Developing Chaotic Artificial Ecosystem-Based Optimization Algorithm for Combined Economic Emission Dispatch

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Abstract: In this paper, Chaotic Artificial Ecosystem-based Optimization Algorithm (CAEO) is proposed and utilized to determine the optimal solution which achieves the economical operation of the electrical power system and reducing the environmental pollution produced by the conventional power generation. Here, the Combined Economic Emission Dispatch (CEED) problem is represented using a max/max Price Penalty Factor (PPF) to confine the system’s nonlinearity. PPF is considered to transform a four-objective problem into a single-objective optimization problem. The proposed modification of AEO raises the effectiveness of the populations to achieve the best fitness solution by well-known 10 chaotic functions and this is valuable in both cases of the single and multi-objective functions. The CAEO algorithm is used for minimizing the economic load dispatch and the three bad gas emissions which are sulfur dioxide (SO2), nitrous oxide (NOx), and carbon dioxide (CO2). To evaluate the proposed CAEO, it is utilized for four different levels of demand in a 6-unit power generation (30-bus test system) and 11-unit power generation (69-bus test system) with a different value of load demand (1000, 1500, 2000, and 2500MW). Statistical analysis is executed to estimate the reliability and stability of the proposed CAEO method. The results obtained by CAEO algorithm are compared with other methods and conventional AEO to prove that the modification is to boost the search strength of conventional AEO. The results display that the CAEO algorithm is superior to the conventional AEO and the others in achieving the best solution to the problem of CEED in terms of efficient results, strength, and computational capability all over study cases. In the second scenario of the bi-objective problem, the Pareto theory is integrated with a CAEO to get a series of Non-Dominated (ND) solutions, and then using the fuzzy approach to determine BCS.

Index Terms: Combined economic and emission dispatch, artificial ecosystem-based optimization, greenhouse gases, Pareto front, price penalty factor, chaotic AEO.

Abbreviations:

| Abbreviation | Description |
|--------------|-------------|
| CEED | Combined Economic and Emission Dispatch |
| CAEO | Chaotic Artificial ecosystem-based optimization |
| BCS | Best Compromise Solution |
| AEO | Artificial ecosystem-based optimization |
| GA | Genetic Algorithm |
| PSO | Particle swarm optimization |
| ACO-ABC-HS | Ant Colony Optimization-Artificial Bee Colony-Harmonic Search |
| RGA | Real coded GA |
| PPF | Price Penalty Factor |
| MOCAEO4 | Multi-objective 4th chaotic function |
| ELD | Economic Load Dispatch |
| DE | Differential Evolution |
| SA | Simulated Annealing |

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power generation system, and accordingly, these polynomials order might represent the actual response of the thermal power generation system makes the solution of this problem deviates from the idealist and therefore nullify the CEED problem is using the 2nd order polynomial function. It had been noted that the functions with an order higher than 2nd order can help to improve the solutions. But the downside of applying these polynomials which have order higher than the 2nd order on the CEED problem makes it more complicated, and subsequently, it is hard to solve it. Therefore, to reach the most accurate solution for these two incompatible issues, several researchers have utilized a 3rd order cost function to represent the CEED problem. The 3rd-order cost function successfully decreases the increasing nonlinearities of the modern thermal generation system when it is utilized to represent the CEED problem [6]. During this analysis, the CEED problem was formulated using the cubic function.

The researchers started to solve the CEED problem by Classical techniques which are the oldest approaches had used to find the solution for this issue [7]. Then, several intelligence methods have been developed as an alternative to the obsolete classical ways of solving the various CEED problems. They have more advantages than the classical approaches which make the researchers used them to solve the CEED problem and reach the best solution between lots of global solutions. Most of these technologies are nature-inspired. A number of the most renowned methods are GA [8], SA [9], PSO [10], flower pollination algorithm [11], Spider Monkey Optimization [12], Kernel search optimization [13], DE [14], and ant lion optimization [15]. Recently, researchers had made modifying and developing standalone ways by combining the effective features of two or more methods to become a hybrid method and thereby to attain superior performance than standalone ways. A number of the most newly introduced hybrid methods to achieve the optimum solution for the CEED problem are ACO-ABC-HS algorithm [16], PSOGSA [17], RGA and DE [18], backtracking search algorithm with sequential quadratic programming [19], MHBA [20], CSA and DE [21], FFA-BA [22], PSO- NN [23], DE-SA [24], and gradient search method and improved Jaya algorithm [25]. But the long computational time is sometimes one of the hybrid algorithm drawbacks wherever every one of the algorithms performs separately into the problem and adds more complexities [5].

Recently, many optimization algorithms depended on chaos theory to improve their performance such as the chaotic differential bee colony [26], chaotic bat algorithm [27], modified artificial bee colony [28], chaotic krill herd [29], modified artificial bee colony based on the chaos [30] and hybrid PSO and GSA integrated with chaotic maps (CPSOGSA) [31] and Enhanced chaotic JAYA algorithm [32]. However, these algorithms have been applied for solving different optimization problem such as the economic dispatch, optimal reactive power dispatch, nonconvex emission/economic dispatch, optimal power flow with stochastic wind and FACTS devices, parameter estimation of photovoltaic, and dynamic economic dispatch with valve-point effects problems in power systems. It is clear from the results of chaotic optimization algorithms that these algorithms have proved a reliable performance, which is more effective than those of the conventional optimization algorithms.

MHBA multi-objective hybrid bat algorithm
PSOGSA PSO-the gravitational search algorithm
CSA crow search algorithm
FFA-BA firefly-bat algorithm
FDM fuzzy decision-making
MBO Modified Biogeography Based Optimization
SSE Sum of squared errors
RE Relative error
MAE Mean absolute error
ISA Interior search algorithm
CSAISA Chaotic self-adaptive interior search algorithm
PSO- NN PSO and Neural Network algorithm
QBA Quantum-Behaved Bat
SCA Sine cosine algorithm
SD Standard deviation
RMSE Root mean square error
ND Non-Dominated
HSA Harmony search algorithm
GSA Gravitational search algorithm

I. INTRODUCTION
The electric power supply system faces its main issues, which are the efficiency of generator and transmission, and distribution grid, or those three issues together. Previous efforts have been tried to find the optimum solutions for these issues by decreasing the operating cost of fuel consumption, which became an objective function besides many other requirements. The speedy development of digital computing has been helping in dealing with these issues by developing numerous algorithms to limit the quantity of energy that the station can generate and transfer through the transmission networks to satisfy consumer requirements within the most economical way possible taking under consideration the calculation of the system limits and all stations [1]. Some of the other requirements are such as scale back greenhouse gas emissions, higher energy quality and improve power grid efficiency, and high reliability [2].

In general, the fuels consumed in the thermal power stations have bad environmental impacts as they produce many types of gases and CO2, SO2, and NOx are considered the most harmful among them [3]. The aim of CEED is reducing the total cost of generating, besides, decreasing the pollutant emission by obliging with all other constraints concurrent [4]. The CEED problem represents a multi-objective optimization problem, and various techniques have been developed to solve this problem. One of the most common methods to represent the CEED problem is using the 2nd order polynomial function [5]. Though, the non-linearity of the actual thermal power generation system makes the solution of this problem deviates from the idealist and therefore nullify the approximation of the 2nd order polynomial function. It had been noted that the functions with an order higher than 2nd order might represent the actual response of the thermal power generation system, and accordingly, these polynomials
In this paper, a new modification of the AEO is proposed and applied for solving the CEED problem. The chaotic maps help the algorithms to increase their performance by replacing the variables with chaotic variables [33]. The application of the CAEO technique for the CEED problem is therefore reasonable if this technique produces optimal results at less computation time. Hence the main contributions of this work are summarized as follows:

- Proposing a Chaotic Artificial ecosystem-based optimization (CAEO) based on chaotic maps. These chaotic maps enhance a variety of the solution spaces in the optimization process and improve the convergence capabilities to achieve the optimum solutions and help the proposed technique to avoid the local minima.
- Proposing Multi-Objective Chaotic Artificial ecosystem-based optimization (MOCAEO).
- Analysing and applying the proposed CAEO and MOCAEO4 to find the optimal solution for CEED problem.
- The effectiveness of the proposed methodology is compared with the conventional AEO and other well-known optimization methods using four different levels of demand in a 6-unit power generation system and 11-generating units (69-bus system) with a different value of load demand (1000, 1500, 2000, and 2500MW).

The proposed technique has been verified for achieving the optimal solution for the CEED problems and its results have been compared with those obtained by various recent optimization techniques such as LR [6], PSO [44], SA [45], QBA [4], MBO [46] and SCA [47] for the 6-unit power system and CSAISA [39], ISA [39], GA [39], PSO [39], DE [39], HAS [39], GA similarity [48], and GSA [49]. All results demonstrate that the proposed CAEO4 provides a more precise solution than original AEO and other techniques.

Finally, the rest of research is prepared as follows: Section II comprises the problem description including the mathematical definition of the CEED, operational limitations, and single and multi-objective functions. Then, the improved single and bi-objective CAEO technique is presented in Section III. After that, the simulation studies, results, and discussion are given in Section IV. Finally, the conclusions are discussed in Section V.

II. PROBLEM FORMULATION

A. 6-UNIT POWER GENERATION SYSTEM

CEED is a multi-objective optimization problem that generally indicates the reduction of fuel cost besides the reduction of risky gases emission at the same time whereas sustaining all operational limitations. In this paper, the reduction of SO$_2$, NO$_x$, and CO$_2$ as independent three objectives have been studied. Consequently, by adding ELD as an objective function to the three emission objectives, CEED becomes a four-objective optimization problem [5]. Firstly, fuel cost $F (P)$ in ($/h$) can be calculated from the cubic equation as follow:

$$F (P) = \sum_{i=1}^{n} a_i P_i^3 + b_i P_i^2 + c_i P_i + d_i,$$  \hspace{1cm} (1)

where $n$ is the total number of generating units, $P_i$ is the actual output power of $i^{th}$ generating unit; $a_i$, $b_i$, $c_i$, and $d_i$ are the coefficients of fuel cost for each generating unit $i$.

Secondly, the Emission of risky gases is separated into independent three objectives and is also expressed as follow:

$$E_{SO_2} (P) = \sum_{i=1}^{n} e_{SO_2} P_i^3 + f_{SO_2} P_i^2 + g_{SO_2} P_i + h_{SO_2},$$ \hspace{1cm} (2)

where $E_{SO_2} (P)$ in (kg/h) is the emission function of SO$_2$, $e_{SO_2}$, $f_{SO_2}$, $g_{SO_2}$, and $h_{SO_2}$ are coefficients of SO$_2$ emission of the generating unit $i$, respectively.

$$E_{NO_x} (P) = \sum_{i=1}^{n} e_{NO_x} P_i^3 + f_{NO_x} P_i^2 + g_{NO_x} P_i + h_{NO_x},$$ \hspace{1cm} (3)

where $E_{NO_x} (P)$ in (kg/h) is the emission function of NO$_x$, $e_{NO_x}$, $f_{NO_x}$, $g_{NO_x}$, and $h_{NO_x}$ are coefficients of NO$_x$ emission of the generating unit $i$, respectively.

$$E_{CO_2} (P) = \sum_{i=1}^{n} e_{CO_2} P_i^3 + f_{CO_2} P_i^2 + g_{CO_2} P_i + h_{CO_2},$$ \hspace{1cm} (4)

where $E_{CO_2} (P)$ in (kg/h) is the emission function of CO$_2$, $e_{CO_2}$, $f_{CO_2}$, $g_{CO_2}$, and $h_{CO_2}$ are coefficients of CO$_2$ emission of the generating unit $i$, respectively.

The equality constraint is Power balance where Total actual output power generation $P_T$ (in MW) must cover both total load demand $P_D$ (in MW) and the total transmission power loss $P_L$ (in MW). This equality constraint can be computed as follow:

$$P_T = \sum_{i=1}^{n} P_i = P_D + P_L,$$ \hspace{1cm} (5)

While the inequality constraint is achieved when each generating unit operates in its operational limits which can be described as:

$$P_{i,min} \leq P_i \leq P_{i,max},$$ \hspace{1cm} (6)

where $P_{i,min}$ and $P_{i,max}$ are operational limits of each generating unit $i$.

1) SINGLE-OBJECTIVE FUNCTION

In this research, a max/max PPF [6] is used to convert the four objectives (decreasing both of the fuel cost and emissions of CO$_2$, SO$_2$, and NO$_x$) into a single objective (total cost) and the goal of CAEO algorithm is minimizing this objective. The total cost FT in ($/h$) can be defined as:

$$OF = \min (F_T)$$

$$F_T = \sum_{i=1}^{n} \{ F(P_i) + hS_i E_{SO_2}(P_i) + hN_i E_{NO_x}(P_i) + hC_i E_{CO_2}(P_i) \},$$ \hspace{1cm} (7)
where \( F(P_i), E_{SO_2}(P_i), E_{NO_3}(P_i), \) and \( E_{CO_2}(P_i) \) are fuel cost ($/h), emission of \( SO_2 \) (kg/h), emission of \( NO_3 \) (kg/h), and emission of \( CO_2 \) (kg/h) of each generating unit \( i \), respectively.

The PPF \( (h_i) \) can be defined as dividing the maximum fuel cost into the maximum emissions for each gas \( SO_2 \), \( NO_3 \), and \( CO_2 \). And it can be computed for each gas from these equations:

\[
h_{Si} = \frac{\sum_{i=1}^{n} F(P_{i,\text{max}})}{E_{SO_2}(P_{i,\text{max}})}
\]

\[
h_{Ni} = \frac{\sum_{i=1}^{n} F(P_{i,\text{max}})}{E_{NO_3}(P_{i,\text{max}})}
\]

\[
h_{Ci} = \frac{\sum_{i=1}^{n} F(P_{i,\text{max}})}{E_{CO_2}(P_{i,\text{max}})}
\]

2) BI-OBJECTIVE FUNCTION

Generally, a Bi-objective optimization algorithm is used to optimize two objectives simultaneously [34]. The solutions that are obtained in each iteration within the algorithm are classified as dominated solutions and ND solutions, based on the objective functions. The Pareto dominance concept is used to execute this classification. Then, the ND solutions are put within the archiving matrix to select the BCS by the FDM. However, numerous approaches are used to determine the BCS [35].

FDM is the most common method that is generally used to find solutions for decision-making problems [36], [37]. In this research, the FDM method is used to determine the BCS from the obtainable selections of final Pareto front as below:

a: PARETO OPTIMIZATION METHOD

First, Pareto optimization reaches a series of reasonable solutions. Then, the optimization of Pareto considers that a solution \( x_1 \) dominates the solution \( x_2 \) when [38]:

\[
\forall i \in \{1, 2, \ldots, M\} \ , \ f_i(x_1) \leq f_i(x_2)
\]

\[
\exists i \in \{1, 2, \ldots, M\} : f_i(x_1) < f_i(x_2)
\]

b: DEFINITION OF THE BC SOLUTION

The fuzzy membership method can normalize the objective function value \( F \) of each ND solution \( k \) (Figure 1) as follows:

\[
\mu^k = \begin{cases} 
1 & F_i \leq F_{i,\text{min}}^\text{max} \\
\frac{F_{i,\text{max}}^\text{max} - F_i}{F_{i,\text{max}}^\text{max} - F_{i,\text{min}}^\text{max}} & F_{i,\text{min}}^\text{max} < F_i < F_{i,\text{max}}^\text{max} \\
0 & F_i \geq F_{i,\text{max}}^\text{max}
\end{cases}
\]

where \( F_{i,\text{max}}^\text{max} \) and \( F_{i,\text{min}}^\text{max} \) are the maximal and minimal values of \( F_i \) between all ND solutions, respectively.

The normalized membership function \( (\mu^k) \) is defined as:

\[
\mu^k = \frac{\sum_{i=1}^{Nobj} \mu^k_i}{\sum_{i=1}^{M} \sum_{k=1}^{Nobj} \mu^k_i}
\]

where \( M \) is the total numeral of ND solutions. The selection of The BCS from all ND solutions through the value of \( \mu^k \), where the BCS which has a maximum value of \( \mu^k \).

In this research, there are 3 cases and two objective functions in each case of the bi-objective optimization problems which are defined as below:

The first objective function in all cases is minimizing of fuel cost and the second objective function is given as follow:

1- In the first case, minimizing the Emission of \( SO_2 \).
2- In the second case, minimizing the Emission of \( NO_3 \).
3- In the third case, minimizing the Emission of \( CO_2 \).

B. 11-UNIT POWER GENERATION (69-BUS SYSTEM)

1) SINGLE-OBJECTIVE FUNCTIONS

The total fuel costs based on the output of thermal generating units along with its constraints is given as [39]:

\[
F_1 = \sum_{i=1}^{N_G} [a_i + b_iP_{Gi} + c_iP_{Gi}^2 + d_i\sin(e_i(P_{min}^{Gi} - P_{Gi}))] 
\]

where \( a_i; b_i; c_i; d_i \) and \( e_i \) represent the cost coefficients for the \( i^{th} \) unit; \( P_{Gi} \) represents the output power of \( i^{th} \) unit \( (i = 1; 2; 3; \ldots; N_G) \) unit, and \( N_G \) represents the number of generating units.

The second objective, the emission function, considers two primary pollutant emissions \( (SO_2 \) and \( NO_3 \) caused by fossil-fuel thermal units. The total pollutant emission is expressed as:

\[
F_2 = \sum_{i=1}^{N_G} \left[ 10^{-2}(\alpha_i + \beta_iP_{Gi} + \gamma_iP_{Gi}^2) + \eta_i\exp(\delta_iP_{Gi}) \right]
\]

where \( \alpha_i; \beta_i; \gamma_i; \eta_i \) and \( \delta_i \) represent the emission coefficients for the \( i^{th} \) unit.

The CEED is calculated as follows:

\[
F_T = \sum_{i=1}^{N_G} (F_1(P_{Gi}) + h_i \times F_2(P_{Gi}))
\]

where, \( h_i \) is max/max PPF.
2) SYSTEM CONSTRAINTS
The equality constraint is the power balance where the total actual output power generation \( P_T \) (in MW) must cover the total load demand \( P_D \) (in MW) and the total transmission power loss \( P_{\text{Loss}} \) (in MW). This equality constraint is expressed as follows:

\[
P_T = \sum_{i=1}^{N_G} P_{Gi} = P_D + P_{\text{Loss}},
\]

(18)

\( P_{\text{Loss}} \) is a function of the real output power of the system generators and it is generally estimated by Kron’s loss formula as follows:

\[
P_{\text{Loss}} = \sum_{i=1}^{N_G} \sum_{j=1}^{N_G} P_{Gi}B_{ij}P_{Gj} + \sum_{i=1}^{N_G} B_{0i}P_{Gi} + B_{00},
\]

(19)

where, \( B_{00}, B_{0i} \) and \( B_{ij} \) are the transmission loss coefficients.

The inequality constraint is achieved when each generating unit operates within its operational limits as:

\[
P_{Gi,\text{min}} \leq P_{Gi} \leq P_{Gi,\text{max}},
\]

(20)

where, \( P_{Gi,\text{min}} \) and \( P_{Gi,\text{max}} \) are the operational limits of each generating unit \( i \).

III. METHODOLOGY
The conventional AEO method and recommended CAEO technique developed by using 10 chaotic maps are described in this section.

A. THE CONVENTIONAL AEO
This subsection presents the conventional AEO algorithm was firstly developed by Zhao et al. This algorithm is based on the energy flow in a natural ecosystem [40]. An ecosystem is a group of living creatures, which exist in a specific area, and it demonstrates the ecological relations among these creatures. As any population-based optimization technique, AEO has included production, consumption, and decomposition behaviours of creatures on the earth and the sequence of those behaviours represent the energy flow in an ecosystem.

Figure 2 shows the energy flow in an ecosystem, wherever most producers (green plants) depend on the photosynthesis process to get their food energy. After the green plants were growing, a number of the consumers (animals) feed only on a part of these plants, and these consumers are known as herbivores. Other animals are dividing into two types. One of them feeds on both plants and animals and they are called omnivores.

The last type of animal is known as carnivores and this type eats only other animals. Decomposers are most bacteria and fungi. This phase starts once the producers and animals die when Decomposers convert them into small particles, like minerals, carbon dioxide, and water. The black arrow in Figure 2.a represents the various energy levels that reduce from plants (producers) to bacteria and fungi (decomposers), whereas the arrows within Figure 2.b refer to the energy transfer path.

Based on the previous discussion, the AEO consists of three operators:

(i) the production is used to strengthen the balance between the exploration and exploitation phases,
(ii) the role of consumption is an improvement of exploration,
(iii) Decomposition is used to enhance the exploitation of the AEO.

The individuals in the population of the AEO algorithm are divided into three groups as follows, only one of them is a producer and only one is a decomposer, while all other individuals are consumers from the three predefined sorts and they have the same probability. The energy level of each individual is set by the fitness function of that individual.

The representation of the AEO technique is shown in Figure 3. The energy flow is represented by the brown arrows. \( x_1 \) (producer) is the worst individual and having the highest function fitness value and \( x_n \) (decomposer) is the best individual having the lowest function fitness value. Consumers are the other individuals, and according to the
A consumption parameter having the Levy flight feature is
and upper limits, respectively.

\[ b \] vector within the range of \([0, 1]\), and \(L_\text{r} \) \( \text{iter} \) is the maximum number of iterations,
where \(x\) depends on the randomly chosen and how each type of them
previous classification of consumers, it is supposed that \(x_2\) and \(x_5\) are the types of herbivores, \(x_3\) and \(x_7\) are omnivores
while \(x_4\) and \(x_6\) are carnivores.

**B. PRODUCTION**
The production operator can be modeled mathematically as follows:

\[ x_1(t + 1) = (1 - a) x_2(t) + a x_{\text{rand}}(t) \] \( (21) \)

\[ a = (1 - \frac{t}{\text{max}_\text{iter}}) r_1 \] \( (22) \)

\[ x_{\text{rand}} = r (U_b - L_b) + L_b \] \( (23) \)

where \(a\) is a linear weight coefficient, \(n\) is the population size,
\(x_{\text{rand}}\) is an individual position of randomly produced in the
search space, \(\text{max}_\text{iter}\) is the maximum number of iterations,
\(r_1\) is a random number within the range of \([0, 1]\), \(r\) is a random
vector within the range of \([0, 1]\), and \(L_b\) and \(U_b\) are the lower
and upper limits, respectively.

**C. CONSUMPTION**
A consumption parameter having the Levy flight feature is
given as [40]:

\[ C = \frac{1}{2} \frac{v_1}{|v_2|} \] \( (24) \)

\[ v_1 \sim N(0, 1) \text{, } v_2 \sim N(0, 1) \] \( (25) \)

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

The following equations of three types of consumers depend on the randomly chosen and how each type of them
deals with the producers and the other consumers where:

1- herbivore can be presented mathematically as follows:

\[ x_i(t + 1) = x_i(t) + C. (x_i(t) - x_{\text{rand}}(t)) \]

\[ i \in [2, \ldots, n] \] \( (26) \)

2- carnivore can be mathematically formulated as follows:

\[
\begin{cases}
  x_i(t + 1) = x_i(t) + C. (x_i(t) - x_{\text{rand}}(t)) \\
  i \in [2, \ldots, n] \\
  j = \text{randi}([2i - 1])
\end{cases}
\]

\( (27) \)

3- omnivore can be modeled mathematically as below:

\[
\begin{cases}
  x_i(t + 1) = x_i(t) + C. (x_i(t) - x_1(t)) + (1 - r_2) \\
  (x_i(t) - x_{\text{rand}}(t)) \text{, } i \in [3, \ldots, n] \\
  j = \text{randi}([2i - 1])
\end{cases}
\]

\( (28) \)

\[ D = 3u \text{, } u \sim N(0, 1) \] \( (30) \)

\[ e = r_3.\text{randi}([12]) - 1 \] \( (31) \)

\[ h = 2. r_3 - 1 \] \( (32) \)

**E. PROPOSED CAEO TECHNIQUES**
The proposed CAEO technique is to improve early convergence of conventional AEO to local optimum or convergence
to near-global optimum with an increase in the number of iterations and enhance the non-dominated solution of the
algorithm to solve multi-objective functions to obtain the best value. This modification is based on chaotic maps. Instead
of using random parameters, a set of chaotic equations [41]
is used to improve the convergence properties of the conventional AEO. Table 1 presents the ten chaotic maps are
applied for the conventional AEO to update the parameter of exploration \(q\) as below [42]:

\[ q = y_{k+1} \] \( (33) \)

where \(y_{k+1}\) is the chaos map that is chosen to solve the problem and it is presented in Table 1. The description of
CAEO is displayed in the flowchart of Figure 4.

**F. MULTI-OBJECTIVE 4th CHAOTIC FUNCTION ARTIFICIAL
ECOSYSTEM-BASED OPTIMIZATION (MOCAEO4) ALGORITHM**
Two main structures called archive, and chaotic maps help to
implement the Multi-objective 4th chaotic function artificial
ecosystem-based optimization (MOCAEO4) algorithm. The
function of the archive is to organize the non-dominated solutions obtained so far while the chaotic maps are used
to enhance the strength of AEO and to lead the individuals
to update their position directly to the next best position. Finally, an appropriate decision-making approach is neces-
sary to obtain the best compromise solution between the
NDS [43]. The flow chart of the (MOCAEO4) algorithm is
shown in Figure 5 which is used to solve the CEED problem.

**IV. SIMULATION RESULTS AND DISCUSSION**
MATLAB (R2019a) is used to simulate conventional AEO
and proposed CAEO techniques to solve the CEED problem
for two power generation systems (6-unit and 11-units). The
description of the portable computer, which is used to solve
this problem, are Intel Core i5-4210U CPU@2. 40GHz with
a 4.00 MB RAM.

**A. 6-UNIT POWER GENERATION SYSTEM**
In this subsection, the CEED problem is solved for 4 levels
of demand, where the first level of demand is 150 MW and
it is increased by 25MW each time to reach 225 MW in the
fourth level of demand.

1) SINGLE-OBJECTIVE FUNCTION
The best-estimated parameters achieved by the proposed
CAEO have been confirmed using measured data of a CEED
problem for the first level of demand (150 MW) provided in
The proposed CAEO with 10 chaotic functions according to the previous section has been confirmed by several operating scenarios. In this research, the following control variables have been assumed: the number of population is 100 and the maximum number of iterations is 200. The number of 50 independent runs has been executed under each chaotic function in addition to the conventional AEO to overcome the randomness of the proposed optimization technique and to check the quality of these chaotic functions. According to the results of these independent runs, the best solution is taken as the lowest value of the fitness function. Tables 2, 3, 4, and 5 display the data of the 6-unit system [6], which is used for this study.

![Flowchart of proposed CAEO technique.](image)

**TABLE 1. Ten Chaotic maps.**

| No. | Name     | Chaotic map formula                  |
|-----|----------|-------------------------------------|
| CAEO1 | Chebyshev | $y_{k+1} = \cos(k \cos^{-1}(y_k))$ |
| CAEO2 | Circle   | $y_{k+1} = \mod(y_k + b_1 - \frac{b_2}{2n} \sin(2\pi y_k), 1)$ |
|      |          | $b_1 = 0.5$; $b_2 = 0.2$            |
| CAEO3 | Gauss/  | $y_{k+1} = \begin{cases} 1 & y_k = 0 \\ 1 \mod(y_k) & \text{otherwise} \end{cases}$ |
|      | mouse    |                                      |
| CAEO4 | Iterative| $y_{k+1} = \sin(\frac{b_1}{y_k}), b = 0.7$ |
| CAEO5 | Logistic | $y_{k+1} = b y_k (1 - y_k), b = 4$ |
| CAEO6 | Piecewise| $y_{k+1} = \begin{cases} \frac{y_k}{H} & 0 \leq y_k \leq H \\ \frac{y_k - H}{H} & H \leq y_k \leq 0.5 \\ 1 - \frac{H - y_k}{H} & 0.5 \leq y_k \leq 1 - H \end{cases}$ |
| CAEO7 | Sine     | $y_{k+1} = b \sin(\pi y_k), b = 4$ |
| CAEO8 | Singer   | $y_{k+1} = u \left( \frac{7.86y_k^2 - 23.31y_k^4 + 28.75y_k^4 - 13.302875y_k^4}{2} \right)^{1/2}$ |
|       |          | $= 1.07$                            |
| CAEO9 | Sinusoidal| $y_{k+1} = b y_k (1 - y_k), b = 2.3$ |
| CAEO10| Tent     | $y_{k+1} = \begin{cases} \frac{y_k}{H} & y_k < 0.7 \\ 10/3 (1 - y_k) & y_k \geq 0.7 \end{cases}$ |

**TABLE 2. The coefficients of fuel cost and operational limits.**

| Unit | $A_i (10^3)$ | $B_i$ | $C_i (10^3)$ | $D_i (10^3)$ | $P_{\text{min}}$ (MW) | $P_{\text{max}}$ (MW) |
|------|--------------|-------|--------------|--------------|-----------------------|-----------------------|
| P1   | 0.1000       | 0.092 | 0.145        | -0.1360      | 50                    | 200                   |
| P2   | 0.4000       | 0.025 | 0.220        | -0.0035      | 20                    | 80                    |
| P3   | 0.6000       | 0.075 | 0.230        | -0.0810      | 15                    | 50                    |
| P4   | 0.2000       | 0.100 | 0.135        | -0.0145      | 10                    | 50                    |
| P5   | 0.1300       | 0.120 | 0.115        | -0.0698      | 10                    | 50                    |
| P6   | 0.4000       | 0.084 | 0.125        | 0.0756       | 12                    | 40                    |

**TABLE 3. The coefficients of SO$_2$ Emission and its max/max PPF.**

| Unit | $\omega_{\text{SO}_2}$ | $\omega_{\text{SO}_2}$ | $\omega_{\text{SO}_2}$ | $\omega_{\text{SO}_2}$ | $\varphi_{\text{SO}_2}$ | $\beta_{\text{SO}_2}$ |
|------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|
| 1    | 0.0005                  | 0.150                   | 17.00                   | -90                     | 1.09                    |
| 2    | 0.0014                  | 0.055                   | 12.00                   | -30.5                   | 1.06                    |
| 3    | 0.0010                  | 0.035                   | 10.00                   | -80                     | 2.11                    |
| 4    | 0.0020                  | 0.070                   | 23.50                   | -34.5                   | 0.60                    |
| 5    | 0.0013                  | 0.120                   | 21.50                   | 19.75                   | 0.68                    |
| 6    | 0.0021                  | 0.080                   | 22.50                   | 25.50                   | 0.62                    |

**TABLE 4. The coefficients of NO$_X$ Emission and its max/max PPF.**

| Unit | $\omega_{\text{NO}_X}$ | $\omega_{\text{NO}_X}$ | $\omega_{\text{NO}_X}$ | $\omega_{\text{NO}_X}$ | $\varphi_{\text{NO}_X}$ | $\beta_{\text{NO}_X}$ |
|------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|
| 1    | 0.0012                  | 0.052                   | 18.5                    | -26                     | 0.94                    |
| 2    | 0.0004                  | 0.045                   | 12.0                    | -35                     | 1.50                    |
| 3    | 0.0016                  | 0.050                   | 13.0                    | -15                     | 1.39                    |
| 4    | 0.0012                  | 0.070                   | 17.5                    | 74                      | 0.83                    |
| 5    | 0.0003                  | 0.040                   | 8.5                     | 89                      | 2.17                    |
| 6    | 0.0014                  | 0.024                   | 15.5                    | 75                      | 1.09                    |

**a: CASE 1: ESTIMATION OF TOTAL COST ($/H) FOR LOAD = 150 mW**

To validate the strength of proposed CAEO for the parameters identification of Total cost ($/h) to solve a CEED problem.
FIGURE 5. MOCAEO technique for the CEED problem.
for load demand equals 150 MW, a statistical analysis is presented for the lowest values of fitness function (SSE) which obtained from 50 individual runs. This analysis is presented to provide a clear estimation of 10 chaotic functions and choose the most precise one for completing the study of the suggested system with other levels of demand in the rest of this research.

The comparisons between the proposed CAEO according to 10 chaotic functions and the conventional AEO are executed regarding nine metrics. The first four of these metrics are the best and worst values of SSE, the mean value of SSE, and Median. The other metrics are SD, RE, RMSE, MAE, and efficiency which can be calculated from the following equations [41]:

\[ SD = \sqrt{\frac{\sum_{i=1}^{50} (SSE_i - \overline{SSE})^2}{50 - 1}} \] (34)

\[ RE = \frac{\sum_{i=1}^{50} (SSE_i - SSE_{\text{min}})}{SSE_{\text{min}}} \] (35)

\[ MAE = \frac{\sum_{i=1}^{50} (SSE_i - SSE_{\text{min}})}{50} \] (36)

\[ RMSE = \frac{\sum_{i=1}^{50} (SSE_i - SSE_{\text{min}})^2}{50} \] (37)

\[ \text{efficiency} = \frac{SSE_{\text{min}}}{SSE_i} \times 100\% \] (38)

where \( SSE_i \) is the lowest value of the objective function in each run. \( \overline{SSE} \) is the mean value of SSE overall. \( SSE_{\text{min}} \) is the lowest best value of SSE over the 50 runs. Table 6 presents the statistical results of ten proposed CAEO and conventional AEO. From this table, it can be noticed that the lowest value of SSE obtained by the 4th chaotic function is the best within all functions and the conventional AEO algorithm and gives the best value of Total cost (10179.349 $/h).

Therefore, the 4th chaotic function is selected to complete study of the suggested system with other levels of demand. Figure 6 illustrates the convergence characteristics of ten proposed CAEO and conventional AEO.

Table 7 displays the comparison between the results obtained by the proposed CAEO techniques and the results of the conventional AEO as well as other recent optimization techniques which studied this problem previously. From Table 7, we can see that the fuel cost, the value of three types of emission, and total cost, for the 150MW load demand obtained by CAEO4 are 2702.94 $/h, 2885.21 kg/h, 2249.1 kg/h, 2448.86 kg/h, 10179.349 $/h, respectively.

We conclude that CAEO4 technique is better than the others proposed CAEO and the conventional AEO as well as other recent optimization techniques such as LR [6], PSO [44], SA [45], QBA [4], MBO [46] and SCA [47] methods. Because CAEO4 has the best values for 150MW load demand, we will continue the next simulation results for other loads as single and multi-objective functions using CAEO4.

b: CASE 2: SIMULATION RESULTS FOR DIFFERENT LOAD DEMANDS

Table 8 and Figure 7.a show a comparison of fuel cost ($/h) considering 4 levels of demand in the 6-unit power generation system. It can be noticed from Table 7 that CAEO4 gives the best value of fuel cost for all levels of demand. The differences between the proposed CAEO4 method and the nearest method (conventional AEO) to it are 0.75 $/h for the first level of demand, 7.97 $/h for the second level of demand, 2.26 $/h for the third level of demand, and 0.59 $/h for the fourth level of demand.

Figure 7.a displays the comparison graph of different methods for levels of demand. According to Table 8 and Figure 7.a, we can conclude that CAEO4 provides the best value of fuel costs, conventional AEO closely follows the proposed CAEO, whereas MBO, QBA, SA, PSO, and LR methods provide the highest value of fuel cost.
TABLE 6. Statistical results of proposed CAEO and conventional AEO for the total cost of the 6-unit system (150MW load).

| Optimization techniques | Min  | Max  | MEAN  | Median | SD    | RE    | MAE    | RMSE   | Eff.  |
|-------------------------|------|------|-------|--------|-------|-------|--------|--------|-------|
| AEO                     | 10180.834 | 10201.468 | 10187.464 | 10187.499 | 601.491 | 0.0242 | 4.917 | 7.7220 | 99.95 |
| CAEO1                   | 10189.257 | 10206.534 | 10193.4787 | 10191.777 | 637.238 | 0.0277 | 5.645 | 8.4655 | 99.94 |
| CAEO2                   | 10182.023 | 10197.209 | 10187.0025 | 10185.448 | 504.950 | 0.0255 | 5.199 | 7.2122 | 99.95 |
| CAEO3                   | 10180.948 | 10206.169 | 10187.8050 | 10185.155 | 677.080 | 0.0282 | 5.741 | 8.8252 | 99.94 |
| CAEO4                   | 10179.349 | 10219.630 | 10186.6464 | 10183.197 | 778.508 | 0.0250 | 5.084 | 9.2329 | 99.95 |
| CAEO5                   | 10180.724 | 10217.198 | 10188.0959 | 10184.764 | 766.531 | 0.0275 | 5.599 | 9.4304 | 99.95 |
| CAEO6                   | 10181.969 | 10204.980 | 10188.2257 | 10184.733 | 576.669 | 0.0187 | 3.814 | 6.6655 | 99.96 |
| CAEO7                   | 10180.402 | 10202.343 | 10186.7732 | 10186.442 | 548.832 | 0.0219 | 4.465 | 7.0324 | 99.96 |
| CAEO8                   | 10188.519 | 10212.684 | 10196.0928 | 10193.216 | 811.825 | 0.0308 | 6.262 | 10.188 | 99.94 |
| CAEO9                   | 10181.087 | 10205.830 | 10189.4777 | 10188.000 | 654.437 | 0.0261 | 5.318 | 8.3818 | 99.95 |
| CAEO10                  | 10183.274 | 10192.094 | 10185.9869 | 10184.137 | 372.765 | 0.0152 | 3.095 | 4.8162 | 99.97 |

TABLE 7. Estimated parameters of Cost for 150MW using CAEO, AEO, and other well-known optimization techniques.

| Optimization techniques | Fuel cost ($/h) | SO2 Emission (kg/h) | NOx Emission (kg/h) | CO2 Emission (kg/h) | Total cost ($/h) |
|-------------------------|-----------------|---------------------|---------------------|---------------------|------------------|
| CAEO1                   | 2703.540        | 3037.750            | 2335.920            | 2502.55             | 10189.260        |
| CAEO2                   | 2702.217        | 2802.343            | 2393.656            | 2605.428            | 10182.023        |
| CAEO3                   | 2704.835        | 2931.922            | 2362.363            | 2528.619            | 10180.948        |
| CAEO4                   | 2702.944        | 2885.210            | 2249.105            | 2448.860            | 10179.349        |
| CAEO5                   | 2702.914        | 3071.733            | 2409.679            | 2649.255            | 10180.724        |
| CAEO6                   | 2704.007        | 2936.314            | 2305.776            | 2642.078            | 10181.969        |
| CAEO7                   | 2702.738        | 3129.145            | 2410.572            | 2571.062            | 10180.402        |
| CAEO8                   | 2701.003        | 3370.514            | 2589.438            | 2932.466            | 10188.519        |
| CAEO9                   | 2702.582        | 3051.836            | 2353.906            | 2551.257            | 10181.087        |
| CAEO10                  | 2701.254        | 2927.012            | 2282.086            | 2480.293            | 10183.274        |
| AEO                     | 2703.686        | 2978.035            | 2349.853            | 2480.418            | 10180.834        |
| SCA [47]                | 2704.923        | 3146.831            | 2406.237            | 2564.567            | 10255.208        |
| MBO [46]                | 2704.922        | 3146.831            | 2406.236            | 2564.572            | 10255.210        |
| QBA [4]                 | 2704.970        | 3147.380            | 2408.100            | 2565.140            | 10255.280        |
| SA [45]                 | 2703.210        | 3138.446            | 2379.350            | 2568.946            | 10261.490        |
| PSO [44]                | 2734.200        | 3193.600            | 2424.690            | 2607.190            | 10385.000        |
| LR [6]                  | 2729.350        | 3091.648            | 2448.218            | 2537.122            | 10264.570        |

TABLE 8. The results of fuel cost considering 4 levels of demand in the 6-unit power generation system.

| Load (MW) | Total fuel cost ($) |
|-----------|---------------------|
| 150       | 2,729.35            |
| 175       | 2,743.2             |
| 200       | 3,475.41            |
| 225       | 4,210.30            |

TABLE 9. The results of SO2 emission considering 4 levels of demand in the 6-unit power generation system.

From Table 9, we can see that the comparison of emission for SO2 considering 4 levels of demand in a 6-unit power generation system. CAEO4 provides the best value (2885.21 kg/h) for the first level, whereas SA provides the best results (3,763.48; 4,553.97 kg/h) for the second and third levels. Finally, AEO has the best value (5,235.67 kg/h) for the fourth level.

From Table 10, we can see that the comparison of emission for NOx. CAEO4 provides the best value (2,249.11 kg/h) for the first level, whereas LR provides the best results (2,604.89; 3,102.08 kg/h) for the second and third levels. Finally, AEO has the best value (3,758.10 kg/h) for the fourth level.

From Table 11, we can see that the comparison of emission for CO2. CAEO4 provides the best value (2,448.86 kg/h) for the first level, whereas SA provides the best results (3,094.69; 3,714.33 kg/h) for the second and third level. Finally, AEO has the best value (4,255.72 kg/h) for the fourth level.
TABLE 10. The results of NOx emission considering 4 levels of demand in the 6-unit power generation system.

| Load (MW) | LR [6] (kg/h) | PSO [44] | SA [45] | QBA [4] | MBO [46] | SCA [47] | AEO | CAEO4 |
|-----------|---------------|----------|---------|---------|----------|---------|-----|-------|
| 150       | 2,448.22      | 2,424.60 | 2,379.35 | 2,408.10 | 2,406.24 | 2406.2374 | 2,349.85 | 2,249.11 |
| 175       | 2,604.89      | 2,879.70 | 2,798.92 | 2,832.40 | 2,854.13 | 2854.0066 | 2,883.36 | 2,847.56 |
| 200       | 3,102.08      | 3,073.20 | 3,285.65 | 3,327.78 | 3,325.35 | 3325.3389 | 3,362.90 | 3,301.53 |
| 225       | 3,798.38      | 3,877.60 | 3,781.19 | 3,822.53 | 3,811.18 | 3820.2984 | 3,758.10 | 3,832.07 |

TABLE 11. The results of CO2 emission considering 4 levels of demand in the 6-unit power generation system.

| Load (MW) | LR [6] (kg/h) | PSO [44] | SA [45] | QBA [4] | MBO [46] | SCA [47] | AEO | CAEO4 |
|-----------|---------------|----------|---------|---------|----------|---------|-----|-------|
| 150       | 2,537.12      | 2,607.10 | 2,568.95 | 2,565.14 | 2,564.57 | 2564.5670 | 2,480.42 | 2,488.86 |
| 175       | 3,613.53      | 3,178.00 | 3,094.69 | 3,129.78 | 3,129.20 | 3129.1869 | 3,136.06 | 3,154.93 |
| 200       | 4,473.37      | 3,771.50 | 3,714.33 | 3,719.64 | 3,715.69 | 3715.6370 | 3,719.48 | 3,725.20 |
| 225       | 5,502.52      | 4,403.00 | 4,324.30 | 4,323.47 | 4,328.07 | 4322.5213 | 4,255.72 | 4,322.68 |

TABLE 12. The results of total cost considering 4 levels of demand in a 6-unit power generation system.

| Load (MW) | LR [6] (S/h) | PSO [44] | SA [45] | QBA [4] | MBO [46] | SCA [47] | AEO | CAEO4 |
|-----------|--------------|----------|---------|---------|----------|---------|-----|-------|
| 150       | 10,264.17    | 10,385   | 10,261.49 | 10,255.28 | 10,255.21 | 10,255.208 | 10,180.83 | 10,179.35 |
| 175       | 13,251.52    | 12,425   | 12,280.04 | 12,241.74 | 12,241.67 | 12241.668 | 12,172.06 | 12,164.36 |
| 200       | 16,077.41    | 14,642   | 14,421.30 | 14,413.88 | 14,413.71 | 14413.709 | 14,293.19 | 14,287.65 |
| 225       | 19,661.33    | 17,125   | 16,790.69 | 16,783.91 | 16,783.44 | 16783.781 | 16,617.10 | 16,603.90 |

Finally, Table 12 and Figure 7.b present a comparison of the lowest value of the total cost (S/h), which is considered the main objective in this studying as a single objective function. From this table, the CAEO4 method provides the best overall results for all levels of demand in the 6-unit power generation system.

Figure 8 illustrates the convergence curves of the proposed CAEO4 technique for obtaining the optimum convergence to single-objective CEED problems using different levels of demand. From this Figure, it can be noticed that the curves tend to converge very fast and they are converging to achieve the optimal value through 200 iterations. It also displays that the CAEO4 technique has the highest computational prowess. The simulation results obtained from the four cases also show that they are robust and reliable. Finally, it can be confirmed that the proposed CAEO4 technique provides accurate and reliable solutions with strong computational competence after it is compared with the conventional AEO, MBO, QBA, SA, PSO, and LR.

Figure 9 shows the comparison between the convergence curves of proposed CAEO4 and the conventional AEO for the total cost at 3 levels of demand in a 6-unit power system. Also, it can be seen from Table 13 that the results of CAEO4 are more reliable and robust than the conventional AEO for different levels of demand.

B. BI-OBJECTIVE FUNCTION

In this subsection, a MOCAEO4 algorithm is applied for obtaining the optimal point to minimize the first objective...
function (the fuel cost) with one of three emission types (SO\(_2\), NO\(_x\), and CO\(_2\)) as the second objective function in the 6-unit power generation system for the fourth level of demand (250MW).

1) CASE 1: THE OPTIMUM VALUES OF THE FUEL COST AND SO\(_2\) EMISSION
In the 1\(^{st}\) case, the MOCAEO4 algorithm is used for obtaining the best values of fuel cost (1\(^{st}\) objective function) and SO\(_2\) emission (2\(^{nd}\) objective function) simultaneously. Figure 10.a shows The Pareto optimal values of this case. The best solutions obtained by the MOCAEO4 algorithm are presented in Table 14. From this table, the best compromise fuel costs and emission of SO\(_2\) are 4348.79 $/h and 5297.95 kg/h, respectively.

2) CASE 2: THE OPTIMUM VALUES OF THE FUEL COST AND NO\(_x\) EMISSION
In the 2\(^{nd}\) case, the MOCAEO4 algorithm is used for obtaining the best values of fuel cost (1\(^{st}\) objective function) and NO\(_x\) emission (2\(^{nd}\) objective function) simultaneously. Figure 10.b shows The Pareto optimal values of this case. The best solutions obtained by the MOCAEO4 algorithm are presented in Table 14. From this table, the best compromise fuel costs and emission of NO\(_X\) are 4332.28 $/h and 3789.72 kg/h, respectively.

3) CASE 3: THE OPTIMUM VALUES OF THE FUEL COST AND CO\(_2\) EMISSION
In the 3\(^{rd}\) case, the MOCAEO4 algorithm is used for obtaining the best values of fuel cost (1\(^{st}\) objective function) and emission of CO\(_2\) (2\(^{nd}\) objective function) simultaneously. Figure 10.c shows The Pareto optimal values of this case. The best solutions obtained by the MOCAEO4 algorithm are presented in Table 14. From this table, the best compromise fuel costs and emission of CO\(_2\) are 4310.178 $/h and 4323.98 kg/h, respectively.

C. 11-UNIT POWER GENERATION 69-BUS SYSTEM
1) CASE 1: THE OPTIMUM VALUES OF THE FUEL COST
This test system consists of 11-generating units (69-bus, 11-generator, coal-fired power system) with different load demand values (1000, 1500, 2000, and 2500MW) and the optimal results obtained by the CAEO-4 are compared with the conventional AEO algorithm. At the load demand = 2500 MW, the results of the proposed algorithm are compared with six-recent methods beside the original AEO algorithm to check the effectiveness of the proposed technique.
FIGURE 9. Convergence Characteristics of AEO and CAEO4 for 3 levels of demand in 6-unit power system (a) Load Demand = 175 MW (b) Load Demand = 200MW (c) Load Demand = 225MW.

TABLE 14. BCS for multi-objective functions using MOCAEO4 (load = 225MW).

| Objective                  | Fuel Cost ($/h) | Emission (kg/h) |
|----------------------------|-----------------|-----------------|
| Case (1)                   |                 |                 |
| Best Fuel Cost             | 4343.48         | 5342.96         |
| Best Emission of SO₂       | 4352.39         | 5285.28         |
| Best Compromise            | 4346.44         | 5310.487        |
| Case (2)                   |                 |                 |
| Best Fuel Cost             | 4313.49         | 3839.79         |
| Best Emission of NOₓ       | 4332.28         | 3798.72         |
| Best Compromise            | 4321.18         | 3811.77         |
| Case (3)                   |                 |                 |
| Best Fuel Cost             | 4309.51         | 4332.88         |
| Best Emission of CO₂       | 4310.93         | 4319.83         |
| Best Compromise            | 4310.178        | 4323.98         |

The number of populations is 20, and the maximum number of iterations is 2000. The Generation limits, Fuel cost coefficients, and emission coefficients of the system are given in Table 15.

In Table 16, the best values of fuel cost attained using the proposed CAEO-4 were 8408.4307, 9623.5203, 10912.3379, and 12274.4028 $/h for the load demand of 1000, 1500, 2000, and 2500 MW, respectively. These results confirm
the superiority of the proposed CAEO-4 method compared with the conventional AEO. The comparative convergence curves between the proposed CAEO4 and AEO are shown in Figure 11.

The best fuel cost results obtained by the proposed CAEO4, original AEO, and other metaheuristic (CSAISA [39], ISA [39], GA [39], PSO [39], DE [39], HAS [39]) techniques are compared in Table 17.

### FIGURE 10. Pareto-optimal front for (a) Fuel cost and SO2 emission (b) Fuel cost and NOx emission (c) Fuel cost and CO2 emission.

### TABLE 15. Data of the 11-unit system: Generation limits, Fuel cost coefficients and Emission coefficients.

| Unit | P_{min}(MW) | P_{max}(MW) | a(S)  | b(S/MW) | c(S/MW^2) | a_i  | b_i  | y_i  |
|------|-------------|-------------|-------|---------|------------|------|------|------|
| 1    | 20          | 250         | 387.85| 1.92699 | 0.00762    | 33.93| -0.67767| 0.00419|
| 2    | 20          | 210         | 441.62| 2.11969 | 0.00838    | 24.62| -0.69044| 0.00461|
| 3    | 20          | 250         | 422.57| 2.19196 | 0.00523    | 33.93| -0.67767| 0.00419|
| 4    | 60          | 300         | 552.5 | 2.01983 | 0.0014     | 27.14| -0.54551| 0.00683|
| 5    | 20          | 210         | 557.75| 2.22181 | 0.00154    | 24.15| -0.40006| 0.00751|
| 6    | 60          | 300         | 562.18| 1.91528 | 0.00177    | 27.14| -0.54551| 0.00683|
| 7    | 20          | 215         | 568.39| 2.10681 | 0.00195    | 24.15| -0.40006| 0.00751|
| 8    | 100         | 455         | 682.93| 1.99138 | 0.00106    | 30.45| -0.51116| 0.00355|
| 9    | 100         | 455         | 741.22| 1.99802 | 0.00117    | 25.59| -0.56228| 0.00417|
| 10   | 110         | 460         | 617.83| 2.12352 | 0.00089    | 30.45| -0.41116| 0.00355|
| 11   | 110         | 465         | 674.61| 2.10487 | 0.00098    | 25.59| -0.56228| 0.00417|
2) CASE 2: THE OPTIMUM VALUES OF THE TOTAL EMISSION
The optimal power generation achieved by proposed CAEO4 and AEO algorithms with system demands rising from 1000 MW to 2500 MW for the best total emission are tabulated in Table 18. When the results are compared, the proposed CAEO4 gives the better values of

TABLE 16. Results of the fuel cost for the 11-unit system using AEO and CAEO4.

| Generating Unit, MW | 1000MW | 1500MW | 2000MW | 2500MW |
|---------------------|--------|--------|--------|--------|
|                     | AEO    | CAEO4  | AEO    | CAEO4  |
| P1                  | 28.1109| 29.7026| 37.9728| 57.0104|
| P2                  | 20.1227| 20.0474| 23.1348| 31.2992|
| P3                  | 20.0881| 20.0600| 29.7579| 57.6054|
| P4                  | 119.0846| 119.5868| 174.2851| 47.4836|
| P5                  | 44.0101| 44.1590| 91.7651| 226.1858|
| P6                  | 126.3340| 120.3953| 166.6362| 225.2687|
| P7                  | 60.2112| 63.4011| 101.0234| 138.7365|
| P8                  | 166.2222| 172.0383| 242.3194| 187.2295|
| P9                  | 154.6643| 153.7968| 215.9341| 187.5444|
| P10                 | 132.8594| 135.7267| 213.5000| 187.5444|
| P11                 | 128.2927| 123.9454| 203.3553| 187.5444|

Fuel cost, $/h

|                      | 8408.4535| 8408.4507| 9623.5203| 10912.3379| 12274.4032|

Emission, ton/h

|                      | 369.9576| 368.8915| 821.0156| 819.0274| 1541.7568|

Computation time (s)

|                      | 4.6609| 4.6550| 4.6613| 4.6579| 4.8261| 4.7930| 4.8812| 4.8626|
FIGURE 12. Total emission convergence curves of AEO and CAEO4 techniques (case study 2) (a) 1000MW (b) 1500MW (c) 2000MW (d) 2500MW.

TABLE 17. The best solution values for the fuel cost of the case study 2 (2500 MW).

| Generating Unit, MW | HSA  | DE   | PSO  | GA   | ISA   | CSAISA | AEO  | CAEO4 |
|---------------------|------|------|------|------|-------|--------|------|-------|
| P1                  | 56.5750 | 57.5683 | 57.6582 | 57.4565 | 57.3520 | 56.9465 | 57.0104 | 57.0440 |
| P2                  | 41.7558 | 39.8234 | 41.7560 | 40.7339 | 40.3501 | 40.5882 | 40.4182 | 40.5110 |
| P3                  | 58.8239 | 57.3622 | 57.0840 | 60.6382 | 58.5628 | 57.9381 | 57.6054 | 58.0606 |
| P4                  | 277.6793 | 277.6343 | 279.6482 | 278.8546 | 278.7029 | 277.9182 | 277.8938 | 278.1442 |
| P5                  | 189.5183 | 189.2732 | 189.7429 | 191.7492 | 189.2024 | 186.7996 | 187.2295 | 186.5444 |
| P6                  | 250.1128 | 249.9246 | 249.7420 | 249.2131 | 249.5435 | 249.2460 | 249.7332 | 249.6237 |
| P7                  | 176.9563 | 175.6345 | 176.6402 | 178.2341 | 176.0364 | 177.6527 | 177.4899 | 177.3503 |
| P8                  | 379.8753 | 378.7465 | 377.7493 | 379.3567 | 379.9651 | 380.7402 | 380.3062 | 380.7580 |
| P9                  | 341.0440 | 340.8126 | 341.8462 | 344.1547 | 340.7782 | 341.7721 | 341.2216 | 341.4758 |
| P10                 | 379.8564 | 378.1122 | 378.7465 | 378.6473 | 378.8541 | 377.8633 | 378.5940 | 377.8372 |
| P11                 | 351.6593 | 352.8493 | 350.8284 | 353.6394 | 350.6525 | 352.5351 | 352.4965 | 352.7109 |

| Fuel cost, $/h   | 12275.46 | 12277.92 | 12276.42 | 12278.42 | 12274.40 | 12274.40 | 12274.40 | 12274.40 |
| Emission, ton/h  | 2538.76  | 2538.74  | 2534.69  | 2531.32  | 2539.69  | 2540.41  | 2541.9545 | 2540.7367 |
| Time (s)         | 12.65    | 12.68    | 12.69    | 12.71    | 12.65    | 12.64    | 4.8812    | 4.8626    |

Figure 12 shows the convergence characteristics of the CAEO4 and AEO. From this Figure, it can be seen that the convergence characteristic curves of the CAEO4 are fast, smooth and smoothly reach to the optimal value of objective function, compared with the original AEO.
Table 18 presents the best solution values for the total emission of the case study 2 using the proposed CAEO4 technique, AEO, GA, and GSA with 2500MW system demands for 51162.

Table 19 gives the best optimal power output of generators for CEED problem using proposed CAEO4 technique, AEO, GA, and GSA with 2500MW system demands for 51162.

Table 20 gives the best optimal power output of generators for CEED problem using proposed CAEO4 technique, AEO, GA, and GSA with 2500MW system demands for 51162.

Table 21 presents the best solution values for the total emission of the case study 2 using the proposed CAEO4, original AEO and other algorithms. From Table 19, it can be observed that the optimal emission obtained using CAEO4 and CISAISA [39] was 1659.35 ton/h.

3) CASE 1: THE OPTIMUM VALUES OF THE COMBINED ECONOMIC EMISSION DISPATCH (CEED)

Table 20 gives the best optimal power output of generators for CEED problem using proposed CAEO4 technique, AEO, GA, and GSA with 2500MW system demands for 51162.
11-generator system. From this table, it is clear that the proposed approach gives the best total cost (18953.49162 $/h). The convergence characteristic curve for the best total cost is shown in Figure 13. It can be observed that the proposed CAEO4 has a steady and faster convergence characteristic than the conventional AEO algorithm.

V. CONCLUSION

In this research, single and multi-objective CEED problems in power grids have been solved to obtain economic and environmental profits. In the 6-unit power system, the target has been achieved by minimizing the total fuel cost and the emission of the three risky gases SO₂, NOₓ, and CO₂. The proposed CAEO4 algorithm has been modified to solve the multi-objective CEED problem according to the Pareto theory. After the determination of the ND solutions, the BCS is chosen using the fuzzy set theory. The MOCAEO4 algorithm has been established for obtaining the best solution of two objective functions simultaneously. Also, the proposed CAEO4 has been tested by the 69-bus 11-unit power system. The results demonstrated the superiority of the developed algorithms for achieving the optimal solution to decrease the total cost and reduce the bad emission for different levels of demand.

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