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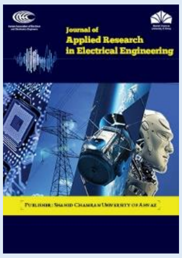

Research Article

Multi-Objective Optimal Power Flow Based Combined Non-Convex Economic Dispatch with Valve-Point Effects and Emission Using Gravitation Search Algorithm

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Abstract: This paper presents a solution of Optimal Power Flow (OPF) problem Combined Economic Dispatch with Valve-Point Effect and Emission Index (EI) in electrical power networks using the physics-inspired optimization method, which is the Gravitational Search Algorithm (GSA). Our main goal is to minimize the objective function necessary for a best balance between the energy production and its consumption which is presented in a nonlinear function, taking into account of equality and of inequality constraints. The objective is to minimize the total cost of active generations, the active power losses and the emission index. GSA method have been examined and tested on the standard IEEE 30-bus test system with various objective functions. The simulation results of used methods have been compared and validated with those reported in the recent literature. The results are promising and show the effectiveness and robustness of used method. It should be mentioned that from the base case, the cost generation, the active power losses and the emission index are significantly reduced to 823 (\$/h), 6.038 (MW) and 0.227 (ton/h), which are considered 5.85%, 61.61%, and 44.63%, respectively.

Keywords: Optimization; optimal power flow; emission index; gravitational search algorithm.

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1. Introduction

Electric power plants that operate on fossil-fuels are among the most prominent sources of air pollution and contribute to causing great harm to the environment due to the burning of raw fuels such as coal, gas, and oil [1].

Electric power systems engineering has the longest history of development compared to the various fields of engineering. In electrical supply systems, there are a wide range of problems involved in system optimization [2]. Among these problems, power system scheduling is one of the most important in system operation, control, and management.

Power plants Coal-fired contribute a large quantity of polluting gases to the Atmosphere, as they produce large amounts of Carbon oxides CO_2, and some toxic and dangerous gases such as emissions of Sulfur oxides SOx, and Nitrogen oxides, NOx [1]-[2].

After implementation of the 1990 amendment to the United States Clean Air Act and increasing public awareness of environmental protection and public utilities, electricity production companies were obligated to adapt their designs and making strategy to reduced pollution rate and emissions of electric power plants [2]-[3]. Several efforts and strategies have been proposed and devoted to reduce atmospheric of pollutant emissions [2].

The OPF problem has a long history in its development for more than 60 years. Since the OPF problem was first discussed by Carpenter in 1962, then formulated by Dommel and Tinney in 1968 [4]. The OPF are non-linear and non-convex very constrained optimization problems.

The ED problem is one of the concerns of statistical optimization in the planning, control and operation of electric power; he is a sub-problem of OPF [5].

The OPF is an important criterion in today's power system operation and control due to scarcity of energy resources, increasing power generation cost and ever-growing demand for electric energy [2].

The main purpose of an OPF is to determine the optimal operating state of a power system and the corresponding settings for economic operation of control variables by optimizing a particular objective while meeting the constraints of economics and security, such as equality and inequality constraints [1], [5]-[6].

In the past, various optimization methods have been applied, and some of them have been implemented into practice. Over the past few years, many methods have been used to solve the OPF and EI problems like; Quadratic programming method (QP) [7], Newton and Qassi-Newton methods [8]-[9], linear and non-linear programming methods [10]-[11] and interior point methods (IPM) [12].

In the last two decades, and in order to solve the OPF and EI problems, several methods of optimization are formulated such as Artificial neutral networks (ANN) [13], Artificial bee colony (ABC) and Incremental artificial bee colony (IABC) [14]-[15], Bacterial foraging algorithms (BFA) [16], Cuckoo search algorithm (CSA) [17], Harmony search (HS) [18], Evolution programming (EP) [19], Differential evaluation (DE) [20], Modified differential evaluation (MDE) [21], Tabu search (TS) [22], Simulated annealing (SA) [23], Gravitational search algorithms (GSA) [24], Evolutionary algorithm [25], Genetic algorithms (GA) [26], Particle swarm optimization (PSO) [27], Modified Particle swarm optimization (MPSO) [28], Ant colony optimization (ACO) [29], Tree-seed algorithm (TSA) [30], Moth Swarm Algorithm (MSA) [31], Sine-cosine algorithm (SCA) [32], Firefly Algorithm [33], Modified imperialist competitive algorithm (MICA) [34], Shuffled frog leaping algorithm (SFLA) [35], Electromagnetism-like mechanism method (ELM) [36], Ant-lion optimizer [37], Interior search algorithm [38], Wind driven optimization (WDO) method [39], Machine learning and modified grasshopper optimization algorithms [40], Rao algorithm [41], Artificial Eco-system optimization [42], Hamiltonian technique [43], Teaching-learning-studying-based optimization [44] and Grey wolf optimizer (GWO) [3], [45]. Variants of these algorithms were proposed to handle multi-objective functions in electric power systems.

The proposed GSA approach is tested and illustrated by numerical examples based on IEEE 30-bus test system.

With comparison, the obtained results validate the advantage of the proposed approach over many other methods in terms of solution quality.

2. PROBLEM FORMULATION

The OPF and EI are nonlinear optimization problems, represented by a predefined objective function f, subject to a set of equality and inequality constraints [46]. Generally, these problems can be expressed as follows.

$$Min\ f(x, u) \tag{1}$$

Subject to

$$h(x, u) = 0 \tag{2}$$

$$g(x, u) \leq 0 \tag{3}$$

$$x_{\min} \leq x \leq x_{\max} \quad \& \quad u_{\min} \leq u \leq u_{\max} \tag{4}$$

where $f(x,u)$ is a scalar objective function to be optimised, $h(x,u)$ and $g(x,u)$ are, respectively, the set of nonlinear equality constraints represented by the load flow equations and inequality constraints consists of state variable limits and functional operating constraints. x and u are the state and control variables vectors respectively. Hence, x and u can be expressed as given

$$x^t = \left\{ P_{G_1}, \left|V_{L_1}\right|, \ldots \left|V_{L_{nL}}\right|, Q_{G_1}, \ldots Q_{G_{ng}}, S_1, \ldots, S_{n_{br}} \right\} \tag{5}$$

where, P_G, Q_G, V_L and S_k are the generating active power at slack bus, reactive power generated by all generators, magnitude voltage of all load buses and apparent power flow in all branches, respectively. n_g, n_L and n_{br} are, respectively, the total number of generators, the total number of load buses and the total number of branches.

The set control parameters are represented in terms of the decision vector as follows:

$$u^t = \left\{ P_{G_2}, \ldots, P_{G_{ng}}, \left|V_{G_1}\right|, \ldots \left|V_{G_{ng}}\right|, Q_{1_{com}}, \ldots Q_{n_{com}}, T_1, \ldots, T_{n_T} \right\} \tag{6}$$

where, P_G are the active power generation excluding the slack generator, V_G are the generators magnitude voltage, T is tap settings transformers, and Q_{com} are the reactive power compensation by shunt compensator, $, n_T$ and n_{com} are the total number of transformers and the total number of compensators units, respectively.

2.1. Single-objective Function

In general, the single-objective function is a nonlinear programming problem. In this paper, four single objectives commonly found in OPF and EI have been considered.

2.1.1. Cost without valve-point optimization

The objective function of cost optimization f_1 of quadratic cost equation for all generators as given below

$$f_1 = \min \sum_{k=1}^{n_g} C(P_{gk}) = \min \sum_{k=1}^{n_g} a_k + b_k P_{gk} + c_k P_{gk}^2 \tag{7}$$

where f_1 is the total generation cost in ($/h). P_{gk} and n_g are the active power output generated by the i^{th} generator and the total number of generators. a_k, b_k and c_k are the cost coefficients of the generator *k*.

2.1.2. Cost with valve-point optimization

When the valve point loading is taken into account, this model can be used as is, except for the shape of the objective function instead of being a quadratic function it is now a non-convex and smooth function as shown in Fig. 1 [14]-[15].

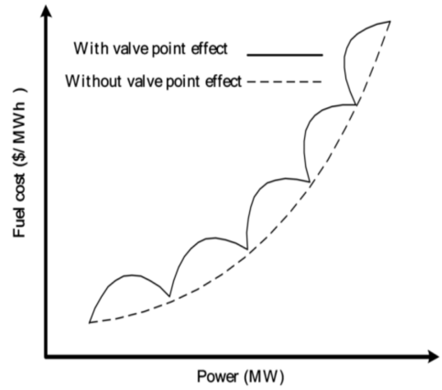

Fig. 1**:** Fuel cost curve of units with valve-point effects.

Generally, when every steam valves begins to open, the valve-point shows rippling. However, the characteristics of input-output of generation units make nonlinear and non-smooth of the fuel costs function. To consider the valve-point effect, the sinusoidal function is incorporated into the quadratic function. Typically, this function is represented as follows [14]-[15], [26].

$$f_2 = \min \sum_{k=1}^{n_g} \left[a_k + b_k P_{gk} + c_k P_{gk}^2 \right] + \left| d_k \sin\left(e_k \left(P_{gk}^{\min} - P_{gk}\right)\right) \right| \tag{8}$$

where d_k and e_k are the cost coefficients of unit with valve-point effect.

2.1.3. *Active power loss optimization*

The active power loss function f_3 in (MW) to be minimized can be expressed as follows

$$f_3 = \sum_{k=1}^{n_b} G_{kj} \left[V_k^2 + V_j^2 - 2V_k V_j \cos\theta_{kj} \right] \tag{9}$$

where, V_k and V_j are the magnitude voltage at buses *k and j*, respectively, G_{kj} is the conductance of line *kj*, θ_{kj} is the voltage angle between buses *k* and *j*, and n_b is total number of buses.

2.1.4. *Emission optimization*

The emission function is the sum of exponential and quadratic functions of real power generating. Using a quadratic equation, emission of harmful gases is calculated in (ton/h) as given below [34], [46]-[47].

$$f_4 = \min \sum_{k=1}^{n_g} 10^{-2} \left(\alpha_k + \beta_k P_{gk} + \gamma_k P_{gk}^2 \right) + \zeta_k \exp\left(\lambda_k P_{gk}\right) \tag{10}$$

where f_4 is the emission function in (ton/h), $\alpha_k, \beta_k, \gamma_k, \zeta_k$ and λ_k are the emission coefficients of the generator *k*.

2.2. Multi-objective Optimization

In all multi-objective functions, we use the weighted aggregation function. The function used in the case of weighted aggregation is given by equation (11).

$$MinF = \sum_{i=1}^{n_f} \omega_i f_i \ \ with\ \ \omega_i \geq 0\ \ and\ \sum_{i=1}^{n_f} \omega_i = 1 \tag{11}$$

where $\sum_{i=1}^{n_f} \omega_i = 1\ \&\ i = 1 : n_f$, ω_i is the weighting factor and n_f is the number of objective function considered.

2.3. Equality Constraints

These equality constraints are the sets of nonlinear load flow equations that govern the power system, i.e.:

$$\begin{cases} P_{gk} = P_k + P_{dk} \\ Q_{gk} - Q_{ComK} = Q_k + Q_{dk} \end{cases} \tag{12}$$

where P_{gk} and Q_{gk} are, respectively, the scheduled active and reactive power generations at bus *k*. P_k, Q_k are the active and reactive power injections at bus *k*. P_{dk}, Q_{dk} and Q_{comk} are the active and reactive power loads at bus *k* and the reactive power compensation at bus *k*.

2.4. Inequality Constraints

The inequality constraints $g(x,u)$ are represented by the system operational and security limits, listed below

$$P_{gk}^{\min} \leq P_{gk} \leq P_{gk}^{\max} \quad \text{where} \quad k = 1, \ldots, n_g \tag{13}$$

$$Q_{gk}^{\min} \leq Q_{gk} \leq Q_{gk}^{\max} \quad \text{where} \quad k = 1, \ldots, n_g \tag{14}$$

$$V_k^{\min} \leq V_k \leq V_k^{\max} \quad \text{where} \quad k = 1, \ldots, n_b \tag{15}$$

$$\theta_k^{\min} \leq \theta_k \leq \theta_k^{\max} \quad \text{where} \quad k = 1, \ldots, n_b \tag{16}$$

$$T_k^{\min} \leq T_k \leq T_k^{\max} \quad \text{where} \quad k = 1, \ldots, n_T \tag{17}$$

$$Q_{Comk}^{\min} \leq Q_{Comk} \leq Q_{comk}^{\max} \quad \text{where} \quad k = 1, \ldots, n_{Com} \tag{18}$$

$$S_{kj} \leq S_{kj}^{\max} \quad \text{where} \quad k = j = 1, \ldots, n_b \tag{19}$$

where, n_T, n_{Com}, T and Q_{Com} are the total number of transformers, total number of compensators, transformers tap settings, the reactive power compensation and $S_{kj}^{\max}$ is the maximum apparent power between buses k and j.

2.5. Gravitation Search Algorithm

Gravity Search Algorithm (GSA) is one of the recent algorithms developed by Rashidi et al. [48]. GSA is also a meta-heuristic method inspired by Newtonian laws of gravitation and mass interactions [24], [47]-[48]. The agents in the GSA method are the targets whose performance is measured by their masses. Each agent attracts another agent by a force of gravity which is inversely proportional to the square of the distance between the agents and directly proportional to the product of their mass. By means of the Newtonian law of motion this force creates a global movement of all agents towards the heavier masses.

Compared to lighter agents, heavier agents move very slowly which correspond to good solutions to the problem [24], [49].

In the GSA method [48]-[50], the agents/vectors of the solution are considered as objects and their performance is measured by their masses. Each mass (agent) has specified by four specifications: position of the mass, inertial mass, active gravitational mass and passive gravitational mass. The position of the mass corresponds to the solution of the problem, and its gravitational and inertial masses are computed using a fitness function. The algorithm is navigated by properly adjusting the gravitational and inertial masses. By lapse of iteration cycles, it is expected that masses be attracted by the heaviest mass. This heaviest mass will present an optimum solution in the search space [24].

The GSA could be considered as an isolated masses system. It is like a small artificial world of masses obeying the Newtonian laws of gravitation and motion. More precisely, masses obey the following two laws [50].

Now, let us consider a system with N_a agents (masses). The position of the i^{th} agent is defined by

$$x_i = \left(x_i^1, \ldots, x_i^d, \ldots, x_i^D \right) \quad \text{where} \quad i = 1, \ldots, N_a \tag{20}$$

where x_i^d represents the positions of the i_{th} agent in the d_{th} dimension, which is a candidate solution to the problem, *D* is the space dimension of the problem and N_a is total number of agents in the swarm [48].

Initially, the agents of the solution are defined according to Newton gravitation theory. At a specific iteration t, the force acting on i^{th} mass from j^{th} mass according to Newton gravitation theory is defined randomly as follows

$$F_{ij}^{d}(t)=G(t)\frac{M_{pi}(t)\times M_{aj}(t)}{R_{ij}(t)+\varepsilon}\left(x_j^d(t)-x_i^d(t)\right) \tag{21}$$

where M_{pi} is the mass of the object i, M_{aj} the mass of the object j, $G(t)$ is the gravitational constant at time t, ε is a small constant and $R_{ij}(t)$ is the Euclidean distance between two agents i and j given as follows.

$$R_{ij}(t)=\left\|x_i(t),x_j(t)\right\|_2 \tag{22}$$

To give a stochastic characteristic to the algorithm, it is expected that the total force that acts on i_{th} agent in d^{th} dimension be a randomly weighted sum of d^{th} components of the forces exerted from other agents given by the following equation

$$F_i^d(t)=\sum_{\substack{j=1\\ j\neq i}}^{N_a} rand_j F_{ij}^d(t) \tag{23}$$

where $rand_j$ is uniform random variable in the interval [0, 1], this random is used to give a randomized characteristic to the search [48], [50].

The law of motion is used directly to calculate the acceleration of i^{th} agent, at time t in the d^{th} dimension. This acceleration is proportional to the force acting on that agent, and inversely proportional to the mass agent. a_i^d is given as

$$a_i^d(t)=\frac{F_i^d(t)}{M_{ii}(t)} \tag{24}$$

where $M_{ii}(t)$ is the inertial mass of the i^{th} agent and and $a_i^d(t)$ is the acceleration of i^{th} agent in the d_{th} dimension at iteration t.

Moreover, a search strategy can be defined on this idea to find the next velocity and position of the agent. Further, the next velocity of any agent is considered a fraction of its current velocity and current acceleration. Therefore, the next velocity and the next position of an agent can be calculated as [50]-[51].

$$v_i^d(t+1)=rand_i\times v_i^d(t)+a_i^d(t) \tag{25}$$

$$x_i^d(t+1)=x_i^d(t)+v_i^d(t+1) \tag{26}$$

v_i^d and x_i^d are, respectively, the velocity and the position of an agent. The gravitational constant, G, which is initialized randomly at the starting, and given in terms of the initial gravitational constant (G_0) and iteration (t) expressed by (27).

$$G=G_0\exp\left(-\alpha\frac{t}{t_{\max}}\right) \tag{27}$$

where α is a user specified constant, t and t_{max} are the current and the total numbers of iterations, respectively. G_0 is set to 100, α is set to 20 [48].

The masses of agents are computed using fitness evaluation. The heavier mass of an agent, the more influential is that agent concerning the solution it represents. The masses are updated as follows:

$$M_{ai}=M_{pi}=M_{ii}\quad for\ \ i=1,2,....N_a \tag{28}$$

$$m_i(t)=\frac{fit_i(t)-worst(t)}{best(t)-worst(t)}$$

(29)

where $fit_i(t)$ represents the fitness of the j_{th} agent at iteration t, $best(t)$ and $worst(t)$ represents the best and worst fitness value of all agents at generation t.

$$M_i(t)=\frac{m_i(t)}{\sum_{1}^{N_a} m_i(t)} \tag{30}$$

where $M_i(t)$ is the agent mass of i at iteration t. For a minimization problem

$$best(t)=\min_{j\in\{1,\ldots\ldots,N_a\}} fit_j(t) \tag{31}$$

$$worst(t)=\max_{j\in\{1,\ldots\ldots,N_a\}} fit_j(t) \tag{32}$$

The total force acting on the i^{th} agent is computed as follows:

$$F_i^d(t)=\sum_{\substack{j\in Kbest\\ j\neq i}}^{N_a} rand_j F_{ij}^d(t) \tag{33}$$

$Kbest$ is the set of first K agents with the best fitness value and the biggest mass, which is a function of time with the initial value, K_0 and it decreases with time. In such a way, all agents apply the forces at the beginning, and as time passes, $Kbest$ is linearly decreased to 1. At the end, there will be only one agent applying force to the others.

2.5.1. Implementation GSA in OPF problem

At the beginning of the GSA algorithm, in the search space each agent is placed at a certain point, which defines a solution to the problem. Then, the customers are retrieved and their next locations are calculated according to equations (18) and (19). Other parameters of the algorithm such as masses M, gravitational constant G, and acceleration a are calculated using equations (27)-(30), and (24), respectively, and updated each iteration. The Flowchart of GSA used in this works is shown in Fig. 2.

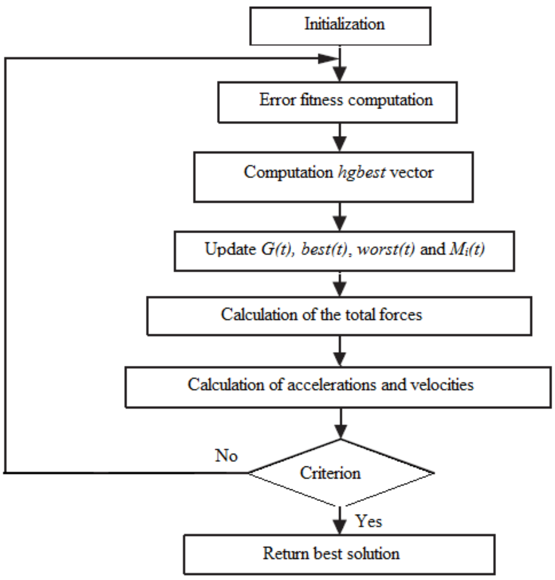

Fig. 2: Flowchart of GSA.

Below we will present the steps of the GSA method to solve the problem of OPF.

Step 1: Initialization the population size of agent vectors, $N_a = 25,\ t_{\max} = 250, G_0 = 100, \alpha = 10$

Step 2: Generation of the initial vectors of the agents N_a having that (n +1)

Step 3: Calculate the values of fitness error of total population, N_a,, as shown by Equation (31).

Step 4: Calculation of population best solution (hgbest).

Step 5: Update *G(t), best(t), worst(t)* and $M_i(t)$ for $i = 1,\ldots, N_a$.

Step 6: Calculate the sum of forces in different directions.

Step 7: Calculate the factor velocities and accelerations.

Step 8: Update the position of agent's.

Step 9: Repeat steps 3 through 8 until the stopping criterion is met (either the maximum number of iterations or near global optimal solution, *hgbest*) is met.

3. SIMULATION & RESULTS

The five generators system, IEEE 30-bus system is used throughout this work to test the proposed algorithm. This system consist, 30 buses, 6 generators units and 41 branches, 37 of them are the transmissions lines and 4 are the tap changing transformers. One of these buses is chosen like as a reference bus (slack bus), the buses containing generators are taken the PV buses, the remaining buses are the PQ buses or loads buses. It is assumed that 9 capacitors compensation is available at buses 10, 12, 15, 17, 20, 21, 23, 24 and 29. The network data, the cost and emission coefficients of the five generators are referred in [52]. The one-line diagram IEEE 30-bus system is shown in Fig. 3.

The total loads of active and reactive powers are 283.4 (MW) and 126.2 (MVAr), respectively, with 24 control variables. The basis apparent power used in this paper is 100 (MVA). The simulation results of load flow problem of test system are summarized in Table 1.

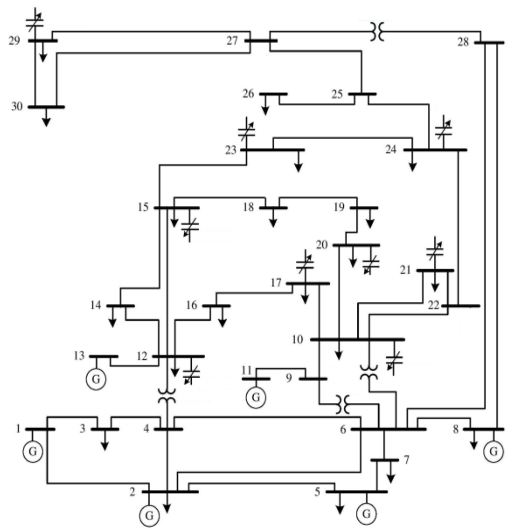

Fig. 3: Single-line diagram of IEEE 30-bus system.

3.1.1. *Case 1: Cost without valve point effect*

In this case, the cost has resulted in 801.7517 (\$/h), which is considered 8.3608 % lower than the initial case (load flow). Fig. 4 shows the convergence characteristic of cost using *GSA*. Table 1 summarizes the optimal control variables setting in this case.

3.1.2. *Case 2: Cost optimization with valve point effect*

In this case, the cost has resulted in 834.85 (\$/h), which is considered 3.837% lower than the initial case. Table 1 summarizes the optimal control variables of this case. Fig. 4 illustrates the convergence algorithms for case 2.

3.1.3. *Case 3: Active power loss optimization*

The optimal control variables of this case are introduced in Table 1. Fig. 5 shows the convergence characteristics of active power losses using GSA algorithm. The active power loss has dramatically decreased to 5.4074 (MW) which is considered 81.5905% lower than the basic case.

3.1.4. *Case 4: Gas emission optimization*

In this case, the emission reduction yielded 0.2162 (ton/h), which is considered 97.7962% lower than initial case. The optimal settings of control variables of this case are detailed in Table 2. The convergence characteristic of emission using GSA method is shown in Fig. 6.

3.1.5. *Case 5: Cost and active loss optimization*

The multi-objective control variables considering cost and active loss are tabulated in Table 2. Fig. 7 shows the trend of optimization for this case using *GSA* method.

3.1.6. *Case 6: Cost and gas emission optimization*

Fig. 8 shows the convergence characteristics obtained in case 6. The results of this case are tabulated in Table 3.

3.1.7. *Case 7: Cost, active power loss and gas emission*

The control variables setting of multi-objectives considering cost, active power loss and emission are given in Table 3. The convergence characteristics of this case are shown in Fig. 9.

In order to obtain the desired set of non-dominant solution points, we run the algorithm with different weight factor. Therefore, the multi-objective problem is transformed into a single objective problem using the linear summation of weight factors according to Equation (34).

$$f_{multi\text{-}objective} = w_c . f_1 + w_l . f_3 + w_e . f_4 \tag{34}$$

where w_c, w_l and w_e are, respectively, the weight factor for cost, losses and emission functions and $w_c + w_l + w_e = 1$.

Table 4 shows the obtained results using different weight factors.

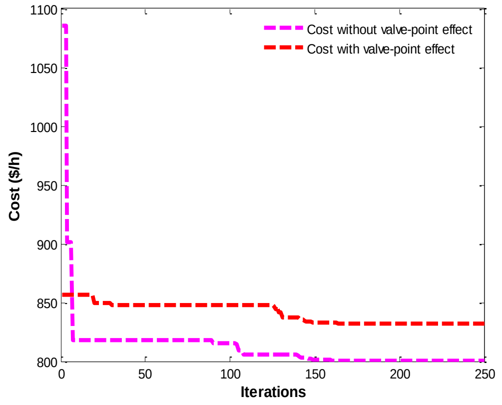

Fig. 4: Convergence of algorithm for cases 1 and 2.

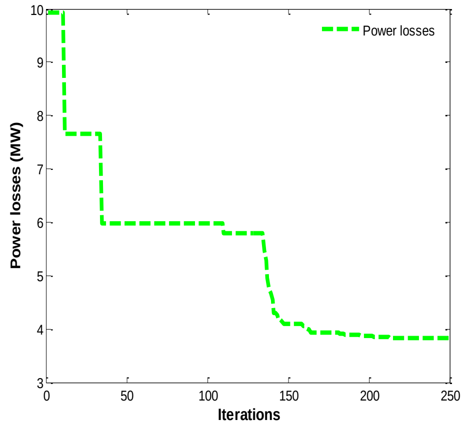

Fig. 5: Convergence of algorithm for case 3.

Table 1: Results of cases 1, 2 and 3 for test system.

Control variables	*Optimal values*		
	Case 1	*Case 2*	*Case 3*
	Cost w/o valve	*Cost w/ valve*	*Losses*
P_{G2} (MW)	49.3452	36.9639	42.1640
P_{G5} (MW)	21.1403	16.3928	49.9853
P_{G8} (MW)	21.2490	10.3052	34.9261
P_{G11} (MW)	11.9704	11.1055	29.8481
P_{G13} (MW)	12.0421	12.0007	37.5303
V_1 (pu)	1.0860	1.0603	1.0696
V_2 (pu)	1.0673	1.0330	1.0559
V_5 (pu)	1.0380	1.0062	1.0326
V_8 (pu)	1.0391	0.9967	1.0396
V_{11} (pu)	1.0926	1.0056	1.0781
V_{13} (pu)	1.0444	1.0668	1.0255
Q_{com10} (MVAr)	1.3214	1.0262	3.2206
Q_{com12} (MVAr)	1.2352	2.0189	0.6561
Q_{com15} (MVAr)	1.9913	2.5747	4.0699
Q_{com17} (MVAr)	3.1741	2.0459	2.8506
Q_{com20} (MVAr)	0.9824	2.5540	2.3771
Q_{com21} (MVAr)	3.8632	3.7772	3.8207
Q_{com23} (MVAr)	3.8792	1.4481	4.3263
Q_{com24} (MVAr)	2.4345	2.1937	2.3369
Q_{com29} (MVAr)	2.6679	2.4615	1.5492
T_{6-9}	1.0042	1.0037	1.0329
T_{6-10}	1.0021	0.9824	0.9452
T_{4-12}	0.9574	0.9404	0.9911

T_{28-27}	0.9762	0.9630	0.9873
Cost in ($/h)	800.751	834.85	912.19
loss in (MW)	9.0937	12.264	3.837
Emission (ton/h)	0.3117	0.3211	0.2161
Slack in (MW)	176.7467	208.899	92.7820
CPU time (s)	87.2648	86.756	77.595

From the results presented in Table 1 and Fig. 4, Fig. 5 and Fig. 6 it can appear that, the GSA method is considered to have given best results for multi-objective OPF based combined economic dispatch and emission because they obtained better results compared to those known references.

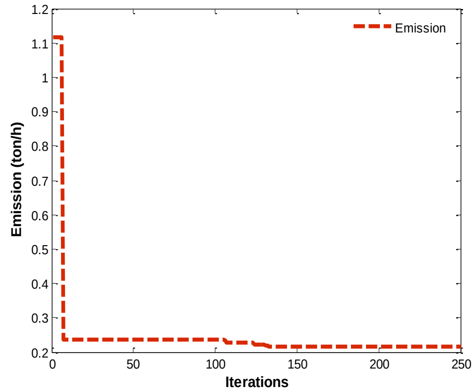

Fig. 6: Convergence of algorithm for case 4.

Table 2: Results of cases 4 and 5 for IEEE 30-bus system.

Control variables	*Optimal values*		
	Case 4	*Case 5*	
	Emission	*w/o valve*	*w/ valve*
P_{G2} (MW)	55.2162	51.7103	48.8408
P_{G5} (MW)	48.4827	30.7894	30.4953
P_{G8} (MW)	22.8868	34.9894	34.9624
P_{G11} (MW)	29.9986	23.4313	19.1652
P_{G13} (MW)	31.4252	21.1699	21.3077
V_1 (pu)	1.0863	1.0713	1.0673
V_2 (pu)	1.0728	1.0581	1.0501
V_5 (pu)	1.0228	1.0321	1.0202
V_8 (pu)	1.0097	1.0420	1.0309
V_{11} (pu)	1.0493	1.0644	1.0623
V_{13} (pu)	1.0248	1.0602	1.0551
Q_{com10} (MVAr)	1.4597	3.7160	4.6011
Q_{com12} (MVAr)	4.2850	2.9271	4.2547
Q_{com15} (MVAr)	1.3286	3.9829	1.4724
Q_{com17} (MVAr)	3.0464	1.2142	4.5426
Q_{com20} (MVAr)	3.3183	2.6623	3.9967
Q_{com21} (MVAr)	3.1756	3.1168	4.9962
Q_{com23} (MVAr)	3.1649	1.3367	4.0620
Q_{com24} (MVAr)	3.0629	4.3422	3.5058
Q_{com29} (MVAr)	2.7770	3.3533	1.4227
T_{6-9}	0.9902	0.9953	0.9658
T_{6-10}	1.0132	0.9589	1.0312

$T_{4\text{-}12}$	0.9408	1.0010	0.9731
$T_{27\text{-}28}$	0.9755	0.9819	0.9557
Cost in ($/h)	1025.9600	824.87	862.78
loss in (MW)	5.245	**05.827**	**06.284**
Emission (ton/h)	0.229	0.2524	0.2557
Slack in (MW)	100.636	127.1374	134.913
CPU time (s)	77.306	81.0773	80.756

The developed *GSA* has been implemented and used to solve the OPF combined economic dispatch with valve-point effect and emission for IEEE 30-bus system under varying operating conditions. The cost function is considered to be quadratic function.

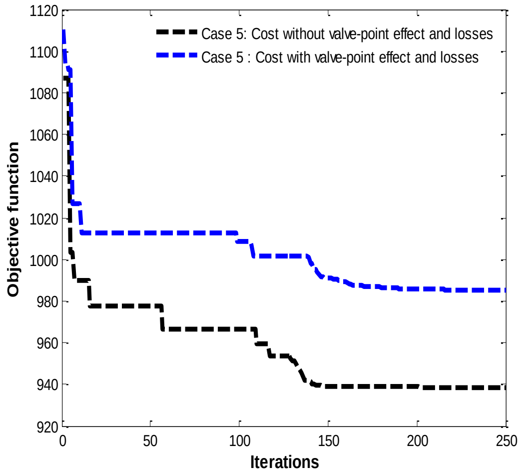

Fig. 7: Convergence of algorithm for case 5.

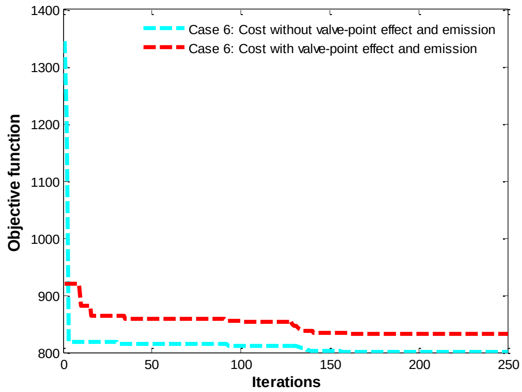

Fig. 8: Convergence characteristics for case 6.

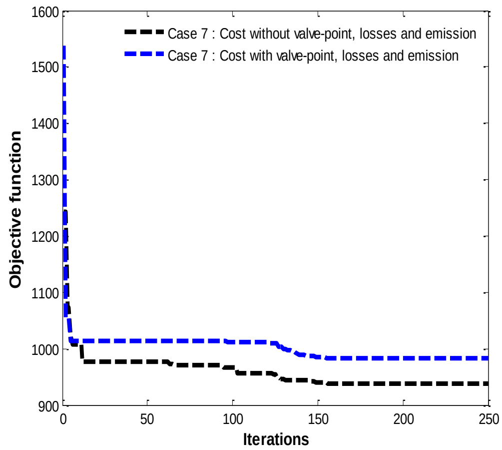

Fig. 9: Convergence characteristics for the case 7.

From Fig. 7, Fig. 8 and Fig. 9, all cases study of multi-objective results obtained the minimum values after 120 iterations.

Table 5 shows a comparison between the obtained single and multi-objective results of costs, power losses and emission with the results obtained in literature.

The proposed method to solve the OPF combined economic dispatch with valve-point effect and emission is considered to have given the best results because the results obtained using the *GSA* method are better compared to those published recently in several researches papers.

Table 3: Results of cases 6 and 7 for IEEE 30-bus system.

Control variables	*Optimal values*			
	Case 6		*Case 7*	
	w/o valve	*With valve*	*w/o valve*	*with valve*
P_{G2} (MW)	48.9786	42.8649	52.2267	47.7413
P_{G5} (MW)	21.1630	16.6036	30.5107	29.2543
P_{G8} (MW)	21.3428	13.9896	35.0000	34.9274
P_{G11} (MW)	11.8295	10.0373	24.4152	25.4630
P_{G13} (MW)	12.0012	12.0919	20.6417	17.2960
V_1 (pu)	1.0809	1.0859	1.0717	1.0722
V_2 (pu)	1.0624	1.0660	1.0577	1.0568
V_5 (pu)	1.0325	1.0365	1.0327	1.0291
V_8 (pu)	1.0375	1.0217	1.0424	1.0366
V_{11} (pu)	1.0459	1.0812	1.0821	1.0777
V_{13} (pu)	1.0180	1.0277	1.0597	1.0507
Q_{com10} (MVAr)	3.9395	2.2226	4.1934	3.0310
Q_{com12} (MVAr)	2.7670	1.6456	1.9471	3.1556
Q_{com15} (MVAr)	3.1526	1.4549	2.1550	2.0520
Q_{com17} (MVAr)	2.4079	3.7126	2.0085	3.9209
Q_{com20} (MVAr)	3.5253	2.0909	3.0977	1.8054
Q_{com21} (MVAr)	4.3362	0.7274	4.8694	4.6344
Q_{com23} (MVAr)	3.7058	1.3824	2.3529	3.5211
Q_{com24} (MVAr)	4.9791	4.1553	4.6928	3.2256
Q_{com29} (MVAr)	1.0175	1.8858	3.1813	1.9244
$T_{6\text{-}9}$	1.0588	0.9958	1.0198	0.9929
$T_{6\text{-}10}$	0.9963	1.0163	0.9503	1.0325
$T_{4\text{-}12}$	1.0190	0.9525	0.9884	1.0253

$T_{27\text{-}28}$	1.0084	0.9633	0.9882	0.9817
Cost in ($/h)	**800.89**	**834.69**	**825.170**	**862.90**
loss in (MW)	09.157	10.951	**5.775**	**6.1693**
Emission (ton/h)	**0.3203**	**0.3203**	**0.3203**	**0.3203**
Slack in (MW)	177.246	198.764	126.381	**134.887**
CPU time (s)	74.072	84.152	83.059	79.020

Table 4: Results of case 7 with different weight factors.

	w_c	w_l	w_e
	0.9	**0.08**	**0.02**
Cost ($/h)	862.90	864.71	865.10
Losses (MW)	6.1693	6.2012	6.1921
Emission (ton/h)	0.3203	0.3101	0.3100
	0.8	**0.15**	**0.15**
Cost ($/h)	863.10	864.71	865.10
Losses (MW)	6.9731	6.9958	6.9547
Emission (ton/h)	0.3199	0.3158	0.30258
	0.5	**0.25**	**0.25**
Cost ($/h)	863.80	864.71	865.10
Losses (MW)	6.3257	6.2012	6.1921
Emission (ton/h)	0.3302	0.3354	0.3434
	0.338	**0.335**	**0.327**
Cost ($/h)	866.65	862.90	862.90
Losses (MW)	6.7000	7.2121	7.123
Emission (ton/h)	0.24156	0.2315	0.3058

Through the results obtained in Table 5, we note that the optimal values of the different objective functions are affected by the change of weight factors. The larger the weight factor, the more optimal the value of the objective function.

Table 5: Comparison of obtained and literature results.

Methods		Cost	Losses	Emission
Methods	Ref.	($/h)	(MW)	($/ton)
		Case 5		
Proposed	-	**824.87**	**5.827**	**0.2524**
MSA	[36]	859.191	4.540	-
IABC	[19]	854.913	4.982	-
PSO	[31]	878.873	7.810	-
MDE	[25]	820.880	5.594	-
		Case 6		
Proposed	-	**800.89**	**9.157**	**0.267**
GA	[30]	820.166	-	0.271
MICA	[39]	865.066	-	0.222
		Case 7		
Proposed	-	**825.17**	**5.775**	**0.227**
GA	[30]	793.605	8.450	0.187
IABC	[19]	851.611	4.873	0.223
ABC	[18]	854.916	4.982	0.228

4. Conclusion

The GSA method was successfully implemented in this paper to find the optimum OPF control variables for single objective and multi-objective optimization. The versatility of the multi-objective OPF optimization is illustrated by different tests systems by changing the parameters of *GSA* method such as population size N_a and control parameters, α and G_0. The analysis performance of used methodology is illustrated by the numerical and graphical results as shown in all tables and figures. The proposed method has fast convergence time in all cases test due of obtained performance. Through the obtained results, the power generation cost, active losses and emission index were significantly reduced to 5.85%, 61.61% and 44.63% %, respectively, from the base case and these results obtained are considered good results compared to some references. The effectiveness and robustness of used method are demonstrated by the obtained results. Therefore, it can be recommended to future researchers as a promising algorithm for solving some more complex engineering optimization problems. However, we have to mention that it becomes slow if the numbers of system variables are increased. It is found that the average CPU time increases rapidly as system size increases and convergence slows down.

CRediT Authorship Contribution Statement

Nabil Mezhoud: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources Software, Supervision, Validation, Visualization, Writing - original draft, Writing - review & editing. **Mohamed Amarouayache:** Conceptualization, Formal analysis, Investigation, Project administration, Resources Software, Supervision, Visualization, Writing - original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The ethical issues; including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy has been completely observed by the authors.

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