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Exchange market algorithm for economic load dispatch

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ABSTRACT

This paper presents exchange market algorithm for solving economic load dispatch problems. Exchange market algorithm (EMA) is a new, robust, and strong algorithm to extract the optimal point for global optimization. Inspired by the stock exchange trading method, EMA strives to solve optimization problem. Meticulous investigation of the stock exchange methods employed by the elites in such markets has yielded to shape this algorithm. This algorithm has two searcher operators as well as two absorbent operators for individuals to be absorbed to the elite person, which leads to creation and organization of random numbers in the best way. In order to show the abilities of the EMA, this algorithm has been implemented on four test systems in different dimensions (3, 6, 15 and 40 units) with convex and nonconvex cost functions. The numerical results have been compared with the results of some new and strong algorithms. The results prove the robustness and effectiveness of the proposed algorithm and show that it could be used as a reliable tool for solving practical ELD problems.

Introduction

Economic load dispatch (ELD) is one of the most important optimization problems in power system operation and planning. The main objective of economic dispatch problem of electric power generation is to schedule the output power of committed generating units so as to meet the required load demand at minimum operating cost, while satisfying system equality and inequality constraints. In the ELD problem, the cost function for each generation unit is approximately represented by a single quadratic function and the problem is solved using mathematical programming based on optimization techniques such as lambda iteration method, gradient method, Newton's method, linear programming, interior point method and dynamic programming [1,2]. However, many mathematical assumptions such as convexity, quadratic, differentiable or linear objectives are required to simplify the problem. In these numerical methods for solving the ELD problem, an essential assumption is that the incremental cost curves of the units are piecewise-linear monotonically increasing functions. Unfortunately, the input–output characteristics of power generating units are inherently highly nonlinear because of prohibited operating zones, valve-point loadings, etc. Furthermore, they may lead to multiple local minimum points of the cost function. Classical dispatch algorithms require that these characteristics be approximated, even though such approximations are not desirable as they may lead to suboptimal [3,4]. Due to the non-convergence behavior of generation units' input/output characteristics the practical ELD problem should be a non-convex problem with constraints, which cannot be solved directly through the mathematical approaches. Dynamic programming (DP) method can solve such types of problems, but it suffers from so-called the curse of dimensionality [5]. From the last decades, advanced heuristic techniques such as genetic algorithm [6,7], evolutionary programming (EP) [8,9], differential evolution (DE) [10–13], particle swarm optimization (PSO) [14–19], and Biogeography-based optimization (BBO) [20,21] are developed to solve these problems.

Exchange Market Algorithm (EMA) is a meta-heuristic algorithm appropriate to solve the optimization problems. This algorithm is inspired by the stock market in which the shareholders buy and sell any types of shares under different market conditions. In this algorithm, it is assumed that the shareholders compete to introduce themselves as the most successful shareholder in the ranked list. In the EMA, shareholders with lower ranks tend to do logical risks to gain more profits and generally it is assumed that the shareholders are intelligent persons and behave similar with the successful traders of the stock market. Unlike the other algorithms, this algorithm has two searcher operators as well as two absorbent operators for individuals to be absorbed to the elite person, which leads to creation and organization of random numbers in the best way. These operators make EMA able to overcome the usual limitations of other algorithms such as local optimal trapping due to premature convergence (i.e. exploration problem), insufficient

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capability to find nearby extreme points (i.e. exploitation problem) and lack of efficient mechanism to treat the constraints (i.e. constraint handling problem). Less execution time, the ability in selecting search area and in turn the ability for optimization of various problems, convergence to the identical solutions in each program iteration, high ability in extraction of global optimum points, are some advantages of EMA [22].

In order to reveal the capabilities of EMA, it is applied to optimize several convex and nonconvex ELD problems aim to decrease the system fuel costs. In order to investigate the performance of the EMA in facing problems with several type of constraints, the ELD problem is optimized considering the existence of system power losses, system equality and inequality constraints, ramp rate limits, valve-point effects, and prohibited operational zones. This algorithm is implemented successfully on systems with 3, 6, 15, and 40 units. The obtained results are compared with other advanced techniques. The results well demonstrate the practical advantage of the exchange market algorithm over the other approaches.

The rest of this paper is organized as follows. Section 'Economic load dispatch problem formulation': gives the formulation of the ELD problem; Section 'Exchange market algorithm': explains the EMA; Section 'Implementation of exchange market algorithm for ELD problem': shows implementation pattern of EMA in solving ELD problem; Section 'Numerical results': shows implementation of the EMA to the test systems and obtained results; and Section ' Conclusions' gives our conclusions.

Economic load dispatch problem formulation

Objective function

The [14–18] have mentioned the formulation and ELD problem constraints in details. The aim of solving ELD problem is to minimize the outputs of the online generating units, while simultaneously satisfying all unit and system equality and inequality constraints. The simplified cost function of each generating unit can be approximated to be a quadratic function of the active power outputs from the generating units. The simplified cost function of each generation unit in ELD problem is as follows [5]:

$$F_t = \sum_{i=1}^{n} F_i(P_i) \tag{1}$$

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 \tag{2}$$

where F_t is the system fuel cost, F_i is the fuel cost of the ith unit, and a_i, b_i, and c_i are the coefficients related to the ith unit fuel. Parameter P_i represents the ith plant's generated power and n is the number of the last power unit of the system.

Equality and inequality constraints

Active powers balance equation

In order to balance the power, an equality constraint should be met. Total generated power of the plants should equal to total system demand power plus total transmission line power losses. In other words, the following should be valid:

$$\sum_{i=1}^{n} P_i = P_{\text{load}} + P_{\text{loss}} \tag{3}$$

where P_{load} is the total system load. Parameter P_{loss} is the power losses of transmission line and is a function of plants output power, which is defined as follows using B factor:

$$P_{\text{loss}} = \sum_{i=1}^{n}\sum_{j=1}^{n} P_i B_{ij} P_j + \sum_{i=1}^{n} B_{0i} P_i + B_{00} \tag{4}$$

Minimum and maximum power limits

The output power of each power unit should fall between the maximum and the minimum values of the power plant proportionally with the following inequality:

$$P_{i,\min} \leqslant P_i \leqslant P_{i,\max} \tag{5}$$

where $P_{i,\min}$ and $P_{i,\max}$ are the minimum and the maximum powers of the ith unit, respectively.

Ramp rate limits

The actual operation interval of all power plants is limited by the ramp-up and ramp-down. In other words, the plant, which used to generate P_i^0 can just increase or decrease its generation to some extent. The constraints of ramp-up and ramp-down are defined as follows:

$$P_i - P_i^0 \leqslant UR_i \tag{6}$$

$$P_i^0 - P_i \leqslant DR_i \tag{7}$$

where P_i^0 is the previous output power of the ith generating unit, UR_i and DR_i are the ramp-up and ramp-down of the ith generating unit, respectively. In order to consider the ramp-up and ramp-down and power output limits constraints simultaneously, (5)–(7) can be redefined as the following inequality:

$$\max\{P_{i,\min}, P_i^0 - DR_i\} \leqslant P_i \leqslant \min\{P_{i,\max}, P_i^0 + UR_i\} \tag{8}$$

ELD problem considering prohibited operational zones

In some cases, whole generation range of a generating unit is not available due to some executive physical limitations. Generating units may have some prohibited operation zones due to the existence of some deficiencies in machineries or in accessories. These defects might result in instability in some specific output power intervals. Therefore, some additional constraints should be added to the unit operation zones as follows for the plants with prohibited operational zones:

$$P_i \in \begin{cases} P_{i,\min} \leqslant P_i \leqslant P_{i,1}^{l} \\ P_{i,k-1}^{u} \leqslant P_i \leqslant P_{i,k}^{l} \\ P_{i,pzi}^{u} \leqslant P_i \leqslant P_{i,\max} \end{cases} \begin{matrix} i = 1, 2, \ldots, npz \\ k = 2, 3, \ldots, pz_i \end{matrix} \tag{9}$$

where $P_{i,1}^{l}$ and $P_{i,k}^{u}$ are respectively the lower and the upper bands of the ith unit prohibited zone, pz_i is the number of ith unit's prohibited zone and npz is the number of units with prohibited zone [25].

ELD problem considering valve-point effects

The generation units with multi steam valve create more variations in plant cost function. Since the existence of steam valves leads to ripple creation in plants characteristics, the cost function would have a more nonlinear formula. Therefore, the cost function (2) should be replaced by the following cost function:

$$F_i(P_i) = a_i + b_i P_i + c_i P_i^2 + |e_i \times \sin(f_i \times (P_{i,\min} - P_i))| \tag{10}$$

where e_i and f_i are the coefficients of generator i reflecting valve-point loading [27].

Exchange market algorithm

Exchange market algorithm is an appropriate meta-heuristic algorithm for optimization problems solving. This algorithm has two searcher operators as well as two absorbent operators. This advantageous enables the algorithm to search around the optimum point and in a vast range simultaneously. In EMA, each member is one of the answers. In the proposed algorithm there exists specific number of shares (in solving the ELD problem the number of shares is the number of generation units), each member intelligently tries to buy a number of them (in the ELD problem are the power output of each generating units), and intelligently performs to gain the maximum possible profit (in the ELD problem, profits can be achieved by reducing fuel costs) at the end of each period by calculating the validity of his own total shares.

In EMA, it is assumed that there exist two major market modes. In the first mode, the market condition is normal and faces with no considerable oscillation and the shareholders try to gain the maximum profit using the experiments of the successful members without performing any non-market risks (searching around the optimum point). In the second mode, the market experiences different oscillations and the shareholders try to perform some intelligent risks identifying the conditions to use the situation maximally to increase their assets (finding out the unknown points). In other words, in each iteration of the EMA, the fitness of the function is evaluated twice. In this algorithm, the shareholders are classified into three groups under any market condition. Here, group means the primary, middle, and the end members of the shareholder population [22].

Exchange market in normal mode

In this mode, the market is in normal condition without any considerable oscillation and the shareholders try to gain the maximum possible profit without performing non-market risks using the experiments of the elite shareholders and investigating the present condition. Therefore, they compete with each other. Here, each member is ranked according to the fitness function and stands in a group [22].

First group: members with high fitness

These members do not change their shares without performing any risk and trade to maintain their ranks. This group of shareholders composes 10–30% of the population. Members of this group are the elite shareholders or the best problem answers, so, they do not required to be changed.

Second group: members with average fitness

This group of shareholders composes 20–50% of the population. The members of this group use the successful experiences of elite stockbrokers and tend to take the least possible risk in changing their shares.

$$\mathrm{pop}_j^{\mathrm{group}\ (2)} = r \times \mathrm{pop}_{1,i}^{\mathrm{group}\ (1)} + (1-r) \times \mathrm{pop}_{2,i}^{\mathrm{group}\ (1)} \tag{11}$$

$$i = 1,2,3,\cdots,n_i \quad \text{and} \quad j = 1,2,3,\cdots,n_j$$

where n_i is the nth person of the first group and n_j is the nth person of the second group. Parameter r is a random number within [01], $\mathrm{pop}_{1,i}^{\mathrm{group}\ (1)}$ and $\mathrm{pop}_{2,i}^{\mathrm{group}\ (1)}$ are the members of the first group and $\mathrm{pop}_j^{\mathrm{group}\ (2)}$ is the jth member of the second group.

Third group: members with weak fitness

These groups of people are the end-list ranks of shareholders. This group of shareholders composes 20–50% of the population. The members of this group utilize the differences of share values of the first group as well as their share values' differences compared to the first group individuals and change their shares based on Eq. (12):

$$S_k = 2 \times r_1 \times \left(\mathrm{pop}_{i,1}^{\mathrm{group}\ (1)} - \mathrm{pop}_k^{\mathrm{group}\ (3)}\right) + 2 \times r_2 \times \left(\mathrm{pop}_{i,2}^{\mathrm{group}\ (1)} - \mathrm{pop}_k^{\mathrm{group}\ (3)}\right) \tag{12}$$

$$\mathrm{pop}_k^{\mathrm{group}\ (3),new} = \mathrm{pop}_k^{\mathrm{group}\ (3)} + 0.8 \times S_k \quad k = 1,2,3,\cdots,n_k \tag{13}$$

where r_1 and r_2 are random numbers, n_k is the nth member of the third group, $\mathrm{pop}_k^{\mathrm{group}\ (3)}$ is the kth member of the third group and s_k is the share variation of the kth member of the third group. The members of this group actually search the optimum point in a vaster domain in compare to the members of the second group.

Exchange market in oscillation mode

In this mode after shareholders reevaluation and members rating, the shareholders perform intelligent risks according to their own rank among other members to gain the maximum possible profit and achieve the higher ranks of the market from fitness function viewpoint. In other words, the algorithm should search in a wider space and try to find out the unknown points in this mode. Here, any member adopts different financial policies based on the gained profit and performs different risks to surpass the elite members. In this mode, members can be sorted in three separate groups considering their performances.

First group: members with high fitness

This part of population is the elite members or the best optimization problem answers, which do not tend to trade their shares and try to maintain their ranks. This group of shareholders composes 10–30% of the population. [22].

Second group: members with average fitness

In this section the sum of the shares held by people tends to be constant and only the number of some of each type of shares increase and some decrease in a way that the sum remains constant. At first, the number of shares held by each person increases based on the following equation:

$$\Delta n_{t1} = n_{t1} - \delta + (2 \times r \times \mu \times \eta_1) \tag{14}$$

$$\mu = \left(\frac{t_{\mathrm{pop}}}{n_{\mathrm{pop}}}\right) \tag{15}$$

$$n_{t1} = \sum_{y=1}^{n} |s_{\mathrm{ty}}| \quad y = 1,2,3,\ldots,n \tag{16}$$

$$\eta_1 = n_{t1} \times g_1 \tag{17}$$

$$g_1^k = g_{1,\max} - \frac{g_{1,\max} - g_{1,\min}}{iter_{\max}} \times k \tag{18}$$

where Δn_{t1} is the amount of shares should be added randomly to some shares, n_{t1} is total shares of tth member before applying the share changes. S_{ty} is the shares of the tth member, δ is the information of exchange market. Because of using penalty factor in the ELD problem and this paper, δ is equal to n_{t1} [22]. r is a random number in interval [1]. η_1 is risk level related to each member of the second group, t_{pop} is the number of the tth member in exchange market. n_{pop} is the number of the last member in exchange market, μ is a constant coefficient for each member and g_1 is the common market risk amount which decreases as iteration number increases. $iter_{\max}$ is the last iteration number and k is the number of program iteration. $g_{1,\max}$ and $g_{1,\min}$ indicate the maximum and minimum values of risk in market, respectively.

In the second part of this section, it is necessary that each person randomly sells some of his shares equal to the number he has purchased so that the sum of each person's shares remains constant. In this section, it is essential that each person reduces the number of his shares in Δn_{t2} amount. In this status, the Δn_{t2} of each person equals:

$$\Delta n_{t2} = n_{t2} - \delta \tag{19}$$

where Δn_{t2} is the share amount should be decreased randomly from some shares and n_{t2} is total share amount of the tth member after applying variations on shares.

Third group: members with weak fitness

In this section, unlike group 2, the sum of the person's number of shares would change after each trade. In other words, in this section, the person purchases or sells a number of shares. The shareholders of this group change some of their shares based on the following equation:

$$\Delta n_{t3} = (4 \times r_s \times \mu \times \eta_2) \tag{20}$$

$$r_s = (0.5 - rand) \tag{21}$$

$$\eta_2 = n_{t1} \times g_2 \tag{22}$$

$$g_2^k = g_{2,\max} - \frac{g_{2,\max} - g_{2,\min}}{iter_{\max}} \times k \tag{23}$$

where Δn_{t3} is totally the share amount should be applied in the shares of each member of third group randomly. Parameter r_s is a random number within $[-0.5\ 0.5]$. Parameter η_2 .is the risk related to each member of third group and g_2 is the market variable risk in third group. In this section, members trade a part of their shares randomly by varying total number of their shares.

Implementation of exchange market algorithm for ELD problem

The ELD problem optimization pattern using by exchange market algorithm is as the following steps:

(1) Selecting initial values and share allocation to the initial shareholders;
(2) Shareholders cost calculation and their rating;

In this section, members are evaluated according to the values of their shares and are classified in three separate groups to indicate different shareholders groups. The fitness function in ELD problem optimization is (1).

(3) Applying variations on the shares of the second group members in normal market mode

In this step, the elite members or the shareholders of the first group experience no variations and the middle members or the members of the second group change some shares according to (11).

(4) Applying variations on the shares of the third group members in normal market mode

This group is the end members of the population with lower fitness function value and they change their share amount from any type using Eq. (13).

(5) Recalculating shareholders cost and rating them

In the previous mode, it was aimed to search around the optimum point and the market was in its normal mode, but, in this mode, according to the variations applied on the shares of the middle and end members, the main population is evaluated from fitness function and members are classified based on their share values and are sorted in separate groups again.

(6) Trade in the shares of the second group members using Eq. (14) in market oscillated mode

In this step, the higher ranked members or the elite shareholders are maintained without any variation and the shareholders of the second group trade their shares considering Eq. (14) and change some of their shares. Initially, each member randomly buys some shares and then sells the same amount so that, there will be no variation in sum shares amount.

(7) Trade in the shares of the third group members using Eq. (20) in market oscillated mode

In this step, the shareholders trade their shares without any consideration on total share amounts according to Eq. (20).

(8) Jump to step 2 until the program ending conditions are not satisfied

In this step, the market oscillation condition is finished and the program starts to operate in order to evaluate the shareholders from step 2 if end up conditions that is the number of program iteration are not satisfied. If end up conditions are satisfied, the program operation is ended up. Flowchart of the EMA for solving the ELD problem is illustrated in Fig. 1.

Numerical results

The EMA is applied on four different power systems: (1) System with 3-unit system with prohibited operating zones, ramp rate limits and network losses; (2) 6-unit system with prohibited operating zones, ramp rate limits and network losses; (3) 15-unit system with prohibited operating zones, ramp rate limits and network losses; (4) 40-units system with valve-point effects.

Fifty independent experimentations are conducted on each problem to compare the problem solution quality and convergence features. In all case studies, the number of generation is 100.

In all experiments, the number of individuals in 1st, 2nd and 3rd groups in non-oscillation market (balanced or normal market) conditions are 25, 25 and 50% of the generation, and the pattern for the oscillated market conditions are equal to 20%, 60% and 20% of initial generation [22]. The individuals' percentage in three groups has approximately constant values, and its optimum value is as the mentioned value. The necessary adjustable parameters of the proposed algorithm are risk factors of 2nd and 3rd groups in oscillated market which its optimum value for each problem are included in Table 1.

System with 3-unit system

The experimentations are accomplished on a system possessing three units, in two separate parts, due to in some papers the results do not satisfy the ramp rate limits. (A) System with network power losses and prohibited operating zones; (B) System with network power losses, prohibited operating zones and ramp rate limits. The total demand is set to 300 MW. It is aimed to minimize the total cost of the system. Input data for 3-unit test system are included in Table 2 and B coefficient of network losses are in [6].

(A) The results obtained from solving the test system *A* by EMA is in Table 3. As it is obvious, the minimum obtained fuel cost is 3619.7555 ($/h) resulted by EMA. (B) The results obtained from ELD problem solution using EMA in a system with three units considering total constraints of case study A plus the ramp rate limits are presented in Table 3. As it is obvious, the minimum fuel cost and the minimum system losses are achieved applying EMA. In order to investigate the convergence pattern of the EMA, fifty independent experimentations are conducted for A and B case studies

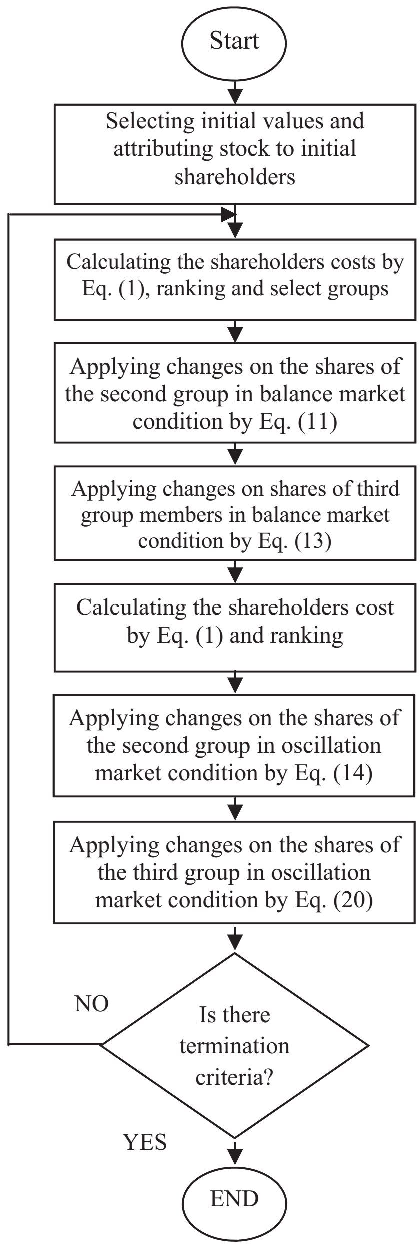

Fig. 1. Program implementation flowchart of exchange market algorithm.

and the average of the results are presented in Table 3. The results show the robust convergence of the proposed algorithm during each program implementation. In Table 4, the result obtained by EMA is illustrated for case study B after fifty program implementations with different iterations. In solving ELD problem with 3-unit system by EMA, the least cost is obtained in 50 implementations with 30 iterations, but the convergence to completely similar answers with four digits of decimal is achieved for 500 iterations due to the random nature of the algorithms operation process.

Table 1
Adjustable parameters of EMA for numerical experimentations.

Risk value	g_1 [max, min]	g_2 [max, min]
3-unit system	[0.005,0.001]	[0.01,0.002]
6-unit system	[0.005,0.001]	[0.01,0.002]
15-unit system	[0.003,0.001]	[0.006,0.002]
40-unit system	[0.001,0.0005]	[0.002,0.001]

Results shown in Table 4 well indicate the fact that this algorithm converges to near the global optimum point during initial iterations, and is able to finding out global optimum point during each program implementation.

System with 6-unit

This test system contained six units with non-convex cost functions considering ramp-rate limits, prohibited operating zones and transmission network losses. Total system load power is 1263 MW. Input data for 6-unit test system are included in Table 2 and B coefficient of power losses are as presented in [14]. {R.4} Results of solving ELD problem through EMA in a 6-unit system are presented in Table 5. As can be seen in Table 5, the lowest fuel cost for the system is 15443.0749 ($) that obtained by EMA and is lower than that of θ-PSO, Self-Organizing Hierarchical Particle Swarm Optimization (SOH-PSO) and BBO. In order to investigate the convergence pattern of the EMA, fifty independent experimentations are conducted for 6 units test system and the average of the results is presented in Table 5. As it is apparent, the presented method found the same solutions in this problem in each program runs indicating the robustness of this method. As can be seen from Table 5, the run time of EMA is lower than θ -PSO, SOH-PSO and BBO.

System with 15 units

This test system contained 15-online units with non-convex cost functions considering ramp-rate limits, prohibited operating zones and transmission network losses. The system supplies a total load of 2630 MW. The input data for 15-unit test system are included in Table 2 and B-matrix for transmission network losses for the system are given in [14]. {R.4 & R.5} The results of solving ELD problem in a 15-unit system are presented in Table 6. In order to investigate the convergence pattern of the EMA, fifty independent experimentations are conducted on 15 units test system and the average of the results in comparison with other methods is presented in Table 7. As can be seen in Tables 6 and 7, the minimum fuel cost obtained for the system is 32704.4503 ($/h), which is achieved using EMA and is less than that of GAAPI, SOH-PSO, modified differential evolution (MDE), PSO, artificial bee colony (ABC), particle swarm optimization with smart inertia factor (PSO-SIF) and θ-PSO techniques. Comparing the results of applying EMA with that of the other approaches shows robustness and the high capabilities of this algorithm in finding out the global optimum point over other compared methods.

As shown in Table 7, the results of EMA are very robust in compare with that of the other methodologies and their full-fledged methods since the EMA algorithm achieves similar answers after 50 program implementations. For example, in comparing the average results of EMA and PSO, it is obvious that PSO technique finds out the average value 33,039 ($/h) in 50 program implementation, which is 181 ($/h) more than the minimum cost amount obtained by PSO, while in EMA, the minimum and the average obtained cost amounts in 50 program implementations are equal. The convergence characteristic of EMA and PSO algorithms are compared in Fig. 2.

In PSO, the search domain in initial iterations is wide and decreases due to the reduction of weight inertia coefficient as the iteration number increases [5]. The effect of wide search domain of PSO in initial 200 iterations is distinctive in Fig. 2. The effect of restricted PSO search domain in 600–800 iterations is also depicted in Fig. 2. EMA has two searcher operators that one of which searches in the restricted domain and the other simultaneously searches in a wider domain. Searching in the restricted domain leads to finding out more optimized points adjacent to

Table 2
Data for 3, 6 and 15 units systems.

Unit	$P_{i,\min}$	$P_{i,\max}$	a_i	b_i	c_i	UR_i	DR_i	P_i^0	Prohibited zones
3-unit test system									
1	50	250	328.13	8.663	0.00525	55	95	215	[105,117][165,177]
2	5	150	136.91	10.04	0.00609	55	78	72	[50,60][92102]
3	15	100	59.16	9.76	0.00592	45	64	98	[25][60,67]
6-unit test system									
1	100	500	240	7	0.0070	80	120	440	[210240][350380]
2	50	200	200	10	0.0095	50	90	170	[90110][140160]
3	80	300	220	8.5	0.0090	65	100	200	[150170][210240]
4	50	150	200	11	0.0090	50	90	150	[8090][110120]
5	50	200	220	10.5	0.0080	50	90	190	[90110][140150]
6	50	120	190	12	0.0075	50	90	110	[7585][100105]
15-unit test system									
1	150	455	671	10.1	0.000299	80	120	400	
2	150	455	574	10.2	0.000183	80	120	300	[185,225][305,335][420,450]
3	20	130	374	8.80	0.001126	130	130	105	
4	20	130	374	8.80	0.001126	130	130	100	
5	150	470	461	10.40	0.000205	80	120	90	[180,200][305,335][390,420]
6	135	460	630	10.10	0.000301	80	120	400	[230,255][365,395][430,455]
7	135	465	548	9.5	0.000364	80	120	350	
8	60	300	227	11.2	0.000338	65	100	95	
9	25	162	173	11.2	0.000807	60	100	105	
10	25	160	175	10.7	0.001203	60	100	110	
11	20	80	186	10.2	0.003586	80	80	60	
12	20	80	230	9.90	0.005513	80	80	40	[30,40][55,65]
13	25	85	225	13.1	0.000371	80	80	30	
14	15	55	309	12.1	0.001929	55	55	20	
15	15	55	323	12.4	0.004447	55	55	20	

Table 3
Results obtained with different algorithms on a system with three units.

Unit (MW)	Case study A		Case study B	
	EMA	DE/BBO [21]	EMA	GA [6]
P1	207.7666	207.9926	200.5892	194.26
P2	87.1567	86.0125	78.2520	50
P3	15.0000	16.0723	34.0000	79.62
TP*	309.9234	310.0774	312.8413	323.89
P_{Loss}	9.9234	10.0774	12.8413	24.011
TC	3619.7555	3620.1748	3634.7683	3737.20
AC	3619.7555	3620.1799	3634.7683	–
T/I	0.0020	0.017	0.0022	0.01

* TP: total power [MW], TC: total cost [$/h], AC: average cost [$/h], T/I: cpu time/iteration [s].

Table 4
EMA results in 50 program implementations with different iterations for B case study.

Iteration	30	50	100	500
Min. cost	3634.8401	3634.7709	3634.7695	3634.7683
Max. cost	3635.4609	3634.9011	3634.8113	3634.7683
Ave. cost	3634.9131	3634.7818	3634.7706	3634.7683

the global optimum point and searching in a wider domain leads to find out unknown points. This optimum search of EMA enables the algorithm to find out cost amount less than 32,850 ($/h) in initial 15 iterations but PSO is not able to find out even in 50 program implementations with 1000 iterations. {R.3} As it can be seen, the capability of extraction of global optimum point in EMA is far better than PSO. The main reasons for this discrepancy include the following points:

1. *Having appropriate absorbent: operators:* There are two absorbent operators toward the elite stockbrokers in the proposed algorithm. In proposed algorithm and in balanced market the shareholders in groups 2 and 3 are responsible to absorb

Table 5
The best output power for a system with 6 units.

Unit (MW)	SOH-PSO [19]	θ-PSO [23]	BBO [20]	EMA
P1	447.49	447.105	447.3997	447.3872
P2	173.32	173.112	173.2392	173.2524
P3	263.47	263.65	263.3163	263.3721
P4	139.06	139.152	138.0006	138.9894
P5	165.47	165.934	165.4104	165.3650
P6	87.13	86.5037	87.07979	87.0781
TP	1275.55	1275.46	1275.446	1275.4443
P_{loss}	12.55	12.4493	12.446	12.4430
TC	15446.02	15443.18	15443.09	15443.0749
AC	15497.35	15443.2117	15443.09	15443.0750
T/I	0.0633	0.0088	0.0325	0.0024

Table 6
The best output power for a system with 15 units.

Unit (MW)	EMA	GAAPI [7]	SOH-PSO [19]
P1	455.0000	454.70	455.00
P2	380.0000	380.00	380.00
P3	130.0000	130.00	130.00
P4	130.0000	129.53	130.00
P5	170.0000	170.00	170.00
P6	460.0000	460.00	459.96
P7	430.0000	429.71	430.00
P8	72.0415	75.35	117.53
P9	58.6212	34.96	77.90
P10	160.0000	160.00	119.54
P11	80.0000	79.75	54.50
P12	80.0000	80.00	80.00
P13	25.0000	34.21	25.00
P14	15.0000	21.14	17.86
P15	15.0000	21.02	15.00
TP	2660.6626	2660.36	2662.29
P_{loss}	30.6626	30.36	32.28
TC	32704.4503	32732.95	32751.39
T/I	0.0033	NA	0.0936

Table 7
Obtained results by different methods for 15-unit test system.

Methods	Min. cost	Ave. cost	Max. cost
MDE [12]	32917.87	33066.76	33245.54
PSO [14]	32858	32989	33031
ABC [24]	32707.85	32707.95	32708.27
PSO-SIF [5]	32706.8800	32707.7900	32709.92
θ-PSO [23]	32706.6856	32711.4955	32744.0306
EMA	32704.4503	32704.4504	32704.4506

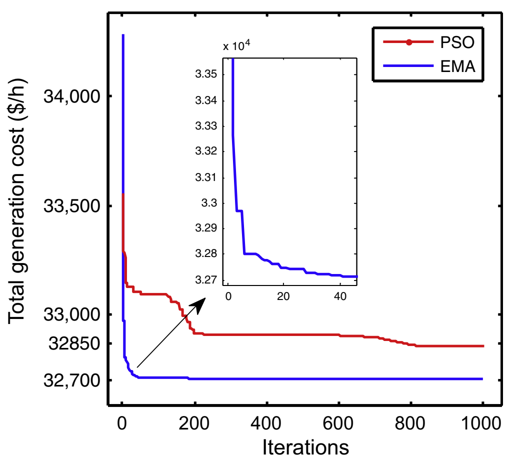

Fig. 2. Convergence characteristics of EMA and PSO in 15 units test system.

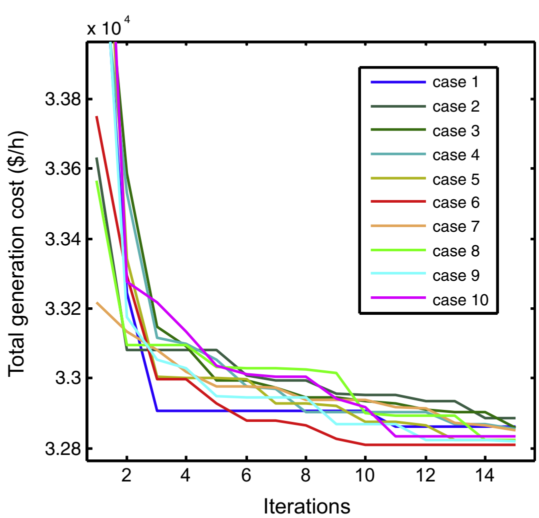

Fig. 3. Characteristics of finding out 32,850 ($/h) cost by EMA.

individuals toward group 1 members or elite stockbrokers. Therefore, the absorption toward group 1 or elite stockbrokers is done as well in EMA.

2. *Robust and efficient searcher operators:* In this algorithm, there are two searcher operators and along with local search, the vaster search is also simultaneously conducted which leads to creation and organization of random numbers in the best way.
3. *Application of unique changes in each shareholder:* In EMA algorithm, shareholders with low fitness, trade with a higher risk, conversely, shareholders with higher fitness levels trade with lower ranks. Hence, considering the fitness rank of shareholders, each person shows a unique trade to increase his possessions.

Table 8
Determination of g_1 and g_2 for EMA in 15-unit test system.

Case	$g_{1,max}$	$g_{2,max}$	Minimum cost ($)	Average cost ($)
1	0.2	0.4	32754.2501	32785.6591
2	0.1	0.2	32719.4698	32731.1390
3	0.05	0.1	32707.1364	32715.3871
4	0.02	0.04	32705.5038	32711.0017
5	0.01	0.02	32704.7894	32706.0102
6	0.005	0.01	32704.4503	32705.2113
7	0.004	0.008	32704.4503	32704.4898
8	**0.003**	**0.006**	**32704.4503**	**32704.4504**
9	0.002	0.004	32704.4503	32705.0015
10	0.001	0.002	32708.1001	32721.0176

Table 9
Data for 40 units system.

Unit	$P_{i,min}$	$P_{i,max}$	a_i	b_i	c_i	e_i	f_i
1	36	114	94.705	6.73	0.00690	100	0.084
2	36	114	94.705	6.73	0.00690	100	0.084
3	60	120	309.540	7.07	0.02028	100	0.084
4	80	190	369.030	8.18	0.00942	150	0.063
5	47	97	148.890	5.35	0.01140	120	0.077
6	68	140	222.330	8.05	0.01142	100	0.084
7	110	300	287.710	8.03	0.00357	200	0.042
8	135	300	391.980	6.99	0.00492	200	0.042
9	135	300	455.760	6.60	0.00573	200	0.042
10	130	300	722.820	12.9	0.00605	200	0.042
11	94	375	635.200	12.9	0.00515	200	0.042
12	94	375	654.690	12.8	0.00569	200	0.042
13	125	500	913.400	12.5	0.00421	300	0.035
14	125	500	1760.400	8.84	0.00752	300	0.035
15	125	500	1760.400	8.84	0.00752	300	0.035
16	125	500	1760.400	8.84	0.00752	300	0.035
17	220	500	647.850	7.97	0.00313	300	0.035
18	220	500	649.690	7.95	0.00313	300	0.035
19	242	550	647.830	7.97	0.00313	300	0.035
20	242	550	647.810	7.97	0.00313	300	0.035
21	254	550	785.960	6.63	0.00298	300	0.035
22	254	550	785.960	6.63	0.00298	300	0.035
23	254	550	794.530	6.66	0.00284	300	0.035
24	254	550	794.530	6.66	0.00284	300	0.035
25	254	550	801.320	7.10	0.00277	300	0.035
26	254	550	801.320	7.10	0.00277	300	0.035
27	10	150	1055.100	3.33	0.52124	120	0.077
28	10	150	1055.100	3.33	0.52124	120	0.077
29	10	150	1055.100	3.33	0.52124	120	0.077
30	47	97	148.890	5.35	0.01140	120	0.077
31	60	190	222.920	6.43	0.00160	150	0.063
32	60	190	222.920	6.43	0.00160	150	0.063
33	60	190	222.920	6.43	0.00160	150	0.063
34	90	200	107.870	8.95	0.00010	200	0.042
35	90	200	116.580	8.62	0.00010	200	0.042
36	90	200	116.580	8.62	0.00010	200	0.042
37	25	110	307.450	5.88	0.01610	80	0.098
38	25	110	307.450	5.88	0.01610	80	0.098
39	25	110	307.450	5.88	0.01610	80	0.098
40	242	550	647.830	7.97	0.00313	300	0.035

4. *Selecting a specific search area:* The structure of EMA is in a way that it allows manipulation of the search area. In Table 1, the risk level of groups 2 and 3 members in oscillated markets or the selected search area have been presented.
5. *Independence of searcher operators from obtained costs:* in PSO, the search area of the algorithm is dependent upon the costs of best individual and group answers. Therefore, there exist the possibility of individuals' costs being equal and the algorithm's getting stuck in local optimum points [5]. In EMA the trade volume does not depend on the cost of elite stockbrokers and only depends on the sum number of the shares of each person. Hence, in the proposed algorithm, the only possibility of getting stuck would be in cases where the sum of the persons'

Table 10
The best output power for a system with 40 units.

Unit	EMA	BBO [20]	QPSO [18]
P1	110.7998	110.0465	111.20
P2	110.7998	111.5915	111.7
P3	97.3999	97.6007	97.40
P4	179.7331	179.7095	179.73
P5	87.7999	88.3060	90.14
P6	140.0000	139.9992	140.00
P7	259.5996	259.6313	259.60
P8	284.5996	284.7366	284.80
P9	284.5996	284.7801	284.84
P10	130.0000	130.2484	130.00
P11	94.0000	168.8461	168.80
P12	94.0000	168.8461	168.80
P13	214.7598	214.7038	214.76
P14	394.2793	304.5894	304.53
P15	394.2793	394.2761	394.28
P16	394.2793	394.2409	394.28
P17	489.2793	489.2919	489.28
P18	489.2793	489.4188	489.28
P19	511.2793	511.2997	511.28
P20	511.2793	511.3073	511.28
P21	523.2793	523.4170	523.28
P22	523.2793	523.2795	523.28
P23	523.2793	523.3793	523.29
P24	523.2793	523.3225	523.28
P25	523.2793	523.3661	523.29
P26	523.2793	523.4362	523.28
P27	10.0000	10.0531	10.01
P28	10.0000	10.0113	10.01
P29	10.0000	10.0030	10.00
P30	87.7999	88.4775	88.47
P31	190.0000	189.9983	190.00
P32	190.0000	189.9881	190.00
P33	190.0000	189.9663	190.00
P34	164.7998	164.8054	164.91
P35	200.000	165.1267	165.36
P36	194.3977	165.7695	167.19
P37	110.0000	109.9059	110.00
P38	110.0000	109.9971	107.01
P39	110.0000	109.9695	110.00
P40	511.2793	511.2794	511.36
TC	121412.5355	121426.953	121448.21

share numbers equals zero. This possibility can exist only when all values converge to zero. This is not possible unless the global optimum point is zero. Therefore, the possibility of this algorithm getting stuck in local optimum points is very negligible, and the algorithm is able to searching until its last iteration.

Fig. 3 shows the Convergence characteristic of EMA with just 15 iterations in 10 program implementations. In solving ELD problem with 15-unit system by EMA, the least cost is obtained in 50 implementations with 200 iterations, but the convergence to completely similar answers with three digits of decimal is achieved for 2000 iterations due to the random nature of the algorithms operation process.{R.4} How selecting optimal values for EMA's adjustable parameters is explained in [22] and the optimal adjustable value for the 15-unit system is presented in Table 1. Adjustable parameters of EMA play a key role in algorithm's convergence to the optimal point in each program implementation. In order to show the effect of EMA's adjustable parameters in converging to optimal point, the results of solving ELD problem in 15-unit system in terms of various values for $g_{1,\max}$ and $g_{2,\max}$ after fifty program implementations are given in Table 8. Obtained results in Table 8, shows that suitable value of adjustable parameters can be guaranteed the algorithm's convergence to the optimal point in 15 units system.

System with 40 units

Total system load power is 10,500 MW. The input data for test system are included in Table 9 [14]. Results of solving ELD problem in a 40-unit system with valve-point effects is presented in Table 10. {R.4 & R.5} In order to investigate the convergence pattern and robustness of proposed algorithm, the program is run for 50 times and the average of results through EMA is compared with other methods in Table 11. As seen in Tables 10 and 11, the minimum fuel cost obtained for the system is 121412.5355 ($/h), which is achieved using EMA and is less than that of BBO, QPSO, ACO, CSO, θ-PSO and FA techniques by 14.42 $, 35.68 $, 398.84 $, 49 $, 8.37 $, 2.43 $ and 2.52 $ respectively. Fig. 4 depicts the convergence characteristics of EMA for the studied system. Comparing the results of applying EMA with that of the other approaches shows the high capabilities of this algorithm in finding out the global optimum point over other advanced techniques.

Table 11
Obtained results by different methods for 40-unit test system.

Methods	Min. cost	Ave. cost	Max. cost
ACO [25]	121811.3700	121930.5800	122048.0600
CSO [13]	121461.6707	121936.1926	122844.5391
BBO [20]	121426.9530	121508.0325	121688.6634
θ-PSO [23]	121420.9027	121509.8423	121852.4249
FA [26]	121415.0500	121416.5700	121424.5600
EMA	121412.5355	121417.1328	121426.1548

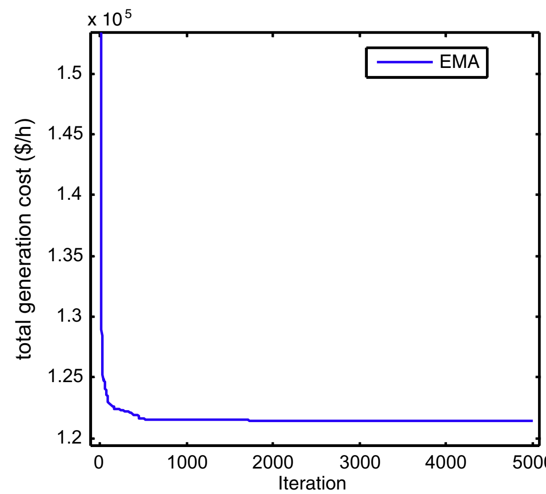

Fig. 4. Convergence characteristic of EMA in 40 units system.

Conclusions

In this paper, the proposed exchange market algorithm has been successfully implemented to solve both convex and nonconvex ELD problems considering practical constraints such as ramp rate limits, valve point effects, and prohibited operating zone. In tests conducted on systems with 3, 6 and 15 units; EMA has been able to find global optimum point for each run of the program. This convergence to the identical solution shows the robustness and search efficiency of the proposed method. In tests conducted on a system with 40 units with valve point effects, EMA could extract cost of 121412.5355 ($/h) which is minimum in comparison to the other methods such as BBO, QPSO, ACO and others. In EMA run-time of the program is the lowest in compared with other compared algorithms. The findings considerably reveal that the EMA method has superior solution quality, convergent characteristics, computational efficiency, and robustness in achieving near global solutions compared by other methods. The results prove the robustness and effectiveness of the EMA and shows that it could be used as a reliable tool for solving the optimization problems.

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