Reactive Power Optimization Using Differential Evolution Algorithm

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Abstract--**In this Reactive power optimization is a nonlinear, multi-variable, multi-constrained programming problem, which makes the optimization process multifaceted. In this paper, based on the characteristics of reactive power optimization, a mathematical model of reactive power optimization, including comprehensive concern of the practical constraints and reactive power regulation means for optimization, is established. Reactive Power reduces power system losses by adjusting the reactive power control variables such as transformer tap-settings, generator voltages and other sources of reactive power such as capacitor banks. Reactive Power provides better system voltage control resulting in improved voltage profiles, system security, power transfer capability and overall system operation. Also Differential Evolution (DE) Algorithm has been studied, and the technique based on improved DE Algorithm for reactive power is going to be taken in this paper Optimization for the IEEE 14-bus and IEEE 57 bus system proves that the improved DE algorithm used for reactive power optimization is valuable. The algorithm is simple, convergent and of high quality for optimization, and thus appropriate for solving reactive power optimization problems, with some application view.**

Keywords-**Reactive Power Optimization, power loss, Voltage Deviation, Differential Evolution (DE) Algorithm.**

I. INTRODUCTION

The purpose of Power system reactive power optimization is to find the reasonably reactive compensation points and best compensation methods with the demand of the reactive load power system, which makes the power system safe and economic. The traditional reactive power optimization methods include linear programming, Newton method, interior-point method [1], etc. In recent years, artificial intelligence such as genetic algorithm, particle swarm algorithm [2], Ant algorithm [3] realizes the algorithm from different approaches, and everyone of them have their own advantages, but also have defects. In the last decades, many computational intelligence-based techniques have been proposed for reactive power optimization problem, such as genetic algorithm (GA), particle swarm optimization (PSO), Social Cognitive Optimization Algorithm (SCOA),Tabu search. In this paper, it is introduced to solve reactive power problem [16]. Two famous examples: IEEE- 14 bus and IEEE-57 bus system are used to test, simulation results show differential evolution (DE) is effective.

The main objective of Reactive power optimization in power system is to identify the reactive control variables settings such as transformer tap-settings, generator voltages and other sources of reactive power such as capacitor banks to present better system voltage control resulting in improved voltage profile, power transfer capability, system security and overall system operation. It is a sub-problem of optimal power flow (OPF) calculation. In general, OPF is a non-linear programming problem (NLP) that is used to find out the optimal control parameters circumstance to minimize or maximize a desired objective function, subject to certain system constraints [4].

In recent years, the problem of reactive power optimization (RPO) for voltage control and for reducing power losses has received much attention [5]. The main objective of RPO is to improve the voltage profile and minimize real power losses through redistribution of reactive power in the system [6]. Reactive power optimization is an effective method to insure the security and economy of the operation of power system, and also acting an imperative role to improving the voltage quality and reducing the electricity loss. Reactive power optimization is known as a multi-modal, mixed variable and nonlinear problem [16]. There are various optimization algorithms used for the solution of such type of problem. These algorithms may be classified into three groups, namely Non-linear Programming, sensitivity analysis and gradient-based optimization, and heuristic methods [6, 7].

Recently Differential Evolution (DE) algorithm has been developed and applied for various optimization problems. DE is an improved version of a genetic algorithm, which provides fast optimization. Differential Evolution is a simple population based search algorithm, which is highly efficient in handling constrained optimization problems. This algorithm can take care of optimality on uneven, discontinuous and multi-modal surfaces. DE has some advantages as compared to other methods. It can find near optimal solutions regardless the initial parameters, its convergence is fast and it requires few number of control parameters. In addition to this, its coding is simple and it can handle integer and discrete optimization [8, 9].

Genetic Algorithm (GA) is a class of stochastic search optimization technique which starts from multiple randomly selected points (initial population) and proceeds towards the better optimal solution based on evolution of genes through various generations. The performance of GA is enhanced for ORPD problem by various researchers by developing many GA variants based on the system variable representation (binary and real) and their genetic operators (such as selection, crossover and mutation)[10]. Both of the simple genetic algorithm (SGA) and the improved genetic algorithm (IGA) will be tested on all the two systems [15].

The constraints include the equality function and non-equality function- the equality functions are related to the reactor power of bus in the power system, as well as the non-equality functions are decided in the upper and lower limit of the design variables .The design of variable related with the objective function are divided as two types [18]: one is the control variable which need to be optimized in the optimization model, while the other is state variable which is obtained with the numerical computation. The control variables include the bus voltage of generator (V), compensation quantity of reactive power of shunt capacitors or reactors (Q_{sh}) and change ratio of transformer (T) in the model of reactive power optimization. The state variables include voltage amplitude of the various buses and input value of active power of generator [19].

II. PROBLEM FORMULATION

The objective of the RPO problem is to identify reactive power control variables which minimize the objective functions. Here the RPO problem is treated as a single objective optimization problem by linear combination of two objective functions i.e. PLOSS and VD which can be written as follows [17].

$$F = W * Ploss + (1 - w) * VD$$

Where w is a weighting factor and varying as a random number w= rand [0, 1].

A. Problem objectives

1) Minimization of system power losses: The mini –mization of system real power losses $Ploss$(MW) can be calculated as follows.

$$f_1 = P_l = \sum_{k=1}^{nl} g_k\left[v_i^2 + v_j^2 - 2v_i v_j \cos(\delta_i - \delta_j)\right]. \quad (1)$$

In equation (1) where nl is the number of transmission lines; g_k is the conductance of the K^{th} line; v_i and v_j are the voltage magnitude at the end buses i and j of the K^{th} line. Respectively, δ_i and δ_j are the voltage phase angles at the end buses i and j.

2) Voltage Deviation (VD)

This objective is to minimize the deviations in voltage magnitudes at the load buses. Bus voltage is one of the most important security and service quality indices. The Improving voltage profile can be obtained by minimizing the load bus voltage deviations from 1.0 per unit (pu). The objective function can be expressed as:

$$f_2 = VD = \sum_{i=1}^{NL} |V - 1.0| \quad (2)$$

In equation (2) Where NL is the number of load buses.

B. System constraints

1) Equality constrain : These constraints are representing load flow equations:

$$P_{gi} - P_{di} - V_i \sum_{j=1}^{NB} Vj\left[G_{ij}\cos(\delta_i - \delta_j) + B_{ij}\sin(\delta_i - \delta_j)\right] = 0 \quad (3)$$

$$Q_{gi} - Q_{di} - V_i \sum_{j=1}^{NB} Vj\left[G_{ij}\sin(\delta_i - \delta_j) - B_{ij}\cos(\delta_i - \delta_j)\right] = 0 \quad (4)$$

In equation (3) and (4) i=1,. . .,NB; NB is the number of buses, P_g is the active power generated, $P_d$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.

2). Inequality constraints

2.1. Generator constraints: Generator voltages and reactive power outputs are restricted by their lower and upper limits as follows:

$$V_{gi}^{min} \le V_{gi} \le V_{gi}^{max} \quad (5)$$

where, i=1 2 3………………NG.

$$Q_{gj}^{min} \le Q_g \le Q_{gj}^{max} \quad (6)$$

where, j=1 2 3 …………….NG.

In equation (5) and (6) NG is the number of the generators.

2.2. Transformer constraints: Transformer tap settings are bounded as follows:

$$T_i^{min} \le T_i \le T_j^{max} \quad (7)$$

where, $i = 1\ 2\ 3 \dots\dots\dots\dots\dots\dots NT$

In equation (7) NT is the number of the transformers.

2.3. Shunt VAR constraints: Shunt VAR compensations are classified by their limits when follows:

$$Q_{ci}^{min} \le Q_c \le Q_{ci}^{max} \quad (8)$$

where, $i = 1\ 2\ 3 \dots\dots\dots\dots N_C$

In equation (8) N_C is the number of switchable VAR sources.

III. DIFFERENTIAL EVOLUTION ALGORITHIM

In 1995, Storn and Price were proposed a new floating point encoded evolutionary algorithm for global optimization and named it differential evolution (DE) algorithm owing to a extraordinary kind of differential operator, which they invoked to create new off-spring from parent chromosomes instead of classical crossover or mutation [8].

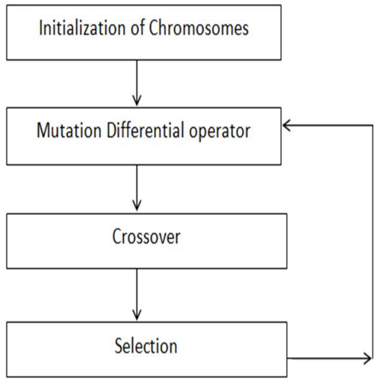

Figure (1): DE cycle of stage

Similar to GAs, DE algorithm is a population based algorithm that uses crossover, mutation and selection operators. The main differences between the genetic algorithm and DE algorithm are the selection process and the mutation scheme that makes DE self-adaptive. In DE, all solutions have the same chance of being selected as parents [14]. DE algorithm is a population based algorithm using three operators such as crossover, mutation and selection. Several optimization parameters must also be tuned. These parameters have connected 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 provide as a stopping condition and low and high boundary constraints of Variables that limit the feasible area.

A. *Initialization*

At the very beginning of a DE run, 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 as x_j^L and x_j^u, respectively, then the jth component of the ith population members may be initialized as,

$$x_{i,j}(0) = x_j^L + rand(0,1).(x_j^u - x_j^l) \quad (9)$$

in equation (9) $rand$ (0,1) is a uniformly distributed random number between 0 and 1.

B. *Mutation*

Mutation is the method of creating this donor vector, which demarcates between the various *differential evolution* schemes. In equation(10) However, in this paper, one such specific mutation strategy known as DE/rand/1 is discussed To create a donor vector $\vec{v_i}(t)$, 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 F scales the difference of any two of the three vectors and the scaled difference is added to the third one whence the donor vector $\vec{v_i}(t)$, is obtained.

$$v_{i,j}(t+1) = x_{r1j} + F\left(x_{r2,j}(t) - x_{r3,j}(t)\right) \quad (10)$$

C. *Crossover*

Two types of crossover schemes can be used with DE techniques. These are exponential crossover and binomial crossover. Although the exponential crossover was proposed in the original work of Storn and Price [8] the binomial variant was much more used in recent applications [12].Moreover, in the case of exponential crossover one has to be aware of the fact that there is a small range of CR values (typically [0.9, 1]) to which the DE is sensitive. This could explain the rule of thumb derived for the original variant of DE. On the other hand, for the same value of crossover (CR), the exponential variant needs a larger value for the scaling parameter F in order to avoid premature convergence [13].

$$u_{i,j}(t) = v_{i,j}(t)x_{i,j}(t) \quad (11)$$

D. Selection

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

Flow chart for step follows for the calculation in the differential evolution algorithm.

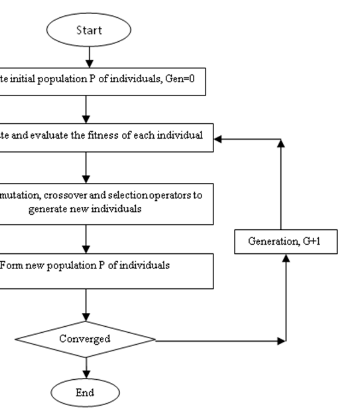

Fig (2) Flow chart of the DE Algorithm

IV. IMPLEMENTATION OF DE ALGORITHM

The suggested DE-based approach has been formulated and implemented using the Matlab software. Several trials have been done with different values of DE key parameters such as differentiation (mutation) constant *F*, crossover constant CR, size of population *NP*, and the maximum number of generations *GEN* which is used here as a stopping criteria to find the optimal DE key parameters. In this paper, the following values of DE key parameters are selected for the simultaneous optimization of the real power loss (PL) and the bus voltage deviations (VDs).

$$F = 0.6, CR\ 0.8, NP = 10, GEN = 100$$

The first step in the DE algorithm is creating an initial population. All the independent variables which include generator voltages and transformer tap settings have to be generated according to (9), where each independent parameter of each individual in the population is assigned a value within its specified feasible region. This creates parent vectors of independent variables for the first generation. After, finding the independent variables, dependent variables like generators reactive power, voltages at load buses and line flows etc [15].

Computational Steps of DE Algorithm:-

DE is utilized to find the best control variable setting starting from a randomly generated initial population. At the end of each generation, the best individuals, based on the fitness value, are stored. The computational steps of the DE algorithm are as follows [15]:

i. Generate an initial population randomly within the control variable bounds.

ii. For each individual in the population, run a load flow program such as NR method, to find the operating points.

iii. Evaluate the fitness of the individuals.

iv. Perform mutation and crossover operation

v. Select the individuals for the next generation

vi. Store the best individual of the current generation.

vii. Repeat steps *ii*–*v*, till the termination criterion is met.

viii. Select the control variable setting corresponding to the overall best individual.

ix. If the solution is acceptable, find out the best individual and its objective value. Otherwise, change the settings of DE and repeat the steps *i* – *viii*.

V. RESULTS AND DISCUSSION

To evaluate the effectiveness and efficiency of DE based reactive power optimization approach, the numerical experiments are made in the standard IEEE 14 bus and standard IEEE 57 bus system. The proposed approach has been tested on two cases, one is the standard IEEE 14-bus and other is the standard IEEE-57 bus system systems. Take in case (1) The system has four generators at buses 2, 3, 4 and 5; and three transformers with off nominal tap ratio and One-switchable VAR source. The lower voltage magnitude limits at all buses are 0.95 pu and the upper limits are 1.1 pu for generator buses and 1.05 pu for the remaining buses. The lower and upper limits of the transformer tapings are 0.9 and 1.1 pu, respectively and showing the single line figure (1) for IEEE-14 bus system.

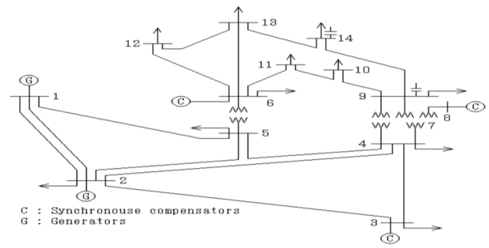

Figure (1) Single Line Diagram of IEEE 14 bus system

Results obtained by simulation of the algorithm using the differential evolution (DE) algorithm, done in MATLAB 7.8.0 (R2009a) environment are provided in this section. Simulation is carried out on IEEE-14 bus system and IEEE-57 bus test systems.

1. TABLE

SETTING OF THE CONTROL VARIABLE FOR P_{Loss} MINIMIZED

S.No	Control Variable	Setting			
		Min	**Max**	**Initial**	**DE**
1	V_2	0.95	1.10	1.0450	1.063
2	V_3	0.95	1.10	1.0100	1.083
3	V_4	0.95	1.10	1.0700	1.073
4	V_5	0.95	1.10	1.0900	1.055
5	T_{6-7}	0.90	1.10	0.9780	0.995
6	T_{6-8}	0.90	1.10	0.9690	1.038
7	T_{6-9}	0.90	1.10	0.9320	1.017
8	Q_9	0.00	0.05	0.1900	0.042
Power losses P_{Loss} (MW)				13.853	**12.45**
Voltage Deviation(VD)				1.1601	**0.149**

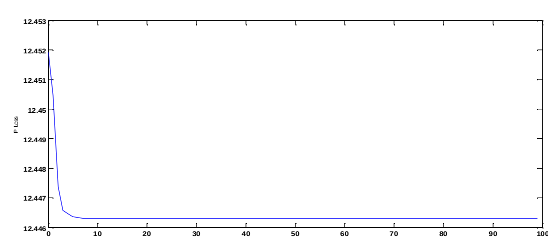

Figure (2) P_{Loss} & Number of iterations

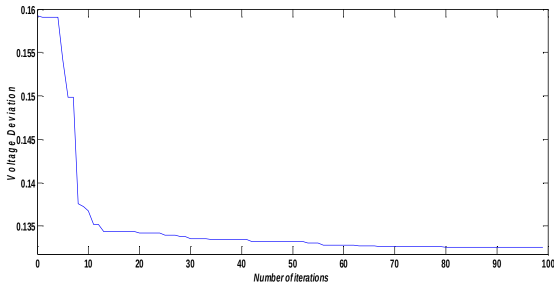

Figure (3) VD and Number of iteration

DE is applying in IEEE-14 bus system and result showing in the table (1) with graph. Figures are showing in power losses and number of iterations, Voltage Deviation (VD) and number of iteration.

Case (2) Study of IEEE-57 bus system

In this section performance of differential evolution algorithm for optimal reactive power dispatch was evaluated on IEEE 57- bus systems with simulation parameter in table (2) The system has seven generators at buses 1,2, 3, 6, 8, 9 and 12; and fifteen transformers with off nominal tap ratio & four-switchable VAR sources. The lower voltage magnitude limits at all buses are 0.95 pu and the upper limits are 1.1 pu for generator buses and 1.05 pu for the remaining buses. Figures are showing in power losses and number of iterations, Voltage Deviation (VD) and number of iteration.

2. TABLE

SETTING OF THE CONTROL VARIABLE FOR P_L AND VOLTAGE DEVIATION (VD) MINIMIZATION

S. No.	Control Variables	Setting			
		Min	**Max**	**Initial**	**Proposed DE**
1	V_1	0.95	1.10	1.0400	1.0814
2	V_2	0.95	1.10	1.0200	1.0605
3	V_3	0.95	1.10	1.0150	1.0227
4	V_6	0.95	1.10	1.0100	1.0413
5	V_8	0.95	1.10	1.0550	1.0132
6	V_9	0.95	1.10	1.0100	0.9980
7	V_{12}	0.95	1.10	1.0250	0.9970
8	T_{4-18}	0.90	1.10	0.9700	1.0333
9	T_{4-19}	0.90	1.10	0.9780	1.0930
10	T_{21-20}	0.90	1.10	0.9670	1.0947
11	T_{24-26}	0.90	1.10	0.9400	0.9736
12	T_{7-29}	0.90	1.10	0.9300	1.0955
13	T_{34-32}	0.90	1.10	0.9550	1.0930
14	T_{11-41}	0.90	1.10	0.9580	1.0228
15	T_{15-45}	0.90	1.10	0.8950	0.9712
16	T_{14-46}	0.90	1.10	0.9000	1.0126
17	T_{10-51}	0.90	1.10	0.9550	1.0126
18	T_{13-49}	0.90	1.10	1.0430	1.0873
19	T_{11-43}	0.90	1.10	1.0430	1.0939
20	T_{40-56}	0.90	1.10	0.9750	1.0688
21	T_{39-57}	0.90	1.10	0.9800	1.0483
22	T_{9-55}	0.90	1.10	0.9580	0.9536
23	Qsh_1	0.00	0.05	0.8500	0.0424
24	Qsh_{11}	0.00	0.05	0.9500	0.0467
25	Qsh_{18}	0.00	0.05	0.8000	0.0339
26	Qsh_{20}	0.00	0.05	0.8500	0.0378
Power Losses(MW)				29.439	**28.254**
Voltage Deviation				1.0670	**0.404**

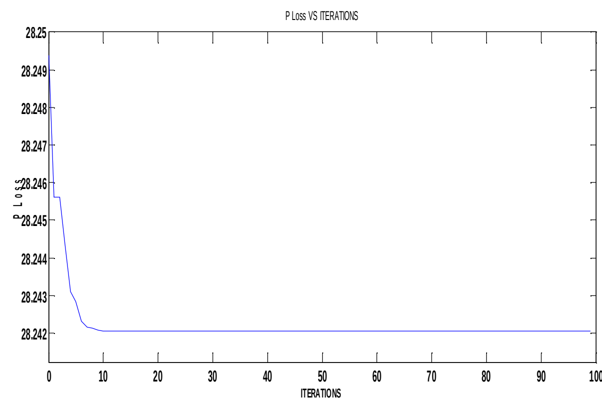

Figure (4) P_{Loss} & Number of iterations

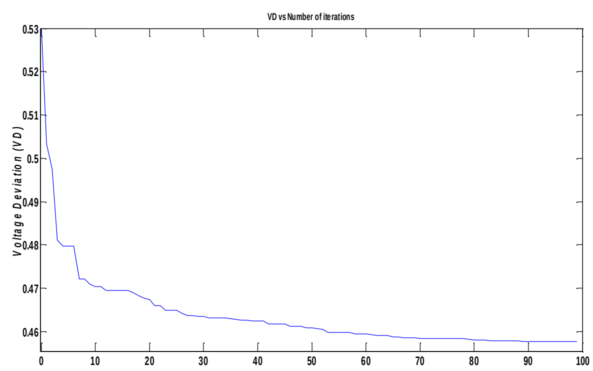

Figure (5) VD and Number of iteration

DE based result comparison in different methods as SGA and IGS. It has find better results to other method. Both of the simple genetic algorithm (SGA) and the improved genetic algorithm (IGA) will be tested on all the two systems [11]. In the reduction rate is reactive power loss to the initial power loss.

VI. CONCLUSION

In this paper, differential evolution based approach has been presented and applied to multi-objective reactive power problem with real power loss and bus voltage deviations as competing objectives. Reactive power optimization is a complex combinational optimization problem. The problem of multi-objective optimization has been solved by converting it into a single objective optimization problem. The results show that the proposed approach is efficient for solving multi-objective reactive power problem. In addition, the non-dominated solutions obtained are well distributed and have satisfactory diversity characteristics. Though the DE based approach has been implemented on IEEE 14-bus and IEEE-57 bus system, the same can be implemented for large size power systems as well. The obtained results are superior compared to previously reported work in the literature.

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