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Optimal power flow using gravitational search algorithm

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ABSTRACT

In this paper, gravitational search algorithm (GSA) is proposed to find the optimal solution for optimal power flow (OPF) problem in a power system. The proposed approach is applied to determine the optimal settings of control variables of the OPF problem. The performance of the proposed approach examined and tested on the standard IEEE 30-bus and 57-bus test systems with different objective functions and is compared to other heuristic methods reported in the literature recently. Simulation results obtained from the proposed GSA approach indicate that GSA provides effective and robust high-quality solution for the OPF problem.

1. Introduction

Optimal power flow (OPF) has become one of the most important problems and commonly studied subjects for optimal operation and planning processes of modern power systems. Recently, the problem of OPF has received much attention by many researchers. The OPF is the fundamental tool that enables electric utilities to specify economic operating and secure states in power systems. Main objective of the OPF problem is to optimize a chosen objective function such as fuel cost, piecewise quadratic cost function, fuel cost with valve point effects, voltage profile improvement, voltage stability enhancement, through optimal adjustments of the power system control variables while at the same time satisfying various system operating such as power flow equations and inequality constraints [1,2]. The equality constraints are as nodal power balance equations, while the inequality constraints are as the limits of all control or state variables. The control variables involve the tap ratios of transformer, the generator real powers, the generator bus voltages and the reactive power generations of VAR sources. State variables involve the generator reactive power outputs, the load bus voltages and network line flows [3,4]. In general the OPF problem is a large-scale, highly constrained nonlinear nonconvex optimization problem.

Dommel and Tinney firstly presented the formulation optimal power flow [5]. Then this topic has been handled by many researchers. The OPF problem has been solved by using traditional and evolutionary based algorithms. Conventional optimization techniques such as interior point method, linear programming, nonlinear programming and quadratic programming have been implemented to solve the OPF problem [6–11]. However, the disadvantage of these techniques is that it is not possible to use these techniques in practical systems because of nonlinear characteristics such as valve point effects, prohibited operating zones and piecewise quadratic cost function. Therefore, it becomes necessary to improve the optimization methods that are capable of overcoming these disadvantages and handling such difficulties [12]. Lately, many population-based optimization techniques have been used to solve complex constrained optimization problems. These techniques have been increasingly applied for solving power system optimization problems such as economic dispatch, optimal reactive power flow and OPF in decades. Some of the population-based methods have been proposed for solving the OPF problem successfully, such that genetic algorithm [13], improved genetic algorithm [14], tabu search [4], particle swarm [15], differential evolution algorithm [16], simulated annealing [17], evolutionary programming [18].

Anitha et al. presented a new variation of particle swarm optimization algorithm to solve the OPF problem with IEEE 30-bus system. The obtained results of proposed approach are compared with tabu search (TS), simulated annealing (SA), evolutionary programming (EP), improved evolutionary programming (IEP) and particle swarm optimization (PSO) methods [19]. Dutta and Sinha used PSO algorithm to solve voltage stability constrained multi-objective OPF problem. The proposed method successfully applied for IEEE 30, IEEE 57 and IEEE 118-bus systems by the authors [20]. Bakirtzis

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et al. utilized enhanced genetic algorithm for solving OPF. The authors tested their approach on IEEE 30-bus system and the three area IEEE RTS-96 which is a 73 bus, 120-branch system [21]. Basu offered differential evolution algorithm (DE) to solve OPF problem with flexible alternating current transmission systems (FACTSs) devices. The author has proposed to minimize generator fuel cost with FACTS devices such as thyristor-controlled series capacitor (TCSC) and thyristor-controlled phase shifter (TCPS) in IEEE 30-bus systems [22]. Basu used multi-objective differential evolution algorithm to solve the OPF problem with FACTS devices in IEEE 30-bus and IEEE 57-bus systems. The results were compared with the literature by the author [23]. Madhad et al. investigated efficient parallel genetic algorithm applied to the OPF problem for large-scale system with shunt FACTS. In this study, authors are presented three test systems IEEE 30-bus, IEEE 118-bus and 15 generation units with prohibited zones and compared with results of other the literature [24].

One of the recently improved heuristic algorithms is the gravitational search algorithm (GSA), which is based on the Newton's law of gravity and mass interactions. GSA has been verified high quality performance in solving different optimization problems in the literature [25–29]. The most substantial feature of GSA is that gravitational constant adjusts the accuracy of the search, so it is to speed up solution process [30–32]. Furthermore, GSA is memory-less, it works efficiently like the algorithms with memory [31,32]. In this paper, a newly developed heuristic optimization called GSA method is proposed to solve the OPF problem which is formulated as a nonlinear optimization problem with equality and inequality constraints in a power system. The objective functions are minimization of fuel cost such as quadratic cost function, piecewise quadratic cost function, cost function with valve point effect, improvement of the voltage profile and improvement of voltage stability in both nominal and contingency situations. The performance of the proposed approach is sought and tested on the standard IEEE 30-bus and 57-bus test systems. Obtained simulation results demonstrate that the proposed method provides very remarkable results for solving the OPF problem. The results have been compared to those reported in the literature.

The rest of the paper is organized as follows: Section 2 defines the mathematical formulation of optimal power flow problem and in Section 3 the proposed approach GSA is presented. Section 4 presents the results of simulation and compares techniques in the literature to solve the case studies of optimal power flow problems with IEEE 30-bus and 57-bus test systems. Finally, conclusion of the implementation of the proposed approach is illustrated in Section 5.

2. Mathematical problem formulation of OPF

The OPF is a nonlinear optimization problem. The essential goal of the OPF is to minimize the settings of control variables in terms of a certain objective function subjected to various equality and inequality constraints. In general, the OPF problem can be mathematically formulated as follows:

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

$$\textit{subject to } g(x,u) = 0 \tag{2}$$

$$h(x,u) \leqslant 0 \tag{3}$$

where F is the objective function to be minimized, $\boldsymbol{x}$ and $\boldsymbol{u}$ are vectors of dependent and control variables respectively. $\boldsymbol{x}$ is the vector of dependent variables including:

I. Generator active power output at slack bus P_{G1}.
II. Load bus voltage V_L.
III. Generator reactive power output Q_G.
IV. Transmission line loading S_l.

$\boldsymbol{x}$ can be represented as:

$$\boldsymbol{x}^T = [P_{G1}, V_{L1} \ldots V_{LNPQ}, Q_{G1} \ldots Q_{GNPV}, S_{l1} \ldots S_{1NTL}] \tag{4}$$

where NPV defines the number of voltage controlled buses; NPQ and NTL depict the number of PQ buses, the number of transmission lines respectively.

In a similar way, the vector of control variables $\boldsymbol{u}$ can be expressed as:

$$\boldsymbol{u}^T = [P_{G2} \ldots P_{GNG}, V_{G1} \ldots V_{GNG}, Q_{C1} \ldots Q_{CNC}, T_1 \ldots T_{NT}] \tag{5}$$

I. P_G defines the active power output of generators at PV bus.
II. V_G depicts the terminal voltages at generation bus bars.
III. Q_C represents the output of shunt VAR compensators.
IV. T stands for the tap setting of the tap regulating transformers.

where NT and NC define the number of tap regulating transformers and number of shunt VAR compensators, respectively.

2.1. Constraints

2.1.1. Equality constraints

g Defines equality constraints representing typical load flow equations:

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j \left[G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)\right] = 0 \tag{6}$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j \left[G_{ij} \sin(\delta_i - \delta_j) + B_{ij} \cos(\delta_i - \delta_j)\right] = 0 \tag{7}$$

where V_i and V_j are the voltages of ith and jth bus respectively, P_{Gi} and Q_{Gi} the active and reactive power of ith generator, P_{Di} and Q_{Di} the demand of active and reactive power of ith bus and G_{ij}, B_{ij} and δ_{ij} are the conductance, susceptance and phase difference of voltages between ith and jth bus and NB is the total number of buses.

2.1.2. Inequality constraints

h defines inequality constraints that contain:

i. Generator constraints: Generator voltage, active and reactive outputs ought to be restricted by their lower and upper limits as follows:

$$\begin{aligned} &V_{Gi}^{\min} \leqslant V_{Gi} \leqslant V_{Gi}^{\max}, \quad i = 1,2,\ldots,NPV \\ &P_{Gi}^{\min} \leqslant P_{Gi} \leqslant P_{Gi}^{\max}, \quad i = 1,2,\ldots,NPV \\ &Q_{Gi}^{\min} \leqslant Q_{Gi} \leqslant Q_{Gi}^{\max}, \quad i = 1,2,\ldots,NPV \end{aligned} \tag{8}$$

where $V_{Gi}^{\min}$ and $V_{Gi}^{\max}$ are the minimum and maximum generator voltage of ith generating unit; $P_{Gi}^{\min}$ and $P_{Gi}^{\max}$ the minimum and maximum active power output of ith generating unit and $Q_{Gi}^{\min}$ and $Q_{Gi}^{\max}$ are the minimum and maximum reactive power output of ith generating unit.

ii. Transformer constraints: Transformer tap settings ought to be restricted by their lower and upper limits as follows:

$$T_i^{\min} \leqslant T_i \leqslant T_i^{\max}, \quad i = 1,.2,\ldots,NT \tag{9}$$

where $T_i^{\min}$ and $T_i^{\max}$ define minimum and maximum tap settings limits of ith transformer.

iii. Shunt VAR compensator constraints: Shunt VAR compensators ought to be restricted by their lower and upper limits as follows:

$$Q_{Ci}^{\min} \leqslant Q_{Ci} \leqslant Q_{Ci}^{\max}, \quad i = 1,2,\ldots,NC \tag{10}$$

where $Q_{Ci}^{\min}$ and $Q_{Ci}^{\max}$ define minimum and maximum Var injection limits of ith shunt capacitor.

iv. Security constraints: These contain the constraints of voltage magnitudes at load buses and transmission line loadings. Voltage of each load bus ought to be restricted by their lower and upper operating limits. Line flow through each transmission line ought to be restricted by their capacity limits. These constraints can be mathematically formulated as follows:

$$V_{Li}^{\min} \leqslant V_{Li} \leqslant V_{Li}^{\max}, \quad i = 1, 2, \ldots, NPQ \tag{11}$$

$$S_{li} \leqslant S_{li}^{\max}, \quad i = 1, 2, \ldots, NTL \tag{12}$$

where $V_{Li}^{\min}$ and $V_{Li}^{\max}$ minimum and maximum load voltage of ith unit. S_{li} defines apparent power flow of ith branch. $S_{li}^{\max}$ defines maximum apparent power flow limit of ith branch.

The inequality constraints of dependent variables contain load bus voltage magnitude; real power generation output at slack bus, reactive power generation output and line loading may be included into an objective function as quadratic penalty function method. In this method, a penalty factor multiplied with the square of the disregard value of dependent variable is added to the objective function and any unfeasible solution obtained is declined. Mathematically, penalty function can be expressed as follows:

$$\begin{aligned} J\,\text{mod} = {} & \sum_{i=1}^{NPV} F_i(P_{Gi}) + \lambda_P (P_{G1} - P_{G1}^{\lim})^2 + \lambda_V \sum_{i=1}^{NPQ} (V_{Li} - V_{Li}^{\lim})^2 \\ & + \lambda_Q \sum_{i=1}^{NPV} (Q_{Gi} - Q_{Gi}^{\lim})^2 + \lambda_S \sum_{i=1}^{NTL} (S_{li} - S_{li}^{\max})^2 \end{aligned} \tag{13}$$

where λ_P, λ_V, λ_Q and λ_S are defined as penalty factors. $x^{\lim}$ is the limit value of the dependent variable x and given as;

$$x^{\lim} \begin{cases} x^{\max}; & x > x^{\max} \\ x^{\min}; & x < x^{\min} \end{cases} \tag{14}$$

3. Gravitational search algorithm

The gravitational search algorithm (GSA) is one of the newest stochastic search algorithm developed by Rashedi et al. [32]. This algorithm, which is based on Newtonian laws of gravity and mass interaction, has a great potential to be a break-through optimization method. In this algorithm, agents are taken into consideration as objects and their performances are measured by their masses. Every object represents a solution or a part of a solution to the problem. All these objects attract each other by the gravity force, and this force causes a global movement of all objects towards the objects with heavier masses. Due to the heavier masses have higher fitness values; they describe good optimal solution to the problem and they move slowly than lighter ones representing worse solutions. In GSA, each mass has four particulars: its position, its inertial mass (M_{ii}), its active gravitational mass (M_{ai}) and passive gravitational mass (M_{pi}). The position of the mass equaled to a solution of the problem and its gravitational and inertial masses are specified using a fitness function [30–32].

At the beginning of the algorithm the position of a system are described with N (dimension of the search space) masses

$$X_i = (x_i^1 \ldots x_i^d \ldots x_i^n) \quad \textit{for } i = 1, 2, \ldots, N \tag{15}$$

where n is the space dimension of the problem and x_i^d defines the position of the ith agent in the dth dimension.

Initially, the agents of the solution are defined randomly and according to Newton gravitation theory, a gravitational force from mass j acts mass i at the time t is specified as follows:

$$F_{ij}^d(t) = G(t)\frac{M_i(t) x M_j(t)}{R_{ij}(t) + \varepsilon}(x_j^d(t) - x_i^d(t)) \tag{16}$$

where M_i is the mass of the object i, M_j the mass of the object j, $G(t)$ the gravitational constant at time t, ε a small constant and $R_{ij}(t)$ is the Euclidian distance between i and j objects defined as follows:

$$R_{ij}(t) = \|X_i(t), X_j(t)\|_2 \tag{17}$$

The total force acting on the ith agent ($F_i^d(t)$) is calculated as follows:

$$F_i^d(t) = \sum_{j \in kbest, j \neq i}^{N} rand_j F_{ij}^d(t) \tag{18}$$

where $rand_j$ is a random number between interval $[0,1]$ and $kbest$ is the set of first K agents with the best fitness value and biggest mass

In order to find the acceleration of the ith agent, at t time in the dth dimension law of motion is used directly to calculate. In accordance with this law, it is proportional to the force acting on that agent, and inversely proportional to the mass of the agent. $a_i^d(t)$ is given as follows:

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \tag{19}$$

Moreover, the searching strategy on this notion can be defined to find the next velocity and next position of an agent. Next velocity of an agent is defined as a function of its current velocity added to its current acceleration. Hence, the next position and next velocity of an agent can be computed as follows:

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t) \tag{20}$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \tag{21}$$

where $v_i^d(t)$ and $x_i^d(t)$ are the velocity and position of an agent at t time in d dimension, respectively. $rand_i$ is a random number in the interval $[0,1]$. It is to give a randomized feature to the search.

The gravitational constant, G, which is initialized randomly at the starting, will be decrease according to time to control the search accuracy.

G is a function of the initial value (G_0) and time (t):

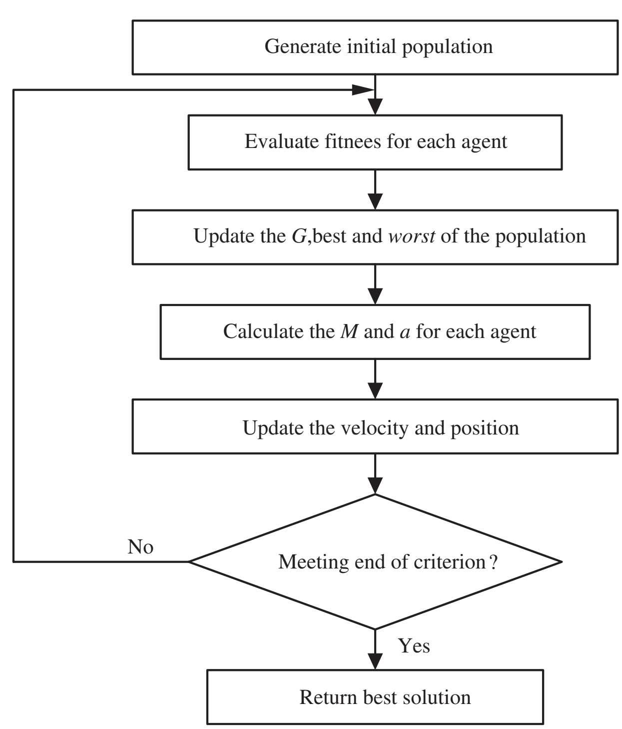

Fig. 1. The flow chart of the GSA.

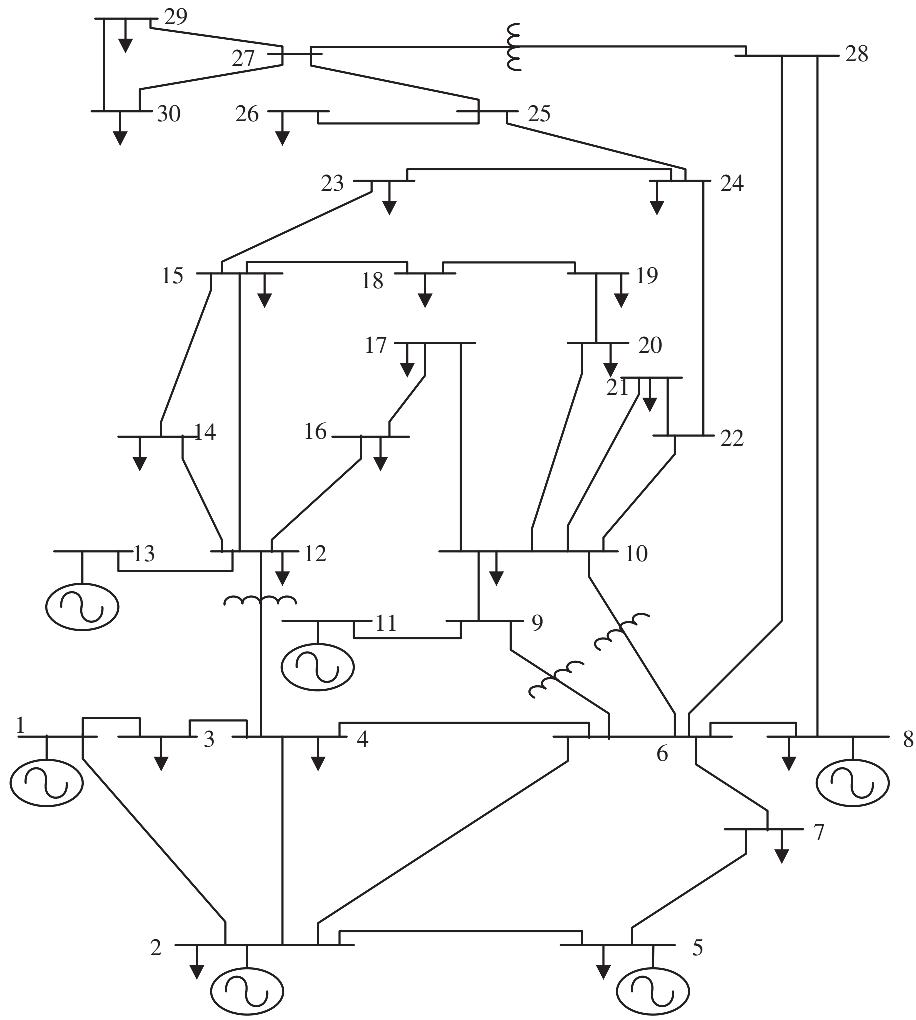

Fig. 2. Single line diagram of IEEE 30-bus test system.

$$G(t) = G(G_0, t) \tag{22}$$

$$G(t) = G_0 e^{-\alpha \frac{t}{T}} \tag{23}$$

where α is a user specified constant, t the current iteration and T is the total number of iterations.

The masses of the agents are computed using fitness evaluation. The heavier mass of an agent, the more influential is that agent, concerning the solution it represents. It is notable that as the Newton's law of gravity and law of motion refer a heavy mass has a higher pull on power and moves slower. The masses are updated as follows:

$$M_{ai} = M_{pi} = M_{ii} = M_i, \quad i = 1, 2, \ldots, N$$

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \tag{24}$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \tag{25}$$

where $fit_i(t)$ represents the fitness value of the agent i at time t, and the $best(t)$ and $worst(t)$ in the population respectively specify the strongest and the weakest agent with regard to their fitness route. For a minimization problem:

$$best(t) = \min_{j \in \{1,\ldots,m\}} fit_j(t) \tag{26}$$

$$worst(t) = \max_{j \in \{1,\ldots,m\}} fit_j(t) \tag{27}$$

For a maximization problem:

$$best(t) = \max_{j \in \{1,\ldots,m\}} fit_j(t) \tag{28}$$

$$worst(t) = \min_{j \in \{1,\ldots,m\}} fit_j(t) \tag{29}$$

In order to solve the optimization problem with GSA, at the beginning of the algorithm every agent is placed at a certain point of the search space which specifies a solution to the problem at every unit of time. Then according to Eqs. (20) and (21), the agents are recovered and their next positions are computed. Other parameters of the algorithm like the gravitational constant G, masses M and acceleration a are computed via Eqs. 22, 23, 24, 25, and (19) respectively, and are updated every cycle of time. The flow diagram of the GSA is shown in Fig. 1 [32,33].

3.1. Application of gravitational search algorithm to the OPF problem

In this section, a new heuristic optimization algorithm based on Newton's law of gravity and mass interactions for solving the OPF problem is described as follows:

Step 1. Search space identification.

Table 1
Best control variables settings for different test cases.

Control variables settings (p.u.)	Case 1: Quadratic cost function	Case 2: Voltage profile improvement	Case 3: Voltage stability enhancement	Case 4: Voltage stability enhancement during contingency condition	Case 5: Piecewise quadratic cost function	Case 6: Quadratic cost function with valve point loadings
P_1	1.75749826	1.73320940	1.77043235	1.84916647	1.39999960	1.99599439
P_2	0.48165537	0.49263900	0.44918179	0.52336057	0.54926800	0.51946406
P_5	0.21381724	0.21567799	0.23962118	0.21451240	0.24995982	0.15000000
P_8	0.21561405	0.23274500	0.14170295	0.11408846	0.30249474	0.10000000
P_{11}	0.12417360	0.13774500	0.17213382	0.10388632	0.19583234	0.10000001
P_{13}	0.12510199	0.11964300	0.16008895	0.12487544	0.20218508	0.12000003
V_1	1.086235	1.026900	1.098204	1.077534	1.049999	1.099002
V_2	1.046685	1.009980	1.087066	1.039057	1.009321	1.018042
V_5	1.035570	1.014280	1.093797	1.039118	1.014509	1.052247
V_8	1.076962	1.008680	1.089740	1.098241	1.034569	0.950000
V_{11}	1.077452	1.050289	1.099999	1.100000	0.950429	0.963430
V_{13}	1.099999	1.016340	1.100000	1.100000	1.003616	0.950702
T_{11}	0.939297	1.071330	0.900001	0.900000	1.100000	0.909096
T_{12}	1.006593	0.900000	0.900000	0.900000	1.099763	0.918200
T_{15}	0.907372	0.996500	0.900000	0.900002	1.099998	0.925648
T_{36}	0.921855	0.973200	1.006570	0.918952	1.079138	0.945975
Q_{C10}	0.02190333	0.04143700	0.04999998	0.05000000	–	–
Q_{C12}	0.05000000	0.03562000	0.04999748	0.05000000	–	–
Q_{C15}	0.00000000	0.05000000	0.04999585	0.05000000	–	–
Q_{C17}	0.02715239	0.00000000	0.05000000	0.05000000	–	–
Q_{C20}	0.00000672	0.05000000	0.04998984	0.05000000	–	–
Q_{C21}	0.00000000	0.05000000	0.04998921	0.04999998	–	–
Q_{C23}	0.00000593	0.05000000	0.04997742	0.05000000	–	–
Q_{C24}	0.00000000	0.04983700	0.04999937	0.00000000	–	–
Q_{C29}	0.00000000	0.02588000	0.03723178	0.00000000	–	–
Fuel cost ($/h)	**798.675143**	804.314844	806.601315	801.183476	**646.848066**	**929.7240472**
Power loss (p.u.)	0.08386049	0.09765939	0.09916103	0.09588964	0.06573957	0.15145848
Voltage deviations	0.872862	**0.093269**	0.900000	0.868275	0.822802	0.577974
L_{max}	0.130759	0.135776	**0.116247**	**0.093073**	0.141948	0.156484

Step 2. Generate initial population between minimum and maximum values of the control variables.
Step 3. Calculate value of fitness function of each agent for the OPF problem.
Step 4. Update $G(t)$, $best(t)$, $worst(t)$ and $M_i(t)$ *for* $i = 1, 2, \ldots, N$.
Step 5. Calculation of the total force in different directions.
Step 6. Calculation of acceleration and velocity.
Step 7. Updating agents' position.
Step 8. Repeat Steps 3–7 until the stop criteria is reached.
Step 9. Stop.

4. Numerical results

4.1. IEEE 30-bus test system

Proposed GSA algorithm has been implemented to solve the OPF problems. In order to test the efficiency and robustness of the proposed GSA approach based on Newtonian physical law of gravity and law of motion which is tested on standard IEEE 30-bus test system shown in Fig. 2. The line, bus data, generator data and the minimum and maximum limits for the control variables are given in Appendix A.

Test system has six generators at the buses 1, 2, 5, 8, 11 and 13 and four transformers with off-nominal tap ratio at lines 6–9, 6–10, 4–12 and 28–27. In addition, buses 10, 12, 15, 17, 20, 21, 23, 24 and 29 were selected as shunt VAR compensation buses [15]. The total system demand is 2.834 p.u. at 100 MVA base. The maximum and minimum voltages of all load buses are considered to be 1.05–0.95 in p.u. The proposed approach has been applied to solve the OPF problem for different cases with various objective functions. In each case, 50 test runs were performed for solving the OPF problem using the GSA approach.

G is set using in Eqs. (22) and (23), where G_0 is set to 100, α is set to 10 and T is the total number of iterations. Maximum iteration numbers are 200 for all case studies. The software was written in MATLAB 2008a computing environment and applied on a 2.63 GHz Pentium IV personal computer with 512 MB-RAM. In the following, the simulation results are presented:

4.1.1. Case 1: quadratic cost function

The generator cost characteristics are defined as quadratic cost function of generator power output and the objective function selected.

$$J = \sum_{i=1}^{NG} F_i(P_{Gi}) = \sum_{i=1}^{NG} (a_i + b_i P_{Gi} + c_i P_{Gi}^2) \tag{30}$$

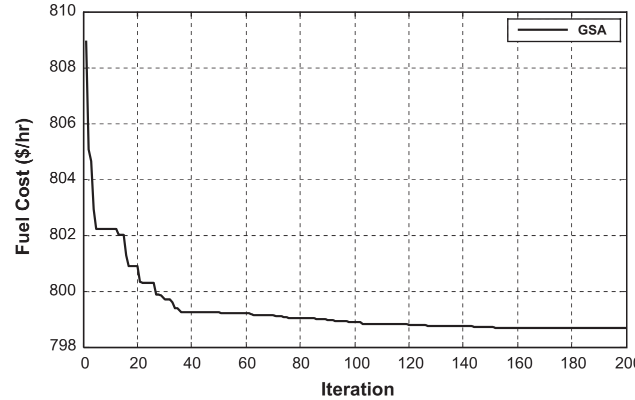

Fig. 3. Convergence of GSA for Case 1.

Table 2
Comparison of the simulation results for Case 1.

Methods	Fuel cost ($/h)			Simulation times
	Min	Average	Max	
GSA	798.675143	798.913128	799.028419	10.7582
BBO [34]	799.1116	799.1985	799.2042	11.02
DE [1]	799.2891	NA	NA	NA
PSO [15]	800.41	NA	NA	NA
Improved GA [14]	800.805	NA	NA	NA
MDE [2]	802.376	802.382	802.404	23.25
Gradient Method [36]	804.853	NA	NA	4.324
EADDE [39]	800.2041	800.2412	800.2784	3.32
EADHDE [40]	800.1579	NA	NA	NA
Enhanced GA [21]	802.06	NA	802.14	76

where F_i and P_{Gi} are the fuel cost of the ith generator and the output of the ith generator, respectively. a_i, b_i and c_i are the cost coefficients of the ith generator and NG is the number of total generator. The values of cost coefficients are given in Table A1. The optimum control parameter settings of GSA algorithm are given in Table 1. The minimum fuel cost obtained from the proposed approach is 798.675143 $/h. GSA is less by 0.054617%, 0.076812% compared to previously reported best results 799.1116 $/h, 799.2891 $/h respectively. Fig. 3 shows the convergence of GSA for minimum fuel cost solution. The result obtained from the proposed GSA algorithm was compared to the other methods in the literature. The results of this comparison are given in Table 2. The average cost obtained from the GSA for this case is 798.913128 $/h with a maximum cost of 799.028419 $/h. From Table 2, it can be seen that the results obtained from the proposed approach are better than those reported in the literature.

4.1.2. Case 2: voltage profile improvement

Bus voltage is one of the most significant safety and service qualification indices. Considering only cost-based objective in the OPF problem may result in a feasible solution, however voltage profile may not be reasonable. Hence, in the present case a twofold objective function is taken in consideration to minimize the fuel cost and enhance voltage profile by minimizing all the load bus deviations from 1.0 per unit [1]. The objective function can be described as follows:

$$J = \sum_{i=1}^{NG}(a_i + b_i P_{Gi} + c_i P_{Gi}^2) + \eta \sum_{i=1}^{NPQ}|V_i - 1.0| \tag{31}$$

where η is a suitable weighting factor, to be selected by the user. Value of η in this case is chosen as 100 [1,34]. The proposed method has been applied to search for the optimal solution of the problem. The obtained optimal settings of the control variables from the proposed GSA method are given in Table 1. Voltage profile in this case is compared to that of Case 1 as shown in Fig. 4. It is quite obvious that voltage profile is enhanced compared to that of Case 1. It is decreased from 0.872862 p.u in Case 1 to 0.093269 p.u in Case 2. The result obtained from the proposed approach reduces 89.314576% in this case. The comparison results are shown in Table 3. The average voltage profile obtained from the GSA for this case is 0.093952 with a maximum voltage profile of 0.094171. From the results in Table 3, it is clear that the results obtained from the GSA method are better than those reported in the literature.

Abou El Ela et al. [1], though fuel cost for Case 1 was 799.2891 $/h, there were load bus voltage violations. Approximately, for voltages of load buses were up to 1.06, 1.07 and 1.08 p.u. It is clear that this may be observed in Fig. 4 of Abou El Ela et al. [1]. The maximum acceptable voltage magnitudes at all load buses are 1.05 p.u for IEEE 30-bus test system [35].

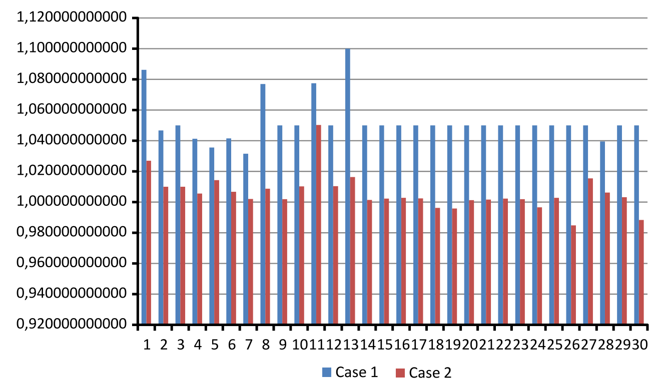

Fig. 4. System voltage profile.

Table 3
Comparison of the simulation results for Case 2.

Methods	Voltage profile improvement along with fuel cost			Simulation times
	Min	Average	Max	
GSA	0.093269	0.093952	0.094171	11.5873
BBO [34]	0.1020	0.1105	0.1207	13.23
DE [1]	0.1357	NA	NA	NA
PSO [15]	0.0891	NA	NA	NA

4.1.3. Case 3: voltage stability enhancement

Voltage stability is interested with the ability of a power system to maintain constantly acceptable bus voltage at each bus in the power system under nominal operating conditions. A system experiences a state of voltage instability when the system is being subjected to a disturbance, rise in load demand, change in system configuration may lead to progressive and uncontrollable reduce in voltage. Consequently, enhancement of voltage stability of a system is a significant parameter of power system operation and planning. Voltage stability can be defined via minimizing the voltage stability indicator L-index values of each bus of a power system [1,34].

The L-index of a bus specifies the proximity of voltage collapse condition of that bus. L-index L_j of bus jth is defined as follows [37]

$$L_j = \left|1 - \sum_{i=1}^{NPV} F_{ji} \frac{V_i}{V_j}\right| \quad \text{where } j = 1, 2, \ldots, NPQ \tag{32}$$

$$F_{ji} = -[Y_1]^{-1}[Y_2] \tag{33}$$

where NPV is number of PV bus and NPQ is number of load bus. Y_1 and Y_2 are the sub-matrices of the system YBUS obtained after separating the PQ and PV bus bars parameters as described in the following equation

$$\begin{bmatrix} I_{PQ} \\ I_{PV} \end{bmatrix} = \begin{bmatrix} Y_1 & Y_2 \\ Y_3 & Y_4 \end{bmatrix} \begin{bmatrix} V_{PQ} \\ V_{PV} \end{bmatrix} \tag{34}$$

L-index is computed for all the PQ bus. L_j is represents no load case and voltage collapse conditions of bus j in the range of zero and one, respectively. Hence, a global system indicator L describing the stability of the complete system is given as follows:

$$L = \max(L_j), \quad \text{where } j = 1, 2, \ldots, NPQ \tag{35}$$

Lower value of L represents more stable system. In the OPF problem, inaccurate tuning of control variable settings may be increase the value of L-index, that is, may decrease the voltage stabil-

Table 4
Comparison of the simulation results for Case 3.

Methods	Voltage stability improvement along with fuel cost			Simulation times
	Min	Average	Max	
GSA	0.116247	0.120538	0.12284	13.6378
BBO [34]	0.1104	0.1186	0.1214	16.29
DE [1]	0.1219	NA	NA	NA
PSO [15]	0.1246	NA	NA	NA

ity margin of a system [34]. In order to improve the voltage stability and move the system far from the voltage collapse point, the following objective function can be defined:

$$J = \sum_{i=1}^{NG}(a_i + b_i P_{Gi} + c_i P_{Gi}^2) + \eta(\max(L_j)) \tag{36}$$

where η is a weighting factor to be selected by the user. Value of η in this case is chosen as 6000. Applying the OPF problem to the proposed technique importantly decrease the value of $L_{\max}$ according to Cases 1 and 2. This state can be seen from Table 1. The simulation results obtained from the proposed GSA technique are compared to other heuristic techniques in the literature. The comparison results are shown in Table 4. From the Table 4 it is clear that in GSA approach, $L_{\max}$ is 0.116247 which is reduce 4.637407%, 6.703852% than in comparison to DE, PSO algorithms, respectively and is more than the BBO algorithm.

4.1.4. Case 4: voltage stability enhancement during contingency condition

A contingency state is simulated as outage of line (2–6). Voltage stability is substantially interested in this case. Hence, in order to enhance of voltage stability is considered as objective function Eq. (36). The results obtained from this case are given in Table 1. The comparison results are shown in Table 5. The proposed GSA algorithm is indicated to improve of voltage stability in the contingency condition. It appears that in the proposed approach $L_{\max}$ is 0.093073 which is less 30.903489% than DE algorithm, for voltage stability enhancement.

4.1.5. Case 5: piecewise quadratic fuel cost functions

In power system operation conditions, many thermal generating units may be supplied with multiple fuel sources like coal, natural gas and oil. The fuel cost functions of these units may be dissevered as piecewise quadratic fuel cost functions for different fuel types [1]. The cost coefficients for these units are given Table A2. The fuel cost coefficients of other generators have the same values as of Case 1 condition. The cost characteristics of generators 1 and 2 are defined as follows:

$$F(P_{Gi}) = \begin{cases} a_{i1} + b_{i1}P_{Gi} + c_{i1}P_{Gi}^2 & P_{Gi}^{\min} \leqslant P_{Gi} \leqslant P_{Gi1} \\ a_{i2} + b_{i2}P_{Gi} + c_{i2}P_{Gi}^2 & P_{Gi1} \leqslant P_{Gi} \leqslant P_{Gi2} \\ \cdots \\ a_{ik} + b_{ik}P_{Gi} + c_{ik}P_{Gi}^2 & P_{Gik-1} \leqslant P_{Gi} \leqslant P_{Gi}^{\max} \end{cases} \tag{37}$$

where a_{ik}, b_{ik} and c_{ik} are cost coefficients of the ith generator for fuel type k. Objective function can be described as:

$$J = \left(\sum_{i=1}^{2} a_{ik} + b_{ik}P_{Gi} + c_{ik}P_{Gi}^2\right) + \left(\sum_{i=3}^{NG} a_i + b_i P_{Gi} + c_i P_{Gi}^2\right) \tag{38}$$

The proposed GSA approach is applied to this case considering the upper limit of voltage magnitude at bus 1 as 1.05 and no shunt VAR compensation buses [1,15]. The results obtained optimal settings of control variables for this case study are given Table 1, which shows that the GSA has best solution for minimizing of fuel

Table 5
Comparison of the simulation results for Case 4.

Methods	Voltage stability improvement along with fuel cost			Simulation times
	Min	Average	Max	
GSA	0.093073	0.096531	0.099846	11.4926
DE [1]	0.1347	NA	NA	NA

Table 6
Comparison of the simulation results for Case 5.

Methods	Voltage stability improvement along with fuel cost			Simulation times
	Min	Average	Max	
GSA	646.848066	646.896273	646.938163	10.2716
BBO [34]	647.7437	647.7645	647.7928	11.94
DE [1]	650.8224	NA	NA	NA
PSO [15]	647.69	647.73	647.87	NA
MDE [2]	647.846	648.356	650.664	37.05

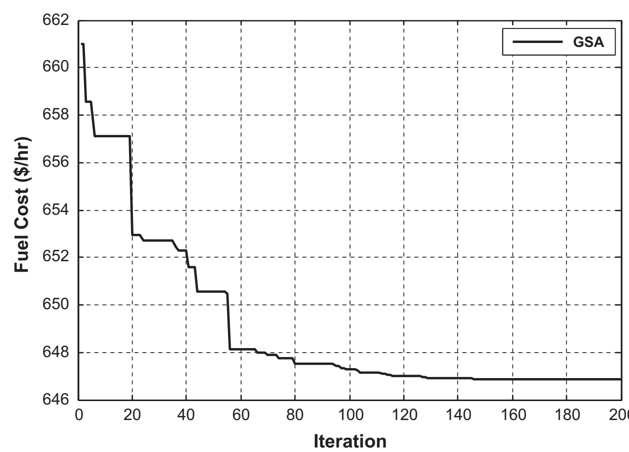

Fig. 5. Convergence of GSA for Case 5.

cost in the OPF problem. The best fuel cost result obtained from the GSA technique is compared with other techniques in Table 6. The convergence of GSA algorithm for the OPF problem with minimum fuel cost is shown Fig. 5. From the results in Table 6, it can be seen that the minimum fuel cost is 646.848066 \$/h, with an average cost of 646.896273 \$/h and a maximum cost of 646.938163 \$/h which are less in comparison to reported results in the literature.

4.1.6. Case 6: quadratic cost curve with valve point loadings

In this case, the generating units of buses 1 and 2 are considered to have the valve-point effects on their characteristics. Fuel cost coefficients of these generators are taken from [39]. The cost coefficients for these units are given in Table A3. The fuel cost coefficients of remaining generators have the same values as of Case 1. The cost characteristics of generators 1 and 2 are described as follows:

$$\begin{aligned} F_i(P_{Gi}) &= a_i + b_i P_{Gi} + c_i P_{Gi}^2 \\ &\quad + \left| d_i \sin\left(e_i\left(P_{Gi}^{\min} - P_{Gi}\right)\right)\right| \quad \text{where } i \\ &= 1 \text{ and } 2 \end{aligned} \tag{39}$$

where a_i, b_i, c_i, d_i and e_i are cost coefficients of the ith generating unit.

Objective function can be defined as:

Table 7
Comparison of the simulation results for Case 6.

Methods	Voltage stability improvement along with fuel cost			Simulation times
	Min	Average	Max	
GSA	929.7240472	930.9246338	932.0487291	9.8374
BBO [34]	919.7647	919.8389	919.8876	11.15
MDE [2]	930.793	942.501	954.073	41.85

$$J = \left(\sum_{i=1}^{2} a_i + b_i P_{Gi} + c_i P_{Gi}^2 + \left| d_i \sin\left(e_i\left(P_{Gi}^{\min} - P_{Gi}\right)\right)\right|\right) + \left(\sum_{i=3}^{NG} a_i + b_i P_{Gi} + c_i P_{Gi}^2\right) \quad (40)$$

The obtained optimal settings of control variables from the proposed method are given in Table 1. Table 7 gives the comparison of the proposed GSA technique other heuristic techniques reported in the literature. It is quite obvious that the minimum fuel cost obtained from the proposed approach is 929.7240472 \$/h with an average cost of 930.9246338 \$/h and a maximum cost of 932.0487291 \$/h, which is less than MDE algorithm and is more than BBO algorithm. But the sum of real power of generating units was given as 294.464 MW in BBO approach and real power loss was 12.18 MW whereas load was 283.4 MW. So power generation is not matching load plus losses. This approach did not meet the load demand for this case. The variation of the total fuel cost is shown in Fig. 6. The results obtained confirm the ability of the proposed GSA approach to find accurate OPF solutions in this case study.

4.2. IEEE 57-bus test system

To evaluate the effectiveness and efficiency of the proposed GSA approach in solving larger power system, a standard IEEE 57-bus test system is considered. The IEEE 57-bus test system consist of 80 transmission lines, seven generators at the buses 1, 2, 3, 6, 8, 9 and 12, and 15 branches under load tap setting transformer branches. The shunt reactive power sources are considered at buses 18, 25 and 53. The total load demand of system is 1250.8 MW and 336.4 MVAR. The bus data, the line data and the cost coefficients and minimum and maximum limits of real power generations are taken from Refs. [41,42]. The maximum and minimum values for voltages of all generator buses and tap setting transformer control variables are considered to be 1.1–0.9 in p.u. The maximum and minimum values of shunt reactive power sources are 0.0 and 0.3 in p.u. The maximum and minimum values for voltages of all load buses are 1.06 and 0.94 in p.u form MATPOWER [42], respectively. In simulation process, minimization of

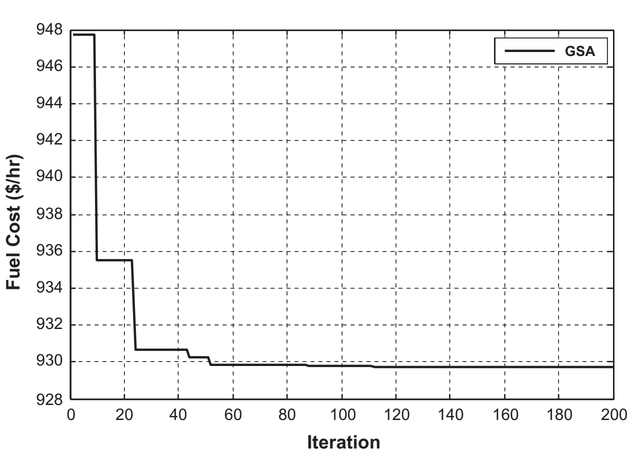

Fig. 6. Convergence of GSA for Case 6.

Table 8
Best control variables settings for IEEE 57-bus test system.

Control variables settings (p.u.)	GSA	Control variables settings (p.u.)	GSA
P_1	1.42369	T_{24-25}	1.05921
P_2	0.92630	T_{24-25}	0.99921
P_3	0.45318	T_{24-26}	0.92201
P_6	0.72355	T_{7-29}	0.93243
P_8	4.64743	T_{34-32}	1.08828
P_9	0.84999	T_{11-41}	1.03902
P_{12}	3.63951	T_{15-45}	1.04318
V_1	1.05941	T_{14-46}	1.02494
V_2	1.05759	T_{10-51}	0.95425
V_3	1.06000	T_{13-49}	0.92897
V_6	1.06000	T_{11-43}	1.09942
V_8	1.05999	T_{40-56}	0.96948
V_9	1.05999	T_{39-57}	1.06200
V_{12}	1.04590	T_{9-55}	1.09388
T_{4-18}	0.90000	Q_{C18}	0.15243
T_{4-18}	0.90000	Q_{C25}	0.14403
T_{21-20}	0.90856	Q_{C53}	0.15102
Fuel cost (\$/h)			41695.8717

Table 9
Comparison of the simulation results for IEEE 57-bus test system.

Methods	Fuel cost (\$/h)
BASE-CASE [39]	51347.86
MATPOWER [39]	41737.79
EADDE [39]	41713.62
GSA	41695.8717

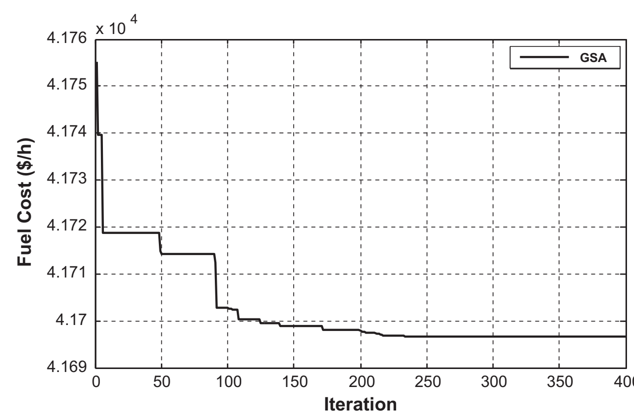

Fig. 7. Convergence of GSA for IEEE 57-bus test system.

Table A1
Generator cost coefficients for Case 1 [35,36].

Bus no.	Cost coefficients		
	a	*b*	*c*
1	0.00	2.00	0.00375
2	0.00	1.75	0.01750
5	0.00	1.00	0.06250
8	0.00	3.25	0.00834
11	0.00	3.00	0.02500
13	0.00	3.00	0.02500

Table A2
Generator cost coefficients for Case 5 [38].

Bus no.	From MW	To MW	Cost coefficients		
			a	b	c
1	50	140	55.00	0.70	0.0050
	140	200	82.5	1.05	0.0075
2	20	55	40.00	0.30	0.0100
	55	80	80.00	0.60	0.0200

Table A3
Generator cost coefficients for Case 6 [38].

Bus no.	P_{Gi}^{min}	P_{Gi}^{max}	Cost coefficients				
			a	b	c	d	e
1	50	200	150.00	2.00	0.0016	50.00	0.0630
2	20	80	25.00	2.50	0.0100	40.00	0.0980

Table A4
Load data [35,36].

Bus no.	Load		Bus no.	Load		Bus no.	Load	
	P (p.u.)	Q (p.u.)		P (p.u.)	Q (p.u.)		P (p.u.)	Q (p.u.)
1	0.000	0.000	11	0.000	0.000	21	0.175	0.112
2	0.217	0.127	12	0.112	0.075	22	0.000	0.000
3	0.024	0.012	13	0.000	0.000	23	0.032	0.016
4	0.076	0.016	14	0.062	0.016	24	0.087	0.067
5	0.942	0.190	15	0.082	0.025	25	0.000	0.000
6	0.000	0.000	16	0.035	0.018	26	0.035	0.023
7	0.228	0.109	17	0.090	0.058	27	0.000	0.000
8	0.300	0.300	18	0.032	0.009	28	0.000	0.000
9	0.000	0.000	19	0.095	0.034	29	0.024	0.009
10	0.058	0.020	20	0.022	0.007	30	0.106	0.019

quadratic cost function is considered as objective function and also to test the performance of the proposed GSA approach. In this test system, 50 test runs were performed for solving the OPF problem using the GSA method. The objective function is described as follow:

$$J = \sum_{i=1}^{NG} F_i(P_{Gi}) = \sum_{i=1}^{NG} (a_i + b_i P_{Gi} + c_i P_{Gi}^2) \quad (41)$$

Table A6
The limits of the control variables [36].

Control variables	Min	Max
P_1	50	200
P_2	20	80
P_5	15	50
P_8	10	35
P_{11}	10	30
P_{13}	12	40
V_1	0.95	1.1
V_2	0.95	1.1
V_5	0.95	1.1
V_8	0.95	1.1
V_{11}	0.95	1.1
V_{13}	0.95	1.1
T_{11}	0.90	1.1
T_{12}	0.90	1.1
T_{15}	0.90	1.1
T_{36}	0.90	1.1
Q_{C10}	0.00	5.0
Q_{C12}	0.00	5.0
Q_{C15}	0.00	5.0
Q_{C17}	0.00	5.0
Q_{C20}	0.00	5.0
Q_{C21}	0.00	5.0
Q_{C23}	0.00	5.0
Q_{C24}	0.00	5.0
Q_{C29}	0.00	5.0

where F_i and P_{Gi} are the fuel cost of the ith generator and the output of the ith generator, respectively. a_i, b_i and c_i are the cost coefficients of the ith generator and NG is the number of total generator. The obtained optimal settings of control variables from the proposed method are given in Table 8. Comparison of the proposed GSA technique other heuristic technique reported in the literature, base case and MATPOWER is given in Table 9. The convergence characteristic of the best fuel cost result obtained from the GSA approach is shown in Fig. 7.

From the results in Table 9, it is quite clear that the best fuel cost result obtained from the proposed GSA technique is 41695.8717 $/h, which is less in comparison to reported best result the literature.

5. Conclusion

In this paper, one of the recently improved heuristic algorithms which are the gravitational search algorithm was demonstrated

Table A5
Line data [35,36].

Line no	From bus	To bus	R (p.u.)	X (p.u.)	B (p.u.)	Tap settings	Line no	From bus	To bus	R (p.u.)	X (p.u.)	B (p.u.)	Tap settings
1	1	2	0.0192	0.0575	0.0264	–	22	15	18	0.1070	0.2185	0.0000	–
2	1	3	0.0452	0.1852	0.0204	–	23	18	19	0.0639	0.1292	0.0000	–
3	2	4	0.0570	0.1737	0.0184	–	24	19	20	0.0340	0.0680	0.0000	–
4	3	4	0.0132	0.0379	0.0042	–	25	10	20	0.0936	0.2090	0.0000	–
5	2	5	0.0472	0.1983	0.0209	–	26	10	17	0.0324	0.0845	0.0000	–
6	2	6	0.0581	0.1763	0.0187	–	27	10	21	0.0348	0.0749	0.0000	–
7	4	6	0.0119	0.0414	0.0045	–	28	10	22	0.0727	0.1499	0.0000	–
8	5	7	0.0460	0.1160	0.0102	–	29	21	22	0.0116	0.0236	0.0000	–
9	6	7	0.0267	0.0820	0.0085	–	30	15	23	0.1000	0.2020	0.0000	–
10	6	8	0.0120	0.0420	0.0045	–	31	22	24	0.1150	0.1790	0.0000	–
11	6	9	0.0000	0.2080	0.0000	1.078	32	23	24	0.1320	0.2700	0.0000	–
12	6	10	0.0000	0.5560	0.0000	1.069	33	24	25	0.1885	0.3292	0.0000	–
13	9	11	0.0000	0.2080	0.0000	–	34	25	26	0.2544	0.3800	0.0000	–
14	9	10	0.0000	0.1100	0.0000	–	35	25	27	0.1093	0.2087	0.0000	–
15	4	12	0.0000	0.2560	0.0000	1.032	36	28	27	0.0000	0.3960	0.0000	1.068
16	12	13	0.0000	0.1400	0.0000	–	37	27	29	0.2198	0.4153	0.0000	–
17	12	14	0.1231	0.2559	0.0000	–	38	27	30	0.3202	0.6027	0.0000	–
18	12	15	0.0662	0.1304	0.0000	–	39	29	30	0.2399	0.4533	0.0000	–
19	12	16	00945	0.1987	0.0000	–	40	8	28	0.0636	0.2000	0.0214	–
20	14	15	0.2210	0.1997	0.0000	–	41	6	28	0.0169	0.0599	0.0065	–
21	16	17	0.0824	0.1932	0.0000	–							

and applied to solve optimal power flow problem. The OPF problem is formulated as a nonlinear optimization problem with equality and inequality constraints in power systems. In this study, different objective functions were considered to enhance the voltage profile, also to enhance the voltage stability in both nominal and contingency conditions, to minimize the fuel cost such as quadratic cost function, piecewise quadratic cost function, cost function with valve point effect. The proposed GSA approach were tested and investigated on the IEEE 30-bus and 57-bus test systems. This approach was successfully and influentially performed to find the optimal settings of the control variables of test system. The simulation results proved the robustness and superiority of the proposed approach to solve the OPF problem. The results obtained from the GSA technique were compared to other methods previously reported in the literature. The comparison verifies the influentially of the proposed GSA approach over stochastic techniques in terms of solution quality for the OPF problem.

Appendix A

See Tables A1–A6.

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