Optimal Power Flow Using Differential Evolution Algorithm With Conventional Weighted Sum Method

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Abstract
Optimal reactive power dispatch is one of most important task in the today's power system operation. This paper present optimal reactive power dispatch with the help of differential evolution algorithm. The optimal reactive power dispatch is a non linear constraints multi objective optimization problem where the real power loss, voltage deviation and fuel cost are to be minimized under control and dependent variables.. Reactive power optimization is a mixed integer nonlinear optimization problem which includes both continuous and discrete control variables. The suggested algorithm is used to find the setting of control variables, such as voltage, transformer tap position and reactive compensation devices to optimize a certain objective. A Differential Evolution Algorithm based approach is proposed to handle the problem as a true multi-objective optimization problem. The standard IEEE 30-bus test system is used and the results show the effectiveness of Differential Evolution Algorithm and confirm its potential to solve the multi-objective optimal reactive power dispatch problem. The results obtained by Differential Evolution Algorithm are compared and validated with conventional weighted sum method to show the effectiveness of the proposed algorithm.

Keywords: - Differential evolution algorithm, Power loss minimization, Voltage deviation, Multi-objective weighted sum method.

I. Introduction
Optimization concerns to the analyze of problems where an objective function is minimized or maximized by consistently choosing the values of real and/or integer variables from within an permitted set. Many real world and theoretical problems may be simulated in the general model of an optimization problem. Power
System is one of the composite fields in electrical engineering, where optimization plays an significant role [1].
Reactive power optimization [2] is one of the difficult optimization problems in power system operation and control. To ameliorate the voltage profile and to decrement the active power losses along the transmission lines beneath various operating conditions, power system operator can choose a number of control tools such as switching reactive power sources, charging generator voltages and adjusting transformer tap settings. Therefore, the trouble of the reactive power bump off can be optimized to ameliorate the voltage profile and minimize the system losses as well [3].
It is a non- linear optimization trouble and various numerical proficiencies have been assumed to solve this optimal reactive power dispatch trouble [5]. These include the gradient method [6-7], Newton method [8] and linear programming [9].The gradient and Newton methods endure from the difficulty in handling inequality constraints. To employ linear programming, the input output function is to be conveyed as a set of linear functions, which may lead to loss of accuracy. Recently, worldwide optimization proficiencies such as genetic algorithms have been suggested to figure out the reactive power optimization problem [10-11]. Genetic algorithm is a random search technique based on the mechanics of natural selection [12].In GA-based RPD problem it starts with the randomly generated population of points, ameliorates the fitness as generation continues through the application of the three operators-selection, crossover and mutation. But in the recent research some inadequacies are identified in the GA execution. This debasement in efficiency is apparent in applications with highly hypostasis objective functions i.e. where the parameters being optimized are highly correlated. In addition, the untimely convergence of GA degrades its performance and abbreviates its search capability. In addition to this, these algorithms are found to take more time to reach the optimal solution.
The reactive power planning is one of the most significant and ambitious problems because it has lots of objective functions like Voltage Deviation, Real power loss and installation cost of the reactive power sources is to be minimized at the same time [13]. The number of variables and parameters of the objective functions are optimized for figuring out the reactive power compensation problem. To solve the reactive power compensation troubles various numerical troubles are formulated.
When an optimization trouble calls for more than one objective function, the project of determining one or more optimum solutions is known as multi-objective optimization [2].
One major trouble consociated with suggesting a multiobjective problem as single objective trouble is that an optimal solution may be extremely contingent on how the weights are set [14-23]. This can be of great business in cases where weights are randomly assigned. To overcome this problem weighted sum methods are to be proposed.
In this paper, the Differential Evolution Algorithm (DE) combine with weighted sum method based approach is proposed for solving the multiobjective VAR dispatch optimization problem [15]. The problem is formulated as a nonlinear constrained multiobjective optimization problem where the real power loss and the bus voltage deviations are treated as contending objectives. A hierarchical bunching technique is carried out to allow for the power system operator with a representative and accomplishable Pareto optimal set. The strength and potential of the proposed approach to figure out the multiobjective VAR dispatch problem are presented.
The new approach introduced in this paper to solve the reactive power compensation problem is based on Differential Evolution Algorithm, proposed by Storn and Price in 1995, a variant of the Differential Evolution Algorithm (DE) that has

tested to be a very competitory algorithm solving several optimization problems [16-17].

II. Problem Formulation

A. Minimization Of System Power Losses

The RPD problem aims at minimizing the real power loss in a power system while satisfying the unit and system constraints. This goal is achieved by proper adjustment [18-19] of reactive power variables like generator voltage magnitudes (V_{Gi}), reactive power generation of capacitor banks (Q_{Ci}) and transformer tap settings (T_k).

This is mathematically stated as:

$$\text{Min } F_1 = P_{Loss} = \sum_{\substack{k\in N_l \\ k=(i,j)}} g_k \left(V_i^2 + V_j^2 - 2V_iV_j\,\mathrm{Cos}(\theta_i - \theta_j)\right) \quad (1)$$

The real power loss given by (1) is a non-linear function of bus voltages and phase angles which are a function of control variables.

B. Voltage Profile Improvement (Voltage Deviation)

Bus voltage is one of the most important security and service quality indices. Improving voltage profile can be obtained by minimizing the load bus voltage deviations from 1.0 per unit. The objective function can be expressed as:

$$\text{Min}F_2 = VD = |V_i - 1.0| \qquad (2)$$

C. Minimization Of Fuel Cost

The objective of the ELD is to minimize the total system cost by adjusting the power output of each of the generators connected to the grid. The total system cost is modeled as the sum of the cost function of each generator (1). The generator cost curves are modeled with smooth quadratic functions, given by:

$$\text{Min } F_3 = F_{cost} = \sum_{i=1}^{NG} a_i + b_i P_{Gi} + c_i P_{Gi}^2 \ \ (\$/h) \qquad (3)$$

Where NG is the number of online thermal units, P_{Gi} is the active power generation at unit i and a_i, b_i and c_i are the cost coefficients of the i^{th} generator.

Iii: System Constraints

The real power loss given by (1) is a non-linear function of bus voltages and phase angles which are a function of control variables. The minimization problem is subjected to the following equality and inequality constraints:

A. Equality Constraints (Load flow constraints)

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{N_B} V_j \left(G_{ij}\,\mathrm{Cos}(\theta_i - \theta_j) + B_{ij}\,\mathrm{Sin}(\theta_i - \theta_j)\right) = 0, \qquad (4)$$

$$i = 1,2 \ldots\ldots N_B$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{N_B} V_j \left(G_{ij}\,\mathrm{Sin}(\theta_i - \theta_j) - B_{ij}\,\mathrm{Cos}(\theta_i - \theta_j)\right) = 0, \qquad (5)$$

$$i = 1,2 \ldots\ldots N_{PQ}$$

B. Inequality constraints includes

- Voltage constraints:

$$V_i^{min} \le V_i \le V_i^{max} \quad ; \quad i \in N_B \qquad (6)$$

- Generator reactive power capability limit:

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max} \quad ; \quad i \in N_g \qquad (7)$$

- Reactive power generation limit of capacitor banks:

$$Q_{ci}^{min} \le Q_{ci} \le Q_{ci}^{max} \quad ; \quad i \in N_c \qquad (8)$$

- Transformer tap setting limit:

$$T_k^{min} \le T_k \le T_k^{max} \quad ; \quad i \in N_T \qquad (9)$$

- Transmission line flow limit

$$S_l \le S_l^{max} \quad ; \quad l \in N_l \qquad (10)$$

- Generation capacity constraint

$$P_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max} \quad ; \quad i \in N_B \qquad (11)$$

- Power balance constraint

The total power generation must cover the total demand P_D and the real power loss in transmission lines P_L. This relation can be expressed as:

$$\sum_{i=1}^{NB} P_{Gi} = P_D + P_L \qquad (12)$$

III. DIFFERENTIAL EVOLUTION ALGORITHM

In 1995, Storn and Price proposed a new floating point encoded evolutionary algorithm for global optimization and named it differential evolution (DE) algorithm owing to a special kind of differential operator, which they invoked to create new off-spring from parent chromosomes instead of classical crossover or mutation [20]. DE algorithm is a population based algorithm 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 [20]. DE works through a simple cycle of stages, presented in Fig. 1.

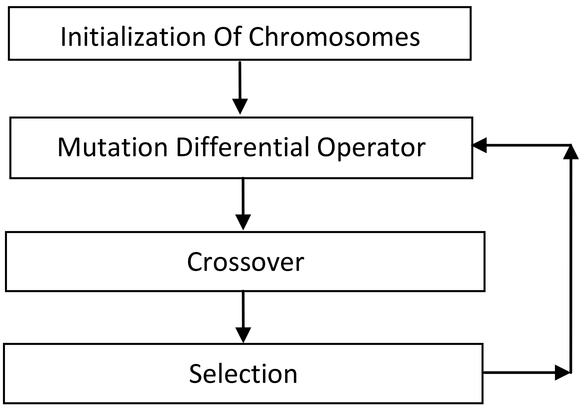

Fig-1 DE Process cycle

These stages can be cleared as follow:

A. Initialization

At the very beginning of a DE run, problem independent variables are initialized in their feasible numerical range. Therefore, if the j^{th} variable of the given problem has its lower and upper bound as x_i^L and x_i^U, respectively, then the jth component of the i^{th} population members may be initialized as:

$$x_{i,j}(0) = x_j^L + \text{rand}(0,1).(x_j^u - x_j^L) \qquad (13)$$

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

B. Mutation

In each generation to change each population member , a donor vector is created. It is the method of creating this donor vector, which demarcates between the various DE schemes. However, in this paper, one such specific mutation strategy known as DE/rand/1 is discussed. To create a donor vector for each i^{th} member, three parameter vectors and are chosen randomly from the current population and not coinciding with the current xi. 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 is obtained. The usual choice for F is a number between 0.4 and 1.0. So, the process for the jth component of each vector can be expressed as:

$$v_{i,j}(t+1) = x_{r1,j}(t) + F.\left(x_{r2,j}(t) - x_{r3,j}(t)\right) \qquad (14)$$

C. Crossover

To increase the diversity of the population, crossover operator is carried out in which the donor vector exchanges its components with those of the current member $\overrightarrow{X_i(t)}$, Two types of crossover schemes can be used with DE technique. These are exponential crossover and binomial crossover. Although the exponential crossover was proposed in the original work of Storn and Price [20], the binomial variant was much more used in recent applications [21]. In this paper, binomial crossover scheme is used which is performed on all D variables and can be expressed as:

$$u_{i,j}(t) = \begin{cases} v_{i,j}(t) & \text{if} \quad \text{rand}(0,1) < CR \\ x_{i,j}(t) & \text{else} \end{cases} \qquad (15)$$

Where $u_{i,j}(t)$ represents the child that will compete with the parent xi,j(t).

D. 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:

$$\vec{X_i}(t+1) = \begin{cases} \vec{U_i}(t) \text{ if } f\left(\vec{U_i}(t)\right) \le f(\vec{X_i}(t)) \\ \vec{X_i}(t) \text{ if } f\left(\vec{X_i}(t)\right) < f(\vec{U}(t)) \end{cases} \qquad (16)$$

Where f ( ) is the function to be minimized. So, if the child yields a better value of the fitness function, it replaces its parent in the next generation; otherwise, the parent is retained in the population. Hence the population either gets better in terms of the fitness function or remains constant but never deteriorates

Flow chart for steps follows for calculation in Differential Evolution Algorithm

IV. RESULTS AND DISCUSSION

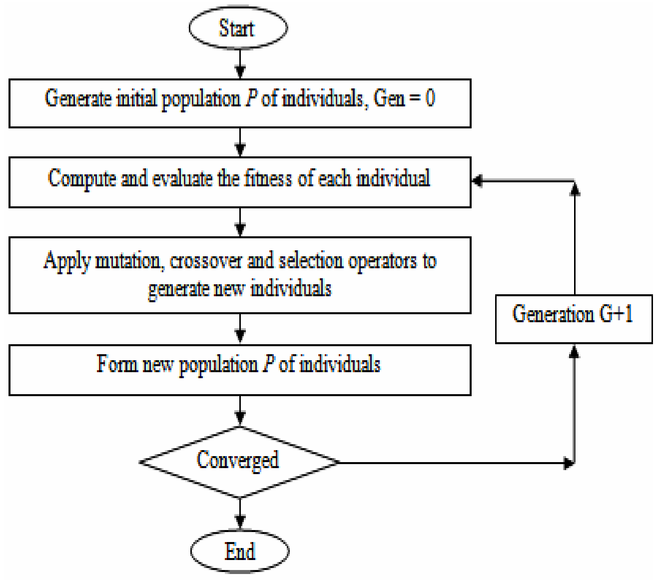

Fig: - 2 Flow Chart Of Algorithm

All the coding for the proposed algorithm using DE was done in MATLAB 7.8.0.347 (2009A) running on Pentium(R) Dual-Core CPU E5200, 2.50GHz, 1.00 GB. Simulation is carried out on IEEE 30 bus test system. In order to compare the results obtained from DE, the optimization problem is also solved using a conventional technique. The all data is and initial value is taken from [22]

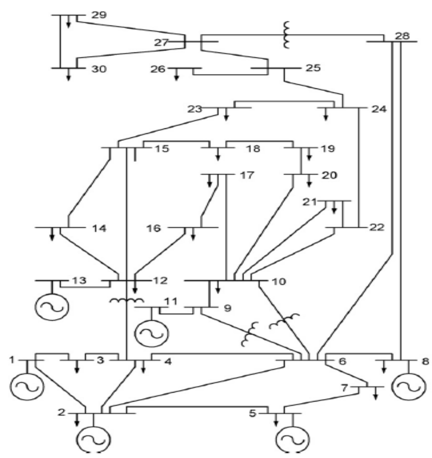

Fig:- 3 One Line Diagram Of Ieee-30 Bus System

Table 1:- Parameter used in calculation

No. Of Population	06
No. Of Iteration	200
Crossover	0.8
Mutation	0.8

Table 2:- Optimal result when objective function taken as multi-objective. See Fig: - 4

P_{loss} vs VD	
W_1= **0.8184**	
P_{loss}	VD
5.3378	**0.2483**

Table 3:- Best results of individually run of Ploss and Voltage Deviation as main function

	Min	Max	Initial	Ploss	VD
V_1	0.95	1.1	1.04	1.10	1.00
V_2	0.95	1.1	1.01	1.09	1.02
V_5	0.95	1.1	1.01	1.07	1.01
V_8	0.95	1.1	1.05	1.08	1.01
V_{11}	0.95	1.1	1.05	1.04	1.09
V_{13}	0.95	1.1	1.07	1.10	1.06
T_{11}	0.9	1.1	1.06	1.03	0.98
T_{12}	0.9	1.1	1.03	0.95	0.95
T_{15}	0.9	1.1	1.06	1.06	1.03
T_{36}	0.9	1.1	0.0	1.00	1.00
Q_{C10}	0.0	5.0	0.0	5.0	2.67
Q_{C12}	0.0	5.0	0.0	5.0	5.00
Q_{C15}	0.0	5.0	0.0	5.0	5.00
Q_{C17}	0.0	5.0	0.0	1.10	1.38
Q_{C20}	0.0	5.0	0.0	2.30	3.38
Q_{C21}	0.0	5.0	0.0	1.41	5.00
Q_{C24}	0.0	5.0	0.0	4.45	4.22
Q_{C29}	0.0	5.0	0.0	2.49	5.00
P loss (MW)			**5.85**	**4.76**	6.40
V D			**1.16**	1.01	**0.19**
@=See Fig :- **5** $= See Fig :- **6**				@	$

To demonstrate the effectiveness of the proposed algorithm, these different cases have been considered as follows:

Case 1:- Minimization of power loss and voltage deviation using weighted sum method considered as multi-objective.

Case 2:- Individual minimization of system power loss and voltage deviation

Case 1:- Minimization of power loss and voltage deviation using weighted sum method considered as multi-objective

The problem was handled as a multi objective optimization problem where both power loss and voltage deviations were optimized simultaneously with the proposed approach. For completeness and comparison purposes, the problem was also treated as a single objective optimization problem by linear combination of PL and VD is considered:-

$$Minimize\ f = W_1 * f1 + (1 - W_1) * f2 \qquad (17)$$

W_1 is a weighting factor. To generate 41 nondominated solutions, the algorithm was applied 41 times with varying W1 as a random number W_1= rand [0, 1]. The best P_{loss} and best VD solutions are given in Table 2.

Case2:- Individual minimization of system power loss and voltage deviation

At first, the P_{loss} and VD objectives are optimized individually in this case we can take power loss and voltage deviation as a main function simultaneously. The best results of P_{loss} and VD functions when optimized individually are given in Table 3. Table 2:- Optimal result when objective function taken as multi-objective. See Fig: - 4

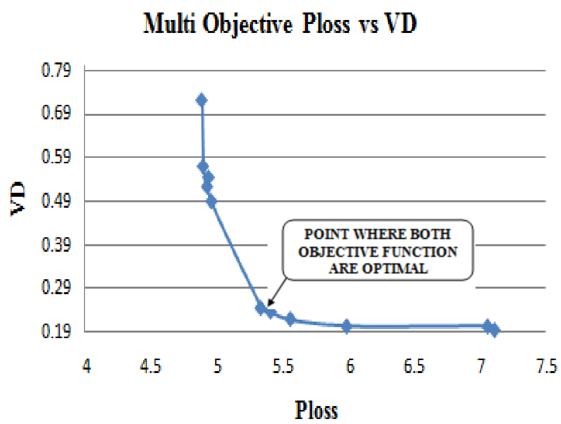

Fig 4 Pareto optimal graph between VD

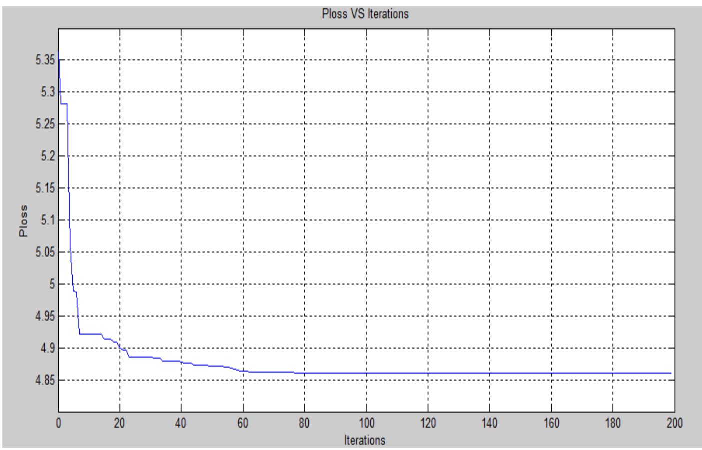

Fig 5 Graph between Ploss and No. of iterations

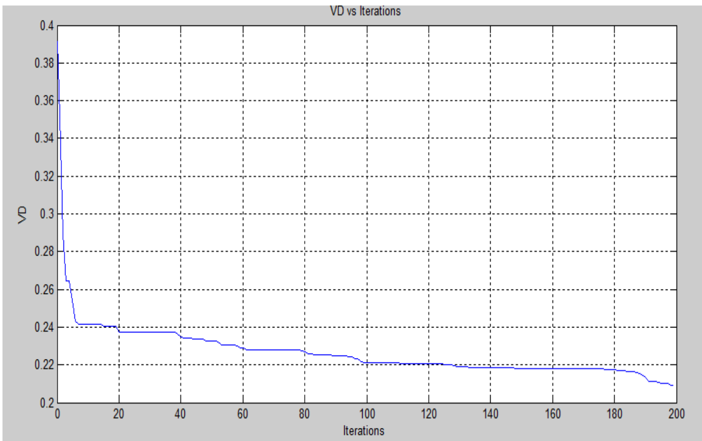

Fig 6 Graph between VD and No. of iterations

Conclusion

In this paper differential evolution algorithm has been proposed and successfully applied to solve the optimal power flow problem for multiobjective. For solving the optimal power flow problem we can consider two objective functions these are Ploss and voltage deviation. Result shows that differential evolution based optimal power flow algorithm is adequate to minimize the P_{loss} and VD in the system. The proposed approach has been tested on standard IEEE-30 bus system. The Pareto graph proves the effectiveness of this proposed algorithm.

Acknowledgement

The authors are thankful to Director, HOD (Electrical Department) Madhav Institute of Technology and Science, Gwalior (M.P.) India for providing support and facilities to carry out this research work

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