FUZZY TAKAGI-SUGENO AND LMS BASED CONTROL TECHNIQUES

BY

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Dedicated to

MY PARENTS AND WIFE

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In the name of Allah, the Most Beneficent, the Most Merciful.

All praise and glory goes to Almighty Allah (Subhanahu Wa Ta'ala) who gave me the courage and patience to carry out this work. Peace and blessing of Allah be upon His last Prophet Muhammad (Sallalaho-Alaihe-Wassalam) and all his Sahaba (Razi-Allaho-Anhum) who devoted their lives towards the prosperity and spread of Islam.

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Contents

List of Figures

Nomenclature

Notations and Symbols

t, k	integer time index
$u(k)$	control input signal
$y(k)$	plant output signal
$\hat{y}(k)$	estimated plant output
$r(k)$	reference signal
$d(k)$	disturbance/white noise
$r(k)$	error signal
q	parameter vector
$\hat{q}$	estimated parameter vector

Abbreviations

IMC	Internal Model Control
nLMS	normalized Least Mean Square algorithm
SISO	Single Input Single Output system
FIR	Finite Impulse Response
TS	Takagi-Sugeno
AIC	Adaptive Inverse Control

THESIS ABSTRACT

Name:	KHALID MOUSA AL-ZAHRANI
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Today's manufacturing processes present many challenging control problems; among these are nonlinear dynamic behavior, uncertain and time varying parameters, and unmeasured disturbances. In the past decade, the control of these systems has received considerable attention in both academia and industry. Surveys and studies indicate that MPC and fuzzy control are the most widely used of the modern control techniques in industries. These tendencies indicate that there is a huge demand in the industry for new fuzzy and MPC solutions. However, most of the available algorithms to control nonlinear systems lead to the use of computationally intensive nonlinear techniques that make industrial application almost impossible. To avoid this problem, this work presents the use of Takagi-Sugeno Fuzzy (TSF) Models and Least Mean Square (LMS) for the design and implementation of new control techniques that incorporate Internal Model Control (IMC) structure and Adaptive Inverse Control (AIC) for the control of nonlinear systems. The proposed control techniques are applied to control nonlinear temperature process module and a robotic arm manipulator in a laboratory scale.

Keywords: *Fuzzy Takagi-Sugeno(TS) modeling, Internal Model Control (IMC), Adaptive Inverse Control (AIC), Least-Mean-Square algorithm (LMS).*

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خلاصة الرساله

الأسم : خالد موسى غرم الله الزهراني

عنوان الرساله : تقنيات تحكم مبنيه على نمذجة تاكاجي-ساجينو الهلاميه و خوارزمية متوسطات المربعات الصغرى

التخصص : هندسة نظم

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العمليات الصناعية ألحديثه تعرض العديد من التحديات في مجال أنظمة التحكم ومنها السلوك الغير خطي الديناميكي ، المعاملات المتغيرة وقتيا والغير أكيده ، والاضطرابات الغير مقاسه. حصل التحكم بهذه الأنظمة في العقد الأخير على اهتمام من المجال الأكاديمي والصناعي. الدراسات الحديثه تشير إلى أن التحكم التنبؤي المنمذج والتحكم الهلامي تعتبر أكثر تقنيات التحكم الحديثه المستخدمه في المصانع. لكن معظم المعادلات الراضية المتوفرة للاسخدام في التحكم بالأنظمة الغير خطيه تؤدي إلى استخدام حسابات غير خطيه مكثفه وتجعل استخدامها في التطبيقات الصناعية مستحيلة. لتجنب هذه المشكلة ، الرسالة تعرض استخدام نمذجة تاكاجي-ساجينو الهلاميه وخوارزمية متوسطات المربعات الصغرى لتصميم وتطبيق تقنيات تحكم جديدة تتضمن نموذج التحكم الداخلي والتحكم العكسي التكيفي للتحكم في الأنظمة الغير خطيه. تقنيات التحكم المعروضة تم تطبيقها بنجاح على نظام عمليات الحرارة الغير خطيه وذراع الروبوت في المختبر.

درجة الماجستير في العلوم

جامعة الملك فهد للبترول والمعادن

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Chapter 1

Introduction

1.1 Fuzzy Modeling

Fuzzy if-then rules, sets and reasoning are the concepts of a computational framework for a fuzzy model. The fuzzy set theory allows elements to have a degree of membership to a particular set in additional to the restriction given by the conventional set theory that allows either belongs to or does not belong to a particular set. This makes fuzzy sets a more natural approach to mathematically represent elements belonging to given sets. Considering, as an example, the case of describing the room temperature as being "hot". Using the conventional set theory, a distinct range of temperatures greater than 25°C will be used to designate the set *hot*. That is:

$$hot = [25, \infty]\,°\mathrm{C} \tag{1.1}$$

In this case any temperature which falls just slightly outside this range would not be a member of the set, even though a human being may not be able to distinguish between it and the one which is just inside the set. In fuzzy set theory, strict limits of a set are not required to be defined; instead a *membership function* is defined. It describes the relationship between a variable and the degree of membership that corresponds to a particular value of that variable. Usually, this degree of membership is defined in terms of a number between 0 and 1, inclusive, where 0 implies total absence of membership, 1.1

implies complete membership, and any value in-between implies partial membership of the fuzzy set. This may be written as:

$$A(x) \in [0,1] \quad for \quad x \in U \tag{1.2}$$

$A(.)$ is the membership function and U is the *universe of discourse* which defines the total range of interest over which the variable x should be defined.

For example, to define membership of the *hot* fuzzy set a function which rises from 0 to 1 over the range between 15°C and 25°C can be used , i.e.,

$$mf(x) = \begin{cases} 0 & x < 15^o C, \\ \dfrac{x-15}{10} & 15 \geq x \geq 25^o C, \\ 1 & x > 25^o C, \end{cases} \tag{1.3}$$

This means that 14°C in not hot; 19°C is a bit hot; 23.5°C is quite hot; and 31°C is truly hot. Specific measurable values, such as 14 and 19 are often referred to as *crisp* values or *fuzzy singletons*, to distinguish them from *fuzzy* values, such as *hot*, which are defined by a fuzzy set. Sometimes fuzzy values are called *linguistic* values. Figure 1.1 illustrates the human or *linguistic* interpretations of temperatures and hence better approximates such concepts.

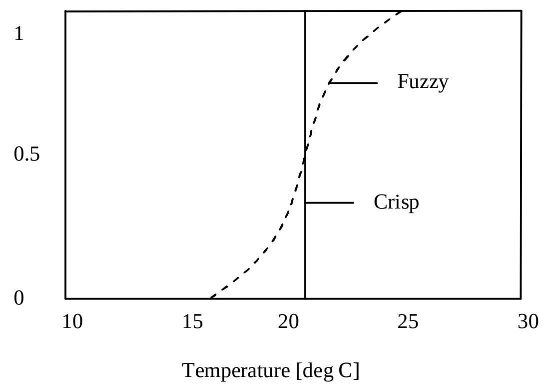

Figure 1.1: High temperature representation

Fuzzy sets are mathematically precise, in that they can be fully represented by exact numbers and at the same time comply with human interpretations. Therefore, they can be seen as a method of tying together human and machine knowledge representations. With the existing capabilities of using computers to represent information, fuzzy models can be applied to information processing methods.

Basics of a fuzzy model are shown in Figure 1.2. As shown in the figure, the fuzzy model includes the following components or stages:

- *Data preprocessing stage:* It is the scaling process for the given physical values of the input to the fuzzy system. It is done by mapping it to proper normalized (but interpretable) domains via scaling. One can instead, work with signals roughly of the same magnitude, which is desirable from an estimation point of view.
- *Fuzzification stage:* It is the mapping of the crisp values of the preprocessed input of the model into a suitable fuzzy sets represented by *membership functions* (MF).

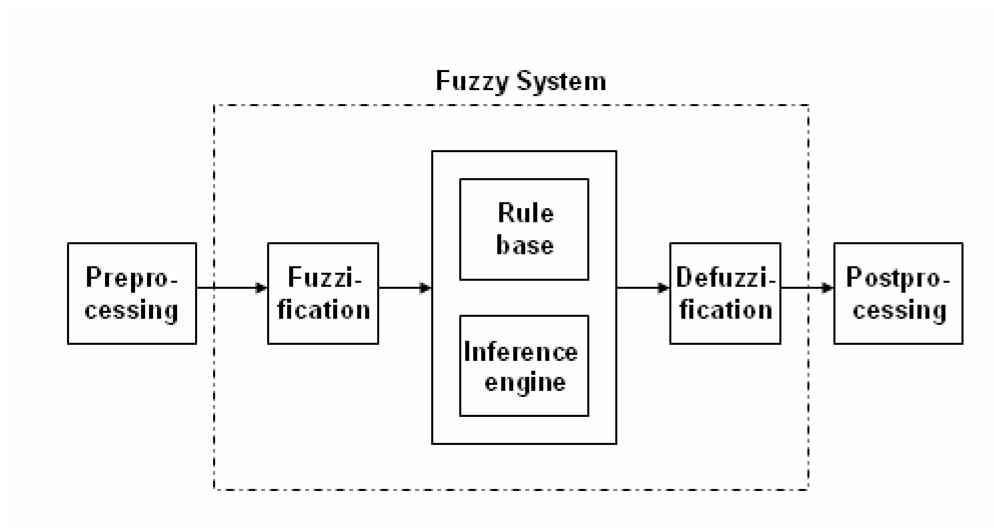

Figure 1.2: Fuzzy system components

- *Rule bas stage:* It houses the if-then rules for the fuzzy system. The relationships between variables are represented by the following general form:

  If there is an antecedent proposition **then** there is a consequent proposition (1.4)

  There are three distinct classes used for the consequent proposition in fuzzy models and they are:

  - *Fuzzy linguistic models (Mamdani models)* [37,38] where both the antecedent and consequent are fuzzy propositions.
  - *Fuzzy relational models* are based on fuzzy relations and relational equations.
  - *Takagi-Sugeno (TS) fuzzy models* where the consequent is a crisp function of the input variables $f_j(x)$ as follows:

$$R_j : \textbf{If } x_1 \text{ is } A_{1,j} \textbf{ and ….. and } x_n \text{ is } A_{n,j} \textbf{ then } y = f_j(x) \qquad (1.6)$$

- *Inference engine stage:* It is the computational method which calculates the degree to which each rule fires for a given fuzzified input pattern by considering the rule and label sets.
- *Defuzzification stage*: It takes care of compiling the information provided by each of the rules and makes a decision from this basis.
- *Postprocessing stage:* It gives the output of the fuzzy system based on the crisp signal obtained after defuzzification. This often means the scaling of the output.

1.2 Takagi-Sugeno Fuzzy Models (TS)

As described by Abonyi [1], Takagi-Sugeno (TS) fuzzy model is a combination of a logical and a mathematical model. This model is also formed by logical rules consisting of a fuzzy antecedent and a mathematical function as a consequent part. The antecedents of fuzzy rules partition the input space into a number of fuzzy regions, while the consequent function describe the system behavior within a given region:

$$R_j: \textbf{If } z_1 \text{ is } A_{1,j} \textbf{ and ….. and } z_n \text{ is } A_{n,j} \textbf{ then } y = f_j(q_1,....,q_m) \tag{1.7}$$

where $z = [z_1,.....,z_n]^T$ is the *n*-dimensional vector of the antecedent variables, and $z \in x$, $q = [q_1,....,q_m]^T$ is the m-dimensional vector of the $y = f(x)$ model. $A_{i,j}(z_i)$ denotes the antecedent fuzzy set for the *i*th input. The antecedents of fuzzy rules partition the input space into a number of fuzzy regions, while the $f_j(q)$ consequent functions describe the system behavior within a given region.

The spirit of fuzzy inference system resembles that of the "divide and conquer" concept – the antecedent of fuzzy rules partition the input-space into a number of local fuzzy regions, while the consequents describe the behavior within a given region via various constituents. Usually, the f_j consequent function is a polynomial in the input variables, but it can be any arbitrarily chosen function that can appropriately describe the output of the system within the region specified by the antecedent of the rule. Where $f_j(q)$ is a first-order polynomial,

$$f_j(q) = p_j^0 + p_j^1 q_1 + \ldots + p_j^m q_m = \sum_{l-0}^{m} p_j^l q_l \text{, where } q_0 = 1, \tag{1.8}$$

The resulting fuzzy inference system is called *first-order Takagi-Sugeno* or simply a *Takagi-Sugeno* fuzzy model. If $f_j(q)$ is a constant (fuzzy singleton), $f_j = p_j^0$, we have a zero-order Takagi-Sugeno or singleton fuzzy model, which is a special case of the linguistic fuzzy inference system and the TS fuzzy model. Using fuzzy inference based on product-sum-gravity at a given input the final output of the fuzzy model, $y = f_j(q_1,\ldots,q_m)$, is inferred by taking the weighted average of the consequent functions as depicted in Figure 1.4:

$$f_j(q_1,\ldots,q_m) = \frac{\sum_{j=1}^{N_r} B_j(z) f_j(q)}{\sum_{j=1}^{N_r} B_j(z)} \tag{1.9}$$

where the weight, $0 \le B_j(z) \le 1$, represents the overall truth value (degree of fulfillment) of the *i*th rule calculated based on the degrees of membership

$$B_j(z) = \prod_{i=1}^{n} A_{i,j}(z_i) \tag{1.10}$$

Figure 1.3 shows the fuzzy reasoning procedure for a TS fuzzy model.

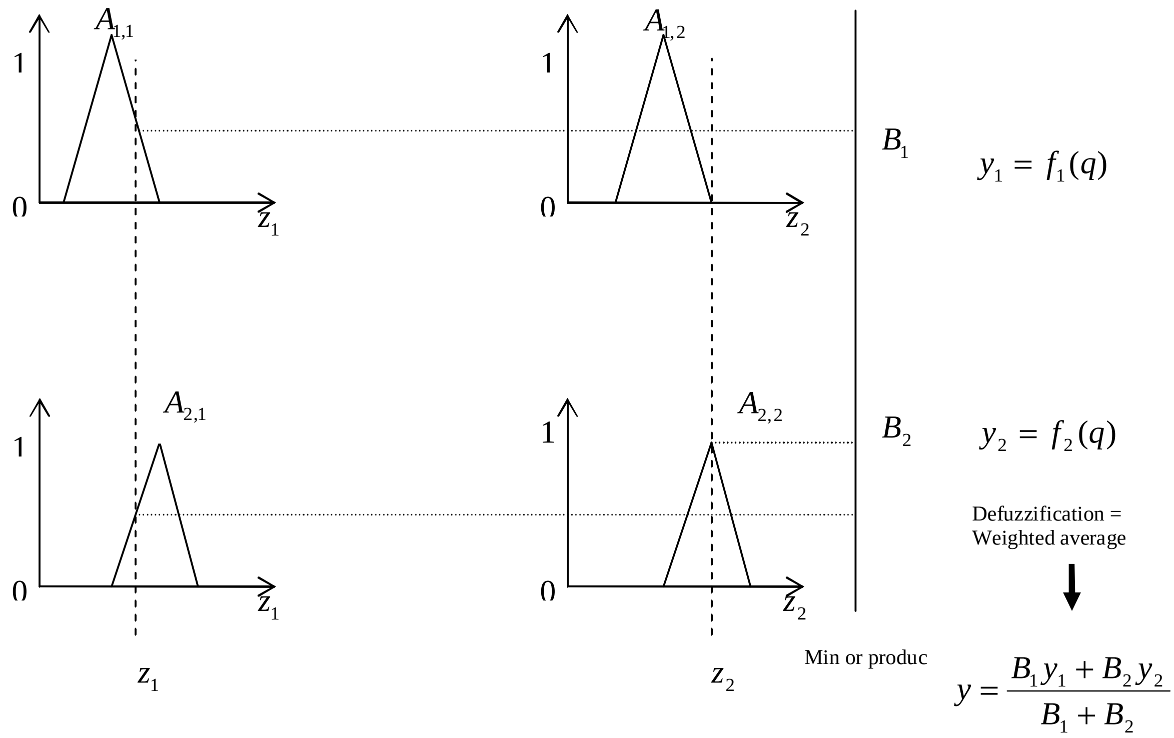

Figure 1.3: Inference method of the Takagi-Sugeno fuzzy model

The membership functions arranged by Ruspini type partition while keeping the sum of the membership degree equal to 1 is shown in Figure 1.4,

$$\sum_{i_l=1}^{M_l} A_{l,i_l}(z_l) = 1,\ l = 1,\dots,n, \tag{1.11}$$

where M_l represents the number of the fuzzy sets on the lth input domain. Hence, the triangular membership functions are defined by:

$$A_{l,i_l}(z_l) = \frac{z_l - a_{l,i_l-1}}{a_{l,i_l} - a_{l,i_l-1}}, \quad a_{l,i_l-1} \le z_l < a_{l,i_l},$$

$$A_{l,i_l}(z_l) = \frac{a_{l,i_j+1} - z_l}{a_{l,i_l+1} - a_{l,i_l}}, \quad a_{l,i_l} \le z_l < a_{l,i_l+1}, \tag{1.12}$$

where a_{l,i_l} cores of the adjacent fuzzy sets determine the support ($\sup_{l,i_l} = a_{l,i_l+1} - a_{l,i_{l-1}}$) of a set.

$$a_{l,i_l} = core(A_{l,i_l}(z_l) = \{z_l \,|\, A_{l,i_l}(z_l) = 1\} \tag{1.13}$$

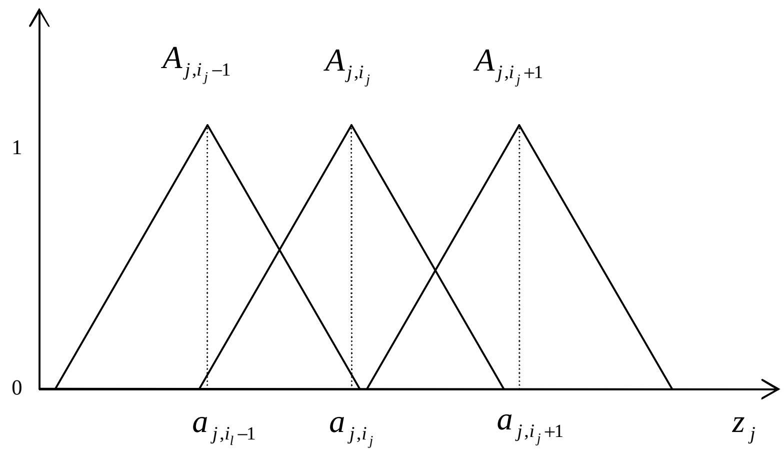

Figure 1.4: Ruspini parameterization of triangular membership functions

1.3 Least Mean Square

The least-squares method can be applied to a large variety of problems. Gauss formulated its principle at the end of the eighteenth century and used it to determine the orbits of planets and asteroids. He stated that the unknown parameters of a mathematical model should be chosen is such a way that the sum of the squares of the differences between the actually observed and the computed values, multiplied by numbers that measure the degree of precision, is a minimum. As explained by Astrom and Wittenmark [3], it is particularly simple for a mathematical model that can be written in (1.14).

$$y(i) = j_1(i)q_1^0 + j_2(i)q_2^0 + ... + j_n(i)q_n^0 = j^T(i)q^0 \quad (1.14)$$

Where y is the observed variable, $q_1^0, q_2^0, ..., q_n^0$ are parameters of the model to be determined, and $j_1, j_2, ..., j_n$ are known functions that may depend on other known variables. The vectors shown in (1.15) and (1.16) have also been introduced.

$$j^T(i) = [j_1(i) \quad j_2(i) \quad .... \quad j_n(i)] \quad (1.15)$$

$$q^0 = [q_1^0 \quad q_2^0 \quad ... \quad q_n^0]^T \quad (1.16)$$

The model is indexed by the variable i, which often denotes time. It will be assumed initially that the index set is a discrete set. The variables j_i are called the regression variable or the regressors, and the model in equation (1.14) is also called a regression model. Pairs of observations and regressors $\{(y(i), j(i)), i = 1,2,...t\}$ are obtained from an experiment. The problem is to determine the parameters in such a way that the outputs computed from the model are as closely as possible with the measured variables $y(i)$ in the sense of least squares. That is, the parameter q should be chosen to minimize the least-square loss function in (1.17).

$$V(q,t) = \frac{1}{2}\sum_{i=1}^{t}(y(i) - j^T(i)q)^2 \quad (1.17)$$

Since the measured variable y is linear in parameters q^0 and the least-squares criterion is quadratic, the problem admits an analytical solution. Introducing the notations:

$$Y(t) = [y(1) \quad y(2) \quad ... \quad y(t)]^T$$

$$e(t) = \left[e(1) \quad e(2) \quad \ldots \quad e(t)^T \right]$$

$$j(t) = \begin{bmatrix} j^T(1) \\ . \\ . \\ j^T(t) \end{bmatrix}$$

$$P(t) = (j^T(t) j(t))^{-1} = (\sum_{i=1}^{t} j(i) j^T(i))^{-1} \tag{1.18}$$

Where the residuals $e(i)$ are defined by:

$$e(i) = y(i) - y(i) = \hat{y}(i) - j^T(i)q$$

With these notations the loss function (1.17) can be written as:

$$V(q,t) = \frac{1}{2}\sum_{i=1}^{t} e^2(i) = \frac{1}{2} e^T e = \frac{1}{2}\|e\|^2$$

Where e can be written as:

$$e = Y - \hat{Y} = Y - j\,q \tag{1.19}$$

Now the solution of the least-squares problem can be obtained by minimizing for the parameter $\hat{q}$ such that:

$$j^T j\,\hat{q} = j^T Y \tag{1.20}$$

If the matrix $j^T j$ is nonsingular, the minimum is unique and given by:

$$\hat{q} = (j^T j)^{-1} j^T Y \tag{1.21}$$

In on-line identification the observations are obtained sequentially in real-time. It is then desirable to make the computation recursively to save computation time. Computation of the least-squares estimate can be arranged in such a way that the results obtained at time $t-1$ can be used to get the estimates at time t. The solution in to the least-squares problem in (1.21) will be written in a recursive form. Let $\hat{q}(t-1)$ denote the least-squares estimate based on $t-1$ measurements. Assuming that the matrix $j^T j$ is nonsingular for all t. It follows from the definition of $P(t)$ in equation (1.18) that:

$$P^{-1}(t) = j^T(t) j(t) = \sum_{i=1}^{t} j(i) j^T(i)$$

$$= \sum_{i=1}^{t-1} j(i) j^T(i) + j(t) j^T(t)$$

$$= P^{-1}(t-1) + j(t) j^T(t) \qquad (1.22)$$

It follows that:

$$\sum_{i=1}^{t-1} j(i) y(i) = P^{-1}(t-1)\hat{q}(t-1) = P^{-1}(t)\hat{q}(t-1) - j(t) j^T(t)\hat{q}(t-1)$$

The estimate at time t can now be written as:

$$\hat{q}(t) = \hat{q}(t-1) - P(t) j(t) j^T(t)\hat{q}(t-1) + P(t) j(t) y(t)$$

$$= \hat{q}(t-1) + P(t) j(t)(y(t) - j^T(t)\hat{q}(t-1))$$

$$= \hat{q}(t-1) + K(t) e(t)$$

Where $\quad K(t) = P(t) j(t)$

$$e(t) = y(t) - j^T(t)\hat{q}(t-1)$$

The residual $e(t)$ can be interpreted as the error in predicting the signal $y(t)$ at one step ahead based on the estimate $\hat{q}(t-1)$. To proceed it is necessary to derive a recursive equation for $P(t)$ rather than for $P(t)^{-1}$ as in equation (1.22). Applying the matrix inversion lemma we get;

$$P(t) = (j^T(t)j(t))^{-1} = (j^T(t-1)j(t-1) + j(t)j^T(t))^{-1}$$

$$= (P(t-1)^{-1} + j(t)j^T(t))^{-1}$$

$$= P(t-1) - P(t-1)j(t)(I + j^T(t)P(t-1)j(t))^{-1}j^T(t)P(t-1)$$

This implies that;

$$K(t) = P(t)j(t) = P(t-1)j(t)(I + j^T(t)P(t-1)j(t))^{-1}$$

Now if we assume that the matrix $j(t)$ has full rank, that is, $j^T(t)j(t)$ is nonsingular, for all $t \geq t_0$. Given $\hat{q}(t_0)$ and $P(t_0) = (j^T(t_0)j(t_0))^{-1}$, the least-squares estimate $\hat{q}(t)$ then satisfies the recursive equations;

$$\hat{q}(t) = \hat{q}(t-1) + K(t)(y(t) - j^T(t)\hat{q}(t-1)) \tag{1.23}$$

$$K(t) = P(t)j(t) = P(t-1)j(t)(I + j^T(t)P(t)j(t))^{-1} \tag{1.24}$$

$$P(t) = P(t-1) - P(t-1)j(t)(I + j^T(t)P(t-1)j(t))^{-1}j^T(t)P(t-1)$$

$$= (I - K(t)j^T(t))P(t-1) \tag{1.25}$$

The recursive least-squares algorithm has two sets of state variables, $\hat{q}$ and P, which must be updated at each step. For large n the updating of the matrix P dominates the computing effort. There are several simplified algorithms that avoid updating the P matrix at the cost of slower convergence. Kaczmarz's projection algorithm is one simple solution which states that:

$$\hat{q}(t) = \hat{q}(t-1) + \frac{g j(t)}{a + j^T(t)j(t)}(y(t) - j^T(t)\hat{q}(t-1) \tag{1.26}$$

Where $a \geq 0$ and $0 < g < 2$.

A further simplification is the least mean square (LMS) algorithm in which the parameter updating is done by using;

$$\hat{q}(t) = \hat{q}(t-1) + g j(t)(y(t) - j^{T}(t)\hat{q}(t-1)) \tag{1.27}$$

Where g is a constant.

1.4 Adaptive Inverse Control

Adaptive inverse control is a novel approach to the design of control systems and regulators. Widrow and Walach [73] stats that if the controller shown in Figure 1.5 were to be ideal for adaptive inverse control system, its transfer function would be

$$C(z) = \frac{M(z)}{P(z)} \tag{1.28}$$

The adaptive controller will generally not be ideal; its transfer function can therefore be designated as

$$\hat{C}(z) = C(z) + \Delta C(z) \tag{1.29}$$

Adaptive filters such as LMS are fundamental building blocks to adaptive inverse control and they require an error referred to the plant input not to the plant output. Hence, the plant and its inverse model are commuted and the error is directly available for the adaptation of $\hat{C}(z)$. Once $\hat{C}(z)$ is obtained, an exact digital copy can be used as a controller for the plant.

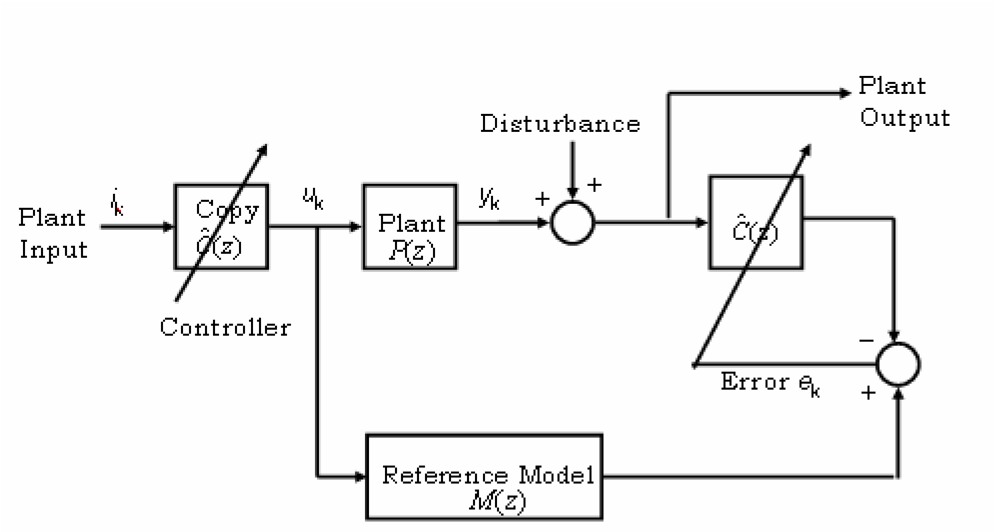

Figure 1.5 Adaptive Inverse Control System

The controller can be thought of as an adaptive filter having the plant output y_k as filter input and the estimated plant input $\hat{u}_k$ as filter output. By comparing the filter output with the desired plant input u_k, the filter adjusts its parameters that control its impulse response. The filter would be finite impulse response (FIR) and the estimated plant input is given by

$$\hat{u}(k) = \sum_{i=0}^{M-1} w_i(k) y(k-i) = w(k)^T y(k) \tag{1.30}$$

where *w(k)* is the weight and *y(k)* is the plant output. The error which is the difference between the estimated and desired plant input needs to be minimized by choosing the best filter coefficients. Using least mean square (LMS) algorithm, we minimize the cost function squared error at each sample time *k* is given by

$$e^2(k) = [\hat{u}(k) - w(k)^T y(k)]^2 \tag{1.31}$$

The adaptive rule for the filter coefficient is given by

$$w(k+1) = w(k) + 2me(k)y(k) \tag{1.32}$$

where $2 > m > 0$ is the adaptation parameter and $e(k)$ is the error.

1.5 Internal Model Control (IMC)

The Internal Model Control (IMC) structure is introduced as an alternative to the classic feedback structure. As per Morari and Zafiriou [4], its main advantage is that closed-loop stability is assured simply by choosing a stable IMC controller. Also, closed-loop performance characteristics (like settling time) are related directly to the controller parameters, which make on-line tuning of the IMC controller very convenient.

The block diagram of the IMC loop is shown in Figure 1.6. Here p denotes the plant and p_m the measurement device transfer functions. In general neither p nor p_m are known exactly but only there nominal models $\hat{p}$ and $\hat{p}_m$ are available. The transfer function p_d describes the effect of the disturbance d' on the process output y. The measurement of y is corrupted by measurement noise n. The controller q determines the value of the input (manipulated variable) u. The control objective is to keep y close to the reference (set point) r. Commonly we use the simplified block diagram in Figure 3.2. Here d denotes the effect of the disturbance of the output. Exact knowledge of the output y is assumed $(p_m = 1, n = 0)$). The complete control system is implemented through computer software or analog hardware. Because in addition to the controller q it includes the plant model $\hat{p}$ explicitly we refer to this feedback configuration as *Internal Model Control* (IMC). The feedback signal is:

$$\hat{d} = (p - \hat{p})u + d \tag{1.33}$$

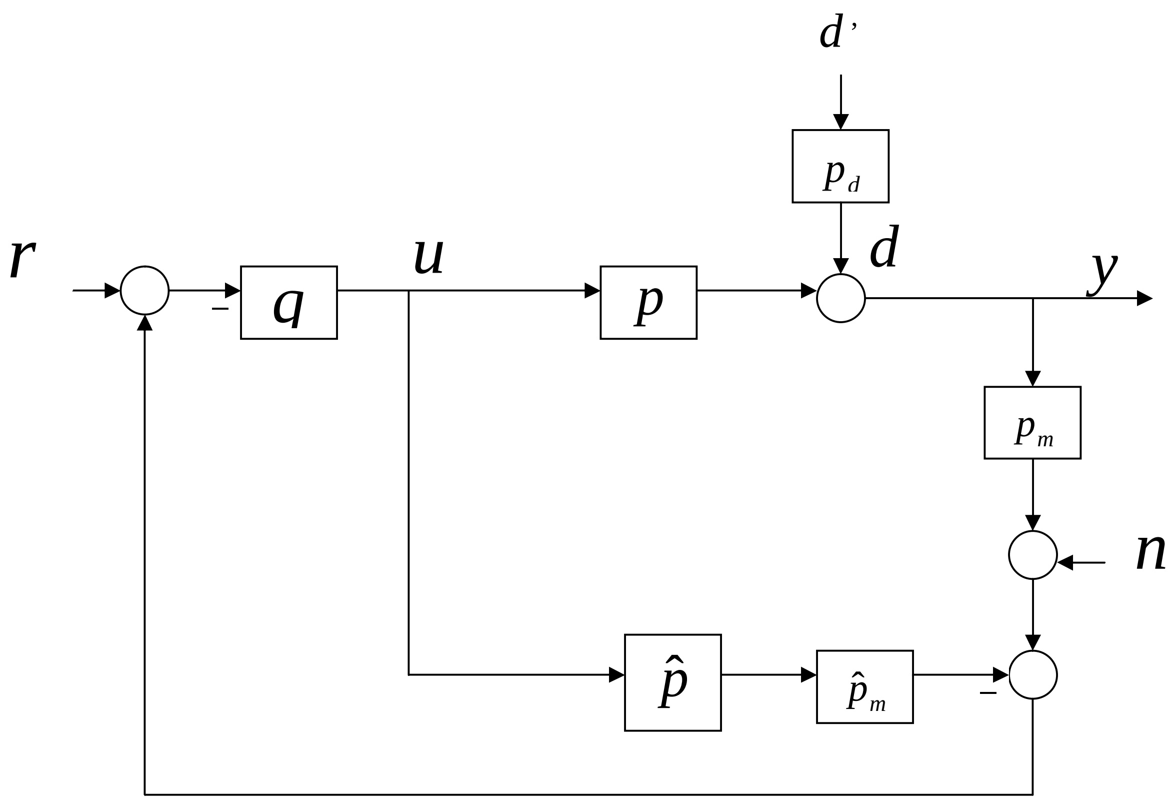

Figure 1.6: General block diagram of Internal Model Control System

If the model is exact $(p = \hat{p})$ and there are no disturbances $(d = 0)$, then the model output $\hat{y}$ and the process output y are the same and the feedback signal $\hat{d}$ is zero. Thus, the control system is an open-loop when there is no uncertainty –i.e., no model uncertainty and no unknown input d. This demonstrates very instructively that for open-loop stable process feedback is only needed because of uncertainty. If a process and all its inputs are known perfectly, there is no need for feedback control. The feedback signal $\hat{d}$ expresses the uncertainty about the process.

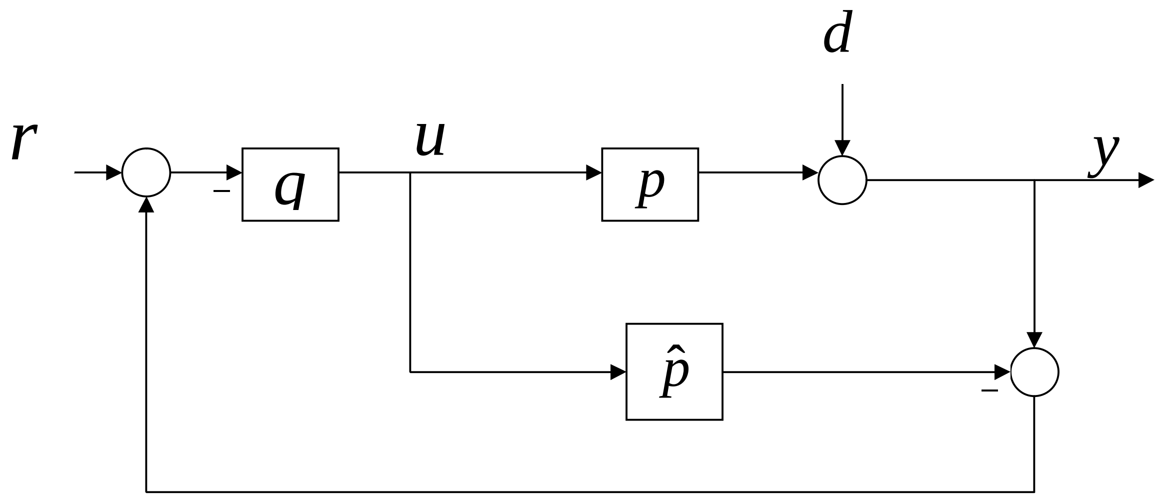

Figure 1.7: A simplified block diagram of Internal Model Control system

In order to test for internal stability we examine the transfer function between all possible system input and outputs. From the block diagram of Figure 1.8 we find that there are three independent system inputs and three independent outputs. As shown in Figure 1.6 and 1.7 we choose the independent inputs to be r, u_1 and u_2 and the independent outputs y, u and $\hat{y}$. If there is no model error $(p = \hat{p})$, then the inputs and outputs are related through the following transfer matrix.

$$\begin{pmatrix} y \\ u \\ \hat{y} \end{pmatrix} = \begin{pmatrix} pq & (1-pq)p & p \\ q & -pq & 0 \\ pq & -p^2 q & p \end{pmatrix} \begin{pmatrix} r \\ u_1 \\ u_2 \end{pmatrix} \tag{3.2}$$

Theorem 1.1 *Assume the model is perfect* $(p = \hat{p})$. *Then the IMC system in Figure 1.7 is internally stable if and only if both the plant p and the controller q are stable.*

This result is not unexpected as the IMC system is effectively an open-loop when there is no uncertainty. Since the stabilization of open-loop unstable systems requires feedback, the IMC structure cannot be applied in this case. It can be argued that the lack of model uncertainty is an artificial assumption. Uncertainty gives rise to feedback and thus it could be possible to stabilize an unstable system with IMC. However in any practical situation it is unacceptable to rely on model uncertainty for stability.

1.6 Objective of the Thesis

The objectives of this thesis work are the following:

1. Identifying fuzzy Takagi-Sugeno (TS) models of nonlinear plants at different operating points to be further used in the proposed control techniques.
2. Use the normalized nLMS algorithm to select the membership function of the fuzzy Takagi-Sugeno models and to develop adaptive TS with IMC structure using nLMS tuning control technique.
3. Implement the adaptive TS with IMC structure using nLMS tuning control technique in a nonlinear heating process.
4. Develop an adaptive inverse control (AIC) with IMC structure control technique.
5. Implement the AIC with IMC structure control technique in a single link robotic arm manipulator.

1.7 Organization of the Thesis

The first chapter of the thesis introduces and defines the main methods that are used to support the proposed control techniques. In addition, the thesis objective and organization summary is stated. The second chapter covers the literature review for the fuzzy Takag-Sugeno modeling and control as well as the adaptive inverse control (AIC). In the third chapter, the proposed control techniques are explained. It includes the adaptive inverse control (AIC) with internal model control (IMC) structure control technique and the adaptive Takagi-Sugeno (TS) with IMC using nLMS tuning control technique. The fourth chapter covers the experimental implementation results for both of the proposed control techniques. The AIC with IMC structure control technique is implemented on a single-link robotic arm manipulator system. The adaptive TS with IMC using nLMS tuning control technique are implemented on a nonlinear heating process. The fifth chapter presents the summery, conclusion and recommendations for the possible future work.

Chapter 2

Literature Review

2.1 Takagi-Sugeno Fuzzy Modeling

The mathematical modeling of fuzzy concepts was first presented by Proffessor Lotfi Zadeh in 1965 to describe, mathematically, class of objects that do not have precisely defined criteria of membership. His contention is that the meaning in a natural language is a matter of degree. Later on, Takagi-Sugeno (TS) fuzzy model [35, 36] was proposed by Takagi, Sugeno, and Kang in 1985-1986 to develop a systematic approach for generating fuzzy rules from a given input-output data set in the application of multilayer incinerator. Since then, researchers started implementing their model in wide range of applications. This work is motivated by the use of TS fuzzy models in adaptive control area. Hence, its implementation in such area is presented. Smith [10] designed a controller with run-time adaptation based on TS format that was wrapped during each step response to a change in structure. His approach combined the quick response of bang-bang like control with the stable convergence properties of more conservative linear control to produce high performance controller. Spooner and Passino [11] introduced a stable direct and indirect adaptive controller that uses TS fuzzy systems to be used for a class of continuous-time nonlinear plant with poorly understood dynamics with a technique for direct adaptive scheme in which linguistic knowledge of the inverse dynamics of the plant may be used to accelerate adaptation. Also, Spooner, Ordonez and Passino [12] introduced an indirect adaptive control scheme for a class of discrete-time nonlinear system based on functional approximation approach which modifies TS fuzzy control system. Kosinski and Weigl [13] introduced an adaptive TS fuzzy expert system which combines the fuzzy inference module with neural network in order to realize a process of fuzzy reasoning and express their parameters by connection weights of a neural network. This was constructed for the need of an opto-computer system for the diagnostic of surface imperfections of technological elements. Sousa, Babuska and Verbruggen [32] proposed a procedure based on product-space fuzzy clustering to find TS fuzzy model and invert it as part of an IMC structure to control highly nonlinear processes. Ordonez and Passino [14] implemented a discrete-time adaptive prediction and control techniques where they used TS fuzzy systems as function approximator and least-square was investigated for use in prediction and control. Kang, Son, Kwon and Park [15] proposed an approach to the indirect adaptive fuzzy algorithm that uses TS fuzzy model to identify the unknown nonlinear SISO system. Barada and Singh [16] published their approach to generate optimal adaptive fuzzye-neural models from I/O data which combine structure and parameter identification of TS fuzzy models. Xie and Rad [33] introduced a fuzzy adaptive IMC with TS fuzzy process model and a fuzzy model-based controller that minimize and H_2-performance objective based on the identified fuzzy model. Cho, Yee and Park [17] proposed an indirect model reference adaptive TS fuzzy control scheme to provide asymptotic tracking of a reference signal for systems having uncertain or slowly time-varying parameters. They compared the measured state with the state of the estimation model and implemented in Robot Manipulator. Song, Smith and Rizk [18] introduced cell state space based TS type fuzzy logic controller with automatic rule extraction and parameter optimization algorithm where the parameters of the rule base antecedents extracted from a discrete optimal control table generated under a predefined cost function and used LMS to train data sets of the rule output parameters, it was implemented in a 4-D inverted pendulum. Boukezzoula, Galichet and Foully [34] proposed an IMC control structure based on TS fuzzy model of the plant and claiming perfect control when the controller is the inverse of the fuzzy model. Hwang [19] introduced two TS fuzzy base robust and adaptive sliding-mode controls that uses fuzzy sets from the system rule of the reference model. Gazi and Passino [20] presented a direct adaptive control scheme for a class of continuous time non-linear systems where strictly dynamic TS fuzzy systems used as on-line function approximator and gradient method for adaptation. Azeem, Hanmandlu and Ahmad [21] proposed a generalized fuzzy model GFM that encompasses both TS fuzzy model and the compositional rule of inference CRI model. Park, Hyun, Lee, Kim and Park [22] presented an adaptive fuzzy control scheme via parallel distributed compensation for MIMO plant of TS model type and implemented to track a flexible-link robot manipulator. Boukezzoula, Galichet and Foulloy [23] proposed an adaptive TS fuzzy controller for continuous nonlinear system where the plant was approximated with TS fuzzy model and the control law used Lyapunov and passivity theories. Yoon and Park [24] presented a control method for general nonlinear systems using TS fuzzy models and developed an adaptation law to adjust the parameters of the fuzzy system. Golea, Boumehrez and Kadjoudj [25] proposed an adaptive scheme that uses TS fuzzy controller which allows the inclusion of a priori information in terms of qualitative knowledge about the plant. Lin [26] developed an adaptive fuzzy gain-scheduled missile autopilot that uses TS fuzzy system to represent the fuzzy relationship between the scheduling variables and controller parameters with an adaptation law that uses scheduling parameter variation information. Boukezzoula, Galichet and Foulloy [27] combined fuzzy feedback linearizing controller with a simple linear controller using a TS fuzzy model for a discrete-time nonlinear system. Cupec, Peric and Petrovic [28] proposed an adaptive control method based on TS fuzzy process model that is applicable when the variables in the premises of fuzzy rules are not measurable. Diao and Passino [29] proposed an adaptive control methodology for a class of nonlinear systems with a time-varying structure composed of interpolations of nonlinear subsystems which are input-output feedback linearizable with TS fuzzy localized model as online approximator to learn the unknown dynamics of the system. Yang and Zhou [30] designed a fuzzy adaptive robust control algorithm FARC for a class of uncertain nonlinear system using small gain approach and dissipative system theory. Zheng, Wang and Lee [31] studied the issue of designing robust adaptive stabilizing controllers for nonlinear systems in TS fuzzy model with both parameter uncertainties and external disturbances. Boukezzoula, Galichet and Foulloy [40] investigated the possible application of dynamical fuzzy systems to control nonlinear plants with asymptotically stable zero dynamics using a fuzzy nonlinear internal model control strategy. The developed strategy consists of a dynamic Takagi-Sugeno fuzzy model of the plant within the control structure. The control design results in a fuzzy model inversion. This framework presents the use of a dynamic fuzzy model and its inversion. The inversion of the global fuzzy system was tackled by inversion of some of the elementary subsystems that represent the fuzzy system. The fuzzy controller was connected in series with a robust filter. Chang and Sun [41] addressed the stability and controller design problem for a discrete Takagi-Sugeno type fuzzy model whose subsystems are made up of controllability canonical forms. Stability conditions and fuzzy controller design were derived by solving the inverse solution of Lyapunove equation. Kadmiry and Diankov [42] addressed the robust fuzzy control problem for discrete-time nonlinear systems in the presence of sampling time uncertainties. The ease of TS fuzzy system was considered and robust controller design was proposed. The sufficient conditions and the design procedure were formulated in the form of linear matrix inequalities (LMI). Angelov and Filer [43] proposed an approach to the online learning of Takagi-Sugeno (TS) type models. The rule-base and parameters of the TS model continually evolve by adding new rules with more summarization power and by modifying existing rules and parameters. It is inherited and updated when new data become available. A new type adaptive model called the Evolving Takagi-Sugeno model (ETS) was achieved by this learning concept. Wai and Chen [44] presented a Takagi-Sugeno-Kang type fuzzy-neural-network control (T-FNNC) scheme for an n-link robot manipulator to achieve high precision position tracking. Due to uncertainties in practical applications (such as friction forces, external disturbances and parameter variations) a T-FNNC system without the requirements of prior system information and auxiliary control design was investigated to the joint position control of an n-link robot manipulator of periodic motion. Boukezzoula, Galichet and Fonlloy [45] examined the tracking control problem for a class of feedback linearizable nonlinear systems for which there is no available analytical model. The unknown nonlinear system was represented by a Takagi-Sugeno (TS) fuzzy system. The parameters were adjusted via adaptive laws according to the Lyapunove and passivity theories. A fuzzy adaptive feedback linearizing controller was designed under the constraint that only the output of the plant is available for measurement. Chiu [46] proposed a robust adaptive controller using a feedforward Takagi-Sugeno fuzzy approximator for a class of multi-input multi-output (MIMO) nonlinear plants that is highly unknown. The desired commands were taken as input variables of a TS fuzzy system. The unknown feedforward terms required during steady state were adaptively approximated and compensated. According to H^{∞} control technique, nonlinear damping design and sliding mode control, the controllers were synthesized to assure either only the minimization of disturbances and estimated fuzzy parameter errors, or globally asymptotic stable tracking. Baranyi, Annamaria, Yam and Patton [47] presented an adaptation of TS fuzzy models without complexity expansion (HOSVD-based approach). The proposed method minimizes the necessary modification of the new information. A focus was given to the Higher Order Singular Value Decomposition (HOSVD) method and Takagi-Sugeno (TS) inference operator based fuzzy rule-bases. The proceeding discussion motivate the use of Takagi-Sugeno fuzzy model as being a powerful tool to model nonlinear systems in addition to using LMS to achieve adaptation to plant output. In addition, the design of adaptive controllers in new control techniques is essential for robust control structure that is implementable.

2.2 Adaptive Inverse Control

Adaptive control is used when the plant characteristics are time variable or non-stationary. Its first introduction was in the 1950s, but the interest diminished partly because it was too hard to deal with using the available techniques at that time. Further researches in the 1960s, lead to its development. In adaptive control, it is necessary to design the controller to vary with the plant. An identification process could be used to estimate the plant characteristics over time, and these characteristics could be used to parameterize the controller and vary the parameters to directly minimize the mean square error. The difficulty with this approach is that, regardless of how the controller is parameterized, the mean square error versus parameter values would be a function not having a unique exteremum and one that could easily become infinite if the controller parameters were pushed beyond the brink of stability. In the 1970's an alternative look at the subject of adaptive control was introduced by Widrow and Walach [73] known as adaptive inverse control. In simple format, it involves an open-loop control with the controller transfer function equals to the inverse of the plant to be controlled. Widrow and McCool [48] presented a comparison of the performance characteristics of three algorithms useful in adjusting the parameters of the adaptive systems, the differential (DSD) and least-mean-square (LMS) algorithms; both are based on the method of steepest descent, and the linear random search (LRS) algorithm, based on a random search procedure derived from Darwinian concept of "natural selection." Analytical expressions were developed to define the relationship between rate of adaptation and "misadjustment" demonstrating their application canceling of broadband interference in sidebars of receiving antenna array and phase control of a transmitting antenna array. Widrow and Walach [49] presented an efficiency analysis of the LMS algorithm with nonstationary inputs where the quality of the exact least square solution was compared with the quality of the solution obtained by orthogonalized and conventional least mean square (LMS) algorithm with stationary and nonstationary inputs data. Widrow, Baudrenghien, Vetterli and Titchener [50] established a relationship between LMS algorithm and the DFT. It was shown that the LMS spectrum analyzer is a new mean from the calculation of the DFT. Widrow, Lehr, Beaufays, Wan and Bilello [51] presented a learning algorithms that were used in both linear and nonlinear adaptive filters, along with applications to signal processing and control problems such as prediction, modeling, inverse modeling, equalization, echo canceling, noise canceling, and inverse control. Hunt and Sbarbaro [52] showed that adaptive inverse control is a further member of the class of control design techniques with an internal model control structure. Artificial neural network architecture for the implementation of nonlinear internal model control (IMC) was presented. Two separate networks in the implementation of nonlinear IMC were used; one network models the plant and the second network models that plant inverse. Widrow and Bilello [53] presented a model-reference inverse control system that can learn to approximate a desired reference-model dynamics. Control of internal plant disturbance was accomplished with an optimal adaptive disturbance canceller. Tao [54] presented a modified parameterization for model reference adaptive control of linear plants with partial knowledge of the stable zero or pole dynamics. Such parameterization was applied to the adaptive inverse control of plants with unknown nonsmooth nonlinearities such as dead-zone, backlash, or hysteresis at the input or output of a linear part whose stable zero or pole dynamics were partially known. Widrow and Plett [55] presented adaptive filtering to achieve feedforward control for both linear and nonlinear plants. Precision was attained by incorporating the adaptive filtering process. Disturbance was optimally controlled by filtering it and feeding it back into the plant input. Klippel [56] presented an adaptive inverse control of weakly nonlinear systems. By linearizing the plant, it was possible to track an input signal if the plant was preceded by a nonlinear controller which approximates the inverse of the plant's transfer function. Novel filtered-A and filtered-E modifications of the stochastic gradient based methods which were applicable to update generic as well as special block-oriented nonlinear filter architecture were presented. Nobari, Chambers, Green, Goodfellow and Smith [57] presented a design and development of a controller through the teaching company scheme and impact of this development on Link Dynamic Systems (LDS), which is a leading manufacturer in the vibration test industry. Widrow and Plett [58] presented nonlinear adaptive inverse control which treats the control of plant dynamics and plant disturbance separately without compromise. The controller approximates the inverse of the plant transfer function. A model-reference version allows system dynamics to closely approximate desired reference-model dynamics. Cochofel, Woten and Principe [59] presented a neurocontroller development environment using the idea of adaptive inverse control. A real-time implementation was done on a motor speed control using the power supply as the control input. Kaelin and Grunigen [60] presented the use of priori knowledge in adaptive inverse control. The controller can be split into a long fixed and a short adaptive filter. The controller can be made more efficient by feed backing the error signal only in a desired frequency range. A modified objective function allows the minimization of the filtered square error plus the norm of the controller. Karshenas, Dunnigan and Williams [61] proposed an adaptive inverse control algorithm for shock testing an arbitrary specimen using an electrodynamic actuator. It approximates an inverse model of the loaded shaker with a finite impulse response adaptive filter, such that the reference input is reproduced at the shaker output. The standard filtered-x least mean square control structure used in the adaptive inverse control algorithm was modified to a block-processing structure, with the frequency-domain adaptive filter as the adaptation algorithm. Harnold and Lee [62] introduced a "free-model" based model reference adaptive inverse control design for a boiler-turbine plant by using functional mapping. In order to obtain smaller error in the initial phase of training, free-model based neural networks were applied as the neuro-identifier and neuro-controller in the control scheme. The functional mapping was applied for the drum pressure set point from the power demand in order to be more economical on the fuel burning at the throttle valve. Plett and Bottrich [63] proposed a modification to the standard nonlinear adaptive inverse control learning methods to be based on dynamic-decoupled-extended-kalman-filter (DDEKF) where training became significantly faster. Li and Jinshon [64] presented nonlinear hybrid adaptive inverse control using neural fuzzy system and its application to CSTR systems. It consists of two control loops, inverse control and PID control. The PID control was a complement for inverse control and was mainly used to eliminate static error existing in direct inverse control when the inverse model is uncertain. The neural fuzzy system was utilized to construct the inverse controller. Plett [65] presented the adaptive inverse control of linear and nonlinear systems dynamic neural networks. Adaptive control was looked at as a three-part adaptive-filtering problem. First, the dynamic system was modeled using adaptive system-identification technique. Second, the dynamic response of the system was controlled using an adaptive feedforward controller. Third, disturbance canceling was performed using an additionally adaptive filter. Jeng, Chuang and Lee [66] presented annealing robust nonlinear adaptive inverse control with fuzzy neural network based support vector regression (FNNBSVR). It was used to overcome initial structure problem and long training time in the nonlinear adaptive inverse control. Besides, the annealing robust learning algorithm was proposed to overcome the outlier in the training procedure. Zhao and Zhan [67] presented a study on ship maneuvering control based on adaptive inverse control technology. Dynamic control and noise elimination of adaptive inverse control were introduced. X-LMS adaptive inverse control algorithm and RLS adaptive inverse control algorithms were used to identify the parameters and design of the controller. Shao-Kuiliu and Yan [68] proposed an adaptive inverse control method for space flexible truss structure vibration control. The purpose was to retain the displacement amplitude or the acceleration amplitude of the structure vibration, to use the artificial neural network to identify the dynamic space flexible truss structure as the control plant, and then obtain the inverse model of the plant utilizing the LMS algorithm. Xing, Zhang, Liu and Feng [69] proposed a neural network based adaptive inverse control structure fit for the decoupling control of the underwater vehicle. The process of decoupling does not depend on the dynamic model and coupling model of the plant. The coupling between different variables was suppressed through a disturbance canceller. Sun, Ru and Rong [70] presented hysteresis compensation for piezoelectric actuator based on adaptive inverse control. Hysteresis hinders the wider applicability of smart materials in actuators. An adaptive inverse control approach based on the so-called Prandtle-Ishlinkii hysteresis operator was presented for reducing hysteresis. The weights of the model were identified by using LMS algorithm. The realization of an inverse feedforward controller for the linearization of a piezoelectric actuator was formulated. Peng, Wang and Yang [71] proposed a strategy of adaptive inverse control based on parallel self-learning neural networks. Aiming at the main steam temperature control system, which has large inertia, long time-delay and time varying in thermal power plant, the proposed method was designed. The plant model and its inverse were represented by neural networks. Liu, Yi, Zhao and Wang [72] presented a king of nonlinear adaptive inverse control systems based on fuzzy neural networks. Feedback compensation was used to counteract the system's direct current zero-frequency drift. Nonlinear filters based on fuzzy neural networks were used in the nonlinear plant modeling the design of the controller and adaptive disturbance canceller.

Chapter 3

Proposed Fuzzy TS and LMS based Control Techniques

3.1 Adaptive AIC with IMC Structure

An adaptive inverse control with internal model control (IMC) structure is proposed. The inverse of the plant is estimated using normalized least mean square (nLMS) algorithm. Radial base transfer function is used as an input mask to the adaptive algorithm. A delayed version of the reference signal is compared with the plant output to produce the error for the adaptive algorithm. The error signal is masked by a hyperbolic tangent sigmoid transfer function and the learning rate is adjusted automatically A rate limiter is used in the model identification part to eliminate oscillatory plant output behavior. Comparison between adaptive inverse control and IMC structure is going to be covered.

The control objective is to develop a link position tracking control strategy for the robotic arm manipulator system using AIC with IMC structure. The introduced integrator backstepping technique that is developed for a DC motor turning a robotic load [10] has an embedded current control input inside an overall control strategy which is designed at the voltage control input. Taking this into consideration, we designed the control input as the applied voltage to the same system of [10]. It is necessary to stabilize the DC motor angular position based on the input voltage before proceeding with the development of the AIC and IMC structure (Figure 3.1). Assuming that the plant has a transfer function *P(s)*, a simple lead-lag controller *LL(s)* is used to stabilize the angular position (1).

$$LL(s) = \frac{b_1 s + b_0}{a_1 s + a_0} \tag{3.1}$$

where the selection of the (b_1, b_0, a_1, a_0) parameters is to stabilize the plant angular position.

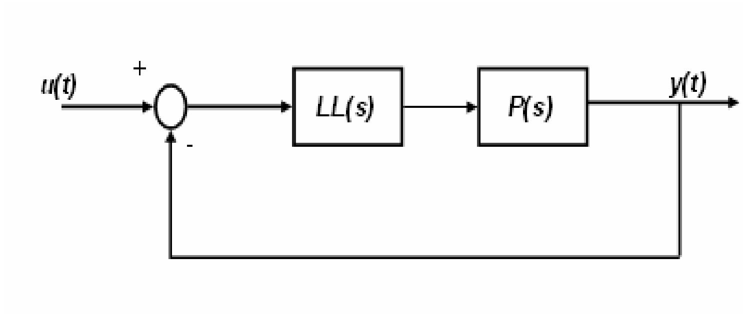

Figure 3.1: Stabilization using Lead-Lag.

The next step is to implement the proposed AIC with IMC structure (Figure 3.2).

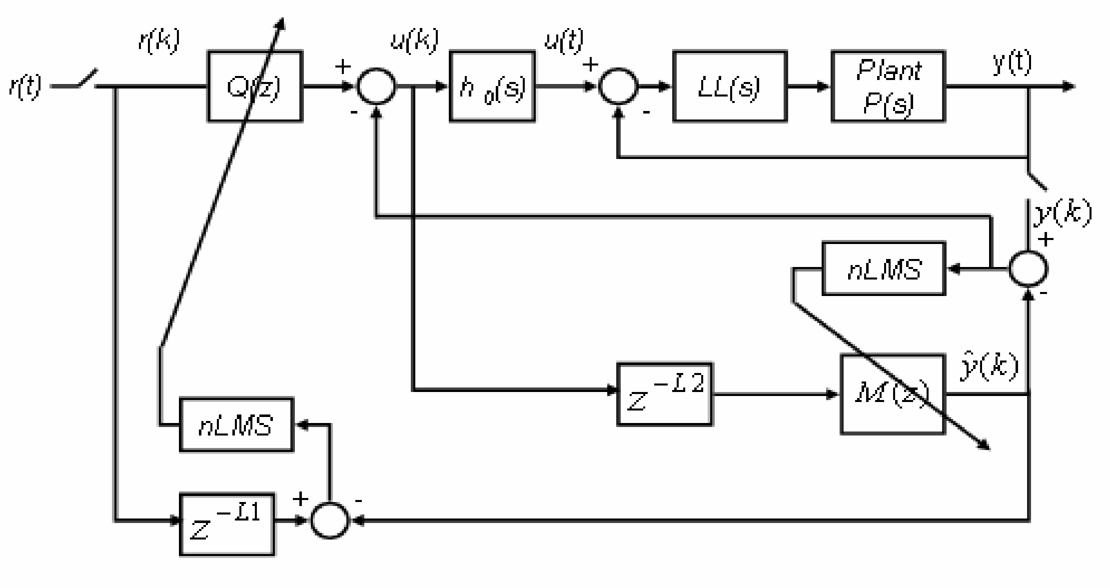

Figure 3. 2: AIC with IMC structure.

Consider the continuous-time unstable plant transfer function *P(s)* that is stabilized by the Lead-Lag controller *LL(s)*. Let $h_0(s)$ denote the zero-order hold. The discrete-time version of the plant and the Lead-Lag controller will be *P(z)* and *LL(z)*. *u(k)* is the control input to the plant and *y(k)* is the plant output. The control objective is to synthesize *u(k)* such that *y(k)* tracks some bounded piecewise continuous desired trajectory *r(k)*.

3.1.1 Adaptive identification of the forward model

As shown in Figure 3.2, the forward model *M(z)* of the IMC structure is adaptively identified using the nLMS algorithm. Let $\hat{y}(k)$ be the identified model output required to track *u(k-L2)*, an *L2*-sample delayed *u(k)*. Then

$$\hat{y}(k) = j_{mdl}^{T}(k)\hat{q}_{mdl}(k-1) \tag{3.2}$$

where the regression variables $j_{mdl}(k)$ holds a masked version of the control input signal using neural networks radial bas transfer function given by

$$j_{mdl}^{T}(k) = [u_{rbf}(k), u_{rbf}(k-1), \ldots\ldots, u_{rbf}(k-p)] \tag{3.3}$$

where the neural networks radial base transfer function is defined as

$$u_{rbf}(k) = e^{-[u(k-L2)]^2} \tag{3.4}$$

The parameter estimation law to identify the forward model based on nLMS is given by

$$\hat{q}_{mdl}(k) = \hat{q}_{mdl}(k-1) + \frac{g_{mdl}^{T}(k) j_{mdl}(k)}{a + j_{mdl}^{T}(k) j_{mdl}(k)} e_{tsg}(k) \tag{3.5}$$

where $a \geq 0$ is a small positive constant and the residual error is masked by a hyperbolic tangent sigmoid neural network transfer function

$$e_{tsg}(k) = \frac{2}{1+e^{-2b_{mdl}(k)}} - 1 \tag{3.6}$$

where $b_{mdl}(k)$ is the residual error and given by

$$b_{mdl}(k) = u(k-L2) - y(k) - \hat{y}(k) \tag{3.7}$$

$g_{mdl}(k)$ is a proposed automatic adjustment of the nLMS learning rate and is inversely proportional to the residual error and given by

$$g_{mdl}(k) = \frac{|b_{mdl}(k)|}{\|b_{mdl}(k)\|^2 + b} \tag{3.8}$$

where $f \leq g_{mdl}(k) \leq g$, $f < g$ and $0 \leq f,g \leq 2$ remains as the learning rate bound and b is the specified normalization bias parameter.

3.2 Adaptive Inverse Design

The inverse model *Q(z)* shown in Figure 3 uses the nLMS algorithm to adaptively satisfy the IMC structure. The control input *u(k)* that is required such that *y(k)* tracks the reference signal *r(k)* and is given by

$$u(k) = u_{inv}(k) - y(k) + \hat{y}(k) \tag{3.9}$$

where $u_{inv}(k)$ is the output of the inverse model and is given by

$$u_{inv}(k) = j^{T}_{inv}(k)\hat{q}_{inv}(k-1) \tag{3.10}$$

In a similar way to the forward model identification method, the regression variables $j_{inv}(k)$ contains a masked version of the reference signal using neural networks radial base transfer function given by

$$j_{inv}(k) = [r_{rbf}(k), r_{rbf}(k-1),...., r_{rbf}(k-p)] \tag{3.11}$$

where

$$r_{rbf}(k) = e^{-[r(k)]^2} \tag{3.12}$$

The nLMS algorithm for the parameter estimation law define it by

$$\hat{q}_{inv}(k) = \hat{q}_{inv}(k-1) + \frac{g^{T}_{inv}(k)j_{inv}(k)}{a + j^{T}_{inv}(k)j_{inv}(k)} e_{inv(k)} \tag{3.13}$$

where the neural network hyperbolic tangent sigmoid transfer function is masking the residual error $e_{inv}(k)$ and is given by

$$e_{inv}(k) = \frac{2}{1+e^{-2b_{inv}(k)}} - 1 \tag{3.14}$$

where $b_{inv}(k)$ is the residual error between a delayed version of the reference signal and the forward model estimated output and is given by

$$b_{inv}(k) = r(k - L1) - \hat{y}(k) \tag{3.15}$$

where $g_{inv}(k)$ is the same proposed automatic learning rate adjustment for the nLMS algorithm in (3.8) with the residual error of $b_{inv}(k)$ and is given by

$$g_{inv}(k) = \frac{|b_{inv}(k)|}{\|b_{inv}(k)\|^2 + b} \tag{3.16}$$

3.2.1 Adaptive identification of the forward model

In this section we discuss the design of adaptive inverse control system that uses the similar introduced algorithm to synthesize *u(k)* such that *y(k)* tracks some bounded piecewise continuous desired trajectory *r(k)* as given in [2]. We will assume using the same lead-lag controller design in (3.1) to stabilize the plant before anything. Figure 4 shows a block diagram of the proposed structure.

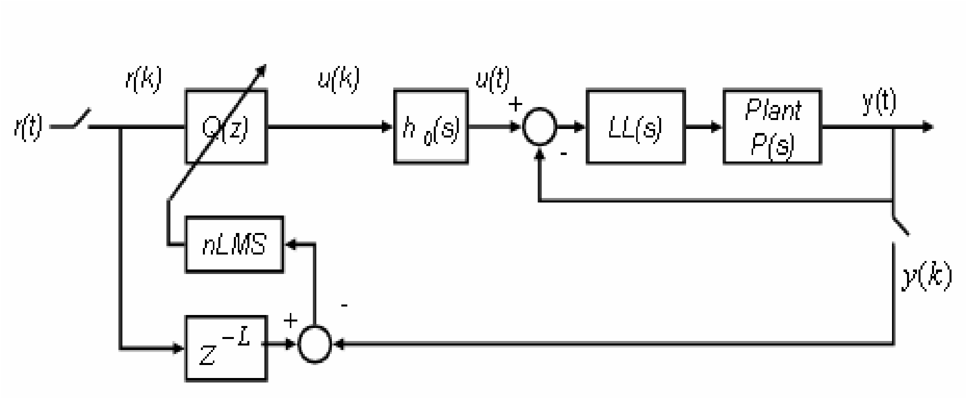

Figure 3.3: Adaptive Inverse Control.

The adaptive inverse controller *Q(z)* produce the system control input *u(k)* that is required to make the plant output *y(k)* tracks the reference input signal *r(k)* and is given by

$$u(k) = j^{T}(k)\hat{q}(k-1) \tag{3.17}$$

where the regression variables of $j(k)$ are given by

$$j(k) = [r_f(k), r_f(k-1), \ldots., r_f(k-p)] \tag{3.18}$$

where $r_f(k)$ is the output of the neural network radial base transfer function layer of a given net reference input signals *r(k)* and is given by

$$r_f(k) = e^{-[r(k)]^2} \tag{3.19}$$

The parameter estimation law uses nLMS algorithm and is given by

$$\hat{q}(k)=\hat{q}(k-1)+\frac{g(k)j(k)}{a+j^{T}(k)j(k)}e(k) \tag{3.20}$$

A neural networks hyperbolic tangent sigmoid transfer function $e(k)$ produces output from the residual error of a delayed version of the reference input and the plant output given by

$$e(k)=\frac{2}{1+e^{-2b(k)}}-1 \tag{3.21}$$

The residual error $b(k)$ in this case is given by

$$b(k)=r(k-L)-y(k) \tag{3.22}$$

Also, the automatic learning rate adjustment given in (8) is implemented here and it is given by

$$g(k)=\frac{|b(k)|}{\|b(k)\|^{2}+b} \tag{3.23}$$

3.3 Adaptive Fuzzy TS using IMC with nLMS Tuning

The Takagi-Sugeno fuzzy model is used to identify a SISO nonlinear plant by incorporating a number of linear continuous-time models of the system taken at different operating range of the input signal. Linear models are found based on the system step response characteristics at different values of the input range. A method presented in [5] is used to find a second order transfer function of the system at a given step response value. First, the response steady state; $K_0 = \lim_{s \to 0} G(s)$ then we calculates the following:

- $f_0(t) = K_0 - y_u(t)$, where $y_u(t)$ denote the system output.

- $y_1(t) = \int_0^\infty f_0(t)dt$.

- Apply step to $y_1(t)$ and find the new steady state K_1.

- $f_1(t) = K_1 - y_1(t)$.

- $y_2(t) = \int_0^\infty f_1(t)dt$.

- Apply step to $y_2(t)$ and find the new steady state K_2.

- Find $a_1 = \dfrac{K_1}{K_0}$ and $a_2 = \dfrac{a_1 K_1 - K_2}{K_0}$.

- The transfer function is $G(s) = \dfrac{K_0}{s^2 + (a_1/a_2)s + 1/a_2}$

A number of different linear transfer functions at different values of the input range can be used to approximate the nonlinear system. The conventional TS fuzzy model will be modified to incorporate the normalized LMS adaptive algorithm to replace the membership selection function. The well known fuzzy TS makes use of the membership function as follows:

$$R_j : \textbf{If } u_1 \text{ is } A_{1,j} \textbf{ then } y = g_j \tag{3.24}$$

where; $y = f(x)$, is a continuous function that equal to the value of calculated transfer function g_j, $j = 1,....,n$ and u_1 is the input to the system. Hence, instead, the input to the system is fed to all the different linear transfer functions, that are representations at different operating points and the collection of the outputs of each system are fed to the adaptive linear combiner subsystem of the normalized LMS adaptive filter. The adaptive linear combiner is shown in Figure 3.4. Its output is a linear combination of its inputs.

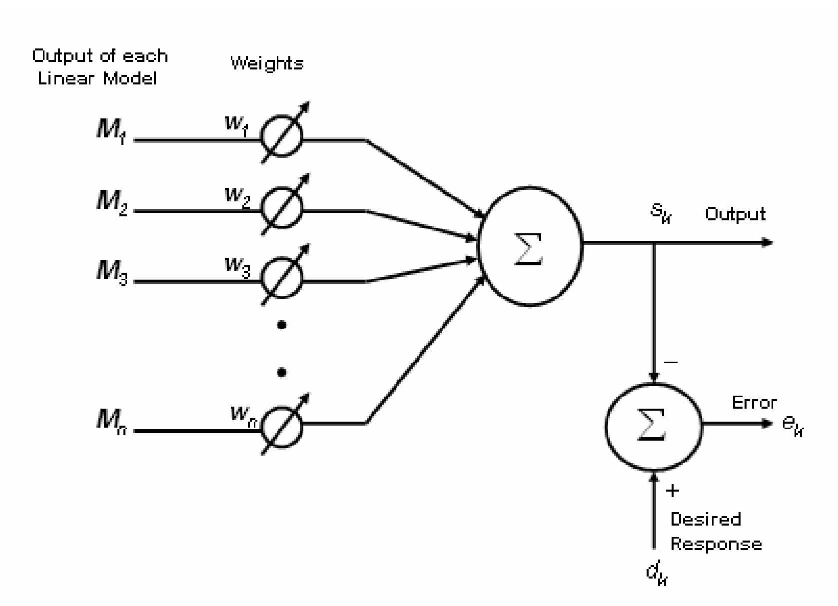

Figure 3.4: Adaptive Linear Combiner for nLMS

This element receives at time k an input signal vector or input pattern vector $M_k = [M_{1k}, M_{2k}, M_{3k}, \ldots, M_{nk}]^T$ and a desired response d_k, a special input used to effect learning. The components of the input vector are weighted by a set of coefficients, the weight vector $W_k = [W_{1k}, W_{2k}, W_{3k}, \ldots, W_{nk}]^T$. The sum of the weighted inputs is then computed, producing a linear output, the inner product $S_k = M_k^T W_k$. During the training process, input patterns and corresponding desired responses are presented to the linear combiner. The nLMS adaptation algorithm automatically adjusts the weights so that the output responses to the input pattern will be as close as possible to their respective desired responses. The nLMS algorithm minimizes the sum of square of the linear errors over the training set. The linear error e_k is defined to be the difference between the desired response d_k and the linear output S_k.

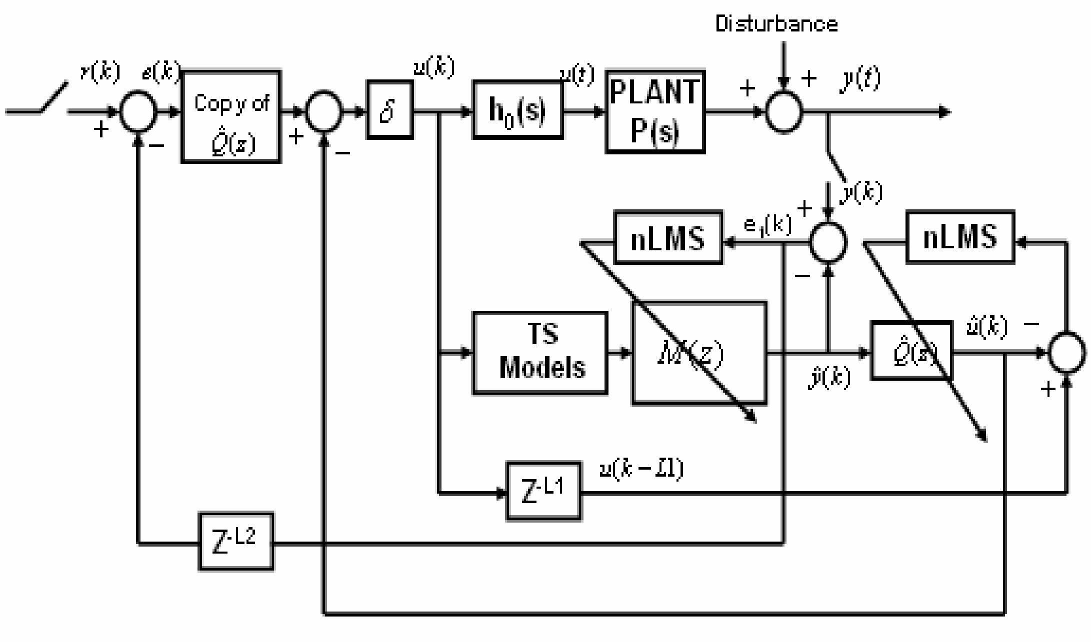

Figure 3.5: Adaptive TS with IMC using nLMS tuning

Considering the continues-time staple plant transfer function $P(s)$, let $h_0(s)$ denote the zero-order hold, $u(k)$ is the control input to the plant and $y(k)$ is the plant output. The control objective is to synthesize $u(k)$ such that $y(k)$ tracks some bounded piecewise continuous desired trajectory $r(k)$. As shown in Figure 3.5, the forward model $M(z)$ of the IMC structure is identified using TS linear models and the nLMS adaptive algorithm. Let $\hat{y}(k)$ be the identified model output required to track $u(k)$. Then

$$\hat{y}(k) = M^T(k)W(k-1) \tag{3.25}$$

where M is a vector of n input signal or pattern that is represented by the different TS models of the plant. Let the local linear transfer functions be a second order given by

$$M_n(s) = \frac{b_{0n}}{s^2 + a_{1n}s + a_{0n}} \tag{3.26}$$

where n is the number of TS models used. The parameter estimation law to adjust the weights and identify the forward model using the nLMS is given by

$$W(k) = W(k-1) + gM(k)(y(k) - \hat{y}(k)) \tag{3.27}$$

where g is a constant or the learning rate $0 \le g \le 2$. The inverse of the plant model is incorporated in the feed-forward path to achieve asymptotic tracking in the IMC structure. It is estimated using an adaptive FIR filter using nLMS. This approximate inverse system is the local inverse of the system and its parameters may change with variation in system excitation signal.

The nLMS given by

$$\hat{u}(k) = j^{T}(k)q(k-1) \tag{3.28}$$

where

$$j^{T}(k) = [\hat{y}(k), \hat{y}(k-1),..., \hat{y}(k-p)] \tag{3.29}$$

and

$$q^{T}(k) = [w_1, w_2, w_3,...., w_p] \tag{3.30}$$

The parameter estimation law to adjust the weights and identify the inverse model using the nLMS is given by

$$q(k) = q(k-1) + g j^{T}(u(k-L1) - \hat{u}(k)) \tag{3.31}$$

The control input is defined by

$$u(k) = d(e(k)\hat{Q}(k) - \hat{u}(k)) \tag{3.32}$$

where d is a small gain in the loop and

$$e(k) = r(k) - e_1(k-L2) \tag{3.33}$$

and

$$e_1(k) = y(k) - \hat{y}(k) \tag{3.34}$$

Chapter 4

Experimental Implementations and Results

4.1 Adaptive AIC with IMC Structure

An implementation on a robotic arm manipulator (single link) system is shown in Figure 4.1 and discussed here. The lead-lag controller design to stabilize the system reveals the parameter selection given in (3.1) for b_1=50, b_0=50, a_1=1 and a_0=200. Due to the nature of the system, the reference signal has a rate limiter to smoothen the adaptive tracking behavior of the system with a rising slew rate equal 1 and a falling slew rate equal -1. For the same purpose, another rate limiter is introduced in the adaptive algorithm. In this section, the two cases of AIC with IMC structure and AIC will be shown.

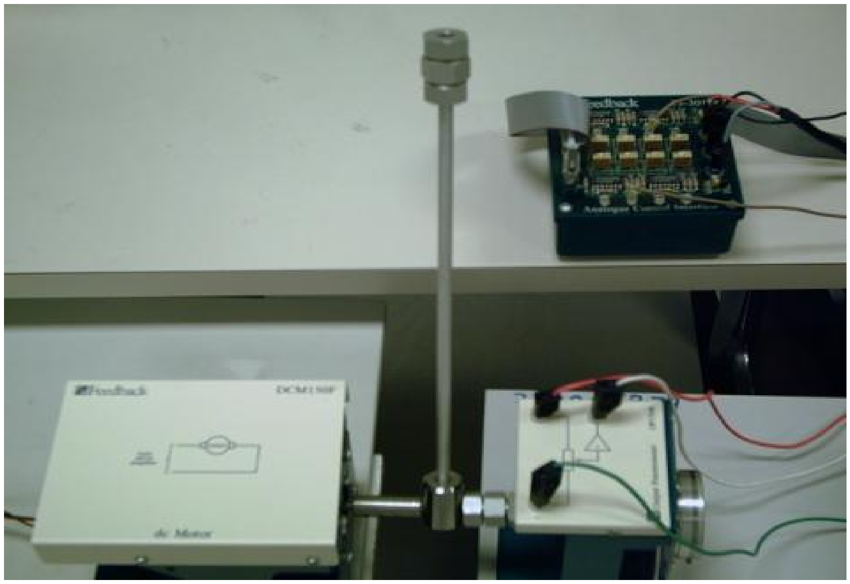

Figure 4.1: Robotic Arm Manipulator

4.1.1 AIC with IMC Structure

The sample time used is 5 milliseconds and the implementation was done with delay *L1*= 5 milliseconds and *L2*= 500 milliseconds. Also, the bounds of (8) for the automatic learning rate adjustment of the forward model are *f*=0.001 and *g*=0.5, while the selection for the inverse model are *f*=0.01 and *g*=0.1.

Figure 5 shows that the output (position) of the plant converges quickly to the desired reference input signal.

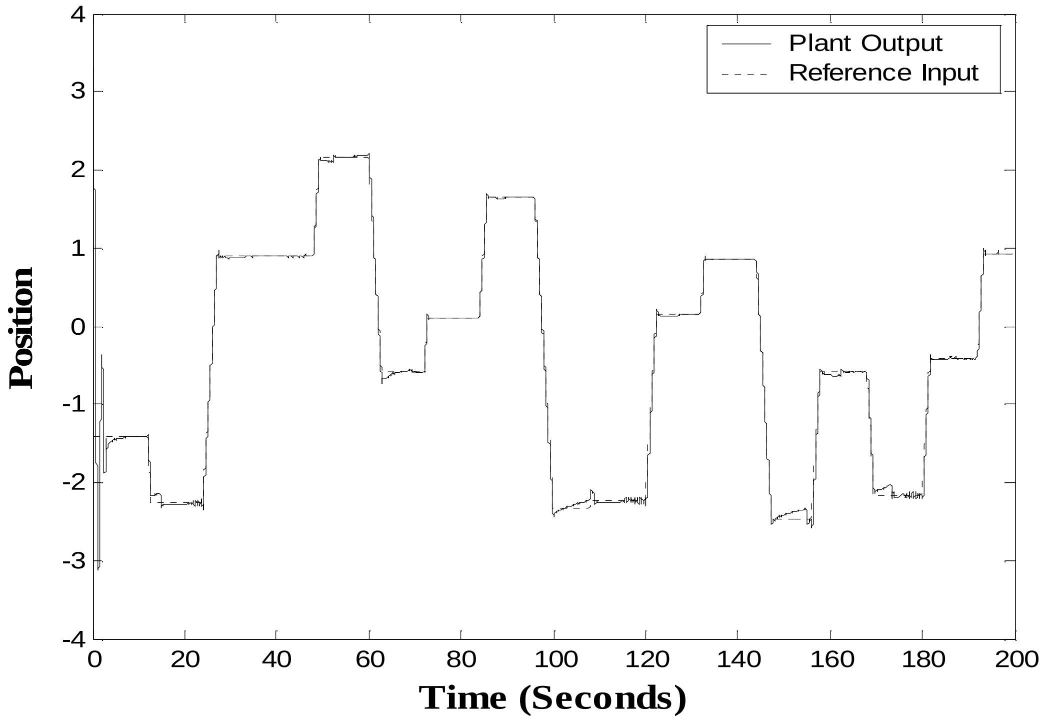

Figure 4.2: Desired output tracking reference input for the AIC with IMC structure.

Figure 4.3 shows the error between the forward model estimated output and the plant output $y(k) - \hat{y}(k)$ and Figure 7 shows the control input *u(t)*

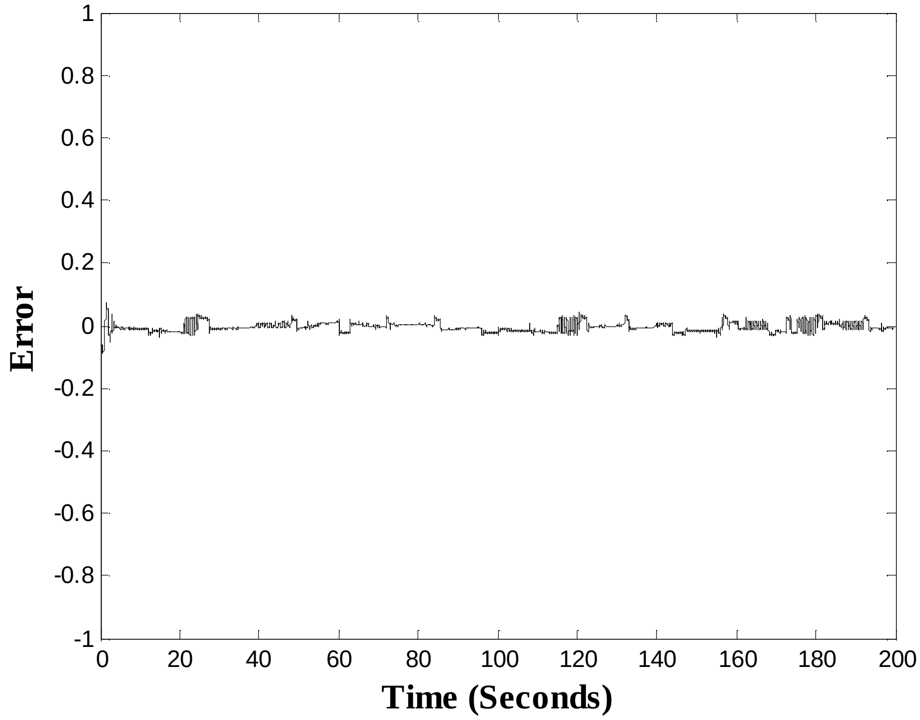

Figure 4.3: Error between the estimated output of forward model and the plant output for the AIC with IMC structure.

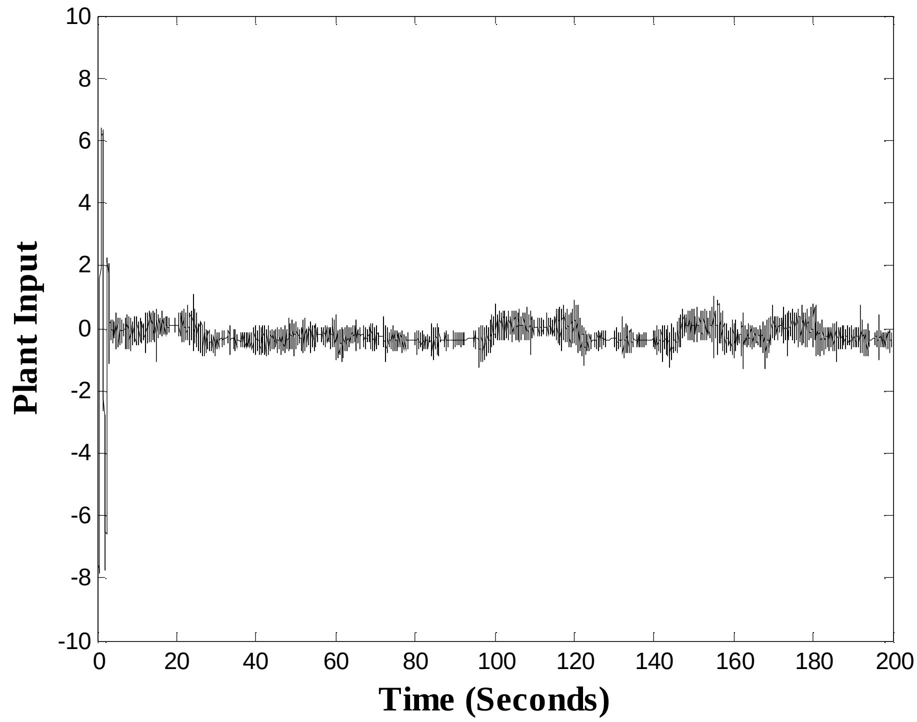

Figure 4.4: Control input for the AIC with IMC structure.

Now, we will show the effect of varying some parameters on the overall system performance. First, it was found that by reducing the time delay (*L2*) will negatively impact the performance of the overall system. Reducing the time delay to *L2* =50 milliseconds results in the tracking between the desired plant output and the reference input is shown in Figure 8. The error and the control input are shown in Figure 9 and 10.

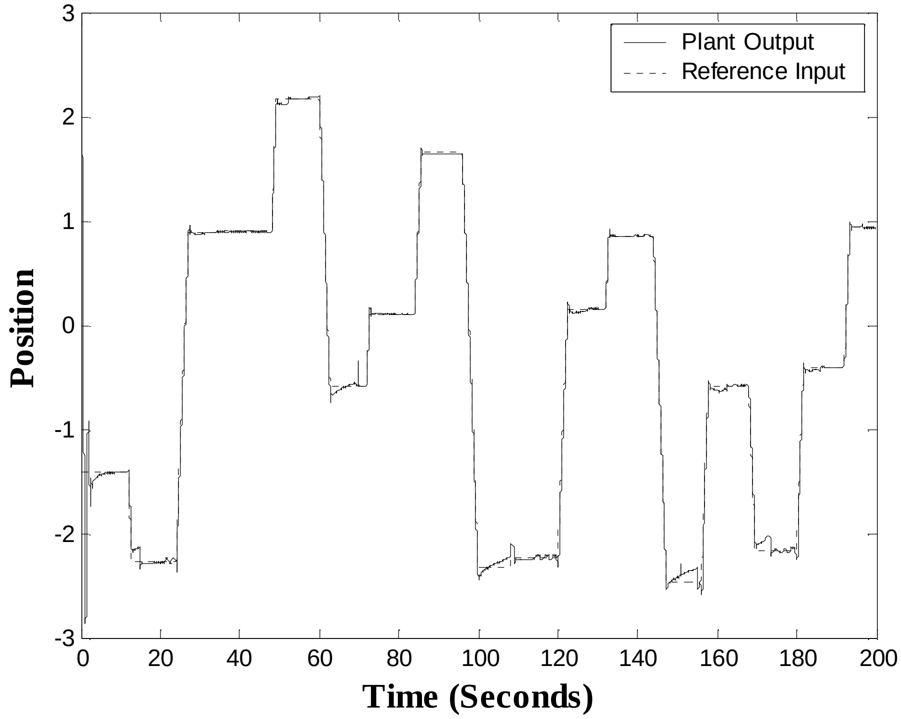

Figure 4.5: Desired output for the AIC with IMC structure with reduction of *L2*.

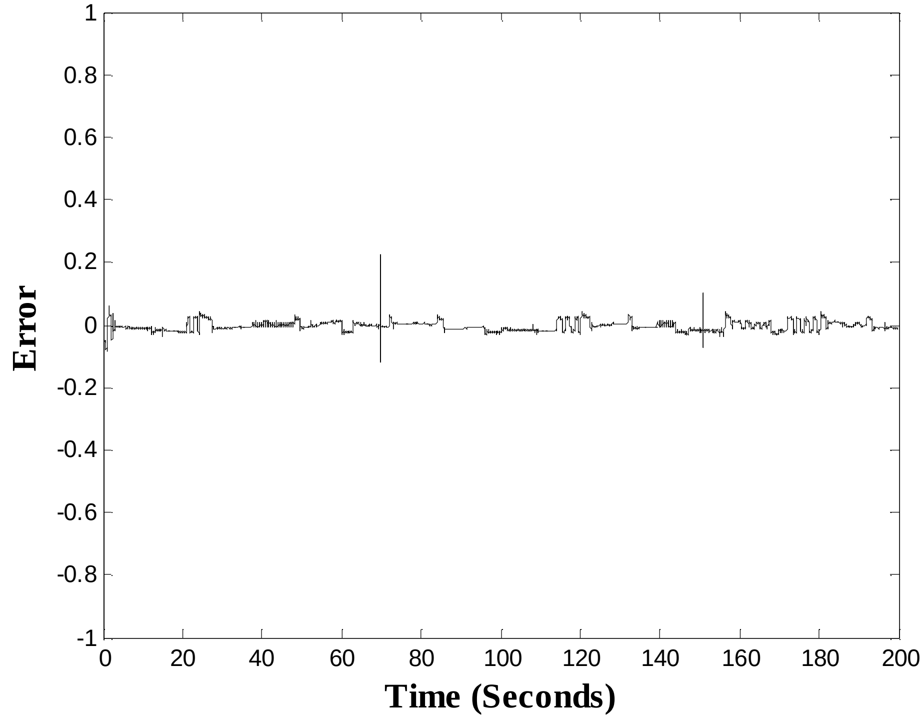

Figure 4.6: Error between the estimated output of forward model and the plant output for the AIC with IMC structure with reduction of *L2*.

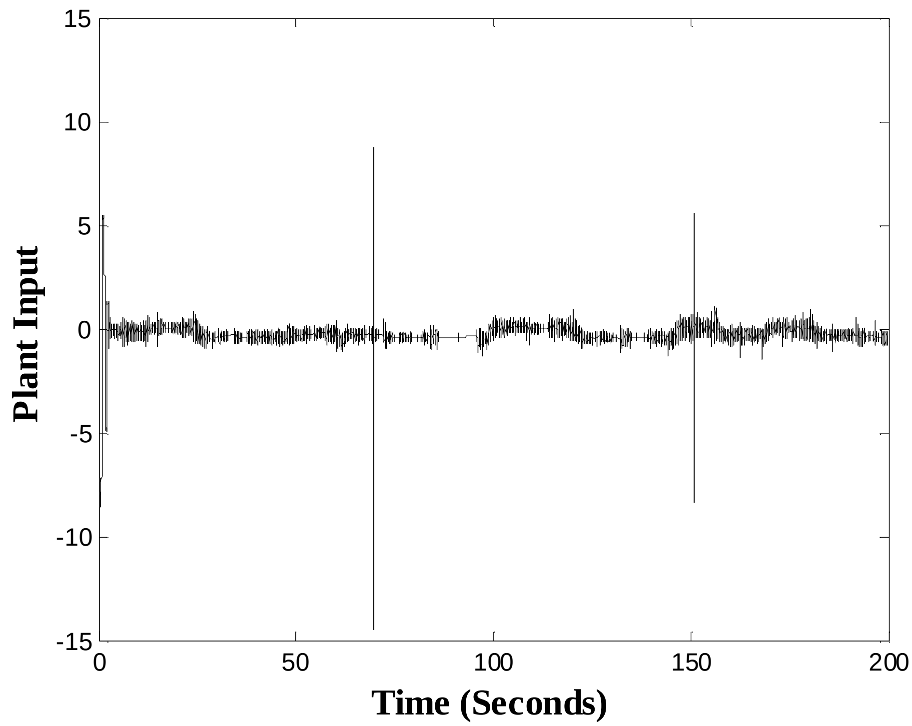

Figure 4.7: Control input for the AIC with IMC structure *L2*= 50 ms.

Next, we will show the impact on changing/eliminating the rate limiter imposed at the forward model adaptive identification algorithm. Figure 4.8 shows the tracking behavior becoming oscillatory and the same impact is observed in the error and control input of Figure 4.9 and 4.10.

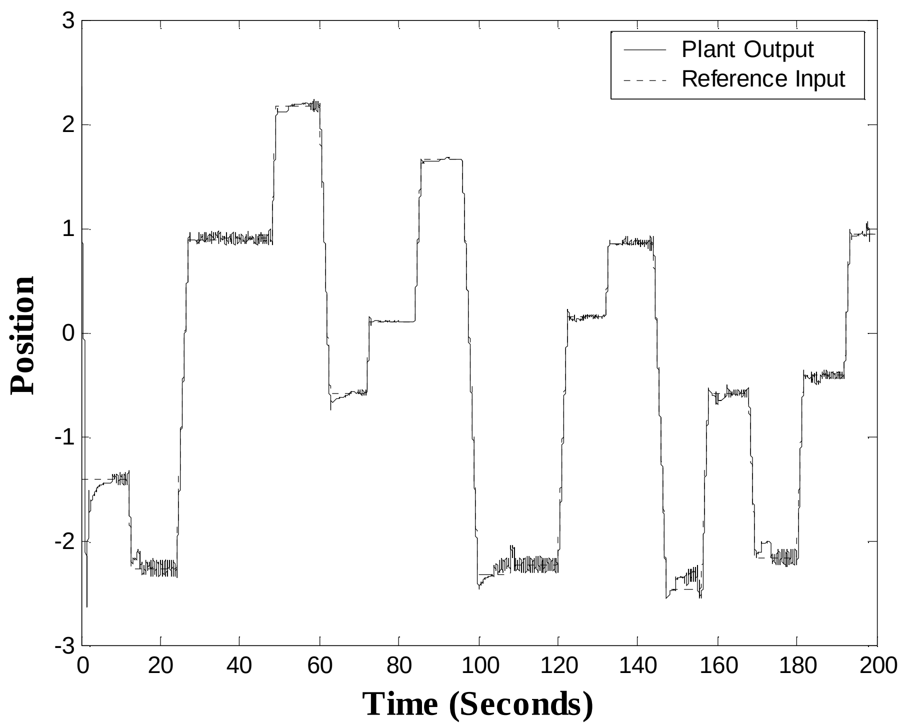

Figure 4.8: Desired output tracking reference input for the AIC with IMC structure with change in rate limiter at the forward model.

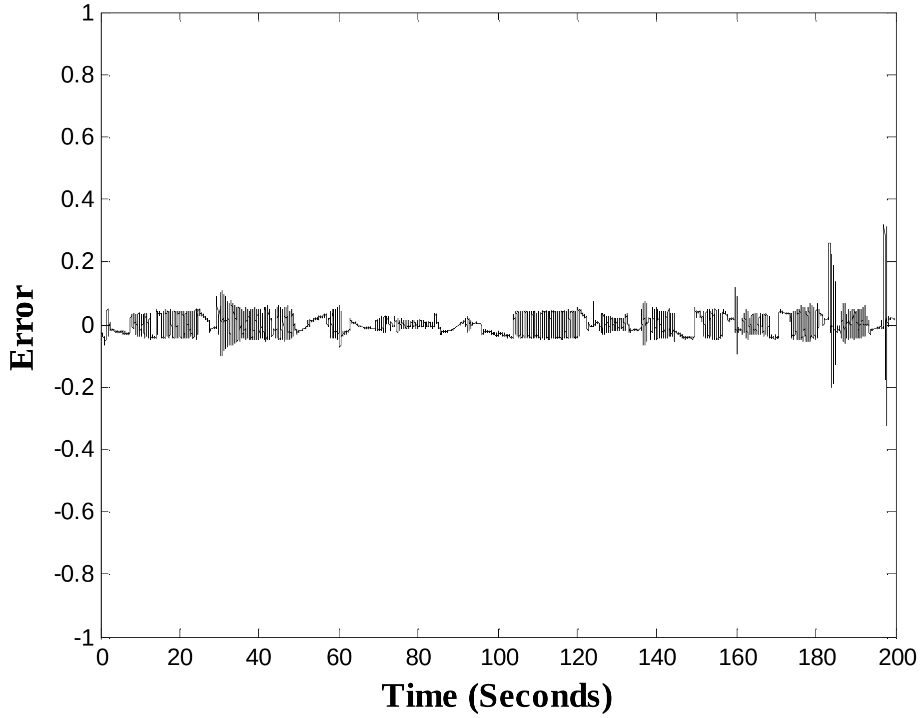

Figure 4.9: Error for the AIC with IMC structure with change in the rate limiter at the forward model.

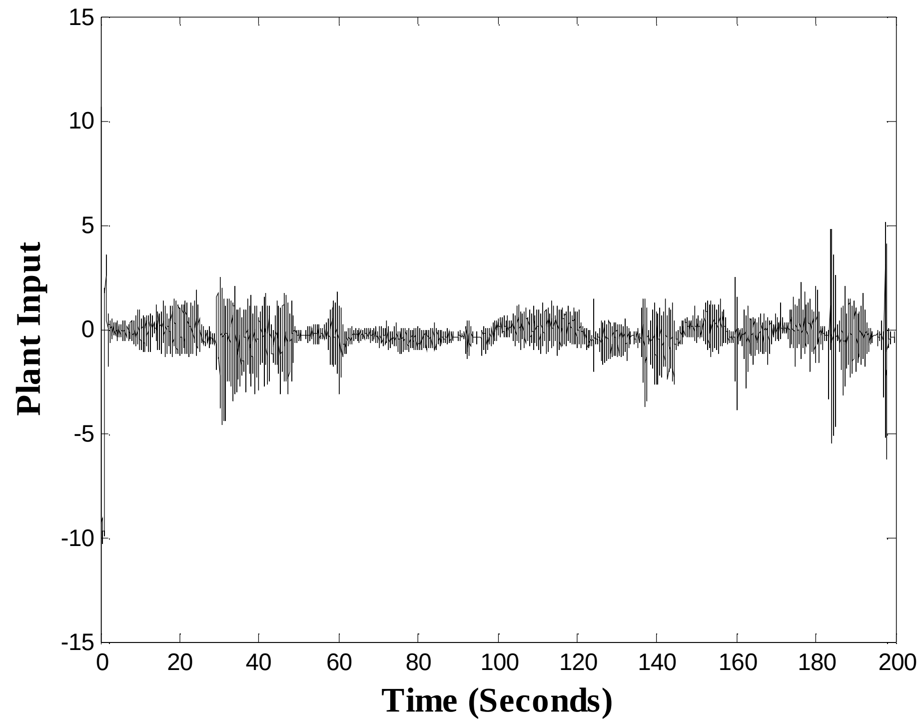

Figure 4.10: Control input with change in the rate limiter at the forward model.

The impact of removing the presented automatic adjustment of the learning rate is shown here. Figure 4.11 shows the difficulty of the tracking process. The error as well as the plant input is shown in Figure 4.12 and 4.13 respectively.

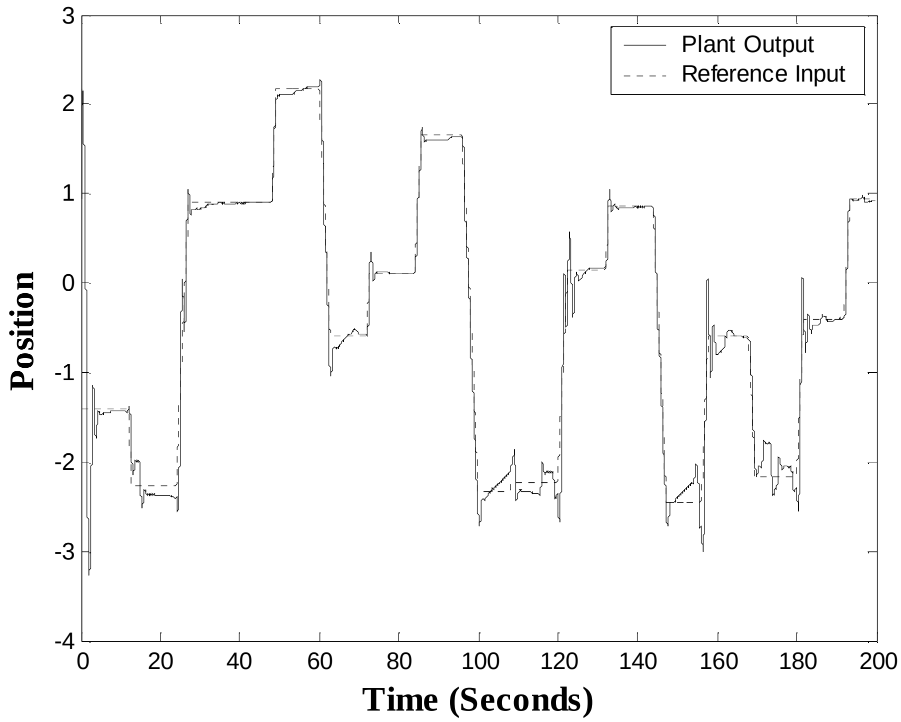

Figure 4.11: Desired output tracking reference input for the AIC with IMC structure without automatic adjustment of the learning rate.

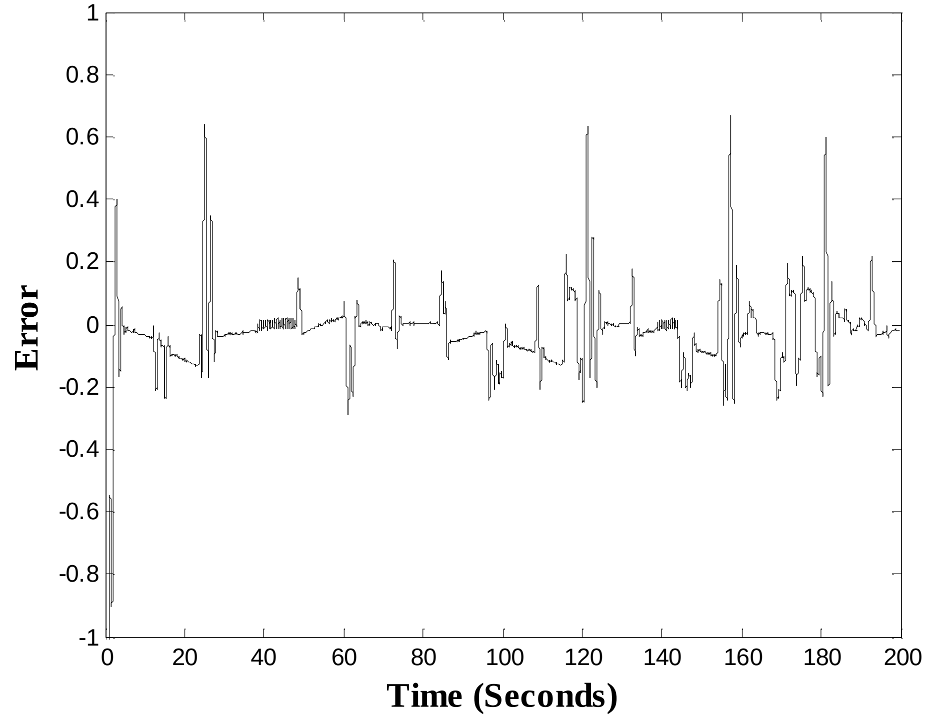

Figure 4.12: Error for the AIC with IMC structure without automatic adjustment of the learning rate.

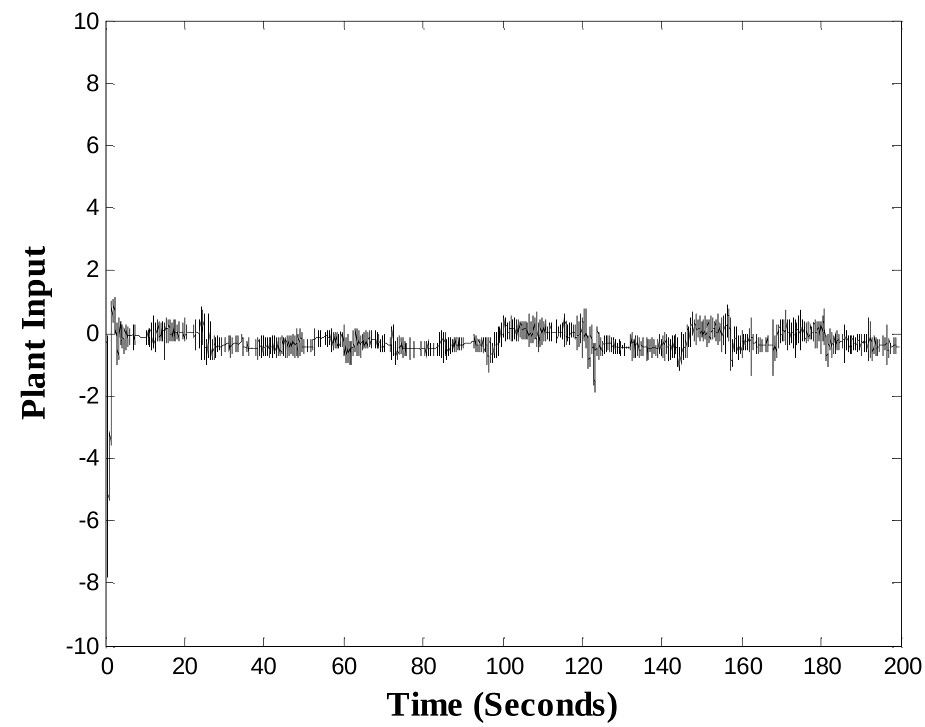

Figure 4.13: Control input for the AIC with IMC structure without automatic adjustment of the learning rate.

4.1.2 Adaptive Inverse Control

The structure shown in Figure 3.3 is implemented in the same robotic arm manipulator system of Figure 4.14 and the results shows that the automatic adjustment of the learning rate has its benefit more when used in AIC with IMC structure. Figure 17 shows the tracking behavior and Figure 18 shows the control input.

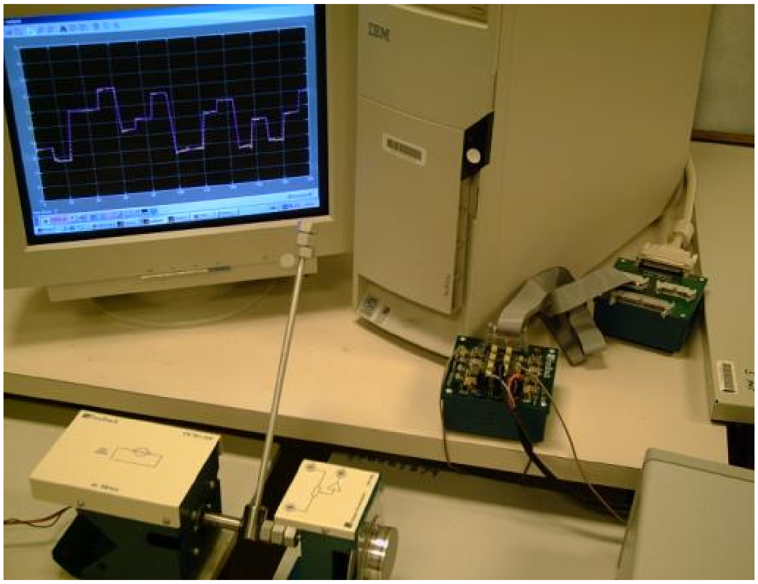

Figure 4.14: Robotic arm manipulator complete system

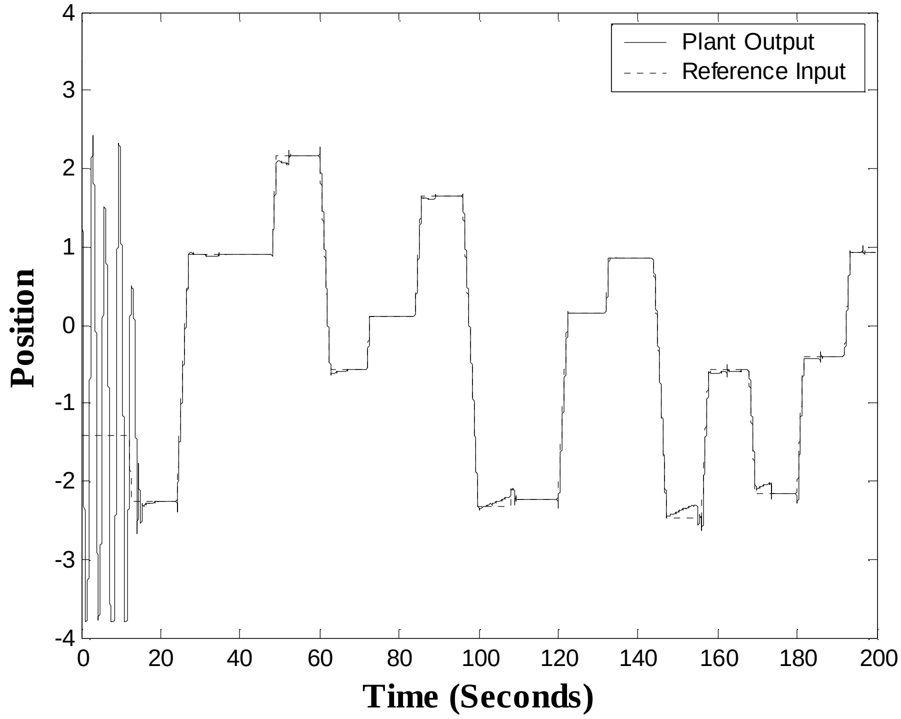

Figure 4.15: Desired output tracking reference input for the AIC system.

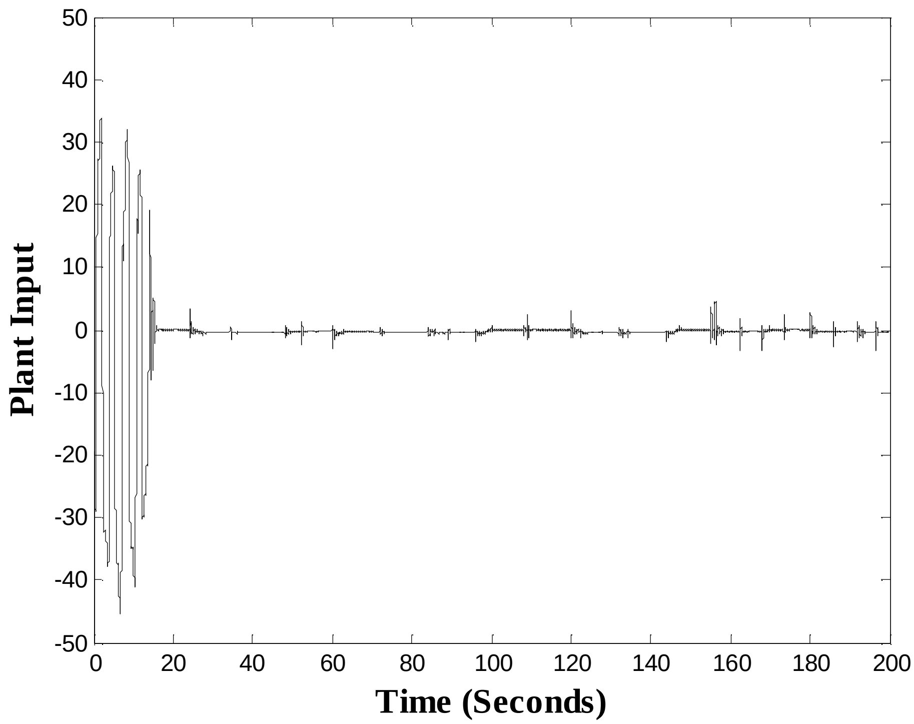

Figure 4.16: Control input for the AIC structure.

4.2 Adaptive Fuzzy TS using IMC with nLMS Tuning Implementation on Thermal Heating Process

The proposed technique was implemented in a real-time system. The real-time system was a thermal heating process (temperature control system) that is a Single Input Single Output (SISO) system. The result shows that technique is successful in terms of achieving the expected results. The temperature control system consists of a heater installed on a pipeline that is open to atmosphere and with a fan installed adjacent to the heater to transfer the heat produced by the heater to the other end of the pipe where a temperature sensor is installed as shown in Figure 4.17. So, the measuring device or sensor of the system is a temperature sensor which is a thermostat. The output of the thermostat is conditioned using signal conditioning module that is installed in the process control trainer to give an output that equal to 0V at ambient temperature (25ºC) and equal to 10V at 80ºC which is the maximum temperature range that the system operate at. The heater, which is the actuator of the control system, is capable of receiving analogue signal between 0V to 10V and will act accordingly to vary the temperature of the airflow inside the pipeline. The fan, the heat transfer mean, of the system can act as a disturbance to the system. The process is a second order system with dead-time or time delay. This kind of system is nonlinear in its behavior and non-minimum-phase.

Linear models of the thermal heating process were first found to be later incorporated in the Takagi-Sugeno fuzzy model.

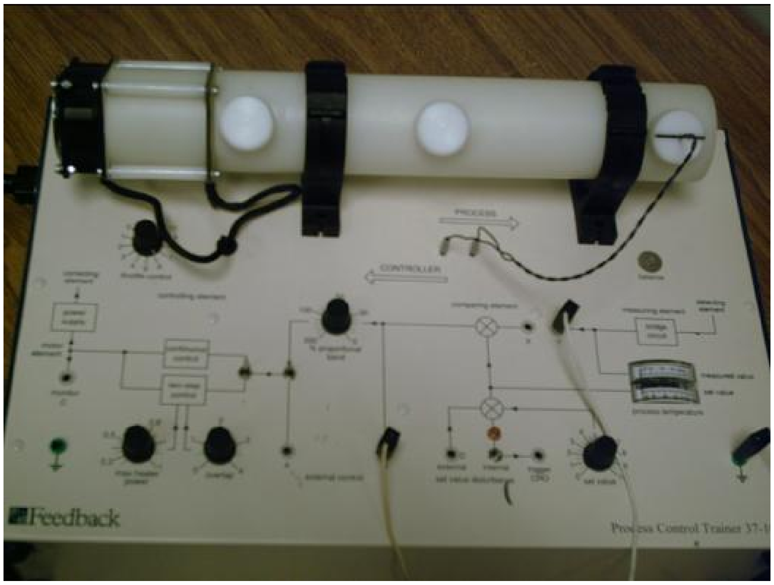

Figure 4.17: Thermal Heating Process

Ten models of the system were taken at different operating points of the input range (0-10 V). These models were taken after getting information about the step responses and finding second order linear models. The results are shown below:

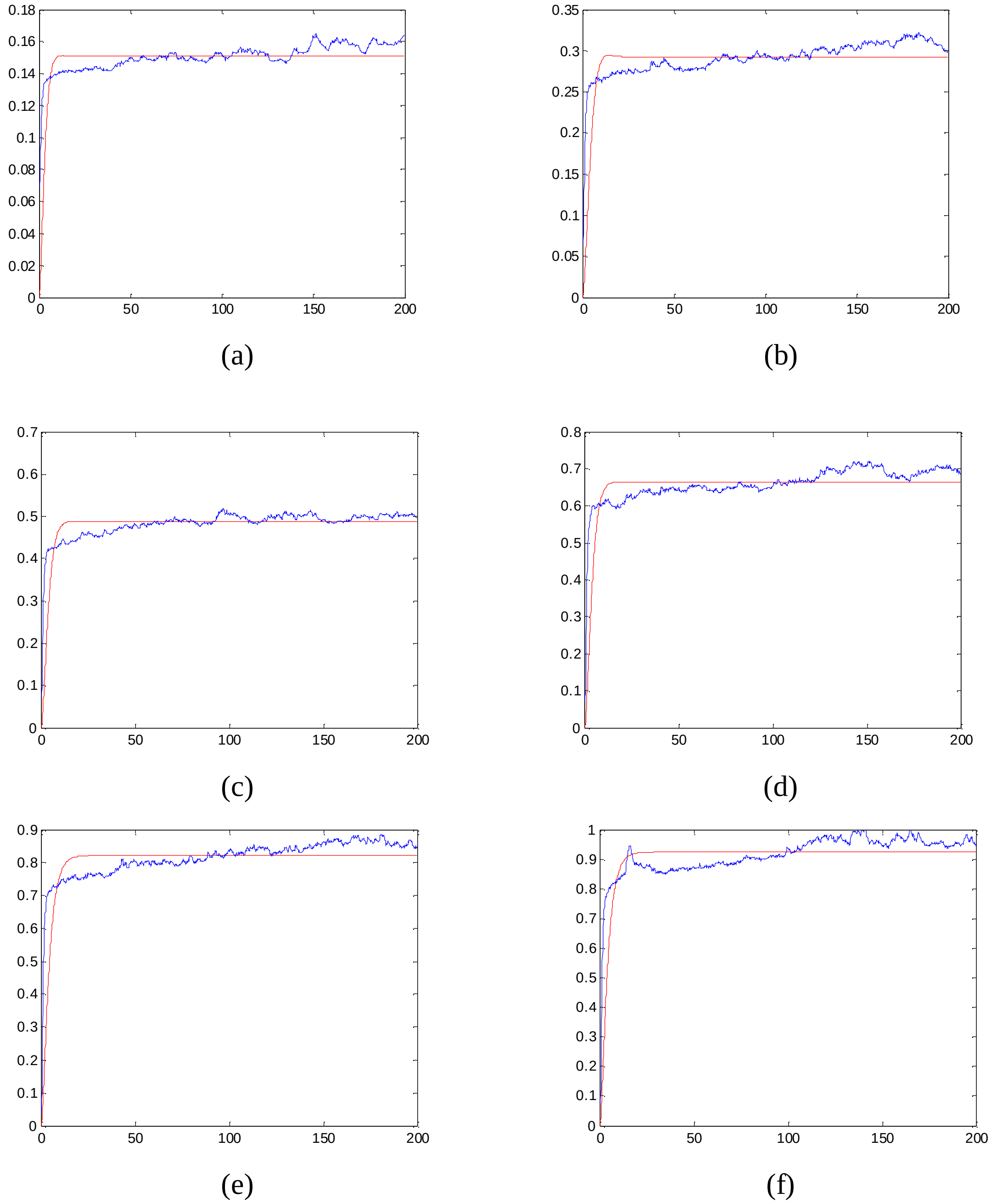

Figure 4.18: Step responses at different step sizes (a), .., (f)

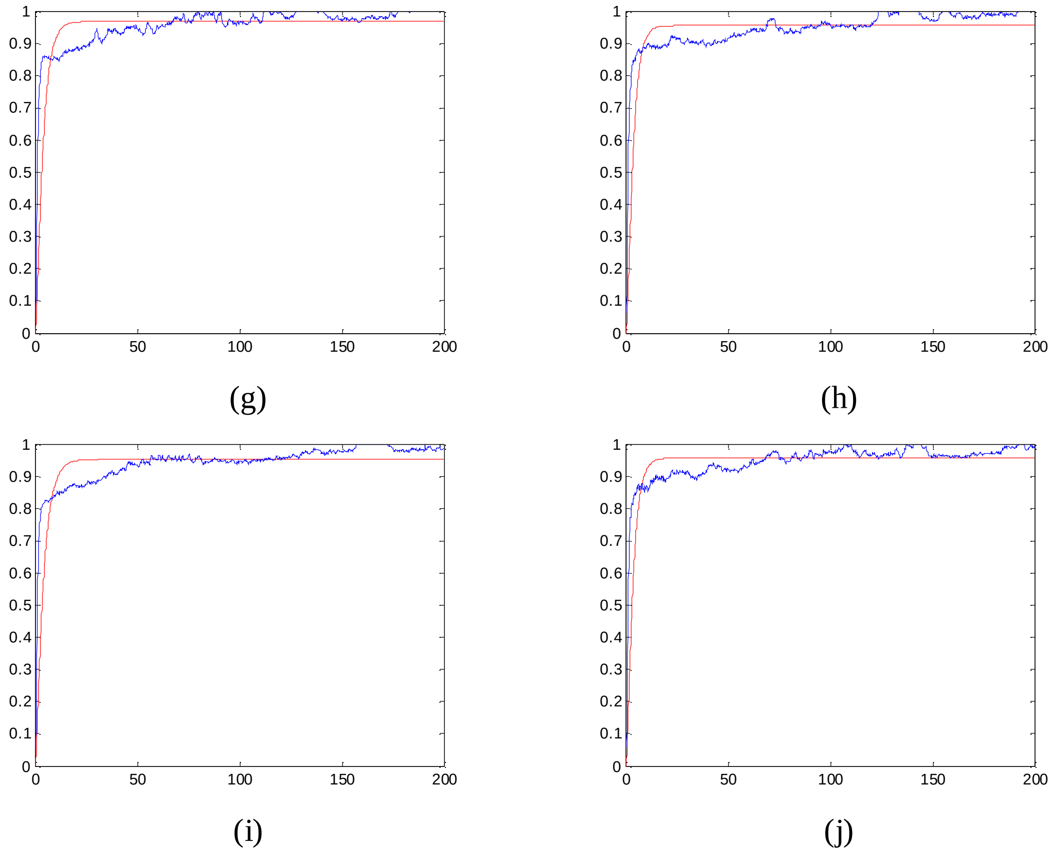

Figure 4.19: Step responses at different step sizes (g), …, (j)

The results shown in Figure 4.18 & 4.19 shows the identified model compared with the measured step response. The first model in Figure 4.18 (a) was taken at step size equal to one while (b) was taken at step size equal to two. The rest of the other eight models were taken with the respective step size (i.e. at –e- the step size was three and so on). The method described in section 3.2 was used and the models are as follows:

(a) $G_1(s) = \frac{0.05051}{s^2 + 1.054s + 0.3344}$

(b) $G_2(s) = \frac{0.05085}{s^2 + 0.7129s + 0.1738}$

(c) $G_3(s) = \frac{0.1048}{s^2 + 0.8666s + 0.2148}$

(d) $G_4(s) = \frac{0.1384}{s^2 + 0.8631s + 0.2083}$

(e) $G_5(s) = \frac{0.1853}{s^2 + 1.034s + 0.2256}$

(f) $G_6(s) = \frac{0.2469}{s^2 + 1.188s + 0.267}$

(g) $G_7(s) = \frac{0.3114}{s^2 + 1.319s + 0.3118}$

(h) $G_8(s) = \frac{0.2977}{s^2 + 1.197s + 0.3118}$

(i) $G_9(s) = \frac{0.3461}{s^2 + 1.584s + 0.3636}$

(j) $G_{10}(s) = \frac{0.3454}{s^2 + 1.355s + 0.3611}$

The implementation of using the adaptive nLMS algorithm to select the membership function of the conventional fuzzy TS model is done here. Figure 4.20 shows the complete system implementation.

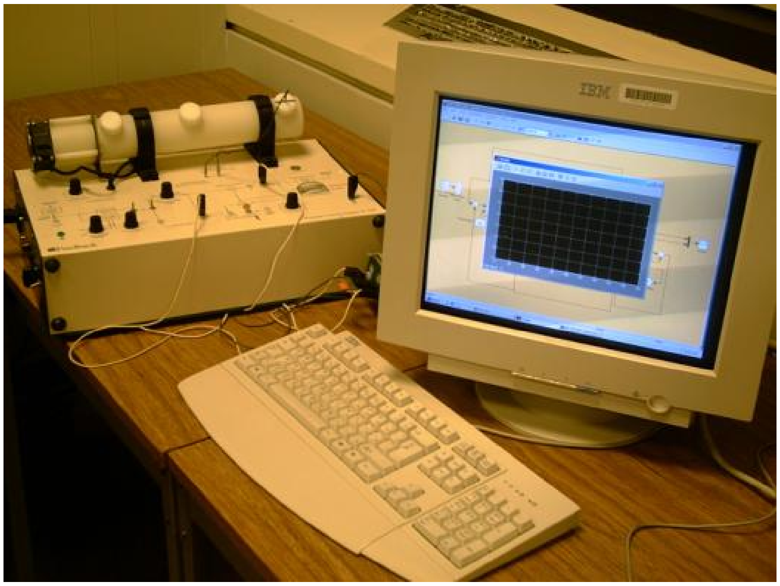

Figure 4.20: System implementation for the Thermal Heating Process

The sample time used is 10 milliseconds and the implementation was done with delay *L1*= 1 seconds, *L2*= 10 milliseconds and $d = 0.1$. Figure 4.21 shows the plant output response to the given reference input signal. This result was taken for 200 seconds. It was found that the nLMS weight at the forward model identification that is used to select the TS membership functions in the IMC structure doesn't get enough time to converge. Hence, the experiment was repeated for a longer time in Figure 4.22 that allows the convergence of the parameters as in Figure 4.23.

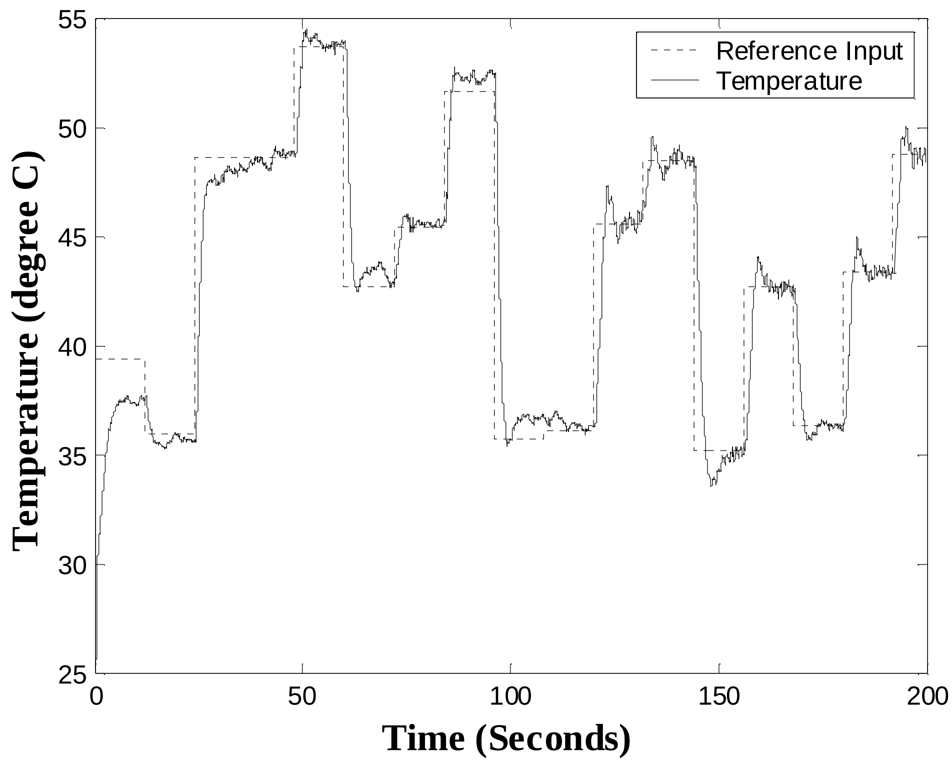

Figure 4.21: Desired output temperature tracking the reference input

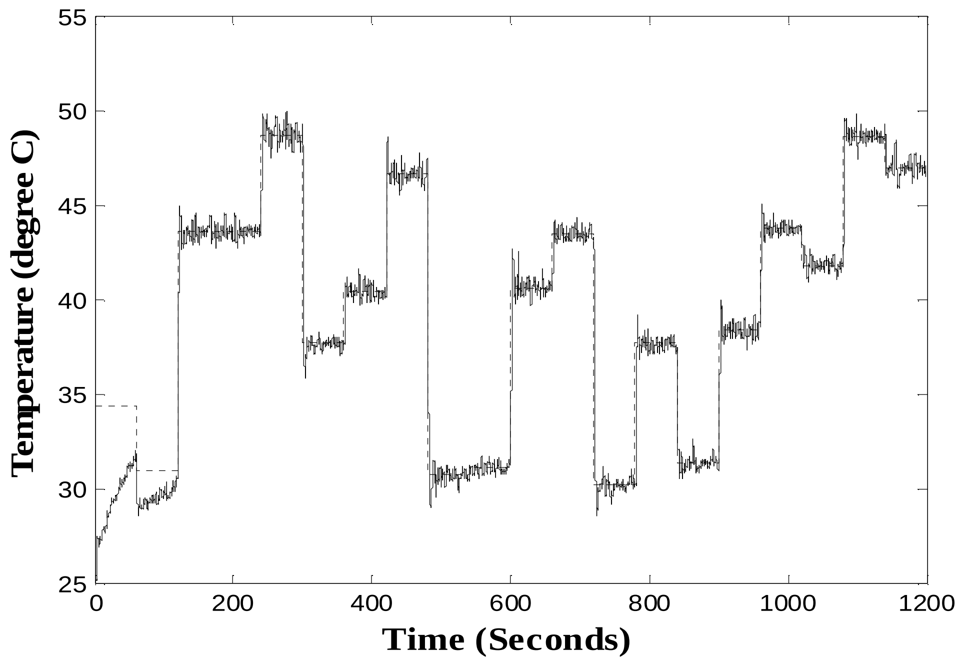

Figure 4.22: Desired output temperature tracking the reference input for a longer time

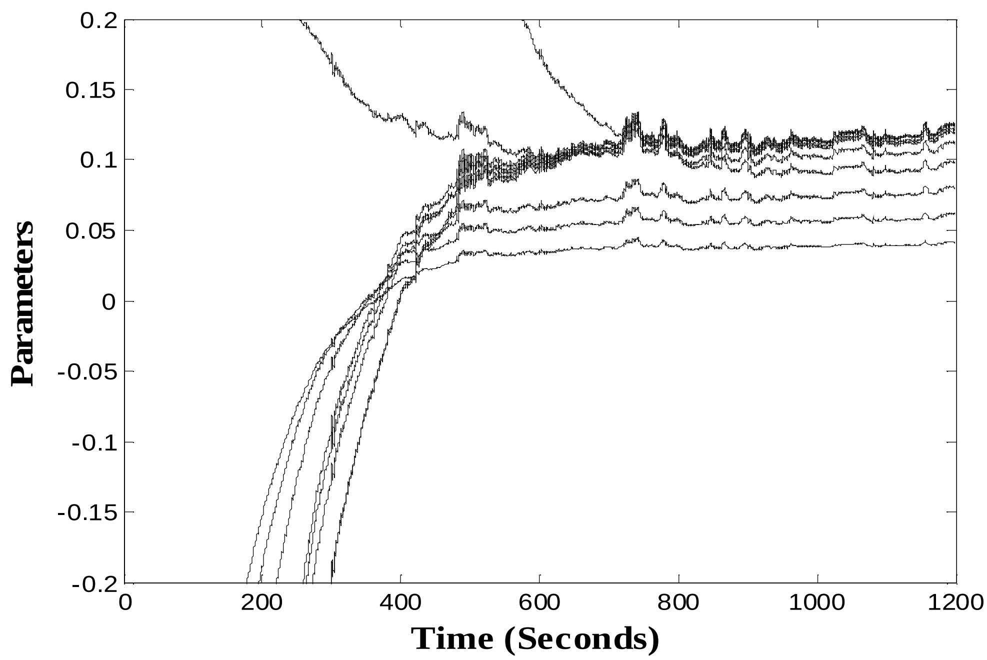

Figure 4.23: TS nLMS parameter convergence for the membership function selection

The error $e_1(k)$ between the TS model in the IMC structure and the plant output is shown in figure 4.24.

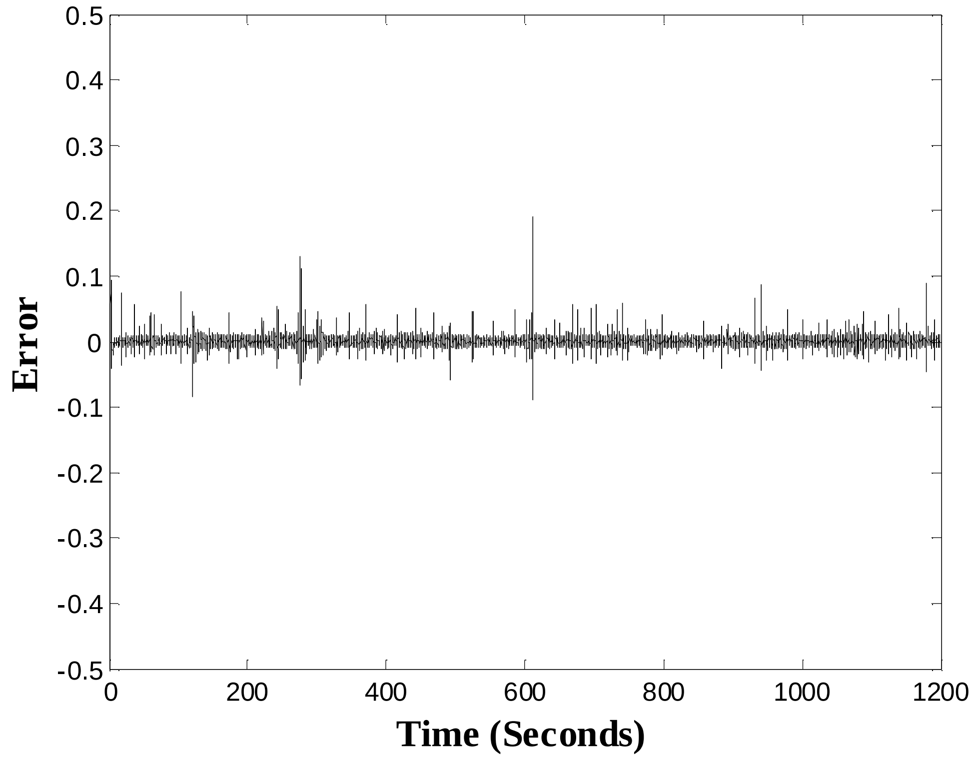

Figure 4.24: Error between the TS model and the plant output

The control input $u(k)$ to the plant is shown in Figure 4.25.

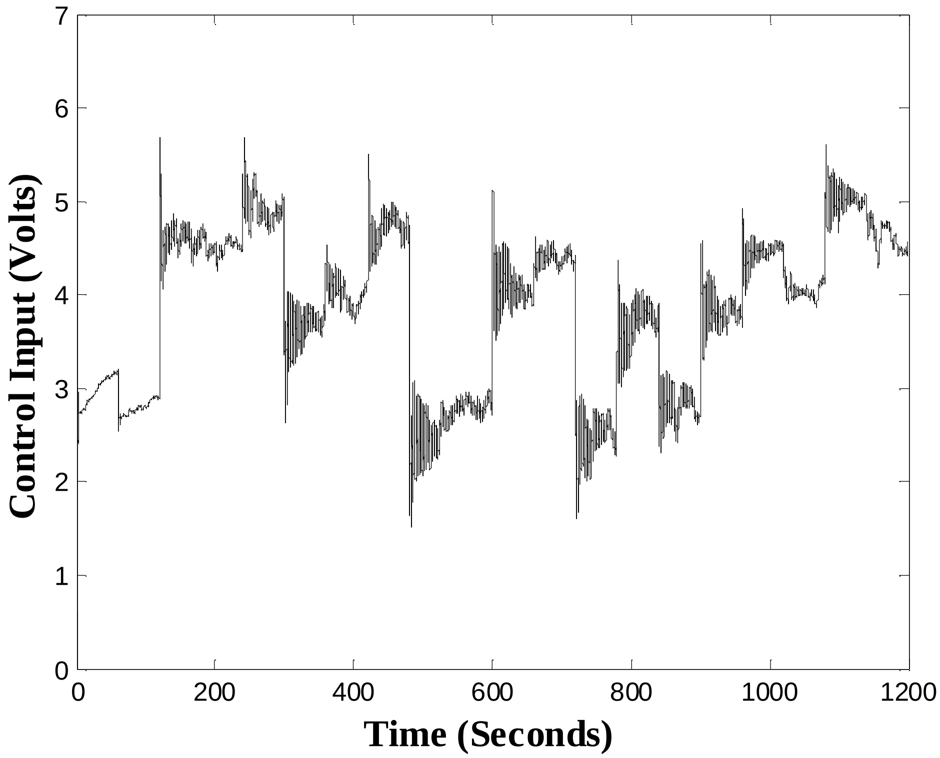

Figure 4.25: Control Input

Chapter 5

Conclusion and Recommendations for Future Work

This chapter concludes the thesis by summarizing the important contributions and highlights some recommendations for the future work.

5.1 Conclusions

In this thesis, the fuzzy Takagi-Sugeno (TS) modeling have been explored and used in the design of adaptive control schemes that incorporates internal model control structure (IMC). Nonlinear plants were approximated by linear models that represent the system behavior at different operating points. The conventional TS modeling approach that uses membership functions to select the degree of relative contribution of each model on the fuzzy universe of discourse was tested by allowing the nLMS algorithm to adaptively select among all the different models that represent the system. In addition, an adaptive inverse control (AIC) scheme was investigated with and without the IMC structure. An automatic adjustment of the learning rate for the nLMS algorithm was developed and showed that the learning rate improves in the IMC structure while the normal AIC structure doesn't show much of improvement. The adaptive fuzzy TS using IMC structure with nLMS tuning is a better control option compared with the AIC with IMC structure when implemented on a laboratory scale systems. This preference is due to relative computational simplicity and less number of tuning parameters. The proposed algorithms have been implemented on real-time systems of nonlinear plants on laboratory scale of heating process and single link robotic arm manipulator. The proposed controller design implementation showed its effectiveness by the demonstrated results.

5.2 Recommendations for Future Work

Research work is ongoing and the potential for new developments is still possible. Some of the recommended extensions of this work are given as follows:

- The use of multi-input-multi-output (MIMO) systems can be further investigated on its use by utilizing the proposed control techniques.
- The use of Fuzzy TS inverse model can be investigated by integrating it with the proposed IMC structure.

- Real-time implementation on the robotic arm manipulator can be further investigated with smaller sample time than 5 milliseconds using the proposed control techniques.

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Appendix: Conference & Publication

- Muhammad Shafiq and Khalid M. Al-Zahrani. Adaptive Inverse Control with IMC Structure Implementation on Robotic Arm Manipulator. *10th International Conference on Emerging Technology and Factory Automation Proceedings,* 1: 537-543, 2005.

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