International Journal of Electrical and Computer Engineering.
ISSN 0974-2190 Volume 6, Number 1 (2014), pp. 9-20

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# Improved Distribution Particle Swarm Optimization (IDPSO) Algorithm for Solving Optimal Reactive Power Dispatch Problem

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## Abstract

This paper presents an algorithm for solving the multi-objective reactive power dispatch problem in power system. Modal analysis of the system is used for static voltage stability assessment. Loss minimization and maximization of voltage stability margin are taken as the objectives. Generator terminal voltages, reactive power generation of the capacitor banks and tap changing transformer setting are taken as the optimization variables. PSO is a powerful evolutionary algorithm used for finding global solution to a multidimensional problem. Particles in PSO tend to re-explore already visited bad solution regions of search space because they do not learn as a whole. This is avoided by restricting particles into promising regions through probabilistic modeling of the archive of best solutions. This paper presents hybrids of improved distribution particle swarm (IDPSO) algorithm to solve optimal reactive power dispatch problem. In order to evaluate the proposed algorithm, it has been tested on IEEE 30 bus system and compared to other algorithms and Results show that IDPSO is more efficient than other algorithms in reducing the real power loss and maximization of voltage stability index.

**Key words—** Modal analysis, optimal reactive power, Transmission loss, improved distribution, Meta heuristic, Optimization.

## INTRODUCTION

Optimal reactive power dispatch problem is one of the difficult optimization problems in power systems. The sources of the reactive power are the generators, synchronous condensers, capacitors, static compensators and tap changing transformers. The problem that has to be solved in a reactive power optimization is to determine the required reactive generation at various locations so as to optimize the objective function. Here the reactive power dispatch problem involves best utilization of the existing generator bus voltage magnitudes, transformer tap setting and the output of reactive power sources so as to minimize the loss and to enhance the voltage stability of the system. It involves a non linear optimization problem. Various mathematical techniques have been adopted to solve this optimal reactive power dispatch problem. These include the gradient method [1-2], Newton method [3] and linear programming [4-7]. The gradient and Newton methods suffer from the difficulty in handling inequality constraints. To apply linear programming, the input- output function is to be expressed as a set of linear functions which may lead to loss of accuracy. Recently global Optimization techniques such as genetic algorithms have been proposed to solve the reactive power flow problem [8, 9]. In recent years, the problem of voltage stability and voltage collapse has become a major concern in power system planning and operation. To enhance the voltage stability, voltage magnitudes alone will not be a reliable indicator of how far an operating point is from the collapse point [11]. The reactive power support and voltage problems are intrinsically related. Hence, this paper formulates the reactive power dispatch as a multi-objective optimization problem with loss minimization and maximization of static voltage stability margin (SVSM) as the objectives. Voltage stability evaluation using modal analysis [12] is used as the indicator of voltage stability. Particle swarm optimization algorithm (PSO), models the dynamics of societies of biological specimen like birds, insects and fish. It is a population based optimization technique in which a collection of test solutions interact with each other and search for the best solution to the given problem [13]. PSO consists of a population (or swarm) of particles, each of which represents an n dimensional potential solution. Particles are assigned random initial positions and they change their positions iteratively to reach the global optimal solution. The direction of position change is influenced by both particle's own experience and the knowledge the particle acquires from the flock. Each particle is evaluated using a fitness function, which indicates how close the particle is to the optimal solution. It is desired to maximize the fitness as the PSO iterations progress. PSO has found extensive applications in many optimization problems. In sensor networks, it has been used for cluster formation [14], optimal multicast routing [15], and distributed sensor placement problems [16]. Maximum likelihood estimation of target position [17] and sink node path optimization [18] are the other problems that have been addressed with PSO. A PSO variant has been applied in wavelength detection in FGB sensor network [19]. PSO has been used for odor source localization in mobile sensor networks [20]. In spite of its advantages like low computational complexity, the PSO suffers from the problem of premature convergence. This is overcome with a mutation operator with adaptive probability, and by replacing particles flying out of the solution space by newly generated random particles during the search process. The variant of PSO that uses adaptive mutation and regeneration is called Improved PSO (IPSO) [21]. Here we introduce Estimation of distribution particle swarm optimization (EDPSO) for solving reactive power dispatch problem and tested in standard IEEE 30 bus test system.

## I. Voltage Stability Evaluation

### A. Modal analysis for voltage stability evaluation

Modal analysis is one of the methods for voltage stability enhancement in power systems. In this method, voltage stability analysis is done by computing Eigen values and right and left Eigen vectors of a jacobian matrix. It identifies the critical areas of voltage stability and provides information about the best actions to be taken for the improvement of system stability enhancements. The linearized steady state system power flow equations are given by.

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = \begin{bmatrix} J_{p\theta} & J_{pv} \\ J_{q\theta} & J_{QV} \end{bmatrix} \quad (1)$$

Where

$\Delta P$ = Incremental change in bus real power.

$\Delta Q$ = Incremental change in bus reactive

Power injection

$\Delta\theta$ = incremental change in bus voltage angle.

$\Delta V$ = Incremental change in bus voltage

Magnitude

$J_{p\theta}$, $J_{PV}$, $J_{Q\theta}$, $J_{QV}$ jacobian matrix are the sub-matrixes of the System voltage stability is affected by both P and Q. However at each operating point we keep P constant and evaluate voltage stability by considering incremental relationship between Q and V.

To reduce (1), let $\Delta P = 0$, then.

$$\Delta Q = [J_{QV} - J_{Q\theta} J_{P\theta^{-1}} J_{PV}] \Delta V = J_R \Delta V \quad (2)$$

$$\Delta V = J^{-1} - \Delta Q \quad (3)$$

Where

$$J_R = (J_{QV} - J_{Q\theta} J_{P\theta^{-1}} JPV) \quad (4)$$

$J_R$ is called the reduced Jacobian matrix of the system.

### B. Modes of Voltage instability:

Voltage Stability characteristics of the system can be identified by computing the Eigen values and Eigen vectors

Let

$$J_R = \xi\eta \quad (5)$$

Where,

$\xi$ = right eigenvector matrix of $J_R$

$\eta$ = left eigenvector matrix of $J_R$

$\Lambda$ = diagonal eigenvalue matrix of $J_R$ and

$$J_{R^{-1}} = \xi^{-1}\eta \quad (6)$$

From (3) and (6), we have

$$\Delta V = \xi^{-1}\eta\Delta Q \quad (7)$$

or

$$\Delta V = \sum_I \frac{\xi_i \eta_i}{\lambda_i} \Delta Q \quad (8)$$

Where $\xi_i$ is the ith column right eigenvector and $\eta$ the ith row left eigenvector of $J_R$.

$\lambda_i$ is the ith eigen value of $J_R$.

The ith modal reactive power variation is,

$$\Delta Q_{mi} = K_i \xi_i \tag{9}$$

where,

$$K_i = \sum_j \xi_{ij^2} - 1 \tag{10}$$

Where

$\xi_{ji}$ is the jth element of $\xi_i$

The corresponding ith modal voltage variation is

$$\Delta V_{mi} = [1/\lambda_i] \Delta Q_{mi} \tag{11}$$

It is seen that, when the reactive power variation is along the direction of $\xi_i$ the corresponding voltage variation is also along the same direction and magnitude is amplified by a factor which is equal to the magnitude of the inverse of the ith eigenvalue. In this sense, the magnitude of each eigenvalue $\lambda_i$ determines the weakness of the corresponding modal voltage. The smaller the magnitude of $\lambda_i$, the weaker will be the corresponding modal voltage. If $|\lambda_i| = 0$ the ith modal voltage will collapse because any change in that modal reactive power will cause infinite modal voltage variation.

In (8), let $\Delta Q = e_k$ where $e_k$ has all its elements zero except the kth one being 1. Then,

$$\Delta V = \sum_i \frac{\eta_{1k}\, \xi_1}{\lambda_1} \tag{12}$$

$\eta_{1k}$ k th element of $\eta_1$

V –Q sensitivity at bus k

$$\frac{\partial V_K}{\partial Q_K} = \sum_i \frac{\eta_{1k}\, \xi_1}{\lambda_1} = \sum_i \frac{P_{ki}}{\lambda_1} \tag{13}$$

## II. Problem Formulation

The objectives of the reactive power dispatch problem considered here is to minimize the system real power loss and maximize the static voltage stability margins (SVSM). This objective is achieved by proper adjustment of reactive power variables like generator voltage magnitude ($V_{gi}$), reactive power generation of capacitor bank ($Q_{ci}$), and transformer tap setting ($t_k$). Power flow equations are the equality constraints of the problems, while the inequality constraints include the limits on real and reactive power generation, bus voltage magnitudes, transformer tap positions and line flows

### *A.* Minimization of Real Power Loss

It is aimed in this objective that minimizing of the real power loss (Ploss) in transmission lines of a power system. This is mathematically stated as follows.

$$P_{loss} = \sum^{n}_{\substack{k=1 \\ k=(i,j)}} g_{k}(V_i^2 + V_j^2 - 2V_i V_j \cos\theta_{ij}) \tag{14}$$

Where n is the number of transmission lines, $g_k$ is the conductance of branch k, $V_i$ and $V_j$ are voltage magnitude at bus i and bus j, and θij is the voltage angle difference between bus i and bus j.

### *B.* Minimization of Voltage Deviation

It is aimed in this objective that minimizing of the Deviations in voltage magnitudes (VD) at load buses. This is mathematically stated as follows.

$$\text{Minimize VD} = \sum_{k=1}^{nl} |V_k - 1.0| \tag{15}$$

Where nl is the number of load busses and $V_k$ is the voltage magnitude at bus k.

### *C.* System Constraints

In the minimization process of objective functions, some problem constraints which one is equality and others are inequality had to be met. Objective functions are subjected to these constraints shown below.

Load flow equality constraints:

$$P_{Gi} - P_{Di} - V_{i\sum_{j=1}^{nb} V_j} \begin{bmatrix} G_{ij} & \cos\theta_{ij} \\ +B_{ij} & \sin\theta_{ij} \end{bmatrix} = 0, i = 1,2 \dots, nb \tag{16}$$

$$Q_{Gi} - Q_{Di} - V_{i\sum_{j=1}^{nb} V_j} \begin{bmatrix} G_{ij} & \cos\theta_{ij} \\ +B_{ij} & \sin\theta_{ij} \end{bmatrix} = 0, i = 1,2 \dots, nb \tag{17}$$

where, nb is the number of buses, $P_G$ and $Q_G$ are the real and reactive power of the generator, $P_D$ and $Q_D$ are the real and reactive load of the generator, and $G_{ij}$ and $B_{ij}$ are the mutual conductance and susceptance between bus i and bus j.

Generator bus voltage ($V_{Gi}$) inequality constraint:

$$V_{Gi}^{min} \le V_{Gi} \le V_{Gi}^{max}, i \in ng \tag{18}$$

Load bus voltage ($V_{Li}$) inequality constraint:

$$V_{Li}^{min} \le V_{Li} \le V_{Li}^{max}, i \in nl \tag{19}$$

Switchable reactive power compensations ($Q_{Ci}$) inequality constraint:

$$Q_{Ci}^{min} \le Q_{Ci} \le Q_{Ci}^{max}, i \in nc \tag{20}$$

Reactive power generation ($Q_{Gi}$) inequality constraint:

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max}, i \in ng \tag{21}$$

Transformers tap setting ($T_i$) inequality constraint:

$$T_i^{min} \le T_i \le T_i^{max}, i \in nt \tag{22}$$

Transmission line flow ($S_{Li}$) inequality constraint:

$$S_{Li}^{min} \le S_{Li}^{max}, i \in nl \tag{23}$$

Where, nc, ng and nt are numbers of the switchable reactive power sources, generators and transformers.

## III. Basic PSO Model

PSO has been developed through simulation of simplified social models. The features of the method are as follows:

(a) The method is based on researches about swarms such as fish schooling and a flock of birds.

(b) It is based on a simple concept. Therefore, the computation time is short and it requires few memories.

According to the research results for a flock of birds, birds find food by flocking (not by each individual). The observation leads the assumption that every information is shared inside flocking. Moreover, according to observation of behavior of human groups, behavior of each individual (agent) is also based on behavior patterns authorized by the groups such as customs and other behavior patterns according to the experiences by each individual. The assumption is a basic concept of PSO. PSO is basically developed through simulation of a flock of birds in two-dimension space. The position of each agent is represented by XY-axis position and the velocity (displacement vector) is expressed by vx (the velocity of X-axis) and vy (the velocity of Y-axis). Modification of the agent position is realized by using the position and the velocity information.

## A. Searching procedure of PSO

Searching procedures by PSO based on the above concept can be described as follows: a flock of agents optimizes a certain objective function. Each agent knows its best value so far (pbest) and its XY position. Moreover, each agent knows the best value in the group (gbest) among pbests, namely the best value so far of the group. The modified velocity of each agent can be calculated using the current velocity and the distance from pbest and gbest as shown below:

$$v^{k+1} = w_i v_i^{k} + c_1 \text{rand x } (\text{pbest}_i, - s_i^k + c_2 \text{rand x } (\text{gbest} - s_i^k) \qquad (24)$$

where, $V_i^k$ : current velocity of agent i at iteration k, $V_i^{k+1}$: modified velocity of agent i, rand: random number between 0 and 1, $s_i^k$: current position of agent i at iteration k, $\text{pbest}_i$: pbest of agent i, gbest: gbest of the group, $W_i$: weight function for velocity of agent i, $C_i$: weight coefficients for each term.

Using the above equation, a certain velocity that gradually gets close to $p_{best}$ and $g_{best}$ can be calculated. The current position (searching point in the solution space) can be modified by the following equation:

$$S_i^{k+1} = s_i^k + V_i^{k+1} \qquad (25)$$

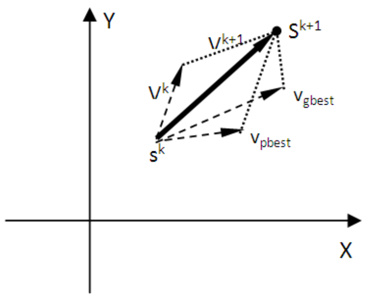


**Figure 1.** Shows the above concept of modification of searching points

Where, $S^k$ : current searching point, $S^{k+1}$ : modified searching point, $V_k$ : current velocity, $V^{k+1}$ : modified velocity, $V_{pbest}$ : velocity based on pbest, $V_{gbest}$ :velocity based on gbest.

In spite of its advantages like low computational complexity, the PSO suffers from the problem of premature convergence. This is overcome with a mutation operator with adaptive probability, and by replacing particles flying out of the solution space by newly generated random particles during the search process. The variant of PSO that uses adaptive mutation and regeneration is called Improved PSO (IPSO) [21]. In the classical PSO, particles depend on their individual memory and peer influence to explore the search space. However, the swarm as a whole does not use its collective experience (represented by the array of previous best positions) to guide its search. This causes re-exploration of already known bad regions in the search space. This paper proposes an approach in which swarm's collective memory is used to guide the particle's movement towards the estimated good regions in the search space. This paper presents hybrid versions of PSO that allow a particle swarm to estimate the distribution of promising solution regions and thus learn through the information assimilated during the process of optimization. This distribution is used to keep the particles within the promising solution regions. This algorithm is fused with two versions of PSO, namely classical PSO and IPSO. The estimation of the distribution is done by means of a mixture of normal distributions of previous best solutions. These hybrids borrow ideas from recent developments in Ant Colony Optimization (ACO) in which an archive of solutions is used to select the next point to explore in the search space.

## VI. IMPROVED DISTRIBUTION PSO (IDPSO) ALGORITHM

Improved distribution algorithms (IDA) use information obtained during optimization to build probabilistic models of distribution of good solution regions and use this information to produce new solutions. IDAs yield fast convergence to global optimal solution because they approximate the joint probability distribution that characterizes the problem. A comprehensive comparison of some best-known IDA algorithms is given in [22]. This paper uses two hybrids, which progress like PSO algorithms but model the joint probability distribution in order to constrain particles in better areas of search space. Ant Colony Optimization (ACO) is another popular swarm intelligence algorithm. This algorithm is used for combinatorial optimization problems. A recent development of ACO that is aimed at continuous optimization is called $ACO_R$ [23]. This algorithm approximates the joint probability distribution, one dimension at a time, by using a mixture of weighted Gaussian functions. The weights represent quality of different search regions in solution space. Therefore, $ACO_R$ can deal with multimodal functions. The algorithm uses an archive of existing solutions of size m (swarm size) as the source of information to parameterize univariate distributions. The $i^{th}$component of $l^{th}$ solution is represented as $s_{il}$. For an n –dimensional Problem For each dimension i, the vector $\mu_i = < s_{i1,} s_{i2,}, \ldots, s_{im} >$ represents vector of means used to model univariate probability distribution for the $i^{th}$ dimension. The vector of weights $w = <w_1, w_2 \ldots w_m>$ is the same across all dimensions because it is based on relative quality of complete solutions. In each iteration, solutions are ranked and weights are determined using (26),

$$w_l = \frac{1}{qm\sqrt{2\pi}} e^{-\frac{(l-1)^2}{2(qm)^2}} \tag{26}$$

where q is the parameter that determines the degree of preference of good solutions. With a small value of q, best solutions are strongly preferred over weaker solutions to guide the search [24]. Because the algorithm samples a mixture of Gaussians, one will need to select one Gaussian function from the kernel probabilistically. The probability of choosing $l^{th}$ Gaussian function is computed using (27).

$$P_l = \frac{w_l}{\sum_{j=1}^{m} w_j} \tag{27}$$

$$\sigma_{li} = \xi \sum_{j=1}^{m} \frac{|s_{ij} - s_{il}|}{m-1} \tag{28}$$

Where $\xi$ is a parameter that allows algorithm to balance its exploration-exploitation behaviour. This has the same value for all dimensions. $ACO_R$ samples a Gaussian function and generates a new solution component in every iteration. This paper borrows the idea from $ACO_R$ [23]. In improved distribution of PSO (IDPSO) hybrid, $ACO_R$ is fused with PSO in order to exploit the useful properties of both the algorithms. The p_best matrix is used here as the archive of solution over which $ACO_R$ builds its probabilistic model. The IDPSO algorithm progresses as the normal PSO does. For every particle in the swarm, two particles are generated, one using PSO and another using estimation of distribution. In each iteration, the location to which a particle will be moved is determined using PSO position update equation. Such a particle is names as PSO version of the particle. In addition, a Gaussian distribution function is probabilistically chosen from the kernel and a new particle is produced by sampling it in all n dimensions. This gives the IDA version of the particle. The fitness functions are evaluated for both versions of a particle. The particle that exhibits the better objective function is selected to enter the next iteration. This paper uses central theme of the work reported in [24] but uses the selection criterion to choose either PSO or IDA version of a particle.

## V. Simulation Results

The legitimacy of the projected Algorithm method is demonstrated on standard IEEE-30 bus system. The IEEE-30 bus system has 6 generator buses, 24 load buses and 41 transmission lines of which four branches are (6-9), (6-10), (4-12) and (28-27) - are with the tap setting transformers. The lower voltage magnitude limits at all buses are 0. 95 p. u. and the upper limits are 1. 1 for all the PV buses and 1. 05 p. u. for all the PQ buses and the reference bus.

**TABLE 1.** VOLTAGE STABILITY UNDER CONTINGENCY STATE

| Sl. No | Contigency | ORPD Setting | Vscrpd Setting |
|---|---|---|---|
| 1 | 28-27 | 0. 1400 | 0. 1422 |
| 2 | 4-12 | 0. 1658 | 0. 1662 |
| 3 | 1-3 | 0. 1784 | 0. 1754 |
| 4 | 2-4 | 0. 2012 | 0. 2032 |

**TABLE 2.** LIMIT VIOLATION CHECKING OF STATE VARIABLES

| State variables | limits | | ORPD | VSCRPD |
|---|---|---|---|---|
| | Lower | upper | | |
| Q1 | -20 | 152 | 1. 3422 | -1. 3269 |
| Q2 | -20 | 61 | 8. 9900 | 9. 8232 |
| Q5 | -15 | 49. 92 | 25. 920 | 26. 001 |
| Q8 | -10 | 63. 52 | 38. 8200 | 40. 802 |
| Q11 | -15 | 42 | 2. 9300 | 5. 002 |
| Q13 | -15 | 48 | 8. 1025 | 6. 033 |
| V3 | 0. 95 | 1. 05 | 1. 0372 | 1. 0392 |
| V4 | 0. 95 | 1. 05 | 1. 0307 | 1. 0328 |
| V6 | 0. 95 | 1. 05 | 1. 0282 | 1. 0298 |
| V7 | 0. 95 | 1. 05 | 1. 0101 | 1. 0152 |
| V9 | 0. 95 | 1. 05 | 1. 0462 | 1. 0412 |
| V10 | 0. 95 | 1. 05 | 1. 0482 | 1. 0498 |
| V12 | 0. 95 | 1. 05 | 1. 0400 | 1. 0466 |
| V14 | 0. 95 | 1. 05 | 1. 0474 | 1. 0443 |
| V15 | 0. 95 | 1. 05 | 1. 0457 | 1. 0413 |
| V16 | 0. 95 | 1. 05 | 1. 0426 | 1. 0405 |
| V17 | 0. 95 | 1. 05 | 1. 0382 | 1. 0396 |
| V18 | 0. 95 | 1. 05 | 1. 0392 | 1. 0400 |
| V19 | 0. 95 | 1. 05 | 1. 0381 | 1. 0394 |
| V20 | 0. 95 | 1. 05 | 1. 0112 | 1. 0194 |
| V21 | 0. 95 | 1. 05 | 1. 0435 | 1. 0243 |
| V22 | 0. 95 | 1. 05 | 1. 0448 | 1. 0396 |
| V23 | 0. 95 | 1. 05 | 1. 0472 | 1. 0372 |
| V24 | 0. 95 | 1. 05 | 1. 0484 | 1. 0372 |
| V25 | 0. 95 | 1. 05 | 1. 0142 | 1. 0192 |
| V26 | 0. 95 | 1. 05 | 1. 0494 | 1. 0422 |
| V27 | 0. 95 | 1. 05 | 1. 0472 | 1. 0452 |
| V28 | 0. 95 | 1. 05 | 1. 0243 | 1. 0283 |
| V29 | 0. 95 | 1. 05 | 1. 0439 | 1. 0419 |
| V30 | 0. 95 | 1. 05 | 1. 0418 | 1. 0397 |

**TABLE 3.** COMPARISON OF REAL POWER LOSS

| Method | Minimum loss |
|---|---|
| Evolutionary programming[25] | 5. 0159 |
| Genetic algorithm[26] | 4. 665 |
| Real coded GA with Lindex as SVSM[27] | 4. 568 |
| Real coded genetic algorithm[28] | 4. 5015 |
| Proposed IDPSO method | 4. 2339 |

## VI. CONCLUSION

In this paper a novel approach IDPSO algorithm used to solve optimal reactive power dispatch problem, The effectiveness of the proposed method is demonstrated on IEEE 30-bus system and the simultion results clearly shows the good performance of the proposed algorithm in reducing the real power loss and volatge profile index are well within the limits.

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