CHAPTER 3
FREQUENCY CONTROL IN AN ISOLATED POWER SYSTEM WITH INTELLIGENT CONTROLLER

In an isolated power system, maintenance of interchange power is not an issue. Therefore, the function of AGC is to restore frequency to the specified nominal value. This chapter presents the fundamentals of load frequency control problem in an isolated power system, its key functions, and operations. The MATLAB SIMULINK model of a single area AGC is presented. The design and simulation of Fuzzy Logic controller is carried out with an aim to compare its performance with the conventional PI controllers. An attempt is made to apply GA and present some crucial design implementation issues to achieve satisfactory design of FLC. Power system operations and frequency control under parametric and load perturbations are discussed. The efficiency of the proposed GA optimized Fuzzy controller has been demonstrated through simulations by using appropriate system model.

3.1 MODELING OF AN ISOLATED POWER SYSTEM

To understand the load frequency control problem, transfer function models of speed governor, turbine and load generator are mathematically derived in the light of control system engineering. The mathematical modeling of a single area load frequency control is given in Appendix A1.

To investigate the dynamics of the AGC process, and to carry out simulation for analysis purposes, a software package, MATLAB, distributed by the MathWorks, Inc. is utilized. MATLAB provides the required dynamic modeling and graphical output capabilities with technical, user-friendly computing environment for high-performance numeric computation and visualization. SIMULINK is an extension to MATLAB and provides an interface for simulating dynamic systems. In addition to the general functions of the MATLAB, SIMULINK has many explicit features pertaining to the dynamic systems. A model is prepared using a block diagram approach in the SIMULINK followed by the analysis using either the options from SIMULINK menus or by entering commands in the MATLAB command window. Graphical analysis is carried out where the simulation results are viewed while it is running. The results can be captured and further manipulated in the MATLAB workspace when the simulation is terminated.

3.2 SIMULINK MODEL OF SINGLE AREA AGC

A simple isolated power system were modeled and analyzed using MATLAB SIMULINK, a practical model of an isolated (single area) load frequency control (see Fig. 3.1 below) is considered; the numerical data for the system are K_P = 120.0, T_P = 20.0 Sec, T_G = 0.08 Sec, T_T = 0.3 Sec A disturbance DP_d=0.03 is given on the generator side.

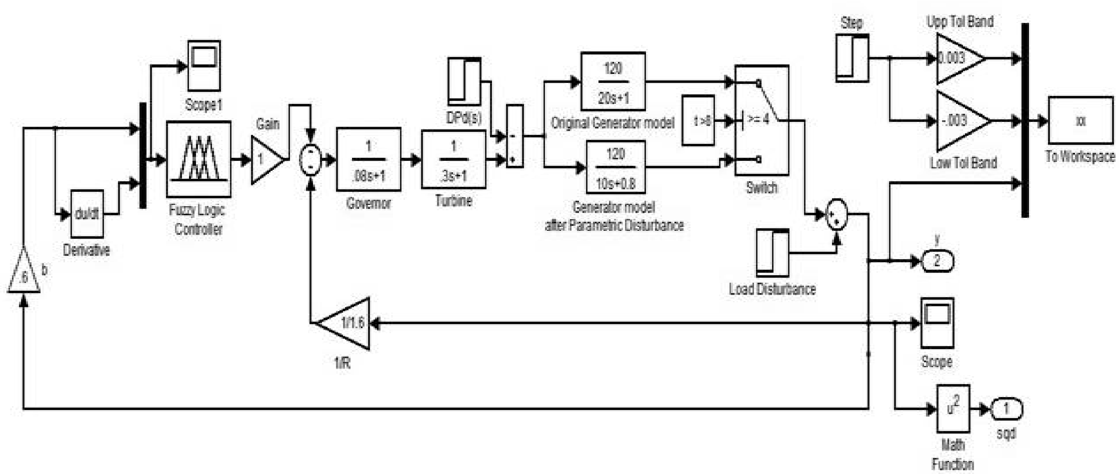


Figure 3.1 Simulink Block diagram of Load Frequency Control (Single Area)

LEGEND

$DP_d(s)$	:	Disturbance on Generator side
R	:	Speed Governor Regulation
b	:	Frequency bias factor
y	:	Frequency deviation

3.3 PI CONTROLLER FOR SINGLE AREA AGC

A Fuzzy Logic controller block is shown in the figure 3.1; however a PI controller can be used on the same model in place of FLC. Conventional control strategy is used to control the dynamic frequency response and make the steady state error near to zero with load perturbations. This is accomplished by adding a reset or integral controller, which acts on the load reference settings of the governors of units on AGC. The integral control action ensures zero frequency error in the steady state. The simulation result of PI control action (frequency deviation Vs time) is shown in Fig. 3.2 in which frequency error becomes zero.

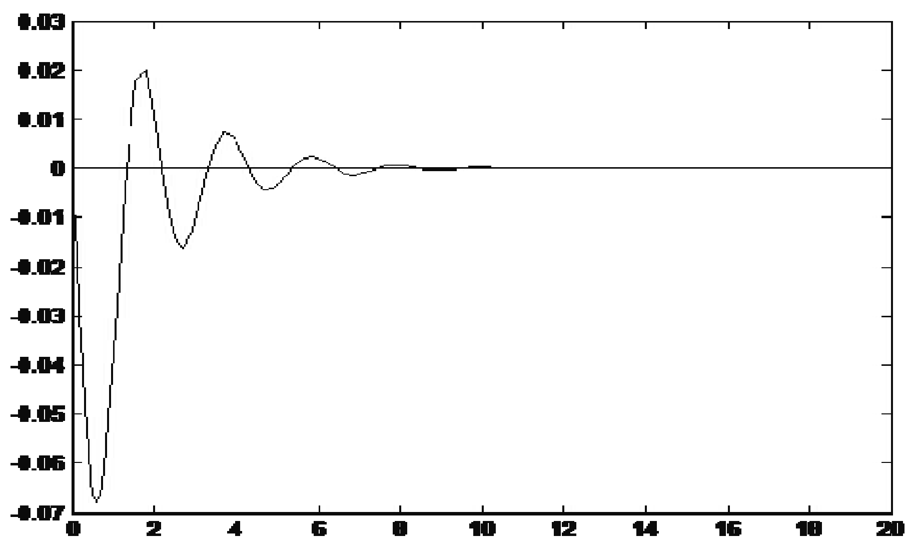


Figure 3.2 Frequency deviation response for an isolated system with PI Controller

3.4 DESIGN AND IMPLEMENTATION OF A FUZZY LOGIC CONTROLLER IN MATLAB

Three membership functions (Positive, Negative & Zero) are defined for each of the two inputs (*Δf and d/dt (Δf))* and 5 mfs (Large Negative, Negative, Zero, Positive and Large Positive) for the output are defined for one output (u). The membership functions correspond to three linguistic variables Negative (NE), Zero (ZE) and Positive (PO) for each of the inputs, and five linguistic variables Large Negative (NL), Negative (NE), Zero (ZE), Positive (PO) and Large Positive (PL) for the output. The nine rules used for the fuzzy controller are tabulated in the fuzzy rule Table 3.1 which prescribes fuzzy sets for control action (speed changer position) as the two variables assume different linguistic values. The rules are interpreted as in [6], for instance: If Δf is PO and d/dt (Δf) is PO then output is NL. The rationale behind the rule is: if frequency deviation (Δf) is positive & the derivative of frequency deviation (d/dt (Δf)) is positive, it results in a large negative control action for the speed changer position.

Table 3.1: Fuzzy Rule Base (9 rules)

d/dt(Δf) \ **(Δf)**	**NE**	**ZE**	**PO**
NE	PL	PO	ZE
ZE	PO	ZE	NE
PO	ZE	NE	NL

As a part of the initial design (hand designed) of the FLC, its all mfs were taken symmetrical [16] as shown in Fig. 3.3

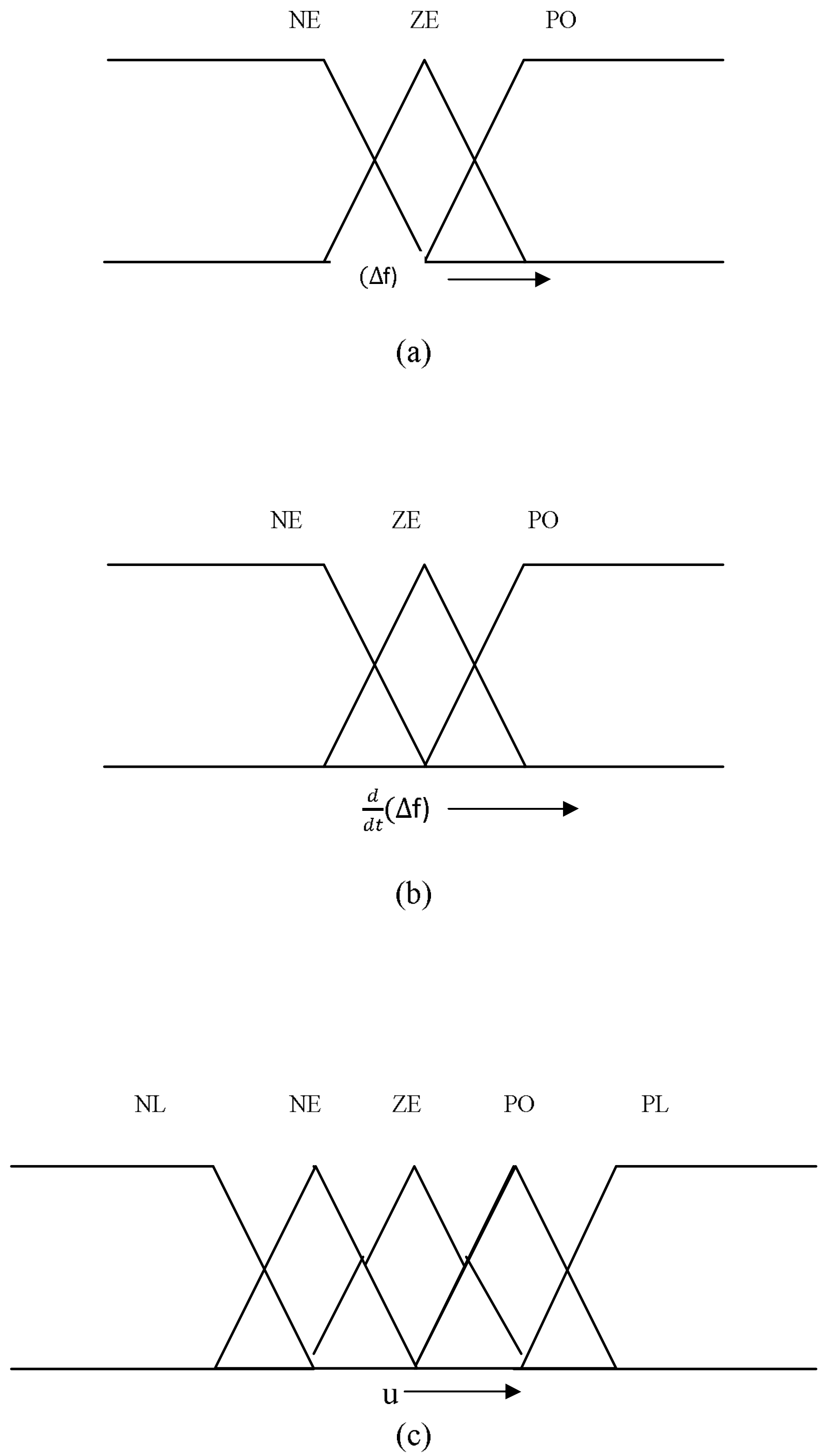


Figure 3.3 Symmetrical mfs of FLC (a) for Δf (b) for d/dt (Δf) (c) for control output u.

3.5 COMPARISON OF PI CONTROLLER AND FLC RESPONSES

The measured values of the performance indices of the system controlled by PI controller and Fuzzy controller are listed in Table 3.2.

Table 3.2 Comparison of PID & FLC Response

Simulated Parameters	**PI Controller**	**Fuzzy Logic Controller**
Settling Time (ts)	7.1124	4.4847
Peak overshoot (% MP)	2.08 %	1.47%

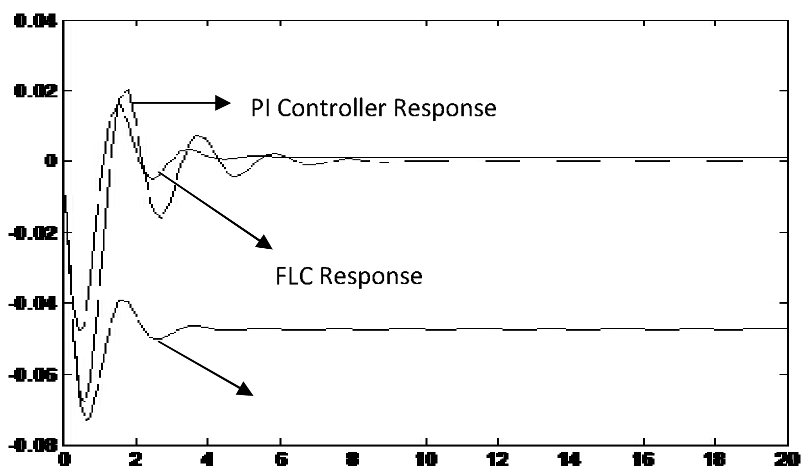
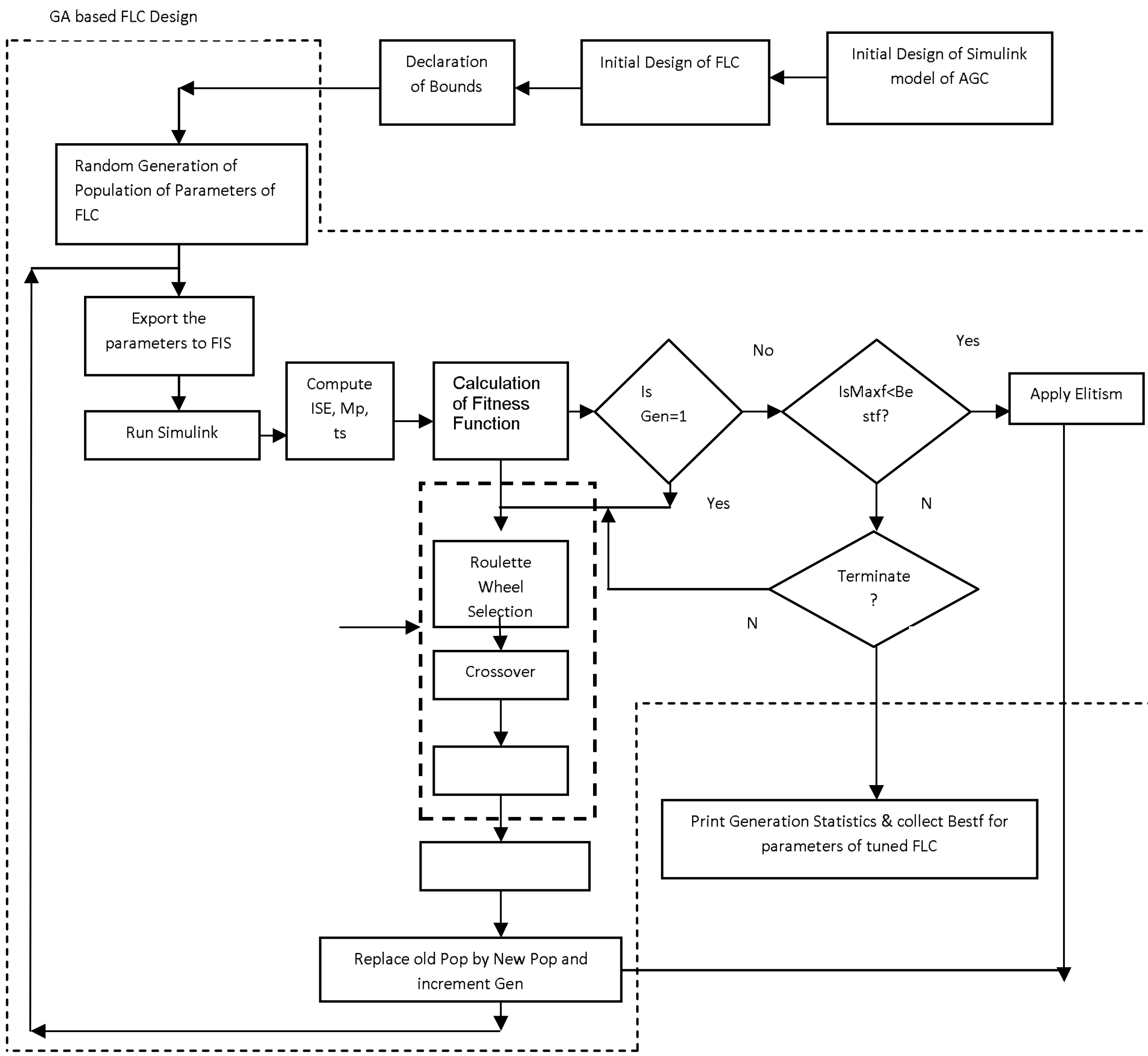


Figure 3.4 Comparison of the Response of PI and Fuzzy Controller

It is shown here that the frequency response in an isolated power system is improved to a large extent by using Fuzzy logic in designing the controllers as compared to the conventional PI controllers [17], [18]. More so, there are several levers, which can be fine-tuned to yield high performance in fuzzy controllers. Evolutionary Computing Algorithms can be used in this situation for finding an optimal FLC [19]-[27].

3.6 FLC TUNING USING GENETIC ALGORITHM

The composite block diagram for evolving FLC with GA is shown in Fig.3.5



LEGEND:

Gen= Generation Count

Maxf = maximum fit chromosome

Pop = Population

Bestf = Best fit chromosome

FIS = Fuzzy Inference System

Figure 3.5 Block diagram for Evolving FLC

The mfs (both input and output) of the FLC is carried out automatically by the GA by fine-tuning the parameters/levers of the mfs. The Tuning of the parameters of FLC is carried out by the maximization of a comprehensive fitness function which is chosen as inverse of a weighted average of Integral Square Deviation (ISD), Peak overshoot (Mp), & Settling time (ts), taking a clue from a previous paper [21]. After the initial design of Simulink model of AGC and initial design of FLC in MATLAB Fuzzy Logic Toolbox (with all mfs chosen symmetrically), the control is passed on to a MATLAB program. This program, after prescribing the lower & upper bounds (within which GA searches for optimal parameters) & after generating the initial population randomly, enters into a loop which runs the GA (with three operators namely selection, crossover & mutation) till termination criterion is met with.

3.7 SOME VITAL GA REALIZATION ISSUES

To apply the GA effectively for tuning the parameters of FLC, some crucial design issues are implemented and discussed in the subsequent sections.

3.7.1 SELECTION OF CHROMOSOME LENGTH

The performance of a fuzzy logic controller can be modified by altering a number of sets of parameters. In this work, the inputs and output mfs of the FLC are tuned/evolved by the GA starting with all symmetrical mfs. The structure of set of parameters which describes a proposed solution to the problem and hence is accordingly determined. Generally the choice of the chromosome is binary, but here the chromosome is represented in real numbers representing each parameter. The chromosome length employed contains 3 alleles for each trimf and 2 for each zmf and smf, thus the length of chromosome becomes:

$$L = [2\times2 + (3-2)\times3]\times2 + [2\times2 + (5-2)\times3] = 27 \text{ alleles}$$

3.7.2 DECLARATION OF BOUNDS

The GA evolves the membership functions for inputs and outputs within a range imposed by lower and upper bounds (Table 3.3) on respective allele values so that the parameters of mfs do not represent obtuse angles and are within rational limits. The selections of these bounds are carried out through a few trial runs of the FLC without GA by placing scopes at relevant points in the Simulink model. This enables understanding of the dynamics of the FLC & ascertaining its Universes of Discourse.

Table 3.3 Bounds for mfs of FLC

Bounds		Fuzzy Set (mf)	LB	UB
Bounds for mfs for I/p	(Δf)	N	-.064, -0.043	-.052 -.032
		Z	-.065, -.045, -0.29	-.05 -.03 -.01
		P	-.043, -0.026	-.032 -.012
	d/dt(Δf)	N	-0.18, -.010	-0.1 -0.05
		Z	-0.17, -0.09, -.051	-0.11 -0.04 -.04
		P	-0.09, -0.051	-0.04 0.04
Bounds for mfs for o/p	u	LN	-0.03, -.015	-0.016 -0.0025
		N	0.03, 0.01, 0.002	-0.012 -0.0024 0
		Z	0.010, -0.002, 0.0024	-0.0024, 0.002 0.01
		P	0, 0.0024, 0.012	0.002,0.01 0.03
		LP	0.00251, 0.016	0.015,0.03

3.7.3 DESIGN OF FITNESS FUNCTION

For starting any GA, a randomly generated population of solutions, i.e., chromosomes within the rational lower and upper bounds specified by the user are required, and there after converges towards better solutions using its genetic operators. In every generation, comparatively better solutions are produced to give offspring that substitute the relatively poor ones, of course, fair play is also allowed for poor solutions. It is the role of the fitness function to act as an environment in distinguishing between good and poor solutions. A general comprehensive fitness function, which covers different facets of time response such as peak overshoot, settling time and Integral Square Deviation, is used as

Fitness Function = (w1+w2+w3)/ (w1*ISD+w2*Mp+w3*ts) Eqn. (3.1)

Where ISD= Integral Square Deviation, Mp=Peak overshoot and ts= settling time w1, w2, & w3 are chosen as free parameters by the user and are respectively the weightages given to ISD, Mp and ts. If any one of these parameters gives illusory performance, then weights may be adjusted so as to avoid weak/smaller values of the corresponding performance index from being numerically dominated by other constituents of the fitness function.

3.7.4 REASONABLE RANDOMNESS IN POPULATION

To give a fair amount of randomness in the population (i.e., no. of chromosomes in any generation), the size of population is taken as significantly large (larger than 20) [60]. Smaller sized populations are likely to soon result in same fitness strings over the whole population, stopping any further chase for improved solutions.

3.7.5 PREVENTION OF SELF- MATING

In a GA program sometimes crossover of identical chromosomes take place which results in no new chromosomes and is termed as self-mating [28]. In order to avoid self mating the population selected is arranged as per the score of fitness values and placed in two equal arrays. For crossover, the first chromosome of the first half of this population is taken, and is paired with the first chromosome from the second half of the population. The same course of action is extended in succession to the next strings from the first half and correspondingly next one from the second half. This will circumvent the pairing of the same fitness strings. However, in a very rare case, this procedure can be unsuccessful if more than half the population has the similar fitness.

3.7.6 ELITISM

With the application of crossover and mutation operators in the GA program, there is always likelihood that most favorable solutions may be lost. In view of the randomness component of these GA operators there is no absolute guarantee that the solution with highest fitness is preserved. Moreover, during the selection process, there is a possibility that even the fittest solution is not selected. To overcome this problem, elitism approach is frequently used [21]. In this approach, the best fit solutions from a population are saved from getting lost while the GA operations take place. In this work, after the new population is created and evaluated, it is ensured that the best chromosome is preserved. If not, the saved copy of the best-so-far chromosome is reinserted back into the population, at the disbursement of the weakest one.

3.7.7 GA PROGRAM TERMINATION NORM

The GA program continues to evolve the parameters of FLC until some termination criterion is followed. The norms for termination used in this work is that the difference between the average value of fitness values of i^{th} and $(i-5)^{th}$ generations is less than the threshold value of fitness which is chosen as=0.0001 (which is approx. 12.5% of the maximum fitness achieved during a trial run of 5-10 generations). Due to randomness in search for the optimal solution, the GA may not give monotonically increasing average fitness over the generations; therefore, the chosen criterion is considered as better compared to the difference between current average fitness and the just previous average fitness going below a certain threshold. However, over a considerable number of generations, it is certain to evolve better fitness solution.

3.8 GA ALGORITHMS AND PARAMETER SETTING

3.8.1 ALGORITHM FOR CHROMOSOMES GENERATION AND SELECTION

- Specify the population as a bit string (chromosome), which includes the size of the string (length of chromosome) and the number of strings (Population size).
- According to population size we toss a fair coin and get the initial population
- Calculate the fitness value fval (v_i) for each chromosome v_i (i =1, 2…pop size)
- Sum up above vector to find the total fitness of population:
  $F=\sum_{i=1}^{N} fval(vi)$
- Calculate the probability, pi, of a selection of each chromosome vi.
- p_i= fval(v_i) / F; (i = 1,2…, popsize).
- Compute the cumulative probability qi, for each chromosome vi:
  $q_i = \sum_{j=1}^{i} p(j)$
- Generate a real valued random number' r' in the range (0 and 1).
- If r< p_i, then select the first chromosome (v_i) for each chromosome vi, otherwise select the i-th chromosome v_i (2< i<popsize), such that $q_{i-1}<r<q_i$.

3.8.2 ALGORITHM FOR CROSSOVER

- Specify the probability of Cross over (Pc).
- Generate a random number 'r' in the range [0 1].
- If r<Pc, select a given chromosome for crossover.
- Generate a random integer number, pos, between 1 and L-1.

(Where L= Chromosome Length). This number is crossover site

Two chosen chromosomes:
(x_1, x_2... $x_{pos}x_{pos+1}$... x_L) and
(y_1, y_2... $y_{pos}y_{pos+1}$... y_L)

are replaced by a pair of their off springs

$(x_1, x_2 \ldots x_{pos} y_{pos+1} \ldots y_L)$ and

$(y_1, y_2 \ldots y_{pos}\, x_{pos+1} \ldots x_L)$

3.8.3 ALGORITHM FOR MUTATION

- Specify the probability of mutation Pm.
- For each chromosome in the current (i.e. after crossover) population and for each bit within the chromosome, generate a random number 'r' in the range [0 and 1].
- If r<Pm, mutate the bit.

3.8.4 PARAMETERS FOR GA

The two most important GA parameters are crossover probability and mutation probability. Crossover probability is chosen such that the crossover takes place in hope that new chromosomes will have some parts of old ones. Mutation probability is chosen to be a low value to give diversity to the population and also to avoid local extreme. The typical values of the GA parameters chosen are tabulated in the Table 3.4.

Table 3.4 Values of GA parameters

S.no	Parameter	Value
1	Population Size (Psize)	30
2	Length of chromosome (lchro)	27
3	Probability of crossover (P_c)	0.6
4	Probability of mutation (P_m)	0.03
5	Weight of integral square deviation (ISD) w_1	0.25
6	Weight of peak overshoot (M_p) w_2	0.3
7	Weight of settling time (t_s)w_1	0.45

3.9 RUNNING THE GA

GA was run for a number of generations, complete population report for the Generation1 is shown in section 3.9.1. This run was continued further, and termination criterion was reached in generation 41 where the best controller was found. For the sake of brevity, however, only the last generation statistics with the best fit and least fit chromosomes is presented. Few landmarks in the time response statistics are shown in Table 3.5.

3.9.1 POPULATION REPORT

GENERATION: 1

#	String	ISE	Mp	ts	Fitness
1)	0.0560 -0.0327 -0.0565 -0.0303 -0.0148 -0.0326 -0.0142 -0.1877 -0.0769 -0.1535 -0.0730 -0.0087 -0.0797 -0.0060 -0.0250 0.0004 -0.0260 0.0005 0.0235 0.0005 0.0295	0.0012	0.0143	2.8532	0.7765
2)	-0.0583 -0.0356 -0.0536 -0.0393 -0.0175 -0.0313 -0.0144 -0.1182 -0.0794 -0.1638 -0.0765 -0.0095 -0.0785 -0.0083 -0.0225 0.0005 -0.0297 0.0005 0.0213 0.0005 0.0225	0.0024	0.02126	16.43	0.1351
3)	-0.0512 -0.0320 -0.0552 -0.0346 -0.0200 -0.0310 -0.0117 -0.1580 -0.0722 -0.1317 -0.0718 -0.0096 -0.0784 -0.0078 -0.0261 0.0005 -0.0297 0.0005 0.0281 0.0005 0.0286	0.0034	0.0247	20	0.1110
4)	-0.0552 -0.0315 -0.0564 -0.0311 -0.0113 -0.0364 -0.0169 -0.1352 -0.0738 -0.1662 -0.0702 -0.0092 -0.0784 -0.0087 -0.0294 0.0004 -0.0240 0.0004 0.0288 0.0004 0.0251	0.0016	0.0174	3.7862	0.5853

#	String	ISE	Mp	ts	Fitness
5)	-0.0526 -0.0382 -0.0559 -0.0397 -0.0177 -0.0362 -0.0121 -0.1515 -0.0748 -0.1760 -0.0725 -0.0067 -0.0763 -0.0073 -0.0218 0.0004 -0.0226 0.0004 0.0231 0.0005 0.0274	0.0012	0.0116	3.1462	0.7047
6)	-0.0503 -0.0303 -0.0549 -0.0332 -0.0171 -0.0391 -0.0156 -0.1889 -0.0746 -0.1139 -0.0720 -0.0064 -0.0700 -0.0079 -0.0263 0.0004 -0.0210 0.0004 0.0214 0.0005 0.0289	0.0021	0.0181	6.909	0.3210
7)	-0.0545 -0.0393 -0.0533 -0.0348 -0.0200 -0.0363 -0.0126 -0.1648 -0.0797 -0.1089 -0.0795 -0.0082 -0.0787 -0.0052 -0.0237 0.0004 -0.0285 0.0004 0.0210 0.0005 0.0240	0.0015	0.0153	2.9093	0.7613
8)	-0.0582 -0.0306 -0.0600 -0.0376 -0.0175 -0.0347 -0.0103 -0.1359 -0.0745 -0.1891 -0.0731 -0.0055 -0.0773 -0.0074 -0.0262 0.0005 -0.0279 0.0005 0.0250 0.0005 0.0234	0.0013	0.0146	2.7762	0.7979
9)	-0.0544 -0.0320 -0.0574 -0.0352 -0.0111 -0.0307 -0.0106 -0.1585 -0.0786 -0.1416 -0.0756 -0.0086 -0.0795 -0.0062 -0.0275 0.0004 -0.0249 0.0005 0.0211 0.0005 0.0268	0.0013	0.0145	2.9677	0.7466
10)	-0.0595 -0.0325 -0.0590 -0.0399 -0.0144 -0.0391 -0.0105 -0.1745 -0.0738 -0.1002 -0.0746 -0.0086 -0.0793 -0.0082 -0.0286 0.0004 -0.0206 0.0004 0.0270 0.0004 0.0283	0.0042	0.0224	4.0923	0.5410
11)	-0.0512 -0.0315 -0.0539 -0.0392 -0.0199 -0.0376 -0.0118 -0.1148 -0.0777 -0.1489 -0.0726 -0.0096 -0.0754 -0.0063 -0.0271 0.0004 -0.0271 0.0004 0.0231 0.0004 0.0299	0.0014	0.0142	2.8439	0.7790

#	String	ISE	Mp	ts	Fitness
12)	-0.0587 -0.0320 -0.0532 -0.0368 -0.0108 -0.0359 -0.0107	0.0013	0.0147	3.9183	0.5658
	-0.1926 -0.0761 -0.1508 -0.0755 -0.0076 -0.0740 -0.0060				
	-0.0296 0.0004 -0.0251 0.0004 0.0256 0.0004 0.0235				
13)	-0.0553 -0.0364 -0.0556 -0.0333 -0.0189 -0.0393 -0.0130	0.0014	0.0161	3.9202	0.5654
	-0.1107 -0.0737 -0.1628 -0.0751 -0.0073 -0.0746 -0.0053				
	-0.0295 0.0005 -0.0251 0.0004 0.0236 0.0005 0.0299				
14)	-0.0512 -0.0338 -0.0549 -0.0391 -0.0121 -0.0353 -0.0161	0.0016	0.0166	3.1084	0.7126
	-0.1318 -0.0744 -0.1262 -0.0709 -0.0074 -0.0717 -0.0054				
	-0.0254 0.0004 -0.0255 0.0004 0.0250 0.0005 0.0243				
15)	-0.0571 -0.0373 -0.0583 -0.0358 -0.0145 -0.0373 -0.0166	0.0012	0.0156	3.5960	0.6163
	-0.1611 -0.0795 -0.1671 -0.0793 -0.0052 -0.0794 -0.0076				
	-0.0279 0.0004 -0.0249 0.0004 0.0245 0.0005 0.0277				
16)	-0.0534 -0.0364 -0.0542 -0.0351 -0.0185 -0.0355 -0.0128	0.0012	0.0149	3.7809	0.5863
	-0.1997 -0.0718 -0.1784 -0.0708 -0.0096 -0.0762 -0.0080				
	-0.0289 0.0005 -0.0286 0.0004 0.0280 0.0005 0.0226				
17)	-0.0512 -0.0371 -0.0538 -0.0306 -0.0133 -0.0354 -0.0144	0.0014	0.0158	2.7712	0.7991
	-0.1666 -0.0754 -0.1287 -0.0765 -0.0097 -0.0767 -0.0100				
	-0.0258 0.0004 -0.0231 0.0004 0.0254 0.0005 0.0242				
18)	-0.0512 -0.0377 -0.0595 -0.0396 -0.0138 -0.0340 -0.0124	0.0024	0.0192	3.6686	0.6037
	-0.1406 -0.0748 -0.1069 -0.0775 -0.0056 -0.0738 -0.0059				
	-0.0263 0.0004 -0.0219 0.0005 0.0215 0.0004 0.0254				

#	String							ISE	Mp	ts	Fitness
19)	-0.0581	-0.0367	-0.0527	-0.0307	-0.0121	-0.0312	-0.0197	0.0013	0.0161	3.7222	0.5954
	-0.1829	-0.0719	-0.1798	-0.0706	-0.0085	-0.0785	-0.0091				
	-0.0283	0.0004	-0.0292	0.0005	0.0273	0.0005	0.0217				
20)	-0.0503	-0.0365	-0.0513	-0.0359	-0.0109	-0.0316	-0.0121	0.0012	0.0152	3.7463	0.5917
	-0.1989	-0.0760	-0.1974	-0.0792	-0.0096	-0.0712	-0.0095				
	-0.0289	0.0005	-0.0228	0.0005	0.0202	0.0005	0.0222				
21)	-0.0577	-0.0310	-0.0527	-0.0316	-0.0110	-0.0343	-0.0127	0.0020	0.0186	3.7823	0.5857
	-0.1294	-0.0735	-0.1213	-0.0741	-0.0092	-0.0724	-0.0067				
	-0.0275	0.0004	-0.0273	0.0004	0.0275	0.0004	0.0297				
22)	-0.0586	-0.0383	-0.0577	-0.0317	-0.0109	-0.0397	-0.0172	0.0019	0.0171	4.8868	0.4535
	-0.1662	-0.0797	-0.1501	-0.0760	-0.0060	-0.0715	-0.0085				
	-0.0225	0.0005	-0.0287	0.0005	0.0236	0.0005	0.0234				
23)	-0.0508	-0.0365	-0.0555	-0.0328	-0.0157	-0.0334	-0.0156	0.0014	0.0137	3.0680	0.7223
	-0.1439	-0.0741	-0.1669	-0.0800	-0.0076	-0.0778	-0.0087				
	-0.0209	0.0005	-0.0206	0.0005	0.0263	0.0004	0.0239				
24)	-0.0562	-0.0367	-0.0579	-0.0342	-0.0125	-0.0313	-0.0127	0.0017	0.0160	3.0475	0.7268
	-0.1064	-0.0755	-0.1287	-0.0753	-0.0099	-0.0711	-0.0087				
	-0.0236	0.0004	-0.0234	0.0005	0.0221	0.0005	0.0271				
25)	-0.0598	-0.0400	-0.0516	-0.0355	-0.0143	-0.0367	-0.0159	0.0020	0.0173	2.9596	0.7481
	-0.1027	-0.0792	-0.1226	-0.0726	-0.0098	-0.0705	-0.0060				
	-0.0230	0.0004	-0.0256	0.0004	0.0286	0.0004	0.0225				

#	String	ISE	Mp	ts	Fitness
26)	-0.0512 -0.0369 -0.0566 -0.0336 -0.0191 -0.0319 -0.0183 -0.1079 -0.0712 -0.1551 -0.0706 -0.0070 -0.0750 -0.0059 -0.0207 0.0005 -0.0205 0.0004 0.0232 0.0005 0.0286	0.0018	0.0155	5.9744	0.3697
27)	-0.0533 -0.0390 -0.0517 -0.0300 -0.0169 -0.0321 -0.0161 -0.1674 -0.0740 -0.1627 -0.0792 -0.0084 -0.0709 -0.0070 -0.0205 0.0004 -0.0216 0.0004 0.0277 0.0004 0.0258	0.0013	0.0121	2.9970	0.7396
28)	-0.0546 -0.0342 -0.0527 -0.0337 -0.0144 -0.0372 -0.0159 -0.1763 -0.0763 -0.1942 -0.0788 -0.0089 -0.0786 -0.0089 -0.0201 0.0005 -0.0276 0.0005 0.0291 0.0005 0.0228	0.0013	0.0129	2.8978	0.7648
29)	-0.0508 -0.0340 -0.0591 -0.0350 -0.0103 -0.0312 -0.0102 -0.1575 -0.0714 -0.1546 -0.0798 -0.0083 -0.0779 -0.0057 -0.0256 0.0005 -0.0249 0.0005 0.0226 0.0005 0.0269	0.0014	0.0142	2.9858	0.7421
30)	-0.0539 -0.0307 -0.0589 -0.0384 -0.0145 -0.0383 -0.0162 -0.1946 -0.0711 -0.1305 -0.0800 -0.0063 -0.0749 -0.0068 -0.0243 0.0004 -0.0236 0.0004 0.0238 0.0004 0.0243	0.0013	0.0136	2.9882	0.7416

It is evident from the Section 3.91 above that there is diversity in the fitness values of different chromosomes from the minimum fitness to the maximum fitness in the fist generation. The aim is to produce a best fit chromosome in the generations to come.

3.9.2 GENERATION 41: STATISTICS

Minimum fitness value (minf) =0.6629

Maximum fitness value (Maxfit) =1.0104

Mean fitness value(Meanf) =0.7120

Bestfitness value (Best) =1.0104

The least fit chromosome in generation 41 (Fitness=0.6629)

[-0.0607 -0.0320 -0.0552 -0.0390 -0.0286 -0.0345 -0.0176 -0.1236 -0.0965 -0.1250 -0.0400 -0.0505 -0.0668 -0.0029 -0.0210 -0.0039 -0.0258 -0.0096 -0.0016 -0.0062 0.0012 0.0049 0.0020 0.0032 0.0300 0.0119 0.0235]

ISD = 0.0021, Mp = 0.0138, ts =3.3420

The Best fit chromosome in generation 41 (Fitness=1.0104)

[-0.0629 -0.0339 -0.0570 -0.0385 -0.0216 -0.0378 -0.0222 -0.1136 -0.0763 -0.1474 -0.0687 -0.0448 -0.0663 -0.0331 -0.0182 -0.0079 -0.0233 -0.0093 -0.0009 -0.0064 0.0013 0.0039 0.0003 0.0049 0.0204 0.0143 0.0294]

ISD = 0.002, Mp = 0.0130, ts =2.1896

3.9.3 Few Landmarks in the Time Response Statistics

The Table 3.5 compares the time response statistics for few fitness values captured during the various generations. The decrease in the settling time from 3.9354 to 2.1896, peak overshoot from 0.179 to 0.0130 is a testimony to the improvement in the time response specifications of the system.

Table3.5 A few landmarks in Time Response Statistics

S.no	**Fitness Value**	**ISE** (Integral Square Error)	**Mp** (Peak Overshoot)	**Ts** (Settling time)
1	0.1110	0.0034	0.0247	20
3	0.3210	0.0021	0.0181	6.909
4	0.5631	0.0019	0.0179	3.9354
5	0.5853	0.0016	0.0174	3.7862
6	0.6108	0.0014	0.0166	3.6278
7	0.7223	0.0014	0.0137	3.0680
8	0.8012	0.0014	0.0147	2.7644
9	0.9791	0.0014	0.0093	2.2637
10	1.0104	0.002	0.0130	2.1896

3.10 PLOTS OF FREQUENCY RESPONSE UNDER DIFFERENT TESTING CONDITIONS

The GA program is run till the termination criterion is reached. The simulation plots of the hand-tuned FLC response and GAFLC response for the best fit chromosomes under different testing conditions are presented.

3.10.1 SYSTEM WITHOUT DISTURBANCE

The simulation is run for the system with the model in Fig. 3.1 but without any disturbance; the GA produced some good solutions. The Figs. 3.6 & 3.7 portrays the plot of frequency deviation for the hand-tuned FLC and GAFLC without disturbance respectively. The plot in Fig. 3.7 shows that settling time is reduced from 3.20 sec for hand-tuned case to 2.1896 sec for the best fit chromosome.

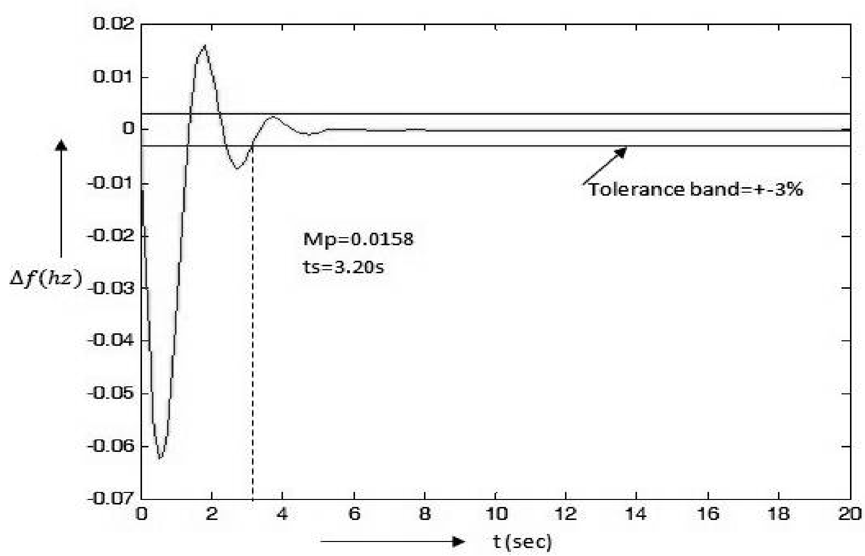


Figure 3.6 Hand-tuned FLC response for frequency deviation without disturbance

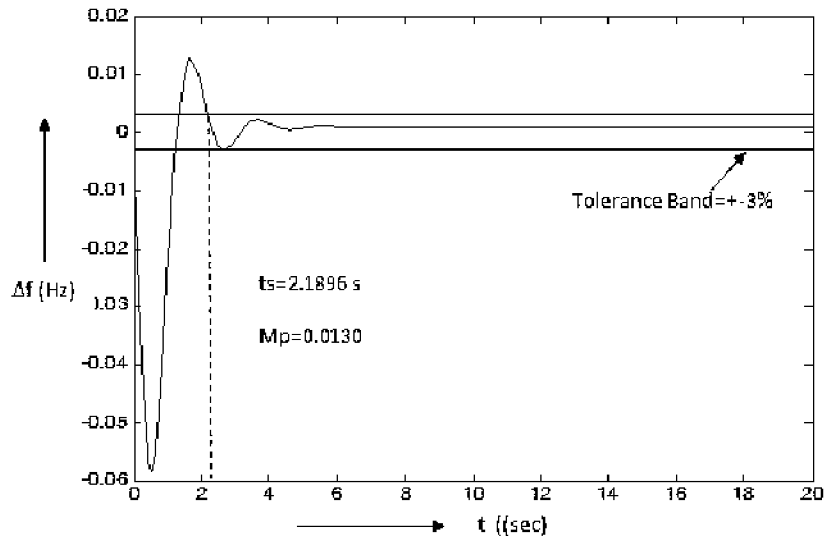


Figure 3.7 GAFLC response for frequency deviation without disturbance

3.10.2 SYSTEM WITH PARAMETRIC DISTURBANCE

A parametric disturbance is injected into the system at t=8 sec (after the response of the controller attains a steady state within the tolerance band) while the simulation is running, by changing the coefficients of the transfer function block of the generator in the denominator from (20s+1) to (10s+0.8).

The best fit chromosome under parametric disturbance:

[-0.0629 -0.0339 -0.0570 -0.0385 -0.0216 -0.0378 -0.0222 -0.1136 -0.076 -0.1474 -0.0687 -0.0448 -0.0663 -0.0331 -0.0182 -0.0079 -0.0233 -0.0093 -0.0009 -0.0064 0.0013 0.0039 0.0003 0.0049 0.0204 0.0143 0.0294]

ISD=0.018, Mp=0.0109, ts=0

Fig. 3.8 demonstrates the response of a hand-tuned FLC under parametric disturbance injected at t=8 sec.

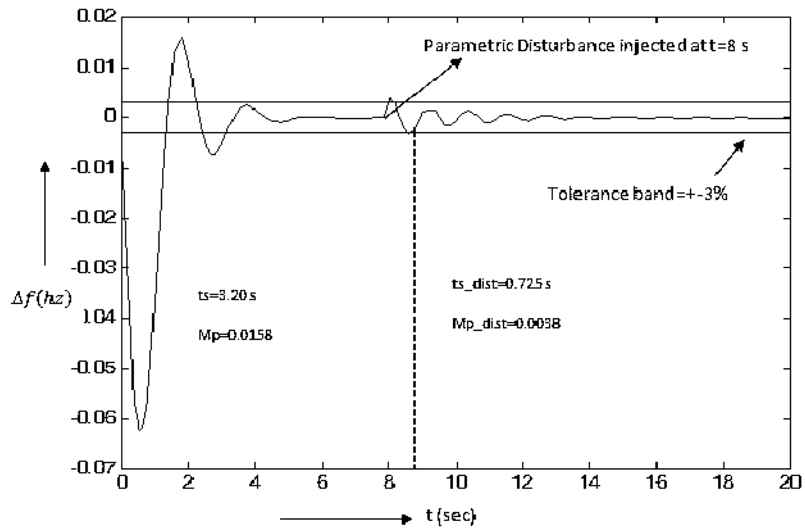


Figure 3.8 Hand-tuned FLC response for frequency deviation with parametric disturbance

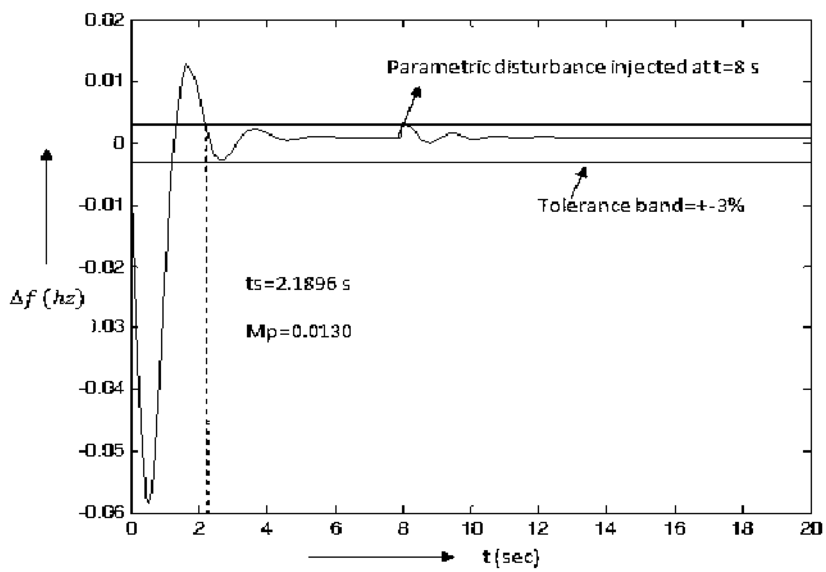


Figure 3.9 GAFLC response for frequency deviation with parametric disturbance

It can be seen from Fig.3.9 that the GAFLC arrests the parametric disturbance well within the tolerance band. Hence GAFLC is capable of producing good solution even under parametric disturbances, addressing the problem of load frequency control.

3.10.3 SYSTEM WITH LOAD DISTURBANCE

A load disturbance (step signal of 0.01) is injected into the system after the response attains a stable steady state within the tolerance band. Plots of the frequency deviation response are captured for hand-tuned FLC and best fit chromosomes with the system subjected to the load disturbance injected at t=8 sec. Fig. 3.10 & Fig. 3.11 displays the response of hand-tuned FLC and GAFLC under load disturbance injected at t=8sec.

The best fit chromosome under load disturbance:

[-0.0629 -0.0339 -0.0570 -0.0385 -0.0216 -0.0378 -0.0222 -0.1136 -0.0763 -0.1474 -0.0687 -0.0448 -0.0663 -0.0331 -0.0182 -0.0079 -0.0233 -0.0093 -0.0009 -0.0064 0.0013 0.0039 0.0003 0.0049 0.0204 0.0143 0.0294]

ISD=0.0021, Mp=0.0109, ts=0.546

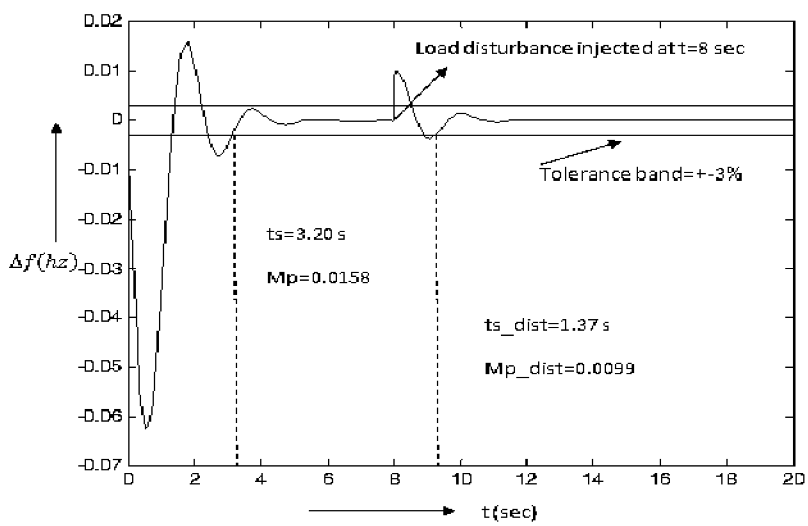


Figure 3.10 Hand-tuned FLC response for frequency deviation with Load disturbance

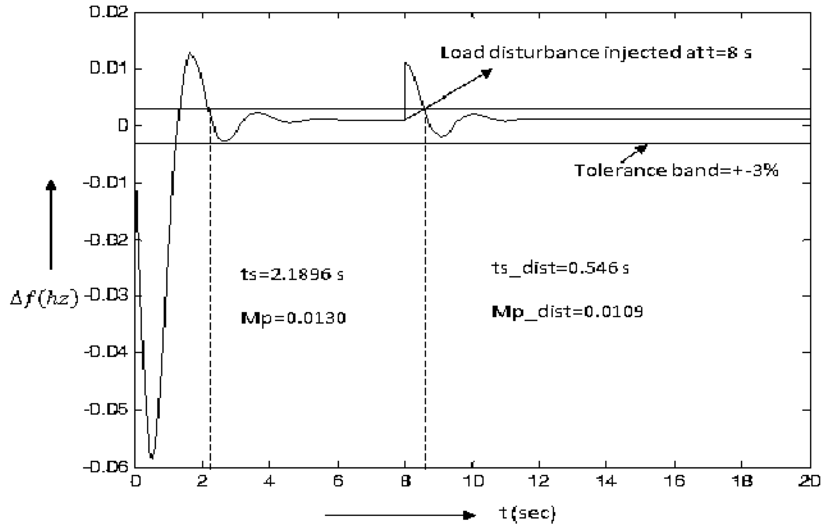


Figure3.11 GAFLC response for frequency deviation with Load disturbance

The measured values of the performance indices of the system shown in Fig.3.1 controlled by PI, a hand-tuned FLC and GAFLC under different testing conditions are illustrated in Table 3.6.

Table 3.6 Performance comparison of a PI, a Hand-Tuned FLC & GAFLC Response

Controller	Settling Time (ts) in secs.	Peak overshoot(Mp)
PI Controller without disturbance	7.1124	0.0208
PI Controller with Parametric disturbance	System becomes Unstable	-
PI Controller with Load disturbance	2.33	0.0102
Hand-tuned FLC without disturbance	3.20	0.0158
GAFLC without disturbance	2.1896	0.0130
Hand-tuned FLC with Parametric disturbance	0.735	0.0038

GAFLC with Parametric disturbance	0 (Response maintained Within Tolerance band)	0.0029
Hand-tuned FLC with Load disturbance	1.37	0.0099
GAFLC with Load disturbance	0.546	0.0109

GA has been shown to effectively improve the system response in terms of time and effort. They can rapidly find optimal solutions and, if used correctly, can avoid local optima [27].

3.11 CONCLUSION

It is shown that GA is a powerful search tool which is used for designing systems for which very little methodical plan strategy exists. They can rapidly find optimal solutions and, if used efficiently, can avoid local optima. Use of genetic algorithm substantially reduces the time and effort involved during the search of the optimal solution.

FLC tuned by GA produced some good solutions (with fitness values 0.8012, 0.9791, 1.0104 in different generations), the best solution evolved was in 41 generations having fitness 1.0104. Various novel testing conditions are applied during the simulation in current work. Also, three different performance indices of the response are reviewed using a comprehensive fitness function. The results demonstrate that the proposed GA optimized FLC is capable of restoring the nominal value of frequency even under parametric and load disturbances in contrast to a hand designed FLC. Thus the controller performance can be enhanced by incorporating an intelligent Genetic Algorithm for tuning Fuzzy logic controller for AGC. The load frequency design and control problem is extended to multi area AGC with a more practical approach in the next chapter.