A MODIFIED PARTICLE SWARM OPTIMIZATION TECHNIQUE FOR SOLVING TRANSIENT STABILITY CONSTRAINED OPTIMAL POWER FLOW

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ABSTRACT

This paper presents an improved Particle Swarm Optimization (PSO) algorithm for solving Transient Stability Constrained Optimal Power Flow (TSCOPF) problem through the application of Gaussian and Cauchy probability distributions. The modified PSO approach introduces new diversification and intensification strategy into the particles thus preventing PSO algorithm from premature convergence. The controllable system quantities are optimized to minimize fuel cost of the power generation. An IEEE 30-bus test system is taken for investigation. The transient stability constrained optimal power flow results obtained using the improved PSO models are compared with those obtained using standard PSO and GA algorithms. The investigations reveal that the proposed algorithm is relatively simple, reliable and efficient and suitable for on-line applications.

KEYWORDS: *Optimal power flow, Transient stability, Particle swarm optimization, Gaussian probability distribution function, Cauchy probability distribution function*

1. INTRODUCTION

Optimal Power Flow (OPF) has been an area of active research since it was proposed in the 1960 [1]. The main objective of an OPF problem is to determine the optimal operating state of the power system. This is achieved by optimizing the objective function while satisfying certain specified constraints [2] - [3]. The OPF problem can be constructed with a number of different operational objectives. The widely considered objective is to minimize the fuel cost subject to network and generator operation constraints. Several mathematical techniques like non linear programming (NLP), quadratic programming (QP), linear programming (LP), Newton method and interior point methods (IPM) have been applied to solve the OPF Problem [4]. These classical methods are limited in handling algebraic functions and unable to consider the dynamic characteristics [5].

The integration of the economic and security aspects of the power system into one mathematical formulation has made OPF as a powerful tool in both planning and operating stages. Hence many researchers and power system planners and operators are attracted towards the solution of this problem. Momoh [6] in 1995 at IEEE winter power meeting in the panel session presented a paper on challenges to OPF where the voltage and angle stability of the power system were discussed. From then on Transient Stability Constrained OPF (TSCOPF) was launched and the research is being carried on. Generally, TSCOPF problem is nonlinear optimization problem with both algebraic and differential equations, which are difficult to solve even for smaller power systems. The main difficulties experienced in solution of TSCOPF are the representation of differential equation which describes the dynamic behavior of the power system. The research in TSCOPF problem has been carried out in two different directions. In first case, the TSCOPF problem is formulated as an extended OPF problem with rotor angle inequality constraints. Here the position of the rotor angle is used to indicate the stability of the system [7] – [8]. In second case, TSCOPF problem is converted into an equivalent optimization problem in Euclidean space [8]. From now on TSCOPF can be viewed as an initial value problem which can be solved by any standard non linear programming technique. As indicated in [9], the conventional methods like nonlinear programming, linear programming, quadratic programming, Newton method and interior point methods apply convexity and gradient principle to reach the global optimum solution. However, the OPF problem in general is a nonconvex multimodal problem. When transient stability constraints are included on the network, further many local minima is introduced in to the solution space. Hence local optimization techniques are not suitable for these problems.

Many Heuristic optimization methods like Evolutionary Programming (EP) [9] – [10], Simulated Annealing (SA) [11], and Genetic Algorithm (GA) [12] have been employed to overcome the drawbacks of conventional techniques. In 2002, Abido [13] employed a new approach called as Particle Swarm Optimization (PSO) which was inspired by the social behaviours of animals such as fish schooling and bird flocking. PSO approach utilizes global and local exploration. He has obtained the results for different objective function of the OPF problem and compared it with the reports available in the literature. The results of his work were promising and had shown effectiveness and superiority over classical techniques and Genetic Algorithms. The other main advantage of using PSO algorithm is that it requires only few parameters to be tuned.

In 2008, Coelho and Lee [14] has employed chaotic and Gaussian function in the PSO algorithm to solve economic load dispatch problem. The proposed method was tested on 15 and 20 unit test systems and it revealed that the new method has outperformed the modern metaheuristic methods. Inspired by this technique, the Gaussian and Cauchy probability distribution technique has been employed in the PSO to solve the transient stability constrained optimal power flow problem. The proposed method has been tested on IEEE 30-bus test system. The simulation results reveal that the proposed PSO approaches developed using Gaussian and Cauchy distributions helps in diversifying and intensifying the search space of the particle's swarm in PSO, thus preventing premature convergence to local minima and hence improving the performance of PSO.

2. PROBLEM FORMULATION

An optimal power solution gives the optimal active and reactive power dispatch for a static power system loading conditions. It is a valuable tool for minimizing the cost of the electric power system. The general optimal power flow problem may now be expressed as:

$$\textit{Minimise}\ f(x,u) \tag{1}$$

Subject to:

$$g(x,u)=0 \tag{2}$$

and

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

where, $f(x,u)$ is the objective function to be optimized, $g(x,u)$ is the set of equality constraints, and $h(x,u)$ is the set of inequality constraints. x is the vector of dependent variable such as slack bus power P_{G1}, load bus voltage V_L, generator reactive power output Q_G and transmission line loadings L_F. Hence x can be represented as

$$x^T=[P_{G1,}V_{L_1},V_{L_2},...V_{L_{NL}},Q_{G_1},Q_{G_2},...Q_{G_{NG}},L_{F_1},L_{F_2},...L_{F_{nl}}]$$

where NL, NG and nl are the number of load buses, number of committed generators and number of transmission lines respectively.

u is a set of independent variable like generator voltages V_G, generator real power outputs P_G except the slack bus power output, transformer tap settings T and shunt Var compensations Q_C. Hence u can be represented as

$$u^T=[P_{G_2},P_{G_3},...P_{G_{NG}},V_{G_1},V_{G_2},...V_{G_{NG}},T_1,T_2,...T_{NT},...\\ Q_{C_1},Q_{C_2},...Q_{C_{NC}}]$$

where NT and NC are the number of tap setting transformers and Number of shunt compensators respectively.

Assuming second order generator cost curves, the total generation cost objective function is

$$f(x,u)=Min\,F_T=\sum_{i=2}^{NG}\left(a_i+b_iP_{Gi}+c_iP_{Gi}^2\right)\\ +\left(a_1+b_1P_{G1}+c_1P_{G1}^2\right)\$/hr \tag{4}$$

where, F_T is the total fuel cost of the generators, P_{Gi} is the real power output generated by the i^{th} generator, a_i, b_i, c_i are the fuel cost coefficients.

The equality constraints $g(x,u)$ of the optimization problem are the equations defining the power flow problem. As mentioned in [2], Newton load flow polar power mismatch formulation is particularly suitable for the optimization study. The relevant equations are

$$P_i(V,\theta)+P_{Di}-P_{Gi}=0 \tag{5}$$

$$Q_i(V,\theta)+Q_{Di}-Q_{Gi}=0 \tag{6}$$

where, Q_{Gi} is the reactive power generations at i^{th} bus.

P_{Di} and Q_{Di} are the active and reactive power demands at i^{th} bus.

P_i and Q_i are the active and reactive power injections at i^{th} bus .

The inequality constraints comprises of limits for equipment loading and operating requirements. The system operation constraints consist of the transmission line loadings L_F, load bus voltages V_L, reactive power output of generator Q_G, and real power generation of slack generator P_{G1}

Generator voltages, real power outputs, reactive power outputs, transformer taps and transmission lines loadings are restricted by their lower and upper limits as follows,

$$V_{Gi}^{\min}\le V_{Gi}\le V_{Gi}^{\max};\ i=1,2,3,...NG \tag{7}$$

$$P_{Gi}^{\min}\le P_{Gi}\le P_{Gi}^{\max};\ i=1,2,3,...NG \tag{8}$$

$$Q_{Gi}^{\min}\le Q_{Gi}\le Q_{Gi}^{\max};\ i=1,2,3,...NG \tag{9}$$

$$T_{\min}^{i}\le T^{i}\le T_{\max}^{i};\ i=1,2,...NT \tag{10}$$

$$L_{F\,i}\le L_{F\,i,\max};\ i=1,2,...nl \tag{11}$$

The transient stability problem in a power system is described by a set of differential-algebraic equations [15], which could be solved in time-domain simulation. The swing equation set for the i^{th} generator is

$$\begin{aligned}&\dot{\delta}_i=\omega_i-\omega_0\\&M_i\dot{\omega}_i=\omega_0\left(P_{mi}-P_{ei}-D_i\omega_i\right)\quad i=1,2,...N_G\end{aligned} \tag{12}$$

where

δ_i : Rotor angle of the i^{th} generator

ω_i : Rotor speed of the i^{th} generator

D_i : Damping constant of the i^{th} generator

P_{mi} : Mechanical input power of the i^{th} generator

P_{ei} : Electrical output power of the i^{th} generator

ω_0 : Synchronous speed

For simplicity the criterion for transient stability is defined as the rotor angle deviation with respect to the centre of inertia (COI), and hence the inequality constraints of transient stability are formulated as

$$\left|\delta_i-\delta_{COI}\right|_{\max}\le\delta_{\max} \tag{13}$$

where $\left|\delta_i-\delta_{COI}\right|_{\max}$ corresponds to maximum rotor angle deviation of the i^{th} generator from COI, and $\delta_{\max}$ is the maximum allowable rotor angle deviation. The setting of $\delta_{\max}$ is often based on operational experience. The position of COI is defined as

$$\delta_{COI}=\frac{\sum_{i=1}^{NG}M_i\delta_i}{\sum_{i=1}^{NG}M_i} \tag{14}$$

where M_i is the moment of inertia of the i^{th} generator.

3. PARTICLE SWARM OPTIMIZATION

3.1 Overview of PSO

The PSO method was introduced in 1995 by Kennedy and Eberhart [16]. The method is motivated by social behaviour of organisms such as fish schooling and bird flocking. PSO provides a population-based search procedure. Here individuals called as particles change their positions with time. These particles fly around in a multidimensional search space. During flight, each particle adjusts its position according to its own experience, and the experience of neighbouring particles. Thus each particle makes use of the best position encountered by itself and its neighbours. The direction of the particle is given by the set of particles neighbouring the particle and its past experience. Let x_i and v_i denote the particle position and its corresponding velocity in the search space. *pbest* is the best previous position of the particle and *gbest* is the best particle among all the particles in the group. The velocity and the position for each particle is calculated by using the following formulae

$$v_i^{t+1}=k\begin{pmatrix}w.v_i^t+\varphi_1.rand()\left(pbest-x_i^t\right)+\\ \varphi_2.rand()\left(gbest-x_i^t\right)\end{pmatrix} \tag{15}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \quad (16)$$

where x_i and v_i are the current position and velocity of the i^{th} generation, w is the inertia weight factor, φ_1 and φ_2 are acceleration constants, $rand()$ is the function that generates uniform random number in the range [0,1] and k is the constriction factor introduced by Eberhart and Shi to avoid the swarm from premature convergence and to ensure stability of the system. Mathematically, k can be determined as follows

$$k = \frac{2}{\left|2-\varphi-\sqrt{\varphi^2-4\varphi}\right|} \quad (17)$$

where $\varphi = \varphi_1 + \varphi_2$ and $\varphi > 4$

The selection of w provides a balance between global and local explorations. In general, the inertia weight w is set as

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{t_{\max}} \times t \quad (18)$$

where $t_{\max}$ is the maximum number of iterations or generations and $w_{\max}$ and $w_{\min}$ are the upper and lower limit of the inertia weight.

3.2 Algorithm for the solution of TSCOPF problem using PSO

The various steps involved for solving the TSCOPF problem using the PSO algorithm is given below.

Step 1: The elements in the swarm are the independent variables like real power outputs of the generating units excluding the slack bus unit, bus voltage magnitudes, switchable shunt capacitors and off-nominal transformer tap ratios. The particles in the swarm of size N_p is generated randomly as follows:

Consider the i^{th} particle,

$$x_i = [P_{G_2}^i, \ldots P_{G_j}^i, \ldots P_{G_{NG}}^i, V_{G_1}^i, \ldots V_{G_j}^i, \ldots V_{G_{NG}}^i, T_1^i, \ldots T_j^i, \ldots T_{NT}^i, Q_{C_1}^i, \ldots Q_{C_j}^i, \ldots Q_{C_{NC}}^i]; i = 1,2 \ldots NP$$

The components of x_i are generated as

$P_{G_j}^i \sim U(P_{G_{j,\min}}, P_{G_{j,\max}})$,

$V_{G_j}^i \sim U(V_{G_{j,\min}}, V_{G_{j,\max}})$,

$T_j^i \sim U(T_{j,\min}, T_{j,\max})$ and

$Q_{c_j}^i \sim U(Q_{c_{j,\min}}, CQ_{c_{j,\max}})$

where $U(P_{G_{j,\min}}, P_{G_{j,\max}})$, $U(V_{G_{j,\min}}, V_{G_{j,\max}})$, $U(T_{j,\min}, T_{j,\min})$ and $U(Q_{c_{j,\min}}, Q_{c_{j,\max}})$ denotes a uniform random variable.

Load flow is run for each particle x_i and the reactive power generations, system transmission loss, slack bus generation and line flows are calculated.

Step 2: The fitness function for each particle of the swarm is computed as:

$$f_i = F_{Ti} + k_1 P_{G1}^{i,\lim} + k_2 \sum_{m=1}^{NL} V_{Lm}^{i,\lim} + k_3 \sum_{m=1}^{NG} Q_{Gm}^{i,\lim} + k_4 \sum_{m=1}^{nl} L_{Fm}^{i,\lim} + k_5 \sum_{m=1}^{NG} \delta_m^{i,\lim}; \quad (19)$$

$i = 1,2,\ldots NP$

where k_1, k_2, k_3, k_4 and k_5 are penalty factors for the constraint violations, F_{Ti} is the total fuel cost of the i^{th} particle.

$$P_{G1}^{i,\lim} = \begin{cases} P_{G1}^{\min} - P_{G1}^i, if\ P_{G1}^i < P_{G1}^{\min} \\ P_{G1}^i - P_{G1}^{\max}, if\ P_{G1}^i > P_{G1}^{\max} \end{cases} \quad (20)$$

$$Q_{G_m}^{i,\lim} = \begin{cases} Q_{G_m}^{\min} - Q_{G_m}^i, if\ Q_{G_m}^i < Q_{G_m}^{\min} \\ Q_{G_m}^i - Q_{G_m}^{\max}, if\ Q_{G_m}^i > Q_{G_m}^{\max} \end{cases} \quad (21)$$

$$V_{G_m}^{i,\lim} = \begin{cases} V_{G_m}^{\min} - V_{G_m}^i, if\ V_{G_m}^i < V_{G_m}^{\min} \\ V_{G_m}^i - V_{G_m}^{\max}, if\ V_{G_m}^i > V_{G_m}^{\max} \end{cases} \quad (22)$$

$$L_{F_m}^{i,\lim} = \begin{cases} \left|L_{F_m}^i\right| - L_{F_m}^{\max}, if \left|L_{F_m}^i\right| > L_{F_m}^{\max} \\ 0, \quad otherwise \end{cases} \quad (23)$$

To determine the violation in the transient stability, transient stability simulation is evaluated to obtain the rotor responses of the generator. The maximum rotor angle deviation from COI, among all the generators and contingencies, is used to compute the transient stability violation as follows:

$$\delta^{i,\lim} = \begin{cases} \left|\delta^i - \delta_{COI}\right|, \ if \left|\delta^i - \delta_{COI}\right| > \delta_{\max} \\ 0, \quad otherwise \end{cases} \quad (24)$$

Step 3: Compare the evaluated fitness value of each particle with its pbest. If current value is better than pbest, then set the current location as the pbest location. Furthermore, if current value is better than gbest, then reset gbest to the current index in particle array.

Step 4: If the maximum iteration number is reached, then go to step 9, else increment the iteration number

Step 5: Update the inertia weight according to equation (18)

Step 6: Update the velocity of each particle according to equation (15)

The particle velocity in k^{th} dimension is restricted by maximum value, $v_k^{\max}$. This limit enhances the local exploration of the problem space. To ensure uniform velocity through all the dimensions, the maximum velocity in the k^{th} dimension is proposed as

$v_k^{\max} = \dfrac{x_k^{\max} - x_k^{\min}}{N}$ where N is the chosen number of intervals.

Step 7: Update the position of each particle according to equation (16)

If the particle violates the position in any dimensions, then set its position at proper limit.

Step 8: Return to step 2 and repeat the evaluation process with the updated position.

Step 9: The particle that generates the latest gbest is the optimal solution.

4. MODIFIED PSO APPROACHES BASED ON GAUSSIAN AND CAUCHY DISTRIBUTION FOR SOLVING TSCOPF PROBLEM

Coelho and Krohling proposed the use of truncated Gaussian and Cauchy probability distribution to generate random numbers for the velocity updating equation of PSO. In this paper, new approaches to PSO are proposed which are based on Gaussian probability distribution (Gd) and Cauchy probability distribution (Cd). In this new approach, random numbers are generated using Gaussian probability function and/or Cauchy probability function in the interval [0,1].

The Gaussian distribution (Gd), also called normal distribution is an important family of continuous probability distributions. Each member of the family may be defined by two parameters, location and scale: the mean and the variance respectively. A standard normal distribution has zero mean and variance of one. Hence importance of the Gaussian distribution is due in part to the central limit theorem. Since a standard Gaussian distribution has zero mean and variance of value one, it helps in a faster convergence for local search.

This work proposes new PSO approaches with combination of Gaussian distribution and Cauchy distribution function. The modification to the conventional PSO (Model 1) proceeds as follows:

Model 2: Here the Gaussian distribution, is used to generate random numbers in the interval [0, 1], in the Cognitive part (Individual Thinking) of the particle. The modified velocity equation is given by

$$v_i^{t+1} = k\begin{pmatrix} w.v_i^t + \varphi_1.Gd()\left(pbest - x_i^t\right) + \\ \varphi_2.rand()\left(gbest - x_i^t\right) \end{pmatrix}$$

Model 3: Here the Gaussian distribution Gd, is used to generate random numbers in the interval [0,1], in the Social Part of the particle. The modified velocity equation is given by

$$v_i^{t+1} = k\begin{pmatrix} w.v_i^t + \varphi_1.rand()\left(pbest - x_i^t\right) + \\ \varphi_2.Gd()\left(gbest - x_i^t\right) \end{pmatrix}$$

Model 4: Here the Gaussian distribution Gd, is used to generate random numbers in the interval [0,1], in the Cognitive and Social Part. The modified velocity equation is given by

$$v_i^{t+1} = k\begin{pmatrix} w.v_i^t + \varphi_1.Gd()\left(pbest - x_i^t\right) + \\ \varphi_2.Gd()\left(gbest - x_i^t\right) \end{pmatrix}$$

Model 5: Here the Cauchy distribution Cd, is used to generate random numbers in the interval [0,1], in the Cognitive Part. The modified velocity equation is given by

$$v_i^{t+1} = k\begin{pmatrix} w.v_i^t + \varphi_1.Cd()\left(pbest - x_i^t\right) + \\ \varphi_2.rand()\left(gbest - x_i^t\right) \end{pmatrix}$$

Model 6: Here the Cauchy distribution Cd, is used to generate random numbers in the interval [0,1], in the Social Part. The modified velocity equation is given by

$$v_i^{t+1} = k\begin{pmatrix} w.v_i^t + \varphi_1.rand()\left(pbest - x_i^t\right) + \\ \varphi_2.Cd()\left(gbest - x_i^t\right) \end{pmatrix}$$

Model 7: Here the Cauchy distribution Cd, is used to generate random numbers in the interval [0,1], in the Cognitive and Social Part. The modified velocity equation is given by

$$v_i^{t+1} = k\begin{pmatrix} w.v_i^t + \varphi_1.Cd()\left(pbest - x_i^t\right) + \\ \varphi_2.Cd()\left(gbest - x_i^t\right) \end{pmatrix}$$

Model 8: Here the Gaussian distribution Gd, is used to generate random numbers in the interval [0,1], in the Social Part and Cauchy Distribution Cd, is used to generate random numbers in the interval [0,1] in the Cognitive Part. The modified velocity equation is given by

$$v_i^{t+1} = k\begin{pmatrix} w.v_i^t + \varphi_1.Cd()\left(pbest - x_i^t\right) + \\ \varphi_2.Gd()\left(gbest - x_i^t\right) \end{pmatrix}$$

Model 9: Here the Cauchy distribution Cd, is used to generate random numbers in the interval

[0,1], in the Social Part and Gaussian Distribution Gd, is used to generate random numbers in the interval [0,1] in the Cognitive Part. The modified velocity equation is given by

$$v_i^{t+1} = k\begin{pmatrix} w.v_i^t + \varphi_1.Gd()\left(pbest - x_i^t\right) + \\ \varphi_2.Cd()\left(gbest - x_i^t\right) \end{pmatrix}$$

The above models that have been developed are implemented in the conventional PSO approach and their performances were studied.

5. TEST CASE AND SIMULATION RESULTS

The standard IEEE 30-bus test system [18] is used to test the effectiveness and robustness of the proposed models.

The IEEE 30 – bus test system consists of 6 generators, 41 transmission lines with a total real power demand of 189.2 MW and reactive power demand of 107.2 MVAR. The generation cost data and the load data for the IEEE 30-bus test system are shown in Table 1 and Table 2 respectively. The objective function is the total fuel cost and the fuel cost curve of the units is represented by quadratic cost functions. The lower voltage-magnitude limits at all buses are 0.95 p.u., and the upper limits are 1.1 p.u. for generator buses and 1.05 p.u. for the remaining buses including the slack bus 1.

Table1 Generator data

Bus No	P_G^{min} Mw	P_G^{max} MW	Q_G^{min} MVAR	S_G^{max} MVA	Cost coefficients		
					a	b	c
1	50	200	-20	250	0.0	2.0	0.00375
2	20	80	-20	100	0.0	1.75	0.0175
5	15	50	-15	80	0.0	1.0	0.0625
8	10	35	-15	60	0.0	3.25	0.00834
11	10	30	-10	50	0.0	3.0	0.025
13	12	40	-15	60	0.0	3.0	0.025

Table 2 Load data

Bus No	Load		Bus No	Load	
	MW	MVAR		MW	MVAR
1	0.0	0.0	16	3.5	1.8
2	21.7	12.7	17	9.0	5.8
3	2.4	1.2	18	3.2	0.9
4	7.6	1.6	19	9.5	3.4
5	0.0	0.0	20	2.2	0.7
6	0.0	0.0	21	17.5	11.2
7	22.8	10.9	22	0.0	0.0
8	30.0	30.0	23	3.2	1.6
9	0.0	0.0	24	8.7	6.7
10	5.8	2.0	25	0.0	0.0
11	0.0	0.0	26	3.5	2.3
12	11.2	7.5	27	0.0	0.0
13	0.0	0.0	28	0.0	0.0
14	6.2	1.6	29	2.4	0.9
15	8.2	2.5	30	10.6	1.9

Two cases are considered to study the effect of incorporating the transient stability constraint into the OPF problem. In case 1, basic OPF problem is solved using the proposed PSO models. In case 2, a disturbance is introduced into the test system and the OPF problem is solved with the inclusion of transient stability constraint. For analysis purpose a disturbance in the form a three phase fault was introduced into the system near the bus 2 of line 2 – 5 at t=0.1 s. The fault was subsequently cleared at t=0.18 s. Each PSO approaches are implemented in Matlab. Power system tool box is used to perform time domain simulations. All the programs are executed on 3 GHz, Pentium Duo processor with 3 GB RAM. The parameters used in the proposed PSO models and GA are shown in Table 3.

Table 3 Parameter settings

PSO Parameters	GA Parameters
Swarm Size = 50	Population Size = 50
Initial Inertia weight = 1.5	Crossover rate p_c = 0.6
Acceleration constants $\varphi_1 = \varphi_2 = 2.05$	Mutation rate p_m = 0.05
Maximum iteration no =50	Maximum generation no = 50

Table 4 Limit violations corresponding to an initial trial solution

Randomly chosen 10 particles in initial trial solution	Source bus numbers having reactive power generation limit violation	Load buses having voltage magnitude limit violation	Line numbers having limit violation
Particle 1	1,7	26,28,29,30	7
Particle 2	1,3	10	3
Particle 3	1	25	4,8
Particle 4	1,2,3,8	18-28, 30	2,6
Particle 5	1,15,19	10-25, 29	4,8
Particle 6	1,8	25-30	3
Particle 7	1,7	26,28,30	2,5
Particle 8	1,2,10	-	4
Particle 9	-	12,13,16, 19, 20-27, 28, 30	7,9
Particle 10	10	12	10

5.1 Base-case OPF results

In this case the OPF problem is solved using the proposed PSO models without any disturbance. The violations in reactive power generation, load bus voltage magnitude and line flow limit in the base case for each randomly chosen 10 initial particle from the swarm size of 50 are given in Table 4. Table 4 reveals that there are several reactive power generation, load bus voltage magnitude, and MVA line flow limit violations of both maximum and minimum limit with each particle. The reactive power generation limit violations are found to be in the range of 0–95% of its minimum or maximum limit. The load bus voltage limit violations are found to be in the range of 0–7% of its minimum or maximum limit. The line flow limit violations are found to be in the range of 0–30% of its line rating.

To evaluate the performance of the proposed models discussed in Section 4, 100 independent runs were made involving 100 different initial trial solutions. The optimum schedule, total fuel cost and transmission loss obtained with the proposed 9 models are shown in Table 5. From the Table 5 it is clear that the results obtained with Model 9 is minimum among all other proposed models. This is because of the fact that social interaction of the particle is enhanced by Cauchy distribution function and the individual cognition thinking of the particle is improved by Gaussian distribution function. Thus the proposed Model 9 has yielded a better performance for the OPF problem. The other models which use the combinations of uniform probability function, Gaussian probability function and Cauchy probability function get struck at suboptimal values. The convergence characteristic of fitness function for one of the trial solution obtained for the proposed 9 models of the PSO are shown in Fig. 2. The fitness function convergence characteristic is drawn by taking the particle with minimum fitness value at the end of every iteration.

It is seen from Fig. 2, that the fitness function converges smoothly to the optimum value without any abrupt oscillations for all the proposed 9 Models. This shows the convergence reliability of the proposed models.

Table 5 Optimized schedules using basic PSO

Models	P_{G1}	P_{G2}	P_{G3}	P_{G4}	P_{G5}	P_{G6}	Total Cost ($/Hr)
Model 1	42.63	38.05	42.29	34.49	19.04	15.54	579.32
Model 2	55.60	30.00	35.76	23.35	18,22	29.15	580.35
Model 3	53.89	59.62	40.84	12.97	11.99	12.73	581.55
Model 4	63.45	28.47	38.02	15.96	17.67	28.48	580.25
Model 5	48.03	36.22	25.91	32.26	14.37	36.15	581.07
Model 6	43.94	53.19	18.91	25.38	20.69	29.93	580.35
Model 7	49.99	52.78	34.77	25.52	10.45	19.31	581.84
Model 8	60.25	42.52	45.12	13.08	12.32	18.74	580.95
Model 9	42.22	55.98	22.83	37.75	15.91	17.35	577.62

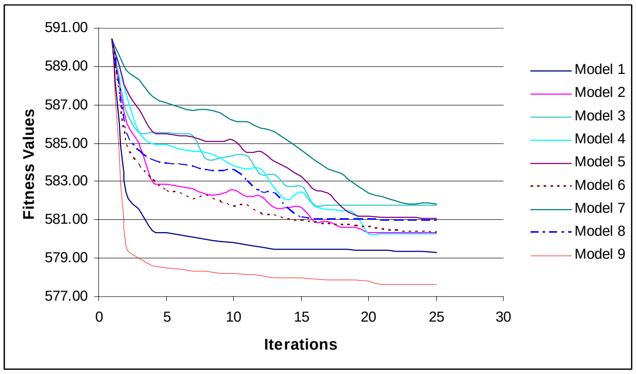

Figure 1 Convergence characteristics of the proposed models

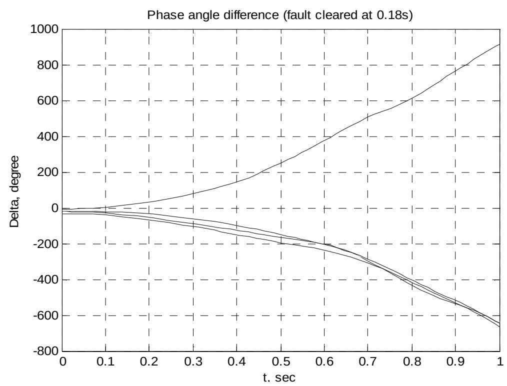

Figure 2 Rotor angle curves for base case

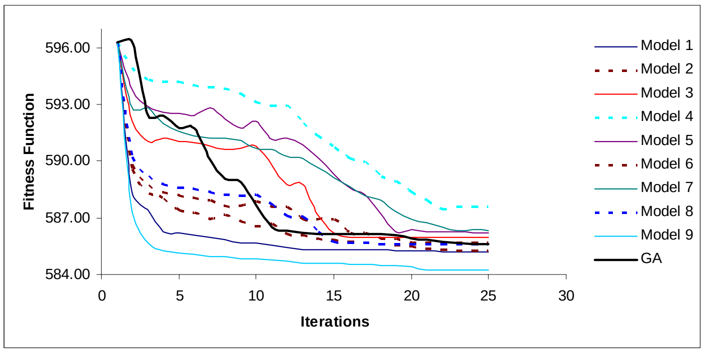

Figure 3 Convergence characteristics of the proposed models with inclusion of TSCOPF

With the optimal control variable settings the disturbance (fault on line 2) is introduced in the test system. The power system tool box is used to perform the transient stability analysis of the system. The rotor angles relative to COI for all generators obtained from the transient analysis program is shown in Fig. 2. From the Fig. 2 it is observed that conventional OPF solution fails to maintain transient stability when subjected to disturbances.

5.2 Transient Stability Constrained OPF (TSCOPF)

From the previous analysis, it is clear that conventional OPF technique does not take into consideration the transient stability constraint of the test system. Hence to overcome the above mentioned problem, the transient stability constraint has been introduced into the OPF problem.

To evaluate the performance of the proposed models discussed in Section 4, 100 independent runs were made involving 100 different initial trial solutions. The optimum schedule, total fuel cost and transmission loss obtained with the proposed Model 9 and standard GA are shown in Table 6.

From the Table 6 it is observed that the results obtained with Model 9 are closely matching with the standard GA method. The convergence characteristic of fitness function for one of the trial solution obtained for the proposed 9 models and from the standard GA is shown in Fig. 3. It is seen from Fig. 3, that the fitness function converges smoothly to the optimum value without any abrupt oscillations for the TSCOPF problem also. This shows the convergence reliability of the proposed models. Also from Fig. 3 it can be observed that the proposed Model 9 has better convergence when compared with the standard GA.

With the optimal control variable settings the disturbance (fault on line 2) is introduced in the test system. The power system tool box was used to perform the transient stability analysis of the system. The rotor angles relative to COI for all generators obtained from the transient analysis program is shown in Fig 4. From the Fig.4 it is observed that introduction of transient stability constraint into the OPF problem has secured the test system.

Table 6 Comparison of model 9 with stanard algorithm

Generators	P_{G1}	P_{G2}	P_{G3}	P_{G4}	P_{G5}	P_{G6}	Total Cost ($/Hr)
Model 9	45.21	57.50	22.01	29.12	19.21	18.99	583.17
Model 1 (Basic PSO)	43.63	58.05	23.29	32.49	17.04	17.54	585.34
GA	41.88	56.38	22.94	37.63	16.7	16.53	585.66

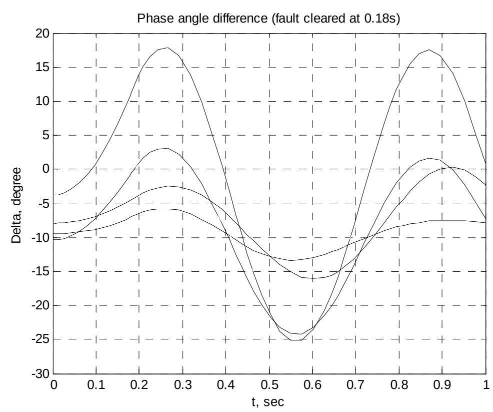

Figure 4 Rotor angle curves with TSCOPF

6. CONCLUSION

This paper has explored the feasibility of employing gaussian and cauchy probability function in the conventional PSO approach for solving of TSCOPF problem. To evaluate the searching capability of PSO algorithm, different PSO models are proposed employing gaussian and cauchy probability distribution functions. The PSO model which employs, Cauchy distribution function in the social part and Gaussian distribution function in the cognitive part has introduced the diversification and faster convergence into the particle thus preventing the PSO algorithm from premature convergence. The result obtained with IEEE 30-bus test system reveal that the proposed method is relatively simple, reliable and efficient and suitable for on-line application.

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