3. PSO BASED DECOUPLED LOAD FLOW

3.1 INTRODUCTION

Attempting solutions of the load flow problem using evolutionary techniques may seem to be rather vain exercises to many because of the fact that load flow is a very well formulated problem and there are efficient solution techniques using conventional procedures. In spite of the above facts, necessity of exploring solutions using the evolutionary techniques has been established by Kit P. Wong et. al [19]-[21] , who have attempted GA and evolutionary programming techniques focusing the problem of obtaining multiple load flow solutions and handling FACTS related variables. Inspired by the above attempts, the author's motivation is to search for the efficient evolutionary tools for solving load flows – for normal solutions, multiple solutions.

Of all the evolutionary techniques available in literature, the author feels that the Particle Swarm Optimization (PSO) is the most appropriate one for solving the power flow problem as PSO algorithm guides the population towards the best solution known so far. Convergence thus can be forced more easily by pushing the PSO population towards the minimum power mismatch solution found so far.

The decoupled property of the power system variables has been utilized to develop a PSO based power flow algorithm which has then been extended to obtain constrained power flow solutions where branch flows, node voltages and the component limitations such as tap changer, shunt capacitors/VAR generator limits may be used as constraints.

In this chapter the author first presents a brief discussion on the Particle Swarm Optimization technique: The development of the PSO based load flow is then discussed. Two algorithms have been developed using the PSO technique. In the present chapter PSO based decoupled algorithm is presented, while a coupled algorithm is reported in the next chapter.

The perturbation based load flows reported in the previous chapter have also been incorporated in the structure of the PSO based load flows. Results obtained from the simple PSO based load flow and the improved algorithms using the hybrid of PSO and perturbation algorithms are also reported.

3.2. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization introduced by Kennedy J. and Eberhart R.C. [24] is a population based evolutionary algorithm. Unlike most of other evolutionary algorithms which are based on the concept of survival of the fittest, PSO is motivated by the social behavior [32]-[35], [38]. 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 :

$$v_{id} = w_i * v_{id} + C_1 * rand() * (p_{id} - x_{id}) + C_2 * Rand() * (p_{gd} - x_{id}) \qquad (3.1)$$

$$v_{id} = x_{id} + v_{id} \qquad (3.2)$$

Where, $C_1 \& C_2$ are the positive constant 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 particle i, i.e., the best position of the particle upto the present iteration. w_i is weight function for velocity of particle i .

3.3. DEVELOPMENT OF THE PSO BASED DECOUPLED LOAD FLOW

The main problem of applying the PSO technique to the load flow problem lies in the identification of the particles and their gbest and pbest positions. The problem may be formulated in two different ways. Perhaps the most natural way that one would like to think of a PSO based load flow is to design a complete solution consisting of a set of voltages and phase angles of all the buses as a single particle. We call this as the natural way as with this approach it becomes easy to measure the goodness of the position of the particle. Particle position is good if it is close to its destination. In case of the load flow problem the distance from the destination can be measured as the sum of the squares of the node power mismatches. Large values of the sum of square of the mismatches indicate that the solution variables are away from their desired values.

The problem with such formulation is that corrections of the variables are to be performed simultaneously on the basis of an aggregate mismatch value. Such method has been found to be very slow. The velocity and position corrections in this approach can never reach the converged solution unless special means are adopted for the satisfaction of the bus mismatch constraint.

The second approach is to treat the individual bus voltages and phase angles as separate particles. The problem with such design is the difficulty associated with the measurement of the goodness of the position of the particles. The problem comes from the fact that bus power mismatches are not the functions of the corresponding bus variables only. They are also dependent upon the variables of the buses directly connected to the bus concerned. As the variables are assigned a wider range of values in the population based approach, individual bus voltage and phase angle should, perhaps, be given more importance while enforcing convergence of the individual bus power mismatches. The load flow algorithm developed in this chapter follows the second approach. Individual bus variables treated as separate particles and their goodness are judged by the measures of the active and reactive power mismatches at the individual buses. Here the decoupling property between the power system quantities has been taken into consideration. For measuring the goodness of the phase angle of a bus the active power mismatch of the bus has been used as an indicator whereas for measuring the goodness of the voltage magnitude the reactive power mismatch of the bus is taken as the indicator.

The above assumption will not be illogical considering the fast decoupled formulation [8] of the load flow problem where active and reactive mismatches ΔP and ΔQ are represented in terms of the phase angle correction $\Delta\delta$ and voltage magnitude correction ΔV respectively and the susceptance matrix B as:

$$\frac{\Delta P_i}{V_i} = B'_{ii}\Delta\delta_i + \sum_m B'_{im}\Delta\delta_m \qquad (3.3)$$

$$\frac{\Delta Q_i}{V_i} = B''_{ii}\Delta V_i + \sum_m B''_{im}\Delta V_m \qquad (3.4)$$

The magnitudes of B'_{ii} & B''_{ii} being much larger than individual value of B'_{im} & B''_{im}, it may be said that the single largest contributors to the mismatches are those corresponding to the diagonal terms. Thus the active & reactive mismatches at bus i , may be used as the measures of the quality of the voltage and phase angles V_i & δ_i respectively.

3.3.1. PARTICLE STRUCTURE

The particles for the load flow problem thus consists of the bus voltages and phase angles represented in polar form. For generator buses, voltages are kept constant, allowing phase angles to vary until the generators Q-limits are violated when the voltage magnitude too is made variable.

3.3.2. FORMATION OF pbest SOLUTION

A complete solution strings of the PSO population is not selected as the pbest solution. Rather, the pbest solution is formed taking the best particles from the whole population. In this approach the pbest is formed taking the components from each possible candidate of the population. For bus i , best δ_i of the swarm is selected by identifying the minimum value of ΔP_i among the particles whereas the best V_i is selected by identifying the minimum ΔQ_i of the population. Minimum active and reactive mismatches for a bus thus correspond to the best estimates for the phase angle and voltage respectively for that bus. Thus, the pbest solutions for δ and V are determined as

$$\delta^i_{pbest} = \delta^i_j \,|_{\min(\Delta P^i_j,\, j=1......population)} \tag{3.5}$$

$$V^i_{pbest} = V^i_j \,|_{\min(\Delta Q^i_j,\, j=1......population)} \tag{3.6}$$

The pbest phase angle and voltage of a bus identified as above may correspond to two different population strings. This proposition thus suggests that the complex voltage of a bus may have the magnitude taken from one and the phase angle taken from another individual of the population in constructing the pbest vector. Moreover, as shown in Fig.3.1, voltage for different buses may be accepted from different individuals. This, therefore, requires that bus mismatches of the newly formed pbest solution be calculated afresh with the new combination of bus voltages and phase angles. There is, however, no guarantee that the mismatches so calculated will be smaller than the reference mismatches responsible for the formation of the pbest solution. But, as the PSO based load flow has been designed to search for the minimum mismatches, the mismatches of the pbest solution, inspite of the local spikes, decrease gradually. It may be noted here that, this particular selection of the pbest has been found to be the key to the convergence of the load flow problem using particle swarm optimization.

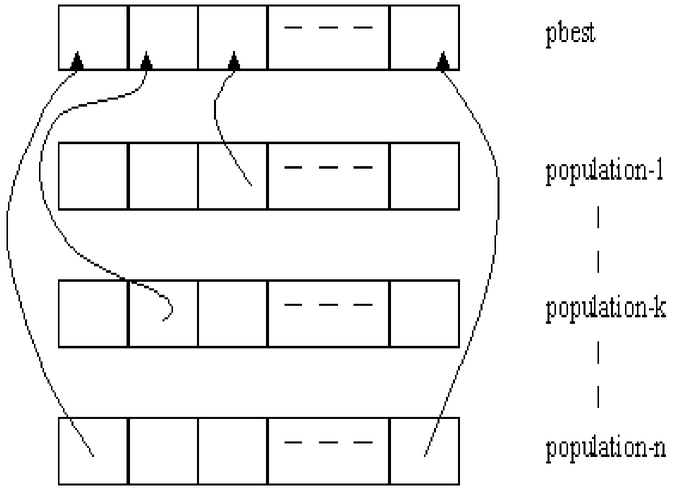

Fig. 3.1: Composition of the pbest solution

3.3.3. FORMATION OF gbest AND CONVERGENCE CRITERION

Selection of gbest follows the same criterion as used in the selection of the pbest. If the active mismatch of node i for the pbest solution is less than that of the gbest, δ_i of the pbest solution replaces δ_i of the gbest solution. Similarly V_i of the pbest solution replaces V_i of the gbest solution if the reactive mismatch of the pbest for node i is less than that of the gbest solution. gbest solution thus contains the voltages and phase angles corresponding to the lowest mismatches of the bus reactive and active power respectively.

Similar to the pbest solution, mismatches are also calculated for the updated gbest solution and these mismatches sometimes may be larger than the reference mismatches of the pbest solution, which has been the resource for updating of the gbest. In the long run, however, the mismatches decrease and converge to the desired solution of the load flow problem. As in the conventional load flow, PSO based decoupled load flow also is said to have converged if all the mismatches are less than the specified limiting values. Flowchart of the PSO based decoupled algorithm is given in Fig. 3.2.

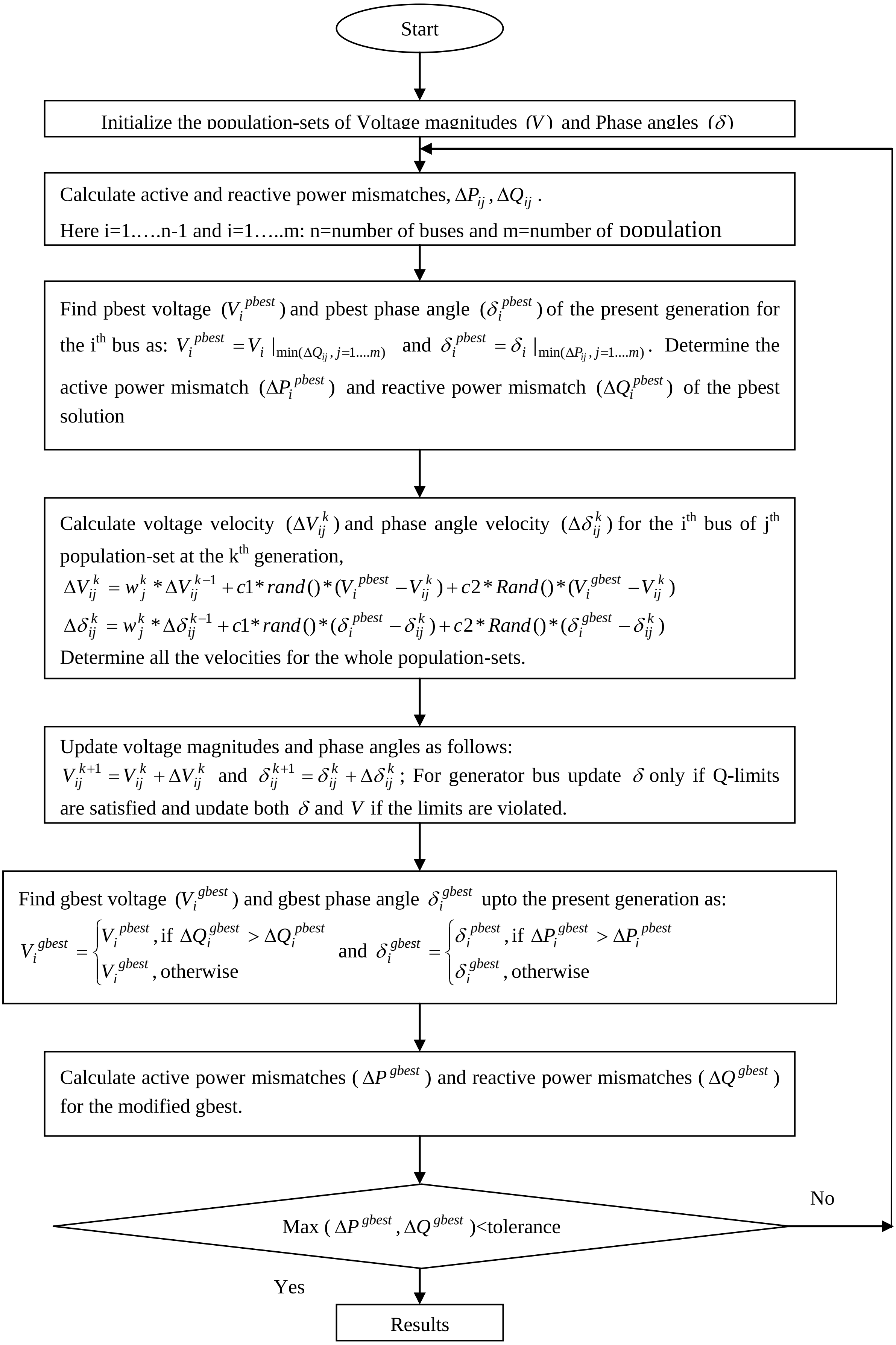

Fig. 3.2: Flowchart of the PSO based decoupled method

3.4. PARAMETER SETTINGS

Parameters of the PSO algorithms such as learning factors (c1, c2), inertia weight (w) and maximum velocity (V_m) which are to be tuned properly to get better results.

Selection of proper values for the learning factors c1 and c2 is very important for the convergence of the PSO based load flow. The optimum value for both c1 & c2 has been found to be 1.5. Convergence difficulties have been experienced if the value of c1 & c2 are selected below 1.2 or above 1.8. Effects of the variation of the constriction factors are shown in Fig. 3.3 for different test systems.

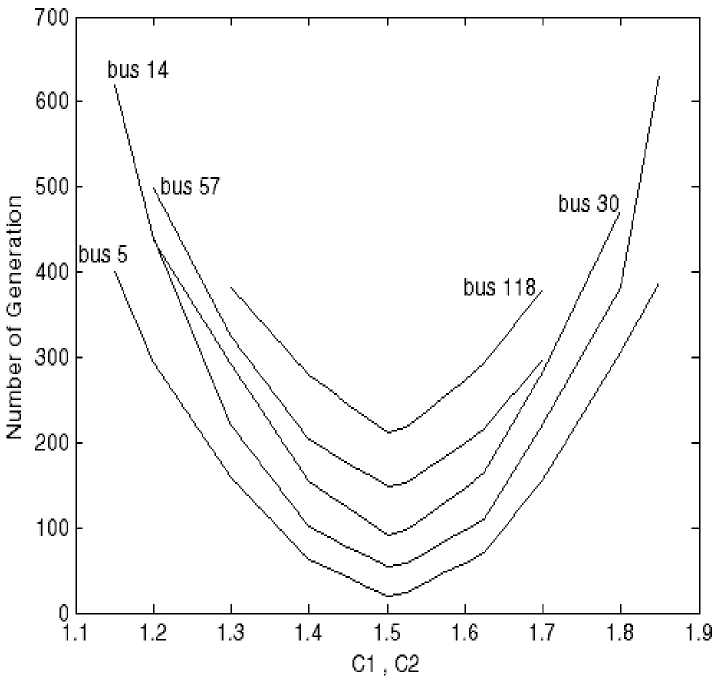

Fig.3.3: Effect of variation of c1 & c2

The decoupled algorithm gives convergence for different voltage ranges. The best results can be observed when voltage magnitudes are initialized between 0.9 and 1.1 p.u. and the phase angles are generated within 0.01 and –0.5 radian randomly. Initializations outside the specified range may require more number of generations for convergence for the same population size.

Maximum velocity limit is also a significant parameter for the particle swarm optimization technique. For the power flow problem the maximum velocity limit is determined empirically. For voltage magnitudes the limiting value is 0.05 p.u., whereas, the maximum limit of phase angles is 0.25 radian.

Inertia weight significantly affects the performance of the PSO based algorithm. The weighting factor is normally taken as w=0.5+rand/2 [25], [30, [37] where rand is a random number between 0 and 1. The decoupled algorithm has shown convergence with conventional w. An adaptive variation of the inertia weight, however, has been found to be very effective. The weighting function has been formulated as a function of the maximum error of the previous and present iteration. The inertia weight for p^{th} population at generation k has been designed to vary depending upon the maximum mismatch values as

$$w_p^k = \frac{\text{Maximum error of } p^{th} \text{ solution at } (k\text{-}1)^{th} \text{ iteration}}{\text{Maximum error of } p^{th} \text{ solution at } k^{th} \text{ iteration}} * rand() \tag{3.7}$$

The logic behind such design is as follows:

A lower maximum error at k^{th} iteration compared to that of the previous iteration indicates that variable values are closer to their desired solutions compared to the previous iteration. Thus, a higher inertia weight will ensure that the variable values remain close to their current values. On the other hand a higher maximum error than the previous iteration indicates that variables are farther from the desired solution. Assigning lower value to w to put less weight on the present value of the variable is thus justified.

The effect of such adaptive selection of w is depicted in Fig. 3.4. For comparison, the effect of conventional selection of w is also presented in Fig. 3.5 in case of IEEE 30 bus test system. The average value of w using the definition w=0.5+rand/2 is 0.75, compared to 0.51, for the newly proposed adaptive definition.

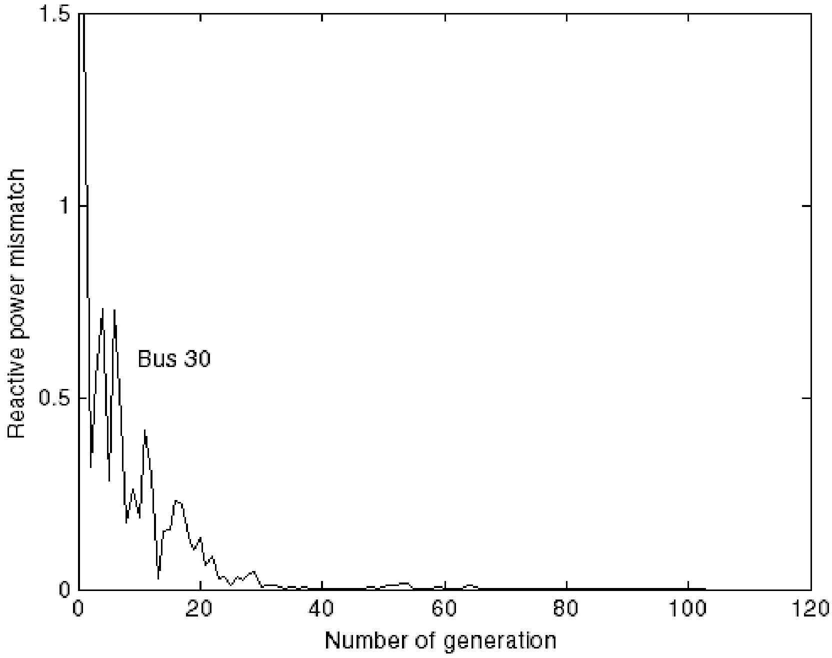

Fig.3.4: Variation of error of bus number 30 for IEEE 30 bus test system for 10 population size using newly proposed ‘w’

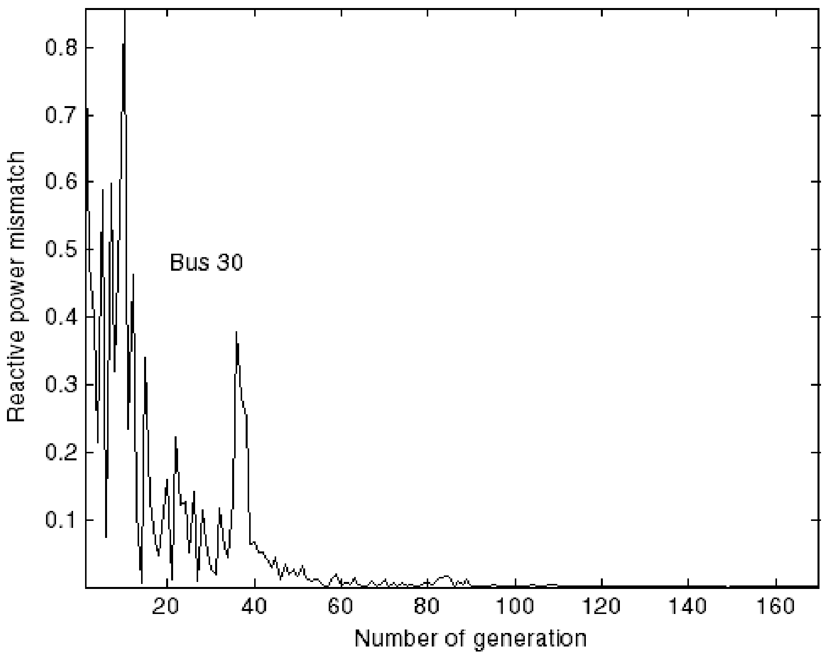

Fig. 3.5: Variation of error of bus number 30 for IEEE 30 bus test system for 10 population size using w=0.5+rand/2.

For IEEE 30 bus test system the smooth reduction in error has been observed in Fig. 3.4 for adaptive w, whereas, sluggish convergence has been noticed for conventional w in Fig.3.5. For adaptive and conventional w, the variations of w with the number of generations have been shown in Fig.3.6 and Fig.3.7 respectively.

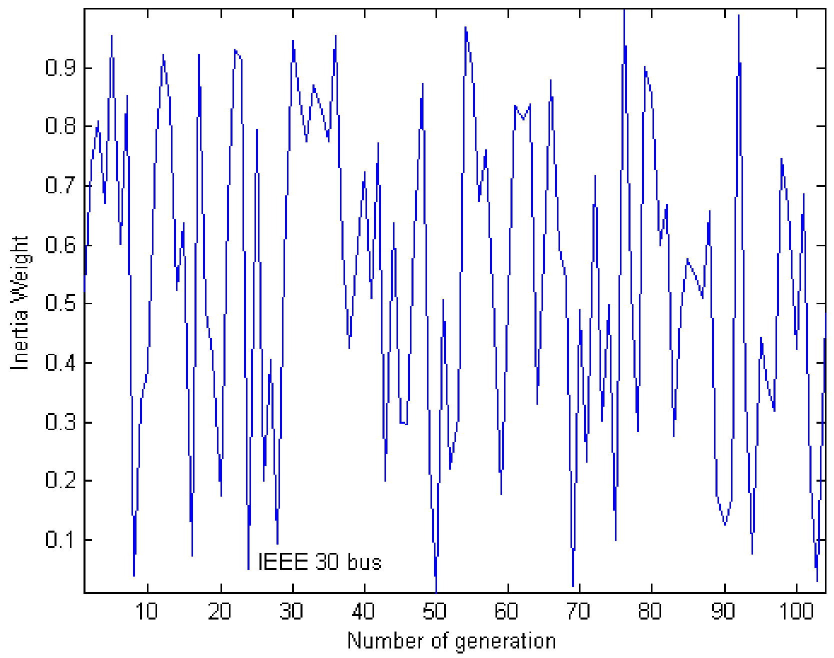

Fig.3.6: Variation of weighting factor with the generation using adaptive w for IEEE 30 bus test system

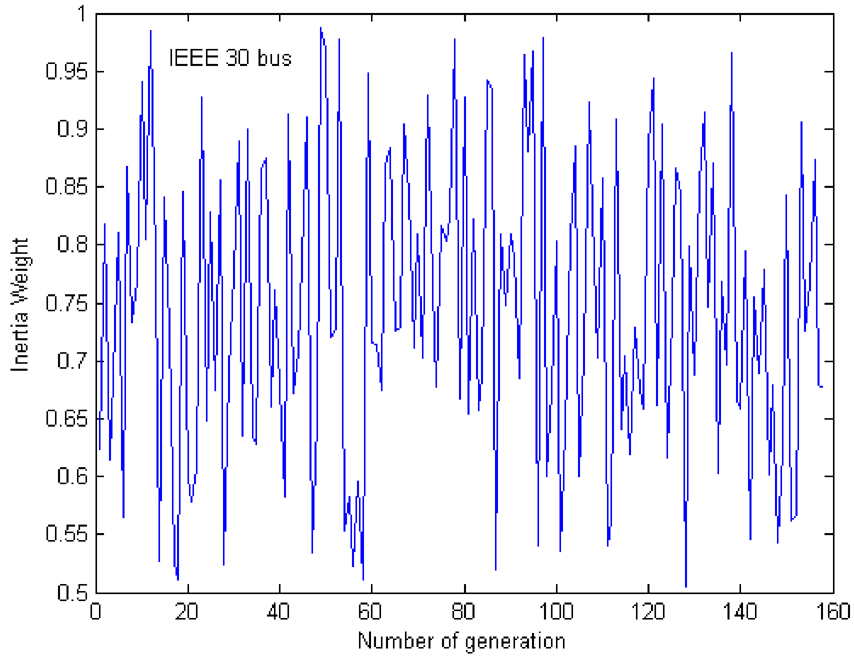

Fig.3.7: Variation of weighting factor with the generation using conventional w for IEEE 30 bus test system

3.5. RESULTS FOR THE DECOUPLED ALGORITHM

The proposed PSO based decoupled load flow has been tested extensively on many standard as well as ill conditioned systems. For each and every such case the proposed algorithm could obtain the solution efficiently. As the PSO is a general purpose search technique, its parameters are to be tuned for specific problems. Constriction factors c1& c2, inertia weight w, population size and velocity limits of the particles had to be adjusted as reported earlier for optimum results. Extensive studies have been carried out by varying the range of values for voltage and phase angle initialization and no problem has been encountered in obtaining the convergence. Table 3.1 shows the test results for the PSO based decoupled algorithm.

TABLE 3.1

Test Results for the PSO based decoupled power flow

Test System →	5-bus	11-bus	IEEE 14-bus	IEEE 30-bus	IEEE 57-bus	IEEE 118-bus	Population size ↓
Number of Generations	19	49	44	102	141	213	100
	19	50	46	102	142	216	40
	22	59	54	108	153	233	10
	24	71	57	111	165	252	08
	25	72	63	125	180	278	06
	38	87	86	152	224	327	04

Simple PSO based load flow is less sensitive to the variation of the size of the population, particularly for a population size above 10. Convergence for all the test cases has been found even with a population size of 4 only. Convergences for population sizes of 3 and 2 were also available in most of the cases, but needed more number of generations.

3.6. IMPROVEMENT SCHEMES

Perturbation based load flows reported in the previous chapter have been applied along with the PSO algorithm in order to have improved performance of the PSO based load flows. The improvement schemes have been applied on the pbest solution of the decoupled algorithm.

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 schemes applied on pbest works better than that applied on the gbest. Both the improvement schemes are able to enhance the speed of the proposed algorithm efficiently and the performances of the schemes are almost similar.

3.7. RESULTS FOR THE DECOUPLED ALGORITHM WITH IMPROVEMENT SCHEMES

The performances of the decoupled algorithm with local search are given in Table 3.2. The test results of the decoupled algorithm with linear perturbation are shown in Table 3.3.

TABLE 3.2

Performance of the PSO based decoupled algorithm with local search

Test System →	5-bus	11-bus	IEEE 14-bus	IEEE 30-bus	IEEE 57-bus	IEEE 118-bus	Population size ↓
Number of Generations	06	14	16	30	43	72	10
	07	15	16	33	44	75	08
	07	18	17	34	47	76	06
	09	19	19	38	48	78	04
	11	21	24	41	51	88	03
	14	23	25	44	59	92	02

Table 3.3

Test results For the PSO based decoupled algorithm with linear perturbation

Test System →	5-bus	11-bus	IEEE 14-bus	IEEE 30-bus	IEEE 57-bus	IEEE 118-bus	Population size ↓
Number of Generation	06	16	15	29	41	68	10
	07	16	16	30	42	71	08
	07	19	17	32	44	74	06
	08	20	19	35	46	75	04
	10	22	22	38	50	80	03
	12	24	23	41	53	84	02

The convergence characteristics have been shown through Fig. 3.8 to Fig. 3.11 for PSO based decoupled algorithm with population size of 10.

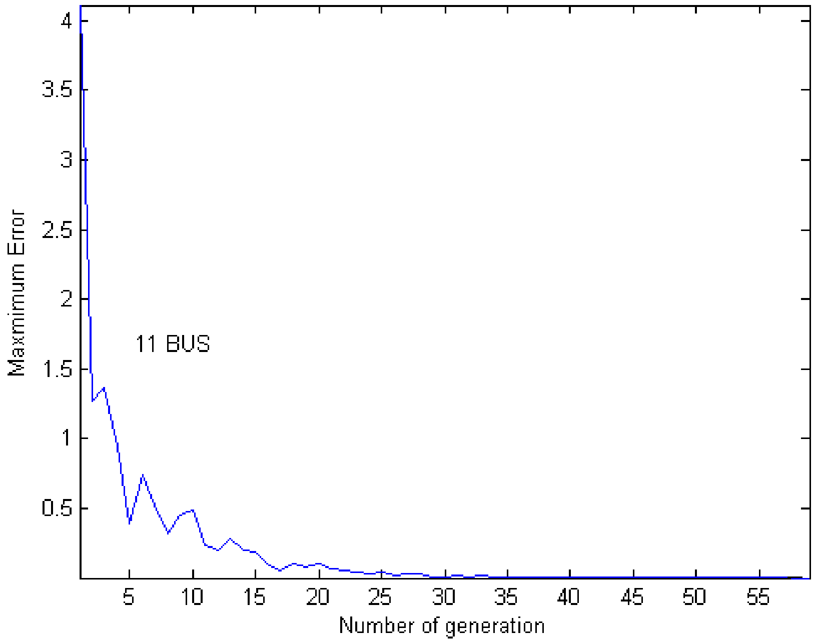

Fig. 3.8: Convergence characteristics of 11-bus test system for PSO based decoupled algorithm with 10-population size

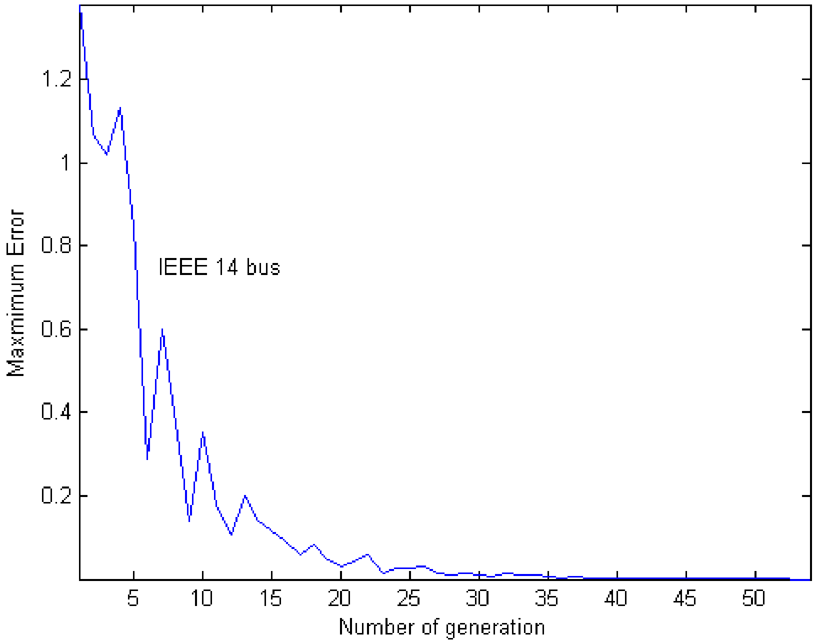

Fig. 3.9: Convergence characteristics of IEEE 14 bus test system for PSO based decoupled algorithm with 10-population size

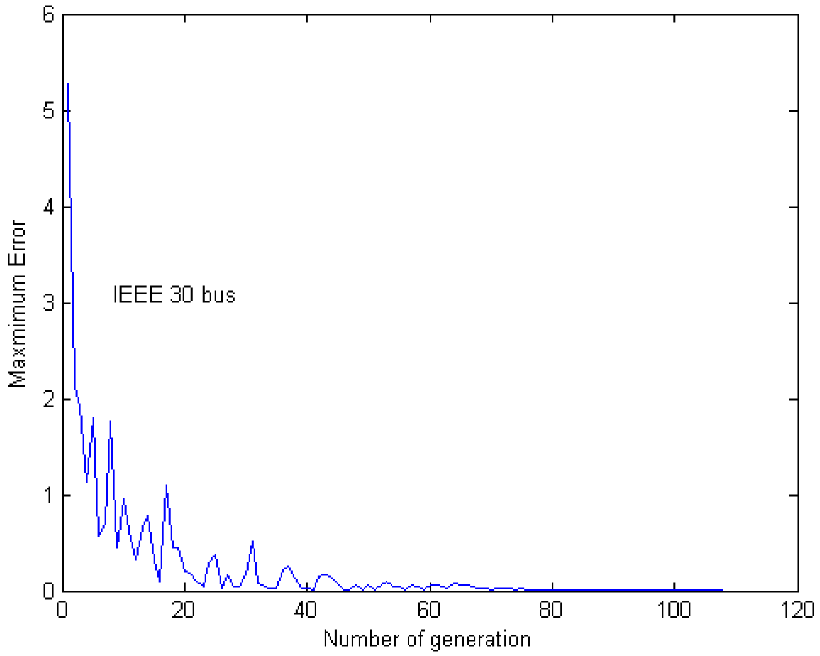

Fig. 3.10: Convergence characteristics of IEEE 30 bus test system for PSO based decoupled algorithm with 10-population size

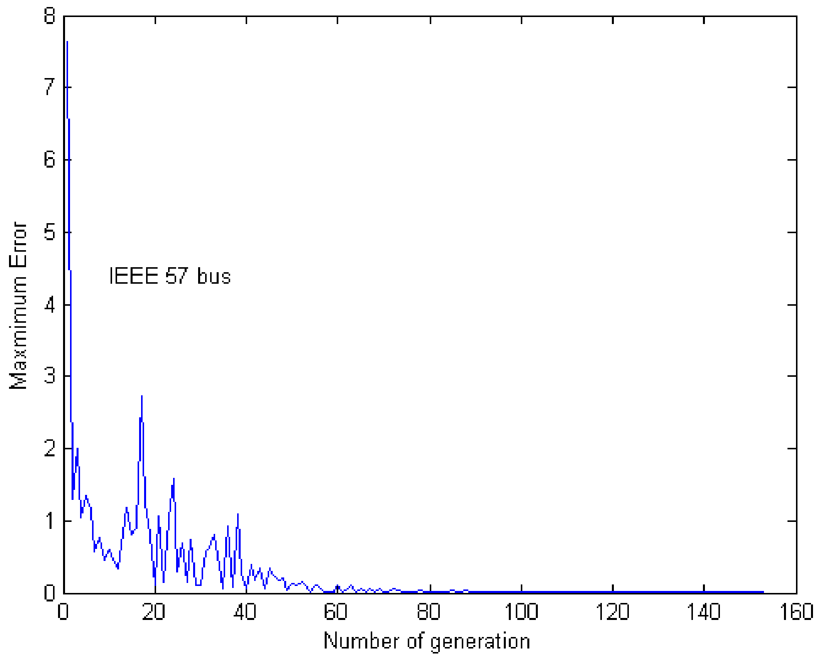

Fig. 3.11: Convergence characteristics of IEEE 57 bus test system for PSO based decoupled algorithm with 10-population size

From the above figures it can be noticed that the maximum error of the gbest solution sometimes become higher than that of the previous iteration but ultimately the maximum error decreases to the specified limit.

The local search improves both the sum square error and maximum error of the pbest solution. Error of the gbest solution with the generations for PSO based decoupled algorithm with local search are given in Fig. 3.12 to Fig. 3.15 for population size of 10.

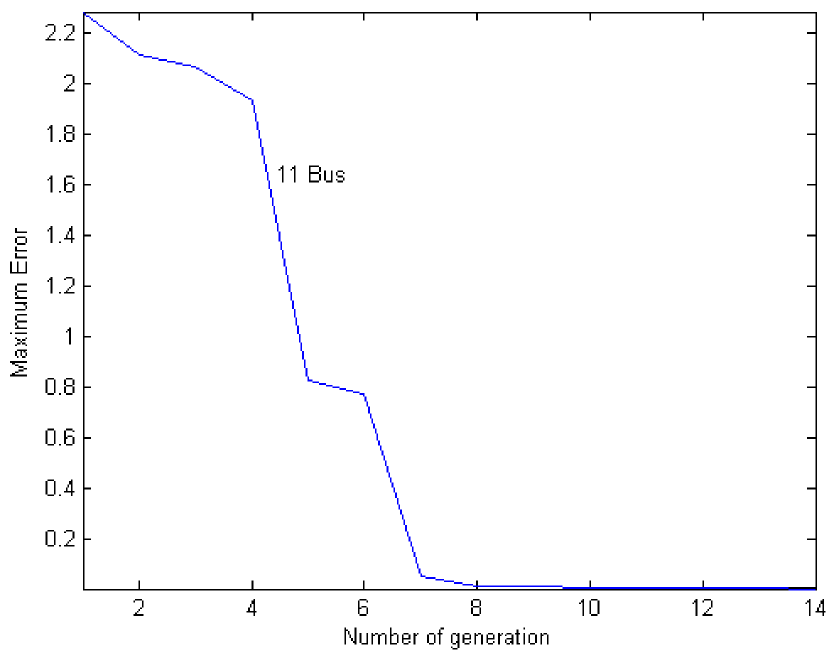

Fig. 3.12: Variation of maximum error of the gbest solution with the generations for PSO based decoupled algorithm with local search for 11-bus test system

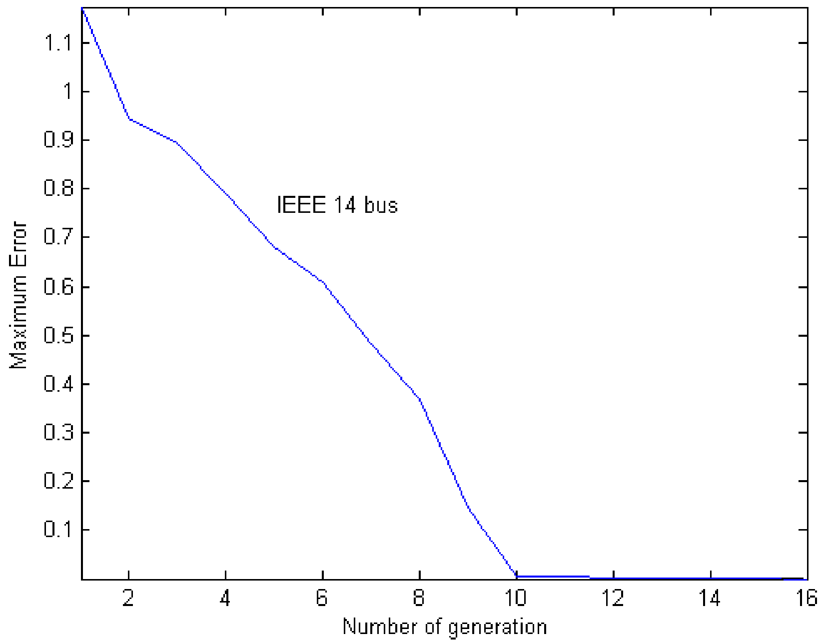

Fig. 3.13: Variation of maximum error of the gbest solution with the generations for PSO based decoupled algorithm with local search for IEEE 14 bus test system

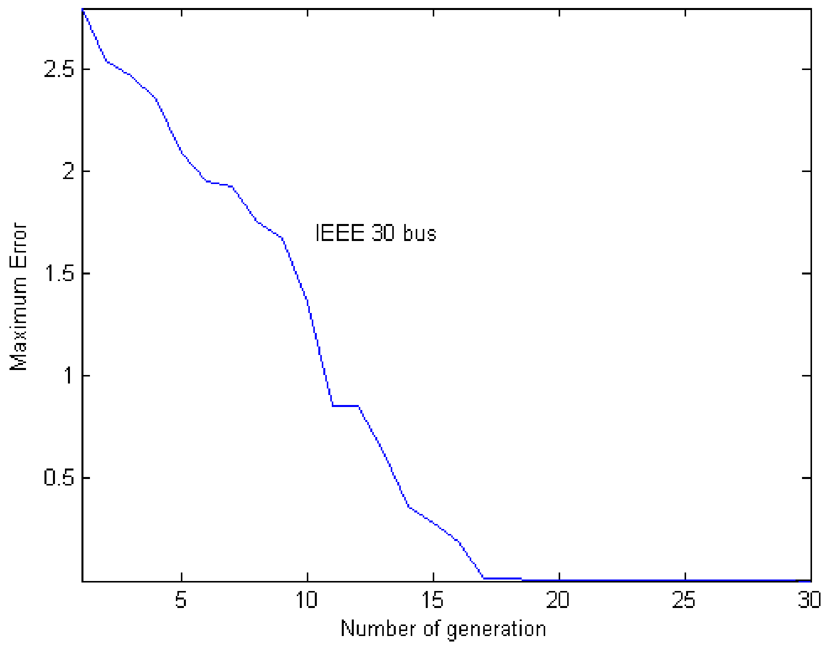

Fig. 3.14: Variation of maximum error of the gbest solution with the generations for PSO based decoupled algorithm with local search for IEEE 30 bus test system

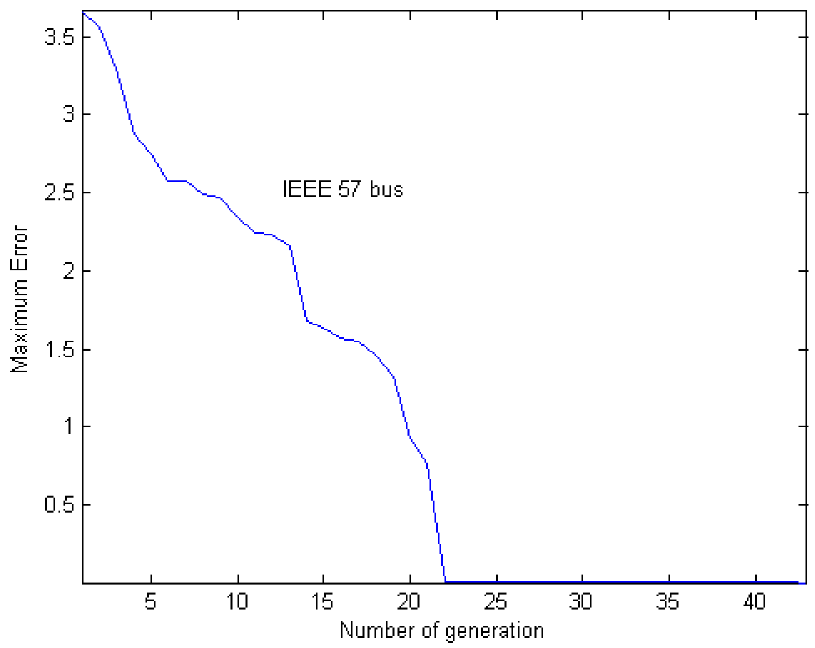

Fig. 3.15: Variation of maximum error of the gbest solution with the generations for PSO based decoupled algorithm with local search for IEEE 57 bus test system

Variations of the maximum error of the gbest solution with the generations for PSO based decoupled algorithm with linear perturbation are given in Fig. 3.16 to Fig. 3.19 for a population size of 10.

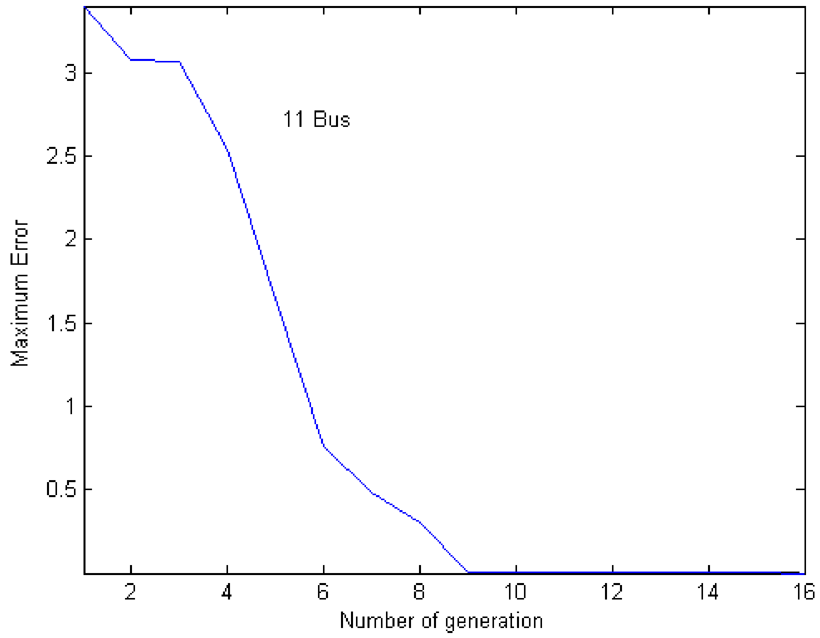

Fig. 3.16: Variation of maximum error of the gbest solution with the generations for PSO based decoupled algorithm with linear perturbation for 11-bus test system

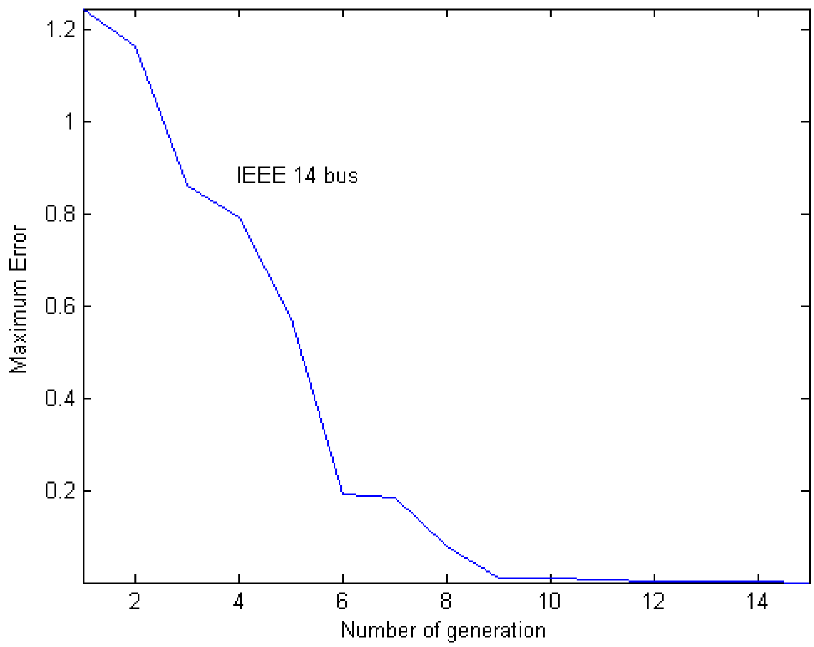

Fig. 3.17: Variation of maximum error of the gbest solution with the generations for PSO based decoupled algorithm with linear perturbation for IEEE 14 bus test system

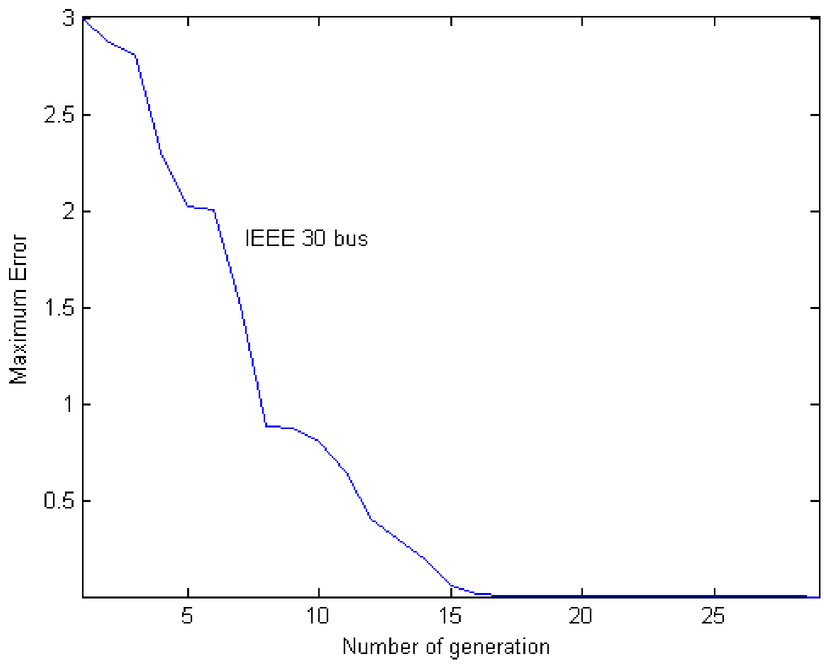

Fig. 3.18: Variation of maximum error of the gbest solution with the generations for PSO based decoupled algorithm with linear perturbation for IEEE 30 bus test system

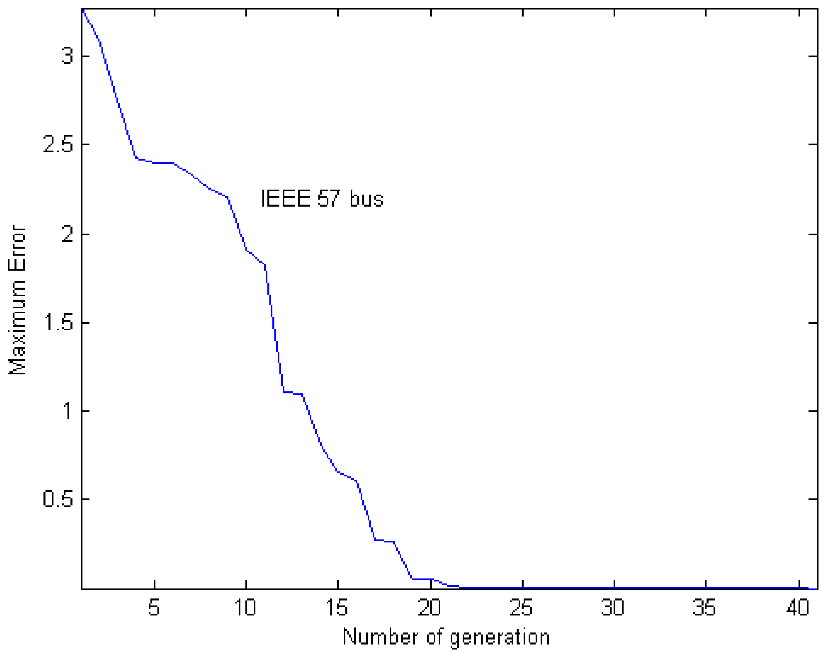

Fig. 3.19: Variation of maximum error of the gbest solution with the generations for PSO based decoupled algorithm with linear perturbation for IEEE 57 bus test system

In case of linear perturbation the similar variations of the maximum error of the gbest solution have been observed like local search. For linear perturbation, the required number of generations for convergence is almost the same as that of the local search for the same population size. Hence both the improvement schemes have shown neck-to-neck performance for PSO based decoupled algorithm.

3.8. PERFORMANCE ANALYSIS

For the PSO based decoupled algorithm without any improvement scheme the variation of the number of generation with population size has been given in Fig. 3.20 and the variation of the product of the number of generation and the population size with the size of population has been shown in Fig. 3.21.

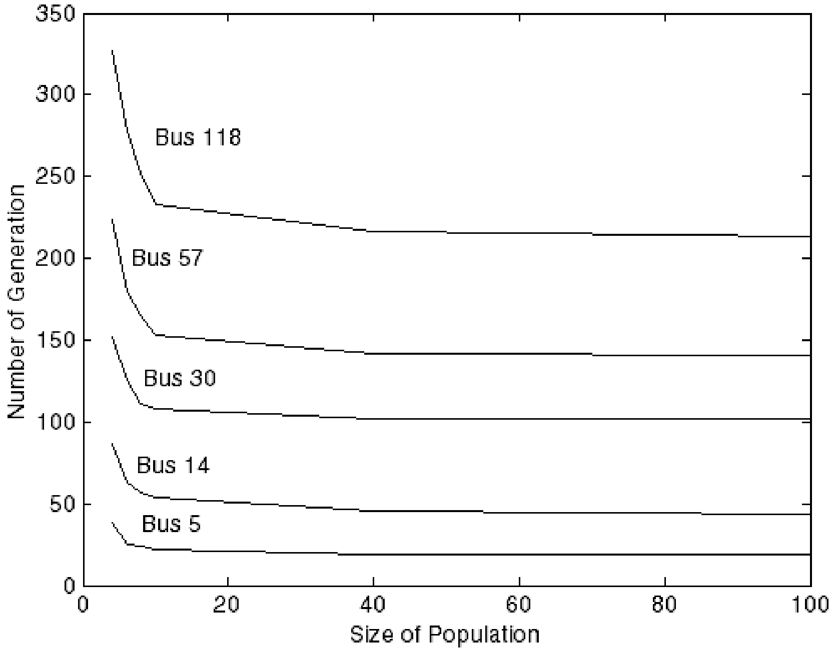

Fig. 3.20: Variation of the number of generation with the population-size for the PSO based decoupled power flow

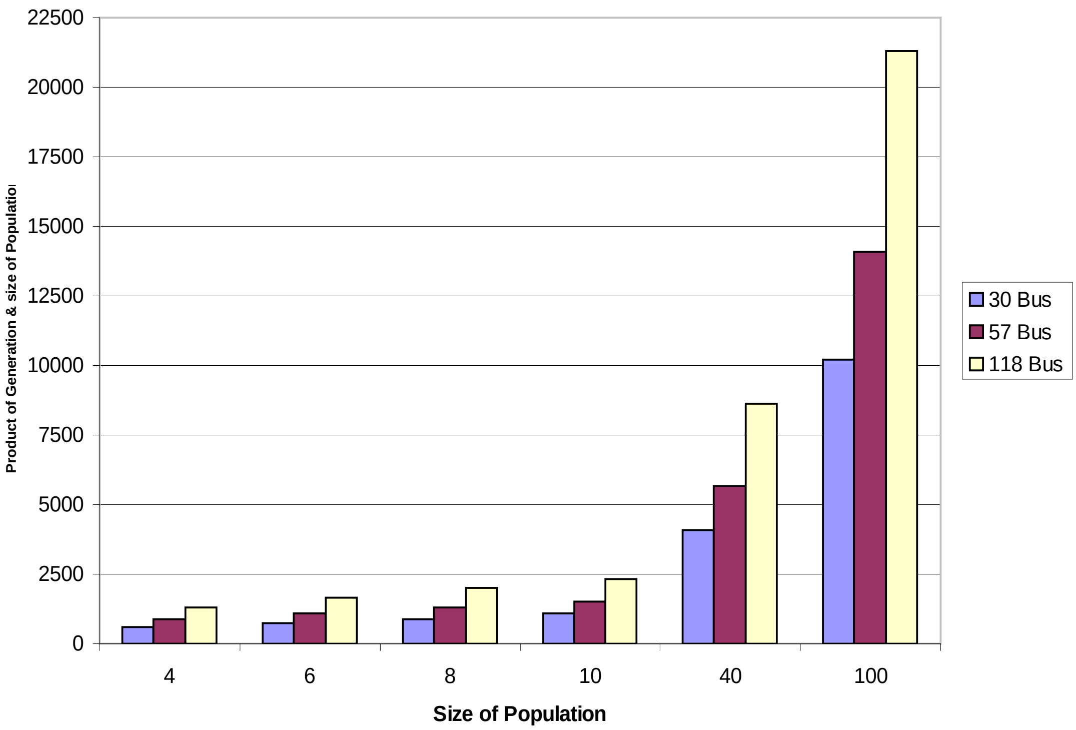

Fig. 3.21: Variation of the product of the number of generation and the population-size with the size of population for the PSO based decoupled power flow

From the Fig. 3.20, it can be noticed that there is no significant change in the required number of generation for the desired convergence above 10-population.

For the PSO based decoupled algorithm with the local search, the variation of the number of generation with population size is given in Fig. 3.22 and the variation of the product of the number of generation and the population size with the size of population is shown in Fig. 3.23.

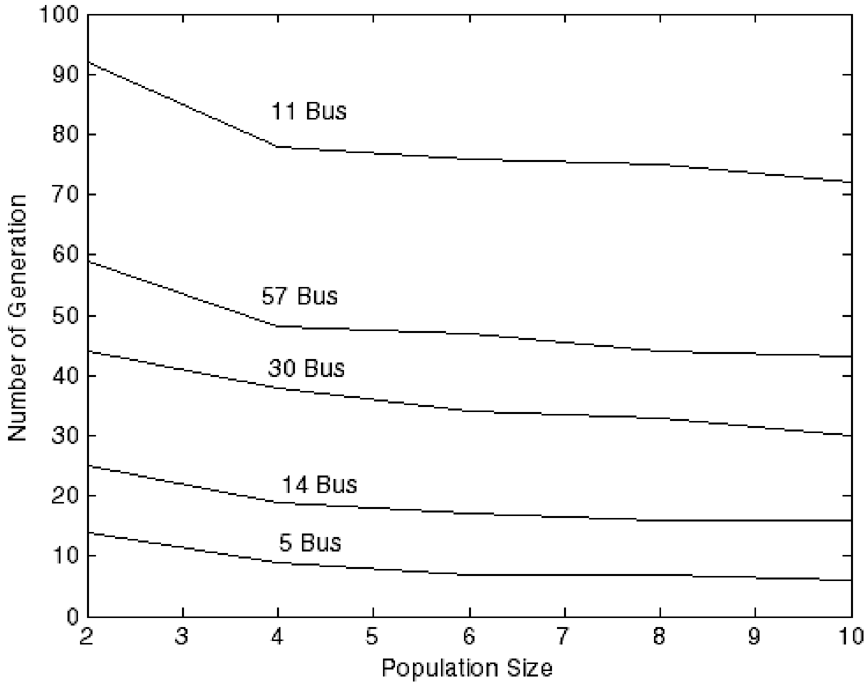

Fig. 3.22: Variation of the number of generation with the population-size for PSO based decoupled power flow with local search

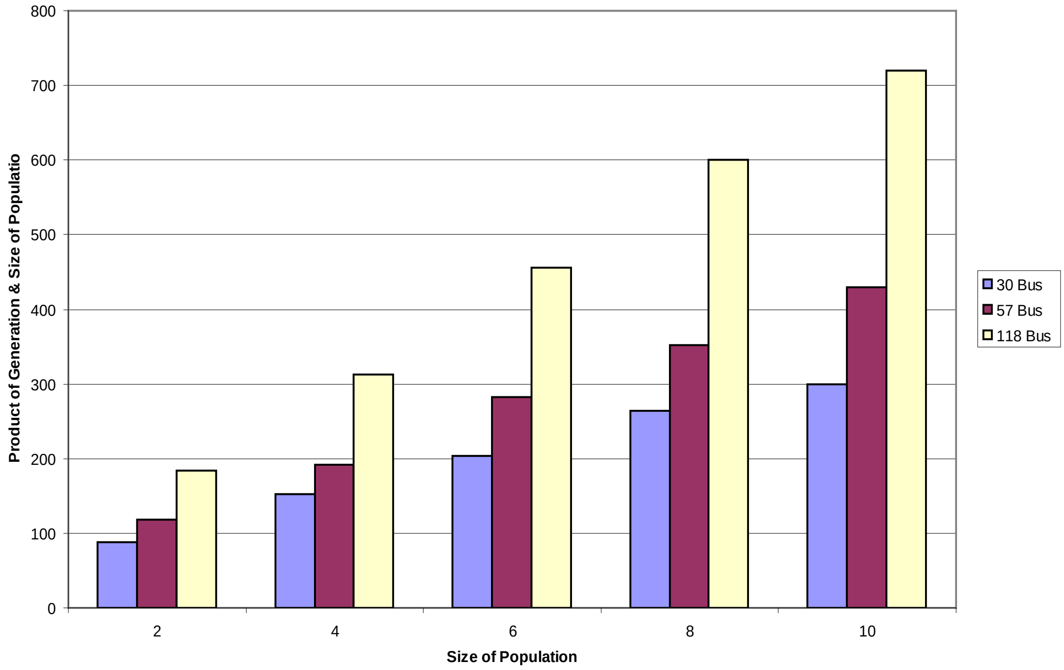

Fig. 3.23: Variation of the product of the number of generation and the population-size with the size of population for PSO based decoupled power flow with local search

It has been observed from the Fig. 3.22 that the decoupled algorithm with local search is almost insensitive to the population size. The proposed algorithm with local search can perform reliably with a population size as low as 2 only.

For the PSO based decoupled algorithm with the linear perturbation, the variation of the number of generation with population size is given in Fig. 3.24 and the variation of the product of the number of generation and the population size with the size of population is shown in Fig. 3.25.

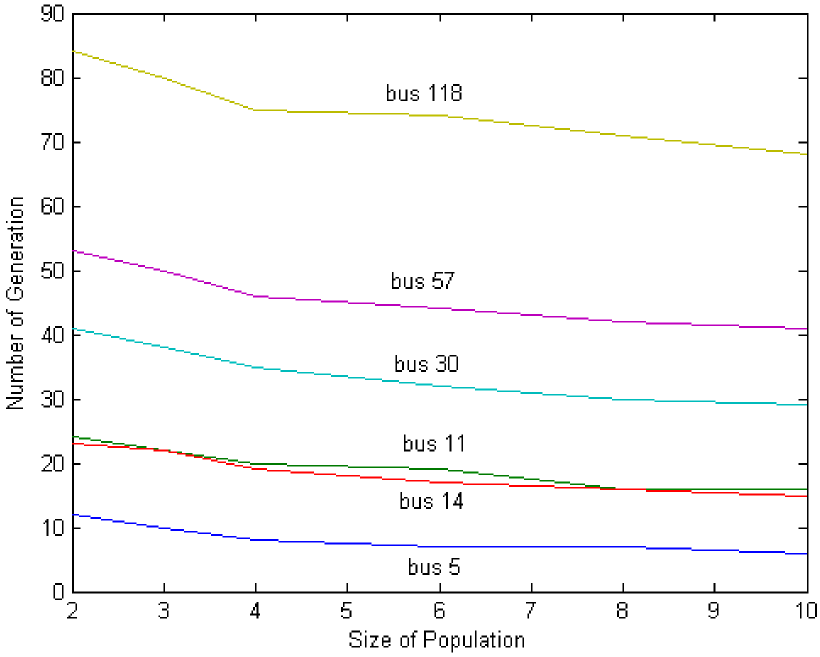

Fig. 3.24: Variation of the number of generation with the population-size for PSO based decoupled power flow with linear perturbation

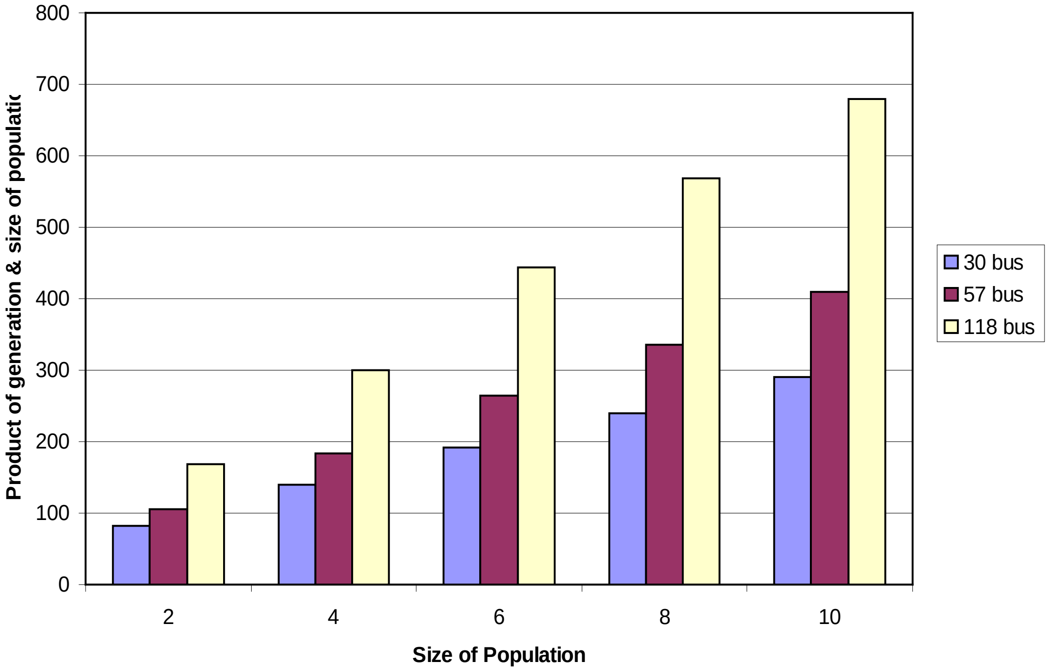

Fig. 3.25: Variation of the product of the number of generation and the population-size with the size of population for PSO based decoupled power flow with linear perturbation

3.9. CONCLUSION

A PSO based decoupled power flow algorithm has been reported in this chapter. The PSO algorithm uses constant value of learning factors and an adaptive formulation of the weighting factor. The proposed algorithm is robust. Initialization of the algorithm with perturbation based power flows improves the solution speed and needs smaller population size for convergence. PSO based power flow can not be the competetor to the conventional power flows for solving normal power flow problem but the PSO based power flow is a superior competetor for solving the power flow problem in certain critical situations.

The author has developed another PSO based load flow named as PSO based coupled algorithm to find out low voltage solutions of the load flow.