A Novel PSOGSA_SQP Algorithm for Solving Optimal Power Flow (OPF) Problem Based on Specific Switching Condition

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Abstract

In this paper, PSOGSA_SQP novel hybrid algorithm is proposed to solve the optimal power flow (OPF) problem. Employing the proposed method aims at optimally adjusting control variables and increasing speed. The performance of the proposed method is studied on a standard system introduced in IEEE standards with 30 buses and specific objective functions which seek to minimize generator fuel costs, voltage stability and voltage profile improvement in different modes. Simulation results certify that this algorithm is faster than other methods such as PSO, GSA, GA, in view of using the SQP classical gradient-based method and its combination with PSOGSA intelligent method. We also propose a new switching method to switch from intelligent optimization method to SQP. This algorithm minimizes cost function value by accurately adjusting control variables.

Key words: Optimal power flow, Particle Swarm Oprimization, Gravitational Search Algorithm, Sequential Quadratic Programming

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I. INTRODUCTION

Power engineers require special tools to optimally analyze, monitor, and control different aspects of power systems operation and planning. Most of these tools are properly formulated as some sort of optimization problems. The optimal power flow (OPF) is a backbone tool that has been extensively researched since its first introduction in the early 1960s [1,2]. It appears that the term "optimal power flow" was first introduced by Dommel and Tinney in 1968.

Originally, the OPF was formulated as a natural extension of the traditional economic dispatch. Differences between the two optimization functions exist even though both of them may share the same objective function. In economic dispatch, the entire power network is reduced to a single equality constraint. By contrast, all major elements of the modeled system are explicitly presented in the OPF problem. The generic term "OPF" is no longer associated exclusively with the extended economic dispatch calculation. Rather, it presents a wide range of optimization problems commonly formulated in power systems related studies. OPF studies are evolving over time from its basic form to cope with the continuous changes that are taking place in power systems. Deregulation of the electric power industry, advances being made in the area of power electronics, and the environmental regulations that are being imposed on power plants are some of the main factors that have played major role in constantly reformulating the OPF. The historical development of the OPF is closely correlated with the advances made in the area of numerical optimization techniques. Researchers have attempted to apply most optimization techniques to solve the OPF.

The purpose of OPF is to find the optimal settings of a given power system network that optimize a certain objective function while satisfying its power flow equations, system security, and equipment operating limits. Different control variables are manipulated to achieve an optimal network setting based on the problem formulation.

In this paper, minimization of fuel cost of generators, improvement of voltage stability and voltage characteristics by optimal adjustment of control variables are considered while equality and inequality constraint of power system are satisfied. The equality constraints are as nodal power balance equations, while the inequality constraints are as the limits of all control or state variables. Control variables consist of 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 non-convex optimization problem.

Methods investigated in previous papers may be divided into three categories: classical, intelligent and hybrid optimization methods. Classical optimization methods include interior point method, linear programming, nonlinear programming and quadratic programming. Although these methods are fast, the algorithm might suffer a local minimum [4-9].

Intelligent optimization methods are including several methods such as Genetic algorithm[11], Improved genetic algorithms[12], tabu search [4], particle swarm [13], differential evolution algorithm [14], improved differential evolution algorithm[15], evolutionary programming[16], Gravitational Search Algorithm (GSA)[17]. Even though intelligent algorithms are global and insensitive to initial point, one of their weak spots is lengthy calculation time. PSO algorithm along with parallel processing system is used in [18] and GA method is used in [19] in order to reduce calculation time. In [20], fuzzy genetic algorithm is addressed in which crossover and mutation operators vary via fuzzy rules. Another category is hybrid optimization methods. By combining SQP and particle swarm optimization algorithms in [21] and SQP, genetic algorithm, and tabu search algorithms in [22], hybrid optimization methods seek to reduce calculation time and increase speed. In fact, efforts have been made in these methods to make use of the positive features of both intelligent and classical algorithms. In hybrid methods where intelligent and classical methods are employed simultaneously, switching rule playsan important role. In [22], switching condition is based on termination of iterations in the intelligent algorithm. In [21], switching condition is based on difference in cost function value in two successive iterations, in this manner that when the difference in cost function value is less than a specific value in two successive iterations, the algorithm switches from the intelligent mode to the classical mode. The only defect is that this condition may be met at the outset of the optimization process in the intelligent algorithm, thus being unable to provide the classical algorithm with an appropriate initial point. In [25], switching condition is based on differences in Lagrange coefficients.

In this paper, the global search feature of PSOGSA algorithm [26] as well as the local search feature of SQP algorithm is used. Bearing in mind that SQP algorithm is sensitive to initial point, the performance of the proposed method is in such a way that that PSOGSA algorithm initiates the optimization process in order to be able to provide the intelligent algorithm with an appropriate initial point. In case switching condition is met, the optimization process continues until arriving at an answer via SQP algorithm.

Using PSOGSA method certainly involves the advantage of not getting caught in local minimums. Its combination with the fast gradient-based SQP method speeds up convergence. In the proposed method, the algorithm switching condition is based on curve steepness. The optimization process starts with great speed and curve steepness in PSOGSA algorithm. As the algorithm approaches the optimal point, the process slows down and curve steepness decreases. In this situation, PSOGSA algorithm switches to the fast classical SQP algorithm and the process continues until reaching the desired point with great speed.

In this paper, a newly developed heuristic optimization called PSOGSA_SQP 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 including fuel cost of generators, fuel cost with non-smooth cost curve and piecewise quadratic cost function. The obtained final optimal solution is compared with other algorithms.

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 PSOGSA_SQP is presented. Section 4 presents the results of simulation and compares techniques which have been proposed previously in the literature to solve optimal power flow.

II. OPF MATHEMATICAL MODEL

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 [20]:

$$\begin{aligned} &\mathbf{Min}\, F(x,u) \\ \textit{subject to}\ & g(x,u) = 0 \\ & h(x,u) \le 0 \end{aligned} \tag{1}$$

where F is the objective function to be minimized, x and u are vectors of dependent and control variables respectively. 'x' is the vector of dependent variables consisting of load bus voltage magnitude limits, reactive capabilities of generators, slack bus active power and branch flow limits:

$$x^t = [P_{G1}, V_{L1}, \ldots V_{L-NPQ}, Q_{G1} \ldots Q_{G-NPV}, S_{L1}, \ldots S_{1NTL}] \quad (2)$$

where NPV, NPG and NTL are number of control buses voltage, number of PQ-buses and number of transmission lines, respectively. u is the vector of control or independent variables consisting of generator-bus voltage magnitudes, active power generations, transformer-tap settings and reactive shunt compensators:

$$u^t = [P_{G2} \ldots P_{G-NG}, V_{G1} \ldots V_{G-NG}, Q_{c1} \ldots Q_{c-NC}, T_1 \ldots T_{NT}] \quad (3)$$

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

A. Objective function

The OPF problem is considered as a general minimization problem with constraints, and can be written in the following form:

$$F = \sum_{i=1}^{NG} f_i = \sum_{i=1}^{NG} a_i + b_i P_{Gi} + c_i P_{Gi}^2 \quad (4)$$

where F is the total generation cost ($/h) [23], a_i, b_i, c_i are the cost function coefficients of the i_{th} unit, P_{Gi} is the real power generation of unit i , N_G is the total number of generation units.

B. Constraints

1. Equality constraints

These constraints are typical load flow equations

$$P_{Gi} - P_{Di} - \sum_{i=1}^{NG} v_j \left[G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)\right] = 0 \quad (5)$$

$$Q_{Gi} - Q_{Di} - \sum_{j=1}^{NG} v_j \left[G_{ij}\sin(\delta_i - \delta_j) + B_{ij}\sin(\delta_i - \delta_j)\right] = 0 \qquad (6)$$

i = 1. . .n. where n is the number of buses in the system. P_{Gi} and Q_{Gi} are active and reactive power generations at bus i , P_{Di} and Q_{Di} are corresponding active and reactive load demands.

C. Inequality constraints

These constraints represent system operating limits.

I. Generator constraints: generator voltage magnitudes VG, Generator active power PG and reactive power QG are restricted by their lower and upper limits.

$$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max}, i = 1,2, \dots, NPV \qquad (7)$$

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max}, i = 1,2, \dots, NPV \qquad (8)$$

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max}, i = 1,2, \dots, NPV \qquad (9)$$

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

II. Transformer constraints: transformer taps have minimum and maximum setting limits:

$$T_i^{min} \leq T_i \leq T_i^{max}, i = 1,2, \dots, NPV \qquad (10)$$

where T_i^{min} and T_i^{max} define minimum and maximum tap settings limits of i_{th} transformer.

III. Switchable VAR sources: the switchable VAR sources have restrictions as follows

$$Q_{ci}^{min} \leq Q_{ci} \leq Q_{ci}^{max}, i = 1,2, \dots, NPV \qquad (11)$$

where Q_{ci}^{min} and Q_{ci}^{max} define minimum and maximum Var injection limits of i_{th} shunt capacitor.

IV. Security constraints: these include the limits on the load bus voltage magnitudes and line flow limits.

$$V_{Li}^{min} \le V_{Li} \le V_{Li}^{max}, i = 1,2,\ldots,NPQ \quad (12)$$

$$S_{li} \le S_{li}^{max}, i = 1,2,\ldots,NTL \quad (13)$$

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

A penalty function [24] is added to the objective function, if the functional operating constraints violate any of the limits. The initial values of the penalty weights are:

$$P(x) = f(x) + \rho(x) \quad (14)$$

$$\rho(x) = \sigma\{g^{2}(x) + [\max(0, k(x))]^{2}\} \quad (15)$$

where $P(x)$, $\rho(x)$, σ, $k(x)$ and g(x) are penalty function, penalty term, penalty coefficient, inequality constraint and equality constraint respectively.

D. Power Losses

Optimal power flow in power transfer lines with short distances may be calculated without taking line losses into consideration. In large scales, however, this is impossible to neglect. Transfer line losses may be considered to constitute 5 to 15 percent of the entire load. Hence, it is necessary to calculate transfer line losses. Using Crone's formula, in which a coefficient of generated power of generators is used, is a simple proper estimation for calculating transfer line losses. Coefficients of matrix B are used for this purpose as follows:

$$P_L = \sum_i \sum_j P_i B_{ij} P_j + \sum_i B_{i0} P_i + B_{00} \quad (16)$$

$$P_{Lmin} \le P_L \le P_{Lmax} \quad (17)$$

III. PSOGSA_SQP ALGORITHM:

PSOGSA is proposed to combine global search capability of PSO algorithm with the local search ability increase the convergence speed and accuracy of PSO. The goals of this combination are increment of convergent speed and reach to better optimal values. Finding global optimum and independence to initial point are exploration as the two main characteristics of intelligent algorithms. Firstly, PSO and GSA algorithms are combined. In this article, optimization process is begun with PSOGSA. The vital exclusivities of classical algorithms are including low calculate volume and high convergence speed. So, for rising convergence rate and accede to optimal solution, SQP algorithm is used. The basic idea of proposed method is to combine the ability of global search in PSOGSA with the local search capability of GSA. In optimal power flow problem using novel algorithm, initial population involve the reactive power of generators, the tap ratio of transformer, parallel compensator and generator voltage. The optimal power flow is an important problem of power systems in which certain control variables are adjusted to minimize an initial objective function. In this section, at first, the well-known algorithms, namely PSO, GSA and SQP are introduced briefly.

A. *Particle Swarm Optimization*

PSO is an evolutionary computation technique which is proposed by Kennedy and Eberhart [28,29]. The PSO was inspired from social behavior of bird flocking. It uses a number of particles (candidate solutions) which fly around in the search space to find best solution. Meanwhile, they all look at the best particle (best solution) in their paths. In other words, particles consider their own best solutions as well as the best solution has found so far. Each particle in PSO should consider the current position, the current velocity, the distance to *pbest*, and the distance to *gbest* to modify its position.

After any iteration, each particle updates its position and velocity to achieve better fitness values according to the following Eqs. (18) and (19).

$$v_{ci}^{(t+1)} = w \cdot v_{ci}^{(t)} + c_1 * rand * \left(x_{gbest}^{(t)} - x_i^{(t)}\right) + c_2 * rand * \left(x_{ipbest}^{(t)} - x_i^{(t)}\right) \tag{18}$$

$$\mathbf{x}_i^{(t+1)} = \mathbf{x}_i^{(t)} + \mathbf{v}_{ci}^{(t+1)} \tag{19}$$

where c_1, c_2 are two constants, called acceleration factors, w is inertia weight is a random number between 0 and 1 denoted by inertia weight, v_{ci}^{t} is velocity of each particle during iteration t, x_i^t is current position of particle at iteration t, x_{ipbest}^{t} is previous best position of each particle till t; x_{gbest}^{t} is the position of the best particle in the group, rand is a random number between 0 and 1, t is the current iteration time or index.

The first part of (18), $w \cdot v_{ci}^{(t)}$ provides exploration ability for PSO. The second and third parts $c_1 * rand * \left(x_{gbest}^{(t)} \quad x_i^{(t)}\right)$ and $c_2 * rand * \left(x_{ipbest}^{(t)} \quad x_i^{(t)}\right)$, represent private thinking and collaboration of particles respectively. The PSO starts with randomly placing the particles in a problem space.

B. *Gravitational Search Aalgorithm*

In 2009, Rashedi et al. [27] proposed a new heuristic optimization algorithm called the Gravitational Search Algorithm (GSA) to find the best solution in problem search spaces using physical rules. In GSA, the position of the mass corresponds to a solution of the problem and the gravitational forces and inertias are determined using a fitness function. It is expected that masses be attracted by the heaviest masses that presents the optimum solution in the search space by lapse of time. According to [27], suppose there is a system with N agents. The position of each agent (masses) which is a candidate solution for the problem is defined as follows:

$$\mathbf{x}_i = \left(x_i^1 \dots x_i^d \dots x_i^n\right) \ for \ i = 1, 2, \dots, N \tag{20}$$

where N is the dimension of the problem and x_i^d is the position of the i_{th} agent in the d_{th} dimension. After evaluating the current population fitness, the mass of each agent is calculated as follows:

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \tag{21}$$

where:

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \tag{22}$$

where $M_1(t)$ and $fit_i(t)$ represent the mass and the fitness value of the agent i at t, respectively. For a minimization problem, $worst(t)$ and $best(t)$ are defined as follows [29]:

$$best(t) = \min_{j\in\{1,\dots,N\}} fit_j(t) \tag{23}$$

$$worst(t) = \max_{j\in\{1,\dots,N\}} fit_j(t) \tag{24}$$

The algorithm starts by randomly placing all agents in a search space. At a specific time t, the force acting on the i_{th} mass from the j_{th} mass is defined as in the following equation

$$F_{ij}^d(t) = G(t)\frac{M_{aj}(t)M_{pj}(t)}{R_{ij}(t) + \varepsilon}\left(x_j^d(t) - x_i^d(t)\right) \tag{25}$$

where M_{aj} is the active gravitational mass related to agent j, M_{pi} is the passive gravitational mass related to agent i, G(t) is a gravitational constant at time t, e is a small constant, and $R_{ij}(t)$ is the Euclidian distance between two agents i and j and the gravitational constant G given by the following equations:

$$R_{ij}(t) = \|X_i(t), X_j(t)\|_2 \tag{26}$$

$$G(t) = (G_0, t), \qquad G(t) = G_0 e^{-\alpha\frac{iter}{maxiter}} \tag{27}$$

where a is the descending coefficient, G0 is the initial gravitational constant, iter is the current iteration, and max-iter is the maximum number of iterations.

To ensure the stochastic characteristic of the GSA, it is expected that the total force that acts on the i_{th} agent in the d_{th} dimension be α randomly weighted sum of d_{th} components of the forces exerted from other agents given by following equation:

$$F_i^d(t) = \sum_{j\epsilon kbest,\ j\neq i}^{N} rand_i\, F_{ij}^d(t) \tag{28}$$

where $rand_i$ is a random number in the interval [0, 1] According to the law of motion, the acceleration of an agent
is proportional to the result force and inverse of its mass, so
the acceleration of all agents should be calculated as follow:

$$ac_i^d(t) = \frac{F_i^d(t)}{M_i} \tag{29}$$

where M_i is the inertial mass of the i_{th} agent. The next velocity and position of an agent is considered as fraction of its current velocity added to its acceleration i.e.

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t) \tag{30}$$
$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \tag{31}$$

The GSA algorithm is composed of the following steps:

Step.1 Search space identification.
Step.2 Randomized initialization.
Step.3 Fitness evaluation of agents.
Step.4 Update $G(t)$, $best(t)$, worst(t) and $M_i(t)$ for $i = 1,2,..,N$.
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 to 7 until the stop criteria is reached.
Step.9 End.

C. *The hybrid PSOGSA algorithm [26]*

Talbi in [31] has presented several hybridization methods for heuristic algorithms. According to [30], two algorithms can be hybridized in high-level or low-level with relay or evolutionary method as homogeneous or heterogeneous. In this paper, we hybridize PSO with GSA using low-level evolutionary heterogeneous hybrid. The hybrid is low-level because we combine the functionality of both algorithms. It is co-evolutionary because we do not use both algorithm one after another. In other words, they run in parallel. It is heterogeneous because there are two different algorithms that are involved to produce final results. The basic idea of PSOGSA is to combine the ability of social thinking (*gbest*) in PSO with the local search capability of GSA. In order to combine these algorithms, (30) is proposed as follow:

$$v_i(t+1) = w \times v_i(t) + c'_1 \times rand \times ac_i(t) + c'_2 \times rand \times (gbest - x_i(t)) \tag{32}$$

Where $V_i(t)$ is the velocity of agent i at iteration *t*, c'_j is a weighting factor, *w* is a weighting function, rand is a random number between 0 and 1, ac_i is the acceleration of agent *I* at iteration *t*, and $gbest$ is the best solution so far. In each iteration, the positions of particles are updated as follow:

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{33}$$

In PSOGSA, at first, all agents are randomly initialized. Each agent is considered as a candidate solution. After initialization, Gravitational force, gravitational constant, and resultant forces among agents are calculated using (25), (27), and (28) respectively. After that, the accelerations of particles are

defined as (29). In each iteration, the best solution so far should be updated. After calculating the accelerations and with updating the best solution so far, the velocities of all agents can be calculated using (32). Finally, the positions of agents are defined as (33). The process of updating velocities and positions will be stopped by meeting an end criterion. The steps of PSOGSA are represented in figure 1.
To see how PSOGSA is efficient some remarks are noted as follow.

- In PSOGSA, the quality of solutions (fitness) is considered in the updating procedure.
- The agents near good solutions try to attract the other agents which are exploring different parts of the search space.
- When all agents are near a good solution, they move very slowly. In this case, g_{best} helps them to exploit the global best.
- PSOGSA uses a memory (g_{best}) to save the best solution found so far, so it is accessible at any time.
- Each agent can observe the best solution (g_{best}) and tend toward it.
- By adjusting c0 as 1 and c0 as 2, the abilities of global searching and local searching can be balanced.

D. *Sequential Quadratic Programming*

Currently, the sequential quadratic programming (SQP) method is considered as the most efficient method for solving nonlinearly constrained optimization problems. SQP is a nonlinear programming method that starts from a single searching point and finds a solution using the gradient information. Although this optimizing method is less time consuming and convergence than the population based search algorithms but it is highly dependent on the initial estimate of solution [30].
SQP algorithm as an iteratively method is solved base on quadratic programming method. At first, Lagrangian function creates by adding constraints of the main problem to cost function:

$$L(x,\gamma) = f(x) + \sum_{i=1}^{m} \gamma_i \varphi_i(x) \tag{34}$$

The procedure for this SQP algorithm can be summarized as follows:

Step.1: Start from initial point x_k

Step.2: Compute the approximate Hessian of Lagrangian function in each iteration (H, k)

Step.3: Generate iteratively the main search direction d_k of the nonlinear problem (NLP) by solving the following QP sub-problem:

$$\begin{aligned} &\min \frac{1}{2} d^T H_k d + \nabla f(x_k)^T d \\ &\quad \nabla \varphi_i(x_k)^T d + \varphi_i(x_k) = 0, \qquad i = 1, \dots, m_e \\ &\quad \nabla \varphi_i(x_k)^T d + \varphi_i(x_k) = 0, \qquad i = m_e, \dots, m \end{aligned} \tag{35}$$

where φ_i are the equal and unequal constraints.

Step.4: update x_k by d_k:

$$x_{k+1} = x_k + \alpha_k d_k \tag{36}$$

The step length parameter α_k is determined by an appropriate line search procedure so that a sufficient decrease in a merit function is obtained. The method is vastly used in optimization problems, but it is also known that it depends on the initial estimate. Switching condition from PSOGSA algorithm to SQP is based on the end of PSOGSA iterations.

E. *Switching Condition*

The optimization process starts rapidly in PSOGSA algorithm and the initial steepness of the optimization process is high. After a number of iterations, as the algorithm approaches the optimal point, the difference in cost function value decreases in successive iterations (curve steepness decreases). Thus, in case the curve steepness reduces to less than 10 degrees in 4 successive iterations, switching to SQP algorithm takes place. In this case, the optimization process continues rapidly until reaching the optimal point and prevents iteration loss in the intelligent algorithm and results in high convergence speed as it is illustrated in simulation part.

F. *PSOGSA_SQP argorithm:*

The overall procedure of the PSOGSA_SQP can be explained as follows:

1) Begin optimization process by PSOGSA algorithm
2) If solution satisfy switch condition (end of iteration), stop optimization process
3) Save the last optimal value from PSOGSA as an initial point of SQP algorithm and continue the optimization process by SQP till reach to solution

The flowchart of proposed method is depicted in figure 1.

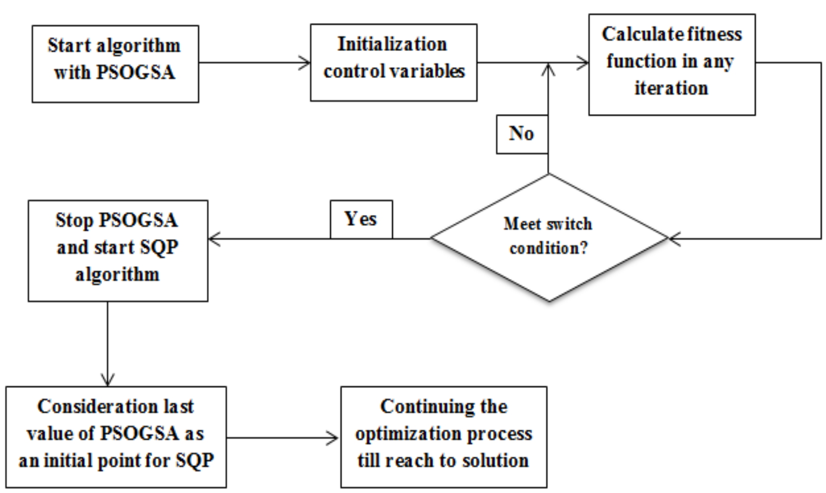

Figure 1. PSOGSA_SQP Algorithm Flowchart.

IV. SIMULATION RESULT

The proposed algorithm has been implemented on standard IEEE 30-bus test system with maximum and minimum of limitation of control variables [17].

Test system consists of 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 [17]. 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 three cases with various objective functions. G is set using in Eqs. (27), where G0 is set to 100, α is set to 10 and T is the total number of iterations. Maximum iteration numbers are 100 for all case studies. In the following, the simulation results are presented:

A. *Case 1: quadratic cost function*

The generator cost characteristics are defined as quadratic cost function of generator power output and the objective function as follow:

$$\mathbf{f_1} = \sum_{i=1}^{NG}\left(a_i + b_i P_{Gi} + c_i P_{Gi}^2\right) \tag{37}$$

where $a_i, b_i,$ c_i are the cost coefficients of generators[17]. Figure (2) shows the convergence diagram of the proposed method compared to that of GA[13] method. According to the figure, the optimization process starts with PSOGSA algorithm in the proposed method which is insensitive to initial point and this phase proceeds quite rapidly. After a number of iterations, as the algorithm approaches the optimal point, the process slows down, and difference in cost function value in successive iterations decreases. In this case, when the switching condition (curve steepness) is satisfied, the process continues with SQP algorithm until reaching an answer. This increases convergence speed and reduces calculation time.

The results of this comparison are given in Table 1. According to table, the minimum value of cost function is 796,010. Also, the sum of real power of generating units and the losses of transmission line are 291.6971 and 8.2971 respectively which decreases effectively in comparison with GA, GSA and PSO algorithm.

Table 1. Comparison of the simulation results of first cost function with other algorithms

Methods	Min of cost fun.	Time
PSOGSA_SQP	796.010	5.01
GSA[17]	798.6751	10.78
GA[12]	800.012	11.03

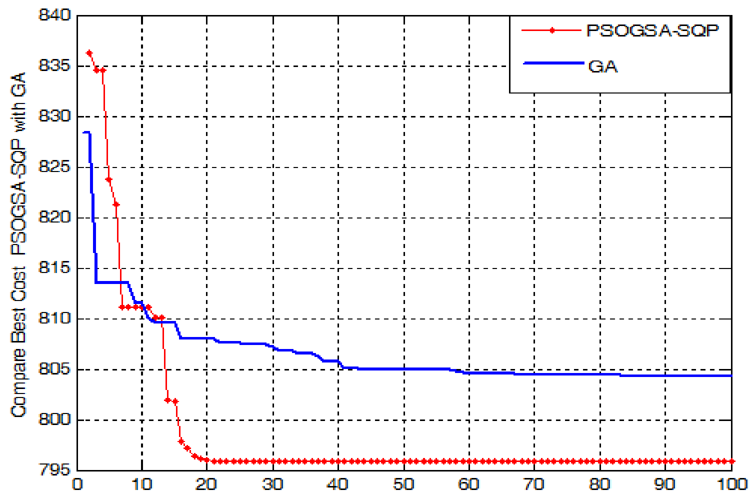

Figure 2. Convergence diagram of proposed algorithm in comparison with GA related to first cost function.

B. *Case 2. Non-smooth cost function of generator fuel:*

In this case, the generating units of buses 1 and 2 are considered to have the valve-point effects on their characteristics. The cost characteristics of generators 1 and 2 are described as follows:

$$\sum_{i=1}^{2} \left(a_i + b_i P_{Gi} + c_i P_{Gi}^2 + \left| d_i \sin\left(e_i\left(P_{Gi}^{min} - P_{Gi}\right)\right)\right|\right) + \left(\sum_{i=3}^{NG} \left(a_i + b_i P_{Gi} + c_i P_{Gi}^2\right)\right) \qquad (38)$$

where a_i, b_i, c_i, d_i and e_i are cost coefficients of the i_{th} generating unit. Table 2 gives the comparison of DE, GA and PSOGSA_SQP methods in terms of minimization of cost function and time convergence. As can be seen, minimum cost function in proposed method is equal to 940.0256 that is less compared to other algorithms. In Figure (3), the convergence diagram of the proposed method is compared to that of GA algorithm. According to the figure, optimization starts with great steepness. As the process slows down and the switching condition is met, PSOGSA algorithm switches to SQP and as a result, convergence speed increases. In this method, power generation of generators and transmission line losses are 292.0063 and 8.6063 MW respectively in which comparison with other references are decreased. Table. 3 gives the amount of power generation of generators and transmission line losses related to first and second cost functions.

Table 2. Comparison of the simulation results of second cost function with other algorithms

Methods	Min of cost fun.	Time
PSOGSA_SQP	940.0256	6.05
DE[32]	945.924	9.83
GA[12]	955.01	41.85
MDE[15]	942.501	41.05

Table 3. Obtained Control variables with proposed method related to first and second cost function

Control Variables (generator)	First Cost Function	Second Cost Function
P1	191.1302	200
P2	48.0993	41.3847
P5	19.4678	18.6216
P8	10.9998	10
P11	10	10
P13	12	12
Transmission line losses	8.2971	8.6063

C. *Case 3: 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 [17]. The fuel cost coefficients of other generators have the same values as of Case 1 condition. The objective function can be described as:

$$f_3 = \left(\sum_{i=1}^{2} [a_{ik} + b_{ik} P_{Gi} + c_{ik} P_{Gi}^2) + \left(\sum_{i=3}^{NG} a_i + b_i P_{Gi} + c_i P_{Gi}^2 \right) \right] \quad (39)$$

where a_{ik}, b_{ik} and c_{ik} are cost coefficients of the i_{th} generator for fuel type k[17]. PSOGSA_SQP method is compared to GSA and DE algorithms in terms of minimization of cost function and time of process (Table 4). Considering to table 4 the minimum cost function is equal to 628.1024 with the best convergence time.

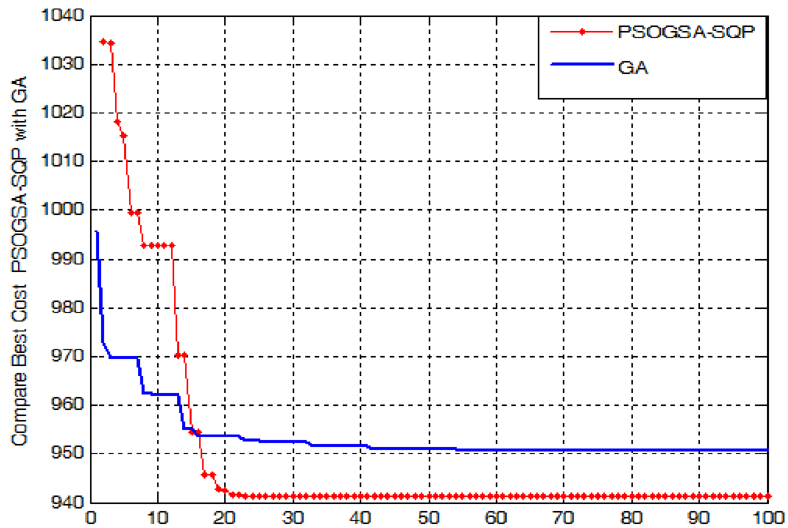

Figure 3. Convergence diagram of proposed algorithm in comparison with GA related to second cost function.

Table 4. Comparison of the simulation results of second cost function with other algorithms

Methods	Min of cost fun.	Time
PSOGSA_SQP	628.1024	4.12
GSA[17]	646.896	9.83
DE[32]	650.822	41.85

V. CONCLUSION

In this paper, a combination of two PSO and GSA intelligent methods and the SQP classical method is utilized to solve the optimal power flow problem. Using SQP algorithm aims at increasing speed; however, considering the fact that this algorithm is sensitive to initial point, optimization starts with PSOGSA algorithm which is global and insensitive to initial point. The goal of this combination is to increase speed in minimizing the fuel cost of generators and transfer line losses concerning power flow. The power flow optimization problem is a non-linear problem with equal and unequal constraints which is formulated in a 30-bus system in IEEE standard in here. Simulation results demonstrate that this algorithm is faster compared to other control methods thanks to using SQP method which is gradient-based and its switching mode. It also minimizes the cost function value of generator fuel and transfer line losses by optimally adjusting control variables.

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