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Optimization of Energy Management in a Hybrid PV-Battery-Diesel System for Rural Electrification in Guinea: A Comparative Performance Study of the PSO, WOA and TDO Optimization Algorithms

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Abstract

Hybrid renewables provide a practical solution for expanding access in rural Guinea, where electrification remains limited. However, their performance highly depends on the efficiency of energy management. In this work, a comparison of three optimization algorithms including Particle Swarm Optimization (PSO), Whale Optimization Algorithm (WOA) and Tasmanian Devil Optimization (TDO) is presented for the management of a stand-alone hybrid system consisting of photovoltaic generation, battery storage and diesel generator. The objective is to identify the most effective algorithm for minimizing the electrical energy generated by the diesel generator while satisfying load demand and respecting operational constraints. The performance of the three algorithms was averaged across 30 independent runs under the same simulation setting. Performance was assessed using convergence curves, mean value of the objective function, standard deviation, mean execution time, and the resulting energy management strategies. All the methods converged to feasible solutions and found the system to operate reliably. TDO produced the strongest overall outcomes, with the lowest mean objective value (586.70), the smallest standard deviation (1.43), and the shortest mean execution time (0.327 s). It also increased the usage of the storage system and further reduced the reliance on the diesel generator compared to the PSO and WOA. These results

indicate that TDO is a very powerful and efficient approach for energy management in stand-alone hybrid systems and a promising option for the electrification of the rural and remote areas of Guinea.

Keywords

Energy Management, Standalone Hybrid System, Photovoltaics, Battery, Diesel Generator, Metaheuristic Optimization, Guinea

1. Introduction

Electricity access is a crucial driver for socioeconomic development in many sub-Saharan African countries. There have been significant improvements in recent years, but most of the continent is still limited in access, particularly in the provinces. In Guinea, data from 2023 shows that 51.1% of the population has access to electricity, with a significant difference between urban (92.5%) and rural areas (25.7%) [1]. This shortfall delays economic growth, limits access to health care and education, and worsens living conditions. Guinea's power system relies mostly on hydropower, which accounts for about 74% of total generation while fossil fuels also contribute significantly to the energy mix [2]. However, annual per capita electricity use is still low, around 281 kWh, significantly below the global average [2]. This situation shows the necessity to find solutions that can sustainably improve the production and distribution of electricity in the country. Guinea has paradoxically a huge energy potential, especially in renewables. Financial Afrik said that hydroelectric capacity may reach more than 6000 MW, whereas solar resources are at average of 5.5 kWh/m^2 per day and over 2700 hours of sunshine par year [3]. These strengths create good conditions for the development of the photovoltaics sector. However, all these resources are set back by a lack of infrastructure, investment constraints and the slow expansion of the national grid. In this context, hybrid configurations that combine renewable and conventional resources offer a practical option to electrify remote areas and to improve grid reliability. In many developing countries, such systems typically integrate photovoltaic generators, battery storage, and diesel gensets to maintain continuous supply despite the intermittency of renewable resources [4]. Interest in these architectures has increased because they can lower fuel consumption, reduce greenhouse gas emissions, and reduce operating costs, while also supporting the integration of renewables into the grid [5]. Managing energy flows in these systems remains challenging, due to uncertain renewable output, demand variability, and the technical limits of storage devices. To address these difficulties, the literature proposes a range of approaches. Early solutions rely on deterministic, rule-based strategies, such as load-following and cycle charging. Although these methods help align power generation with demand by prioritizing certain energy sources, they do not capture the nonlinear dynamics inherent to hybrid energy systems

[6]. To achieve better performance, many studies adopt mathematical optimization and metaheuristic techniques. These methods are well suited to the nonlinear and multi-objective form of microgrid energy management. Evolutionary approaches, like genetic algorithms and particle swarm optimization, are widely used both to derive optimal operating policies and to size hybrid systems [4]. For example, particle swarm optimization has been extensively used to allocate generation among sources and reduce fuel consumption in photovoltaic hybrid configuration [7]. More recently, nature-inspired algorithms have been proposed, such as the Whale Optimization Algorithm and other bio-inspired methods that explore the search space efficiently to identify high-quality solutions to complex energy optimization problems [8] [9]. These approaches typically offer strong performance while requiring only a small number of tuning parameters. In addition to metaheuristic approaches, many studies have been examined in energy management strategies based in artificial intelligence and predictive control. Fuzzy logic offers a way to model complex system behavior by incorporating decision rules derived from expert knowledge [10]. Similarly, model predictive control anticipates variations in generation and demand to optimize management over a defined temporal horizon [11] [12]. Recent publications show a growing interest in adding further criteria to the optimization of hybrid systems. Beyond traditional goals such as reduce energy costs or fuel consumption, numerous works now, consider battery degradation, system reliability, and uncertainties associated with renewables resources [13] [14]. Adopting a multi-criteria approach therefore provides a more accurate representation of the constraints actually encountered during microgrid operation. Nevertheless, notable gaps persist in the literature. A large share of research targets the optimal sizing of hybrid systems, while comparatively few studies assess, within a consistent experimental framework, different optimization methods for energy management [15]. In addition, most analyses emphasize European, Asian, or North American contexts, whereas sub-Saharan African countries face specific challenges related to electricity access, renewable resource availability, and economic constraints. In the Republic of Guinea, electricity access remains limited, particularly in rural area. According to the World Bank and the International Renewable Energy Agency (IRENA), deploying solar-dominant hybrid microgrids is a promising way to expand energy access and support national socio-economic development [16] [17]. Guinea's significant solar potential, combined with the implementation of energy storage systems and backup generators, opens up particularly promising prospects for the deployment of optimized hybrid systems. Finally, it is vital to analyse the performance of some optimization methods used for energy management of hybrid photovoltaic systems. Several proposed nature-inspired algorithms have been derived from these approaches such as Particle Swarm Optimization (PSO), Whale Optimization Algorithm (WOA), and Tasmanian Devil Optimization (TDO). The methods are useful in exploring the solution space for management solutions that reduce fuel usage, while not imposing undue demands on storage. This work intends, there-

fore, to analyze and evaluate these three optimization metaheuristics, in order to find the energy management techniques best adapted to photovoltaic-battery-diesel generator systems for decentralized electrification in Guinea. More precisely, it studies the impact of these approaches on the distribution of production among the numerous sources, on the ways of utilization of storage capabilities, but also on the contribution of the generator set.

2. Methodology

First, Figure 1 presents the study system, which is representative of a hybrid microgrid constituted by three energy sources: photovoltaic (PV) generator, battery storage and diesel generator. Such type of design is extensively used in autonomous microgrids to provide the reliable supply of energy despite the irregularity of the renewable resources [4] [5]. The meteorological data used in this study were obtained from RETScreen for Kankan, Guinea, and comprise monthly solar irradiance, ambient temperature and wind speed profiles covering the twelve months of the year. The electrical load profile was obtained from a village in the Kankan region.

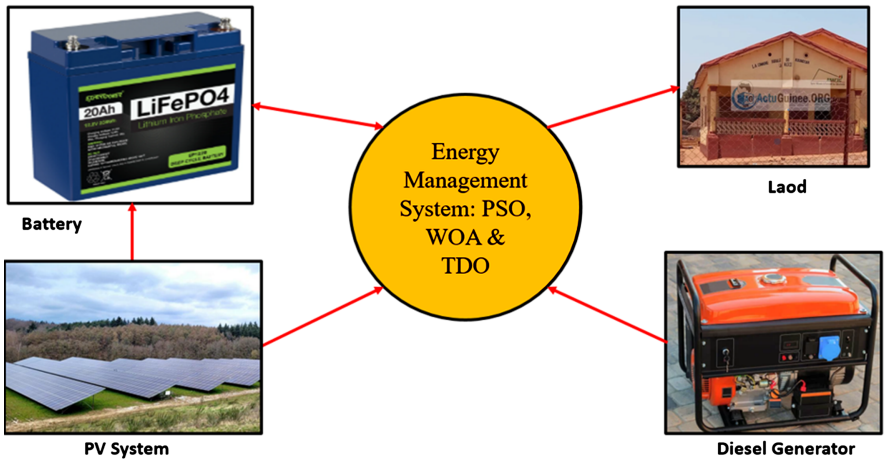

Figure 1. Study system.

In this architecture, the main source of renewable energy is the photovoltaic generation. The battery allows to store the excess of the panels and to release it when the solar production is not enough. The diesel generator serves as a backup to ensure the continuity of electricity supply when the renewable production and storage capacity available is not sufficient to supply demand.

Equation (1) must be satisfied in order to keep the energy balance of the system [18]:

$$P^{Load}(t) = P^{PV}(t) + P^{Batt}(t) + P^{DG}(t) \quad (1)$$

where:

$P^{Load}(t)$ is the power required by the load, $P^{PV}(t)$ is the power generated by the PV array, $P^{Batt}(t)$ is the power injected into or extracted from the storage system, and $P^{DG}(t)$ is the power supplied by the generator.

2.1. Modelling of the PV System

The key factors determining the output of a photovoltaic generator are the solar irradiance and the temperature of the modules under the sun. It can be estimated with Equation (2) which enables the PV production to be calculation at each instant t [4].

$$P^{PV}(t) = P^{PV,STC}\frac{I(t)}{I^{Ref}}\left(\gamma\left(T(t) - T^{Ref}\right) + 1\right) \tag{2}$$

where:

$P^{PV,STC}$: nominal power of the photovoltaic system (W), $I(t)$: solar irradiance (W/m²), I^{Ref}: reference irradiance (1000 W/m²), $T(t)$: temperature of the PV cells, T^{Ref}: reference temperature of the PV cells (25˚C), γ: temperature coefficient of the module.

2.2. Modelling of the Battery

The battery is an important element for the hybrid system stability. It stores surplus energy from the photovoltaic array and supplies it when PV generation is not sufficient to feed the load. Equation (3) is used to update the state of charge SOC [19] [20].

$$\mathrm{SOC}(t) = \mathrm{SOC}(t-1) + \frac{\Delta t}{C^{Batt}}\left(\tau^{ch}\cdot P^{Batt,ch} - \frac{P^{Batt,desch}}{\tau^{desch}}\right) \tag{3}$$

In this expression, $\mathrm{SOC}(t)$: means the respective state of charge at time t, C^{Batt} is the nominal capacity of the battery, τ^{ch} and τ^{desch} is the efficiencies of charge and discharge, and Δt is the time step of the simulation.

To avoid premature aging of the storage device, the SOC is constrained between the lower limit SOC^{min} and the upper limit SOC^{max}, as shown in Equation (4). These limits are enforced to reduce dep discharges and to extend the battery's service life [13] [14].

$$\mathrm{SOC}^{min} \le \mathrm{SOC}(t) \le \mathrm{SOC}^{max} \tag{4}$$

2.3. Generator Set Modeling

The diesel generator supplies the residual electrical demand when photovoltaic generation and the available battery power are insufficient. Its contribution is evaluated in terms of electrical power and energy output.

2.4. Optimization Problem

The energy management of the hybrid is developed as an optimization problem. At each time step it allocates the contributions of the photovoltaic generator, the battery and the diesel generator in order to satisfy the electrical demand minimising the use of the generator. The objective function therefore represents the total electrical energy supplied by the diesel generator over the simulation horizon. The objective function is provided by Equation (5) [6]:

$$\min J = \sum_{i=1}^{n} P^{DG}(t) \cdot \Delta t \tag{5}$$

where:

J denotes the cumulative energy delivered by the diesel generator over the simulation horizon, $P^{DG}(t)$ is the Diesel generator power at time t, Δt is the simulation time step (1 h in this study) and n is the total number of time intervals. The Diesel generator power is derived from the residual energy deficit as follows:

$$P^{DG}(t) = \min\left[P^{DG,max}, \max\left(0, P^{Load}(t) - P^{PV}(t) - P^{Batt}(t)\right)\right] \tag{6}$$

where $P^{Load}(t)$ is the load demand, $P^{PV}(t)$ is the power produced by the photovoltaic generator, $P^{Batt}(t)$ is the power exchanged by the battery and $P^{DG,max}$ is the Diesel generator's maximum power.

The term represented by Equation (7) guarantees that the power output of the generator is always non-negative. The generator is off when the photovoltaic production and the batteries are able to satisfy the electrical load completely. If that production is not enough, the generator only supplies the missing power, till its rated capacity ($P^{DG,max}$).

$$\max\left(0, P^{Load}(t) - P^{PV}(t) - P^{Batt}(t)\right) \tag{7}$$

2.5. Optimisation Methods

The optimal energy management of autonomous hybrid PV-Battery-Diesel systems is a nonlinear optimization issue, characterized by the intermittency of the solar production, the operating limits of the battery and the minimization of the diesel generator use. Metaheuristic algorithms are quite popular to handle this kind of problem because they are efficient to explore complex search spaces without requiring information on the gradient of the objective function [21] [22]. In this work, the Particle Swarm Optimization (PSO), Whale Optimization Algorithm (WOA) and Tasmanian Devil Optimization (TDO) are selected to compare their performances for the energy management of a hybrid system designed for rural electrification in Guinea. These three algorithms use the same optimization idea, but employ distinct search techniques. Each candidate solution represents a vector of power demands of the battery. The energy management model to determine the power of the diesel generator uses this vector and the objective function given by Equation (5) is computed. Hence, the algorithms come up with the solution that results in minimum total energy generation by the generator.

In the next sections, the working principles of the three algorithms are discussed.

2.5.1. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is an optimization technique based on the group behavior of birds and fish schools. Each particle is a unique candidate solution that is shifted in the search space, and the particle's velocity and position are updated using its own and the group best experiences [23]. The velocity of particle i at iteration $k+1$ is determined by Equation (8):

$$v_i^{k+1} = \omega v_i^k + \mu_1 \delta_1 \left(g_i - x_i^k \right) + \mu_2 \delta_2 \left(G - x_i^k \right) \tag{8}$$

where:

ω is the inertia weight, μ_1 and μ_2 are the learning factors, δ_1 and δ_2 are two random values uniformly distributed in [0, 1], g_i is the best position of the individual and G is the best position of the group.

The position is then updated by Equation (9):

$$x_i^{k+1} = x_i^k + v_i^{k+1} \tag{9}$$

Figure 2 shows the flowchart of the PSO algorithm used in this study for optimal energy management of the PV-battery-diesel hybrid system.

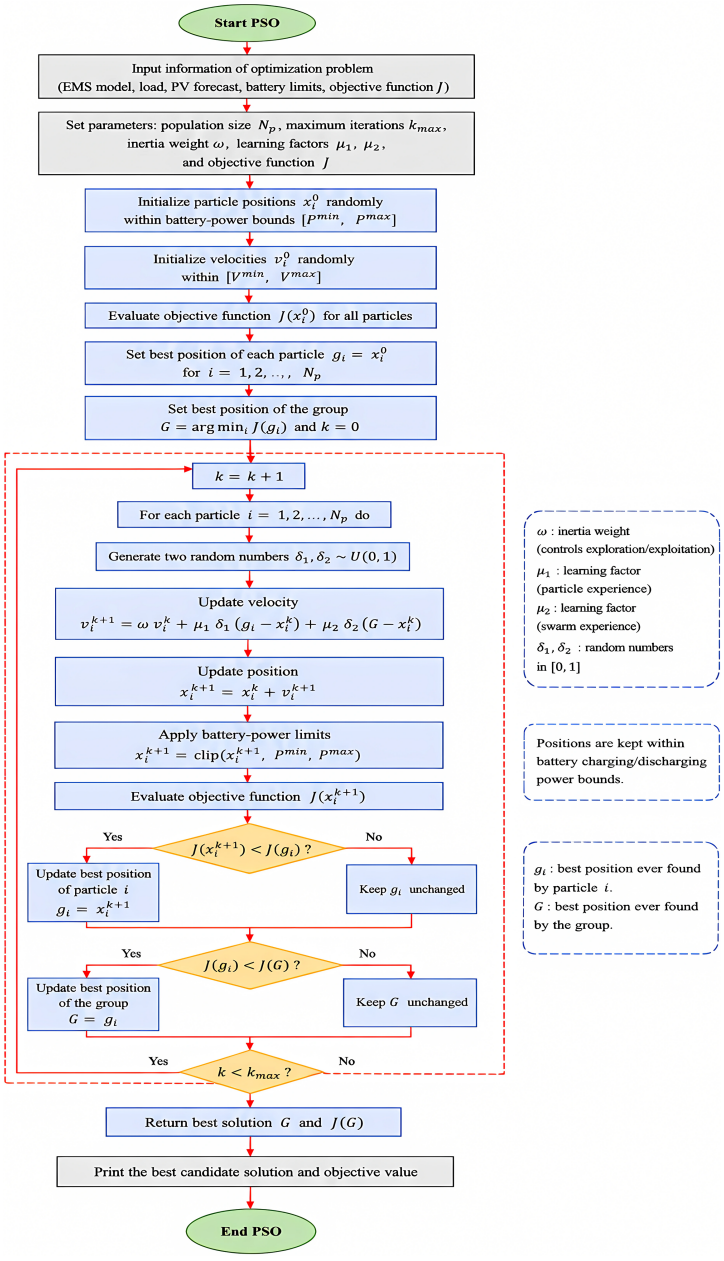

Figure 2. Optimization flowchart of the PSO.

2.5.2. Whale Optimization Algorithm

The Whale Optimization Algorithm (WOA) used for optimizing the battery power trajectory and minimizing the energy consumption of the diesel generator is presented in Figure 3.

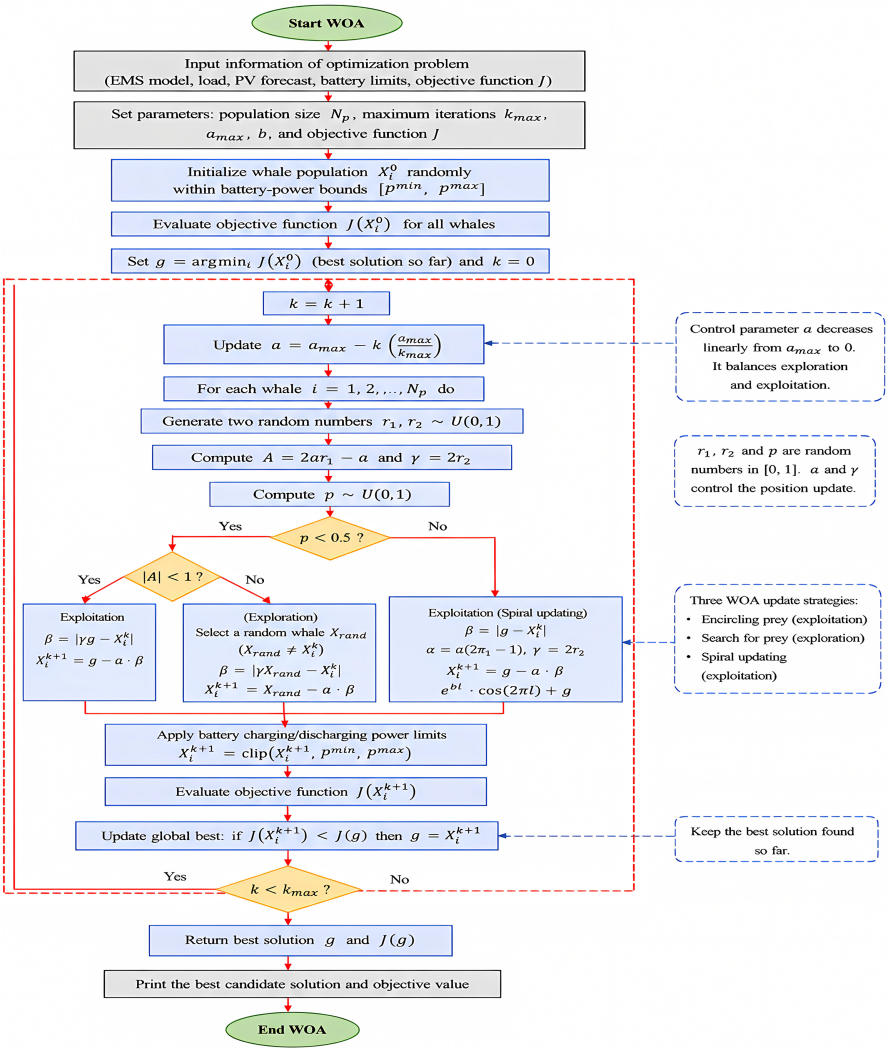

Figure 3. Optimization flowchart of WOA.

Whale Optimization Algorithm (WOA) is a bio-inspired metaheuristic algorithm inspired by the spiral hunting tactic of humpback whales. The method alternates between exploitation periods around the best known solution and exploration phases of new regions of the search space [24].

The position update is done according to Equation (10):

$$y_i^{k+1} = y^*(k) - \alpha \cdot \beta \tag{10}$$

with:

$$\beta = \left|\gamma \cdot y^*(k) - y(k)\right|$$

where:

y is the position of whale at iteration k, y^* is the best solution achieved till the iteration k and β is the distance between the current whale and the best solution, $\alpha = q(2r_1 - 1)$ is the control vector for exploration and exploitation and $\gamma = 2r_2$ is the distance weighting vector, q is a linear decreasing parameter from 2 to 0 during the iterations to assure the shift from exploration to exploitation and r_1 and r_2 are uniform random values [0, 1].

2.5.3. Tasmanian Devil Optimization (TDO)

Tasmanian devil optimization (TDO) is a bio-inspired metaheuristic which imitates the foraging behaviour of the Tasmanian devil. In the selected implementation, we do the search using a Gaussian perturbation of the solutions and then choose the improved solutions in a greedy way [25]-[27]. In this work, a modified version of the TDO is applied for optimizing the energy management of PV-Battery-Diesel hybrid system. In classical variants of the TDO, the method operates on a population of N_p candidate solutions, each solution being a vector of battery power levels throughout the whole optimization horizon. After population initialization, each solution is evaluated by using the objective function defined by Equation (5). In each iteration a new solution for each individual is generated using a Gaussian perturbation:

$$X_{i,new}^k = X_i^k + \rho(0,\sigma) \tag{11}$$

where: $\rho(0,\sigma)$ is a Gaussian perturbation with zero mean and $\sigma = \varphi P^{Batt,max}$ is the search standard deviation.

The new solution is accepted only if it improves the objective function value.

$$X_i^{k+1} = \begin{cases} X_{i,new}^k & \text{if } J\left(X_{i,new}^k\right) < J\left(X_i^k\right), \\ X_i^k & \text{else} \end{cases} \tag{12}$$

J is the objective function stated in Equation (5).

The best global solution is updated at the conclusion of each iteration in whole population. We do this repeatedly till the maximum number of iterations is achieved. The approach of this search can explore the solution space well and maintain the best solutions found during the optimization phase [25].

The Tasmanian Devil Optimization (TDO) method to find the optimal battery power trajectory by minimizing the objective function is provided in **Figure 4**.

2.5.4. Algorithms Performance

The algorithms were tested on three complementary metrics: mean objective value, standard deviation and mean runtime. These statistics indicators are commonly used in metaheuristics comparative studies. There are utilized to evaluate the quality of the solutions, robustness and computational efficiency of the stochastic algorithms respectively [28].

Objective value mean

The objective value mean (Equation (13)) measures the average quality of the solutions generated by each algorithm. A lower figure represents a higher performance of the energy management plan.

$$\bar{J} = \frac{1}{N}\sum_{i=1}^{N} J_i \tag{13}$$

where $N = 30$ and J_i is the objective function value in ith run.

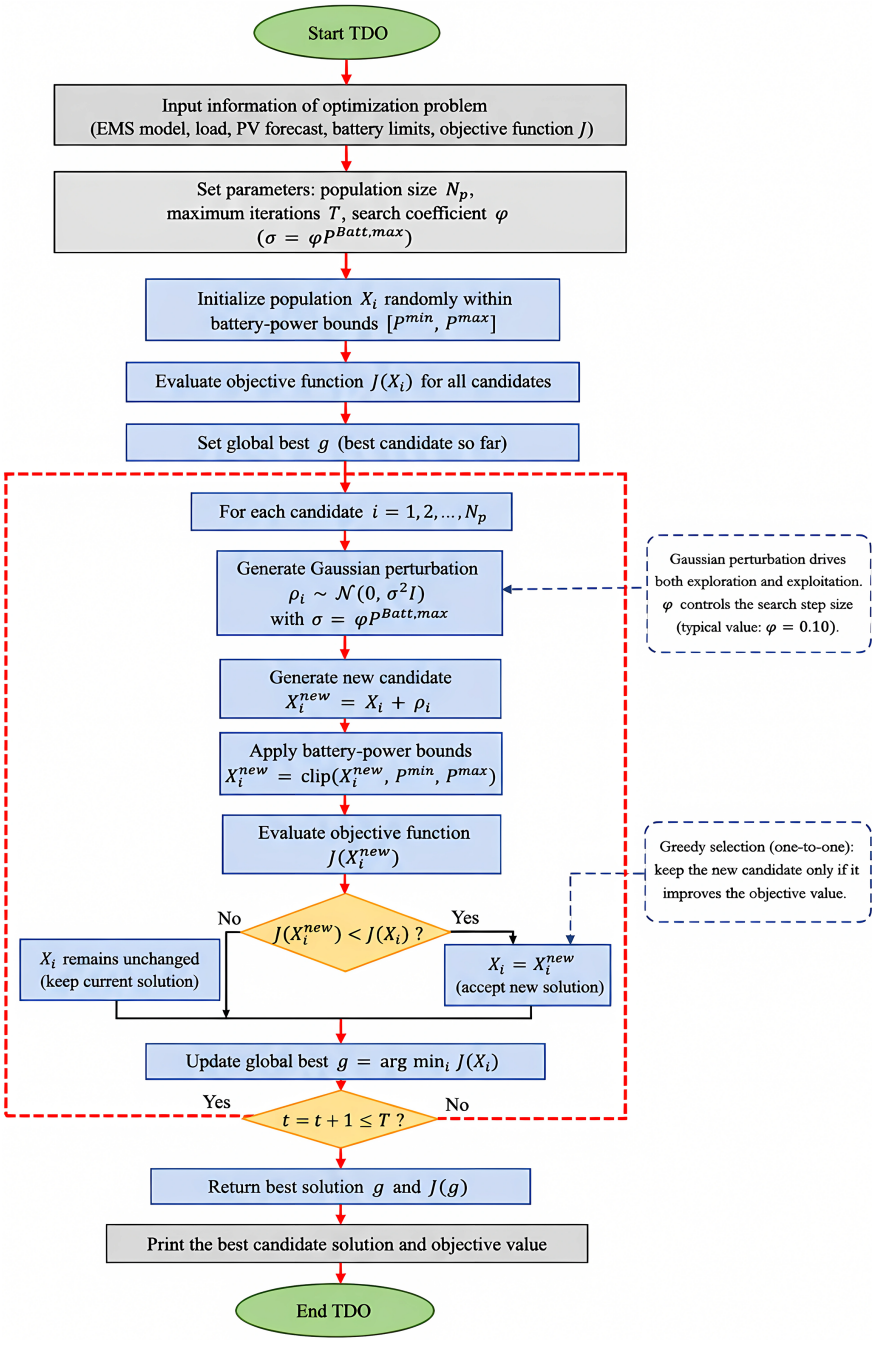

Figure 4. Optimization flowchart of the modified TDO.

Standard Deviation

The standard deviation (Equation (14)) is a measure of robustness of the method. A low number means the solutions obtained are less subject to random initialization and hence more reproducible.

$$s = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left(J_i - \bar{J}\right)^2} \tag{14}$$

Mean runtime

The Mean runtime (15) makes it possible to estimate computational efficiency of the methods. Lower number indicates lower computational cost.

$$\bar{\tau} = \frac{1}{N}\sum_{i=1}^{N}\tau_i \tag{15}$$

where τ_i is the execution time of the ith simulation.

3. Results and Discussion

All parameters used in the simulations are presented in Table 1, including the hybrid system's characteristics and the optimization algorithms' variables. These settings were kept fixed for all of the three approaches for a fair evaluation of their performance.

Table 1. Parameters of the system.

component	Parameters	Value	Unit
PV panel	Rated power	500	kW
	Reference solar radiation	1000	W/m^2
	Thermal coefficient	0.0045	$^\circ$C^{-1}
Battery	Capacity	2000	kWh
	Maximum charge power	250	kW
	Minimum charge power	−250	
	Initial SOC	50	
	Minimum SOC	20	%
	Maximum SOC	90	
Diesel Generator	Maximum Power	500	kW
Algorithms			
PSO	Cognitive coefficient	1.5	
	Social coefficient	1.5	
	Inertia	0.5	
WOA	Control parameter	2 à 0	
	Spiral parameter	[−1, 1]	
	Probability	[0, 1]	
TDO	Strategy	Exploration	
	update	Random	

The meteorological inputs used in the simulation show modest fluctuations in solar irradiance, air temperature, and wind speed across the twelve time points examined (Figure 5). The irradiance is maximum at time points 3 and 4, which are the most, favorable window for photovoltaic generation whereas time points 7 and 8 are the least favorable conditions. The air temperature ranges from 24 to 30 ˚C, the maximum occurs simultaneously with the peak of solar irradiance; it is expected to slightly reduce the efficiency of photovoltaic modules. Wind speed is low and fairly steady, giving a limited but useful cooling effect to the panels. In general, these patterns confirm the strong influence of weather on photovoltaic output and support the adoption of an appropriate energy management strategy for the hybrid system under study.

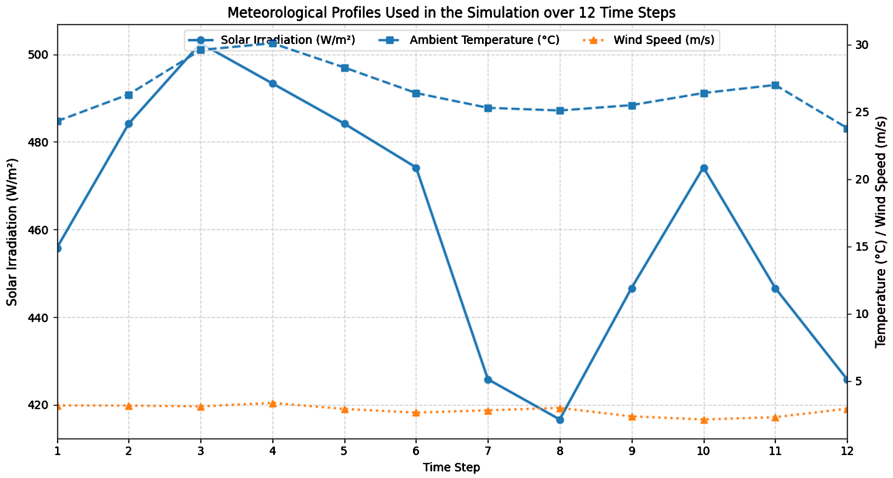

Figure 5. Meteorological profiles used in the simulation.

3.1. Optimization Algorithms Convergence Analysis

Figure 6 shows the comparison of the convergence curves of PSO, WOA and TDO algorithms in 100 iterations. It can be observed that the objective function value decreases rapidly in the initial phase for all the three approaches and then enters the stabilization phase, indicating that the three methods can converge to a solution. The PSO has a faster convergence speed in the first many iterations, while WOA has a slower convergence speed. TDO improves the objective function over a larger number of iterations and achieves the lowest end value. The results show that TDO has a better balance between exploration and exploitation, and avoids premature convergence leading to better quality final solution. Such behaviours were reported by Mirjalili *et al.* [24] and Dehghani *et al.* [25].

3.2. Statistical Evaluation over 30 Independent Runs

To verify the robustness of the methods, each optimization algorithm was performed 30 times separately in the same simulated settings. The statistical results are shown in Table 2. Figure 7 shows the distribution of the objective function values in the form of box plots.

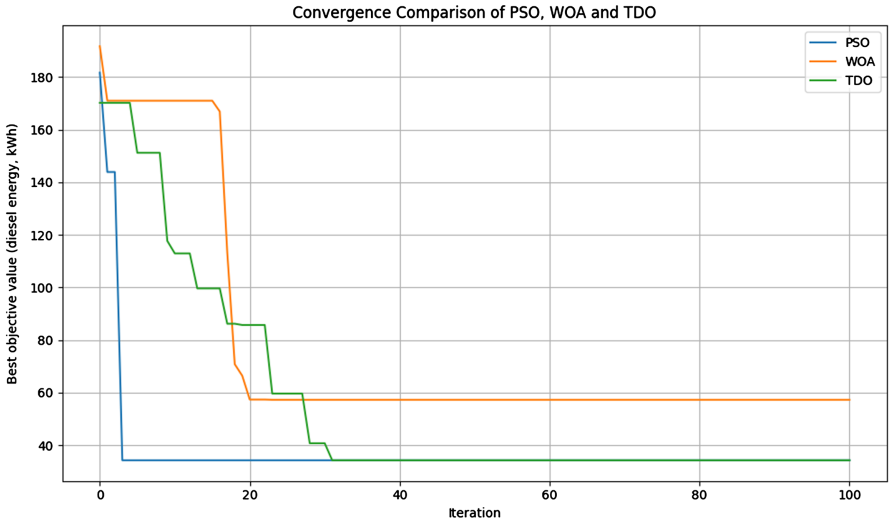

Figure 6. Convergence curves of the PSO, WOA and TDO algorithms.

Table 2. Statistical comparison of the optimization algorithms over 30 independent runs.

Algorithm	Mean objective value	Standard deviation	Mean runtime (s)
PSO	590.5089	8.3792	0.3620
WOA	606.8290	26.1191	0.3525
TDO	586.7032	1.4343	0.3267

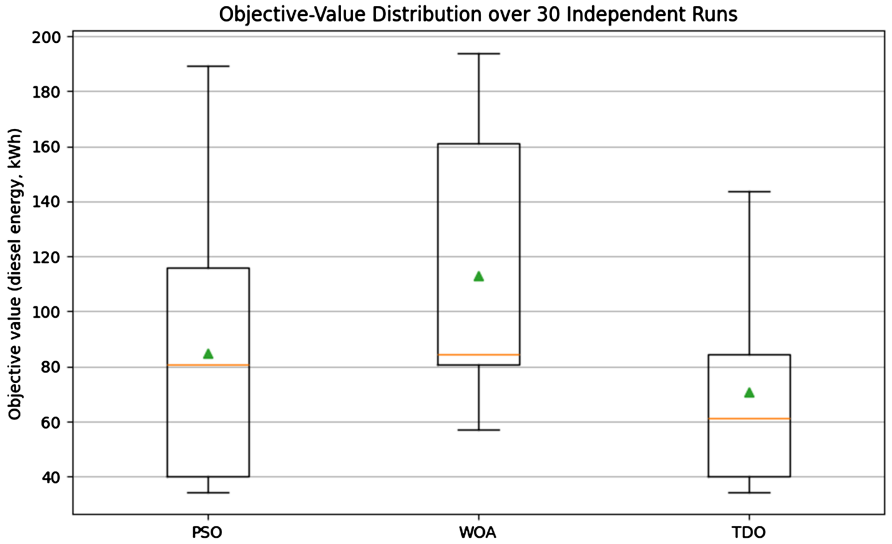

Figure 7. Objective function distribution over 30 independent runs.

As can be observed in Table 2, TDO has the lowest mean value of the objective function, the lowest standard deviation, and the shortest mean run time. The findings prove that the proposed method is superior than PSO and WOA in terms of solution quality, resilience and computational efficiency. The boxplots in Figure 7 confirm this tendency. The findings achieved with TDO are the less dispersed

i.e. better reproducibility of the solutions. In contrast, WOA presents the highest variability and PSO an intermediate behavior.

3.3. Energy Management Strategies Comparison

Figures 8-10 show the energy management techniques obtained by PSO, WOA and TDO algorithms. Each next graphic displays the power profiles of the photovoltaic, battery and diesel generator and the growth of the battery's state of charge (SOC). The photovoltaic power profile is the same for the three algorithms as it is dependent on the weather conditions and on the specified photovoltaic model. The differences seen between techniques are related to the distribution of the solar energy produced between the storage system and the generator. The power profiles of the batteries indicate distinct storage techniques. All three algorithms are operating constraint respecting, *i.e.* they respect the operating constraints imposed to

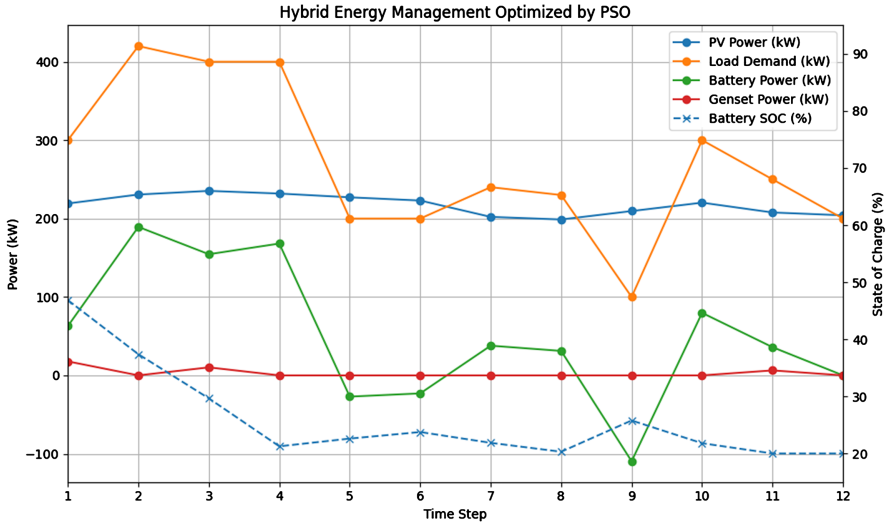

Figure 8. Optimal energy management using PSO.

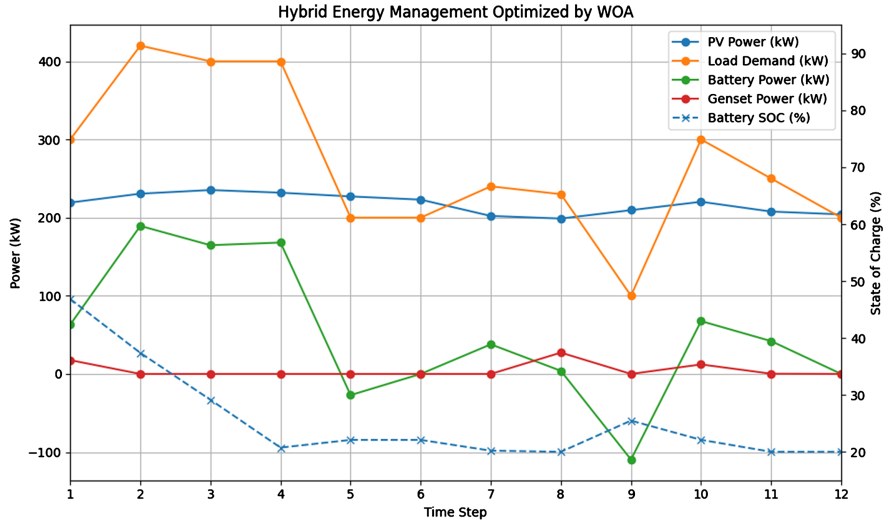

Figure 9. Optimal energy management using WOA.

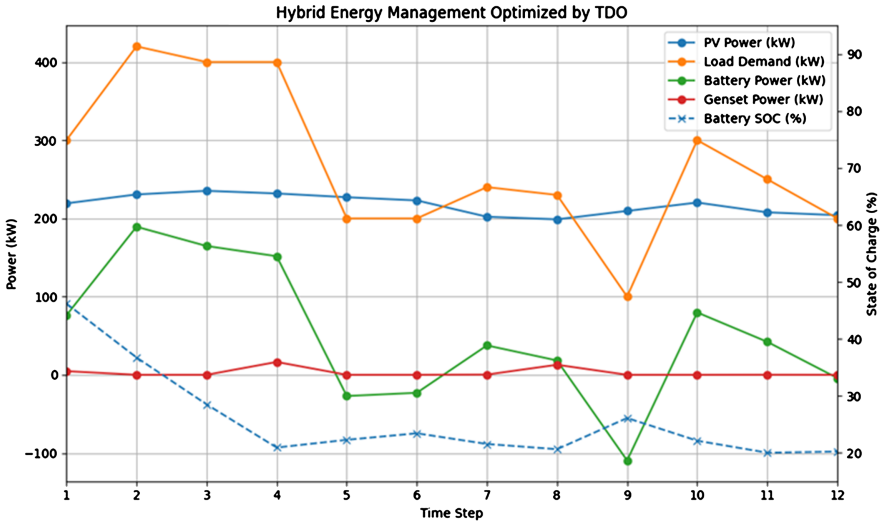

Figure 10. Optimal energy management using TDO.

the system. The modified TDO strategy makes greater use of battery storage, thereby reducing the electrical energy supplied by the diesel generator compared with the other strategies. PSO has intermediate behavior and WOA demands more from diesel generator. This is shown by generator power profiles. It intervenes only when photovoltaic production and the battery are insufficient to meet demand. The TDO also further limits this contribution. This is consistent with the reduced average value of the objective function determined during the statistical analysis. Finally, the evolution of the SOC indicates that all the three techniques respect the operational constraints imposed to the battery, thus ensuring the feasibility of the found solutions. All the three algorithms preserve the balance between energy output and demand. The TDO is characterized by greater use of storage and more efficient use of the generator.

4. Conclusions

This paper evaluates the performance of the Particle Swarm Optimization (PSO), the Whale Optimization Algorithm (WOA) and Tasmanian Devil Optimization (TDO) algorithms for the energy management of a stand-alone hybrid photovoltaic-battery-diesel generator system for rural electrification in Guinea. The results reveal that the three algorithms converge to plausible solutions and enable a dependable operation of the system. However, the modified TDO obtains the best mean value of the objective function, the standard deviation and the execution time. The developed energy management approach utilizes more battery storage and decreases electrical energy provided by the diesel generator than PSO and WOA.

These results confirm the high-performance of TDO as a technique of energy management of standalone hybrid systems and an interesting possibility for enhancing the rural electrification in Guinea. The viewpoints of this work are related to the incorporation of techno-economic criteria to evaluate the energy perfor-

mance, the investment costs, the operating costs and the profitability of autonomous hybrid systems simultaneously.

Author Contributions

A.S. and M.T. conceptualized the study and developed the research methodology. M.T. implemented the PSO, WOA, and modified TDO algorithms, performed the numerical simulations, analyzed the energy management strategies, and prepared the original draft of the manuscript. A.B., D.G., and S.B.O. contributed to the analysis and interpretation of the optimization results. A.N., S.M. and F.E.M. contributed to the scientific supervision and critical review of the study.

Conflicts of Interest

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

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