ANALYSIS OF OPTIMAL POWER FLOW USING GRAVITATIONAL SEARCH ALGORITHM

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ABSTRACT

The operation of an electric power system is a complex one due to its nonlinear and computational difficulties. One task of operating a power system economically and securely is optimal scheduling, commonly referred to as the Optimal Power Flow (OPF) problem. It optimizes a certain objective function while satisfying a set of physical and operating constraints. Optimal power flow has become an essential tool in power system planning and operation. In this paper, a gravitational search algorithm is presented to solve OPF problems while satisfying system equality, in-equality constraints. The effect of security limits such as transmission line limits and load bus voltage magnitudes is also analyzed on OPF problem. The developed methodology is tested on the standard IEEE-30 bus test system, supporting numerical as well as graphical results.

Keywords: Optimal Power Flow, Gravitational Search Algorithm, Security Constraints, Quadratic Fuel Cost.

INTRODUCTION

For secure operation of the system without any limit violation, complete modeling of the system through load flow equations and operational constraints is necessary. Thus the Optimal Power Flow (OPF) is a good choice. The solution of formulated Optimal Power Flow (OPF) model gives the optimal operating state of a power system and the corresponding settings of control variables for economic and secure operation, while at the same time satisfying various equality and inequality constraints. The equality constraints are the power flow equations, while the inequality constraints are the limits on control variables and the operating limits of power system dependent variables. Amongst a number of different operational objectives that an OPF problem may be formulated, a widely considered objective is to minimize the fuel cost subject to equality and inequality constraints.

The goal of optimal power flow is to determine optimal control variables and quantities for efficient power system planning and operation. Several optimization techniques have been proposed to handle the OPF problem [1-3]. A wide variety of optimization techniques have been applied to solve the OPF problems such as Nonlinear Programming (NLP) [1, 4-10, 11-13], Quadratic Programming (QP) [6,7], Linear Programming (LP) [14, 15], Newton-based techniques [8, 9], and sequential unconstrained minimization technique [10]. Generally, NLP based procedures have many drawbacks such as insecure convergence properties and algorithmic complexity.

Another evolutionary computation technique called Particle Swarm Optimization (PSO), has been proposed and introduced [16-19]. This technique combines social psychological principles in socio-cognition human agents and evolutionary computations. PSO has been motivated by the behavior of organisms such as fish schooling and bird flocking. Generally, PSO is characterized as simple in concept, easy to implement and computationally efficient. Unlike, the other heuristic techniques, PSO has a flexible and well-balanced mechanism to enhance and adapt to the global and local exploration abilities.

In this paper, the PSO and GSA (Gravitational Search Algorithm) based algorithms for solving OPF problems, with generation fuel cost as objective, is presented. The effect of security constraints on OPF problem is investigated by considering security limits. The proposed

approach has been tested on the Standard IEEE-30 bus system. The potential and effectiveness of the proposed approach are demonstrated.

1. OPF Problem Formulation

The aim of the Optimal Power Flow solution is to optimize the selective objective function through proper adjustment of control variables by satisfying various constraints. The OPF problem can be represented as follows:

$$\text{Min } [A_m(x,u)] \tag{1}$$

Subjected to $g(x,u) = 0$ and

$$h_{min} \leq h(x,u) \leq h_{max}$$

where,

$A_m(x,u)$ is the function which is to be minimized,

$g(x,u)$, $h(x,u)$ represents equality and inequality constraints,

'x' and 'u' are dependent and independent variables.

Optimal power flow solution gives an optimal control variable leads to the minimum generation fuel cost, emission and total power loss, etc. subjected to all the various equality and inequality constraints. Here, the vector 'x' consists of slack bus real power output (P_{G1}), generator VAr output (Q_G), load bus voltage magnitude (V_L), and line flow limits (S_l).

Thus 'x' can be written as,

$$x^T = [P_{G1}, V_{L1}, \dots, V_{LNL}, Q_{G1}, \dots, Q_{GNG}, S_{l1}, \dots, S_{lnl}] \tag{2}$$

where,

NL = Number of load buses,

NG = Number of generator buses,

nl = Number of lines,

u = the independent variable vector such as continuous and discrete variables that consists of,

- Generator active output 'P_G' at all generators without slack bus,
- Generator voltages V_G,
- Tap settings of transformer 'T',
- Shunt VAr compensation (or) reactive power injections Q_C.

Here P_G, V_G are continuous variables and T and Q_C are the discrete variables. Hence 'u' can be expressed as,

$$u^T = [P_{G2}, \dots, P_{GNG}, V_{G1}, \dots, V_{GNG}, Q_{C1}, \dots, Q_{Cnc}, T_1, \dots, T_{NT}] \tag{3}$$

'NT' and 'nc' are the number of tap controlling transformers and shunt compensators.

2. Quadratic Fuel Cost

The main aim of OPF problem is to optimize the total generation fuel cost in a system. Generators for which fuel cost characteristics are given by,

$$A_1 = \sum_{i=1}^{NG} (a_i P_{Gi}^2 + b_i P_{Gi} + c_i); \text{ \$/h} \tag{4}$$

where, a_i, b_i, c_i are the fuel cost coefficients of ith unit. P_{Gi} is the active power generation of ith unit.

3. Constraints

Constraints made in this OPF problem are usually two types. They are equality constraints and inequality constraints.

3.1 Equality Constraints

These constraints mentioned in Equation (2) are usually load flow equations described as,

$$P_{G,k} - P_{d,k} - \sum_{m=1}^{N_{bus}} |V_k| |V_m| |Y_{km}| \cos(\theta_{km} - \delta_k + \delta_m) = 0 \tag{5}$$

$$Q_{G,k} - Q_{d,k} - \sum_{m=1}^{N_{bus}} |V_k| |V_m| |Y_{km}| \sin(\theta_{km} - \delta_k + \delta_m) = 0 \tag{6}$$

where, $P_{G,k}$, $Q_{G,k}$ are the active and reactive power generation at the kth bus, P_{dk}, Q_{dk} are the active and reactive power demands at the kth bus, $|V_k|$ $|V_m|$ are the voltage magnitudes at the kth and m^{th} buses, δ_k, δ_m are the phase angles of the voltage at the kth and m^{th} buses, and $|Y_{km}|$, θ_{km} are the bus admittance magnitude and its angle between the kth and m^{th} buses.

3.2 Inequality Constraints

These are the constraints that represents the system operation and security limits which are continuous and discrete constraints.

Generator bus voltage limits:

$$V_{G_i}^{min} \leq V_{G_i} \leq V_{G_i}^{max} \quad \forall i \in NG \tag{7}$$

Active power generation limits:

$$P_{G_i}^{min} \leq P_{G_i} \leq P_{G_i}^{max} \quad \forall i \in NG \tag{8}$$

Transformers tap setting limits:

$$T_i^{min} \leq T_i \leq T_i^{max} \quad \forall i \in nt \tag{9}$$

Capacitor reactive power generation limits:

$$Q_{sh_i}^{min} \leq Q_{sh_i} \leq Q_{sh_i}^{max} \quad \forall i \in nc \tag{10}$$

Transmission line flow limit:

$$S_{l_i} \leq S_{l_i}^{max} \quad \forall i \in nl \qquad (11)$$

Reactive power generation limits:

$$Q_{G_i}^{min} \leq Q_{G_i} \leq Q_{G_i}^{max} \quad \forall i \in NG \qquad (12)$$

Load bus voltage magnitude limits:

$$V_i^{min} \leq V_i \leq V_i^{max} \quad \forall i \in NL \qquad (13)$$

The control variables in this problem are self-constrained, whereas the in-equality constraints such as P_{Gi}, V_i, Q_{Gi}, and S_{li} are non-self-constrained by nature. Hence, these inequalities are incorporated into the objective function using a penalty approach [8]. The augmented function can be formulated as:

$$A_{aug}(x,u) = A(x,u) + R_1 \left(P_{G_1} - P_{G_1}^{lim}\right)^2 + R_2 \sum_{i=1}^{NL} \left(V_i - V_i^{lim}\right)^2$$
$$+ R_3 \sum_{i=1}^{NG} \left(Q_{G_i} - Q_{G_i}^{lim}\right)^2 + R_4 \sum_{i=1}^{nl} \left(S_{l_i} - S_{l_i}^{max}\right)^2 \qquad (14)$$

where, R_1, R_2, R_3 and R_4 are the penalty quotients, which take large positive values. The limit values of the dependent variable x^{lim} can be given as:

$$x^{lim} = \begin{cases} x, & x^{min} \leq x \leq x^{max} \\ x^{max}, & x \geq x^{max} \\ x^{min}, & x \leq x^{min} \end{cases} \qquad (15)$$

where, x^{lim} can be P_{G1}, V_i, Q_{Gi}

4. Particle Swarm Optimization (Existing)

Particle Swarm Optimization (PSO) is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling [20].

PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random solutions and searches for optima by updating generations. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles, fly through the problem space by following the current optimum particles.

PSO has been successfully applied in many research and application areas. It is demonstrated that, PSO gives better results in a faster, cheaper way compared with other methods [21].

4.1 PSO Operation

PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations, the particles are "flown" through the problem space by following the current optimum particles. Each particle keeps track of its coordinates in the problem space, which are associated with the best solution (fitness) that it has achieved so far. This implies that each particle has a memory, which allows it to remember the best position on the feasible search space that it has ever visited. This value is commonly called p_{best}. Another best value that is tracked by the particle swarm optimizer is the best value obtained so far by any particle in the neighborhood of the particle. This location is commonly called g_{best}. The basic concept behind the PSO technique consists of changing the velocity (or accelerating) of each particle toward it's p_{best} and the g_{best} positions at each time step. This means that each particle tries to modify its current position and velocity according to the distance between its current position and p_{best}, and the distance between its current position and g_{best}.

PSO, simulation of bird flocking in two-dimension space can be explained as follows. The position of each agent is represented by XY-axis position and the velocity is expressed by V_x (the velocity of X-axis) and V_y (the velocity of Y-axis). Modification of the agent position is realized by the position and velocity information. PSO procedures based on the above concept can be described as follows. Bird flocking optimizes a certain objective function. Each agent knows its best value so far (p_{best}) and its XY position. Moreover, each agent knows the best value in the group (g_{best}) among p_{best}. Each agent tries to modify its position using the current velocity and the distance from p_{best} and g_{best}. The modification can be represented by the concept of velocity. The new velocity and updated positions are calculated using the following expressions,

$$Vel_{ij}^{k+1} = W \times Vel_{ij}^{k} + C_1 \times rand_1 \times \left(L_{ij}^{best} - X_{ij}^{k}\right) + C_2 \times rand_2 \times \left(G_{ij}^{best} - X_{ij}^{k}\right) \quad (16)$$

$$X_{ij}^{k+1} = X_{ij}^{k} + Vel_{ij}^{k+1} \qquad (17)$$

where, $'X_{ij}^{k'}$ and $'Vel_{ij}^{k'}$ are the present position and velocities of ith particle in j^{th} dimension in k^{th} iteration. These new velocities and updated positions are calculated

repeatedly for a pre-defined number of iterations reached. For minimization of the objective functions, the fitness function is evaluated using the following expression,

$$\text{Fitness} = \frac{1}{1 + J_{aug}} \qquad (18)$$

Expressions (16) and (17) describe the velocity and position update, respectively. Expression (16) calculates a new velocity for each particle based on the particle's previous velocity, the particle's location at which the best fitness has been achieved so far, and the population global location at which the best fitness has been achieved so far. Usually $C_1 = C_2 = 2$.

4.2 Flow Chart of PSO

The complete procedure of PSO is shown in Figure 1.

5. Gravitational Search Algorithm (Proposed)

In this section, the developed algorithm is based on the law of gravity. In the proposed algorithm, agents are considered as objects and their performance is measured by their masses. 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. Hence, masses co-operate using a direct form of communication, through gravitational force. The heavy masses – which correspond to good solutions – move
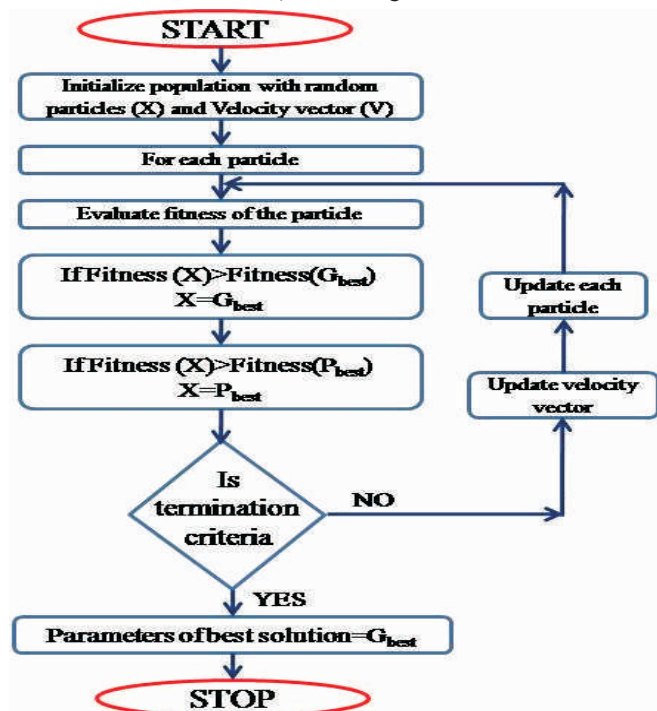

Figure 1. Flow Chart of Existing PSO

more slowly than lighter ones, this guarantees the exploitation step of the algorithm.

In GSA, each mass (agent) has four specifications: position, inertial mass, active gravitational mass, and passive gravitational mass. The position of the mass corresponds to a solution of the problem, and its gravitational and inertial masses are determined by using a fitness function.

In other words, each mass presents a solution, and the algorithm is navigated by properly adjusting the gravitational and inertia masses. By lapse of time, we expect that the masses be attracted by the heaviest mass. This mass will present an optimum solution in the search space.

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

Law of Gravity

Each particle attracts every other particle and the gravitational force between two particles is directly proportional to the product of their masses and inversely proportional to the distance between them, R. The authors use R instead of R^2 because according to the experiment results, R provides better results than R^2 in all experimental cases.

Law of Motion

The current velocity of any mass is equal to the sum of the fraction of its previous velocity and the variation in the velocity. Variation in the velocity or acceleration of any mass is equal to the force acted on the system divided by mass of inertia.

The gravitational constant, G, is initialized at the beginning and will be reduced with time to control the search accuracy. In other words, G is a function of the initial value (G_0) and time (t):

$$G(t) = G(0) \times \exp^{\left(\frac{-\alpha t_i}{T} \right)} \qquad (19)$$

where, α is a constant, t_i is the iteration number and 'T' is the total number of iterations.

Consider a system of N agents. The position of ith agent is

defined as,

$$X_i = \left(x_i^1, \ldots, x_i^d, \ldots, x_i^n\right) \quad ; \quad i = 1, 2, 3, \ldots, N \quad (20)$$

For each position, fitness function is evaluated.

5.1 Calculation of Masses

Let, $fit_i(t)$ be the fitness function of ith particle at t^{th} iteration.

Now, the authors introduce new variables worst (t) and best (t).

For a minimization problem, best (t) and worst (t) are defined as follows:

$$best(t) = \min(fit_j(t)) \quad ; \quad j = 1, 2, \ldots, N \quad (21)$$

$$worst(t) = \max(fit_j(t)) \quad ; \quad j = 1, 2, \ldots, N \quad (22)$$

For a maximization problem, best (t) and worst (t) are defined as follows:

$$best(t) = \max(fit_j(t)) \quad ; \quad j = 1, 2, \ldots, N \quad (23)$$

$$worst(t) = \min(fit_j(t)) \quad ; \quad j = 1, 2, \ldots, N \quad (24)$$

Gravitational and inertia masses are simply calculated by the fitness evaluation. A heavier mass means a more efficient agent. This means that, better agents have higher attractions and walk more slowly. Assuming, the equality of the gravitational and inertia mass, the values of masses are calculated using the map of fitness. The gravitational and inertial masses are updated by the following equations:

$$M_{ai} = M_{pi} = M_{ii} = M_i \quad (25)$$

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \quad (26)$$

$$M_i(t) = \frac{m_i(t)}{\sum\limits_{j=1}^{N} m_i(t)} \quad (27)$$

5.2 Calculation of Force

For iteration t, the force acting on mass i from mass j is defined as the following,

$$F_{ij}^d(t) = G(t) \frac{M_{pi}(t) M_{aj}(t)}{R_{ij} + \epsilon} \left(x_j^d - x_i^d\right) \quad (28)$$

where, M_{aj}, M_{pi} are the active and passive gravitational masses related to agent j, G(t) is gravitational constant at iteration t, ε is a small constant and R_{ij} is the Euclidian distance between two agents i and j given by,

$$R_{ij}(t) = ||X_i(t) X_j(t)||_2 \quad (29)$$

To give a stochastic characteristic to the algorithm, the total force that acts on agent i in a dimension d be a randomly weighted sum of dth components of the forces exerted from other agents:

$$F_i^d(t) = \sum\limits_{j=1, j \neq i}^{N} rand_i F_{ij}^d(t) \quad (30)$$

One way to perform a good compromise between exploration and exploitation is to reduce the number of agents with lapse of time. Hence, the authors propose only a set of agents with bigger mass apply their force to the other. However, we should be careful of using this policy because it may reduce the exploration power and increase the exploitation capability.

The authors remind that, in order to avoid trapping in a local optimum, the algorithm must use the exploration at beginning. By lapse of iterations, exploration must fade out and exploitation must fade in. To improve the performance of GSA by controlling exploration and exploitation only the K_{best} agents will attract the others. K_{best} is a function of time, with the initial value K_0 at the beginning and decreasing with time. In such a way, at the beginning, all agents apply the force, and as time passes, K_{best} is decreased linearly and at the end there will be just one agent applying force to the others.

Therefore, equation (30) can be modified as:

$$F_i^d(t) = \sum\limits_{j=K_{best}, j \neq i}^{N} rand_i F_{ij}^d(t) \quad (31)$$

where, K_{best} is the set of first K agents with the best fitness value and biggest mass given by,

$$k_{best} = final_{per} + \left(1 - \frac{t}{T}\right)(100 - final_{per}) \quad (32)$$

where, $final_{per}$ is the percentage of particles that remain at the end (generally 2). Since M is a function of m, which is function fitness, in every iteration, one value of m is zero. Hence, M is zero at this value of m. At this value of M, acceleration becomes an indefinite value from above equations. To obtain integer value of K_{best}, it is rounded in terms of population. Hence, we introduce another variable E which is defined as follows:

$$E_{ij}^d = \frac{F_{ij}^d}{MG} = \frac{M}{R_{ij} + \epsilon} \left(x_j^d - x_i^d\right) \quad (33)$$

$$E_i^d(t) = \sum\limits_{j=1, j \neq i}^{N} rand_i E_{ij}^d(t) \quad (34)$$

5.3 Calculation of Acceleration

Hence, by the law of motion, the acceleration of the agent 'i' at iteration t, and in direction d, is given as:

$$a_i^d = E_i^d(t) \times G(t) \qquad (35)$$

Furthermore, the next velocity of an agent is considered as a fraction of its current velocity added to its acceleration. Therefore, its position and its velocity could be calculated as follows:

$$V_i^d(t+1) = rand_i \times V_i^d(t) + a_i^d(t) \qquad (36)$$

$$x_i^d(t+1) = x_i^d(t) + V_i^d(t+1) \qquad (37)$$

5.4 Step by Step Procedure of GSA

The different steps of the proposed algorithm are following.

- Search space identification.
- Randomized initialization.
- Fitness evaluation of agents.
- Update $G(t)$, best(t), worst(t) and $M_i(t)$ for i = 1,2,...,N.
- Calculation of the total force in different directions.
- Calculation of acceleration and velocity.
- Updating agents' position.
- Repeat steps 3 to 7 until the stop criteria is reached.
- End.

5.5 Flow Chart of GSA

The complete procedure of GSA is shown in Figure 2.

6. Results and Analysis

In order to demonstrate the effectiveness and robustness of the proposed GSA method, the Standard IEEE 30 bus system is considered. The existing an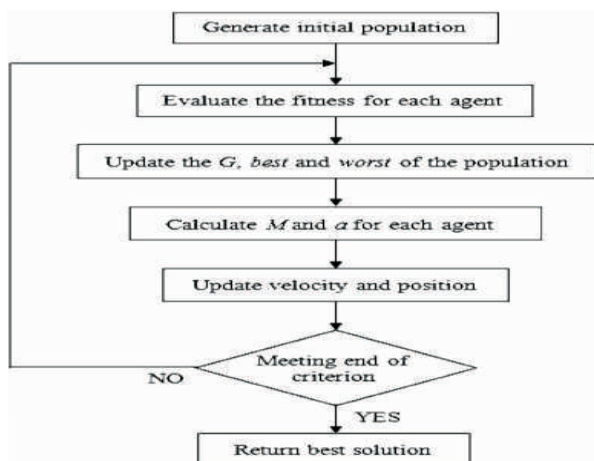d proposed methodologies are implemented on a personal computer with Intel Core2Duo 1.18 GHz processor and 2 GB RAM. The input parameters of the existing PSO method and the proposed GSA method for the considered test system are given in Table 1.

This section presents the details of the study carried out on the Standard IEEE-30 bus test system to analyze OPF problem. The network and load data for this system is taken from [1]. In the Standard IEEE-30 bus system consist of 41 branches, six generator buses and 21 load buses. Four branches 6-9, 6-10, 4-12 and 27-28 have tap changing transformers. The buses with possible reactive power source installations are 10 and 24.

The effectiveness of SCOPF (Security Constrained Optimal Power Flow) over OPF is verified using existing PSO and proposed GSA. The respective results are tabulated in Table 2. From this table, it is observed that, less generation fuel cost is obtained with the proposed GSA when compared to the existing PSO algorithm in OPF and SCOPF problems.

Using the proposed GSA, the total generation and there by the total transmission power losses are decreased. It is also observed that, because of the increased number of constraints in SCOPF, the generation fuel cost is increased when compared to OPF. In OPF problem, using the proposed GSA, the generation fuel cost in decreased by 0.4107 $/h and whereas in SCOPF problem, the generation fuel cost is decreased by 0.6916 $/h.

The convergence characteristics for the OPF and SCOPF problems using the existing and proposed methods are shown in Figures 3 and 4. From these Figures 3 and 4, it is

Figure 2. Flow Chart of GSA

S.No	Method	Parameters	Quantity
1	PSO method	Population size	5
		Number of generations	100
		Initial weight function, ω_{max}	0.9
		Final weight function, ω_{min}	0.4
		Acceleration coefficients c_1 and c_2	2
2	GSA method	Population	50
		Maximum iterations	100
		Initial gravitational constant (G_0)	100
		Decay constant (a)	5/10
		Constant (ε)	8.854×10^{-12}
		Percentage of number of particles in final iteration	2
		Rnorm	2

Table 1. Input Parameters for Test System

S.No	Control Parameters		OPF		SCOPF	
			Existing PSO	Proposed GSA	Existing PSO	Proposed GSA
1	Real power Generation (MW)	P_{G1}	176.689	174.3426	176.382	175.9074
		P_{G2}	48.3217	49.64299	48.2966	49.51213
		P_{G5}	21.3454	21.8549	21.3100	21.21016
		P_{G8}	23.1939	21.79141	22.8044	20.91668
		P_{G11}	11.4869	13.14502	12.3677	13.07669
		P_{G13}	12	12	12	12.35759
2	Generator voltages (p.u.)	V_{G1}	1.05	1.05	1.05	1.05
		V_{G2}	1.03381	1.039274	0.94015	1.035991
		V_{G5}	1.01015	1.012427	1.01053	1.010529
		V_{G8}	1.01274	1.019376	1.04743	1.018665
		V_{G11}	1.01537	1.05	1.01463	1.007666
		V_{G13}	1.04928	1.05	1.05	1.05
3	Transformer tap setting (p.u.)	T_{6-9}	0.96095	1.002329	0.96522	0.988997
		T_{6-10}	0.94748	0.999802	1.03427	0.966031
		T_{4-12}	1.01572	0.989838	1.02057	1.027439
		T_{28-27}	0.94073	0.974107	0.98408	0.978148
4	Shunt compensators (MVAr)	$Q_{C,10}$	10.1511	22.4211	23.8126	10.91058
		$Q_{C,24}$	16.0914	13.46823	13.0653	13.20759
5	Total generation (MW)		293.037	292.7769	293.161	292.9806
6	Quadratic fuel cost ($/h)		802.925	802.5149	803.441	802.7499
7	Total power losses (MW)		9.63776	9.376908	9.76158	9.58063

Table 2. OPF and SCOPF Results of Generation Fuel Cost for Standard IEEE-30 Bus System
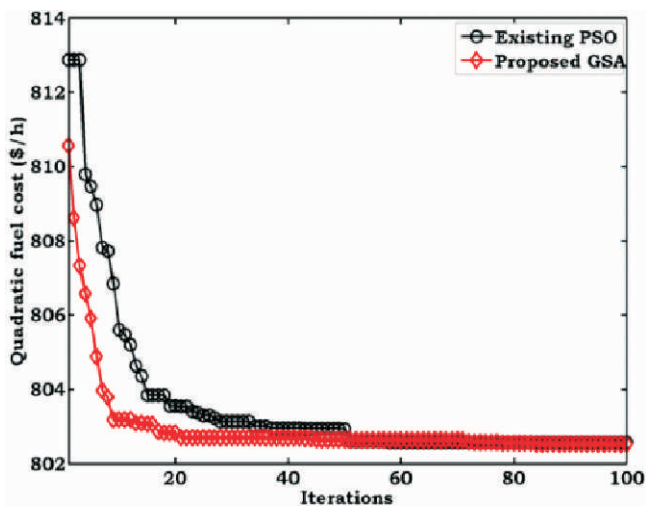

Figure 3. Convergence Characteristics of OPF with Quadratic Cost for IEEE-30 Bus System
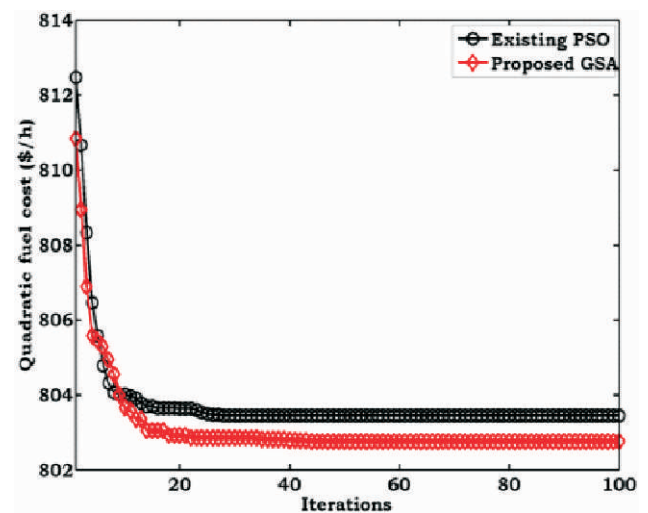

Figure 4. Convergence Characteristics of SCOPF with Quadratic Cost for IEEE-30 Bus System

observed that, in both of the problems, the proposed GSA algorithm starts the iterative process with better initial value and converges to a best value in less number of iterations when compared to the existing PSO algorithm. It is also identified that, because of the increased number of constraints in SCOPF problem, the convergence starts with higher generation fuel cost value when compared to that of OPF problem.

The voltage magnitudes at buses in OPF and SCOPF problems are tabulated in Table 3. Similarly, the variation

Bus No	OPF		SCOPF	
	PSO	GSA	PSO	GSA
1	1.05	1.05	1.05	1.05
2	1.0338099	1.0392735	1.03599084	1.0252456
3	1.023003	1.0276981	1.02658537	1.0279858
4	1.0163374	1.0220096	1.02066874	1.0223658
5	1.0101587	1.0124268	1.01052911	1.011053
6	1.0085361	1.0190805	1.0141517	1.0197274
7	1.0013885	1.0086115	1.0048899	1.0084307
8	1.0127406	1.0193756	1.01866452	1.0298365
9	1.0279167	1.0304091	1.01277126	1.0278281
10	1.0241939	1.0283828	1.00990145	1.0208056
11	1.0153761	1.05	1.00766592	1.0146308
12	1.0217949	1.0309191	1.0156231	1.0207211
13	1.0492814	1.05	1.05	1.05
14	1.0103291	1.0182547	1.00242241	1.0082015
15	1.0092109	1.0158622	0.99974737	1.0060747
16	1.0153909	1.0224689	1.00573499	1.0133121
17	1.0160827	1.0211697	1.00312949	1.0130711
18	1.0020398	1.007892	0.99072919	0.9987695
19	1.0010064	1.0063673	0.98863678	0.9976692
20	1.0060003	1.0110722	0.99314235	1.002646
21	1.0154761	1.0183278	0.99999601	1.0104518
22	1.0172498	1.0196641	1.00146326	1.0117288
23	1.0106095	1.0130431	0.99655693	1.0036236
24	1.0211206	1.0178873	1.00103812	1.0090372
25	1.0280064	1.0158606	1.00184443	1.0073429
26	1.0105196	0.9981566	0.98388279	0.9894833
27	1.04074	1.0231726	1.01104984	1.0149381
28	1.0045315	1.0154692	1.01106194	1.0183262
29	1.0212698	1.003332	0.99094491	0.9949187
30	1.0100071	0.9918565	0.97931759	0.9833405

Table 3. Voltage Magnitudes of OPF and SCOPF
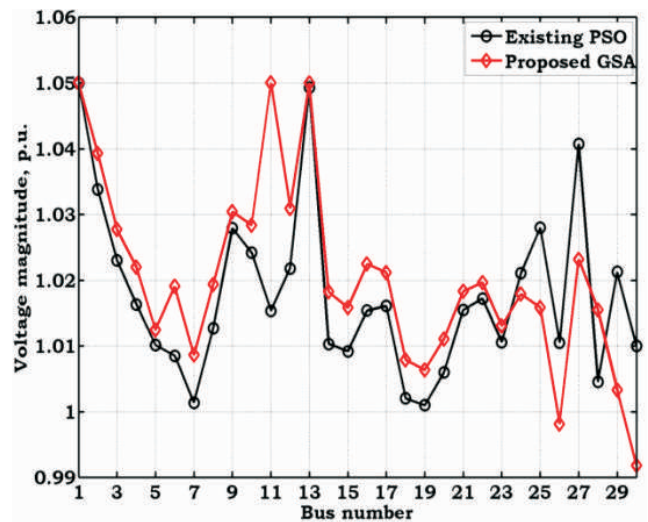with Quadratic Cost for IEEE-30 Bus System

Figure 5. Variation of Voltage Magnitudes of OPF
with Quadratic Cost for IEEE-30 Bus System
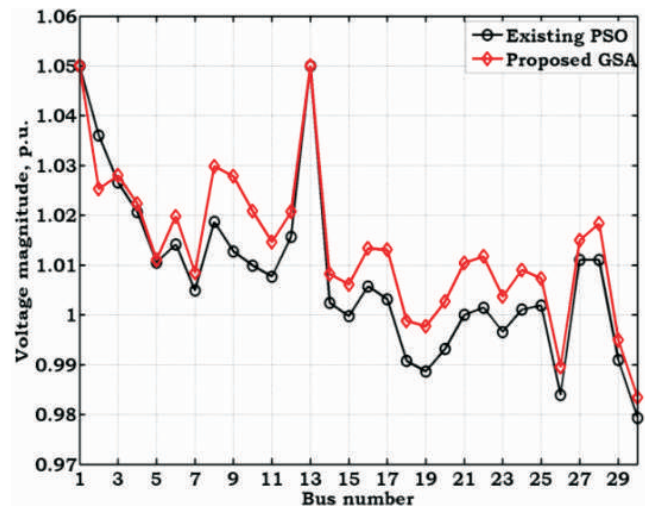
Figure 6. Variation of Voltage Magnitudes of SCOPF
with Quadratic Cost for IEEE-30 Bus System

of voltage magnitudes in OPF and SCOPF problems using the existing and proposed methods is shown in Figures 5 and 6. From Figure 5, it is observed that, because of solving OPF problem without security limits, voltage magnitude deviations are high at some of buses and majority of buses are operating nearer to maximum voltage limit. From Figure 6, it is observed that, because of SCOPF problem, the voltage magnitude at buses is within its voltage limits. It is also observed that, in both of the problems, with the proposed GSA, the voltage magnitude at buses is enhanced when compared to the existing PSO algorithm.

Similarly, the transmission line power flows in OPF and SCOPF problems using existing and proposed methods are tabulated in Table 4 and the respective variation is

shown in Figures 7 and 8. From Figure 7, it is observed that, because of solving OPF problem without security constraints, the power flow in some of the lines is operating nearer to the maximum MVA limit. From Figure 8, it is observed that, because of SCOPF, the power flow in all lines is within limits. In this problem, the power flow in some of the lines is reduced with the proposed GSA when compared to the existing algorithm.

To support the effectiveness of the proposed method, obtained results are compared with the existing literature methods. The comparison results is given in Table 5. From this table, it is identified that, the proposed method yields good results when compared to the

Line No	OPF		SCOPF		MVA Limit
	PSO	GSA	PSO	GSA	
1	118.58923	117.66726	117.59952	118.04218	130
2	58.465331	58.106942	58.97925	58.547977	130
3	33.695453	33.895374	35.082238	34.036904	65
4	54.643444	54.420379	55.274202	54.818077	130
5	63.860637	63.111099	63.671463	63.7444	130
6	44.926912	44.949618	46.093901	45.16888	65
7	50.238842	49.110583	50.155039	49.835576	90
8	15.435622	12.888982	12.729458	13.850837	70
9	34.134329	34.193146	34.579622	34.234051	130
10	16.553976	11.508245	29.567665	18.656065	32
11	22.489145	19.504944	24.741637	19.423453	65
12	15.95031	13.131913	14.138645	15.611208	32
13	13.115116	16.241415	14.053543	13.344512	65
14	31.206987	31.677095	32.882916	31.512531	65
15	30.553153	30.989444	31.159019	31.158701	65
16	23.295615	18.406835	24.406593	27.742596	65
17	7.4372823	7.7335177	7.6582792	7.751248	32
18	16.962592	17.770038	17.533633	17.72761	32
19	6.2519348	6.7863481	6.5435735	6.8026593	32
20	1.2635863	1.3357483	1.291789	1.304483	16
21	3.1010764	3.1946544	3.1701121	2.9642617	16
22	5.4184223	5.6935724	5.5406616	5.7330867	16
23	2.1560346	2.373722	2.2791709	2.3613325	16
24	8.2215903	7.8939907	8.1176284	7.7679596	32
25	10.739833	10.397281	10.631457	10.276169	32
26	9.7452386	8.7945921	9.2822486	8.3749702	32
27	16.181094	17.139934	17.296203	16.915986	32
28	7.4711249	7.9891802	8.0770564	7.8644642	32
29	6.9199655	5.2104912	4.9356191	5.6259293	32
30	5.0558992	4.8784794	4.7795617	4.7316863	16
31	7.5443262	6.4633763	6.36329	6.6630826	16
32	4.5280591	3.0124336	3.0636556	2.7696838	16
33	2.6665257	1.9195494	1.8950464	1.7030546	16
34	4.2605518	4.262361	4.263671	4.2645353	16
35	6.8520487	4.9731364	5.0359842	5.4021057	16
36	21.03537	19.052656	19.141018	19.569332	65
37	6.4046256	6.4110887	6.4142476	6.4157692	16
38	7.2766468	7.2844887	7.2883219	7.2901684	16
39	3.7512091	3.7529791	3.7538444	3.7542613	16
40	3.1553816	2.6858103	3.9070057	2.6144364	32
41	16.601932	15.780857	15.774988	16.029469	32

Table 4. Power Flows of OPF and SCOPF with Quadratic Cost for IEEE-30 Bus System

existing methods.

From the above analysis, it has been concluded that, because of including security constraints in SCOPF problem, this problem is more efficient when compared to OPF problem. From this, it is assumed that, further analysis is performed using SCOPF only.
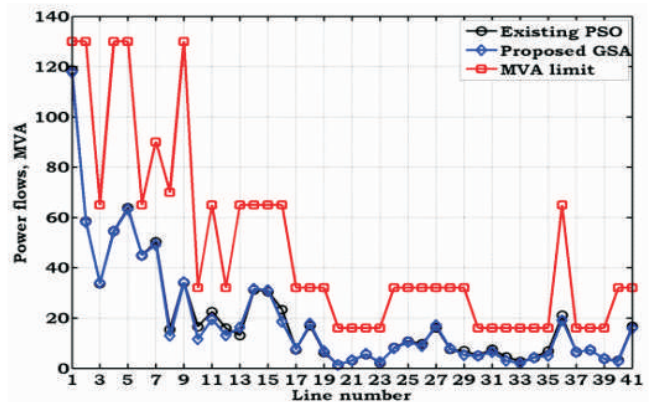

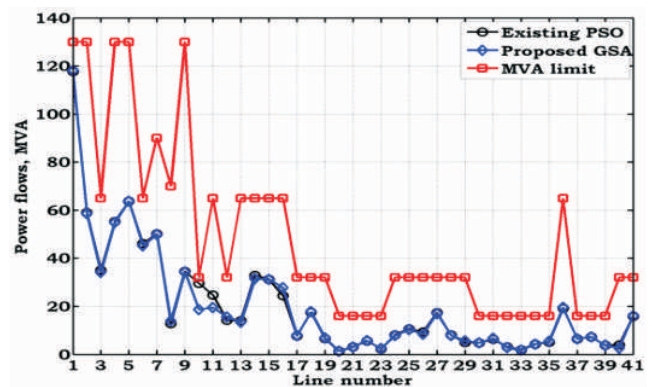Figure 7. Variation of Power Flows of OPF with Quadratic Cost for IEEE-30 Bus System

Figure 8. Variation of Power Flows of SCOPF with Quadratic Cost for IEEE-30 Bus System

S.No	Method	Quadratic cost ($/h)
1	EP [22]	802.9070
2	TS/SA [23]	802.7880
3	ITS [24]	804.5560
4	GA [25]	803.0500
5	Proposed GSA	802.7499

Table 5. Validation of SCOPF results of quadratic cost for IEEE-30 bus system

Conclusion

In this paper, to show the effect of security constraints on OPF problem which has been demonstrated by performing OPF and SCOPF problems by considering generation fuel cost as objective. To solve this problem, Gravitational Search Algorithm (GSA) is proposed. The effectiveness of the proposed algorithm is compared with the existing Particle Swarm Optimization (PSO). The effect of security constraints on voltage magnitudes and line power flows has been analyzed. The complete methodology has been tested on the standard IEEE-30

bus test system. The obtained results are validated with the existing literature.

References

[1]. Alsac O, and Stott B. (1974). "Optimal load flow with steady state security". *IEEE Trans Pwr Appar Syst*, Vol.93, pp.745-751.

[2]. Po-Hung Chen and Hong-Chan Chang, (1995). "Large-Scale Economic Dispatch By Genetic Algorithm". *IEEE Transactions on Power Systems*, Vol.10, No.4, pp.1919-1926.

[3]. J. Z. Zhu and G. Y. Xu, (1992). "A new real power economic dispatch method with security". *Electric Power Systems Research*, Vol.25, No.1, pp. 9-15.

[4]. Shoults R, and Sun D. (1982). "Optimal power flow based on P-Q decomposition". *IEEE Trans Pwr Appar Syst*, Vol.101, No.2, pp.397-405.

[5]. Habiabollahzadeh H, Luo, and Semlyen A. (1989). "Hydrothermal optimal power flow based on combined linear and nonlinear programming methodology". *IEEE Trans Pwr Appar Syst*, Vol.4, No.2, pp.530-537.

[6]. Burchet RC, Happ HH, and Vierath DR. (1984). "Quadratically convergent optimal power flow". *IEEE Trans Pwr Appar Syst*, Vol.103, pp.3267-3276.

[7]. Aoki K, Nishikori A, and Yokoyama RT. (1987). "Constrained load flow using recursive quadratic programming". *IEEE Trans Pwr Syst*, Vol.2, No.1, pp.8-16.

[8]. Mota-Palomino R, and Quintana V H. (1986). "Sparse reactive power scheduling by a penalty function linear programming technique". *IEEE Trans Pwr Syst*, Vol.1, No.3, pp.31-39.

[9]. Sun DI, Ashley B, Brewer B. Hughes A, and Tinney WF. (1984). "Optimal power flow by Newton approach". *IEEE Trans Pwr Appar Syst*, Vol.103, No.10, pp.2864-2875.

[10]. Santos A, and da Costa GR. (1995). "Optimal power flow solution by Newton's method applied to an augmented lagrangian function". *IEEE Proc Gener Transm Distrib*, Vol.142, No.1, pp.33-36.

[11]. Dommel H, Timmy W, (1968). "Optimal power flow solution". *IEEE Trans Pwr Appar Syst*, Vol.87, No.10, pp.1866-1876.

[12]. Happ HH, (1977). "Optimal power dispatch: a comprehensive survey". *IEEE Trans Pwr Appar Syst*, Vol.96, pp.841-854.

[13]. Mamandur KRC, (1981). "Optimal control of reactive power flow for improvements in voltage profiles and for real power loss minimization". *IEEE Trans Pwr Appar Syst*, Vol.100, No.7, pp.3185-3193.

[14]. Abou El-Ela AA, and Abido MA, (1992). "Optimal operation strategy for reactive power control, modeling, simulation and control". *AMSE Press*, Vol.41, No.3, pp.19-40.

[15]. Stadlin W, and Fletcher D, (1982). "Voltage versus reactive current model for dispatch and control". *IEEE Trans Pwr Appar Syst*, Vol.101, No.10, pp.3751-3758.

[16]. Kennedy J, (1997). "The particle swarm; social adaptation of knowledge". *Proc of IEEE Int Conf Evol Comput ICEC-97*, Indianapolis, IN, USA, pp.303-308.

[17]. Angeline P, (1998). "Evolutionary optimization versus particle swarm optimization: Philosophy and performance differences". *Proc 7th Annu Conf Evol Prog*, pp.601-610.

[18]. Shi Y, and Eberhart R, (1998). "Parameter selection in particle swarm optimization". *Proc 7th Annu Conf Evol Prog*, pp.591-600.

[19]. Ozcan E, and Mohan C, (1998). "Analysis of a simple particle swarm optimization system". *Intel Engng Syst Artif Neural networks*, Vol.8, pp.253-258.

[20]. R.J. Ringlee and D.D. William, (1963). "Economic dispatch operation considering valve throttling losses. Part II: Distribution of system loads by the method of dynamic programming". *IEEE Transactions on Power Apparatus and Systems*, Vol.82, No.1.

[21]. IEEE Committee Report, (1971). "Practices in the economic operation of power systems". *IEEE Trans. Power Apparatus and Systems*, Pas-90, pp.1768-1775.

[22]. Yang H, Yang P, and Huang C., (1996). "Evolutionary programming based economic dispatch for units with non-smooth fuel cost functions". *IEEE Trans. Power Syst.*, Vol.11, pp.112-118.

[23]. W. Ongsakul and T. Tantimaporn, (2006). "Optimal

power flow by improved evolutionary programming". *Electric Power Components and Systems*, Vol.34, pp.79-95.

[24]. Lin W, Cheng F, and Tasy M., (2002). "An improved search for economic dispatch with multiple minima". *IEEE Trans. Power Syst.*, Vol.17, pp.108-112.

[25]. D Devaraj, and B. Yegnanarayana, (2005). "Genetic Algorithm based optimal power flow for security enhancement". *IEE Proc. on Gener. Trans. Distr.*, Vol.52, No.6, pp.899-905.

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