IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received February 21, 2021, accepted March 9, 2021, date of publication March 17, 2021, date of current version April 8, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3066914

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

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 Artificial ecosystem-based optimization
ELD	Economic Load Dispatch
DE	Differential Evolution
SA	Simulated Annealing

The associate editor coordinating the review of this manuscript and approving it for publication was Pavlos I. Lazaridis.

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 can help to improve the solutions [5]. But the downside of applying these polynomials which have order higher than the 2^{nd} 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.

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 Appling 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:

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

where n is the total number of generating units, Pi 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:

$$E_{SO2}(P) = \sum_{i=1}^{n} e_{SO2i} P_i^3 + f_{SO2i} P_i^2 + g_{SO2i} P_i + h_{SO2i}, \tag{2}$$

where $E_{SO2}(P)$ in (kg/h) is the emission function of SO_2. e_{SO2i}, f_{SO2i}, g_{SO2i}, and h_{SO2i} are coefficients of SO_2 emission of the generating unit i, respectively.

$$E_{NOx}(P) = \sum_{i=1}^{n} e_{NOxi} P_i^3 + f_{NOxi} P_i^2 + g_{NOxi} P_i + h_{NOxi}, \tag{3}$$

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

$$E_{CO2}(P) = \sum_{i=1}^{n} e_{CO2i} P_i^3 + f_{CO2i} P_i^2 + g_{CO2i} P_i + h_{CO2i}, \tag{4}$$

where $E_{CO2}(P)$ in (kg/h) is the emission function of CO_2. e_{CO2i}, f_{CO2i}, g_{CO2i}, and h_{CO2i} 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:

$$P_T = \sum_{i=1}^{n} P_i = P_D + P_L, \tag{5}$$

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

$$P_{i,min} \le P_i \le P_{i,max}, \tag{6}$$

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 CO2, SO2, and NOx) 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:

$$\begin{aligned} OF &= min(F_T) \\ F_T &= \sum_{i=1}^{n} \{F(P_i) + h_{Si} E_{SO2i}(P_i) + h_{Ni} E_{NOxi}(P_i) \\ &\quad + h_{Ci} E_{CO2i}(P_i)\}, \end{aligned} \tag{7}$$

where $F(P_i)$, $E_{SO2i}(P_i)$, $E_{NOxi}(P_i)$, and $E_{CO2i}(P_i)$ are fuel cost ($/h), emission of SO_2 (kg/h), emission of NO_x (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_x, and CO_2. And it can be computed for each gas from these equations:

$$h_{Si} = \sum_{i=1}^{n} \frac{F(P_{i.max})}{E_{SO2}(P_{i.max})} \tag{8}$$

$$h_{Ni} = \sum_{i=1}^{n} \frac{F(P_{i.max})}{E_{NOx}(P_{i.max})} \tag{9}$$

$$h_{Ci} = \sum_{i=1}^{n} \frac{F(P_{i.max})}{E_{CO2}(P_{i.max})} \tag{10}$$

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 x1 dominates the solution x2 when [38]:

$$\forall_i \in \{1, 2, \ldots, M\},\ f_i(x_1) \leq f_i(x_2) \tag{11}$$

$$\exists_i \in \{1, 2, \ldots, M\}:\ f_i(x_1) < f_i(x_2) \tag{12}$$

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:

$$\mu_i^k = \begin{cases} 1 & F_i \leq F_i^{min} \\ \dfrac{F_i^{max} - F_i}{F_i^{max} - F_i^{min}} & F_i^{min} < F_i < F_i^{max} \\ 0 & F_i \geq F_i^{max} \end{cases} \tag{13}$$

where F_i^{max} and F_i^{min} are the maximal and minimal values of F_i between all ND solutions, respectively.

The normalized membership function (μ_k) is defined as:

$$\mu^k = \frac{\sum_{i=1}^{Nobj} \mu_i^k}{\sum_{k=1}^{M} \sum_{i=1}^{Nobj} \mu_i^k} \tag{14}$$

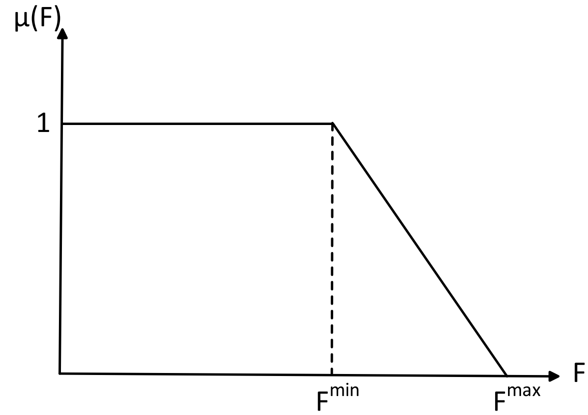


FIGURE 1. Flowchart membership of objective functions.

where M is the total numeral of ND solutions. The selection of The BCS from all ND solutions through the value of μ^k, where the BCS which has a maximum value of μ^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_x.
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]:

$$F_1 = \sum_{i=1}^{N_G} [a_i + b_i P_{Gi} + c_i P_{Gi}^2 + \left| d_i \sin\left(e_i\left(P_{Gi}^{min} - P_{Gi}\right)\right)\right|] \tag{15}$$

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} ($i = 1; 2; 3; \ldots; N_G$) unit, and N_G represents the number of generating units.

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

$$F_2 = \sum_{i=1}^{N_G} \left[10^{-2}(\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2) + \eta_i \exp(\delta_i P_{Gi})\right] \tag{16}$$

where α_i; β_i; γ_i; η_i and δ_i represent the emission coefficients for the i^{th} unit.

The CEED is calculated as follows:

$$F_T = \sum_{i=1}^{N_G} \{F_1(P_{Gi}) + h_i \times F_2(P_{Gi})\} \tag{17}$$

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_{Loss} (in MW). This equality constraint is expressed as follows:

$$P_T = \sum_{i=1}^{N_G} P_{Gi} = P_D + P_{Loss}, \tag{18}$$

P_{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:

$$P_{Loss} = \sum_{i=1}^{N_G}\sum_{j=1}^{N_G} P_{Gi}B_{ij}P_{Gj} + \sum_{i=1}^{N_G} B_{0i}P_{Gi} + B_{00}, \tag{19}$$

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:

$$P_{Gi,min} \leq P_{Gi} \leq P_{Gi,max}, \tag{20}$$

where, $P_{Gi,min}$ and $P_{Gi,max}$ 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 gets 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.

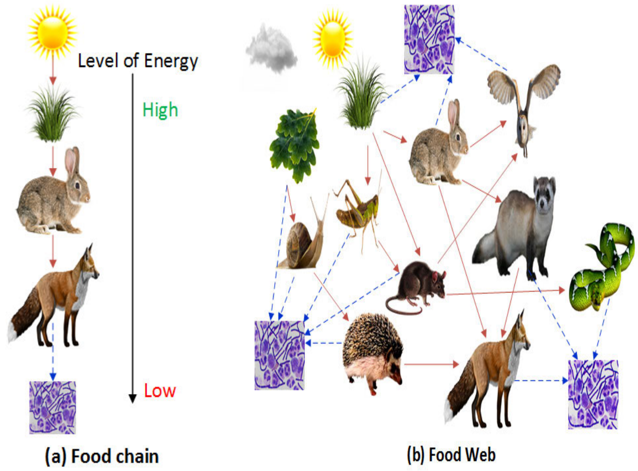


FIGURE 2. The energy flow in an ecosystem.

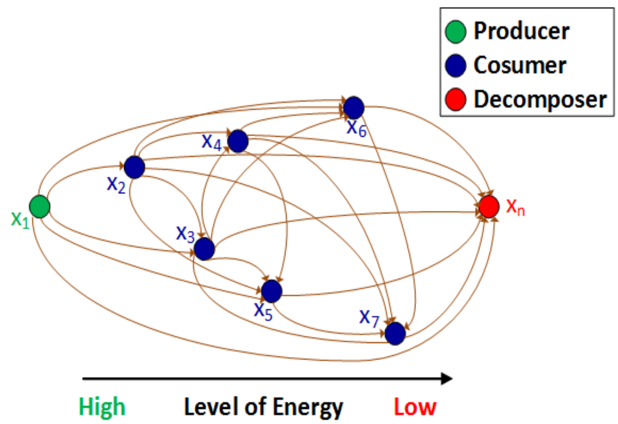


FIGURE 3. An ecosystem representation in the AEO technique.

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 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:

$$x_1(t+1) = (1-a)\,x_n(t) + a x_{rand}(t) \tag{21}$$

$$a = (1 - \frac{t}{max\_iter})r_1 \tag{22}$$

$$x_{rand} = r\,(U_b - L_b) + L_b \tag{23}$$

where a is a linear weight coefficient, n is the population size, x_{rand} is an individual position of randomly produced in the search space, max_*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]:

$$C = \frac{1}{2}\frac{v_1}{|v_2|} \tag{24}$$

$$v_1 \sim N(0,1),\, v_2 \sim N(0,1), \tag{25}$$

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:

$$x_i(t+1) = x_i(t) + C.\,(x_i(t) - x_1(t)),\quad i \in [2, \ldots, n] \tag{26}$$

2- carnivore can be mathematically formulated as follows:

$$\begin{cases} x_i(t+1) = x_i(t) + C.\left(x_i(t) - x_j(t)\right), \\ i \in [2, \ldots, n] \\ j = randi([2i-1]) \end{cases} \tag{27}$$

3- omnivore can be modeled mathematically as below:

$$\begin{cases} x_i(t+1) = x_i(t) + C.\,(x_i(t) - x_1(t)) + (1-r_2) \\ \left(x_i(t) - x_j(t)\right), i = 3, \ldots, n \\ j = randi\,([2i-1]) \end{cases} \tag{28}$$

D. DECOMPOSITION

The i-th individual position x_i in the population can be improved to the better position depending on the decomposer x_n, the decomposition factor D, and the weight coefficients e and h as follow:

$$x_i(t+1) = x_n(t) + D.\,(e.x_n(t) - h.x_i(t)),\quad i = 1, \ldots, n \tag{29}$$

$$D = 3u,\, u \sim N(0,1) \tag{30}$$

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

$$h = 2.r_3 - 1 \tag{32}$$

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]:

$$q = y_{k+1} \tag{33}$$

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 necessary 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

TABLE 1. Ten Chaotic maps.

No.	Name	Chaotic map formula
CAEO1	Chebyshev	$y_{k+1} = \cos(k \cos^{-1}(y_k))$
CAEO2	Circle	$y_{k+1} = \mathrm{mod}\left(y_k + b_1 - \left(\frac{b_2}{2\pi}\right)\sin(2\pi y_k), 1\right)$ $b_1 = 0.5, b_2 = 0.2$
CAEO3	Gauss/ mouse	$y_{k+1} = \begin{cases} 1 & y_k = 0 \\ \frac{1}{mod(y_k)} & otherwise \end{cases}$
CAEO4	Iterative	$y_{k+1} = \sin\left(\frac{b\pi}{y_k}\right), b = 0.7$
CAEO5	Logistic	$y_{k+1} = by_k(1\text{-}y_k), b = 4$
CAEO6	Piecewise	$y_{k+1} = \begin{cases} \frac{y_k}{H} & 0 \le y_k \le H \\ \frac{y_k - H}{0.5 - H} & H \le y_k \le 0.5 \\ \frac{1 - H - y_k}{0.5 - H} & 0.5 \le y_k \le 1 - H \\ \frac{1 - y_k}{H} & 1 - H \le y_k \le 1 \end{cases}, H$ $= 0.4$
CAEO7	Sine	$y_{k+1} = \frac{b}{4}\sin(\pi\, y_k), b = 4$
CAEO8	Singer	$y_{k+1} = u\left(\begin{matrix} 7.86{y_k}^1 - 23.31{y_k}^{12} \\ -28.75{y_k}^3 - 13.302875{y_k}^4 \end{matrix}\right), u$ $= 1.07$
CAEO9	Sinusoidal	$y_{k+1} = by_k^1 \sin(\pi y_k), b = 2.3$
CAEO10	Tent	$y_{k+1} = \begin{cases} \frac{y_k}{0.7} & y_k < 0.7 \\ \frac{10}{3}(1 - y_k) & y_k \ge 0.7 \end{cases}$

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

Unit	Ai (10^{-3})	Bi	ci (10^2)	di (10^3)	$P_{i,min}$ (MW)	$P_{i,max}$ (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	- 0.0098	10	50
P6	0.4000	0.084	0.125	0.0756	12	40

the research. 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.

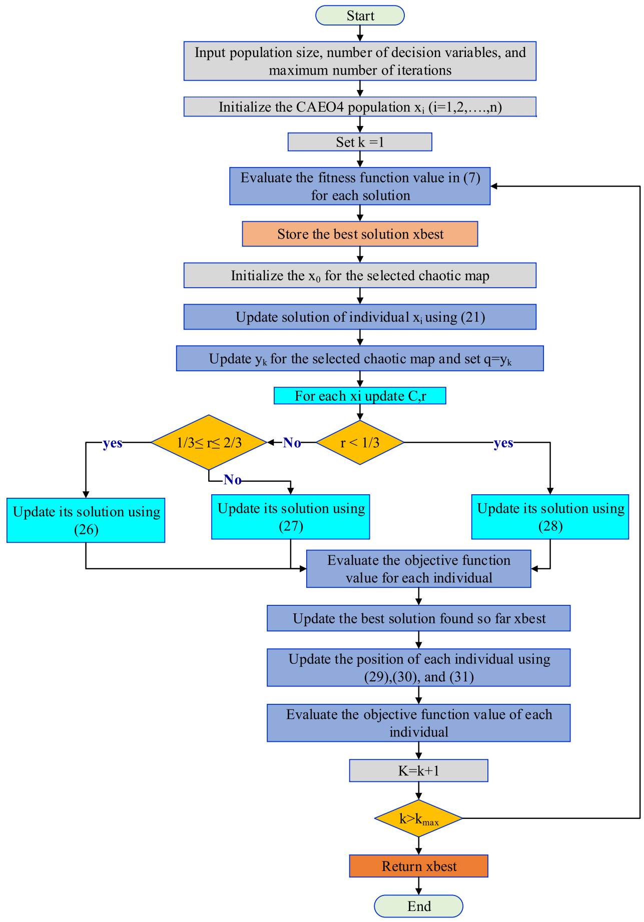


FIGURE 4. Flowchart of proposed CAEO technique.

TABLE 3. The coefficients of SO_2 Emission and its max/max PPF.

Unit	The coefficients of SO_2 emission				max/max PPF of SO_2
	e_{SO2i}	f_{SO2i}	g_{SO2i}	h_{SO2i}	h_s
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	25.60	0.62

TABLE 4. The coefficients of NO_X Emission and its max/max PPF.

Unit	The coefficients of NO_x emission				max/max PPF of No_x
	e_{NOxi}	f_{NOxi}	g_{NOxi}	h_{NOxi}	h_n
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

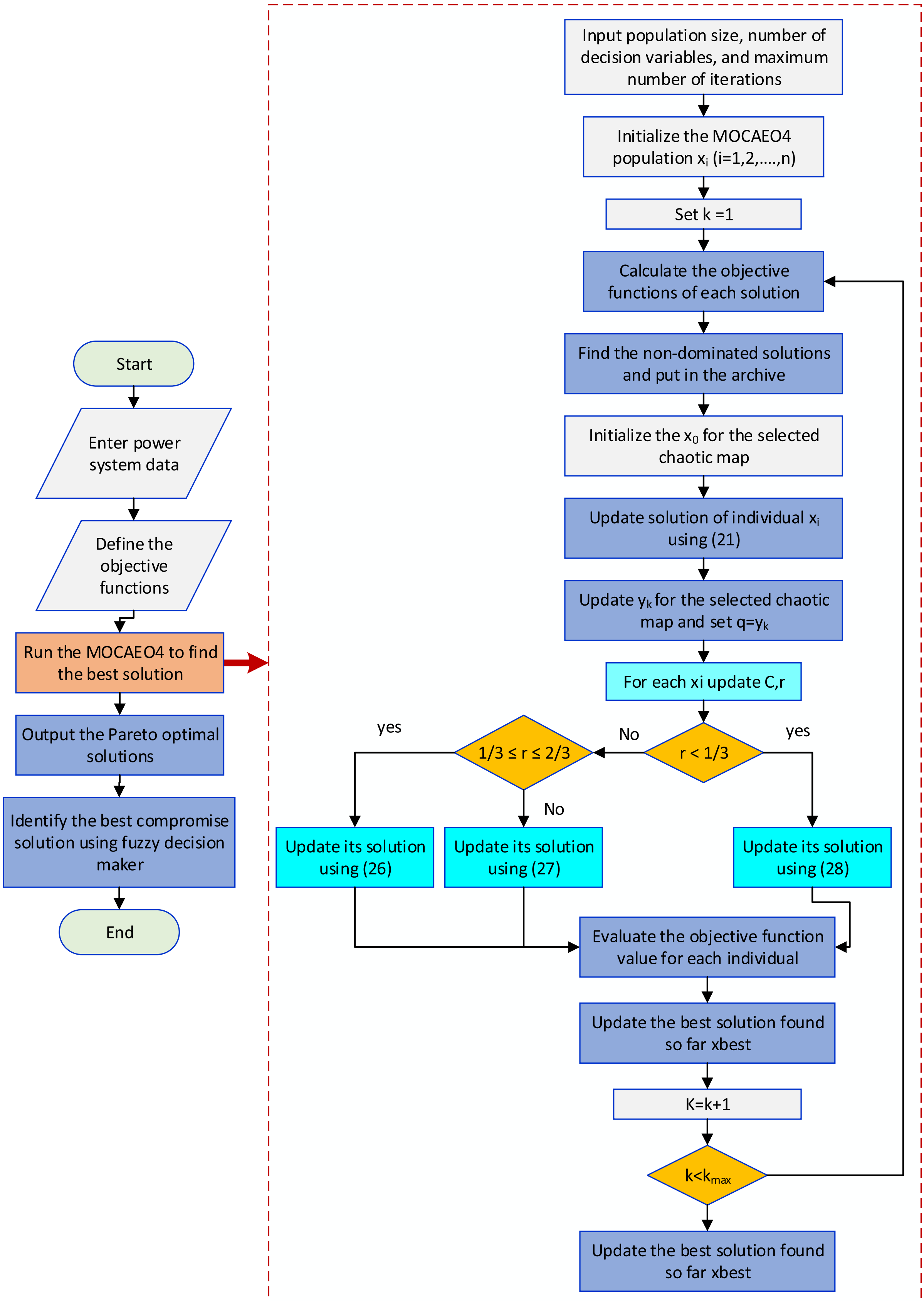


FIGURE 5. MOCAEO technique for the CEED problem.

TABLE 5. The coefficients of CO_2 Emission and its max/max PPF.

Unit	The coefficients of CO2 emission				max/max PPF of CO_2
	e_{CO2i}	f_{CO2i}	g_{CO2i}	h_{CO2i}	h_c
1	0.0015	0.092	14.0	- 16.0	0.78
2	0.0014	0.025	12.5	- 93.5	1.19
3	0.0016	0.055	13.5	- 85.0	1.44
4	0.0012	0.010	13.5	- 24.5	1.13
5	0.0023	0.040	21.0	- 59.0	0.75
6	0.0014	0.080	22.0	- 70.0	0.7158

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 and these metrics can be calculated from the following equations [41]:

$$SD = \sqrt{\frac{\sum_{i=1}^{50} (SSE_i - \overline{SSE})}{50-1}} \tag{34}$$

$$RE = \frac{\sum_{i=1}^{50} (SSE_i - SSE_{min})}{SSE_{min}} \tag{35}$$

$$\mathrm{MAE} = \frac{\sum_{i=1}^{50} (\mathrm{SSE_i} - \mathrm{SSE_{min}})}{50} \tag{36}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{50} (SSE_i - SSE_{min})^2}{50}} \tag{37}$$

$$efficiency = \frac{SSE_{min}}{SSE_i} \times 100\% \tag{38}$$

where SSE_i is the lowest value of the objective function in each run. $\overline{SSE}$ is the mean value of SSE overall. SSE_{min} is the lowest best value of SSE over the 50 runs. Table 6 presents the statistical results of ten proposed CAEO as well as the 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.

The results for the 6-unit system considering the first level of demand equals 150MW are provided in Table 7. These results include the value of fuel cost, the value of three types of emission (SO2, NOx, and CO2, respectively), and the value

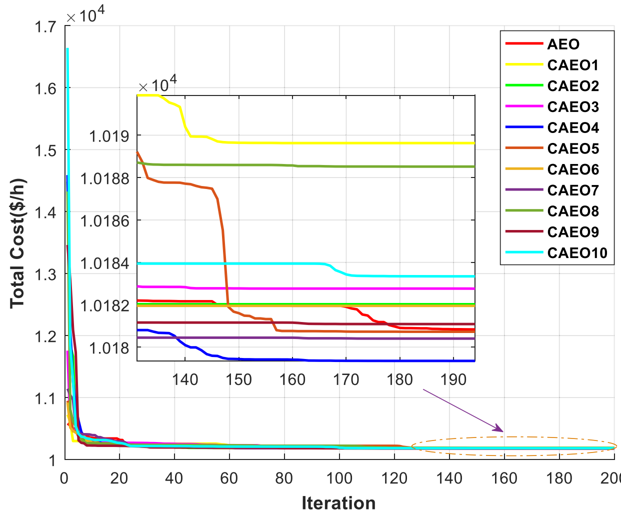


FIGURE 6. Convergence characteristics of proposed CAEO and AEO.

of total cost. Table 7 displays the comparison between the results obtained by the proposed CAEO techniques and the results of the conventional AEO as well as the 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	10187.4646	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	6.8655	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	10185.9889	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 ($/h)	SO_2 Emission (kg/h)	NO_x Emission (kg/h)	CO_2 Emission (kg/h)	Total cost ($/h)
CAEO1	2703.540	3037.750	2335.920	2502.55	10189.260
CAEO2	2702.217	3028.343	2339.656	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	2462.078	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	2703.582	3051.836	2335.906	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]	2705.210	3138.446	2379.350	2568.946	10261.490
PSO [44]	2734.200	3193.600	2424.600	2607.100	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	Total fuel cost ($/h)							
(MW)	LR [6]	PSO [44]	SA [45]	QBA [4]	MBO [46]	SCA [47]	AEO	CAEO4
150	2,729.35	2,734.2	2,705.2	2,704.97	2,704.92	2704.92	2,703.69	**2,702.94**
175	3,475.41	3,236.3	3,220.5	3,188.10	3,188.13	3188.15	3,187.31	**3,179.34**
200	4,210.30	3,784.9	3,735.7	3,726.08	3,727.43	3727.45	3,724.71	**3,722.45**
225	5,130.53	4,402.3	4,321.5	4,314.63	4,315.63	4315.05	4,314.97	**4,314.38**

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

Load	Emission of SO_2(kg/h)							
(MW)	LR [6]	PSO [44]	SA [45]	QBA [4]	MBO [46]	SCA [47]	AEO	CAEO4
150	3,091.65	3,193.60	3,138.45	3,147.38	3,146.83	3146.8310	2,978.03	2,885.21
175	4,142.18	3,904.90	3,763.48	3,858.96	3,859.49	3859.3593	3,829.72	3,891.64
200	5,053.58	4,670.60	4,553.97	4,598.20	4,592.64	4592.4934	4,618.24	4,589.87
225	6,106.50	5,426.10	5,287.31	5,344.75	5,335.81	5339.9612	5,235.67	5,360.57

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 (2,249.11kg/h) for the first level, whereas LR provides the best results (2,604.89; 3,102.08kg/h) for the second and third levels. Finally, AEO has the best value (3,758.10kg/h) for the fourth level.

From Table 11, we can see that the comparison of emission for CO2. CAEO4 provides the best value (2,448.86kg/h) for the first level, whereas SA provides the best results (3,094.69; 3,714.33kg/h) for the second and third level. Finally, AEO has the best value (4,255.72kg/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)	Emission of NO_x (kg/h)							
	LR [6]	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	2,789.92	2,853.40	2,854.13	2854.0066	2,883.36	2,847.56
200	**3,102.08**	3,373.20	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	3820.2894	**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)	Emission of CO_2(kg/h)							
	LR [6]	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	**2,448.86**
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)	Total cost ($/h)							
	LR [6]	PSO [44]	SA [45]	QBA [4]	MBO [46]	SCA [47]	AEO	CAEO4
150	10,264.57	10,385	10,261.49	10,255.28	10,255.21	10255.208	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	16,784.34	16783.781	16,617.10	**16,603.90**

TABLE 13. Results of CEED for the 6-unit system using AEO and CAEO4.

Load (MW)	**AEO**	**CAEO4**	**AEO**	**CAEO4**	**AEO**	**CAEO4**	**AEO**	**CAEO4**
	150 MW		175 MW		200 MW		225 MW	
P1 (MW)	50.000	50.000	50.074	50.00823	50.010	50.002	50.0	50.004
P2 (MW)	20.024	20.007	22.683	21.24516	29.909	29.602	37.2	39.421
P3 (MW)	15.000	15.000	15.999	15.01373	15.213	15.002	16.8	16.079
P4 (MW)	24.096	23.968	30.159	32.97348	40.223	38.672	44.8	45.271
P5 (MW)	16.179	18.988	24.745	26.27831	27.354	30.327	36.4	34.260
P6 (MW)	24.701	22.038	31.339	29.48110	37.297	36.396	39.7	39.965
Fuel cost ($/h)	2703.686	2702.944	3187.307	3179.337	3724.708	3722.450	4315.0	4314.380
Emission of SO_2 (kg/h)	2978.035	2885.210	3829.720	3891.639	4618.244	4589.868	5235.7	5360.573
Emission of No_x (kg/h)	2349.853	2249.105	2883.358	2847.565	3362.898	3301.527	3758.102	3832.066
Emission of CO_2 (kg/h)	2480.418	2448.860	3136.058	3154.931	3719.476	3725.202	4255.7	4322.681
Total Cost ($/h)	10,180.8	**10,179.35**	12,172.1	**12,164.4**	14,293.19	**14,287.65**	16,617.1	**16,603.9**

Finally, Table 12 and Figure 7.b present a comparison of the lowest value of the total cost ($/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.

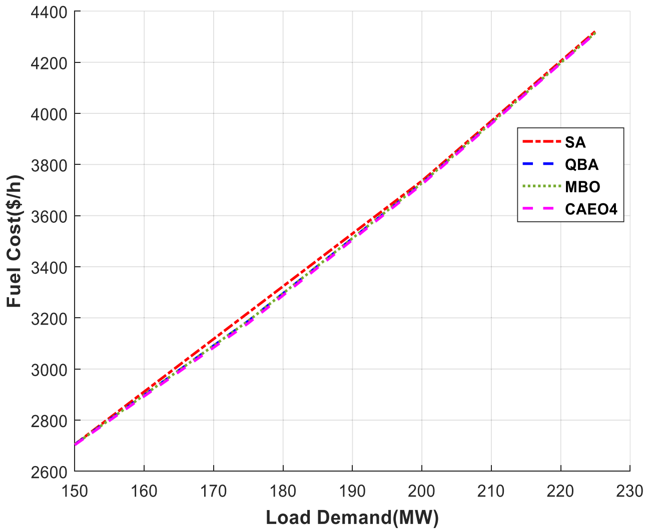
Figure 8 illustrates the convergence curves of the proposed CAEO4 technique for obtaining the optimum convergence to single-objective CEED problems using different levels of demand. From this Figure, it can be noticed that the curves tend to converge very fast and they are converging to achieve the optimal 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.

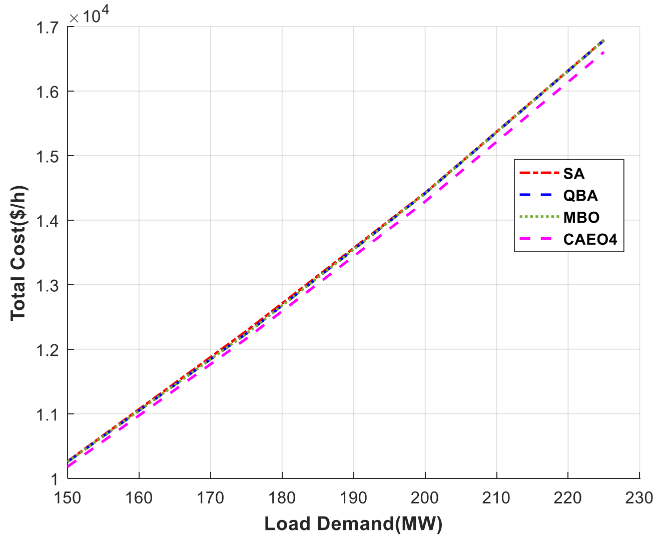
Also, it can be seen from Table 13 that the results of CAEO4 are more reliable and robust than the conventional AEO for different levels of demand.

B. BI-OBJECTIVE FUNCTION

In this subsection, a MOCAEO4 algorithm is applied for obtaining the optimal point to minimize the first objective



(a)



(b)

FIGURE 7. **Variations of methods for different levels of demand in 6-unit system (a) Fuel cost ($/h) (b) Total cost ($/h).**

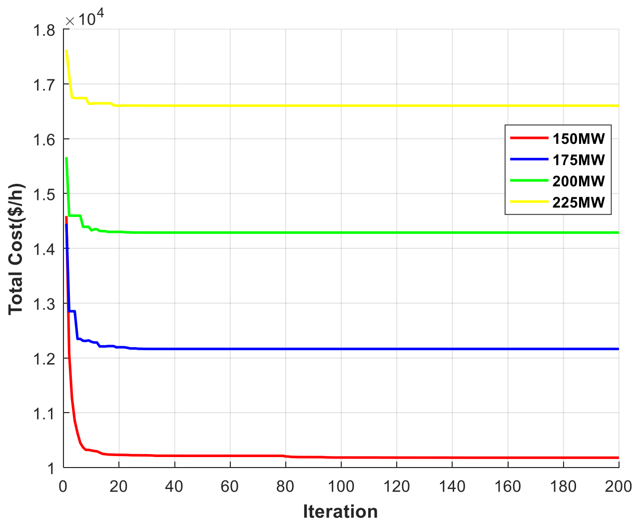


FIGURE 8. **Convergence curves of the CAEO4 method for different levels of demand.**

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 1st case, the MOCAEO4 algorithm is used for obtaining the best values of fuel cost (1st objective function) and SO_2 emission (2nd 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 2nd case, the MOCAEO4 algorithm is used for obtaining the best values of fuel cost (1st objective function) and NOx emission (2nd 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 NOX 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 3rd case, the MOCAEO4 algorithm is used for obtaining the best values of fuel cost (1st objective function) and emission of CO_2 (2nd 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.

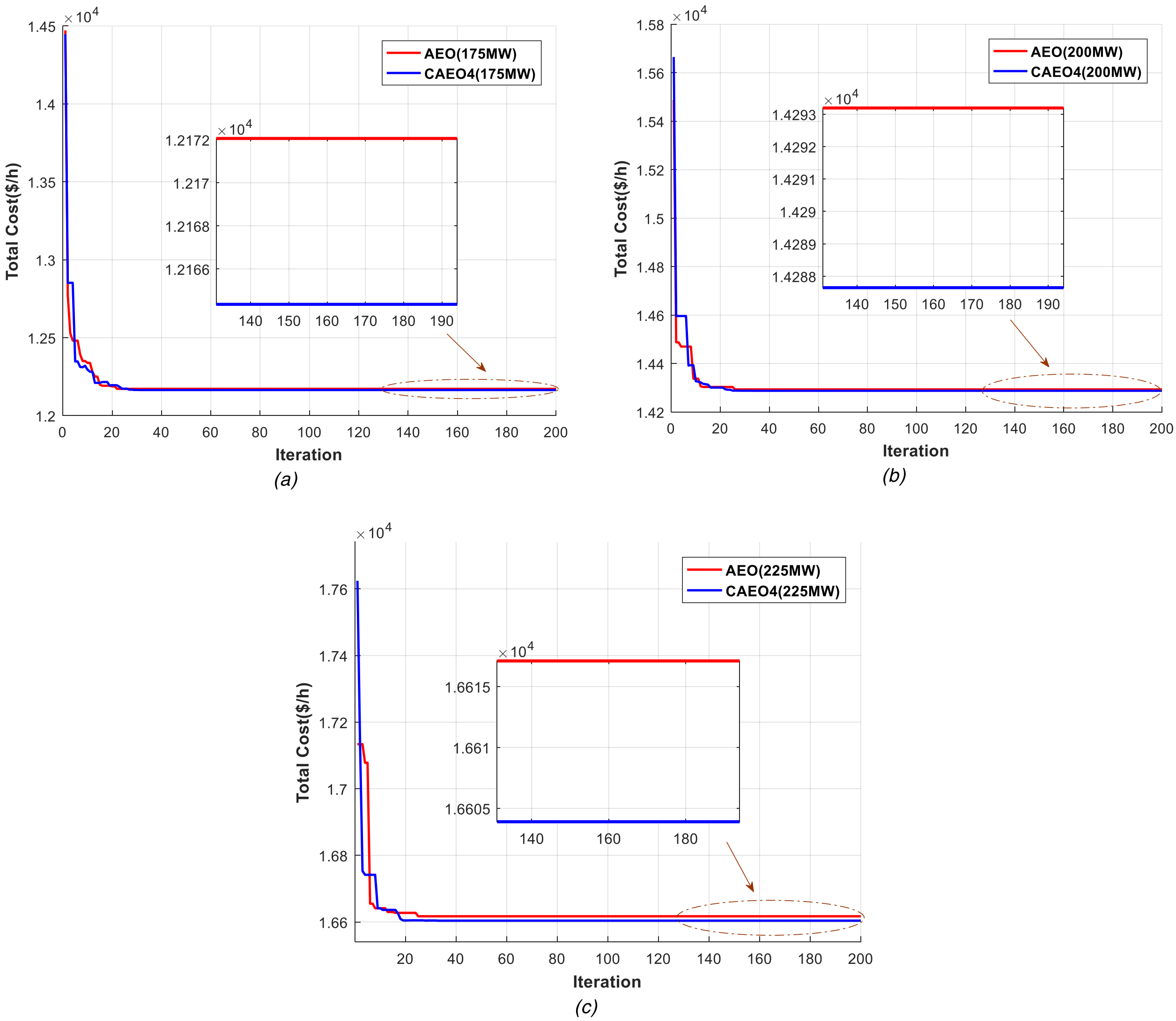


FIGURE 9. Convergence Characteristics of AEO and CAEO4 for 3 levels of demand in 6-unit power system (a) Load Demand = 175 MW (b) Load Demand = 200MW (c) Load Demand = 225MW.

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 SO_2	4352.39	5285.28
	Best Compromise	4346.44	5310.487
Case (2)	Best Fuel Cost	4313.49	383979
	Best Emission of NO_x	4332.28	3798.72
	Best Compromise	4321.18	3811.77
Case (3)	Best Fuel Cost	4309.51	4332.88
	Best Emission of CO_2	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

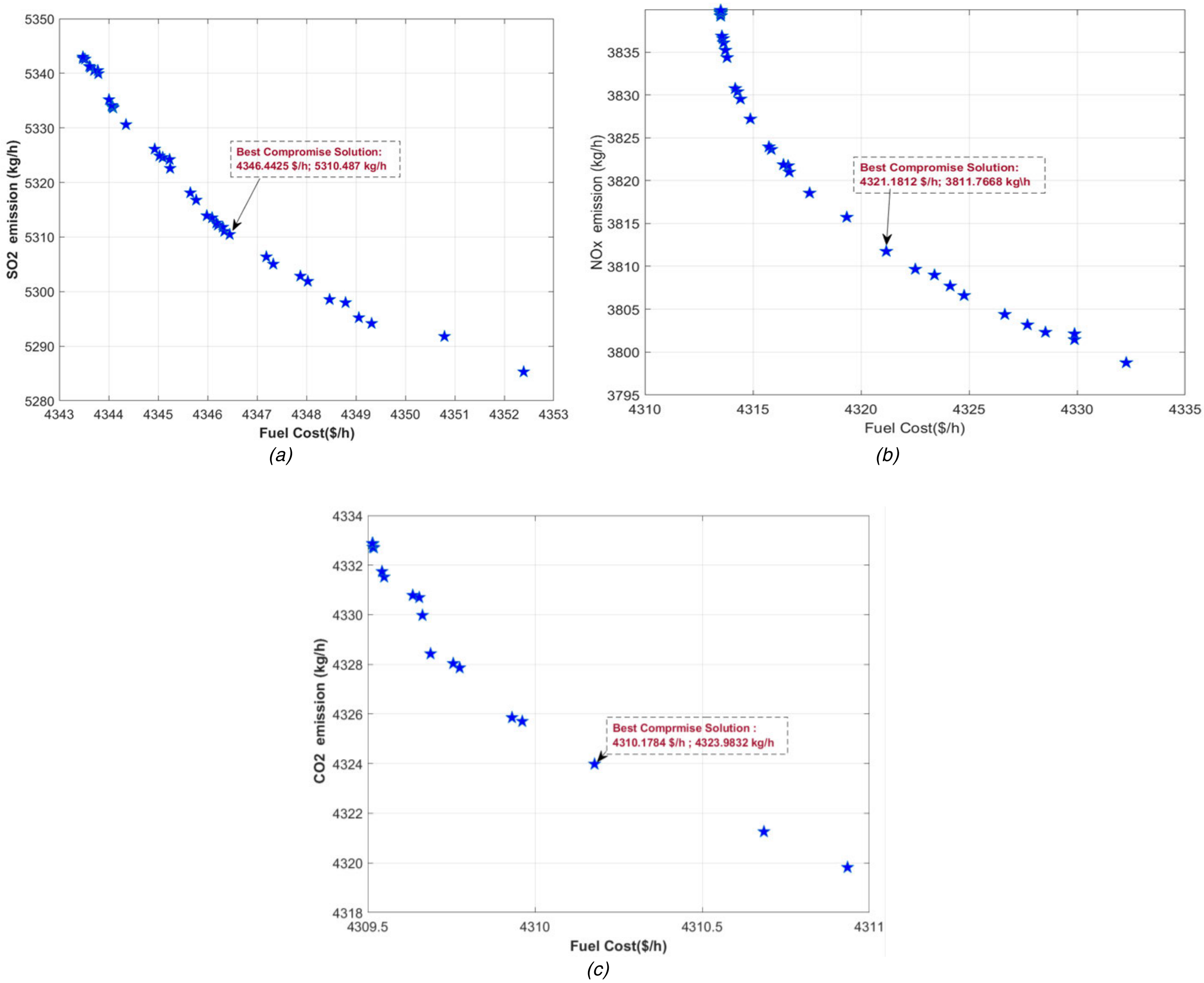


FIGURE 10. Pareto-optimal front for (a) Fuel cost and SO2 emission (b) Fuel cost and NO*x* emission (c) Fuel cost and CO2 emission.

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

Unit	$P_{i,min}$(MW)	$P_{i,max}$(MW)	a_i($)	b_i($/MW)	c_i($/MW^2)	α_i	β_i	γ_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

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.

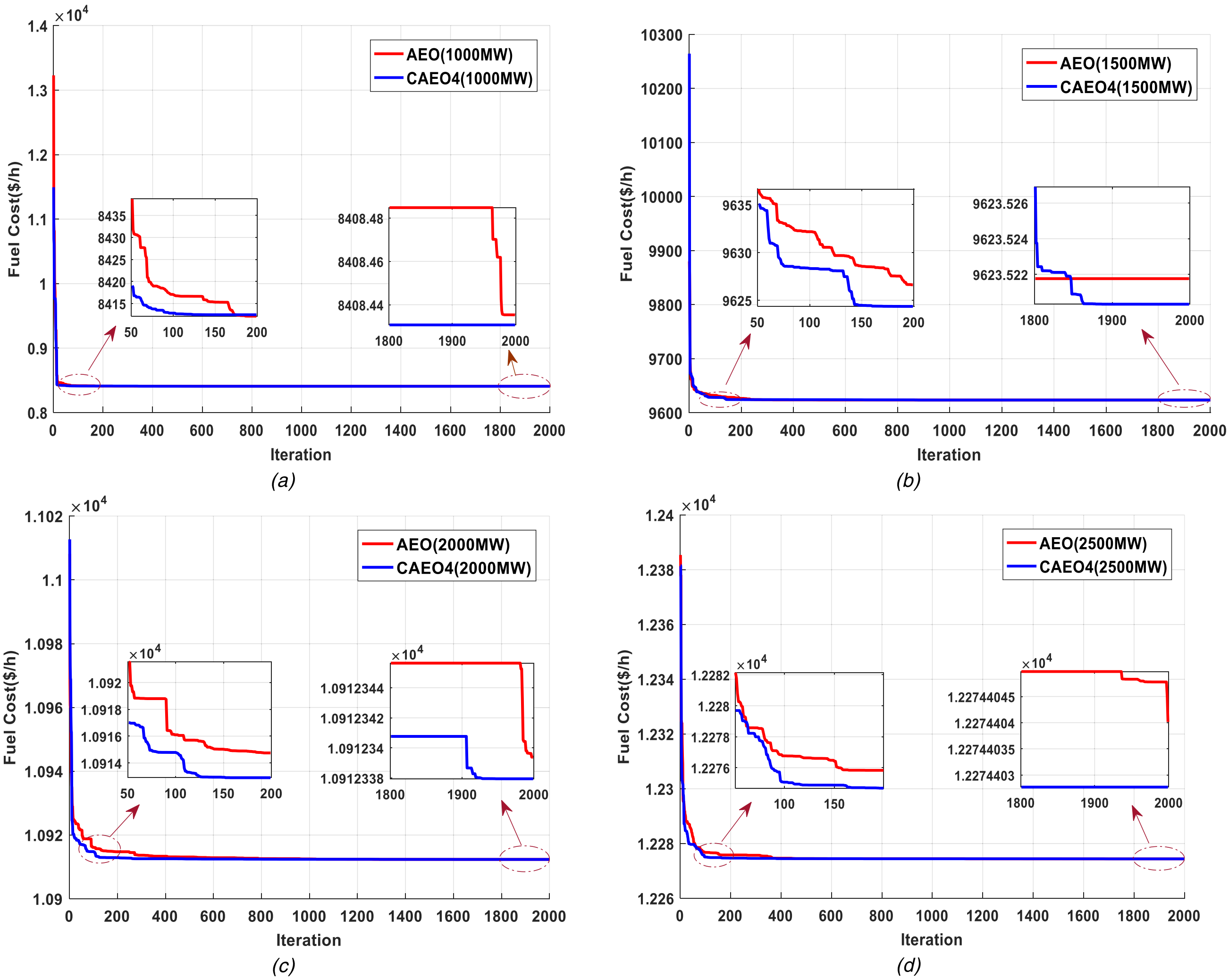


FIGURE 11. Fuel cost convergence curves of AEO and CAEO4 techniques (case study 2) (a) 1000MW (b) 1500MW (c) 2000MW (d) 2500MW.

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

Generating Unit, MW	1000MW AEO	1000MW CAEO4	1500MW AEO	1500MW CAEO4	2000MW AEO	2000MW CAEO4	2500MW AEO	2500MW CAEO4
P1	28.1109	26.9032	38.2802	37.9728	47.6185	47.6678	57.0104	57.0440
P2	20.1227	20.0474	23.1434	23.1548	31.7279	31.2992	40.4182	40.5110
P3	20.0881	20.0000	29.7579	30.1502	43.4838	43.6162	57.6054	58.0006
P4	119.0846	119.5868	174.2851	171.9100	226.1858	225.2687	277.8938	278.1442
P5	44.0101	44.1590	91.7651	92.2375	138.7365	138.5868	187.2295	186.5444
P6	126.3340	120.3953	166.6362	166.4011	208.0531	207.9147	249.7332	249.6237
P7	60.2112	63.4011	101.0234	102.3885	139.8906	139.7655	177.4899	177.3503
P8	166.2222	172.0383	242.3194	242.4297	309.2088	312.7202	380.3062	380.7580
P9	154.6643	153.7968	215.9341	216.3218	278.0736	279.7097	341.2216	341.4758
P10	132.8594	135.7267	213.5000	214.2392	297.6213	296.3373	378.5940	377.8372
P11	128.2927	123.9454	203.3553	202.7944	279.3999	277.1138	352.4965	352.7109
P_T	1000	1000	1500	1500	2000	2000	2500	2500
Fuel cost, \$/h	8408.4353	**8408.4307**	9623.5218	**9623.5203**	10912.3394	**10912.3379**	12274.4032	**12274.4028**
Emission, ton/h	369.9576	368.8915	821.0156	819.0274	1541.7568	1541.4073	2541.9545	2540.7367
Computation time (s)	4.6609	4.6550	4.6613	4.6579	4.8261	4.7930	4.8812	4.8626

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

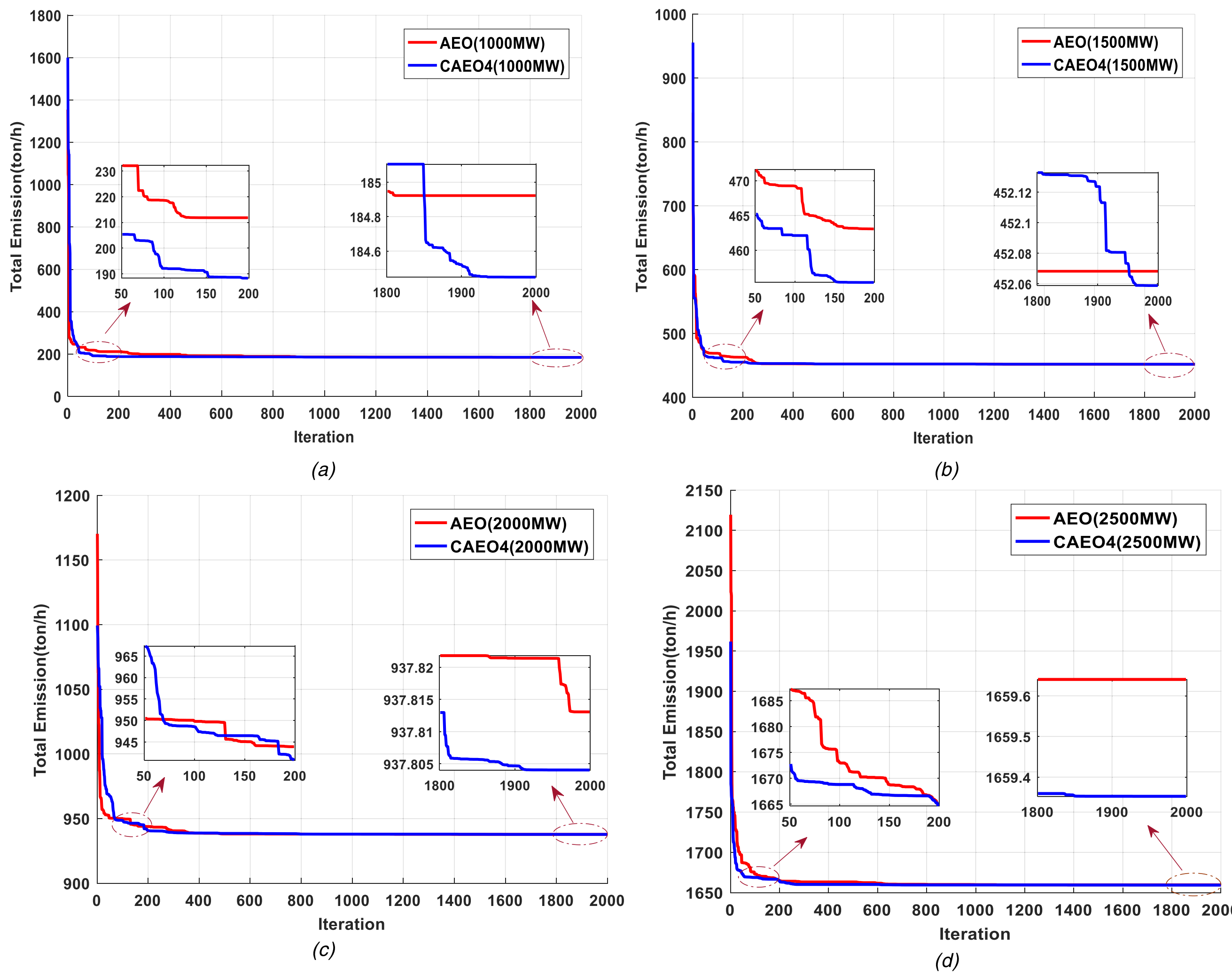


FIGURE 12. Total emisssion convergence curves of AEO and CAEO4 techniques (case study 2) (a) 1000MW (b) 1500MW (c) 2000MW (d) 2500MW.

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	58.0006
P4	277.6793	277.6343	279.6482	279.8546	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	379.3367	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	12274.42	**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

total emission with different load demand than the AEO algorithm.

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 is fast, smooth and smoothly reach to the optimal value of objective function, compared with the original AEO.

TABLE 18. Results of the Total Emission for the 11-unit system using AEO and CAEO4.

Generating Unit, MW	1000MW		1500MW		2000MW		2500MW	
	AEO	CAEO4	AEO	CAEO4	AEO	CAEO4	AEO	CAEO4
P1	114.9310	115.6166	170.3952	169.9899	222.3402	222.5858	250.0000	250.0000
P2	110.4444	106.6322	157.8394	157.9584	203.2599	203.9822	210.0000	210.0000
P3	108.5783	117.1041	168.7295	171.1396	222.5538	223.4453	249.9905	250.0000
P4	63.5394	62.9325	95.1658	94.9936	127.2490	127.3814	170.6799	166.5864
P5	50.0853	48.1375	77.0199	76.7260	105.7898	105.9247	145.3686	142.1694
P6	61.4376	60.9420	95.2664	94.0723	126.8799	126.9826	166.7993	166.7366
P7	47.0821	47.2607	76.9046	76.9785	105.3808	105.8052	142.5525	142.0880
P8	116.3723	117.6070	178.7900	177.4586	239.7585	238.9238	313.1171	316.3717
P9	105.8973	103.2849	158.6913	157.6715	210.4395	209.8031	274.0111	276.1787
P10	110.0000	110.0001	164.2761	164.2563	226.9829	225.8490	305.3927	302.5881
P11	111.6323	110.4824	156.9217	158.7554	209.3656	209.3168	272.0884	277.2812
P_T	1000	1000	1500	1500	2000	2000	2500	2500.0000
Fuel cost, $/h	8606.9017	8610.7957	10042.1191	10045.6046	11607.8374	11612.4854	13046.2434	13046.8016
Emission, ton/h	184.9225	**184.4483**	452.0682	**452.0588**	937.8131	**937.8040**	1659.6402	**1659.3528**
Computation time (s)	4.92856	4.82575	5.04369	4.84046	4.89423	4.80766	7.88432	7.81721

TABLE 19. The best solution values for the Total Emission of the case study 2.

Generating Unit, MW	HAS	DE	PSO	GA	ISA	CSAISA	AEO	CAEO4
P1	249.5765	249.2256	249.3756	249.2323	249.5639	250.0000	250.0000	250.0000
P2	209.2341	209.0785	209.5345	209.1423	209.5641	209.9829	210.0000	210.0000
P3	248.7676	248.6894	248.0876	248.4236	248.9627	250.0000	249.9905	250.0000
P4	169.0712	169.0586	169.8945	169.6453	169.6364	169.9912	170.6799	166.5864
P5	145.5326	145.2794	145.0675	145.9786	145.8813	142.9608	145.3686	142.1694
P6	171.6924	171.5923	171.5547	171.3854	171.0137	166.0797	166.7993	166.7366
P7	145.3356	145.4902	145.2246	145.3782	145.8453	142.2710	142.5525	142.0880
P8	300.5643	300.4168	300.1156	300.2742	300.8375	316.6614	313.1171	316.3717
P9	275.5923	275.4901	275.3345	275.1153	275.8335	275.4746	274.0111	276.1787
P10	300.2686	300.4233	300.6754	300.7655	300.7452	300.8140	305.3927	302.5881
P11	282.2216	282.5901	282.5646	282.3766	282.1124	275.7644	272.0884	277.2812
Fuel cost, $/h	13040.46	13040.83	13039.39	13036.95	13041.04	13046.31	13046.2434	13046.8016
Emission, ton/h	1661.96	1661.58	1663.74	1662.96	1661.36	**1659.35**	1659.64	**1659.35**
Time (s)	12.70	12.69	12.73	12.72	12.69	12.66	7.88432	**7.81721**

TABLE 20. The best solution values for the CEED of the case study 2 (2500MW).

Generating Unit, MW	GA similarity	GSA	AEO	CAEO4
P1	138.8618	138.9382	139.7138708	139.5510382
P2	112.1312	110.2728	112.7197442	112.7841557
P3	146.7169	147.9728	145.8199968	145.8042388
P4	222.1041	221.1072	221.7609406	221.6021175
P5	137.1962	137.7986	136.8983313	136.739107
P6	217.3208	217.9015	218.4680741	218.6680504
P7	140.4711	141.3801	140.3670688	140.2660913
P8	348.9008	349.6497	344.7404472	344.9562373
P9	326.5188	327.3178	329.3798993	329.6177547
P10	363.5275	363.4766	363.5154487	363.8805598
P11	346.2508	344.1847	346.6159412	346.1306494
Fuel cost, $/h	12423.7667	12422.66	12424.90013	12424.77517
Emission, ton/h	2003.10456	2003.024	2003.420114	2003.613181
Total Cost, $/h	18953.9567	18954.73	18953.49305	**18953.49162**
Time (s)	-	-	10.8593	**10.4268**

Table 19 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 CSAISA [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 [48], and GSA [49] with 2500MW system demands for

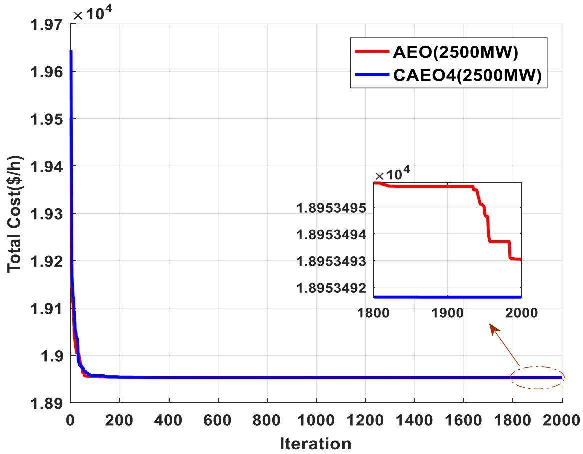


FIGURE 13. **Total cost convergence curves of AEO and CAEO4 techniques (case study (2) - 2500MW).**

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 SO_2, NO_x, and CO_2. 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.

ACKNOWLEDGMENT

The authors thank the support of the National Research and Development Agency of Chile (ANID), ANID/Fondap/ 15110019.

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