Chapter 5

Multiobjective Optimization : Evolutionary Algorithm

Multiobjective optimization of 2DOF controller parameters using evolutionary NSGA-II and NSGA-III algorithms are discussed in this chapter. The above mentioned algorithms are implemented in the software MATLAB and results are discussed.

5.1 Introduction

Multiobjective optimization is required to find widely spread nondominated set of solutions on the Pareto front. Finding multiple solutions in a single simulation run is a rare quality of evolutionary and swarm based algorithms. Evolutionary algorithms (EAs) are a part of evolutionary computations, in which EAs follows mechanism inspired by biological evolution. It includes following one or more mechanisms like, generation, recombination, mutation, and selection of the fittest. Genetic algorithm (GA) is the most popular type of evolutionary algorithm used in optimization problems realized by John Holland of the University of Michigan Ann Arbor and it became popular in the early 1970s.
Here, 2DOF controller parameters of feed forward type structure are optimized using multiobjective optimization of NSGA-II and NSGA-III algorithms. The comparison of results are provided in following sections in the form of graphs and tabulated in tables.

5.2 Working of GA

GA is population based search and optimization algorithm. As the name suggest genetic algorithms (GAs) borrow their working principle from natural genetics. Genetic algorithms (GAs) can find multiple optimal solutions in a single simulation run due to population based approach. Hence, GA is used for solving multiobjective optimization problems. The result of multiobjective optimization algorithm is a set of Pareto-optimal solutions so, it is not possible to find out a unique solution which minimizes or maximizes all objectives simultaneously. Hence, user has to select only one solution based on his/her preference [13].

Genetic algorithm begins with a population of chromosomes (It is combinations of 2DOF controller parameters). An objective function value for each chromosome is required to be calculated in order to find the optimum value. The fitness value of all the chromosomes in each generation will be evaluated using the performance objectives. Based on the fitness of objective function value, parent chromosomes will be chosen for the next generation. The crossover and mutation carried out among the selected parent chromosomes. The above mentioned process is repeated till objective functions are optimized or for assigned maximum number of iterations [33]. The working principle of GA is described in the form of flow chart as shown in Figure 5.1.

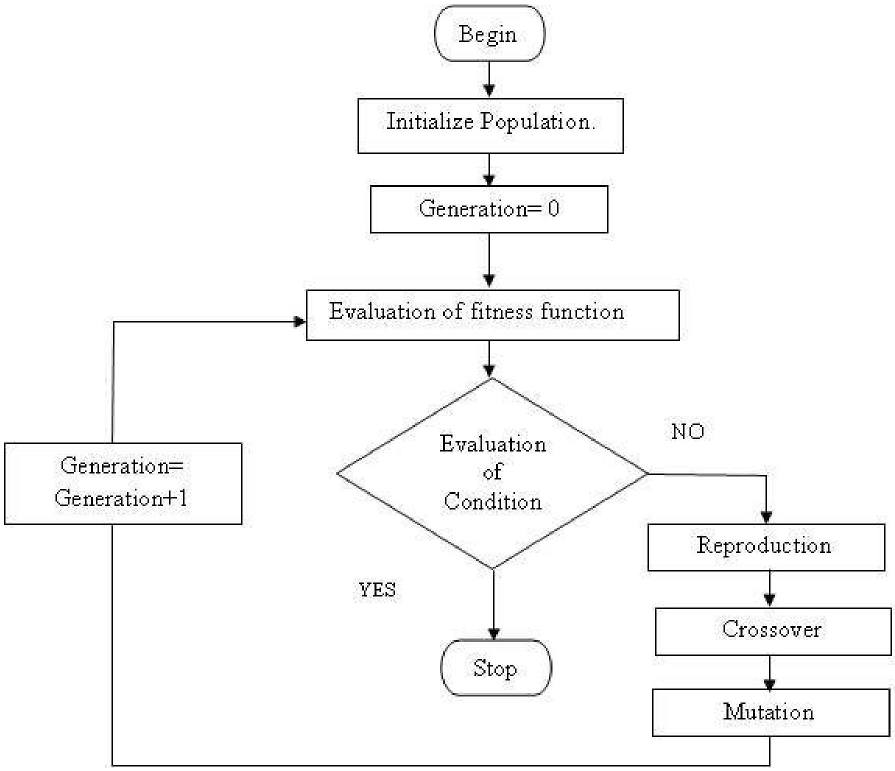

Figure 5.1: Flow chart for working principle of GA.

5.3 Tuning of 2DOF controller using Genetic algorithm

Step 1: Define the dimension of 2DOF controller parameters optimization problem (number of decision variables **'NVARS'** =5).

Step 2: Set the upper bound values UB= [100 100 100 1 1] & lower bound values LB= [0 0 0 0 0]. M Araki et al. [3] has tested different processes using 2DOF controller optimization and maximum value of any parameters of $C_s(s)$ is not greater than **'60'** hence, for safe side maximum value in $C_s(s)$ is selected to be **'100'**.

Step 3: Derive transfer function of plant **'plant'**, actuator **'actuator_tf'**, sensor **'sensor_tf'**, temperature disturbance **'distb_temp'**, flow disturbance **'distb_flow'**, serial controller **'C'**, and feed forward controller **'C_f'**.

Step 4: Define the step magnitude of input, flow disturbance and temperature disturbance as **1**, **0.1**, and **0.01** respectively [59].

Step 5: The type of solver used for computing fitness function is **'ga'**.

Step 6: Option for problem type is **'boundconstraints'**.

Step 7: In order to start genetic algorithm with same initial condition the default settings are the **'Mersenne Twister'** with seed **'0'** is selected.

Step 8: The maximum number of iterations before the algorithm halts is **'100'** (positive integer only).

Step 9: The function that algorithm uses to create crossover children is default type **'crossoverscattered'**.

Step 10: The fraction of population at the next generation, not including elite children, that is created by the crossover function is default positive scalar value **'0.8'**.

Step 11: The algorithm stops if the weighted average relative change in the best fitness function value over **'StallGenLimit '** generations is less than or equal to **'TolFun '** is default **'1e-6'**.

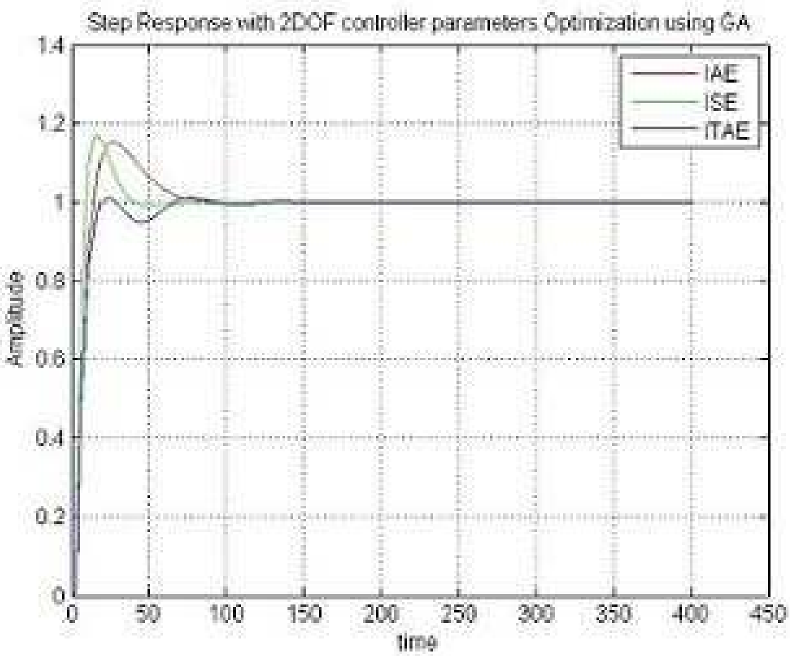

Figure 5.2: Step response of 2DOF controller optimization using GA.

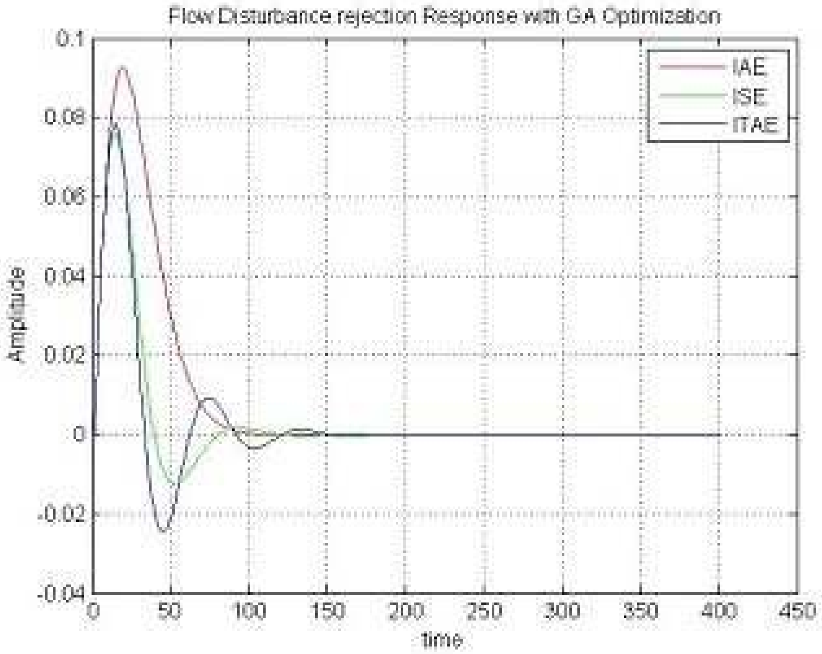

Figure 5.3: Flow disturbance response of 2DOF controller optimization using GA.

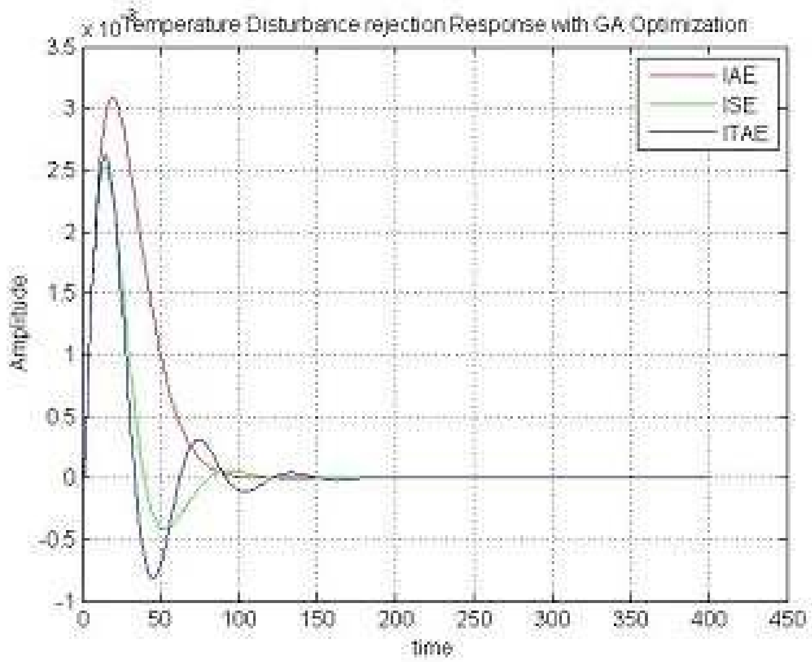

Figure 5.4: Temperature disturbance response of 2DOF controller optimization using GA.

Table 5.1: Result of 2DOF controller parameter optimization using GA.

GA optimization of 2DOF controller parameters $[K_p, K_i, K_d, \alpha, \beta]$	Peak overshoot of of Step Response In (%)	Reduction Flow Disturbance Response In (%)	Reduction Temperature Disturbance Response In (%)
IAE $[2.540, 0.152, 22.529, 0.707, 0.363]$	2.1	54.3	85
ISE $[2.238, 0.235, 31.598, 0.389, 0.549]$	29.98	58.2	86
ITAE $[2.3065, 0.1153, 17.035, 0.574, 0.431]$	20.75	50.4	83

From the Figure 5.2 ,5.3, 5.4 and parameters tabulated in Table 5.1, it is concluded that IAE criterion for optimizing simultaneously all the five parameters of 2DOF controller using GA method has minimum peak overshoot of step response(2.1%). The maximum reductions of flow(58.2%) and temperature (86%) disturbances are obtained under the criterion of ISE compared to other two criteria IAE and ITAE. Here, results are obtained using single objective optimization by assigning equal weights(unity) to all three objective functions under three separate evaluation criteria. As being multiobjective optimization problem, it is first required to obtain multiple pareto optimal solutions and select best one using multi-criteria decision. Following section discusses prevalent multiobjective optimization algorithms NSGA-II and NSGA-III for the 2DOF controller parameter optimization.

5.4 Working of Nondominated Sorting Genetic Algorithm-II (NSGA-II)

Nondominated Sorting Genetic Algorithm-II falls under the category of elitist genetic algorithm. Unlike Rudolf method of using only an elite preservation, NSGA-II uses an explicit diversity preservation mechanism based on crowding comparison (calculated on objective function space) along with tournament selection procedure. In NSGA-II, first of all offspring population Q_t of size N is created by using the parent population P_t of size N. Two populations Q_t and P_t are combined to form R_t of size 2N then, nondominated sorting is used to classify the entire population R_t. To achieve this, the combined population R_t is sorted according to different nondomination levels (F_1, F_2, and so on). Then, each nondomination level is selected one at a time to construct a new population S_t, starting from F_1, until the size of S_t is equal to N or for the first time exceeds N. An objective in NSGA-II is to derive number of dominated and nondominated set of solutions. The NSGA-II computes density of solution in the population based on crowding distance. NSGA-II considers rank of nondomination of an individual in the population and its crowding distance to select solution. If two solutions has same nondomination rank then solution comprising larger crowding distance value is selected [63], [14].

5.5 Algorithm for tuning 2DOF controller using NSGA-II

Step 1: Define the dimension of 2DOF controller parameters optimization problem (number of decision variables **'NVARS'** =5).

Step 2: Set the upper bound values UB= [100 100 100 1 1] & lower bound values LB= [0 0 0 0 0]. M Araki et al. [3] has tested different processes using 2DOF controller optimization and maximum value of any parameters of $C_s(s)$ is not greater than **'60'** hence, for safe side maximum value in $C_s(s)$ is selected to be **'100'**.

Step 3: Derive transfer function of plant **'plant'**, actuator **'actuator_tf'**, sensor **'sensor_tf'**, temperature disturbance **'distb_temp'**, flow disturbance **'distb_flow'**, serial controller **'C'**, and feed forward controller **'C_f'**.

Step 4: Define the step magnitude of input, flow disturbance and temperature disturbance as **1**, **0.1**, and **0.01** respectively [59].

Step 5: Choose the population size (number of individuals in each generation) **'PopulationSize'** (default is 15*NVARS) = 100, Data type of each decision variable is double vector (**'PopulationType'** is **'doubleVector'**), Initial population matrix will be **'PopulationSize* rows'** and **'NVARS'** columns. Create population using MATLAB function **'gacreationuniform'**, termination criterion **'MaxGenerations'**= **'100'**. Initialize the generation counter. Formulate problem with a vector of three objectives.

Step 6: Evaluate the objective function for the population, and use those values to create scores for the population. The performance indices considered for evaluation of objective functions are Integral of Absolute Error (IAE), Integral of Squared Error (ISE), and Integral of Time-weighted Absolute Error (ITAE) one at a time. This establishes the basis for selecting populations that will be mated during reproduction.

Step 7: Rank the population according to solution of objective functions based on non-dominated sorting approach front wise.

Step 8: Select a pair of population for mating from the current population for the next generation using the selection function **'selectiontournament'**. In the tournament randomly two solutions are selected from the current population and the one having better nondominated rank is selected. If solutions are on the same nondominated front then one having higher crowding distance (function **'distancecrowding'**) will be selected.

Step 9: Use the genetic operators crossover (Cross over percentage **'0.8'**) and mutation

(Mutation rate **'0.09'**) to generate offspring solution of size N. Create offspring by built in MATLAB crossover function **'crossoverintermediate'** and mutation function **'mutationadaptfeasible'**.

Step 10: Calculate objective functions of the offspring population.

Step 11: Combine the current population **(N)** and the offspring population **(N)** into one matrix, the combined population **(2N)**.

Step 10: Compute the rank by sorting non-inferior individuals above inferior ones, so it uses elite individuals automatically (function **'Rank'**) and crowding distances (function **'distancecrowding'**) for all individuals in the combined population.

Step 11: Trim the combined population **2N** to have **'PopulationSize' N** by retaining the non-inferior solutions front wise. If solutions are on same front apply crowding distance operator to select solution best **N** populations and other solutions are rejected.

Step 12: Replace the initial population with the new population. Increment generation counter.

Step 13: If generation counter is less than **MaxGenerations** (the termination criterion), Go to **Step 8**.

The output of algorithm is variable **x** which is a matrix with **'NVARS'** columns. The number of rows in **x** is the same as the number of Pareto solutions. All solutions in a Pareto set are equally optimal; it is up to the designer to select a solution in the Pareto set depending on the application or solutions are ranked using algorithm and highly ranked solution is selected.

5.6 Working of Nondominated Sorting Genetic Algorithm-III (NSGA-III) [5]

This algorithm is the extension of the NSGA-II algorithm for optimization of many objective problems. NSGA-III was presented by Kalyanmoy Deb [5]. The basic framework of NSGA-III is identical to the NSGA-II though there is a sound change in its selection procedure. In the case of many objective optimization problems, proportion of nondominated solutions becomes exponentially large due to increase in number of objectives. Since, nondominated solutions occupy most of the population slots, any elite preserving algorithm faces difficulty in accommodating adequate number of new solutions in the populations.

This slow down the search process. Here, diversity among the population members is maintained by supplying and adaptively updating reference points. The crowding distance operator of NSGA-II is replaced in NSGA-III by following methods.

5.6.1 Classification of population into nondominated levels

The number of nondominated fronts are identified at first using prevailing nondominated method. Then, population members from the nondominated front level '1' to level 'l' are incorporated in set S_t . If $|S_t| = N$ (Number of population), no other process is required and subsequent generation is started with $P_{(t+1)} = S_t$. For $|S_t| > N$, members from '1' to 'l-1' are chosen and remaining members $K = N - |P_{(t+1)}|$ are selected from last front F_l.

5.6.2 Determination of reference points on a hyper plane

The set of reference points (denoted as H) are used in order to maintain diversity among solutions. The reference points can be predefined in a structured manner or determined by the user. The algorithm is expected to obtain near Pareto optimal solutions corresponding to the given reference points. This feature of algorithm is used for two combined application one is decision making and second is optimization. Das and Dennis's systematic approach is used to place points on a normalized hyper-plane a M-1 dimensional unit simplexes inclined to all objective axes and has an intercept of one on each axis. The total number of reference point in M objective problem considering 'p' number of divisions along each objective is given as under:

For example, in a three-objective problem (M = 3), the reference points are created on a triangle with apex at (1, 0, 0), (0, 1, 0) and (0, 0, 1). If four divisions (p = 4) are chosen for each objective axis, H= 15 reference points are created. The reference points are shown in below Figure 5.5 for understanding. In the case of user supplied set of preferred reference points, user marks H number of reference points on a normalized hyper plane.

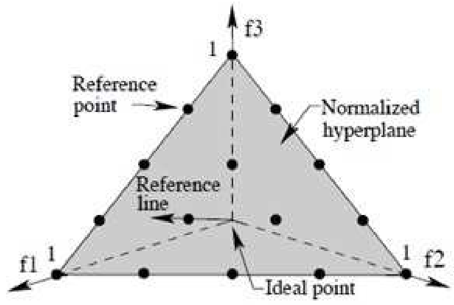

Figure 5.5: Reference point (H=15) shown on normalized 3 objective problem with p=4 [15].

5.6.3 Adaptive normalization of population members

The main objective of normalization of an objective functions is to solve problems with Pareto optimal front whose objective function values are scaled differently. The procedure used for normalization of objective function includes creation of hyper plane on objective space. The normalization of objective functions and creation of hyper plane is carried out every generation to maintain diversity among population hence, it is known as adaptive normalization of population. First, an ideal point of the population S_t is determined by identifying the minimum value (Z_j^{min}), for each objective function. Each objective value of S_t is then translated by subtracting objective f_j by Z_j^{min} , so that the ideal point of translated S_t becomes a zero vector. This is called translated objective as $f_j^{'}$ (x) = $f_j(x) Z_j^{min}$. Then, maximum point in each objective is calculated using following function called as Achievement Scalarizing Function (ASF). ASF(x,w) = $max_{i=1}^{M}$ $f_j^{'}$ (x)$/w_j$ for w_j=0 replace with small value 1e-6. From this, calculate extreme maximum value of M objective function vector Z_j^{max}. Using the M extreme vectors, M dimensional linear hyper plane is constructed. Now, the intercept a_j with objective axis and linear hyper plane is computed and objective functions are normalized as under:

$$f_j^n(x) = \frac{f_i(x) - Z_j^{min}}{a_j - Z_j^{min}} \tag{5.1}$$

Here, intercept on each normalized axis is at f_j^n (x)= 1 and hyper plane constructed with these intercept points will make, $\sum_{j=1}^{M} f_j^n = 1$. The procedure for computing intercept and forming hyper plane is in Figure 5.6.

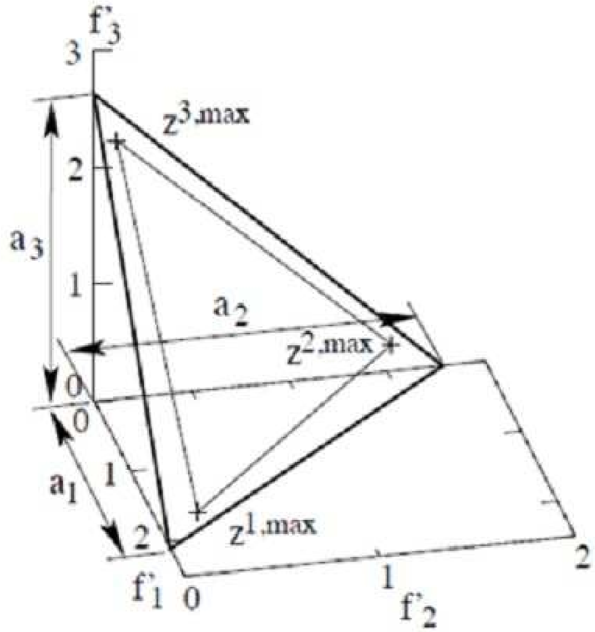

Figure 5.6: Computing intercepts and forming hyper-plane for a three objective problem [15].

5.6.4 Association operation

Once adaptive normalization of population members is completed, population members are required to associate with reference point. The aim of this operation is to find population members associated with reference point or not. In order to do this, a reference line corresponding to each reference point on the hyper plane is determined by joining the reference point with the origin. Then, perpendicular distance of each population member from each of the reference lines is calculated. The reference point is said to be associated with the population member if its reference line is closest to a population member in the normalized objective space. This is shown in Figure 5.7.

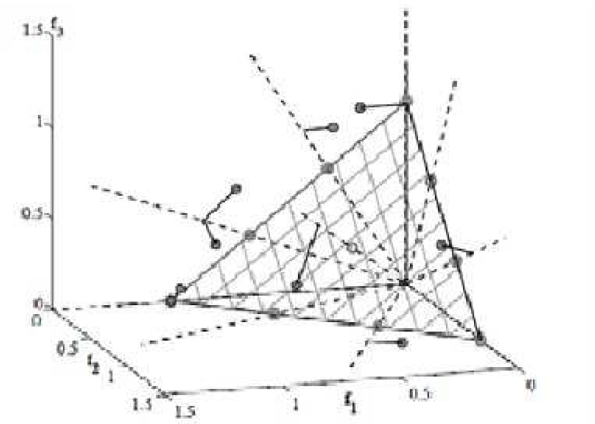

Figure 5.7: Association of population members with reference points [15].

5.6.5 Niche preservation operation

From, the above association operation it will come to know the number of population members associated with reference points. The number of population members associated with particular reference points are denoted as niche count for that reference point only. The niching procedure is used to select population for next generation.

It can be concluded from the above process mentioned for NSGA-III that, this algorithm does not require setting any new parameters other than usual GA parameters, similar to NSGA-II. The parameter number of reference point (H) is not an algorithmic parameter; it is directly related to the desired number of trade-off points. The overall computational complexity of NSGA-III algorithm is higher than that of NSGA-II algorithm.

5.7 Algorithm for tuning 2DOF controller using NSGA-III

Step 1: Define the dimension of 2DOF controller parameters optimization problem (number of decision variables **'NVARS'** =5).

Step 2: Set the upper bound values UB= [100 100 100 1 1] & lower bound values LB= [0 0 0 0 0]. M Araki et al. [3] has tested different processes using 2DOF controller optimization and maximum value of any parameters of $C_s(s)$ is not greater than **'60'** hence, for safe side maximum value in $C_s(s)$ is selected to be **'100'**.

Step 3: Derive transfer function of plant **'plant'**, actuator **'actuator_tf'**, sensor **'sensor_tf'**, temperature disturbance **'distb_temp'**, flow disturbance **'distb_flow'**, serial controller **'C'**, and feed forward controller **'Cf'**.
Step 4: Define the step magnitude of input, flow disturbance and temperature disturbance as **1**, **0.1**, and **0.01** respectively [12].
Step 5: Choose the population size (number of individuals in each generation) **'nPop'** = 100, Data type of each decision variable is double vector (**'PopulationType'** is **'doubleVector'**), Initial population matrix P_t will be PopulationSize* rows and **'NVARS'** columns. Create population using **'unifrnd'**, termination criterion **'MaxIt'**=100, Crossover Percentage **'pCrossover'** = 0.8, Mutation Percentage **'pMutation'** = 0.5, **'nObj'** is number of objectives, number of divisions are considered along each objective **'nDivision'**=10, **Zr = GenerateReferencePoints(nObj, nDivision)** total number of reference points generated based on Das and Dennis's technique. Initialize the generation counter. Formulate problem with a vector of three objectives.
Step 6: Evaluate the objective function for the population, and use those values to create scores for the population. The performance indices considered for evaluation of objective functions are Integral of Absolute Error (IAE), Integral of Squared Error (ISE), and Integral of Time-weighted Absolute Error (ITAE) one at a time.
Step 7: Sort population and perform selection according to solution of objective functions based on nondominated sorting approach front wise using function **SortAndSelectPopulation(pop, params)**.
Step 8: While **it** < **MaxIt** do

1. Create offspring population Q_t using arithmetic crossover operator **'Crossover(p1.Position, p2.Position)'** and Gaussian mutation **'Mutate(p.Position, mu, sigma)'**.
2. Set R_t= P_t U Q_t i.e. combine parent and offspring populations of size 2* nPop.
3. Apply non-dominated sorting **'NonDominatedSorting(newpop)'** on R_t and obtain solutions front wise F_1, F_2, ...
4. Starting from F_1, the individuals in the higher non-dominance levels are added to S_t until its size reaches **'nPop'** or exceed **'nPop'** for the first time, assuming number of non-dominance levels **'l'**. Solutions from non-dominance level greater than **'l'** are discarded.

S_t=[ ] and i=1

While $|S_t| \leq$ nPop

$S_t = S_t U F_i$

i=i+1

End

Solutions S_t are selected for next generation $P_{(t+1)}$. If the size of the $P_{(t+1)}$ is **'nPop'** algorithm then repeats previous step in next iteration by generating new offspring solutions (if termination criteria of the algorithm is not met). Else, the other **nPop** - $P_{(t+1)}$ solutions are selected from F_l based on reference points. Since the objectives may be on different scales, they are normalized and reference points are generated in the normalized space. Each member of S_t is associated with the reference point which has the closest euclidean distance from it. The goal is to assign higher priority to those reference points in F_l that are not well represented in $S_t \backslash F_l$ to be in the next generation $P_{(t+1)}$. After generating the reference points, the distance of each individual from the reference line, the line that connects the origin of the space of the normalized objectives to the reference point are calculated. Then, each individual is assigned to the closest reference point.

IF $|S_t|$ = nPop **do**

$P_{(t+1)} = S_t$; **break**

Else

$P_{(t+1)} = U_{j=1}^{(l-1)} F_j$

Normalize S_t using function **'NormalizePopulation(pop, params)'** minimum and intercept points of each objective.

Associate each member of S_t to the reference point using function **'AssociateToReferencePoint(pop, params)'**.

Select **nPop** = $P_{(t+1)}$ members from F_l using niche preserving operator.

End

it= it+1

End

The output of algorithm is variable P_t is a matrix with **'NVARS'** columns. The number of rows in P_t is the same as the number of Pareto solutions. All solutions in a Pareto set are equally optimal; it is up to the designer to select a solution in the Pareto set depending on the application or solutions are ranked using algorithm and highly ranked solution is selected.

5.8 Comparison of results using NSGA-II and NSGA-III algorithms

The system of heat exchanger with controller and disturbances are considered as shown in Figure 3.6. The step response and both flow and temperature disturbance rejection responses of the system are simulated in the software tool MATLAB. The reference signal and disturbances (both flow and temperature) applied as a step input has magnitude of 1, 0.1 and 0.01 respectively [59]. The process of tuning 2DOF controller for multiobjective optimization using NSGA-II and NSGA-III algorithm is shown in the previous section.

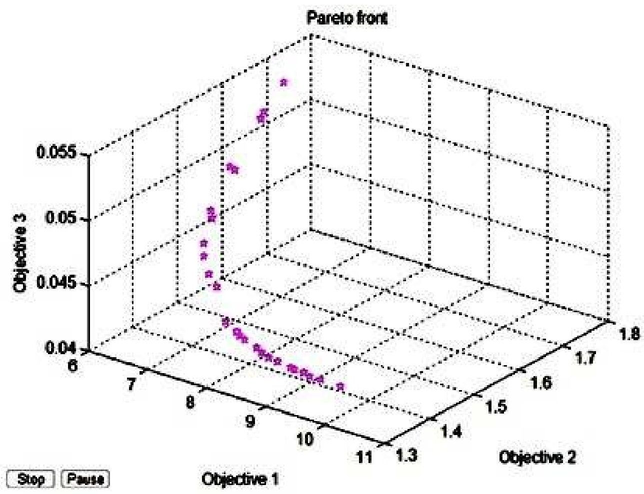

Figure 5.8: Plot of Pareto optimal front using NSGA-II based optimization under IAE Criterion.

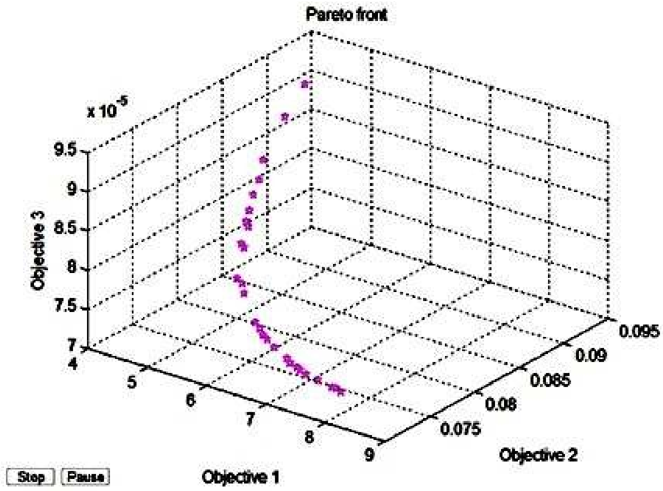

Figure 5.9: Plot of Pareto optimal front using NSGA-II based optimization under ISE Criterion.

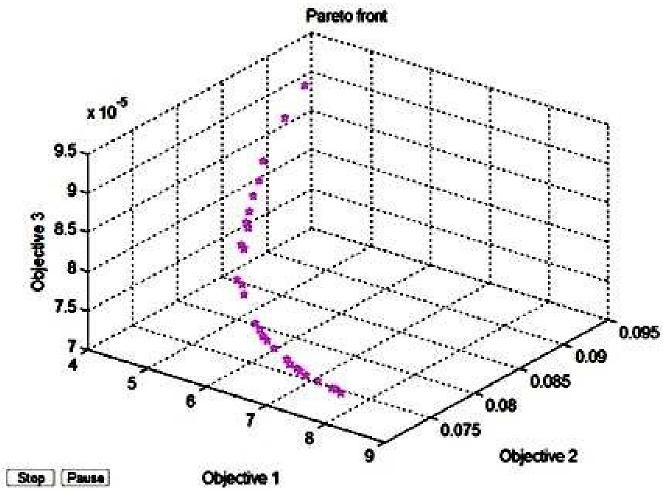

Figure 5.10: Plot of Pareto optimal front using NSGA-II based optimization under ITAE Criterion.

The Figure 5.8 to Figure 5.10 are plots of Pareto optimal front of optimization of three distinct objective functions i.e. set point tracking and disturbance rejections (Both flow and temperature) obtained for all three criteria IAE, ISE & ITAE. The Pareto front has 27 nondominated set of solutions, which are obtained under different criteria are tabulated as under.

Table 5.2: Non-dominated set of solutions obtained using NSGA-II optimization under IAE criterion.

Sr.No	K_p	K_i	K_d	α	β
1	1.024007	0.048362	6.608518	0.486411	0.292564
2	1.362449	0.052017	6.854668	0.601088	0.439414
3	1.113922	0.051042	6.790711	0.527548	0.330018
4	1.149686	0.051746	6.837209	0.547475	0.363404
5	0.995107	0.046072	6.465139	0.471004	0.285858
6	1.142566	0.052012	6.811436	0.53246	0.36453
7	1.061573	0.0482	6.668703	0.489134	0.341552
8	1.253998	0.051724	6.84518	0.559015	0.399582
9	1.350209	0.051231	6.852343	0.577602	0.417164
10	1.333592	0.05177	6.839711	0.565704	0.36669
11	1.026934	0.048259	6.654233	0.487695	0.304087
12	1.192237	0.05188	6.76109	0.538246	0.348068
13	1.329296	0.051252	6.851525	0.57615	0.4176
14	1.233943	0.051778	6.837104	0.54654	0.369673
15	1.362205	0.052017	6.854668	0.601088	0.439581
16	1.294361	0.051796	6.837073	0.546528	0.376135
17	1.316415	0.051891	6.839923	0.563724	0.385974
18	1.267034	0.051803	6.835596	0.547901	0.380322
19	1.112907	0.051771	6.807975	0.530331	0.347839
20	1.338831	0.051908	6.844837	0.566669	0.391565
21	1.248228	0.051773	6.838224	0.562774	0.367966
22	1.276698	0.051557	6.833231	0.55156	0.410129
23	1.349177	0.05144	6.851313	0.570992	0.385513
24	0.995107	0.046072	6.465139	0.471004	0.285858
25	1.305848	0.051984	6.847643	0.556222	0.39363
26	1.163408	0.050888	6.802661	0.523014	0.339921
27	1.083258	0.052036	6.741211	0.523123	0.31271

Table 5.3: Non-dominated set of solutions obtained using NSGA-II optimization under ISE criterion.

Sr.No	K_p	K_i	K_d	α	β
1	1.696144	0.045715	4.894663	0.604138	0.228633
2	1.676746	0.045378	4.886081	0.6193	0.215132
3	1.12004	0.054174	4.830019	0.603224	0.115752
4	1.156798	0.05391	4.834612	0.601096	0.108425
5	1.632394	0.048476	4.889907	0.606914	0.209064
6	1.256848	0.053329	4.851208	0.606097	0.125689
7	1.234446	0.0533	4.848767	0.604842	0.136053
8	1.202035	0.053501	4.875281	0.603063	0.118119
9	1.692167	0.047096	4.890637	0.604381	0.228432
10	1.535643	0.049876	4.880562	0.609287	0.206677
11	1.409286	0.053676	4.886552	0.606422	0.110776
12	1.330287	0.051077	4.864312	0.606479	0.14383
13	1.3083	0.054096	4.874194	0.60833	0.17808
14	1.413978	0.052716	4.875266	0.607019	0.169175
15	1.279894	0.053249	4.857112	0.604928	0.142454
16	1.32216	0.051512	4.879703	0.604255	0.137026
17	1.539822	0.051603	4.884958	0.605085	0.203346
18	1.550184	0.04867	4.887196	0.606408	0.203231
19	1.608952	0.048967	4.89097	0.603107	0.219779
20	1.628257	0.048833	4.886023	0.607083	0.203008
21	1.594193	0.048788	4.87988	0.607308	0.196674
22	1.430709	0.051995	4.878397	0.60782	0.179276
23	1.665038	0.047606	4.890524	0.603808	0.161112
24	1.506493	0.049876	4.876303	0.608933	0.193128
25	1.282773	0.050966	4.869333	0.603866	0.124228
26	1.636219	0.047434	4.893375	0.604517	0.217247
27	1.520018	0.053782	4.895455	0.609287	0.206677

Table 5.4: Non-dominated set of solutions obtained using NSGA-II optimization under ITAE criterion.

Sr.No	K_p	K_i	K_d	α	β
1	0.852827	0.033659	5.324272	0.439655	0.463838
2	0.836627	0.032942	5.230666	0.421576	0.417012
3	0.869257	0.033901	5.315995	0.439526	0.474888
4	0.894934	0.034171	5.316161	0.437792	0.480781
5	0.870821	0.033758	5.308657	0.436979	0.475201
6	0.853539	0.033408	5.321049	0.437744	0.467873
7	0.858643	0.033344	5.321461	0.431966	0.470431
8	0.856807	0.033583	5.322067	0.424024	0.467221
9	0.868056	0.033656	5.319998	0.437607	0.471322
10	0.86372	0.033441	5.32166	0.427881	0.468131
11	0.866127	0.034088	5.281864	0.444645	0.472936
12	0.857191	0.03308	5.321088	0.42873	0.471637
13	0.889773	0.034101	5.369274	0.441436	0.482245
14	0.878432	0.034095	5.316452	0.437786	0.476991
15	0.911885	0.034239	5.313478	0.471491	0.479922
16	0.895713	0.034053	5.310828	0.43612	0.479032
17	0.910474	0.034142	5.302916	0.441588	0.474148
18	0.886536	0.034076	5.340969	0.439622	0.477364
19	0.945207	0.035115	5.27583	0.443237	0.480697
20	0.905041	0.034167	5.301803	0.440695	0.476445
21	0.892192	0.033976	5.335683	0.442162	0.474603
22	0.912436	0.034314	5.297286	0.471881	0.47975
23	0.869928	0.033664	5.314661	0.436995	0.473112
24	0.873633	0.033829	5.305953	0.441525	0.477943
25	0.900335	0.034297	5.305991	0.440605	0.478676
26	0.880645	0.033852	5.34835	0.435275	0.478134
27	0.836627	0.032942	5.230666	0.421576	0.417012

The values of 2DOF controller parameters tabulated in Table 5.2, 5.3, & 5.4 are nondominated set of solutions. Hence, any of the above result can be selected by the user for the problem of shell and tube heat exchanger system. The Figure 5.11 to Figure 5.19 are plots of set point tracking and disturbance rejections for all values of 2DOF controller parameters obtained under the criteria IAE, ISE and ITAE as nondominated set of solutions using NSGA-II. The best value obtained from the list of nondominated set of solutions are plotted as symbol '*' has red color.

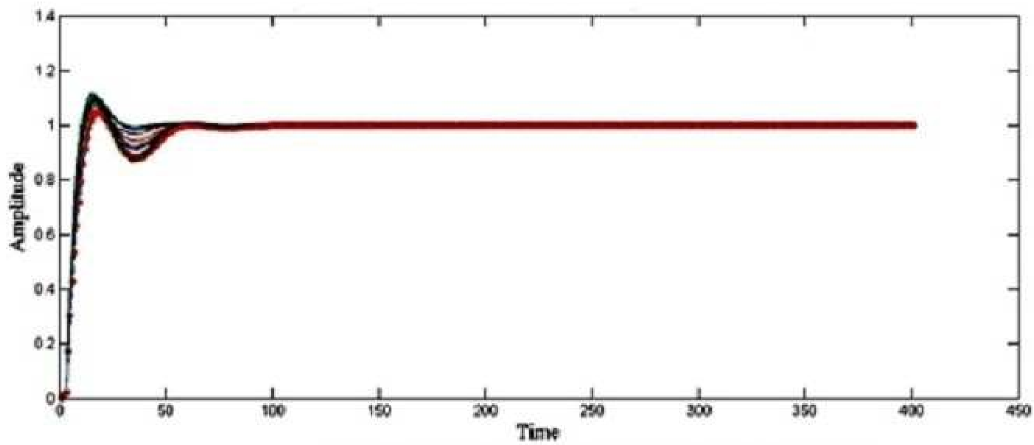

Figure 5.11: Set point response obtained using NSGA-II optimization of 2DOF controller under IAE.

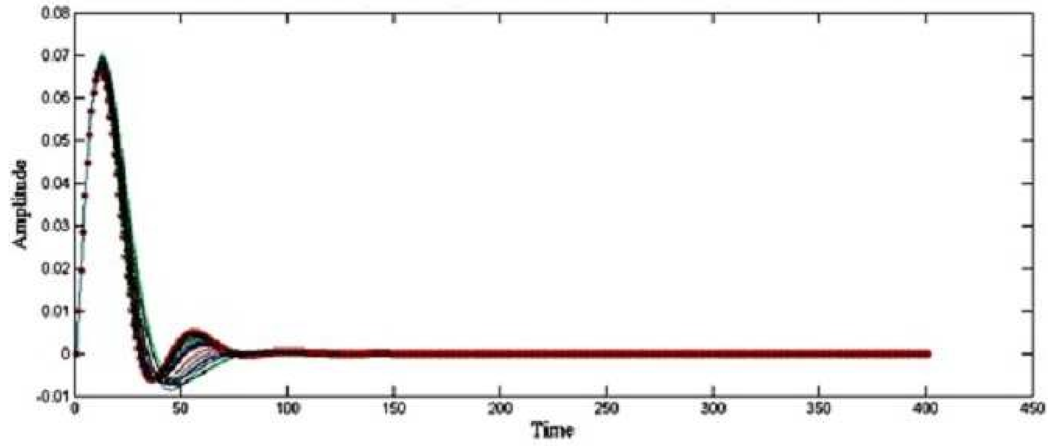

Figure 5.12: Flow disturbance rejection response obtained using NSGA-II optimization of 2DOF controller under IAE.

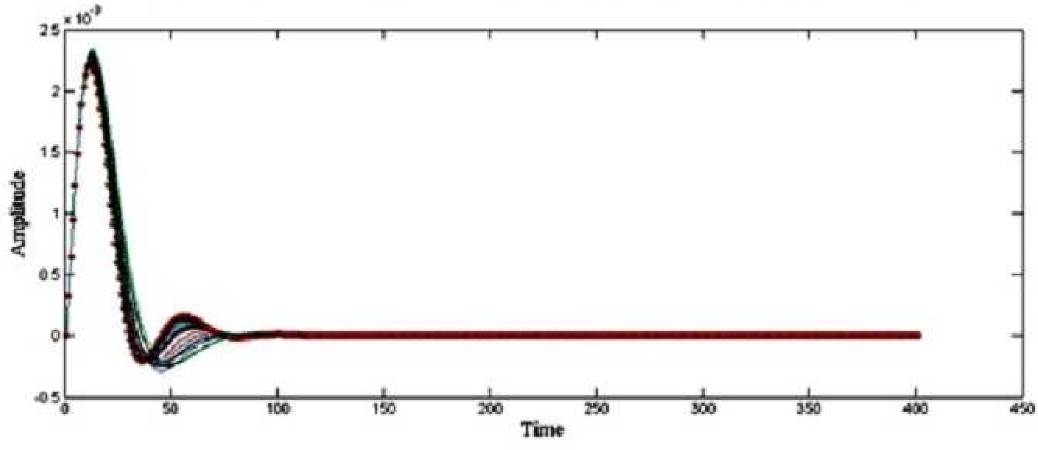

Figure 5.13: Temperature disturbance rejection response obtained using NSGA-II optimization of 2DOF controller under IAE.

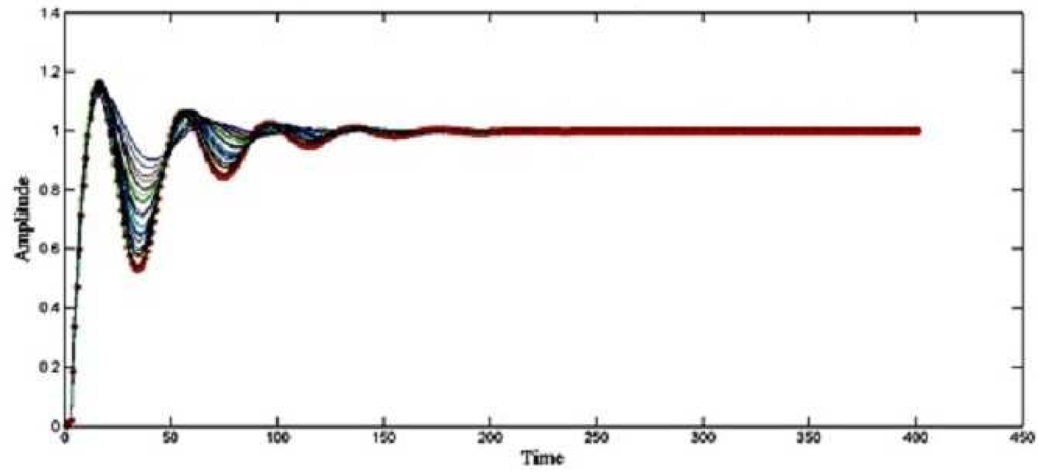

Figure 5.14: Set point response obtained using NSGA-II optimization of 2DOF controller under ISE.

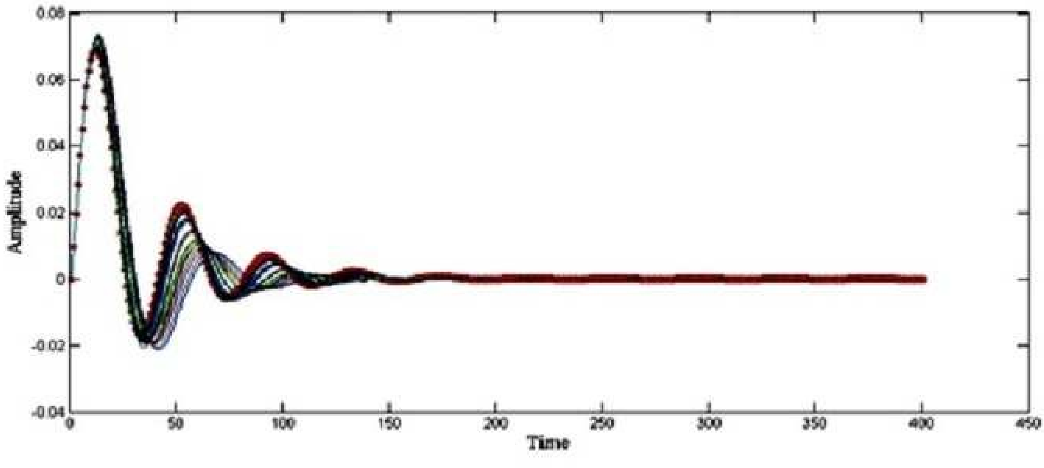

Figure 5.15: Flow disturbance rejection response obtained using NSGA-II optimization of 2DOF controller under ISE.

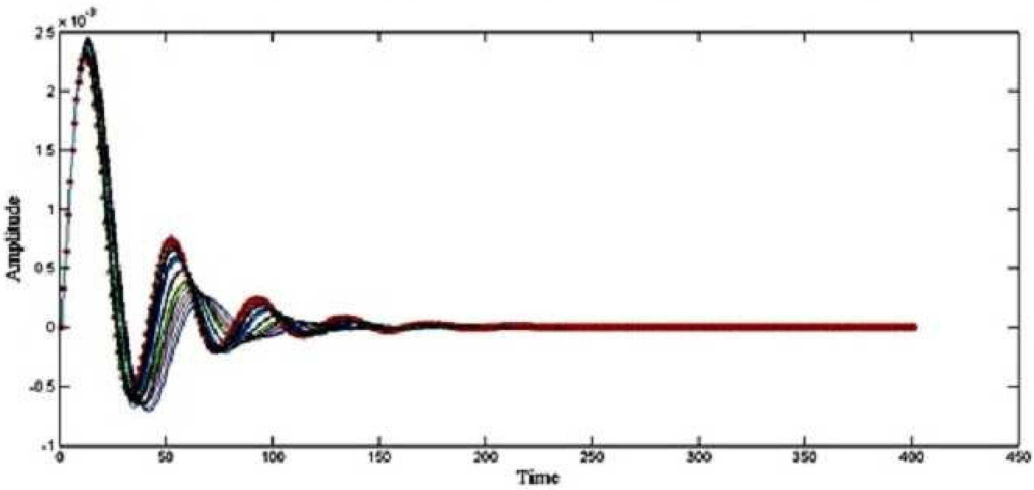

Figure 5.16: Temperature disturbance rejection response obtained using NSGA-II optimization of 2DOF controller under ISE.

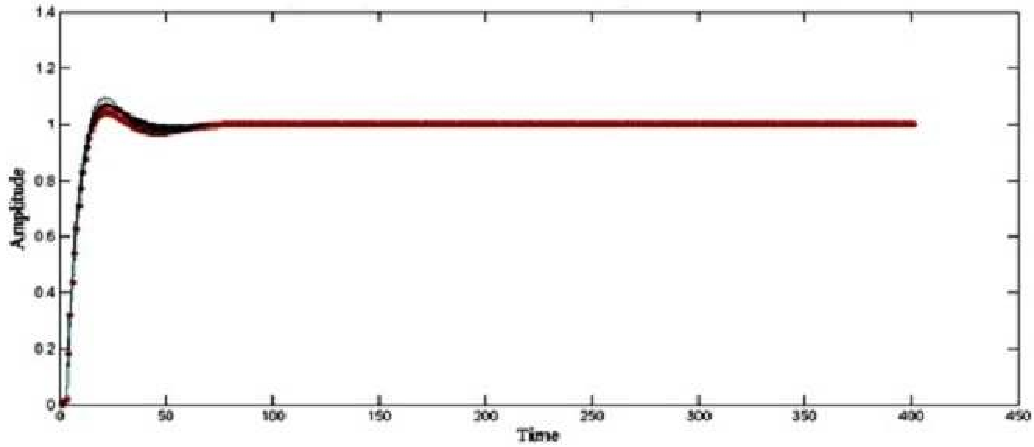

Figure 5.17: Set point response obtained using NSGA-II optimization of 2DOF controller under ITAE.

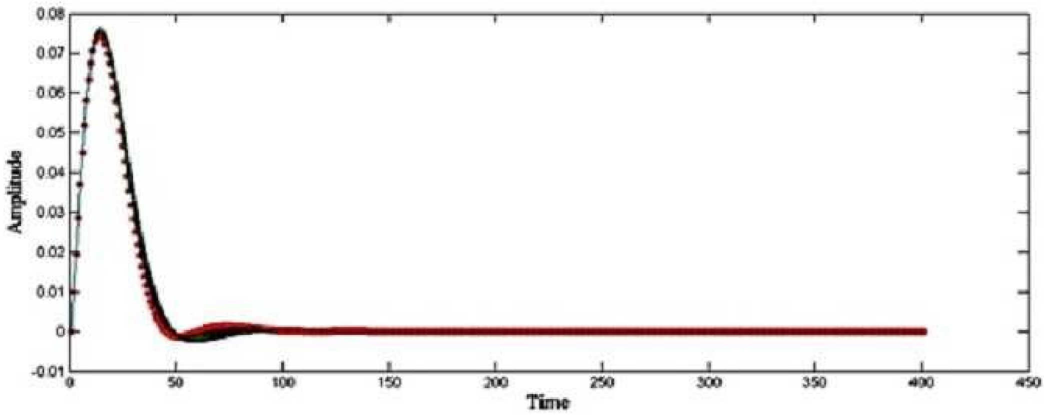

Figure 5.18: Flow disturbance rejection response obtained using NSGA-II optimization of 2DOF controller under ITAE.

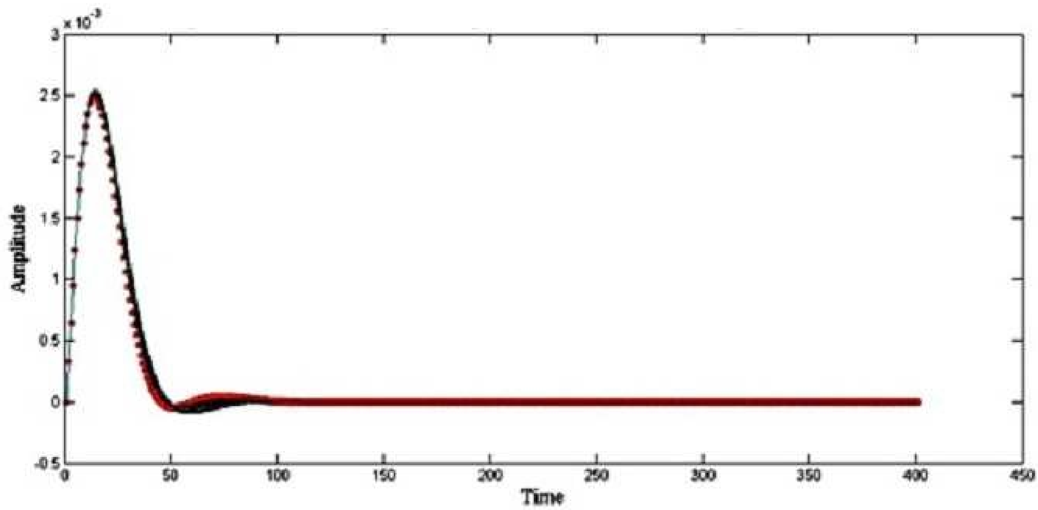

Figure 5.19: Temperature disturbance rejection response obtained using NSGA-II optimization of 2DOF controller under ITAE.

From the Figure 5.11 to Figure 5.19 and parameters tabulated in Table 5.5, it is concluded that ITAE criterion for optimizing simultaneously all the five parameters of 2DOF controller using multiobjective optimization of NSGA-II has minimum peak overshoot of step response for nondominated set of solution [0.911884974,0.034239346,5.313477873,0.471490705,0.479921627] (Sr.No-15, from Table 5.4). The maximum reductions of flow and temperature disturbances are obtained under the criterion of IAE for nondominated set of solution [1.36244, 0.0520165, 6.8546, 0.60108, 0.439414] (Sr.No-15, from Table 5.2).

Table 5.5: Result of 2DOF controller parameter optimization using NSGA-II.

Multiobjective optimization 2DOF controller parameter NSGA-II $[K_p, K_i, K_d, \alpha, \beta]$	Peak overshoot of of Step Response In (%)	Reduction Flow Disturbance Response In (%)	Reduction Temperature Disturbance Response In (%)
IAE (Sr.No-15, Table 5.2) $[1.362, 0.052, 6.85, 0.601, 0.439]$ (Best Set point tracking & disturbance rejections)	4.79	33.43	77.82
ISE (Sr.No-1, Table 5.3) $[1.676, 0.045, 4.88, 0.619, 0.215]$ (Best Set point tracking)	12.5	31.02	77.01
ITAE (Sr.No-15, Table 5.4) $[0.911, 0.034, 5.31, 0.471, 0.479]$ (Best Set point tracking)	4.44	24.8	74.94
ITAE (Sr.No-19, Table 5.4) $[0.945, 0.035, 5.27, 0.443, 0.480]$ (Best Disturbance rejections)	9.52	25.11	75.1

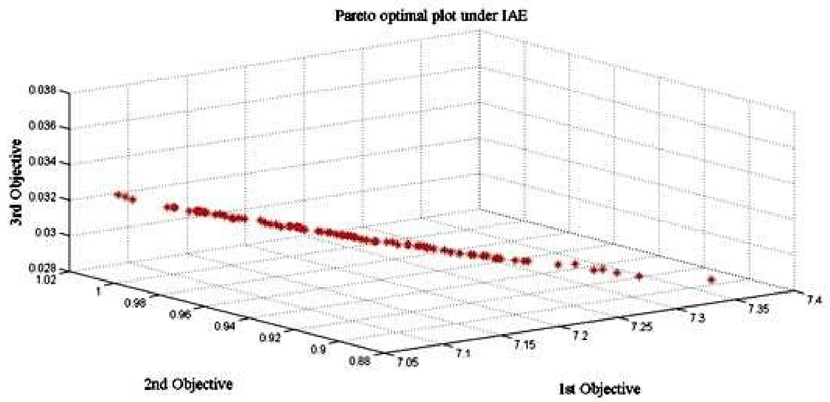

Figure 5.20: Plot of Pareto optimal front using NSGA-III based optimization under IAE Criterion.

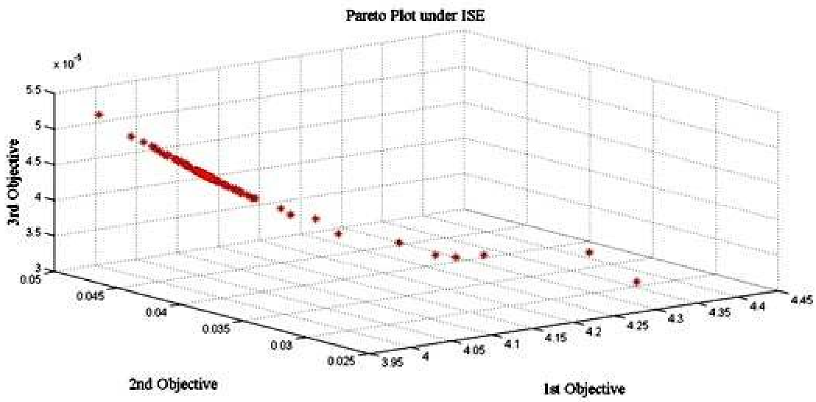

Figure 5.21: Plot of Pareto optimal front using NSGA-III based optimization under ISE Criterion.

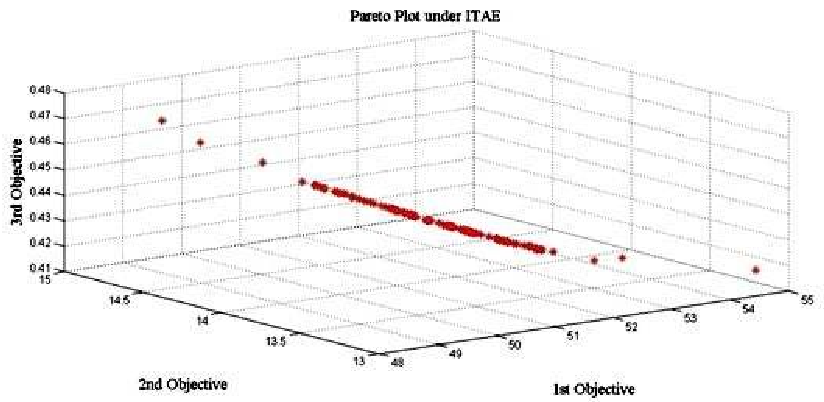

Figure 5.22: Plot of Pareto optimal front using NSGA-III based optimization under ITAE Criterion.

The Figure 5.20 to Figure 5.22 are plots of Pareto optimal front of optimization of three distinct objective functions i.e. set point tracking and disturbance rejections (Both flow and temperature) obtained for all three criteria IAE, ISE & ITAE. The Pareto front has 80 nondominated set of solutions, which are obtained under different criteria are tabulated as under.

Table 5.6: Nondominated set of solutions obtained using NSGA-III optimization under IAE criterion.

Sr.No	K_p	K_i	K_d	α	β
1	1.5620	0.0747	10.3879	0.5645	0.3978
2	1.5381	0.0737	10.1711	0.5671	0.3981
3	1.5557	0.0745	10.2929	0.5671	0.3979
4	1.6258	0.0757	11.1012	0.5605	0.4015
5	1.5461	0.0741	10.2436	0.5680	0.3977
6	1.5808	0.0750	10.4887	0.5649	0.3991
7	1.5501	0.0740	10.2770	0.5663	0.3975
8	1.5822	0.0750	10.6929	0.5620	0.3982
9	1.5301	0.0735	10.0894	0.5673	0.3980
10	1.5514	0.0748	10.2189	0.5688	0.3978
11	1.5861	0.0751	10.5896	0.5650	0.3978

Sr.No	K_p	K_i	K_d	α	β
12	1.5919	0.0757	10.6840	0.5577	0.3989
13	1.5884	0.0752	10.6801	0.5663	0.3977
14	1.5945	0.0752	10.8216	0.5587	0.4009
15	1.5846	0.0747	10.5988	0.5661	0.3976
16	1.5919	0.0750	10.6700	0.5648	0.3988
17	1.5751	0.0747	10.4876	0.5664	0.3977
18	1.5297	0.0735	10.0840	0.5692	0.3962
19	1.5683	0.0748	10.3699	0.5668	0.3966
20	1.5450	0.0739	10.1616	0.5669	0.3977
21	1.5178	0.0734	9.9859	0.5690	0.3977
22	1.5650	0.0755	10.4903	0.5639	0.3984
23	1.5486	0.0739	10.2677	0.5664	0.3974
24	1.5919	0.0757	10.6840	0.5577	0.3989
25	1.5568	0.0750	10.4014	0.5644	0.3980
26	1.5329	0.0737	10.0695	0.5673	0.3965
27	1.5698	0.0746	10.4395	0.5644	0.3976
28	1.6043	0.0753	10.8488	0.5607	0.4009
29	1.6086	0.0753	10.8854	0.5622	0.3981
30	1.6002	0.0752	10.8939	0.5614	0.4002
31	1.5297	0.0733	10.0964	0.5726	0.3972
32	1.5505	0.075	10.4026	0.5653	0.3969
33	1.5628	0.075	10.3995	0.5642	0.3978
34	1.5898	0.0752	10.6625	0.5634	0.3981
35	1.5326	0.0737	10.0699	0.5674	0.3962
36	1.5692	0.0748	10.384	0.5664	0.3974
37	1.5564	0.0742	10.2887	0.5661	0.3978
38	1.5135	0.0735	9.9835	0.5641	0.3971
39	1.5325	0.074	10.1527	0.568	0.3979
40	1.5134	0.0737	10.0476	0.5644	0.3957
41	1.558	0.0743	10.3165	0.5649	0.3981

Sr.No	K_p	K_i	K_d	α	β
42	1.5481	0.0739	10.2525	0.5651	0.3967
43	1.5919	0.075	10.6840	0.5577	0.3989
44	1.5244	0.073	10.0665	0.5679	0.3969
45	1.5567	0.074	10.3022	0.5658	0.3978
46	1.5728	0.0752	10.5443	0.5643	0.398
47	1.5861	0.0753	10.5366	0.5648	0.3979
48	1.5365	0.0737	10.1346	0.574	0.3979
49	1.5706	0.0754	10.4832	0.5646	0.3983
50	1.5518	0.0747	10.2805	0.569	0.3979
51	1.5718	0.075	10.5874	0.5656	0.3978
52	1.578	0.0756	10.5092	0.5632	0.3983
53	1.5754	0.0753	10.4826	0.5649	0.3981
54	1.5767	0.0749	10.5184	0.5664	0.3981
55	1.5486	0.0739	10.2695	0.5663	0.3981
56	1.5229	0.0732	10.0459	0.5678	0.3954
57	1.5394	0.0743	10.2501	0.5666	0.3981
58	1.5492	0.0739	10.2401	0.5679	0.398
59	1.5698	0.0754	10.4897	0.5642	0.3981
60	1.5935	0.0756	10.749	0.5578	0.3996
61	1.5441	0.0745	10.1785	0.5708	0.3979
62	1.5899	0.0756	10.824	0.5627	0.3986
63	1.5632	0.0746	10.3182	0.5663	0.3972
64	1.6002	0.0744	10.6852	0.562	0.3989
65	1.5381	0.0745	10.2606	0.568	0.3977
66	1.5826	0.075	10.4411	0.5655	0.3978
67	1.5874	0.0753	10.5535	0.5667	0.398
68	1.5635	0.0747	10.3949	0.5652	0.3979
69	1.5606	0.0744	10.3742	0.5625	0.3976
70	1.5238	0.073	10.0236	0.5673	0.3953
71	1.5887	0.0753	10.5864	0.5641	0.398

Sr.No	K_p	K_i	K_d	α	β
72	1.5756	0.0751	10.5162	0.5614	0.3981
73	1.6174	0.0756	10.9185	0.5614	0.4003
74	1.5695	0.0751	10.4988	0.5614	0.3978
75	1.5325	0.0737	10.0704	0.5674	0.3969
76	1.562	0.0748	10.3791	0.5645	0.3978
77	1.5335	0.0737	10.1415	0.5675	0.3974
78	1.5464	0.0739	10.2238	0.5656	0.3972
79	1.5803	0.0751	10.5592	0.5636	0.3979
80	1.5365	0.0738	10.1135	0.5655	0.3966

Table 5.7: Nondominated set of solutions obtained using NSGA-III optimization under ISE criterion.

Sr.No	K_p	K_i	K_d	α	β
1	1.4321	0.0843	10.5769	0.5787	0.2771
2	1.4161	0.0841	10.4796	0.5792	0.2726
3	1.479	0.0861	10.9209	0.5778	0.2898
4	1.3921	0.0833	10.3181	0.5795	0.2703
5	1.4112	0.0836	10.3778	0.5789	0.2705
6	1.4566	0.0851	10.7506	0.579	0.277
7	1.4233	0.084	10.5172	0.5791	0.2763
8	1.4207	0.084	10.5293	0.5788	0.2751
9	1.3943	0.0831	10.3132	0.5797	0.2706
10	1.4355	0.0849	10.6477	0.579	0.277
11	1.3776	0.0827	10.1824	0.5838	0.2679
12	1.6476	0.0911	13.1916	0.5758	0.2755
13	1.4187	0.0843	10.5345	0.579	0.2764
14	1.4292	0.0841	10.5305	0.5788	0.2763
15	1.4049	0.0836	10.3788	0.5792	0.2713
16	1.4263	0.0838	10.5119	0.5789	0.2763

Sr.No	K_p	K_i	K_d	α	β
17	1.4246	0.0841	10.5252	0.5792	0.276
18	1.3896	0.0828	10.2103	0.5795	0.2639
19	1.4349	0.084	10.5761	0.5785	0.2775
20	1.4476	0.0854	10.8604	0.5782	0.2781
21	1.402	0.0835	10.2976	0.5792	0.2686
22	1.3841	0.083	10.3396	0.5798	0.2702
23	1.4272	0.084	10.5286	0.5789	0.276
24	1.43	0.0841	10.5663	0.5785	0.277
25	1.4806	0.0861	10.8053	0.5782	0.2778
26	1.4328	0.0841	10.5775	0.5785	0.2773
27	1.4724	0.0862	10.7815	0.5784	0.2776
28	1.5359	0.0899	11.1511	0.5789	0.2825
29	1.4294	0.084	10.5381	0.5787	0.2765
30	1.447	0.0854	10.7573	0.5787	0.2774
31	1.4379	0.084	10.6376	0.5785	0.2797
32	1.7863	0.0954	13.8225	0.5756	0.2856
33	1.5767	0.0948	11.6566	0.579	0.2856
34	1.4262	0.0843	10.6246	0.579	0.2807
35	1.4843	0.0856	11.2806	0.5771	0.2885
36	1.4279	0.0841	10.5567	0.5786	0.2765
37	1.418	0.0837	10.4685	0.5791	0.2742
38	1.4461	0.085	10.6136	0.5791	0.2746
39	1.3923	0.0833	10.2041	0.5807	0.2674
40	1.431	0.0848	10.6535	0.5788	0.2764
41	1.4423	0.0847	10.6054	0.579	0.2752
42	1.4037	0.0836	10.38	0.5795	0.2731
43	1.4527	0.0862	10.7185	0.5791	0.2779
44	1.4277	0.084	10.5192	0.5787	0.2764
45	1.5722	0.0923	11.1516	0.5762	0.2791
46	1.3719	0.0823	10.156	0.5847	0.2701

Sr.No	K_p	K_i	K_d	α	β
47	1.3576	0.0817	9.9175	0.5952	0.2596
48	1.4176	0.084	10.4877	0.5794	0.2763
49	1.476	0.086	10.9548	0.5784	0.278
50	1.4211	0.0838	10.4611	0.5792	0.2754
51	1.43	0.0844	10.5784	0.5787	0.2769
52	1.3897	0.0827	10.207	0.5794	0.2638
53	1.4311	0.0842	10.5062	0.5786	0.2762
54	1.461	0.0854	10.8097	0.5788	0.2777
55	1.4461	0.0854	10.7215	0.5783	0.2779
56	1.4636	0.087	10.841	0.5789	0.2789
57	1.4277	0.0847	10.5989	0.579	0.275
58	1.4247	0.0843	10.4814	0.5791	0.2753
59	1.418	0.0837	10.4122	0.5941	0.2727
60	1.626	0.0981	12.6792	0.5763	0.2778
61	1.4097	0.0835	10.3611	0.5786	0.2721
62	1.3221	0.0819	9.6583	0.5806	0.2397
63	1.4295	0.0845	10.5808	0.5787	0.2762
64	1.4145	0.0837	10.4618	0.5788	0.2724
65	1.3969	0.083	10.1393	0.5894	0.26
66	1.3895	0.0827	10.2002	0.5796	0.2631
67	1.626	0.0981	12.4959	0.5763	0.2778
68	1.7483	0.1066	12.1525	0.5745	0.2838
69	1.6322	0.1012	11.9297	0.5746	0.2843
70	1.4187	0.0839	10.5248	0.5789	0.2758
71	1.3718	0.0832	10.093	0.5802	0.2633
72	1.626	0.0981	12.6792	0.5763	0.2778
73	1.4437	0.0843	10.7053	0.5785	0.2853
74	1.4057	0.0836	10.2906	0.5789	0.2694
75	1.3669	0.0818	9.9974	0.5796	0.2629
76	1.4221	0.0838	10.5005	0.5788	0.2759

Sr.No	K_p	K_i	K_d	α	β
77	1.4296	0.0842	10.5687	0.5785	0.2764
78	1.4024	0.0834	10.2917	0.5794	0.2707
79	1.4295	0.0845	10.5769	0.5785	0.2774
80	1.4206	0.0838	10.4821	0.5791	0.2747

Table 5.8: Nondominated set of solutions obtained using NSGA-III optimization under ITAE criterion.

Sr.No	K_p	K_i	K_d	α	β
1	1.457	0.0633	9.3165	0.5835	0.5028
2	1.4381	0.0631	9.086	0.5881	0.5025
3	1.4445	0.0633	9.15	0.5895	0.5027
4	1.4606	0.0634	9.3094	0.5827	0.5027
5	1.4417	0.0632	9.1277	0.5902	0.5023
6	1.4432	0.0631	9.1174	0.5896	0.5027
7	1.4607	0.0634	9.3164	0.5831	0.5028
8	1.4497	0.0633	9.2287	0.5857	0.5026
9	1.436	0.0631	9.0792	0.5877	0.5025
10	1.4322	0.0629	9.0067	0.5903	0.5022
11	1.45	0.0634	9.2308	0.5857	0.5027
12	1.4425	0.0632	9.1273	0.5885	0.5026
13	1.4531	0.0633	9.2304	0.5856	0.5026
14	1.4417	0.0632	9.1438	0.5898	0.5026
15	1.4347	0.063	9.0427	0.5887	0.5026
16	1.4397	0.0633	9.1376	0.5931	0.5028
17	1.4371	0.0631	9.0826	0.5872	0.5024
18	1.4482	0.0634	9.2265	0.5865	0.5027
19	1.451	0.0632	9.202	0.5867	0.5026
20	1.4556	0.0634	9.2643	0.5864	0.5027
21	1.4304	0.063	9.0434	0.5903	0.5022

Sr.No	K_p	K_i	K_d	α	β
22	1.4423	0.0632	9.1545	0.588	0.5026
23	1.434	0.063	9.0489	0.5908	0.5025
24	1.4396	0.063	9.096	0.5879	0.5025
25	1.4435	0.0633	9.1385	0.5881	0.5027
26	1.4445	0.0633	9.1465	0.5902	0.5026
27	1.4485	0.0632	9.1905	0.5871	0.5026
28	1.4342	0.063	9.0775	0.5877	0.5024
29	1.4512	0.0634	9.2681	0.5841	0.5027
30	1.4504	0.0633	9.2229	0.5875	0.5026
31	1.4399	0.0631	9.126	0.5863	0.5026
32	1.4315	0.0629	9.048	0.5891	0.5023
33	1.4448	0.0633	9.1685	0.5897	0.5026
34	1.4557	0.0633	9.261	0.5834	0.5026
35	1.456	0.0634	9.2739	0.5857	0.5027
36	1.4351	0.0629	9.037	0.5884	0.5026
37	1.436	0.0631	9.0538	0.5885	0.5025
38	1.4341	0.063	9.0751	0.5903	0.5023
39	1.4599	0.0634	9.3136	0.5834	0.5026
40	1.4143	0.0629	8.8144	0.593	0.5028
41	1.4703	0.0631	9.398	0.5828	0.5036
42	1.4317	0.0628	9.028	0.5883	0.5022
43	1.4616	0.0636	9.3389	0.5881	0.5028
44	1.4534	0.0633	9.2185	0.5865	0.5026
45	1.4455	0.0633	9.1713	0.5875	0.5026
46	1.44	0.0633	9.142	0.589	0.5025
47	1.4408	0.0632	9.107	0.5878	0.5024
48	1.4608	0.0634	9.3182	0.5828	0.503
49	1.4521	0.0632	9.2669	0.5834	0.5026
50	1.4413	0.0632	9.1146	0.5894	0.5028
51	1.4283	0.063	8.9217	0.5924	0.5027

Sr.No	K_p	K_i	K_d	α	β
52	1.4573	0.0633	9.2964	0.5832	0.5026
53	1.4567	0.0634	9.2913	0.586	0.5026
54	1.4313	0.063	9.0278	0.5904	0.5024
55	1.4492	0.0634	9.1888	0.5861	0.5026
56	1.4458	0.0633	9.1641	0.5895	0.5027
57	1.4479	0.0633	9.1906	0.5888	0.5027
58	1.4574	0.0635	9.268	0.5839	0.5026
59	1.4379	0.0632	9.1057	0.5893	0.5024
60	1.4494	0.0633	9.2186	0.5877	0.5026
61	1.4463	0.0633	9.1869	0.5873	0.5027
62	1.4325	0.0629	9.02	0.5908	0.5025
63	1.4524	0.0633	9.2146	0.5872	0.5026
64	1.4494	0.0632	9.1852	0.5861	0.5026
65	1.4516	0.0634	9.2308	0.585	0.5026
66	1.4538	0.0633	9.2588	0.586	0.5026
67	1.4477	0.0631	9.1889	0.5873	0.5025
68	1.4675	0.0636	9.3994	0.5844	0.5036
69	1.424	0.0629	8.8408	0.599	0.5026
70	1.445	0.0632	9.1733	0.5876	0.5024
71	1.4458	0.0633	9.1638	0.5901	0.5026
72	1.4494	0.0633	9.1969	0.5873	0.5026
73	1.4562	0.0634	9.2846	0.5855	0.5027
74	1.4298	0.0629	8.9989	0.5903	0.5023
75	1.4425	0.0632	9.1524	0.5885	0.5026
76	1.4571	0.0633	9.309	0.5832	0.5026
77	1.4573	0.0634	9.3116	0.5851	0.5026
78	1.4488	0.0633	9.1819	0.5903	0.5026
79	1.4971	0.0636	9.5291	0.5853	0.5039
80	1.451	0.0634	9.2351	0.5855	0.5027

The Figure 5.23 to Figure 5.31 are plots of set point tracking and disturbance rejections for all values of 2DOF controller parameters obtained under the criteria IAE, ISE and ITAE as nondominated set of solutions using NSGA-III. The best value obtained from the list of nondominated set of solutions are plotted as symbol * has red color.

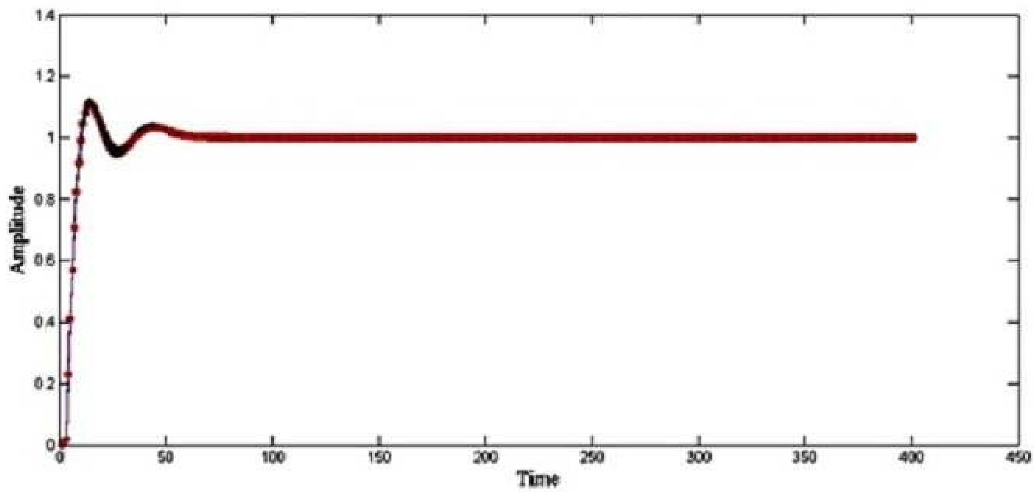

Figure 5.23: Set point response obtained using NSGA-III optimization of 2DOF controller under IAE.

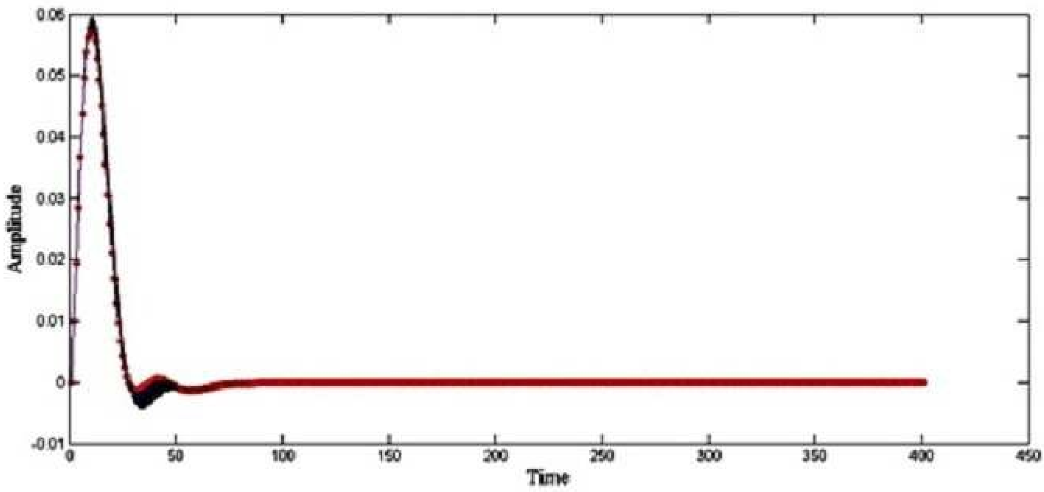

Figure 5.24: Flow disturbance rejection response obtained using NSGA-III optimization of 2DOF controller under IAE.

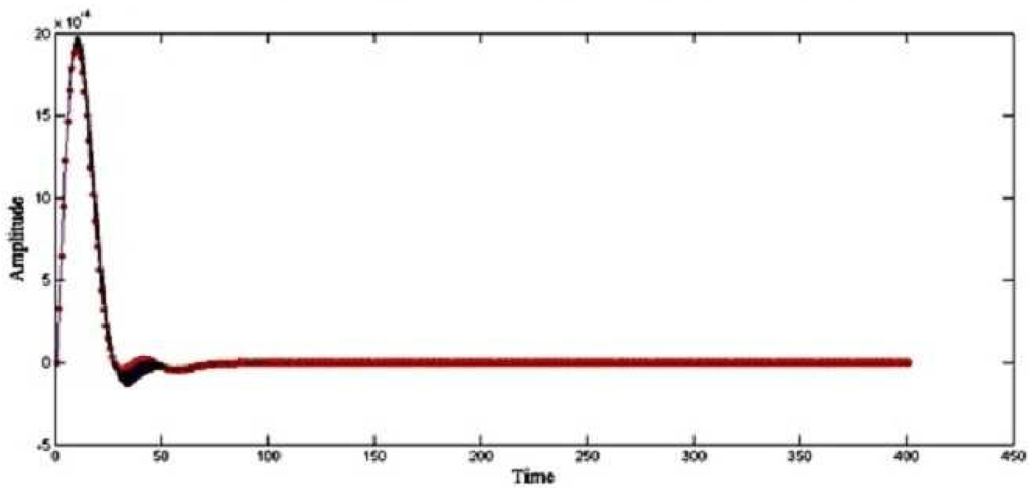

Figure 5.25: Temperature disturbance rejection response obtained using NSGA-III optimization of 2DOF controller under IAE.

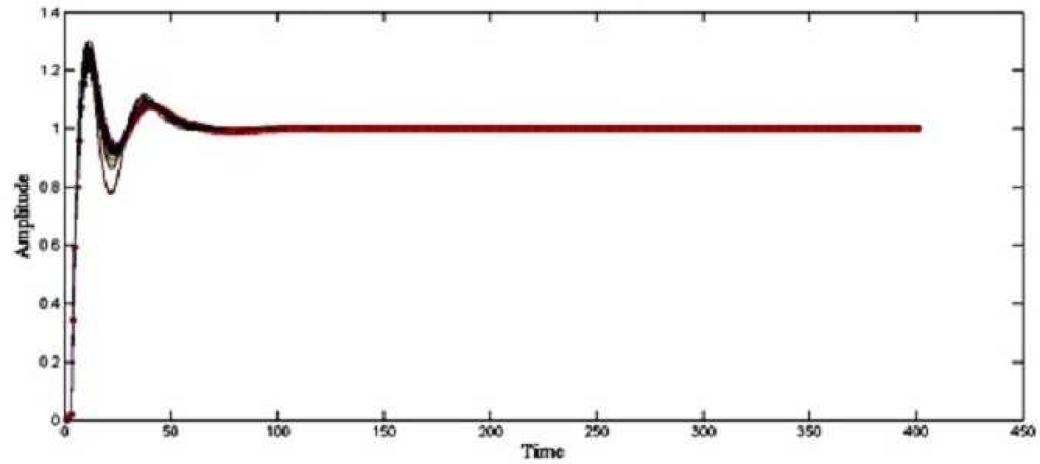

Figure 5.26: Set point response obtained using NSGA-III optimization of 2DOF controller under ISE.

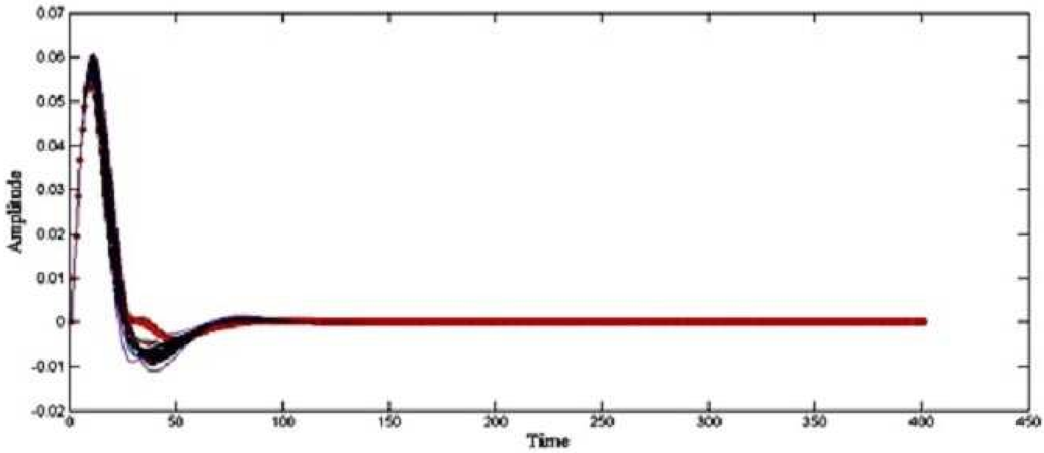

Figure 5.27: Flow disturbance rejection response obtained using NSGA-III optimization of 2DOF controller under ISE.

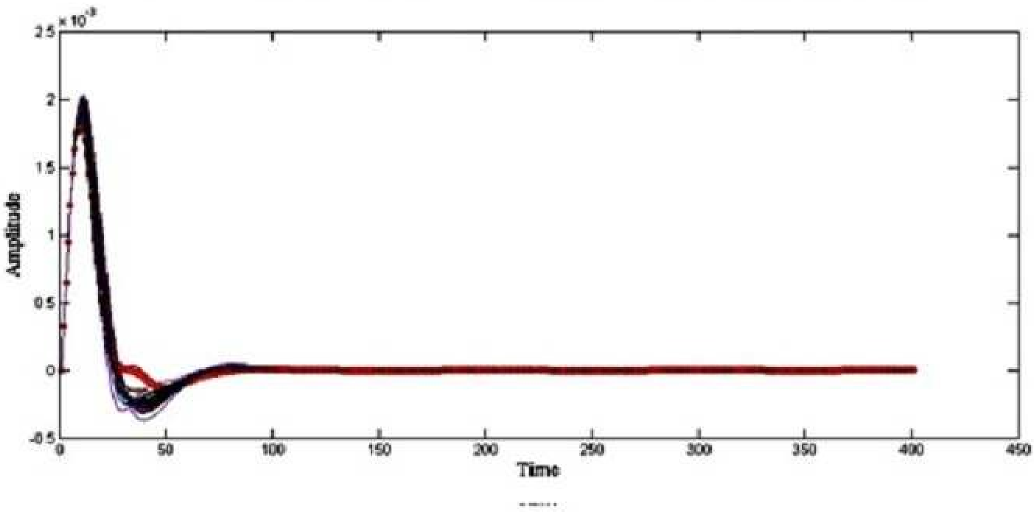

Figure 5.28: Temperature disturbance rejection response obtained using NSGA-III optimization of 2DOF controller under ISE.

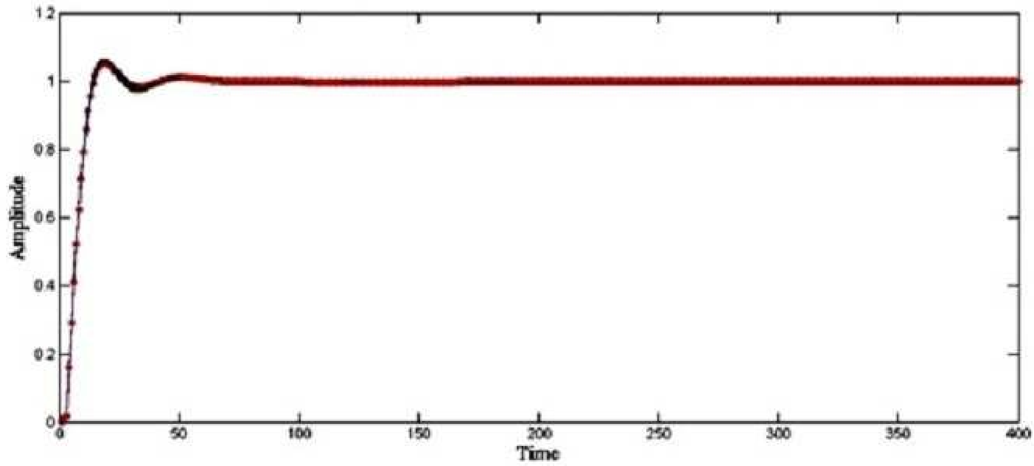

Figure 5.29: Set point response obtained using NSGA-III optimization of 2DOF controller under ITAE.

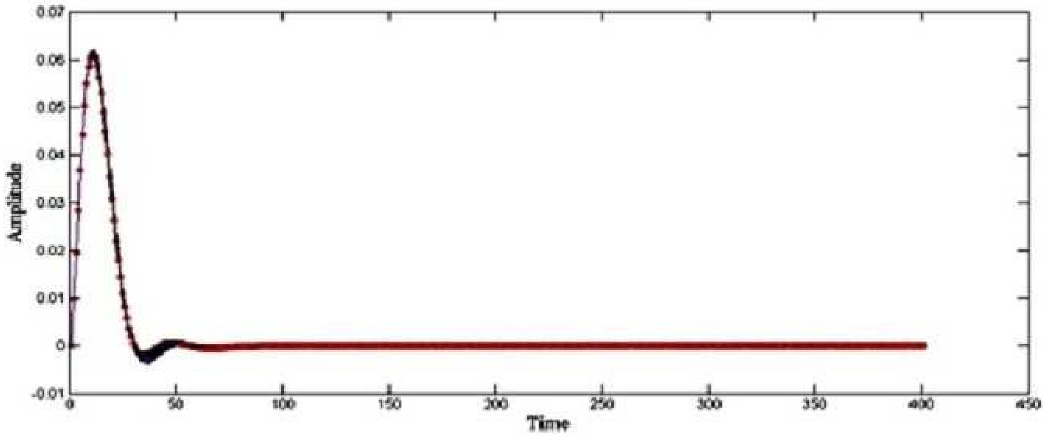

Figure 5.30: Flow disturbance rejection response obtained using NSGA-III optimization of 2DOF controller under ITAE.

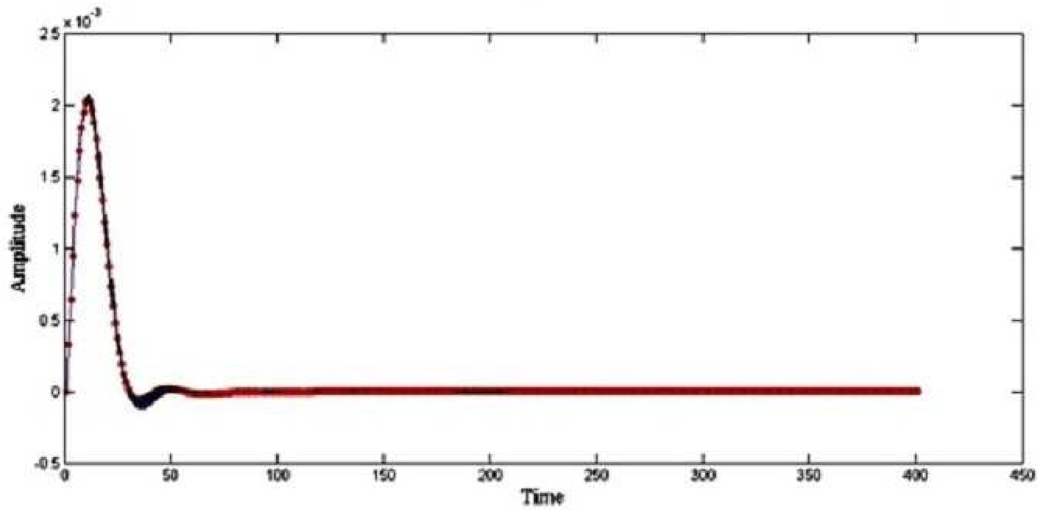

Figure 5.31: Temperature disturbance rejection response obtained using NSGA-III optimization of 2DOF controller under ITAE.

Table 5.9: Result of 2DOF controller parameter optimization using NSGA-III.

Multiobjective optimization 2DOF controller parameter NSGA-III $[K_p, K_i, K_d, \alpha, \beta]$	Peak overshoot of of Step Response In (%)	Reduction Flow Disturbance Response In (%)	Reduction Temperature Disturbance Response In (%)
IAE (Sr.No-18 Table 5.6) $[1.529, 0.074, 10.08, 0.56, 0.392]$ (Best Set point tracking)	11.34	40.63	80.21
IAE (Sr.No-4 Table 5.6) $[1.626, 0.076, 1.10, 0.560, 0.401]$ (Best disturbances rejections)	11.62	42.46	80.82
ISE (Sr.No-11 Table 5.7) $[1.377, 0.083, 10.18, 0.58, 0.268]$ (Best Set point tracking)	21.87	40.20	80.07
ISE (Sr.No-12 Table 5.7) $[1.647, 0.091, 13.19, 0.57, 0.276]$ (Best disturbances rejections)	29.59	45.34	81.78
ITAE (Sr.No-16 Table 5.8) $[1.439, 0.0633, 9.08, 0.59, 0.502]$ (Best Set point tracking)	5.64	38.52	79.50
ITAE (Sr.No-7 Table 5.8) $[1.460, 0.063, 9.31, 0.583, 0.502]$ (Best disturbances rejections)	9.52	38.92	79.64

From the Figure 5.23 to Figure 5.31 and parameters tabulated in Table 5.9, it is derived that ITAE criterion for optimizing concurrently all the five parameters of 2DOF controller using NSGA-III algorithm has minimum peak overshoot of step response(5.64%) for nondominated set of solution [1.439,0.0633,9.08,0.593,0.502] (Solution.No-16, Table 5.8). The maximum rejection of flow (45.34%) and temperature (81.78%) disturbances are attained beneath the criterion of ISE for nondominated set of solutions [1.647, 0.091, 13.19, 0.576, 0.276] (Solution.No-12, Table 5.7).

5.9 Conclusion

The results of GA based multiobjective optimization algorithms NSGA-II and NSGA-III are compared. From the responses shown in Figure 5.8 to Figure 5.31 and parameters tabulated in Table 5.5 & 5.9, it is derived that multiobjective optimization of 2DOF controller using NSGA-III algorithm gives more number of nondominated set of solutions (Here, 80 each for three criteria IAE, ISE and ITAE) as compared to NSGA-II algorithm (Here, 27 each for three criteria IAE, ISE and ITAE). Among all the solutions obtained under three tests criteria using NSGA-II & NSGA-III approaches, ITAE criterion for NSGA-III gives (mentioned in ITAE Solution No-16, Table 5.8) considerably balanced solution in terms of minimizing peak overshoot (5.64%), flow disturbance rejections (38.52%) and temperature disturbance rejections (79.50%). Hence, out of total available nondominated set of solution one from ITAE (Solution No-16, Table 5.8) is preferred one.
NSGA-II and NSGA-III optimization algorithms give number of nondominated set of solutions called Pareto optimal solutions. Practically, user needs only one solution from the set of Pareto optimal solutions for particular problem. Generally, user is not aware of exact trade-off among objective functions. Hence, it is desirable to first obtain maximum possible Pareto optimal solutions and select best one using multi-criteria decision making technique. TOPSIS based multi-criteria decision making technique is applied to nondominated set of solutions discussed in the chapter 7.