Available Online at http://www.recentscientific.com

ISSN: 0976-3031

International Journal of Recent Scientific Research
Vol. 8, Issue, 1, pp. 15041-15047, January, 2017

International Journal of Recent Scientific Research

Research Article

SOLVING TRANSIENT SECURITY CONSTRAINED OPTIMAL POWER FLOW PROBLEM USING DIFFERENTIAL EVOLUTION ALGORITHM

Venkateswarlu, B[1]*., Vaisakh, K[2] and Sujatha, P[3]

[1]Department of Electrical and Electronics Engineering, JNTUA, Anantapur, AP, India
[2]Department of Electrical Engineering, AUCE (A), Andhra University, Visakkhapatnam, AP,India
[3]Department of Electrical and Electronics Engineering, JNTUA, Anantapur, AP, India

ARTICLE INFO

Article History:

Received 06th October, 2015
Received in revised form 14th November, 2016
Accepted 23rd December, 2016
Published online 28th January, 2017

Key Words:

Differential evolution, optimal power flow, parallel computation, power system operation, power system transient stability.

ABSTRACT

The increase of power transmission and interconnection of power system have led to an increasingly complex system which has to be operated close to the limits of security/stability. The problems related to voltage/transient instability have become a major concern for secure operation of many power systems. Consideration of voltage/transient stability constraints in optimal power flow (OPF) problems is increasingly important in the modern power systems operation. The OPF problem with voltage/transient stability constraints is however a nonlinear optimization problem with both algebraic and differential equations, which is difficult to be solved even for small power systems. This paper develops a robust and efficient method for solving OPF problems with voltage/transient stability constraints in the power system operation. The proposed method is based on differential evolution (DE), which is a branch of evolutionary algorithms with strong ability in searching global optimal solutions of highly nonlinear and non-convex problems. Numerical tests on the IEEE six-generator, 30-bus system have demonstrated the robustness and effectiveness of the proposed approach for solving optimal operation of power systems.

INTRODUCTION

Optimal power flow (OPF) is an important tool for power system operators both in planning and operating stages. The main purpose of an OPF program is to determine the optimal operating state of a power system and the corresponding settings of control variables for economic and secure operation. Moreover, with increased loading of existing power transmission systems, the problem of voltage stability and voltage collapse, has also become a major concern in power system planning and operation [1]. Therefore, it is necessary to consider voltage stability indices in the OPF problem [2].

Transient stability testing for the optimal solution obtained from the OPF has to be performed under all the credible disturbances to ensure the system stability performance. If the system is transiently unstable for any one of the disturbances, the OPF solution is then modified by heuristic trial-and-error methods based on engineering experience and judgment. Due to the rapid increase of electricity demand, power systems tend to operate closer to stability boundaries. The consideration of the transient stability limit in the OPF problem is becoming more and more imperative in the power system operation [3].

Many mathematical programming techniques such as nonlinear programming (NLP), quadratic programming (QP), linear programming (LP), Newton method, and interior point methods (IPM) have been applied to solve the OPF problem successfully. However, these classical optimization methods are limited in handling algebraic functions and unable to consider the dynamic characteristic such as the transient stability performance in the optimization. Classical optimization methods for OPF and OPF with transient stability constraint problems are indeed suffering from the high sensitivity problem of initial conditions. They may either converge to local optimum solutions or, under some situations, diverge in their solution processes.

Owing to the computational difficulties, the degree of freedom in the objective functions and the types of constraints in OPF problems such as transient stability limit are restricted. These weaknesses can be solved by modern heuristic optimization techniques such as evolutionary algorithms (EAs). As a new branch of EA, differential evolution (DE) developed by Storn and Price [4] has gained more and more attention recently due to its strong ability in searching global optimal solution [5].

**Corresponding author:* *Venkateswarlu, B*
Department of Electrical and Electronics Engineering, JNTUA, Anantapur, AP, India

In this chapter, in order to exploit the exploration and the exploitation capabilities of DE, it is being proposed for solving TSOPF problems. Numerical tests on the IEEE six-generator, 30-bus system have demonstrated the robustness and effectiveness of the proposed approach for solving optimal operation of power systems.

Formulation of Tsopf Problem

A standard OPF problem with transient stability constraint can be formulated as follows:

$$\text{Min} \quad f(\mathbf{u},\mathbf{x}) \tag{1}$$

$$\text{Subject to} \quad g(\mathbf{u},\mathbf{x}) = 0 \tag{2}$$

$$h(\mathbf{u},\mathbf{x}) \le 0 \tag{3}$$

$$TSI_k \ge \varepsilon \tag{4}$$

where $\mathbf{u}$ is the vector of control variables; and $\mathbf{x}$ is the vector of dependent variables corresponding to $\mathbf{u}$.

Objective function

The OPF problem has the following objective function:

Objective Function : $Min \quad F_T = \sum\left(a_i P_{gi}^2 + b_i P_{gi} + c_i\right)$ is the cost of generation

where P_{gi} is the active power generation of unit i; a_i, b_i and c_i are the fuel cost coefficients of unit i.

Constraints

The OPF problem has two categories of constraints:

Equality Constraints: These are the sets of nonlinear power flow equations that govern the power system, i.e,

$$P_{gi} - P_{di} - \sum_{j=1}^{nb} |V_i||V_j||Y_{ij}| \cos(\theta_{ij} - \delta_i + \delta_j) = 0 \quad i \in nl \tag{5}$$

$$Q_{gi} - Q_{di} + \sum_{j=1}^{nb} |V_i||V_j||Y_{ij}| \sin(\theta_{ij} - \delta_i + \delta_j) = 0 \quad i \in ng \tag{6}$$

where P_{gi} is the real power generation at i^{th} bus, P_{di} is the real power demand at i^{th} bus, Q_{gi} is the reactive power generation at i^{th} bus, Q_{di} is the reactive power demand at i^{th} bus, Y_{ij} is the admittance of the line connected between i and j^{th} bus, nb is the total number of buses, nl is the number of load buses and ng is the number of generator buses in the system.

Inequality Constraints: These are the set of constraints that represent the system operational and security limits like the bounds on the following:

generator voltages, real and reactive power outputs

$$V_{gi}^{\min} \le V_{gi} \le V_{gi}^{\max}, \quad i = 1, \ldots, ng$$

$$P_{gi}^{\min} \le P_{gi} \le P_{gi}^{\max}, \quad i = 1, \ldots, ng \tag{7}$$

$$Q_{gi}^{\min} \le Q_{gi} \le Q_{gi}^{\max}, \quad i = 1, \ldots, ng \tag{8}$$

voltage magnitudes at each load bus in the network

$$V_{li}^{\min} \le V_{li} \le V_{li}^{\max}, \quad i = 1, \ldots, nl \tag{9}$$

transformer tap settings

$$T_{ti}^{\min} \le T_{ti} \le T_{ti}^{\max}, \quad i = 1, \ldots, nt \tag{10}$$

reactive power injections due to capacitor banks

$$Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max}, \quad i = 1, \ldots, nc \tag{11}$$

transmission lines loading

$$S_{li} \le S_{li}^{\max}, \quad i = 1, \ldots, ntl \tag{12}$$

voltage stability index

$$L_j \le L_j^{\max}, i = 1, \ldots, nl \tag{13}$$

Equation (4) is the transient stability associated constraints, implying that the system should maintain stability after the contingency k. Transient stability index (TSI) is the indicator of the ability of a power system to maintain itself within the stable domain of attraction and bring it back to a new stable equilibrium.

Transient stability assessment

Transient stability assessment (TSA) is the evaluation of the stability of a power system to withstand specified contingencies by surviving the subsequent transient events and arrive at an acceptable steady state operating condition [6]. Many advanced methods have been developed for transient stability assessment. These methods include time-domain simulation, transient energy function (TEF) methods [7], and hybrid methods [8]. Most of the researches in OPF problems consider the transient stability constraints through time domain simulation and constrain the relative rotor angle within a predefined limit, for example 100 degree [9] or π *rad* [10].

In this paper, the time-domain simulation, which is simple and easy to implement is used. Time-domain simulation is performed to calculate the generator rotor angles are calculated to determine the system stability based on the results of time-domain simulation, in which the detailed models can be incorporated. The transient behavior of a ng -generator power system is described by a set of differential and algebraic equations as follows:

$$M_i \frac{d^2\delta_i}{dt^2} = P_{mi} - P_{ei} \tag{14}$$

$$\delta_i = \omega_i \tag{15}$$

where δ_i and ω_i are rotor angle and angular speed of generator i ; P_{mi} and are P_{ei} the mechanical power input and electrical power output of generator i; and M_i is the moment of inertia of generator i.

The center of inertia (COI) of a power system can be represented by a linear combination of all generator rotor angles as follows:

$$\text{¢}_{COI} = \frac{1}{M_T}\sum_{i=1}^{ng} M_i \text{¢}_i \tag{16}$$

where $M_T = \sum_{i=1}^{ng} M_i$ is the inertia of the center.

Then we have the rotor angle and speed in COI frame as follows:

$$\bar{-}_i = \text{¢}_i - \text{¢}_{COI} \tag{17}$$

$$\dot{-}_i = \mu_i \tag{18}$$

Thus the system equations with respect to the COI frame are denoted here as

$$M_i \dot{\mu}_i = P_{mi} - P_{ei} - \frac{M_i}{M_T} P_{COI} = PAC_i \tag{19}$$

$$P_{COI} = \sum_{i=1}^{N_g} (P_{mi} - P_{ei}) \tag{20}$$

where PAC_i is the accelerating power of generator i.

Differential Evolution

The differential evolution algorithm evolves a population of NP D–dimensional parameter vectors, which are called individuals and encode the candidate solutions, i.e. $X_{i,G} = X_{i,G}^1, \dots, X_{i,G}^D$, $i = 1, \dots, NP$, towards the global optimum. The initial population cover the entire search space as much as possible by uniformly randomizing individuals within the search space constrained by the prescribed minimum and maximum parameter bounds $X_{min} = X_{min}^1, \dots, X_{min}^D$ and $X_{max} = X_{max}^1, \dots, X_{max}^D$.
For example, the initial value of the jth parameter in the ith individual at the generation G=0 is generated by

$$x_{i,0}^j = x_{min}^j + rand\ 0{,}1 \cdot x_{max}^j - x_{min}^j, \quad j = 1,2,3, \dots, D \tag{21}$$

where $rand\ 0{,}1$ represents a uniformly distributed random variable within the range [0,1].

***Mutation Operation*:** After the generation of initial population, the differential evolution algorithm employs the mutation operation to produce a mutant vector $V_{i,G}$ with respect to each individual $X_{i,G}$, so-called target vector, in the current population. For each target vector $X_{i,G}$ at the generation, its associated mutant vector $V_{i,G} = v_{i,G}^1, v_{i,G}^2, \dots, v_{i,G}^D$ is generated by using any one of the following mutation strategies. The five most frequently used mutation strategies implemented in the differential algorithm are as follows:

"$DE/rand/1$"

$$V_{i,G} = X_{r_1^i,G} + F \cdot X_{r_2^i,G} - X_{r_3^i,G} \tag{22}$$

"$DE/best/1$":

$$V_{i,G} = X_{best,G} + F \cdot X_{r_1^i,G} - X_{r_2^i,G} \tag{23}$$

"$DE/rand - to - best/1$":

$$V_{i,G} = X_{i,G} + F \cdot X_{best,G} - X_{i,G} + F \cdot X_{r_1^i,G} - X_{r_2^i,G} \tag{24}$$

4) "$DE/best/2$":

$$V_{i,G} = X_{best,G} + F \cdot X_{r_1^i,G} - X_{r_2^i,G} + F \cdot X_{r_3^i,G} - X_{r_4^i,G} \tag{25}$$

5) "DE/rand/2":

$$V_{i,G} = X_{r_1^i,G} + F \cdot X_{r_2^i,G} - X_{r_3^i,G} + F \cdot X_{r_4^i,G} - X_{r_5^i,G} \tag{26}$$

The indices $r_1^i, r_2^i, r_3^i, r_4^i, r_5^i$ are randomly generated and mutually exclusive integers and are also different from the index. These indices are randomly generated once for each mutant vector. The F is a scaling factor and a positive control parameter for scaling the difference vector. $X_{best,G}$ is the best individual vector with the best fitness value in the population of a particular generation.

***Crossover Operation*:** After the application of mutation operation, crossover operation is applied to each pair of the target vector $X_{i,G}$ and its corresponding mutant vector $V_{i,G}$ to generate a trial vector: $U_{i,G} = u_{i,G}^1, u_{i,G}^2, \dots, u_{i,G}^D$. In the basic version, DE employs the binomial (uniform) crossover defined as follows:

$$u_{i,G}^j = \begin{cases} v_{i,G}^j, & if\ \ rand_j\ 0{,}1 \le CR\ or\ (j = j_{rand}) \\ x_{i,G}^j, & otherwise \end{cases} \quad j = 1,2, \dots, D. \tag{27}$$

In (7), the crossover rate CR is generally a specified constant within the range [0, 1) and also controls the fraction of parameter values copied from the mutant vector. j_{rand} is a randomly chosen integer in the range [1,D]. The binomial crossover operator copies the jth parameter of the mutant vector $V_{i,G}$ to the corresponding element in the trial vector $U_{i,G}$ if $rand_j\ 0{,}1 \le CR$ or $j = j_{rand}$. Otherwise, it is copied from the corresponding target vector $X_{i,G}$. The remaining parameters of the trial vector $U_{i,G}$ are copied from the corresponding target vector $X_{i,G}$. The condition j_{rand} ensures that the trial vector $U_{i,G}$ will be different from its corresponding target vector $X_{i,G}$ by at least one parameter.

***Selection Operation*:** If there are violations in a newly generated trial vector which exceed the corresponding upper and lower bounds, then randomly and uniformly reinitialize them within the pre-specified range and the objective function values of all trial vectors are evaluated. After that, a selection operation is performed to obtain the best population. The objective function value of each trial vector $f(U_{i,G})$ is compared with the corresponding target vector $f(X_{i,G})$ of the current population. If the trial vector has less or equal objective function value than the corresponding target vector, the trial vector will replace the target vector and it enters into the population of the next generation. Otherwise, the target vector will remain in the population for the next generation. The selection operation is expressed by the following equation:

$$X_{i,G+1} = \begin{cases} U_{i,G}, & if\ f\ U_{i,G} \le f\ X_{i,G} \\ X_{i,G}, & otherwise \end{cases} \quad (28)$$

The above procedure is repeated until some specific termination criteria are satisfied.

Differential Evoltion Algorithm for Tsopf Problem

The differential evolution algorithm, which is based on the principles of natural evolution, uses a population composed of N_p individuals to evolve over several generations to reach an optimal solution. In this section the differential evolution algorithm is applied to solve TSCOPF problem. In the differential evolution algorithm several strategies are proposed for the initialization, selection and assessment of solution individuals in the population to reduce the computational time. The flow chart of the proposed DE algorithm for solving the TSCOPF problem is illustrated in Fig.1 This section will explain it in detail.

Encoding the control variables in the individuals: The control variables of the problem to be optimized are first identified before applying the differential evolution algorithm to solve the TSCOPF problem, and are embedded in the individuals of differential evolution. In our problem, the set of control variables u are generator active power outputs P_{gi} except the slack unitP_{g1}, generator voltage magnitudes V_{gi}, tap changing transformers T_{ti}, and shunt reactive power injections Q_{ci} There fore, u can be expressed as

$$u^T = [P_{g2}, \ldots\ldots . P_{gNg}, V_{g1}, \ldots\ldots . V_{gNg}, T_{t1}, \ldots\ldots . T_{tNt}, Q_{C1}, \ldots\ldots . Q_{CNc}] \quad (29)$$

Selection of population size: The proper selection of the population size N_P generally dependents on the size of the problem. For the real-world engineering problems with C control variables, N_P=20C will probably be sufficient and it is difficult to obtain the optimal solutions with N_P<2C[16]. The population size N_P=3-5C is best suited for getting the possible optimal solutions.

Generation of initialization of population: *A*ll the control variables in an individual u are randomly generated within their limits according to (30) and are used as the parent population of the first generation

$$u_{i,j}^0 = rand\ 0,1\ \ u_j^{max} - u_j^{min}\ + u_j^{min} \quad (30)$$

where i ∈ {1,2,3,. . . . .,N_p}, j ∈ {1,2,. . . . . . . .C}, and $u_{i,j}^k$ denotes the control variables j in individual i at the kth generation. u_j^{min} And u_j^{max} are the lower and upper limits of the control variable j.

To satisfy the slack bus active power constraints, the following procedure is incorporated. Suppose that the total active load of the system is P_L, sum of the power that has been dispatched to all generators excluding the slack unit is P_{ds}, then it is subtracted from the total active load of the system P_L, and is assigned to the slack bus generator active power. If the assigned slack bus active power exceeds its lower or upper bounds of slack bus generator, then its active power is fixed to the limit P_{slack}^{min} or P_{slack}^{max}. The remaining active power is redistributed among the other generators proportionally.

Run the load flow method: For each individual, the Newton-Raphson power flow program is run to evaluate the power flow solutions. This step also calculates the generation of the independent generator (slack bus), and checks the power system operation constraints such as reactive power outputs, load bus voltages, line flows and voltage stability indices.

Fitness Evaluation: For each individual solution, a fitness value F_i is evaluated including the penalty functions to measure the quality of the individual as follows:

$$F_i = 1\ (f_i + K_Q F_{Qi} + K_v F_{Vi} + K_S F_{Si} + K_L F_{Li}) \quad (31)$$

$$F_{Qi} = \sum_{i=1}^{N_g} (|Q_{Gii} - Q_{Gii}^{lim}|)^2 \quad (32)$$

$$F_{Vi} = \sum_{i=1}^{N_{pq}} (|V_{PQii} - V_{PQii}^{lim}|)^2 \quad (33)$$

$$F_{Si} = \sum_{i=1}^{Nl} (|S_{li} - S_{li}^{lim}|)^2 \quad (34)$$

$$F_{Li} = \sum_{i=1}^{Npq} (|L_j - L_j^{lim}|)^2 \quad (35)$$

where f_i is the system generating fuel cost, F_{Vi} and F_{Qi} denote the sum of the normalized violations of PQ-bus voltages and generator reactive power outputs of individual i, respectively ; N_{pq} is the total number of PQ buses; V_{PQii}^{lim} and Q_{Gii}^{lim} denote the violated upper and lower limits of the voltages of the load buses ($V_{PQii}^{max}, V_{PQii}^{min}$) and the generator's reactive power outputs($Q_{Gii}^{max}, Q_{Gii}^{min}$), respectively; K_Q and K_v are the corresponding penalty coefficients. F_{PS}, denotes the violation of slack bus active power limitation of individual i. P_{slack}^{min}, and P_{slack}^{max} are the limits of it. Generally an individual is better if its fitness value is higher.

Transient stability assessment: Since the transient stability is a condition to be satisfied and not an objective for optimization, the transient stability is not included into the fitness function. Therefore, each individual is assigned an index if that particular individual can maintain the stability of the system under the selected contingency and it will take the effect in the selection procedure during evolution.

Since transient stability assessment will be very time-consuming because the searching space is huge for TSCOPF optimization problems, only certain percentages of the population with better fitness will undergo the TSA calculation to evaluate some stable individuals to push the population converging to a feasible and stable space. This operation reduces the computational burden without deteriorating the reproduction characteristics of the evolution.

Global best individual: It is just the best one in the initial population the global best individual u_{best} denotes the best individual obtained from all the generations. To find u_{best} individuals, two individuals u_a and u_b are compared in a particular generation, u_a is defined " better" than u_b if one of the following conditions is matched:

If both of them are stable, u_a, has higher fitness value:
If both of them are unstable, u_a, has higher fitness value:
If u_a, is stable, while u_b is unstable.

Reproduction: *The* offspring population is reproduced by perturbing the value of each control variables of each individual in the present population. The following reproduction scheme is used to reproduce the offspring for an individual i.e in the kth generation.

$$u_{i,j}^{\prime k} = u_{i,j}^{k} + d1\ u_{best,j} - u_{i,j}^{k}\ + d2(u_{r1,j}^{k} - u_{r2,j}^{k}) \quad (36)$$

where $u_{best,j}$ is the control variable j of the best individual, r1 ≠r2≠I are integers randomly selected in rage of [1,N_p]; the parameters d_1 and d2 take values randomly from the range of [0,1] once per individual,. If $u_{i,j}^{\prime k}$ is outside the feasible range of [u_j^{min}, u_j^{max}], it is fixed to the limit u_j^{min} or u_j^{max} .

Selection: The selection scheme can be denoted as a "one- to-one" selection. An offspring individual $u^{\prime k}$ is compared with its parent individual u_i^k, and the better one is finally selected. The selected individuals form the updated population of generation k, and it will be used as the parent population of the next generation.

Global best individual updation: The best individual of the updated population of generation k is found out and noted as u_{best}^k. If u_{best}^k is better than u_{best}, then u_{best} is replaced by u_{best}^k ; otherwise u_{best} remains unchanged. The updated u_{best} will be used in the reproduction of the next generation.

SIMULATION RESULTS

IEEE 30-bus system results

In this section, the proposed DE method is tested on the IEEE six-generator, 30-bus system. In test system, the classical generator model is used for synchronous generator and loads are modeled as constant impedances. Integration time step is 0.01 s for transient stability simulation, the whole simulation period is 2.0s. For each test case, totally 20 trial runs are performed to verify the robustness of the proposed method. The developed MATLAB program is run using MATLAB 7.8 running on Intel Core 2 Duo, 2 GHz, and 2.0 GB RAM PC.

The differential evolution the following set of control parameters were implemented and tested. The values of control parameters used in this algorithm are, namely CR = 0.8 and F = 0.1,

The test system consists of six generating units interconnected with 41 branches of a transmission network with a total load of 283.4 MW and 126.2 MVAR as shown in Fig. 1. The bus data and the branch data are taken from [11]. There are 4 transformers with off-nominal tap ratio. The shunt injections are provided at buses 10, 12, 15, 17, 20, 21, 23, 24 and 29. In this case study, bus 1 is considered as the swing bus. The maximum and minimum values for the generator voltage and tap changing transformer control variables are 1.1 and 0.9 in per unit respectively. The maximum and minimum voltages for the load buses are considered to be 1.1 and 0.95 in per unit. The line flow limits are taken from [11, 12].

In the simulation studies, a fuzzy logic composite criteria (FLCC) based network contingency ranking is carried out to determine the rank-1 network contingency [13]. The FLCC based network contingency method takes the pre/post contingency line loadings, load bus voltages, voltage stability indices, and reactive power outputs of generators for ranking. Instead of assessing the transient stability under the randomly selected network contingency, TSA is done under the rank-1 network contingency for testing the effectiveness of the proposed algorithm. Various equality and inequality constraints, including the voltage stability and transient stability constraints are considered during the solution of the OPF problem.

The proposed DE algorithm is applied for solving the optimal power flow problems without and with induction motor loads and with different equality and inequality constraints including voltage/transient stability constraints. The best values of control parameters F and CR obtained are 0.1 and 0.8 respectively. The population size is set as 50 and the maximum generation number is 150. As a rough try 1/4th of the population will undergo the transient stability assessment under the rank-1 contingency case. A three phase to ground fault at bus 8 and cleared by tripping line 8–11 is considered as large disturbance. All the solutions satisfy the constraints on reactive power generation limits and line flow limits. Fig. 2 show the convergence of the cost of generation with the DE algorithm for the best run under normal operation. From the Fig.2 it can be observed that the DE algorithm reaches the best solution within 100 iterations.

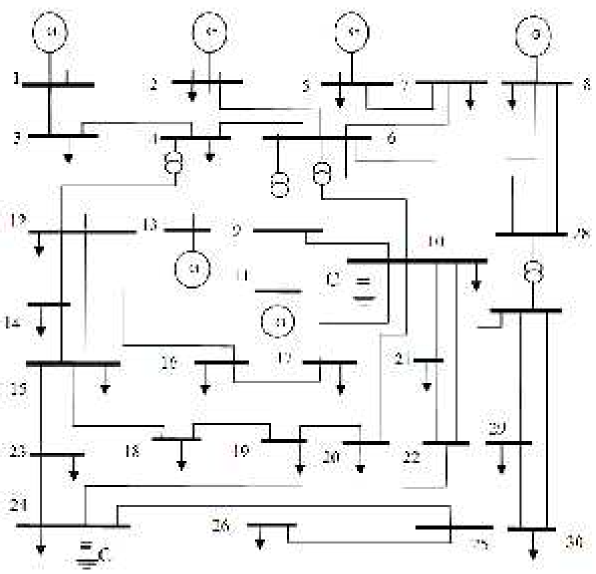

Figure 1 Single line diagram of IEEE 30-bus test system

The optimal settings of the control variables for the best result of OPF problem obtained by the DE, method re given in Table 1. The cost of generation, real power loss, maximum voltage stability index, are also given in Table 1. It can be found that the proposed DE method gives lower values for cost of generation, power loss and voltage stability index than the values obtained with Base case.

The Fig. 3 show the stable trajectories of relative rotor angles of best solutions obtained with DE algorithm. The load bus voltages, voltage stability indices and percentage line loadings are maintained within their lower and upper limits after optimization. The comparison of the cost of generation with other methods reported in the literature is given in Table 2. It can be seen from the Table 2 that the proposed DE algorithm gives best cost of generation for OPF compared with other methods reported in the literature.

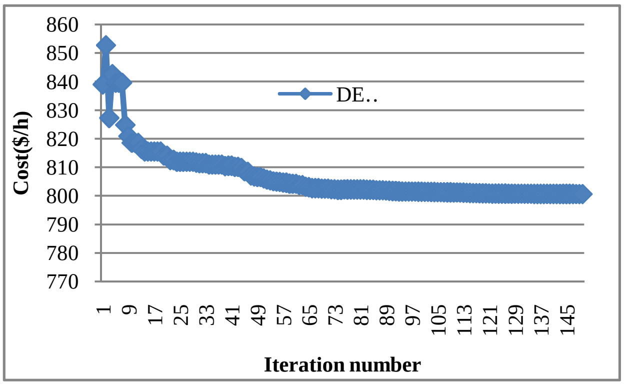

Figure 2 Convergence of cost of generation of IEEE 30-bus system

Table 1 Optimal settings of control variables for IEEE 30-bus system

Control variables(p.u.)	Base Case	
P_{g1}	0.9873	1.7772
P_{g2}	0.80	0.5019
P_{g3}	0.20	0.2047
P_{g4}	0.20	0.1061
P_{g5}	0.50	0.2136
P_{g6}	0.20	0.1200
V_{g1}	1.050	1.1000
V_{g2}	1.045	1.0860
V_{g3}	1.010	1.0620
V_{g4}	1.050	1.0547
V_{g5}	1.010	1.0583
V_{g6}	1.050	1.0553
T_{t1}	0.978	0.9700
T_{t2}	0.969	1.0900
T_{t3}	0.932	1.0600
T_{t4}	0.968	0.9900
Q_{c10}	0	0
Q_{c12}	0	0.1800
Q_{c15}	0	0.0600
Q_{c17}	0	0.1200
Q_{c21}	0	0.1800
Q_{c22}	0	0
Q_{c23}	0	0
Q_{c24}	0	0.0600
Q_{c29}	0	0
Cost($/h)	900.5995	800.1386
Ploss(p.u.)	0.0533	0.0915
Ljmax	0.1456	0.1200

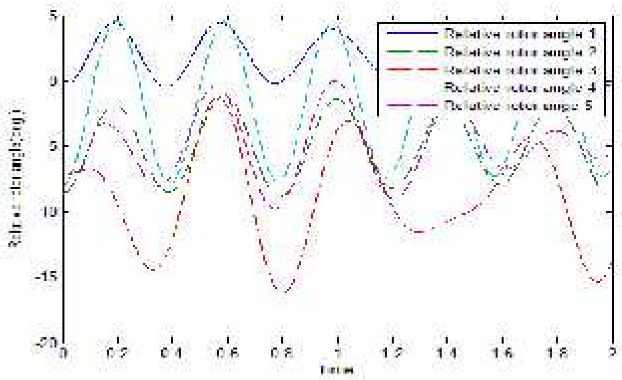

Figure 3 Stable trajectory of rotor angles of IEEE 30-bus

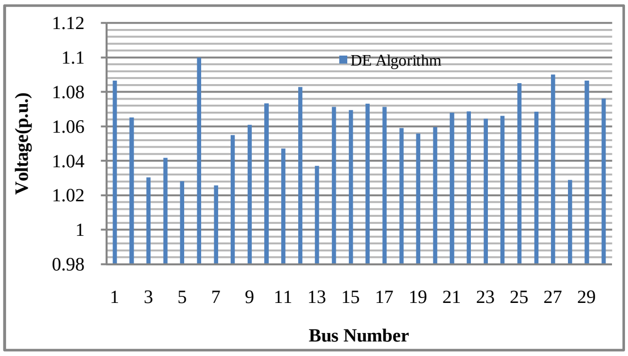

Figure 4 Voltage stability indices IEEE 30-bus system

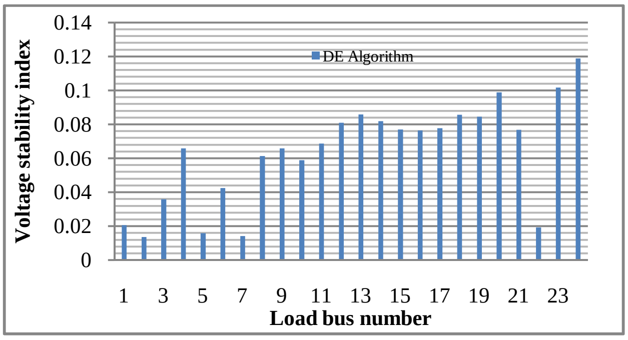

Figure 5 Load bus voltage stability indices of IEEE 30-bus system

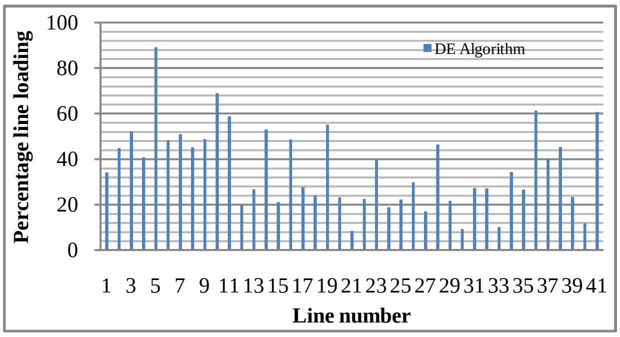

Figure 6 Percentage line loadings of IEEE 30-bus system

Table 2 Comparison of fuel costs

Method	Cost($/h)
Base Case	900.5995
MATPOWER [14]	804.0600
IPM	803.986
IEP [15]	802.4650
GA	805.3076
EP	801.1315
PSO	800.3484
DE	800.1386

CONCLUSION

In this paper, a robust and efficient E method for solving TSOPF problems has been developed to meet the pressing need of the modern power systems. The robustness and effectiveness of the proposed method have also been verified based on the simulation results. The proposed approach has been successfully and effectively implemented on the IEEE 30–bus test system. The results clearly indicate that better solutions are obtained using this proposed approach when compared with other methods reported in the literature. It is found that the proposed method is not only able to ensure the lower fuel cost solution compared with other reported results in the literature but also maintain transient stability of the system.

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How to cite this article:

Venkateswarlu, B., Vaisakh, K and Sujatha, P.2017, Solving Transient Security Constrained Optimal Power Flow Problem Using Differential Evolution Algorithm. *Int J Recent Sci Res.* 8(1), pp. 15041-15047.