5. TWO-STAGE GA BASED LOAD FLOW

5.1 INTRODUCTION

The development of Genetic Algorithm precedes the development of all other population based methods. It is, therefore, interesting to know the performance of the genetic algorithm in solving a problem that is being solved by any other evolutionary techniques. The load flow problem was first solved using the genetic algorithm by K.P. Wong, Li A., and M.Y. Law [20]. The main focus of these authors was, however, to obtain the multiple load flow solutions. Later on in [19]-[21], K.P. Wong, J.Yuryevich and A. Li have applied the evolutionary programming technique in solving the load flow problem for systems having FACTS devices. The presence of FACTS devices increases the complexity of the load flow problem due to the increase in the number of variables and the range specified values of their variables. The authors of [20] have reported several constraint enforcement techniques which were very useful in satisfying the power balance conditions at the system buses. The present author first wishes to examine the impact of those constraint enforcement techniques in obtaining the convergence of the evolutionary load flows and then proposes new algorithm for the solution of the problem.

5.2. THE GENETIC ALGORITHM

The genetic algorithm, in brief, is reported in the appendix section. It basically consists of three operators- Reproduction, Crossover and Mutation. GA initializes a population of solution string called chromosomes. The qualities of the solution strings are measured by their fitness values. GA searches for maximizing the fitness values of the solution strings. Based on the fitness values two solution strings are selected. This procedure is known as the selection or reproduction. Solution strings such selected undergoes mating through the process of crossover whereby parent strings recombine to generate the child strings. The child strings transform to the final stage after mutation by which either bit compliment or small perturbations are performed depending upon the binary or real coding of the GA variables. The GA iterations (generations) follow the steps as given below:

Initialization

Loop: {fitness evaluation

Selection

Crossover

Mutation}

End

The above steps are known as the 'Simple Genetic Algorithm' in GA literature. GA includes many variations for improved performance. Moreover, several other problem specific operations are also included in the GA architecture as the general structure of the GA does not always work efficiently in real life problems. For the solution of the load flow problem, for example, constraint enforcement operations are incorporated in [20], [21].

5.3. CONSTRAINT ENFORCEMENT PROCEDURE FOR LOAD FLOW SOLUTION

The stochastic variation of the load flow variables does not ensure satisfaction of the power balance conditions at the network buses. Constraint enforcement at the load and generator buses has been proposed in [21] to ensure convergence. The constraint equations for the satisfaction of the specified active and reactive powers at any PQ node i by updating the nodal voltage of a PQ node d are developed in the following. Let the real and imaginary voltages of node d be E_{id} and F_{id} respectively. The power mismatches ΔP_i, and ΔQ_i for node i are now set to zero. When d $\neq$ i, E_{id} and F_{id} can be calculated according to

$$E_{id} = \frac{(E_i G_{id} + F_i B_{id})P_i^{sp} + (F_i G_{id} - E_i B_{id})Q_i^{sp}}{(G_{id}^2 + B_{id}^2)(E_i^2 + F_i^2)} - \frac{(X_{id} G_{id} + Z_{id} B_{id})}{(G_{id}^2 + B_{id}^2)}$$

$$F_{id} = \frac{(F_i G_{id} - E_i B_{id})P_i^{sp} - (E_i G_{id} + F_i B_{id})Q_i^{sp}}{(G_{id}^2 + B_{id}^2)(E_i^2 + F_i^2)} + \frac{(X_{id} B_{id} - Z_{id} G_{id})}{(G_{id}^2 + B_{id}^2)}$$

Where,

$$X_{id} = \sum_{\substack{j=1 \\ j \neq d}}^{N} (G_{ij} E_j - B_{ij} F_j) \qquad Z_{id} = \sum_{\substack{j=1 \\ j \neq d}}^{N} (G_{ij} F_j + B_{ij} E_j)$$

P_i^{sp} , Q_i^{sp} = Specified active and reactive powers at node *i*

P_i , Q_i = Calculated active power and reactive power at node i

G_{ij} , B_{ij} = Real and imaginary parts of the (i, j) th element of the admittance matrix

E_i , F_i = real and imaginary parts of the nodal voltage at node i

E_{id} , F_{id} = updated real and imaginary parts of the nodal voltage at node d

V_i^{sp} , V_i = specified and calculated voltage magnitude at node *i*

V_k = nodal voltage vector at node k

ΔP_i , ΔQ_i =Active and reactive power mismatches respectively

When d = ***i*,** the power constraints at PQ node d itself are required to be met. The constraint equations for calculating E_{id} and F_{id} of node *d* can be derived by the same procedure above and by setting the subscript ***i*** to *d*. The two resultant expressions are lengthy and are therefore omitted here for clarity.

The constraint equations for the satisfaction of the voltage magnitude constraint at any PV node d by updating its own nodal voltage are developed in the following. Let the real and imaginary voltages of the PV node *d* in the chromosome be E_{dd} and F_{dd}. The mismatches ΔP_d and ΔV_d for node *d* can now be set to zero. Now, the expressions for E_{dd} and F_{dd} are:

$$E_{dd} = \frac{X_{dd}(P_d^{sp} - V_d^{sp^2} G_{dd})}{X_{dd}^2 + Z_{dd}^2} \pm \frac{Z_{dd}\sqrt{V_d^{sp^2}(X_{dd}^2 + Z_{dd}^2) - (P_d^{sp} - V_d^{sp^2} G_{dd})^2}}{X_{dd}^2 + Z_{dd}^2}$$

$$F_{dd} = \frac{Z_{dd}(P_d^{sp} - V_d^{sp^2} G_{dd})}{X_{dd}^2 + Z_{dd}^2} \mp \frac{X_{dd}\sqrt{V_d^{sp^2}(X_{dd}^2 + Z_{dd}^2) - (P_d^{sp} - V_d^{sp^2} G_{dd})^2}}{X_{dd}^2 + Z_{dd}^2}$$

Where,

$$X_{dd} = \sum_{\substack{j=1 \\ j \neq d}}^{N} (G_{dj} E_j - B_{dj} F_j) \qquad Z_{dd} = \sum_{\substack{j=1 \\ j \neq d}}^{N} (G_{dj} F_j + B_{dj} E_j)$$

The problem with the proposed constraint enforcement process is that it involves complex and lengthy computations. It seems that not the GA steps but the constraint enforcement procedure is more responsible for the convergence of the GA or EP based load flows. In order to have a better understanding the present author has attempted a load flow implementation using only the operators of the simple genetic algorithm.

5.4. DEVELOPMENT OF THE TWO-STAGE GA BASED LOAD FLOW

The experience of the author with simple GA implementation of the power flow problem is rather uninspiring. Simple GA based power flow, based on reproduction, crossover and mutation operators is very unreliable and occasionally does not converge. Fig. 5.1 shows the convergence characteristics for simple GA based power flow. It, therefore, shows that the constraint enforcement as reported in [20], [21] is the key to the convergence of the GA and EP based power flows. The author, however, could develop a novel two-stage GA based power flow that is reliable in convergence but not as efficient as the PSO based Power Flows.

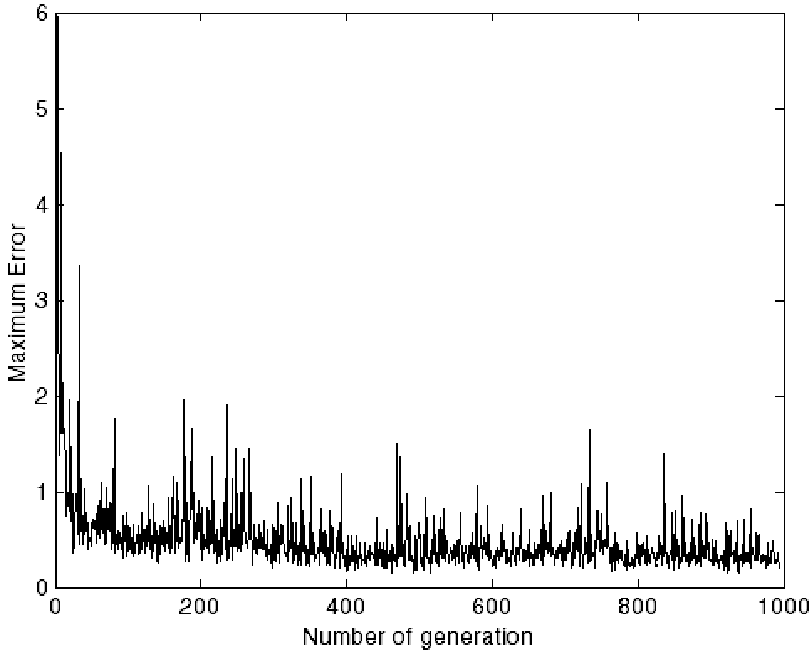

Fig. 5.1: Convergence characteristics of simple GA based power flow for IEEE 30 bus test system with 500-population size

The first stage of the proposed algorithm does not include the mutation operator. The first stage, for this reason, is termed as incomplete GA. The second stage of the GA based power flow implements all the three genetic operators and hence is termed complete GA.

5.4.1. INCOMPLETE GA

Incomplete GA stage does not use the mutation operator. Here the population strings are selected randomly restricting the selection of each strings only once. Generation of the child solutions has been related with the power mismatches of the parent populations. As voltage magnitudes are more responsible for reactive power mismatches and phase angles for active power mismatches, the voltage magnitudes in the child solutions have been made dependent on the reactive mismatches of the participating parents. Similarly, phase angles of the child solutions have been made dependant on the active power mismatches of the parent solutions. Incomplete GA thus has been made to work using the decoupled property of the power systems. Steps involved in the incomplete GA are shown in Fig. 5.2.

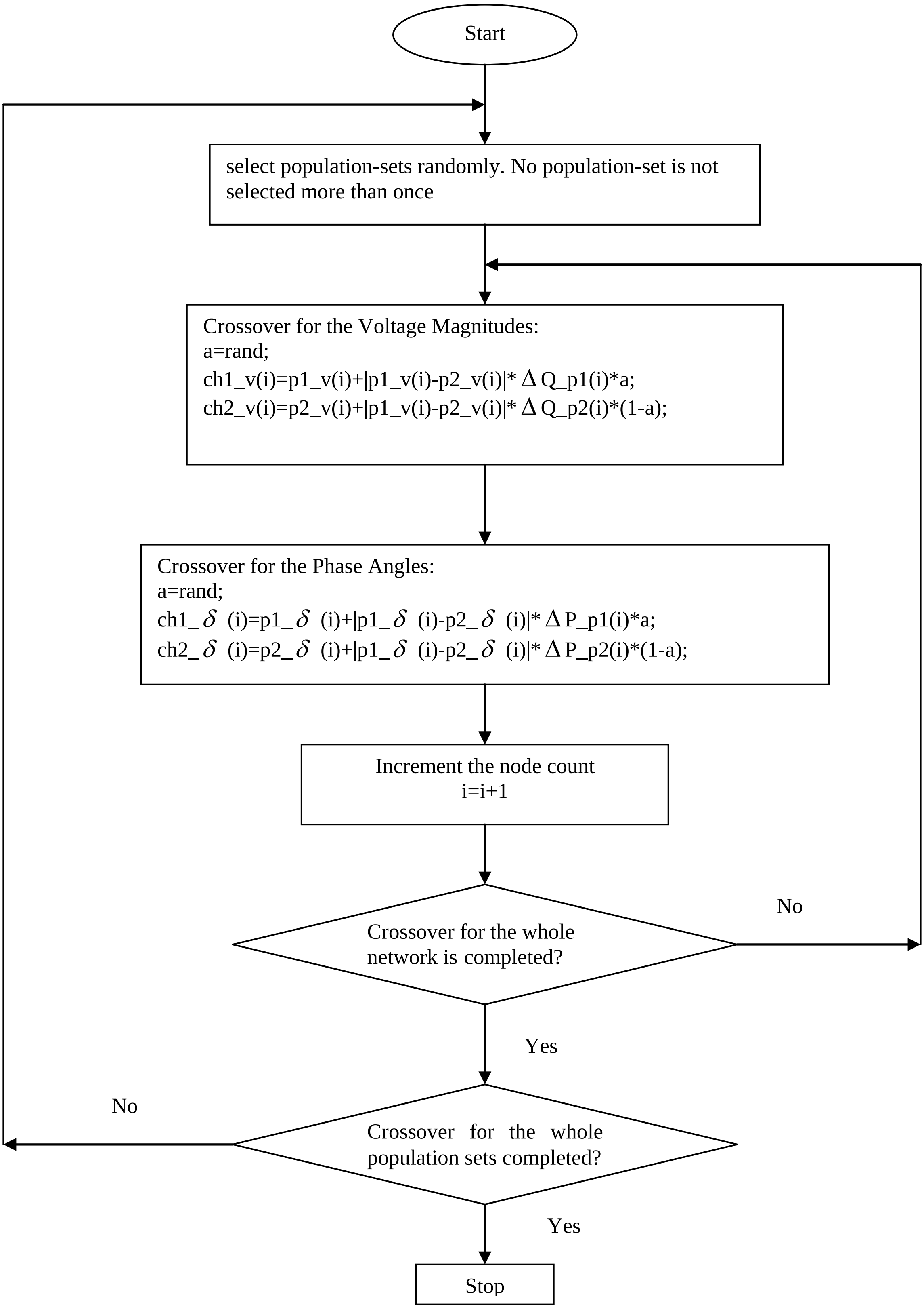

Fig.5.2. Flowchart of the crossover operation used in the incomplete GA stage

Here, for Voltage magnitudes the following notations are used in Fig. 5.2:

ch1_v(i) : i^{th} voltage magnitude of child1

ch2_v(i) : i^{th} voltage magnitude of child2

p1_v(i) : i^{th} voltage magnitude of parent1

p2_v(i) : i^{th} voltage magnitude of parent2

ΔQ_p1(i) : i^{th} Reactive power mismatch of parent1

ΔQ_p2(i) : i^{th} Reactive power mismatch of parent2

Here, for Phase angles magnitudes the following notations are used in Fig. 5.2:

ch1_δ(i) : i^{th} phase angle of child1

ch2_δ(i) : i^{th} phase angle of child2

p1_δ(i) : i^{th} phase angle of parent1

p2_δ(i) : i^{th} phase angle of parent2

ΔP_p1(i) : i^{th} Active power mismatch of parent1

ΔP_p2(i) : i^{th} Active power mismatch of parent2

5.4.2. COMPLETE GA

In the complete GA crossover is implemented by exchanging the values of the variables between the participating parents to generate the child solutions, while the mutation operation introduces small perturbation on the variables. Such operations are, however, performed probabilistically. The flowcharts of Fig. 5.3 & Fig. 5.4 show the crossover and mutation used in the complete GA. In both crossover and mutation, two solution strings are randomly selected but none is selected more than once. After crossover two best solutions are chosen among the parent-sets and the child-sets. The solution with lower sum square error is considered to be the better solution. Like the crossover, for the mutation also, the selection criterion of the best solution is the least sum square error. The convergence, however, is determined on the basis of the maximum nodal power mismatch.

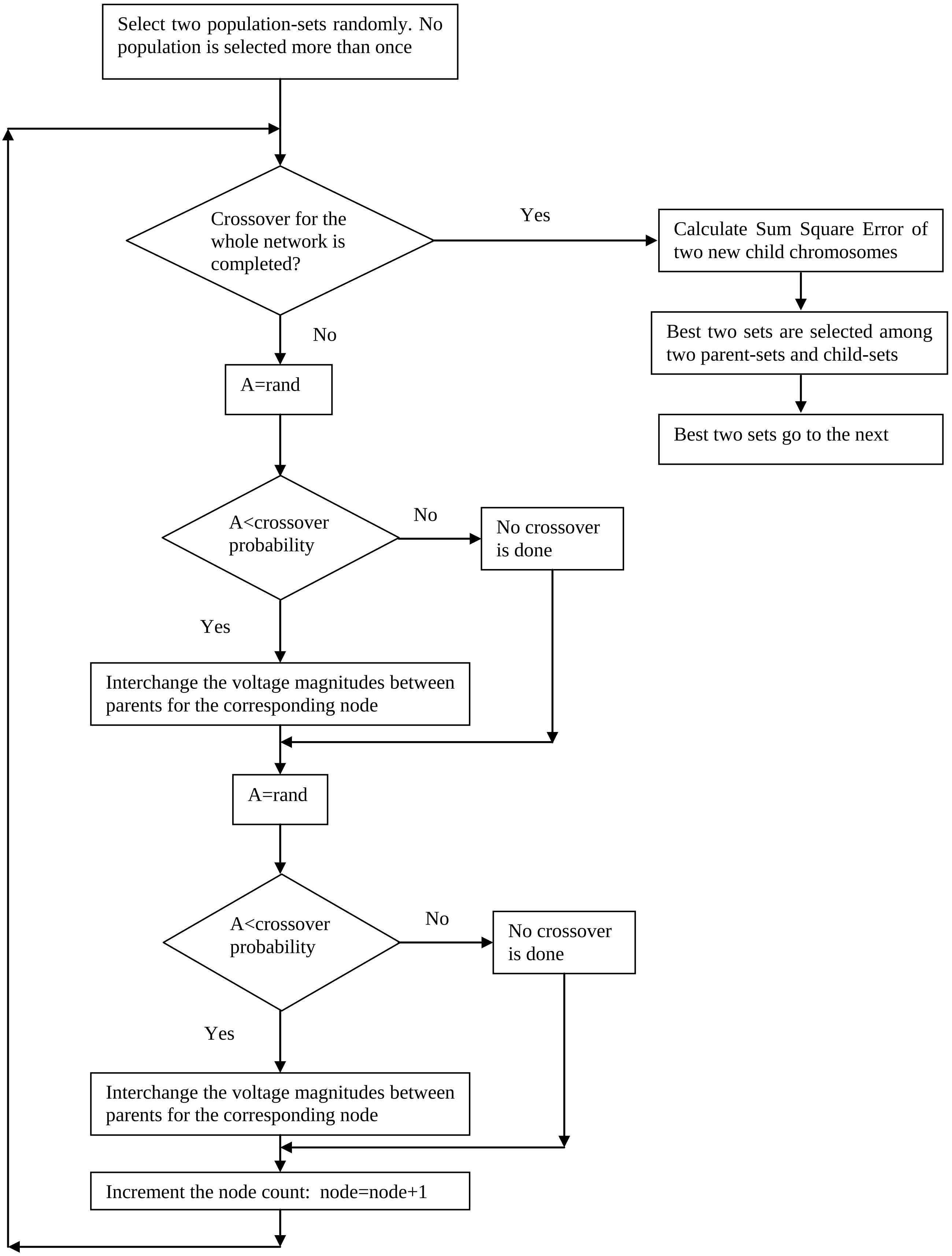

Fig.5.3. Flowchart of the crossover operation used in the complete GA stage

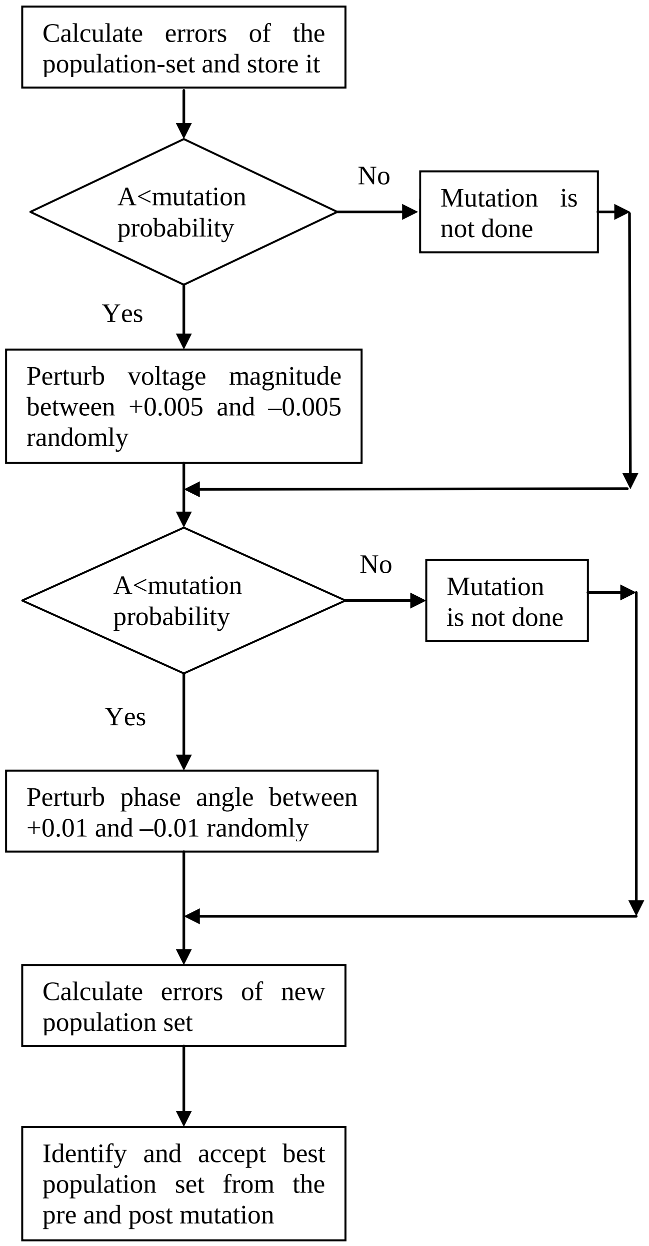

Fig. 5.4: Flowchart of the mutation operation used in the complete GA stage

5.4.3. FLOWCHART OF THE TWO-STAGE GA BASED LOAD FLOW

The incomplete and the complete GAs are applied sequentially on the solution population until the convergence, determined by the maximum mismatch values of the nodal active and reactive powers being within the acceptable limit, is achieved. The flowchart of the two-stage GA based power flow is shown in Fig. 5.5.

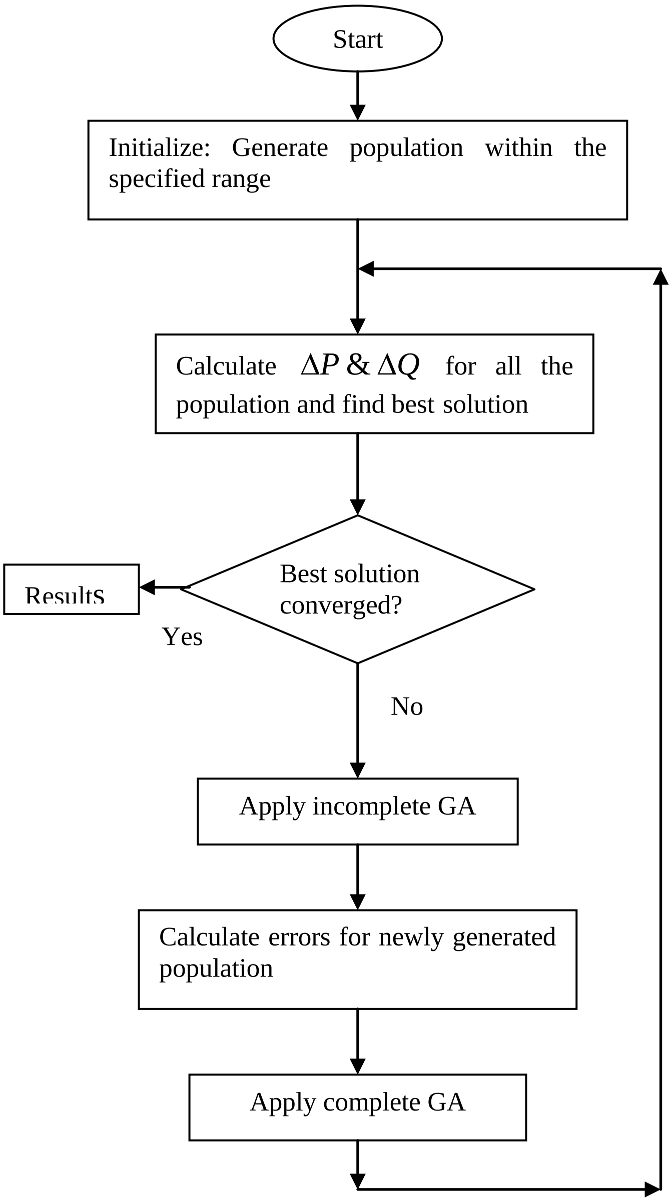

Fig. 5.5: Flowchart of the two-stage GA based load flow

5.5. GA PARAMETER SETTINGS

Two basic parameters of GA are crossover probability and mutation probability. Population size, selection and encoding of chromosomes also play very important role in the performance of the GA based solution algorithms.

Generally crossover rate is set very high.. In the two-stage GA based load flow the crossover probability of 0.95 has been found to give the best results. Generally mutation rate are very low. Best rates seem to be 0.5 for the proposed algorithm. Good population size is about 20-30, however sometimes sizes 50-100 are reported as the best. In the two-stage GA based load flow, the size of population may be taken as low as 8. If the population-size increases, the number of generations for convergence decreases. There are many methods in selecting the best chromosomes. But in the proposed method, two population-sets are selected randomly (not according to the fitness function). Every population set will be selected only once i.e. no population-set will be chosen twice. Value encoding has been used in the proposed algorithm. Real values have been generated randomly within the specified range. The voltage magnitudes are initialized randomly between 0.9 and 1.1, whereas, the phase angles are generated randomly between –0.5 and –0.01.

5.6. TEST RESULTS OF TWO-STAGE GA BASED LOAD FLOW

The two-stage GA based load flow has been tested on standard test systems. The method converged successfully in all type of test cases. A summary of the results obtained for various test systems are given in Table 5.1.

Table 5.1

Test results of two-stage GA based load flow

Test System →	5-bus	11-bus	IEEE 14-bus	IEEE 30-bus	IEEE 57-bus	IEEE 118-bus	Population size ↓
Number of Generations	61	140	109	196	258	404	100
	98	191	183	288	349	517	40
	162	289	252	303	472	798	10
	217	408	342	598	763	1012	08

5.7. IMPACT OF THE IMPROVEMENT SCHEMES

Like the PSO based load flows, linear perturbation and local search techniques have been used to speed up the proposed method. In PSO based load flows, the improvement schemes have been applied only on the pbest solution. But in the proposed GA based algorithm, the improvement schemes have been applied on all the solution strings in each iteration. The GA based power flow, as shown in Table 5.1 converges with population size as low as 8. With the applications of the local search on the GA chromosomes, convergence has been achieved with a population size of two only. The performances of the proposed method with the local search have been tested on different test systems for different population-size and are shown in Table 5.2 and Table 5.3.

Table 5.2

Performances of the two-stage GA based load flow 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	25	48	49	92	118	169	10
	31	64	55	111	132	184	08
	48	82	76	147	201	312	06
	172	318	296	523	811	1083	04

From Table 5.2 it is observed that the speed of the proposed method with the local search has increased significantly. Table 5.3 shows the test results of the proposed method with linear perturbation for varied population size.

Table 5.3

Test results of two-stage GA based load flow 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 Generations	12	23	21	32	45	72	10
	13	25	22	35	48	76	08
	15	29	27	41	53	84	06
	24	42	40	63	78	104	04
	37	64	58	89	102	154	02

It is noticed that linear perturbation technique as improvement scheme for the two-stage GA based load flow gives better results than that of the local search technique. For the linear perturbation, number of required generations for convergence with the same population size is comparatively less.

5.8. CONVERGENCE CHARACTERISTICS OF THE PROPOSED METHOD

The variations of the sum square error of the best solution among the whole population with the generations are shown through Fig. 5.6 to Fig.5.9 for population size of 10.

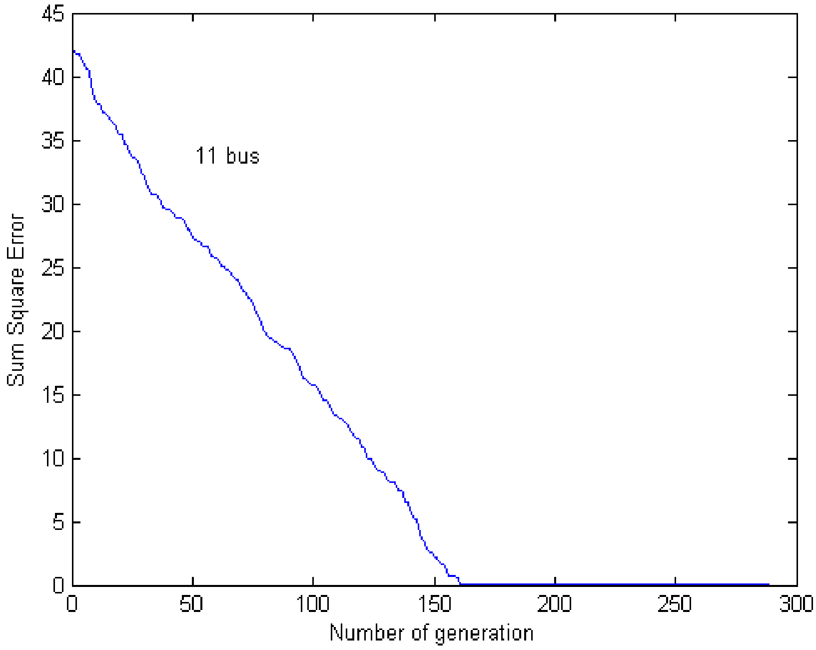

Fig. 5.6: Variations of the sum square error with the generations for 11 bus test system for two-stage GA based load flow with 10-population size

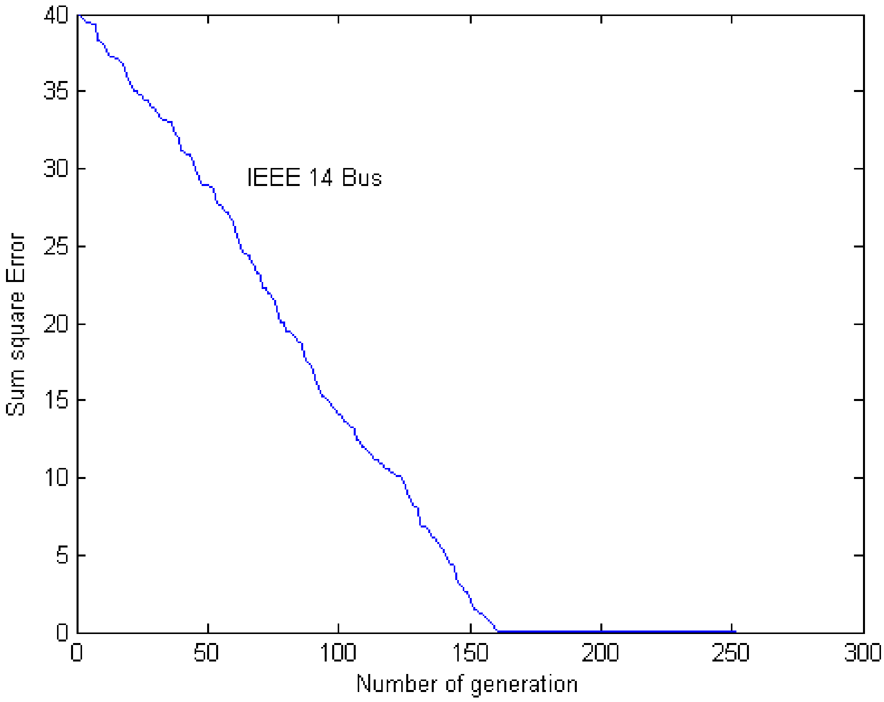

Fig. 5.7: Variations of the sum square error with the generations for IEEE 14 bus test system for two-stage GA based load flow with 10-population size

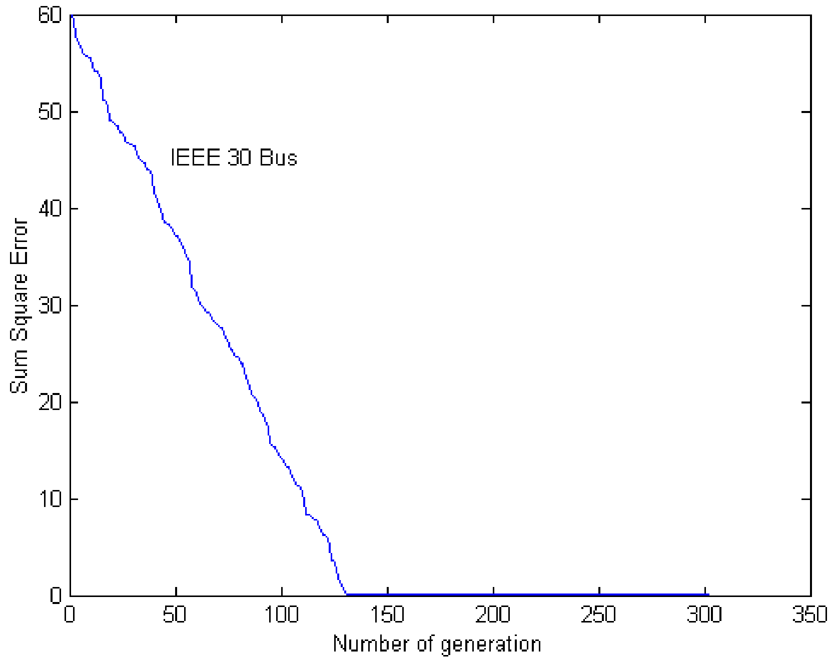

Fig. 5.8: Variations of the sum square error with the generations for IEEE 30 bus test system for two-stage GA based load flow with 10-population size

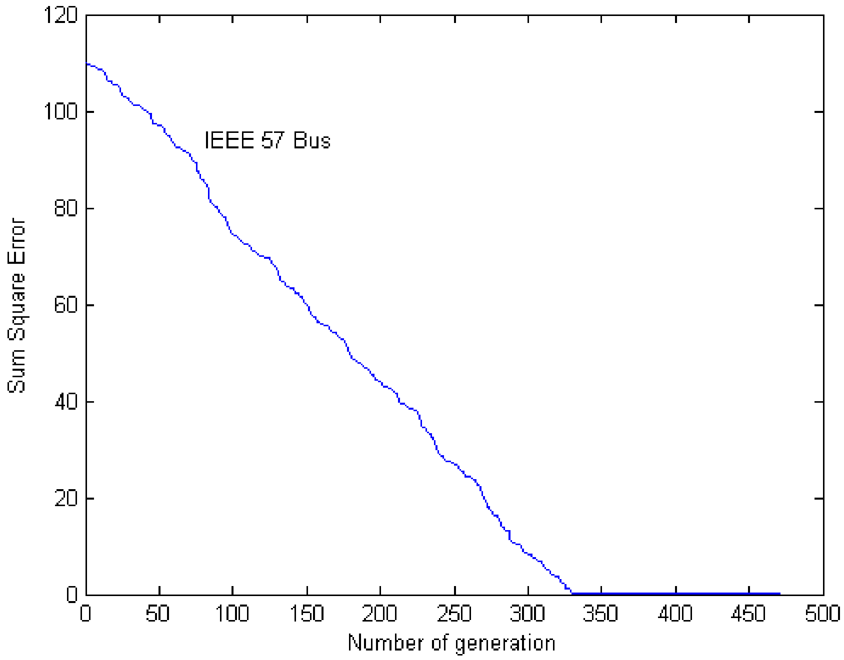

Fig. 5.9: Variations of the sum square error with the generations for IEEE 57 bus test system for two-stage GA based load flow with 10-population size

The sum squared error maintains more or less a uniform rate of reduction throughout the iterative process.

Like PSO based load flow, considerable improvement can be observed when the two-stage GA based load flow works with the local search technique. The convergence characteristics of different test systems with 10-population size are given in Fig.5.10 to Fig. 5.13 for the novel two-stage GA based load flow with local search.

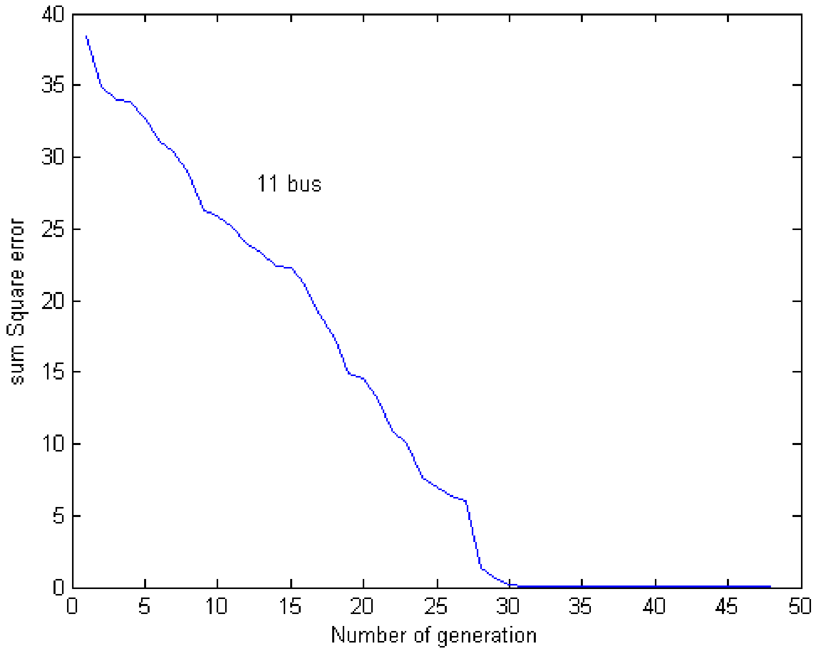

Fig. 5.10: Convergence characteristic of 11-bus test system with 10-population size for the two-stage GA with local search

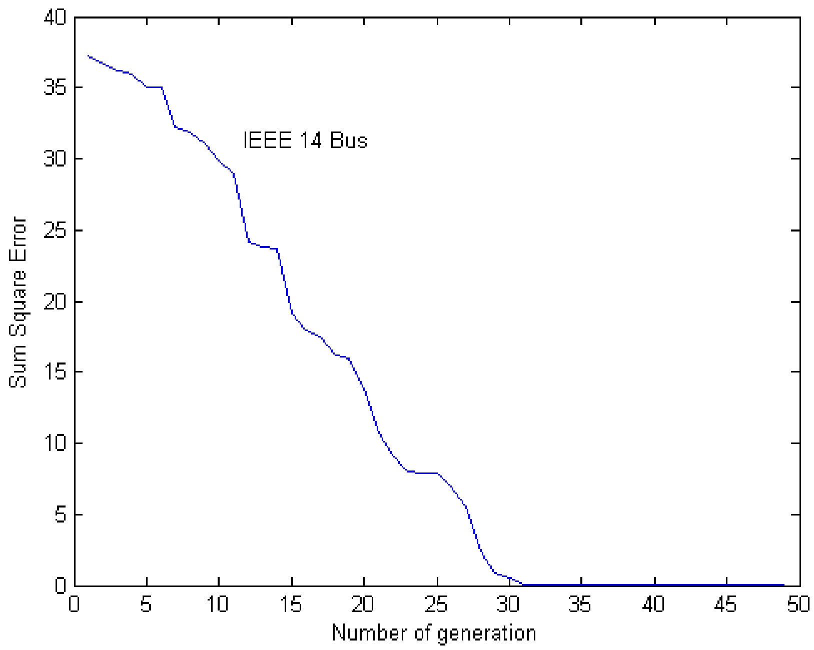

Fig. 5.11: Convergence characteristic of IEEE 14 bus test system with 10-population size for the two-stage GA with local search

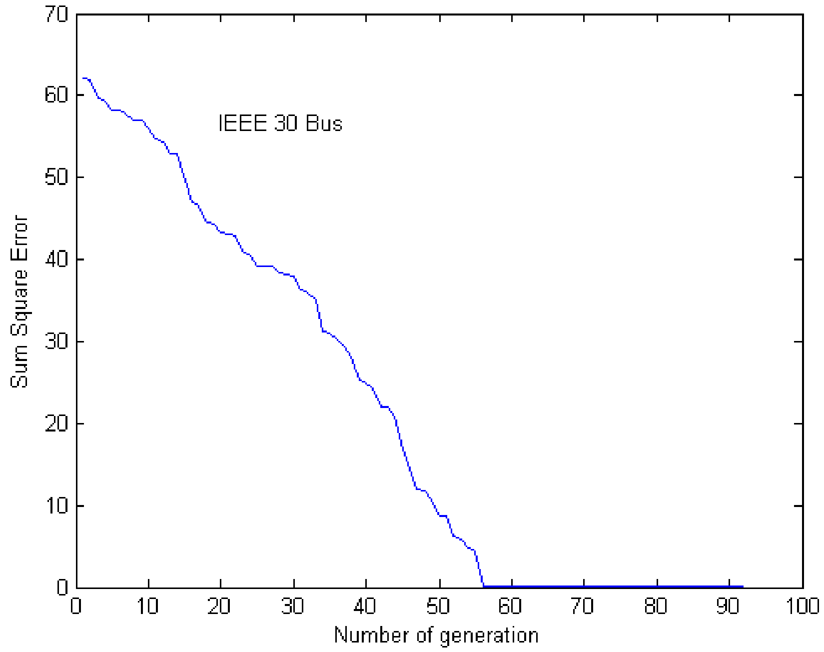

Fig. 5.12: Convergence characteristic of IEEE 30 bus test system with 10-population size for the two-stage GA with local search

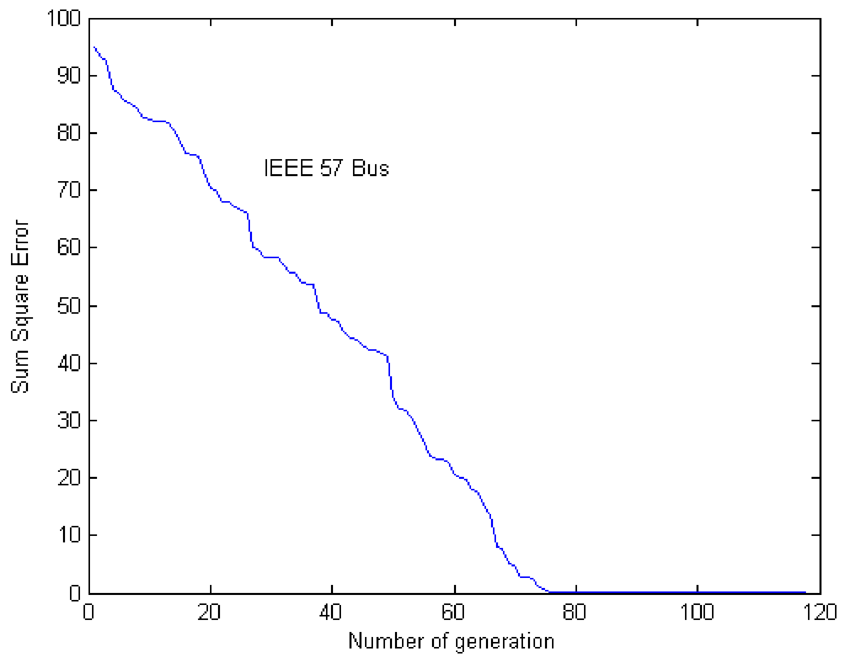

Fig. 5.13: Convergence characteristic of IEEE 57 bus test system with 10-population size for the two-stage GA with local search

With the linear perturbation, the convergence is still better. The variations of the sum square error with the generations for the proposed algorithm with linear perturbation are shown through 5.14 to 5.17 for the population size of 10. The convergence pattern now can be divided into smaller number of segments of uniform slopes.

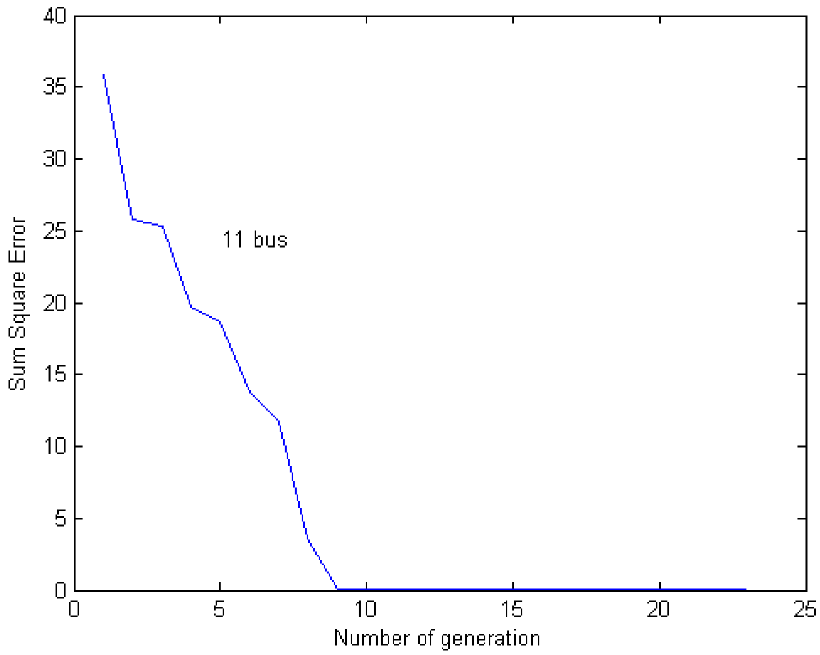

Fig. 5.14: Variations of the sum square error with the generations for 11 bus test system for the two-stage GA based load flow with linear perturbation for the population size of 10

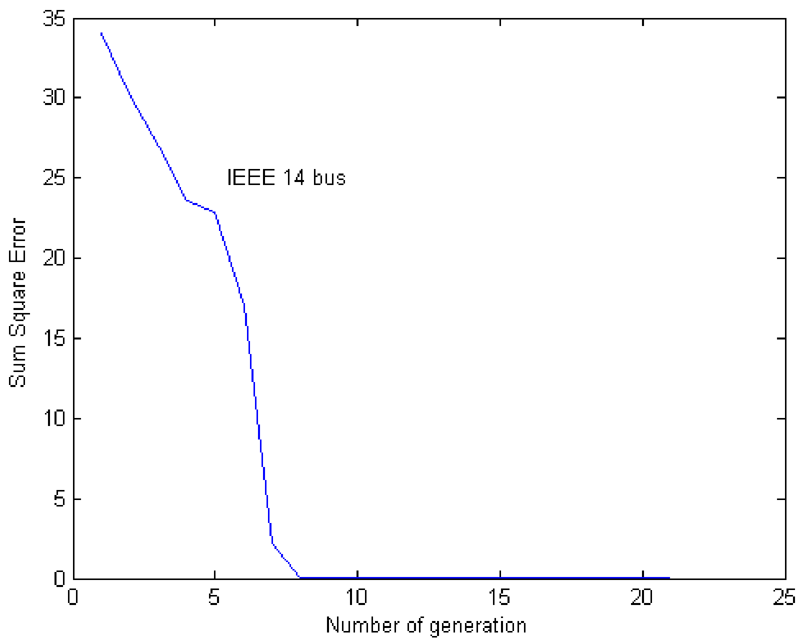

Fig. 5.15: Variations of the sum square error with the generations for IEEE 14 bus test system for the two-stage GA based load flow with linear perturbation for the population size of 10

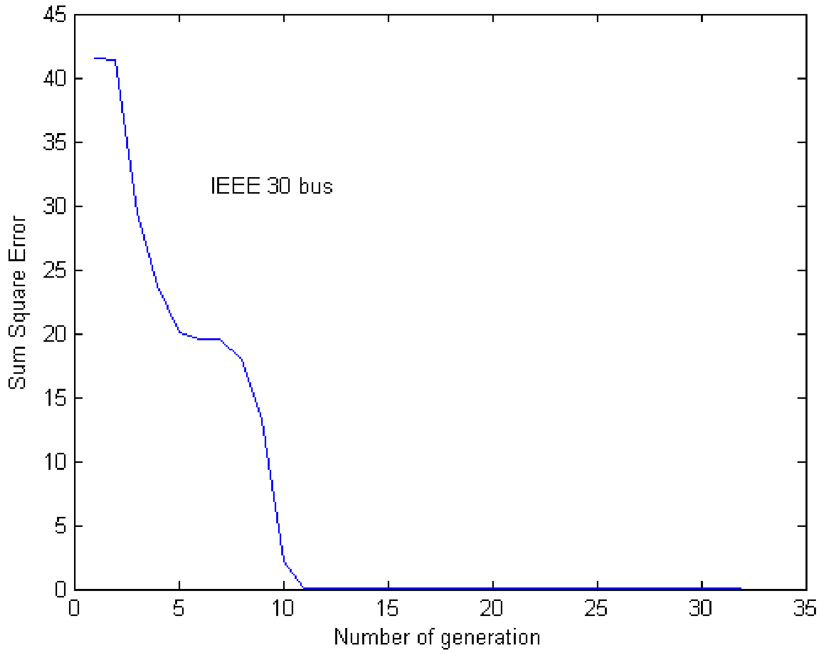

Fig. 5.16: Variations of the sum square error with the generations for IEEE 30 bus test system for the two-stage GA based load flow with linear perturbation for the population size of 10

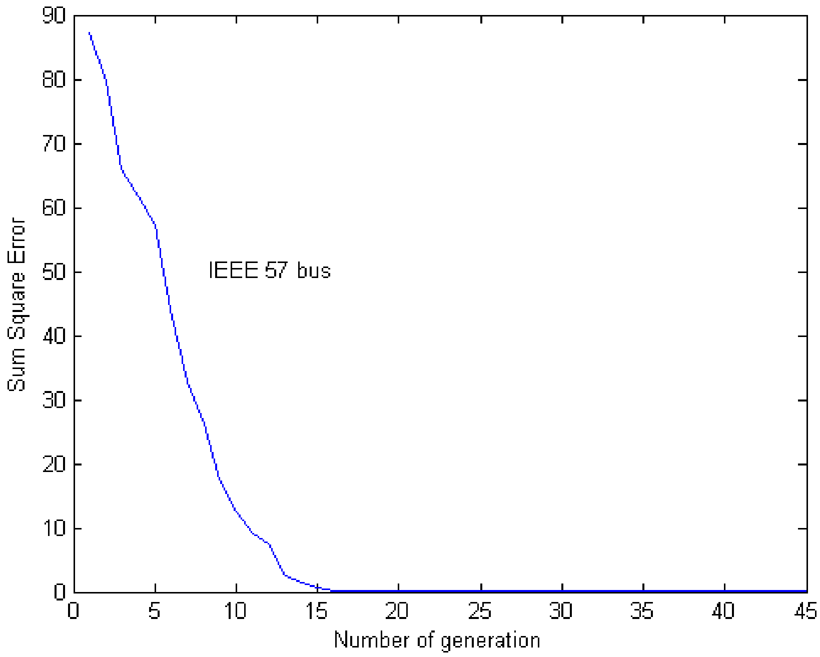

Fig. 5.17: Variations of the sum square error with the generations for IEEE 57 bus test system for the two-stage GA based load flow with linear perturbation for the population size of 10

5.9. PERFORMANCE ANALYSIS

Variation of the product of the number of generation and the population-size with the size of population for the two-stage GA method has been given in Fig. 5.18 and variation of the number of generation with the size of population has been shown in Fig. 5.19.

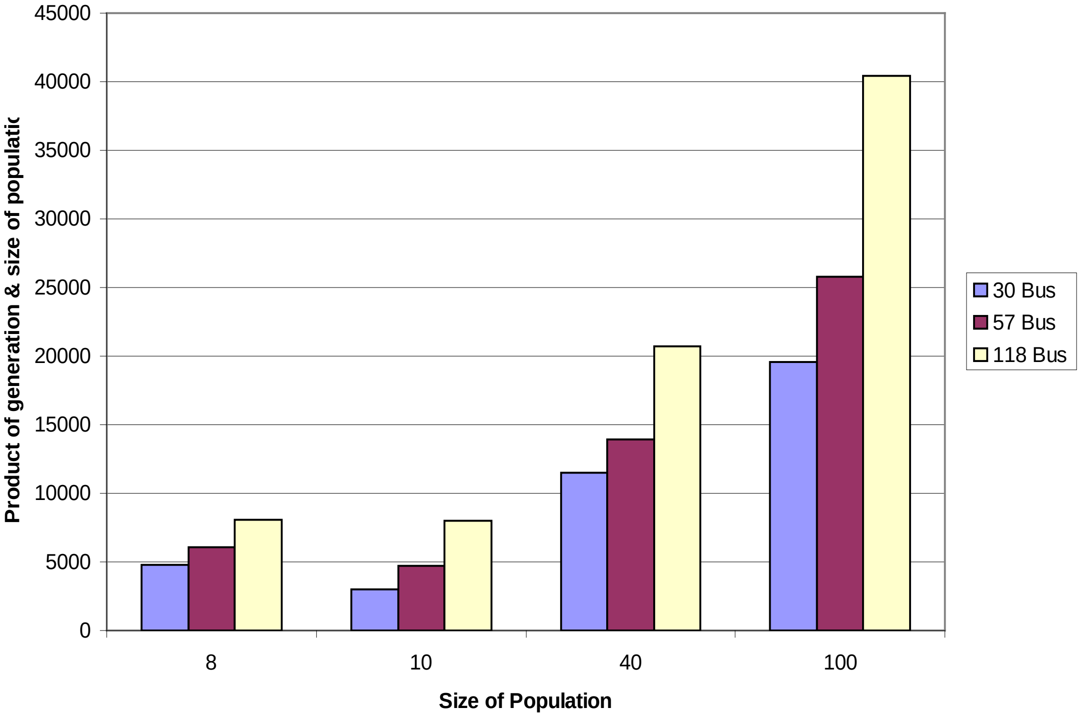

Fig. 5.18: Variation of the product of the number of generation and the population-size with the size of population for the two-stage GA method

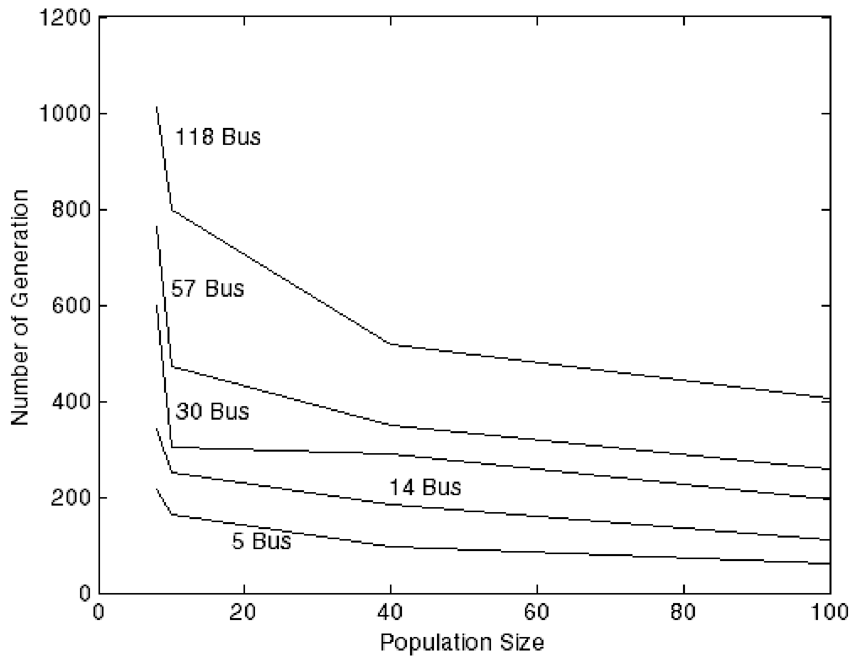

Fig. 5.19: Variation of the number of generation with the size of population for the two-stage GA method

The two-stage GA based algorithm also works better with smaller population size though requiring much greater computing efforts than the decoupled PSO based algorithm. From Fig. 5.19 it has been noticed that the number of generations for convergence decreases with the increase of population size. According to the performance index for the proposed load flow, the best performance has been observed when the population size is 10.

The performances of the proposed method with the local search have been shown in Fig. 5.20 and 5.21.

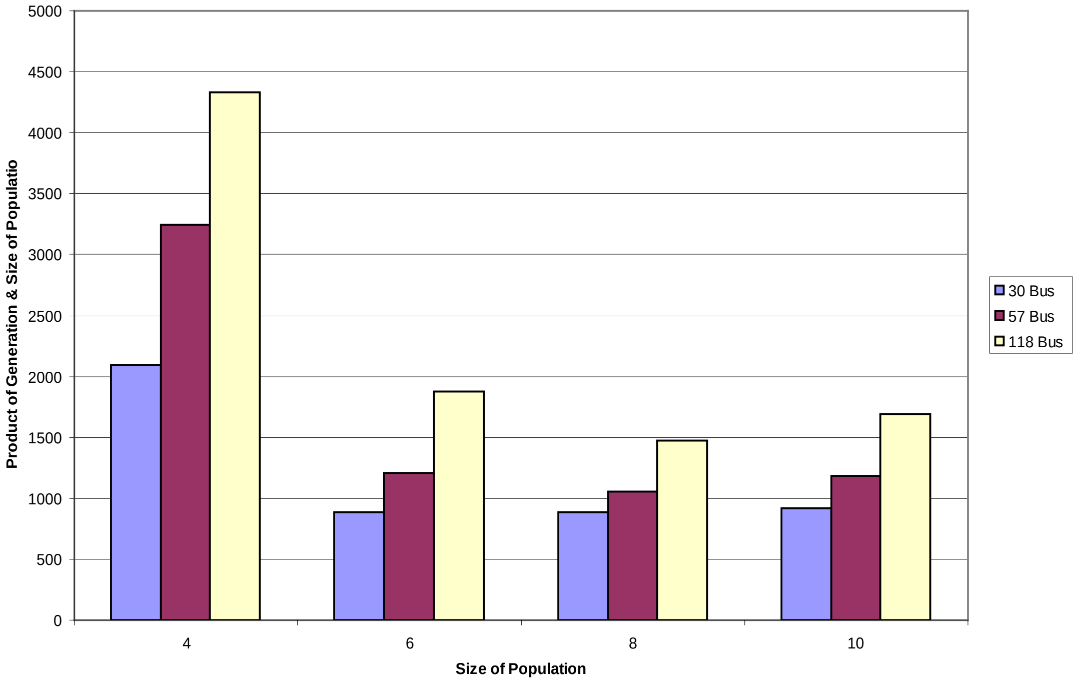

Fig. 5.20: Variation of the product of the number of generation and the population-size with the size of population for two-stage GA method with local search

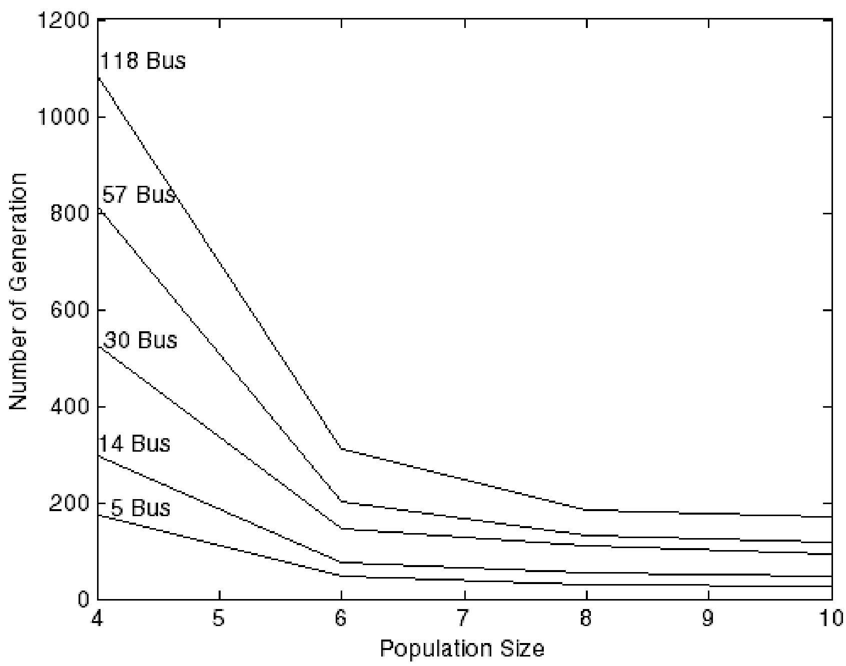

Fig. 5.21: Variation of the number of generation with the population-size for two- stage GA method with local search

If local search is used with the proposed method, then the method is almost independent of the size of population. The best performance has been observed when the population size is 8.

Fig. 5.22 shows the variation of the product of the number of generation and the population-size with the size of population for two-stage GA method with linear perturbation and with the population size the changes in number of generations has been given in Fig. 5.23 for the projected method with linear perturbation.

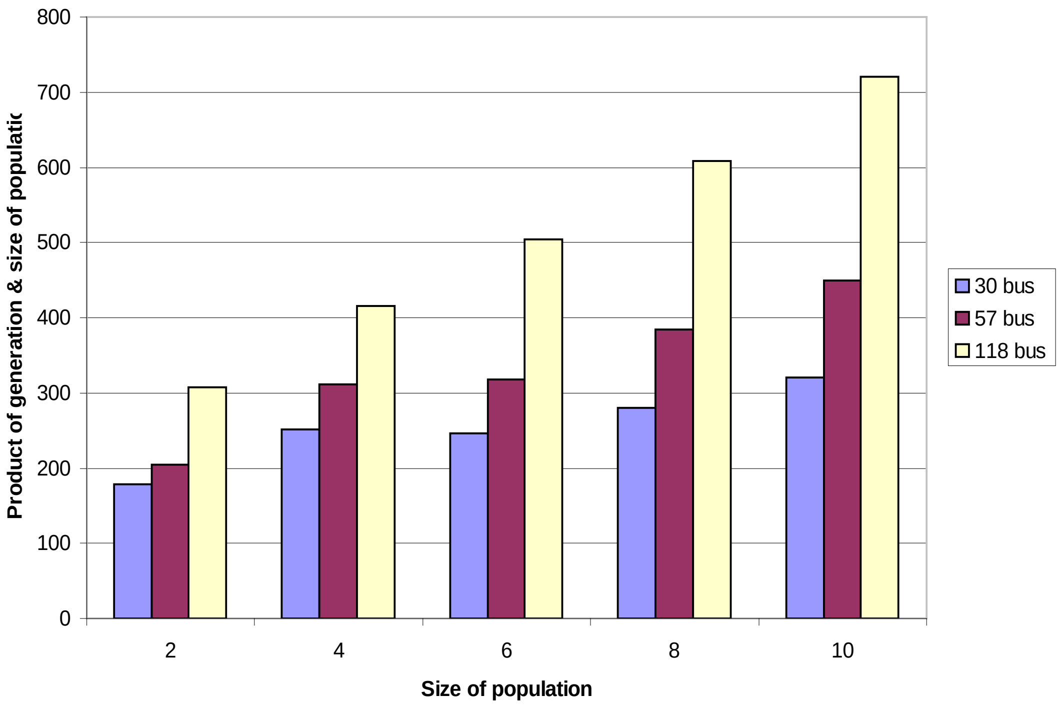

Fig. 5.22: Variation of the product of the number of generation and the population-size with the size of population for two-stage GA method with linear perturbation

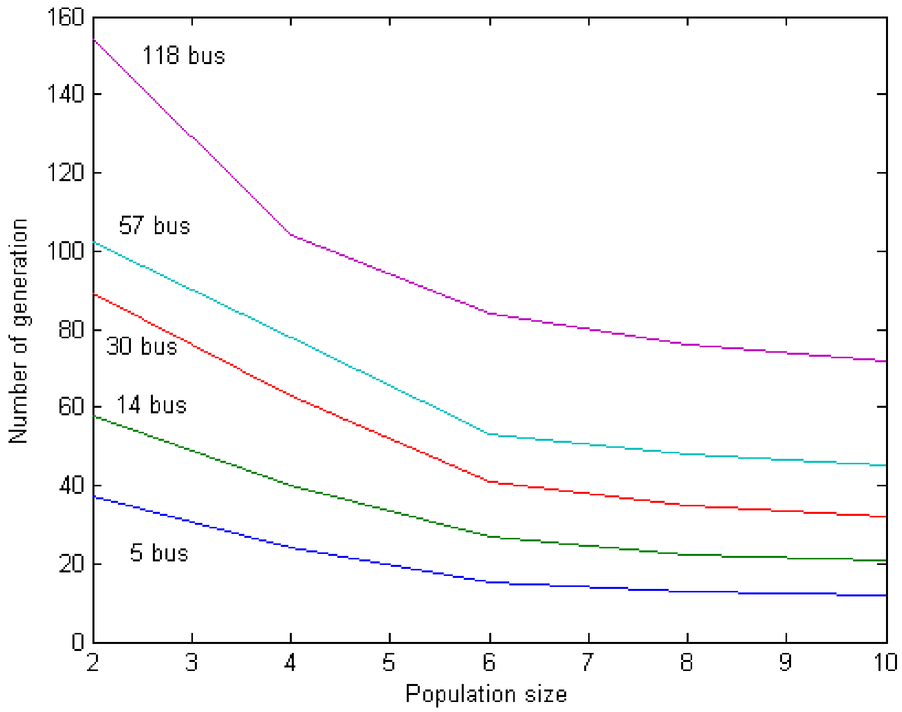

Fig. 5.23: Variation of the number of generation with the population-size for two- stage GA method with linear perturbation

The two-stage GA based power flow with linear perturbation is insensitive to the size of population according to Fig. 5.23. From Fig.5.22 it can be concluded that the proposed method with linear perturbation has given best performance for population size 2 only. The performance of the proposed method with linear perturbation is better than that of the local search.

5.10. CONCLUSION

A two-stage GA based load flow is proposed in the chapter. The first stage contains only the crossover operator and the second stage consists of both crossover and mutation operators. In the proposed algorithm the mutation probability is higher than the conventional mutation probability.

For the proposed algorithm the required number of generations for convergence is more than the PSO based decoupled algorithm. But the performance of this method is better than the PSO based coupled algorithm.

The perturbation based load flows iterations have been used along with the GA algorithm for improved performance. Unlike the PSO algorithms, improvement steps had to be applied on all the solution populations. The two-stage GA based load flow with linear perturbation gives better performance than that of the local search. With the improvement scheme this method give convergence reliably with the population size of 2 only.

The population based load flows can handle the FACTS variables efficiently. Treatment of the FACTS devices and Q-limit constraints of the generator buses remain same in all the implementations reported in this thesis. The author has, therefore, arranged to present them separately in the next chapter. Moreover, it now perhaps is a requirement to have a comparative study on the performance of all the population based load flows presented in this thesis. The next chapter thus contains a report on the performance of the population based load flows developed by the author.