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Optimal reconfiguration of distribution systems considering reliability: Introducing long-term memory component AEO algorithm

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ABSTRACT

This article introduces a modified version of the Artificial Ecosystem Optimization (AEO) algorithm, called Long-term Memory Component AEO (LMAEO), for optimizing the reconfiguration of radial distribution networks. The LMAEO algorithm incorporates a long-term memory component, enabling individuals in the population to make decisions based on past experiences. This integration of long-term memory allows the algorithm to explore a wider range of potential solutions during the optimization process, potentially leading to improved performance and better exploration of the solution space. To verify the effectiveness and superiority of the LMAEO technique, it is compared with the conventional AEO algorithm and other well-known algorithms using seven benchmark functions. The proposed LMAEO algorithm successfully addresses the reconfiguration of distribution systems considering reliability for the modified 12-bus, 33-bus and 69-bus IEEE test systems. Leveraging the strengths of AEO and the long-term memory component, the LMAEO algorithm achieves efficient solutions for this problem. To assess the performance of the proposed LMAEO, a comparison is made with the original AEO algorithm. The results demonstrate that the LMAEO technique surpasses the AEO optimizer in terms of optimal reconfiguration of distribution systems jointly considering reliability, system losses and voltage deviations.

1. Introduction

Nowadays, the electric power systems play a fundamental role in the electricity/energy markets. Any failure or disruption to comply with the normal function of a distribution network will incur important economic and social costs. To prevent this from happening in radial networks, the reconfiguration of the network topology is carried out by inserting additional tie switches. Many studies based on multi-parameter optimization, have addressed the reconfiguration of radial distribution networks since Baran and Wu (1989) published the first study on losses reduction in distribution systems employing "a search method using Branch exchanges". For example, a reconfiguration approach based on the Particle Swarm Optimization method (PSO) was proposed by Olamaei et al. (2008); in this work the authors used the voltage deviation, the number of switching operations and the active power generation cost as the objective function's parameters. Mena and García (2012) employed a heuristic meshed algorithm, based on the active and reactive power flow directions, to minimize the distribution losses objective function. Kavousi-Fard et al. (2014) solved the Multi-objective Probabilistic Distribution Feeder Reconfiguration problem by an optimization method based on the Self Adaptive Modified Teacher Learning Optimization algorithm; in this case their objective function's parameters were the total losses and the voltage deviations. Another approach to increase the hosting capacity of Active Distribution Systems, by network reconfiguration, was done by Capitanescu et al. (2015); where authors maximized the hosting capacity under both thermal and voltages restrictions, studying the non-linear and mix periods of the power flow. A new approach of stochastic reconfiguration optimization, based on Gravitational Search Algorithm, that minimize the resistive losses and the radial distribution networks cost, was presented by Kavousi-Fard et al. (2015). Kanwar et al. (2016) minimized the annual energy loss, while keeping the best bus voltage profiles, with a Dedicated Search Teaching Learning Based Optimization method. López et al. (2016) presented a comprehensive optimization model that combines reactive power optimization and network reconfiguration to minimize power

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Nomenclature

c_{lss}	Cost of power losses ($/kW)
c_{SAIDI}	Cost due to violation of $SAIDI_{max}$ ($)
c_{SAIFI}	Cost due to violation of $SAIFI_{max}$ ($)
c_V	Cost due to voltage deviation ($/V)
P_{lss}	Total power loss in the system (kW)
L	Number of system lines
L_a	Number of additional ties
N	Number of system buses
N_j	Number of users connected at bus j
U_j	Average annual time out of service for bus j (h/year)
$SAIDI_{max}$	Average interruption duration limit index (h/year)
$SAIFI_{max}$	Average Interrupt Frequency Limit Rate (faults/year)
λ_j	Mean failure rate at bus j (failures/year)
λ_i	Failure rate of line i (failures/year)
$V_{nom,j}$	Nominal voltage for the bus j (V)
V_j	Voltage at bus j (V)
P_j	Active power injected at bus j (kW)
Q_j	Reactive power injected at bus j (kVAr)
G_{jk}	Real part of element jk of the system bus matrix (Siemens)
B_{jk}	Imaginary part of the element jk of the system bar matrix (Siemens)
$b_{sh,jk}$	Susceptance of the line jk (Siemens)
δ_{jk}	Angle difference between bus voltages jk, $\delta_j - \delta_k$ (°)
$V_{max,j}$	Maximum voltage limit for bus j (V)
$V_{min,j}$	Minimum voltage limit for bus j (V)
S_{jk}	Apparent power flow circulating through the line from bus j to bus k (kVA)
$S_{max,jk}$	Transmission limit of the line jk (kVA)
P_{jk}	Active power flow circulating through the line from bus j to bus k (kW)
Q_{jk}	Reactive power flow circulating through the line from bus j to bus k (kVAr)
Lp	Number of closed loops in the system
r_i	Average restoration time of the line i (h)
t_{jk}	Transformer tap between buses j and k
A	Bus incidence matrix
R	Line resistence (p.u.)
X	Line reactance (p.u.)
OF	Objective function
OF_{aug}	Augmented objective function
Eq	Number of equality constraints
Ieq	Number of inequality constraints
k_{eq}	Penalty coefficient for equality constraints
k_{ieq}	Penalty coefficient for inequality constraints
$\overline{X}_i$	State variable vector
$h_m(\overline{X}_i)$	Equality constraints
$g_m(\overline{X}_i)$	Inequality constraints

losses and maximize the reliability, based on a Mixed-Integer Second-Order Cone Programming model. The Ant Colony Optimization algorithm for network reconfiguration is proposed by Ameli et al. (2016) to minimize network costs; they proposed a method for simultaneous dynamic programing for feeder reconfiguration and capacitor banks on Distributed Generation (DG) units. A novel solution method called Multi-objective Hybrid Big Bang-Big Crunch was implemented by Esmaeili et al. (2016) to solve the optimization problem; among the energy losses and the operation cost, also the polluting gases is input as one of the objective function's parameters. A hybrid Improved PSO – Improved Grey Wolf Optimization algorithm was employed by Azizivahed et al. (2018) to study the dynamic feeder reconfiguration problem with several objective functions that takes into account the operation cost, the power loss and the energy not supplied. When considering the load variations of the systems, through a stochastic reconfiguration process, López et al. (2018) used the Monte Carlo method; the reconfiguration optimization problem is solved by Genetic Algorithm. Another approach to minimize losses with objective functions is the Shuffled Frog Leaping Algorithm as shown in Dong et al. (2018). Linearization techniques are employed, by Bao et al. (2019), to formulate the dynamic reconfiguration problem into a Mixed-Integer Linear Programing model, which tries to minimize the total costs with respect to various operating constraints. Mukhopadhyay and Das. (2020) used PSO for the optimized allocation of photovoltaic DG and battery energy storage systems; the reconfiguration objectives considered are loss minimization as well as voltage, and loadability improvement. Other analytical methods for evaluating the reliability of radial distribution networks were proposed by Li et al. (2020); they approached the problem with a linear programing model, which includes precisely assessing reliability and considers post-fault network reconfiguration strategies involving operational constraints. A joint framework was presented by Harsh and Das (2021) to integrate an incentive-based demand response and reconfiguration method in the energy management problem of microgrid; they minimized the fuel cost and the cost of the power purchased from the grid.

However, the literature review conducted reveals a lack of studies that simultaneously consider active power losses, voltage deviations, and system reliability in the objective function. Previous works have predominantly focused on minimizing system losses, neglecting the consideration of reliability or voltage deviations.

All these variables play crucial roles in the efficient operation of an electrical system and also contribute to operating costs. Therefore, this study aims to minimize the combined cost associated with compromising system reliability, power losses, and voltage deviations from nominal values at the buses. By incorporating these factors into the objective function, a more comprehensive and realistic assessment of the system's performance and cost can be achieved.

These novel optimization techniques can be used to find solutions to a multitude of problems in different fields, as can be seen in Eliwa et al. (2023), Omar and Abd El-Hafeez (2023a, 2023b), Hady and Abd El-Hafeez (2023), Hamed et al. (2023), and Nguyen et al. (2022).

In this paper, it is proposed an improved Artificial Ecosystem Optimization (AEO), called long term AEO (LMAEO), to optimize the reconfiguration of radial distribution networks. The AEO algorithm offers numerous advantages. Firstly, it efficiently balances global exploration and local exploitation, permitting it to competently search through the solution space. This characteristic leads to a rapid convergence rate, allowing the AEO technique to converge toward best solutions in a shorter amount of time. Furthermore, the AEO algorithm proves suitable solution precision, confirming that the attained solutions are consistent and effective. Though, in spite of its strengths, the AEO algorithm also has some restrictions. One weakness is its susceptibility to getting stuck in local optima, which can delay the technique's capability to explore the whole solution space and possibly bound the superiority of the solutions gotten. Also, the AEO technique may show sensitivity to parameter settings, demanding careful tuning for optimum performance in different problem domains. To address these limitations, the proposed LMAEO algorithm presents improvements to overcome the challenges handled by its predecessor. The LMAEO algorithm builds upon the strengths of the AEO algorithm while qualifying its weaknesses. It combines further mechanisms to escape local optima and improve exploration. In this article, the multi objective optimization problems takes into account the following costs: (i) power losses, (ii) bus voltage violations and (iii) reliability index violations. The inclusions of these terms into the proposed objective function, along with the use of improved optimization techniques, differentiate our work from the above-mentioned studies. This paper aims to significantly enhance and improve upon existing classification methods in several key aspects. The proposed approach introduces a state-of-the-art feature extraction technique that surpasses the capabilities of traditional methods. By leveraging advanced algorithms and incorporating the latest developments in signal processing, the proposed method captures complicated patterns and distinctions in the data, leading to more robust and accurate classification results. The main contributions of this paper are:

- The AEO algorithm is improved by incorporating a long-term memory component, which serves to assess the performance of the original algorithm and prevent it from being trapped in local optima, thereby enhancing its ability to achieve better optimal solutions.
- The effectiveness and superiority of the LMAEO technique are demonstrated by comparing it with both the conventional AEO algorithm and other recently developed optimizers. This comparison is conducted using seven benchmark functions.
- The proposed LMAEO algorithm is utilized for the optimal reconfiguration of distribution systems in the modified 12-bus, 33-bus, and 69-bus IEEE test systems. The objective function takes into account power losses in the system as well as voltage deviations at the buses and system reliability. The aim is to maximize system reliability while minimizing power losses and voltage deviations.

This document is structured as follows. In Section 2 we define the scope of the problem and also the objective function. The method used to solve the objective function is presented in Section 3. In Section 4, we explain how to deal with the details of the proposed methodology. The LMAEO algorithm is tested on the 12-bus, 33-bus and 69-bus IEEE distribution test systems. The results and a discussion are shown in Section 5. Finally, in Section 6, we draw the main conclusions from the studies carried out.

2. Problem formulation

2.1. Objective functions

Due to the high losses in distribution networks, and consequently high costs, the reduction of the active power losses is a very important task (Nguyen, 2021). Moreover, in order to maintain a correct functioning of the network, the voltage limits at the buses must comply with national standards and regulations to guarantee the continuity of the service and the quality of the voltage wave (IEEE, 2001). Aiming at reducing the operation costs by constraining these parameters, we proposed the following objective function:

$$\mathrm{OF} = \min c_{lss}P_{lss} + c_{SAIDI}\left[\sum_{j=1}^{N} N_j\left(U_j - SAIDI_{max}\right)\right] + c_{SAIFI}\left[\sum_{j=1}^{N} N_j\left(\lambda_j - SAIFI_{max}\right)\right] + c_V\sum_{j=1}^{N}\left|\left|V_{nom,j}\right| - \left|V_j\right|\right| \tag{1}$$

The first term refers to the cost of active power losses in the system, where P_{lss} are the total losses in the system, in kW, and c_{lss} is the cost associated with the losses in \$/kW. The power losses in an electrical system can be calculated with the following expression:

$$P_{lss} = \sum_{i=1}^{L}\left|\left|P_{jk,i}\right| - \left|P_{kj,i}\right|\right| \tag{2}$$

where $P_{jk,i}$ and $P_{kj,i}$ are the active power flows circulating from bus j to bus k, and from bus k to bus j, respectively, on line i. These flows are calculated in the following way (Gomez-Exposito et al., 2009):

$$\begin{aligned} P_{jk} &= -\frac{1}{t_{jk}}\left|V_j\right|^2 G_{jk} + \left|V_j\right|\left|V_k\right|\left(G_{jk}cos\delta_{jk} + B_{jk}sin\delta_{jk}\right) \\ P_{kj} &= -\frac{1}{t_{kj}}\left|V_k\right|^2 G_{kj} + \left|V_k\right|\left|V_j\right|\left(G_{kj}cos\delta_{kj} + B_{kj}sin\delta_{kj}\right) \end{aligned} \tag{3}$$

The second and third terms of Eq. (1) refer to the cost of violating the SAIDI and SAIFI reliability indices (López et al., 2016; IEEE, 2001). These indices are widely used in evaluating the reliability of electrical distribution systems. SAIDI indicates the average duration of interruptions perceived by a user, while SAIFI shows the average number of times an interruption occurs for a user.

The costs of violating the SAIDI and SAIFI reliability indices, in \$, are represented by the variables c_{SAIDI} and c_{SAIFI}, respectively. The evaluation of reliability according to these indices is determined through the following expressions:

$$\begin{aligned} SAIFI &= \frac{\sum_{j=1}^{N}\lambda_j N_j}{\sum_{j=1}^{N} N_j} \\ SAIDI &= \frac{\sum_{j=1}^{N} U_j N_j}{\sum_{j=1}^{N} N_j} \end{aligned} \tag{4}$$

where λ_j is the average failure rate for bus j, and U_j is the average annual out-of-service time for bus j, determined as follows (López et al., 2016):

$$\begin{aligned} \lambda_j &= \sum\nolimits_i \lambda_i \\ U_j &= \sum\nolimits_i \lambda_i \cdot r_i \end{aligned} \tag{5}$$

where λ_i and r_i represent the expected failure rate and restoration time of each line i between bus j and its source (Billinton and Allan, 1996). Eqs. (4) and (5) will allow us to define some important restrictions for the optimization problem, as will be seen later.

The fourth term of Eq. (1) represents the cost of the voltage violation (Olamaei et al., 2008). Although the legislation of each country establishes that the voltage at each bus of an electrical system must be within limits, usually ± 10 % with respect to the nominal value (IEEE, 2001), more and more receivers are sensitive to voltages out of range, causing its malfunction or even its stoppage, with the consequent economic damages. Hence, some consumers with this type of sensitive loads choose to install voltage stabilizers, with the associated cost of this equipment. This is why in this study the voltage deviation of a bus is associated with a cost, c_V, which will allow the evaluation of the damage caused to consumers when the voltage deviates from its nominal value.

2.2. Constraints and limits

To operate with the objective function shown in the previous section, a series of restrictions are established to ensure the proper functioning and operation of the electrical distribution system. Commonly, constraints can be classified into two types: equality and inequality constraints or limits. Next, we explain these limits.

2.2.1. Equality constraints

The equality constraints established for the present study are the following:

$$P_j = \left|V_j\right|\sum_{k=1}^{N}\left[\left|V_k\right|\left(G_{jk}cos\delta_{jk} + B_{jk}sin\delta_{jk}\right)\right] \tag{6}$$

$$Q_j = \left|V_j\right|\sum_{k=1}^{N}\left[\left|V_k\right|\left(G_{jk}sin\delta_{jk} - B_{jk}cos\delta_{jk}\right)\right] \tag{7}$$

$$P_{lss} = \sum_{i=1}^{L}\left|\left|P_{jk,i}\right| - \left|P_{kj,i}\right|\right| \tag{8}$$

$$det(A) = 1 \ \ or \ \ -1 \tag{9}$$

$$\lambda_j = \sum_i \lambda_i \tag{10}$$

$$U_j = \sum_i \lambda_i \cdot r_i \tag{11}$$

Constraints (6) and (7) correspond to the load flow equations. Constraint (8) is related to the calculation of the active power lost in the system, calculated from equations (3). Constraint (9) ensures the radial topology for the electrical system (Shaheen and El-Sehiemy, 2020), since it must operate in this way, with A being the incidence matrix of the system calculated as can be seen in Grainger and Stevenson (1994). If the determinant of matrix A is equal to 1 or -1, then the system is radial. If the determinant of matrix A is equal to 0, this means that the system is not radial or that there are areas isolated from the rest of the system. Finally, constraints (10) and (11) mark the determination of the system reliability indices for a given topology.

2.2.2. Inequality constraints

The inequality constraints, or limits, established in this study are:

$$V_{min,j} \leq V_j \leq V_{max,j} \tag{12}$$

$$S_{jk} \leq S_{max,jk} \tag{13}$$

$$\frac{\sum_{j=1}^{N} N_j \lambda_j}{\sum_{j=1}^{N} N_j} \leq SAIFI_{max} \tag{14}$$

$$\frac{\sum_{j=1}^{N} N_j U_j}{\sum_{j=1}^{N} N_j} \leq SAIDI_{max} \tag{15}$$

Constraint (12) ensures that the voltages at each bus of the system are not outside the range established by the standards of each country. This constraint is independent of the cost associated with the voltage deviation (fourth term of the Objective Function). That is, as long as (12) is met, a cost associated with the voltage deviations will be calculated. If (12) does not hold, then that is not a feasible solution to this problem. Constraint (13) limits the power transported by each line of the system. Constraints (14) and (15) limit the reliability indices SAIFI and SAIDI (López et al., 2016), respectively, to a maximum value, which is normally established by the standards of each country (IEEE, 2012).

3. The proposed LMAEO algorithm

3.1. Original conventional AEO

Zhao et al. firstly proposed the Artificial Ecosystem Optimization (AEO) technique, taking motivation from the energy flow detected in natural ecosystems (Zhao et al., 2020). The technique integrates three distinct behaviors: production, consumption, and decomposition, which reflect the energy flow dynamics inside an ecosystem. The AEO technique mixes three fundamental operators, each satisfying a different role inside the optimization procedure:

- Production: This operator is responsible for keeping a balance between the exploration and exploitation stages, confirming an inclusive search for optimum solutions.
- Consumption: The consumption operator improves exploration by spreading the search space, permitting for the exploration of a widespread range of solutions.
- Decomposition: The decomposition operator improves the exploitation stage of the original AEO, allowing the technique to professionally exploit the exposed solutions.

These operators work together to develop the functionality and efficiency of the AEO technique.

A. *Production*

The production operator is mathematically showed as (Hassan et al., 2021):

$$x_1(t+1) = (1-a)x_n(t) + a \times x_{rand}(t) \tag{16}$$

$$a = (1 - \frac{t}{\max\_it})r_1 \tag{17}$$

$$x_{rand} = r(u_b - l_b) + l_b \tag{18}$$

In the given context, the variable a denotes a linear weighting coefficient. The term x_{rand} represents an individual location produced randomly inside the search space. $\max\_it$ means the maximum number of iterations. The value r_1 signifies a random number within the range of [0, 1]. The term r is a random vector with values between 0 and 1. The variables u_b and l_b denote the upper and lower bounds, respectively.

B. *Consumption*

There are three types of consumers, as the following equations:

(1) herbivore is mathematically expressed as follows (Abd-El Wahab et al., 2023):

$$x_i(t+1) = x_i(t) + C \times (x_i(t) - x_1(t)), i \in [2, \cdots, n] \tag{19}$$

$$C = \frac{1}{2} \frac{v_1}{|v_2|} \tag{20}$$

$$v_1 \ N(0,1), v_2 \ N(0,1), \tag{21}$$

where $N(0,1)$ is a normal distribution.

(2) carnivore is obtainable mathematically as below:

$$\begin{cases} x_i(t+1) = x_i(t) + C \times (x_i(t) - x_j(t)), \\ \quad i \in [2, \cdots, n] \\ \quad j = randi([2i-1]) \end{cases} \tag{22}$$

(3) omnivore is displayed mathematically as follows:

$$\begin{cases} x_i(t+1) = x_i(t) + C \times (x_i(t) - x_1(t)) + (1-r_2) \\ \quad (x_i(t) - x_j(t)), i = 3, \cdots, n \\ \quad j = randi([2i-1]) \end{cases} \tag{23}$$

C. *Decomposition*

The decomposition operator is exhibited mathematically as follows (Youssef et al., 2023):

$$x_i(t+1) = x_n(t) + D \times (s \times x_n(t) - q \times x_i(t)), \quad i = 1, \cdots, n \tag{24}$$

$$D = 3u, u \ N(0,1) \tag{25}$$

$$s = r_3 \times randi([12]) - 1 \tag{26}$$

$$q = 2 \times r_3 - 1 \tag{27}$$

where D represents the decomposition factor D, while s and q are the weighting coefficients.

3.2. Proposed LMAEO algorithm

Although the AEO optimization technique displays ability, there is

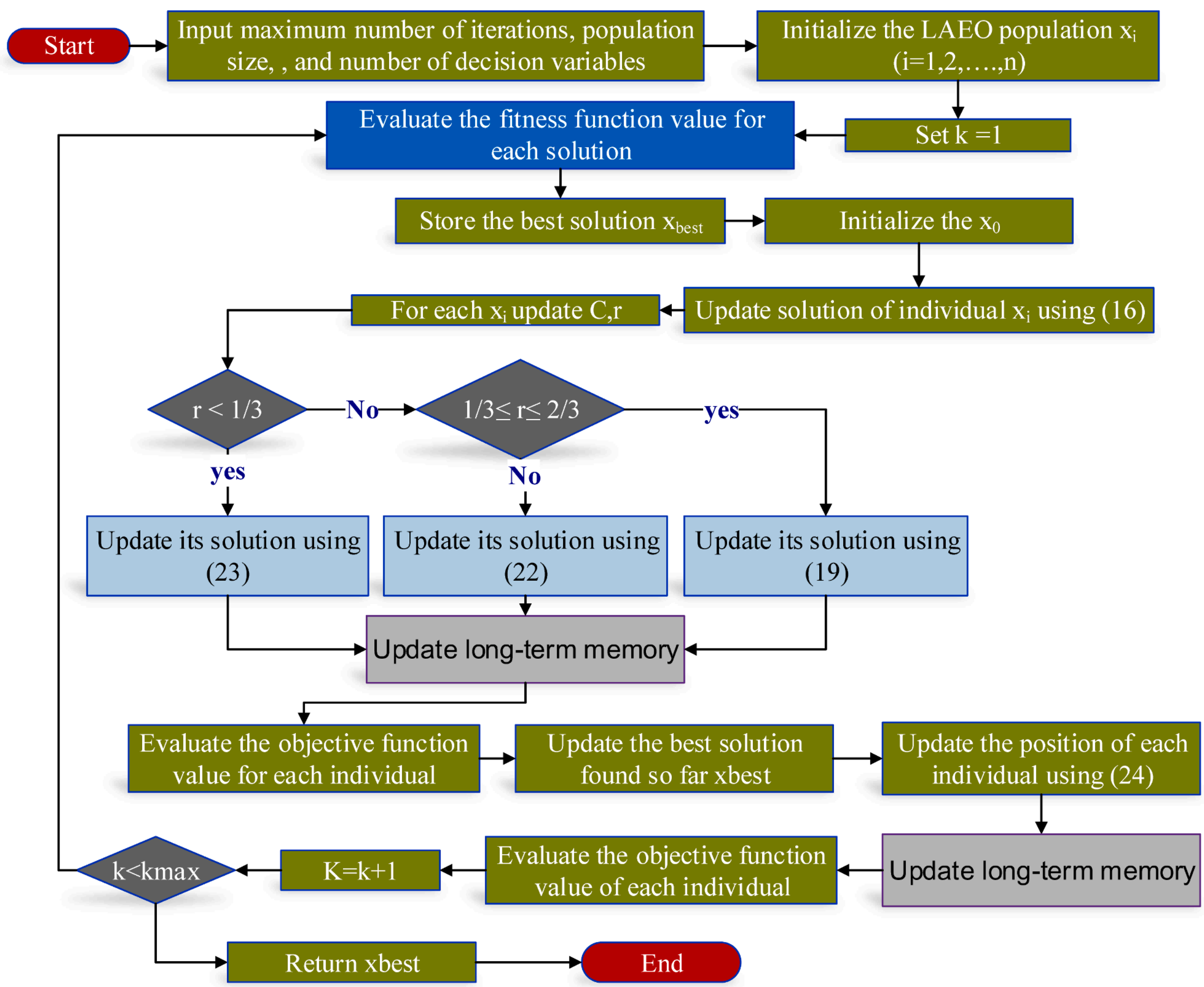

Fig. 1. Flow chart of LMAEO algorithm.

room for additional development to attain even better results. Like to many other metaheuristic methods, AEO relies on searching around a single global best location. Though, this method of having a single guiding location for the whole residents may not confirm convergence to the global best location. The confidence on a single global best location often leads to early convergence in metaheuristic methods. To address this restriction, this paper presents the idea of long-term memory in AEO. By integrating long-term memory, the population of individuals can make decisions based on multiple previous skills. This method offers a wider view of numerous promising positions, thus qualifying the risk of early convergence or stagnation. The proposed technique, called Long-Term Memory AEO (LMAEO), presents an extra parameter known as Memory Length (ML). ML is a user-defined control parameter that regulates how many previous skills the swarm or population can remember at any given time (Hussain et al., 2019). By combining long-term memory into AEO, LMAEO improves the algorithm's capability to explore diverse solutions and evade early convergence.

The updating procedure of the long-term memory in LMAEO follows a First-In-First-Out (FIFO) queue mechanism. The memory stores the ML best positions exposed thus far. In the FIFO method, when a new item is added, the oldest item is removed to keep the queue's length. In the case of AEO, during each iteration t, the memory is updated by adding the most recent best position initiate while removing the oldest entry. Once the memory is updated, the swarm regulates its next transfer by choosing one item from the long-term memory. The choice is made probabilistically, using a possibility calculation for each item in memory, signified as pi for the i_{th} item, as shown in Eq. (28):

$$pi = \frac{f(x_i^d)}{\sum_{j=1}^{ML} f(x_j^d)} \tag{28}$$

In Eq. (28), $f(x_i^d)$ or $f(x_j^d)$ denotes the fitness value of the ith or j_{th} item in the long-term memory. Once the possibility of choice is calculated for each item in the long-term memory, the choice procedure is achieved using the Roulette Wheel Selection method. Upon choosing an item from the long-term memory, it can be used in all location update equations. In LMAEO, instead of using a single global best position, x_{best}, as in AEO, LMAEO employs x_{best}^k, which corresponds to the kth global best position stored in the long-term memory. The index k is chosen through the Roulette Wheel Selection method. As a result, all the position update equations in LMAEO remain the same as AEO, with the exception of replacing x_{best} with x_{best}^k. Fig. 1 illustrates the intricate process flow of the proposed LMAEO algorithm. The flow chart encapsulates the sequential steps and decision points that characterize the functioning of the algorithm, providing a visual representation of its underlying logic and structure. Moreover, Algorithm 1 describes the LMAEO algorithm's pseudocode. This pseudocode serves as a detailed guide, articulating the step-by-step procedures and computational operations involved in the

Table 1
Parameter settings of the selected techniques.

Algorithms	Parameters setting
Common settings	*Population size: nPop = 50.* *Maximum iterations: Max_iter = 200.* *Number of independent runs: 20.*
HPO	$C \in [1, 0.02]$, $\beta = 0.1$. *(Default)*
GBO	$\beta_{min} = 0.2, \beta_{max} = 1.2$, $pr = 0.5$. *(Default)*
POA	*No such parameter.*
ARO	
AEO	
LMAEO	*Long term memory limit LM = 10. (Default)*

execution of the algorithm.

Algorithm 1: Pseudocode of the LMAEO algorithm

Set the control parameter (Dimension of problem (d), maximum iteration (kmax), population size), and long-term memory limit (LM).
Initialize the population randomly
Evaluate the fitness of the new solution
Obtain the best solution
While $k \leq kmax$
% Production
For individual X1, Update the new location of the individual using Eq. (16)
% Consumption
For individual Xi, (i = 2,….,n),
% Herbivore
If $r < 1/3$
Update the new location of the individual using Eq. (23).
% Omnivore
Else If $1/3 \leq r \leq 2/3$
Update the new location of the individual using Eq. (22).
% Carnivore
Else *Update the new location of the individual using Eq. (19).*
End If
Check the limits of the new locations and evaluate the fitness values
Update long-term memory
Find the new solution if the fitness is better
% Decomposition
Update the new location of the individual using Eq. (24).
Check the limits of the new locations and evaluate the fitness values
Update long-term memory
Find the new solution if the fitness is better
Check the limits of the new locations and evaluate the fitness values
Find the new solution if the fitness is better
k = k + 1
End while
Output the best solution

3.3. Computational complexity analysis of LMAEO

Computational complexity provides a valuable tool for assessing the effectiveness of algorithms in solving optimization problems. The complexity of an algorithm is influenced by several factors, including the number of individuals involved (n), the dimensionality of the problem's variables (d), the maximum number of iterations (T), and long-term memory (ML). In the case of LMAEO, the total computational complexity can be expressed as follows:

$$O(LMAEO) = O(initialization) + O(function\ evaluation) + O(Position\ updating\ in\ production) + O(Position\ updating\ in\ Consumption) + O(updating\ long-term\ memory) + O(selection\ of\ items\ from\ the\ memory) + O(Position\ updating\ in\ Decomposition) = O\left(n + T\times n + \frac{1}{n}\times T\times d + \frac{n-1}{n}\times Td\times + T\times ML\times d + T\times ML + T\times n\times d\right) = O(n + T\times n + 2\times T\times n\times d + T\times ML\times d + T\times ML).$$

4. Application

4.1. Benchmark functions

Prior to delving into the reconfiguration problem, we conduct a comparative study of our proposed method against various preceding techniques, including gradient-based optimization (GBO) (Ahmadianfar et al., 2020), hunter-prey optimization (HPO) (Naruei et al., 2022), artificial rabbits optimization (ARO) (Wang et al., 2022), pelican optimization algorithm (POA) (Trojovský and Dehghani, 2022), and the original AEO. This analysis aims to showcase the superior effectiveness of our approach.

To confirm a balanced estimation, all methods were thoroughly tested under comparable situations, as long as a fair basis for comparison. The assessment involved the employment of 50 search agents and a maximum iteration of 200. Moreover, each technique was independently executed 20 times, considering the essential stochastic nature of the techniques. This method permitted for a complete assessment of their performance. The parameters specified in the original reference were employed for each method. Table 1 displays the parameter configurations for these techniques.

The execution of the techniques was carried out using the MATLAB R2016a software on a high-performing computer running Windows 10 64-bit Professional and equipped with 8 GB RAM. This confirmed a consistent and reliable computing environment for the experiments. A key aspect considered in this evaluation was the influence of parameter settings on algorithm performance. To confirm an objective comparison, the parameter values employed for all algorithms were directly derived from the original articles authored by their respective developers. This approach-maintained consistency and removed any possible bias arising from arbitrary parameter choices. Markedly, the LMAEO technique stood out among the compared algorithms such as GBO, HPO, ARO, POA, and original AEO, exhibiting exceptional performance across the 7 benchmark functions. Its results, as demonstrated in Table 2, consistently surpassed those of other recent algorithms. LMAEO achieved the best outcomes in terms of the best, average, median, and worst results across multiple benchmark functions. The LMAEO algorithm's strength lies in its ability to consistently find optimal solutions, as evident from its top ranking across different benchmark functions. Its superior performance, as compared to other recent algorithms, underscores its effectiveness in tackling complex optimization problems. These results highlight the LMAEO technique as a robust and reliable approach for addressing a wide range of optimization challenges.

The convergence curves of all algorithms for the seven benchmark functions, including F1, F2, F3, F4, F5, F6, and F7, are illustrated in Fig. 2. This graphical representation provides insights into the convergence behavior of each algorithm over the iterations for the respective benchmark functions. Additionally, Fig. 3 presents the boxplots showcasing the performance of all algorithms across the seven benchmark functions, F1, F2, F3, F4, F5, F6, and F7. These boxplots offer a comprehensive overview of the algorithm's performance in terms of the best, average, and worst results achieved.

Especially, the LMAEO technique demonstrates remarkable convergence behavior in Fig. 2, showcasing its ability to converge toward optimal solutions for all benchmark functions. Moreover, in Fig. 3, the boxplots consistently position LMAEO as a leading algorithm, further emphasizing its competitive performance compared to other algorithms. These convergence curves and boxplot results highlight the robustness and effectiveness of the LMAEO algorithm, underscoring its strength in achieving convergence and generating favorable outcomes across a diverse set of benchmark functions.

A. Wilcoxon's rank test results

In this subsection, we conduct a detailed statistical analysis of the variances between LMAEO and other methods using the Wilcoxon rank-sum test (WRST), a paired assessment employed to identify significant differences between the two techniques. The results of the test comparing LMAEO with each method, conducted at a significance level of $\alpha = 0.05$, are presented in Table 3. The symbols "+/=/-" indicate whether LMAEO performs better, similarly, or worse than the compared

Table 2
The statistical Results of seven benchmark functions by the LMAEO technique and other recent algorithms.

Function		LMAEO	AEO	GBO	HPO	ARO	POA
F1	Best	2.8E−99	1.49E−85	9.06E−52	1.17E−77	1.59E−26	1.18E−45
	Average	1.03E−84	3.69E−72	4.1E−46	1.49E−69	1.07E−21	1.62E−37
	Median	3.89E−91	1.58E−73	1.73E−49	3.09E−72	4.68E−23	1.86E−41
	Worst	1.82E−83	4.72E−71	4.79E−45	1.92E−68	7.08E−21	3.09E−36
	std	4.06E−84	1.08E−71	1.27E−45	4.51E−69	2.18E−21	6.9E−37
	Rank	1	2	4	3	6	5
F2	Best	1.2E−48	1.67E−41	2.03E−28	5.41E−41	1.34E−14	3.79E−23
	Average	4.07E−43	4.65E−38	1.95E−24	2.69E−38	1.15E−12	3.15E−20
	Median	6.99E−46	3.89E−39	1.77E−25	1.64E−39	1.22E−13	5.04E−21
	Worst	7.67E−42	3.79E−37	1.95E−23	2.64E−37	1.78E−11	1.67E−19
	std	1.71E−42	9.33E−38	4.64E−24	6.13E−38	3.94E−12	4.9E−20
	Rank	1	3	4	2	6	5
F3	Best	1.03E−86	7.95E−75	3.42E−42	4.64E−68	4.28E−21	1.74E−43
	Average	9.11E−76	2.57E−63	2.56E−38	1.72E−59	5.08E−15	8.76E−39
	Median	1.64E−79	6.73E−70	5.51E−40	5.21E−63	6.99E−17	3.91E−41
	Worst	6.75E−75	5.05E−62	2.05E−37	3.12E−58	6.41E−14	1.19E−37
	std	2.19E−75	1.13E−62	5.68E−38	6.95E−59	1.51E−14	2.76E−38
	Rank	1	2	5	3	6	4
F4	Best	2.16E−49	5.72E−43	1.54E−24	2.1E−35	8.35E−13	2.06E−24
	Average	3.86E−43	9.09E−36	8.59E−22	7.25E−32	2.6E−09	5.73E−20
	Median	4.57E−45	2.8E−37	1.22E−22	1.31E−32	7.79E−10	4.04E−21
	Worst	4.73E−42	5.78E−35	1.08E−20	7.27E−31	2.28E−08	4.68E−19
	std	1.19E−42	1.92E−35	2.47E−21	1.69E−31	5.09E−09	1.29E−19
	Rank	1	2	4	3	6	5
F5	Best	4.41E−06	24.57729	24.25387	23.80007	0.048127	27.59768
	Average	0.000921	25.40966	25.13063	24.34554	2.57084	28.57786
	Median	0.000309	25.32669	25.117	24.16784	1.069097	28.75691
	Worst	0.004024	26.19623	26.10917	25.98622	16.26736	28.8694
	std	0.001285	0.437327	0.565603	0.511546	3.783419	0.376116
	Rank	1	5	4	3	2	6
F6	Best	8.03E−08	0.001169	0.00018	3.7E−07	0.009568	2.287489
	Average	1.38E−05	0.006	0.00108	0.000811	0.044563	3.220579
	Median	3.17E−06	0.005046	0.000875	1.8E−06	0.039666	3.076281
	Worst	5.94E−05	0.015412	0.002836	0.015867	0.098375	4.6641
	std	1.61E−05	0.004129	0.000702	0.003544	0.026373	0.548631
	Rank	1	4	3	2	5	6
F7	Best	6.49E−05	0.000105	0.000111	2.71E−05	3.22E−05	1.74E−05
	Average	0.000375	0.000681	0.001192	0.000529	0.001407	0.000404
	Median	0.000275	0.000588	0.000985	0.000167	0.00115	0.000328
	Worst	0.001328	0.001961	0.004017	0.001566	0.003564	0.001649
	std	0.000335	0.000455	0.001008	0.000569	0.001071	0.000361
	Rank	1	4	5	3	6	2
Average Rank	1	3.142857	4.142857	2.714286	5.285714	4.714286	
Final ranking	1	3	4	2	6	5	

technique. Furthermore, the table includes statistical findings for LMAEO across various dimensions and functions, indicating its comparative performance. Notably, LMAEO demonstrates superior statistical performance in F1-F7 with Dim = 30 when compared to other techniques, affirming its significant superiority across most functions. Consequently, we confidently assert that the proposed LMAEO technique exhibits the best overall performance when compared to other methods.

B. Friedman's rank test results

The statistical outcomes obtained through Friedman tests for seven benchmark functions using the examined algorithms are presented in Table 4. A lower ranking value signifies superior algorithm performance. Based on the results, the ranking order of the six techniques is as follows: LMAEO, HPO, AEO, GBO, POA, and ARO.

Furthermore, Fig. 4 illustrates the mean ranks derived from Friedman's rank test for the seven benchmark functions employing various algorithms. This graphical representation offers a distinct comparison of the algorithms' performances across the cases, facilitating the identification of any noteworthy disparities in their ranks. The prominently elevated position in the rankings unequivocally establishes LMAEO as the most effective algorithm among the six considered.

4.2. The studied system

To solve the proposed problem, an algorithm has been implemented in MATLAB to perform the necessary simulations. This is a complex problem to solve, due to the large number of combinations that can be obtained. For a system with L lines and L_a additional ties, the

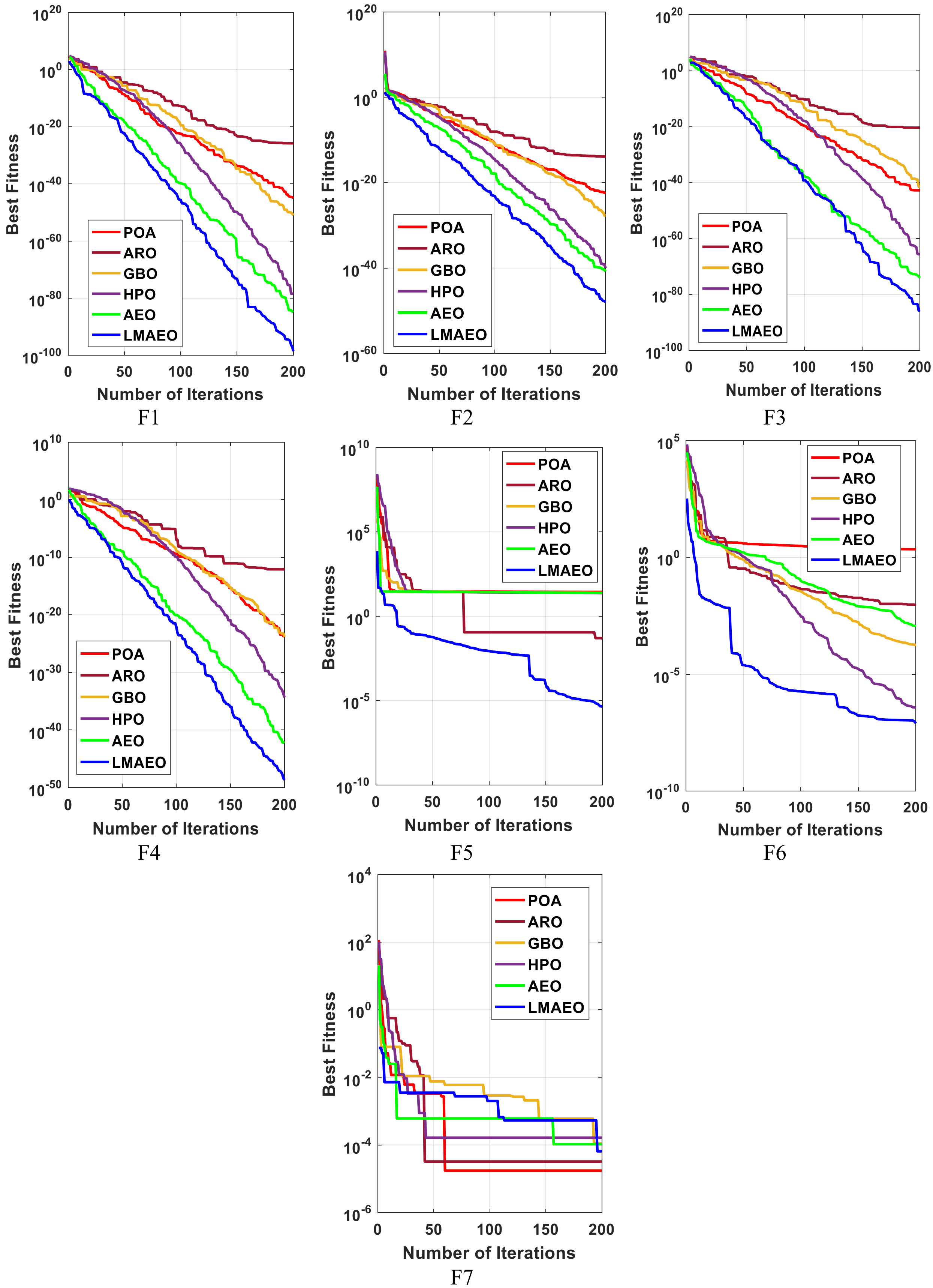

Fig. 2. The convergence curves of all algorithms for seven benchmark functions, F1-F7.

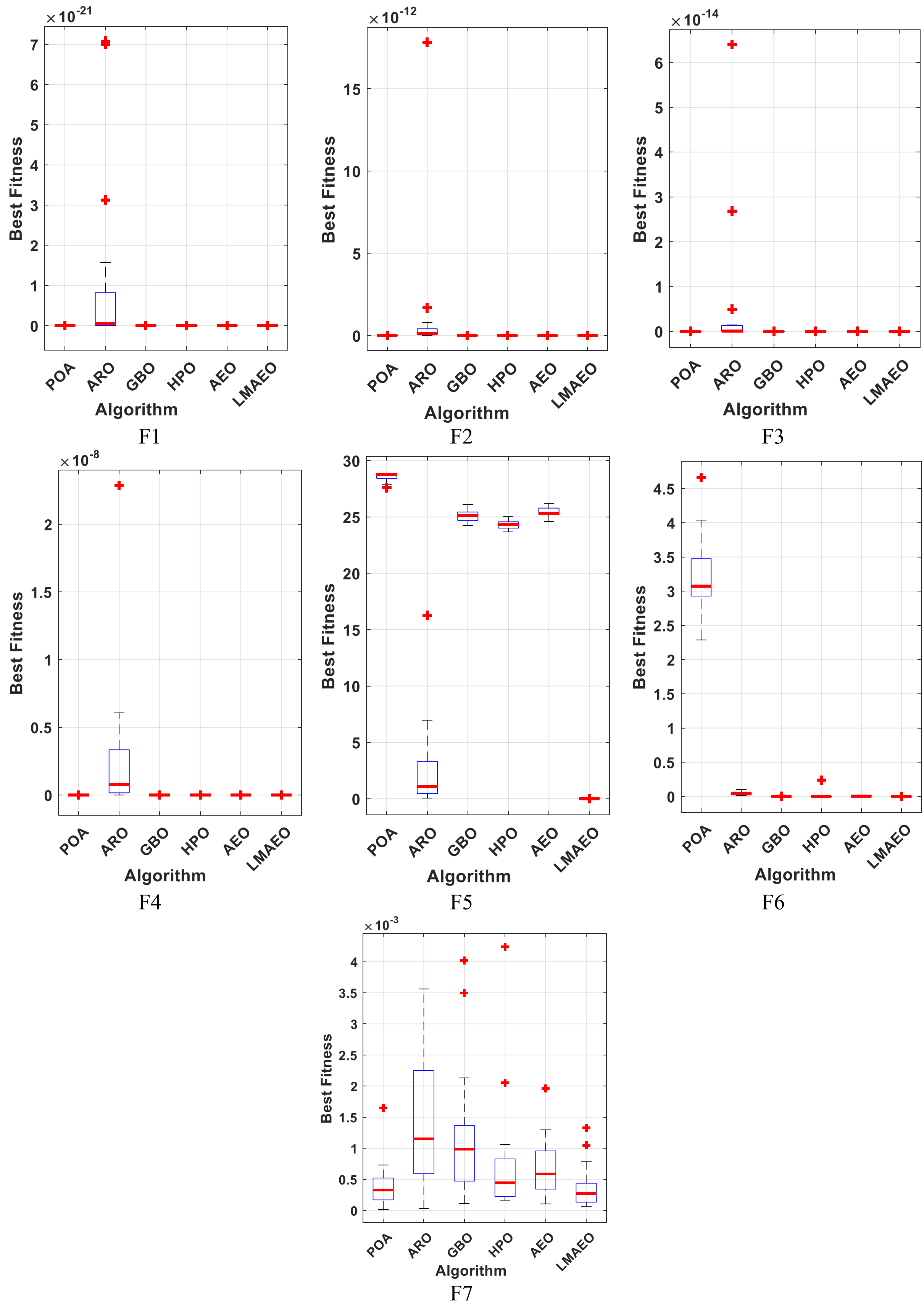

Fig. 3. Boxplots for all algorithms for seven benchmark functions, F1-F7.

Table 3
Statistical results of the Wilcoxon rank-sum test.

LMAEO vs	AEO		HPO		GBO		ARO		POA	
Function	P	winner	P	winner	P	winner	P	winner	P	winner
F1	9.17E−08	+	6.80E−08	+	6.80E−08	+	6.80E−08	+	6.80E−08	+
F2	6.80E−08	+	6.80E−08	+	6.80E−08	+	6.80E−08	+	6.80E−08	+
F3	6.80E−08	+	6.80E−08	+	6.80E−08	+	6.80E−08	+	6.80E−08	+
F4	9.17E−08	+	6.80E−08	+	6.80E−08	+	6.80E−08	+	6.80E−08	+
F5	6.80E−08	+	6.80E−08	+	6.80E−08	+	6.80E−08	+	6.80E−08	+
F6	6.80E−08	+	4.39E−02	−	6.80E−08	+	6.80E−08	+	6.80E−08	+
F7	1.44E−02	+	4.39E−02	+	4.60E−04	+	4.16E−04	+	6.55E−01	=
WRST (+/=/-)	7/0/0		6/0/1		7/0/0		7/0/0		6/1/0	

Table 4
Friedman test for the six algorithms.

Function	LMAEO	AEO	HPO	GBO	ARO	POA
F1	1	2.3	2.7	4	6	5
F2	1	2.55	2.45	4	6	5
F3	1	2.1	2.9	4.6	6	4.4
F4	1	2.05	2.95	4.15	6	4.85
F5	1	4.7	3.1	4.2	2	6
F6	1.65	4.05	1.5	2.95	4.85	6
F7	2.15	3.65	3.4	4.6	4.65	2.55
Mean ranks	1.257143	3.057143	2.714286	4.071429	5.071429	4.828571

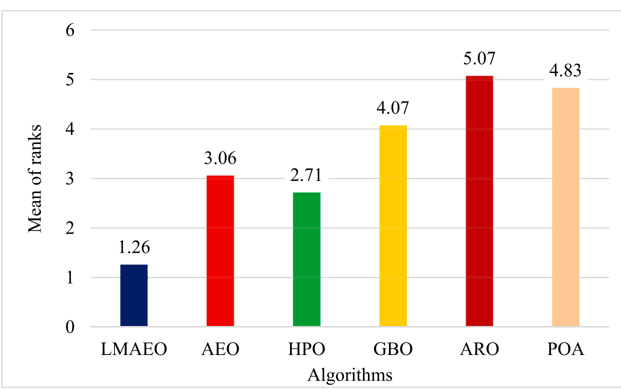

Fig. 4. Mean ranks achieved using Friedman's rank test for the seven benchmark functions using various algorithms.

mathematically possible combinations, *Comb*, are determined as:

$$Comb = \frac{(L + L_a)!}{L! \cdot L_a!} \tag{29}$$

For example, in a system of 60 lines and 7 additional ties, the total number of mathematically possible combinations would be Comb = 869,648,208. The amount of data to be analyzed is enormous, although some of these combinations would not be feasible because they do not meet the radiality condition, Eq. (9).

As can be deduced from the above, the state variables in solving the optimal reconfiguration problem are the state of the lines. These can be in active state (on) or disconnected (off). Mathematically, 1 is assigned to active lines and 0 to inactive lines. It is understood that a line in the "on" state must have its two header switches closed and a line in the "off" state must have these switches open. Therefore, it can be seen that the solution to the problem is binary in nature, being contained in a vector, $\overline{X}_i$, whose elements are 0 s or 1 s, and its size is equal to the total number of lines in the system, including the additional ties. In order to do this with the proposed optimization algorithm, 0 s and 1 s are assigned to the limits of the state variables in the LMAEO and AEO methods. Additionally, for intermediate values the MATLAB *round* function is used.

The purpose of this study is to verify the greater effectiveness of the improved LMAEO method over the already known AEO method, using a novel and complex optimization function, in order to verify the desired effectiveness.

As shown in Section 2, the objective function is composed of four terms. The reliability terms only depend on the topology of the system, while the loss and voltage deviation terms depend on the state of the system. These are two elements added to the complexity of the proposed problem.

The proposed problem must be transformed into an unconstrained one by constructing an augmented objective function that incorporates penalty factors for any value that violates the constraints (Olamaei et al., 2008):

$$OF_{aug} = OF + k_{eq}\left(\sum_{m=1}^{Eq}\left(h_m(\overline{X}_i)^2\right)\right) + k_{ieq}\left(\sum_{m=1}^{Ieq}\left(Max[0, -g_m(\overline{X}_i)]^2\right)\right) \tag{30}$$

where $h_m(\overline{X}_i)$ y $g_m(\overline{X}_i)$ are the equality and inequality constraints, respectively. k_{eq} and k_{ieq} being their respective penalty factors.

Considering that methods like the proposed one may not assure the attainment of the global optimum, we conducted a brute force attack on the problem before implementing the proposed methodology. In other words, we simulated all possible combinations (Eq. (29)) to identify the global optimum. Although this approach incurs a substantial computational cost, it has proven valuable in assessing whether the proposed method can reach the global optimum.

5. Case studies

To show the efficiency of the proposed algorithm, it is tested on three different IEEE distribution systems, a 12-bus, 33-bus, and 69-bus. The simulation algorithm was performed in MATLAB (version 9.11.0.1809720 (R2021b)) employing a PC Intel(R) Core (TM) i7-10700 CPU @ 2.90 GHz, 16.0 GB RAM.

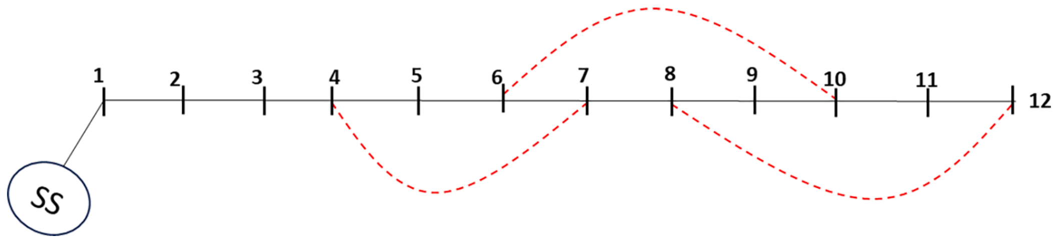

Fig. 5. Modified 12-bus IEEE test system with three ties.

Table 5
Bus data for the modified 12-bus IEEE test system.

Bus	P_d (p.u.)	Q_d (p.u.)	V_{min} (p.u.)	V_{max} (p.u.)	N_j
1	0	0	–	–	0
2	0.06000	0.06000	0.9	1.1	171
3	0.04000	0.03000	0.9	1.1	100
4	0.05500	0.05500	0.9	1.1	156
5	0.03000	0.03000	0.9	1.1	85
6	0.02000	0.01500	0.9	1.1	50
7	0.05500	0.05500	0.9	1.1	156
8	0.04500	0.04500	0.9	1.1	128
9	0.04000	0.04000	0.9	1.1	114
10	0.03500	0.03000	0.9	1.1	93
11	0.04000	0.03000	0.9	1.1	101
12	0.01500	0.01500	0.9	1.1	43

Table 6
Line data for the modified 12-bus IEEE test system.

Line	From bus	To bus	R (p.u.)	X (p.u.)	S_{max} (p.u.)	λ (faults/year)	r (h)
1	1	2	0.000090	0.000038	0.8918	0.20	2
2	2	3	0.000098	0.000041	0.7646	0.20	3
3	3	4	0.000173	0.000072	0.6899	0.20	2
4	4	5	0.000263	0.000110	0.5733	0.20	3
5	5	6	0.000090	0.000038	0.5097	0.15	2
6	6	7	0.000083	0.000034	0.4724	0.20	3
7	7	8	0.000364	0.000100	0.3558	0.10	2
8	8	9	0.000466	0.000132	0.2604	0.20	3
9	9	10	0.000239	0.000068	0.1758	0.15	2
10	10	11	0.000125	0.000035	0.1067	0.20	3
11	11	12	0.000102	0.000029	0.0318	0.10	2
12	4	7	0.000098	0.000041	0.9000	0.10	3
13	6	10	0.000083	0.000034	0.4500	0.10	3
14	8	12	0.000239	0.000068	0.1800	0.10	3

Table 7
Bus data for the modified 33-bus IEEE test system.

Bus	P_d (p.u.)	Q_d (p.u.)	V_{min} (p.u.)	V_{max} (p.u.)	N_j
1	0	0	–	–	0
2	0.0010	0.0006	0.9	1.1	85
3	0.0009	0.0004	0.9	1.1	71
4	0.0012	0.0008	0.9	1.1	105
5	0.0006	0.0003	0.9	1.1	49
6	0.0006	0.0002	0.9	1.1	46
7	0.0020	0.0010	0.9	1.1	162
8	0.0020	0.0010	0.9	1.1	162
9	0.0006	0.0002	0.9	1.1	46
10	0.0006	0.0002	0.9	1.1	46
11	0.00045	0.0003	0.9	1.1	39
12	0.0006	0.00035	0.9	1.1	50
13	0.0006	0.00035	0.9	1.1	50
14	0.0012	0.0008	0.9	1.1	104
15	0.0006	0.0001	0.9	1.1	44
16	0.0006	0.0002	0.9	1.1	46
17	0.0006	0.0002	0.9	1.1	46
18	0.0009	0.0004	0.9	1.1	71
19	0.0009	0.0004	0.9	1.1	71
20	0.0009	0.0004	0.9	1.1	71
21	0.0009	0.0004	0.9	1.1	71
22	0.0009	0.0004	0.9	1.1	71
23	0.0009	0.0005	0.9	1.1	75
24	0.0042	0.0020	0.9	1.1	338
25	0.0042	0.0020	0.9	1.1	338
26	0.0006	0.00025	0.9	1.1	47
27	0.0006	0.00025	0.9	1.1	47
28	0.0006	0.0002	0.9	1.1	46
29	0.0012	0.0007	0.9	1.1	100
30	0.0020	0.0060	0.9	1.1	458
31	0.0015	0.0007	0.9	1.1	120
32	0.0021	0.0010	0.9	1.1	169
33	0.0006	0.0004	0.9	1.1	52

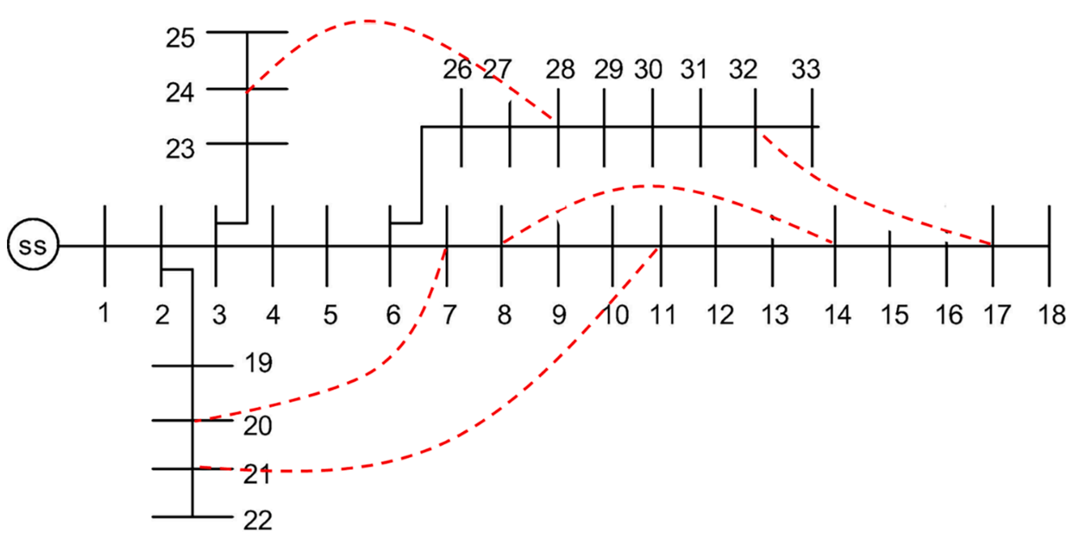

Fig. 6. Modified 33-bus IEEE test system with five ties.

Table 8
Line data for the modified 33-bus IEEE test system.

Line	From bus	To bus	*R* (p.u.)	*X* (p.u.)	S_{max} (p.u.)	*λ* (faults/year)	*r* (h)
1	1	2	0.057500	0.029300	0.1339	0.1	2
2	2	3	0.307600	0.156600	0.1189	0.1	3
3	3	4	0.228400	0.116300	0.1546	0.1	2
4	4	5	0.237800	0.121100	0.2306	0.1	3
5	5	6	0.511000	0.4411009	0.0766	0.1	2
6	6	7	0.116800	0.386100	0.0983	0.1	3
7	7	8	1.068000	0.771000	0.0253	0.1	2
8	8	9	0.642600	0.461700	0.0902	0.1	3
9	9	10	0.651400	0.461700	0.0708	0.1	2
10	10	11	0.122700	0.040600	0.5087	0.1	3
11	11	12	0.233600	0.077200	0.4945	0.1	2
12	12	13	0.915900	0.720600	0.0551	0.1	3
13	13	14	0.337900	0.444800	0.1175	0.1	2
14	14	15	0.368700	0.328200	0.0264	0.1	3
15	15	16	0.465600	0.340000	0.0800	0.1	3
16	16	17	0.804200	1.073800	0.0305	0.1	3
17	17	18	0.456700	0.358100	0.0995	0.1	3
18	2	19	0.102300	0.097600	1.3024	0.1	3
19	19	20	0.938500	0.845700	0.0378	0.1	3
20	20	21	0.255500	0.298500	0.0931	0.1	3
21	21	22	0.442300	0.584800	0.0508	0.1	3
22	3	23	0.281500	0.192400	0.5142	0.1	3
23	23	24	0.560300	0.442400	0.0542	0.1	3
24	24	25	0.559000	0.437400	0.0470	0.1	3
25	6	26	0.126700	0.064500	1.6539	0.1	3
26	26	27	0.177300	0.090300	0.1943	0.1	3
27	27	28	0.660700	0.582600	0.0501	0.1	3
28	28	29	0.501800	0.437100	0.0655	0.1	3
29	29	30	0.316600	0.161300	0.1314	0.1	3
30	30	31	0.608000	0.600800	0.0044	0.1	3
31	31	32	0.193700	0.225800	0.0212	0.1	3
32	32	33	0.212800	0.330800	0.0041	0.1	3
33	7	20	1.247851	1.247851	0.6000	0.1	3
34	8	14	1.247851	1.247851	0.6000	0.1	3
35	11	21	1.247851	1.247851	0.6000	0.1	3
36	17	32	0.311963	0.311963	0.6000	0.1	3
37	24	28	0.311963	0.311963	0.6000	0.1	3

Table 9
OF y OF_{aug} data.

Parameter	Value	Parameter	Value
C_{lss}	4.5 ($/kW)	$SAIDI_{max}$	2.3
C_{SAIDI}	0.1 ($)	$SAIFI_{max}$	1.5
C_{SAIFI}	0.1 ($)	k_{eq}	1000
C_V	0.8 ($/kV)	k_{ieq}	10,000

5.1. Data systems

Fig. 5 shows a modified 12-bus IEEE distribution test system. It has 12 buses and 11 lines, with bus 1 being the root bus connected to the substation. Three additional loops (dashed red lines) are considered in the test system. A base power of 1000 kVA and a base voltage of 11 kV (nominal system's voltage) are considered. The data of the buses and the lines are shown in Tables 5 and 6 respectively.

Fig. 6 shows a modified 33-bus IEEE distribution test system with five additional ties (red dashed lines). It has 33 buses and 32 lines, with bus 1 being the root bus connected to the substation. A base power of 100 MVA and a base voltage equal to the nominal voltage of the system, 12.66 kV, are considered. The data of the buses and the lines are shown in Tables 7 and 8 respectively.

5.2. Results and discussion

We will present the simulation results employing the objective functions (*OF* and OF_{aug}) parameters' value given in Table 9, for all the modified 12-bus, 33-bus, and 69-bus IEEE test systems. For the sake of clarity, we have inserted a switch symbol close to the bus where the additional line is connected.

5.2.1. Modified 12-bus IEEE test system

The minimum value of the objective function was given by the network configuration shown in Fig. 7, which yielded a cost of 19.33$. The vector of state variable for the lines is shown in Table 10. It can be seen that the three additional lines were left in an active state, while three of the lines of the original network configuration were disconnected (lines 5, 8 and 11).

Fig. 8 shows the convergence of the two methods used, LMAEO and AEO, using 15 search agents. It can be seen how the proposed LMAEO method achieved the optimum value in approximately 145 iterations, while AEO not even in 200 iterations reached the optimal value of the objective function, i.e. 19.33$. The computation times were 68.51 sec for LMAEO and 79.68 sec for AEO.

A convergence analysis was carried out to optimize de process. Fig. 9 shows the number of iterations versus the number of search agents for both methods the AEO and the LMAEO. Setting a limit of 200 iterations, the number of search agents should be 17 for LMAEO and 20 for AEO. The symbols represent the average value for 100 search agent simulations performed. To guide the eye of the reader, fitting lines were added.

5.2.2. Modified 33-bus IEEE test system

The minimum value of the objective function was given by the network configuration shown in Fig. 10, which yielded a cost of 4287.88 $. The vector of state variable for the lines is shown in Table 11. All the additional lines were working and lines 10, 11, 15, 18 and 25 were out of service.

Fig. 11 shows the convergence of the two methods used, LMAEO and AEO, using 150 search agents. It can be seen how the proposed LMAEO method achieved the optimum in approximately 97 iterations, while AEO in 200 iterations did not reach the optimal value of the objective function. The computation times were 352.28 sec for LMAEO and 444.42 sec for AEO.

Once again, a convergence analysis was performed for different numbers of search agents. The results show that the LMAEO method reaches the optimum before AEO, as shown in Fig. 12.

In order not to exceed 200 iterations, the number of search agents should be 170 for LMAEO and 195 for AEO.

Since power losses and voltage deviations are within the objective function, during the optimization process these variables experience an

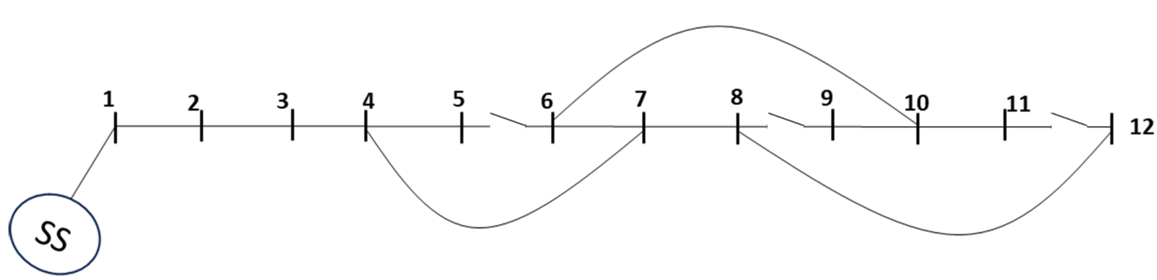

Fig. 7. Optimal configuration for 12-bus IEEE test system.

Table 10
Optimal state of the 12-bus IEEE test system lines.

Line	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Status variable	1	1	1	1	0	1	1	0	1	1	0	1	1	1

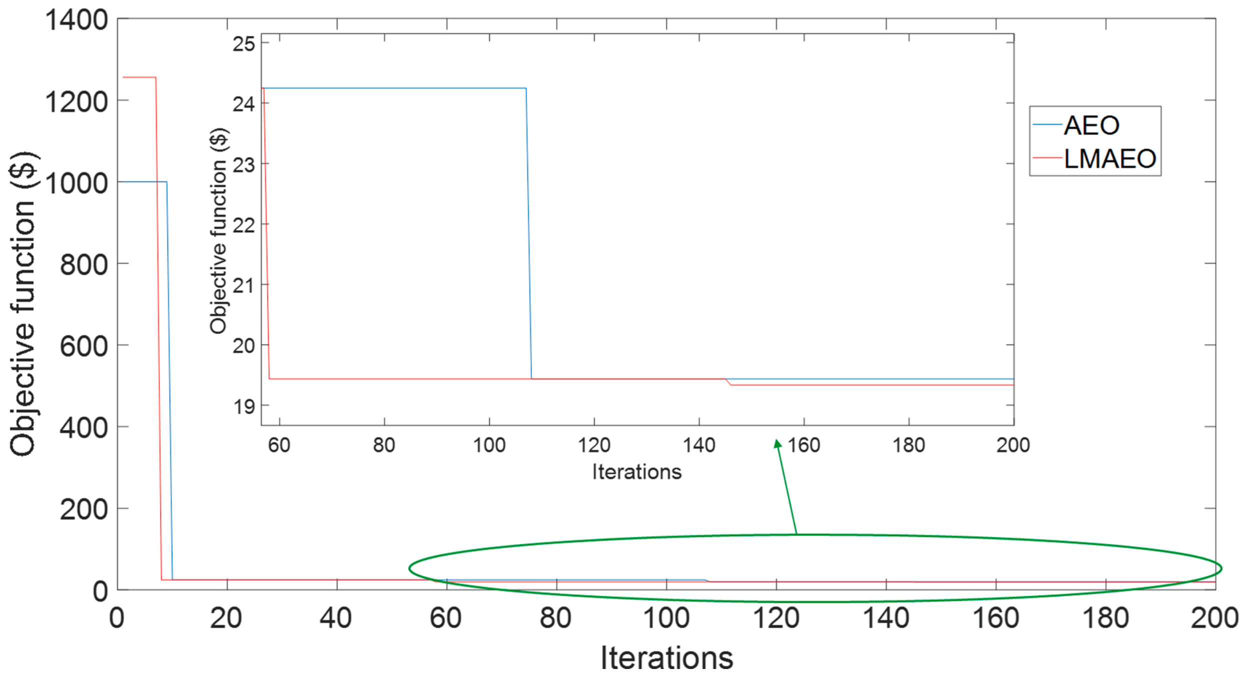

Fig. 8. LMAEO and AEO Convergence for 12-bus IEEE test system.

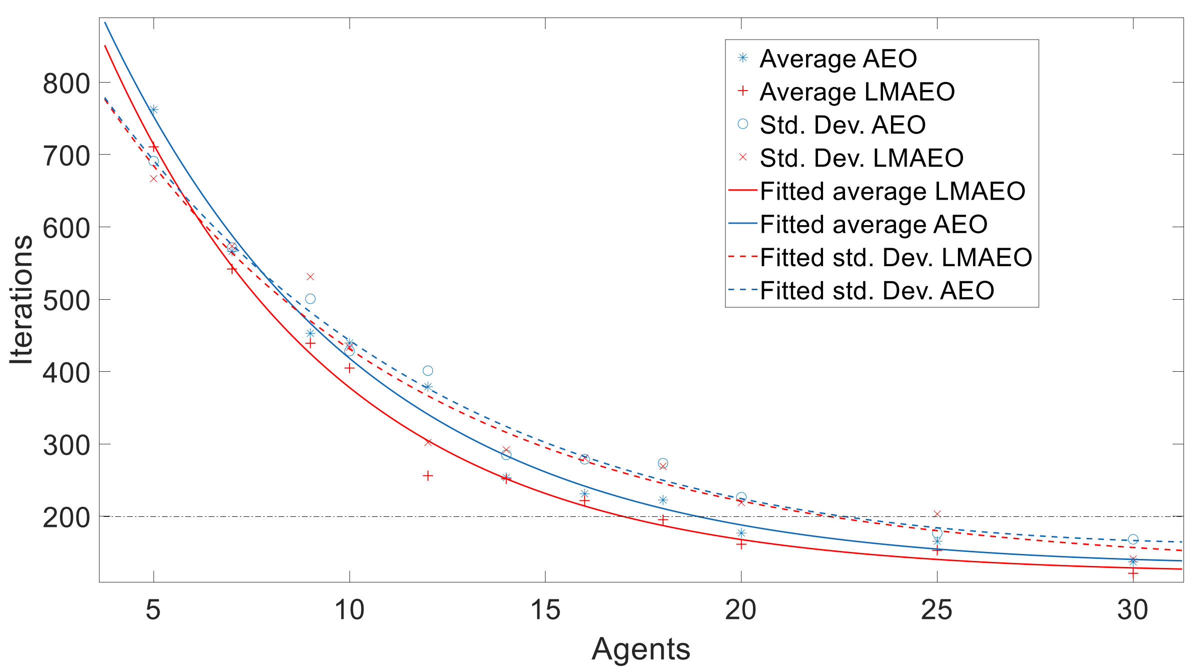

Fig. 9. Required iterations depending on search agents.

improvement. Fig. 13 shows the voltage profiles before and after optimization for the IEEE12 and IEEE33 systems. It can be clearly seen how, in the case of the 12-bus system, the voltage profile improves. In the case of the 33-bus system, the voltage profile is smoothed and homogenized after optimization.

5.2.3. *Modified 69-bus IEEE test system*

Additionally, and to verify the good performance of the proposed method for larger systems, results have been obtained for the IEEE 69 system, whose data can be seen in (Mukhopadhyay and Das, 2020). It is a system of 69 buses and 68 lines, with 5 additional lines. The minimum value of the objective function was given by the network configuration

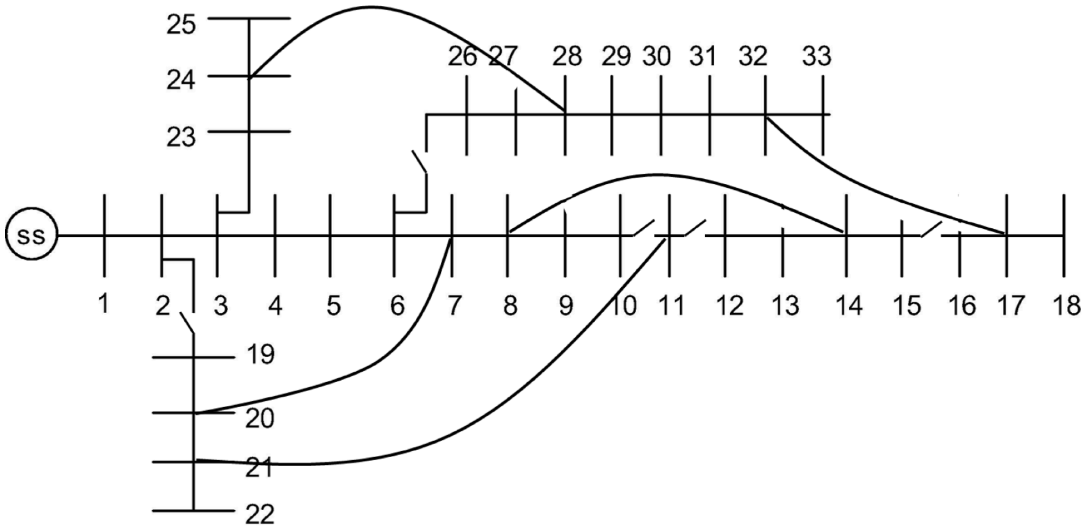

Fig. 10. Optimal configuration for 33-bus IEEE test system.

Table 11
Optimal state of the IEEE 33 system lines.

Line	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
Status variable	1	1	1	1	1	1	1	1	1	0	0	1	1	1	0	1	1	0	1
Line	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	
Status variable	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	

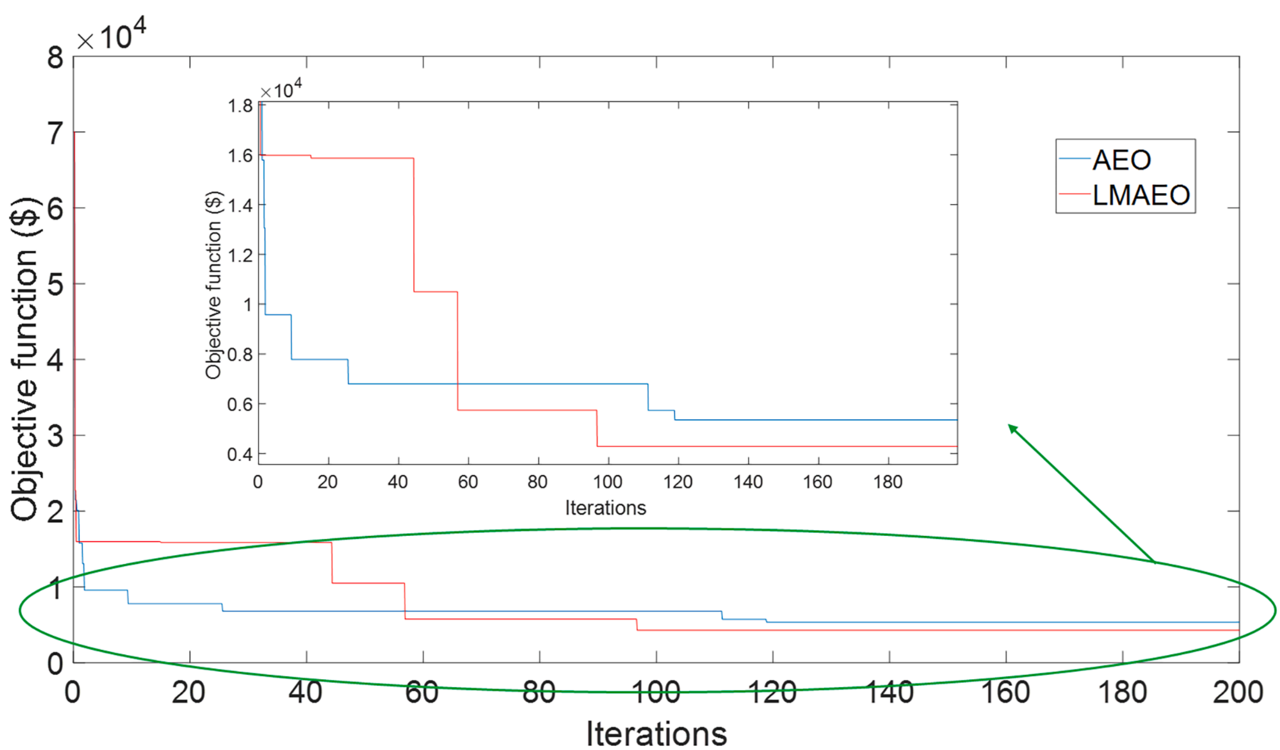

Fig. 11. LMAEO and AEO Convergence for IEEE 33.

shown in Fig. 14, which yielded a cost of 259.182$. The vector of state variable for the lines is shown in Table 12. Only the additional lines 69, 70 and 72 were working and lines 8, 20, 58, and additional lines 71 and 73 were out of service.

Fig. 15 shows the convergence of the two methods used, LMAEO and AEO, using 515 search agents. It can be seen how the proposed LMAEO method achieved the optimum in approximately 60 iterations, while AEO in 200 iterations did not reach the optimal value of the objective function. The computation times were 1426.85 sec for LMAEO and 1860.54 sec for AEO.

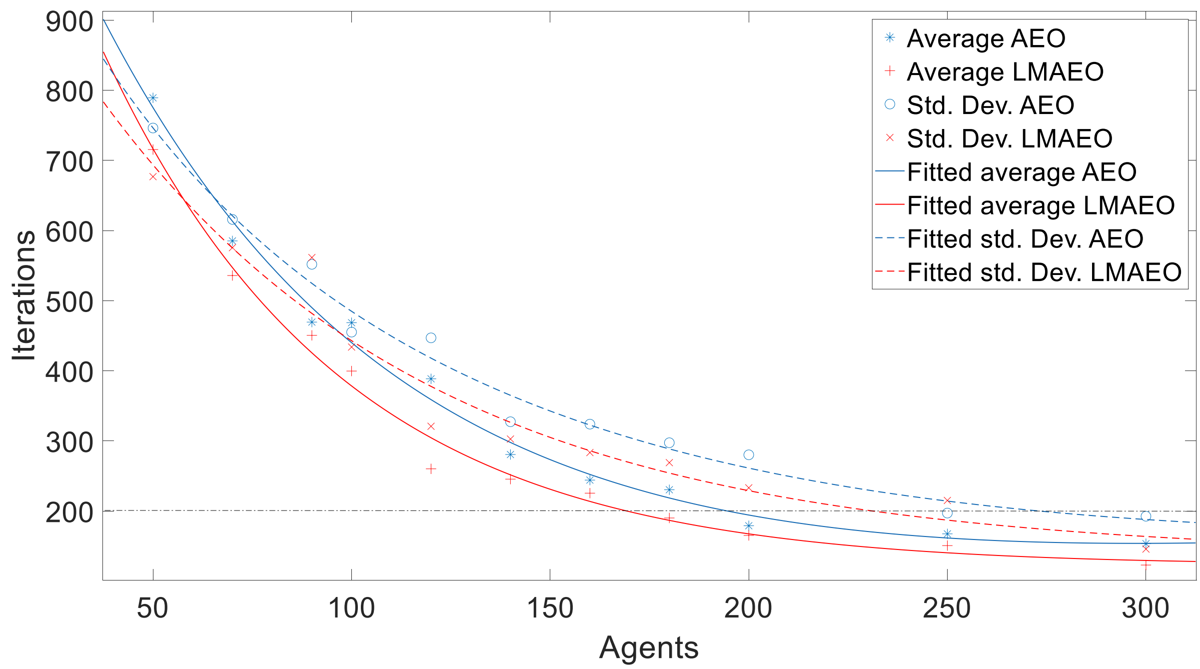

Fig. 12. Required iterations depending on search agents.

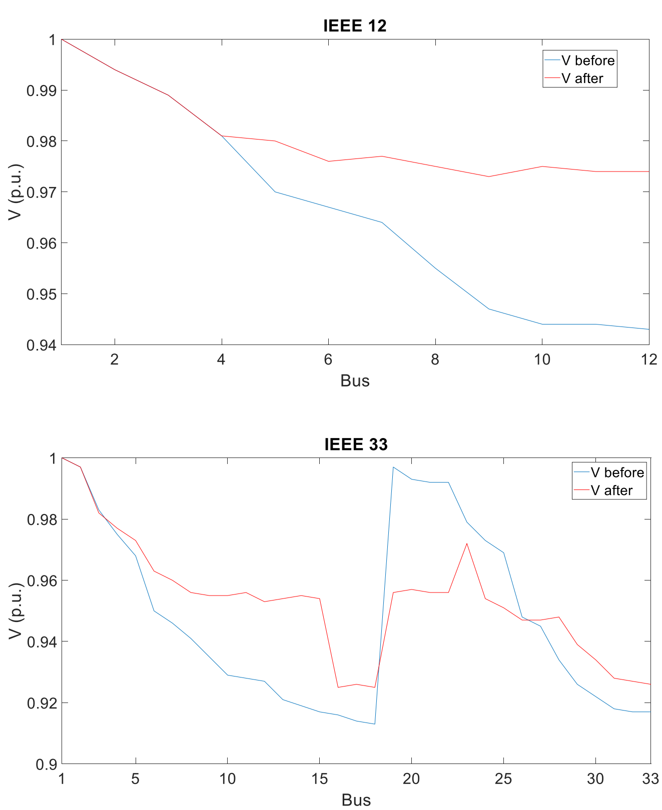

Fig. 13. Voltage profiles for IEEE12 and IEEE33 systems.

Once again, a convergence analysis was performed for different numbers of search agents. The results show that the LMAEO method reaches the optimum before AEO, as shown in Fig. 16.

In order not to exceed 200 iterations, the number of search agents should be 530 for LMAEO and 575 for AEO.

To conclude this section, Table 13 presents a summary of the results obtained for the three electrical systems studied, considering 200 iterations. The last two columns show the improvement of the computational time and the objective function achievement when comparing the LMAEO method and its predecessor AEO. This improvement is calculated as the percentage difference with respect to the reference value as follow:

$$Imp\ \ Time = \frac{Time\ \ AEO - Time\ \ LMAEO}{Time\ \ AEO} \cdot 100 \tag{31}$$

$$Imp\ \ OF = \frac{OF\ \ AEO - OF\ \ LMAEO}{OF\ \ AEO} \cdot 100 \tag{32}$$

It can be seen how the LMAEO method presents improvements with respect to the AEO method, both in computing time and in achieving the objective function for a given number of search agents. Furthermore, it is observed that as the size of the problem to be solved increases, the LMAEO method is more precise and faster than AEO.

6. Conclusion

This paper has introduced an LMAEO algorithm designed to tackle the reconfiguration problem in electrical distribution systems. The algorithm aims to simultaneously minimize the costs due to the total losses of active power, the violation of the reliability indices, SAIDI and SAIFI, and the costs produced by the deviations from the nominal voltage at the buses of the system. The motivation behind adopting this novel LMAEO algorithm lies in its unique combination of a long-term memory component for exploring a broader range of positions during optimization, coupled with the effective exploration capabilities of the AEO algorithm. Before applying the proposed technique to the given problem, the authors conducted tests using seven benchmark functions to assess the LMAEO algorithm's performance. The results of this algorithm were then compared to recent optimization algorithms, including GBO, HPO, ARO, and POA, as well as the original AEO algorithm. Notably, the LMAEO algorithm consistently demonstrated its strength by finding optimal solutions for various benchmark functions. Subsequently, the methodology was applied to three modified test systems: a 12-bus system, a 33-bus system and a 69-bus system. In the evaluation of the proposed LMAEO algorithm, comparisons were made with the original AEO algorithm. The results unequivocally demonstrate that the LMAEO

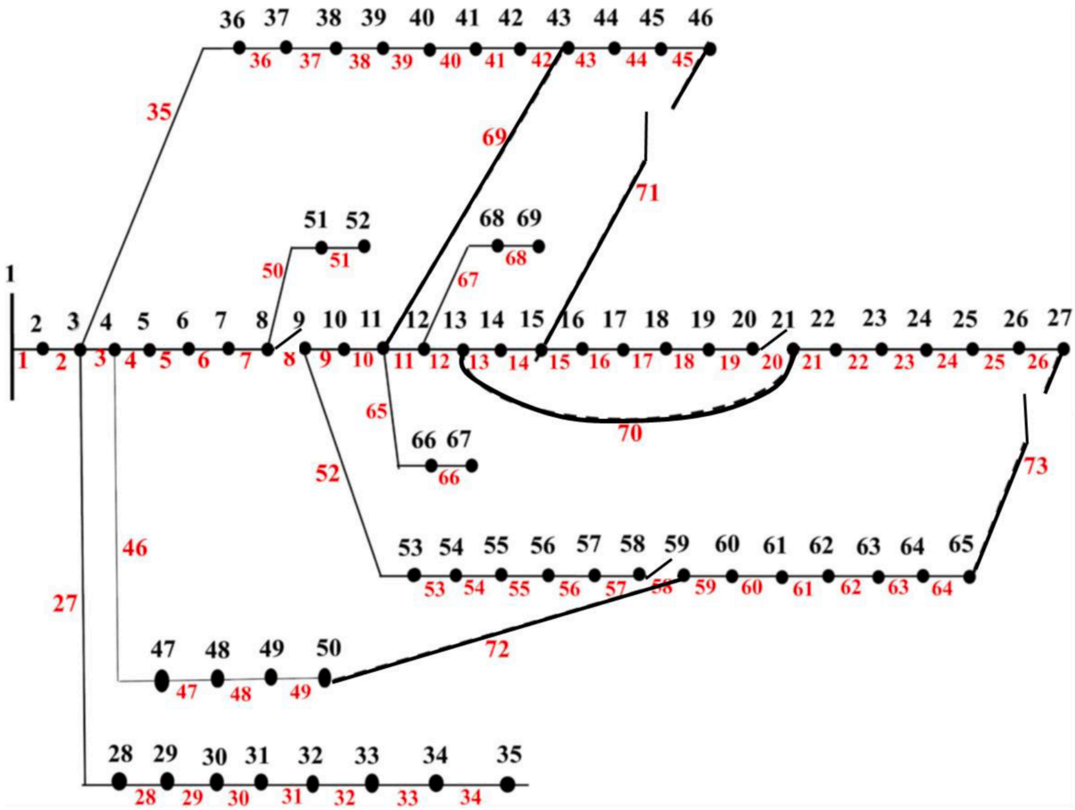

Fig. 14. Optimal configuration for 69-bus IEEE test system.

Table 12
Optimal state of the IEEE 69 system lines.

Line	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Status variable	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1
Line	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
Status variable	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Line	37	38	39	40	41	42	43	44	45	46	47	48	49	50	51	52	53	54
Status variable	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Line	55	56	57	58	59	60	61	62	64	65	66	67	68	69	70	71	72	73
Status variable	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	0	1	0

technique outperforms the AEO optimizer when it comes to optimizing the reconfiguration of distribution systems while addressing reliability and voltage deviation issues. In addition to the current findings, future work in this area could delve into the integration of renewable energy sources within distribution systems, allowing for the optimization of their placement and operation alongside reconfiguration. The development of dynamic reconfiguration strategies that adapt to changing load and fault conditions in real-time presents an intriguing avenue for research. Advanced machine learning and artificial intelligence techniques, such as deep learning and reinforcement learning, can be explored to enhance the performance of reconfiguration algorithms. Additionally, investigating how these algorithms can bolster system resilience against natural disasters and cyber threats is an essential aspect of future research. Lastly, extending the scope to multi-objective optimization approaches can provide a more comprehensive understanding of the trade-offs and opportunities in distribution system reconfiguration.

CRediT authorship contribution statement

Francisco J. Ruiz-Rodríguez: Conceptualization, Methodology, Software, Investigation, Writing – original draft, Supervision. **Salah Kamel:** Conceptualization, Data curation, Software, Investigation, Writing – original draft. **Mohamed H. Hassan:** Visualization, Investigation, Writing – original draft. **José A. Dueñas:** Visualization, Investigation, Writing – original draft.

Declaration of competing interest

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

Data availability

Data will be made available on request.

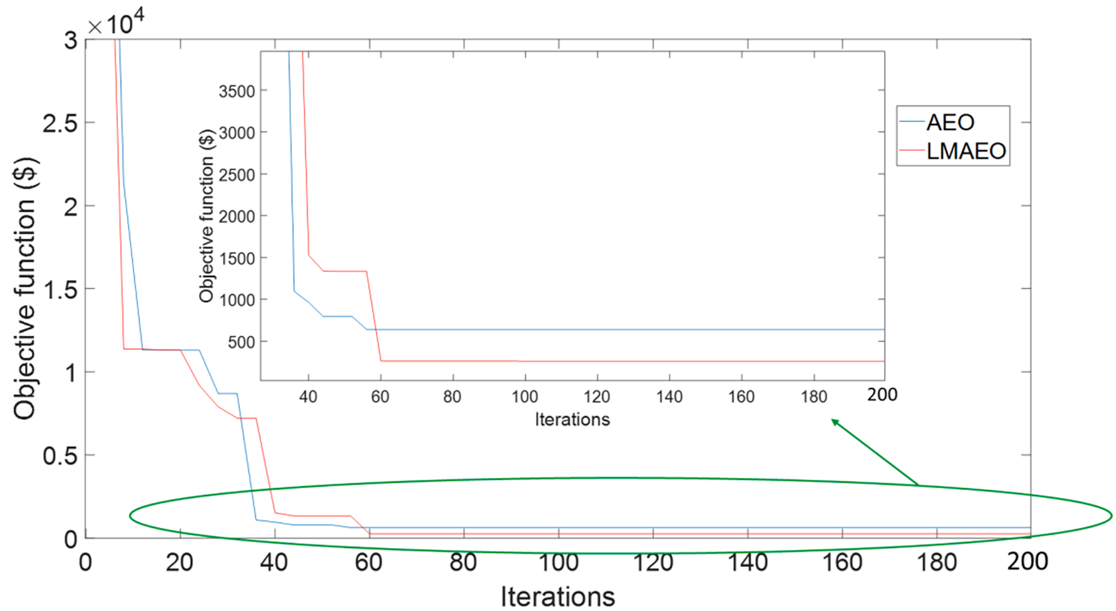

Fig. 15. LMAEO and AEO Convergence for IEEE 69.

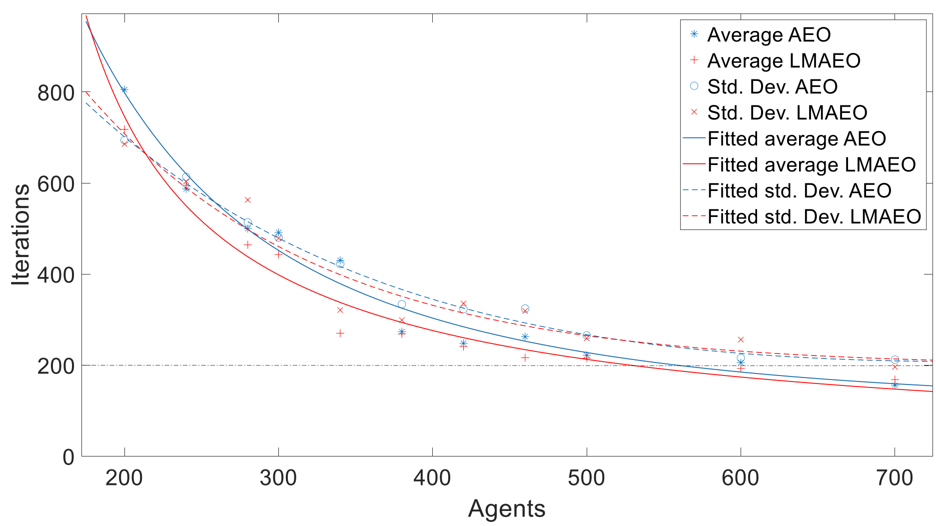

Fig. 16. Required iterations depending on search agents, IEEE 69.

Table 13
Improvement rates of the proposed methodology.

	Search agents	Time AEO (s)	Time LMAEO (s)	OF AEO ($)	OF LMAEO ($)	*Imp Time* (%)	*Imp OF* (%)
IEEE 12	15	79.68	68.51	19.72	19.33	14.02	1.97
IEEE 33	150	444.42	352.28	5437.25	4287.88	20.73	21.13
IEEE 69	515	1860.54	1426.85	639.33	259.182	23.31	59.46

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