An Efficient Differential Evolutionary approach to Optimal Reactive Power Dispatch with Voltage Profile Improvement

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Abstract - *In any power system faults occur due to unexpected outages of lines or transformers or other disturbances which are referred to as contingencies may cause voltage instability in the power system. Reactive power plays a very important role in the power system. In a power system when reactive power absorbed is greater than reactive power generated, the system voltage falls from its normal operating value and system voltage rises from its normal operating range when reactive power generated is greater than reactive power absorbed. Therefore optimization of reactive power dispatch and maintaining voltage at the load buses are two important tasks to be performed in a power system. This paper proposes an efficient differential evolutionary algorithm (DEA) to solve the optimal reactive power dispatch (ORPD) problems. The main objective of optimal reactive power dispatch is to minimize the real power loss with the optimal setting of the control variables. The continuous control variables are-generator bus voltage magnitudes and the discrete control variables are-transformer tap settings. The proposed approach employs differential evolution algorithm for optimal setting of reactive power dispatch control variables. The differential evolution solution has been tested on two standard IEEE systems. i.e. 14 and 30 bus test systems to minimize the total active power loss and to improve the voltage profile.*

Key Words: Active Power loss, Differential Evolution Algorithm, Reactive power, Voltage Profile, etc...

1. Introduction:

The purpose of the reactive power dispatch (RPD) in power system is to identify the control variables which minimize the given objective function while satisfying the unit and system constraints. This goal is achieved by proper adjustment of reactive power variables like generator voltage magnitudes and transformer tap setting. 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. To solve the RPD problem, a number of conventional optimization techniques [1, 2] 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 solving the reactive power dispatch problem, 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 RPD problem, majority of the techniques converge to a local optimum. Recently, Evolutionary Computation techniques like Genetic Algorithm (GA) [3], Evolutionary Programming (EP) [4] and Evolutionary Strategy [5] have been applied to solve the optimal dispatch problem. In this paper, a new evolutionary computation technique, called Efficient Differential Evolution (DE) algorithm is used to solve RPD problem. The DE [6] has three main advantages: it can find near optimal solution regardless the initial parameter values, its convergence is fast and it uses few number of control parameters. In addition, DE is simple in coding and easy to use. It can handle integer and discrete optimization. The performance of DE algorithm was compared to that of different heuristic techniques. It is found that, the convergence speed of DE is significantly better than that of GAs [7].

This paper is organized as follows: the problems of optimal reactive power dispatch and voltage profile improvement are formulated in section 2. Section 3 gives an overview of differential evolution algorithm. Application of differential evolution algorithm in ORPD, simulation results and comparison with other approaches are given in section 4. Finally conclusion is presented in section 5.

2. Problem Formulation:

The objective of RPD is to identify the reactive power control variables, which minimizes the objective functions stated as follows:

2.1 Minimization of system power losses:

The minimization of system real power losses *Ploss* (MW) can be calculated as follows:

$$f_1 = Ploss = \sum_{k=1}^{nl} g_k [V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_i - \delta_j)] \qquad 2.1$$

where nl is the number of transmission lines; g_k is the conductance of the kth line; V_i and V_j are the voltage magnitude at the end buses i and j of the kth line, respectively, and δ_i and δ_j are the voltage phase angle at the end buses i and j.

2.2 Voltage profile improvement:

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:

$$f_2 = \sum_{i \in NL} |V_i - 1.0| \qquad 2.2$$

Where NL is the number of load buses.

2.3. System Constraints:

2.3.1. Equality constraints:

These constraints represent load flow equations:

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)] = 0 \qquad 2.3$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{NB} V_j [G_{ij} \sin(\delta_i - \delta_j) - B_{ij} \cos(\delta_i - \delta_j)] = 0 \qquad 2.4$$

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.

2.3.2. Inequality Constraints:

These constraints include:

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

$$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max}, \quad i = 1, ..., NG$$

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max}, \quad i = 1, ..., NG$$

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

$$T_i^{min} \leq T_i \leq T_i^{max}, \quad i = 1, ..., NT$$

Security constraints:

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

$$V_{Li}^{min} \leq V_{Li} \leq V_{Li}^{max}, \quad i = 1, ..., NL$$

$$S_{li} \leq S_{li}^{max}, \quad i = 1, ..., nl$$

By adding the inequality constraints to the objective function, the augmented fitness function to be minimized becomes:

$$F_T = F + \lambda_v \sum_{i=1}^{NL} (V_i - V_i^{lim})^2 + \lambda_p \sum_{i=1}^{nbr} (S_{li} - S_{li}^{max})^2 + \sum_{i \in T} \lambda_t (t_{ik} - t_{ik}^{lim})^2 \qquad 2.5$$

Where λ_v, λ_p and λ_t are the penalty factors, these penalty factors are large positive constants. NL is the number of load buses (PQ buses) and nbr is the total number of transmission lines.

$$V_i^{lim} = \begin{cases} V_i^{min} & \text{if } V_i < V_i^{min} \\ V_i^{max} & \text{if } V_i > V_i^{max} \end{cases} \qquad 2.6$$

$$t_{ik}^{lim} = \begin{cases} t_{ik}^{min} & \text{if } t_{ik} < t_{ik}^{min} \\ t_{ik}^{max} & \text{if } t_{ik} > t_{ik}^{max} \end{cases} \qquad 2.7$$

3. Differential Evolution Algorithm:

3.1. Overview:

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.

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. DE employs a greedy selection process that is the best new solution and its parent wins the competition providing significant advantage of converging performance over genetic algorithms.
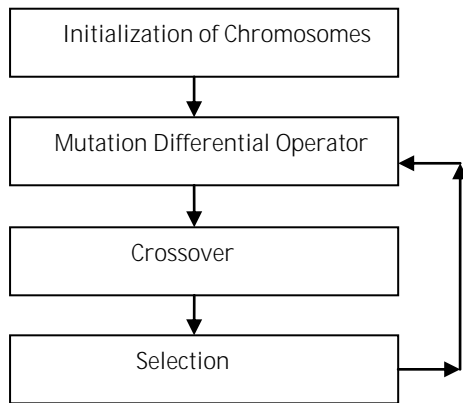

Fig 3.1: DE cycle of stages

3.2. DE computational flow:

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. The proper setting of NP is largely dependent on the size of the problem. Storn and Price remarked that for real-world engineering problems with D control variables, NP=20D will probably be more than adequate, NP as small as 5D is often possible, although optimal solutions using NP<2D should not be expected. Storn and Price set the size of population less than the recommended NP=10D in many of their test tasks. It is recommended using of NP≥4D. NP=5D is a good choice for a first try, and then increase or decrease it by discretion. So, as a rough principle, several tries before solving the problem may be sufficient to choose the suitable number of the individuals. The DE algorithm works through a simple cycle of stages, presented in Fig.3.1. These stages can be cleared as follow:

3.2.1. 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:

$$X_{i,j}(0) = X_j^L + rand(0,1).\left(X_j^u - X_j^L\right) \qquad 3.1$$

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

3.2.2. Mutation:

In each generation to change each population member _Xi(t), a donor vector _vi(t) is created. It is the method of creating this donor vector, which demarcates between the various DE schemes. However, in this project, one such specific mutation strategy known as DE/rand/1 is discussed. To create a donor vector _vi(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 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 _vi(t) 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:

$$V_{i,j}(t + 1) = X_{r1,j}(t) + F.\left(X_{r2,j}(t) - X_{r3,j}(t)\right) \qquad 3.2$$

3.2.3. 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 _Xi(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, the binomial variant was much more used in recent applications. In exponential type, the crossover is performed on the D variables in one loop as far as it is within the CR bound. The first time a randomly picked number between 0 and 1 goes beyond the CR value, no crossover is performed and the remaining variables are left intact. In binomial type, the crossover is performed on all D variables as far as a randomly picked number between 0 and 1 is within the CR value. So for high values of CR, the exponential and binomial crossovers yield similar results. 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 CR, the exponential variant needs a larger value for the scaling parameter F in order to avoid premature convergence [8].

In this paper, binomial crossover scheme is used which is performed on all D variables and can be expressed as:

$$u_{i,j}(t) = \begin{cases} v_{i,j}(t) \; if \; rand(0,1) < CR \\ X_{i,j}(t) \qquad else \end{cases} \qquad 3.3$$

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

3.2.4. 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:

$$\vec{X}_i (t+1) = \begin{cases} \vec{U}_i(t) \; if \; f(\vec{U}_i(t)) \le f(\vec{X}_i(t)) \\ \vec{X}_i(t) \; if \; f(\vec{X}_i(t)) < f(\vec{U}_i(t)) \end{cases} \qquad 3.4$$

Where, f ( ) is the function to be minimized. From Equation we noticed that:

If $\vec{U}_i(t)$ yields a better value of the fitness function, it replaces its target $\vec{X}_i(t)$ in the next generation.

Otherwise, $\vec{X}_i(t)$ is retained in the population.

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

### 4. Simulation Results and discussion:

In this paper the main emphasis is given to reduce power system losses and improve the voltage profile by using differential evolution algorithm.

The control variables are generator bus voltages and tap settings of the regulating transformers. The upper and lower bounds of the control variables are given in the table1 below:

Table 1: Initial Variable limits

Control Variables	Min. Value	Max. Value	Type
Generator V	0.9	1.1	Continuous
Load Bus V	0.9	1.05	Continuous
Tap	0.9	1.05	Discrete

4.1 Flow chart of the proposed algorithm:
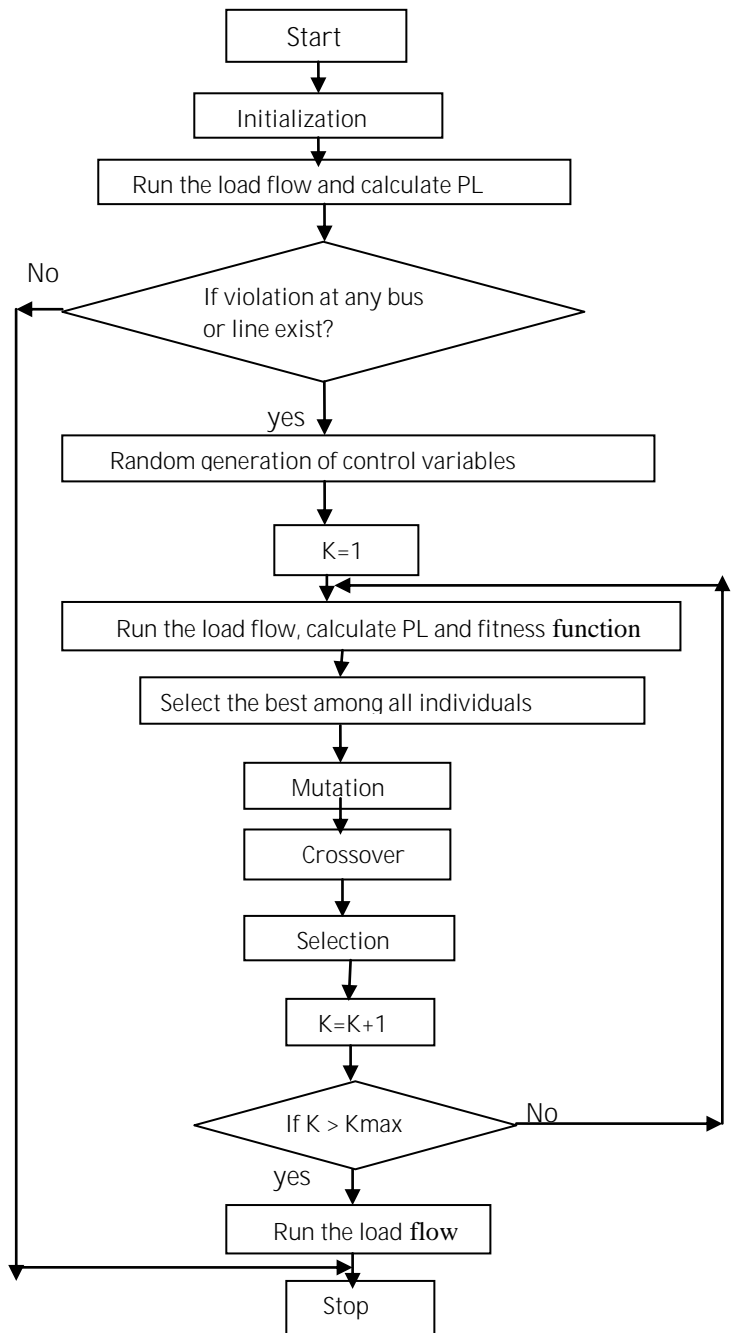
4.2 DE algorithm:

The DE algorithm is given below:

Step1: Generate an initial population randomly within the control variable bounds.

Step2: For each individual in the population, run power flow algorithm such as Newton Raphson method, to find the operating points.

Step3: Evaluate the fitness of the individuals according to Equations

Step4: Perform differentiation (mutation) and crossover as described in above Sections to create offspring from parents.

Step5: Perform Selection as described in above Section between parent and offspring. While using the penalty parameter-less method of constraint handling the following criteria are enforced while selecting the individuals for the next generation.

- Any feasible solution is preferred to any infeasible solution.
- Among two feasible solutions, the one having better objective function value is preferred.
- Among two infeasible solutions, the one having smaller constraint violation is preferred.

Step6: Store the best individual of the current generation.

Step7: Repeat steps 2 to 6 till the termination criteria is met (maximum number of generations).

4.3 Case Study:

To prove the effectiveness of the proposed algorithm, it has been tested on two standard IEEE test systems. Results obtained by simulation using differential evolutionary algorithm done in MATLAB, are provided in this section. Simulation is carried out on IEEE 14 and IEEE 30 bus test systems.

Case 1: IEEE-14 bus test system:

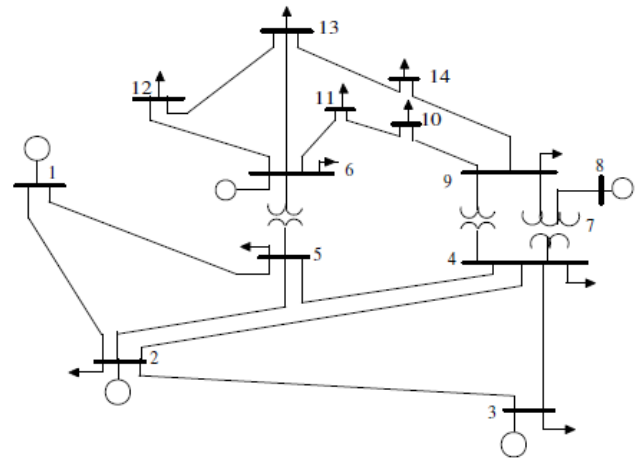The single line diagram of an IEEE 14-bus test system is shown below:

Fig-4.3.1: Network diagram of IEEE 14-bus test system

This system has 8-control variables as follows:
5-generators bus voltage magnitudes and 3-tap settings of transformers. Table2 shows the optimal setting of the control variables of 14-bus system.

Table 2: optimal setting of the control variables of 14-bus system:

Serial Number	Control Variable	Initial Value	Final Value (DEA)
1	V1	1.0600	1.0425
2	V2	1.0450	1.0309
3	V3	1.0100	0.9956
4	V4	1.0700	0.9969
5	V5	1.0900	1.0179
6	T1	0.9320	0.9512
7	T2	0.9780	0.9855
8	T3	0.9690	0.9782
Power loss in MW		13.89	12.57
Voltage Deviation Index		0.9962	0.0446

Fig: 4.3.2 shows the convergence characteristics of 14 bus test system obtained by using the proposed algorithm:
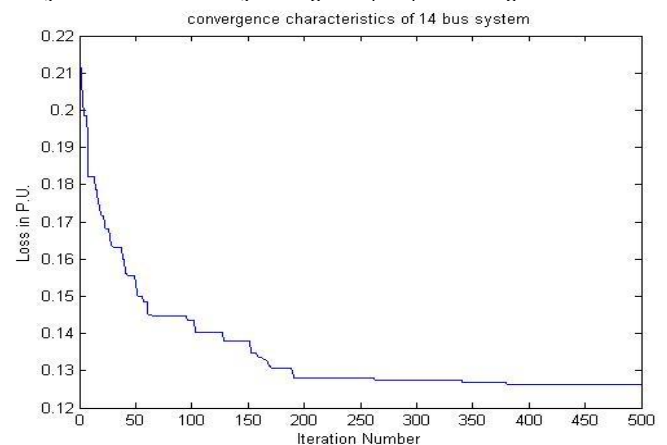

Fig: 4.3.2: convergence characteristics of 14 bus system

Fig: 4.3.3 shows the voltage profile of 14 bus test system obtained by using the proposed algorithm.
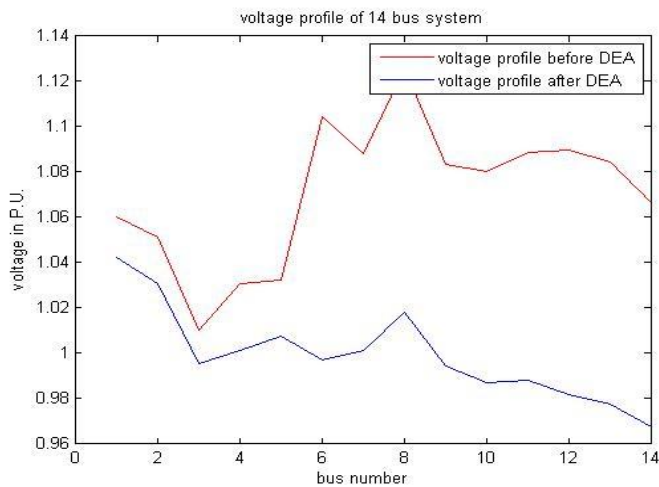

Fig: 4.3.3: voltage profile of 14 bus test system

Table3: comparison of results with different methods:

PSO[9]	IPM[10]	Proposed Algorithm
13.327 MW	13.246 MW	12.57 MW

From the initial value of 13.89 MW the power loss is reduced to 12.57 MW. In order to evaluate the performance of differential evolutionary computation, the results were compared with popular Particle Swarm Optimization (PSO) and conventional Interior Point Method (IPM).

The proposed algorithm is also capable of reducing the total voltage deviation from an initial value of 0.9962 to 0.0446.

Case2: IEEE-30 bus test system:
The single line diagram of an IEEE 30-bus test system is shown below:
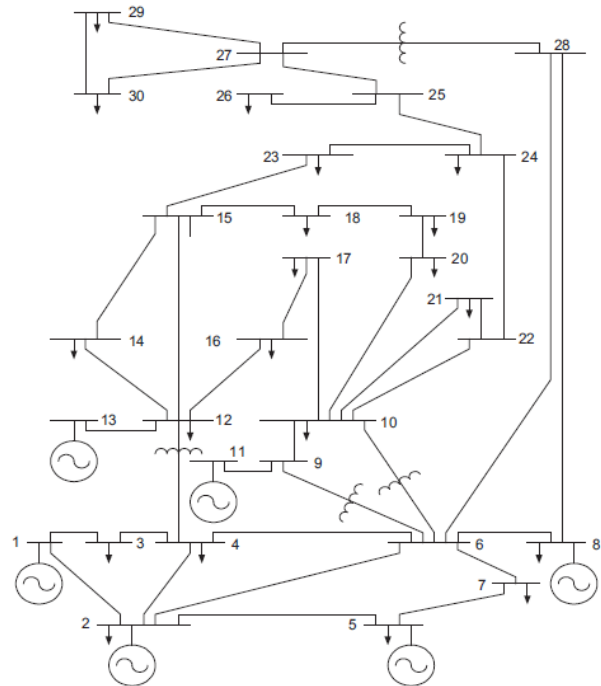

Fig-4.3.4: Network diagram of IEEE 30-bus test system

This system has 10-control variables as follows:
6-generators bus voltage magnitudes and 4-tap settings of transformers. Table: 4 Shows the optimal setting of the control variables of 30-bus system:

Table 4: optimal setting of the control variables of 30-bus system:

Serial Number	Control Variable	Initial Value	Final Value (DEA)
1	V1	1.0500	1.0191
2	V2	1.0338	1.0283
3	V3	1.0058	1.0069
4	V4	1.0230	1.0500
5	V5	1.0913	1.0128
6	V6	1.0880	1.0468
7	T1	1.0155	0.9983
8	T2	0.9629	1.0268
9	T3	1.0129	0.9850
10	T4	1.0120	1.0450

Power loss in MW	5.822	4.720
Voltage Deviation Index	1.9035	0.3079

Fig: 4.3.5 shows the convergence characteristics of 30 bus test system obtained by using the proposed algorithm.
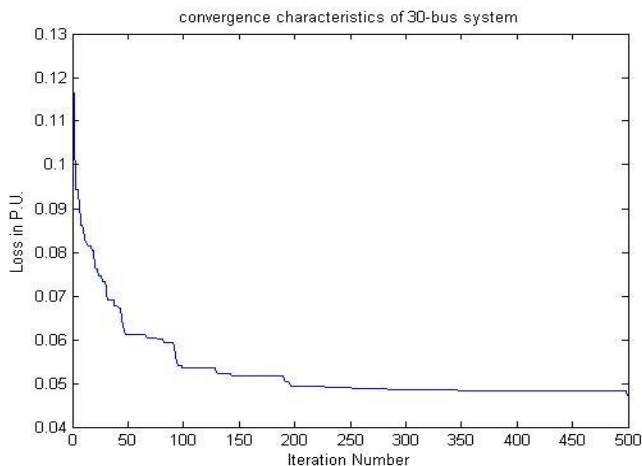

Fig: 4.3.5: convergence characteristics of 30 bus system

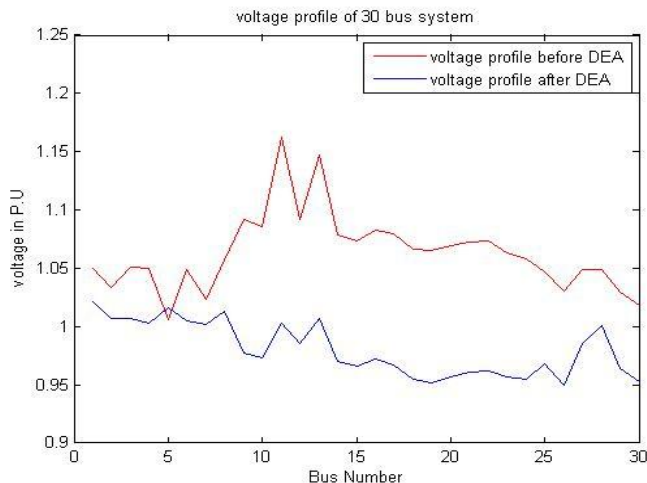Fig: 4.3.6 shows the voltage profile of 30 bus test system obtained by using the proposed algorithm.

Fig: 4.3.6: voltage profile of 30 bus test system

Table5: comparison of results with different methods:

SGA[12]	PSO[11]	Proposed Algorithm
4.98 MW	4.9262 MW	4.720 MW

From the initial value of 5.822 MW the power loss is reduced to 4.720 MW. In order to evaluate the performance of differential evolutionary computation, the results were compared with popular Particle Swarm Optimization (PSO) and standard genetic algorithm (SGA). The proposed algorithm is also capable of reducing the total voltage deviation from an initial value of 1.9035 to 0.3079.

For both the cases, the DE population size is taken equal to 30. The maximum number of generations is 500, Mutation factor is F=0.6, and crossover rate is RC=0.8. The penalty factors in equation (2.5) are chosen as the multiples of 100. For both the cases, 20 runs have been performed for the objective function and the results which follow are the best solution of these 20 runs.

5. CONCLUSIONS

In this paper, an efficient DE solution to the ORPD problem has been presented for determination of the global or near-global optimum solution for optimal reactive power dispatch and voltage deviation in PQ buses. The main advantages of this DE to the ORPD problem are optimization of different type of objective function, real coded of both continuous and discrete control variables, and easily handling nonlinear constraints. The proposed algorithm has been tested on two IEEE bus systems i.e.IEEE-14 bus and IEEE-30 bus systems, to minimize the active power loss. The optimal setting of control variables are obtained in both continuous and discrete value.

The results were compared with the other heuristic methods such as SGA. IPM and PSO algorithm reported in the literature and demonstrated its effectiveness and robustness.

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