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Particle Distribution Algorithm for Solving Optimal Reactive Power Dispatch Problem

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Abstract

In this paper, a novel perception of the particle swarm optimization (PSO) system called Particle Distribution Algorithm (PDA) is proposed to solve Reactive power problem. In that swarm individual particles are moved away, but discreetly characterize each particle by a field or by distribution & its behaviour absolutely dissimilar from the family of old PSO scheme. The projected PDA has been tested in standard IEEE 30 bus test system and simulation results show clearly the better performance of the proposed algorithm in reducing the real power loss.

Keywords

Particle Swarm Optimization; Particle Distribution; Optimal Reactive Power; Transmission Loss;

Introduction

Various numerical methods like the gradient method [1, 2] Newton method [3] and linear programming [4-7] have been utilized to solve the optimal reactive power dispatch problem. The problem of voltage stability and collapse play a key role in power system planning and operation [8]. Enhancing the voltage stability, voltage magnitudes within the limits alone will not be a reliable indicator to indicate that, how far an operating point is from the collapse point. The reactive power support and voltage problems are internally related to each other.This paper formulates by combining both the real power loss minimization and maximization of Static Voltage Stability Margin (SVSM) as the objectives. Numerous Evolutionary algorithms have been already utilized to solve the reactive power flow problem [9-20]. This paper proposes Particle Distribution Algorithm (PDA) to solve reactive power dispatch problem. Proposed algorithm has better exploration and exploitation capabilities in searching the global near optimal solution & each particle can be abstracted by a field or distribution. The parameters of the distribution are modernized by using a scheme alike to Thompson's sampling, leading to a completely new and unique perspective on particle swarm systems [21-40]. Proposed PDA has been evaluated in standard IEEE 30 bus test system. Simulation results show that our proposed approach outperforms all the entitled reported algorithms in minimization of real power loss and voltage profile index is enhanced.

Voltage Stability Evaluation

Modal analysis for voltage stability evaluation

Modal analysis is one among best methods for voltage stability enhancement in power systems. The steady state system power flow equations are given by.

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

Where

ΔP = Incremental change in bus real power.

ΔQ = Incremental change in bus reactive Power injection

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

ΔV = 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.

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

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

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

Where

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

J_R is called the reduced Jacobian matrix of the system.

Modes of Voltage instability

Voltage Stability characteristics of the system have been identified by computing the Eigen values and Eigen vectors.

Let

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

Where,

ξ = right eigenvector matrix of JR

η = left eigenvector matrix of JR

Λ = diagonal eigenvalue matrix of JR and

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

From (5) and (8), we have

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

or

$$\Delta V = \sum \frac{\hat{\imath}_i \varsigma_i}{\ddot{e}} \Delta Q \tag{8}$$

Where ξi is the ith column right eigenvector and η the ith row left eigenvector of JR.

λi is the ith Eigen value of JR.

The ith modal reactive power variation is,

$$\Delta Q_{mi} = K_\iota \xi_\iota \tag{9}$$

where,

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

Where

ξji is the jth element of ξi

The corresponding ith modal voltage variation is

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

If | λi | =0 then the ith modal voltage will collapse .

In (10), let ΔQ = ek where ek has all its elements zero except the kth one being 1. Then,

$$\Delta V = \sum_i \frac{\eta_{1k}\ \xi_1}{\ddot{e}_1} \tag{12}$$

η_{1k} k th element of η_1

V –Q sensitivity at bus k

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

Problem Formulation

The objectives of the reactive power dispatch problem is to minimize the system real power loss and maximize the Static Voltage Stability Margins (SVSM).

Minimization of Real Power Loss

Minimization of the real power loss (P_{loss}) in transmission lines is mathematically stated as follows.

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

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.

Minimization of Voltage Deviation

Minimization of the voltage deviation magnitudes (VD) at load buses is mathematically stated as follows.

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

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

System Constraints

Objective functions are subjected to these constraints shown below.

Load flow equality constraints:

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

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

where, nb is the number of buses, PG and QG are the real and reactive power of the generator, PD and QD are the real and reactive load of the generator, and Gij and Bij are the mutual conductance and susceptance between bus i and bus j.

Generator bus voltage (VGi) inequality constraint:

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

Load bus voltage (VLi) inequality constraint:

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

Switchable reactive power compensations (QCi) inequality constraint:

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

Reactive power generation (QGi) inequality constraint:

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

Transformers tap setting (Ti) inequality constraint:

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

Transmission line flow (SLi) 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

Particle Distribution Algorithm (PDA)

In the basic particle swarm optimization (PSO) model, an individual particle consists of: A current position, a current velocity and a personal best found position. Each of these components is required in order to decide the succeeding position of the particle for the subsequent iteration. The particle's position in the succeeding iteration depends upon its present position and the particle's velocity. The modernized velocity, in turn, depends on the particle's current velocity, the particle's personal best found position and the population's global best found position. The representation of a swarm of particles "flying" through space no longer aptly describes the high-level concept of the algorithm. Rather, the algorithm now consists of a population of "particle fields" which move throughout the space in a different way. Because the "positions" of these "particle fields" are defined as arbitrary distributions, "evaluating" a "particle field's" existing "position" is nondeterministic, and so these "particle fields" do not certainly have to "move" to discover new points. These "particle fields" remain "stationary" in the space until either the individual's personal best point changes, or the population's global best point changes. This population of "particle fields" can, itself, be alleged as an arbitrary field of particles defined as a mixture distribution made up of each individual distribution. This population level distribution can be thought of as an abstract depiction of a particle swarm, representing a probability distribution of all possible particle locations for the consequent iteration. With this new outlook, it is possible to discover new directions in refining or altering the behaviour of the algorithm. With these changes taken into account, we have now moved away from the traditional PSO paradigm and arrived at a new, distinct algorithm, which will be hereafter referred to as Particle Distribution Algorithm (PDA). This algorithm consists of a population of "particle field" individuals and a "point pool" of candidate solution points. The population of particle field individuals uses PSO principles to guide the exploration of the solution space, which is carried out by creating and weighing, the pool of candidate solution points. Similar to traditional PSO algorithms, the PDA algorithm consists of an initialization phase and a simulation phase which loops until some end criteria is met, at which point the best solution found by the algorithm is returned as output. A particle field individual is designated at an arbitrary position from the population, according to some weighting scheme. Then, the point is produced by sampling the arbitrary distribution defined by the selected individual. This arbitrary distribution is constructed using the individual's personal best, and the global best points.

Given a particle field with personal best point $\vec{p}_i$ and for which the global best point is $\vec{p}_g$, the position of the candidate solution point, $\vec{c}$ is determined according to:

$$\vec{p}_m = \frac{\vec{p}_i + \vec{p}_g}{2} \tag{24}$$

$$\overrightarrow{\sigma^2} = \left|\overrightarrow{p_i} - \overrightarrow{p_g}\right| \tag{25}$$

$$\vec{c} = \vec{N}\left(\overrightarrow{p_m} - \overrightarrow{\sigma^2}\right) \tag{26}$$

Once the candidate solution has been produced, the objective function is weighed, using this produced point as its input, in order to assign it a value. After each candidate solution in the point pool has been produced, the second phase begins. In this phase, the population of particle field individuals is modernized. Each individual updates its own best found point using the set of candidate solutions produced from its own distribution. Each individual selects the best point from the set of associated candidate solutions. If the best associated candidate solution is better than the individual's personal best found point, the individual sets its personal best found point to be equal to that candidate solution point. The pool of candidate solutions is then "emptied", and the simulation endures to the succeeding iteration. Once the termination criteria have been met, the global best found point is returned as output of the algorithm.

Input:

Function f ( ) to be optimized

Initialization range lbound, ubound

Particle field population size $_{pop}$

Candidate solution point pool size n_{pool}

Weighting function ù ( )

Output:

Point $\vec{p}_i$ representing best found solution

Method:

Generate particle field population P with size n_{pop}

Generate candidate solution point pool C with size n_{pool}

For each particle field $i \in p$ do

$$\vec{p}_i = \vec{U}\left[\text{lbound, ubound}\right]$$

If $f\left(\vec{p}_i\right) < f\left(\vec{p}_j\right)$ Then

$\vec{p}_i \Leftarrow \vec{p}_j$

End if

End for

While termination criteria not met do

For each candidate solution point $\vec{c} \in C$ do

Select particle field $i \in p$ with probability $\frac{ù(i)}{\sum p \in P^{ù(p)}}$

$$\vec{c} \Leftarrow \vec{N}\left(\frac{\vec{p}_i + \vec{p}_g}{2}, \left[\vec{p}_i - \vec{p}_g\right]\right)$$

$$\vec{s}_i \Leftarrow s_i \bigcup \left\{\vec{c}\right\}$$

End for

For each particle field $i \in p$ do

Choose point $\vec{c}_{min}$ from S_i which minimizes $f\left(\vec{c}_{min}\right)$

If $f\left(\vec{c}_{min} < f\left(p\right)_i\right)$ then

$\vec{p}_i \Leftarrow \vec{c}_{min}$

If $f\left(\vec{p}_i\right) < f\left(\vec{p}_j\right)$

Then $\vec{p}_i \Leftarrow \vec{p}_j$

End if

End if

$S_i \Leftarrow \varnothing$

End for

End

Simulation Results

The efficiency of the proposed Particle Distribution Algorithm (PDA) is demonstrated by testing it 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. The simulation results have been presented in Tables 1, 2, 3 &4. And in the Table 5 shows the proposed algorithm powerfully reduces the real power losses when compared to other given algorithms. The optimal values of the control variables along with the minimum loss obtained are given in Table 1. Corresponding to this control variable setting, it was found that there are no limit violations in any of the state variables.

Table 1: Results of PDA – ORPD optimal control variables

Control Variables	Variable Setting
V1	1.047
V2	1.046
V5	1.041
V8	1.030
V11	1.004
V13	1.031
T11	1.00
T12	1.00
T15	1.01
T36	1.01
Qc10	3
Qc12	3
Qc15	2
Qc17	0
Qc20	2
Qc23	3
Qc24	3
Qc29	2
Real power loss	4.2869
SVSM	0.2479

Table 2: Results of PDA -Voltage Stability Control Reactive Power Dispatch Optimal Control Variables

Control Variables	Variable Setting
V1	1.049
V2	1.047
V5	1.044
V8	1.032
V11	1.005
V13	1.034
T11	0.090
T12	0.090
T15	0.090
T36	0.090
Qc10	3
Qc12	3
Qc15	2
Qc17	3
Qc20	0
Qc23	2
Qc24	2
Qc29	3
Real power loss	4.9896
SVSM	0.2484

Table 3: Voltage Stability under Contingency State

Sl.No	Contingency	ORPD Setting	VSCRPD Setting
1	28-27	0.1419	0.1434
2	4-12	0.1642	0.1650
3	1-3	0.1761	0.1772
4	2-4	0.2022	0.2043

Optimal Reactive Power Dispatch problem together with voltage stability constraint problem was handled in this case as a multi-objective optimization problem where both power loss and maximum voltage stability margin of the system were optimized simultaneously. Table 2 indicates the optimal values of these control variables. Also it is found that there are no limit violations of the state variables. It indicates the voltage stability index has increased from 0.2479 to 0.2484, an advance in the system voltage stability. To determine the voltage security of the system, contingency analysis was conducted using the control variable setting obtained in case 1 and case 2. The Eigen values equivalents to the four critical contingencies are given in Table 3. From this result it is observed that the Eigen value has been improved considerably for all contingencies in the second case.

Conclusion

In this paper, Particle Distribution Algorithm (PDA) has been successfully applied to solve Optimal Reactive Power Dispatch problem. The proposed algorithm has been tested on the standard IEEE 30 bus system. Simulation results show the heftiness of projected Particle Distribution Algorithm (PDA) method in decreasing the real power loss & voltage profile index has been enhanced. The control variables obtained after the optimization by Particle Distribution Algorithm (PDA) is within the limits.

Table 4: 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 5: Comparison of Real Power Loss

Method	Minimum loss
Evolutionary programming [41]	5.0159
Genetic algorithm [42]	4.665
Real coded GA with Lindex as SVSM [43]	4.568
Real coded genetic algorithm [44]	4.5015
Proposed PDA method	4.2869

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