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# Solution to economic emission dispatch problem including wind farms using Exchange Market Algorithm Method

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ABSTRACT

This paper presents an Exchange Market Algorithm (stocktickerEMA) method for solving the Economic Emission Dispatch (EED) problem including wind farms in the power systems. The stocktickerEMA algorithm is a powerful and useful method for finding the optimal value of an optimization problem with high accuracy. In recent years, because of the emission of harmful gases from fossil fuels and global warming issues, the penetration level of cleaner energies such as the wind and solar energy has been increased in order to produce the desired electrical energy. Therefore, it is vital to consider the wind turbines and wind farms in the EED optimization problem. Due to the probabilistic nature of wind speed in wind turbines, the generated power by wind turbines and wind farms has uncertain nature. Hence, the Weibull probability distribution function is used to model the wind power in the EED problem. The proposed method is tested on the IEEE 40-units test system. The analysis shows that, compared to other algorithms the EMA method has faster convergence and better ability in finding the optimal solution for the EED problem.



## 1. Introduction

Economic dispatch (ED) problem is very important for the economical operation of power systems. The purpose of the ED problem is to determine the optimal output values for the generation units to fulfill the load demand and other constraints of a power system, as well as minimizing the cost of electrical energy produced [1]. In the recent years the diffusion of harmful gases such as sulfur oxides ($SO_X$) and nitrogen oxides ($NO_X$), which pollutes the atmosphere and exacerbates the global warming situation, has become a critical issue. The main source of these greenhouse gases are the thermal units. One way to limit the emission of these gasses is to impose stricter policies on the thermal units. To apply the new regulations and tax issues for excessive generated greenhouse gases, a combination of economic dispatch and constraints on emission has been introduced which is known as Economic Emission Dispatch (EED) problem. In the EED optimization problem, in addition to minimizing the cost of energy, minimization of the amount of emission has been considered as well [2]. EED is an optimization problem with the following two main goals [3]:

(1) Minimizing the fuel cost of thermal units.

(2) Minimizing the emission of harmful gases into the air.

As mentioned above, the objective function of the EED problem has two main parts where the emission criteria is added to the fuel cost of the thermal unit. In order to integrate the emission part to the ED problem, different methods are introduced, for example, Dhillon et al. [4] and Kulkarni et al. [5] presented a method in which a penalty factor coefficient is multiplied to the emission part of the objective function. This technique allows both components to become commensurately involved in the optimization. Zou et al. [6] implemented a new global particle swarm optimization (NGPSO) algorithm to find the minimum cost of economic emission problem. The authors normalized each objective of the problem according to their candidate solutions and then the problem is transformed into a single objective problem.

Numerous methods are proposed in the literature to solve the EED optimization problem. Dosoglu et al. [7], solved the issue of EED in term of thermal generators, used a symbiotic organisms search (SOS) algorithm in order to minimize operating costs and emission levels and satisfy the load demand and all equality–inequality constraints. Devi et al. [8] and Hamedi et al. [9] solved the EED problem by the combination of evolutionary and intelligent algorithms. Aydin et al. [10] optimized the EED problem with the bee colony method. System security constraints are taken into account in [11] to solve the EED problem in which the multi-population ant colony has been applied.

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Abdelaziz et al. [12], implemented flower pollination algorithm (FPA) to solve the EED problem. A more realistic approach has been put forth by Naderi et al. [13] tackling EED with a hybrid optimization method. Singh et al. [14] utilized a novel method – adaptive predator–prey optimization (APPO) – for solving thermal power load dispatch in a multiobjective form considering the emission. Increase in the penetration level of wind farms in power systems, has attracted a great attention to solving the EED problem including wind farms [15].

Qu et al. [16] proposed a summation based multi-objective differential evolution (SMODE) algorithm to find the optimum point of the economic emission dispatch problem with stochastic wind power. The Weibull probability distribution function is used to model the stochastic nature of the wind power and the uncertainty is preserved as the system constraints with stochastic variables. The algorithm is combined with the advantage of feasible solution constraint handling technique. The author in [17] presented a dynamic economic emission dispatch (DEED) model in order to consider the uncertainty of wind energy alongside the effect of energy storage systems and demand-side management on cost and emission. Jadha et al. [18] solved the EED optimization problem taking into account both thermal power plants and wind farms by craziness-based differential evolution algorithm and some characteristics of thermal plants such as valve point effect and generated power limitations. Hu et al. [19] handled DEED problem by defining bi-level programming in which the leader level deals with minimizing fuel cost and emission simultaneously and minimization of output power deduction periods are assigned to the follower level. Linear programming and intelligence base algorithm are used in this paper. Jadhav et al. [20] stimulated the effects of wind power in EED problem and used the Gbest guided artificial bee colony algorithm for simulation. Liu et al. [21] solved the EED problem including the environmental constraints and different wind farms. The objective function is optimized by stochastic methods. Zhan et al. [22] analyzed the EED problem considering high penetration of wind farms in the test power system and the results show that the EED problem has probabilistic nature when the wind farms are added into the power system. Wang et al. [23] and Hetzer et al. [24] compared the power systems consisting of wind farms with the conventional power systems and the characteristics of wind farms are discussed in these papers. Shaw et al. [25] solved the EED problem along with wind farms by hybrid based PSO methods. Jiang et al. [26] proposed a gravitational acceleration enhanced particle swarm optimization algorithm (GAEPSO) to find the optimum fuel cost, emission level in wind–thermal economic emission dispatch (WTEED) problem. Roy et al. [27] presented a chemical reaction optimization algorithm, based on the chemical molecular reaction to optimize economic dispatch problem in presence of wind turbine. Ghasemi et al. [28] focused on modeling the wind-based energy production in economic dispatch problem introducing an online meta-heuristic learning method. Kheshti and Ding in [29] introduced a revolutionized PSO method namely double weighted PSO (DWPSO) to solve an EED problem with penetration of wind energy sources. Furthermore, a secure EED problem has been discussed in [30] solved by a novel parallel hurricane optimization algorithm.

Ghorbani et al. [31] presented a new meta-heuristic algorithm called Exchange Market Algorithm (EMA). The EMA algorithm which is introduced in 2014 is based on the stock exchange trading method in the stock market. The EMA intelligent algorithm has some advantages such as faster convergence and yielding better optimal values over other algorithms like PSO, Bee colony and Ant colony. Ghorbani et al. [32] solved the economic dispatch problem by EMA method and the results show that the EMA method is able to find the best and convex response for this problem successfully.

In this paper, the solution to EED problem with the EMA method including wind farms is considered. It is obvious that the wind speed bares a stochastic nature. As a result, the generated power by wind turbines and wind farms add uncertainty to power system studies. Therefore, in this paper, the EED optimization problem has probabilistic nature, too. The main contribution of this work is the fast convergence and superiority of EMA compared to other algorithms in finding the optimum solution of the economic emission dispatch including wind power penetration problem.

## 2. Characterization of wind energy

In the EED problem with wind energy, the optimization process constitutes dispatching the generation power between fossil fuel power plants and wind farms in addition to satisfying the system constraints. As a result of the random nature of wind speed, the generated power by a wind turbine is variable in different wind speeds, which are expressed as follows [26]:

$$w = 0 \quad for \quad v < v_i \quad and \quad v > v_o \tag{1}$$

$$w = w_r \frac{(v - v_i)}{(v_r - v_i)} \quad for \quad v_i \leq v \leq v_r \tag{2}$$

$$w = w_r \quad for \; v_r \leq v \leq v_o \tag{3}$$

where $v$ is the current wind speed in (m/s), $v_i$, $v_o$ and $v_r$ are cut-in, cut-out and rated wind speed, respectively, $w$ is the output power of turbine (MW) and $w_r$ is the rated power of the turbine.

Eqs. (1), (2), and (3) illustrate that: (1) the power produced by a wind turbine is set to zero if the wind velocity is out of the turbine's speed limits; (2) at the range of cut-in wind speed and rated wind speed a linear formulation can be defined between output power and wind speed; (3) power output is equal to rated power output between rated wind speed and cut-out wind speed.

In order to use wind turbine in economic dispatch problem and due to a stochastic characteristic of wind energy, the Weibull probability and cumulative distribution functions are used for modeling the wind speed which are expressed as follows [26]:

$$F_V(v) = 1 - \exp\left[-\left(\frac{v}{c}\right)^k\right], [v \geq 0] \tag{4}$$

$$f_V(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} \exp\left[-\left(\frac{v}{c}\right)^k\right] \tag{5}$$

Eq. (4) is the cumulative distribution function (CDF) and Eq. (5) is the probability distribution function (PDF) where $v$ is wind speed in (m/s), $k$ is shape factor at a given location (dimensionless) and $c$ is scale factor at a given location (m/s).

By using Eqs. (1), (3), and (4), the probability of scenario $w = 0$ and $w = w_r$ are expressed as follows [26]:

$$P_r\{w = 0\} = F_V(v_i) + (1 - F_V(v_o)) = 1 - \exp(-(\frac{v_i}{c})^k) + \exp(-(\frac{v_o}{c})^k) \tag{6}$$

$$P_r\{w = w_r\} = F_V(v_o) - F_V(v_r) = \exp(-(\frac{v_r}{c})^k) - \exp(-(\frac{v_o}{c})^k) \tag{7}$$

where $v_i$, $v_o$ and $v_r$ are cut-in, cut-out and rated wind speed, respectively and $F_V$ is the cumulative distribution function. Parameter k is the shape factor at a given location.

In order to modify the two random variables of wind speed and wind turbine output power in continues span two ratios are used as following [26]:

$\rho = \frac{w}{w_r}$ This ratio presents wind power output to rated wind power ratio; and

$l = \frac{(v_r - v_i)}{v_i}$ This ratio presents a linear range of wind speed to cut-in wind speed ratio.

The Weibull PDF of the wind turbine power output random variable in the continuous range takes from [26]:

$$f_w(w) = \frac{klv_i}{w_r c}\left(\frac{(1+\rho l)v_i}{c}\right)^{k-1} \exp\left(-\left(\frac{(1+\rho l)v_i}{c}\right)^k\right) \qquad 0 < w < w_r \tag{8}$$

## 3. Problem formulation

This section provides the formulation of the EED problem delineating the objective function and the constraints enforced by the power system such as transmission losses, power balance and limitations on power generated by thermal and wind source power plants.

### 3.1. Objective function

The objective function implemented in this paper is as follow [27]:
Minimize

$$\begin{aligned} FC_{total} = &\left(\sum_{j=1}^{N_w} C_{ov,j}(W_{ov})\right) + \left(\sum_{j=1}^{N_w} C_{un,j}(W_{un})\right) + \left(\sum_{j=1}^{N_w} C_{dir,j}(W_j)\right) \\ &+ \left(\sum_{i=1}^{N_t} C_{th,i}(P_{g,i})\right) + \left(\sum_{i=1}^{N_t} C_{emi,i}(P_{g,i})\right) \end{aligned} \tag{9}$$

where $N_t$ and $N_w$ are the number of thermal units and number of wind turbines, respectively; $C_{ov,j}$, $C_{un,j}$ and $C_{dir,j}$ are the overestimation, underestimation and direct costs of $j$th wind turbine, respectively; $C_{th,i}$ and $C_{emi,i}$ are the fuel and emission costs of thermal units, respectively.

In Eq. (9), the first part shows the overestimation penalty cost. It means that the operator purchases the additional power when the scheduled wind power is more than the actual power and pays the overestimation penalty cost function, which is as follows [26]:

$$\begin{aligned} C_{ov,j}(W_{ov}) = &c_{ov,j} \times [w_j \times [1 - \exp(-(\frac{v_{i,j}}{c_j})^{k_j}) + \exp(-(\frac{v_{o,j}}{c_j})^{k_j})] \\ &+ (\frac{w_{r,j}v_{i,j}}{(v_{r,j} - v_{i,j})} + w_j) \\ &\times [\exp(-(\frac{v_{i,j}}{c_j})^{k_j}) - \exp(-(\frac{v_{1,j}}{c_j})^{k_j})] + (\frac{w_{r,j}c_j}{(v_{r,j} - v_{i,j})}) \\ &\times \{\Gamma[1 + 1/k_j, (v_{1,j}/c_j)^{k_j}] - \Gamma[1 + 1/k_j, (v_{i,j}/c_j)^{k_j}]\}] \end{aligned} \tag{10}$$

where $v_{1,j} = v_{i,j} + (v_{r,j} - v_{i,j})w_j/w_{r,j}$; $w_j$, $w_{r,j}$ and $c_{ov,j}$ are the output power, rated output power and the overestimation coefficient of $j$th wind-powered generator, respectively; $\Gamma(.)$ is the incomplete gamma function, which is supported by Matlab software.

In Eq. (9), the second part shows the underestimation penalty cost. It means that the operator must be paid the generator's cost when the scheduled power is less than the actual wind power. Underestimation penalty cost function is expressed as follows [26]:

$$\begin{aligned} C_{un,j}(W_{un}) = &c_{un,j} \times [(w_{r,j} - w_j) \times [\exp(-(\frac{v_{r,j}}{c_j})^{k_j}) \\ &- \exp(-(\frac{v_{o,j}}{c_j})^{k_j})] + (\frac{w_{r,j}v_{i,j}}{(v_{r,j} - v_{i,j})} + w_j) \\ &\times [\exp(-(\frac{v_{r,j}}{c_j})^{k_j}) - \exp(-(\frac{v_{1,j}}{c_j})^{k_j})] + (\frac{w_{r,j}c_j}{(v_{r,j} - v_{i,j})}) \\ &\times \{\Gamma[1 + 1/k_j, (v_{1,j}/c_j)^{k_j}] - \Gamma[1 + 1/k_j, (v_{r,j}/c_j)^{k_j}]\}] \end{aligned} \tag{11}$$

In Eq. (9), the third part shows the direct cost of wind power which is known as non-utility operator and it is not considered when the operator owns the wind farm. If wind energy conversion systems have owners, based on the special contractual agreements, the wind generation will have a cost which is expressed as follows [24]:

$$C_{dir,j}(w_j) = d_i w_j \tag{12}$$

where $d_i$ is the direct cost coefficient for the $j$th wind generator.

In Eq. (9), the fourth part shows the cost function of thermal units which is expressed as follows [26]:

$$FC = \sum_{i=1}^{N_t} C_{th,i}(P_{g,i}) = \sum_{i=1}^{N_t} (a_i P_{g,i}^2 + b_i P_{g,i} + c_i) \tag{13}$$

With considering valve-point effect at thermal units, the cost function can be expressed as follows [32]:

$$\begin{aligned} FC = \sum_{i=1}^{N_t} C_{th,i}(P_{g,i}) = \sum_{i=1}^{N_t} (&a_i P_{g,i}^2 + b_i P_{g,i} + c_i \\ &+ \left|d_i \sin(e_i \times (P_{g,i}^{\min} - P_{g,i}))\right|) \end{aligned} \tag{14}$$

where $P_{g,i}$ are output power of $i$th thermal unit and $a_i$, $b_i$, $c_i$ are the coefficients related to the $i$th unit and $d_i$, $e_i$ are the coefficients of generator $i$ reflecting valve-point loading.

In Eq. (9), the last part shows the total carbon emissions of thermal units. The total emission cost for six-unit system is expressed as follows [27]:

$$EC = \sum_{i=1}^{N_t} C_{emi,i}(P_{g,i}) = \sum_{i=1}^{N_t} ef_i(f_i + g_i P_{g,i} + h_i P_{g,i}^2) C_{tax} \tag{15}$$

The total emission cost for a 40 unit system is expressed as follows [26]:

$$EC = \sum_{i=1}^{N_t} (10^{-2} \times (\alpha_i + \beta_i P_{g,i} + \gamma_i P_{g,i}^2) + \zeta_i \exp(\lambda_i P_{g,i})) \tag{16}$$

where $\alpha_i$, $\beta_i$, $\gamma_i$, $\zeta_i$ and $\lambda_i$ are the pollution coefficients of the $i$th thermal unit.

### 3.2. System constraints

In this paper, system constraints are considered as equality and inequality constraints.

#### 3.2.1. Equality constraints

The power balance, which is considered in the constraints, shows that the sum of the generated power by thermal and wind power plants should be equal to the transmission losses plus load demand of the power system. The power balance equation is as follows:

$$\sum_{j=1}^{N_w} w_j + \sum_{i=1}^{N_t} P_{g,i} = P_{demand} + P_{losses} \tag{17}$$

In Eq. (17), $P_{losses}$ is expressed as follows:

$$P_{losses} = \sum_{i=1}^{N_t}\sum_{j=1}^{N_t} P_{g,i}B_{ij}P_{g,j} + \sum_{i=1}^{N_t} B_{i0}P_{g,j} + B_{00} \tag{18}$$

In Eq. (18), $B_{ij}$, $B_{i0}$ and $B_{00}$ are elements of matrix B.

*3.2.2. Non equality constraints*

The non-equality constraints indicate the minimum and maximum of generated power by thermal and wind power plants as follows:

$$P_{g,i}^{\min} \le P_{g,i} \le P_{g,i}^{\max} \qquad i = 1, 2, \ldots, N_t \tag{19}$$

$$0 \le w_j \le w_{r,j} \qquad j = 1, 2, \ldots, N_w \tag{20}$$

In Eq. (20), the $w_{r,j}$ is the rated power of the $j$th wind turbine and the minimum generated power by a wind turbine is zero.

## 4. Exchange market algorithm (EMA)

The Exchange Market Algorithm (EMA) is based on the performance of shareholders in the stock market. In each running of this algorithm for solving the optimization problem, two different forms of the market are considered, which are called balanced and unbalanced conditions of the market. In a balanced condition, the oscillation of the market is not considerable and shareholders use elite member's experiences to gain more profit (searching around optimum point). In the unbalanced mode, the market faces different oscillations and members take risks to achieve more profit (finding out the unknown points). At the end of each market condition, the traders in the stock market are divided into three groups based on their finance which are called group one, two and three. Because of having two explorer and absorptive operators in each market condition, the EMA algorithm has faster Convergence than other algorithms. When the market condition is in a balanced position the EMA algorithm uses the absorptive operators and when the market condition is in an unbalanced position this algorithm uses the explorer operators to find the optimal value.

*4.1. The operation of EMA algorithm in the balanced market*

This section introduces the performance of shareholders in the different mentioned groups in the balanced market condition. Because of having the maximum finance and rank market, the members of the first group, do not have any tendency to change their amounts of shares. The members in the first group are 10 to 30% of the population in the market. Since the members in the second group have the lower finance and rank market than the members of the first group and bear the least risk, they change in their amounts of shares. The members in the second group are 20 to 50% of the population in the market. In this group, the shareholders change their amounts of shares based on the difference between the shares of the members in the first group. Changing in the shares of the second group members is expressed as follows [31]:

$$pop_j^{group(2)} = r \times pop_{1,i}^{group(1)} + (1-r) \times pop_{2,i}^{group(1)}$$
$$i = 1, 2, \ldots, n_i \quad and \quad j = 1, 2, \ldots, n_j \tag{21}$$

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

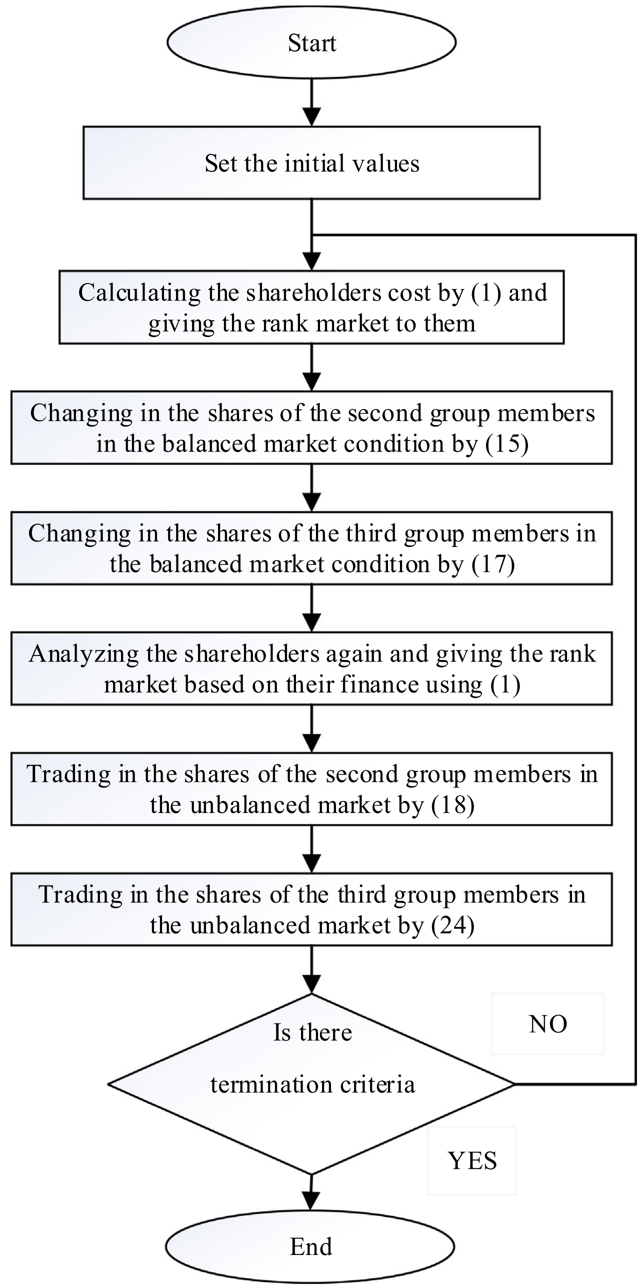


**Fig. 1.** Flowchart of EMA method.

In addition, the members in the third group have the lowest finance and rank market than other groups and like the second group they change their amounts of shares based on the difference between the shares of the members in the first group to achieve the maximum profit but they are faced with higher risks than the second group members. The members in the third group are 20 to 50% of the population in the market. Change in the shares of the third group members is expressed as follows [31]:

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

$$pop_k^{group(3),new} = pop_k^{group(3)} + 0.8 \times S_k \qquad k = 1, 2, \ldots, n_k \tag{23}$$

**Table 1**
Data for 40 thermal units test system with valve-point effect.

| Unit | $P_{i,min}$ (MW) | $P_{i,max}$ (MW) | $a_i$ (\$/MW$^2$) | $b_i$ (\$/MW) | $c_i$ (\$) | $d_i$ (\$) | $e_i$ (1/MW) |
|---|---|---|---|---|---|---|---|
| 1 | 36 | 114 | 94.705 | 6.73 | 0.0069 | 100 | 0.084 |
| 2 | 36 | 114 | 94.705 | 6.73 | 0.0069 | 100 | 0.084 |
| 3 | 60 | 120 | 309.54 | 7.07 | 0.02028 | 100 | 0.084 |
| 4 | 80 | 190 | 369.03 | 8.18 | 0.00942 | 150 | 0.063 |
| 5 | 47 | 97 | 148.89 | 5.35 | 0.0114 | 120 | 0.077 |
| 6 | 68 | 140 | 222.33 | 8.05 | 0.01142 | 100 | 0.084 |
| 7 | 110 | 300 | 287.71 | 8.03 | 0.00357 | 200 | 0.042 |
| 8 | 135 | 300 | 391.98 | 6.99 | 0.00492 | 200 | 0.042 |
| 9 | 135 | 300 | 455.76 | 6.6 | 0.00573 | 200 | 0.042 |
| 10 | 130 | 300 | 722.82 | 12.9 | 0.00605 | 200 | 0.042 |
| 11 | 94 | 375 | 635.2 | 12.9 | 0.00515 | 200 | 0.042 |
| 12 | 94 | 375 | 654.69 | 12.8 | 0.00569 | 200 | 0.042 |
| 13 | 125 | 500 | 913.4 | 12.5 | 0.00421 | 300 | 0.035 |
| 14 | 125 | 500 | 1760.4 | 8.84 | 0.00752 | 300 | 0.035 |
| 15 | 125 | 500 | 1728.3 | 9.15 | 0.00708 | 300 | 0.035 |
| 16 | 125 | 500 | 1728.3 | 9.15 | 0.00708 | 300 | 0.035 |
| 17 | 220 | 500 | 647.85 | 7.97 | 0.00313 | 300 | 0.035 |
| 18 | 220 | 500 | 649.69 | 7.95 | 0.00313 | 300 | 0.035 |
| 19 | 242 | 550 | 647.83 | 7.97 | 0.00313 | 300 | 0.035 |
| 20 | 242 | 550 | 647.81 | 7.97 | 0.00313 | 300 | 0.035 |
| 21 | 254 | 550 | 785.96 | 6.63 | 0.00298 | 300 | 0.035 |
| 22 | 254 | 550 | 785.96 | 6.63 | 0.00298 | 300 | 0.035 |
| 23 | 254 | 550 | 794.53 | 6.66 | 0.00284 | 300 | 0.035 |
| 24 | 254 | 550 | 794.53 | 6.66 | 0.00284 | 300 | 0.035 |
| 25 | 254 | 550 | 801.32 | 7.1 | 0.00277 | 300 | 0.035 |
| 26 | 254 | 550 | 801.32 | 7.1 | 0.00277 | 300 | 0.035 |
| 27 | 10 | 150 | 1055.1 | 3.33 | 0.52124 | 120 | 0.077 |
| 28 | 10 | 150 | 1055.1 | 3.33 | 0.52124 | 120 | 0.077 |
| 29 | 10 | 150 | 1055.1 | 3.33 | 0.52124 | 120 | 0.077 |
| 30 | 47 | 97 | 148.89 | 5.35 | 0.0114 | 120 | 0.077 |
| 31 | 60 | 190 | 222.92 | 6.43 | 0.0016 | 150 | 0.063 |
| 32 | 60 | 190 | 222.92 | 6.43 | 0.0016 | 150 | 0.063 |
| 33 | 60 | 190 | 222.92 | 6.43 | 0.0016 | 150 | 0.063 |
| 34 | 90 | 200 | 107.87 | 8.95 | 0.0001 | 200 | 0.042 |
| 35 | 90 | 200 | 116.58 | 8.62 | 0.0001 | 200 | 0.042 |
| 36 | 90 | 200 | 116.58 | 8.62 | 0.0001 | 200 | 0.042 |
| 37 | 25 | 110 | 307.45 | 5.88 | 0.0161 | 80 | 0.098 |
| 38 | 25 | 110 | 307.45 | 5.88 | 0.0161 | 80 | 0.098 |
| 39 | 25 | 110 | 307.45 | 5.88 | 0.0161 | 80 | 0.098 |
| 40 | 242 | 550 | 647.83 | 7.97 | 0.00313 | 300 | 0.035 |

**Table 2**
Parameters of EMA for numerical testing.

| | Number of pop | 100 |
|---|---|---|
| Risk values | $g_1$[max, min] | [$1 * 10^\wedge - 1, 5 * 10^\wedge - 10$] |
| | $g_2$[max, min] | [$5 * 10^\wedge - 5, 1 * 10^\wedge - 5$] |
| Balanced mode | Group 1 | 24% |
| | Group 2 | 24% |
| | Group 3 | 52% |
| Unbalanced mode | Group 1 | 20% |
| | Group 2 | 60% |
| | Group 3 | 20% |

where $r_1$ and $r_2$ are random numbers, $n_k$ is the $n$th member of the third group, $pop_k^{group(3)}$ is the $k$th member and $S_k$ is the share variation of the $k$th member of the third group.

### 4.2. The operation of EMA algorithm in the unbalanced market

In this section, the performance of the members in the different mentioned groups in the unbalanced market condition is considered. The members of the first group like the first group in the balanced market have not any tendency to change their amounts of shares and they try to keep their rank in the stock market. In the market process, sometimes the shares of the second group members rise and sometimes the shares drop but at the end the total shares of the members in the second group are constant. At first, the shares of the members in the second group rise by the following equation [31]:

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

$$\mu = \left(\frac{t_{pop}}{n_{pop}}\right) \tag{25}$$

$$n_{t1} = \sum_{y=1}^{n} |s_{ty}| \qquad y = 1, 2, 3, \ldots, n \tag{26}$$

$$\eta_1 = n_{t1} \times g_1 \tag{27}$$

$$g_1^k = g_{1,\max} - \frac{g_{1,\max} - g_{1,\min}}{iter_{\max}} \times k \tag{28}$$

where $\Delta n_{t1}$ is the number of shares should be added randomly to some shares, $n_{t1}$ is total shares of the t$th$ member. Factors $s_{ty}$ and $\delta$ are the shares of the t$th$ member and information of exchange market, respectively. Parameter $r$ is a random number between 0 and 1, $t_{pop}$ is the number of the t$th$ member and $n_{pop}$ is the last member's number in the market, $\mu$ is a constant number, $\eta_1$ is the risk level, $g_1$ is the common market risk. Factors $k$, $iter_{max}$ are number of program iteration and maximum number of iteration, respectively. Parameter $g_{1,max}$ and $g_{1,min}$ indicate the maximum and minimum values of risk in the market, respectively.

In order to sustain the number of shares constant in this condition, each person randomly must sell some of his shares. The following equations show this statement [31]:

$$\Delta n_{t2} = n_{t2} - \delta \tag{29}$$

**Table 3**
Results of using different algorithms for economic dispatch problem with valve point effect on 40 units test system.

| Output | EMA | PSO [12] | BBO [33] | FPA [12] |
|---|---|---|---|---|
| Thermal 1 (MW) | 108.332 | 113.116 | 110.0465 | 72.4810 |
| Thermal 2 (MW) | 112.903 | 113.010 | 111.5915 | 103.0314 |
| Thermal 3 (MW) | 110.4308 | 119.702 | 97.6007 | 83.2726 |
| Thermal 4 (MW) | 157.698 | 81.647 | 179.7095 | 182.3106 |
| Thermal 5 (MW) | 96.4871 | 95.062 | 88.3060 | 76.1669 |
| Thermal 6 (MW) | 139.4160 | 139.209 | 139.9992 | 126.1346 |
| Thermal 7 (MW) | 290.0277 | 299.127 | 259.6313 | 258.8452 |
| Thermal 8 (MW) | 299.0464 | 287.491 | 284.7366 | 297.1636 |
| Thermal 9 (MW) | 275.3247 | 292.316 | 284.7801 | 290.8899 |
| Thermal 10 (MW) | 130.0000 | 279.273 | 130.2484 | 274.8232 |
| Thermal 11 (MW) | 94.00000 | 169.766 | 168.8461 | 356.9806 |
| Thermal 12 (MW) | 155.12014 | 94.344 | 168.8461 | 124.4054 |
| Thermal 13 (MW) | 125.00000 | 214.871 | 214.7038 | 493.3764 |
| Thermal 14 (MW) | 321.23775 | 304.790 | 304.5894 | 344.9029 |
| Thermal 15 (MW) | 297.39311 | 304.563 | 394.2761 | 372.3864 |
| Thermal 16 (MW) | 481.93555 | 304.302 | 394.2409 | 345.4624 |
| Thermal 17 (MW) | 493.87094 | 489.173 | 489.2919 | 422.6378 |
| Thermal 18 (MW) | 489.92728 | 491.336 | 489.4188 | 434.4065 |
| Thermal 19 (MW) | 511.47443 | 510.880 | 511.2997 | 461.3107 |
| Thermal 20 (MW) | 513.00495 | 511.474 | 511.3073 | 434.3828 |
| Thermal 21 (MW) | 523.62103 | 524.814 | 523.4170 | 545.2846 |
| Thermal 22 (MW) | 525.12629 | 524.775 | 523.2795 | 490.3572 |
| Thermal 23 (MW) | 549.41438 | 525.563 | 523.3793 | 506.0639 |
| Thermal 24 (MW) | 526.94583 | 522.712 | 523.3225 | 467.3109 |
| Thermal 25 (MW) | 543.65718 | 503.211 | 523.3661 | 488.1203 |
| Thermal 26 (MW) | 524.61198 | 524.199 | 523.4362 | 486.9019 |
| Thermal 27 (MW) | 10.7388 | 10.082 | 10.0531 | 16.8002 |
| Thermal 28 (MW) | 10.4742 | 10.663 | 10.0113 | 39.3475 |
| Thermal 29 (MW) | 10.8417 | 10.418 | 10.0030 | 23.6359 |
| Thermal 30 (MW) | 93.85314 | 94.244 | 88.4775 | 86.3295 |
| Thermal 31 (MW) | 179.3785 | 189.377 | 189.9983 | 165.9924 |
| Thermal 32 (MW) | 188.87791 | 189.796 | 189.9881 | 174.5707 |
| Thermal 33 (MW) | 189.41675 | 189.813 | 189.9663 | 184.0570 |
| Thermal 34 (MW) | 162.42366 | 199.797 | 164.8054 | 193.6668 |
| Thermal 35 (MW) | 198.03820 | 199.284 | 165.1267 | 191.6152 |
| Thermal 36 (MW) | 189.50969 | 198.165 | 165.7695 | 196.1763 |
| Thermal 37 (MW) | 109.62129 | 109.291 | 109.9059 | 90.0101 |
| Thermal 38 (MW) | 109.28931 | 109.087 | 109.9971 | 37.5421 |
| Thermal 39 (MW) | 109.16065 | 109.909 | 109.9695 | 89.4239 |
| Thermal 40 (MW) | 543.71235 | 512.348 | 511.2794 | 471.4405 |
| TC($)*10^5 | 1.208453 | 1.22323 | 1.21426 | 1.21074 |

**Table 4**
Statistical comparison between EMA and different algorithms.

| Algorithms | Best cost ($) | Mean cost ($) | Worst cost ($) | Time (s) |
|---|---|---|---|---|
| NPSO-LSR [12] | 121 664.43 | 122 209.31 | 122 981.59 | 16.81 |
| DE [12] | 121 416.29 | 121 422.72 | 121 431.47 | NA |
| CDEMD [12] | 121 423.4 | 121 526.73 | 121 696.98 | 44.3 |
| HMAPSO [12] | 121 586.9 | 121 586.9 | 121 586.9 | NA |
| FAPSO-NM [12] | 121 418.3 | 121 418.8 | 121 419.8 | 40 |
| EMA | 120 845.3 | 121 422.13 | 121 512.4 | 5.1 |

where $\Delta n_{t2}$ and $n_{t2}$ are the share amount that should be decreased randomly and total share amount of the $t$*th* member, respectively.

Unlike the second group, in the third group, the total shares of the members can be changed at the end and the risk is higher than group two. The change in the shares of the third group members is expressed by the following equation [31]:

$$\Delta n_{t3} = (4 \times r_s \times \mu \times \eta_2) \quad (30)$$

$$r_s = (0.5 - rand) \quad (31)$$

$$\eta_2 = n_{t1} \times g_2 \quad (32)$$

$$g_2^k = g_{2,\max} - \frac{g_{2,\max} - g_{2,\min}}{iter_{\max}} \times k \quad (33)$$

where $\Delta n_{t3}$ is the amount of share which changes in the shares of the members in group three. Parameter $r_s$ is a random number between −0.5 and 0.5 and $\eta_2$ is the risk of each member and $g_2$ is the market variable risk.

## 5. Application of the EMA method for solving the optimization problem

The EMA method follows the following steps to solve the problem and finds the best optimal values. Fig. 1, illustrates the flowchart of the proposed algorithm to find the optimum point of Wind/Environment/Economic Dispatch (WEED) problem:

(1) Assuming the first values.

(2) Calculating the shareholder's cost and giving the rank market for them.

(3) Changes in the shares of the second group members in the balanced market condition.

(4) Changes in the shares of the third group members in the balanced market condition.

**Table 5**
Emission coefficients of 40 units test system.

| Unit | $\alpha_i$ | $\beta_i$ | $\gamma_i$ | $\zeta_i$ | $\lambda_i$ |
|---|---|---|---|---|---|
| 1 | 60 | −2.22 | 0.048 | 1.31 | 0.0569 |
| 2 | 60 | −2.22 | 0.048 | 1.31 | 0.0569 |
| 3 | 100 | −2.36 | 0.0762 | 1.31 | 0.0569 |
| 4 | 120 | −3.14 | 0.054 | 0.9142 | 0.0454 |
| 5 | 50 | −1.89 | 0.085 | 0.9936 | 0.0406 |
| 6 | 80 | −3.08 | 0.0854 | 1.31 | 0.0569 |
| 7 | 100 | −3.06 | 0.0242 | 0.655 | 0.02846 |
| 8 | 130 | −2.32 | 0.031 | 0.655 | 0.02846 |
| 9 | 150 | −2.11 | 0.0335 | 0.655 | 0.02846 |
| 10 | 280 | −4.34 | 0.425 | 0.655 | 0.02846 |
| 11 | 220 | −4.34 | 0.0322 | 0.655 | 0.02846 |
| 12 | 225 | −4.28 | 0.0338 | 0.655 | 0.02846 |
| 13 | 300 | −4.18 | 0.0296 | 0.5035 | 0.02075 |
| 14 | 520 | −3.34 | 0.0512 | 0.5035 | 0.02075 |
| 15 | 510 | −3.55 | 0.0496 | 0.5035 | 0.02075 |
| 16 | 510 | −3.55 | 0.0496 | 0.5035 | 0.02075 |
| 17 | 220 | −2.68 | 0.0151 | 0.5035 | 0.02075 |
| 18 | 222 | −2.66 | 0.0151 | 0.5035 | 0.02075 |
| 19 | 220 | −2.68 | 0.0151 | 0.5035 | 0.02075 |
| 20 | 220 | −2.68 | 0.0151 | 0.5035 | 0.02075 |
| 21 | 290 | −2.22 | 0.0145 | 0.5035 | 0.02075 |
| 22 | 285 | −2.22 | 0.0145 | 0.5035 | 0.02075 |
| 23 | 295 | −2.26 | 0.0138 | 0.5035 | 0.02075 |
| 24 | 295 | −2.26 | 0.0138 | 0.5035 | 0.02075 |
| 25 | 310 | −2.42 | 0.0132 | 0.5035 | 0.02075 |
| 26 | 310 | −2.42 | 0.0132 | 0.5035 | 0.02075 |
| 27 | 360 | −1.11 | 1.842 | 0.9936 | 0.0406 |
| 28 | 360 | −1.11 | 1.842 | 0.9936 | 0.0406 |
| 29 | 360 | −1.11 | 1.842 | 0.9936 | 0.0406 |
| 30 | 50 | −1.89 | 0.085 | 0.9936 | 0.0406 |
| 31 | 80 | −2.08 | 0.0121 | 0.9142 | 0.0454 |
| 32 | 80 | −2.08 | 0.0121 | 0.9142 | 0.0454 |
| 33 | 80 | −2.08 | 0.0121 | 0.9142 | 0.0454 |
| 34 | 150 | −2.06 | 0.0542 | 0.655 | 0.02846 |
| 35 | 130 | −2.32 | 0.041 | 0.655 | 0.02846 |
| 36 | 150 | −2.11 | 0.0435 | 0.655 | 0.02846 |
| 37 | 100 | −1.98 | 0.095 | 1.42 | 0.0677 |
| 38 | 100 | −1.98 | 0.095 | 1.42 | 0.0677 |
| 39 | 100 | −1.98 | 0.095 | 1.42 | 0.0677 |
| 40 | 220 | −2.68 | 0.0151 | 0.5035 | 0.02075 |

(5) Analyzing the shareholders again and giving the rank market based on their finance.

(6) Trading in the shares of the second group members in the unbalanced market.

(7) Trading in the shares of the third group members in the unbalanced market.

(8) Returning to step two until the completion of the program is achieved.

## 6. Numerical results

To determine the efficiency of the EMA method, a test system with 40 thermal units is used in three cases of study. Table 1 shows the parameters of the test system [32]. In the first case, the economic dispatch problem solved for 40 thermal units test system and the minimum cost of power system operation obtained. In the second case, emission cost added to the fitness function (operation cost of thermal units) and the economic emission dispatch problem solved for this case. In the third case, wind farms penetration considered and the objective function which is introduced in Section 3, minimized. The parameters of the EMA method are mentioned in Table 2 and three cases results are considered as follows:

*Case 1: economic dispatch (ED) problem without contemplating emission and wind turbine*

In this part, to evaluate the superiority of the EMA method, this method is used to solve the ED problem by considering valve-point effect. In this case, the total load demand is 10 500 MW.

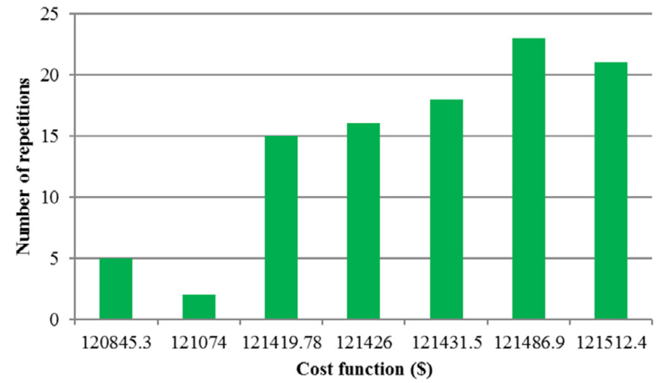


**Fig. 2.** Frequency of each answer for 100 consecutive runs of EMA.

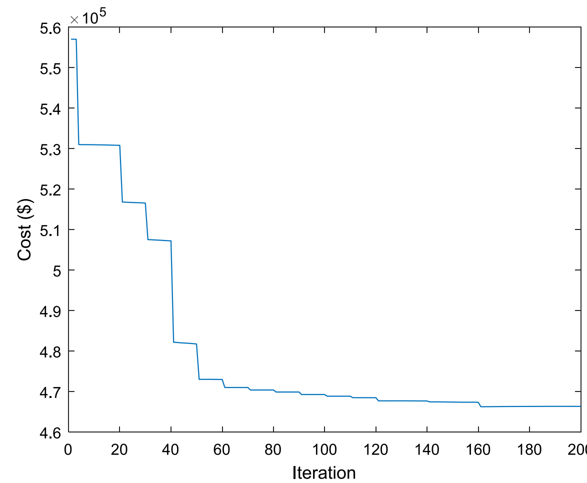


**Fig. 3.** Convergence characteristic of EMA for third case.

The results of the optimization are shown in Table 3. As seen in Table 3, the best answer to the ED problem is 12 0845 $ which is obtained by the EMA algorithm. The core goal of using different methods in economic dispatch is to optimize the cost function leading to the minimum cost which is achieved by EMA. The total cost (TC) of EMA is 1478 $, 581 $ and 229 $ less than PSO, BBO and FPA heuristic methods, respectively. Therefore, utilizing the EMA method yields a better solution for optimizing the cost function. Fig. 2 shows the frequency of each answer in the 100 consecutive runs of the EMA algorithm. In Table 4, the best, worst and mean of the presented data are compared with the other algorithms. The results shows the superiority of the EMA algorithm in finding the best solution.

*Case 2: economic emission dispatch problem (EED)*

In this case, the problem is solved by considering the emission's objective function. Emission coefficient of 40 units test system are included in Table 5 and the system's load demand is 10 500 MW. The results are shown in Table 6 and indicate that EMA is able to find the optimum point of the combined economic emission problem. Total cost (TC) and emission cost (EC) of EMA is less than GSA, MODE, PDE and FPA, which is an indication of the strength of EMA in finding global minima of the objective function.

*Case 3: economic emission dispatch with wind turbine*

This case represents a multi-objective function considering wind turbine, emission and fuel costs of thermal units. The emission cost coefficient of the system is 1.8655 ($/ton) and two wind

**Table 6**
Results of second case (economic emission dispatch).

| Outputs | EMA | MODE [12] | PDE [12] | GSA [34] | FPA [12] |
|---|---|---|---|---|---|
| Thermal 1 (MW) | 113.987 | 113.5295 | 112.1549 | 113.9989 | 43.405 |
| Thermal 2 (MW) | 113.795 | 114 | 113.9431 | 113.9896 | 113.95 |
| Thermal 3 (MW) | 119.687 | 120 | 120 | 119.9995 | 105.86 |
| Thermal 4 (MW) | 163.980 | 179.8015 | 180.2647 | 179.7857 | 169.65 |
| Thermal 5 (MW) | 96.987 | 96.7716 | 97 | 97 | 96.659 |
| Thermal 6 (MW) | 128.354 | 139.276 | 140 | 139.0128 | 139.02 |
| Thermal 7 (MW) | 296.582 | 300 | 299.8829 | 299.9885 | 273.28 |
| Thermal 8 (MW) | 279.141 | 298.9193 | 300 | 300 | 285.17 |
| Thermal 9 (MW) | 292.277 | 290.7737 | 289.8915 | 296.2025 | 241.96 |
| Thermal 10 (MW) | 130.003 | 130.9025 | 130.5725 | 130.3850 | 131.26 |
| Thermal 11 (MW) | 253.529 | 244.7349 | 244.1003 | 245.4775 | 312.13 |
| Thermal 12 (MW) | 224.444 | 317.8218 | 318.284 | 318.2101 | 362.58 |
| Thermal 13 (MW) | 419.527 | 395.3846 | 394.7833 | 394.6257 | 346.24 |
| Thermal 14 (MW) | 419.0212 | 394.4692 | 394.2187 | 395.2016 | 306.06 |
| Thermal 15 (MW) | 424.179 | 305.8104 | 305.9616 | 306.0014 | 358.78 |
| Thermal 16 (MW) | 420.0415 | 394.8229 | 394.1321 | 395.1005 | 260.68 |
| Thermal 17 (MW) | 484.9416 | 487.9872 | 489.304 | 489.2569 | 415.19 |
| Thermal 18 (MW) | 478.645 | 489.1751 | 489.6419 | 488.7598 | 423.94 |
| Thermal 19 (MW) | 455.747 | 500.5265 | 499.9835 | 499.2320 | 549.12 |
| Thermal 20 (MW) | 415.1129 | 457.0072 | 455.416 | 455.2821 | 496.7 |
| Thermal 21 (MW) | 446.878 | 434.6068 | 435.2845 | 433.4520 | 539.17 |
| Thermal 22 (MW) | 451.4312 | 434.531 | 433.7311 | 433.8125 | 546.46 |
| Thermal 23 (MW) | 424.7311 | 444.6732 | 446.2496 | 445.5136 | 540.06 |
| Thermal 24 (MW) | 429.5494 | 452.0332 | 451.8828 | 452.0547 | 514.5 |
| Thermal 25 (MW) | 464.30627 | 492.7831 | 493.2259 | 492.8864 | 453.46 |
| Thermal 26 (MW) | 444.3183 | 436.3347 | 434.7492 | 433.3695 | 517.31 |
| Thermal 27 (MW) | 10.4061 | 10 | 11.8064 | 10.0026 | 14.881 |
| Thermal 28 (MW) | 10.1509 | 10.3901 | 10.7536 | 10.0246 | 18.79 |
| Thermal 29 (MW) | 10.0715 | 12.3149 | 10.3053 | 10.0125 | 26.611 |
| Thermal 30 (MW) | 96.9925 | 96.905 | 97 | 96.9125 | 59.581 |
| Thermal 31 (MW) | 188.0112 | 189.7727 | 190 | 189.9689 | 183.48 |
| Thermal 32 (MW) | 189.9040 | 174.2324 | 175.3065 | 175 | 183.39 |
| Thermal 33 (MW) | 189.8771 | 190 | 190 | 189.0181 | 189.02 |
| Thermal 34 (MW) | 199.994 | 199.6506 | 200 | 200 | 198.73 |
| Thermal 35 (MW) | 199.998 | 199.8662 | 200 | 200 | 198.77 |
| Thermal 36 (MW) | 199.961 | 200 | 200 | 199.9978 | 182.23 |
| Thermal 37 (MW) | 109.827 | 110 | 109.9412 | 109.9969 | 39.673 |
| Thermal 38 (MW) | 109.742 | 109.9454 | 109.8823 | 109.0126 | 81.596 |
| Thermal 39 (MW) | 109.813 | 108.1786 | 108.9686 | 109.4560 | 42.96 |
| Thermal 40(MW) | 484.045 | 422.0628 | 421.3778 | 421.9987 | 537.17 |
| TC($) ∗10^5 | 1.23112 | 1.2579 | 1.2573 | 1.2578 | 1.23170 |
| EC (ton) ∗10^5 | 2.0496 | 2.1119 | 2.1177 | 2.1093 | 2.0846 |

turbines are added to the 40 units test system. The parameters of wind turbines are shown in Table 7. These parameters are adopted from [26] in order to compare our result with [26]. The results of the EMA implementation are presented in Table 8. The results achieved in this case is another indicator of the dominance of the EMA method over other heuristic methods including PSO and GEAPSO. The value of TC which is reached using EMA method has the least value in comparison with PSO and GEAPSO. To determine the quickness of the algorithm, the convergence characteristic of the EMA algorithm has been displayed in Fig. 3.

Results of case 1, case 2 and case 3 illustrate that EMA has the superiority compared to studied algorithms in finding the minimum value of cost functions which is the main contribution of the paper. However, there are some limitations to this work such as simplicity of the wind power curve which can be assumed as a polynomial or exponential power curve which is closer to reality.

## 7. Conclusion

This paper presented the solution for the economic emission dispatch problem including wind farms. Economic emission dispatch problem including wind energy is a nonlinear problem which is difficult to solve with mathematical solutions and for a large number of generation units, therefore using Meta-heuristic methods become popular for solving WEED problem. In this paper, the exchange market algorithm (EMA) has been implemented for solving WEED problem. The EMA algorithm is based on human intelligence and proved to be a powerful and useful method for finding the optimal value with high accuracy especially for non-linear problems with myriad variables. Due to two absorptive and explorer operators in each market conditions, EMA avoids getting stuck in the local minima. In order to determine the superiority of the EMA, the proposed method is tested on 40 thermal units test system with two wind turbine. The results have shown that the EMA method is effective in minimizing the problem and presents better simulation results than other algorithms in the literature. The EMA presents a faster convergence, it takes less than 200 iterations to find the best answer of WEED problem. In terms of improvements the future works, the WEED problem can be examined for a system with higher penetration of wind turbines and the modeling of the wind power curves can be replaced by a more realistic nonlinear form. Moreover, the stochastic nature of demand can be studied for further validating the work.

**Declaration of competing interest**

No author associated with this paper has disclosed any potential or pertinent conflicts which may be perceived to have impending conflict with this work. For full disclosure statements refer to https://doi.org/10.1016/j.asoc.2019.106044.

**Table 7**
Parameters of wind turbines.

| | $k$ | $C$ | $w_{min}$ (MW) | $w_{max}$ (MW) | $C_{ov,j}$ | $C_{un,j}$ | $v_o$ (m/s) | $v_i$ (m/s) | $v_r$ (m/s) | $d$ |
|---|---|---|---|---|---|---|---|---|---|---|
| $W_1$ | 2.2 | 15 | 10 | 100 | 310 | 100 | 45 | 5 | 15 | 120 |
| $W_2$ | 2.2 | 15 | 10 | 100 | 310 | 100 | 45 | 5 | 15 | 150 |

**Table 8**
Results of implementation of EMA with wind turbines.

| Outputs (MW) | EMA | PSO [26] | GAEPSO [26] | Outputs (MW) | EMA | PSO [26] | GAEPSO [26] |
|---|---|---|---|---|---|---|---|
| Thermal 1 | 113.9978 | 114.0000 | 110.3346 | Thermal 24 | 436.2640 | 538.0536 | 436.6102 |
| Thermal 2 | 114 | 106.2356 | 108.0659 | Thermal 25 | 436.3564 | 545.0089 | 343.2251 |
| Thermal 3 | 119.9878 | 118.2564 | 122.2268 | Thermal 26 | 436.2608 | 426.2278 | 407.8362 |
| Thermal 4 | 168.0691 | 182.6634 | 183.5638 | Thermal 27 | 25.4306 | 121.2238 | 100.2835 |
| Thermal 5 | 96.9998 | 97.0000 | 97.0000 | Thermal 28 | 25.2202 | 126.0343 | 104.2249 |
| Thermal 6 | 123.5121 | 102.1987 | 121.2663 | Thermal 29 | 25.6125 | 106.2268 | 124.9365 |
| Thermal 7 | 298.6488 | 134.0531 | 289.3386 | Thermal 30 | 96.9989 | 96.0892 | 67.0836 |
| Thermal 8 | 295.3222 | 292.2256 | 291.0248 | Thermal 31 | 171.2491 | 172.0086 | 126.2364 |
| Thermal 9 | 294.9185 | 290.1165 | 268.1832 | Thermal 32 | 171.2214 | 181.6147 | 175.2238 |
| Thermal 10 | 130 | 133.8941 | 185.0362 | Thermal 33 | 171.2614 | 170.1243 | 168.0834 |
| Thermal 11 | 297.3430 | 101.2368 | 226.5547 | Thermal 34 | 199.9997 | 191.3843 | 152.7525 |
| Thermal 12 | 296.5167 | 154.7289 | 300.0362 | Thermal 35 | 199.9974 | 189.5371 | 160.3315 |
| Thermal 13 | 431.0401 | 308.2166 | 362.8566 | Thermal 36 | 200 | 172.0034 | 176.6257 |
| Thermal 14 | 420.4353 | 368.3325 | 422.0695 | Thermal 37 | 100.14834 | 97.6206 | 93.0638 |
| Thermal 15 | 421.0584 | 371.2215 | 452.1836 | Thermal 38 | 100.03489 | 94.4833 | 86.1743 |
| Thermal 16 | 421.1593 | 381.2681 | 411.6642 | Thermal 39 | 99.8474 | 86.0853 | 104.2263 |
| Thermal 17 | 437.1676 | 416.2678 | 456.0281 | Thermal 40 | 434.6385 | 462.2264 | 489.0264 |
| Thermal 18 | 437.1425 | 482.9655 | 426.3377 | Wind 1 | 40.487141 | 46.0468 | 53.6275 |
| Thermal 19 | 435.6283 | 506.2201 | 468.9534 | Wind 2 | 31.9771 | 80.0468 | 76.0742 |
| Thermal 20 | 436.129 | 516.2468 | 501.5378 | Fuel cost($) | 144 356 | 142 068 | 146 035 |
| Thermal 21 | 436.1449 | 502.7719 | 424.2835 | EC(ton) $*10$^5 | 1.72595 | 1.78432 | 1.72268 |
| Thermal 22 | 435.6814 | 435.4741 | 456.7872 | TC($) $*10$^5 | 4.66332 | 4.74934 | 4.67402 |
| Thermal 23 | 436.0896 | 482.1264 | 369.0365 | | | | |

## CRediT authorship contribution statement

**Mehrdad Tarafdar Hagh:** Conceptualization, Methodology, Validation, Writing - review & editing, Supervision. **Seyed Mohammad Sajjadi Kalajahi:** Conceptualization, Software, Validation, Writing - original draft. **Naser Ghorbani:** Conceptualization, Methodology, Software, Resources.

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