# Hybrid PSOGSA Method of Solving ORPD Problem with Voltage Stability Constraint

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***Abstract***
*This paper presents a new hybrid evolutionary based algorithm based on PSO and GSA for solving optimal reactive power dispatch problem in power system. The problem was designed as a Multi-Objective case with loss minimization and voltage stability as objectives. Generator terminal voltages, tap setting of transformers and reactive power generation of capacitor banks were taken as optimization variables. Modal analysis method is adopted to assess the voltage stability of system. The above presented problem was solved on basis of efficient and reliable technique which takes the advantages of both PSO and GSA. The proposed method has been tested on IEEE 30 bus system where obtained results were found satisfactorily to a large extent that of reported earlier.*

*Keywords: optimal reactive power dispatch, modal analysis, PSO, GSA.*

## 1. Introduction

Optimal power flow (OPF) is an optimization tool used to schedule the control parameters of power systems in such a manner that the objective function is minimized or maximized. Operating constraints of equipments, security requirement and stability limits are enforced to the solution [1]. Optimal reactive power dispatch problem is an OPF sub-problem which has a significant impact on economic and secure operation of power systems [2]. One of the principal tasks of a system operator is to guarantee that network parameters such as voltage and line loads are kept within predefined limits for high quality of services to the consumer load point and power system stability. However, changes in network topology and/or loading conditions often cause corresponding variation in voltage profiles of present day power systems. This problem can be addressed through re-distribution of reactive power sources with concomitant decrease in transmission losses [3]. The reactive power dispatch has a twofold goal thus: to improve system voltage profiles and minimizes system losses at all times [4]. Reactive power flow can be controlled by suitably adjusting the following facilities: tap changing under load transformers, generating units' reactive power capability variation, switching of capacitors, switching of unloaded or unused lines and flexible AC transmission system (FACTS) devices [5]. It is therefore clear that reactive power and voltage control is a constrained, nonlinear problem of considerable complexity.

## 2. Modal Analysis for Voltage Stability evaluation:

Modal analysis is one of methods for voltage stability assessment in power systems. This method is based on eigen value analysis of jacobian matrix.

The system steady state power flow equations are written as:

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} J_{p\theta} & J_{pv} \\ J_{Q\theta} & J_{Qv} \end{bmatrix} \begin{bmatrix} \Delta\theta \\ \Delta V \end{bmatrix} \tag{1}$$

$\Delta P$- incremental change in bus real power
$\Delta Q$-incremental change in bus reactive power
$\Delta\theta$-incremental change in bus voltage angle
$\Delta V$-incremental change in bus voltage magnitude

$J_{P\theta}$, $J_{PV}$, $J_{Q\theta}$, $J_{QV}$ are the sub matrices of jacobian matrix.
   If in above equation ΔP is made equal to zero, then:

$$\Delta Q = \left[J_{QV} - J_{Q\theta} J_{P\theta}^{-1} J_{PV}\right]\Delta V = J_R \Delta V \; and \; so$$
$$\Delta V = \left[ J_R^{-1}\right]\Delta Q \; where$$
$$J_R = \left[J_{QV} - J_{Q\theta} J_{P\theta}^{-1} J_{PV}\right] \tag{2}$$

Called the reduced Jacobian matrix of system [6].
   The system is voltage stable if the Eigen values of Jacobian are all positive. Thus the results for voltage stability enhancement using modal analysis for the reduced Jacobian matrix is when:
   Eigen values $\lambda_i > 0$, the system is under stable condition
   Eigen values $\lambda_i < 0$, the system is unstable condition
   Eigen values $\lambda_i = 0$, the system is in critical condition and may collapse.


## 3. Problem Formulation

   The objective of the ORPD problem is to minimize one or more objective functions while satisfying a number of constraints such as load flow, generator bus voltages, load bus voltages, switchable reactive power compensations, reactive power generation, transformer tap setting and transmission line flow. In this paper two objective functions are minimized separately as single objective. Objective functions minimized in this paper and constraints are formulated as shown as follows.

### 3.1. Minimization of Real Power Loss

$$P_{loss} = \sum G_{ij}(V_i^2 + V_j^2 - 2V_i V_j \cos\theta_{ij}) \tag{3}$$
i,j $\in$ 1,2 ---N$_l$

### 3.2. Maximizing the Voltage Stability Margin

   The stability stating factors which is almost used in all application to assess the proximity of voltage collapse. This is based on eigen value analysis of power flow jacobian matrix. This state's how a particular bus can sustain for given loading which is can be above than the base case [7].

### 3.3. Equality Constraints

   This are normal power flow equations, such that every possible solution must satisfy this constraints.

$$P_{Gi} - P_{Di} = \sum V_i V_j (G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij})$$
$$Q_{Gi} - Q_{Di} = \sum V_i V_j (G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}) \tag{4}$$

N$_B$ Number of buses in the power system
N$_G$ Number of generators
P$_i$ and Q$_i$ are real and reactive power injected at bus *i*
G$_{ij}$ and B$_{ij}$ are conductance and susceptance between bus *i* and *j*, can be self or mutual values

### 3.4. Inequality Constraints

   These include the system operating constraints that are included here. The particular quantity of interest must be operated with in this possible range only, then the system is said to operate in secure and stable state.
   These are handled by considering penalty for each of constraint that are included in the objective function to construct a fitness function for searching the optimal solution in search space [8].

$$\mathbf{Q_{Gi \; min}} \leq \mathbf{Q_{Gi}} \leq \mathbf{Q_{Gi \; max}} \qquad i \in N_{PV}$$

$$V_{Gi\,min} \leq V_{Gi} \leq Q_{Gi\,max} \qquad i \in N_{PV}$$

$N_{PV} =$ Number of voltage buses

$$V_{Li\,min} \leq V_{Li} \leq V_{Li\,max} \qquad i \in N_{PQ}$$

$N_{PQ} =$ Number of load buses

$$Q_{Ci\,min} \leq Q_{Ci} \leq Q_{Ci\,max} \qquad i \in N_c$$

$N_c =$ Number of Switchable Capacitors

$$t_{k\,min} \leq t_k \leq t_{k\,max} \qquad i \in N_T$$

$N_T =$ Number of Tap changing Transformers

## 4. The Hybrid PSOGSA Algorithm

In recent years, many heuristic evolutionary optimization algorithms have been developed. The goal of them is to find the best outcome (global optimum) among all possible inputs. In order to do this, a heuristic algorithm should be equipped with two major characteristics to ensure finding global optimum. These two main characteristics are exploration and exploitation. Exploration is the ability of an algorithm to search whole parts of problem space whereas exploitation is the convergence ability to the best solution near a good solution. The ultimate goal of all heuristic optimization algorithms is to balance the ability of exploitation and exploration efficiently in order to find global optimum. In the present context, two algorithms namely PSO and GSA are combined to define a new hybrid PSOGSA algorithm for solving non-linear optimization problems [9].

### 4.1. Standard PSO

PSO is an evolutionary computation technique which is proposed by Kennedy and Eberhart. 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. PSO was mathematically modeled as follow:

$$v_i^{t+1} = wv_i^t + c_1 * rand(pbest_i - x_i^t) + c_2 * rand(gbest_i - x_i^t) \qquad (5)$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \qquad (6)$$

Where $v_i^t$ is the velocity of particle $i$ at iteration $t$, $w$ is a weighting function, $c_j$ is a weighting factor, rand is a random number between 0 and 1, $x_i^t$ is the current position of particle $i$ at iteration $t$, $pbest_t$ is the $pbest$ of agent $i$ at iteration $t$, and $gbest_t$ is the best solution so far.

The first part of (5), $wv_i^t$ provides exploration ability for PSO. The second and third parts, $c_1 * rand(pbest_i - x_i^t)$ and $c_2 * rand(gbest_i - x_i^t)$, represent private thinking and collaboration of particles respectively. The PSO starts with randomly placing the particles in a problem space. In each iteration, the velocities of particles are calculated using (5). After defining the velocities, the position of masses can be calculated as (6). The process of changing particles' position will continue until meeting an end criterion.

### 4.2. Standard GSA

GSA is a novel heuristic optimization method which has been proposed by E. Rashedi et al in 2009. The basic physical theory which GSA is inspired from is the Newton's theory that states: Every particle in the universe attracts every other particle with a force that is directly proportional to the product of their masses and inversely proportional to the square of the distance between them.

The GSA was mathematically modeled as follows. Suppose a system with N agents. The algorithm starts with randomly placing all agents in search space. During all epochs, the gravitational forces from agent *j* on agent *i* at a specific time *t* is defined as follow:

$$F_{ij}^d(t) = G(t)\frac{M_{pi}(t)*M_{aj}(t)}{R_{ij}(t)+\text{Є}}(x_j^d(t)- x_i^d(t)) \tag{7}$$

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 gravitational constant at time *t*, Є is a small constant, and $R_{ij}$ (t) is the Euclidian distance between two agents *i* and *j*.
The *G(t)* is calculated as (8):

$$G(t)=G_o*\exp(-\alpha*iter/maxiter) \tag{8}$$

Where α and $G_0$ are descending coefficient and initial value respectively, *iter* is the current iteration, and *maxiter* is maximum number of iterations.nTotal force that acts on agent *i* is

$$F_{ij}^d(t)=\sum_{j=1,j\neq i}^N rand_j * F_{ij}^d(t) \tag{9}$$

Where $rand_j$ is a random number in the interval [0,1]. The acceleration of all agents should be calculated as follows:

$$ac_i^d(t)=\frac{F_i^d(t)}{M_{ii}(t)} \tag{10}$$

Where *t* is a specific time and $M_i$ is the mass of object *i*. The velocity and position of agents are calculated as follows:

$$vel_i^d(t + 1) = rand_i * vel_i^d(t) + ac_i^d(t) \tag{11}$$

$$x_i^d(t + 1) = x_i^d(t) + vel_i^d(t + 1) \tag{12}$$

Where $rand_i$ is a random number in the interval [0, 1].

### 4.3. The Hybrid PSOGSA Algorithm

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, (13) is proposed as follows:

$$V_i^{t+1}=wV_i^t+c_1'*rand* ac_i(t)+c_2'*rand*(gbest_i-x_i^t) \tag{13}$$

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, $ac_i(t)$ is the acceleration of agent *i* at iteration *t*, and g*best* is the best solution so far. In each iteration, the positions of particles are updated as follows:

$$X_i(t+1)=X_i(t)+V_i(t+1) \tag{14}$$

The process of updating velocities and positions will be stopped by meeting an end criterion. The steps of PSOGSA are represented in Figure 1.
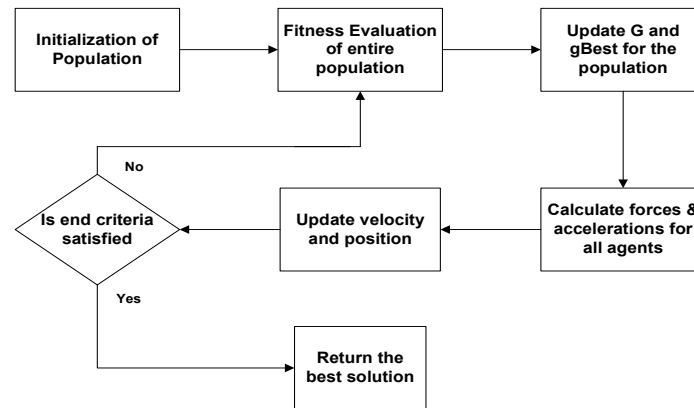
Figure 1. Process Involved in PSOGSA

## 5. PSOGSA Approach to ORPD Problem

The present ORPD problem is implemented in the new proposed method to make the objective function of interest as minimum as possible without making the solution variables going out of the limits. Already the unitary GSA algorithm has been applied for the same problem in[10], to which a hybrid method is discussed here. Also there exists variant methods, for example as stated in [11].

The decision variables such as generator bus voltages, reactive power generated by capacitors and transformer tap settings are represented as candidate solution vector, such that they are initialized according to their nature of variation in its practical situation.The function of each individual in the population is evaluated according to its fitness which is the non-negative number that is to be minimized as made by objective function.

The fitness function for the present problem looks to be:

$$\text{Min } F = P_{loss} + w*(E_{max}) + Pen_V + Pen_Q \tag{15}$$

Where:

$P_{loss}$ is the total power loss in system
$E_{max}$ is max eigen value of reduced Jacobian
$w$ is penalty for eigen value of matrix
$Pen_V$ is penalty for load bus variation
$Pen_Q$ is penalty for generator reactive power limit violation.

## 6. Simulation and Results

To test the effectiveness of the proposed approach IEEE 30 bus system was chosen as the standard model that has 6 generators, 24 load bus and 41 transmission lines with 4 tap changing transformers. The initial range for solutions were taken as shown in Table 1.

Table 1 Initial Range of Population

| Sl.No. | Variable | Min | max |
|---|---|---|---|
| 1 | Generator bus voltage | 0.95 | 1.05 |
| 2 | Tap setting | 0.9 | 1.1 |
| 3 | Reactive power generation by Capacitor | 0 | 5 |

## 6.1. Only Loss Minimization as Objective:

Here the objective is to minimize the power loss in the system without considering the voltage stability of system. It was run with different control parameter settings and minimal solution was obtained for some fixed values by repeated program runs. The similar

implementation by method of Differential Evolution (DE) is proposed in [12], which is as taken as one of reference for present study.

The optimal values for the solution vector was obtained for optimum condition of function and it was found to be lie within the range of its minimum and maximum values as given in Table 2.

The optimal control variables obtained in this case are as follows:

Table 2. Solution with Loss Minimization as only Objective

| Variable | Value obtained |
|----------|----------------|
| $V_1$ | 1.094 |
| $V_2$ | 1.025 |
| $V_5$ | 1.091 |
| $V_8$ | 0.950 |
| $V_{11}$ | 1.051 |
| $V_{13}$ | 1.068 |
| $T_{11}$ | 0.995 |
| $T_{12}$ | 1.022 |
| $T_{15}$ | 1.100 |
| $T_{36}$ | 0.989 |
| $Q_{C10}$ | 3.984 |
| $Q_{C12}$ | 1.012 |
| $Q_{C15}$ | 0.002 |
| $Q_{C17}$ | 3.956 |
| $Q_{C20}$ | 3.836 |
| $Q_{C21}$ | 3.945 |
| $Q_{C23}$ | 3.992 |
| $Q_{C24}$ | 3.012 |
| $Q_{C29}$ | 2.948 |
| $P_{loss}$ | 4.578 |
| $E_{min}$ | 0.412 |

## 6.2. Multi-Objective Case of Loss Minimization with Voltage Stability

Now the case where both the objectives of loss minimization and voltage stability enhancement has been considered with the fitness function as given in previous section to obtain the candidate solution by PSOGSA mechanism. Since both the objectives are considered it is difficult to obtain the minimum of both objectives so we get the solution in the search space was both are acceptable in narrow difference as compared to the previous case. The results of this case is depicted in Table 3.

Table 3. Solution with Loss Minimization & Voltage Stability as Objectives

| Variable | Value obtained |
|----------|----------------|
| $V_1$ | 1.035 |
| $V_2$ | 0.995 |
| $V_5$ | 0.950 |
| $V_8$ | 1.046 |
| $V_{11}$ | 0.974 |
| $V_{13}$ | 1.050 |
| $T_{11}$ | 0.987 |
| $T_{12}$ | 1.100 |
| $T_{15}$ | 1.081 |
| $T_{36}$ | 0.900 |
| $Q_{C10}$ | 4.546 |
| $Q_{C12}$ | 2.561 |
| $Q_{C15}$ | 1.456 |
| $Q_{C17}$ | 3.554 |
| $Q_{C20}$ | 3.574 |
| $Q_{C21}$ | 1.256 |
| $Q_{C23}$ | 2.578 |
| $Q_{C24}$ | 4.789 |
| $Q_{C29}$ | 5.000 |
| $P_{loss}$ | 4.077 |
| $E_{min}$ | 0.897 |

Also in present context the penetration of FACTS devices in system is increasing, hence the same problem has to be formulated with consideration of such device's operational and control constraints, as presented in [13]. The obtained values of power loss and minimum Eigen values are the utmost minimum values as far reported in the literature. On comparison with the previously solved algorithms the comparison table can be framed as depicted in Table 4.

Table 4. Comparision with other Methods

| Method | $P_{loss}$ |
|---|---|
| EP[4] | 5.015 |
| GA[7] | 4.665 |
| Real Coded GA[6] | 4.501 |
| PSOGSA [Proposed] | 4.077 |

## 7. Conclusion

This paper presented a dynamic multi modal evolutionary algorithm approach for ORPD problem with voltage stability enhancement as main constraint. The decision variables chosen to achieve the above objective were the generator bus voltages, reactive power generation by capacitor banks and transformer tap settings, more over this algorithm provides a new dimension in solving such kind of multi variable problem such that the obtained decision variables are within their boundaries. The modal analysis provides the better information about voltage stability assessment than any other index referred in literature, so that the problem becomes more complex, where this proposed hybrid PSOGSA can able to solve with minimum iterations and time as possible.So, from the proposed work it can be concluded that this mode of solving multi modal real valued optimization problems can be effectively applied with variants in other power system problems as well.

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