



Modeling of Combined Economic and Emission Dispatch Using Improved Sand Cat Optimization Algorithm

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Abstract: Combined Economic and Emission Dispatch (CEED) task forms multi-objective optimization problems to be resolved to minimize emission and fuel costs. The disadvantage of the conventional method is its incapability to avoid falling in local optimal, particularly when handling nonlinear and complex systems. Metaheuristics have recently received considerable attention due to their enhanced capacity to prevent local optimal solutions in addressing all the optimization problems as a black box. Therefore, this paper focuses on the design of an improved sand cat optimization algorithm based CEED (ISCOA-CEED) technique. The ISCOA-CEED technique majorly concentrates on reducing fuel costs and the emission of generation units. Moreover, the presented ISCOA-CEED technique transforms the equality constraints of the CEED issue into inequality constraints. Besides, the improved sand cat optimization algorithm (ISCOA) is derived from the integration of traditional SCOA with the Levy Flight (LF) concept. At last, the ISCOA-CEED technique is applied to solve a series of 6 and 11 generators in the CEED issue. The experimental validation of the ISCOA-CEED technique ensured the enhanced performance of the presented ISCOA-CEED technique over other recent approaches.

Keywords: Economic and emission dispatch; multi-objective optimization; metaheuristics; fuel cost minimization; sand cat optimization

1 Introduction

Smart grids can be defined as a set of technologies, approaches, and concepts, permitting the integration of distribution, generation, and transmission, employing them into one internet by using



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information technology, advanced sensor measurement technologies, communications technologies, new energy technologies, computer technology, control technology [1]. But Smart Grid employs digital technologies for controlling the grid and selecting the optimal mode of power dispersal to increase reliability, minimize energy consumption, increase transparency and reduce costs in the network. Thus, the intelligent system will have an important effect in the domains of economics and finance of the energy sector [2]. The economic dispatch (ED) is the power managing tool that can be utilized for determining the real-time power output of thermal production units to address essential load demand. The ED has minimal fuel production cost, and minimal transmission energy loss while fulfilling all units, along with that system restraint [3]. Fig. 1 illustrates the infrastructure of CEED.

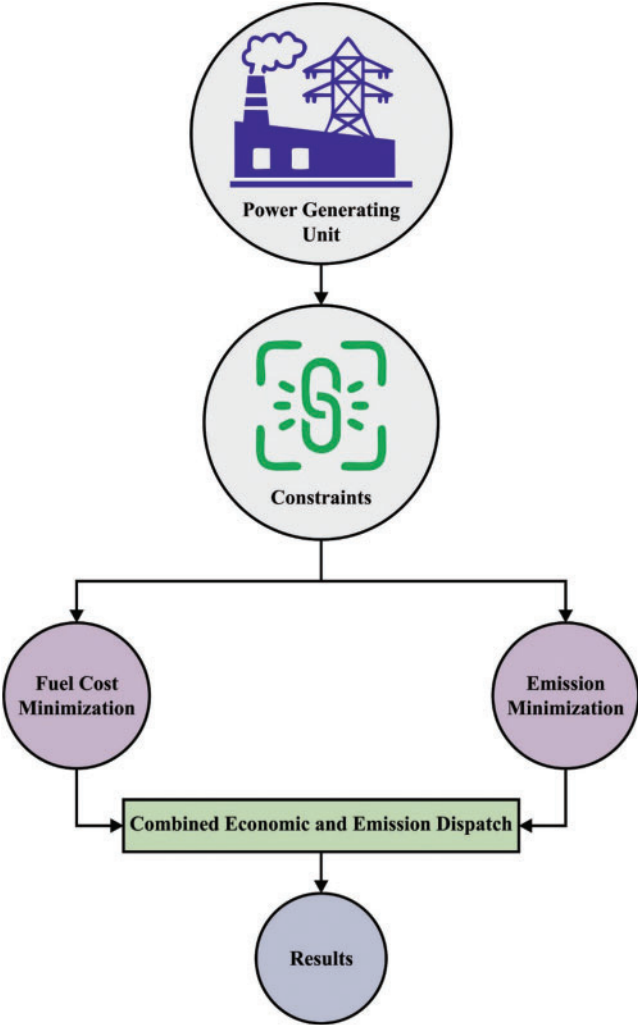


Figure 1: Structure of CEED

The conventional ED issue was to determine the best active power allotment from every involved unit for reducing the whole working cost irrespective of emissions formed while fulfilling every unit and system limitation [4]. But with growing public awareness of environmental protection and the increasing seriousness of the energy crisis, higher-efficacy consumption for renewable energy resources like wind, along with a decrease in pollutant emission extracted from fossil fuels, was paid

much interest globally [5]. In this condition, adapting the current allocation technology tactics for minimizing fuel costs and emission levels of pollutants is becoming an urgent research problem. Hence, a novel dispatch method called the combined economic and emission dispatch (CEED) issue was offered for following the minimum emission level and minimal production cost of an energy system [6]. To detect quality solutions to the CEED issue, various optimized methods were formulated. Traditional optimization methods like recursive quadratic programming (QRP) and linear programming (LP) were modeled by researchers [7]. But, the real CEED issue can be a nonlinear and non-smooth constrained optimized issue with nonconvex and complex features, which makes it difficult to search for the best solution. Thus, certain conventional gradient data-related optimized approaches do not solve the CEED problem effectively [8].

Recently, as a replacement to the conventional optimized techniques, many population-related nature-inspired heuristic approaches were widely presented to solve several complicated optimization issues in the real world like electric power system planning, feature selection, image processing, neural networks training, and robotic path planning. Certain heuristic techniques were reported in the literature for solving CEED issues [9]. But the aforementioned CEED issue just relies upon how best to decline the contaminant discharge in the fossil-fuel energy sector through regulation of the prevailing dispatch approaches. Now, renewable energy like wind energy in the energy sector has obtained widespread attention because of its main benefit of zero-emission and less fuel cost [10]. Later, the CEED or ED model by combining wind power was devised for gaining viable scheduling solutions for authors to reach the objective of reducing emissions.

This paper focuses on the design of an improved sand cat optimization algorithm based CEED (ISCOA-CEED) technique. The presented ISCOA-CEED technique majorly concentrates on the reduction of fuel cost and emission of generation units. Moreover, the presented ISCOA-CEED technique transforms the equality constraints of the CEED issue into inequality constraints. Besides, the improved sand cat optimization algorithm (ISCOA) is derived from the integration of traditional SCOA with the Levy Flight (LF) concept. At last, the ISCOA-CEED technique is applied to solve a series of 6 generators as well as 11 generators in the CEED issue. The experimental validation of the ISCOA-CEED technique ensured the enhanced performance of the presented ISCOA-CEED technique over other recent approaches. In short, the key contributions of the study are given as follows.

- Develop a new ISCOA-CEED technique for reducing fuel cost and emission of generation units
- Converts the equality constraints of the CEED issue into the inequality constraints
- Propose an ISCOA by the integration of the conventional SCOA with the LF concept
- Validate the proposed model on a series of 6 generators as well as 11 generators in the CEED issue

2 Related Works

The author in [11], developed an Ensemble Multi-objective Differential Evolution (EMODE) to address the problems of ED. Firstly, the equality constraint of the problems was converted into an inequality constraint. Then, two mutation approaches differential evolution (DE)/current-to-rand/1 and DE/rand/1 were employed for improving the traditional DE. The accuracy of the presented model has been estimated on 6 test functions and the mathematical solution has shown that the presented model is effective. Li et al. [12] present an enhanced sailfish optimization technique for handling the problem of large pollution emissions and high operation costs in hybrid dynamic economic emission dispatch (HDEED). The arbitrariness of wind energy can be demonstrated using Weibull

distribution and integrated into the dynamic economic emission dispatch (DEED); therefore, it is necessary to establish the presented method. The conventional sailfish optimization (SFO) approach can be optimized by presenting the global search formula, weight inertia, and Levy flight approach to enhance the solution speed and search performance. The improved sailfish optimization (ISFO) technique is to handle the constraint conditions namely slope constraint, power balance constraints, and valve point effect of the thermal power unit.

Deb et al. [13] designs a novel Metaheuristic algorithm (MH) named the Turbulent Flow of Water Optimization (TFWO), which depends on the behaviors of whirlpools made in turbulent water flow, to solve various forms of CEED and economic load dispatch (ELD). To authenticate the effectiveness of the TFWO, numerous test networks of CEED with valve effects and ELD with loss of communication are integrated. The outcomes establish the robustness and potential of the grey wolf optimizer (GWO) to be a promising method to resolve different ELD challenges. Rex et al. [14] developed a new hybrid mechanism to resolve CEED problems that exploit the Whale optimization algorithm (WOA) and genetic algorithm (GA). The performance of the presented algorithm has been tested on 4 distinct test systems and the effectiveness is compared to other heuristic models. Hussien et al. [15] present an adapted moth-flame optimization technique (MMFO) to find the optimum solution to the CEED problem. The presented method is based mainly on the mayfly optimization (MFO) concept with path modification of moths in a new spiral around the flame. The proposed mode is utilized for improving the convergence features of CEED optimum solutions more than others.

The author in [16], developed the Moth Swarm Algorithm to resolve the CEED problems for a twenty-four-hour period. The algorithm has been carried out on the test system composed of solar photovoltaic and thermal plants while considering spinning reserve allocation. Jadoun et al. [17] suggest a Dynamically Controlled Whale Optimization Algorithm (DCWOA) to resolve the Multi-objective non-convex MO-CHPEED problems. The presented method is a better variant of conventional WOA by dynamically adding a controlled constriction function. The contradictory aims of mass emissions and fuel costs are managed through Fuzzy Framework. Li et al. [18] recommend an improved tunicate swarm algorithm (ITSA) for optimizing and solving DEED problems. The presented method aims to minimize the pollutant emission and energy cost of the power system. Furthermore, the presented model is a complicated optimization problem and has numerous optimization goals.

3 The Proposed Model

In this study, a new ISCOA-CEED technique has been developed for CEED. The presented ISCOA-CEED technique aims at the effectual reduction of fuel costs and the emission of generation units. Following, the presented ISCOA-CEED technique transforms the equality constraint of the CEED issues into an inequality constraint.

3.1 Problem Statement

The solution to CEED problems can be accomplished by minimalizing the objective function (OF) incorporated with weighted sum methodology under the system constraint [19].

$$OF = \text{Min} \left\{ w \sum_{n \in N_G} F_n(P_{G,n}) + (1 - w) \gamma \sum_{n \in N_G} E_n(P_{G,n}) \right\}. \quad (1)$$

From the expression, the fuel cost rate (\$/h) can be demonstrated with $F_n(P_{G,n})$ and the emission rate (ton/h) with $E_n(P_{G,n})$. γ , w , ($0 \leq w \leq 1$), and N_G correspondingly indicates the Scaling factor, and

weight factor, along with a set of thermal generation units; $w = 1$ relates to the reduction of overall fuel cost only, similarly, $w = 0$ relates to the reduction of overall emission.

3.1.1 Fuel Cost Function

The fuel cost function of every generator in the system might be characterized by the quadratic function of real power production:

$$F_n(P_{G,n}) = a_n + b_n P_{G,n} + c_n P_{G,n}^2 (\$/h), \quad (2)$$

whereas a_n , b_n , and c_n indicate the cost coefficient. Since the unit loading rises, the input to the unit rises, and the increasing heat rate reduces among the opening point for any two valves. But once the valve is initially opened, the throttling loss increases suddenly and the incremental heat rate increases rapidly. It is named the valve point effect which results in non-convex input-output, non-smooth features. Generally, valve point effects are modeled with the inclusion of recurring rectified sinusoid to the quadratic cost function:

$$F_n(P_{G,n}) = a_n + b_n P_{G,n} + c_n P_{G,n}^2 + |d_n \sin(e_n (P_{G,n}^{\min} - P_{G,n}))| \left(\frac{\$}{h}\right), \quad (3)$$

whereas d_n and e_n denotes the fuel cost coefficient for the valve point effect.

3.1.2 Emission Function

Fossil-fuelled thermal unit causes atmospheric waste emission made up of gases and particles namely nitrogen oxide (NO_x), carbon dioxide (CO_2), and sulfur dioxide (SO_2). (Bhattacharya and Chattopadhyay 2011) Diverse mathematical modelling was introduced to characterize the emission function of thermal generating units. In the presented method, the sum of quadratic and exponential functions determines the emission function of the thermal unit:

$$E_n(P_{G,n}) = \alpha_n + \beta_n P_{G,n} + \eta_n P_{G,n}^2 + \xi_n \exp(\lambda_n P_{G,n}) \left(\frac{ton}{h}\right), \quad (4)$$

where α_n , β_n , η_n , ξ_n , and λ_n denotes the coefficient of n -th generator emission.

3.1.3 Constraints

In the minimization method, inequality and equality constraints should be fulfilled. In the presented model, inequality constraints are named generation capacity constraints and equality constraints are termed power balance.

3.1.4 Power Balance Constraint

The overall power production should cover the real power loss in transmission line P_{loss} and the overall load demand P_{load} . Consequently, the power balance constraints are characterized by the following equation:

$$\sum_{n \in N_G} P_{G,n} - P_{load} - P_{loss} = 0. \quad (5)$$

The communication loss of the system is denoted as loss coefficients (B_{nj}), generally known as B -loss matrices and approximated the system loss as a quadratic function of the generator's real power:

$$P_{loss} = \sum_{n \in N_G} \sum_{j \in N_G} P_{G,n} B_{nj} P_{G,j} + \sum_{n \in N_G} B_{0n} P_{G,n} + B_{00}. \quad (6)$$

In Eq. (6), B_{nj} , B_{0n} , and B_{00} refer to the coefficient of B -loss matrices.

3.1.5 Generation Capacity Constraint

The real power output of all the generators is constrained using minimal $P_{G,n}^{\min}$ and maximal $P_{G,n}^{\max}$ power limits for stable operation:

$$P_{G,n}^{\min} \leq P_{G,n} \leq P_{G,n}^{\max} \quad (n \in N_G). \quad (7)$$

3.2 Algorithm Design of ISCOA

The SCOA technique is called based on a special feature of sand cat (SC) performance in the environment which is the size to classify lower-frequency sound [20]. The attacking and foraging of the prey are the 2 main performances of SC. According to the research study, the SC frequency absorption to frequency under 2 kHz was remarkable. SCs are nearby 8 decibels further searching than house cats at this frequency. Due to these unique behaviors, the SC identifies sound (prey movements), follows prey, and hunts effectively dependent upon the prey place. All the SCs in the SCOA technique signify the problem variable. To start with the SCOA technique, the candidate matrix of SC populations was created arbitrarily betwixt the low and high restrictions of the design variable.

The dimensional of the candidate matrix to a d -dimension optimized space with n SCs is equivalent to $N_{pop} \times N_d$, ($pop = 1, \dots, n$). All the SC's solution was represented as $X_i = (x_{i1}, x_{i2}, \dots, x_{id})$, ($i = 1, \dots, n$). The SCOA technique proceeds to benefit SC's lower-frequency hearing abilities. As already noted, the SC identifies frequencies under 2 kHz. Consequently, it can be offered that the sensitivity range of SCs starts at 2 kHz and ends at 0 kHz once examined for prey. For representing this process, and in a mathematical model of technique, the vector \vec{r}_G was established, which is linearly reduced in [2–0] as the iterations enhance based on the subsequent formula:

$$\vec{r}_G = S_M - \left(\frac{S_M \times t}{t_{Max}} \right) \quad (8)$$

The S_M value has assumed that 2 as it can be dependent upon the hearing features of SCs. In addition, t defines the present iteration, and t_{Max} is the maximal count of iterations. In the searching phase, the place of all the searching agents is upgraded by utilizing the subsequent formula dependent upon the best-candidate position (\vec{Pos}_b), their present position (\vec{Pos}_c), and their sensitivity range (\vec{r}).

$$\vec{Pos}(t+1) = \vec{r} \cdot \left(\vec{Pos}_b(t) - rand(0, 1) \cdot \vec{Pos}_c(t) \right) \quad (9)$$

For escaping the local optimal trap, all the SCs have a distinct sensitivity range (\vec{r}) that is computed by utilizing Eq. (10).

$$\vec{r} = r_G \rightarrow \times rand(0, 1) \quad (10)$$

Therefore, \vec{r}_G signifies the general sensitivity range that is linearly decreased from two to zero. In addition, \vec{r} illustrates the sensitivity range of all the cats. After looking, and during the attacking phase of SCOA, all the SCs place are upgrading dependent upon the subsequent formula:

$$\vec{Pos}(t+1) = \vec{Pos}_b(t) - \vec{r} \cdot \vec{Pos}_{rnd} \cdot \cos(\theta) \quad (11)$$

In which θ denotes the arbitrary angle betwixt 0 and 360, and \vec{Pos}_{rnd} demonstrates the position of an arbitrarily chosen SC dependent upon the subsequent formula:

$$\vec{Pos}_{rnd} = \left| rand(0, 1) \cdot \vec{Pos}_b(t) - \vec{Pos}_c(t) \right| \quad (12)$$

At last, the R parameter that is defined in Eq. (13), is the last and very essential parameter of this technique in defining the transition between exploitation (attacking) and exploration (searching) phases.

$$\vec{R} = 2 \times r_G \rightarrow \times rand(0, 1) - \vec{r}_G \quad (13)$$

Once R is lesser than or equivalent to 1, the SCOA technique pushes the searching agents for exploiting; then, it can be driven to exploring and discovering prey. So, Eq. (14) implies the last upgrading position formula of the SCOA technique.

$$\vec{X}(t+1) = \begin{cases} \vec{Pos}_b(t) - \vec{pos}_{rnd}(t) \cdot \cos(\theta) \cdot \vec{r} & |R| \leq 1; \text{exploitation} \\ \vec{r} \cdot (\vec{Pos}_b(t) - rand(0, 1) \cdot \vec{Pos}_c(t)) & |R| > 1; \text{exploration} \end{cases} \quad (14)$$

Algorithm 1. Pseudocode of SCOA

Initializing the population

Compute the fitness function dependent upon the main function

Initializing the r, r_G, R

While ($t \leq t_{Max}$)

 For all the SCs

 Obtain an arbitrary angle $\theta(0^\circ \leq \theta \leq 360^\circ)$

 If ($|R| \leq 1$)

 Upgrade the searching agent dependent upon the exploitation phase of Eq. (17),
 $\vec{pos}_b(t) - \vec{pos}_{rnd}(t) \cdot \cos(\theta) \cdot \vec{pos}_{rnd}$

 Else

 Upgrade the searching agent dependent upon the exploration phase of Eq. (17), $\vec{pos}_{rnd} \cdot$
 $(\vec{pos}_b(t) - rand(0, 1) \cdot \vec{pos}_c(t))$

 End

 End

$t = t + 1$

End

In Eq. (14), SCs are orderly for attacking their victim if $|R| \leq 1$, then, the cats are simulated to search for a novel possible solution in the global area. Fig. 2 illustrates the steps involved in the SCOA technique.

Moreover, the ISCOA is derived from the integration of traditional SCOA with the LF concept. LF is a type of chaotic system where the leap magnitude can be defined using the likelihood function [21].

$$x_{new} = x_{prey} \times Levy(D) + X_R(t) + (y - x) * rand, \quad (15)$$

In Eq. (15), x_{new} refers to the novel location that is generated using the search method (x). The dimensionality space can be represented as D , and the LF distribution is indicated as Levy (D). In the i -th cycle, $X(t)$ refers to the random integer ranges from [1N].

$$Levy(D) = s \times \frac{u \times \sigma}{|r|^{1/p}}, \quad (16)$$

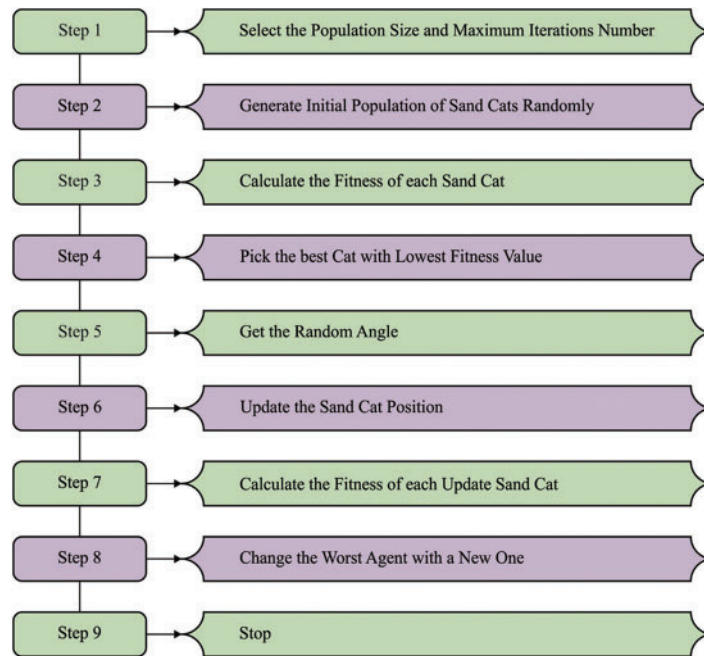


Figure 2: Steps involved in SCO

Now, s indicates a constant fixed as 0.01, u denotes the random number within $[0,1]$, and r indicates a random value ranging from zero to one.

$$\sigma = \left(\frac{\Gamma(1 + \beta) \times \sin e \left(\frac{\pi\beta}{2} \right)}{\Gamma\left(1 + \frac{\beta}{2}\right) \times \beta \times 2^{(\beta - \frac{1}{2})}} \right), \quad (17)$$

In Eq. (17), β denotes the constant fixed as 1.5. y and x are utilized for displaying the circular form as follows.

$$\begin{aligned} y &= r \times \cos(\theta), \\ x &= r \times \sin(\theta), \\ r &= r_1 + U \times D_1, \\ \theta &= -w \times D_1 + \theta_1, \\ \theta_1 &= \frac{3 \times \pi}{2}. \end{aligned} \quad (18)$$

For the provided number of search iterations, r_1 indicates the values within $[1, 20]$, w signifies a small value fixed as 0.005, U refers to the smaller value fixed as 0.00565 and D_1 characterizes integer ranges from 1 to Dim (search space length).

3.3 Process Involved in ISCOA for CEED Problem

During this phase, the CSBO algorithm derives a fitness function to resolve the CEED problems. The fitness function for CEED is the total costs of the estimated system and the fitness function for effective EED is the total emitted emission evaluated as follows:

$$Z = F + hE + \lambda \times MV \quad (19)$$

In Eq. (19), λ denotes the penalty factor and MV represents the mismatch value. Furthermore, some penalty coefficients can be used for constant handling techniques.

$$Z = Z + \Lambda [CV] \quad (20)$$

In Eq. (20), Λ denotes the penalty coefficient, and CV indicates the group of constraints violation. The fitness function should be reduced while satisfying all the constraints. In each iteration, inequality constraints are checked beforehand evaluating the fitness value and if it isn't bound feasibly, it can be fixed on lower or upper bounds. CEED has an equality constraint that is, inequality and power balance constraints are generators of lower and upper limits.

4 Results and Discussion

The proposed model is simulated using the MATLAB tool. The performance validation of the ISCOA-CEED model has been validated through two scenarios a test system with 11 generators and a test system with 6 generators. The test system with eleven generators involves emission level and quadratic cost functions. The power demand ranges from 1000 to 2500 MW. As well, the test system with six generators involves emission level and quadratic cost functions. The power demand ranges from 500 to 1100 MW.

Table 1 and Fig. 3 exhibits a comparative fuel cost (FC) examination of the ISCOA-CEED model with recent models on six generators. The experimental values depicted that the ISCOA-CEED model has shown maximum performance with the least FC values. At the same time, it is noticed that the recursive and improved recursive models have exhibited poor performance with maximum FC values. Although the particle swarm optimization (PSO) and DE models have demonstrated moderately closer FV values, the ISCOA-CEED model has surpassed them with minimal FC values.

Table 1: FC analysis of ISCOA-CEED system with existing approaches under six generator

Load	Fuel cost (\$)				
	Recursive	Improved recursive	PSO	Differential evaluation	ISCOA-CEED
500	30890	28432	26949	26408	25312
600	32873	30155	30099	29997	27422
700	38985	36879	34944	34926	30947
800	43977	42426	41891	37242	31406
900	45728	43945	42667	42554	40923
1000	54124	52384	51734	49996	48364
1100	59962	59116	58999	58033	54314

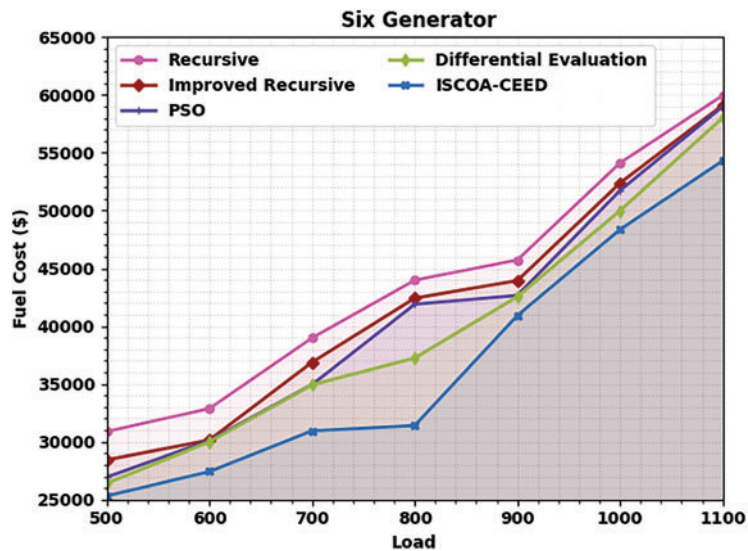


Figure 3: FC analysis of ISCOA-CEED system under six generator

Table 2 and Fig. 4 show a comparative fuel emission (FE) analysis of the ISCOA-CEED with current methods on six generators. The experimental value depicts that the ISCOA-CEED technique has exhibited maximal performance with minimum FE values. Simultaneously, it is noted that the recursive and improved recursive approaches have displayed poor performance with maximal FE values. Even though the PSO and DE techniques have demonstrated reasonably nearer FV values, the ISCOA-CEED method has surpassed them with the least FE values.

Table 2: FE analysis of ISCOA-CEED system with existing approaches under six generator

Load	Fuel emission (kg)				
	Recursive	Improved recursive	PSO	Differential evaluation	ISCOA-CEED
500	154.57	152.37	140.88	124.09	94.45
600	189.03	177.40	175.28	169.99	158.19
700	228.00	195.48	193.71	186.58	185.56
800	271.48	264.61	256.60	253.96	228.77
900	325.00	321.63	307.84	285.79	274.74
1000	417.81	386.24	383.93	346.65	339.75
1100	479.49	478.27	473.56	442.58	421.34

In Table 3, the EED optimal compromise solutions of the ISCOA-CEED model are examined under distinct loads and six generators. The experimental values demonstrated that the ISCOA-CEED model has reached an effectual outcome under each load value.

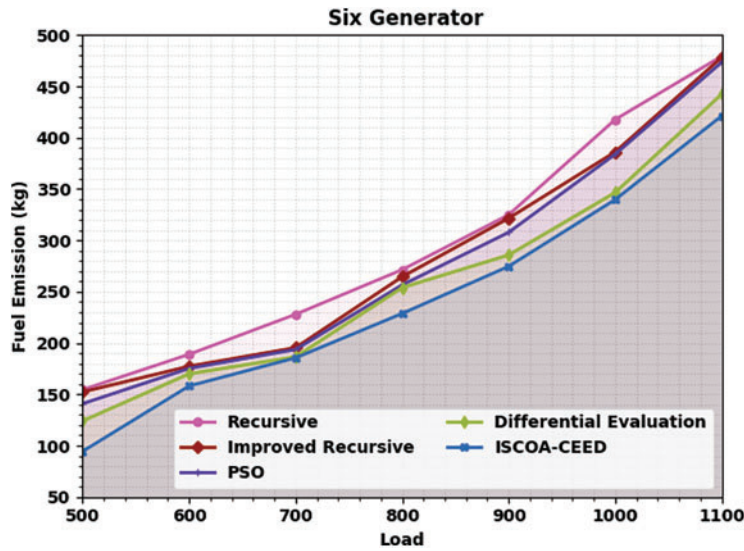


Figure 4: FE analysis of ISCOA-CEED system under six generator

Table 3: EED analysis of ISCOA-CEED system under a six-generator system with distinct loads

Load	500	600	700	800	900	1000	1100
P1	9.94	17.84	80.01	104.74	143.45	147.29	159.71
P2	37.57	43.14	109.05	148.42	202.16	219.65	237.14
P3	25.43	40.62	105.58	125.61	195.61	203.8	225.68
P4	17.38	38.58	86.06	112.26	165.71	198.41	207.25
P5	82.37	90.28	141.16	156.68	221.94	243.33	282.46
P6	82.91	95.33	146.99	198.22	243.74	256.62	289.57

Table 4 and Fig. 5 display a comparative FC inspection of the ISCOA-CEED with current techniques on eleven generators. The experimental value depicts that the ISCOA-CEED model has presented maximal performance with minimum FC values. Simultaneously, it is noted that the recursive and improved recursive techniques have demonstrated poor performance with maximal FC values. Even though the PSO and DE techniques have illustrated reasonably closer FV values, the ISCOA-CEED approach has surpassed them with the least FC values.

Table 4: FC analysis of ISCOA-CEED system with existing approaches under eleven generator

Load	Fuel cost (\$)				
	Recursive	Improved recursive	PSO	Differential evaluation	ISCOA-CEED
1000	7560.54	6072.59	5467.60	5363.81	3633.09
1250	8738.53	7223.51	7011.49	6673.60	6606.49

(Continued)

Table 4: Continued

Load	Fuel cost (\$)				
	Recursive	Improved recursive	PSO	Differential evaluation	ISCOA-CEED
1500	12178.87	10733.49	7731.90	7110.32	6724.36
1750	13053.54	12188.72	10852.45	10454.39	7466.58
2000	14288.96	12595.19	11449.69	11403.29	10770.98
2250	15401.53	14410.58	13171.69	12896.60	12116.40
2500	17614.45	16871.59	14823.51	13401.53	13270.60

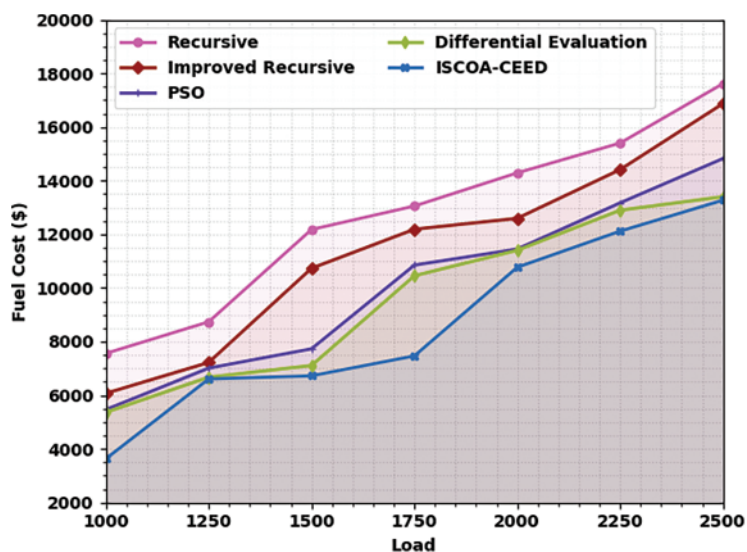
**Figure 5:** FC analysis of ISCOA-CEED system under eleven generator

Table 5 and Fig. 6 display a comparative FE inspection of the ISCOA-CEED with recent systems on eleven generators. The experimental values portrayed that the ISCOA-CEED method has displayed maximal performance with minimum FE values. Simultaneously, it is noted that the recursive and improved recursive approaches have shown poor performance with maximum FE values. Even though the PSO and DE techniques have illustrated reasonably closer FV values, the ISCOA-CEED method has surpassed them with the least FE values.

Table 5: FE analysis of ISCOA-CEED system with existing approaches under eleven generator

Load	Fuel emission (kg)				
	Recursive	Improved recursive	PSO	Differential evaluation	ISCOA-CEED
1000	120.04	113.09	106.20	97.53	61.68
1250	188.64	168.10	160.73	160.64	127.79

(Continued)

Table 5: Continued

Load	Fuel emission (kg)				
	Recursive	Improved recursive	PSO	Differential evaluation	ISCOA-CEED
1500	287.49	242.61	227.08	221.83	189.3
1750	398.44	391.14	361.17	360.97	309.63
2000	545.40	517.83	490.54	487.10	439.78
2250	695.35	691.92	682.22	681.25	629.33
2500	951.13	937.76	933.35	930.19	877.67

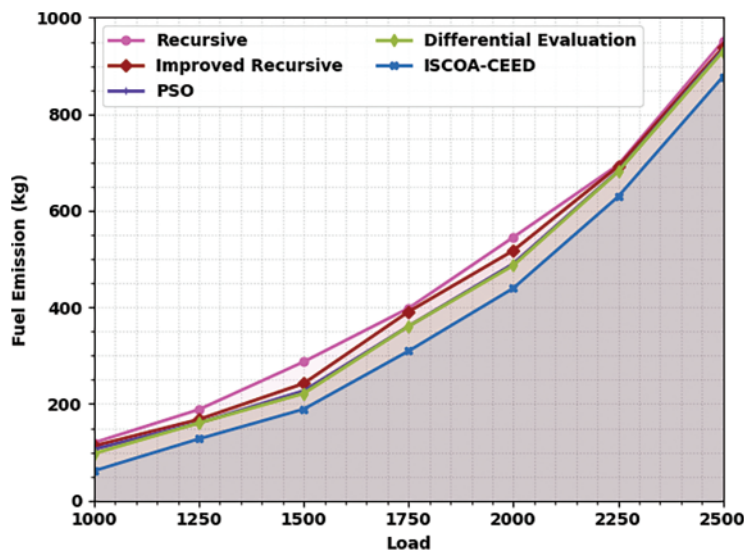


Figure 6: FE analysis of ISCOA-CEED system under eleven generator

In Table 6, the EED optimum compromise solutions of the ISCOA-CEED method are inspected under dissimilar loads and eleven generators. The experimental values show that the ISCOA-CEED technique has obtained effective results under each load value.

Table 6: EED analysis of ISCOA-CEED system under an eleven-generator system with distinct loads

Load	1000	1250	1500	1750	2000	2250	2500
P1	54.50	70.57	94.87	103.18	97.92	148.79	136.25
P2	47.72	54.89	80.07	83.88	87.34	101.78	136.02
P3	98.20	101.29	115.64	122.98	150.28	180.84	163.56
P4	61.55	85.26	100.49	109.45	102.08	152.09	139.42
P5	77.23	95.64	103.89	117.19	111.39	158.10	147.00
P6	105.79	147.83	167.36	200.31	226.04	256.97	304.37
P7	100.00	103.47	122.00	141.85	151.58	189.20	194.00

(Continued)

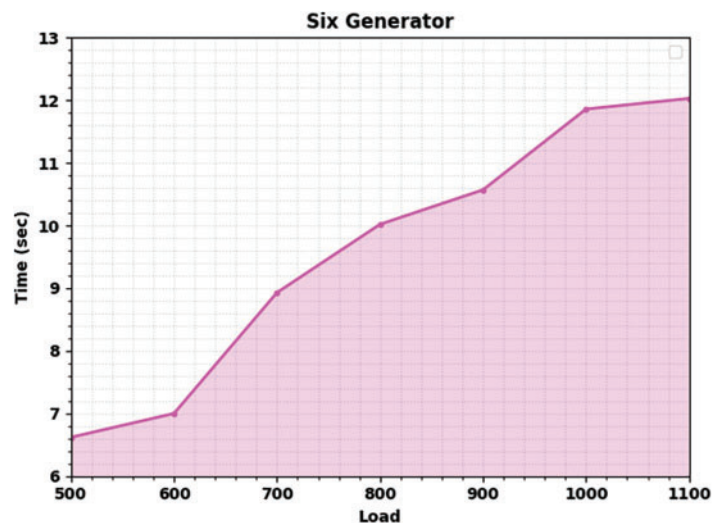
Table 6: Continued

Load	1000	1250	1500	1750	2000	2250	2500
P8	100.45	112.15	141.44	175.29	162.92	200.91	213.41
P9	119.65	154.60	185.24	221.02	263.54	303.68	346.65
P10	107.05	151.54	182.72	206.79	235.35	289.87	345.35
P11	164.09	158.72	212.30	227.46	291.78	335.35	376.80

The computation time (CT) analysis of the ISCOA-CEED model under varying loads of six generators is given in Table 7 and Fig. 7. These results inferred that the ISCOA-CEED model has reached effectual outcomes with minimal CT values under all loads. For instance, with 500 loads, the ISCOA-CEED model obtained a CT of 6.62s. At the same time, with 600 loads, the ISCOA-CEED method has acquired a CT of 7s. Moreover, with 900 loads, the ISCOA-CEED method has attained a CT of 10.57s. Next, with an 1100 load, the ISCOA-CEED approach has accomplished a CT of 12.03s.

Table 7: CT analysis of ISCOA-CEED system with distinct loads under six generator

Load	Six generator time-(s)
500	6.62
600	7.00
700	8.93
800	10.02
900	10.57
1000	11.86
1100	12.03

**Figure 7:** CT analysis of ISCOA-CEED system under six generator

The CT examination of the ISCOA-CEED approach under varying loads of eleven generators is demonstrated in Table 8. The result depicts that the ISCOA-CEED approach has obtained effective results with the least CT values under each load. For example, with 1000 loads, the ISCOA-CEED method has attained a CT of 10.29s. Simultaneously, with a 1250 load, the ISCOA-CEED technique has attained a CT of 10.98s. Furthermore, with a 2250 load, the ISCOA-CEED technique has accomplished a CT of 16.80s. Then, with a 2500 load, the ISCOA-CEED approach attained a CT of 18.28s. These results assured the enhanced performance of the ISCOA-CEED model over other models.

Table 8: CT analysis of ISCOA-CEED system with distinct loads under eleven generator

Load	Eleven generator time–(s)
1000	10.29
1250	10.98
1500	11.18
1750	13.85
2000	15.11
2250	16.80
2500	18.28

5 Conclusion

In this study, a new ISCOA-CEED technique has been developed for CEED. The presented ISCOA-CEED technique aims at the effectual reduction of fuel cost and emission of generation units. Following, the presented ISCOA-CEED technique transforms the equality constraint of the CEED issues into the inequality constraint. Moreover, the ISCOA is derived from the integration of traditional SCOA with the LF concept. Finally, the ISCOA-CEED technique is applied to solve a series of 6 generators as well as 11 generators in the CEED issue. The experimental validation of the ISCOA-CEED technique ensured the enhanced performance of the presented ISCOA-CEED technique over other recent approaches. Therefore, the ISCOA-CEED technique can resolve the CEED in a real-time environment. In the future, the presented ISCOA-CEED technique can be extended by the use of deep learning (DL) models.

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