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A novel parallel hurricane optimization algorithm for secure emission/economic load dispatch solution

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ABSTRACT

This paper proposes a parallel hurricane optimization algorithm (PHOA) for solving economic emission load dispatch (EELD) problem in modern power systems. In PHOA, several sub-populations moving independently in the search space with the aim of simultaneously optimizing the problem objectives considering the local behavior between sub-populations. By this way, it is intended to search for the Pareto optimal solutions which are contrasting to the single optimal solution. The inherent characteristics of parallelization strategy can enhance the Pareto solutions and increase the convergence to reach the Pareto optimal solutions. Simulations are conducted on three test systems and comparisons with other optimization techniques that reported in the literature are demonstrated. The obtained results demonstrate the superiority of the proposed PHOA compared to other optimization techniques. Additional economic benefits with secure settings are fulfilled, while preserving all system constraints within their permissible limits. Added to that, two security indices are proposed from generation units and transmission lines. The highest security index from generation units reflects that the operating condition achieves more power reserve. In transmission lines, the highest security index means that the transmission lines operated beyond their congestion limits. For justification of the proposed security indices, the proposed solution methodology is employed to assure their benefits in terms of economical and environmental issues. The proposed algorithm improves the economic issue as well as enhances the power system operation in the technical point of view with acceptable levels of emissions. Moreover, design of experiments using the Taguchi approach is employed to calibrate the parameters of the algorithms. So, it can be considered as a promising alternative algorithm for solving problems in practical large-scale power systems.

1. Introduction

A rapid growth has been witnessed of the search-based optimization algorithms in recent years for power systems due to the dramatic variation in fuel costs and the increased concerns of environmental impacts. The EELD problem is considered as a challenge for researchers due to its high non-linear constraints. It aims to meet the load demand at minimum total fuel cost while satisfying equality and inequality constraints. However, due to the seriousness of the environmental pollution induced by fossil fuel fired thermal power plants, this led to optimize the cost and emission simultaneously. This is becoming more and more desirable for obtaining the optimum scheduling of the committed generating unit outputs [1,2].

Thus, the EELD problem is considered as a mathematical optimization issue that has non-convex objective functions with nonlinear constraints [3]. These nonlinearities increase even more in practical applications due to the opening process of the steam admission valves that resulting in a sharp increase in losses [4]. Generally, non-convexities arise from valve points or combined cycle units, zones of prohibited operation of unit, and nonlinear power-flow equality constraints [5].

These characteristics of nonlinearities increase often result in an unsatisfactory solution, characterized by a slow convergence

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and stuck on local optimum in case of using any mathematical algorithms [3]. Reduction of the overall fuel cost used to be the main objective of electric power systems ignoring the amount of emission produced in the system.

However, the aim of EELD problem is to consider the importance of the environmental impacts that is, the amount of the emission produced must be taken into consideration as well as fuel cost [6–9].

Recently, the dramatic growing of fuel costs and the increased concerns of environmental issues of power generating units present early alarms for the necessity of continuous improvement of optimization methodologies for solving EELD problems efficiently. From power system operation point of view, it is necessary to minimize both emission impacts and generation costs simultaneously. The EELD problem can be formulated as a multi-objective constrained nonlinear problem. The optimization technique needed to solve the EELD problem must take into consideration: types of units, the characteristics of units, costs of operation and maintenance, models of available generation units, the operational constraints, capabilities of equipment and transmission line limits, and the reliability of the available generations for operational points [10,11].

Recently, various optimization techniques have been proposed by many researchers to deal with the EELD problem. Lambda iteration and gradient methods were used as alternatives to solve the Economic Load Dispatch "ELD" problems [12]. However, due to the existence of nonlinearities in generators, previous methods fail to give accurate decisions in power systems. Other optimization methods including nonlinear and dynamic programming were also applied to the same problem. However, these methods suffer from non-differential and non-convex objective function, resulting in being stuck in local optima [12]. Meanwhile, convex EELD problems are efficiently solved through traditional local search algorithms such as lambda iteration "which ignores network constraints" [1] and linear programming [2].

In addition, several scholars have been worked on the flourishing of meta-heuristic search algorithms to overcome the drawbacks of the traditional methods. Meta-heuristic search algorithms are characterized by a fast convergence and a high precision, thus they can provide a more effective behavior and a robust flexibility when dealing with practical applications and large-scale problems. The most well-known paradigms of meta-heuristics contain genetic algorithms (GAs) [13], ant colony optimization (ACO) [14], firefly algorithm (FA) [15] and fruit fly optimization algorithm (FOA) [16]. Over the recent years, many scientists have been enhanced the mentioned meta-heuristics through various variants. Some of the recent developments are reported in [17–25].

A promising new meta-heuristic algorithm denoted as hurricane optimization algorithm (HOA). HOA is one of the latest meta-heuristic methods presented in the literature [26]. HOA emulates the nature phenomena of hurricanes, the radial wind and pressure portraits in the real world. Ismail Rbouh [26] proposed HOA for global optimization. In HOA, the parcels of wind move in a spiral course going out from a low-pressure region called the eye of the hurricane. Through this move, wind parcels seek for a lower pressure zone (new eye position), which is considered as the optimal solution. The HOA has many advantages such as easy to build the program code, ease to implement and can immediately apply for more applications.

This paper is concerned with solving the EELD problem using PHOA. The considered problem is solved using the proposed optimization PHOA with the aim of simultaneously optimizing the economic and emission objectives at the same time that yields the Pareto optimal solution or the Pareto front. Three test systems are employed to check the capability of the proposed PHOA compared with reported methods in the literature. To assure the security analysis, two performance indices that reflect the reserve degree from generators or transmission lines are proposed.

The rest of the paper is organized as follows. In Section 2 we describe some preliminaries of the EELD problem. The proposed PHOA algorithm is explained in details in Section 3. Section 4 describes the tested case studies with a comparative analysis to previous work reported. Finally we summarize the paper with some comments in Section 5.

2. Problem description

The non-linear EELD problem of searching for the optimal combination of power generation, that minimizes the total fuel cost function of each generator while satisfying the total required demand, can be mathematically stated as:

$$\min\ ,\ F_t = \sum_{i=1}^{NG} (a_i + b_i PG_i + c_i PG_i^2) \tag{1}$$

Generally, the generation production costs are represented by quadratic functions with superimposed sine components that represent the rippling effects produced by the steam admission valve opening. The total $/h fuel cost considers the non-smooth valve point effects can be modeled as [2,5,6,27]:

$$\min\ F_t = \sum_{i=1}^{NG} (\mathrm{a}_i + \mathrm{b}_i\ PG_i + \mathrm{c}_i\ PG_i^2) + \left| d_i\ \sin[e_i[PG_i - PG_i^{\min}]] \right| \tag{2}$$

where F_t is a mixed objective function (i.e., quadratic and exponential) defining the total fuel cost of the power generation for the system. a_i, biand c_i are the coefficients of the fuel cost function and diand e_i are the coefficients of non-smooth operation of valves. *NG* is the number of generation buses. The main objective is to minimize value of F_t.

The second objective aims at minimizing the emission effects. The atmospheric pollutants such as nitrogen and sulphur oxides produced by fossil fueled thermal units that can be stated as [27].

$$\min\ E_t = \sum_{i=1}^{NG} 10^{-2}(\alpha_i + \beta_i PG_i + \gamma_i PG_i^2) + \left| \zeta_i \exp[\lambda_i PG_i] \right| \tag{3}$$

where, α_i, β_i, γ_i, ζ_i and λ_i are the coefficients of power generation emissions. The previous objective functions are subjected to the following constraints: generated power outputs must be equal to sum of the total load demand and transmission line losses, thus this constraint can be defined as follows:

$$\sum_{i=1}^{NG} P_{Gi} = \sum_{j=1}^{NL} P_{Dj} + P_{Loss} \tag{4}$$

where, P_{Gi} is the power generation at bus *i*, P_{Dj} is the load demand at load bus *j*, *NL* is the number of load buses and PLoss is the total power losses in the system.

The generation hard constraints include generator voltages, real power outputs, these constraints are defined as hard constraints as they are restricted by their physical lower and upper limits. The generation constraints can be simulated as:

$$P_{Gi\min} \le P_{Gi} \le P_{Gi\max} \tag{5}$$

where $P_{G\min}$ is the minimum limit for the generated power, and $P_{G\max}$ is the maximum limit for the generated power.

Mathematically, the security EELD problem formulation involves large number of constraints. For typical power systems, a huge number of lines have a rather small possibility of becoming congested. The EELD problem must consider only the small number of lines in congestion condition that the power flows in these transmission lines are violated or near to their upper security limits. The critical lines term is identified for the congested lines. In this work, it considers only the critical lines that are binding in the optimal solution [28]. The flow of the i^{th} line is expressed in terms of the decision variables P_{Gi}, by using the generalized generation distribution factors “GGDF” [29] and is given below.

$$T_j(\mathrm{P}_G) = \sum_{i=1}^{n}(D_{ji}P_{Gi}) \tag{6}$$

where, D_{ji} is the generalized GGDF for line j, due to generator i and $T_j(PG)$ is the real power flow.

The total power generation from traditional power plants and DG units should be covered the total load demand (*TLD*) and the active power losses (*LL*):

$$\sum_{p=1}^{N_p}P_{Gp} + \sum_{d=1}^{N_{Gd}}P_{Gd} = TLD + LL \tag{7}$$

where, P_{Gp} is the power generated from traditional power plant and P_{Gd} is the power generated from distributed generations at bus d and N_p is the total number of traditional power plants.

The power flow in line k is restricted by its upper limit ${PF_k}^{max}$ as:

$$PF_k \le PF_k^{\max} \quad , k = 1, 2, ..., N \tag{8}$$

where, PF_k is the power flows in line k and N is the total number of lines.

Two security indices are proposed to measure the security levels from generation units and transmission lines. The highest security index from generation units reflects that the operating condition achieves more power reserve. In transmission lines, the highest security index means that the transmission lines operated beyond congestion limits. The proposed indices can be computed as:

$$SI_k^{PF} = \frac{PF_k - PF_k^{\min}}{PF_k^{\max} - PF_k^{\min}} \tag{9}$$

$$SI_i^{G} = \frac{PG_i - PG_i^{\min}}{PG_i^{\max} - PG_i^{\min}} \tag{10}$$

3. Proposed methodology

In this section, the framework for the proposed approach PHOA is presented that is based on parallelization strategy to enhance the diversity of the non-dominated solutions for EELD. The proposed algorithm operates in two phases. The first phase employs a parallelization strategy on original HOA with the aim of simultaneously exploring Pareto optimal solutions at the same time, while the second one, a cooperative strategy among the populations are also employed, this is also a kind of local search which aims to achieve robust exploration and improve the obtained solutions quality.

In the proposed approach, a multi-population of wind parcels is adopted where each population of wind parcels is responsible to optimize only one of the objective functions of the problem under consideration. That is, for K objective functions, K populations each of size m would be generated. Each population uses only one of the K objective functions for EELD. After the generation step, the evaluation step is utilized to obtain the set of the non-dominated solutions. Then the next iteration starts with of non-dominated solution as a new eye that is selected randomly. The main steps of the PHOA are outlined as follows.

Attempting to deal with several objectives via parallel hurricane optimization algorithm necessitates answering four questions: (1) How to build Pareto optimal solutions using PHOA (2) How does a new eye is generated according to Pareto optimal solutions (3) How the given eye location evolves its location (4) How the parallelization strategy emphases the Pareto optimal solutions. The main steps of this phase can be stated as follows:

Step 1 (Initialization): Instead of having one population trying to find the Pareto optimal solution, the PHOA algorithm assumes that K populations, $POP_1, POP_2, ..., POP_K$, with K regions, $R_1, R_2, ..., R_K$, each of size m of wind parcels aim to optimize simultaneously K-objective functions.

Step 2 (Initial eye location): Each eye location of the k-th region $(R_k^{(t=0)})$ is initialized within the search space randomly, that is for $NG-1$ generation units, the eye location is denoted as $P_{Gj,eye} = (P_{G1,eye}, P_{G2,eye}, ..., P_{GNG-1,eye})$ and initialized as follows:

$$P_{Gj,eye,R_i} = P_{Gj,\min} + rand \times (P_{Gj,\max} - P_{Gj,\min}), \; j = \{1,:NG-1\} \tag{11}$$

Step 3 (Reserve unit): in this step, the reserve unit is exploited to deal efficiently with the equality constraints and then it serves the power system operates in power balance condition, as shown in Fig. 1.

Step 4 (Migration of parcels): In this step, each parcel is migrated to new location starting from the current eye location according to incorporate two modifications. First, the rand term of the inner radius is modulated so that it diminishes progressively as the optima are approaching instead of working randomly as in traditional HOA. Second, the new population of each region is created through selecting one of Pareto optimal solution from the archive randomly, then the new position starting from the Pareto eye position for each population as follows:

$$r_i(t) = R_0\, e^{(rand.(1-t/t_{\max}).\,\varphi_i(t))}, \quad t = 1, 2, ..., t_{\max} \tag{12}$$

$$P_{ij}^{Gi} = \begin{cases} r_i\,\cos(\varphi_{initial}^{i} + \varphi_i(t)) + P_{eye,j} & \text{if } j = d \\ r_i\,\sin(\varphi_{initial}^{i} + \varphi_i(t)) + P_{eye,j} & \text{if } j = d+1 \\ P_{eye,j} & \text{otherwise} \end{cases} \quad i = 1, 2, ..., m \tag{13}$$

where d = i mod (NG − 1)).

Step 5 (Evaluation of solutions): In this step the m parcels of region are evaluated according to objective function that is associated with it and the eye location for each population is determined. Then the non-dominated solutions are obtained and stored in an external archive (denoted by $A^{(t)}$) and the dominated solutions are stored in an archive (denoted by D(t)). At each generation, the solutions that obtained in current generation are compared with the stored solutions in the archive; the dominated ones are stored in $D^{(t)}$ and the non-dominated ones are added to the archive $A^{(t)}$, see Fig. 2.

Step 6 (Update the angular coordinate): In this step the angular coordinate is updated as the basic HOA [26].

Step 7 (Cooperative of sub-populations): Since each subpopulation is responsible for searching for the eye location using its own parcel pressure (fitness function), it may be trapped into local optima that caused the premature convergence. Therefore, subpopulations must be cooperated to improve the information exchange between subpopulations and improve the solution quality. This cooperation is implemented by introducing the concept of linear combination of two solutions, one solution is the eye location of the kth subpopulation and the other solution is selected randomly from the archive $A^{(t)}$ as follows:

$$P_{G,eye,R_k} = \begin{cases} \alpha_k\, P_{G,eye,R_k} + (1-\alpha_k) P_{Gpareo} & \text{if } \xi_k \le 0.5 \\ P_{Gpareo} \in A^t & O.\,W. \end{cases} \tag{14}$$

where ξ_k and α_k are a uniformly random real number within (0, 1) for the kth sub-population, P_{G,eye,R_k} is the current position of the eye location for kth sub-population and P_{Gpareo} is a Pareto optimal solution is selected randomly from the archive $A^{(t)}$.

Reserve unit

Input: $P_D = P_{Load} + P_{Losses}$ **;**, P_{Gj} , $P_{Gj,\max}$, $P_{Gj,\min}$.

$\forall i, i = 1, 2, \ldots, m$

$P_{G,NG} = P_D - \sum_{j=1}^{NG-1} P_{Gj}$

If $P_{GNG} > P_{GNG,\max}$

$\delta = P_{GNG} - P_{GNG,\max}$; $\gamma = \left\{P_{Gj}\right\}_{j=1}^{NG-1} - \left\{P_{Gj,\max}\right\}_{j=1}^{NG-1}$; $P_{GNG} = P_{GNG,\max}$

$\Re = \left\{\gamma(j)/\delta \sum \gamma + P_{Gj}\right\}_{j=1}^{NG-1}$

$P_G = [\Re \quad P_{GNG}]$

Else if $P_{GNG} < P_{GNG,\min}$

$\delta = P_{GNG,\min} - P_{GNG}$; $\gamma = \left\{P_{Gj,\min}\right\}_{j=1}^{NG-1} - \left\{P_{Gj}\right\}_{j=1}^{NG-1}$; $P_{GNG} = P_{GNG,\min}$

$\Re = \left\{-\gamma(j)/\delta \sum \gamma + P_{Gj}\right\}_{j=1}^{NG-1}$

$P_G = [\Re \quad P_{GNG}]$

output : P_G

Fig. 1. The process for reserve mechanism.

Step 8 (Stopping criteria): If $t \geq t_{\max}$, stop the PHOA search; otherwise, go to Step 3.

In Steps 3–5, each population searches its best solution associated with its objective function, then the overall solutions from each population are evaluated according to all objective functions at which the Pareto optimal solutions are obtained. In the manner of parallel strategy, several populations can improve the solution equality and accelerated the convergence to the Pareto optimal solutions.

Step 9 (Selection of the best compromise solution): Multi-objective optimization problem is characterized by multiple of criteria for judging the alternatives, and the decision making process is required to select a possible alternative. Therefore, the first step is to give a reference point (i.e. minimum value). With a given reference point, the decision-making aims to select the alternative that is closest to the reference point (minimum value). Thus, the decision is established based on selecting the minimum distance ($\mathrm{d}_{\min}$) from the reference point. The solution that satisfies the lowest distance is called the best compromise solution. Additionally, in some problems, reference point is defined as the worst alternative (i.e. maximum value). Therefore, the decision-making aims to select the alternative that is farthest from the reference point (maximum value). Thus, the decision is established based on selecting the maximum distance ($\mathrm{d}_{\max}$) from the reference point. These distances reflect the closeness to the best solutions and the farthest from the worst solutions. The computation of the distances is carried out as follows:

$$d_i = \sqrt{\left(\frac{F_{t,i} - F_t^{\min}}{F_t^{\max} - F_t^{\min}}\right)^2 + \left(\frac{E_{t,i} - E_t^{\min}}{E_t^{\max} - E_t^{\min}}\right)^2}, \quad i = 1, 2, \ldots N \qquad (15)$$

$$d'_i = \sqrt{\left(\frac{F_t^{\max} - F_{t,i}}{F_t^{\max} - F_t^{\min}}\right)^2 + \left(\frac{E_t^{\max} - E_{t,i}}{E_t^{\max} - E_t^{\min}}\right)^2}, \quad i = 1, 2, \ldots N \qquad (16)$$

$$d_{\min} = \min\{d_i\}_{i=1}^{N} \qquad (17)$$

$$d_{\max} = \max\{d'_i\}_{i=1}^{N} \qquad (18)$$

Table 1
Combinations of parameter values of PHOA.

Parameters	Factor level			
	1	2	3	4
m	15	20	25	30
$R_{\max}$	0.2	0.33	0.46	0.6
ω	π/10	11π/15	41π/30	2π

Where, d_i andd'_i are the distances from the ith solution to the minimum and maximum values respectively; $\mathrm{d}_{\min}$ and $\mathrm{d}_{\max}$ are the minimum and maximum distances to the best and worst objective function values, respectively. N is number of solutions. Max and min denote to the maximum and minimum values of the variables, respectively.

4. Simulation results

In order to validate the effectiveness of the proposed PHOA, the proposed PHOA is tested for solving the EELD problems with three test systems. These systems are standard IEEE 30 bus system with 283.4 MW load demand [30], ten unit system with 2000 MW load demand, IEEE 118 bus system with 4242 MW load demand. The algorithm is coded in MATLAB 7, running on a computer with an Intel Core I 5 (1.8 GHz) processor and 4GB RAM memory and Windows XP operating system.

4.1. Parameter calibration

In this subsection, the parameters of the proposed PHOA are calibrated. The set of the parameters that affect the algorithm's performance is adjusted by applying the Taguchi method of design of experiment (DOE) [31] through optimizing the cost function of Case 1. PHOA contains five key parameters: population size (m), the radius of the maximum ($R_{\max}$) and angular velocity (ω) while maximum number of iterations (t_{max}) and eye radius (R_0) are fixed. Different combinations of the values are listed in Table 1.

Evaluation of Pareto solutions

Input: $A^{(t)}$ □ ϕ; D □ ϕ ; $\{P_{G,i}\}_{i=1}^{m}$.

$\forall i, j = 1, 2, \ldots, m$.

If $P_{G,i} \prec \forall P_{G,j} \ \wedge i \neq j$ **then**

$D = D \cup \{P_{G,i}\}$

Else

$A^{(t)} = A^{(t)} \cup \{P_{G,i}\}$

End ; $i = i + 1$

output : $A^{(t)}$ (Pareto solutions)

($\prec$ denote worse than in the point of view of optimality)

Updating Pareto solutions

Input: $A^{(t)}, P_G$

If $\nexists P'_G \in A^{(t)} \mid P_G \succ P'_G$ **then**

$A^{(t)} = A^{(t)} \cup P_G$

Else if $\exists P'_G \in A^{(t)} \mid P_G \succ P'_G$ **then**

$A^{(t)} = \{A^{(t)} \cup P_G\} \backslash \{P'_G\}$

Else $A^{(t)} = A^{(t)}$

End

output : $A^{(t)}$

($\succ$ denote better than in the point of view of optimality)

Fig. 2. Evaluation of solutions via Pareto optimality.

For each combination of these values, the PHOA is run 20 times independently, where the average value of cost (Ave. Cost) for Case 1 obtained by the PHOA is recorded. The L_{16} orthogonal design of Taguchi is used in this study and the obtained Ave. Cost values in Table 2.

Using the statistical analysis tool Minitab based on the signal-to-noise ratio (S/N ratio), we can obtain the trend of each factor level, as shown in Fig. 3. According to the DOE test based investigation, the best settings are determined as $m = 30$, $R_{\max} = 0.46$ and $\omega = 11\pi/15$, which will be used for the following testing. In addition, maximum number of iterations (t_{max}) is set to 300 iterations, eye radius (R_0) is set 10^{-5} and initial polar angle ($\varphi_{initial}$) returns a random number form [0,2 π]. Additionally, Table 3 shows the parameter configurations for the comparative algorithms as the authors' suggestions in the literature.

4.2. Studied systems

To assess the efficiency of the proposed PHOA algorithm, it has been applied to EELD problems where the objective functions can be either smooth or non-smooth. The studied cases can be classified under the following three categories:

Case 1: Minimization of the fuel costs only without loss consideration.

Case 2: Minimization of the generation emissions only without loss consideration.

Case 3: All objectives are optimized simultaneously when the transmission losses are ignored. Two sub cases, 3.a and 3.b, are considered. Case 3.a reflects the highest priority of cost function minimization while Case 3.b reflects the highest priority of emission minimization. This case is employed using random generation of weighing factors,

Case 4: minimization of the fuel costs only considering the transmission loss consideration.

Case 5: Minimization of the generation emissions only with loss consideration.

Case 6: All objectives are optimized simultaneously when the transmission losses are considered. In this case, the ultimate goal of this experiment is to analyse the performance of the proposed PHOA that explores best solution or explores the Pareto front when

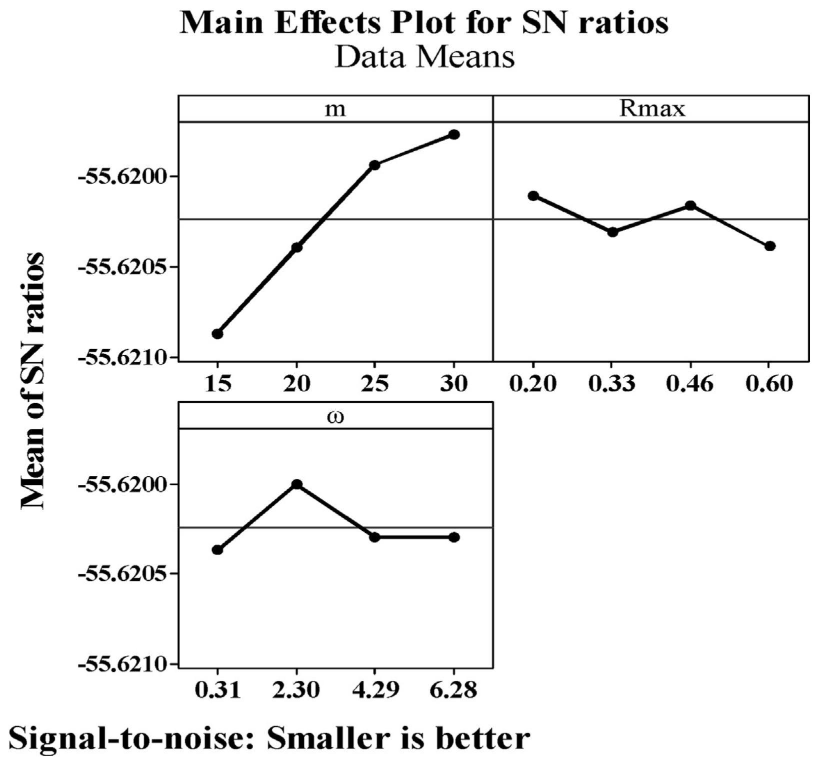

Fig. 3. Fact level trend of PHOA.

Table 2
Orthogonal array and Ave. Cost value.

Experiment number	Factors			Ave. Cost
	m	R_{max}	ω	
1	1	1	1	604.0399
2	1	2	2	603.9791
3	1	3	3	604.0084
4	1	4	4	604.0099
5	2	1	2	603.9248
6	2	2	1	604.0016
7	2	3	4	603.9750
8	2	4	3	604.0026
9	3	1	3	603.9315
10	3	2	4	603.9641
11	3	3	1	603.9220
12	3	4	2	603.9576
13	4	1	4	603.9276
14	4	2	3	603.9346
15	4	3	2	603.9336
16	4	4	1	603.9324

Table 3
Parameter configurations for the comparative algorithms.

Algorithm	Pop. size	Max. generation	Other parameters
NSGA	50	30	Mutation probability = 0.2, Crossover probability = 0.9,
NSGAII	50	30	Mutation probability = 0.2, Crossover probability = 0.9,
MODE	20	30	Scaling factor = 0.75, Crossover factor = 1.
PDE	20	30	Scaling factor = 0.75, Crossover factor = 1.
GSA	50	1000	Gravitational constant (G0) = 100, User specified constant (α) = 20.
ABC_PSO, PSO	15	1000	c1 = c2 = 2; r1, r2 = rand(0,1)
ABC	30	500	Food Number = 15, Limit of trials = 90.
EMOCA	50	30	Situational space NQ = 20, Acceleration constants of the PSO c1 = 2, c2 = 2, Inertia weight factor w = 0.8, Local search control h = 10, Generated local search points NL = 5, Local area parameter σ = 0.2, Range shrinking parameter ε = 0.9.

optimizing all objectives simultaneously. Case 6.a presents the best compromise solution when the d_{min} criterion is considered to achieve the best closeness to the best solution while, Case 6.b is considered for d_{max} criterion to achieve the best farthest from the worst solution. The test systems are considered for lossless and lossy networks. The security constraints are released by preserving the power flow in transmission lines below their maximum limitations.

For further justification of the proposed security indices, additional two cases are proposed to assure the benefits of the proposed security indices as:

Case 7: maximizing the security index from a single generator

Case 8: maximizing the security indices from all generator simultaneously

For Cases 7 and 8, SIG is considered as the primary objective function while other system constraints are preserved within their permissible limits.

4.3. Simulation results for test system 1

This test system involves 41 lines and six generating units with quadratic cost and emission level functions. Fig. 4 shows the single line diagram for IEEE 30-bus test system. Tables 4 and 5 present the generation cost and emission coefficients for IEEE 30–bus test system. To investigate the effectiveness of the proposed algorithm, the system is considered as lossless in Cases 1–3. In case 1, the fuel cost is optimized individually by taking the effect of valve term

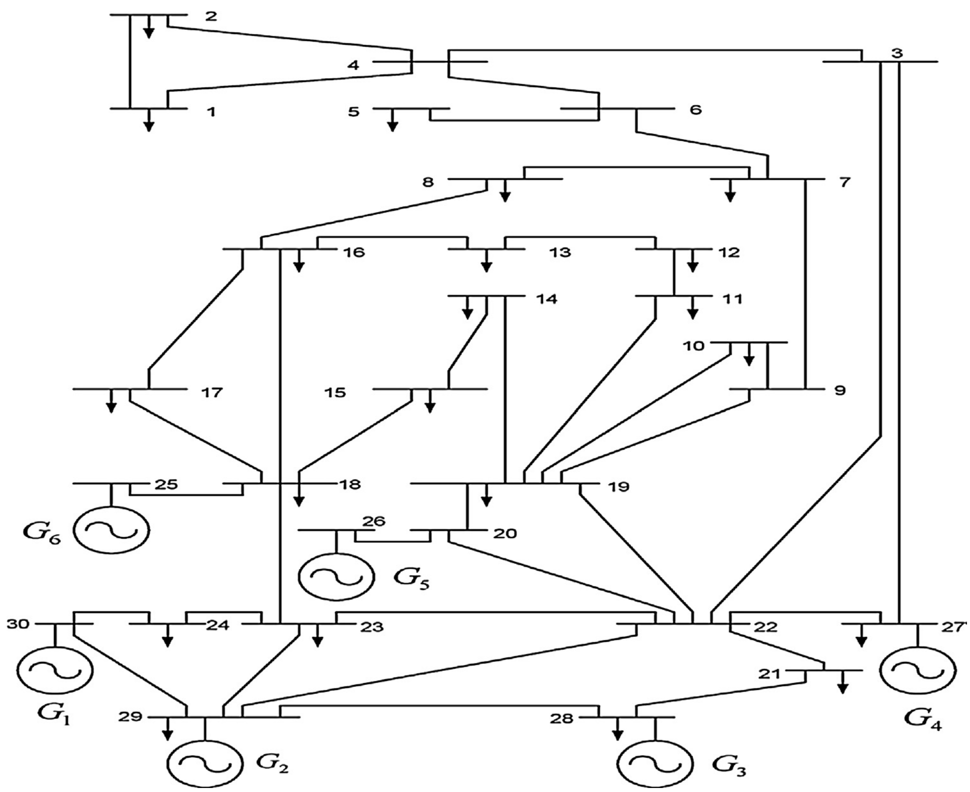

Fig. 4. Single-line diagram of IEEE 30-bus test system [30].

Table 4
Generation limits and cost coefficients.

Generator	Min MW	Max MW	a ($/MW^2)	b ($/MW)	c $	d $	e MW^{-1}
PG_1	0.05	0.5	10	200	100	32.4	0.047
PG_2	0.05	0.6	10	150	120	32.4	0.047
PG_3	0.05	1	20	180	40	32.4	0.047
PG_4	0.05	1.2	10	100	60	23.4	0.063
PG_5	0.05	1	20	180	40	24	0.063
PG_6	0.05	0.6	10	150	100	24	0.063

Table 5
Generator emission coefficients.

Coefficient	PG_1	PG_2	PG_3	PG_4	PG_5	PG_6
α	4.091	2.543	4.258	5.326	4.258	6.131
β	−5.554	−6.047	−5.094	−3.550	−5.094	−5.555
γ	6.490	5.638	4.586	3.380	4.586	5.151
ξ	2.0E-4	5.0E-4	1.0E-6	2.0E-3	1.0E-6	1.0E-5
λ	2.857	3.333	8.000	2.000	8.000	6.667

and without the valve term and the obtained results are shown in Table 6. Table 6 shows the PHOA based solution for EELD problem compared with real code genetic algorithm [32].

From Table 6, the fuel cost equals 603.9163 $/hr when the valve term is considered while the pollutant emission is 0.2218 ton/hr. Additionally, Table 6 outlines the settings of the control variables through optimizing the fuel cost as a single objective using the proposed PHOA. The statistical measures, after 20 independent runs, in terms of the best, mean, worst and the standard deviation obtained. It is also shows that the proposed PHOA is better than the RCGA in terms of the mean value, where the mean value (average value) of the fuel cost with 20 independent runs is 600.1321 while the mean value by RCGA is 623.3722. Further the corresponding value of emission objective is calculated. The obtained value of emission by the proposed PHOA is 0.2218 while the mean value by RCGA is

Table 6
Best Fuel costs-based EELD solution of Case 1.

Variable	RCGA [32]	PHOA	
PG_1(per unit)	0.1727	0.1099	0.1099
PG_2(per unit)	0.3966	0.3027	0.3027
PG_3(per unit)	0.5679	0.5269	0.5269
PG_4(per unit)	1.1079	1.0121	1.0121
PG_5(per unit)	0.2194	0.5227	0.5227
PG_6(per unit)	0.3949	0.3597	0.3597
Mean (Fuel cost) $/h	623.3722	603.9341	**600.1321**[a]
Best (Fuel cost) $/h	615.5482	603.9163	600.1138[a]
Worst (Fuel cost) $/h	634.9026	604.6256	600.8281[a]
Standard-deviation	5.7289	0.0734	0.0738[a]
Emission at best fuel costs	0.2285	0.2218	0.2218[a]
Run time	0.29364	0.8567	0.8567[a]

[a] Without valve effect.

0.2285. Based on the obtained results, it can be concluded that proposed PHOA outperform the RCGA in terms of statistical measures. Furthermore, the convergence behavior of fuel cost is illustrated in Fig. 5. It is obvious from Fig. 5 that with increasing in the number of iterations, convergence is guaranteed by the proposed PHOA, where the cost function is depicted with and without the valve influence.

In case 2, the emission objective is considered as the primary objective function (single objective). The obtained results are presented in Table 7. Table 7 shows that the proposed algorithm is better than the RCGA in terms of statistical measures. In addition, Fig. 6 shows the convergence of the emission function, where the proposed algorithm reaches the best value after 160 iterations. Additionally, Table 5 outlines the outputs of each unit through optimizing the emission objective as a single objective function (the prime objective) using the proposed PHOA .The statistical measures are given in Table 7, where the mean value after 20 runs is 0.1943 with a standard deviation of 1.4697E-4 which is better than the compared algorithm. Further the corresponding value of

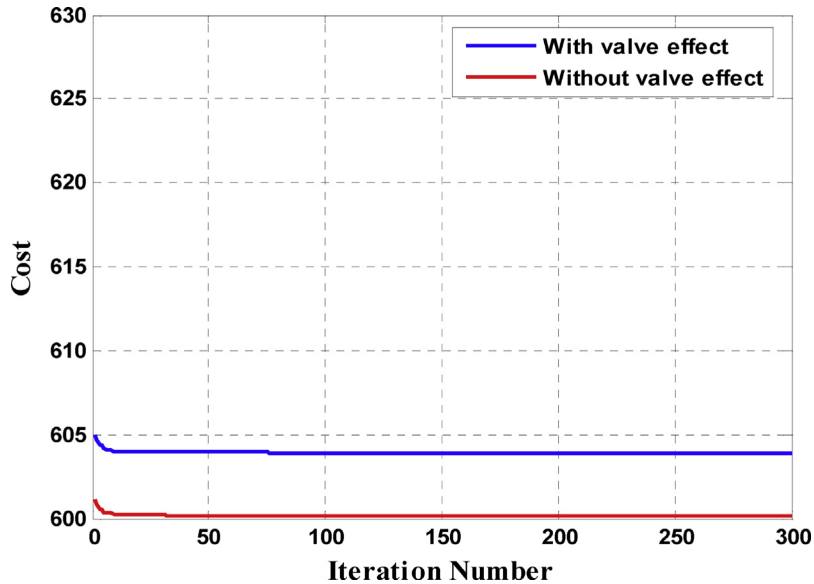

Fig. 5. The convergence of fuel cost for case 1.

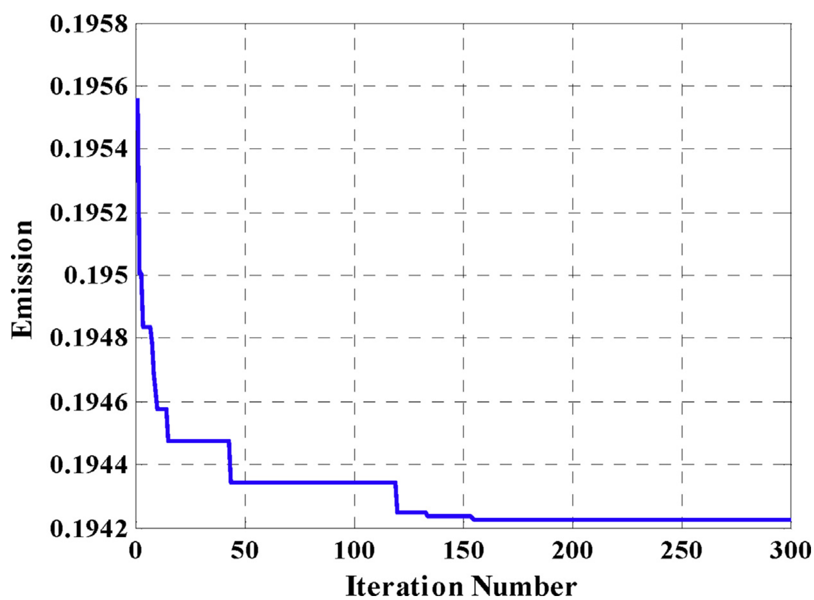

Fig. 6. The convergence of emission for case 2.

Table 7
Best emission EELD solution for Case 2.

Variables	RCGA [32]	PHOA
PG_1(per unit)	0.3969	0.4142
PG_2(per unit)	0.4566	0.4615
PG_3(per unit)	0.6015	0.5398
PG_4(per unit)	0.3853	0.3799
PG_5(per unit)	0.5366	0.5211
PG_6(per unit)	0.5064	0.5175
Mean (Emission) ton/h	0.2018	**0.1943**
Best (Emission)	0.1932	0.1942
Worst (Emission)	0.2194	0.1956
Standard-deviation	0.0056	1.4697E-4
Fuel costs at best emission	691.3766	643.1455, 639.3133*
Run time	0.0502	0.7354

Bold value refers to the primary objective in each case.
* Refers to minimizing the fuel cost without valve point effect.

cost objective is calculated. Based on the results obtained as in Tables 6 and 7, it is concluded that the proposed algorithm achieves better performance in terms of the average value (mean).

In case 3, multi-objective optimization is employed. Therefore, a set of solutions is obtained which is denoted as Pareto optimal solution. By applying the proposed PHOA in Case 3, the Pareto front is obtained and it has been depicted in Fig. 7. The graphical results significantly reveal that the obtained solutions are well-distributed and covered the entire Pareto front of Case 3. The proposed PHOA algorithm is compared with some algorithms such as LP [33], NSGA [34], NPGA [35], SPEA [30] and NSGA-II [36]. Tables 8 and 9 demonstrate the best results for total fuel cost and emission objective for Cases 3.a and 3.b, respectively. Further, Fig. 7 shows the Pareto from using the proposed PHOA for case 3.

In Tables 8 and 9, comparative studies are presented to assess the performance of the proposed algorithm concerning Pareto optimal solutions, superiority and computational time. It can be noted that the proposed algorithm provides a diverse and well-

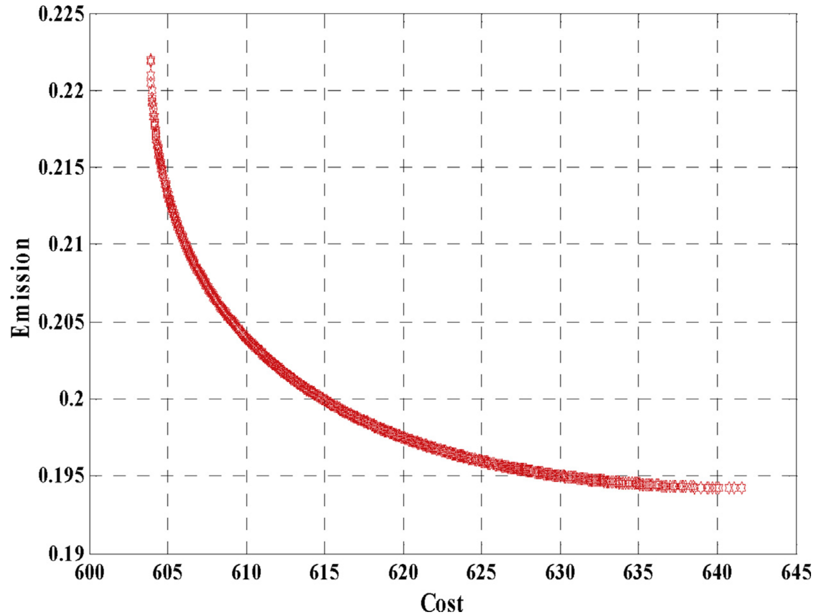

Fig. 7. Pareto front of the proposed algorithm for case 3.

Table 8
Best solutions for cost with six algorithms for Case 3.a.

Variable	LP [33]	NSGA [34]	NPGA [35]	SPEA [30]	NSGA-II [36]	proposed PHOA
PG_1	0.1500	0.1567	0.1080	0.1062	0.1059	0.1132
PG_2	0.3000	0.2870	0.3284	0.2897	0.3177	0.3043
PG_3	0.5500	0.4671	0.5386	0.5289	0.5216	0.5183
PG_4	1.0500	1.0467	1.0067	1.0025	1.0146	1.0167
PG_5	0.4600	0.5037	0.4949	0.5402	0.5159	0.5223
PG_6	0.3500	0.3729	0.3574	0.3664	0.3583	0.3592
Fuel cost	606.314	600.572	600.259	600.150	600.155	603.9190 600.1167*
emission	0.22330	0.22282	0.22116	0.22151	0.22188	0.2220

* Refers to minimizing the fuel cost without valve point effect.

Table 9
Best solutions for emission with six algorithms for Case 3.b.

Variable	LP [33]	NSGA [34]	NPGA [35]	SPEA [30]	NSGA-II [36]	Proposed PHOA
PG_1	0.4000	0.4394	0.4002	0.4116	0.4074	0.4079
PG_2	0.4500	0.4511	0.4474	0.4532	0.4577	0.4567
PG_3	0.5500	0.5105	0.5166	0.5329	0.5389	0.5427
PG_4	0.4000	0.3871	0.3688	0.3832	0.3837	0.3883
PG_5	0.5500	0.5553	0.5751	0.5383	0.5352	0.5352
PG_6	0.5000	0.4905	0.5259	0.5148	0.5110	0.5033
emission	0.194227	0.194356	0.194327	0.194210	0.194204	0.1942
Fuel cost	639.600	639.209	639.180	638.507	638.249	641.5259 637.6941*

* Refers to minimizing the fuel cost without valve point effect.

distributed optimal Pareto front within 10,000 evaluations, and hence is a viable alternative for solving the EELD problem. In addition, Table 8 shows that the best solution for the PHOA is better than for the fuel cost for all other algorithms and Table 9 shows that the proposed PHOA is superior to all other algorithms for both cost and emission, and then it dominates these solutions. On the other hand, the cooperation with the parallelization mechanism helps to save computational time. Finally, the superiority of using the proposed algorithm to handle multi-objective EELD has been empirically approved.

Case 4–6 analyze the system performance when the power losses are considered. The obtained results of the proposed PHOA for minimum cost and emission are shown in Table 10 for cases 4 and 5. Table 10 demonstrates the extreme points on optimizing the fuel cost and emission objectives individually. In addition, the cost and emission are separated and each one is optimized individually, where the convergence behavior of fuel cost and emission objectives are shown in Figs. 8 and 9, respectively. Finally, the Pareto front is depicted in Fig. 10 to demonstrate the overall non-

Table 10
Best solutions for cost and emission optimized individually for cases 4 and 5.

Variable	Best cost (case 4)	Best emission (case 5)
PG_1	0.0992	0.4043
PG_2	0.3228	0.4577
PG_3	0.5295	0.5427
PG_4	1.0122	0.3865
PG_5	0.5110	0.5346
PG_6	0.3622	0.5135
Fuel cost ($/h)	604.6342, 600.8273*	642.9709, 639.1311*
Emission (ton/h)	0.2218	0.1942
Losses (MW)	0.0029	0.0053

* Refers to minimizing the fuel cost without valve point effect.

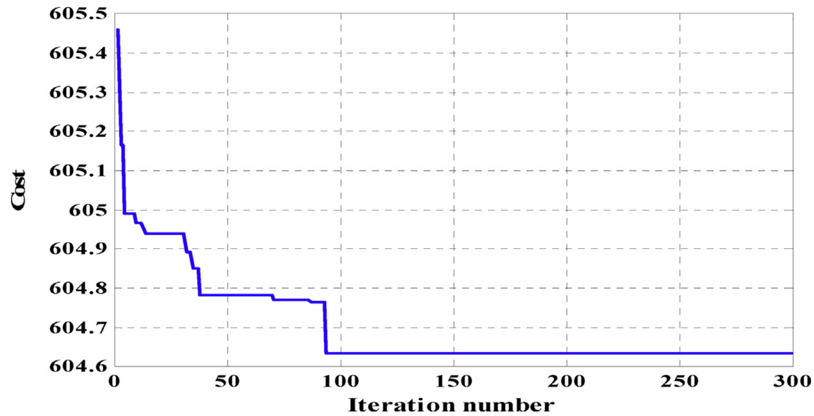

Fig. 8. The convergence of cost for case 4.

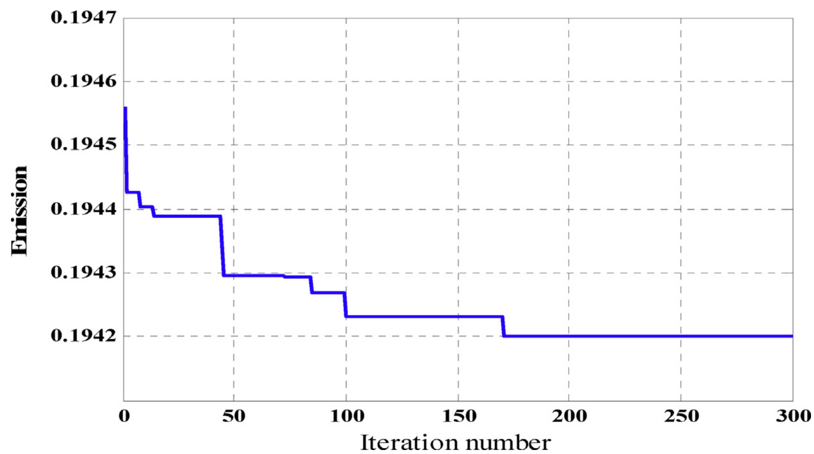

Fig. 9. The convergence of emission for case 5.

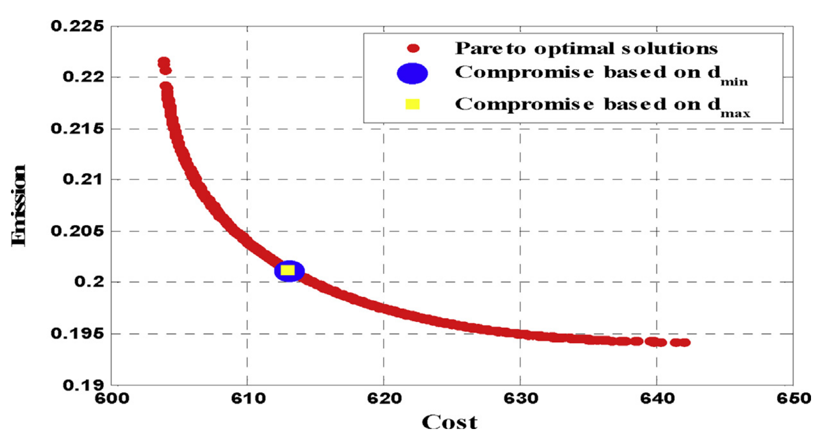

Fig. 10. Pareto front in case 6 of the proposed algorithm for test system1.

dominated solutions that helps the operator to take a right decision about the suitable operation point.

Table 11 presents the best compromise solutions, Case 6, that are obtained based on minimum and maximum distances and also these solutions are showed on the Pareto front as depicted in Fig. 10. The obtained best compromise solutions in this case are 613.1449 $/hr and 0.2011 ton/hr based on minimum distance and 612.9922 $/hr and 0.2012 ton/hr based on maximum distance. To assess the security analysis of the IEEE 30-bus test system, Table 12 present the power flow solution for cases 1–6. The power flows in transmission lines are preserved within their permissible limits.

4.4. Simulation results for test system 2

The second test system has10 units with non-smooth fuel cost and emission issues to verify the proficiency of proposed PHOA. Table 13 shows the generation cost and emission coefficients for 10 unit test system with 2000 MW for the load demand. The fuel cost and emission are optimized individually, Case 1 and 2. Table 14 shows the scheduling of control variables of these two cases and the corresponding statistical measures (i.e., best, mean, worst and standard deviation). Further the convergence performance of fuel cost and emission objectives are shown in Figs. 11 and 12.

Table 11
Best compromise solutions for case 6.

Variable	d_{min}	d_{max}
PG1	0.2538	0.2538
PG2	0.3743	0.3743
PG3	0.5436	0.5367
PG4	0.6992	0.7038
PG5	0.5386	0.5386
PG6	0.4245	0.4268
Fuel cost	613.1449	612.9922
Emission	0.2011	0.2012
d_{min}	0.2469	0.2470
d_{max}	0.7532	**0.7532**

Bold value refers to the primary objective in each case.

Table 15 demonstrates the best compromise solutions for case 3 where the non-dominated solutions are depicted in Fig. 13. By considering the non-dominated solutions, the best cost and the corresponding emission are recorded. Also the best emission and the corresponding cost are obtained from the non-dominated set. Table 16 shows the best solutions for cost and emission when they optimized separately, Cases 4 and 5. Thestatistical measures of these two cases are reported also. The convergence of the cost and emission against iterations are depicted in Figs. 14 and 15, respectively.

Fig. 16 shows the set of non-dominated solutions, where we can see that the proposed algorithm gives two fronts of the non-dominated solution (i.e., Best front and worst front). According to

Table 12
Power flow in transmission lines in cases 1–6.

		PF_{max}	Case 1	Case 2	Case 3.a	Case 3.b	Case 4	Case 5	Case 6.a	Case 6.b
1	2	130	50.95299	35.62092	50.74985	35.88588	52.35634	36.47465	44.08747	44.0736
1	3	130	28.95654	17.15114	28.79573	17.40544	29.08676	17.69737	23.54621	23.53901
2	4	65	21.4042	11.76821	21.26891	11.98671	21.10735	12.13788	16.78734	16.78186
3	4	130	31.15102	19.43382	30.99126	19.68673	31.28026	19.97997	25.80269	25.79576
2	5	130	9.557817	6.714774	9.511904	6.712426	9.467433	6.70185	7.505739	7.503528
2	6	65	26.3864	13.29594	26.24532	13.55124	26.12381	13.6613	19.81098	19.80296
4	6	90	27.92829	14.779	27.86698	14.68902	27.99285	14.71929	18.89817	18.89496
5	7	70	11.34204	8.654195	11.30147	8.664538	11.261	8.66025	9.493783	9.49175
6	7	130	27.40408	20.81602	27.33455	20.97256	27.28289	21.05319	24.39736	24.3938
6	8	35	29.59043	32.83524	29.58303	32.75276	29.59453	32.76192	30.74548	30.7262
6	9	65	21.7336	19.20152	21.41205	19.46432	21.59792	19.63283	21.15896	20.97656
6	10	32	12.4192	10.9723	12.23546	11.12247	12.34167	11.21876	12.09083	11.98661
9	10	65	21.66241	19.15975	21.34431	19.41985	21.52834	19.58667	21.09014	20.90951
4	12	65	33.28729	35.16369	33.05855	35.05603	33.04347	35.64344	34.49124	34.50494
12	13	65	39.98222	53.5246	39.91368	52.25296	40.13707	53.20654	45.35556	45.55032
12	14	32	3.934938	3.465574	3.927319	3.46252	3.875097	3.462076	3.642309	3.637324
12	15	32	14.82244	6.933097	14.7491	7.780457	14.37171	7.575471	11.9307	11.84973
12	16	32	4.554755	8.770076	4.624634	8.499226	4.539728	8.687365	6.262329	6.37034
14	15	16	6.50585	4.462695	6.486449	4.685262	6.392758	4.631512	5.761243	5.739709
16	17	16	1.155947	5.570755	1.245402	5.301287	1.109825	5.495004	2.979359	3.101002
15	18	16	10.47299	11.98136	10.51592	11.96673	10.36526	12.05996	11.19153	11.25575
18	19	16	7.188122	8.714168	7.233861	8.70194	7.074422	8.796152	7.918238	7.985061
19	20	32	4.922243	4.907687	4.927622	4.923241	4.917045	4.940385	4.864433	4.875995
10	20	32	6.91801	6.465206	6.911368	6.484362	6.941548	6.470403	6.667747	6.659298
10	17	32	10.49446	8.818888	10.45789	8.881184	10.48828	8.853879	9.567837	9.532097
10	21	35	32.3435	26.89125	31.97841	27.28062	32.28349	27.28794	30.37975	30.11889
10	22	32	21.85096	18.68384	21.6379	18.91083	21.81425	18.91614	20.70811	20.55643
21	22	65	52.99168	47.7756	52.6381	48.15398	52.9237	48.1666	51.10616	50.85606
15	23	65	38.18827	29.74465	38.14024	30.81695	37.51552	30.65038	35.27978	35.24242
22	24	32	26.9554	13.05499	27.24128	13.51161	26.55611	13.49979	20.15304	20.42193
23	24	32	9.990748	18.94888	10.00335	19.29225	9.50048	19.40771	14.80756	14.85021
24	25	32	21.27391	2.346497	21.5525	2.202011	21.40303	2.330809	9.295945	9.52769
25	26	16	4.265922	4.265709	4.265931	4.265706	4.265928	4.265707	4.26567	4.265672
25	27	32	23.66633	4.097738	23.94184	4.081037	23.79524	4.091666	11.97811	12.19735
28	27	70	64.96014	23.24938	65.15878	23.94753	64.84279	23.88063	44.63241	44.88245
27	29	16	6.399435	6.399435	6.399435	6.399435	6.399435	6.399435	6.399435	6.399435
27	30	16	7.316602	7.316602	7.316602	7.316602	7.316602	7.316602	7.316602	7.316602
29	30	16	3.734281	3.734281	3.734281	3.734281	3.734281	3.734281	3.734281	3.734281
8	28	32	17.40197	10.31789	17.43723	10.42951	17.38124	10.41801	13.86025	13.90301
6	28	65	47.80042	14.23741	47.9595	14.80521	47.70632	14.75185	31.49687	31.69769
SIF			15.9485	20.1016	15.9668	19.9629	16.0348	19.8934	15.6039	15.6265
SIG			1.4908	1.0098	1.4860	0.9996	1.4981	0.9990	3.3219	3.3228

Table 13
characteristics of the ten unit generator.

Unit	α $/h	β $/MWh	γ $/MW2h	e ($/h)	f (rad/MW)	min (MW)	max (MW)	a (Ib/MW^{2}h)	b (Ib/MWh)	c (Ib/h)	η (Ib/h)	δ (1/MW)
P1	0.12951	40.5407	1000.403	33	0.0174	10	55	0.04702	−3.9864	360.0012	0.25475	0.01234
P2	0.10908	39.5804	950.606	25	0.0178	20	80	0.04652	−3.9524	350.0056	0.25475	0.01234
P3	0.12511	36.5104	900.705	32	0.0162	47	120	0.04652	−3.9023	330.0056	0.25163	0.01215
P4	0.12111	39.5104	800.705	30	0.0168	20	130	0.04652	−3.9023	330.0056	0.25163	0.01215
P5	0.15247	38.539	756.799	30	0.0148	50	160	0.0042	0.3277	13.8593	0.2497	0.012
P6	0.10587	46.1592	451.325	20	0.0163	70	240	0.0042	0.3277	13.8593	0.2497	0.012
P7	0.03546	38.3055	1243.531	20	0.0152	60	300	0.0068	−0.5455	40.2669	0.248	0.0129
P8	0.02803	40.3965	1049.998	30	0.0128	70	340	0.0068	−0.5455	40.2669	0.2499	0.01203
P9	0.02111	36.3278	1658.569	60	0.0136	135	470	0.0046	−0.5112	42.8955	0.2547	0.01234
P10	0.01799	38.2704	1356.659	40	0.0141	150	470	0.0046	−0.5112	42.8955	0.2547	0.01234

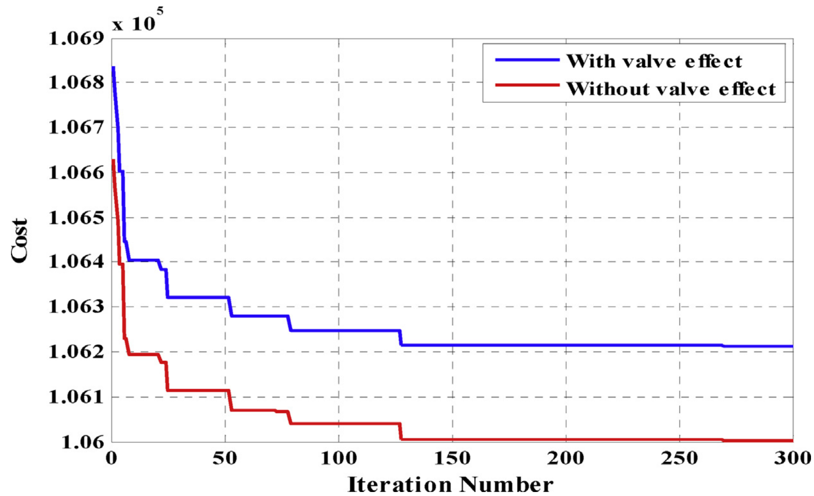

Fig. 11. The convergence of cost (case 1).

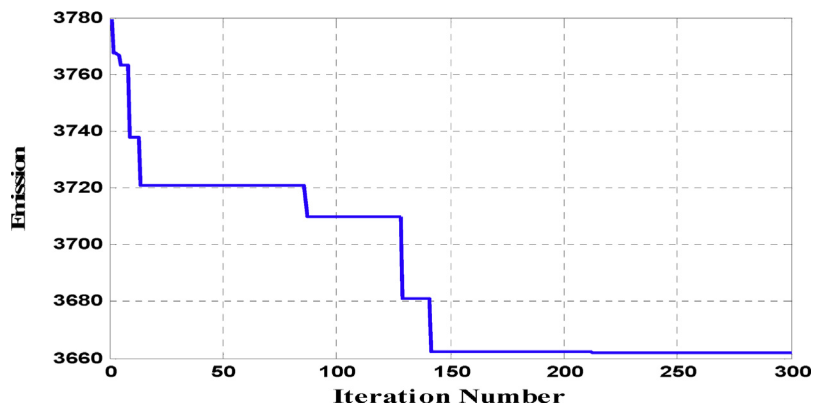

Fig. 12. The convergence of emission (case 2).

Table 14
Best solutions for cost and emission for cases 1 and 2.

Unit	Case 1	Unit	Case 2
PG_1	55.0000	PG_1	55
PG_2	80.0000	PG_2	68.0479
PG_3	98.2792	PG_3	73.4161
PG_4	73.2943	PG_4	70.4446
PG_5	70.2278	PG_5	160.0000
PG_6	72.7025	PG_6	240.0000
PG_7	270.4959	PG_7	275.2700
PG_8	340.0000	PG_8	289.1154
PG_9	470.0000	PG_9	371.9836
PG_{10}	470.0000	PG_{10}	396.7219
Best (Fuel cost) $/h	1.0621E5	Best Emission	3661.8815
Mean (Fuel cost) $/h	1.0621E5	Mean (Fuel cost) $/h	3661.8815
Worst (Fuel cost) $/h	1.0621E5	Worst	3661.8815
Standard-deviation	1.7822E-11	Standard-deviation	0.0000
Emission at best fuel costs ton/h	4285.4729	Cost at best Emission	1.1182E+5 1.1167E+5
Run time	2.9855	Run time	2.2581

Table 15
Best solution for cases 3.a and 3.b.

Unit	Best Cost	Best Emission
PG_1	45.1990	54.3594
PG_2	75.5307	76.8520
PG_3	87.1554	69.8664
PG_4	77.8913	83.2299
PG_5	94.7194	150.7724
PG_6	107.5802	240.0000
PG_7	300.0000	300.0000
PG_8	303.9946	237.3870
PG_9	437.9292	418.0927
PG_{10}	470.0000	369.4403
Fuel cost	**1.0672E+5**	4.1025E+3
Emission	1.1170eE+5 1.1151E+5[a]	**3.6993E+3**

Bold value refers to the primary objective in each case.
[a] Without valve term.

the dominance concept we found that the best front dominates the worst front. Many algorithms in the literature give the solutions around the worst front, and consequently the proposed algorithm is effective and robust than the other algorithms. Table 17 demonstrates the best compromise solutions for the two fronts. Based on the obtained results as recorded in Table 17, it is noted that the solutions of two fronts are obtained namely, Best Front and Worst Front. For each front the generation units of minimizing the cost are recorded and the corresponding emission value is computed. Also the generation units of minimizing the emission are listed and the corresponding cost value is calculated. In this sense, the most appropriate solution is 1.1196E+5 and 3824.6645 for cost and emission respectively. From optimization point of view this solution dominates the solutions of other algorithms. While comparisons, the solutions of the comparative algorithms are ranged from 1.1342E+5 to 1.13539E+5 for cost value and from 4109.1 to 4130.2 for emission value (See Table 18). Thus, it is concluded that the solutions of the comparative algorithms are close to the worst front.

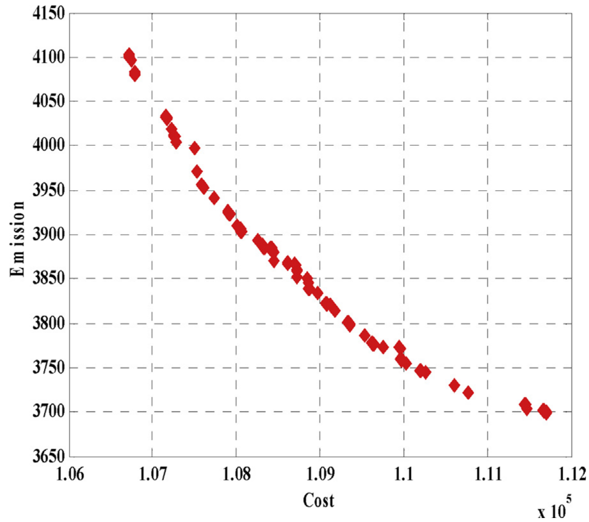

Fig. 13. The set of non-dominated solutions for Case 3.

Table 16
Best solutions for cost and emission optimized individually for case 4 and 5.

Unit	Case 4	Unit	Case 5
PG_1	34.2892	PG_1	55
PG_2	79.5228	PG_2	65.0908
PG_3	116.4348	PG_3	87.7902
PG_4	105.4548	PG_4	83.7240
PG_5	110.0841	PG_5	160
PG_6	108.3113	PG_6	238.7892
PG_7	285.1402	PG_7	258.0059
PG_8	319.0626	PG_8	269.7862
PG_9	457.6793	PG_9	357.8647
PG_{10}	470.0000	PG_{10}	470
Best (Fuel cost) $/h	1.1213E+5	Best Emission	3888.7281
Mean (Fuel cost) $/h	1.1213E+5	Mean (Fuel cost) $/h	3888.7281
Worst (Fuel cost) $/h	1.1213E+5	Worst	3888.7281
Standard-deviation	0.0000	Standard-deviation	0.0000
Emission at best fuel costs ton/h	4520	Cost at best Emission	1.1432E+5 1.1413E+5
losses	85.9792		46.0514
Run time	2.0121	Run time	2.3480

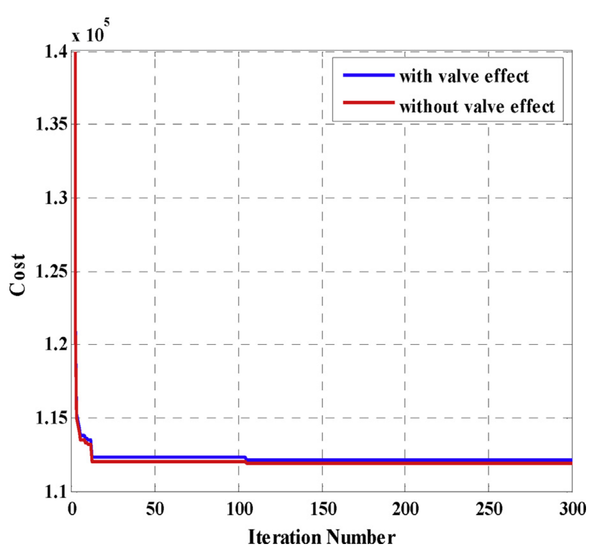

Fig. 14. The convergence of cost for case 4.

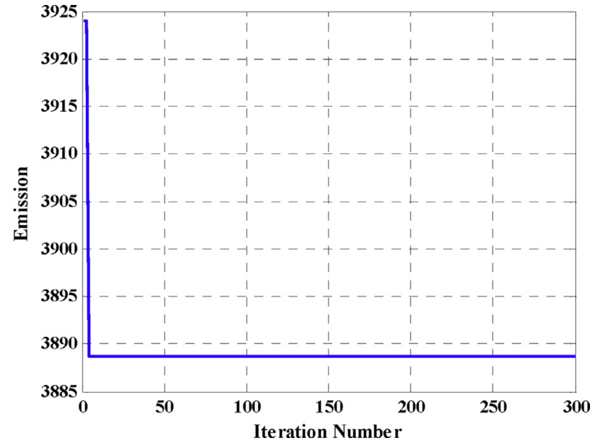

Fig. 15. The convergence of emission for case 5.

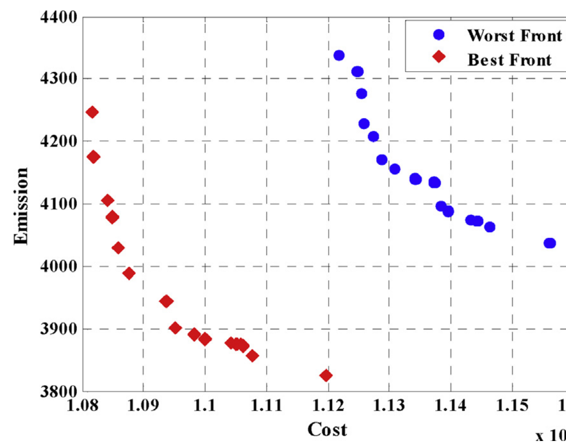

Fig. 16. Best and worst Pareto solutions for case 6.

Table 17
Best solution for optimizing cost and emission simultaneously for case 6.

Unit	Best Front		Worst Front	
	Best Cost	Best Emission	Best Cost	Best Emission
PG_1	26.4173	54.9763	40.0295	54.9806
PG_2	60.3172	66.2297	66.3583	68.7189
PG_3	103.3296	86.9187	106.7688	92.8987
PG_4	91.1715	88.4442	92.3418	95.9560
PG_5	83.4825	158.4767	141.5731	158.7521
PG_6	36.1716	226.0765	112.9903	228.5934
PG_7	283.5391	215.2617	286.8813	230.6529
PG_8	333.7698	258.0727	310.2724	272.9146
PG_9	426.0849	389.9519	450.6735	404.4218
PG_{10}	470.0000	469.8751	470.0000	470.0000
Fuel cost	**1.0815E+5**	1.1196E+5	**1.1218E+5**	1.1561E+5
Emission	4247.5800	**3824.6645**	4337.8091	**4036.5608**
Losses (MW)	14.2840	14.2840	77.8893	77.8893

Bold value refers to the primary objective in each case.

Table 18 demonstrates the comparisons between the proposed algorithms with different algorithms [36,38–40]. Results show that the proposed PHOA outperforms and outlasts other algorithms in obtaining better cost and better emission than the other algorithms. The simulation results indicate that the PHOA has effective performance in realizing the ability of obtaining the global solution. In addition, the convergence characteristics and better performance in solution's quality than other algorithms proposed in the literature have been proved. So, it is believed that the proposed PHOA

Table 18
Comparisons between the proposed PHOA with different algorithms for10-unit system at demand of 2000 MW (Case 6).

Outputs	MODE[36]	NSGAII[36]	PDE[36]	SPEA-2[36]	GSA[38]	ABC_PSO[39]	EMOCA[40]	PHOA
PG_1(MW)	54.9487	51.9515	54.9853	52.9761	54.9992	55	55	54.9763
PG_2 (MW)	74.5821	67.2584	79.3803	72.813	79.9586	80	80	66.2297
PG_3(MW)	79.4294	73.6879	83.9842	78.1128	79.4341	81.14	83.5594	86.9187
PG_4(MW)	80.6875	91.3554	86.5942	83.6088	85.0000	84.216	84.6031	88.4442
PG_5(MW)	136.8551	134.0522	144.4386	137.2432	142.1063	138.3377	146.5632	158.4767
PG_6(MW)	172.6393	174.9504	165.7756	172.9188	166.5670	167.5086	169.2481	226.0765
PG_7(MW)	283.8233	289.4350	283.2122	287.2023	292.8749	296.8338	300	215.2617
PG_8(MW)	316.3407	314.0556	312.7709	326.4023	313.2387	311.5824	317.3496	258.0727
PG_9(MW)	448.5923	455.6978	440.1135	448.8814	441.1775	420.3363	412.9183	389.9519
PG_{10}(MW)	436.4287	431.8054	432.6783	423.9025	428.6306	449.1598	434.3133	469.8751
Fuel cost *105$	1.13484	1.13539	1.1351	1.1352	1.1349	1.1342	1.13445	1.1196E+5
Emission(Ib)	4124.9	4130.2	4111.4	4109.1	4111.4	4120.1	4113.98	3824.6645
Losses(MW)	84.33	84.25	83.9	84.1	83.9869	84.1736	83.56	14.2840
CPU(s)	3.82	6.02	4.23	7.53	NA	NA	2.90	2.1201

Table 19
Optimal settings of generation outputs and the related security indices of IEEE 118-bus test system for case 1.

Control variables	Proposed PHOA	SI_G	Control variables	Proposed PHOA	SI_G
PG_1 (MW)	63.81	0.36	PG_{65} (MW)	150.31	0.69
PG_4 (MW)	23.66	0.76	PG_{66} (MW)	315.74	0.36
PG_6 (MW)	23.11	0.77	PG_{69} (MW)	281.08	0.65
PG_8 (MW)	27.31	0.73	PG_{70} (MW)	56.71	0.43
PG_{10} (MW)	319.25	0.42	PG_{72} (MW)	38.12	0.62
PG_{12} (MW)	61.72	0.67	PG_{73} (MW)	39.42	0.61
PG_{15} (MW)	27.99	0.72	PG_{74} (MW)	45.02	0.55
PG_{18} (MW)	46.61	0.53	PG_{76} (MW)	23.66	0.76
PG_{19} (MW)	25.87	0.74	PG_{77} (MW)	30.74	0.69
PG_{24} (MW)	52.56	0.47	PG_{80} (MW)	339.36	0.41
PG_{25} (MW)	107.16	0.67	PG_{85} (MW)	23.09	0.77
PG_{26} (MW)	280.27	0.32	PG_{87}(MW)	22.89	0.78
PG_{27} (MW)	40.33	0.60	PG_{89} (MW)	279.94	0.60
PG_{31} (MW)	29.88	0.72	PG_{90} (MW)	47.99	0.52
PG_{32} (MW)	23.96	0.76	PG_{91} (MW)	30.55	0.69
PG_{34} (MW)	36.11	0.64	PG_{92} (MW)	30.92	0.69
PG_{36} (MW)	43.85	0.56	PG_{99} (MW)	22.34	0.78
PG_{40} (MW)	22.19	0.78	PG_{100} (MW)	177.04	0.50
PG_{42} (MW)	33.76	0.66	PG_{103} (MW)	43.57	0.69
PG_{46} (MW)	32.77	0.72	PG_{104} (MW)	28.00	0.72
PG_{49} (MW)	167.97	0.45	PG_{105} (MW)	26.95	0.73
PG_{54} (MW)	47.75	0.68	PG_{107} (MW)	48.01	0.52
PG_{55} (MW)	24.39	0.76	PG_{110} (MW)	27.38	0.73
PG_{56} (MW)	23.04	0.77	PG_{111} (MW)	31.33	0.77
PG_{59} (MW)	98.96	0.61	PG_{112} (MW)	57.91	0.42
PG_{61} (MW)	161.50	0.38	PG_{113} (MW)	47.97	0.52
PG_{62} (MW)	30.17	0.70	PG_{116} (MW)	100.00	0.00
COST = 134630.3845 $/h		Total generator security index = 33.15		PD = 4242 MW	

in this study is capable of effectively and quickly solving several optimization problems in power systems.

4.5. Simulation results for test system 3

The third test system in this paper is the IEEE 118-bus test system. The total load demand is 4242.0 MW. The number of committed generators is 54. The number of connected transmission lines is 177 line and 9 transformers. The cost coefficients of the IEEE 118-bus test system are taken from MATPOWER package [41].

Tables 19 and 20 present the proposed solution settings for Case 1. In Table 19, the optimal settings of control variables (54 generators) are recorded and the corresponding security index from generators. It was found the total generation costs equals 134630.3845 $/h for total load of 4242 MW. The lowest security index is appeared to PG_{116}. The generator at bus 116 is operated at its maximum limit so its security index equals to zero. In the other side, the highest security index is appeared with generator at bus 40 (78%). In Table 20, the power flows in light loading transmission lines with the highest security indices. The lower security indices refer to that the closeness to congestion condition.

4.6. Security indices justification

In this section, Table 21 and Fig. 17 show the further justification of the proposed security indices benefits on the economic emission dispatch problem. In Case 7, the SIG is maximized from each generator individually. While in Case 8, the SIG of all generators are optimized simultaneously. For describing the obtained results, Cases 7.a-7.f are presented to maximize the SIG from generators 1–6, respectively. Case 7.a has the lowest power generator' outputs from the Gen. # 1 (0.05 p. u.), the SIG is maximized from generator 1 only. The corresponding SIG and SIF levels are 3.4458 and 17.4812 respectively. In this case the fuel costs and emission levels are 670.2157 $/h and 0.2136 ton/hr. In Case 7.b, the lowest power generator' outputs from the Gen. # 2 (0.05 p. u.). The corresponding SIG and SIF levels are 3.328 and 18.3453 respectively. In this case the fuel costs and emission levels are 629.3589 $/hr and 0.2239 ton/hr. The highest SIG level is obtained from the largest generator Case 7.d (from generator 4). For Case 8.a, the SIGs from all generators are maximized simultaneously. The SIG and SIF equal 4.0357 and 16.2556, respectively. When the considered objective aims to minimize the SIG level from all generators simultaneously,

Table 20
Power flows of in light loading transmission lines and the related security indices of test system 3 for case 1.

line #	Max Limit	Power flow	SI^F	line #	Max limit MVA	Power flow	SI^F
3	500	75.98	0.8480	112	175	28.12	0.8393
4	175	44.87	0.7436	115	175	37.35	0.7866
5	175	65.80	0.6240	116	500	62.96	0.8741
6	175	36.34	0.7923	119	175	66.94	0.6175
11	175	65.04	0.6283	120	175	20.54	0.8827
21	500	94.51	0.8110	121	175	64.18	0.6333
25	175	5.94	0.9661	124	500	36.76	0.9265
26	175	19.35	0.8894	128	200	29.34	0.8533
29	175	48.25	0.7243	129	200	15.47	0.9226
34	175	29.26	0.8328	132	175	21.68	0.8761
35	175	13.34	0.9237	135	175	11.59	0.9338
43	175	10.59	0.9395	139	500	61.08	0.8778
44	175	28.80	0.8354	140	175	26.21	0.8502
45	175	23.82	0.8639	144	175	25.14	0.8563
47	175	22.41	0.8720	145	175	20.81	0.8811
50	500	71.33	0.8573	147	175	39.93	0.7718
51	500	203.18	0.5936	148	175	30.54	0.8255
59	175	11.79	0.9326	149	175	14.96	0.9145
60	175	26.66	0.8476	154	175	11.47	0.9345
63	175	18.59	0.8938	156	175	21.20	0.8788
64	175	10.73	0.9387	157	175	24.18	0.8618
65	175	12.16	0.9305	158	175	15.39	0.9121
68	175	34.04	0.8055	159	175	17.21	0.9017
78	175	11.61	0.9337	161	175	14.34	0.9180
81	175	36.49	0.7915	163	500	13.45	0.9731
94	500	168.36	0.6633	165	175	22.76	0.8699
97	500	183.72	0.6326	166	175	25.99	0.8515
110	175	60.00	0.6572	168	175	17.27	0.9013

Table 21
Generation security indices as objective functions of IEEE 30 buses for Cases 7 and 8.

Variable	Case 7						Case 8	
	Case 7.a	Case 7.b	Case 7.c	Case 7.d	Case 7.e	Case 7.f	Case 8.a	Case 8.b
P_{G1} (p. u.)	0.05	0.4660	0.2094	0.4812	0.2736	0.3870	0.5	0.05
P_{G2}	0.5796	0.05	0.6	0.3261	0.3613	0.4761	0.6	0.05
P_{G3}	0.8176	0.2093	0.05	0.7625	0.8411	0.5309	0.2694	0.6316
P_{G4}	0.09078	0.8645	1.0959	0.05	1.0728	0.9236	0.0502	1.1969
P_{G5}	0.7490	0.7716	0.3022	0.9158	0.05	0.4664	0.8144	0.8556
P_{G6}	0.5469	0.4726	0.5765	0.2984	0.2352	0.05	0.6	0.05
Cost ($/h)	670.2157	629.3589	627.9742	678.7878	618.0055	621.7745	693.8880	624.3551
Emission (ton/h)	0.2136	0.2239	0.2369	0.2131	0.2391	0.2196	0.2086	0.2638
SIF	17.4812	18.3453	15.8952	16.9417	16.6239	15.0479	16.2556	21.9908
SIG	3.4458	3.3283	3.4865	3.5732	3.1218	3.2278	4.0357	2.4574

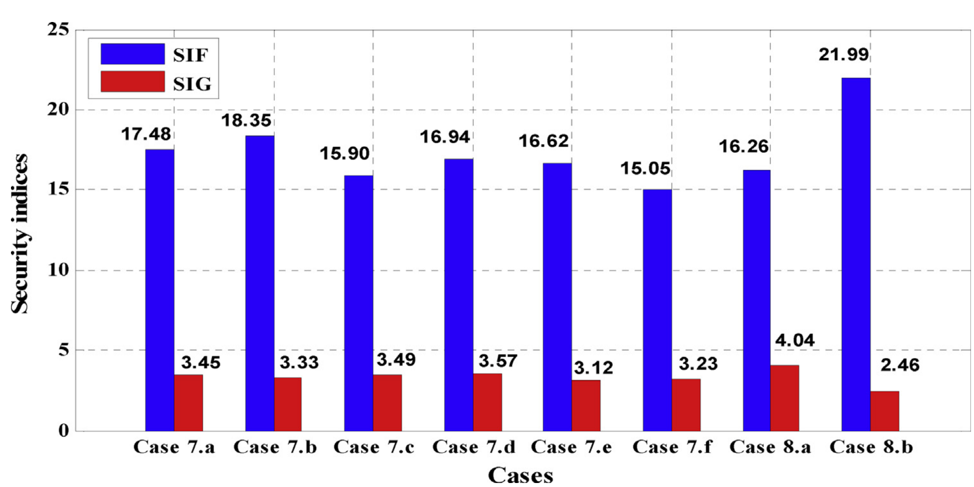

Fig. 17. Security indices from generators and transmission lines for cases 7 and 8.

Case 8.b has the lowest SIGs level from all generators, which equals 2.4574. it is noticed that, in Case 8.b the cost has its minimum level (624.3551 \$/h) as most of the generated power is assigned to the most economical generator (Gen. 4)

5. Conclusions

This paper is concerned with solving the nonlinear constrained economic emission dispatch problem. The main aim is to enhance the operation of power plants and to help for building up effective generating management plans. This paper investigated a new improved search algorithm based on the parallel hurricane search optimization for non-smooth constrained economic emission dispatch problems. Experiments were conducted on IEEE 30-bus, 10-unit and IEEE 118-bus test systems. The results are compared with other optimization techniques those reported in the literature. The obtained results demonstrate the superiority of the proposed PHOA compared with other competitive optimization techniques in the literature. The comparisons confirm the robustness and the superiority of the proposed PHOA algorithm over the other methods in terms of solution quality. So, it can be considered as a promising alternative algorithm for solving problems in practical large-scale power systems. The main characteristics of the proposed algorithm are simplified as follows:

a) The proposed PHOA has been effectively applied to solve the single and multi-objective EELD problems.
b) The mechanism of parallelization for the proposed algorithm has some merits over other algorithms reported such as simplicity of the approach, low computational time.
c) The Pareto front solutions have satisfactory diversity characteristics and well distributed in the search space. This is useful in getting a reasonable freedom in taking the best operating point from the available finite set of alternatives.
d) The proposed PHOA is efficient for solving convex and non convex multi-objective optimization problems where multiple Pareto-optimal solutions can be obtained in one simulation run.
e) Two security indices are proposed to measure the closeness of the operating condition to the boundary limits of generation units and the closeness to congestion limit of transmission lines.
f) Different security operating modes are proposed according to different security levels.
g) Best compromise solution for multiobjective cases are obtained according to minimum and maximum distances from the best and worst solutions, respectively.
h) The obtained Pareto solutions reflect the closeness to the best solution and the extreme from the worst solution therefore, the search space is enhanced.
i) The capability of the proposed PHOA is achieved for lossless and lossy networks at acceptable economical and emissions levels.

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