



Enhanced Whale Optimizer: An Enhanced Approach Using Opposition Learning Solving PV maximum power point tracking problem

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ARTICLE INFO	ABSTRACT
Article type: Research Paper Article History: Received 1 November 2025 Accepted 7 September 2026 Keywords: Metaheuristics, Complex Optimization Problems, Opposition-Based Learning, Golden-Sine Strategy, Enhanced Whale Optimizer.	This paper proposes an Enhanced Whale Optimizer (EWO), a variant of the recently introduced Whale Optimizer (WO), motivated by the cooperative and foraging behaviors of groups of Whales. Although the original WO achieves a good exploration–exploitation balance, it often gets trapped in premature convergence and reduces population diversity at later search stages. To overcome these limitations, two adaptive strategies are combined: Opposition-Based Learning (OBL) and the Golden-Sine Strategy (GSS). The OBL mechanism ensures diversity of the initial population and global exploration, and assures a more comprehensive exploration of the search domain. The GSS, conversely, adaptively balances exploration and exploitation, resulting in improved convergence and enhanced local optimization capabilities. Performance of the proposed EWO is also confirmed with the CEC-2019 benchmark suite and several difficult real-world engineering problems, such as economic load dispatch, microgrid energy management, and Traveling Salesman Problem (TSP). Comparative analyses with well-known algorithms such as Particle Swarm Optimization (PSO), Dwarf Mongoose Optimization Algorithm (DMO), and White Shark Optimizer (WO) confirm EWO's better accuracy, convergence rate, and stability. Statistical tests and boxplot visualization also confirm its stability and consistency. It is evidenced that EWO has smaller mean errors, lower standard deviations, and higher reliability across multiple problem areas, citing its strength as a strong and general-purpose optimization algorithm suitable for both benchmark and engineering problems.
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1. Introduction

In the past decades, a wide variety of metaheuristic algorithms have been developed that are inspired by natural evolution [1-6], animal behavior [7-14], human creativity, and physical laws [14-16]. These algorithms usually come under four general categories based on the inspiration drawn from them: Swarm intelligence-based algorithms, Evolutionary algorithms, Physics-based algorithms, and Human or socio-inspired algorithms. Swarm intelligence-based algorithms such as Particle Swarm Optimization (PSO) [16], Grey Wolf Optimizer (GWO) [17], Dwarf Mongoose Optimization Algorithm (DMO) [18], Artificial Rabbits Optimization (ARO) [19], White Shark Optimizer (WSO) [20], Horse Herd Optimization (HHO) [21], Crested Porcupine Optimizer [22], Snake Optimizer (SO) [23], Beluga Whale Optimization (BWO) [24], Dandelion Optimizer (DO) [25], Golden Jackal Optimization (GJO) [26], Aquila Optimizer (AO) [27], and Red Deer Algorithm (RDA) [28] are inspired by the social behavior of social organisms such as insects, birds, or sea creatures.

These methods rely on cooperation in the social framework and information exchange between individuals to navigate through the search space. Swarm methods tend to be simple to employ with high global search ability, but are likely to suffer from premature convergence as the population diversity reduces or when the agents become too attracted to the best global position. Evolutionary algorithms (EAs) trace their origins in natural selection and evolutionary adaptation principles. Typical examples are the Genetic Algorithm (GA) [29], Differential Evolution (DE) [30], and Evolution Strategies (ES) [31]. Other new variants recently proposed, such as the Coronavirus Search Optimizer (CVSO) [32], Ebola Optimization Search Algorithm (EOSA) [33], and Coronavirus Herd Immunity Optimizer (CHIO) [34], also belong to this category. These algorithms use crossover, mutation, and selection operators to evolve candidate solutions through generations. Evolutionary

algorithms are likely to possess strong global optimization capability and resilience but are usually computationally expensive due to iterated population assessment and gradual local exploitation. Physics-based metaheuristics rely on mathematical models of physical processes such as annealing, gravity, electromagnetism, or arithmetic laws. Some of the algorithms are Simulated Annealing (SA) [35], Gravitational Search Algorithm (GSA) [36], Electromagnetic Field Optimization (EFO) [37], Arithmetic Optimization Algorithm (AOA) [38], Chernobyl Disaster Optimizer (CDO) [39], Atomic Orbital Search (AOS) [40], and Propagation Search Algorithm (PSA) [41]. The above algorithms all use physical metaphors to optimize for minimizing energy, attraction–repulsion forces, or laws of motion. They possess strong exploitation behavior and deterministic search patterns, but miss exploration capability in rough terrain. Human or socio-inspired algorithms simulate cognitive learning, instruction, or strategic group activity in human populations. Some such noteworthy examples include Teaching-Learning-Based Optimization (TLBO) [42], Brain Storm Optimization (BSO) [43], Human Evolutionary Optimization Algorithm (HEOA) [44], Mountaineering Team-Based Optimization (MTBO) [45], Stock Exchange Trading Optimization (SETO) [46], Poor and Rich Optimization (PRO) [47], Human Felicity Algorithm (HFA) [48], and Musical Chairs Algorithm (MCA) [49]. Such algorithms imitate cooperation, competition, and knowledge sharing among individuals or groups. While they are prone to yielding rapid convergence and lower parameter dependency, they are extremely sensitive to population diversity and adaptive trade-off between learning and innovation. Each class of metaheuristics has been found with specific strengths, yet none excels over the others in all categories of problems according to the no-free-lunch theorem [50]. Hence, hybrid metaheuristic algorithm development combining the strengths of different methods has been a thriving research domain. Hybridization enhances convergence

accuracy, accelerates performance, and reduces the danger of becoming entrapped in local optima—critical in the case of high-dimensional and engineering design optimization problems in real-world applications.

2. PV maximum power point tracking problem

Maximum Power Point Tracking (MPPT) is a crucial procedure in PV systems with the objective of extracting the maximum available power from the system and making the system work at the Global Maximum (GM). The Maximum Power Point (MPP) of a PV cell is not constant since it varies with different parameters such as temperature, irradiation, load impedance, weather conditions, and other environmental conditions. These variations make MPPT a requirement to ensure the optimal operation of PV panels by maintaining them at their maximum power production at all times. PV systems can be generally classified as grid-connected and standalone systems. For a grid-connected system, the interface between the PV system and the grid is provided by a voltage source converter, and for a standalone system, the interface between the PV panel and the load is provided by a DC/DC converter. The duty cycle of this converter, d , is used as the control variable in the MPPT method. The duty cycle is limited in a range so that $d_{\min}=0$ and $d_{\max}=1$, which forms the search space in MPPT optimization. Fig. 1 presents the block diagram of a traditional MPPT controller used in PV systems, which efficiently controls the power flow by adjusting the duty cycle to track the maximum power point.

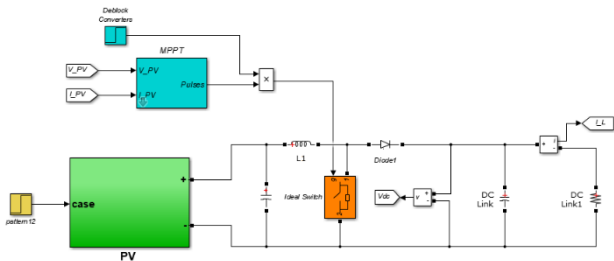


Fig. 1. Block diagram of a typical MPPT controller used in the PV system.

The output current of an ideal PV cell, which is derived according to Kirchhoff's first law, is expressed as follows [54]:

$$I_{pv} = I_{ph} - I_D + I_{sh} \quad (1)$$

Where, I_{pv} is the output current, I_{ph} is the photoelectric current, and I_{sh} is the shunt current.

The diode current in the system is controlled by Shockley's equation, as given in [54].

$$I_D = I_0 \left[\exp \left(\frac{q}{nkT} (V_{PV} + I_{PV}R_s) \right) - 1 \right] \quad (2)$$

Where, I_D is the diode current, I_0 is the diode reverse saturation current, and V_{pv} is the voltage across the diode.

The shunt current can be determined using the below equation [54]:

$$I_{sh} = \frac{V_{PV} + I_{PV}R_s}{R_p} \quad (3)$$

Substituting the value of I_D in Eq. (33) yields the expression for the output current I_{pv} of an ideal PV cell, as presented in [54].

$$I_{PV} = I_{ph} - I_0 \left[\exp \left(\frac{q}{nkT} (V_{pv} + I_{pv}R_s) \right) - 1 \right] - \frac{V_{pv} + I_{pv}R_s}{R_p} \quad (4)$$

The current–voltage characteristic of a solar cell is also explained by the equation. In the equation, q is the charge of an electron, T is the temperature of the junction, k is Boltzmann's constant, and n is the diode ideality factor.

Since a PV panel generates a DC output, the panel power can be calculated as:

$$P_{PV} = V_{PV} \times I_{PV} \quad (5)$$

The efficiency of all GMPPT algorithms is calculated by:

$$\eta_{PV} = \frac{\text{Steadystate Power}}{\text{GMPP Power}} \times 100 \quad (6)$$

Table 1 shows the PV module parameters used in the MPPT problem. The module has a max power of 80 W, a voltage of open-circuit equal to 22.1 V, and a current of short-circuit equals to 4.8 A. At standard operating

conditions, the MPP is located at a voltage of 17.6 V and a current of 4.6 A.

Table 1. The PV module parameters [54].

Parameter	Value
Maximum power (W)	80
Voltage of open circuit (V)	22.1
Current of short circuit (A)	4.8
Maximum power voltage (V)	17.6
Maximum power current (A)	4.6

In Table 2, two irradiance patterns are employed to investigate the performance of the EWO in resolving the MPPT problem. The PV panels are exposed to constant irradiance levels of 1000 W/m² in Pattern 1, which is an ideal, unshaded condition and yields a global power output of 159.652 W. On the contrary, Pattern 2 generates partial shading conditions under which the irradiance values are [1000 W/m², 700 W/m², 100 W/m², 1000 W/m²] and result in non-uniform illumination of the PV array. For this shading condition, the global power decreases to 88.948 W, which is an indicator of the influence of partial shading on energy generation. These patterns are applied as test cases for assessing how robust and versatile the EWO algorithm is in identifying the global maximum power point accurately under uniform and non-uniform environmental conditions.

Table 2. Shading patterns and global power values [54].

Pattern Number	Shading Pattern	Global Power
Pattern 1	[1000 W/m ² , 1000 W/m ² , 1000 W/m ² , 1000 W/m ²]	159.652 W
Pattern 2	[1000 W/m ² , 700 W/m ² , 100 W/m ² , 1000 W/m ²]	88.948 W

The dynamic output power response of the PV and the matching duty cycle for the considered shading conditions, such as the transition from the first-to-second pattern, is depicted in Fig. 2. The sampling period (T_s) of the MPPT controller is set to be 0.06 seconds, and the oscillation amplitude of the power in the steady-state is maintained within 2%, ensuring stable operation close to the maximum power point.

As shown, when, upon changing from a uniform state (Pattern 1) to an partially shaded

state (Pattern 2) of the irradiation pattern at the 10th second, the new GMPP under the new environment is accurately detected and followed by the presented IWO-based MPPT algorithm, this demonstrates not only the algorithm's rapid dynamic response within the transient time but also its high steady-state accuracy after the new operating point is reached.

Overall, the simulated results also confirm the high flexibility, superb convergence capability, and high robustness of the evolved IWO algorithm against partial shading variations, indicative of its applicability to real-time PV power management under highly varying weather condition.

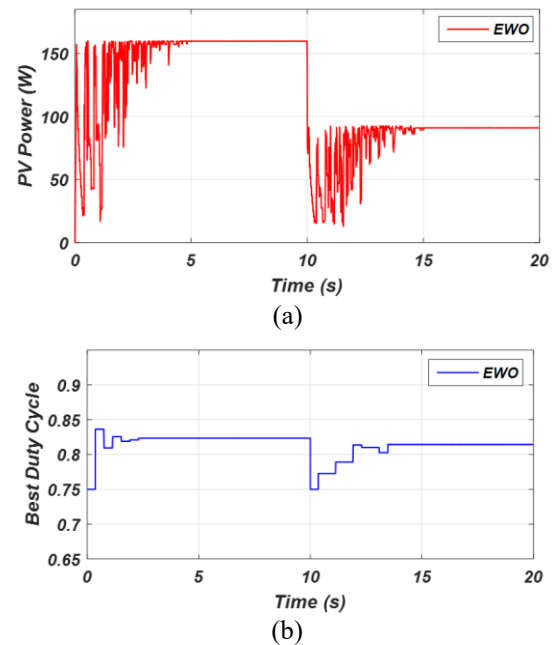


Fig. 2. Variation of a) PV power b) Best duty cycle.

Table 3 displays the MPPT efficiency results of several optimization algorithms, such as EWO, WO, PSO, DMO, WSO, and the Artificial Bee Colony (ABC) algorithm published in [54], for Pattern 1 that describes uniform irradiance conditions. As seen, the EWO algorithm has the maximum mean efficiency of 99.83% compared to all other algorithms. On comparison, the traditional WO algorithm performs a mean efficiency of 99.76%, signifying an enhancement of approximately 0.07% compared to EWO, and represents improved accuracy and convergence capability. Moreover, EWO

possesses the lowest standard deviation (0.52) among all the algorithms, meaning greater stability and uniformity to locate the global maximum power point. Although algorithms like PSO, DMO, and WSO exhibit similar performances (99.78%, 99.79%, and 99.81% mean efficiencies, respectively), their greater standard deviations reflect somewhat weaker reliability. The highest efficiency reported by EWO (99.86%) is identical to that of the ABC algorithm (99.83%), which reflects its excellent optimization capability even compared with well-established metaheuristics. Overall, EWO performs the best among all the algorithms tried in terms of illustrating its efficiency, stability, and rapid convergence in optimal power harvesting under ideal irradiance.

Table 3. The results of different optimizers in solving the MPPT for pattern 1.

Function/ Algorithm	EWO	WO	PSO	DMO	WSO	ABC [54]
Mean	99.83	99.76	99.78	99.79	99.81	--
Std	0.52	0.71	0.74	0.79	0.68	--
Best	99.86	99.82	99.81	99.81	99.83	99.83
Worst	99.78	99.73	99.72	99.69	99.75	--
Rank	1	5	4	3	2	--

The bottom row of Table 3 and Fig. 3 present the ranking results of the algorithms according to overall MPPT performance for Pattern 1. The EWO algorithm ranks first, verifying its better efficiency, accuracy, and convergence consistency relative to the other optimization algorithms. WSO and DMO rank second and third, respectively, with acceptable but comparatively less stable performance. PSO stands at fourth position, and the classical WO algorithm at fifth position, meaning that the original version does not possess the adaptability and robustness that have been added in EWO. This standing confirms that the addition of OBL and Golden-Sine strategies to EWO indeed makes it far superior to converge to the global maximum power point more quickly and reliably compared to its counterparts, and thus it is the best technique

to be used under uniform irradiance conditions.

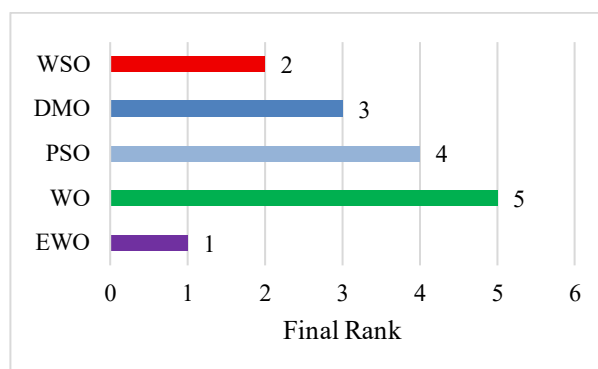


Fig. 3. The final rank for different algorithms in solving the MPPT for pattern 1.

The boxplot of Fig. 4 reveals that the EWO algorithm yields a better median value of fitness and smaller variation than WO, reflecting superior stability, accuracy, and quicker convergence in resolving the MPPT issue for Pattern 1.

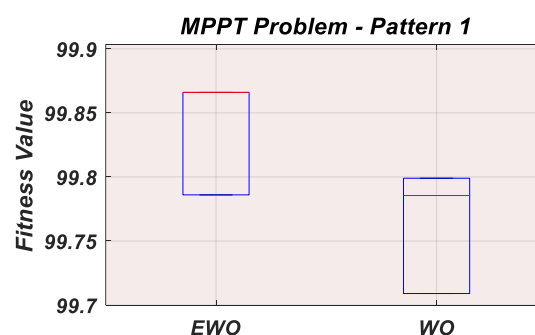


Fig. 4. The Boxplots visualization of EWO, and WO in solving the MPPT problem for pattern 1.

Table 4 summarizes the MPPT efficiency outcomes of various optimization algorithms under Pattern 2, which reflects partial shading conditions where irradiance across PV modules is non-uniform. As can be seen, the EWO attains the best mean efficiency of 99.39%, reflecting its excellent adaptability and robustness in tracing the global maximum power point under complicate and irregular illumination patterns. The standard deviation (0.33) of EWO is also minimal among all the algorithms, and it speaks well of its superior stability and stable convergence under changing shading conditions. In comparison, the traditional WO algorithm possesses a mean efficiency of 99.28%, and what this means is that the improvement provided by EWO is

approximately 0.11%, which, although numerically small, speaks well of an appreciable increase in energy capture consistency. The other algorithms, PSO (99.32%), DMO (99.31%), and WSO (99.34%), perform a little less than EWO, and ABC [54] performs with an identical best value of 99.36%.

Table 4. The results of different algorithms to solve the MPPT for pattern 2.

Function/ Algorithm	EWO	WO	PSO	DMO	WSO	ABC [54]
Mean	99.39	99.28	99.32	99.31	99.34	--
Std	0.33	0.62	0.51	0.55	0.48	--
Best	99.42	99.31	99.36	99.35	99.37	99.36
Worst	99.35	99.24	99.29	99.28	99.31	--
Rank	1	5	3	4	2	--

Ranking outcomes listed in Table 4 and Fig. 5 validate this observation, with EWO at the top, followed by WSO, PSO, DMO, and WO, respectively. This ranking verifies that the hybrid mechanisms incorporated in EWO, especially OBL and the Golden-Sine strategy, largely enhance its global search performance and local optima resistance, which enables faster and more precise MPPT convergence under partial shading.

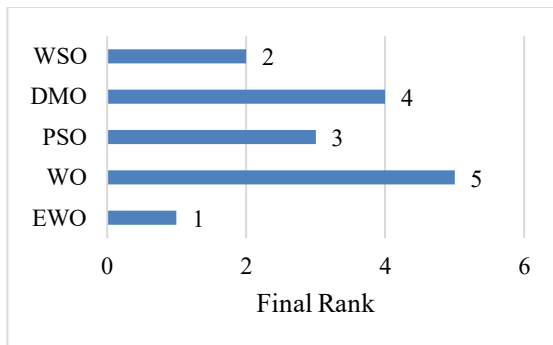


Fig. 5. The final rank for different algorithms in solving the MPPT for pattern 2.

Fig. 6 is a comparison between WO and EWO's performance in solving the MPPT problem for Pattern 2 (partial shading). A larger median fitness value is achieved by the EWO algorithm and with smaller variability, which proves its better stability and reliability of convergence even with non-uniform irradiance. Conversely, WO shows a lower

median and higher spread, which illustrates weaker adaptability. Generally, EWO presents better accuracy and stability in following the overall peak power point under intricate shading scenarios.

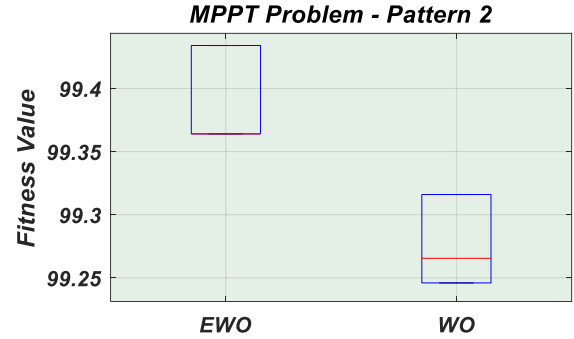


Fig. 6. The Boxplots visualization of EWO, and WO in solving the MPPT problem for pattern 2.

4.3.3 Economic load dispatch

Economic Load Dispatch (ELD) is a key optimization problem in the planning and operation of power systems. The primary purpose is to determine the most optimal distribution of power generation among available diesel generator (DG) units in order to reduce the total cost of fuel while simultaneously optimizing the utilization of renewable energy resources. This allocation must satisfy the system requirement for load and respect the operating limits for each generating unit, such as capacity constraints and ramp rates. The generation cost of each unit is typically characterized by quadratic cost functions so that the fuel consumption as a function of output power can be properly modeled. The overall cost of fuel for the system can be quantitatively expressed as in [55], providing the foundation upon which optimization algorithms are based to calculate the most cost-effective dispatch approach under the reliability and efficiency constraints of the system. The problem is further complicated when various renewable resources and actual operating considerations are taken into account.

$$F_G(t) = \sum_{t=1}^{24} \sum_{i=1}^g (\delta_i G_i^2(t) + \theta_i G_i(t) + \lambda_i) \quad (7)$$

Where, $FG(t)$ denotes the fuel cost in dollars per hour (\$/h), while δ_i (\$/MW²h), θ_i (\$/MWh), λ_i (\$/h) represent the cost coefficients of generator i . The variable t refers to the hourly time index within a 24-hour period.

The work discusses a generator-based islanded microgrid with the aim of serving local or community power demands, as presented in Fig. 7. In this operating mode, the microgrid runs in isolation without any power sharing or exchange with the host utility grid. Everything is self-contained, including generation and load management. The whole system power load is defined as follows, upon which optimization and control strategies are based.

$$P_d(t) = \sum_{i=1}^g G_{pi}(t) \quad (8)$$

$$+ P_w(t) + P_s(t) \quad (9)$$

$$G_{pi}^{min} \leq G_{pi} \leq G_{pi}^{max}$$

Where, $P_d(t)$ is the sum of the power demand at time t , $G_{pi}(t)$ is the i th generator's power output at the same time, and g is the system generators number. $P_s(t)$ and $P_w(t)$ are the power produced by the PV panels and wind turbines, respectively, at time t . These parameters collectively decide the generation–demand balance of the microgrid, which is critical for optimal energy management and optimization.

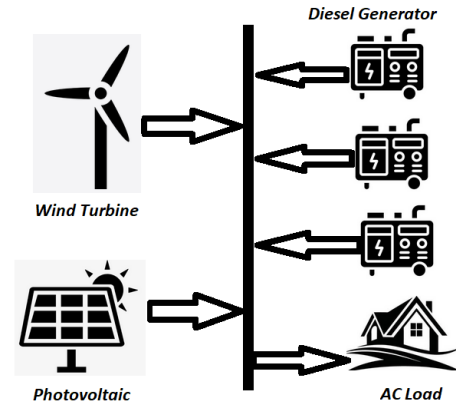


Fig. 7. Schematic of a Microgrid with generation units.

The proposed EWO is applied to minimize the total fuel price in the ELD problem for a distributed energy resource microgrid consisting of PV and wind WT under load demand conditions considering no power loss. The system information is presented in [55], and the outputs of the generators are determined using different optimization algorithms. All algorithms are executed for 500 iterations with the population size of 50, 30 independent runs in a statistically sound manner. As illustrated in Table 11, EWO produces the lowest mean fuel cost of 1.663×10^5 , outperforming other algorithms such as WO, PSO, DMO, and WSO by approximately 2.0%, 0.7%, 1.1%, and 0.36%, respectively. In addition, EWO demonstrates the lowest standard deviation (1.72×10^4), which reflects the greatest stability and solution consistency. Its performance values at optimal and worst performances (1.658×10^5 , 1.670×10^5) also confirm its power in finding near-optimal solutions. Compared to other algorithms reported in the literature, such as AOA (166,820.33) [55] and LAA (166,793.09) in [55], EWO is comparable or better with higher convergence consistency. Overall, the outcome verifies that the suggested EWO is efficient in minimizing the operation cost of the microgrid and proves to be more accurate and robust compared to other conventional optimization approaches.

Table 5. The outcomes of different optimizers in solving the economic load dispatch.

Item/Algorithm	EWO	WO	PSO	DMO	WSO	AOA [55]	LAA [55]
Mean	1.663E+05	1.697E+05	1.675E+05	1.681E+05	1.669E+05	--	--
Std	1.72E+04	5.04E+04	3.61E+04	3.61E+04	3.28E+04	--	--
Best	1.658E+05	1.693E+05	1.669E+05	1.67E+05	1.667E+05	166820.3313	166793.0971

Worst	1.670E+05	1.704E+05	1.686E+05	1.702E+05	1.671E+05	--	--
Rank	1	5	3	4	2	--	--

According to Table 5, and Fig. 8 the optimum overall performance (Rank = 1) is achieved by the EWO to solve the ELD problem and it proves to be more accurate and stable than any other algorithm. WSO stands second, with fairly good but less dependable outcomes, then comes PSO and DMO at third and fourth positions, respectively. The traditional WO comes last as anticipated, thereby confirming that the enhancements of EWO thoroughly promote convergence accuracy and dependability in optimizing the aggregate fuel cost of the microgrid.

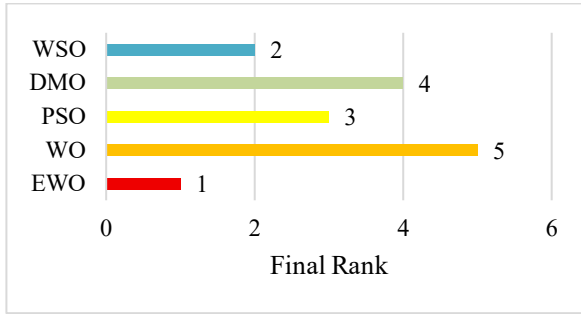


Fig. 8. The final rank for different algorithms in solving the economic load dispatch problem.

The boxplot in Fig. 9 provides a comparison of the EWO against the traditional WO in solving the economic load dispatch problem. It can be clearly observed that EWO receives a significantly lower median fitness value ($\approx 1.663 \times 10^5$) than WO ($\approx 1.697 \times 10^5$) and therefore has a superior capability of optimization in minimizing the total fuel cost. The interquartile range (IQR) of EWO is also significantly smaller, presenting greater stability and reliability with multiple runs, whereas WO presents greater dispersity, indicating greater volatility in its result. The presence of few outliers in EWO proves that it is robust even in the presence of stochastic environments. Overall, the plot validates that the improvements incorporated in EWO lead to higher convergence precision, lower variance, and more stable behavior than the conventional WO algorithm in solving the ELD optimization problem.

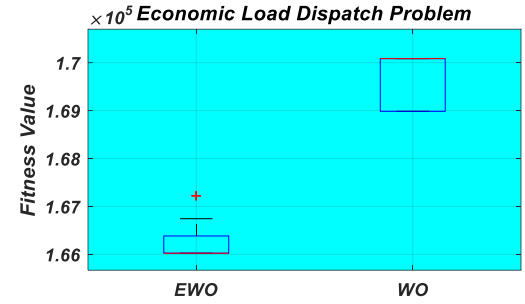


Fig. 9. The Boxplots visualization of EWO, and WO in solving the economic load dispatch problem.

4.3.4 Microgrids energy management problem

In the microgrid energy management problem, the objective is to determine the optimal sizes and capacities of various microgrid components, including PV systems, wind turbines (WT), microturbines (MT), fuel cells (FC), battery energy storage systems (BES), and the grid, to reduce the cost of operation of each component while satisfying diverse constraints. These constraints cover capacity limits of the components, system stability, and power source availability and reliability so that the microgrid is efficient under different load conditions [56]. The configuration and design of the entire microgrid energy management system are illustrated in Fig. 10, emphasizing the connections and operation flows between all the components. The EWO is utilized for this problem to optimize power distribution and minimize overall operating costs. Its performance is tested to the extreme, demonstrating its ability to handle complex interactions in the system and to generate cost-effective and reliable microgrid operation [56].

$$\begin{aligned}
 \text{Minimize } F(X) &= \sum_{i=1}^T C_o(x) \\
 \text{Subjected to:} \\
 0 \leq x_1 \leq 25; & 0 \leq x_2 \leq 15; 6 \leq x_3 \\
 & \leq 30; 3 \leq x_4 \\
 & \leq 30; -30 \leq x_5 \\
 & \leq 30; -30 \leq x_6 \leq 30
 \end{aligned} \tag{10}$$

The capacities of the PV, WT, MT, FC, BES, and the grid are represented by the decision variables x_1 , x_2 , x_3 , x_4 , x_5 , and x_6 , respectively.

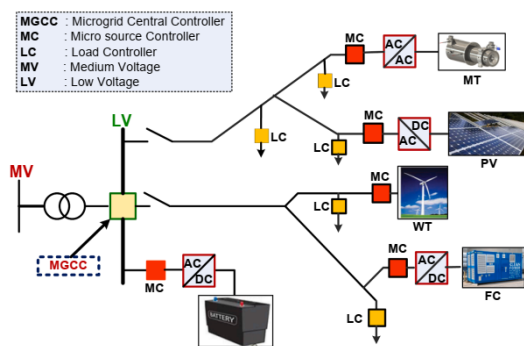


Fig. 10. Schematic of the microgrid energy management problem.

Optimum size of each unit in a hybrid renewable energy system depends crucially on design parameters. Problem constraints are related to balancing different sources' power generated and load demand at any given time. This balance is imperative in a bid to balance the system in a way that energy generation does not either surpass or fall short of the required demand, ultimately maximizing the utilization of energy while maintaining costs at the lowest. Besides, these constraints accommodate other aspects such as the dependability of the system, power quality, and incorporation of renewable resources in a bid to reduce the environmental impact of the system.

As can be seen in Table 6, by means of advanced mechanisms such as the OBL and

golden-sine strategies, the EWO algorithm is able to generate an optimized microgrid component sizing design with significantly lower operation cost compared to traditional algorithms such as WO and other algorithms. The numbers in Table 6 are comparative performance evaluation of various optimization algorithms to solve the microgrid (MG) energy management problem with the aim of minimizing the overall cost of operation. The proposed EWO shows the best performance among all algorithms with an average cost of 1.09×10^2 , which is significantly lower than the traditional WO (1.33×10^2), PSO (1.23×10^2), DMO (1.27×10^2), and WSO (1.18×10^2). This indicates that EWO achieves about 17.9%, 11.4%, 14.1%, and 7.6% lower operational expenditures, respectively, indicating its greater efficiency in microgrid energy dispatch optimization. Regarding stability, EWO has the smallest standard deviation (3.15×10^1) compared with WO (6.47×10^1) and DMO (7.20×10^1), indicating more stable and trustworthy convergence behavior. Moreover, the best cost achieved by EWO (1.04×10^2) is far less than the costs achieved by WO (1.28×10^2) and DMO (1.21×10^2), while the worst case achieved by EWO (1.13×10^2) is still far better than others, confirming its robustness and global convergence capability. In contrast to the algorithms of reference [56] denoted as BES (111.252) and BWO (154.917), EWO performs better again, with 2.2% and 29.6% less operation cost realized, respectively.

Table 6. The results of different optimizers in solving the MG energy management problem.

Function/Algorithm	EWO	WO	PSO	DMO	WSO	BES [56]	BWO [56]
Mean	1.09E+02	1.33E+02	1.23E+02	1.27E+02	1.18E+02	--	--
Std	3.15E+01	6.47E+01	5.74E+01	7.20E+01	5.38E+01	--	--
Best	1.04E+02	1.28E+02	1.19E+02	1.21E+02	1.12E+02	111.252	154.917
Worst	1.13E+02	1.37E+02	1.28E+02	1.30E+02	1.24E+02	--	--
Rank	1	5	3	4	2	--	--

According to the ranking outcomes in Table 6 and Fig. 11, EWO ranks first, then WSO (rank 2), followed by PSO (rank 3), then DMO (rank 4) and WO (rank 5). This ranking confirms that the addition of adaptive features

such as OBL and the GSS in EWO significantly improves the accuracy of the optimization process as well as its stability, which therefore converges faster and

optimizes energy management in the microgrid system at lower costs.

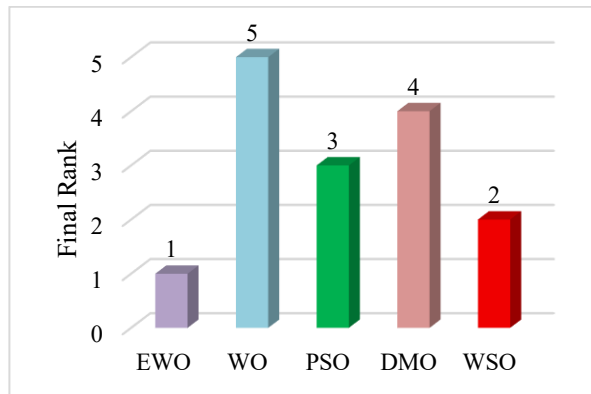


Fig. 11. The final rank for different algorithms in solving the microgrid energy management problem.

The boxplot in Fig. 12 compares the performance between EWO and the conventional Whale Optimizer (WO) for solving microgrid energy management problem. As shown, the EWO is much lower in fitness values, indicating enhanced optimization capability in minimizing the overall operating cost of microgrid. The median value of EWO is significantly lower than that of WO, demonstrating that EWO always converges to a better and more economically efficient solution. In addition, the low IQR and short whiskers of EWO demonstrate its excellent stability and robustness, implying that its performance will not shift significantly under various runs. WO's box is much wider and has more spread, which implies more variability in results and local optimum biasing. The absence of significant outliers in EWO also suggests its convergence behavior's stability. In summary, this visualization confirms that the integration of OBL and GSS in the EWO actually improves its convergence precision, stability, and global exploration capacity, and therefore a more efficient tool for optimal energy scheduling of microgrid operation.

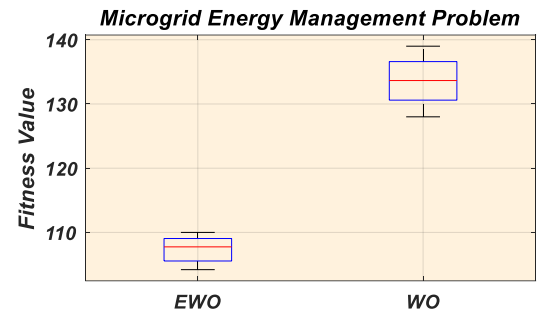


Fig. 12. The Boxplots visualization of EWO, and WO in solving the microgrid energy management problem.

The results as shown in Fig. 13 illustrate the optimal power dispatch of various components of the microgrid system over a period of 24 h. The figure demonstrates how all the different distributed energy sources like wind turbine (PWT), PV system (PPV), battery storage (PBAT), microturbine (PMT), and fuel cell (PFC) work and schedule to meet the fluctuating load demand (PLoad) at the least cost of operation. During peak solar hours (around 10:00–15:00), the maximum contribution towards generation is from the PV system, thus reducing the dependency upon the main grid. By way of contrast, fuel cell and wind power production provide steady input day after day, bridging the diurnal fluctuations of solar energy.

The battery system operates dynamically—charging when there is low-demand period or peak generation hours (early mornings and late evenings) and discharging when there is high demand—to optimally balance energy supply and demand. Microturbine and fuel cell function as dispatchable resources to stabilize the system during sudden changes of load, offering reliability and continuity of supply. The low use of the grid power (PGrid) shows the efficacy of the proposed energy management strategy since most of the demand is being satisfied locally within the microgrid. Overall, the coordinated operation of the renewable sources and storage units under optimized control of the EWO-based management architecture properly reduces the operational expenses while maintaining the load satisfaction and system stability for the complete simulation duration.

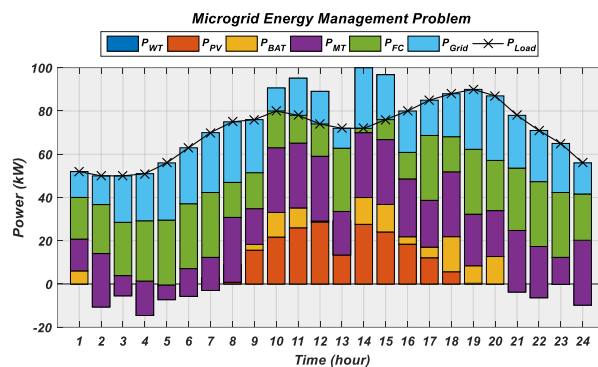


Fig. 13. Optimal power dispatch of different devices of the microgrid and load demand changes.

3. Conclusion

In this study, an EWO is built on top of two adaptive mechanisms— OBL and GSS — applied in the original WO framework. The main motivation of this enhancement is to remove WO's default weaknesses, such as premature convergence and insufficient population diversity, and to achieve improved exploration–exploitation balance. The new proposed EWO was intensively tested on the CEC-2019 benchmark test functions and several complex engineering problems, such as the TSP, partial shading MPPT, ELD, and microgrid energy management. The outcomes were compared with a diversity of well-known algorithms such as PSO, DMO, WSO, BES, and BWO, and the In solving the TSP, EWO demonstrated quicker and smoother convergence to the global optimum, even achieving much lower travel cost than that of traditional algorithms compared to PSO, DMO, WSO, ISO [53], and ESO [53]. Its efficient search mechanism allowed it not to be stuck in local minima and to perform consistently in multiple runs. In the MPPT problem with oscillating patterns of irradiation, EWO provided the optimal energy tracking efficiency compared to PSO, DMO, WSO, and ABC [54], especially under the transition from uniform to partially shaded irradiation conditions. With adaptive learning techniques, it adapted rapidly to new operating points and extracted maximum power with minimal oscillations in steady-state operation.

For the microgrid energy management issue, minimum operating cost and maximum stability was attained by EWO compared to

WO, PSO, DMO, WSO, BES [56], and BWO [56]. OBL-GSS integration provided increased convergence rate and reliability, generating optimal power balance and reduced energy cost. The consistent performance and high robustness of EWO support its feasibility as a complex optimization tool for effective and cost-minimized microgrid management. Future research can expand the EWO framework through hybridization with adaptive control mechanisms and machine learning to further enhance its real-time decision-making capability. Additionally, distributed or parallel implementations of EWO can enhance computational efficiency significantly for large-scale optimization problems, so that it is more practical to be used in industrial and energy management systems in reality.

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