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Sine Cosine Algorithm for Solving Economic Load Dispatch Problem With Penetration of Renewables

Diwakar Verma, Institute of Technology, Nirma University, India
Jatin Soni, Institute of Technology, Nirma University, India*
Dhruv Kalathia, Institute of Technology, Nirma University, India
Kuntal Bhattacharjee, Institute of Technology, Nirma University, India

ABSTRACT

Economic load dispatch is used to allocate power demand economically among connected generators by considering various constraints. The thermal generating units are incorporated with renewable sources like wind and solar units to reduce pollution and dependency on fuel cost. The uncertainty of output power from wind and solar plants is considered here. The 2-m point estimation method is used to get generated power from wind and solar units. The population-based Sine Cosine Algorithm is proposed to get the optimum solution of the presented complex ELD problem. The randomly placed search agents find an optimum solution according to their fitness values and keep path towards best solution attained by each search agent. The search agents avoid local optima in exploration stage and move towards the solution exploitation stage using sine and cosine functions. The proposed algorithm has been tested in various four test systems. The results proved that the proposed algorithm gives quite an effective, efficient, and promising solution compared to other techniques.

KEYWORDS

2-m Point Estimation Method, Economic Load Dispatch, Renewable Energy Sources, Sine Cosine Algorithm, Valve Point Effect

1. INTRODUCTION

Due to increased power demand by commercial and residential users, the cost of power generation becomes a huge concern in power system operation and control. If there is a slight decrease in the cost of power generation, it will create a major effect on the economics of the power system. Researchers and engineers have introduced Economic Load Dispatch (ELD) term to run power generating units at minimum cost with satisfying power demand. The economics of power systems encourage researchers to invent techniques that reduce the cost of power generation significantly. The traditional numerical techniques like lambda iteration method (Zhan et al., 2014), gradient method (Ray, 2014), linear programming method and quadratic programming method (dos Santos Coelho & Mariani, 2006) used

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to solve ELD problem. These methods are based on linear cost approximation. The practical ELD problem becomes highly nonlinear after considering various operating constraints like generating operating constraints and valve point loading effect (VPLE). Many metaheuristic techniques like Genetic Algorithm (GA) (Bakirtzis, 1994), Differential Evaluation (DE) (Roy et al., 2014), Particle Swarm Optimization (PSO) (Gaing, 2003), Evolutionary Programming (EP) (Dao et al., 2015), Hybrid Evolutionary Programming (HEP) (Sinha et al., 2003), Civilized Swarm Optimization (CSO) (Narang et al., 2017), Modified PSO (MPSO) (Kamboj et al., 2016), Adaptive Real Coded GA (ARCGA) (Ni et al., 2017), Bacteria Foraging Optimization (BFO) (Ali & Abd-Elazim, 2ss011), Search Group Optimization (SGO) (Bhattacharjee & Patel, 2019), Seeker Optimization Algorithm (SOA) (Shaw et al., 2012) used due to capable of finding high dimensional ELD problem. Sometimes, these methods converge to local optima and do not guarantee the global best solution.

To solve the issue of an energy shortage and environmental effect, the renewable energy sources (RES) incorporated with the ELD problem have received much attention (Sujatha et al., 2020). The power generation from RES is very less and could not meet the demand (Soni et al., 2020). Thus, they are interconnected with thermal generating units to supply power demand. Wind and solar units are incorporated in the ELD problem due to their lower operating cost (Kaluri & CH, 2018). The power generation from wind and solar units is uncertain due to their dependency on wind velocity and solar irradiance respectively. The Weibull and beta Probability Density Function (PDF) are used to randomly generate wind velocity and solar irradiance (Azad et al., 2014). The 2-m Point Estimation Method (PEM) is used to get mean and standard deviation (SD) (Bhattacharjee et al., 2014). Thus, the objective function of the renewable-based ELD problem becomes highly nonlinear and complex (Kaluri & Pradeep Reddy, 2017). Many hybrid techniques like Strength Pareto Evolutionary Algorithm (SPEA) (Kamboj et al., 2017) and a combination of Sequential Quadratic Programming (SQP) and PSO (Bhattacharjee & Patel, 2020) were applied. These hybrid methods give premature results because the problem has multiple minima. Many metaheuristic techniques like Artificial Bee Colony (ABC) (Dubey et al., 2020), Harmony Search Algorithm (HAS) (Ravikumar Pandi et al., 2010), Flower Pollination Algorithm (FPA) (Shilaja & Ravi, 2017), Teaching-Learning Based Optimization (TLBO) (Bhattacharjee et al., 2015), Backtracking Search Algorithm (BSA) (Jin & Yin, 2020), and Tabu Search (TS) (Soni & Pandya, 2018)used all thermal ELD problems without renewables. Unfortunately, these methods have very low efficiency and are frequently stuck in local optima. Many artificial techniques like Firefly Algorithm (FFA) (Banerjee & Sarkar, 2021), Dragonfly Algorithm (DA) (Das et al., 2020), Multiple Group Search Optimization (MGSO)(Gou, 2021), Artificial Immune System Algorithm (AISA) (Naderi et al., 2009), Imperialist Competitive Algorithm (ICA) (Morshed & Asgharpour, 2014), Jaya Algorithm (JA)(Trivedi et al., 2016), Cuckoo Search Algorithm (CSA) (Bhoye et al., 2016), Ant Lion Optimizer (ALO)(Hatata & Hafez, 2019), Oppositional Real-Coded Chemical Reaction Optimization (ORCCRO)(Bhattacharjee et al., 2014), Biogeography-Based Optimization (BBO) (Xiong et al., 2013), Adaptive Jaya Algorithm (AJA) (R. V. Rao et al., 2020), Bat Algorithm (BA)(Algburi & Karataş, 2021), Plant Grow Simulation Algorithm (PGSA) (R. S. Rao et al., 2011), Magnetic Optimization Algorithm (MOA)(Kushwaha et al., 2018), Gravitational Search Algorithm (GSA) (Younes et al., 2021) and Charged System Search (CSS) (Zakian & Kaveh, 2018) have been applied to solve renewable-based ELD problem. However, some of the above-mentioned methods have a low convergence rate and some may stick in finding local optima. Thus, a powerful optimization technique is needed to overcome all of these disadvantages.

Recently, the population-based Sine Cosine Algorithm (SCA) has been proposed by Mirjalili et al. (Mirjalili, 2016). The nineteen unimodal, multimodal, and composite benchmark functions have been solved by Mirjalili et al. (Mirjalili, 2016).In SCA, the multiple initial random populations are generated and moved outward or toward the best solution. The trigonometric sine and cosine function of SCA is used to find the fitness value of populations. SCA has the exploration and exploitation property. The randomly generated solution by SCA gets to benefit from higher exploration and avoids local optima value. Such a feature is not available in other algorithms. These properties help to avoid

local optima and move directly to global optima in very less computational time. The advantages of SCA have encouraged present authors to use this newly developed algorithm to resolve highly nonlinear and complex renewable-based ELD problems. The key contributions of this paper have been listed as follows:

- The trigonometric functions sine and cosine based SCA algorithm has been proposed first time to solve highly complex and non-linear ELD problem with high penetration of renewable energy sources.
- The various operating constraints like VPLE, generator operating limit, and power balancing constraints have been considered to make system more realistic.
- The probability density functions like Weibull and beta distribution have been used to get uncertain values of wind velocity and solar irradiance respectively.
- The 2-m point estimation method has been used to estimate output power from wind farms and solar units.
- The proposed algorithm has been tested in different small, medium, and large test system to prove robustness of the algorithm.
- The results obtained by proposed algorithm have been compared with the results of some recently developed algorithms to prove better performance of the proposed algorithm.

The problem formulation of the ELD problem with RES is given in Section 2. The mathematical modeling of wind and solar is explained in Section 3. Section 4 provides information on the original SCA method. The PEM is explained in Section 5. The steps involved for the solution of the renewable-based ELD problem using SCA are discussed in Section 6. Section 7 shows the simulation results of various test cases. Finally, the conclusion of the manuscript is pointed out in Section 8.

2. PROBLEM FORMULATION

The main aim of this research is to supply power demand by minimizing the total power generation cost of wind-solar-thermal units and by satisfying all equality and inequality constraints. The objective function of the renewable-based ELD problem is formulated below.

2.1 Objective Function

2.1.1 The Total Cost Function of ELD Incorporating With Wind-Solar Without VPLE

The objective function of cost for the thermal unit is a second-order polynomial equation. The objective function of cost for wind-solar ELD without VPLE is shown as below:

$$Total\cos t = min\left[\sum_{iT=1}^{N} a_{iT} + b_{iT}T_{iT} + c_{iT}T_{iT}^{2} + \sum_{k=1}^{N_w} W_{p,k} \times C_{wk} + \sum_{l=1}^{N_s} S_{pl} \times Bid_l\right] \quad (1)$$

where a_{iT}, b_{iT} and c_{iT} are thermal cost co-efficient of ith unit; N is total connected thermal units; T_{iT} is the power generated by each thermal unit; T_i^{min}, T_i^{max} are the minimum and maximum power limit of each unit; W_p, S_p are the output power of wind and solar in MW; C_w is cost coefficient of wind in \$/h; N_w, N_s is Total number of wind and solar plant; Bid_l is Bid rate of lth solar plant.

2.1.2 The Total Cost Function of ELD Incorporating With Wind-Solar With VPLE

To consider the realistic and practical application of the ELD problem, the sinusoidal phrase of VLPE is added in the objective function. The cost function of wind-solar ELD with VPLE is stated as:

$$Total\,cost = min\left[\begin{array}{c}\sum_{iT=1}^{N} a_{iT} + b_{iT}T_{iT} + c_{iT}T_{iT}^{2} + \left|e_{iT}sin\left\{f_{iT}\times\left(T_{iT}^{min} - T_{iT}\right)\right\}\right| + \\ \sum_{k=1}^{N_w} W_{p,k}\times C_{wk} + \sum_{l=1}^{N_s} S_{pl}\times Bid_{l}\end{array}\right] \tag{2}$$

where e_{iT} and f_{iT} are co-efficient of thermal i^{th} unit representing VPLE. The objective function (1) and (2) are minimized subject to subsequent constraints.

2.2 Constraints

The following equality and inequality constraints are considered while optimizing the total cost function.

2.2.1 Thermal Generator Operating Limit

The power generated by each generator has a minimum and maximum permissible power limit for efficient operation:

$$T_{iT}^{\min} \le T_{iT} \le T_{iT}^{\max}; iT = 1,2,3,\ldots,N \tag{3}$$

2.2.2 Power Balance

The total real power generated must balance total load demand:

$$\sum_{iT=1}^{N} T_{iT} + \sum_{k=1}^{N_w} W_{pk} + \sum_{l=1}^{N_s} S_{pl} - \left(T_D + T_L\right) = 0 \tag{4}$$

where T_D is Total load demand and T_L is Total transmission loss.

3. MODELING OF WIND AND SOLAR POWER

The RES has got much attention from researchers due to its many advantages. These RES are integrated with conventional sources to decrease the use of fossil fuels. The mathematical model of RES like wind and solar is formulated as the following.

3.1 Modelling of Wind Power

The output power of wind is uncertain due to dependency on wind speed. Many methods were used to get uncertain curve of wind speed characteristics (He et al., 2019). Weibull PDF is used to describe stochastic wind speed profiles. The PDF for wind speed is formulated as (Azad et al., 2014):

$$PDF\left(v\right) = \frac{S_{shf}}{S_{scf}}\left(\frac{v}{S_{scf}}\right)^{S_{shf}-1} \exp\left[1 - \left(\frac{v}{S_{scf}}\right)^{S_{shf}}\right]; for 0 < v < \infty \tag{5}$$

where S_{shf} and S_{scf} are shape factor and scale factor of wind turbine; v is instantaneous wind speed. After calculating the uncertain behavior of wind speed as an arbitrary variable, the wind power is

computed as an arbitrary variable through a conversion from wind speed to output power. The wind power is computed using the speed-power curve as:

$$W_p = \begin{cases} 0; v\left\langle v_{in}, v\right\rangle v_{out} \\ W_{pt}\left(\dfrac{v - v_i}{v_r - v_i}\right); v_{in} < v < v_r \\ W_{pr}; v_r < v < v_{out} \end{cases} \tag{6}$$

where v and v_r are instantaneous speed and rated speed of wind unit; v_{in} and v_{out} are cut in and cut out speed of wind unit; W_p and W_{pt} are output power and rated power of wind turbine.

3.2 Modelling of Solar Power

The output power of solar depends upon irradiance and temperature. beta PDF is used to show uncertain behavior of solar irradiance (Sheng & Wang, 2018). The beta distribution is expressed as:

$$PDF\left(r\right) = \begin{cases} \dfrac{\Gamma\left(w+\psi\right)}{\Gamma\left(w\right)\Gamma\left(\psi\right)} \times r^{w-1}\left(1-r\right)^{\psi-1}; 0 \le r \le 1, w \ge 0, \psi \ge 0 \\ 0; otherwise \end{cases} \tag{7}$$

where ω are ψ beta distribution parameters; Γ is the gamma function. The reactive power of the solar system is assumed zero to inject solar power into the grid at a unity power factor (Namilakonda & Guduri, 2021). The. The relation between them is formulated as:

$$S_P\left(t\right) = \left[S_{P,stc} \times \frac{S_{rad}\left(t\right)}{S_{rad,stc}} \times \left\{1 - \gamma \times \left(T_{cell} - T_{cell,stc}\right)\right\}\right] \times N_{sc} \times N_{pc} \tag{8}$$

where $S_{rad}(t)$ is solar radiation of cell at time t; $S_{rad,stc}$ is solar radiation for the standard condition; $S_{P,stc}$ is solar power for standard condition; γ is coefficient of temperature in %/°C; T_{cell} is the temperature of solar cell; $T_{cell,stc}$ is temperature of solar cell in standard test condition; N_{sc} are N_{pc} are number of series and parallel solar cell. The temperature of cell T_{cell} can be computed using the following formula:

$$T_{cell} = T_{amb} + \frac{S_{rad}\left(t\right)}{S_{rad.stc}} \times \left(NTC - 20\right) \tag{9}$$

where T_{cell} is ambient temperature in °C and NTC is the normal temperature of solar cell.

4. POINT ESTIMATION METHOD

PEM is presented by Rosenblueth in 1975 to solve probabilistic problems. However, it was not useful for symmetric variables. Therefore, Hongs proposed 2-m PEM to get the probabilistic behavior of the arbitrary variable. The probabilistic renewable-based ELD problem is mathematically denoted as:

$$S_e = f\left(I_k\right) \tag{10}$$

where S_e is total power generation including wind and solar and I_k is input variables. The predicted value is different from actual values in a probabilistic problem. If b is the number of an arbitrary variable, the equation is modified as:

$$S_e = f\left(c, z_1, z_2, ..., z_b\right) \tag{11}$$

The PDF $f(z_l)$ of each arbitrary variable z_b is changed by two-point using three moments namely mean μ, variance σ, and skewness λ coefficient. The function f is computed 2b times to get these moments:

$$S_{e(l,p)} = f\left(c, \mu_{z1}, \mu_{z2}, ..., \mu_{zb}\right); p = 1,2; y = 1,2,...b \tag{12}$$

The steps of 2-m PEM are summarized as below:

1. Decide b (input arbitrary variable).

2. Set all moments (first and second) of output arbitrary variable equal to zero:

$$E_x\left(S_i^t\right) = 0; t = 1,2 \tag{13}$$

3. Decide uncertain parameter z_y.
4. Compute skewness λ_{zy}:

$$\lambda_{zy,3} = \frac{E_x\left[\left(z_y - \mu_{zy}\right)^3\right]}{\left(\sigma_{zy}\right)^3}$$

where:

$$E_x\left[\left(z_y - \mu_{zy}\right)^3\right] = \sum_{j=1}^{N}(z_{y,j} - \mu_{zy})^3 \times prob\left(z_{y,j}\right) \tag{14}$$

5. Compute two standard location:

$$\Delta = \frac{\lambda_{zy,3}}{2} + \left(-1\right)^{3-p}\sqrt{\left(b + \left(\frac{\lambda_{zy,3}}{2}\right)\right)}; p = 1,2 \tag{15}$$

6. Calculate two projected location:

$$z_{y,k} = \mu_{zy} + \Delta_{zy,k}\sigma_{zy}; p = 1,2 \tag{16}$$

7. Compute deterministic ELD for two projected location:

$$S_{e(y,p)} = f\left(\mu_{z1}, \mu_{z2}, .., z_{yp}, ..., \mu_{zb}\right); p = 1,2; y = 1,2,...b \tag{17}$$

8. Compute two weighting factors:

$$w_{y,p} = \frac{(-1)^p}{b} \frac{\Delta_{y,3-p}}{\Delta_{y,1} - \Delta_{y,2}}; p = 1,2 \tag{18}$$

9. Update the moment of each output arbitrary variable:

$$E_x\left(S_e^t\right) = E_x\left(S_e^t\right) + \sum_{p=1}^{2} w_{y,p}\left(S_e\left(y,p\right)\right)^t; t = 1,2 \tag{19}$$

10. Repeat steps 3 to 9 until all unpredictable parameter are taken into account.
11. Calculate mean and SD:

$$\begin{aligned} mean\left(\mu\right) &= E_x\left(S_e^1\right) \\ std\left(\sigma\right) &= \sqrt{E_x\left(S_e^2\right) - \left(E_x\left(S_e^1\right)\right)^2} \end{aligned} \tag{20}$$

5. SINE COSINE ALGORITHM

SCA starts the optimization using a random search agent because it is a population-based technique (Mirjalili, 2016). The random search population is evaluated repetitively and upgraded using a set of rules. SCA has an exploration and exploitation stage. In the exploration stage, all the random solutions are combined at a higher randomness rate to get search space area where higher possibility of getting the global solution. In the exploitation stage, the random solutions are changed slowly and that variation is very less as compared to the exploration stage.

The four parameters g_1, g_2, g_3 and g_4 are the main in SCA. The g_1 parameter represents the next position that can be in space between the solution and destination or exterior of it. The g_2 parameter represents distance that population have to go in the direction of the solution. The g_3 parameter helps to find weights for destination. The weights greater than one and less than one represents emphasize and deemphasize on solution respectively. The g_4 parameter switches between sine and cosine terms in (23). The trigonometric sine and cosine function is involved in this formulation. Thus, it is called as SCA. The following equations of SCA are used to update results in every iteration:

$$P_h^{t+1} = P_i^t + g_1 \times \sin\left(g_2\right) \times \left|g_3 PO_h^t - P_h^t\right| \tag{21}$$

$$P_h^{t+1} = P_h^t + g_1 \times \cos\left(g_2\right) \times \left| g_3 PO_h^t - P_h^t \right| \tag{22}$$

where g_1, g_2 and g_3 are constant variables. the g_4 variable is given a random variable between 0 and 1. The equations (21) and (22) are modified as below:

$$P_h^{t+1} = \begin{cases} P_h^t + g_1 \times \sin\left(g_2\right) \times \left| g_3 PO_h^t - P_h^t \right|; & g_4 < 0.5 \\ P_h^t + g_1 \times \cos\left(g_2\right) \times \left| g_3 PO_h^t - P_h^t \right|; & g_4 \geq 0.5 \end{cases}$$

where P_h^{t+1} is the position of the population at current (t+1)th iteration and hth dimension; P_h^t is position of population at previous tth iteration and hth dimension; PO_h^t is position of destination point at previous tth iteration and hth dimension. The sequential steps of SCA are given below.

5.1 Sequential Steps of SCA

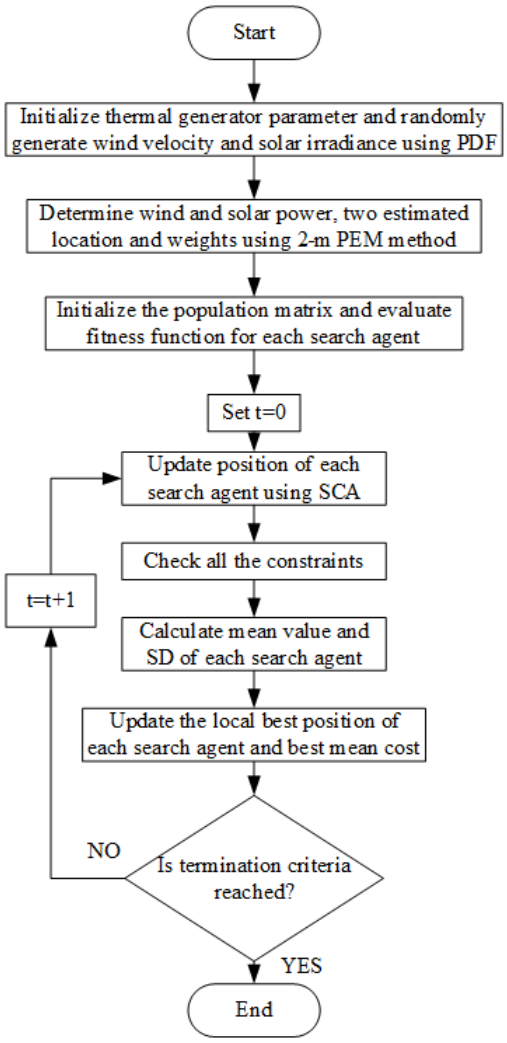
1. Initialization of lower and upper bound limit of each search agent. Decide the total number of iteration and population size.
2. The objective is computed by considering input variables.
3. Evaluate the fitness function value of each population using an objective function.
4. If the fitness function value is lower than the previous one, it is considered as local minima. The parameters g_1, g_2 and g_3 are initially assigned. After each iteration, the value of parameters will change. The parameter g_4 switches between sine and cosine function.
5. The changed values of the population is checked if it violated or not. If yes, fix their boundary limits.
6. The search agents will move in the whole search space to find global optima in the exploration stage.
7. Once the destination point is found, the population will move in that direction in the exploitation stage.
8. Repeat steps 3 to 7 until termination criteria is reached.

6. SCA USED IN RENEWABLE BASED ELD PROBLEM

The steps for solving the renewable-based ELD problem by using SCA are discussed in this section. The flowchart of the SCA used in solving the renewable-based ELD problem is given in Figure 1. The steps to solve the problem as shown below:

Step 1: Initialize the number of generators, population size, lower bound and upper bound of thermal generators, wind and solar parameters.
Step 2: Generate wind velocity and solar irradiance using Weibull distribution and beta distribution function respectively using Equations (5) and (7).
Step 3: Implement the 2m-PEM Method and find mean wind and solar power, two estimated locations, and their corresponding weighting factor using equations from (13) to (18).
Step 4: For each search agents randomly initialize the population matrix for thermal power plants and evaluate the fitness function.
Step 5: Randomly generate g_2, g_3 and g_4 parameters and determine the value of g_1.
Step 6: Update the position of each search agents using equation (23).
Step 7: Check for constraint limits of each generator based on equations (3) and (4).
Step 8: Compute the fitness function and update the local best position of each search agent. Update best mean cost and SD.
Step 9: Repeat step (5) until the termination criterion is reached.

Figure 1. Flowchart of SCA used in solving renewable-based ELD problem



7. RESULTS AND DISCUSSION

To check and validate the effectiveness of the SCA algorithm, four test systems have been considered in this manuscript as shown in Table 1. These four test systems include small and large thermal generating units with two solar and two wind units. The final results of SCA are compared with results of other well-known algorithms like DA (Das et al., 2020), CSA (Bhoye et al., 2016), ALO (Hatata & Hafez, 2019), BBO (Xiong et al., 2013), PSO (Gaing, 2003), GA (Bakirtzis, 1994) and ORCCRO (Bhattacharjee et al., 2014). MATLAB 2021a software is used to simulate the problem and validated in 1.7GHz intel core, 4GB RAM personal computer.

7.1 Test Case 1

Three thermal generators are considered with two wind and two solar plants in this test system. The VPLE is considered. The input data for solar and wind units are taken from (Das et al., 2020). The input data for thermal units are taken from (Mallikarjuna et al., 2014). The generating capacity of

Table 1. Details of test system

Case	1	2	3	4
No. of Thermal Units	3	5	6	15
No. of Wind plant	2	2	2	2
No. of Solar Plant	2	2	2	2
Total Demand (MW)	1050	730	1263	2630
Valve Point Loading	Yes	Yes	No	No

each solar and wind unit is 10 MW and 0.8 MW respectively. The power demand of the system is 1050 MW. The algorithm requires 200 iterations and 3.6585 seconds to get the optimum solution. The 2-m sets of attained output power are shown in Figure 2. The mean cost and SD attained by SCA are compared with DA (Das et al., 2020), GA (Bakirtzis, 1994), PSO (Gaing, 2003), CSA (Bhoye et al., 2016), ORCCRO (Bhattacharjee et al., 2014), BBO (Xiong et al., 2013) and ALO (Hatata & Hafez, 2019) as shown in Table 2. It is noticed that the minimum cost attained by SCA is 10,023.93 $/h which is very less compared to DA (Das et al., 2020), GA (Bakirtzis, 1994), PSO (Gaing, 2003), CSA (Bhoye et al., 2016), ORCCRO (Bhattacharjee et al., 2014) and ALO (Hatata & Hafez, 2019). It is also observed that SCA gets the optimum solution in very less time as compared to other techniques. The convergence characteristic by SCA is shown in Figure 3.

7.2 Test Case 2

Five thermal generators are considered with two wind and two solar plants. The VPLE is considered in this case. The generating capacity of each solar and wind unit is 10 MW and 0.8 MW respectively. The input data for solar and wind units are available in (Das et al., 2020). The input data for thermal units are taken from (Roy et al., 2014). The power demand of the system is 730 MW. The algorithm requires 600 iterations and 9.28 seconds to get the optimum solution. The 2-m sets of attained best output power in this case are given in Figure 4. The mean cost attained by the SCA algorithm is 2014.1967 $/h which is very less as compared to other algorithms like DA (Das et al., 2020), GA (Bakirtzis, 1994), PSO (Gaing, 2003), CSA (Bhoye et al., 2016), ORCCRO (Bhattacharjee et al., 2014), BBO (Xiong et al., 2013) and ALO (Hatata & Hafez, 2019) as shown in Table 3. The convergence characteristic by the SCA algorithm is shown in Figure 5.

Figure 2. 2-m set of attained best output power for test case 1

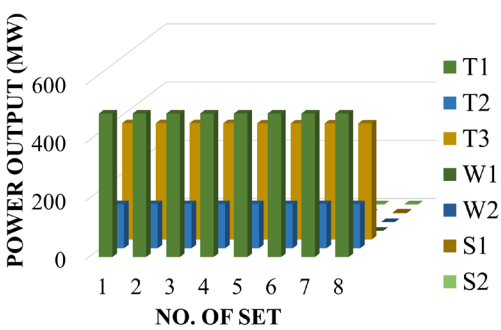


Table 2. Performance study of well-known methods for test case 1

Methods	Mean Cost ($/h)	Simulation Time (seconds)	SD
SCA	10,023.9367	3.6585	0.1147
DA (Das et al., 2020)	10,049.1948	8	0.5394
CSA (Bhoye et al., 2016)	10,065.7013	10	1.2365
ALO (Hatata & Hafez, 2019)	10,079.2323	12	3.0214
ORCCRO (Bhattacharjee et al., 2014)	10,080.8028	14.6	8.7412
BBO (Xiong et al., 2013)	10,088.8563	17.8	13.2557
PSO (Gaing, 2003)	10,089.0073	20.5	15.3369
GA (Bakirtzis, 1994)	10,096.199	24.2	18.3698

Figure 3. Convergence characteristics by SCA algorithm for case 1

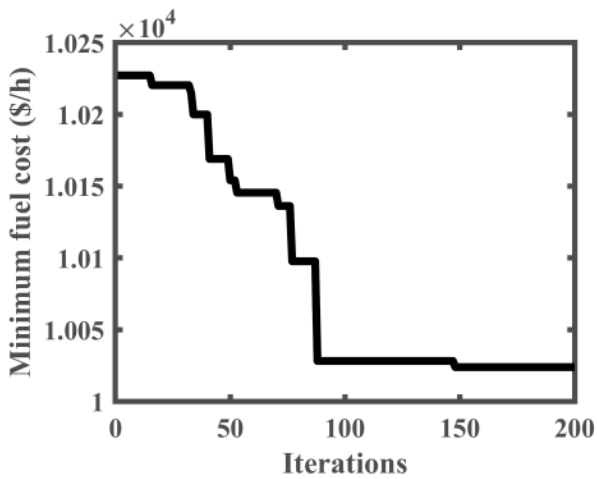


Figure 4. 2-m set of attained best output power for test case 2

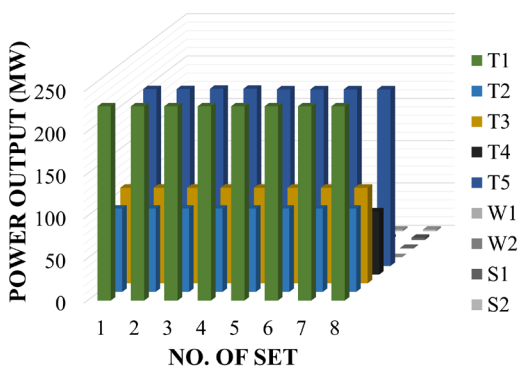
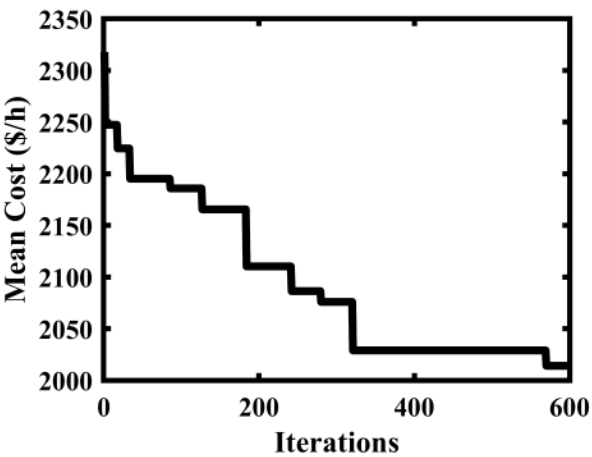


Table 3. Performance study of well-known methods for test case 2

Methods	Mean Cost ($/h)	Simulation Time (seconds)	SD
SCA	2014.1967	9.28	2.2582
DA (Das et al., 2020)	2018.0762	12	2.5111
CSA (Bhoye et al., 2016)	2021.5229	12.6	4.2210
ALO (Hatata & Hafez, 2019)	2025.8236	14.5	6.3258
ORCCRO (Bhattacharjee et al., 2014)	2046.6344	17.2	9.8871
BBO (Xiong et al., 2013)	2058.5299	21	14.2558
PSO (Gaing, 2003)	2060.8011	25	18.7324
GA (Bakirtzis, 1994)	2073.8957	28	23.1892

Figure 5. Convergence characteristic by SCA algorithm for case 2



7.3 Test Case 3

Six thermal generating units are connected with two solar and two wind plant. The input data for solar and wind units are available in (Das et al., 2020). The input data for thermal units are provided in (Roy et al., 2014). The generating capacity of each solar and wind unit is 10 MW and 0.8 MW respectively. The power demand is 1263 MW. The algorithm requires 150 iterations and 4.58 seconds to get the optimum solution. The 2-m sets of attained best output power in this case are shown in Figure 6. The mean cost attained by the SCA algorithm is 15,203.842 $/h which is very less as compared to other algorithms like DA (Das et al., 2020), GA (Bakirtzis, 1994), PSO (Gaing, 2003), CSA (Bhoye et al., 2016), ORCCRO (Bhattacharjee et al., 2014), BBO (Xiong et al., 2013) and ALO (Hatata & Hafez, 2019) as shown in Table 4. It is also observed that SCA requires very less time to get the optimum solution as compared to other techniques. The convergence characteristic by the SCA algorithm is shown in Figure 7.

7.4. Test Case 4

The 15 thermal generating units are connected with two solar and two wind plant. The input data for solar and wind units are available in (Das et al., 2020). The input data for thermal units are provided

Figure 6. 2-m set of attained best output power for test case 3

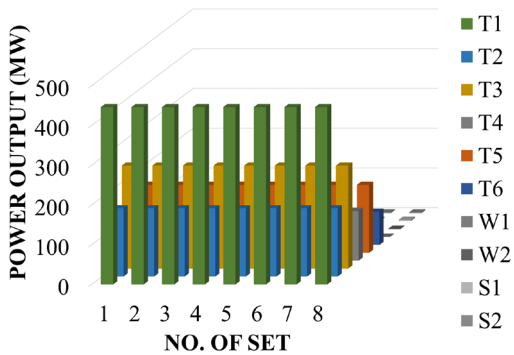
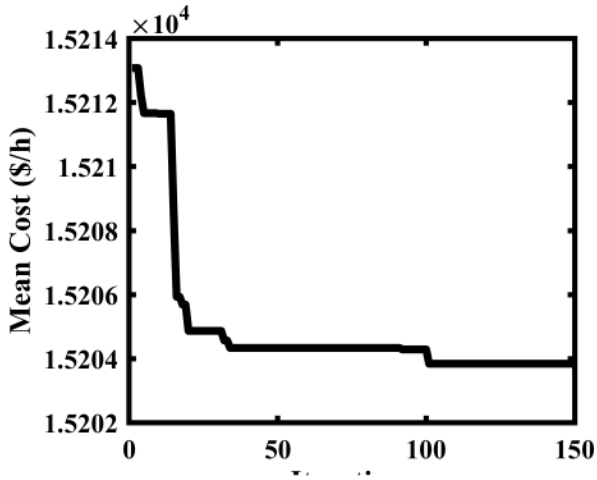


Table 4. Performance study of well-known methods for test case 3

Methods	Mean Cost ($/h)	Simulation Time (seconds)	SD
SCA	15,203.8424	4.58	4.2867
DA (Das et al., 2020)	15,268.8325	15	13.1266
CSA (Bhoye et al., 2016)	15,277.2396	18	15.3321
ALO (Hatata & Hafez, 2019)	15,278.2188	19.2	16.9127
ORCCRO (Bhattacharjee et al., 2014)	15,280.1136	23.9	18.2114
BBO (Xiong et al., 2013)	15,284.9752	24	21.4785
PSO (Gaing, 2003)	15,286.3639	27.6	26.9874
GA (Bakirtzis, 1994)	15,287.8373	28	28.7745

Figure 7. Convergence characteristic by SCA algorithm for case 3



in (Bhattacharjee et al., 2013). The generating capacity of each solar and wind unit is 10 MW and 0.8 MW respectively. The power demand is 2630 MW. The algorithm requires 100 iterations and 10.04 seconds to get the optimum solution. The 2-m sets of attained best output power in this case are given in Figure 8. The mean cost attained by the SCA algorithm is 32285.3935 $/h. which is very less as compared to other algorithms like DA (Das et al., 2020), GA (Bakirtzis, 1994), PSO (Gaing, 2003), CSA (Bhoye et al., 2016), ORCCRO (Bhattacharjee et al., 2014), BBO (Xiong et al., 2013) and ALO (Hatata & Hafez, 2019) as shown in Table 5. The convergence characteristic by the SCA algorithm is given in Figure 9.

7.4.1. Tuning the Parameter of the SCA

The parameters of the SCA algorithm should be tuned to obtain optimum solution in less computational time. The different values of the parameters 'g_1, g_2, g_3, and g_4' give different minimum fuel costs. For single values of g_1 parameter, the values of other parameters 'g_2, g_3 and g_4' have to be varied in all possible combinations. It takes very large space to show here. Thus, the summarized results of minimum fuel costs, after 50 trails run, for all possible combinations have been shown in Table 6. The optimal values of the parameters are listed as g_1=0.5, g_2=0.6, g_3=0.3, g_4=0.5.

Figure 8. 2-m set of attained best output power for test case 4

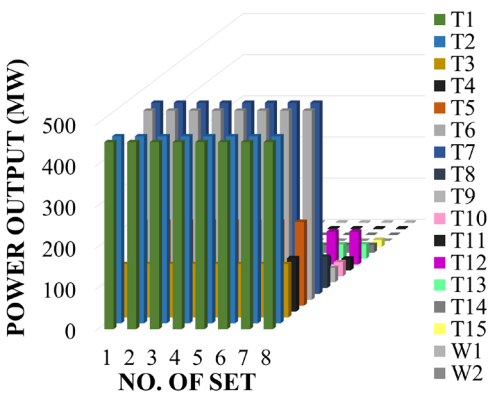


Table 5. Performance study of well-known methods for test case 4

Methods	Mean Cost ($/h)	Simulation Time (seconds)	SD
SCA	32,285.39352	10.04	3.7468
DA (Das et al., 2020)	32,310.2922	20	10.5017
CSA (Bhoye et al., 2016)	32,318.1056	24.3	14.2357
ALO (Hatata & Hafez, 2019)	32,329.5536	26.8	16.6912
ORCCRO (Bhattacharjee et al., 2014)	32,358.0926	29	19.7439
BBO (Xiong et al., 2013)	32,260.2696	31.4	21.3321
PSO (Gaing, 2003)	32,365.9862	35	24.9874
GA (Bakirtzis, 1994)	32,388.5473	36.7	26.1234

Figure 9. Convergence characteristic by SCA algorithm for case 4

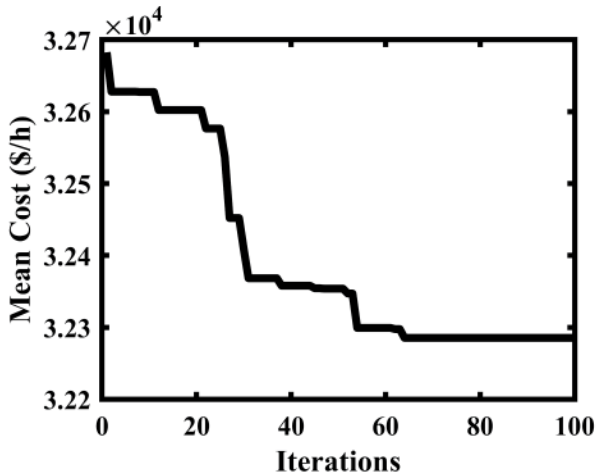


Table 6. The minimum fuel cost for different values of SCA parameters

g_1	g_2	g_3	g_4	Minimum fuel cost ($ / hr.)
0.1	0.40	0.10	0.1	32301.9654
0.2	0.45	0.15	0.2	32295.3621
0.3	0.50	0.2	0.3	32300.1542
0.4	0.55	0.25	0.4	32290.7845
0.5	0.60	0.30	0.5	**32285.3935**
0.6	0.65	0.35	0.6	32289.9652
0.7	0.70	0.40	0.7	32296.1004
0.8	0.75	0.45	0.5	32306.9865

7.5. Discussion

The mean cost obtained by the SCA algorithm and power generated by each unit of thermal, wind-solar for various test systems is shown in Table . The total power generated by the system and total load demand for various test system is shown in Figure 10, Figure 11, Figure 12, Figure 13. For cases 1,2,3 and 4, the total power generated by thermal units is 1042.8003 MW, 724.3609 MW, 1256.0108 MW and 2624.1559 MW respectively. It is observed that the power from the thermal generator is reduced due to load sharing by renewable sources. The use of fossil fuels is reduced due to integrated with renewable sources. Therefore, the greenhouse effect is also reduced. From the results, it is observed that SCA gives a promising and satisfactory performance in terms of quality and efficient optimum solution as compared to other well-known optimization techniques.

8. CONCLUSION

The efficient technique SCA have been presented to solve the renewable-based ELD problem. The uncertainties of wind and solar power have been generated using Weibull and beta PDF. The power

Table 7. The output power from generating unit and mean cost obtained by SCA

	3 thermal generator with renewable energy	5 thermal generator with renewable energy	6 thermal generator with renewable energy	15 thermal generator with renewable energy
T1	493.3122	229.5500	444.4860	455.0000
T2	151.1492	98.4855	169.3774	455.0000
T3	398.3387	112.9003	261.9042	130.0000
T4		74.8061	124.3520	130.0000
T5		208.6187	175.1840	203.7708
T6			80.7070	460.0000
T7				465.0000
T8				76.0636
T9				34.8050
T10				34.8050
T11				28.6470
T12				80.0000
T13				34.8050
T14				19.0094
T15				17.2496
Total Thermal Generation	1042.8003	724.3609	1256.0108	2624.1559
Total Wind and Solar Generation	7.1996	5.6390	6.9891	5.8440
Iteration	200	600	150	100
Mean Cost ($/h)	**10,023.9367**	**2014.1967**	**15,203.842**	**32,285.3935**

Figure 10. The total power generated by system and power demand for case 1

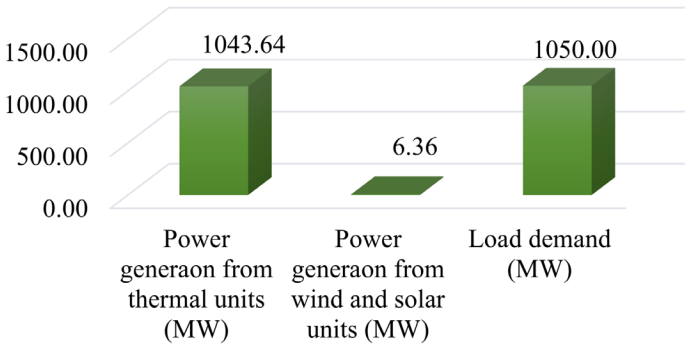


Figure 11. The total power generated by system and power demand for case 2

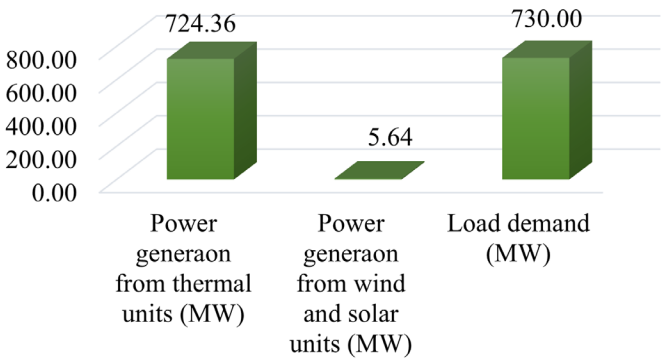


Figure 12. The total power generated by system and power demand for case 3

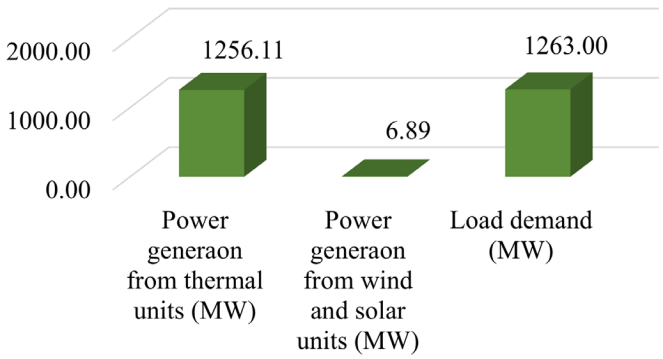
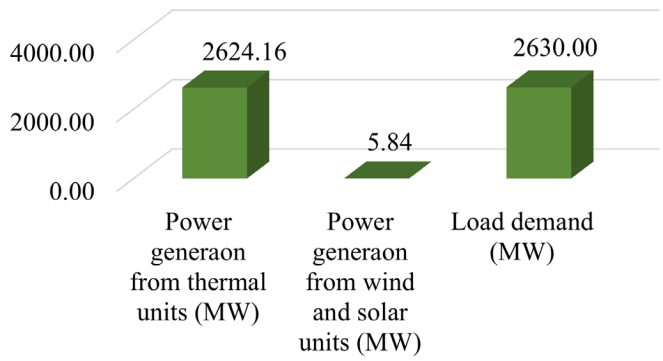


Figure 13. The total power generated by system and power demand for case 4



generated by renewable sources is computed by the 2-m PEM. The various types of operating constraints like VPLE and generator operating constraints have been considered here. To validate the effectiveness and performance of SCA, the algorithm has been applied in four different test systems. The results attained from SCA have been compared with other well-known algorithms DA, GA, PSO, CSA, ORCCRO, BBO and ALO. The results were shown in tabular and graphical form. The proposed algorithm gives quite promising and effective results in solving the renewable-based ELD problem. After getting superior results using SCA algorithm, it was concluded that the SCA algorithm may be used in highly complex optimization problem in power system, electrical vehicle and electrical discharge system.

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This is to acknowledge that there is no any financial interest or benefit that has arisen from the direct applications of our research.

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Diwakar Verma was born in Ajmer city, in the Rajasthan state of India on December 27, 1998. He completed his B.Tech. degree (2017-2021) in Electrical Engineering Department, Institute of Technology, Nirma University, Ahmedabad, India. His research interests include different power system problems, renewable energy, and soft computing techniques.

Jatin Soni is pursuing a Ph.D. (part-time) in electrical engineering at the Institute of Technology, Nirma University since September 2020. He is working as an assistant professor in the electrical engineering department at Ganpat University, Mehsana. He obtained his B.E. degree from Birla Vishvakarma Mahavidyalaya (BVM) engineering college and M.E. degree from Lukhdhirji engineering college (Govt.), Gujarat from 2016 and 2018 respectively. His area of research are power system optimization, power system operation and control, optimization technique, and hydro-thermal scheduling problems.

Kuntal Bhattacharjee received a BE degree from BIET, Suri Private College, Burdwan University, and MTech degree from NIT, Durgapur, India, in 2003 and 2005, respectively, both in Electrical Engineering. He is currently in the Electrical Engineering Department, Institute of Technology, Nirma University, India. His research interests include power system optimization, ELD, EELD, and hydrothermal applications.