Solution of Constrained Optimal Active Power Dispatch Problems Using Exchange Market Algorithm

Abhishek Rajan, T. Malakar and Abhimanyu

Abstract OAPD is basically a Generation Scheduling (GS) problem which is commonly formulated as an Optimal Power Flow (OPF) problem. OPF is a power system optimization tool which aims to optimize certain objective and provide the optimal operating state of power system simultaneously satisfying both physical and operational constraints of power system. The basic aim of OAPD problem is to determine the optimal GS for the committed generators in such a manner that the total fuel cost is optimized. The presence of nonlinear constraints like Valve-Point Loading (VPL), Prohibited Operating Zone (POZ), and Ramp Rate Limits (RRLs) makes the objective function nonlinear, non-convex, and sometimes discontinuous. This paper attempts to investigate the newly developed meta-heuristic algorithm called Exchange Market Algorithm (EMA) in solving highly nonlinear non-convex Optimal Active Power Dispatch (OAPD) problems of power system with VPL, POZ, and RRLs effect. Both continuous and discrete control variables are present in the problem which makes the optimization more complex. The problem is implemented on the standard IEEE-30 bus system. The results are compared with several other meta-heuristic algorithms, and it is found that EMA outperforms many contemporary algorithms in terms of the convergence rate and objective function value.

Keywords Optimal Power Flow · Optimal Active Power Dispatch · POZ
Ramp Rate Limits · Exchange Market Algorithm

1 Introduction

Power system economy is one of the crucial issues for both power system practitioners and researchers. The electric power system operation has to be economical to ensure a cost-efficient electric energy supply to the consumer's terminal. The load demand at

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J. C. Bansal et al. (eds.), *Soft Computing for Problem Solving*, Advances in Intelligent Systems and Computing 817, https://doi.org/10.1007/978-981-13-1595-4_48

consumer's terminal is continuously varying, and it is required to distribute this load in real time among already running generating units so as to meet the load demand at every interval of time satisfactorily. Active power dispatch problem of power system is basically an optimization problem [1] where scheduling of generators' real power output is performed in a most economic manner, satisfying all physical and operational constraints related to generation and transmission of real power. In such type of optimization problem, the basic aim of power system planner is to gain power system operational economics. So as far as power system economics is concerned, the system operation economics deals with minimum cost of power production. In this case, the problem is called Optimal Active Power Dispatch (OAPD). In realizing any OAPD problems, the optimization is performed by adjusting certain problem variables. These power system variables are usually termed as control variables. These variables are guessed initially, and having initial assumptions, it checks that the given aim is satisfied or not. If it is not, then the value of control variables is adjusted following some optimization techniques and the process is repeated until the objective is satisfied. OAPD problem for a particular power system can be solved as an Optimal Power Flow (OPF) problem. The OPF was first proposed and defined by Dommel and Tinney [2] and developed by Carpentier [3]. Since then, OPF has become most important tool for analyzing power system operation and had been in use for over last few decades. OPF is a power system optimization tool which aims to optimize a given objective function and provide optimal operating state of power system, simultaneously satisfying all physical and operational constraints of the power system [4]. It is a particular case where the power flow in an electrical system occurs optimally [5]. In general, the objectives of OPF problems are nonlinear non-convex and sometimes discontinuous too. Hence, when viewed as an optimization problem, OPF is highly nonlinear non-convex and complex optimization problem.

The most commonly used objective function for OAPD problem is the minimization of generation cost for thermal unit [4]. Some classical optimization techniques [4, 6, 7] were successfully implemented to solve OPF problems. In [4], Lee et al. proposed unified method for real and reactive dispatch for economic operation of power system. Gradient projection method is used as the optimization technique. In [6] of Zehar and Sayah, a multi-objective environmental/economic load dispatch problem, based on an efficient successive linear programming technique, is solved. The problem is solved on Algerian 59-bus power system. The OPF-based real power dispatch problem using linear programming (LP) technique is modeled and discussed in [7]. Though these algorithms have fast convergence speed, their differential calculus-based approach restricts them to solve the non-convex and discontinuous objective functions. Moreover, they have higher tendency to trap into local optimal if the function is multimodal in nature. Hence, as an alternative, since last few decades, researchers and practitioners have begun to show their interest in population-based algorithms instead. In order to overcome the drawbacks of gradient-based optimization techniques, solution based on the behavior of natural evolution and natural objects has been developed and applied to solve many engineering as well as power system problems. In terms of solution methods, these algorithms are termed as metaheuristic algorithms. Some examples of these types are Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Differential Evolution (DE), etc. These algorithms are generally population-based and work meticulously toward finding the optimal solution for both constrained and unconstrained optimization problems.

Genetic Algorithm [8], Evolutionary Programming [9], Tabu Search [10], Particle Swarm Optimization [11], Differential Evolution [12], Biogeography-Based Optimization [13], Harmony Search Algorithm [14], Gravitational Search Algorithm [15], Black-Hole-Based Algorithm [16], Teaching–Learning-Based Algorithm [17], etc., have shown promising results when applied to solve power system problems. In [18, 19], the solution methodologies have been improved by researchers to eliminate the drawback associated with the above optimization techniques by either improving its evolution process or by hybridizing it with suitable classical optimization techniques. Multi-objective optimization is also reported in [20], where two or more than two optimization objectives are solved at a time to check the efficiency and capability of the algorithm in finding the global optimal solution. In the above-mentioned works, authors have tried to implement several nonlinearities like VLP, POZ, and RRLs together with the optimization of simple fuel cost.

In this work, relatively new and promising algorithm called Exchange Market Algorithm (EMA) is implemented to solve the OAPD problem with several nonlinearities like VLP, POZ, and RRLs. This algorithm is developed by Ghorbani and Babaei in 2014 which is based on the behavior of shareholders in stock market [21]. In order to prove the efficiency and capability of EMA, many benchmark problems have been solved by authors and results looks promising when compared with other reported literatures. The unique feature of double exploitation and exploration attracts the present authors to use this algorithm in solving complex problems of power system. Till date, EMA has not been applied to solve many power system problems. Therefore, in this paper, authors intend to solve OAPD problems using EMA. The problem is formulated as nonlinear optimization with various objectives associated to OAPD. These problems are implemented on the standard IEEE test systems. The results are compared with other well-established contemporary algorithms.

2 Problem Formulation

OAPD problems are mathematically modeled as Optimal Power Flow (OPF) problems. OPF is a power system optimization tool which aims to optimize a given objective function and provide an optimal operating state through the proper adjustments of various power system controllers while simultaneously satisfying the equality and inequality constraints present in the system. It is expressed as [1]:

$$\text{Minimize} \quad f(x, u) \tag{1}$$

$$\text{Subjected to} \quad \begin{cases} g(x, u) = 0 \\ h_{min} \leq h(x, u) \leq h_{max} \end{cases} \tag{2}$$

where f, x, u, g(x, u), and h(x, u) are the objective function, set of dependent variables, set of independent variables, sets of equality, and inequality constraints, respectively. Slack generators' real (P_{G1}) and reactive power outputs (Q_{G1}), load bus voltage magnitudes ($V_{L1}, \ldots V_{L_{N_{PQ}}}$), reactive power generations ($Q_{G1}, \ldots Q_{G_{N_{PV}}}$), and line loadings $\left(S_{L1}, \ldots S_{L_{N_{TL}}}\right)$ are considered as dependent variables in power system. Hence, the vector of dependent variables '**x**' can be expressed as:

$$x^T = \left[P_{G1}, V_{L1}, \ldots V_{L_{N_{PQ}}}, Q_{G1}, \ldots Q_{G_{N_{PV}}}, S_{L1}, \ldots S_{L_{N_{TL}}}\right] \tag{3}$$

The vector of independent/control variables '**u**' comprise of all real power generations ($P_{G2}, \ldots P_{G_{N_{PV}}}$) and their generation voltages ($V_{G1}, \ldots V_{G_{N_{PV}}}$), tap-changing transformer's positions ($Tap_1, \ldots Tap_{NT}$), capacitors VAr output ($Q_{C1}, \ldots Q_{C_{NC}}$). Similarly, the vector **u** is represented mathematically as

$$u^T = [\overbrace{P_{G2}, \ldots P_{G_{N_{PV}}}, V_{G1}, \ldots V_{G_{N_{PV}}}}^{continuous} \overbrace{Tap_1, \ldots Tap_{NT}, Q_{C1}, \ldots Q_{C_{NC}}}^{discrete}] \tag{4}$$

where NT and NC represent number of tap changers and switchable capacitors, respectively.

3 Objective Functions

In this work, the major objective is to find the optimal scheduling of thermal generators to meet the load demand economically by simultaneously maintaining the various physical and operational constraints present in the power system. The nonlinearities present in power generating units such as Valve-Point Loading (VPL), Prohibited Operating Zone (POZ), and Ramp Limits (RLs) are also considered. Inclusion of these nonlinearities makes the cost function non-convex and discontinuous, and hence, the optimization problem becomes a complex one.

(a) ***Minimization of fuel cost with Valve-Point Loading effect***

Simple fuel cost expression is an approximated cost expression. In real-time practice, cost expression is not so simple; rather they are complex and nonlinear in nature. Practical cost functions are generally non-convex and contain multiple ripples. This is because, practically, valve is used to control the steam flow to the turbine with the help of nozzle. Nozzles generally achieve high efficiency at full output. To achieve maximum efficiency, sequence operation of nozzle group is required. This results in a rippled efficiency curve which makes the curve non-convex in nature. This effect is called Valve-Point Loading (VPL) effect [18]. Mathematically, the cost function with VPL is expressed as [18]

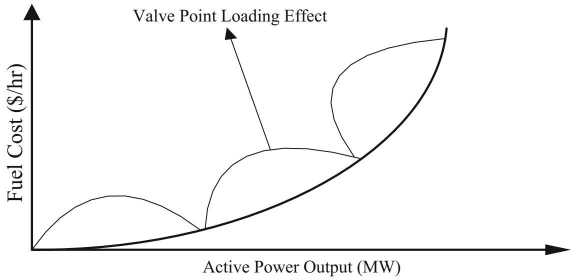

Fig. 1 Graphical representation of Valve-Point Loading (VPL) effect

$$F_{cost}^{valvepoint} = \sum_{i=1}^{i=N_g} \left[c_i + b_i P_{Gi} + a_i P_{Gi}^2 + \mid e_i \sin\left(f_i\left(P_{Gi}^{min} - P_{Gi}\right)\right) \mid \right] \$/\text{hr}. \quad (5)$$

e_i and f_i are the coefficient related to Valve-Point Loading. The numerical values of these coefficients are given in the corresponding result section. From Fig. 1, it can be seen that the simple fuel cost curve which is convex in nature is changed to a non-convex function with multiple ripples.

4 Constraints

There are two types of constraints present in the power system operation, i.e., equality constraints and inequality constraints.

Equality constraints

The mathematical expression of active and reactive power balance equation at each node of the power system network is given below [15]:

$$P_i - P_{Di} - |V_i| \sum_{j=1}^{NB} |V_j| \left\{ G_{ij} cos\left(\theta_i - \theta_j\right) + B_{ij} sin\left(\theta_i - \theta_j\right) \right\} = 0 \quad (6)$$

$$Q_i - Q_{Di} - |V_i| \sum_{j=1}^{NB} |V_j| \left\{ G_{ij} sin\left(\theta_i - \theta_j\right) - B_{ij} cos\left(\theta_i - \theta_j\right) \right\} = 0 \quad (7)$$

where P_i and Q_i are the real power injections at ith node of the network, and P_{Di} and Q_{Di} are the active and reactive load associated with the ith node. NB is the total number of busses. V_i and V_j are the voltage of the ith and jth bus, and θ_i and θ_j are the corresponding angles. G_{ij} and B_{ij} are the conductance and susceptance of the transmission line connected between ith and jth bus.

Inequality constraints
In power system, generally two types of constraints are there: (i) inequality constraints on independent variable side and (ii) inequality constraints on dependent variable side.

(1) Inequality constraints on independent variable side

$$\mathrm{P_{Gi}^{min}} \le \mathrm{P_{Gi}} \le \mathrm{P_{Gi}^{max}} \qquad \mathrm{i} \in \mathrm{NG} \tag{8}$$

$$\mathrm{V_{Gi}^{min}} \le \mathrm{V_{Gi}} \le \mathrm{V_{Gi}^{max}} \qquad \mathrm{i} \in \mathrm{NPV} \tag{9}$$

$$\mathrm{Tap_{i}^{min}} \le \mathrm{Tap_{i}} \le \mathrm{Tap_{i}^{max}} \qquad \mathrm{i} \in \mathrm{NT} \tag{10}$$

$$\mathrm{SC_{i}^{min}} \le \mathrm{SC_{i}} \le \mathrm{SC_{i}^{max}} \qquad \mathrm{i} \in \mathrm{NC} \tag{11}$$

POZ constraints
Due to the several steam valve operation and vibration in a shaft bearing of thermal generators, some physical limitations are imposed by the manufacturers. These limitations may result in the non-operation of thermal units within certain range of the power output. These restricted zones are called Prohibited Operating Zone (POZ). The presence of POZs makes the cost function discontinuous and it becomes difficult to determine the exact shape of the cost curve. By using Eq. (8), the feasible operating zones (FOZs) of the *i*th thermal generating unit are given by

$$P_{Gi}^{min} \le P_{Gi} \le P_{Gi,1}^{l} \tag{12}$$

$$P_{Gi,K-1}^{u} \le P_{Gi} \le P_{Gi,K}^{l} K = 2, 3 \ldots N_{i,PZ} \tag{13}$$

$$P_{Gi,N_{i,PZ}}^{u} \le P_{Gi} \le P_{Gi}^{max} \tag{14}$$

where $P_{Gi,K}^{l}$ and $P_{Gi,K}^{u}$ are the lower and upper bonds of the *k*th POZs of *i*th unit. $N_{i,PZ}$ is the total number of POZs of *i*th generating unit.

RRL constraints
The physical limits of thermal generating units restrict the operating range of all units by their Ramp Rate limits (RRLs) [22]. After incorporating the RRLs, Eq. (8) becomes as follows

$$max\left\{P_{Gi}^{min}, \left(P_{Gi}^{o} - DR_i\right)\right\} \le P_{Gi} \le min\left\{P_{Gi}^{max}, \left(P_{Gi}^{o} + UR_i\right)\right\} \tag{15}$$

where P_{Gi}^{o} is the power output at previous time interval and P_{Gi} is the power output at current time interval. UR_i and DR_i are the up ramp limit and down ramp limit of ith generating unit in (MW/hr), respectively.

(2) Inequality constraints on dependent variable side.

$$\mathrm{P_{G1}^{min}} \le \mathrm{P_{G1}} \le \mathrm{P_{G1}^{max}} \tag{16}$$

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max} \qquad i \in NG \tag{17}$$

$$V_{Li}^{min} \leq |V_{Li}| \leq V_{Li}^{max} \qquad i \in NPQ \tag{18}$$

$$S_{Li} \leq S_{Li}^{max} \tag{19}$$

5 Exchange Market Algorithm

Exchange Market Algorithm is designed by Ghorbani and Babaei after carefully observing the behavior of shareholders of exchange market under different market conditions. The algorithm is designed on the basis of maximizing the profit in the exchange market. Hence, the algorithm is initially developed for maximizing the objective function. However, it can also be used to solve the minimization problem [21]. As a general fact, in the exchange market, shareholders trade different shares in the virtual stock market, under diverse market scenarios. Political and economic policies of country sometimes drag the stock market from non-oscillated to oscillated market condition. If the market is balanced (non-oscillated mode), it is easier to predict the market condition and shareholder can increase their shares as well as profit without taking any unconventional risk. On the contrary, when the market condition is unbalanced (oscillated mode), situation becomes adverse and it involves certain risk in selecting shares for trading. It becomes difficult to predict the behavior of market, and thus, the action of the shareholders can be profitable or disadvantageous. In this algorithm, each shareholder is considered as the potential solution to the problem. Shareholders who are active and experienced are elite stock dealers. Profit of each shareholder is calculated and termed as fitness of the objective function. Based on the fitness values of each individual in both balanced and unbalanced market modes, sorting of the population is done. The individuals with highest, average, and low fitness as first, second, and third groups, respectively. Since first group members are highly experienced and can earn more profit at any market conditions, they remain unaffected in all stages of algorithm.

The steps of EMA in solving any optimization problem are given below:

Step 1: Initialization of the shareholders and their shares

In this step, share quantity (dimension of the problem), initial shareholders desired iterations, and the values of shares (control variable values $x_{ij}, \{i = 1, 2 \ldots m; j = 1, 2 \ldots n\}$ where m is the total dimension of the control variables and n is the population size) are initialized. The following formula is used for initialization.

$$x_i = x_i^L + rand \times \left(x_i^U - x_i^L\right) \tag{20}$$

Step 2: Computation of fitness and sorting

The total population is divided into high-, middle-, and low-ranked shareholders. In this step, the fuel costs are calculated and classified into three different groups depending on the effectiveness of their total shares.

Step 3: Updating of the shares of the second group in balanced market condition

The changes in the second group members are carried out in the following manner:

$$pop_j^{group(2)} = r \times pop_{1,i}^{group(1)} + (1 - r) \times pop_{2,i}^{group(1)} \tag{21}$$

$i = 1, 2, 3 \ldots n_i$ and $j = 1, 2, 3 \ldots n_j$

Step 4: Updating the shares of the third group in balanced market condition

$$S_k = 2 \times r_1 \times \left(pop_{i,1}^{group(1)} - pop_k^{group(3)}\right) + 2 \times r_2 \times \left(pop_{i,2}^{group(1)} - pop_k^{group(3)}\right) \tag{22}$$

$$pop_k^{group(3),new} = pop_k^{group(3)} + 0.8 \times S_k \tag{23}$$

where S_k is the variation in the share of the kth shareholder of the third group.

Step 5: Computation of shareholders cost (fitness) and ranking

Based on the fitness, the shareholders are sorted and divided into three groups.

Step 6: Adjustment of shares of second group members under market unbalanced market condition

In this step, mean members of shareholders vary some of their shares according to the following equations.

$$\Delta n_{t1} = n_{t1} - \delta + (2 \times r \times \mu \times \eta_1) \tag{24}$$

The detailed process of calculation of these parameters and the meaning associated with it are described in [21].

Step 7: Change of shares of third group members under unbalanced condition

In this step, contrary to the previous step, shareholders exchange some shares according to Eq. (24), irrespective of their total share amount.

$$\Delta n_{t3} = (4 \times r_s \times \mu \times \eta_2) \tag{25}$$

The calculation methods and meanings associated with the parameters are given in [21].

Step 8: End-up criteria

Maximum number of iterations is considered as the terminating criteria in this paper.

Table 1 POZs data for case-1

Prohibited zones
Pg_1 [55–66], [200–230]
Pg_2 [24–30], [45–55]
Pg_5 [10–18]
Pg_8 [10–15]
Pg_{11} [10–15]
Pg_{13} [11–18]

6 Results and Analysis

In this section, EMA is explored in solving OAPD problems of power system. The simulation is performed on IEEE-30 bus system [23]. Both continuous and discrete variables are considered as the control variables. Nonlinearities like VPL, POZ, and RRL are also considered to verify the efficiency of EMA in solving complex optimization problem. A population size of 50 is taken for all case studies. First 20% population is chosen as first, next 60% as second, and rest 20% as third group members. Constraints are handled by well-known penalty function method. Maximum cycle and trial runs are taken as 200 and 100, respectively. The results are compared by implanting the problem on some well-established meta-heuristic algorithms like FA, GSA, ABC, CSA. The results are compared with that of EMA both numerically and graphically. The control variable range and cost coefficients data are taken from [18].

Result Analysis of Case-1 (Fuel cost with VPL and POZ)

In this case, altogether, 25 control variables are used to optimize the fuel cost. The control variable includes active power output of generators, its voltages, transformers tap positions, and shunt capacitors. In addition to VPL, POZs are used with fuel cost in this case which makes the problem more complicated. Along with EMA, problem is also simulated on some promising meta-heuristic algorithms like ABC [24], FA [19], CSA [25], and GSA [15], and results so obtained are compared with that of EMA. The POZs data used in this case are given in Table 1. The combined convergence plots of EMA and other algorithms for the best solution obtained after 100 trials are represented in Fig. 2, whereas the best control settings obtained from these algorithms are compared with EMA in Table 2.

From Fig. 2, it can be seen that the convergence of EMA is very fast in comparison to other algorithms, and it also took very less iterations to converge. Thought convergence plot reflects that the GSA converges little earlier than EMA, but the optimal results obtained from EMA **(830.9393 $/h)** are lesser than that of GSA (831.44075 $/h). From Table 2, it can be seen that the optimal control settings of each variable obtained from different algorithms including EMA are within their given range and they also followed the POZs restrictions, which signifies the successful implementation all the above-mentioned algorithms. Both numerical and graphical presentations

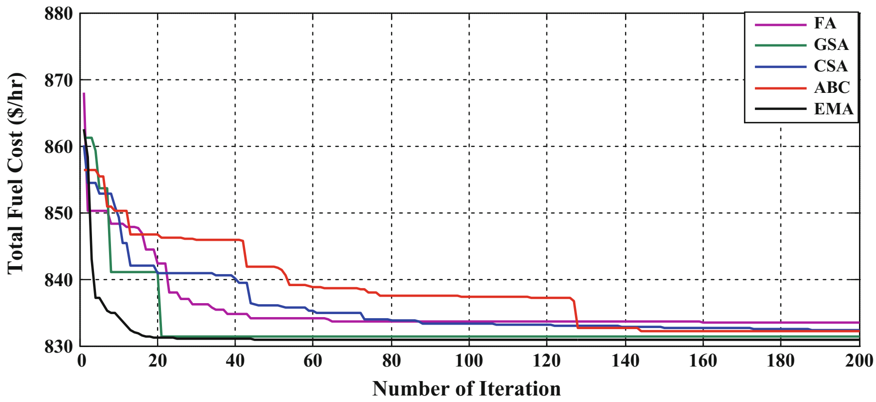

Fig. 2 Convergence plot for case-1

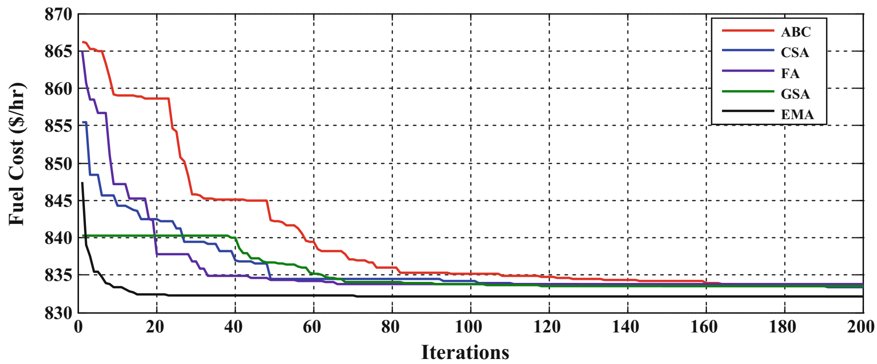

Fig. 3 Convergence plot for case-2

reveal that the EMA outperforms several other promising algorithms in solving such a complex nonlinear and discontinuous objective function.

Results for Case-2 (Fuel cost with VLP, POZ, and RRLs)

As mentioned in Sect. 3, the generators cannot increase or decrease its generation suddenly to any value when the system experiences a load change. Their increment and decrement in generations depend on the up ramping and down ramping limits, respectively. In this case study, same IEEE-30 bus system is taken as previous cases, and the ranges of control variables, POZ data, and cost coefficients are taken from [18]. The UR limit, DR limits, and initial generations (P^o_{Gi}) are given in Table 3 [22].

In this case, the problem is simulated with EMA and the results are compared graphically and numerically with several contemporary algorithms like ABC, FA, CSA, and GSA. The combined convergence plot of all the algorithms mentioned above along with that of EMA is presented in Fig. 3. The optimal control settings found for each method after 100 trials are given in Table 4. From Fig. 2, it can be seen that EMA converges faster than its contemporary algorithms. EMA converges at

Table 2 Comparison of simulation results for case-4 (b)

Variables	ABC	CSA	FA	GSA	EMA
Pg_1	199.98142	199.94782	200.00051	199.741	199.7859
Pg_2	45	43.248285	39.397676	45	45
$\boldsymbol{Pg_5}$	18.106504	19.844703	18.566638	19.652582	18
Pg_8	10	10	15	10	10
Pg_{11}	10	10	10	10	10
Pg_{13}	11	11	11	11	11
Vg_1	1.09173	1.0885275	1.0451061	0.9549027	1.1
Vg_2	1.07171	1.0656825	1.0120227	1.0143829	1.0516363
Vg_5	1.0380489	1.0415522	0.9838249	1.0215506	1.0542925
Vg_8	1.0333034	1.039999	0.9927971	0.963568	1.0795661
Vg_{11}	0.9842589	0.9630442	1.1876888	0.4184401	1.1
Vg_{13}	1.0473202	1.0330667	3.0346211	1.9638265	1.1
T_{6-9}	1.0258657	1.1	1.7580171	1.6781856	0.9642508
T_{6-10}	0.9610222	0.9	1.7848064	4.5385482	0.9471938
T_{4-12}	0.9786692	0.9816544	2.8781137	2.479595	0.9706705
T_{28-27}	0.9853553	0.9904716	3.4673909	3.6978057	0.9208261
Qc_{10}	1.1379254	2.7591335	2.5386399	4.1823588	4.9976107
Qc_{12}	4.9995384	3.9574064	2.9179724	1.4860359	0.5385628
Qc_{15}	5	2.9890051	2.918599	2.4881503	4.9813202
Qc_{17}	5	5	1.0890878	1.0606953	0.0025519
Qc_{20}	4.7864185	5	1.0674744	1.0345174	4.6090319
Qc_{21}	5	3.6265382	1.0276487	0.9697528	5
Qc_{23}	4.9602783	1.357168	1.0396423	0.9677014	2.6363138
Qc_{24}	3.8667484	5	1.0333033	1.009063	4.919458
Qc_{29}	2.396309	3.8220988	0.9995657	1.0468263	0.4915342
Cost ($/h)	832.10769	832.30725	833.42228	831.44075	**830.9393**
Loss (MW)	10.68792	10.640804	10.564819	11.993581	**10.38593**

Table 3 Ramp Rate Limits of IEEE-30 bus system [22]

Units	P_{Gi}^{o} (MW/h)	UR_i (MW/h)	DR_i (MW/h)
1	150	60	80
2	35	28	10
3	39	10	20
4	20	10	05
5	18	10	05
6	20	15	06

Table 4 Optimal control settings of different methods for case-2

Control settings	ABC	CSA	FA	GSA	EMA
Pg_1	207.92777	207.92747	208.06596	207.96852	207.5132
Pg_2	25	25	25	25	25
Pg_5	19	19.004729	19	19	19
Pg_8	15	15.00854	15	15	15
Pg_{11}	13.009165	13.004599	13	13	13
Pg_{13}	14	14	14	14	14
Vg_1	1.0946403	1.0904963	1.0852024	1.0917504	1.1
Vg_2	1.0688301	1.065443	1.0605096	1.0683272	1.08
Vg_5	1.0326919	1.0332523	1.0262487	1.036175	1.058
Vg_8	1.0425804	1.0361277	1.0346637	1.0403727	1.066
Vg_{11}	1.0061195	0.9696367	1.006751	1.0539735	1.1
Vg_{13}	1.0204623	1.0496216	1.0422215	1.0316439	1.1
T_{6-9}	0.9795929	1.0521864	1.0179205	1.0807292	1.047
T_{6-10}	1.0634502	0.9130505	1.007955	0.9	0.9016
T_{4-12}	0.9597269	0.9727112	1.0150316	0.9477566	0.9989
T_{28-27}	0.9916507	0.9786864	1.0109243	0.9745052	0.9781
Qc_{10}	1.9739053	2.2729398	2.6973317	0.0009942	1.2
Qc_{12}	3.7964077	0.1875152	2.4849725	3.8797133	5
Qc_{15}	5	2.7080108	2.0377753	4.9013219	5
Qc_{17}	5	5	3.2786065	0.5169132	5
Qc_{20}	4.0458936	4.4030709	3.4339994	0.5886965	5
Qc_{21}	3.9367355	4.4293553	1.3465702	2.6584298	5
Qc_{23}	5	4.8790692	1.8397726	0.4824813	5
Qc_{24}	4.2248185	3.9794151	1.3397933	2.0041334	5
Qc_{29}	2.1774603	2.6063759	3.1384295	2.0907184	2.369
Cost ($/h)	833.51004	833.42519	833.71745	833.42938	**832.0843**
Loss (MW)	10.536939	10.54534	10.665958	10.568525	**10.11**

the lower value while other algorithms prematurely converged at a value higher than that of EMA. The optimal fuel cost obtained from EMA is **832.0843 $/h** where the results obtained from CSA which is closer to that of EMA are found to be 833.4252 $/h. Other algorithms such as ABC, FA, and GSA settles down at 833.51, 833.71, and 833.4294 $/h, respectively. These can be also verified from the optimal control settings given in Table 4. From the graphical as well as numerical results, it can be concluded that EMA performs better than other well-established algorithms in solving such a complex nonlinear discontinuous objective functions.

7 Conclusion

In this work, a newly developed meta-heuristic algorithm called Exchange Market Algorithm is applied to solve the complex, nonlinear, non-convex OAPD problems of power system. The problem is implemented on IEEE-30 bus system. The basic objective is to optimize the fuel cost of thermal generating units by simultaneously satisfying all the physical and operational constraints of the power system. The various nonlinear constraints VLP, POZ, and RRLs are incorporated in order to test the applicability and efficiency of EMA in solving the non-convex and discontinuous objectives. The optimal control settings in both the cases suggest that EMA is successfully implemented to solve such a complex optimization problem. The comparison results with various other methods confirm that EMA has faster convergence and provides better near-optimal solution over other methods. Hence, EMA can be treated as one of the efficient members of evolutionary algorithms and can further be used to solve the other complex power system optimization problems.

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