International Journal of Enhanced Research in Science Technology & Engineering, ISSN: 2319-7463
Vol. 2 Issue 12, December-2013, pp: (29-34), Available online at: www.erpublications.com

Optimization of reactive power for line loss reduction and voltage profile improvement using Differential Evolution Algorithm

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Abstract: This paper presents the application of Differential Evolution (DE) algorithm for line loss reduction and simultaneously improves the voltage profile in power transmission network. In this approach optimal setting of Reactive power control variable are carried out with the help of DE. The proposed approach is implemented on three standard IEEE system and obtained results reflect power losses reduction and voltage profile improvement.

Keywords: Load flow, Reactive power control variable, Differential Evolution, Line loss, Voltage stability.

1. Introduction

The optimal power flow (OPF) problem, which was Introduced in 1960s by Carpentier, [1] is an important and powerful tool for power system operation and planning. Reactive power optimization is a sub problem of OPF calculation, which determines all the controllable variables, such as tap ratio of transformers, output of shunt capacitors/reactors, reactive power output of generators and static reactive power compensators etc., and minimizes transmission losses or other appropriate objective functions. Reactive power optimization problem for improving economy and security of power system operation has received much attention. The main objective of optimal reactive power control is to improve the voltage profile and minimizing system real power losses via redistribution of reactive power in the system.

For the Optimization of Reactive power problem, a number of conventional optimization techniques [2]-[3] have been proposed. These include the Gradient method, Non-linear Programming (NLP), Quadratic Programming (QP), Linear programming (LP) and Interior point method. Though these techniques have been successfully applied for optimization of reactive power, still some difficulties are associated with them. One of the difficulties is the multimodal characteristic of the problems to be handled. Also, due to the non-differential, non-linearity and non-convex nature of the Reactive power dispatch problem, majority of the techniques converge to a local optimum. Recently, Evolutionary Computation techniques like Genetic Algorithm (GA) [4], Evolutionary Programming (EP) [5] and Evolutionary Strategy [6] have been applied for optimization of reactive power. In this paper a evolutionary computation technique, Differential Evolution (DE) algorithm is used to solve reactive power optimization problem.
Differential Evolution algorithm is developed by Price and Storn in 1995[7-10] to be a reliable and versatile function optimizer that is also easy to use. Main advantage of DE are, it can find near optimal solution regard less the initial parameters values, its convergence is fast and it uses few number of control parameters. It can handle integer and discrete optimization [7]-[10]. In [11]-[13], the DE algorithm is used for optimization of reactive power with the propose of reduction the system power losses while maintaining the dependant variable including voltages of PQ-buses and reactive power outputs of generators, within limits.

2. Problem Formulation

The objective of optimization of reactive power (control variables), which reduces the objective functions. This is mathematically stated as follows.

2.1 Minimization of system real power losses (MW)

$$F_1 = \min P_{Loss} \qquad (1)$$

2.2 System constraints
The equality constraints are power/reactive power equalities, the inequality constraints include bus voltage constraints, generator reactive power constraints, reactive source reactive power capacity constraints and the transformer tap position

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constraints, etc. The equality constraints can be automatically satisfied by load flow calculation, while the lower/upper limit of control variables corresponds to the coding on the Differential Evolution Optimization (DE) Algorithm, so the inequality constraints of the control variables are satisfied.
The Equality constraints are the power flow equation given by:

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)] = 0 \quad (2)$$
$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \sin(\delta_i - \delta_j) - B_{ij} \cos(\delta_i - \delta_j)] = 0 \quad (3)$$

where i=1,. . .,NB; NB is the number of buses, P_G is the active power generated, Q_G is the reactive power generated, P_D is the load active power, Q_D is the load reactive power, G_{ij} and B_{ij} are the transfer conductance and susceptance between bus i and bus j, respectively.

The inequality constraints are:
Generator constraints: generator voltages, and reactive power outputs are restricted by their lower and upper limits as follows:

$$V_{Gi}^{min} \le V_{Gi} \le V_{Gi}^{max}, \ i=1,\ldots\ldots\ldots,NG \quad (4)$$
$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max}, \ i=1,\ldots\ldots\ldots,NG \quad (5)$$

Transformer constraints: transformer tap settings are bounded as follows:

$$T_{Gi}^{min} \le T_{Gi} \le T_{Gi}^{max}, \ i = 1,\ldots\ldots\ldots,NT \quad (6)$$

Shunt VAR constraints: shunt VAR compensations are restricted by their limits as follows:

$$Q_{ci}^{min} \le Q_{ci} \le Q_{ci}^{max}, i=1,\ldots\ldots\ldots, N_c \quad (7)$$

Security constraints: these include the constraints of voltages at load buses and transmission line loadings as follows:

$$V_{Li}^{min} \le V_{Li} \ge V_{Li}^{max}, i=1......NL \quad (8)$$
$$S_{li} \le S_{li}^{max}, \ i=1.......nl \quad (9)$$

3. Differential Evolution Algorithm

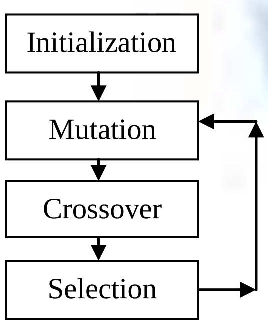


Fig.1: DE cycle of stages

3.1 DE computational flow

DE algorithm is a population based algorithm developed by Price and Storn using three operators; crossover, mutation and selection. Several optimization parameters must also be tuned. These parameters have joined together under the common name control parameters. In fact, there are only three real control parameters in the algorithm, which are differentiation (or mutation) constant F, crossover constant CR, and size of population NP. The rest of the parameters are dimension of problem D that scales the difficulty of the optimization task; maximum number of generations or iterations GEN, which may serve as a stopping condition; and low and high boundary constraints of variables that limit the feasible area [7]-[8].

The DE algorithm works through a simple cycle of stages, presented in Fig. 1.

These stages can be cleared as follow:

3.1.1 Initialization

Initial population of size 'N' is generated as follows:

$$x_{i,j}(0)=x_j^L+ \text{rand}(0,1) . (x_u^L - x_j^L)$$

In above $x_{i,j}$ is j^{th} component of the i^{th} population.

Problem independent variables are initialized in their feasible numerical range. Therefore, if the jth variable of the given problem has its lower and upper bound asx_j^Landx_u^L , respectively

where rand(0,1) is a uniformly distributed random number between 0 and 1.

3.1.2 Mutation

In each generation to change each population member $X_i(t)$, at donor vector $v_i(t)$ is created.

To create a donor vector $v_i(t)$for each ith member, three parameter vectors x_{r1}, x_{r2} and $x_{r3}$are chosen randomly from the current population and not coinciding with the current x_i. Next, a scalar number S scales the difference of any two of the three vectors and the scaled difference is added to the third one whence the donor vector $v_i(t)$ is obtained. The usual choice for S is a number between0.4 and 1.0. So, the process for the jth component of each vector can be expressed as,

$$v_{i,j}(t+1) = x_{r1,j}(t) + S. (x_{r2,j}(t) - x_{r3,j}(t))$$

3.1.3 Crossover [14]

Following the mutation stage, the crossover (recombination) operator is applied on the population. For each mutant vector $v_{i,j}(t+1)$, a trial vector $u_{i,j}(t)$ is generated with

$$u_{i,j}(t) = \begin{cases} v_{i,j}(t+1) & \text{if} \quad \text{rand}(0,1) < CR \\ x_{i,j}(t) & \text{else} \end{cases}$$

Where CR is the DE control parameter that is called the crossover rate and user defined parameter with in the range [0,1]
$u_{i,j}(t)$ represents the child that will compete with the parent $x_{i,j}(t)$

3.1.4 Selection

To keep the population size constant over subsequent generations, the selection process is carried out to determine which one of the child and the parent will survive in the next generation, i.e., at time t=t+1. DE actually involves the Survival of the fittest principle in its selection process. The selection process can be expressed as,

$$X_i(t+1) = \begin{cases} U_i(t) & \text{if} \quad f\big(U_i(t)\big) \le f(X_i(t)) \\ X_i(t) & \text{if} \quad f(X_i(t)) < f(U(t)) \end{cases}$$

Where , f () is the function to be minimized as given in (1)-. From Eq. we noticed that:

- If $u_i(t)$ yields a better value of the fitness function, it replaces its target $X_i(t)$ in the next generation
- Otherwise, $X_i(t)$ is retained in the population.

Hence, the population either gets better in terms of the fitness function or remains constant but never deteriorates.

DE Based Approach Implementation

Step-1 Data input: Reactive power control variables and system parameters (resistance, reactance and susceptance etc.)
Step-2 Base case transmission loss calculated based on NR method.
Step-3 Generate an initial population randomly with in the control variable bounds
Step-4 Run the load flow solution with these control variables and calculate loss.
Step-5 Perform differentiation (mutation) and crossover to create offspring from parents
Step-6 Perform selection between parent and offspring.
Step-7 store the best individual of the current generation.
Step-8 Repeat step 2 to 6 till the termination criteria is met. i,e iteration procedure can be terminated when any of the following criteria is met, i,e, an acceptable solution has been reached, a state with no further improvement in solution is reached, control variables has converged to a stable state or a predefined number of iterations have been completed.

Results

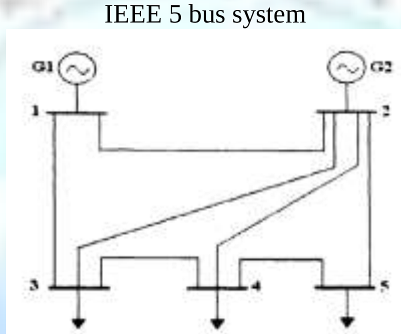
The developed DE based algorithm has been applied to three standard IEEE systems. The results in Table 1,2 and 3 shows losses is minimized with voltage profile improve in all three system which demonstrate the effectiveness of the algorithm. Initial data of three system taken from [15],[16] & [17] respectively.

For 5 bus system Generator bus voltages ranges 0.95pu -1.10pu, Tap settings ranges 0.9pu-1.1pu, Generator reactive power ranges 1pu – 5pu, load bus voltages ranges 0.95pu – 1.05pu.

Table:1 Optimal setting of control variables for different cases in IEEE 5 bus system

Control variable	Initial value	Minimization of power losses & Voltage profile improvement
T_4	1	0.9761
Q_3	2	2.7963
Power loss (MW)	5.147	5.1010

IEEE 5 bus system

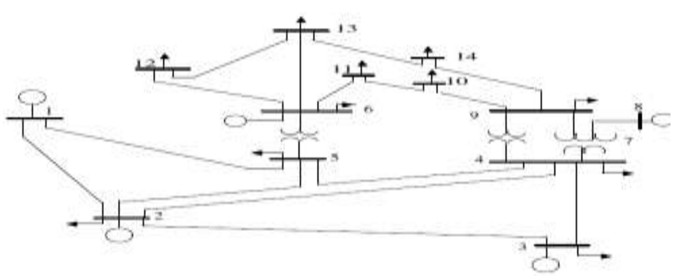


For 14 bus system Generator bus voltages ranges 0.95pu -1.10pu, Tap settings ranges 0.9pu-1.1pu,

Table 2: Optimal setting of control variables for different cases in IEEE 14 bus system.

Control variable	Initial value	Minimization of power losses & Voltage profile improvement
T_8	1	1.0063
T_9	1	1.0140
T_{11}	1	.9176
Q_9	18	18
Q_{14}	18	6
Power loss (MW)	13.402	13.337

IEEE 14 BUS SYSTEM

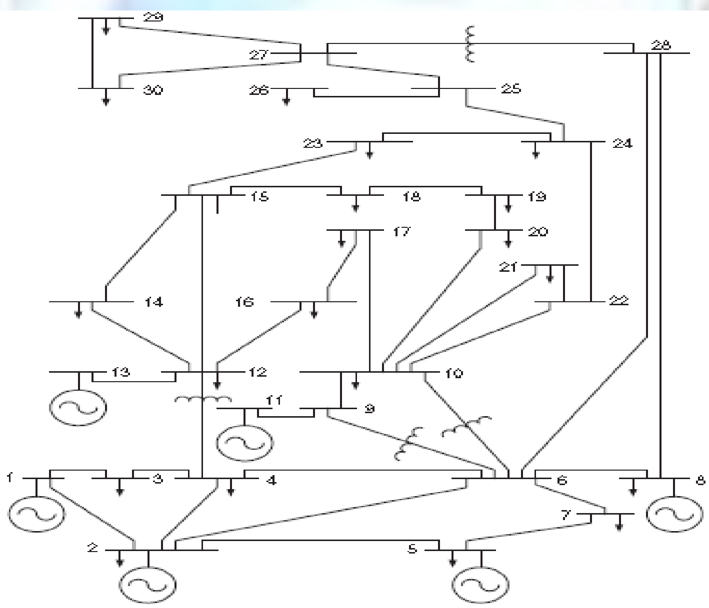


For 30 bus system Generator bus voltages ranges 0.95pu -1.10pu, Tap settings ranges 0.9pu-1.1pu, Generator reactive power ranges 1pu – 5pu, load bus voltages ranges 0.95pu – 1.05pu

Table 3: Optimal setting of control variables for different cases in IEEE 30 bus system

Control variable	Initial value	Minimization of power losses & Voltage profile improvement
T_{11}	1.069	0.9376
T_{12}	1.078	1.0165
T_{15}	1.032	1.0646
T_{36}	1.068	0.9509
Q_{10}	2	4.2877
Q_{12}	0	3.0011
Q_{15}	0	3.9597
Q_{17}	0	3.2073
Q_{20}	3	6.5059
Q_{21}	0	3.0732
Q_{23}	0	3.4412
Q_{24}	2	5.9356
Q_{29}	2	6.7578
Power loss (MW)	5.679	5.4120

IEEE 30 BUS SYSTEM



Conclusion

In this paper, a Differential evolution (DE) optimization algorithm has been successfully applied to solve the optimized problem. The computation of this method is simple and easy mechanization to execute it. Developed algorithm has been implemented on three IEEE standard systems, obtained results proves the significance of developed methodology.

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