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Chaotic self-adaptive interior search algorithm to solve combined economic emission dispatch problems with security constraints

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Summary
The main goal behind the combined economic emission dispatch (CEED) is to reduce the costs incurred upon fuel and emission for the generating units available without any intention to violate the generator and security constraints. Hence, the CEED must be handled after considering two challenging goals such as the costs involved with emission and fuel. In this paper, chaotic self-adaptive interior search algorithm (CSAISA) was proposed to solve the CEED problems, considering the nonlinear behavior of generators in terms of valve point effects, prohibited operating zones, and security constraints. The proposed algorithm was tested for its effectiveness using 11-generating units (without security), IEEE-30 bus system, and IEEE-118 bus system with security constraints. The results of the proposed CSAISA were compared with interior search algorithm (ISA), harmony search algorithm (HSA), differential evolution (DE), particle swarm optimization (PSO), and genetic algorithm (GA). To conclude, the proposed CSAISA outperformed all other algorithms in terms of convergence speed, implementation time, and solution quality, which was tested using performance metrics.

KEYWORDS
chaotic self-adaptive interior search algorithm, combined economic emission dispatch, interior search algorithm, multiobjective optimization problem, performance metrics, security constraints

1 | INTRODUCTION

The sole aim of the combined economic emission dispatch (CEED) is to guarantee both less fuel cost and reduced emission in the available generating units simultaneously. In general, the fossil fuel–based electricity generation methods discharge a lot of pollutants into the atmosphere such as nitrogen oxides, sulfur dioxides, and carbon dioxide. Because of various measures taken after the implementation of "American Clear Air Act" amendments in the year 1990 and other such acts in different countries, the power generation utilities started focusing on environmental protection, whereby its operational procedures were changed to generate maximum electricity at low cost and low pollution level. A number of methods were proposed in the literature[1,2] to minimize the atmospheric emissions. These studies proposed a simple and easy to implement emission dispatch (ED) method that reduces the fuel costs and emission rate simultaneously without any violations in terms of equality and inequality constraints. Numerous conventional optimization techniques have been used to mitigate problems in CEED such as Newton-Raphson, quadratic programming, and continuation and linear programming

(LP) methods.[3] These mathematical methods usually suffer from convergence problem and might operate with the available local best solution. Further, it is also forced to tolerate the dimensionality problem especially in case of large-scale power systems. Recent advances in evolutionary computing techniques have proved that they possess powerful searching capacity to achieve global optimal solutions in complex and multimodel optimization problems. Evolutionary algorithms such as genetic algorithm (GA),[4] evolutionary programming (EP),[5] hybrid EP, LP,[6] and improved particle swarm optimization (IPSO)[7] have been used to solve economic load dispatch (ELD) problems with security constraints as alternative techniques to achieve the best solution when compared with conventional techniques. Evolutionary algorithms seem to exhibit great efficiency in finding solution to nonlinear ELD problems in addition to providing a speedy reliable solution that is suboptimal or nearly the global optimal.[8] In recent studies, a lot of new algorithms were proposed to solve ELD problems, one of which is backtracking search optimization (BSA)[9] method in which two new crossover and mutation operators were introduced to find a global solution. In the literature, Jianzhong et al,[10] the researchers proposed a multiobjective multipopulation–based ant colony optimization to solve continuous domain problems (MMACO_R). This method had Gaussian function–based niche search method in order to improve the Pareto-optimal front solutions' distribution and accuracy. Multiobjective Ɛ-constrained method (ƐBiODE) was proposed earlier,[11] in which multiobjective optimization techniques were hybridized with Ɛ-constrained method so as to arrive at the optimal solution. Real-coded chemical reaction (RCCRO) algorithm was proposed in the study[12] in which the algorithm mimics the molecular interaction as in the chemical reaction so as to achieve the low energy (global) state. Modulated particle swarm optimization (MPSO)[13] was proposed by researchers in which a special truncated sinusoidal constriction function was introduced to control the velocity of particles. Comprehensive learning strategy was introduced to enhance the learning ability of population in hybrid bat algorithm (RCBA).[14] Flower pollination algorithm (FPA) as suggested in the literature[15] has only one key parameter for tuning the algorithm. "Modified artificial bee colony based on chaos" (CIABC) has been introduced in the literature[16] to solve multiobjective optimization problems (MoPs). Symbiotic organisms search (SOS)[17] algorithm has been developed with a new procedure in updating the solutions during iterative process and the elimination of parasitism phase. Chaotic self-adaptive differential harmony search (CSADHS) algorithm was developed in the earlier study[18] to solve MoPs. A modified harmony search method (MHSA)[19] was proposed with a new improved method using wavelet mutation and new memory consideration scheme based on roulette wheel mechanism in order to increase the search capability. Mine blast algorithm (MBA) was discussed in Ali and Elazim[20] to solve MoPs, and other recent search techniques that were proposed to solve ELD, ED, and MoPs are floating search space,[21] enhanced moth-flame optimizer,[22] immune algorithm,[23] multiobjective biogeography–based optimization,[24] artificial bee colony algorithm,[25] ant colony optimization,[26] Franklin and Coulomb law–based algorithm,[27] population variant differential evolution,[28] stochastic fractal search algorithm,[29] quantum-inspired particle swarm optimization (QPSO),[30] quadratic approximation–based hybrid artificial cooperative search algorithm,[31] opposition-based harmony search algorithm (OHS),[32] spiral optimization algorithm,[33] chaotic firefly algorithm,[34] mixed integer optimization problem,[35] stochastic weight trade-off chaotic Non-dominated Sorting Particle Swarm Optimization (NSPSO),[36] and interior search algorithm (ISA).[37] Generally, there is no satisfactory performance registered from meta-heuristic algorithm in the multimodel fitness landscapes. This might be due to the reason that it gets confined to the local optima. So a number of investigations are being conducted to enhance the performance of this meta-heuristic algorithm through novel strategical implementation. Apart from this, security constraints have not been taken into account in many the research works. So, in the current research work, the researchers proposed a new chaotic self-adaptive interior search algorithm (CSAISA) method after considering the security constraints to explore the proposed algorithm's performance on 11-generating units (without security) and IEEE-30 bus and IEEE-118 bus systems. The performance of the proposed algorithm was compared with ISA, HSA, differential evolution (DE), PSO, and GA. The compromised solutions were generated using weighted sum method, and the best compromised solution (BCS) was chosen using fuzzy logic. The proposed CSAISA produced better quality solutions, which was inferred by conducting performance metric analysis for ELD, ED, and CEED problems considered in the study and the exhibited speedy convergence characteristics that took lesser computational time.

2 | FORMULATION OF CEED PROBLEM (FORMULAE)

2.1 | Minimization of fuel cost

Minimize

$$\mathrm{F_{t,cost}} = \mathrm{F_i(P_i)} = \sum_{i=1}^{N} = \mathrm{F}_i(\mathrm{P_i}) = \mathrm{a_i} + \mathrm{b_iP_i} + \mathrm{c_iP_i^2} + |\mathrm{e_i}\sin(\mathrm{f_i}{*}(\mathrm{P_i},\ \min - \mathrm{P_i})| \tag{1}$$

where the fuel cost of the ith generation is denoted by $F_i(P_i)$ and the total fuel cost is expressed through $F_{t,cost}$. The fuel cost coefficients of the ith unit are a_i, b_i, c_i, e_i, and f_i with valve point effects. In the formula above, P_i denotes the power output of the ith generator whereas the total number of generating units is expressed through N.

2.2 | Minimization of emission

The total emission F_2 can be expressed as follows:

$$F_2 = E_i(P_i) = \sum_{i=1}^{N} 10^{-2}\left(\alpha_i + \beta_i P_i + \gamma_i P_i^2\right) + \delta_i \exp(\lambda_i P_i) \tag{2}$$

where the ith generator's emission curve coefficients are denoted as α_i, β_i, γ_i, δ_i, and $\lambda_{i.}$

2.3 | Real power balance constraint

The power balance equation of the system is as follows:

$$\sum_{i=1}^{N} P_i = P_D + P_L \tag{3}$$

where P_L denotes the total loss and P_D denotes the total demand. Using Equations 4 and 5, the power loss can be calculated as follows:

$$P_i - P_{di} = \sum_{j=1}^{Nb} |V_i||V_j|Y_{ij}|\mathrm{Cos}\left(\theta_{ij} - \delta_i + \delta_j\right), \ i = 1, ..., Nb \tag{4}$$

$$Q_{gi} - Q_{di} = \sum_{j=1}^{Nb} |V_i||V_j|Y_{ij}|\mathrm{Sin}\left(\theta_{ij} - \delta_i + \delta_j\right), \ i = 1, ..., Nb \tag{5}$$

where P_i denotes the real power production at bus i, P_{di} denotes the real power requirement at bus i whereas the reactive power production at bus i is denoted through Q_{gi}, Q_{di} denotes the reactive power requirement at bus i, $|V_j|$ denotes the voltage level at bus j, $|V_i|$ denotes the voltage level at bus i, $|Y_{i\,j}|$ is the magnitude of the ijth element of Ybus, $\theta_{i\,j}$ is the angle of the ijth element of Ybus, the total number of buses is denoted by Nb, δ_i is the voltage angle at bus i, and δ_j is the voltage angle at bus j. The system inequality limitations $h\ (x,\ u)$ are as follows:

2.4 | Generation limit constraint

Every unit's electrical power output must fall between the minimum and maximum values, which are defined and given below.

$$P_{i,\min} \le P_i \le P_{i,\max} \text{ for } i = 1, 2, 3, ..., N \tag{6}$$

where $P_{i,\min}$ and $P_{i,\max}$ are the minimum and maximum power limits of ith generator.

2.5 | Prohibited operating zones

$$P_{\mathrm{i}} = \begin{bmatrix} P_{\mathrm{i,\,min}} \le P_{\mathrm{i}} \le P_{\mathrm{i,1}}^{\mathrm{L}} & \text{or} \\ P_{\mathrm{i,k-1}}^{\mathrm{U}} \le P_{\mathrm{i}} \le P_{\mathrm{i,k}}^{\mathrm{L}} & \text{or} \\ P_{\mathrm{i,n_i}}^{\mathrm{U}} \le P_{\mathrm{i}} \le P_{\mathrm{i,\,max}}, & k = 2,\,3,\,\ldots,\,n_{\mathrm{i}} \end{bmatrix} \tag{7}$$

2.6 | Security constraints

Security constraints considered are load bus voltages, transmission line flow, and their bounds, which are given herewith:

$$V_{\mathrm{i,\,min}} \le V_{\mathrm{i}} \le \mathrm{V}_{\mathrm{i,\,max}} \qquad \text{for i} = 1,\,2,\,3,\,\ldots,\,\mathrm{NB} \tag{8}$$

$$\mathrm{LF}_{\mathrm{i,j}} \le \mathrm{LF}_{\mathrm{i,j}}^{\mathrm{max}}, \qquad \mathrm{i} = 1,\,\ldots,\,\mathrm{NL} \text{ and } \mathrm{j} = 1,\,\ldots,\,\mathrm{NL} \tag{9}$$

where $V_{i,\mathrm{min}}$and $V_{i,\mathrm{max}}$ denote the minimum and maximum voltage limits of ith PQ bus. NB is the total number of PQ busses. $\mathrm{LF}_{i,j}$ is apparent power flow from ith bus to jth bus. $\mathrm{LF}_{i,j}^{\mathrm{max}}$ denotes the highest rating of transmission line connecting bus i and j. The total number of transmission lines is denoted by NL.

2.7 | Calculation of fitness function value

The fitness value is calculated as given below:

$$\mathrm{F}_1 = \mathrm{F}_{\mathrm{t,cost}} + \lambda_{\mathrm{eq}}\left(\sum_{\mathrm{i=1}}^{N} P_{\mathrm{i}} - P_{\mathrm{D}} - P_{\mathrm{L}}\right)^2 + \lambda_{\mathrm{poz}}\left(\sum_{\mathrm{i=1}}^{N}\left(P_{\mathrm{poz}}^{\mathrm{limit}}\right)\right)^2 + \lambda_V\left(\sum_{\mathrm{i=1}}^{\mathrm{NB}}\left(V_{\mathrm{i}}^{\mathrm{limit}}\right)\right)^2 + \lambda_{\mathrm{LF}}\left(\sum_{\mathrm{i=1}}^{\mathrm{NL}}\left(\mathrm{LF}_{\mathrm{i,j}}^{\mathrm{limit}}\right)\right)^2 \tag{10}$$

As per Equation 10, $V_i^{\mathrm{limit}}$and $V_{i,\mathrm{max}}$ are meant to be equal, and if in case V_i is higher than the maximum limit and if V_i is lesser than the minimum limited defined, then it should be defined as $V_{i,\mathrm{min}}$. Following is the information regarding penalty factor values.

Test System	λ_{eq}	λ_{poz}	λ_V	λ_{LF}
11-units	1000	–	–	–
IEEE-30 bus	1000	1000	500	500
IEEE-118 bus	2000	1500	500	500

Through the following equations, the inequality constraints limits can be calculated.

$$P_{poz}^{limit} = \begin{bmatrix} \min\left(P_{\mathrm{i}} - P_{\mathrm{i,k}}^{\mathrm{L}}, P_{\mathrm{i,k}}^{\mathrm{U}} - P_{\mathrm{i}}\right), & \text{if } \mathrm{P}_{\mathrm{i,k}}^{\mathrm{L}} \le P_{\mathrm{i}} \le P_{\mathrm{i,k}}^{\mathrm{U}} \\ 0 & \text{otherwise} \end{bmatrix} \tag{11}$$

$$\mathrm{LF}_{\mathrm{i,j}}^{\mathrm{limit}} = \begin{bmatrix} 1 & \text{if } \mathrm{LF}_{\mathrm{i,j}} \ge \mathrm{LF}_{\mathrm{i,j}}^{\mathrm{max}} \\ 0 & \text{otherwise} \end{bmatrix} \tag{12}$$

2.8 | CEED problem

The formulation of CEED problem is as follows:

$$\text{Minimize C}\,(\mathrm{F_1}, \mathrm{F_2}) \tag{13}$$

where F_1 denotes the objective function to minimize cost and F_2 denotes the objective function for emission minimization. By introducing price penalty factor via (h), the bi-objective CEED problem can be changed into singular objective optimization problem and is given in Equation 14. The procedure to calculate "h" value is given in Venkatesh et al.[5]

$$\text{Minimize } \mathrm{F_t} = \sum_{i=1}^{N} (w^*\mathrm{F_1} + \mathrm{h}^*(1 - w)^*\mathrm{F_2}) \tag{14}$$

Here, the "w" value denotes the "objective function," which is given more significance. If the value of w is equal to 1, the problem turns into classical ELD and reduces only the fuel cost. If zero value is assigned to w, then the problems change to ED, which decreases only the emission. The w value is reduced in CEED from steps 1 to 0, and for each decrement, a compromised solution is created. Finally, the fuzzy selection method, as mentioned in Section 2.9, is utilized to determine the BCS from a group of solutions. The fuel cost value increases and the emission rate decreases simultaneously when w is decreased in a step-by-step manner.

2.9 | Selection of best compromised solution

The solution achieved from single objective function cannot be enhanced without losing the solution accuracy of the other objective. For practical implementation, one solution has to be selected from a set of compromised solutions such that it fulfills all the objectives to some level; such a solution is known as the BCS. It is important to choose BCS among the available ones, and decision making plays a significant role here. Here, the fuzzy method was chosen to select one BCS. Since the situation was vague at the time of decision-making process, the ith objective function f_i of individual k is denoted through a membership function, ie, μ_i^k as defined earlier in Equation 15:

$$\mu_i^k = \begin{cases} 1 & f_i \le f_i^{min} \\ \dfrac{f_i^{max} - f_i}{f_i^{max} - f_i^{min}} & f_i^{min} < f_i < f_i^{max} \\ 0 & f_i \ge f_i^{max} \end{cases} \tag{15}$$

For every nondominated solution k, the researchers considered standardized membership function μ^k as per Equation 16.

$$\mu^k = \frac{\sum_{i=1}^{NF} \mu_i^k}{\sum_{k=1}^{p} \sum_{i=1}^{NF} \mu_i^k} \tag{16}$$

In the equation, the number of objective functions is denoted through NF whereas the number of nondominated solutions is denoted via p. The BCS can be identified when the solution has the maximum value of μ^k.

3 | LOGISTIC MAP METHOD TO PRODUCE CHAOTIC VARIABLES

Chaos occurs in nonlinear dynamic system. It has deterministic value, random-like movement, nonperiod characteristics and is surrounded. It is more sensitive to its preliminary condition. The performance of heuristic optimization algorithm can be enhanced by combining the chaotic variables generated by logistic map.[38] The expression of logistic map is given in Equation 17.

$$\alpha_{n+1} = 4^*\alpha_n{}^*(1 - \alpha_n) \tag{17}$$

where α_n is a chaotic variable. It is distributed between [0, 1]. The initial conditions to generate chaotic variable are $\alpha_n \in$ (0, 1) and $\alpha_n \notin$ {0, 0.25, 0.5, 0.75, 1}, where "n" denotes the iteration number.

4 | CHAOTIC SELF-ADAPTIVE INTERIOR SEARCH ALGORITHM—AN INTRODUCTION

Being an optimization technique, ISA has two stages and is primarily motivated by decoration and interior design.[39] The initial stage is "composition stage" where the composition of elements (solution vectors) is altered to get an environment that looks enhanced (better fitness value). The final stage is mirror search in which it mimics the work of the mirror worker. The mirror worker utilizes different mirrors to create a more attractive environment. It is imperative that the mirrors are positioned in such a way that it is present in between "each element" and the "fittest element" in order to bring furthermore catchy environment. The details about ISA, algorithm steps, and pseudo code are given in the literature.[39] The advantage of ISA with that of other algorithms is that it has only one tuning parameter (α). Normally, an optimal α value is chosen from 0 to 1. In the proposed CSAISA, the tuning parameter α value was generated between 0 and 1 using logistic map method, and the value of α gets self-adaptively changed on the basis of the fitness values obtained. The flow chart for the proposed CSAISA is shown in Figure 1.

4.1 | Summary of computational steps of CSAISA for CEED problem

Step 1: Read system data.

Start $w = 1$ to 0 with a decrement value of −0.001.

Step 2: Randomly generate elements (solutions) between lower bound (LB) and upper bound (UB). Check equality and inequality constraints violation for all the elements. If any of the elements violate, it is penalized. The fitness value is calculated for all the elements along with embedded penalizing method as given in (10).

Step 3: The variant with the finest fitness is portrayed as the global best, which is referred as ${x_{gb}}^j$, where j and gb represent jth iteration and global best solution, respectively.

Step 4: Generate α value using logistic map. This procedure is detailed under Section 3.

Step 5: The elements are to be divided in a random manner such as mirror group and composition group. If in case, the value of r (rand) is below α, then the element is placed under mirror group, and if not, it is segregated under composition group.

Step 6: In the composition group, the element values are altered within the narrow search space using (18).

$$x_i^j = LB^j + \left(UB^j - LB^j\right) r_2 \tag{18}$$

Step 7: In mirror group, a mirror is placed at any place, ie, in a random manner in between each element and the global best solution. According to Equation 19, the mirror location for ith element in the jth iteration is provided herewith.

$$x_{m,i}^j = r_3 x_i^{j-1} + (1 - r_3) x_{gb}^j \tag{19}$$

The location of the image for every element is based on the mirror location, which can be devised as follows:

$$x_i^j = 2x_{m,i}^j - x_i^{j-1} \tag{20}$$

Step 8: To some extent, the position of the global best solution gets modified using random walk, which is in association with local search.

$$x_{gb}^j = x_{gb}^{j-1} + \lambda r_n \tag{21}$$

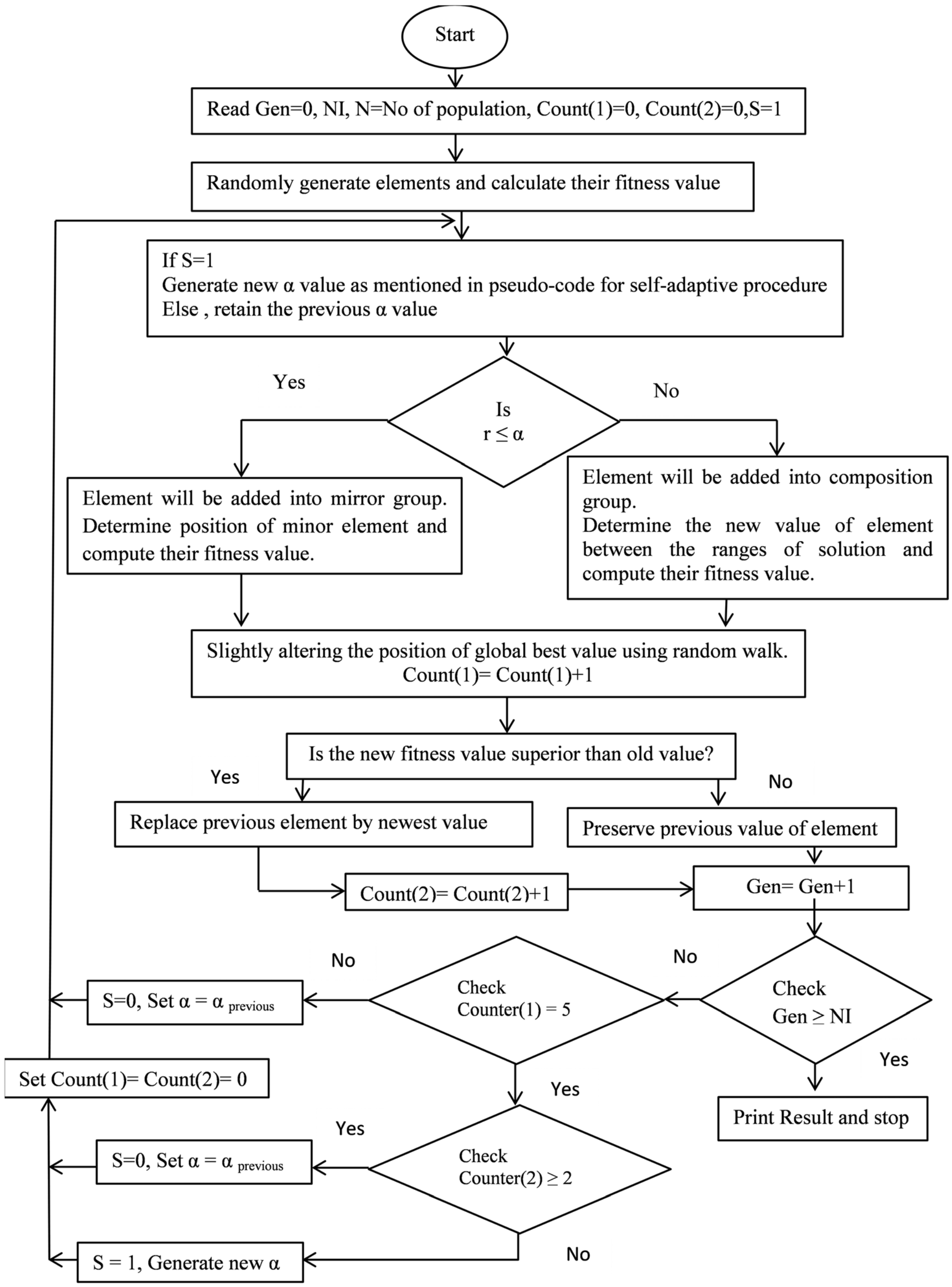

FIGURE 1 Flow chart for combined economic emission dispatch (CEED) problem using the proposed chaotic self-adaptive interior search algorithm (CSAISA)

In the above equation, the scale factor, which is decided on the basis of solution space size, is denoted through λ. Here, λ is considered as the value of $0.01 \times (\mathrm{UB} - \mathrm{LB})$ whereas r_n denotes the random value from 0 to 1.

Step 9: Determine the fitness values for new locations of the elements and images. Check for violation in equality and inequality constraints. If the fitness value of new location is superior, then replace the previous best with the fitness value of new location. Otherwise, previous best is to be preserved.

Step 10: Check for maximum number of iterations, and once the maximum is reached, the algorithm should be stopped, and the results are to be printed. Otherwise, count (1) is verified whether it reached the preset value, which was 5. If different (set $S = 0$), then step 4 must be followed in which the next iteration is performed without changing the "α" value. Alternatively, if it is a yes, then count (2) needs to be verified whether it reached the preset value "2."

If different (set $S = 1$), then counts (1) and (2) are to be reset and step 4 must be followed. A new α value is produced for the following iteration. If yes (set $S = 0$; reset count (1) and count (2)), then go to step 4. The next iteration is to be executed without any change in the "α" value. The steps from 4 to 9 are to be repeated until the stopping criterion is reached, and it should be ended for weight w loop.

Step 11: The compromised solution is nothing but the result obtained at every w value, and the BCS is chosen on the basis of the fuzzy logic method.

5 | ANALYSIS OF SOLUTION QUALITY

The performance evaluations of MoP are more complicated. To examine and compare the performance of MoP techniques, there are several metrics suggested in the literature. Here, three metrics, namely, generational distance (GD), spacing (SP), and diversity metric (D-metric), were considered to evaluate the performance of the proposed algorithm with other algorithms considered. These metrics are highly helpful in the evaluation of closeness to the true or reference Pareto-optimal front. Further, these are also helpful in the measurement of diversity among the nondominated solutions.

5.1 | Generational distance

This method was proposed by van Veldhuizen and Lamont[40] in order to analyze the value of being far off the elements in the set of nondominated vectors identified from the Pareto-optimal set. This is denoted as

$$\mathrm{GD} = \frac{\sqrt{\sum_{\mathrm{i}=1}^{n} d_{\mathrm{i}}^{2}}}{n} \tag{22}$$

where n denotes the number of vectors in the set of nondominated solutions found. The Euclidean distance (measured in objective space) is denoted by d_i and is measured as the distance between each of these solutions and the nearest member of the Pareto-optimal set. It is evident that the value of $\mathrm{GD} = 0$ denotes that the generated elements are placed under Pareto-optimal set. In case of small GD value, it can be understood that it has a better convergence to the Pareto front.

5.2 | Spacing

Distribution of the Pareto solutions is another critical factor in these Pareto fronts. This finds out the distance between the neighboring points in the nondominated Pareto solution set.[41] This is calculated as follows:

$$\mathrm{SP} \triangleq \sqrt{\frac{1}{\mathrm{S}-1} \sum_{\mathrm{i}=1}^{\mathrm{S}} \left(\bar{\mathrm{d}} - \mathrm{d}_{\mathrm{i}}\right)^{2}} \tag{23}$$

TABLE 1 Optimal parameters of proposed and other algorithms

Algorithm	Control Parameters Case 1 (N = 20, NI = 2000)	Case 2 (N = 30, NI = 500)	Case 3 (N = 30, NI = 2000)
CSAISA	$\alpha_n = 0.21$	$\alpha_n = 0.27$	$\alpha_n = 0.26$
ISA	$\alpha = 0.22$	$\alpha = 0.22$	$\alpha = 0.22$
DE	$F = 0.2$	$F = 0.2$	$F = 0.2$
HSA	HMCR = 0.8, PAR = 0.4, $b = 0.012$	HMCR = 0.8, PAR = 0.4, $b = 0.012$	HMCR = 0.8, PAR = 0.4, $b = 0.012$
PSO	C1 = 2, C2 = 2, $W = 1$	C1 = 2, C2 = 2, $W = 1$	C1 = 2, C2 = 2, $W = 1$
GA	Pc = 0.95, Pm = 0.05	Pc = 0.95, Pm = 0.05	Pc = 0.95, Pm = 0.05

Abbreviations: CSAISA, chaotic self-adaptive interior search algorithm; DE, differential evolution; GA, genetic algorithm; HMCR, harmony memory consideration rate; HSA, harmony search algorithm; ISA, interior search algorithm; PAR, pitch adjusting rate; PSO, particle swarm optimization.

where

$$d_i = \min_j \left(\sum_{k=1}^{NF} |X_{ki} - X_{ki}| \right), \ i, \ j = 1, 2, \ldots, S \tag{24}$$

TABLE 2 Optimal generation schedule for ELD for case 1

Generating Unit, MW	Best Fuel Cost					
	Proposed CSAISA	**ISA**	**HSA**	**DE**	**PSO**	**GA**
P_1	56.9465	57.3520	56.5750	57.5683	57.6582	57.4565
P_2	40.5882	40.3501	41.7558	39.8234	41.7560	40.7339
P_3	57.9381	58.5628	58.8239	57.3622	57.0840	60.6382
P_4	277.9182	278.7029	277.6793	277.6343	279.6482	279.8546
P_5	186.7996	189.2024	189.5183	189.2732	189.7429	191.7492
P_6	249.2460	249.5435	250.1128	249.9246	249.7420	249.2131
P_7	177.6527	176.0364	176.9563	175.6345	176.6402	178.2341
P_8	380.7402	379.9651	379.8753	378.7465	377.7493	379.3367
P_9	341.7721	340.7782	341.0440	340.8126	341.8462	344.1547
P_{10}	377.8633	378.8541	379.8564	378.1122	378.7465	378.6473
P_{11}	352.5351	350.6525	351.6593	352.8493	350.8284	353.6394
Fuel cost, $/h	**12274.40**	**12274.42**	**12275.46**	**12277.92**	**12276.42**	**12278.42**
Emission, ton/h	2540.41	2539.69	2538.76	2538.74	2534.69	2531.32
Time, s	12.64	12.65	12.65	12.68	12.69	12.71

Abbreviations: CSAISA, chaotic self-adaptive interior search algorithm; DE, differential evolution; ELD, economic load dispatch; GA, genetic algorithm; HSA, harmony search algorithm; ISA, interior search algorithm; PSO, particle swarm optimization.

Bold indicates the best solutions generated by each methods.

TABLE 3 Optimal generation schedule for ED for case 1

Generating Unit, MW	Best Emission					
	Proposed CSAISA	**ISA**	**HSA**	**DE**	**PSO**	**GA**
P_1	250.0000	249.5639	249.5765	249.2256	249.3756	249.2323
P_2	209.9829	209.5641	209.2341	209.0785	209.5345	209.1423
P_3	250.0000	248.9627	248.7676	248.6894	248.0876	248.4236
P_4	169.9912	169.6364	169.0712	169.0586	169.8945	169.6453
P_5	142.9608	145.8813	145.5326	145.2794	145.0675	145.9786
P_6	166.0797	171.0137	171.6924	171.5923	171.5547	171.3854
P_7	142.2710	145.8453	145.3356	145.4902	145.2246	145.3782
P_8	316.6614	300.8375	300.5643	300.4168	300.1156	300.2742
P_9	275.4746	275.8335	275.5923	275.4901	275.3345	275.1153
P_{10}	300.8140	300.7452	300.2686	300.4233	300.6754	300.7655
P_{11}	275.7644	282.1124	282.2216	282.5901	282.5646	282.3766
Fuel cost, $/h	13046.31	13041.04	13040.46	13040.83	13039.39	13036.95
Emission, ton/h	**1659.35**	**1661.36**	**1661.96**	**1661.58**	**1663.74**	**1662.96**
Time, s	12.66	12.69	12.70	12.69	12.73	12.72

Abbreviations: CSAISA, chaotic self-adaptive interior search algorithm; DE, differential evolution; ED, emission dispatch; GA, genetic algorithm; HSA, harmony search algorithm; ISA, interior search algorithm; PSO, particle swarm optimization.

Bold indicates the best solutions generated by each methods.

$\bar{d}$ denotes the mean of all d_i. S denotes the number of nondominated vectors found so far, and the number of objectives is denoted via NF. When this metric has zero or less than zero value, it is understood that the members of Pareto front are equally spaced in their current positions. This metric can be used to measure whether the solutions are distributed in a uniform and smooth manner.

5.3 | Diversity metric

In spite of the fact that there is no optimal Pareto front required for this metric, it has a correlation with Hamming and Euclidean distance between solutions.[42] In a scenario where S number of points is available on a Pareto front and the space is N-dimensional (no. of objectives), then the centroid C_i for ith dimension is given by

TABLE 4 Optimal generation schedule for CEED for case 1

Generating Unit, MW	BCS					
	Proposed CSAISA	ISA	HSA	DE	PSO	GA
P_1	145.8432	147.0312	146.4564	147.5733	147.3745	146.3641
P_2	125.7652	126.6103	126.3841	126.6855	123.1573	126.6463
P_3	168.9363	170.6024	171.2867	170.2890	170.4892	171.6452
P_4	201.5166	199.9273	199.4352	199.7902	197.3367	199.9956
P_5	163.2154	163.0421	164.6445	163.4531	164.3689	163.0023
P_6	199.0507	198.9784	198.7285	198.0701	198.7900	196.3217
P_7	161.9231	161.8036	161.2784	161.2265	161.8462	161.3521
P_8	358.6520	357.9313	356.5635	357.5873	357.6421	357.4533
P_9	313.6074	315.8803	315.7464	315.1890	316.6904	315.5623
P_{10}	345.6316	344.5631	345.7463	344.3781	343.5687	345.4421
P_{11}	315.8764	313.6583	313.2636	313.5834	314.5903	312.4628
Fuel cost, $/h	**12476.29**	**12532.83**	**12535.67**	**12536.84**	**12538.12**	**12568.83**
Emission, ton/h	**1913.96**	**1926.86**	**1930.74**	**1926.89**	**1926.65**	**1936.76**
Time, s	12.69	12.70	12.70	13.08	12.72	12.69

Abbreviations: BCS, best compromised solution; CEED, combined economic emission dispatch; CSAISA, chaotic self-adaptive interior search algorithm; DE, differential evolution; GA, genetic algorithm; HSA, harmony search algorithm; ISA, interior search algorithm; PSO, particle swarm optimization.

Bold indicates the best solutions generated by each methods.

TABLE 5 Comparison of result for case 1

Method	Best Fuel Cost		Best Emission		BCS	
	Fuel Cost, $/h	Emission, ton/h	Fuel Cost, $/h	Emission, ton/h	Fuel Cost, $/h	Emission, ton/h
Proposed CSAISA	**12274.40**	2540.41	13046.31	**1659.35**	**12476.29**	**1913.96**
ISA	**12274.42**	2539.69	13041.04	**1661.36**	12532.83	1926.86
HSA	**12275.46**	2538.76	13040.46	**1661.96**	12535.67	1930.74
DE	**12277.92**	2538.74	13040.83	**1661.58**	12536.84	1926.89
PSO	**12276.42**	2534.69	13039.39	**1663.74**	12538.12	1926.65
GA	**12278.42**	2531.32	13036.95	**1662.96**	12568.83	1936.76
DP[44]	–	–	–	–	12424.9400	2003.3000
GSA[45]	–	–	–	–	12422.6626	2002.9499

Abbreviations: BCS, best compromised solution; CSAISA, chaotic self-adaptive interior search algorithm; DE, differential evolution; DP, dynamic programming; GA, genetic algorithm; GSA, gravitational search algorithm; HSA, harmony search algorithm; ISA, interior search algorithm; PSO, particle swarm optimization.

Note: "–" Not available in the referred literature.

Bold indicates the best solutions generated by each methods.

$$C_i = \frac{\sum_{j=1}^{S} x_{ij}}{S}, \tag{25}$$

For $i = 1, 2, ..., N$, x_{ij} denotes the ith dimension of the jth point. Then the diversity measuring D-metric is given by

$$D - \text{metric} = \sum_{i=1}^{N} \sum_{j=1}^{S} \left(x_{ij} - C_i\right)^2 \tag{26}$$

When the D-metric value is high, then the Pareto front diversity is also high.

6 | RESULTS AND DISCUSSIONS

The novel algorithm proposed in the current study was applied in the following test systems to solve ELD, ED, and CEED and to validate the viability and efficiency.

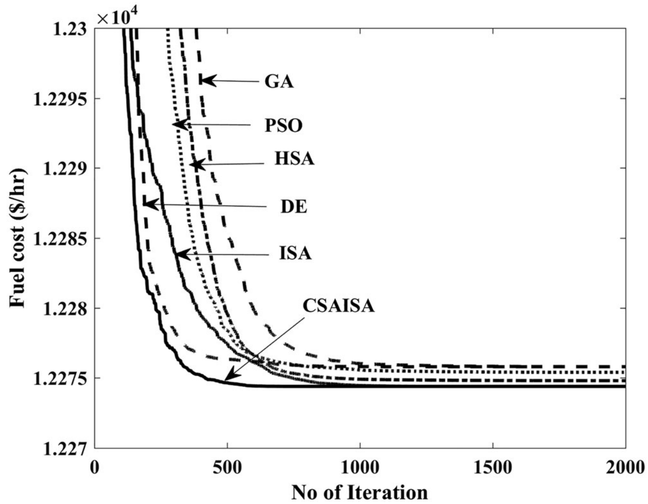

FIGURE 2 Convergence characteristic curve for the ELD (case 1). CSAISA, chaotic self-adaptive interior search algorithm; DE, differential evolution; ELD, economic load dispatch; GA, genetic algorithm; HSA, harmony search algorithm; ISA, interior search algorithm; PSO, particle swarm optimization

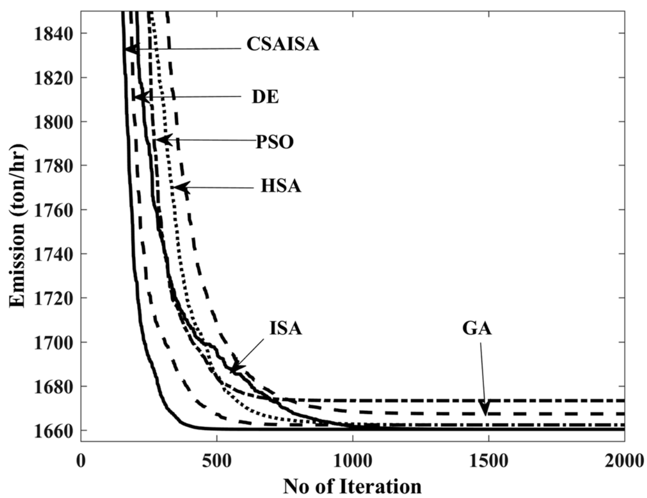

FIGURE 3 Convergence characteristic curve for the ED (case 1). CSAISA, chaotic self-adaptive interior search algorithm; DE, differential evolution; ED, emission dispatch; GA, genetic algorithm; HSA, harmony search algorithm; ISA, interior search algorithm; PSO, particle swarm optimization

Case 1: 11-generating units with quadratic cost curve and without security constraints;
Case 2: IEEE-30 bus system with quadratic cost functions, valve point effects, prohibited operating zones, and security constraints;
Case 3: IEEE-118 bus system with quadratic cost functions, prohibited operating zones, and security constraints.

The proposed and existing algorithms considered for comparison were coded in MATLAB 7.4 and executed in a personal computer configured with 1.6 GHz, Pentium-IV and 4 GB RAM. The optimal control parameters for all the algorithms were obtained by trial and error method and are presented in Table 1.

TABLE 6 Statistical comparison of performance metric (case 1)

Performance Metric	Algorithm	Best	Mean	Worst	Standard Deviation
GD	Proposed CSAISA	0.0176	0.1023	0.2845	0.0028
	ISA	0.2394	0.2865	0.3267	0.0586
	HSA	0.2186	0.3264	0.3365	0.0732
	DE	0.1164	0.2185	0.3056	0.0675
	PSO	0.2296	0.2575	0.3223	0.0787
	GA	0.3286	0.3654	0.3343	0.0853
SP	Proposed CSAISA	0.1037	0.1586	0.3745	0.0172
	ISA	0.2744	0.3659	0.4645	0.0354
	HSA	0.2967	0.3755	0.4754	0.0467
	DE	0.1674	0.2768	0.3863	0.0399
	PSO	0.2985	0.3003	0.4779	0.0671
	GA	0.3856	0.4887	0.5796	0.0725
D-metric	Proposed CSAISA	575	541	534	354
	ISA	467	387	345	316
	HSA	326	295	283	267
	DE	486	432	405	312
	PSO	376	278	258	235
	GA	365	225	214	206

Abbreviations: CSAISA, chaotic self-adaptive interior search algorithm; D-metric, diversity metric; DE, differential evolution; GA, genetic algorithm; GD, generational distance; HSA, harmony search algorithm; ISA, interior search algorithm; PSO, particle swarm optimization; SP, spacing.

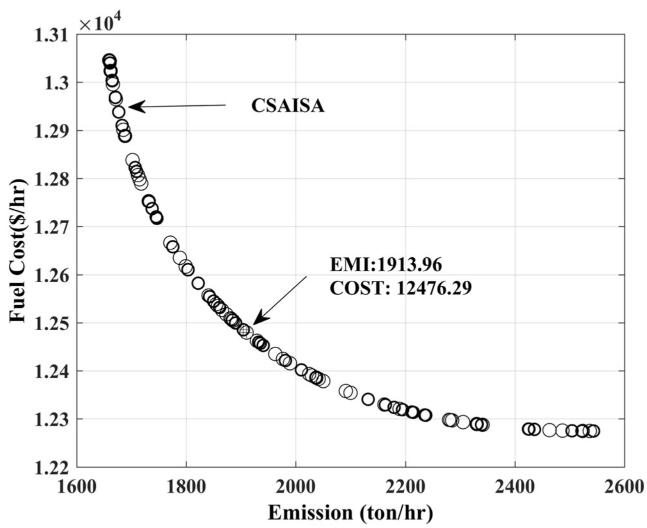

FIGURE 4 Emission-cost trade-off curve obtained using the proposed chaotic self-adaptive interior search algorithm (CSAISA) (case 1)

6.1 | Case 1 (11-generating units)

In this test system, there were 11-generating units consisted of quadratic cost curve and emission function along with it. From the previous study,[43] the costs related to generators, the emission data, and its generation limits were retrieved. The total load demand was 2500 MW. The ELD, ED, and CEED problems were executed as discussed under Section 2.8 using the proposed and existing methods considered. The BCS was selected by applying fuzzy method from the results achieved, ie, by changing the *w* value from 1 to 0 in small steps. The BCS attained using the proposed CSAISA was 12476.29 $/h, and corresponding emission was 1913.96 ton/h. The emission-cost trade-off curve with BCS generated by the proposed CSAISA is presented in Figure 4. The optimal generation schedule achieved using the proposed and existing methods for ELD, ED, and CEED problems is given in Tables 2–4 and also found to be within the limits. The best cost, emission, and BCS obtained by the proposed and other algorithms were compared. The solution found by the proposed CSAISA method was better than all other algorithms and is presented in Table 5. The convergence characteristic curves for the best fuel cost and emission are shown in Figures 2 and 3. It is proven from Figures 2

TABLE 7 Optimal generation schedule obtained for ELD problem (case 2)

Generating Unit, MW	ELD					
	Proposed CSAISA	**ISA**	**HSA**	**DE**	**PSO**	**GA**
P_{g1}	198.4532	199.2870	199.7300	199.3003	199.0203	199.7392
P_{g2}	25.1641	25.0000	25.7594	25.8224	25.7392	25.6400
P_{g5}	19.0000	19.0000	19.2208	19.7292	19.8476	19.8433
P_{g8}	16.1627	19.5201	19.0488	19.6484	19.6392	19.9843
P_{g11}	17.7700	13.0006	13.8583	13.8304	13.7201	13.8443
P_{g13}	14.0000	14.7426	14.0955	14.9498	14.2084	14.9842
P_{Loss}	7.1500	7.1503	7.1535	7.1624	7.1654	7.1682
Fuel cost, $/h	**807.47**	**808.84**	**810.24**	**808.92**	**809.35**	**810.51**
Emission, ton/h	43.62	43.15	42.85	42.36	41.75	39.75
Avg CPU time, min	1.84	1.89	1.94	1.92	1.90	1.91

Abbreviations: CSAISA, chaotic self-adaptive interior search algorithm; DE, differential evolution; ELD, economic load dispatch; GA, genetic algorithm; HSA, harmony search algorithm; ISA, interior search algorithm; PSO, particle swarm optimization.

Bold indicates the best solutions generated by each methods.

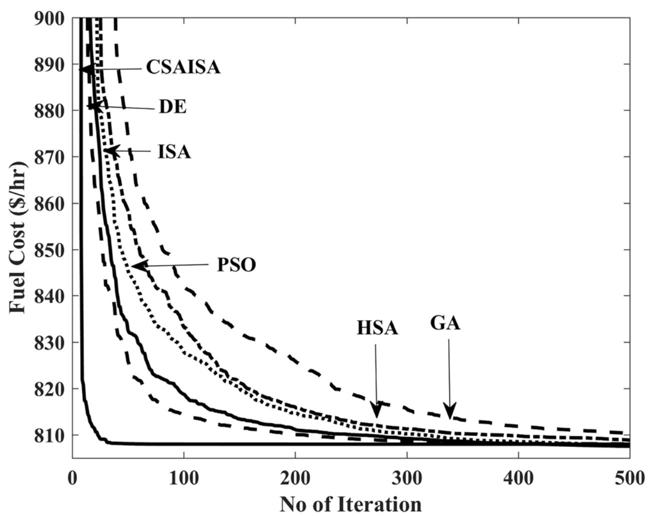

FIGURE 5 Convergence characteristic curve of IEEE-30 bus system for ELD (case 2). CSAISA, chaotic self-adaptive interior search algorithm; DE, differential evolution; ELD, economic load dispatch; GA, genetic algorithm; HSA, harmony search algorithm; ISA, interior search algorithm; PSO, particle swarm optimization

and 3 that the proposed CSAISA has a steady and faster convergence characteristic than other algorithms. In order to further validate the superiority of the proposed algorithm over other algorithms, 100 independent runs were carried out for each performance metrics to check the accuracy and diversity of the nondominated solutions. The best, worst, mean and standard deviation obtained for the GD, SP, and D-metric are shown in Table 6. The best values obtained by the proposed CSAISA for GD and SP were lesser, and D-metric value was higher. From these results, it can be concluded that the proposed algorithm has the capability to generate quality solutions compared with others (Figure 4).

6.2 | Case 2 (IEEE-30 bus system)

The proposed algorithm was tested on IEEE-30 bus system with security constraints, quadratic cost function, valve point loading effects, and prohibited operating zones. In this system, there were totally six thermal generating units with a load demand of 283.4 MW. As per the literature,[46,47] the information regarding line mega volt ampere (MVA) rating

TABLE 8 Optimal generation schedule obtained for ED problem (case 2)

Generating Unit, MW	ED					
	Proposed CSAISA	ISA	HSA	DE	PSO	GA
P_{g1}	85.9097	92.0837	92.4884	92.2984	92.8228	92.8363
P_{g2}	63.7636	61.0296	61.2975	61.0821	61.2029	61.2084
P_{g5}	47.9061	49.0000	49.9755	49.4283	49.8476	49.2928
P_{g8}	30.0000	30.0000	30.0484	30.4973	30.8373	30.6382
P_{g11}	27.9705	23.4368	23.1921	23.0283	23.9728	23.8635
P_{g13}	35.0000	35.0000	35.9483	35.4084	35.1123	35.7453
P_{Loss}	7.1499	7.1501	7.1515	7.1563	7.1574	7.1594
Fuel cost, $/h	918.58	911.68	911.26	911.47	910.68	910.28
Emission, ton/h	**21.75**	**22.78**	**22.24**	**21.88**	**22.18**	**22.98**
Avg CPU time, min	1.83	1.90	1.91	1.91	1.92	1.91

Abbreviations: CSAISA, chaotic self-adaptive interior search algorithm; DE, differential evolution; ED, emission dispatch; GA, genetic algorithm; HSA, harmony search algorithm; ISA, interior search algorithm; PSO, particle swarm optimization.

Bold indicates the best solutions generated by each methods.

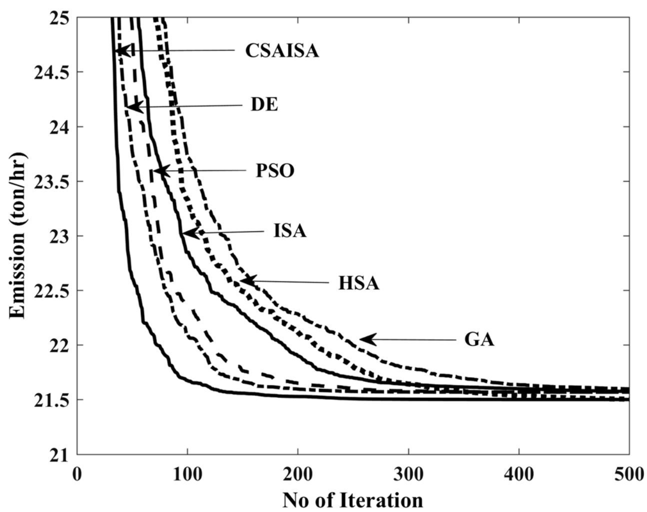

FIGURE 6 Convergence characteristic curve of IEEE-30 bus system for ED (case 2). CSAISA, chaotic self-adaptive interior search algorithm; DE, differential evolution; ED, emission dispatch; GA, genetic algorithm; HSA, harmony search algorithm; ISA, interior search algorithm; PSO, particle swarm optimization

and the cost curve data were retrieved. From the earlier study,[48] the data regarding the prohibited operating zones were retrieved for all the units. The lower and upper voltage limits were 0.95 and 1.05 pu set for all the busses including slack bus. The ELD problem, with security constraints, was done by assigning $w = 1$ in (14). In Table 7, the optimal generation schedule obtained by proposed and other algorithms is tabulated. Figure 5 gives the convergence characteristics of the proposed CSAISA and other algorithms. From Figure 5, it can be inferred that the convergence characteristic of the proposed CSAISA is fast enough and at the same time smooth, when compared with all other algorithms.

From the proposed CSAISA, the optimal generation cost obtained was 807.47 \$/h, and the corresponding emission was 43.62 ton/h. When compared with other algorithms, both the values (optimal generation cost and the corresponding emission value) seem to be better. In the proposed CSAISA, the total transmission loss with regard to the optimal generation cost was 7.15 MW. This is much lesser when compared with the transmission loss incurred in other algorithms. By substituting $w = 0$ in Equation 14, the optimal ED was performed. From the proposed CSAISA, the optimal emission obtained was 21.75 ton/h whereas the corresponding fuel cost value obtained was 918.58 \$/h. When compared, the proposed CSAISA generated better values than other algorithms in terms of optimal emission. This is presented in Table 8. When reviewing the convergence characteristic curve with reference to optimal ED of the proposed CSAISA, it

TABLE 9 Optimal generation schedule obtained for CEED problem (case 2)

Generating Unit, MW	BCS					
	Proposed CSAISA	**ISA**	**HSA**	**DE**	**PSO**	**GA**
P_{g1}	113.0654	113.0344	113.3938	113.4742	113.1093	113.2918
P_{g2}	58.745	63.0000	63.6274	63.1983	63.7332	63.7493
P_{g5}	24.1398	24.8788	24.1974	24.0832	24.9464	24.9363
P_{g8}	30.0000	30.0000	30.9473	30.8464	30.0839	30.7292
P_{g11}	27.7560	27.9950	27.0847	27.0183	27.9273	27.0828
P_{g13}	33.8581	30.3522	30.2974	30.6483	30.8493	30.5473
P_{Loss}	5.1643	5.8604	5.2098	5.8474	5.8392	5.7498
Fuel cost, \$/h	**836.28**	**839.92**	**840.46**	**840.53**	**840.74**	**841.92**
Emission, ton/h	**24.26**	**24.31**	**24.97**	**24.95**	**25.09**	**25.91**
Avg CPU time, min	1.94	1.95	1.96	1.95	1.97	1.98

Abbreviations: BCS, best compromised solution; CEED, combined economic emission dispatch; CSAISA, chaotic self-adaptive interior search algorithm; DE, differential evolution; GA, genetic algorithm; HSA, harmony search algorithm; ISA, interior search algorithm; PSO, particle swarm optimization.

Bold indicates the best solutions generated by each methods.

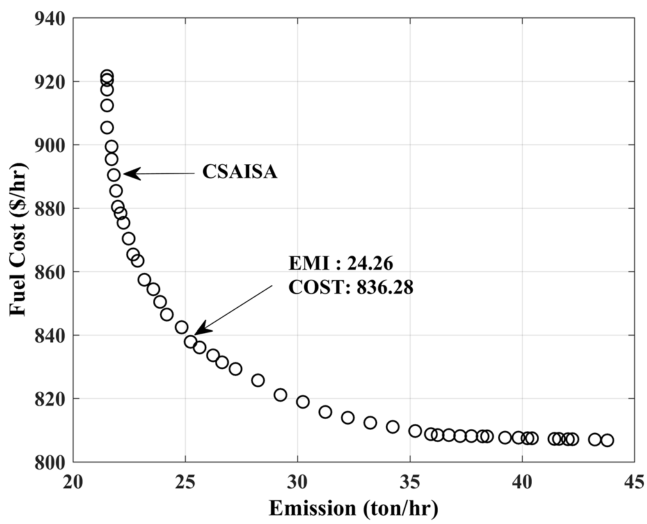

FIGURE 7 Emission-cost trade-off curve obtained using the proposed chaotic self-adaptive interior search algorithm (CSAISA) (case 2)

TABLE 10 Line flows obtained by the proposed algorithm for ELD, ED, and BCS (case 2)

Line Number	Line Flow Limits, MVA	Line Flow, MVA, for ELD	Line Flow, MVA, for ED	Line Flow, MVA, for CEED
1	130	95	94	113
2	130	110	100	122
3	65	53	56	45
4	130	122	122	128
5	130	116	122	126
6	65	57	56	46
7	90	84	87	87
8	70	65	65	64
9	130	122	124	124
10	32	26	30	27
11	65	53	62	56
12	32	25	28	28
13	65	43	62	46
14	65	24	62	47
15	65	32	54	63
16	65	56	53	62
17	32	22	27	28
18	32	25	26	26
19	32	25	27	26
20	16	15	15	15
21	16	14	13	14
22	16	15	13	14
23	16	14	15	15
24	32	31	27	29
25	32	30	28	29
26	32	28	29	29
27	32	28	27	28
28	32	27	26	28
29	32	18	28	28
30	16	14	13	15
31	16	12	13	12
32	16	13	12	14
33	16	14	13	14
34	16	15	14	14
35	16	15	14	15
36	65	55	51	58
37	16	13	12	14
38	16	13	09	14
39	16	13	09	15
40	32	30	30	30
41	32	31	27	30

Abbreviations: CEED, combined economic emission dispatch; ED, emission dispatch; ELD, economic load dispatch; MVA, mega volt ampere.

seems to be rapid and smooth in comparison with other algorithms as illustrated in Figure 6. The loss resulted in the minimum emission gained by the proposed CSAISA was 7.1499 MW, which is less than other algorithms. By varying w and applying the fuzzy logic, the BCS value obtained using the proposed CSAISA was 836.28 $/h and 24.26 ton/h, which is better than the results of all other algorithms shown in Table 9. The trade-off curve of the proposed CSAISA is shown in Figure 7. The prohibited operating zones limits and active power generation limits were also examined for ELD, ED, and CEED problems and found to be well within the bounds. In the proposed algorithm, the total transmission loss with regard to the optimal solution of ELD, ED, and CEED is much lesser compared with other algorithms. The security constraints (the line flows and load bus voltages) resultant to the optimal solutions gained by the proposed and other algorithms were examined and found to be well inside the limits stated. The line flows corresponding to the proposed algorithm alone are shown in Table 10 for ELD, ED, and CEED problems. The load bus voltages, resultant to the optimal solution done using the proposed CSAISA for CEED problem, are shown in Figure 8. It is proven from Figure 8 that the load bus voltages are within the limits considered. The performance metric tests were conducted for

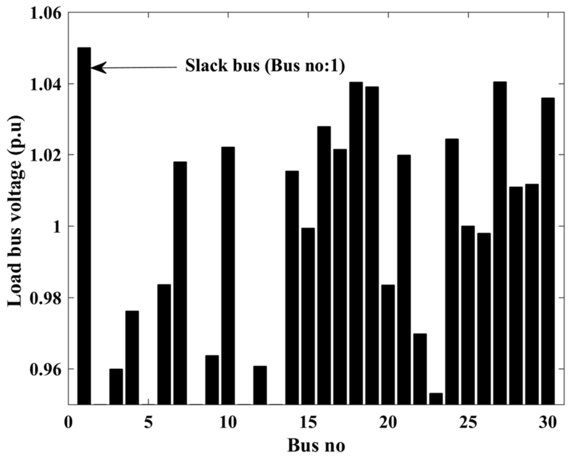

FIGURE 8 Load bus voltage obtained using the proposed chaotic self-adaptive interior search algorithm (CSAISA) for best compromised solution (BCS) (case 2)

TABLE 11 Statistical comparison of performance metric (case 2)

Performance Metric	Algorithm	Best	Worst	Mean	Standard Deviation
GD	Proposed CSAISA	0.1654	0.1874	0.2865	0.0268
	ISA	0.2258	0.2586	0.4653	0.0372
	HSA	0.2454	0.3267	0.5297	0.0475
	DE	0.2243	0.2745	0.4050	0.0392
	PSO	0.3185	0.3164	0.3986	0.0845
	GA	0.3283	0.3237	0.4465	0.0934
SP	Proposed CSAISA	0.2685	0.2767	0.3195	0.0298
	ISA	0.3859	0.3748	0.5986	0.0356
	HSA	0.2984	0.3867	0.5488	0.0552
	DE	0.2847	0.3436	0.4956	0.0305
	PSO	0.3476	0.3566	0.4967	0.0427
	GA	0.3696	0.3745	0.4995	0.0992
D-metric	Proposed CSAISA	756	695	557	379
	ISA	423	365	285	264
	HSA	352	263	243	236
	DE	426	384	346	316
	PSO	434	278	324	302
	GA	463	394	363	286

Abbreviations: CSAISA, chaotic self-adaptive interior search algorithm; D-metric, diversity metric; DE, differential evolution; GA, genetic algorithm; GD, generational distance; HSA, harmony search algorithm; ISA, interior search algorithm; PSO, particle swarm optimization; SP, spacing.

all the algorithms and are shown in Table 11. The best value obtained by the proposed CSAISA for GD and SP was lesser, and D-metric value was higher. It can be concluded from the above tests that the proposed algorithm is capable enough to generate quality solutions compared with other algorithms. Further, the proposal algorithm has better convergence speed and execution time.

TABLE 12 Optimal generation schedule obtained for ELD problem (case 3)

Generating Unit, MW	ELD					
	Proposed CSAISA	ISA	HSA	DE	PSO	GA
P_{g10}	118.3499	111.4335	111.9484	111.5483	111.4938	111.6473
P_{g12}	74.9394	76.6429	76.9550	76.9394	76.8658	76.7392
P_{g25}	50.0374	51.3193	51.6473	51.5440	51.2010	51.7754
P_{g26}	54.0025	72.5879	72.5372	72.3536	72.0373	72.2730
P_{g46}	50.5251	50.0000	50.5371	50.5373	50.2029	50.0383
P_{g49}	50.0000	53.8147	53.0747	53.4262	53.2192	53.0202
P_{g54}	50.0000	50.0000	50.7739	50.4372	50.7493	50.7302
P_{g59}	50.0000	50.0000	50.4382	50.3739	50.6403	50.0844
P_{g61}	58.9198	57.1157	57.5489	57.9638	57.0933	57.7393
P_{g65}	63.4520	52.8252	52.6458	52.4383	52.1943	52.4343
P_{g66}	50.0000	59.3695	59.4373	59.6497	59.9320	59.2383
P_{g69}	186.9806	159.6054	159.6203	159.7483	159.7943	159.1930
P_{g80}	50.0000	52.5218	52.6484	52.5343	52.0837	52.5922
P_{g87}	50.0000	59.9712	59.8403	59.3225	59.6748	59.7859
P_{Loss}	7.2067	7.2071	7.2083	7.2082	7.2095	7.2137
Fuel cost, $/h	**4291.64**	**4329.99**	**4367.25**	**4340.63**	**4372.03**	**4385.65**
Emission, ton/h	306.51	301.93	301.52	301.85	300.84	299.38
Avg CPU time, min	3.22	3.23	3.23	3.24	3.26	3.25

Abbreviations: CSAISA, chaotic self-adaptive interior search algorithm; DE, differential evolution; ELD, economic load dispatch; GA, genetic algorithm; HSA, harmony search algorithm; ISA, interior search algorithm; PSO, particle swarm optimization.

Bold indicates the best solutions generated by each methods.

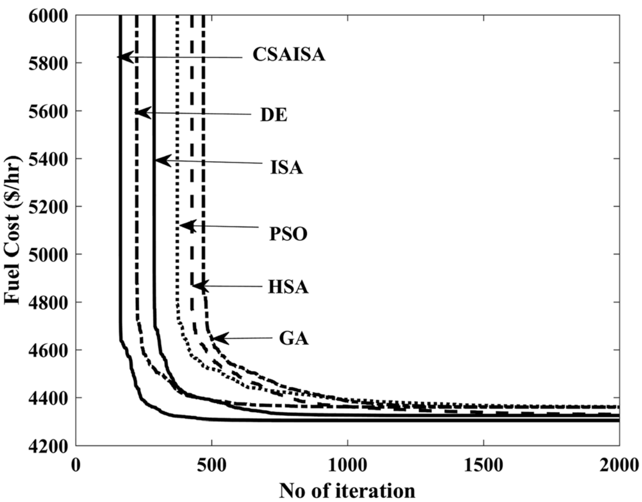

FIGURE 9 Convergence characteristic curve of IEEE-118 bus system for ELD (case 3). CSAISA, chaotic self-adaptive interior search algorithm; DE, differential evolution; ELD, economic load dispatch; GA, genetic algorithm; HSA, harmony search algorithm; ISA, interior search algorithm; PSO, particle swarm optimization

6.3 | Case 3 (IEEE-118 bus system)

This system consisted of 14 generators and 186 transmission lines. In this system, quadratic cost function with prohibited operating zones and security constraints was considered. The total load demand was 950 MW. The system data are available in literature.[44,45,49] The voltage limits were set as 0.95 and 1.05 pu respectively for all the busses

TABLE 13 Optimal generation schedule obtained for ED problem (case 3)

Generating Unit, MW	ED					
	Proposed CSAISA	**ISA**	**HSA**	**DE**	**PSO**	**GA**
P_{g10}	70.9063	69.2964	69.2983	69.3928	69.5387	69.1242
P_{g12}	50.0296	50.3507	50.6482	50.0747	50.8330	50.2310
P_{g25}	79.5189	77.9228	77.8463	77.0102	77.6372	77.7939
P_{g26}	93.1976	93.2497	93.8494	93.3242	93.5463	93.5498
P_{g46}	64.5653	64.5154	64.4943	64.3536	64.4363	64.5302
P_{g49}	50.0000	50.2352	50.8473	50.7483	50.4373	50.9301
P_{g54}	71.2999	69.5680	69.7938	69.5373	69.4422	69.6493
P_{g59}	73.1069	72.7860	72.6480	72.6483	72.5473	72.6420
P_{g61}	71.4609	72.5459	72.7203	72.5446	72.4262	72.4383
P_{g65}	89.7778	85.4308	85.6339	85.6383	85.5363	85.3262
P_{g66}	50.0000	52.2386	52.5327	52.2298	52.6252	52.4397
P_{g69}	69.1690	70.7889	70.7302	70.7339	70.7353	70.3092
P_{g80}	74.1178	78.2788	78.5438	78.6483	78.7648	78.5373
P_{g87}	50.0569	50.0000	50.6483	50.7483	50.3232	50.2933
P_{Loss}	7.2069	7.2072	7.2173	7.2279	7.2506	7.2847
Fuel cost, $/h	4549.68	4548.13	4534.76	4528.93	4468.17	4343.46
Emission, ton/h	**23.72**	**25.49**	**26.69**	**25.84**	**28.85**	**32.72**
Avg CPU time, min	3.22	3.24	3.28	3.26	3.34	3.53

Abbreviations: CSAISA, chaotic self-adaptive interior search algorithm; DE, differential evolution; ED, emission dispatch; GA, genetic algorithm; HSA, harmony search algorithm; ISA, interior search algorithm; PSO, particle swarm optimization.

Bold indicates the best solutions generated by each methods.

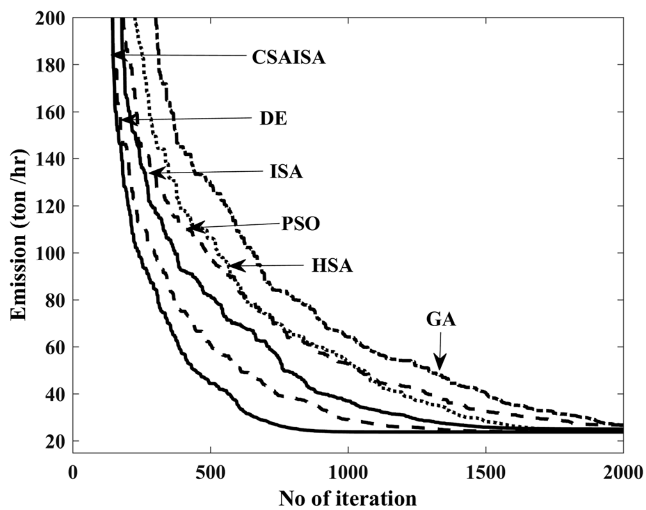

FIGURE 10 Convergence characteristic curve of IEEE-118 bus system for ED (case 3). CSAISA, chaotic self-adaptive interior search algorithm; DE, differential evolution; ED, emission dispatch; GA, genetic algorithm; HSA, harmony search algorithm; ISA, interior search algorithm; PSO, particle swarm optimization

including slack bus. The maximum rating of all the transmission lines was taken as 99 MVA. The ELD, ED, and CEED problems with security constraints and prohibited operating zones were carried out as discussed under Section 2.8. The optimal cost attained by the proposed CSAISA was 4291.64 \$/h, and its emission value was 306.51 ton/h, which is minimum compared with other algorithms. In Table 12, the optimal values for proposed and other algorithms considered are tabulated. Figure 9 shows the convergence characteristic of the proposed and other algorithms for ELD problem. From Figure 9, it can be concluded that the proposed CSAISA can gain steady-state optimal solution at the earliest

TABLE 14 Comparison of CEED result for case 3

Generating Unit, MW	BCS					
	Proposed CSAISA	**ISA**	**HSA**	**DE**	**PSO**	**GA**
P_{g10}	102.6468	100.3485	100.3839	100.5473	100.7363	100.8578
P_{g12}	59.1816	58.8270	58.6583	58.5372	58.2314	58.3547
P_{g25}	50.0599	50.8309	50.8302	50.8474	50.5242	50.9943
P_{g26}	70.3498	73.3932	73.5292	73.0932	73.3238	73.4352
P_{g46}	63.1042	59.1153	59.1846	59.9323	59.7272	59.4636
P_{g49}	51.0080	50.1468	50.9231	50.7397	50.2726	50.6254
P_{g54}	50.0000	50.7470	50.2832	50.5360	50.8362	50.5363
P_{g59}	51.0166	53.2494	53.0220	53.2324	53.5242	53.1321
P_{g61}	83.9497	85.1551	85.8231	85.4235	85.4355	85.3546
P_{g65}	98.1409	92.1870	92.6484	92.5426	92.0388	92.7522
P_{g66}	58.6019	61.3470	61.9233	61.5243	61.6493	61.4368
P_{g69}	119.1476	121.8597	121.4353	121.6357	121.7468	121.2463
P_{g80}	50.0000	50.0000	50.4352	50.5367	50.6484	50.7468
P_{g87}	50.0000	50.0000	50.5327	50.6382	50.8202	50.4373
P_{Loss}	7.2070	7.2069	7.3536	7.6388	7.8447	7.4357
Fuel cost, \$/h	**4352.39**	**4353.57**	**4366.27**	**4387.44**	**4427.26**	**4453.85**
Emission, ton/h	**135.23**	**136.46**	**144.85**	**153.42**	**176.75**	**184.38**
Avg CPU time, min	3.22	3.24	3.27	3.24	3.32	3.35

Abbreviations: BCS, best compromised solution; CEED, combined economic emission dispatch; CSAISA, chaotic self-adaptive interior search algorithm; DE, differential evolution; GA, genetic algorithm; HSA, harmony search algorithm; ISA, interior search algorithm; PSO, particle swarm optimization.

Bold indicates the best solutions generated by each methods.

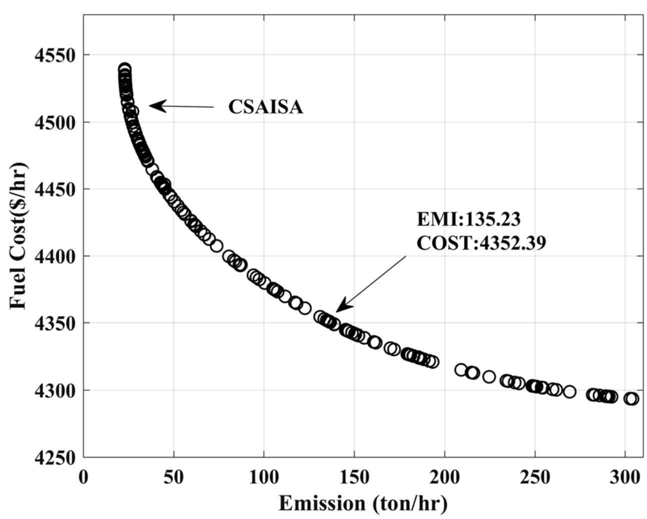

FIGURE 11 Emission-cost trade-off curve obtained using the proposed chaotic self-adaptive interior search algorithm (CSAISA) (case 3)

when compared with other algorithms. In the proposed CSAISA, the optimal emission value of 23.71 ton/h was achieved with the fuel cost of 4549.68 \$/h. As per Table 13, the optimal emission value obtained when using the proposed CSAISA is better when compared with other algorithms. A faster convergence characteristic curve was observed for ED in case of the proposed CSAISA whereas it was slow in other algorithms as inferred through Figure 10. *w*, the weight factor, got differed in steps, and the best BCS was finalized using the fuzzy method. The fuel cost was 4352.39 \$/h, and the corresponding emission was 135.23 ton/h in BCS, which was obtained with the help of the proposed CSAISA. When compared between others and the proposed CSAISA, the BCS obtained was better in the latter, which is tabulated in Table 14. In Figure 11, the trade-off curve of the proposed CSAISA is shown. According to Tables 12–14, the proposed CSAISA had exhibited best fuel cost, emission, and BCS values when compared with other algorithms. The prohibited operating zones limits and active power generation limits were also examined for ELD, ED, and CEED problems and found to be well within the bounds. In the proposed algorithm, the total transmission loss with regard to the optimal solution of ELD, ED, and CEED is much lesser compared with other algorithms. With regard to the security constraints, the line flows corresponding to the optimal values were examined for all algorithms and found to be within the limits specified for ELD, ED, and CEED problems. The line flows corresponding to BCS obtained by the proposed algorithm were within the limits and are shown in Figure 12.

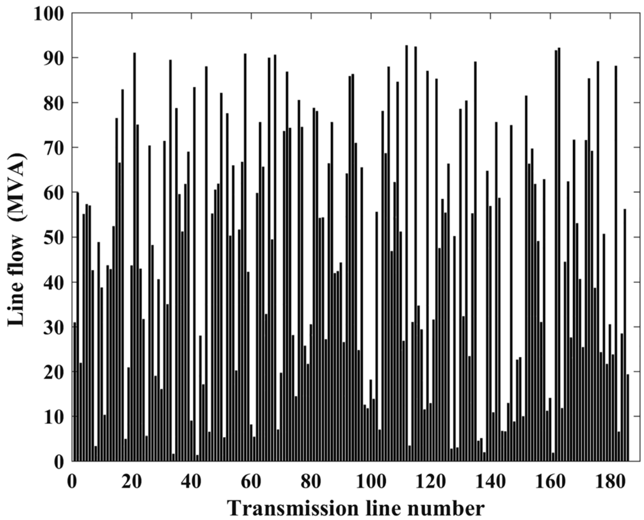

FIGURE 12 Line flow obtained using the proposed chaotic self-adaptive interior search algorithm (CSAISA) for best compromised solution (BCS) (case 3)

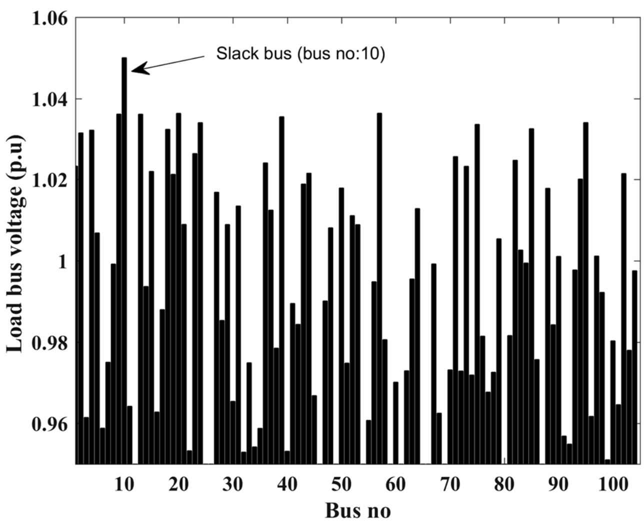

FIGURE 13 Load bus voltage obtained using the proposed chaotic self-adaptive interior search algorithm (CSAISA) for best compromised solution (BCS) (case 3)

TABLE 15 Statistical comparison of performance metric (case 3)

Performance Metric	Algorithm	Best	Worst	Mean	Standard Deviation
GD	Proposed CSAISA	0.1154	0.1494	0.2865	0.0124
	ISA	0.2176	0.2764	0.3965	0.0243
	HSA	0.2443	0.2675	0.3926	0.0284
	DE	0.1354	0.2346	0.3545	0.0214
	PSO	0.2243	0.2453	0.3875	0.0357
	GA	0.3198	0.3127	0.4387	0.0392
SP	Proposed CSAISA	0.1385	0.1765	0.3584	0.0102
	ISA	0.2856	0.3276	0.4745	0.0258
	HSA	0.2934	0.3635	0.4854	0.0291
	DE	0.1575	0.2457	0.3956	0.0242
	PSO	0.2696	0.2745	0.4864	0.0343
	GA	0.3864	0.4535	0.5764	0.0387
D-metric	Proposed CSAISA	878	785	753	368
	ISA	439	385	342	327
	HSA	395	326	269	240
	DE	567	492	463	343
	PSO	573	457	425	342
	GA	459	536	388	304

Abbreviations: CSAISA, chaotic self-adaptive interior search algorithm; D-metric, diversity metric; DE, differential evolution; GA, genetic algorithm; GD, generational distance; HSA, harmony search algorithm; ISA, interior search algorithm; PSO, particle swarm optimization; SP, spacing.

The load bus voltage of the proposed CSAISA and other algorithms for ELD, ED, and CEED problems was examined and found to be within the limits specified. The load bus voltage of the proposed CSAISA is illustrated in Figure 13. The performance metric tests were conducted for all the algorithms and are shown in Table 15. The best value obtained by the proposed CSAISA for GD and SP was lesser, and D-metric value was higher. It can be concluded from the above tests that the proposed algorithm is capable enough to generate quality solutions compared with other algorithms. Further, the proposed algorithm exhibits better convergence speed and execution time.

7 | CONCLUSION

In the current study, a novel CSAISA was proposed and successfully applied in 11-generating units and IEEE-30 bus and IEEE-118 bus systems to solve the CEED problems with nonlinearity such as valve point effects, prohibited operating zones, and security constraints. Fuzzy decision-making method was chosen for the current study to finalize the BCS from the set of compromise solutions obtained through differentiation of w value from 1 to 0. A comparison was performed with the optimal results retrieved from ISA, HSA, DE, PSO, and GA as well as the proposed algorithm without violating the constraints.

The following are the specific findings:

In all the case studies, the proposed CSAISA produced better quality solution for ELD, ED, and CEED problems considered. The performance of the proposed and other algorithms was also analyzed by comparing performance metrics.

The proposed CSAISA has fast convergence characteristics and less computational time compared with other algorithms. In future, to validate the efficiency of the proposed algorithm further, it can be applied to solve optimal power flow problems in smart grid environment and optimization problems related to electric vehicles.

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LIST OF SYMBOLS AND ABBREVIATIONS

a_i, b_i, c_i, e_i, and f_i	fuel cost coefficients of the ith unit
BSA	backtracking search optimization
BCS	best compromised solution
CEED	combined economic emission dispatch
C_i	centroid
CIABC	modified artificial bee colony based on chaos
CSAISA	chaotic self-adaptive interior search algorithm
CSADHS	chaotic self-adaptive differential harmony search algorithm
count (1) and count (2)	no. of counts made for consecutive generations and no. of times better harmony has generated
DP	dynamic programming
D-metric	diversity metric
d_i	Euclidean distance
DE	differential evolution
EP	evolutionary programming
ED	emission dispatch
ELD	economic load dispatch
FPA	flower pollination algorithm
$F_i(P_i)$	fuel cost
$F_{\mathrm{t,cost}}$	total fuel cost
F_1	objective function for cost minimization
F_2	objective function for emission minimization
$f_i^{\min}$ and $f_i^{\max}$	minimum and maximum value of ith objective function among all nondominated solutions
GA	genetic algorithm
GD	generational distance
GSA	gravitational search algorithm
HSA	harmony search algorithm
H	price penalty factor
ISA	interior search algorithm
IPSO	improved particle swarm optimization
K	index of the prohibited operating zones
LP	linear programming
$\mathrm{LF}_{i,j}$	apparent power flow from ith bus to jth bus.
$\mathrm{LF}_{i,j}^{\mathrm{limit}}$	line flow limits
$\mathrm{LF}_{i,j}^{\max}$	maximum rating of transmission line connecting bus i and j
LB	lower bound
MMACO_R	multiobjective multipopulation–based ant colony optimization
MoP	multiobjective optimization problem
MBA	mine blast algorithm
MHSA	modified harmony search method
MPSO	modulated particle swarm optimization
MVA	mega volt ampere
N	no. of elements generated/population, no. of generating units
Nb	total no. of busses
NF	no. of objective functions
NI	no. of iterations
NB	total no. of PQ busses
NL	total no. of transmission lines
n_i	no. of prohibited operating zones in the ith generating unit
n	no. of vectors in the nondominated solutions

P_i	power output of the ith generator
P_{D}	total demand
P_{L}	transmission loss
P_i	total real power generation at bus i
$P_{\mathrm{d}i}$	total real power demand at bus i
p	the no. of nondominated solutions
PSO	particle swarm optimization
poz	prohibited operating zones
$P_{\mathrm{poz}}^{\mathrm{limit}}$	prohibited operating zones limits
$P_{i,\min}$ and $P_{i,\max}$	ith generator minimum and maximum power limits
$P_{i,k}^{\mathrm{L}}$ and $P_{i,k}^{\mathrm{U}}$	lower and upper bounds of kth prohibited operating zones of unit i
$Q_{\mathrm{g}i}$	total reactive power generation at bus i
$Q_{\mathrm{d}i}$	total reactive power demand at bus i
RCCRO	real-coded chemical reaction algorithm
RCBA	hybrid bat algorithm
r,r_2,r_3	random no between 0 to 1
SOS	symbiotic organisms search
SP	spacing
S	no. of nondominated vectors
UB	upper bound
$\lvert V_j \rvert$	voltage magnitude at bus j
$\lvert V_i \rvert$	voltage magnitude at bus i
$V_{i,\min}$ and $V_{i,\max}$	minimum and maximum voltage limits of ith PQ bus
$x_{\mathrm{gb}}{}^{j}$	global best element in the jth iteration
W	weight factor
$\lvert Y_{i\ j} \rvert$	magnitude of the ijth element of Ybus
α_i,β_i,γ_i,δ_i,and λ_i	emission curve coefficients of the ith generator
α (alpha)	tuning parameter
δ_i	voltage angle at bus i
δ_j	voltage angle at bus j
λ_{eq}	penalty factor for equality constraints
λ_{poz}	penalty factor for prohibited operating zones
λ_V	penalty factor for voltage constraints
λ_{LF}	penalty factor for line flow constraints
μ_i^k	membership function
θ_{ij}	angle of the ijth element of Ybus
ƐBiODE	multiobjective Ɛ-constrained method

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