

# Multiple Power Flow Solutions Using Particle Swarm Optimization with Embedded Local Search Technique

P. Acharjee, S. K. Goswami

**Abstract**—Particle Swarm Optimization (PSO) with elite PSO parameters has been developed for power flow analysis under practical constrained situations. Multiple solutions of the power flow problem are useful in voltage stability assessment of power system. A method of determination of multiple power flow solutions is presented using a hybrid of Particle Swarm Optimization (PSO) and local search technique. The unique and innovative learning factors of the PSO algorithm are formulated depending upon the node power mismatch values to be highly adaptive with the power flow problems. The local search is applied on the pbest solution obtained by the PSO algorithm in each iteration. The proposed algorithm performs reliably and provides multiple solutions when applied on standard and ill-conditioned systems. The test results show that the performances of the proposed algorithm under critical conditions are better than the conventional methods.

**Keywords**—critical conditions, ill-conditioned systems, local search technique, multiple power flow solutions, particle swarm optimization.

## I. INTRODUCTION

IN recent years evolutionary/meta-heuristic/ soft-computing techniques like Genetic Algorithm (GA), Particle Swarm Optimization (PSO), fuzzy logic, Artificial Neural Network (ANN) and others have emerged as very powerful general purpose solution tools to be applied in different engineering fields such as civil, mechanical, electrical etc. [1]-[17]. Basically these tools are search techniques capable of finding the optimum solution of a problem. The most remarkable feature of these tools is that they do not impose any restriction to the nature of the search space and type of the variables [1]-[6]. Such tools are in wide use in solving many power system problems [7]-[17]. Power flow problem has also been treated as optimization problem and solved using such meta-heuristic techniques [11], [17]. Finding multiple power flow solutions, constrained power flow solutions considering physical limitations of power system components has been thought to

be the area of applications of the meta-heuristics based power flow methods.

Both the population based algorithms, GA and PSO shares many similarities [1], [6], [15], [16], [18]. In GA, the whole population moves like a one group towards an optimal area as chromosomes share information with each other [1]. In PSO the information sharing mechanism is significantly different from GA. PSO is one-way information sharing mechanism [6]. Here best solution gives the information to the others. Change in genetic populations results in destruction of previous knowledge of the problem [15]. In PSO, individuals who fly past optima are tugged to return toward them, good solutions are retained by all the particles. PSO only looks for the best solution [16], [18]. All the particles have a tendency to converge to the best solution quickly in most cases. Genetic algorithms are known to be rather inefficient in solving problems having epistatic objective functions i.e. where the parameters being optimized are highly correlated as the representation of the weights is difficult and the genetic operators have to be carefully selected or developed [1], [6], [15], [16], [18]. The power flow or the load flow of electrical power system is such a problem as it has non-linear complex characteristics with many variables. The field of swarm intelligence is an emerging research area that presents features of self-organization and cooperation principles among group members. The swarm optimization technique is now widely used in power system applications [7]-[17].

The conventional methods such as Newton Raphson, fast decoupled load flow fail to give satisfactory results under heavy loading situations [19]-[21] and can not provide multiple solutions which are important for voltage stability analysis. To overcome the drawback, the different approaches have been used in the current literature [22]-[25]. Since power flow has wide range of applications, methods have been developed giving very high as well as low level of accuracies [21]-[23]. For better accuracy local network power flow is studied developing new equations [23]. A new power flow with preconditioned conjugate gradient is developed by F. De Leon [24]. To obtain fast response nonlinear predictors and hybrid corrector is used in continuation power flow [25].

Due to the deregulated energy system, geographical constrains and increased loading situation, more and more attention has been taken for the problems associated with the voltage instability and voltage collapse. For the purpose of voltage stability assessment and to overcome voltage collapse,

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multiple load flow solutions are used [26], [27]. The power flow problem can be represented as a set of non-linear simultaneous equations. So the multiple solutions in power system can be possible [11], [28]-[33]. Unstable solutions are important to assess the stability of power system [26], [27]. Application of the Genetic Algorithm to solve the load flow problem is discussed in [11]. In [11] also multiple load flow solutions have been found out using the genetic algorithm. Overbye and Klump [28] proposed a method of determining the type-one low voltage solutions. The structure of the power equations is used to determine good initial guesses for these solutions. In [29], the multiple load flow solutions are obtained by tracing the homotopy curves. Perhaps the simplest of all the methods for finding the unstable equilibriums is the method of optimum multiplier [30]. The method is based on the rectangular version of the Newton-Raphson power flow. The optimal multiplier method determines a pair of load flow solutions- one of which is the unstable equilibrium solution of the power system. The limitation of this method is that only one of the multiple low voltage solutions can be found out. The parameterized load flow equations are solved in [31] to find all the solutions. W. Zhigang et. al. [32] proposed a new method to determine multiple power flow solutions. For three phase unbalanced circuits multiple solutions are obtained in [33].

The present paper proposes an algorithm to find the multiple solutions of the power flow problem based on a combination of Particle Swarm Optimization (PSO) and a local search technique. During each iteration of the PSO algorithm, the local search employs a perturbation mechanism on the pbest solution obtained by the PSO algorithm with an aim to obtain a better estimate of the phase angles and node voltages. To ensure convergence at the low voltage solutions instead of the normal power flow solution, voltages are initialized with lower values, whereas phase angles are assigned higher starting values. The proposed algorithm gives normal and low voltage solutions reliably for all type of systems i.e. large network systems, standard test systems and ill-conditioned systems. The performances of the PSO based power flow algorithm are better than the conventional approaches such as Newton-Raphson Load Flow (NRLF), Fast-Decoupled Load Flow (FDLF).

## II. PARTICLE SWARM OPTIMIZATION TECHNIQUE

Particle swarm optimization [18] is a population based meta-heuristic algorithm. PSO, unlike other evolutionary techniques, uses a leader-follower approach. In each generation, the fittest of the population is selected as the leader and the rest of the population then orient themselves towards the leader until the optimum solution is reached. Thus, convergence of the algorithm will mostly depend on the judicious selection of the leader [15], [34]. In PSO, candidate solutions, called particles, are associated with a velocity and a position. The particle velocity is constantly adjusted according to the experience of the particles and its companions. In a D-dimensional space the velocity  $v_{id}$  and position  $x_{id}$  of particle i are adjusted as:

$$v_{id} = w_i * v_{id} + c1 * rand() * (p_{id} - x_{id}) + c2 * Rand() * (p_{gd} - x_{id}) \quad (1)$$

$$x_{id} = x_{id} + v_{id} \quad (2)$$

Where,  $c1$  &  $c2$  are the positive constants known as learning factors and  $rand()$  &  $Rand()$  are two random functions in the range of [0,1].  $p_{id}$  represents pbest position of particle i, i.e., the best position of the particle in the current iteration, and  $p_{gd}$  denotes the gbest position of the particle i, i.e., the best position of the particle upto the present iteration.  $w_i$  is weight function for velocity of particle i.

## III. POWER FLOW PROBLEM

Power flow problem is non-linear complex problem. Power flow solution is essential for designing a new power system and for planning extension of the existing one for increased load demand. These analyses require the calculation of numerous load flows under both normal and abnormal operating conditions like outage of transmission lines, outage of some generating source. Power flow solution also provides the initial conditions of the system when the transient behaviour of the system is to be studied. In power system each node or bus is associated with four parameters such as bus voltage magnitude ( $V$ ), phase angle ( $\delta$ ), real power ( $P$ ) and reactive power ( $Q$ ). In a power flow solution two out of the four parameters are specified and the remaining two unknown quantities are required to be obtained through the solution of the equations (3) to (6).

$$P_i + jQ_i = V_i e^{j\delta_i} \sum Y_{im} e^{-j\theta_m} V_m e^{-j\delta_m} \quad (3)$$

Where,

$V_i, V_m$  = Voltage magnitude of  $i^{\text{th}}$  and  $m^{\text{th}}$  bus

$\delta_i, \delta_m$  = Phase angle of  $i^{\text{th}}$  and  $m^{\text{th}}$  bus

$Y_{im}, \theta_{im}$  = Admittance matrix element and its corresponding phase angle

$P_i, Q_i$  = Active and Reactive power respectively of  $i^{\text{th}}$  bus

$\Delta P_i, \Delta Q_i$  = Active and Reactive power mismatches of the  $i^{\text{th}}$  bus

The power flow problem solves the active and reactive power equations of the nodes of a power system. The power specified at the nodes  $P_i^{\text{specified}}$  and  $Q_i^{\text{specified}}$  are compared with the power calculated as functions of the bus voltages and phase angles  $P_i(V, \delta)$  and  $Q_i(V, \delta)$ . Small mismatch values at the buses  $\Delta P_i, \Delta Q_i$  are given by

$$\Delta P_i = P_i^{\text{specified}} - P_i(V, \delta) \quad (4)$$

$$\Delta Q_i = Q_i^{\text{specified}} - Q_i(V, \delta) \quad (5)$$

For a power system having N number of buses and G number of generator buses excluding the slack bus, (N-1) active power equations (or P-equations) and (N-G-1) reactive power equations (or Q-equations) are to be solved to determine (N-1) phase angles and (N-G-1) voltages. Load

flow equations being non-linear, iterative techniques are used for solution. The iterative techniques must estimate the voltage and phase angles such that calculated values of P & Q at each bus match closely with the specified values. When solved as an optimization problem, the load flow problem may be formulated as a problem having (2N-G-2) objective functions that are to be minimized simultaneously. As the errors may be of both the polarities, sum of their squares will be minimum when individual errors are also minimum. The second approach has been utilized in [11], [17] while applying GA and EP in the load flow problem. As the PSO needs a single value to indicate the quality of a solution, sum of the squares of the mismatches is used as the cost function. Cost function  $C_k$  for  $k^{\text{th}}$  individual of the solution population is taken as:

$$C_k = \sum_i \Delta P_i^2 + \sum_j \Delta Q_j^2 \quad (6)$$

Where  $i$  is the set of all buses except the slack bus, and  $j$  is the set of all load buses.

#### IV. PROPOSED MULTIPLE SOLUTION ALGORITHM

PSO is a general purpose optimization technique and has been successfully applied to many power system problems [2]-[6]. This characteristic of the PSO algorithm, as the authors think, makes it an appropriate tool for application in the load flow problem because it is known that the optimality condition of the power flow is the zero (negligible) node-power mismatch condition and therefore arrangement may be made to push the leader (pbest/gbest solution) towards the reduced mismatch condition and the followers will then automatically adjust themselves along the leader. It may be noted here that when multiple low voltage solutions are of interest, reactive limits of the voltage controlled buses become meaningless. Thus, the number of reactive mismatch equations equals the number of the load buses. Designing a power flow algorithm to find the multiple low voltage solutions using PSO requires identifying a suitable cost function, developing methods for the selection of the values for  $c1$ ,  $c2$  and formulating the composition of the pbest and gbest particles.

Particles of the power flow problem are the vectors of the voltages and the phase angles. The particle position corresponds to the magnitude of the voltage and phase angle, and the velocity corresponds to the correction vector. At  $k^{\text{th}}$  iteration the solution string (vectors of voltage and phase angle) corresponding to minimum value of the sum of square of mismatches is the pbest solution. The solution string corresponding to the minimum sum of the square of mismatches upto  $k^{\text{th}}$  iteration is the gbest solution at  $k^{\text{th}}$  iteration. The PSO updating rule is applied as:

$$[\Delta V]^k = w * [\Delta V]^{k-1} + c1 * rand1 * ([V]^{pbest} - [V]^k) + c2 * Rand1 * ([V]^{gbest} - [V]^k) \quad (7)$$

$$[V]^{k+1} = [V]^k + [\Delta V]^k \quad (8)$$

$$[\Delta \delta]^k = w * [\Delta \delta]^{k-1} + c1 * rand1 * ([\delta]^{pbest} - [\delta]^k) + c2 * Rand1 * ([\delta]^{gbest} - [\delta]^k) \quad (9)$$

$$[\delta]^{k+1} = [\delta]^k + [\Delta \delta]^k \quad (10)$$

$[V]$ ,  $[\delta]$  are the vectors of voltages and phase angles respectively and  $[\Delta V]$ ,  $[\Delta \delta]$  are their corresponding corrections.  $w$ ,  $c1$ ,  $c2$  are the parameters of the PSO algorithm. The PSO algorithm can give normal solutions reliably but it alone cannot find the multiple low voltage solutions unless supported by a local search technique. Local search technique is used to improve the pbest solution for faster and sure convergence. After application of local search technique whole population sets are updated through PSO technique using equations (7) to (12).

##### A. Local Search Technique

A perturbation based algorithm, local search technique is developed to update the evolutionary/meta-heuristic methods. The nodes which are directly connected to the concern node to be updated are formed local network for the concerned node as shown in Fig. 1. Local networks around  $p$  and  $q$  are shown by the encircled zones in Fig. 1. The local search is applied on the pbest solution after the application of the PSO updating rule and function evaluation. The local search searches for the availability of a better solution around the pbest solution. Since the particles always follow their leaders' pbest and gbest, it is obvious that convergence can be accelerated if the gbest/pbest can be pushed faster towards the final solutions. Though either or both of gbest and pbest may be improved for better convergence, it has been found that it is more effective to improve the pbest. The reason behind this is that, being the best solution in a particular generation, pbest changes more frequently than gbest, the best solution obtained so far. Thus improvement scheme applied on pbest works better than that applied on the gbest. Voltage magnitude and phase angle of node, say  $k$ , are perturbed at a time by small steps keeping other node-variables of the local network fixed. Since we assume constant voltage in the network outside the concerned node, computations involved in such corrections are very little, as we need to compute the changes in the flows of the lines connected to the node only. If the solution improves after perturbation, the perturbation is continued on the same bus; otherwise it is applied on the next bus in the network. Such corrections are applied to all nodes of the system and corrections leading to reduced sum square error as well as maximum error of the local networks are accepted.

##### B. Design of Constriction Factor

The constriction factors or learning factor, however, are designed to be adaptive depending upon the objective function value of the individual population with respect to the objective function of the pbest and the gbest solutions.

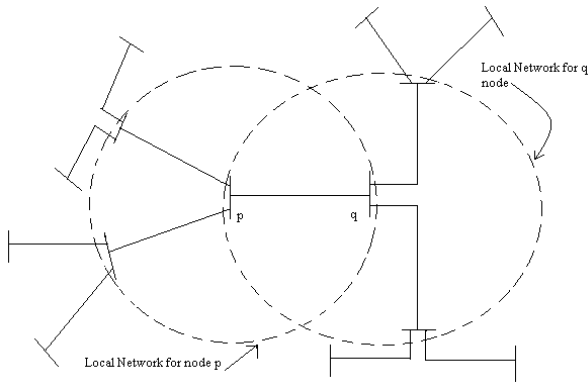


Fig.1 The formation of Local Network

For the  $p^{th}$  population, learning factors  $c_1^p$  and  $c_2^p$  (superscript p is used to indicate the population number) are designed as:

$$c_1^p = \frac{\text{Sum Square Error of } p^{th} \text{ Population}}{\text{Sum Square Error of pbest Solution}} \quad (11)$$

$$c_2^p = \frac{\text{Sum Square Error of } p^{th} \text{ Population}}{\text{Sum Square Error of gbest Solution}} \quad (12)$$

During the initial iterations  $c_1, c_2$  will take higher values as the individual population error (objective function value) will generally have higher values. But, as the convergence approaches, all the solution strings will approach the gbest and pbest solutions and  $c_1, c_2$  approach a value of unity. The inertia weight ( $w$ ) has been set to be  $w=0.5+\text{rand}/2$  as in standard PSO technique [3], [4], [15], [34].

**C. Parameter Settings**

Initialization of the population plays a very important role in this context. For multiple-low-voltage solutions, the ranges of values for which voltages and phase angles are initialized are 0.06 to 0.7 p.u. for the voltage magnitudes and 0.01 to -3.0 radian for the phase angles while for normal power flow solution these ranges are 0.9 to 1.1 p.u. and -0.01 to -0.4 radian respectively. Initializations outside the specified range may require more number of generations for convergence for the same population size. Because of highly adaptive learning factors and proper implementation of local search technique on the pbest solution, preferred low voltage solution can also be obtained according to the range-selection of the starting values of power flow variables. For assured and faster convergence, particle velocities (corrections for voltage and phase angle) are kept limited within 0.05 p.u. for voltage magnitudes and 0.25 radian for phase angles. These values are determined empirically.

**D. Flowchart of the Proposed Method**

The local search plays a key role in the convergence of the proposed multiple-power flow solution algorithm. Besides the local search, proper choices of  $c_1, c_2$  values are also very crucial for the convergence of the power flow algorithm. The solution algorithm is given in the flowchart of Fig.2.

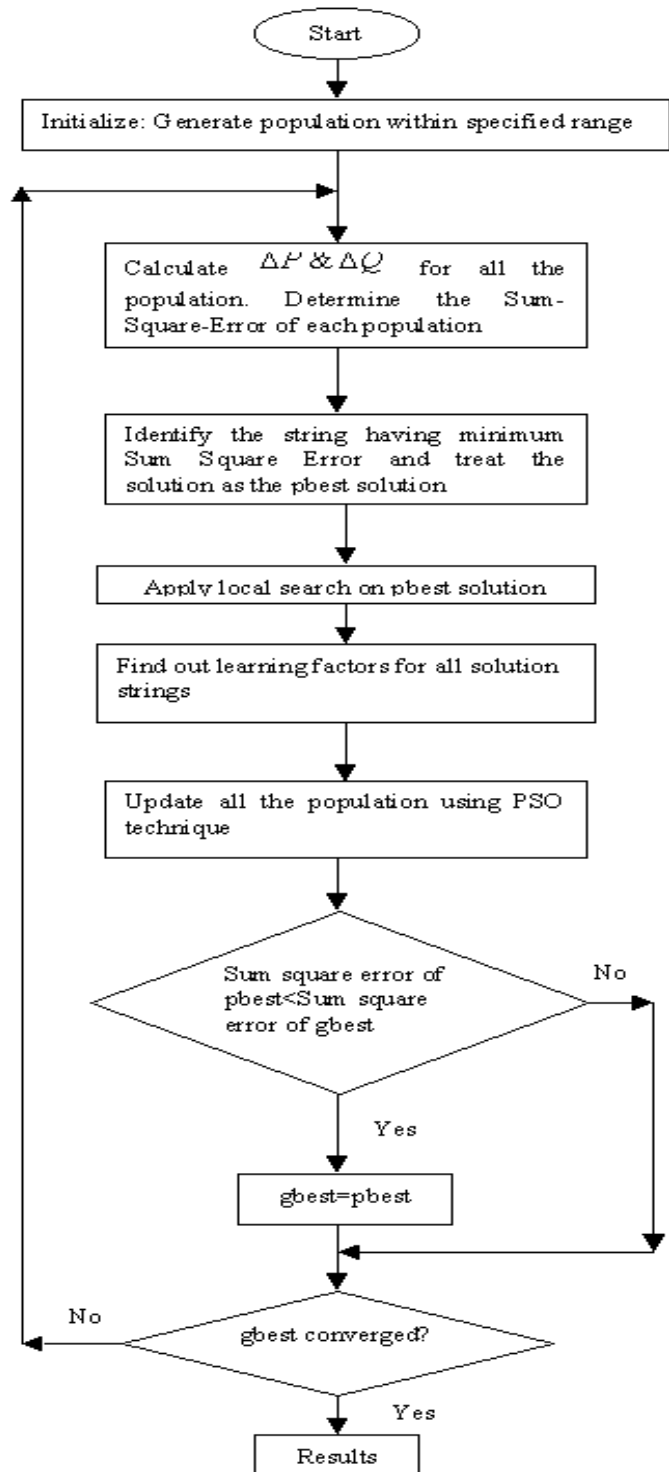


Fig. 2 Flowchart of the PSO based Load flow

V.PERFORMANCE ANALYSIS OF THE PROPOSED ALGORITHM

A. Multiple Power Flow Solutions

The proposed PSO based power flow algorithm with embedded local search can efficiently find the low voltage solutions of power networks for both standard and ill-conditioned systems. The same power flow algorithm can find the normal power flow solutions as well. Some of the low voltage solutions obtained for IEEE 30 bus test system are shown in Table I. Low voltage solutions of ill-conditioned 11 bus system are given in Table II for evidence.

TABLE I  
SOME OF THE LOW VOLTAGE SOLUTIONS OF THE 30 BUS TEST SYSTEM

Bus No.	Voltage magnitude in p.u.	Phase angle in degree	Bus No.	Voltage magnitude in p.u.	Phase angle in degree
1	1.0500	0	1	1.0500	0
2	1.0338	-6.0495	2	1.0338	-3.9579
3	0.9487	-9.2965	3	1.0003	-6.3439
4	0.9274	-11.3159	4	0.9890	-7.6393
5	1.0058	-14.7615	5	1.0058	-11.1110
6	0.9267	-12.5767	6	0.9881	-8.7363
7	0.9506	-14.0318	7	0.9873	-10.2509
8	1.0230	-14.4112	8	1.0230	-9.3577
9	0.6798	-20.0381	9	0.9125	-11.9544
10	0.3559	-34.9622	10	0.7888	-15.6175
11	1.0913	-17.1579	11	1.0913	-9.8130
12	0.7864	-32.1740	12	0.9120	-16.3713
13	1.0883	-30.5901	13	1.0883	-15.0084
14	0.6979	-35.1293	14	0.8328	-17.3473
15	0.6212	-34.3905	15	0.7708	-15.3399
16	0.5889	-33.3605	16	0.8512	-16.4193
17	0.4124	-35.3390	17	0.8008	-16.1890
18	0.4990	-37.5092	18	0.5780	-12.3497
19	0.4336	-39.1698	19	0.4712	-8.6304
20	0.4120	-38.5056	20	0.5471	-11.5751
21	0.0564	-41.7206	21	0.7448	-15.7179
22	0.1105	-38.2747	22	0.7371	-15.4309
23	0.4474	-36.5774	23	0.6984	-14.0048
24	0.2362	-40.9678	24	0.6154	-10.9226
25	0.3567	-33.5001	25	0.7567	-14.9690
26	0.2941	-37.7020	26	0.7321	-15.7693
27	0.4648	-28.9700	27	0.8587	-16.0894
28	0.8872	-12.9368	28	0.9738	-9.2722
29	0.4067	-35.7047	29	0.8472	-18.3096
30	0.3734	-41.5057	30	0.8476	-20.0381

B. Characteristics and Results

Adaptive variation of the learning factors  $c1$ ,  $c2$  is a necessity for the PSO based multiple power flow. For faster and reliable convergence the maximum limit on the learning factor is set at 25 which is determined empirically. For IEEE-30 bus system with 100 population size, variations of the maximum and average values of  $c1$  &  $c2$  are shown in Fig. 3, 4 & 5, 6 respectively. It is to be noted that the PSO based load flow algorithm fails to converge with constant values for  $c1$  &  $c2$ . From Fig. 3 to Fig. 6, it can be concluded that the learning factors are initially high as power mismatches of population are high because of wide range of starting values of the power flow variables. But the learning factors are adaptive. So with the generation, these values reduce automatically and lie

between 1 and 2 at the end of iteration.

TABLE II  
SOME LOW VOLTAGE SOLUTIONS OF 11 BUS SYSTEM

Solution 1		Solution 2			
Bus No.	Voltage magnitude in p.u.	Phase angle in degree	Bus No.	Voltage magnitude in p.u.	Phase angle in degree
1	1.0500	0	1	1.0500	0
2	0.6555	-1.9534	2	0.7404	-2.4572
3	0.4560	-4.4977	3	0.6633	-5.4055
4	0.0234	-18.0771	4	0.4600	-11.2587
5	1.0500	-33.1041	5	1.0500	-14.4411
6	0.3684	-13.1049	6	0.6580	-9.0746
7	0.8868	-20.0495	7	0.9712	-10.7052
8	0.9471	-17.5077	8	0.9991	-9.9330
9	1.0375	-14.1638	9	1.0375	-8.7705
10	0.8749	-10.6776	10	0.8188	-6.5375
11	0.3183	-10.2593	11	0.0644	-0.9340

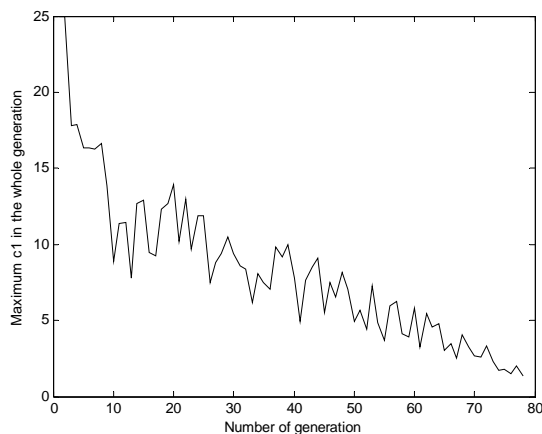


Fig. 3 Variation of the maximum value of  $c1$  in the whole population for multiple solutions for IEEE 30 bus test system

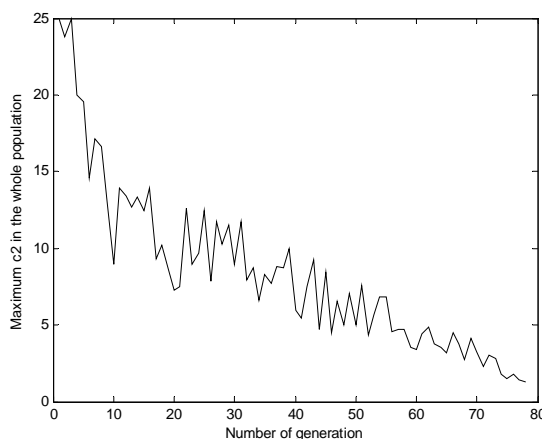


Fig. 4 Variation of the maximum value of  $c2$  in the whole population for multiple solutions for IEEE 30 bus test system

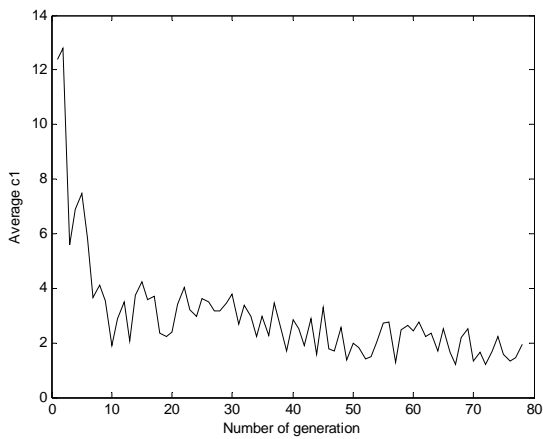


Fig. 5 Variation of the average value of c1 for multiple solutions for IEEE 30 bus test system

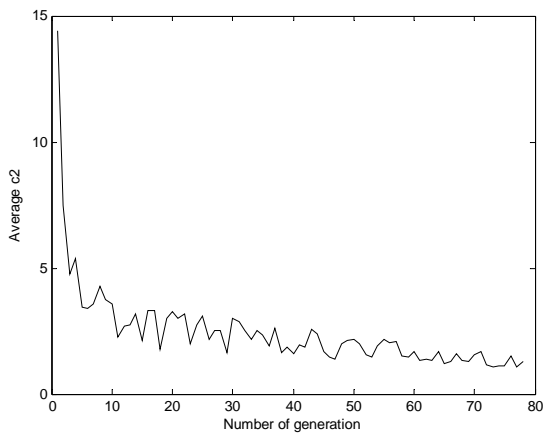


Fig. 6. Variation of the average value of c2 for multiple solutions for IEEE 30 bus test system.

Best and worst results are given in Table 3 for PSO based power flow algorithm with embedded local search technique for different size of population. The impact of the population size can be visualized from Table III.

The convergence characteristics of Sum Square Error and maximum error of the best solution for IEEE 30 bus test system for multiple solutions are given in Fig.7 and Fig. 8 respectively. The error decreases smoothly with the generation. It is noticed from the convergence characteristics that the proposed algorithm sluggish but ensure sure convergence.

### C. Performances under critical conditions

Recently for socio-economic developments, many large power plants are installed in hilly/rural/remote areas because of geographical problems and the deregulated power markets bring about the uncertain events and increases the degree of uncertainty in a power system [6], [16]. In addition to that, the mass of ill-type load such as heaters, air-conditioners and

some type motors, which have negative exponential load characteristics, suddenly increase. So in the present scenario it is essential to find out the loadability limits of the power systems in relation to voltage stability and security monitoring [22]-[25]. As the Jacobian matrix becomes singular under critical conditions, no solution can be obtained by the conventional methods [22]-[23], [25]. The justification of the application of the meta-heuristic approaches in the power flow problem lies in the fact that these approaches are not based on the power flow derivatives. So, these methods need not face the problem of Jacobian singularity as the maximum loading conditions are approached. Table IV shows the maximum loadability limits for different methods such as Newton Raphson load flow (NRLF) [19], NRLF with optimal multiplier [30], GA based load flow (GALF) [11] and proposed algorithm. The performance of various algorithms under critical condition, high R/X ratio, is shown in Table V. From the shown Tables, it can be concluded that the performances of proposed algorithm is superior to the conventional approaches.

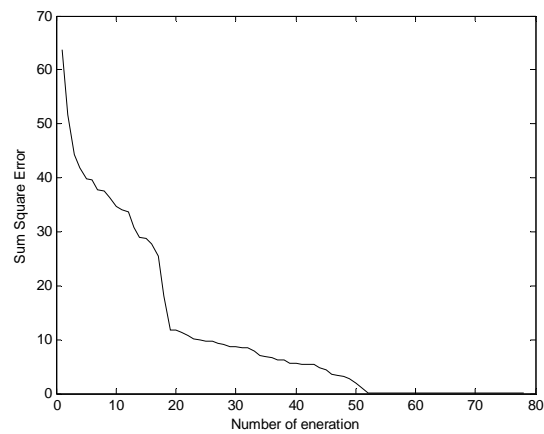


Fig. 7 Convergence characteristics of IEEE 30 bus test system considering the least Sum Square Error with 100-population size

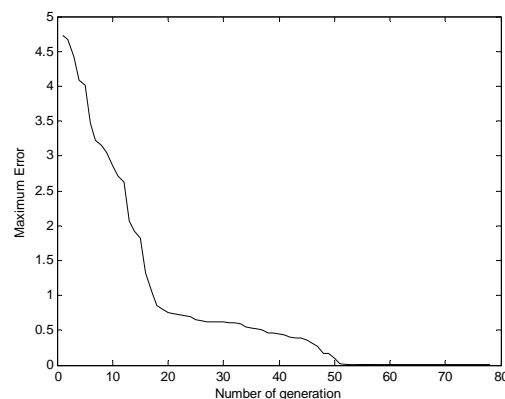


Fig. 8 Variation of the maximum error with the number of generation of IEEE 30 bus test system with 100 population size

TABLE III  
NUMBER OF GENERATIONS FOR MULTIPLE SOLUTIONS FOR PSO BASED ALGORITHM WITH EMBEDDED LOCAL SEARCH TECHNIQUE

Population Size	Test Systems									
	11-bus		IEEE 14- bus		IEEE 30-bus		IEEE 57-bus		IEEE 118 bus	
	Best	Worst	Best	Worst	Best	Worst	Best	Worst	Best	Worst
50	82	186	81	183	102	243	144	322	213	512
100	64	144	59	138	78	186	112	258	184	417
200	52	125	48	121	64	159	96	212	160	387

TABLE IV  
MAXIMUM LOADABILITY LIMIT FOR DIFFERENT TEST SYSTEMS

Test systems	Solution Methods			
	NRLF	NRLF with Optimal Multiplier	GALF	Proposed method
IEEE 14 bus	4.0627	4.0631	4.0657	4.0657
IEEE 30 bus	3.1611	3.1616	3.1648	3.1651
IEEE 57 bus	1.8952	1.8969	1.9024	1.9024
IEEE 118 bus	2.8162	2.8174	2.9003	2.9005

TABLE V  
LINE RESISTANCE MULTIPLIER FOR THE CRITICAL CONDITIONS

Test systems	Solution Methods			
	NRLF	NRLF with Optimal Multiplier	GALF	Proposed method
IEEE 14 bus	4.4223	4.4225	4.4371	4.4371
IEEE 30 bus	5.1212	5.1212	5.1304	5.1304
IEEE 57 bus	4.4102	4.4102	4.4252	4.4252
IEEE 118 bus	5.0705	5.0706	5.0732	5.0732

## VI. COMPARISON AND CONCLUSION

A method for finding the multiple power flow solutions has been proposed in this paper using Particle Swarm Optimization with an embedded local search. Adaptive variation of the PSO parameters, a local search technique and proper initializations are the three key factors for convergence to the low voltage solutions. In [3], [4], [34], generalized PSO-parameter selection is described. The proper selection of PSO parameters are designed first time for non-linear complex power flow problem under practical constrains. If  $n$  are the total nodes of a standard system,  $2^n - 1$  solutions can theoretically be located using the algorithm developed by the Ma & Thorp [31]. Salam F. M. et. al. proposed a homotopy method to find out low voltage solutions [29]. Though the homotopy method needs no improvement scheme to get solutions, it is difficult to implement for ill-conditioned systems. Effective and efficient method developed by Overbye & Klump [28] can find only type-one low voltage solutions. Though the Optimal multiplier method [30] is very simple and efficient, it can only find out a pair of multiple power flow solutions. Evolutionary technique, Genetic Algorithm (GA) is used to find multiple solutions in ref. [11]. GA based algorithm can find low voltage solutions for both standard as well as ill-conditioned systems. Innovative complex constrains satisfaction and accelerating techniques are the key factors for obtaining abnormal solutions. But 41% convergence is obtained for the GA based power flow algorithm. But PSO

based power flow algorithm gives 100% convergence though only one improvement scheme, local search is used.

In the presented paper, the pioneering learning factors are such formulated that these become highly adaptive for power flow problems. The proposed method can find normal and abnormal solutions for both standard and ill-conditioned systems reliably. The beauty of the proposed algorithm is that depending on the starting values of the power flow quantities, we can get preferred low voltage solutions for adaptive learning factors and local search.

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