Differential Evolution approach to Optimal Reactive Power Dispatch with Voltage Stability enhancement by Modal Analysis

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Abstract

This paper presents an evolutionary based algorithm 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 among all evolutionary based algorithms, the Differential Evolution Technique. The proposed method has been tested on IEEE 30 bus system where the obtained results were found satisfactorily to a large extent that of reported earlier.

Key words: Optimal Reactive Power Dispatch, Modal Analysis, Differential Evolution.

I. 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. Optimal reactive power dispatch problem is an OPF sub-problem which has a significant impact on economic and secure operation of power systems. 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. The reactive power dispatch has a twofold goal thus: to improve system voltage profiles and minimizes system losses at all times. 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. It is therefore clear that reactive power and voltage control is a constrained, nonlinear problem of considerable complexity.

Differential evolution is an improved version of GA for faster optimization. It was initially presented by Storn and Price as in as heuristic optimization method which can be used to minimize nonlinear and non-differentiable continuous space functions with real-valued parameters. This has been extended to handle mixed integer discrete continuous optimization problems. The main advantages of differential evolution are its simple structure, ease of use, robustness and its effectiveness for nonlinear constraint optimization problems with penalty functions.

II. 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

$$\begin{bmatrix}\Delta P\\ \Delta Q\end{bmatrix}=\begin{bmatrix}Jp\theta & Jpv\\ JQ\theta & JQv\end{bmatrix}\begin{bmatrix}\Delta\theta\\ \Delta V\end{bmatrix} \quad \text{--(1)}$$

ΔP- incremental change in bus real power
ΔQ-incremental change in bus reactive power
$\Delta\theta$-incremental change in bus voltage angle
ΔV-incremental change in bus voltage magnitude
$J_{P\theta}$, J_{PV}, $J_{Q\theta}$, J_{QV} are the sub matrices of jacobian matrix
If in above equation ΔP is made equal to zero, then
$\Delta Q=[J_{QV} - J_{Q\theta} J_{P\theta}^{-1} J_{PV}]\Delta V=J_R\Delta V$
and so
$\Delta V=J_R^{-1}\Delta Q$
where

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

called the reduced jacobian matrix of system

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.

III. 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.

A. Minimization of Real Power Loss

$$P_{loss} = \sum G_{i,j}(V_i + V_j - 2 V_i V_j \cos(\theta_{ij}))$$

$i,k \in 1,2 \text{---} N_l$ --(3)

B. 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.

C. Equality Constraints

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

$$P_{Gi} - P_{Di} = \sum V_i V_j \, (G_{i,j} \cos(\theta_{ij}) + B_{i,j} \sin(\theta_{ij}))$$

$$Q_{Gi} - Q_{Di} = V_i \sum V_J \, (G_{i,j} \sin(\theta_{ij}) - B_{i,j} \cos(\theta_{ij}))$$

$i = 1,2,\text{-------} N_B$ --(4)

where

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

D. 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.

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

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

N_{PV} = Number of voltage buses

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

N_{PQ} = Number of load buses

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

N_c= Number of Switchable Capacitors

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

N_T= Number of Tap changing Transformers

IV. Differential Evolution

One extremely powerful algorithm from Evolutionary Computation due to convergence characteristics and few control parameters is differential evolution. Differential Evolution is an optimization algorithm that solves real-valued problems based on the principles of natural evolution using a population P of N_p floating point encoded individuals that evolve over G generations to reach an optimal solution. Each individual, or candidate solution, is a vector that contains as many parameters as the problem decision variables D. In Differential Evolution, the population size (N_p) remains constant throughout the optimization process.

$$P^{(G)} = [X_1^{(G)}, \text{----} X_{Np}^{(G)}] \quad \text{---} (5)$$

$$X_i^{(G)} = [X_{1,i}^{(G)}, \text{----} X_{D,i}^{(G)}]^T \quad \text{---} (6)$$

$i= 1, \text{----} N_P$

Differential Evolution creates new offspring by generating a noisy replica of each individual of the population. The individual that performs better from the parent vector (target vector) and the replica (trial vector) advances to the next generation. This optimization process is carried out with three basic operations: Mutation, Crossover and Selection.

The first step in the DE optimization process is to create an initial population of candidate solutions by assigning random values to each decision parameter of each individual of the population. Such values must lie inside the feasible bounds of the decision variable, and can be generated by equation,

$$X_{j,i}^{(0)} = X_j^{min} + \eta_j (X_j^{max} - X_j^{min}), \quad \text{---} (7)$$

$i= 1, \text{----} N_P\,;\ j= 1, \text{----} D$

Where X_j^{min} and X_j^{max} are respectively, the lower and upper bound of the j^{th} decision parameter and η_j is the uniformly distributed random number within [0, 1] generated a new for each value of j.

After the population is initialized, this evolves through the operators of mutation, crossover and selection. The mutation operator is in charge of introducing new parameters in to the population. To achieve this, the mutation operator creates mutant vectors by perturbing a randomly selected vector (X_a) with the difference of two other randomly selected vectors (X_b and X_c)) according to. All of these vectors must be different from each other, requiring the population to be of at least four individuals to satisfy this condition. To control the perturbation and improve convergence, the difference vector is scaled by a user defined constant in the range [0, 1.2]. This constant is commonly known as the scaling constant (F). This is illustrated in Fig 1.

$$X_i^{'(G)} = X_a^{(G)} + F\,(X_b^{(G)} - X_c^{(G)}) \quad \text{- - - (8)}$$
$$i = 1, \text{- - - -}\ N_P;$$

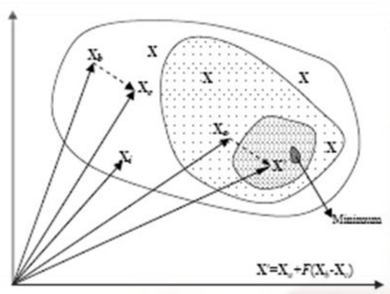

Fig 1 Method of creating Mutant Vector

Where X_a, X_b, X_c are randomly chosen vectors €{1, - - - - Np} and a ≠b≠c≠ i. X_a, X_b, and X_c are generated anew for each parent vector. F is the scaling constant.

The crossover operator creates the trial vectors which are used in the selection process. A trial vector is a combination of a mutant vector and a parent (target) vector performed based on probability distributions. For each parameter, a random value based on binomial distribution (preferred approach) is generated in the range [0, 1] and compared against a user defined constant referred to as the crossover constant. If the value of the random number is less or equal than the value of the crossover constant the parameter will come

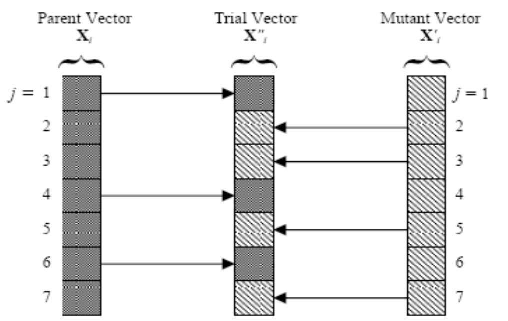

Fig 2 Method of Crossover operation

from the mutant vector, otherwise the parameter comes from the parent vector. The figure2 shows how the crossover operation is performed.

The cross operation maintains diversity in the population, preventing local minima convergence. The crossover constant (C_R) must be in the range of [0, 1]. A crossover constant of one means the trial vector will be composed entirely of mutant vector parameters. A crossover constant near zero results in more probability of having parameters from the target vector in the trial vector. A randomly chosen parameter from the mutant vector is always selected to ensure that the trial vector gets at least one parameter from the mutant vector even if the crossover constant is set to zero.

$$X_{j,i}^{''(G)} = \begin{cases} X_{j,i}^{'(G)} & \text{if } \eta_j' \le C_R \text{ or } j=q \\ X_{j,i}^{(G)} & \text{otherwise} \end{cases} \quad \text{- - - (9)}$$
$$i = 1, \text{- - - -}\ N_P;\ j = 1, \text{- - - -}\ D$$

Where q is a randomly chosen index € {1, - - - - D} that guarantees that the trial vector gets at least one parameter from the mutant vector; η_j' is a uniformly distributed random number with [0, 1) generated anew for each value of j. $X_{j,i}^{(G)}$ is the parent (target) vector, $X_{j,i}^{'(G)}$ the mutant vector and $X_{j,i}^{''(G)}$ the trial vector.

The selection operator chooses the vectors that are going to compose the population in the next generation. This operator compares the fitness of the trial vector and the fitness of the corresponding target vector, and selects the one that performs better. The selection process is repeated for each pair of target/trial vector until the population for the next generation is complete.

$$X_i^{(G+1)} = \begin{cases} X_{j,i}^{''(G)} & \text{if } f(X_{j,i}^{''(G)}) \le f(X_{j,i}^{(G)}) \\ X_i^{(G)} & \text{otherwise} \end{cases}$$
$$i = 1, \text{- - - -}\ N_P; \quad \text{- - - (10)}$$

V. DE approach to ORPD Problem

The present ORPD problem is implemented in DE to make the objective function of interest as minimum as possible without making the solution variables going out of the limits.

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,

$$\text{Min } F = P_{loss} + w^*(E_{max}) + Pen_V + Pen_Q$$
--(11)

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.

VI. 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,

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

a. 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 optimal values for the solution vector was obtained for optimum condition of function and it was found to be lie with in the range of its minimum and maximum values as given in table 1.

The optimal control variables obtained in this case are as follows

Variable	Value obtained
V_1	1.029
V_2	1.054
V_5	1.035
V_8	0.998
V_{11}	1.024
V_{13}	1.032
T_{11}	0.998
T_{12}	1.066
T_{15}	1.003
T_{36}	0.958
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}	4.456
E_{min}	0.344

b. 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 DE 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.

Variable	Value obtained
V_1	1.035
V_2	0.995
V_5	1.011
V_8	1.024
V_{11}	0.985
V_{13}	1.041
T_{11}	0.978
T_{12}	1.052
T_{15}	1.030
T_{36}	0.988
Q_{C10}	3.998
Q_{C12}	1.112
Q_{C15}	0.010
Q_{C17}	3.854
Q_{C20}	3.548
Q_{C21}	3.654
Q_{C23}	3.988
Q_{C24}	3.015
Q_{C29}	3.002
P_{loss}	4.987
E_{min}	0.354

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 following comparison table can be framed.

Method	P_{loss}
EP[2]	5.015
GA[4]	4.665
Real Coded GA[6]	4.501
DE[Proposed]	4.456

VII. 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 DE 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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