CHAPTER 4

AGC OF INTERCONNECTED TWO AREA SYSTEM WITH INTELLIGENT CONTROLLER

In the previous chapter, single-area load frequency control was explained where the power systems were operated as an isolated unit and the frequency deviations were represented by a single variable Δf. Due to huge demand of power and increased consistency, neighbouring areas are interconnected. The generating stations are interconnected to form a state grid, a regional grid and a national grid. The interconnection provides an economic operation as lesser machines are required for meeting the peak loads and unexpected loads. The power system is divided into sub-areas which are tied up tightly and all the generators swing in unison with change in load or speed changer setting. These areas are termed as control area.

disturbances caused by load, result in, changes to the nominal value of frequency. In an interconnected system if there is a load disturbance in any one area, the frequency of other areas also get affected. Therefore, to improve the overall stability of the system, automatic generation control is required.

In this chapter AGC of an interconnected two area system is carried out .It is assumed that each area is strong and is interconnected through a tie line. A widely used model of a two area non-reheat thermal system is chosen for the purpose of modeling and simulation. A conventional PI controller and Fuzzy logic controller are designed for the system and further both the controllers are optimized using Genetic Algorithm.

4.1 MODELING OF A TWO AREA THERMAL SYSTEM (NON-REHEAT) USING INTEGRAL CONTROLLER

The schematic block diagram created in MATLAB SIMULINK with conventional PI controller is shown in Fig. 4.1 below

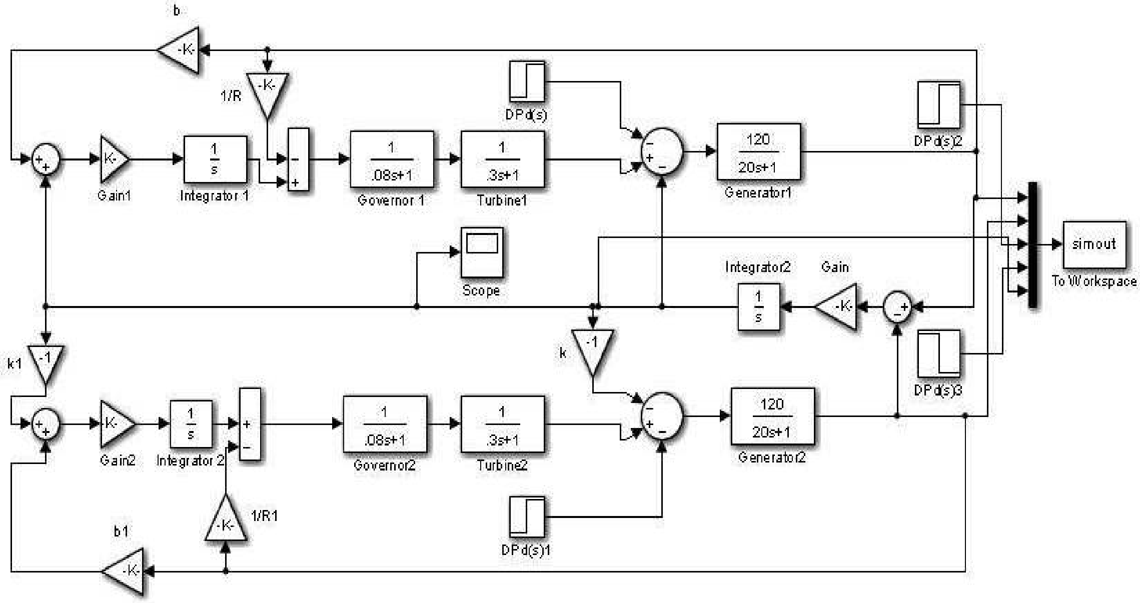


Figure 4.1 Two area thermal non-reheat system with PI controller

AGC problem is resolved by applying Area Control Error (ACE) as input to a PI controller which calculates an error value as the difference between measured value and the set point. The control inputs are adjusted by the controller in order to minimize the error.

For the design of PI controller, the optimal values of controller gains can be obtained through various existing tuning method [28]-[30]. By tuning these parameters, the desired performance can be obtained.

In this thesis, the GA is used to find the optimal values of gain of PI controller in both the areas to meet the designs specifications. The weighted average of ITAE, IAE and ISE criterion is used to evaluate the fitness of each chromosome [31]. The flowchart for tuning PI Controller using GA is shown in Fig. 4.2.

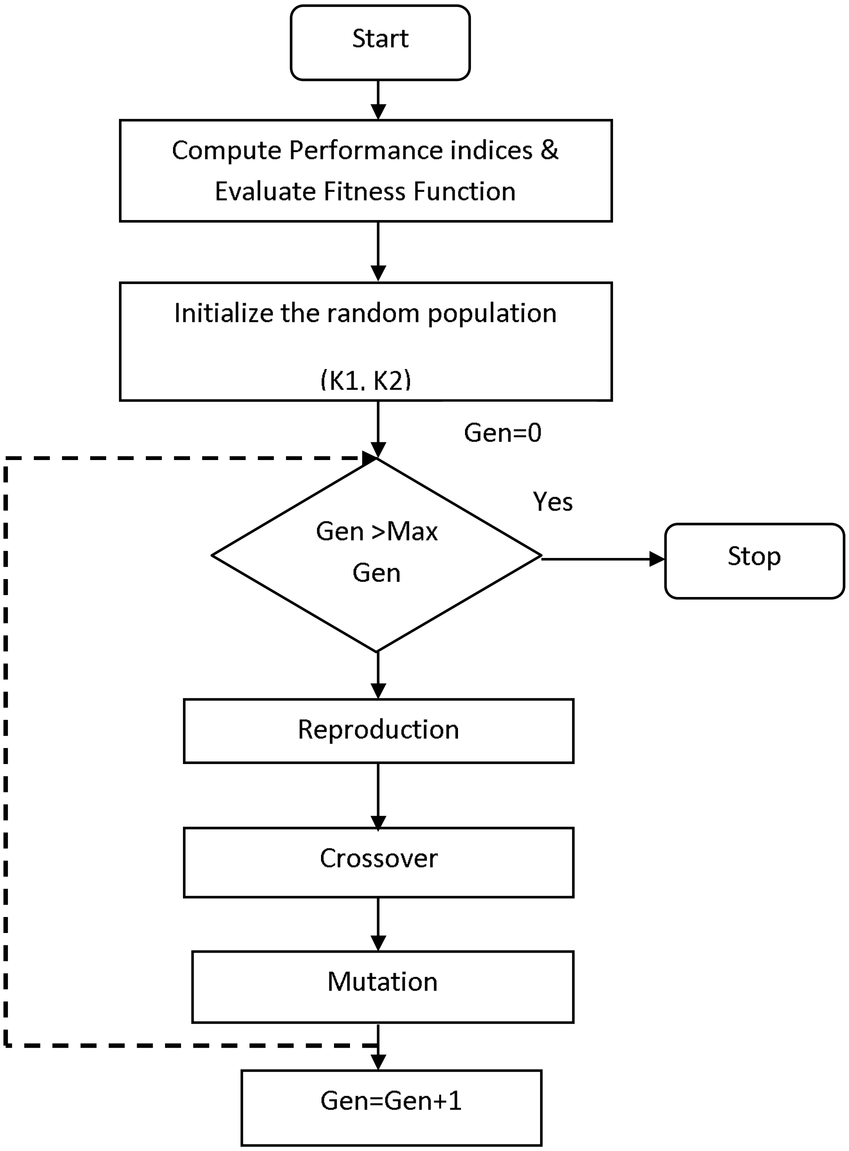


Figure 4.2 Flow Chart of GA tuned PI controller

4.2 DESIGN CRITERION FOR GA OPTIMISED PI CONTROLLER

4.2.1 GA PARAMETERS

The parameters chosen for the GA program are illustrated in Table 4.1

Table 4.1 GA Parameters for PI Controller

POP SIZE	30
LENGTH OF CHROMOSOME	2
PROBABILITY OF CROSSOVER	0.6
PROBABILITY OF MUTATION	0.003
WEIGHT OF INTEGRAL SQUARE ERROR (ISE) W_1	0.4
WEIGHT OF INTEGRAL ABSOLUTE ERROR (IAE) W_2	0.3
WEIGHT OF INTEGRAL OF TIME ABSOLUTE ERROR (IATE) W_3	0.3

4.2.2 DECLARATION OF BOUNDS

The GA evolves the optimal values of the gains of PI controller in both areas within a range imposed by lower and upper bounds as shown in Table 4.2 below

Table 4.2 Bounds for Gain of PI controller

GAIN	LB	UB
K1	-0.05	-0.1
K2	-0.05	-0.1

4.2.3 CHOICE OF FITNESS FUNCTION

A general comprehensive fitness function, which takes into account different performance evaluation criterion such as IAE, IATE and ISE is used as:

Fitness Function = $(\boldsymbol{w1} + \boldsymbol{w2} + \boldsymbol{w3})/\ (\boldsymbol{w1} \times \boldsymbol{ISE} + \boldsymbol{w2} \times \boldsymbol{IAE} + \boldsymbol{w3} \times \boldsymbol{IATE})$

Eqn. 4.1

Where ISE= Integral Square Error, IAE=Integral Absolute error and
IATE= Integral of absolute time error
w1, w2, & w3 are chosen as free parameters by the user and are respectively the weightages given to ISE, IAE and IATE.

4.2.4 SIMULATION RESULT

GA was run for a number of generations, until the performance criterion is met with. The optimal parameters were evolved by the GA program in 28 generations. The complete population report for the Generation1 is shown below.

POPULATION REPORT OF GENERATION 1

S.no	String	Fitness
1	-0.0843 -0.0592	1.0295
2	-0.0922 -0.0597	1.1129
3	-0.0723 -0.0653	1.0783
4	-0.0614 -0.0718	0.9830
5	-0.0719 -0.0556	1.0933
6	-0.0906 -0.0766	1.3713
7	-0.0774 -0.0648	1.0258
8	-0.0822 -0.0689	0.9702
9	-0.0611 -0.0559	1.0556
10	-0.0712 -0.0754	1.3059
11	-0.0715 -0.0592	1.1097
12	-0.0872 -0.0594	1.2473
13	-0.0938 -0.0856	1.0115
14	-0.0801 -0.0775	1.2897
15	-0.0735 -0.0615	1.1435
16	-0.0801 -0.0856	0.8109
17	-0.0743 -0.0556	0.9650
18	-0.0719 -0.0718	1.1706
19	-0.0675 -0.0970	0.7925
20	-0.0843 -0.0592	0.8514

S.no	String	Fitness
21	-0.0648 -0.0659	0.9806
22	-0.0723 -0.0653	0.9267
23	-0.0604 -0.0651	1.3936
24	-0.0909 -0.0897	0.9090
25	-0.0811 -0.0794	0.8677
26	-0.0614 -0.0718	1.0489
27	-0.0743 -0.0718	1.1539
28	-0.0890 -0.0541	0.7752
29	-0.0938 -0.0592	0.8757
30	-0.0715 -0.0775	1.0000

Fitness function of best fit chromosome (Bestf) in generation 1 = 0.7752

Best fit chromosome (bestfchro) in generation 1 = -0.0611 -0.0559

STATISTICS OF GENERATION 28

Fitness function of best fit chromosome (Bestff) in generation 1 = 0.0592

Best fit chromosome (bestfchro) in generation 1 = -0.0990 -0.0990

Hence the optimal value of K1 and K2 obtained by the GA in 28 generations are -0.099 and 0.099 respectively

4.2.5 PLOTS OF THE RESPONSE OF GA PI CONTROLLER

The simulation plots of the GA tuned PI controller for the best fit chromosomes are presented in Fig.4.3, Fig.4.4. and Fig.4.5.

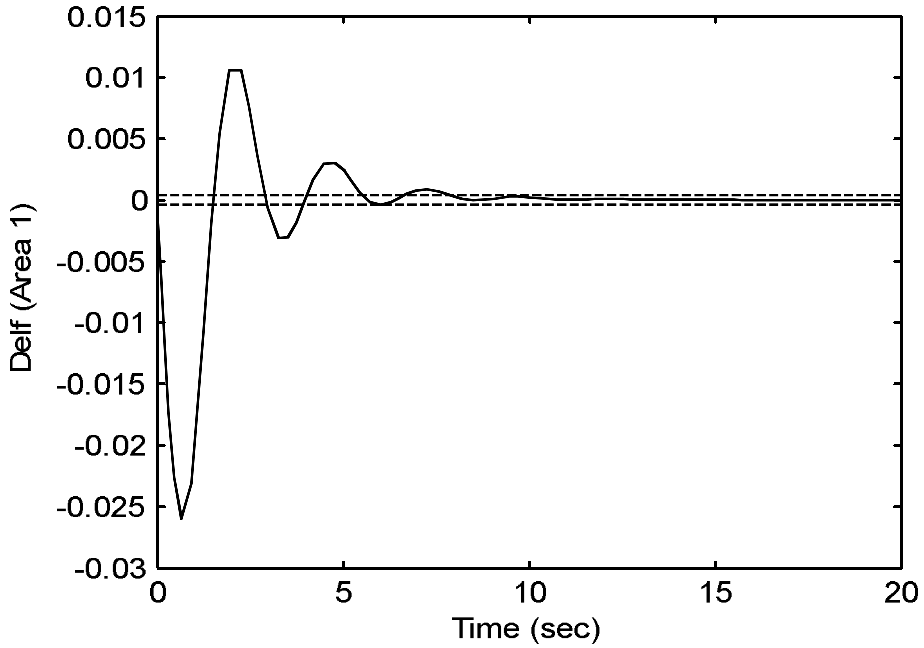


Figure 4.3 GA PI response for frequency deviation in Area 1 (ΔF_1)

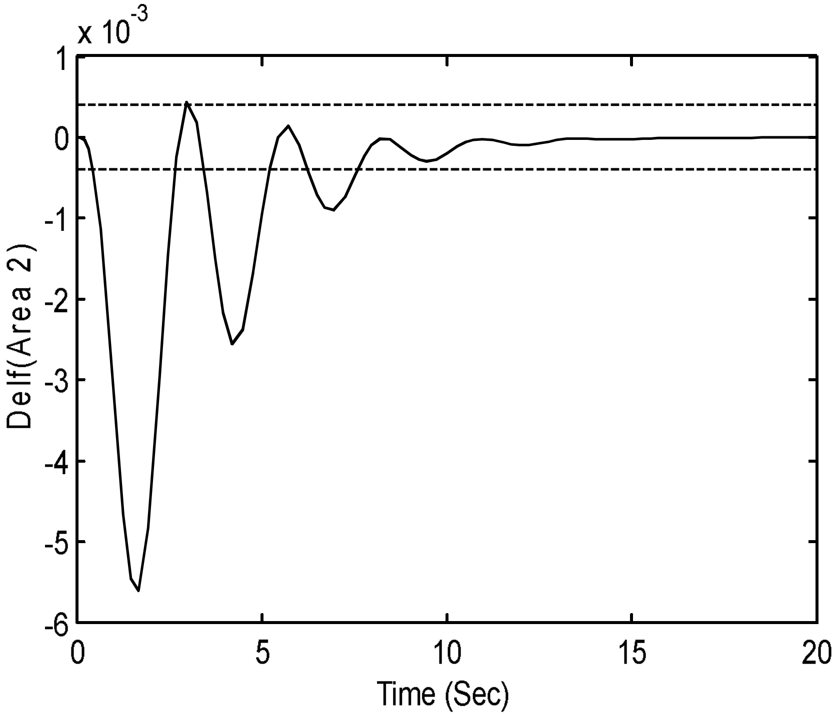


Figure 4.4 GA PI response for frequency deviation in area2 (ΔF_2)

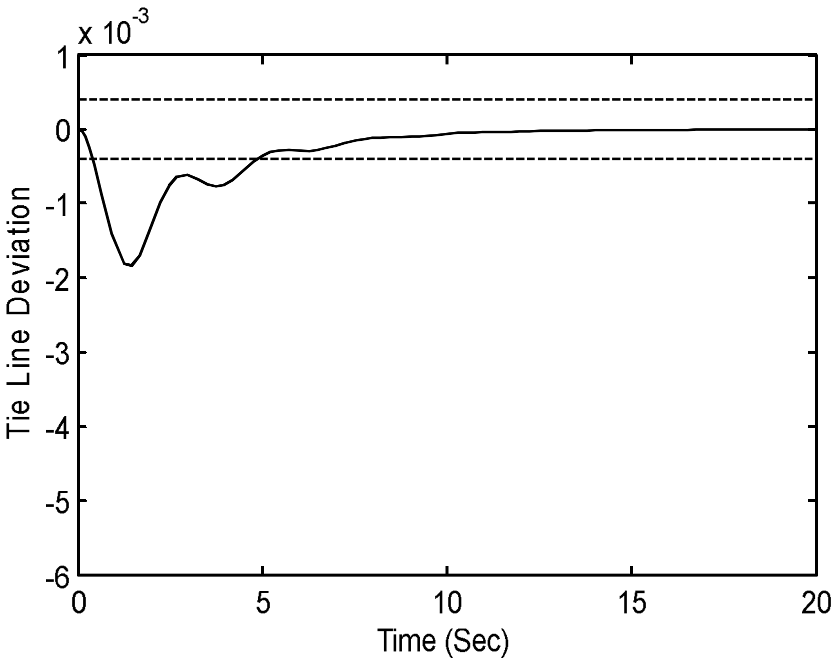


Figure 4.5 GA PI response for tie-line deviation

It is observed that the GA tuned PI controller reveals a better time response specifications as compared to the other conventional available methods. However new intelligent techniques may be applied to enhance the capabilities of the AGC [32]-[36]. The next section presents the Fuzzy Logic controller and its optimization using GA for the same model of two area AGC used in this section.

4.3 MODELING OF A TWO AREA THERMAL SYSTEM (NON-REHEAT) USING FUZZY LOGIC CONTROLLER

The schematic block diagram is created in MATLAB SIMULINK as shown in Fig. 4.6. FLC is designed using MATLAB fuzzy logic tool box (all mfs are taken as symmetrical).

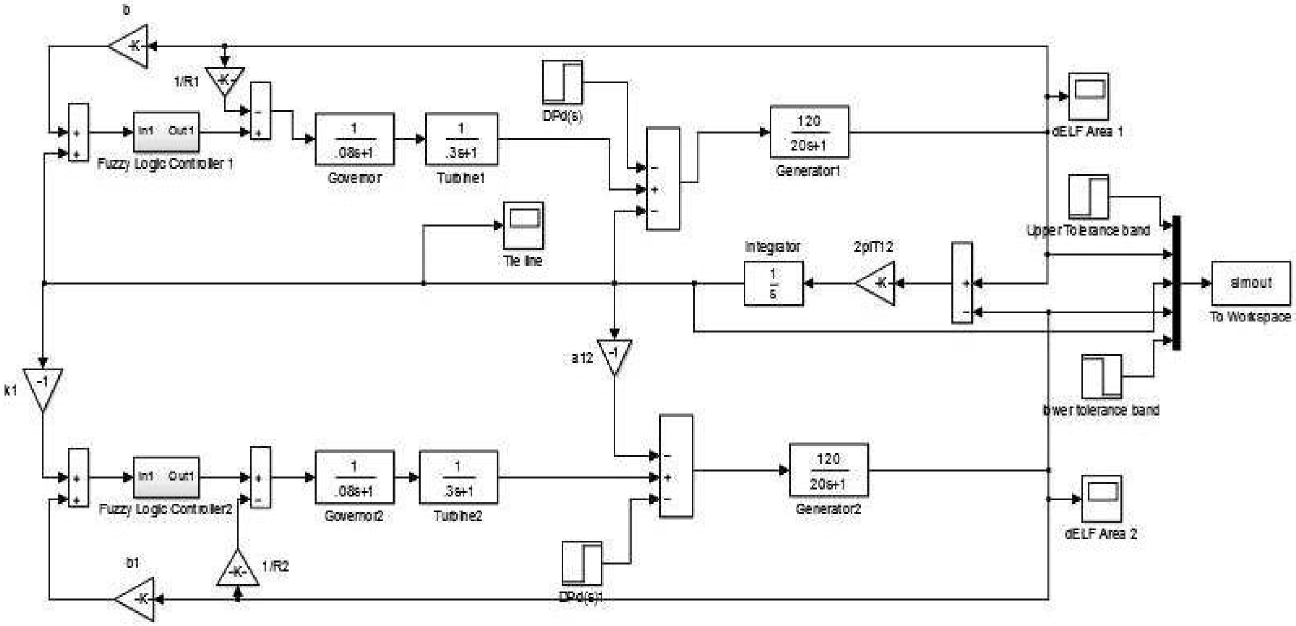


Figure 4.6 Simulink model of a two Area non-reheat thermal System with FLC.

4.3.1 Design of Fuzzy Logic Controller

Inputs to the FLC are chosen as ACE and d/dt(ACE) as shown in fig 4.6. Five membership functions for each of the two inputs (ACE and d/dt(ACE)) and one output are defined. as negative large(NL), negative smal(NS), zero(Z), positive small(PS), positive large(PL).

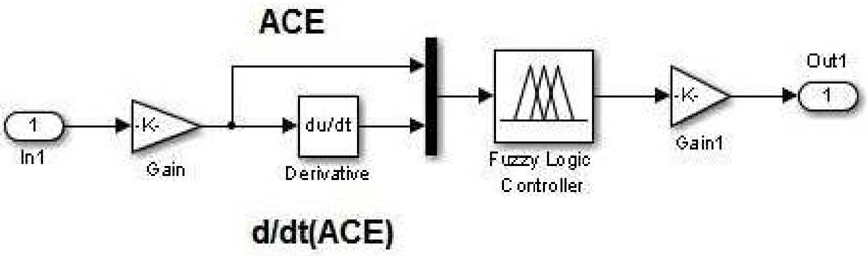


Figure 4.7 Fuzzy Logic Controller Structure

The rule base [24] used for the fuzzy controller are described in Table 4.3. The rules has a rationale as follows: if ACE is PL and d/dt(ACE) is PL then ACE-out is PL, etc

Table 4.3 Fuzzy Rule Base (25 Rules)

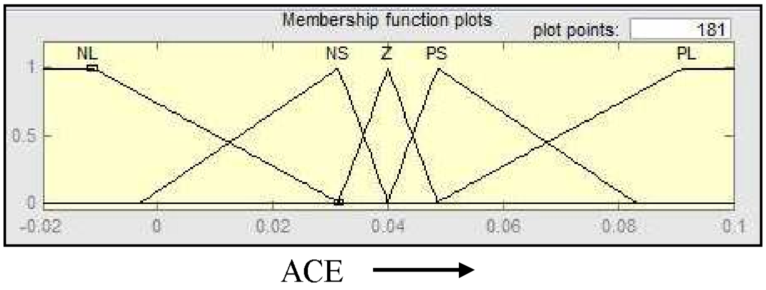
d/dt(ACE)

ACE	**NL**	**NS**	**Z**	**PS**	**LP**
NL	**NL**	**NL**	**NS**	**NS**	**Z**
NS	**NL**	**NS**	**NS**	**Z**	**PS**
Z	**NS**	**NS**	**Z**	**PS**	**PS**
PS	**NS**	**Z**	**PS**	**PS**	**PL**
PL	**Z**	**PS**	**PS**	**PL**	**PL**

4.3.2 Membership Function of FLC

Initial design of the FLC is hand tuned with all mfs taken as symmetrical as shown in Fig. 4.8.

a)



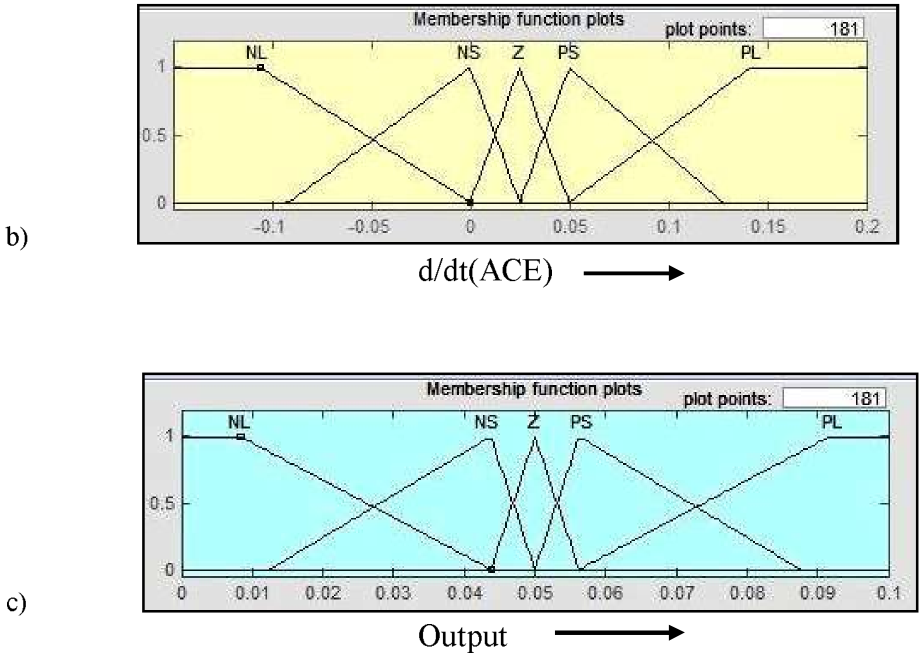


Figure 4.8 Symmetrical mfs of FLC, a) for ACE, b) for d/dt(ACE), c) for output

4.4 OPTIMIZATION OF THE PARAMETERS OF FLC USING GA

The input and output membership functions of the FLC are designed automatically by the optimization process carried out by GA. The interfacing of the system model designed in SIMULINK and the FLC is done through the separately written MATLAB program of the GA. The GA program computes the parameters of mfs based on fitness function and returns to the FLC in the Simulink model.

4.4.1 FITNESS COMPUTATION

The optimisation of the parameters of mfs are carried out based on the minimization of integral time multiply absolute error (ITAE) criterion. It has been shown in the literarture [31] that IATE gives a better performance as compared to other criterion used in the control design, such as, ISE and IAE and therefore is used in this thesis.

$$\boldsymbol{J = ITAE = \int_0^{tsim}(|\Delta F1| + |\Delta F2| + |\Delta Ptie|).t.dt} \qquad \text{Eqn.4.2}$$

4.4.2 SIZE OF CHROMOSOME

In this thesis the symmetrical untuned mfs of the FLC are tuned using GA to improve the controller response. The size of the chromosome is decided based on the parameters of the mfs of FLC to be optimized. The chromosome for the FLC in each area consists of three alleles for each triangular membership functions (trimf) and two for each Sigmoidal membership functions(smf), thus the size of chromosome in each area is calculated as:

$s = [2 \times 2 + (5 - 2) \times 3] \times 3 = 39$ alleles.

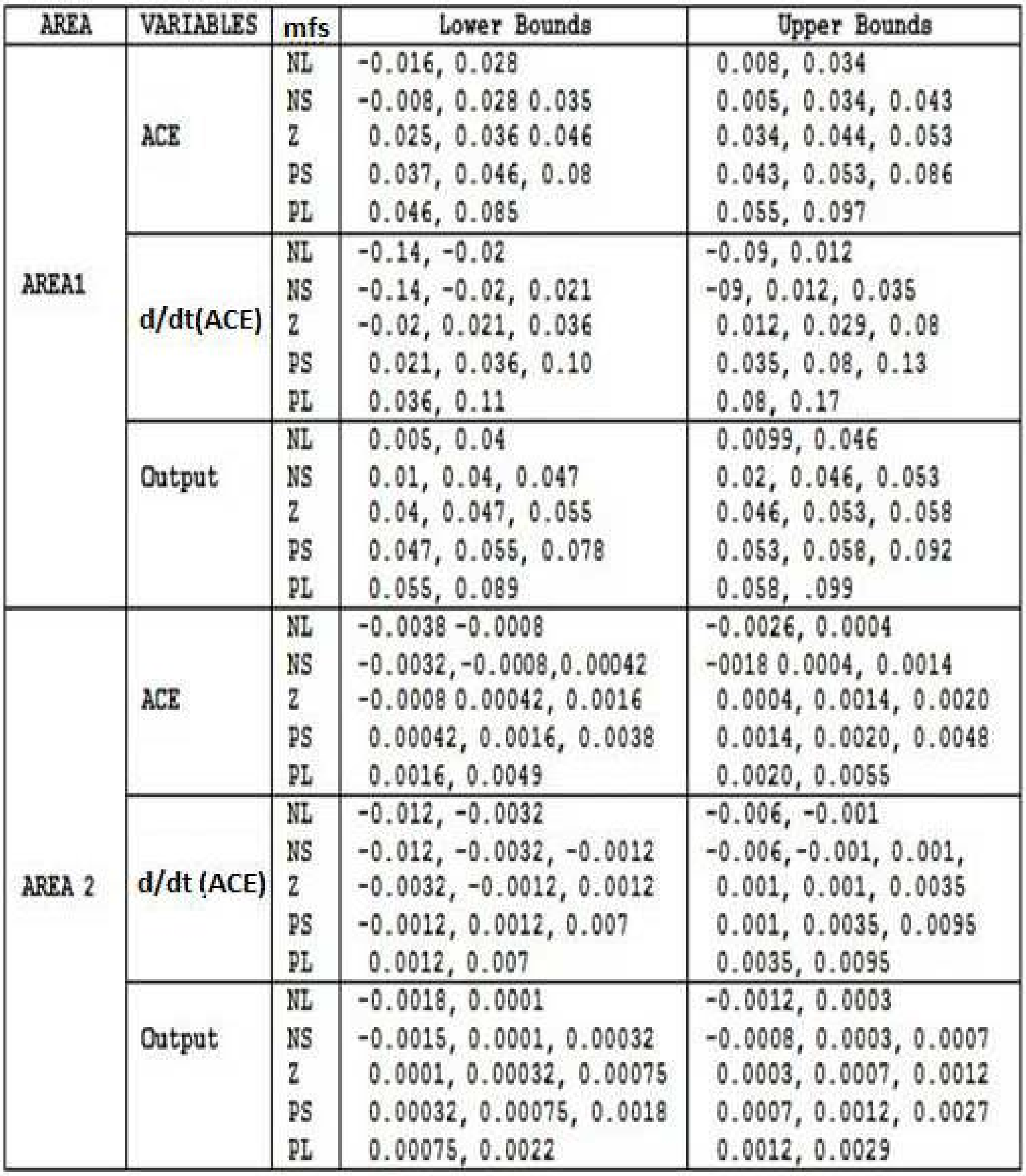
Therefore, for two FLC's in two area AGC, the size of chromosome becomes:

$2 \times s = 78$.

4.4.3 BOUNDS SELECTION FOR PARAMETERS

Trial runs are performed on the FLC to find out the lower and upper bounds on each allele value so as to get the parameters of mfs within acceptable limits. GA searches for the optimal parameters within these bounds. The Table 4.4 depicts the typical values of these bounds

Table 4.4 Membership function bounds for FLC



AREA	VARIABLES	mfs	Lower Bounds	Upper Bounds
AREA1	ACE	NL	-0.016, 0.028	0.008, 0.034
		NS	-0.008, 0.028 0.035	0.005, 0.034, 0.043
		Z	0.025, 0.036 0.046	0.034, 0.044, 0.053
		PS	0.037, 0.046, 0.08	0.043, 0.053, 0.086
		PL	0.046, 0.085	0.055, 0.097
	d/dt(ACE)	NL	-0.14, -0.02	-0.09, 0.012
		NS	-0.14, -0.02, 0.021	-09, 0.012, 0.035
		Z	-0.02, 0.021, 0.036	0.012, 0.029, 0.08
		PS	0.021, 0.036, 0.10	0.035, 0.08, 0.13
		PL	0.036, 0.11	0.08, 0.17
	Output	NL	0.005, 0.04	0.0099, 0.046
		NS	0.01, 0.04, 0.047	0.02, 0.046, 0.053
		Z	0.04, 0.047, 0.055	0.046, 0.053, 0.058
		PS	0.047, 0.055, 0.078	0.053, 0.058, 0.092
		PL	0.055, 0.089	0.058, .099
AREA 2	ACE	NL	-0.0038 -0.0008	-0.0026, 0.0004
		NS	-0.0032,-0.0008,0.00042	-0018 0.0004, 0.0014
		Z	-0.0008 0.00042, 0.0016	0.0004, 0.0014, 0.0020
		PS	0.00042, 0.0016, 0.0038	0.0014, 0.0020, 0.0048
		PL	0.0016, 0.0049	0.0020, 0.0055
	d/dt (ACE)	NL	-0.012, -0.0032	-0.006, -0.001
		NS	-0.012, -0.0032, -0.0012	-0.006,-0.001, 0.001,
		Z	-0.0032, -0.0012, 0.0012	0.001, 0.001, 0.0035
		PS	-0.0012, 0.0012, 0.007	0.001, 0.0035, 0.0095
		PL	0.0012, 0.007	0.0035, 0.0095
	Output	NL	-0.0018, 0.0001	-0.0012, 0.0003
		NS	-0.0015, 0.0001, 0.00032	-0.0008, 0.0003, 0.0007
		Z	0.0001, 0.00032, 0.00075	0.0003, 0.0007, 0.0012
		PS	0.00032, 0.00075, 0.0018	0.0007, 0.0012, 0.0027
		PL	0.00075, 0.0022	0.0012, 0.0029

4.4.4 PARAMETERS FOR GA

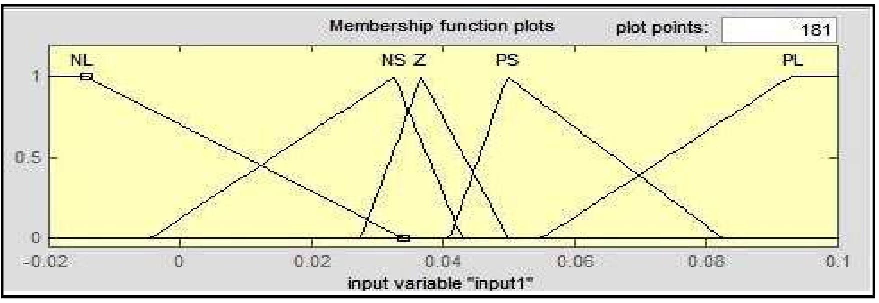
Parameters chosen for the GA program are listed in Table 4.5 below

Table 4.5 GA Parameters

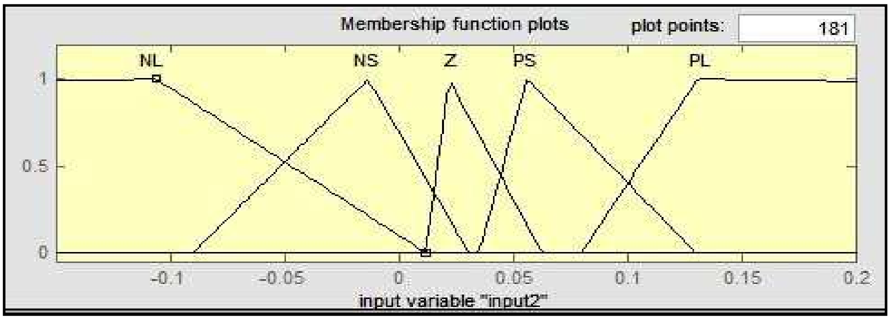
Population Size=30	30
Length of chromosome	78
Probability of Cross over	0.6
Probability of mutation	0.03

4.4.7 SIMULATION RESULTS AND DISCUSSIONS

The model of the system (Fig. 4.1) with Fuzzy controller developed in MATLAB/SIMULINK interacts with the separately written GA program (in .mfile). The GA computes the fitness value in various generations and in the process captures good fitness values till the program terminates based on termination criterion. The parameters of the FLC tuned by GA are 78. The tuned mfs of the FLC for the two inputs and output obtained from the best solution in 32 generations are shown in figure 4.9



a



b

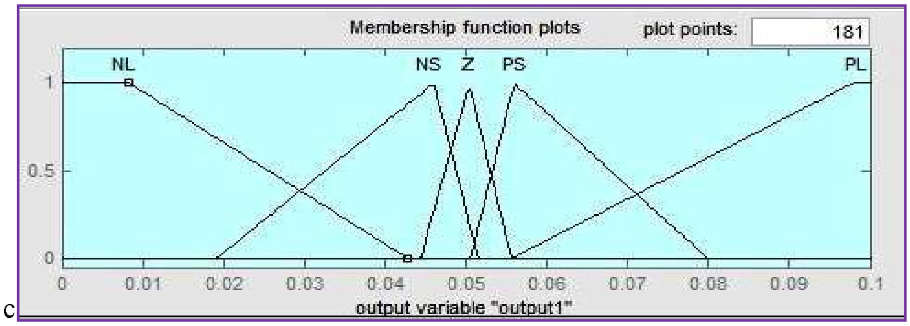


Figure 4.9 GA tuned mfs of FLC a) for ACE, b) for d/dt(ACE) and c) for output of FLC

For the sake of brevity the generation statistics of the first and the last generation is presented. Some good solutions having fitness (0.0861, 0.0451 and 0.0351) in different generations are produced by GA.

Generation 1: Statistics

Minimum fitness = 1.7126, Maximum fitness =0.1425, Mean of Fitness =0.9501

Best fit chromosome

[-0.0111 0.0308 -0.0034 0.0330 0.0397 0.0299 0.0433 0.0480 0.0415 0.0513 0.0823 0.0511 0.0859 -0.1373 -0.0030 -0.1010 0.0099 0.0228 -0.0018 0.0248 0.0365 0.0257 0.0431 0.1238 0.0497 0.1417 0.0058 0.0436 0.0126 0.0439 0.0511 0.0445 0.0497 0.0553 0.0484 0.0577 0.0801 0.0575 0.0944 -0.0026 -0.0007 -0.0026 -0.0007 0.0014 -0.0008 0.0012 0.0019 0.0013 0.0016 0.0042 0.0017 0.0054 -0.0094 -0.0012 -0.0109 -0.0026 -0.0009 -0.0029 0.0007 0.0025 0.0000 0.0015 0.0091 0.0026 0.0079 -0.0015 0.0002 -0.0014 0.0001 0.0004 0.0001 0.0004 0.0009 0.0003 0.0012 0.0027 0.0010 0.0025]

Generation 32: Statistics

Minimum fitness = 1.7120, Maximum fitness =0.0733, Best fitness=0.0351, Mean Fitness =0.5990
Bestfit chromosome

[-0.0141 0.0340 -0.0045 0.0326 0.0430 0.0276 0.0367 0.0500
0.0411 0.0498 0.0826 0.0550 0.0928 -0.1060 0.0120 -0.0900 -0.0133
0.0309 0.0120 0.0220 0.0627 0.0350 0.0562 0.1300 0.0800 0.1310
0.0083 0.0428 0.0191 0.0460 0.0515 0.0444 0.0504 0.0556 0.0506
0.0559 0.0799 0.0556 0.0979 -0.0037 -0.0005 -0.0031 -0.0003 0.0014
0.0003 0.0006 0.0020 0.0007 0.0018 0.0039 0.0020 0.0051 -0.0102
-0.0031 -0.0102 -0.0031 -0.0001 -0.0015 0.0002 0.0035 -0.0005 0.0027
0.0076 0.0035 0.0095 -0.0015 0.0002 -0.0011 0.0003 0.0007 0.0002
0.0005 0.0010 0.0004 0.0011 0.0027 0.0009 0.0029]

The response plots for Δf_1 , Δf_2 and ΔP tie for the model shown in fig.4.1 with GAFLC and GAPI controller are presented in Fig. 4.10, Fig. 4.11 and Fig. 4.12.

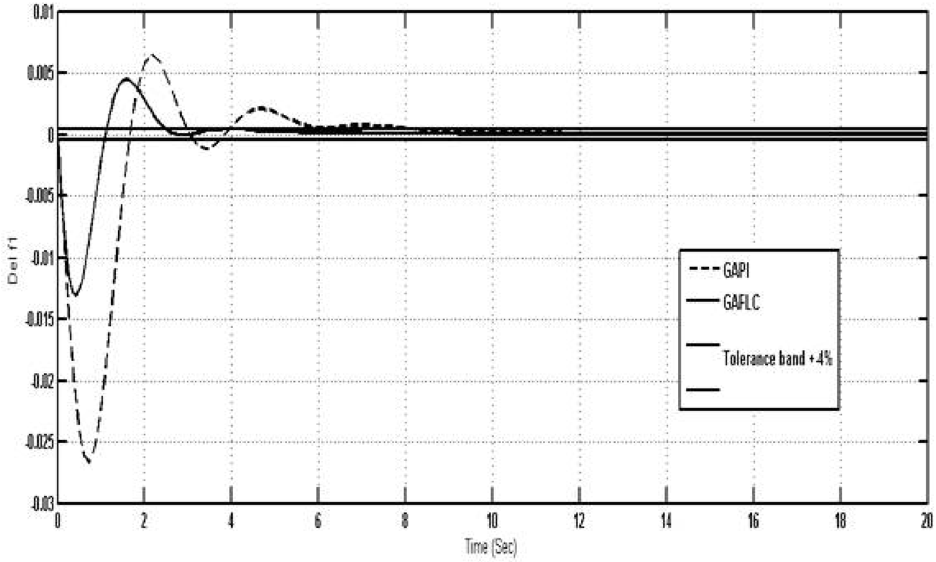


Figure 4.10 Plot of frequency deviation in Area -1(Δf_1) with GAPI and GAFLC controllers.

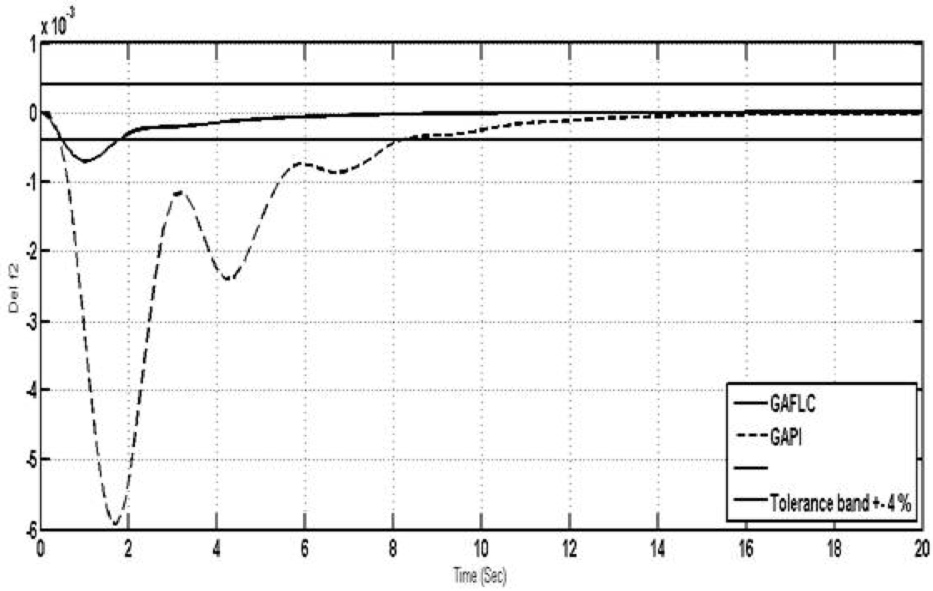


Figure 4.11 Plot of frequency deviation in Area 2(Δf_2) with GAPI and GAFLC controllers.

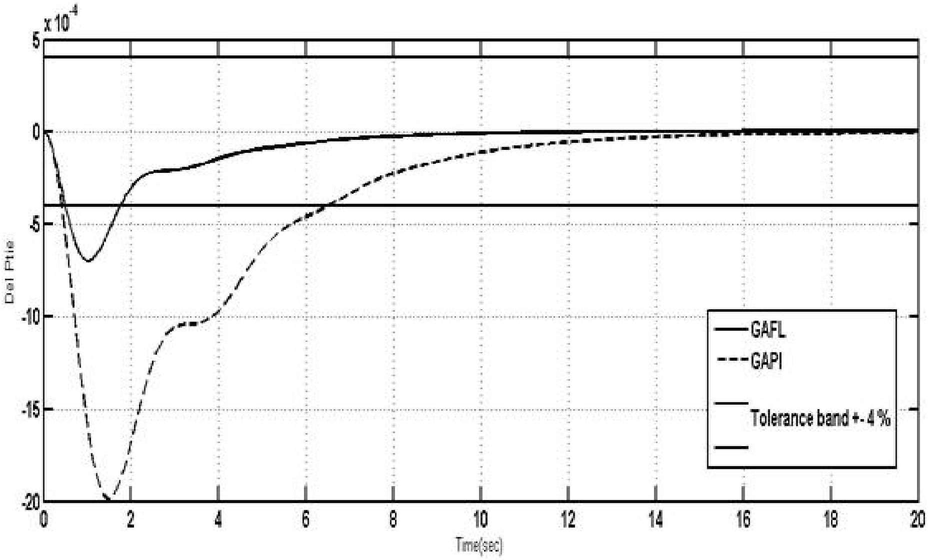


Figure 4.12 Plot of Tie Line power deviation (ΔP_{tie}) with GAPI and GAFLC controllers

The comparison of both the controllers in terms of performance indices are tabulated in Table 4.6

Table 4.6 Performance Comparision of GAPI and GAFLC response

Controller	**Overshoot in Hz. (x10^{-3})**			**Undershoot in Hz. . (x10^{-3})**			**Settling time in sec (ts)**			**IATE**
	Δf_1	**Δf_2**	**ΔP tie line**	**Δf_1**	**Δf_2**	**ΔP tie line**	**Δf_1**	**Δf_2**	**ΔP tie line**	
GAFLC	4.461	0	0	-13.06	-1.98	-0.7	4.2	2.358	1.81	0.0351
GAPI	6.475	0	0	-26.62	-5.92	-1.98	8.12	8.097	6.624	0.1581

4.5 CONCLUSION

In this chapter design of conventional PI and Fuzzy Logic Controller has been proposed for a standard two area AGC. Tuning of the proposed controllers is carried out by Genetic Algorithm technique by minimizing an IATE-based fitness function.

To show the preeminence of the proposed GA optimized Fuzzy controllers, results are compared with that of a GA optimized PI controller implemented on the same model as shown in Table 4.6. Fig. 4.10, Fig.4.11 and Fig 4.12 demonstrates the comparison of various performance indexes such as undershoot, overshoot and settling time between GAFLC and GAPI controllers. It is observed that the response of GAFLC is better both in terms of overshoots, undershoots and settling time as compared to GAPI.

The multi area design of the AGC problem is extended to a restructured power system scenario. Modeling of AGC systems under deregulated environment with various configurations, and characteristics is presented in the next chapter.