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Artificial Electric Field Algorithm Applied to the Economic Load Dispatch Problem With Valve Point Loading Effect:

AEFA Applied to ELD With VPLE

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ABSTRACT

Economic load dispatch is to operate thermal generators economically with fulfilling load demand. This economic dispatch problem becomes highly complex and non-linear after considering various operating constraints like valve-point loading effect, generator operating constraints, and prohibited operating zone. The recently developed physics law-based artificial electric field algorithm has been applied to solve highly complex and non-linear ELD problems. The exploration and exploitation strategy of the algorithm helps to avoid local optimum value, and to get global optimum value in less computation time. The AEFA method has been applied to 10, 13, 15, 40, and large 110 thermal generators to validate the effectiveness of the proposed algorithm. The results obtained by the proposed algorithm have been compared with other recently developed algorithms.

KEYWORDS

Artificial Electric Field Algorithm, Economic Load Dispatch, Prohibited zone, Soft Computing, Valve point loading effect

1. INTRODUCTION

In recent scenarios, the electrical energy market has become liberal and highly competitive because of increasing load demand. Economic load dispatch (ELD)s beneficial in the operation and planning of power system management (Soni et al., 2020). ELD is used to maintain the economy of the power system by reducing production costs and increasing reliability by maximizing the capability of the thermal unit (Soni & Pandya, 2018). The main aim of ELD is to predict variables for sharing all load to make the system economical by considering equal and unequal constraints. In practical ELD problems, other constraints should consider, like valve point effect, ramp rate, and prohibited

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operating zones(POZ). This ELD problem is initially solved by some classical methods like quadratic programming (Shah et al., 2019), Dynamic Programming, Linear Programming, gradient method, Lagrangian relaxation, and Hopfield framework (Dieu & Schegner, 2012). The main issue with this method is that they are susceptible to starting points and mostly converge and diverge at a local optimum solution. The solution to the ELD problem by DP technique makes large dimensions that require more computational efforts. These methods are not feasible due to nonlinear characteristics like ramp rate limits, discontinue POZ, and non-smooth cost function. Therefore, classical calculus-based methods are not used. To overcome these drawbacks, robust and reliable techniques are developed. Hence, some new optimization techniques like artificial intelligence (AI) were found to overcome the disadvantages of classical techniques. Hopfield neural network (HNN) is an example of an AI-based algorithm used to solve non-convex and non-differentiable ELD optimization problems. However, they require a large number of iterations to reach global optima. Hence, it takes more time to reach the solution (Bhattacharjee & Patel, 2020).

In recent times, A new population based modern intelligent heuristic and stochastic optimization methods is proposed like Backtracking search algorithm (BSA), search group optimization (SGO), hybrid version particle swarm optimization with mutation (HPSO) (Jiang et al., 2014), Bacterial forge optimization (BFO), artificial bee colony (ABC), Evolutionary programming (EP) (Bhattacharjee et al., 2022), lightning flash algorithm (LFA), Kinetic gas molecule optimization (KGMO) (Basu, 2016), Improved genetic algorithm with mutation (IGA MU), sine cosine algorithm (SCA) (Verma et al., 1 C.E.), A full mixed-integer linear programming (FMILP), A modified symbiotic organisms search (MSOS), Differential evaluation with multi population (MPDE), swarm base optimization (SBO) (Article et al., 2018), Civilized swarm optimization (CSO) (Narang et al., 2017), Modified cuckoo search algorithm (MCSA), Emended salp swarm algorithm (ESSA) (Bhattacharjee & Patel, 2020), Ant Direction Hybrid Differential Evolution (ADHDE) (Priyadarshi et al., 2020), Jaya Algorithm With Self-Adaptive Multi-Population (Jaya SML) (Yu et al., 2019), evolutionary approach for particle swarm optimization (EPSO) (Kamboj et al., 2016), conglomerated ion-motion and crisscross search optimizer (C-MIMO-CSOO), Water cycle algorithm (WCA) (Elhameed & El-Fergany, 2017), Two-phase mixed integer programming (TPMIP) (Wu et al., 2016), Rooted tree optimization (RTO), Exchange market algorithm (EMA) (Ghorbani & Babaei, 2016), Phasor particle swarm optimization (PPSO) (Gholamghasemi et al., 2019), Density-Enhanced Multi-objective Evolutionary Approach (DMOA) (Ji et al., 2021), Particle swarm inspired optimization (PARPSO), Improved PSOG (IODPSO-G), Improved PSOL (IODPSO-L) (Dou et al., 2020), chaotic bat algorithm (CBA) (Adarsh et al., 2016), Crow search algorithm (CSA), immune algorithm (IA EDP), Turbulent Flow of Water-based Optimization (TFWO) (Ghasemi et al., 2020), oppositional invasive weed optimization (OIWO), Ameliorated grey wolf optimization (AGWO). A teaching-learning-based optimization (TLBO) was proposed to solve the heat and power dispatch problem. It divides the search agents into the teaching and learning phases. Thus, the main drawback of the TLBO method is that it requires more memory space and consumes more time. Modified TLBO named quasi oppositional TLBO (QOTLBO) is proposed in (YANG et al., 2014). The OHSA algorithm used opposite numbers to improve the convergence rate. Gandomi and Alavi have proposed a krill herd algorithm (KHA) in (Kaur et al., 2021), which was also successfully applied to solve the ELD problems. Oppositional real coded chemical reaction optimization (ORCCRO) has a special ability to solve the non-linear and non-quadratic equations with a smoother transition. Oppositional KHA was proposed to solve the ELD problem in small, medium, and large power systems.

However, these heuristic methods have poor results for different sets of problems. Some of these algorithms have corrupted local and global search at the final stage of optimization. Some methods have good capability to find global search, but they have less capability to find local search. Thus a strong optimization technique is needed to overcome these disadvantages.

This paper uses a new algorithm called the Artificial electric field algorithm (AEFA) (Anita & Yadav, 2019). The solution does not stick at the local optimum point in complex optimization problems and gives diverse solutions for the complex ELD problem. The idea of the AEFA algorithm is based on Coulomb's law of electrostatic force and Newton's law of motion, that the charged particle in an isolated system of charges exerts an electrostatic force (attraction or repulsion) on each other charged particles and moves in space such that the electrostatic potential energy of the system becomes minimum. The proposed AEFA method is applied to various test systems with ramp rate limits, valve point effect, and POZ to prove this algorithm's usefulness. The results are compared with other existing methods in this paper.

The organization of the presented paper is as follows: Section 2 gives information on problem formulation. Section 3 gives a brief introduction to the AEFA algorithm. Section 4 gives information on AEFA applied to ELD. Section 5 gives simulations and results. And Section 6 gives the conclusion and validation of this algorithm, followed by references.

2. PROBLEM FORMULATION

The ELD is important in the optimization of power system management. The objective function and constraint are taken into consideration as follows.

2.1 Objective Function

The ELD is used to minimize total fuel cost with equal and unequal constraints. The full cost function in ELD is as follows.

$$Total\, fuel\, cost = min\sum_{i=1}^{N} F\left(i\right) \text{ i=1,2,3,…., N} \tag{1}$$

Considering the quadratic cost of each unit, the objective function of ELD is as follows,

$$F_T = \min\sum_{i=1}^{N}(\alpha_i + \beta_i P_i + \gamma_i P_i^2) \quad \mathrm{i} = 1,2,3,\ldots,\mathrm{N} \tag{2}$$

There is a ripple effect of entering steam at the valve in the turbine. Thus, the valve point effect makes the system more practical and flexible. It makes objective cost function as a summation of quadratic and sinusoidal functions.

$$F_T = \sum_{i=1}^{N} F_i = \sum_{i=1}^{N}\left[\begin{array}{c}\alpha_i + \beta_i P_i + \gamma_i P_i^2 + \\ \left|\delta_i \times sin\left\{\varepsilon_i\left(P_i^{\min} - P_i\right)\right\}\right|\end{array}\right] \quad \mathrm{i} = 1,2,3,\ldots,\mathrm{N} \tag{3}$$

2.2 Constraints

The active power generation ion in each unit should be less than or equal to the maximum permitted active power and greater than or equal to the minimum allowed active power. It is expressed as

$$P_i^{\min} \le P_i \le P_i^{\max} \text{ i=1,2,3,..,N} \tag{4}$$

The total generated power must fulfill total load demand and transmission losses; this is known as equality or real power balance constraint of ELD problem,

$$\sum_{i=1}^{N} P_i = P_D + P_{Loss} \text{ i=1,2,3,…,N} \tag{5}$$

Transmission loss is calculated using Kron's loss formula or B-matrix loss coefficients formula which is expressed as,

$$P_{Loss} = \sum_{m=1}^{N}\sum_{n=1}^{N} P_m B_{mn} P_n + \sum_{m=1}^{N} B_{m0} P_m + B_{00} \tag{6}$$

Due to presence of vibration in shift bearing and faults in the boiler or feed pump, The units have POZ in input-output characteristics. For safe operation of the generator, each unit must not operate in prohibited operating zones, expressed mathematically as:

$$\left.\begin{array}{c} P_i^{min_{ii,1}} \\ P_{i,j-1} \le P_i \le P_{i,j} \\ P_{i,ni} \le P_i \le P_i^{max} \} \end{array}\right\} \tag{7}$$

The operating range of each unit is limited by ramp rate limit by considering the unit's operation repeatedly between specific operational zone. The change in power generation of each unit should be within a limit, the upper limit is known as the upper ramp rate limit (URL), and the lower limit is known as the down ramp rate limit (DRR_i). It is expressed mathematically as

$$\max\left(P_i^{min_{i0i}}()_i \min\left(P_i^{max_{i0i}}()\right)\right) \tag{8}$$

Calculation of slack generator is one of the essential parts of ELD problem formulations. If *N* is the total number of generators, then initially calculate (*N–1*) the number of power generations randomly based on equations (1) to (6). The remaining generator (say N^{th}) is called the slack generator, and its power generation is given by

$$P_N = P_D + P_{Loss} - \sum_{i=1}^{N-1} P_i \tag{9}$$

Transmission loss P_{loss} calculated from (6) are modified and given as

$$P_{Loss} = \sum_{m=1}^{N-1}\sum_{n=1}^{N-1} P_m B_{mn} P_n + 2P_N\left(\sum_{m=1}^{N-1} B_{Nm} P_m\right) + B_{NN} P_N^2 + \sum_{m=1}^{N-1} B_{0m} P_m + B_{0N} P_N + B_{00} \tag{10}$$

3. ARTIFICIAL ELECTRIC FIELD ALGORITHM (AEFA)

AEFA is based on the coulomb's law of electrostatic force. It says that an electrostatic force (repulsion or attraction) between two charged particles is directly proportional to the product of their charges and inversely proportional to the square of the distance between them. Search agents are viewed as charged particles, and their costs calculate their strength in this algorithm. These particles move in space due to electrostatic force between them.

Hence the position of charge gives the solution to the problem. A charged particle with the greatest charge attracts other lower charges by attraction force and moving in space.

A system of *N-charged* particles in d-dimensional search space is considered. The position of the i^{th} particle in the d-dimensional search space be $X_i = (x_i^1, x_i^2, \ldots\ldots, x_i^d)$ for $i = 1,2,3,\ldots\ldots, N$, where x_i^d is the position of the i^{th} particle in d^{th} dimension. The following equation gives the position of the ith particle at any time t:

$$\mathrm{p}_\mathrm{i}^\mathrm{d}\left(\mathrm{t}+1\right)=\begin{cases}\mathrm{p}_\mathrm{i}^\mathrm{d}\left(t\right) & if\ \ \mathrm{f}(\mathrm{P}_\mathrm{i}\left(t\right))<\mathrm{f}(\mathrm{X}_\mathrm{i}\left(t+1\right)) \\ \mathrm{x}_\mathrm{i}^\mathrm{d}\left(t+1\right) & if\ \ \mathrm{f}(\mathrm{X}_\mathrm{i}\left(t+1\right))\leq\mathrm{f}(\mathrm{P}_\mathrm{i}\left(t\right))\end{cases} \tag{11}$$

For the best fitness value, overall particle $P_{best} = X_{best}$. At any time *t,* the force acting between the charges *i* and *j* are:

$$F_{ij}^d\left(t\right)=K\left(t\right)\frac{Q_i\left(t\right)\times Q_j\left(t\right)\left(P_j^d\left(t\right)-X_i^d\left(t\right)\right)}{R_{ij}\left(t\right)+\varepsilon} \tag{12}$$

Where $R_{ij}\left(t\right)$ is the Euclidian distance between particles *i* and *j* and is given by the following equation:

$$R_{ij}\left(t\right)=X_i\left(t\right),X_j\left(t\right)_2 \tag{13}$$

K(t) is a coulomb's constant which is a function of the number of maximum iteration, and calculated as follows:

$$K\left(t\right)=K_0\times e^{\left(-\alpha\times\frac{iteration}{\max iteration}\right)} \tag{14}$$

Where K_0 and α are initial value and parameter respectively. The current iteration and the maximum number of iterations are called iteration and max iteration. If N is a total number of charges, the total electric force on the i^{th} charge by all other charges at any time t is:

$$F_i^d\left(t\right)=\sum\nolimits_{j=1,j\neq i}^{N}rand()F_{ij}^d\left(t\right) \text{ (15),}$$

Where *rand()* is a random number between 0 and1. The electric field of the i^{th} particle at any time t is:

$$E_i^d\left(t\right) = \frac{F_i^d\left(t\right)}{Q_i\left(t\right)} \tag{16}$$

The acceleration of charge is given by newton's second law of motion (*F=ma*) and using the equation (16):

$$a_i^d\left(t\right) = \frac{Q_i\left(t\right) \times E_i^d\left(t\right)}{M_i\left(t\right)} \tag{17}$$

The velocity and the position of the particle are updated as follows:

$$V_i^d\left(t+1\right) = rand() \times V_i^d\left(t\right) + a_t^d\left(t\right) \tag{18}$$

$$X_i^d\left(t+1\right) = X_i^d\left(t\right) + V_i^d\left(t+1\right) \tag{19}$$

The flow chart of AEFA algorithm is shown in Fig. 1.

4. AEFA ALGORITHM IN ELD PROBLEM

The steps for the AEFA algorithm for solving ELD problems are discussed below.

Step1:Restrict the search space. Put a lower and upper bound limit on each decision variable.
Step2: Initialization of various parameters. The initial value of position and velocity of each particle should be selected such that each candidate solution is feasible.

$X=X_i=[X_1, X_2, X_3,\ldots\ldots, X_{Popsize}]$

For the ELD problem, search agent matrix as active power generation.

$[P_{ij}] = [P_{i1}, P_{i2}, P_{i3}, \ldots.., P_{im}]=X_i$

Step3: The transmission loss P_{Li} is calculated by the B coefficient matrix for each P_i.
Step4:Calculate the fitness value of each P_i.
Step5: Store non-dominated solution as archive data.
Step6:Memory of each particle should be initialized where the local optimum solution Pbest is stored by equation (11).
Step7:Increase the number of generations.
Step8:Calculate and store the local best, local worst, the force between particles, and acceleration of particles by equation (12) to (14). Find the global best and global worst values from fuzzified regions.
Step9: The global best particle has the largest charge value and attracts the other particle to its direction using equation (15).
Step10:Update the velocity of each particle by equation (18) to get a feasible solution.
Step11:Check all constraints to ensure a feasible solution.

Step12:If stopping criteria are satisfied, then go to step 13. Otherwise, go to step7.
Step13:Output as the feasible solution to the ELD problem.

5. SIMULATIONS AND RESULTS

In this paper, to prove the effectiveness of the recently developed AEFA algorithm, it is used to solve nonlinear and complex ELD problems considering transmission losses, POZ, and ramp rate limit. MATLAB-2017b software used to simulate ELD problem and validated in 1.7GHz intel core,4 GB RAM personal computer. The AEFA algorithm is applied to five different test systems with varying levels of complexity to verify its efficiency and feasibility, as detailed in Table 1.

5.1 Test Case -1

A test system with ten generating units and a power demand of 2700 MW is analyzed in this case. Multi-fuel options and valve point loading effect are both considered. Transmission losses are neglected. Required input data are taken from (Arumugam et al., 2019). Obtained minimum fuel cost is 623.8812 $/hr which is superior than other existing techniques like BSA (Bhattacharjee, 2018), SGO (Bhattacharjee & Patel, 2019), HPSO (Das et al., 2021), IGA_MU (Barisal, 2013). Obtained results are much better than existing techniques, as shown in table-3. The output of each generator is shown in table 2. Convergence characteristics are shown in figure 2.

Figure 1. Flowchart of AEFA algorithm

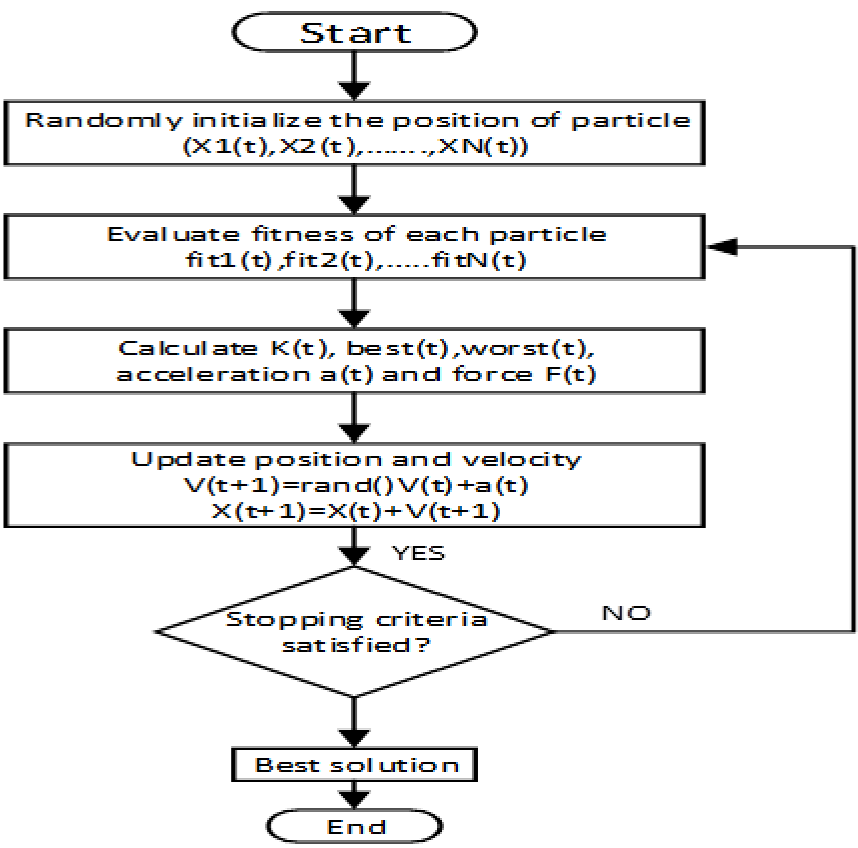


Table 1. Details of Test Systems

Case	1	2	3	4	5
No. of Generator Units	10	13	15	40	110
Input Data	(Arumugam et al., 2019)	(Alkoffash et al., 2021)	(Ghorbani & Babaei, 2016)	(Alkoffash et al., 2021)	(Hassan et al., 2021)
Total Demand (MW)	2700	2520	2630	10500	15000
Valve Point Loading	Yes	No	No	Yes	No
Ramp Rate	No	No	Yes	No	No
POZ	No	No	Yes	No	No
Transmission Loss	No	Yes	Yes	No	No
Multi-Fuel Option	Yes	No	No	No	No

Table 2. Power output of 10 generator units for test case 1. (Power demand: 2700MW)

Unit		Generator Output		
	Fuel Type	AEFA	BSA (Bhattacharjee, 2018)	SGO (Bhattacharjee & Patel, 2019)
1	2	217.205383	218.5777	217.0407
2	1	212.159802	211.2153	211.8944
3	1	282.556704	279.5619	281.6792
4	3	239.955568	239.5024	238.2056
5	1	279.615562	279.9724	279.8321
6	3	239.929841	241.1174	239.2547
7	1	287.894902	289.7965	290.2798
8	3	239.551340	240.5785	240.2228
9	3	425.014566	426.8873	425.5958
10	1	276.116332	272.7907	275.9942
Fuel Cost($/hr.)		**623.8812**	623.9016	623.9170

Table 3. Comparison of a result obtained by AEFA and other techniques for test case 1

Method	Minimum Fuel Cost($/hr.)	Maximum Fuel Cost($/hr.)	Average Fuel Cost ($/hr.)	Simulation Time	Number of hits to best solution
AEFA	**623.8812**	**623.8812**	**623.8812**	**0.35**	**50**
SGO (Bhattacharjee & Patel, 2019)	623.9170	625.5478	623.9170	0.51	49
HPSO(Das et al., 2021)	623.9588	624.2930	624.0816	NA	NA
IGA-MU (Barisal, 2013)	624.5178	630.8705	625.8692	NA	NA
BSA (Bhattacharjee, 2018)	623.9016	624.0838	623.9757	NA	NA

5.2 Test Case -2

13 generating unis are considered in this test system with multiple constraints. The power demand is 2520MW. Transmission losses are considered here. Required input data is taken from (Alkoffash et al., 2021). The minimum cost and simulation time is obtained at 24512.60 $/hr. And 0.30 seconds, respectively. Obtained results are superior to other existing techniques. The number hits to best solution is 50. The output of each generator unit is shown in table 4. A comparison of Obtained results is shown in Table 5 convergence characteristic is shown in figure 3.

5.3 Test Case 3

In this system total 15 number of generator units are taken with multiple constraints. The POZ, ramp rate limit is considered here. Transmission losses are considered. Power demand is 2630MW. Required input data is taken from (Ghorbani & Babaei, 2016). Obtained minimum cost and simulation time is 32697.2819 $/hr. and 0.59 seconds respectively. Obtained results are superior than other existing techniques like ESSA (Alkoffash et al., 2021), Jaya SML (Yu et al., 2019) etc. The number hits to best solution is 49 out of 50 trials. Output of each generator unit is show in Table 6. A comparison of obtained results is shown in Table 7. Convergence characteristic is shown in figure 4.

5.4 Test Case 4

This system consist 40 generating units with power demand of 10500MW. Valve point loading effect is considered here. Transmission losses are ignored. This is non-convex optimization problem. Input data is taken from (Alkoffash et al., 2021). Obtained minimum cost is 121412.5355 $/hr and number of hits best solution 49 with simulation time 6 seconds. Obtained result is superior than existing techniques in terms of fuel cost, simulation time and no hits to best solution. Convergence

Figure 2. Convergence characteristics for test case 1

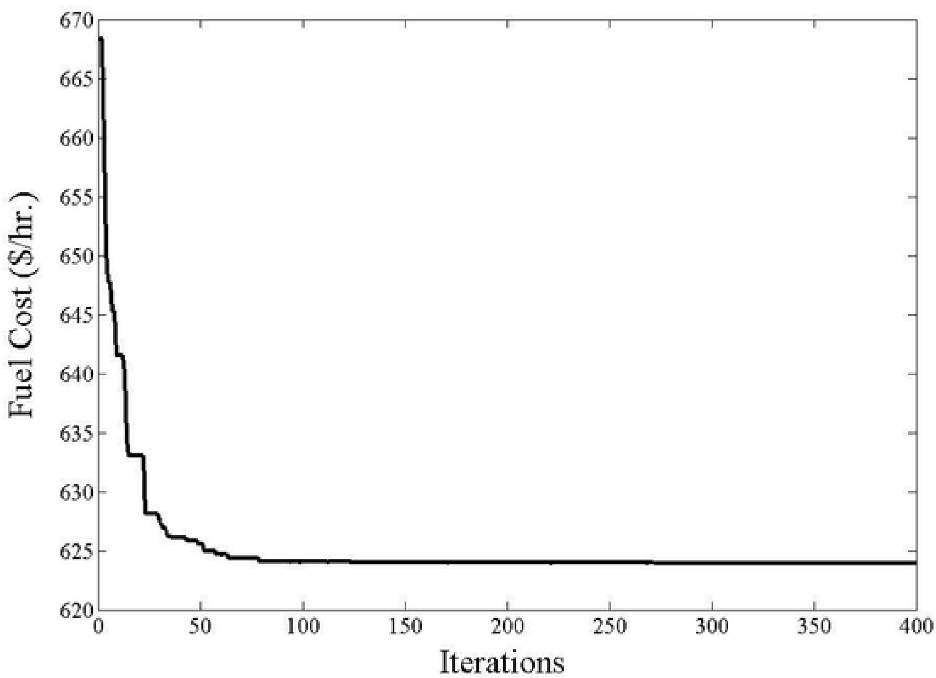


Table 4. Power output of 13 generator units for test case 1. (Power demand: 2520MW)

Unit	*Generator Output*		
	AEFA	*SCA (Bhattacharjee & Patel, 2018)*	*F-MILP (Hamilton et al., 2020)*
1	628.318383	628.3179	628.318530
2	299.199400	299.1992	299.199300
3	297.446434	297.4468	299.199300
4	159.732553	159.7327	159.733100
5	159.732964	159.7327	159.733100
6	159.732834	159.7328	159.733100
7	159.733055	159.7331	159.733100
8	159.733178	159.7325	159.733100
9	159.732636	159.7328	159.733100
10	77.399699	77.3995	77.399912
11	114.799604	114.7993	113.49589
12	92.399434	92.3997	92.399912
13	92.399553	92.4000	92.399912
Total Power Generate (MW)	2560.35	2559.8000	2560.811356
Total Loss (MW)	**40.35**	39.8000	40.811358
Fuel Cost($/hr.)	**24512.60656**	24512.6085	24,515.2258

Table 5. Comparison of result obtained by AEFA and other techniques for test case 2

Method	**Minimum Fuel Cost**	**Maximum Fuel Cost**	**Average Fuel Cost**	**Simulation Time(s)**	**Number of hits to best solution**
AEFA	**24512.60656**	**24512.60656**	**24512.60656**	**0.30**	**50**
F-MILP (Hamilton et al., 2020)	24,515.2258	NA	NA	4.24	NA
MSOS (Secui, 2016)	24,515.2258	24,515.2258	24,515.2258	2.6535	NA
ORCCRO (Bhattacharjee et al., 2014)	24513.91	24513.91	24513.91	0.04	50
MCSA (Chandrasekaran et al., 2014)	24514.8756	24514.8756	24514.8756	12.80	NA
SCA	24512.6085	24512.6085	24512.6085	0.041	50
MPDE (Li et al., 2019)	24514.8756	24514.8756	24514.8756	5	NA

characteristic is shown in figure 5. Obtained results are shown in table 8. Comparison of obtained results are in table 9.

5.5 Test Case-5

In this case total 110 generating unit system is considered. Transmission loss is neglected here. Required input data are taken from (Hassan et al., 2021). Total Power demand is 15000 MW. Obtained results are shown in table 10. Comparison of obtained results are in table 11. Convergence characteristic is shown in figure 6.

Figure 3. Convergence characteristics for test case 2

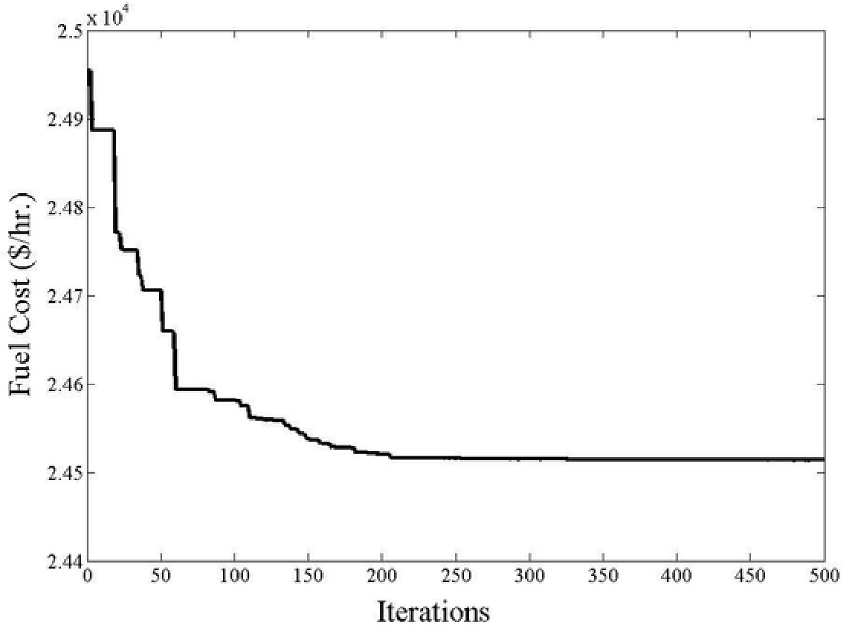


Table 6. Schedule of generation for test case 3 with 15 generator and power demand 2630 MW

Unit	**Power Output**		
	AEFA	**ESSA (Alkoffash et al., 2021)**	**Jaya SML (Yu et al., 2019)**
1	455.000000	454.9995	454.9999
2	380.000000	379.9996	380.0000
3	130.000000	130.0000	130.0000
4	130.000000	130.0000	130.0000
5	170.000000	170.0000	170.0000
6	460.000000	460.0000	460.0000
7	430.000000	430.0000	430.0000
8	71.429057	70.1478	71.4456
9	58.596432	60.2593	59.3587
10	160.000000	159.9599	160.0000
11	80.000000	79.9996	79.9997
12	80.000000	79.9999	80.0000
13	25.000000	25.0007	25.0000
14	15.000000	15.0000	15.0000
15	15.000000	15.0009	15.0000
Total Power Generated (MW)		2660	2660.8039
Total Loss (MW)		30.3679	30.8039
Fuel Cost ($/hr.)	**32697.2819**	32701.21	32706.3587

Table 6. Schedule of generation for test case 3 with 15 generator and power demand 2630 MW

Unit	Power Output		
	AEFA	ESSA (Alkoffash et al., 2021)	Jaya SML (Yu et al., 2019)
1	455.000000	454.9995	454.9999
2	380.000000	379.9996	380.0000
3	130.000000	130.0000	130.0000
4	130.000000	130.0000	130.0000
5	170.000000	170.0000	170.0000
6	460.000000	460.0000	460.0000
7	430.000000	430.0000	430.0000
8	71.429057	70.1478	71.4456
9	58.596432	60.2593	59.3587
10	160.000000	159.9599	160.0000
11	80.000000	79.9996	79.9997
12	80.000000	79.9999	80.0000
13	25.000000	25.0007	25.0000
14	15.000000	15.0000	15.0000
15	15.000000	15.0009	15.0000
Total Power Generated (MW)		2660	2660.8039
Total Loss (MW)		30.3679	30.8039
Fuel Cost ($/hr.)	**32697.2819**	32701.21	32706.3587

Table 7. Comparison of result obtained by AEFA and other techniques for test case 3

Method	Minimum Fuel Cost	Maximum Fuel Cost	Average Fuel Cost	Simulation Time(s)	Number of hits to best solution (50 trials)
AEFA	**32697.2819**	**32697.7845**	**32697.2918**	**0.59**	**49**
SGO (Bhattacharjee & Patel, 2019)	32697.2819	32698.1574	32697.3344	0.75	47
BSA (Bhattacharjee, 2018)	32704.4504	32704.5816	32704.4721	NA	NA
ESSA (Alkoffash et al., 2021)	32701.21	32701.22	32701.22	NA	NA
SSA (Bhattacharjee & Patel, 2020)	32702.43	32911.32	32785.45	NA	NA
C-MIMO CSOO (Zakian & Kaveh, 2018)	32701.21	32701.22	32701.2102	NA	NA
Jaya SML (Yu et al., 2019)	32706.3578	32707.2925	32706.6774	5.14	NA
WCA (Elhameed & El-Fergany, 2017)	32704.44	32704.51	32704.50	NA	NA
TPMIP (Wu et al., 2016)	33013.98	NA	NA	NA	NA
RTO (Labbi et al., 2016)	32701.81	32715.18	32704.53	NA	NA
EMA (Ghorbani & Babaei, 2016)	32704.45	32704.45	32704.45	NA	NA
TLBO (Bhattacharjee et al., 2014)	32770.72	33073.88	32819.74	NA	NA

Figure 4. Convergence characteristics for test case 3

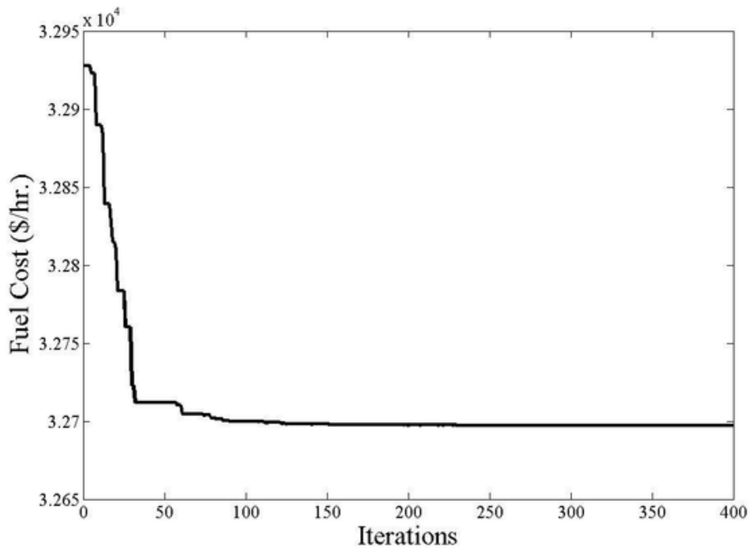


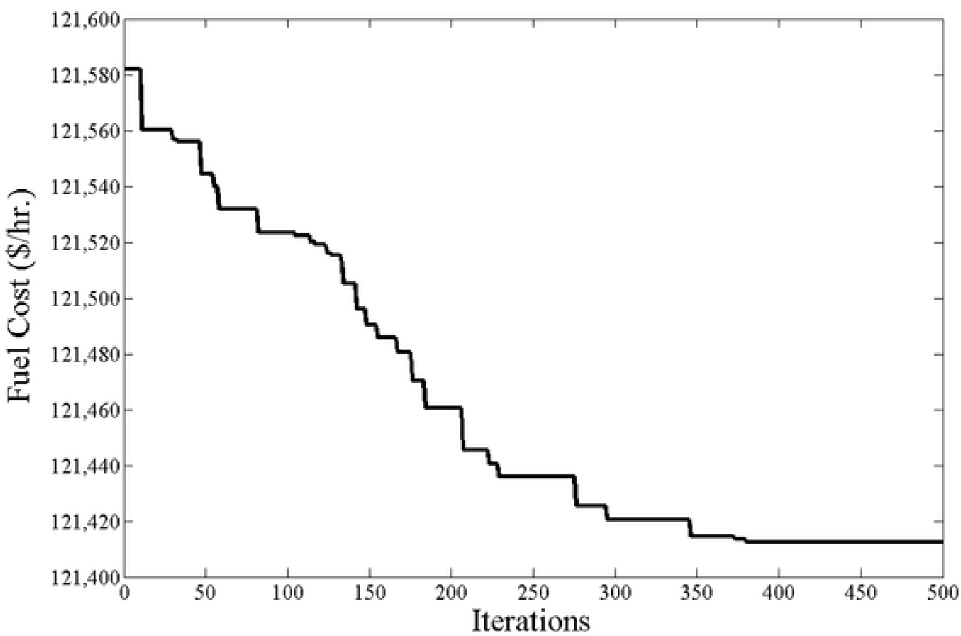
Table 8. Schedule of generation for test case 4 with 40 generator and power demand 6000MW

Unit	Power Output		Unit	Power Output	
	AEFA	PPSO (Gholamghasemi et al., 2019)		AEFA	PPSO (Gholamghasemi et al., 2019)
1	110.799825	110.7998	22	523.279370	523.2794
2	110.799825	110.7998	23	523.279370	523.2794
3	97.399913	97.3999	24	523.279370	523.2794
4	179.733100	179.7331	25	523.279370	523.2794
5	87.799905	87.7999	26	523.279370	523.2794
6	140.000000	140.0000	27	10.000000	10.0000
7	259.599650	259.5997	28	10.000000	10.0000
8	284.599650	284.5997	29	10.000000	10.0000
9	284.599650	284.5997	30	87.799905	87.7999
10	130.000000	130.0000	31	190.000000	190.0000
11	94.000000	94.0000	32	190.000000	190.0000
12	94.000000	94.0000	33	190.000000	190.0000
13	214.759790	214.7598	34	164.799825	164.7998
14	394.279370	394.2794	35	200.000000	194.3973
15	394.279370	394.2794	36	194.397778	200.0000
16	394.279370	394.2794	37	110.000000	110.000000
17	489.279370	489.2794	38	110.000000	110.000000
18	489.279370	489.2794	39	110.000000	110.000000
19	511.279370	511.2794	40	511.279370	511.2794
20	511.279370	511.2794	Total Power Generated (MW)		400500
21	523.279370	523.2794	Fuel Cost ($/hr.)		121,412.5421

Table 9. Comparison of result obtained by AEO and other techniques for test case 4

Method	Minimum Fuel Cost($/hr.)	Maximum Fuel Cost($/hr.)	Average Fuel Cost($/hr.)	Simulation Time (sec.)	Number of hits to best Solution (50 trials)
AEFA	**121412.5355**	**121413.4123**	**121412.5530**	**6**	**49**
DMOA (Kushwaha et al., 2018)	121412.5443	NA	121420.8076	66.42	NA
PPSO (Gholamghasemi et al., 2019)	121412.5421	121413.9525	121412.5890	NA	NA
MPDE (Li et al., 2019)	121412.5355	121414.6185	121412.6188	NA	NA
PARPSO (Azizivahed et al., 2020)	122256.3000	NA	122634.0000	NA	NA
IODPSO-G (Hamedi, 2013)	121414.93	121426.42	121416.54	17.75	NA
IODPSO-L (Selvakumar & Thanushkodi, 2007)	121420.98	121431.62	121424.62	18.69	NA
CBA (Lu et al., 2010)	121412.5468	121436.1500	121418.9826	NA	NA
CSA (Basak et al., 2022)	121425.6100	NA	NA	NA	NA
IA_EDP (Aragón et al., 2015)	121436.9729	121648.4401	121492.7018	NA	NA

Figure 5. Convergence characteristics for test case 4



5.6 Result Summary

In Test Case 1, average and minimum fuel costs are 623.8812 $/hr. and 623.8812 $/hr. respectively which is better than other existing techniques like BSA (Bhattacharjee, 2018), SGO (Bhattacharjee

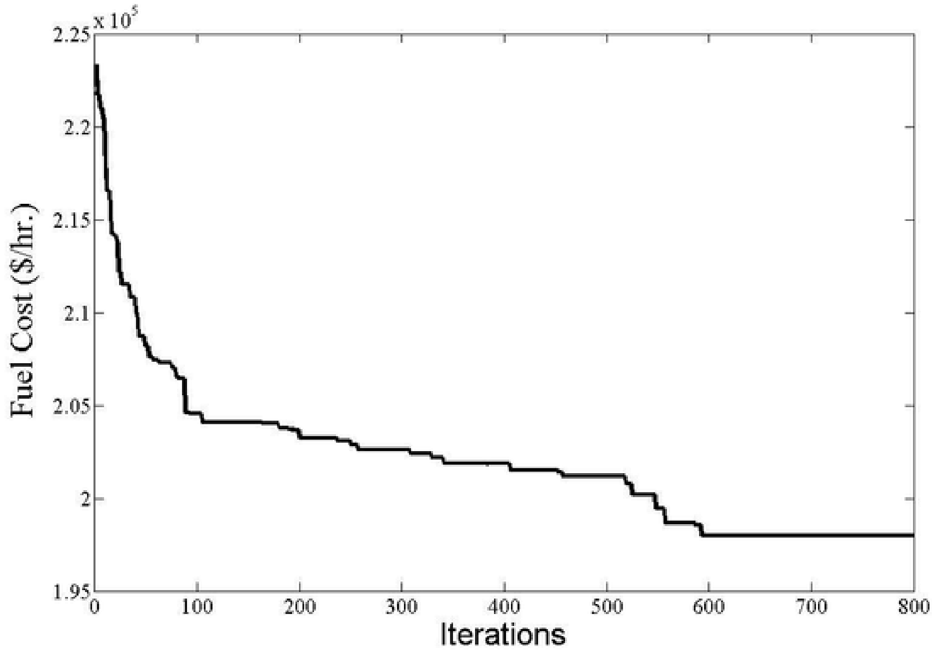
Table 10. Schedule of generation for test case 5 with 110 generator and power demand 15000MW

Unit	Power Output	Unit	Power Output	Unit	Power Output
1	2.4000	38	70.0000	75	90.0000
2	2.4000	39	100.0000	76	50.0000
3	2.4000	40	120.0000	77	160.0000
4	2.4000	41	157.1559	78	295.7505
5	2.4000	42	220.0000	79	175.0689
6	4.0000	43	440.0000	80	98.0059
7	4.0000	44	560.0000	81	10.0000
8	4.0000	45	660.0000	82	12.0000
9	4.0000	46	616.2389	83	20.0000
10	64.4000	47	5.4000	84	200.0000
11	62.1600	48	5.4000	85	325.0000
12	36.2885	49	8.4000	86	440.0000
13	56.6371	50	8.4000	87	14.3811
14	25.0000	51	8.4000	88	24.3110
15	25.0000	52	12.0000	89	82.4198
16	25.0000	53	12.0000	90	89.2470
17	155.0000	54	12.0000	91	57.8600
18	155.0000	55	12.0000	92	100.0000
19	155.0000	56	25.2000	93	440.0000
20	155.0000	57	25.2000	94	500.0000
21	68.9000	58	35.0000	95	600.0000
22	68.9000	59	35.0000	96	471.5000
23	68.9000	60	45.0000	97	3.6000
24	350.0000	61	45.0000	98	3.6000
25	400.0000	62	45.0000	99	4.4000
26	400.0000	63	185.0000	100	4.4000
27	500.0000	64	185.0000	101	10.0000
28	500.0000	65	185.0000	102	10.0000
29	200.0000	66	185.0000	103	20.0000
30	100.0000	67	70.0000	104	20.0000
31	10.0000	68	70.0000	105	40.0000
32	20.0000	69	70.0000	106	40.0000
33	80.0000	70	360.0000	107	50.0000
34	250.0000	71	400.0000	108	30.0000
35	360.0000	72	400.0000	109	40.0000
36	400.0000	73	104.9493	110	20.0000
37	40.0000	74	191.4957	**Fuel Cost ($/hr.)**	**197987.7386**

Table 11. Comparison of result obtained by AEO and other techniques for test case 5

Method	Minimum Fuel Cost ($/hr.)	Maximum Fuel Cost($/hr.)	Average Fuel Cost ($/hr.)	Simulation Time (sec.)	No of hits to best Solution (50 trials)
AEFA	**197987.7386**	**197987.7386**	**197987.7386**	**0.8**	**50**
TFWO (Ghasemi et al., 2020)	197,988.1790	197988.1904	197988.1823	NA	NA
OIWO (Pradhan et al., 2017)	197989.14	197989.93	197989.41	NA	NA
AGWO (Kamboj et al., 2017)	197988.00	197988.00	197988.00	NA	NA
ORCCRO (Bhattacharjee et al., 2014)	198016.29	198016.89	198016.32	0.15	48

Figure 6. Convergence characteristics for test case 5



& Patel, 2019), HPSO (Das et al., 2021), and IGA_MU (Chiang, 2005). Simulation time and 'number of hits to best solution' are 0.35 seconds and 50 (out of 50 trials).

In Test Case 2, the average and minimum fuel costs are 24512.60656 $/hr. and 24512.60656 $/hr. respectively. Simulation time and 'number of hits to best solution' are 0.30 seconds and 50 (out of 50 trials).

In Test Case 3, the average and minimum fuel costs are 32697.2918 $/hr. and 32697.2819 $/hr. respectively, better than other existing techniques like ESSA (Alkoffash et al., 2021), Jaya SML (Yu et al., 2019), etc. The number of hits to the best solution is 49 out of 50 trials with a simulation time of 0.59 seconds.

In Test Case 4, the average and minimum fuel costs are 121412.5530 $/hr. and 121412.5355 $/hr. The number of hits best solution 49 with a simulation time of 6 seconds.

In Test Case 5, the average and minimum fuel costs are 197987.7386 \$/hr. and 197987.7386 \$/hr. respectively. Simulation time and 'number of hits to best solution' is 0.8 seconds and 50 (out of 50 trials).

5.7 Discussion

For obtaining the best result, two things play an important role in any optimization technique. (i) Determination of population size (ii) Determination of tuning Parameter. Determination of population size can change in population size also affects the performance of the AEFA. The large or small value of population size may not give the optimum value. For each population size of 20, 50, 100, 150, and 200, 50 trials have been run using test system-5. Table 12 shows the performance of the BSA for different population sizes. A population size of 50 resulted in achieving global solutions more consistently.

5.8 Determination of Tuning Parameter

Tuning of different parameters like, K_0 and α is required to search out an optimum solutions using AEFA algorithm. For different values of these parameters, minimum fuel cost has been evaluated for all Test cases, and table 13 shows the same for Test Case-5. At K_0=500 and α=30 minimum value has been obtained.

6. CONCLUSION

In this paper, a new and efficient algorithm named AEFA is proposed to solve the ELD problem with constraints like valve point loading effect, prohibited operating zone, and multiple fuel and ramp rate limits. The five test systems are employed to show the applicability of the AEFA method. The advantage of AEFA is that it converges to a stable stage. Numerical results show that the AEFA

Table 12. Determination of population size for Test Case-5

Population Size	No. Hits to Best Solution	Simulation Time (S)	Min. Fuel Cost (\$/hr)	Max. Fuel Cost (\$/hr)	Avg. Fuel Cost (\$/hr)
20	47	0.6	197990.8963	197996.6398	197991.12
50	**50**	**0.8**	**197987.7386**	**197987.7386**	**197987.73**
100	45	1.2	197993.5368	197996.37	197993.82
150	43	1.9	197995.1255	197999.145	197995.60
200	41	2.6	197997.9658	197999.9888	197998.24

Table 13. Determination of tuning parameter for Test Case-5

K_0	α				
	10	20	30	40	50
100	197992.9638	19792.5698	197991.7386	197993.5698	197993.5241
200	197991.8795	197991.8562	197990.8521	197991.7385	197992.5638
300	197991.7412	197990.5896	197989.7884	197990.9856	197991.7896
400	197990.8545	197989.7896	197988.8928	197989.9639	197990.2358
500	197989.4569	197988.8388	**197987.7386**	197988.8569	197988.9856

algorithm performs better than other algorithms in terms of robustness, premature convergence, and less computational effort. Although the AEFA algorithm is applied to the ELD problem in the current study, it seems that AEFA can be used to solve many optimization problems in power system operation and planning.

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APPENDIX

Table 14

NomenclatureF_T	Total Fuel cost
P_i	Power generation of i^{th} unit
N	total number of generating unit
P	Population size
maxiter	the maximum number of iteration
α_i, β_i, γ_i, δ_i	Fuel coal coefficient for i^{th} generating unit
P_i^{min}	minimum value of power generation of i^{th} unit
P_i^{max}	maximum value of power generation of i^{th} unit
P_D	Total power demand
P_{Loss}	Total transmission loss
B_{ij}, B_{i0}, B_{00}	Loss coefficient of the line between i and j bus
URR_i, DRR_i	Up ramp rate and Down ramp rate limit of i^{th} unit
ni	number of prohibited zone in i^{th} unit
P_{i0}	Previous operating zone of i^{th} unit

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