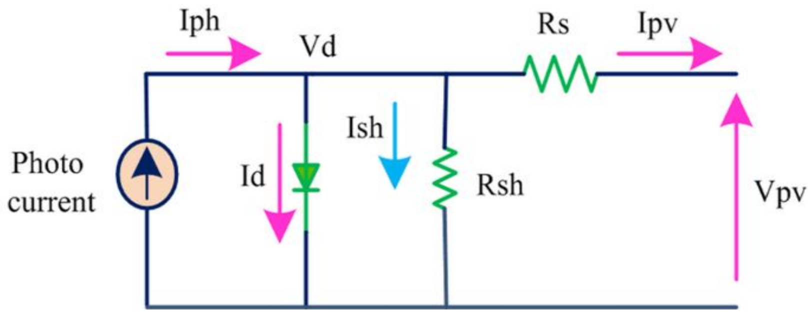

Figure. 3 Single-diode solar cell concept

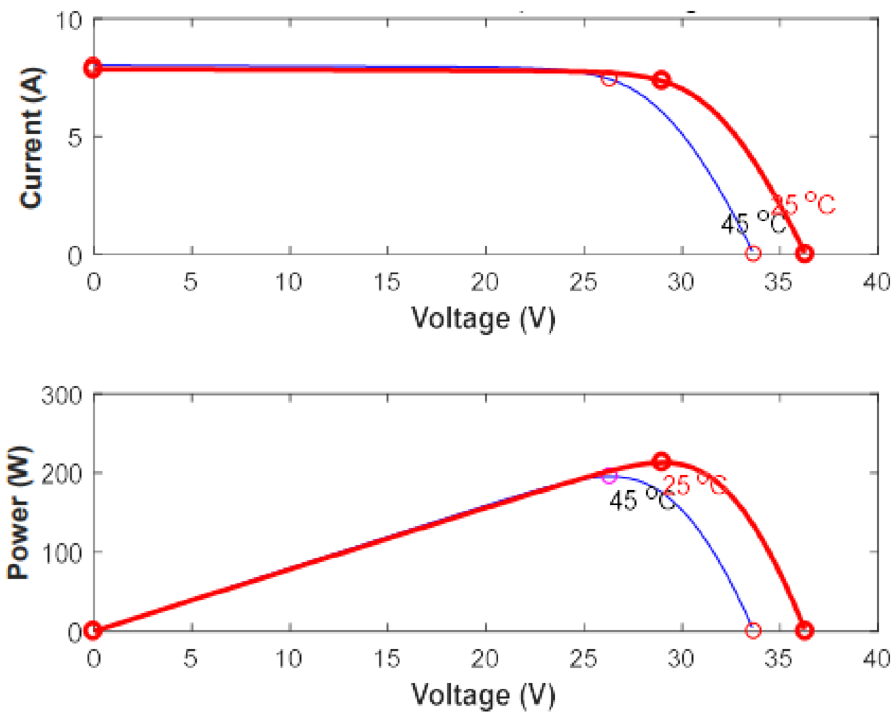

Figure. 4 Characteristics of Solar PV Cell: I-V and P-V Curves

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Table 1. PV module specifications

Parameters	Values
Maximum Power (W)	250.1234
Cells per module (N_{cell})	72
Open Circuit Voltage(V_{OC}), V	37.50
Short Circuit Current (I_{SC}),A	9.20
Voltage at Maximum Power Point (V_{MP}), V	30.40
Current at Maximum Power Point (I_{MP}),A	8.80

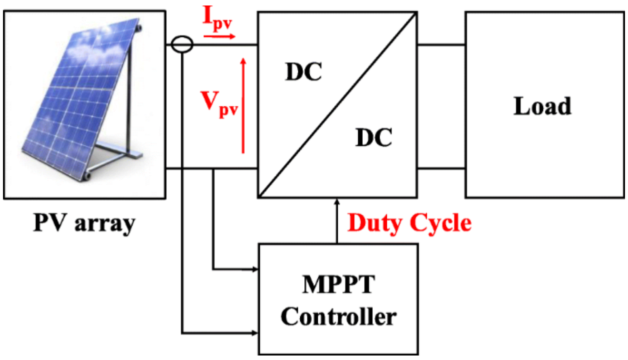

Figure. 5 Solar PV combined with a DC/DC Converter

3.2 DC/DC converter modeling

A DC-DC boost converter is used in the illustrated DC microgrid system to meet the particular need in which the output voltage created by the solar PV system is less than the standard DC-bus voltage. This converter efficiently raises the PV array's output voltage to match the voltage level of the common DC bus, ensuring seamless integration and distribution of the generated solar power within the microgrid. In the setup illustrated in Fig. 5, a DC/DC boost converter is interposed among the PV module and the DC/AC inverter. In this configuration, the circuit following the PV module can be viewed as the load.

The output voltage (V_{out}) in a switching circuit is determined by the input voltage (V_{in}) and the duty cycle (D) of the switching operation. The Eq. (3) describes the functioning of a solar PV system using a DC-DC boost converter.

$$V_{out} = \frac{V_{in}}{1-D} \tag{3}$$

The Perturb and Observe (P&O) approach is harnessed to regulate the duty cycle of the converter. This control mechanism allows for the adjustment of the voltage as well as current output of the converter, thereby facilitating the achievement of impedance matching. Consequently, when the internal resistance of the system equals the impedance of the equivalent circuit downstream from the PV module (Ri = RL), the PV module can function at its MPP.

This approach assures that the PV system runs at peak efficiency, optimizing power conversion and energy output. The P&O method involves a straightforward process of incrementally adjusting the reference voltage value or duty ratio of the converter and monitoring its impact on the power output from the system as shown in Fig. 6. If the power at the kth iteration (P(k)) exceeds that at the previous iteration (P(k-1)), the controller maintains the same direction of change; otherwise, it reverses the direction. This change is implemented by perturbation, and its consequences are observed. This iterative process is aptly named "perturb and observe" and serves as a means to enhance the PV array's efficiency and power output by continuously monitoring the MPP.

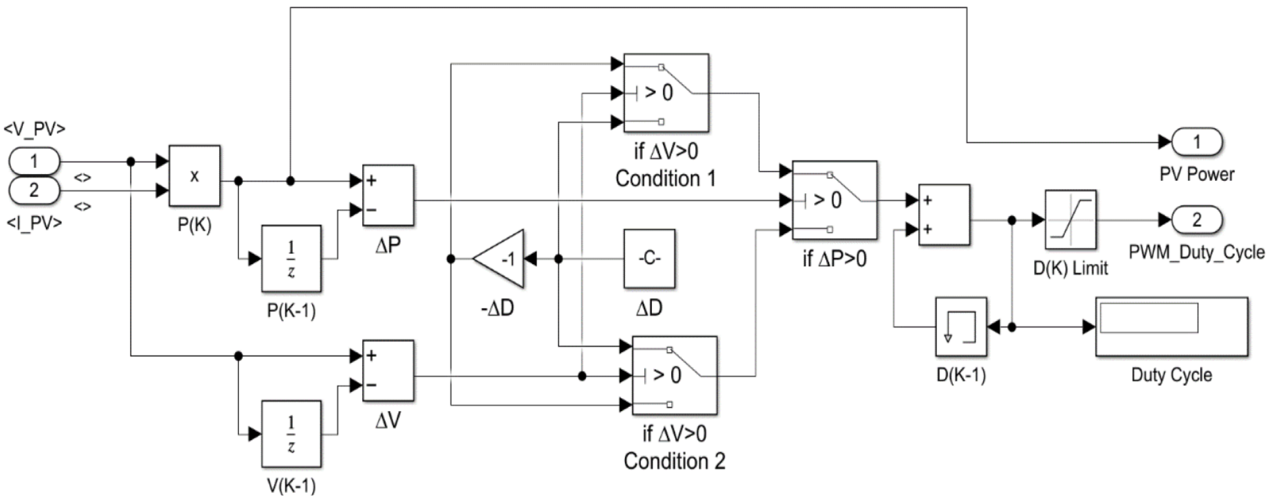

Figure. 6 MPPT P&O algorithm

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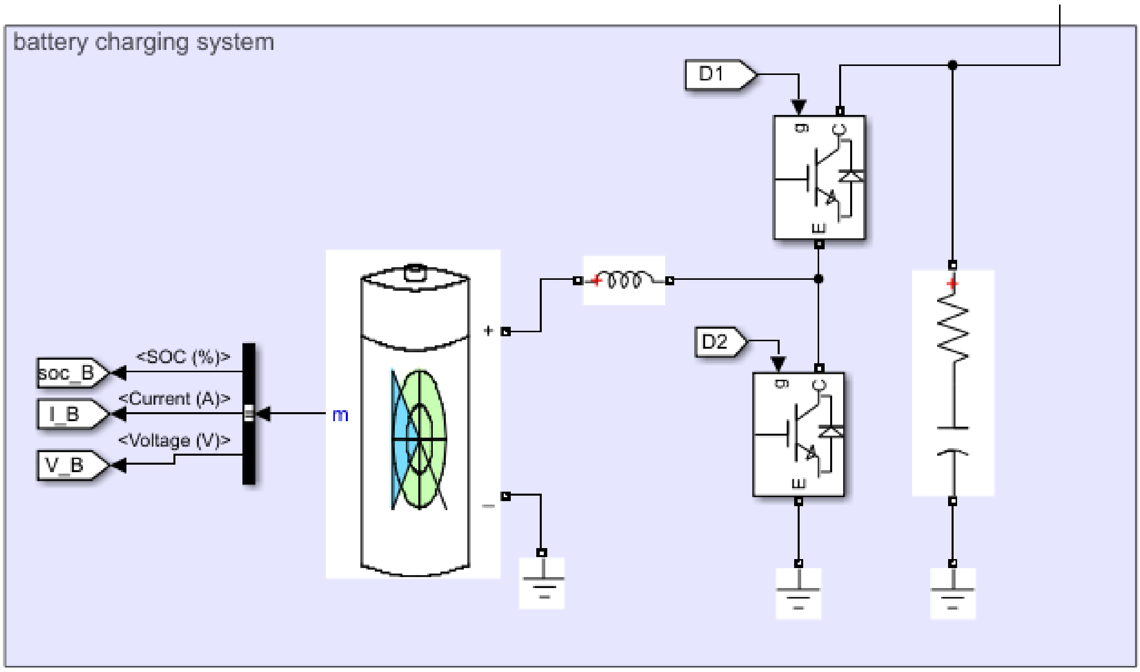

Figure. 7 Modelling of battery

The D of the converter continually adapts to accommodate variations in load conditions and source output, striving to align with the peak point of power until the maximum power output is achieved. This control scheme ensures that the PV system operates efficiently by continuously seeking the maximum power output while adapting to changing environmental conditions and load requirements.

3.3 Modelling the battery

In the domain of DC microgrids, BESSs assume a pivotal role by not only ensuring the steady maintenance of a consistent common-mode DC-bus voltage but also by compensating for both surplus and deficit energy. This function is particularly vital when dealing with the fluctuating nature of solar power output. The quantity of excess or inadequate energy in the microgrid is to be ascertained by the EMS. This energy surplus or deficit data from the EMS directs the management of switching control activities, guaranteeing the efficient maintenance of the DC microgrid's power balance. When controlling switching control operations for the DC-DC converter, it is vital to consider the state-of-charge (SoC) as the BESS's functioning, including charging and discharging, depends on whether there is an energy surplus or deficit. Consequently, the control strategy for the BESS must be meticulously planned, taking into consideration critical parameters such as the DC-bus voltage and the SoC, to guarantee the optimal performance and consistency of the DC MG.

Renewable energy resources are inherently intermittent in nature, and to mitigate the challenges posed by periods of low or non-existent sunlight, energy storage systems are considered integral components of the solution. The core of these power storage systems typically consists of a battery and a battery charging controller, as illustrated in Fig. 7. By coupling solar PV systems with energy storage, uncertainties surrounding the local availability of renewable energy sources can be significantly reduced. During instances of insufficient energy generation or high demand, the energy stored in the battery system can be harnessed to supply the required power, ensuring a more dependable and stable microgrid power system. It is worth noting that the performance and efficiency of the battery are sensitive to various factors, including environmental temperature, charge level, voltage influences, and the rate of charging and discharging.

Table 2. Battery Specifications

Parameters	Values
Internal Resistance	0.195 ohms
Volumetric Energy Density	210-260 Wh/L
Exponential Zone	230.237 V, 1.48 Ah
Fully Charged Voltage	225.782 V
Energy Capacity	8.100 Ah
Maximum Capacity	9.042 Ah
Discharging Current Range	60, 120 A
Nominal Discharge Current	148 A

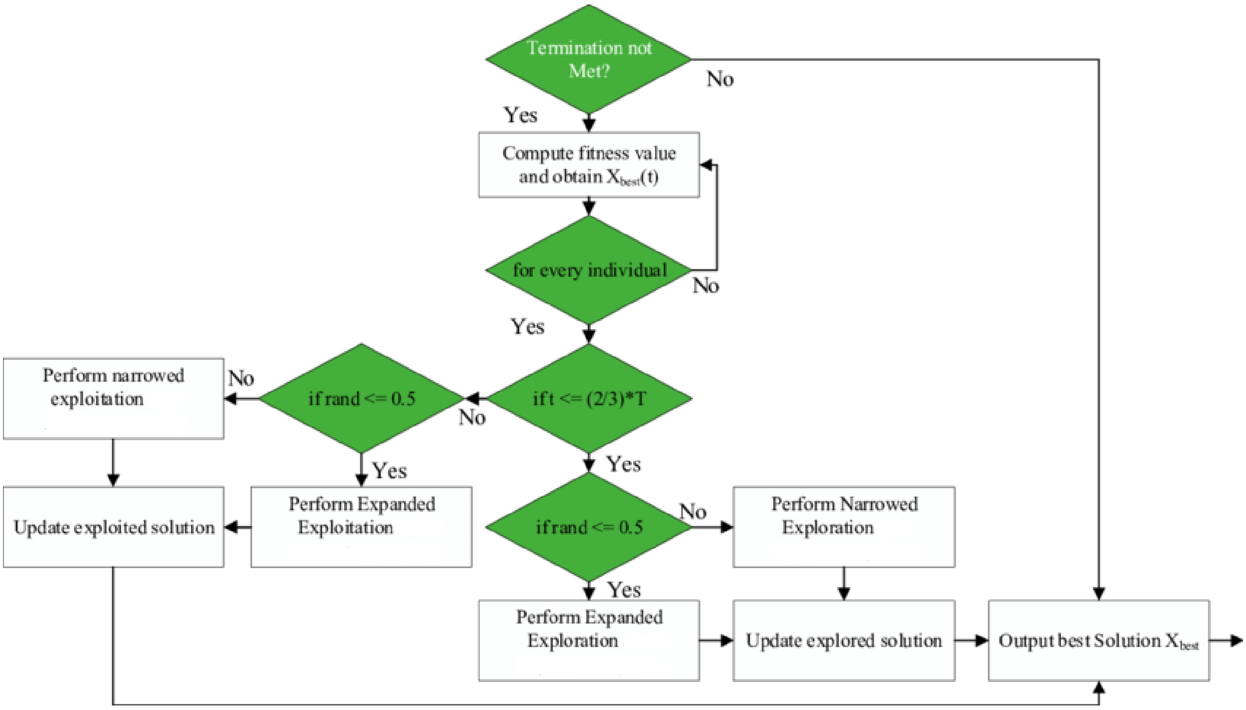

Figure. 8 Aquila Algorithm flowchart

The longevity of a battery is influenced by a set of parameters, and these parameters can have varying effects depending on the type of battery used. In the proposed study, lithium-ion batteries have been chosen due to their favorable attributes such as cost-effectiveness, durability, safety, and high efficiency when compared to other battery types. To ensure the durability of these batteries, it is imperative that they are not overcharged, as excessive charging can diminish their effectiveness and lead to a shortened lifespan. Similarly, over-discharging the battery is detrimental, as it can also result in a reduced lifespan. A key requirement for maintaining the battery's durability is to set its SoC to match its nominal capacity. Furthermore, it is essential to ensure that the battery's SoC does not fall below 30% at any given time.

When the DC microgrid is operating, the SoC of the BESS is constrained within defined limits, $SoC_{BES,max}$ and $SoC_{BES,min}$, which in turn restrict the charging and discharging currents of the BESS to fall within the allowable range, delineated by $i_{bs,max}$ and $i_{bs,min}$. These limitations are put in place to safeguard the BESS from potential over-charging or over-discharging, and they are succinctly described by the conditions outlined in Eqs. (4) and (5).

$$SoC_{BES,min} \leq SoC_{BES}(t) \leq SoC_{BES,max} \quad (4)$$

$$i_{bs,min} \leq i_{bs}(t) \leq i_{bs,max} \quad (5)$$

3.4 Proposed Aquila optimization algorithm

3.4.1 Inspiration and behavior

The Aquila hawk, a popular raptor in the Northern Hemisphere, exhibits remarkable adaptability and hunting skills. Similarly, in the realm of PV optimization for DC microgrid energy management, adaptability and efficiency are key goals. The Aquila's ability to swiftly switch between hunting techniques has inspired the development of innovative algorithms like the Aquila Optimizer (AOA) for optimizing PV systems in DC microgrids [28]. Just as the hawk employs various hunting techniques based on the circumstances, an effective PV system in a DC microgrid must adapt to changing environmental factors to maximize energy capture. The Aquila's adeptness at catching prey serves as an inspiration for developing an optimization algorithm that can swiftly and intelligently adjust the PV system's parameters for optimal energy utilization. By modeling and simulating these dynamic activities, the proposed algorithm aims to enhance the efficiency and adaptability of energy management in DC microgrids with PV arrays.

Aquila, employs four distinct approaches that it can swiftly switch between depending on the circumstances.

- Involves flying high and stooping vertically, is intended to be used for bird hunting. This tactic involves soaring high above the ground, followed by a rapid dive to capture prey.

- Involves contour flying combined with a brief glide, is the most commonly employed and is ideal for chasing ground-dwelling prey.
- Slow-down attack in low flight, suitable for targeting slower-moving prey that lacks an effective escape response.
- Involves walking and grabbing prey, often used to pull the young of large prey out of their hiding places.

These adaptive hunting techniques enable Aquila to effectively capture a wide range of prey in various situations. The proposed AO algorithm draws its primary inspiration from the above-mentioned hunting methods of the Aquila.

3.4.2 Initialization

In the AO, being a population-based optimization method, the optimization process commences with a population of potential solutions denoted as X, following the probabilistic generation method described in Eq. (6). These solutions are stochastically generated within the defined upper bound (UB) and lower bound (LB) constraints of the specific challenge at hand. The best solution achieved up to the current iteration is regarded as the approximate optimal solution. This population-driven approach underlines the quest for the best possible solution in each iteration, making AO an effective optimization technique.

$$X = \begin{bmatrix} x_{1,1} & \cdots & x_{1,j} & x_{1,Dim-1} & x_{1,Dim} \\ x_{2,1} & \cdots & x_{2,j} & \cdots & x_{2,Dim} \\ \cdots & \cdots & x_{i,j} & \cdots & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{N-1,1} & \cdots & x_{N,1-j} & \cdots & x_{N-1,Dim} \\ x_{N,1} & \cdots & x_{N,j} & x_{N,Dim-1} & x_{N,Dim} \end{bmatrix} \quad (6)$$

where X represents the collection of current candidate solutions, each of which is produced through a random process defined by Eq. (7). $X_i$corresponds to the decision scores or locations of the i-th solution within this set. Whereas Dim denotes the dimension size, N is the total number of potential solutions in the population.

$$X_{ij} = rand * \left(UB_j - LB_j\right) + LB_j \quad (7)$$

where i=1, 2…., Dim and term "rand" represents a randomly generated number.

3.4.3 Theoretical framework of AO

As previously mentioned, the AOA operates through four primary global steps. The shift among exploration and exploitation stages in the AO algorithm is determined based on the scenario "if $t \leq \left(\frac{2}{3}\right) \times T$," where exploration phases are initiated. Following this, the exploitation phases are executed. The fundamental mathematical model for these four main steps within the AO algorithm is presented as follows:

In the initial stage, Expanded exploration (X_1), the Aquila adeptly locates the prey's location and strategically selects the best hunting ground using a high soar followed by a vertical stoop. To replicate this behavior, the AO employs an extensive exploration approach, akin to the bird's high soar, to pinpoint the region within the search arena where the prey is likely located. This process is illustrated in Fig. 9, depicting the mathematical representation as expressed in Eq. (8). This method mimics the bird's systematic approach to identifying the ideal hunting zone in the search space.

$$X_1(t+1) = X_{best}(t) \cdot \left(1 - \frac{t}{T}\right) + (X_M(t) - X_{best}(t) \cdot rand) \quad (8)$$

X_1 (t+1) denotes the solution for the next generation produced by the initial search stepX_1. X_{best} (t) signifies the best solution achieved in the current generation. To guide the expanded exploration, the formula $\left(1 - \frac{t}{T}\right)$ is employed, where t represents the current generation, and T is the total number of generations. Additionally, X_M stands for the mean value of the location in the current solution of the i^{th} generation, computed using Eq. (9).

$$X_M(t) = \frac{1}{N}\sum_{i=1}^{N} X_i(t), \forall_j=1, 2\ldots, \text{Dim} \quad (9)$$

where the population size, or N, is the number of candidate solutions.

In the second phase, Narrowed exploration (X_2), also known as "contour flight with short glide attack," the Aquila, after spotting the prey from a higher altitude, engages in a circling maneuver above the intended target area as shown in Fig. 10. This technique involves a careful preparation and narrowing of focus before launching the attack. Mathematically, this behavior is represented by Eq. (10).

$$X_2(t+1) = X_{best}(t) \cdot \text{Levy(D)} + X_R(t) + (y - x) \cdot rand \quad (10)$$

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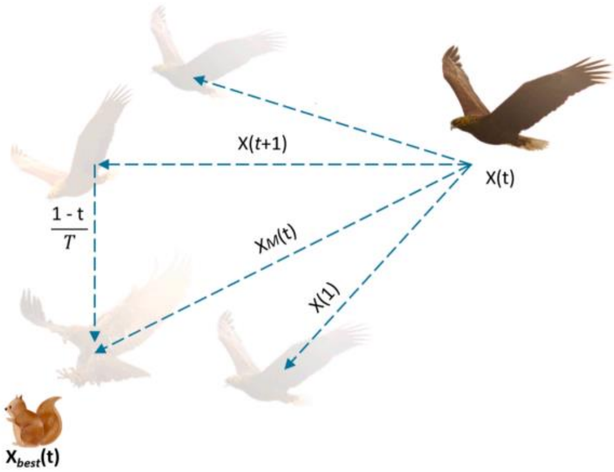

Figure. 9 The Aquila's vertical stoop and high soar behavior

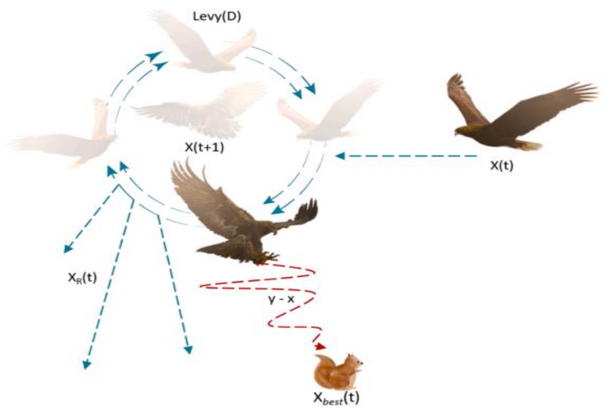

Figure. 10 Aquila's short glide attack characteristic during contour flight

Where $X_2(t+1)$ represents the solution in the next iteration (t + 1) produced by the second method (X_2). The variable D stands for the dimension space, while Levy(D) represents the "Levy flight distribution function". Additionally, $X_R(t)$ corresponds to a randomly selected solution within the range of [1, N] at the i^{th} iteration.

In the third hunting method, Expanded exploitation (X_3), the Aquila drops vertically, and attacks the victim in order to determine how it will react. This approach, is employed when the prey's location is exactly known. The Aquila utilizes this method to exploit the selected target area, gradually closing in on the prey for a calculated attack. This behavior is illustrated in Fig. 11 and is mathematically represented by Eq. (11).

$$X_3(t+1) = \left(X_{best}(t) - X_M(t)\right) \cdot \alpha - rand + \left((UB - LB) \cdot rand + LB\right) \cdot \delta \quad (11)$$

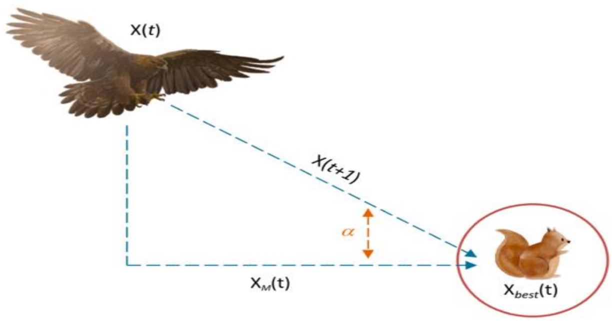

Figure. 11 Aquila's low-flying, slow-descending assault behavior

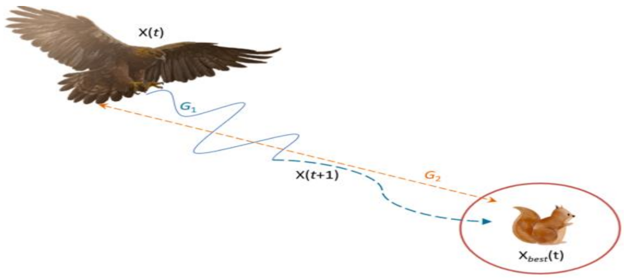

Figure. 12 Aquila's walk-and-grab method of hunting

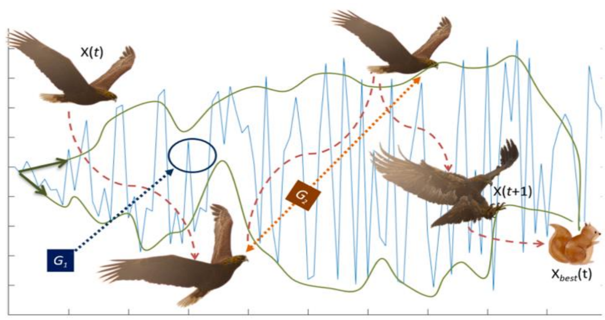

Figure. 13 The impact of the G1, G2, and QF on the AO's behavior

Where, $X_3(t+1)$ signifies the solution in the subsequent iteration produced by the third method (X_3). $X_{best}(t)$ indicates the best solution attained until the i^{th} iteration, which serves as an approximation of the prey's location. $X_M(t)$ represents the mean value of the current solution at the t^{th} iteration, determined using Eq. (9). The variable "rand" ranges from 0 to 1. Additionally, the parameters δ and α, which are set at a small value of 0.1, are exploitation adjustment parameters.

In the fourth hunting method, Narrowed exploitation (X_4), known as "walk and grab prey" (X4), involves the aquila approaching its target on land and engages in a pursuit that considers the unpredictable motions of the prey. This method involves a final attack by the Aquila, ensuring a successful capture. The way the Aquila behaves during this "walk and grab prey" method is illustrated in Fig. 12, and its mathematical representation is presented in Eq. (12).

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$$X_4(t+1) = QF \cdot X_{best}(t) - (G_1 \cdot X(t) \cdot rand) - G_2 \cdot levy(D) + rand \cdot G_1 \quad (12)$$

Where the result of the fourth search technique (X_4) is the solution for the subsequent iteration of t, denoted as $X_4(t+1)$. QF is computed using Eq. (13), and it is utilized to balance the search techniques.

$$QF(t) = t^{\frac{2*rand-1}{(1-T)^2}} \quad (13)$$

$$G_1 = 2 \cdot rand - 1 \quad (14)$$

$$G_2 = 2\left(1 - \frac{t}{T}\right) \quad (15)$$

In Fig. 13, the impact of the quality function (QF), as well as the parameters G1 and G2, on the behavior of the optimization algorithm (AO), is illustrated.

3.5 Problem formulation

This study's main goal is to improve energy management by effectively optimizing the deployment of PV panels in a DC microgrid that includes a battery storage system. The central focus revolves around determining the ideal locations and sizes of PV panels within the microgrid, leveraging the Aquila Algorithm for optimization. In the context of load flow simulation, PV panels are integrated as a source of power generation. The candidate buses for PV panel deployment encompass all system buses, except for the substation bus. The study formulates an objective function, akin to [27], where the locations and sizes of PV panels serve as control variables. The proposed algorithm seeks to identify the optimal values for these variables, ensuring the efficient utilization of PV resources. The selection of the most suitable PV panel configuration is driven by an objective function (OF), which aggregates weighted criteria aimed at maximizing the efficiency and effectiveness of PV energy generation in the DC microgrid.

3.5.1 Objective function (OF)

The objective function aims to optimize the utilization of PV panels in the DC micro grid while ensuring power balance and minimizing power losses. The objective function is formulated as follows:

OF=Maximize $\sum_{i=1}^{N} P_{PV_i}$
Subject to following constraints:
Power Balance Constraint:

$$\sum_{i=1}^{N} P_{PV_i} - P_{load} - P_{battery} = 0$$

Power Loss Minimization

$$P_{loss} = \sum_{i=1}^{N} P_{PV_i} - P_{load} - P_{battery}$$

Voltage Deviation Constraint

$\sum_{i=1}^{N} V_i$-$V_{ref} \leq \Delta V$

Where, N represents the quantity of PV panels used in the system, P_{PV_i} is the power output generated by a specific PV panel, i is the panel's index, P_{load} signifies the electrical power utilized by the load within the system, $P_{battery}$is the electric power supplied or discharged by the battery storage, V_i corresponds to the voltage measurement at the i^{th} bus or location in the micro grid, V_{ref} is the designated reference voltage level used as a benchmark, ΔV designates the acceptable voltage variation or deviation from the reference level.

4. Results and discussion

The efficiency of the suggested PV system optimization was validated through the utilization of the MATLAB/Simulink system model. The simulation was executed with specific settings to ensure accurate results. We conducted a comprehensive performance evaluation of our PV panel optimization strategy, meticulously examining how the system behaves under varying control approaches and different levels of PV power. As depicted in Fig. 14, a notable event occurs at t = 0.025 s when there is a rapid surge in the model's load, leading to a temporary imbalance within the micro grid. This, in turn, results in deviations in several critical parameters. However, through the application of the Aquila algorithm, our research effectively mitigated these imbalances and brought the system back to a stable state.

Our focus extended to ensuring equilibrium in key system aspects, and the outcomes depicted in Fig. 14 demonstrate the positive impact of our PV panel optimization, especially when considering critical variables like grid power, battery power, load power, and DC load. The Aquila algorithm's effectiveness is evident as it aids in maintaining these system variables within desirable ranges. Furthermore, the study delved into improving the overall performance of PV panels within the microgrid, making certain that they operate at their maximum efficiency and generate power effectively. By harnessing the Aquila algorithm, we aimed to enhance the system's operation by optimizing the placement and size of PV panels, thereby ensuring that the microgrid operates with increased efficiency and improved performance.

In the initial phase, the PV system commences its operation under an irradiance level of 1000 W/m². This condition is associated with a voltage reading of 320V and a current flow of 30A. Fig. 15 visually depicts the AC side voltage and current attributes influenced by our optimization approach using the Aquila algorithm. It strikingly demonstrates a substantial decrease in system oscillations, yielding a remarkably smoother performance profile. Notably, at t=0.025 seconds, a sudden increase in system fluctuation is observed. The algorithm ensures that the PV system operates with a higher degree of consistency and precision, minimizing discrepancies and fluctuations.

Fig. 16 illustrates the performance characteristics of DC link voltage, current, and power, showcasing the remarkable outcomes achieved through the implementation of our optimization technique. This study focuses on a PV system operating under conditions of 700 W/m^2 solar radiation, with an incoming solar power of 7.5 kW, while the anticipated PV output is set at 8 kW. The controlled power supply from the system is established at 10 kW. At the critical time point of t = 0.025 s, the PV generation experiences a decline due to a decrease in illumination, necessitating the microgrid to provide the remaining power required to fulfill the system's energy demands. This transition triggers fluctuations in the DC circuit's voltage levels while introducing minimal changes in other critical parameters, such as frequency.

An essential aspect of this scenario is the synergy of competitive power and solar system-generated power, which not only serves to maintain grid frequency within acceptable limits but also remarkably reduces the system's settling time. Also, it becomes evident that the system attains a remarkably swift settling time of merely 0.2 seconds, underscoring the efficiency of our proposed optimization technique. This outcome is a proof to the technique's effectiveness in ensuring that the PV system promptly and seamlessly adapts to variations in solar generation, ultimately enhancing the reliability and responsiveness of the DC microgrid.

4.1 Convergence study

A maximum iteration count of 100 was chosen to control the optimization process effectively. Furthermore, to minimize errors and enhance reliability, the simulation was run a maximum of 10 times. In this optimization process, the fitness function was designed to focus on attaining the maximum power point for the solar system, represented as a negative value. This unique representation simplifies the optimization process, given that the maximum power aligns with the minimum fitness function value. Initially, the simulation was executed under uniform irradiation conditions, with all three PV panels exposed to an insolation level of 1000 W/m^2.

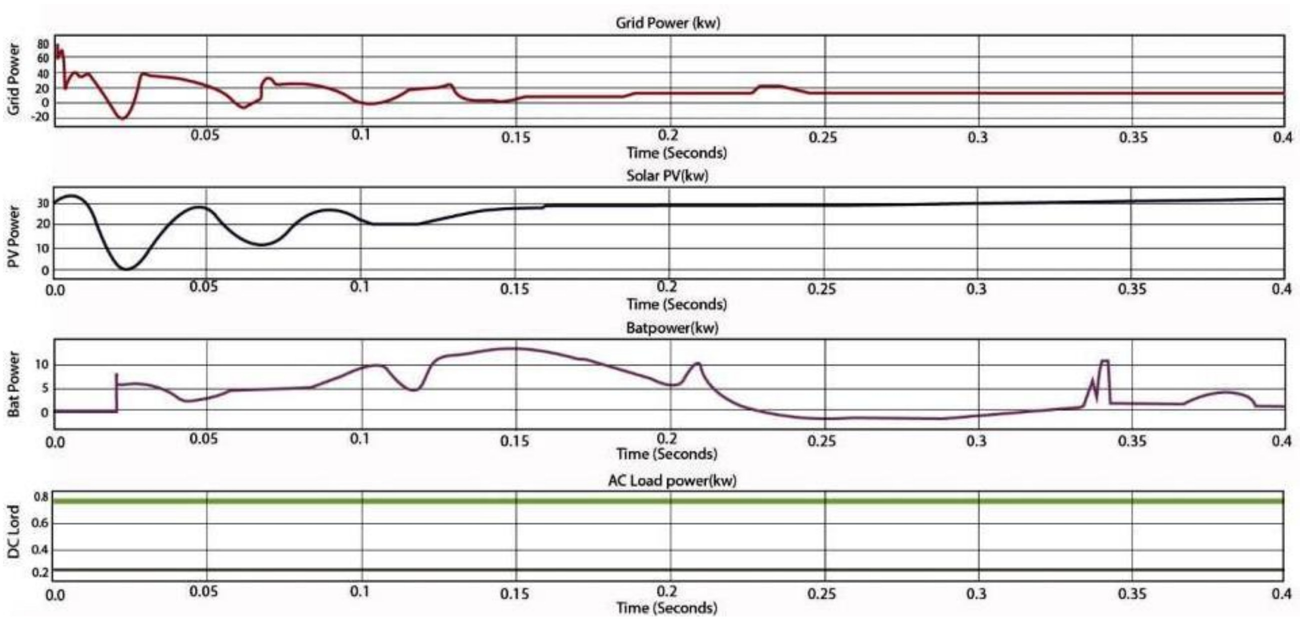

Figure. 14 Load Variation using Aquila Algorithm

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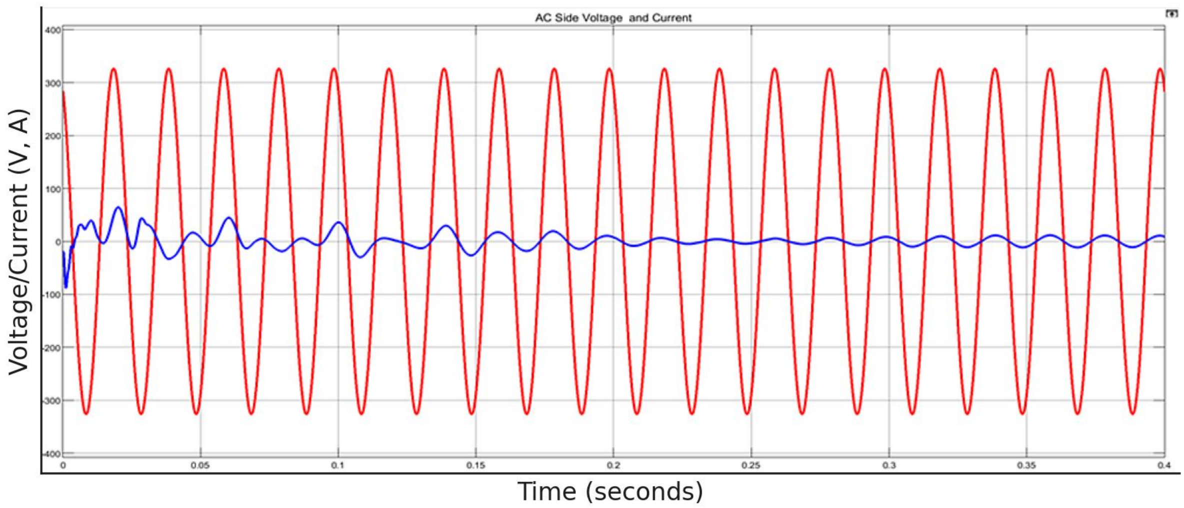

Figure. 15 AC side Voltage and current from PV battery system

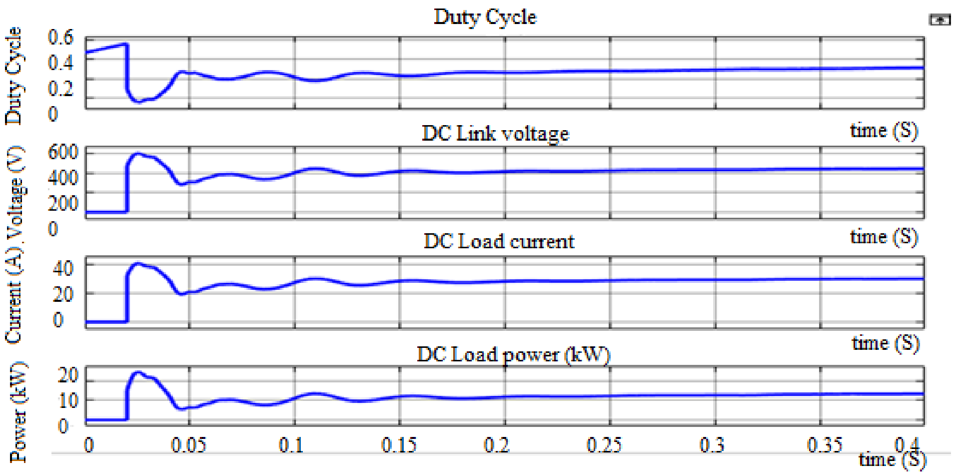

Figure. 16 DC link Voltage, current and power using Aquila Optimizer

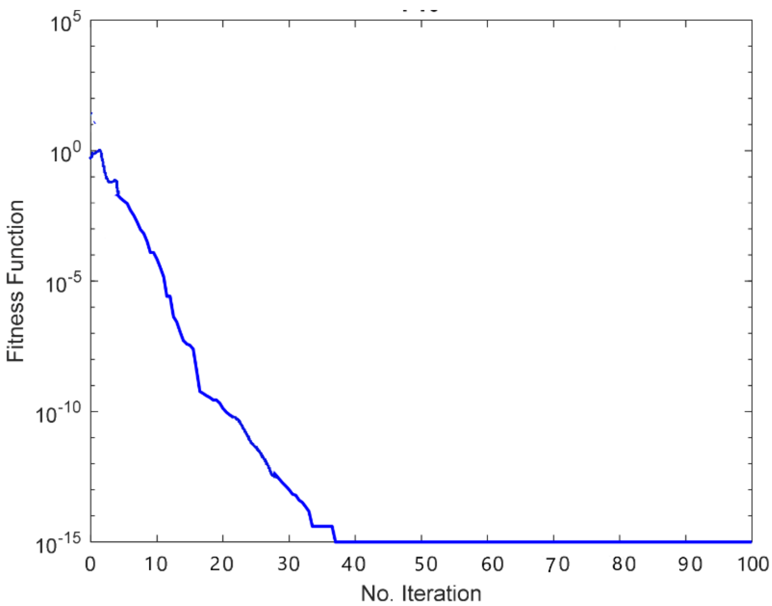

Figure. 17 Fitness function vs. iteration curve for Aquila optimizer

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Table 3. Performance Comparison of the proposed model with existing methods

Algorithm	Settling Time (s)	Voltage Fluctuations (V)	Power Loss (%)	Stability (%)	Response Time (s)	Oscillation Amplitude (V)
Particle Swarm Optimization (PSO)	0.5	±6	5	91	0.05	12
Genetic Algorithm (GA)	0.4	±5	4	93	0.045	10
Perturb and Observe (P&O)	0.8	±8	7	85	0.07	15
Incremental Conductance (IC)	0.6	±7	6	88	0.06	13
Artificial Bee Colony (ABC)	0.35	±4	3	95	0.03	8
Aquila Algorithm (Proposed)	**0.2**	**±2**	**2**	**98**	**0.025**	**5**

The optimization performance is effectively illustrated in Fig. 17, where we can observe the evolution of the best fitness value over time. It assesses how effectively the Aquila algorithm optimizes the PV panel configuration by examining the behavior of the fitness function over multiple iterations, ultimately ensuring that the DC microgrid operates at its peak efficiency. The optimized operation showcased in this study bodes well for the resilience and stability of PV systems within the DC microgrid, offering a promising solution for improved energy management and performance.

The Table 3 clearly illustrates the superiority of the proposed Aquila algorithm in optimizing photovoltaic (PV) systems within a DC microgrid across multiple performance metrics. The Aquila algorithm achieves a significantly faster settling time of 0.2 seconds, indicating its ability to stabilize the system more quickly compared to conventional methods like PSO (0.5 seconds) and P&O (0.8 seconds). This rapid response is crucial for adapting to sudden changes in solar irradiance or load conditions. Furthermore, the voltage fluctuations are minimized to just ±2V, showcasing better control over voltage stability, whereas traditional techniques like P&O exhibit greater fluctuations (±8V). The Aquila algorithm also demonstrates improved energy efficiency with only 2% power loss, compared to higher losses in PSO (5%) and P&O (7%), underscoring its ability to minimize energy wastage. In terms of system stability, the proposed model maintains 98% stability, outperforming other methods in managing grid and load power with minimal oscillations. Additionally, the response time to sudden load changes (0.025 seconds) and reduced oscillation amplitude (5V) highlight its superior transient handling capabilities. These factors collectively contribute to the overall enhanced performance and reliability of the Aquila algorithm in PV system optimization, making it a more effective solution for energy management in DC microgrids.

5. Conclusion

The proposed research focused on optimizing photovoltaic (PV) systems within a direct current (DC) microgrid, utilizing the Aquila algorithm to enhance energy management and performance. The methodology involved developing a MATLAB/Simulink model to simulate the PV system's behavior under various control approaches and solar irradiance levels, specifically starting from an initial condition of 1000 W/m². Performance evaluations demonstrated that the Aquila algorithm effectively mitigated load imbalances, particularly evident at t = 0.025 s when a sudden surge in load led to deviations in critical system parameters. Results indicated a significant improvement in system stability, with the algorithm maintaining grid power, battery power, load power, and DC load within desirable ranges. Additionally, the simulation illustrated a remarkable reduction in oscillations and fluctuations in AC side voltage and current, enhancing the overall operational efficiency of the PV panels. The study also achieved a swift settling time of just 0.2 seconds during conditions of fluctuating illumination, showcasing the ability of the optimization technique to adapt to changes in solar generation seamlessly. Overall, the findings substantiate the effectiveness of the Aquila algorithm in optimizing the configuration of PV systems, thus contributing to the advancement of reliable and sustainable energy solutions in DC microgrid applications.

NOTATIONS

I	Current produced by PV array
I_{ph}	Photo-generated current
I_0	Diode's reverse saturation current
q	Elementary charge
V	Voltage across PV array
n	Ideality factor
k	Boltzmann constant
T	Temperature (in Kelvin)
R_s	Series resistance
R_{sh}	Shunt resistance
V_{th}	Thermal voltage
V_{out}	Output voltage
V_{in}	Input voltage
D	Duty cycle
X_{ij}	Candidate solution
QF	Quality function
P_{pvi}	Power output of PV panel
P_{load}	Electrical power used by load
$P_{battery}$	Power supplied/discharged by battery
V_{ref}	Reference voltage
ΔV	Acceptable voltage variation
N	Total number of PV panels

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

The paper conceptualization, methodology, software, validation, formal analysis, investigation, resources, data curation, writing—original draft preparation, writing—review and editing, and visualization, have been done by 1st author. The paper conceptualization, methodology, data curation, supervision, and project administration have been done by 2nd author. The supervision and project administration, have been done by 3rd author.

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