

Performance Evaluation of Different Conventional and Intelligent Controllers for Temperature Control of Shell and Tube Heat Exchanger System

A Thesis submitted in partial fulfillment of the requirements for the award of degree of

Master of Engineering

in

Electronic Instrumentation and Control



Submitted by

Subhransu Padhee

Roll No: 800951023

Under the Guidance of

Dr. Yaduvir Singh

Associate Professor

Department of Electrical and Instrumentation Engineering

Thapar University

(Established under the section 3 of UGC act, 1956)

Patiala, 147004, Punjab, India

July 2011

DECLARATION

I hereby certify that the work which is being presented in the thesis entitled "Performance Evaluation of Different Conventional and Intelligent Controllers for Temperature Control of Shell and Tube Heat Exchanger System" in partial fulfillment of award of degree of **Master of Engineering in Electronics Instrumentation and Control** submitted in Electrical and Instrumentation Engineering department, Thapar University, Patiala is an authentic record of my own work carried under the supervision of **Dr. Yaduvir Singh**, Associate Professor, Department of Electrical and Instrumentation Engineering, Thapar University, Patiala, Punjab.

Date: 25/5/2011


Subhransu Padhee
 Roll No: 800951023

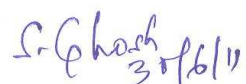
I certify that the above statement made by the student is correct to the best of my knowledge and belief.

Date:



Dr. Yaduvir Singh
 Associate Professor
 Department of Electrical and
 Instrumentation Engineering
 Thapar University, Patiala
 Punjab

Countersigned By


Dr. Smarajit Ghosh
 Head of Department
 Department of Electrical and Instrumentation
 Engineering
 Thapar University, Patiala
 Punjab


Dr. Saroj Kumar Mohapatra
 Dean of Academic Affairs
 Thapar University, Patiala
 Punjab

ABSTRACT

In any of the control application, controller design is the most important part. There are different types of controller architectures available in control literature. The controller can be conventional in nature or can be intelligent in nature. The conventional controller doesn't possess the human intelligence; where in the intelligent controller human intelligence is embedded with the help of certain soft computing algorithms. After the design of controller is performed, the performance evaluation part comes in to light. The designed controller has to give optimal control results irrespective of every situation like plant and equipment non linearity, equipment saturation.

This dissertation looks in to performance evaluation of different conventional and intelligent controllers implemented with a clear objective to control the outlet fluid temperature of shell and tube heat exchanger system. First of all mathematical modeling of the process is performed using experimental plant data. After the mathematical modeling the control objective is set and different kind of controllers are designed to meet the control objective. Feedback controller, feedback plus feed forward controller are implemented to meet the control objective, but due to their inherent disadvantages and more tuning parameters, these controllers were unable to give satisfactory results. So, a model based controller is designed which has only one tuning parameter as compared to three tuning parameters of PID controller. The model based controller gives a satisfactory result. But to embed some kind of intelligence in the controller, fuzzy logic based controller is designed. The fuzzy logic based controller meets the control objective. Comparative analyses of performance evaluation of all controllers are performed.

During the design of fuzzy based hybrid controller, the designer meets two key design challenges namely, optimization of existing fuzzy rule base and identification, estimation of new membership function or optimization of existing membership function. These issues play a vital role in controller design in real time. In real time controller hardware design there is memory and computational power constraints, so a designer needs to optimize these two design aspects. This dissertation also looks in to these key design challenges. For optimization of existing mamdani based fuzzy rule base, a genetic algorithm approach is used and for identification and estimation of fuzzy membership function, a neural network based approach is used.

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RELATED PUBLICATIONS

International Conference

- [1] Subhransu Padhee and Yaduvir Singh, “A comparative analysis of various control strategies implemented on heat exchanger system: A case study,” in Proceedings of the World Congress of Engineering, vol. II, London, Jul 2010, pp. 873-877.
http://www.iaeng.org/publication/WCE2010/WCE2010_pp873-877.pdf
- [2] Subhransu Padhee and Yaduvir Singh, “An efficient neuro-fuzzy control of heat exchanger system: A comparative analysis,” in Proceedings of International Conference on Clean Energy Technologies and Energy Efficiency for Sustainable Development, Dehradun, Dec 2010.
- [3] Subhransu Padhee and Yaduvir Singh, “Data logging and supervisory control of process using LabVIEW,” in Proceedings of 2011 IEEE Student’s Technology Symposium, (Poster Session), IIT Kharagpur, Jan 2011
- [4] Subhransu Padhee, Yaduvir Singh and Yuvraj Bhushan Khare, “Internal model based PID control of shell and tube heat exchanger system,” in Proceedings of 2011 IEEE Student’s Technology Symposium, IIT Kharagpur, Jan 2011

National Conference

- [1] Subhransu Padhee, Yaduvir Singh and Gagandeep Kaur, “An efficient fuzzy logic based control of heat exchanger system,” in Proceedings of National Conference on Trends in Instrumentation and Control Engineering, Patiala, Oct 2009.
- [2] Subhransu Padhee, Yaduvir Singh, “Signal acquisition and analysis system using LabVIEW,” in Proceedings of Conference on Signal Processing and Real Time Operating System, Mar 2011

* Photo copy of certificates of publications are attached for reference

Chapter 1

Introduction

1.1 Overview

The transformation of raw material in to desired products usually cannot be achieved in a single step in any chemical process. The overall transformation is broken in to individual transformation to achieve the desired objective. Simulation is a mathematical model of a process, which attempts to predict how the process would behave if it is constructed in real life. After simulation of the model, control of the model is necessary. There are different ways to control a chemical process. This dissertation gives a brief idea of different controlling techniques and different aspects of controller design for a chemical plant taken in to consideration.

1.2 Motivation

In any of the control application, controller design is the most important part. There are different types of controller. The controller can be conventional in nature or intelligent in nature. The conventional controller doesn't posses the human intelligence; where in the intelligent controller human intelligence is embed with the help of certain soft computing algorithms. After the design of controller is performed, the performance evaluation part comes in to light. The designed controller has to give optimal control results irrespective of every situation like plant and equipment non linearity, equipment saturation.

1.3 Objective and scope of the dissertation

The objective of this dissertation is to evaluate the performance of different conventional and intelligent controllers. Figure 1.1 shows the performance evaluation scheme implemented in this dissertation. To evaluate the performance of the controller, time response and frequency response analysis is carried out. The time response analysis consists of two type of analysis. One is unit step response analysis and other is performance indices analysis. The frequency response

analysis also consists of two kind of analysis. One is robustness analysis and other one is sensitivity analysis.

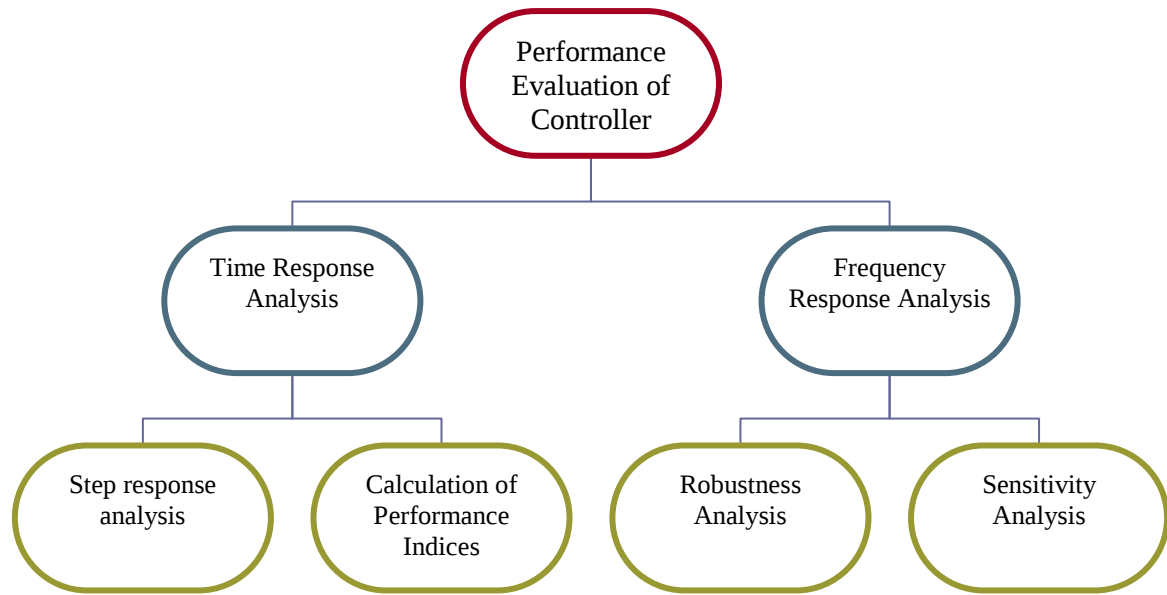


Figure 1.1: Performance evaluation scheme implemented for controller

The other objective of the dissertation is to find out the key design challenges in design of intelligent controllers. This dissertation implements a fuzzy logic based hybrid controller and faces two design challenges. The challenges are optimization of existing fuzzy rule base with N rules and identification and estimation of the optimal number of membership functions and optimization of existing membership function. This dissertation addresses this design issues.

1.4 Organization of the dissertation

The dissertation is organized as follows.

Chapter 2 is takes a case study of shell and tube heat exchanger and performs the mathematical modeling of the heat exchanger system with the help of available experimental data. The control objective is to control the outlet temperature of the shell and tube heat exchanger system to a desired temperature. In chapter 2 different conventional control strategies like feedback control, feedback plus feed forward control, internal model based control is used to control the outlet temperature of the shell and tube heat exchanger system. But the conventional controllers don't provide satisfactory performance.

Chapter 3 introduces fuzzy based controller and designs and implements a fuzzy based hybrid controller to control the outlet temperature of the shell and tube heat exchange system. The

hybrid fuzzy based controller gives an intelligent touch to the controller and gives satisfactory control results. But while designing the fuzzy based controller, there are some key challenges. The key challenges are optimization of existing rule base and identification, estimation and optimization of new and existing membership functions of fuzzy logic.

Chapter 4 discusses a GA based optimization technique to optimize the existing fuzzy rule base, so that the fuzzy rule base can be efficiently used.

Chapter 5 discusses the identification and estimation of fuzzy membership functions and fuzzy membership values using Kalman filtering and optimization of existing membership functions.

Chapter 6 gives the detailed performance analysis of conventional controller and fuzzy based controller. Time response analysis and frequency response analysis is carried out to evaluate the performance of the controllers.

Chapter 7 gives the concluding remarks and addresses the issues which can be taken up for further work.

Chapter 2

Conventional Controllers

A typical chemical process for heating consists of a chemical reactor and a shell and tube heat exchanger system. The process fluid which is the salt solution of sodium sulphate and aluminum sulphate is stored in the storage tank at a temperature of 32°C. The storage tank pumps the salt solution to the shell and tube heat exchanger system. The heat exchanger heats up the salt solution to a temperature of 52°C using super heated steam at 180°C to get a concentrated salt solution. The super heated steam comes from the boiler and flows through the shell side, whereas, the salt solution flows through the tube side of the shell and tube heat exchanger system. After the steam heats up the salt solution, the condensed steam at 93°C goes out of the steam trap. The steam trap removes the condensate and non condensing gases. The control objective is to control the temperature of the concentrated salt solution. Different control architectures and different conventional controllers like PID, feed forward controller and internal model based controller can be implemented to achieve the control objective.

2.1 Heat Exchanger

In practice, all chemical processes involve the production or absorption of energy in the form of heat. Heat exchanger is commonly used in industrial chemical processes to transfer heat from a hot liquid through a solid wall to a cooler fluid [2.1]. A heat exchanger is a device that is used to transfer thermal energy (enthalpy) between two or more fluids, between a solid surface and a fluid, or between solid particulates and a fluid, at different temperatures and in thermal contact [2.17].

There are different types of heat exchanger used in the industry but most of the industry use shell and tube type heat exchanger system. It consists of parallel tubes enclosed in a shell. One of the fluid flows in the tubes and the other flows inside the shell around the tube. These heat exchangers are very flexible and adaptable, can operate over full range of pressures and

temperatures encountered in chemical plants. They have larger ratios of heat transfer surface to volume than double-pipe heat exchangers, and they are easy to manufacture in a large variety of sizes and configurations. They can operate at high pressures, and their construction facilitates disassembly for periodic maintenance and cleaning. A shell-and-tube heat exchanger is an extension of the double-pipe configuration. Instead of a single pipe within a larger pipe, a shell-and-tube heat exchanger consists of a bundle of pipes or tubes enclosed within a cylindrical shell.

In shell and tube heat exchanger one fluid flows through the tubes, and a second fluid flows within the space between the tubes and the shell [2.33].

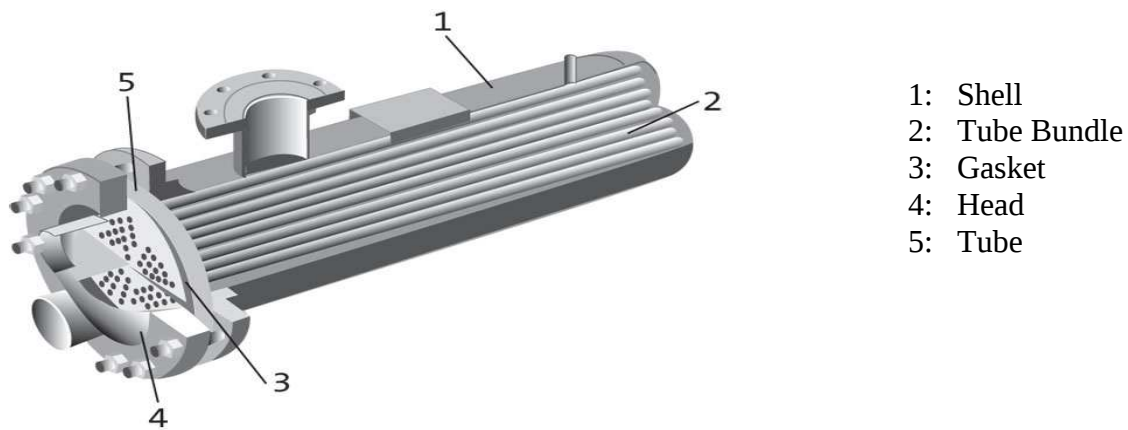


Figure 2.1: Schematic diagram of shell and tube heat exchanger system

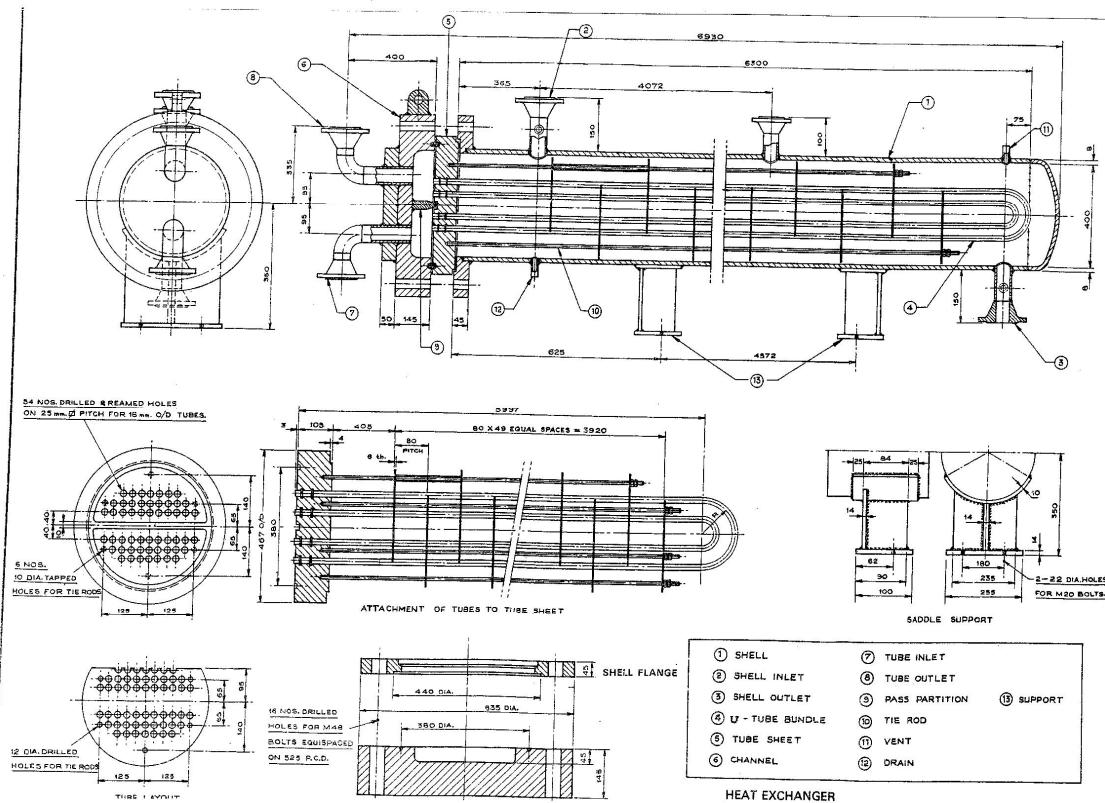


Figure 2.2: Mechanical diagram of shell and tube heat exchanger system

Figure 2.1 shows the parts of shell and tube heat exchanger system and figure 2.2 shows the detail mechanical diagram of shell and tube heat exchanger system.

2.2 Construction of Shell and Tube Heat Exchanger

This section describes the different materials and dimensions of shell and tube heat exchanger system [2.26].

Sl. No	Parts	Dimensions
1	Shell material	PVC
2	Outer dimension of shell	0.166m
3	Inner dimension of shell	0.16m
4	Tube bundle	0.12 m
5	Number of tubes	18 net
6	Tube material	Aluminum
7	Inner dimension of tubes	10mm
8	Outer dimension of tubes	12 mm
9	Flange material	Acrylate

10	Flange thickness	20mm
11	Gasket width	0.3 cm
12	Pitch	Triangular

2.3 Application of Heat Exchanger

Shell-and-tube heat exchangers find widespread use in refrigeration, power generation, heating and air conditioning, chemical processes, manufacturing, and medical applications.

2.4 Literature Review

Y. S. N. Malleswararao et.al, developed a model reference non linear controller with PID control action for heat exchanger system. The proposed controller is efficient from other controllers and is robust to modelling errors and disturbances [2.2].

Rajiv Mukherjee in his research paper gave a basic overview of shell and tube heat exchanger system: components, classifications in details [2.6].

G P Liu et.al, presented three kind of optimal tuning of PID controller design. These types are time domain optimal tuning PID control, frequency domain optimal tuning PID control and multi objective optimal tuning PID control. These are applied to three industrial systems, a hydraulic position control system, a rotary hydraulic speed control system and a gasifier, respectively [2.10].

K J Astrom et.al, in his paper presented the state of the art of PID control and reflects on its future. Particular issues discussed include specifications, stability, design, applications, and performance of PID control. The paper ends with a discussion of alternatives to PID and its future [2.12].

G K I Mann et.al, analyzed different time domain based design and analysis of PID tuning for FOPTD process. The proposed PID tuning rule is capable of handling actuator saturation and can handle process and controller non linearity in an effective manner [2.13].

Clark K Colton et.al, developed a remote controlled heat exchanger system for laboratory application. All other inlet and outlet temperatures are monitored. Monitoring and control is carried out with a web server using LabVIEW. Data is published to web-accessible LabVIEW graphical user interfaces or via a Data Socket Server to a Java2 GUI. A Microsoft SQL database is used for registering, authentication, and scheduling (ASP.NET) and for collaboration management software, which provides for chat capabilities and ability to pass local control between team members who

are collaborating on carrying out the experiment from their own computers in different locations [2.18].

Kiam heong Ang et.al, has given a complete overview of modern tuning methods of PID controller, different patents in PID controllers, commercial hardware modules and software packages of PID controller available in market. This paper also reviews the contemporary intelligent PID controllers and reviews the future PID controller like plug and play PID controller [2.20].

Fernando G Martins has proposed a PID controller tuning method based on ITAE criteria. ITAE is a performance criteria which should be minimized for a better control action but the computation of ITAE is a difficult task [2.21].

Wen Tan et.al has compared the performance of some well known PID controllers. He has taken two criteria for the comparison and those are disturbance rejection and system robustness [2.22].

S A Mandavgane et.al, applied ANN architecture to model the shell and tube heat exchanger system. In this research paper ANN is used for estimation of exit temperature of both fluids as a function of inlet temperature condition and flow rates [2.26].

S Haugwitz et.al, in his research paper developed a non linear model of open plate reactor developed by Alfa Laval AB. In his research paper he developed the control strategies for the heat exchanger system and experimentally verified the control strategy. He used a model predictive controller with extended Kalman filter [2.30].

Orlando Duran et.al, in his research paper proposed a test model of cost estimating of shell and tube heat exchanger system using ANN. The proposed ANN test model reduces the uncertainties related to cost estimation of shell and tube heat exchanger system [2.33].

M. Thirumarimurugan et.al, experimentally investigated heat transfer study on a solvent and solution with a 1-1 shell and tube heat exchanger. The experimental findings were compared with the mathematical model of the system [2.34].

S Dudzik in his research paper proposed a new method for calculation of heat power consumption in a heat exchanger. The method is based on the analysis of phenomena occurring between the heat exchanger and the ambient. An artificial neural network, trained with data obtained from infrared thermography measurements is used to calculate the heat power consumption in steady state [2.37].

Vikas Gupta et.al, in there paper explain a method for the design and implementation of multiplier-less digital PID controller based on FPGA device. It is more compact, power efficient and provides high speed capabilities as compared to software based PID controllers. The proposed method is based on Distributed Arithmetic (DA) architecture [2.39].

M. Thirumarimurugan studied the performance of plate type heat exchanger with miscible and immiscible systems. The experimental studies involved in the determination of outlet temperature of both cold and hot fluid for various flow rates. The experimental data were used to develop neural networks using general regression neural network (GRNN) model. These networks were tested with a set of testing data and then the simulated results were compared with the actual results of the testing data and found that the experimental data are very close to the simulated data. [2.40].

2.5 Mathematical Modelling

Many of the engineering devices like turbines, compressors, pumps, nozzles and heat exchangers operate at steady state condition. It is assumed that the mass flows into the control volume at a constant rate and leaves the control volume at the same rate. Therefore, there is no accumulation of mass inside the control volume. Thus, $\dot{m}_i = \dot{m}_e = \dot{m}$

$$\text{So, } \frac{d}{dt} \int_v \rho dV = \frac{dm}{dt} = 0 \quad (1)$$

The state of the matter at the inlet, exit and at any given point inside the control volume does not change with respect to time. Therefore $\frac{d}{dt} \int_v \rho e dV = \frac{dE}{dt} = 0$ (2)

The rate of energy transfer as heat $\dot{Q}$ and work across the control surface $\dot{W}_s$ is constant.

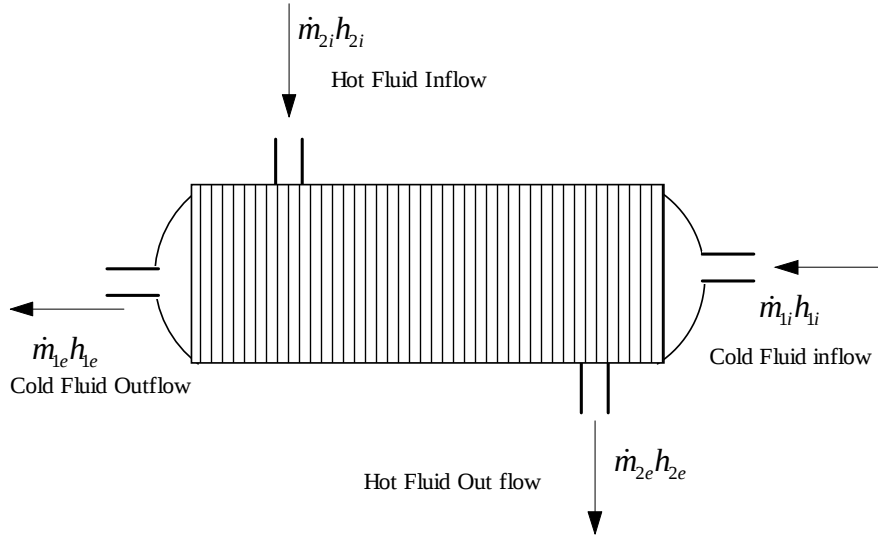


Figure 2.3: Inputs and outputs of heat exchanger system

Figure 2.3 shows the working of a simple heat exchanger system. The governing equation can be modified for multiple inputs and multiple outputs as

$$\sum \dot{m}_e \left(h_e + \frac{v_e^2}{2} + gz_e \right) - \sum \dot{m}_i \left(h_i + \frac{v_i^2}{2} + gz_i \right) = \dot{Q} - \dot{W}_s \quad (3)$$

No shaft work is done and energy losses are negligible. Change in potential energy and kinetic energy is also neglected.

$$\sum \dot{m}_e h_e = \sum \dot{m}_i h_i \quad (4)$$

$$\Rightarrow \dot{m}_{1e} h_{1e} + \dot{m}_{2e} h_{2e} = \dot{m}_{1i} h_{1i} + \dot{m}_{2i} h_{2i} \quad (5)$$

$$\dot{m}_{1e} = \dot{m}_{1i} = \dot{m}_1 \quad (6)$$

$$\dot{m}_{2e} = \dot{m}_{2i} = \dot{m}_2 \quad (7)$$

$\dot{m}_1$ and $\dot{m}_2$ are the mass flow rates of cold fluid and hot fluid, respectively.

Here, the heat exchanger system, actuator, valve, sensor are mathematically modelled using the available experimental data. The experimental process data is summarized below [2.31].

Exchanger response to the steam flow gain	50°C/(kg/sec)
Time constants	30 sec
Exchanger response to variation of process fluid flow gain	1°C/(kg/sec)
Exchanger response to variation of process temperature gain	3°C/°C
Control valve capacity	1.6 kg/sec of steam

Time constant of control valve	3 sec
The range of temperature sensor	50°C to 150°C
Time constant of temperature sensor	10 sec

From the above experimental data the transfer function model of the system is derived. The transfer functions of different component of the transfer function model are summarized below.

Transfer function of process	$\frac{50e^{-s}}{30s+1}$
Gain of valve	0.13
Transfer function of valve	$\frac{0.13}{3s+1}$
Gain of current to pressure converter	0.75
Transfer function of disturbance variables (flow and temperature disturbances respectively)	$\frac{1}{30s+1}, \frac{3}{30s+1}$
Transfer function of temperature sensor	$\frac{0.16}{10s+1}$

Figure 2.4 shows the block diagram of feedback control architecture of a general system. The controller gives the controlling action to the final control element via the actuator. The sensor senses the output and gives feedback to the controller.

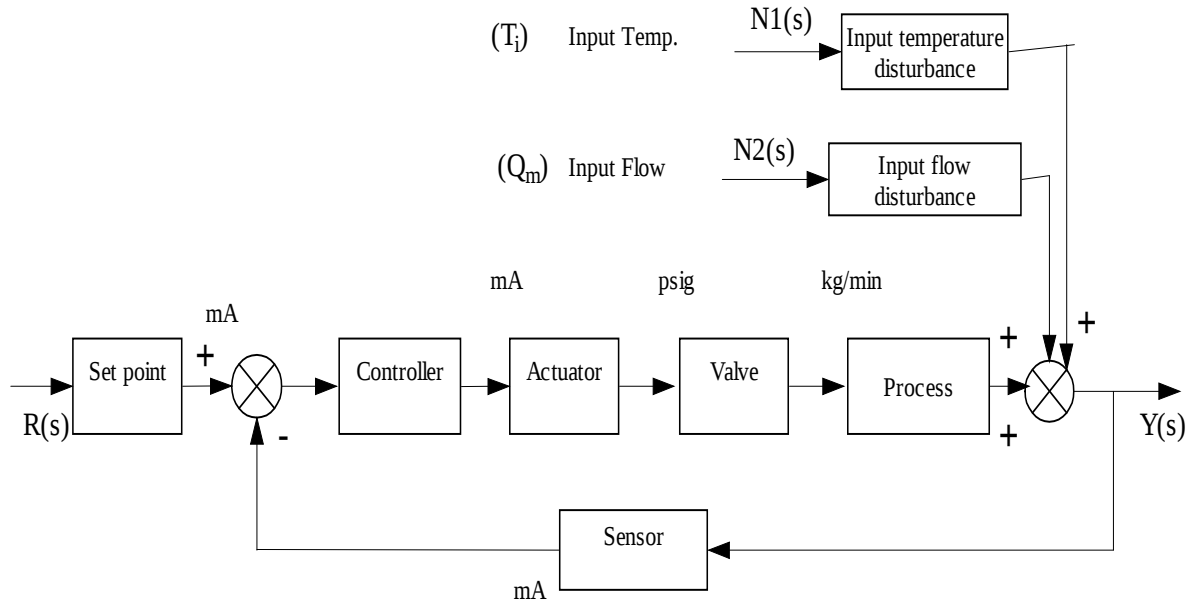


Figure 2.4: Block diagram for feedback control of heat exchanger system

Figure 2.5 shows the transfer function model of the feedback control of shell and tube heat exchanger system. The transfer functions are derived from the experimental data. In this transfer function model K_{cu} is the critical gain implemented in the forward path of the system.

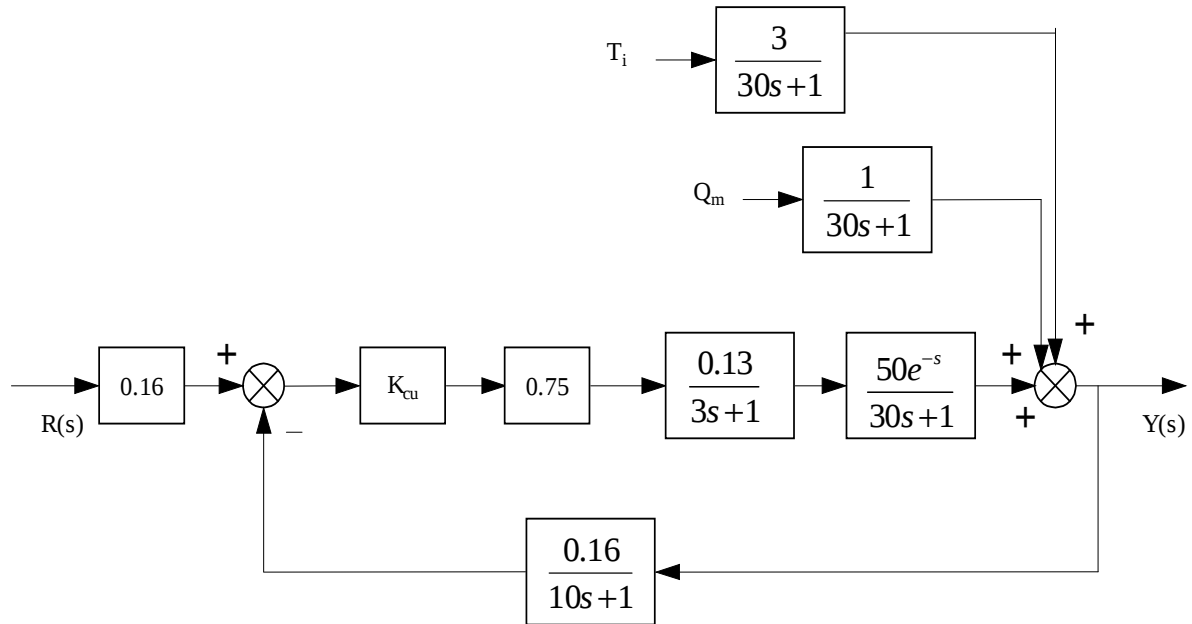


Figure 2.5: Transfer function model of heat exchanger system

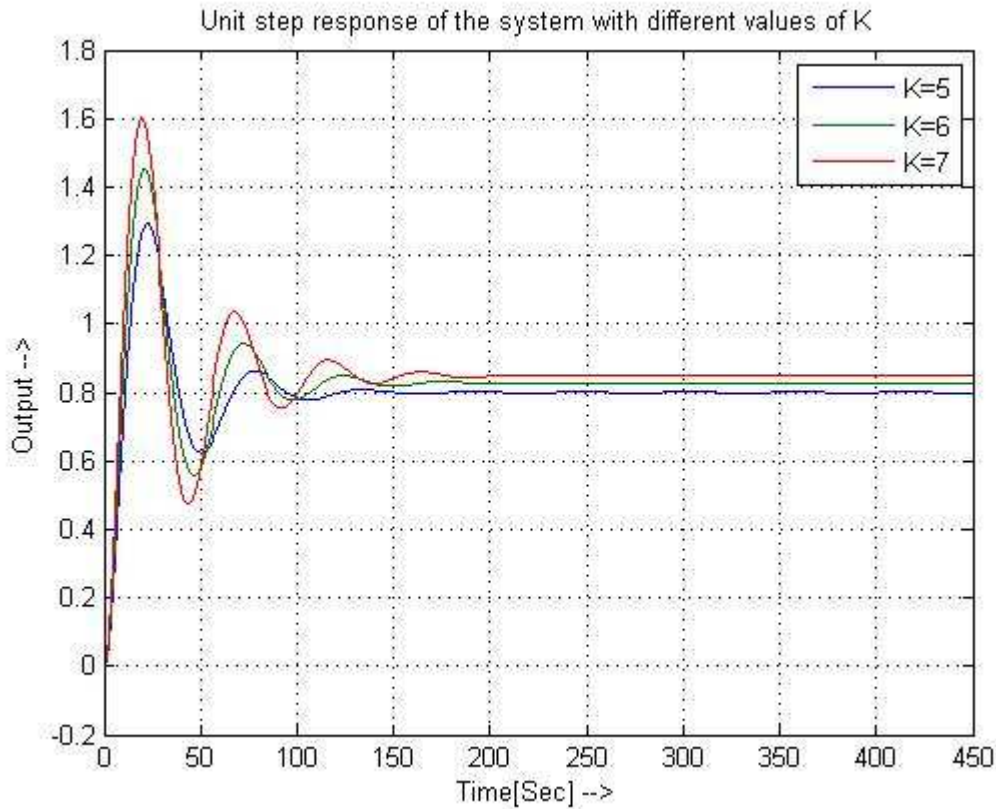


Figure 2.6: Unit step response of the process at different values of gain

Figure 2.6 shows the unit step response of the system at the values of K equal to 5, 6 and 7.

2.6 Control of Shell and Tube Heat Exchanger System

Different assumptions have been considered to develop the control architecture of the shell and tube heat exchanger system. The first assumption is that the inflow and the outflow rate of fluid are same, so that the fluid level is maintained constant in the heat exchanger. The second assumption is the heat storage capacity of the insulating wall is negligible. In this feedback process control loop, the controller is reverse acting, the valve used is of air to open (fail-close) type. A thermocouple is used as the sensing element, which is implemented in the feedback path of the control architecture. The temperature of the outgoing fluid is measured by the thermocouple and the output of the thermocouple (voltage) is sent to the transmitter unit, which eventually converts the temperature output to a standardized signal in the range of 4-20 mA. This output of the transmitter unit is given to the controller unit. In this heat exchanger system a PID controller has been taken as the controlling unit. The PID controller implements the control algorithm, compares the output with the set point and then gives necessary command to the final control element via the actuator unit. The actuator unit is a current to pressure converter and the final control unit is an air

to open (fail-close) valve. The actuator unit takes the controller output in the range of 4-20 mA and converts it into a standardized pressure unit, i.e in the range of 3-15 psig. The valve actuates according to the controller decisions.

2.7 Feedback Control

Feedback control is a control mechanism which regulates the controlled variable by taking negative feedback from the output and taking regulatory action through the controller and changing the manipulating variable accordingly.

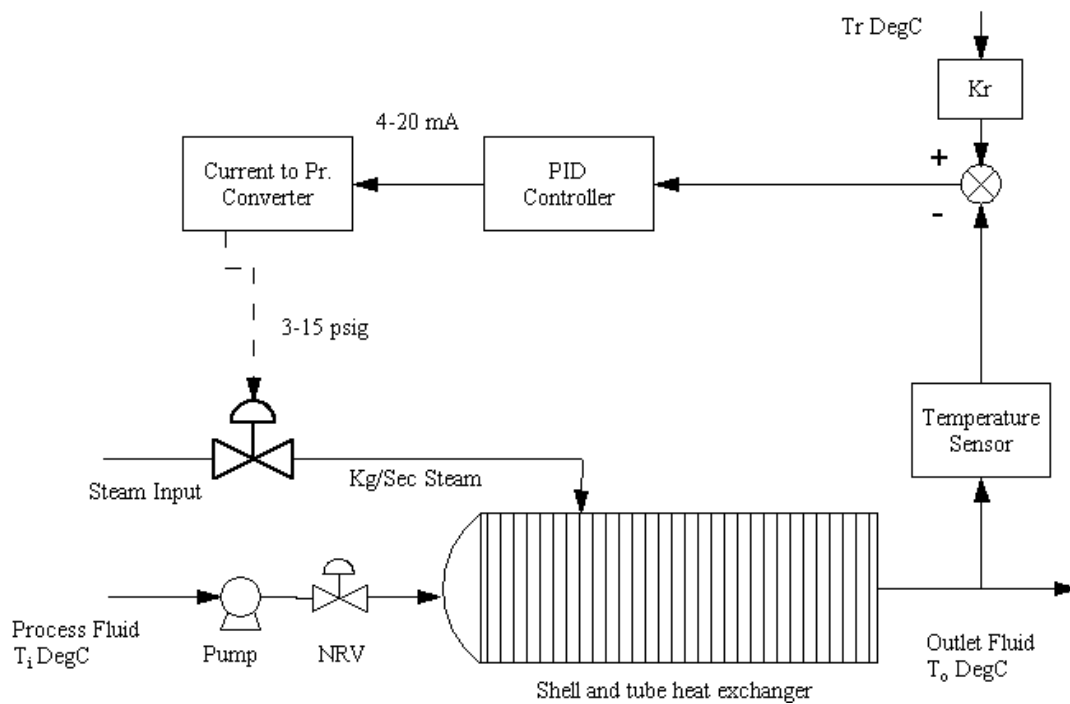


Figure 2.7: Feedback control scheme for shell and tube heat exchanger system

Figure 2.7 shows the feedback control scheme for shell and tube heat exchanger system. PID controller is used as the controlling element to control the outlet temperature of shell and tube heat exchanger.

2.7.1 PID Controller

The mnemonic PID refers to the first letters of the names of the individual terms that make up the standard three-term controller. These are P for the proportional term, I for the integral term and D for the derivative term in the controller. Three-term or PID controllers are probably the most widely used industrial controller. Even complex industrial control systems may comprise a control network whose main control building block is a PID control module. The three-term PID controller

has had a long history of use and has survived the changes of technology from the analog era into the digital computer control system age quite satisfactorily. It was the first (only) controller to be mass produced for the high-volume market that existed in the process industries.

Ideal PID controller in continuous time is given as $u(t) = K_c \left(e(t) + \frac{1}{\tau_i} \int_0^t e(t) dt + \tau_d \frac{de(t)}{dt} \right)$ (8)

In eq(8), $e(t)$ is the error signal, $u(t)$ is the controller output, K_c is the controller gain, τ_i and τ_d are integral gain and derivative gain respectively. Eq(9) represents the Laplace domain representation of ideal PID controller.

$$G_{PID}(s) = \frac{u(s)}{e(s)} = K_c \left(\frac{\tau_i \tau_d s^2 + \tau_i s + 1}{\tau_i s} \right) \quad (9)$$

The equation for real PID controller is represented as $G_{PID}(s) = \frac{u(s)}{e(s)} = K_c \left(\frac{\tau_i s + 1}{\tau_i s} \right) \left(\frac{\tau_d s + 1}{1 + \tau_f s} \right)$ (10)

Here τ_f represents the filter parameter. Eq(10) can be rewritten as

$$G_{PID}(s) = \frac{u(s)}{e(s)} = K_c \left(\frac{\tau_i s + 1}{\tau_i s} \right) \left(\frac{\tau_d s + 1}{1 + \alpha \tau_d s} \right) \quad (11)$$

By substituting $\tau_f = \alpha \tau_d$. Here α is the filter coefficient

2.7.1.1 Anti Reset Windup Protection

Figure 2.8 shows the parallel form of PID controller. In this parallel form three terms like proportional, integral and derivative are added to generate the PID action.

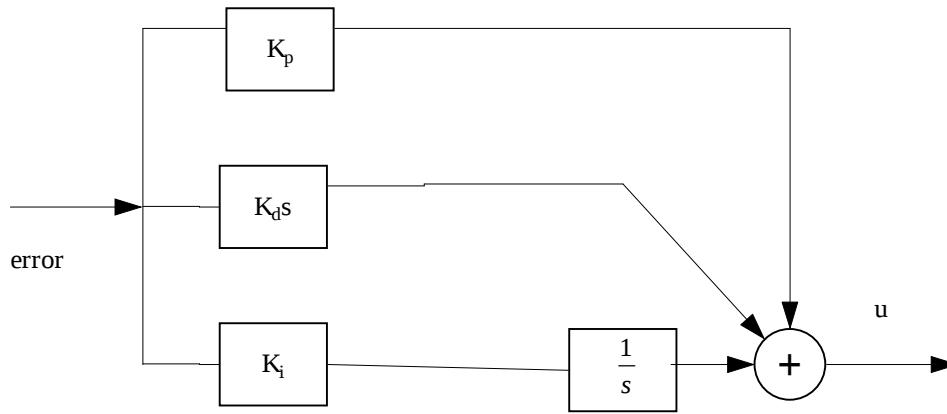


Figure 2.8: Parallel form of PID controller

But the ideal form of PID controller lacks the solution to some practical problems encountered in industrial process. So different modifications of this parallel form are suggested and

employed. Two of the major modifications are anti reset windup and derivative kick. Figure 2.9 shows the block diagram of anti reset windup of PID controller.

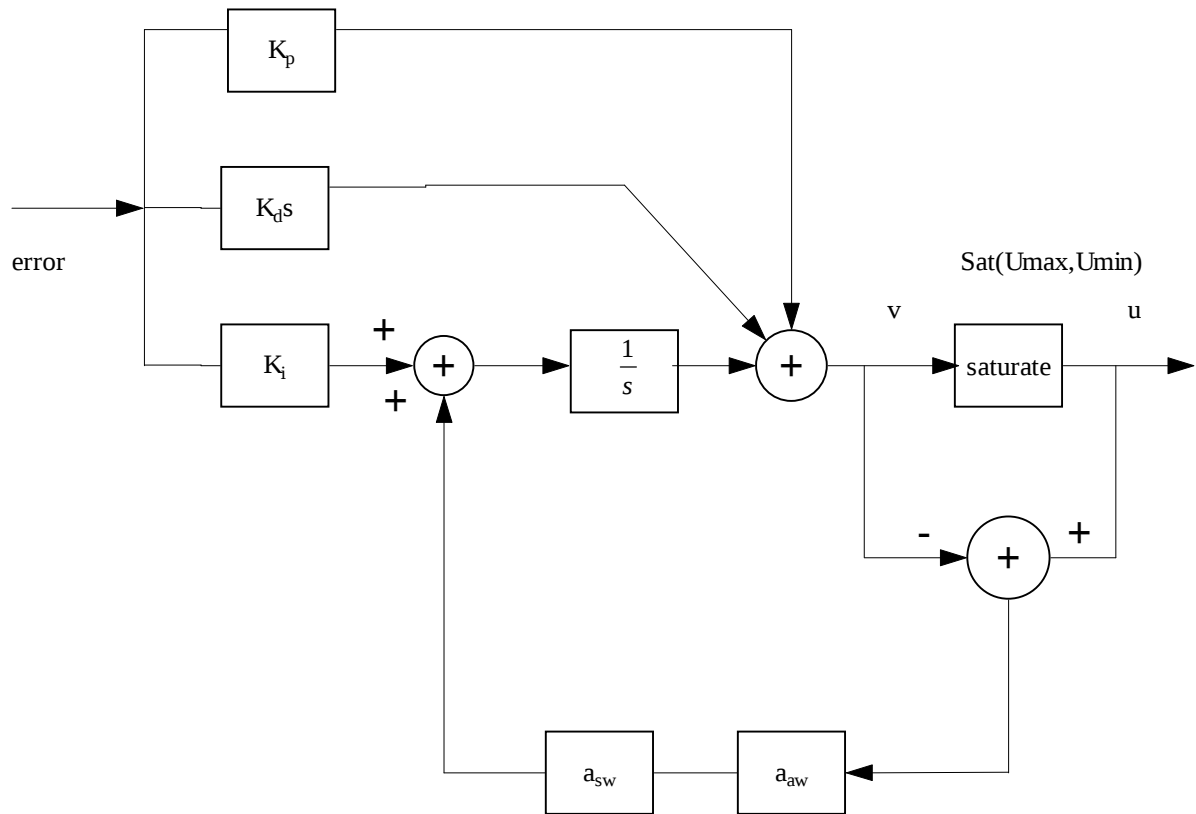


Figure 2.9: Anti reset windup scheme of parallel form of PID controller

In many real life applications output of the actuator can saturate because the dynamic range of the real actuator is limited. The final control element saturates when it is open or closed to the maximum limit. When the actuator saturates the control action stops. At this moment if the error signal is applied, then it results in very high overshoot and poor transient response. So anti reset windup structure is implemented in PID controller.

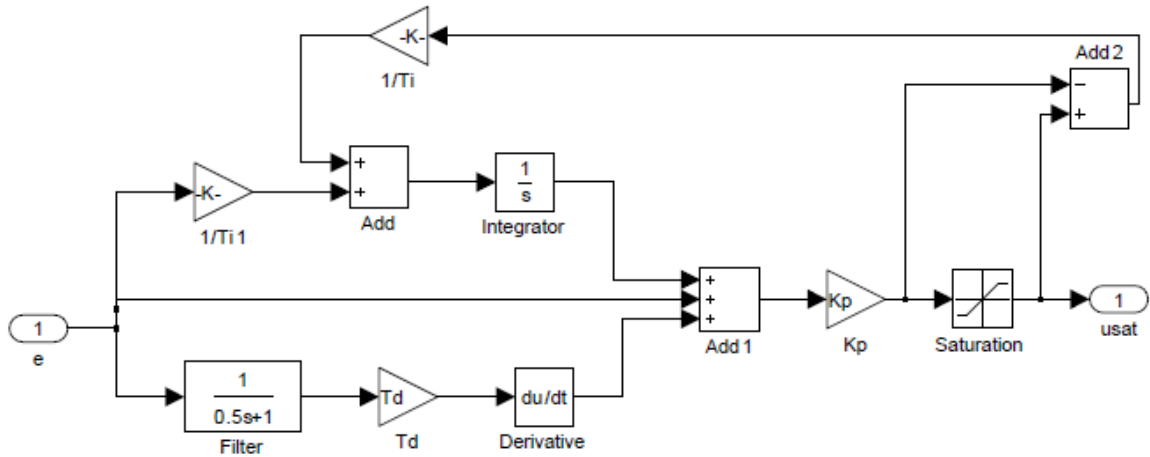


Figure 2.10: Anti reset windup scheme in Simulink

Figure 2.10 shows the Simulink representation of anti reset windup scheme in PID controller. For v in saturation zone the controller output is limited at $u_{\max}$ or $u_{\min}$. The corresponding plant error will also be fixed if the plant is open loop stable. Also, the anti windup feedback loop is now switched on ($a_{sw} = 1$). Its effect is to replace the integrator component with one with a stable first order transfer function. Windup action is therefore halted so that the controller output remains at or near either saturation limit. The loop is deactivated when the system exits saturation; then $a_{sw} = 0$ so that integrator action will resume using the last integrator output (under saturation) as the initial condition.

$$\text{sat}(v, u_{\max}, u_{\min}) = \begin{cases} v & u_{\max} \geq v \geq u_{\min} \\ u_{\max} & v > u_{\max} \\ u_{\min} & v < u_{\min} \end{cases} \quad (12)$$

$$A_{sw} = 0 \text{ (anti windup OFF)}$$

$$= 1 \text{ (anti windup ON)} \quad (13)$$

$$\text{Gain parameter } A_{aw} > 0 \quad (14)$$

2.7.1.2 Derivative Kick

In real life control applications, when there is a step change in set point, then the derivative action increases many fold.

$$u(t) = K_c \left(e(t) + \frac{1}{\tau_i} \int_0^t e(t) dt + \tau_d \frac{de(t)}{dt} \right) \quad (15)$$

Eq (15) shows the ideal PID controller. Where error is represented by eq(16).

$$e(t) = y_{sp}(t) - y(t) \quad (16)$$

When the derivative action is implemented in error signal, following equation is obtained.

$$\frac{d}{dt}(e(t)) = \frac{d}{dt}(y_{sp}(t)) - \frac{d}{dt}(y(t)) \quad (17)$$

Under normal conditions when there is no step change in set point, we can write eq(18) as

$$\frac{d}{dt}(e(t)) = -\frac{d}{dt}(y(t)) \quad (18)$$

So eq(15) can be rewritten as

$$u(t) = K_c \left(e(t) + \frac{1}{\tau_i} \int_0^t e(t) dt - \tau_d \frac{dy(t)}{dt} \right) \quad (19)$$

Eq(19) can be used to eliminate derivative kick from PID controller.

2.7.2 Discrete PID Controller

This section describes the discrete PID controller. A sample time t and index k is used to represent the continuous time signal at discrete step k .

$$u(k) = u_0 + K_c \left[e(k) + \frac{\Delta t}{\tau_i} \sum_{i=0}^k e(i) + \frac{\tau_d}{\Delta t} (e(k) - e(k-1)) \right] \quad (20)$$

Eq (12) is the position form of discrete PID controller. The velocity form of discrete PID controller can be found out by subtracting position form at step $k-1$ from that at step k .

$$u(k) = u_0 + K_c \left[e(k) + \frac{\Delta t}{\tau_i} (e(0) + e(1) + \dots + e(k-1) + e(k)) + \frac{\tau_d}{\Delta t} (e(k) - e(k-1)) \right] \quad (21)$$

Eq (21) is the extended form of eq (20)

$$u(k) = u_0 + K_c \left[\left(1 + \frac{\Delta t}{\tau_i} + \frac{\tau_d}{\Delta t} \right) e(k) + \frac{\Delta t}{\tau_i} e(k-1) - \frac{\tau_d}{\Delta t} e(k-1) \right] \quad (22)$$

Substituting k as $k-1$ in the position form we get eq (20)

$$u(k-1) = u_0 + K_c \left[e(k-1) + \frac{\Delta t}{\tau_i} \sum_{i=0}^{k-1} e(i) + \frac{\tau_d}{\Delta t} (e(k-1) - e(k-2)) \right] \quad (23)$$

Eq (23) can be extended and written as follows

$$u(k-1) = u_0 + K_c \left[e(k-1) + \frac{\Delta t}{\tau_i} (e(0) + e(1) + \dots + e(k-2) + e(k-1)) + \frac{\tau_d}{\Delta t} (e(k-1) - e(k-2)) \right] \quad (24)$$

$$u(k-1) = u_0 + K_c \left[\left(1 + \frac{\Delta t}{\tau_i} + \frac{\tau_d}{\Delta t} \right) e(k-1) - \frac{\tau_d}{\Delta t} e(k-2) \right] \quad (25)$$

$$u(k) - u(k-1) = u_0 + K_c \left[\left(1 + \frac{\Delta t}{\tau_i} + \frac{\tau_d}{\Delta t} \right) e(k) + \frac{\Delta t}{\tau_i} e(k-1) - \frac{\tau_d}{\Delta t} e(k-1) \right] - u_0 - K_c \left[\left(1 + \frac{\Delta t}{\tau_i} + \frac{\tau_d}{\Delta t} \right) e(k-1) - \frac{\tau_d}{\Delta t} e(k-2) \right] \quad (26)$$

$$u(k) - u(k-1) = K_c \left[\left(1 + \frac{\Delta t}{\tau_i} + \frac{\tau_d}{\Delta t} \right) e(k) + \left(-\frac{\tau_d}{\Delta t} - 1 + \frac{\Delta t}{\tau_i} - \frac{\Delta t}{\tau_i} - \frac{\tau_d}{\Delta t} \right) e(k-1) + \frac{\tau_d}{\Delta t} e(k-2) \right] \quad (27)$$

$$u(k) - u(k-1) = K_c \left[\left(1 + \frac{\Delta t}{\tau_i} + \frac{\tau_d}{\Delta t} \right) e(k) + \left(-1 - \frac{2\tau_d}{\Delta t} \right) e(k-1) + \frac{\tau_d}{\Delta t} e(k-2) \right] \quad (28)$$

Eq (28) is known as velocity form of discrete PID controller. The major advantage of velocity form of PID controller is that it is naturally anti reset windup.

2.7.2.1 Digital PID Controller

The velocity form of PID controller can be re written as follows

$$u(k) - u(k-1) = b_0 e(k) + b_1 e(k-1) + b_2 e(k-2) \quad (29)$$

Here

$$b_0 = K_c \left(1 + \frac{\Delta t}{\tau_i} + \frac{\tau_d}{\Delta t} \right) \quad (30)$$

$$b_1 = -K_c \left(1 + \frac{2\tau_d}{\Delta t} \right) \quad (31)$$

$$b_2 = \left(\frac{K_c \tau_d}{\Delta t} \right) \quad (32)$$

Representing eq(29) in z domain, we get

$$(1 - z^{-1})u(z) = (b_0 + b_1 z^{-1} + b_2 z^{-2})e(z) \quad (33)$$

$$\Rightarrow u(z) = \left(\frac{b_0 + b_1 z^{-1} + b_2 z^{-2}}{1 - z^{-1}} \right) e(z) \quad (34)$$

$$\frac{u(z)}{e(z)} = \frac{b_0 + b_1 z^{-1} + b_2 z^{-2}}{1 - z^{-1}} \quad (35)$$

$$\frac{u(z)}{e(z)} = \frac{b_0 z^2 + b_1 z + b_2}{z^2 - z} \quad (36)$$

Eq (36) is the digital representation of PID controller. The values of coefficient are shown in eq (30), (31) and (32) respectively.

2.7.3 Tuning of PID Controller

Closed loop oscillation based PID tuning method is a popular method of tuning PID controller. In this kind of tuning method, a critical gain K_{cu} is induced in the forward path of the control system. The high value of the gain takes the system to the verge of instability. It creates oscillation and from the oscillations, the value of frequency and time are calculated. Table 2.1 gives different experimental tuning rules based on closed loop oscillation method.

Table 2.1: Different closed loop oscillation based tuning methods

Type of tuning methods	K_c	τ_i	τ_d
Zeigler-Nichols	$0.6K_{cu}$	$0.5T$	$0.125T$
Tyreus-Luyben	$0.45K_{cu}$	$2.2T$	$0.15T$

2.7.4 Analog PID Controller Using Operational Amplifier

Simple operational amplifiers can be used to implement different controlling action of a PID controller. This section gives a detail overview of analog PID controller using op-amp. The values of PID controller gains can be found out by following equation (37), (38) and (39).

$$K_p = \frac{R_2}{R_1} \quad (37)$$

$$K_i = \frac{1}{R_i C_i} \quad (38)$$

$$K_d = R_d C_d \quad (39)$$

K_p , K_i and K_d denotes the proportional gain, integral gain and derivative gain respectively.

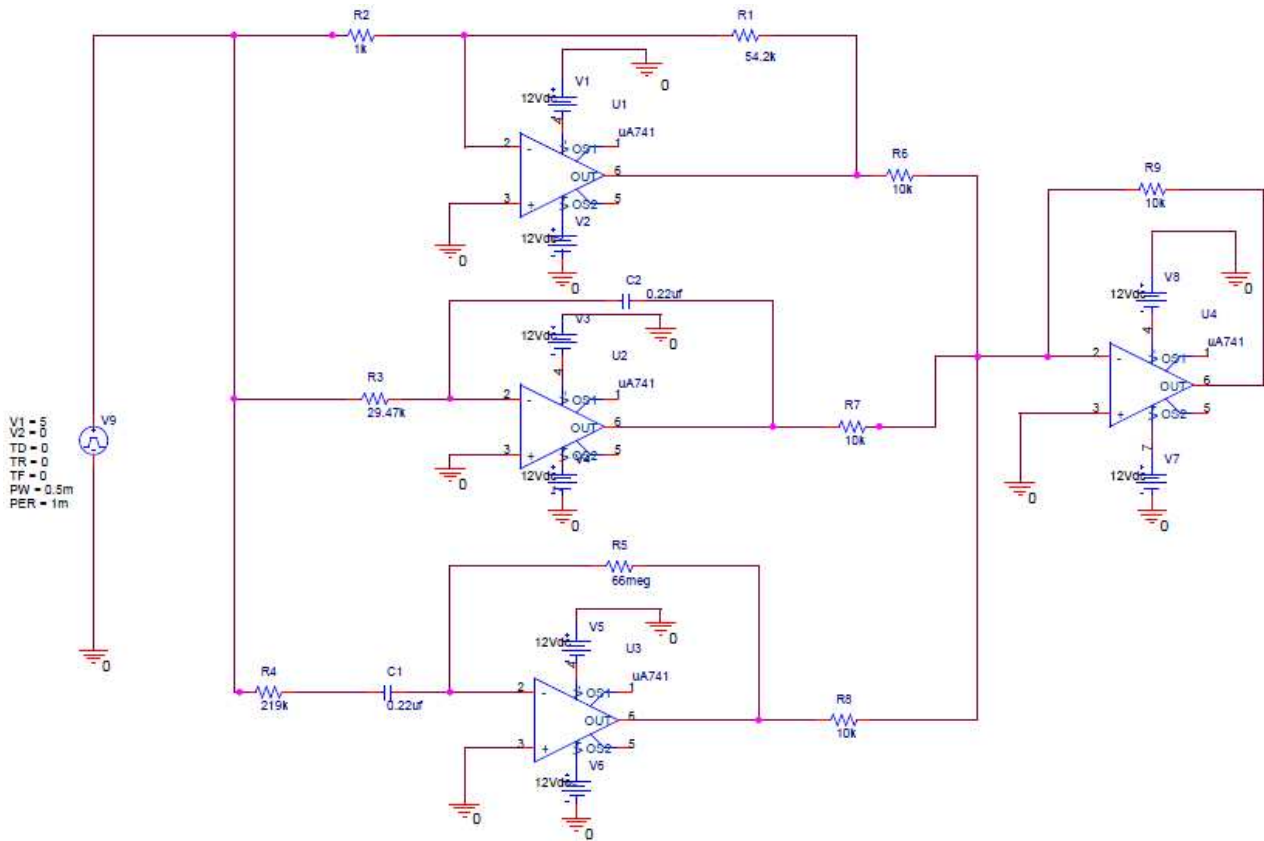


Figure 2.11: Op-amp. based realization of parallel form of PID controller

Figure 2.11 shows the analog form of PID controller designed using IC-741 op-amp. Proportional action, integral action, derivative action can be implemented using op-amp.

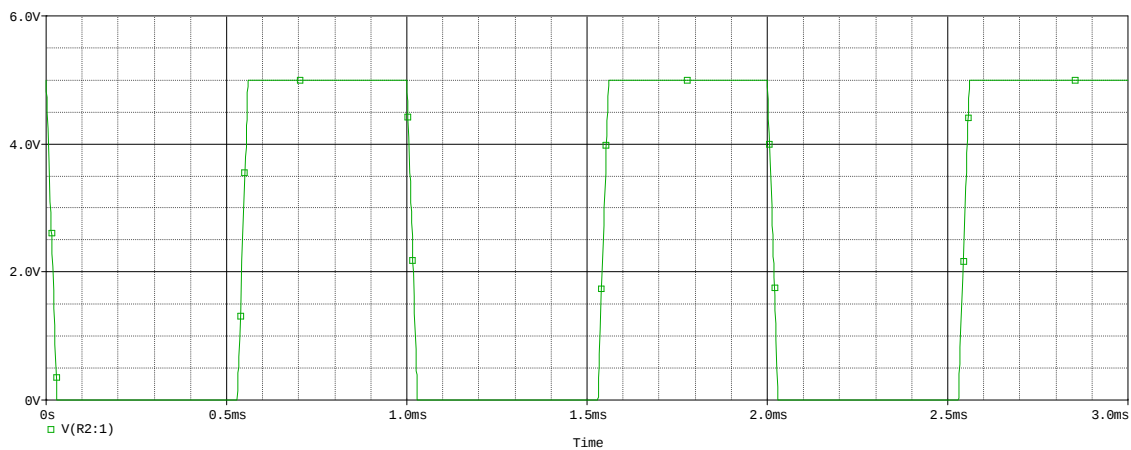


Figure 2.12: Input error signal

Figure 2.12 shows the error waveform taken for the evaluation of PID controller. A pulse wave with 50% duty cycle is considered as the error signal.

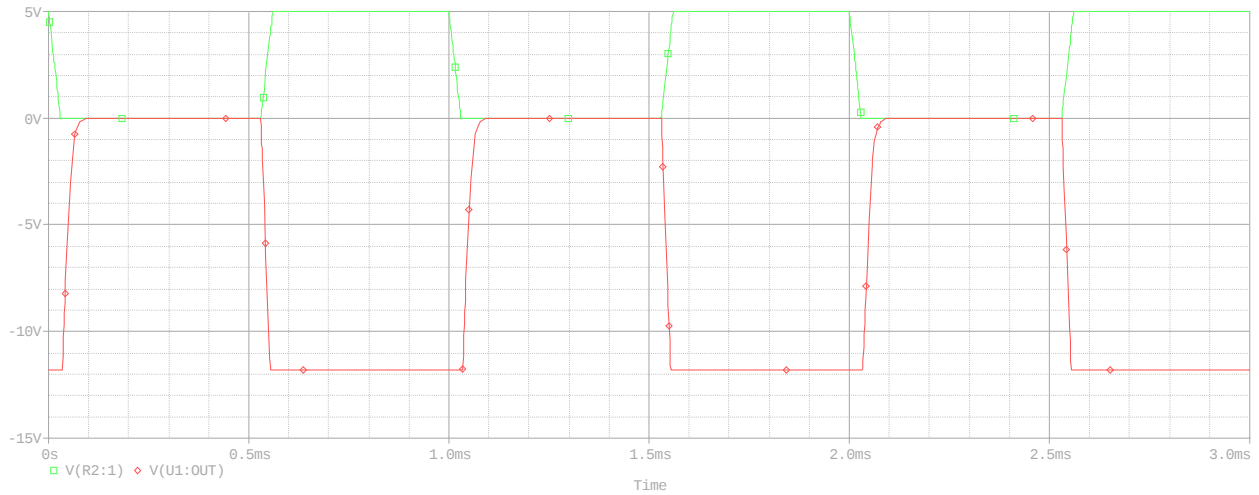


Figure 2.13: Output of proportional term

Figure 2.13 shows the error curve and output of proportional term of the PID controller. The green curve is the error curve while the red curve is the graph for proportional term. Because of the inverting nature of the operational amplifier, the output of proportional controller is inverted from the error signal.

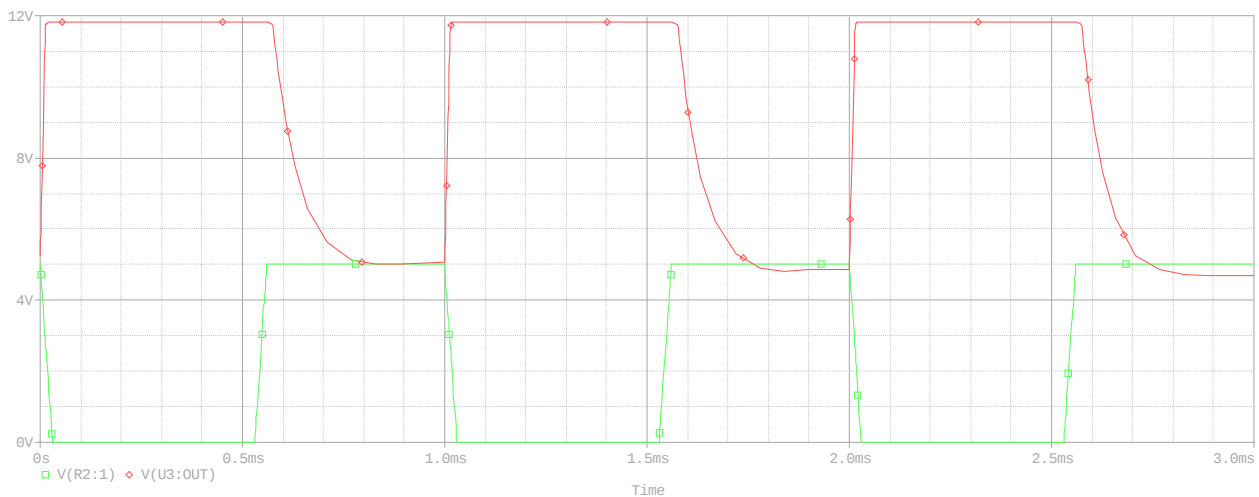


Figure 2.14: Output of derivative term

Figure 2.14 shows the error curve and the derivative curve. The green pulse signal is the error signal and the red curve shows the derivative term.

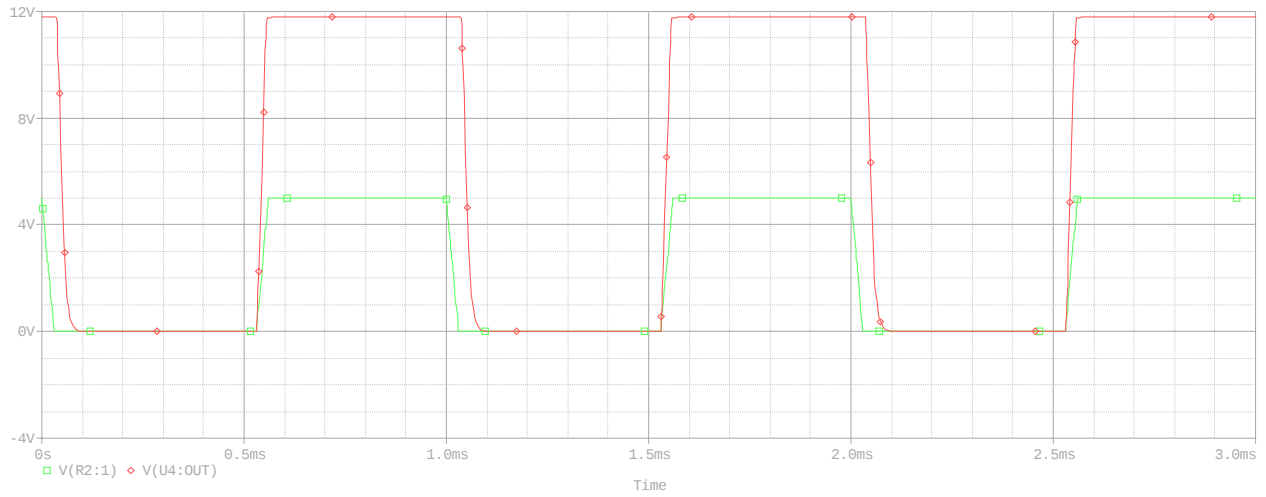


Figure 2.15: Output of PID controller

Figure 2.15 shows the output of the summer circuit and figure 2.16 shows graph for error signal, proportional term, integral term, derivative term and graph of the summer circuit.

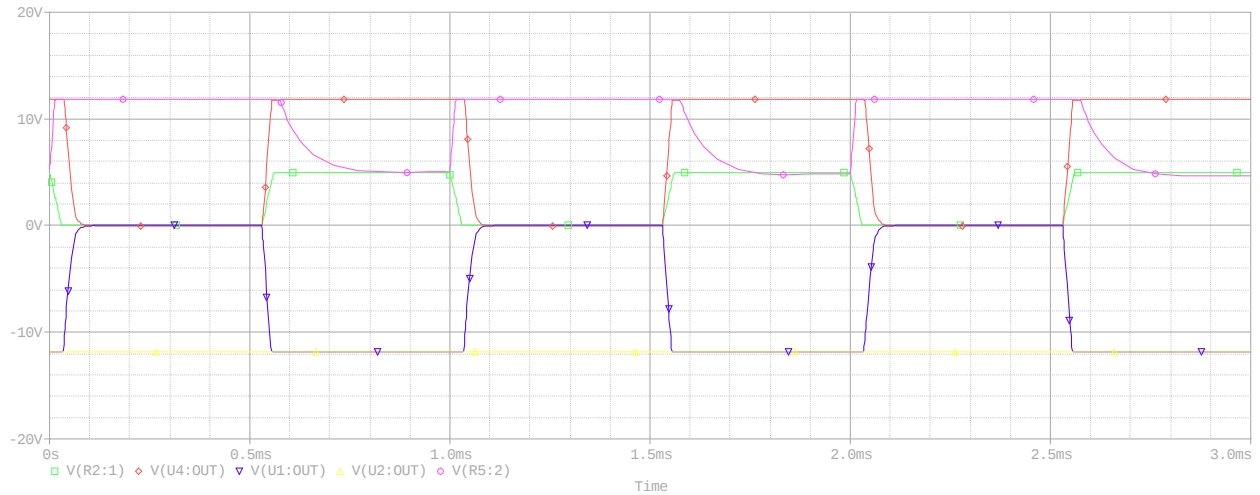


Figure 2.16: Output of all the inputs and output terms of PID controller

This figure shows all the signals, like error signal, proportional output signal, derivative output signal and summer output signals.

2.7.5 PID Controller in Shell and Tube Heat Exchanger System

The characteristic equation $(1+G(s)H(s)=0)$ in this case is obtained as below.

$$900s^3 + 420s^2 + 43s + 0.798K_{cu} + 1 = 0 \quad (40)$$

Applying Routh stability criterion in eq. (40) gives K_{cu} as 23.8.

$$\text{Auxiliary equation } 420s^2 + 0.798K_{cu} + 1 = 0 \quad (41)$$

Substituting $s=j\omega$ in eq. (41), $\omega=0.218$ and $T=28.79$

For the PID controller the values of parameters (K_c , τ_i , τ_d) obtained using closed loop oscillation based tuning methods like Zeigler-Nichols method and Tyreus- Luyben methods are summarized in table 2.2.

Table 2.2: PID parameters using different tuning methods

Tuning Methods	K_c	τ_i	τ_d
Zeigler-Nichols	14.28	14.395	3.59
Tyreus – Luyben	10.71	63.33	4.31

In this case study we have taken the parameters tuned using Zeigler-Nichols method. Usually, initial design values of PID controller obtained by all means needs to be adjusted repeatedly through computer simulations until the closed loop system performs or compromises as desired. This stimulates the development of “intelligent” tools that can assist the engineers to achieve the best overall PID control for entire operating envelopes. Figure 2.17 shows the Simulink model of feedback control of shell and tube heat exchanger system. The feedback control is achieved using PID controller. A relay block is also attached in parallel to the PID controller, which acts like an auto tuner. The PID controller and the relay blocks are connected using a manual switch. The operator can manually change the switch to either PID controller or the auto tuner.

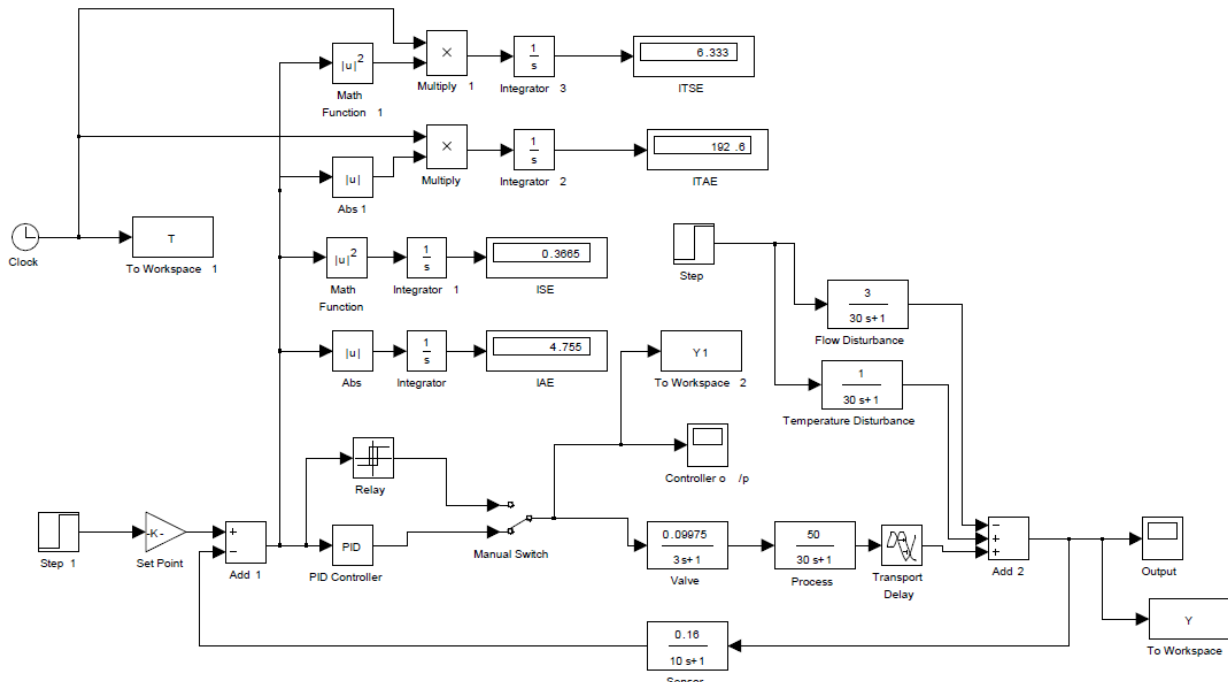


Figure 2.17: Simulink representation of feedback controller of shell and tube heat exchanger system

Figure 2.18 shows the unit step response of feedback control of shell and tube heat exchanger system. Figure 2.19 shows the controller output and process output when the relay block is activated using the manual switch.

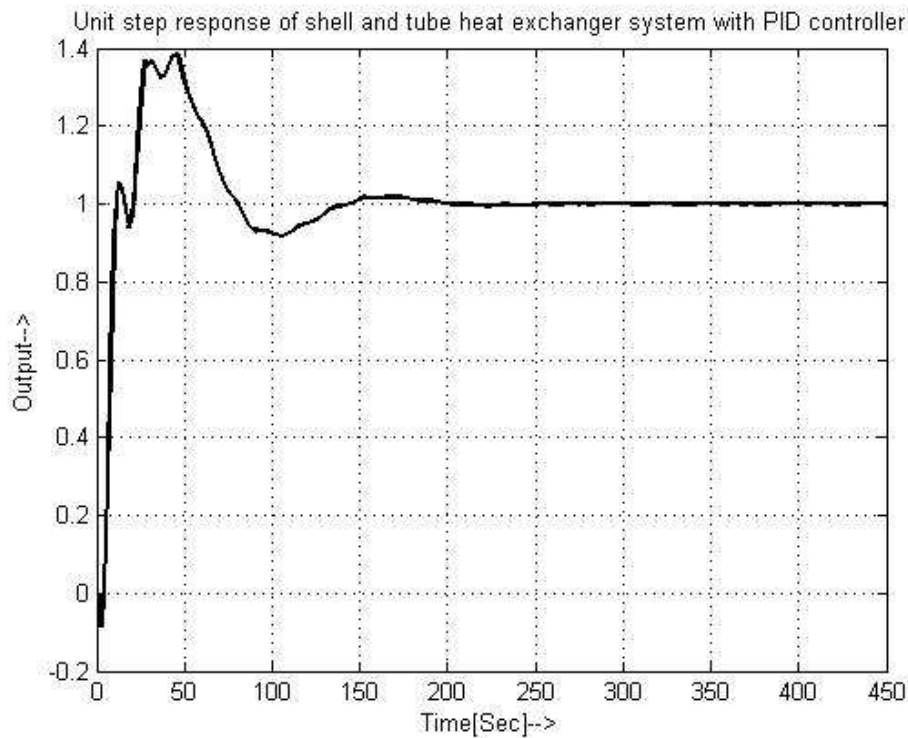


Figure 2.18: Unit step response of shell and tube heat exchanger system with PID controller

The step response analysis shows a very high overshoot on the range of 38% which is completely unacceptable in a process plant. To further reduce the overshoot and settling time a feed forward plus feedback controller is designed in section 2.8.

2.7.6 Relay Based Auto Tuning of PID Controller

Most of the process control systems have an auto tune option. The operator can simply push the auto tune button and have the controller tune for itself. Auto tuning means determining the values of tuning parameters of the controller automatically. There are many methods of auto tuning. Some methods employ simple relay blocks where as other methods employ sophisticated soft computing techniques or hybrid soft computing techniques.

The most common method of auto tune method is to place a relay block in parallel to the controller block. The relay block acts as an ON-OFF controller. The resulting oscillatory behaviour of the controller and process is further analysed to determine the proper controller setting. Figure

2.19 shows the oscillatory behaviour of controller and process when the operator manually switches the relay block.

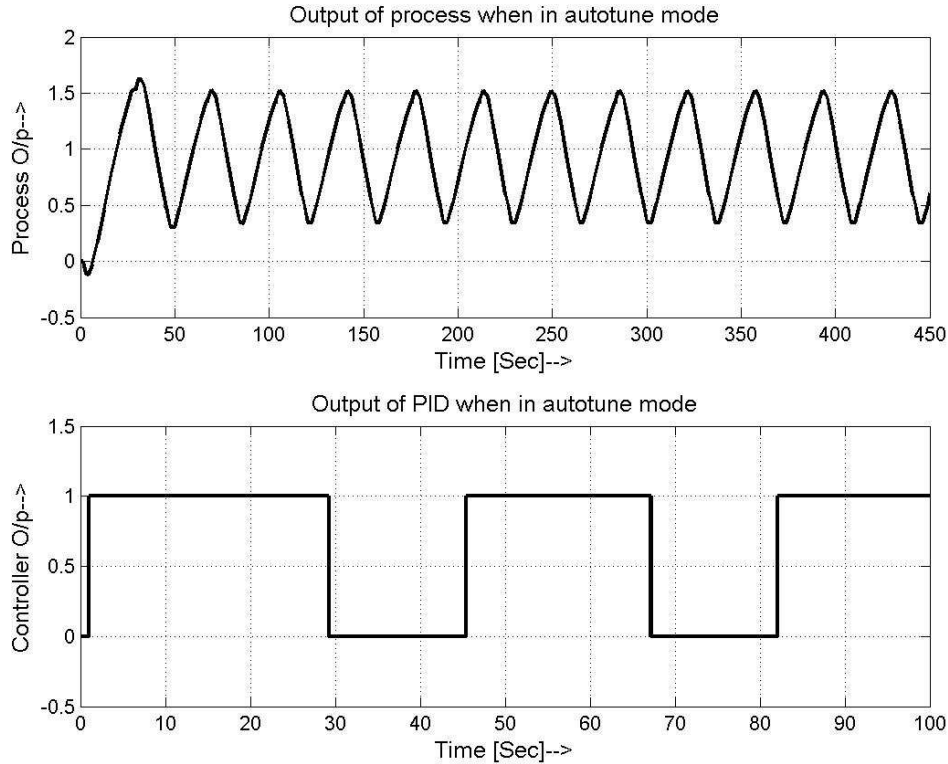


Figure 2.19: Unit step response of process and controller when PID controller in auto tune mode

When the auto-tune function is required, then the manual switch is set to the relay block. The relay block represents a nonlinear behaviour. In auto-tune mode, the closed loop system oscillates and the manipulated variable action is ON-OFF. From the auto-tune mode, two parameters are obtained. These parameters are ultimate gain and ultimate frequency.

$$\text{Ultimate gain} \quad K_{cu} = \frac{4h}{\pi a} \quad (42)$$

$$\text{Ultimate frequency} \quad \omega_u = \frac{2\pi}{P} \quad (43)$$

Here, P is the period between the successive peaks, a is the amplitude of process output and h is the height of controller output

The behavior obtained from auto tuning mode is very similar to the behavior obtained from Zeigler- Nichols closed loop cycling method.

If an ideal relay is implemented there can be problems if there is process noise. To handle the process noise in relay based auto tuning of controller a dead band with a magnitude ε is added

to the relay switch. The magnitude of the dead band is selected to be at least twice or thrice the standard deviation of the process noise.

2.7.7 Root Locus Technique

Root locus technique is used to locate the roots of characteristic equation in a graphical manner in s-plane. This method indicates the manner in which the open loop poles and zeros should be modified such that the response meets the system performance specifications.

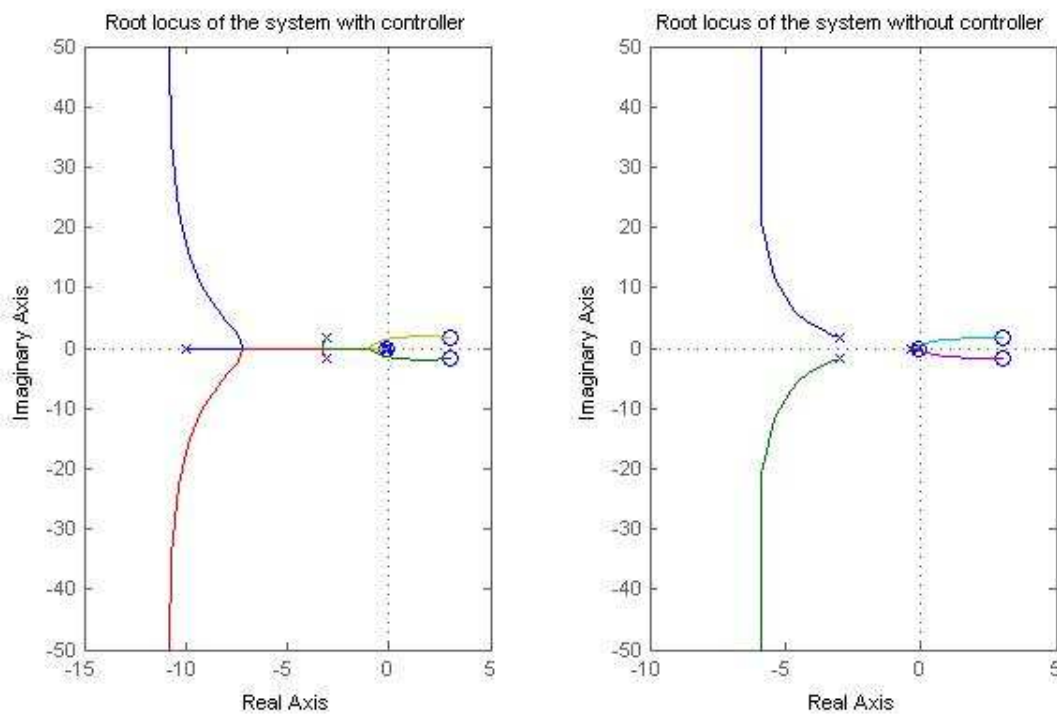


Figure 2.20: Root locus of the shell and tube heat exchanger system with and without controller

Figure 2.20 shows the root locus of the shell and tube heat exchanger system with and without controller. It investigates the effects of variation of system parameters on location of closed loop poles.

2.8 Feedback plus Feed Forward Controller

There can be two types of disturbances in this process, one is the flow variation of input fluid and the second is the temperature variation of input fluid. But in practice the flow variation of input fluid is a more prominent disturbance than the temperature variation in input fluid.

The input fluid flow disturbance introduces error in the system performance. In several systems the disturbance can be predicted and its effect can be eliminated with the help of feed forward controller before it can change the output of the system. In the previous section a feedback

controller was designed to control the outlet temperature. But due to high overshoot and high settling time the controller's performance is poor. To improve the control a feed forward controller is designed in this section. The control action of feedback and feed forward controller is summed up to give a combined control signal. The combined control signal improves the controller performance. Figure 2.21 shows the control scheme for the combined controller. In this control scheme the main disturbance (volume change in input fluid flow) is measured and controlled using a feed forward controller. For this reason an orifice plate along with a differential pressure transmitter is used to measure the input fluid flow. The output of the DPT is given to the feed-forward controller. The control action of feedback and feed forward controller is summed up and provided to the valve via the actuator.

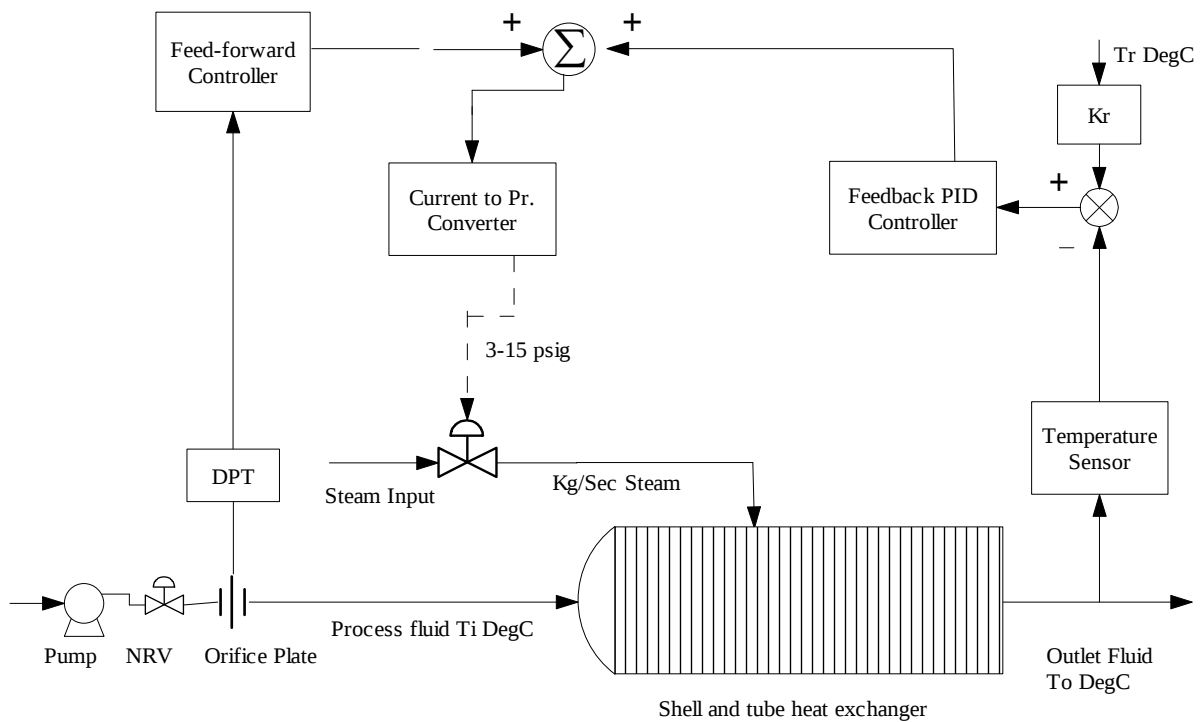


Figure 2.21: Feed-forward plus feedback control scheme of shell and tube heat exchanger system

The flow through the orifice is represented by eq(44)

$$v_0 = \frac{C_0}{\sqrt{1-\beta^4}} \sqrt{\frac{2g_c(P_1 - P_2)}{\rho}} \quad (44)$$

Here, v_0 is average velocity through the orifice, β is the ratio of orifice to pipe diameter, C_0 is orifice coefficient. The value of orifice coefficient is 0.61, P_1 and P_2 are upstream and down stream pressure, g_c is Newton's law of gravitational constant and ρ is the fluid density

$$\text{The volumetric flow is represented by } F = v_0 \frac{\rho D_0^2}{4} \quad (45)$$

Substituting the value of v_0 in eq (45)

$$F = \frac{\rho D_0^2}{4} \frac{C_0}{\sqrt{1-\beta^4}} \sqrt{\frac{2g_c (P_1 - P_2)}{\rho}} \quad (46)$$

$$F = C_1 \sqrt{P_1 - P_2} \quad (47)$$

$$C_1 = \frac{\rho D_0^4}{4} \frac{C_0}{\sqrt{1-\beta^4}} \sqrt{\frac{2g_c}{\rho}} \quad (48)$$

In feedback control scheme the sensor is used to detect the process output and gives the error to the controller which in turn takes appropriate controlling action. But till the controlling action reaches the process, the output has been changed. A feed forward control estimates the error and changes the manipulating variable before the disturbance can affect the output. Figure 2.22 shows the control scheme of feedback and feed forward controller.

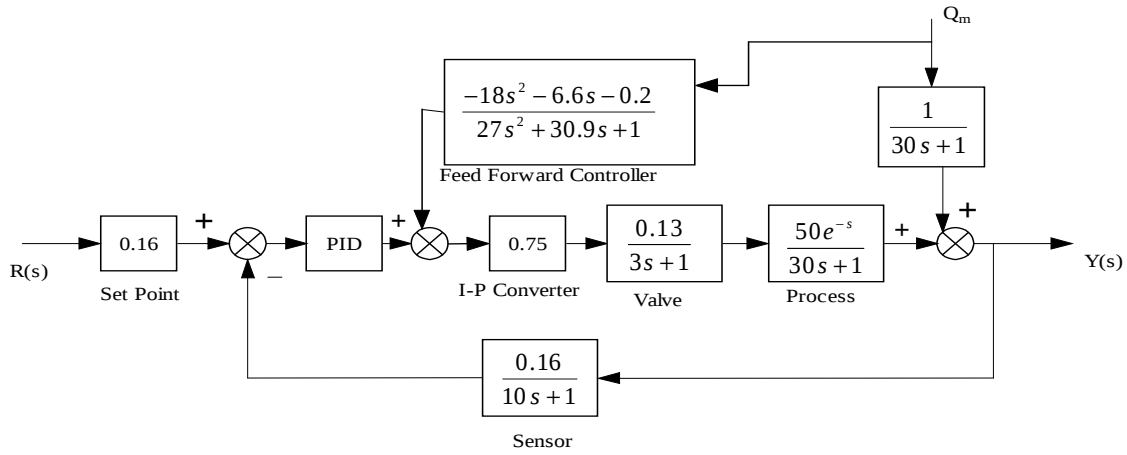


Figure 2.22: Feed-forward plus feedback control system block diagram of shell and tube heat exchanger system

$G_p(s)$ shows the transfer function of the process and $G_d(s)$ shows the transfer function of the flow disturbances.

$$G_p(s) = \frac{5e^{-s}}{90s^2 + 33s + 1} \text{ and } G_d(s) = \frac{1}{30s + 1}$$

$$\text{The transfer function of the feed-forward controller is } G_{cf}(s) = \frac{-G_d(s)}{G_p(s)} \quad (49)$$

$$G_{cf}(s) = \frac{-18s^2 - 6.6s - 0.2}{27s^2 + 30.9s + 1} \quad (50)$$

Here, ' λ ' is the filter parameter, whose range is from 0 to 1. It has been used to make the transfer function semi proper. The controller transfer function neglects the effects of process delay. Here the value of $\lambda = 0.9$. In this case, there is no time delay between the unit step input and unit step disturbance.

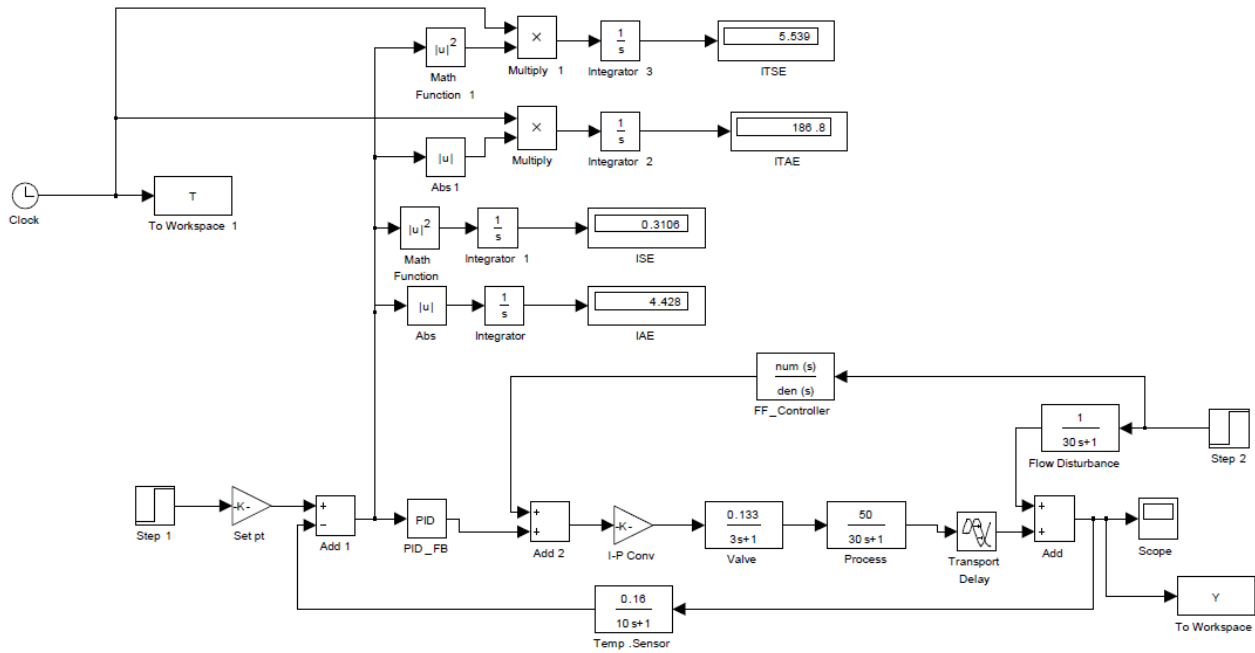


Figure 2.23: Simulink representation of feedback plus feedforward controller of shell and tube heat exchanger system (No time delay between step input and step disturbance)

Figure 2.23 shows the Simulink representation of feedback and feedforward control of shell and tube heat exchanger system. Figure 2.24 shows the unit step response of feedback plus feed forward controller. In this case there is no time delay between unit step input and unit step disturbance. The designed feedback plus feed forward controller shows 30% overshoot which is an improvement from the feedback controller. The feedback controller showed 38% overshoot and the feedback plus feed forward controller reduced the overshoot to 30%.

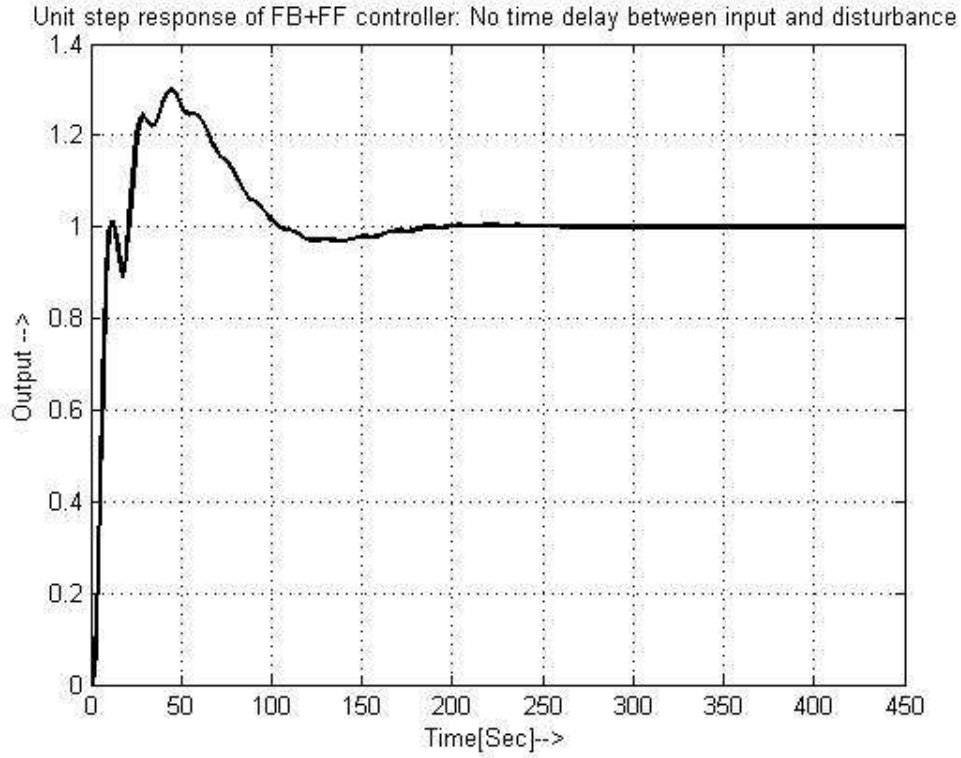


Figure 2.24: Unit step response of shell and tube heat exchanger system with feed forward controller, (No delay between step input and step change in disturbance)

$$G_p(s) = \frac{5e^{-s}}{90s^2 + 33s + 1} \text{ and } G_d(s) = \frac{1e^{-s}}{30s + 1}$$

The transfer function of the feed-forward controller is $G_{cf}(s) = \frac{-G_d(s)}{G_p(s)}$ (51)

$$G_{cf}(s) = \frac{-18s^2 - 6.6s - 0.2}{135s^2 + 150.9s + 1} \quad (52)$$

Here, ' λ ' is the filter parameter, whose range is from 0 to 1. It has been used to make the transfer function semi proper. The controller transfer function neglects the effects of process delay. Here the value of $\lambda = 0.9$. In this case there is a unit time delay between the unit step input and unit step disturbance.

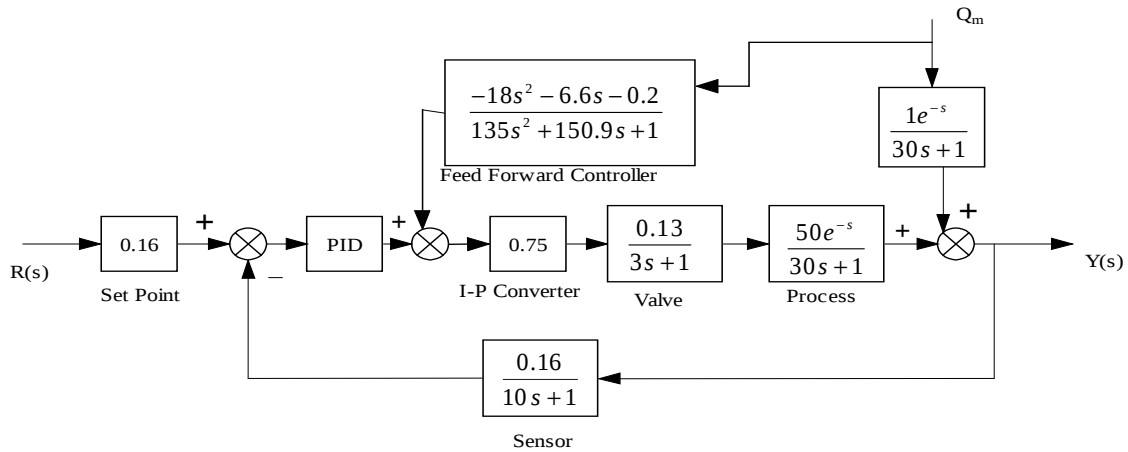


Figure 2.25: Feedback plus feed forward control of shell and tube heat exchanger (With unit time delay between unit step input and unit step disturbance)

Figure 2.25 shows the control scheme of feedback plus feed forward control of shell and tube heat exchanger system. In this case we have considered a unit delay between unit step input and unit step change in disturbance.

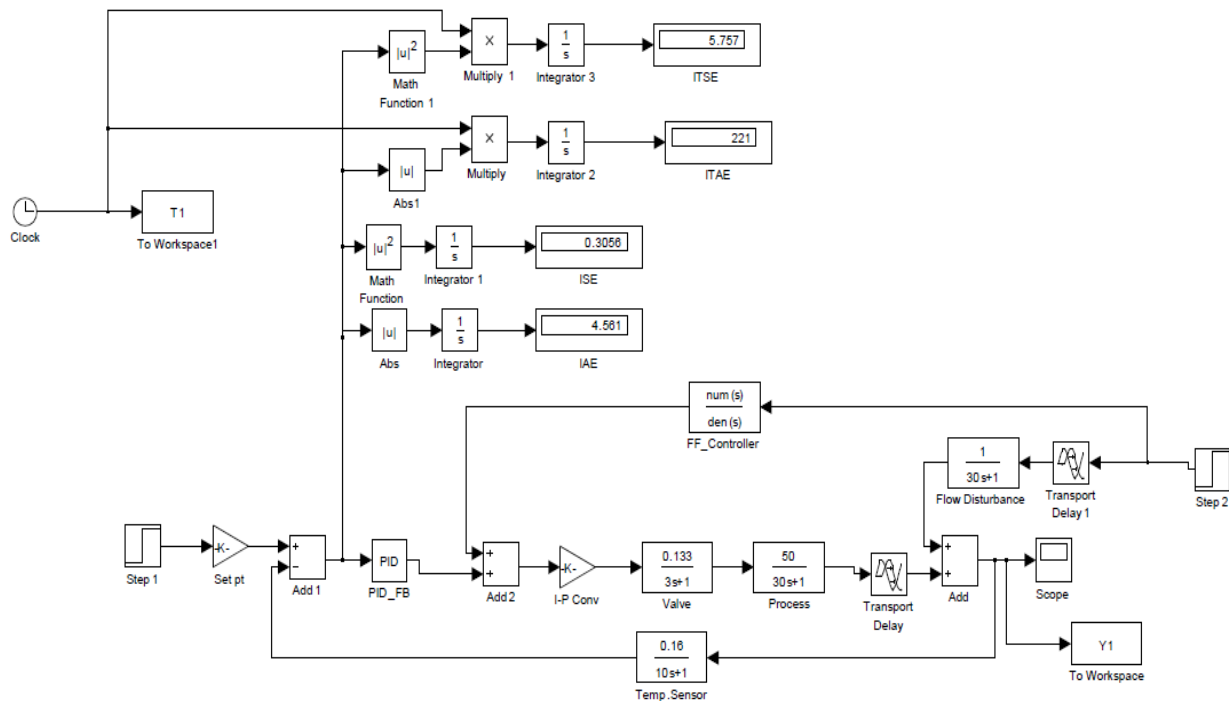


Figure 2.26: Simulink representation of feedback plus feed forward control of shell and tube heat exchanger system

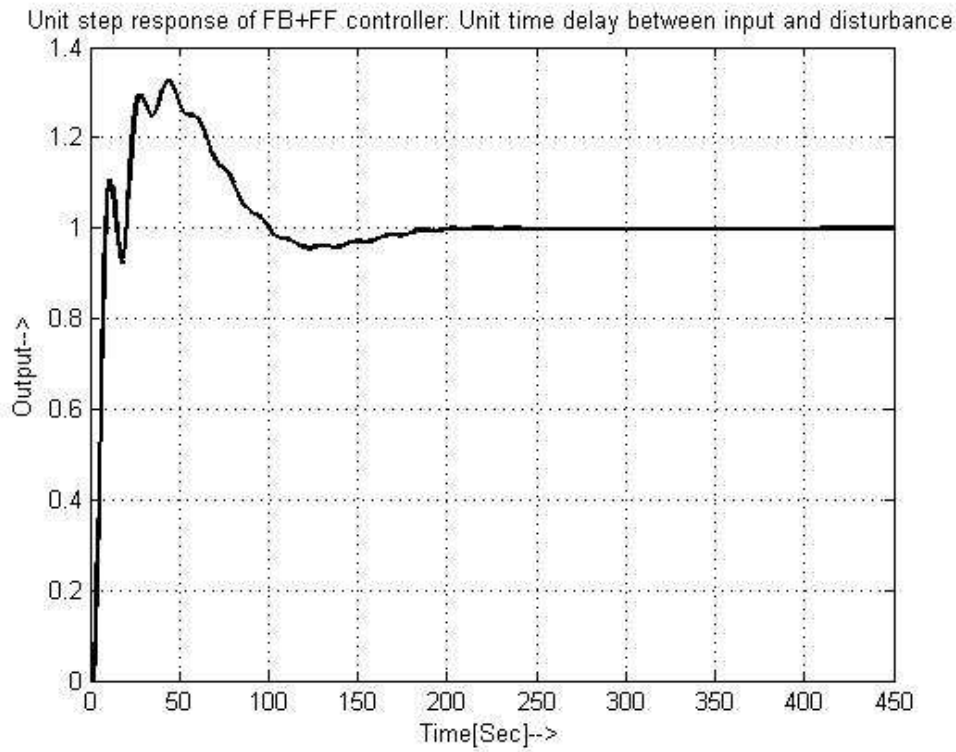


Figure 2.27: Unit step response of feedback plus feed forward controller of shell and tube heat exchanger system (With unit time delay between unit step input and unit step disturbance)

Figure 2.26 shows the Simulink representation of feedback plus feed forward controller of shell and tube heat exchanger system. Figure 2.27 shows the step response of feedback plus feed forward controller with a unit time delay between unit step input and unit step change in disturbance.

2.9 Internal Model Controller

Internal model controller is that it provides a transparent framework for control system design and tuning. The structure of internal model controller is shown in figure 2.28. The main feature of internal model controller is that the process model is in parallel with the actual process. The transfer function of the process is shown in eq (53).

$$G_p(s) = \frac{5e^{-sT_d}}{90s^2 + 33s + 1} \quad (53)$$

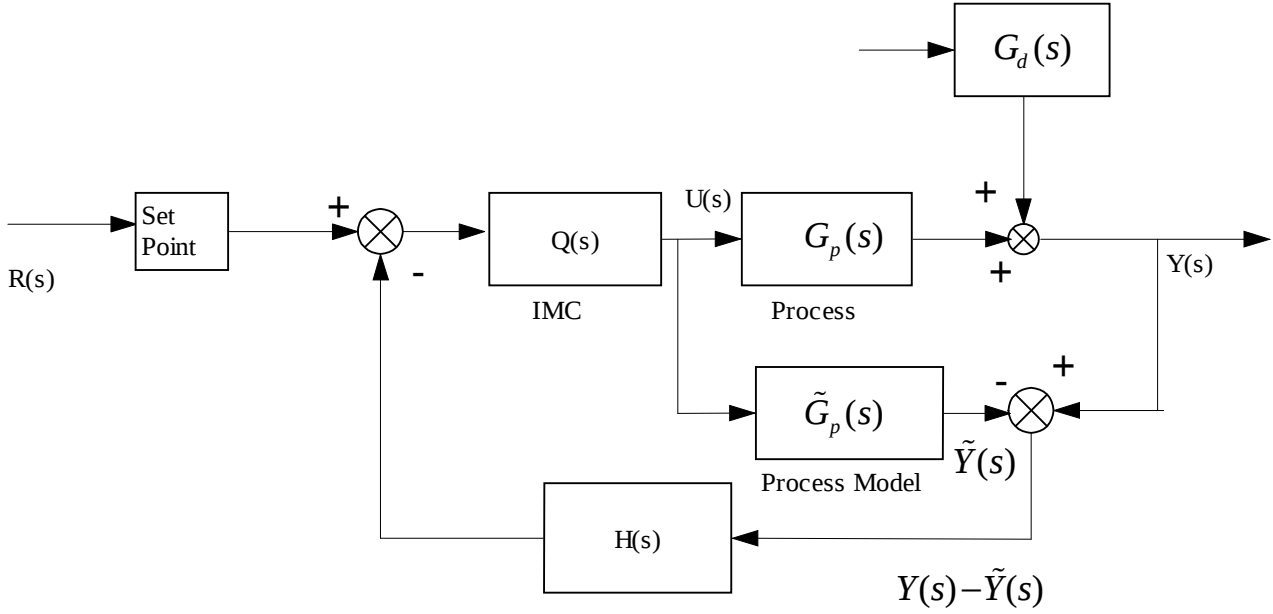


Figure 2.28: Control scheme of internal model control

The process consists of a time delay in the form of $e^{-T_d s}$. Pade's approximation for time delay can be used for process with time delays. The first order Pade's approximation is described as

$$e^{-T_d s} = \frac{-\frac{T_d}{2}s + 1}{\frac{T_d}{2}s + 1} \quad (54)$$

A second order Pade's approximation is described as

$$e^{-T_d s} = \frac{-\frac{T_d}{12}s^2 - \frac{T_d}{2}s + 1}{\frac{T_d}{12}s^2 + \frac{T_d}{2}s + 1} \quad (55)$$

Implementing first order Pade's approximation in process the process transfer function can be re written as

$$G_p(s) = \frac{5}{(30s+1)(3s+1)} \left(\frac{-0.5s+1}{0.5s+1} \right) \quad (56)$$

The step response for Pade's first order approximation is shown in figure 2.28. Implementing second order Pade's approximation in process the process transfer function can be re written as

$$G_p(s) = \frac{5}{(30s+1)(3s+1)} \left(\frac{-0.083s^2 - 0.5s + 1}{0.083s^2 + 0.5s + 1} \right) \quad (57)$$

The step response for Pade's second order approximation is shown in figure 2.29.

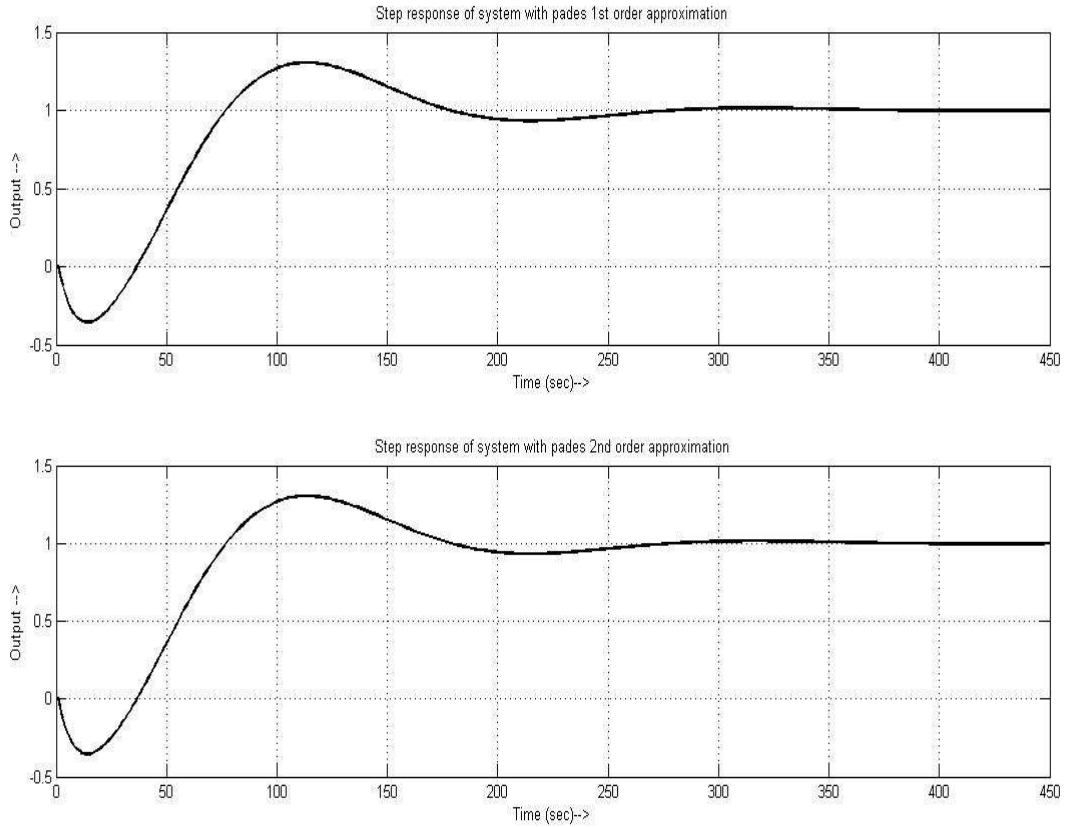


Figure 2.29: Pade's 1st order and 2nd order response

The process model $\tilde{G}_p(s)$ is factored in to two parts. That is invertible part $\tilde{G}_{p+}(s)$ and non invertible part $\tilde{G}_{p-}(s)$ elements. The non invertible part consists of RHP zeros and time delays. This factorization is performed so as to make the resulting internal model controller stable.

$$\tilde{G}_p(s) = \tilde{G}_{p-}(s)\tilde{G}_{p+}(s) \quad (58)$$

$$\tilde{G}_p(s) = \frac{5(-0.083s^2 - 0.5s + 1)}{(30s + 1)(3s + 1)(0.083s^2 + 0.5s + 1)} \quad (59)$$

The internal model controller can be designed by taking the inverse of process model along with the filter transfer function. The transfer function representation of internal model controller is

$$Q(s) = \tilde{G}_{p-}^{-1}(s)f(s) \quad (60)$$

$$Q(s) = \frac{(30s + 1)(3s + 1)(0.083s^2 + 0.5s + 1)}{5(\lambda s + 1)^4} \quad (61)$$

The process shows an over damped response, so damping coefficient $\xi > 1$.

The process transfer function can be factored as

$$90s^2 + 33s + 1 = (\tau_1 s + 1)(\tau_2 s + 1) \quad (62)$$

Time constant expressions are obtained as

$$\tau_1 = \frac{\tau}{\xi - \sqrt{\xi^2 - 1}} \text{ and } \tau_2 = \frac{\tau}{\xi + \sqrt{\xi^2 - 1}} \quad (63)$$

In practice λ is taken as one third or one fifth of the time constant. So, the values of λ are obtained as 11.4 and 17. Substituting the values of λ as 11.4 in eq(61) we get

$$Q(s) = \frac{1.494s^4 + 603s^3 + 235.966s^2 + 6.7s + 0.2}{16889.6s^4 + 5926.17s^3 + 779.76s^2 + 45.6s + 1} \quad (64)$$

Substituting the values of λ as 17 in eq(61) we get

$$Q(s) = \frac{1.494s^4 + 603s^3 + 235.966s^2 + 6.7s + 0.2}{83521s^4 + 19652s^3 + 1734s^2 + 68s + 1} \quad (65)$$

The transfer function of internal model controller denoted by $Q(s)$ for different values of the filter parameter is shown in eq (64) and eq (65).

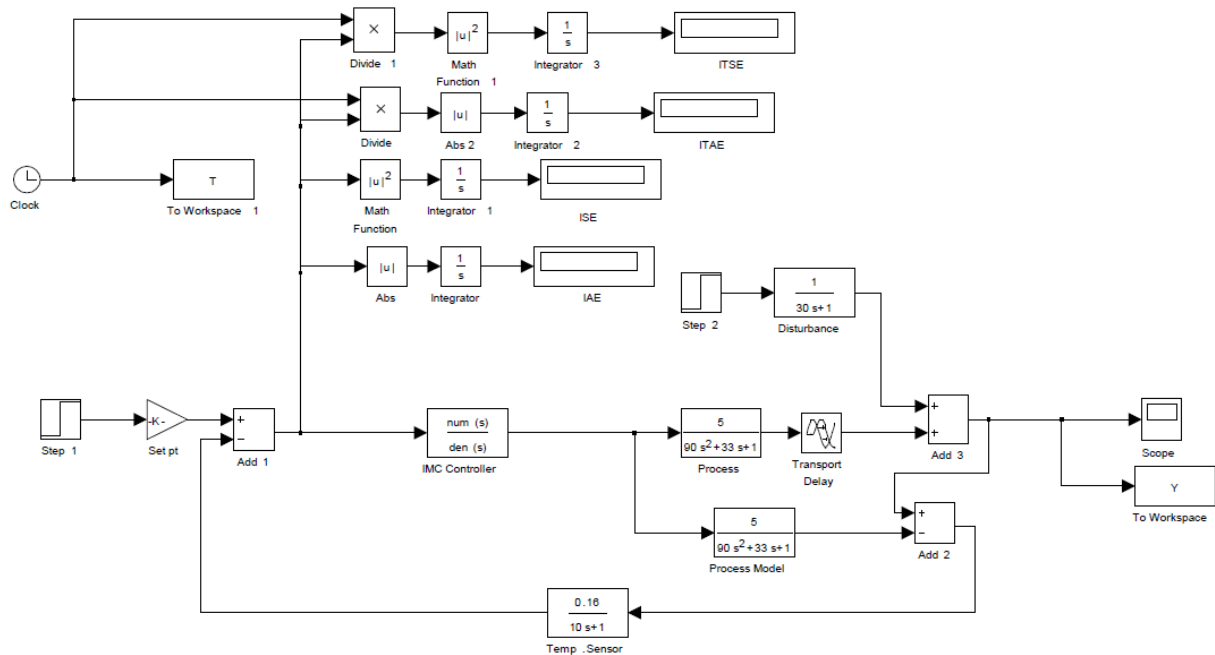


Figure 2.30: Simulink representation of IMC in shell and tube heat exchanger system

Figure 2.30 shows the Simulink representation of internal model based controller for shell and tube heat exchanger system.

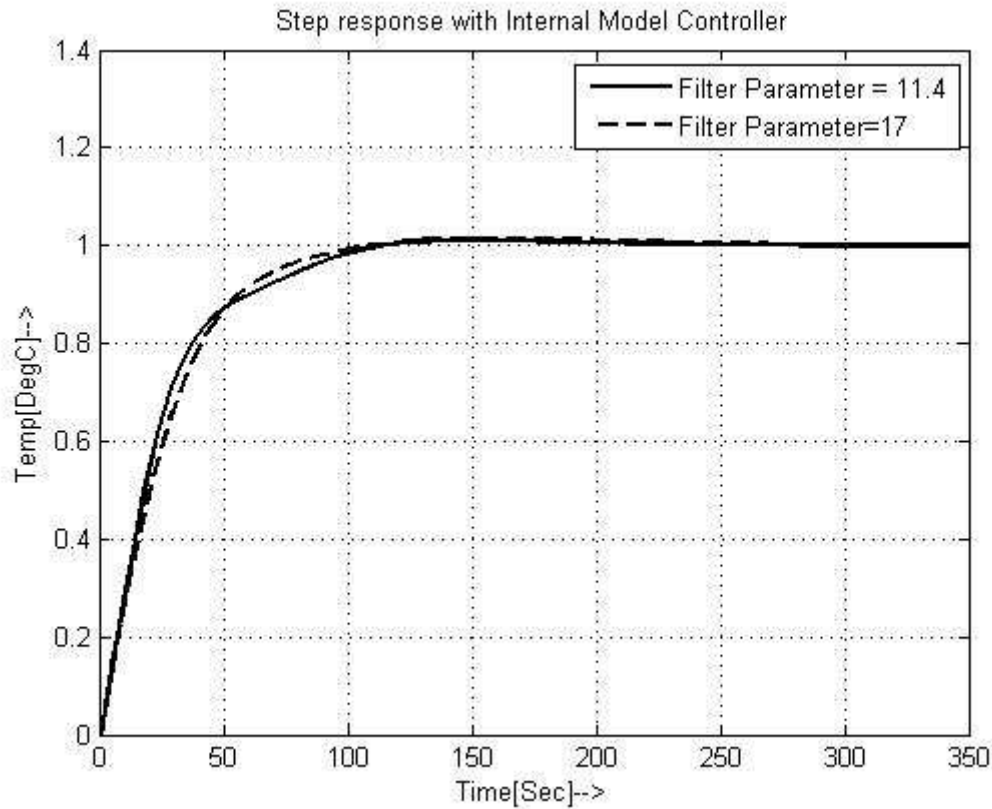


Figure 2.31: Unit step response of shell and tube heat exchanger system with IMC with different filter parameters

Figure 2.31 shows the unit step response of internal model based controller in shell and tube heat exchanger system with different values of filter parameter. As the graph shows the maximum overshoot is nearly 1%. In the previous sections we have designed feedback and feedback plus feed forward controller for temperature control of shell and tube heat exchanger system. The feedback controller shows 38% overshoot while feedback plus feed forward controller shows 30% overshoot. The designed internal model controller is very much effective because it shows very low overshoot and has only one tuning parameter which is the filter parameter.

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Chapter 3

Fuzzy Based Feedback Controller

Fuzzy logic is a form of logic that is the extension of boolean logic, which incorporates partial values of truth. Instead of sentences being "completely true" or "completely false," they are assigned a value that represents their degree of truth. In fuzzy systems, values are indicated by a number (called a truth value) in the range from 0 to 1, where 0.0 represents absolute false and 1.0 represents absolute truth. Fuzzification is the generalization of any theory from discrete to continuous. Fuzzy logic is important to artificial intelligence because they allow computers to answer 'to a certain degree' as opposed to in one extreme or the other. In this sense, computers are allowed to think more 'human-like' since almost nothing in our perception is extreme, but is true only to a certain degree. Through fuzzy logic, machines can think in degrees, solve problems when there is no simple mathematical model. It solves problems for highly nonlinear processes and uses expert knowledge to make decisions.

3.1 Fuzzy Logic Controller

The fuzzy logic controller provides an algorithm, which converts the expert knowledge into an automatic control strategy. Fuzzy logic is capable of handling approximate information in a systematic way and therefore it is suited for controlling non linear systems and is used for modeling complex systems, where an inexact model exists or systems where ambiguity or vagueness is common. The fuzzy control systems are rule-based systems in which a set of fuzzy rules represent a control decision mechanism for adjusting the effects of certain system stimuli. With an effective rule base, the fuzzy control systems can replace a skilled human operator. The rule base reflects the human expert knowledge, expressed as linguistic variables, while the membership functions represent expert interpretation of those variables.

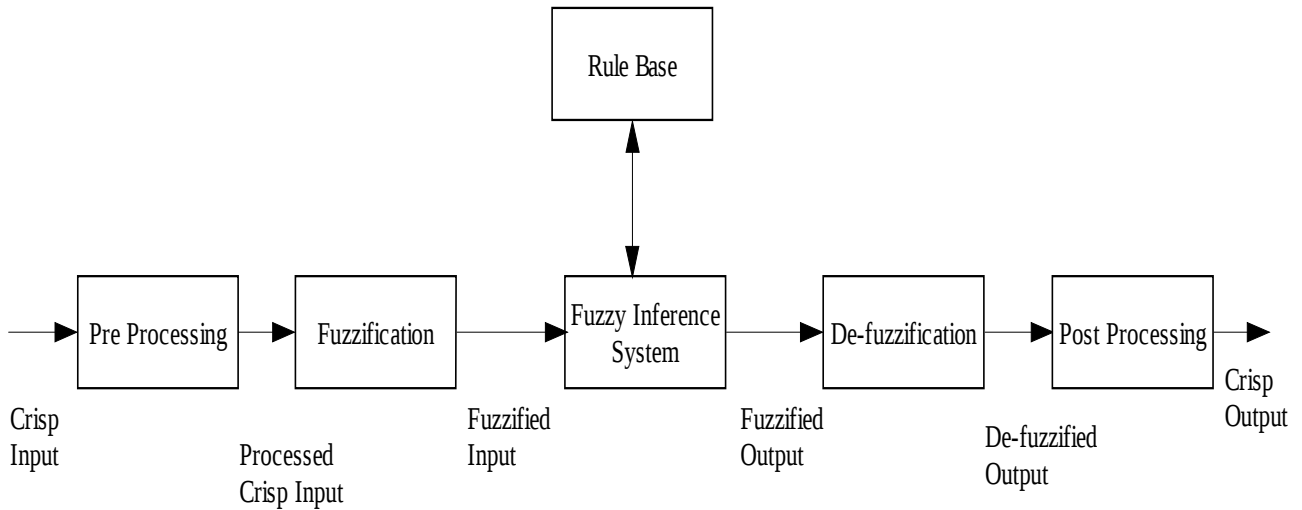


Figure 3.1: Block diagram of fuzzy control system

Figure 3.1 shows the block diagram of fuzzy control system. The crisp inputs are supplied to the input side Fuzzification unit. The Fuzzification unit converts the crisp input in to fuzzy variable. The fuzzy variables are then passed through the fuzzy rule base. The fuzzy rule base computes the input according to the rules and gives the output. The output is then passed through de-fuzzification unit where the fuzzy output is converted to crisp output.

3.2 Hybrid Fuzzy-PID Controller

Although it is possible to design a fuzzy logic type of PID controller by a simple modification of the conventional ones, via inserting some meaningful fuzzy logic IF- THEN rules into the control system, these approaches in general complicate the overall design and do not come up with new fuzzy PID controllers that capture the essential characteristics and nature of the conventional PID controllers. Besides, they generally do not have analytic formulas to use for control specification and stability analysis. The fuzzy PD, PI, and PI+D controllers to be introduced below are natural extensions of their conventional versions, which preserve the linear structures of the PID controllers, with simple and conventional analytical formulas as the final results of the design. Thus, they can directly replace the conventional PID controllers in any operating control systems (plants, processes).

The main difference is that these fuzzy PID controllers are designed by employing fuzzy logic control principles and techniques, to obtain new controllers that possess analytical formulas very similar to the conventional digital PID controllers.

3.3 Different Structures of Hybrid Fuzzy PID Controller

Han Xiong Li et.al, has proposed a two dimensional configuration for PID type FLC. In this paper optimal fuzzy reasoning model for control is proposed and is compared with conventional fuzzy control [3.14].

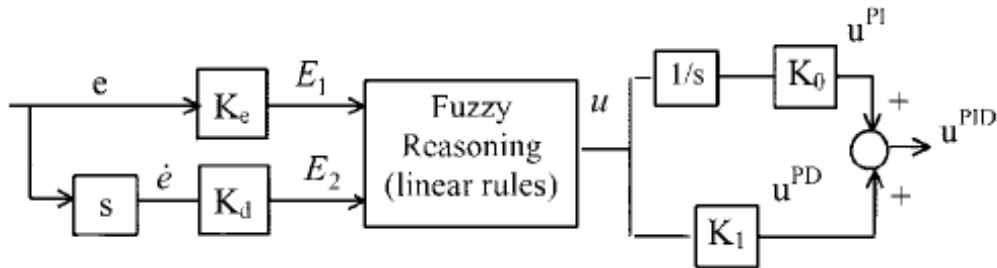


Figure 3.2: Architecture of fuzzy PID controller [3.14]

Y Zhang et.al, implemented a fuzzy PID hybrid controller for temperature control of melted aluminum in atomized furnace. In this architecture the input of fuzzy controller is error and change in error. α is the weighing factor. The total controller output is the summation of the output of fuzzy controller and PID controller. The output of Fuzzy-PID hybrid controller denoted by u is a combination of the output of fuzzy controller and the output of PID controller, symbolized as u_1 and u_2 respectively, involving a weighting calculation for bumpless switch between the two controllers. The weighting coefficient ' α ' as a function of e can decide which controller operating mainly according to e . The fuzzy controller works mostly if e is larger than set point, or else the PID controller becomes the main controller with a bumpless switch [3.17].

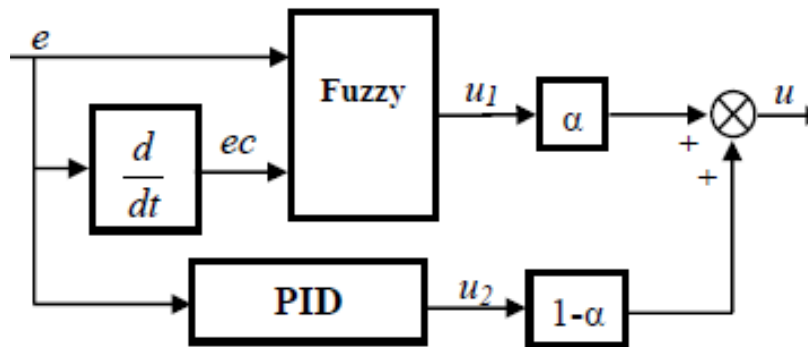


Figure 3.3: Architecture of fuzzy PID controller [3.17]

Seema Chopra et.al, has proposed an architecture for fuzzy PI controller shown in figure [3.18,3.22].

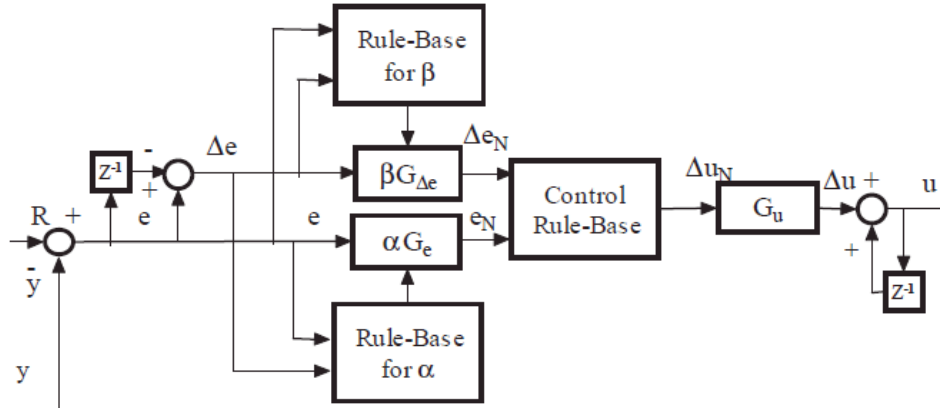


Figure 3.4: Architecture of fuzzy PID controller [3.18,3.22]

A M F Fileti et.al, has described another type of architecture for hybrid fuzzy PID control architecture [3.19].

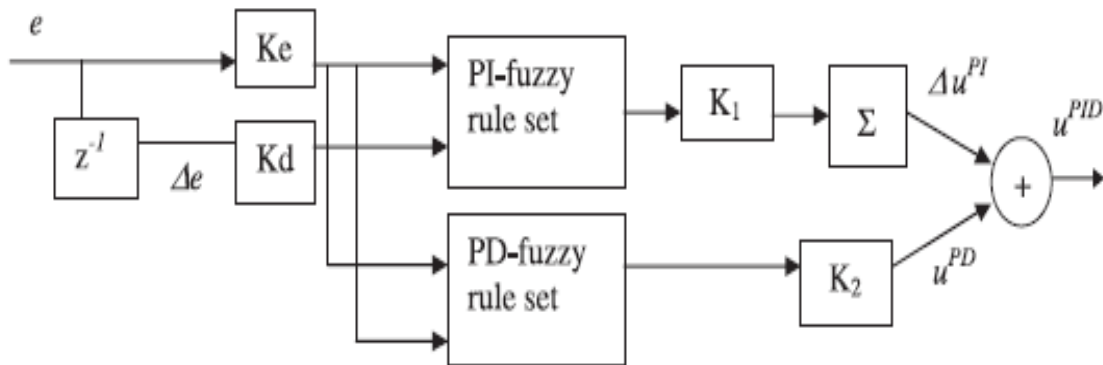


Figure 3.5: Architecture of hybrid fuzzy PID controller [3.19]

In this architecture the controller output value has two components, evaluated independently. One is the output of a PI-fuzzy controller in a velocity form. The other represents a PD-fuzzy controller in the position form. Besides the advantage of using two-dimensional rule set, instead of three-dimensional, the hybrid approach simplifies the control tuning.

Sufian Ashraf Mazhari et.al, has proposed a fuzzy PD+I controller for PUMA 560 robot and used different swarm intelligence and evolutionary techniques to tune the fuzzy PD+I controller. This paper also gives a comparative study of different swarm intelligence and evolutionary algorithm based tuning methods [3.25].

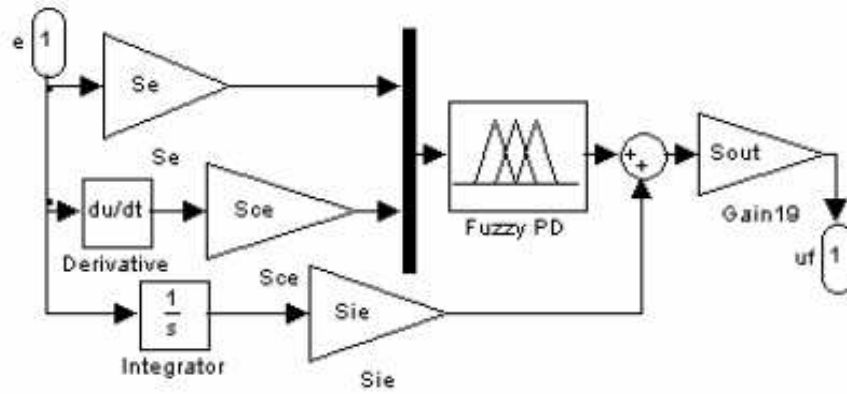


Figure 3.6: Architecture of fuzzy PID controller [3.25]

The scale factors are calculated as follows. The output equation is given by

$$u = (s_e e(k) + s_{ce} \dot{e}(k) + s_{ie} ie(k)) s_{out} \quad (66)$$

$$u = s_e s_{out} \left(e(k) + \frac{s_{ce}}{s_e} \dot{e}(k) + \frac{s_{ie}}{s_e} ie(k) \right) \quad (67)$$

From the above two equations we get the values of the tuning parameters

$$k_p = s_e s_{out} \quad (68)$$

$$\tau_d = \frac{s_{ce}}{s_e} \quad (69)$$

$$\frac{1}{\tau_i} = \frac{s_{ie}}{s_e} \quad (70)$$

3.4 Tuning of Fuzzy PID Controller

Seema Chopra et.al, proposed a method for tuning of fuzzy PI controller. The input scaling factors are tuned online by gain updating factor whose values are determined by fuzzy rule base [3.18].

Seema chopra et.al have proposed a neural network tuned fuzzy controller for MIMO systems from the given set of input and output data. An appropriate coupling tuned fuzzy controller is incorporated to control MIMO system to compensate for the dynamics of coupling [3.20].

3.5 Scaling Factor in Fuzzy Logic Controller

Scaling factor in a fuzzy logic controller is very important. Selection of suitable values for scaling factors are made based on the knowledge about the process to be controlled and sometimes through trial and error to achieve the best possible control performance. This is so because, unlike conventional non-fuzzy controllers to date, there is no well-defined method for good setting of scaling factors for fuzzy logic controllers. But the scaling factors are the main parameters used for tuning the fuzzy logic controller because changing the scaling factors changes the normalized universe of discourse, the domains, and the membership functions of input /output variables of fuzzy logic controller.

3.6 Hybrid Fuzzy Controller

This section gives a detail view of hybrid fuzzy controller designed to control the outlet temperature of shell and tube heat exchanger system. Figure 3.7 shows the parallel form of PID controller where all the elements (proportional, integral and derivative) are summed together to produce the control effect.

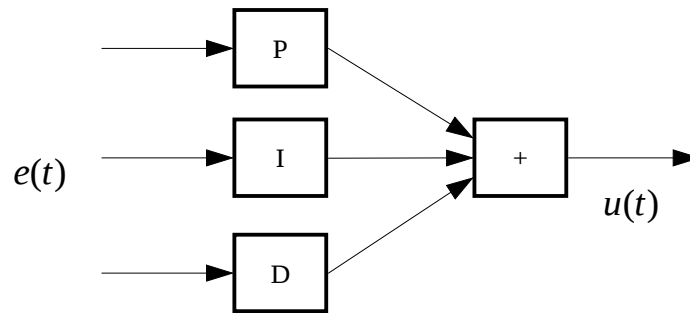


Figure 3.7: Parallel form of PID controller

The conventional design of PID controller was some what modified and a new hybrid fuzzy PID controller was designed. Instead of summation effect a mamdani based fuzzy inference system is implemented. The inputs to the mamdani based fuzzy inference system are error and change in error. Figure 3.8 shows the fuzzy inference system developed for hybrid fuzzy controller.

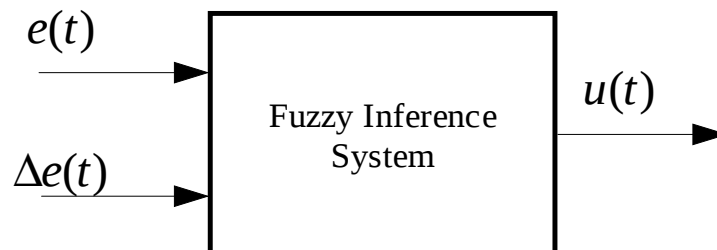


Figure 3.8: Mamdani based fuzzy inference system

Figure 3.9 shows the structure of hybrid fuzzy logic controller, which keeps the general architecture of PID controller as shown in figure 3.7 with some slight modifications. A mamdani based fuzzy inference system is implemented in between proportional and derivative term. The integral term is then added to the output of fuzzy inference system.

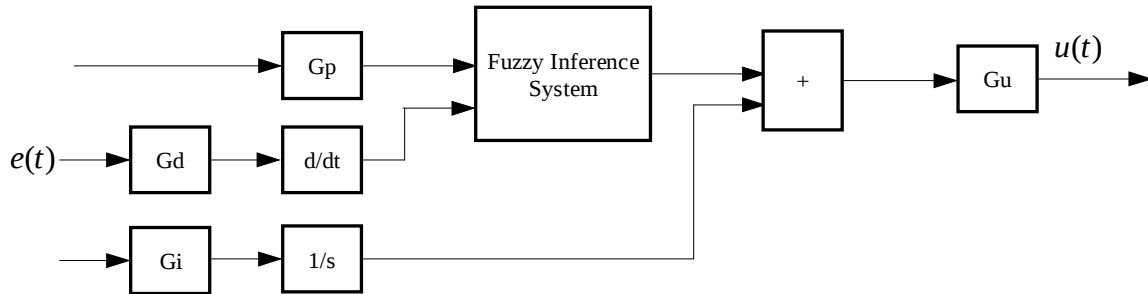


Figure 3.9: Proposed structure of hybrid fuzzy controller

G_p , G_d and G_i are scaling factors for the input where as G_u is the scaling factor for the output. In this design the input and output scaling factors are determined by trial and error methods and are taken very small. Figure 3.10 shows the fuzzy inference system for error and change in error.

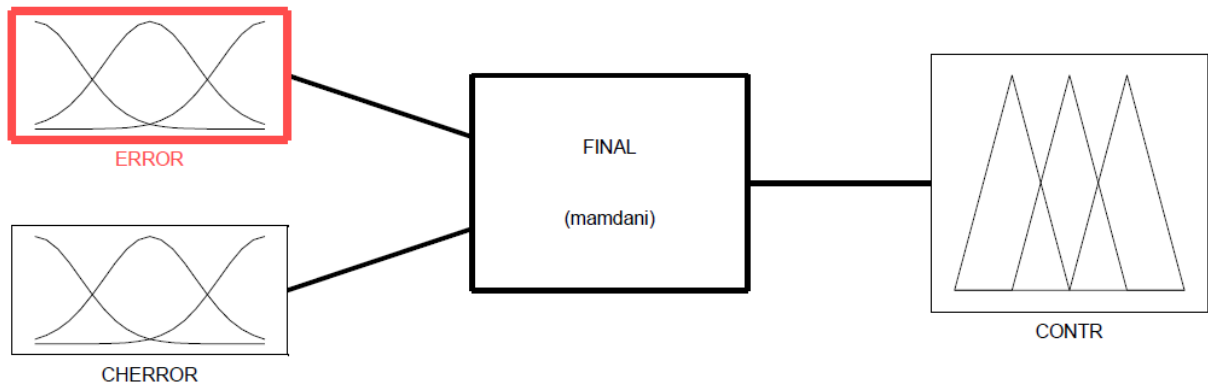


Figure 3.10: Mamdani fuzzy inference system for fuzzy controller

The mamdani based fuzzy inference system uses linear membership function for both inputs and outputs. The ranges of the values are normalized between -1 to 1. Figure 3.11 shows the membership functions for the input error.

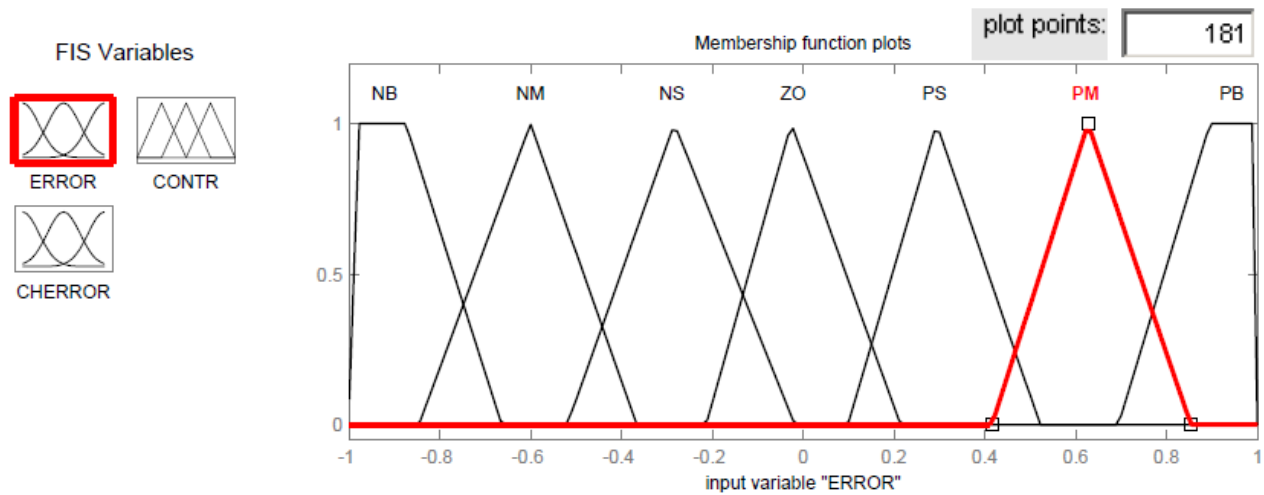


Figure 3.11: Membership function for input-1

Figure 3.12 shows the membership function for the input change in error.

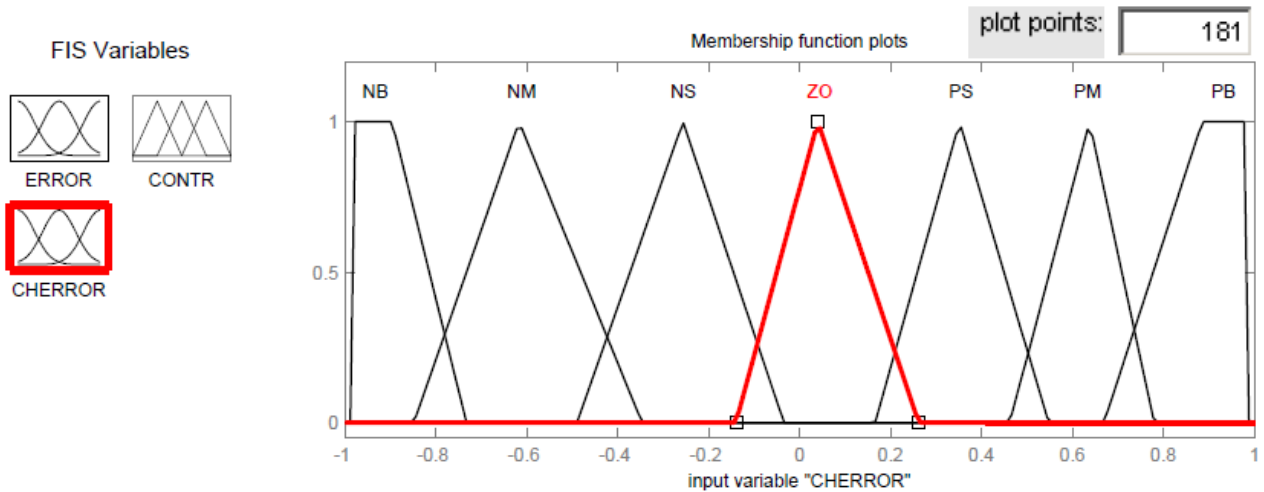


Figure 3.12: Membership function for input-2

Figure 3.13 shows the membership function for output.

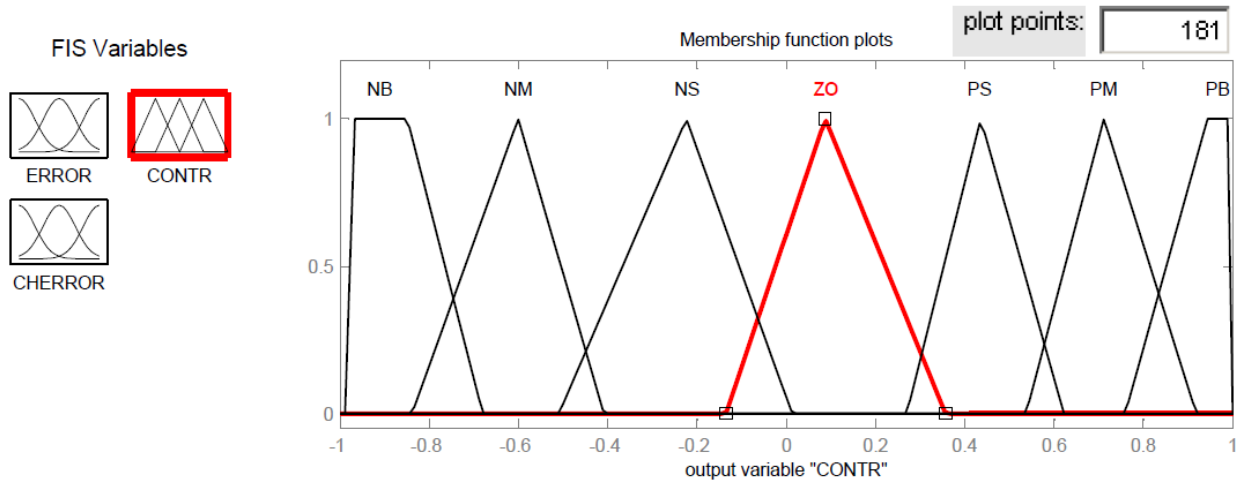


Figure 3.13: Membership function for output

The linguistic variables used in the membership functions are described in table 3.

Table 3.1: Linguistic variables in fuzzy inference system

Error $e(t)$		Change in error $\Delta e(t)$		Controller output $u(t)$	
NB	Negative Big	NB	Negative Big	NB	Negative Big
NM	Negative Medium	NM	Negative Medium	NM	Negative Medium
NS	Negative Small	NS	Negative Small	NS	Negative Small
ZO	Zero	ZO	Zero	ZO	Zero
PS	Positive Small	PS	Positive Small	PS	Positive Small
PM	Positive Medium	PM	Positive Medium	PM	Positive Medium
PB	Positive Big	PB	Positive Big	PB	Positive Big

In mamdani based fuzzy inference system IF-THEN rules are created. The IF-THEN rules of mamdani type fuzzy inference system is summarized in table 4.

Table 3.2: IF-THEN rules for fuzzy inference system

$u(t)$	$e(t)$							
		NB	NM	NS	ZO	PS	PM	PB
$\Delta e(t)$	NB	NB	NB	NB	NB	NM	NS	ZO
	NM	NB	NB	NB	NM	NS	ZO	PS
	NS	NB	NB	NM	NS	NS	PS	PS
	ZO	NB	NM	NS	ZO	ZO	PM	PM

	PS	NM	NS	ZO	PS	PS	PB	PB
	PM	NS	ZO	PS	PM	PM	PB	PB
	PB	ZO	PS	PM	PB	PB	PB	PB

The fuzzy rule base can be read as follows

IF $e(t)$ is NB and $\Delta e(t)$ is NB **THEN** $u(t)$ is NB

IF $e(t)$ is <negative big> and $\Delta e(t)$ is <negative big> **THEN** $u(t)$ is <negative big>

Figure 3.14 shows the Simulink representation of temperature control of shell and tube heat exchanger system with hybrid fuzzy controller.

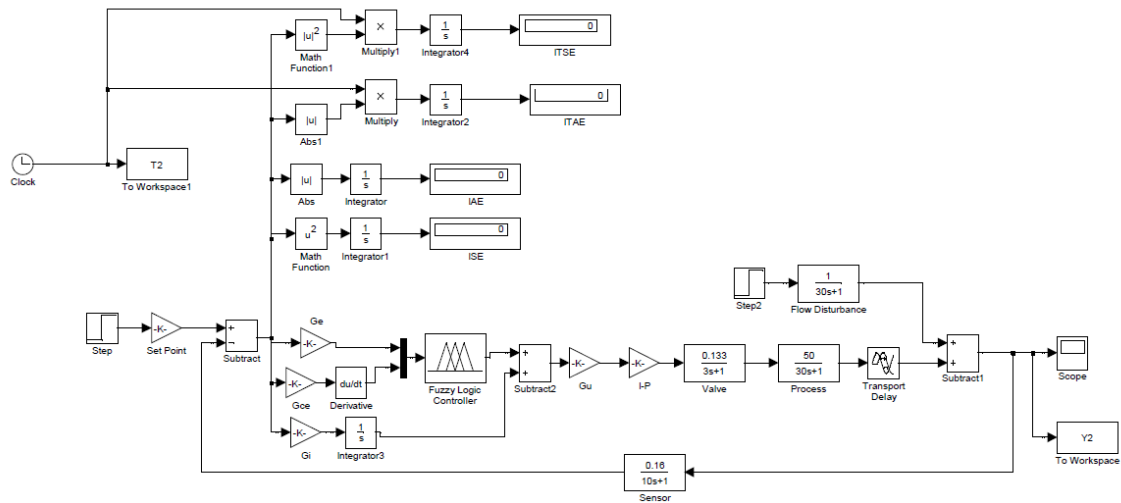


Figure 3.14: Simulink representation of shell and tube heat exchanger system with hybrid fuzzy controller

In chapter 2 feedback, feedback plus feed forward controller and internal model controller were implemented to control the outlet temperature of shell and tube heat exchanger system. But the conventional controller showed overshoot in the unit step response which is not at all desired. So in this chapter a hybrid fuzzy controller is implemented to control the outlet temperature of shell and tube heat exchanger system.

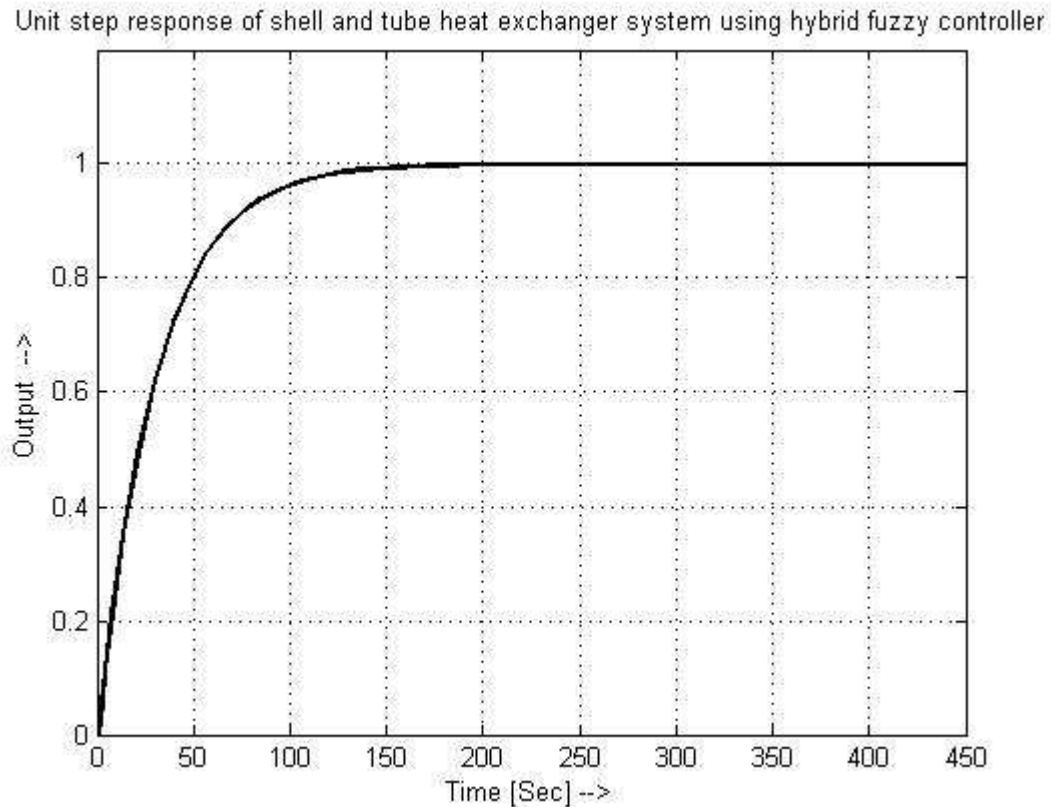


Figure 3.15: Unit step response of shell and tube heat exchanger system using hybrid fuzzy controller

Figure 3.15 shows the unit step response of shell and tube heat exchanger system using hybrid fuzzy controller. When fuzzy based hybrid controller is used to control the outlet temperature of shell and tube heat exchanger system, the peak overshoot becomes zero and settling time also reduces as compared to the different conventional controllers designed in chapter 2.

3.7 Fuzzy Based Auto Tuning of PID Controller

In section 2.7.6 a relay based auto tuning method of PID controller was discussed. In relay based auto tuning method a relay is placed in parallel to the PID controller and both the elements are connected with a manual switch. In this section a fuzzy based auto tuning of PID controller is proposed where PID controller and hybrid fuzzy controller is placed in parallel to each other and a manual switch or selector button is used to change between PID controller and hybrid fuzzy controller. Figure 3.16 shows the Simulink representation of fuzzy based auto tuning of PID controller.

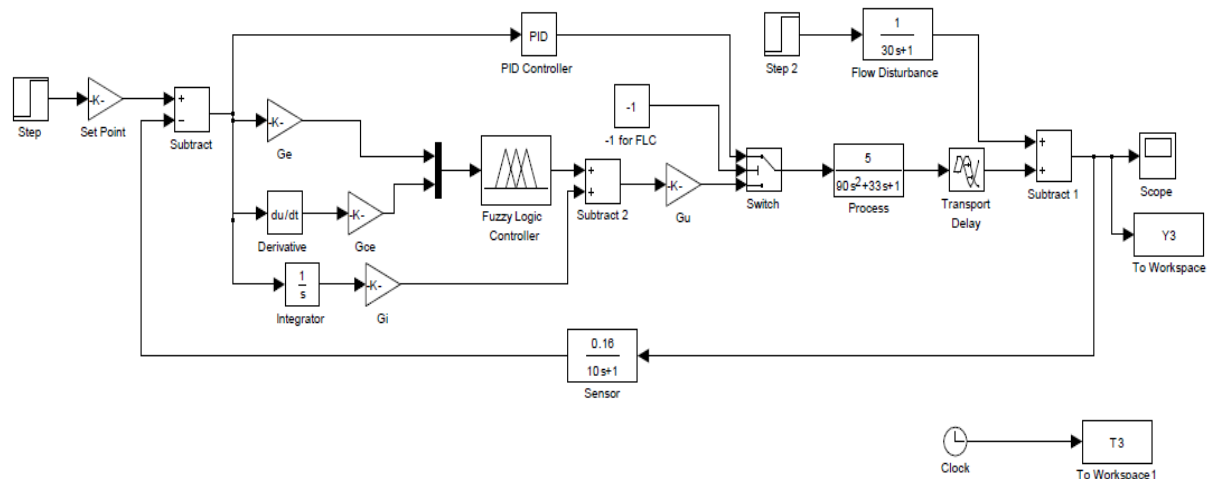


Figure 3.16: Simulink representation of fuzzy based auto tuning method of PID controller

As shown in figure 3.16 a hybrid fuzzy controller and a PID controller is placed in parallel to each other and a manual selector switch is used to change the controller choice between PID controller and hybrid fuzzy controller. If the selector switch is set to “-1” the hybrid fuzzy controller is activated or else PID controller is activated.

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Chapter

4

GA Based Optimization of Fuzzy Rule Base

In chapter 3 a hybrid fuzzy controller is proposed to control the outlet temperature of shell and tube heat exchanger system. In the hybrid fuzzy controller a two input fuzzy inference system was used and each inputs and output had 7 membership functions each. With each input having 7 membership functions, the rule base has 49 rules. This chapter looks in to the methods of reducing the size of the fuzzy rule base with the help of optimization algorithm.

4.1 Problems in Existing Fuzzy Inference System

A fuzzy inference system consists of fuzzy if-then rules such as “If x_1 is small and x_2 is small than y is large” in MAMDANI type and “If x_1 is small and x_2 is small than $y = f(x_1, x_2)$ ” in SUGENO type fuzzy inference system. The problem with existing fuzzy rule-based systems is that the size of the rule-base (number of rules) increases exponentially with the increase in the number of fuzzy sets. This exponential increase in size of the rule-base increases the search time and hence the computation time and memory space required also increases. The membership function selection process is done with trial and error and it runs step by step which is too long in completing the problem.

To minimize the computation time and memory space required different optimization techniques can be implemented in fuzzy rule base system. The optimization techniques will reduce the size of the rule base by eliminating the un-necessary rules and streamlining and organizing the existing rules.

4.2 Related Works

Khaled Belarbi et.al, proposed a new method for designing fuzzy logic controller. This method uses network implementation of fuzzy logic controller with real and binary weights with constraints [4.2].

France Cheong et.al, in his research paper proposes a genetic algorithm based method to produce near optimal fuzzy logic controller. This paper utilizes parallel GA method in different size

of rule bases. The paper compares the performance of the unconstrained fuzzy logic controller with constrained fuzzy logic controller [4.3].

A A Lofti Neyestanak et.al, presented an optimized E-shaped patch antenna which is optimized by genetic algorithm and based on fuzzy decision making [4.6].

Nanna Suryana Herman et.al, studies the use of GA in the design of fuzzy logic controller and shows how population size, probability of crossover and rate of mutation can affect the performance of the GA. This research develops a system that may help users to determine the membership function of fuzzy logic controller using the technique of GA optimization for the fastest processing in completing the problems. The system developed is very helpful to determine membership function and it is clear that the GA is very promising in improving the performance of the fuzzy logic controller to get more accurate in order to find the optimum result [4.23].

Mahesh Kumar et.al, reviewed the concept of genetic algorithm based optimization of fuzzy inference system [4.26].

Chia Feng Jhuang et.al, proposes the design of fuzzy-rule-based systems using continuous ant-colony optimization. Ant colony optimization determines the number of fuzzy rules and optimizes all the free parameters in each fuzzy rule. It uses an online-rule generation method to determine the number of rules and identify suitable initial parameters for the rules and then optimizes all the free parameters using continuous ant-colony optimization. In contrast to traditional ant colony optimization, which optimizes in the discrete domain, the RCACO optimizes parameters in the continuous domain and can achieve greater learning accuracy [4.28].

R. P Prado et.al, introduces a new method for the fuzzy-rule evolution that forms an expert system knowledge: the knowledge acquisition with a swarm-intelligence approach. Specifically, this strategy is based on the use of particle swarm optimization to obtain the antecedents, consequences, and connectives of the rules [4.30].

Asif Iqbal et.al, presents a two-stage approach for enhancing accuracy of prediction results. The first stage seeks best possible assignment of fuzzy sets of a response variable to the rules of a fuzzy rule-base, while the second stage looks for further improvement by adjusting shapes of the fuzzy sets of the response variable. For accomplishment of both of the stages, simulated annealing algorithm has been utilized and the approach has been practically applied on experimental data related to a turning process. The process has resulted in development of a rule-base Q1 that predicts with highly acceptable levels of accuracy [4.32].

4.3 Genetic Algorithm

Genetic algorithm introduced by Holland in 1975 can be used for optimization of existing rule base of fuzzy inference system. Genetic algorithm belongs to the group of optimization methods called as non traditional optimization methods. GA tries to imitate natural genetics and natural selection. The main philosophy behind GA is survival of the fittest. As a result GA is used primarily for maximization problems in optimization. GAs do not suffer from the basic setback of traditional optimization methods such as getting stuck in local minima. This is because GAs work on the principle of natural genetics, which incorporates large number of randomness.

4.3.1 Advantages of Genetic Algorithm

Advantages of GA's are given below

1. Simple to understand and to implement
2. It solves problems with multiple solutions.
3. Since the genetic algorithm execution technique is not dependent on the error surface, we can solve multi-dimensional, non-differential, non-continuous, and even non-parametrical problems.
4. Is well suited for parallel computers.
5. Optimizes variables with extremely complex cost surfaces (they can jump out of a local minimum).
6. Provides a list of optimum variables, not just a single solution.
7. Can encode the variables so that the optimization is done with the encoded variables i.e. it can solve every optimization problem which can be described with the chromosome encoding.
8. Works with numerically generated data, experimental data, or analytical functions. Therefore, works on a wide range of problems. For each problem of optimization in GAs, there are number of possible encodings. These advantages are intriguing and produce stunning results where traditional optimization approaches fail miserably. Due to various advantages as discussed above, GAs are used for a number of different application areas.

4.3.2 Limitations of Genetic Algorithm

In spite of its successful implementation, GA does possess some weaknesses leading to

1. Certain optimization problems (they are called variant problems) cannot be solved by means of genetic algorithms. This occurs due to poorly known fitness functions which generate bad chromosome blocks in spite of the fact that only good chromosome blocks cross-over.
2. There is no absolute assurance that a genetic algorithm will find a global optimum. It happens very often when the populations have a lot of subjects.
3. Genetic algorithm applications in controls which are performed in real time are limited because of random solutions and convergence, in other words this means that the entire population is improving, but this could not be said for an individual within this population. Therefore, it is unreasonable to use genetic algorithms for on-line controls in real systems without testing them first on a simulation model.
4. One well-known problem that can occur with a GA is known as premature convergence. If an individual that is more fit than most of its competitors emerges early on in the course of the run, it may reproduce so abundantly that it drives down the population's diversity too soon, leading the algorithm to converge on the local optimum that that individual represents rather than searching the fitness landscape thoroughly enough to find the global optimum.
5. One type of problem that genetic algorithms have difficulty dealing with are problems with "deceptive" fitness functions, those where the locations of improved points give misleading information about where the global optimum is likely to be found.

4.3.3 Flow chart of Genetic Algorithm

Figure 4.1 shows the flow chart of genetic algorithm. First of all an initial population (parents) is considered. Crossover operation is applied on the parents to produce offspring's. Fitness value is assigned in the population.

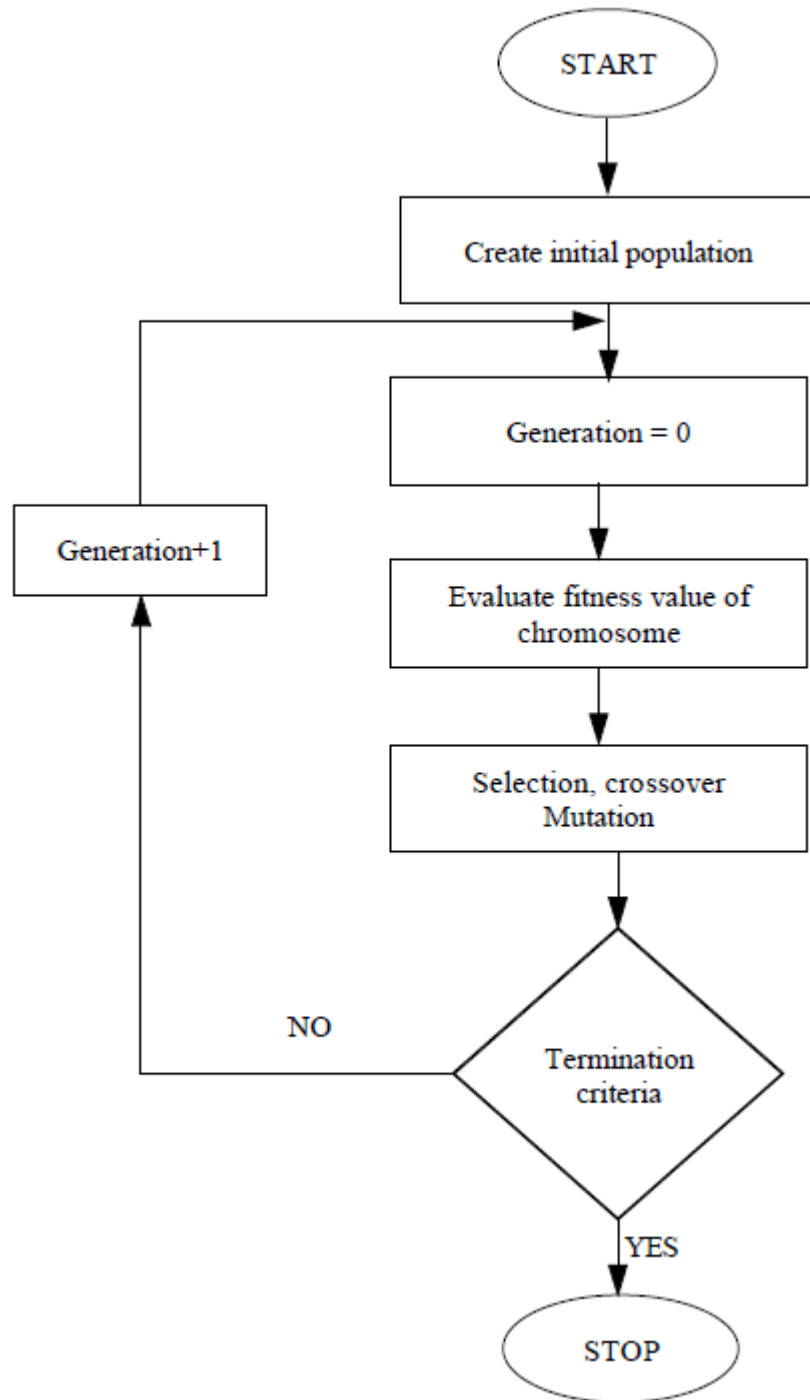


Figure 4.1: Flow chart of genetic algorithm

Again crossover operation is applied on the fittest two chromosomes. The termination criteria for a genetic algorithm can be epoch based or error based. If after repeated crossover the error fails to converge then mutation is applied, which gives the best results.

4.4 Operators of Genetic Algorithm

There are three basic operators of genetic algorithm namely

1. Reproduction
2. Crossover
3. Mutation

4.4.1 Reproduction

This operator is also called selection operator. This operator decides the strings to be selected for the next generation. This operator creates a mating pool where above average strings are copied in a probabilistic manner. The probability of selection of i^{th} string in to the mating pool is given by

$$P_i = \frac{F_i}{\sum_{j=1}^n F_j} \quad (71)$$

Here F_i is the fitness of i^{th} string and F_j is the fitness of j^{th} string. n is the population size

4.4.2 Crossover

Crossover operator introduces some amount of randomness in to the population in order to avoid getting trapped in to local searches. In crossover operation, new strings are formed by exchange of information among strings of the mating pool.

4.4.3 Mutation

Mutation operation aims to flip randomly selected bits in certain strings. The aim of mutation is to change the population members by small amount to promote local searches when the optimum is nearby.

4.5 Different Approaches of Optimization of Fuzzy Inference System

The optimization of the fuzzy inference system can be viewed in two approaches

1. Automatic rule base generation (Adaptation or learning)
2. Optimization of the existing rule base using genetic algorithm (Optimization)

The first method constitutes an automated design method of generation of fuzzy rules from scratch and the second method is concerned with optimization of an existing fuzzy inference system.

4.6 Challenges in Optimization of Existing Rule Base

From the viewpoint of optimization, the task is to find out an appropriate rule base for a particular problem, and to find those parameter values that are optimal with respect to the design

criteria. The rule base parameters constitute the optimization space, which is transformed into a suitable genetic representation in which the search process operates. The rule base of a fuzzy inference system does not constitute a homogeneous structure but is rather the union of qualitatively different components. The decision on which part of the rule base to adapt depends on two conflicting objectives:

1. Dimensionality
2. Efficiency of search

A search space of a smaller dimension results in a faster and simpler learning process, but the obtainable solutions might be suboptimal. A larger, complete search space that comprises the entire rule base and has a finer dimensionality is therefore more likely to contain optimal solutions, but the search process itself might become prohibitively inefficient and slow. With these considerations there is an obvious trade-off between the completeness and dimensionality of the search space and the efficiency of the search.

4.7 Steps of Optimization of Existing Rule Base Using GA

The optimization of fuzzy inference system with an existing rule base can be done in three phases

1. Knowledge Acquisition
2. Encoding
3. Optimization

In knowledge acquisition phase information from various knowledge sources i.e. experts and machine learning methods is integrated into a single knowledge base. In encoding phase rule set and corresponding membership functions from different knowledge sources is encoded into a variable length string or chromosomes so that they can contribute to the genetic optimization approach. In optimization phase genetic algorithm that results in an optimal or nearly optimal set of fuzzy rules and membership functions from the initial set of rules and membership function is proposed.

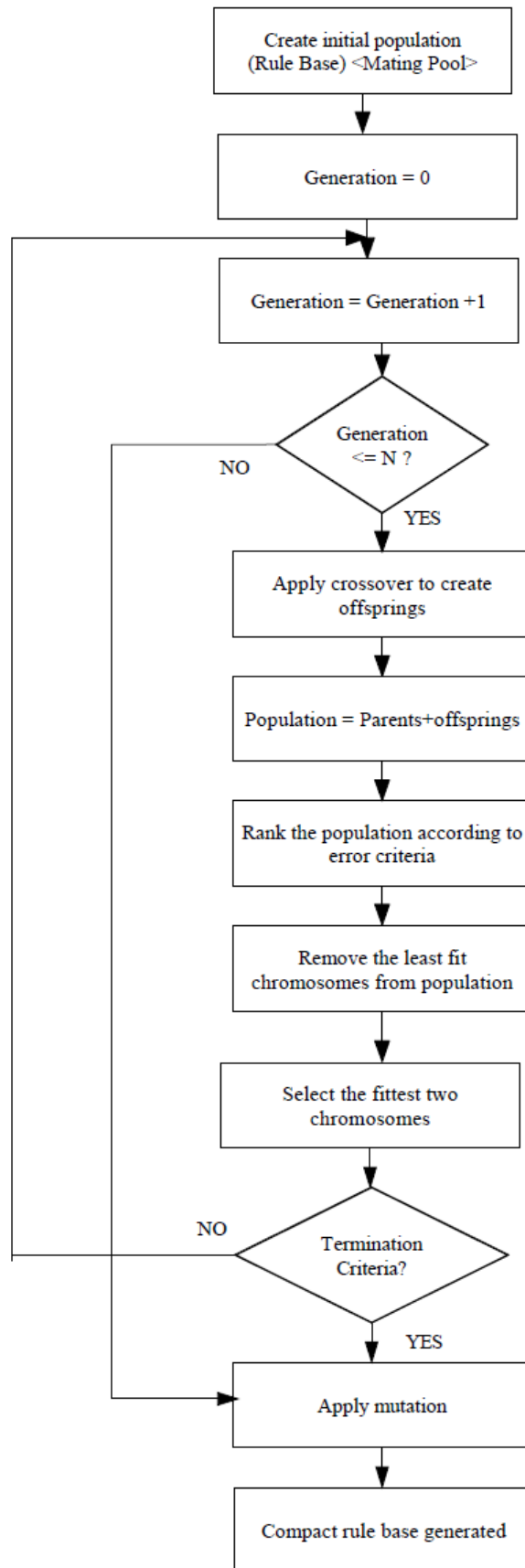


Figure 4.2: Flow chart for GA based optimization of existing rule base of fuzzy inference system

Figure 4.2 shows the flow chart for GA based optimization of existing rule base. As shown in the flow chart a optimized rule base is generated using genetic algorithm, by taking two fuzzy rule bases as parent chromosomes. The main problem of GA is that the optimal solution can get trapped in global optima and to get rid of that the generation counter concept is implemented.

4.8 Optimization of Existing Rule Base Using Genetic Algorithm

This section shows the step by step approach of optimizing an existing rule base using genetic algorithm. The hybrid fuzzy controller designed in chapter 3 uses the fuzzy if-else rule base shown in table 4.1.

The first step of genetic algorithm is to create initial population (parents). Here the objective is to optimize the rule base so the initial population is also rule base. Table 4.1 and table 4.3 represent the parent rule base. These rule bases gives satisfactory results. So these rule bases are considered as parents.

Table 4.1: Fuzzy rule base used as parent-1

u(t)	e(t)							
		NB	NM	NS	ZO	PS	PM	PB
$\Delta e(t)$	NB	NB	NB	NB	NB	NM	NS	ZO
	NM	NB	NB	NB	NM	NS	ZO	PS
	NS	NB	NB	NM	NS	NS	PS	PS
	ZO	NB	NM	NS	ZO	ZO	PM	PM
	PS	NM	NS	ZO	PS	PS	PB	PB
	PM	NS	ZO	PS	PM	PM	PB	PB
	PB	ZO	PS	PM	PB	PB	PB	PB

Table 4.2 represents the encoded rule base of table 4.1. Usually binary encoding is used in genetic algorithm but due to the complexity of the problem this kind of encoding is used.

Table 4.2: Encoded rule base of parent-1

u(t)	e(t)							
		0	1	2	3	4	5	6
0	0	0	0	0	0	1	2	3

$\Delta e(t)$	1	0	0	0	1	2	3	4
	2	0	0	1	2	2	4	4
	3	0	1	2	3	3	5	5
	4	1	2	3	4	4	6	6
	5	2	3	4	5	5	6	6
	6	3	4	5	6	6	6	6

Table 4.3 represents the fuzzy rule base used as parent-2.

Table 4.3: Fuzzy rule base used as parent-2

$u(t)$	$e(t)$							
		NB	NM	NS	ZO	PS	PM	PB
$\Delta e(t)$	NB	NB	NB	NM	NM	NM	NS	ZO
	NM	NB	NB	NM	NM	ZO	ZO	ZO
	NS	NB	NB	NS	NS	ZO	PS	PS
	ZO	NB	NM	NS	ZO	PS	PM	PB
	PS	NM	NS	ZO	PS	PS	PM	PB
	PM	NS	ZO	PS	PM	PM	PM	PB
	PB	ZO	PS	PM	PB	PM	PB	PB

Table 4.4 shows the encoded rule base of parent 2.

Table 4.4: Encoded rule base of parent-2

$u(t)$	$e(t)$							
		0	1	2	3	4	5	6
$\Delta e(t)$	0	0	0	1	1	1	2	3
	1	0	0	1	1	3	3	3
	2	0	0	2	2	3	4	4
	3	0	1	2	3	4	5	5
	4	1	2	3	4	4	5	5
	5	2	3	4	5	5	5	5
	6	3	4	5	6	5	6	5

Encoding Scheme is as follows. NB: 0, NM: 1, NS: 2, ZO: 3, PS: 4, PM: 5, PB: 6

4.8.1 Parameters of Genetic Algorithm

1. Maximum size of the population = 4
2. Maximum number of generation = 4
3. Type of crossover = Two point
4. Error criteria = ITAE (integral time absolute error)
5. Type of optimization = Minimize
6. Percentage of crossover = 70%
7. Probability of mutation = 0.01

Table 4.2 and table 4.4 represent the parent population of genetic algorithm. Each parent has 7 individual chromosomes. The next step of genetic algorithm is crossover between the parents to produce the offspring's. After cross over the parents RB1 and RB2 produce the offspring's RB3 and RB4. RB3 and RB4 are rule bases with 7 chromosomes each. Table 4.5 summarizes the individual chromosomes of parents and chromosomes produced after crossover of parents.

Table 4.5: Individual chromosomes of parents and offsprings

Chromosomes	Initial Population		After Crossover	
	Parent1(RB1)	Parent2(RB2)	Offspring1(RB3)	Offspring2(RB4)
C1	0000123	0011123	0001032	0011132
C2	0001234	0011333	0002143	0013133
C3	0012244	0022344	0021424	0023244
C4	0123355	0123455	0132535	0124355
C5	1234466	1234455	1236446	1235445
C6	2335566	2345555	2335665	2354555
C7	3456666	3456565	3456666	3455656

Table 4.6 and table 4.7 shows the detail rule base generated after crossover of parents rule base RB1 and RB2. These are represented as RB3 and RB4.

Table 4.6: Offspring's-I created after crossover of parent 1 and parent 2

u(t)	e(t)							
		0	1	2	3	4	5	6
$\Delta e(t)$	0	0	0	0	1	0	3	2
	1	0	0	0	2	1	4	3
	2	0	0	2	1	4	2	4
	3	0	1	3	2	5	3	5
	4	1	2	3	6	4	4	6
	5	2	3	3	5	6	6	5
	6	3	4	5	6	6	6	6

Table 4.7: Offspring's-II created after crossover of parent 1 and parent 2

u(t)	e(t)							
		0	1	2	3	4	5	6
$\Delta e(t)$	0	0	0	1	1	1	3	2
	1	0	0	1	3	1	3	3
	2	0	0	2	3	2	4	4
	3	0	1	2	4	3	5	5
	4	1	2	3	5	4	4	5
	5	2	3	5	4	5	5	5
	6	3	4	5	5	6	5	6

The size of population and the number of iteration is kept fixed at 4. The objective is to reduce the integral time absolute error. So the integral time absolute error is calculated for every rule base. The fittest rule bases are taken forward for crossover and the worst fit rule base (high value of ITAE) are removed from the population.

Table 4.8: Step by step approach of optimization of existing fuzzy rule base

Number of generations	Ranking of population according to ITAE	Selection of best population and rejection of worst
1 st Generation	RB1 = 179.7	RB1 and RB4 are best and are taken to next generation for crossover
	RB4 = 181.9	
	RB3 = 183.8	

	RB2 = 184.5	RB2 & RB3 are removed
2 nd Generation	RB1 = 179.7	RB1 and RB5 are best and are taken to next generation for crossover
	RB5 = 180.8	
	RB4 = 181.9	RB4 & RB6 are removed
	RB6 = 182.1	
3 rd Generation	RB1 = 179.7	RB1 and RB7 are best and are taken to next generation for crossover
	RB7 = 179.8	
	RB5 = 180.8	RB5 & RB8 are removed
	RB8 = 183.5	
4 th Generation	RB7 = 178.4	RB1 and RB7 are best and are taken to next generation for crossover
	RB1 = 179.7	
	RB9 = 182.4	RB9 & RB10 are removed
	RB10 = 183.6	

After 4 generations, the chromosomes don't meet the termination criteria. So, apply mutation in best chromosome (RB7). After mutation the value of ITAE for RB7 is 169.5

4.9 Limitations of the Proposed Method

Though the use of GA can produce near optimal FLC, it raises problems such as messy overlapping of fuzzy sets and rules not in agreement with common sense.

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Chapter 5

Identification, Estimation and Optimization of Fuzzy Membership Functions

Design of an efficient fuzzy logic controller involves the optimization of parameters of fuzzy sets (membership function) and proper choice of rule base. There are several techniques reported in recent literature that use neural network architecture and genetic algorithms to learn and optimize a fuzzy logic controller. The first step to build an efficient fuzzy inference system is to identify the membership function from the experimental data. There is no pre defined rules for calculating number of membership functions and range of membership functions. At this point system identification comes in to act. With the help of system identification and estimation the designer can determine the number of membership functions and ranges of membership functions. After membership function is designed, rule base is created. A new fuzzy rule base can be created by neural network learning approach or else the existing rule base can be optimized by the help of evolutionary or swarm optimization techniques, the later aspect was discussed in chapter 4. Like the existing rule base optimization, the pre defined membership functions can also be optimized using evolutionary and swarm intelligence techniques. In chapter 5 different approaches of identification, estimation of a new fuzzy membership function is described and different methods of optimization of existing fuzzy membership function is also discussed.

5.1 System Identification

System identification is the art and science of building mathematical models of dynamic systems from observed input–output data. It can be seen as the interface between the real world of applications and the mathematical world of control theory and model abstractions [5.17]. System identification is an essential requirement in areas such as control, communication, power system and instrumentation for obtaining a model of a system (plant) of interest or a new system to be developed and for the purpose of development of control law, analysis fault diagnosis, etc. Major advances have been made in adaptive identification and control, in past few decades for identifying

linear time-invariant plants with unknown parameters. The choice of the identifier structure is based on well established results in linear systems theory. Stable adaptive laws for the adjustment of parameters in these which assures the global stability of the relevant overall systems are also based on properties of linear systems as well as stability results that are well known for such systems.

The area of system identification is one of the most important areas in engineering because most of the dynamical system behavior can be obtained exploiting system identification techniques. For identifying an unknown dynamic systems two things are important i.e. model structure and then parameters. Adaptive modeling and system identification are prerequisite before going to design a controller for an on-line plant, say for a scenario an on-line plant requires a controller for improving its performance. The controller cannot be operated on the on-line plant as it may disturb the entire production which may be cost effective, so a model is required which represents the on-line plant. If there is adaptability in modeling there is more chance of controlling the model on-line thus System identification concerns with the determination of a system, on the basis of input output data samples. The identification task is to determine a suitable estimate of finite dimensional parameters which completely characterize the plant. The selection of the estimate is based on comparison between the actual output sample and a predicted value on the basis of input data up to that instant. An adaptive automaton is a system whose structure is alterable or adjustable in such a way that its behavior or performance improves through contact with its environment. Depending upon input-output relation, the identification of systems can have two groups

1. Static system identification
2. Dynamic system identification

5.1.1 Static System Identification

In this type of identification the output at any instant depends upon the input at that instant. These systems are described by the algebraic equations. The system is essentially a memory less one and mathematically it is represented as $y(n) = f[x(n)]$ where $y(n)$ is the output at the n th instant corresponding to the input $x(n)$.

5.1.2 Dynamic System Identification

In this type of identification the output at any instant depends upon the input at that instant as well as the past inputs and outputs. Dynamic systems are described by the difference or differential equations. These systems have memory to store past values and mathematically

represented as $y(n) = f[x(n), x(n-1), x(n-2) \dots y(n-1)]$ where $y(n)$ is the output at the n^{th} instant corresponding to the input $x(n)$.

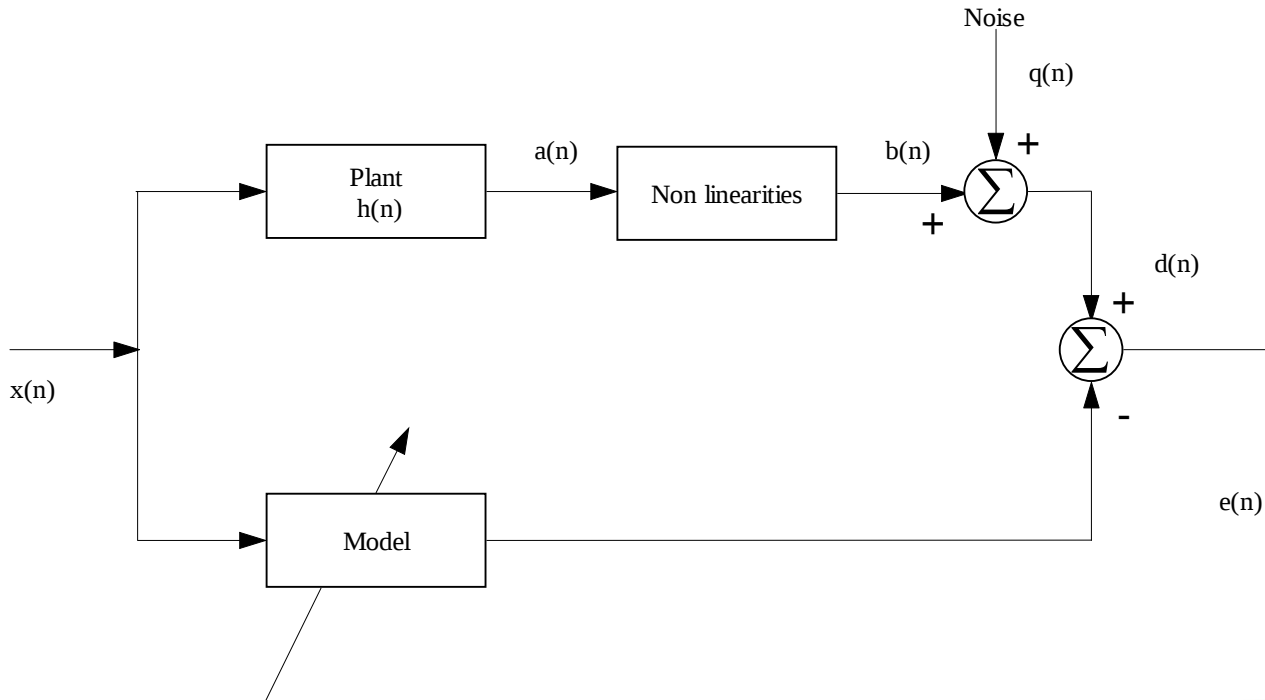


Figure 5.1: Structure of system identification

A system identification structure is shown in figure 5.1. The model is placed parallel to the nonlinear plant and same input is given to the plant as well as the model. The impulse response of the linear segment of the plant is represented by $h(n)$ which is followed by nonlinearity (NL) associated with it. White gaussian noise $q(n)$ is added with nonlinear output accounts for measurement noise. The desired output $d(n)$ is compared with the estimated output $y(n)$ of the identifier to generate the error $e(n)$ which is used by some adaptive algorithm for updating the weights of the model. The training of the filter weights is continued until the error becomes minimum and does not decrease further. At this stage the correlation between input signal and error signal is minimum. Then the training is stopped and the weights are stored for testing. For testing purpose new samples are passed through both the plant and the model and their responses are compared. System identification is the experimental approach to process modeling. System identification includes the following steps

- Step 1: Experimental design
- Step 2: Choice of the criterion to fit
- Step 3: Parameter estimation

Step 4: Model validation

Experiment Design: Its purpose is to obtain good experimental data and it includes the choice of the measured variables and of the character of the input signals.

Selection of model structure A suitable model structure is chosen using prior knowledge and trial and error.

Choice of the Criterion to Fit: A suitable cost function is chosen, which reflects how well the model fits the experimental data.

Parameter Estimation: An optimization problem is solved to obtain the numerical values of the model parameters.

Model Validation: The model is tested in order to reveal any inadequacies.

Modeling is also important outside the traditional engineering discipline such as modeling of social systems, modeling of economic systems and modeling of biological systems. An adaptive filter can be used in modeling. This filter imitates the behavior of physical systems which may be regarded as unknown system termed as “black boxes” having one or more inputs and one or more outputs. The essential and principal property of an adaptive system is its time-varying, self-adjusting performance. The adaptive systems have following characteristics

1. They can automatically adapt (self-optimize) in the face of changing (non-stationary) environments and changing system requirements.
2. They can be trained to perform specific filtering and decision making tasks.
3. They can extrapolate a model of behavior to deal with new situations after trained on a finite and often small number of training signals and patterns.
4. They can repair themselves to a limited extent.
5. They can be described as nonlinear systems with time varying parameters.

The adaptation is of two types

1. Open-loop adaptation
2. Closed-loop adaption

The open-loop adaptive process is shown in figure 5.2 (a). It involves making measurements of input or environment characteristics, applying this information to a formula or to

a computational algorithm, and using the results to set the adjustments of the adaptive system. The adaptation of process parameters don't depend upon the output signal.

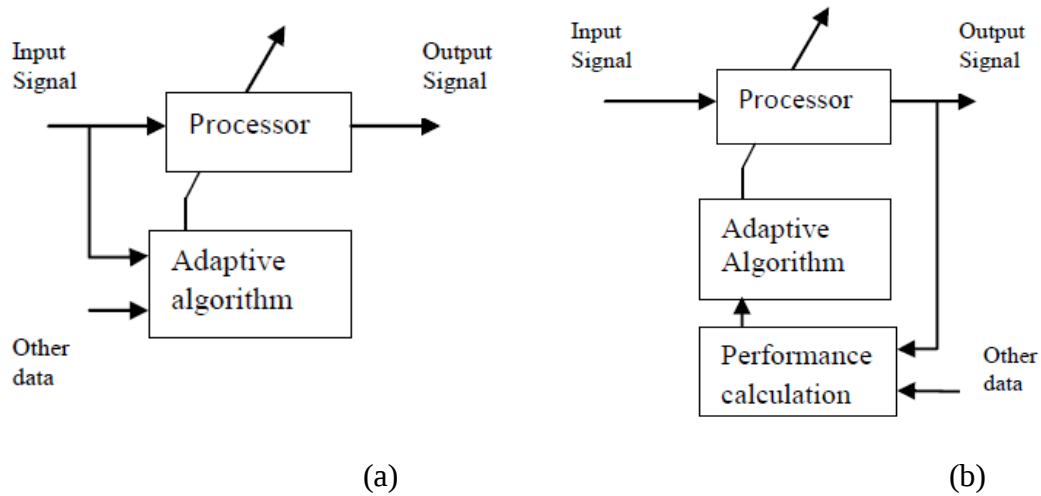


Figure 5.2 (a) Open loop adaption

(b) Closed loop adaption

Closed-Loop Adaptation: Close-loop adaptation (as shown in figure 5.2 (b)) on the other hand involves the automatic experimentation with these adjustments and knowledge of their outcome in order to optimize a measured system performance. The latter process may be called adaptation by performance feedback. The adaptation of process parameters depends upon the input as well as output signal.

System identification techniques are two types

1. Direct Modeling
2. Indirect Modeling

Direct Modeling: In this type of modeling the adaptive model is kept parallel with the unknown plant. Modeling a single-input, single-output system is illustrated in figure 5.3. Both the unknown system and adaptive filter are driven by the same input. The adaptive filter adjusts itself in such a way that its output is match with that of the unknown system. Upon convergence, the structure and parameter values of the adaptive system may or may not resemble those of unknown systems, but the input-output response relationship will match. In this sense, the adaptive system becomes a model of the unknown plant. Let $d(n)$ and $y(n)$ represent the output of the unknown system and adaptive model with $x(n)$ as its input

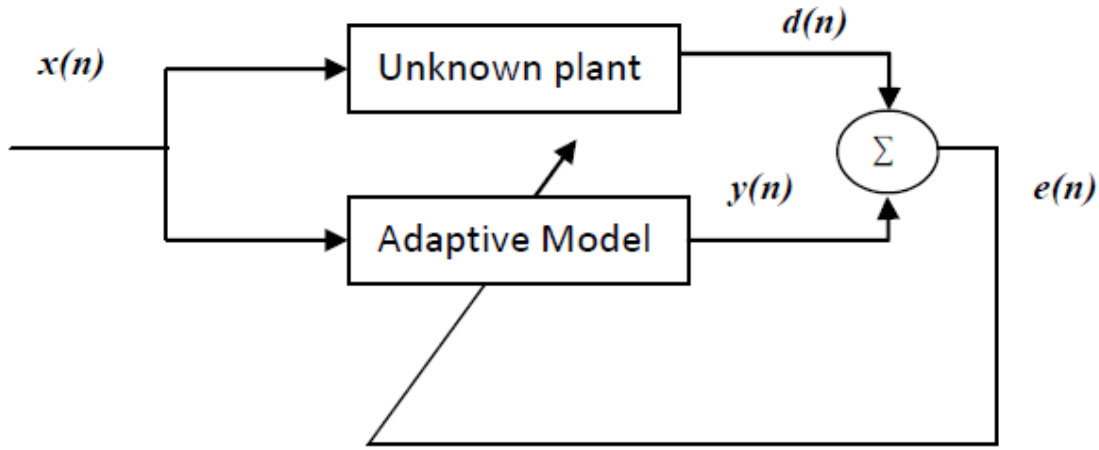


Figure 5.3: Direct modeling system identification

Here, the task of the adaptive identifier is to accurately represent the signal $d(n)$ at its output. If $y(n) = d(n)$, then the adaptive identifier has accurately modeled or identified the portion of the unknown system that is driven by $x(n)$. Since the model typically chosen for the adaptive identifier is a linear identifier, the practical goal of the adaptive identifier is to determine the best linear model that describes the input-output relationship of the unknown system. Such a procedure makes the most sense when the unknown system is also a linear model of the same structure as the adaptive identifier, as it is possible that $y(n) = d(n)$ for some set of adaptive filter parameters.

Inverse Modeling: We now consider the general problem of inverse modeling, as shown in figure 5.4. In this diagram, a source signals $s(n)$ is fed into a plant that produces the input signal $x(n)$ for the adaptive identifier. The output of the adaptive identifier is subtracted from a desired response signal that is a delayed version of the source signal, such that $d(n) = s(n - \Delta)$

Here Δ is a positive integer value.

The goal of the adaptive identifier is to adjust its characteristics such that the output signal is an accurate representation of the delayed source signal.

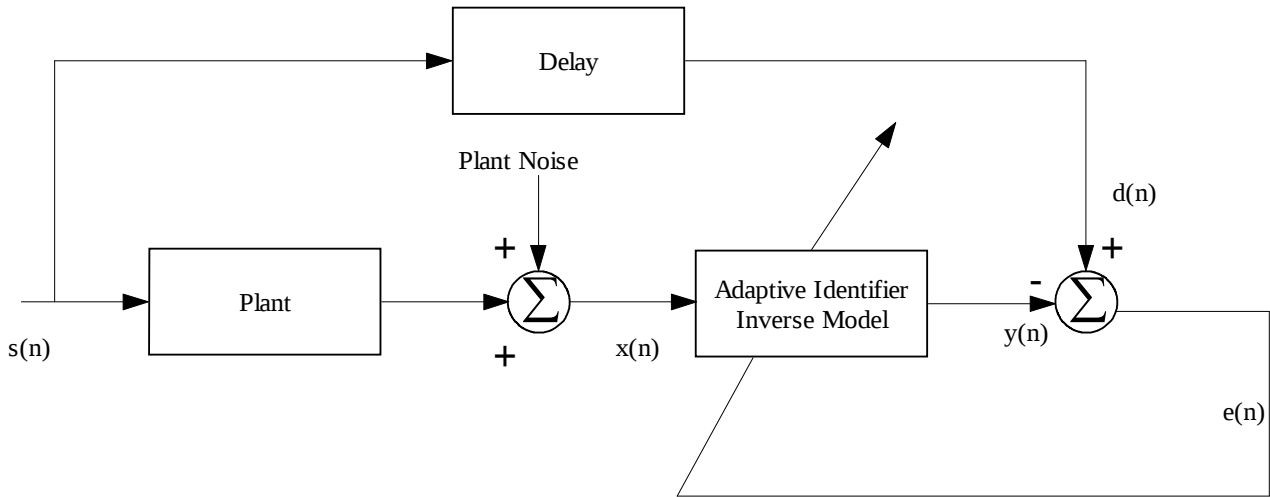


Figure 5.4: Inverse modeling of system

Channel equalization is an important application of inverse modeling. In channel equalization the inverse model of the channel is modeled and the channel effects of multi-path and inter symbol interference (ISI) are reduced.

5.2 Related Works

M Delgado et.al, has studied the use of non linear membership functions in fuzzy linear programming model [5.1].

Kit sang Tang et.al, implemented hierarchical genetic algorithm to fine tune the membership functions and fuzzy rule base in a water pressure pumping system [5.2].

J Valente de Oliveira addresses the difficulty of fuzzy sets and points out a set of constraints that when used within an optimization scheme obviate the subjective task of interpreting membership functions. To achieve this a comprehensive set of semantic properties that membership functions should have is postulated and discussed. These properties are translated in terms of nonlinear constraints that are coded within a given optimization scheme, such as backpropagation. Implementation issues and one example illustrating the importance of the proposed constraints are included [5.4].

Sushmita Mitra et.al, proposes a novel attempt in providing an exhaustive survey of neuro-fuzzy rule generation algorithms [5.5].

Hector Pomares et.al, presents a reliable method to obtain the structure of a complete rule-based fuzzy system for a specific approximation accuracy of the training data, i.e., it can decide which input variables must be taken into account in the fuzzy system and how many membership

functions (MFs) are needed in every selected input variable in order to reach the approximation target with the minimum number of parameters [5.6].

Tandar Pal et.al, presents a self-organized genetic algorithm based rule generation (SOGARG) method for fuzzy logic controllers. It is a three-stage hierarchical scheme that does not require any expert knowledge and input-output data. The first stage selects rules required to control the system in the vicinity of the set point. The second stage starts with the rules resulted from the first stage and extends its span of operation to the entire input space. Thus, the second stage ends up with a rule base that can bring the system to its set point from almost all initial states of the input space. The third stage then refines the rule base and reduces the number of rules in the rule base [5.9].

Manish Kumar et.al, propose a method to learn and optimize the parameters of fuzzy logic controllers with the help of neural network and genetic algorithm. This strategy is applied to control inverted pendulum. It is observed that neuro-fuzzy approach and GA-fuzzy approach is suitable to train the fuzzy logic controller and optimize the controller [5.11].

Yongshang Zhao et.al, proposes a new method utilizing ant colony algorithm (ACA) to optimize the fuzzy membership function's parameters, which overcoming the subjectivity and blindness in the process of designing the input or output membership functions. The fuzzy controller, which is optimized by ACA, is applied to a second order model and the simulation results shown a better result [5.13].

H Kharati et.al, presents a hybrid approach to determine fuzzy rules and membership functions simultaneously. This approach consists of GA which determines the fuzzy rule base and H filtering which fine tunes the membership function. Automotive cruise control is taken as a case study to implement this hybrid approach [5.14].

Gu Fang et.al, presents the particle swarm optimization technique is employed to automatically tune the MFs of a Mamdani-type of fuzzy controller. The effectiveness of the proposed controller is demonstrated by the control performance of such an FLC of a nonlinear water tank system. The results are compared favourably to a PSO tuned PID controller [5.15].

Chairul Saleh et.al, used GA to optimize the fuzzy membership function. The fuzzy inference system in the case study is used to predict the credit status of a bank [5.16].

5.3 Identification of Fuzzy Membership Function

Membership optimization problem can be reduced to a parameter optimization problem. The parameter optimization problem can then be formulated as a nonlinear filtering problem. In this chapter the nonlinear filtering problem is solved using H^∞ state estimation theory. But this approach has a drawback that the membership values don't add up to unity. So a state constraint is added up with the H^∞ filtering. H^∞ is similar to Kalman filtering but it is more robust than Kalman filtering in presence of noise, modeling error and non linearity. Membership function optimization involves high level of non linearity so H^∞ approach is used.

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Chapter

6

Results and Discussions

In chapter 2 different conventional controller were designed to control the outlet temperature of shell and tube heat exchanger system. In chapter 3 hybrid fuzzy controller was designed to control the outlet temperature of shell and tube heat exchanger system. This chapter evaluates the performance of the conventional and intelligent controller. The performance evaluation scheme is shown in figure 1.1. Performance evaluation scheme of controller is done using both time response analysis and frequency response analysis. In time response analysis unit step response of the respective controller is evaluated and maximum overshoot and settling time is calculated. To study the performance of the controller different performance indices (IAE, ISE, ITAE and ITSE) are calculated.

In frequency domain analysis robustness analysis and sensitivity analysis is performed. In robustness analysis bode plot is studied and gain margin, phase margin are calculated. In sensitivity analysis sensitivity of the controller is calculated.

6.1 Controller Performance Evaluation in Time Domain

Control systems are inherently time domain systems subject to time varying inputs and are to be analyzed and tested using time domain test signals like unit step signal.

6.1.1 Controller Performance Evaluation Using Unit Step Response Method

In step response analysis different parameters are considered. From those parameters there are two most important parameters, these are peak overshoot and settling time.

Peak Overshoot: It indicates the normalized difference between the time response peak and steady

output. It is defined as $\%M_p = \frac{c(t_p) - c(\infty)}{c(\infty)} * 100\%$ (72)

Settling Time: It is the time required for the response to reach and stay within a specified tolerance band of its final value. The tolerance band is taken randomly as 5%.

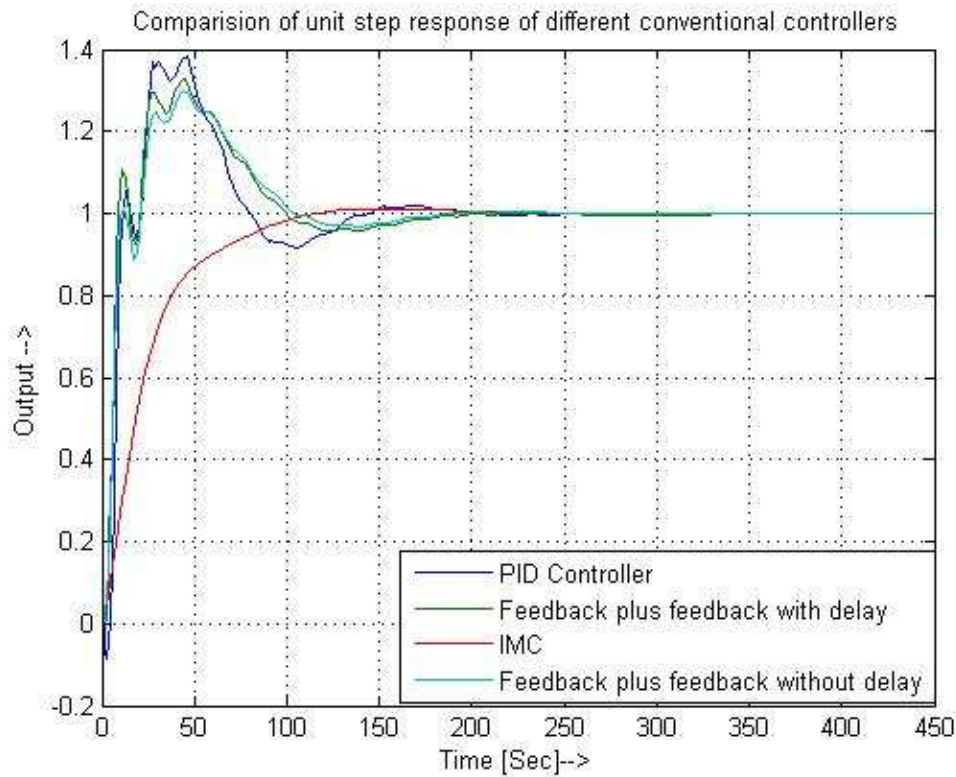


Figure 6.1: Comparison of unit step response of different conventional controllers

Figure 6.1 shows the comparison of unit step response of different conventional controllers. The PID controller shows a peak overshoot of 38%, a feed forward and feedback controller reduces the peak overshoot to 30% and the model based controller (IMC) significantly reduces the peak overshoot and the peak overshoot of IMC is 1%. It is clear from the step response analysis that the model based controllers give a better control than the conventional feedback and feed forward controllers.

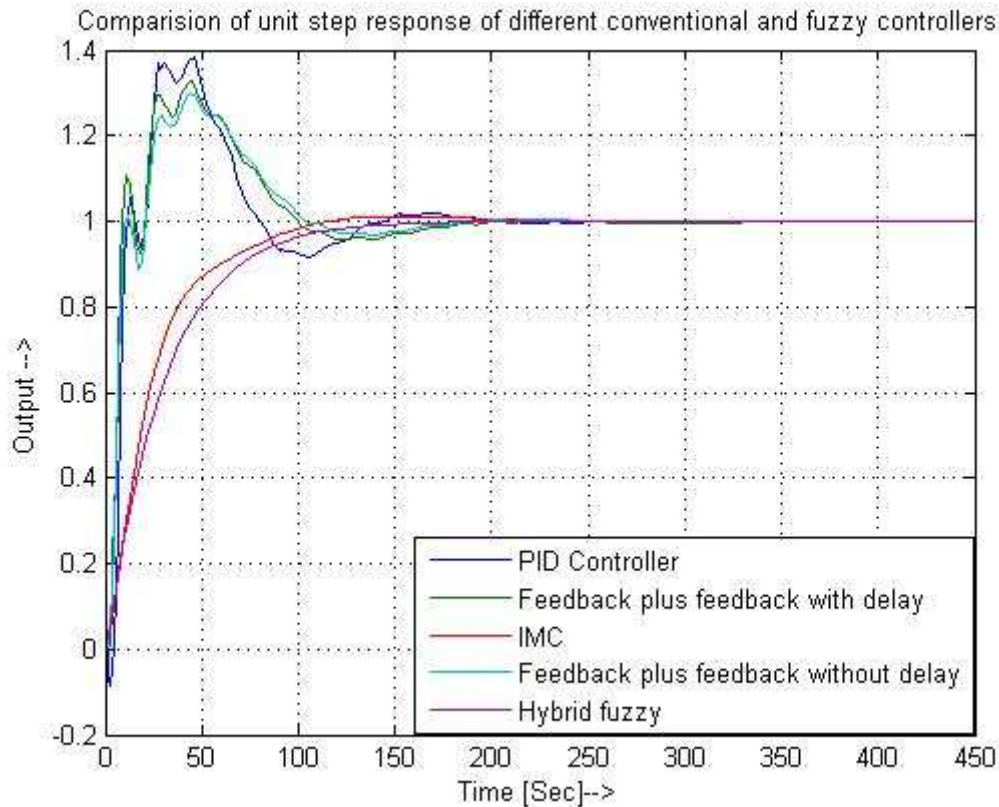


Figure 6.2: Comparison of unit step response of different conventional and hybrid fuzzy controllers

Figure 6.2 shows the comparison of unit step response of different conventional and fuzzy controller. The model based controller IMC significantly reduced the overshoot but to give some intelligence to the controller and to get near zero overshoot, a fuzzy based hybrid controller is used. The hybrid fuzzy controller retains the linearity characteristics of PID controller and gives a fuzzy touch to it. The unit step response of hybrid fuzzy controller gives a near zero peak overshoot or no overshoot. Table 6.1 summarizes all the results.

Table 6.1: Comparison of peak overshoot and settling time of different controllers

Sl.No	Type of Controller	Peak Overshoot	Settling Time
1	Feedback	38.38%	115.2 sec
2	Feedback plus feed forward (No delay in disturbance)	30.04%	91.34 sec
3	Feedback plus feed forward (Unit delay in disturbance)	32.51%	86.16 sec
4	Internal model controller	1.13%	77.79 sec
5	Hybrid fuzzy	0%	74.38 sec

Table 6.1 gives a comparative analysis of peak overshoot and settling time of different controllers designed to control the outlet temperature of shell and tube heat exchanger system.

The feedback controller (PID controller) gives 38.38% peak overshoot and 115.2 sec settling time. The peak overshoot is in a higher side. To compensate the high peak overshoot, feed-forward controller was designed. The feed forward controller estimates the error and compensates it. In this project two types of feed forward controller is developed. In the first case it is assumed that there is no time delay between the unit step input to the process and unit step disturbance. In this case the combined effect of feedback and feed forward controller gives a peak overshoot of 30% and settling time is 91.3 sec. in the second case, it is assumed that there is a unit time delay between unit step input to the process and unit step disturbance. In the second case though the peak overshoot somewhat rises to 32.51% but the settling time reduces to 86.16 sec. but after the implementation of feed forward plus feedback controller still the peak overshoot is 30% which is very high. To further reduce the peak overshoot, model based controller (internal model controller) was designed. The internal model controller reduces the peak overshoot to 1.13% and reduces the settling time to 77.79 sec. To further improve the peak overshoot, fuzzy based hybrid controller was designed. The fuzzy based hybrid controller gives a peak overshoot of 0% (no overshoot) and reduces the settling time to 74.38 sec.

From the table 6.1 it is clear that the model based and fuzzy based controller gives a better control results as compared to feedback and feed forward controller when a unit step input is applied and controller are evaluated in terms of peak overshoot and settling time.

6.1.2 Controller Performance Evaluation Using Performance Indices

In section 6.1.1 the designed controllers were subjected to unit step input and their performance were evaluated according to the peak overshoot and settling time. In this section the controllers will be evaluated according to the performance indices.

A performance index is a quantitative measure of the performance of a system and is chosen so that emphasis is given to the important system specifications. A system is considered an optimum control system when the system parameters are adjusted so that the index reaches an extreme, commonly a minimum value. To be useful a performance index must be a number that is always positive or zero. Then the best system is defined as the system that minimizes the index.

There are different performance indices of a control system and most common performance indices are IAE (integral absolute error), ISE (integral square error), ITAE (integral time absolute error) and ITSE (integral time square error).

$$IAE = \int_0^{\infty} |e(t)| dt \quad (73)$$

$$ISE = \int_0^{\infty} e^2(t) dt \quad (74)$$

$$ITAE = \int_0^{\infty} t |e(t)| dt \quad (75)$$

$$ITSE = \int_0^{\infty} t e^2(t) dt \quad (76)$$

Table 6.2: Comparison of performance indices of different controllers

Sl.No	Type of Controller	IAE	ISE	ITAE	ITSE
1	Feedback	4.755	0.366	192.6	6.33
2	Feedback plus feed forward (No delay in disturbance)	4.441	0.311	188.1	5.569
3	Feedback plus feed forward (Unit delay in disturbance)	4.456	0.305	221	5.757
4	Internal model controller	4.37	0.27	181.9	5.15
5	Hybrid fuzzy	3.56	0.18	179.7	4.75

From the table 6.2 it is clear that IAE of feedback controller is 4.755 and IAE of feedback plus feed forward controller is 4.441, the IAE of internal model controller is 4.37 and IAE of hybrid fuzzy controller is 3.56. It is observed that feedback controller showed 38% overshoot, so the IAE was a little bit higher. As the overshoot decreases the value of IAE also decreases. For this reason IAE of hybrid fuzzy controller is 3.56.

ISE of feedback controller is 0.366 and ISE of feedback plus feed forward controller is 0.311, the ISE of internal model controller is 0.27 and ISE of hybrid fuzzy controller is 0.18. It is observed that feedback controller showed 38% overshoot, so the ISE was a little bit higher. As the overshoot decreases the value of ISE also decreases. For this reason ISE of hybrid fuzzy controller is 0.18.

From the table 6.2 it is clear that ITAE of feedback controller is 192.6 and ITAE of feedback plus feed forward controller is 188.1, the ITAE of internal model controller is 181.9 and ITAE of hybrid fuzzy controller is 179.7. It is observed that feedback controller showed 38% overshoot, so the ITAE was a little bit higher. As the overshoot decreases the value of ITAE also decreases. For this reason ITAE of hybrid fuzzy controller is 179.7.

From the table 6.2 it is clear that ISE of feedback controller is 6.33 and ISE of feedback plus feed forward controller is 5.569, the ISE of internal model controller is 5.15 and ISE of hybrid fuzzy controller is 4.75. It is observed that feedback controller showed 38% overshoot, so the ISE was a little bit higher. As the overshoot decreases the value of IAE also decreases. For this reason ISE of hybrid fuzzy controller is 4.75.

6.2 Controller Performance Evaluation in Frequency Domain

A control system must satisfy desired performance characteristics for nominal operating conditions. In real world the model is never perfect, so the controller has to be robust. Robust controller literally means the controller should remain stable, even when the true plant characteristics are different from the process model.

6.2.1 Robustness Analysis

Frequency response analysis is performed because, it primarily provides a measurement of robustness of the controller tuning. It provides a measure of the amount of model uncertainty that can be tolerated before the controller will become unstable.

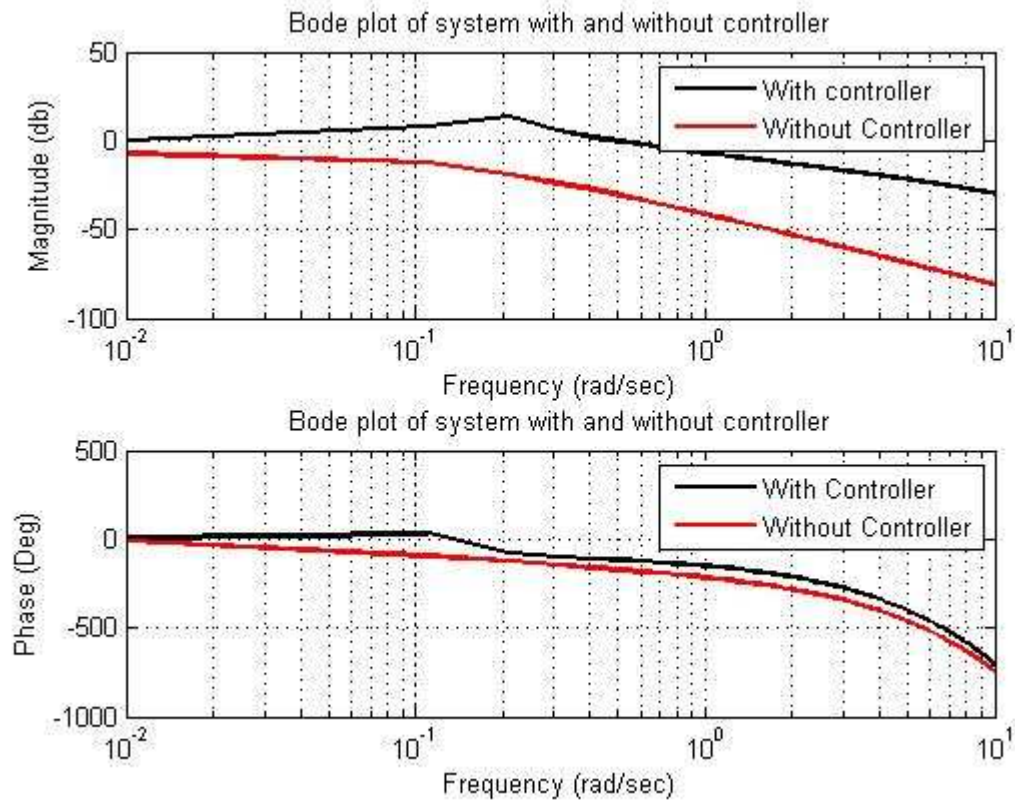


Figure 6.3: Frequency response of system with and without controller

Figure 6.3 shows the frequency response of the system with and without controller. The frequency response of a system consists of the magnitude response and phase response. Different process disturbance is effects the stability of the system. To investigate the effect of stability due to addition of disturbance, bode plot is plotted.

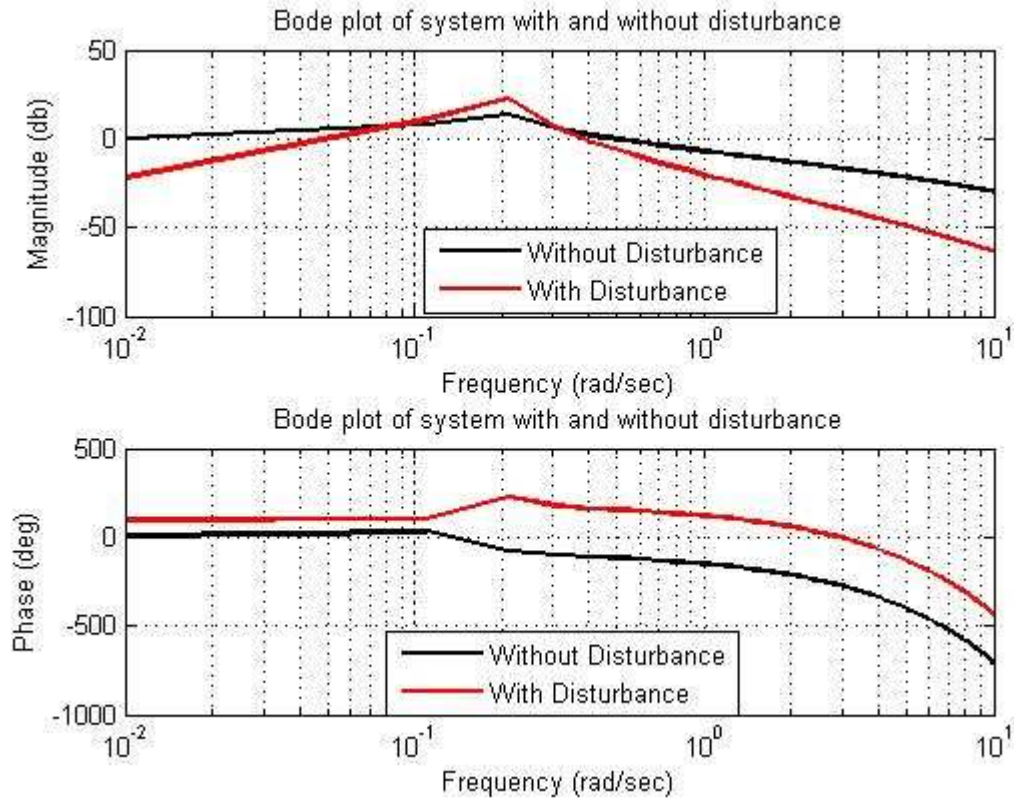


Figure 6.4: Frequency response of controlled system with and without disturbance

Figure 6.4 shows the frequency response of controlled system with disturbance and without disturbance. Table 6.3 represents the different robustness factors of different systems.

Gain margin: The gain margin is the reciprocal of the magnitude $|G(j\omega)|$ at the frequency at which the phase angle is -180° . If gain margin is greater than unity it means that the system is stable, where as if the gain margin is less than unity it means that the system is unstable.

Phase margin: The phase margin is that amount of additional phase lag at gain crossover frequency required to bring the system to the verge of instability.

Gain crossover frequency: The gain crossover frequency is the frequency at which $|G(j\omega)|$, the magnitude of open loop transfer function is unity.

Phase crossover frequency: It is the frequency at which the phase angle of open loop transfer function is -180° .

Bandwidth: The frequency range $0 \leq \omega \leq \omega_b$ in which the magnitude of the closed loop doesn't drop -3dB is called bandwidth of the system. The bandwidth indicates the frequency where in gain starts to fall from its low frequency values. Thus the bandwidth represents how well the system tracks the input. A large bandwidth corresponds to a small rise time or fast response. Bandwidth

and rise time are inversely proportional to each other. The necessary filtering characteristic is filtering of high frequency noise.

Table 6.3: Robustness analysis of different system configurations

	GM (dB)	PM (rad/sec)	ω_{cg}	ω_{cp}
System with controller	10.29	63.33	1.45	0.48
System without controller	32.72	∞	0.57	--
System without disturbance	10.29	63.33	1.45	0.48
System with disturbance	-8.35	-15.33	0.28	0.38

Table 6.3 shows the comparative study of robustness of system with different configurations, like system with and without controller, system with and without disturbance. The robustness factors considered here are gain margin denoted as GM, phase margin denoted as PM, gain crossover frequency denoted by ω_{cg} and phase crossover frequency denoted by ω_{cp} .

6.2.2 Sensitivity Analysis

$S(s)$ is the sensitivity function, which can be defined as
$$S(s) = \frac{1}{1 + G_p(s)G_c(s)} \quad (82)$$

Complementary sensitivity function is defined as
$$T(s) = \frac{G_c(s)G_p(s)}{1 + G_c(s)G_p(s)} \quad (83)$$

It should be noted that by definition $T(s) + S(s) = 1$. The sensitivity function describes the system response sensitivity to reference signal changes, whereas the complementary sensitivity function describes the system sensitivity to measurement noise. Moreover, they describe the system sensitivity to modeling errors which is important to notice in this study.

The PID controller in frequency domain can be defined as
$$G_c(j\omega) = K_p + \frac{K_i}{j\omega} + K_d j\omega \quad (84)$$

The H_∞ sensitivity constraint is defined as,
$$\|S(j\omega)\|_\infty \leq \gamma \quad (85)$$

Here $S(j\omega)$ is defined as
$$S(j\omega) = \frac{1}{1 + G_p(j\omega)G_c(j\omega)} \quad (86)$$

γ is a positive real scalar quantity.

Eq(84) for a SISO system for each value of ω can be re written in terms of its magnitude and phase angle as $\left\|S(j\omega)e^{j\angle S(j\omega)}\right\| \leq \gamma$ (87)

The sensitivity specification is defined as $M_s = \max_{0 \leq \omega < \infty} \left| \frac{1}{1 + G_p(j\omega)G_c(j\omega)} \right|$ (88)

A_m and ϕ_m are gain margin and phase margin respectively.

$$A_m > \frac{M_s}{M_s - 1} \quad (89)$$

$$\phi_m > 2 \sin^{-1} \frac{1}{2M_s} \quad (90)$$

Sensitivity of controllers is also analyzed separately for category one and category two controllers. For category one controllers the sensitivity analysis is done with the help of Nyquist diagrams and the M-circles. Controllers with greater M values (smaller circles) are more sensitive to disturbances and measurement noise than ones with smaller M values (larger circles).

6.2.3 Design Considerations and Sensitivity Analysis

To design a high performance control system following steps are considered

1. The tracking error should be small
2. Sensitive to modeling errors
3. Disturbance rejection
4. Stability margin
5. Sensitive to sensor noises

To improve the disturbance rejection and make the system sensitive to modeling errors $S(j\omega)$ should be small. To make the system sensitive to sensor noise and improve the stability margin $T(j\omega)$ should be small. Here $S(j\omega)$ is the sensitivity function and $T(j\omega)$ is complimentary sensitivity function.

Chapter 7

Conclusions

In this dissertation, a comparative study of performance of different conventional and fuzzy based controllers is studied. The aim of the proposed controller is to regulate the temperature of the outgoing fluid of a shell and tube heat exchanger system to a desired temperature in the shortest possible time and minimum or no overshoot irrespective of step change in load and process disturbances, equipment saturation and non-linearity of different control equipments. After time response and frequency response based analysis carried out on different controllers it is observed that hybrid fuzzy controller provides a satisfactory performance in both steady state and transient state and overcomes the drawbacks of conventional PID controller, feedback plus feed-forward controller and internal model based controller. The proposed hybrid fuzzy controller has demonstrated 100% improvement in the overshoot and 35.43% improvement in settling time as compared to the conventional PID controller.

The fuzzy based controller gives the best performance, but the control engineer faces different kind of challenges to design such a controller. This dissertation identified the key design challenges. The key design challenge is to generate an optimized fuzzy rule base with minimum number of rules. An existing rule base of N number of rules can be optimized using different optimization techniques like genetic algorithm, PSO, ant colony optimization. This dissertation proposes a genetic algorithm based optimization of existing fuzzy rule base of N number of rules.

The second challenge is to reduce the size of the rule base. To reduce the size of the rule base, optimal number of membership function has to be chosen and the optimal width of membership function has to be calculated. To achieve this objective system identification and estimation approach is used. This dissertation proposes Kalman filter based H_∞ estimation to achieve the objective.

In future scope of the dissertation, the Kalman filter based H_∞ estimation technique can be used to identify and estimate the new fuzzy membership function and optimize the existing one.