MODELING AND CONTROL OF BASIS WEIGHT AND MOISTURE USING FUZZY LOGIC CONTROL SYSTEM

A THESIS

Submitted in partial fulfilment of the requirements for the award of the degree

of

DOCTOR OF PHILOSOPHY

by

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled **"MODELING AND CONTROL OF BASIS WEIGHT AND MOISTURE USING FUZZY LOGIC CONTROL SYSTEM"** in partial fulfillment of the requirements for the award of the Degree of Doctor of Philosophy and submitted in the Department of Paper Technology of the **Indian Institute of Technology Roorkee, Roorkee** is an authentic record of my own work carried out during a period from January 2005 to December 2009 under the supervision of Dr.M.C.Bansal, Professor, Department of Paper Technology and Dr.S.Mukherjee, Professor, Department of Electrical Engineering, Indian Institute of Technology Roorkee, Roorkee.

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other University/ Institute.

(ANAMIKA BHATIA)

This is to certify that the above statement made by the candidate is correct to the best of our knowledge.

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Abstract

The thesis starts with the brief introduction on the status of pulp and paper industry. The description of the paper making process and control of basis weight and moisture as interactive and non interactive system is discussed. The fuzzy logic controller, and different types of fuzzy control systems used in the work i.e. the P-Type Fuzzy controller, PD-Type Fuzzy controller and PD+I-Type Fuzzy controller are discussed. Different scaling gains used in these systems and there relationship with each other and how these gains are related to different constants of conventional PID controllers are then discussed. The second chapter puts some light on the Literature review of the process i.e. the basis weight and the moisture as an interactive system and also as a non-interactive system and Fuzzy Logic in general and tuning methods used to tune various scaling gains. The third and fourth chapters deal with the non interacting systems (SISO) relating the basis weight and moisture respectively. It also describes the effect of various scaling gains on performance parameters and gain to tune the system for a particular parameter, which scaling gain should be changed and how. In chapter five the interacting system as a whole is taken, and on the basis of the tuning methods applied in chapter three and four, the system is tuned for optimum values of scaling gains to get the desired output. Conclusions based on the work done in chapter 3, 4 and 5 are given in chapter 6. The recommendations and limitations are also mentioned.

The chapter 1 starts with the status of Indian paper mills and the technologies dealing with its processes that are ranging from oldest to the most modern. It describes the paper industry operations and processes, the interactive system relating the description of the controlled variables i.e. the basis weight and the moisture, the manipulated variables i.e. the Pulp flow and the Steam flow. The Process description is given, which gives the detail of the MIMO system used in the system. The chapter also introduces a brief description of the Fuzzy logic Controller and its design parameters which includes the number of fuzzy sets for each input and output, fuzzy rule base structure, shapes and place of the membership functions by which the output

can be monitored. After that the Fuzzy controller is made to work like a Fuzzy-P, Fuzzy-PD and Fuzzy-PD+I. Thus the description of all these types of Fuzzy controllers is given in detail, along with the relationship between the different scaling gains i.e. GE, GCE, GIE and GU.

Two control loops are formed by coupling pulp flow with basis weight and steam flow with moisture and two controllers are used in the two loops. Here the pulp flow is controlled by the Basis weight valve opening and the steam flow is changed by Steam Shower Valve Opening. First the results are analyzed for SISO system i.e. a non-interacting system, and then the interacting system is analyzed. To understand the nature of interaction between the two control loops, we have studied the effects of input changes on the outputs when one loop is closed and the other is open and when both the loops are closed. The system is simulated for the above process using both FLC and Conventional PID controllers and the results are compared.

Chapter 2 attempts to review the literature pertaining to the work done in the past on the basis weight and moisture control as an interactive system and as the individual systems and some economic factors related to the paper industry. A survey has been done on the FLC in general and the hybrid system combining P, PD and PD+I type of systems with Fuzzy. As the work deals with the tuning of the scaling factors, thus emphasis has been laid on the self tuning of FLC and how the variations in the scaling gains have been done. A collection of hybrid techniques where Fuzzy system is made to work as PD- Type Fuzzy and PI- Type Fuzzy Logic Control and its comparison with Conventional PID is also taken into consideration. FLC, how and where these controllers are used and implemented in the industry. Study of the Simulink environment using MATLAB, optimization using Neuro-Fuzzy and GA has also been analyzed.

Chapter 3 deals with a SISO system, in which only one parameter i.e. Basis weight is taken into consideration. The variations of Basis Weight output are analyzed according to the changing values of basis weight valve opening. Major emphasis has been laid on the design parameters of Fuzzy logic controller. The effects of various scaling gains have been analyzed on the output of the system. The system is made to work like a Fuzzy-P, Fuzzy-PD and Fuzzy-PD+I type systems separately. It has been analyzed that the four scaling gains have different effects on the output of the system. The denormalization gain (GU) is mainly responsible for the system offset, thus the offset can be easily minimized by the proper choice of GU. The three normalization gains i.e. GE, GCE, and GIE have the affects on the oscillatory behavior, Rise time and the system stability respectively. A similar type of simulation is performed using a conventional PID controller instead of a fuzzy controller. The effects of the three constants K_P, K_D and K_I on the system response are also discussed. All these tests are done both for the step input and the varying input of the basis weight set-point. A Fuzzy Logic Controller gives much better output in comparison to the conventional PID controller. The regulator problem has also been analyzed for the basis weight control using the Fuzzy control system, and it was found that the fuzzy control worked well for regulator problem also. Thus the PID controllers presently used in the industry can be replaced by the Fuzzy control systems.

Chapter 4 also deals with a SISO non-interacting system, thus the variations of the moisture output with respect to the change in the Steam Shower Valve Opening are only taken into consideration. The system has been simulated using both Fuzzy and PID controller. Similar types of tests are performed to select the optimum values of the scaling gains for this system when a fuzzy controller is used. Also tests are performed for finding the optimum values of the three constants used in the PID controller for the same system. All these tests are done both for the step input and the varying input of the basis weight set-point and it was found that the Fuzzy controller can be tuned in a far better way to get good results.

Chapter 5 shows a detailed description of the MIMO system and the implementation of the controllers (PD+I-Fuzzy Controller and Conventional PID) in the system. The system is simulated for the cases when one loop is closed and the other is open and vice-versa, also the results are compared and discussed when both the loops are closed. The comparisons show that as it is an interacting system, the effect of change in any one of the controlling parameters i.e. the BWVO and the SSVO have its impact on both the controlled variables i.e. the BW and the Moisture. The simulation is done for the step input as well as the varying inputs of set-point for both moisture and BW using both FLC and PID controllers. It has been observed that for both the cases i.e. the step input and the varying input using a PID controller, the system becomes unstable for the case when the moisture loop is closed. It means that when the BWVO is not under control, the outputs for both moisture and basis weight are also not under control. While the case is different, when the BWVO is under control and SSVO is not under control, both the outputs are under control. Thus it can be said that the major controlling factor is the BW valve opening, and by varying the value of BWVO both the parameters can be controlled. The SSVO has an insignificant effect in case of the PID controller. But this is not the case for the FLC model. For the FLC model, both the controlling parameters (BWVO and SSVO) have a significant effect on both the controlled outputs (BW and M). Moreover the performance parameters i.e. the RT, delay and overshoot were also calculated for these controllers for step input as well as the varying input and it was observed that the in case of the PID controllers the rise-time and the delay is more, also the overshoot was introduced for the varying input.

Chapter 6 give the conclusions based on the work done in chapter 3, 4 and 5 and how the tuning process helps in getting the desired outputs. As the paper industry requires up-gradation of process equipments, especially the paper machines, process automation and control. Thus conventional PID controllers can easily be replaced by the FLC's as Fuzzy logic controller has a better performance in comparison with the PID controller. Even further optimization of the design parameters can be done by using the Hybrid intelligent techniques such as: Neuro-Fuzzy model and Fuzzy controllers using GA.

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(Anamika Bhatia)

Research Papers

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2. Anamika Bhatia, M.C.Bansal, S.Mukherjee; Control of Moisture of Paper using FLC, National Conference on Electron Transfer Reaction in Chemistry Physics and Molecular Biology, M.S. Collage, Saharanpur, India, Dec 23-24, 2007.

3. Anamika Bhatia, M.C.Bansal, S.Mukherjee; Fuzzy Logic Application for modeling of recycled fiber blended pulp, International journal of Hybrid Computation Intelligence (IJHCI), ISSN: 0975-3680, Vol.1, No.1, Jan-June 2008.

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7. Anamika Bhatia, M.C.Bansal, S.Mukherjee; Performance Comparison between FLC and PID Controller for Basis Weight Servo Control in Pulp and Paper

Industry Using Simulink, Asian Journal of Control, Manuscript ID: FR-09-063, Submission Date: 24-Jul-2009. (communicated)

3. Anamika Bhatia, M.C.Bansal, S.Mukherjee; Simulation of Fuzzy Logic Controller for Moisture Control in Pulp and Paper Industry, Journal of Process Control, Manuscript Number: JPROCONT-D-09-00157, Submission Date: 9-Jul-2009. (communicated)

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Chapter 1
Introduction

1.1 Status of Indian Pulp and Paper Industry

The Indian Paper Industry accounts for about 1.6% of the world's production of paper and paperboard. The estimated turnover of the industry is Rs 25,000 crore (USD 5.95 billion) approximately and its contribution to the exchequer is around Rs. 2918 crore (USD 0.69 billion) in the year 2008. The industry provides employment to more than 0.12 million people directly and 0.34 million people indirectly. The industry was delicenced effective from July, 1997 by the Government of India; foreign participation is permissible. Many of the paper mills are in existence for a long time and hence, present technologies fall in a wide spectrum ranging from oldest to the most modern.

India is the fastest growing market for paper globally and it presents an exciting scenario; paper consumption is poised for a big leap forward in synchronism with the economic growth and is estimated to touch 13.95 million tons by 2015-16. The futuristic view is that growth in paper consumption would be in multiples of GDP and hence an increase in consumption by one kg per capita would lead to an increase in demand of more than 1 million tons. As per industry estimates, paper production is likely to grow at a CAGR of 8.4% while paper consumption will grow at a CAGR of 9% till 2012-13. The import of pulp & paper products is likely to show a growing trend. Foreign funds interest in the Indian paper sector is growing. IFC, the investment arm of the World Bank is already associated with at least three of the IPMA member mills.

The Paper Industry accounts for 3.5% of the world's industrial production and 2.0% of world trade with an employment potential of over 3.5 million people. India, with 16.0% of the worlds population consumes approximately only 1.6%-2% of the World's paper production. In India the paper industry has been considered as one of the 35 high –priority industries in terms of pollution and capital intensiveness for investment and being an essential commodity material.

The paper industry belongs to a core sector industry. The number of paper mills at present is approximately 666 with overall 80-85 % capacity utilization. Per capita consumption of paper in a country is an index of civilization and directly proportional to its literacy rate .In India through per capita consumption is low, on an average as low as 9 kg in India as against the world average of 45 kg and the Asian average of 28 kg. The US tops in per capita paper consumption at 300 kg, followed by Sweden and Japan at 247 kg and 242 kg, respectively, developing country's average of 12.0 kg and developed country's average of 152.0 kg. The growth in the paper industry has been to the extent of 8-9% during the last few years. However due to slowdown in economy, the reported present growth rates of Indian paper mills are: 4-5 % for cultural paper and paper board –the largest segment (45 %) of the market share, 3-4 %for newsprint, and 7 % plus for packaging compared to paper consumption of the order of 1.5% to 2% in average in the North America and Europe and global growth of 2.6%. In 2010, the growth rate of the pulp and paper industry the world over and in Asia will be almost the same of the order of 2.2% and 4.4% respectively. Thus the rate of growth is however higher than those in USA and Europe .This data amply indicates that there is higher GDP and GNP even in this period of economic recession, compared to developed countries though India's economic growth is likely to slow down further in 2009-10, to six per cent as against the Government's estimate of above seven per cent. In the year 2006, the production achieved was 5.48 million tons of paper and paper board, 1.09 million tones of newsprint, totaling 6.57 million tons, and 8.3-8.5 million tons in 2009 with Newsprint consumption of 1.6 million tones, 50 % of which is imported. It has also been predicted that in the year 2010-2011 and 2015-2016 the demand forecasts will be in the range of 10 -15.0 million tons respectively. With the expected increase in literacy rate, the growth of the economy and an increase in the per capita consumption, a very high growth rate is expected in the future. Massive investment in terms of capacity and technology will be required in the Indian pulp, paper and allied Industries, therefore one has to take up the challenges for meeting the demand of around 14-16 million tons by 2015. As a result, Indian Paper Industry inducts an attractive proposition to the global market for necessary investment in this sector.

This Industry is however, capital intensive in terms of consumption of raw materials, chemicals, energy (both thermal and electrical), water and labor. It also generates huge amount of pollutants (solid, particulates, liquids and gaseous emission).Approximately 2.5-3.0 t of raw materials, 130-200 m^3 of water, 8-15 t of steam and 900-1500 kWh of electrical energy are required for one ton of paper. This leads to generation of pollution loads to an extent of 24 - 45 kg of BOD, 80 -150 kg of AOX in the effluents. The consumption of the above inputs are therefore disproportionately high and at the same time due to high cost of energy and other inputs compared to North American or European Industry , the Indian industry is struggling hard for its sustainability . There are around efforts in India to reduce all these inputs to the level of international standards for mere survival, for sustained production and to stand the stiff competition in international market. The main reasons for low profit –investment ratio, low capacity utilization are due to lower production capacity, adopting relatively older technology, obsolete equipment and low degree of automation. The industry today is grapping with issues of global competitiveness in terms of quality and cost as is most of the manufacturing sector. Environmental compliance is the other critical dimension emerging in the pursuit of global competitiveness. The positive factors for the paper industry are that the domestic market continues to grow and the technology is available for meeting the challenges of quality as well as environment.

In order to keep pace with sustainable production, for compliance of environmental friendliness, to meet the ever increasing demand of paper in India, meeting international quality norms, some of the measures to be taken by the Indian industry are: to upgrade their process and equipment technology, scaling up the process and equipment, to seek optimum design and operational parameters, introducing up-to-date process instrumentation, measurements and control. This in turn requires immediate upgradation of process equipments, especially the paper machines, process automation and control. In fact, the use of automation and control which are demanded by modern sophisticated equipments is not very widespread unlike many chemical process industries in Indian industry. The low degree of automation (2.0-3.0% of investment) is one of the causes for low profit to investment status of this industry.

Thus the main requirement for today is that, the companies must be more productive, flexible and produce high quality goods for customers and market requirements in the world market's conditions. Therefore, every stage in organization & production systems can be used for continuous improvement. For this purpose, many tools, techniques, subsystems and systems can be used.

Paper has played a vital role in the cultural development of mankind. It still has a key role in communication and is needed in many other areas of our society. Paper making is a vast, multidisciplinary technology that has expanded tremendously in recent years. Significant advances have been made in all areas of paper making, including raw materials, production technology, process control and end products [87].

The papermaking process is a very complicated process with varying; heat and mass transfer steps at different stages. Along with the change of parameters, at different stages, their mathematical model also changes. Paper machine controls try to keep quality variables at their target levels with minimum variability. Each paper grade has its specific targets and limits for many quality variables such as Basis weight, Moisture, Caliper, Ash content, smoothness, Gloss, Formation, strength properties, Fault distribution etc. [87].Out of these properties some are measured and controlled, while some are only measured to be taken care otherwise. Basis weight and moisture content are the two important parameters of quality which are measured and controlled on line. We should implement necessary tools to optimize papermaking process and increase control precision under the precondition for stable operation and quality production.

1.2 Paper Industry Unit Operations and Processes

It is well known that paper is produced through a number of unit operations and processes in a paper industry (Figure 1.1).

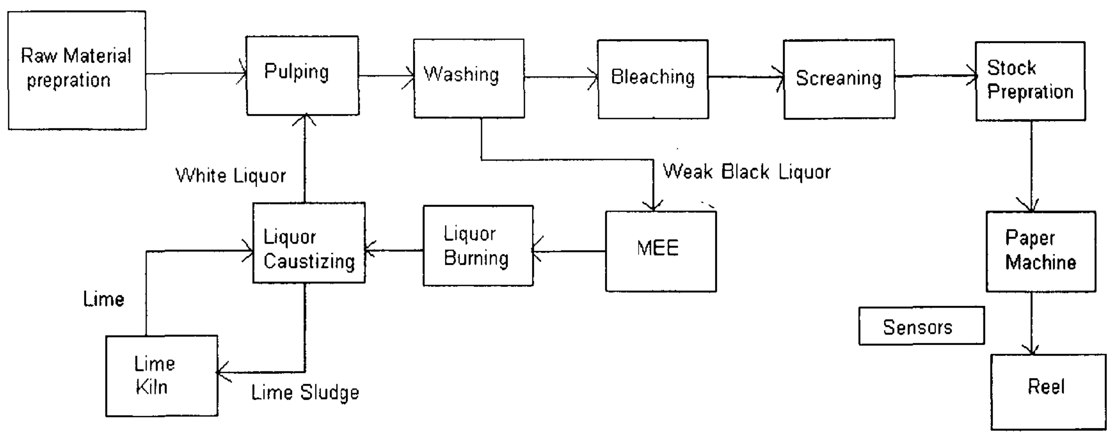

Figure1.1 Pulp and Paper making System

These are in fact, very complex. These include raw material preparation, pulping (single or multi-stage digestion), multistage brown stock washing, multi stage bleaching, stock preparation and refining of pulp, approach flow system, wet end of paper machine – the formation of paper, pressing and drying – the dry end of paper machine operation, machine calendering and winding. For converting operations OFF-machine or ON-machine coating, super calendering and now soft calendering techniques are practiced. For energy and chemical recovery, chemical recovery operations include multiple effect evaporation for concentration of weak black liquor, combustion or incineration in recovery boiler operation, causticization/recausticizing, mud washing, and calcinations in lime kiln are important. For environmental compliance, effluent treatment plant (ETP) is required.

Two problems make paper machine control difficult from the control engineering point of view: severe interactions between the controlled variables and long time delays for controlling some variables. In MD control, the most common interaction is between basis weight control and moisture control. For example when the basis weight controller increases the stock flow, the amount of water i.e. the moisture content of the paper increases. If steam flow is now increased to correct the moisture, the basis weight will decrease; therefore, it becomes difficult to maintain the balance between the two controlled variables. Control engineering techniques must decouple such an interaction [12]. Computer control system for controlling the basis weight and moisture content of paper has a very complicated interacting configuration.

In the papermaking process, the paper sheet contains fiber, water and filler. The basis weight of the paper sheet is the total weight per unit area [124]. The basis weight of the paper from a papermaking machine is measured by scanning the paper with a gamma gauge. The gamma gauge develops corresponding analog outputs which are converted to digital equivalents. A digital computer from these digital equivalents determines the difference between the measured basis weight and the desired basis weight [99]. Necessary corrective actions are taken on this error signal.

The degree of uniformity of moisture content of the web, across the machine width, as the web leaves the forming section determines to a large extent the average moisture level that can be maintained in finished paper at the reel. The moisture level the web depends on the opening of the steam shower valve. A typical shower impinges dry, saturated or superheated steam onto the traveling web. The web, supported on a forming wire or drying belt, is simultaneously subjected to vacuum. The vacuum pulls the steam into the sheet interior where it condenses, giving up its heat of condensation. The water content of the web absorbs the heat. It is known that the removal rate from the web, when subjected to a vacuum, is proportional to the square root of surface tension to viscosity. Both surface tension and viscosity are directly proportional to temperature. Therefore, increasing moisture removal rate is a linear function of increasing sheet temperature [65]. Thus a similar process is adopted for measuring the analog values of moisture of the paper sheet through moving sensors. These analog values are then converted to digital values and then compared with the set points for that paper. The error signal is transmitted for valve opening for regulating the steam flow rate in steam showers. The basis weight and moisture values are measured by n number of sensors, the average basis weight is calculated and this average value is compared with the setpoint and the error signal so generated is given to the basis weight controller, which accordingly generates the signal which is given to the basis weight valve and the corrective action thus begins. While in the case of moisture, corresponding n sensors give signal to the n comparators, which is further given to the same number of moisture controllers from where the respective signal to change the n number of steam shower valve openings are carried out in the respective cross direction settings.

The parameter G(s) (Pulp flow) is monitored by varying the basis weight valve opening and P(s) (Steam flow) is changed by the steam shower valve opening. Figure1.2 shows the basic process for paper making with the two control loops for basis weight and moisture control.

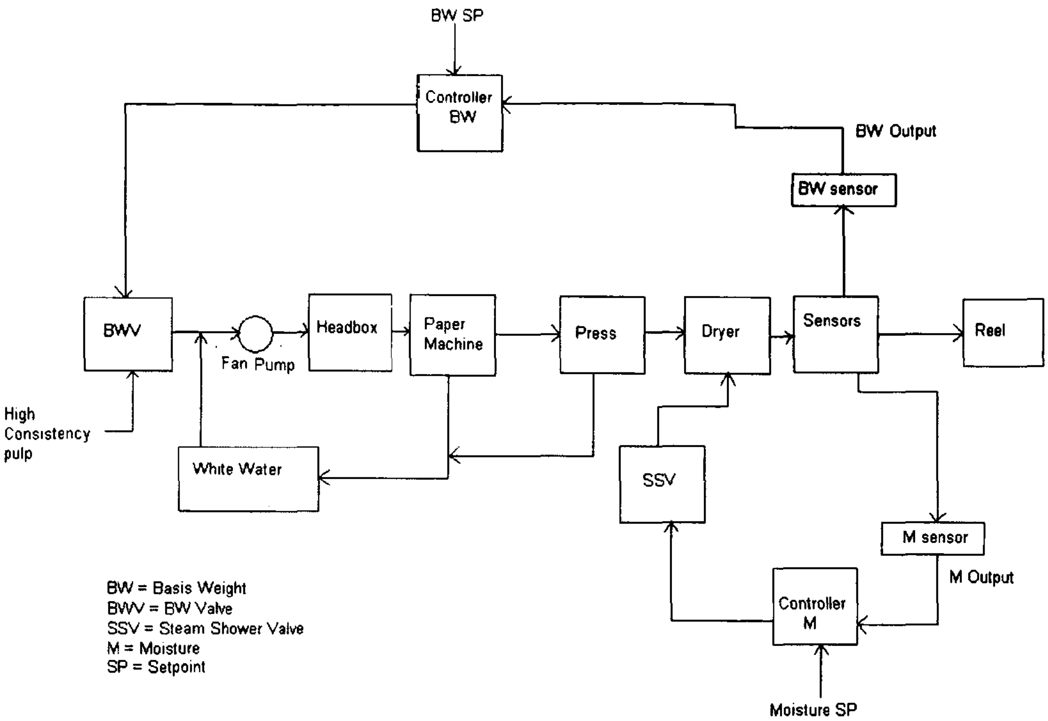

Figure 1.2 Flow Diagram for Paper Making with basic controls

The process thus has two controlled outputs i.e. Basis weight (B) and Moisture (M) and two manipulated inputs i.e. pulp flow (G) and steam flow (P). The input output relationship is given by the equation (1.1) [149].

[B(s); M(s)]=A*[G(s); P(s)] .... (1.1)

Where

A= [a b; c d]

and

a= [5.15*exp (-144*s)]/ (105*s+1)

b= [0.2*exp (-66*s)]/ (132*s+1)

c= [0.44*exp (-144*s)]/ (105*s+1)

d= [1.26*exp (-66*s)]/ (132*s+1).

where

exp (-144*s) Transportation Lag for BW loop

exp (-66*s) Transportation Lag for Moisture loop

105 is the (τ_1) time constant (in seconds) for pulp flow change.

132 is the (τ_2) time constant (in seconds) for steam flow change.

5.12, 0.2, 0.44 and 1.26 are the constants that represent the dimensional conversion factors based on equipments involved in the system.

This matrix can be expressed in the form of equations as

B(s) = a G(s) + b P(s) .... (1.2)

M(s) = c G(s) + d P(s) .... (1.3)

Where

B(s) = Basis weight per meter square

M(s) = Moisture content (%)

G(s) = Pulp flow, m^3/ sec

P(s) = Steam flow, m^3/ sec (at specified pressure)

From the above equations it is clear that a change in any of the input functions G(s) or P(s) will affect both controlled outputs B(s) and M(s) i.e. the system outputs are interdependent on both the inputs and also on each other.

The transport delay for the basis weight loop is 144 seconds; this signifies time taken to calculate the average weight of the BW by the sensor. The sensor moves along the CD of the web and senses the BW output at *n* points and thus the average of these readings is taken to get the average BW output, this process takes about 144 seconds. Similarly the transport delay for the moisture loop is 66 seconds which is lesser than that of the basis weight loop; this is because in this case the average moisture is not calculated. The moisture is sensed at *n* points and the signal is fed back to *n* different steam showers.

τ time constant reflects the sluggishness of the system i.e. Time constant is the time taken for the system to incorporate the changes induced by the valve opening at the web end. Time constant for the change in pulp flow τ_1 (due to the variation in the BWVO) is about 1.8 min (105 sec), while the time constant for the change in steam flow τ_2 (due to the variation in SSVO) is about 2.23 min (132 sec). The time constant for the later is more due to the heat and mass transfer effect; hence the moisture change is slower than the basis weight change.

K is a constant that represents the dimensional conversion factor based on equipments involved in the paper machine section.

The data for basis weight and moisture has been collected from a middle basis weight mill, where the speed of the paper machine is 250m/min and length of paper traveled from the head box to the reel is approximately 600 meters.

Similarly the length of paper traveled from the steam shower to the reel is approximately 275 meters.

The equations for the transfer functions can be obtained using Matlab:

```
>> H = tf({5.15 0.2;0.44 1.26},...
       {[105 1] [132 1];[105 1] [132 1]},...
       'iodelay',[144 66 ;144 66],...
       'inputname',{'G' , 'P'},...
       'outputname',{'B' , 'M'})
```

Transfer function from input function "G(s)" to output...

$$B(s) = \exp(-144*s)\,\frac{5.15}{105\,s + 1} \quad \ldots\ldots\ldots\ldots\ldots\ldots (1.4)$$

$$M(s) = \exp(-144*s)\,\frac{0.44}{105\,s + 1} \quad \ldots\ldots\ldots\ldots\ldots\ldots (1.5)$$

Transfer function from input function "P(s)" to output...

$$B(s) = \exp(-66*s)\,\frac{0.2}{132\,s + 1} \quad \ldots\ldots\ldots\ldots\ldots\ldots (1.6)$$

$$M(s) = \exp(-66*s)\,\frac{1.26}{132\,s + 1} \quad \ldots\ldots\ldots\ldots\ldots\ldots (1.7)$$

The above relationship can be expressed in form the of a block diagram of the Process as shown in Figure 1.3.

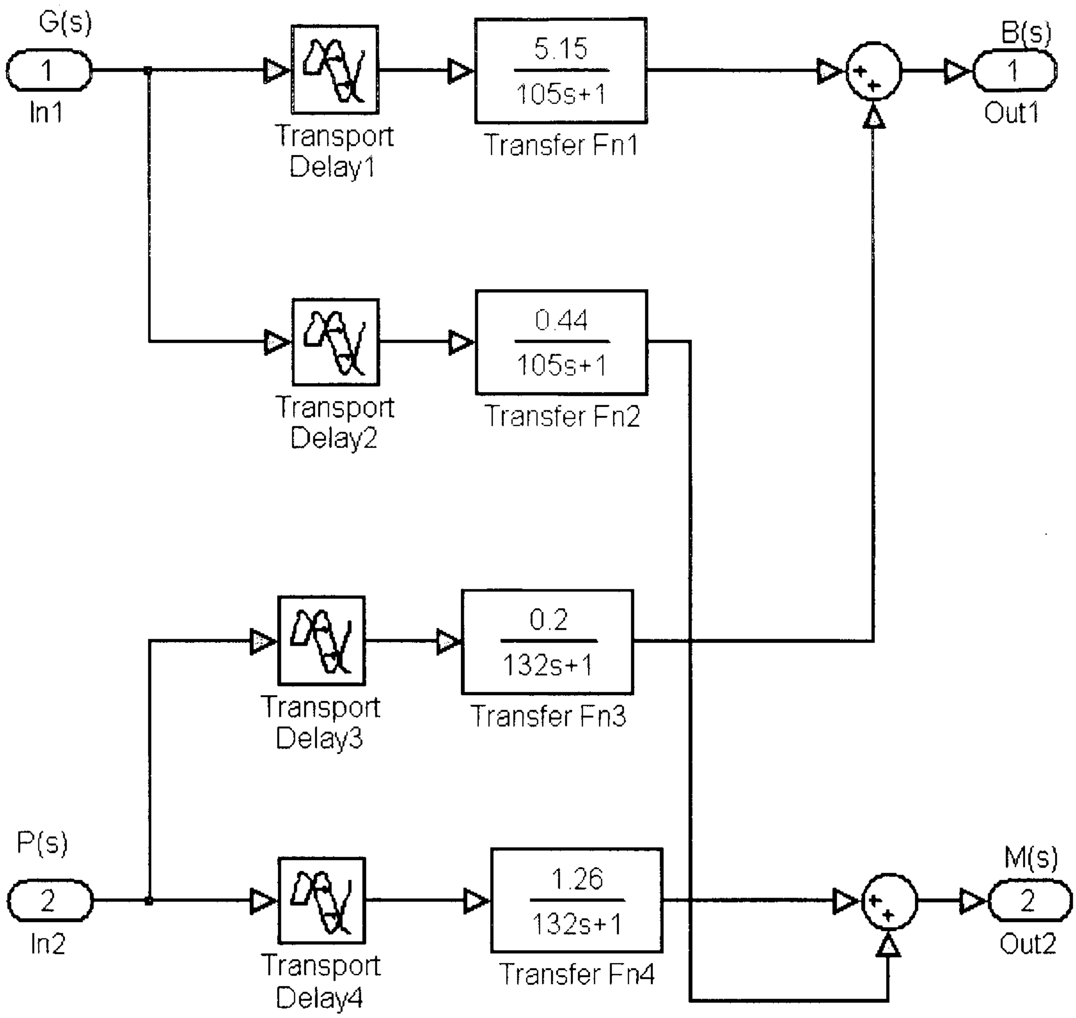

Figure 1.3 Block diagram of the process with open loop

Let us form two control loops by coupling G(s) with B(s) and P(s) with M(s) as can be seen in Figure 1.4. To simplify the presentation, we have assumed that the transfer functions of the measuring devices and final control elements in both the loops are equal to unity.

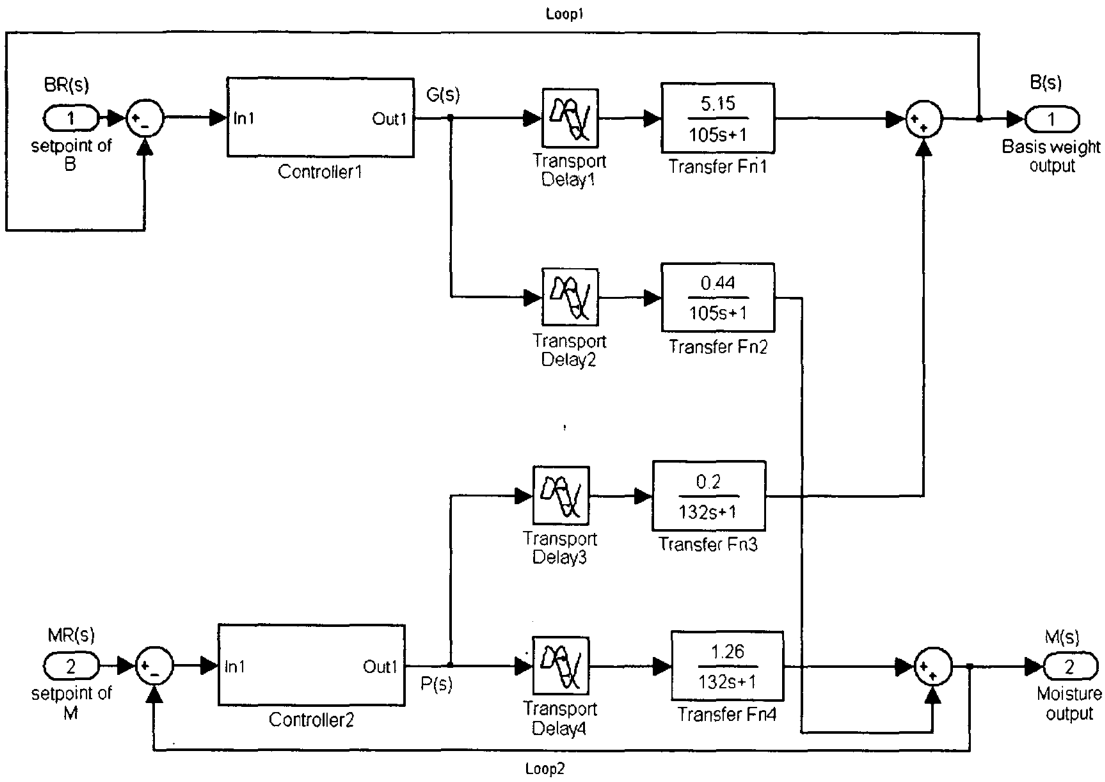

Figure 1.4 Block diagram of the process with closed loop

Let C1 (Controller1) and C2 (Controller2) be the transfer functions of the two controllers [132], the values of the manipulations are given by:

$G(s) = C1\ [B_R(s)\text{-}B(s)]$.................. (1.8)

$P(s) = C2\ [M_R(s)\text{-}M(s)]$.................. (1.9)

Where:

$B_R(s)$ = Setpoint of Basis Weight

$M_R(s)$ = Setpoint of Moisture

This kind of process is too complicated, to be modeled precisely, moreover due to the continuously developing automation systems and more demanding control performance requirements, conventional control methods are not always adequate. On the other hand, practical control problems are usually imprecise. The input-output relations of the system may be uncertain and they can be changed by unknown external disturbances. New schemes are needed to solve such problems. One such an approach is to utilize fuzzy control. Fuzzy control is based on fuzzy logic, which provides an efficient method to handle inexact information as a basis of reasoning. With fuzzy logic, it is possible to convert knowledge, which is expressed in an uncertain form, to an exact algorithm. In fuzzy control, the controller can be represented with linguistic if-then rules. The interpretation of the controller is fuzzy but the controller is processing exact input-data and is producing exact output-data in a deterministic way. Fuzzy Logic provides a certain level of artificial intelligence to the conventional PID controllers. Fuzzy PID controllers have self-tuning ability and on-line adaptation to nonlinear, time varying, and uncertain systems. Fuzzy PID controllers provide a promising option for industrial applications with many desirable features [1].

Fuzzy logic has been available as a control methodology for over three decades and its application to engineering control systems is well proven. In a sense, fuzzy logic is a logical system that is an extension of multi-valued logic although in character it is quite different. It has become popular due to the fact that human reasoning and thought formation is linked very strongly with the ways fuzzy logic is implemented. Far – ranging applications exist including space-rocket control, advanced in-car control systems, and not to mention the myriad of potential industrial applications. In more recent years the use of fuzzy logic in combination with neuro computing and genetic algorithms has become popular in control system design. The purpose of this amalgamation of methods is to produce systems whose MIQ (Machine IQ) is considerably higher than those developed using conventional methods [45].

1.3 Fuzzy Logic

Theory of fuzzy sets was introduced by Lotfi A. Zadeh, Professor for computer science at the University of California in Berkeley in 1965 [153] and the industrial application of the first fuzzy controller was initiated by E. H. Mamdani in 1974 [94]. Fuzzy systems have obtained a major role in engineering systems and consumer products in the 1980s and 1990s. New theoretical results [40, 89] and new applications [69, 7] are presented continuously. A reason for this significant role is that fuzzy computing provides a flexible and powerful alternative to construct controllers, supervisory blocks, computing units and compensation systems in different application areas [40]. With fuzzy sets, very nonlinear control actions can be formed easily. The transparency of fuzzy rules and the locality of parameters are helpful in the design and maintenance of the systems [16].

Therefore, preliminary results can be obtained within a short development period. Basically, Fuzzy Logic (FL) is a multi-valued logic that 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 [104].

Fuzzy logic is a powerful problem solving methodology with a myriad of application in control and information processing. It provides a remarkably simple way to draw definite conclusions from vague, ambiguous or imprecise information [85]. In a sense, fuzzy logic resembles human decision making with its ability to work from approximate data and find precise solutions. Complex systems are described using knowledge and experience of experts in simple English-like rules. It does not require any system modeling and complex mathematical equations governing the relationship between inputs and outputs. Most real life physical systems are actually nonlinear systems. Conventional design approaches use different methods to handle non-linearity. Fuzzy logic provides an alternative solution to nonlinear control. Non-linearity is handled by rules, membership functions, and inference process which results in improved performance, simpler implementation and reduced design costs.

Fuzzy logic control systems have the capability of transforming linguistic information and expert knowledge into control signals and therefore, are preferred over traditional approaches such as optimal and adaptive control techniques. Despite the advantages of conventional Fuzzy Logic Controller over traditional approaches, there remain a number of drawbacks in its implementation. Fuzzy Logic Controllers are characterized by a number of parameters that need to be configured in priori, such as input/output scaling gains, center and width of the membership function and selection of appropriate fuzzy control rules etc. The complexity in selection of these parameters increases with the complexity of the process.

A fuzzy system is a knowledge-based system which utilizes fuzzy if-then rules and fuzzy logic in order to obtain the output of the system. When the system is considered as a fuzzy block, the computing algorithm can be divided into three parts: fuzzification, reasoning and defuzzification [104, 60, 40, 82, and 156] and this can be seen in Figure 1.5. Fuzzy sets of the inputs are defined by the membership functions [68]. The sets can be labeled by adjectives which represent the meaning of the sets. The membership function gives the grade of the membership which tells how well the current input value belongs to the fuzzy set. The part of the algorithm where the grades are calculated is usually called fuzzification [68]. After fuzzification the computing handles only the grades and the exact input values are ignored.

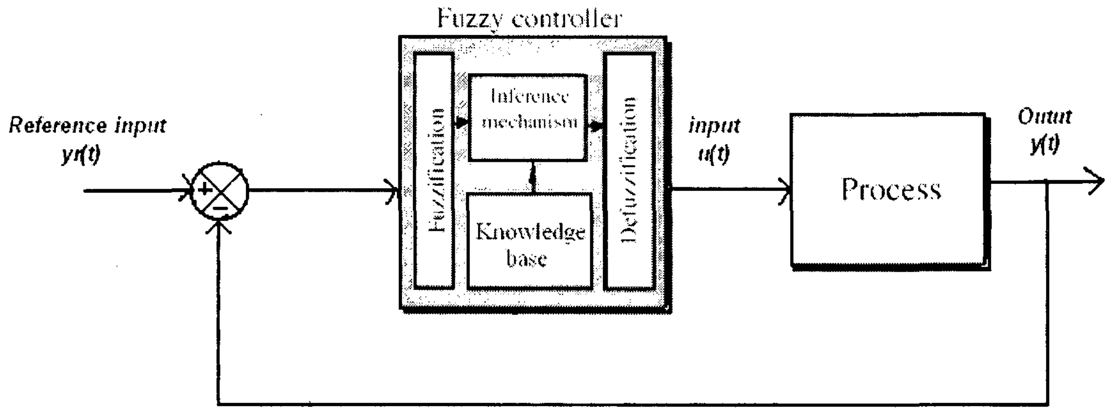

Figure 1.5 Fuzzy logic control loop system

The reasoning is performed based on the if-then rules and the grades calculated in the fuzzification [68]. In the design stage, different input fuzzy sets are combined together with fuzzy connectives, and a certain area of the input space can be detected, where only one rule is active. Selecting suitable values for the outputs in the situation and choosing them as consequences of the rule, the fuzzy system can be constructed element-by-element. Normally we have two types of reasoning; Mamdani and Sugeno. Mamdani reasoning usually produces a fuzzy set as a consequence. It must be converted to an exact value before it can be used. This part is called defuzzification. Sugeno reasoning does not need defuzzification. The main feature of a Sugeno fuzzy model is to express the local dynamics of each fuzzy implication (rule) by a linear system model. The overall fuzzy model of the system is achieved by fuzzy "blending" of the linear system models. The Mamdani model is preferred when a linguistic description of both the input and output membership function is desired. We have used Mamdani Type of model in our analysis.

The behavior of the system is expressed in the form of the membership functions and the fuzzy if-then rules. This facilitates the validation and correction by experts, and provides a way to communicate with users. Most fuzzy systems are transparent because they can be represented in a linguistic form. In the case of fuzzy computing, the parameters include parameters of the membership functions, and connections between the fuzzy sets, i.e., the rules. The fuzzy system has a property that the rules interact together to produce the final value of the output. Thus the value of the output can be calculated from the membership function of the output fuzzy set.

1.4 Fuzzy control

A fuzzy controller is a fuzzy system, which is used to control a target system or it is used for supervisory control. The fuzzy controller has a linguistic interpretation which can be expressed with the help of fuzzy sets, membership functions, and fuzzy rules. However, it processes exact input data and produces exact output data in a deterministic way. Fuzzy controllers can be used when nonlinear control action is needed, or when the controller is to be tuned manually. Dynamical behavior of the controller is implemented in pre-filtering and post-filtering parts [106] to obtain delayed signals, differences, integral actions, etc.

Design of the fuzzy controller means selection of fuzzy rule base structure, including the number of fuzzy sets for each input and output. After that places and shapes of the membership functions are tuned to obtain behavior of the controller as wanted. Often the tuning must be done on a trial-and-error basis which is time-consuming and needs patience. With fuzzy logic, very versatile control strategies can be implemented and improvements to the control performance can be made by altering the shape of membership functions and the number of fuzzy sets and rules.

The most widely used controller in industrial applications is PID-controller (proportional- integral-derivative). It is easy to tune and it has good disturbance attenuation properties. A disadvantage of the PID controller is that it is linear and cannot successfully control a plant, which has strong nonlinearities. In fuzzy control [72], PD-type and PI-type fuzzy controllers are the best-known counterparts of the PID controller. They are used to achieve better performance with nonlinear processes. Good experiences have been obtained especially with the PD-type fuzzy controllers in servo applications [93]. When the number of the inputs of the fuzzy system are increased, the dimension of the rule base also increases. Thus, the maintenance of the rule base is more time-consuming. Another disadvantage of fuzzy controllers is the lack of systematic, effective and useful design methods, which can use a priori knowledge of the plant dynamics. Deficiencies of the PID controller and the fuzzy controller can be reduced by combining them together. In this work an effort has been made to combine PID controller with Fuzzy Logic systems.

Usually the design problem is well-defined with respect to the output variables of the fuzzy system, i.e., the signals u(t) which affect the process output y(t) are known (Figure 1.5). Because the fuzzy controller is a static mapping, the outputs of the fuzzy system can vary and finally the post-filtering produces u(t). Another part is the selection of the input variables for the fuzzy controller. In practice, there are several signals which should be taken into account when the control signal is calculated.

In feedback control, the error signal between the set-point and the measurement

$e(t) = y_r(t) - y(t)$ ....(1.10)

is observed. The control objective is to keep the error signal small. Usually the changing rate of the error signal in the form of the change in the error

$\Delta e(t) = e(t) - e(t-1)$ ....(1.11)

is also considered. The signs of the change and the error indicate, if the process output is going towards the set-point or not. With those two inputs, the fuzzy system can perform PI or PD type control depending on whether the output is the change in the control signal $\Delta u(t)$ or the pure control signal u(t). The error and the change in the error do not include information about the operation point of the system. Thus the controller behaves in the same manner in different conditions even if the controller is nonlinear. Additional information is needed. Thus the measurement y(t) or the set-point $y_r(t)$ can be appropriate.

The fuzzy controller includes a number of if-then rules, the form of which is choice of the designer. Usually they are of the form

if x1 is X^i_1 and x2 is X^i_2 and ...... and x_{nx} is X^i_{nx} then z1 is Z^i_1 and z2 is Z^i_2 and ..... and z_{nz} is Z^i_{nz} , where X^i_j is the fuzzy set of the jth input (nx is the number of inputs) and Z^i_j is the fuzzy set of the jth output (nz is the number of outputs) both related to the ith rule.

In constructing the rule base, the numerical completeness must be kept in mind in order to prevent dividing zero by zero in the center-of-gravity defuzzification. It is easily caught by including all combinations of the input fuzzy sets into the rule base by means of fuzzy and connectives. The number of rules demanded can be decreased by dropping some fuzzy conditions away from the antecedent. This can be done, if the controller output is constant with respect to the input in a certain area.

The fuzzy parameters include the place and the shape of membership functions. The most important point in the selection of the membership functions is the transparency of the obtained controller. The placing of the membership functions can be seen as a tuning problem. Used T-norms and T-conorms, the reasoning method, and the defuzzification method can be included in the choices which are decided at a very early stage of the design and are not changed in the tuning stage. They can rather be classified to strategy choices than to design parameters.

The application area of fuzzy logic ranges from consumer products to automation systems. The wide range of consumer products shows that fuzzy logic is also applicable in very cheap and simple platforms. It shows that the requirements of fuzzy logic are not high because the operation of a fuzzy system does not need very heavy computing facilities. When fuzzy computing is applied, the system can operate like an input-output mapping as a black box without any linguistic interpretation and if-then rules. The inside functionality can be hidden from the users. Hence, the application platform does not need any special user interface. The possibility to load parameters into it and logging the inputs and the outputs of the fuzzy system during operation are enough. Another possibility to change the parameters on-line might be also useful, but no graphical interface is necessary. On-line capability can be used to fine-adjust the rules, but it is dedicated only for skilled operators. More complicated redesign and retuning tasks are done in the development environment. The power of fuzzy computing is said to be in the user-friendly and understandable knowledge presentation in the form of linguistic if-then rules.

Fuzzy systems are very useful in two general contexts:

1. In situations involving highly complex systems whose behaviors are not well understood
2. In situations where an approximate, but fast, solution is warranted.

There is a distinction between models of systems and models of uncertainty. A fuzzy system can be thought of as an aggregation of both because it attempts to understand a system for which no model exists, and it does so with information that can be uncertain in a sense of being vague, or fuzzy, or imprecise, or altogether lacking. Systems whose behaviors are both understood and controllable are of the kind which exhibits certain robustness to spurious changes. In this sense, robust systems are the ones whose output doses not change significantly under the influence of changes in the inputs, because the system has been designed to operate within some window of uncertain conditions. It is maintained that fuzzy systems too are robust. This is because the uncertainties contained in both the inputs and outputs of the system are used in formulating the system structure itself, unlike conventional system analysis which first poses a model, based on a collective set of assumptions needed to formulate a mathematical form, and then uncertainties in each parameters of that mathematical abstraction are considered.

Fuzzy logic uses a different approach than conventional controllers. Conventional Proportional, Integral, and Differential (PID) controllers model the desired system or process being controlled. Alternatively, in a fuzzy logic controller, it is the human operator's behavior that is modeled. The PID controller uses a set of differential equations to analytically model the system. It is the solution to these equations that tells the PID controller how to adjust the system. In a fuzzy controller, adjustments are handled by a fuzzy rulebased expert system (an expert system is a logical model of an expert human operator's reasoning to control the system). The shift in focus from the process to the operator changes the whole approach to control problems.

A fuzzy logic controller or fuzzy engine code has the advantage of being shorter than their PID controllers. In some cases they only require 250 bytes of code to implement a two input, one output controller. This translates into less cost for computing and faster response times than traditional controllers.

As one can see, fuzzy controllers are much easier to read and understand than using a set of differential equations. Additionally, fuzzy controllers are simpler than classical controllers. That is because they can tolerate some imprecision when dealing with the desired system. This ease of use translates into lower costs and faster time to implement. That is why so many companies are using fuzzy logic controllers in their applications. The reason for the widespread use of fuzzy logic lies in that they are easier to design than conventional PID controllers, and cheaper to produce as well.

When the control problem is to regulate the process output around a setpoint, it is natural to consider *error* as an input, even to a fuzzy controller, and it follows that the integral of the error and the derivative of the error may be useful inputs as well. Since fuzzy controllers are nonlinear, it is more difficult to set the controller gains compared to proportional-integral-derivative (PID) controllers. But a systematic tuning procedure would make it easier to install fuzzy controllers, and it might pave the way for auto-tuning of fuzzy controllers. Fuzzy controllers show similarities with PID controllers under certain assumptions [99]. But there is still a gap; it seems, between the PID tuning methods and a design strategy for fuzzy controllers of the PID type.

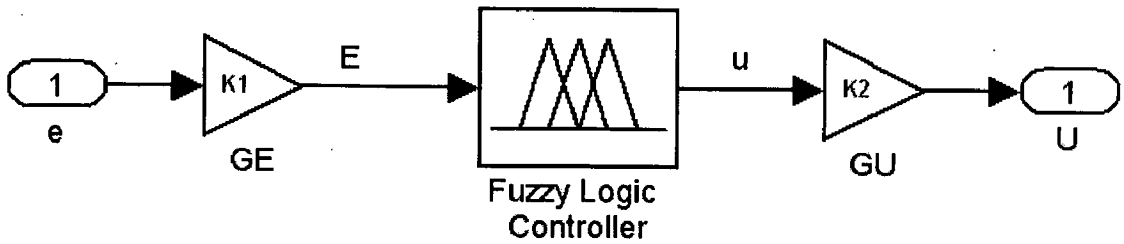

Figure 1.6 Fuzzy-Proportional controller (FP)

Input to a *Fuzzy Proportional* (FP) controller (Figure 1.6) is *error* and the output is the control signal. This is the simplest fuzzy controller available. It is relevant for state- or output-feedback in a state space controller. Compared to crisp proportional control, the fuzzy P controller has two gains GE and GU instead of just one and the values of gains are given by the constants K1 and K2 respectively. As a convention, signals are written in lower case before gains and upper case after gains, for instance E = GE * e. The gains are mainly for tuning the response, but since there are two gains, they can also be used for scaling the input signal onto the input universe to exploit it better.

The controller output at any time t is the control signal U_t, it is a nonlinear function of e_t.

$U_t = f\,(GE * e_t) * GU$ ....(1.12)

The function f is the fuzzy input-output map of the fuzzy controller. Using the linear approximation $f\,(GE * e_t) = GE * e_t$ then

$U_t = GE * e_t * GU = GE * GU * e_t$ ....(1.13)

So we can say that the product of the gain factors is equivalent to the proportional gain,

i.e.

$GE * GU = K_P$ ....(1.14)

The accuracy of the approximation depends mostly on the membership functions and the rules. Because of the process dynamics it will take some time before a change in the control signal is noticeable in the process output, and the proportional controller will be more or less late in correcting an error. Derivative action helps to predict the error and the proportional-derivative controller uses the derivative action to improve closed-loop stability. The basic structure of a PD controller is shown in Figure 1.7.

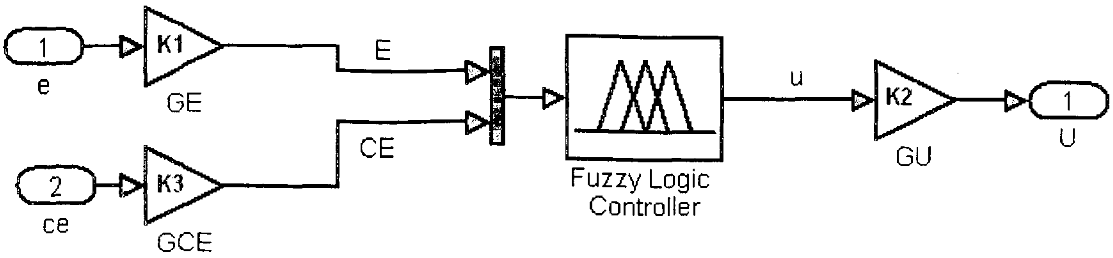

Figure 1.7 Fuzzy-PD controller (FPD)

Input to the *Fuzzy Proportional Derivative* (FPD) controller is the *error* and the *derivative of the error*. In fuzzy control the latter term is usually called *change in error (ce)*.

Where

$ce = e_t - e_{t-1}$ ....(1.15)

The controller output is a nonlinear function of *error* and *change in error*

$U_t = f\,(GE * e_t, GCE * e_t) * GU$ ....(1.16)

Again the function *f* is the input-output map of the fuzzy controller, only this time it is a surface. Using the linear approximation $GE * e_t + GCE * e_t$, then

$U_t = (GE * e_t + GCE * e_t) * GU$ ....(1.17)

$U_t = GE * GU\,(e_t + (GCE / GE) * e_t)$ ....(1.18)

The gains are related in the following way:

$GE * GU = K_P$ ....(1.19)

and

$GCE / GE = \tau_D$ ....(1.20)

The fuzzy PD controller may be applied when fuzzy proportional control is inadequate. The derivative term reduces overshoot, but it may be sensitive to noise as well as an abrupt change of the reference causing a *derivative Kick*.

If there is a sustained error in steady state, integral action is necessary. The integral action will increase the control signal if there is a small positive error, no matter how small the error is; the integral action will decrease it if the error is negative. A controller with integral action will always return to zero in steady state. It is straight forward to envision a *fuzzy PID controller* with three input terms: *error, integral error*, and *derivative error.* A rule base with three inputs, however, easily becomes rather big and, as mentioned earlier, rules concerning the integral action are troublesome. Therefore, it is common to separate the integral action as in the *fuzzy PD+I* (FPD+I) controller as shown in Figure 1.8 [72].

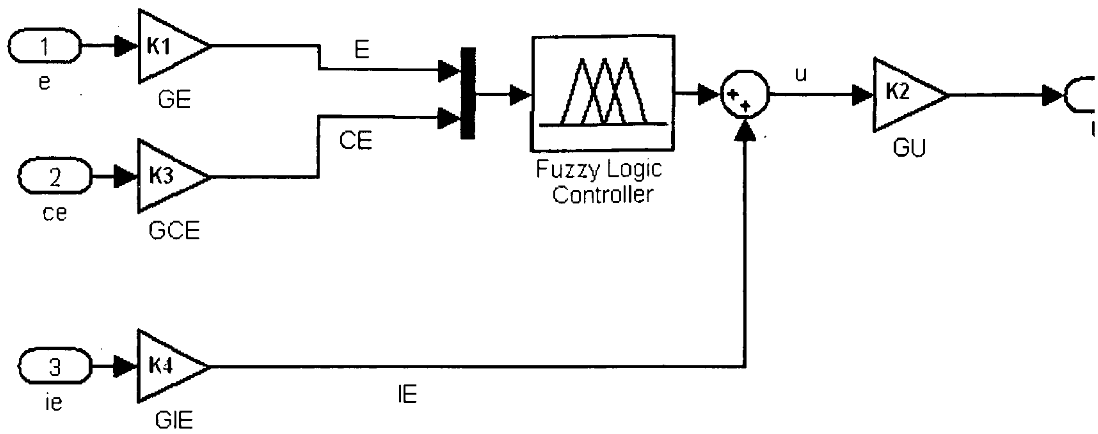

Figure 1.8 Fuzzy PD+I controller (FPD+I)

The integral error is computed as,

$ie_t = \sum (e_i * T_s)$ ....(1.21)

The controller is thus a function of the three inputs

$U_t = [f(GE * e_t, GCE * e_t) + GI * ie_t]* GU$ ....(1.22)

Its linear approximation is

$U_t = [GE * e_t + GCE * e_t + GI * ie_t]* GU$ ....(1.23)

$U_t = GE * GU [e_t + (GCE / GE) * e_t + (GI / GE) * ie_t]$......(1.24)

Thus the gains are related in the following way:

$GE * GU = K_P$ ....(1.25)

$GCE / GE = \tau_D$ ....(1.26)

and

$GI / GE = 1 / \tau_I$...(1.27) s controller provides all the benefits of PID control, but also the disadvantages arding derivative kick and integrator windup.

Controller	Advantage	Disadvantage
Fuzzy-P	Simple	Maybe too simple
Fuzzy-PD	Less overshoot	Noise sensitive, derivative kick
Fuzzy-PD+I	All in one	Windup, derivative kick

Table 1.1 Comparison of different types of Fuzzy Controller

1.4 Objective of the present work:

The objective of the work is to develop a model for controlling the Basis weight and Moisture of an interactive system using a Fuzzy Logic Controller.

It is done in two steps:

1.4.1 Considering the individual systems as Non-Interacting Systems.

1.4.1(a) Variations in the BW output due to the variations in the Basis weight valve opening, assuming no variation in moisture due to BW variation. The Servo model is developed for both step input and varying input, using both FLC and PID controller.

- Developing three types Fuzzy Logic model:

(1)Fuzzy-P Model

(2)Fuzzy-PD Model

(3)Fuzzy-PD+I Model

- Developing three types Conventional controller model:

(1) P-Type Controller

(2) PD-Type Controller

(3) PID-Type Controller

1.4.1(b) Variations in the Moisture content due to the variations in the steam shower valve opening, assuming no variation in BW due to the moisture variation. The Servo model is developed for both step input and varying input, using both FLC and PID controller.

- Developing three types Fuzzy Logic model:

(1)Fuzzy-P Model

(2)Fuzzy-PD Model

(3)Fuzzy-PD+I Model

- Developing three types Conventional controller model:

(1)P-Type Controller

(2)PD-Type Controller

(3)PID-Type Controller

The two non interacting systems are analyzed and the model for the same is developed using the Fuzzy Controller and the PID controller and the system is made to work in a manner to find the optimum values of different scaling gains for the two systems. The effect of different gains on the output of the system is also discussed.

1.4.2 Considering the Interactive system.

To understand the nature of interaction between two control loops, we have studied the effects of the inputs i.e. Pulp flow (G) and Steam flow (P) on the outputs i.e. Basis weight (B) and Moisture (M) using a Fuzzy Logic Controller (FLC) and a conventional PID controller, both for Step input and Varying input when:

a) One loop is closed and other is open.
b) Both the loops are closed.

The Simulation for all the above cases is done using Matlab. The tuning for both the Fuzzy Control System and the conventional PID controllers is carried out by hit and trial method. The tuning of the Fuzzy controller could easily be done by Neuro-Fuzzy techniques or by using Genetic Algorithm, while the tuning of PID controller could be done by Z-N method, provided we have a well defined objective function. As we cannot define the objective function for this process with all the performance parameters such as Risetime, Offset, Settling time, Overshoot etc. as all have to be simultaneously regulated. The main aim is to keep the system stable for bounded inputs, thus we are not in the position to use any suitable optimization technique with so many objective functions Moreover the hit and trial method used here is simply to analyze the effect of various scaling gains individually on the performance parameters of the system. This has been worked out in Chapter 3(Basis weight) and Chapter 4 (Moisture). In Chapter 5 (Interactive system) the tuning of various parameters is not shown rather directly the optimum values of various scaling gains are used and the effect of the interactions between the moisture and basis weight are analyzed. As can be clearly seen from the work done in Chapter 3 and Chapter 4, the individual scaling gains can be monitored to achieve the desired results. Thus if the objective functions of the specific problem are known, one can easily tune the system according to their requirements, but unfortunately no specific values can be given for the objective functions. Only the responses obtained for the assumed parameters gives a check for them.

Chapter 2
Literature Review

A survey was done on the modeling and control of BW and moisture and it was found that a lot of work has been done in the past few years in this field. The control system has a complicated interactive configuration and is difficult to model. Various researchers have tried to model the system using various techniques.

Xin, Kaixiang and Sun [149] have tried to model the system using Petri net model. According to them, basis weight and moisture content are two important parameters of paper's quality. One can preferably pledge quality of production, increase output, economize material, save energy sources through control of these parameters. Computer control system for controlling the basis weight and moisture content of paper machine has a very complicated configuration, is more disturbed, and has great pure lag. In this paper, they have analyzed the arts and crafts flow of the papermaking system, and modeled it using Petri net. The simulation is done and it is proved that the model is an advantage.

Sankarnarayanan and his co-workers [116, 117] reviewed exhaustively the use of electronic control and the parameters of importance for monitoring/ control to maintain the paper quality in mills; such as basis weight, moisture content, thickness or caliper, brightness, color and opacity of paper, ash content, consistency of stock, headbox consistency and quality of pulp. Development of indigenous microprocessor based instruments for designing real time scanning or measurement of basis weight with wide range (40gsm-500gsm) by neucleonic technique, moisture monitor, and profile control of paper machine for basis weight & moisture by both analogue and digital techniques have been made. Further, dynamic measurement of thickness, measurement of color and turbidity, nondestructive technique for measuring tensile strength and breaking length using sonic wave propagation and coat thickness measurement have been demonstrated. In all the cases of measurement of parameters field testing were performed. For control of Basis weight, dynamic models were developed, simulated and used for testing in mills for single loop feedback control in paper mill. Beside it, the principles of computer control of digester were reported.

Singhal [127, 128] designed low cost basis weight control system for small paper mill. Basis weight control particularly when manufacturing reel orders is very important and discussed manual control and feed forward control systems. Basis weight control with feed forward control is a good choice for the small paper mills who cannot afford costly QCS system. Scott [121] developed a new headbox design featuring consistency profiling decoupled from fiber orientation response which provided narrower basis weight response than a slice blending system. Bergeron. M et al. [12] worked on simultaneous measurement of moisture and basis weight of paper.

Shen, Zhang, Wang, and Xinmin [124] proposed a new decoupling measure approach, which can avoid the shortcomings of the paper sheet basis-weight and ash-content sensors available now. A new type of sensor is designed and produced. A test has been performed, and the experimental results show that the new type sensor gives excellent performance.

Ola Slatteke [129] indicated that control of the moisture content is accomplished by adjusting the steam pressure in the drying cylinders. This paper presents a nonlinear dynamic model, based on heat and mass balances for steam, cylinder and paper. It is implemented in the object-oriented modeling language Modelica and is used to evaluate control of a new process structure in the drying section.

Hojjatie, Abedi, and Coffin [66] determined the correlation between surface temperature distribution measured by an Infrared Thermography technique and moisture content distribution determined by a gravimetric method. Paper sheets were constrained such that diffusion would predominantly be in one in-plane direction. Both measurements were taken as a function of time for a sorption process. The results proved that thermal imaging method could provide a useful technique to quantify in-plane moisture distribution in a paper web during apermaking and diffusion of water vapor in paper sheets during end-use.

Garceau and his co-workers [48] developed the control strategy for on-line haracterization of the fiber size of pulp by acousto-optical methods in various perations of paper industry including the wet end operations. The models eveloped for this purpose for both optical and acoustical techniques have been simulated through experimental results. Further models are also developed for kraft pulping delignification kinetics for making pulp and then post treatment pulps have also been characterized through on-line methods.

Ghosh [53, 54] worked extensively on modeling and simulation, wet end chemistry, paper drying and optimization, refining and screening. Bernateau. J. P and Hix. S. H [11] and Shead. R. P [123] worked on CD moisture control of paper. Wang. H [145] applied the Neuro-Fuzzy Modeling and Control to MD Moisture content systems in Paper Machines.

As seen above both these parameters i.e. the basis weight and the moisture affect the economy of the system. A few researches in their work have put light on the economic factor, energy conservation and also how other parameters can affect these parameters.

Rao, Bansal, and Ray [113] studied the application of various methods to measure the relevant parameters in pulp and paper mill emphasizing the status of instrumentation in paper mill with particular reference to paper machine. They have further treated the selection of instrumentation in terms of cost and added that in paper machine section the measurement and control of headbox temperature along with headbox level are essential.

The necessity of various types of process control applications in pulp and paper mill have been dealt with by Rao [109,110, 111], and Bihani et al.[13, 14, 15]. However most of the work of above researchers is devoted to pulping and bleaching of woods, mixed hardwoods and non woods. Economic utilization of alum in sizing has been emphasized by Rao [112].

Banerjee et al [8, 9] carried out extensive investigation on various aspects of many operations of a paper mill. Some of the processes include improving energy efficiency, improving centrifugal cleaner efficiency, modeling, simulation and control. S.L Keswani [80] had given a view on indigenous capabilities for electronic process control in pulp and paper industry.

In the present work, we have used a similar type of interacting system for the control of Basis Weight and Moisture using the Fuzzy Logic Controller and the models developed are of Fuzzy-P, Fuzzy-PD, Fuzzy-PD+I. Thus a general survey of Fuzzy controllers and the tuning of various parameters, along with the hybrid techniques of Artificial Intelligence to optimize the system has been surveyed in detail.

Literature review on fuzzy logic

The idea of fuzzy sets was first proposed in July 1964 by Lofti A. Zadeh, a well-respected professor in the department of electrical engineering and computer science at University of Califonia, Berkeley. Even though there was strong resistance to fuzzy logic, many researchers around the world became Zadeh's followers. Important concepts introduced by Zadeh during this period included fuzzy multistage decision-making, fuzzy similarity relations, fuzzy restrictions, and linguistic hedges. Other contributions include Bellman's work (with Zadeh); in fuzzy multistage decision making [10]; Lakoff's work from a linguistic view [84]; Goguen's work on the category-theoretic approach to fuzzy mathematical structure [57]; Kohout and Gaines on the foundation of fuzzy logic [47]; Klir, worked on fuzzy sets and logic [82]; Kandel's work on fuzzy switching function [77, 78], and Zimmermann's work on; fuzzy optimization [156].

One of the early fuzzy logic journals in the world is Chinese journal on fuzzy mathematics. While in the late 1970s, a few small university research groups on fuzzy logic were established in Japan. Professor T. Terano and Professor H. Shibata from Tokyo University led one such group in Tokyo.

An important milestone in the history of fuzzy logic control was established by Assilian and E. Mamdani in the United Kingdom in 1974. They developed the first fuzzy logic controller, which was for controlling a steam generator. Pioneering efforts to use fuzzy logic applications in civil engineering were made by C.B. Brown, D. Blockley and D. Dubois. In April 1971, Brown and Leonardo [23] introduced and discussed civil engineering applications of fuzzy sets during the ASCE Structural Engineering Meeting in Baltimore, Maryland. In 1975, Blockley [19] published a paper on the likelihood of structural accidents, which was followed by a continuous flow of simulating papers [17, 18] and a thought-provoking book [16]. In 1979, Brown [22] presented a fuzzy safety measure, with which more realistic failure rates were obtained by utilizing both subjective information and objective calculations. Later Brown treated entropy constructed probabilities [21].

In 1976, the first industrial application of fuzzy logic was developed by Blue Circle Cement and SIRA in Denmark. The system is a cement kiln controller that incorporates the "know-how" of experienced operators to enhance the efficiency of a clinker through smoother grinding. The system went to operation in 1982.

After eight years of persistent research, development, and deployment efforts, Seiji Yasunobu and his colleagues at Hitachi put a fuzzy logic-based automatic train operation in Sendai city's subway system in 1987. Another early successful industrial application of fuzzy logic is a water-treatment system developed by Fuji Electric. The development of water treatment systems enabled Fuji Electric to introduce the first Japanese general-purpose fuzzy logic controller (named FRUITAX) into the market in 1985. Various other applications and implementation of FLC have been tried and are still under progress all over the world. P. Javadi, A. Tabatabaee, M .Omid [74] have put some light on the Automation of Greenhouse Irrigation systems using Fuzzy logic. Areas like liquid level control [60,119]; Image processing [136, 150]; induction motor [4,141]; Boiler Control [118]; industrial robot [46, 56]; HVAC systems [126]; Yaw Vector Control [107]; servo control [2] have also been tried using Fuzzy Control by various researches. Tseng and Chen [139] Robust Fuzzy Observer-Based Fuzzy Control Design for Nonlinear Discrete-Time Systems with Persistent Bounded Disturbances. Brovis [20] compared the Fuzzy Logic Control with other Automatic Control Approaches.

The fuzzy boom in Japan was a result of close collaboration and technology transfer between universities and industries. Matsushita Electric Industrial Co. (also known as Panasonic outside Japan) was the first to apply fuzzy logic to consumer product, a shower head that controlled water temperature, in 1987. In late January 1990, Matsushita Electric Industrial Co. named their newly developed fuzzy controlled automatic washing machine "Asai-go Day Fuzzy" and launched a major commercial campaign for the "fuzzy" product. Many other home electronic companies followed Panasonic's approach and introduced fuzzy vacuum cleaners, fuzzy rice cookers, fuzzy refrigerators, and others. This resulted in a fuzzy vogue in Japan. As a result consumers in Japan recognized the word "fuzzy", which won the gold prize for a new word in 1990.This fuzzy boom in Japan, triggered a broad and serious interest in this technology in Europe, and, to a lesser extent, in the United States, where fuzzy logic was invented.

Another important milestone in the history of fuzzy logic is the first VLSI chip for performing fuzzy logic inferences. It was developed by M. Togai and H. Watanabe in 1986 [138]. These special-purpose VLSI chips can enhance the performance of fuzzy rule-based systems for real-time applications. Togai later formed a company (Togai Infralogic) that sold hardware and software packages for developing fuzzy logic applications. Several other companies (e.g. APTRONIX, INFORM) were formed in late 1980s and early 1990s. Later the vendors of conventional control design software such as Math Works started introducing add-on toolboxes for designing fuzzy systems. The Fuzzy Logic Toolbox for MATLAB was introduced as an add-on component to MATLAB in 1994.This helped in the exposure of toolkits such as Simulink [81, 90].

A good summary of fuzzy logic research progress during the first decade can be found in collection edited by Gupta, Saridis, and Gaines [58]. In this volume M.M. Gupta describes some of the events that took place during the first decade of fuzzy logic [59]; E.H. Mamdani gives a survey of fuzzy logic control and points out several important issues regarding the design and application of fuzzy logic controllers [95].

Hirota presented a history of the development of fuzzy logic technology in Japan in [64]. The fuzzy washing machine that triggered the fuzzy boom was discussed by N. Wakami et al. [143] and by S. Kondo et. al.[83]. D.G. Schwartz and G. Klir discussed several key milestones of fuzzy logic technology development and applications [120]. Constantin von Altrock summarizes the historic development and the industrial applications of fuzzy logic in Europe [7]. H. Takagi surveys the applications of fuzzy logic and neuro-fuzzy systems in consumer products [137]. Industrial fuzzy control applications have been published in collected volumes edited by M. Sugeno [133, 134] and by Yen, Langari [151]. An update on fuzzy logic applications in civil engineering has been compiled by Wong, Chou and Yao [148]. Dotoli. M with his co-workers [29-39] has contributed a lot in the field of fuzzy logic; he has worked in the areas of development of FLC systems. A large body of literature on fuzzy control exists; some comprehensive survey papers [41, 44, 50, 55, 67, 73, 92, 95, 101, 103, 105,114, 130,146, 147,151, 154] are helpful for quick access to this field.

Hybrid techniques of Artificial intelligence also gained importance and much work has been done in this field [61, 71, 81, 141] and optimization was successfully analyzed in 2008 using Genetic Algorithms by Khan, Salami and Adetunji [81] Seema, Mitra and Vijay have used Neural network to tune Fuzzy Logic Controller for MIMO systems in 2007 [122]. Aliyari. S.M, et. al, have done

Identification using ANFIS with intelligent hybrid stable learning Algorithm approaches, Training ANFIS as an identifier with intelligent hybrid stable learning Algorithm based on particle swarm optimization and extended Kalman Filter [5, 6].

People are trying to replace PID controller with these intelligent controllers and a lot of work has been done in this field in the recent years. Moreover hybrid systems combining Fuzzy with PID have gained much importance [43, 51, 52, 70, 98, 135]; Akbiyik et. al. have Evaluated the Performance of various Fuzzy PID Controller Structures on Benchmark systems [3].

Tuning of Fuzzy controller was done to improve the performance of the system. He S.Z, Tan S & Xu F.L[63]; Chen. J.Y and Lin. Y.H [25]; Chiricozzi. E [26] worked on self-tuning of fuzzy controller design; Karasakal. O, et. al.[79] have implemented a Self- Tuning Fuzzy PID Controller on PLC.

Haiguo.P and Zhixin.W [62] had worked on enhancing the stability and robust of yawing system effectively, carrying out the simulation research of fuzzy-PID synthesis control. They designed the yawing vector control system with the synthesis controller of fuzzy-PID, modeled the system with Matlab simulation software, and simulated the test. Then compared the simulation curves with common PID control and fuzzy PID subsection control.

Cao and Zhang [24] introduced the Modified Fuzzy PID Controller to deal with random delays in Networked Control System (NCS), to implement real-time control adaptively. Via adjusting the control signal dynamically, the system performance is improved. In this paper, the design process and the ultimate simulation results are represented. Fuzzy PID controller has shown its benefit in dealing with random delays in NCS due to its flexibility and adaptation to uncertain elements. In this paper Modified PID controller supplies high-order information that can accurately track the nonlinear of delays. It is noticeable that this method presents good performance. As Fuzzy Logic is a study process, what kind of membership functions is better and how many fuzzy parameters are proper are still problems. In addition, with the growing requirement of the system performance, the fuzzy membership functions and the inference rules becomes more and more complicated. From this paper high-order information gives additional information that can improve the system performance.

P. J. Escamilla-Ambrosio and N. Mort [42] In their work made a novel approach to deal with the noise issue in both the auto-tuning procedure and the control performance for a PID-type fuzzy logic controller in a multi-sensor environment is proposed. This approach combines a low order modeling method with a fuzzy logic-based adaptive decentralized Kalman filtering approach. The proposed methodology is tested in several simulated benchmark processes. Good results are obtained.

Dotoli, Bruno and Turchiano[37] presented some results about the design and implementation of a fuzzy supervised PID controller for a flow rate process. Since the process is quite nonlinear, a fixed tuning of the PID algorithm cannot guarantee good performances for any operating condition. In this work the use of a fuzzy supervisor that modifies the PID tuning online was suggested, depending on the set point, the error and the actual control action. First, a simplified fuzzy supervisor with only the set point as an input is designed on the basis of the responses with an unsupervised and optimized PID to different set points. Afterwards, the fuzzy rule base is modified and refined introducing two additional inputs: the error and control action. The control strategy is implemented in a C/C++ software module, including a user-friendly graphical user interface (GUI). Results are fully analyzed and discussed in comparison with traditional PID algorithms.

Gao, Trautzsch and Dawson [49] developed a closed loop control system incorporating fuzzy logic for a class of industrial temperature control problems. A unique fuzzy logic controller (FLC) structure with an efficient realization and a small rule base that can be easily implemented in existing industrial controllers was proposed. It was demonstrated in both software simulation and hardware test in an industrial setting that the fuzzy logic control is much more capable than the current temperature controllers. It has also been found that the FLC utilizes self-tuning mechanisms to effectively overcome issues not easily addressed in the PID controller.

Jan Jantzen[72] proposed a design procedure and a tuning procedure that carries tuning rules from the PID domain over to fuzzy single-loop controllers. The idea was to start with a tuned, conventional PID controller, replace it with an equivalent linear fuzzy controller, make the fuzzy controller nonlinear, and eventually fine-tune the nonlinear fuzzy controller. This is relevant whenever a PID controller is possible or already implemented. Since fuzzy controllers are nonlinear, it is more difficult to set the controller gains compared to PID controllers.

Ying [152] investigated the analytical structure of the Takagi-Sugeno (TS) type fuzzy controllers. The TS fuzzy controllers employ a new and simplified TS control rule scheme in which all the rule consequents use a common function and are proportional to one another, greatly reducing the number of parameters needed in the rules. Other components of the fuzzy controllers are general: arbitrary input fuzzy sets, any type of fuzzy logic and the generalized defuzzifier, which contains the popular centroid defuzzifier as a special case.

It has been proved that all these TS fuzzy controllers are non linear, variable gain controllers and the characteristics of the gain variation are parameterized and governed by the rule proportionality. All these results come from the analytical investigations and from the comparison with the conventional counterpart (PID controllers).

Chung et al. [27] proposed a self-tuning fuzzy controller with a smart and easy structure. The tuning scheme allows tuning the scaling factors by only seven rules. The aim of the controller is to obtain a satisfactory performance, for rise time, overshoot and steady-state error for the step response. The structure of this controller consists of two fuzzy logic controllers: one is a PI-type fuzzy controller at low level directly applied to the process; the other one is the fuzzy supervisory tuner controller which adjusts the scaling factors of each MF of the low level controller. This means that the self-tuning controller adjusts three scaling factors for the three linguistic variables of the PI-type fuzzy controller, i.e. G_e (scaling factor of error) G_{ce} (scaling factor of change of error) and G_{cu} (scaling factor of change of manipulated variable).

Mudi & Pal [100] present a simple but robust model for self-tuning FLC's. Because this method will be later applied to the pilot plant dryer it will be presented quite detailed as follows. According to Mudi & Pal the adaptive tuning of a FLC is based on adjusting the output scaling factor (SF) of a FLC on-line by fuzzy rules according to the current trend of the controlled process. The rule-base for tuning the output SF is defined based on the error (e) and the change of error (Δe) of the controlled variable using the most common and unbiased membership functions (MF's). The error e is taken as the difference between the set point and the output controlled variable. The proposed selftuning technique is applied to both PI and PD-type FLC's by making the simulation analysis for a wide range of different linear and non linear second order processes including a marginally stable system. The performance of the proposed STFLC is compared with the corresponding conventional FLC in terms of several performance measures such as peak overshoot, settling time, rise time, integral absolute error (IAE) and integral-of-time absolute error (ITAE) in addition to the responses due to stepwise set point changes and load disturbances.

For the successful design of a FLC, the right selection of the input-output SF's and/or the tuning of the other controller parameters are crucial tasks, which in many cases are done through trial and error or based on some training data. From the various tuneable parameters, SF's have the highest effect due to their global effect on the control performance.

The scaling factors for the inputs and the output (G_u) of the low level FLC are determined based on the knowledge about the process to be controlled and sometimes through trial and error to achieve the best possible control performance.

Visavadia and Brown [142] have performed a comparison between traditional and fuzzy PID controllers and have indicated that the fuzzy controllers perform better and are more robust. Their paper explains what advantages nonlinear fuzzy PID controllers have over their linear counterparts and show several simulations which illustrate this behavior. In particular, the underlying properties of the fuzzy PID controllers are described and some design and analysis methods are outlined.

Ramkumar & Chidambaram [108] present a fuzzy self-tuning PI controller for controlling a bioreactor. The basic idea is to parameterize the Ziegler-Nichols tuning formula by two parameters α and β and then to use an on-line fuzzy inference mechanism to tune the PI controller parameters i.e. proportional gain and reset time. The fuzzy self-tuning method uses the process output error as input and the tuning parameters α and β as outputs. The ranges of membership functions are selected based on the simulation study. In real situation these ranges will be fixed from the knowledge of the operators. The rules are developed and examined for their correctness. The rule base is formed after an iterative process, in which new rules are added and some existing rules are deleted or changes are made in the existing ones. After several simulation runs, a set of seven rules is extracted. Simulation studies of the non linear bioreactor model show that the present method is superior to that of fixed parameters conventional PI controller for both servo and regulatory problems. The present fuzzy logic controller is robust to process parameter uncertainties and to changes in magnitude and direction of the disturbances.

Daugherity *et al.* [28] describe a self-tuning fuzzy controller where the scaling factors of the inputs are changed in the tuning procedure. In this case the process in which the tuning method was applied was a simple gas-fired water heater, since it is widely used in the petrochemical industry and an accurate simulation model is available. The aim is to replace an existing PID controller with a fuzzy controller, using initial guesses as to the fuzzy membership functions and rules to tune the fuzzy controller for optimum performance and to compare the performance of three control regimes i.e. PID, not tuned FLC and self-tuning FLC. Here a single input / single output process is considered. The FLC has two control inputs: the current error and the change of error. The control action is the change in the manipulated variable. The tuning of the two scaling factors for the two control inputs is done automatically by a fuzzy set of meta rules. The performance measures for tuning are the overshoot, rise time and the amplitude of oscillation of the transient response of the process. The rules for tuning are of the form: IF performance measure IS X, THEN scaling factor IS Y, where performance measure is one of three above mentioned performance measures. X is a fuzzy set describing the performance measures and Y is a fuzzy set describing the scaling factor correction.

Many more researches have done the work in the area of tuning of Fuzzy controllers [75, 76, 86, 88, 91, 97, 115, 125, 140, 144, 155]. Implementation of Fuzzy logic on chips has been done by Togai and Watanabe [138] and Mohammed et. al [98].

Chapter 3
Non-Interacting system for Basis weight

New generations of Fuzzy Logic Controllers are based on the integration of conventional and Fuzzy controllers. Thus an effort has been made to develop the three types of hybrid controllers i.e. Fuzzy-P, Fuzzy-PD and Fuzzy-PD+I and the effects of different scaling gains is analyzed. In the present work, the setpoint tracking control problem is taken into consideration, hence a servo model is developed using Simulink and Fuzzy Logic toolbox. The Fuzzy control system developed in this chapter is mainly dealing with the online setpoint variations in the basis weight as per demand by the costumer in the industry. To develop the three types of Fuzzy control systems, tuning of the different scaling gains is also required besides the tuning of the parameters of the Fuzzy controller.

3.1 Basis weight

The grammage per square meter (GSM) is considered as the target end product of paper. It not only reflects the quality of the end product, but also affects the economy. Therefore it must be controlled. The primary factor influencing the basis weight is the pulp flow that can be controlled by the basis weight valve opening at the headbox. Thus the process as a whole has one controlled output i.e. Basis weight (B) and one manipulated input i.e. pulp flow (G) monitored by the basis weight valve opening (BWVO) at the head box. The input-output relationship is given by equation (1.4) [chap 1].

Transfer function between input function "G(s)" to output function "B(s)" is given by:

$$\frac{B(s)}{G(s)} = \exp(-144{*}s)\,\frac{5.12}{105\,s + 1} \quad \ldots\ldots\ldots\ldots\ldots\ldots(1.4)$$

where

G(s) = Pulp Flow at head box

B(s) = Basis weight per square meter

For the above system

exp (-144*s) Transportation Lag

105 refer to as τ time constant of the system, in seconds.

5.12=K, a constant that represents the dimensional conversion factor based on equipments involved in the system.

The basis weight is continuously measured online on the reel and any variation required in its setpoint is accordingly adjusted by varying the basis weight valve opening at the headbox. The data for basis weight has been collected from a middle density basis weight mill, where the speed of the paper machine is around 250 m/min and length of paper traveled from the head box to the reel is approximately 600 meters.

The Fuzzy logic controller here is used to adjust the basis weight valve opening according to the changing values of the basis weight setpoint. The sensors are incorporated at the end of the paper machine section. These sensors measure the online variations in the basis weight output and calculate the average value of the basis weight and give this average value to the controller for proper corrective action by the basis weight valve. For simplicity, the transfer functions of the measuring devices and final control elements are assumed equal to unity. The simulation is performed using Matlab, Simulink and Fuzzy Logic toolbox software.

3.2 Fuzzy Logic Controller (FLC) for Basis Weight

Presently a two-input single-output fuzzy logic controller is designed with the input variables as: the error (e) and change in error (che), and the output variable as basis weight valve opening (bwvo). This can be seen in the Figure3.1. The program describing the details of FLC and type of Fuzzification and Defuzzification methods used in the designing of the controller are given in Appendix P3.1.

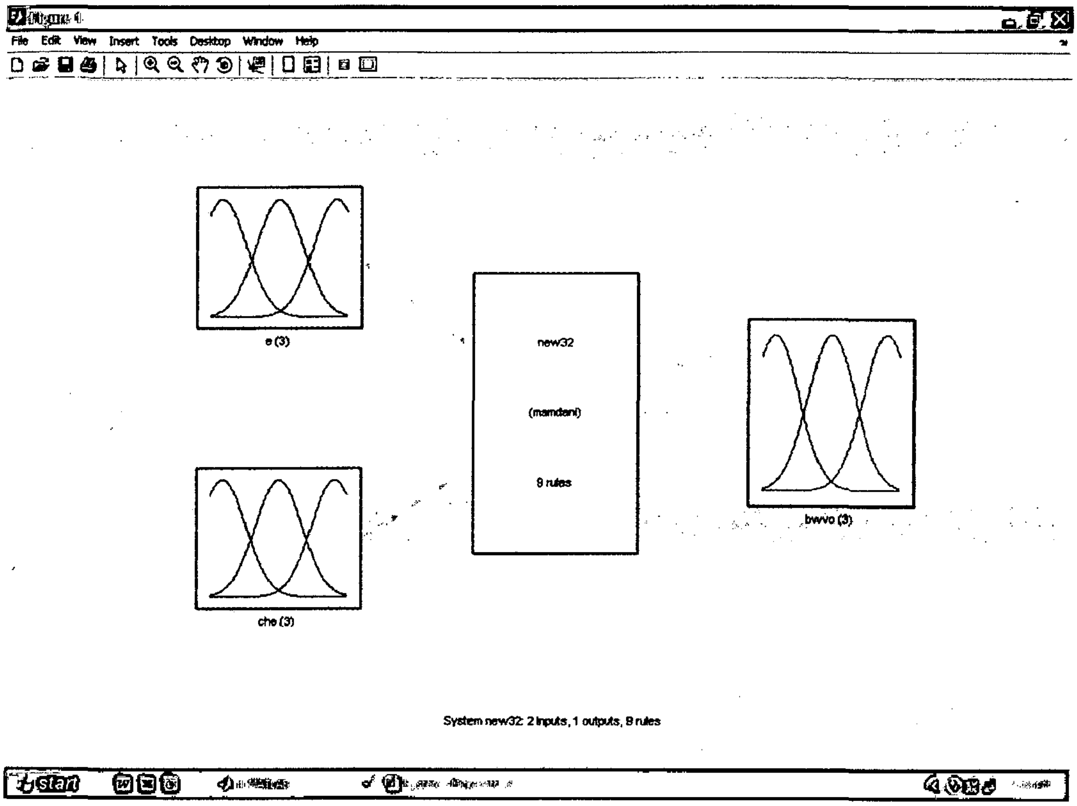

Figure 3.1 Matlab window showing the input-output variables of the FLC.

Basis weight is measured online and accordingly the error and change in error is found and accordingly the adjustments of BWVO are done.

The error and change in error can be found by using the following equations:

e (t)= Setpoint value - Measured value ....(3.1)

che(t)= $e(t)_2$- $e(t)_1$...(3.2)

$er(t)_x$ = value of the error at different intervals of time.

x= 1,2,3,----------.

The fuzzy system implemented here is using the following FIS (Fuzzy Inference System) properties:

And method: Min

Or method: Max

Implication: Min

Aggregation: Max

Defuzzification: Centroid

The input variables in a fuzzy control system are mapped by sets of membership functions known as "fuzzy sets". The process of converting a crisp input value to a fuzzy value is called "fuzzification". Given "mappings" of input variables into membership functions and truth values, the controller then makes decisions for what action is to be taken based on a set of "rules"[43]. The universe of discourse for both the input variables is chosen to be [-1, +1] for the step input and the range of the input variables can be changed according to the changing demand for the varying input. The universe of discourse for the output variables is chosen to be as [0, 1] for both the step and the varying input as the pulp flow is monitored by the basis weight valve opening, which will be varied from fully open to fully close.

Using heuristic rules, the contiguous fuzzy subsets in each library are overlapped to about 50%.The crossover point is one of the important parameters that affects the properties of the FLC. According to Brovis [20], a cross point level of 0.5 provides less overshoot, faster Risetime and less Undershoot in the dynamic response. Also the number of control laws is directly related to cross point values. Like all controllers, a FLC has a number of parameters, which must be chosen by the designer a priori. These parameters include the number and type of membership functions used the position of each membership function and also the degree of overlapping. In the present case uniformly distributed gaussian membership functions for the fuzzy subsets are taken for each fuzzy variable. The gaussian membership curve has the advantage of being smooth and nonzero at all points.

The system was tested for five subsets for each input and for crossover point <, = and > than 0.5 and based on these tests the controller with 3 subsets for each input and a crossover point of 0.5 was selected. The comparative study for the same is given below in Table 3.1.

Performance parameters	No of Membership Functions =5 (Gaussian Type)			No of Membership Functions =3 (Gaussian Type)		
	Cross over point <0.5	Cross over point =0.5	Cross over point >0.5	Cross over point <0.5	Cross over point =0.5	Cross over point >0.5
Overshoot	1.187	1.182	1.15	1.12	1.117	1.1
Undershoot	0.87	0.85	0.85	0.88	0.85	0.85
Settling time(sec)	40	70	93	25	40	35
Offset	0.024	0.0237	0.005	0.0007	0.0001	0.0006

Table 3.1Comparision between the performance parameters using different number of membership functions

From the results of Table 3.1 the controller with the inputs having three membership functions had a lesser offset in comparison to that with five membership functions. Thus three membership functions were taken for the two inputs. In the present work, it is assumed that all crosspoint values are 0.5. The Matlab window of Figures (3.2, 3.3, 3.4) shows the two inputs and an output used in this case.

The input 1 error function (e) is divided into three membership functions as: **en** = error negative, **em** = error medium, **ep** = error positive.

The input 2 change in error function (che) is also divided into three membership functions as: **chen** = change in error negative, **chem** = change in error medium, **chep** = change in error positive.

The output basis weight valve opening (bwvo) is divided into three membership functions as: **bwvos** = basis weight valve opening small, **bwvom** = basis weight valve opening medium, **bwvol** = basis weight valve opening large [24].

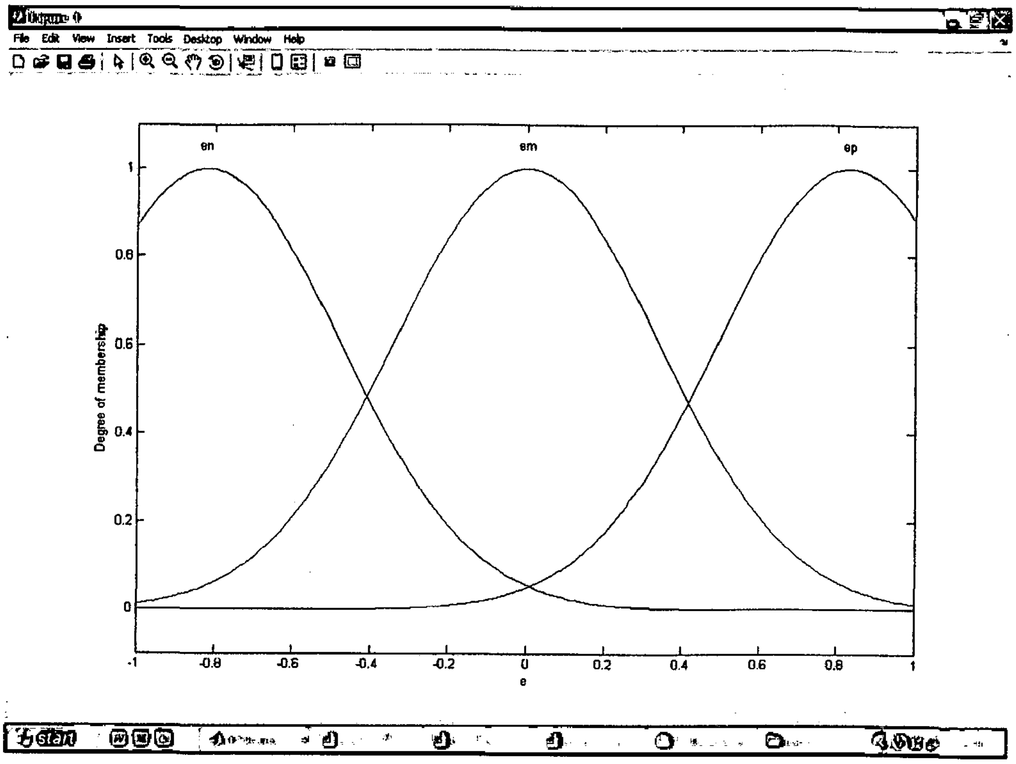

Figure3.2 Matlab window showing the input 1 as error (e) with three membership functions as Gaussian and the cross point approximately equal to 0.5.

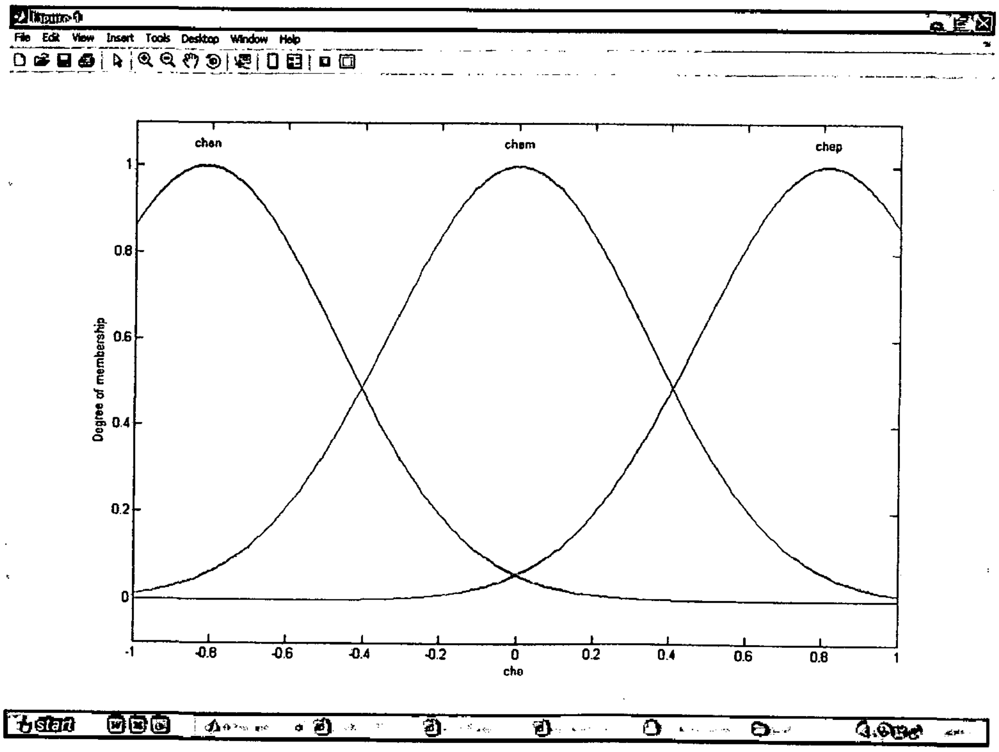

Figure 3.3 Matlab window showing the input 2 as change in error (che) with three membership functions as Gaussian and the cross point approximately equal to 0.5.

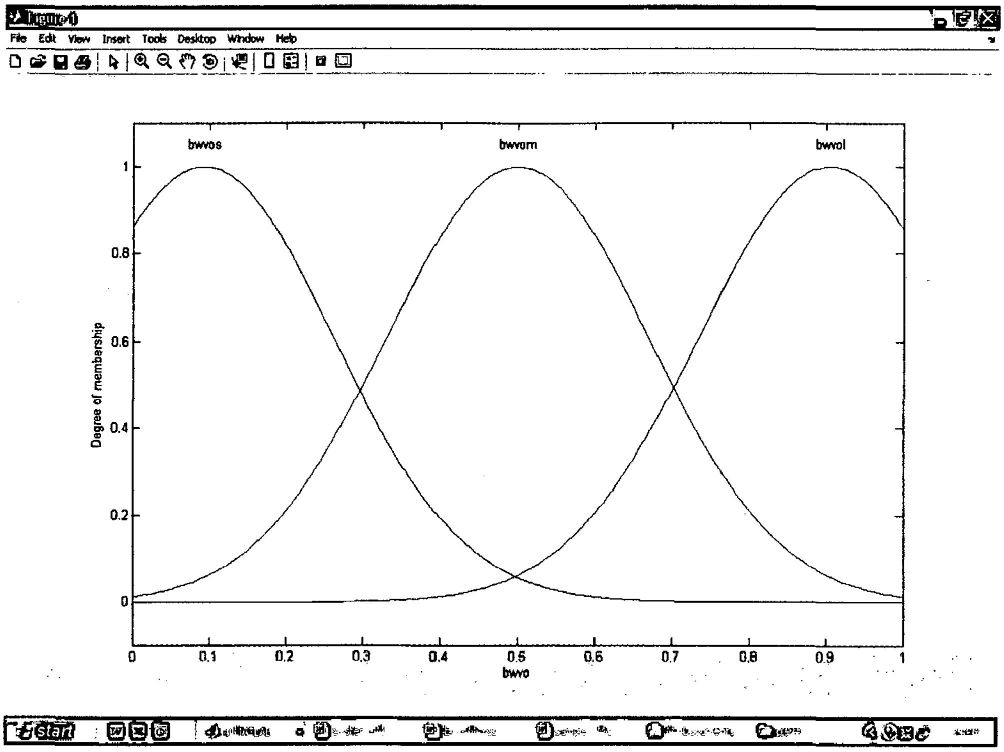

Figure3. 4 Matlab window showing the output as basis weight valve opening (bwvo) with three membership functions as Gaussian and the cross point approximately equal to 0.5

3.2.1 Knowledge Based

The distinguishing mark of Fuzzy Logic in rule based systems is its ability to deal with situations in which making a sharp distinction between the boundaries of application in the use of rules or constraints is very difficult. The Knowledge Base is structured in frames, which represent the operator knowledge about the plant in the form of geometrical structure, process representations and control sequences [126]. The basic function of the rule base is to represent the expert knowledge in a form of IF-THEN rule structure [99]. The fuzzy logic can be derived into a 3×3-rule matrix that consists of 9 rules. Figure 3.5 shows the fuzzy logic rules formulated for the present case.

Rules for Fuzzy Logic Controller				
		error (e)		
		en	em	ep
Change in error (che)	chen	bwvos	bwvos	bwvom
	chem	bwvos	bwvom	bwvol
	chep	bwvom	bwvol	bwvol

Antecedent Consequent

Figure 3.5 Fuzzy logic rule matrix

A Fuzzy IF-THEN rule is a knowledge representation scheme for capturing knowledge (typically human knowledge) that is imprecise and inexact in nature. This can be achieved by using linguistic variables to describe elastic conditions (i.e. conditions that can be satisfied to a degree) in the IF part of Fuzzy rule. As can be said for the present case that if the basis weight demand is increasing i.e. the setpoint of basis weight is increased then the basis weight valve opening has to be increased. The Fuzzy controller developed for the same is a two input controller where error in basis weight and the change in error in the basis weight are taken as the two inputs, thus taking the error and change in error from equations 3.2 and 3.3 respectively. The rules for this controller are formulated in the manner given below:

IF error is **en** AND change in error is **chen** THEN basis weight valve opening is **bwvos**

IF error is **en** AND change in error is **chem** THEN basis weight valve opening is **bwvos**

IF error is **en** AND change in error is **chep** THEN basis weight valve opening is **bwvom**

IF error is **em** AND change in error is **chen** THEN basis weight valve opening is **bwvos**

IF error is **em** AND change in error is **chem** THEN basis weight valve opening is **bwvom**

IF error is **em** AND change in error is **chep** THEN basis weight valve opening is **bwvol**

IF error is **ep** ANDchange in error is **chen** THEN basis weight valve opening is **bwvom**

IF error is **ep** AND change in error is **chem** THEN basis weight valve opening is **bwvol**

IF error is **ep** AND change in error is **chep** THEN basis weight valve opening is **bwvol.**

On the basis of these rules developed, the system works, and the implication method is applied. After the implication method, the output for each rule is aggregated and the defuzzification is done to find the crisp output.

The Defuzzification method gives a quantitative summary, i.e. given the possibility distribution of fuzzy output, defuzzification amounts to selecting a single representative value that captures the essential meaning of the given distribution. The Defuzzification method used for the present case is the centroid method as this is the most prevalent and physically appealing of all the defuzzification methods. It is given by the algebraic expression:

$Z^* = \int \mu c(z).z \, dz \, / \int \mu c(z) \, dz$ ....(3.3)

Where Z* is the defuzzfied value, c(z) represents the Union of the membership functions and is found by the MAX aggregation method and μc(z) is the degree of the membership function [114].

The entire process of Implication, Aggregation and Defuzzification of the system is shown in the Rule View window of Fuzzy Logic Toolbox. Figure3.6 shows the rule viewer for an arbitrarily selected input (e = -0.275, che = 0.625) and accordingly the output (bwvo = 0.64) is generated.

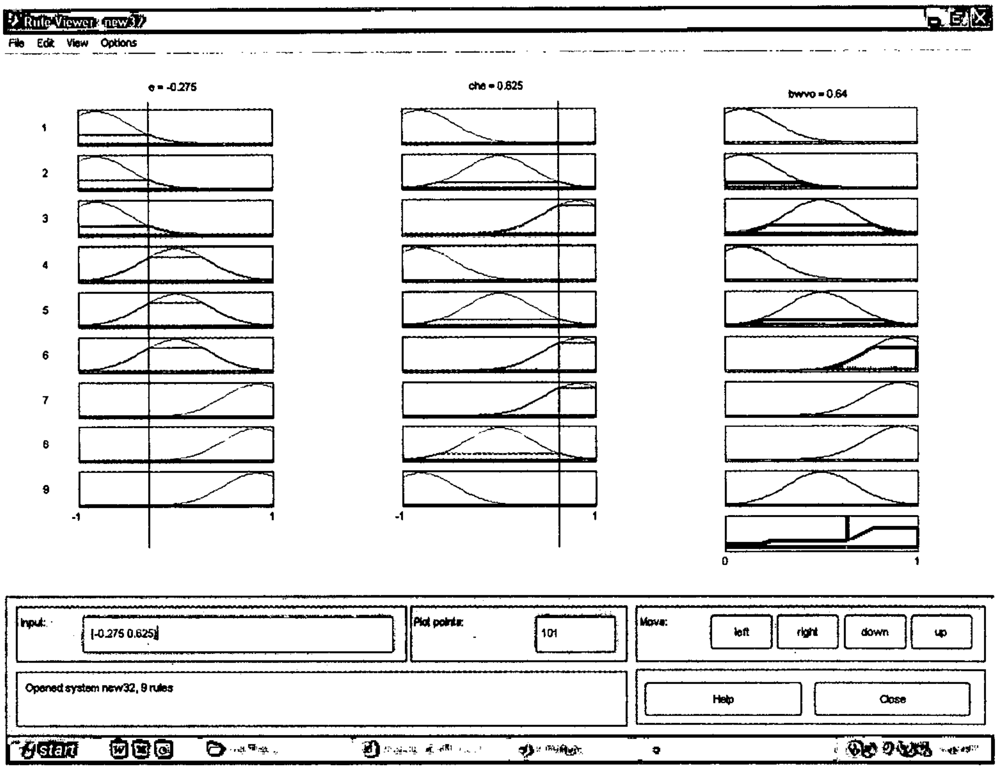

Figure 3.6 Matlab window showing the rule viewer.

This Fuzzy controller developed in Section 3.2 is used for the control of setpoint variations for the basis weight. Integrating this model with the conventional parameters, the hybrid control system is developed. Thus besides the tuning of the above parameters of the Fuzzy controller, there are some parameters to be tuned to get the optimum output. In this fuzzy controller, there are four scale factors, one for the process error (e); GE, second for change in error (che); GCE, and third for integration of error; GIE and fourth for the controller's output (bwvo); GU. GE, GCE and GIE are also called normalization factors and GU is also called denormalization factor [68]. The selection of these scaling factors is akin to the selection of the PID controller parameters and the user defined polynomials of some adaptive controllers [72]. The scaling gains have been tuned on hit-and-trail basis and the results for different values for the gains are shown. The values which give the best results in terms of the overshoot, settling time and offset are then finally chosen for the controller. Further emphasis will be laid on the performance of different types of Fuzzy logic Controllers i.e. Fuzzy-P, Fuzzy-PD and Fuzzy-PD+I models for different values of normalization and denormalization factors and their effects on the system response in terms of Rise time (RT), Settling time (ST), Overshoot (OS) and Offset (OF).

3.3 Model development

3.3.1 Servo model for Step input using FLC

A Servo model using Simulink, shown in (Figure3.7) is developed which has a Fuzzy Logic Controller with a rule viewer, two summing elements, a process (Gb), a multiplexer, a derivative element, a input block from where the different types of inputs can be given, four gain elements representing the scaling gains as GE, GCE, GIE and GU, and finally an output block which can be further connected to a scope window to show the output as the basis weight. Here the measuring element is considered to be ideal so the output of the process which is the basis weight, is directly given to the summing element from where the error is evaluated and the change in error is evolved using the differentiator function, as it is a two input fuzzy logic controller. A multiplexer is used to give the two inputs to the controller. The step input block is used as the input of this servo model and the scope block from the Simulink library is taken to see the output. All the three models i.e. Fuzzy-P, Fuzzy-PD and Fuzzy-PD+I can be made from the servo model of Figure3.7 by changing the values of the scaling gains.

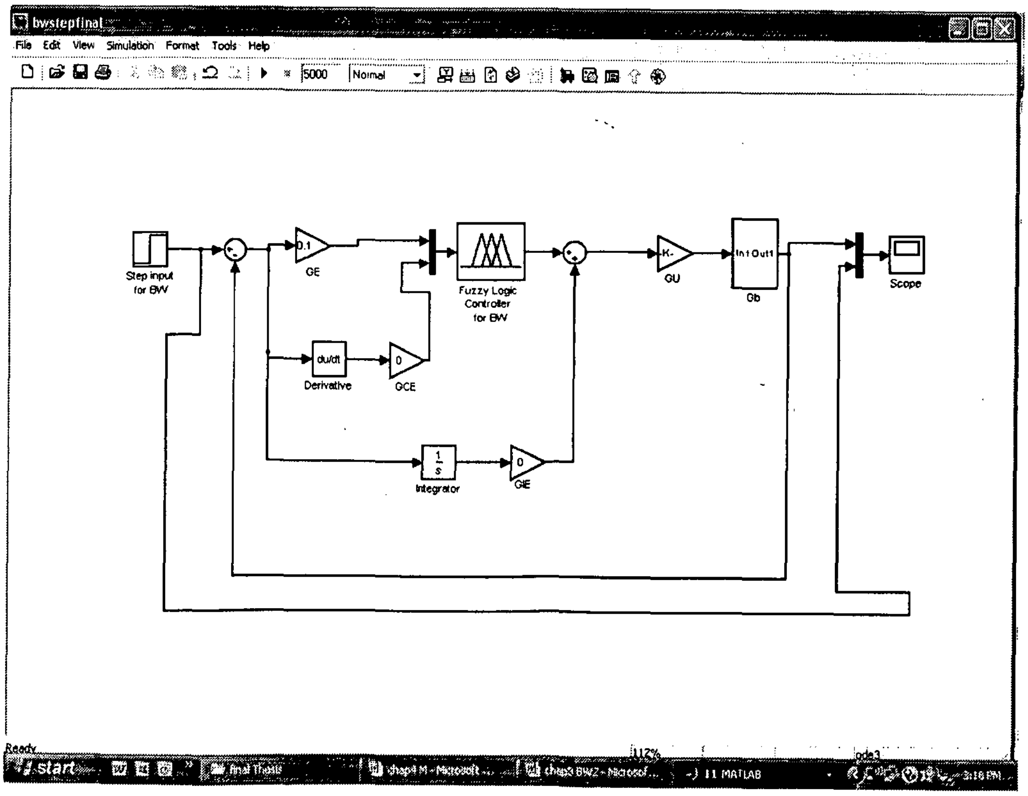

Figure3.7 Servo model for basis weight control using FLC.

For the above model to work, the first thing is to decide the values of the scaling gains as these gains are responsible for the variations in the output of the system. As discussed above, there are four gains; three normalization gains GE, GCE, GIE and one demoralization gain GU. The values of these gains are responsible for the proportional constant (K_P), the derivative rate (τ_D) and the reset rate (τ_I).The aim of this work is to analyze the effect of changing gains on the response of the system and how it can be compared with the conventional PID controller.

Initially the value of GU is chosen, as it is responsible for the proportional constant by the relation as shown below:

$GE * GU = K_P$ .... (1.19)

Experiments were conducted and it was found that the value of GU is responsible for the steady state error. As can be seen from equation (1.19), the value of proportional constant is controlled by the two factors GE and GU so once the value of GU is decided, the value of GE can be changed and even better response can be achieved by monitoring GE. Now if GE is fixed, the values of the derivative rate (τ_D) and the reset rate (τ_I) can be changed by changing the value of GCE and GIE respectively. Here one major advantage over a conventional controller can be seen that in case of a conventional controller the value of K_P affects all other constants. If this is changed it will directly affect the derivative rate (τ_D) and the reset rate (τ_I). These are related to each other by equations (3.4) and (3.5) given below.

For a conventional controller:

$\tau_D = K_D/K_P$ ....(3.4)

$1/\tau_I = K_I/K_P$ .... (3.5)

Thus for tuning a FLC, the values of derivative rate (τ_D) and the reset rate (τ_I) can remain unaffected and the proportional gain K_P can only be changed by changing GU.

First the tests were preformed for different values of GU while keeping all other gains at zero. To find out the optimum value of GU, the other gains were taken as GE=0, GCE=0, GIE=0. Different values of GU are taken as: GU=0.5, 0.3905, 0.3 and 0.2 and the output is shown in Figure3.8.

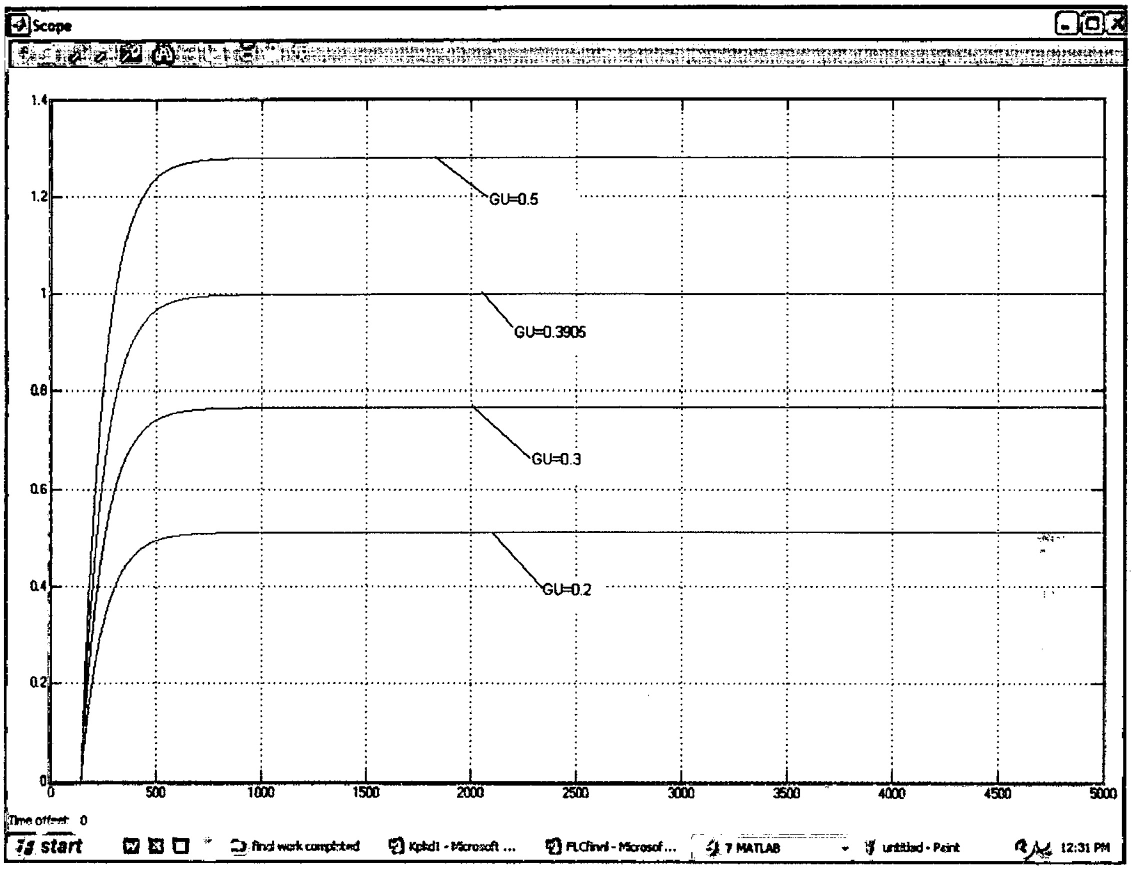

Figure 3.8 Simulation results of BW for step input servo model for different values of GU

The Figure 3.8 shows that the value of GU is responsible for the steady state error and hence the offset, and it is clear from the above results that a value of GU=0.3905 almost nullifies the offset for the step input. Thus the major factor which eliminates the offset is the demoralization gain. Now the value of GE is introduced to the system and the joint effect of both the gains is analyzed on the system and can be seen in the Figure3.9. The simulation is now performed for GE=1, GCE=0, GIE=0 and different values of GU are taken as: GU=0.5, 0.3905, 0.3, 0.2.

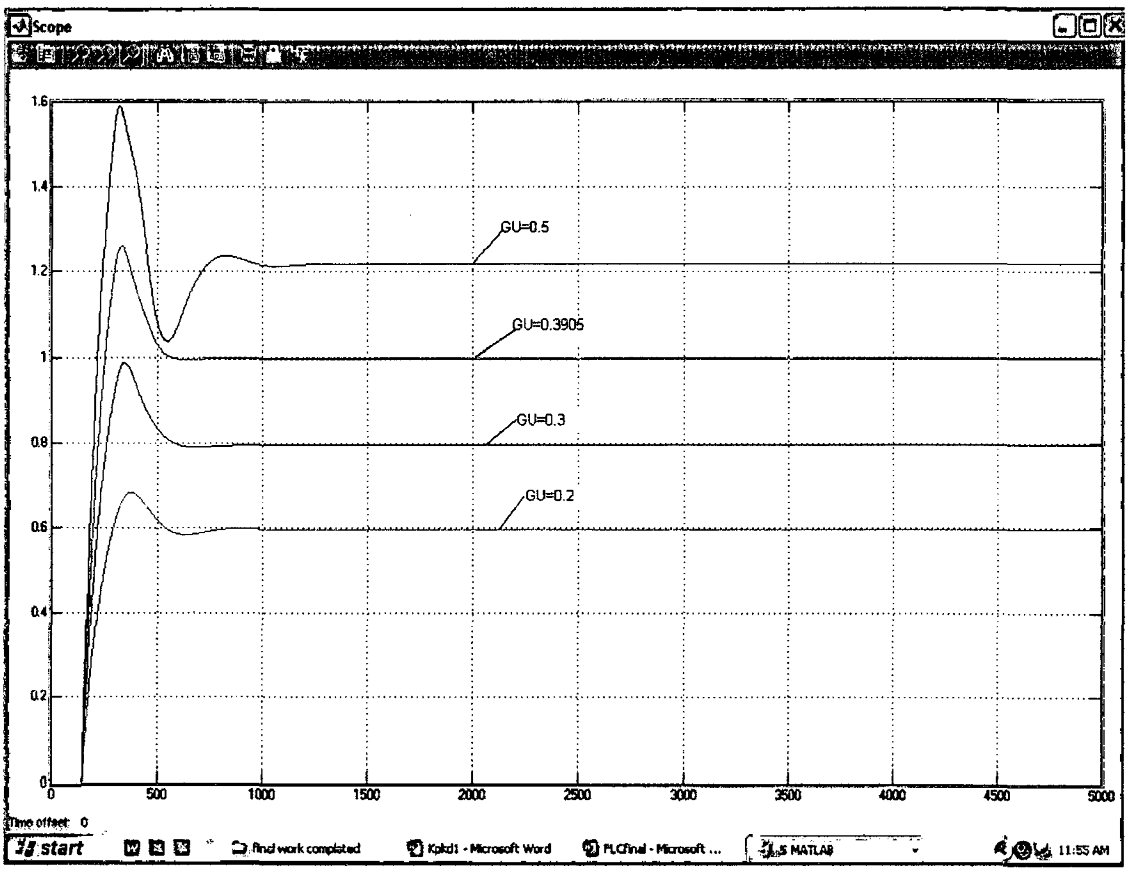

Figure 3.9 Simulation results of BW for step input servo model for different values of GU when GE = 1

It can be seen from Figure 3.9 that the value of GU was responsible for the offset in the system and on introducing the GE gain in the system, the overshoots and undershoots also came into picture. From these tests, the value of GU= 0.3905 will be taken for further study. To find the optimum values of all other gains, the simulations were performed and the results for the same are discussed below.

3.3.1(a) Fuzzy-P model:

To develop a Fuzzy –P model, in the model of Figure 3.7, only the proportional gain (GE) were taken into consideration and the other normalization gains i.e. the derivative gain (GCE) and the integral gain (GIE) were taken as zero, while the demoralization gain will now onwards be taken as 0.3905. Hence it is named as Fuzzy-P model. Now the effect of changing the value of GE is examined and the simulation results of four such models are compiled and shown in the scope window of Figure 3.10. For the above model, the input is taken as the step input and the different values of GE are taken as 1, 2, 2.5 and 3.5, GCE = 0, GIE = 0 and GU = 0.3905.

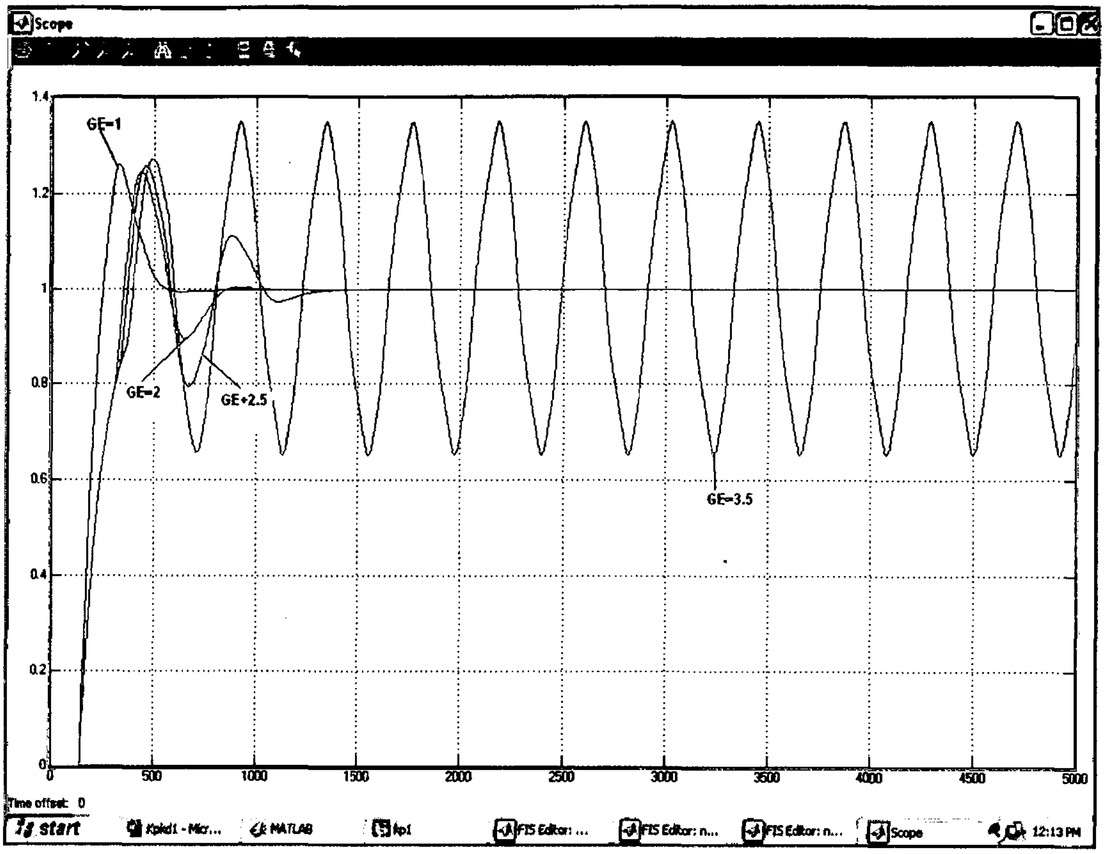

Figure 3.10 Simulation results of BW for step input servo model for different values of GE

Now as can be seen from Figure 3.10, as the value of GE increases, the oscillatory behavior increases; even the rise time (RT) and settling time (ST) increases with increases in K_P. The readings for the same can be seen in Table3.2.

GE	1	2	2.5	3.5
RT	83.16	178.8	195.26	219.7
ST	516	801	1164	Very oscillatory
OS	0.2624	0.2463	0.2587	0.2729
OF	nil	Nil	nil	--

Table 3.2 Performance comparison for different values of GE

Again Simulation was performed for some more values, and the optimum value of GE for the step input servo model used in Figure 3.7 was found. Simulation is done for different values of GE as: 0.1, 0.5, 1, 2 and the results for the same can be seen in Figure 3.11.

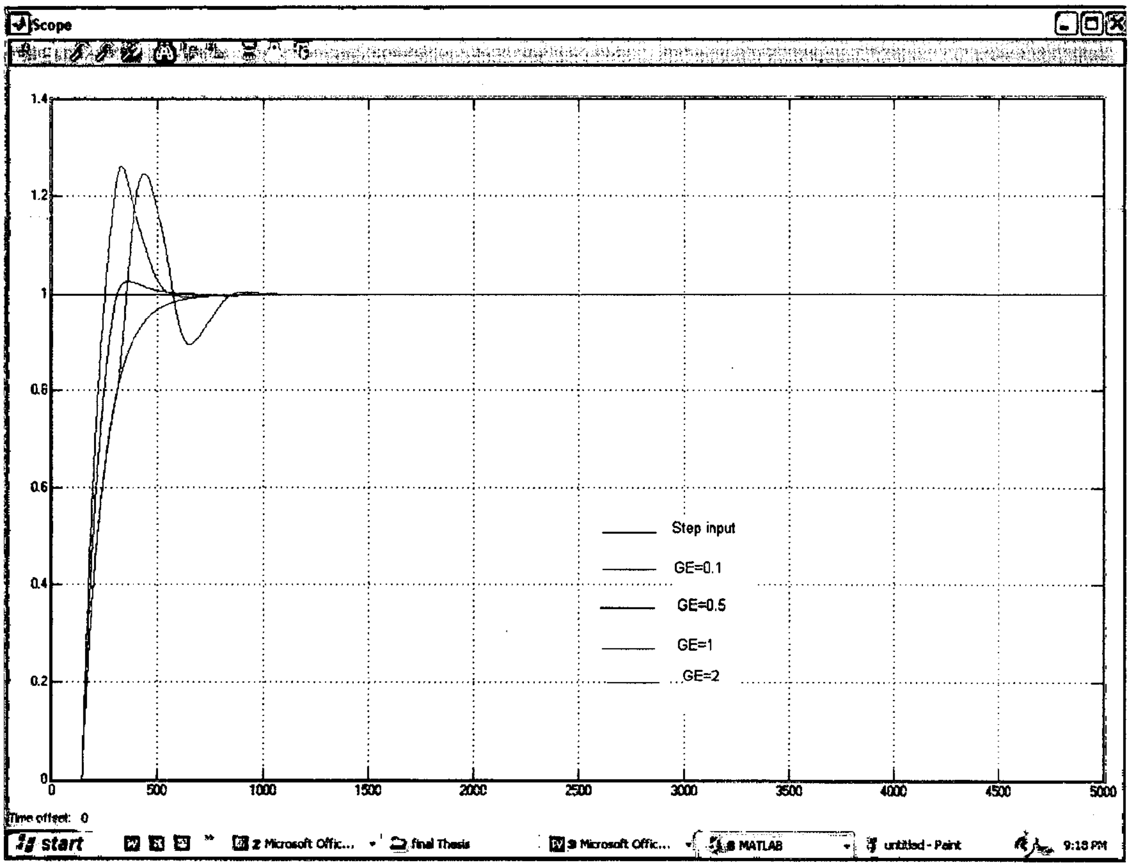

Figure 3.11 Simulation results of BW for step input servo model for different values of GE = 0.1, 0.5, 1, 2.

From the above tests the value of GE =0.1 showed the overdamped system while on increasing GE = 0.5, the system showed an overshoot. Hence the simulation was performed again to get an optimum value of GE. The simulation results for GE = 0.1, 0.2, 0.3, 0.4 can be seen in Figure 3.12

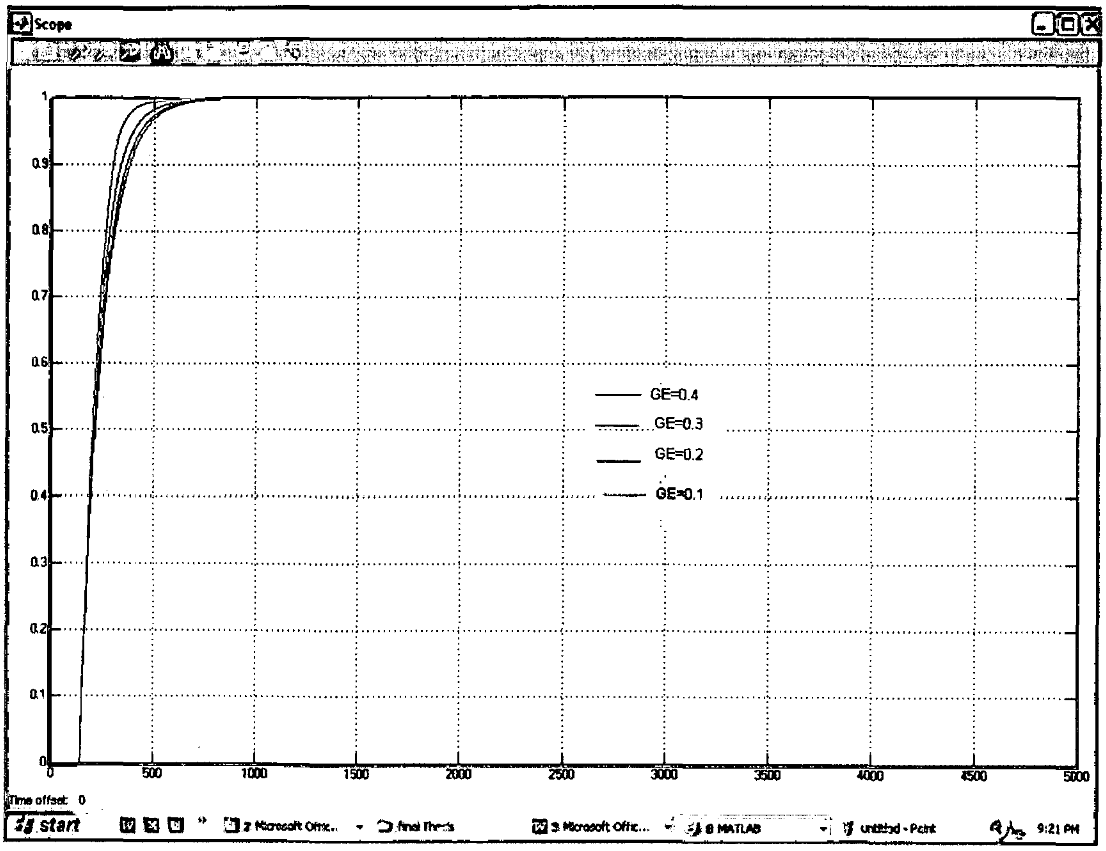

Figure 3.12 Simulation results of BW for step input servo model for different values of GE=0.1, 0.2, 0.3, 0.4

It was found that for GE=0.4, the Rise Time was minimum and the overshoot was nil, but when GE=0.5 the overshoot appears therefore a value of GE=0.4 is taken as the optimum value. From the simulation results of Figures (3.10, 3.11, 3.12) and Table3.1, it is clear that as the value of GE increases the system becomes more and more oscillatory but still remains bounded and hence marginally stable (Test were even performed for higher values of GE i.e. GE = 6, 10 and even 20). The value of RT, ST, increases as the value of GE increases. Out of these values the value that gives the best results is taken i.e. GE = 0.4 is selected and further a Fuzzy-PD model is developed.

Thus it can be concluded that the value of K_P [equation (1.25), Chapter1] has a joint effect on the systems output, It is responsible for both the offset and the oscillatory behavior in the system. Major part of offset can be reduced by adjusting the value of GU, while the oscillations can be reduced by adjusting the value of GE. Further analysis will be done for the changing values of GCE (and hence τ_D) while keeping the value of GU and GE (hence K_P) constant.

3.3.1(b) Fuzzy-PD model:

For Fuzzy-PD model, the value of GCE is added to the model of Figure 3.7 i.e. the gain of GCE is given some value instead of zero. Thus the Fuzzy-PD model is developed. The simulation is performed for various values of GCE, while keeping GE = 0.4, GIE = 0, and GU = 0.3905. It was seen that for GCE = 0.1, 1, 2, 3, 4, 10 the results of simulation were almost coinciding , but as the value of GCE is increased to 100 the system became a bit oscillatory and on changing the value of GCE to 1000 the system became unstable, as the response was very oscillatory. Thus we can say that by increasing the value of GCE, instability is introduced in the system. To choose the optimum value again, the simulation is performed for some values of GCE between 10 to110. The different values of GCE are taken as 30, 50, 90, 110 and the results for their simulation can be seen in the scope window of Figure 3.13.

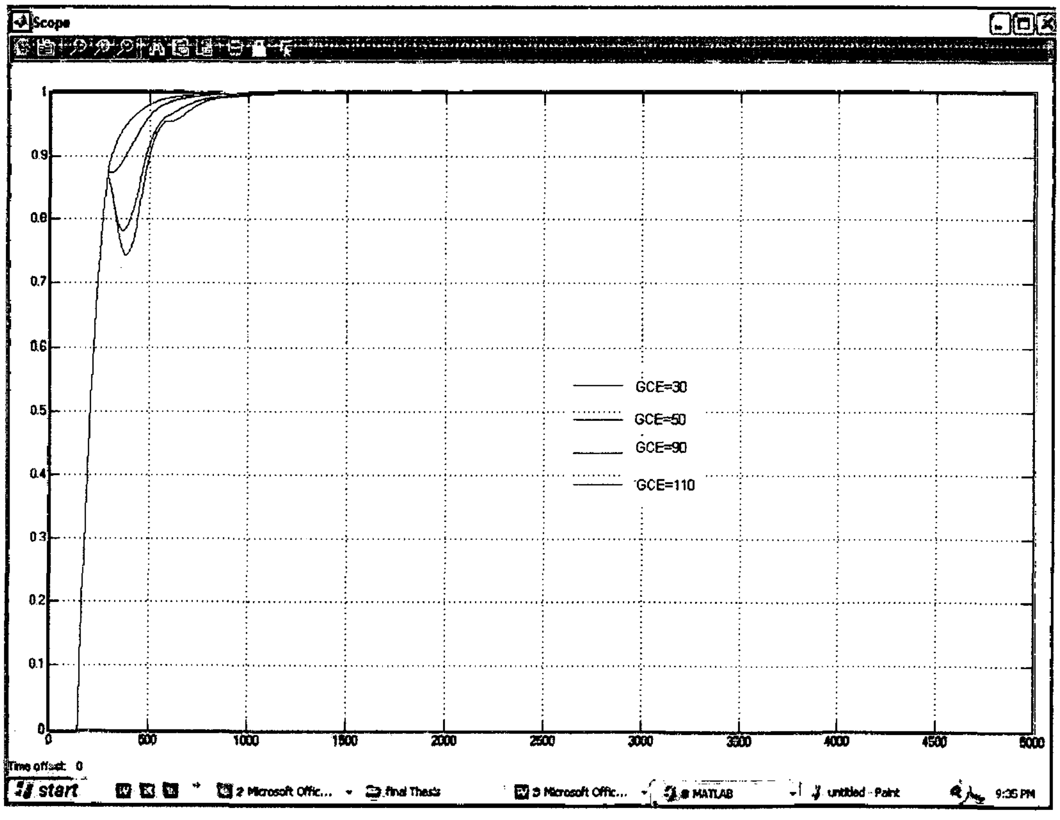

Figure 3.13 Simulation results of BW for step input servo model for different values of GCE=30, 50, 90, 110.

Out of these values the value of GCE= 30 gave satisfactory results, but this cannot be assumed as the optimum value, thus some more tests were performed for GCE = 1, 5, 10, 20. Again it was found that on decreasing the values of GCE, an improvement in the rise time was observed. Further tuning of the system was done by changing the scaling this gain, and thus the tests were performed for GCE= 0.01, 0.1, 0.5 and 1. The results for the same can be seen in the scope window of Figure 3.14

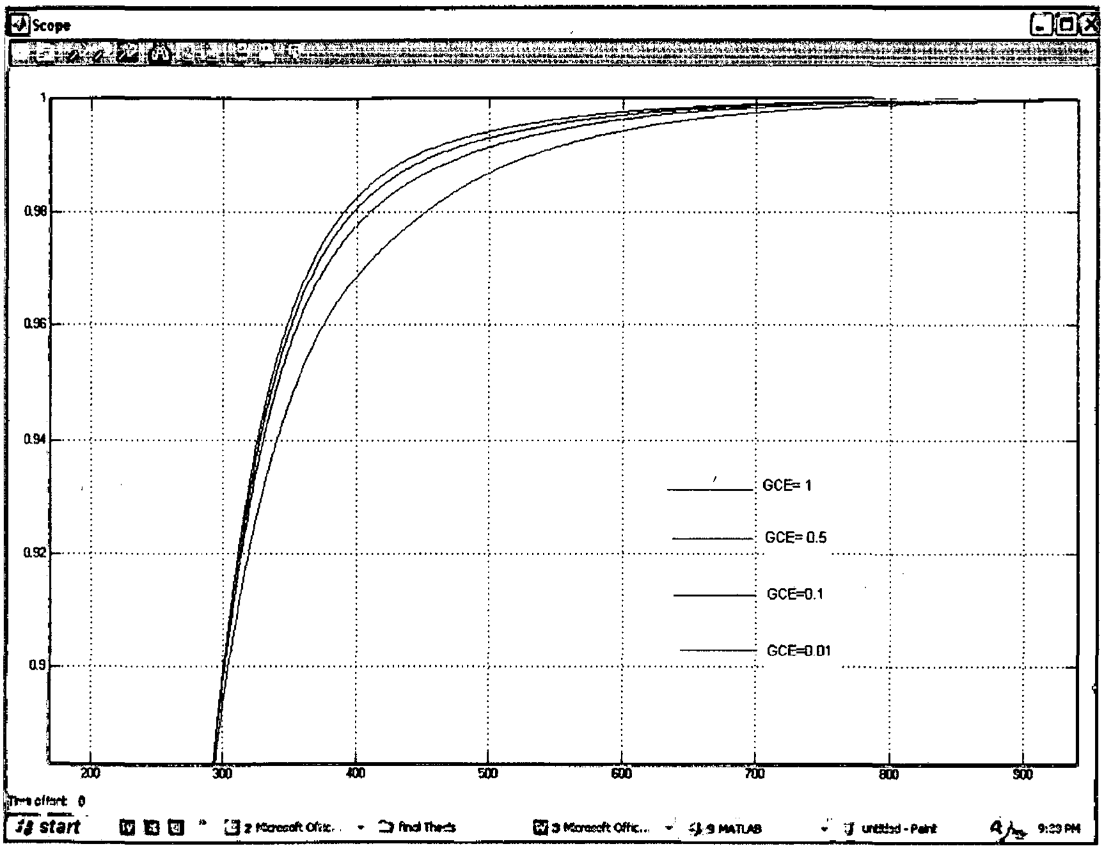

Figure 3.14 Simulation results of BW for step input servo model for different values of GCE = 0.01, 0.1, 0.5, 1.

Looking at the enlarged view in Figure 3.14, it can be seen that by changing the values of GCE from 1 to 0.01, minor variations in the risetime are observed. In the normal view for all these values of GCE, all the curves overlapped, so no significant improvement in the risetime is found. Thus the optimum value of GCE was taken as 0.01.

Once the optimum values of GE, GU and GCE are selected, the value of GIE is to be taken into consideration so that the reset gain can be decided, so Fuzzy-PD+I model is made by assigning some values to GIE block of Figure 3.7 instead of zero.

3.3.1(c) Fuzzy-PD+I model:

The model of Figure 3.7 is given the values as: GE = 0.4, GCE = 0.01, GU = 0.3905, and GIE is assigned various values and it was observed that as the value of GIE is increased beyond 0.001 the system becomes quite unstable and the y-axis was found to be of the order of 10^5 , for GIE= 0.01. Various values of GIE between 0.01 and 0.0001 were further taken but still the output of the system was unbounded. To find the optimum value of GIE, the system was again tuned and simulated for GIE = 0.0001, 0.00007, 0.00003, 0.000001. These models are simultaneously simulated and the results can be seen in the scope window of Figure 3.15.

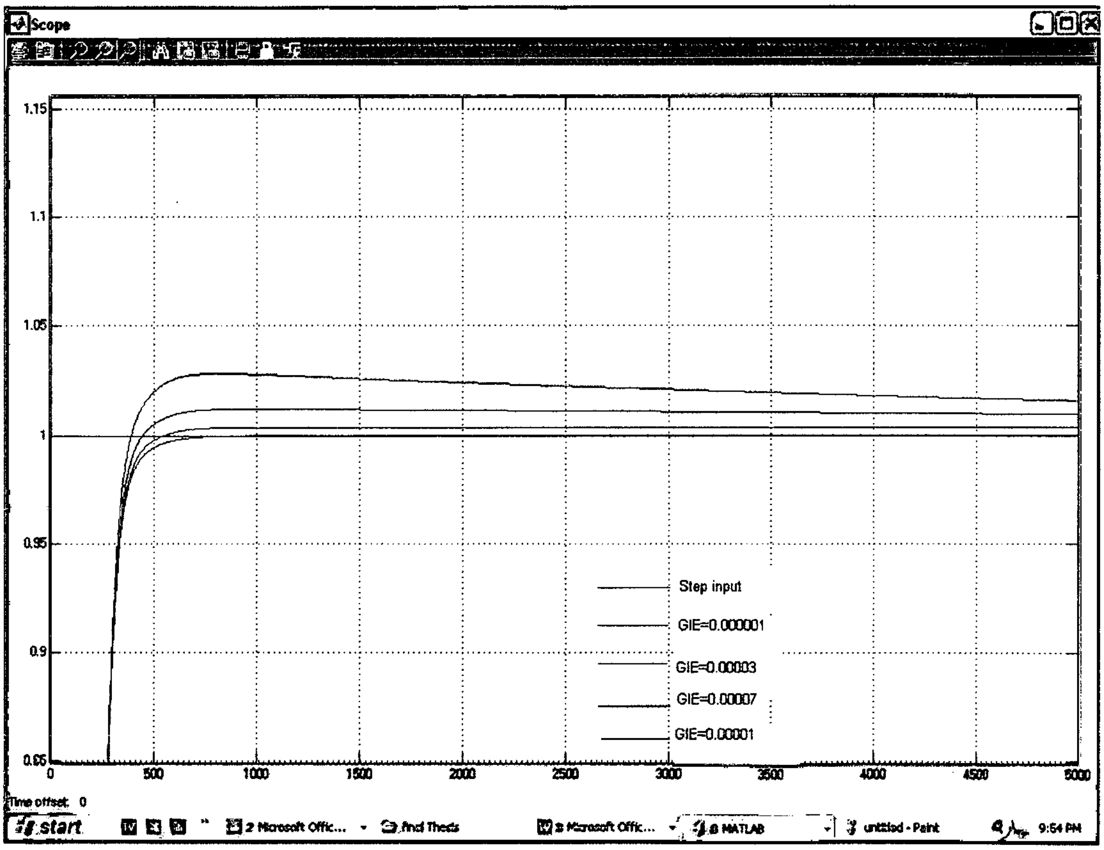

Figure 3.15 Simulation results of BW for step input servo model for different values of GIE = 0.0001, 0.00007, 0.00003, 0.000001.

It can be seen from Figure 3.15 that for GIE = 0.0001 the overshoot has considerably reduced but an offset has been introduced. Increasing the values of GIE introduces some offset in the system. If the value of GIE is reduced below 0.000001, there is no significant change in the response. Thus the value of GIE= 0.000001 is taken as the optimum value. Thus the best results for the step input for a servo model using FLC are observed for: GE = 0.4, GCE = 0.01, GU = 0.3905, GIE=0.000001.

This was the case with the step input. The similar types of tests are done for varying inputs and the test results for the same are shown below.

3.3.2 Servo model for varying inputs using FLC

The system designed to track the reference signal are referred as the tracking or servo systems, generally the real life problems have the varying setpoints. For the present case, the demand of basis weight of the paper in the mill changes with time. Thus the variations in the setpoints are required; these variations in the setpoints are taken care by the controllers implemented in the industry. Generally the controllers used in the Indian paper mills are the conventional controllers. This exercise would help the mills to replace the conventional controllers by the Fuzzy controllers. The servo model developed in this section tracks the setpoint variations in the basis weight.

Here the simulation is done for variable inputs i.e. the data for the reference inputs is collected from the mill where online sensors are incorporated and the value of the inputs i.e. the basis weight continuously changes according to the demand, This data has been saved in the m-file of Matlab and is collected from the workspace from where it is given as the input to model of Figure3.16. The details of the varying inputs can be seen from the Appendix (Table 3.3)

Using the values of Table 3.3 for the Basis Weight, the model of Figure 3.16 is developed, using two Fuzzy Logic Controllers. The model of Figure 3.16 is almost similar to the model of Figure 3.7, except for the case that this model has a variable input block instead of a step input, also the GU block is replaced by another Fuzzy Logic controller for finding the values of GU. This value is implemented in the system with the help of a product block shown in the model.

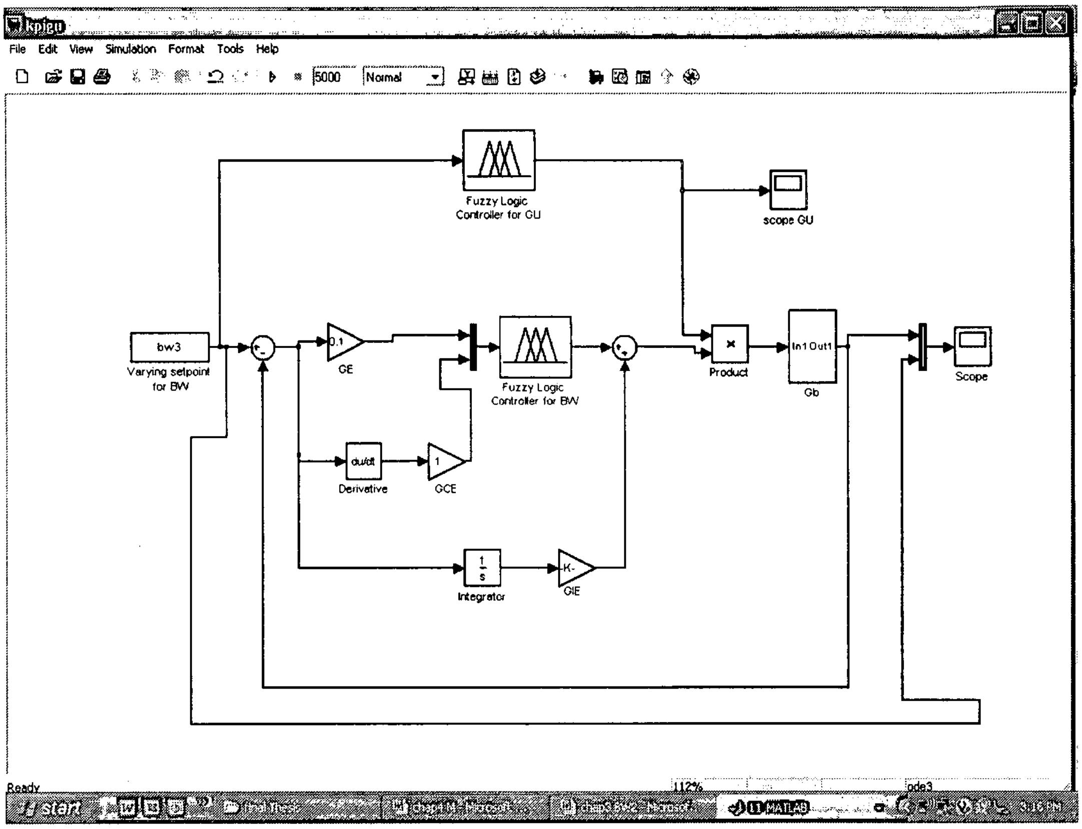

Figure3.16 Varying input Servo model for basis weight control using FLC

The Fuzzy Logic Controller for BW control is now modeled according to the changing input values. The design parameters for this FLC are now set accordingly i.e. the universe of discourse for the input variables i.e. error in basis weight (e) is now taken according to the maximum error, found from the data of Table3.4 in the Appendix. The error in the basis weight is calculated by using the equation (3.1). The universe of discourse of the error is thus taken as [-20 35]. Similarly the change in error in basis weight (che) is found using the data from the Table3.4 (Appendix) and implementing equation (3.2). Thus the universe of discourse for the change in error is taken as [-37 35], while the range of the output variable i.e. the basis weight valve opening (bwvo) is taken as [0 1]. The entire range of inputs as well as the output variables is again divided into three subsets each and the Gaussian type membership function is taken for all the three cases. The degree of overlapping is taken as 50%. According to the number of subsets taken for the input the nine rules are formulated, and the implication method used in this case is the max-min method. The detailed view for the same can be seen in the Fuzzy wizard window of Figure 3.17. Also the program developed to build the Fuzzy controller for the varying input of basis weight is given in the Appendix P3.2.

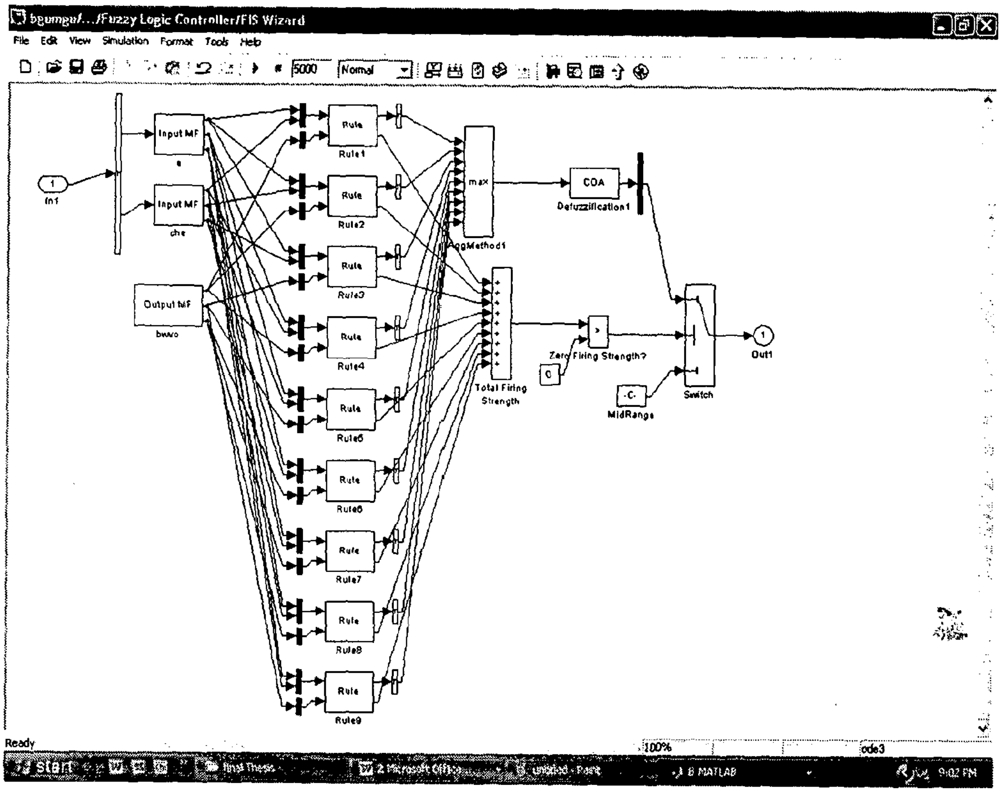

Figure 3.17 Fuzzy wizard window for Basis weight controller

The Fuzzy controller so developed is now implemented in the servo model of Figure 3.16, and the system is made to work like the Fuzzy Control system after integrating it with the hybrid controller components. As discussed in section 3.3.1, the value of GU is the prime factor which is responsible for the offset in the system. In case of the step input (section 3.3.1) the reference input was a single value equal to unity, the value of GU was tuned according to the fixed value of input. But for the variable inputs the case is different, here the reference input varies with time so the value of GU should also change with time. Taking this into consideration some tests were performed and the value of GU was found for the changing reference input. Thus a single-input single-output Fuzzy logic controller was developed (as shown in Figure3.16) to set the values of GU as the reference input changes in the system. This controller was then implemented in the system and it was used so as to supply the values of the denormalization gains i.e. GU. Therefore the model of Figure 3.7 is modified a bit and the GU block is replaced by a FLC and a product block whose combined output gives the value of GU. The FLC for GU is a single input single output controller, with the input taken as the varying input having the range from [99 138], and the output of the controller is taken as the value of GU, having a range from [37.2 61.9]. Both input output variables are divided into three subsets each, indicated as low, medium, and high for each case. The membership functions for each case are taken as triangular and trapezoidal. The method of implication used in this case is the max-min method and the type of defuzzification applied is centroid. The program describing the details of FLC and type of Fuzzification and Defuzzification methods used in the designing of the controller are given in Appendix P3.3

The optimum value of GU for each varying input is thus found by the program developed by the controller and its values can be seen in the scope window inserted in the model (Figure 3.18). Now to find the optimum value of GE for the system, Fuzzy-P model is developed.

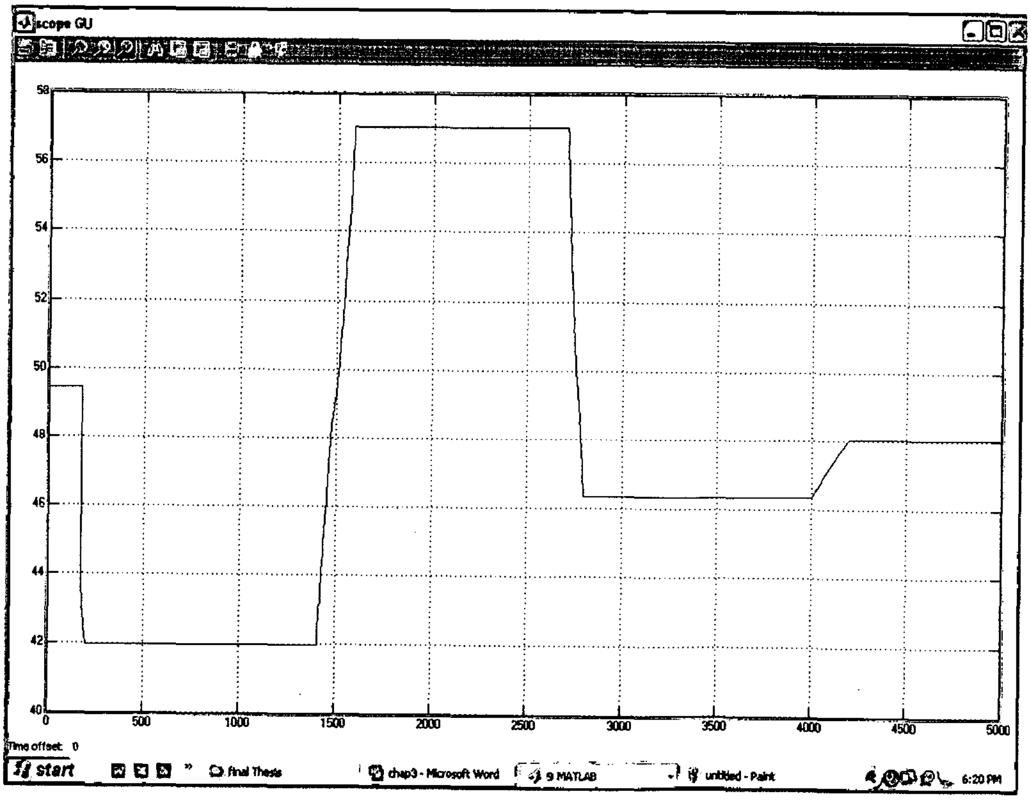

Figure 3.18 Varying values of GU as given by the Fuzzy controller.

As can be seen from the above results the values of GU, for the varying values of the moisture controller vary according to the varying setpoint inputs.

3.3.2(a) Fuzzy-P Model

The values of GU are decided according to the program developed, To develop the Fuzzy –P model the values of different scaling gains are taken as: GCE = 0, GIE = 0 and different values of GE as: 0.1, 0.15, 0.25 and 0.4, The model of Figure 3.16 is made to run for these values of scaling gains and the results of simulation can be seen in Figure 3.19.

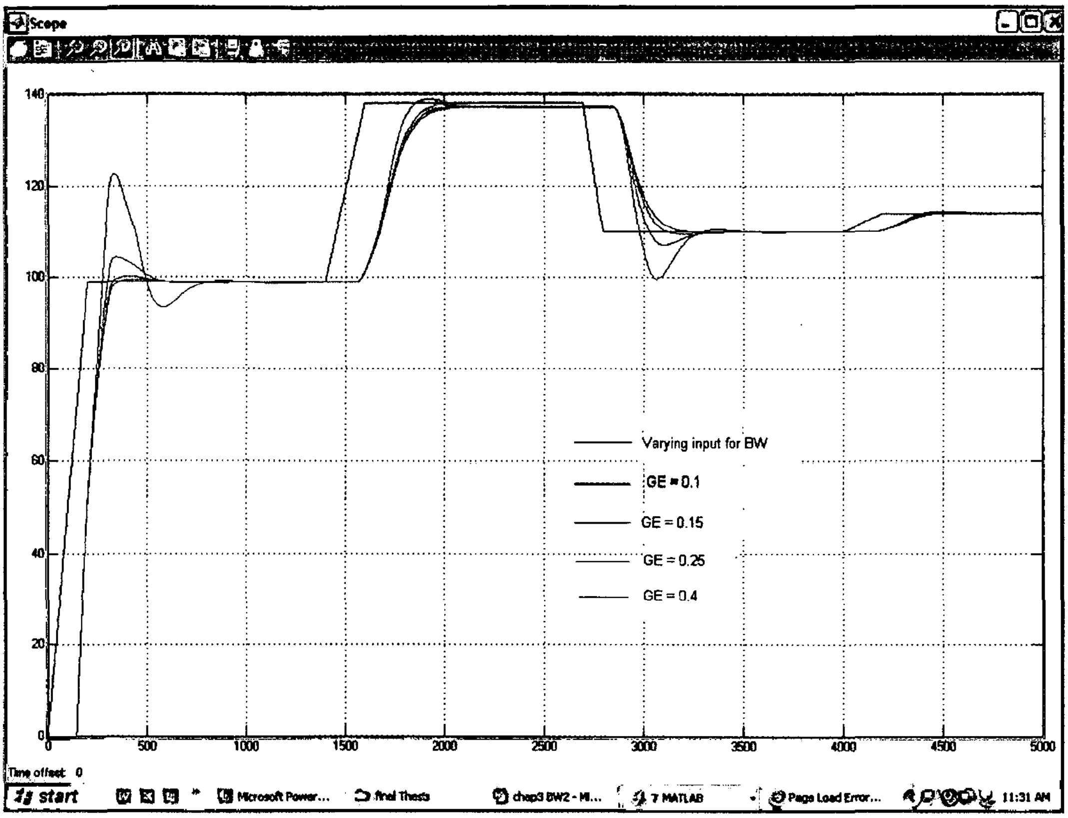

Figure 3.19 Simulation results of BW for varying input servo model for different values of GE = 0.1, 0.15, 0.25 and 0.4.

This Figure 3.19 shows that as the value of GE increases, the oscillatory behavior increases and the Risetime decreases. For higher values of GE, the output of the system is oscillatory but not unstable. Out of these values, GE=0.1 is taken as the optimum value. Further tests are carried out to find out the value of GCE, hence a Fuzzy-PD model is now developed.

3.3.2(b) Fuzzy-PD model:

When the value of GCE is added along with the value of GE, to the model of Figure 3.16, the system becomes Fuzzy-PD model. The different values for the scaling factors are now taken as: GE= 0.1, GIE= 0 and various values of GCE are taken as: 1, 2, 5 and 10. The simulation results for the same are shown in Figure 3.20.

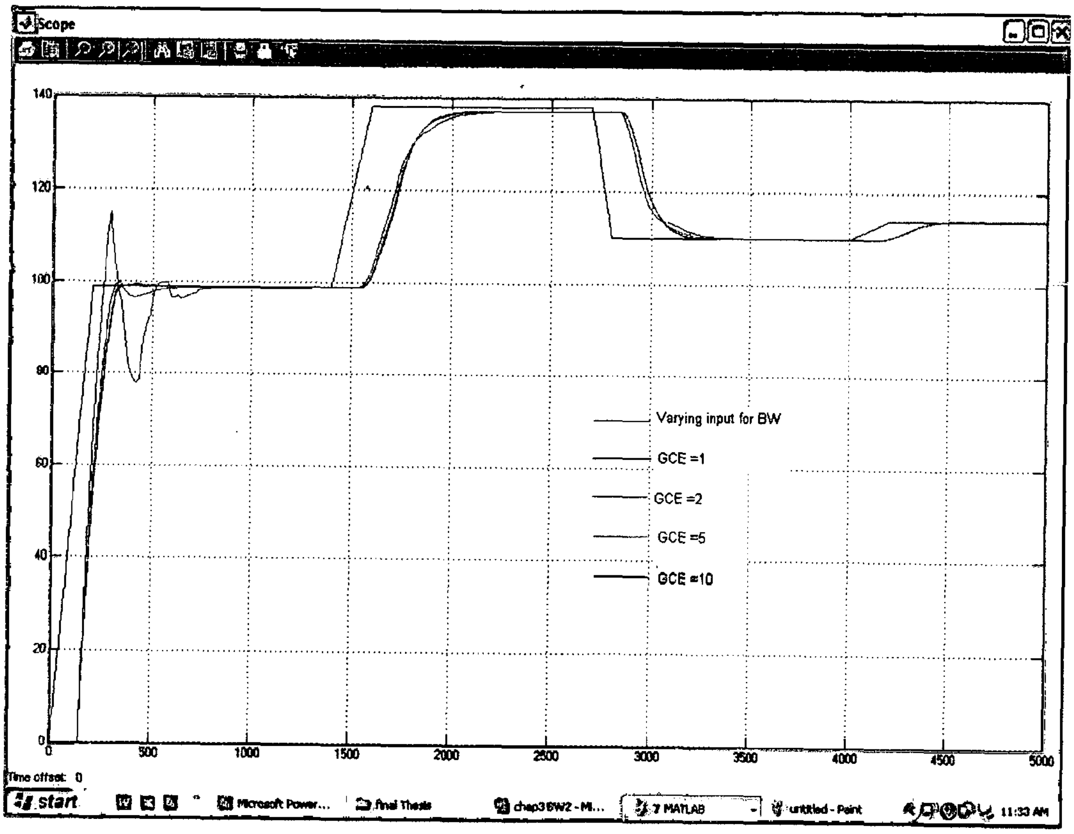

Figure 3.20 Simulation results of BW for varying input servo model for different values of GCE = 1, 2, 5, and 10.

The response for GCE= 1, 5 and 10 is almost coinciding. For GCE=20, the response is a bit oscillatory in the beginning, but becomes stable after some time. It has also been tested that as the value of GCE is increased beyond 20, the response becomes more oscillatory. From the results the value of GCE = 1 is taken as the optimum value as it has comparatively lower Risetime.

3.3.2(c) Fuzzy-PD+I model:

For adding the integral effect to the system, the value of GIE is added to the model of Figure 3.16. The system is now simulated for GE= 0.1, GCE = 1. Various values of GIE are taken as 0.00001, 0.000001, 0.0000001 and 0.00000001 and the results for the same can be seen in Figure 3.21.

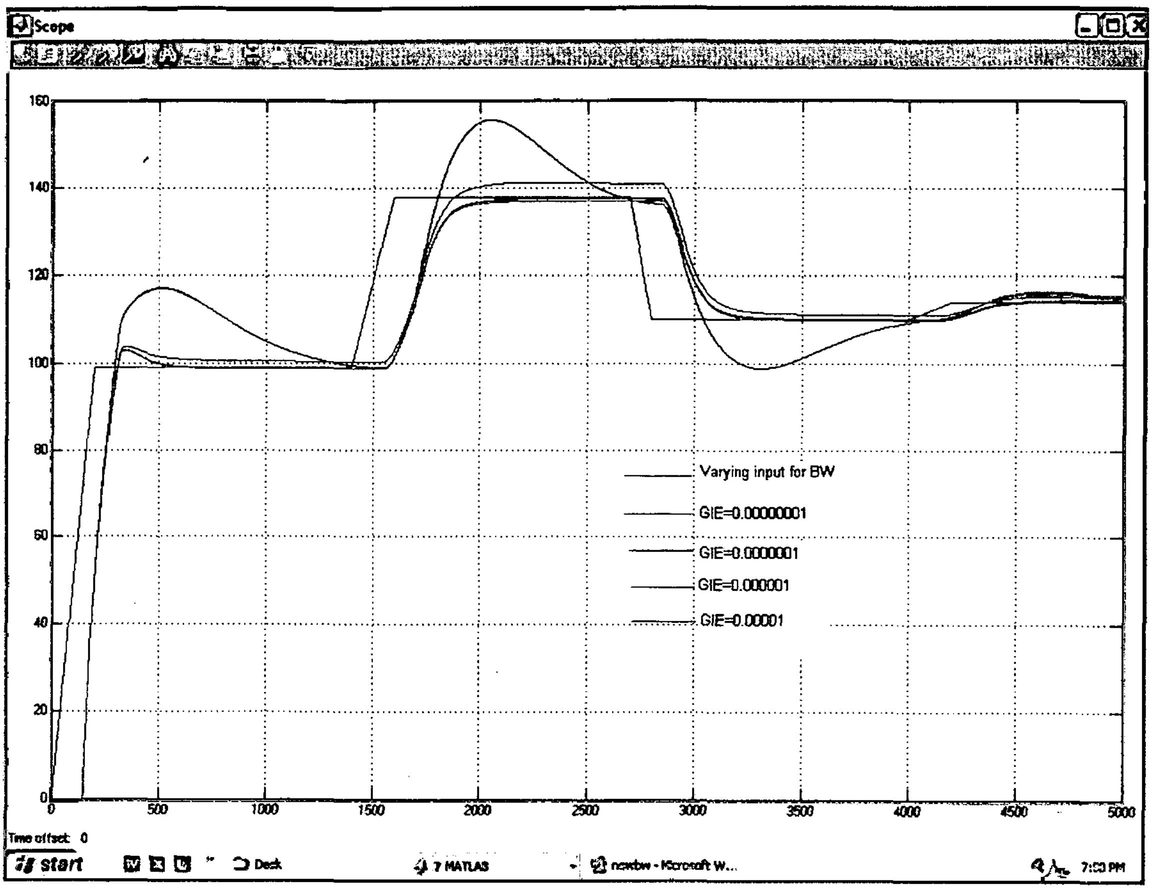

Figure 3.21 Simulation results of BW for varying input servo model for different values of GIE = 0.00001, 0.000001, 0.0000001 and 0.00000001.

It is observed from the results shown in Figure 3.21 that as the value of GIE increases, the overshoot increase. It also has a little effect on the offset. It has also been tested that if the value of GIE is increased beyond 0.00001, the system becomes unstable. From the above tests, the value of GIE = 0.0000001 is selected as the optimum value for the above system as a higher value of GIE eliminates the steady state error quickly.

The performance of different types of Fuzzy Logic Controllers have been analyzed and it has been seen that GU is responsible for the offset, GE affects the oscillatory behavior, GCE has a lesser effect on the system response. It affects the risetime of the system, but gives oscillations if the value of GCE is increased to a large extent, while GIE has an effect on the stability of the system.

From all the above tests performed in Section 3.2.2, the tuned values of various scaling gains are taken as: GE=0.1, GCE = 1 and GIE = 0.0000001 and using these values the model of Figure 3.16 is simulated and its output can be seen in the scope window of Figure 3.22.

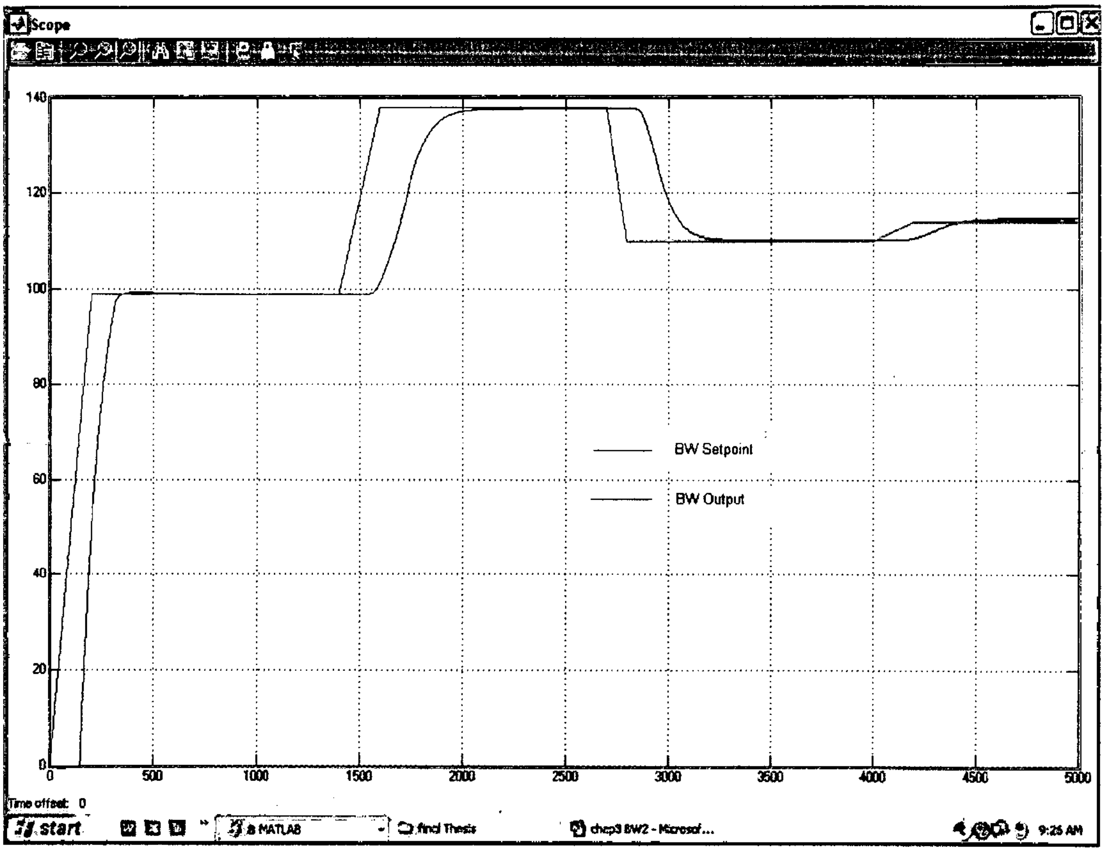

Figure 3.22 The BW output using the Fuzzy Logic Controller

The output of the basis weight (BW Output) moves according to the basis weight setpoint (BW Setpoint) but after a delay. The delay measured was 144 seconds. This delay is there in the system because of the process itself. The Fuzzy controller introduces no delay of its own. Now the simulation results for the same process, using the step input and the varying input is performed with a conventional controller. Tuning is done for the constants to get the optimum values for the three constants, and then the results for both types of controllers are compared.

3.4 Conventional PID Controllers

PID controller is one of the earliest industrial controllers. It has many advantages: It is cost economic, simple and easy to be tuned and is robust. However, in spite of these advantages of the PID controller, there remain several drawbacks [96]. It can not cope well in some cases such as:

- Non-linear processes.

- Time-varying parameters.
- Compensation of strong and rapid disturbances.
- Supervision in multivariable control.

The servo model for the above nonlinear system using a conventional PID controller is developed and can be seen in Figure 3.23. The model shows a simple feedback loop which has a summing element to evaluate error; the evaluated error is given to a PID controller, the output of which is given as an input to the Process (Gp) through valve. The transfer function of the valve is assumed to be unity with no lag. The output of the process is given to the output block as well as feedback to the summing element to evaluate error by comparing it with the setpoint that comes through the input block. The input will be the step input as well as the varying input. The model has been simulated for different values of K_P, K_D and K_I and has been discussed accordingly.

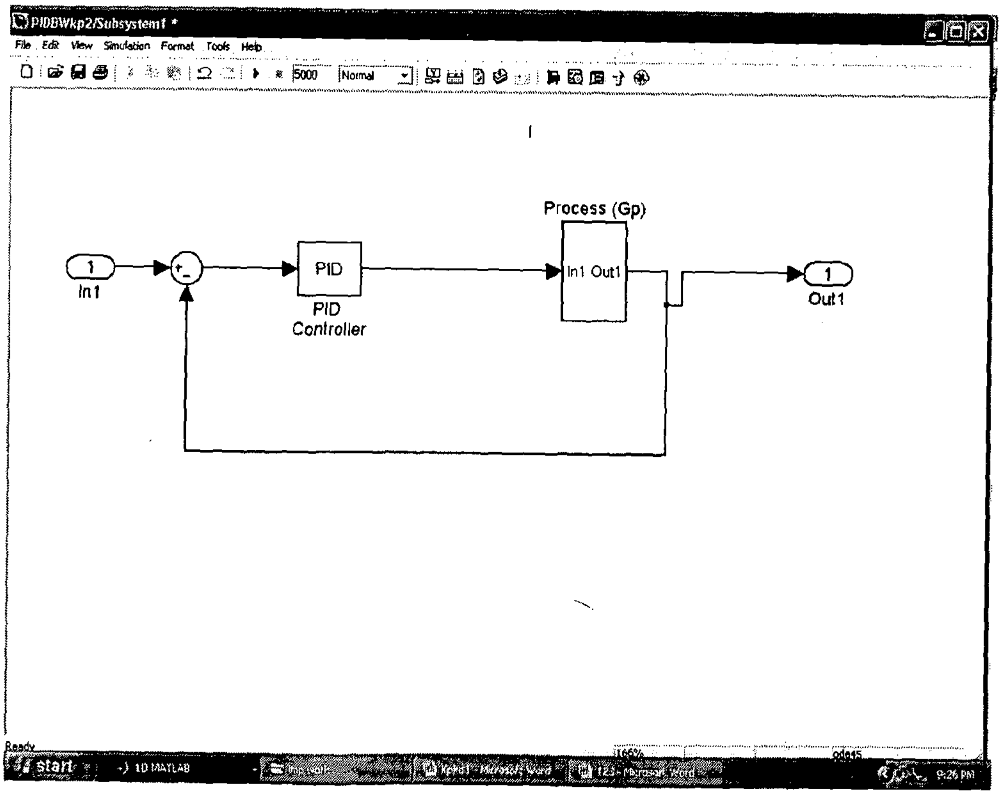

Figure 3.23 Conventional PID Controller for Servo problem

3.4.1 Servo model for step input using PID controller

3.4.1(a) P-Type servo model for step input

In this case, only the Proportional gain constant i.e. K_P is given some specified value and the other two gains i.e. the differential (K_D) and integral (K_I) gains are kept at zero. Different values are assigned to K_P while K_D and K_I were kept zero. It was found that for a step input, on increasing the value of K_P, the system response became more and more oscillatory and hence the system became unstable. First the test was done for K_P = 0.1, 0.2, 0.3 and 0.5 and the simulation results for the same can be seen in the Figure 3.24.

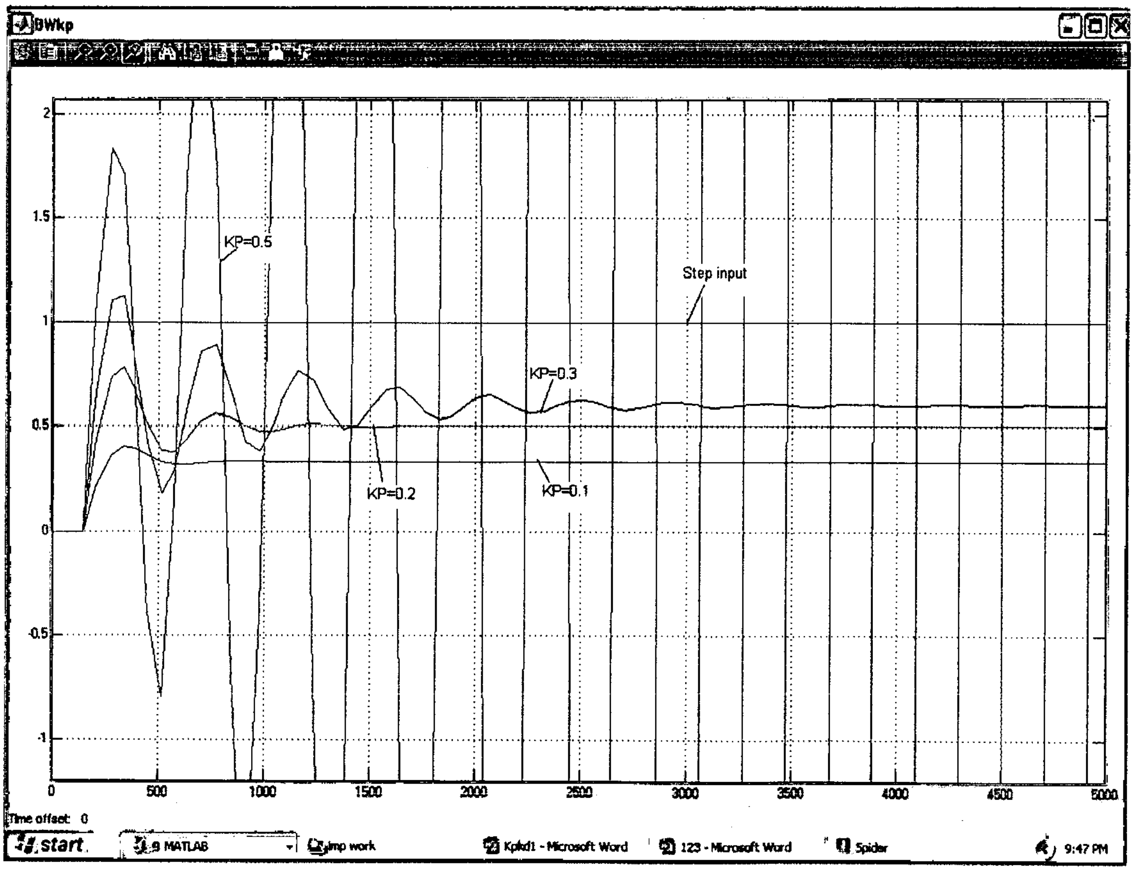

Figure 3.24 Output for step input- servo model for the basis weight for varying values of K_P (a)

As can be seen from Figure3.24 that the system becomes unstable at K_P = 0.5.It is also observed that though the oscillatory behavior increases with the increase in K_P but the offset is also reduced to some extent. Again tests were performed for some more values of K_P, to find the out optimum value of K_P for the step input of the system. Now the test values were taken as K_P = 0.3, 0.32, 0.34, 0.38. The simulation results for the same can be seen in Figure 3.25.

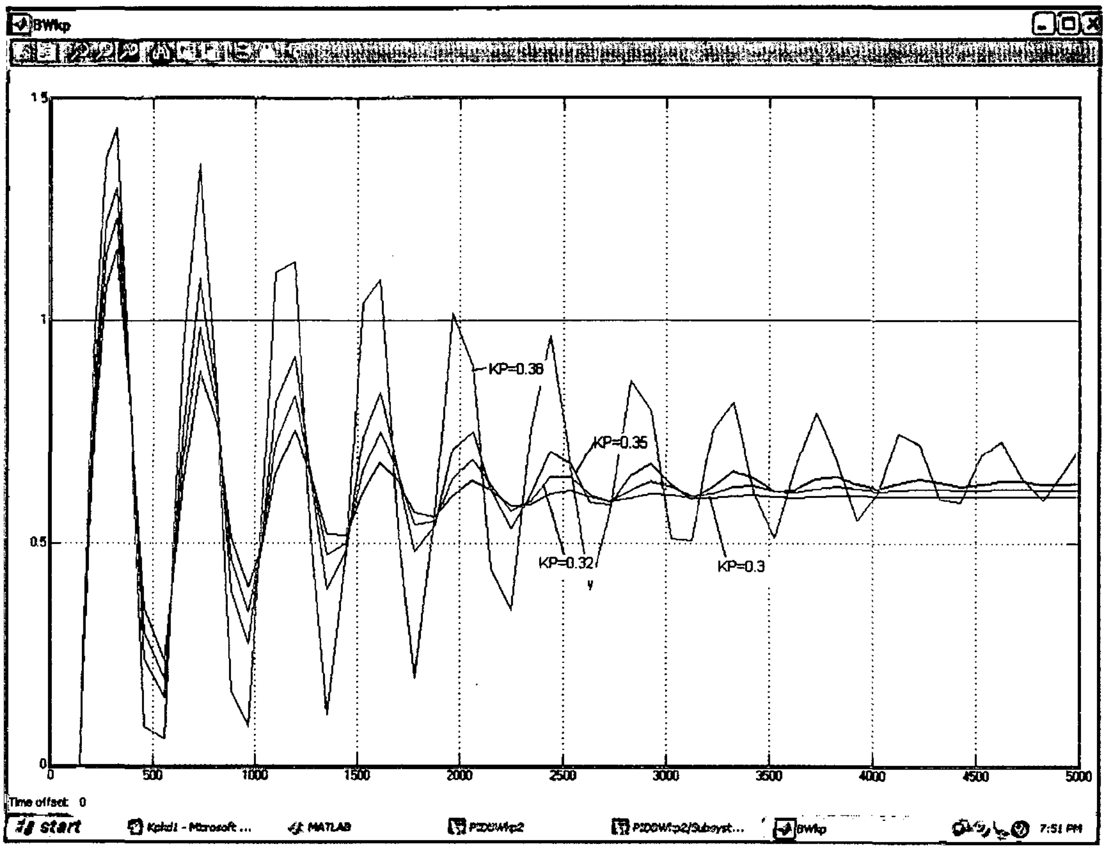

Figure 3.25 Output for step input- servo model for the basis weight for varying values of K_P (b)

It can be clearly seen from Figure 3.25 that for values of K_P equal to and below 0.38, the system gives the bounded output and hence it is stable though very oscillatory. But as can be seen in the next simulation result (Figure 3.26) that as the value of K_P increases beyond 0.4 the system suddenly becomes unstable. In case of a conventional controller the value of K_P is responsible both for the offset as well as the oscillatory behavior. If offset has to be reduced the value of K_P has to be increased, but increasing the value of K_P increases the oscillations in the system. Hence tuning becomes difficult, unlike that for as in case of a FLC model where the system remains marginally stable even on increasing the value of GE. Also the value of offset can simultaneously be monitored by changing GU. Both GE and GU can be individually monitored to remove oscillations and offset respectively. The simulation results for different values of K_P = 0.35, 0.38, 0.4, 0.42 are shown in Figure 3.26.

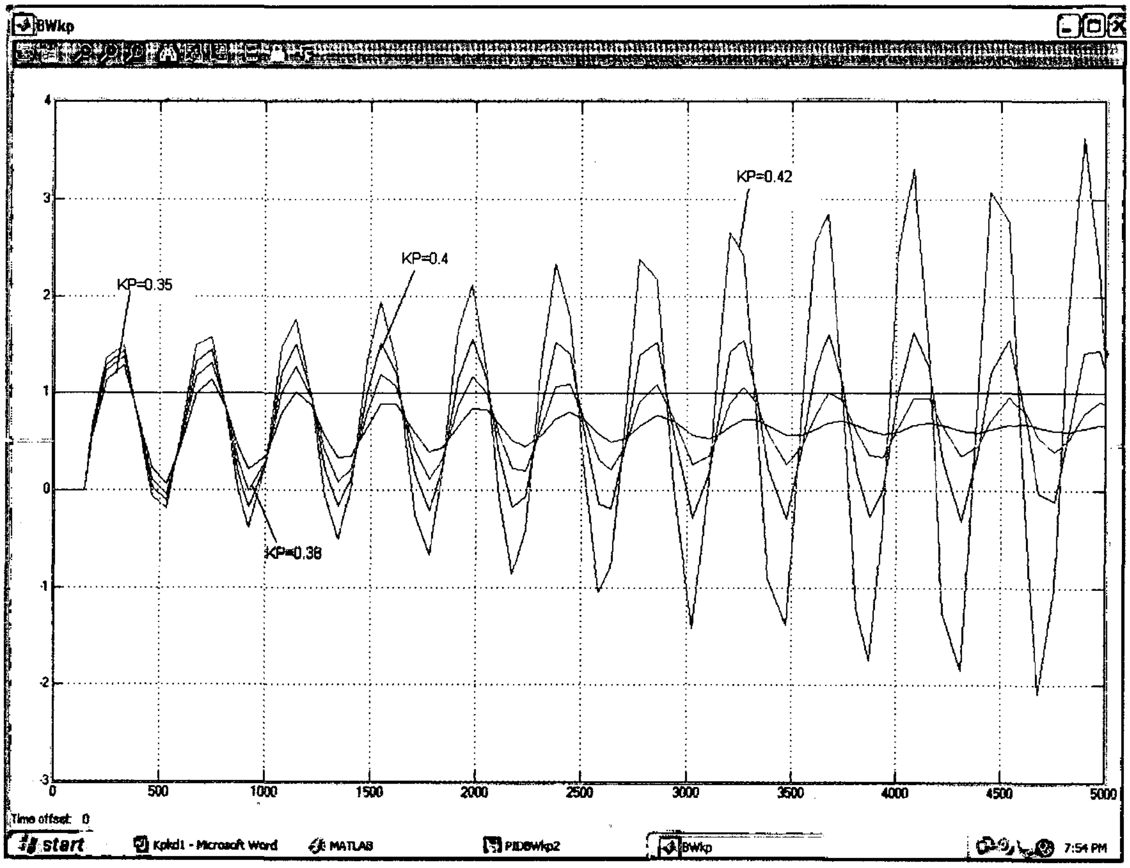

Figure 3.26 Output for step input- servo model for the basis weight for Varying values of K_P (c)

Out of all these test values, K_P = 0.1 was selected as the optimum value as it had the minimum oscillatory behavior.

3.4.1(b) PD-Type servo model for step input

Once the value of K_P has been selected, now the system is tuned for optimum value of K_D. As it is a PD type of controller, therefore K_I is kept zero. Thus the simulation is performed for K_P as 0.1 and K_I as zero and different values of K_D are taken as 0.1, 1, 10, and 20, the results for the same can be seen in the Figure 3.27.

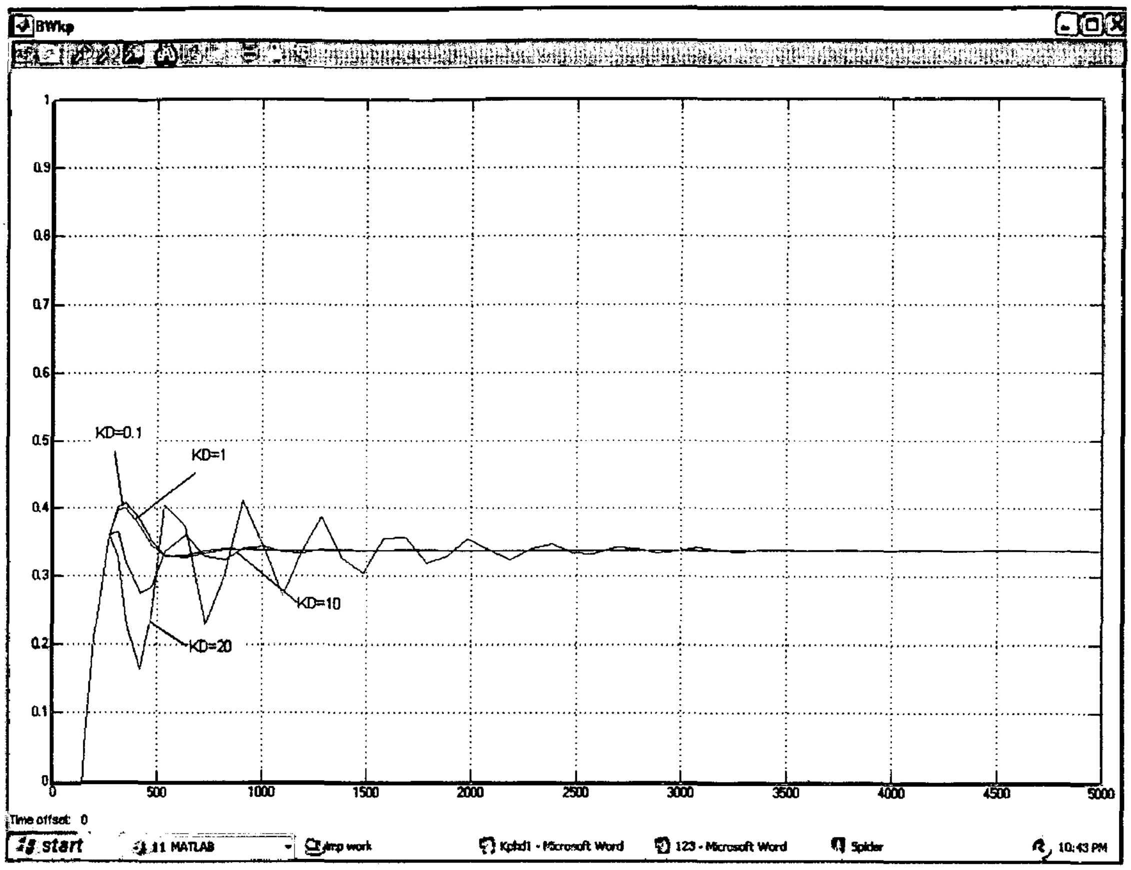

Figure 3.27 Output for step input- servo model for the basis weight for varying values of K_D

It can be clearly seen from Figure 3.27 that as the value of K_D increases the overshoot is decreased i.e. the derivative action dampens the system and tries to improve the stability of the system, though for higher values of K_D the response is oscillatory but yet stable. Tests are also performed for K_D = 0.001, 0.01, 0.1 and the results for all the three values were almost coinciding. Thus out of all these values K_D = 0.1 gives the best results; hence it is taken as the optimum value. It can be said here that the value of K_D if increased to a large extent affects the system output, for smaller values of K_D the output has minor affect on its dynamics. From these results it can be concluded that the effect of introducing the differential part is almost the same for both conventional and FLC controller for the step input in servo model.

3.4.1(c) PID-Type servo model for step input

Now the effect of integral part is analyzed by introducing the K_I part in the system. The optimum values of K_P and K_D are taken from the above results.

K_P = 0.1 and K_D = 0.1 is taken and Different values of K_I are taken as K_I = 0.001, 0.0005, 0.0001, 0.00001. The results for the same can be seen in Figure 3.28.

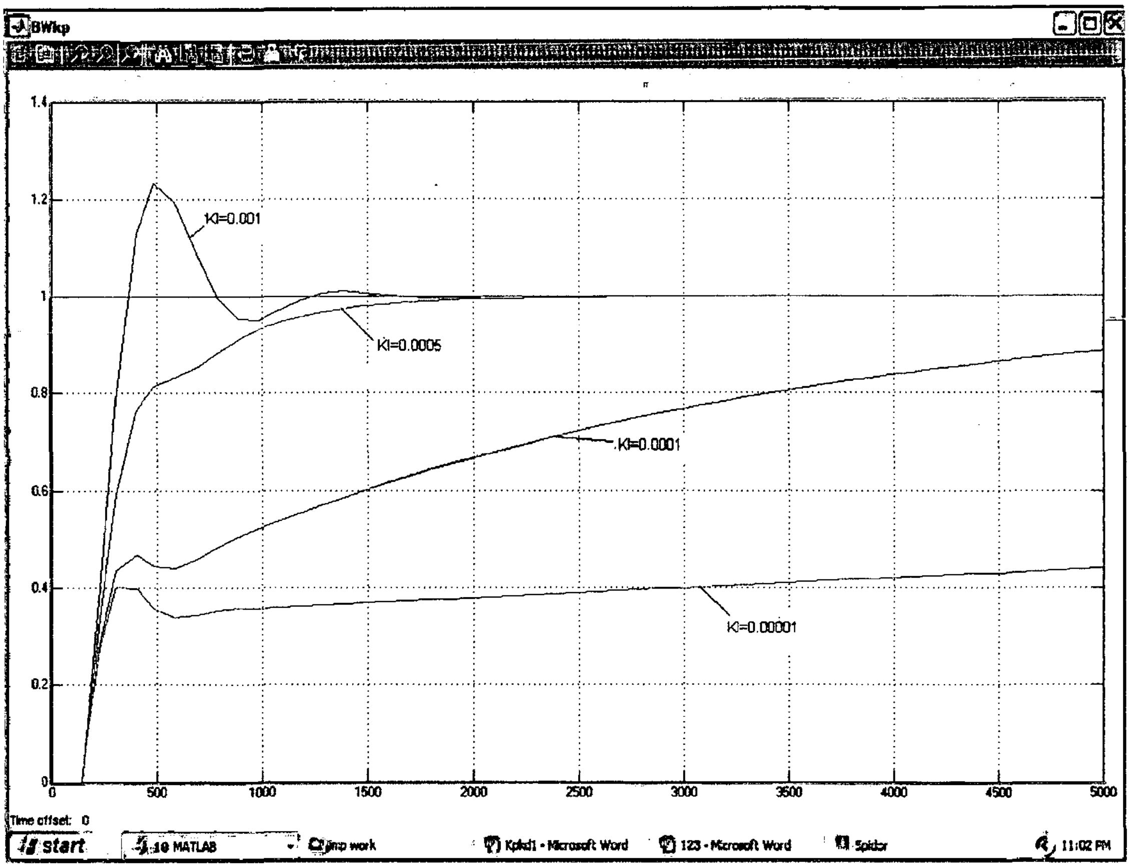

Figure 3.28 Output for step input- servo model for the basis weight for different values of K_I

It can be seen from Figure3.28 that as the value of K_I increases, the offset is decreased. For K_I = 0.001, the offset is zero, even for K_I = 0.0005 the offset is zero. But for the values of K_I above this, the offset appears. It can be clearly seen from the graph of Figure3.28 that on decreasing the value of K_I the offset appears in the system output and on increasing the value of K_I the offset is removed but overshoots come into picture. Again as both the parameters are important for the system performance, hence tuning the system becomes difficult. Hence the tests are again performed for values of K_I between 0.0005 and 0.001. Therefore the simulation is again performed for some other values i.e. for K_I = 0.0006, 0.0007, 0.0008 and 0.0009, K_P = 0.1and K_D = 0.1 and the results for the same can be seen in Figure 3.29.

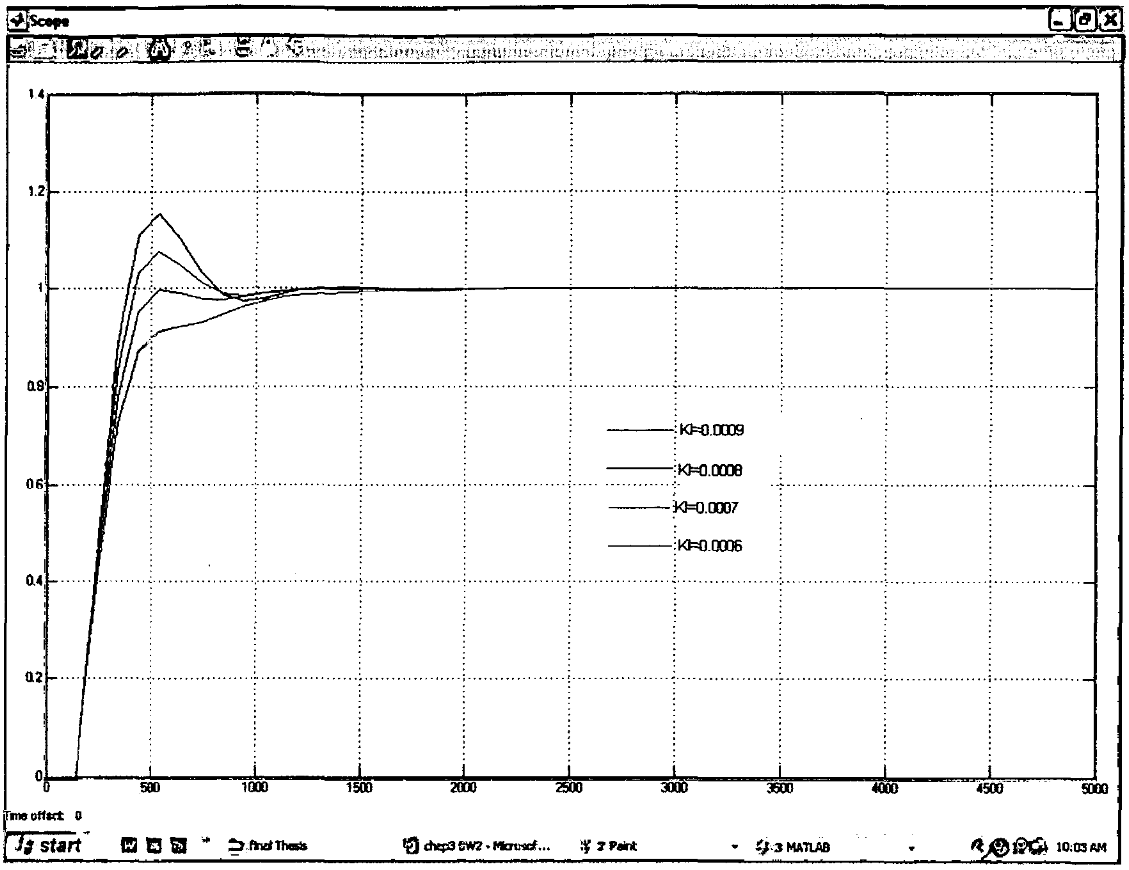

Figure 3.29 Output for step input- servo model for the basis weight for varying values of K_I (b)

As can be seen in Figure 3.29 that the value of K_I between 0.0007 and 0.0008 would give the optimum value. Tests were done and the value of K_I = 0.00073 which gave a minimum overshoot and zero offset was taken as the optimum value. Also it is observed that the integral part is responsible for the offset and also the overshoot in both Conventional and Fuzzy controller for servo model with step input.

Thus a conventional controller with an optimum output for the step input-servo model has been developed with values for different gains as: K_P =0. 1, K_I = 0.00073, K_D = 0.1.

3.4.2 Servo model for varying input using PID controller

The same model of Figure 3.23 using a PID controller is simulated for varying values of basis weight and these values are taken from Table 3.2 (Appendix). First a P-Type controller is made to run and then further PD and then PID models are simulated.

3.4.2(a) P-Type servo model for varying input

Different values are assigned to K_P, the Proportional gain and the other two gains i.e. the integral (K_I) and the differential (K_D) gains are kept at zero. Thus the different values assigned to the gains are $K_D=0$, $K_I=0$ and different values of K_P are as such: K_P = 0.1, 0.2, 0.3, and 0.4. It can be seen from Figure 3.30 that as the value of K_P increases the response of the system becomes more and more oscillatory, but it is also clear from the response that the effect of change in the values of the reference input on the output response is almost nil for different values of K_P. Thus the system response is very poor. Moreover it is also seen that as the value of K_P is increased beyond 0.4 the system becomes highly unstable. For K_P = 1 the Y- axis becomes 1×10^{10}. So from the above results the optimum value of K_P is selected as 0.1 for further work.

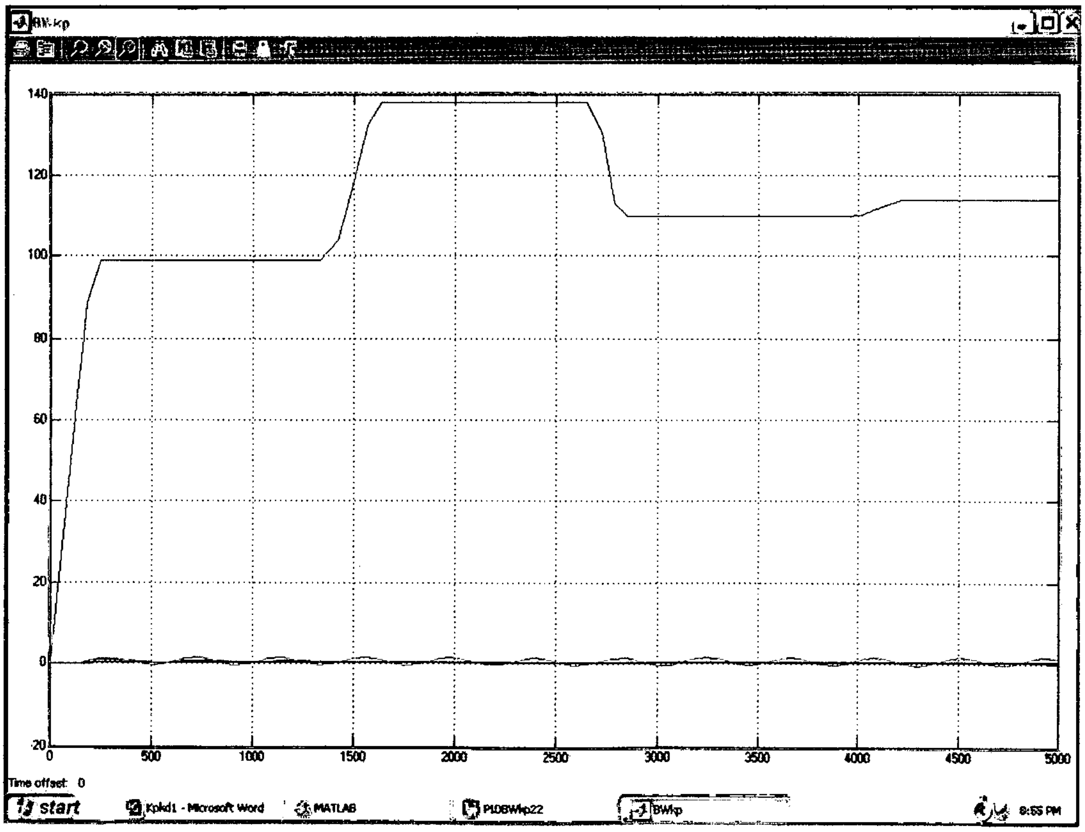

Figure 3.30 Output for varying input- servo model for the basis weight for varying values of K_P

3.4.2(b) PD-Type servo model for varying input

For the model of Figure 3.23 to behave like a PD-Type of Controller, the term K_D is assigned some value instead of zero. Now K_P = 0.1, and K_I = 0 and different values of K_D are taken as: K_D=1, 0.1, 0.01 and 0.001. As seen from the simulation result shown in Figure 3.31 that the output of all the values of K_D almost coincide. A minor difference is seen in the overshoot but rest curves are almost the same for all values.

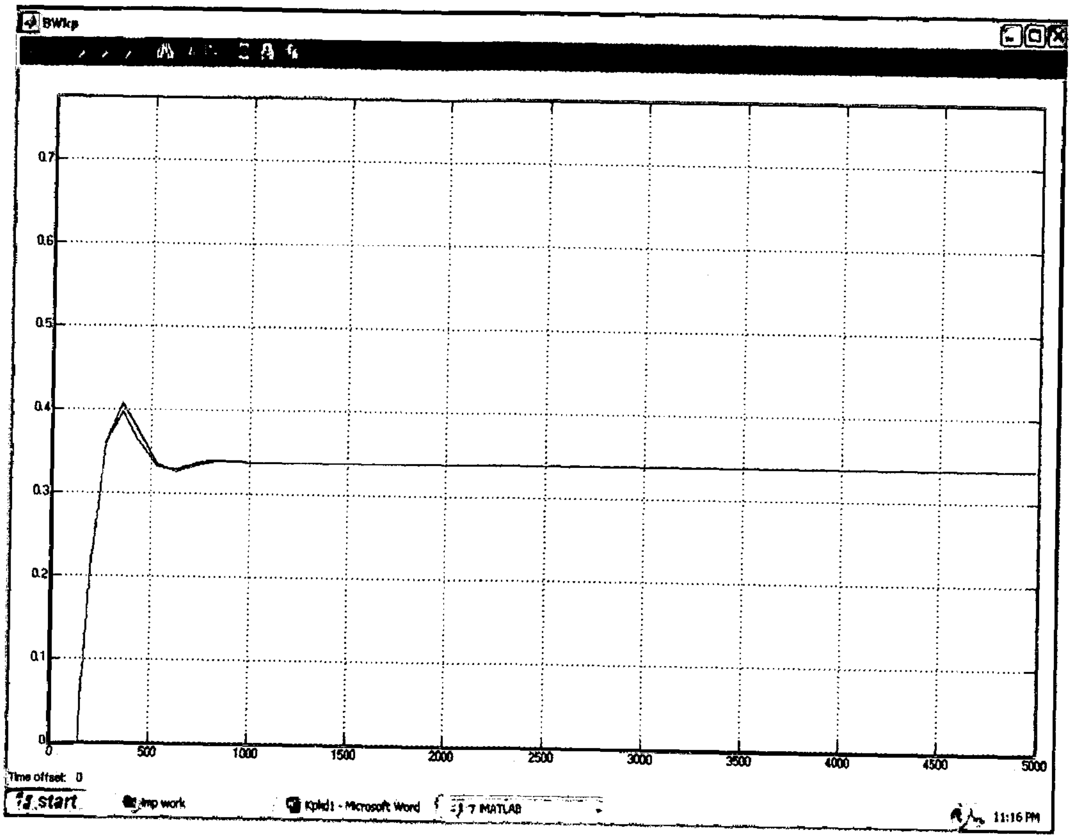

Figure 3.31 Output for varying input- servo model for the basis weight for Varying values of K_D (a)

Simulation is again performed for more values of K_D such as K_D = 1, 10, 15 and 20 keeping K_P = 0.1, and K_I = 0, and it was observed that as the value of K_D is increased, the oscillatory behavior increases as can be seen in Figure 3.32, but there is no effect of changing input on any of these values. The system output does not vary according to the Basis weight setpoint changes. Thus from the above results the value of K_D =1 is taken as the optimum value.

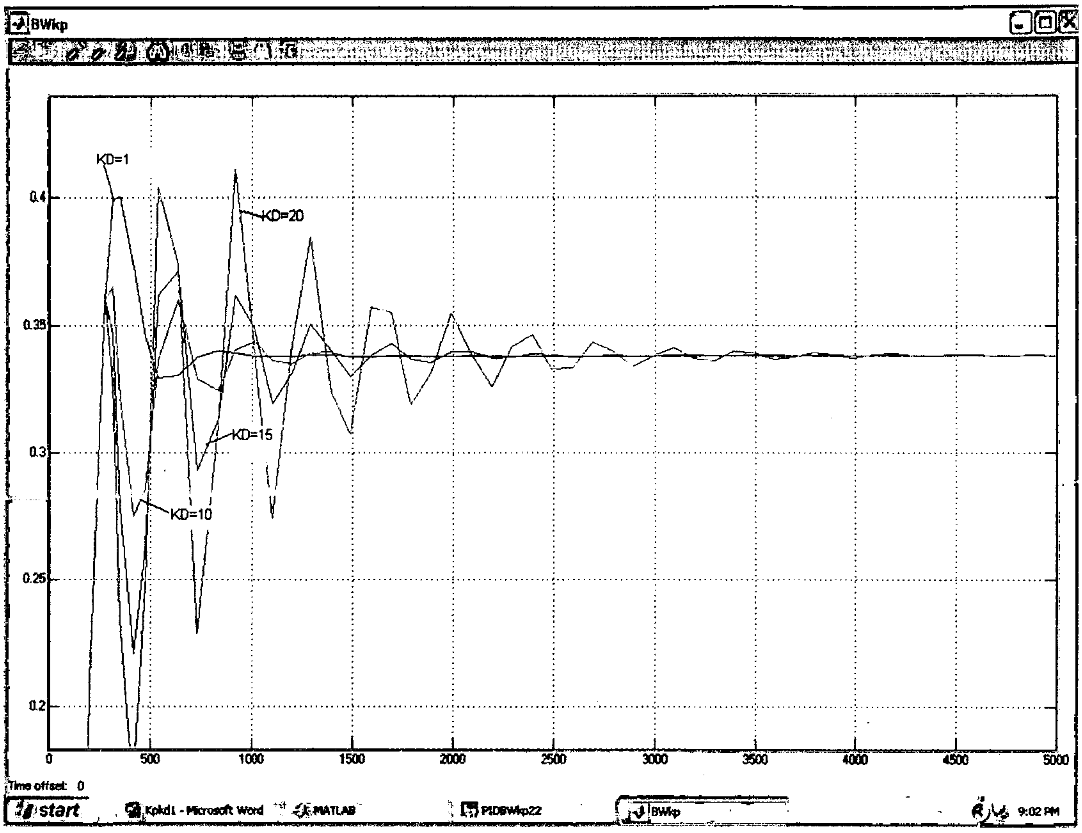

Figure 3.32 Output for varying input- servo model for the basis weight for varying values of K_D (b)

3.4.2(c) PID-Type servo model for varying input

Now the integral term K_I term is introduced to the model of Figure 3.23. The simulation was performed for various values of K_I as can be seen from the Figures 3.33, 3.34 and 3.35. The different values of K_I in Figure 3.21 are 0.00005, 0.00001, 0.000005, and 0.000001 while the values of K_P and K_D are taken as 0.1 and 1 respectively. As can be seen, the response for all the values does not vary with the changing input. Also it is observed that as the value of K_I increases, the offset is reduced to some extent.

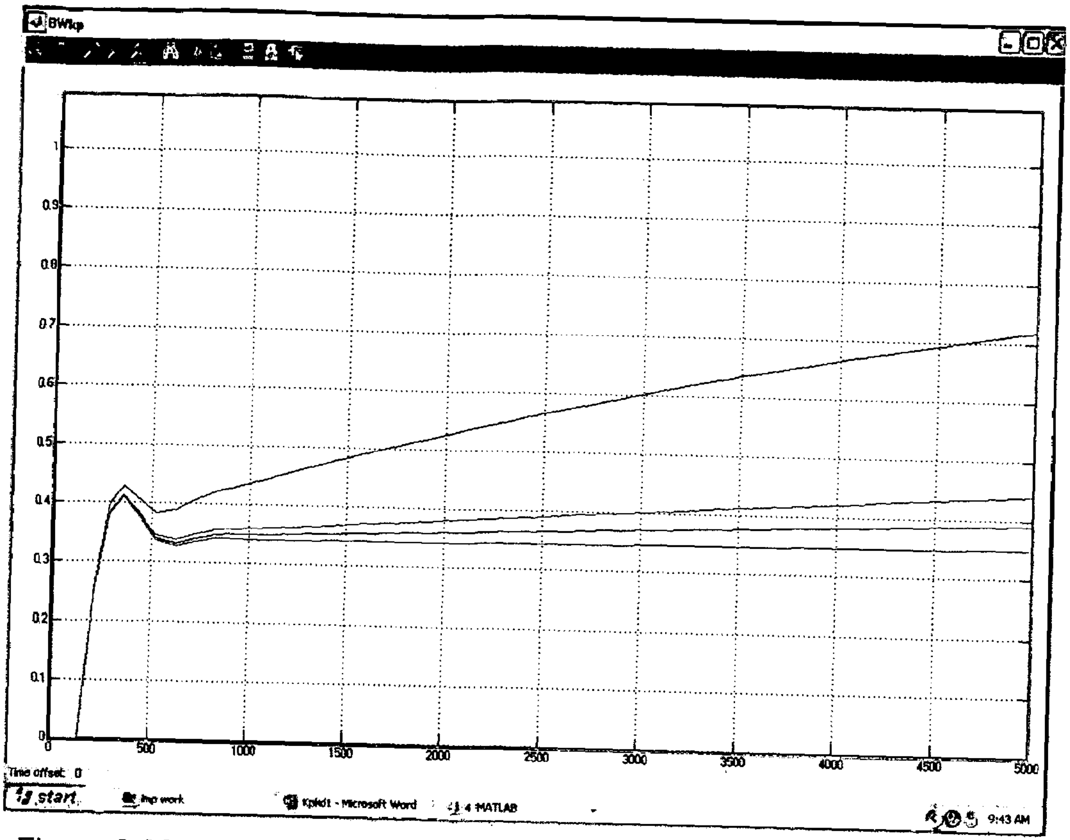

Figure 3.33 Output for varying input- servo model for the basis weight for varying values of K_I (a)

Again the simulation is performed for more values of K_I i.e. K_I = 0.0005, 0.0001, 0.00007, 0.00001 while K_P and K_D are taken as 0.1 and 1 respectively. The results for the same can be seen in Figure 3.33. For these values also same observations are made as above i.e. as the value of K_I increases, the offset is reduced.

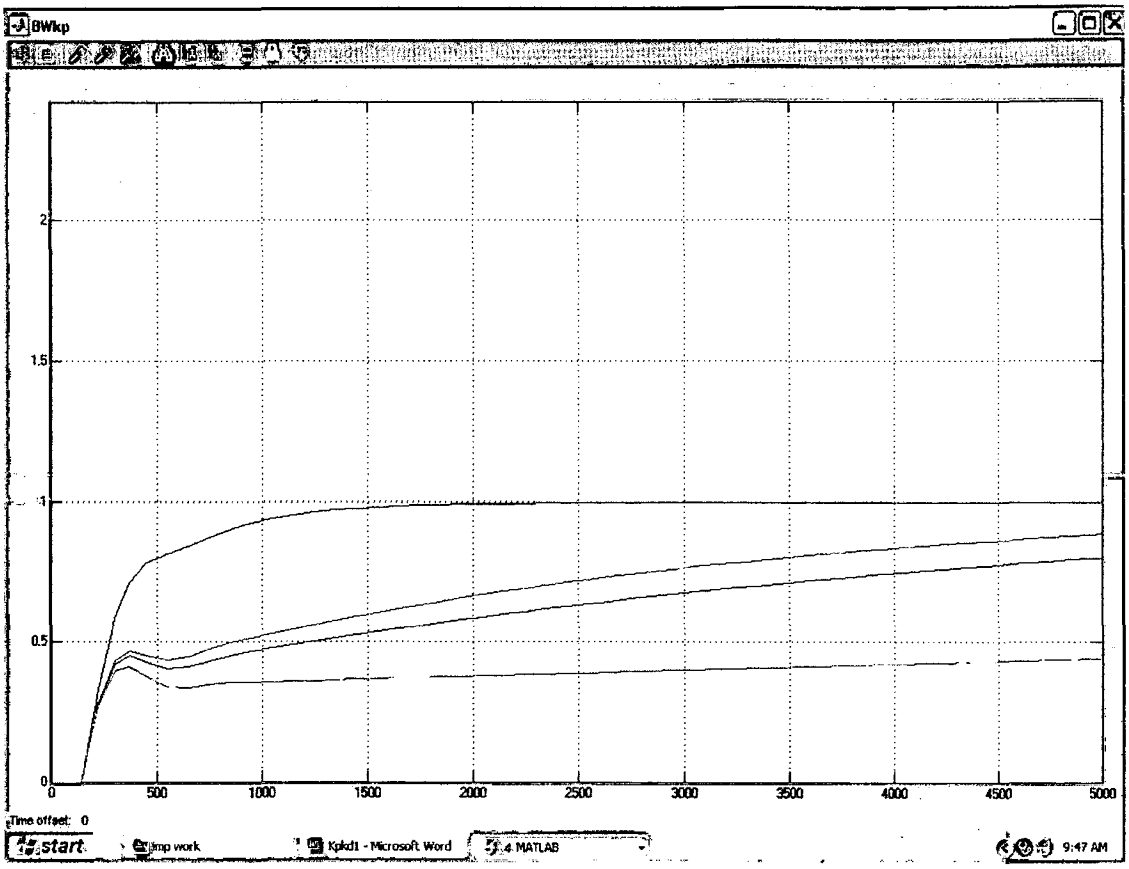

Figure 3.33 Output for varying input- servo model for the basis weight for varying values of K_I (b)

It has been observed from the simulation results that for none of the values of K_I, the system is giving a good output. The system is giving a bounded output for some values but as the value of K_I is increased beyond 0.001, the output becomes quite unstable. The same can be seen in the scope window of Figure 3.34 where different values of K_I are taken as K_I = 0.005, 0.001, 0.0007 and 0.0001, keeping the value of K_D and K_P same as for the above cases. Moreover for none of the cases the output is changing along with the input hence the system response is very poor.

Figure 3.34 Output for varying input- servo model for the basis weight when the value of K_I is 0.001

It is worth mentioning here that as the value of K_I increases beyond 0.001, the system becomes unstable, as it gives the unbounded output for the bounded input. Moreover it can also be seen from the above simulation results that the system output does not vary with the change in the setpoint of the input. But in case of the Fuzzy Logic Controller, the output varies according to the setpoint variations; also the system gives a stable output.

Once the system has been analyzed for setpoint variations, tests are also done to take care for the disturbances i.e. the regulator problem. The regulator model is now developed for the process.

3.5 Regulator model using FLC for the Process Gb:

All industrial systems often exhibit load variations that undermine the performance of the controllers. In real world the system performance generally depends on both setpoint and load change variations. Hence it is desirable to provide some means of uniform optimal performance over a wide operating range. The paper making as already discussed is a multidisciplinary process, and the disturbances can be there due to a number of reasons. It is basically an interactive process where the variations in any one of the parameter can adversely affect the system performance of the other parameters too. The system discussed in this chapter was a fuzzy system for the servo model, and it has been found the Fuzzy system worked well for the servo problem. It becomes equally important to use the Fuzzy controller discussed above for the real world system. Thus a regulator model is developed using the Fuzzy Logic Control system and the same can be seen in the Figure 3.35.

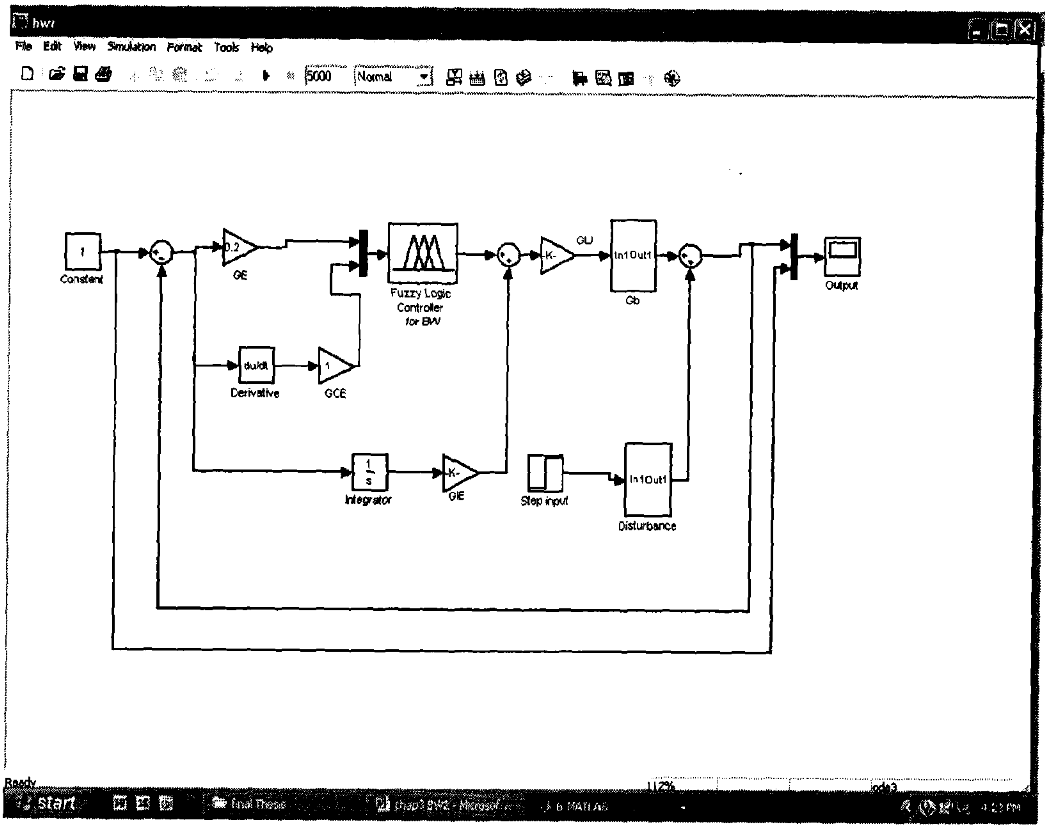

Figure 3.35Regulator model for the process using FLC

The model has been developed using a Fuzzy PD+I type of controller and the system is tested for a step input. The process used is the same as given by equation (1.4). The disturbance is added to the system and the system is tuned for the optimum values of the different scaling gains. The values of the scaling gains are taken as GU=0.163, GE= 0.2, GCE=1 and GIE= 0.0018. Taking these values the model is simulated and the simulation results for the same can be seen in the scope window of Figure 3.35.

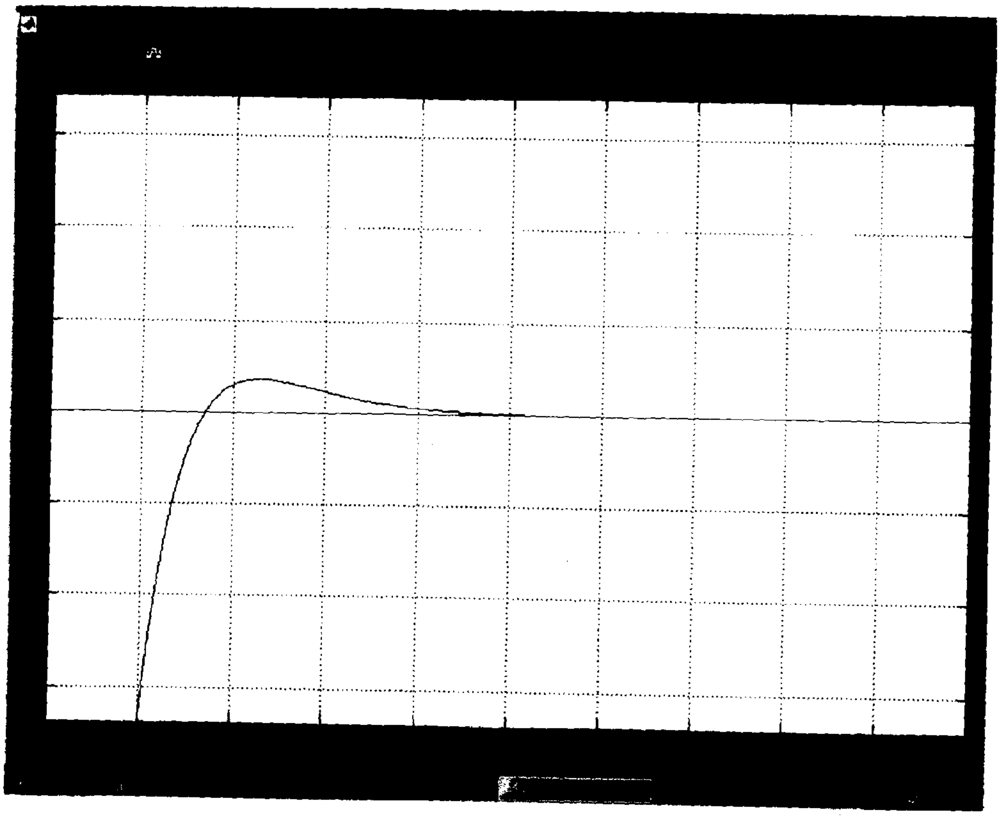

Figure 3.35 System response for the regulator model using FLC

It can be seen from the results of Figure 3.35 that the output of the system is under control, even when the disturbance is added to the system. The permissible range of the basis weight output is within ±2% after a time of about 757 seconds. This time can further be reduced even more by finer tuning. This means that the output for 12.6 minutes is wasted and after that the output moves in a controlled manner. The regulator model developed in this section is just to show that the Fuzzy controller works equally well for the servo as well as the regulator problem. Hence it can be easily implemented in the industry.

3.6 Conclusion:

A Fuzzy Logic Controller gives much better output in comparison to the conventional PID controller. The response of the system using a FLC is stable and can be easily varied according to the changing demand in the input by simply developing a single input/output Fuzzy Logic Controller. Once the effect of each scaling gain is examined, the scaling gains can easily be tuned to get the perfect output both for the step input as well as the varying input. But these things are not observed while using a conventional PID controller as in this case the system output is very poor. The system does not respond according to the changing reference input, though the effect of the three constants (K_P,K_D and K_I)are analyzed but they are difficult to monitor according to the varying input. In case of the Fuzzy controllers the scaling gains can individually be tuned to monitor the system performance, but in case of the PID controller the performance parameters of the system are interdependent on all the three constants. Thus trying any attempt to improve one parameter can have an adverse effect on the other parameter. Also for real world problems, the Fuzzy Control system can be made to work for setpoint variations (servo problem)and also for load variations (regulator problem).

Chapter 4
Non-Interacting system for Moisture

In this chapter, an efficient solution to control the set-point variations in moisture content of paper (Servo problem), in pulp and paper industry is done using a Fuzzy Logic Control System. The traditional systems are based on operator's experience and data provided by the mill. The decision of the operator is not exact but good enough or appropriate for normal functioning in the mill. Fuzzy Logic offers a promising solution to this conceptual design through fuzzy modeling. Fuzzy logic control systems, as is known, are designed with the intension of replacing an expert human operator with an automated rule -based system. In this chapter, simulation tools have been reviewed for a non-interacting system i.e. the change in moisture variations only due to the variations in the steam shower valve opening, and the output of the system is analyzed. The chapter contains, a comparative study of the performance of the system using both Fuzzy Logic Controller and a conventional PID controller in terms of Settling time, Rise time, Overshoot and Steady state error; even the effect of scaling gains on the performance of the system for both the controllers are discussed.

4.1 Moisture

Moisture content is defined as the percentage of water inside the finished sheet. It is one of the most important quality parameters of the final paper product therefore it is important to keep this property well regulated, both at steady-state and at state transitions. Moreover a well tuned moisture control system provides economic yield because many of the paper properties depend on the moisture content, e.g. curl, stretch, tear, strength and stiffness. Also large variations in moisture can adversely affect post processing units like calendaring, the converting or packaging line, or even the customer's printing press. During production, moisture content is therefore measured and monitored online, and the paper product is rejected if it deviates outside the specified limits in CD and MD both A stable and uniform moisture content during normal operation guarantees low reject and consequently high production rates [129].

Here onwards, the system is considered to be a non-interacting system i.e. only the relation between moisture M(s) and steam flow P(s) will be taken and the transfer function relating M(s) and P(s) is given by:

$$\frac{M(s)}{P(s)} = \exp(-66^{*}s) \frac{1.26}{132\,s + 1} \quad \ldots\ldots\ldots\ldots\ldots\ldots (1.7) \quad \text{[Chap 1]}$$

M(s) = Moisture

P(s) = Steam Shower flow.

Equation (1.7) is taken in the form of process Transfer function and a servo model is developed using both Fuzzy Logic Control system and a PID controller. The models are developed in Matlab using Simulink, for step input as well as the varying input. The Fuzzy logic controller taken here is used to adjust the steam shower valve opening as that is considered as the prime factor influencing the moisture content in the web [65]. For simplicity, the transfer functions of the measuring devices and final control elements are assumed to be unity. Similar type of conditions are assumed for both Fuzzy models and the model made by using the conventional controller. The simulation is performed using Matlab, Simulink and Fuzzy Logic toolbox software.

4.2 Fuzzy Logic Controller for Moisture

A Fuzzy Logic controller is a fuzzy system, which is used to control a target system or it is used for supervisory control. The fuzzy controller has a linguistic interpretation which can be expressed with the help of fuzzy sets, membership functions, and fuzzy rules. However, it processes inexact input data but produces exact output data in a deterministic way. Fuzzy controllers can be used when nonlinear control action is needed, or when the controller is to be tuned manually [114]. A Mamdani type of Fuzzy Logic Controller is developed for controlling the moisture content, for step input variations. The controller designed here has two inputs and one output. The error in moisture (em) and change in error in moisture (chem) taken as the inputs of the controller and steam shower valve opening (ssvo) is taken as the output of the controller/ final control element. This can be seen in the window of Figure 4.1.

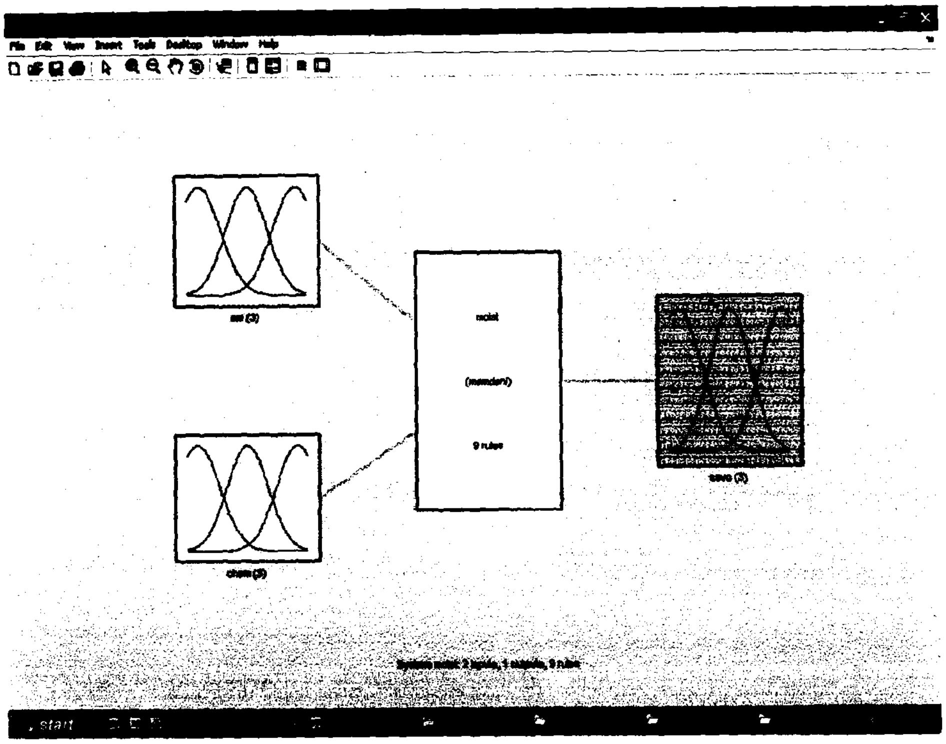

Figure 4.1 Matlab window showing the Fuzzy logic controller for moisture control.

The window of Figure 4.1 shows a two input single output Fuzzy Logic Controller. The behavior of the system is expressed in the form of the membership functions and the fuzzy if-then rules. Each input and the output is divided into three subsets, thus nine rules are formulated.

The input em (error in moisture), has a universe of discourse having the range taken as [-1 1]. This universe is further divided into three subsets each of which is assigned by a Gaussian type membership function, a similar type of exercise was done as discussed in section 3.2, to divide each input and output parameter into subsets. Tests were done for three and five membership functions, and it was analyzed that the input when divided into three subsets gave satisfactory results. The results for the input, when divided into five subsets were also good, but it increased the rule base to a maximum of twenty five rules. The rule base could even be reduced to a lesser number of rules, as some of the conditions never occur practically, but it was found that with each input divided into three membership functions gave good results. Thus it was not necessary to increase the number of membership functions. Also the rule base with nine rules (3×3) was covering all the practical conditions. Thus the three subsets for the input em were taken and the same are named as emn, emm, emp

where emn: error in moisture negative.

emm: error in moisture medium.

emp: error in moisture positive.

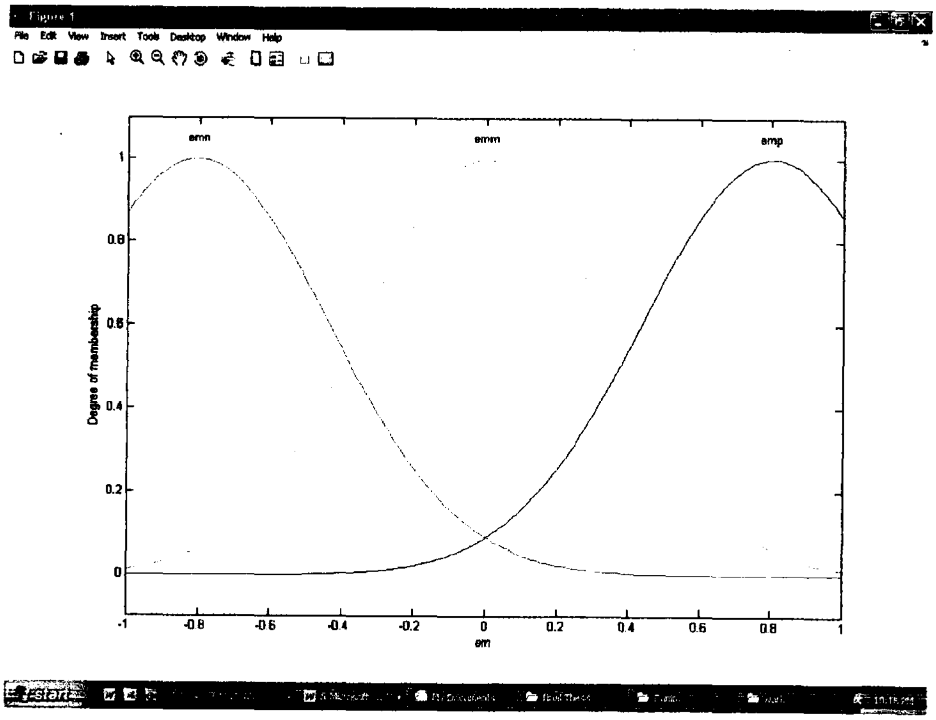

Figure 4.2 Matlab window showing the subsets of input em (error in moisture).

Figure 4.3 shows the input chem (change in error in moisture), range of chem is taken as [-1 1] which is further divided into three subsets each of which is assigned by a membership function i.e. the Gaussian type and are named as chemn, chemm, chemp,

where chemn: change in error of moisture negative.

chemm: change in error of moisture medium.

chemp: change in error of moisture positive.

Figure 4.4 shows the output ssvo (steam shower valve opening), range of the output is taken as [0 1] which is further divided into three subsets each, which are assigned by a membership function i.e. the Gaussian type and are named as ssvos, ssvom, ssvob:

Where ssvos: steam shower valve opening small

ssvom: steam shower valve opening medium

ssvob: steam shower valve opening big.

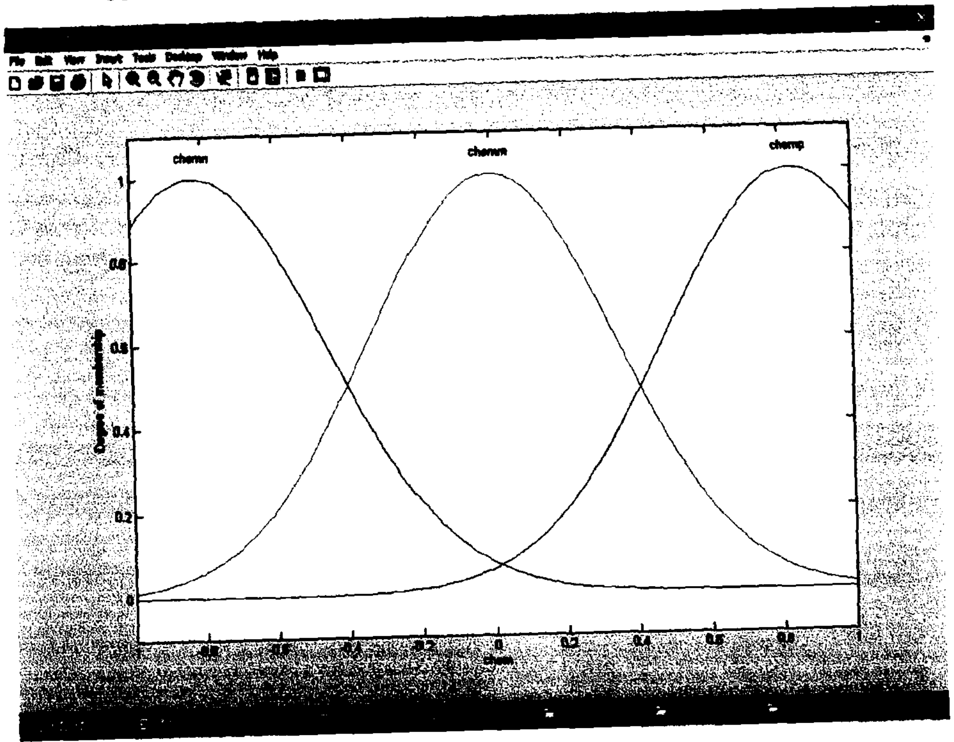

Figure 4.3 Matlab window showing the subsets of input chem (change in error in moisture).

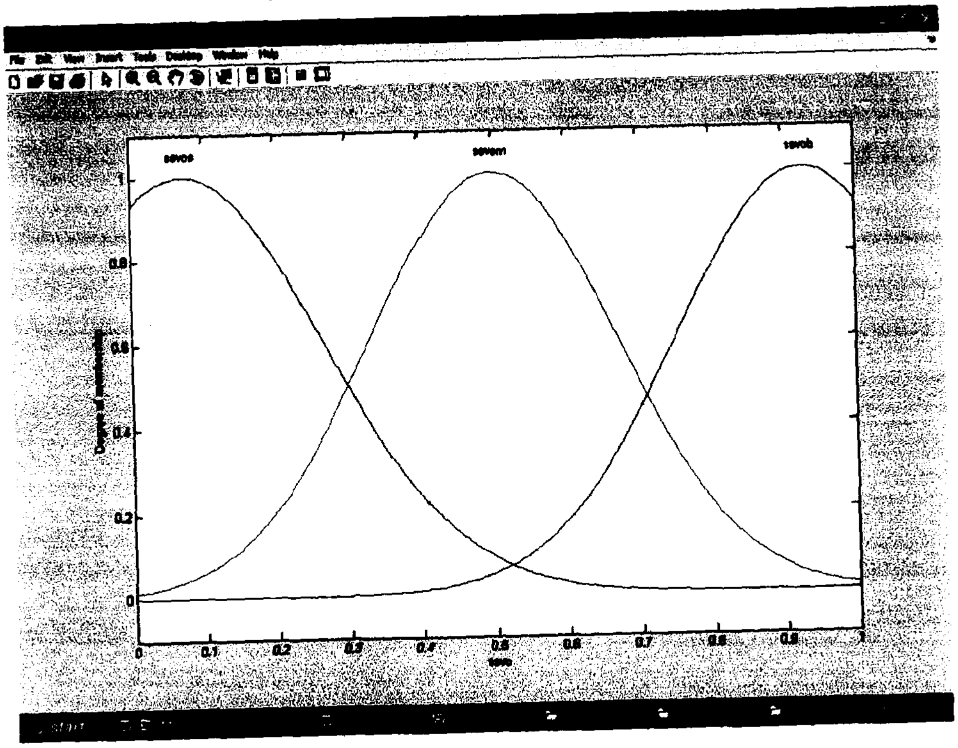

Figure 4.4 Matlab window showing the output ssvo (steam shower valve opening).

The main feature of Fuzzy rule base inference is its capability to perform under partial matching i.e. it computes the degree, the input data matches the condition of a rule. The rule base has a rule for each possible situation [10]. This property is called completeness of the rule base. In this case as there are three subsets for each input therefore the rule base has 3×3 i.e. a total of nine rules. These rules can be shown in the matrix form and forms the rule matrix which can be seen in Figure 4.5.

Rules for Fuzzy Logic Controller				
	error (e)			
		en	em	ep
Change in error (che)	chen	ssvos	ssvos	ssvom
	chem	ssvos	ssvom	ssvol
	chep	ssvom	ssvol	ssvol

Antecedent   Consequent

Figure 4.5 Fuzzy logic rule matrix.

The fuzzy logic rule-base for the moisture controller has the following rules:

IF error is **en** AND change in error is **chen** THEN basis weight valve opening is **ssvos**

IF error is **en** AND change in error is **chem** THEN basis weight valve opening is **ssvos**

IF error is **en** AND change in error is **chep** THEN basis weight valve opening is **ssvom**

IF error is **em** AND change in error is **chen** THEN basis weight valve opening is **ssvos**

IF error is **em** AND change in error is **chem** THEN basis weight valve opening is **ssvom**

IF error is **em** AND change in error is **chep** THEN basis weight valve opening is **ssvol**

IF error is **ep** AND change in error is **chen** THEN basis weight valve opening is **ssvom**

IF error is **ep** AND change in error is **chem** THEN basis weight valve opening is **ssvol**

IF error is **ep** AND change in error is **chep** THEN basis weight valve opening is **ssvol.**

These rules are written in rule editor of the FIS and are fired when the input is given to the controller. The program describing the details of FLC and type of Fuzzification and Defuzzification methods used in the designing of the controller are given in Appendix P4.1. The fuzzy system implemented here is using the following FIS (Fuzzy Inference System) properties:

And method: Min

Or method: Max

Implication: Prod

Aggregation: Sum

Defuzzification: Centroid

In the rule viewer, the output of all the rules are aggregated using sum method and then defuzzified. The output value for each input can be seen by moving the scale about the input values in the screen of the rule viewer shown in Figure 4.6.

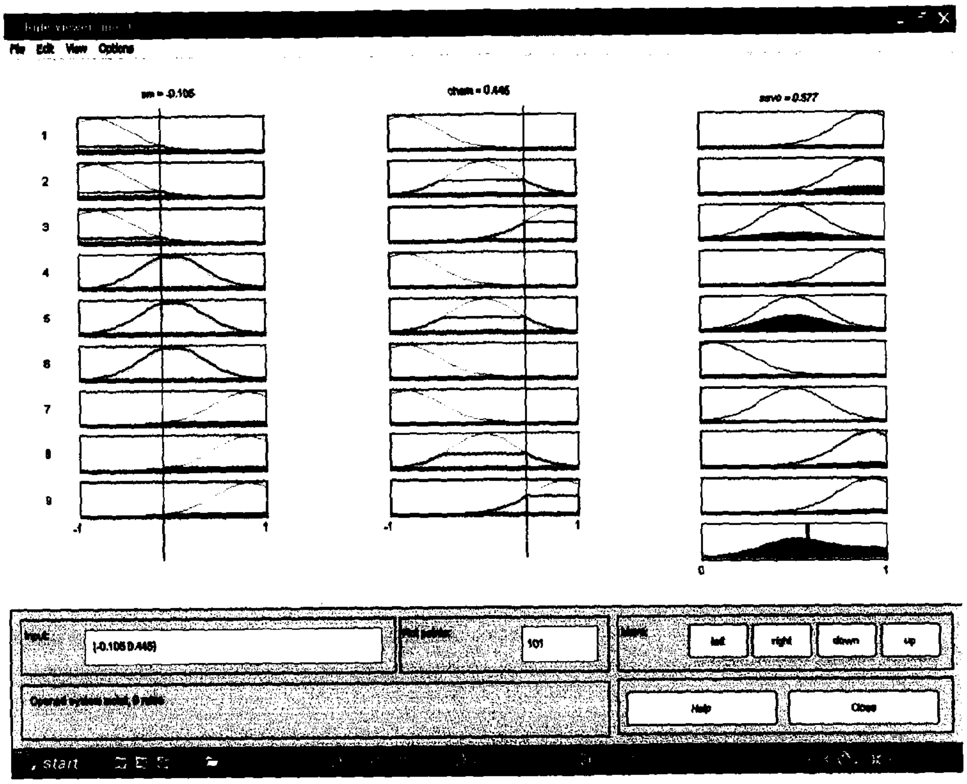

Figure 4.6 Matlab window showing the rule viewer.

The surface viewer is a three dimensional view of the input-output; hence a graph can be seen in the window of Figure 4.7, It shows the relation between the inputs and the output. The x-axis is marked with the input em (error in moisture) and the y-axis is marked with the input chem (change in error in moisture), while the z-axis is labeled as the output ssvo (steam shower valve opening). The graphs relating the variations of the individual inputs with the output can also be seen from this window on the Matlab.

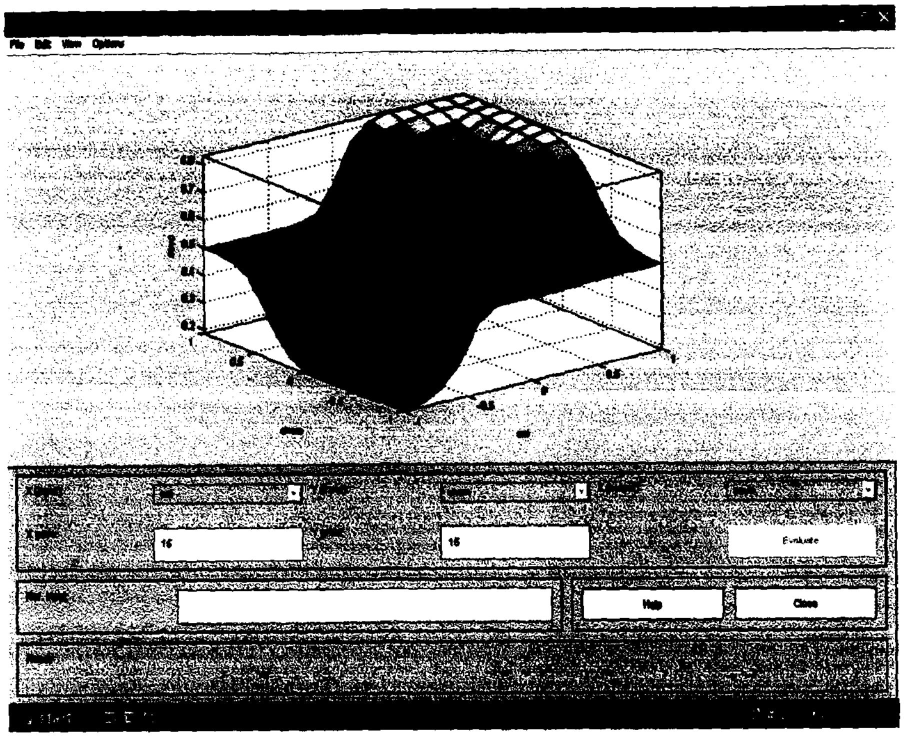

Figure 4.7 Matlab window showing the surface viewer

By tuning the above parameters and formulating the proper rule matrix this Fuzzy logic controller is made and used in the model of Figure 4.8. The system is now made to work as a Fuzzy-P, Fuzzy-PD, Fuzzy-PD+I using the FLC and is further tuned for optimum values of different scaling gains i.e. GE, GCE, GIE and GU.

4.3 Model Development

4.3.1 Servo model for Step input using FLC

A Servo model using Simulink is shown in Figure 4.8. It has a Fuzzy logic controller with a rule viewer, two summing elements, a process (Gm), two multiplexers, a differentiator, an input block, four gain elements representing the scaling gains as: GE, GCE, GIE and GU, a subsystem is taken which represents the steam shower valve, This steam shower valve opening parameter is the parameter for controlling the steam flow, it is known that as we change the steam shower valve opening the moisture content varies, thus the output of the FLC is given to the valve whose output is fed to the process. The transfer function of the valve is assumed to be unity for simplicity and finally a scope window is taken showing the output as the moisture variation with respect to simulation time. Here the measuring element is considered to be ideal so the output of the process which is the moisture is directly given to the summing element used as a comparator from where the error is evaluated and the change in error is evolved using the differentiator block. As it is a two input fuzzy logic controller therefore a multiplexer is used to give the two inputs to the controller. The servo model of Figure 4.9 is used to examine the response of the system using step input.

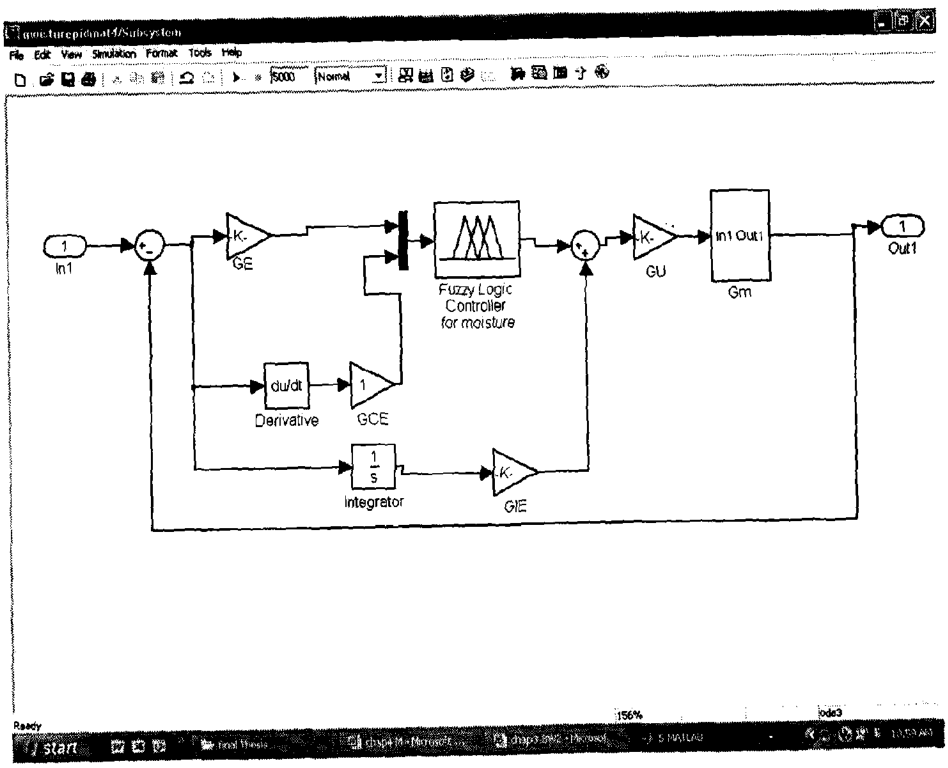

Figure 4.9 Matlab window showing the model developed for the control of moisture using FLC.

Using the model of Figure 4.9, the simulation is performed and the system is tuned for the scaling gains i.e. GE, GCE, GIE and GU to get the optimum value of the output. Different types of fuzzy controllers are developed such as FP type, FPD type FPD+I type. This is done by assigning different values to the scaling parameters i.e. GE, GCE, GIE and GU and the effect of each parameter is also analyzed.

To develop the step input-servo model, the model of Figure 4.9 is given the step input in place of the input block. First the system is tuned for optimum value of GU. The simulation tests are performed by keeping all other gains i.e.

GE, GCE and GIE as zero and taking different values of GU as: 2, 1.5,1 and 0.5. The simulation results for the same can be seen in the scope window of Figure 4.10.

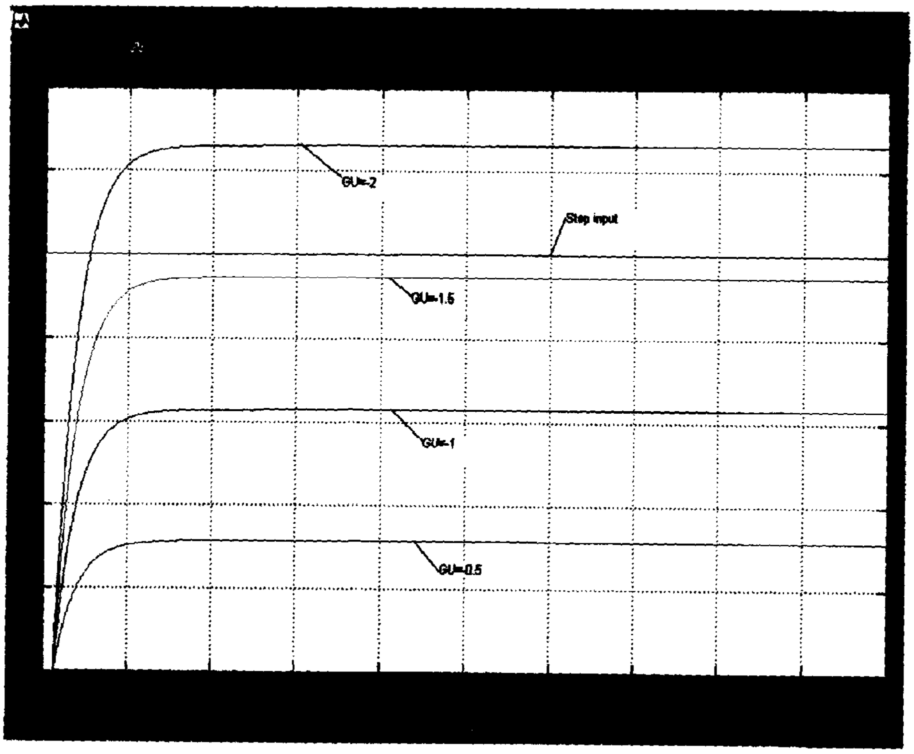

Figure 4.10 Simulation results of moisture for step input servo model for different values of GU as: 2, 1.5,1 and 0.5.

The results of Figure 4.10 clearly show that the demoralization factor (GU) is responsible for the offset in the output response. The value of GU for the above process should be greater than 1.5 but less than 2 for the above model. Thus the system is again simulated and the value of GU is tuned in a way to get a minimum offset. The simulation results for the same can be seen in Figure 4.11.

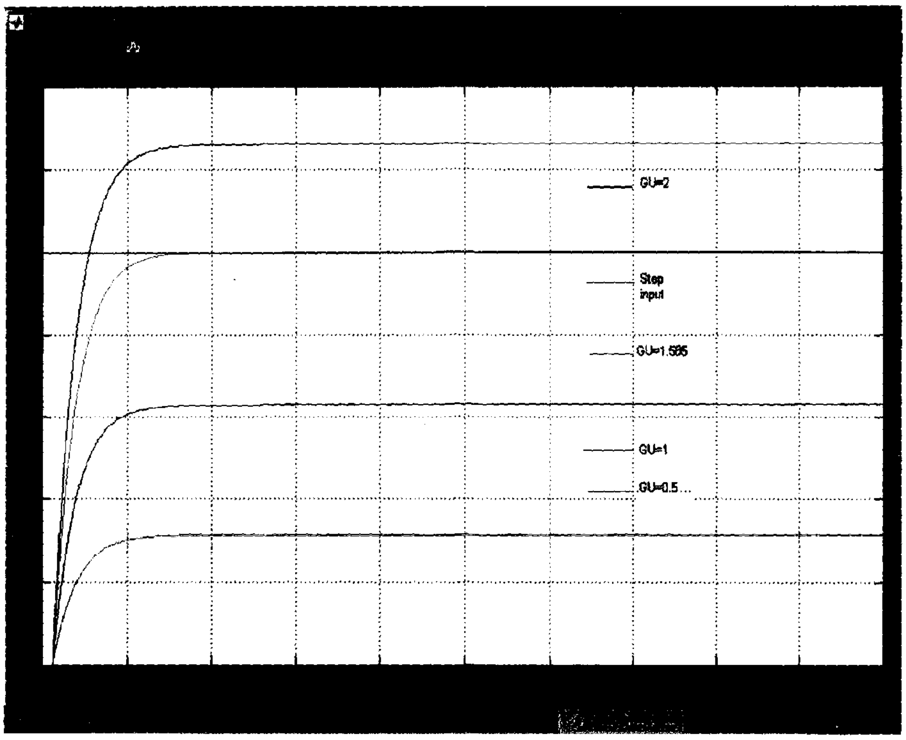

Figure 4.11 Simulation results of moisture for step input servo model for different values of GU as: 2, 1.585,1 and 0.5.

Thus the optimum value of GU is taken as GU = 1.585. Further this value will be used for the step input servo model for moisture control. Now the value of GE is introduced in the system and the joint effect of both GU and GE are analyzed, GE = 1and the different values of GU are taken as: 2, 1.585,1 and 0.5, and the results for the same can be seen in the Figure 4.12.

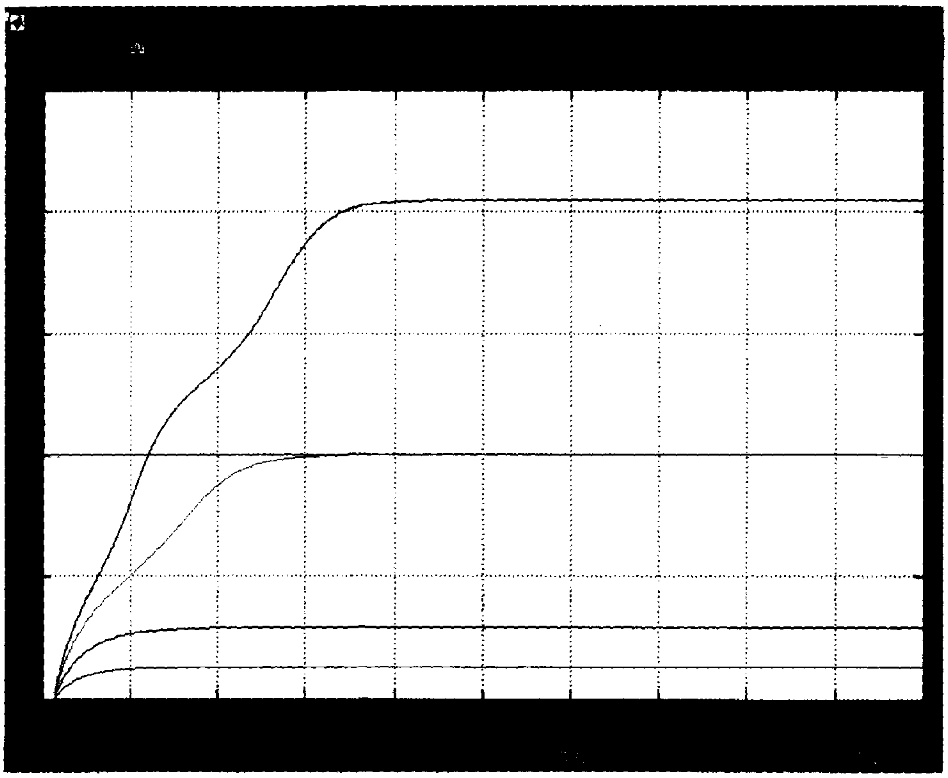

Figure 4.12 Simulation results of moisture for step input servo model for different values of GU when GE = 1

From Figure4.12 it can be seen that by introducing GE into the system the rise time of the system is adversely effected. Now to select the optimum value of GE, different values are assigned to the gain, keeping the value of GU constant i.e. 1.585.

4.3.1(a) Fuzzy-P model:

To develop a Fuzzy-P Type of model, only the proportional gain (GE) is taken into consideration and the other normalization gains that is the derivative gain (GCE) and the integral gain (GIE) are taken as zero. The value of GU is taken as above i.e. 1.585, hence it is named as Fuzzy-P model and these values of gains are applied to the model of Figure 4.9. The effect of changing the value of GE is examined and the simulation results of four such models are compiled and are shown in the scope window of Figure 4.13. Presently the input is taken as the step input and the different gains are assigned the values as: GCE = 0, GU =1.585 and GIE = 0 and four different values of GE are taken as 2, 1.5, 1 and 0.5.

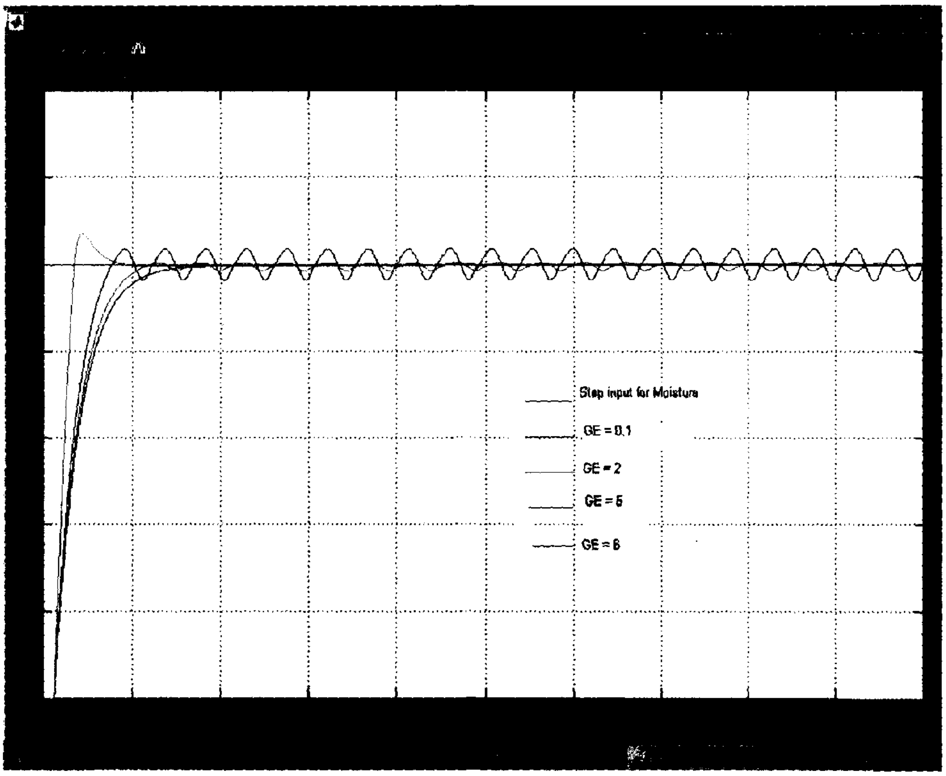

Figure 4.13 Simulation results of moisture for step input servo model for different values of GE taken as: 0.1, 2, 5 and 6

It can be clearly seen from Figure 4.13 that as the value of GE decreases, the oscillations in the output also decrease. The response for GE =2 shows an overshoot, while for GE = 0.1 the system behaves in an overdamped manner. Thus to find the optimum value, some more tests were performed. After subsequent tests, it was found that the system output was with no overshoot for values below 0.5. Again the test values are taken as GE = 0.5, 0.3, 0.1, 0.01 and the simulation results for the same can be seen in the scope window of Figure 4.14.

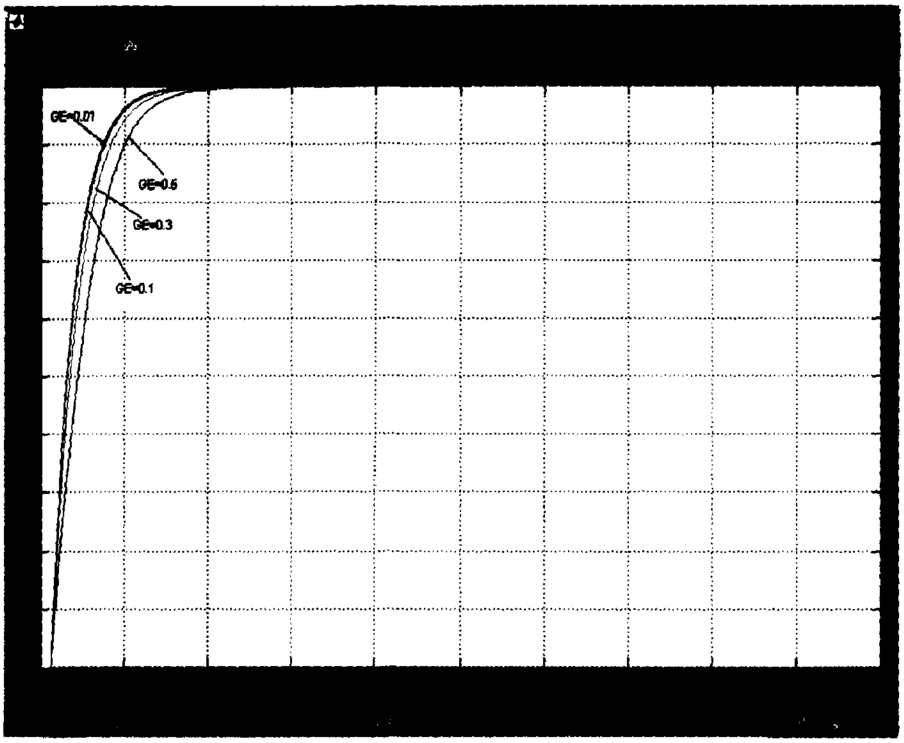

Figure 4.14 Simulation results for Fuzzy-P models for step input where four different values of GE are 0.5, 0.3, 0.1 and 0.01

It is clear from the Figure 4.14 that as the value of GE decreases, the rise time decreases and still further decreasing the value of GE below 0.01 has no significant improvement in the output, hence the value of GE is taken as 0.01. Now the model is simulated for GE =0.01 and different values of GCE are introduced so that the model behaves like Fuzzy-PD model.

As optimum value of GE=0.01 has been selected and a Fuzzy-PD model is made by assigning some values to GCE, the differential gain instead of zero, while keeping the integral gain at a value of zero i.e. GIE = 0.

4.3.1(b) Fuzzy-PD model:

The model of Figure 4.9 is now simulated for GE = 0.01, GU = 1.585, GIE = 0 and different values of GCE are taken as: 0.1, 1, 5 and 10. This model is simulated and the results can be seen from the window of Figure 4.15. It can be clearly seen from the results that the value of GCE has no significant effect on the output. For various values of GCE, the output is almost the same.

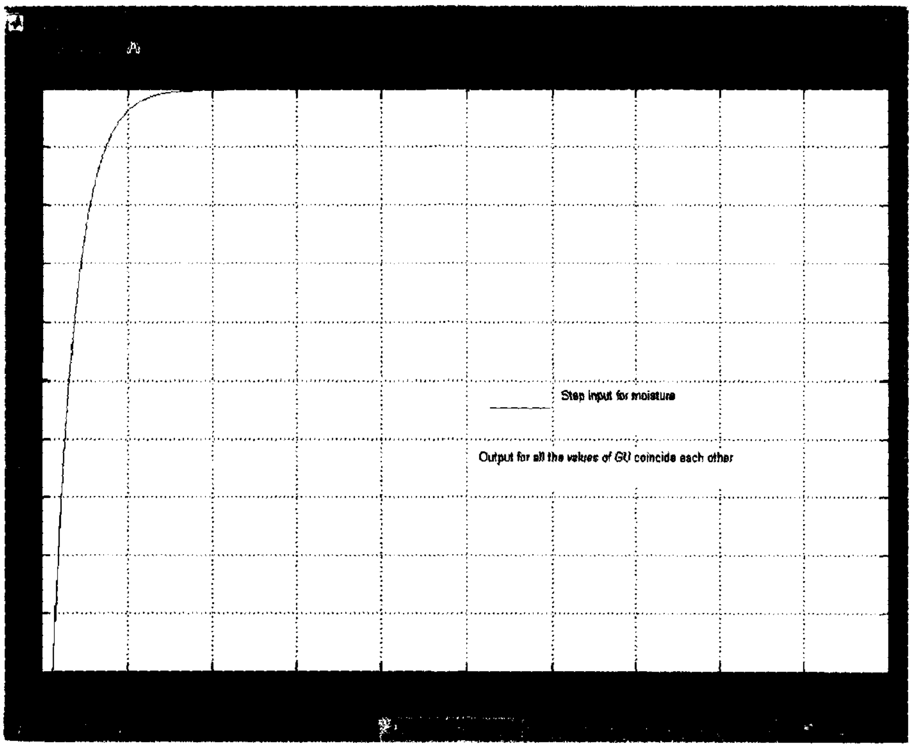

Figure 4.15 Simulation results for Fuzzy-PD models for step input where four different values of GCE are 0.1, 1, 5 and 10

As the value of the output coincides for all the above taken values, thus it is clear that the value of GCE has no significant affect on the output so any of the above values of GCE can be selected for further work. The value of GCE is then taken as 1.

Moving a step ahead the integral constant (GIE) is now added to the system with some numerical value instead of zero to make the model work like a Fuzzy-PD+I model.

4.3.1(c) Fuzzy-PD+I model:

To make the model of Figure 4.9 to run as the Fuzzy-PD+I model, the different types of gains are given the value as: GE=0.01, GU= 1.585, GCE= 1, and GIE = 0.000001, 0.00001, 0.0001, 0.001. The simulated results for this can be seen in the scope window of Figure 4.16.

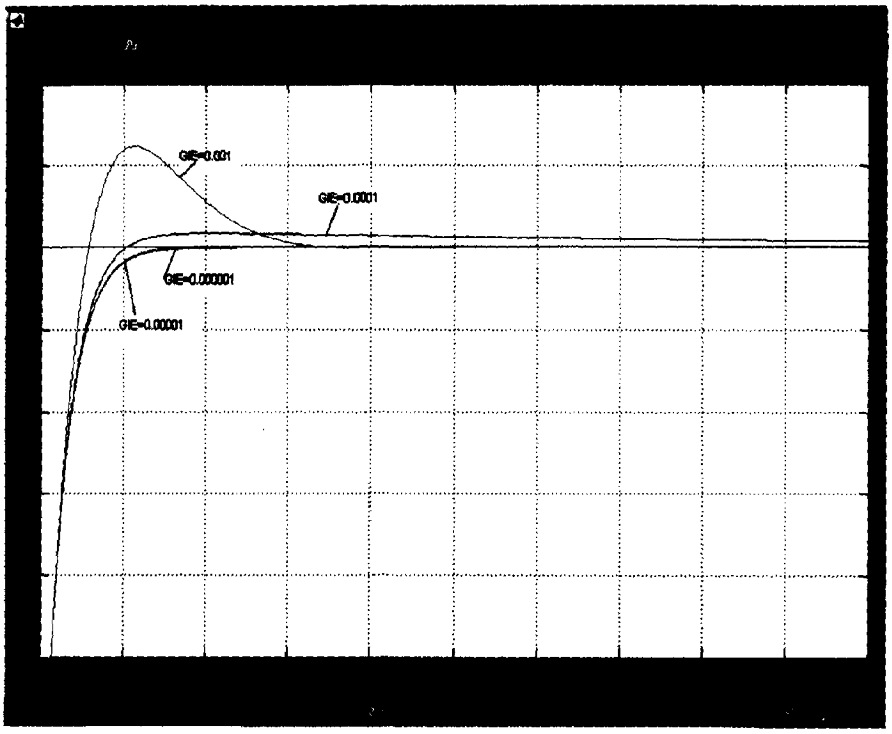

Figure 4.16 Simulation results for Fuzzy-PD+I models for step input where four different values of GIE = 0.000001, 0.00001, 0.0001 and 0.001 are used.

Figure 4.16 show that increasing the value of GIE, introduces the overshoot in the output. Also it can be seen that by increasing the value of GIE, the value of offset also increases up to a certain value. Again some more tests were performed for GIE= 0.001, 0.005, 0.01 and 0.05 using the model of Figure 4.9 keeping the other gain values same as for the above case. The simulation results for the same can be seen in Figure 4.17.

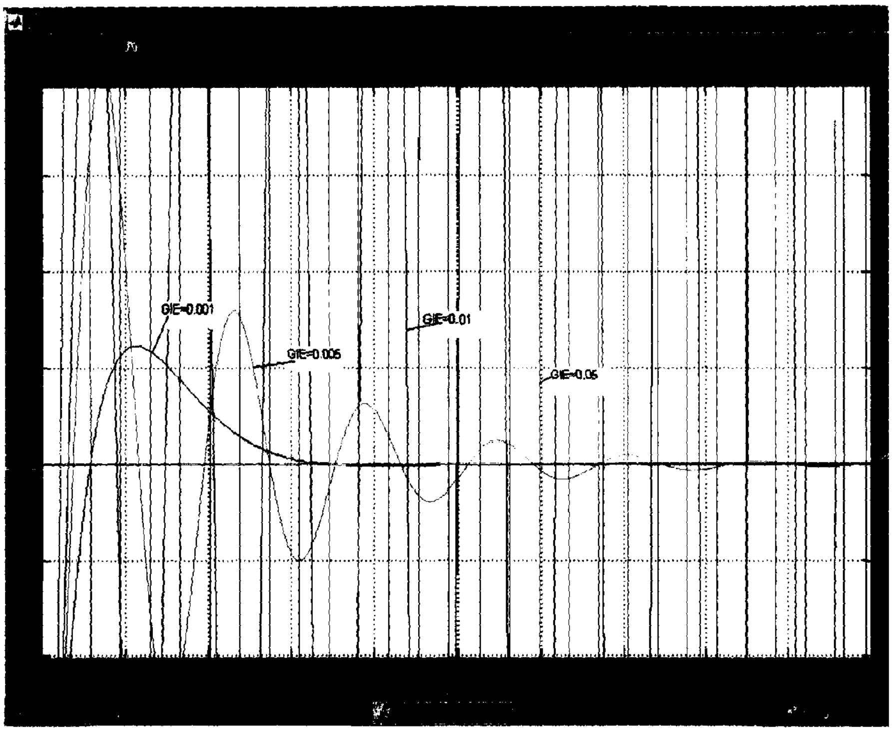

Figure 4.17 Simulation results for Fuzzy-PD+I models for step input where four different values of GIE =0.001, 0.005, 0.01, 0.05 are used.

It is clear from the Figure 4.17 that the integral value affects the stability of the system. As can be seen from the above simulation results that on increasing the value of GIE, the system becomes more and more oscillatory and hence unstable. Therefore a stable system can be obtained with value of GIE=0.00001. Also from all the above tests, it can be concluded that the optimum output of the system can be achieved by using different gains as GE = 0.01, GCE = 1, GIE = 0.00001, GU = 1.585.

This was the case with the step input-servo model. Similar tests are performed for the varying values of reference input and the optimum values of the gains are found by simulating the model of Figure 4.18. The variable input data of Table 4.1 is taken from the workspace of the Matlab window.

4.3.2 Servo model for variable input using FLC

A setpoint tracking system is developed to track the setpoint variations in the moisture as per the requirement of the changing demand. The output or response of the control system is adjusted as required by the error signal. The error signal is the difference between the desired response and the actual response as measured by the sensor system. Thus a closed loop (feedback) control system is developed for the moisture control. The data for the reference input of the moisture is collected from the mill where online sensors are incorporated and the value of the input i.e. the moisture continuously changes according to the demand. The data of Table 4.1 (Appendix) shows these varying values of moisture% with time. This data have been saved in the m-file of Matlab and is collected from the workspace and is given as the input to the model developed (Figure 4.18).

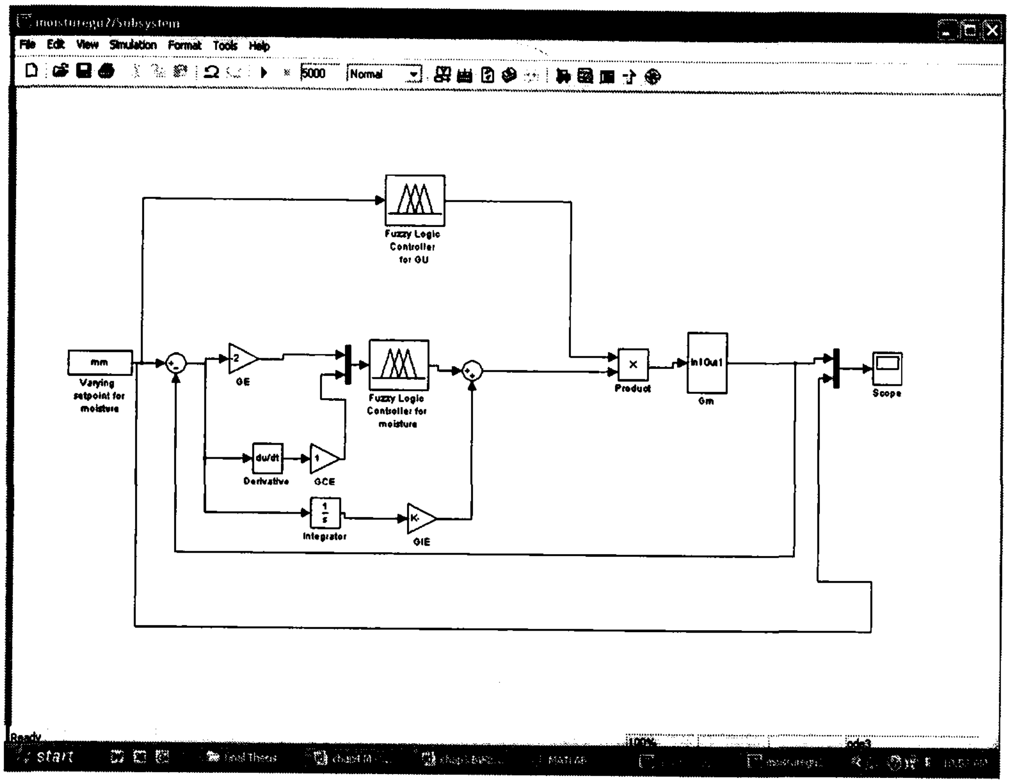

Figure4.18 Varying input Servo model for moisture control using FLC.

The Fuzzy model for varying input has two Fuzzy controllers, one for controlling the moisture as in case of the model of Figure 4.9, and the other for controlling the value of GU according to the changing input values of moisture.

The FLC developed for moisture control in this case is a two input-single output Fuzzy controller. The range of the two input variables i.e. error and change in error is decided according to the data collected from the mill (Table 4.2 Appendix). The universe of discourse for the error em(t) is taken as [-2 2] and the universe of discourse for the change in error chem(t) is taken as [-2 2], while the range of the output variable i.e. the steam shower valve opening ssvo(t) is taken as [0 1]. The membership function for all the three subsets are taken as the Gaussian type, while the implication method used in this case is the max-product method. The Defuzzification scheme used here is the centroid type. The details for the same can be seen in the Fuzzy wizard shown in Figure 4.17 and the program for the FLC can be seen in Appendix P4.2.

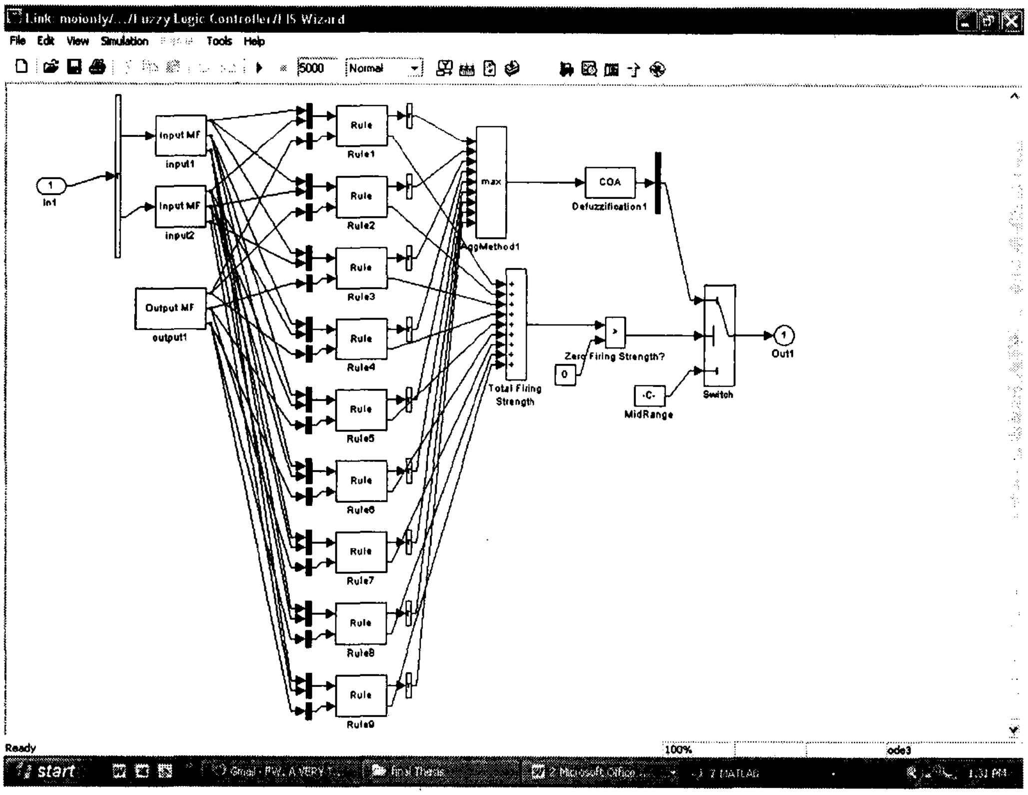

Figure 4.18 Fuzzy Wizard for moisture controller

As each input is divided into three subsets therefore the rule matrix has nine rules in all, the rules can be seen in the rule matrix of Figure 4.5. Tuning of these parameters was done to get an appropriate output and the system is made to work like a Fuzzy-P, Fuzzy-PD and Fuzzy-PD+I.

Using the varying input values from Table 4.1, the model is simulated and the tests are performed to find out the optimum values of different gains. As the input is varying with time, thus the output should also vary with the changing input and as the value of GU is responsible for the final value as seen in the above tests, therefore the value of GU should also change with the varying input. To find out the optimum value of GU for the system, a single input- single output FLC is developed, with the varying input taken from the Table 4.1, as the input to the controller and the value of GU as the output of the controller. As we know that the value of GU is responsible for the offset in the output, thus the offset can be easily removed by making a proper Fuzzy Logic Controller for manipulating GU as per need.

The FLC used for controlling the GU for moisture is a single input-single output controller. The input variable is taken in the range of [4 6] and the output variable is taken in the range of [0.1 0.307]. The input and output variable is divided into three subsets each, the membership function taken in this case is the triangular type. The three rules are made by the three subsets of the input. Using this controller, the value of GU for the moisture controller varies according to the varying input. The Fuzzy controller for developing the values of GU according to the varying values the moisture is a single input-single output fuzzy controller, the details for the same can be seen in the Appendix P4.3.

The system is now tuned for other values of scaling gains. Thus further tests are performed so that the optimum values of GE, GCE and GIE can be found.

4.3.2(a) Fuzzy-P model:

A Fuzzy-P model is developed by assigning different values to GE, and their effects on the system output are analyzed. The values of the different scaling gains are taken as: GIE= 0, GCE=0, GE = 1, 2, 3 and 4 and the changing values of GU is taken from the output of FLC and the results for the same can be seen in scope window of Figure 4.19.

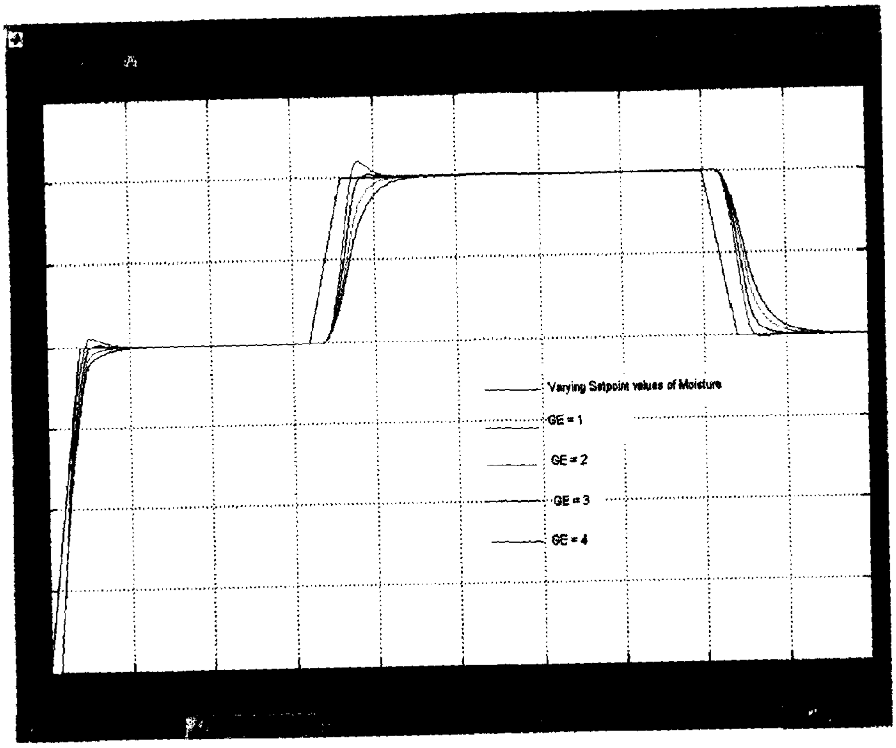

Figure 4.19 Simulation results of moisture for varying input servo model for four different values of GE = 0.1, 0.15, 0.25 and 0.4.

It can be seen from the Figure 4.19 that as the value of GE increases, the overshoot also increases, but the risetime decreases i.e. the response becomes more abrupt to the changing values of the input. The changing values of GE are not at all affecting the offset value of the system. The optimum value of GE has thus been selected as 2 as this value gives almost no overshoot and responds a bit faster than the value of GE = 1.

Now the model of Figure 4.18 is further made to run as Fuzzy –PD model, therefore the value of GCE is introduced in the system along with the above tested values of GU and GE, while keeping GIE=0.

4.3.2(b) Fuzzy-PD model:

Different values of scaling gains are taken as GE = 2, GIE = 0, GCE = 1, 5, 10 and 20. The simulation results for the same can be seen in the Figure 4.20.

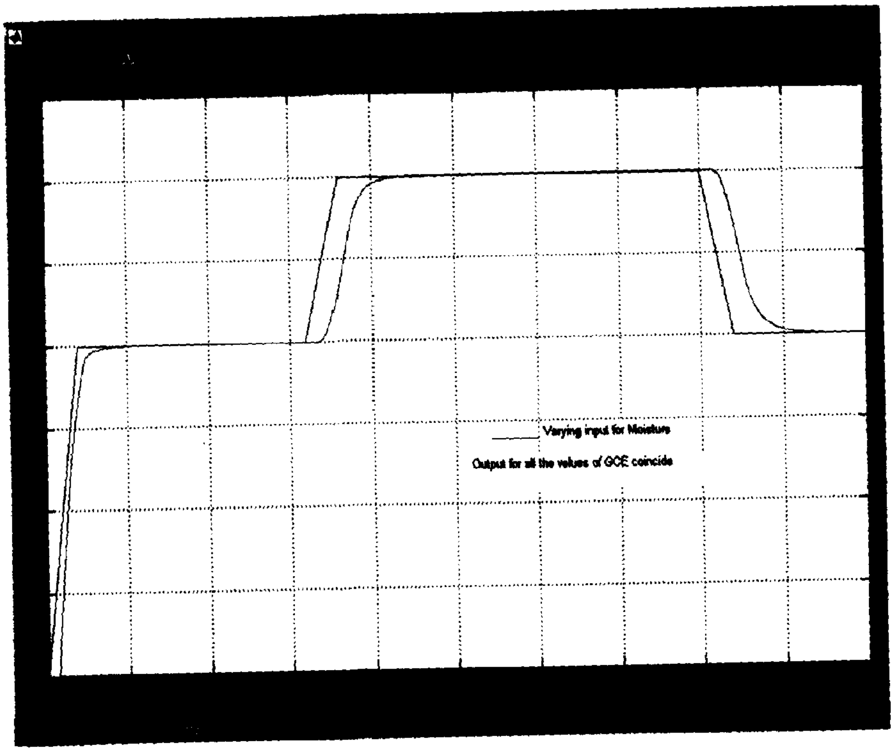

Figure 4.20 Simulation results for Fuzzy-PD models for variable input for four different values of GCE = 1, 5, 10, 20.

As can be seen from Figure 4.20, the graphs for all these values of GE almost coincide each other, hence the effect of GCE is almost insignificant in the response.

The value of GCE has no significant effect on the response of the system, except for the value of risetime that too in a very small ratio. As the value of GCE increases, the risetime decreases. Thus from the above experiments, the optimum value of GCE for the above process is taken as 1. Now the integral constant (GIE) is introduced into the system so that it works like Fuzzy-PD+I model.

4.3.2(c) Fuzzy-PD+I model:

Different values of the scaling gains are given as: GE = 2, GCE = 1, GIE = 0.0001, 0.00001, 0.000001, 0.0000001.The output can be seen in the scope window of Figure 4.21.

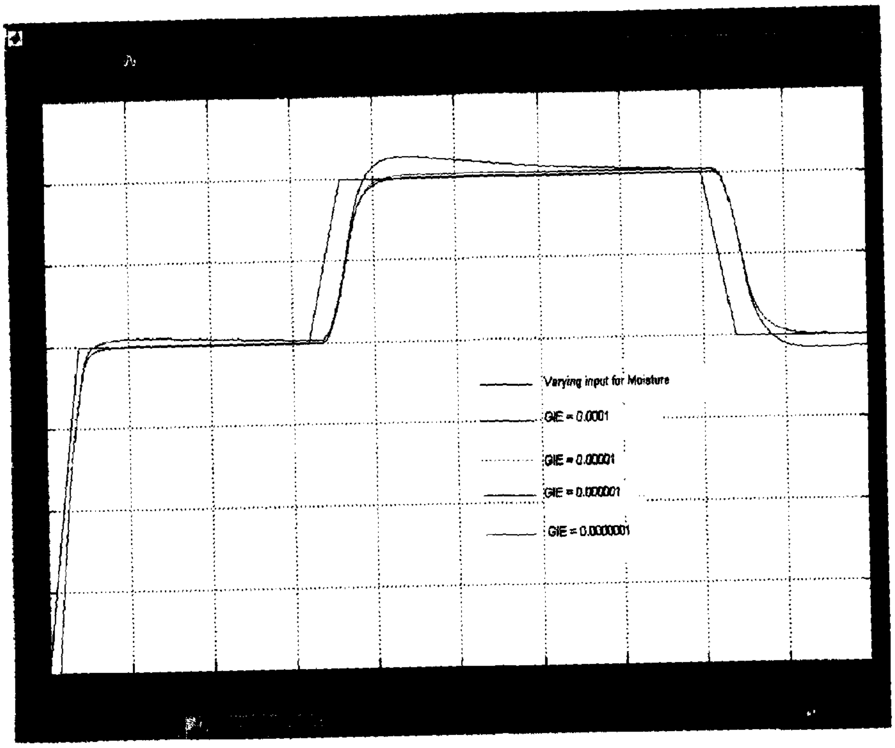

Figure4.21 Simulation results of moisture for varying input servo model when different values of gains are GE = 2, GCE = 1, GIE = 0.0001, 0.00001, 0.000001 and 0.0000001

Increasing the value of GIE introduces the overshoot in the system. As the value of GIE is increased, the offset is also increased. As seen from these results that lesser the value of GIE better is the response, but for GIE=0.00001, 0.000001 and 0.0000001 the response is almost overlapping. Thus we take GIE= 0.00001 as the optimum value, as larger values implies that steady state error are eliminated more quickly.

As can be seen from the above tests that the optimum value of all the scaling gains can be found and the system can be tuned for a better response. Here the optimum values selected from the above tests are GE= 2, GCE= 1, GIE= 0.00001and the response for the system using these values of gains is shown in Figure 4.22. Still further improvements can be done by changing the gains if required, as individual tuning of gains is also possible.

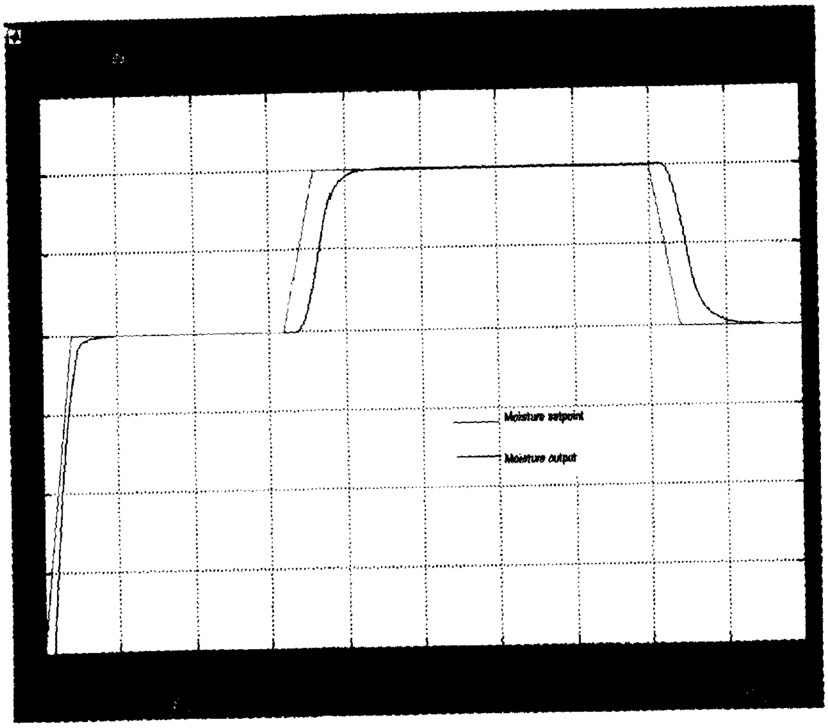

Figure4. 22 The moisture output using the Fuzzy Logic Controller

Further the tests are performed for the conventional PID controller and the results are analyzed.

4.4 Conventional PID

The servo model for the above nonlinear system using a conventional PID controller is developed and can be seen in Figure 4.23. The model shows a simple feedback loop which has a summing element used as a comparator to evaluate error; the evaluated error is given to a PID controller the output of which is given as input to the Process (Gm) through a final control element with unity gain and no delay. The output of the process is given to the output block as well as feedback to the comparator to evaluate error by comparing it with the input that comes through the input block. The model has been tested for different values of K_P, K_D and K_I and after simulation the results are compared with the output of the Fuzzy Logic Controller.

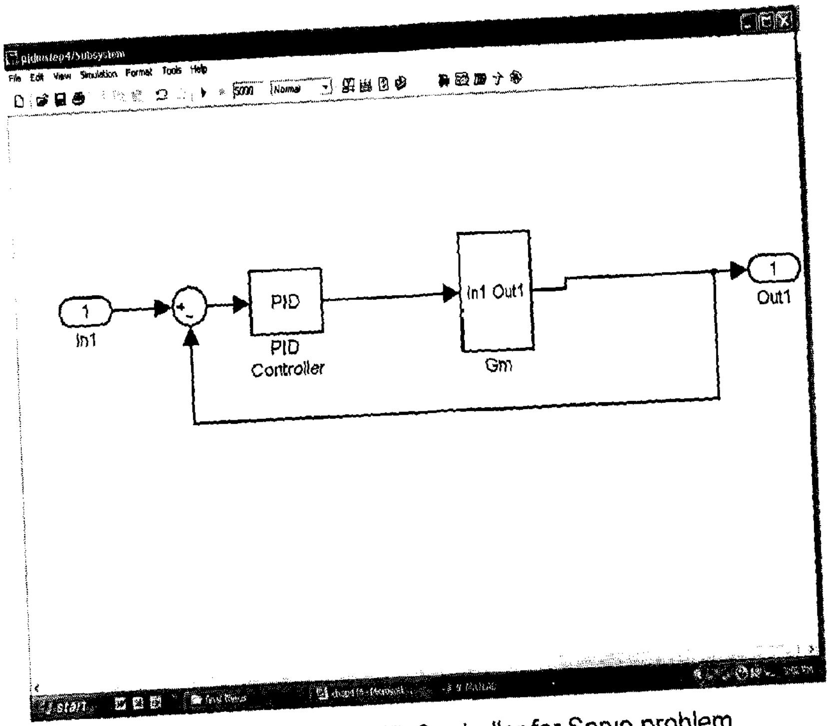

Figure 4.23 Conventional PID Controller for Servo problem

Now the systems response is found using a conventional PID controller for the step input. Different values are assigned to the constants and the response is analyzed. First the effect of the Proportional constant (K_P) is seen on the system, thus all other gains are kept zero and K_P is assigned some value.

4.4.1 Servo model for step input using PID controller

4.4.1(a) P-Type Controller

In this case only the Proportional gain constant, K_P is given some specified value and the other two gains i.e. the differential (K_D) and integral (K_I) gains are kept zero. Tests were performed for $K_D = 0$ and $K_I = 0$ and different values of K_P are taken as: 3, 2, 1 and 0.1. The simulation results for the same can be seen in the scope window of Figure 4.24.

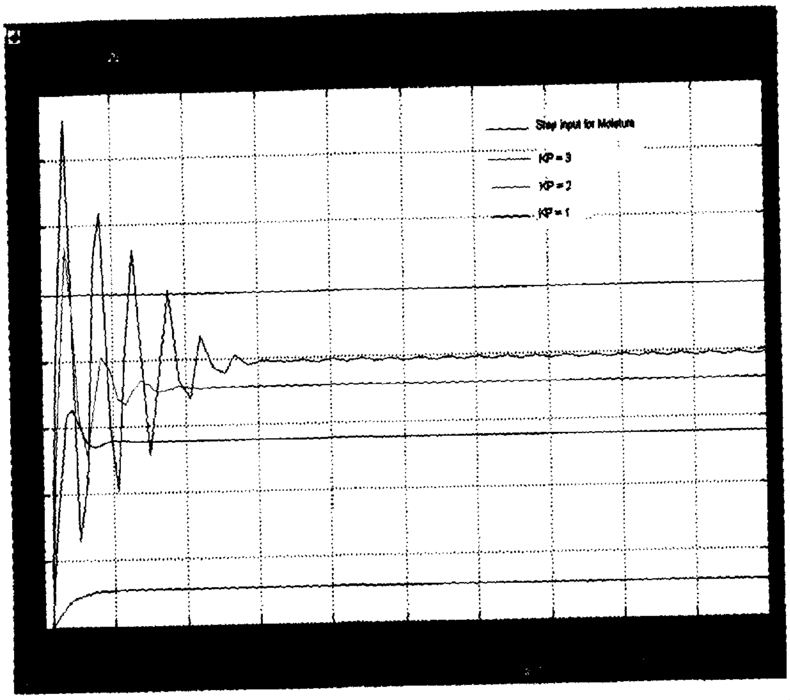

Figure 4.24 Output for step input- servo model for moisture control when the values of different gains are: $K_P = 3, 2, 1$ and 0.1, $K_D = 0$, $K_I = 0$

It was found that when the step input is given to the model of Figure 4.23, increasing the value of K_P, the offset is reduced but the system response became more and more oscillatory and hence the system became unstable. On further increasing the value of K_P the response became even more oscillatory. Thus it can be said that the offset is reduced at the cost system stability. From the above tests the optimum value of K_P was taken as 2. Further tests are performed to find the results for different values of K_D and hence the system works as a PD type of controller.

4.4.1(b) PD-Type Controller

As it is a PD type of controller therefore K_I is kept zero. Thus the simulation is performed for K_P as 2 and K_I as zero and different values of K_D are taken as 1, 10, 20, and 50 and the results of simulation can be seen in Figure 4.25.

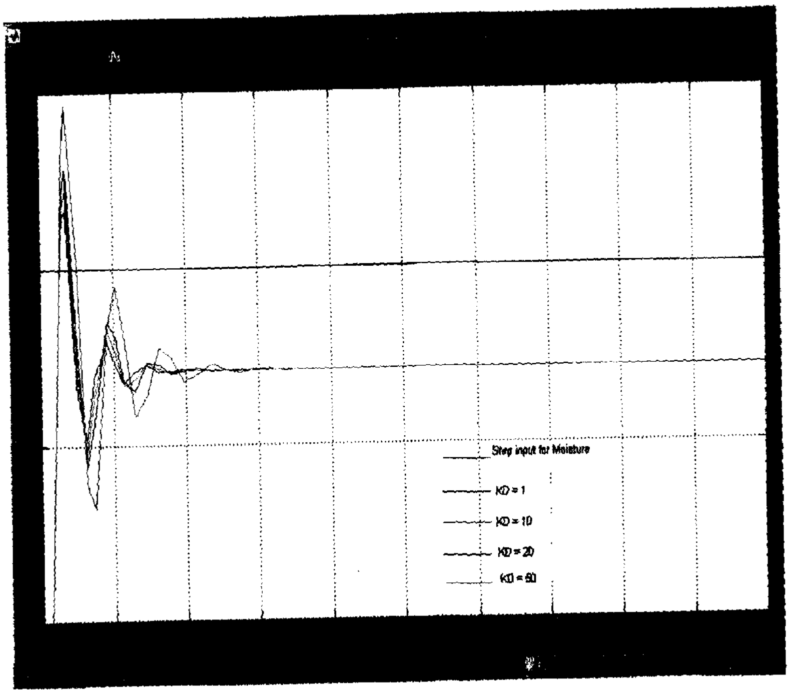

Figure 4.25 Output for step input- servo model for moisture control when the values of different gains are: $K_P = 2$, $K_I = 0$, $K_D = 1, 10, 20, 50$.

It is clear from Figure 4.25 that as the value of K_D increases the overshoot increases and also the settling time, but the change in the value of K_D has no effect on the rise time and offset of the system, thus a value of $K_D = 1$ will be taken as the optimum value.

4.4.1(c) PID-Type Controller

Now the effect of integral part is analyzed by introducing the K_I part in the system. The optimum values of K_P and K_D are taken as: $K_P = 2$ and $K_D = 1$ and different values of K_I are taken as $K_I = 0.0001$, 0.00005, 0.00001 and 0.000005. The model is simulated and the results for the same can be seen in Figure 4.26.

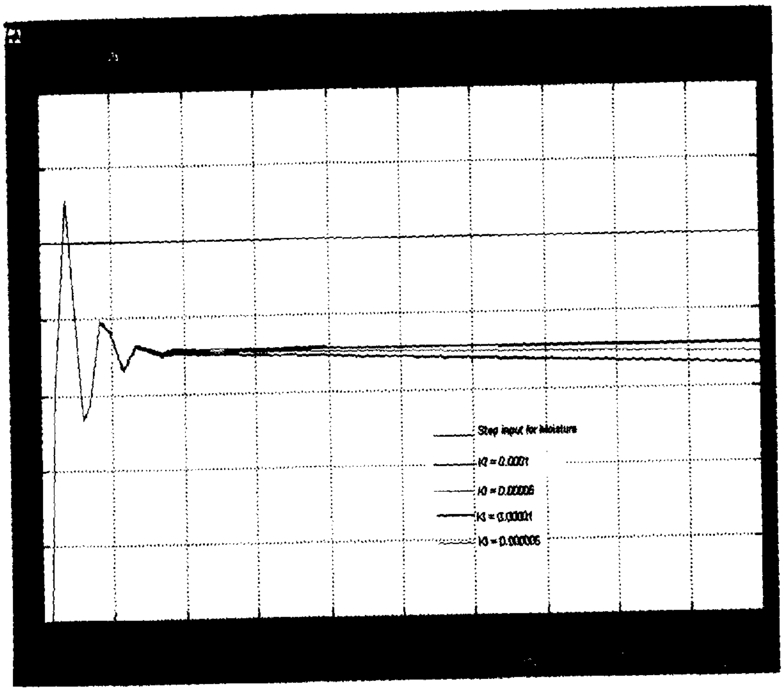

Figure 4.26 Output for step input- servo model for moisture control when the values of different gains are: $K_P = 2$, $K_D = 1$, $K_I = 0.0001, 0.00005, 0.00001$ and 0.000005

From the simulation results of Figure 4.26 it is clear that larger the value of K_I more is the offset in the system, rather the system becomes unstable. But a value smaller than 0.00001 has almost insignificant affect on the offset. Thus from the above tested values the value of $K_I = 0.00001$ is taken as the optimum value.

If we compare the results for the FLC and a PID controller the results of a FLC are far better than the results for a PID controller. Again tuning for the scaling gains of the FLC can be easily done to remove the offset in the system without increasing the oscillations as both the offset and the oscillatory behavior are controlled by different parameters. The similar type of tests is now performed for the variable input servo model instead of the step input.

4.4.2 Servo model for variable input using PID controller

The same model of Figure 4.23 using a PID controller is simulated for varying setpoint values of moisture and these varying values are taken from

Table 4.1. First a P-Type controller is made to run and then further PD and PID models are simulated.

4.4.2(a) P-Type Controller

In this case only the Proportional gain constant i.e. K_P is given some specified value and the other two gains i.e. the differential (K_D) and integral (K_I) gains are kept zero. Tests are first performed for K_P = 2.5, 2, 1 and 0.5, while K_D and K_I are kept to zero and the simulation results for the same can be seen in the scope window of Figure 4.27. It is found that for the varying setpoint for moisture, on increasing the value of K_P, the offset is reduced but the system response became more and more oscillatory and hence the system became unstable. On further increasing the value of K_P the response became even more oscillatory.

Figure 4.27 Response for a conventional PID controller for moisture with gain values as K_P = 2.5, 2, 1and 0.5, K_D =0, K_I =0.

As can be seen from Figure 4.27 that as the value of K_P increases the offset is reduced but the oscillatory behavior increases. Tests were also made for some more values of K_P and it was found that the system became quite unstable as the value of K_P increased further, for K_P = 10 the y-axis takes the value of 8×10^{26}. This shows that the system becomes quite unstable on increasing the value of K_P. Thus we can say that the offset can be reduced to some extent but at the cost of an unstable system, while this was not the case for the FLC as there were two factors which were controlling the value of K_P i.e. GU and GE, where GU was mainly responsible for the system offset and GE for the oscillatory behavior. Thus both the parameters can be improved simultaneously, which is not possible in case of a normal Conventional PID controller.

From the above tested values, $K_P = 1$ is taken as the optimum value for the proportional constant. Further tests are performed to find the optimum value of K_D.

4.4.2(b) PD-Type Controller

For the model of Figure 4.23 to behave like a PD-Type of Controller, the term K_D is assigned some value instead of zero. Now $K_P = 1$, and $K_I = 0$ and different values of K_D are taken as: $K_D = 0, 1, 10$ and 100. The simulation results for these values can be seen in the scope window of Figure 4.28.

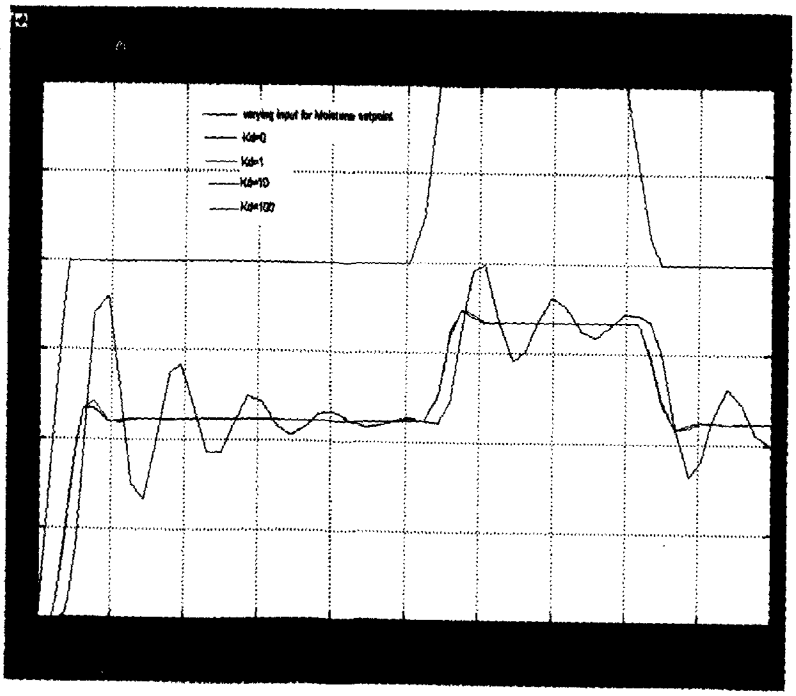

Figure 4.28 Response for a conventional PID controller for moisture with gain values as $K_D = 0, 1, 10$and 100, $K_P = 1$, and $K_I = 0$.

From the simulation results of Figure 4.28 it can be seen that for the values of K_D up till 10, there is no significant effect on the output. But as the value of K_D is increased to 100 the oscillatory behavior increases, also the overshoot increases. Some more tests were performed and it was found that K_D = 1 was giving the best output for the system.

4.4.2(c) PID-Type Controller

To make the model to run as a PID controller, the K_I term is introduced to the model of Figure 4.28. Different values are assigned to the integral term and the simulation is performed. The different values of K_I are taken as K_I = 0.0000001, 0.000001, 0.00001, 0.0001 and the other constants are given the values as K_P = 1, and K_D =1. The simulation for these values is performed and the results for the same are seen in the scope window of Figure 4.29.

Figure 4.29 Response for a conventional PID controller for moisture with gain values as K_P = 1, K_D =1 and K_I =0.0000001, 0.000001, 0.00001, 0.0001.

As can be seen from Figure 4.29 that for first three values the results are almost same, while for the last value, the offset is increased. If the value is increased beyond this limit (tests were done for K_I = 0.0005 and even higher values) makes the system quite unstable. If the value of K_I is decreased still further there is no significant change in the output, moreover small values of K_I implies that the steady state errors are eliminated slowly. Thus the optimum value of K_I for the above system is taken as K_I = 0.00001.

4.5 Conclusion

From the above tests it can be concluded that the Fuzzy controller can be tuned in a far better way to get good results. Also it is worth mentioning here that the varying values of moisture are not too large i.e. the maximum value recorded here was only 6%, so the output of a conventional controller was able to reach it to some extent with some offset. Thus it can be said that a fuzzy logic controller gave appreciable results for step input and varying input for the moisture control SISO system.

Chapter 5
Interactive system

5.1 Interactive model development

Severe interactions between the two controlled variables i.e. the basis weight and moisture make the control system of paper making process difficult. It is well known that when the basis weight controller increases the stock flow by regulating the basis weight valve opening, the amount of water i.e. the moisture content of the paper increases. Now to control the moisture content in the web the steam flow is regulated, the basis weight will decrease; therefore it becomes difficult to maintain the balance between the two controlled variables. Control engineering techniques decouple such interactions. Thus the Process (Gp) as a whole is taken as an interactive system in which both the controlled variables i.e. the BW and the Moisture are affected by the variations in any one of the controlling parameters i.e. the basis weight valve opening (BWVO) and the steam shower valve opening (SSVO). In the previous chapters (Chapter 3 & 4) the system was assumed to be Non-interacting and the individual controlled parameters i.e. the BW was individually monitored by the BWVO and the Moisture was individually controlled by varying the SSVO. Different types of Fuzzy logic controllers were developed and the effects of various scaling gains were discussed in detail.

In this chapter the effects of variations due to various scaling gains are not discussed, as this thing has already been discussed in Chapter 3 and 4 for basis weight and moisture respectively and these effects remain same and affect both the outputs in a similar manner. Using the results of Chapter 3 & 4, the optimum values of various scaling gains for PD+I type FLC, and the constants for PID controllers for both step and varying inputs are found. Here emphasis has been laid on the interaction between the two parameters i.e. the basis weight and moisture and their effects on each other have be estimated and discussed.

First the system has been simulated for one loop closed and other open and vice versa and the effect of one closed loop has been analyzed on both the parameters. Simulation is also done when both the loops are closed and their affects on each other are also discussed. All these cases are simulated using both Fuzzy logic controller and a Conventional PID controller and the results for both these cases are discussed.

(i) Using a Fuzzy Logic controller.
(ii) Using a Conventional PID controller.

The simulation results for all the three cases i.e. when one loop is closed and other is open and vice versa and when both the loops are closed has been shown on the same scope window so that a proper comparative study can be made for the outputs.

First the controller is tested for the step input and then the simulation is done for the varying input.

5.2 Servo model for Step input using FLC

In the step input servo model developed in this case, two Fuzzy Control systems are used one for the basis weight control and other for the moisture control. The number and type of membership functions used for the FLC for basis weight control is the same as used in section 3.2 (Appendix P3.1), only the system was tuned for the optimum values of scaling gains. The values of scaling gains obtained for the basis weight controller are taken as: GU = 0.0648, GE =0.1, GCE = 1, GIE = 0.00000001. The FLC used for the moisture control is the same as used in section 4.2 (Appendix P4.1). The different values for scaling gains for the moisture are obtained as: GU =1.472, GE = 0.01, GCE = 1, GIE = 0.0000001. These details will be used for the three cases discussed in this section.

5.2.1 Case I: One loop is closed and other is open.

a) The BW loop is closed and M loop is open:

When the basis weight loop is closed and the moisture loop is open, the basis weight output is controlled by taking a feedback of this output, while the moisture output is left uncontrolled i.e. open. The model of Figure 5.1 is used. In this model we have a process Gp from which the two variables BW and M are simultaneously measured on-line. The system has two Fuzzy Logic Control systems one for controlling the basis weight and other for controlling the moisture. The loop for the basis weight is closed while that for the moisture is open. The setpoint variations for both basis weight and moisture are taken in the form of step input in this case. A scope window is provided to analyze the effect of closed basis weight loop and open moisture loop on both the outputs i.e. the basis weight output and moisture output.

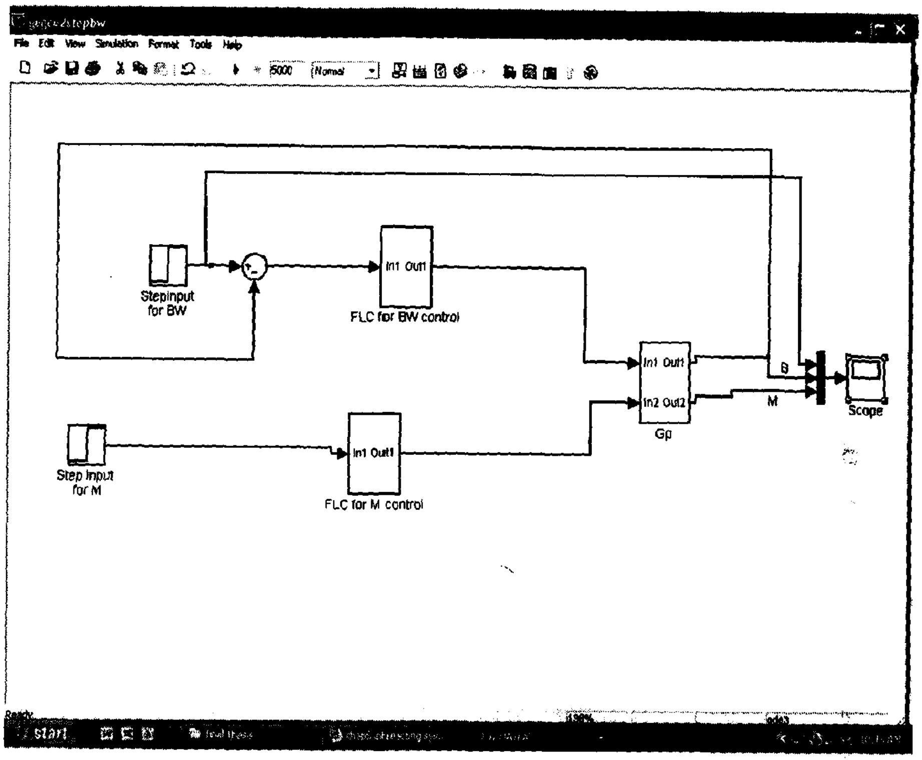

Figure 5.1 Servo model for step input when the BW loop is closed and M loop is open

As the BW loop is closed while the moisture loop is open, the BW output is fedback to the comparator so that the error (in comparison with the basis weight setpoint) in the basis weight is calculated. The error so obtained is given to the Fuzzy logic control system. The output of this FLC system is given to the basis weight valve opening (BWVO) which is the controlling the basis weight at the headbox. The moisture loop is open and the moisture input (setpoint) is given to the FLC system for the moisture. The output of this FLC system is given to the steam shower valve, but as this loop is open hence the steam shower valve is not being monitored according to the variations in the moisture output. The variations in the BW output is due to the basis weight setpoint variations and the variations in the moisture output is due to the basis weight setpoint variations and can be seen on the same scope window, of Figure5.2.

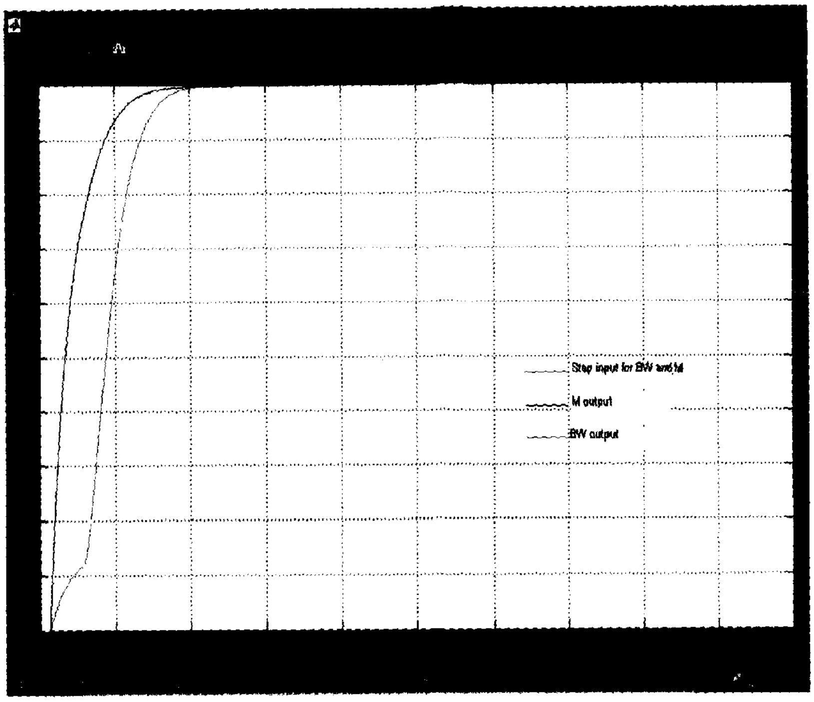

Figure 5.2 Simulation results of step input for BW and M output when BW loop is closed and M loop is open.

The scope window of Figure 5.2 shows the results for the BW output and the Moisture output for step input servo model. It is observed that both BW and M outputs move in a controlled manner, though one of the loop is open.

b) The M loop is closed and BW loop is open:

When the BW loop is open and the Moisture loop is closed as shown in the model of Figure 5.3. In this case, the moisture output is controlled while the basis weight output variations are left uncontrolled. In this case, both the outputs vary according to the moisture setpoint variations. The details for the FLC systems used both for BW and Moisture are same as that mentioned above.

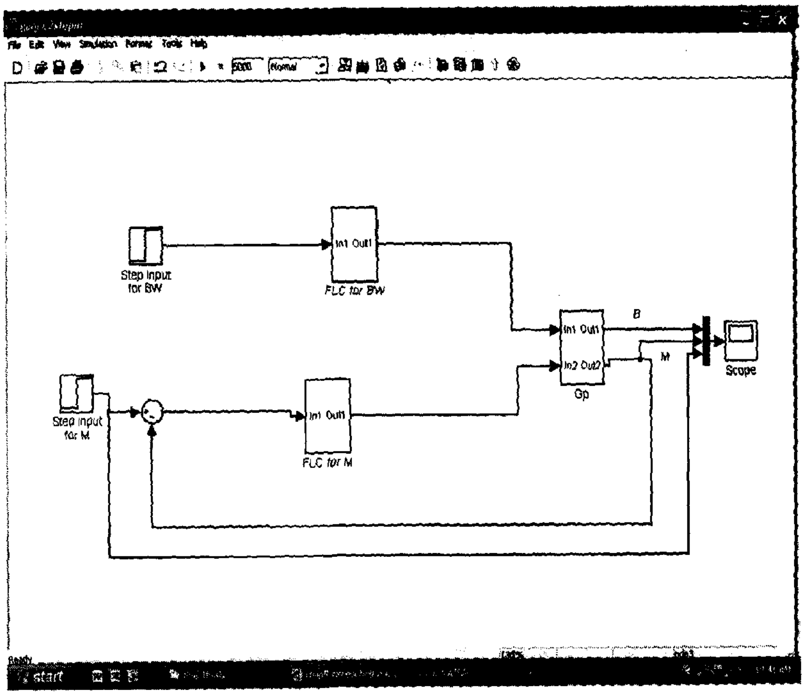

Figure 5.3 Servo model for step input when M loop is closed and BW loop is open

Now as the BW loop is open thus the BWVO is not being monitored in accordance to the BW output changes. Thus the output for both BW and M are now being affected due to the variations in the steam shower valve opening. The simulation results for the same can be seen in the scope window of Figure5.4

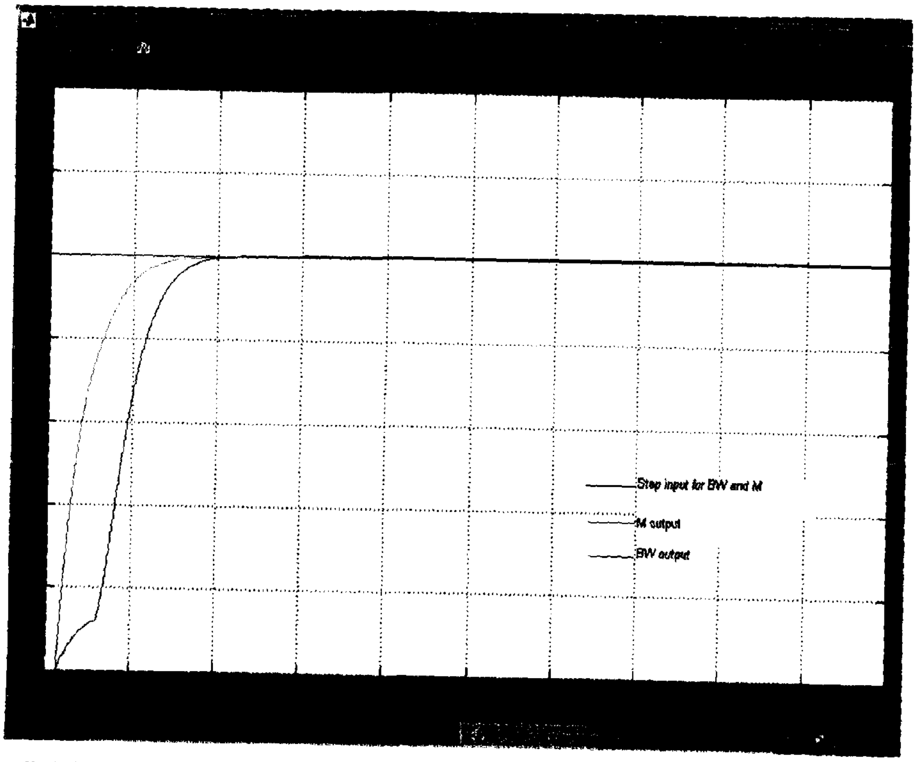

Figure 5.4 Simulation results of step input for BW and M output when M loop is closed and BW loop is open.

Again as can be seen from Figure 5.4 both the outputs for the basis weight and moisture move in a controlled manner, when only the moisture loop is closed while the BW loop is open. Now the system output is analyzed when both the loops are closed.

5.2.2 Case II: Both the loops are closed.

When both the basis weight and moisture loops are closed the model developed can be seen in the simulink window of Figure 5.5. It has two Fuzzy Logic Control Systems one for the basis weight control and the other for moisture control. The step input is given as setpoint for both basis weight and moisture.

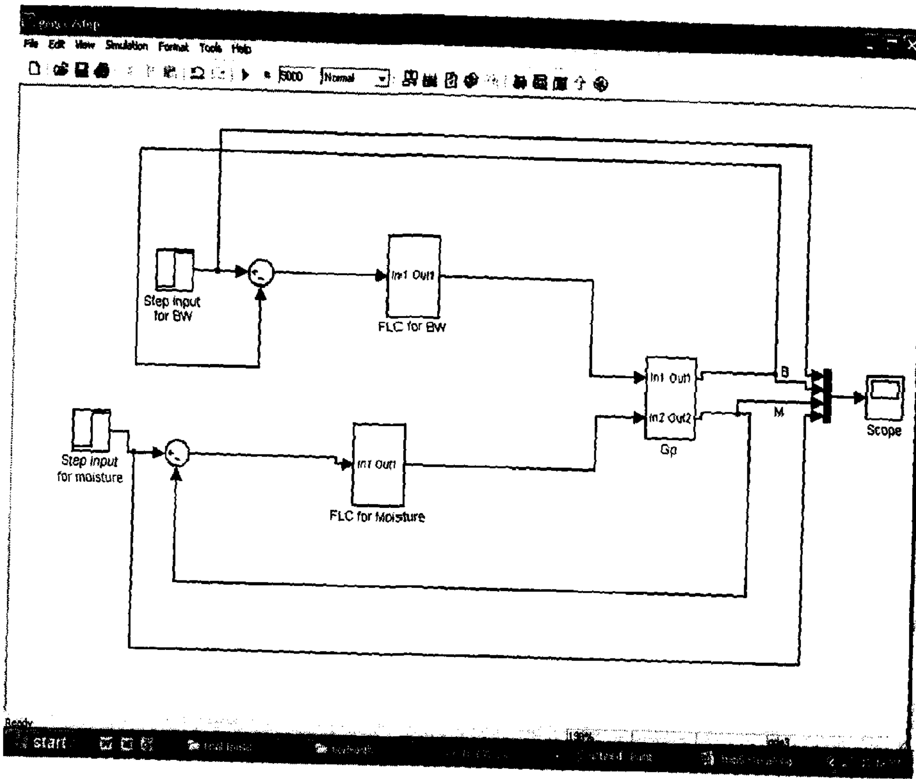

Figure 5.5 Servo model for step input when both the loops are closed

According the model of Figure 5.5 the variations in both the outputs i.e. the Basis Weight and Moisture will simultaneously be monitored by the change in the BWVO and the SSVO. The model is simulated and the output for both the basis weight and the moisture can be seen in the scope window of Figure 5.6.

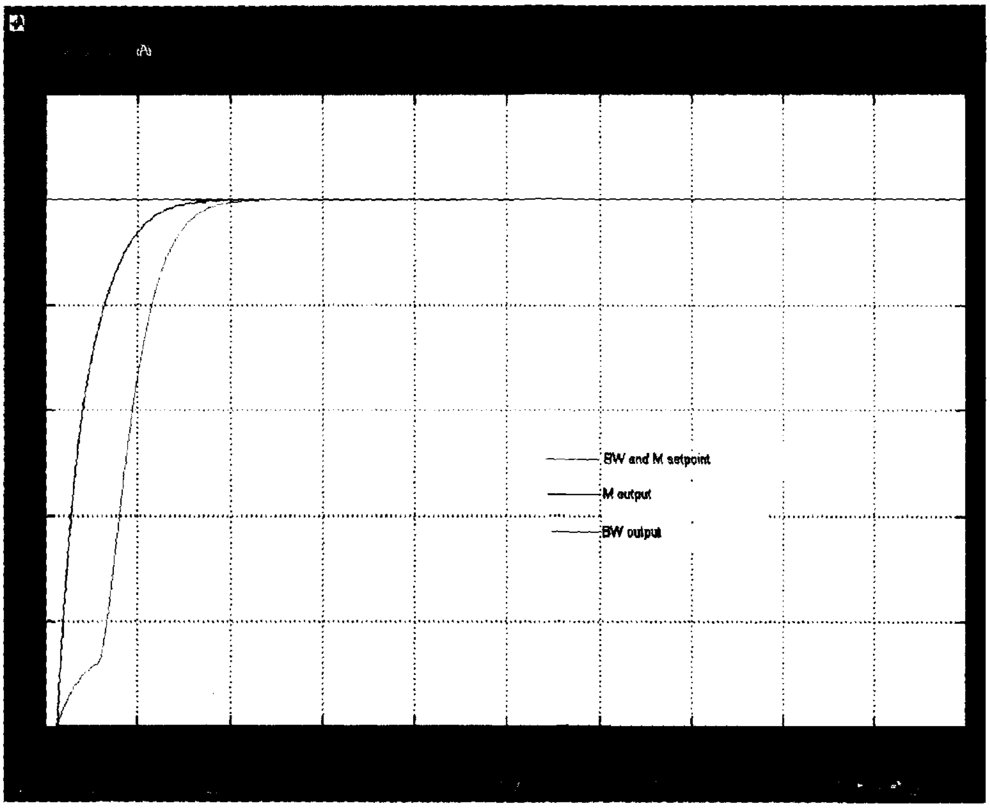

Figure 5.6 Simulation results of step input for BW and M output when both the loops are closed

As can be seen from Figure 5.6, the output for both basis weight and moisture moves in a controlled manner according to the setpoint variations i.e. the step input for both basis weight and moisture.

The combined effect of all the three cases on the basis weight output can be seen in the scope window of Figure 5.7 & 5.8. Similarly the combined effects of all the three cases on the moisture output can be seen in the scope window of Figure 5.9 & 5.10.

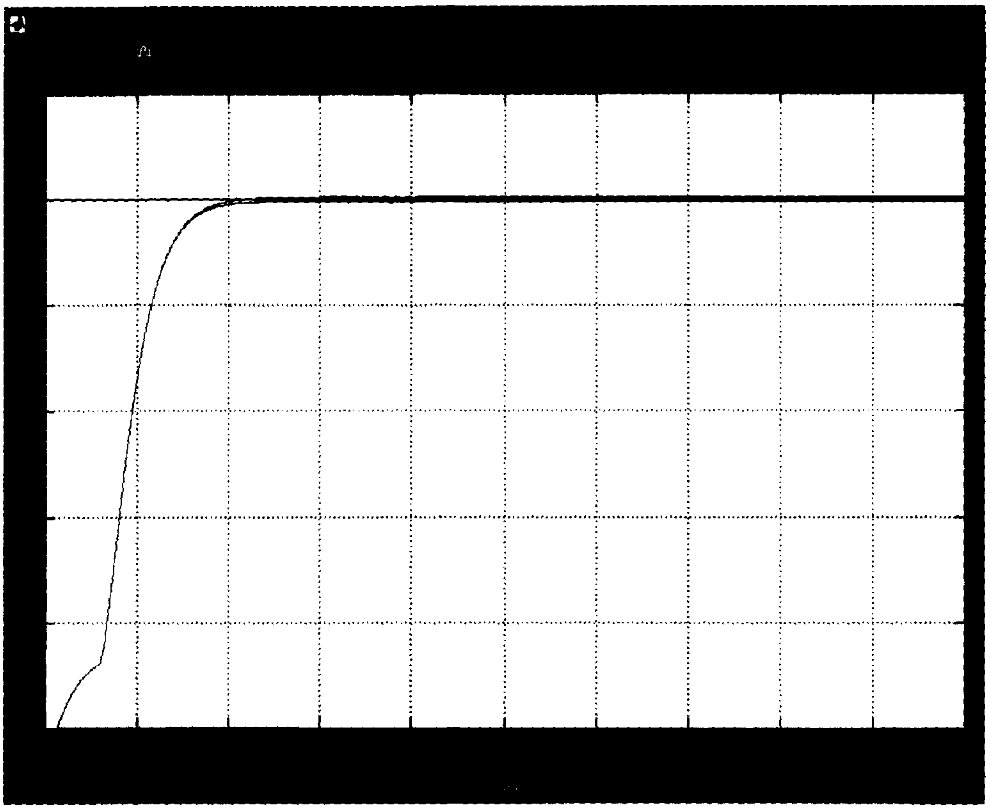

Figure 5.7 Combined simulation results for the basis weight output for the step input servo model using a Fuzzy Logic controller.

As can be seen from Figure 5.7 that all these curves almost coincide with each other, the explanation for the simulation results of all the above cases can be done by taking the enlarged view of Figure 5.7 which is given in Figure 5.8.

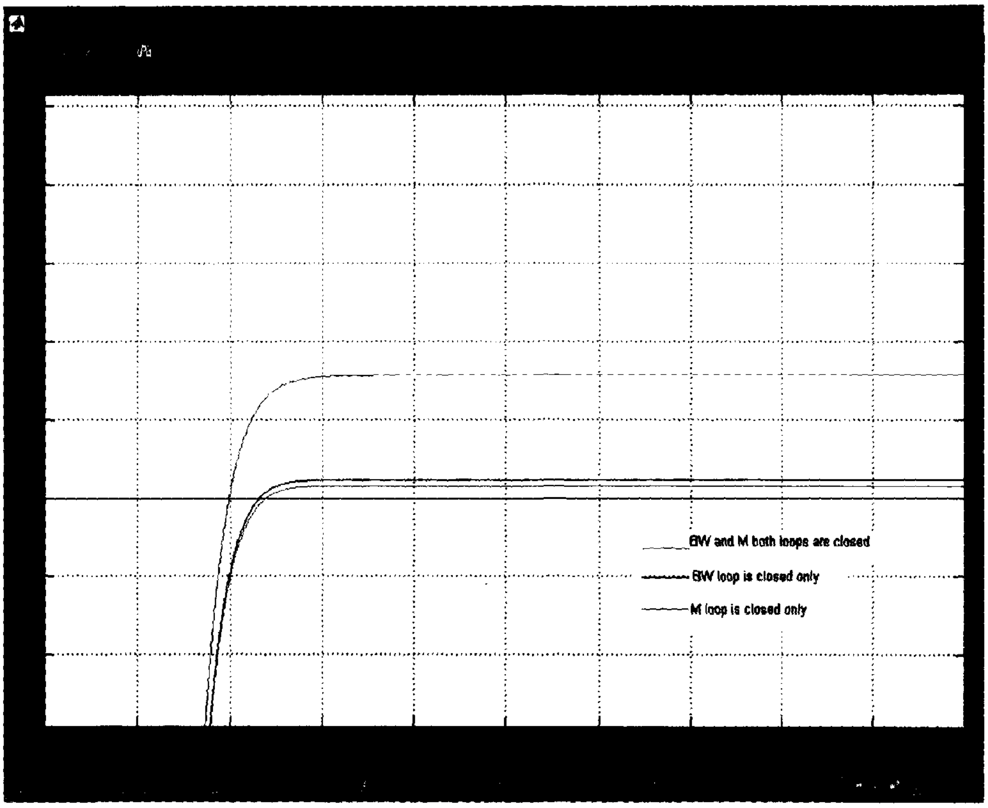

Figure 5.8 Enlarged view of combined simulation results for the basis weight output for the step input servo model using a Fuzzy Logic controller.

Both loops are closed: In this case both the loops are closed i.e. both BWVO and SSVO are the controlling factor, hence the output i.e. the BW output is affected by changing both these factors.

BW loop is closed: For this case only the BW loop is closed therefore the BW output is only monitored due to the change in the BWVO i.e. only BWVO is the controlling factor, thus the output in this case is a bit more in comparison to that when both the loops are closed.

M Loop is closed: In this case only the SSVO is the controlling factor, as the moisture loop is closed and the BW loop is open, thus the BW output is varied according to the change in SSVO. It is clear from the above results that the effect of change in the output due to the variations in SSVO is the minimum. In the present case the BW output is monitored only by the change in the SSVO. The BW loop is open, hence no control in the BW output due to the BWVO. As the BWVO is set to a fixed value by the FLC, hence the BW output only moves according to the SSVO.

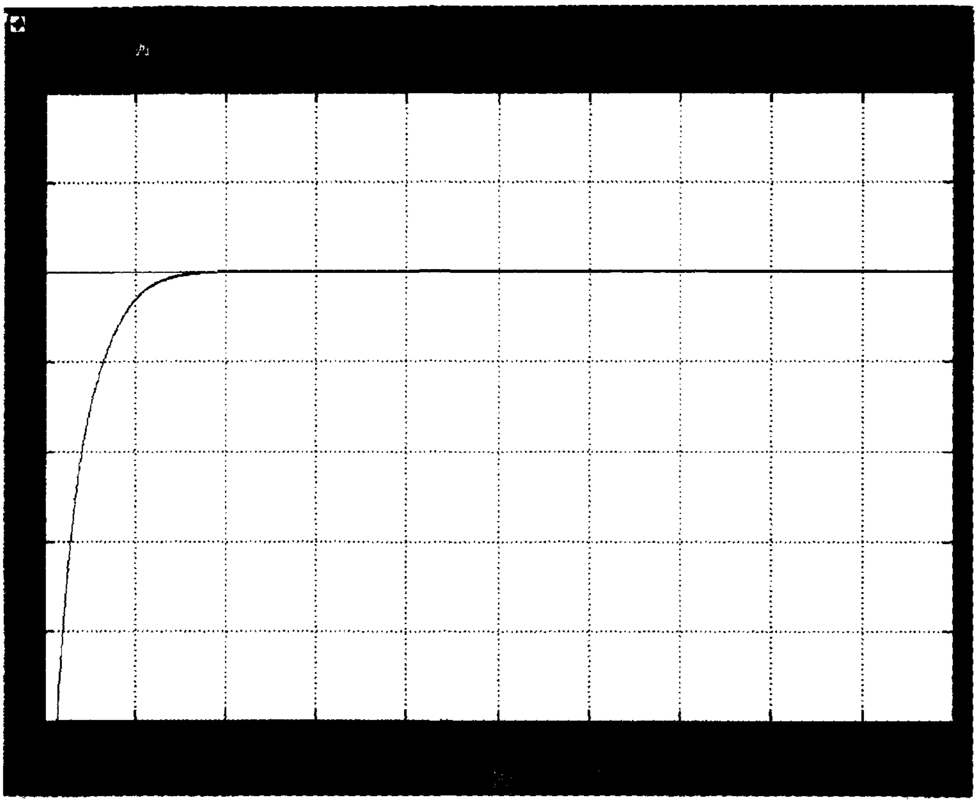

Figure 5.9 Combined simulation results for the moisture output for step input servo model using a Fuzzy Logic controller.

As can be seen from Figure 5.9 that all these curves almost coincide with each other. The explanation for the simulation results of all the above cases can be done by taking the enlarged view of Figure 5.9 which is given in Figure 5.10.

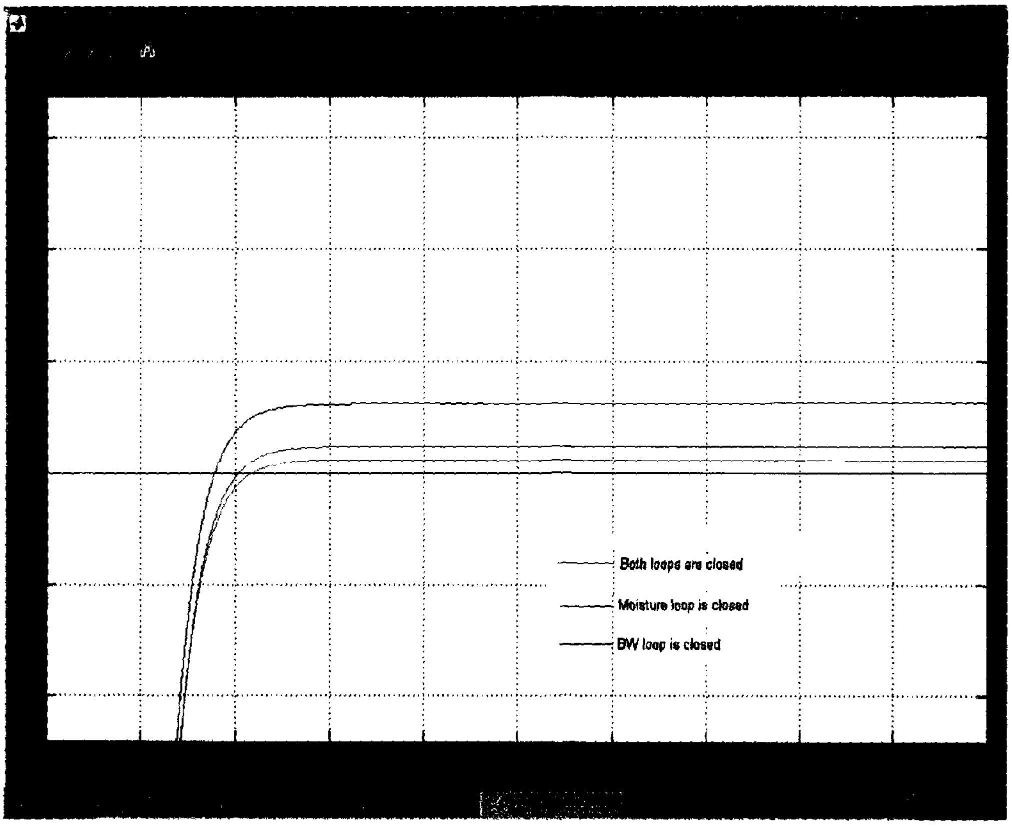

Figure 5.10 Enlarged view of moisture curve of Figure 5.9

Both the loops are closed: When both the loops are closed in that case the moisture output is affected by changing both the BWVO and SSVO, thus the Moisture output is having the minimum value.

BW loop is closed: In this case only the BW loop is closed while the moisture loop is open therefore, the changes in the moisture output is affected only by the variation in the BWVO i.e. BWVO is the only controlling factor, thus as can be seen from Figure 5.10, the output of moisture in this case is least affected in comparison to the other two curves.

Moisture loop is closed: When the moisture loop is closed and the basis weight loop is open, only SSVO is the controlling factor, thus the moisture output is affected by variations in the steam shower valve opening.

From the above simulation results it can be concluded that the change of any one parameter has its effect on both the controlled variables as discussed in Chapter 1. As seen from Figure 5.8 and 5.10 the basis weight valve opening change has more affect on the basis weight output while the steam shower valve opening has its effect more on the moisture output.

Now the simulation is done for the varying inputs servo model using FLC and the results for the same are discussed in section 5.3.

5.3 Servo model for varying input using FLC

Control engineering refers to a discipline whose main concern is with problems of regulating and generally controlling the behavior of a physical system. Here the physical system is the paper making process. The paper making is a vast multidisciplinary process, as discussed in the work we have only considered the two parameters i.e. the basis weight and moisture. Only the setpoint tracking is discussed thus the model developed for this case has two Fuzzy Logic Control systems one of them is used for the BW control and the other is used for the Moisture control. The system has four Fuzzy logic controllers in all, two controllers are of FPD+I type; which is used for the moisture/BW control in the loop and the other two are simple Fuzzy logic controllers, used to change the values of GU according to the changing demand of the input. The Fuzzy control system used for the basis weight is the same as used in section 3.3.2 (Appendix P3.2). The model is simulated and after a number of tests, the optimum values of the scaling gains are selected as: GE= 0.05, GCE=0.1 and GIE= 1×10^{-7}. The value of GU for the basis weight comes from the output of the fuzzy logic controller (Appendix P5.1). The varying setpoint values for the basis weight are taken from Table 3.3(Appendix). The Fuzzy control system used for the moisture is the same as used in section 4.2.3 (Appendix P4.2). The model is simulated and after a number of tests, the optimum values of the scaling gains are selected as: GE= 10, GCE=1 and GIE= 1×10^{-6}. The value of GU for the moisture comes from the output of the fuzzy logic controller (Appendix P5.2). The varying setpoint values for the moisture are taken from Table 4.1(Appendix).

The Fuzzy Logic Control system discussed above is used and the models for the two cases are developed.

5.3.1 Case I: One loop is closed and other is open.

a) The BW loop is closed and M loop is open:

When the basis weight loop is closed and the moisture loop is open, the model of Figure5.11 is developed. Here there are two Fuzzy control systems;

one for the basis weight control and the other for the moisture control. As the moisture loop, is open we have kept the moisture setpoint at a constant value of 3.96, while the value of BW is varied from 99 gsm to 138 gsm as per demand and these changing values are taken according to the readings of Table 3.3(Appendix). The data is stored in the m-file and is given as input from the workspace of Matlab.

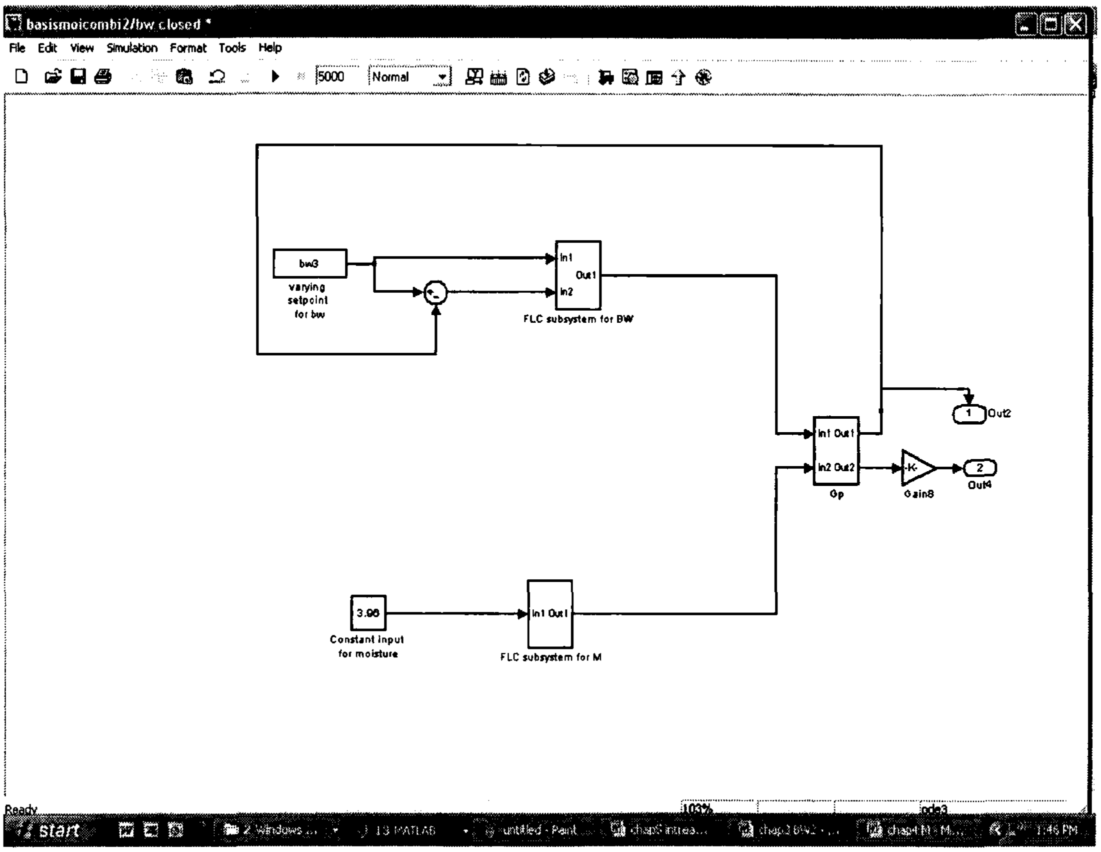

Figure 5.11 Servo model for varying input when The BW loop is closed and M loop is open

The above model has a constant value of the moisture thus the value of the SSVO is also maintained to a constant value, set by the Fuzzy logic control system used in the model. The value of the BW set-point is varying and so does the values of the BWVO vary according to the Fuzzy systems output. The effect of variations in the basis weight valve opening will have its affect both on the basis weight output and the moisture output. The model is simulated and the results of both Basis Weight and Moisture output can be seen on the scope window of Figure 5.12.

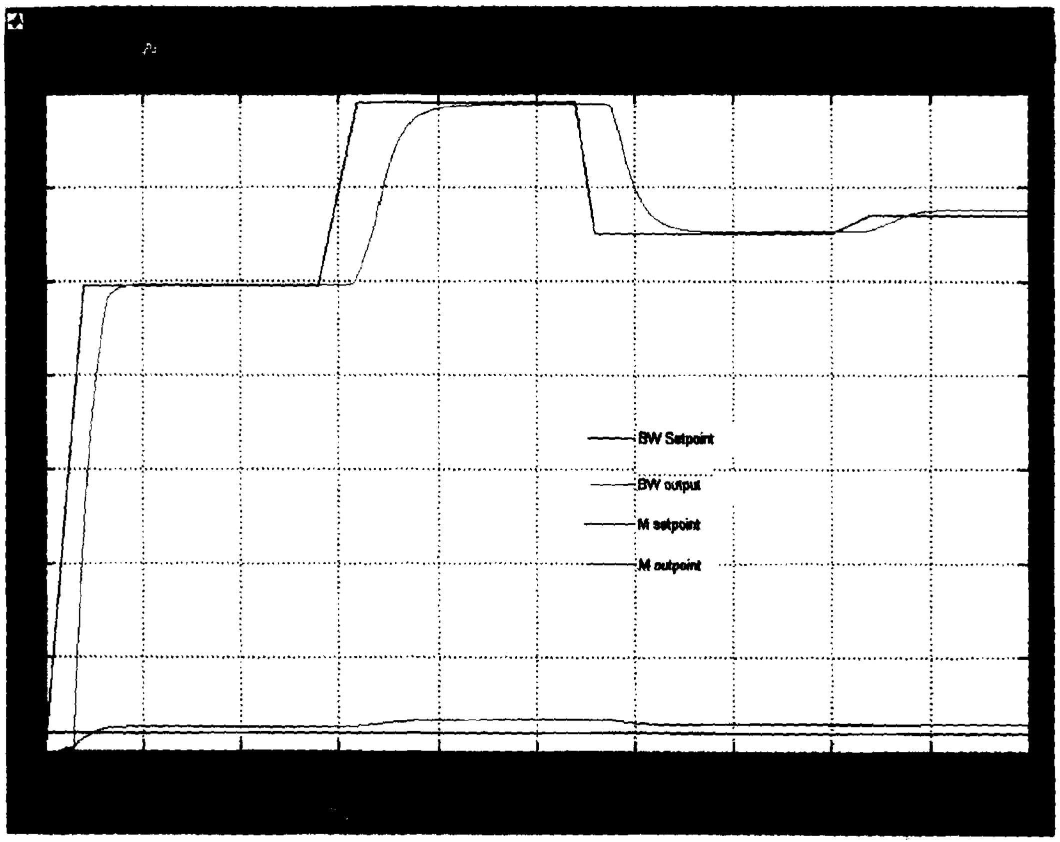

Figure 5.12 Simulation results of varying input for BW and M output when BW loop is closed and M loop is open.

It can be clearly seen from Figure 5.12 that as the value of basis weight setpoint varies so do the values of the basis weight output vary. This is so because the basis weight loop is closed and the output is thus fed back and the FLC system monitors the BWVO accordingly. Looking at the moisture curve in the Figure 5.12, it can be seen that though the moisture setpoint is kept at a constant value but the moisture output is no more a constant. The moisture curves moves according to the variations in the basis weight output curve. This means that the moisture output is monitored according to the changing values of BWVO. As the basis weight setpoint increases so does the basis weight output as governed by the FLC system. This increase in the basis weight output increases the moisture content of the paper as discussed in Chapter 1. The details for the same can be seen in the Table 5.1.

BW SP	BW O/P	M% RQ	M SP	M O/P	M% OB
99	98.79	4%	3.96	3.728	3.77%
138	136.95	2.86%	3.96	5.065	3.69%
110	109.85	3.6%	3.96	4.116	3.47%
114	114.62	3.47%	3.96	4.283	3.73%

Table 5.1 Data for the output of BW and M when BW loop is closed and M loop is open

Where:

BW SP= Basis weight setpoint

BW O/P= Basis weight output

M SP= Moisture setpoint

M O/P= Moisture output

M% RQ= Moisture% Required

M% OB= Moisture% Obtained.

b) The M loop is closed and BW loop is open:

A model developed for this case has the closed loop for the moisture while the basis weight loop is kept open. The model so made can be seen in Figure 5.13. The model has two Fuzzy Control Systems one for the basis weight and other for the moisture. The details for these Fuzzy Control Systems are given above. In the present case as the basis weight loop is open thus a constant value of 100 gsm is taken as the setpoint for the BW, and the varying values of the moisture are taken from the Table 4.1(Appendix). The data is stored in the m-file and is given as input from the workspace of Matlab.

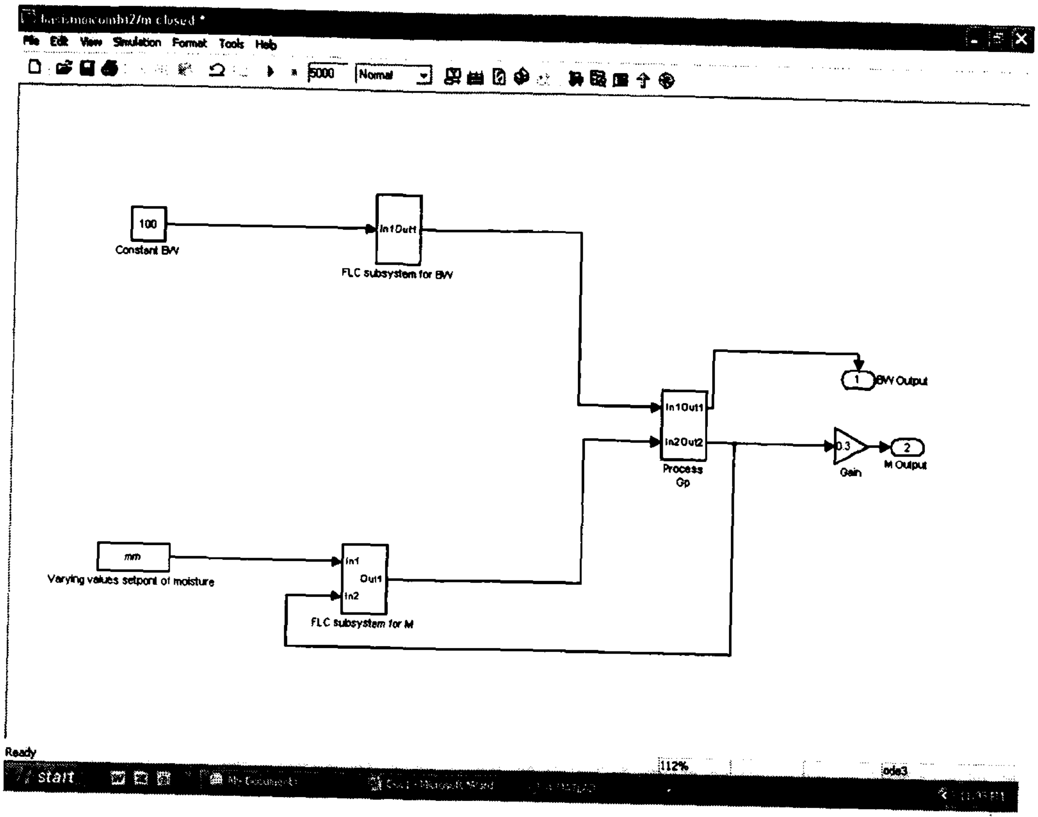

Figure 5.13 Servo model for varying input when The M loop is closed and BW loop is open

The model of Figure 5.13 is simulated and the results for basis weight output and the moisture output can be seen in the scope window of Figure 5.14.

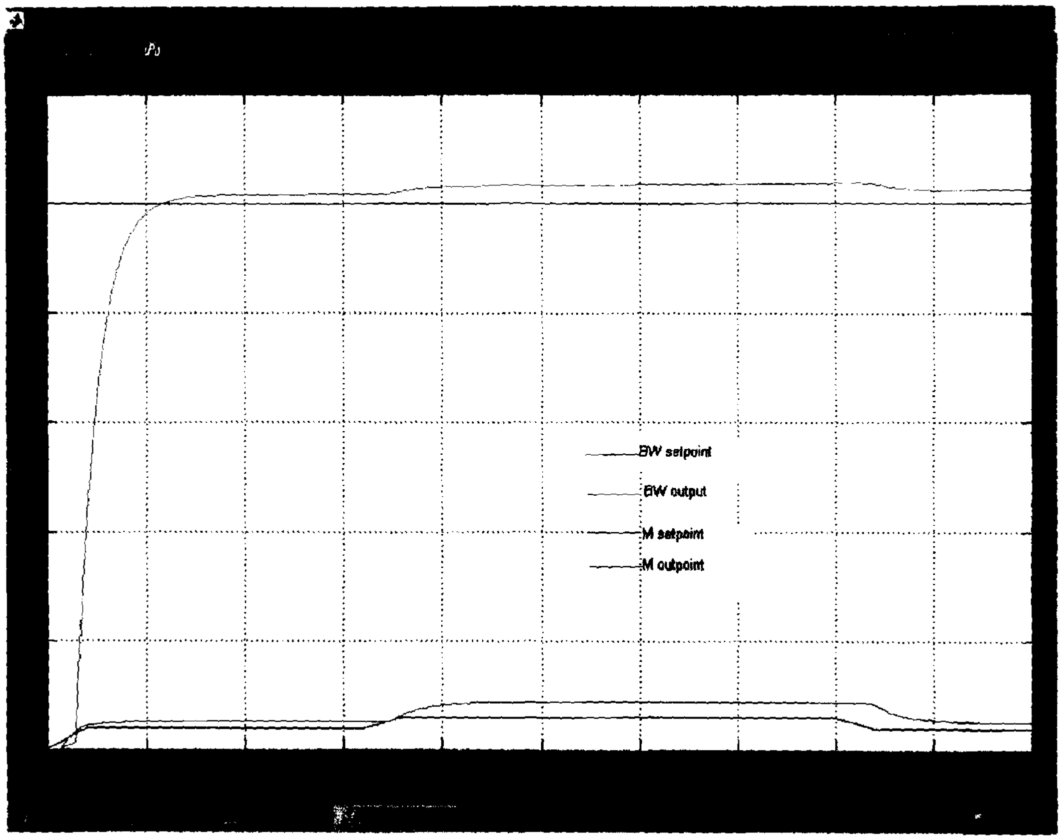

Figure 5.14 Simulation results of varying input for BW and M output when M loop is closed and BW loop is open.

As can be seen from the simulation result of Figure 5.14, the moisture setpoint varies according to the values taken from Table 4.1 (Appendix). As the moisture setpoint varies, so does the steam shower valve opening varies too, thus the moisture output changes according to the changing values of the moisture setpoint. The setpoint for the BW was kept at a constant value of 100gsm, but still the basis weight output varies according to the changes in the moisture output. This shows that change in the steam shower valve opening directly affects the change in the basis weight variations. As the moisture setpoint changes the FLC for moisture control changes the settings of the steam shower valve opening to incorporate the change in the moisture output. This change in the moisture profile directly affects the gsm of the web. This can be clearly be seen from the data of Table 5.2.

BW SP	BW O/P	M% RQ	M SP	M O/P	M% OB
100	101.3	4%	4	3.995	3.94%
100	102	6%	6	4.987	4.89%

Table 5.2 Data for the output of BW and M when M loop is closed and BW loop is open

Once the system has been analyzed for the one loop closed and the other open and vice versa, it has been observed that as it is an interacting system the change in the value of any one controlling parameter has the significant effect on the output of the other. Now the system is simulated for both the loops closed.

5.3.2 Case II: Both the loops are closed

The model of Figure 5.15 shows the combined effect when both the basis weight and moisture loops are closed. Thus the model has two Fuzzy Control Systems one for the moisture control and other for basis weight control. The optimum values of the scaling gains for both these controllers are used and the model is simulated.

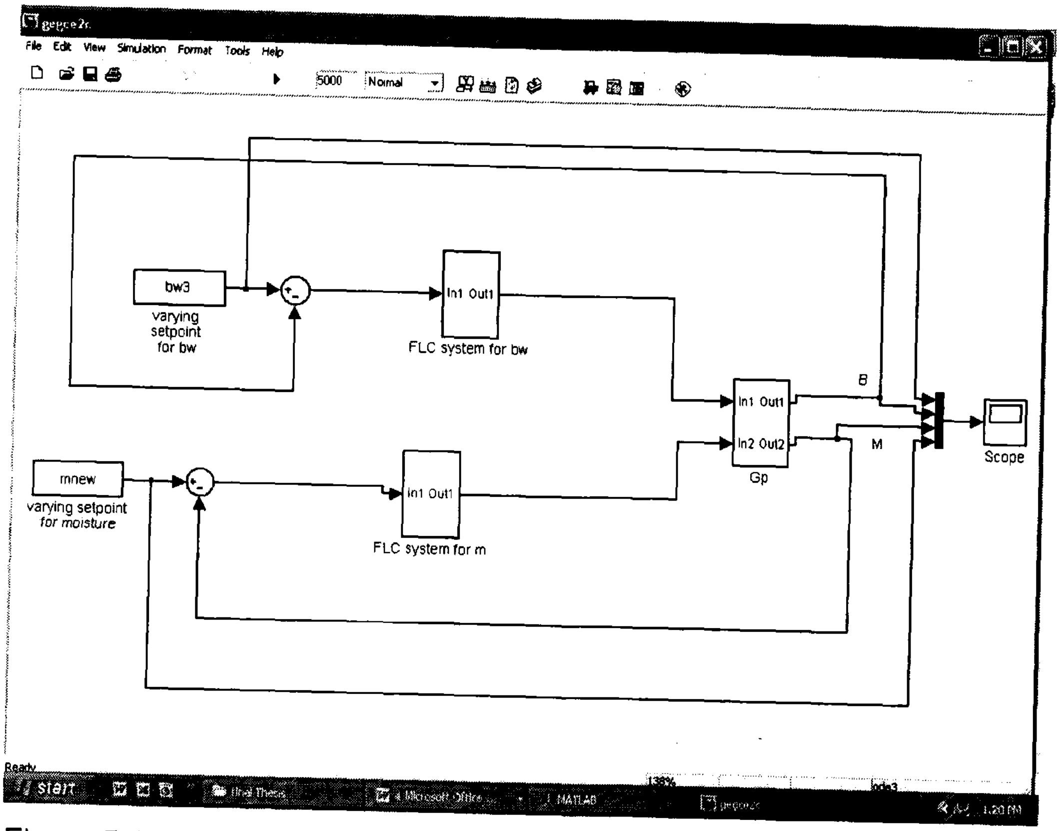

Figure 5.15 Servo model for varying input when both the loops are closed

The results for basis weight output and moisture output variations due to the simultaneous variations in the basis weight valve opening and the steam shower valve opening can be seen in the Figure 5.16.

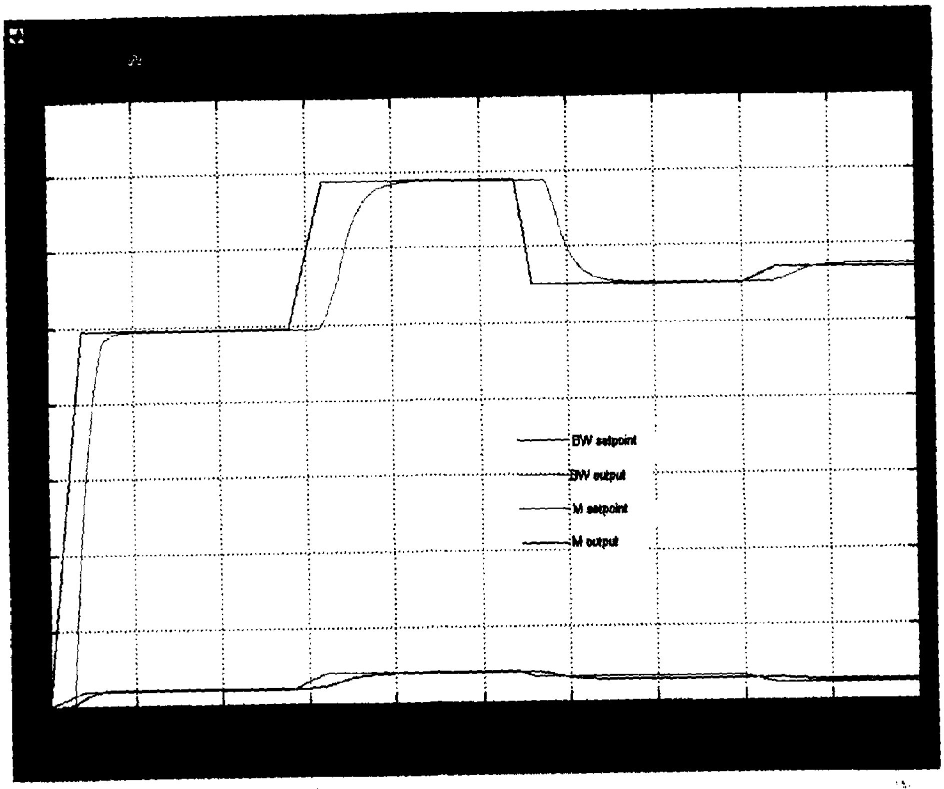

Figure 5.16 Simulation results of varying input for BW and M output when both the loops are closed

As seen from Figure 5.16, both the outputs are affected when both the loops are simultaneously closed. When the basis weight setpoint is at a low value of 99gsm and the moisture setpoint is also at a low value of 3.96 i.e. 4%. The Fuzzy control system for the basis weight control sets the value of the BWVO at a low value to maintain the BW output at a low value. Also the Fuzzy control system for the moisture control sets the value of the SSVO at a low value to maintain the moisture output to a low value. When the BW setpoint increases, the FLC for the basis weight sets the output of the controller to increase the BWVO such that the pulp flow increases, which in turn increases the BW output. As can be seen from the figure, increase in the BWVO also increases the moisture output. Now when the moisture setpoint is increased, the FLC system for the moisture changes the SSVO in a manner so as to increase the moisture content in the web, thus the moisture output increases. Increase in the moisture output also increases the basis weight output and this can be clearly seen in the curve of Figure 5.16. The details for the same can be seen in the Table 5.3.

BW SP	BW O/P	M %RQ	M SP	M% OB	M O/P
99	98.861	4%	3.96	4%	3.96
138	137.73	6%	8.28	5.28%	7.281
110	110.28	6%	6.60	4.84%	5.345
114	114.79	4%	4.56	4.2%	4.83

Table 5.3 Data for the output of BW and M when both loops are closed.

Figure 5.17 shows the simulation results for the basis weight output, for all the three cases discussed above on the same window.

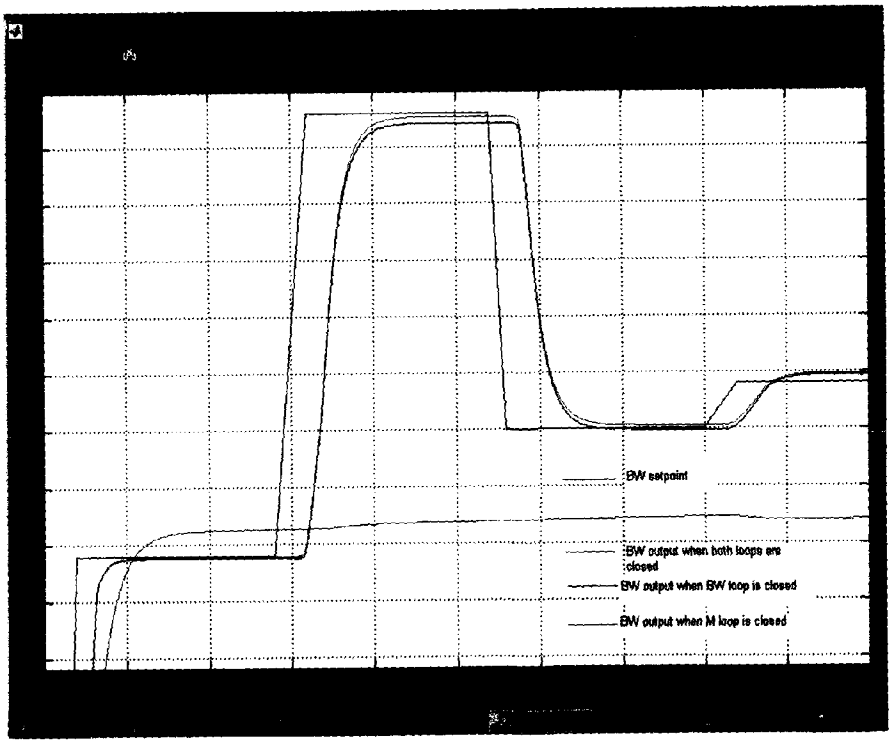

Figure 5.17 Combined Output response curves of BW for all the three cases

Figure 5.18 shows the simulation results for the moisture output, for all the three cases discussed above on the same window.

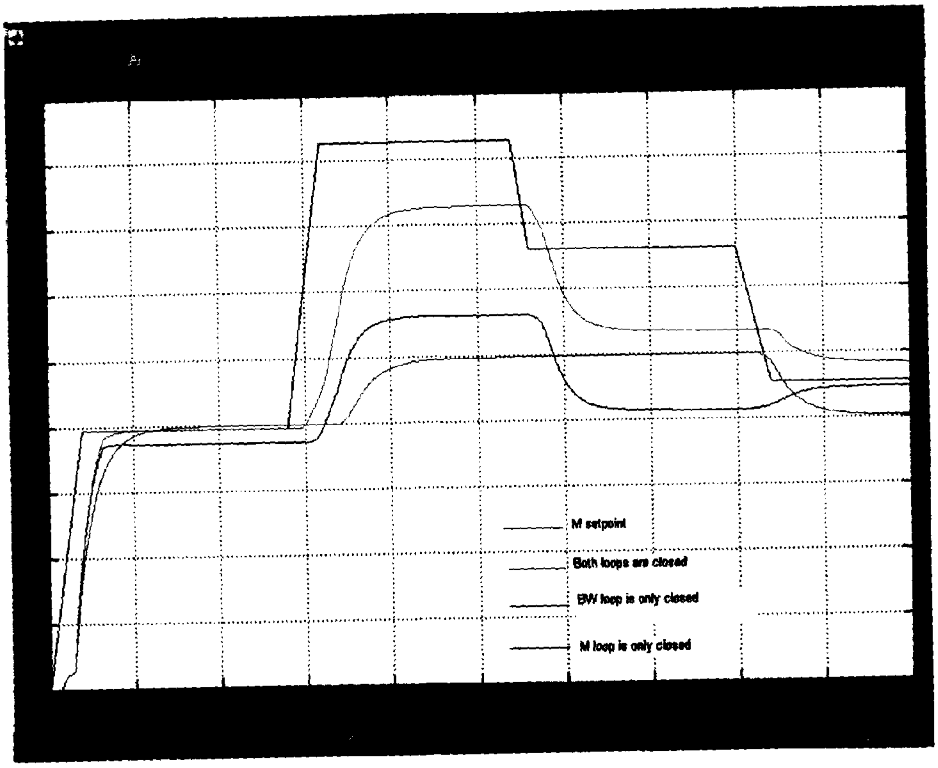

Figure 5.18 Combined Output response curves of moisture for all the three cases

Similar types of tests were carried out for the step input and varying input-servo model using the Conventional PID controller.

5.4 Servo model for step input using a Conventional PID controller:

When the model is developed using a conventional PID controller, the tests were carried out to find out the optimum value of the three constants i.e. the proportional constant (K_P), differential constant (K_D) and the integral constant (K_I) for both the controllers are taken as:

The optimum constants for the BW controller: KP = 0.05, KD = 0.5×10^{-3} and KI = 1.

The optimum constants for the moisture controller: KP =0.05, KD =0.5×10^{-8} and KI = 1.

These controllers are used and the models are developed when one loop is closed and the other is open and vice versa and when both the loops are closed.

5.4.1 Case I: One loop is closed and the other loop is open.

a) The BW loop is closed and M loop is open:

The model of Figure 5.19 is similar to that of Figure 5.1; only a conventional PID controller is used instead of a FLC system. The optimum values of the three constants are taken as mentioned above. In this case, the BW loop is closed and the moisture loop is open, both the outputs will be affected only due to the variations in the BW. This BW output is monitored by the Basis weight valve opening.

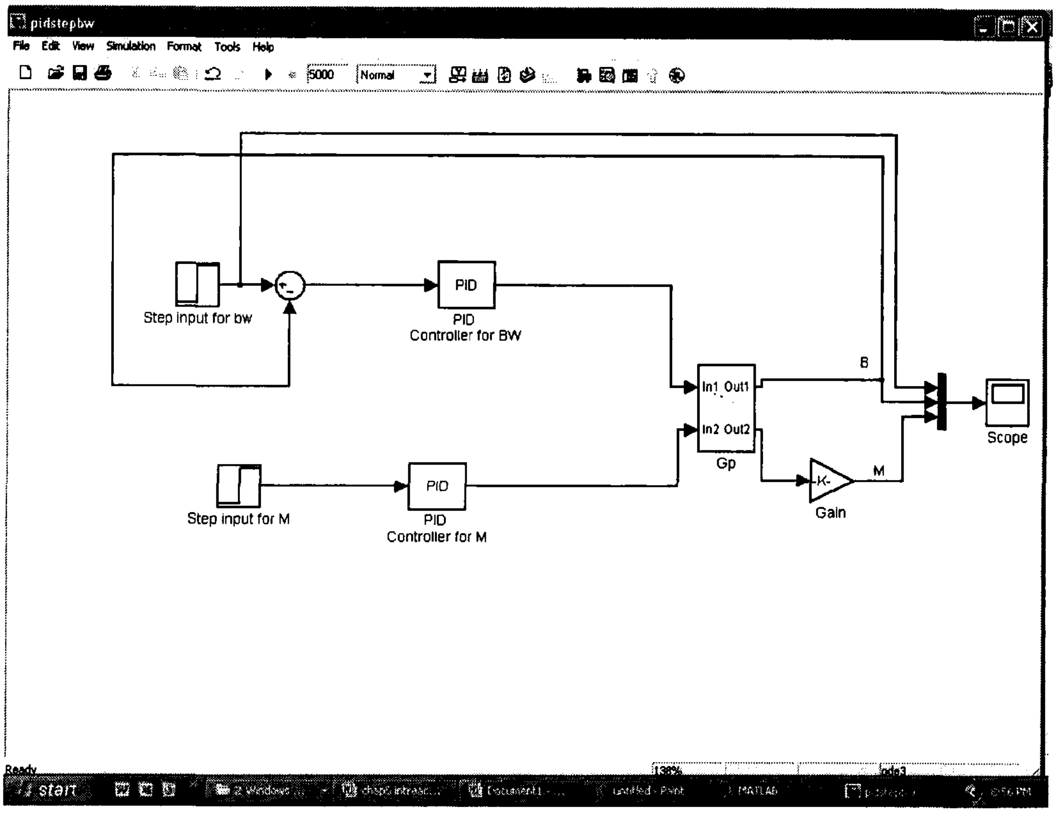

Figure 5.19 Servo model for step input using PID controller when the BW loop is closed.

The model of Figure 5.19 is simulated and the results for the same can be seen on the scope window of Figure 5.20.

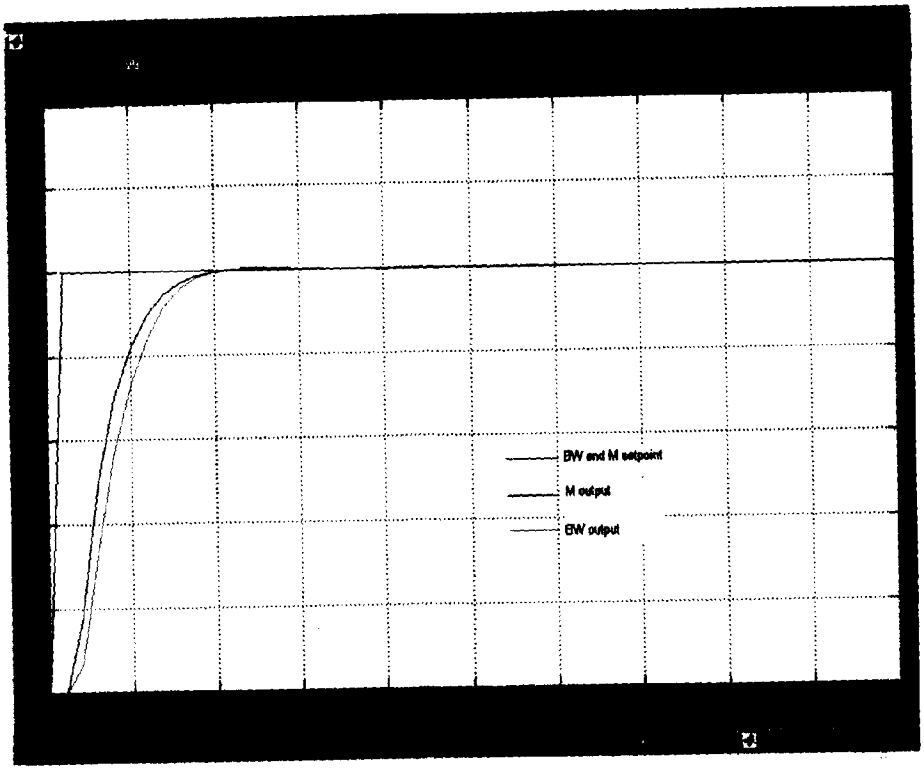

Figure 5.20 Simulation results of step input for BW and M output using PID controller when BW loop is closed and M loop is open.

Figure 5.20 shows the basis weight output and the moisture output when the basis weight loop is closed. Both the outputs move according to the step input.

Now the model is developed with the moisture loop closed and the basis weight loop open.

b) The M loop is closed and BW loop is open:

The model for this type of system is shown in Figure 5.21. When the moisture loop is closed and the basis weight loop is open, moisture output is fedback and the error signal is generated, which is given to the conventional moisture controller. The output of this controller sets the value of the steam shower valve opening accordingly and the variation in the moisture output as well as the corresponding basis weight output is governed by the change in the SSVO.

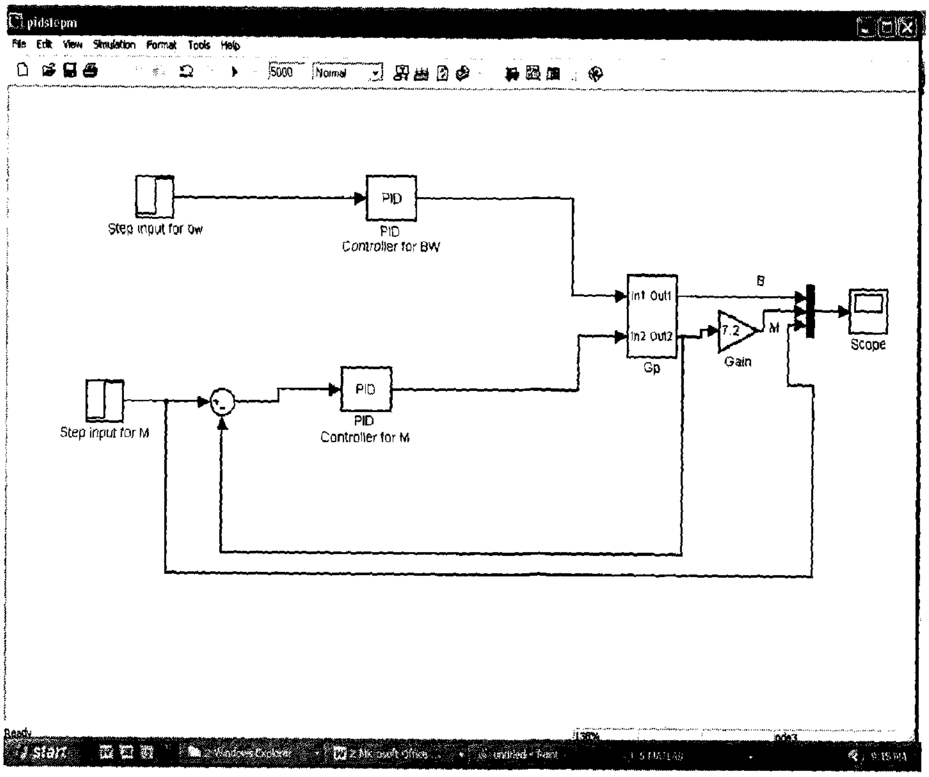

Figure5.21 Servo model for step input using PID controller when the moisture loop is closed.

The model of Figure 5.21 is simulated and the output for both basis weight and moisture can be seen in the scope window of the Figure 5.22. It is observed that the output is only governed due to the variations in the steam shower valve opening. The basis weight loop is kept open, this means the basis weight output is left uncontrolled, and hence the basis weight valve opening is kept at a constant value as given by the basis weight controller.

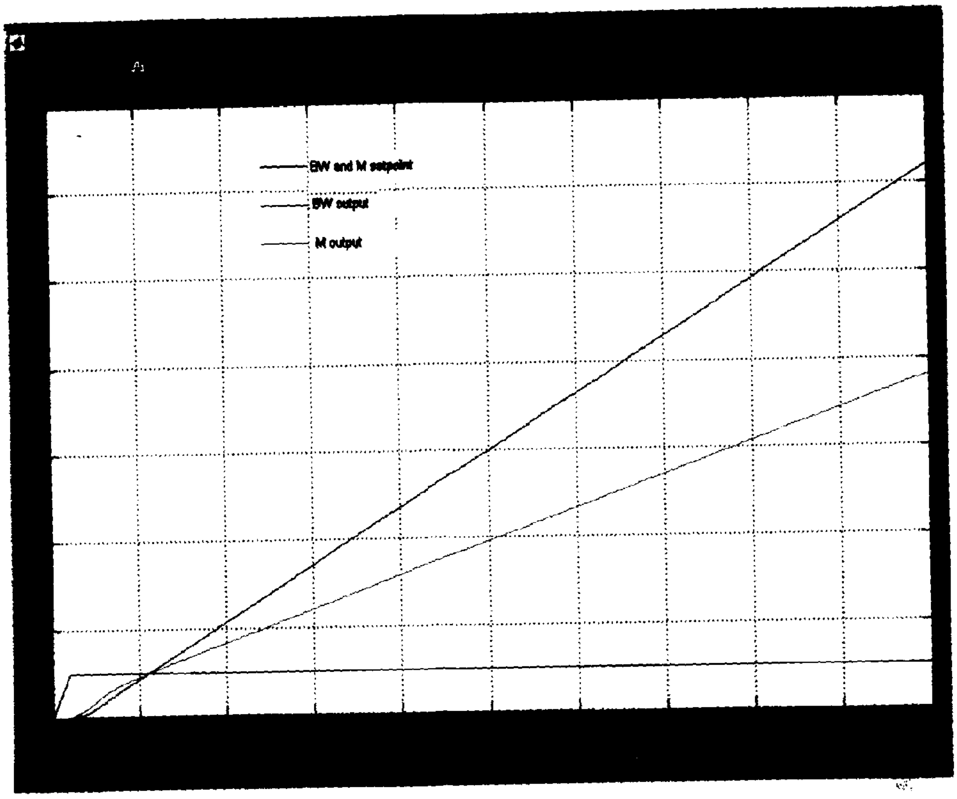

Figure 5.22 Simulation results of step input for BW and M output using PID controller when M loop is closed and BW loop is open

Looking at the simulation result of Figure 5.22 it is clear that when the moisture loop is closed and the basis weight loop is open, the output is monitored by the change in the steam shower valve opening. The basis weight valve opening is kept at a constant value resulting in the constant flow of pulp, without being monitored. This increases the value of the basis weight output in every cycle which is very clear from the results of Figure 5.22. Thus when the basis weight output increases, this increases the value of the moisture content in the web, and this can also be seen from the output of the moisture shown in the scope window. This clearly shows that the effect of change in the steam shower valve opening is almost negligible on both the outputs. Thus if the basis weight is left open the entire system goes out of control and hence the system stability is adversely affected. Now the model is developed for both loops closed.

5.4.2 Case II: Both the loops are closed

When both the loops are closed the output for the basis weight and moisture is fed back, and thus the error signal so generated is given to the two controllers's; one for the basis weight control and the other for the moisture control. The output of the two controllers is then given to the two valves i.e. the basis weight valve and the steam shower valve and the two outputs are varied according to the changing values of basis weight valve opening and steam shower valve opening simultaneously. The model for the same can be seen in the Simulink window of Figure 5.23.

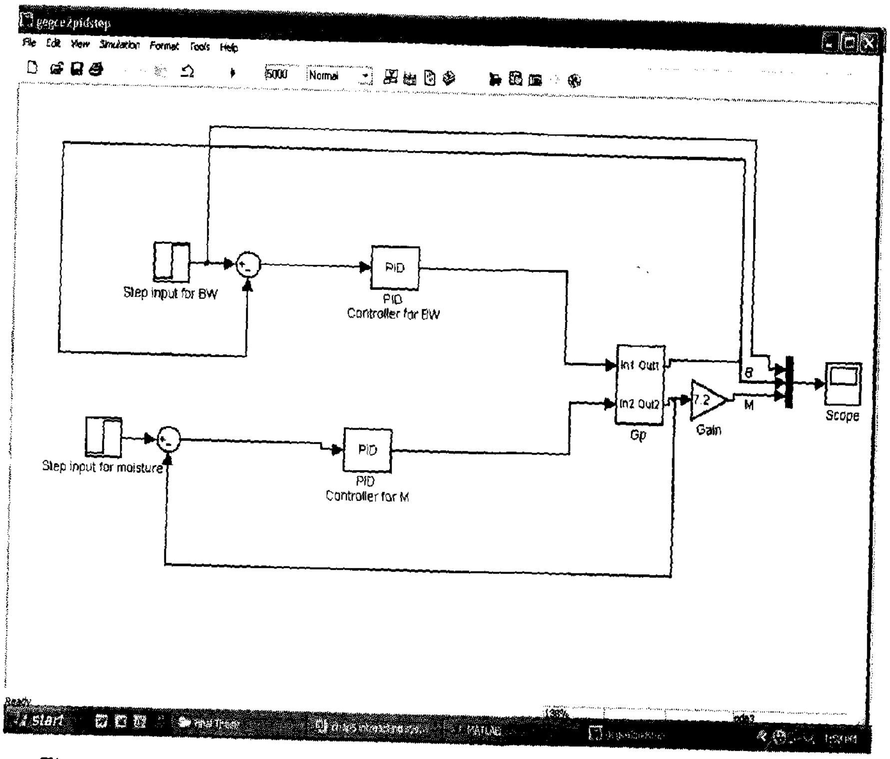

Figure5.23 Servo model for step input using PID controller when the both the loops are closed.

The model is simulated and the results for the same can be seen in the scope window of Figure 5.24.

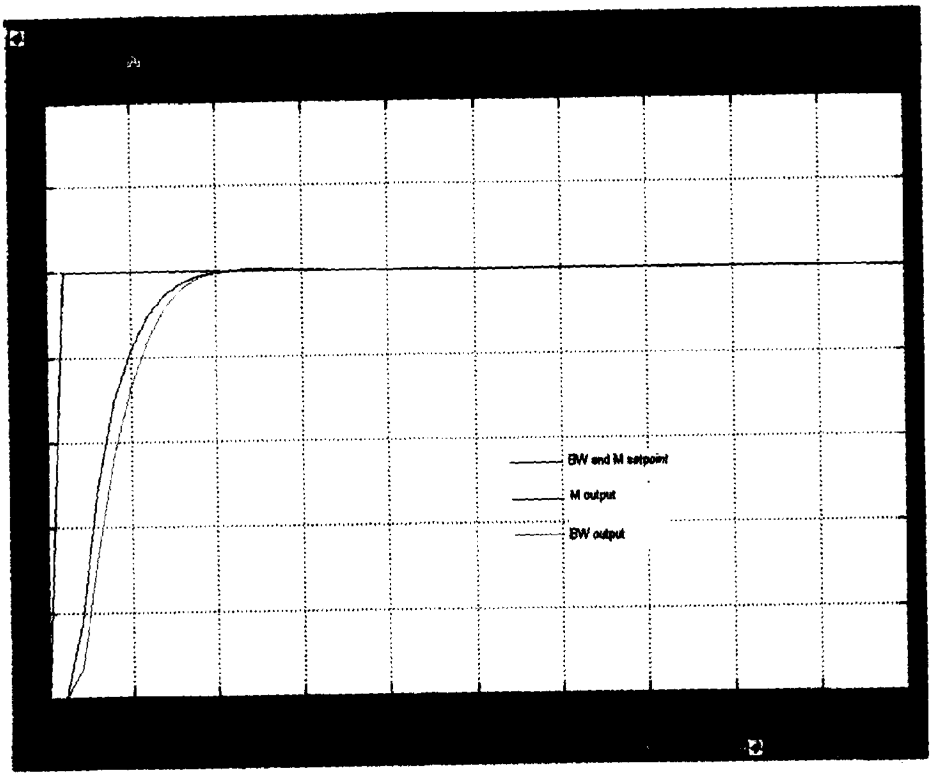

Figure 5.24 Simulation results of step input for the basis weight and moisture output using PID controller when both the loops are closed

The simulation results of Figure 5.24 shows that both the outputs i.e. the basis weight output and the moisture output move according to the step input. The combined output for all the three cases can be seen in the Figure 5.25.

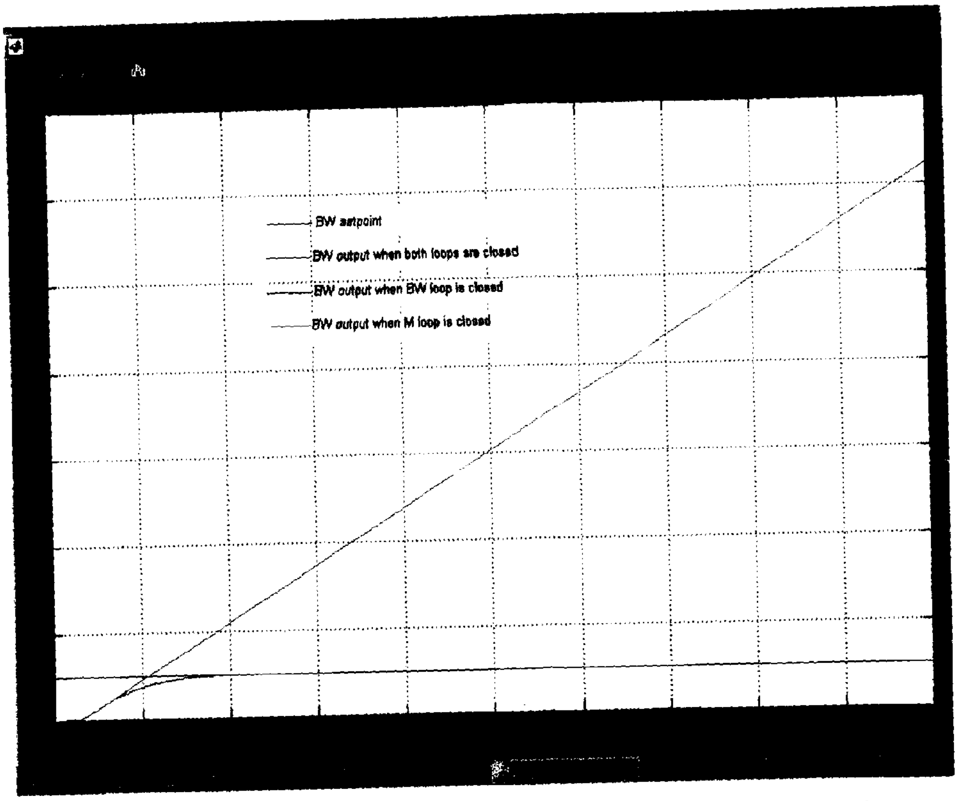

Figure 5.25 Combined simulation results for the basis weight output for step input servo model using PID controller.

Looking at the curves of Figure 5.25, it is clear that the effect of variations in the steam shower valve opening is almost negligible. The curves for the basis weight output when both the loops are closed and when the basis weight loop is closed coincide each other. Thus using a PID controller does not give a good output; moreover the system becomes unstable as soon as the basis weight loop opens. This type of instability was not observed in case of the FLC system.

Similarly the combined results for the moisture output can be seen in the Figure 5.26.

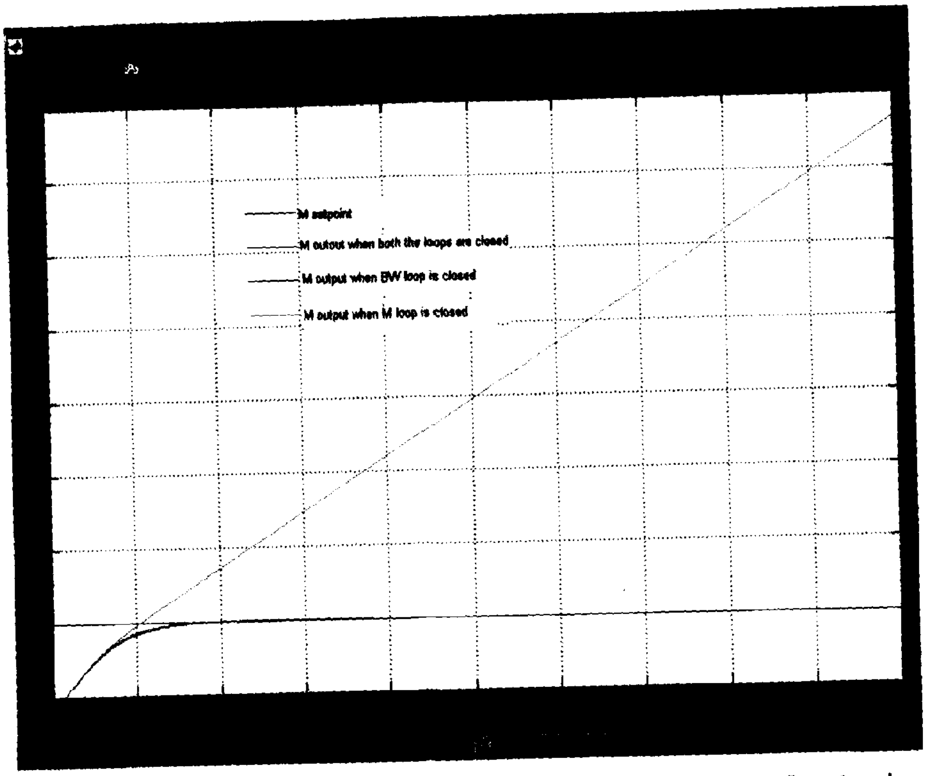

Figure 5.26 Combined simulation results for the moisture output for step input servo model using PID controller.

From Figure 5.26 it is clear that the moisture output depends mainly on the changing values of basis weight valve opening, the output is almost independent of the variations in the steam shower valve opening. The system becomes unstable and gives an unbounded output for the bounded input, when the moisture loop is only closed i.e. the basis weight valve is left uncontrolled.

As can be seen from the above simulation results, the system is under control and the outputs vary according to the step input variations, only when the BWVO and SSVO both are changed according to the changing input or when the BWVO is only varied according to the step input of BW, keeping the SSVO constant. The system response becomes uncontrolled as soon as the BWVO is maintained to a constant value. Hence it can be concluded that by using a conventional controller, the system responds only due to the changing values of BWVO and do not vary according to SSVO variations, but this was not the case with the FLC. The variations were clearly seen and were quite significant for all the three cases. Now the system is simulated for varying input using the PID controller.

5.5 Servo model for varying input using a Conventional PID controller

For developing the varying input-servo model for the process Gp, two PID controllers are used. The details of the three optimum constants for both the controllers are given as:

Constants for the BW controller: $K_P = 0.09$, $K_D = 0.7\times10^{-3}$ and $K_I = 1$.

Constants for the moisture controller: $K_P = 0.6$, $K_D = 1\times10^{-7}$ and $K_I = 1$.

The varying inputs for the BW setpoint are used in this case and the values of these are taken from Table3.2. Similarly the varying setpoint values of the moisture are taken from Table 4.1(Appendix).

The three models are now developed using the above details.

5.5.1 Case I: One loop is closed and other is open.

a) The BW loop is closed and M loop is open:

The model for the same is shown in Figure5.27. In this case as the BW loop is only closed thus the setpoint of moisture is kept at a constant value of 3.96, hence maintaining the steam shower valve opening at a constant value, as no feedback is provided in this loop. The values of the basis weight valve opening are given by the conventional controller for the basis weight used in that loop. The opening of the basis weight valve is varied according to the variation in the set-point of the BW.

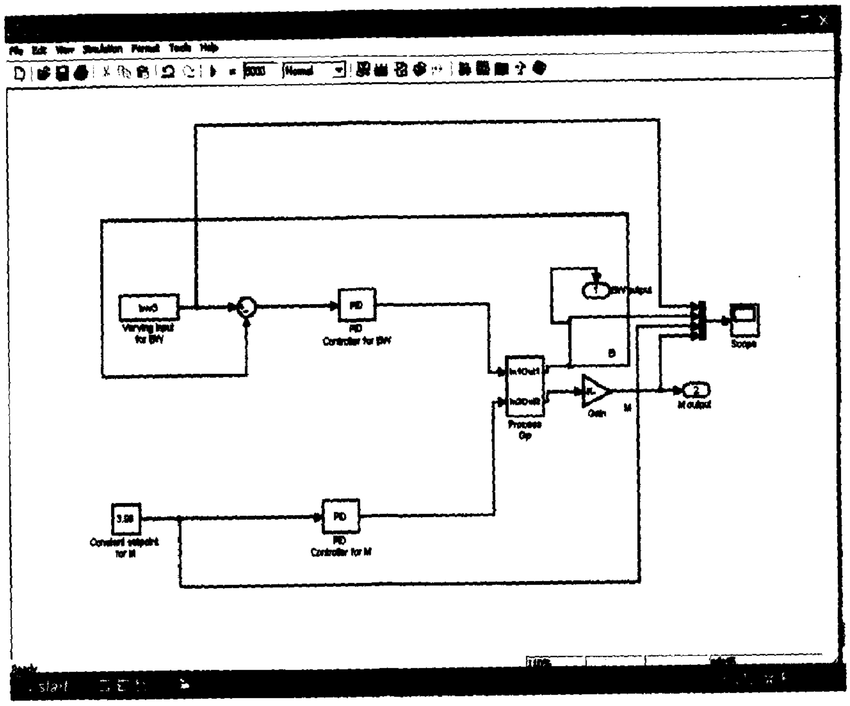

Figure 5.27 Servo model for varying input using PID controller when the BW loop is closed

The model of Figure 5.27 is simulated and the results for the basis weight and moisture output can be seen in the scope windows of Figure 5.28.

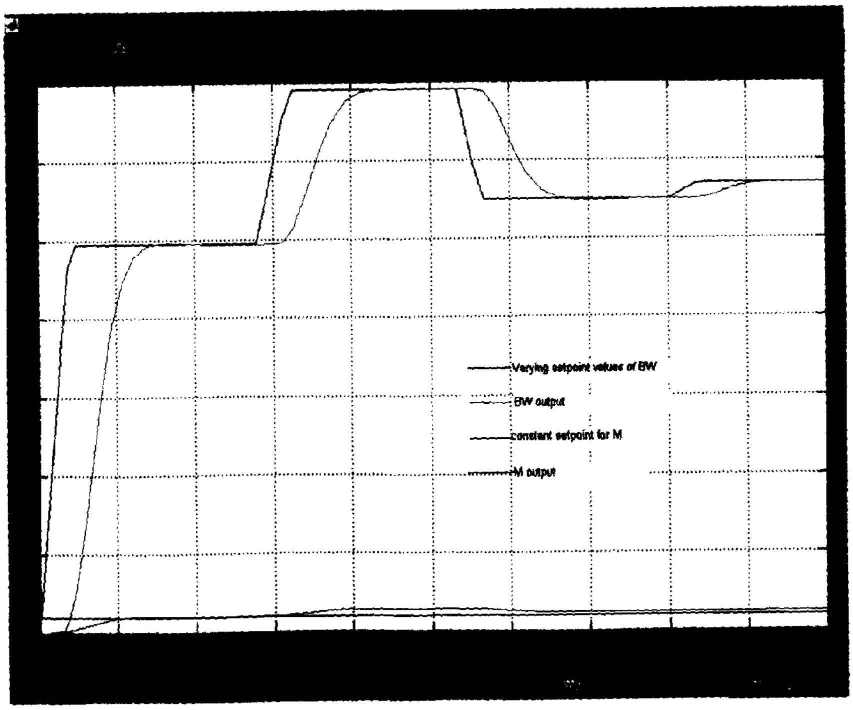

Figure 5.28 Simulation results of step input for the basis weight and moisture output using PID controller when BW loop is closed and M loop is open

From the Figure 5.28, it is clear that as the basis weight setpoint changes, the basis weight output moves according to the changing values of the input. When the basis weight setpoint increases, the basis weight valve opening is increased by the controller action which in turn increases the basis weight output. The increase in the basis weight output simultaneously affects the moisture output. The moisture output also increases due to the increases in the basis weight output. This increase in the moisture output can be clearly seen from the results of Figure 5.28. The moisture output moves in the same manner as the basis weight output curve moves. Now the model shall be developed for the moisture loop open and the basis weight loop closed.

b) The M loop is closed and BW loop is open:

When the moisture loop is closed and the basis weight loop is open, the moisture output is measured online and is fedback to calculate the error. This error is given to the conventional controller, which gives the output signal to the steam shower valve. The signal given to the valve opens the valve in a manner so as to reduce the error. Thus the output so generated is a controlled output, which depends on the opening of the steam shower valve. Figure 5.29 shows the model for the same.

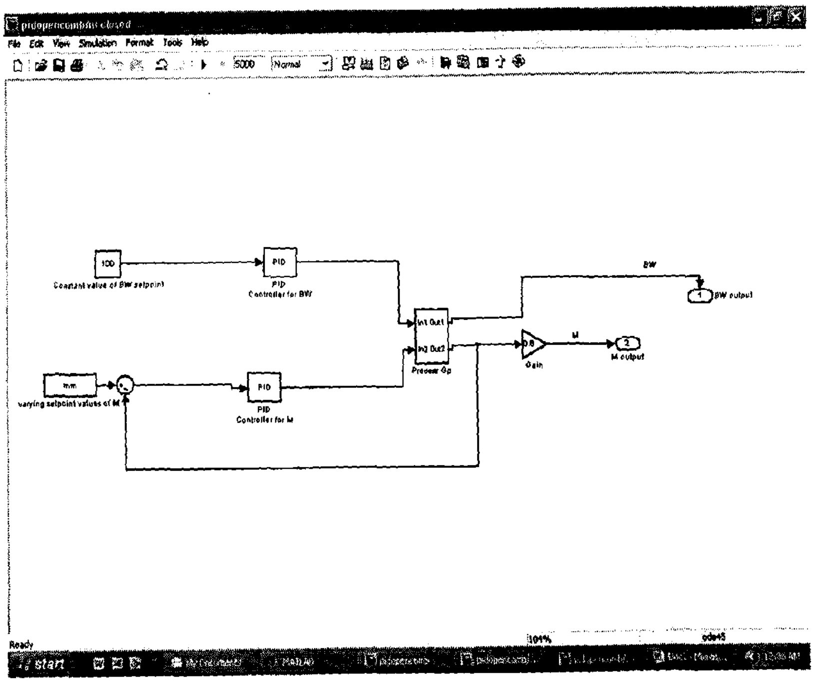

Figure 5.29 Servo model for varying input using PID controller when the M loop is closed

The model of Figure 5.29 is simulated and the results for both basis weight and moisture output is shown in the Figure 5.30.

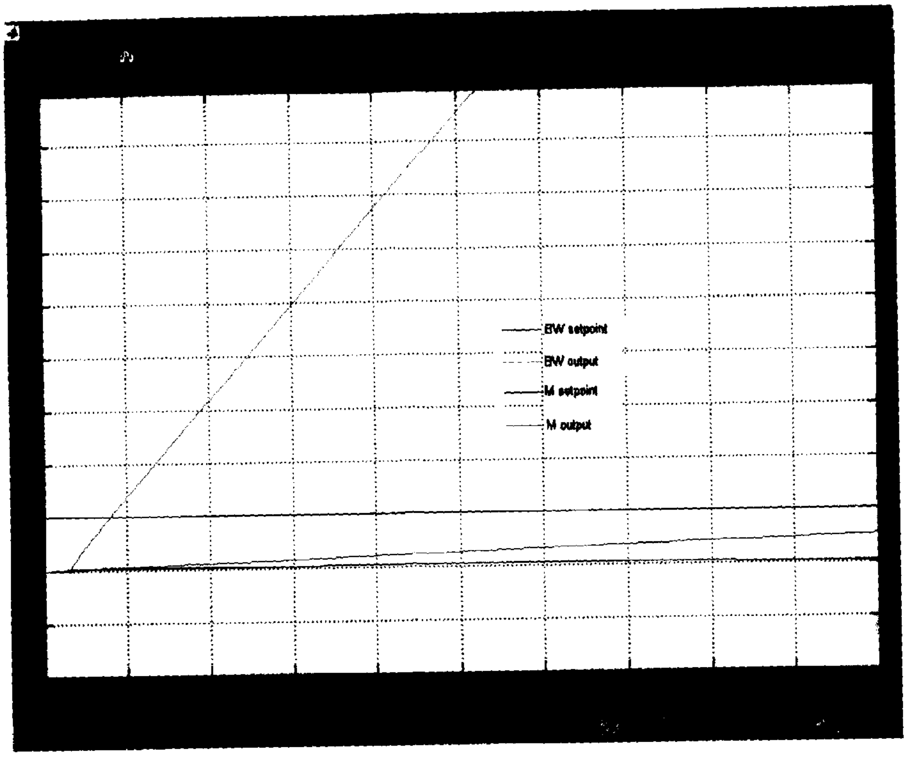

Figure 5.30 Simulation results of step input for the basis weight and moisture output using PID controller when M loop is closed and BW loop is open

It can be clearly seen from the output curves of Figure 5.30, that both the outputs i.e. the basis weight as well as the moisture output move in an uncontrolled manner. The system output does not depend on the variations in the steam shower valve opening monitored by the conventional PID controller according to the changing values of the moisture setpoint. For the present case the basis weight loop was open i.e. the basis weight valve was set to a fixed value, due to which there is a continuous increase in the basis weight output as well as the moisture output. Thus it is clear that both the outputs only depend on the variations in the basis weight valve opening. Once the basis weight valve is left uncontrolled, the system output becomes unbounded for the given bounded inputs. Thus the system becomes unstable.

Now the model is developed for both the loops closed.

5.5.2 Case II: Both the loops are closed

When both the loops are closed, both the outputs are measured online and fedback to generate the two error signals, one for the moisture and the other for the basis weight. These signals are then given to the two controllers as shown in the Figure 5.31. The two controllers then generate the actuating signals one for the basis weight valve and the other for the steam shower valve. These valves accordingly govern the outputs.

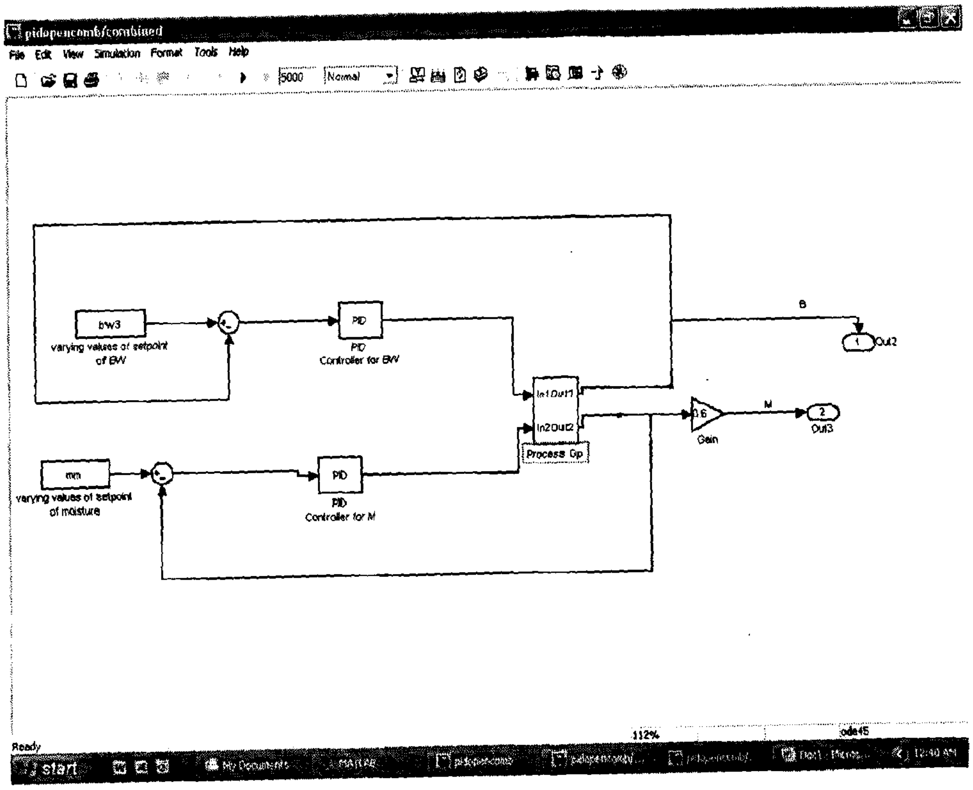

Figure 5.31 Servo model for varying input using PID controller when the both the loops are closed.

The model of Figure 5.31 is simulated and the simulation results for the same can be seen in the scope window of Figure 5.32.

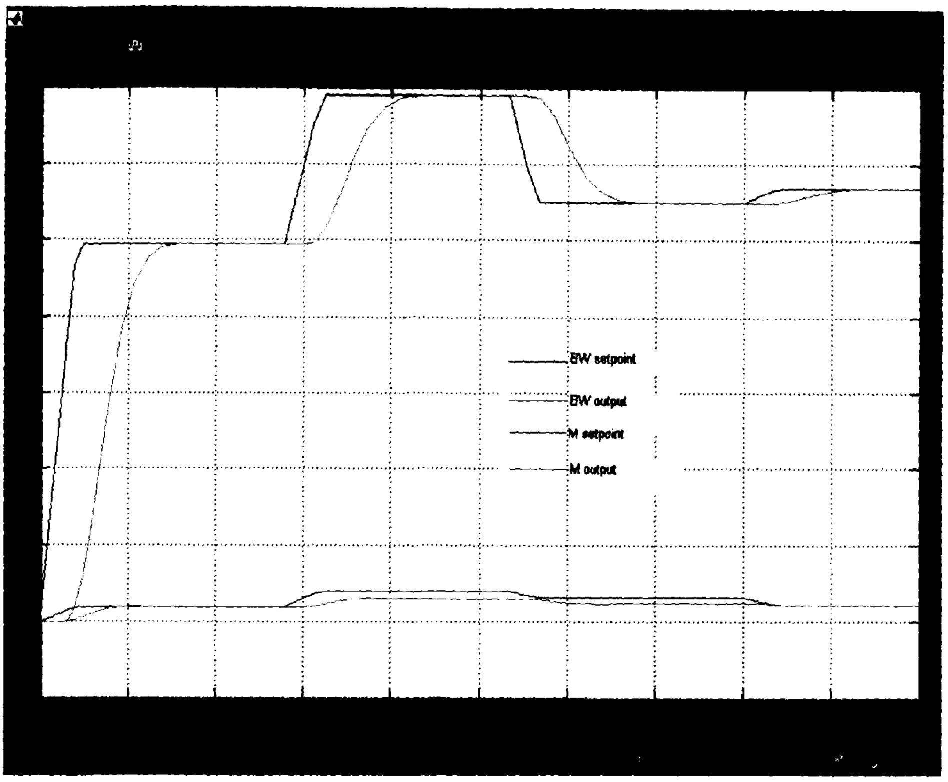

Figure 5.32 Simulation results of step input for the basis weight and moisture output using PID controller when both the loops are closed

The simulation results for both the loops closed can be seen in Figure 5.32. This figure shows that both the outputs i.e. the basis weight output and the moisture output, move according to the changing values of the input.

A comparative study is done by analyzing the results of basis weight output and the moisture output for all the three cases discussed above. Figure 5.33 shows the results for the basis weight output and Figure 5.34 shows the results for the moisture output.

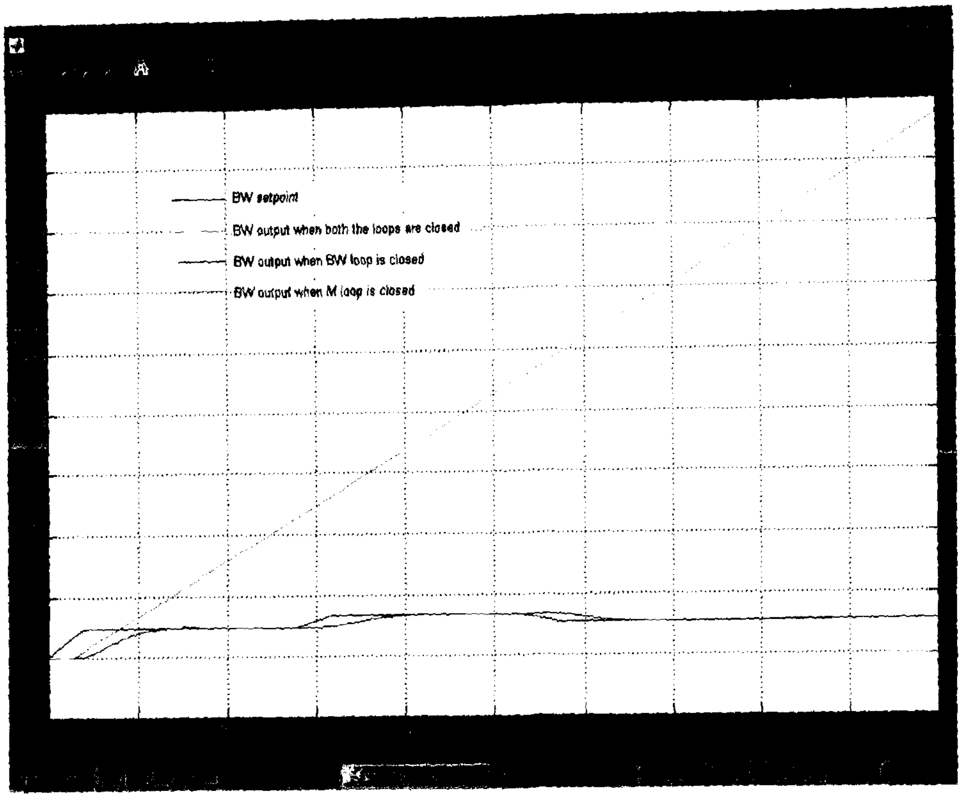

Figure 5.33 Combined simulation results for the basis weight output for the varying input servo model using a PID controller.

The window of Figure 5.33 shows the combined simulation results for the basis weight output for the varying input servo model using a PID controller. It is clear from this figure that when both the loops are closed and when the basis weight loop is only closed, the basis weight output varies according to the changing values of the setpoint. When the basis weight setpoint is low, the controller sets the basis weight valve opening to a lower value and thus the output of basis weight follows the input but after some delay. As the basis weight setpoint value increases the basis weight valve opening is changed accordingly hence increasing the pulp flow, thus the value of basis weight output follows the input. The effect of steam shower valve opening is almost insignificant as both the curves Green and red overlap each other. When the Moisture loop is only closed keeping the basis weight loop open, the steam shower valve opening is monitored according to the variations in the setpoint, while the basis weight valve opening is independent to these variations and is kept constant. In such a case, the basis weight output no more follows the varying input, rather it becomes unstable as it increases monotonously. This is because the steam shower valve opening, though varied according to the changing values of basis weight setpoint, is yet unable to control the basis weight. The basis weight continuously increases as the basis weight valve opening is kept constant and the flow of pulp is not monitored.

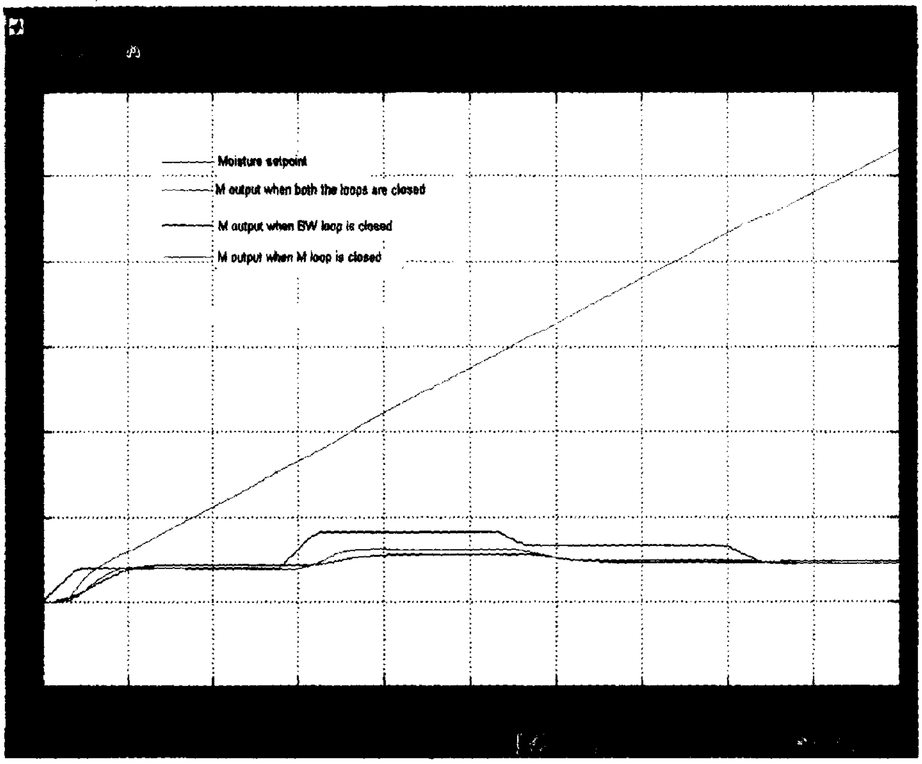

Figure 5.34 Combined simulation results for the moisture output for the varying input servo model using a PID controller.

It has been observed that for both the cases i.e. the step input and the varying input using a PID controller, the system becomes unstable for the case when the moisture loop is closed. It means that when the basis weight valve opening is not under control, the output for both moisture and basis weight is also not under control. While the case is different when the basis weight valve opening is under control and steam shower valve opening is not under control, both the outputs are under control.

Thus it can be said that the major controlling factor is the basis weight valve opening, and by varying the value of basis weight valve opening both the parameters can be controlled. The steam shower valve opening has an insignificant effect in case of the PID controller. But this is not the case for the FLC model; for an FLC model both the controlling parameters (basis weight valve opening and steam shower valve opening) have a significant effect on both the controlled outputs (Basis Weight and Moisture).

Now once these results are analyzed, a comparative graph between the PID and the Fuzzy controller using both step input and the varying input, can be seen when both the loops are closed. The Basis Weight and Moisture outputs for the varying input are shown in Figure 5.35 and Figure 5.36 respectively.

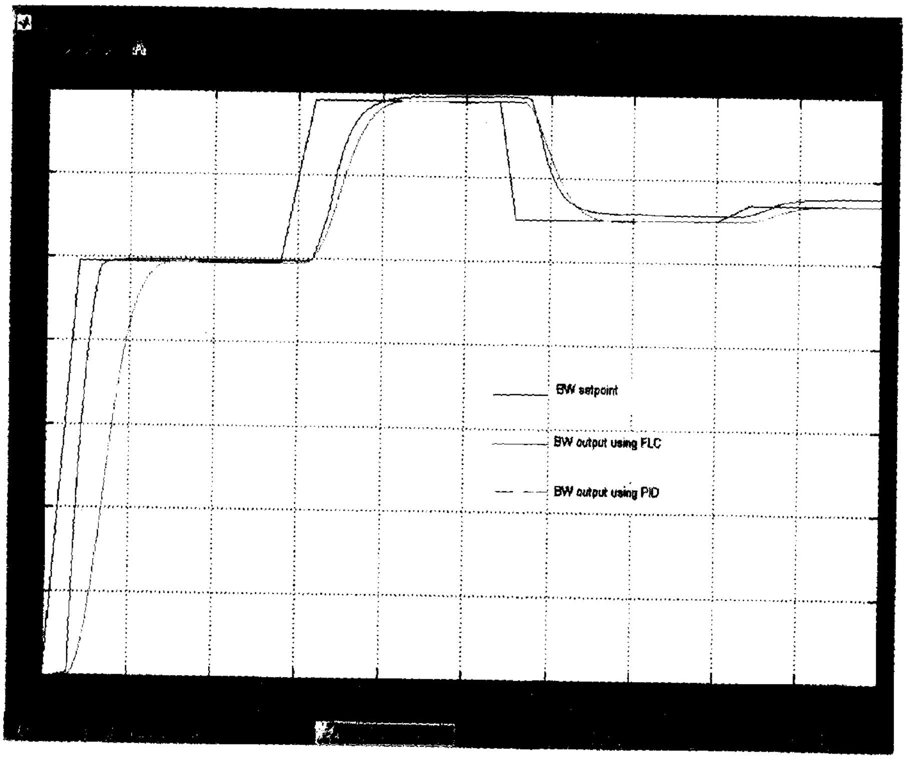

Figure5.35 Curves Comparing the basis weight of the process using FLC and PID controller

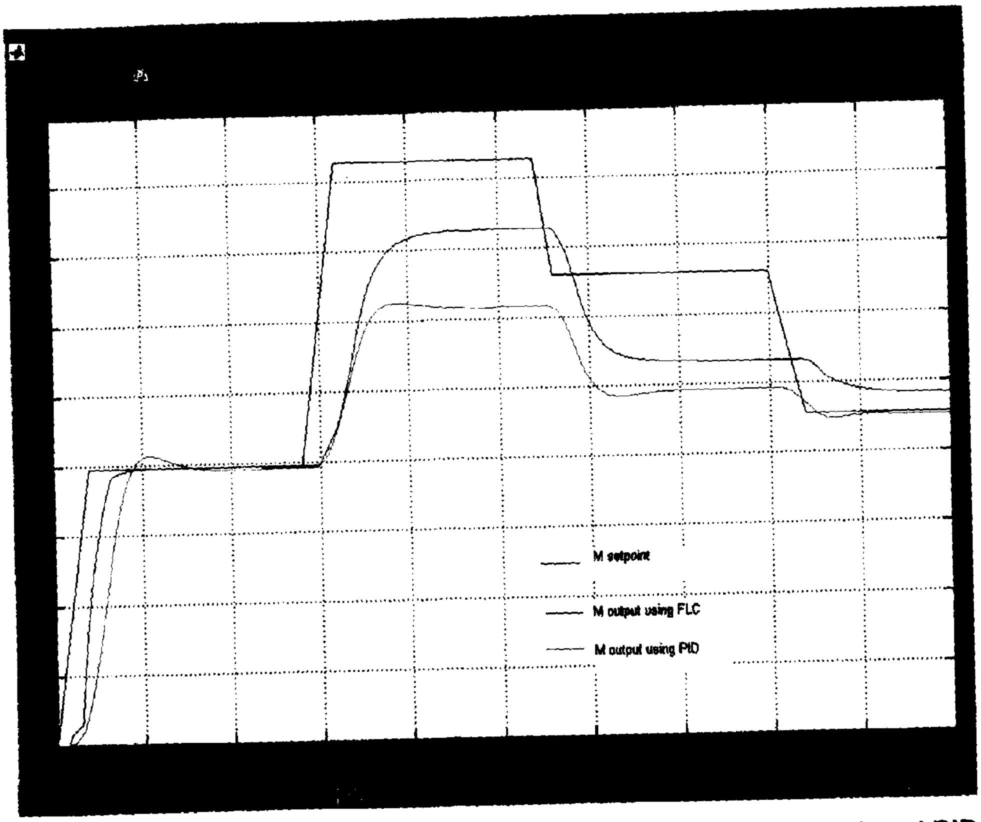

Figure 5.36 Curves comparing the moisture of the process using FLC and PID controller

A comparison was done for the curve of basis weight output and moisture output using a conventional PID controller and a Fuzzy Logic control system when both the loops are closed. It has thus been observed that a PID controller introduces a delay of its own, while the Fuzzy controller does not introduce a delay of its own. The Table 5.1, 5.2 shows the details for the basis weight and moisture output respectively for the varying input. While Tables 5.3 and 5.4 give the details of the output for the basis weight and moisture output respectively for the step input.

	FLC output for BW	PID output for BW
RT (sec)	136.138	306.035
Delay(sec)	144	147
OS	nil	0.002

Table 5.4 Performance comparison between FLC and PID output for basis weight for varying input

	FLC output for Moisture	PID output for Moisture
RT (sec)	180.2	220.73
Delay(sec)	66	79
OS	nil	0.17

Table 5.5 Performance comparison between FLC and PID output for moisture for varying input

From Figure 5.35& 5.36 and the data of Table 5.4 & 5.5, it is clear that the PID controllers introduce a significant amount of delay. The delay in the FLC output is because of the system itself, while an additional delay in the PID controller is caused due to the controller itself.

Similar types of results were observed for the step input servo model. Tables 5.6 and 5.7 show the performance comparison between FLC and PID output for basis weight and moisture output respectively for the step input.

	FLC output for BW	PID output for BW
RT (sec)	453.18	498.58
Delay(sec)	67	109

Table 5.6 Performance comparison between FLC and PID output for basis weight for step input

	FLC output for Moisture	PID output for Moisture
RT (sec)	350.08	444.96
Delay(sec)	66	85.68

Table 5.7 Performance comparison between FLC and PID output for moisture for step input

5.6 Conclusion:

In this chapter, the effect of the interaction between the two parameters has been analyzed using the Fuzzy control system and the conventional PID controller. From the various tests performed, it can be concluded that the performance of the system was not good while using the PID controller. In case of the conventional controller the major controlling factor is the basis weight valve opening, and by varying the value of basis weight valve opening both the parameters can be controlled. The effect of variations in the steam shower valve opening is almost insignificant in case of the PID controller. But this is not the case for the FLC model; for the FLC model both the controlling parameters i.e. basis weight valve opening and steam shower valve opening have a significant effect on both the controlled outputs i.e. the Basis Weight and the Moisture.

Chapter 6
Conclusions and Recommendations

Paper making is a vast, multidisciplinary technology that has expanded tremendously in recent years. The main requirement for today is that, the companies must be more productive, flexible and produce high quality goods for customers and market requirements in the world market's conditions. Significant advances have been made in all the areas of paper making, including raw materials, production technology, process control and end products. As per demand, implementation of necessary tools to optimize papermaking process and to increase the control precision under the precondition for stable operation and quality production is necessary. Hence in the present work an effort has been made to replace the conventional PID controllers with the Fuzzy controllers. Basis weight and moisture content at the web are the two parameters which have been measured and an exercise has been done to control (on-line) these parameters using the Fuzzy control system.

In the present work the process has two controlled outputs i.e. Basis weight (B) and Moisture (M) and two manipulated inputs i.e. pulp flow (G) and steam flow (P). The transport delay for basis weight loop and the moisture loop has been estimated, also the time constants for both the systems have been estimated, while the machine constants for the systems have been assigned some constant values. The data for basis weight and moisture has been collected from a middle basis weight mill. All the details of the work has been discussed in chapter1.

In view of the discussions in chapter 1, a survey has been done on the modeling and control of Basis Weight and Moisture control systems. As the present work, deals with the modeling of the interacting and non-interacting system using Fuzzy Logic Control system, thus a general survey of Fuzzy controllers and the tuning of various parameters, along with the hybrid techniques has also been surveyed and has been shown in Chapter 2.

In Chapter 3 & 4 the non-interacting systems for basis weight and moisture are developed and the effect of each scaling gain is examined. It has been analyzed that when using a Fuzzy control system for both basis weight and moisture respectively the scaling gains can be easily tuned to get the perfect output, both for the step input as well as the varying input. But these things are not observed while using a conventional PID controller, as in this case the system output is poor. The system does not respond according to the changing reference inputs of Basis weight and moisture respectively. Though the effect of the three constants K_P, K_D and K_I are analyzed but they are difficult to monitor according to the varying inputs. In case of Fuzzy controllers, the scaling gains GU, GE, GCE and GIE can individually be tuned to monitor the system performance, but in case of the PID controller, the performance parameters of the system are interdependent of all the three constants. Thus an effort to improve one parameter can have an adverse effect on the other parameter. The system also worked well for the regulator problem as analyzed by adding a disturbance to the control system. Thus from the results of chapter 3 and chapter 4 it can be concluded that:

- A Fuzzy Logic Controller gives much better output in comparison to the conventional PID controller. The response of the system using a FLC is stable and can be easily varied according to the changing demand in the input by simply developing a single input/output Fuzzy Logic Controller.
- The effects of the three constants are analyzed but they are difficult to monitor according to the varying inputs for the non-interacting systems for PID controllers.
- FLC can be easily tuned according to the desired output by varying the design parameters as each scaling gain is individually responsible for a performance parameter:

1. GU= Responsible for variations in the Offset.
2. GE= Responsible for the Oscillatory behavior.
3. GCE= Responsible for variations in the RT.
4. GIE= Responsible for minor Offsets and also the system stability.

Once the effect of each scaling gain is examined, the scaling gains can easily be tuned to get the perfect output; both for the step input as well as the varying input. But these results are not observed while using a conventional PID controller. Also one can see, fuzzy controllers are much easier to read and understand than using a set of differential equations. Additionally, fuzzy controllers are simpler than classical controllers. That is because they can tolerate some imprecision when dealing with the desired system. This ease of use translates into lower costs and faster time to implement.

The Chapter 5 dealt with the severe interactions between the controlled variables i.e. the basis weight and moisture, and long time delays for controlling these variables. And it is well known and also discussed in chapter 1 that these are the two major problems in paper machine control and are also difficult to monitor from the control engineering point of view. It has been shown in the simulation results of chapter 5 that when the basis weight controller increases the stock flow, the amount of water i.e. the moisture content of the paper increases. Further if steam flow is increased to correct the moisture, the basis weight will decrease; therefore it is difficult to maintain the balance between these two controlled variables and the results of chapter 5 shows the same. The conventional control system for controlling the basis weight and moisture content of paper has a very complicated interacting configuration and this has been shown in the results of chapter 5. Fuzzy control system handled these interactions in a well defined manner as fuzzy control is based on fuzzy logic which provides an efficient method to handle inexact information as a basis of reasoning. Thus from the results of Chapter 5 it can be concluded that:

- The Fuzzy Control system monitors the output of an interacting system in a well defined manner.
- The system output remains under control, even if any of the feedback loops stops responding accidentally.
- The conventional PID controllers can easily be replaced by the FLC as Fuzzy logic controller gives better performance in comparison with the PID controller.
- Conventional controller introduces delays in the system, also the risetime of the output response increases with conventional controllers.

Thus it can be said that a fuzzy logic controller gives satisfactory results for step input and varying input for both the cases i.e. the basis weight and moisture control for both SISO (basis weight and moisture as non-interacting system) and MIMO systems.

From the entire work done we come to the conclusion that:

- The paper industry needs to upgrade their process and equipment technology. This in turn requires up-gradation of process equipments, especially the paper machines, process automation and control.
- There are many more areas in the paper industry where the FLC can be introduced.
- FLC requires only 250 bytes of code to implement a two input, one output controller. This translates into less cost for computing and faster response times than traditional controllers.
- Even further optimization of the design parameters can be done by using the Hybrid intelligent techniques such as: Neuro-Fuzzy model, and Fuzzy controllers using Genetic Algorithm.

The practical implementation of Fuzzy controllers has also been surveyed [138, 98]. Moreover Fuzzy tech provides with all the tools to design and test a fuzzy logic system. Once designed, fuzzy tech stores the work as an FTL format file. FTL stands for "Fuzzy Technology Language", and can be considered "the programming language of fuzzy logic". Fuzzy Tech provides an all-graphical user interface Fuzzy Tech converts this FTL description to code that can be used on target hardware that is, the hardware where fuzzy logic solution shall finally run on.

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Appendix

Chapter3

P3.1

```
[System]
Name='new32'
Type='mamdani'
Version=2.0
NumInputs=2
NumOutputs=1
NumRules=9
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

[Input1]
Name='e'
Range=[-1 1]
NumMFs=3
MF1='en':'gaussmf',[0.34 -0.819417989417989]
MF2='em':'gaussmf',[0.3398 0]
MF3='ep':'gaussmf',[0.339 0.831746031746032]

[Input2]
Name='che'
Range=[-1 1]
NumMFs=3
MF1='chen':'gaussmf',[0.34 -0.815075132275132]
MF2='chem':'gaussmf',[0.3398 0]
MF3='chep':'gaussmf',[0.34 0.813693121693122]

[Output1]
Name='bwvo'
Range=[0 1]
NumMFs=3
MF1='bwvos':'gaussmf',[0.17 0.0926]
MF2='bwvom':'gaussmf',[0.1699 0.5]
MF3='bwvol':'gaussmf',[0.171 0.90478253968254]

[Rules]
1 1, 1 (1) : 1
```

```
1 2, 1 (1) : 1
1 3, 2 (1) : 1
2 1, 1 (1) : 1
2 2, 2 (1) : 1
2 3, 3 (1) : 1
3 3, 3 (1) : 1
3 2, 3 (1) : 1
3 1, 2 (1) : 1
```

P3.2

```
[System]
Name='new323'
Type='mamdani'
Version=2.0
NumInputs=2
NumOutputs=1
NumRules=9
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

[Input1]
Name='e'
Range=[-20 35]
NumMFs=3
MF1='en':'gaussmf',[9.35 -15.03]
MF2='em':'gaussmf',[9.342 7.5]
MF3='ep':'gaussmf',[9.326 30.36]

[Input2]
Name='che'
Range=[-37 35]
NumMFs=3
MF1='chen':'gaussmf',[12.24 -30.34]
MF2='chem':'gaussmf',[12.23 -1]
MF3='chep':'gaussmf',[12.24 28.29]

[Output1]
Name='bwvo'
Range=[0 1]
NumMFs=3
MF1='sos':'gaussmf',[0.17 0.0926]
MF2='som':'gaussmf',[0.1699 0.5]
MF3='sol':'gaussmf',[0.171 0.90478253968254]
```

[Rules]
1 1, 1 (1) : 1
1 2, 1 (1) : 1
1 3, 2 (1) : 1
2 1, 1 (1) : 1
2 2, 2 (1) : 1
2 3, 3 (1) : 1
3 3, 3 (1) : 1
3 2, 3 (1) : 1
3 1, 2 (1) : 1

P3.3
[System]
Name='gu'
Type='mamdani'
Version=2.0
NumInputs=1
NumOutputs=1
NumRules=3
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

[Input1]
Name='step'
Range=[99 138]
NumMFs=3
MF1='l':'trapmf',[86.7195238095238 98.6895238095238 106.309523809524 118.309523809524]
MF2='m':'trimf',[101.412698412698 119.412698412698 135.412698412698]
MF3='h':'trapmf',[118.187301587302 130.487301587302 138.287301587302 150.587301587302]

[Output1]
Name='gu'
Range=[37.2 61.9]
NumMFs=3
MF1='l':'trapmf',[30.56 35.06 42.53 49.94]
MF2='m':'trimf',[38.86 48.92 60.11]
MF3='h':'trapmf',[49.86 56.13 66.38 66.38]

[Rules]
1, 1 (1) : 1

2, 2 (1) : 1
3, 3 (1) : 1

Time (sec)	Basis Weight (gsm)	Time (sec)	Basis Weight (gsm)
0	0	2700	138
200	99	2800	110
400	99	3000	110
600	99	3200	110
800	99	3400	110
1000	99	3600	110
1200	99	3700	110
1400	99	3800	110
1600	138	4000	110
1800	138	4200	114
2000	138	4400	114
2200	138	4600	114
2400	138	4800	114
2600	138	5000	114

Table 3.3 Data for varying values of Basis weight with respect to time (bw3.m)

Time (sec)	BW setpoint (gsm)	BW output (gsm)	Time (sec)	BW setpoint (gsm)	BW output (gsm)
0	0	0	2700	138	136.4
200	99	98.1	2800	110	117.6
400	99	99.2	3000	110	117.2
600	99	99.1	3200	110	110.1
800	99	98.7	3400	110	110.1
1000	99	99.2	3600	110	109.9
1200	99	99	3800	110	109.2
1400	99	99.3	4000	110	109.5
1600	138	103.1	4200	110	110.1
1800	138	113.7	4400	114	112.3
2000	138	139.2	4600	114	115.1
2200	138	139.9	4800	114	113.9
2400	138	138.2	5000	114	114.1
2600	138	137.7			

Table 3.4 Input and Output values of Basis Weight as per the changing demand

Chapter4

P4.1

```
[System]
Name='moist'
Type='mamdani'
Version=2.0
NumInputs=2
NumOutputs=1
NumRules=9
AndMethod='min'
OrMethod='max'
ImpMethod='prod'
AggMethod='sum'
DefuzzMethod='centroid'

[Input1]
Name='em'
Range=[-1 1]
NumMFs=3
MF1='emn':'gaussmf',[0.366893536426007 -0.805]
MF2='emm':'gaussmf',[0.3397 1.388e-017]
MF3='emp':'gaussmf',[0.364345571025143 0.802]

[Input2]
Name='chem'
Range=[-1 1]
NumMFs=3
MF1='chemn':'gaussmf',[0.360561819936029 -0.824]
MF2='chemm':'gaussmf',[0.3397 2.776e-017]
MF3='chemp':'gaussmf',[0.3493 0.8315]

[Output1]
Name='ssvo'
Range=[0 1]
NumMFs=3
MF1='ssvos':'gaussmf',[0.19336046569245 0.0726]
MF2='ssvom':'gaussmf',[0.1699 0.5]
MF3='ssvob':'gaussmf',[0.1753 0.928]

[Rules]
1 1, 3 (1) : 1
1 2, 3 (1) : 1
1 3, 2 (1) : 1
2 1, 3 (1) : 1
2 2, 2 (1) : 1
```

```
2 1, 1 (1) : 1
3 1, 2 (1) : 1
3 2, 3 (1) : 1
3 3, 3 (1) : 1
```

P4.2

```
[System]
Name='moi2'
Type='mamdani'
Version=2.0
NumInputs=2
NumOutputs=1
NumRules=9
AndMethod='min'
OrMethod='max'
ImpMethod='prod'
AggMethod='max'
DefuzzMethod='centroid'

[Input1]
Name='input1'
Range=[-2 2]
NumMFs=3
MF1='mf1':'gaussmf',[0.734 -1.61]
MF2='mf2':'gaussmf',[0.6792 0]
MF3='mf3':'gaussmf',[0.7288 1.604]

[Input2]
Name='input2'
Range=[-2 2]
NumMFs=3
MF1='mf1':'gaussmf',[0.7212 -1.648]
MF2='mf2':'gaussmf',[0.6796 0]
MF3='mf3':'gaussmf',[0.6984 1.663]

[Output1]
Name='output1'
Range=[0 1]
NumMFs=3
MF1='mf1':'gaussmf',[0.19336046569245 0.0726]
MF2='mf2':'gaussmf',[0.1699 0.5]
MF3='mf3':'gaussmf',[0.1753 0.928]

[Rules]
1 1, 1 (1) : 1
```

```
1 2, 1 (1) : 1
1 3, 2 (1) : 1
2 1, 1 (1) : 1
2 2, 2 (1) : 1
2 1, 3 (1) : 1
3 1, 2 (1) : 1
3 2, 3 (1) : 1
3 3, 3 (1) : 1
```

P4.3

```
[System]
Name='mgu'
Type='mamdani'
Version=2.0
NumInputs=1
NumOutputs=1
NumRules=3
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

[Input1]
Name='m'
Range=[4 6]
NumMFs=3
MF1='mf1':'trimf',[3.2 4 4.8]
MF2='mf2':'trimf',[4.2 5 5.8]
MF3='mf3':'trimf',[5.2 6 6.8]

[Output1]
Name='gum'
Range=[0.1 0.307]
NumMFs=3
MF1='mf1':'trimf',[0.0172 0.1 0.1828]
MF2='mf2':'trimf',[0.1207 0.2035 0.2863]
MF3='mf3':'trimf',[0.2242 0.307 0.3898]

[Rules]
1, 1 (1) : 1
2, 2 (1) : 1
3, 3 (1) : 1
```

Time(s)	Moisture%	Time(s)	Moisture%
0	0	2700	6
200	4	2800	6
400	4	3000	6
600	4	3200	6
800	4	3400	6
1000	4	3600	6
1200	4	3800	6
1400	4	4000	6
1600	4	4200	4
1800	6	4400	4
2000	6	4600	4
2200	6	4800	4
2400	6	5000	4
2600	6		

Table 4.1 Data for varying values of moisture with respect to time

Time (sec)	Moisture % Setpoint	Moisture % Output	Time (sec)	Moisture % Setpoint	Moisture % Output
0	0	0	2700	6	6.5
200	4	4.6	2800	6	6.3
400	4	4.4	3000	6	6.0
600	4	4.2	3200	6	5.9
800	4	4.2	3400	6	5.9
1000	4	3.7	3600	6	6.3
1200	4	3.9	3800	6	6.2
1400	4	4.1	4000	6	6.2
1600	4	4.0	4200	4	5.9
1800	6	5.1	4400	4	5.0
2000	6	5.7	4600	4	4.5
2200	6	6.3	4800	4	4.4
2400	6	5.7	5000	4	4.2
2600	6	5.9			

Table 4.2 Input and Output values of Moisture as per the changing demand (mm.m)

Chapter 5

P5.1

```
[System]
Name='bgubest'
Type='mamdani'
Version=2.0
NumInputs=1
NumOutputs=1
NumRules=3
AndMethod='min'
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

[Input1]
Name='b'
Range=[99 138]
NumMFs=3
MF1='mf1':'trapmf',[88 98 100.599206349206 118]
MF2='mf2':'trapmf',[104 118.345238095238 121 129]
MF3='mf3':'trimf',[118 137.845238095238 148]

[Output1]
Name='gub'
Range=[34.8 57.2]
NumMFs=3
MF1='mf1':'trimf',[25.93 35 48.16]
MF2='mf2':'trapmf',[39.12 46.05 48.88 53.91]
MF3='mf3':'trimf',[48.3 57.26 66.22]

[Rules]
1, 1 (1) : 1
2, 2 (1) : 1
3, 3 (1) : 1
```

P5.2

```
[System]
Name='mgubest'
Type='mamdani'
Version=2.0
NumInputs=1
NumOutputs=1
NumRules=3
AndMethod='min'
```

```
OrMethod='max'
ImpMethod='min'
AggMethod='max'
DefuzzMethod='centroid'

[Input1]
Name='m'
Range=[3.96 8.28]
NumMFs=3
MF1='mf1':'trimf',[2.232 3.96 5.688]
MF2='mf2':'trimf',[4.392 6.12 7.848]
MF3='mf3':'trimf',[6.552 8.28 10.01]

[Output1]
Name='gum'
Range=[0.2 8]
NumMFs=3
MF1='mf1':'trimf',[-2.92 0.2 3.32]
MF2='mf2':'trimf',[0.98 4.1 7.22]
MF3='mf3':'trimf',[4.88 8 11.12]

[Rules]
1, 1 (1) : 1
2, 2 (1) : 1
3, 3 (1) : 1
```

Time	Moisture	Time	Moisture
0	0	2700	8.28
200	3.96	2800	6.60
400	3.96	3000	6.60
600	3.96	3200	6.60
800	3.96	3400	6.60
1000	3.96	3600	6.60
1200	3.96	3700	6.60
1400	3.96	3800	6.60
1600	8.28	4000	6.60
1800	8.28	4200	4.56
2000	8.28	4400	4.56
2200	8.28	4600	4.56
2400	8.28	4800	4.56
2600	8.28	5000	4.56

Table 5.7 Varying values of moisture setpoint (mnew.m)