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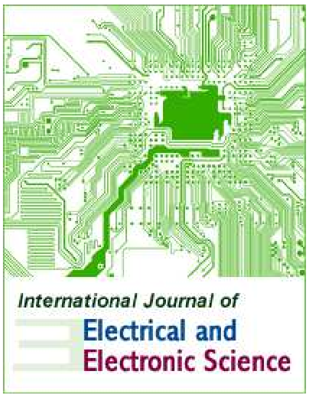


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# New hybrid particle swarm optimization algorithm for solving optimal reactive power dispatch problem

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## Abstract
This paper presents a hybrid particle swarm algorithm for solving the multi-objective reactive power dispatch problem. 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. Evolutionary algorithm and Swarm Intelligence algorithm (EA, SI), a part of Bio inspired optimization algorithm, have been widely used to solve numerous optimization problem in various science and engineering domains. The standard Particle Swarm Optimization (PSO) algorithm is a novel evolutionary algorithm in which each particle studies its own previous best solution and the group's previous best to optimize problems. One problem exists in PSO is its tendency of trapping into local optima. This paper proposes a hybrid approach by combining a Euclidian distance (EU) based genetic algorithm (GA) and particle swarm optimization (PSO) method - New hybrid particle swarm optimization (NHPSO). The simulation results demonstrate good performance of the NHPSO in solving an 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 reported those before in literature. Results show that NHPSO is more efficient than others for solution of single-objective optimal reactive power dispatch (ORPD) problem.

## 1. 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 [10]. 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 [10] is used as the indicator of voltage stability. During the last decade, genetic algorithm-based approaches have received increased attention from the engineers dealing with problems, which could not be solved using conventional problem solving techniques. A typical task of a GA in this context is to find the best values of a predefined set of free parameters associated with either a process model or a control vector. A possible solution to a specific problem can be encoded as an individual (or a chromosome), which consists of group of genes. Each individual represents a point in the search space and a possible solution to the problem can be formulated. A population consists of a finite number of individuals and each individual is decided by an evaluating mechanism to obtain its fitness value. Using this fitness value and genetic operators, a new population is generated iteratively which is referred to as a generation. The GA uses the basic reproduction operators such as crossover and mutation to produce the genetic composition of a population. Many efforts for the enhancement of conventional genetic algorithms have been proposed. Among them, one category focuses on modifying the structure of the population or on the individual's role while another category is focused on modification/efficient control of the basic operations, such as crossover or mutation, of conventional genetic algorithms [11]. This chapter introduces a hybrid approach consisting of genetic algorithm and particle swarm optimization (PSO) algorithm. To obtain an advanced learning structure, there are two processing steps in the proposed method. In the first step, Euclidean distance is used to select the global data for crossover and mutation operators to avoid local minima, and to obtain fast convergence. In the second step, in order to enhance the learning efficiency of GA, PSO strategy is applied. The proposed approach focuses on the advantage of PSO into the mutation process of GA, for improving the GA learning efficiency. A PSO like search proceeds through the problem space, with the moving velocity of each particle represented by a velocity vector. The performance of NHPSO has been evaluated in standard IEEE 30 bus test system and the results analysis shows that our proposed approach outperforms all approaches investigated in this paper. The performance of NHPSO has been evaluated in standard IEEE 30 bus test system and the results analysis shows that our proposed approach outperforms all approaches investigated in this paper.

# 2. Voltage Stability Evaluation

## 2.1. 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.

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

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.

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

$$\Delta V = J^{-1} - \Delta Q \tag{3}$$

Where

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

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

Modes of Voltage instability:

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

Let

$$J_R = \xi\eta \tag{5}$$

Where,
$\xi$ = right eigenvector matrix of $J_R$
$\eta$ = left eigenvector matrix of $J_R$
$\wedge$ = diagonal Eigen value matrix of $J_R$ and

$$J_{R^{-1}} = \xi^{-1}\eta \tag{6}$$

From (5) and (8), we have

$$\Delta V = \xi^{-1}\eta\Delta Q \tag{7}$$

or

$$\Delta V = \sum_I \frac{\xi_i\eta_i}{\lambda_i}\Delta Q \tag{8}$$

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 $j_{th}$ 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 Eigen value. In this sense, the magnitude of each Eigen value $\lambda_i$ 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 $i_{th}$ modal voltage will collapse because any change in that modal reactive power will cause infinite modal voltage variation.

In (10), let $\Delta Q = e_k$ where $e_k$ has all its elements zero except the $k_{th}$ one being 1. Then,

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

${}_{1k}$ k th element of ${}_1$
V –Q sensitivity at bus k

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

# 3. 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). 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

## 3.1. 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.

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

Where n is the number of transmission lines, gk is the conductance of branch k, Vi and Vj are voltage magnitude at bus i and bus j, and θij is the voltage angle difference between bus i and bus j.

## 3.2. 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.

## 3.3. 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:

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

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

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:

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in nt \quad (22)$$

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

$$S_{Li}^{min} \leq S_{Li}^{max}, i \in nl \quad (23)$$

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

# 4. Hybrid Approach using Euclidean Distance Genetic Algorithm and Particle Swarm Optimization Algorithm

## 4.1. Particle Swarm Optimization Algorithm

The PSO algorithm conducts search using a population of particles which correspond to individuals in a genetic algorithm [12, 13]. A population of particles is initially randomly generated. Each particle represents a potential solution and has a position represented by a position vector. A swarm of particles moves through the problem space, with the moving velocity of each particle represented by a velocity vector. At each time step, a function representing a quality measure is calculated by using as input. Each particle keeps track of its own best position, which is associated with the best fitness it has achieved so far in a vector. Furthermore, the best position among all the particles obtained so far in the population is kept track as output. In addition to this global version, another local version of PSO keeps track of the best position among all the topological neighbours of a particle. At each time step, by using the individual best position, and global best position, a new velocity for particle is updated. The computation for PSO is easy and adds only a slight computational load when it is incorporated into the conventional GA. Furthermore, the flexibility of PSO to control the balance between local and global exploration of the problem space helps to overcome premature convergence of elite strategy in GA, and also enhances search ability.

## 4.2. Genetic Algorithm with Euclidean Data Distance

When individuals in a genetic algorithm are differentiated to search for optimal solutions, there is a high chance for obtaining local optimal solutions. Using the conventional GA or PSO approach, optimal solutions are obtained mostly with some initial differentiated data and there is a high possibility for obtaining local optimal solutions. The proposed approach uses data points with the longest Euclidean distance for crossover process to avoid such local optimization. The idea is to obtain global solutions by considering the entire search space (all the data points).We consider the Euclidean distance for the function

$$F_1(x) = \sum_{i=1}^{2} x_i^2 \quad (24)$$

As per proposed method, all the data points have a higher chance to be included in the search and thus a local solution could be avoided. The distance between two points on n search space is defined by

$$\text{distance} = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + .. + (x_n - y_n)^2} \quad (25)$$

The influence of mutation in GA or in a hybrid system of PSO and GA has been studied to speed up the running time to obtain optimal solutions [14, 15]. We used the position and speed vector of PSO as follows:

$$v_{f,g}^{(t+1)} = wv_{j,g}^{(t)} + c_1^* rand()^* \left(pbest_{j,g} - k_{j,g}^{(t)}\right) + c_2^* Rand()^* \left(gbest_g - k_{j,k}^{(t)}\right) \quad (26)$$

Where j= 1,2,..,n g=1,2,..,m

$$k_{j,g}^{(t+1)} = k_{j,g}^{(t)} + v_{j,g}^{(t+1)}, k_g^{min} \leq k_{j,g}^{(t+1)} \leq k_g^{max} \quad (27)$$

Where n is the number of agents in each group; m the number of members in each group; t the number of reproduction steps; $v_{j,g}^{(t+1)}$ the speed vector of agent j in reproduction step of $t_{th}$,

$$v_g^{min} \leq v_{j,g}^{(t)} \leq v_g^{max} \, k_{j,g}^{(t)} \quad (28)$$

The position vector of agent j in reproduction step of $t_{th}$; w the weighting factor; $c_1$,$c_2$ the acceleration constant; rand(),Rand() the random value between 0 and 1; $p_{best}$ j the optimal position vector of agent j; and $g_{best}$ is the optimal position vector of group. The value of position vector and speed vector is determined by the acceleration constants $c_1$, $c_2$ . If these values are large, each agent moves to the target position with high speed and abrupt variation. If vice versa, agents wander about target place. As weighting factor w is for the search balance of the agent, the value for optimal search is given by

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} \times iter, \quad (29)$$

Where $W_{max}$ is the maximum value of W(0.9); $W_{min}$ the minimum value of W(0.4); $iter_{max}$ the number of iterations; and iter is the number of iterations at present.

The speed vector is limited by

$$v_g^{min} \leq v_{j,g}^{(t)} \leq v_g^{max} \quad (30)$$

## 4.3. Algorithm NHPSO for Solving Reactive Power Dispatch Problem

[Step 1] Initialize all GA variables.

[Step 2] Initialize all PSO variables.

[Step 3] Calculate affinity of each agent for condition of optimal solution of GA. At this point, optimal position condition of PSO is introduced into the GA loop.

[Step 4] Arrange the group of PSO and agents in GA.

[Step 5] Update position vector pbest and speed vector gbest.

[Step 6] Perform crossover in GA using Euclidian distance and position vector of PSO.

[Step 7] Perform mutation in GA.

[Step 8] If condition of GA is satisfied with the target condition (iteration number or target value), reproduction procedure is halted. Otherwise, it goes to step 3.

## 5. Simulation Results

The validity of the proposed Algorithm technique is demonstrated on 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 Lower | upper | ORPD | VSCRPD |
|---|---|---|---|---|
| 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[16] | 5.0159 |
| Genetic algorithm[17] | 4.665 |
| Real coded GA with Lindex as SVSM[18] | 4.568 |
| Real coded genetic algorithm[19] | 4.5015 |
| Proposed NHPSO method | 4.1103 |

## 6. Conclusion

In this paper a novel approach NHPSO algorithm is used to solve optimal reactive power dispatch problem, with considering various constraints. The effectiveness of the proposed method is demonstrated by testing on IEEE 30-bus system and the real power loss has been considerably reduced when compared to other standard algorithms, also the voltage profile are well within the specified limits .

## 7. Future Scope of the Paper

The NHPSO algorithm has been successfully applied to the reactive power dispatch problem. The real power loss has been reduced and voltage profile index also within limits. By refining the algorithm further, it can be applied to large systems networks and practical utility systems.

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