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MULTI-OBJECTIVE OPTIMAL REACTIVE POWER DISPATCH USING DIFFERENTIAL EVOLUTION

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Abstract:

Reactive power optimization is a major concern in the operation and control of power systems. In this paper a new multi-objective differential evolution method is employed to optimize the reactive power dispatch problem. It is the mixed–integer non linear optimization problem with continuous and discrete control variables such as generator terminal voltages, tap position of transformers and reactive power sources. The optimal VAR dispatch problem is developed as a nonlinear constrained multi objective optimization problem where the real power loss and fuel cost are to be minimized at the same time. A conventional weighted sum method is inflicted to provide the decision maker with a example and accomplishable Pareto-optimal set. This method underlines non-dominated solutions and at the same time asserts diversity in the non-dominated solutions. Thus this technique treats the problem as a true multi-objective optimization problem. The performance of the suggested differential evolution approach has been tested on the standard test system IEEE 30-bus.

Keywords: Reactive Power Management; Differential Evolution Algorithm; Power Loss Minimization; Voltage Deviation, Pareto-Optimal Solutions.

1. Introduction

Optimal reactive power expedition problem is one of the difficult optimization worries in power systems. The origins of the reactive power are the generators, synchronous condensers, capacitors, static compensators and tap changing transformers. The problem that has to be figured out in a reactive power optimization is to find out the optimal values of generator bus voltage magnitudes, transformer tap setting and the output of reactive power origins so as to minimize the transmission loss. In recent years, the problem of voltage stability and voltage collapse has become a major worry in power system designing and procedure.

It is a non- linear optimization problem and several mathematical techniques have been followed to solve this optimal reactive power dispatch problem. These admit the gradient method [1-2], Newton method [3] and linear programming [4]. The gradient and Newton methods suffer from the difficulty in dealing inequality constraints. Recently, global optimization techniques such as

genetic algorithms have been proposed to solve the reactive power optimization problem [5]. Genetic algorithm is a random search technique based on the mechanics of natural selection. But in the recent research some insufficiencies are distinguished in the GA performance. This abasement in efficiency is apparent in applications with highly hypostasis objective functions i.e. where the parameters being optimized are extremely correlated. In addition, the untimely convergence of GA degrades its performance and reduces its search capability. In addition to this, these algorithms are found to take more time to reach the optimal result.

More recently, a new evolutionary computation technique, called differential evolution (DE) algorithm, has been proposed and introduced [6-7]. The algorithm is motivated by biological and sociological motivations and can take care of optimality on bumpy, discontinuous and multi modal surfaces. The DE has three main advantages: it can find near optimal solution apart from the initial parameter values, its convergence is fast and it uses not many number of control parameters. In addition, DE is simple in coding, effortless to use and it can handle integer and discrete optimization. The performance of the DE algorithm was equated by the different heuristic techniques. It is determined from that compression, the DE is considerably better than that of other process. Also it is determined that DE is robust; it is able to replicate the same results consistently over many trials. In addition, DE algorithm has been used to solve high dimensional function optimization [8]. It is found that, it has better functioning on a set of generally used bench mark function. Therefore, the DE algorithm seems to be a predicting advance for engineering optimization problem [9].

The traditional approach is to formulate this problem as a single objective optimization problem with constraints. In this approach, the objective may consist of a single term or it may consist of multiple terms [10].The multi objective VAR dispatch problem was converted to a single objective problem by linear compounding of different objectives as a weighted sum [11]. Contrariwise, the studies on evolutionary algorithms, over the past few years, have shown that these methods can be expeditiously used to wipe out most of the difficulties of classical methods [12-13]. Since they use a population of solutions in their search, multiple Pareto-optimal solutions can, in principle, be found in one single run. The multi objective evolutionary algorithms have been carried out to environmental/economic power bump off problem with telling achiever.

The goal of this paper is to develop the RPD problem as a multi-objective optimization and exemplify its solution using Pareto based multi-objective optimization Differential evolution. Two different multi-objective problem formulations are provided.

In this paper, Differential Evolution based approach has been proposed for solving the multi-objective RPM problem. The problem has been developed as a non-linear constrained multi-objective optimization problem, where the real power loss, bus voltage deviations (VDs) and Fuel cost are to be optimized simultaneously. The two objectives are convinced to a single objective problem by linear combination of different objectives as a weighted sum. DE algorithm has been employed to obtain Pareto-optimal. The strength of the proposed approach to solve multi-objective VAR management problem has been established on the standard IEEE-30 bus system [14].

2. Problem Formulation

The optimal VAR management problem is to optimize the steady state performance of a power system in terms of one or more objective functions while satisfying several equality and inequality constraints. Generally the problem can be formulated as follows.

2.1. Objective Functions

Real power loss (PL)
This objective is to minimize the real power loss in transmission lines of the power system and is expressed as

$$f_1 = Ploss = \sum_{k=1}^{nl} g_k [V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_i - \delta_j)] \tag{1}$$

where nl is the number of transmission lines; g_k is the conductance of the kth line; $V_i \angle \delta_i$ and $V_j \angle \delta_j$ are the voltages at the end buses i and j of the kth line, respectively.

Fuel Cost Minimization
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:

$$f_2 = F_{cost} = \sum_{i=1}^{NG} a_i + b_i P_{Gi} + c_i P_{Gi}^2 \ (\$/h) \tag{2}$$

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 ith generator

2.2. Problem Constraints

Equality Constraints
The equality constraints represent typical load flow equations as follows

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

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j |G_{ij} \sin(\partial_i - \partial_j) + B_{ij} \cos(\partial_i - \partial_j)| = 0 \tag{4}$$

for $\qquad i = 1,.........NB$

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

Inequality Constraints
The inequality constraints represent the system operating constraints as follows.

Generation Constraints: Generator voltages V_G and reactive power outputs Q_G are restricted by their lower and upper limits as follows:

$$V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max}, \quad i = 1,2,........, NG.$$
(5)

$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max}, i = 1.......NG$$
(6)

where *NG* is the number of generators.

Transformer constraints: Transformer tap T settings are bounded as follows:

$$T_i^{\min} \le T_i \le T_i^{\max}, i = 1........NT$$
(7)

where *NT* is the number of transformers.

Switchable VAR sources constraints: Switchable VAR compensations Q_C are restricted by their limits as follows

$$Q_{ci}^{\min} \le Q_{ci} \le Q_{ci}^{\max}, i = 1.....NC$$
(8)

where *NC* is the number of switchable VAR sources.

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

$$V_{Li}^{\min} \le V_{Li} \le V_{Li}^{\max}, i = 1...NL.$$
(9)

$$S_{li} \le S_{li}^{\max}, i = 1.......nl$$
(10)

Aggregating the objectives and constraints, the problem can be mathematically formulated as a nonlinear constrained multi-objective optimization problem as follows.

Minimize [$P_L(x,u)$, $VD(x,u)$]
(11)

Subject to;

$g(x,u) = 0$
(12)

$$h(x,u) = 0 \tag{13}$$

where x is the vector of dependent variables consisting of load bus voltages V_L, generator reactive power outputs Q_G, and transmission line loadings S_L. Hence, x can be expressed as

$$x^T = [V_{L1}.... V_{NL}, Q_{G1}....Q_{GNG}, S_{l1}....S_{lnl}] \tag{14}$$

u is the vector of control variables consisting of generator voltages V_G transformer tap settings T, and shunt VAR compensations Qc. Hence, u can be expressed as

$$u^T = [V_{G1}.... V_{GNG}, T_1....T_{NT}, Q_{C1}....Q_{CNC}] \tag{15}$$

Differential Evolution algorithm has been applied for this multi-objective reactive power management problem. This RPM problem is a combinatorial optimization problem with multi-extremism and non-linear property. To overcome the difficulties, the optimization variables, namely generator voltages and transformer tap-settings are considered as continuous values in this paper.

3. Multi-Objective Optimization

In many practical problems, several optimization criteria need to be satisfied simultaneously [15]. Moreover, it is often not advisable to combine them into a single objective. While it may sometimes happen that a single solution optimizes all of the criteria, the more likely scenario is when one solution is optimal with respect to a single criterion while other solutions are best with respect to the other criteria. The increase of the "goodness" of the solution with respect to one objective will produce a decrease of its "goodness" with respect to the others. While there are no problems in understanding the notion of optimality in single objective problems, multi objective optimization requires the concept of *Pareto-optimality*.
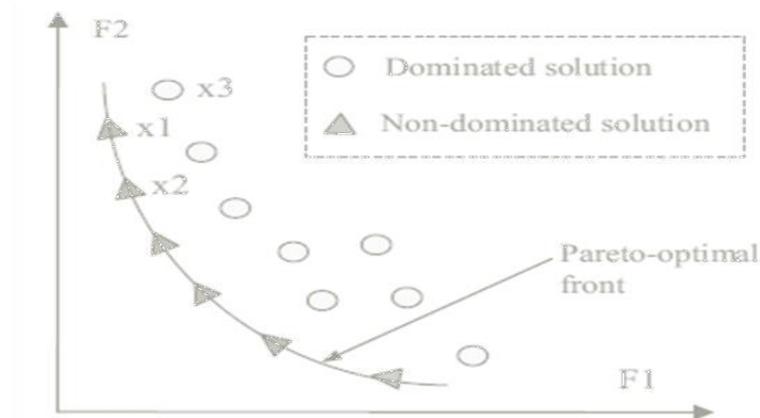

Figure 1: Pareto-optimality, non dominated and dominated solutions

A general multi-objective optimization problem consists of a number of objectives to be optimized simultaneously and is associated with a number of equality and inequality constraints. It can be formulated as follows:

Minimize F $=[f_1, f_2]$ (16)

Subject to the constraints (3) – (10)

For a multi-objective optimization problem, any two solutions x_1 and x_2 can have one of two possibilities - one covers or dominates the other or none dominates the other. In a minimization problem, without loss of generality, a solution x_1 dominates x_2 if the following two conditions are satisfied

$$\forall\, i \in \{1,2\} : f_i(x_1) \leq f_i(x_2)$$ (17)

$$\exists\, j \in \{1,2\} : f_j(x_1) < f_j(x_2)$$ (18)

If any of the above conditions is violated, the solution x_1 does not dominate the solution x_2. If x_1 dominates the solution x_2, x_1 is called the non-dominated solution. The solutions that are non-dominated within the entire search space are denoted as Pareto-optimal and constitute the Pareto-optimal set or Pareto-optimal front. The Pareto-optimal front depicts the optimal tradeoffs that exist between the competing objectives. There are different approaches to solve multi-objective optimization problems like aggregating, population based non-Pareto, and Pareto based techniques. In aggregating technique, the different objectives are generally combined into one using weighing or goal-based method.

The present paper implements aggregating technique for solving the multi-objective RPM problem. The RPM problem has been treated as a single objective optimization problem by linear combination of P_L and V_D objectives as follows:

Minimize $w \times P_L + (1-w) \times fuel\ cost$ (19)

Where *w* is a weighing factor. For example to generate 20 non-dominated solutions, the algorithm has been applied 20 times with varying weighing factor *w* which is a random number *rand* [0,1], a uniformly distributed random number between 0 and 1.

4. Differential Evolution Algorithm

DE algorithm is a population based algorithm that employs crossover, mutation (differential) and selection operators [2]. In DE, all solutions have the same probability of being selected as parents. DE employs a greedy selection process that is the best new solution and its parent win the competition providing significant advantage of converging performance over genetic algorithms. Differential evolution algorithm works through a simple cycle of the stages shown in Figure 1. The various stages of DE are as follows;
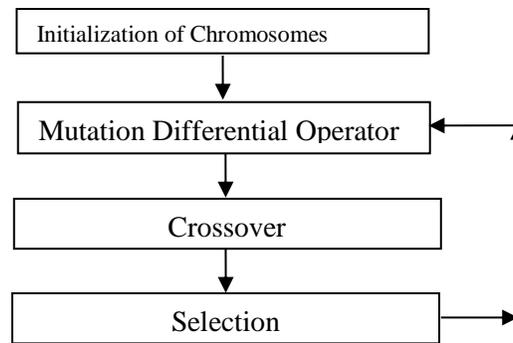
Initialization of Chromosomes

↓

Mutation Differential Operator

↓

Crossover

↓

Selection

Figure 2: DE Process

Initialization

At the beginning of DE algorithm implementation, i.e. at $t = 0$, the problem independent variables are initialized somewhere in their feasible numerical range. Therefore, if the ith variable has its lower and upper bounds as x_i^l and x_i^u, respectively, then
the jth component of the ith population member may be initialized as:

$$x_{ij}(0) = x_j^l + rand(0,1) \times (x_j^u - x_j^l) \tag{20}$$

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

Mutation

In each generation, a donor vector $v_i(t)$ is created in order to change the population member vector $x_i(t)$. Generally, the method of creating this donor vector is different in various DE schemes. However, in this paper, DE/rand/1 mutation strategy is implemented. In this mutation strategy, creation of the donor vector $v_i(t)$ for the ith member x_i, three parameter vectors x_{r1}, x_{r2} and x_{r3}, are selected randomly from the current population and not coinciding with the current member x_i.

Next, a scalar number F scales the difference between any two of the three vectors and this scaled difference is added to the third one. Thus, the donor vector $v_i(t)$ is obtained. The jth component of each vector can be expressed as:

$$v_{i,j}(t+1) = x_{r1,j}(t) + F(x_{r2,j}(t) - x_{r3,j}(t) \tag{21}$$

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 $x_i(t)$. Two types of crossover schemes can be used by DE algorithm. These are exponential crossover and binomial crossover. Although the exponential crossover was presented in the original work of Storn and Price [3], the binomial variant is much more used in recent applications [7]. On the other hand, for the same value of CR, the exponential variant needs a larger value for the scaling parameter F in order to avoid premature convergence [1]. In this paper, binomial crossover scheme is used which is performed on all the D variables and can be expressed as:

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

$$(22)$$

Selection

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

$$\vec{X}_i(t+1) = \begin{cases} \vec{U}_i(t) & if \quad f\left(\vec{U}_i(t)\right) \le f\left(\vec{X}_i(t)\right) \\ \vec{X}_i(t) & if \quad f\left(\vec{X}_i(t)\right) < f\left(\vec{U}_i(t)\right) \end{cases}$$

$$(23)$$

Where $f(.)$ is the function to be minimized. So, if the child $\vec{U}_i(t)$ yields a better value of the fitness function, it replaces its parent in the next generation; otherwise, the parent $\vec{X}_i(t)$ is retained in the population. Thus, the population either gets better in terms of the fitness function or remains fixed but never degenerates. Hence, the population either gets better in terms of the fitness function or remains constant but never deteriorates.

5. Flow Chart and Steps Followed in DE Algorithm

Computational Steps of DE Algorithm

DE is utilized to find the best control variable setting starting from randomly generated initial population. At the end of each generation, the best individuals, based on the fitness value, are stored [8]. The detail of the proposed DE algorithm is as follows:

1) Generate an initial population randomly within the control variable bounds.
2) For each individual in the population, run load flow program such as NR method, to find the operating points.
3) Evaluate the fitness of the individuals.
4) Perform mutation and crossover operation
5) Select the individuals for the next generation
6) Store the best individual of the current generation.
7) Repeat steps *ii–v,* till the termination criterion is met.
8) Select the control variable setting corresponding to the overall best individual.

If the solution is acceptable, output the best individual and its objective value. Otherwise, take the settings corresponding to the next best individual and repeat the Step viii.

6. Results and Discussion

The proposed approach has been tested on the standard IEEE 30-bus system [21] in order to investigate its effectiveness. The system has six generators at buses 1, 2, 5, 8, 11, and 13 and four transformers with off-nominal tap ratio in lines 6–9, 6–10, 4–12, and 27–28. 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. Subsequently, the problem was handled as a multi-objective optimization problem where both power loss P_L and Fuel cost were optimized simultaneously by converting it into a single objective optimization problem by linear combination of P_L and Fuel cost objectives using (19). The DE algorithm was applied 41 times with varying weighing factor w generated randomly in the range of 0 to 1. The non-dominated solutions were selected by removing the inferior solutions from the total set of solution. Thus the Pareto-optimal set obtained has 12 non-dominated solutions and is shown in Fig. 3. Out of them, two non-dominated solutions that represent the best PL and best Fuel cost are given in Table 1. In this paper, the following values of DE key parameters are selected for the simultaneous optimization of the real power loss (P_L) and Fuel cost.
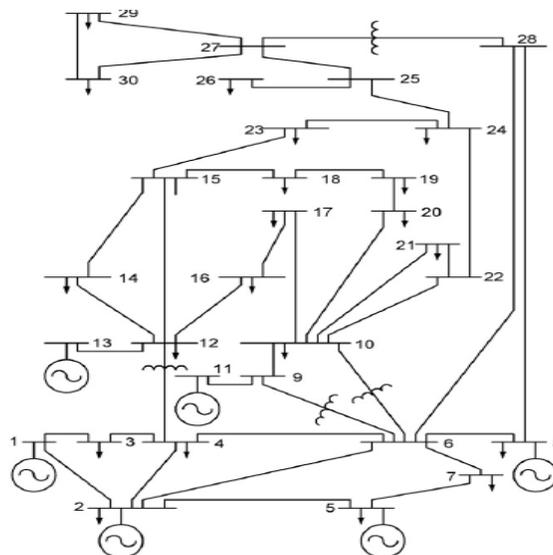
$F = 0.2$, CR $= 0.8$, NP $= 15$, GEN $= 1000$

Figure 3: Single line diagram of IEEE-30 bus system

Case1: Minimization of system power losses.

In this first case we run the algorithm for the minimization of power loss as a main objective function. The real power setting of the generator is taken from [12]. Table 1 shows the best result of Ploss function minimization.

Table1: Best result and control variable settings of Ploss

S. No.	Control Variables	Initial Value	Value After DE
1	V1	1.10000	1.1000
2	V2	1.09437	1.0979
3	V5	1.07457	1.0786
4	V8	1.07610	1.0800
5	V11	1.10000	1.1000
6	V13	1.10000	1.0969

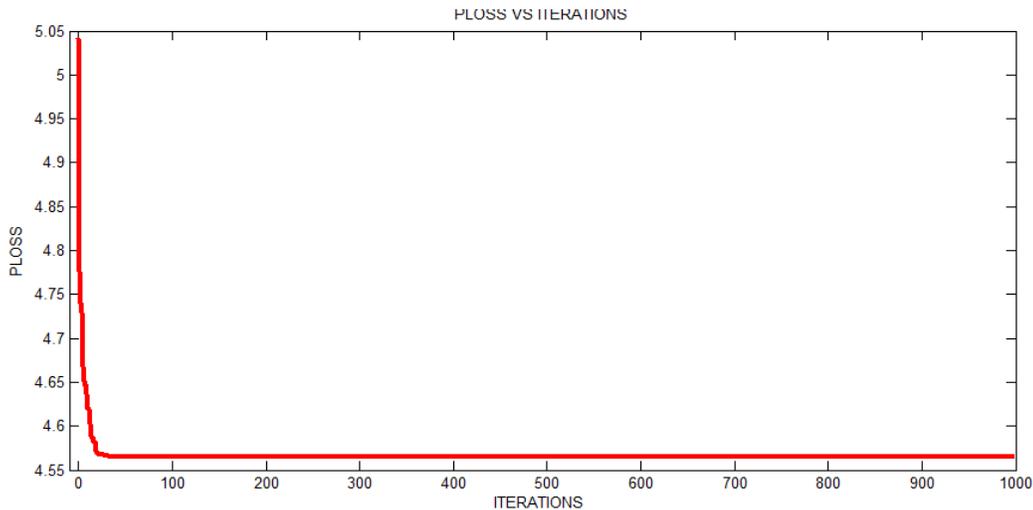| 7 | T11 | 1.06718 | 1.1000 |
8	T12	0.9000	0.9500
9	T15	1.04797	1.0924
10	T36	0.98354	1.000
Ploss (MW)		5.84230	**4.5653**
Fuel Cost			613.0778

Figure 5: Graph between Fcost and No. of Iteration

Case 2: Minimization of system Fuel cost.

In this second case we run the algorithm for the minimization of fuel cost as a main objective function. The real power setting of the generator is taken from [12]. Table 2 shows the best result of fuel cost function minimization.

Table 2: Best result and control variable settings of Fuel cost

S. No.	Control Variables	Initial Value	Value After DE
1	V1	1.10000	1.0770
2	V2	1.09437	1.0800
3	V5	1.07457	1.0492
4	V8	1.07610	1.0067
5	V11	1.10000	0.9796
6	V13	1.10000	0.9800
7	T11	1.06718	0.9700
8	T12	0.9000	0.9500
9	T15	1.04797	1.0600
10	T36	0.98354	1.1000
Ploss (MW)		5.8423	6.2182
Fuel Cost			**612.584**
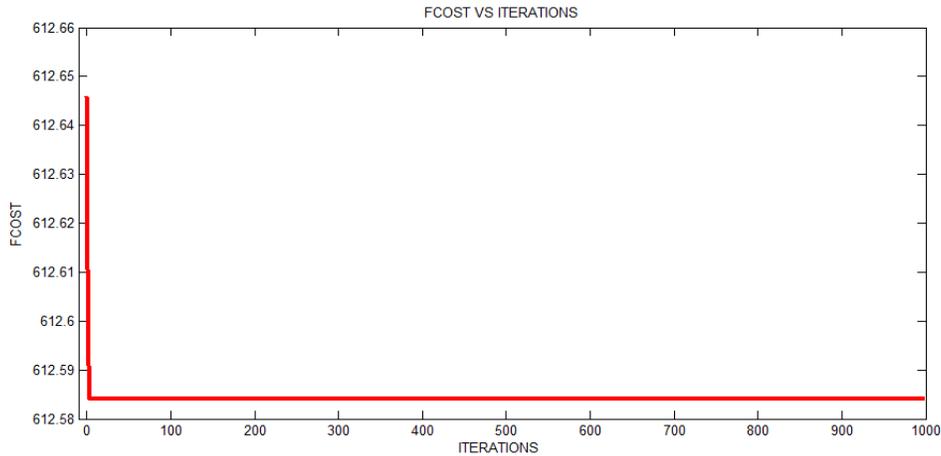
Table 3: Control variables for P_L and Fuel cost Minimization

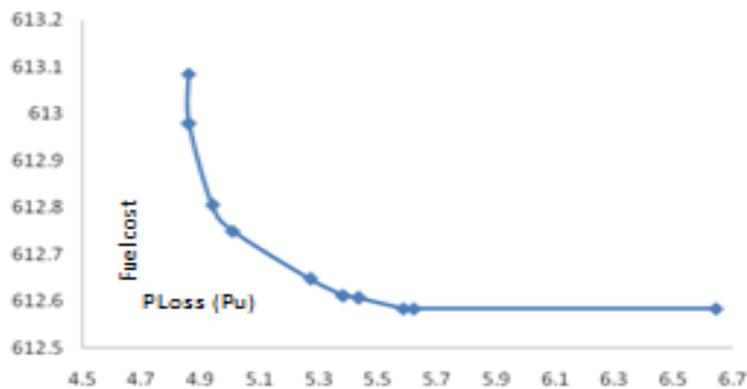| S. No.	Control Variable	Setting	
		Best PL	*Best Fuel cost*
1	V1	1.1000	1.1000
2	V2	1.0894	1.0922
3	V5	1.0705	1.0701
4	V8	1.0700	1.0700
5	V11	1.1000	1.1000
6	V13	1.1000	1.1000
7	T11	0.9702	0.9698
8	T12	0.9500	0.9500
9	T15	1.0021	1.0010
10	T36	0.9533	0.9500
Power Loss (MW)		**4.9380**	4.9352
Fuel Cost		612.8096	**612.47**

Figure 5: Pareto optimal graph between Ploss Fuel cost

7. Conclusion

In this paper differential evolution algorithm has been proposed and successfully applied to solve the optimal power flow problem. In this paper for solving the optimal power flow problem we can consider two objective functions these are Ploss and fuel cost these two objectives considered as single as well as multi objective to shows the effectiveness of the proposed algorithm. The proposed approach has been tested on standard IEEE-30 bus system; the same can be implemented for large size power systems as well.

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