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Multi-objective Dynamic Environmental Economic Dispatch Problem Considering Plug in Electric Vehicles by Using the Improved Exchange Market Algorithm

Hossein Nourianfar[1], Hamdi Abdi[1,*]

[1] *Electrical Engineering Faculty, Razi University, Kermanshah, Iran*

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ABSTRACT

Global Warming and progression of modern power networks have profoundly changed traditional power grids in terms of fossil fuel consumption and emission of toxic gases. Therefore, auxiliary power plants and ancillary services have been introduced as an effective alternative, to overcome these new challenges in power systems. In this work, the dynamic environmental economic dispatch (DEED) problem, is investigated by considering the plug-in electric vehicles (PEVs), minimizing the fuel cost and greenhouse gas emissions from fossil fuel units. In the mentioned problem, to make it more practical, various operational constraints, including valve-point loading effect (VPLE), ramp rate limits (RRLs) and generation capacity limits are considered. This paper proposes a new multi-objective exchange market algorithm (EMA) based on the non-dominated sorting theory to find the Pareto front. In addition, the impacts of PEVs, as an uncertainty source, on the mentioned problem are analysed in four different charging scenarios. The efficiency of the proposed method has been detailed on three experimental systems and the obtained results are compared with other algorithms in this field. The results show that the maximum percentage reduction in costs for test cases 1 to 3, are about 2.13, 2.69, and 39.48, respectively, and bout 45.96, 48.20 and 44.07, for emission, respectively. The comparative analysis verify the proposed method efficiency, and accuracy in solving the suggested problem.

Nomenclature

List of symbols

$FC_i(P_i)$	Fuel cost function of the i[th] thermal unit
A_i ، B_i *and* C_i	Coefficients of thermal unit cost function *i*.
D and θ	Coefficients of VPLE
P_i	Generated power by thermal unit *i*
$E_i(P_i)$	Emission function of the i[th] thermal unit
α, β, γ, ζ and λ	Emission coefficients of thermal unit
$P_{i,t}^{min}$ and $P_{i,t}^{max}$	Minimum and maximum power generated by unit *i* at time *t*
$P_{D,t}$ and $P_{L,t}$	Demand load and the power loses at time *t*.
$l_{ev,t}$	Charging load of PEVs, at time *t*
P_i^0	previous output power of the *i*[th] unit
DR_i and UR_i	Down and up ramp rate limits of the *i*[th] unit
$IND_{1,i}^{group1}$ and $IND_{2,i}^{group1}$	Individuals in the first category

* Corresponding author
E-mail address: hamdiabdi@razi.ac.ir
https://www.orcid.org/0000-0002-7625-0036
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R	A random number in the range of 0 and 1
δ_k	Value of the change in the share of the k member in the third group
W_k	Feedback coefficient of the k member in the third group
$Rank_k$	Rank of the k member in the third group
N_{POP}	Number of total population
Δn_{t1}^i and Δn_{t2}^i	Amount of change in the variables of the members of the second and third groups
Ψ_t^i	Exchange market information
ω_1	Risk factor for each member of group 2
μ	Risk increase coefficient that makes the last individuals of the ranking take more risks
$g_1^k and\ g_2^k$	common market risk for the second and third groups
$iter_{max}$	Maximum iteration
$g_{min}\ and\ g_{max}$	Minimum and maximum common market risk
$f_i(x)$ and $f_i(y)$	Output of the ith objective function for solutions x and y
CD_i	Crowding distance of the ith solution
φ	Penalty coefficient

Abbreviations

DEED	Dynamic Environmental Economic Dispatch
PEVs	Plug-in Electric Vehicles
VPLE	Valve-Point Loading Effect
RRLs	Ramp Rate Limits
ELD	Economic Load Dispatch
EED	Economic Emission Dispatch
AI	Artificial Intelligence
DE	Differential Evolution
MCSA	Modified Crow Search Algorithm
Dy-NSBBO	Dynamic Non-dominated Sorting Biogeography-Based Optimization
NSGA-II	Non-dominated Sorting Genetic Algorithm
KKO	Kho-Kho Optimization
WOA	Whale Optimization Algorithm
COA	Coyote Optimization Algorithm
MSFLA	Modified Shuffle Frog Leaping Algorithm
ICA	Imperialist Competitive Algorithm
EPRI	Electric Power Research Institute
PDF	Probability Distribution Function

1. Introduction

Power generation units play a significant role in the power system, to provide a reliable and safe electricity to consumers, in an economical and controllable manner. With the development of technology and industrialization, the need for electrical power is increasing gradually. On the other hand, meeting the increased power demand entails significant costs. Accordingly, reducing the power generation costs is remarkably involved in promoting the economic development of countries [1].

Supplying reliable energy at the minimum cost can be a very challenging subject that is highly dependent on grid operation and control strategies. So far, different operation concepts are considered to minimize the total cost of power generation units. In this regard, Economic load dispatch (ELD) is the most basic problem, as the cornerstone of operation studies, to provide the quality power to the customers, economically and safely. The ELD problem is defined as determining the optimal generations of power plants satisfying a set of different constraints, while minimizing total operating costs [2].

Mathematical methods cannot be used properly to address these problems due to the need for differentiable or continuous objective functions. Hence, various artificial intelligence (AI)-based optimization methods that randomly seek the optimal solutions are used effectively to solve the EED problem. As a result, these methods can be a suitable candidate. Some of these optimization techniques include Kho-Kho Optimization algorithm (KKO) [3], Whale Optimization Algorithm (WOA) [4], Coyote Optimization Algorithm (COA) [5], Modified Shuffle Frog Leaping Algorithm (MSFLA) [6], Modified Crow Search Algorithm (MCSA) [7], and Imperialist Competitive Algorithm (ICA) [8].

Integrating the environmental issues caused by produced emission gases from fossil fuel-based generators to the ELD problem, results in extending a single-objective problem to a multi-objective economic emission dispatch (EED) problem [9]. The EED problem is mentioned as a type of multi-objective problems with conflicting objectives. In other words, reducing the value of one-goal leads to increasing the value of another. Therefore, the appropriate solution must be obtained through an acceptable trade-off between different objectives.

This new problem is more complex than the earlier one, which needs applying some new techniques to solve it. The purpose of this new problem is to minimize the fuel cost and emissions simultaneously, which has made it as one of the most important research topics, and directions in modern power system operation studies. Solving this complex problem considering practical system-operating constraints such as valve-point loading effect (VPLE), due to its very nonlinear and non-convex nature, is a very challenging problem that cannot be solved by using traditional and classical methods [10].

As the literature confirms, there are many researches focussed on this issue, some of them are addressed in following.

One of the effective techniques to solve this problem is converting this two-objective problem to a single objective framework by using the classical optimization techniques. In this method the emission rate is considered as an operational constraint [11]. Depending on the problem model and solving strategy, this method has some complexities in finding a compromise solution among the fuel cost and emissions.

Another method is addressed in [12], which applied the goal-based programming to solve the EED problem. However, this method needs more run-time to be converged.

The classical optimization techniques are applied to solve the EED problem based on coordination equations that are not suitable for discontinuous cost functions. Therefore, in classical optimization methods, the cost curve must be estimated in proportion to the necessity of the problem.

A popular strategy is to convert the multi-objective EED problem into a single-objective problem using the price penalty factor and then extract the Pareto Front by varying the values of weighted coefficients for cost and emission. The weighted coefficients method suffers from two main drawbacks [13]. First, the uniform distribution of weighted coefficients does not always result in a uniform distribution of solutions. Second, the solutions existing on the non-convex portions of the Pareto front cannot be found using this method.

In [14], the authors investigated various optimization problems in the field of operation of power systems, such as ELD, ELD in multi-area, ELD in the presence of combined heat and power (CHP) units, on the small- and large-scale cases and taking into account the effect of renewable energy resources. In this work, a modified version of the EMA is employed to solve the mentioned problems. In [15], the multi-objective EED problem is addressed using the combination emission with cost by the price penalty factor. In that research, a hybridization of adaptive inertia weight particle swarm optimization (PSO) and EMA, integrated with an effective constraint handling method is used for problem optimization. In [16], the bi-objective EED problem is solved by employing an improved bare-bone multi-objective PSO algorithm. In this algorithm, to extract the Pareto front and maintain the distribution diversity of Pareto-optimal solutions, the slope method and crowding distance are integrated in the algorithm. In addition, two operators' p_{best} and g_{best} are improved to enhance the performance of the algorithm. In [17], to deal with conflicting objectives in the EED problem, the concept of non-dominated sorting is embedded in the squirrel search algorithm. In this work, the crowding distance mechanism along with an external depository is utilized to distribute the solutions well in the target space.

On the other hand, the use of plug-in electric vehicles (PEVs) in recent years has received much attention due to their significant impacts on reducing emission and being a good option for storing electrical energy. Hence, many large automobile companies have turned to the production of these cars [18]. Increasing the number of EVs has caused the charging and discharging programs of these cars to be done in accordance with the load curve of the network. Therefore, it is always tried to direct the car charging mainly to non-peak times, and a portion of the stored energy in batteries of these cars is sold to the grid during peak hours.

In [19], the economic unit commitment examines power systems integrated with renewable energy resources and PEVs, considering only the unit costs and regardless of emissions. In [20], an energy storage model with network vehicles is proposed for ELD in the smart grid. In this work, weighting coefficients are used to convert the two objectives optimization problem, including emission and cost objectives, into a single objective function. In [21], in addition to PEVs, the effect of wind turbines on the DEED problem is analysed. The solution approach used in this work is the multi-objective virus colony search, and the non-dominated sorting procedure is employed to extract the Pareto front.

With the integration of PEVs in the power grid, the mentioned problem changes from optimal static power dispatch to dynamic ones. As a result, the complexity of the problem will be increased in the dynamic condition than in the static condition.

So far, several methods have been proposed for solving the mentioned problem in dynamic condition, which, in general terms, they can be grouped into two major categories. The first category includes different classical methods based on mathematical equation used to solve the DEED problem, such as linear, quadratic programming and gradient methods [22, 23]. Most mathematical methods are based on iteration. Although these methods offer somewhat accurate solutions to the problem, they are faced with several limitations in real-world problems, including the fact that the fuel cost curve of the units must be continuous.

In addition, although this is not the case with dynamic programming methods and there is no limit to the continuity of the fuel cost curve, it will take a lot of time and memory to solve the problem if the number of units increases.

Nevertheless, in intelligent algorithms, not only are they applicable to any problem without if the number of units any limitations, but also the time and dimensions required to solve the problem increase linearly with the number of units, making them a more suitable option for solving practical problems of ELD [21].

Among the algorithms used in recent researches to solve the DEED problem are the combination of multi-objective crisscross optimization and differential evolution (DE) [24] constriction factor-based particle swarm optimization [25] and the self-adaptive parameter operator multi-objective differential evolution integrated with local search operator based on non-dominant sorting [26].

In this paper, an improved EMA is used to solve the dynamic environmental economic dispatch (DEED) problem considering PEVs. This meta-heuristic algorithm has two operators that generate intelligent random numbers and two operators that strongly and efficiently absorb random numbers towards optimal numbers, simultaneously.

The main contributions of this paper are: improving the EMA, integrating the fast non-dominated sorting approach in the suggested method to find the pareto front of the problem, applying the addressed technique to the mentioned problem with modelling the PEVs, and evaluating the performance and effectiveness of the proposed method, by comparing the results obtained with the results of recent methods.

The rest of the paper is organized as follow. The formula for the DEED problem and the mathematical model of PEV charging are shown in section 2. Section 3 addresses the suggested technique in detail. The simulation results on different case studies are described in section 4. Finally, main conclusions and some suggestions for future works are stated in section 5.

2. Problem Formulation

In this section, the formulation of the EED problem is detailed.

2.1. Fuel Cost Function

The fuel cost function of thermal generation units is assumed to be a quadratic equation as [8]:

$$FC_i(P_i) = A_i + B_i P_i + C_i P_i^2 \tag{1}$$

A_i (\$/h) ،B_i (\$/MW/h) and C_i (\$/MW^2/h) are the coefficients of thermal power plant cost function *i*.

2.2. The VPLE

The fuel cost function considering the VPLE is modeled by adding a sine term to the objective function of Eq. (1) as [10]:

$$FC_i(P_i) = A_i + B_iP_i + C_iP_i^2 + |D * sin\ \{\theta(\ P_{min} - P\ )\}| \quad (2)$$

Where D (\$/h), and θ (rad/MW) are the coefficients of VPLE, and P_{min} is the minimum generated power by thermal unit i.

2.3. Emission Function

The emission produced by each generation unit can be expressed in terms of generator output power as follow [9]:

$$E_i(P_i) = \alpha + \beta P_i + \gamma P_i^2 + \zeta\ exp(\lambda P_i) \quad \left(\frac{Kg}{h}\right) \quad (3)$$

In which, α, β, γ, ζ and λ are the emission coefficients.

2.4. The DEED Formulation

The DEED problem formulation is similar to the static ELD, except that in the dynamic condition, the problem is investigated within 24 hours, and constraints such as the ramp rate limits (RRLs) are added to the problem. The DEED problem can be expressed as:

$$min\left\{\sum_{t=1}^{24}\sum_{i=1}^{N_P} E(P_i), \sum_{t=1}^{24}\sum_{i=1}^{N_P} FC(P_i)\right\} \quad (4)$$

2.5. The Effect of PEVs

Despite the advantages of EVs over conventional vehicles, one of the biggest challenges in using these vehicles is that if they are connected to the power grid suddenly during peak consumption, there is a possibility of network disruption and equipment damage. This is mainly due to the coincidence of the time of return of car owners to the place of residence at the end of office hours with the peak consumption to the place of residence time [21].

Severe fluctuations and sometimes sudden ascent in the load curve typically occur due to power consumption for home chargers and superchargers [21]. To prevent such disturbances in the power system, it is necessary to exercise appropriate control and coordination between car charging and the grid. Generally, four different strategies to charge the PEVs are addressed. These techniques are including EPRI forecasted load profile according to the PEVs driver behavior, stochastic charging, peak and off-peak charging.

According to EPRI, more than 60% of the power is consumed in seven hours, from 10 pm to 4 am. The Peak and Off-Peak profiles indicate the worst and best situations of vehicles charge, respectively. Finally, the stochastic profile based on the uncertainty of the charge of EVs is a daily casual charge distribution. In this scenario the probability distribution function (PDF) is considered with a normal distribution by mean value of 0.05. Table I shows the PDF for charging EVs based on different scenarios.

2.6. Maximum and Minimum Generation Capacity Limits

Each generation units must be operated within a certain range, due to some technical and economic reasons. The upper limit of this range is the nominal value of the generator and the lower one is the value that is necessary for the boiler stable operation.

$$P_{i,t}^{min} \leq P_{i,t} \leq P_{i,t}^{max} \quad (5)$$

$P_{i,t}^{min}$ and $P_{i,t}^{max}$ show the minimum and maximum generated powers by unit i at time t.

2.7. Power Balance

The sum of total power demand and power losses must be equal to the total power generated, as:

$$\sum_{i=1}^{N_P} P_{i,t} = P_{D,t} + P_{L,t} + l_{ev,t} \quad (6)$$

$P_{D,t}$ is the demand load, and $P_{L,t}$ is the electrical power losses at time t. $l_{ev,t}$ represents the charging load of PEVs, at time t. The power losses is determined by using the B-matrix coefficient method.

Table I. Charging scenarios of electric vehicles.

	Charging Scenario	Time			
		01:00-06:00	07:00-12:00	13:00-18:00	19:00-24:00
Probability Distribution	EPRI	0.100	0.010	0.021	0.016
		0.100	0.003	0.021	0.036
		0.095	0.003	0.021	0.054
		0.070	0.013	0.001	0.095
		0.050	0.021	0.005	0.100
		0.030	0.021	0.005	0.100
	Off-Peak	0.185	0	0	0
		0.185	0	0	0
		0.090	0	0	0
		0.090	0	0	0
		0.040	0	0	0.185
		0.040	0	0	0.185
	Peak	0	0	0.185	0.040
		0	0	0.185	0.040
		0	0	0.185	0
		0	0	0.185	0
		0	0	0.090	0
		0	0	0.090	0
	Stochastic	0.057	0.087	0.038	0.028
		0.049	0.048	0.02	0.022
		0.048	0.011	0.021	0.055
		0.024	0.032	0.061	0.025
		0.026	0.021	0.032	0.035
		0.097	0.057	0.022	0.082

2.8. Ramp Rate Limits

The RRLs are the dynamic constraints, in terms of mechanical constraints and in the form of increasing or decreasing rates the output power. By considering this subject, the static EED problem is converted into a dynamic EED problem that prevents possible damage to the rotor. These RRLs are expressed as:

$$Max(P_i^{min}, P_i^0 - DR_i) \leq P_i \leq Min(P_i^{max}, P_i^0 + UR_i) \quad (7)$$

In which, P_i^0 (MW) is the previous output power of the i^{th} unit, and DR_i (MW/h), and UR_i (MW/h) are the down and up ramp rate limits of the i^{th} unit, respectively.

3. Proposed Approach

The approach used in this work, consists of three general components:

I. Employing the improved EMA
II. Non-dominated sorting procedure and crowding distance calculations
III. Constraint handling

The main component of this approach is to use the improved EMA to optimize the intended problem. How this algorithm works is described in detail in Section 3.2. Nevertheless, since this algorithm is designed to address single-objective optimization problems, a mechanism is needed to find the Pareto front. For this purpose, non-dominated sorting and crowding distance are embedded in the algorithm.

3.1. Improved EMA

In this algorithm, there are two different market modes in each iteration, and after each mode, the viability is examined and individuals are sorted based on the value of their assets [28]. At the end of each market situation, the primary, middle, and final members of the population are known as members of groups one, two, and three. How to trade stocks in different market conditions and in different groups is as follows:

- **Normal Mode**

After producing the initial population and calculating the value of individuals' stocks, in normal mode, individuals are divided into three categories based on the amount of assets and the value of their stocks.

Then the first category, which includes individuals with the highest stock value, makes no effort to change their stock because of their position. [27].

However, individuals who are in the second category, change their shares according to the experience of the first category to reach the position of individuals in the first category and increase the value of their shares. The method of changing the shares of these individuals is as [28]:

$$IND_j^{group2} = R \times IND_{1,i}^{group1} + (1-R) \times IND_{2,i}^{group1} \quad (8)$$

$IND_{1,i}^{group1}$ and $IND_{2,i}^{group1}$ are the individuals in the first category. R is a random number in the range of (0,1).

In the third category, individuals change their stocks at greater risk than those in the second category because of the much lower stock value than those in the first category, as: [28]:

$$\delta_k = 2 \times W_k \times \left(IND_{1,i}^{group1} - IND_k^{group3}\right) \quad (9)$$

$$IND_k^{group3,new} = IND_k^{group3} + \delta_k \quad (10)$$

$$W_k = 2 \times {(Rank_k - N_{POP}/2)}/{N_{POP}} \quad (11)$$

δ_k is the value of the change in the share of the k member in the third group.

- **Oscillation Mode**

Similar to normal mode, the individuals are divided into 3 groups and the members of first group try to maintain their rank and remained unchanged. However, in the second group, the total shares of individuals is fixed and only the amount of some shares of each type increases and the amount of others decreases, so the total amount of shares of each individual remains unchanged. Initially, the number of shares of each individual increases according to [28]:

$$\Delta n_{t1}^i = n_{t1}^i - \Psi_t^i + (2 \times R \times \mu \times \omega_1) \quad (12)$$

$$\mu = t_{POP}/N_{POP} \quad (13)$$

$$n_{t1}^i = \sum_{y=1}^{n} |S_{ty}| \quad (14)$$

$$\omega_1 = n_{t1}^i \times g_1^k \quad (15)$$

$$g_1^k = g_{1,max} - \frac{g_{1,max} - g_{1,min}}{iter_{max}} \times k \quad (16)$$

$$\Psi_t^i = \phi^i + \theta_t^i(x) \quad (17)$$

Δn_{t1}^i is the amount of change in the variables of the members of the second group and Ψ_t^i is the exchange market information. R is a random number, ω_1 is the risk factor for each member of group 2. μ is the risk increase coefficient that makes the last individuals of the ranking take more risks. $g_1^k$is a common market risk and decreases with increasing the iteration.

In the second part of this section, it is necessary for each individual to sell some of his stocks of any kind at random in the same amount as he bought additional stocks, so that the total stocks of each individual remain unchanged. In this part, it is necessary for each individual to reduce his stocks by a total of Δn_{t2}^i. In this case, the value of each individual is equal to:

$$\Delta n_{t2}^i = n_{t2}^i - \Psi_t^i \quad (18)$$

Δn_{t2}^i is the amount of stock that each individual must sell.

In this section, unlike group two, the total number of stock of individuals changes with trading and each member buys or sells some shares. The shareholders of the third group change some of their stock according to the following relation [28]:

$$\Delta n_{t3} = (4 \times r_s \times \mu \times \omega_2) \quad (19)$$

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

$$\omega_2 = nt_1 \times g_2 \quad (21)$$

$$g_2^k = g_{2,max} - \frac{g_{2,max} - g_{2,min}}{iter_{max}} \times k \qquad (22)$$

Δn_{t3} is the amount of change in the variables of the members of the third group. *rand* is a random number, ω_2 is the risk factor for each member of group 2. μ is the risk increase coefficient that makes the last members in the ranking take more risks. Finally, g_2^k is the usual market risk for the third group in the oscillation mode and decreases with increasing iteration. The flowchart of the proposed approach is drawn in Figure 1.

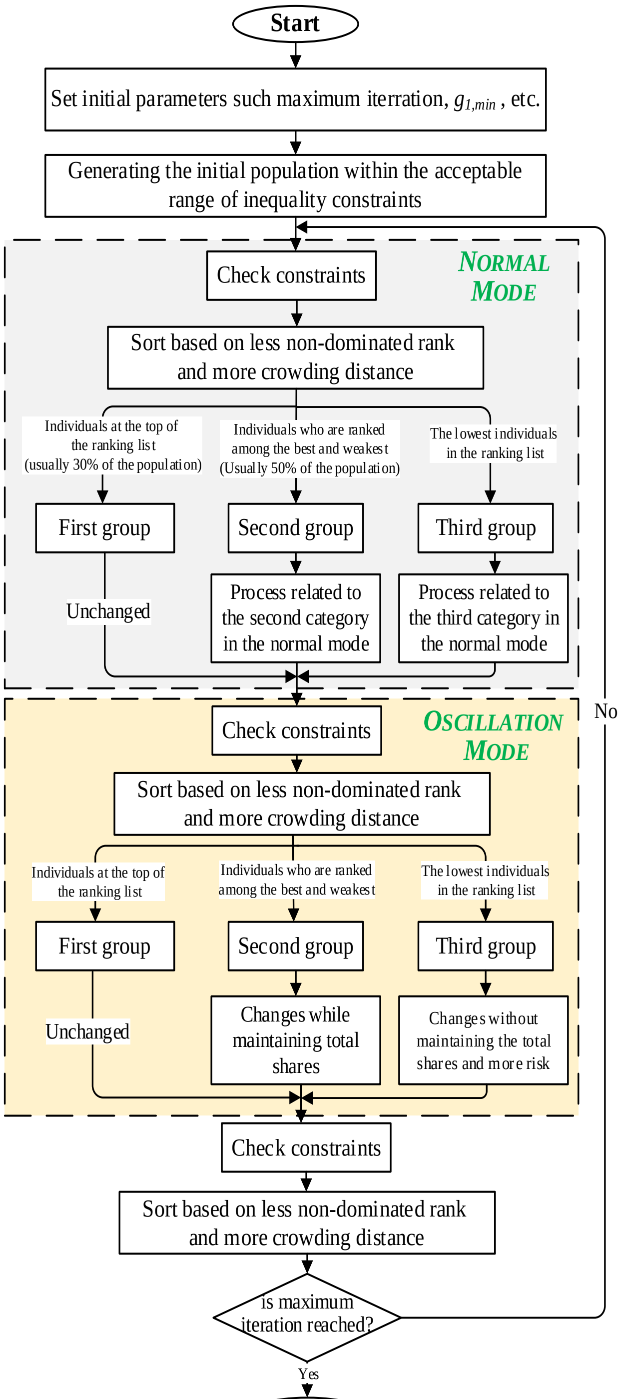

Fig. 1. The flowchart of the proposed approach

3.2. Non-Dominated Sorting Procedure and Crowding Distance Calculations

In the multi-objective EED problem, the aim is to reduce both costs and emissions. Therefore, solutions cannot be sorted on the basis of less cost alone. In these cases, the concept of dominance is used. One solution dominates another, if the following equations are met simultaneously [29].

$$f_i(x) \le f_i(y) \qquad \forall i = 1,2,\dots,n \qquad (23)$$

$$f_i(x) < f_i(y) \qquad \exists i = 1,2,\dots,n \qquad (24)$$

Where, $f_i(x)$ and $f_i(y)$ are the output of the i^{th} objective function for solutions *x* and *y*, respectively. In addition, n represents the number of objectives. In the non-dominated sorting procedure, the solutions that are not dominated by any other solution form the first front. Regardless of the available solutions in the first front, the same procedure is repeated, and the non-dominated solutions form the second front, and so on. In addition, to maintain diversity, in each front, the crowding distance of the solutions is calculated according to the following equation [10].

$$CD_i = \frac{1}{n}\sum_{o=1}^{n} |f_{i+1}^o - f_{i-1}^o| \qquad (25)$$

Where CD_i is the crowding distance of the i^{th} solution in that front, n is the number of objectives, and f_{i+1}^o and f_{i-1}^o represent the output of the o^{th} objective function for solutions *i*+1 and *i*-1, respectively.

First, the solutions are ranked based on the front which they are on it (solutions on the first front are better than solutions on the second front, and so on). Then, solutions on the same front are ranked based on the greater crowding distance. Table II shows a comparison between the features of the proposed modeling and solution approach.

Table II. Comparison between the features of the DEED problem and the proposed method.

Proposed method	DEED problem
Individual	Solution
Shares	Power output of units
Total shares	Total power
Information of exchange market	Problem data (e.g. power balance)
Buying/selling shares	Increasing/decreasing power outputs of units
Number of shareholders	Population (the number of solutions)
Sorting based on the value of Assets or stocks	Sorting based on front and crowding distance

3.3. Constraint Handling

Two steps are taken to satisfy inequality constraints such as generation capacity limits. In the first step, it tries to generate power within the acceptable range; in the second step, whenever it is violated, the power is corrected to the nearest margin of the feasible solution. Two actions are taken for equality constraints. In the first one, the penalty function with a small value for the penalty coefficient is considered. The following equation shows the new fuel cost function by applying the penalty function.

$$FC_{new} = FC_{old} + \varphi \times \left|\sum_{i=1}^{N_P} P_i - P_D - P_L - l_{ev}\right| \quad (26)$$

Where, φ is the penalty coefficient, its value is considered small here, and FC_{old} is the fuel cost function before applying the penalty function. On the one hand, a small value cannot guarantee the exact fulfilment of the constraint; on the other hand, a large value for the penalty coefficient can lead to premature convergence. Hence, in the second action, to accurately satisfy the constraint, an intelligent search is performed during the algorithm optimization process according to Equations (12-17). In this way, it is tried that the total shares of individuals are always in such a way that the equality constraints are met.

4. Simulation

To confirm the effectiveness of the proposed algorithm in solving bi-objective DEED problems, three test systems including 6-unit static and dynamic systems, and 10-unit dynamic system with four electric vehicle-charging scenarios are used. The parameter settings of the proposed algorithm for solving each of the test systems are presented in Table III.

4.1. Test case I

In the first case, a simple test system without PEV is used to test the effectiveness of the proposed algorithm on a 6-unit test system. Load demand is set to PD=500 MW and other coefficients of generation units are selected based on [18].

The Pareto front obtained by the proposed method for this test system is shown in Figure. 2. As can be seen from this figure, the proposed method can obtain extreme solutions (minimum cost and minimum emission) well, and although the solutions do not have a uniform distribution, due to the low run-time and high accuracy of the outputs, the diversity of solutions is acceptable.

In addition, the best-compromised solution obtained by the proposed method is compared with the results of other methods in this field in Table IV.

As can be seen, the results of the proposed method are better than the other methods in terms of fuel cost and emission. In addition, the proposed method, unlike the other two methods, despite the losses, satisfies the power balance well.

Table II. Settings of algorithm parameters to solve different test cases.

Parameters	Test Case 1	Test Case 2	Test Case 3
Maximum Iteration	100	100	100
Population	50	50	100
g1 [max, min]	[0.005, 0.0005]	[0.01, 0.05]	[0.01, 0.05]
g2 [max, min]	[0.01, 0.001]	[0.02, 0.005]	[0.02, 0.005]

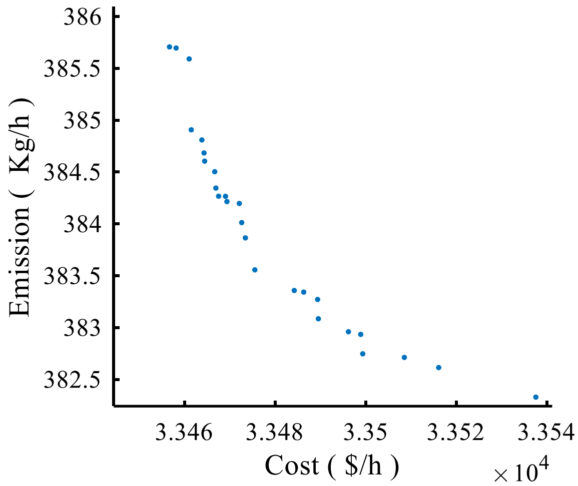

Fig. 2. Pareto front obtained by the proposed method for the test case 1.

Table III. Comparison of results for test case 1.

Method	Dy-NSBBO [18]	Dy-NSGA-II [18]	Proposed method
P1	173.11	165.87	125.047
P2	149.52	158.13	130.376
P3	65.36	78.78	51.295
P4	47.41	55.44	60.097
P5	30.07	22.61	106.949
P6	34.51	19.23	81.591
Cost	34141.32	34214.25	33484.34
Emission	709.26	711.32	384.357

4.2. Test case 2

In this case, the same 6-unit test system with PEVs is employed to examine the proposed algorithm performance. The four PEV charging scenarios described in the previous section are applied. As the amount of charge changes over time, the problem will change to DEED.

In this case, it is assumed that there are some EVs, 18000 of low-hybrid vehicles equipped with 15 kWh batteries, 10000 of medium-sized hybrid vehicles with 25 kWh batteries, and 12000 of pure electric vehicles equipped with 40 kWh [21]. As a result, the total charge of PEVs for one day will be 1000MWh. This amount of charge is significant for the current network.

Figures 3 to 6 show the cost and emission for 4 different charging scenarios of EVs during 24 hours, respectively.

As can be seen from these figures, the best case is related to the Off-Peak scenario, in which the vehicles charging time is shifted to non-peak hours. Figure 3 shows that in the EPRI scenario, costs and emissions are almost the same at all day-hours, due to the almost uniform distribution of PEVs charges during the day, and figure 5 shows that costs and emissions peaked during peak hours. In the stochastic scenario, due to the fact that the amount of charge per hour is random, the cost and emission increase or decrease irregularly, at any day-hour.

The total cost and emission obtained by the proposed method for different scenarios is compared with the results of other methods in Table V.

Table IV. Total cost and emission for the test case 2.

Method		EPRI	Off-Peak	Peak	Stochastic
Dy-NSBBO [18]	Total Cost	836509	835211	852666	849959
	Total Emission	18327	18250	18395	18338
Dy-NSGA-II [18]	Total Cost	852419	851100	869407	858470
	Total Emission	18542	18425	18772	18669
Proposed method	Total Cost	840130	845152	845983	844670
	Total Emission	13374.7	9768.6	9722.4	9940.3

Table V shows that for both peak and stochastic scenarios, the results of the proposed method are better than the results of the other two methods, in terms of both cost and emission. In other words, for these two scenarios, the results of the proposed method dominate the results of the other two methods. In addition, for the other two scenarios, the results of the proposed method dominate the results of the Dy-NSGA-II method.

It should be noted that in the case of the Dy-NSBBO method, for both EPRI and Off-Peak scenarios, we cannot speak with confidence about the superiority between the methods. Because the Dy-NSBBO costs less, while its emission is higher than the proposed method.

The total cost of the EPRI scenario is lower than the Off-Peak scenario. This is due to the fact that load demand used in the test system is considered the same at all hours. As a result, since the vehicles is charged more uniformly in the EPRI scenario, the total cost will be lower.

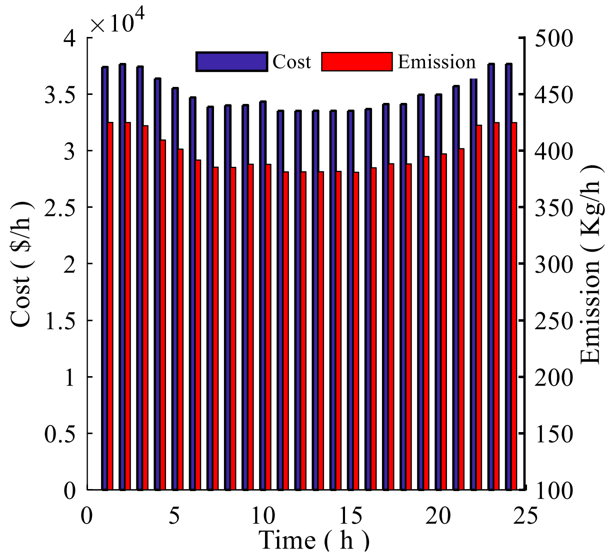

Fig. 3. The cost and emission for test case 2, in EPRI scenario.

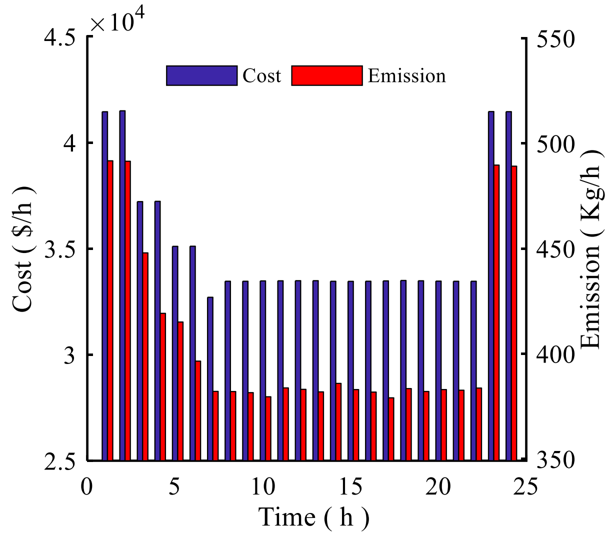

Fig. 4. The cost and emission of test case 2, in Off-Peak scenario.

4.3. Test Case 3

The third test system is a 10-unit system that takes into account the practical system constraints, including the VPLE, RRLs, losses and generation capacity limits, in the form of DEED over 24 hours. The demand load in this system is 900 MW and the system data are extracted from [18].

Since the complexity and scale of this test system is greater than the previous system, it is more appropriate to evaluate the performance of the proposed method.

The best compromising solutions for 24 hours in four different scenarios are given in Figures 7 to 10. Also, the total cost and emission of the proposed method compared to other methods are presented in Table VI.

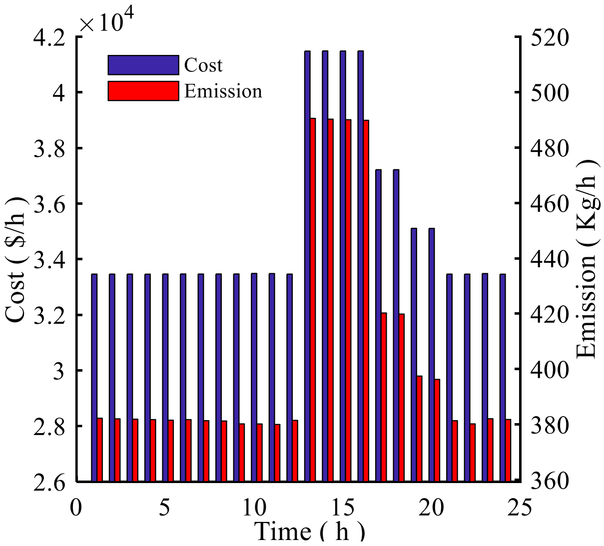

Fig. 5. The cost and emission for test case 2, in Peak scenario.

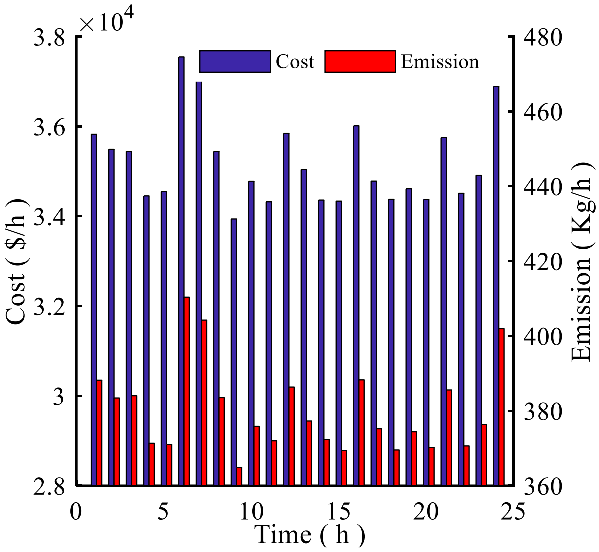

Fig. 6. The cost and emission for test case 2, in Stochastic scenario.

The proposed method for all scenarios is less costly and less emission than the other two methods. In other words, the results of the proposed method dominate the results of the other two methods for all four scenarios.

Furthermore, with the increasing problem scale, the superiority of the proposed method over the other two methods is more clearly demonstrated.

The percentage improvement in cost and emission for all three test cases and for different scenarios is shown in Table VII. As can be seen from this table, the costs and emissions obtained by the proposed method have been significantly improved, especially concerning emissions. The results in Table VII confirm the reduction up to 39% in costs and up to 48% in emissions.

Table V. Total cost and emission for the test case 3.

method		EPRI	Off-Peak	Peak	Stochastic
Dy-NSBBO [18]	Total Cost	2061738	2061330	2067307	2062806
	Total Emission	153483	153321	154178	153778
Dy-NSGA-II [18]	Total Cost	2069298	2065476	2073424	2073017
	Total Emission	155443	154685	155932	155801
Proposed method	Total Cost	1448453	1456437	1456329	1449608
	Total Emission	92851	88506	87198	93063

Table VII. The percentage improvement in cost and emission for all 3 test cases.

Scenario		**Method**	**Percentage improvement** Cost (%)	Emission (%)
Test case 1	-	Dy-NSBBO	1.92	45.80
		Dy-NSGA-II	2.13	45.96
Test case 2	EPRI	Dy-NSBBO	-0.43 [1]	27.02
		Dy-NSGA-II	1.44	27.86
	Off-Peak	Dy-NSBBO	-1.19	46.47
		Dy-NSGA-II	0.69	46.98
	Peak	Dy-NSBBO	0.78	47.14
		Dy-NSGA-II	2.69	48.20
	Stochastic	Dy-NSBBO	0.62	45.79
		Dy-NSGA-II	1.60	46.75
Test case 3	EPRI	Dy-NSBBO	29.74	39.50
		Dy-NSGA-II	30.00	40.26
	Off-Peak	Dy-NSBBO	29.34	42.27
		Dy-NSGA-II	39.48	42.78
	Peak	Dy-NSBBO	29.55	43.44
		Dy-NSGA-II	29.76	44.07
	Stochastic	Dy-NSBBO	29.72	39.48
		Dy-NSGA-II	30.07	40.26

[1] A minus sign means higher cost of the proposed method

5. Conclusion

Investigating different power system operation studies in modern power systems is an important task, which should be discussed, especially by considering some new concepts such as uncertainty, and environmental impacts. In this regard, in this paper, a new version of EMA, known as improved EMA is implemented to solve the DEED problem in the presence of PEVs, as an uncertainty sources in new power systems, with conflicting objectives of fuel cost and emission. This optimization technique was applied to three test cases.

In the first test case, the Pareto front obtained by the proposed method had an acceptable diversity and spread, which shows the proper performance of applying the non-dominated sorting and crowding distance. In the second and third test cases, PEVs were also considered, which converted the static EED problem into a dynamic one. In these test cases, the results of the proposed method compared to state of the art methods, showed up to 48% reduction in emissions and up to 39% reduction in costs. From these results, it can be concluded that the proposed method can be a suitable candidate to solve the multi-objective DEED problems by considering the practical constraints. In addition, a comparison of four scenarios EPRI, Off-Peak, Peak, and Stochastic, showed that shifting the charging time of EVs to non-peak hours reduces costs and emissions.

Increasing the search ability of the algorithm by combining it with other optimization methods, and introducing some hybridizing optimization techniques, to apply it to multi-objective optimization problems of DEED with more practical constraints in a microgrid can be considered as future work in this field. Furthermore, considering a complete package of uncertainties in power systems, including the uncertainty of load, and renewable energy resources, can be mentioned as the most prominent topics for future researches.

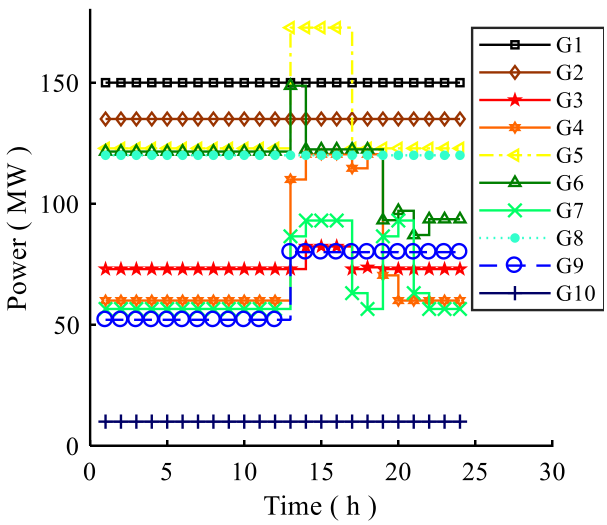

Fig. 7. Generated powers in test case 3 during 24 hours for Peak scenario.

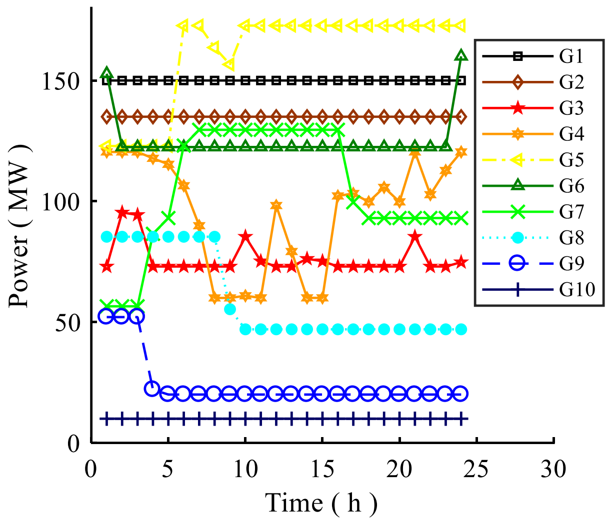

Fig. 8. Generated powers in test case 3 during 24 hours for Stochastic scenario.

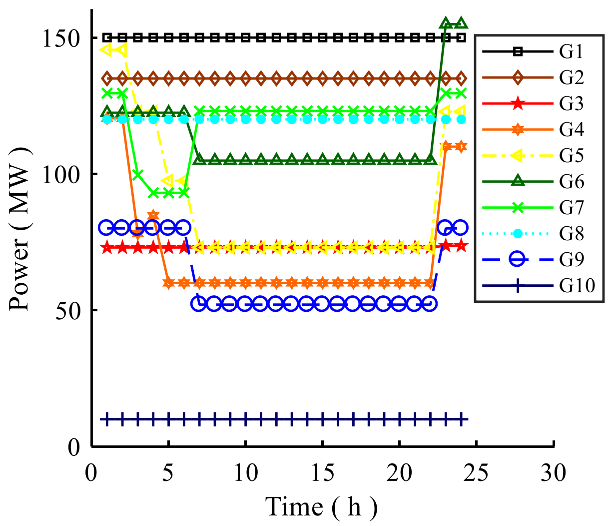

Fig. 9. Generated powers in test case 3 during 24 hours for Off-Peak scenario.

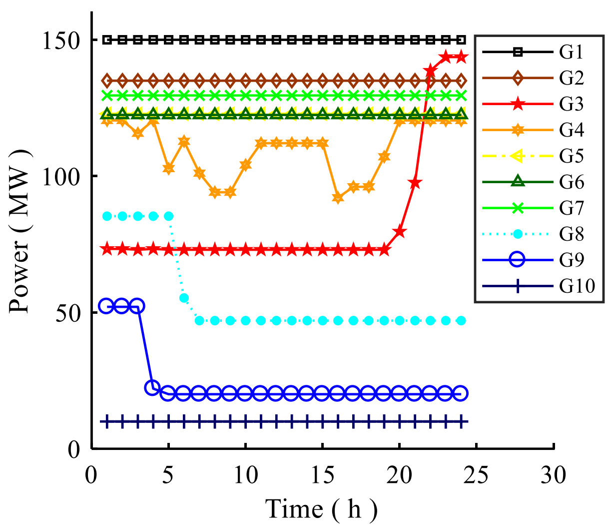

Fig. 10. Generated powers in test case 3 during 24 hours for EPRI scenario.

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