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Original Article

New Hybrid Optimization Algorithm based on COA and WCA for Hybrid Microgrid System

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Abstract *- This paper shows the developments and evaluations of a hybrid optimization algorithm combining the Coyote Optimization Algorithm (COA) and the Water Cycle Algorithm (WCA) for energy management in hybrid microgrid systems. Hybrid microgrids, which are the integration of renewable energy sources such as solar panels and wind turbines with energy storage and diesel generators, require optimization to minimize both the Cost of Energy (COE) and the Loss of Power Supply Probability (LPSP). While COA is known for its strong exploration capabilities, and WCA excels in local exploitation, both algorithms face challenges in optimizing complex multi-objective systems. Simulation results using MATLAB demonstrate that the COA-WCA hybrid algorithm overcomes the limitations of the individual algorithms. The hybrid approach achieves faster convergence, improved stability, and higher efficiency, reducing the standard deviation of results by 61.8% compared to COA. Additionally, the COA-WCA hybrid produces the highest hypervolume (31.63174), which means that this system has the ability to explore a broader solution space and achieve more optimal solutions. In sensitivity analysis, the COA-WCA hybrid is more robust to variations in parameters such as fuel prices and weather conditions. This study shows the significant contribution to the development of more efficient and reliable energy management systems, especially for off-grid microgrid applications in remote locations.*

Keywords *- COA-WCA, COE, Hybrid Microgrid, LPSP, Metaheuristics, Multi-Objective Optimization.*

1. Introduction

The demand for clean, sustainable, and resilient energy systems has driven people to find an integration of Renewable Energy Sources (RES) and a decentralized power generation system, such as microgrids. These microgrids have the ability to operate independently or connected to the grid, which is one of the best solutions for energy security challenges in remote areas, and also an off-grid system. However, increasing the number of RES such as solar PV and wind energy creates some problems in terms of variability in power generation, so there is a need for efficient energy management and optimization strategies [1, 2]. Some research in optimization of microgrid has been conducted to balance energy efficiency, operation stability, and cost in a dynamic system and heterogeneous energy environment [3, 4].

The integration of RES, Battery Energy Storage Systems (BESS), and conventional generators increases the complexity of the microgrid system. It needs to have advanced optimization techniques for handling large-scale, nonlinear, multi-objective decision problems. Conventional optimization methods, such as linear programming and classical heuristics, have some drawbacks, such as slow convergence, getting trapped in local optima, and struggling with system nonlinearities-especially in energy management, sizing, and scheduling tasks [5]. This means that a sophisticated optimization technique is needed to effectively explore the solution space and balance trade-offs between cost, reliability, and environmental impact [6].

In recent research, hybrid algorithms show strong potential in addressing microgrid optimization challenges. These hybrid methods use a combination of the strengths of different heuristics-such as Particle Swarm Optimization (PSO) and Imperialist Competitive Algorithm (ICA)-to enhance both exploration and exploitation across complex solution landscapes [7, 8]. Although interest in hybrid metaheuristics for microgrid optimization is growing, the combination of Coyote Optimization Algorithm (COA) with Water Cycle Algorithm (WCA) in this domain remains very limited. The potential of this pairing to improve power dispatch efficiency in hybrid microgrids-particularly in terms of cost reduction, reliability, and overall performance-needs further exploration. Integrating COA and WCA in hybrid microgrid optimization offers significant promise for improving both exploration and exploitation capabilities, leading to more effective solutions for multi-objective, constrained, non-convex problems commonly found in microgrid systems. COA is known for its fast and diversified search across the solution space, while WCA excels at intensifying and refining solutions through its water-flow-inspired mechanisms [9, 10]. However, this hybrid approach to microgrid power management remains low, and no validation for the effectiveness of this method in the real world.

In this study, the lack of comprehensive research on the COA-WCA hybrid algorithm for energy management in hybrid microgrid systems becomes the main problem. While metaheuristic hybridization has become a dominant trend in microgrid optimization [11], studies combining COA with WCA are scarce-especially at the system level where multi-objective optimization is crucial. Moreover, there is limited theoretical analysis of the COA-WCA hybrid, including its convergence behavior and solution quality, which adds to the challenge of proving its real-world applicability. Therefore, this research aims to fill that gap by developing and testing the COA-WCA hybrid algorithm for optimizing power supply in hybrid microgrids.

Previous studies have demonstrated the advantages of metaheuristic hybridization for various microgrid optimization tasks, including sizing, scheduling, and energy management [7, 10]. Hybrid algorithms often outperform standalone methods in solution quality, convergence stability, and robustness across different problem types. For example, integrating Harris Hawks Optimizer (HHO) with Arithmetic Optimization Algorithm (AOA) has shown better performance in microgrid sizing, achieving a superior cost-reliability balance [12]. Similarly, combining Invasive Weed Optimization (IWO) with Backtracking Search Algorithm (BSA) proved effective in optimizing the techno-economic and ecological aspects of hybrid renewable energy systems [7]. This research has explored the potential of metaheuristic hybridization for tackling complex, multi-dimensional microgrid optimization problems.

Despite these advances, hybridization of COA-WCA still needs to be explored-especially at the microgrid system level. The application of COA in microgrid optimization is still rare, making a significant gap in the literature, especially in component sizing, energy dispatch, storage management, and real-time scheduling under dynamic conditions. In addition, metaheuristic hybridization has proven effective in improving optimization outcomes, but insufficient in-depth analysis of convergence behavior, parameter sensitivity, and solution quality. So, it needs to explore a more comprehensive evaluation of the COA-WCA hybrid, both in algorithmic performance and real-world applicability. The primary objective of this study is to develop and evaluate the effectiveness of the COA-WCA hybrid algorithm in optimizing power supply for hybrid microgrid systems. This work aims to contribute to existing literature by introducing a new hybrid metaheuristic that combines COA's rapid exploration with WCA's intensification capabilities for multi-objective microgrid optimization. It also seeks to provide practical solutions for improving the efficiency and reliability of hybrid microgrids. Furthermore, the study assesses the scalability and practical feasibility of the COA-WCA hybrid through robustness validation under uncertain conditions, convergence performance analysis, and evaluation of solution quality. The novelty of this research lies in the introduction of a new hybrid algorithm for microgrid optimization and its theoretical and practical validation. The findings are expected to offer new insights into the potential of metaheuristic hybridization in microgrid optimization and contribute to the development of more robust and efficient energy management systems. Moreover, by integrating stochastic formulations and real-world constraints, this study provides a more holistic approach to microgrid optimization that considers both economic and technical factors-thereby advancing the field in a more comprehensive way.

2. Hybrid Microgrid System

A hybrid microgrid system is a system that integrates renewable and non-renewable energy sources to provide an efficient, reliable, and sustainable electricity supply. This system can support energy resilience and reduce dependence on fossil fuels. This system in this paper consists of solar PV, batteries, wind turbines, and diesel generators.

2.1. Modeling of the Hybrid Microgrid

The total energy generation that can be produced by all SHM components in a hybrid microgrid needs to be calculated, including solar PV, wind turbines, batteries, and diesel generators. The potential energy generation of the SHM components is calculated using modeling.

2.1.1. Solar PV

The electrical power generated by solar PV is determined by the characteristics of the PV module, solar radiation (G in W/m²), and temperature (Tc in °C), which can be expressed in Equation (1) [13].

$$P_{PV}(t) = \eta_{ref}\eta_{inv}\left[1 - \beta_c\left\{T_{a(t)} + G_{(t)}\left(\frac{NOCT-20}{800}\right) - T_{ref}\right\}\right]N_m A_m G_{(t)} \tag{1}$$

Where, $P_{PV(t)}$, η_{ref}, η_{inv}, β_c, $T_{a(t)}$, T_{ref}, N_m, A_m, G, G_o, NONC are, respectively, the estimated power generation of the PV system (W), reference efficiency under Standard Test Conditions (STC) (%), inverter efficiency (%), temperature coefficient of efficiency (0.004–0.006 per °C for silicon cells) (per °C), surface temperature of the solar PV (°C), module temperature under STC (°C), number of modules in the PV system (units), area of each module ($ m^2 $), solar radiation on the PV surface W/m^2), solar radiation under STC (W/m^2), solar cell temperature when the PV operates under 800 $ W/m^2 $ radiation, and the temperature below 20°C (NOCT value between 42°C–46°C).

2.1.2. Wind Turbine

The output power of the Wind Turbine (WT) can be estimated using Equations (2)-(4) [14]

$$P_{wt} = 0 \quad jika \;\; V < Vcut_{in} \;\; or \;\; V > Vcut_{out} \tag{2}$$

$$P_{wt} = V^3\left(\frac{P_r}{V_r{}^3 - Vcut_{in}{}^3}\right) - \left(\frac{Vcut_{in}{}^3}{V_r{}^3 - Vcut_{in}{}^3}\right)\mathrm{Pr} \tag{3}$$

$$if \;\; V > Vcut_{in} \;\; and \quad V < V_r$$

$$P_{wt} = P_r \quad if \;\; V > V_r \;\; and \, V < Vcut_{out} \tag{4}$$

Where P_{wt}, P_r, V_r, V, $V_{cut\ in}$, $V_{cut\ out}$ are the Wind Turbine (WT) Power Generation (kW), the WT Rated Power (kW), the WT Rated Wind Speed (m/s), the Measured Wind Speed (m/s), the Cut-in Wind Speed (m/s), and the Cut-Out Wind Speed (m/s) respectively.

2.1.3. Battery

In its operation, the battery has two functions: as a load and as a generator. During the energy charging process, the battery acts as a load, while during discharging, the battery functions as a generator. The charging and discharging processes of the battery can be expressed using Equations (5) and (6) [15].

Charging Process

$$E_B(t) = E_B(t-1) * (1-\sigma) + (E_G(t) - \frac{E_L(t)}{\eta_{inv}}) * \eta_B\,(t) \tag{5}$$

Discharging Process

$$E_B(t) = E_B(t-1) * (1-\sigma) - \left(\frac{E_L(t)}{\eta_{inv}} - E_G(t)\right) \tag{6}$$

2.1.4. Diesel Generator

The diesel generator must generate electrical power greater than the existing peak load. The hourly fuel Consumption Cost (CF) of the diesel generator can be expressed using Equation (7) [13].

$$C_F = P_{fuel} \,.\, F_{GBD} \tag{7}$$

Where P_{fuel} and F_{GBD} are the fuel price, which refers to the market price, and the fuel consumption of the diesel generator (liters per hour), respectively, the maximum output power generated by the diesel generator is 85% of its rated power as per the manufacturer's recommendation.

2.2. Cost of Energy (COE)

There are several important parameters commonly used as objective functions in SHM optimization, such as COE (Cost of Energy), LPSP (Loss of Power Supply Probability), and dummy load. COE is the total annual cost ($C_{ann.tot(\$)}$) required to generate electricity divided by the total electrical load served in a year ($P_{load\ (kWH)}$) as expressed in Equation (8) [16].

$$COE = \frac{C_{ann.T}}{\sum_{h=1}^{h=8760} P_{load}} \tag{8}$$

The total annual cost ($C_{ann.T}$) is the sum of the annual investment cost ($C_{ann.cap}$), the annual operation and maintenance cost (Cann.o&m), and the annual replacement cost ($C_{ann.rep}$), as expressed in Equation (9).

$$C_{ann\_T} = C_{ann\_cap} + C_{ann\_o\&p} + C_{ann\_rep} \tag{9}$$

2.3. Loss of Power Supply Probability (LPSP)

LPSP evaluates microgrid reliability. It is the ratio of total energy deficit to total load over the study period (usually one year). This LPSP value can be calculated using Equation (10) [16]. The calculation results are 1, which means complete failure; while 0 means perfect supply.

$$LPSP = \frac{\sum_0^T (P_L(t) - [P_{PV}(t) + P_{WT}(t)] + P_{Bat(t-1)} + P_{DG(t)})}{\sum_{t=1}^T P_L(t)} \tag{10}$$

Where LPSP, $P_L(t)$, $P_{PV}(t)$, $P_{WT}(t)$, $P_{DG}(t)$, $P_{Batt}(t-1)$, and T are *Loss of Power Supply Probability*, load power at t time, Power produced by solar PV, wind turbine, diesel generator power, battery power, and periode of study for *microgrid system* in one year period of time (8760 hours). In this study, LPSP is treated as a constraint. To ensure reliable 100% renewable-based operation, the maximum allowable LPSP (εLPSP) is set to 0.04 (4%). The reliability of the LPSP can be written as follows [16].

$$LPSP \;\leq \varepsilon \, LPSP. \tag{11}$$

Where εLPSP is a reliability value that is less than 4%.

2.4. Optimization Sizing of the Hybrid Microgrid System

2.4.1. Objective Function

The Hybrid COA-WCA algorithm minimizes two conflicting objectives: COE and LPSP. The Weighted Sum Method (WSM) combines them into a single aggregate function [12, 17, 18]

$$F(x) = w_1 \cdot f_1(x) + w_2 \cdot f_2(x) \tag{12}$$

With $w_1 + w_2 = 1$, and w_1, $w_2 > 0$. WSM is chosen due to its simplicity, flexibility, and effectiveness in scalarizing multi-objective problems [17]. In this study, $w_1 = w_2 = 0.5$.

2.4.2. Constrain

In its operation, the SHM must satisfy the specified constraints. The constraint in this discussion is that the total energy generated by the Solar Pv (P_{PV}), Wind Turbine (P_{WT}), Battery (P_{bat}), and Diesel Generator (P_{DG}) must equal the total Load Demand (P_{load}), If the energy generated exceeds the load demand, the surplus energy will be directed to the Dummy Load (P_{dummy}), as expressed in Equation (13).

$$(P_{PV} + P_{WT} + P_{PV} + P_{PV}) - P_{dummy} = P_{load} \qquad (13)$$

2.5. Optimization Algorithm

2.5.1. COA

The Coyote Optimization Algorithm (COA) is a metaheuristic algorithm first introduced by researchers Juliano Pierezan and Carlos A. Coelho in 2018 in a scientific article titled "Coyote Optimization Algorithm: A new metaheuristic for global optimization problems" [9].

COA is a metaheuristic optimization method inspired by the species Canis latrans, which is predominantly found in North America. The algorithm is designed by considering the social organization of coyotes and their adaptation to the environment, contributing to an algorithmic structure distinct from other metaheuristic methods. It also provides a novel mechanism for balancing exploration and exploitation during the optimization process [9].

2.5.2. WCA

The Water Cycle Algorithm (WCA) is a metaheuristic algorithm developed by Ezatolah Salari et al. in 2012 [19] through the publication of a paper titled "Water Cycle Algorithm – A Novel Metaheuristic Optimization Method for Solving Constrained Optimization Problems." This algorithm is inspired by the hydrological cycle that occurs in nature. Water flows in the form of rivers and streams from mountain peaks toward the sea. During their descent, rivers and streams collect water from rainfall and other tributaries. These waters and streams evaporate, and vegetation also releases water into the atmosphere as clouds. These clouds are compressed in the cooler atmosphere, making rain and creating new streams.

Like other metaheuristic algorithms, the WCA begins with an initial population referred to as the "stream population," which originates from rain or hail.

2.5.3. Hybrid Optimization Algorithm

A Hybrid Optimization Algorithm (HOA) is an optimization algorithm that combines two or more optimization algorithms with the aim of enhancing exploration and exploitation of the solution space, accelerating convergence to the optimal solution, avoiding local optima traps, and improving the stability and reliability of results. In general, metaheuristic optimization methods possess a balanced capability in terms of exploration and exploitation of the best solution to be selected. The Coyote Optimization Algorithm (COA) has strong exploration capabilities [20, 21], while hybrid approaches combining the Water Cycle Algorithm (WCA) with Particle Swarm Optimization (PSO) [22], the Moth Flame Algorithm (MFA) [23], and Simulated Annealing (SA) [24] leverage WCA's strengths in exploration.

Hybrid optimization algorithms can be categorized into three types; (i) sequential hybrid, where the first algorithm is used to search for promising areas of the solution space, and the second algorithm performs a refined search around those solutions; (ii) Parallel hybrid, where two or more algorithms are run in parallel and exchange information (co-evolution); (iii) Embedded hybrid, where one algorithm is executed as part of another algorithm (one serves as a component within the optimization process) [10, 25, 26].

3. Material and Method

3.1. Technical and Economic Characteristics of Microgrid Components

The hybrid microgrid system at Menjangan Island mainly consists of solar PV, a wind turbine, a battery, and a diesel generator, with characteristics as displayed in Table 1.

Table 1. Technical and economic characteristics of hybrid microgrid components

Component	Parameter	Value
Solar PV (LR6-72)	Nominal Max. Power	330 W
	Module efficiency	17%
	Open circuit voltage	46.1V
	Short circuit voltage	9.3 A
	Power temperature coefficient	−0.41%/°C
	Capital cost	256.2$
	O & M cost	3.8$
Wind Turbine L1000	Rated power	1kW
	Rated voltage	24/48/98 V
	Cut in speed	2.5 m/s
	Rated wind speed	12 m/s
	Cut off speed	25 m/s
	Capital cost	13658 $
	O & M cost	205 $
	Replacement cost	10926$
Battery VRLA	Nominal capacity	100 Ah
	Nominal voltage	12V
	Max charging current	30A
	Efficiency	86 %
	Design lifetime	7year
	Capital cost	584 $
	O & M cost	9 $
	Replacement cost	468 $
Diesel generator	Rated capacity	4 kW
	Fuel consumption	0.8 L/h
	Capital cost	1327 $
	O & M cost	929 $
	Replacement cost	1062$

3.2. Menjangan Island

For this case study, data were collected from Menjangan Island, Bali. Located 5 miles northwest of Bali, this island is part of the West Bali National Park and Sumberklampok Village area, Gerokgak sub-district, Buleleng Regency, Bali Province, Indonesia (8°03'–8°07' S and 114°25'–114°35' E) as shown in Figure 1. The island is known for snorkeling and diving, with an area of 165 hectares. The main electrical load consists of lighting for the temple areas only, which operates automatically using timers and LDRs (Light-Dependent Resistors), as there is no electricity grid. Currently, the electricity supply is served by a generator that is operated irregularly, only when needed.

Fig. 1 The Menjangan Island

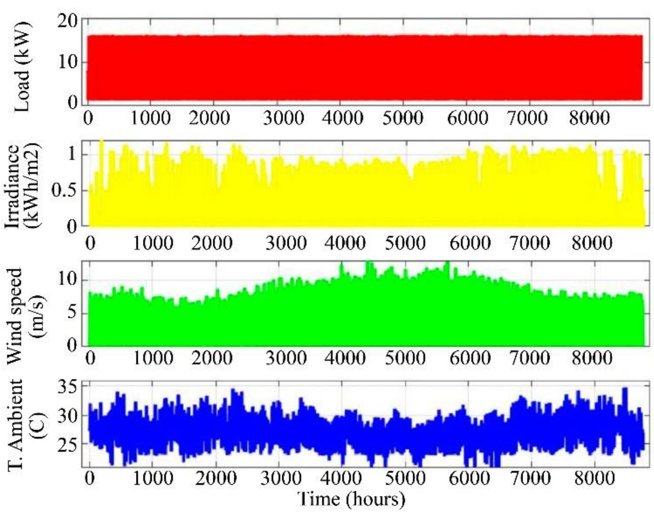


Fig. 2 Menjangan Island yearly data: load, irradiance, wind speed, and ambient temperature

The data on solar radiation intensity over a horizontal surface, ambient temperature, and wind speeds were obtained from NASA. Figures 3 and 4 show the detailed potential of solar radiation and wind speed on Menjangan Island. The annual average data (8,760 hours) and a 25-hour segment of electrical load, solar irradiance, wind speed, and ambient temperature have been recorded from hour 5,495 to hour 5,520, for the Menjangan Island area, which are shown in both figures.

The data have been recorded annually, where the electrical load has an average value of 6.12 kW, with a minimum of 1.3 kW and a maximum of 15.78 kW. Solar irradiance is 5.643 kWh/m² on average, with a maximum of 1.2 kWh/m², while the wind speed data shows a value of 7.64 m/s, with a minimum and maximum value at 0.06 m/s and 26 m/s, respectively. The ambient temperature lies between 19.73°C and 34.74°C, with an average of 27 °C.

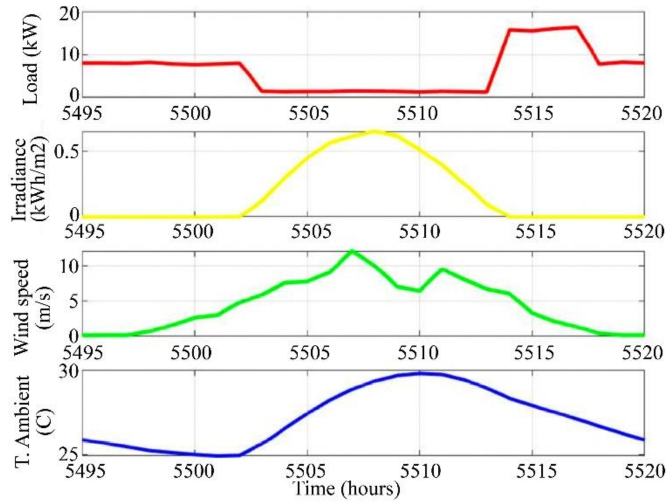


Fig. 3 Menjangan Island 24-hour data: load, irradiance, wind speed, and ambient temperature

3.3. Method

This section describes the methodology used in the study, which adopts a numerical simulation approach to optimize power dispatch in a hybrid microgrid system using the hybrid COA-WCA optimization algorithm. The research aims to evaluate the effectiveness and robustness of this hybrid algorithm in optimizing both technical and economic objectives within the microgrid system. This section is divided into several subsections that detail the system configuration, algorithm implementation, simulation setup, and performance evaluation methods.

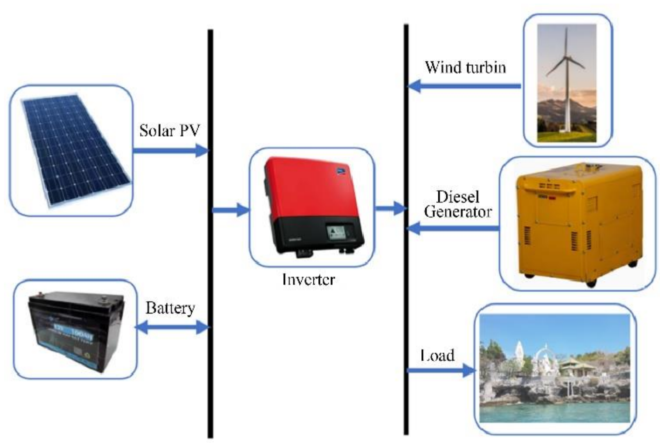


Fig. 4 Schematic configuration of the proposed hybrid microgrid system

3.3.1. System Configuration

General off-grid hybrid microgrid configurations, such as solar, wind, battery, and diesel generator, need to be autonomous and have good reliability in remote settings with variable renewable availability [27]. Designers of microgrids have to consider the balance between storage and backup to achieve operational stability [28] and diversify energy sources to avoid instability from over-reliance on one type [29]. System configuration in this paper consists of solar PV, batteries, wind turbines, and diesel generators, as shown in Figure 4.

3.3.2. Hybrid COA-WCA Algorithm

The Coyote Optimization Algorithm (COA) and the Water Cycle Algorithm (WCA), two well-known metaheuristics, are combined in this study's hybrid algorithm optimization process. Both algorithms have proven effective in solving complex optimization problems across various engineering domains. While WCA concentrates on heavily exploiting promising local solutions, COA is used to more efficiently explore the solution space. In order to achieve an ideal balance between exploration and exploitation, this sequential hybrid approach makes use of the advantages of both algorithms: COA conducts global exploration while WCA refines solutions locally [30]. Better global solutions can be found thanks to COA's superior ability to explore a wide solution space [28]. WCA, on the other hand, places more emphasis on deeper local exploitation, which is advantageous for refining and enhancing solutions found during global exploration. The integration of these two algorithms is expected to optimize power supply in hybrid microgrid systems more effectively, as their approaches are complementary in handling the exploration–exploitation trade-off [29].

3.3.3. Objectives and Constraints

The optimization model in this study involves two primary objectives-technical and economic. Reducing the Loss of Power Supply Probability (LPSP), which gauges power supply dependability, is the technical goal. A more dependable system that can meet load demand with fewer interruptions is indicated by a lower LPSP. Minimizing the Cost of Energy (COE), which represents the entire cost of producing and delivering electricity from the hybrid microgrid, is the economic goal. COE is influenced by factors such as capital and operational costs of renewable energy systems, battery storage, and diesel generators [28].

Several constraints are also considered in the optimization process, including capacity limits of renewable energy systems, battery storage, and diesel generators. The optimization also accounts for the time-varying load profile. All of these constraints focus on resulting solutions, both in practical and in implementable terms. The system design can meet the required energy demands within technical and economic limitations. Capacity constraints and load variability are key factors in designing efficient microgrid systems, as explained by Kavadias and Triantafyllou (2021) in their research [31].

3.3.4. Simulation Setup

Simulations were conducted using MATLAB R2023b, which has a robust system for implementing and testing optimization algorithms. The hybrid COA-WCA algorithm was programmed in MATLAB, and system parameters were configured according to the specifications of the Menjangan Island microgrid. The simulation environment was designed to model the island's actual power generation and consumption patterns using real-world data, including solar irradiance profiles, wind speed, and load demand [32]. In the COA algorithm configuration, a population size of 49 individuals is used with parameters n_pack = 7 and n_c = 7, which define the pack size and the number of individuals selected for crossover, respectively. The configuration of WCA contains a population size of 29 (Npop) and a number of river-stream cycles (Nsr) set to 7. Both algorithms were set to run for 25 iterations to evaluate their convergence behavior. In the simulation, changes were also made to the population number parameters for both COA, WCA, and hybrid COA-WCA as material for performance evaluation.

3.3.5. Performance Evaluation

The performance evaluation for the hybrid COA-WCA algorithm was conducted by comparing its results against those obtained from COA and WCA individually. Some evaluation metrics were used, such as solution quality, convergence behavior, robustness, and sensitivity to uncertainty. These metrics are used to understand the trade-offs among competing objectives and constraints.

- Sensitivity Analysis and Robustness Testing: Robustness can be shown in the stability of solutions under varying conditions, such as changes in weather, load profiles, and energy prices. Sensitivity analysis was performed to assess the impact of parameter variations on system performance, using scenario reduction and disturbance analysis to test the system's response to different input conditions [27].
- Sensitivity analysis and robustness testing are complementary tools: sensitivity analysis is diagnostic-it identifies "what matters" at the parameter or model level-whereas robustness testing evaluates "whether decisions remain good" when uncertainties are realized. Both are integrated into the microgrid design/ optimization pipeline by best practices: robustness testing assesses the quality of decisions made within the test space, sensitivity analysis reduces the test space, and their combined outcomes strengthen the basis for technical and policy recommendations [33].
- Statistical Analysis: To determine if the performance analysis has significant differences statistically, non-parametric tests were applied to 30 independent runs of each algorithm. Statistical metrics included the mean, median, standard deviation, and minimum/maximum values of the objective function. The significance of algorithmic performance differences was evaluated using the Wilcoxon signed-rank test [28].

- Convergence Behavior: The objective function values (LPSP and COE) were plotted against the number of iterations in order to analyze convergence. This offers insights into algorithmic efficiency and aids in identifying premature or slow convergence [29].
- Solution Quality: Solution quality was visualized using Pareto front diagrams. The Pareto front is used to evaluate multi-objective solutions, and the distance between obtained solutions and the ideal front is measured [28]. Hypervolume analysis and descriptive statistics were employed to assess solution quality. Hypervolume is a widely used quantitative metric in multi-objective optimization that measures the "objective space" dominated by a set of solutions relative to a reference point, thereby combining convergence and diversity into a single value [10, 34]. To evaluate algorithm performance using hypervolume, the following procedure was followed:

  1) Obtain the set of nondominated (Pareto) solutions from multiple independent runs,
  2) Define a consistent reference point and normalize the objective space if needed,
  3) Compute the hypervolume for each run, and
  4) Compare hypervolume distributions across algorithms using appropriate statistical tests and effect size measures, supported by Pareto front plots and hypervolume boxplots for interpretation [10, 34].

3.3.6. Benchmarking and Dataset

To ensure fair and reproducible comparisons, a standardized benchmarking protocol was followed. Simulations used multi-year datasets for load profiles, solar irradiance, ambient temperature, and wind speed-representative of actual conditions on Menjangan Island. Extreme scenarios-including cloudy days (irradiance variation), wind speed fluctuations, load demand changes, and fuel price shifts-were also included to test system robustness. [32] This dataset provides a realistic representation of operational conditions faced by hybrid microgrids, enabling a comprehensive evaluation of the optimization algorithm. This methodology integrates a hybrid optimization approach with rigorous performance evaluation techniques to assess the effectiveness of the COA-WCA algorithm in optimizing power dispatch in hybrid microgrid systems. Strong statistical analysis, scenario-based simulation, and multi-objective optimization are used to guarantee that the final solutions are reliable and optimal under a variety of circumstances. By using this approach, the study hopes to offer insightful information for hybrid microgrid design and operation, especially in isolated areas like Menjangan Island.

4. Results and Discussion

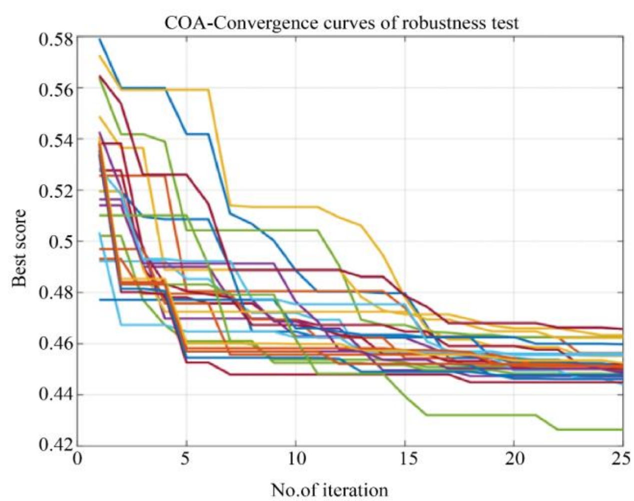
The three optimization algorithms-COA, WCA, and Hyb_COA-WCA-were simulated using MATLAB software and applied to the case study of the hybrid microgrid system on Menjangan Island, Bali, Indonesia. Table 2 presents the values of the objective function, COE, LPSP, and the number of units for solar PV, wind turbines, batteries, and diesel generators, as obtained from simulations conducted using MATLAB. The simulation results were tested using sensitivity and robustness tests, convergence performance, and kualitas solusi, with the results and discussion presented below.

Table 2. Result of simulation COA, WCA, and Hyb_COA-WCA

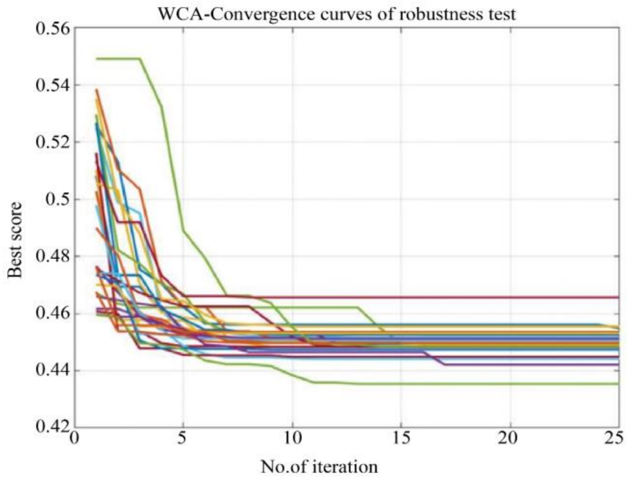
Parameter	COA	WCA	Hyb_COA-WCA
f	0.45226	0.45044	0.45036
COE ($/kWh)	0.823692	0.818973	0.819454
LPSP (kWh)	1346.632	1346.632	1332.757
Solar PV (unit)	707	670	655
Wind Turbine (unit)	15	15	19
Battery (unit)	100	99	99
Generator Diesel (unit)	1	1	1

4.1. Sensitivity Analysis and Robustness Test

Sensitivity analysis and robustness testing were conducted to compare the performance of the three algorithms-COA, WCA, and Hyb_COA-WCA-in achieving the minimum objective function value (f). The algorithms were evaluated under various uncertain conditions. In this simulation, 30 uncertain scenarios were created, representing realistic variations such as changes in population size, fuel price fluctuations, weather variations (solar irradiance, temperature, wind speed), and population size constraints. All optimizations were run for a maximum of 25 iterations. A lower objective function value (best score) indicates better algorithm performance. Figure 5 presents the results of the sensitivity and robustness tests for all three algorithms in the form of convergence curves of the objective function values.



(a)



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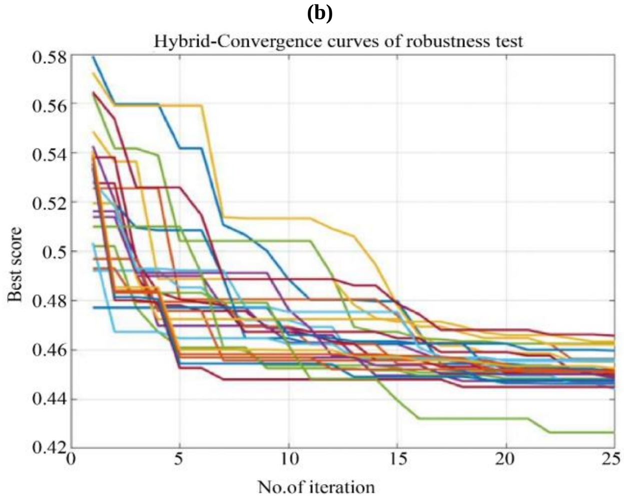

(c)

Fig. 5 Convergence curve, (a) COA, (b) WCA, (c) Hyb COA-WCA.

The results of the sensitivity and robustness tests can be seen in Table 3. The Hyb_COA-WCA achieves the lowest mean and median values (0.457 and 0.450, respectively) and the smallest standard deviation (0.013). It means that this method has the most stable performance among the three algorithms. On the other hand, COA has the highest mean value (0.493) and the largest spread of results (SD = 0.034), making it the least stable performance.

Table 3. Descriptive statistics of the objective function values for COA, WCA, and COA-WCA

Algorithm	Mean	Median	S.dev	Min	Max
COA	0.493	0.478	0.034	0.426	0.573
WCA	0.461	0.451	0.018	0.435	0.516
Hyb_COA-WCA	0.457	0.450	0.013	0.423	0.465

As the data did not show a normal distribution, a non-parametric Friedman test was carried out to evaluate the performance of differing algorithms. Analysis using these algorithms shows the results are significantly different ($\chi^2(2) = 18.72$, p = 0.00008). The following results were obtained with the Wilcoxon signed rank test, which was used for post-hoc pairwise comparison:

- Hyb_COA-WCA vs COA → p = 0.001 (signifikan**)**
- Hyb_COA-WCA vs WCA → p = 0.018 (signifikan**)**
- COA vs WCA → p = 0.124 **(**tidak signifikan**)**

Thus, statistically, Hyb_COA-WCA demonstrates significantly better and more stable performance than both COA and WCA.

These findings indicate that Hyb_COA-WCA successfully overcomes the main limitations of its base algorithms. Generally, COA exhibits strong exploration capability due to the social interaction mechanism among coyote packs, but often lacks effective exploitation, making it prone to local convergence. Conversely, WCA tends to converge quickly thanks to its stream flow and rainflow mechanisms, but easily stagnates at suboptimal points due to low solution diversity.

In Hyb_COA-WCA, COA's information-sharing mechanism is combined with WCA's rainflow update strategy, enabling the hybrid algorithm to balance global exploration and local exploitation dynamically.

This is evident from:

- A 7.3% reduction in average objective function value compared to COA and approximately 0.9% compared to WCA,
- A 61.8% reduction in standard deviation compared to COA, indicating significantly improved result consistency across runs,
- A narrower value range (max–min = 0.042 for Hyb_COA-WCA vs. 0.147 for COA), demonstrating high robustness to variations in initial conditions.

Moreover, the lower median and symmetric distribution observed in boxplots indicate that Hyb_COA-WCA not only achieves the best objective values but also maintains consistently optimal performance across all 30 test scenarios.

Conceptually, the superior performance of Hyb_COA-WCA can be attributed to the successful integration of two key processes:

- Adaptive global exploration (from COA) → maintains solution diversity and prevents premature convergence.
- Convergent exploitation (from WCA) → accelerates convergence toward the optimum via water-flow-like movement toward a sink (best solution).

Consequently, Hyb_COA-WCA not only enhances optimization accuracy but also improves robustness and convergence efficiency, making it a powerful alternative for solving complex, multivariate optimization problems.

4.2. Convergence Performance

The convergence performance of the three optimization algorithms was compared with each other based on their best scores using convergence curves to assess their relative effectiveness. Figure 6 shows the convergence curves of COA, WCA, and Hyb_COA-WCA over 25 iterations.

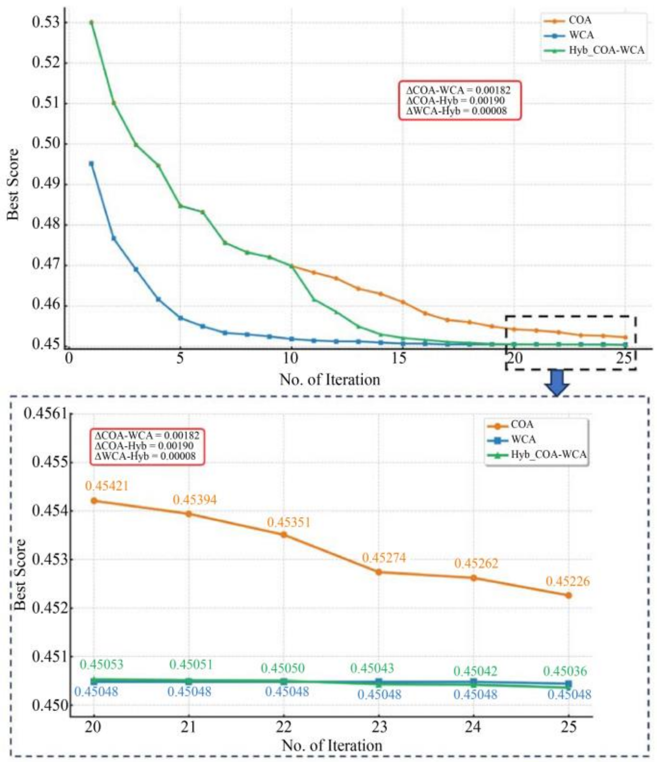

Fig. 6 Convergence curve COA, WCA, and Hyb_COA-WCA

The analysis shows that all three algorithms consistently reduce their objective function values until reaching a stable state in the final iterations. During the first 10 iterations, COA indicates a moderate rate of decline with minor fluctuations due to dominant exploration behavior. On the other hand, WCA gives a faster initial decline, reflecting the effectiveness of its stream flow mechanism in enhancing local exploitation. For Hyb_COA-WCA, it indicates a stable behavior consistently, where the best scores are always lower than those of the other two algorithms at every iteration stage.

For another result at iteration 25, the best scores were 0.45226 (COA), 0.45044 (WCA), and 0.45036 (Hyb_COA-WCA). Hyb_COA-WCA achieves the best convergence performance by achieving the lowest differences between them, which are Δ(COA–WCA) = 0.00182, Δ(COA–Hyb) = 0.00190, and Δ(WCA–Hyb) = 0.00008. These results indicate the efficiency improvements of approximately 0.42% over WCA and 0.80% over COA.

The convergence pattern from iterations 1 to 25 shows that COA requires more cycles to stabilize due to its exploration-focused nature, driven by social interactions among coyote packs. While this helps avoid local optima, it results in slower convergence.

Conversely, WCA demonstrates more efficient exploitation due to its stream and rainfall mechanisms, which balance global and local search. However, WCA tends to stagnate between iterations 10 and 15 before stabilizing again toward the minimum.

The best performance is achieved by Hyb_COA-WCA, which successfully combines COA's exploration strength with WCA's exploitation stability. During iterations 20–25, Hyb_COA-WCA exhibits a smooth and stable convergence curve, with inter-iteration changes in the best score of ≤ 0.0001.

This result means that the algorithm has reached a near-global optimum. This adaptive combination strengthens the algorithm's ability to accelerate solution discovery while keeping the high accuracy.

Overall, these results confirm that the COA–WCA hybrid approach yields significant improvements in both convergence speed and solution quality, making Hyb_COA-WCA a more efficient and stable method for solving complex nonlinear optimization problems compared to COA and WCA used individually.

4.3. Solution Quality

The simulation results were also evaluated based on the quality of solutions produced by each algorithm. Solution quality was assessed using the two primary optimization objectives: Cost of Energy (COE) as the economic metric and Loss of Power Supply Probability (LPSP) as the technical (reliability) metric. Solution quality is thus defined by the balance achieved between economic and technical aspects.

The COE and LPSP values from simulations across 30 scenarios under varying conditions are visualized in the Pareto front shown in Figure 7.

The two-dimensional LPSP–COE Pareto front is an effective and quantifiable tool for evaluating optimization algorithm performance in microgrid design and operation, as it integrates technical (reliability) and economic (cost) aspects into a visually and quantitatively analyzable trade-off. In multi-objective optimization, hypervolume measures how extensively an algorithm explores the optimal solution space by calculating the area dominated by the Pareto front relative to a reference point worse than all obtained solutions. A larger hypervolume means a better solution quality. These results reflect the algorithm's ability to find optimal solutions across a broader multi-objective space.

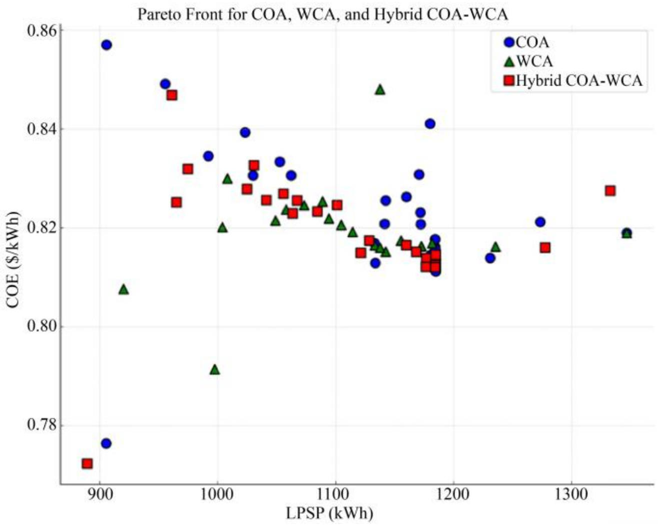

Fig. 7 Pareto Front COE dan LPSP, Hybrid COA-WCA, COA, WCA

Using a reference point of COE = 0.8 and LPSP = 1400, the calculation of hypervolume values can be seen as:

- COA: 30.13447
- WCA: 20.85942
- Hyb_COA-WCA: 31.63174

Based on these results, significant differences in solution space exploration performance are observed:

- COA shows a hypervolume of 30.13447 as an indication that COA finds reasonably good solutions but does not explore as broadly as other algorithms.
- WCA achieved the lowest hypervolume (20.85942), showing the least effectiveness at exploring the solution space widely. This method has solutions that are more concentrated in a limited optimal region but do not cover as many high-quality trade-offs as COA or Hyb_COA-WCA.
- Hyb_COA-WCA, a combination of COA's exploration strength and WCA's exploitation capability, found the highest hypervolume (31.63174). This means it is successful in balancing exploration and exploitation, discovering more optimal solutions, and exploring a wider and higher-quality portion of the solution space than either algorithm alone.

Overall, Hyb_COA-WCA shows the best performance by achieving the largest hypervolume. This hybrid algorithm effectively merges COA's global search capability with WCA's local refinement strength, producing more optimal solutions for both objectives: minimizing COE and LPSP.

Table 4. Minimum and maximum values of COE and LPSP parameters

Parameter	Algorithm	Min	Max
COE ($/kWh)	COA	0,8230	0,8491
	WCA	0,8124	0,8246
	Hyb	0,8120	0,8326
LPSP (kWh)	COA	905	1184
	WCA	1008	1346.63
	Hyb	889	1332.76

Table 4 presents the statistical min–max ranges of COE and LPSP for all three algorithms. It shows that each method produces solutions with distinct trade-off characteristics. Notably, Hybrid COA-WCA demonstrates the potential to achieve lower energy costs (COE) without significantly compromising energy reliability. The following provides a more detailed analysis of each algorithm's behavior based on Table 4.

4.4. Coyote Optimization Algorithm (COA)

- Solutions (blue circles) span an LPSP range of 900–1180 kWh and a COE range of 0.76–0.85 $/kWh.
- While COA can produce competitive COE values, it shows high variability in LPSP. Some solutions achieve low LPSP at a higher cost, indicating a significant trade-off.
- This suggests that although COA is effective at finding good solutions, it struggles to consistently balance COE and LPSP, especially at higher cost levels.

4.5. Water Cycle Algorithm (WCA)

- Solutions (green triangles) are more evenly distributed across LPSP values, ranging from 900 to over 1300 kWh.
- WCA generally achieves lower COE than COA, but with noticeable variation. Some solutions show low COE accompanied by high LPSP, indicating better cost control but reduced reliability.
- Despite its ability to minimize COE, WCA often produces high-LPSP solutions even at moderate costs, suggesting a stronger bias toward cost minimization at the expense of reliability.

4.6. Hybrid COA-WCA

- Solutions (red squares) are more concentrated in regions of low COE without significant LPSP degradation. The LPSP distribution is comparable to COA and WCA, but with more competitive COE values.
- This method demonstrates superior ability to simultaneously optimize both objectives, with more solutions clustered in the optimal zone of low cost and high reliability.
- This indicates that the hybrid combination of COA and WCA creates effective synergy, achieving a better balance between reducing energy cost and ensuring a reliable power supply, making it a more effective choice than either algorithm used alone.

The hybrid COA–WCA approach outperforms other methods in the literature by combining WCA's global search ability with COA's exploration method. This mix stops early convergence and speeds up the path to good results. The proposed method gets lower objective function values, better system efficiency, trustworthy results, and less variability across runs. The better results come from an algorithmic design that fits the optimization problem.

This work has important practical considerations. It can improve performance, make systems more productive and dependable, and be used for many power system problems. Still, some limits are not checked in real time, and it may require more calculations for large systems. Plus, we have not fully tested it with uncertain data or hard working conditions.

5. Conclusion

This study develops and evaluates a hybrid optimization algorithm that combines the Coyote Optimization Algorithm (COA) with the Water Cycle Algorithm (WCA) for energy management in hybrid microgrid systems. The research aims to address the challenges of multi-objective optimization involving the minimization of both the Cost of Energy (COE) and the Loss of Power Supply Probability (LPSP), while considering technical and economic factors.

Simulation results show that the COA-WCA hybrid algorithm delivers more stable and efficient performance compared to COA and WCA when used individually. In terms of convergence, COA-WCA reaches optimal solutions faster, reduces the standard deviation of results by 61.8% compared to COA, and achieves the highest hypervolume-indicating greater effectiveness in exploring a broader solution space. Furthermore, sensitivity analysis demonstrates that COA-WCA is more robust against uncertainties such as fluctuations in fuel prices and weather variability.

By integrating COA's strong exploration capability with WCA's refined exploitation ability, the hybrid algorithm produces superior solutions for power dispatch optimization in hybrid microgrids. Pareto front analysis reveals a better trade-off between energy cost and system reliability, achieving lower COE and more tightly controlled LPSP compared to either algorithm used alone.

In this research, a significant contribution can be seen in the development of renewable-based microgrid systems by offering a more efficient and reliable optimization approach. This also opens opportunities for applying hybrid algorithms in practical, real-world applications, especially in remote locations and off-grid systems.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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