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Optimal Sizing of Stand-Alone Photovoltaic Systems using Meerkat Optimization Algorithm: A Cost-Based Performance Assessment

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ABSTRACT

Stand-Alone Photovoltaic (SAPV) systems play a vital role in providing clean and reliable electricity for remote and off-grid communities where grid expansion is economically or technically unfeasible. Their economic feasibility and technical reliability, however, depend strongly on accurate component sizing and system configuration, which require advanced optimization techniques. In this study, the Meerkat Optimization Algorithm (MOA) is applied to optimize two SAPV configurations. System 1 integrates a photovoltaic array, battery storage, and a hybrid inverter, while System 2 consists of a photovoltaic array, battery storage, a solar inverter, and a charge controller. The optimization focuses on minimizing Life Cycle Cost (LCC) and Levelized Cost of Energy (LCOE), which are widely recognized as reliable indicators of long-term cost-effectiveness and financial viability. To validate the performance of MOA, its results are benchmarked against three well-established metaheuristic algorithms: Particle Swarm Optimization (PSO), Firefly Algorithm (FA), and Slime Mould Algorithm (SMA). Simulation results show that System 1 consistently achieves lower LCC and LCOE compared to System 2, primarily due to its reduced component count and simplified integration. Moreover, MOA demonstrates enhanced optimization performance by converging more rapidly and delivering more stable solutions across multiple independent runs. In contrast, PSO, FA, and SMA exhibit slower convergence and greater variability in outcomes. Importantly, the performance differences are statistically meaningful, as MOA achieved consistently lower mean values and smaller standard deviations. These findings highlight MOA as an effective and reliable optimization tool for SAPV systems and provide practical insights to support sustainable rural electrification planning.

1. Introduction

Access to reliable, affordable, and sustainable energy is widely recognized as a cornerstone of socio-economic development. Yet, according to the International Energy Agency (IEA), more than 675 million people worldwide still lack electricity, with the majority concentrated in rural and remote regions of sub-Saharan Africa and South Asia [1]. These communities often face severe developmental constraints due to the absence of modern energy services, including limitations in healthcare, education, and small-scale industries. Extending centralized grid infrastructure to such areas has proven economically and technically challenging, owing to factors such as low population density, difficult terrain, and high capital investment requirements [2]. Consequently, decentralized renewable energy solutions have become essential alternatives for bridging the global energy access gap.

Among renewable options, solar photovoltaic (PV) technology is particularly attractive because of its modular design, scalability, and rapidly declining costs. The International Renewable Energy Agency (IRENA) reported that the levelized cost of electricity (LCOE) for solar PV fell by over 80% between 2010 and 2020, making it one of the most cost-competitive energy sources globally [3]. Stand-alone photovoltaic (SAPV) systems, in particular, provide a practical solution for rural electrification, enabling households, schools, clinics, and businesses to gain access to clean and reliable electricity [4].

SAPV systems have been increasingly adopted in applications ranging from rural household electrification to water pumping, telecommunication towers, and emergency power supply [5], [6]. Their significance extends beyond energy provision: they contribute to environmental protection by reducing reliance on fossil fuels and mitigating greenhouse gas emissions. Replacing diesel generators with SAPV systems substantially reduces both operating costs and carbon dioxide emissions, directly supporting global commitments under the Paris Agreement and Sustainable Development Goals (SDGs), particularly SDG 7 (Affordable and Clean Energy) and SDG 13 [5], [7].

From an environmental perspective, several studies have quantified these benefits. A.Dolatabadi and B.Mohammadi-Ivatloo [6] applied a stochastic optimization model to a PV/diesel/storage hybrid system for maritime applications, showing significant fuel savings and emission reductions. Similarly, P.Z.Pedro and L.G.Juan [7] emphasized the importance of sensitivity analysis in PV/diesel/battery systems, demonstrating how design variations strongly influence sustainability outcomes. At a broader scale, O.Krishan and S.Suhag [8] confirmed that SAPV systems provide not only cleaner energy but also long-term cost savings for rural communities when compared to diesel-based systems.

The socio-economic impact of SAPV systems is equally important. By powering educational institutions, healthcare facilities, and small businesses, SAPV systems promote human development and economic growth in underserved regions [9]. Access to reliable electricity improves healthcare delivery, enables refrigeration for vaccines, supports lighting in schools and enhances communication infrastructure, directly contributing to improved quality of life [10].

Despite their advantages, SAPV systems face significant technical challenges in terms of sizing, performance, and reliability. Accurate component sizing is essential to balance cost-effectiveness with long-term operational sustainability. Undersized systems fail to meet energy demand reliably, while oversized systems impose unnecessary capital costs [11].

PV modules, the primary energy-generating components, are particularly sensitive to environmental conditions such as temperature, shading, and dust accumulation. High ambient temperatures reduce conversion efficiency through thermal losses, while partial shading and soiling can reduce output by as much as 30% [12]. Moreover, PV modules undergo gradual degradation of 0.5%–1% annually, reducing their energy yield and increasing replacement costs over time [13].

Battery storage is another critical element of SAPV systems, ensuring energy supply during periods without sunlight. However, batteries are highly susceptible to degradation due to deep discharges, temperature extremes, and overcharging, resulting in shortened lifespans and higher replacement costs [8], [14]. Inverters, which convert DC power into AC electricity, typically operate for only 5–10 years, substantially shorter than PV modules and batteries. Their performance also declines under partial load conditions, further reducing system efficiency [15]. Charge controllers, meanwhile, regulate power flows but are prone to mismatches when poorly sized, reducing reliability and contributing to component stress [16]. Hybrid inverters, while reducing component count by integrating multiple functions, often suffer from higher operational stress, leading to shorter lifespans and costly failures [17-18]. These component-related challenges underscore the importance of performance optimization methods that can ensure SAPV systems achieve both cost-effectiveness and reliability.

Historically, deterministic sizing methods based on rules of thumb and empirical formulas were used in SAPV system design. While simple, these methods often ignored stochastic variations in solar irradiance and load demand, leading to suboptimal designs [11], [19]. Analytical methods, which rely on average daily energy balance equations, provide a more structured framework but still fail to capture hourly and seasonal variations in demand and resource availability [20-21].

Simulation tools such as HOMER Pro, TRNSYS, and PVsyst have since become widely used for SAPV system design [15], [22]. HOMER has been particularly effective in techno-economic optimization, TRNSYS in time-dependent simulations, and PVsyst in PV module performance analysis [23-24]. However, while useful, these tools rely heavily on predefined search spaces and require intensive computation, making them less suitable for identifying globally optimal solutions in large, complex design problems [15].

To overcome these limitations, metaheuristic algorithms have been widely adopted for renewable energy system optimization. These nature-inspired methods are well-suited to solving nonlinear, constrained, and multi-objective optimization problems. Early applications of metaheuristics in SAPV sizing employed Genetic Algorithms (GA), Particle Swarm Optimization (PSO) and Firefly Algorithm (FA) [26-27]. More recent studies have introduced advanced bio-inspired techniques such as the Aquila Optimizer and Jellyfish Search Algorithm for renewable hybrid systems, achieving higher convergence stability and reduced computational cost, [28-30].

Hanta et al. [10] applied Cat Swarm Optimization (CSO) for SAPV sizing, demonstrating improved reliability and reduced Loss of Power Supply Probability (LPSP). M.Jamshidi and A.Askarzadeh [18] conducted a techno-economic feasibility study of off-grid PV/fuel cell/diesel systems, finding that hybrid metaheuristic frameworks outperform single-algorithm approaches in terms of cost and reliability. Similarly, A.Alsharif et al. [31] compared Cuckoo Search with other heuristics for PV–wind–battery optimization, reporting faster convergence and reduced costs. J.Zhao and Z.M.Gao [32] introduced a hybridized Harris Hawks Optimization and Slime Mould Algorithm (HHO-SMA) that achieved improved convergence stability. Building on this, Güven and Yörükeren [33] conducted a comparative study on hybrid GA–PSO for stand-alone hybrid energy systems and found that the hybrid algorithm provided better cost efficiency and system reliability compared to single-algorithm approaches. Xu et al. [34] proposed a hybrid Differential Evolution–Particle Swarm Optimization (DE–PSO) with dynamic adaptive strategies, successfully preventing premature convergence and improving stability across benchmark optimization problems. Likewise, Fathi et al. [35] carried out a comparative analysis of Differential Evolution, PSO, Arithmetic Optimization Algorithm (AOA), and Henry Gas Solubility Optimization (HGSO) for photovoltaic parameter estimation, concluding that DE achieved the highest accuracy with the fastest convergence speed. These recent contributions reinforce the importance of benchmarking emerging algorithms such as MOA against both classical and modern metaheuristics to ensure robust and context-specific optimization outcomes in SAPV system design.

Although PSO, FA, and SMA are widely used swarm algorithms, each suffers from inherent limitations. PSO relies heavily on velocity and position updates, which can cause premature convergence and stagnation in local optima [36-37]. FA uses attractiveness and light intensity to guide solutions, but diversity decreases as the population converges [38]. SMA employs oscillatory search patterns, which enhance exploration but still risk local entrapment in high-dimensional problems [39].

Nevertheless, PSO, FA, and SMA remain highly relevant benchmarks because they represent three generations of swarm-based optimization: PSO as a classical algorithm with extensive applications in renewable energy, FA as an algorithm designed for multimodal optimization, and SMA as a recent bio-inspired algorithm that has demonstrated strong convergence stability. Their inclusion in comparative studies ensures that new algorithms such as MOA are evaluated against diverse and representative approaches.

The Meerkat Optimization Algorithm (MOA), introduced by Al-Mahdi et al. [40], presents a novel bio-inspired metaheuristic that incorporates unique mechanisms to address the limitations of classical swarm algorithms. The sentry strategy adaptively balances exploration and exploitation based on environmental vigilance, the emergency response mechanism enables the algorithm to escape local minima, and Levy flights provide long-range randomization for improved global search [40]. Recent applications of MOA have shown superior performance in engineering design, scheduling, and energy optimization problems [41-42]. Moreover, 2024–2025 studies have demonstrated continued progress in swarm intelligence for renewable energy, including Enhanced Honey Badger and Hybrid Slime Mould–Harris Hawks algorithms, both yielding improved balance between exploration and exploitation [32,43-44].

Compared with PSO, FA, and SMA, MOA offers mechanisms that explicitly maintain population diversity and convergence stability, potentially reducing the risk of premature convergence. However, its performance in renewable energy optimization, and specifically in SAPV system sizing, remains underexplored. Despite growing interest in metaheuristics for renewable energy, few studies have directly benchmarked MOA against PSO, FA, and SMA in SAPV system optimization. Most MOA studies have been limited to general engineering applications or hybrid renewable systems, leaving a gap in stand-alone PV system research.

This study addresses the gap by applying MOA to optimize two SAPV system configurations: one with a hybrid inverter and another with separate inverters and charge controllers. By benchmarking MOA against PSO, FA, and SMA, this study aims to evaluate whether MOA's unique mechanisms translate into meaningful performance advantages. The contributions of this work are threefold. First, it provides one of the earliest comparative evaluations of MOA in SAPV design. Second, it analyzes the trade-offs between hybrid and modular system architectures in terms of cost-effectiveness and reliability. Third, it advances methodological knowledge in renewable energy optimization by demonstrating how MOA achieves statistically meaningful improvements in convergence stability and cost optimization under real-world solar irradiance and load conditions.

2. Methodology

This study focuses on the optimal sizing of Stand-Alone Photovoltaic (SAPV) systems tailored for rural educational facilities, using a case study of a school located in Pos Musoh, Perak, Malaysia. Several researchers have investigated the design and optimization of SAPV systems in rural and off-grid settings. For example, A. Mahmud [45] analyzed the load characteristics of rural schools in Malaysia and proposed component sizing methods that reflect typical energy consumption patterns. Similarly, A. Alsharif et al. [31] emphasized the importance of tailoring SAPV configurations to match daily usage cycles, including educational facility loads and seasonal variations. The modeling of SAPV systems has been widely studied in the context of cost reduction and energy reliability. System configurations that integrate hybrid inverters have been found to reduce capital costs by minimizing the number of discrete components, as shown in studies focusing on inverter-controller integration [46-47].

Component configuration plays a critical role in determining the efficiency, reliability, and cost-effectiveness of SAPV systems. A system that combines a PV array, battery, and hybrid inverter, which is referred to as System 1 in this study, is often preferred because it offers simplified wiring, shorter installation time and lower maintenance requirements [42]. In comparison, System 2 uses separate devices for the inverter and charge controller functions. This configuration may be more suitable for implementing site-specific control strategies and for allowing phased expansions, although it typically involves a higher initial cost [48].

Numerous studies have confirmed the relevance of optimization algorithms and component modeling in achieving reliable and economical off-grid energy systems [8], [9]. These works underscore the importance of using accurate environmental data, practical component datasets, and cost-based objective functions (such as Life Cycle Cost (LCC) and Levelized Cost of Electricity (LCOE)) to inform the design of systems intended for remote deployment. The integration of simulation with optimization frameworks provides a structured approach to solving complex sizing problems in renewable energy applications.

2.1 Site and system configuration

This study focuses on a school located in the rural area of Pos Musoh, Perak, Malaysia. The load profile was directly obtained from on-site measurements of the school's energy consumption, rather than from assumed or generic load models. The data reflect the actual energy requirements of six classrooms, five laboratories, a canteen, an administrative office, restrooms, and a prayer room (surau). As expected, the load demand exhibited significant variation between school days and public holidays. Hourly solar irradiation (in kWh/m^2) data were collected for the same location at latitude 4°15′55.2″N and longitude 101°24′12.1″E [42]. As shown in Fig. 1, the annual load profile represents the measured variation in energy demand throughout the year, while Fig. 2 illustrates the hourly solar irradiation data recorded over 8,760 hours.

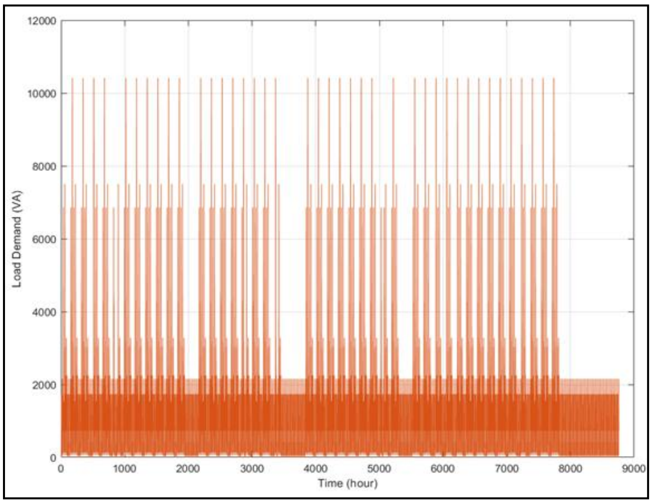


Fig. 1 Load profile during a year (8760 h).

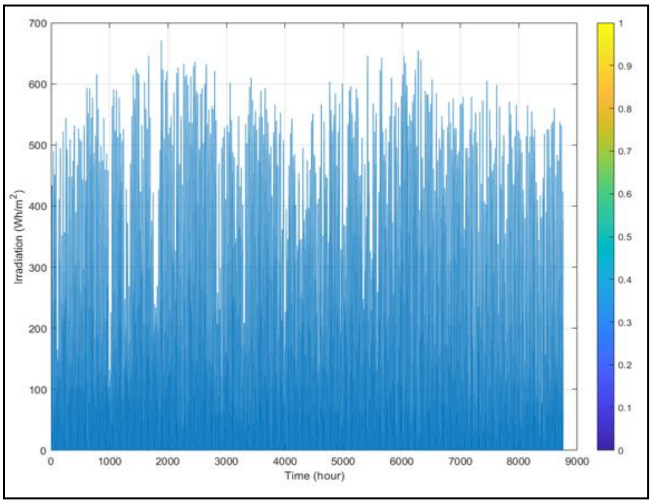


Fig. 2 Solar irradiation profile during a year (8760 h).

Table 1 Average daily solar irradiation for Pos Musoh, Perak [42].

Month	Jan	Feb	Mac	April	May	June	July	August	Sept	Oct	Nov	Dec
Irradiation, G (kWh/m^2)	4.05	4.59	4.32	4.3	4.08	4.18	4.02	3.52	3.34	3.3	3.15	3.3

According to Table 1, the monthly average daily peak sun hours (PSH) in Pos Musoh were calculated using historical data from January 1984 to December 2013. These values are subsequently utilized in the system sizing process to ensure realistic solar resource estimation.

Two configurations of Stand-Alone Photovoltaic (SAPV) systems were designed for comparison. The first configuration, referred to as System 1, consists of a photovoltaic (PV) array, battery storage, and a hybrid inverter. The second configuration, referred to as System 2, includes a PV array, battery storage, charge controller, and a solar inverter. Each component in the database was assigned an integer code according to its index position.

Consequently, System 1 resulted in 10 × 10 × 10 = 1,000 possible component combinations, while System 2 produced 10 × 10 × 10 × 10 = 10,000 combinations. These models were selected from commercially available products to capture realistic variations in cost, efficiency and operational performance. The MOA was used to determine the optimal combination of components by evaluating their performance based on life cycle cost (LCC, unit: RM) and levelized cost of energy (LCOE, unit: RM/kWh).

2.2 System Modelling

In this study, the Stand-Alone Photovoltaic (SAPV) system is modeled using a components-based energy flow approach that accounts for hourly solar irradiance, load demand and system efficiency parameters. The energy output from photovoltaic (PV) array in the *n*th hour, $E_{PV}(n)$ is computed using [49] the following equation:

$$E_{PV}(n) = P_{array\_stc} \times PSH(n) \times f_{temp}(n) \times \ldots \\ f_{mm} \times f_{dirt} \times \eta_{cable} \times \eta_{inv} \times \eta_{cc} \times \eta_{batt} \quad (1)$$

where P_{array_stc} is the rated power output of the PV array under Standard Test Conditions (STC) in watts, *PSH(n)* is the peak sun hour in hours, f_{mm} is the reduction factor due to mismatch of power on PV modules, f_{dirt} represents the factor of dust and dirt accumulation on PV modules, η_{cable} is the efficiency of cabling set as 95%, η_{cc} is efficiency of charge controller, η_{batt} is the efficiency of battery and $f_{temp}(n)$ is the derating factor.

The operation of battery storage is determined by the energy generated by the PV system, $E_{PV}(n)$ and the AC demand from the load, $E_{load}(n)$. When $E_{load}(n) < E_{PV}(n)$, the battery operates in charging mode and continues to charge until it reaches its maximum kWh capacity. Conversely, the battery operates in discharging mode when the energy generated by the PV system is insufficient to meet the load demand, $E_{PV}(n) > E_{load}(n)$. The battery storage capacity in kWh at the *nth* hour for both charging and discharging modes is formulated based on the system configuration illustrated in Fig. 1 and Fig. 2. The equations for battery capacity in these modes are as follows:

Charging mode:

$$E_{battcharge}(n) = E_{batt}(n-1)(1-\sigma) \ldots \\ + \left(E_{PV}(n) - \frac{E_{load}(n)}{\eta_{inv}}\right)\eta_{batt} \quad (2)$$

Where $E_{batt}(n\text{-}1)$ is the previous amount of the battery capacity in kWh, σ is the battery self-discharge rate.

Discharging mode:

$$E_{\mathrm{battdischarge}}(n) = E_{\mathrm{batt}}(n-1)(1-\sigma).. \\ -\left(\frac{E_{\mathrm{load}}(n)}{\eta_{inv}} - E_{PV}(n)\right)\eta_{batt} \quad (3)$$

The sizing process is based on the methodology outlined in [36], which integrates energy balance constraints and design rules for system components. These principles are applied within the objective function during the optimization. While specific equations are not presented in this paper, the method ensures that all components are compatible in terms of voltage, current, and power requirements.

2.3 Performance Indicators

In this study, two key performance indicators are adopted for the evaluation and optimization of stand-alone photovoltaic (SAPV) systems: the Life Cycle Cost (LCC), expressed in Malaysian Ringgit (RM) and the Levelized Cost of Electricity (LCOE), expressed in RM per kilowatt-hour (RM/kWh). These metrics are selected due to their ability to reflect both economic and technical aspects of system performance across the system's lifetime. Each indicator is optimized independently to provide insights into trade-offs between cost-efficiency and long-term energy generation.

The Life Cycle Cost (LCC) represents the total expenditure incurred by the system owner throughout the operational lifetime of the SAPV system. This user-focused approach accounts for all direct costs borne during system ownership and use, making it especially relevant in evaluating decentralized renewable energy applications [50-52]. The LCC includes three main cost components: the initial capital cost (C_{ini}); the present value of the replacement cost (C_{rep}) and the present value of the operation and maintenance cost ($C_{o\&m}$). It is expressed as [23,53-54],

$$LCC = C_{ini} + C_{rep} + C_{O\&M} \quad (4)$$

The initial capital cost, C_{ini} comprises the total upfront investment required to procure and install all major system components. This includes photovoltaic modules, battery banks, inverters (whether hybrid or conventional), charge controllers, as well as installation labor and commissioning services [30]. Depending on the system configuration (e.g., System 1 using hybrid inverters or System 2 with modular inverters and controllers), this cost can vary significantly. The replacement cost C_{rep} accounts for components with limited operational life spans that must be replaced periodically. For instance, battery banks typically require replacement every 5 to 10 years depending on usage depth and temperature exposure, while inverters often have a service life of 10–15 years [44]. The present value of these future costs is computed using a discount rate, acknowledging the time value of money over a 25–30 years project horizon. Operation and maintenance costs $C_{O\&M}$ cover annual inspections, system performance monitoring, preventive maintenance, and potential corrective actions. These costs are often underestimated in design but can significantly affect long-term affordability, especially in remote or harsh environments where technician access and spare parts availability may be constrained [39,55-56]. Studies have shown that for small-scale PV systems, O&M costs can represent 1–2% of the initial capital expenditure annually [48].

The second performance indicator is the Levelized Cost of Electricity (*LCOE*), which expresses the average cost per kilowatt-hour (kWh) of electricity generated over the system's operational lifetime. It integrates both economic and energy production data to evaluate long-term cost-effectiveness. The *LCOE* is calculated as [57-58] :

$$LCOE = \frac{LCC}{\sum_{n=1}^{t}(EPV(1-n)^t)} \quad (5)$$

where *t* is the project lifetime in year.

LCOE is particularly useful for policymakers, energy planners, and system designers, as it standardizes costs across different energy technologies. For SAPV systems, it reflects not only investment efficiency but also the reliability and consistency of electricity production. Factors influencing LCOE include component efficiency, system sizing, geographical irradiance conditions, and system losses due to soiling, shading, or temperature [59-61]. An effective LCOE analysis also requires accurate estimation of energy yield. In this study, the PV energy output is computed hourly using site-specific irradiance and temperature data, factoring in thermal derating, module mismatch losses, inverter efficiency, cable losses, and battery round-trip efficiency. Moreover, the application of a degradation factor (typically 0.5–1% annually) simulates real-world PV performance over time [62].

Combining LCC and LCOE as dual performance indicators provides a balanced and comprehensive framework for assessing SAPV system viability. While LCC is more sensitive to financial parameters and replacement schedules, LCOE emphasizes energy generation sustainability and operational effectiveness. This dual approach enables decision-makers to identify configurations that not only minimize total ownership cost but also deliver cost-effective electricity generation throughout the system lifespan.

2.4 Meerkat Optimizer Algorithm (MOA)

The Meerkat Optimization Algorithm (MOA) is inspired by the behavior of meerkats, small diurnal mammals that are found in desert environments. Their unique behavioral patterns, such as hunting in groups, standing guard as sentinels and responding to predators, have been modeled to create an optimization algorithm. The key behavioral strategies of meerkats, which mimic the search, vigilance and defensive behaviors, are utilized in the MOA to guide optimization processes [40]. The main components of the algorithm are outlined below.

Step 1: Input Initialization

Load the component specifications, including models of PV modules, batteries, hybrid inverter, inverters and charge controllers. Solar irradiance data and hourly load demand profiles are also imported as part of the simulation inputs. These datasets define the system’s operating environment and boundary constraints. The decision variables differ depending on the system configuration:

1. For System 1 (PV-battery-hybrid inverter):
   - x_1: PV model
   - x_2: Battery model
   - x_3: Hybrid inverter model
2. For System 2 (PV-battery-charge controller-solar inverter):
   - x_1: PV model
   - x_2: Battery model
   - x_3: Charge controller model
   - x_4: Solar inverter model

Each candidate solution (meerkat agent) in the population encodes one unique combination of the above decision variables, depending on the system being optimized. Similar representations are common in other population-based metaheuristics, where each agent holds a distinct configuration for system-level evaluation [41].

Step 2: Objective Function Formulation

Case 1: Optimize LCC

Case 2: Optimize LCOE

Step 3: Population Initialization

A population of meerkat agents is randomly initialized, where each agent represents a different combination of system components. Initialization parameters include the population size (P), *scaling* factor (for movement adaptation), and the *sentry* probability (which controls behavioral switching between exploration and exploitation modes).

Step 4: Fitness Function Evaluation

Each meerkat agent is evaluated based on an objective function that quantifies system performance. In this study, two optimization cases are considered: (1) minimizing the Life Cycle Cost (LCC), and (2) minimizing the Levelized Cost of Electricity (LCOE). For the LCOE-based case, each agent's fitness corresponds directly to its computed LCOE value, which reflects the economic efficiency of the system over its lifetime. The agent with the lowest fitness score (i.e., the minimum LCOE or LCC, depending on the case) is recorded as the global best solution in that iteration.

Step 5: Meerkat Movement and Exploration

The core of MOA is executed [40]:

- Group coordination is applied to direct agents toward superior solutions based on social learning and position updates.
- Emergency response behavior is triggered to escape poor-performing areas when threats (e.g., infeasible or stagnant solutions) are detected.
- Levy flight mechanism introduces randomness for escaping local optima and improving global search.

Step 6: Boundary Control

Each updated position is verified to ensure it lies within allowable bounds for each component. Boundary correction is applied to restore feasibility for out-of-bound solutions.

Step 7: Convergence Criteria

The algorithm checks whether convergence has been achieved by monitoring population diversity or reaching the maximum number of iterations.

Step 8: Best Solution Extraction

The solution with the best fitness value based on the optimize LCC/LCOE is stored as the final optimal configuration.

2.5 Benchmark Algorithms for Comparison

To assess the effectiveness of the Meerkat Optimization Algorithm (MOA), this study conducts a comparative analysis with three well-established metaheuristic algorithms: Particle Swarm Optimization (PSO), Firefly Algorithm (FA) and Slime Mould Algorithm (SMA). All four algorithms were applied to both System 1 and System 2 configurations and the parameter settings for each are summarized in Table 2 [42]. For the MOA, the tuning involves three key parameters: the probability factor, *P* = 0.1, , the sentry value, sentry = 0.5 and the scale factor, scale = 0.3. The probability factor determines the chance of performing a local exploitation step, while the sentry value balances exploration by mimicking the behavior of sentry meerkats that scan for optimal zones. The scale parameter adjusts the step size during solution updates, controlling convergence speed. In the case of PSO, the acceleration coefficients, C1 = 0 and C2 = 2 were used, consistent with prior studies [40]. These parameters govern how much influence a particle’s personal best and the global best have on its velocity update.

Table 2 The parameter set of algorithms.

Algorithms	Parameters
MOA	P = 0.1, sentry = 0.5, scale = 0.3
PSO	C1 = 0, C2 = 2[40]
SMA	Z = 0.03 [44]
FA	α = 0.5, β = 1, γ = 1 [44]

In this configuration, the algorithm emphasizes global exploration while suppressing local search. The SMA was configured with Z = 0.03, where Z is a dynamic weight parameter that simulates the oscillatory movement of slime mould toward food sources [44]. This parameter controls the adaptive behaviour of the search agents, helping the algorithm switch between exploration and exploitation modes. Finally, the FA was tuned with three parameters: α = 0.5, β = 1 and γ = 1 [44]. Here, α (alpha) represents the strength of random movement, β (beta) governs the attractiveness between fireflies and γ (gamma) controls the rate at which attractiveness decreases with increasing distance. These parameters collectively guide fireflies toward brighter and more optimal regions in the solution space. By adopting these parameter settings, each algorithm was ensured to operate under standard and literature-supported configurations, allowing for a fair and rigorous performance comparison across the two system configurations.

3. Result and discussion

This section presents the optimization results for sizing the Stand-Alone Photovoltaic (SAPV) system using the Meerkat Optimization Algorithm (MOA) and compares its performance with three other metaheuristic algorithms: Particle Swarm Optimization (PSO), Firefly Algorithm (FA), and Slime Mould Algorithm (SMA). The evaluation focuses on two critical performance metrics, namely Life Cycle Cost (LCC) and Levelized Cost of Electricity (LCOE), to determine the overall cost-effectiveness and energy performance of two distinct SAPV system configurations, referred to as System 1 and System 2.

3.1 Optimization Result Based on LCC

Table 3 illustrates the optimization outcomes for both System 1 and System 2 when the objective is to minimize the Life Cycle Cost (LCC). These results were obtained using MOA under consistent simulation parameters. In both configurations, the optimal PV module (code 4) and battery (code 9) were identical, indicating a uniform preference for these components due to their balance of cost, efficiency, and durability. However, divergence occurred in inverter and control strategies. System 1 employed a hybrid inverter (code 1), integrating the functions of both an inverter and a charge controller, which simplifies system design and reduces the number of discrete components. On the other hand, System 2 utilized a separate solar inverter (code 10) and charge controller (code 1), resulting in a more modular but complex architecture. In terms of PV module sizing, both systems maintained the same total number of PV modules (N_{s_PV} = 24), however, the total of PV modules per charge controller differed, with System 1 utilizing 8 modules per charge controller compared to 5 for System 2. In terms of cost performance, System 1 achieved a significantly lower LCC of RM 262,550.25 compared to RM 278,086.57 for System 2, demonstrating its greater cost-effectiveness. This 5.6% cost reduction confirms the economic advantage of integrating functionalities through hybrid components. Furthermore, System 1 completed its optimization process slightly faster (2.7851 seconds) than System 2 (2.8818 seconds), indicating computational benefits stemming from reduced complexity. Overall, System 1's design proved more cost-efficient and computationally leaner.

Table 3 MOA sizing result of SAPV system for System 1 and System 2 (LCC).

Sizing results	**System 1**	**System 2**
Optimal PV module code	4	4
Optimal battery code	9	9
Optimal hybrid inverter code	1	-
Optimal inverter code	-	10
Optimal charge controller code	-	1
N_{s_PV} in integer	10	2
N_{t_PV} in integer	24	24
$N_{total\_PV\ per\ charge\ controller}$ in integer	8	5
N_{s_batt} in integer	4	4
N_{p_batt} in integer	63	63
N_{t_batt} in integer	252	252
$N_{t\_hybrid\_inv}$ in integer	4	-
$N_{t\_hybrid\_inv}$ in integer	-	5
N_{t_inv} in integer	-	7
Optimal life cycle cost (LCC) in RM	262,550.25	278,086.57
Overall computation time, in seconds	2.7851	2.8818

3.2 Optimization Result Based on LCOE

Table 4 summarizes the optimization results when the objective function was LCOE. Unlike the LCC case, both systems showed variation in selected PV modules. System 1 used PV module code 4, while System 2 used code 5, indicating a potential trade-off between module performance and energy yield. Although both systems again shared the same battery model (code 9), their inverter strategies differed: System 1 used a hybrid inverter (code 3), while System 2 retained the modular solar inverter (code 10) and charge controller (code 1). These selections reflect the algorithms' preference for compact integration in minimizing unit energy cost. In terms of configuration, System 1 used fewer PV modules in series (N_{s_PV} = 3) compared to System 2 (N_{s_PV} = 2), but both maintained nearly the same total PV count (24 vs. 25). This indicates that while total array capacity was similar, the internal arrangement differed to accommodate system-level efficiency goals.

The calculated LCOE for System 1 was RM 1.0151/kWh, which is 9.2% lower than the RM 1.1183/kWh achieved by System 2. The relatively low LCOE suggests that System 1 not only requires lower capital investment but also delivers more cost-effective electricity over time. Moreover, the computational time for System 1 (3.6439 seconds) was slightly less than that of System 2 (3.8115 seconds), reinforcing the operational simplicity of the hybrid design.

Table 4 MOA sizing result of SAPV system for System 1 and System 2 (LCOE).

Sizing results	**System 1**	**System 2**
Optimal PV module code	4	5
Optimal battery code	9	9
Optimal hybrid inverter code	3	-
Optimal inverter code	-	10
Optimal charge controller code	-	1
N_{s_PV} in integer	3	2
N_{t_PV} in integer	24	25
$N_{total\_PV\ per\ charge\ controller}$ in integer	10	5
N_{s_batt} in integer	4	4
N_{p_batt} in integer	62	62
$N_{t\_hybrid\_inv}$ in integer	248	248
$N_{t\_hybrid\_inv}$ in integer	5	-
$N_{t\_hybrid\_inv}$ in integer	-	5
N_{t_inv} in integer	-	7
Optimal Levelized Cost of Energy (LCOE), in (RM/kWh)	1.0151	1.1183
Overall computation time, in seconds	3.6439	3.8115

3.3 Convergence Analysis and MOA, PSO, FA and SMA

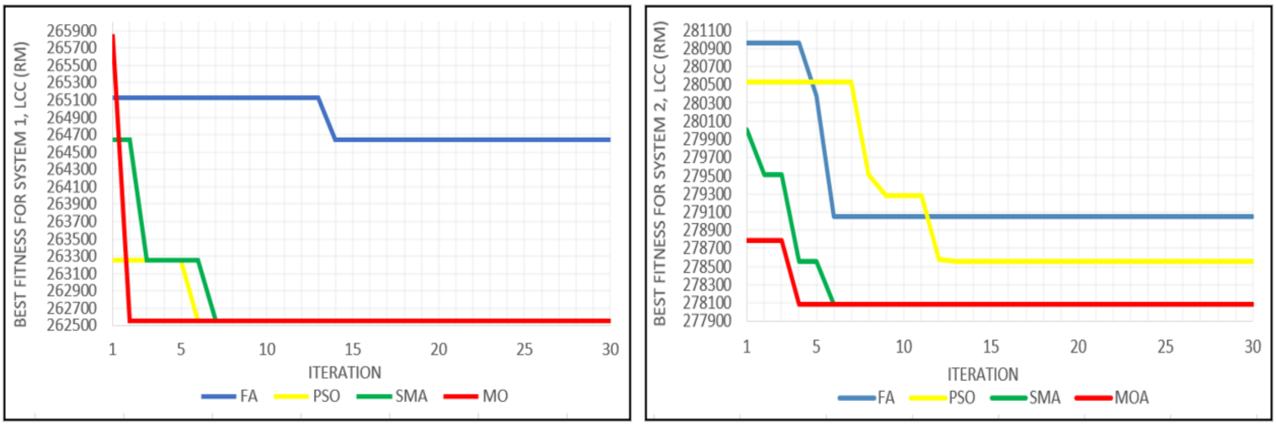
Fig. 3(a) and Fig. 3(b) present the convergence characteristics of MOA, PSO, FA, and SMA in minimizing the Life Cycle Cost (LCC) for System 1 and System 2, respectively. For System 1, the MOA achieves the most rapid and stable convergence, reaching its optimal LCC value of approximately RM 262,550.25 at the second iteration and maintaining this best value throughout the remaining simulation period up to iteration 30. In contrast, the PSO and SMA attain near-optimal performance after approximately five iterations, exhibiting transient fluctuations before stabilizing. The FA demonstrates the slowest convergence behaviour, stagnating at a higher cost level (around RM 264,500), indicating a weaker ability to escape local optima and limited exploitation capability.

A similar trend is observed for System 2, where the MOA again achieves the lowest LCC (approximately RM 278,086.57) by iteration 4. The SMA converges faster than the PSO for this configuration and stabilizes by iteration 6, whereas the PSO reaches a plateau around iteration 13. The FA continues to exhibit the slowest response and converges at a noticeably higher cost value.

Fig. 4(a) and Fig. 4(b) illustrate the convergence characteristics of MOA, PSO, FA, and SMA in minimizing the Levelized Cost of Electricity (LCOE) for System 1 and System 2, respectively. For System 1, the MOA again demonstrates the fastest and most stable convergence, reaching its optimal LCOE value of approximately 1.0151 RM/kWh at the second iteration and maintaining this optimum throughout the 30-iteration period. The PSO achieves its minimum LCOE at iteration 8, while the FA reaches its lowest value at iteration 10, both showing slower convergence compared to the MOA. In contrast, the SMA exhibits the slowest convergence, with a gradual decline in cost and final stabilization around iteration 12 at approximately 1.12 RM/kWh, indicating weaker exploitation ability and limited efficiency in minimizing the cost function compared with the other algorithms.

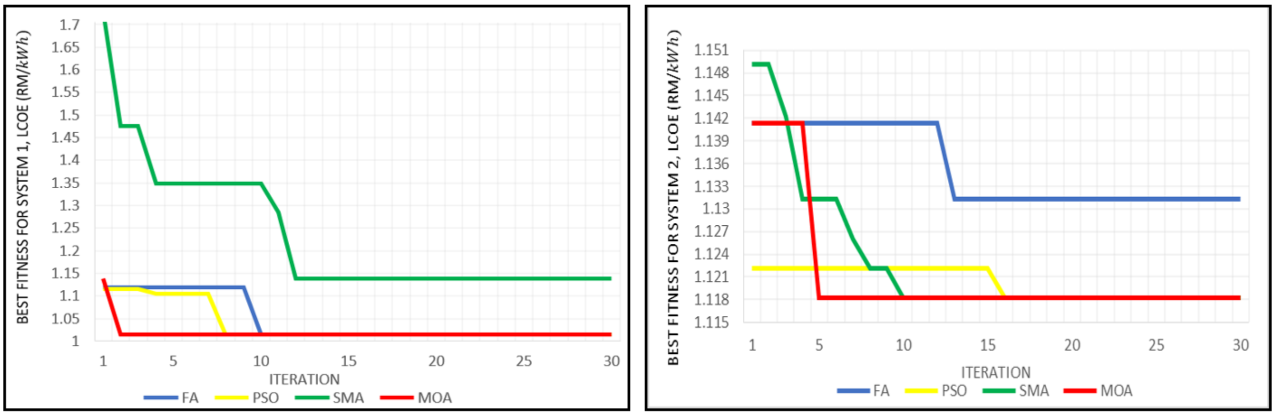
For System 2, a similar pattern is observed. The MOA achieves the most rapid and consistent convergence, reaching its lowest LCOE value of approximately 1.1183 RM/kWh within the first five iterations and maintaining this best value until the end of the simulation. The SMA converges next, achieving its minimum cost around iteration 10, while the PSO reaches its lowest value near iteration 16. The FA, however, shows the slowest convergence behaviours, stabilizing at a noticeably higher LCOE (about 1.135 RM/kWh), suggesting lower exploitation capability and a higher tendency to remain trapped in local optima.

In conclusion, the convergence analyses presented in Fig. 3 and 4 collectively demonstrate that the Meerkat Optimization Algorithm (MOA) consistently delivers outstanding performance in optimizing both Life Cycle Cost (LCC) and Levelized Cost of Energy (LCOE) for the two SAPV configurations. In both cases, MOA rapidly attains the optimal solution within the first few iterations and maintains stable convergence without oscillation, reflecting its effective balance between exploration and exploitation. In contrast, PSO and SMA show slower convergence with minor fluctuations before stabilizing, while FA exhibits the weakest search ability and remains trapped at higher cost levels.



(a) (b)

Fig. 3 Convergence of MOA, PSO, FA, and SMA for Minimizing the Life Cycle Cost (LCC) for (a) System 1 and (b) System 2.



(a) (b)

Fig. 4 Convergence of MOA, PSO, FA, and SMA for Minimizing the Levelized Cost of Energy (LCOE) for (a) System 1 and (b) System 2.

4. Conclusion

The comparative analysis presented in this study reveals that System 1, which integrates a photovoltaic (PV) array, battery storage, and a hybrid inverter, demonstrates greater efficiency and cost-effectiveness compared to System 2, which utilizes separate inverter and charge controller components. Optimization results for both life cycle cost (LCC) and levelized cost of energy (LCOE) consistently favor System 1. This advantage is primarily attributed to its simpler configuration, reduced number of components, and easier integration process. The hybrid inverter, which consolidates multiple power conditioning functions into a single device, not only minimizes the overall system cost but also streamlines the control architecture, leading to faster convergence during the optimization process. Consequently, System 1 emerges as the most suitable configuration for stand-alone photovoltaic (SAPV) systems, especially in rural or off-grid regions where cost-performance trade-offs are critical.

Among the four metaheuristic algorithms evaluated Meerkat Optimization Algorithm (MOA), Particle Swarm Optimization (PSO), Firefly Algorithm (FA) and Slime Mould Algorithm (SMA), the MOA consistently produced the most favorable optimization results across both objective functions. The MOA demonstrated strong convergence behavior, often reaching near-optimal solutions in fewer than five iterations. This performance underscores the algorithm's strength, computational efficiency, and capacity to deliver stable outcomes even under constrained processing resources or real-world conditions. Its search mechanism, inspired by cooperative animal behavior and supported by adaptive parameter control, allows it to maintain an effective balance between exploration and exploitation phases throughout the optimization process.

Furthermore, the results affirm that the MOA is a reliable and effective tool for addressing multi-objective optimization problems in SAPV system design. By simultaneously considering both economic (LCC) and energy-based (LCOE) performance metrics, the MOA facilitates well-informed decision-making for engineers and system planners. Its ability to rapidly identify cost-optimal configurations makes it particularly suitable for applications involving real-world load profiles, variable irradiance data, and geographically diverse deployment scenarios.

Overall, this study contributes a novel and practical framework for optimizing SAPV systems using a bio-inspired algorithm under dual-configuration analysis. The findings serve as a valuable reference for the design and implementation of standalone renewable energy systems, particularly in remote or resource-constrained areas. Future work may extend this research by incorporating additional objectives such as system reliability, battery degradation modeling, and carbon footprint minimization, thereby enhancing the comprehensiveness of sustainability-focused optimization in off-grid energy planning.

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Author Contributions

Mazwin Mazlan: Conceptualization, Methodology, Software, Investigation, Data curation, Formal analysis, Validation, Visualization, Writing – original draft. **Shahril Irwan Sulaiman**: Supervision, Resources, Writing – review and editing. **Azralmukmin Azmi:** Supervision, Resources, Validation, Investigation. **Hedzlin Zainuddin:** Supervision, Resources. **Ismail Musirin:** Supervision, Resources.

Declaration of Interest Statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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