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Combined Economic and Emission Dispatch Solution Using Exchange Market Algorithm

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Abstract

This paper proposes the exchange market algorithm (EMA) to solve the combined economic and emission dispatch (CEED) problems in thermal power plants. The EMA is a new, robust and efficient algorithm to exploit the global optimum point in optimization problems. Existence of two seeking operators in EMA provides a high ability in exploiting global optimum point. In order to show the capabilities of EMA in solving CEED problem, several experimentations are conducted on systems with 6, 10, and 40 generation units applying valve-point effects and network power losses in a multi objective function consists of system fuel cost and emission level. 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.

Keywords: Exchange Market Algorithm, Economic Dispatch, Emission; Valve-point effects, Optimization;

1. Introduction

Exchange market algorithm (EMA) is a new, robust, and efficient algorithm in exploiting the global optimum point of optimization problems [1]. This algorithm is inspired by stock market in which the shareholders try to buy and sell variety of shares under different market conditions. Here, it is assumed that the shareholders compete to mark themselves as the most successful members of the market in the ranking list. In this markets, members with low ranks tend to accomplish logical risks to gain more profit and it is generally assumed that the shareholders are intelligent and perform as the same as the elite members of the real stock market. In EMA, each member is an answer of the problem. There exists certain number of shares (variables of optimization problem) each member intelligently buys a number of them (variables initialization) and conducts his intelligent proceedings at the end of each period calculating the validity of total share amounts to gain the maximum possible profit in market.

In EMA, generation and organization of random numbers are performed in best way due to the existence of two absorbent operators and two searching operators leading to high capability in global optimum point extraction.They enable the EMA to overcome the limitations of other algorithms such as trapping in local points and consequently premature convergence (exploration problem), non-sufficient ability in finding out the adjacent points of the optimum point (exploitation problem), and convergence to non-similar points in every program implementation.

Economic dispatching in thermal power plants aims to minimize the fuel costs of the plants. Utilization of plants consuming fossil fuel is with release of high amounts of NO_X , CO_X , SO_X , etc. Extensive researches on using plants with low emission levels have been accomplished. In some cases, the emission is considered as a constraint in economic dispatch (ED) problem solution and in some others, the emission is applied on the objective function [2-4]. Researches depict that applying a constraint for emission to influence on the ED problem is with some problems such as difficulty of creating a relation between fuel cost and emission level. The weighting approach simply allots several weights to the functions according to their importance in objective function. In solving problems through such technique, the solution considerably depends on the functions weights. The heuristic algorithms do not face with the mentioned problems, where the advanced techniques such as genetic algorithm [5], artificial bee colony [6], evolutionary algorithms [7], differential evolution [8-10], particle swarm optimization [11-13], bacterial foraging algorithm [14-15], gravitational search algorithm [16-18], etc have been developed to solve the economic and emission dispatch (EED) problem. The operational process of the heuristic algorithms is based on the random values. Therefore, this element causes disability in exploring global optimum point and convergence to non-similar answers in each program implementation. Therefore, the answers are less trustable. The exchange market algorithm does not face with these limitations because of possessing two searching operators. In this paper, it is aimed to use the high abilities of EMA in solving CEED problem and global optimum point exploitation. In order to show the capabilities of EMA in solving EED problems, several experimentations are conducted on systems with 6, 10, and 40 units applying valve-point effects and network power losses in a multi objective function consists of system fuel cost and emission level. The results are then compared with that of the efficient algorithms and their developed techniques. Techniques such as Strength Pareto evolutionary algorithm (SPEA), non-dominating sorting genetic algorithm II (NSGA II), multi objective evolutionary algorithm (MOEA), fuzzy clustering-based particle swarm optimization (FCPSO), Differential evolution (DE), multi objective differential evolution (MODE), gravitational search algorithm (GSA), modified bacterial foraging algorithm (MBFA). The results show the high ability of exchange market algorithm over the other methods.

The rest of this paper is organized as follows. Section 2: gives the formulation of the EED problem; Section 3: explains the EMA; Section 4: shows implementation pattern of EMA in solving EED problem; Section 5: shows implementation of the EMA to the test systems and obtained results; and Section 6 gives our conclusions.

2. Formulation of Problem

The detailed data about the formulation and the constraints of CEED are presented in [8-13]. Generally, in solving EED problem, it is aimed to decrease the system fuel costs along with reducing emission level. The multi objective function of the problem is as follows:

$$\min F = [F_{FC}, F_E] \tag{1}$$

Function F is a multi objective function of the investigated problem aimed to be minimized. The objective function separately consists of fuel costs minimization (F_{FC}) and emission level minimization (F_E).

A) Economic Dispatch

It is aimed to minimize the thermal power plants' fuel costs the objective function of which is a second order function defined as follows:

$$F_{FC} = \min \sum_{i=1}^{Ng} (a_i + b_i P_{Gi} + C_i P_{Gi}^2) \quad (\$/h) \tag{2}$$

where a_i, b_i and c_i are the constants related to the thermal plants' fuel costs. The fuel cost is in terms of (\$/h). If the valve-point effects are considered, (2) is redefined as follows [23]:

$$F_{FC} = \sum_{i=1}^{Ng} (a_i + b_i P_i + c_i P_i^2 + |e_i \times \sin(f_i \times (P_{i,\min} - P_i))|) \quad (\$/h) \tag{3}$$

where e_i and f_i are the coefficients of the i^{th} plant and reflect the valve-point effects.

B) Emission Dispatch

It is aimed to minimize the released emission level of fossil fuel of power plants objective function of which is a second order function as follows:

$$F_E = \min \sum_{i=1}^{Ng} (\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2) \quad (ton/h) \tag{4}$$

where α_i, β_i, and γ_i are the constants related to the emission release and F_E shows the emission level. The emission is in terms of (ton/h) or (kg/h). If the valve-point effects are considered, (4) is redefined as follows:

$$F_E = \sum_{i=1}^{Ng} (\alpha_i + \beta_i P_{Gi} + \gamma_i P_{Gi}^2) + \xi_i \exp(\lambda_i P_i) \quad (ton/h) \tag{5}$$

where ξ_i and λ_i represent the valve-point effects [24].

C) Constraints

The power of generation units equals to the sum of load amount and transmission line losses. In other words, the equality constraint is as follows:

$$\sum_{i=1}^{Ng} (P_{Gi}) - P_{load} - P_{loss} = 0 \tag{6}$$

where P_{load} is the load demand power and P_{loss} is the power losses of the transmission line and is obtained as follows:

$$P_{loss} = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} P_{Gi} B_{ij} P_{Gj} + \sum_{i=1}^{Ng} B_{0i} P_{Gi} + B_{00} \tag{7}$$

The inequality constraint of the problem is the generated powers of units and falls within a maximum and minimum allowed values. In other words, the following is valid:

$$P_{Gi\ \min} \le P_{Gi} \le P_{Gi\ \max} \tag{8}$$

D) Combining Economic Dispatch and Emission

The fuel costs and the emission functions are separate and independent. Fuel cost is in terms of (\$/h) and emission is in terms of (ton/h). The value of each function can be several times greater than the other one's value. In order to combine these functions and to form a single-objective function, it is necessary to adopt an attitude to assimilate the units of several functions as well as equiponderating their values in objective function to enable the algorithm to consider the influences of functions similarly in optimizing the problem. The price penalty factor (PPF) method [19] is able to transform the independent functions to an objective function with similar unit. PPF is selected based on the maximum fuel cost of plant. Maximum amount of each emission is divided to ppf to have functions with similar weight in objective function. If the objective function consists of two separate fuel cost and emission functions, the investigated objective function obtained applying ppf method is as follows:

$$\min F = F_{FC} + ppf \times F_{NX} \quad (\$/h) \tag{9}$$

where ppf is the penalty factor related to emission. The ppf calculation steps of objective function are detailed in [20-21].

3. Exchange Market Algorithm

The exchange market algorithm is an appropriate meta-heuristic algorithm to solve the optimization problems. This algorithm is composed of two operators that attract members to market elite members and two searching operators. This advantage leads to a simultaneous exploration around the optimum point in a wider domain. In other algorithms, these two advantages do not exist at the same time. In EMA, each member of the market is one of the answers. Here, there exist a certain number of shares (optimization problem variable) each person intelligently tries to buy some (variables initialization) and conducts his intelligent proceedings at the end of each period calculating the validity of total share amounts to gain the maximum possible profit in market. Generally, the main population is classified in three groups and each group searches a specific domain.

In EMA, it is assumed that there exist two general market states. In the first state, market is in its normal condition without any considerable oscillation and the shareholders try to use the experiments of the elite members to gain the maximum possible profit without performing non-market risks (search around the optimum point). In the second state, the market experiences several oscillations and instabilities and the shareholders try to perform intelligent risks identifying market condition to use the existing condition to increase their assets as more as possible (exploring unknown points). In other words, in any iteration, the fitness of the function is evaluated twice in EMA. In this algorithm, the members are classified in three groups under any market condition. Group means the primary, middle, and the end members of the population not separated from the main population. They are named as above just to be able to apply some specific variations on the primary, middle, and the end members of the population [1].

A) Exchange Market in Normal Condition

In this section, the market is in normal condition without experiencing considerable oscillations. Shareholders try to use the experiments of the elite members to gain the maximum possible profit investigating the existing condition without performing non-market risks. Therefore, they compete with each other. Here, each person is ranked based on the fitness function according to the number of his shares from any type. Members are classified in three groups [1]. Under normal condition of the market, the main target is to attract members toward the elite members of the market.

First Group: Members with High Fitness

The members of this group form the highest ranked members of the list. They do not change their shares and perform no risk in shares trading. These members are estimated to form 10% to 30% of the main population.

Second Group: Members with Average Fitness

This group forms 20% to 50% of the population and the members are the middle ranked members of the shareholders. They vary their share amounts from any type performing logical and intelligent risks using the value differences of the first group members' shares to gain the maximum possible profit according to the following relation based on the cumulative probability:

$$pop_j^{group(2)} = r \times pop_{1,i}^{group(1)} + (1-r) \times pop_{2,i}^{group(1)} \tag{10}$$

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

where n_i is the n^{th} member of the first group and n_j is the n^{th} member of the second group. Parameter r is a random number within [0 1], $pop_{1,i}^{group(1)}$ and $pop_{2,i}^{group(1)}$ are some members of the first group, and $pop_j^{group(2)}$ is the j^{th} member of the second group.

Third Group: Members with Weak Fitness

This group of members, which is formed by the end members of the shareholders, try to find shares with short differences from the shares of the first group members performing risks and identifying the share differences exist between them and the first group members. In other words, the members of this group search the more points adjacent to the optimum point wider from the second group members. This group's members are estimated to form 20% to 50% of market members. The following relation is applied to determine the share number of this group's members:

$$S_k = 2\times r_1 \times\left(pop_{i,1}^{group(1)} - pop_k^{group(3)}\right) + 2\times r_2 \times\left(pop_{i,2}^{group(1)} - pop_k^{group(3)}\right) \quad (11)$$

$$pop_k^{group(3),new} = pop_k^{group(3)} + 0.8\times S_k \qquad k = 1,2,3,\cdots,n_k \quad (12)$$

where r_1 and r_2 are random numbers within [0 1], n_k is the n^{th} member of the third group, $pop_k^{group(3)}$ is the k^{th} member of the third group, and s_k is the shares variations of the k^{th} member of third group.

B) Exchange Market in Oscillation Condition

In this section, after reassessing and ranking shareholders, they perform intelligent risks according to their ranks among the other shareholders to gain the maximum possible profit and to stand among the higher ranked members of the market from fitness function viewpoint. Here, the algorithm intends to explore and exploit the unknown points. In this section, each member adopts different financial policies and performs different risks to surpass the elite member of the market depend on the gained profit. Here, members are classified in three separate groups considering their performance in the market.

First Group: Members with High Fitness

This group of the population consists of the elite members of the market or the best answers of the optimization problem, which do not tend to trade their shares and try to keep their ranks. This group forms 10% to 30% of the main population [1].

Second Group: Members with Average Fitness

These members try to find better costs varying their share amounts. The risk percentage of this group's members differs and it increases, as the rank of their cost is lower. In this section, total share amount of the members is constant and just some share amounts increase and some decrease in a way that the total share amount of each member does not vary. Initially, the share amounts of each member increase according to the followings:

$$\Delta n_{t1} = n_{t1} - \delta + \left(2\times r\times \mu \times \eta_1\right) \quad (13)$$

$$\mu = \left(\frac{t_{pop}}{n_{pop}}\right) \quad (14)$$

$$n_{t1} = \sum_{y=1}^{n}\left|s_{ty}\right| \qquad y = 1,2,3,\cdots,n \quad (15)$$

$$\eta_1 = n_{t1}\times g_1 \quad (16)$$

$$g_1^k = g_{1,\max} - \frac{g_{1,\max} - g_{1,\min}}{iter_{\max}}\times k \quad (17)$$

where Δn_{t1} is the share amount should be added to some shares randomly, n_{t1} is total share amount of the t^{th} member before share amounts variations, S_{ty} is the y^{th} share of the t^{th} member, δ is the exchange market data, and r is a random number within [0 1]. Parameter η_1 is the risk associated to each member of the second group, t_{pop} is the number of the t^{th} member of population, and n_{pop} is the number of last member in market. Parameter μ is a constant related to each member and g_1 is the common risk of the market, which decreases as the number of iteration 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 value of risk in market, respectively. In other words, $g_1 = [g_{1,\max},\ g_{1,\min}]$.

In the second part of this section, it is necessary for members to equalize their share amounts to the initial state. Therefore, each member should sell randomly some shares from any type equal to the bought amount to equalize the share amounts to the initial state. Therefore, each member should totally decrease Δn_{t2} of his shares. Here, Δn_{t2} of each member is indicated as follows:

$$\Delta n_{t2} = n_{t2} - \delta \quad (18)$$

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

Third Group: Members with Weak Fitness

These members try to find better costs by varying their share amounts values. The risk percentage of the members differs in this group and increases as their ranks from cost stand point decreases. Here, total members a share amount is variable and is composed of just one part despite the previous section and the shareholders try to explore new and unknown combinations of the shares and change the numbers of some shares as follows:

$$\Delta n_{t3} = \left(4 \times r_s \times \mu \times \eta_2\right) \quad (19)$$

$$r_s = \left(0.5 - rand\right) \quad (20)$$

$$\eta_2 = n_{t1} \times g_2 \quad (21)$$

where Δn_{t3} is generally the share amount should be applied randomly on the shares of each member of the third group. Parameter r_s is a random number within [-0.5 0.5]. Parameter η_2 is the risk coefficient related to each member of group 3 and g_2 is the variable risk of the market in this group. Parameter μ is the risk increase factor makes the lower ranked members from fitness function viewpoint to accomplish more risks in compare with the other more successful competitors to increase their assets [1].

4. Exchange Market Algorithm Implementation in Solving EELD Problem

The implementation of EMA in solving EELD problem is as the following step:

Step 1: Algorithm initialization

Step 2: Calculating shareholders costs and ranking them. Here, in order to identify different groups of shareholders, members are assessed due to the validity of their total shares and stand in three distinct groups. In solving the EELD problem, the fitness function is (9).

Step 3: Applying changes on shares of the second group under non-fluctuated market condition. In this section, the members of the first group or the primary members of the population even called the elite members of the market are kept with no change. The middle members of the population or the members of the second group vary their some shares according to (10).

Step 4: Applying changes on shares of the third group under non-oscillated market condition. These members are the end members of the population with the lowest validities from fitness function standpoint change their share amounts from any type according to (12).

Step 5: Recalculating the shareholders costs and ranking them again. Until this section, it was aimed to explore around the optimum point and the market was in non-oscillated condition. Here, according to the changes occurred in the shares of the middle and the end members, the population is assessed from fitness viewpoint and members are rearranged in separate groups.

Step 6: Trade in the shares of the second group members through (16) under oscillated market condition. Here, the members of the first group or the elite members of EM are kept with no variation and the middle members or the members of the second group try to trade their shares and change some shares considering (13). Initially, each member buys some shares from any type randomly and tries to sell the similar amount of shares from any type. This results in random variations in some shares, without facing with any changes in total share amount of each member.

Step 7: Trade in the shares of the third group members through (19) under fluctuated market condition

Step 8: Go to step 2 until the program ending conditions are not satisfied

5. Numerical Results

The proposed technique is applied on three different power systems: 1) 6-unit system with valve-point effects and objective function consists of fuel cost and emission functions; 2) 10-unit system with network power losses and valve-point effects and objective function consists of fuel cost and emission functions; 40-unit system with valve-point effects and objective function consists of fuel cost and emission functions.

The algorithm was implemented in MATLAB 7.8 and executed on an Intel Core 2 Duo 1.66 GHz personal computer. Fifty independent tests are conducted on each sample of problem to be able to compare the problem solving quality and convergence features. The initial population number is considered 100 members in all tests. 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 initial population, and the pattern for the oscillated market conditions are equal to 20, 60 and 20% of initial population [1]. The main 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.

A) Test System#1

Tests are conducted on a system with six generation units considering valve-point effects on emission. Total system load is 2.834 p.u. and the system data are included in Table 2 and Table 3 [21]. The tests are accomplished in two separate sections.

The first part of tests relates to minimization of fuel costs and the second part is involved with emission amount minimization. The results of this problem optimization using EMA are presented in Table 4.

In Table 5, the results of solving this problem through EMA are compared with the results obtained applying LP, MOSST, NSGA, NPGA, MBFA, FCPSO, DE, and SPEA and trust-region algorithm (TRA) methods. The minimum fuel cost obtained through EMA is 600.1111 ($/h) with 0.222144 (ton/h) emission level. As it is obvious from Table 5, the fuel costs amount obtained through EMA is lower than cost amount obtained through LP, MOSST, NSGA, NPGA, MBFA, FCPSO, TRA and SPEA techniques, which shows the superiority of the exchange market algorithm over the mentioned techniques. Here, the EMA and DE have been able to exploit the global optimum point.

In Table 4, the least emission level obtained applying EMA is 0.194202 (ton/h), where the fuel cost amount is 638.2734 ($/h). This emission amount is compared with the other methods. As it is obvious, the obtained emission level is lower than emission levels obtained through DE, LP, NSGA, NPGA, and SPEA. The MOSST, MBFA, FCPSO, and EMA have been commonly able to exploit the global optimum point of emission level. As it is seen, each method has more capability in a specific type of objective function but the exchange market algorithm is able to exploit the global optimum point in both sections.

Existence of two operators attract members to elite member as well as presence of two exploration factors are the superiority elements of the EMA results over other algorithms results. In Table 4, the average obtained results after 50 independent trials for fuel costs and emission level are presented.

As it is obvious, the average obtained fuel cost after 50 independent trials equals to the minimum cost amount. The average obtained value of emission level similarly equals to the minimum level. This convergence to similar answers indicates the robustness of this algorithm.

Table.1.
Adjustable parameters of EMA

Risk value	g_1 [max, min]	g_2 [max, min]
Case study 1	[0.005, 0]	[0.01, 0.005]
Case study 2	[0.005, 0]	[0.01, 0.005]
Case study 3	[0.001, 0]	[0.01, 0.003]

Table.2.
Fuel cost coefficients and capacity limits-Test system#1.

Unit	a_i	b_i	c_i	$P_{i,\min}$	$P_{i,\max}$
1	10	200	100	0.05	0.5
2	10	150	120	0.05	0.6
3	20	180	40	0.05	1.0
4	10	100	60	0.05	1.2
5	20	180	40	0.05	1.0
6	10	150	100	0.05	0.6

Table.3.
Emission coefficients-Test system#1.

Unit	α_i	β_i	γ_i	ξ_i	λ_i
1	0.04091	-0.0555	0.06490	0.000200	2.857
2	0.02543	-0.0604	0.05638	0.000500	3.333
3	0.04258	-0.0509	0.04586	0.000001	8.0
4	0.05326	-0.0355	0.03380	0.002000	2.0
5	0.04258	-0.0509	0.04586	0.000001	8.0
6	0.06131	-0.0555	0.05151	0.000010	6.667

Table.4.
Best results obtained by EMA-Test system#1

Unit (pu)	Economic Dispatch	Emission Dispatch
P1	0.109719	0.406073
P2	0.299766	0.459069
P3	0.524298	0.537938
P4	1.0161988	0.382953
P5	0.524298	0.537938
P6	0.359719	0.510027
TP	2.834000	2.834000
TC	600.1111	638.2734
TE	0.222144	0.194202
Average	600.1111	0.194202
T/I	0.0031	0.0031

* TP: total power [PU], TC: total cost [$/h], TE: total emission [ton/h], T/I: time/iteration [sec.]

Table.5.
Comparison of results of each method-Test system #1

Methods	Min. fuel cost	Min. emission
LP [14]	606.310	0.2230
MOSST [14]	605.890	0.1942
NSGA [26]	600.34	0.1946
NPGA [7]	600.31	0.1943
MBFA [14]	600.17	0.1942
FCPSO [14]	600.13	0.1942
DE [9]	600.11	0.1952
SPEA [7]	600.22	0.1943
TRA [25]	602.55	0.2000
HPSO-GSA [11]	600.2982	0.1942
EMA	600.1111	0.194202

B) *Test System#2*

Tests are conducted on a system with ten units considering valve-point effects and network power losses with an objective function consisting of non-smooth fuel costs and emission level functions.

Tests are conducted in three distinctive parts aiming to minimize fuel cost and emission level separately as well as minimizing fuel costs and emission level simultaneously. Total system load demand is 2000 MW and the data about generation units and power losses is included in Table 6 [8].The system optimization results are presented in Table 7. As it is obvious, the minimum fuel cost amount obtained using EMA is 111497.6580 ($/h) the related emission level of which is 4571.2163 (ton/h). The minimum emission level obtained through EMA is 3932.2701.

Table.6.
Ten-unit generator characteristics-Test system#2

Unit	$P_{i,\min}$	$P_{i,\max}$	a_i	b_i	c_i	e_i	f_i	α_i	β_i	γ_i	ξ_i	λ_i
1	10	55	1000.403	40.5407	0.12951	33	0.0174	360.0012	−3.9864	0.04702	0.25475	0.01234
2	20	80	950.606	39.5804	0.10908	25	0.0178	350.0056	−3.9524	0.04652	0.25475	0.01234
3	47	120	900.705	36.5104	0.12511	32	0.0162	330.0056	−3.9023	0.04652	0.25163	0.01215
4	20	130	800.705	39.5104	0.12111	30	0.0168	330.0056	−3.9023	0.04652	0.25163	0.01215
5	50	160	756.799	38.5390	0.15247	30	0.0148	13.8593	0.3277	0.00420	0.24970	0.01200
6	70	240	451.325	46.1592	0.10587	20	0.0163	13.8593	0.3277	0.00420	0.24970	0.01200
7	60	300	1243.531	38.3055	0.03546	20	0.0152	40.2669	−0.5455	0.00680	0.24800	0.01290
8	70	340	1049.998	40.3965	0.02803	30	0.0128	40.2669	−0.5455	0.00680	0.24990	0.01203
9	135	470	1658.569	36.3278	0.02111	60	0.0136	42.8955	−0.5112	0.00460	0.25470	0.01234
10	150	470	1356.659	38.2704	0.01799	40	0.0141	42.8955	−0.5112	0.00460	0.25470	0.01234

The simultaneous fuel cost and emission level minimization results are depicted in the last column of Table 7, which are compared with that of other algorithms in Table 8. The least fuel cost and emission level obtained in this mode are 113450.2966 ($/h) and 4111.3398 (ton/h), respectively. Comparing these with the results obtained applying MODE technique in Table 8, it is obvious that the fuel cost amounted the emission level obtained through EMA are 29.7 ($/h) and 13.56 (ton/h) lower than the amounts obtained applying MODE technique. In addition, it is shown that the fuel cost amount and the emission level obtained through EMA are 59.7 ($/h) and 0.6 (ton/h) lower than PDE and 89.7 ($/h) and 18.86 (ton/h) lower than NSGA-II methods. As it is obvious, in this test, the obtained fuel cost amount and emission level are lower than other methods.

In Table 8, the time/iteration ratio of each method is presented. As it is obvious, in this problem, the run time of any iteration applying EMA is less than MODE, PDE, NSGA, and SPEA methods. As it is depicted, the lower run time, high ability in exploring global optimum points, and convergence to similar answers during each program implementation are distinctive advantageous of the EMA over other algorithms.

C) Test System #3

Tests are conducted on a system with 40 units considering non-smooth fuel cost and emission level functions. The system load is 10500 MW and the generation units' data are included in Table 9 [8]. Test are conducted in three separate parts of fuel cost minimization, emission level minimization, and simultaneous cost and emission level minimization, the results of which are shown in Table 10. The minimum fuel cost obtained applying EMA is 121412.53554 ($/h) and the corresponding emission level is 359900.97251 (ton/h). The minimum emission level obtained applying EMA is 176682.2647 (ton/h).

Table.7.
Best results obtained by EMA-Test system# 2

Unit (MW)	Economic Dispatch	Emission Dispatch	Best results for both
P1	55.0000	55.0000	55.0000
P2	80.0000	80.0000	80.0000
P3	106.6157	80.7795	85.5191
P4	100.7217	80.9836	84.1663
P5	81.3797	160.0000	143.0110
P6	83.3187	240.0000	162.9909
P7	30.0000	294.0945	298.5036
P8	34.0000	296.7213	314.2054
P9	470.0000	397.5342	428.5971
P10	470.0000	396.5199	431.8751
TP	2087.036	2081.6333	2083.8487
TC	111497.6580	116406.6914	113450.2966
TE	4571.2163	3932.2701	4111.3398

Table.8.
Comparison of the best compromising solutions-Test system#2

Methods	Min. fuel cost	Min. emission	Time/ Iteration
MODE [8]	113480	4124.90	0.0382
PDE [8]	113510	4111.40	0.0423
NSGA-II [17]	113540	4130.20	0.0602
SPEA [5]	113520	4109.10	0.0753
$\varepsilon v - MOGA$ [5]	113422.34	4120.5204	
EMA	113450.30	4111.3398	0.00851

In the third part of this section, tests are conducted aiming to simultaneously minimize fuel cost and emission level. Here, the minimum obtained fuel cost and emission level are 125728.3498 ($/h) and 195271.3402 (ton/h), respectively. Comparing results obtained applying EMA and MODE shows that the fuel cost and the emission level obtained through EMA are respectively 61.65 ($/h) and 15918.65 (ton/h) less than MODE technique. In addition, comparing the results obtained applying EMA and PDE depicts that the fuel cost and the emission level obtained through EMA are 1.65 ($/h) and 16498.65 (ton/h) less than MODE technique, respectively. Comparing obtained results in Table 11 it is shown that the fuel cost and emission level achieved applying EMA are respectively 51.65 ($/h) and 158658.65 (ton/h) less than that of GSA method. As it is obvious, in this test, the EMA has an absolute superiority over the other algorithms and their evolutionary techniques and is able to obtain the best possible powers of generators to decrease fuel cost and emission level amounts simultaneously.

The convergence pattern of EMA to minimum fuel cost is illustrated in Fig. 1. As it is obvious, EMA is able to explore the points adjacent to the optimum points in first 200 iterations and in continuous, does not trap in local optimum points and can explore the global optimum point in the 1500th iteration. In algorithms such as PSO in which the search domain decreases as the iteration number increases, if the algorithm is not able to explore the optimum point in the initial iterations, the shortened search domain cannot explore the global optimum point of this non-convex problem [22]. In EMA, due to existence of two exploration elements one searches in limited domain and the other in wider domain, the trapping probability of the algorithm in local optimum points is seldom. As it is shown in Fig.1, the algorithm continues to search in 500th to 1500th iterations, does not trap in local points, and is able to explore the global optimum point in the 1500th iteration. Fig.2 shows the convergence characteristic of EMA in objective function consists of emission level function. This does not face with the complex nature of fuel cost problem and explores the global optimum point in the first 150 iterations of algorithm.

Table.9.
Forty-unit generator characteristics-Test system#3.

Unit	$P_{i,\min}$	$P_{i,\max}$	a_i	b_i	c_i	e_i	f_i	α_i	β_i	γ_i	ξ_i	λ_i
1	36	114	94.705	6.73	0.00690	100	0.084	60	−2.22	0.0480	1.3100	0.05690
2	36	114	94.705	6.73	0.00690	100	0.084	60	−2.22	0.0480	1.3100	0.05690
3	60	120	309.540	7.07	0.02028	100	0.084	100	−2.36	0.0762	1.3100	0.05690
4	80	190	369.030	8.18	0.00942	150	0.063	120	−3.14	0.0540	0.9142	0.04540
5	47	97	148.890	5.35	0.01140	120	0.077	50	−1.89	0.0850	0.9936	0.04060
6	68	140	222.330	8.05	0.01142	100	0.084	80	−3.08	0.0854	1.3100	0.05690
7	110	300	287.710	8.03	0.00357	200	0.042	100	−3.06	0.0242	0.6550	0.02846
8	135	300	391.980	6.99	0.00492	200	0.042	130	−2.32	0.0310	0.6550	0.02846
9	135	300	455.760	6.60	0.00573	200	0.042	150	−2.11	0.0335	0.6550	0.02846
10	130	300	722.820	12.9	0.00605	200	0.042	280	−4.34	0.4250	0.6550	0.02846
11	94	375	635.200	12.9	0.00515	200	0.042	220	−4.34	0.0322	0.6550	0.02846
12	94	375	654.690	12.8	0.00569	200	0.042	225	−4.28	0.0338	0.6550	0.02846
13	125	500	913.400	12.5	0.00421	300	0.035	300	−4.18	0.0296	0.5035	0.02075
14	125	500	1760.400	8.84	0.00752	300	0.035	520	−3.34	0.0512	0.5035	0.02075
15	125	500	1760.400	8.84	0.00752	300	0.035	510	−3.55	0.0496	0.5035	0.02075
16	125	500	1760.400	8.84	0.00752	300	0.035	510	−3.55	0.0496	0.5035	0.02075
17	220	500	647.850	7.97	0.00313	300	0.035	220	−2.68	0.0151	0.5035	0.02075
18	220	500	649.690	7.95	0.00313	300	0.035	222	−2.66	0.0151	0.5035	0.02075
19	242	550	647.830	7.97	0.00313	300	0.035	220	−2.68	0.0151	0.5035	0.02075
20	242	550	647.810	7.97	0.00313	300	0.035	220	−2.68	0.0151	0.5035	0.02075
21	254	550	785.960	6.63	0.00298	300	0.035	290	−2.22	0.0145	0.5035	0.02075
22	254	550	785.960	6.63	0.00298	300	0.035	285	−2.22	0.0145	0.5035	0.02075
23	254	550	794.530	6.66	0.00284	300	0.035	295	−2.26	0.0138	0.5035	0.02075
24	254	550	794.530	6.66	0.00284	300	0.035	295	−2.26	0.0138	0.5035	0.02075
25	254	550	801.320	7.10	0.00277	300	0.035	310	−2.42	0.0132	0.5035	0.02075
26	254	550	801.320	7.10	0.00277	300	0.035	310	−2.42	0.0132	0.5035	0.02075
27	10	150	1055.100	3.33	0.52124	120	0.077	360	−1.11	1.8420	0.9936	0.04060
28	10	150	1055.100	3.33	0.52124	120	0.077	360	−1.11	1.8420	0.9936	0.04060
29	10	150	1055.100	3.33	0.52124	120	0.077	360	−1.11	1.8420	0.9936	0.04060
30	47	97	148.890	5.35	0.01140	120	0.077	50	−1.89	0.0850	0.9936	0.04060
31	60	190	222.920	6.43	0.00160	150	0.063	80	−2.08	0.0121	0.9142	0.04540
32	60	190	222.920	6.43	0.00160	150	0.063	80	−2.08	0.0121	0.9142	0.04540
33	60	190	222.920	6.43	0.00160	150	0.063	80	−2.08	0.0121	0.9142	0.04540
34	90	200	107.870	8.95	0.00010	200	0.042	65	−3.48	0.0012	0.6550	0.02846
35	90	200	116.580	8.62	0.00010	200	0.042	70	−3.24	0.0012	0.6550	0.02846
36	90	200	116.580	8.62	0.00010	200	0.042	70	−3.24	0.0012	0.6550	0.02846
37	25	110	307.450	5.88	0.01610	80	0.098	100	−1.98	0.0950	1.4200	0.06770
38	25	110	307.450	5.88	0.01610	80	0.098	100	−1.98	0.0950	1.4200	0.06770
39	25	110	307.450	5.88	0.01610	80	0.098	100	−1.98	0.0950	1.4200	0.06770
40	242	550	647.830	7.97	0.00313	300	0.035	220	−2.68	0.0151	0.5035	0.02075

6. Conclusion

This paper introduces the exchange market algorithm to solve the EELD problem. The exchange market algorithm has two search elements results in simultaneously exploration in two limited and wide search domains. Searching in limited domain leads to exploration of points adjacent to the optimum point and searching in wide domain results in exploiting unknown points. These factors provide higher ability of exploring global optimum point during each program implementation through exchange market algorithm. For example, in test system 1, the least fuel cost and emission level amounts in each program implementation are respectively 600.1111 ($/h) and 0.194202 (ton/h). These amounts are considerably lower than the amounts obtained applying LP, MOSST, NSGA-II, NPGA, MBFA, FCPSO, DE, and SPEA techniques. In test system#2 with objective function consists of fuel cost and emission level functions, the least fuel cost and emission level amounts are 113450.2966 ($/h) and 4111.3398 (ton/h), respectively, which are less than that of other methods such as MODE, PDE, NSGA-II, and SPEA. As another example and in test system# 3, the minimum fuel cost and emission level amounts are respectively 125728.3498 ($/h) and 195271.3402 (ton/h). These values are considerably less than that of other techniques such as NSGA-II, SPEA, PDE, MODE, and GSA. According to the obtained results it seems that the points explored through EMA are the least possible values of these systems and are the global optimum points of these problems. In EMA and unlike other algorithms, just some amounts of variables of each population intelligently vary. Therefore, the program run time through EMA is short. For example, the time/iteration ratio of EMA in test system 2 is 0.00851 seconds, which is less than MODE, PDE, NSGA-II, and SPEA techniques. The results well demonstrate the practical advantage of the exchange market algorithm over the other approaches.

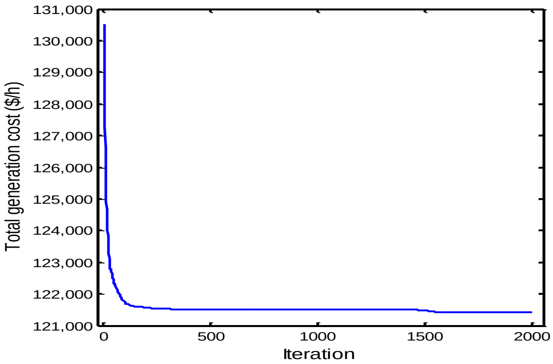

Fig. 1. The convergence characteristic of fuel cost

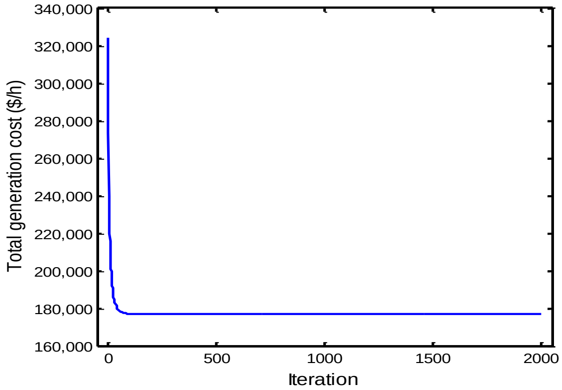

Fig. 2. The convergence characteristic of the emission level

Table.10.
Best results obtained by EMA-Test system#3

Unit	Economic Dispatch	Emission Dispatch	Best results for both
P1	110.7998	114.0000	114.0000
P2	110.7998	114.0000	114.0000
P3	97.3999	120.0000	120.0000
P4	179.7331	169.3687	179.7331
P5	87.7999	97.00000	97.0000
P6	140.0000	124.5932	140.0000
P7	259.5996	299.7097	300.0000
P8	284.5996	297.9134	300.0000
P9	284.5996	297.2595	300.0000
P10	130.0000	130.0000	130.0000
P11	94.0000	298.4103	318.3991
P12	94.0000	298.0236	318.3994
P13	214.7598	433.5579	394.2847
P14	394.2793	421.7297	394.2833
P15	394.2793	422.7792	394.2795
P16	394.2793	422.7793	394.2797
P17	489.2793	439.4139	489.2768
P18	489.2793	439.4046	489.2783
P19	511.2793	439.4121	425.3278
P20	511.2793	439.4136	425.0142
P21	523.2793	439.4487	434.0574
P22	523.2793	439.4463	434.0215
P23	523.2793	439.7728	434.9175
P24	523.2793	439.7710	434.9288
P25	523.2793	440.1099	433.6218
P26	523.2793	440.1093	433.6520
P27	10.0000	28.9922	11.6839
P28	10.0000	28.9960	11.6617
P29	10.0000	28.9929	11.6765
P30	87.7999	97.0000	97.0000
P31	190.0000	172.3316	190.0000
P32	190.0000	172.3322	190.0000
P33	190.0000	172.3315	190.0000
P34	164.7998	200.0000	200.0000
P35	200.000	200.0000	200.0000
P36	194.3977	200.0000	200.0000
P37	110.0000	100.839	110.0000
P38	110.0000	100.8401	110.0000
P39	110.0000	100.8390	110.0000
P40	511.2793	439.4118	425.2225
TP	10500	10500	10500
TC	121412.5355	129995.2453	125728.3498
TE	359900.97	176682.2647	195271.3402

Table.11.
Comparison of the best compromising solutions -Test system#3

Methods	Min. fuel cost	Min. emission
MODE [8]	125790	211190
PDE [8]	125730	211770
NSGA-II [5]	125830	210950
SPEA [17]	125810	211100
GSA [17]	125780	210930
$\varepsilon v-MOGA$ [5]	125750.2510	211744.4600
EMA	125728.3498	195271.3402

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