International Journal of Electrical and Electronic Engineering & Telecommunications

ISSN 2319 – 2518 www.ijeetc.com
Vol. 2, No. 2, April 2013

Research Paper

AN ADAPTIVE DIFFERENTIAL EVOLUTION ALGORITHM BASED MINIMIZATION OF POWER LOSS AND VOLTAGE INSTABILITY

K Naga Sujatha[1] and K Vaisakh[2]*

*Corresponding Author: K Vaisakh, ✉ vaisakh_k@yahoo.co.in

This article introduces an Adaptive Differential Evolution (ADE) method for dealing with optimal reactive power dispatch aiming at power loss reduction. The optimum reactive power dispatch of power systems is to allocate reactive power control variables so that the objective function composed of power losses is minimized and the prescribed voltage limits are satisfied. The proposed method determines the optimum settings of reactive power control variables such as, generator excitation, tap changing transformers, and SVC that reduces the power loss, while maintaining the voltage stability. Mathematically, the problem of this research is a nonlinear programming problem with integer variables. This article presents a new approach that employs the ADE algorithm to solve the problem. IEEE-30 bus test system from the literature is used to exemplify the performance of the proposed method. Numerical results show that the proposed method is better than the other methods.

Keywords: Adaptive differential evolution, Reactive power dispatch, Power loss reduction, L-index

INTRODUCTION

To solve the RPD problem, a number of conventional optimization techniques (Lee *et al.*, 1985; and Granville, 1994) 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, nonlinearity 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) (Iba,

[1] Department of Electrical and Electronics Engineering, JNTUH, Jagityal, Nachupally, AP, India.
[2] Department of Electrical Engineering, Andhra University, Visakhapatnam, AP, India.

1994), Evolutionary Programming (EP) (Wu and Ma, 1995) and Evolutionary Strategy (Bhagwan Das and Patvardhan, 2003) have been applied to solve the optimal dispatch problem. In this paper, GA based approach has been proposed to solve the RPD problem.

Evolutionary Algorithms (EAs) are optimization techniques based on the concept of a population of individuals that evolve and improve their fitness through probabilistic operators like recombination and mutation. These individuals are evaluated and those that perform better are selected to compose the population in the next generation. After several generations these individuals improve their fitness as they explore the solution space for optimal value. The field of evolutionary computation has experienced significant growth in the optimization area. These algorithms are capable of solving complex optimization problems such as those with a non-continuous, non-convex and highly nonlinear solution space. In addition, they can solve problem that feature discrete or binary variables, which are extremely difficult.

Several algorithms have been developed within the field of Evolutionary Computation (EC) being the most studied Genetic Algorithms were first conceived in the 1960's when Evolutionary Computation started to get attention. Recently, the success achieved by EAs in the solution of complex problems and the improvement made in computation such as parallel computation have stimulated the development of new algorithms like Differential Evolution (DE), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO) and scatter search present great convergence characteristics and capability of determining global optima. Evolutionary algorithms have been successfully applied to many optimization problems within the power systems area and to the economic dispatch problem in particular (IEEE Committee Report, 1971; Walters and Sheble, 1993; Rainer Storn and Kenneth Price, 1995; Hong-TzerYang *et al.*, 1996; Wood and Woolenberg, 1996; Jason Yuryevich and Kit Po Wong, 1999; Venkatesh *et al.*, 2003; Dervis Karaboga and Selcuk Okdem, 2004; Gnanadass *et al.*, 2004; Sinha *et al.*, 2004; Somasundaram *et al.*, 2004; Somasundaram *et al.*, 2004; Tarek Bouktir and Linda Slimani, 2004; Gnanadas *et al.*, 2005; Jayabarathi *et al.*, 2005; Raul and Jose, 2005a and 2005b; and Balamurugan and Subramanian, 2007).

Voltage Stability is becoming an increasing source of concern in secure operation of present-day power systems. The problem of voltage instability is mainly considered as the inability of the network to meet the load demand imposed in terms of inadequate reactive power support or active power transmission capability or both. Voltage collapse is a local load bus problem and depends mostly on load conditions in the system. There exist two major techniques viz., static approach and dynamic approach for this analysis. Although not very accurate, yet the static technique has gained wide acceptance for its inherent virtues, eg, simplistic approach, faster execution and less memory consumption. The static voltage stability is primarily associated with the reactive power support.

The real power (MW) loadability of a bus in a system depends on reactive power support that the bus can receive from the system.

Several analytical tools have been presented in the literature for the analysis of the static voltage stability of a system. This paper is mainly concerned with analysis and enhancement of steady state voltage stability based on L-index (Kessel and Glavitsch, 1986).

VOLTAGE STABILITY L-INDEX

The L-indices for a given load condition are computed for all load buses (Kessel and Glavitsch, 1986). The equation for the L-index for j^{th} node can be written as

$$L_j = \left| 1.0 - \sum_{i=1}^{i=g} \left| F_{ji} \right| \frac{|V_i|}{|V_j|} \angle \bar{}_{ji} + \text{¢}_i - \text{¢}_j \right|$$

$$L_j = \left| 1.0 - \sum_{i=1}^{i=g} \frac{|V_i|}{|V_j|} \left(F_{ji}^r + jF_{ji}^m \right) \right|$$

It can be seen that when a load bus approaches a steady state voltage collapse situation, the index L approaches the numerical value 1.0. Hence for an overall system voltage stability condition, the index evaluated at any of the buses must be less than unity. Thus the index value L gives an indication of how far the system is from voltage collapse. This feature of this indicator has been exploited in our proposed algorithm to evolve a voltage collapse margin incorporated in RPD routine.

ADE ALGORITHM

The proposed algorithm is based on Differential Evolution which uses adaptation based optimization techniques. DE is a floating-point encoding evolutionary algorithm for global optimization over continuous spaces. ADE employs mutation, crossover, and selection operations during the evolutionary process, in each generation. Our algorithm uses the idea of adaptation based optimization.

Like any other evolutionary algorithm, the ADE also starts with a population of NP D-dimensional parameter vectors. We will represent subsequent generations in the ADE by discrete time steps like $t = 0, 1, 2, ..., t, t + 1$, etc. Since the vectors are likely to be changed over different generations we may adopt the following notation for representing the i^{th} vector of the population at the current generation (i.e., at time $t = t$) as:

$$\vec{X}_i(t) = [x_{i,1}(t), x_{i,2}(t), x_{i,3}(t), \ldots, x_{i,D}(t)] \quad ...(1)$$

For each parameter of the problem, there may be a certain range within which value of the parameter should lie for better search results. At the very beginning of a DE run or at $t = 0$; problem parameters or independent variables are initialized somewhere in their feasible numerical range. So, if the j^{th} parameter of the given problem has its lower and upper bound as $x_{\min,j}$ and $x_{\max,j}$ respectively, then we may initialize the j^{th} component of the i^{th} population members as:

$$x_{i,j}(0) = x_{\min,j} + rand_j(0,1) \cdot (x_{\max,j} - x_{\min,j}) \quad ...(2)$$

where $rand_j(0, 1)$ is the j^{th} instantiation of a uniformly distributed random number lying between 0 and 1. The following steps are taken next.

Mutation

After initialization, the ADE creates a donor vector $\vec{V}_i(t)$ corresponding to each population member or target vector $\vec{X}_i(t)$ in the current generation through mutation. It is the method of creating this donor vector, which demarcates between the various *DE* schemes. For example, five most frequently referred mutation strategies implemented in the public-domain *DE* codes available online at http://www.icsi.berkeley.edu/»storn/ code.html are listed as follows:

$$"DE/rand/1": \vec{V}_i(t) = \vec{X}_{r_1^i}(t) + F \cdot \left(X_{r_2^i}(t) - \vec{X}_{r_3^i}(t) \right) \quad ...(3a)$$

$$"DE/best/1": \vec{V}_i(t) = \vec{X}_{best}(t) + F \cdot \left(X_{r_1^i}(t) - \vec{X}_{r_2^i}(t) \right) \quad ...(3b)$$

$$"DE/target-to-best/1": \vec{V}_i(t) = \vec{X}_i(t) + F \cdot \left(\vec{X}_{besr}(t) - \vec{X}_i(t)\right) + F \cdot \left(X_{r_1^i}(t) - \vec{X}_{r_2^i}(t) \right) \quad ...(3c)$$

$$"DE/best/2": \vec{V}_i(t) = \vec{X}_{best}(t) + F \cdot \left(\vec{X}_{r_1^i}(t) - \vec{X}_{r_2^i}(t) \right) + F \cdot \left(X_{r_3^i}(t) - \vec{X}_{r_4^i}(t) \right) \quad ...(3d)$$

$$"DE/rand/2": \vec{V}_i(t) = \vec{X}_{r_1^i}(t) + F \cdot \left(\vec{X}_{r_2^i}(t) - \vec{X}_{r_3^i}(t) \right) + F \cdot \left(X_{r_4^i}(t) - \vec{X}_{r_5^i}(t) \right) \quad ...(3e)$$

The indices $r_1^i, r_2^i, r_3^i, r_4^i$ *and* r_5^i are mutually exclusive integers randomly chosen from range [1, NP], which are also different from index *i*. These indices are randomly generated once for each mutant vector. The scaling factor *F* is a positive control parameter for scaling the difference vectors. $\vec{X}_{best,G}$ is the best individual vector with the best fitness function value in the population at generation *G*. The general convention used for naming the various mutation strategies is *DE*/*x*/*y*/*z*, where *DE* stands for the Differential Evolution, *x* represents a string denoting the vector to be perturbed and *y* is the number of difference vectors considered for perturbation of *x*.*z* stands for the type of crossover being used (exp: exponential; bin: binomial). The following section discusses the crossover step in the DE.

Adaptive Mutation

Adaptive mutation generates a mutant population $P_{V,g}$, from the current population P_g, using mutant strategy and adaptive mutation scale factor *F*. For each vector from the current population, mutation (using one of the mutation strategies) creates a mutant vector $\vec{V}_{g,i}$, which is an individual of mutant population.

$$\vec{V}_{g,i} = \{V_{g,i,1}, V_{g,i,2}, \ldots, V_{g,i,D}\} \; i = 1, 2, \ldots, NP$$

DE includes various mutation strategies for global optimization. In our algorithm we used the *rand*/2 mutation strategy, which is given by the equation:

$$\vec{V}_{g,i} = \vec{X}_{g,r1} + F_g \cdot \left(\vec{X}_{g,r2} - \vec{X}_{g,r3}\right) + F_g \cdot \left(\vec{X}_{g,r4} - \vec{X}_{g,r5}\right)$$

The indexes r_1, r_2, r_3, r_4, r_5 are random and mutually different integers generated within the range [1, NP] and also different from index *i*. F_g is a mutation scale factor in the g^{th} generation within the range [0, 2] but usually less than 1.0. Because F_g scales the distance between the new and old individuals, it is responsible for exploration and exploitation balance in the evolutionary process. Therefore, we used adaptive F_g defined as the ratio of the standard deviations between parameters of the initial and current populations, as shown in the following equations:

$$F_g = \frac{\sum_{i=1}^{D} \pm_{g,i}}{\sum_{j=1}^{NP}\left(X_{g,i,j} - \bar{X}_{g,i}\right)^2}$$

$$\pm_{g,i} = \sqrt{\frac{\sum_{j=1}^{NP}\left(X_{g,i,j} - \bar{X}_{g,i}\right)^2}{NP-1}}$$

where $\pm_{g,i}$ is a standard deviation of the i^{th} parameter in the current population.

Crossover

Next, to increase the potential diversity of the population a crossover scheme is undertaken. The DE family of algorithms can use two kinds of cross over schemes, namely exponential and binomial. The donor vector exchanges its "body parts", i.e., components with the target vector $\vec{X}_i(t)$ under this scheme to form the trial vector $\vec{U}_i(t)$. We here outline the binomial crossover scheme, which comes into play in our present analysis. In this case the crossover is performed on each of the *D* variables whenever a randomly picked number between 0 and 1 is within the CR value. In this case the number of parameters inherited from the mutant has a (nearly) binomial distribution. The scheme may be outlined as:

$$u_{i,j}(t) = v_{i,j}(t) If \left(rand_i(0,1) \le CR\right) or \ \left(j = rn(i)\right)$$

$$x_{i,j}(t) If \left(rand_i(0,1) \le CR\right) or \ \left(j = rn(i)\right) \quad ...(4)$$

where $rand_j(0, 1) \in [0, 1]$ is the j^{th} evaluation of a uniform random number generator. $rn(i) \in [1, 2, ..., D]$ is a randomly chosen index which ensures that $\vec{U}_i(t)$ gets at least one component from $\vec{V}_i(t)$. It is instantiated once for each vector. In this article we have not taken into account the term $rn(i)$ so that CR may be exactly equal to the cross-over probability P_{Cr}.

Selection

In this way for each target vector $\vec{X}_i(t)$ a trial vector $\vec{U}_i(t)$ is created. To keep the population size constant over subsequent generations, the next step of the algorithm calls for 'selection' to determine which one of the target and the trial vector will survive in the next generation, i.e., at time $t = t + 1$. The DE actually involves the Darwinian principle of "Survival of the fittest" in its selection process, which may be outlined as,

$$\vec{X}_i(t+1) = \begin{cases} \vec{U}_i(t) & if \ f\left(\vec{U}_i(t)\right) \le f\left(\vec{X}_i(t)\right) \\ \vec{X}_i(t) & if \ f\left(\vec{U}_i(t)\right) > f\left(\vec{X}_i(t)\right) \end{cases} \quad ...(5)$$

where *f* is the function to be minimized. So if the new trial vector 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 (w.r.t the fitness function) or remains constant but never deteriorates.

In this study, the ADE for solving the reactive power dispatch is proposed. In order to demonstrate the effectiveness, the proposed approach is applied to a test system with two different case studies. One is normal operating condition and the other is network contingency condition; both are solved respectively by the proposed method.

ORPD PROBLEM FORMULATION

The objective of RPD is to identify the reactive power control variables, which minimizes the real power loss (P_{loss}) of the system. This is mathematically stated as follows:

Minimize $F = [f_1]$

$$f_1 = P_{loss} \sum_{\substack{k \in N_§ \\ k=(i,j)}} g_k \left(V_i^2 + V_j^2 - 2V_iV_j \cos^{-}{}_{ij}\right) \quad ...(6)$$

The reactive power optimization problem is subjected to the following constraints.

Equality Constraints

These constraints represent load flow equation such as

$$P_i - V_i \sum_{j=1}^{N_g} V_j \left(G_{ij} \cos^{-}{}_{ij} + B_{ij} \sin^{-}{}_{ij}\right) = 0,\ i \in N_B - 1$$

$$Q_i - V_i \sum_{j=1}^{N_g} V_j \left(G_{ij} \sin^{-}{}_{ij} - B_{ij} \cos^{-}{}_{ij}\right) = 0,\ i \in N_B - 1 \quad ...(7)$$

Inequality Constraints

These constraints represent the system operating constraints. Generator bus voltages (V_{gi}), reactive power generated by the capacitor (Q_{ci}), transformer tap setting (t_k), are control variables and they are self-restricted. Load bus voltages (V_{load}) reactive power generation of generator (Q_{gi}) and line flow limit (S_1) are state variables, whose limits are satisfied by adding a penalty terms in the objective function. These constraints are formulated as

- Voltage limits

$$V_i^{min} \le V_i \le V_i^{max};\ i \in N_B \quad ...(8)$$

- Generator reactive power capability limit

$$Q_{gi}^{min} \le Q_{gi} \le Q_{gi}^{max};\ i \in N_g \quad ...(9)$$

- Capacitor reactive power generation limit

$$Q_{ci}^{min} \le Q_{ci} \le Q_{ci}^{max};\ i \in N_c \quad ...(10)$$

- Transformer tap setting limit

$$t_k^{min} \le t_k \le t_k^{max};\ k \in N_T \quad ...(11)$$

- Transmission line flow limit

$$S_l \le S_l^{max};\ l \in N_l \quad ...(12)$$

- Voltage stability constraint

$$L_j \le L^{max};\ j \in N_{PQ} \quad ...(13)$$

The equality constraints are satisfied by running the power flow program. The active power generation (*P*) (except the gi generator at the slack bus), generator terminal bus voltages (*V*) and transformer tap-settings (*t*) are the optimization *gi k* variables and they are self-restricted by the optimization algorithm. The active power generation at the slack bus (*Pgs*), load bus voltages (*V*) and reactive power generation (*Q*) and voltage stability load gi level (*L*) are state variables which are restricted through penalty function approach.

AODE SOLUTION TECHNIQUE

In the ORPD problem, the elements of the solution consist of all the control variables, namely, generator bus voltages (*V*), the *gi* transformer tap-setting (t_k), and the reactive power generation (*Qci*). These variables are represented continuous variables in the DE population.

Fitness Function: In the ORPD problem under consideration the objective is to minimize the total power loss satisfying the constraints given by equations (2) to (9). For each individual, the equality constraints given by equations (2) and (3) are satisfied by running Newton-Raphson algorithm and the constraints on the state variables are taken into consideration by adding a quadratic penalty function to the objective function.

With the inclusion of penalty function, the new objective function then becomes,

$$\min F = P_{loss} + K_v \sum_{i=1}^{N_{PQ}} \left(V_i - V_i^{\lim}\right)^2 + K_q \sum_{i=1}^{N_g} \left(Q_{gi} - Q_{gi}^{\lim}\right)^2 + K_f \sum_{i=1}^{N_l} \left(S_i - S_i^{\lim}\right)^2 + K_l \sum_{j=1}^{N_{PQ}} \left(L_j - L^{\lim}\right)^2 \qquad ...(20)$$

where K_v, K_q, K_f and K_l are the penalty factors for the bus voltage limit violation, generator reactive power limit violation, line flow violation and voltage stability limit violation, respectively. In the above objective function $V_i^{\lim}$ and $Q_{gi}^{\lim}$ are defined as;

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

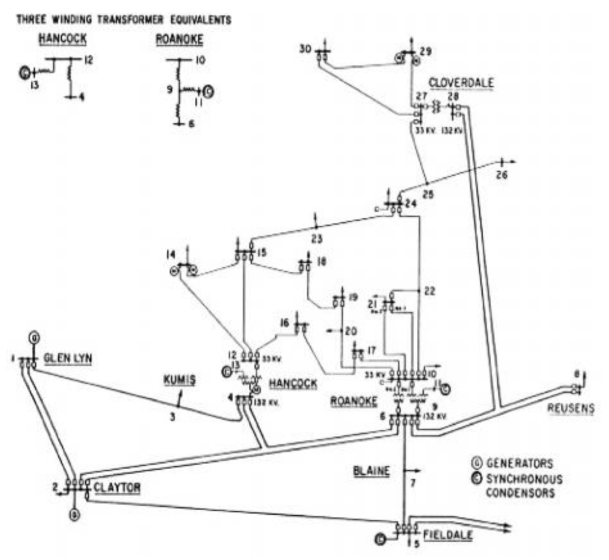
$$Q_{gi}^{\lim} = \begin{cases} Q_{gi}^{\min} & \text{if } Q_{gi} < Q_{gi}^{\min} \\ Q_{gi}^{\max} & \text{if } Q_{gi} > Q_{gi}^{\max} \end{cases} \qquad ...(21)$$

The minimization objective function given by Equation (20) is transformed to a fitness function (f) to be maximized as, where k is a large constant. This is used to amplify, the value of 1/F which is usually small, so that the fitness value of the chromosome will be in a wider range.

SIMULATION RESULTS

The details of the simulation study carried out on IEEE 30-bus system using the proposed ADE-based method are presented here. It is chosen as it is a benchmark system, has more control variables and provides results for comparison of the proposed method. The approach can be generalized and easily extended to large-scale systems. IEEE 30-bus system consists of 6 generator buses, 24 load buses and 41 transmission lines of which 4 branches (6-9), (6-10), (4-12) and (28-27) are with the tap-setting transformer. Generator parameters are given in the Appendix. The transmission line parameters of this system and the base loads are given in Lee *et al.* (1985). Number of population Np = 20, maximum generations =150.

Figure 1: IEEE 30-Bus System



Case 1: Base Case

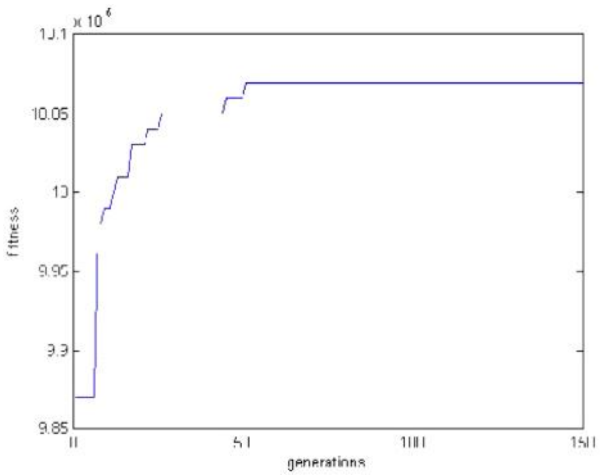
For the ORPD problem, the candidate buses for reactive power compensation are 10, 12, 15, 17, 20, 21, 23, 24 and 29. The ADE-based ORPD algorithm was implemented using MATLAB code and was executed on a PC. Two different studies were performed with this system to show the significance of the proposed method and the use of the algorithm in a bigger system. In case 1 RPD problem is solved by the proposed method with 100% load level, case 2 is reactive power dispatch under network contingency with the incorporation of the voltage stability limit in both the cases.

The real power settings of the generator are taken from Lee *et al.* (1985). To obtain the optimal values of the control variables the ADE-based algorithm was run. The optimal values of the control variables and power loss obtained are presented in Table 1. The minimum transmission loss obtained is 4.8500 MW which is smaller than the result obtained in Lee *et al.* (1985) for the same IEEE 30-bus system. To illustrate the convergence of the algorithm, the relationship between the best fitness value of the ORPD results and the objective function (P_{loss}) are plotted against the number of generations in Figure 2. From the figure it can be seen that the proposed algorithm converges rapidly towards the optimal solution. This shows the effectiveness of the proposed method for the ORPD problem.

Table 1: Control Variables for the 30-Bus System

Generator Voltages		Shunt Compensation		Transformer Taps	
Gen Bus	**Value**	**SVC**	**Value**	**Tran. Tap**	**Value**
1	1.07	Q_{c10}	0.043	$T_{6–9}$	0.91
2	1.0629	Q_{c12}	0.0261	$T_{6–10}$	0.902
5	1.0451	Q_{c15}	0.0275	$T_{4–12}$	1.0092
8	1.0429	Q_{c17}	0.0282	$T_{28–27}$	1.012
11	1.0974	Q_{c20}	0.0458		
13	1.0612	Q_{c21}	0.0381		
		Q_{c23}	0.0532		
		Q_{c24}	0.0258		
		Q_{c27}	0.0309		

Figure 2: Fitness Function Value vs Generations (Case 1)



Case 2: Contingency Case

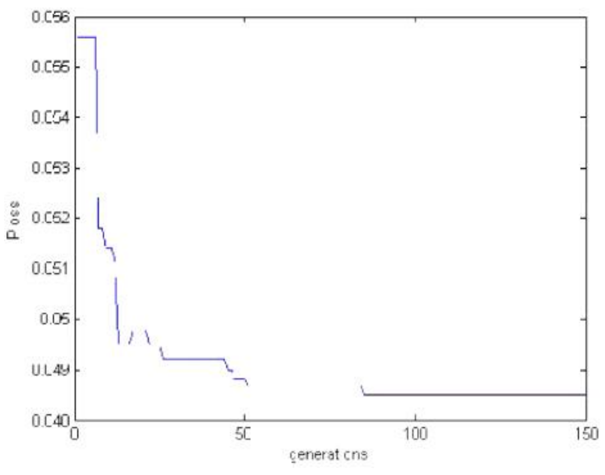
Again in this case, the same values of load condition and generator setting as in case 1 are followed. But a network contingency is considered in this case. Additional constraint in the form of limit on the maximum value of L-index as in normal condition is incorporated.

This is done to restrict the maximum value of L-index under contingency condition from reaching a dangerously high value. For the network contingency, namely, line outage (4-12), with the inclusion of the voltage stability constraint the ADE-based algorithm was applied to obtain the optimal values of the control variables under normal condition, the result of which is given in the Table 2.

Table 2: Control Variables for the 30-Bus System

Generator Voltages		Shunt Compensation		Transformer Taps	
Gen Volt.	**Value**	**SVC**	**Value**	**Tran. Tap**	**Value**
$\|V_{G1}\|$	1.0700	Q_{c10}	0.0140	$T_{6–9}$	1.0284
$\|V_{G2}\|$	1.0630	Q_{c12}	0.0554	$T_{6–10}$	0.9001
$\|V_{G5}\|$	1.0390	Q_{c15}	0.0421	$T_{4–12}$	1.0137
$\|V_{G8}\|$	1.0402	Q_{c17}	0.0261	$T_{28–27}$	0.9851
$\|V_{G11}\|$	1.0864	Q_{c20}	0.0484		
$\|V_{G13}\|$	1.0646	Q_{c21}	0.0159		
		Q_{c23}	0.0195		
		Q_{c24}	0.0497		
		Q_{c27}	0.0288		

Figure 3: Objective Function Value vs Generations for Case 1



For these optimal values of control variables when line (4-12) was removed it was found that the maximum value of L-index reached by the system is 0.1780 only. This improvement in voltage stability was achieved because of the restriction put on the maximum L-index value in the base case condition. Table 3 shows the performance parameters of the reactive power dispatch obtained using ADE-based RPD. This shows the effectiveness of the proposed algorithm for voltage security enhancement.

Table 3: Performance Parameters

Parameter	Values	
	Case 1	**Case 2**
P_{g1} (pu) (slack bus)	0.9979	1.0230
L_{max}	0.1322	0.17781
P_{loss} (pu)	0.04969	0.0501

Figure 4: Fitness Function Value vs Generations for Case 2

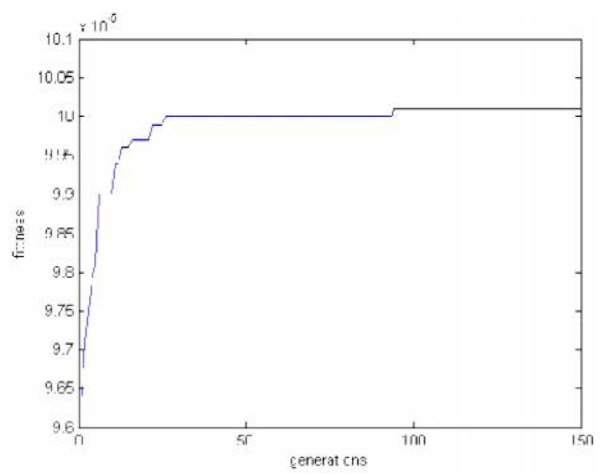
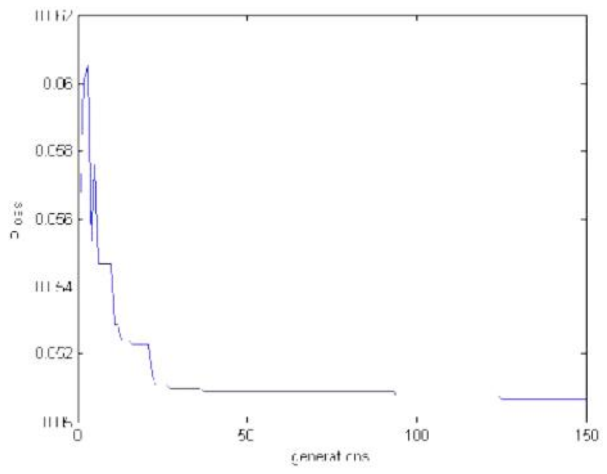


Figure 5: Objective Function Value vs Generations for Case 2



CONCLUSION

This paper presented a ADE solution to the optimal reactive power allocation problem and is applied to an IEEE 30-bus power system. The main advantage of ADE over other modern heuristics is modeling flexibility, sure and fast convergence, less computational time than other heuristic methods. And it can be easily coded to work on parallel computers. The main disadvantage of ADE is that it is heuristic algorithms, and it does not provide the guarantee of optimal solution for the RPD problem. The ADE approach is useful for obtaining highquality solution in a very less time compared to other methods. Simulation results shows that the ADE-based reactive power dispatch algorithm is able to improve voltage stability condition along with loss minimization in the system. Also, it is found that the results of the ADE-based algorithm are always better than that obtained using conventional methods.

REFERENCES

1. Balamurugan R and Subramanian S (2007), "Fuzzy Adaptive Differential Evolution Based Power Economic Dispatch of Generators with Valve Point Effects and Multiple Fuel Options", *International Journal of Computer Science and Engineering*, Vol. 1, No. 1, pp. 10-17, ISSN 1307-3699.
2. Bhagwan Das and Patvardhan C (2003), "A New Hybrid Evolutionary Strategy for Reactive Power Dispatch", *Electric Power Research*, Vol. 65, pp. 83-90.
3. Chiou J P and Wang F S (1998), "A Hybrid Method of Differential Evolution with Application to Optimal Control Problems of a Bioprocess System", Proc. IEEE on Evolutionary Computation Conf., pp. 627-632.
4. Chiou J P and Wang F S (1999), "Hybrid Method of Evolutionary Algorithms for Static and Dynamic Optimization Problems with Application to Fedbatch Fermentation Process", *Computers & Chemical Engineering*, Vol. 23, pp. 1277-1291.
5. Chiou J P and Wang F S (2001), "Estimation of Monod Parameters by Hybrid Differential Evolution", *Bioprocess and Biosystems Engineering*, pp. 109-113.
6. Dervis Karaboga and Selcuk Okdem (2004), "A Simple and Global Optimization Algorithm for Engineering Problems: Differential Evolution Algorithm", *Turk. J. Elec. Engin.*, Vol. 12, No. 1, pp. 53-60.
7. Gnanadas R, Venkatesh P and Narayana Prasad Padhy (2005), "Evolutionary Programming Based Optimal Power Flow for Units with Non-Smooth Fuel Cost Functions", *Electric Power Components and Systems*, Vol. 33, pp. 1245-1250.
8. Gnanadass R, Venkatesh P, Palanivelu T G and Manivannan K (2004), "Evolutionary Programming Solution of Economic Load Dispatch with Combined Cycle Co-Generation Effect", *Institute of Engineers Journal-EL*, Vol. 85, September, pp. 124-128.
9. Granville S (1994), "Optimal Reactive Power Dispatch Through Interior Point Methods", *IEEE Trans. on Power Systems*, Vol. 9, No. 1, pp. 98-105.
10. Hong-TzerYang, Pai-Chuan Yang and Ching-Lein Huang (1996), "Evolutionary Programming Based Economic Dispatch for Units with Non-Smooth Fuel Cost Functions", *IEEE Transactions on Power Systems*, Vol. 11, No. 1, pp. 112-118.
11. Iba K (1994), "Reactive Power Optimization by Genetic Algorithms", *IEEE Trans. on Power Systems*, Vol. 9, No. 2, pp. 685-692.
12. IEEE Committee Report (1971), "Present Practices in the Economic Operation of Power Systems", *IEEE Transactions on Power Apparatus Systems*, Vol. PAS-90, July/August, pp. 1768-1775.

13. Jason Yuryevich and Kit Po Wong (1999), “Evolutionary Programming Based Optimal Power Flow Algorithm”, *IEEE Transactions on Power Systems*, Vol. 14, No. 4, pp. 1245-1250.
14. Jayabarathi T, Jayaprakash K, Jeyakumar D N and Raghunathan T (2005), “Evolutionary Programming Techniques for Different Kinds of Economic Dispatch Problems”, *Electric Power Systems Research*, Vol. 73, pp. 169-176.
15. Kessel P and Glavitsch H (1986), “Estimating the Voltage and Lability of a Power System”, *IEEE Trans. Power Deliv.*, Vol. PWRD-1, No. 3, pp. 346-354.
16. Lampinen J and Zelinka I (2000), On Stagnation of the Differential Evolution Algorithm”, in Ošmera Pavel (Ed.), Proceedings of MENDEL 2000, 6th International Mendel Conference on Soft Computing, June 7-9, Czech Republic, Brno.
17. Lee K Y, Park Y M and Ortiz J L (1985), “A United Approach to Optimal Real and Reactive Power Dispatch”, *IEEE Trans. on Power Apparatus and Systems*, Vol. PAS. 104, No. 5, pp. 1147-1153.
18. Lee K Y, Park Y M and Ortiz J L (1985), “A United Approach to Optimal Real and Reactive Power Dispatch”, *IEEE Transactions on Power Apparatus and System*, Vol. 104, pp. 1147-1153.
19. Price K V (1997), “Differential Evolutionary vs. the Functions of the 2nd ICEC”, Proc. IEEE on Evolutionary Computation Conf., pp. 153-157.
20. Rainer Storn and Kenneth Price (1995), “Differential Evolution—A Simple and Efficient Adaptive Scheme for Global Optimization Over Continuous Spaces”, TR-95-012, March.
21. Raul E Perez-Guerrero and Jose R Cedeno-Maldonado (2005a), “Differential Evolution Based Economic Environmental Power Dispatch”, pp. 191-197.
22. Raul E Perez-Guerrero and Jose R Cedeno-Maldonado (2005b), “Economic Power Dispatch with Non-Smooth Cost Functions Using Differential Evolution”, pp. 183-190.
23. Sinha N, Chakravarthi R and Chattopadhyay P K (2004), “Improved Fast Evolutionary Program for Economic Load Dispatch with Non-Smooth Cost Curves”, *Institute of Engineers Journal-EL*, Vol. 84, September pp. 110-114.
24. Somasundaram P, Kuppuswamy K and Kumudini Devi R P (2004), “Economic Dispatch with Prohibited Operating Zones Using Fast Computation Evolutionary Programming Algorithm”, *Electric Power Systems Research*, Vol. 70, pp. 245-252.
25. Somasundaram P, Kuppuswamy K and Kumidini Devi R P (2004), “Evolutionary Programming Based Security Constrained Power Flow”, *Electric Power Systems Research*, Vol. 72, July, pp. 137-145.
26. Storn R (1999), “System Design by Constraint Adaptation and Differential Evolution”, *IEEE Trans. Evolutionary Computation*, Vol. 3, April, pp. 22-34.
27. Storn R and Price K V (1996), “Minimizing the Functions of the ICEC’96 Contest by Differential Evolution”, Proc.

IEEE on Evolutionary Computation Conf., pp. 842-844.

28. Tarek Bouktir and Linda Slimani (2004), "Economic Power Dispatch of Power Systems with A NOx Emission Control Via: An Evolutionary Algorithm".

29. Venkatesh P, Gnanadass R and Narayana Prasad Padhy (2003), "Comparison and Application of Evolutionary Programming Techniques to Combined Economic Emission Dispatch with Line Flow Constraints", *IEEE Transactions on Power Systems*, Vol. 18, No. 2, pp. 688-697.

30. Vesterstrøm J and Thomson R (2004), "A Comparative Study of Differential Evolution, Particle Swarm Optimization, and Evolutionary Algorithms on Numerical Benchmark Problems", Proc. 6th Congress on Evolutionary Computation (CEC-2004), IEEE Press.

31. Walters D C and Sheble G B (1993), "Genetic Algorithm Solution of Economic Dispatch with Valve Point Loadings", *IEEE Trans. Power Systems*, Vol. 8, No. 3, pp. 1325-1332.

32. Wang F S and Sheu J W (2000), "Multiobjective Parameter Estimation Problems of Fermentation Process Using a High Ethanol Tolerance Yeast", *Chemical Engineering Science*, Vol. 55, pp. 3685- 3695.

33. Wang F S, Jing C H and Taso G T (1998), "Fuzzy-Decision-Making Problems of Fuel Ethanol Production Using a Genetically Engineering Yeast", *Ind. & Eng. Chem. Research*, Vol. 37, pp. 3434-3443.

34. Wood A and Woolenberg B (1996), *Power Generation, Operation and Control*, Wiley, New York.

35. Wu Q H and Ma J T (1995), "Power System Optimal Reactive Power Dispatch Using Evolutionary Programming", *IEEE Trans. on Power System*, Vol. 10, No. 3, pp. 1243-1249.