IDENTIFICATION OF A FUZZY MODEL AND ITS APPLICATION IN A CONTROLLER

Submitted by:

NIDA QAMAR

Supervised by:

DR. MUHAMMAD BILAL KADRI

THESIS

Submitted to:

Department of Electronic and Power Engineering

Pakistan Navy Engineering College Karachi

National University of Science and Technology, Islamabad Pakistan

In fulfillment of requirement for the award of the degree of

MASTER OF SCIENCE IN ELECTRICAL ENGINEERING

With Specialization in Control Engineering

TABLE OF CONTENTS

TABLE OF FIGURES

ABSTRACT

This thesis aims at designing a fuzzy-model of a plant for a Controller. Modeling of a non linear plant is considered to be a very important task for integration and application in non linear systems. Certain algorithms have been proposed that provide efficient modeling of a non linear system and later validate the identified model via application in a controller.

In the recent years, the fuzzy logic has gained immense importance. Today, it is a major tool for modeling and designing a control strategy for many industrial processes. The main reasons for this popularity include the ability to handle constraints and dynamic nonlinearities in an explicit manner, plus the possibility to consider multi-variable processes with many dependent and independent variables. In this thesis, Internal Model Control has been used to validate the identified model, because of its straightforward inner structure.

A model predicts the change in dependent variables in a plant that is caused by the change in independent variables of the plant. Independent variables that cannot be adjusted by the controller are used as disturbances. Dependent variables are other measurements that represent control objectives. The identification process has been simulated using MATLAB and its performance has been tested by its integration in an Internal Model Control scheme.

ACKNOWLEDGEMENT

The transparency of feelings of one human being towards another is usually translated or quoted as a blessing in disguise. In my singularly exceptional case, however, the boon can well be interpreted as a bane; for the gratitude that my heart beholds for my benefactors could only be felt but never be expressed.

However, I shall use the granted confined space of the page to the best of its merit to reflect some of these emotions. First of all, I bow before the Creator for bestowing upon me the faculty that enabled me to carry out this errand with finesse.

Amongst the ephemeral counterparts who leaned their helping shoulders, the good name of Dr.M.Bilal Kadri tops the hall of fame. His unerring guidance, infallible technical insight & unprecedented supervision served the purpose of beacon light to channel my thoughts & vision. He is as personable personally as he is sound professionally. My GEC members have also been very supportive throughout and have been mentors of great class & caliber.

Last but not the least; I would also like to thank my parents & families, who contributed immensely in giving me emotional & moral support. I have been motivated by their countless efforts in helping me to complete the project on time.

CHAPTER 1

INTRODUCTION

1.1 MOTIVATION

Fuzzy Logic has achieved a great deal in modeling, controlling and engineering applications since it has been introduced in 1965 by Lotfi Zadeh [14]. This is mainly because of the increasing number of researchers in this area who have developed appealing conclusions. For the modeling of non linear processes, fuzzy logic and fuzzy systems have proved to be much useful [10] and [25]. The transparent nature of fuzzy logic eases the treatment of qualms and opaqueness usually found in real systems. Furthermore, the if-then rule methodology is straightforward to interpret and is domain independent. Distinct techniques such as Fuzzy Clustering and Least Squares algorithm have been proposed for data driven fuzzy modeling in this thesis [30] and [21].

1.2 FUZZY MODELING AND ITS VALIDATION

The application and regulation of model-based control is based on a crucial step of the design and improvement of a suitable model that depicts the dynamics and non linearity. Many different algorithms have been designed for the development of fuzzy models and tuning them derived from given numerical data. Putting it simply, the if-then rules consist of a collection of translation of expert knowledge expressed verbally. Therefore, a specific model structure is formed. The parameters of the created model structure (weights of rules, membership functions etc.) can be fine tuned using given input-output data [22] and [25].

Based wholly on the given numerical data, fuzzy logic helps to generate a fuzzy model. Here, in this dissertation, data-driven fuzzy modeling has been addressed using fuzzy clustering and least squares algorithm. The identified model is then used to elucidate the performance of the target system in connection with the input-output data pairs.

For the validation of the identified model, a controller based on the IMC scheme has been used which is a classical version of predictive controller [20] and [30].

1.3 SCOPE OF WORK

The main objective of this thesis is to model a plant making the use of certain techniques that have been discovered and studied by various researchers and scientists. To identify the substructures of the observations, in the domain of available observations, fuzzy clustering can be used. Each cluster characterizes a fuzzy space or domain in which the fuzzy scheme can be fairly approximated locally by a sub model or subsets of the observations. The cluster centers are then used to represent the rules of the fuzzy system [6], [19] and [22]. The use of MATLAB fuzzy system toolbox and clustering toolbox was made for modeling the plant. This methodology is tailored specifically for SISO and MISO systems.

We emphasize on the basics of modeling i.e. Adaptation & Learning. These terms are more explicitly defined below [29]:

Adaptation: Adaptation is defined as the state of the controller gradually changing to deal with new environments and compensating for the drift in dynamics of the plant.

Learning: Learning is defined as retrieving trained up models and applying to similar anticipated environments with no/small modifications.

1.4 CHAPTERS ORGANIZATION

This thesis has been organized as follows:

Chapter 2 briefly discusses the literature review of the work done in modeling of a plant using fuzzy techniques.

Chapter 3 as discusses the various concepts and theories regarding the modeling of plant and its validation.

Chapter 4 includes the actual data generation procedure and the training of TS model and its identification.

Chapter 5 elucidates the integration of a controller with the identified model and contains its simulated results.

And the final Chapter 6 concludes the thesis work and contains future recommendations.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

In this chapter, we will discuss the literature review of the work done in related field. Various modeling strategies were adopted by researchers for modeling of a plant. The detail of all the research papers and books is given in the references at the end of this report. This chapter discusses a few, most relevant research papers, briefly regarding modeling of a plant using clustering and least squares algorithm.

2.2 BRIEF DISCUSSION ON REVIEWED LITERATURE

In [24] the authors of the paper "Adaptation and Learning of a Fuzzy System by nearest neighborhood clustering" have discussed the multiple models scheme that is proposed for parameter-varying systems with special initialization technique to ensure smooth transition between different rapid changing environments. The algorithm in this paper is based on adaptive fuzzy nearest neighborhood clustering algorithm. The fast adaptation is realized by the switching between different models; learning is achieved by recording and retrieving the trained up models. The authors have discussed clustering algorithms as compact representations of data sets, through which the data points are classified based on their built-in resemblance in disjoint subsets. The model library is generally too large for memory storage and a fast changing environment evolves the concept of adaptation between the different models. Hence, this paper introduces the concept of the breakdown of large model library in small trained model fragments. This is known as multiple model approach.

The main target for this approach is type of systems which are generally complex in nature. A complex plant is broken down into several sub plants and the learning and adaptation of the models via these sub plants takes place in accordance with the algorithm presented in this paper. Since the system used in this thesis is not a very complex system, also the data points do not need to be classified into sub model, the final identified model can be implemented in any controller without the multiple models approach. Hence, the above given algorithm is ideal for complex systems.

Some basic methods to estimate model parameters from both open loop and closed loop step responses have been proposed in “Novel Identification method from Step Response” [29]. The significance of this method is its flexibility with which the model parameters are estimated from a single step test, a special case being the step input application even when the process is not in a steady state. Another outstanding feature is that the estimation equations are acquired in terms of raw values of variables which facilitate the straightforward use of industrial data without having it processed first.

The two main concerns about the form of data have been reviewed. First, usually identification procedures are designed to deal with variables in deviation form while the data collected from industries is not available in that form. For obtaining the data in deviation form, subtraction is carried out between the initial steady state values and the raw values. Sometimes a hindrance occurs because of the presence of disturbances in the system or because of the application of input before the steady state conditions of the system have been achieved. The second concern that arises is whether any method can estimate the parameters of the system in the existence of initial conditions. Hence, in this paper, the new approach for identification facilitates the use of industrial raw data, is applicable for non-zero initial conditions and estimates the initial conditions as well as the delay, [12] and [13].

The plant that is taken in consideration in this paper is a simple water heater plant being used in a laboratory, the data has been considered in raw form and initial conditions are not required. The above proposed method is appropriate for industrial data but for a less complex data, we can easily deal with simple clustering algorithm and multiple model approach is not required.

We are now moving towards the idea of developing a model from the techniques of Clustering and Least Squares. The Least Squares estimation procedure is very basic and has been discussed in the upcoming chapters. Clustering is a special methodology that has been researched upon in detail by many scholars and engineers, [17], [32] and [33].

In the paper “A Comparative Study of Data Clustering Techniques” [18], Khaled Hammouda has discussed 4 major clustering algorithms, namely, Soft or C-Means Clustering, Hard or K-means Clustering, Subtractive Clustering and Mountain Clustering. Clustering is regarded to be an ideal approach for estimating similarities between the data by any special parameter and classifying them in groups. Such clustering algorithms are used widely for model development and characterizing/organizing large sets of data. Out of the four methods that have been mentioned in this paper, C-means and K-means clustering methods require the number of clusters a priori; the algorithm then tries to categorize the data into the given number of clusters. Whereas, Mountain type and Subtractive clustering do not require the number of clusters, instead the algorithm initializes by forming the initial large cluster and then goes on to find the second.

This thesis covers the C-means clustering procedure that has been described in this paper. The discussion about online and offline clustering is also an important part of this paper that made the decision to imply either of them in this thesis. Online clustering works on the methodology of updating each cluster center to its required vector position, each time the input is applied. In offline clustering, the input is in the form of a training data set. The cluster centers are then created by the analysis of all the input vectors in the training data set. The clustering methods discussed in this paper are of offline type. In C-means clustering each data point belongs to a cluster to a degree specified by a membership grade and works on the conditions that minimize a cost function of dissimilarity measure [17], [25] and [32].

This is the algorithm for fuzzy c-means that has been implemented and validated in this thesis. The iterative steps have been carried out and the results have been validated by observation of the model’s performance in a controller.

C-means clustering approach has been further discussed in the paper “A Clustering Based Approach to Fuzzy Systems Identification” [32]. Out of the two phases of the given approach, the initial phase involves a baseline design for effective identification of the target system from the given set of input-output data pairs. For this purpose, subtractive clustering was used to establish the number of clusters. Then, fuzzy c-means clustering algorithm is applied to construct the rule base. If there is any discrepancy in the performance of the fuzzy model, the second phase fine tuning is applied to adjust the parameters. This process is carried out using recursive least square methods, [31].

This paper makes use of subtractive clustering which is an algorithm other than fuzzy c-means. It makes use of the data points as cluster centers. This might results in loss of information in some cases when the cluster center is far from the actual data point. It also uses the density feature for evaluating the number of clusters. The algorithm presented in this paper does not give one step results, rather we also have to fine tune the process and the output of the clustering procedure. This makes the whole process time consuming, although the use of c-means clustering makes the prototype fuzzy model much promising with reduced computational efforts.

A method for cluster estimation is proposed in [19] which computes the potential of each data point and then diminishes their potential as they approach new cluster centers. The computation grows linearly with the dimension of problem. For c-means algorithm, the initialization mainly depends on the number of clusters and their locations in the vector space. The method discussed in this paper involves consideration of every data point as a cluster center itself. Hence, the number of clusters is equal to number of data points. Furthermore, each cluster center forms a rule that identifies the system’s performance. The method of estimation of clusters provided in this paper when combined with the least squares algorithm produces a robust algorithm for identification of fuzzy models. The validity of this idea has been checked in this thesis by generating the antecedents of the rule base using clustering and the premise has been generated using least squares. Also if the non linear optimization methods are avoided at this stage, the initialization of the variables involved in the algorithm becomes easier, [21] and [25].

Another method for generating the rule base has been proposed in [17]. This paper "Fuzzy Clustering and Fuzzy Rules" reviews certain approaches for generating rules from clusters of data obtained. The proposition is to generate a rule base in which each cluster induces a rule by the position of its projection in coordinate space. This projection of a cluster is acquired by taking the respective coordinate of each data point and assigning to it the membership degree of the original data point to the cluster. Hence, a fuzzy set is obtained. The discretion of the fuzzy set then results in a suitable approximation like a triangular or trapezoidal membership function.

The above approaches have to face the problem that the fuzzy clustering algorithm results in a fuzzy partition of the product space of all data, whereas fuzzy if-then rules are defined on the basis of fuzzy partitions for single domains. This means that loss of information caused by the approximation of the discrete fuzzy sets will occur. Also, the original fuzzy cluster cannot be recreated from the fuzzy sets appearing in the rule base derived from the cluster. Hence, the validity of the clusters containing all the information in the data is doubtful. The grid clustering method is introduced in this paper which involves the generation of rule base according to the number of grid points as cluster centers. And only those clusters are allowed to induce a rule that is non empty.

After the estimation of clusters, the idea of making a compact rule base from a précised number of clusters has been furnished. In "Compatible Cluster Merging" [27], a compatible cluster merging algorithm for finding the best possible number of rules in a rule-base of a fuzzy system, has been discussed in detail. System modeling requires the evaluation of actual number of clusters of the data; an accurate specification of this feature is immensely important as a huge number makes a complicated rule-base that is very time-consuming and tedious to de-fuzzify, whereas a very tiny number results in a poor model. Hence, with the application of CCM, one may initialize with a large number of clusters and goes on reducing the number of clusters until no more clusters can be merged. An upper bound estimation on number of clusters is also mandatory for CCM.

The algorithm works on the degree of compatibility between the clusters. It depends on the Eigen values and Eigen vectors of the covariance matrices of the clusters, evaluated by the clustering algorithm. Using above-mentioned criteria, the initial number of clusters comes down to a specific value; the output of each iteration is used as an initial approximation for the subsequent stage of cluster merging. An important aspect of CCM algorithm is that the final identified model is described locally by the rules and the same is described globally by the initial rule base before the application of CCM.

Although it is an attractive way to merge clusters, the only problem that arises while using the CCM criteria is that the algorithm requires a priori determination of many parameters. One need to have an expert knowledge about these variables or else the algorithm cannot be implemented. The simulations in this thesis do not implement the CCM algorithm because of the above mentioned reasons requiring expert knowledge of the variables.

Hence, after the review of above literature, the idea for identification of fuzzy model is very clear and straightforward. The cluster estimation procedure will be applied in coherence with least squares method. The combination of these two algorithms results in a robust and less complicated model. Furthermore, the model will be identified in offline mode and the final results will be simulated and used for further engineering applications.

2.3 SUMMARY

In this chapter, a brief research overview was presented that has been done to get familiar with various approaches for modeling a system. The remaining chapters will discuss the procedure adapted for this thesis work and the concluding results.

CHAPTER 3

FUZZY MODELING

3.1 INTRODUCTION

In this chapter, fuzzy modeling has been carried out using various techniques. From the several AI modeling techniques known, modeling via fuzzy techniques is one of the most appealing. In fact, when the system cannot be described totally by first principles because of the non linearity present, it is beneficial to use fuzzy modeling as a combination of first principles and information obtained from linguistic rules describing the system and its parameters. This gives rise to gray-box modeling approach. Considering a case in which no a priori knowledge (linguistic rules, physical measurements, and knowledge of various parts of the system) is available, procedures such as Neural Learning methods, Least Squares and Fuzzy Clustering are used to extract rules and membership functions directly from measurements taken from the process [21].

3.2 SIGNIFICANCE OF FUZZY MODELS

In computational terms, fuzzy models have been termed as universal function approximators because of their flexible mathematical structures. Hence, the general form of if-then rules in fuzzy modeling is:

If *antecedent proposition* **then** *consequent proposition*

Fuzzy models make use of “If-Then” rules and coherent connectives to create an interface among the variables allocated for the system’s model. The fuzzy sets in the rules represent a relation between the quantitative input output variables and the qualitative model parameters. The knowledge represented by the model of the system is described in linguistic manner by the rule based nature of the fuzzy model. The fuzzy modeling approach is much advantageous in comparison to other techniques of non linear modeling. In general, fuzzy systems and methodologies can provide a much more transparent depiction of the system under consideration and facilitate a linguistic analysis by the help of rules [7].

3.3 CLASSIFICATION OF FUZZY MODELS

Various types of rule based fuzzy models are eminent depending upon the rule-base structure and the general form of antecedent and consequent propositions [14]. The two most commonly used being:

1. Mamdani fuzzy models: where both the antecedents and consequents are represented by fuzzy propositions.

2. Takagi-Sugeno (TS) fuzzy models: The antecedent is a fuzzy proposition and the consequent is a crisp function.

Here TS fuzzy models will be discussed in this thesis.

3.3.1 TAKAGI-SUGENO FUZZY MODELS

Takagi and Sugeno introduced a fuzzy rule based modeling technique that enables the researchers to analyze almost all classes of non linear systems [22]. The TS fuzzy model is mainly an approximation of the singleton model, where the rule consequents are represented by crisp functions of the model input instead of being constants as in the case with Mamdani Fuzzy models.

$$\mathbf{R_j}\text{: If } \mathbf{x} \text{ is } A_j \text{ then } y_j = f_j(x),\ j=1, 2 \ldots N$$

Where $\mathbf{R_j}$ denotes the jth rule, N denotes the number of rules, x represents the antecedent variable, y represents the one-dimensional consequent function variable and A_j is the antecedent fuzzy set of the jth rule. Above representation is for MIMO fuzzy model, which can later be partitioned into a group of MISO or SISO fuzzy models for the sake of simplicity, [12]. The antecedent proposition can be a combination of simple propositions whereas the consequent functions are preferred as constrained functions, where the general structure remains identical for the whole rule-base. The simplest and extensively used function yielding the rules is:

$$R_j\text{: If } x \text{ is } A_j \text{ then } y_j = a_j^T x + b_j$$

Where a_j represents parameter vector and b_j represents a scalar offset.

Usually, the antecedent fuzzy sets define discrete, but overlapping regions in its space. In such a case, the TS model is viewed as a smooth piece wise linear approximation of a non linear function.

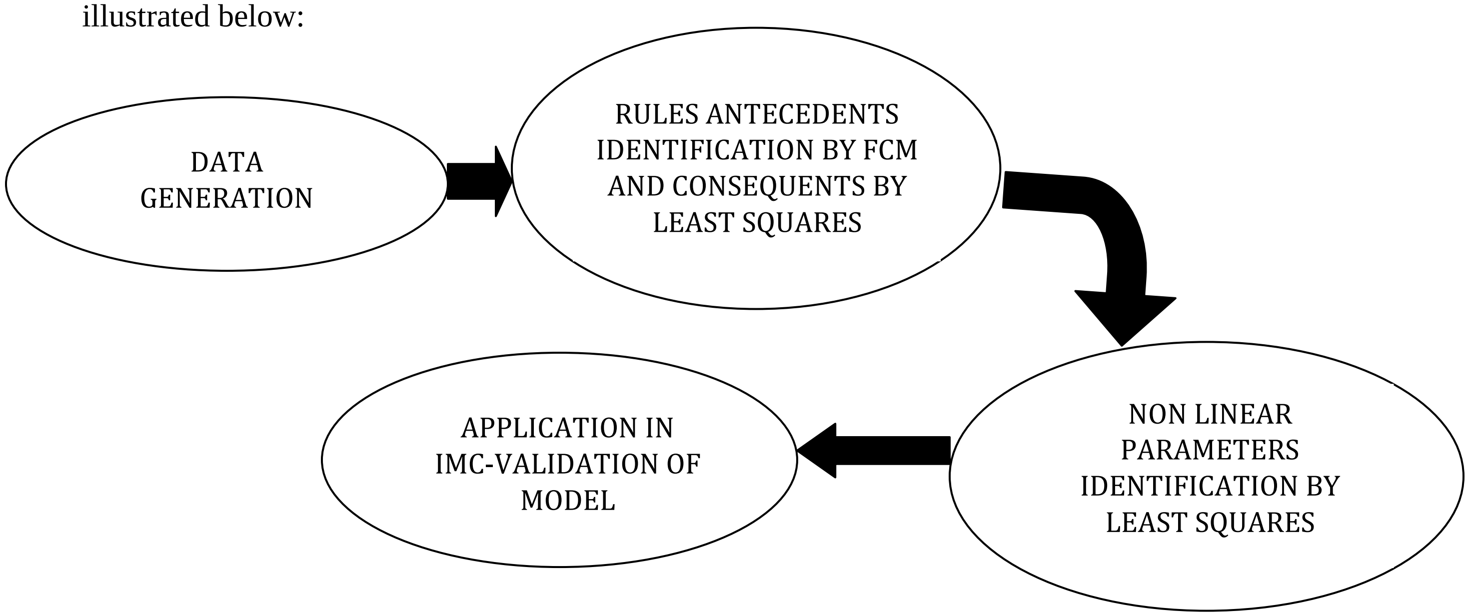
3.4 FUZZY HAMMERSTEIN MODEL

The fuzzy model which is going to be discussed and obtained in this thesis is a special class known as Fuzzy Hammerstein model [23] and [26]. The static non linearity and linear dynamics are combined in series to obtain the FH model. This basic structure provides assistance in the identification and assimilation of Fuzzy Hammerstein models in modern and classical control schemes. Several experiments in which non linear effects are encountered are various industrial processes such as distillation columns, pH neutralization procedures, heat exchangers or electro mechanical systems. Such processes can be effectively modeled as an amalgamation of a linear dynamic element and static non linearity part. Since the knowledge of the steady state attributes of Hammerstein models is usually known a priori, they have been proven to be appropriate for gray box modeling [11].

The identification of FH models is easily carried out with the linguistic rules and data, collected from the system; therefore it has the potential of being transparent and easily interpretable. This is also the main motive behind using the Hammerstein models in this thesis.

3.5 OUTLINE OF MODELING APPROACH

The major outline of the modeling approach and hence its application in a controller is illustrated below:



For this thesis, the plant under consideration is a water heating plant where the input being the control signal that is given to heat the water to a certain temperature and the output is the outlet temperature. This plant is modeled using Fuzzy techniques involving Clustering and Least Squares.

The first step is the collection of data from the plant. Each input output data pair is analyzed and then further used for identification purposes. Approximately 400 samples of data pairs were accumulated.

The second step involves the modeling of linear dynamics part using FCM and Least Squares. The consequents have been identified using Least squares and the antecedent fuzzy sets have been identified by FCM. The rule base is formed and compacted to form a generalized rule base.

In the third step, the parameters for static non linearity have been modeled using Least Squares, giving the best approximate result for the considered plant.

In the final step, the model is integrated in a controller working in an IMC scheme. The results have been simulated and discussed in the later chapters.

3.6 FUZZY CLUSTERING

Clustering, by definition, is the partitioning of data into subsets or groups based on similarities between the data. Clustering divides a data set into several sets such that a relationship forms among the members of the set; also the degree of similarity decreases as we consider several sets. This idea of data partitioning or data clustering is very close to human way of thinking and is quite simple in nature. Whenever a large amount of data is available, a common man's way of thinking is to recapitulate this large data into small number of factions or categories which further simplifies its analysis [17], [18] and [22].

Moreover, in many studies and researches, the data collected is seen to have inherent attributes that impart immediate categorizations. Even though, trying to assemble the data on the basis of similarities is not an easy task for engineers or researchers unless the data has low dimensionality (two or three dimensions at maximum). Hence, clustering methods have been introduced to overcome this problem.

Clustering algorithms are being used extensively for data compression, modeling construction and in soft computing by not only organizing the data but also the classification on the basis of their dimensions and behavior [1] and [3]. Having the knowledge of the similarities in the data, fewer symbols can be used for representation, and hence the model of the system can be analyzed based on these groupings.

Another motive for using clustering is to discern relevant knowledge in the data. Francisco Azuaje [2] introduced a Case Based Reasoning (CBR) system depending upon a Growing Cell Structure (GCS) model. Data that has been indexed and categorized by cases can be stored in a knowledge base, known as a Case Base. Each group represents a certain group of cases. In a GCS scheme, data can be added or subtracted on the basis of learning scheme used. Next, the system retrieves the most appropriate cases from the original case base in the presence of a query, depending on the relevance to the query.

3.7 FUZZY C-MEANS CLUSTERING

As mentioned earlier, data clustering deals with the formation of subsets of the data into several number of groups taking into account the fact that the similarity within a group is larger than the similarity among the groups. This entails that if the data set is uniformly distributed; clustering will either fail or will generate artificially introduced groups/clusters; whereas for implementing clustering the data set must have an intrinsic grouping to some extent. An additional problem that usually arises is the overlapping of data subsets; which results in efficiency reduction in proportion to the degree of overlap between the subsets of the data [10] and [11].

The common idea of all clustering techniques is to estimate cluster centers that will serve as representation of each data. A cluster center denotes the location of the heart of each cluster, so that when the system is encountered with an input vector, a similarity measure among the input vector and the cluster centers can determine the belongingness of the given vector to a cluster. It also interprets which cluster is the nearest one incase exact belongingness is not established, [22].

Some of the clustering techniques rely on the a priori knowledge of the number of clusters. In such case the algorithm groups the data according to the specified number of clusters. Fuzzy C-means is of the same type.

Clustering algorithms may be implemented in offline or online mode. In online clustering the system learns the location of each cluster by the introduction of a new input every time; this input vector updates the position of each cluster according to the vector position of the input presented to the system. In offline mode, a training data set finds the cluster centers by examining all the input vectors in that set. Once the clusters are located, they are fixed and later classify new input vectors [1].

In Fuzzy C-means clustering, a degree of membership grade identifies the belongingness of each data point to a specific cluster. The algorithm depends upon finding a minimal value of the cost function measuring the dissimilarity.

Fuzzy C-means algorithm works on the fundamental idea of Hard C-means Clustering (HCM) with the difference that in FCM, a degree of membership grade is assigned to each data point, while HCM works on the principle that every data point either fits in a cluster or not. So FCM involves fuzzy partitioning in a way that each data point belongs to various clusters with a certain membership grade varying from 0 to 1. FCM also minimizes a cost function while making subsets of the data points [33].

The membership matrix consists of the degrees of belongingness of a specific data point to a cluster. The summation of all the elements of membership matrix U is always equal to unity.

$$\sum_{p=1}^{c} u_{pq} = 1, \forall q = 1, 2, \ldots\ldots n \tag{3.1}$$

The basic cost function for minimization is given below:

$$J(U, c_1 \ldots\ldots c_c) = \sum_{p=1}^{c} J_p = \sum_{p=1}^{c} \sum_{q=1}^{n} u_{pq}{}^{z} d_{pq}{}^{2} \tag{3.2}$$

Where, u_{pq} ranges from 0 to 1; c_p is the cluster center of fuzzy group; $d_{pq} = \| c_p - x_q \|$ is the Euclidean Distance between the p^{th} cluster and the q^{th} data point; $z \in [1,\infty)$ is a weighting exponent.

The requirements for the cost function to be minimum are:

$$c_p = \frac{\sum_{q=1}^{n} u_{pq}^{z} x_q}{\sum_{q=1}^{n} u_{pq}^{z}} \tag{3.3}$$

And

$$u_{pq} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{pq}}{d_{kq}} \right)^{\frac{2}{z-1}}} \tag{3.4}$$

The algorithm runs according to a number of iterations with the above mentioned criteria until convergence is achieved. In the presence of the data in the form of a batch, FCM follows the below steps to estimate the cluster centers c_p and the elements of membership matrix U:

1. Initiate the membership matrix U with random values within the range of 0 and 1 for meeting the constraints in Eq 3.1.
2. Compute c cluster centers, $c_{p,}$ and p=1, 2 …c, using Eq 3.3.
3. Calculate the cost function according to Eq 3.2. If it generates a value that is below a certain threshold or the difference between the results of previous iterations is minimal, bring the calculation to a halt.
4. Determine a new membership matrix U using Eq 3.4. Then go to Step 2.

The FCM behavior relies on the initial values of the membership matrix. Therefore it is desirable to precede with the algorithm a number of times while beginning each time with discrete values of elements of membership matrix for data points [30] and [34].

3.8 LEAST SQUARES ALGORITHM

As per the basic configuration of the FH model under study, the parameters of linear dynamic part are a_p and b_p. Then the parameter $d = [\mathrm{d}_1, \ldots\ldots \mathrm{d}_{N_R}]$ of the non linear part (static non linearity) can be computed by obtaining a solution of the regression equation, as given below:

$$y_d = \phi_d d + \varepsilon \tag{3.5}$$

Where ε denotes the modeling error that has been distributed normally, having zero mean. The y_d vector and the ϕ_d matrix are given for N data pairs as below:

$$y_d = \begin{bmatrix} y_d(1) \\ y_d(2) \\ \vdots \\ y_d(\mathrm{N}) \end{bmatrix}, \ \phi_d = \begin{bmatrix} \phi_d(1) \\ \phi_d(2) \\ \vdots \\ \phi_d(\mathrm{N}) \end{bmatrix} \tag{3.6}$$

With,

$$y_d\left(k\right)=y(k)-\sum_{p=1}^{n_a}a_p y(k-p) \tag{3.7}$$

$$\phi_d(k)=\left[\sum_{p=1}^{n_b}b_p\beta_1(u(k-p-n_d)),.....,\sum_{p=1}^{n_b}b_p\beta_{N_R}(u(k-p-n_d))\right] \tag{3.8}$$

The final solution of least squares regression problem may be given as:

$$d=\left[\phi_d^T\phi_d\right]^{-1}\left(\phi_d\right)^T y_d \tag{3.9}$$

Having computed **d**, the input to the linear dynamic block v(k) is given as:

$$v(k)=\sum_{q=1}^{N_R}\beta_q(u(k))d_q \tag{3.10}$$

Now the linear dynamic parameters $\theta_l=[a_1,a_2,.....a_{n_y},b_1,....,b_{n_u}]^T$ will be computed by evaluating below given regression equation:

$$y_l=\phi_l\theta_l+\varepsilon \tag{3.11}$$

Where,

$$y_l=\begin{bmatrix}y(1)\\y(2)\\\vdots\\y(N)\end{bmatrix},\phi_l=\begin{bmatrix}\phi_l(1)\\\phi_l(2)\\\vdots\\\phi_l(N)\end{bmatrix} \tag{3.12}$$

And,

$$\phi_l(k) = \left[\sum_{q=1}^{N_R} \beta_q d_q(u(k-n_d-1)), ..., \sum_{q=1}^{N_R} \beta_q d_q(u(k-n_d-n_b)), y(k-1), ..., y(k-n_a) \right] \quad (3.13)$$

Finally, the least square estimation of the linear dynamic parameters can be found by:

$$\theta_l = \left[\phi_l^T \phi_l \right]^{-1} \phi_l^T y_l \quad (3.14)$$

After evaluating the linear parameters by the above equation, the parameter of static non linearity **d** are computed once more and the whole method is repeated in certain iterations until convergence is achieved.

The gains of both the blocks of static non linearity and linear dynamic part are used to compute the static gain of the fuzzy model. This is an iterative procedure for the identification of a Fuzzy Hammerstein model and the steps can be stated point wise as below:

Step 1: Initializing the fuzzy model in its steady state based on the given steady state data or at random.

Step 2: Estimating **d** which represents the static non linearity of the fuzzy model.

Step 3: Estimate $\boldsymbol{\theta_l}$ which denotes the linear dynamic part of the fuzzy model.

Step 4: Repeat the iterations until convergence in both the linear and non linear parameters occur.

If the infinity norm of the dissimilarity in the results of two consecutive iterations is below a certain threshold value, then this condition is termed as “**Convergence**”. The above algorithm is much high-priced computationally as it requires solving the Clustering procedure as well as at least one least squares problem during each iteration, [10] and [11]. Also, since this is an offline algorithm, it must be repeated according to the required iterations, if a new input output data is presented to the system.

3.9 SUMMARY

In this chapter, the theory behind fuzzy modeling procedure has been elucidated. Types of fuzzy models and the modeling strategy involving the use of Fuzzy Clustering and Least Squares algorithm used in this thesis have been discussed. Later on, the advantages of fuzzy modeling over different types of modeling will be discussed at the end of this thesis.

CHAPTER 4

DATA GENERATION AND MODELING

4.1 INTRODUCTION

System modeling is an important tool for engineering applications, both from research perspective and a practical point of view. Data-driven models play an important role for processes such as intelligent systems and other control applications, many researches in this field have proved that fuzzy logic is much handy when dealing with model based control, [4]. This is due to the fact that fuzzy logic is very transparent in nature and this makes it easier to deal with any kind of uncertainty present in the real systems due to its expressiveness. Moreover, the rule base that is generated is mostly domain independent and is very easy to manipulate. An effective modeling procedure always produces good models, [9].

This chapter describes the data generation procedure from a non linear water heating plant and further on the modeling procedure, along with the Simulink models and the results. This has been ensured that the model exhibits the following properties:

1. The algorithm should be fast in producing the model.
2. It is constructive such that it has no backtracking procedures.
3. It belongs to a class of model free modeling.

4.2 BASIC CONFIGURATION OF FUZZY MODEL

The Fuzzy Model consists of a static non linearity, f, and linear dynamics G, combined in series according to the given figure. Here, u= $[u_1,\ldots\ldots u_{nu}]^T$ represents the input vector, v= $[v_1,\ldots\ldots v_{nv}]^T$ denotes the transformed input variables and y= $[y_1,\ldots\ldots y_{ny}]^T$ represents the output vector.

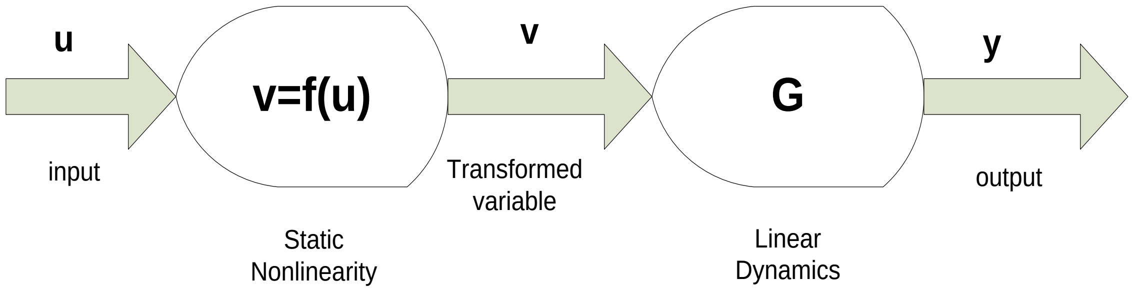


FIGURE 1: BASIC STRUCTURE OF HAMMERSTEIN MODEL; STATIC NONLINEARITY AND LINEAR DYNAMIC SYSTEM CONNECTED IN SERIES

In case, static nonlinearity is to be parameterized distinctly, f(.) can be devised as a group of functions $v_h=f_h(u_h)$, for $h=1,n_u$. For this study, according to [21], the $f_{h(.)}$ functions are denoted by Takagi Sugeno (TS) fuzzy models of zeroth order. The rules of the system are given as below:

$$R^h_{p_1,\ldots,p_{n_u}} : \text{ If } u_1 \text{ is } A_{1,p_1} \text{ and ..... and } u_n \text{ is } A_{n,p_{n_u}} \text{ then } v_h = d^h_{p_1,\ldots,p_{n_u}}$$

Where $A_{q,pq}$ (u_q) is the p_q^{th} fuzzy set in antecedent proposition for q^{th} input, $d^h_{p_1,\ldots,p_{n_u}}$ is the rule consequent which is a constant number in most of the cases. Given the input vector, u, the fuzzy model output, v_h, is evaluated by the weighted average of rule consequents:

$$v_h = \frac{\sum_{p_1=1}^{M_1} \cdots \sum_{p_{n_u}=1}^{M_{n_u}} \beta_{p_1,\ldots,p_{n_u}}(u) d^h_{p_1,\ldots,p_{n_u}}}{\sum_{p_1=1}^{M_1} \cdots \sum_{p_{n_u}=1}^{M_{n_u}} \beta_{p_1,\ldots,p_{n_u}}(u)} \tag{4.1}$$

Where M_q denotes the quantity of fuzzy sets in the q^{th} input domain. The weight $0 \leq \beta_{p_1,\ldots,p_{n_u}} \leq 1$, denotes the final truth value of the $p_1,\ldots,p_{nu}{}^{th}$ rule evaluated below:

$$\beta_{i1,\ldots,i_{n_u}}(u) = \prod_{j=1}^{n_u} A_{j,i_j}(u_j) \tag{4.2}$$

For simplicity, triangular membership functions have been used in this thesis, that generate a summation of unity as evident by the below figure:

$$A_{q,p_q}(u) = \frac{u_q - a_{q,p_q-1}}{a_{q,p_q} - a_{q,p_q-1}}, a_{q,p_q-1} \le u_q \le a_{q,p_q}$$
$$A_{q,p_q}(u) = \frac{a_{q,p_q+1} - u_q}{a_{q,p_q+1} - a_{q,p_q}}, a_{q,p_q} \le u_q \le a_{q,p_q+1} \quad (4.3)$$

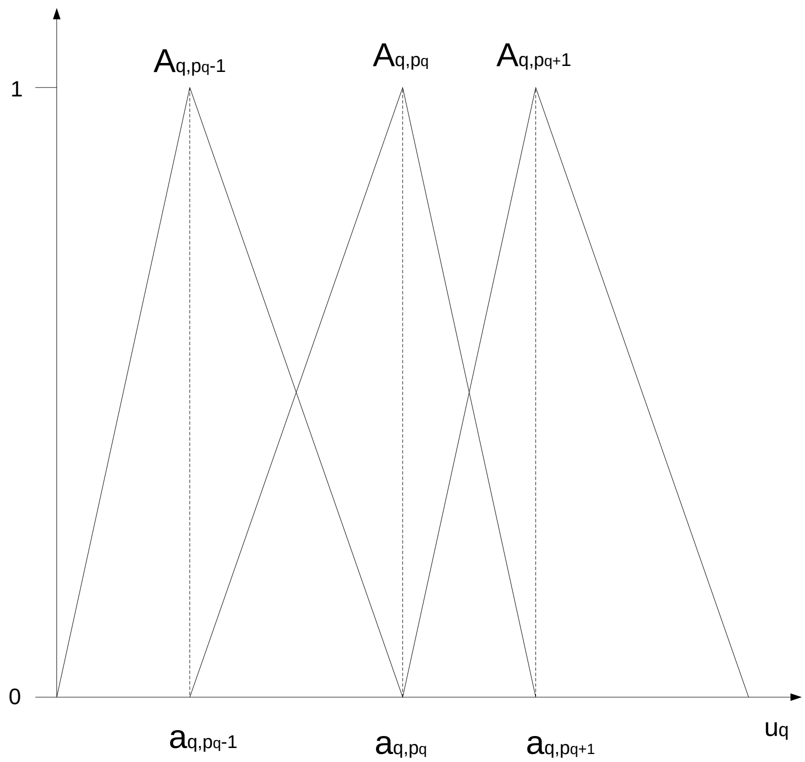


FIGURE 2: TRIANGULAR MEMBERSHIP FUNCTIONS

The cores of fuzzy sets determine the support of each set. This also guarantees that the summation of all membership functions is always unity and helps to acquire a rule base that can be interpreted and analyzed easily. The method for estimation of consequents is independent of the triangular membership functions. The weighted truth values of the rules meets below equality:

$$\sum_{i_1=1}^{M_1}.....\sum_{i_{n_u}=1}^{M_{n_u}}\beta_{i_1,......i_{n_u}}(u)=1 \tag{4.4}$$

And hence the output equation maybe simplified as:

$$v_h=\sum_{i_1=1}^{M_1}.....\sum_{i_{n_u}=1}^{M_{n_u}}\beta_{i_1,......i_{n_u}}(u)d^h_{i_1,....i_{n_u}} \tag{4.5}$$

Next comes the representation of linear dynamics after the static non linearity. For a MIMO system, the linear dynamics are of the form:

$$y(k+1)=\sum_{p=1}^{n_a}A_p y(k+1-p)+\sum_{p=1}^{n_b}B_p f(u(k+1-p-n_d)) \tag{4.6}$$

Where $y(k),.....,y(k+1-n_a)$ and $u(k-n_d),.....,u(k+1-n_d-n_b)$ are the outputs and inputs of the above mentioned linear dynamic part of the model with delays; n_a and n_b symbolize maximum delays for the previous outputs and inputs and n_d is the distinct time lag. $A_1,....,A_{na}$ and $B_1,....B_{nb}$ are the n_y x n_y and n_y x n_u matrices associated with the output and input vectors respectively.

In this thesis, SISO processes are being considered for the sake of simplicity, [26]. A generalized format for the rules of fuzzy system is given as follows:

$$q=p_n+\sum_{l=1}^{n-1}(\mathrm{p}_l-1)\prod_{k=l+1}^{n}M_k \tag{4.7}$$

Where q=1,….N_R.

Also, $N_R=\prod_{p=1}^{n_u}M_p$ denotes the total number of rules. Hence, a precise form of Fuzzy Hammerstein model representing a SISO system is given below:

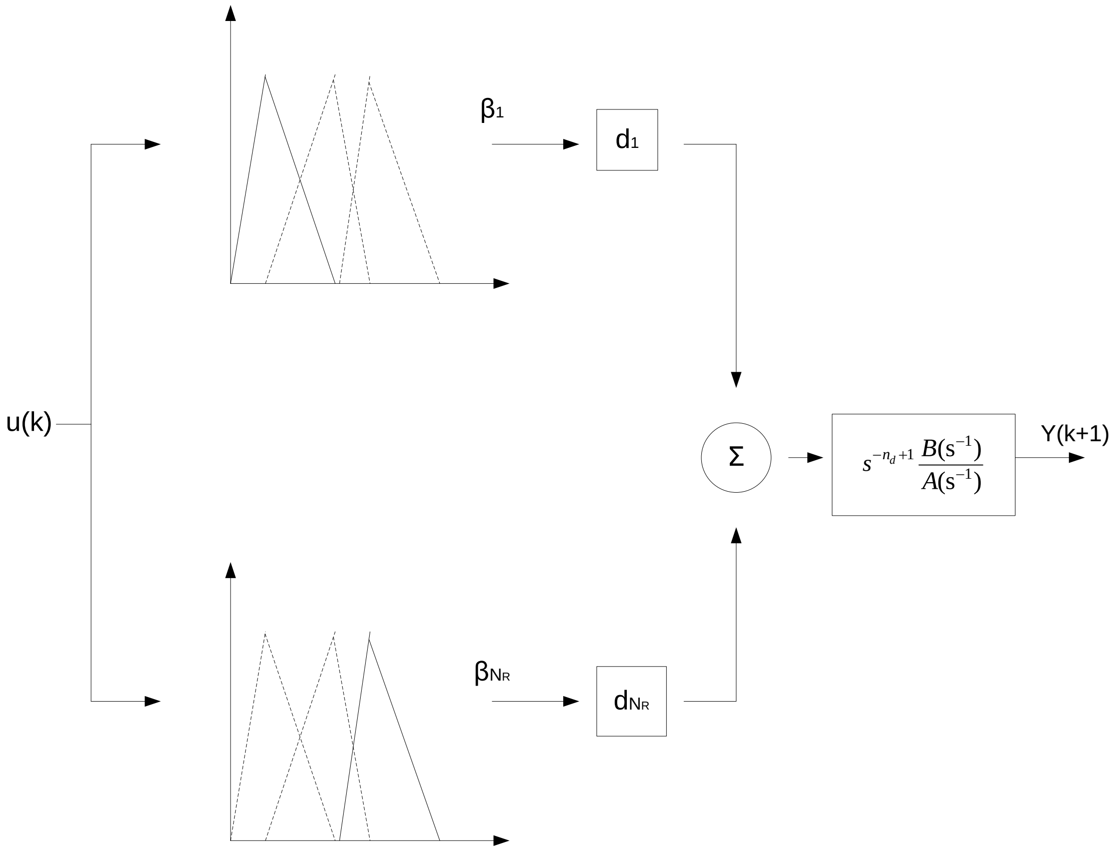


FIGURE 3: BASIC CONFIGURATION OF SISO FUZZY HAMMERSTEIN MODEL

$$\begin{aligned} y(k+1) &= \sum_{p=1}^{n_a} a_p y(k-p+1) + \sum_{p=1}^{n_b} b_p \sum_{q=1}^{N_R} \beta_q (u(k-p-n_d+1)) d_q \\ y(k+1) &= \sum_{p=1}^{n_a} a_p y(k-p+1) + \sum_{q=1}^{N_R} \sum_{p=1}^{n_b} d_q b_p \beta_q (u(k-p-n_d+1)) \end{aligned} \tag{4.8}$$

In the given model, a_p and b_p are the parameters belonging to the linear dynamic model and are termed as "linear parameters" while the parameter d_q represents the static non linearity and is termed as the non linear parameter. The resulting model is shown as a simplified structure in Figure 3; here s represents the shift operator i.e. $u(k)s^{-1} = u(k-1)$.

For steady state condition, we must define the gain of the static non linearity as equal to 1 such that:

$$\frac{\sum_{i=1}^{n_u} b_i}{1-\sum_{i=1}^{n_y} a_i} = 1 \tag{4.9}$$

Under the above mentioned conditions, the fuzzy model qualitatively shows the performance of the system $y_{ss} = f(u_{ss})$ in steady state, where y_{ss} and u_{ss} represent the equivalent input-output data pair at steady state.

4.3 PLANT UNDER CONSIDERATION

The plant under consideration in this thesis is an electrical water heater, which is heating a laboratory cartridge in this process. The proposed scheme of fuzzy modeling is illustrated here which represents the control of temperature in a water heater. Initially, the identification algorithm will facilitate the construction of a Hammerstein model making use of the input output data pairs. Here, the heater's power is considered to be a nonlinear static function of the heating or control signal, and the temperature of the heater at the outlet is taken to be a function of heating power which is linear dynamic in nature.

The schematic diagram depicting the process is shown in Figure 4. The control valve CV is used to control the rate of flow F_w of cold water streaming in the pipeline. Then, the water flows along metal pipes which consist of the cartridge heater. By adjusting the heating signal, u, of the cartridge heater, the output temperature T_{out} of the water becomes controllable.

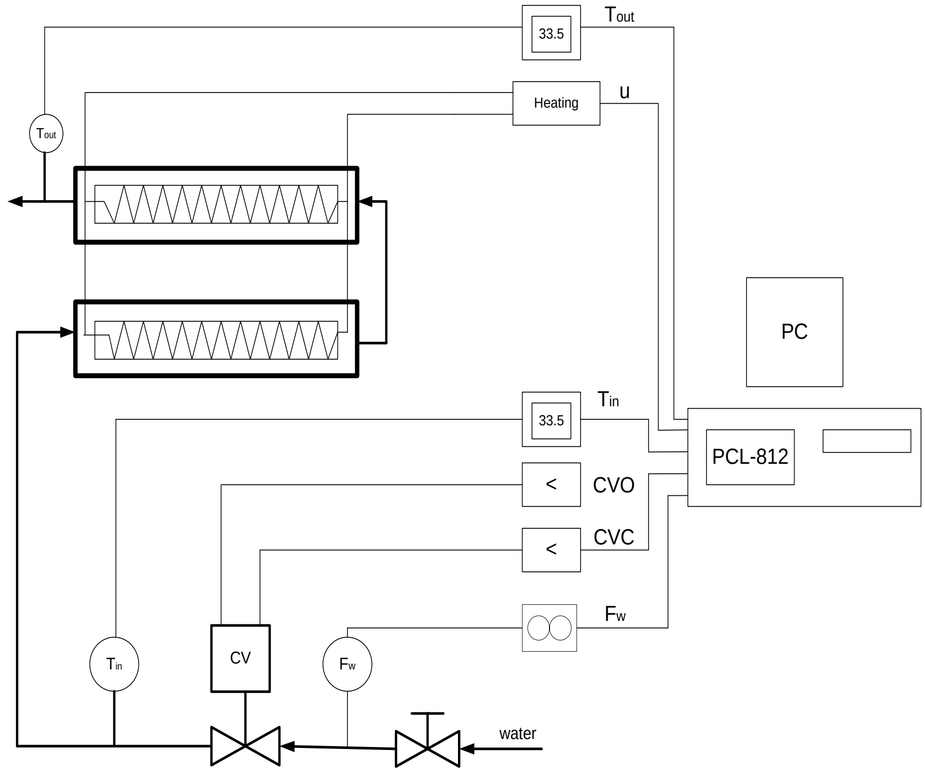


FIGURE 4: A SCHEMATIC DIAGRAM OF THE PROCESS

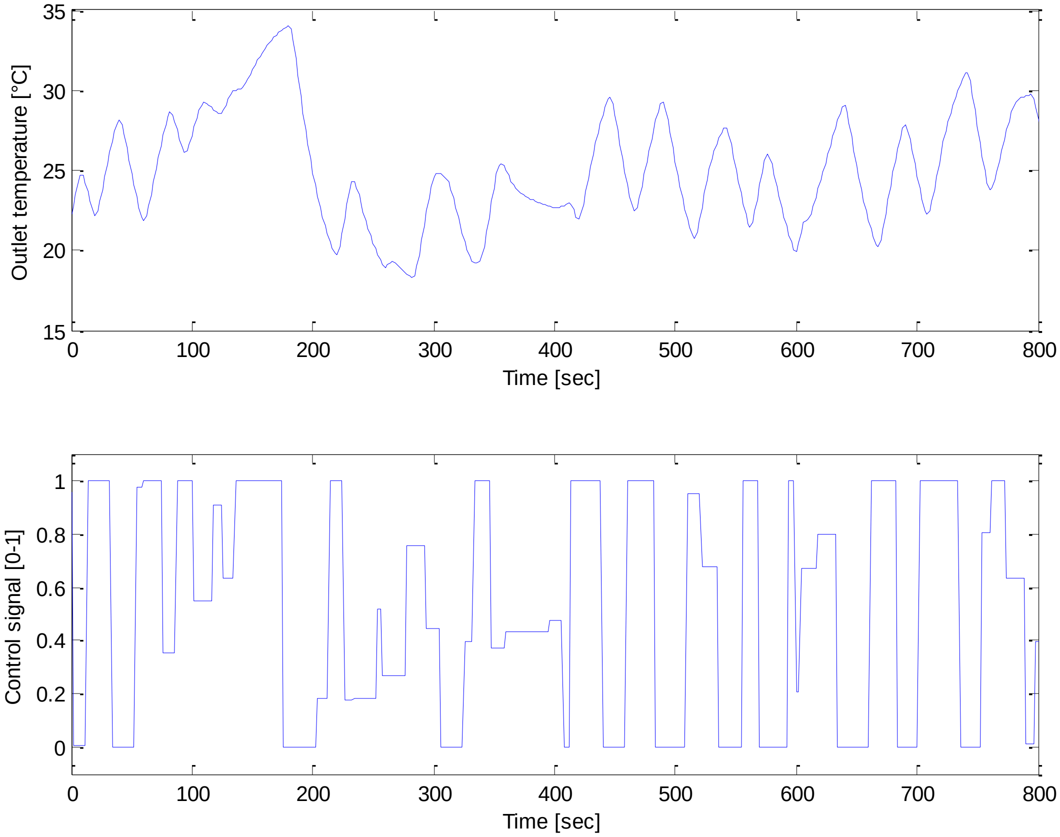


FIGURE 5: ACQUIRED DATA-INPUT OUTPUT DATA PAIRS

4.4 IDENTIFICATION PROCESS OF FUZZY MODEL

This section of the chapter describes briefly the procedure for the Fuzzy Hammerstein Model identification. This algorithm does not depend on the data collected when the system is at steady state. It uses the dynamic data which helps to identify the non linearity present at steady state and the parameters of linear dynamics, simultaneously.

The fuzzy sets in the antecedent proposition of the fuzzy model are estimated on the basis of the a priori knowledge. In this thesis, the antecedents of the fuzzy model have been determined by clustering (FCM), according to the procedure elucidated in Chapter 3. The identification algorithm then determines the parameters d_q, a_p, b_p which represent the consequent of the rules. This has been carried out by an iterative offline procedure of Least Squares, briefly described in the previous chapter.

4.5 DATA GENERATION AND CONSTRUCTION OF FUZZY MODEL

We have considered the above process of the cartridge heater to generate the data. This data is then used to construct the model. To model the given system, the structure was disintegrated into four connective elements:

- The cartridge heater-sub fix “h”
- The flowing water-sub fix “w”
- The wall of pipe-sub fix “p”
- The environment-sub fix “e”

Here, the partial differential equations have been used to represent the heat balances. They are given below:

$$V_h\rho_h C_{p_h}\frac{\partial T_h}{\partial t}(t,j)=Q(u)-\alpha_1 A_1(T_h-T_w)$$
$$V_w\rho_w C_{p_w}\frac{\partial T_w}{\partial t}(t,j)+(F\rho C_p)_w\frac{\partial T_w}{\partial z}(t,z)=\alpha_1 A_1(T_h-T_w)-\alpha_2 A_2(T_w-T_p) \tag{4.10}$$
$$V_p\rho_p C_{p_p}\frac{\partial T_p}{\partial t}(t,j)=\alpha_2 A_2(T_w-T_p)-\alpha_e A_e(T_p-T_e)$$

Here j ϵ [0,L] where L is the lengthwise measurement of the pipe. The cartridge heater works by the following principle:

$$Q(u)=Q_{\max}\left[u-\frac{\sin(2\pi u)}{2\pi}\right] \tag{4.11}$$

Here, $Q_{\max}$ is the maximum power, and u is the voltage signal for heating. In this plant, the flow rate is maintained at a constant, F_w=65 1/hr. The above differential equations have been simulated by approximating them to ten equal sections of volume. The description and theoretical values of the other attributes have been listed in [10]. As evident by the above equation, the heating principle is a static non linear function of the control input which is the heating signal. Hence the Hammerstein model is appropriate to model this system of laboratory water heater.

Now a dynamic model for the outlet temperature of the system will be constructed. This will be depicted by a function of the input heating signal u, $y=T_{out}=T_w(\mathrm{t},\mathrm{i}=\mathrm{L})$ from the provided data. The system is a proximate of a second order model having a discrete time delay. The linear dynamics part of Fuzzy Hammerstein model is given by:

$$y_{out}(n+1)=a_1 y(n)+a_2 y(n-1)+b_1 v(n-2)+b_2 v(n-3) \tag{4.12}$$

And static non linear part is depicted by 6 linguistic rules:

$$R_q:\text{If u is }\mathrm{A}_q\text{ then v=d}_q\text{, q=1,2,3....,6}$$

Clustering was performed to design the antecedent part of the rules (fuzzy sets). Triangular fuzzy sets A_q have been designed on the universe of discourse of the control input signal, u. The training data set collected during the data generation consists of N=400 samples, that were obtained within a sampling time of 4 seconds. The control signal u was defined containing significant frequencies in the projected range of the dynamics of the process. The Fuzzy Model was identified by the above mentioned algorithm taking into account the nominal values of the process parameters and the evaluated values after Clustering and Least Square Estimation.

The linear dynamics parameters resulted after applying Least Squares algorithm, as:

$$\frac{b_1 z^{-1} + b_2 z^{-2}}{1 - a_1 z^{-1} - a_2 z^{-2}} z^{-2} = \frac{0.0093 z^{-3} + 0.0019 z^{-4}}{1 - 1.8 z^{-1} + 0.8112 z^{-2}}$$

The fuzzy sets obtained after performing FCM are uniformly distributed and given as the antecedents of the rules:

$$A_q = [0, 0.2, 0.4, 0.6, 0.8, 1]$$

And, hence the parameters for the static non linearity of the fuzzy model are:

$$d_q = [14.90,\ 15.40,\ 20.94,\ 29.19,\ 34.63,\ 34.97]$$

The simulink model for generating the model generated from the data set is given as:

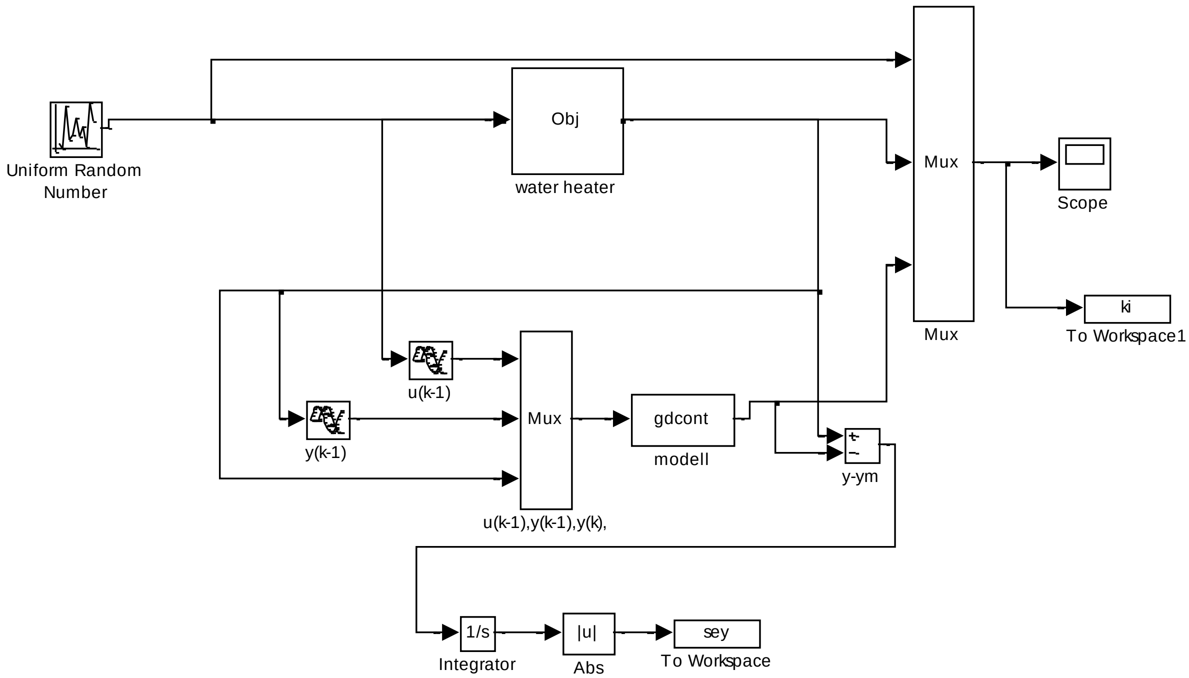


FIGURE 6: SIMULATION SETUP FOR MODEL GENERATION

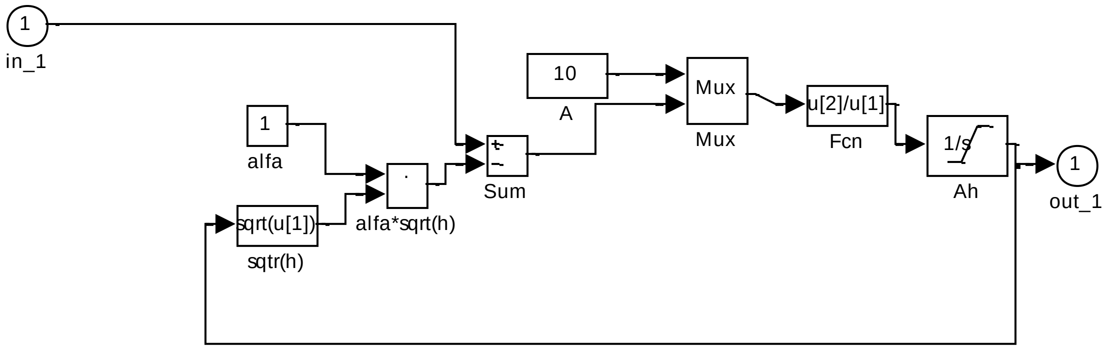


FIGURE 7: THE BASIC INTERNAL FUNCTION OF PLANT

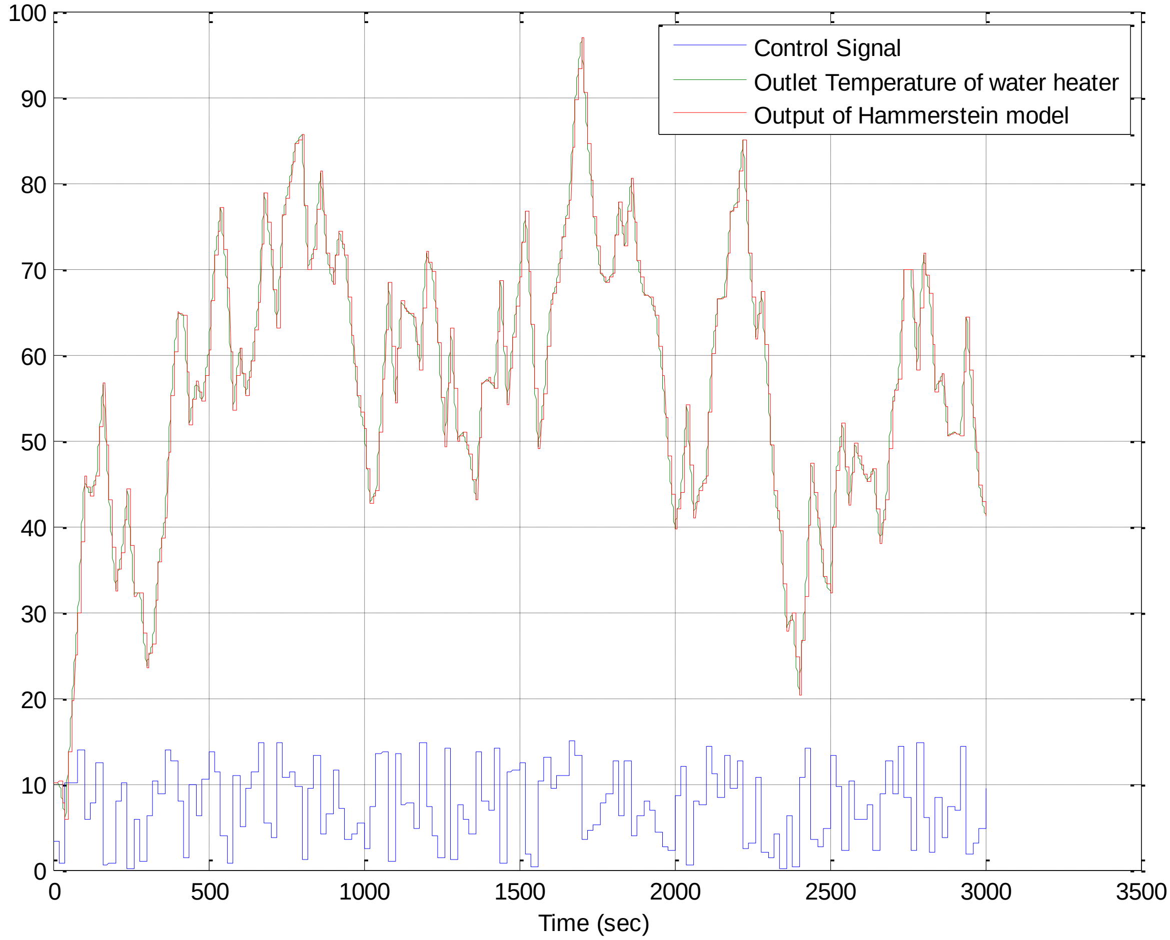


FIGURE 8: COMPARISON OF OUTPUT OF PLANT AND OUTPUT OF GENERATED FUZZY HAMMERSTEIN MODEL

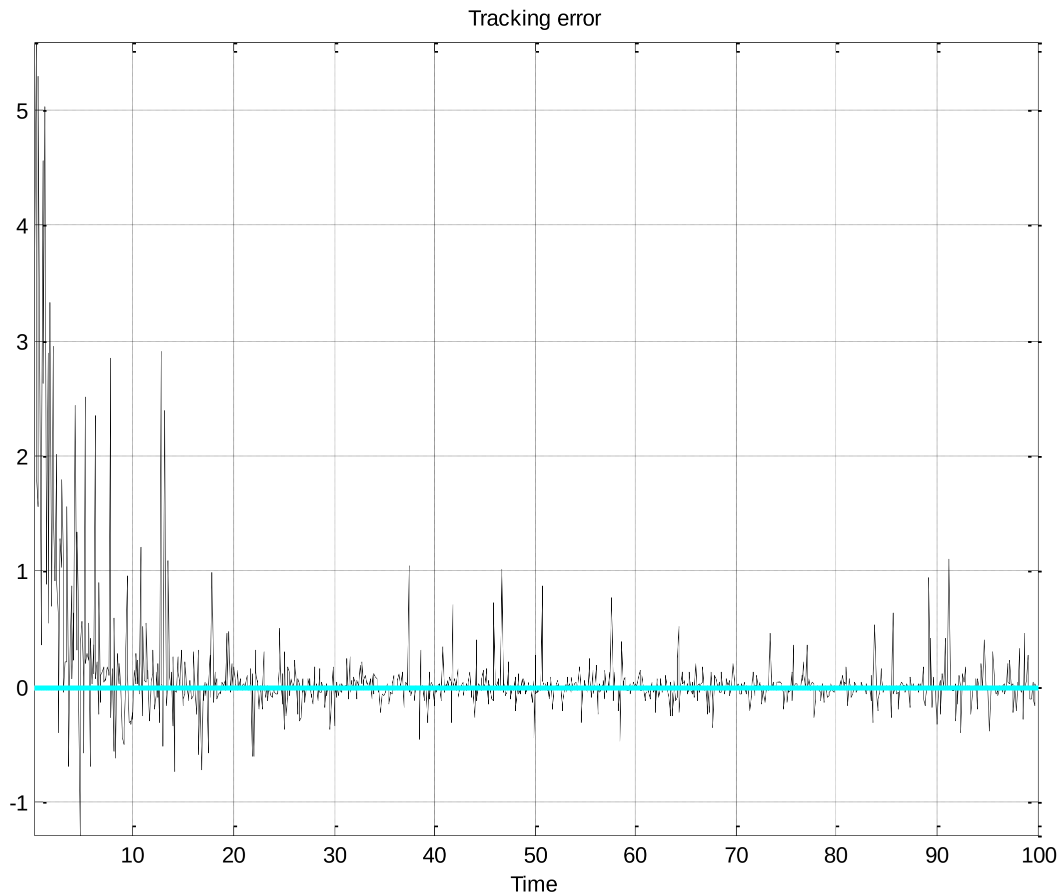


FIGURE 9: ERROR PLOT-DIFFERENCE BETWEEN THE PLANT OUTPUT AND MODEL OUTPUT

4.6 ASSESSMENT OF THE RESULTS

From the above figures, we can clearly observe that the Fuzzy Hammerstein model shows satisfactory behavior over the entire operating range. The training data set provided to make the prototype model behaves in the same way as the plant itself, gives adequate results for identification around the operating region. However, there are occasional errors that can be seen during sharp transitions of the plant output, this is where the model does not track the plant output but it follows a smooth trajectory at the sharp edges. This was not unexpected because these results are based on 6 fuzzy rules; it may be improved if the number of rules is increased. The TS fuzzy model obtained here is much simpler to interpret, unlike the fuzzy relational models that are more complex than transparent linguistic ones, with respect to computations. Therefore they imply greater computing times and also suffer loss of linguistic meaning of the rules in the fuzzy model.

However, the results obtained after modeling via the algorithm given in the previous chapter, the performance of fuzzy systems has been validated and its simplicity in obtaining a prototype model can be seen. Hence we can say that fuzzy logic holds an attractive property of accurate representation of any physical system.

This model is suitable enough to be used in IMC scheme that will be discussed in the next chapter. The inverse of the static non linear part of the model can be used in this scheme and the linear dynamic part is used in the feedback. Since the tuning filter which is low pass in nature, cuts off the disturbances and perturbations to quite an extent, hence we can use this model for the IMC scheme.

4.7 CHAPTER SUMMARY

This chapter elucidated the methodology for modeling a plant incorporating fuzzy clustering as well as least squares algorithm. It also helped to understand the static non linearity and linear dynamics of the system hence making the algorithm available for any real system that requires modeling for its control.

CHAPTER 5

APPLICATION OF MODEL IN A CONTROLLER

5.1 INTRODUCTION

This chapter mainly depicts the performance of the controller when integrated with the model identified in this thesis, in the previous chapters. Among the control development techniques that have been researched upon, the idea of internal model control based on identified model has been proclaimed as the most highlighted development in this field, [15]. The Hammerstein model is an appropriate choice because of its simpler block oriented structure that makes it easier to evaluate the performance via an MPC.

5.2 PERFORMANCE OF THE FUZZY MODEL IN IMC SCHEME

In this thesis, the fuzzy Hammerstein model is integrated in a controller that works on IMC scheme. A brief description of the IMC scheme is elucidated below:

5.2.1 THE INTERNAL MODEL CONTROL SCHEME

The Internal Model Control scheme works on the Internal Model Principle, which states that "If the system encapsulates some form of the process to be controlled, only then the control can be achieved for the system", [21]. Hence, the perfect control of any system is theoretically possible if the controlling scheme is based on a precise model of the process.

However, generally, model-process disparity is very frequent. The reason being the model of the process may not have an exact inverse because of its irreversible features and sometimes the system is also influenced by unidentified external parameters/disruption. In such cases, feedback linearization serves the purpose of nearly accurate control of the process [30]. A low pass filter is usually inserted in the feedback path to attenuate the degree of mismatch between the model and process output and to ensure robustness.

5.2.2 THE IMC SETUP

To setup the IMC scheme, the block of the Fuzzy Hammerstein model has been placed in the feedback and this process maybe be termed as an exclusive case of feedback linearization and is a candid systematic procedure [3] and [15]. A recognizable feature of IMC is the assimilation of the process model in parallel with the actual plant. This scheme is illustrated below:

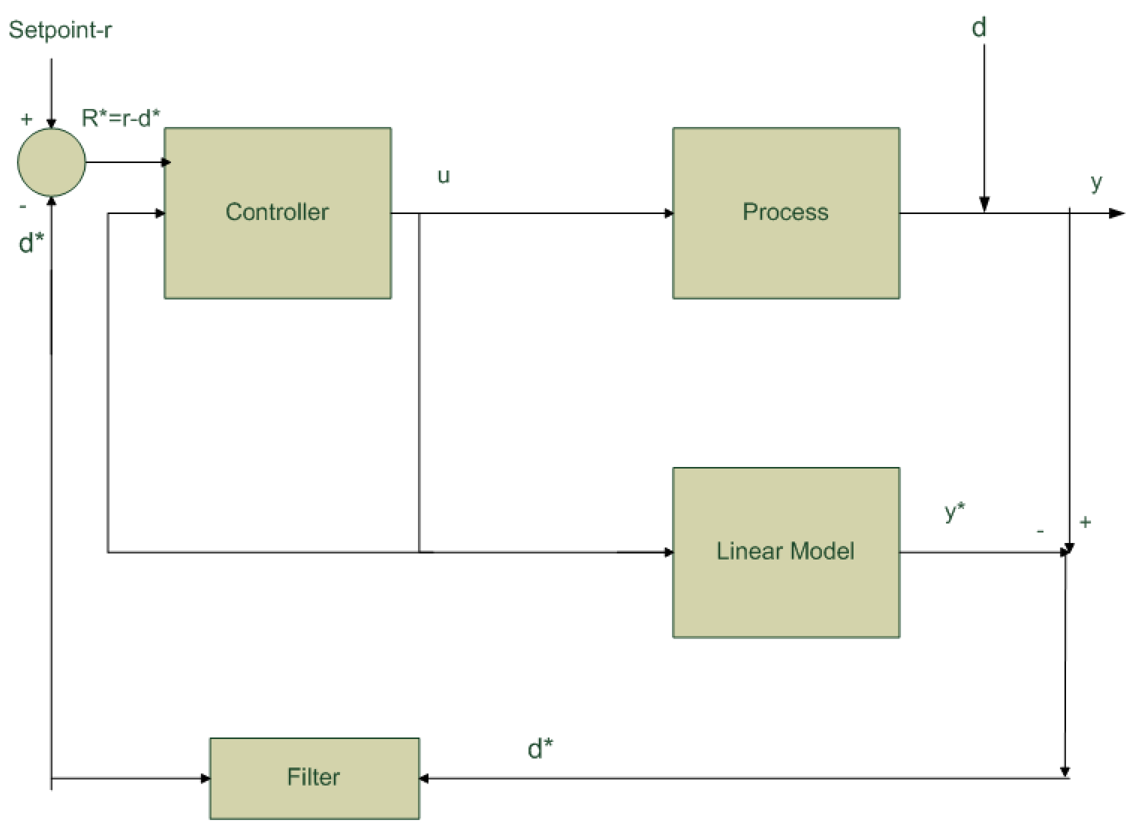


FIGURE 10: BLOCK DIAGRAM OF FUZZY HAMMERSTEIN MODEL BASED IMC SCHEME

The IMC scheme is the classical approach of controller design whereas the GPC is a modern technique for the same purpose. In this thesis, the most generalized procedure for observing the performance of the controller with the Fuzzy model has been considered.

The parameters used for deriving the transfer function for IMC are listed below:

- Controller: Qc
- Actual plant: Gp
- Plant model: Gp*
- Set point: r
- Transformed input: v (output of controller)
- Disturbance: d
- Estimated disturbance: d*
- Process output: y
- Model output: y*
- Feedback signal: d*=(Gp-Gp*)u+d

For the model to be perfect, zero disturbances are taken into account. In such case, the model will be the same as the process.

$$d = 0$$

Therefore, the relationship between set point r and the output y is given as:

$$y = Gp.Qc.r \tag{5.1}$$

The above relationship holds true if the controller and the process both are stable. But usually in real life cases, disturbances exist and the model and plant are never totally same. This condition is termed as process-model mismatch and is very customary because of the uncertainties present in practical systems. For acquiring perfect control, instead of open loop, a closed loop system is implemented incorporating the disturbances present in real systems, [5] and [9].

In Figure 8, d is the disturbance affecting the system. The transformed input v out of the controller is introduced to both the process and its model. The process output y, is then measured with output of the model y*, and this gives out the resultant signal as d*.

The feedback signal can then be stated as below:

$$d^* = [Gp - Gp^*]u + d \tag{5.2}$$

If zero disturbances are there, then the feedback signal depends on the difference of process and its model only.

If the process model is exactly equal to the plant then the feedback signal will depend on the external disturbances only.

Considering the above two cases, we can say that the information contained in d* is missing in the identified model and hence it can be used as a factor to improve robustness and control of the IMC system.

An error signal R* is generated which represents the process-model disparity. This is the control signal sent to the controller and is given below:

$$R^* = r - d^* \tag{5.3}$$

The transformed input sent to the model and the process is estimated as:

$$\begin{aligned} u &= R^*.Gc = [\mathrm{r} - \mathrm{d}^*]\mathrm{Gc} \\ &= [r - \{(Gp - Gp^*)u + d\}].Gc \end{aligned} \tag{5.4}$$

$$u = \frac{[r-d]\mathrm{Gc}}{[1+\{Gp-Gp^*\}Gc]} \tag{5.5}$$

Also,

$$y = Gp.u + d \tag{5.6}$$

Therefore the closed loop transfer function of the IMC scheme is:

$$y = \frac{Gc.Gp.r + [1 - Gc.Gp^*].d}{1 + [\mathrm{Gp} - \mathrm{Gp}^*]\mathrm{Gc}} \tag{5.7}$$

For accurate set point tracking and disturbance rejection, following two conditions hold true:

- If Gc is equal to inverse of process model Gp*
- If model and plant are exactly equal, Gp=Gp*

The improvement of robustness of the system is accomplished if model-plant disparity is minimal. Generally, this disparity takes place at the high frequency end of the system's frequency response, a low pass filter is usually added to alleviate the effects of process-model disparity.

5.3 SIMULATION SETUP FOR CONTROLLER

The model of the plant was replicated in Simulink, the linear dynamics part being used in the feedback and the static non linearity is being used with the controller as its inverse. The system was provided with a minimal delay of 4 seconds, so as to suppress the initial overshoots that may arise. The controller parameters were selected according to [12] and the system was found to behave in the optimal manner. The parameter value of the linear filter was selected in order to achieve a middle ground between robustness and performance. The output of the real process and the fuzzy model were compared as below:

The simulink model for the process is shown below:

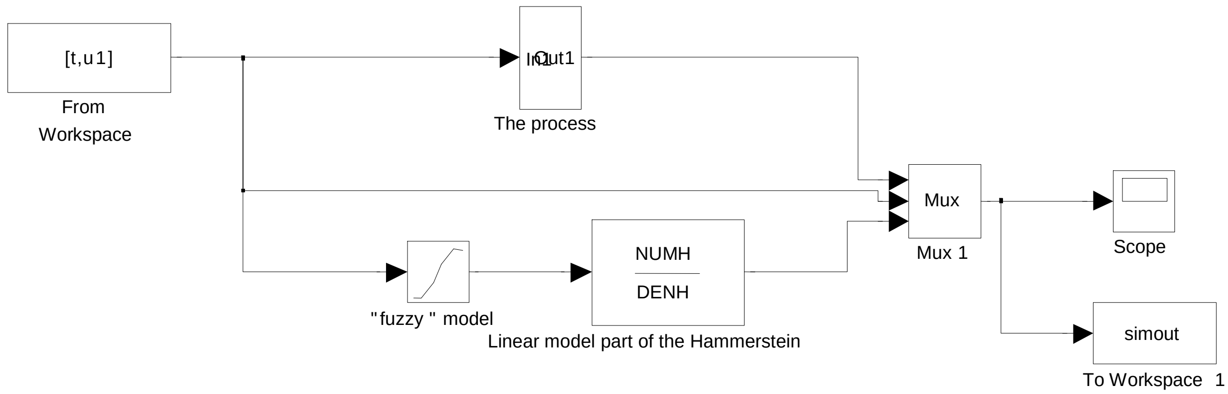


FIGURE 10: THE PROCESS SIMULINK MODEL

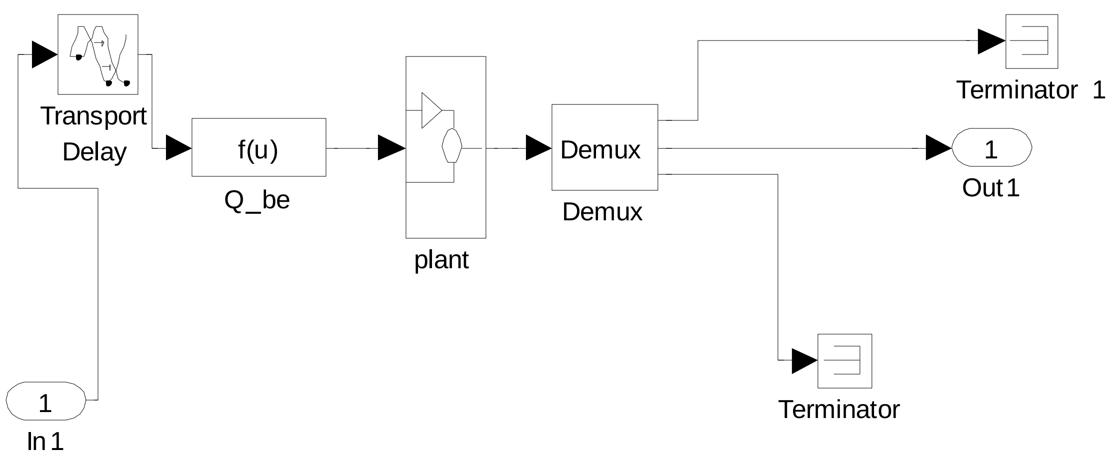


FIGURE 12: ACTUAL PROCESS WITHIN THE CONTROLLER

The simulation results are given in the below figures:

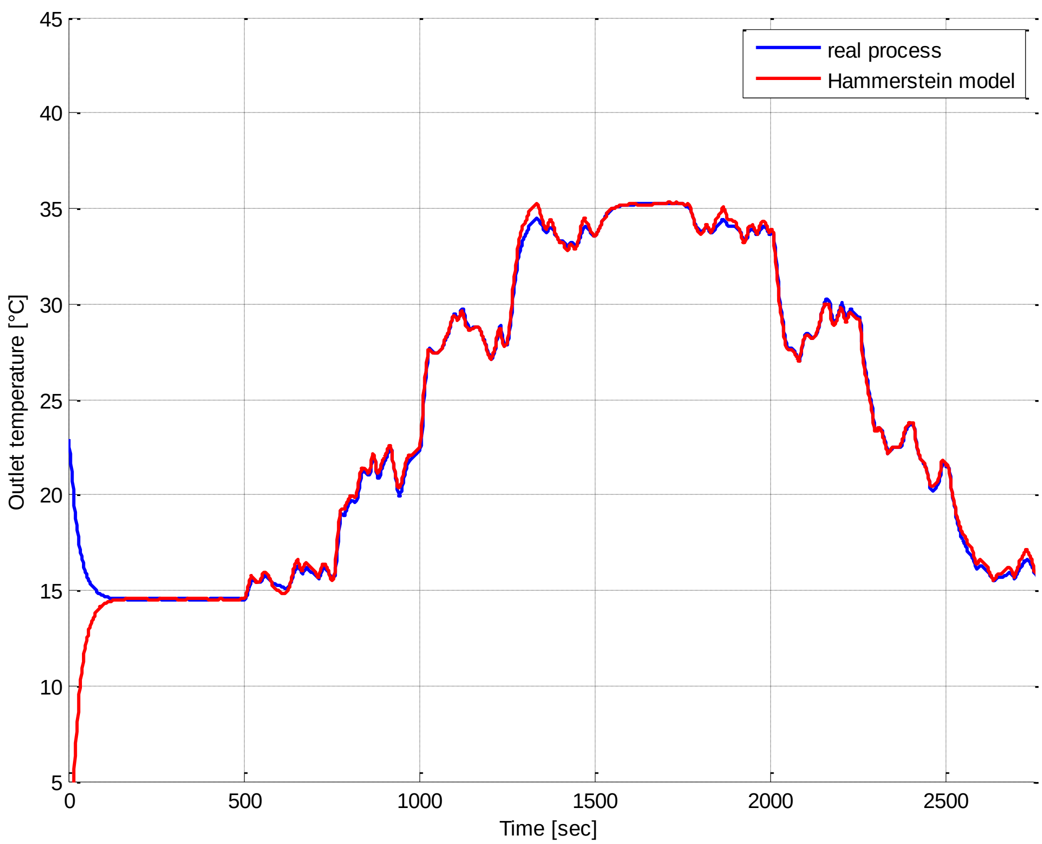


FIGURE 13: OUTPUT OF REAL PROCESS (BLUE) AND OUTPUT OF IDENTIFIED FUZZY MODEL (RED)

The steady state behavior of the model is shown by the below figure:

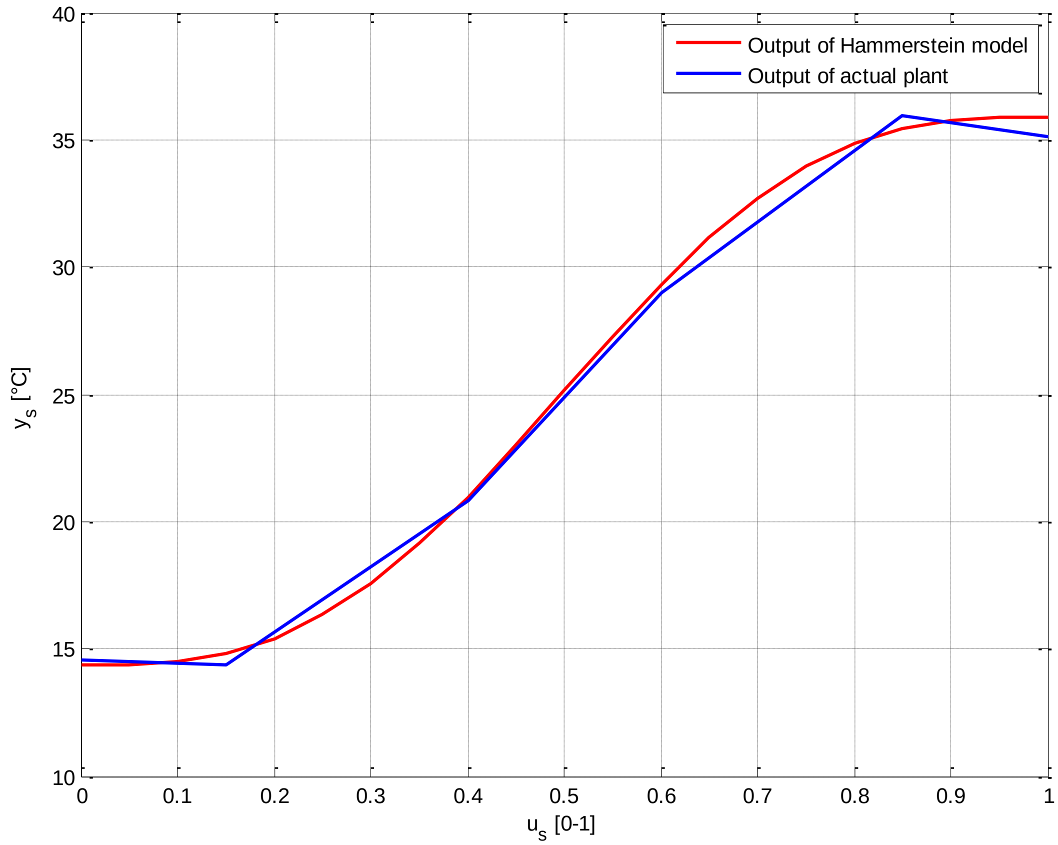


FIGURE 14: STEADY STATE BEHAVIOR OF THE PROCESS (BLUE) AND OF THE IDENTIFIED FUZZY MODEL (RED)

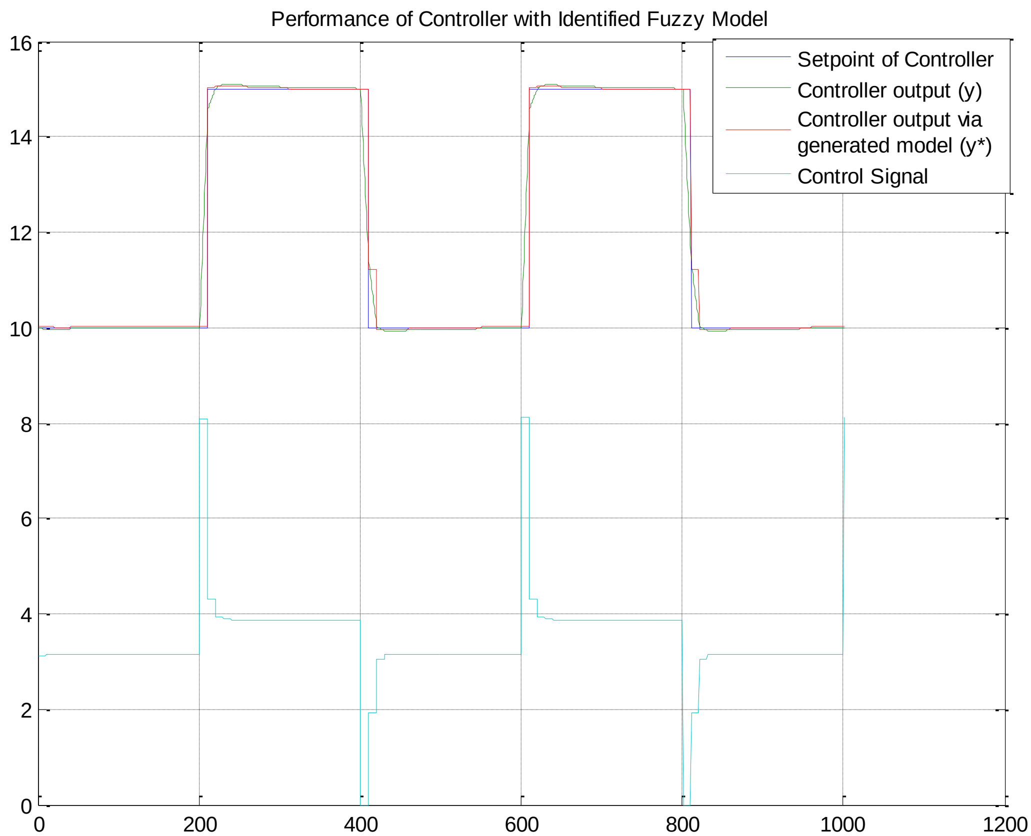


FIGURE 15: PERFORMANCE OF CONTROLLER IN PRESENCE OF ACTUAL PLANT AND THE IDENTIFIED MODEL

5.4 ASSESSMENT OF THE OUTPUTS

The outputs of the real process and of the identified Fuzzy model were compared and the results were found to be much satisfactory over the entire operating range, with the rapid change in control action. The steady state behavior of both the processes can also be seen in the above figure. Except for sharp edges, the Fuzzy model tracks the plant's output throughout. This is because of the over estimation of the gain of the fuzzy model. However, we can say that the model obtained via Fuzzy identification techniques is much simpler to interpret because of linguistic rules and data gathered from the process itself. Also the fuzzy model incorporates lowest degree of complexity.

5.5 CHAPTER SUMMARY

In this chapter, the identified fuzzy model from the previous chapters was integrated with a controller and its performance parameters were found to be more than satisfactory. The Fuzzy Hammerstein model behaves smoothly under steady state conditions and also under dynamic conditions. The process outputs were compared via Matlab and Simulink and the results are shown above in Figures 8 and 9.

CHAPTER 6

CONCLUSION AND FUTURE RECOMMENDATIONS

6.1 CONCLUSION

In this thesis, plant modeling was achieved via clustering and least squares algorithm. This provides an efficient but expensive way to model a plant, which in our work, is an electrical water heater that is heating a laboratory cartridge. The training data set was generated by some known values and some assumed values. This new methodology to the identification of parameters and control of Fuzzy Hammerstein systems whose validity is measured via IMC scheme has been discussed in detail. The most prominent advantage of the proposed scheme if that fuzzy model obtained eventually is much transparent and easy to interpret because of its linguistic nature. Also, by certain researches, it has been studied that the Fuzzy Hammerstein model has a lower complexity as compared to other models, [4], [11], and [25].

For identifying a Fuzzy Hammerstein model, the proposed scheme is to first categorize a basic and linguistic structure of FH model and then using an optimized algorithm to estimate the parameters of that model. The simple structure of FH model assists its effectual application in internal model or predictive control, [22], [23]. Hence, the convergence to a viable control solution is guaranteed in the presence of an iterative control algorithm for the given process.

The simulation results for the control of a laboratory water heater process depict the behavior of the system being tracked well by the identified Fuzzy Hammerstein model, and it also shows good dynamic modeling performance.

6.2 FUTURE RECOMMENDATIONS

Application of fuzzy systems in other model based control structures is a very interesting topic for future research. This can be done in a straightforward manner according to [28], [31] in the case of block oriented models having a feedback and Wiener models. The algorithm presented in this thesis, can be successfully applied to Wiener models after some modifications, where the fuzzy model represents the inverse of static non linearity. Furthermore, the Wiener model identification can be applied in robust model predictive control where the static non linearity is presented as a polytrophic description of uncertainty.

REFERENCES

1. A.Bodizs, F. S. a. T. C. (1999). "Convolution Model Based Predictive Controller for a non linear process." Ind. Eng. Chem. Res **38**: 154-161.

2. Azuaje, F. D., W.Black, N.Adamson.K (June 2000). "Discovering Relevance Knowledge in Data: A Growing Cell Structure Approach." IEEE Transaction Systems, Man and Cybernetics, part B, Cybernetics **30**(03): 448.

3. D.W.Clarke, C. M. a. P. S. C. T. (1989). "Generalized Predictive Control-part I, the basic algorithm." Automatica **23**: 137-148.

4. E.Eskinat, S. H. J. a. W. L. (1991). "Use of Hammerstein models in identification of nonlinear systems." AIChE Journal **37**(2): 255-268.

5. F.Klawonn, R. K. (1995). "Automatic Generation of Fuzzy Controllers by Fuzzy Clustering." IEEE International Conference on Systems; Man and Cybernetics: 2040-2045.

6. F.Klawonn, R. K. (1995). "Clustering Methods in Fuzzy Control." Theoretical and Practical Aspects of Classification, Data Analysis and Knowledge Organization: 195-202.

7. G.Chen, T. T. P. (2001). "Introduction to Fuzzy Sets, Fuzzy Logic." CRC Press: 98-102.

8. H.A.Barker, D. E. R., A.H.Tan, K.R.Godfrey (2006). "Perturbation Signal Design." 14th IFAC Symposium on System Identification, Newcastle, Australia.

9. J.Abonyi, L. N., F.Szeifert (1999). "Adaptive Fuzzy Inference system and its application in modelling and model based control." Chemistry, Engineering Research (Trans.IChemE) **77**: 281-290.

10. J.Abonyi, R. B. (2000). "Local and global identification and interpretation of parameters in TS Fuzzy models." Proceedings 9th IEEE International Conference on fuzzy systems-FUZZ-IEEE 2000: 835-840.

11. J.Abonyi, R. B., M.Ayala Botto, F.Szeifert, L.Nagy (2002). "Identification and Control of Non Linear Systems Using Fuzzy Hammerstein Models." Cite Seer-Industrial and Engineering Chemistry Research **02**: 4204-4214.

12. J.Abonyi, R. B., M.Setnes, H.B.verbruggen and F.Szeifert (1999). "Constrained parameter estimation in fuzzy modelling." Proceedings FUZZ-IEEE 99: 951-956.

13. J.Zhao, V. W. a. R. G. (1994). "A Fuzzy Clustering Method for the identification of fuzzy models for dynamical systems." 9th IEEE International Symposium on Intelligent Control.

14. K.M.Passino, S. Y. (1998). "Fuzzy Control." Addison Weasely: 235-264.

15. K.P.Fruzetti, A. P. a. K. A. M. (1997). "Non Linear Model Predictive Control using Hammerstein Models." Journal of Process Control **7**(1): 31-41.

16. K.Tanaka, M. S. a. (1991). "Successive Identification of a fuzzy model and its application to prediction of a complex system." Fuzzy Sets and Systems 42: 315-334.

17. Keller, F. K. a. A. (1994). "Fuzzy Clustering and Fuzzy Rules." Fuzzy Sets and Systems 66: 207-221.

18. Khaled Hammouda, P. F. K. "A Comparative Study of Data Clustering Techniques." University of Waterloo, Ontario, Canada.

19. L.Chiu, S. (1994). "Fuzzy Model Identification Based On Cluster Estimation." Journal of Intelligent and Fuzzy Systems **2**: 267-278.

20. M.Morari, C. E. G. a. (1982). "Internal Model Control; Aunifying review and results." Ind.End. Chem. Process Res **21**: 308-323.

21. M.Sugeno, T. Y. (1993). "A Fuzzy Logic based Approach to Qualitative Modelling." IEEE Transaction on Fuzzy Systems **01**: 7-31.

22. Muhammad Salaheen Aftab, D. M. B. K. (2012). "Parameter Identification of TS Fuzzy Model of Surge Tank System."

23. P.G.Gallman, K. S. N. a. (1966). "An iterative method for the identification of nonlinear systems using the Hammerstein model." IEEE Transaction on Automatic Control **12**: 546.

24. P.T.Chan, A. B. R. (2002). "Adaptation and Learning of a Fuzzy System by nearest neighbourhood clustering." Fuzzy Sets and Systems 126: 353-366.

25. R.Babuska, H. B. V. (1995). "A New Identification Method for Linguistic Fuzzy Models." Joint Conferences of Fourth IEEE Intern. Fuzzy Engineering Symposium, Yokohama: 905-912.

26. R.Babuska, H. B. V. (1997). "Fuzzy Identification of Hammerstein Systems." Proceedings Seventh IFSA World Congress **2**: 348-353.

27. R.Babuska, U. K. a. (1995). "Compatible Cluster Merging for Fuzzy Modelling." IEEE Transaction Systems, Man and Cybernetics, part B, Cybernetics: 897-904.

28. R.K.Pearson, M. P. a. (1998). "Block Oriented NARMAX models with output multiplicities." Artificial Intelligence ChE **44**(01): 131-140.

29. Salim Ahmed, B. H., Sirish L.Shah (2006). "Novel Identification Method from Step Response." Control Engineering Practice **15**: 545-556.

30. Sugeno, T. T. a. M. (1985). "Fuzzy Identification of Systems and its Applications to modelling and control." IEEE Transaction Systems, Man and Cybernetics **15**(01): 116-132.

31. T.Wiegren (1994). "Convergence Analysis of recursive identification algorithms based on the non linear Wiener model." IEEE Transaction on Automatic Control **39**: 2191-2206.

32. Ta Wei Hung, S. C. F. a. H. L. W. N. (1999). "A Clustering Based Approach to Fuzzy System identification." International Fuzzy Systems Association World Congress.

33. W.C.Kessel, D. E. G. a. (1979). "Fuzzy Clustering with a Covariance matrix." Proceedings of IEEE CDC: 761-766.

34. Y.Yoshinari, W. P. a. K. H. (1993). "Construction of Fuzzy Models through clustering techniques." Fuzzy Sets and Systems **54**: 157-165.