Analysis of Fuzzy PID and Immune PID Controller for Three Tank Liquid Level Control

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
Sharad Kumar Tiwari
Roll No. 800951020

Under the Guidance of

Ms. Gagandeep Kaur
Guide
Assistant Professor, EIED

Dr. Hardeep Singh
Co-Guide
Assistant Professor, ECED

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 "**Analysis of Fuzzy Pid and Immune PID Controller For Three Tank Liquid Level Control**" 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 **Ms. Gagandeep Kaur**, Assistant Professor, Department of Electrical and Instrumentation Engineering, Thapar University, Patiala, Punjab and **Dr. Hardeep Singh**, Assistant Professor, Department of Electronics and Communication Engineering, Thapar University, Patiala, Punjab.

Date: 30/06/11

Sharad Kumar Tiwari
800951020

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

Date:

Ms. Gagandeep Kaur
Assistant Professor
Department of Electrical and
Instrumentation Engineering
Thapar University, Patiala
Punjab

Dr. Hardeep Singh
Assistant Professor
Department of Electronics and
Communication Engineering
Thapar University, Patiala
Punjab

Countersigned By

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

Dr. S K Mohapatra
Dean of Academic Affairs
Thapar University, Patiala
Punjab

ACKNOWLEDGEMENT

I would like to express my gratitude to **Ms. Gagandeep Kaur**, Assistant Professor**,** Electrical and Instrumentation Engineering Department, Thapar University, Patiala and **Dr. Hardeep Singh**, Assistant Professor**,** Electronics and Communication Engineering Department, Thapar University, Patiala for their patient guidance and support throughout this thesis work. I am truly very fortunate to have the opportunity to work with them. They have also provided me help in technical writing and presentation style, and I found this guidance to be extremely valuable. I am very thankful to head of the Department, **Dr. Smarajit Ghosh,** for his encouragement, support and providing the facilities for the completion of this thesis. I am also thankful to entire faculty and staff members of Electrical and Instrumentation Engineering Department for their unyielding encouragement. I am greatly indebted to all my friends, who have graciously applied themselves to the task of helping me with ample morale support and valuable suggestions. Finally, I would like to extend my gratitude to all those persons who directly or indirectly helped me in the process and contributed towards this work.

Sharad Kumar Tiwari

ABSTRACT

Biological immune system (BIS) is a special type of control system that has strong robustness and self-adaptability. This thesis report proposes an artificial immune system algorithm to develop an immune controller. The idea of immune controller is adopted and derived from biological vertebrate immune system, mimicking and imitating of biological immune system which is better known as the artificial immune system .

This thesis show how proposes to apply and implement the algorithm of the artificial immune system (AIS) to develop an immune controller (IC) for three tank level control. There are various models of artificial immune controller (AIC). The most suitable for their particular application is selected. The selected artificial immune controller has the resemblance of a PID controller. The immune controller enhances the performance and stability of the system. The approach is to prove that an immune controller using artificial immune system algorithm can be used as a controller to obtain steady state output response. In industrial control systems the liquid level is carrying its significance as the control action for level control in tanks containing different chemicals or mixtures is essential for further control linking set points. The three level control models are considered in our thesis work. The conventional control algorithms are difficult to reach required control quality with more strict restriction on overshoot. Designed a parameter self-tuning PID-controller based on fuzzy control, which can adjust PID-parameters according to error and change in error. Biological immune system is a control system that has strong robusticity and self-adaptability in complex disturbance and indeterminacy environments. The artificial intelligence technique of fuzzy logic and immune controller is adopted for more reliable and precise control action which incorporate the uncertain factors also. In this thesis the comparison of the conventional model, fuzzy model and immune feedback mechanism has been analyzed.

ORGANISATION OF THESIS

Chapter-1 It includes the introduction of the thesis.

Chapter-2 It is a literature review that contains most of the previous work in this field which has been carried out till date, are given.

Chapter-3 Basics of control theory has been elaborated in this chapter.

Chapter-4 Introduction of Fuzzy Logic and its utilization in control system has been discussed in this chapter.

Chapter-5 It includes the introduction of Artificial Immune System (AIS) and basic biological terminology related to the immune system are described in this chapter. It also includes the proposition of immune controller algorithms and feedback principle of immune system also describe the relation between the terminology of immune system and control system.

Chapter-6 It includes the mathematical modeling for the tank liquid level control system.

Chapter-7 This chapter include the simulation of process and controller in MATLAB simulink and results are shown in this chapter.

Chapter-8 Thesis has been concluded with future scope in this chapter.

TABLE OF CONTENTS

LIST OF FIGURE

LIST OF TABLE

.

LIST OF SYMBOLS AND ABBREVIATIONS

Ag	Antigen
Ab	Antibody
T(k)	T-cell concentration
B(k)	B-cell concentration
e(t)	Error of the control system
y(t)	Output of the immune controller
r(t)	Reference input signal
f(e,u)	Immune controller
G(s)	Object controlled by the immune controller
K_p	Proportional gain, a tuning parameter
K_i	Integral gain, a tuning parameter
K_d	Derivative gain, a tuning parameter
Ɛ(k)	Consistency of antigen at the k_{th} generation
AI	Artificial intelligence
AIS	Artificial immune system
AIC	Artificial immune controller
FL	Fuzzy logic
FLC	Fuzzy logic controller
APC	Antigen presenting cell
PID	Proportional integral and derivative
IC	Immune Controller
h	Height of the tank
A	Area of the tank
F(t)	Flow rate
T	Time
T(h)	Helper T-cells
T(s)	Killer T-cells

CHAPTER 1
INTRODUCTION

1.1 Overview

The objectives of this thesis work are to study and analyze the mathematical model and algorithm of artificial immune system (AIS). Here are various types of mathematical mode of applicable immune algorithm can be found from different sources books, journals, papers, internet etc. The artificial immune algorithm chosen in this analysis have the similarity to the artificial immune controller (AIC) and the conventional control system itself. By selecting artificial immune algorithm an immune controller is to be developed. The immune controller is then tested and simulated using MATLAB Simulink to observe its output response and performance. Once the desired immune controller is obtained, the immune controller is implemented to a control system. The main objective of the immune controller is to enhance the quality of the control system.

Liquid level control is a typical representation of process control and is widely used in iron and steel, chemicals, petroleum and other industries. The control quality directly affects the quality of products and safety of equipments. However, the liquid level control system of water tank is a large lag, time-varying and nonlinear complex system and is very difficult to control. Now, the liquid level control has been an active area in the process control over last decades and various different approaches have been devised.

In industrial applications liquid level control is very important as in food processing industry, dairy, filtration, effluent treatment, nuclear power generation plants, pharmaceutical industries, water purification systems, industrial chemical processing and spray coating and boilers in all the industries. The typical actuators used in liquid level control systems include pumps , motorized valves , on-off valves and level sensors such as displacement float, capacitance probe and pressure sensor provide liquid level measurement for feedback control purpose so that as per the process requirements the fluids could be controlled. In this exercise, the system is modeled, calibrated, and controlled for level determination in a three tank level control system. In particular, this exposes the fundamental modeling principle of fluid mass balance, pressure sensor calibration, and a feedback control design methodology for a state-coupled, three-tank level control system.

The level control is a type of control method for common in process system. It must be controlled by the proper controller. The objective of the controller in the level control is to maintain a level set point at a given value and be able to accept new set point values dynamically. The conventional proportional-integral-derivative (PID) is commonly utilized in controlling the level, but the parameter of those controllers must be turned by tuning method either in time response or frequency response to meet their required.

Fuzzy system theory can have utility in the assessing some of our more necessary. but fast solution can be useful in making preliminary design decision, or as an initial estimate in a more accurate numerical technique to save computational coasts, or in the myriad of situations where the inputs to a problem are vague , ambiguous , or not know at all.

The three level control models are considered in our work. In conventional model for three tank liquid level, the control is done with conventional control PID model. The artificial intelligence technique of fuzzy logic is used to adjust the parameter of PID controller. The artificial immune system is adopted for more reliable and precise control action which incorporate the uncertain factors also. In this work the comparison of the conventional model and fuzzy –PID tuning ,immune model and immune PID tuning is analyzed.

1.2 Scope of Work

The scope of work is to study and analyze various mathematical model of immune algorithm in order to design immune controller. The mathematical model of the immune algorithm must have the quality or other relation or characteristics of the control system. With a selected artificial immune system elements and algorithm the purpose of the project is to design an artificial immune controller. The controller then has to be tested and simulated using a MATLAB Simulink. When the appropriate immune algorithm has been obtained than the artificial immune system algorithm technique can be used to develop a satisfactory process so as to enhance the stability of the control system. The immune controller is to be implemented into the process control system. From there we can observe the output response. Improvement and adjustment of the immune controller variables need to be conducted from time to time in order to obtain a good result and performance of the output response of the control system.

Recently researchers have begun to argue that intelligent behavior and cognition are much more about effective interaction between agent and environment, rather than an agent's capability to handle abstract world models internally. Based on these influences the field of behavior-oriented AI has emerged, which unlike its traditional counter part, is mainly concerned with the study of autonomous agents, situated in and interacting with an environment. Typical criticisms of conventional artificial intelligent systems are that these systems show brittleness for environmental changes, and required much computing time for mapping complex sensory inputs into complex internal models before action can be taken. Therefore, in recent years much attention has been focused on the reactive planning systems, which have demonstrated robustness and flexibility against dynamically changing world. On the other hand, biological information processing systems have many interesting functions and are expected to provide various feasible ideas to engineering fields, especially robotics. Biological information processing systems in living organisms can be mainly classified into the following four systems: (1) nervous system, (2) genetic system, (3) endocrine system, and (4) immune system. Nervous and genetic systems have already been applied to engineering fields by modeling as neural networks, and genetic algorithms, and they have been widely used in various fields. Immune system, in particular, have various interesting features such as immunological memory, immunological tolerance, micro-pattern recognition, nonhierarchical distributed structure, and so on that can be applied to many engineering fields. In the following lines we will brief some of the basic features of the immune system.

• **Recognition:** The immune system can recognize and classify different patterns and generate selective responses. Recognition is achieved by intercellular binding the extent of this binding is determined by molecular shape and electrostatic charge. Self-non-self discrimination is one of the main tasks of the immune system deals with during the recognition process.

• **Feature Extraction:** Antigen Presenting Cells (APCs) interpret the antigenic context and extract its features, by processing and presenting antigenic peptides on its surface. These APC servers as a filter and a lens: a filter that destroy molecular noise, and a lens that focuses the attention of the lymphocyte receptors.

• **Diversity:** It uses combinatory, usually done by a genetic process for generating a diverse set of lymphocyte receptors to ensure that at least some lymphocytes can bind to any known or unknown antigen.

• **Learning:** It learns, by experience, the structure of a specific antigen. Changing Lymphocyte concentration is the mechanism for learning and takes place during the primary response of Ag interception. So the learning ability of the immune system lies primarily in the mechanism which generates new immune cells on the basis of the current state of the system.

• **Memory:** When lymphocytes are activated, a few of each kind become special memory cells which are content-addressable, and continues to circulate in the blood. The life time of immune memory cells is dynamic and requires stimulation by antigens. The immune system keeps an ideal balance between economy and performance in conserving a minimal but sufficient memory of the past, and this is done normally by using short-term and long-term memory mechanisms.

•**Distributed Detection:** The immune system is inherently distributed. The immune cells, in particular lymphocytes, circulate through the blood, lymph, lymphoid organs, and tissue spaces. As lymphocytes recirculate, if they encounter antigenic attacks, they stimulate specific immune responses.

• **Self-regulation:** The basic mechanisms of immune responses are self-regulatory in nature. There is no central organ that controls the functions of the immune system. The regulation of immune responses can be either local or systemic, depending on the route and property of the antigenic challenge.

• **Co-stimulation:** Activation of B cells are closely regulated through co-stimulation. The second signal coming from helper T cells helps to ensure tolerance and judge the invader is dangerous, harmless, or false alarm.

CHAPTER-2

LITERATURE REVIEW

The following section describes the literature survey that is relevant with the work carried out for this thesis work.

Freddy Prasetia Ridhuan and Mohd Fauzi Othman et.al. presented design of power system stabilizer using artificial immune controller. Conventional power system stabilizers contain a phase lag/lead network for phase compensation and have played a very significant role to enhance the stability of power systems. Various new approaches have been proposed in the past 30 years to improve the performance of power system stabilizers such as modern control and artificial intelligence techniques. They used a new method of control will be implemented to a power systems stabilizer. That approaches uses the artificial immune controller called improved verela immune network controller or IVINC. The purposes of IVINC controller are to enhance the stability of power systems and to damp low frequency oscillations [36].

Tao C. W. et. al. had proposed a flexible complexity reduced design approach for PID-like fuzzy controllers. With the linear combination of input variables as a new input variable, the complexity of the fuzzy mechanism of PID-like fuzzy controllers is significantly reduced. However, the performance of the complexity reduced fuzzy PID controller may be degraded since the degree of freedom is decreased by the combination of input variables. To alleviate the drawback and improve the performance of the complexity reduced PID-like fuzzy controller, a flexible complexity reduced design approach is introduced in which the functional scaling factors are heuristically generated. Since the functional scaling factors are heuristically created, they can be easily adjusted for the flexible complexity reduced PID-like fuzzy controller without a priori knowledge of the exact mathematical model of the plant. Moreover, heuristic scaling factors are implemented as functional. Therefore, the complexity of the flexible PID-like fuzzy controller will not be increased. Further, the stability of the fuzzy control system with a flexible complexity reduced PID-like fuzzy controller is discussed [17].

Wei Wang, X. Z. Gao and Changhong Wang et.al. had presented the material-level control of preheating cylinder in the thermo finer of the hot-grinding system is highly nonlinear, and also has a pure delay. They proposed a promising fusion of immune algorithm and PID algorithm to deal with this challenging problem. The MATLAB-based simulations demonstrate that the proposed hybrid controller has the remarkable properties of quick response, good robustness, and satisfactory overshoot. It is considerably effective in improving the control performance of the hot-grinding system. A new immune PID controller is proposed in this paper, and applied to the material-level control of the preheating cylinder as well. Computer simulations show that this method results in a quicker response with a smaller overshoot than the conventional PID controller. Moreover, it has a strong ability to adapt to the significant change of system parameters. To summarize, the immune PID controller has been proved to be an effective method in the material-level control of the preheating cylinder. It can be also used in a variety of nonlinear control systems with time-varying, pure delay, and large time constants [38].

Fu Dongmei and Zheng Deling et. al. analyze the Stability of Immune Control' System Based on Small Gain Theorem in which the biological immune system has many characteristics that can be used to the artificial intelligence for reference. Based on the biological T cell and the B cell immune response mechanism, he was established one general immune controller (T-B-IC).The immune controller model obtained from former some research is concrete realization of which the T-B-IC model is proposed in this article. It is well It known, the boundary and stability of the control system are the most important factor for evaluating the system performance. For the control system is made up of the T-B-IC model, the analytical study of the boundedness and stability for the control system has a little been published. He used, an 10 boundedness theorem and a stability theorem have been made and the certification has been also given for a kind of SISO immune control system based on the small gain theorem. The similar result of the theorems can be achieved easily for other immune control system which composes to B kindred immune controller [33].

Yuan Guili, Liu Jizhen, TanWen, Liu Xiangjie presented an Immune Feedback Control in the Load Control System of Tube Mill. At the tube mill burthen controlled object with the characteristics of large delay, large inertia, nonlinear and time-variant, he was design a tube mill burthen control system basing at fuzzy immune PID control. The system combines the cascade control with the fuzzy immune PID control, and adopts P control in the inner loop and fuzzy immune PID control in the outer loop , taking full advantage of the cascade control, fuzzy control, immune feedback control and PID control, which makes the system have not only better track ability but also stronger robust and anti-disturbance. In order to show the superior of the control strategy, simultaneously the paper carries out cascade PID control Simulation, and the result manifests that the control effect has better regulation-quality than cascade PID control, in some sense equaling with the internal model control and Smith predictive control. But because of consisting the immune fuzzy control, its non-linear control effect is better than internal model control, Smith predictive control, PID control Cascade. What's more, the control algorithm is very simple and practical [40].

Dasgupta et. al. conducted a research that focuses on investigating immunological principles in designing a multi-agent system for intrusion detection and response in networked computers . In this approach, the immunity-based agents roam around the machine, and look for changes such as malfunctions, faults, abnormalities, misuse, deviations, intrusions, etc. These agents can mutually recognize each other's activities and can take appropriate actions according to the underlying security policies. Their activities are coordinated in a hierarchical fashion while sensing, communicating and generating responses. Such an agent can learn and adapt to its environment dynamically and can detect both known and unknown intrusions. Their research is the part of an effort to develop a multi-agent detection system that can simultaneously monitor networked computer's activities at different levels in order to determine intrusions and anomalies. Their proposed intrusion detection system is designed to be flexible, extendible, and adaptable that can perform real-time monitoring in accordance with the needs and preferences of network administrators [10].

Detecting anomalies in time series data is a problem of great practical interest in many manufacturing and signal processing applications. Dasgupta et. al. presented a novel detection algorithm inspired by the negative-selection mechanism of the immune system, which discriminates between self and non-self. Self is defined to be normal data patterns and non-self is any deviation. exceeding an allowable variation. Experiments with this novelty detection algorithm are reported for two data sets: simulated cutting dynamics in a milling operation and a synthetic signal. The results of the experiments exhibiting the performance of the algorithm in detecting novel patterns were reported [22].

Anomaly detection in a system or a process behavior is very important in many real world applications such as manufacturing, monitoring, signal processing etc. Dasgupta et. al. presented an anomaly detection algorithm inspired by the negative-selection mechanism of the immune system, which discriminates between self and other. Here self is defined to be normal data patterns and non-self is any deviation exceeding an allowable variation. Experiments with this anomaly detection algorithm are reported for two data sets: time series data, generated using the Mackey-Glass equation and a simulated signal. Compared to existing methods, this method has the advantage of not requiring prior knowledge about all possible failure modes of the monitored system. Results are reported to display the performance of the detection algorithm [21]

Jiao Licheng and Hunt et. al. described an artificial immune system (AIS) which is based upon models from the natural immune system. This natural system is an example of an evolutionary learning mechanism which possesses a content addressable memory and the ability to forget little used information. It is also an example of an adaptive non-linear network in which control is decentralized and problem processing is efficient and effective. As such, the immune system has the potential to offer novel problem solving methods. The AIS is an example of a system developed around the current understanding of the immune system. It illustrates how an artificial immune system can capture the basic elements of the immune system and exhibit some of its chief characteristics. They illustrate the potential of the AIS on a simple pattern recognition problem. Then, they apply the AIS to a real world problem: the recognition of promoters in DNA sequences. The results obtained are consistent with other approaches, such as neural networks and are better than the nearest neighbor algorithm. They concluded that the primary advantages of the AIS are that it only requires positive examples, and the patterns it has learnt can be explicitly examined. In addition, because it is self-organizing, it does not require effort to optimize any system parameters [27].

According to Baba, Y. et. al. proposed PID control is widely used as a basic control technology in industries, but tuning of PID control systems is not always easy. Based on model-driven control concept, they developed a model-driven PID control system, named MD PID controller, combining with PD local feedback, IMC and set point filter. Their paper provides a brief introduction of new model driven two-degrees of freedom PID control system, named MD TDOF PID controller, and shows some case studies results. They have confirmed that MD TDOF PID can show better control results compared with conventional PID control [28].

Gang Liul and Lina Yang et. al. described the robustness of high-performance induction motor variable frequency speed regulation system is weak owing to the uncertainty of parameters. As a complicated self-adaptable system, the biological immune system can effectively and smoothly deal with various antigen and virus intruded into organism. It is possible to improve the self-learning capability; adaptive capability and robustness of the control system if artificial immunity controller designed by using for reference biological immune system is embed. To solving the control problems of model parameter uncertainty and external disturbance existing in PMSM motor, the traditional problem in the application of the control theory are studied, such as the controller design, realization and application, based on the artificial immune model. They presented a artificial immune controller is to reduce the tracking error and to improve the transient performance and stability of PMSM drive control system [44].

Meshref, and VanLandingham et. al. proposed a paper that applies an AIS technique to a Distributed Autonomous Robotics System (DARS) problem. One of the classic problems in DARS is the dog and sheep problem. In their paper they tried to benefit from the features of the natural immune system in the development of the dog and sheep problem. On the other hand, they found that Natural immune systems are sophisticated information processors. They learn to recognize relevant patterns, they remember patterns that have been seen previously, and they use diversity to promote robustness. Furthermore, the individual cells and molecules that comprise the immune system are distributed throughout the body, encoding and controlling the system in parallel, with no central control mechanism. The immune system uses several weapons to attack the foreign antigen. Abstractly, these weapons are the helper T-cells, B-cells, and antibodies. We simulated the dog as a B cell, the sheep as an antigen, the antibody as the dog behavior, the antigen response as the sheep behavior, and the sheep-to-pen distance as a helper T cell. The system interacts in an equivalent manner similar to the immune response trying to restore the environment to its original state, which is the sheep inside the pen [20].

CHAPTER 3

BASICS OF CONTROL SYSTEM

3.1 Introduction

A control system is an interconnection of components forming a system configuration that will provide a desired system response. The basis for analysis of a system is the foundation provided by linear system theory, which assumes a cause–effect relationship for the components of a system. Therefore a component or process to be controlled can be represented by a block, as shown in Figure 3.1. The input–output relationship represents the cause-and-effect relationship of the process, which in turn represents a processing of the input signal to provide an output signal variable, often with a power amplification. An open-loop control system utilizes a controller or control actuator to obtain the desired response, as shown in Figure 3.2.

An open-loop controller, also called a non-feedback controller, is a type of controller that computes its input into a system using only the current state and its model of the system.A characteristic of the open-loop controller is that it does not use feedback to determine if its output has achieved the desired goal of the input. This means that the system does not observe the output of the processes that it is controlling.

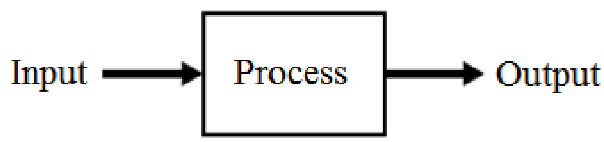

Figure 3.1: Process to be controlled.

An open-loop control system utilizes an actuating device to control the process directly without using feedback.

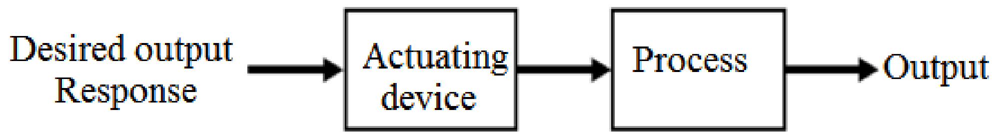

Figure 3.2: Open-loop control system.

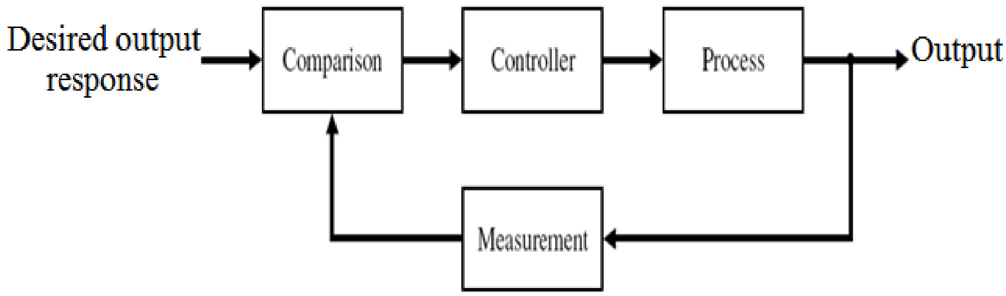

Figure 3.3: Closed-loop control system.

In contrast to an open-loop control system, a closed-loop control system utilizes an additional measure of the actual output to compare the actual output with the desired output response. The measure of the output is called the feedback signal. A simple closed-loop feedback control system is shown in Figure 3.3. A feedback control system is a control system that tends to maintain a prescribed relationship of one system variable to another by comparing functions of these variables and using the difference as a means of control. A feedback control system often uses a function of a prescribed relationship between the output and reference input to control the process. Often the difference between the output of the process under control and the reference input is amplified and used to control the process so that the difference is continually reduced. The feedback concept has been the foundation for control system analysis and design. A closed-loop control system uses a measurement of the output and feedback of this signal to compare it with the desired output.

Due to the increasing complexity of the system under control and the interest in achieving optimum performance, the importance of control system engineering has grown in the past decade. Furthermore, as the systems become more complex, the interrelationship of many controlled variables must be considered in the control scheme. A block diagram depicting a multivariable control system is shown in Figure 3.4. A common example of an open-loop control system is an electric toaster in the kitchen. An example of a closed-loop control system is a person steering an automobile (assuming his or her eyes are open) by looking at the auto's location on the road and making the appropriate adjustments. The introduction of feedback enables us to control a desired output and can improve accuracy, but it requires attention to the issue of stability of response.

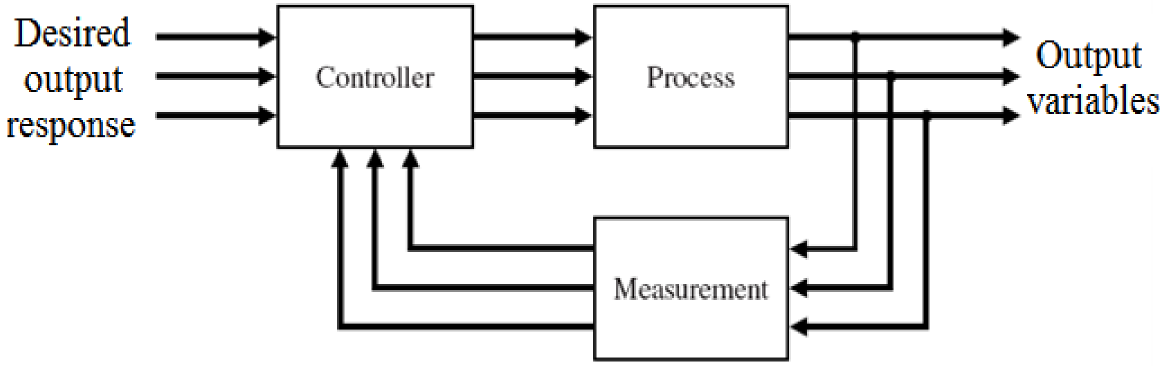

Figure 3.4: Multivariable control system

3.2 Historical View

Although control systems of various types date back to antiquity, a more formal analysis of the field began with a dynamics analysis of the centrifugal governor, conducted by the physicist James Clerk Maxwell in 1868 entitled an governors. This described and analyzed the phenomenon of "hunting", in which lags in the system can lead to overcompensation and unstable behavior. This generated a flurry of interest in the topic, during which Maxwell's classmate Edward John Routh generalized the results of Maxwell for the general class of linear systems. Independently, Adolf Hurwitz analyzed system stability using differential equations in 1877. This result is called the Routh-Hurwitz theorem. A notable application of dynamic control was in the area of manned flight. The Wright Brothers made their first successful test flights on December 17, 1903 and were distinguished by their ability to control their flights for substantial periods (more so than the ability to produce lift from an airfoil, which was known). Control of the airplane was necessary for safe flight.

3.3 Control Loop Basics

A familiar example of a control loop is the action taken when adjusting hot and cold faucet valves to maintain the faucet water at the desired temperature. This typically involves the mixing of two process streams, the hot and cold water. The person touches the water to sense or measure its temperature. Based on this feedback they perform a control action to adjust the hot and cold water valves until the process temperature stabilizes at the desired value. Sensing water temperature is analogous to taking a measurement of the process value or process variable (PV). The desired temperature is called the setpoint (SP). The input to the process is called the manipulated variable (MV). The difference between the temperature measurement and the setpoint is the error (e), that quantifies whether the water is too hot or too cold and by how much.

After measuring the temperature (PV), and then calculating the error, the controller decides when to change the tap position (MV) and by how much. When the controller first turns the valve on, they may turn the hot valve only slightly if warm water is desired, or they may open the valve all the way if very hot water is desired. This is an example of a simple proportional control. In the event that hot water does not arrive quickly, the controller may try to speed-up the process by opening up the hot water valve more-and-more as time goes by. This is an example of an integral control. By using only the proportional and integral control methods, it is possible that in some systems the water temperature may oscillate between hot and cold, because the controller is adjusting the valves too quickly and over-compensating or overshooting the setpoint. In the interest of achieving a gradual convergence at the desired temperature (SP), the controller may wish to damp the anticipated future oscillations. So in order to compensate for this effect, the controller may elect to temper their adjustments. This can be thought of as a derivative control method.

Making a change that is too large when the error is small is equivalent to a high gain controller and will lead to overshoot. If the controller were to repeatedly make changes that were too large and repeatedly overshoot the target, the output would oscillate around the setpoint in either a constant, growing, or decaying sinusoid. If the oscillations increase with time then the system is unstable, whereas if they decrease the system is stable. If the oscillations remain at a constant magnitude the system is marginally stable. A human would not do this because we are adaptive controllers, learning from the process history; however, simple PID controllers do not have the ability to learn and must be set up correctly. Selecting the correct gains for effective control is known as tuning the controller.

If a controller starts from a stable state at zero error (PV = SP), then further changes by the controller will be in response to changes in other measured or unmeasured inputs to the process that impact on the process, and hence on the PV. Variables that impact on the process other than the MV are known as disturbances. Generally controllers are used to reject disturbances and/or implement setpoint changes. Changes in feedwater temperature constitute a disturbance to the faucet temperature control process.

3.4 Closed-Loop Transfer Function

The output of the system y(t) is fed back through a sensor measurement F to the reference value r(t). The controller C then takes the error e (difference) between the reference and the output to change the inputs u to the system under control P. This is shown in the figure 3.5. This kind of controller is a closed-loop controller or feedback controller. This is called a single-input-single-output (SISO) control system; MIMO (i.e. Multi-Input- Multi-Output) systems, with more than one input/output, are common. In such cases variables are represented through vectors instead of simple scalar values. For some distributed parameter systems the vectors may be infinite-dimensional.

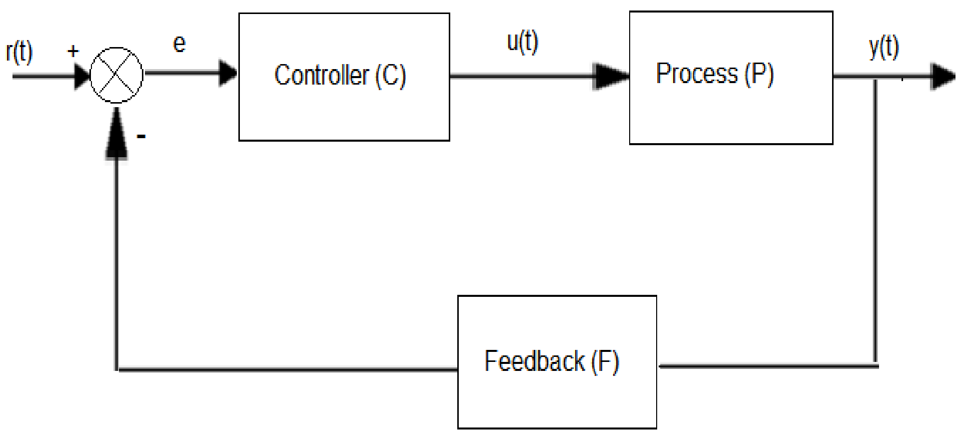

Figure 3.5: Closed loop control system

If we assume the controller C, the plant P, and the sensor F are linear and time-invariant (i.e.: elements of their transfer function C(s), P(s), and F(s) do not depend on time), the systems above can be analyzed using the Laplace transform on the variables.

This gives the following relations:

$$Y(s) = P(s)U(s) \qquad 3.1$$

$$U(s) = C(s)E(s) \qquad 3.2$$

$$E(s) = R(s) - F(s)Y(s) \qquad 3.3$$

Solving for Y(s) in terms of R(s) gives

$$Y(s) = \left(\frac{P(s)C(s)}{1+F(s)P(s)C(s)}\right)R(s) = H(s)R(s) \qquad 3.4$$

$$H(s) = \frac{P(s)C(s)}{1+F(s)P(s)C(s)} \qquad 3.5$$

The above expression is referred to as the closed-loop transfer function of the system. The numerator is the forward (open-loop) gain from r to y, and the denominator is one plus the gain in going around the feedback loop, the so-called loop gain. If $|P(s)C(s)| >> 1$, i.e. it has a large norm with each value of s, and if $|F(s)| = 1$, then Y(s) is approximately equal to R(s). This simply means setting the reference to control the output.

3.5 PID Controller

In the following sections we will describe the introduction of the PID controller.

3.5.1 Introduction to PID Controller

A proportional–integral–derivative controller (PID controller) is a generic control loop feedback mechanism widely used in industrial control systems – a PID is the most commonly used feedback controller. A PID controller calculates an "error" value as the difference between a measured process variable and a desired setpoint. The controller attempts to minimize the error by adjusting the process control inputs. In the absence of knowledge of the underlying process, PID controllers are the best controllers. However, for best performance, the PID parameters used in the calculation must be tuned according to the nature of the system – while the design is generic, the parameters depend on the specific system.

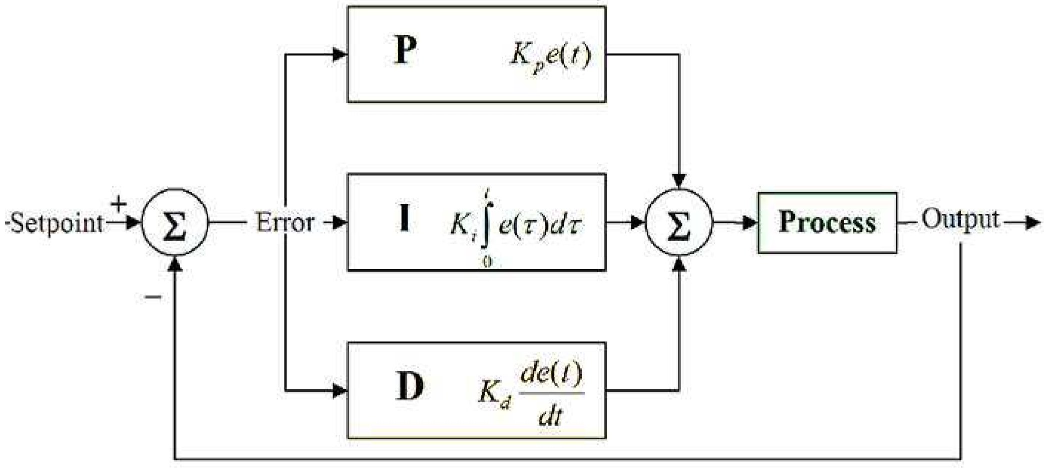

Figure 3.6: Block diagram of PID controller.

The PID controller calculation involves three separate parameters, and is accordingly sometimes called three-term control: the proportional, the integral and derivative values, denoted P, I, and D. The proportional value determines the reaction to the current error, the integral value determines the reaction based on the sum of recent errors, and the derivative value determines the reaction based on the rate at which the error has been changing. The weighted sum of these three actions is used to adjust the process via a control element such as the position of a control valve or the power supply of a heating element. Heuristically, these values can be interpreted in terms of time: P depends on the present error, I on the accumulation of past errors, and D is a prediction of future errors, based on current rate of change. By tuning the three constants in the PID controller algorithm, the controller can provide control action designed for specific process requirements. The response of the controller can be described in terms of the responsiveness of the controller to an error, the degree to which the controller overshoots the setpoint and the degree of system oscillation. Note that the use of the PID algorithm for control does not guarantee optimal control of the system or system stability.

3.5.2 PID Control Theory

The PID controller is probably the most-used feedback control design. PID is an acronym for Proportional-Integral-Derivative, referring to the three terms operating on the error signal to produce a control signal. If u(t) is the control signal sent to the system, y(t) is the measured output and r(t) is the desired output, and tracking error e(t) = r(t) − y(t), a PID controller has the general form.

$$u(t) = K_P e(t) + K_I \int e(t)dt + K_D \frac{d}{dx} e(t) \text{ ……………………….3.6}$$

The desired closed loop dynamics is obtained by adjusting the three parameters K_P, K_I and K_D, often iteratively by "tuning" and without specific knowledge of a plant model. Stability can often be ensured using only the proportional term. The integral term permits the rejection of a step disturbance. The derivative term is used to provide damping or shaping of the response. PID controllers are the most well established class of control systems: however, they cannot be used in several more complicated cases, especially if MIMO systems are considered.

Applying Laplace transformation results in the transformed PID controller equation

$$u(s) = K_P e(s) + K_I \frac{1}{s} e(s) + K_D s e(s) \text{ …………………………3.7}$$

With the PID control transfer function

$$C(s) = K_P + K_I \frac{1}{s} + K_D s \text{ …………………………………...3.8}$$

3.5.3 Proportional Term

The proportional term (sometimes called gain) makes a change to the output that is proportional to the current error value. The proportional response can be adjusted by multiplying the error by a constant Kp, called the proportional gain.

The proportional term is given by:

$$P_{out}=K_p e(t) \text{……………………….…………………..3.9}$$

where

P_{out}: Proportional term of output

K_p: Proportional gain, a tuning parameter

e: Error = SP − PV

t: Time or instantaneous time (the present)

A high proportional gain results in a large change in the output for a given change in the error. If the proportional gain is too high, the system can become unstable. In contrast, a small gain results in a small output response to a large input error, and a less responsive or sensitive controller. If the proportional gain is too low, the control action may be too small when responding to system disturbances. In the absence of disturbances, pure proportional control will not settle at its target value, but will retain a steady state error that is a function of the proportional gain and the process gain.

3.5.4 Integral Term

The contribution from the integral term sometimes called reset is proportional to both the magnitude of the error and the duration of the error. Summing the instantaneous error over time gives the accumulated offset that should have been corrected previously. The accumulated error is then multiplied by the integral gain and added to the controller output. The magnitude of the contribution of the integral term to the overall control action is determined by the integral gain, Ki.

The integral term is given by:

$$I_{out} = K_I \int e(t)dt \qquad \ldots\ldots 3.10$$

where

I_{out}: Integral term of output

K_I: Integral gain, a tuning parameter

e: Error = SP − PV

t: Time or instantaneous time (the present)

τ: a dummy integration variable

The integral term when added to the proportional term accelerates the movement of the process towards setpoint and eliminates the residual steady-state error that occurs with a proportional only controller. However, since the integral term is responding to accumulated errors from the past, it can cause the present value to overshoot the setpoint value.

3.5.5 Derivative Term

The rate of change of the process error is calculated by determining the slope of the error over time i.e., its first derivative with respect to time and multiplying this rate of change by the derivative gain Kd. The magnitude of the contribution of the derivative term to the overall control action is termed the derivative gain, Kd. The derivative term is given by:

$$D_{out} = K_D \frac{d}{dx} e(t) \quad \ldots\ldots\ldots\ldots\ldots\ldots 3.11$$

where

D_{out}: Derivative term of output

K_D: Derivative gain, a tuning parameter

e: Error = SP − PV

t: Time or instantaneous time (the present)

The derivative term slows the rate of change of the controller output and this effect is most noticeable close to the controller setpoint. Hence, derivative control is used to reduce the magnitude of the overshoot produced by the integral component and improve the combined controller-process stability. However, differentiation of a signal amplifies noise and thus this term in the controller is highly sensitive to noise in the error term, and can cause a process to become unstable if the noise and the derivative gain are sufficiently large. Hence an approximation to a differentiator with a limited bandwidth is more commonly used. Such a circuit is known as a Phase-Lead compensator.

The proportional, integral, and derivative terms are summed to calculate the output of the PID controller. Defining u(t) as the controller output, the final form of the PID algorithm is:

$$u(t) = MV(t) = K_p e(t) + K_i \int_0^t e(t)dt + K_d \frac{d}{dx} e(t) \quad \ldots\ldots\ldots 3.12$$

where the tuning parameters are three types:

i) Proportional gain, Kp

Larger values typically mean faster response since the larger the error, the larger the proportional term compensation. An excessively large proportional gain will lead to process instability and oscillation.

ii) Integral gain, Ki

Larger values imply steady state errors are eliminated more quickly. The trade-off is larger overshoot: any negative error integrated during transient response must be integrated away by positive error before reaching steady state.

iii) Derivative gain, Kd

Larger values decrease overshoot, but slow down transient response and may lead to instability due to signal noise amplification in the differentiation of the error.

3.6 Loop Tuning

Tuning a control loop is the adjustment of its control parameters i.e. gain/proportional band, integral gain/reset, derivative gain/rate to the optimum values for the desired control response. Stability is a basic requirement, but beyond that, different systems have different behavior, different applications have different requirements, and some desiderata conflict. Further, some processes have a degree of non-linearity and so parameters that work well at full-load conditions don't work when the process is starting up from no load; this can be corrected by gain scheduling. PID controllers often provide acceptable control even in the absence of tuning, but performance can generally be improved by careful tuning, and performance may be unacceptable with poor tuning. PID tuning is a difficult problem, even though there are only three parameters and in principle is simple to describe, because it must satisfy complex criteria within the limitations of PID control. There are accordingly various methods for loop tuning, and more sophisticated techniques are the subject of patents; this section describes some traditional manual methods for loop tuning.

3.6.1 Stability

If the PID controller parameters are chosen incorrectly, the controlled process input can be unstable, i.e. its output diverges, with or without oscillation, and is limited only by saturation or mechanical breakage. Instability is caused by excess gain, particularly in the presence of significant lag. Generally, stability of response is required and the process must not oscillate for any combination of process conditions and set points, though sometimes marginal stability is acceptable or desired.

3.6.2 Optimum Behavior

The optimum behavior on a process change or set point change varies depending on the application. Two basic desiderata are regulation and command tracking these refer to how well the controlled variable tracks the desired value. Specific criteria for command tracking include rise time and settling time. Some processes must not allow an overshoot of the process variable beyond the setpoint if, for example, this would be unsafe. Other processes must minimize the energy expended in reaching a new setpoint.

3.6.3 Tuning Methods

There are several methods for tuning a PID loop. The most effective methods generally involve the development of some form of process model, then choosing P, I, and D based on the dynamic model parameters. Manual tuning methods can be relatively inefficient, particularly if the loops have response times on the order of minutes or longer. The choice of method will depend largely on whether or not the loop can be taken "offline" for tuning, and the response time of the system. If the system can be taken offline, the best tuning method often involves subjecting the system to a step change in input, measuring the output as a function of time, and using this response to determine the control parameters.

3.6.4 Manual Tuning

If the system must remain online, one tuning method is to first set Ki and Kd values to zero. Increase the K_p until the output of the loop oscillates, then the K_p should be set to approximately half of that value for a "quarter amplitude decay" type response. Then increase K_i until any offset is correct in sufficient time for the process. However, too much K_i will cause instability. Finally, increase Kd, if required, until the loop is acceptably quick to reach its reference after a load disturbance. However, too much K_d will cause excessive response and overshoot. A fast PID loop tuning usually overshoots slightly to reach the setpoint more quickly; however, some systems cannot accept overshoot, in which case an over-damped closed-loop system is required, which will require a K_p setting significantly less than half that of the K_p setting causing oscillation.

Table 3.1: Effects of increasing a parameter independently

Parameter	**Rise Time**	**Overshoot**	**Settling Time**	**Steady-State Error**	**Stability**
K_P	Decrease	Increase	Decrease	Decrease	Degrade
K_I	Decrease	Increase	Decrease	Decrease Significantly	Degrade
K_D	Minor Decrease	Minor Decrease	Minor Decrease	No effect in theory	Improve if K_D small

3.6.5 Ziegler–Nichols Method

Another heuristic tuning method is formally known as the Ziegler–Nichols method, introduced by John G. Ziegler and Nathaniel B. Nichols. As in the method above, the Ki and Kd gains are first set to zero. The P gain is increased until it reaches the ultimate gain, Ku, at which the output of the loop starts to oscillate. Ku and the oscillation period Pu are used to set the gains as shown:

Table 3.2: Ziegler–Nichols method

Control Type	K_P	K_I	K_D
P	$0.50K_u$	-----	----
PI	$0.45K_u$	$1.2K_p/P_u$	----
PID	$0.60K_u$	$2K_p/P_u$	$K_pP_u/8$

The closed – loop Ziegler-Nichols method consist of following steps.

1. With P-only closed loop control, increase the magnitude of the proportional gain until the closed loop is in a continuous oscillation. For slightly larger values of controller gain, the closed loop system is unstable, while the slightly lower values the system is stable.

2. The value of controller proportional gain that causes the continuous oscillation is called the critical gain, K_u. The peak- to - peak period is called critical period $P_{u.}$

3. Depending upon controller chosen, P, PI, or PID, use the value in table3.2 for tuning parameters , based on the critical gain and period.

CHAPTER-4

INTRODUCTION TO MULTIVALUED LOGIC

4.1 Introduction; A Multi-valued Logic

Multi-valued logic is fuzzy logic. fuzzy logic is derived from fuzzy set theory. It deals with reasoning, approximations rather than precise values. The concept of Fuzzy Logic (FL) was conceived by Lotfi Zadeh, a professor at the University of California at Berkley, and presented not as a control methodology. Multi-valued logic allows intermediate values to be defined between conventional evaluations like true/false, yes/no, high/low, etc. Notions like rather tall or very fast can be formulated mathematically and processed by computers, in order to apply a more human-like way of thinking in the programming of computers. Fuzzy systems is an alternative to traditional notions of set membership and logic that has its origins in ancient Greek philosophy. The precision of mathematics owes its success in large part to the efforts of Aristotle and the philosophers who preceded him. In their efforts to devise a concise theory of logic, and later mathematics, the so-called ”Laws of Thought” were posited. One of these, the ”Law of the Excluded Middle,” states that every proposition must either be True or False. Even when Parmenides proposed the first version of this law, there were strong and immediate objections: for example, Heraclitus proposed that things could be simultaneously True and not True. It was Plato who laid the foundation for what would become fuzzy logic, indicating that there was a third region where these opposites ”tumbled about.” Other, more modern philosophers echoed his sentiments, notably Hegel, Marx, and Engels. But it was Lukasiewicz who first proposed a systematic alternative to the bi–valued logic of Aristotle.

4.2 Multivalued Logic; Working

FL requires some numerical parameters in order to operate such as what is considered significant error and significant rate-of-change-of-error, but exact values of these numbers are usually not critical unless very responsive performance is required in which case empirical tuning would determine them. For example, a simple temperature control system could use a single temperature feedback sensor whose data is subtracted from the command signal to compute "error" and then time-differentiated to yield the error slope or rate-of-change-of-error, hereafter called "error-dot". Error might have units of degs F and a small error considered to be 2F while a large error is 5F. The "error-dot" might then have units of degs/min with a small error-dot being 5F/min and a large one being 15F/min. These values don't have to be symmetrical and can be "tweaked" once the system is operating in order to optimize performance. Generally, FL is so forgiving that the system will probably work the first time without any tweaking. Fuzzy reasoning, approximate reasoning, is an inference procedure whose outcome is conclusion for a set of fuzzy if-then rules. The steps of fuzzy reasoning can be given as follows:

i) “Input variables are compared with the MFs on the premise part to obtain the membership values of each linguistic label fuzzification.

ii) The membership values on the premise part are combined through specific fuzzy set operations such as: min, max, or multiplication to get firing strength of each rule.

iii) The qualified consequent either fuzzy or crisp is generated depends on the firing strength.

iv) The qualified consequents are aggregated to produce crisp output according to the defined methods such as: centroid of area, bisector of area, mean of maximum, smallest of maximum and largest of maximum defuzzification.

4.3 Fuzzy Logic; Features

FL offers several unique features that make it a particularly good choice for many control problems.

i) It is inherently robust since it does not require precise, noise-free inputs and can be programmed to fail safely if a feedback sensor quits or is destroyed. The output control is a smooth control function despite a wide range of input variations.

ii) Since the FL controller processes user-defined rules governing the target control system, it can be modified and tweaked easily to improve or drastically alter system performance. New sensors can easily be incorporated into the system simply by generating appropriate governing rules.

iii) FL is not limited to a few feedback inputs and one or two control outputs, nor is it necessary to measure or compute rate-of-change parameters in order for it to be implemented. Any sensor data that provides some indication of a system's actions and reactions is sufficient. This allows the sensors to be inexpensive and imprecise thus keeping the overall system cost and complexity low.

iv) Because of the rule-based operation, any reasonable number of inputs can be processed and numerous outputs generated, although defining the rule base quickly becomes complex if too many inputs and outputs are chosen for a single implementation since rules defining their interrelations must also be defined. It would be better to break the control system into smaller chunks and use several smaller FL controllers distributed on the system, each with more limited responsibilities.

v) FL can control nonlinear systems that would be difficult or impossible to model mathematically. This opens doors for control systems that would normally be deemed unfeasible for automation.

4.4 Fuzzy Sets And Crisp Sets; Comparative study

The very basic notion of fuzzy systems is a fuzzy set. In classical mathematics we are familiar with what we call crisp sets. For example, the possible interferometric coherence g values are the set X of all real numbers between 0 and 1. From this set X a subset A can be defined. The characteristic function of A is shown in figure. 4.1. The elements which have been assigned the number 1 can be interpreted as the elements that are in the set A and the elements which have assigned the number 0 as the elements that are not in the set A.

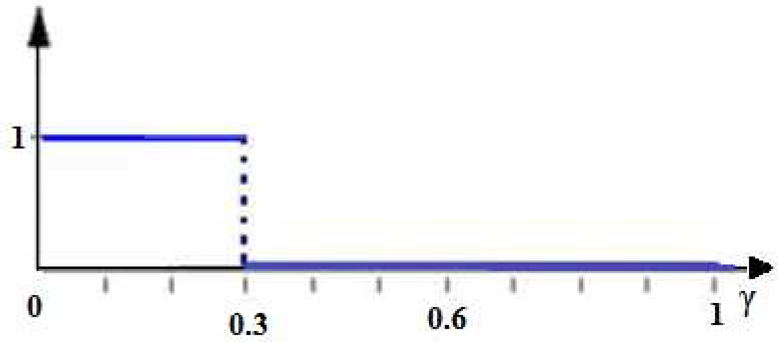

Figure 4.1: Characteristic function of a crisp set

4.5 Fuzzy Logic Expert System

A fuzzy expert system is an expert system that uses a collection of fuzzy membership functions and rules, instead of Boolean logic, to reason about data. The rules in a fuzzy expert system are usually of a form similar to the following:

if x is low and y is high then z = medium where x and y are input variables, z is an output variable, low is a membership function defined on x, high is a membership function defined on y, and medium is a membership function defined on z. The antecedent describes to what degree the rule applies, while the conclusion assigns a membership function to each of one or more output variables. Most tools for working with fuzzy expert systems allow more than one conclusion per rule. The set of rules in a fuzzy expert system is known as the rule base or knowledge base. The general inference process proceeds in three or four basic steps.

1. Under FUZZIFICATION, the membership functions defined on the input variables are applied to their actual values, to determine the degree of truth for each rule premise.
2. Under INFERENCE, the truth value for the premise of each rule is computed, and applied to the conclusion part of each rule. This results in one fuzzy subset to be assigned to each output variable for each rule. Usually only min or product are used as inference rules. In MIN inferencing, the output membership function is clipped off at a height corresponding to the rule premise's computed degree of truth. In product inferencing, the output membership function is scaled by the rule premise's computed degree of truth.
3. Under COMPOSITION, all of the fuzzy subsets assigned to each output variable are combined together to form a single fuzzy subset for each output variable. Again, usually MAX or SUM are used. In MAX composition, the combined output fuzzy subset is constructed by taking the point wise maximum over all of the fuzzy subsets assigned to variable by the inference rule. In SUM composition, the combined output fuzzy subset is constructed by taking the point wise sum over all of the fuzzy subsets assigned to the output variable by the inference rule.
4. Finally is the defuzzification, which is used when it is useful to convert the fuzzy output set to a crisp number. There are many defuzzification methods than you can choose. Two of the more common techniques are the centroid and maximum methods. In the centroid method, the crisp value of the output variable is computed by finding the variable value of the center of gravity of the membership function for the fuzzy value. In the MAXIMUM method, one of the variable values at which the fuzzy subset has its maximum truth value is chosen as the crisp value for the output variable.

4.6 Operation of Fuzzy Logic

Fuzzy logic requires some numerical parameters in order to operate such as what is considered significant error and significant rate-of-change-of-error, but exact values of these numbers are usually not critical unless very responsive performance is required in which case empirical tuning would determine them.

4.7 Type of Fuzzy sets

There are two types of fuzzy set

i) Type I Fuzzy Set

Let X be a collection of objects called universe of discourse. A fuzzy set A $\in$X is characterized by membership function $\mu_A(x)$ (represents the degree of membership), Degree of membership maps each element between 0 and 1. It is defined as

$$A = \{(x, \mu_A(x)); x \in X\} \text{.......................................}4.1$$

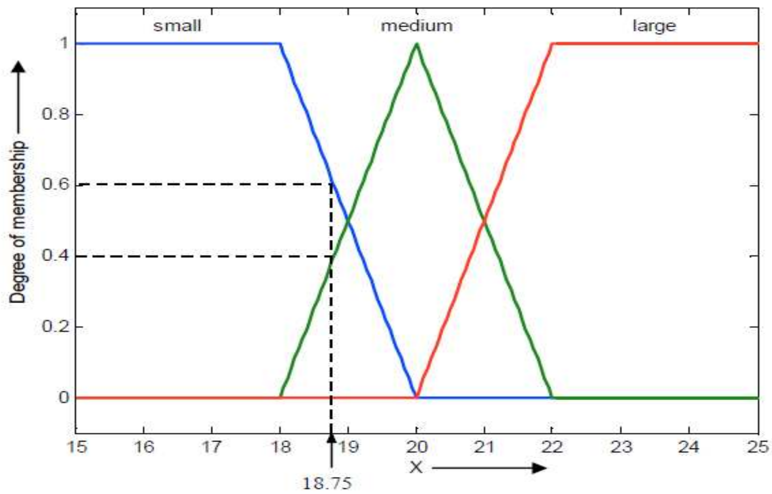

Figure 4.2: Fuzzy Logic Membership Function

i) Type II Fuzzy Set

Type-2 fuzzy sets and systems generalize (type-I) <u>fuzzy sets and systems</u> so that more uncertainty can be handled. A type-2 fuzzy set lets us incorporate uncertainty about the membership function into fuzzy set theory, and is a way to address the above criticism of type-I fuzzy sets head-on. And, if there is no uncertainty, then a type-II fuzzy set reduces to a type-I fuzzy set, which is analogous to probability reducing to determinism when unpredictability vanishes.

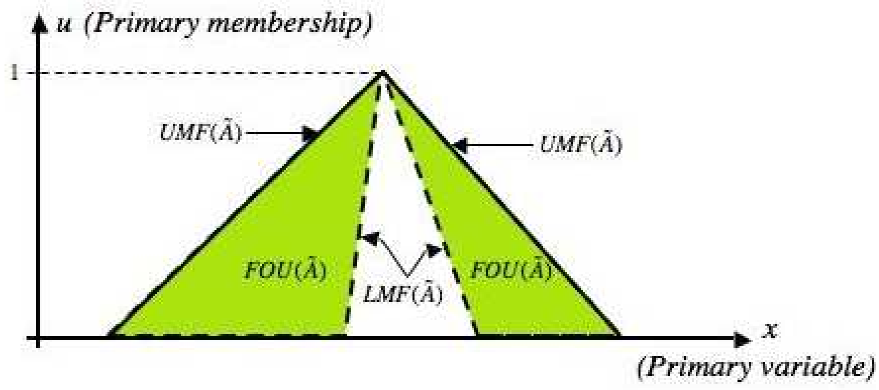

Figure 4.3: FOU for an interval type-2 fuzzy set.

The membership function of a general type-II fuzzy set, Ã, is three-dimensional (Figure 4.3), where the third dimension is the value of the membership function at each point on its two-dimensional domain that is called its footprint of uncertainty (FOU).

4.8 Fuzzy Inference System

Fuzzy inference systems (FIS) are rule-based systems. It is based on fuzzy set theory and fuzzy logic. FIS are mappings from an input space to an output space. FIS allows constructing structures which are used to generate output responses for certain stimulations. Response of FIS is based on stored knowledge. Knowledge is stored in the form of a rule base. Rule base is a set of rules. Rule base expresses relations between inputs of system and its expected outputs.

Knowledge is obtained by eliciting information from specialists. These systems are usually known as fuzzy expert systems. Another common denomination for FIS is fuzzy knowledge-based systems. It is also called as data-driven fuzzy systems. FIS are usually divided in two categories viz. multiple input and multiple output (MIMO) systems and Multiple Input and Single Output (MISO) systems, the system returns several outputs based on the inputs which it receives. Multiple input and single output (MISO) systems are those where only one output is returned from multiple inputs. MIMO systems are decomposed into a set of MISO systems which work in parallel.

In terms of inference process there are two main classes of FIS viz.

1. Mamdani-type FIS and

2. Takagi-Sugeno- Kang (TSK) type FIS.

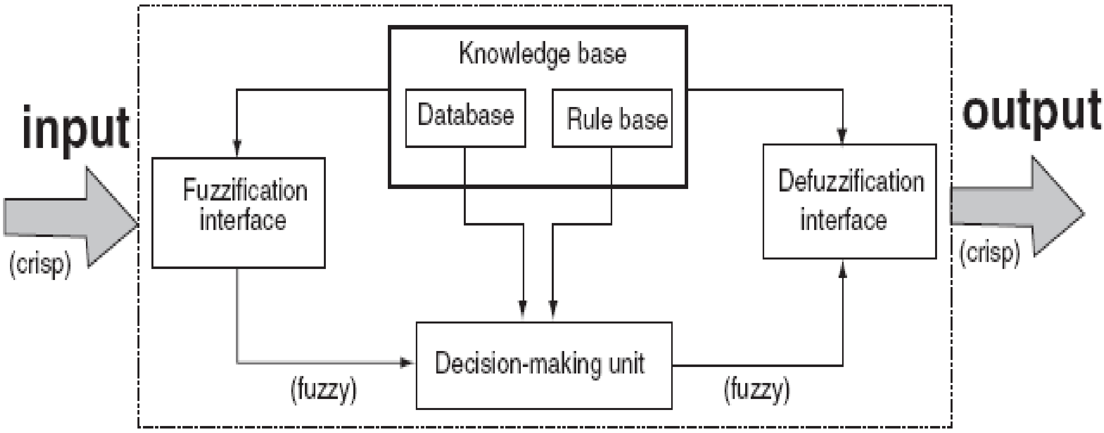

Figure 4.4: Fuzzy inference system

4.8.1 Mamdani Based FIS

In mamdani based fuzzy inference system, inputs and output have an If-Then rules. A typical rule in a sugeno fuzzy model is: IF X is Negative Big AND Y is Negative Small THEN Z is Zero.

4.8.2 Sugeno Based FIS

Sugeno-type systems are used to model any inference system in which output membership functions are either linear or constant. This fuzzy inference system was introduced in 1985. It is also called as Takagi-Sugeno-Kang. Sugeno output membership functions (z) are either linear or constant. A typical rule in a Sugeno fuzzy model is:

If Input 1 = x and Input 2 = y, then Output is $z = ax + by + c$

For a zero-order Sugeno model, the output level z is a constant ($a=b=0$).

Both Sugeno and Mamdani FIS can be used to perform the similar tasks. Rule base and fuzzification remain same for the variables. There are various defuzzifiers that can be chosen for a Mamdani FIS. These defuzzifiers also originate similar results in a Sugeno FIS. There is a certain overlap between both types of systems. Mamdani FIS is more widely used. It is used for decision support applications, because its intuitive and interpretable nature. Consequents of the rules in a Sugeno FIS do not have a direct semantic mean. This means that they are not linguistic terms. Also, this interpretability is partially lost. Sugeno FIS rules consequents can have many parameters per rule as per input values. Thus, Sugeno FIS gets translated into more degrees of freedom in its design as compared to Mamdani FIS. Thus it provides more flexibility. Many parameters can be used in the consequents of the rules of a Sugeno FIS. A zero order Sugeno FIS can reasonably approximate a Mamdani FIS. In computational terms, a Sugeno FIS is more efficient than a Mamdani FIS. It is so because; Sugeno FIS does not involve computationally expensive defuzzification process. Also, a Sugeno FIS always generates continuous surfaces. The continuity of the output surface is quite important. Any existence of discontinuities will result in similar inputs originating substantially different outputs. It will be a situation which is undesirable from the control monitoring perspective. Because of continuous structure of output functions, a Sugeno FIS is also better and adequate for functional analysis than a Mamdani FIS.

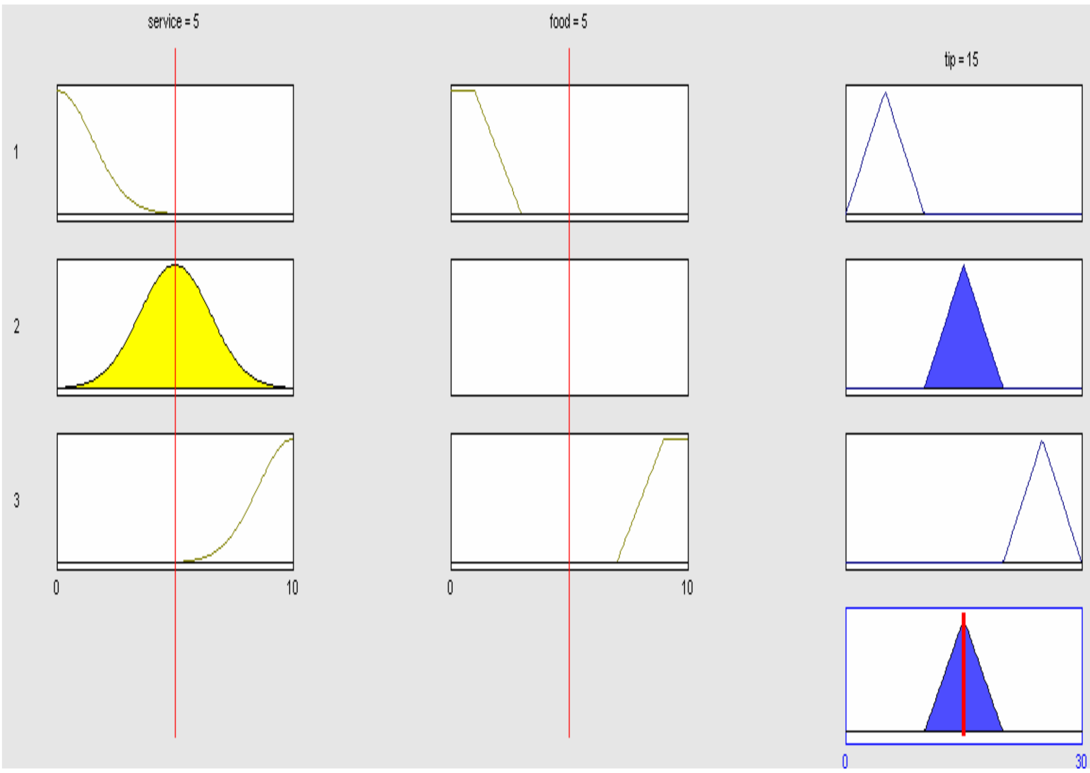

Figure 4.5: Fuzzy Rule Base in the case of a Mamdani Fuzzy Inference System

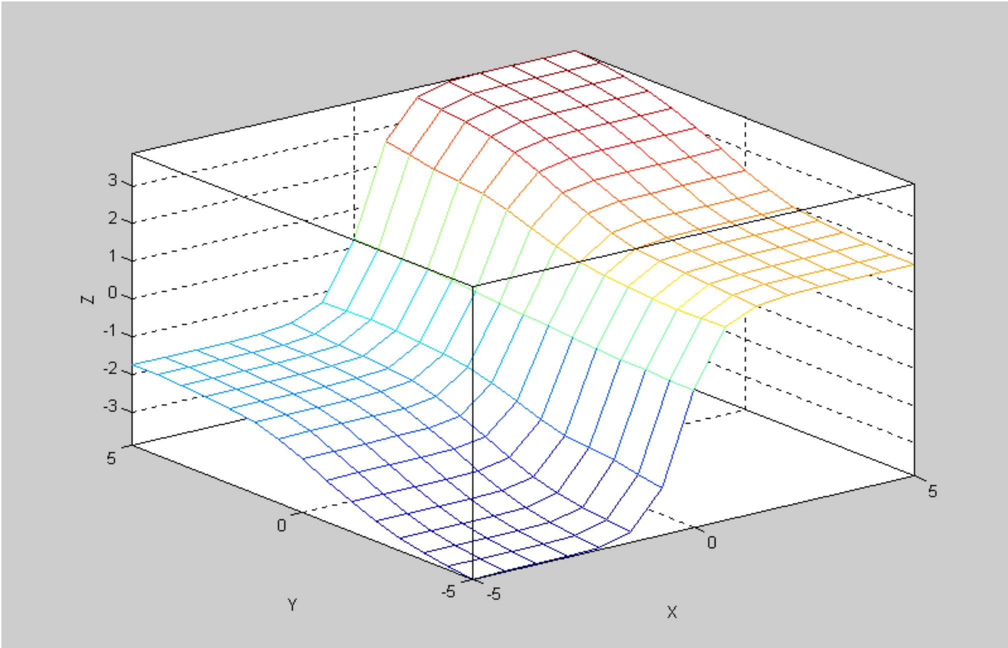

Figure 4.5: Fuzzy Rule Base in the case of a Mamdani Fuzzy Inference System

4.9 Defuzzification

Defuzzification is a processin which fuzzy output converts back to crisp values. There are different types defuzzification methods given as

- Max Membership $\mu_c(z^*) \geq \mu_c(z)$ for all $z \in Z$ …………………………..4.2
- Centroid $z^* = \dfrac{\int \mu_c(z).zdz}{\int \mu_c(z)dz}$ …………………4.3
- Weighted average $z^* = \dfrac{\sum \mu_c(z).z}{\sum \mu_c(z)}$ …………………4.4
- Mean-Max $z^* = \dfrac{a+b}{2}$ ………………………4.5
- Center of Sum $z^* = \dfrac{\int_z z * \sum_{k=1}^{n} \mu_c(z)dz}{\int_z \sum_{k=1}^{n} \mu_c(z)dz}$ ……………4.6
- Center of Largest Area $z^* = \dfrac{\int \mu_c(z)zdz}{\int \mu_c(z)dz}$ …………………4.7

4.10 Fuzzy Control

This section describes the classical control scheme and fuzzy control scheme. In classical control scheme we have open loop and closed loop control architecture. Figure 27 shows the classical feedback control structure of a plant. In fuzzy control scheme the conventional controller is replaced by fuzzy logic controller. The fuzzy control scheme is shown in figure 27.

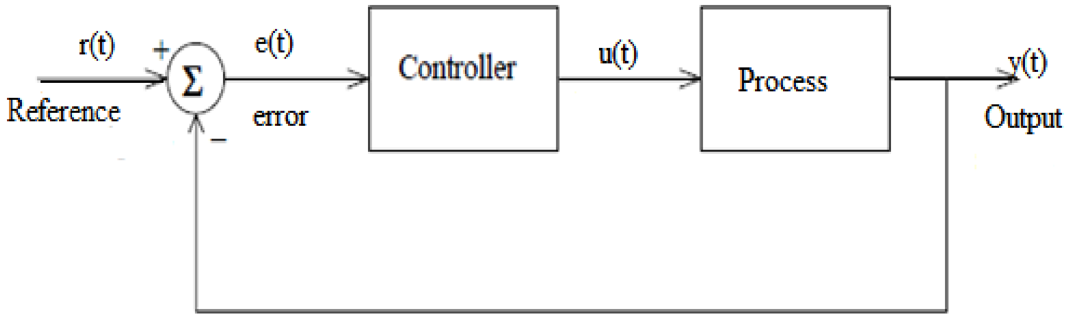

Figure 4.7: Classical Feedback Control Structure

The majority of fuzzy logic control systems are knowledge-based systems in that either their fuzzy models or their fuzzy logic controllers are described by fuzzy IF-THEN rules, which have to be established based on experts' knowledge about the systems, controllers, performance, etc. Moreover, the introduction of input-output intervals and membership functions is more or less subjective, depending on the designer's experience and the available information. However, we emphasize once again that after the determination of the fuzzy sets, all mathematics to follow are rigorous. Also, the purpose of designing and applying fuzzy logic control systems is, above all, to tackle those vague, ill-described, and complex plants and processes that can hardly be handled by classical systems theory, classical control techniques, and classical two-valued logic. This is the first type of fuzzy logic control system: the fuzzy logic controller directly performs the control actions and thus completely replaces a conventional control algorithm. Yet, there is another type of fuzzy logic control system: the fuzzy logic controller is involved in a conventional control system and thus becomes part of the mixed control algorithm, so far as to enhance or improve the performance of the overall control system.

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 modelling 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.

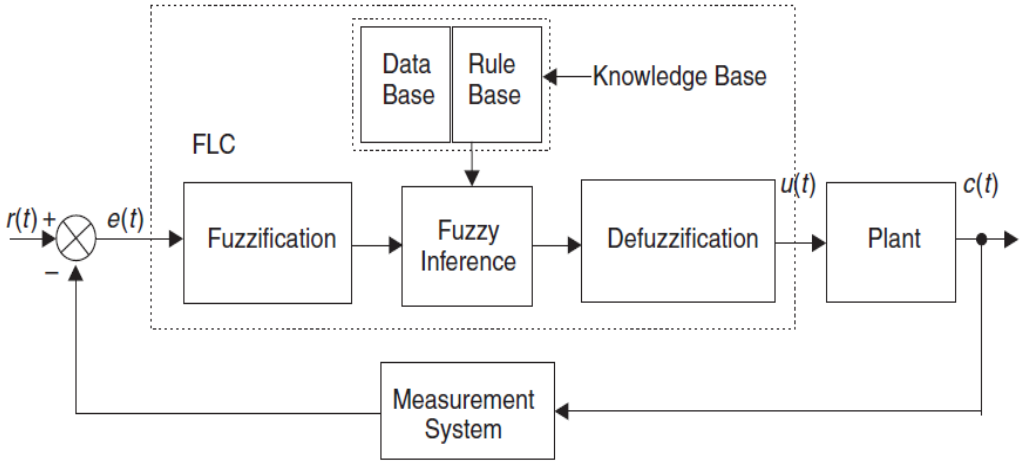

Figure 4.8: Fuzzy Logic Control Structure

Designing a good fuzzy rule base is the key to obtain satisfactory control performance for a particular operation. Classical analysis and control strategy are incorporated in the rule base. The control literature has worked towards reducing the size of the rule base and optimizing the rule base using different optimization techniques like GA, PSO for intelligent controller. At last defuzzified output is obtained from the fuzzy inputs. Table 1 shows the linguistic variables for fuzzy control.

4.12. The Self-Tuning Control Principle of Fuzzy PID Parameter

PID control requirements model structure very precise, and in practical applications, to different extent, most of industrial processes exist to the nonlinear, the variability of parameters and the uncertainty of model, thus using conventional PID control can not achieve the precise control of the process. But the dependence on the mathematical model of the fuzzy control is weak, so it isn't necessary to establish the precise mathematical model of the process, and the fuzzy control has a good robustness and adaptability. According to their own characteristics, we combine fuzzy control with PID control, and provide a based on fuzzy PID parameters self-tuning controller with MATLAB. Fuzzy PID parameters Self-tuning Control takes error "e" and Change-in-error "ec" as the input of Fuzzy PID controller, meets the request of the different moments of "e" and "ec" to PID parameters self-tuning. Using fuzzy control rules on-line, PID parameters "kp", "ki", "kd" are amended, which constitute a self-tuning fuzzy PID controller, the principle of which control program as shown in Figure 4.9

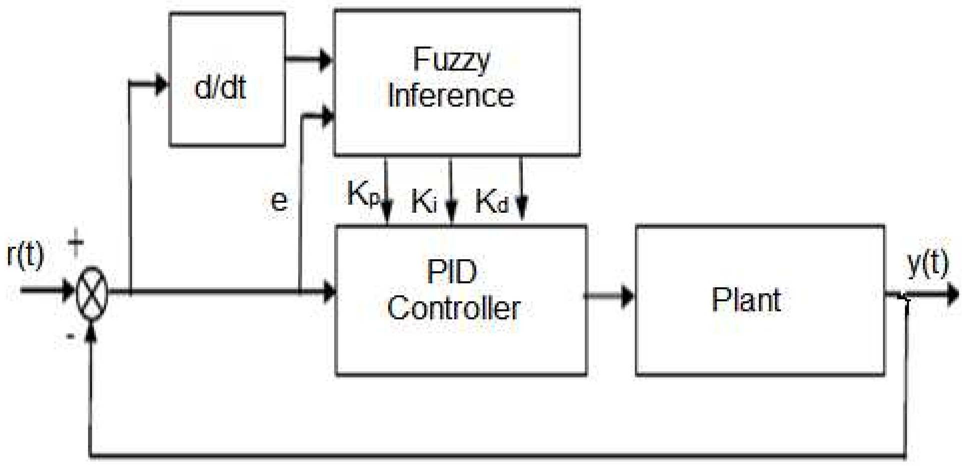

Figure 4.9 :The structure of self-tuning fuzzy PID controller

Fuzzy logic consists of three parts: Fuzzification, inference and defuzzification. Fuzzification is an interface that produces a fuzzy subset from the measurement; that is, it is a mapping from the set of measurements. The inference is an interface that produces a new fuzzy subset from the result of the fuzzification using for example a set of rules. The results of the inference are a fuzzy subset associated with the output. The defuzzification is an interface that produces a crisp output from the results of the interface. The fuzzy inputs (error and the change rate of error) are classified into seven equal-span triangular membership functions. NB, NM, NS, ZE, PS, PM, PB are negative big, negative medium, negative small, zero, positive small, positive medium and positive big.

One of the important steps of fuzzy logic controller is the rule table. The total number of rules is 49 in this study. The output is partitioned into seven fuzzy sets:

negative big (NB), negative medium (NM), negative small (NS), zero (ZE), positive small (PS), positive medium (PM) and positive big (PB). The design of a fuzzy logic controller consists of the selection of membership functions and definition of a rule base. In this study, fuzzy logic controller has two inputs and one output: the position error, change of the error and the temperature of the boiler. Input and output fuzzy members functions are symmetric.

A membership function characterizes a fuzzy set. The value of membership function represents a degree of membership to the fuzzy set, which is between 0 and 1. A fuzzy set with the sharp membership function curve has higher resolution and control sensitivity. With the smooth one, the stability of system is better but resolution is lower. Fuzzy control rules is a set expressed by fuzzy language, which describes the mapping relationship of inputs and outputs.

Run fuzzy function in MATLAB command window to enter the fuzzy logic editor, and create a new FIS file, choosing the control type as Mamdani. According to the analysis above, by inputting the membership degree function and quantizing intervals of e, ec, ΔK_p, ΔK_i and ΔK_d respectively, the figure of membership degree function can be achieved. Opening the window of Ruler Editor, inputting the fuzzy control rules with the form of if……then, and taking min as the And method, max as the Or method, min as the Implication, max as the Aggregation, and defuzzification as the centroid, a FIS file named Fuzzypid.fis can be created. Then creating a file named fpid.m in MATLAB's file editor with the content of matrix=readfis ('Fuzzypid.fis'), the link between fuzzy toolbox and SIMULINK has been established, which lays the foundation for building the whole system.

CHAPTER -5

ARTIFICIAL IMMUNE SYSTEM

5.1 Introduction

The main function of the immune system is to protect the body from pathogens and cancer. Vertebrate immune systems are more complex than the invertebrates. They are characterized by two important properties, which are memory and specificity. In the case of invertebrate, the immune system consists mainly of Phagocytes which are nonspecific. This means that it will not remember any previous antigen, and will use the same attacking strategy each time. Phagocytes has no receptors for specific pathogens, which means that these cells will engulf and try to kill any pathogen. On the other hand, the vertebrate host has evolved more specialized cells called Lymphocytes. These Lymphocytes are pathogen specific, which means that they have distinct receptors to interact with different pathogens. To combat antigens, nature has provided us with the immune system. The blood, lymph nodes, and bone marrow act with the liver, spleen, thymus, and tonsils to produce and deliver specialized cells, including B-lymphocytes, T lymphocytes, and phagocytes. These cells limit the severity and duration of colds, Fight infections in the nose and throat, help wounds to heal, destroy some cancers, and much more.

There are two types of immune models

1) Immune model based on the immune system theory (mainly clones choice theory nowadays).
    a) The somatic theory describes that somatic recombination and mutation contribute to increasing the diversity of antibody.
    b) The network hypothesis describe that a mutual recognition network among antibody contributes to control of the proliferation of clones.
2) Immune network model based on the immune network theory.
    a) All the continuous immune network models at present are the ordinary differential equation of time, which conforms to the real control system.

b) The discrete immune network model is not the common discrete model based on time control system, but it means that the immune cells or molecules are separated among each others.

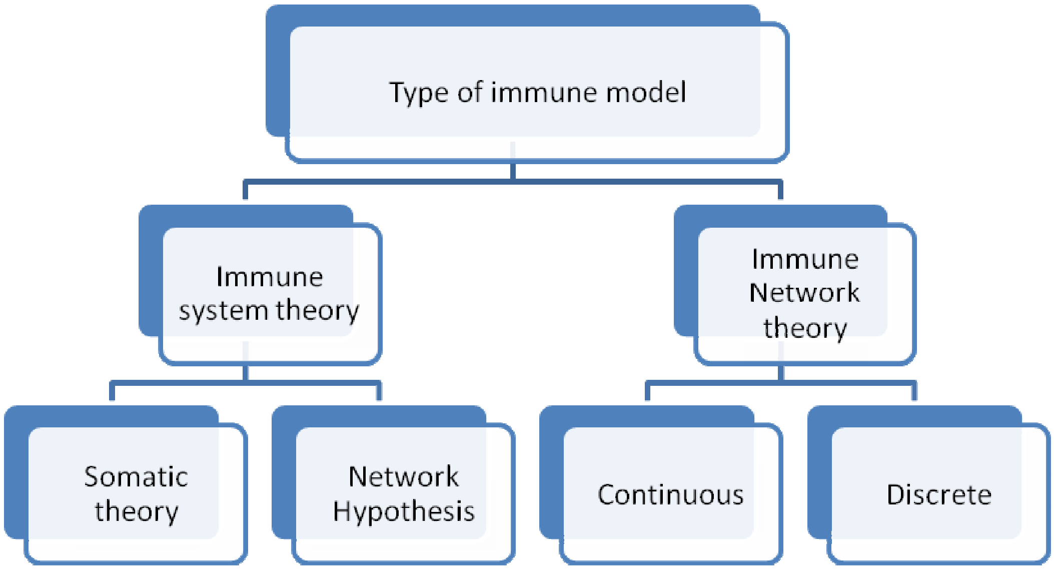

Figure 5.1: Types of immune model

5.2 Innate Versus Acquired Immunity

There are two types of immunity, innate immunity and adaptive or acquired immunity. Also, the immune system response can be divided into humoral immunity, and cell mediated response.

5.2.1 Innate Immunity

The innate immunity can be regarded as natural resistance of the host to foreign pathogens. There are a number of external and internal lines of defenses in the innate immunity. As an examples we find Lysozymes in tears, and skin inflammation as a resistance to a penetrating pathogen. The innate immunity is the first line of defense against the foreign pathogens, and it uses the non-specific strategy while attacking it. Phagocytes engulf the foreign pathogen, and try to kill it. Some examples on the same line of defense are Monocytes, Macrophages, and Neutrophils. There are other types of cells that is called Natural killer cells NK-cells that also use non-specific response to protect the host against the foreign pathogen.

5.2.2 Acquired Immunity

In contrast to the innate immune system, the acquired immune system uses a specific response to pathogens. The important advantage of the acquired immunity is the use of memory through lymphocytes. After getting rid of the foreign pathogen the lymphocytes change into memory cells. These memory cells will recognize rapidly the same pathogen when it evades the host again, and eliminate it before causing any damage. The two major types of lymphocytes are T-cells, and B-cells. B-cells have direct contact with the antigen when interacting with it. On the other hand, T-cell can bind to the antigen only after it is processed and presented by other cells. B-cells are the basic building block of the humoral immunity through the production of antibodies. Cell mediated immunity is contributed by T-cells mediated response. T cells have many forms like the helper T-cell which helps either B-cells, or phagocytic macrophages. Another form that the T-cell can be is the cytotoxic T-cells, which recognize cells infected by virus or cancer, and eliminate them.

5.3 Antigens

An antigen (Ag) can be defined as a substance that triggers specific immune response. In vertebrates, the host system does not respond to its own proteins, and that is called tolerance. T-cells and B-cells that are capable of recognizing self-cells are eliminated during maturation phase,. An antigen may carry several epitops, and consequently this will trigger the production of several antibodies, see Figure 5.2. Generally, T or B cells do not recognize all of these epitopes, instead they recognize part of it. So, a single Ag may attract the attention of several T or B cells. Also, two different antigens may carry the same cross reactive epitopes, which means that an antibody produced for that antigen can interact with another one.

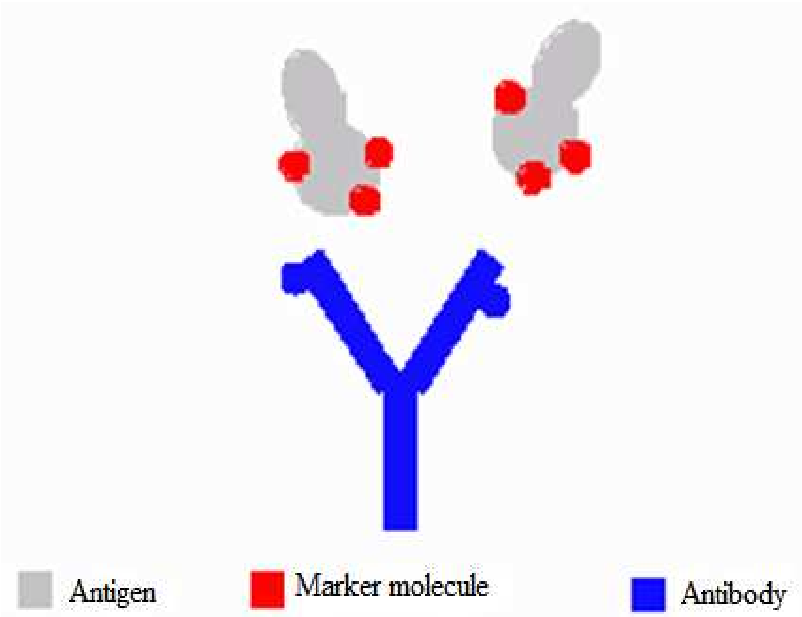

Figure:5.2: antigen antibody interactions

5.4 Immune Cells

Cells destined to become immune cells are produced in the bone marrow. The descendants of some stem cells become lymphocytes, while others develop into a second group of immune cells known as phagocytes. The two major classes of lymphocytes are B cells and T cells. B cells complete their maturation in the bone marrow. On the other hand, T cells migrate to the thymus; an organ that lies high behind the breastbone. Each lymph node contains specialized compartments that house a great number of B lymphocytes, T lymphocytes, capable of presenting antigen to T cells. Thus, the lymph node brings together the several components needed to start an immune response.

5.5 B-Cells and Antibodies

B-Cell is one of the major arms of the immune system mechanisms, and it is responsible for the humoral response. The name humoral comes from these fluids that circulate around the body known as humors. Each B cell is programmed to make one specific antibody. When a B cell encounters its triggering antigen, it produces many large plasma cells. Every plasma cell is a factory for producing antibody. Each of the plasma cells descended from a given B cell produces millions of identical antibody molecules and pours them into the bloodstream, see Figure 5.3. A given antibody matches an antigen as a key matches a lock, and marks it for destruction.

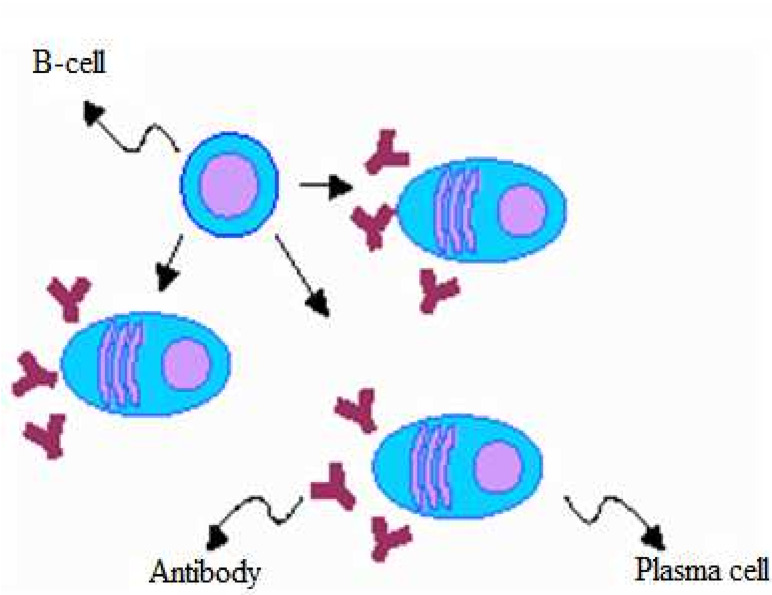

Figure5.3: Production of antibody

5.6 T-Cells And Lymphokines

T-Cells play two rolls in the immune system defense. B cells cannot make antibody against most substances without regulatory T-cell help. On the other hand, Cytotoxic T-cells, directly attack body cells that are infected. Another important regulatory T cells are "helper" cells. Typically identifiable by the T4 cell marker, helper T cells activate B cells and other T cells as well as natural killer cells and macrophages. Another subset of T cells contributes by turning off or "suppress" these cells. T cells work by secreting cytokines or, Lymphokines which are considered to be chemical messengers.

5.7 Macrophages

Macrophages are responsible for carrying the initial attack against an invasion launched by antigens. Macrophages are distributed throughout body tissues , and they rid the body of worn-out cells and other debris. Foremost among the cells that "present" antigen to T cells, having first digested and processed it, macrophages play a crucial role in initiating the immune response. As secretory cells, Monocytes and Macrophages are essential to the regulation of immune responses and the development of inflammation; they produce an array of powerful chemical called Monokines including enzymes, complement proteins, and regulatory factors such as interleukin-1. Sometimes antigens change themselves, and that is why we continue to get sick.

4.8 An Overview of the Immune System

When foreign antigen enters the body, it triggers B-cells to produce antibodies, which bind to the antigen and clear it from the body; this is called Humoral immune response. The cell-mediated response involves helper T-cells and T cytotoxic (CTL) cells. Helper T-cells (Th) can be divided into two sub fields: Th1 and Th2. Th1 cells help B-cells, where Th1 cells activate macrophages. CTL cells kill virtually infected or Cancer cells, see Figure 5.4.

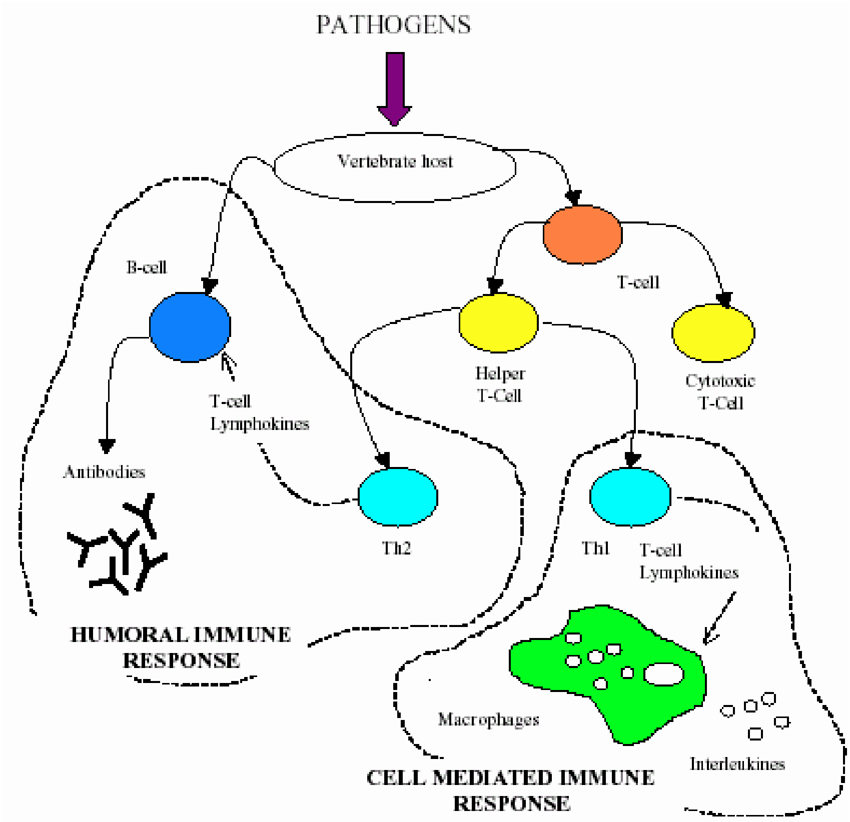

Figure 5.4 : An Overview of an Immune System

5.8.1 Humoral Response

When the B-cell proliferates, all of its descendants will make this uniquely rearranged set of antibodies. B-cells continue to multiply, various mutants arise; these allow for the natural selection of antibodies that provide better and better "fits" for antigen elimination. The result of this entire process is that a limited number of B-cells can respond to an unlimited number of antigens. Antibodies are triggered when a B-cell encounters its matching antigen, and digest it. Antigen fragments are displayed on B-cell distinctive markers. The combination of antigen fragments, and marker molecules attract the mature matching helping cells. T-Cells secrete Lymphokines allow B-cells to multiply and mature into antibody producing Plasma cell. Antibodies are released into the blood stream, and they lock into matching antigens. These antigen-body complexes are soon overcome either by the complement cascade, or by the liver and spleen, see Figure 5.5.

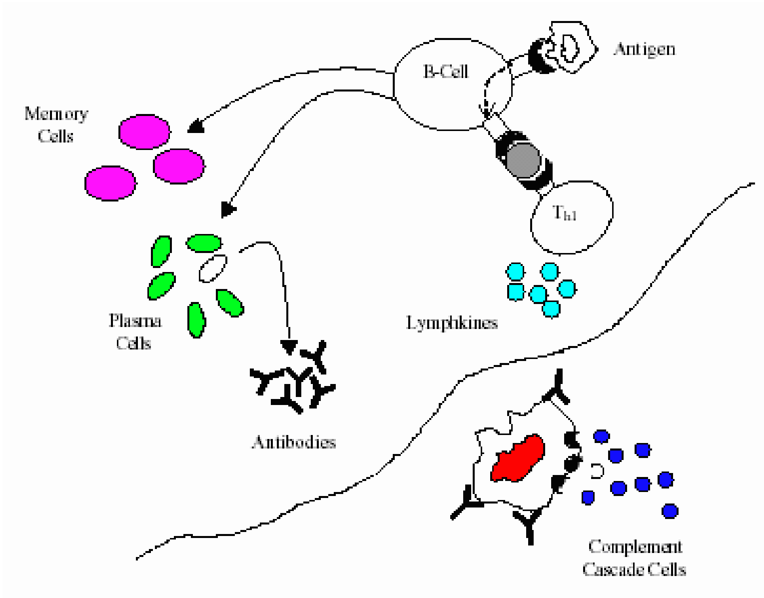

Figure 5.5 : Humoral Response

5.8.2 Cell Mediated Response

Machrophages initiate the cell mediated response, or by other antigen-presenting cell. The antigen-presenting cell digest the antigen, and then displays antigen fragments on its own surface. Bound to the antigen fragment is an MHC molecule. These fragments capture the T cell's attention. A T cell whose receptor fits this antigen binds to it. This bond stimulates the antigen-presenting cell to secrete Interleukins required for T cell activation and performance.

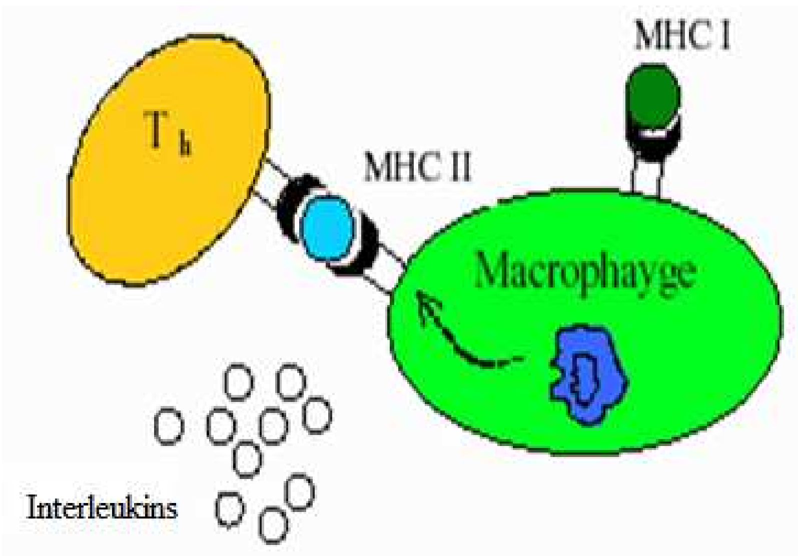

Figure 5.6: Cell mediated response

5.9 Analysis of Lines of Defense

The human immune system attempts to quickly control the spread of antigens once they have been identified. There are several other lines of defense against antigens besides the immune system. The first line of defense is the skin, which prevents the invasion of most micro organisms. The proteins and acidity of the saliva in the mouth and stomach digest harmless microorganisms. However, if there is a cut in the skin, or fluid transmission occurs, pathogens can invade the body. The second line of defense is the cell-mediated response of the immune system. Macrophages are circulating throughout the body that destroy the invading microorganisms by phagocytosis. The last line of defense is known as the humoral immune response. Many types of immune cells are triggered to move into the affected area, and a great deal of antibodies and phagocytes destroy the invading antigen.

5.10 Memory Cells

Some of the lymphocytes activated during the primary immune response remain dormant and keep circulating in the immune system for a long time. These lymphocytes carry the memory of the encountered antigen, and therefore these long-lived cells are called memory cells. Memory can also be maintained by long-lived antigen. Whenever T cells and B cells are activated, some of the cells become "memory" cells. Then, the next time that an individual encounters that same antigen, the immune system is primed to destroy it quickly. The degree and duration of immunity depend on the kind of antigen, its amount, and how it enters the body. An immune response is also dictated by heredity; some individuals respond strongly to a given antigen, others weakly, and some not at all.

5.10.1 Memory T Cells

Memory T cells are formed during an immune response. As the term implies, memory T cells remember past attacks by antigens, and can respond with increased strength during subsequent invasions by a particular pathogen. Memory T cells are long lasting immune cells, and react to particular antigens. Unlike T cells that recirculate in the blood and lymph, memory T cells often circulate throughout the entire body, especially in the site they were originally activated. Memory T cells rely on memory helper T cells for launching a global immune response.

5.10.2 Memory Helper T Cells

Memory helper T cells are also known as memory effector T cells. Memory helper T cells are used by memory T cells to launch an immune response against an attack by pathogens. Memory helper T cells react in much the same way as helper T cells, except that they are stimulated by memory T cells. Memory helper T cells can differentiate into a cytotoxic T cell that attacks abnormal cells, or into a helper T cell that stimulates an immune response from B cells.

5.10.3 Memory B Cells

Little is currently known about memory B cells. However, memory B cells are probably similar to memory T cells in that they retain a strong affinity to low concentrations of antigen, and are able to launch a strong immune response following stimulation by a particular antigen that they are sensitive to. Like normal B cells, memory B cells circulate throughout the entire body. However, they are significantly longer lived, on scales of a few months to years.

5.11 Proposition of Artificial Immune Controller Algorithm

The Biological immune system is a control system that has strong robusticity and self-adaptability in complex disturbance and indeterminacy environment. The artificial immune algorithm has fundamental ability to produce new types of antibody or to find the best fitted antibody which is able to attack the antigen invading into the body. The principal function of the immune system is to limit damage to the host organism by pathogens. Such organisms generate an immune response, and are thus called antigens. Immune system has fundamental ability to produce new types of antibody or to find the best fitted antibody which able to attack the antigen invading into the body. Against the unnumerable types of unknown antigen, the immune system produces a great many types of antibody by trial and error.

Design of the controller aims to enhance the quality of the control system and obtain requested control goal. It is the key for guaranteeing the quality and the characteristic of the control system once the model of the object is determinate. Therefore the design and the analysis of controller is a focal point which the whole control domain pays attention to. There are two method for design traditional controller: One is the classical control theory design method, including linear method such as the method of the root-locus, the method of frequency domain, PID adjustment and non-linear method such as phase plane, description function; Another is the modern control theory design method, including the state feedback controller, the auto-adapted adjustment controller, change the structure controller, based on H. and so on. The design and realization of controller mentioned above already had a series of relative more complete and strict theory methods, but still some defaults left, For example, the object is often limited strictly to be linear, or having been known at least.

5.12 Immune PID control

Introduction of immune PID controller are describe in the following section

5.12.1 Feedback principle of immune system

Immune is a characteristic physiological reaction of biological body. Immune system of biology could produce relative antibody to resist invading anti-source from extraneous. After antibody combines with anti source, a serial reaction will be brought to destroy antibody by swallowing effect or producing special enzyme. In immune system, there is a feedback mechanism that enables human survival of infection and disease. Fig.5.7 presents the principle of feedback mechanism. The basic cells that are involved in the process are antigens Ag, antibodies Ab, B-cells B, helper T-cells T_H and suppressor T-cells T_S. According to Fig.5.7, we know that antigens will be recognized by APC (Antigen Presenting Cell) when they invade into organisms, then, the message will be sent to T-cells. After receiving the message, B-cells will be stimulated by T-cells and create antibodies immediately to eliminate the antigen. When the number of antigens is increasing, the number of T_H-cells will increase and the human body can create more B-cells to protect itself. Along with the decrease of antigens, the amount of T_S-cells in the body would increase and the number of B-cells would reduce accordingly. After a period of time, the immune system inclines to balance. Table 1 summarizes the regulation actions of T-cells in the process of the above immune response.

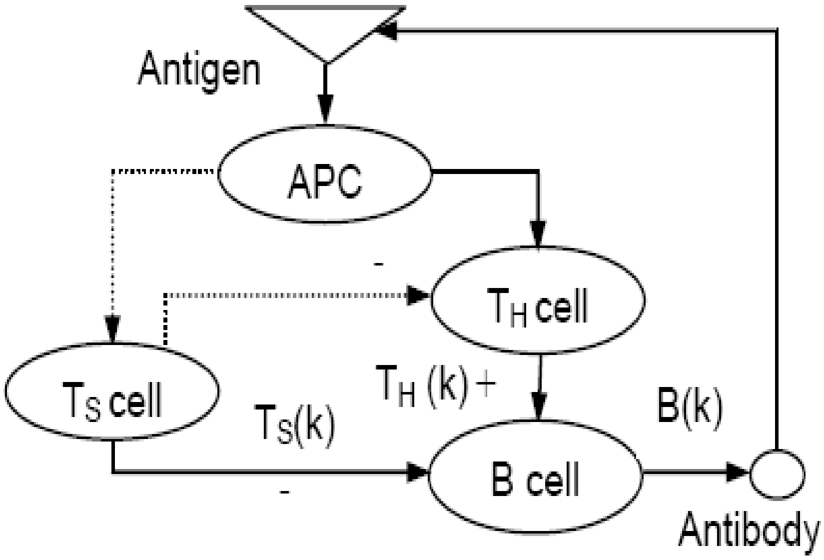

Figure 5.7: Schematic diagram of immune humoral response

Table 5.1.Regulations actions of T-cells in immune response

Immunity response process	**Antigen consistency**	**Antibody consistency**	**T-cells consistency**
Antigen invasion	High	minimum	----
Prophase	High	Low	Promotion
Anaphase	Low	High	Suppression
Telophase	Minimum	Low	-----

As aforementioned, the T_S cells have the function of restraining the T_H cells and B-cells. This paper mainly focuses on the suppression action of the B-cells. For the invasion of the antigen, the B-cells are activated and restrained by the T_S cells. Therefore, the consistency of the kth generation B-cells can be given by

$$B(k)=T_H(k)-T_S(k) \quad \ldots\ldots 5.1$$

$$T_H(k)=K_1\varepsilon(k) \quad \ldots\ldots 5.2$$

$$T_S(k)=K_2\{f[\Delta B(k-d)]\}\varepsilon(k) \quad \ldots\ldots 5.3$$

where $\varepsilon(k)$ is the consistency of antigen at the kth generation; K_1 is the helper gene of T_H; K_2 is the suppressor gene of T_S; $\triangle B(k)$ is the change of B-cell's consistency $\triangle B(k\text{-}d)=B(k\text{-}d)\text{-}B(k\text{-}d\text{-}1)$, and d is the delay-time of immune response; $f(x)$ is an nonlinear function that represents the interaction between antibody which emerge from B-cells and antigen.

From (5.1)~(5.3), we can obtain the relationship formula about the consistency of B-cells and antigen. It is shown as follows:

$$B(k)=K_1\mathcal{E}(k)-K_2\{f[\Delta B(k-d)]\}\mathcal{E}(k)$$
$$=K\{1-\eta f[\Delta B(k-d)]\}\mathcal{E}(k) \qquad \ldots\ldots\ldots\ldots\ldots\ldots 5.4$$

where $\eta= K_2/K_1$ denotes the proportional coefficient of effecting between T_H and T_S.

Table 5.2: Comparison between artificial immune system and control system

Immune System	Control System
1) The kth generation reproduction of antigens and antibodies. 2) $\mathcal{E}(k)$ is the antigen concentration of the kth generation. 3) B(k) is the B cell concentration of the kth generation.	1) The kth sampling time of discrete system. 2) e(k) is the deviation of the set value and output value at the kth sampling instant. 3) u(k) is the output value of the controller at kth sampling instant

5.12.2. Immune PID Controller Design

The principal function of the appropriate immune response lies in ensuring the stability of the immune system and simultaneously responding to the antigen invasion in a fast way, since all the antigens attacking the biological body have to be removed. On the other hand, a high antibody consistency also does harm to the body, and must be controlled. Therefore, the general target of the immune system is to minimize the total injury of the biological body. In the dynamic regulation of a control system, it is requested that deviation should be slaked on the promise of the system stability, which is actually consistent with the target of immune system. Table 5.2 summarizes the comparison between the immune system and control system.

Let the amount of antigen $\varepsilon(k)$ as error $e(k)$, total stimulation that is accepted by B-cells is the input of the control $u(k)$. And then the law of feedback control can be expressed as follows.

$$u(k)=K\{1-\eta f[\Delta u(k-d)]\}e(k)$$
$$=K_I e(k)\ldots\ldots 5.5$$

where K{1-ηf[Δu(k-d)]}=K_I is the proportional gain of immune controller. η= *K*2/*K*1 is called steady gene which controls the amount of proportional gain K_I; *f*(x) is a nonlinear function about Δ*u*(*k*-*d*).

According to the antigen consistency's influence on antibody in immune response, we selected nonlinear function as T-cells regulating action function based on simulation. It is showed as follows

$$f(x)=1-\frac{2}{1+\exp(-cx)} \quad c>0;\ldots\ldots 5.6$$

Where - 1 < *f* (x) < 1, the value of c determines the zone of action of variable x.
The output of Immune controller can be computed as follows:

$$u(k)=K\left[1-\eta\left(1-\frac{2}{1+\exp(-cx)}\right)\right]e(k)\ldots\ldots 5.7$$

It is obvious that Immune Controller （IC） is a nonlinear P controller, its proportional gain will transform with the transformation of the output of controller. Therefore, Immune P Controller cannot compensate noises and errors arose by nonlinear disturbance. Thus, the fusion of the immune controller and conventional PID controller, namely immune PID controller, can learn from each other's strengths and overcome the weaknesses to improve the system performance.

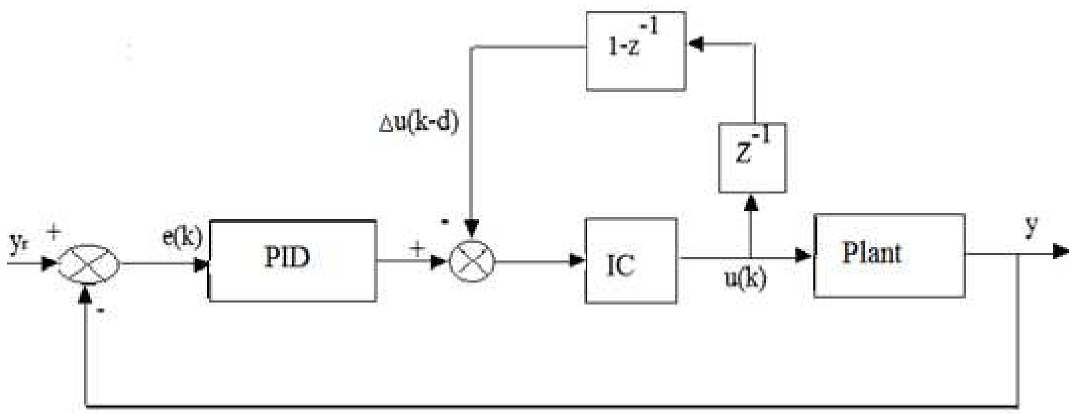

Figure.5.8: The structure of immune PID controller.

The structure of our immune PID controller is described in Fig. 3, whose output is:

$$u(k) = K_I * k_p \left[1 + \frac{K_I}{1 - z^{-1}} + k_d \left(1 - z^{-1}\right) \right] e(k) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..5.8$$

$$u(k) = K_{pI} \left[1 + \frac{K_I}{1 - z^{-1}} + k_d \left(1 - z^{-1}\right) \right] e(k) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots...\ldots\ldots5.9$$

where k_{pI} represents k_p which adjusted by mechanism of immune feedback.

CHAPTER 6

MATHEMATICAL MODELING OF THREE TANK LIQUID LEVEL SYSTEM

6.1 Introduction

Liquid level control is a typical representation of process control and is widely used in iron and steel, chemicals, petroleum and other industries. The control quality directly affects the quality of products and safety of equipments. However, the liquid level control system of water tank is a large lag, time-varying and nonlinear complex system and is very difficult to control. Now, the liquid level control has been an active area in the process control over last decades and various different approaches have been devised.

In industrial applications liquid level control is very important as in food processing industry, dairy, filtration, effluent treatment, nuclear power generation plants, pharmaceutical industries, water purification systems, industrial chemical processing and spray coating and boilers in all the industries. The typical actuators used in liquid level control systems include pumps , motorized valves , on-off valves and level sensors such as displacement float, capacitance probe and pressure sensor provide liquid level measurement for feedback control purpose so that as per the process requirements the fluids could be controlled. In this exercise, the system is modeled, calibrated, and controlled for level determination in a three tank level control system. In particular, this exposes the fundamental modeling principle of fluid mass balance, pressure sensor calibration, and a feedback control design methodology for a state-coupled, three-tank level control system.

In this thesis, the liquid level control system of a - container water tank system is discussed. A 3 – container water tank is usually connected by three first-order non periodic inertia links in series, and its structure can be schematically shown in Figure.6.1. A level sensor is used to measure the water height inside the tank 3. The design model consist of a controller that will either maintain that liquid level at a desired point , a disturbance rejection problem ,or one that can be used to move the level set- point . The idea is to fill the tank to the desired set- point as quickly and smoothly as possible. The additional liquid flows out of the tank through an open valve. This flow is represented by q. Liquid is allowed to flow into the tank by mean of pump. The pump flow Q, can be regulated by controller. The tank cross –sectional area is represented by A.

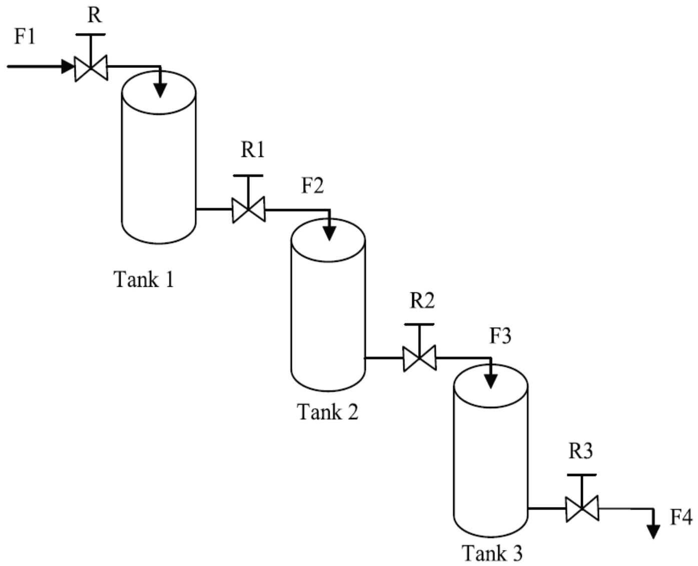

Figure.6.1: Three tank level system

6.2. Mathematical model

For Tank 1;-

$$F_1(t) - F_2(t) = A_1 \frac{dh_1}{dt} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 6.1$$

Where

$F_1(t)$ =tank1 inflowing liquid (m^3/s), $F_2(t)$ =tank1 outflowing liquid(m^3/s), A_1 =area of the tank1 (m2) and h_1 =liquid level in tank1 (m).

For Tank 2:-

$$F_2(t) - F_3(t) = A_2 \frac{dh_2}{dt} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 6.2$$

Where

$F_2(t)$ =tank2 inflowing liquid (m^3/s), $F_3(t)$ =tank2 outflowing liquid(m^3/s), A_2 =area of the tank2 (m2) and h_2 =liquid level in tank2 (m).

For Tank 3:-

$$F_3(t) - F_4(t) = A_3 \frac{dh_3}{dt} \quad \text{...................................6.3}$$

Where

F_3 (t) =tank3 inflowing liquid (m^3/s), $F_4(t)$ =tank3 outflowing liquid(m^3/s), A_3 =area of the tank2 (m^2) and h_3 =liquid level in tank3 (m).

F_2 (t)=h_1/R_1

F_3 (t)=h_2/R_2

F_4 (t)=h_3/R_3

where R_1, R_2 and R_3 are linear resistance of tank1,tank2 and tank 3 (m/(m^3/s)).

The overall transfer function of three tank system is

$$\frac{H_3(s)}{F_1(s)} = \left(\frac{R_1}{A_1R_1s+1}\right)\left(\frac{R_2/R_1}{A_2R_2s+1}\right)\left(\frac{R_3/R_2}{A_3R_3s+1}\right) \quad \text{..........................6.4}$$

By considering

A_1=A_2 =1m^2 ; A_3=0.5m^2 and R_1 =2 (m/(m^3/s)),R_2 =2 (m/(m^3/s)); R_3 =4 (m/(m^3/s)).

$$\frac{H_3(s)}{F_1(s)} = \left(\frac{2}{2s+1}\right)\left(\frac{1}{2s+1}\right)\left(\frac{2}{2s+1}\right) \quad \text{.................................6.5}$$

$$G_p(s) = \frac{H_3(s)}{F_1(s)} = \left(\frac{4}{8s^3+12s^2+6s+1}\right) \quad \text{..............................6.6}$$

Transfer function of valve (R)= $\left(\frac{.133}{3s+1}\right)$

Where $G_p(s)$ is the transfer function of the plant

6.3 Control Valve

Process plants consist of hundreds, or even thousands, of control loops all networked together to produce a product to be offered for sale. Each of these control loops is designed to keep some important process variable such as pressure, flow, level, temperature, etc. within a required operating range to ensure the quality of the end product. Each of these loops receives and internally creates disturbances that detrimentally affect the process variable, and interaction from other loops in the network provides disturbances that influence the process variable. To reduce the effect of these load disturbances, sensors and transmitters collect information about the process variable and its relationship to some desired set point. A controller then processes this information and decides what must be done to get the process variable back to where it should be after a load disturbance occurs. When all the measuring, comparing, and calculating are done, some type of final control element must implement the strategy selected by the controller.

The most common final control element in the process control industries is the control valve. The control valve manipulates a flowing fluid, such as gas, steam, water, or chemical compounds, to compensate for the load disturbance and keep the regulated process variable as close as possible to the desired set point.

6.4 Flow Through Valves

The flow through valve is often described by the relationship

$$F = C_v f(x) \sqrt{\frac{\Delta P_v}{s.g.}} \quad \ldots\ldots\ldots\ldots\ldots\ldots 6.7$$

Where F is the volumetric flow rate, C_v the valve coefficient ,x the function of the valve is open $(0 \le x \le 1)$, ΔP_v the pressure drop across the valve, s.g. the specific gravity of the fluid, and f(x) the flow characteristic (varies from 0 to 1, as a function of x).

Three common valve characteristics are

(i) Linear

(ii)Equal- percentage

(iii)Quick – opening

For a linear valve, f(x)=x. For an equal percentage valve, $f(x)=\alpha^{x-1}$, .For a quick opening valve ,$f(x)=\sqrt{x}$. Theses flow characteristics are plotted in figure 6.2.

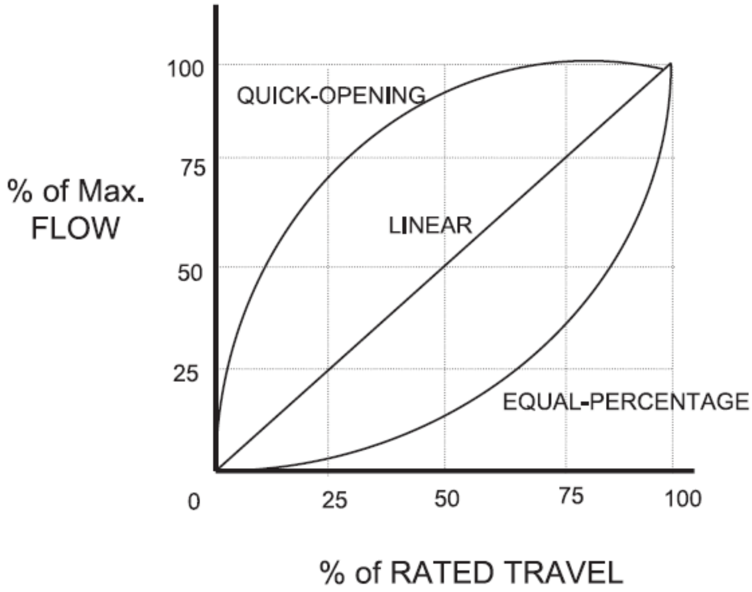

Figure 6.2: valve floe characteristics

Notice that for quick opening valve , the sensitivity (or gain) of flow to valve position is high at low openings and the low at high opening; the opposite is true for an equal percentage valve. The sensitivity of linear valve does not change as a function of valve position . The equal percentage valve is commonly used in chemical process because of desirable characteristics when installed in piping system where a significant piping pressure drop occurs at high flow rates. Knowledge of these characteristics will be important when developing feedback control system.

CHAPTER 7

RESULTS AND DISCUSSION

7.1 Performance with PID controller

In this section we have taken a three tank liquid level control system whose transfer function is

$$G_p(s) = \frac{H_3(s)}{F_1(s)} = \left(\frac{4}{8s^3 + 12s^2 + 6s + 1} \right)$$

Transfer function of valve (R)= $\left(\frac{.133}{3s+1} \right)$

Where $G_p(s)$ is the transfer function of the plant

Using this model, the unit step response was simulated with Matlab. Ziegler–Nichols method of tuning is used to calculate the PID parameters. The values of PID parameter is K_p=7.4382K_i=0.7158 and K_d=18.9753

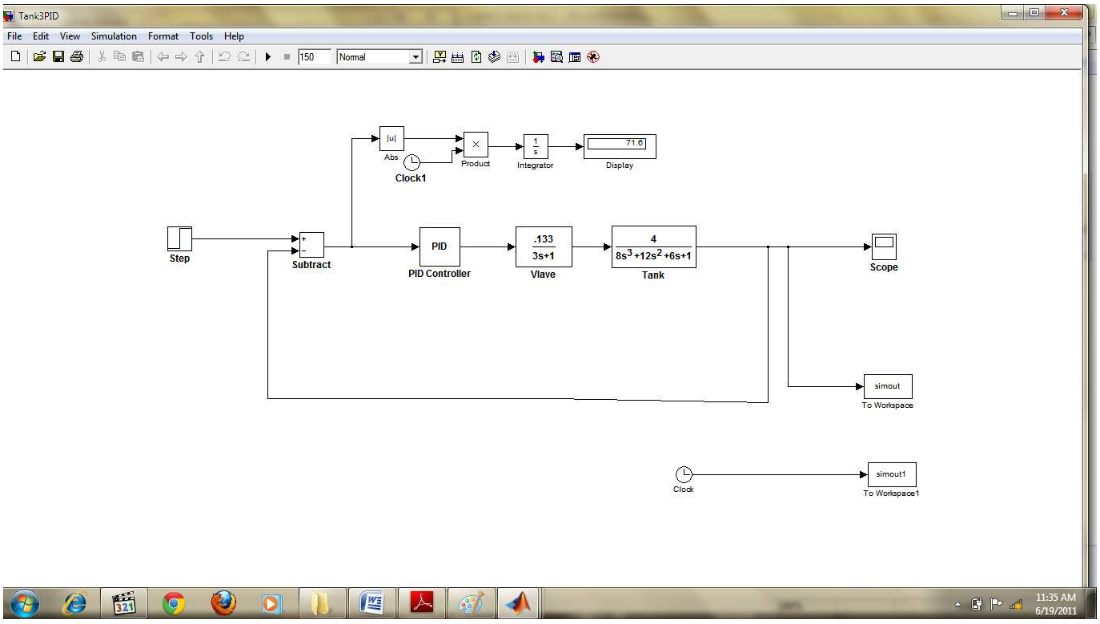

Figure 7.1: Simulink diagram of PID controller for three tank

The above figure 7.1 shows that the simulink block diagram in MATLAB for the three tank liquid level process and the transfer function of the valve with unity feedback control system. Unit step response is the reference input given to the process which is controlled by conventional PID controller.

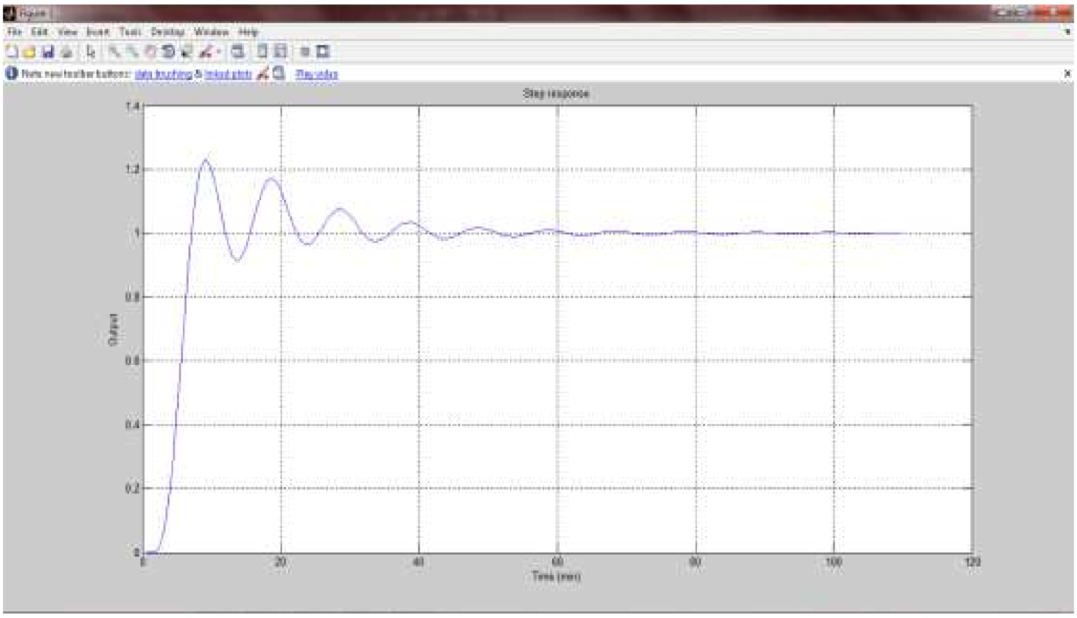

Figure 7.2: Graph showing output of PID controller for three tank

Figure 7.2 show the output response of three tank system with PID controller whose tuning parameter is tune by Ziegler–Nichols method (K_p=7.4382,K_i=0.7158, and K_d=18.9753). By using this controller the peak time is 9.4132 sec, peak overshoot is 22.9169 and the response is settle in 29.8016 sec.

7.2 Performance with self tuning of Fuzzy- PID controller

Fuzzy logic block is prepared using fis file in Matlab 8.0 and the basic structure of this file is as shown in figure 7.1. For the above FIS system Mamdani type of rule-base model is used. This produces output in fuzzified form. Normal system need to produce precise output which uses a defuzzification process to convert the inferred possibility distribution of an output variable to a representative precise value. In the given fuzzy inference system this work is done using centroid defuzzification principle. In this min implication together with the max aggregation operator is used.

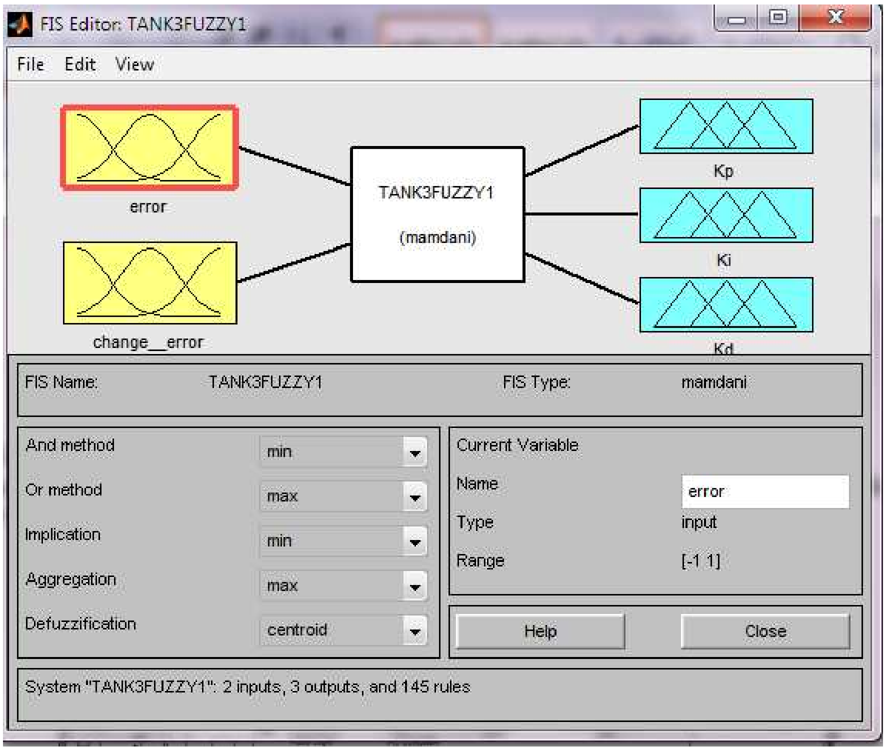

Figure 7.3 :Fuzzy inference system

Given FIS is having seven input member function for both input variables leading to 7*7 i.e. 49 rules. Figure 7.4 shows these rules using rule viewer.

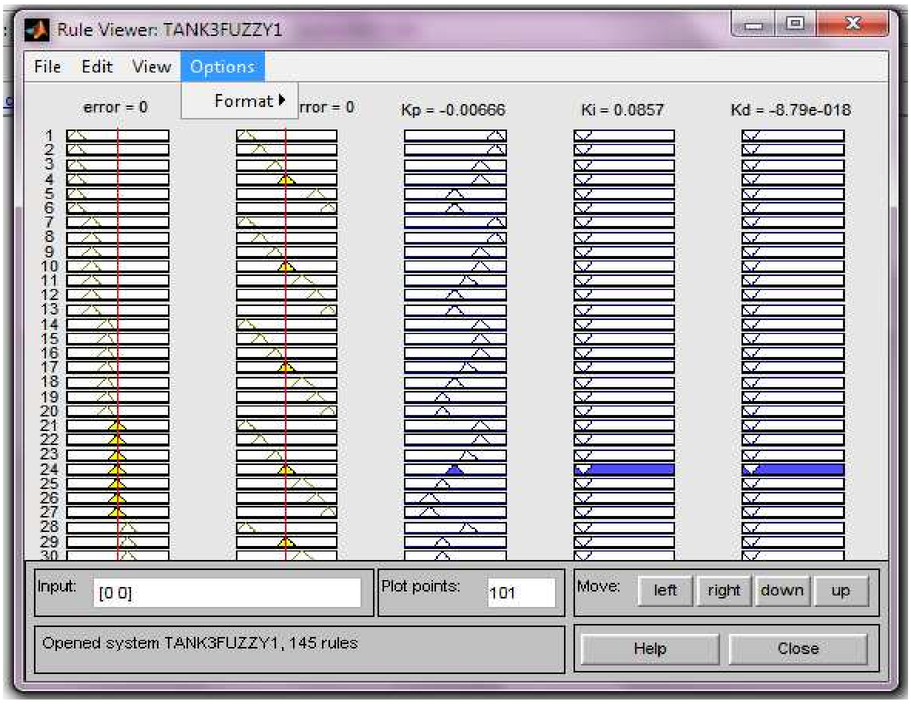

Figure 7.4 Rule viewer of fuzzy logic based PID

The Rule Viewer displays a roadmap of the whole fuzzy inference process. The first two columns of plots show the membership functions referenced by the antecedent, or the if-part of each rule. The third column of plots shows the membership functions referenced by the consequent, or the then-part of each rule. The yellow color (or shading) in first two plots represents the antecedent rules fired for a particular value and blue color (or shading) in third column represents the consequence of the antecedent on the output. Blue color line in the last block of third column represents the final precise value calculated using centroid defuzzification method.

The Rule Viewer shows one calculation at a time and in great detail. In this sense, it presents a sort of micro view of the fuzzy inference system. If the entire output surface of system is to be viewed, that is, the entire span of the output set based on the entire span of the input set, The Surface Viewer is required. Figure 8.5 shows the surface view of the system under consideration.

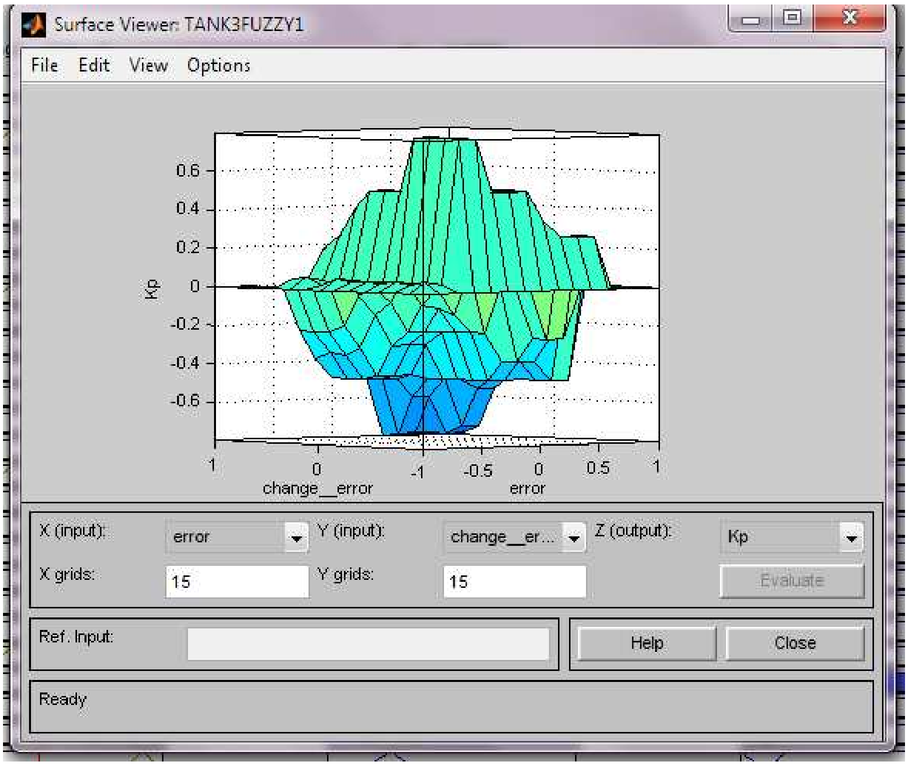

Figure 7.5: Surface viewer of fuzzy logic based PID

The Surface Viewer has a special capability that is very helpful in cases with two or more inputs and one output: we can actually grab the axes and reposition them to get a different three-dimensional view on the data.

A membership function characterizes a fuzzy set. The value of membership function represents a degree of membership to the fuzzy set, which is between 0 and 1. A fuzzy set with the sharp membership function curve has higher resolution and control sensitivity. With the smooth one, the stability of system is better but resolution is lower. Fuzzy control rules is a set expressed by fuzzy language, which describes the mapping relationship of inputs and outputs

The fuzzy rules of K_p, K_i and K_d for the controllers are expressed in the rule matrices as shown in Table 7.1,7.2, and 7.3 respectively.

Table 7.1 The fuzzy rules table of k_p

E \ Ec	NB	NM	NS	ZO	PS	PM	PB
NB	PB	PB	PM	PM	PS	ZO	ZO
NM	PB	PB	PM	PS	PS	ZO	NS
NS	PM	PM	PM	PS	ZO	NS	NS
ZO	PM	PM	PS	ZO	NS	NM	NM
PS	PS	PS	ZO	NS	NS	NM	NM
PM	PS	ZO	NS	NM	NM	NM	NB
PB	ZO	ZO	NM	NM	NM	NB	NB

The above table 7.1 shows the fuzzy rule base for tuning the PID parameter of proportional gain kp. There are total 49 rules in the above table.

Table 7.2: The fuzzy rules table of k_i

E \ Ec	NB	NM	NS	ZO	PS	PM	PB
NB	NB	NB	NM	NM	NS	ZO	ZO
NM	NB	NB	NM	NS	NS	ZO	ZO
NS	NM	NM	NS	NS	ZO	PS	PS
ZO	NM	NM	NS	ZO	PS	PM	PM
PS	NM	NS	ZO	PS	PS	PM	PB
PM	ZO	ZO	PS	PS	PM	PB	PB
PB	ZO	ZO	PS	PM	PM	PB	PB

The above table 7.1 shows the fuzzy rule base for tuning the PID parameter of integral gain ki. There are total 49 rules in the above table.

Table 7.3: the fuzzy rules table of k_d

E \ Ec	NB	NM	NS	ZO	PS	PM	PB
NB	PS	NS	NB	NB	NB	NM	PS
NM	PS	NS	NB	NB	NM	NS	ZO
NS	ZO	NS	NM	NM	NS	NS	ZO
ZO	ZO	NS	NS	NS	NS	NS	ZO
PS	ZO	ZO	ZO	ZO	ZO	ZO	ZO
PM	PB	NS	PS	PS	PS	PS	PB
PB	PB	PM	PM	PM	PS	PS	PB

The above table 7.1 shows the fuzzy rule base for tuning the PID parameter of derivative gain kd. There are total 49 rules in the above table.

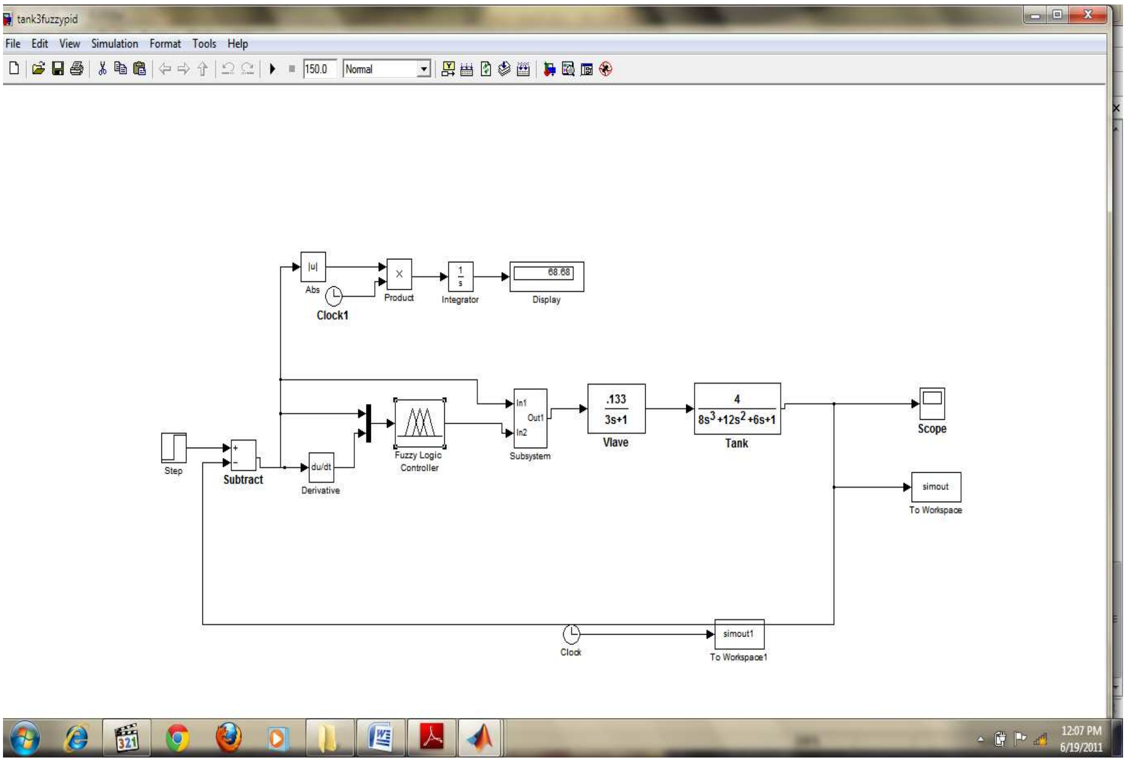

Figure 7.6: Simulink diagram of Fuzzy-PID controller for three tank

The above figure 7.6 shows that the simulink block diagram in MATLAB for the three tank liquid level process and the transfer function of the valve with unity feedback control system. Unit step response is the reference input given to the process which is controlled by self tune fuzzy- PID controller.

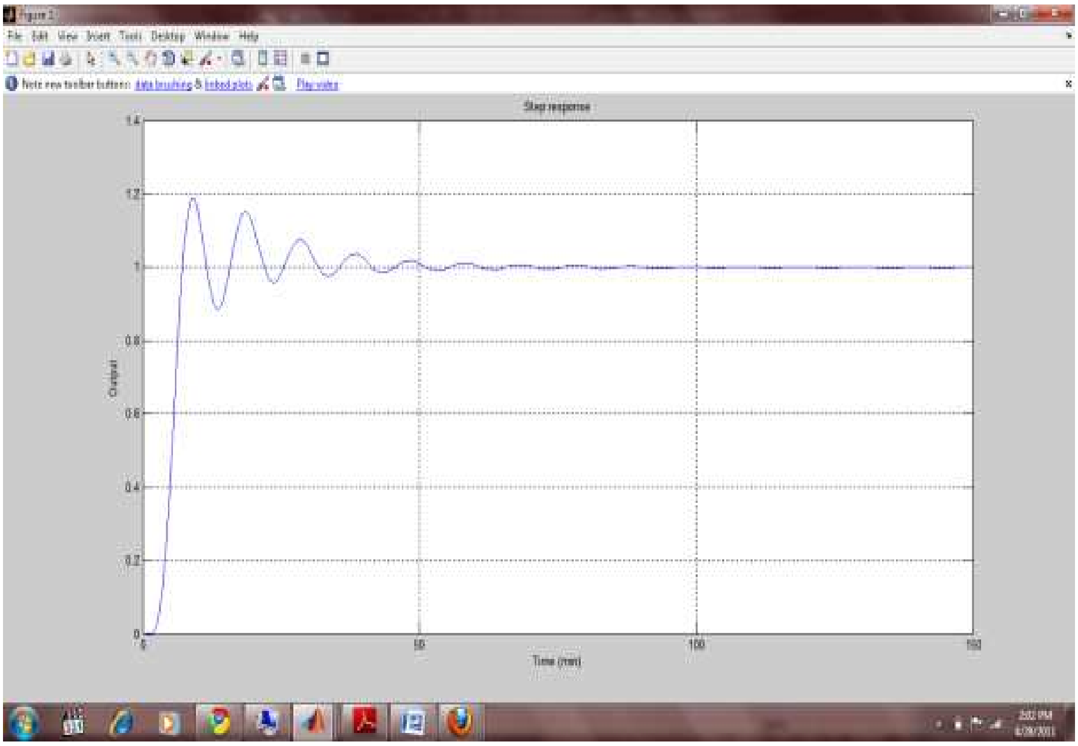

Figure 7.7: Graph showing output response of fuzzy PID controller for three tank

Figure 7.8 show the output response of three tank system with Fuzzy-PID controller. By using this controller the rise time is peak time is 8.8426 sec, peak overshoot is 18.8555 and the response is settle in 29.7961 sec.

7.3 Performance with Immune Controller

The Biological immune system is a control system that has strong robusticity and self-adaptability in complex disturbance and indeterminacy environment. The principal function of the appropriate immune response lies in ensuring the stability of the immune system and simultaneously responding to the antigen invasion in a fast way, since all the antigens attacking the biological body have to be removed.

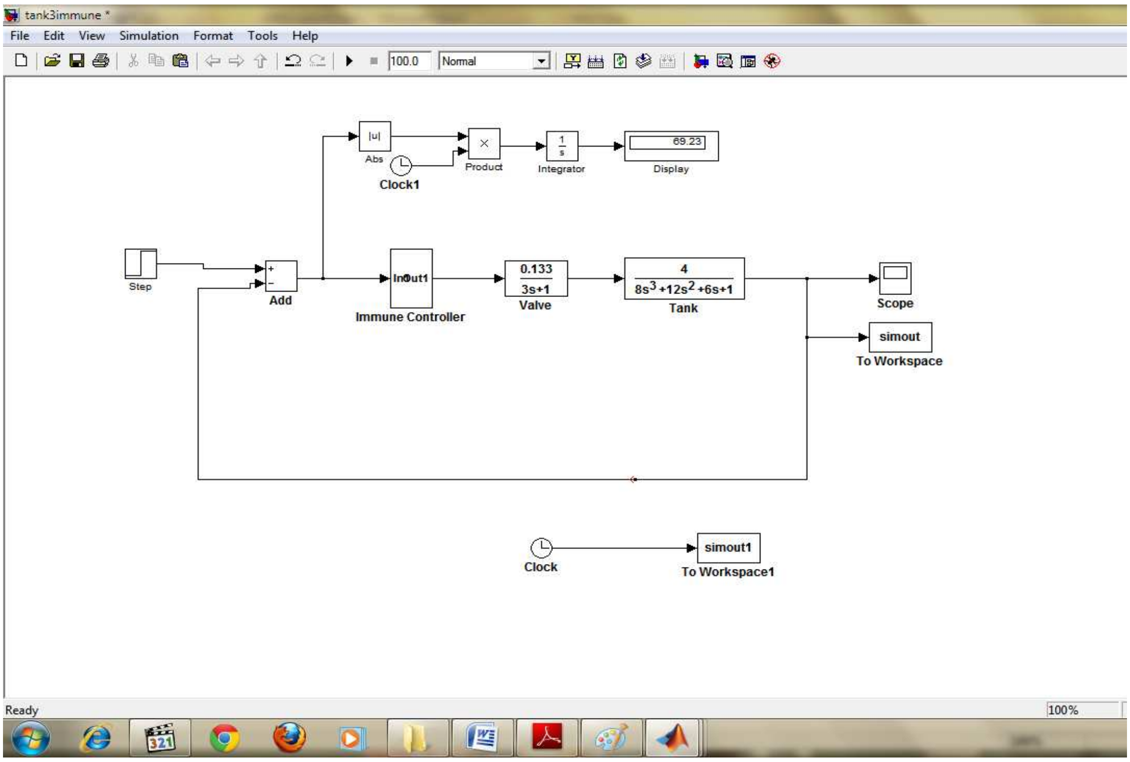

Figure 7.8 Simulink diagram of Immune controller for three tank

The above figure 8.1 shows that the simulink block diagram in MATLAB for the three tank liquid level process and the transfer function of the valve with unity feedback control system. Unit step response is the reference input given to the process which is controlled by immune controller.

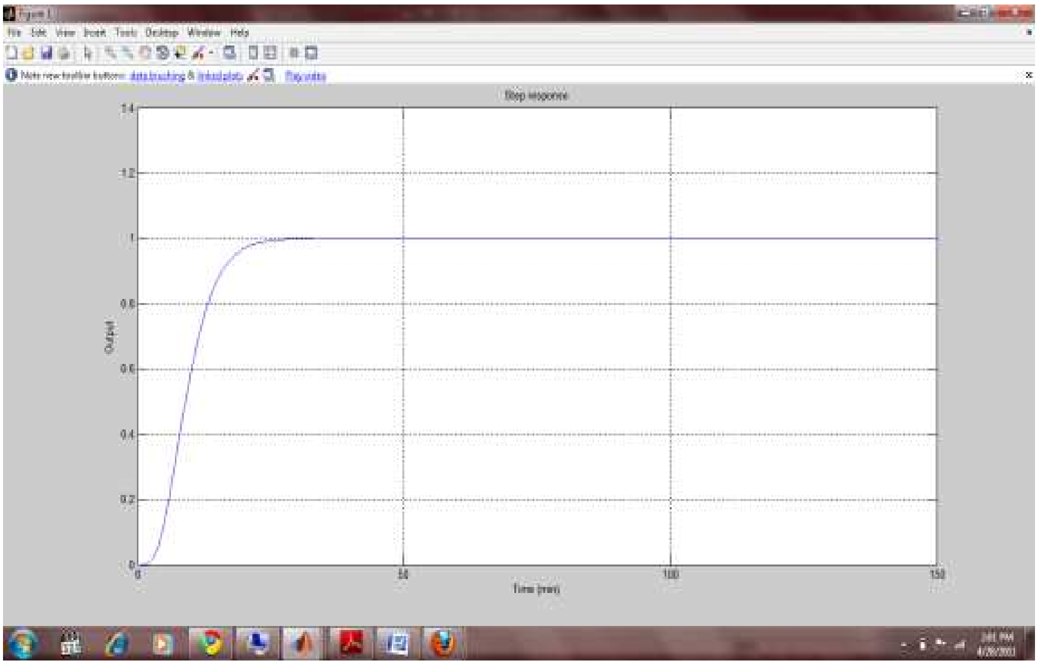

Figure 7.9 :Graph showing the output response Immune controller for three tank

Figure 7.10 show the output response of three tank system with Immune controller. By using this controller there is no any peak times , peak overshoot is 0.2288 and the response is settle in 17.5197 sec.

7.4 Performance with Immune-PID Controller

It is obvious that Immune Controller （IC） is a nonlinear P controller, its proportional gain will transform with the transformation of the output of controller. Therefore, Immune P Controller cannot compensate noises and errors arose by nonlinear disturbance. Thus, the fusion of the immune controller and conventional PID controller, namely immune PID controller, can learn from each other’s strengths and overcome the weaknesses to improve the system performance.

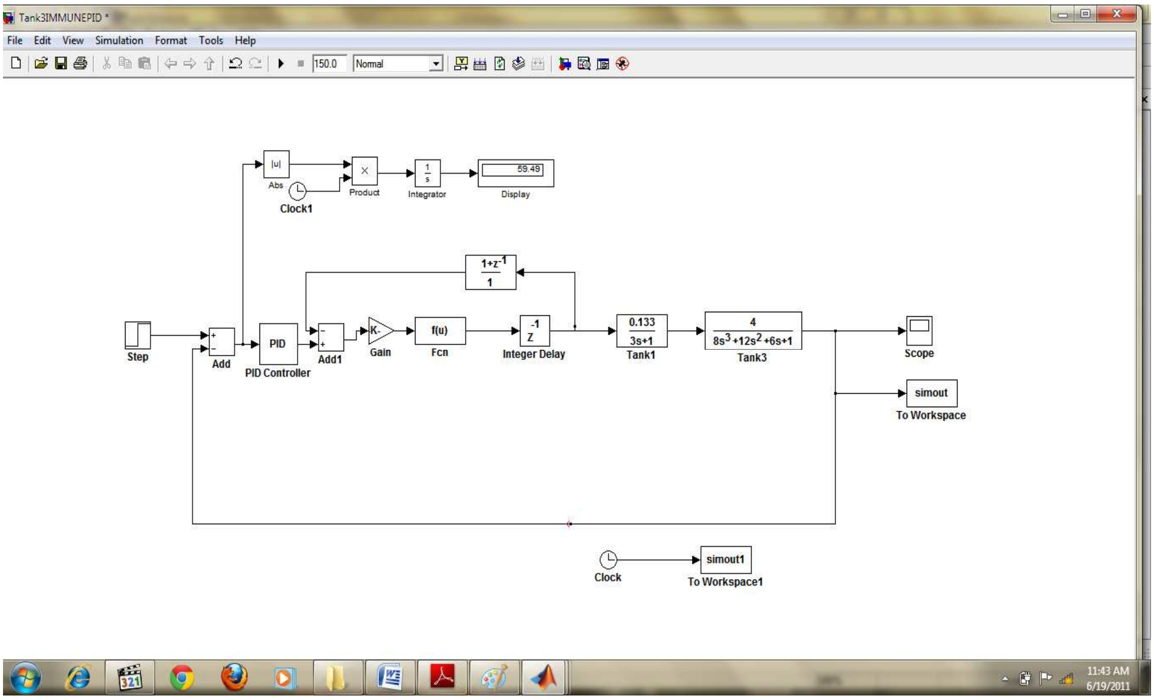

Figure 7.10: Simulink diagram of Immune PID controller for three tank

The above figure 8.1 shows that the simulink block diagram in MATLAB for the three tank liquid level process and the transfer function of the valve with unity feedback control system. Unit step response is the reference input given to the process which is controlled by conventional PID controller.

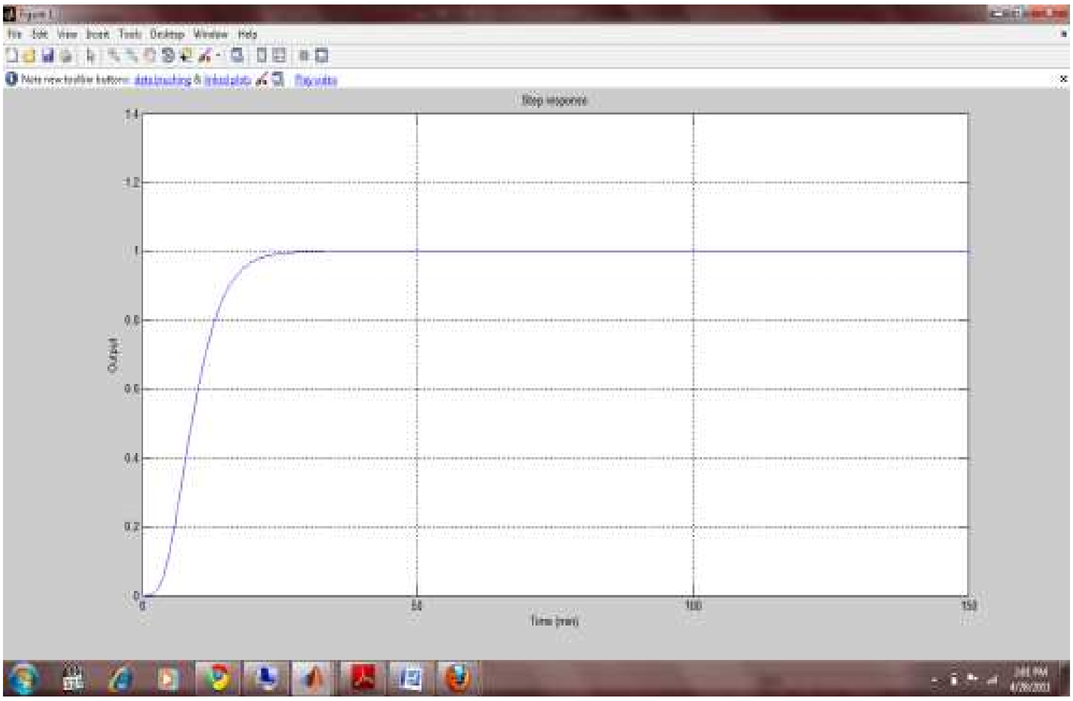

Figure 8.11: Graph showing the output response Immune PID controller for three tank

Figure 7.12 show the output response of three tank system with Immune PID controller. By using this controller there is no any peaks and no overshoot and the response is settle in 17.4107 sec.

7.5 Comparison of results using different controller

Table 7.4: Comparisons of results

	PID	FUZZY-PID	IMMUNE	IMMUNE-PID
PEAK TIME	9.4132	8.8426	NO PEAK	NO PAEK
PEAK OVERSHOOT	22.9169	18.8555	0.2288	NO OVERSHOOT
SETTLING TIME	29.8016	29.8961	17.5197	18.00
ITAE	71.6	68.68	69.23	59.49

Matlab simulations results show that Immune PID control method results in a quicker response with no overshoot than the conventional PID controller and Fuzzy-PID controller. The settling time of immune PID controller and immune controller are better than the conventional PID controller and self tunning fuzzy PID controller. The integral time of weighted absolute error (ITEA) performance criteria also shows that the immune PID controller has better performance. Moreover, The immune control system has a strong ability to adapt to the significant change of system parameters. The peak time ,settling time, peak overshoot and ITEA criteria of different control method for three tank liquid level control are shown in table 7.4.

CHAPTER 8

CONCLUSION AND FUTURE SCOPE

Different types of controllers are proposed in this thesis, and applied to the three tank level control system. Matlab simulations show that the new Immune-PID controller method results in a quicker response with no overshoot than the conventional PID controller and Fuzzy-PID controller. It also improves the settling time of the process. Moreover, it has a strong ability to adapt to the significant change of system parameters. The integral time of weighted absolute error (ITEA) performance criteria also shows that the immune PID controller has better performance. Results of simulation indicates that the effect by using the way to control three tank liquid level process is better than regular PID control, reflecting fine control quality, possessing well practical value, and besides, the principle is simple and easy to understand, convenient to realize.

For the future work, it can be used in a variety of nonlinear control systems with time-varying, pure delay, and large time constants. There are various types of Immune Controller that can be used in control system. The artificial immune system can be configure with the specification for the required works which resemble the similarity of a proportional integral derivative controller or artificial neural networks or fuzzy logic expert control system and many more.

REFERENCES

[1] Bersini, H. and Verela,F.J. The immune recruitment mechanism: Reinforcement, Recruitment and Their Applications. Computing with Biological Metaphors, Vol 1. 1994.

[2] R.Fierro and F.L.Lewis, "Control of a nonholonomic mobile robot: backstepping kinematic into dynamics," in Pro. 34th IEEE Conf. Decision Control, pp.3805-3810, 1995.

[3] Balluchi, A.; Bicchi, A.; Balestrino, A.; Casalino, G.;" Path tracking control for Dubin's cars", Robotics and Automation, 1996. Proceedings. 1996 IEEE International Conference on, Vol 4, pp. 3123-3128, April 1996.

[4] T.J. Ross; "Fuzzy Logic with Engineering Applications", McGraw-Hill, ISBN: 0070539170 37, 1997.

[5] An Shen.X, & Chan Ying. D. Nonlinear Models in Immunity [M]. Shang Hai Scientific and Technological Education Publish House, 1998.

[6] Dipanker Dasgupta, "An Overview of Artificial Immune Systems and Their Applications," Artificial Immune Systems and their applications, Springer, 1998.

[7] K. Takahashi, T. Yamada, "Application of an immune feedback mechanism to control system," JSME Int JSeriesC, Vol.41, 1998.

[8] Takahashi K, Yamada T. Application of an immune feedback mechanism to control systems.JSME IntJ,41(2):pp184-191,1998.

[9] De Castro L N, Zuben F J V. Artificial immune system: part1-basic theory and application. Technical Report-RT DCA 01/99,FEEC/UNICAMP,1999.

[10] D. Dasgupta, "Artificial immune systems and their applications," Berlin: Springer-Verlag, 1999.

[11] Kametuku.M. & Sosaki.M & TakahashiK. Adaptive Leaming Method of Neural Network Controller Using an Immune Feedback , I999.

[12] M. Kawafuku, M. Sasaki, Takahashi, "Adaptive learning method of neural network controller using an immune feedback law," In 1999 IEEE/ASME International Conference on Advanced Intelligent Mechatronics. Piscataway NJ USA: IEEE, 1999.

[13] M.Wooldridge, Multiagent systems: a Modern Approach to Distributed Artificial Intelligence, Gerhard Weiss (Eds.), The MIT press, Massachusetts, USA.1999.

[14] A. Tarakanov and D. Dasgupta, “A formal model of an artificial immune system,” BioSystem, vol. 55, pp. 151–158, 2000.

[15] J.I. Timmis, “Artificial immune systems: A novel data analysis technique inspired by the immune network theory,” Ph.D. dissertation, University of Wales, Aberystwyth, UK, 2000.

[16] Ding Yongsheng, Ren Lihong. A new fuzzy self-tuning immune feedback control system.Control And Decision,pp.443-446,2000

[17] C. W. Tao and J.-S. Taur; “Flexible Complexity Reduced PID-like Fuzzy Controllers” , IEEE Transactions on Systems, Man, and Cybernetics, Part B, Vol. 30, No. 4, pp. 510-516, 2000.

[18] Lydyard P M. & Whelan A. and M.W. Panger. Instant Notes in Immunology. Science Publish House, Beijing 2001.

[19] P.D. Williams, K.P. Anchor, J.L. Bebo, G.H. Gunsh, and G.D. Lamont, “Cdis: Towards a computer immune system for detecting network intrusions” Lecture notes in Computer Science, vol. 2212, pp. 117–133, 2001.

[20] Meshref, and VanLandingham, ‘AIS Technique to A Distributed Autonomous Robotics System’, J.Robot syst., vol 18, No3, pp.119-133, 2001.

[21] D. Dasgupta, “An Immunogenetic Technique to Detect Anomalies in Network Traffic,” In the Proceedings of the International Conference Genetic and Evolutionary Computation, New York, July 9–13, 2002.

[22] D. Dasgupta, and R. Kozma, “Combining negative selection and classification techniques for anomaly detection,” In Proceedings of the Congress on Evolutionary Computation, pp.705–710,2002.

[23] Kim.D.H. Tuning of 2-DOF PID controhr by immune algorithm. Evolutionary Computation. CEC ,pp.675 – 680,2002.

[24] Yingzi, Shen Jiong, Lu Zhenzhong. Study of immune PID controller for surperheated system temperature control system. Proceedings of the Chinese Society for Electrical Engineering. Vol.22 No.10 pp.148-152,2002.

[25] Y. Tan, J. Shen, Z. Lv, “Study of immune PID controller for superheated steam temperature control system,” Proceedings of the Chinese Society of Electrical Engineering,Vol.22, 2002.

[26] ZhenQiangQ. and GuangDa.H and Zha.O.Hua.Y and FuEn. A novel control algorithm based on immune feedback principle. Machilie Learning and Cybemetics ,pp.1089 – 1092,2002.

[27] Jiao Licheng and Hunt, ‘Artificial Immune System Based Upon Models from the Natural Immune System’, ACTA ELECTRONICA SINICA,pp.1540-1548,2003.

[28] Y. Baba, T. Shigemasa , M. Yukitomo, F. Kojima, M. Takahashi and E. Sasamura;“Model-driven PID control system in single-loop controller”, in Proceedings of the SICE annual conference Fukuri, Vol. 1, pp. 187-190, 2003

[29] Dong Mei. Fu and De Ling. Zheng. Design for Biological Immune Controllers and Simulation on Its Control Features. Journal of University of Science and Technology Beijing. 2004.

[30] Dong Mei. Fu and De Ling. Zheng, Designing and analysis of immune controller based on improvement Verela immune network model,IEEE,2004

[31] Kim.D.H & Cho.J.H. Intelligent tuning of PID controller with disturbance function using immune algorithm. Fuzzy Information, 2004. Processing NAFIPS 'pp.286 – 291,2004

[32] L. Tong. Computer Immunology. Publish House of Electronics Industry. Beijing, 2004

[33] Fu Dongmei and Zheng Deling, The Analysis of Stability of Immune Control System Based on Small Gain Theorem,IEEE,2005

[34] Peng Daogang, Yang Ping, Wang Zhiping. Immune PID Cascade Control of Fresh Steam Temperature Control System in Fossil-fired Power Plant. Chinese Journal of Power Engineering,pp. 234-238,2005.

[35] J. Twycross and U. Aickelin, “Libtissue-Implementing Innate Immunity, In the Proceedings of IEEE World Congress on Computational Intelligence, Vancouver, Canada, July 17–21, 2006.

[36] Freddy Prasetia Ridhuan and Mohd Fauzi Othman ,Application OfArtificial Immune System To Design Power Systems Stabilizer,IEEE,2007

[37] Peng Yang, Hongyu Zhao, Ying Zhou and Zhiwei Liu, Study of Immune PID-PI Controller for FG-3000 Temperature Control System,IEEE,2007

[38] Wei Wang, X. Z. Gao and Changhong Wang , A New Immune PID Controller in Material-Level Control, Third International Conference on Natural Computation (ICNC),IEEE,2007

[39] Y.Kanayama, Y.Kimura, F.Miyazaki,T.Noguchi, ”A Stable Tracking Control Method for an Autonomous Mobile Robot”, in Proc. IEEE Int. Conf. Robotics and automation, pp.384-389,2007.

[40] Yuan Guili, Liu Jizhen, TanWen, Liu Xiangjie, 'The Research and Application of Immune Feedback Control in the Load Control System of Tube Mill', Proceedings of the 26th Chinese Control Conference, Zhangjiajie, Hunan, China, July 26-31, 2007.

[41] Jing xin, Ding Liu, Yan-xi Yang, "Robot trajectory tracking control based on fuzzy immune PD-type controller", Proc. Of the 5th world congress on intelligent control and automation, Vol 6, 15-19, pp.4942 – 4945, June 2008.

[42] Jun Liu, Wan-li Wang and Xiu-hua Dou; "Multiple Model Internal Model Control Based on Fuzzy Membership Function", in proceedings of IEEE International Conference on Automation and Logistics, pp. 881-885, 2008.

[43] P.M. Mary and N.S. Marimuthu; "Design of self-tuning fuzzy logic controller for the control of an unknown industrial process", IET control theory & applications, vol. 3, pp. 428-436, 2009.

[44] Gang Liul and Lina Yang, 'Artificial Immune Controller for PMSM Speed Regulation System',IEEE,2010.