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An Enhanced Dwarf Mongoose Optimization Algorithm for Solving Engineering Problems

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Abstract: This paper proposes a new Enhanced Dwarf Mongoose Optimization Algorithm (EDMOA) with an alpha-directed Learning Strategy (LS) for dealing with different mathematical benchmarking functions and engineering challenges. The DMOA's core concept is inspired by the dwarf mongoose's foraging behavior. The suggested algorithm employs three DM social categories: the alpha group, babysitters, and scouts. The family forages as a team, with the alpha female initiating foraging and determining the foraging course, distance traversed, and sleeping mounds. An enhanced LS is included in the novel proposed algorithm to improve the searching capabilities, and its updating process is partially guided by the updated alpha. In this paper, the proposed EDMOA and DMOA were tested on seven unimodal and six multimodal benchmarking tasks. Additionally, the proposed EDMOA was compared against the traditional DMOA for the CEC 2017 single-objective optimization benchmarks. Moreover, their application validity was conducted for an important engineering optimization problem regarding optimal dispatch of combined power and heat. For all applications, the proposed EDMOA and DMOA were compared to several recent and well-known algorithms. The simulation results show that the suggested DMOA outperforms not only the regular DMOA but also numerous other recent strategies in terms of effectiveness and efficacy.

Keywords: Dwarf Mongoose Optimization; alpha-directed Learning Strategy; benchmark functions; CEC 2017; heat and electrical power dispatch problem

MSC: 68N30

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1. Introduction

In many branches of research, optimization is a broad idea. A challenge type with multiple workable solutions is an optimization problem. Additionally, finding the optimum option out of all these workable options in order to fulfill design, planning, or operation activities at the lowest cost possible is the purpose of optimization. Artificial intelligence applications are typically unrestricted or discrete [1]. Moreover, finding the best options using conventional mathematically based programming algorithms is challenging. Besides, conventional optimization strategies offer a single-based solution only [2]. Hence, several optimization methods have been developed in recent years to improve the effectiveness of various systems and reduce computational expenses. Convergence to local optima and an indeterminate search space are two drawbacks and limitations of conventional optimization strategies [3].

An optimization issue is described mathematically in terms of three components: choice variables, constraints, and objective function [4]. The methods used to solve problems in optimization research can be divided into two categories: deterministic algorithms and stochastic algorithms [5]. The two categories of deterministic algorithms—gradient-based and non-gradient-based—are useful for resolving linear, convex, straightforward, low-dimensional, continuous, and differentiable optimization issues [6]. However, when these optimization issues become more complex, the performance of deterministic algorithms is disrupted, and these approaches become stuck in the wrong local optima. However, many optimization issues in research and real-world applications have traits such as high complexity, large dimensionality, non-continuous, unknowable search space, a non-convex, non-differentiable, and nonlinear objective function [7]. Researchers have developed novel algorithms known as stochastic algorithms as a result of these optimization task characteristics and the shortcomings of deterministic algorithms.

One of the most popular stochastic algorithms for solving challenging optimization problems is the employment of metaheuristic algorithmic algorithms [8]. They are effective in resolving high-dimensional, NP-hard, non-differentiable, non-convex optimization issues [9]. Among the benefits that have contributed to the success of metaheuristic algorithms are their effectiveness in solving unknown search spaces, nonlinear, discrete, and the simplicity of their principles, and their independence, their ease of implementation from the nature of the issue [10].

These metaheuristic algorithms are based on the application of random operators and random search in the domain of problem solution. Candidate solutions are initially produced at random. The position of the candidate solutions in the problem-solving space is then modified through a repetition-based process depending on the stages of the algorithm to increase the quality of these initial solutions. Ultimately, the problem can be solved with the top potential solution. The accomplishment of the global optimal by a metaheuristic algorithm is not guaranteed by the use of random search during the optimization process. According to that, solutions produced by metaheuristic algorithms are referred to as pseudo-optimal [11].

Metaheuristic algorithms should be able to provide and manage search operations well, at both global and local levels, in order to organize an efficient search in the problem-solving domain. A global search with the idea of exploration results in a thorough search in the space of problem-solving and a diversion from the best local areas [12]. A local search combined with the idea of exploitation triggers a thorough investigation of the most promising answers in order to converge on potentially superior ones. Given that exploration and exploitation have opposing objectives, striking a balance between them during the search process is essential for metaheuristic algorithms to succeed [13]. Researchers have created a large number of metaheuristic algorithms as a result of the notions of the random search process and quasi-optimal solutions as well as their goal to find better quasi-optimal solutions for these optimization challenges.

The primary categories of metaheuristic algorithms are four, which are named evolutionary algorithms, physics-based algorithms, human-based algorithms, and swarm intelligence algorithms. As explained in [14,15], the genetic algorithm and the evaluation strategy [16], evolutionary algorithms have been built by modelling biological evolutionary traits such as crossovers, mutations, and selections. Physics-based algorithms are motivated by physical laws, such as the equilibrium algorithm (EA) [10,13] and the Henry gas solubility algorithm [12]. Swarm intelligence algorithms, such as the whale optimization algorithm (WOA) [17], jellyfish search optimization (JFSO) [18], heap-based technique (HT) [19], grasshopper optimization (GO) [20], particle swarm optimization [21], manta rays foraging optimization (MRFO) [22], artificial bee colony [23], and marine predators algorithm (MPA) [24] are a series of algorithms influenced by swarming and animal group behavior.

Numerous optimization applications in science use metaheuristic algorithms, including energy [25] and electrical engineering [26]. Additionally, one of the optimization issues

is the dispatch of combined power and heat (DCPH) issue. A DCPH is a type of cogeneration system where the heat and power producers generate energy at the lowest possible cost while reducing pollutants [27]. The DCPH issue has been approached in a variety of ways over time, including computational and metaheuristic methods. Thermal power plants produce energy using fossil fuels such as coal, gas, or oil. High-temperature heat is utilized to generate steam power, which is then used to produce electricity. The thermal power plant's efficiency has dropped to between 50 and 60% as a result. However, various pollutants, including sulphur, carbon dioxides, and nitrogen, are created during the heating process, contributing to the warming effect and endangering the biological landscape.

A variety of optimization issues have been handled using metaheuristic algorithms, which have attracted a lot of attention. They assign several characteristics, such as the two-stage search method [28] that consists of the stages of intensity (exploit) and diversification (explore), respectively. To study diverse searching space areas, the metaheuristic algorithm first generates randomized operations. In the second stage, the optimization strategy looks for the optimum solution inside the search space. An effective metaheuristic optimization strategy must balance the exploitation and exploration stages in order to avoid entrapment at its best.

Distributed beetle antennae search (DBAS) has been employed to enhance multiportfolio selection issues without violating the individual portfolios' privacy [29]. In addition, Egret swarm optimization algorithm (ESOA) has been illustrated in [30] and assessed on 36 benchmark functions using aggressive strategy with encirclement mechanisms and random wandering to provide optimal solution exploration. In [31], an online solution to the static nonlinear programming problem with time-varying has been provided using the beetle antennae search (BAS). The multilayer perceptrons model of neural network has been identified in [32], and the regarding weights for the prediction of polymeric-based composite materials under changing amplitude loading were optimized using a genetic algorithm. In [33], a gradient-based algorithm has been implemented and designed around Newton's gradient-based concept by combining a crossover operator for increasing the variety of solutions provided. In order to analyze material life span using neural networks, a framework of system identification technique based on nonlinear autoregressive exogenous inputs (NARX) has been established as manifested in [34]. Also, the fatigue lifetimes of composite materials under multiaxial and multivariable loadings have been estimated using radial basis functions (RBFNN)-NARX models and the multilayer perceptron-NARX. The optimization of forecasting of fatigue life for polymeric-based composites over varied amplitude loading under diverse stress ratio circumstances has been investigated [35] in connection with the availability of restricted fatigue data. The behavior of a beetle has emerged with Deep Convolutional Neural Networks (CNNs) in [36] for image classification tasks and has been applied on ResNet and LeNet-5 architecture. In [37], human intellectual and reflective capabilities in socially growing actions have been used to formulate a growth optimizer which has been developed for parameter identification of solar photovoltaic cells and modules.

The Dwarf Mongoose Optimization Algorithm (DMOA) is a novel technique developed by the dwarf mongoose's foraging behavior that was presented in 2022 by J.O. Agushaka et al. [38,39]. It has been used to address various real engineering optimizing issues because of its high globally searching ability and resilience [40–47].

This paper proposes a new Enhanced Dwarf Mongoose Optimization Algorithm (EDMOA) with an alpha-directed Learning Strategy (LS) for dealing with different mathematical benchmarking functions and engineering challenges. First, the proposed EDMOA and DMOA were tested on seven unimodal and six multimodal benchmarking tasks. Second, the proposed EDMOA was compared against the traditional DMOA for the CEC 2017 single-objective optimization benchmarks. Further, their application validity was conducted for an important engineering optimization problem regarding optimal dispatch of combined power and heat. For all applications, the proposed EDMOA and DMOA were compared to several other recent and well-known algorithms. The simulation results show

that the suggested DMOA outperforms not only the regular DMOA but also numerous other recent strategies in terms of effectiveness and efficacy.

2. EDMOA Version with Alpha-Directed LS

2.1. Standard DMOA

In the DMOA, the population of the dwarf mongoose (DM) employs three social categories: the alpha group, babysitters, and scouts. The family forages as a team, with the alpha female initiating foraging and determining the foraging course, distance traversed, and sleeping mounds. A subset of the DM population, which is generally a combination of male and female types, provides babysitters. They stay behind with the children until the rest of the party arrives in the afternoon. The babysitters are first swapped to begin foraging alongside the group (exploitation phase). The DM group does not create a place to nest to house the young; instead, they always change the sleeping mound, seeking a new foraged spot. The DMs have established a seminomadic manner of existence in an area sufficiently large to accommodate everyone in the party (exploration phase). Nomadic behavior avoids excessive use of a certain region. It additionally assures that the whole terrain is explored to guarantee that no previously visited sleeping mounds are returned to [38].

In the DMOA, the initial DM populations of the candidate solutions of N_{DM} individuals are randomly generated as follows:

$$D_{j,d}(0) = D_{\min,d} + rand(0,1).\left[D_{\max,d} - D_{\min,d}\right], j = 1 : N_{DM},\ d = 1 : Dim \tag{1}$$

where $D_{j,d}$ represents the location as a searching individual regarding each DM (j) and each control variable (d); $D_{\min,d}$ and $D_{\max,d}$ denote the minimum and maximum bounds of each control variable (d); Dim refers to the number of the decision variables related to the optimizing task.

The fitness of every solution is calculated once the population has been initialized. Equation (2) calculates the probability worth of every group's fitness, and the alpha female (α) is chosen according to this probability [38].

$$\alpha = \frac{F_j}{\sum_{j=1}^{N_{DM}} F_j} \tag{2}$$

In the alpha group, the number of DMs correlates to the difference between the whole group number (N_{DM}) and the number of babysitters (Bst). The number of babysitters is denoted by bs. Peep represents the alpha female's vocalization, which maintains the DM family on track. Each DM sleeps in the first sleeping mound, which has been assigned to $\emptyset$. The DMOA employs the formula provided in Equation (3) to generate a potential food position.

$$D_{k,d}(i+1) = D_{k,d}(i) + rand(0,1) \times peep, k = 1 : N_{DM} - Bst,\ d = 1 : Dim \tag{3}$$

where i refers to the existing iteration. The sleeping mound may be formulated after each iteration as follows:

$$SM_j = \frac{F_{j+1} - F_j}{\max\left(\left|F_{j+1} - F_j\right|\right)} \qquad j = 1 : N_{DM} - Bst \tag{4}$$

where j refers to each DM in the scout group which are the difference between the whole group number (N_{DM}) and the number of babysitters (Bst).

According to that, Equation (5) gives the mean value (ψ) of the sleeping mound discovered.

$$\psi_j = \frac{\sum_{j=1}^{N_{DM}} SM_j}{N_{DM}} \qquad j = 1 : N_{DM} - Bst \tag{5}$$

The DMOA technique advances to the scouting stage, when a subsequent source of food or sleeping mound will be determined once the babysitting exchange criterion is reached. In DMOA, scouting occurs concurrently with foraging, where the scouts search for an alternative sleeping mound, ensuring exploration. The resulting motion is depicted as an effective or unsuccessful assessment of establishing a fresh mound, based on the mongooses' total performance. The scout mongoose can be simulated by Equation (6).

$$D_{k,d}(i+1) = \begin{cases} D_{k,d}(i) - CF \times rand(0,1) \times \left(D_{k,d}(i) - M\right) & if \psi_{j+1} > \psi_j \\ D_{k,d}(i) + CF \times rand(0,1) \times \left(D_{k,d}(i) - M\right) & Else \end{cases} \\ k = 1 : N_{DM},\ d = 1 : Dim \tag{6}$$

where CF is decreasing linearly as iterations progress, as represented in Equation (7), and M indicates a vector that decides the mongoose's migration to the next sleeping mound, as represented in Equation (8). The CF parameter signifies the parameter that regulates the mongoose group's collective–volitive motion.

$$CF = \left(1 - \frac{i}{Iter_{\max}}\right)^{\left(\frac{2 \times i}{Iter_{\max}}\right)} \tag{7}$$

$$M = \sum_{j=1}^{N_{DM}} \frac{D_j \times SM_j}{D_j} \tag{8}$$

where $Iter_{\max}$ refers to the highest number of iterations.

2.2. Proposed EDMOA

In this section, a new EDMOA with an alpha-directed Learning Strategy (LS) for dealing with different mathematical benchmarking functions and engineering challenges is proposed. An enhanced LS is included in the novel proposed solver to improve the searching capabilities, and its updating process is partially guided by the updated alpha. The alpha-directed LS is merged with the formula provided in Equation (3) to generate a potential food position in an effort to enhance the searching capability. Therefore, the change in position of every searching solution within the search space is upgraded as follows:

$$D_{k,d}(i+1) = \begin{cases} BestDM_d(i) + rand(0,1) \times \left(D_{k,d}(i) - D_{R,d}(i)\right) & if \text{ rand} < \text{CP} \\ D_{k,d}(i) + rand(0,1) \times peep & Else \end{cases} \\ k = 1 : N_{DM} - Bst,\ d = 1 : Dim \tag{9}$$

where $BestDM_d$ represents the location as the alpha regarding the searching individual with the best fitness score; $D_{R,d}$ is a randomly picked searching individual from the DM population; *CP* denotes the choice probability. *CP* is set to 50% to establish a balance between the exploration features given in Equation (3) and the increased exploitation qualities mentioned in Equation (9). The exploitation features are considerable and strong while employing the aforementioned structure, whereas the exploratory seeking qualities are kept and obtained using the usual method at the same time. Figure 1 depicts the critical phases of the proposed EDMOA.

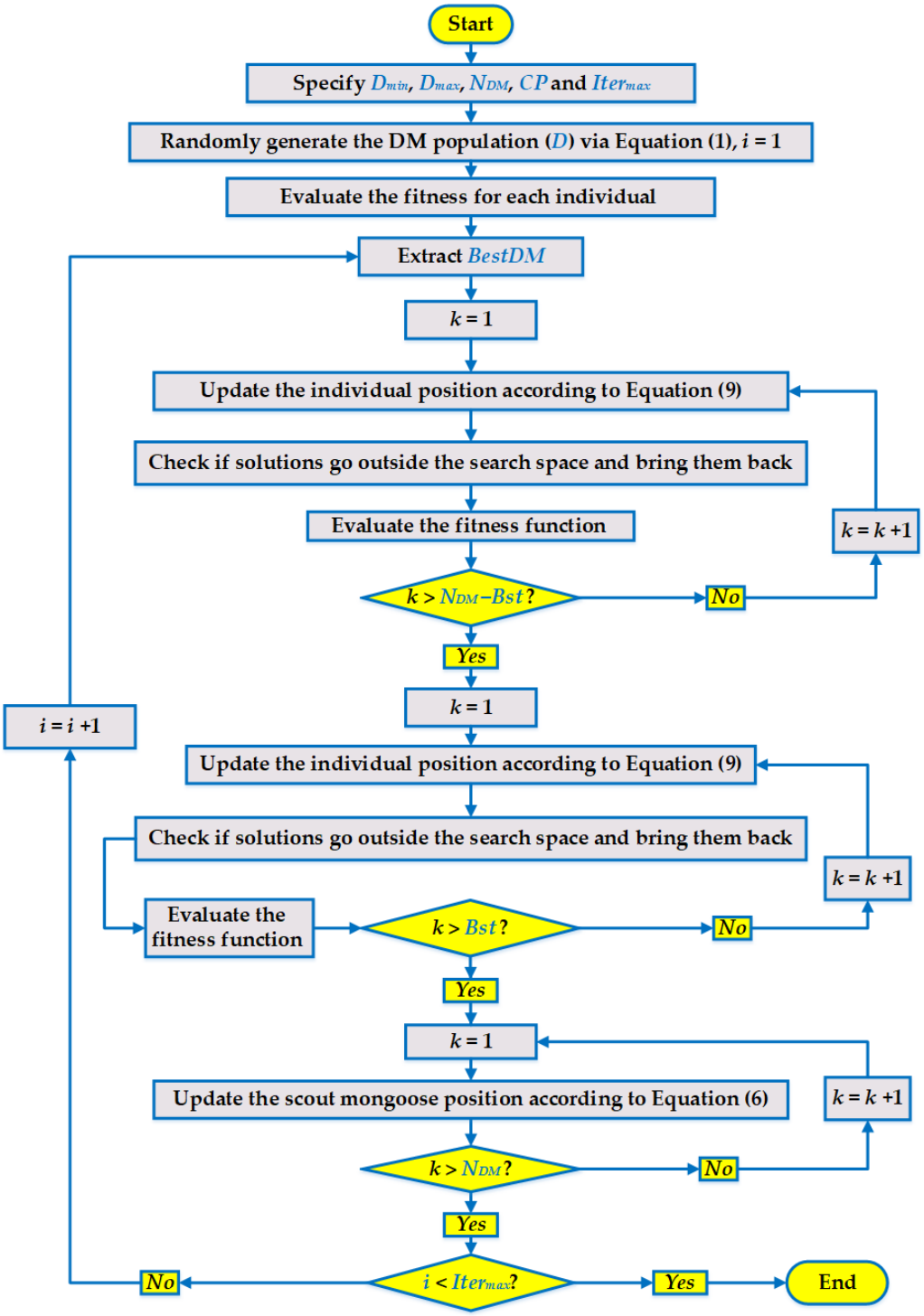


Figure 1. Proposed EDMOA flowchart.

3. Application Assessment for Benchmarking Models

This part assesses the efficacy and functioning of the prescribed EDMOA and DMOA. They are tested on seven unimodal and six multimodal benchmarking tasks. Their comprehensive information regarding the nature of mathematical frameworks, variable dimensions, and acceptable ranges are outlined in Tables 1 and 2.

Table 1. Test data for unimodal benchmarking tasks.

Function	Minimum	*Dim*	Bounds
$Fn_1 = \sum_{j=1}^{Dim} \left(y_j\right)^2$	0	30	$[-100, 100]$
$Fn_2 = \sum_{j=1}^{Dim} \left(\left\|y_j\right\| + \Pi_{j=1}^{Dim} \left\|y_j\right\|\right)$	0	30	$[-10, 10]$
$Fn_3 = \sum_{j=1}^{Dim} \left(\sum_{k-1}^{j} y_k\right)^2$	0	30	$[-100, 100]$
$Fn_4 = \max_j \left\{\left\|y_j\right\|, 1 < j < Dim\right\}$	0	30	$[-100, 100]$
$Fn_5 = \sum_{j=1}^{Dim-1} \left[100(y_{j+1} - {y_j}^2) + (y_j - 1)^2\right]$	0	30	$[-30, 30]$
$Fn_6 = \sum_{j=1}^{Dim} \left(\left[j_j + \frac{1}{2}\right]\right)^2$	0	30	$[-100, 100]$
$Fn_7 = \sum_{k=1}^{Dim} \left(k \times (y_k)^4 + random[0,1]\right)$	0	30	$[-128, 128]$

Table 2. Test data for multimodal benchmarking tasks [48].

Function	Min.	*Dim*	Bounds
$Fn_8 = \sum_{j=1}^{Dim} \left(-y_j \times \sin(\sqrt{\left\|y_j\right\|})\right)$	$-418.9829 \times Dim$	30	$[-500, 500]$
$Fn_9 = \sum_{j=1}^{Dim} \left({y_j}^2 + 10 - 10 \times \cos(2\pi y_j)\right)$	0	30	$[-5.12, 5.12]$
$Fn_{10} = 20 - 20 \times \exp\left(-\left(\frac{1}{25Dim} \sum_{j=1}^{Dim} \left(y_j\right)^2\right)^{\frac{1}{2}}\right) - \exp\left(\frac{1}{Dim} \sum_{j=1}^{Dim} \cos(2\pi y_j)\right) + e$	0	30	$[-32, 32]$
$Fn_{11} = 1 + \frac{1}{4000} \sum_{j=1}^{Dim} \left(y_j\right)^2 - \Pi_{k=1}^{Dim} \cos\left(\frac{y_k}{\sqrt{k}}\right)$	0	30	$[-600, 600]$
$Fn_{12} = \frac{10\pi}{Dim} \times \sin(\pi x_1) + \sum_{j=1}^{Dim-1} \left[\left(x_j - 1\right)^2 \left(1 + 10 \sin^2(\pi x_{j+1})\right)\right] + (x_d - 1)^2 + \sum_{j=1}^{Dim} Z\left(x_j, 10, 100, 4\right)$ $where, x_j = \frac{1+y_j}{4} + 1,\ Z(y_k, \alpha, \beta, \gamma) = \begin{cases} \beta(-\alpha + y_k)^\gamma & if\ y_k > \alpha \\ 0 & if\ -a < y_k < \alpha \\ \beta(-\alpha - y_k)^\gamma & if\ y_k < \alpha \end{cases}$	0	30	$[-50, 50]$
$Fn_{13} = \frac{1}{10} \times \left(\sum_{j=1}^{Dim} (y_j - 1)^2 \left[1 + \sin^2(3\pi y_j + 1)\right] + \sin^2(3\pi y_1) + (y_d - 1)^2 \left[1 + \sin^2(3\pi y_d)\right] \right) + \sum_{j=1}^{Dim} Z\left(y_{j,}, 5, 100, 4\right)$	0	30	$[-50, 50]$

The proposed EDMOA is evaluated against the conventional DMOA. Both strategies are used in comparable circumstances. Assigned to 30 and 1000, respectively, were the number of solutions per population and iterations. To quantify the results, the terms' best, average, worst, and standard deviation (STd) are utilized. Table 3 shows the corresponding outcomes based on both EDMOA and DMOA for unimodal and multimodal tasks, accordingly. As shown, the proposed EDMOA has greater strength with regard to obtaining the least mean, STd, and median in more than 80% of benchmark functions.

Table 3. Statistical outcomes of proposed EDMOA and DMOA for benchmarking tasks.

Task	Standard DMOA				Proposed EDMOA				Average
	Best	Average	Worst	Std	Best	Average	Worst	Std	Improvement
Fn_1	1.79×10^{-5}	8.76×10^{-5}	0.000296	5.90×10^{-5}	6.61×10^{-27}	1.17×10^{-24}	9.46×10^{-24}	2.28×10^{-24}	100%
Fn_2	1.03×10^{-5}	2.00×10^{-5}	3.54×10^{-5}	6.11×10^{-6}	7.96×10^{-17}	1.06×10^{-14}	1.06×10^{-13}	2.03×10^{-14}	100%
Fn_3	5743.5	8781.6	12,966	1668.8	2.8971	27.368	83.87	21.48	99.40%
Fn_4	14.815	20.841	27.163	3.221	0.33587	1.5053	3.4605	0.77068	88.50%
Fn_5	77.956	237.03	393.41	83.866	0.78762	32.275	88.215	28.605	82.20%
Fn_6	1.65×10^{-5}	7.08×10^{-5}	0.000165	3.21×10^{-5}	9.37×10^{-27}	1.09×10^{-24}	1.13×10^{-23}	2.30×10^{-24}	100%
Fn_7	0.11238	0.5481	1.0747	0.27023	0.084286	0.52282	0.93326	0.28925	8.90%
Fn_8	−7211.4	−5642.5	−4571.6	681.27	−11,207	−9752.5	−7496.1	846.28	−34.1%
Fn_9	104.94	153.31	197.11	26.503	27.902	40.152	66.662	9.0548	69.80%
Fn_{10}	0.001129	0.002626	0.004452	0.000796	3.29×10^{-14}	0.044681	1.3404	0.24473	−48.4%
Fn_{11}	0.000112	0.032583	0.40399	0.079176	0	0.009682	0.032006	0.010785	87.20%
Fn_{12}	2.719	7.6682	12.87	2.4431	3.43×10^{-25}	0.096802	0.82919	0.19629	96.10%
Fn_{13}	1.2364	9.3512	24.069	5.0609	2.30×10^{-25}	0.078774	1.2225	0.25351	97.30%

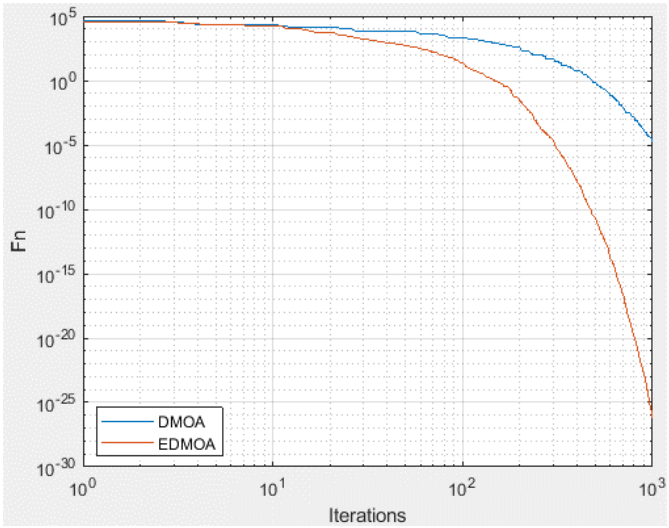
Also, Figure 2 displays the converging properties of the proposed EDMOA and DMOA for the 13 benchmarking tasks. As shown, the proposed EDMOA records average improvement over the standard DMOA of 100%, 100%, 99.4%, 88.5%, 82.2%, 100%, 8.9%, 69.8%, 87.2%, 96.1%, and 97.3% for the optimization benchmarks Fn_1, Fn_2, Fn_3, Fn_4, Fn_5, Fn_6, Fn_7, Fn_9, Fn_{11}, Fn_{12}, and Fn_{13}, respectively. On the other side, the standard DMOA records average improvement over the EDMOA of 34.1% and 48.4% for only two optimization benchmarks: Fn_8 and Fn_{10}, respectively.

The proposed EDMOA is contrasted to other contemporary and well-known applied optimization strategies for benchmarking task functions including the basic DMOA, PSO [21], DE [49], Multi-Verse Optimizer (MVO) [50], salp swarm algorithm (SSA) [51], and sine–cosine algorithm (SCA) [52].

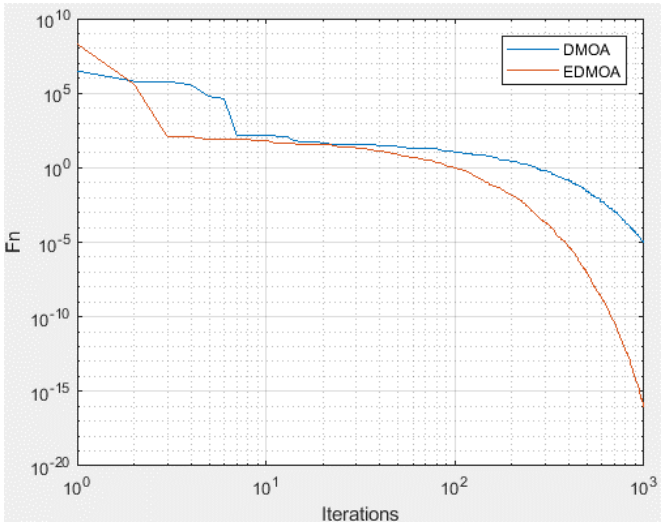
In order to judge the advantage of the proposed algorithm over the well-known ones, the size of the population, the number of iterations, and the number of calculations of the criterion function in these algorithms are displayed in Table 4. Not only that, but this table provides the specified metaparameters of the compared algorithms. To avoid the impact of randomness, thirty different implementations of each method for each benchmark were tested. Based on these circumstances, Table 5 displays the regarding obtained results of the mean and STd of the objective value for the 13 benchmarking tasks under study.

Table 4. Compared algorithms for benchmarking tasks (Fn_1:Fn_{13}): circumstances and metaparameters.

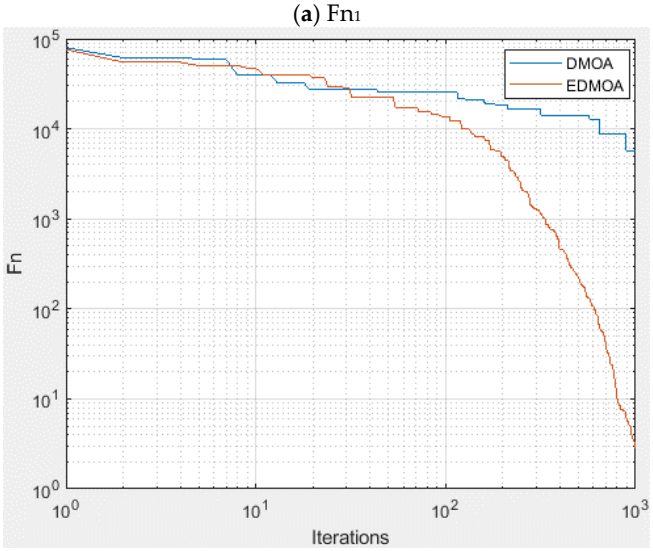
Algorithm	Specified Metaparameters	Size of Population	Number of Iterations	Number of Fitness Calculations
SCA	Parameter constant (a) = 2	30	1000	30,000
SSA	Parameters c1 = c2 are random numbers ∈ [0, 1]	30	1000	30,000
MVO	Travelling distance rate is random number ∈ [0.6, 1] Existence probability is random number ∈ [0.2, 1]	30	1000	30,000
PSO	Parameters c1 = c2 = 2 Maximum Velocity (v^{Max}) = 6	30	1000	30,000
DE	Crossover probability = 0.5 Scaling factor = 0.5	30	1000	30,000
DMOA	Number of babysitters = 3 Alpha female vocalization (peep = 2)	30	1000	30,000
EDMOA	Number of babysitters = 3 Alpha female vocalization (peep = 2)	30	1000	30,000



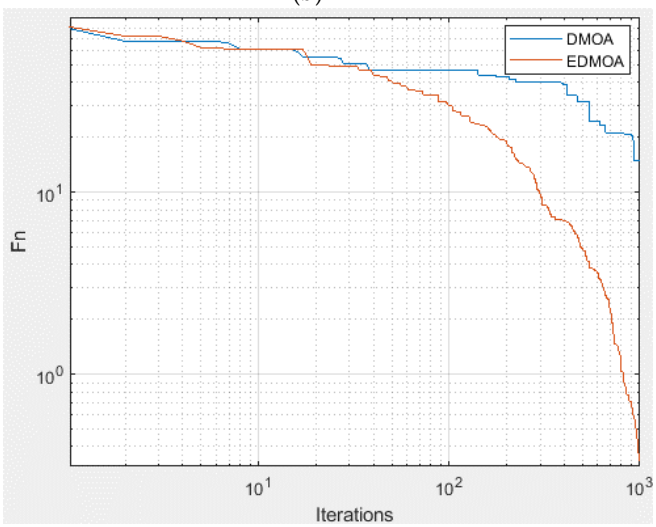
(**a**) Fn_1



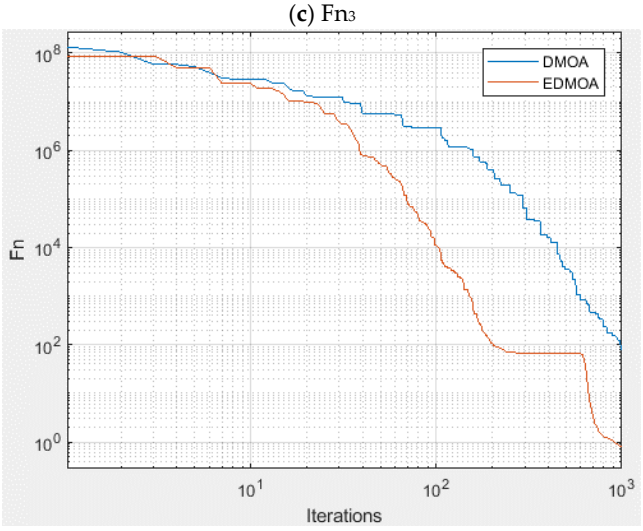
(**b**) Fn_2



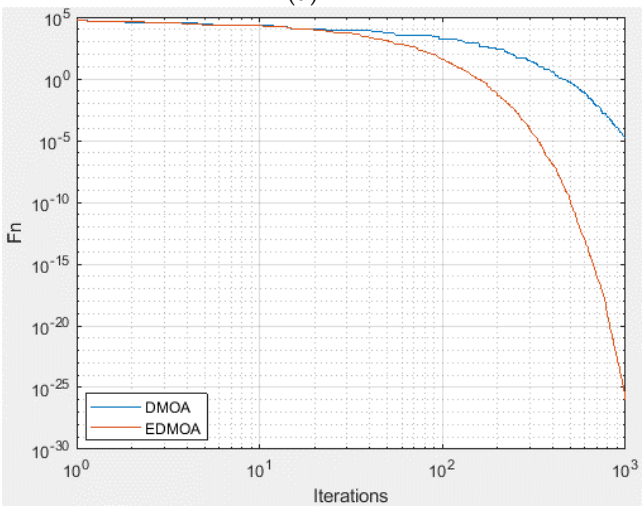
(**c**) Fn_3



(**d**) Fn_4

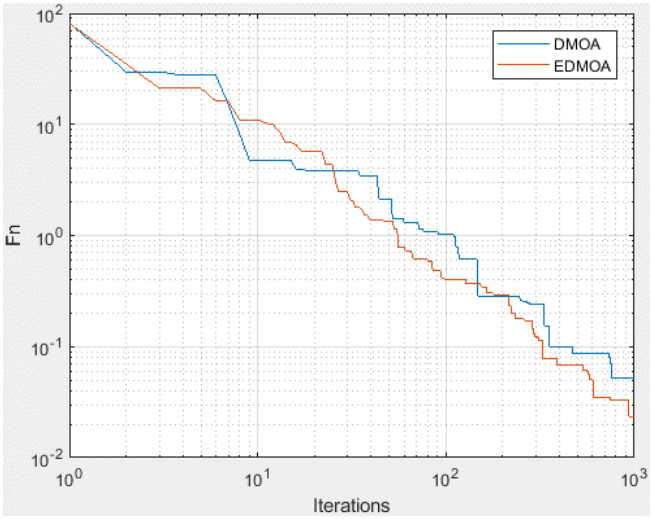


(**e**) Fn_5

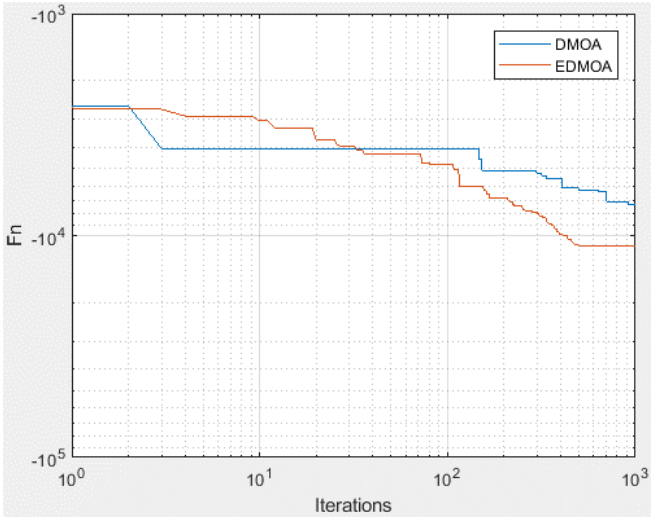


(**f**) Fn_6

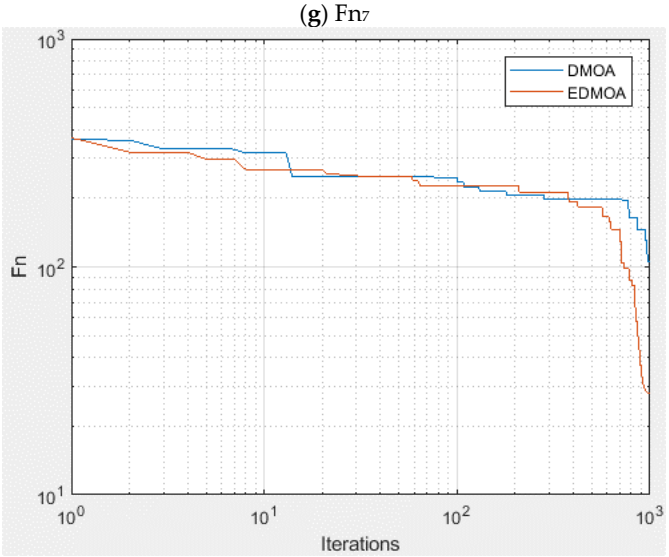
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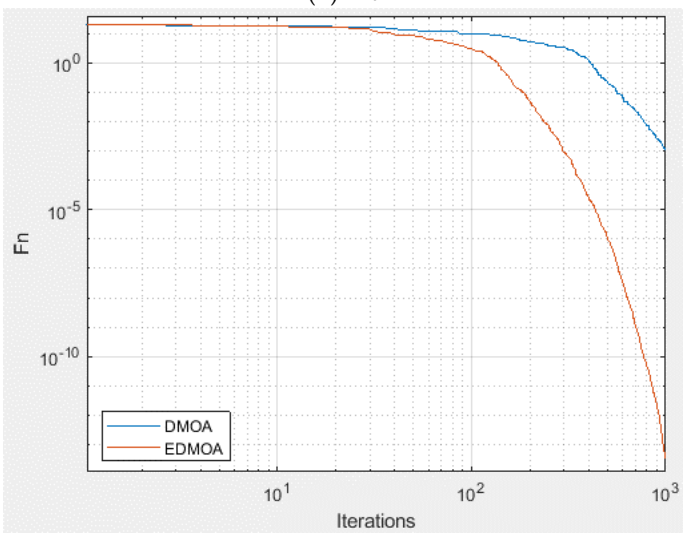
(**g**) Fn7



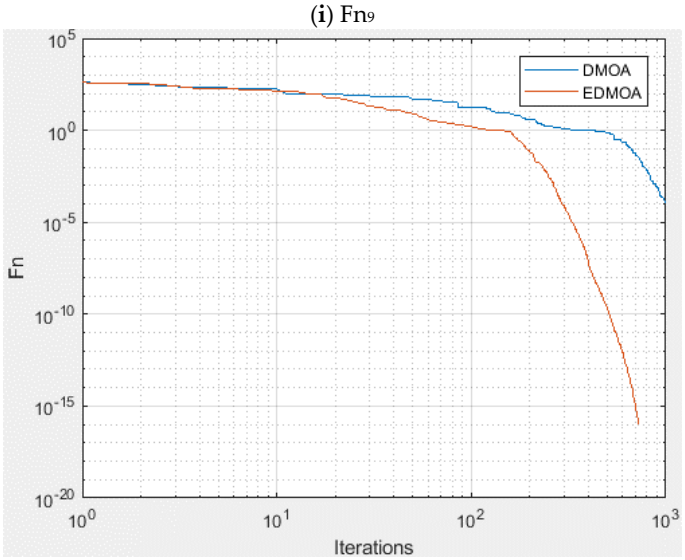
(**h**) Fn8



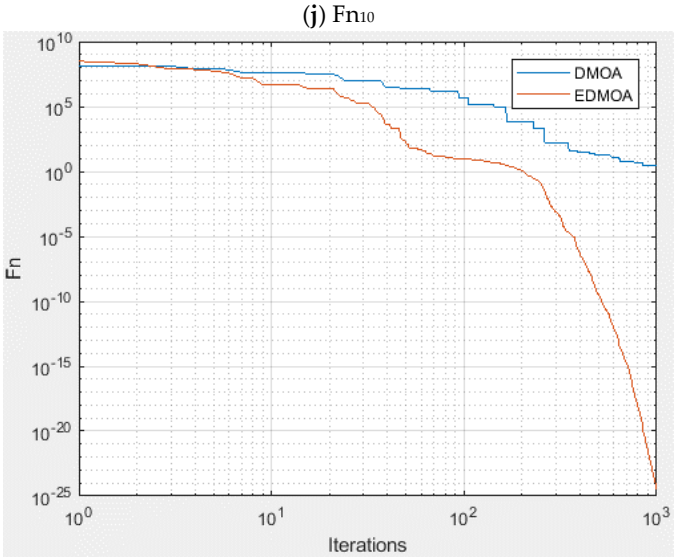
(**i**) Fn9



(**j**) Fn10

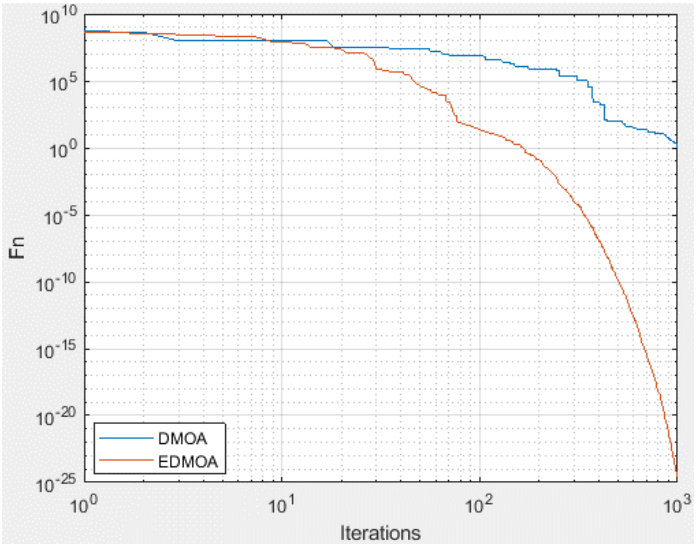


(**k**) Fn11



(**l**) Fn12

Figure 2. *Cont.*



(**m**) Fn_{13}

Figure 2. Converging properties of proposed EDMOA and DMOA for benchmarking tasks.

Table 5. Comparisons of mean and STd of the compared algorithms for benchmarking tasks.

Task	Index	SCA	SSA	MVO	PSO	DE	DMOA	EDMOA
Fn_1	Mean	1.52×10^{-2}	1.23×10^{-8}	3.19×10^{-1}	1.29×10^{2}	3.03×10^{-12}	1.79×10^{-5}	6.61×10^{-27}
	STd	3.00×10^{-2}	3.54×10^{-9}	1.12×10^{-1}	1.54×10^{1}	3.45×10^{-12}	5.90×10^{-5}	2.28×10^{-24}
Fn_2	Mean	1.15×10^{-5}	8.48×10^{-1}	3.89×10^{-1}	8.61×10^{1}	3.72×10^{-8}	1.03×10^{-5}	7.96×10^{-17}
	STd	2.74×10^{-5}	9.42×10^{-1}	1.38×10^{-1}	6.53×10^{1}	1.20×10^{-8}	6.11×10^{-6}	2.03×10^{-14}
Fn_3	Mean	3.26×10^{3}	2.37×10^{2}	4.81×10^{1}	4.07×10^{2}	2.42×10^{4}	5.74×10^{3}	2.9
	STd	2.94×10^{3}	1.56×10^{2}	2.18×10^{1}	7.13×10^{1}	4.17×10^{3}	1.67×10^{3}	2.15×10^{1}
Fn_4	Mean	2.05×10^{1}	8.25	1.08	4.5	1.97	1.48×10^{1}	3.36×10^{-1}
	STd	1.10×10^{1}	3.29	3.11×10^{-1}	3.29×10^{-1}	4.31×10^{-1}	3.22	7.71×10^{-1}
Fn_5	Mean	5.33×10^{2}	1.36×10^{2}	4.08×10^{2}	1.55×10^{5}	4.61×10^{1}	7.80×10^{1}	7.88×10^{-1}
	STd	1.91×10^{3}	1.74×10^{2}	6.15×10^{2}	3.60×10^{4}	2.73×10^{1}	8.39×10^{1}	2.66×10^{1}
Fn_6	Mean	4.55	0	3.24×10^{-1}	1.33×10^{2}	3.10×10^{-12}	1.65×10^{-5}	9.37×10^{-27}
	STd	3.57×10^{-1}	0	9.74×10^{-2}	1.52×10^{1}	1.46×10^{-12}	3.21×10^{-5}	2.30×10^{-24}
Fn_7	Mean	2.44×10^{-2}	9.55×10^{-2}	2.09×10^{-2}	1.11×10^{2}	2.69×10^{-2}	1.12×10^{-1}	8.43×10^{-2}
	STd	2.07×10^{-2}	5.05×10^{-2}	9.58×10^{-3}	2.15×10^{1}	6.32×10^{-3}	2.70×10^{-1}	2.89×10^{-1}
Fn_8	Mean	-3.89×10^{3}	-7.82×10^{3}	-7.74×10^{3}	-6.73×10^{3}	-1.24×10^{4}	-7.21×10^{3}	-1.12×10^{4}
	STd	2.26×10^{2}	8.42×10^{2}	6.93×10^{2}	6.50×10^{2}	1.49×10^{2}	6.81×10^{2}	8.46×10^{2}
Fn_9	Mean	1.84×10^{1}	5.66×10^{1}	1.13×10^{2}	3.69×10^{2}	5.93×10^{1}	1.05×10^{2}	2.79×10^{1}
	STd	2.14×10^{1}	1.29×10^{1}	2.46×10^{1}	1.87×10^{1}	6.08	2.65×10^{1}	9.05
Fn_{10}	Mean	1.13×10^{1}	2.26	1.15	8.42	4.64×10^{-7}	1.13×10^{-3}	3.29×10^{-14}
	STd	9.66	7.21×10^{-1}	7.03×10^{-1}	4.11×10^{-1}	1.38×10^{-7}	7.96×10^{-4}	2.45×10^{-1}
Fn_{11}	Mean	2.35×10^{-1}	1.01×10^{-2}	5.75×10^{-1}	1.03	9.76×10^{-11}	1.12×10^{-4}	0
	STd	2.25×10^{-1}	1.07×10^{-2}	8.75×10^{-2}	4.89×10^{-3}	2.13×10^{-10}	7.92×10^{-2}	1.08×10^{-2}
Fn_{12}	Mean	2.29	5.54	1.29	4.8	3.63×10^{-13}	2.72	3.43×10^{-25}
	STd	2.96	3.12	1.1	8.67×10^{-1}	3.40×10^{-13}	2.44	1.96×10^{-1}
Fn_{13}	Mean	5.19×10^{2}	1.01	8.13×10^{-2}	2.32×10^{1}	1.69×10^{-12}	1.24	2.30×10^{-25}
	STd	2.78×10^{3}	4.7	4.32×10^{-2}	4.2	1.16×10^{-12}	5.06	2.54×10^{-1}

Additionally, Table 6 shows the results of a Friedman ranking test for the implemented benchmark functions. As demonstrated, the presented EDMOA successfully acquires the best performance by recording the first rank by achieving the smallest mean rank with 2.12.

Secondly, the DE comes with mean rank of 2.27, while MVO achieves the third rank by 4.04. After that, the SSA, DMOA, SCA, and PSO come subsequently with mean ranks of 4.27, 4.54, 5.35, and 5.42.

Table 6. Friedman ranking of the compared algorithms for benchmarking tasks.

Task	Index	SCA	SSA	MVO	PSO	DE	DMOA	EDMOA
Fn_1	Mean	5	3	6	7	2	4	1
	STd	5	3	6	7	2	4	1
Fn_2	Mean	4	6	5	7	2	3	1
	STd	4	6	5	7	2	3	1
Fn_3	Mean	7	3	2	4	5	6	1
	STd	6	4	2	3	7	5	1
Fn_4	Mean	7	5	2	4	3	6	1
	STd	7	6	1	2	3	5	4
Fn_5	Mean	6	4	5	7	2	3	1
	STd	6	4	5	7	2	3	1
Fn_6	Mean	6	1	5	7	3	4	2
	STd	6	1	5	7	3	4	2
Fn_7	Mean	2	6	1	7	3	5	4
	STd	3	4	2	7	1	5	6
Fn_8	Mean	7	3	4	6	1	5	2
	STd	2	5	4	3	1	7	6
Fn_9	Mean	1	3	6	7	4	5	2
	STd	5	3	6	4	1	7	2
Fn_{10}	Mean	7	5	4	6	2	3	1
	STd	7	6	5	4	1	2	3
Fn_{11}	Mean	5	4	6	7	2	3	1
	STd	7	3	6	2	1	5	4
Fn_{12}	Mean	4	7	3	6	2	5	1
	STd	6	7	4	3	1	5	2
Fn_{13}	Mean	7	4	3	6	2	5	1
	STd	7	5	2	4	1	6	3
Summation		139	111	105	141	59	118	55
Mean Rank		5.35	4.27	4.04	5.42	2.27	4.54	2.12
Final Ranking		6	4	3	7	2	5	1

4. Application Assessment for Benchmarking Models

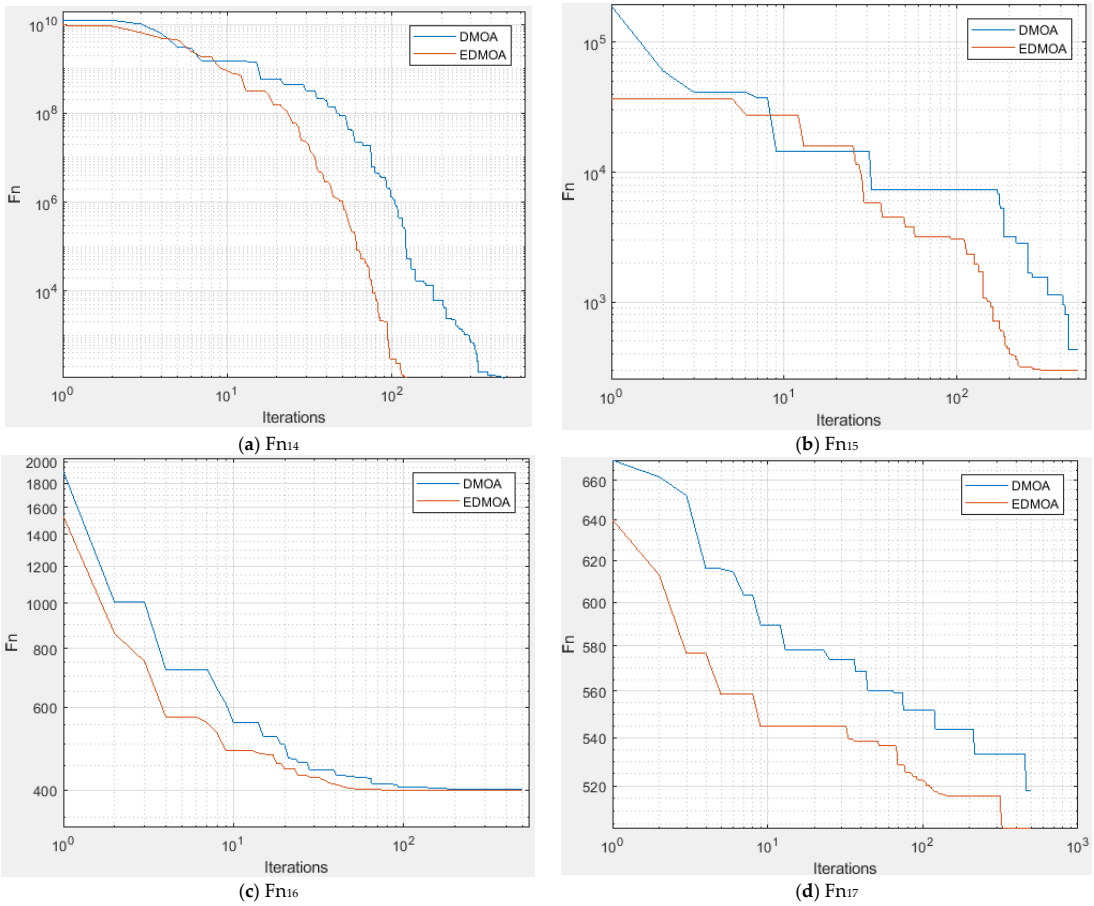
Typically, it can be difficult to measure the level of "good" of an efficient optimization technique because of lacking a mathematical proof; hence, the benchmark functions play a significant part in assessing the efficacy of these techniques. As a result, the performance of the proposed EDMOA and DMOA algorithms is assessed in this study considering 12 benchmark functions related to the CEC 2017 competition [53]. The functions considered include unimodal, multimodal, mixed, and composite. Table 7 depicts those unconstrained benchmarking functions.

The proposed EDMOA is compared against the traditional DMOA for the CEC 2017 single-objective optimization benchmarks presented in Table 7. Both methods are employed in similar situations. Table 8 displays the best, average, and worst outcomes based on both EDMOA and DMOA. As demonstrated, the suggested EDMOA has a higher strength in terms of obtaining the lowest mean, STd, and median in more than 85% of benchmark functions. Figure 3 further shows the convergence features of the proposed

EDMOA and DMOA for twelve benchmarks considered for the CEC 2017 benchmarking tasks. As demonstrated, in acquiring the best fitness score, the proposed EDMOA records average improvement over the standard DMOA of approximately 15%. Based on the derived average fitness score, the suggested EDMOA shows a 20.5% improvement over the traditional DMOA. Based on the derived worst fitness score, the suggested EDMOA shows a 21% improvement over the traditional DMOA.

Table 7. Mathematical information of the CEC 2017 single-objective optimization benchmarks being considered.

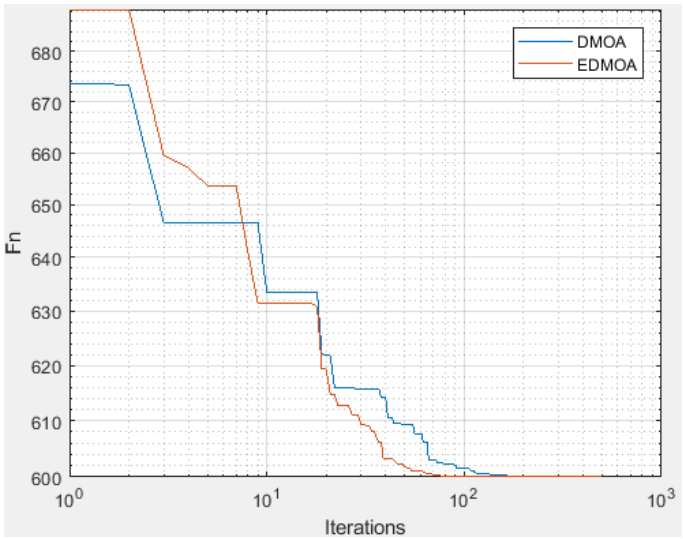
Function No.	Function	Minimum	*Dim*	Bounds
Fn_{14}	Shifted and Rotated Bent Cigar Function	100	30	[−100, 100]
Fn_{15}	Shifted and Rotated Zakharov Function	300	30	[−100, 100]
Fn_{16}	Shifted and Rotated Rosenbrock's Function	400	30	[−100, 100]
Fn_{17}	Shifted and Rotated Rastrigin's Function	500	30	[−100, 100]
Fn_{18}	Shifted and Rotated Expanded Scaffer's F6 Function	600	30	[−100, 100]
Fn_{19}	Shifted and Rotated Lunacek Bi-Rastrigin Function	700	30	[−100, 100]
Fn_{20}	Shifted and Rotated Noncontinuous Rastrigin's Function	800	30	[−100, 100]
Fn_{21}	Shifted and Rotated Levy Function	900	30	[−100, 100]
Fn_{22}	Shifted and Rotated Schwefel's Function	1000	30	[−100, 100]
Fn_{23}	Hybrid Function 1 (N = 3)	1100	30	[−100, 100]
Fn_{24}	Hybrid Function 2 (N = 3)	1200	30	[−100, 100]
Fn_{25}	Hybrid Function 3 (N = 3)	1300	30	[−100, 100]



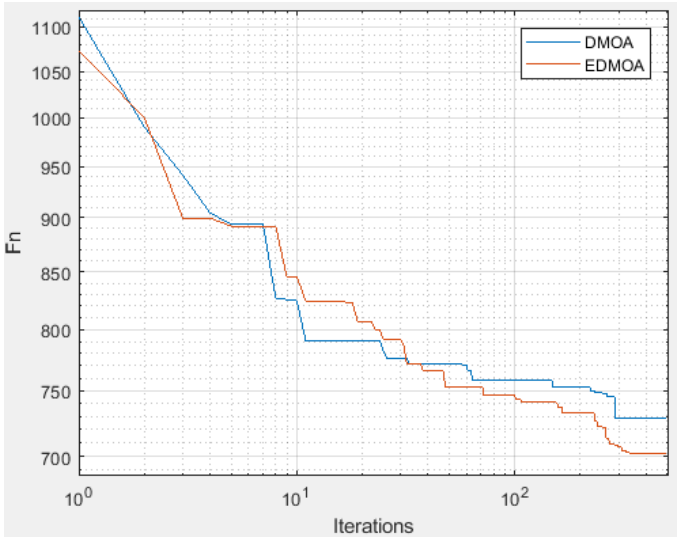
(**a**) Fn_{14} (**b**) Fn_{15}

(**c**) Fn_{16} (**d**) Fn_{17}

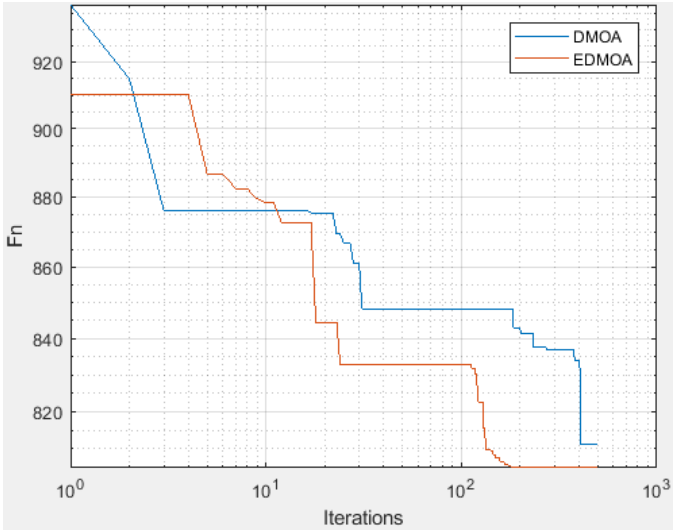
Figure 3. *Cont.*



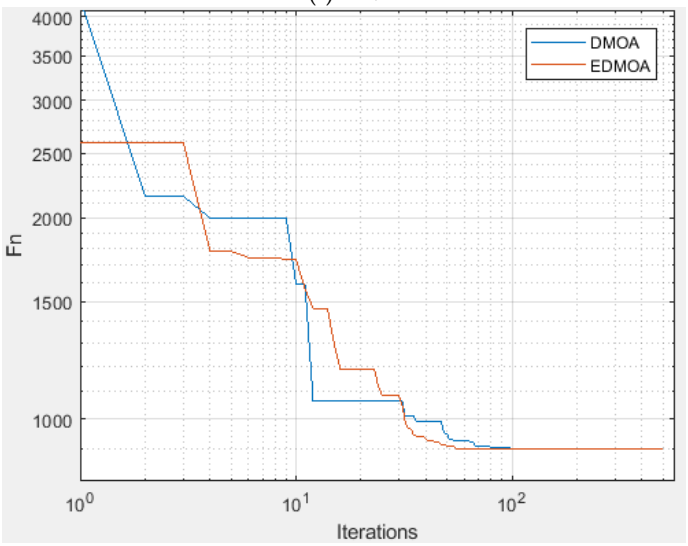
(**e**) Fn_{18}



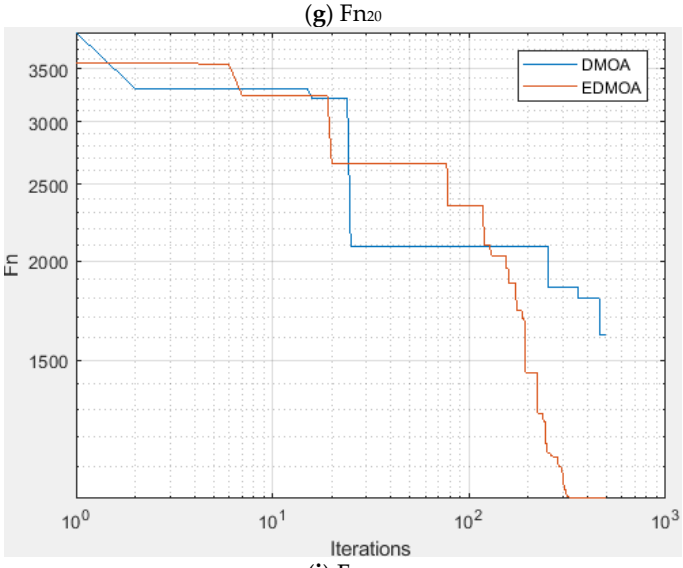
(**f**) Fn_{19}



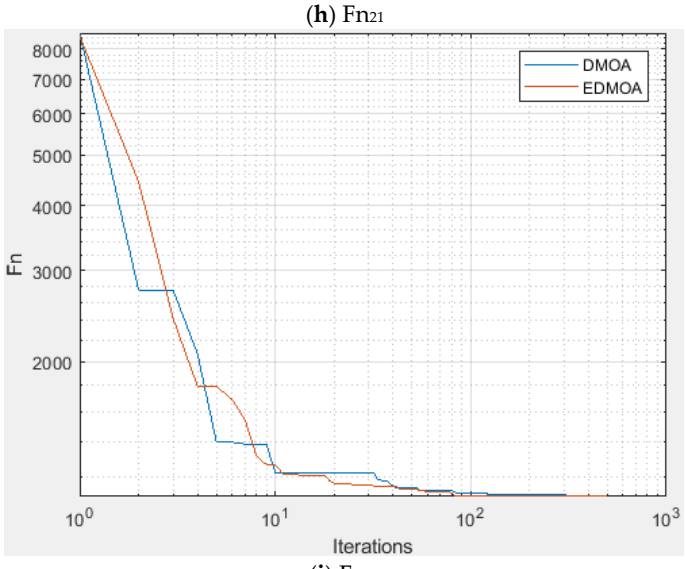
(**g**) Fn_{20}



(**h**) Fn_{21}

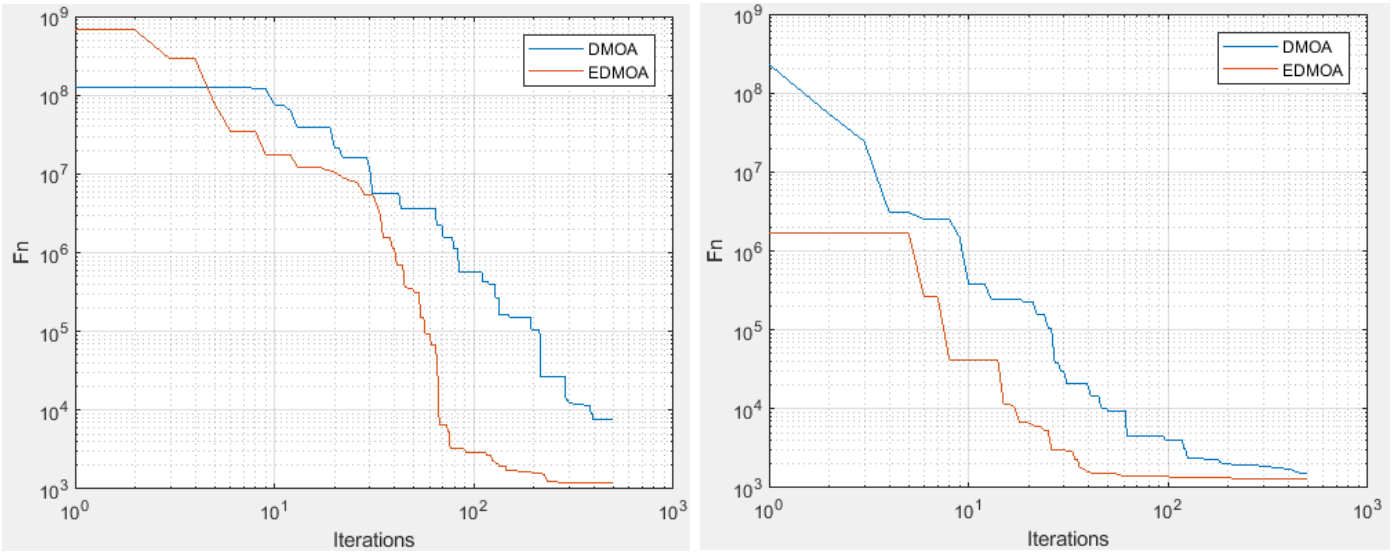


(**i**) Fn_{22}



(**j**) Fn_{23}

Figure 3. *Cont.*



(**k**) Fn24 (**l**) Fn25

Figure 3. Converging properties of proposed EDMOA and DMOA for some samples of the CEC 2017 benchmarking tasks.

Table 8. Statistical outcomes of proposed EDMOA and DMOA for CEC 2017 benchmarking tasks.

Task	Best			Average			Worst		
	DMOA	EDMOA	Improve	DMOA	EDMOA	Improve	DMOA	EDMOA	Improve
Fn_{14}	103.10	100.79	2%	4947.71	1833.43	63%	63,834.88	10,627.66	83%
Fn_{15}	426.95	300.00	30%	1075.82	300.00	72%	2487.44	300.07	88%
Fn_{16}	400.56	400.01	0%	405.29	403.16	1%	406.86	405.07	0%
Fn_{17}	518.01	502.98	3%	530.04	510.00	4%	539.60	521.85	3%
Fn_{18}	600.00	600.00	0%	600.00	600.00	0%	600.00	600.00	0%
Fn_{19}	728.61	701.99	4%	743.07	724.95	2%	753.99	750.16	1%
Fn_{20}	811.29	804.97	1%	829.65	811.34	2%	841.71	826.86	2%
Fn_{21}	900.00	900.00	0%	900.00	900.02	0%	900.00	900.45	0%
Fn_{22}	1615.59	1003.66	38%	2276.48	1528.55	33%	3534.00	2498.38	29%
Fn_{23}	1103.03	1100.35	0%	1107.10	1104.63	0%	1112.53	1113.66	0%
Fn_{24}	7581.32	1215.06	84%	1.48×10^5	1.76×10^4	88%	8.49×10^5	5.58×10^5	93%
Fn_{25}	1471.09	1309.99	11%	4806.37	5704.65	−19%	14,058.03	2.06×10^5	−47%

To discuss the convergence properties of the proposed algorithm towards the optimum fitness, Figure 4 displays the obtained fitness based on the proposed EDMOA, the optimum value, and the difference percentage of both. As shown, the proposed algorithm is certified to be convergent due to the great coincidence between the obtained fitness based on the proposed EDMOA, the optimum value for the considered benchmarks. Similarly, a very small difference in percentage is illustrated. There is no difference for the functions Fn_{15}, Fn_{16}, Fn_{18}, Fn_{21}, and Fn_{23}, while the maximum difference does not exceed 1.5% for Fn_{24}.

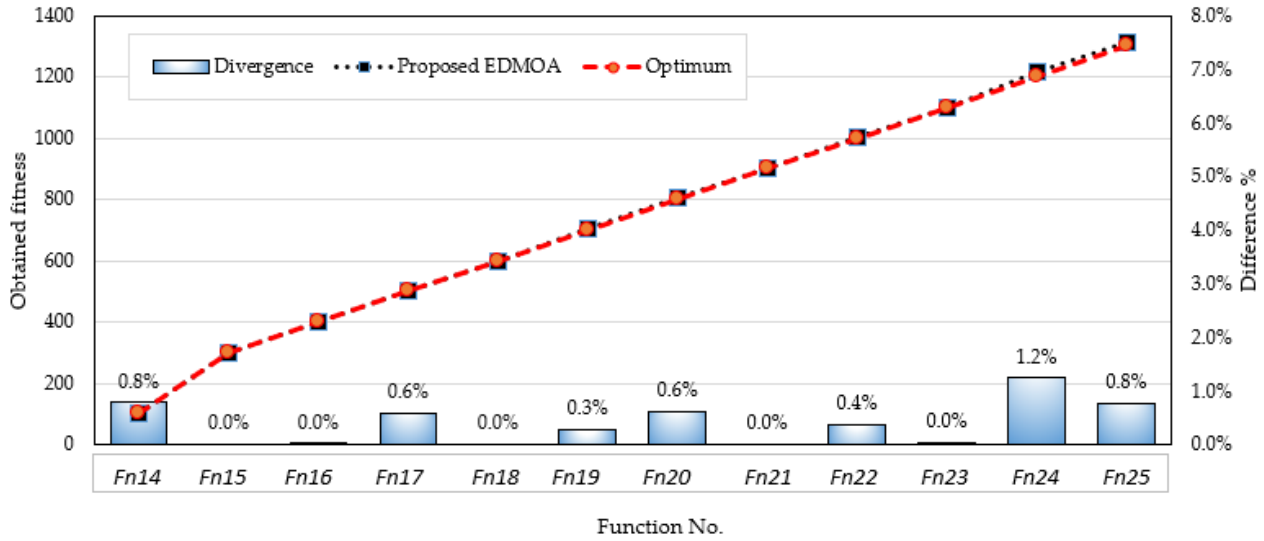


Figure 4. Converging evaluation of the proposed EDMOA and the optimum solution for some samples of the CEC 2017 benchmarking tasks.

The proposed EDMOA is compared to various commonly used optimization approaches for benchmarking task functions, such as the basic DMOA, PSO [21], circle search algorithm [54], gray wolf algorithm (GWO) [55,56], slime mould algorithm (SMA) [48,57], BAS [31], and Eagle Perching Optimizer (EPO) [58].

Table 9 displays the size of the population, the number of iterations, and the number of computations of the criteria function in the aforementioned algorithms to determine the benefit of the proposed method over the comparative algorithms. Furthermore, this table contains the defined metaparameters of the comparing methods. To avoid the influence of randomization, thirty distinct implementations of each method were examined for each benchmark.

Table 9. Compared algorithms for CEC 2017 benchmarking tasks (Fn_{14}:Fn_{25}): circumstances and metaparameters.

Algorithm	Parameters	Population Size	Number of Iterations	Number of Fitness Calculations
Circle	% Parameter (p) decreases linearly from 1 to 0.05 % Parameter c = 0.8	30	500	15,000
GWO	% Parameter (a) decreases linearly from 2 to 0	30	500	15,000
PSO	% Parameters c1 = c2 = 2 % Maximum Velocity (v^{Max}) = 6	30	500	15,000
SMA	% z parameter = 0.03	30	500	15,000
DMOA	% Number of babysitters = 3 % Alpha female vocalization (peep = 2)	30	500	15,000
EDMOA	% Number of babysitters = 3 % Alpha female vocalization (peep = 2)	30	500	15,000
EPO	% The Area to Search: l_scale = 1000; % Resolution Range: res = 0.05; % Shrinking Coefficient: eta = (res/l_scale)^(1/MaxIt);	30	500	15,000

BAS	% antenna distance:
	d0 = 0.001; d1 = 3; d = d1; eta_d = 0.95;
	% random walk:
	l0 = 0.0; l1 = 0.0; l = l1; eta_l = 0.95;
	% steps:
	step = 0.8; % step length
	eta_step = 0.95;
		30	500	15,000

Table 10 shows the findings of the average objective value for the CEC 2017 benchmarking tasks. Table 11 also displays the results of a Friedman ranking test for the implemented benchmark functions. As demonstrated, the provided EDMOA achieves the best performance by recording the top rank with the smallest mean rank with 1.36. Secondly, the SMA comes with a mean rank of 2.46, while the basic DMOA achieves the third rank by 2.714. After that, the GWO, Circle, PSO, EPO, and BAS come subsequently with mean ranks of 4.14, 4.39, 5.89, 6.83, and 7.67, respectively.

Table 10. Comparisons of the average objective value for CEC 2017 benchmarking tasks.

Task	Circle	GWO	PSO	SMA	DMOA	EDMOA	EPO	BAS
Fn_{14}	1.33×10^9	94,119,626	1.12×10^9	4047.105	4947.71	1833.43	8,814,768	2.3×10^{10}
Fn_{15}	14,241.48	3268.186	1578.377	300.0529	1075.82	300	16,333,666	783,773.90
Fn_{16}	506.2511	420.6218	458.378	407.543	405.29	403.16	2353.768	3390.97
Fn_{17}	561.921	519.452	527.4131	514.8857	530.04	510	528.8325	658.1569
Fn_{18}	645.2603	601.8139	603.4523	600.1722	600	600	645.6735	686.2571
Fn_{19}	789.0027	735.5862	726.2797	725.503	743.07	724.95	737.4825	1131.222
Fn_{20}	846.8571	815.9346	819.8598	816.6209	829.65	811.34	823.9785	934.9389
Fn_{21}	1631.005	915.9064	906.119	900.2505	900	900.02	1738.447	3657.722
Fn_{22}	2610.173	1763.644	1725.071	1511.829	2276.48	1528.55	2691.075	3454.588
Fn_{23}	2005.97	1157.378	1205.218	1137.776	1107.1	1104.63	1,003,627	25,751.55
Fn_{24}	2.49×10^8	1.14×10^6	1.18×10^7	2.08×10^5	1.48×10^5	1.76×10^4	2.75×10^9	2.6×10^9
Fn_{25}	10,842,625	12,488.38	15,339.44	8132.892	4806.37	5704.65	4.64×10^8	3.02×10^8

Table 11. Friedman ranking of the compared algorithms for the obtained average objective value for CEC 2017 benchmarking tasks.

Task	Circle	GWO	PSO	SMA	DMOA	EDMOA	EPO	BAS
Fn_{14}	7	4	6	3	2	1	5	8
Fn_{15}	4	6	5	2	3	1	7	8
Fn_{16}	6	4	5	3	2	1	7	8
Fn_{17}	8	3	4	2	5	1	6	7
Fn_{18}	6	4	5	3	1	1	7	8
Fn_{19}	8	4	3	2	5	1	6	8
Fn_{20}	7	2	4	3	5	1	6	8
Fn_{21}	6	5	4	3	1	2	7	8
Fn_{22}	6	4	3	1	5	2	7	8
Fn_{23}	6	4	5	3	2	1	8	7
Fn_{24}	6	4	5	3	2	1	8	7
Fn_{25}	6	4	5	3	1	2	8	7
Summation	70	47	53	31	34	15	82	92
Mean Rank	5.892857	4.142857	4.392857	2.464286	2.714286	1.357143	6.8333	7.6667
Final Ranking	6	4	5	2	3	1	7	8

To assess the computational complexity and run time of EDMOA and DMOA in solving the considered benchmarking models, the "Big O notation" is considered [59]. First,

Dim, N_{DM}, and $Iter_{\max}$ are specified for each considered benchmark. For both the DMOA and EDMOA, the computational complexity in the searching space can be estimated as O ($Iter_{max}$ × N_{DM} × Dim) × O (F(x)). Therefore, Table 12 provides the computational complexity for each considered benchmark and the regarding computing run time. As shown, the standard DMOA records slightly lower computing time than the EDMOA with additional learning strategy.

Table 12. Computational complexity and run time of DMOA and EDMOA.

Task	Computational Complexity	Average Run Time (Seconds)/Iteration		Task	Computational Complexity	Average Run Time (Seconds)/Iteration	
		DMOA	EDMOA			DMOA	EDMOA
Fn_1	O (30 × 30 × 1000)	0.001763	0.001772	Fn_{14}	O (30 × 30 × 500)	0.0023906	0.002345
Fn_2	O (30 × 30 × 1000)	0.001851	0.001798	Fn_{15}	O (30 × 30 × 500)	0.0027801	0.002817
Fn_3	O (30 × 30 × 1000)	0.001592	0.001608	Fn_{16}	O (30 × 30 × 500)	0.0029567	0.002966
Fn_4	O (30 × 30 × 1000)	0.001723	0.001739	Fn_{17}	O (30 × 30 × 500)	0.0021253	0.002111
Fn_5	O (30 × 30 × 1000)	0.001577	0.001528	Fn_{18}	O (30 × 30 × 500)	0.0024131	0.002387
Fn_6	O (30 × 30 × 1000)	0.001414	0.001464	Fn_{19}	O (30 × 30 × 500)	0.0026615	0.0026914
Fn_7	O (30 × 30 × 1000)	0.001695	0.001691	Fn_{20}	O (30 × 30 × 500)	0.0027411	0.002802
Fn_8	O (30 × 30 × 1000)	0.001823	0.001854	Fn_{21}	O (30 × 30 × 500)	0.0030125	0.002929
Fn_9	O (30 × 30 × 1000)	0.002011	0.001902	Fn_{22}	O (30 × 30 × 500)	0.0022145	0.0022941
Fn_{10}	O (30 × 30 × 1000)	0.001886	0.001935	Fn_{23}	O (30 × 30 × 500)	0.0023897	0.0023014
Fn_{11}	O (30 × 30 × 1000)	0.001698	0.001725	Fn_{24}	O (30 × 30 × 500)	0.0023187	0.002408
Fn_{12}	O (30 × 30 × 1000)	0.001598	0.001554	Fn_{25}	O (30 × 30 × 500)	0.0024519	0.002415
Fn_{13}	O (30 × 30 × 1000)	0.001821	0.001875	DCPH	O (60 × 100 × 3000)	0.4152	0.4211

5. Application for Engineering Optimization Problem: Optimal Dispatch of Combined Power and Heat

In this section, the application validity is conducted for one of the important engineering optimization problem regarding optimal Dispatch of Combined Power and Heat (DCPH) [60–64]. Figure 5 depicts the important stakeholders in the DCPH's attempts to provide the power and heat requirements in the facilities and structures. The primary goal of the DCPH framework could be to determine the economical prospective rates for heating produced by heat units, electricity produced by power units, and the heat and power produced by CPH units, in order to keep fuel costs low while meeting heat and power demands and limits.

In this context, the DCPH concern is addressed using a large-scale testing scenario involving 84 different units. Its goal was to reduce the system's overall production expenses. As a consequence, the costs of production as a reduction target (*Fn*) could be stated as follows:

$$F_n = \sum_{a=1}^{N_{PG}} C_a(PG_a) + \sum_{b=1}^{N_{HT}} C_b(HT_b) + \sum_{c=1}^{N_{CPH}} C_c(PG_c, HT_c) \quad (10)$$

where N_{PG}, N_{HT}, and N_{CPH} symbolize the numbers of power, heat, and CPH co-facilities, correspondingly, and $C_a(PG_a)$ [65], $C_b(HT_b)$, and $C_c(PG_c,HT_c)$ represent the cost functions for the power, heat, and CPH components, correspondingly, which can be mathematically modelled in Equations (11)–(13):

$$C_a(PG_a) = A_{1,a} \times {PG_a}^2 + A_{2,a} \times PG_a + A_{3,a} + |A_{4,a} \times \sin(A_{5,a} \times (PG_{a,\min} - PG_{ak}))| \quad (11)$$

$$C_b(HT_b) = B_{1,b} \times {HT_b}^2 + B_{2,b} \times HT_b + B_{3,b} \quad (12)$$

$$C_c(PG_c, HT_c) = C_{1,c} \times {PG_c}^2 + C_{2,c} \times PG_{ci} + C_{3,c} + C_{4,c} \times {HT_c}^2 + C_{5,c} \times HT_c + C_{6,c} \times HT_c \times PG_{ci} \quad (13)$$

where A_1:A_5 constitute the parameters of the costs regarding power units; B_1:B_3 are the parameters of the costs regarding heat units; C_1:C_6 illustrate the parameters of the costs regarding CPH units.

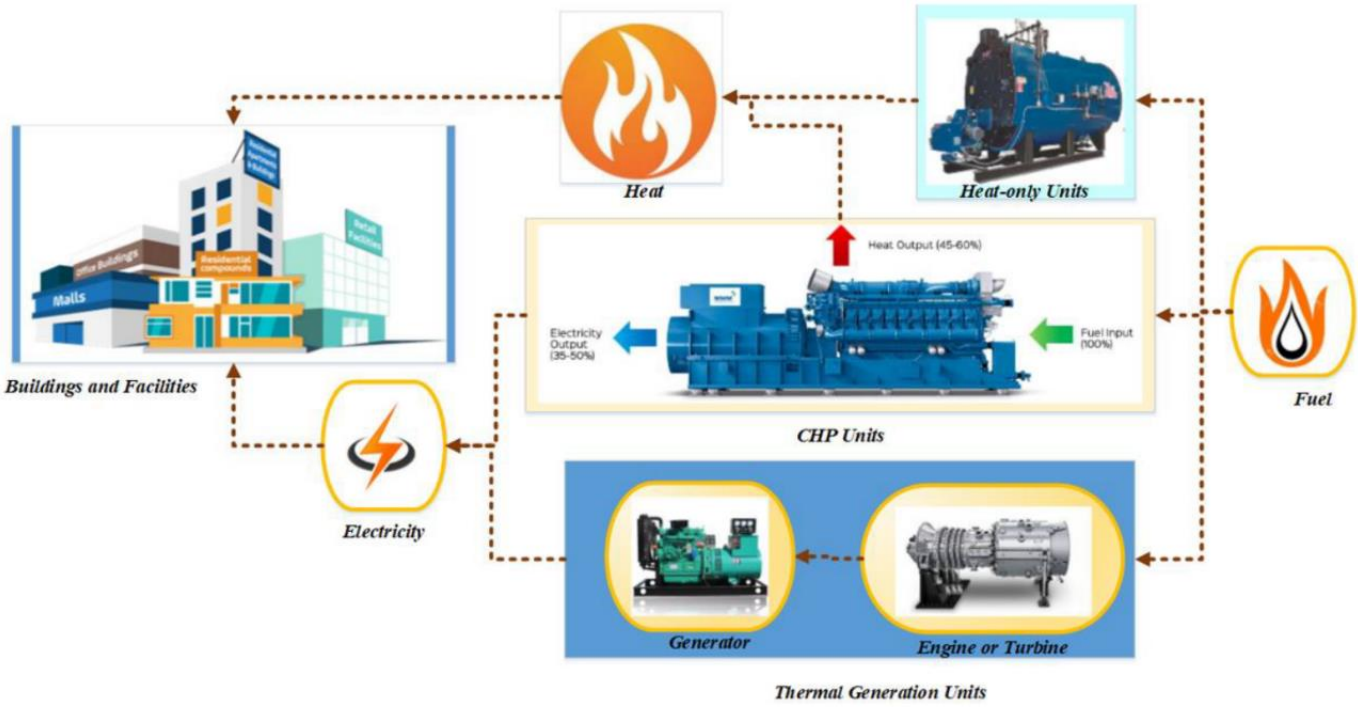


Figure 5. DCPH operation framework [62].

A large case investigation comprising 48 separate units is examined for the DCPH problem. This system, which consists of twelve CPH facilities, twenty-six power facilities, and ten heat facilities, has an electricity burden of 4700 MW and a heating demand of 2500 MWth. The entire data for the investigated system can be found in [66]. Table 13 displays both the electricity and heating productions from the power, heat, and CPH units based on both the proposed EDMOA and DMOA approaches. Figure 6 also depicts the convergence characteristics of the developed EDMOA and DMOA approaches. In terms of overall production costs, the suggested EDMOA obviously outperforms the DMOA, with a reduced fuel cost in the DCPH system of \$116,406.3772 compared to \$121,431.6763 by the standard DMOA. With 4.13%, the percentage decrease is pretty large.

Table 13. Outcomes of costs minimization for 48-unit DCPH system by DMOA and proposed EDMOA.

Variable	DMOA	EDMOA	Variable	DMOA	EDMOA	Variable	DMOA	EDMOA
PG1	410.919	538.715	PG22	91.269	159.899	HT31	42.388	40.211
PG2	236.598	225.129	PG23	75.045	78.120	HT32	17.572	22.192
PG3	320.459	150.068	PG24	108.805	77.390	HT33	108.227	105.055
PG4	70.230	159.774	PG25	94.984	94.666	HT34	88.715	79.077
PG5	174.784	161.645	PG26	115.530	92.638	HT35	111.902	105.339
PG6	159.518	109.808	PG27	98.847	97.820	HT36	82.122	89.306
PG7	110.100	110.431	PG28	61.626	40.246	HT37	34.690	41.207

Table 13. *Cont.*

Variable	DMOA	EDMOA	Variable	DMOA	EDMOA	Variable	DMOA	EDMOA
PG8	130.571	112.748	PG29	99.781	85.629	HT38	21.411	25.351
PG9	105.985	109.874	PG30	54.100	53.532	HT39	479.032	442.594
PG10	88.365	77.377	PG31	16.333	10.502	HT40	54.581	59.883
PG11	82.701	77.516	PG32	42.676	39.931	H41	56.888	59.970
PG12	95.346	92.383	PG33	92.902	81.538	H42	103.343	119.627
PG13	79.876	92.440	PG34	56.262	44.747	H43	117.539	119.798
PG14	533.413	450.161	PG35	105.643	82.097	H44	459.364	447.482
PG15	12.329	224.017	PG36	49.405	56.616	H45	54.980	59.976
PG16	292.225	150.102	PG37	15.492	12.834	H46	57.474	59.996
PG17	109.793	161.726	PG38	43.820	46.780	H47	110.577	119.681
PG18	65.965	159.664	HT27	112.829	114.220	H48	108.102	119.984
PG19	158.946	110.029	HT28	89.529	75.174	Sum (PG)	2500.0000	2500.0000
PG20	139.222	111.665	HT29	108.118	107.347	Sum (HT)	4700.0000	4700.0000
PG21	100.136	159.743	HT30	80.615	86.532	*Fn* ($)	121,431.6763	116,406.3772

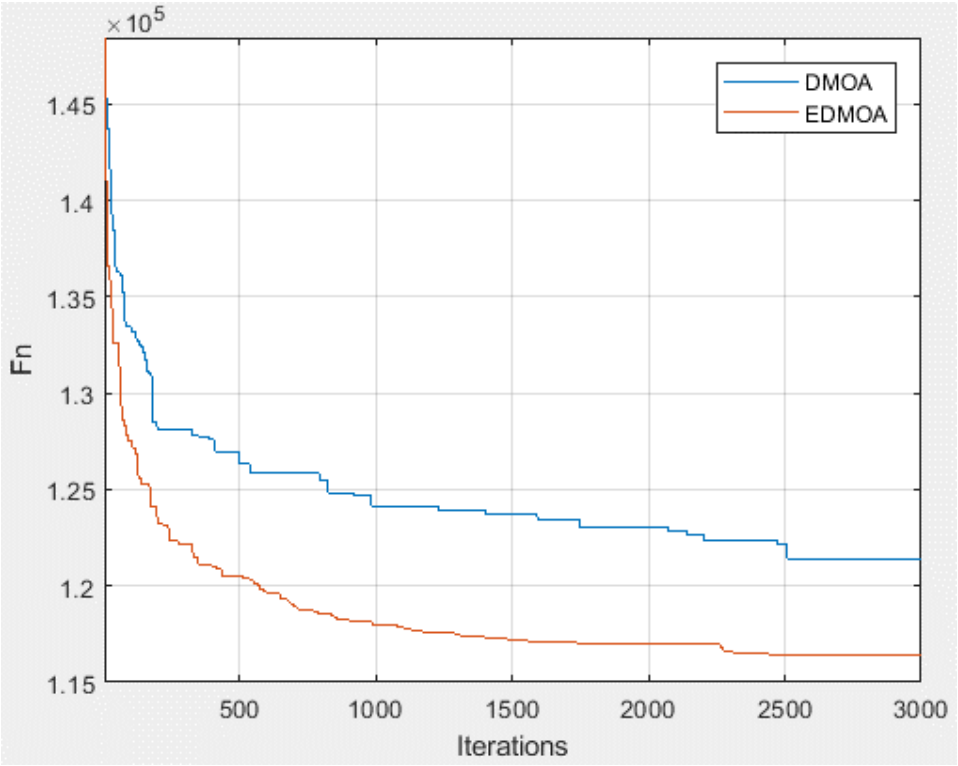


Figure 6. Convergences for minimizing the DCPH costs using DMOA and EDMOA.

Added to that, Figure 7 shows the distribution of the different obtained costs over the different thirty executions for both the proposed EDMOA and the standard DMOA techniques for the DCPH system. In this way, Figure 8 shows the regarding improvement percentages of EDMOA over DMOA considering the different thirty executions for the DCPH system.

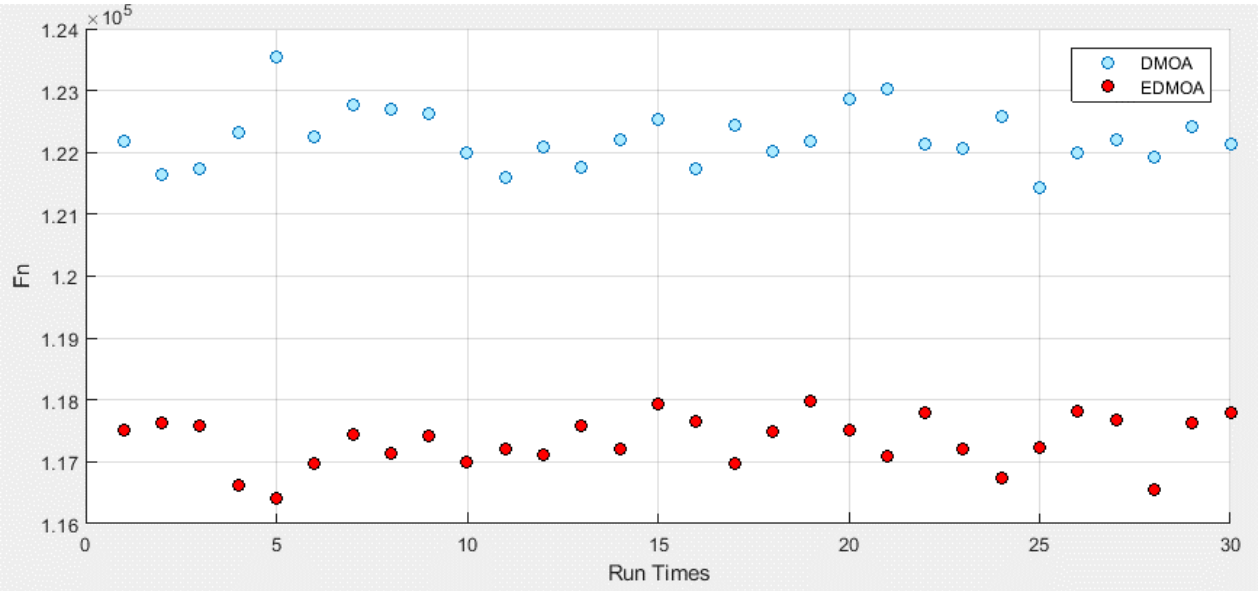


Figure 7. Distribution of the obtained costs over the different thirty executions for EDMOA and DMOA for the DCPH system.

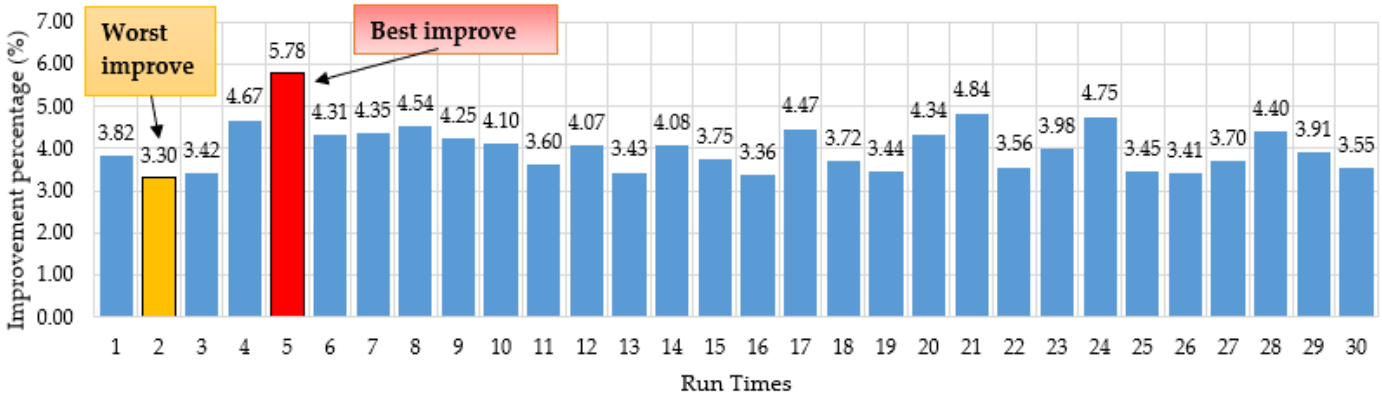


Figure 8. Improvement percentages of EDMOA over DMOA considering the different thirty executions for the DCPH system.

As demonstrated, the proposed EDMOA outperforms the basic DMOA by obtaining lower costs in all completed runs. The suggested EDMOA achieves a maximum reduction of 5.78% in the fifth run and a minimum reduction of 3.3% in the second run; the least minimum, mean, maximum, and standard deviation of $116,897.89, $118,004.35, $119,424.03, and $597.05 per hour with improvements of 1.69, 1.7, 4, and 46.03%, respectively.

Also, comparisons are made with the results of powerful optimization algorithms used in solving ED problems in the literature, as shown in Table 14. As shown, the suggested EDMOA provides superior performing features compared to the others. It provides the capability to achieve the smallest worst, average, and best production costs with $117,973.7, $117,331.3 and $116,406.4 per hour, respectively, compared to all other previously reported results. These findings demonstrate the great effectiveness and efficacy of the proposed DMOA not only over the standard DMOA but also over several other recent techniques.

Table 14. Comparative results for 48-unit DCPH system.

Optimizer	Worst F_n ($/hr)	Average F_n ($/hr)	Best F_n ($/h)
Proposed EDMOA	117,973.7	117,331.3	116,406.4
Standard DMOA	123,551.6	122,238.4	121,431.7
Improved artificial ecosystem algorithm [67]	119,424.033	118,004.349	116,897.888
Artificial ecosystem algorithm [67]	124,396.472	120,045.695	118,881.447
Jellyfish search algorithm [68]	-	-	117,365.09
Gravitational search algorithm [69]	-	-	119,775.9
Manta Ray Foraging Optimizer [70]	118,217.5	117,875.4	117,336.9
CPSO [71]	-	-	120,918.9
TVAC-PSO [71]	-	-	118,962.5
MVO [70]	119,249.3	118,724	117,657.9
SSA [70]	122,636.8	121,110.2	120,174.1

In this regard, Table 15 displays the specified parameters and several successful applications regarding the compared algorithms. For the sake of avoiding the influence of randomness, fifty separate implementations have been examined depending on each algorithm for each benchmark.

Table 15. Compared algorithms for DCPH problem: circumstances and metaparameters.

Algorithm	Parameters	Population Size	No. of Iterations	No. of Fitness Calculations
DMOA	Number of babysitters = 3 Alpha female vocalization (peep = 2)	100	3000	300,000
EDMOA	Number of babysitters = 3 Alpha female vocalization (peep = 2)	100	3000	300,000
Improved artificial ecosystem algorithm [67]	Adaptive parameters a = (1 − iter/MaxIt) × r1;	100	3000	300,000
Artificial ecosystem algorithm [67]	Adaptive parameters a = (1 − iter/MaxIt) × r1;	100	3000	300,000
Jellyfish search algorithm [68]	Adaptive parameters Ar = (1 − iter × ((1)/MaxIt)) × (2 × rand − 1)	100	3000	300,000
Gravitational search algorithm [69]	Parameters: G0 = 400, δ = 0.01	100	500	50,000
Manta Ray Foraging Optimizer [70]	Adaptive parameters Coef = iter/MaxIt	100	3000	300,000
CPSO [71]	Parameters: ω^{max} = 0.9, ω^{min} = 0.4; $C_{1f} = C_{2i}$ = 0.5, $C_{1i} = C_{2f}$ = 2.5; R_{min} = 5, R_{max} = 10	500	300	150,000
TVAC-PSO [71]	Parameters: ω^{max} = 0.9, ω^{min} = 0.4; $C_{1f} = C_{2i}$ = 0.5, $C_{1i} = C_{2f}$ = 2.5; R_{min} = 5, R_{max} = 10	500	300	150,000

Table 15. *Cont.*

Algorithm	Parameters	Population Size	No. of Iterations	No. of Fitness Calculations
MVO [70]	Travelling distance rate is random number ∈ [0.6, 1] Existence probability is random number ∈ [0.2, 1]	100	3000	300,000
SSA [70]	Parameters c1 = c2 are random numbers ∈ [0, 1]	100	3000	300,000

6. Conclusions

For coping with various mathematical benchmarking functions and engineering issues, this work introduces a novel EDMOA with an alpha-directed LS. The proposed method makes use of three DM social groups: the alpha group, babysitters, and scouts. The family forages as a group, with the alpha female starting foraging and deciding on the foraging route, distance travelled, and sleeping mounds. The innovative suggested approach includes an enhanced LS to boost searching capabilities, and its updating process is partially led by the revised alpha. First, the proposed EDMOA and DMOA are evaluated on seven unimodal benchmarking tasks and six multimodal benchmarking tasks. Second, using the CEC 2017 single-objective benchmarks, the proposed EDMOA is compared to the standard DMOA. Furthermore, their applicability is investigated for the DCPH engineering problem. The suggested EDMOA and DMOA are compared to numerous other contemporary and well-known algorithms for all applications. In quantitative speaking, it can be illustrated the following:

- For the first 13 benchmarks, the proposed EDMOA outperforms the regular DMOA in terms of obtaining the lowest mean, STd, and median in more than 80% of benchmark functions. Furthermore, the provided EDMOA achieves the greatest performance by ranking first among DE, MVO, SSA, DMOA, SCA, and PSO.
- For the CEC 2017 benchmarks, the suggested EDMOA has a higher strength compared to the standard DMOA in terms of obtaining the lowest mean, STd, and median in more than 85% of benchmark functions. Also, the provided EDMOA achieves the best performance by recording the top rank compared to SMA, DMOA, GWO, Circle, and PSO.
- For the DCPH engineering problem, the proposed EDMOA outperforms the basic DMOA by obtaining lower costs in all completed runs with savings ranging from 3.3% to 5.78%. Furthermore, the suggested DMOA surpasses not only the standard DMOA but also a number of other recent methods.

Given the great efficacy of the proposed novel technique in the preceding investigations, it is advised that the proposed method be evaluated for sufficiency in future attempts to address the optimal integration of photovoltaic energies in electrical power networks. Also, it can be developed for optimal mathematical representations of these sources and others such as fuel cells and batteries.

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