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Adaptive Inferential Control of Wood Chip Refiner

Steven Boon-Lam Kooi

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ABSTRACT

Adaptive Inferential Control of Wood Chip Refiner

Steven Boon-Lam Kooi

The chip refiner is considered the most critical piece of equipment in the process of manufacturing high yield thermomechanical pulp (TMP). In chip refining process, the measurement of primary controlled output, the freeness, is not readily available owing to the limitation of on -line continuous realiable sensor and the long sampling time to obtain the test result. The measuring of the rapidly sampled secondary output, specific energy, can be inferred to the primary controlled output for feedback control of the refiner.

Chip refining process is stochastic and non stationary in nature. The process dynamics are subject to changes caused by the wear of the refiner plate. System Identific- aion using Recursive Least Square is used in process

modelling. The process can be modelled as a slowly time varying , single input single output system.

The theories of adaptive and linear stochastic control have been reviewed. The control scheme based on an adaptive inferential control is derived and implemented to the pulp freeness control. The method allows closed-loop freeness control of refining process.

Minimum variance control using self tuning regulator based on secondary output measurement is also considered. Simulations of different control schemes are carried out. The results of the study for closed-loop identifiability and performance are presented. The simulation results indicate that the adaptive inferential control strategy can be tuned to a sub-optimal control and the control method has a potential application to the pulp and paper industry.

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I would like to express my gratitude to Professor A.Hemami for his guidance and advice during the research of this thesis. Professor Hemami besides being a professor, has constantly encouarged and advised me on matters in life not related to academic works. For these, I would like to expres my thanks.

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Last but not the least, I would like to thank my family Julia, Donna and Sarah for their understanding and patience.

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List of Symbols and Abbreviations

A	System matrix of dimension n x n
$A(q^{-1})$ $B(q^{-1})$ $C(q^{-1})$	Polynomial in backward shift operator q^{-1}
B	Control input vector of dimension n x 1
D	Primary controlled output vector of dimension 1 x n
e	Gaussian white noise
d	Laboratory sampling time for primary output
E	Mathematical expectation
I	Identity matrix
k_p	Process gain
L	Process time delay
N(t)	Exponential disturbance defined in equation (3-10)
P	Covariance matrix
T	Refiner plate life
T_1	Process time constant
u	Manipulated variable, an input
x	State variable
y	Secondary output, specific energy
y_2	Primary controlled output, the freeness
h	Sampling interval

t	Discrete time
k	Defined in equation 2-33 and equation 2-20
m_1	Time delay of primary output in response to change in u(t)
m_2	Time delay of secondary output in response to change in u(t)
z^{-1}	Unit delay
Mw	Mega Watt ,motor load
K(t)	Kalman gain vector defined in equation (2-42)
w_1	Chip quality variation,process disturbance
w_2	Production fluctuation,process disturbance

Greek Letters

α , β , γ, θ	Parameters to be estimated by RLS
λ	Fixed forgetting factor
$\lambda(t)$	Variable forgetting factor defined in equation (4-34)

$\mathcal{E}$	Performance index defined in equations 2-48 and 2-49
e	Equation error

Abbreviations

CSF	Canadian Standard Freeness , ml
SISO	Single-input single-output
MIMO	Multi-input multi-output
admt/d	Production in air dried metric tonnes per day
Kw-hr/admt	Kilowatt-hour per air dried metric tonnes
TMP	Thermomechanical Pulp
PID	Proportional Integral Derivative
LQG	Linear Quadratic Gaussian
ARMAX	Autoregressive Moving Average with X variable u
ARIMA	Autoregressive Integrated Moving Average
AR	Autoregressive

IMA	Integrated Moving Averag
RLS	Regressive Least Square
STR	Self Tuning Regulator

.

Superscript

^	Estimated
T	Transpose

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CHAPTER I

INTRODUCTION

In recent years, thermomechanical pulp (TMP) has gained great importance in the pulp and paper industry to replace groundwood and sulphite pulp in the manufacturing of newsprint and other specialty grades of paper. In the thermomechanical pulping process (Figure 1.1), the chip refining is considered to be a critical step of the operations. Refiner requires huge amount of electrical energy supplied by the motor for the conversion of wood chip into pulp. The degree of refining is reflected on the pulp by its drainage characteristics and is measured by the property called "**freeness**". Controlling the freeness is the first step in refiner operation in order to optimise energy input before controlling other pulp properties can be considerd.

Owing to the limitation of the availablity of continuous and reliable on line freeness sensor, the present method of freeness control in the refiner operations depends very much on operator's intervention for closing the loop. The present thesis proposes the adaptive inferential control method to overcome the present difficulty in closed loop

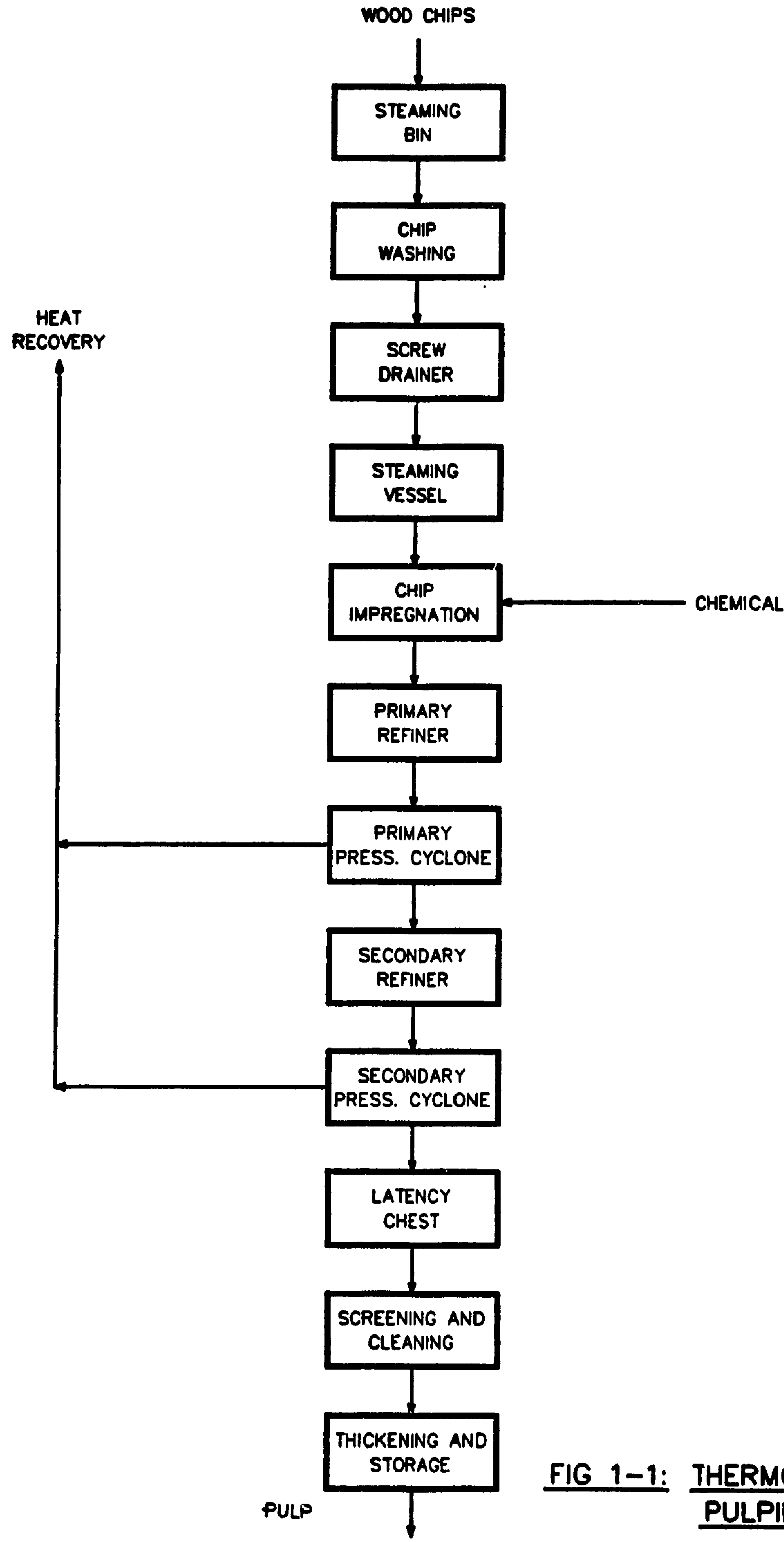


FIG 1-1: THERMOMECHANICAL PULPING PROCESS

control of freeness in refiner operation. The method is based on measurement of the more frequently sampled secondary output, the specific energy and inferred to the primary controlled output for feedfack control. Various control schemes such as minimum variance control, self tuning control as well as their simulation results are the subject of discussion in this research.

1.1 Refining Process Description

A typiacal chip refiner used in the thermomechanical pulping plant is shown in Figure 1.2. Wood chip is regulated and fed to the refiner through the infeed screw for converting into pulp in the refiner. In the refiner there are two refining discs, a stationary stator and a rotating disc driven by the external motor. In the course of refining action occuring between the plates, the chip is being converted into pulp. The degree of refining is reflected on the pulp by its drainage characteristics and is normally measured by the freeness (CSF) expressed in mlilitre (ml).

The freeness is controlled by specific energy applied to the refiner defined as energy input per unit mass of wood chip refined. This implies that the wood feed rate and motor load have to be controlled. The plate gap is adjusted by an integral stepping motor installed in the refiner. As the motor load is increased by closing the plate gap, more refining energy is applied on the chip. However, there is a limitation in the plate gap that further decrease in the gap will result in the collapse of pulp pad in the refiner as shown in Figure 1.3. The process and control variables as well as disturbance of the refining system is shown in Figure 1.4. Chip refining is a very complicated multi- variable process, which can be represented as a multi input and multi output (MIMO) system; and also the process is stochastic in nature. The output of the pulp properties such as freeness, shive content, opacity, fibre length, tear and tensile depend very much on the control of variables in the refiner such as plate gap, plate conditons (plate life and plate pattern), consistency and refining pressure. The manipulating variables which control the refining process are dilution water flow and motor load, regulated by adjusting the plate through a stepping motor. The control is further complicated by the presence of the disturbances such as chip quality variation and production rate fluctuation.

Thermomechanical pulping plant normally consists of two stage of refining as shown in Figure 1.5, the primary and secondary refiner. The refiners can be operated under pressurised condition or atmospheric pressure. For the pressurised refining, refined pulp from primary stage is blown under pressure through a blow line to primary cyclone for steam spearation and the pulp is then fed to secondary refining stage. The pulp from secondary refiner is then blown to secondary cyclone before it is discharged to latency chest.

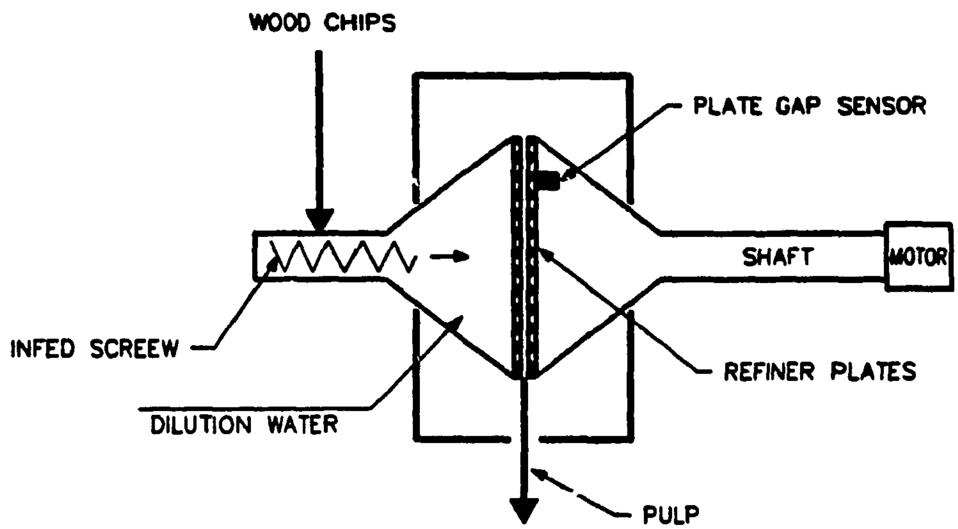


FIG 1-2: CHIP REFINER

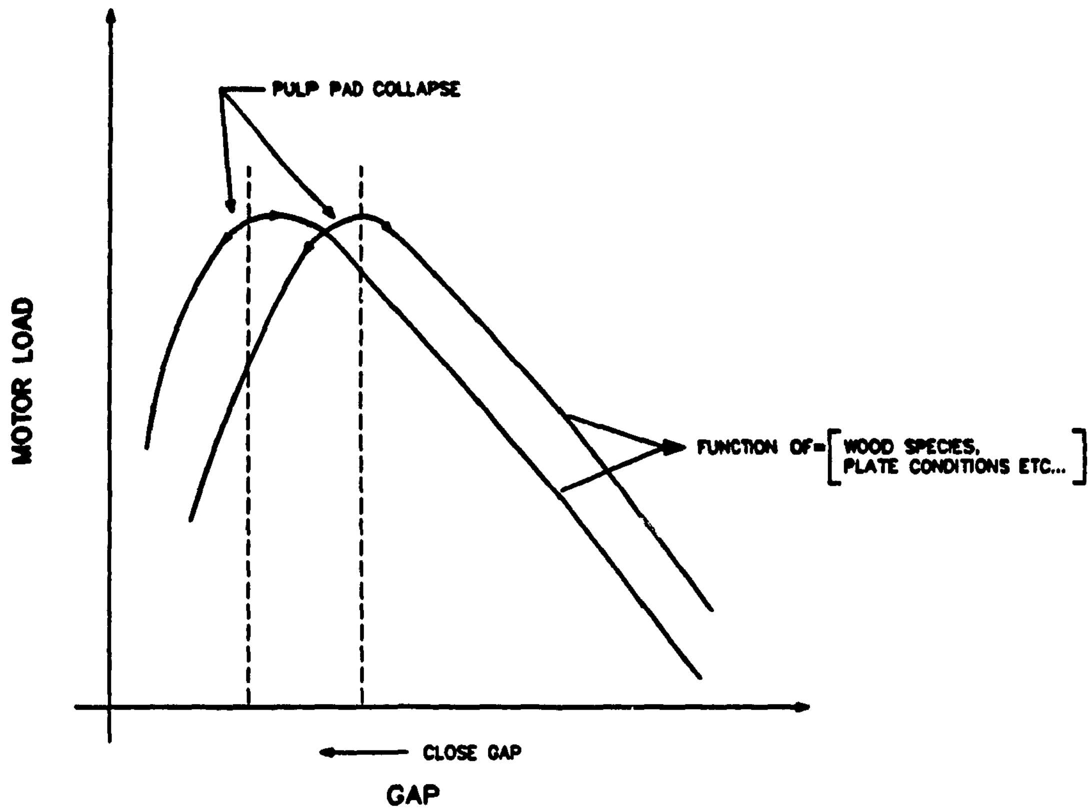


FIG 1-3: MOTOR LOAD VS PLATE GAP

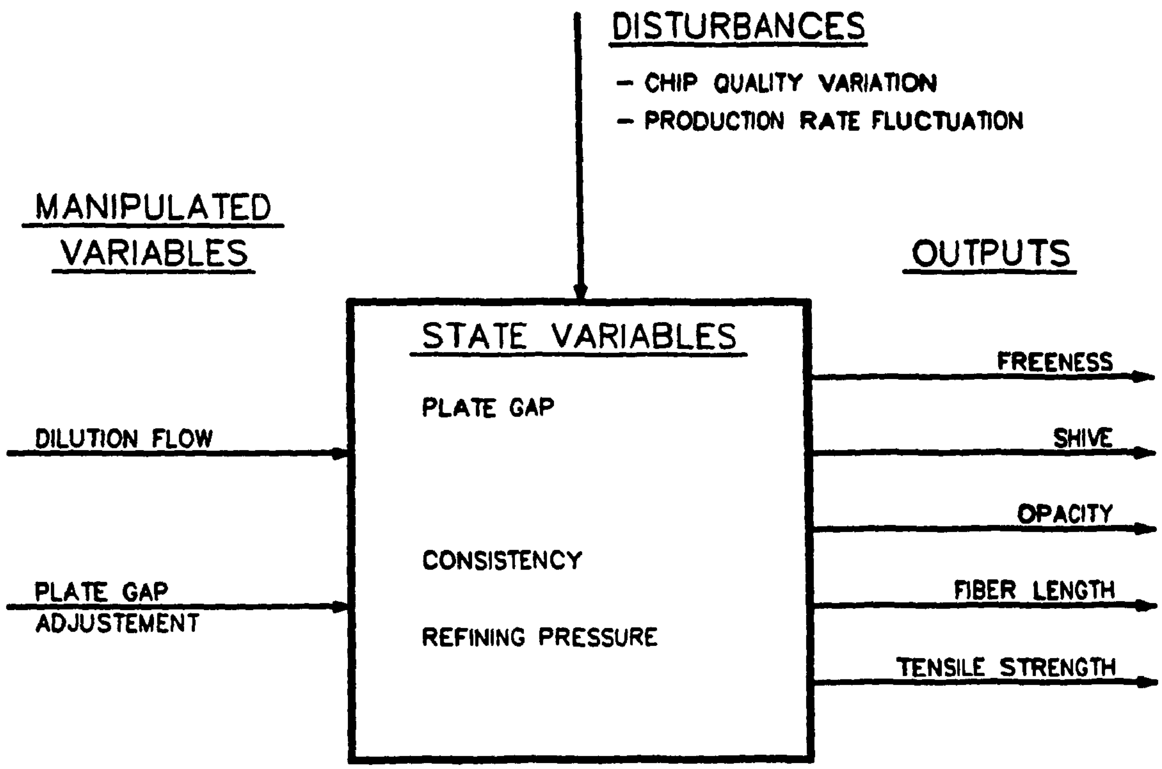


Figure 1.4 Process and Control Variables in Chip Refining System

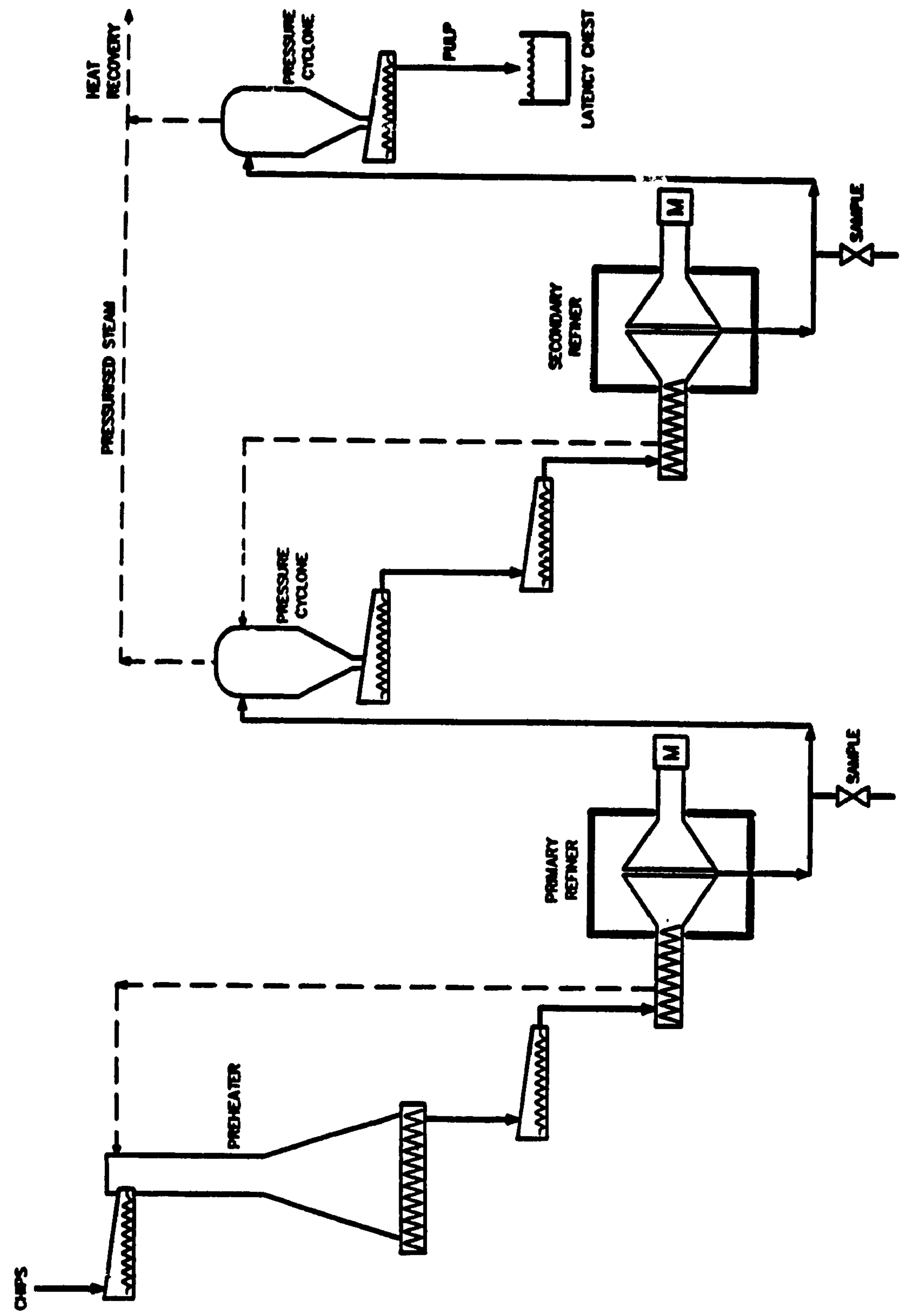


FIG 1–5: TWO STAGE PRESSURISED REFINING SYSTEM

1.2. Control Problem

1.2.1 CONTROL OBJECTIVES

In refining process, the freeness of the pulp produced is dependent on the energy input which is controlled by the plate gap and production rate. The objectives of controlling the refining are twofold as given below:

(i) Energy Optimisation

. To provide a pulp at a specified given freeness by minimising the variability of the specific energy input. Hence, reduced variation makes it possible to shift the freeness set point to give increased production.

(ii) Quality Optimisation

To provide a pulp for a given physical property such as fibre length, tear, tensile strength, shive content etc by optimising the specific energy input to the refiner. The quality optimisation of the pulp in the refining process is next higher level of control strategy and it can be acheived after energy optimisation is realised. The objectives of the thesis will be the following:

. *Propose a closed-loop freeness control based on implicit self tuning regulator using adaptive inferential control method.*

. *The result of the closed-loop freeness control can be used for energy optimisation and increased production.*

1.2.2 PROCESS PERTURBATIONS

For a given freeness target, the control of specific energy during the refining process does not necessarily follow one unique relationship between the two variables. The specific energy required to produce a pulp with specified freeness depends also on the wood species employed such as hardwood and softwood. Within the softwood, for example, there are even large variations of specific energy requirement in refining depending on the type of softwood used. Other variations such as species mix and chip size distribution have also great influence on refining control.

Chip feed rate is another source of disturbance for refining control, mainly because the feed rate is calculated from volumetric flow and chip moisture. There is no on line reliable moisture sensor available and it is normally determined by periodic sampling and laboratory test. Finally the dilution flow rate fluctuation will affect the refiner consistency.

1.2.3 PROCESS VARIABLE AND MEASUREMENT

Several major process measurements are available in the refiner, such as, refining pressure, dilution flow, plate gap etc .

The specific energy is normally determined by measuring the motor load in kilowatt and dividing the figure by production rate.

Refining gap is the most important variable which influences the specific energy input. Measurement of the gap is normally done by the gap sensor or using relative shaft position to infer the gap position. The gap measurement is used for interlocking purpose to prevent refiner plate to plate contact. No TMP mill has attempted to use the gap measurement for closed-loop control of the freeness.

Pulp quality such as freeness, fibre length, tear, shive, are tested manually by periodic sampling in the blow line. Pulp quality monitor, a device which allows on-line measurement of some physical properties is available on the market. However, the device is installed after the latency chest mainly for monitoring purposes. The physical properties obtained from the pulp quality monitor are seldom used for feedback control purposes.

1.2.4 MANIPULATED VARIABLES

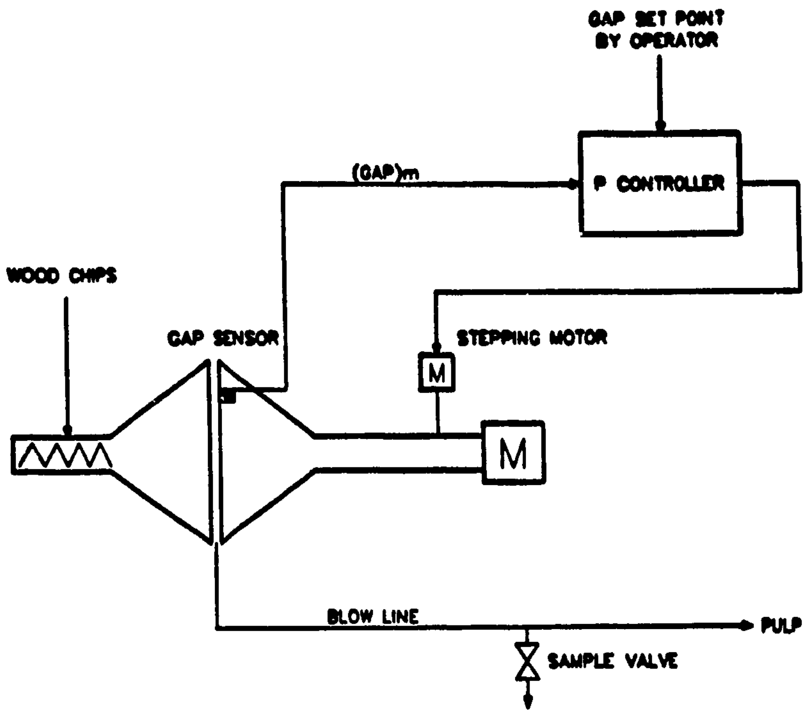
The manipulated variables which control the refining process are the dilution water flow and motor load. The motor load is regulated by adjusting the plate gap through the stepping motor which is an integral part of the refiner. Dilution water flow control is normally a separate control loop.

1.3 Review of Present Method of Refiner Control

1.3.1 MANUAL FEEDBACK CONTROL OF FREENESS

For most of the refiner operation in thermomechanical pulping plants, the control of specific energy is the common means for regulating the pulp freeness. The control is mostly carried out with operator's intervention as shown in Figure 1.6. Gap sensor or relative shaft position proximity sensor is used to indicate the gap clearance between the refiner plates and for interlocking purposes to prevent plate to plate contact which normally results in great damage and causes safety hazard.

The operator samples the pulp through blow line sampler at regular interval and tests for freeness, and other physical properties. Based on operator intuition and experience the gap set point is entered to the proportional controller for gap control. The major drawback of this method lies with the intervention of the operator to close the loop which is often based on the erratic freeness measurement. The method is not satisfactory and fast enough to reject any disturbance owing to the process upset and other equipment failure. Other process variables, such as set point for dilution flow, production rate and consistency test, are also carried manually depending only on operator's intuitive law and experience, as shown in Figure 1.7.



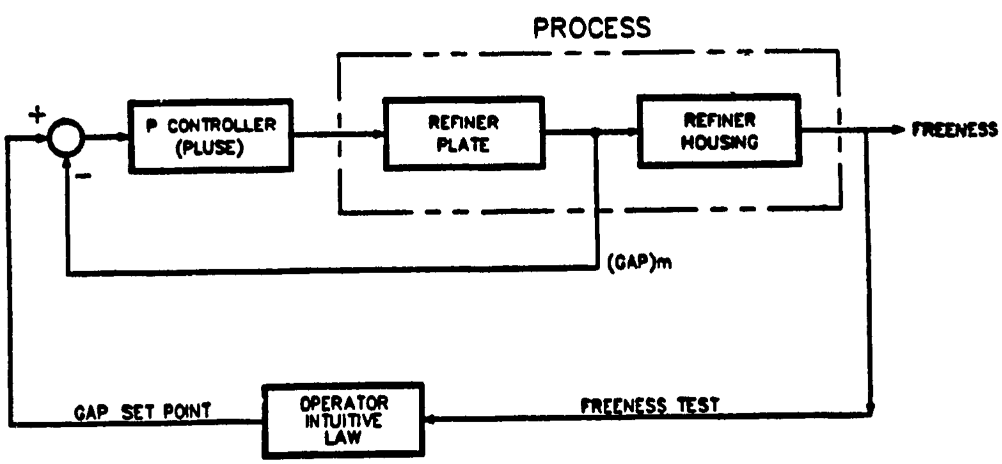


Figure 1.6 Manual Control For Freeness Feedback

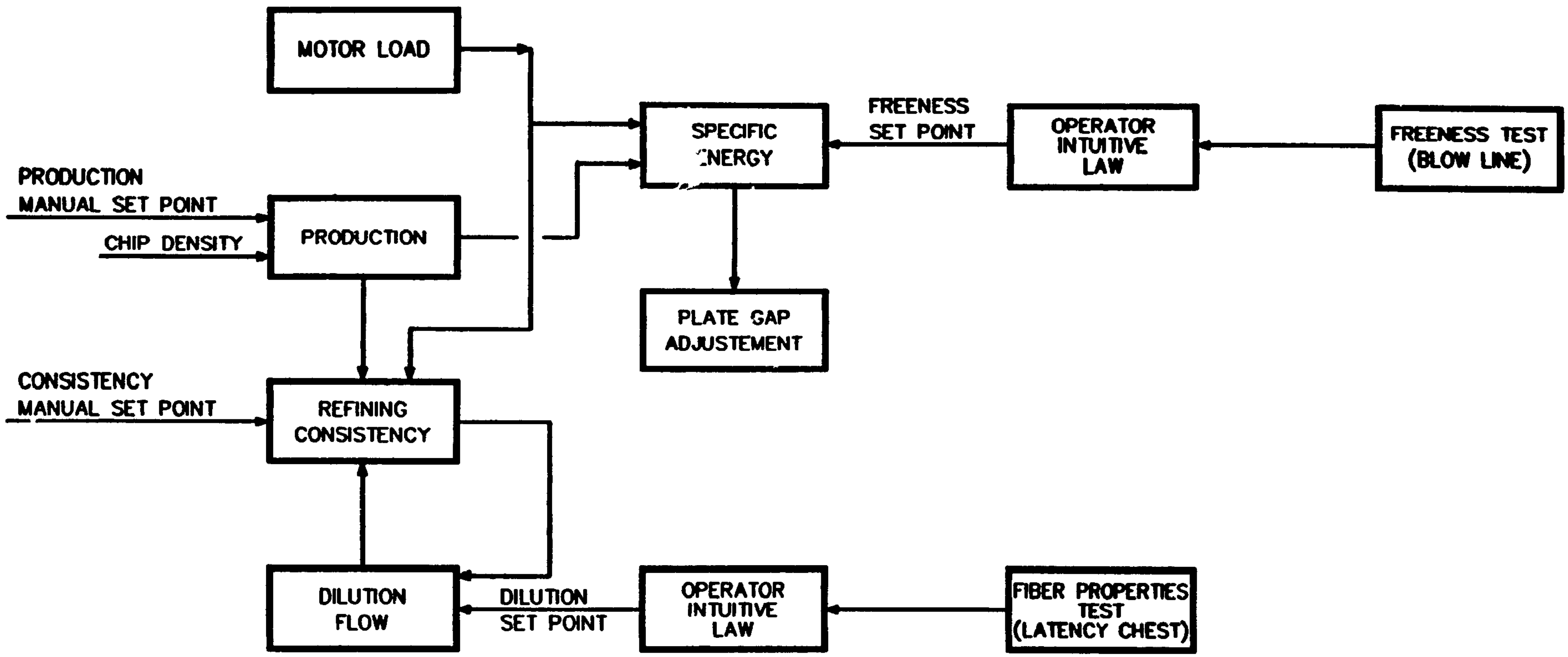


FIG 1–7: OVERVIEW OF REFINER CONTROL STRATEGY

1.3.2 CONSTANT REFINER GAP CONTROL

Speicifc energy input to the refiner is based on the motor load ,(kw), and production rate, (admt/hr), normally expressed as kw-hr/admt. It is assumed that the production rate is known and held constant. In pratice, production rate fluctautes owing to the variation in chip density. To overcome the uncertainty of chip moisture variation and species mix of raw material, some mills have implemented a constant gap control scheme as shown in Figure 1.8.

In this control scheme, the refiner gap is held constant and any change of specific energy output is corrected by feedforward control of production rate through the regulation of screw speed. The advanatge of this control scheme is to take care of the chip moisture variation. However the drawback of this control method is to operate the refiner at a fixed specific energy which will not allow the optimization of the energy set point.

1.4 Literature Survey

A short survey of literature on refiner control and inferential control are briefly discussed in this section. The survey is not intended to be exhaustive but only to review the previous refiner control work carried out related to the author's research in this thesis.

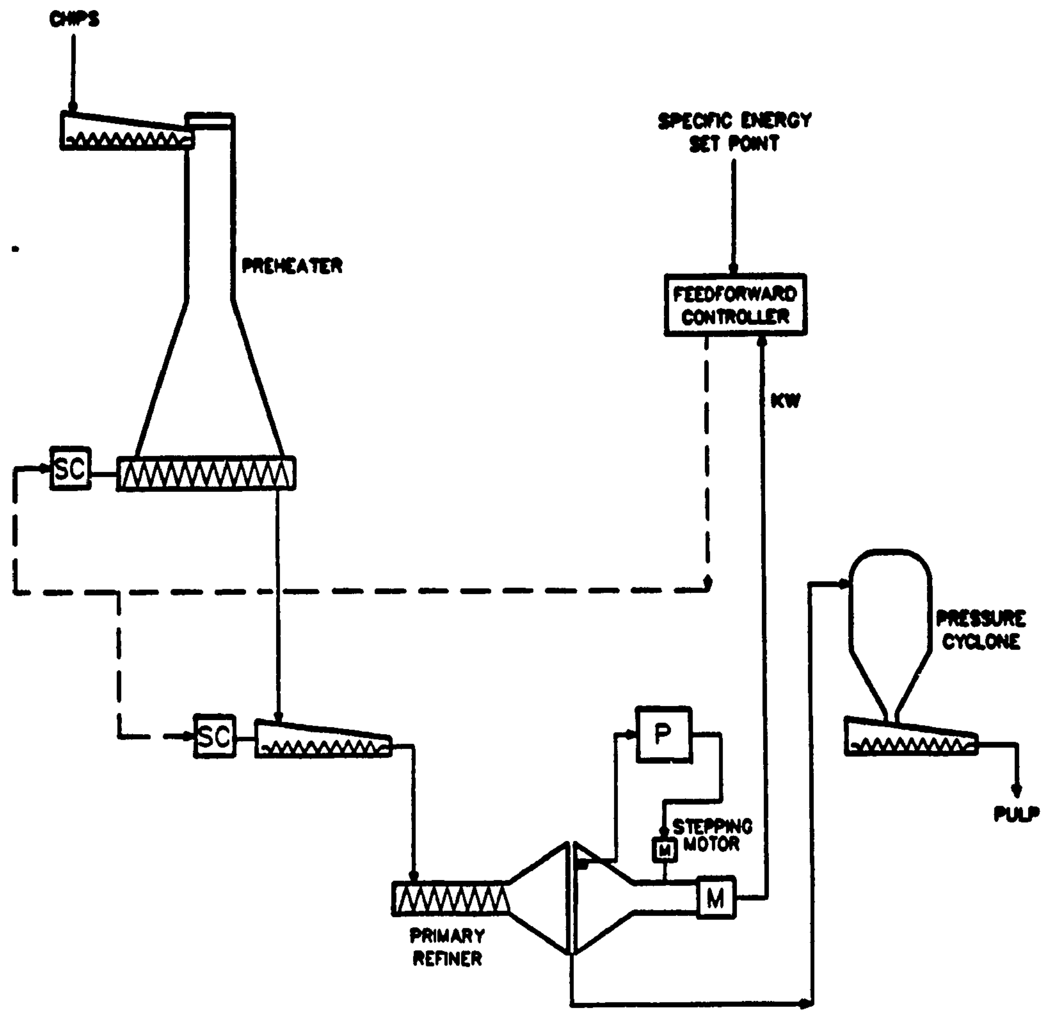


Figure 1.8 Constant Gap Control

1.4.1 REFINER CONTROL

Ever since the thermomechanical pulping (TMP) process gained the acceptance from the paper industry in the late seventies, it is realised how important the impact of this process is to the industry. There is a good economic incentive to implement control to reduce quality variability and to minimise the energy consumption. Attempts had been made by many authors to automate the TMP plant,[1],[2],[3].

The process dynamics of a refiner changes with time due to the wear of refiner plates. Horner [4] used gain scheduling technique to compensate the wear of refiner. The refiner gain between the motor load and gap is subject to drift due to plate wear and the collapse of plate pad in the refiner results in sudden change of sign in the gain. Dumont [5] studied the use of self tuning regulator to control motor load by regulating the plate gap. Manner [6] described the consistency control in the refiner operations. The effects of consistency on refiner operation and pulp quality are studied through process modelling. Tamminen [7] conducted mill trial for comparing three different types of on line freeness testers installed on the latency chest. The information is used for feedback control. It is reported that freeness variation and shive variation drop, production rate increases and energy consumption decreases. In a recent paper [8] a passive adaptive control with fault detection was proposed to control the refiner where incremental gain between the motor load and the plate gap is subject to sudden changes due to pad collapse. The method is applied only to certain type of refiner where the refiner is likely to operate in the cririca1 gap region which results in pulp pad collapse. Gap sensor, available from certain suppliers, will ensure that the refiner operates above the critical gap region.

Strand [9] applied the comminution theory used in the crushing and grinding industry to model the refiner operation. Attempts had been made to predict the fibre size distribution and fibre properties.

Toivonen [10] applied minimax robust LQ method to control the freeness in the closed loop manner. The freeness is measured using on line tester at the latency chest and the information is used for feedback in regulating the production feed screw speed. The approach is based on the process model which considered the whole two stage refiners as a lumped system. The method requires that the model be indentified for different operating conditions. The authors do not discuss the rejection of short term disturbance experienced during process upset conditions.

1.4.2 INFERENTIAL CONTROL

In most of the industrial process, the measurement of primary controlled output variable is often hindered by the limitation of availability of the sensor and the long sampling period to obtain the test result. The measurement of the rapidly sampled secondary output can be infered to the primary controlled output and used for plant control in order to have an early detection of load disturbance. An industrial application of inferential control can be found in [11],[12] and [13]. In Morris and Stephanopoulos [14], the criteria for selecting the secondary output measurement was discussed. The selection of secondary measurement is based on minimising the estimation error caused by the difference between physical system and the model. The most recent work on inferential control is found in [15]. The paper described several schemes and structures where inferential control can be implemented. Depending on the nature and complexicity of the process being controlled, inferential control scheme can be combined together with PID controller. For adaptive control scheme, the inferential control can be incorporated with self tuning regulator.

1.5 Scope of the Work

The organisation of this thesis is outlined as below.

Chapter II describes the process modelling of the refiner and open loop system indentification using parameter estimation. Refining process can be modelled by state space and input output approach. Comparison of two approaches are given. Parameter estimation using recursive least square as well as analysis of parameter convergence are discussed.

Chapter III presents the closed-loop control of specific energy based on constant inferential strategy using self tunung regulator. The theory of self tuning regulator and structure of estimation model is outlined. Simulation studies for set point and load change are presented. Discussion of noise structure such as white noise versus non stationary noise, time varying parameter, persistent excitation as well as convergence properties of parameter estimate are given. Finally the results of minimum variance control of specific energy are also presented.

Chapter IV uses the approach of adaptive inferential control method for closed loop control of freeness. Discussion of the selection of secondary output variable to be used to infer the freeness is given.

The theory of adaptive inferential control and the structure of estimation model for refining process are presented. Simulation studies and comparison of the results between constant inferential control strategy and adaptive inferential control are carried out.

Chapter V gives conclusions of this thesis work and suggestion for potential industrial application of this control method to the pulp and paper industry. Finally recommendated future research work in this area is outlined.

CHAPTER II

PROCESS MODELLING, SIMULATION AND IDENTIFICATION

2.1 Introduction

As discussed before refining is a multi-input multi-output process. However, a research work carried out by Pearson [16] indicates that the applied specific energy is a single variable that has the most significant influence on the freeness of pulp. Specific energy is defined as applied motor load per unit production rate. At constant production rate the motor load is regulated by the refiner plate gap; the motor load increases as plate gap decreases and vice versa. However, at some critical minimum gap, further decrease in gap results in pulp pad collapse.

The above finding leads to the conclusion that the refining process controlling the freeness can be modelled as a single input- single output (SISO) process. The input is the manipulating variable , plate gap, and the output being motor load or specific energy. The assumptions are made that the dilution flow and chip feed are independently controlled.

It is diffcult to model the refining process from first principle, namely because the chip refining process is not fully understood. However, different approach of modelling the process will be presented. The selection of the appropriate model will be discussed. Simulation showing the response of different process variables of the selected model using mill data will be presented. Open loop indentification technique based on parameter estimation will be used for model verification.

In carrying out the process modelling of refining process, the following assumptions are made.

(1) The refiner under study is equipped with gap sensor for gap measurement.

(2) The pulp pad collapse is avoided by the protection of interlocking security logic which allows refiner to operate above the pad collapse region.

(3) The change of the process dynamics is slowly time varying.

(4) The relationship between the gap and control signal is linear with negligible dynamics.

(5) The refining process under study is considered as an LQG (Linear Quadratic Gaussian) problem.

(6) The refining process is modelled as a single input-single output system.

In assumption 3, the change of process gain is due to the wear of refining plate in the course of refining action. Assumption 4 is made to simplify the transformation of control signal, normally in voltage to plate gap. The LQG (Linear Quadratic Gaussian) assumption in 5 leads to an optimal solution in parameter estimation. However, a suboptimal case resulting from different noise structure other than white noise will be discussed.

2.2 Process Modelling

2.2.1 COMMINUTION MODEL

Kano et al [17] uses the comminution theory to describe the refining process. The theory originally used in grinding and crushing industry was applied to model the refining process based on the breakdown of chips into single fibres and broken fibres. The theory predicts the different weight fraction of chip based on the following model.

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \end{bmatrix} = \begin{bmatrix} -(k_1+k_2) & 0 & 0 \\ k_1 & -k_3 & 0 \\ k_2 & k_3 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \qquad (2\text{-}1)$$

where x_1, x_2, x_3 are weights fraction of chip, single fibres and broken fibres, respectively.

k_1, k_2, k_3 are the corresponding respective breakdown constants.

$\dot{x}_1, \dot{x}_2, \dot{x}_3$ are the derivatives of $x_1, x_2,$ and x_3

with respect to total specific energy.

The model is useful in the prediction of different fraction of broken fibre in the pulp.

2.2.2 STATE SPACE MODEL

The chip refining process relating plate gap and motor load can be described by single input and single output (SISO) discrete time stochastic state space model as given below.

$$x(t+1) = Ax(t) + Bu(t-m) + Lw(t) \quad (2\text{-}2)$$

$$y(t) = Hx(t) + v(t) \quad (2\text{-}3)$$

where x(t) is a state variable defined by

$$x(t) = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

where x_1 : plate gap ,mm

x_2 : consistency, % oven dried pulp

x_3 : refiner housing pressure, Kpa

y(t) : controlled output, motor load, Mw (Mega watt)

v(t) : measurement noise assumed to be independent Gaussian sequence.

m : delay in response of output to input change w(t): process disturbance, assumed zero means independent Gaussian sequence defined by the following.

$$w(t) = \begin{bmatrix} w_1(t) \\ w_2(t) \end{bmatrix}$$

where w_1 :chip quality variation

w_2 :production rate fluctuation

A, B, L, and H are matrices of proper dimension, the variation of measurement noise v(t) and disturbance w(t) are defined as:

$$E[(v(t))^2] = r_1 \tag{2-4}$$

$$E[\overline{x}(0)] = \overline{x_0} \tag{2-5}$$

$$E[(\overline{x}(0)-\overline{x_0})(\overline{x}(0)-\overline{x_0})^T] = P_0 \tag{2-6}$$

$$E[w(t)\ (w(t))^T] = Q \tag{2-7}$$

where r_1 and Q are noise covariances , P_0 is covariance and $\overline{x_0}$ is the mean.

The state estimation of equation (2-2) can be obtained from Kalman filter equation using innovation process.

$$x(t+1) = Ax(t)+Bu(t-m) + K(t)\,[v(t)-Hx(t)] \qquad (2\text{-}8)$$

where K(t) : Kalman filter gain matrix

x(t+1):New state estimate

Ax(t) :Predicted estimate based on old estimate

Bu(t-m) :Input

[illegible](t): New estimate of output

Hx(t):Predicted measurement based on old estimate

The design of a control system will involve solving of state equation (2-8) , and also all the matrices A,B,H have to be obtained from field experiment of accurate process model structure, and K(t) has to be obtained from solving the time variant Riccati equation. To avoid solving Riccati equation, the Kalman filter equation (2-8) can be converted into input output model using observable canonical transformation as suggested in [8]. For a stable system, the steady state Kalman filter is expressed as below:

$$\hat{x}(t+1) = A\hat{x}(t)+Bu(t-m)+Kw(t) \qquad (2\text{-}9)$$

$$y(t) = C\hat{x}(t)+w(t) \qquad (2\text{-}10)$$

Equation (2-9) can be written in an observable canonical form

$$x(t+1)= \begin{bmatrix} -a_1 & & \\ -a_2 & I_{n-1} & \\ \cdot & & \\ \cdot & & \\ -a_n & \cdots & 0 \end{bmatrix} x(t) + \begin{bmatrix} b_1 \\ b_2 \\ \cdot \\ \cdot \\ b_n \end{bmatrix} u(t-m) + \begin{bmatrix} k_1 \\ k_2 \\ \cdot \\ \cdot \\ k_n \end{bmatrix} w(t) \quad (2\text{-}11)$$

$$y(t) = [1,0,\ldots\ldots\ldots\ldots 0]\hat{x}(t)+w(t) \quad (2\text{-}12)$$

$$\hat{y}(t) = \hat{x}(t) \quad (2\text{-}13)$$

By successive substitution, the above atate space model (2-9) and (2-10) can be written as input output ARMAX model as below:

$$y(t)+a_1y(t-1)+a_2y(t-2)+\ldots\ldots\ldots\ldots+a_ny(t-n) \quad (2\text{-}14)$$

$$= b_1u(t-m-1)+b_2u(t-m-2)+\ldots\ldots\ldots+b_nu(t-m-n)$$

$$+w(t)+c_1w(t-1)+c_2w(t-2)+\ldots\ldots+c_nw(t-n)$$

$$\text{where} \quad c_i = a_i+k_i$$

Using backward shift operator equation (2.14) can be written

$$A(q^{-1})y(t) = B(q^{-1})u(t-m) + C(q^{-1})w(t) \qquad (2-15)$$

where

$$A(q^{-1}) = 1 + a_1 q^{-1} + a_2 q^{-2} + \ldots\ldots + a_n q^{-n} \qquad (2-16)$$

$$B(q^{-1}) = b_1 q^{-1} + b_2 q^{-2} + \ldots\ldots + b_n q^{-n} \qquad (2-17)$$

$$C(q^{-1}) = 1 + (k_1 + a_1) q^{-1} + \ldots\ldots\ldots + (k_n + a_n) q^{-n} \qquad (2-18)$$

The parameters in the above equations can be estimated easily and the order of polynomials are assumed to be n.

2.2.3 INPUT OUTPUT MODEL

Most of the industrial processes can be represented by linear time invariant, single input - single output model using the following two different approaches.

(i) Åström Approach

Åström [19] suggests that the time invariant linear stochastic system of nth order with single input, single output can be described as below for optimal control problem formulation.

$$y(t)+a_1y(t-1)+........+a_ny(t-n)$$

$$= b_1u(t-k-1)+b_2u(t-k-2)+........+b_nu(t-k-n)$$

$$+e(t)+c_1e(t-1)+........+c_ne(t-n) \qquad (2-19)$$

Where y(t) is the output, u(t) is the input and e(t) is the Gaussian white noise.

The system described by (2-19) can be represented by the following block diagram in Figure 2-1.

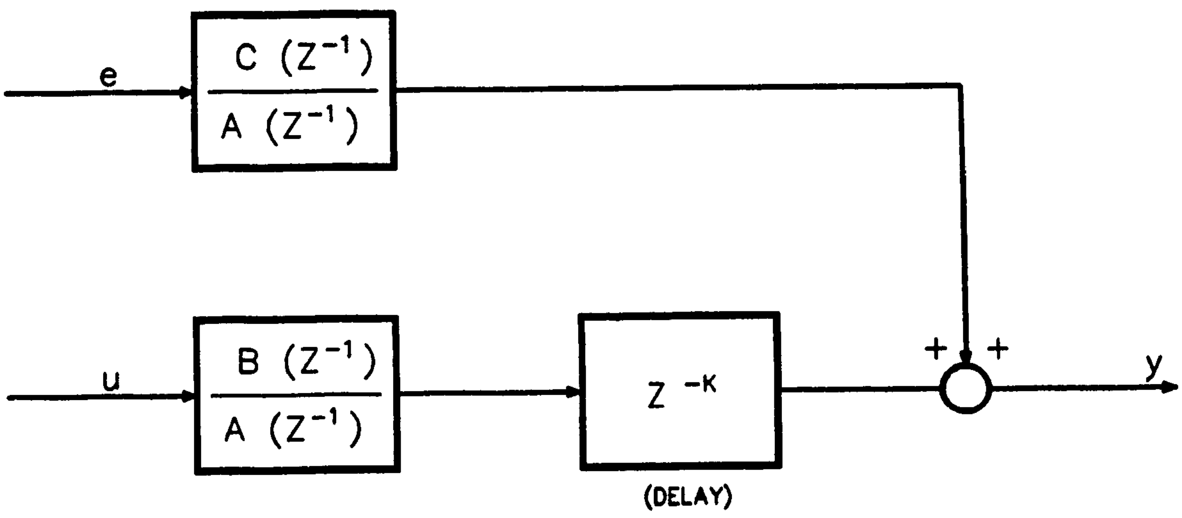


Figure 2-1 ARMAX Model - Åström Approach

Equation (2-19) can be written as the following ARMAX model.

$$A(q^{-1})y(t) = B(q^{-1})u(t-k) + C(q^{-1})e(t) \qquad (2\text{-}20)$$

where k is time delay expressed as integral multiple of sampling interval, L/h ($k \geq 1$), $A(q^{-1})$, $B(q^{-1})$ and $C(q^{-1})$ are polynomials in backward shift operator defined as below and e(t) is white noise sequence, $a_0 = 1$, $b_0 = 0$, and $c_0 = 1$.

$$A(q^{-1}) = a_0 + a_1 q^{-1} + a_2 q^{-2} + \ldots + a_n q^{-n} \qquad (2\text{-}21)$$

$$B(q^{-1}) = b_0 + b_1 q^{-1} + b_2 q^{-2} + \ldots + b_n q^{-n} \qquad (2\text{-}22)$$

$$C(q^{-1}) = c_0 + c_1 q^{-1} + c_2 q^{-2} + \ldots c_n q^{-n} \qquad (2\text{-}23)$$

The ARMAX model (2-20) is a standard tool used in system indentification and control design. In the model the autoregressive part (AR) is $A(q^{-1})y(t)$, a moving average part(MA) is $C(q^{-1})e(t)$ and the control part is $B(q^{-1})u(t)$.

(ii)Box and Jenkins Approach

In Box and Jenkins [20] approach, the stochastic time invariant linear system is described by the following model.

$$y(t) = \frac{B(q^{-1})}{A(q^{-1})}u(t-k) + \frac{C(q^{-1})}{D(q^{-1})}e(t) \qquad (2\text{-}24)$$

where $B(q^{-1})/A(q^{-1})$ respresents the process model and $C(q^{-1})/D(q^{-1})$reperesents the noise model.

$$D(q^{-1})=1+d_1q^{-1}+d_2q^{-2}+\ldots d_pq^{-p} \qquad (2\text{-}25)$$

$$C(q^{-1})=1+c_1q^{-1}+c_2q^{-2}+\ldots c_qq^{-q_1} \qquad (2\text{-}26)$$

Equation (2-24) can be represented by the following block diagram in Figure 2-2.

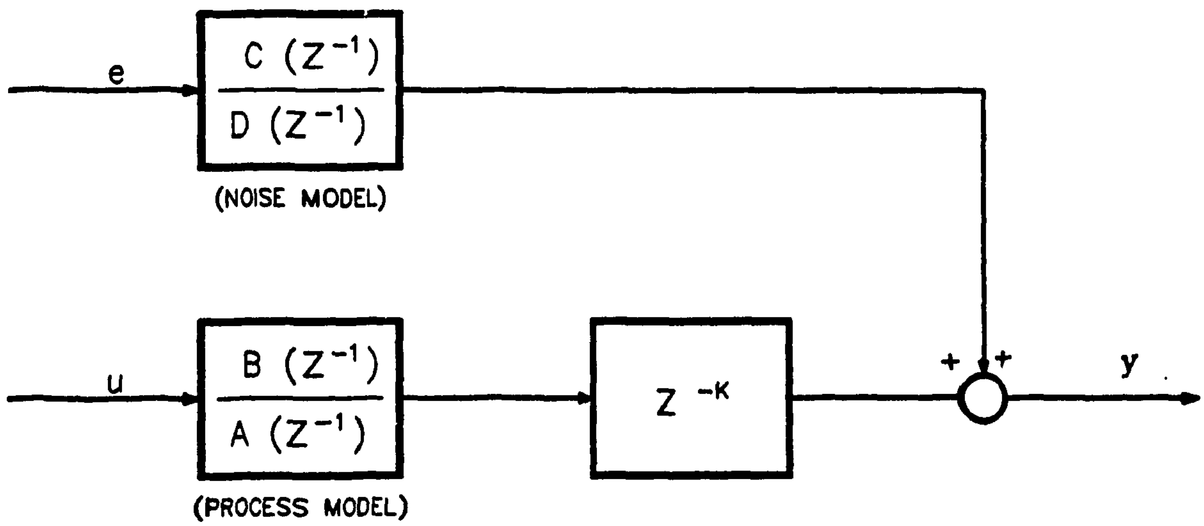


Figure 2-2 ARIMA Model - Box and Jenkins Approach

The noise model $C(q^{-1})/D(q^{-1})$ can be written as the following structure given in [21].

$$\frac{C(q^{-1})}{D(q^{-1})}e(t)=\frac{\theta(q^{-1})}{\nabla^{d}\phi(q^{-1})}e(t)=\frac{(1-\theta_1 q^{-1}..-\theta_q q^{-q_1})}{(1-q^{-1})^{d}(1-\phi q^{-1}..-\phi_p q^{-p})}e(t)$$

(2-27)

The model represented by (2-24) and (2-27) is called Autoregressive Integrated Moving Average model ARIMA(p,d,q^{-1}) , ∇^d is integrator defined as $(1-q^{-1})$. The model is suitable for most of the industrial processes whose p=q=1 for first order system and d=1 for non-stationary noise with slow drifting disturbance. ARIMA provides more information on the noise structure. Control law design using the ARIMA model will eliminate the offset. ARIMA model in equation (2-24) had a different denominator while Äström model has a common denominator in the process and noise model.

In this thesis, Åström approach will be used in the process. However, the integral action will be incorporated in the model replacing y(t) in equation(2-20) by

$\nabla y(t)$ =y(t)-y(t-1), detail will be given in later chapter.

2.2.4 MODELLING OF REFINING PROCESS

The refining process relating plate gap and motor load is described as first order with dead time [22] as shown in continous Laplace domain as below:

$$\frac{y(s)}{u(s)} = \frac{k_p e^{-Ls}}{(1+T_1 S)} \qquad (2\text{-}28)$$

where k_p : Process gain

L : Process time delay

T_1 : Process time constant

y : Output, motor load

u : Input, plate gap

Taking inverse transform of equation (2-28) assumig initial conditions is zero gives the following expression.

$$\dot{y}(t) = -\frac{1}{T_1} y(t) + \frac{k_p}{T_1} u(t-L) \qquad (2\text{-}29)$$

OR

$$\dot{y}(t) = \alpha y(t) + \beta u(t-L) \qquad (2\text{-}30)$$

$$\alpha = -\frac{1}{T_1} \qquad (2\text{-}31)$$

$$\beta = \frac{k_p}{T_1} \qquad (2\text{-}32)$$

2.2.5 DISCRETIZATION OF CONTINOUS SYSTEM

Discretization of equation (2-30) can be written as the following input output form [23], assuming zero order hold reconstruction and $0 \le L \le h$; h is a sampling interval.

$$y(kh) = a_1 y(kh-h) + b_1 u(kh-h) + b_2 u(kh-2h) \tag{2-33}$$

where

$$a_1 = e^{(-\frac{1}{T_1})h} \tag{2-34}$$

$$b_1 = k_p \, [1 - e^{\frac{-(h-L)}{T_1}}] \tag{2-35}$$

$$b_2 = k_p [e^{\frac{-(h-L)}{T_1}} - e^{-\frac{h}{T_1}}] \tag{2-36}$$

and kh=t, k in here is defined as sampling index.

Equation (2-33) is the input output model relating plate gap and motor load, with parameters a_1 ,b_1,b_2 expressed in terms of process dynamics; the equation contains a term representing fractional delay.

2.3 Process Simulation

&6The process simulation of chip refining system is carried out for both time invariant and time variant cases in order to study the relationship between the different process variables.

(i) Time Invariant Case

• The described model of chip refining process used in the simulation study is given in equation (2-33) as shown below where kh=t as defined before.

$$y(kh) = a_1 y(kh-h) + b_1 u(kh-h) + b_2 u(kh-2h)$$

The process model can be viewed as the output of a linear filter driven by white noise process as shown in Figure 2-3.

Figure 2.3 Linear Stochastic Model

The system is modelled as Autoregressive (AR) process which has its transfer function consists of all poles only. Figure 2.4 shows the simulation plot of the constant parameter model; where Gaussian white noise N(o,σ) with zero mean, constant variance is used as an input to generate a

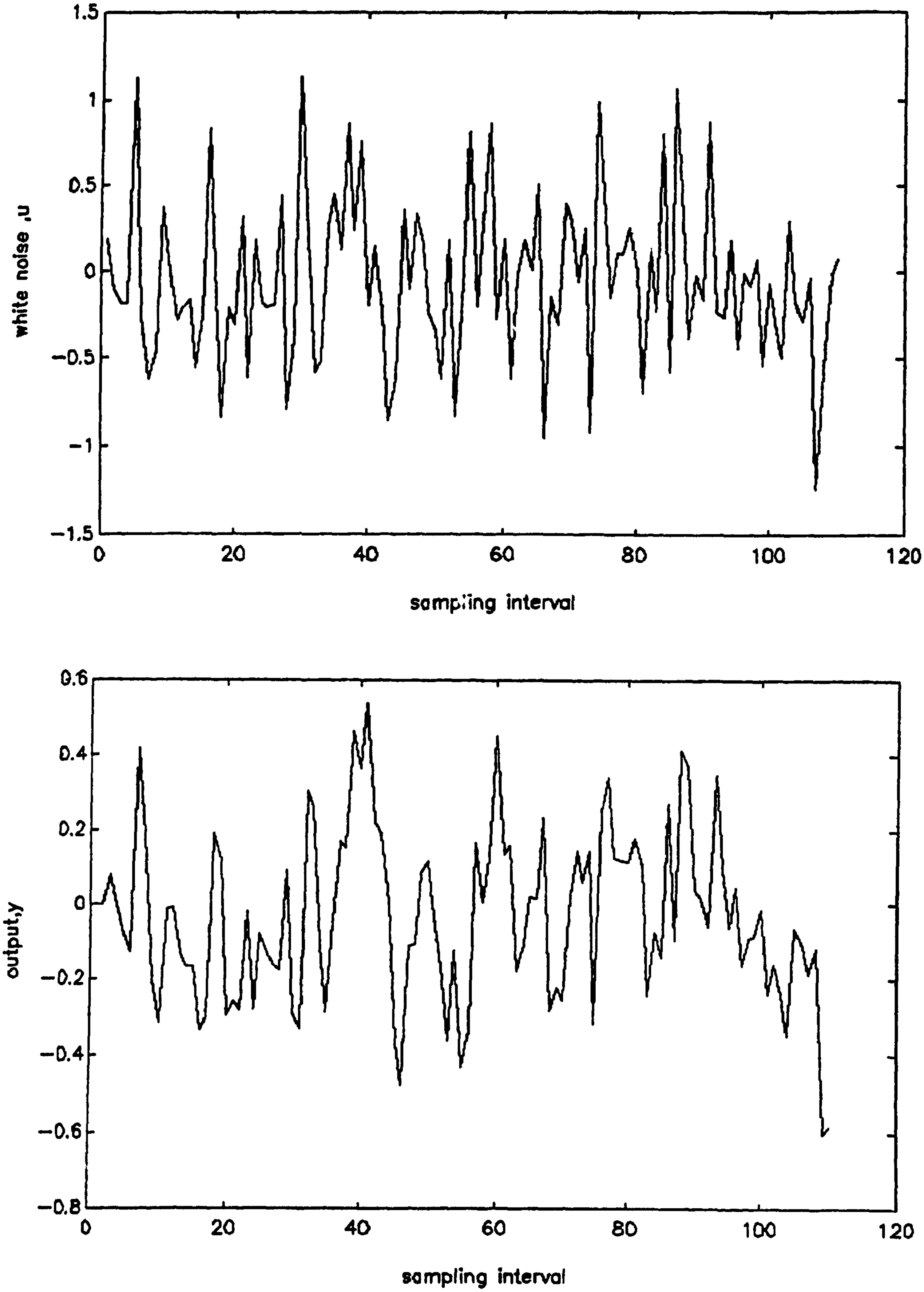


Figure 2.4 Input (white noise) and Process Output for Constant Parameter Model

filtered output. For comparison purposes Figure 2.5 shows the input, the plate gap and output, motor load of data obtained from industrial refiner operations [24]. Figure 2.6 shows the mill data input and model simulated output. It is noted that the output in Figure 2.6 follows the same trend as that in Figure 2-5. In the simulated model the process dynamics used is different from that in the industrial refiner. Other relationship between different variables from refiner operation are shown in Figure 2-7.

(ii) Time Variant Case

In the course of refining, the refiner plate wears gradually from several hundred hours to several thousand hours. The plate life depends on factors such as plate pattern, the removal of corrosive materials during chip washing, stage etc. As the plate wears, the process gain changes accordingly. In practice, plate wear can be modelled as 1st order exponential decay with time constant T, being the plate life [22] which can vary typically from 500 to 300 hours. Thus the time variant incremental process gain can be expressed as below :(refer to equations (2-33) to (2-36)

$$k_p(t) = k_p(t-1) - \frac{1}{T} e^{-\frac{1}{T}kh} \qquad (2\text{-}37)$$

where k_p is the steady state process gain before the plate wear. For the slowly time varying process, the refining model given in equation (2-33) can be modified as below:

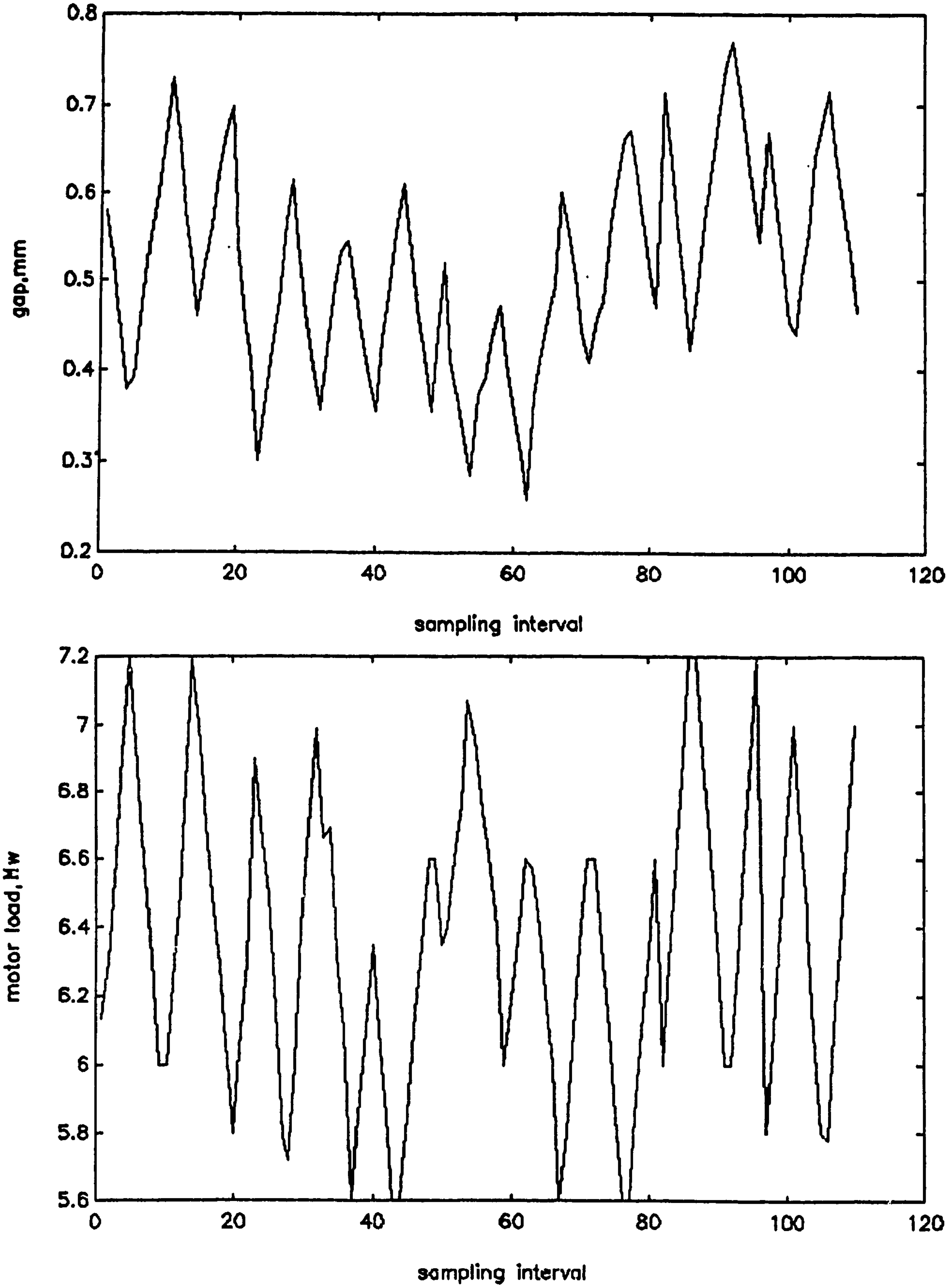


Figure 2.5 Input (plate gap) and Output (motor load) from Industrial Refiner

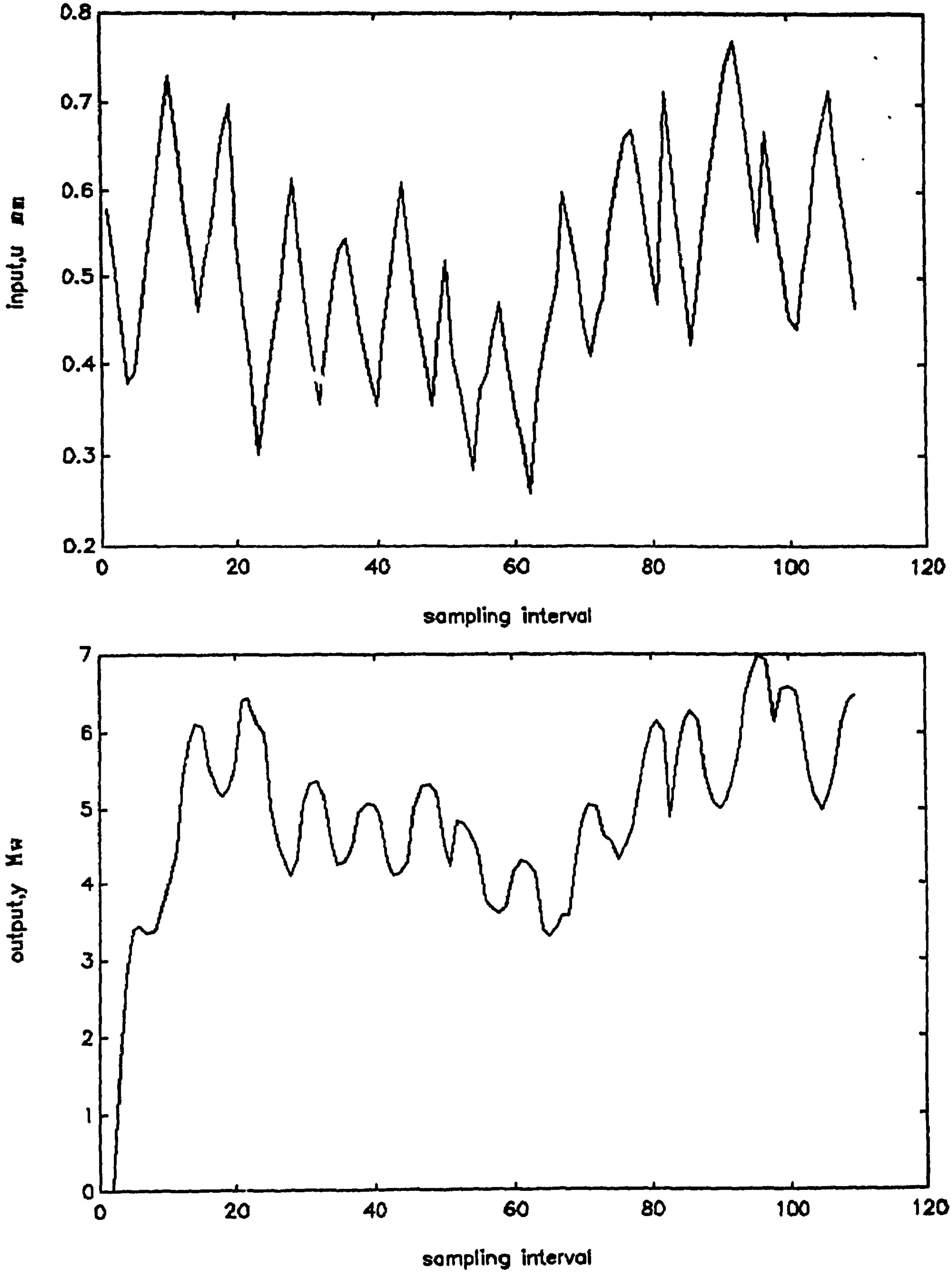


Figure 2.6 Mill Data input (plate gap) and Simulated Model Output (motor load)

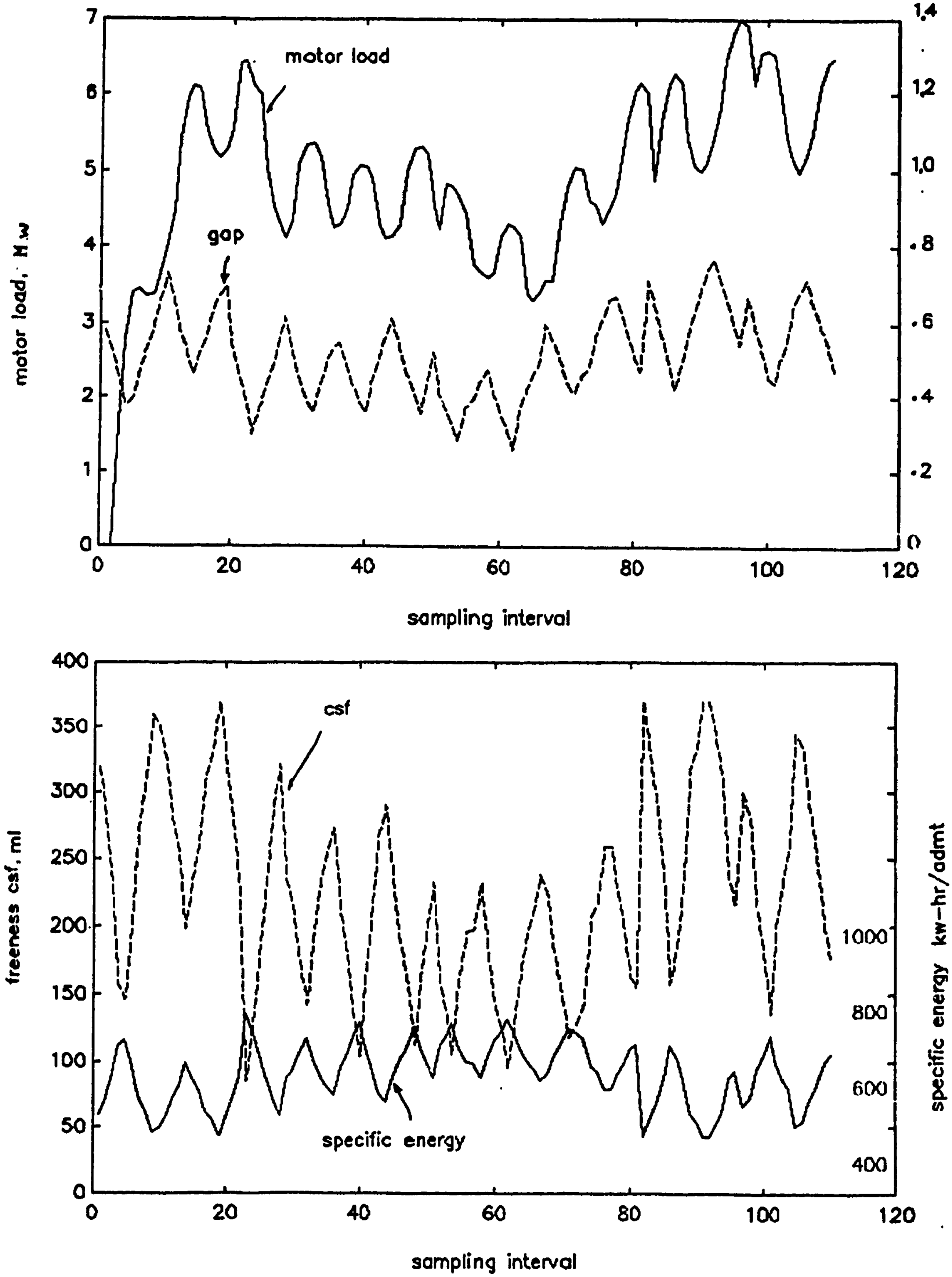


Figure 2.7 Relationships Beteween Motor Load & Gap and Specific Energy & Freeness as function of sampling interval

$$y(t) = a_1 y(t-h) + b_1(t)\,u(t-h) + b_2(t)\,u(t-2h) \qquad (2\text{-}38)$$

where $b_1(t)$ and $b_2(t)$ are time variant parameters defined as

$$b_1(t) = k_p(t)\,[1 - e^{-\frac{(h-L)}{T_1}}] \qquad (2\text{-}39)$$

$$b_2(t) = k_p(t)\,[e^{-\frac{(h-L)}{T_1}} - e^{-\frac{h}{T_1}}] \qquad (2\text{-}40)$$

Figure 2.8 shows the simulated process gain for the slowly time varying system given in equation (2.38). When the mill data of plate gap as input is used in the time varying model, the simulated motor load exhibits a slowly decay as shown in Figure 2.9. To compensate the time varying parameter of the process dynamics, an adaptive scheme is required to regulate the plate gap in order to produce a targeted pulp property, the freeness.

2.4 Open Loop Identification

2.4.1 TIME INVARIANT SYSTEM

The open loop system identification technique is often used to identify an unknown process model. The structure shown in Figure 2.10 uses the adaptive filter in the form of transversal filter to model the process, and the process plant is represented by the invariant system with unknown parameters.

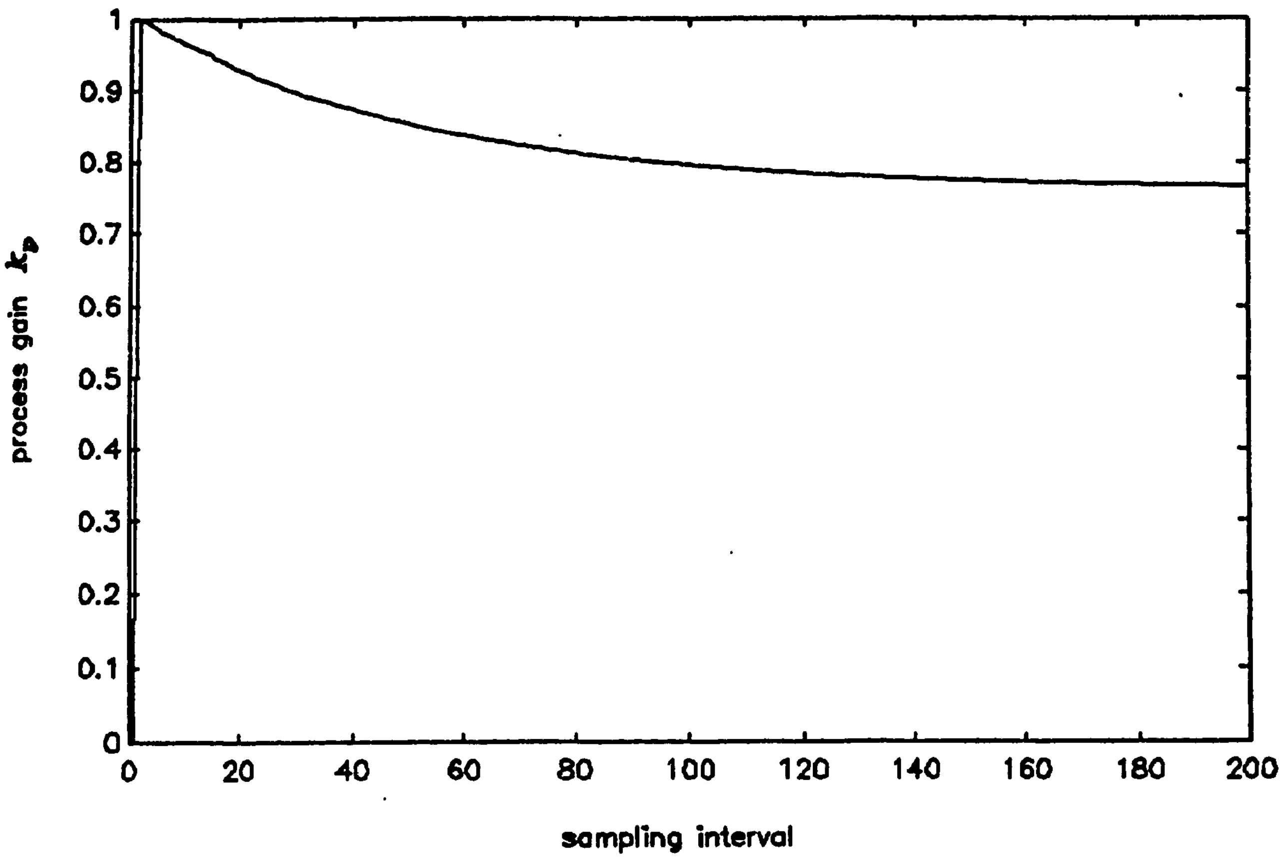


Figure 2.8   Process Gain Decay for Slowly Time Varying Model of Equation (2-38)

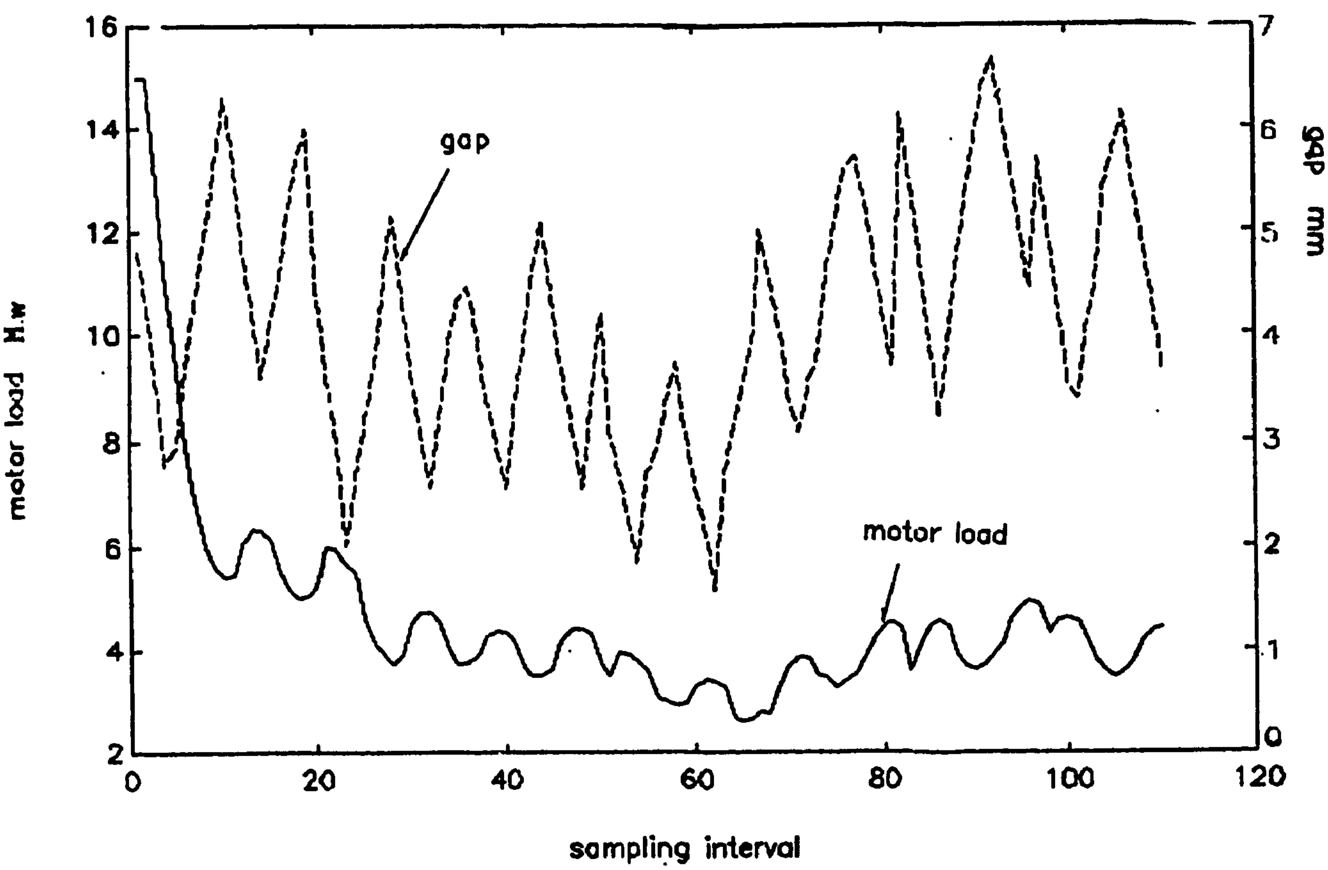


Figure 2.9   Output (motor load) of Time Varying System when input (gap) from Mill Data is used

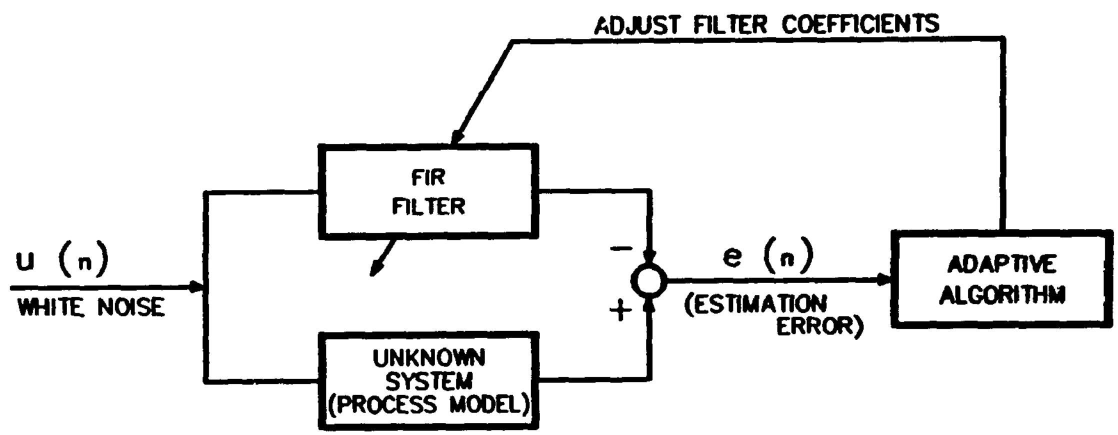


Figure 2.10 System Identification Block Diagram

Gaussian white noise is used as an input for the adaptive filter and the unknown plant. The estimation error is generated between the adaptive filter output and process plant output. The parameters of the adaptive filter are estimated using Recursive Least Square (RLS). The RLS algorithm is derived using matrix inversion lemma [25] as shown in the following equations:

$$\theta(t)=\theta(t-1)+K(t)\,[y(t)-x^{T}(t-b)\,\theta(t-1)] \qquad (2\text{-}41)$$

$$K(t)=\frac{P(t-1)\,x(t-b)}{1+x^{T}(t-b)\,P(t-1)\,x(t-b)} \qquad (2\text{-}42)$$

$$P(t)=P(t-1)-\frac{P(t-1)\,x(t-b)\,x^{T}(t-b)\,P(t-1)}{1+x^{T}(t-b)\,P(t-1)\,x(t-b)} \qquad (2\text{-}43)$$

$x^{T}(t)$ is the regression vector defined by

$$x^{T}(t)=[-y(t-1),\ldots,-y(t-n),u(t-1),\ldots,u(t-m)] \qquad (2\text{-}44)$$

$$\theta^{T}=[\theta_1\ ,\theta_2\ ,\ldots\ldots.\theta_n] \qquad (2\text{-}45)$$

and b is the number of whole period of delay. In equation (2-41), $x^{T}(t-b)\ \ \theta\ (t-1)$, the inner product represents an estimate of desired process plant output y(t) based on old least square estimate of parameter θ at time t-1. The difference between plant output and the estimated plant output is called a priori estimate error defined by

$$\alpha(t) = y(t) - x^T(t-b)\theta(t-1) \qquad (2\text{-}46)$$

In equation (2-42) P(t) is symmetric covariance matrix and K(t) is gain vector. The performance criterion for RLS is to minimise the mean square error of $\alpha(t)$.

If the process model is properly selected, the estimated parameter using white noise as an input will converge to the true parameters in the minimum mean square sense. The estimate is then unbiased and optimal.

Example (2-1)

The time invariant model (2-33) reprenenting the process plant is identified using the identification technique. The following parameters and data are assumed.

$K_p = 1.0$; $L = 4$ sec; $h = 5$ sec; $T_1 = 7$ sec

$a_1 = e^{-h/T1} = 0.4895$

$b_1 = k_p [1 - e^{-(h-L)/T1}] = 0.1331$

$b_2 = k_p (e^{-(h-L)/T1} - e^{-h/T1}) = 0.3773$

u: input, independent Gaussian white noise $N(o,\sigma)$ with zero mean and constant variance. The model is given as following.

$$y(kh) = 0.4895y(kh-h) + 0.1331u(kh-h) + 0.3773u(kh-2h) \quad (2\text{-}47)$$

Figure (2.11) shows the plot of the estimated parameters of the model when Gaussian white noise N(o,σ) is used. It is noted that estimated parameters (θ_1, θ_2, θ_3) converges to the calculated parameters (a_1, b_1, b_2) of the process plant. This validates that the model of the process is properly selected. The estimation is said to be unbias because the parameters converge to the optimal value in the minimum mean square sense.

Example (2-2)

Mill data for refiner gap is used as input in time invariant model (2-47) for process plant indentification, the estimated parameters are shown in Figure 2.12. The results indicates that the parameters do not converge to the calculated values. The comparison of the results of RLS estimate using white noise and mill data input are summarised in Table 2-1.

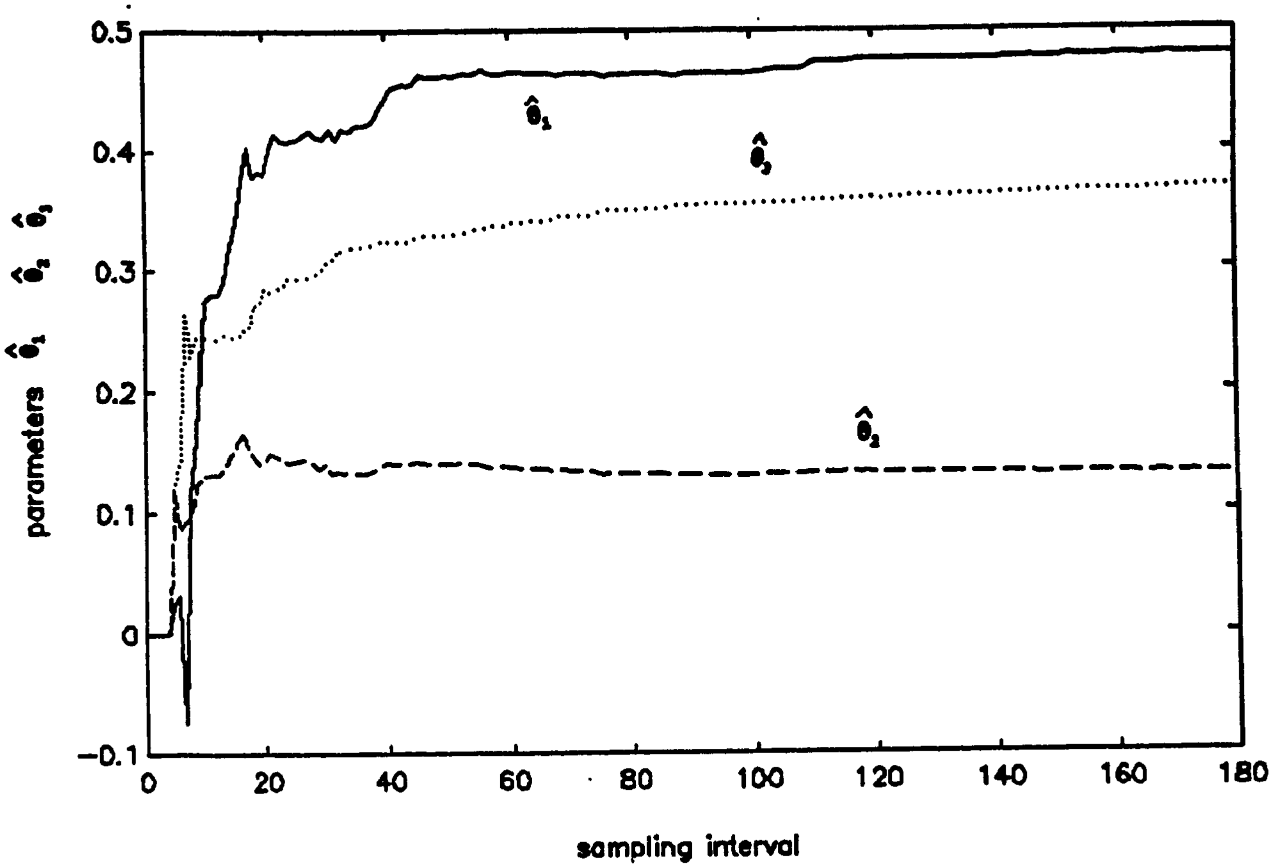


Figure 2.11 Parameter Estimation of Time Invariant Process Model from Equation (2-47) using White Noise as input

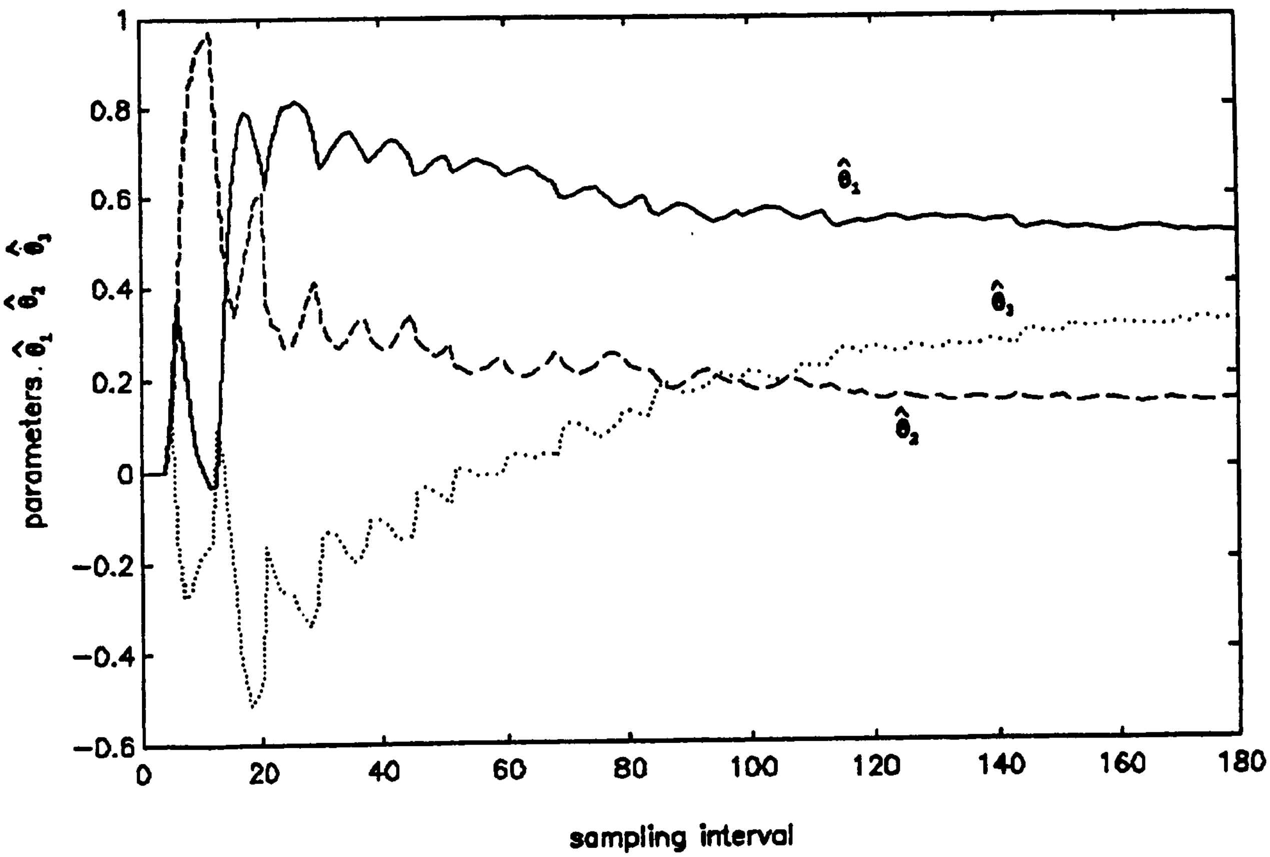


Figure 2.12 Parameter Estimation of Time Invariant Process Model from Equation (2-47) using Mill Data as Input (gap)

	Process Model Parameters		
	θ_1	θ_2	θ_3
(I) Calculated values from model in example (2-1)	0.4895	0.1331	0.3773
(II) Estimated values from RLS using white noise input	0.4793	0.1321	0.3677
% error	-2.0	-0.7	-2.5
(III) Estimated values from RLS using mill gap data as input	0.5095	0.1474	0.3177
% error	4	10.7	-15.7

Table 2-1: Parameters estimation of time invariant system using white noise and plant data as input

As the number of sampling point increases,the error of the converged values will diminish for the case of RLS estimate using white noise input. The parameter estimation using mill data as input gives an bias estimate, and the solution of the least square is not optimal. The signal from the mill data can be considered as colored noise generated by white noise passing through a filter. When the plant is operating under open loop conditions, the gap input could be considered as non-stationary nature due to the sudden changes of the production rate, moisture etc. The exponential forgetting factor λ of 0.99 is used in the RLS algorithm. The purpose is to keep track of the fluctuating parameters as shown in Fig 2.12. The role of λ will be explained in later chapters.

2.4.2 TIME VARIANT SYSTEM

The recursive least square algorithm in equations (2-41),(2-42), and (2-43) can be used for parameters estimation for plant having slowly time varying parameters as given in equations (3-39) and (3-40) with some modifications. In the least square estimation, the following performance index is minimised.

$$\textit{Performance Criteria}: \mathscr{E}(n) = \sum_{i=1}^{N} |\alpha(i)|^2 \qquad (2\text{-}48)$$

Where n is defined as variable length of the observable data, and $\alpha(i)$ is the difference between the desired output and the system output.

It is customary to introduce the weighting or forgetting factor λ in the definition of performance index , by doing so the index is defined as below.

$$\mathscr{E}(n) = \sum_{i=1}^{N} \lambda^{n-i} |\alpha(i)|^2 , \quad 0<\lambda<1 \qquad (2\text{-}49)$$

The value of $\lambda(n,i)$ can be considered as a discounting factor that the current data will be weighted heavily and the data in the distant past are "forgetten". The factor can be used to track the slowly time varyimg parameters as well as to follow the observable data when the input is in the non-stationary environment. The inverse of 1-λ is the measure of memory of RLS algorithm. The practical range of λ is $0.95 \le \lambda \le 1.0$ for $\lambda = 1$ we have the original least square estimate, corresponding to infinite memory, the performance criteria in equation (2-48) gives an equal weighting of the error. Recursive least square (RLS) for estimating the slowly time variant system can be written as below:

$$\theta(t) = \theta(t-1) + K(t)\,[y(t) - x^T(t-b)\theta(t-1)] \qquad (2\text{-}41)$$

$$K(t) = \frac{P(t-1)\,x(t-b)}{\lambda + x^T(t-b)\,P(t-1)\,x(t-b)} \qquad (2\text{-}50)$$

$$P(t) = \frac{P(t-1)}{\lambda} - \frac{1}{\lambda}\cdot\frac{P(t-1)\,x(t-b)\,x^T(t-b)\,P(t-1)}{\lambda + x^T(t-b)\,P(t-1)\,x(t-b)} \qquad (2\text{-}51)$$

Alternatively, the time varying parameter could be postulated as random walk as described below:

$$\theta(t+1) = \theta(t) + w(t) \qquad (2\text{-}52)$$

where w(t) is sequence of disturbance assumed white and Gaussian.

$$E[w(t)\,w^T(t)] = R_1(t) \qquad (2\text{-}53)$$

$$E[v(t)v^T(t)] = R_2(T) \quad (2\text{-}54)$$

where v(t) is measurement noise in output assumed white and Gaussian as defined in equation(2-3). The recursive least square (RLS) is given as below [26].

$$K(t) = \frac{P(t-1)x(t-b)}{R_2(t)+x^T(t-b)P(t-1)x(t-b)} \quad (2\text{-}55)$$

$$P(t) = P(t-1) - \frac{P(t-1)x(t-b)x^T(t-b)P(t-1)}{R_2(t)+x^T(t-b)P(t-1)x(t-b)} + R_1 \quad (2\text{-}56)$$

$R_1(t)$ is positive semi-definite and it will prevent P(t) from tending to zero. $R_1(t)$ would be made as a diagonl matrix and the larget its elements the faster the adaptation for the parameters.

Example (2-3)

In practice, the refining process is the slowly time varying process as given in equation (2-38) represented by the following.

$$y(kh) = a_1 y(kh-h) + b_1(t) u(kh-h) + b_2(t) u(kh-2h)$$

The following data are used in the simulation run k_p =1.0; h=5 sec;L=4 sec; T_1=7.0 sec; T=1500 hrs; a_1=0.4895; $b_1(t)$ $b_2(t)$ are calculated from equations (2-39) and (2-40) as :

$b_1(t) = (1-1/1500\ e^{-(t/300)})0.1331$

$b_2(t) = (1-1/1500\ e^{-(t/300)})0.3773$

Figure 2-13 shows the estimated parameters for time variant system using mill data of refiner gap as input. It is also noted from the figure that the open loop system parameters tend to diverge as the plate continues to wear.

2.5 Convergence of the Parameter Estimates

In the recursive least square (RLS) parameter estimation, the initial values of the parameters and P(0), covariance matrix are assumed as below:

$$\theta = [0,\ 0,\ 0]$$

$$P(O) = \begin{bmatrix} 100 & 0 & 0 \\ 0 & 100 & 0 \\ 0 & 0 & 100 \end{bmatrix}$$

The P(O) matrix relects the confidence of the initial values of the model parameters. If the prior information of the model parameters is completely unknown, the P(O) values is choosen large e.g $P(O) = 10^3 I$. This will allow the

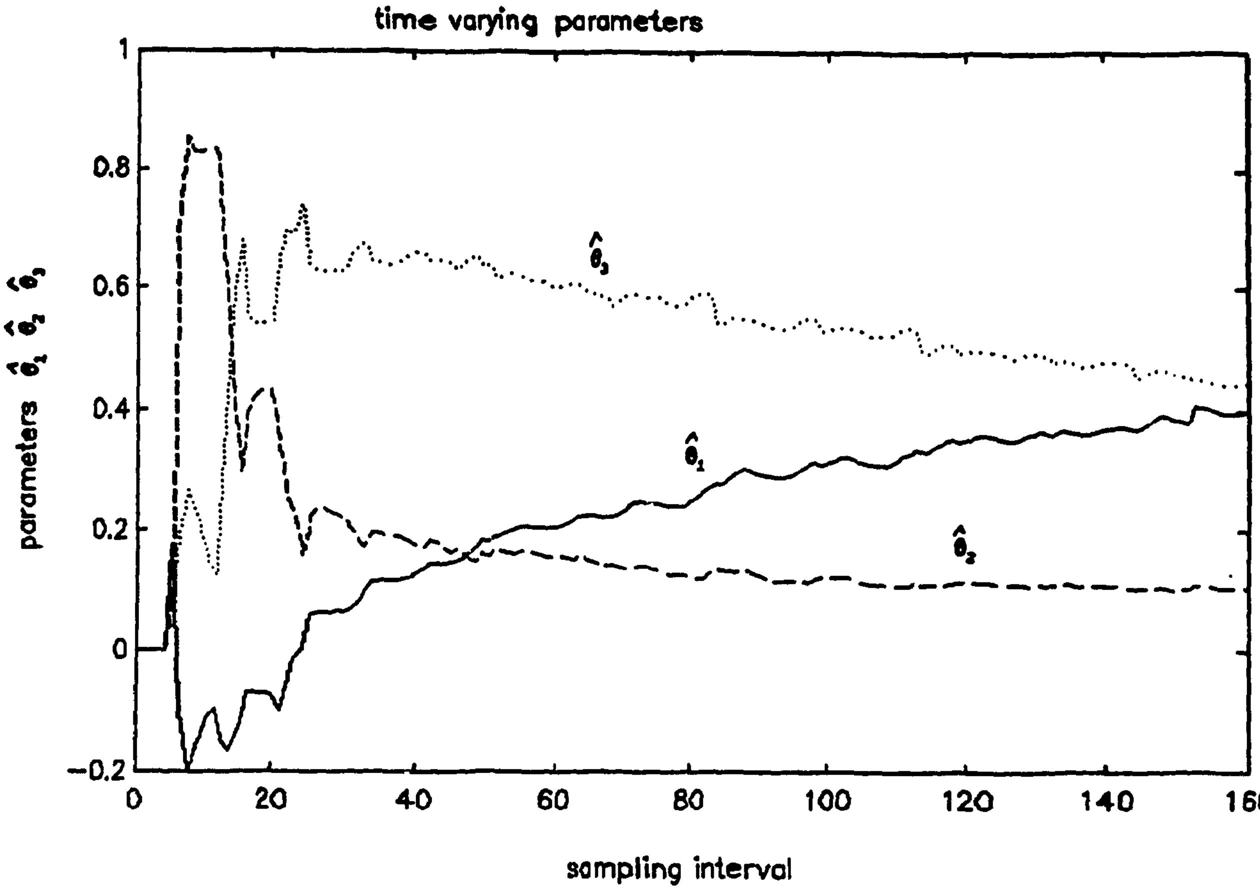


Figure 2.13 Parameter Estimation of Time Variant Model Model from Equation (2-38) using Mill Data as input

parameter estimation to take a large step and a good final estimate will converge in a few steps. On the contrary, if the initial model parameters are known, P(0) can be chosen as small quantity such as $P(0)=10^{-3} I$. This will reflect the

estimation has a large confidence. However, too small a value of P(0) can give rise to a slow rate of convergence. For time variant system, the introduction of forgetting factor λ will allow RLS to keep track of slowly changing of parameter and prevent P(t) tending to zero.

For open loop identification, the Gaussian white noise input gives an unbias estimation. The least square problem gives a minimum mean square error in the optimal sense. The Gaussian white noise has the following given properties [25]. The correlation matrix R(n) is Toeplitz.

$$R(n)=E[u(n)\ u^H(n)] = \begin{bmatrix} r(0) & r(1) \ \ldots\ldots & r(M-1) \\ r(1) & r(0) \ \ldots\ldots & r(M-2) \\ \vdots & & \\ r(M-1) & r(M-2) \ldots\ldots & r(0) \end{bmatrix} \qquad (2\text{-}57)$$

where H denotes Hermitian transpose, M denotes order of AR process and u(n), the input is defined as below:

$$u^T(n)=[\ u(n),u(n-1)\ldots\ldots\ldots\ldots u(n-M+1)] \qquad (2\text{-}58)$$

The parameter estimate $\theta(t)$ converges to a stationary optimal solution. This optimal estimation represents a LQG (Linear Quadratic Gaussian) system when the system is linear, the cost function in the performance index is quadratic and the input signal is Gaussian white noise.

For non-stationary input, parameter for time invariant system converges to a bias estimate.

2.6 Summary

This chapter describes different approaches and modelling for refining process, such as comminution model, state space model, input output model. The cannonical transformation of state space model to input output model is given. Refining process relating motor load and plate gap can be described as a single input single output (SISO) discrete time stochastic model. Process simulation using white noise as well as actual plant data are carried out. System identification of the chosen model using white noise confirms the correct choice of the model chosen. Identification of time invariant and time variant system are carried out.

CHAPTER III

SELF TUNING CONTROL

3.1 Introduction

The problem with freeness control in chip refining is that the process dynamics change as the refiner plates wear. In addition the process is subject to stochastic disturbance such as the changes of raw material properties and production fluctuation. The present method of freeness control used by the TMP mill is based on specific energy measurement and operator's intervention. The method of control has not been satisfactory because of the changing process dynamics cannot be adjusted effectively by manual means. When operating under open loop conditions the time varying system will become unstable as the process parameters continue to change with the wear of the plates.

Owing to the fact that different wood species would be used in the refining process for manufacturing of same grade of pulp, the specific energy required to produce a refined pulp of a given freeness varies according to wood species and production rate. In other words,the relationship between specific energy and freeness is species dependent.

In this chapter a constant inferential control is used to provide the closed loop control of the specific energy. There is a constant inferential relationship between the specific energy and freeness for a constant wood species. Hence the result of specific energy can be easily inferred to freeness. Self tuning regulator is used in the control design. For controlling the chip refining using different type of wood or mixed species, a more elaborate method of adaptive inferential control will be described in Chapter IV.

3.2 Theory of Self Tuning Regulator (STR)

3.2.1 DEVELOPMENT OF SELF TUNING REGULATOR

The original idea of self optimising and self adjusting control strategy was proposed by Kalman [27]. However, because of unavailability of the hardware to implement the control strategy, the technique was not adopted until Peterka [28] proposed the idea of adaptive regulation of noisy system. Parallel to this development, a stochastic control theory was outlined by Box and Jenkins [20] and Åström [19]. A major breakthrough of self tuning regulator came with the landmark paper given by Åström and Wittenmark [29]. The important papers on STR can also be found in Clark and Gawthrop [30] and Harris and Billings [31]. This led to the significant development in the industrial application of STR in different areas such as paper machine [32], [33], ore crusher [34], titanium dioxide [35] and wood chip refiner control [5], [8].

3.2.2 THEORY

Most of the industrial process can be modelled as ARMAX model given in equation (2-20) in Chapter II reproduced as below.

$$y(t)=\frac{B(q^{-1})}{A(q^{-1})}u(t-k)+\frac{C(q^{-1})}{A(q^{-1})}e(t) \tag{2-20}$$

where y(t) is the controlled output, u(t) is a manipulating variable, e(t) is zero mean white noise, t is the discrete time and k is defined as discrete time delay. $A(q^{-1})$,$B(q^{-1})$ and $C(q^{-1})$ are defined before in equation (2-21),(2-22) and (2-23). Equation (2-20) is written in the form of equation (2-19) as below.

$$y(t)+a_1y(t-1)+\ldots\ldots\ldots\ldots+a_ny(t-n)$$

$$=b_1u(t-k-1)+b_2u(t-k-2)+\ldots\ldots\ldots+b_nu(t-k-n)$$

$$+e(t)+c_1e(t-1)+\ldots\ldots\ldots\ldots+c_ne(t-n) \tag{2-19}$$

Åström [19] has shown that the process model of equation (2-19) can be represented by the following predictor form.

$$y(t+k+1)+\alpha_1 y(t)+\ldots\ldots\ldots+\alpha_n y(t-n+1) =$$

$$\beta_0[u(t)+\beta_1 u(t-1)+\ldots+\beta_{n+k-1}u(t-n-k+1)]+\varepsilon(t+k+1) \qquad (3\text{-}1)$$

where α's and β's are estimated parameters corresponding to a's and b's in equation (2-19). Equation (3-1) allows the model to predict process output after time delay k, given the knowledge of past inputs and outputs, $\varepsilon(t)$ is the disturbance acting on the process, called the residuals. $\varepsilon(t)$ is the moving average of order k of the driving noise e(t), β_0 is normally assumed a constant value. For minimum variance control, the process output is forced to equal the residual $\varepsilon(t)$ and the control is given as below .

$$u(t)=\frac{1}{\beta_0}[\alpha_1 y(t)+\ldots\ldots+\alpha_n y(t-n+1)]$$

$$-\beta_1 u(t-1)-\ldots\ldots-\beta_{n+k-1}u(t-n-k+1) \qquad (3\text{-}2)$$

Self tuning control is applied to the process where the parameters are unknown but constant. The basic idea of STR is based on the assumption that it is possible to separate the estimation of the parameters in the model and the control law design. The parameters are estimated using Recursive Least Square (RLS) method. The value of parameters estimated are assumed to be the true process parameter. The principle is known as certainty equivalence Harris [31]. Self tuning regulator (STR) can be implemented either in implicit form or in explicit form. In implicit STR , the process model equation is reformulated such that the estimated parameters are used directly in the controller design. However, explicit STR involves estimation of process parameters and the control law design. Implicit STR will be used in this thesis; its structure is shown in Figure 3.1.

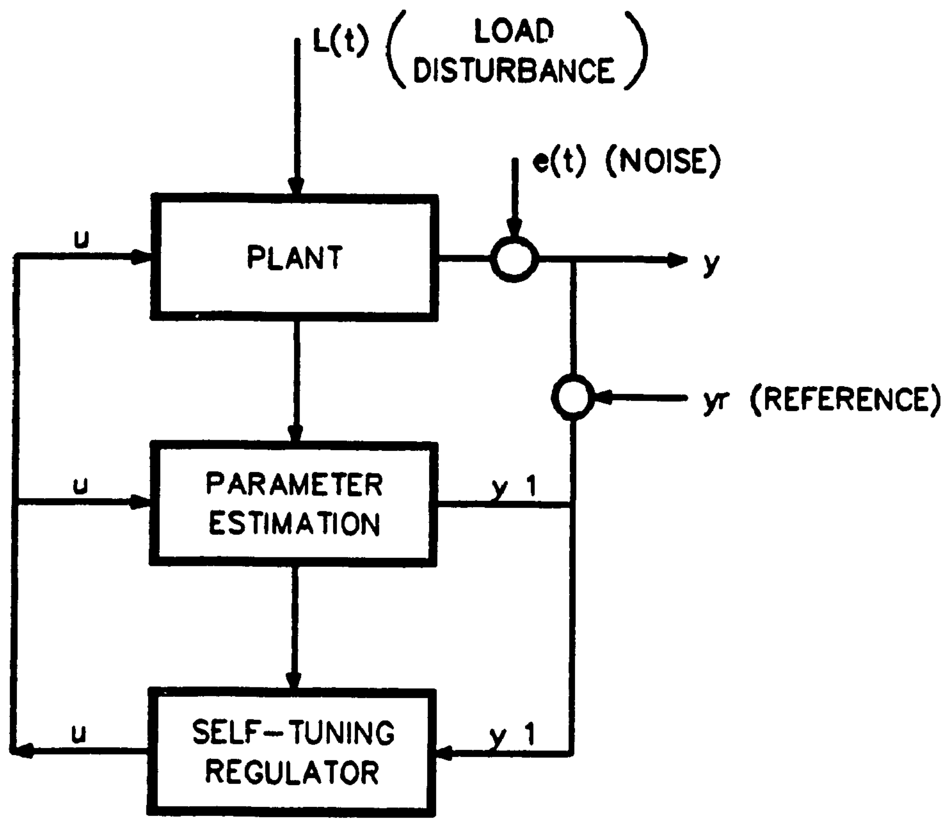


Figure 3.1 Self Tuning Regulator Structure

Introducing the vectors

$$x(t)=[-y(t),-y(t-1)..........-y(t-n+1),$$

$$\beta_0u(t-1),\beta_0u(t-2),..........,\beta_0u(t-n-k+1)] \qquad (3\text{-}3)$$

$$\theta=[\alpha_1\ \alpha_2......\alpha_n,\ \beta_1\ \beta_2......\beta_{n+k-1}]^T \qquad (3\text{-}4)$$

Equation (3-1) can be written as

$$y(t)=\beta_0u(t-k-1)+x(t-k-1)\theta+\varepsilon(t) \qquad (3\text{-}5)$$

The recursive least square estimate is given by the following equation where b=k+1.

$$\theta(t)=\theta(t-1)+K(t)[y(t)-\beta_0u(t-b)-x^T(t-b)\theta(t-1)] \qquad (3\text{-}6)$$

Equations (3-6) together with K(t) amd P(t) as given in (2-42) and (2-43) provide the updating of the parameters after one iteration. To implement the STR control algorithm the following assumptions are made.

- .the parameters in the model (2-20) are constant and unknown.
- .all roots in the polynomial $B(q^{-1})$ in (2-22) are inside or on the unit circle (Conditions required for the system to be a minimum phase).

The following selection of parameters in the algorithm can be specified.

- cale factor β_0 be constant and known
- Sampling time in the process.
- Time delay in the model, k.
- Number of parameter in the regulator.

3.2.3 PARAMETER ESTIMATION AND CONTROL

Self tuning control algorithm is briefly described as below.

At each sampling interval, the parameters defined as $\theta^T=[\alpha_1\ ,\alpha_2\ ,....\alpha_n, \beta_1, \beta_2, ...\beta_{n+k-1}]$ of the model (3-1) are estimated based on input and output data at t using method of least square to minimise the performance index given in the following expression.

$$Performance\ Index = \sum_{i=o}^{N-t} \alpha(i)^2 \qquad (3-7)$$

Using the estimated α_i, β_i the control action is calculated using equation (3-2). Åström [19] proved two theorems to assess the performance of self tuning regulator. If STR converges to a minimum variance, the autocorrelation and cross correlation will have the following properties.

Theorem 1

If the parameters of model (3-1) converges, at $t=\infty$, the colsed loop output using the control law (3-2) is ergodic, and having the following properties.

The Autocorrelation Function ($\gamma_y(\tau)$)

$$\gamma_y(\tau)=Ey(t+\tau)y(t)=0 \quad , \quad \tau=k+1,.....k+n \qquad (3-8)$$

The cross correlation Function ($\gamma_{yu}(\tau)$)

$$\gamma_{yu}(\tau)=Ey(t+\tau)u(t)=0 \quad , \quad \tau=k+1,......k+n \qquad (3-9)$$

Theorem 2

If the parameters α_i , β_i converge such that $A(q^{-1})$,

$B(q^{-1})$ have no common factor then the controller converges to minimum variance regulator.

If the noise is white and Gaussian and in the term $C(q^{-1})$ where $c_0 = 1$, and $c_1 e(t-1)......=0$, the estimated parameter will be a minimum variance estimate or the estimation is unbias. For non white sequence, for example IMA (Integrated Moving Average) noise, where $c_0, c_1 e(t-1) \neq 0$, the estimation of the parameters will be biased, however the controller may still converge to a minimum variance regulator.

3.2.4 STR FOR TIME VARIANT SYSTEM

For process with constant parameter as given in equation (3-1), the parameter estimation in STR will eventually converge to a constant value using the performance index in equation (3-7) and " go to sleep ". However, in most industrial process the process is time variant with slowly changing parameters and when using equation (3-7), the parameter might change after convergence. Thus the STR will not be able to adapt for the new parameters. By introducing the forgetting factor λ, the least square estimate minimising the performance index is given by equation (2-49). The gain vector K(t) and covariance matrix P(t) in RLS algorithm are shown in equations (2-50) and (2-51). The forgetting factor will allow the estimator to track the slowly varying parameters giving a more weighting of the most recent data and less weight of the old data.

3.2.5 STR WITH INTEGRAL ACTION

As discussed in Chapter II Box and Jenkins model given in equation (2-24) contains a noise structure shown in (2-27). The resulting STR control law in equation (2-24) contains an integral control action to eliminate any steady state offset in the controlled system. However an alternative approach given below will be used for the elimination of offset in the closed loop control. Consider the noise model N(t) in equation (2-20) given by.

$$N(t) = \frac{C(q^{-1})}{A(q^{-1})} e(t) \tag{3-10}$$

Equation (3-10) assumes a stationary noise input where e(t) is a white Gaussian sequence N(0,σ). The STR control law based on this noise model does not have integral action to eliminate the offset. To overcome this deficiency, a STR control law capable of handling non-stationary noise is postulated with a noise structure as shown below.

$$\Delta N(t) = \frac{C(q^{-1})}{A(q^{-1})} e(t) \tag{3-11}$$

Δ in equation (3-11) is a differential operator $(1-q^{-1})$, and the equation is a disturbance process with staionary increments. By substituting equation (3-11) in equation (2-20) the modified discrete stochastic model can be described as

$$y(t)=\frac{B(q^{-1})}{A(q^{-1})}u(t-k)+\frac{C(q^{-1})}{A(q^{-1})}\frac{e(t)}{\Delta} \tag{3-12}$$

that is

$$A(q^{-1})\Delta y(t)=q^{-k}B(q^{-1})\Delta u(t)+C(q^{-1})e(t) \tag{3-13}$$

where

$$\Delta y(t)=y(t)-y(t-1) \tag{3-14}$$

$$\Delta u(t)=u(t)-u(t-1) \tag{3-15}$$

Equation (3-13) can be written as

$$\Delta y(t)+a_1\Delta y(t-1)+a_2\Delta y(t-2)+........+a_n\Delta y(t-n)$$

$$= b_0\Delta u(t-k)+b_1\Delta u(t-k-1)+........+b_n\Delta u(t-k-n)$$

$$+e(t)+c_1e(t-1)+........+c_ne(t-n) \tag{3-16}$$

In tne recursive least square, the regressor is given by

$$x(t)=[-\Delta y(t),-\Delta y(t-1),...........-\Delta y(t-n+1),$$

$$\beta_0\Delta u(t-1),\beta_0\Delta u(t-2),............\beta_0\Delta u(t-n-k+1)]$$

(3-17)

The parameter vector θ is the same as in (3-4), in the RLS algorithm the parameter updating equation is given by

$$\theta(t)=\theta(t-1)+K(t)[\Delta y(t)-\beta_0\Delta u(t-b)-x^T(t-b)\theta(t-1)] \quad (3-18)$$

The gain vector K(t) and covariance matrix P(t) incorporating the forgetting factor remains the same as given in equatons (2-50) and (2-51).

In most practical processes, the noise is non - stationary, characterised by occasional step disturbance in changing feed rate or raw material variations. If the step disturbance occurs during the period when the parameters converge, the controller might have a difficulty to keep the process output at the set point. By incorporating the forgetting factor λ of non unity, the diffculty can be overcome. The minimum variance solution of the closed loop control can then be tested with the two theorems given by Åström in (3-8) and (3-9).

3.3 Application to Chip Refiner Control

3.3.1 OBJECTIVES

In the application of self tuning control, the process input u and output y are measured and used in parameter estimation and control law design. In chip refining, the measurement of the controlled output variable is not reaυily available owing to the limitation of continuous reliable on line sensor. Normally the freeness test is done every one to three hours by manual sampling through a blow line (refer to Fig (1.6). The sampling and testing time is long before the test results can be useful for controlling process. Industry often uses the specific energy measurement to infer the freeness. There is a relationship between freeness and specific energy, however the relationship depends on factors such as wood species, degree of chemical treatment, etc. Specific energy is defined by energy input divided by production rate and expressed for example as kw-hour/admt. Kw is direct reading from refiner motor as load is applied for closing the gap and production admt/hr is based on volumetric flow rate of chips and assuming a constant chip density. Chip density sensor is not available at the present time for continous measurement. Most mills use the screw speed control to regulate the production rate, based on the assumption that the chip density is constant.

The change of chip density through species and quality variations represents a stochastic disturbance to the process which the present control methods are not able to detech and correct.Morever, the parameters of the refining system is slowly changing which indicates that there is a need of using adaptive control method for controlling the process.

The objective of this section is to propose a Self Tuning Regulator for a closed loop control of freeness. The method is suitable for a single species of wood based on the constant inferential relationship of specific energy and freeness. The method is superior to present method in the way that the fluctuation of production rate in specific energy calculation is considered as a random noise and has been taken into account in the controller design.

3.3.2 CONTROL DESIGN

The following assumptions are made in the design of STR for the closed-loop control of freeness.

(1) The process parameters are slowly time varying due to the slow wear of refiner plate in the course of refiner operations.

(2) The refiner is equipped with gap measurement sensor. The existing refiner gap controller for plate protection logics remains unchanged.

(3) The refiner is assumed to operate above the gap region where pulp pad collapse is avoided.

(4) The relationship between freeness and specific energy is linear within the operating range under study in this thesis.

The refining process is simulated using the following stochastic input output models.

(i) For White Noise Input

The model is given as

$$y(t)=a_1y(t-1)+b_1u(t-1)+b_2u(t-2)+e(t) \qquad (3\text{-}19)$$

where e(t) is Gaussian white noise sequence N(0,σ), y(t) is the process output and u(t) is the input.

(ii) For Exponential Disturbance Input

The model is given as

$$y(t)=a_1y(t-1)+b_1u(t-1)+b_2u(t-2)+N(t) \qquad (3\text{-}20)$$

where N(t) is exponential disturbance defined by

$$N(t)=0.5N(t-1) + e(t) \qquad (3\text{-}21)$$

and e(t) is Gaussian white sequence N(0,σ).

The implicit self tuning control for the chip refining process relating specific energy and refiner gap can be modelled as ARMAX model [19] for 1st order system with the following conditions, n=1, k=L/h+1=2. Process model in prediction form is obtained from equation (3-1) as

$$y(t+3)+\alpha_1y(t)=\beta_0[u(t)-\beta_1u(t-1)+\beta_2u(t-2)]+\varepsilon(t+3)$$

(3-22)

Introducing the following vectors.

$$\theta = [\alpha_1 , \beta_1 , \beta_2]^T \tag{3-23}$$

$$x = [-y(t), \beta_0 u(t-1), \beta_0 u(t-2)] \tag{3-24}$$

The minimum variance control law is obtained for $\varepsilon(t)$ assumed as white Gaussian noise as:

$$u(t) = -\frac{1}{\beta_0} x(t)\theta \tag{3-25}$$

The parameters (α_1, β_1, β_2) can be estimated using RLS algorithm given in equation (3-6),(2-42) and (2-43). For eliminating the steady state offset, the STR with integral action is used, and the parameters are estimated using equations (3-17), (3-18), (2-50) and (2-51). The structure of implicit self tuning regulator for controlling specific energy is shown in Figure (3.2). The process plant operates with a gap sensor for maintaining a gap based on the set point entered by the operator. The plate adjustment is carried out using stepping motor installed in the refiner. The local gap controller controls the plate gap within the dead band based on pulse modulator signal generated from the controller. The operation of existing controller is assumed unchanged and is considered.

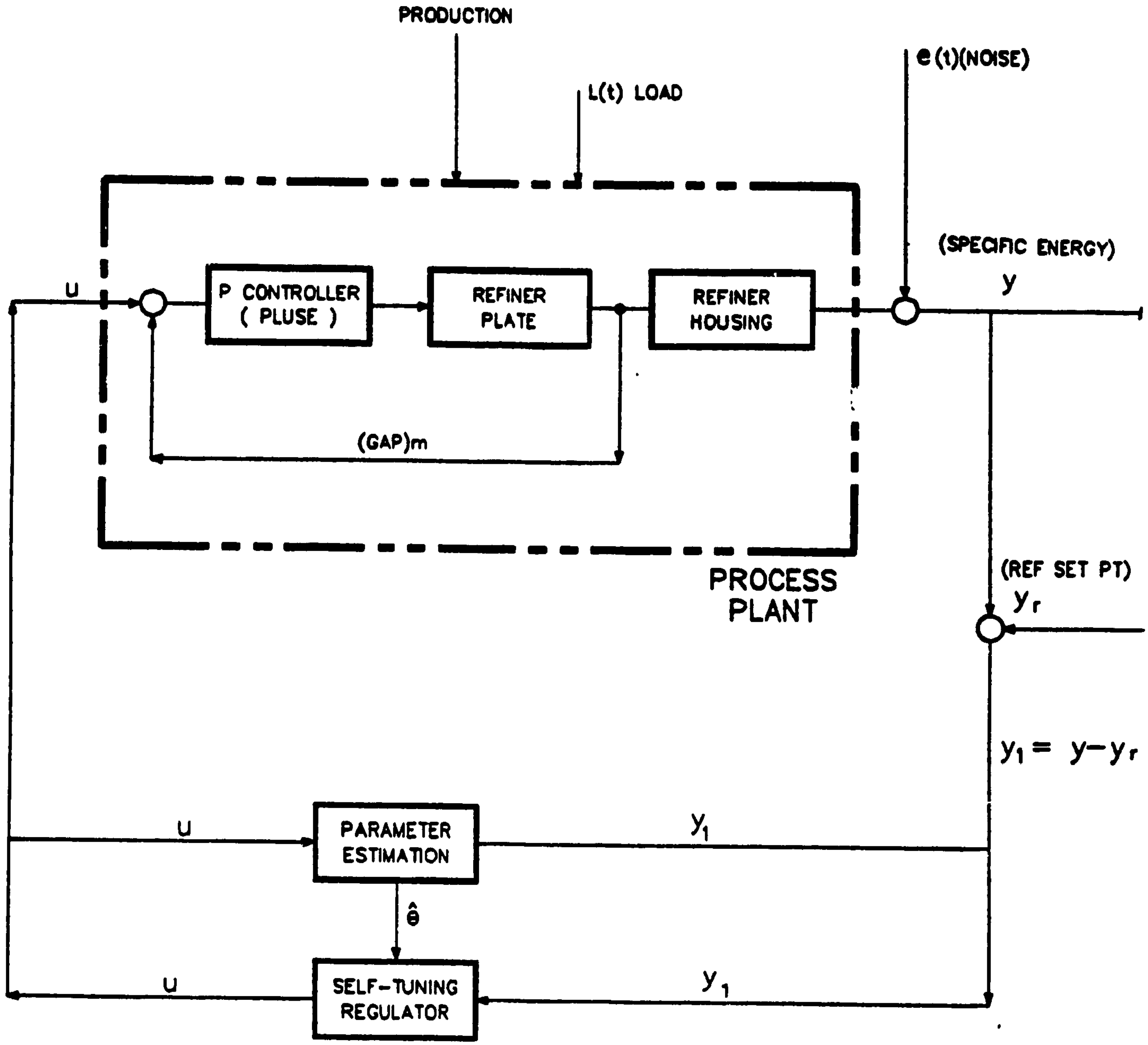


Figure 3.2 Constant Inferential Control Strategy using Implicit Self Tuning Regulator

as part of the process plant.

The proposed STR is based on constant relationship between specific energy and freeness. Specific energy is used for parameter estimation. For STR with integral action, Δy and Δu are used in the parameter estimation.

3.4 Simulation

The simulation of implicit self tuning control is carried out to provide a closed-loop control of the refining process which exhibits time invariant as well as time variant parameters. Under a limited conditions, for example for a new set of refiner plates, the refining process can be considered as time invariant system. As the plates begin to wear, the parameters change. Hence, the process gain decays exponentially.

Closed-loop simulation for set point change and load disturbance are carried out. Comparison of results are given based on white noise as well as filtered white noise in the process model.

<u>Example 3-1 Time Invariant System,Optimal Control</u>

Closed-loop simulation using implicit STR structure shown in Fig 3.2 is considered. White noise is assumed in the process plant which is simulated as time invariant system as below.

$$y(kh) = 0.651y(kh-h) - 0.153u(kh-h) + 0.424u(kh-2h) + e(kh) \quad (3\text{-}26)$$

where e(kh) is white Gaussian noise. The forgetting factor, $\lambda = 1.0$ and $\beta_0 = 1$ are used in the simulation. Figures 3.3 and 3.4 show the closed loop control action and output. The parameter estimation tends to converge asymptotically after 200 iterations as shown in Fig 3-5. Minimum variance control is obtained as shown in the autocorrelation plot given in Fig 3-6. The entire data set of controlled output is used in calculating the autocorrelation function. Fig 3.7 shows the control signal and output when control signal is limited to $|u| = 8.0$ at sampling interval 150. The parameter estimation is given in Fig 3.8. It is noted that limiting the control signal has improved the transient behavior of self tuning regulator as shown in the parameter estimation plot. Wittenmark [36] states that the control signal can be limited for smooth start-up of the regulation. However if control signal is limited too hard it is diffcult to obtain good parameter estimation if the system is unstable.

Example 3-2 STR with Integral Action,Set Point Change

The refining process used in the simulation is represented by the following time invariant system.

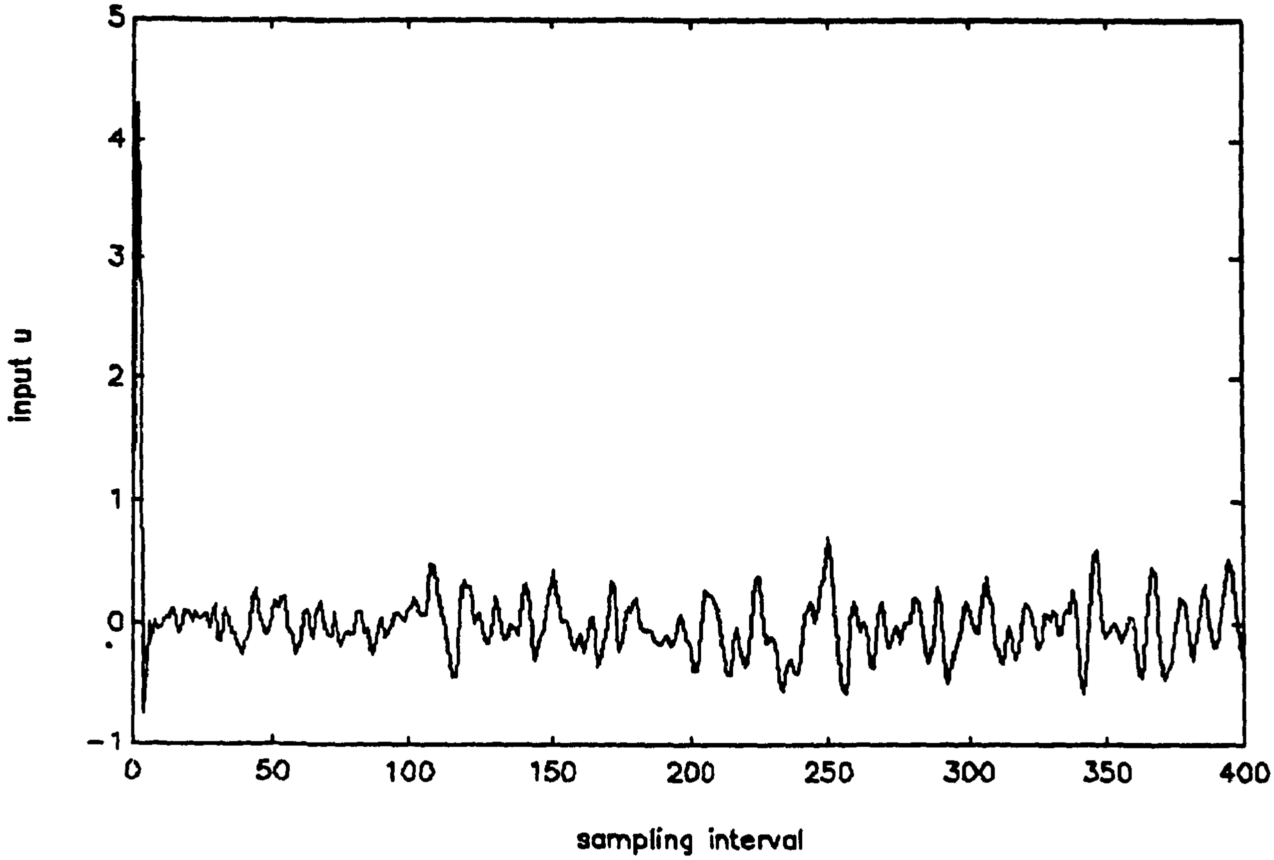


Figure 3.3 Control Action of Time Invariant System for Closed-Loop Simulation

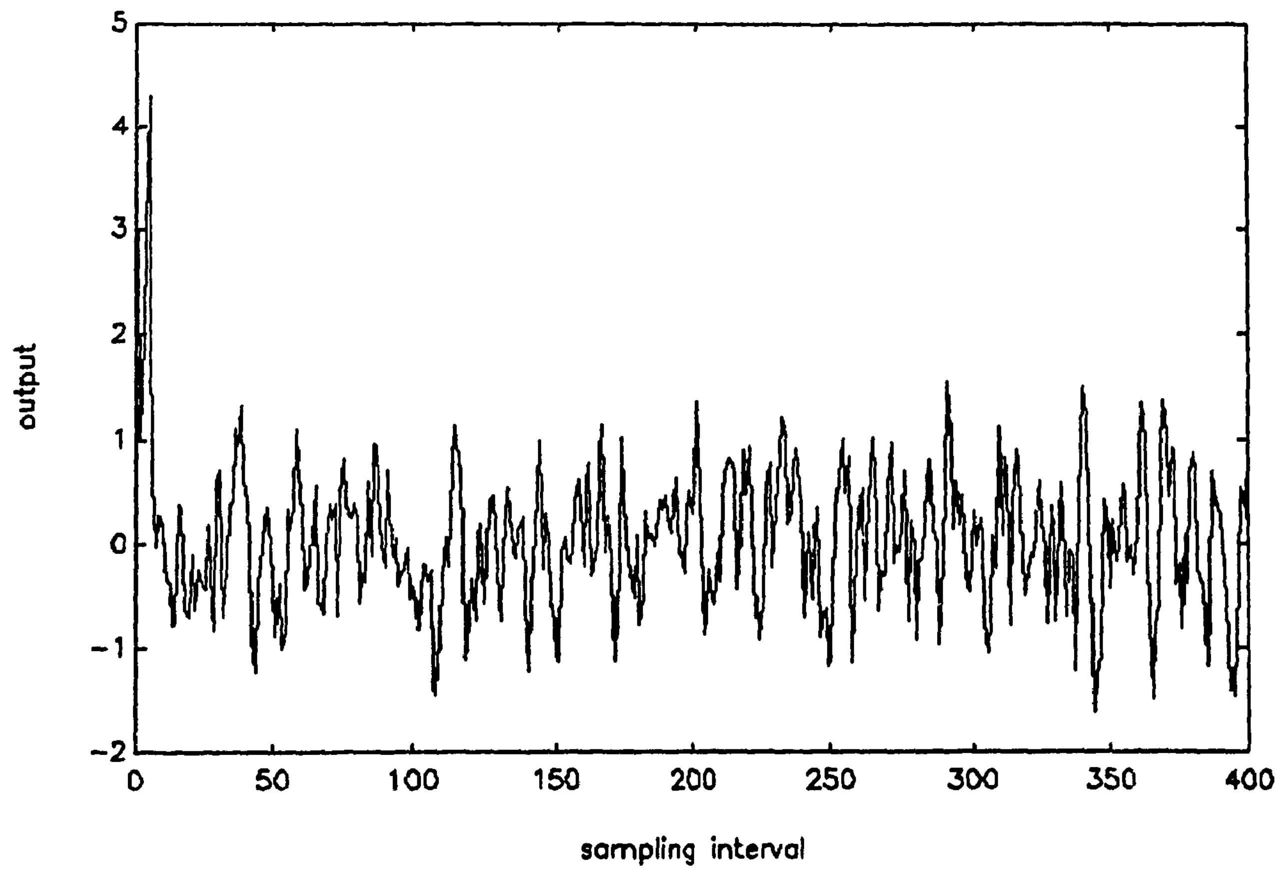


Figure 3.4 Output of Time Invariant System for Closed Loop Simulation

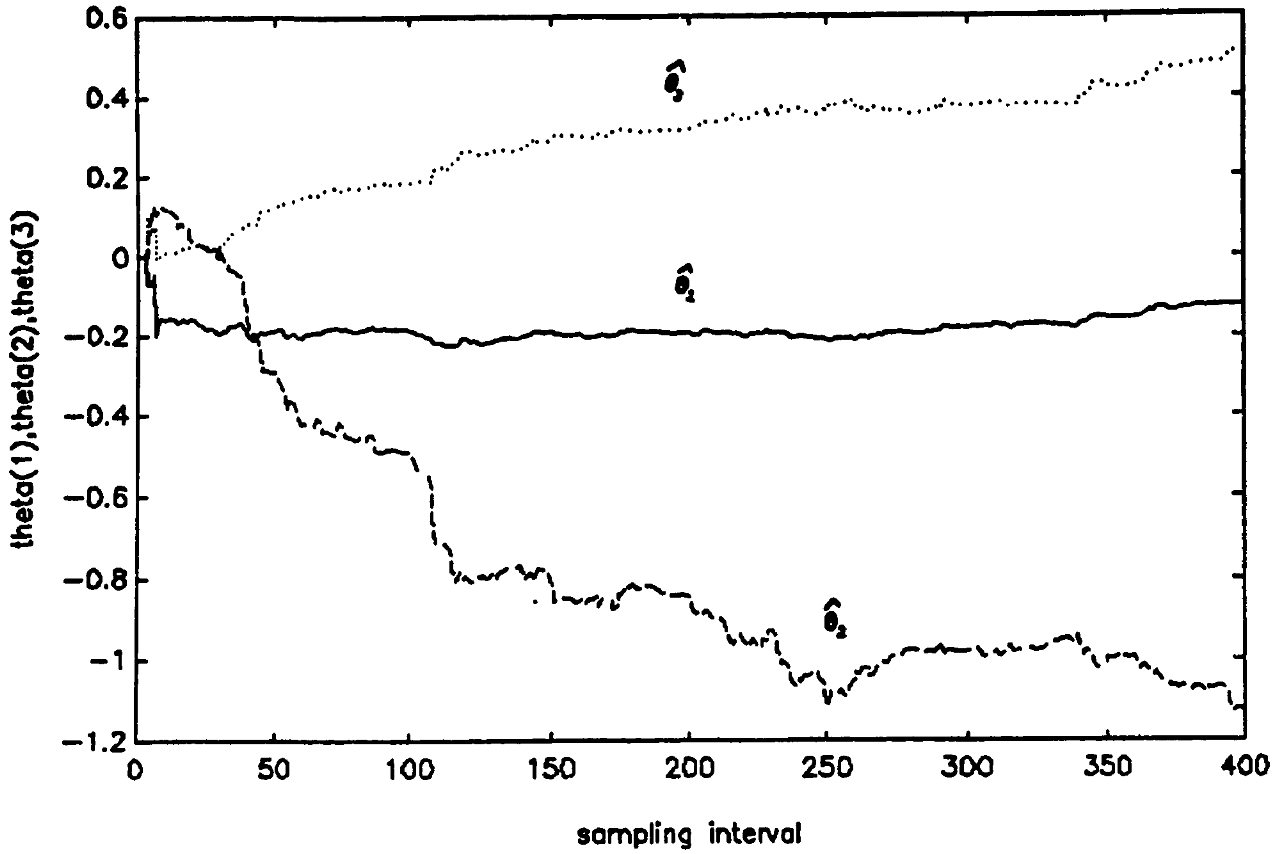


Figure 3.5 Closed-Loop Parameters Estimation of Time Invariant System

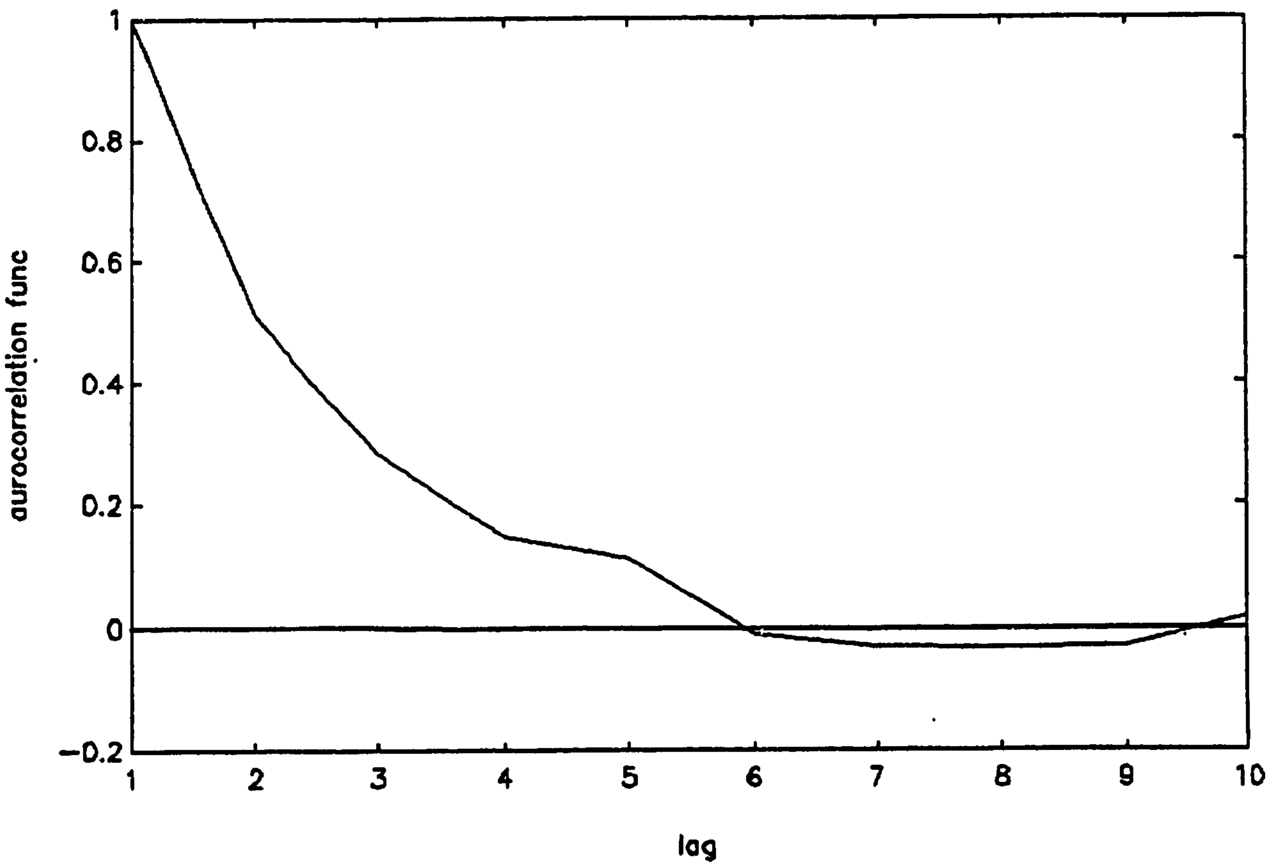
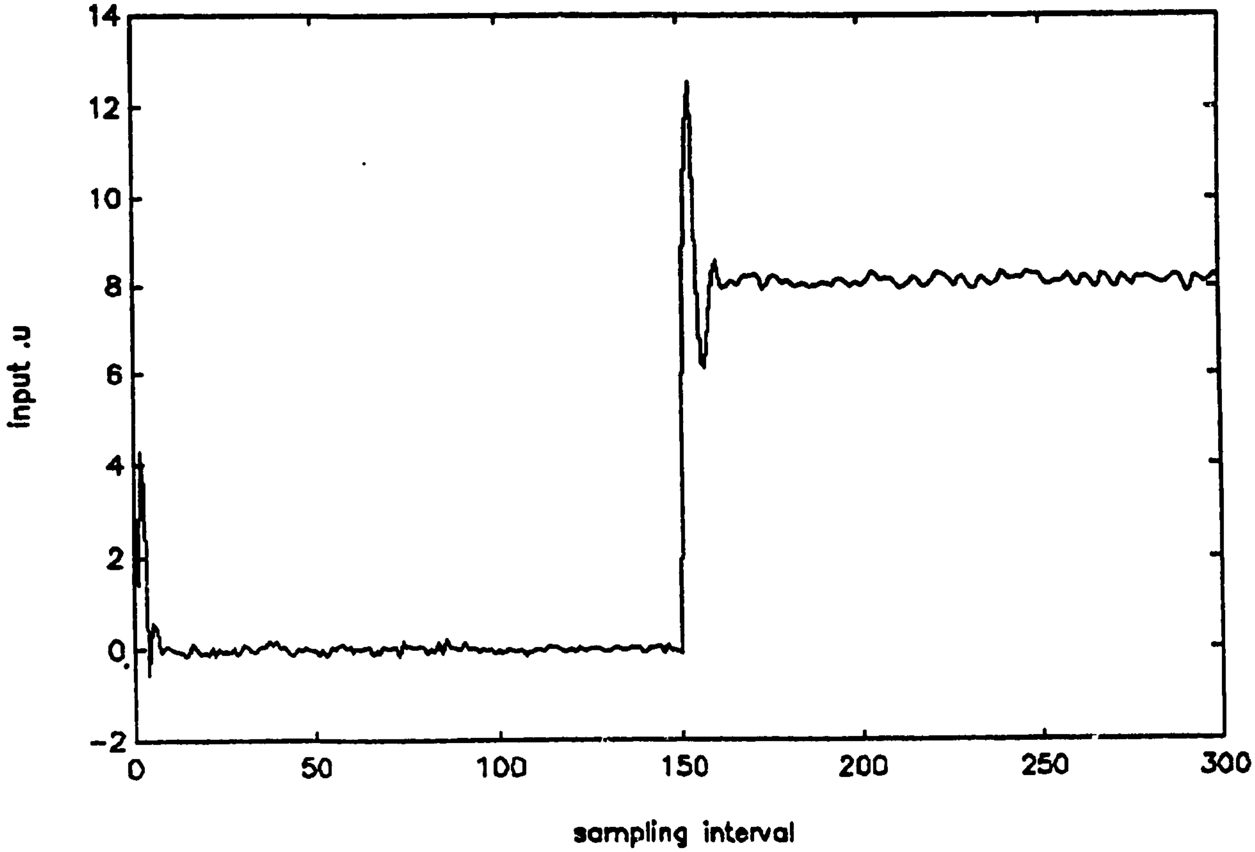


Figure 3.6 Autocorrelation Plot of Output of Closed-Loop Control for Time Invariant System



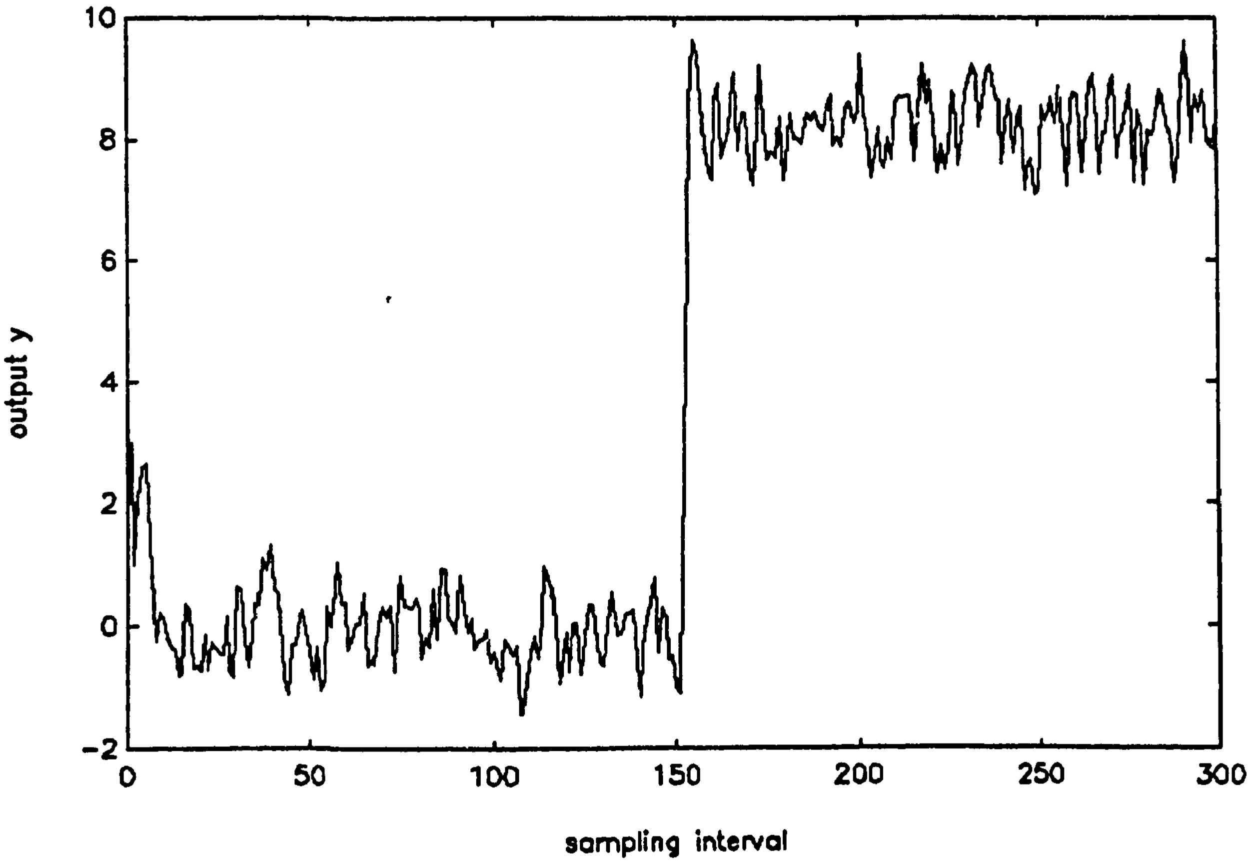


Figure 3.7 Control Signal (u) and Output (y) of Time Invariant System when Control Signal is Limited to $|u|=8$ at sampling interval of 150

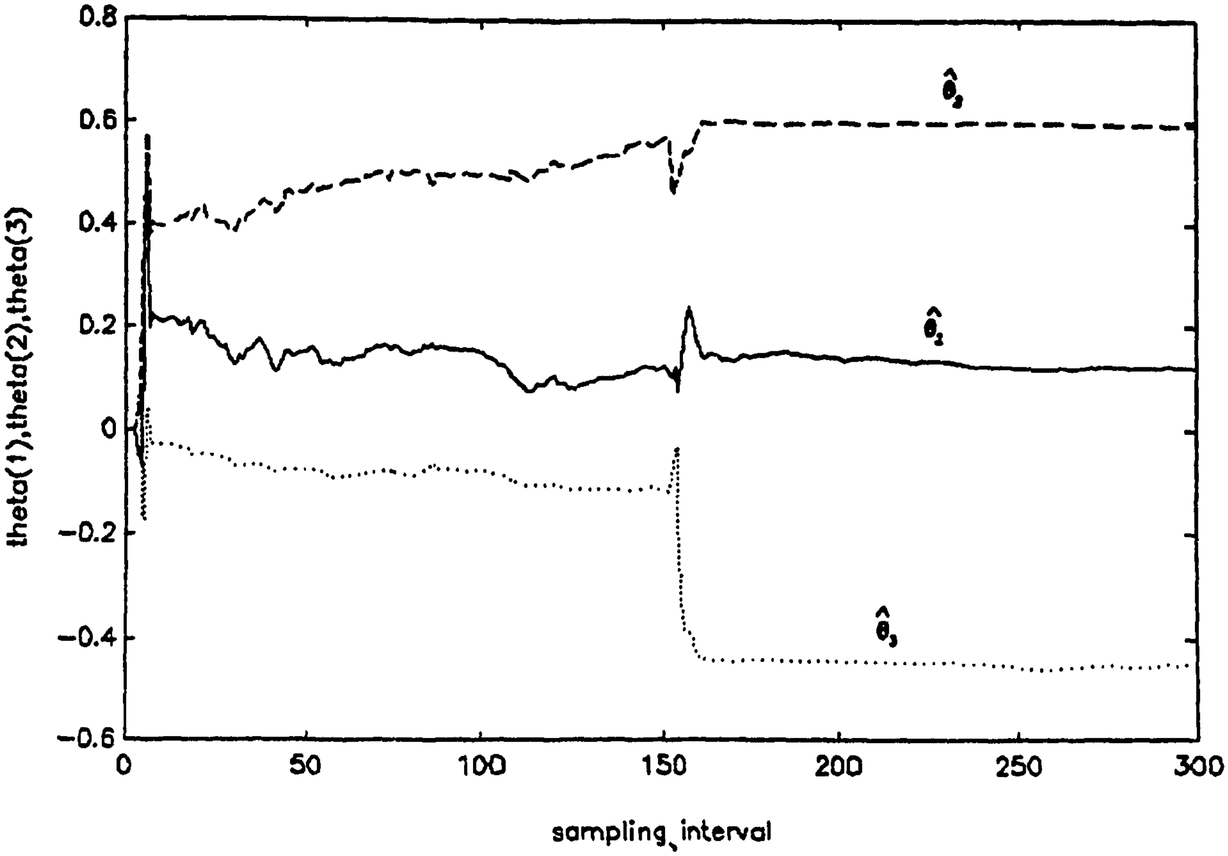


Figure 3.8 Parameters Estimation of Time Invariant System with Limitation of Control Signal for $|u| = 8$.

$$y(t) = 0.535y(t-h) + 0.117u(t-h) + 0.347u(t-2h) + N(t)$$

(3-26)

where sampling interval h=5 sec, time delay L=4 sec and time constant T_1=8 sec are used. N(t), the stochastic disturbance is modelled as exponential type random walk given below.

$$N(t) = \frac{e(t)}{1-0.5q^{-1}} \qquad (3\text{-}27)$$

e(t) is white Gaussian zero mean sequence with constant variance N(0,σ). The parameter estimation structure for self tuning regulator is based on Fig 3.2. The optimal control for eliminating the offset for set point change is provided by using Δu,Δy in the ARIMA model as given in equation (3-13) and also in RLS algorithm for parameter estimation. The initial conditions for RLS algorithm were P(0)=100 I, θ(0)=0, λ=0.98, β_0=1. The control signal Δu and output y are shown in Fig 3-9. The response of the output to set point change is shown in Fig 3-10. The STR with integral action used in the control is based on equation 3-12. The integral action assures the eliminating of offset. Minimum variance control will be obtained after the parameters converge as shown in in Figure 3.11, entire data is used to compute autocorrelation function. The parameters estimation are shown in Figure 3.12.

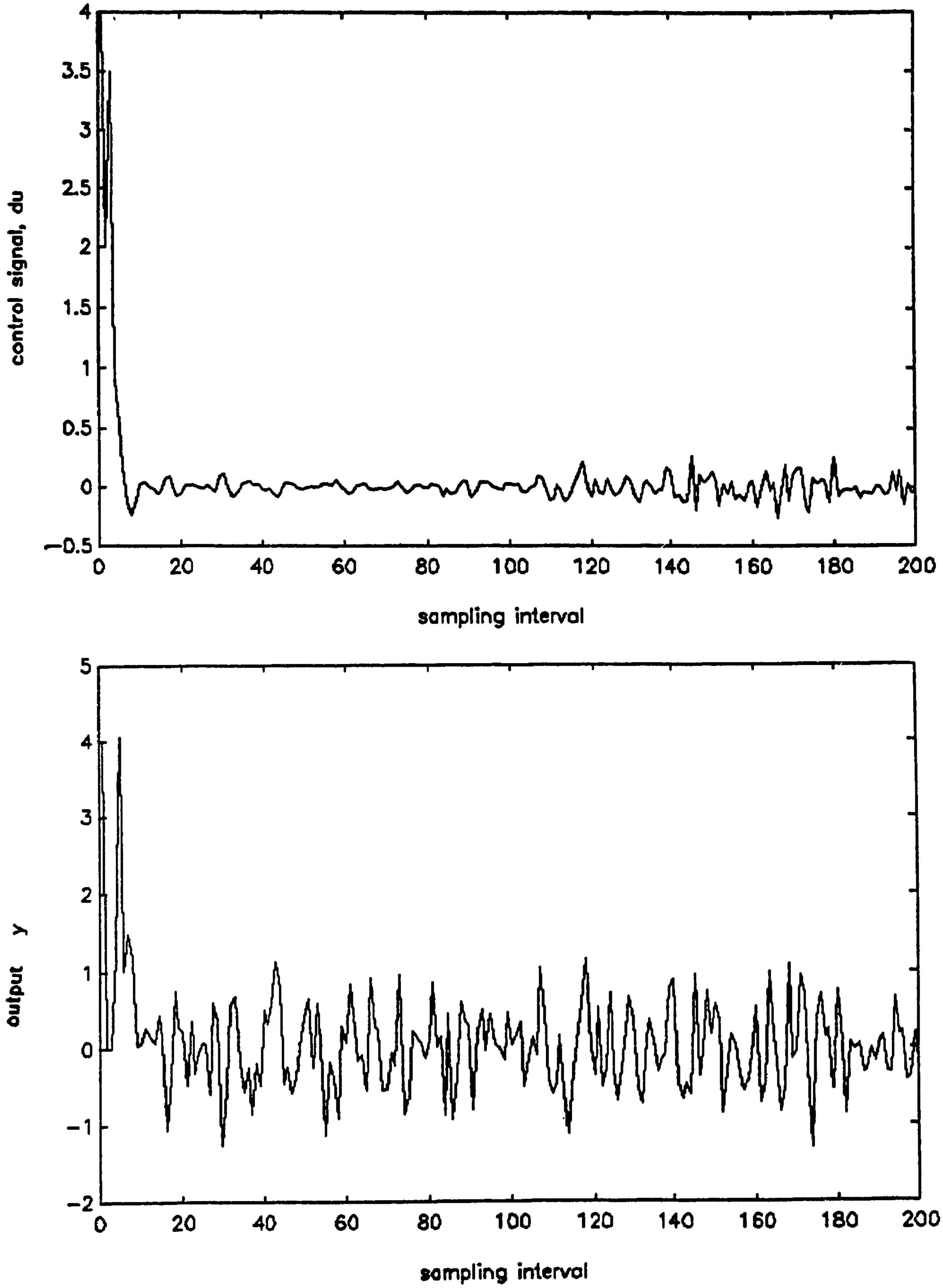


Figure 3.9 **Control Signal and Output for Time Invariant System using Exponential Disturbance in the Model.**

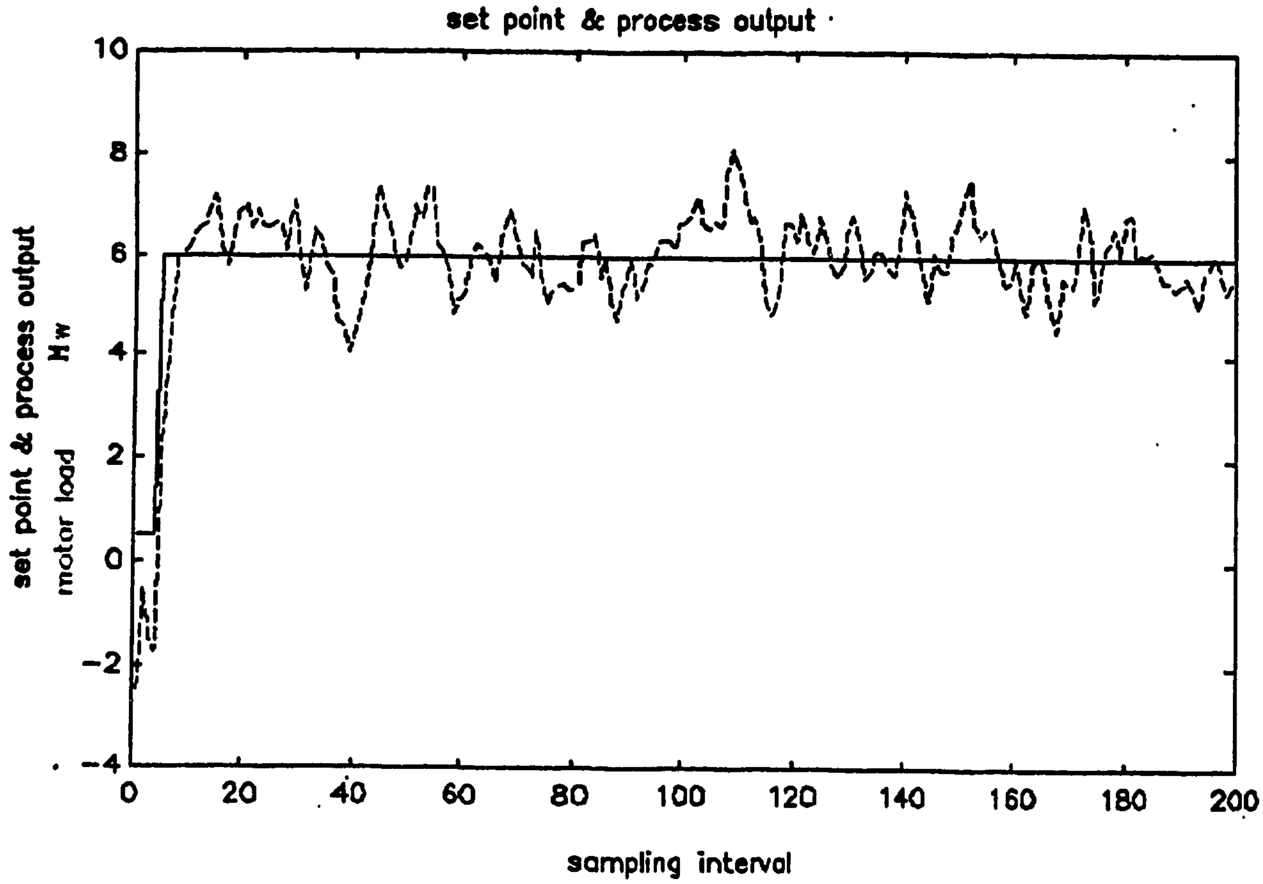


Figure 3.10 Set Point and Output for Example 3-2.

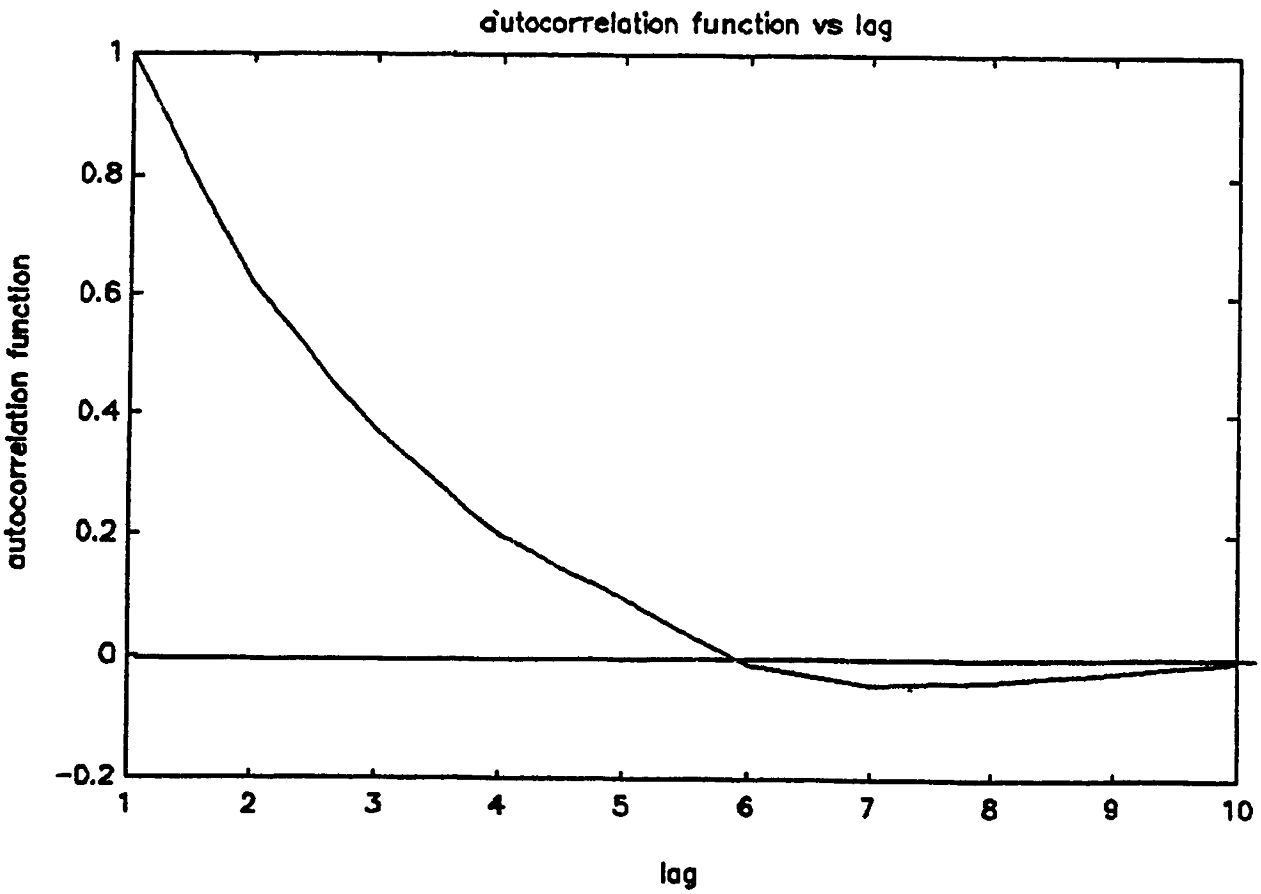


Figure 3.11 Autocorrelation plot of output for Example 3-2.

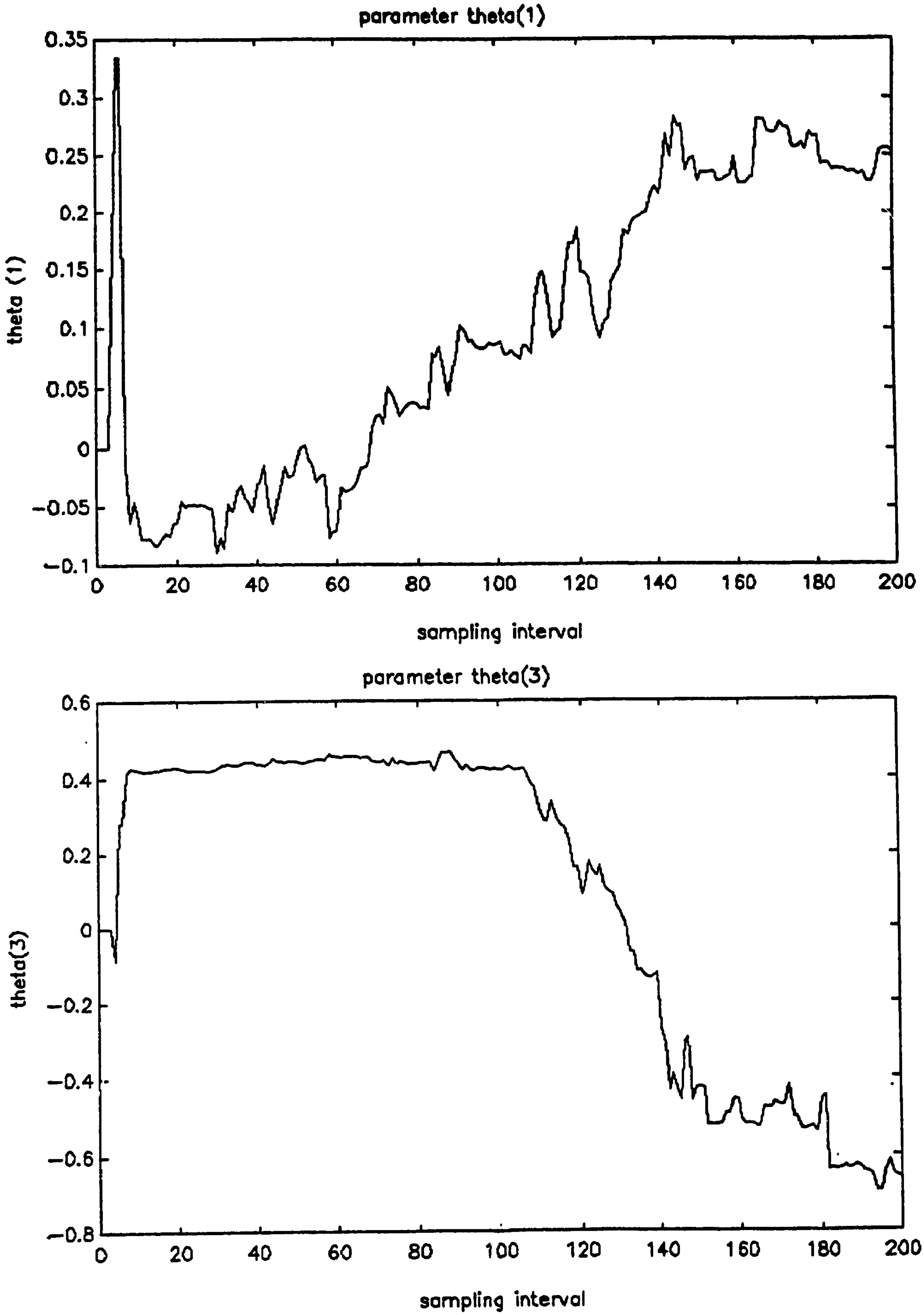


Figure 3.12 Parameters Estimation for Examaple 3-2.

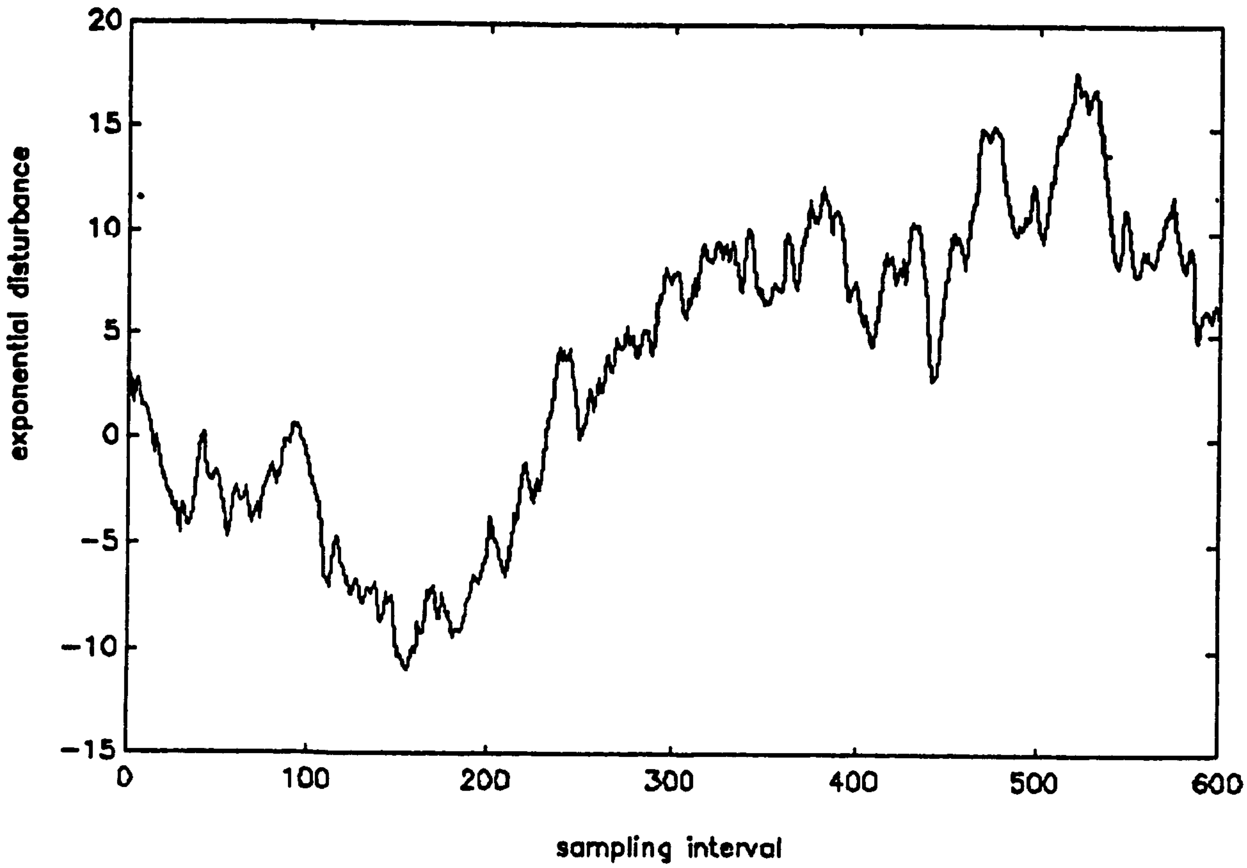


Figure 3.13 **Stochastic Disturbance**
$\Delta N(t)=0.5\Delta N(t-1) + e(t)$ used in Example 3-3

Example 3-3 STR Without Integral Action

The following stochastic disturbance is considered as shown in Figure 3.13.

$$\Delta N(t) = 0.5\Delta N(t-1) + e(t) \qquad (3\text{-}28)$$

where Δ is defined as $(1-q^{-1})$ and e(t) is Gaussian white noise. The refining system is simulated with time invariant system using the process conditions as follow, sampling interval h=5 sec, process delay L=4 sec, time constant t_1=7 and stochastic disturbance $\Delta N(t)$. The parameter estimation algorithm is initialised with P(0)=100I, $\theta(0)=0$, $\lambda=0.98$, $\beta_0=1$. Δu and Δy are not used in the RLS algorithm as no integral action is included in the STR control law. The simulation for the close loop set point change gives non optimal control as shown in the autocorrelation plot in Fig 3.14, the accumulated loss Σy^2 plot is given in Fig 3.15. Figures 3.16 and 3.17 show the response of output and input to set point change.

Example 3-4 Sub-Optimal Control for Pulp Freeness

The estimation structure of STR showm in Fig 3.2 was used to simulate the time variant system of chip refiner running at constant production. The following conditions are used in the simulation.

Sampling interval 5 sec, initial process gain =0.97, time constant for plate life =1000 hrs, production rate is

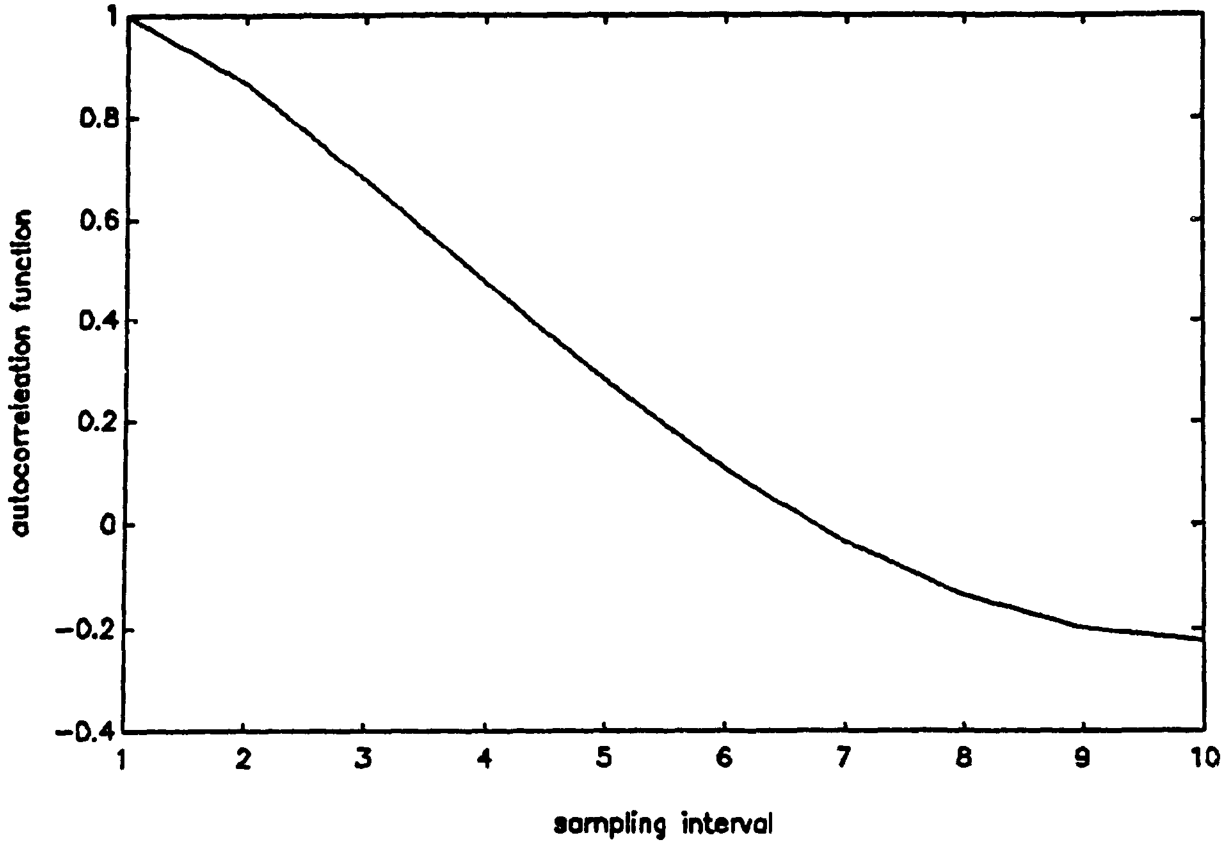


Figure 3.14 Autocorrelation plot of output for Example 3-3.

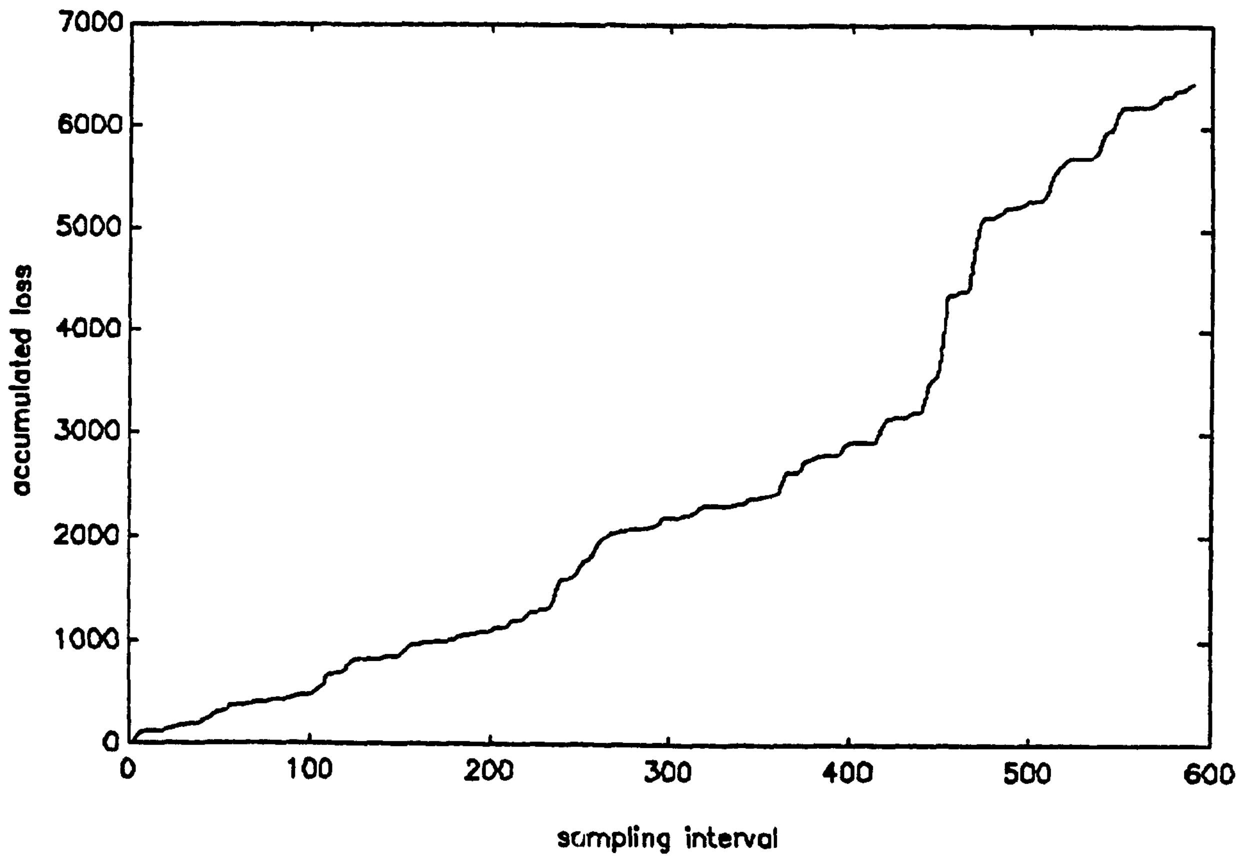


Figure 3.15 Accumulated Loss of STR Control Without Integral Action

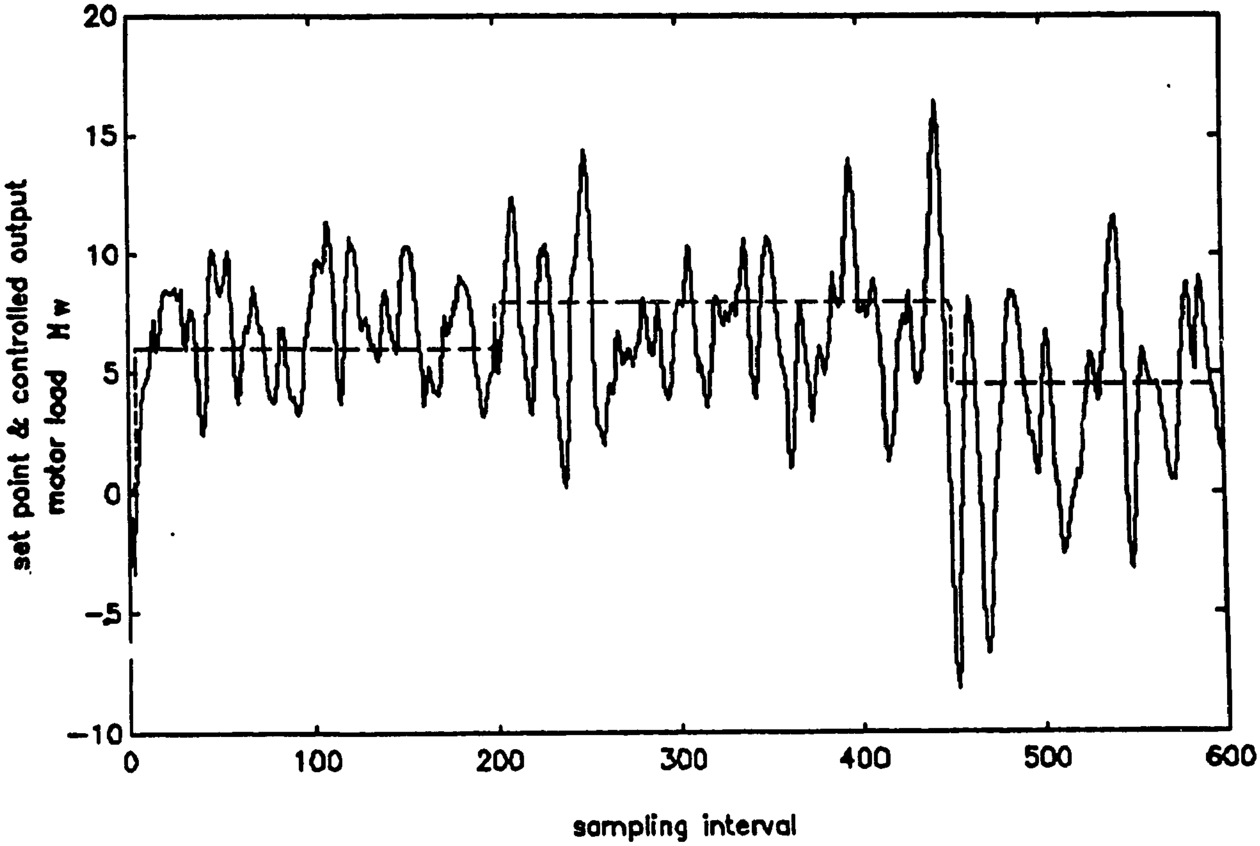


Figure 3.16 Set point vs Output for Example 3-3

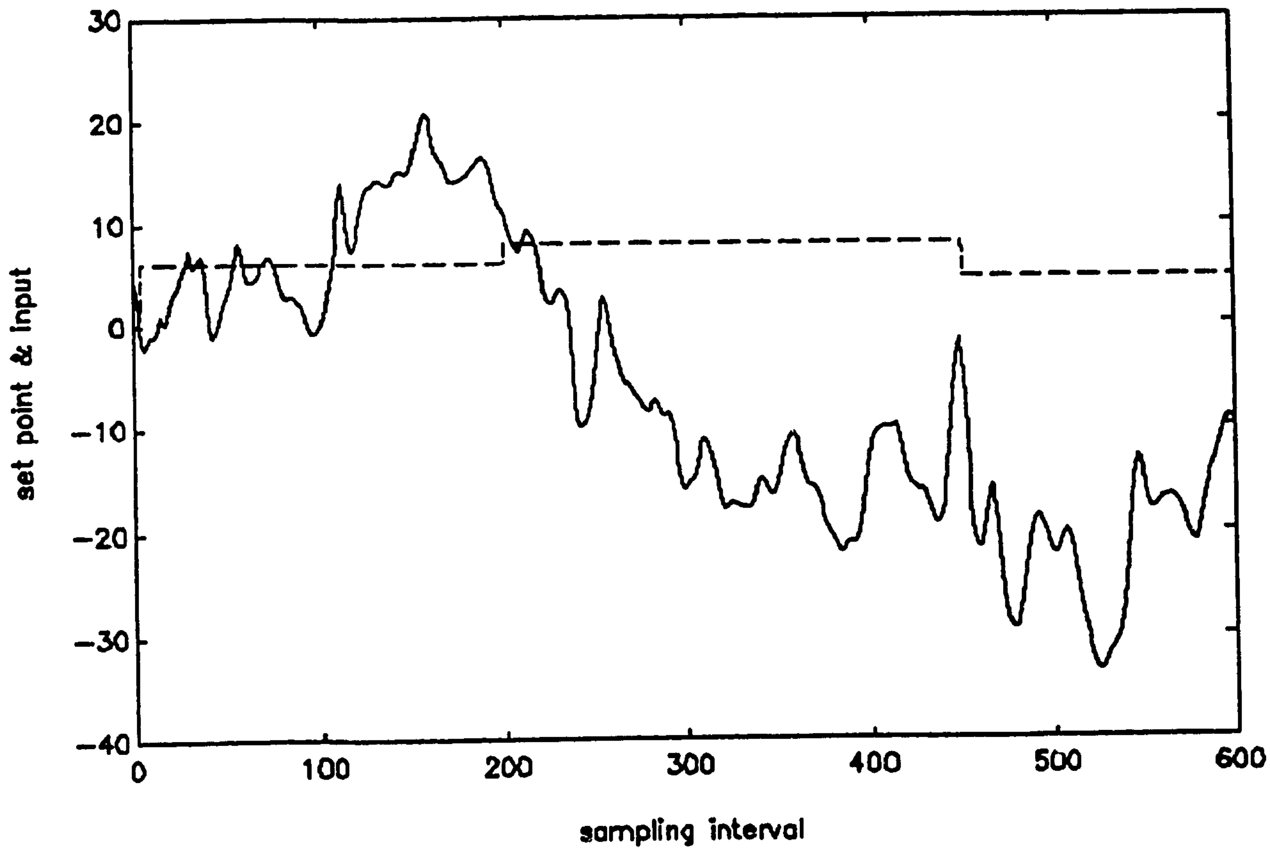


Figure 3.17 Set point vs Input for Example 3-3

80 admt/day. The refiner is assumed to operate using a constant wood species where the constant inferential or relationship between the freeness and specific energy is known. The stochastic disturbance is modelled with exponential disturbance as $N(t)=e(t)/(1-q^{-1})$. The refining system used in the simulation is represented by the following equation.

$$y(kh)=a_1y(kh-h)+b_1(t)u(kh-h)+b_2(t)u(kh-2h)+N(t)$$

$b_1(t),b_2(t)$ are time variant expressed in equation (2-38), (2-39), (2-40); y(kh) is a specific energy, the STR is designed with integral action with the initial conditions used in the parameter estimation algorithm, $b_0=1$, $\lambda=0.98$, $P(0)=100I$, $\theta(0)=0$. A set point change in specific energy is introduced and the response follows closely to the set point as shown in Fig 3.18. The controlled output, freeness in response to step change is given in Figure 3.19. The autocorrelation and cross correlation function are computed using entire data set of freeness as output and control signal du as input. Sub-optimal control is obtained as shown in the two plots given in Figure 3.20. Response of specific energy to gap change is given in Fig 3.21.The control signal du and change of y, the specific energy is given in Fig 3.22. The forgetting factor $\lambda=0.98$ is used in the RLS algorithm to track the slowly changing parameters shown in Figure 3.23.

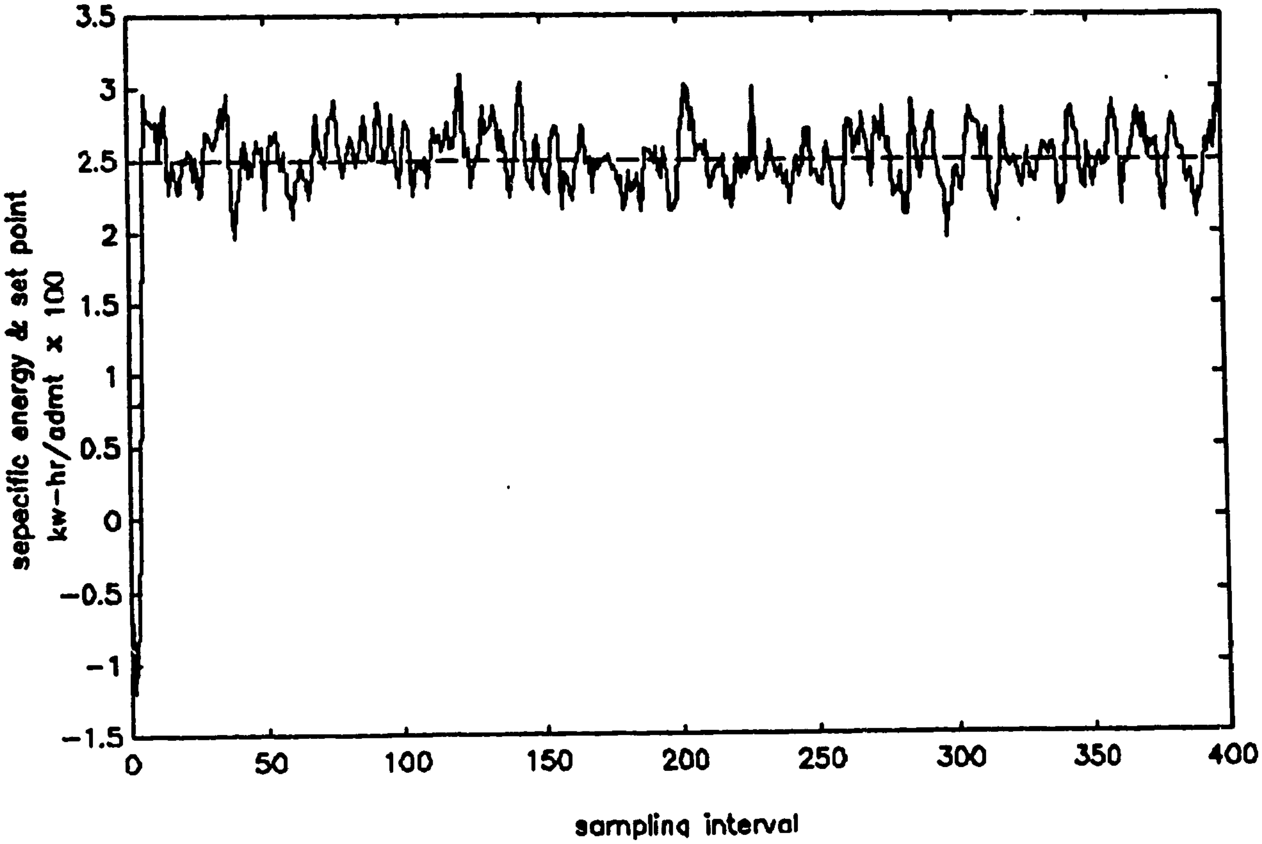


Figure 3.18 Set Point Change of Specific Energy for Example 3.4

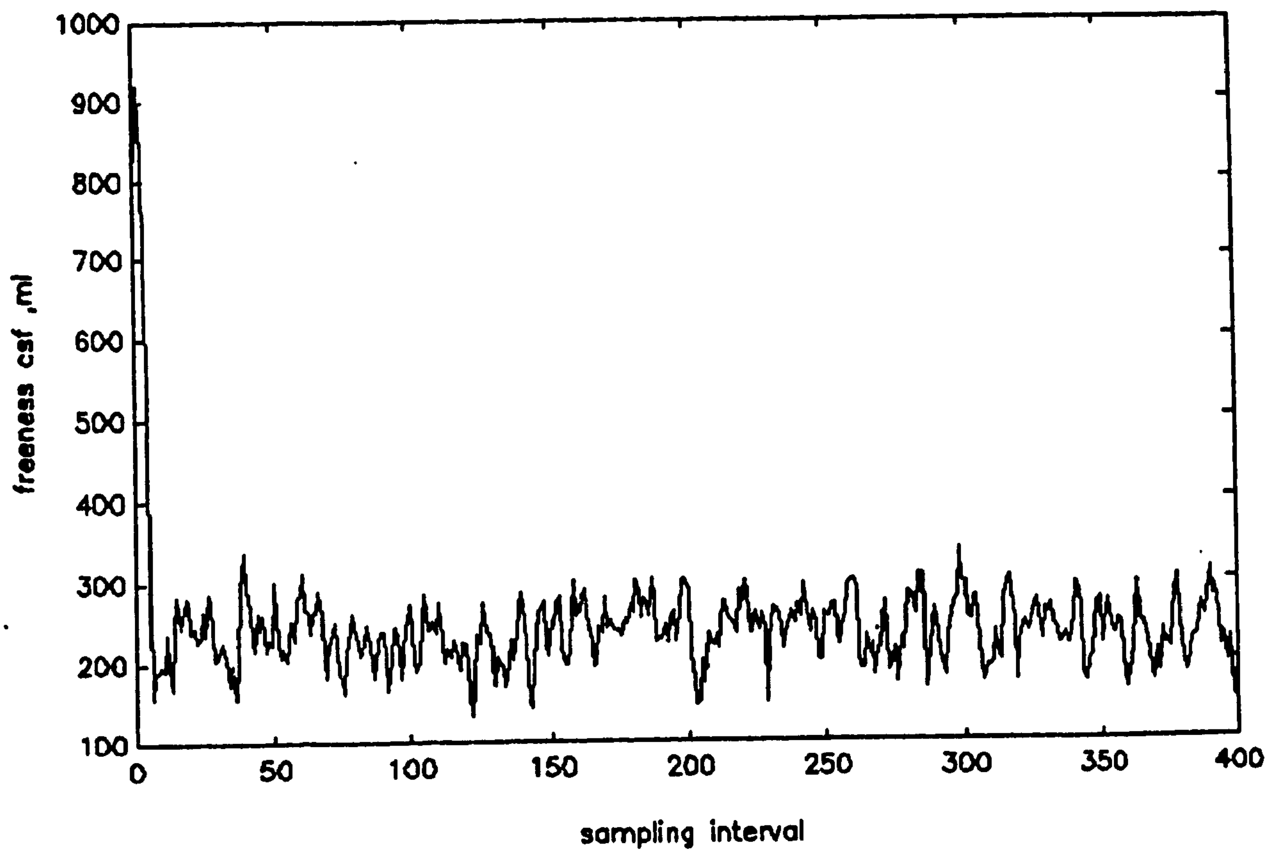


Figure 3.19 The Controlled Output, Freeness to Set Point Change in Specific Energy in Example 3-4.

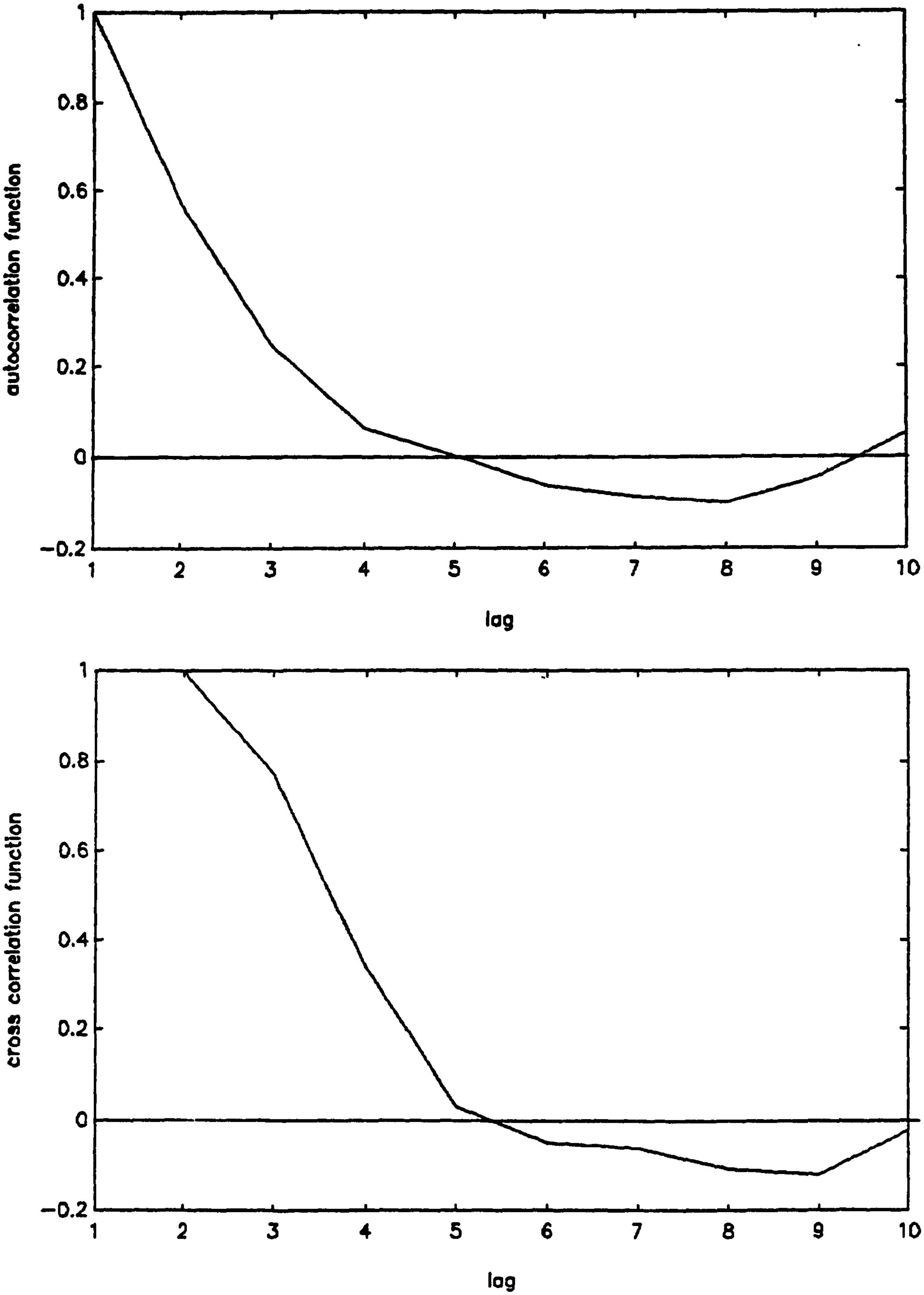


Figure 3.20 Autocorrelation and Cross-correlation Plot vs Lag for Sub-optimal Control in Example 3-4.

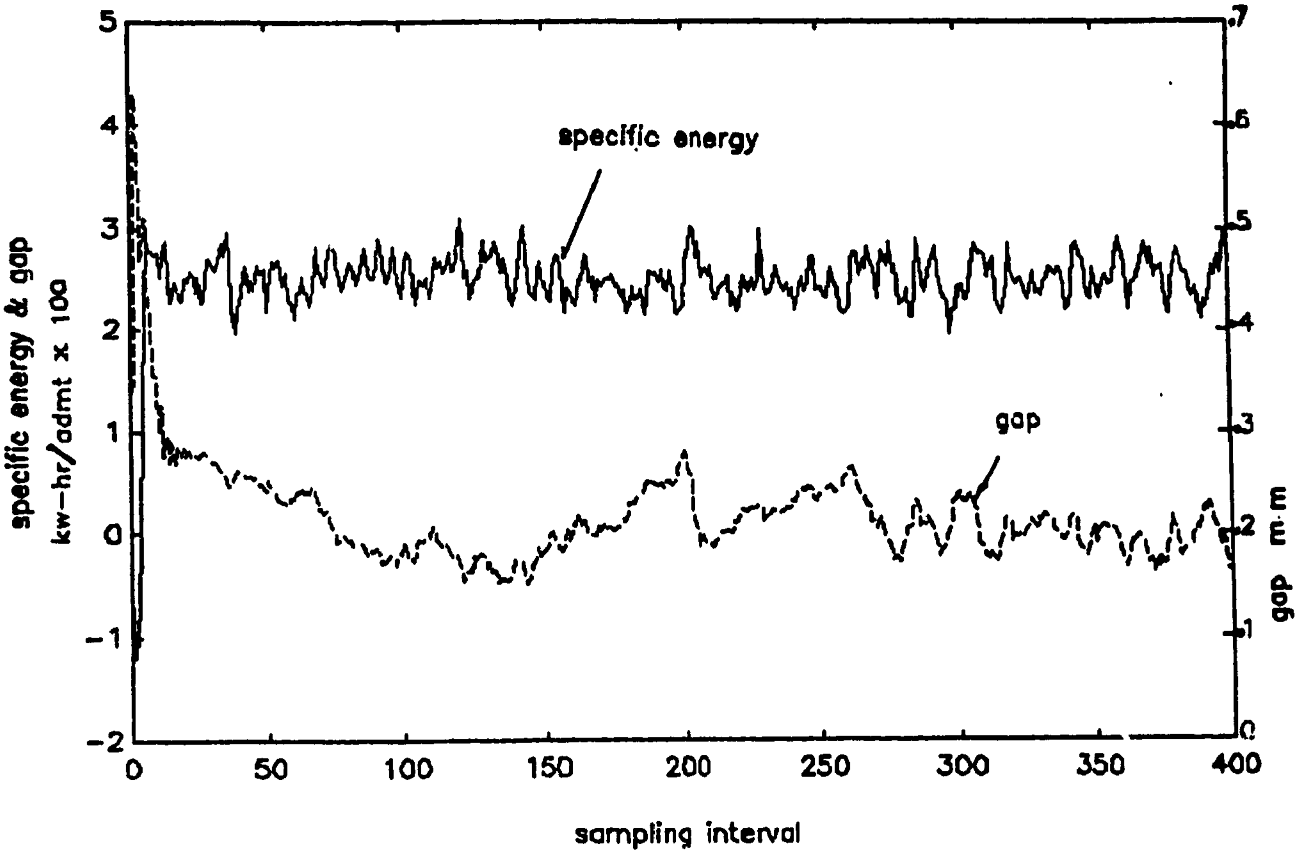


Figure 3.21 Response of Specific Energy to Gap in Closed-Loop System in Example 3-4

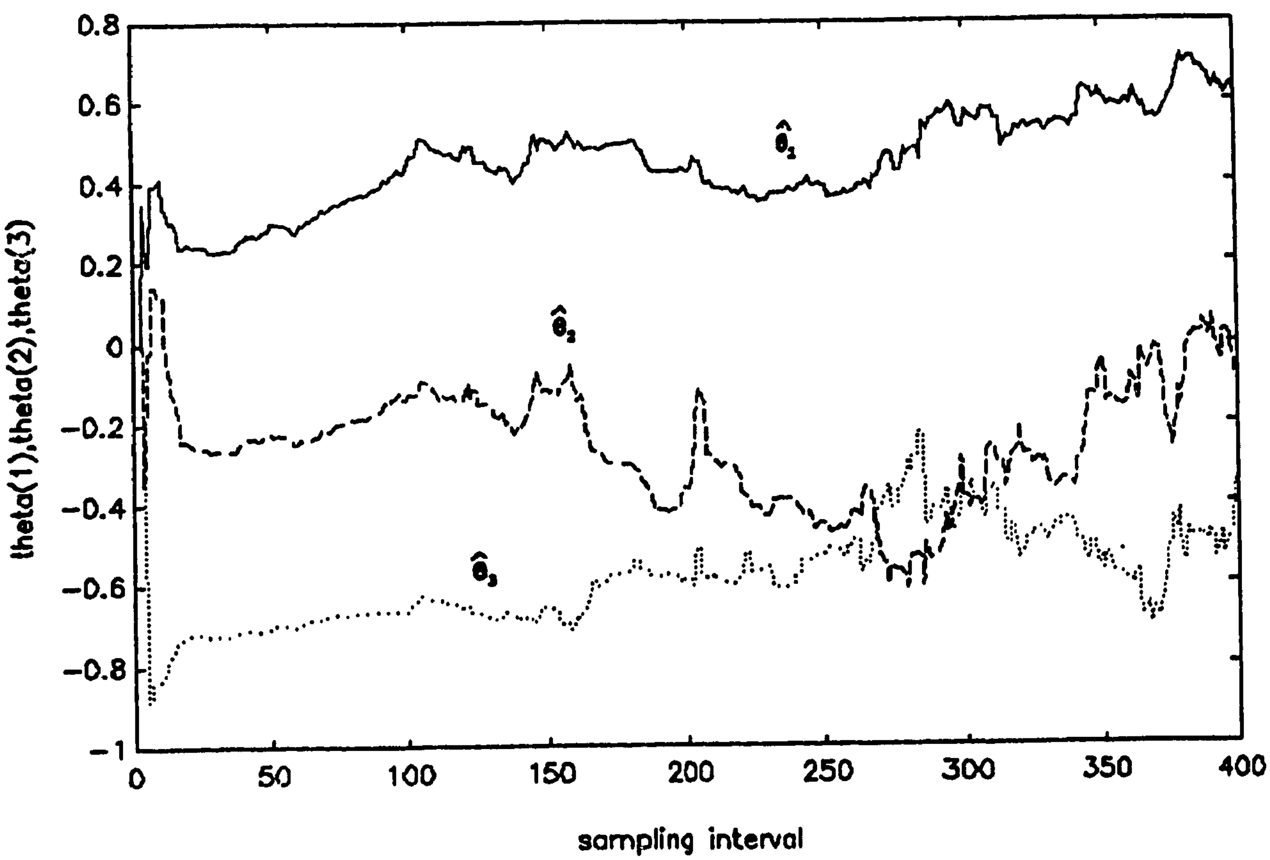


Figure 3.23 Parameter Estimation for Time Variant System for Example 3-4 ,λ=0.98 is used.

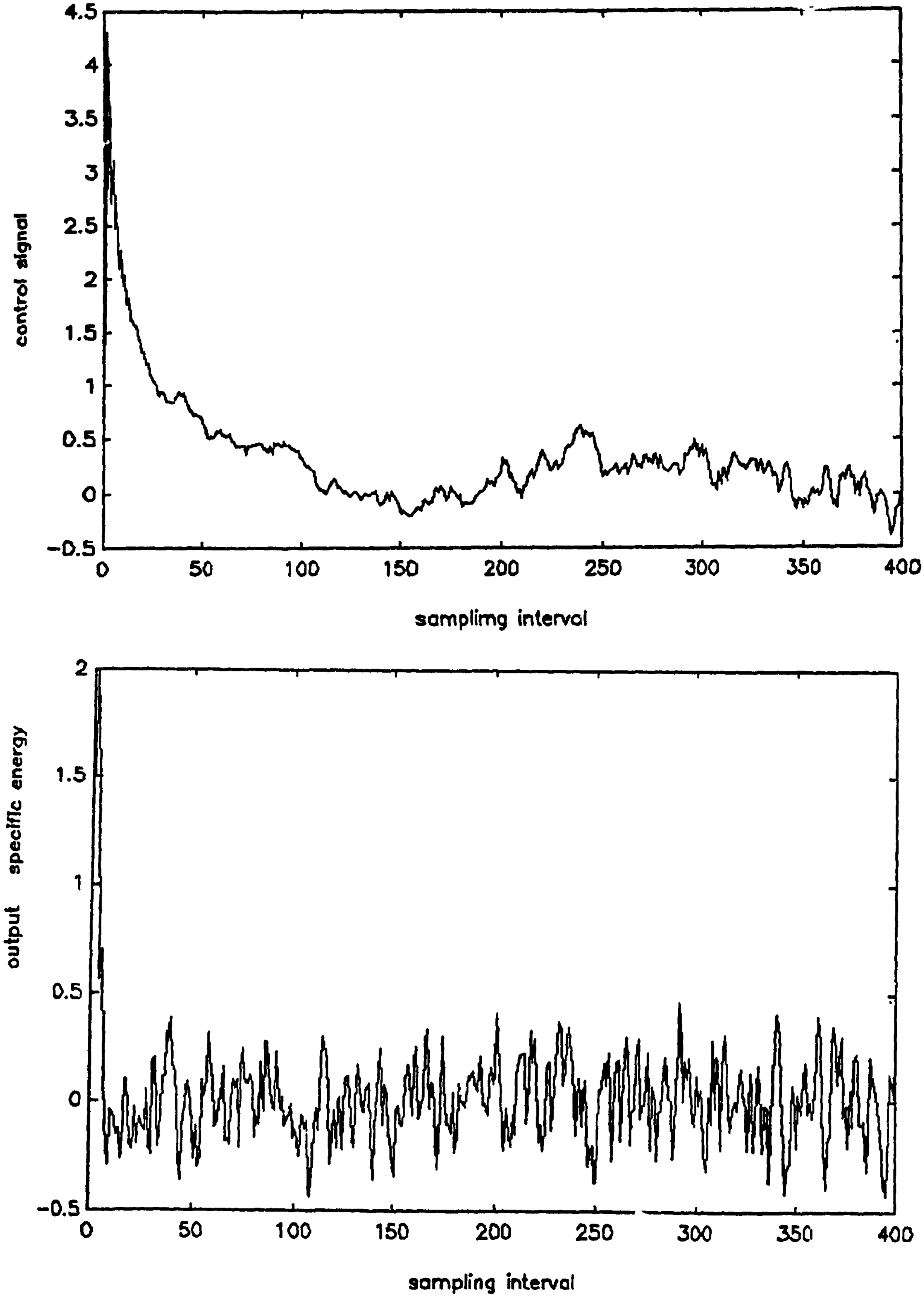


Figure 3.22 Control Signal and Specific Energy Output for Example 3-4

Example 3-5 STR Control Without Integral Action for Motor Load

Closed loop set point control for motor load is simulated for the time variant refining process using the conditions as h=3 sec, L=4 sec, T_1=7sec, the initial process gain k_p=1.0. The noise structure in the system is assumed exponential disturbance $N(t)=e(t)/(1-q^{-1})$. The initial conditions for RLS algorithm are $\beta_0=1$, $P(0)=100\ I$, $\theta(0)=0$, and $\lambda=0.98$, no integral action is provided in the STR control design. Response of output to set point is given in Figures 3.24. The autocorrelation and cross-correlation plot in Fig 3.25 indicate that the closed-loop control is not optimal. The accumulated loss given in Figure 3.26 indicates the loss is greater than the case for optimal control. Parameter estimation is carried out using forgetting factor of $\lambda=0.98$ given in Fig 3.27 which indicates that the parameters are noisy during the adaptation process.

Example 3-6 STR with Integral Action for Load Change

Consider the time varying refining process with the following conditions; h=5 sec , L=3 sec, $k_p(0)=0.97$, T_1=7,sec refining plate life is 1000 hrs.First order disturbance noise is assumed acting on the system. Simulation of closed-loop control of specific energy is carried out for load change. Load change is caused by the production upset, chip density fluctuation which occurs in the cause of operations.

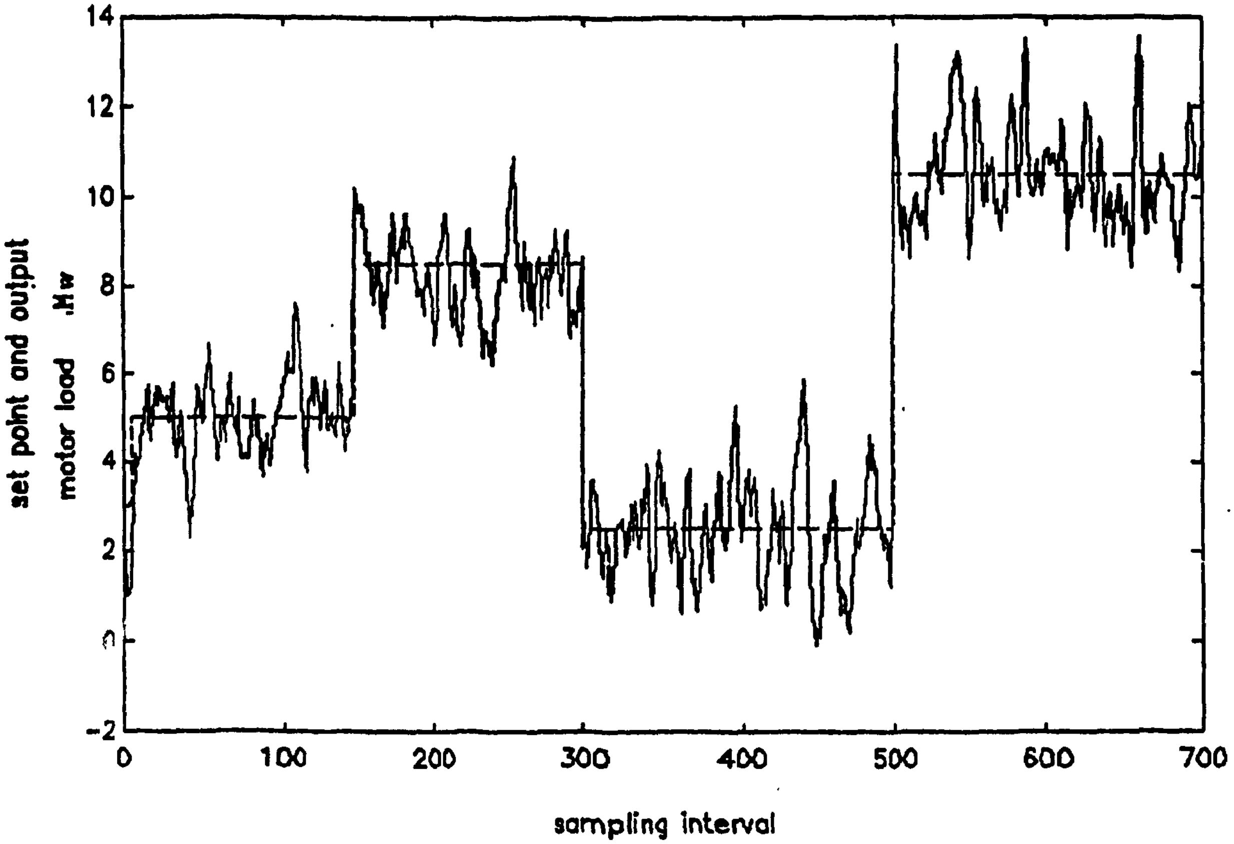


Figure 3.24 Response of Output to Set Point Change for Example 3-5

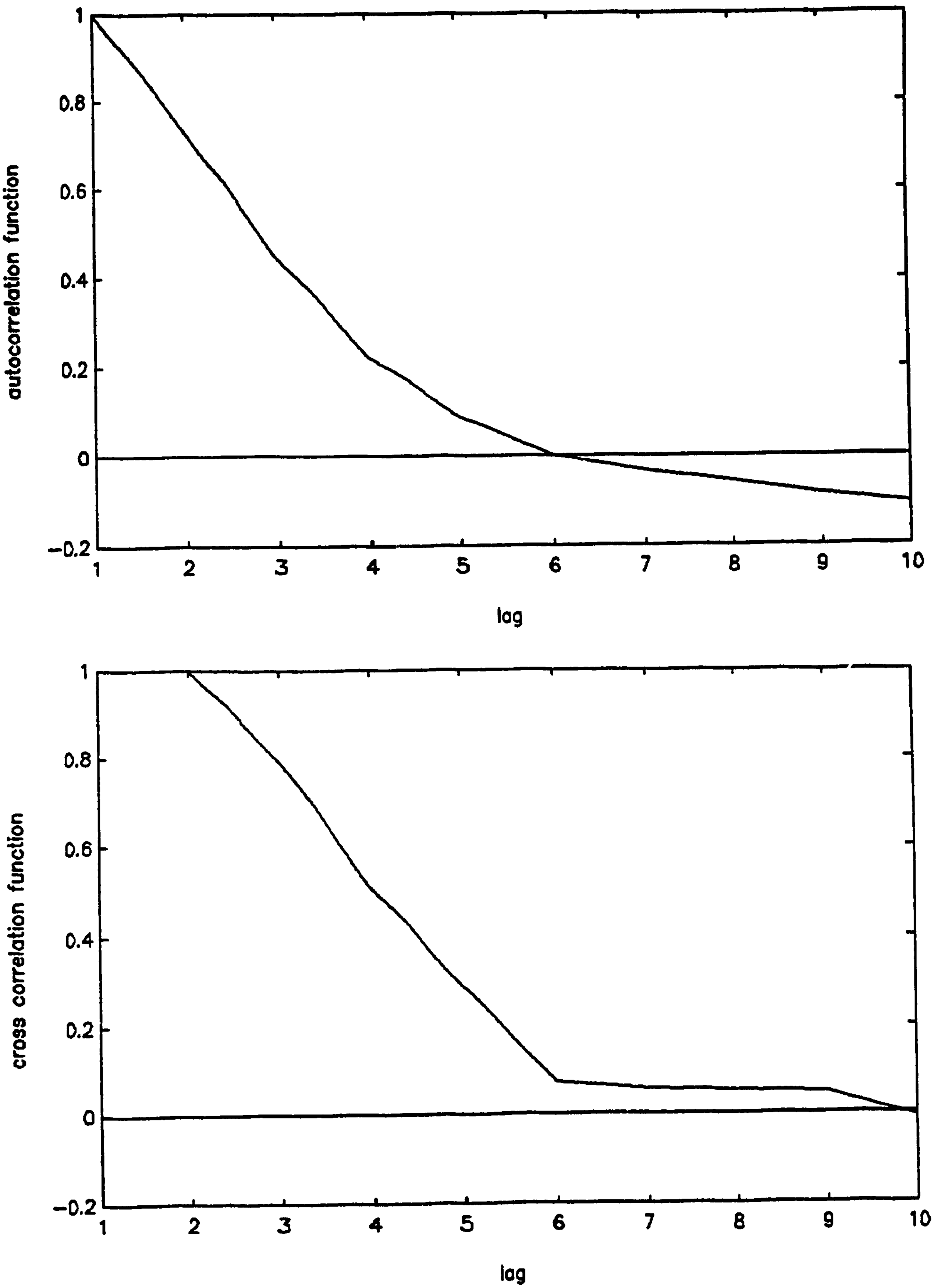


Figure 3.25 Autocorrelation and Cross-correlation of output vs Lag for Example 3-5

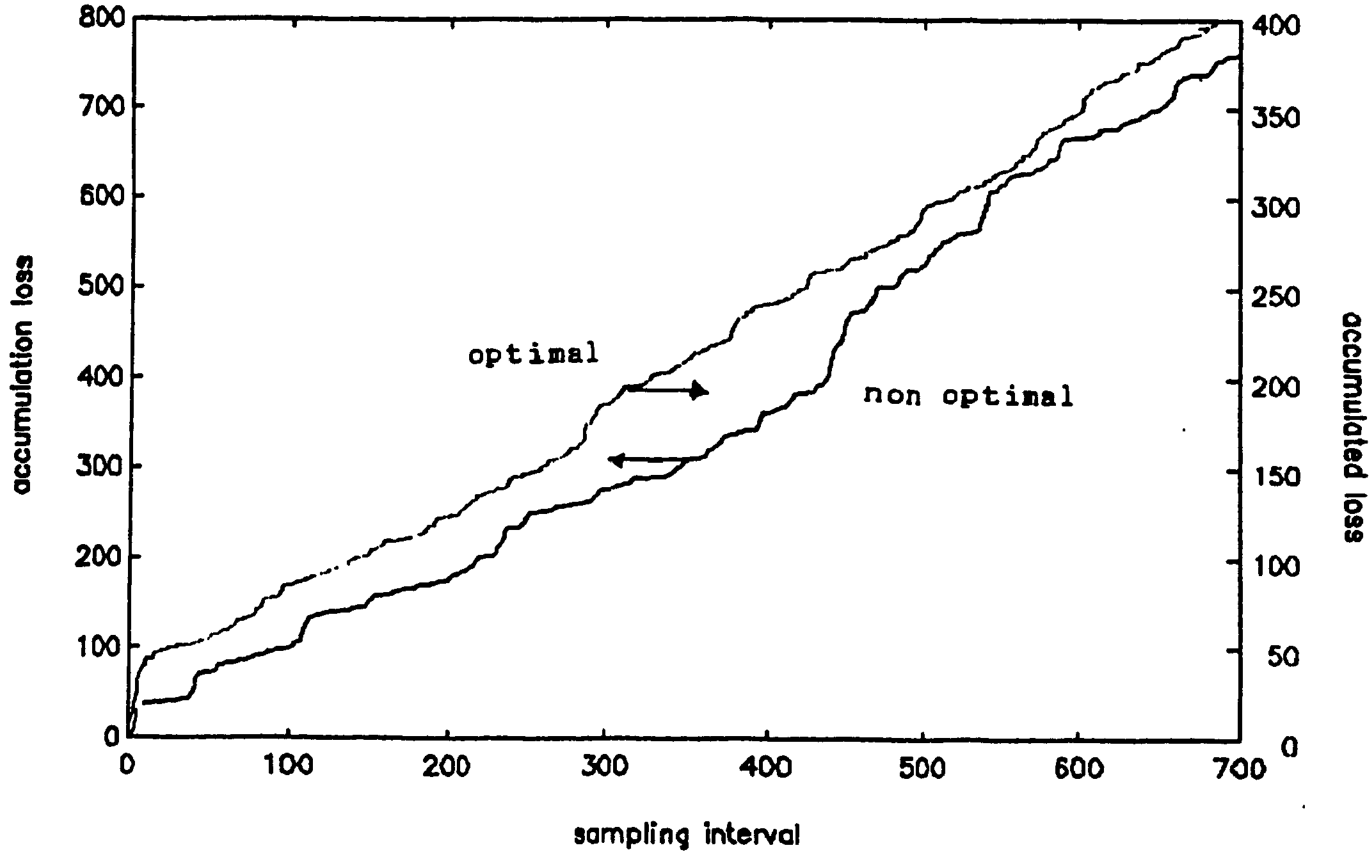


Figure 3.26 Accumulated Loss of output for Example 3-5

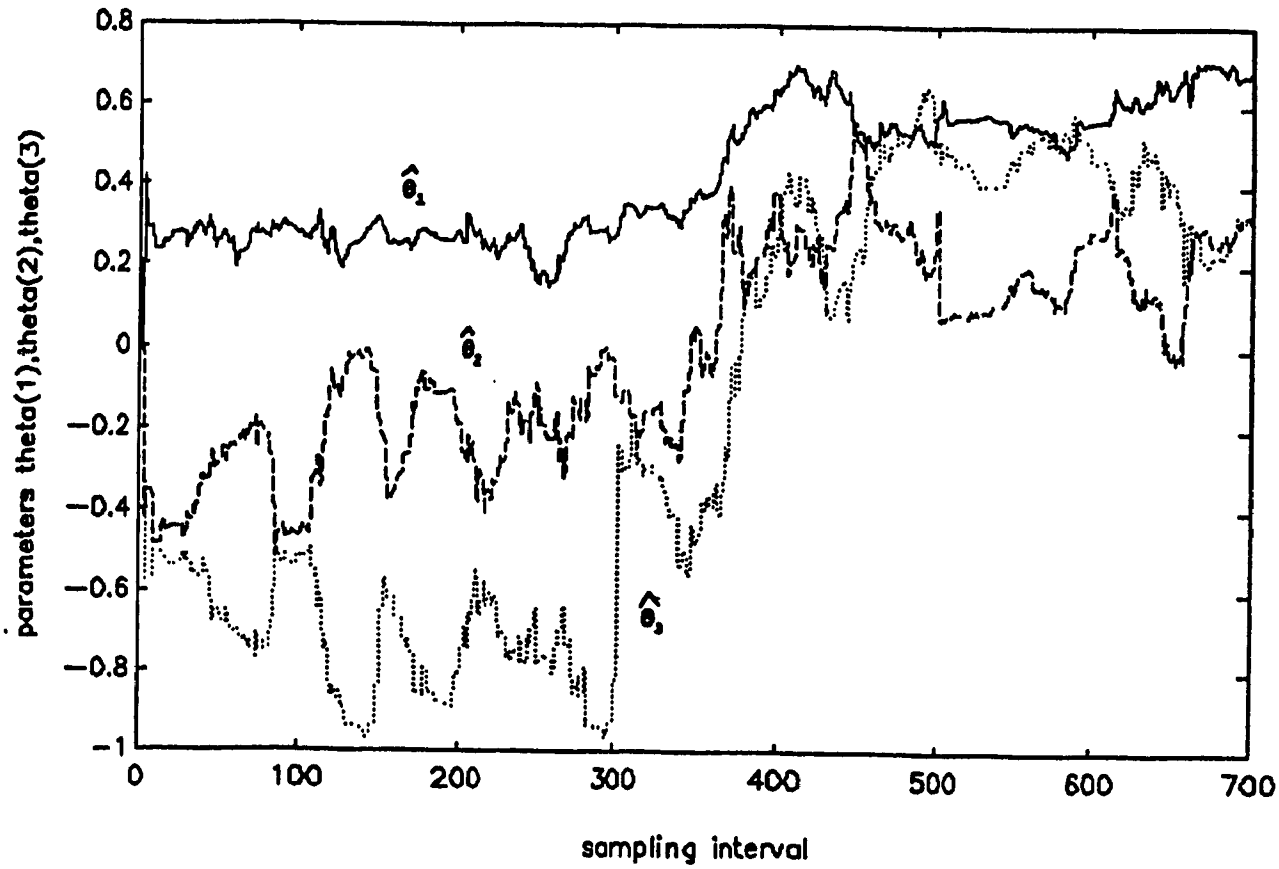


Figure 3.27 Parameter Estimation for Example 3-5

STR with integral action is designed to provide a closed-loop control of specific energy. For a constant wood species, a specific energy is uniquly related to freeness. Figure 3.28 indicates the response of closed loop control of freeness to a load change. The results show that STR is capable of rejecting the disturbance and bring the controlled variable back to a steady state.

3.5 Conclusions of Simulation Results

Comparisons of the control performance are made between refiner operating under conditions of time invariant versus time variant, white noise versus non stationary noise and self tuning regulator incorporated with and without integral action.

Example 3-1 shows a regulatory control where minimum variance control is obtained for time invariant system with white noise acting on the process.

Example 3-2 simulates the time invariant refiner and its control performance is compared with Example 3-4 where time variant system is assumed. In both examples, a self tuning regulator is incorporated with integral action, and also first order exponential disturbance is used. In the time invariant case, the STR converges to a minimum variance

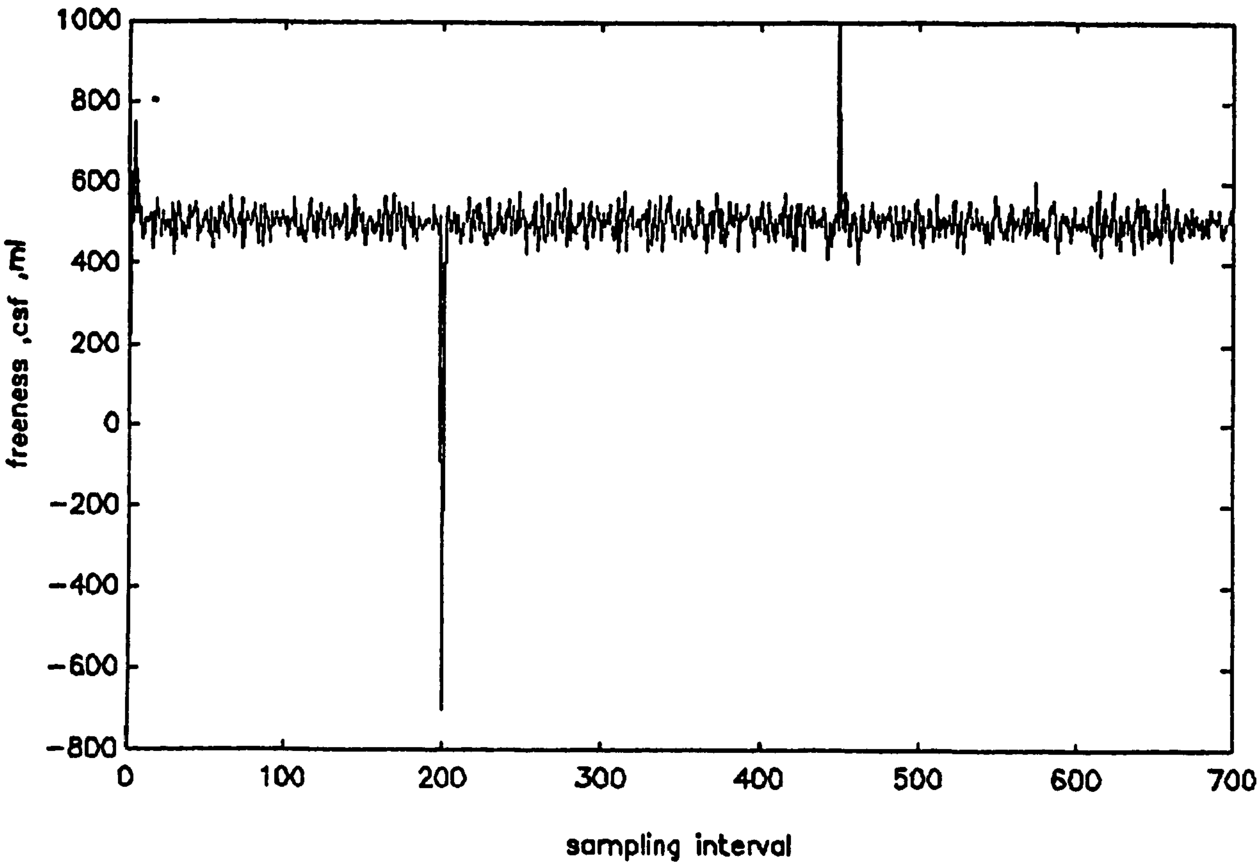


Figure 3.28 Response of the Closed-Loop Control of Freeness to Load Change for Example 3-6

control. However, for time variant case a sub-optimal solution is obtained. Using the forgetting factor of 0.98, the STR is able to track the time varying parameters and providing a satisfactory closed-loop control of specific energy to set point change. The conditions given in Example 3-4 represents closely the typical refiner operations in the TMP mill. The simulation indicates that sub-optimal solution can be obtained if the control strategy is tried to control the industrial refiner.

The effect of self tuning regulator without integral action is studied in Example 3-3 for time invariant system and in Example 3-5 for time variant system. Control performance indicates that the control is non-optimal as shown in the autocorrelation plots given in Fig 3.14 and Fig 3.25 respectively.

Example 3-6 represents a typical scenario in TMP mill where sudden change in feed or process upset can occur. The control performance shown in Fig 3.28 indicates that control strategy could be used in the mill trial.

3.6 Summary

The chapter describes the proposed implicit self tuning regulator for closed-loop control of freeness in the refining process. The method of control is particulary suitable for controlling the refiner operating under constant wood species.

The inferential relationship between secondary output, specific energy and primary output, freeness , is constant and can be established beforehand.

The simulation of refining process based on time invariant and time variant system as well as different noise disturbance models are carried out. Forgetting factor is incorporated in the parameter estimation for the case of time variant system. The performance of implicit self tuning regulator is simulated with and without integral action.

The modelling of noise structure used in ARIMA model gives an optimal solution for the case of non-stationary disturbance acting on the process. The simulation study shows that the proposed implicit self tuning regulator is capable of giving closed loop control of freeness provided the factors such as time varying nature of the process, noise structure are considered in the designed of the controller.

CHAPTER IV

ADAPTIVE INFERENTIAL CONTROL

4.1 Introduction

An adaptive inferential control strategy is proposed for the closed loop control of freeness in refining process. The control method is obtained by measuring secondary output and infer its measurement to the primary output for feedback purposes. In Chapter III, a method of controlling freeness is outlined based on the constant inferential relationship between secondary and primary output applied to single wood species. In constrast, the control strategy given in this chapter applies to wide range of wood species under different operting conditions. Owing to the fact that different wood species would be used in the refining process for manufacturing of same grade of pulp, the specific energy required to produce a refined pulp of a given freeness varies according to wood species. In other words, the relationship between specific energy and freeness is dynamic and species dependent.

System identification method is used for on line identification of the dynamic parameters between the specific energy and freeness. The identified model gives an estimation of the freeness which could be used for the design of an adaptive control scheme for closed loop control of freeness.

4.2 Theory of Adaptive Inferential Control

In adaptive inferential control on line identification between secondary and primary controlled variables will be performed to estimate the primary output to be used in designing the controller. Consider the process dynamics of the refiner plant that can be given by the following input-output representation.

$$y_{2,0}(t) = A_1(q^{-1})u(t-m_1)+B_1(q^{-1})w(t) \tag{4-1}$$

$$y_0(t) = A_2(q^{-1})u(t-m_2)+B_2(q^{-1})w(t) \tag{4-2}$$

$$y_2(t) = y_{2,0}(t-d)+e_1(t) \tag{4-3}$$

$$y(t) = y_0(t)+e_2(t) \tag{4-4}$$

where

$y_{2,0}(t)$: primary controlled output (freeness)

$y_0(t)$: secondary measurable output(specific energy)

$y_2(t)$: observed $y_{2,0}(t)$ contaminated with zero mean white noise $e_1(t)$

$y(t)$: observed $y_0(t)$ contaminated with zero mean white noise $e_2(t)$

m_1 : time delay of primary output in response to change in $u(t)$

m_2 : time delay of secondary output in response to change in $u(t)$

$w(t)$: stationary random and unmeasurable load disturbance

$u(t)$: process input,manipulating variable (plate gap)

d : laboratory sampling time for freeness

$A_1(q^{-1})$, $A_2(q^{-1})$, $B_1(q^{-1})$,$B_2(q^{-1})$ are polynomial ratios with the order of numerator less than or equal to that of the denominator.

In order to apply the inferential control method, the refining plant has to be completely observable from the secondary output, the specific energy, measurement. The specific energy, $y(t)$ is assumed measurable at each sampling instant. The freeness $y_2(t)$ is available from laboratory test after d time steps. Both $y(t)$ and $y_2(t)$ are affected by the load disturbances acting on the refiner, such as production changes, species variation etc. It is assumed $m_1 > m_2$, the primary output response time of observed $y_2(t)$, freeness to input change in $u(t)$ is larger than the response time of secondary output $y(t)$, specific energy, considering the extra time required for latency removal before freeness measurement is made.

4.2.1 INFERENTIAL MODEL IDENTIFICATION

Morris et al [37] had shown that the inference relationship between primary and secondary output can be represented by the following pseudo ARMAX model:

$$y_2(t+d) = \frac{B(q^{-1})}{A(q^{-1})}u(t-m) + \frac{C(q^{-1})}{A(q^{-1})}y(t) + e(t+d) \qquad (4\text{-}5)$$

y(t), a secondary output, is known signal and $y_2(t)$, a primary output is only available after time interval d from freeness test in the laboratory, u(t) is a manipulating variable, e(t) is Gaussian white noise $N(0,\sigma)$ and $A(q^{-1})$, $B(q^{-1})$, $C(q^{-1})$ are polynomials in backward shift operator defined in equations (2.21),(2.22) and (2.23). Equation (4-5) can be rewritten as:

$$y_2(t) = -\alpha_d\hat{y}_2(t-d) - \ldots\ldots\ldots - \alpha_{nd}\hat{y}_2(t-nd)$$

$$+\beta_1 u(t-m-d-1) + \ldots\ldots\ldots\ldots\ldots\ldots + \beta_{n-1}u(t-m-n-d+1)$$

$$\alpha_0 y(t-d) + \ldots\ldots\ldots\ldots\ldots + \alpha_{n-1}y(t-n-d+1) + e(t) \qquad (4\text{-}6)$$

where $e(t)$ is equation error, n is order of model, and

$[\alpha_d \ldots\ldots\ldots \alpha_{nd}, \beta_d \ldots\ldots\ldots \beta_{n-1}, \ldots\ldots \alpha_0 \ldots\ldots\ldots \alpha_{n-1}]$ are model parameters. Equation (4-6) can be further rewritten in compact form as:

$$y_2(t) = \theta^T \phi(t-d) + e(t) \tag{4-7}$$

$$\theta^T = [\alpha_d, \ldots\ldots \alpha_{nd}, \beta_1 \ldots\ldots \beta_{n-1}, \alpha_0 \ldots\ldots \alpha_{n-1}] \tag{4-8}$$

$$\phi(t-d) = [-\hat{y}_2(t-d), \ldots\ldots, u(t-m-d-1), \ldots\ldots, y(t-d), \ldots\ldots] \tag{4-9}$$

At time t, the estimated parameter θ is used to compute $y_2(t) = \theta^T \phi(t-d)$ as " a posterior" value in order to update $\phi(t-d)$ after d. The inferential equation for estimating primary output between t+d and t+2d is given by:

$$\hat{y}_2(t+d) = \theta^T \phi(t)$$

$$= -\alpha_d \hat{y}_2(t) - \ldots\ldots\ldots\ldots - \alpha_{nd} \hat{y}_2(t-(n-1)d)$$

$$+ \beta_1 u(t-m-1) + \ldots\ldots\ldots\ldots + \beta_{n-1} u(t-m-n+1) \tag{4-10}$$

Expression (4-10) estimate $y_2(t)$, the freeness, at the same sampling rate as the secondary output $y(t)$ is measured. The parameters for $\hat{y}_2(t)\theta^T$ are only updated whenever the

freeness test result from the laboratory is available.

In practice the estimation of primary controlled output can be simplified as proposed in [37] as below. Since parameter α_d relates to a_1 in $A(q^{-1})$ given in equation (2-21) for first order estimator $\alpha_d = (-a_1)^d$, and $|a_1| \leq 1$; hence for large d, $\alpha_d << 1$, and becomes negligible, then equation (4-10) reduced to

$$\hat{y}_2(t+d) = \beta_1 u(t-m-1) + \ldots\ldots\ldots\ldots + \beta_{n-1} u(t-m-n+1)$$

$$+ \gamma_0 y(t) \ldots\ldots\ldots\ldots \gamma_{n-1} y(t-n+1) \qquad (4\text{-}11)$$

The Recursive Least Square (RLS) algorithm for estimating the parameter $[\beta_1 \ldots\ldots\ldots \beta_{n-1}, \gamma_0 \ldots\ldots\ldots\ldots \gamma_{n-1}]$ is given :

$$\theta(t) = \theta(t+1) + K(t)\,[y_2(t) - \hat{y}_2(t)] \qquad (4\text{-}12)$$

$$K(t) = \frac{P(t-1)\phi(t-1)}{\lambda + \phi^T(t-1)P(t-1)\phi(t-1)} \qquad (4\text{-}13)$$

$$P(t) = \frac{1}{\lambda}\,[I - K(t)\phi^T(t-1)]\,P(t-1) \qquad (4\text{-}14)$$

where $y_2(t)$, the freeness is obtained from laboratory test after d time steps. I is the identity matrix, and the forgetting factor λ is included to track the time variant characteristics of the process and also for non-stationary stochastic disturbances. The parameter estimation is to find an estimated θ that will minimise the mean square error given by the performance index $\mathscr{E}(n) = \sum_{t=1}^{t=n} \lambda^{n-t} |\alpha(t)|^2, 0 < \lambda < 1,$

where n is a variable length of observable data, and $\alpha(t)$ is error defined as $\alpha(t) = y_2(t) - \hat{y}_2(t)$.

The estimated primary output $\hat{y}_2(t+d)$ can be used as a feedback signal for existing controller. In dealing with chip refiner, with slowly time varying dynamics, the estimated primary output signal can be used for design of adaptive control system using self-tuning regulator.

The method of controlling freeness using implicit self-tuning regulator is described. The adaptive inferential method allows on-line system identification of the parameters of the inferential equation relating specific energy and freeness when refiner is operating using different wood-mix or wood species. The relationship between specific energy and freeness varies depending on the wood species and degree of chemical treatment [16]. The specific energy and freeness are both subjected to stochastic disturbance such as changes in wood species and wood-mix etc.

4.2.2 IMPLICIT SELF TUNING REGULATOR

Implicit self-tuning regulator (STR) for closed loop control of freeness will be described below. The chip refining process is modelled as ARMAX model given as:

$$y_2(t) = \frac{B(q^{-1})}{A(q^{-1})}u(t-k) + \frac{C(q^{-1})}{A(q^{-1})}e(t) \tag{4-15}$$

where $y_2(t)$ is the primary output obtained through inferential estimation, the freeness, u(t) is a manipulating variable, e(t) is zero mean white noise, t is discrete time, and k is discrete process time delay.

$A(q^{-1})$, $B(q^{-1})$ and $C(q^{-1})$ are polynomials in backward shift operator q^{-1}, defined as follow:

$$A(q^{-1})=a_0+a_1q^{-1}+a_2q^{-2}+.......+a_nq^{-n} \tag{4-16}$$

$$B(q^{-1})=b_0+b_1q^{-1}+b_2q^{-2}+......+b_nq^{-n} \tag{4-17}$$

$$C(q^{-1})=c_0+c_1q^{-1}+c_2q^{-2}+.......+c_nq^{-n} \tag{4-18}$$

where $a_0=1$, $b_0=0$ and $c_0=1$ and all roots of $B(q^{-1})$ are assumed inside a unit circle. Åström [19] has shown that the process model of equation (4-15) can be represented by the following predictor form:

$$y_2(t+k+1)+\alpha_1 y_2(t)+.........+\alpha_n(t-n+1)$$

$$=\beta_0[u(t)+\beta_1 u(t-1)+......+\beta_{n+k-1}u(t-n-k+1)]+\varepsilon(t+k+1)$$

(4-19)

where α's and β's are parameters corresponding to a's and b's in equation (4-15). Equation (4-19) allows the model to predict process output after the discrete process time delay k, given the knowledge of past inputs and outputs, $\varepsilon(t)$ is the disturbance acting on the process, called the residuals. $\varepsilon(t)$ is the moving average of order k of the driving noise e(t); β_0 is normally assumed a constant value. For minimum variance control, the process output is forced to equal the residual ε, and control law is given by :

$$u(t)=\frac{1}{\beta_0}[\alpha_1 y_2(t)+..+\alpha_n y_2(t-n+1)]-\beta_1 u(t-1)-..-\beta_{n+k-1}u(t-n-k+1)$$

(4-20)

By introducing the vectors:

$$\Phi(t)=[-y_2(t),\ -y_2(t-1),.......,\ -y_2(t-n+1),$$

$$\beta_0 u(t-1),\ \beta_0 u(t-2),........,\beta_0 u(t-n-k+1)] \qquad (4\text{-}21)$$

$$\theta=[\alpha_1,\ \alpha_2\ ,.....,\alpha_n\ ,\beta_1\ ,\beta_2\ ,.....,\beta_{n+k-1}]^T \qquad (4\text{-}22)$$

Model (4-19) can be written in simplified form as below:

$$y_2(t)=\beta_0 u(t-k-1)+\Phi(t-k-1)\theta+\varepsilon(t) \qquad (4\text{-}23)$$

The parameters are estimated using Recursive Least Square algorithm incorporating with forgetting factor λ as given in equations (4-12),(4-13) and (4-14).

4.3 Application of Adaptive Inferential Control to Refiner

The implementation of the adaptive inferential control of closed loop freeness control is simulated using the structure as shown in Fig (4.1). The control structure consists of two steps of identification; namely

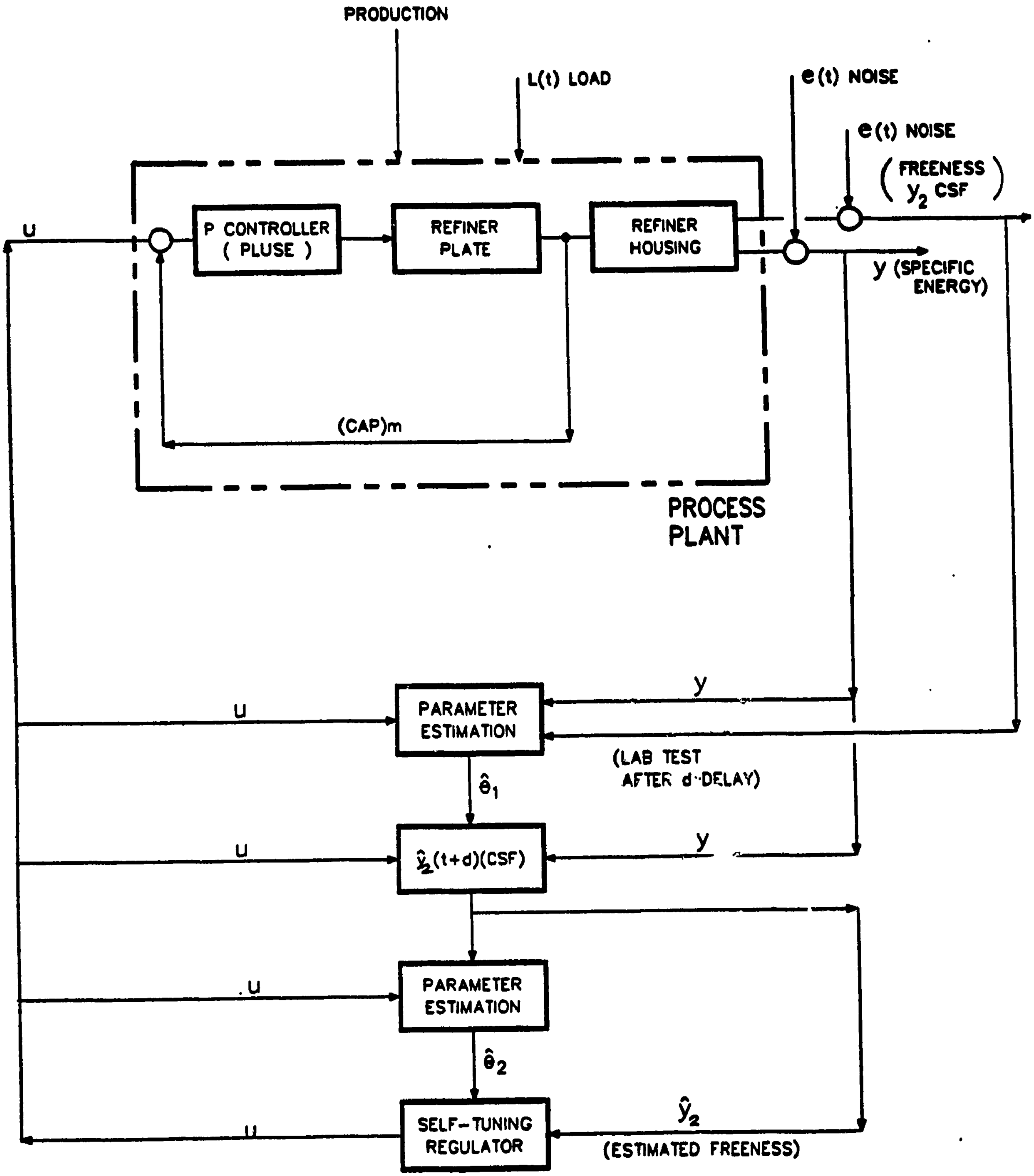


Figure 4.1 Adaptive Inferential Control Strategy

identification of inferential equation parameters using pseudo ARMAX model and identification of refining process described by ARMAX model for the control law design.

4.3.1 REFINING PROCESS MODEL

Refining process relating plate gap and motor load described as 1st order with dead time was already given in equation (2-28). At given production rate, the motor load is directly proportional to specific energy. Hence the refining process relating plate gap and specific energy in Laplace domain is given by:

$$\frac{y_0(s)}{u(s)} = \frac{\tilde{K}_p e^{-\tilde{L}s}}{1+\tilde{T}_1 s} \qquad (4\text{-}24)$$

where $y_0(s)$, u(s) are specific energy and plate gap; $\tilde{K}_p$ is process gain; $\tilde{L}$ is process dead time and $\tilde{T}_1$ is process time constant. The discretised model of equation (4-24) assuming zero order hold reconstruction is given by the following:

$$y_0(kh) = \tilde{a}_1 y(kh-h) + \tilde{b}_1 u(kh-h) + \tilde{b}_2 u(kh-2h) \qquad (4\text{-}25)$$

$$\text{where} \quad \tilde{a}_1 = e^{-\frac{1}{\tilde{\tau}_1}h} \tag{4-26}$$

$$\tilde{b}_1 = \tilde{K}_p[1-e^{\frac{-(h-\tilde{L})}{\tilde{\tau}_1}}] \tag{4-27}$$

$$\tilde{b}_2 = \tilde{K}_p[e^{\frac{-(h-\tilde{L})}{\tilde{\tau}_1}} - e^{-\frac{h}{\tilde{\tau}_1}}] \tag{4-28}$$

For time variant system which describes the process where process gain decays due to the wear of refiner plate, the gain $\tilde{K}_p(t)$ is modelled as slowly exponential dacay, with time constant depending on the refiner plate life.

4.3.2 IDENTIFICATION

The inferential equation describing the dynamic relationship between secondary output, the specific energy and primary output, the freeness is given in equation (4-11). For the case of 1st order estimator and large lab sampling time, equation (4-11) can be reduced to as below:

$$\hat{y}_2(t+d) = \beta_1 u(t-m-1) + \gamma_0 y(t) + \gamma_1 y(t-1) \tag{4-29}$$

where y(t) is secondary output, specific energy, $\hat{y}_2(t)$ is primary output and u(t) is input, a manipulating variable and $m = \min(m_1, m_2)$. Both y(t) and $\hat{y}_2(t)$ are subject to stochastic disturbances such as wood species variation and production fluctuation. The parameters can be estimated using RLS algorithm given in equations (4-12), (4-13) and (4-14).

In order to verify the proposed inferential model given in equation (4-11) , open loop identification is performed using the data of plate gap, u(t), the freeness, $y_2(t)$ and specific energy y(t) obtained from the industrial operating refiner [24]. Solid line shown in Fig (4.2) indicates freeness obtained from the refiner. The dotted line shows the estimated freeness using the same plate gap and specific energy in the model identification process.

The error between freeness generated from the industrial refiner and estimated model is calculated from $\{y_2(\text{actual}) - y_2(\text{estimated})\}^2 / y_2(\text{actual})^2$. The result is plotted as shown in Fig (4.3). Except for a few spikes, the error correlation is considered satisfactory given the fact that the estimation error is affected by freeness sampling time. Large laboratory freeness sampling time is used in the estimation in order to reflect the actual refiner operations in current practice. The continuous estimation of freeness to allow for closed-loop control represents an improvement over the present method used by the operator.

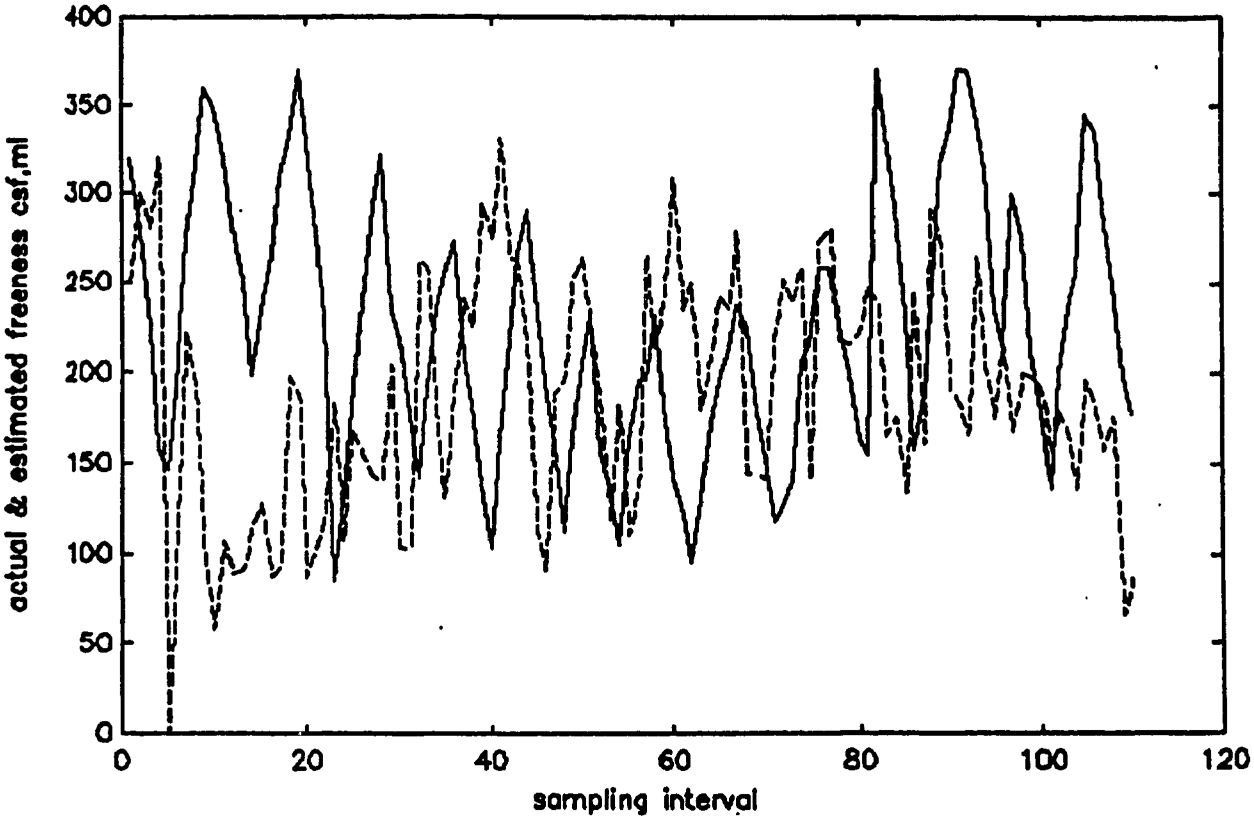


Figure 4.2 Comparision of Freeness Between Actual and Estimated based on Same Plate Gap and Specific Energy Input

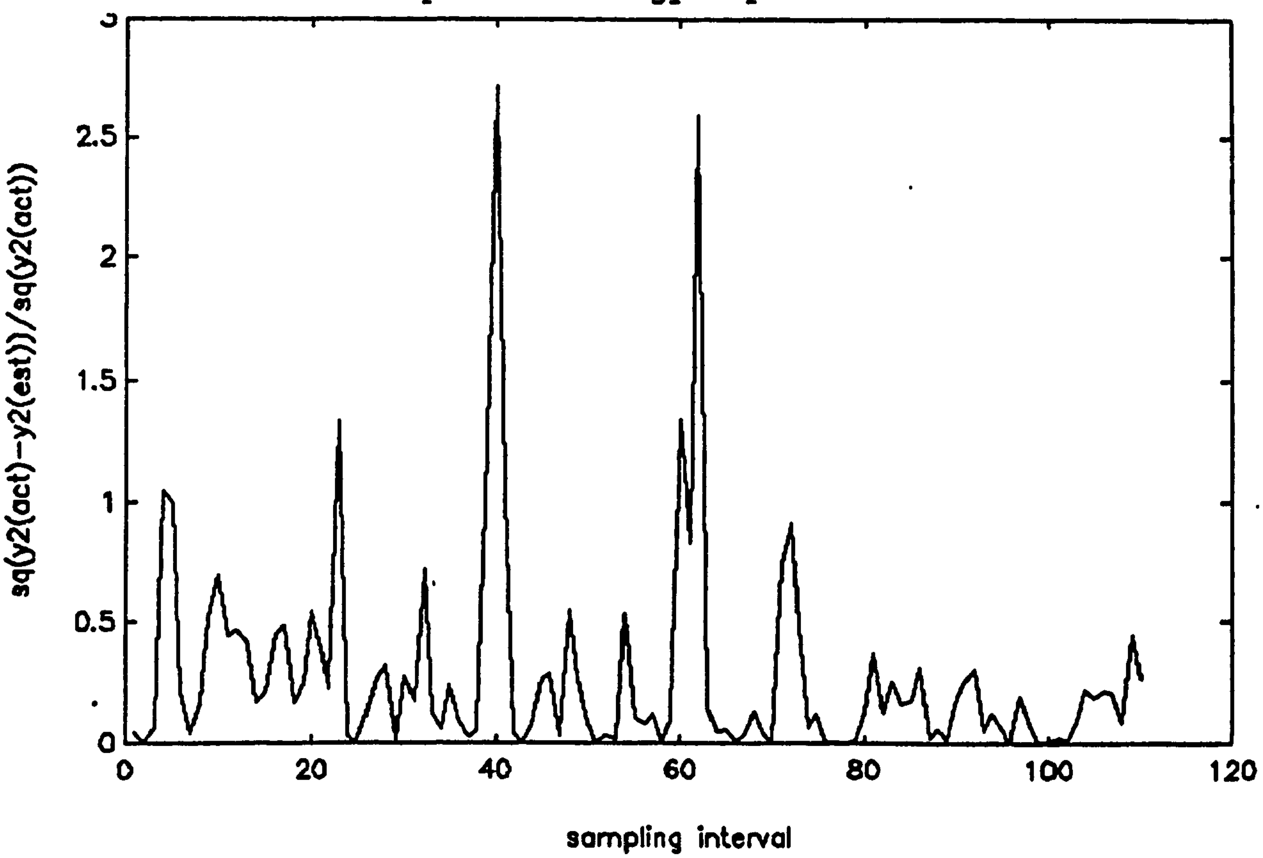


Figure 4.3 Error Between Freeness Generated by True System and Model Estimation (d=2 is used)

4.3.3 CONTROL DESIGN

Using the estimated primary output $\hat{y}_2(t)$, obtained from the identification steps in the inferential equation, an implicit self tuning regulator can be designed for a closed loop freeness control. For refining process the control design given in equation (4-21), (4-22) and (4-23) reduced to the following with k=2, n=1.

$$\hat{\Phi}(t) = [-y_2(t),\ \beta_0 u(t-1),\ \beta_0 u(t-2)] \qquad (4-30)$$

$$\hat{\theta} = [\ \alpha_1,\ \beta_1,\ \beta_2\ ]^T \qquad (4-31)$$

$$y_2(t) = \beta_0 u(t-k-1) + \hat{\Phi}(t-k-1)\hat{\theta} + e(t) \qquad (4-32)$$

Control law is derived as below:

$$u(t) = \frac{1}{\beta_0}\ [\alpha_1 y_2(t)]\ - \beta_1 u(t-1)\ - \beta_2 u(t-2) \qquad (4-33)$$

Parameters $\hat{\theta}$ can be estimated using standard Recursive Least Square. The design of implicit STR is based on the identification of the refining model relating freeness $y_2(t)$ to input u(t), the plate gap. The estimated parameters are used directly in the design of control law to generate feedfack manipulating variable u(t) to regulate the secondary output, the specific energy.

STR control law based on disturbance model having white noise will not have integral action. To design a STR having an integral action the procedure given in Chapter III can be followed.

4.4 Simulation

The simulation program of the proposed inferential control method is written in PC Mathlab code. Simulation is carried out for slowly time varying chip refining process given in equation (4-25) with h=5 sec, $\hat{L}$=3 sec, $\hat{T}_1$ =7 sec. .

The process gain $\hat{K}_p(t)$ is modelled as first order exponential decay with time constant corresponding to refiner plate life of 1000 hrs.

Recursive Least Square (RLS) is used both in the estimation of inferential model parameters, $\theta(t)$, as well as estimation of process model parameters, $\theta(t)$, used in control law design. Initial conditions used in both steps of parameters are $P(0)=100I$, $\theta(0)=0$, $\tilde{\theta}(0)=0$, where $P(0)$ is covariance matrix. $\theta(0)$, $\tilde{\theta}(0)$ are initial parameters used in inferential as well as STR control law parameter identification, respectively. Both fixed and variable forgetting factor are used in the RLS algorithm. Laboratory freeness test data used in the inferential identification stage is generated using a typical freeness values with noise additions. First order inferential estimators given in equation (4-29), is used to estimate the freeness value.

__Example 4.1 Regulatory Control__

Using implicit self tuning regulator, closed loop freeness control is studied. Figure (4.4) shows the regulation of secondary output, the specific energy, while Figure (4.5) shows the primary output. The parameter estimation of inferential model used for estimating freeness is given in Figure (4-6). The conditions used in the estimation algorithm are, fixed forgetting factor of $\lambda=0.98$; laboratory freeness sampling time d=2.

Figure (4.7) shows the parameter estimations of the implicit process model used in the design of self tuning regulator. The process is subject to stochastic disturbance characterised by white noise. The design of STR does not include an integral action.

To assess the control performance, the autocorrelation function using the entire data set is plotted. Figure (4-8) shows the autocorrelation function plot for regulated secondary output, which indicates that the control is not optimal. The fixed forgetting factor is used in parameter estimation.

The simulation is repeated assumimg a first order exponential disturbance acting on the process as described by $N(t)=0.5\ N(t-1)+e(t)$ where $e(t)$ is Gaussian white noise. Integral action is included in the STR design, and variable forgetting factor suggested in [38] is employed in the RLS algorithm as below:

$$\lambda(t) = 0.95\lambda(t-1) + 0.05 x 0.999 \qquad (4-34)$$

Figure (4.9) shows the results of autocorrelation function plot for entire secondary output data. Using the variable forgetting factor the results indicate that the sub-optimal control is obtained. This represents an improvement over the previous simulation results as given in Figure (4.8).

<u>Example (4-2) Set Point Change</u>

Closed-loop identification of the proposed adaptive inferential control is simulated with a set point change on the primary output, the freeness. Procedures for analyzing the closed loop identifiability given in [39] was followed.

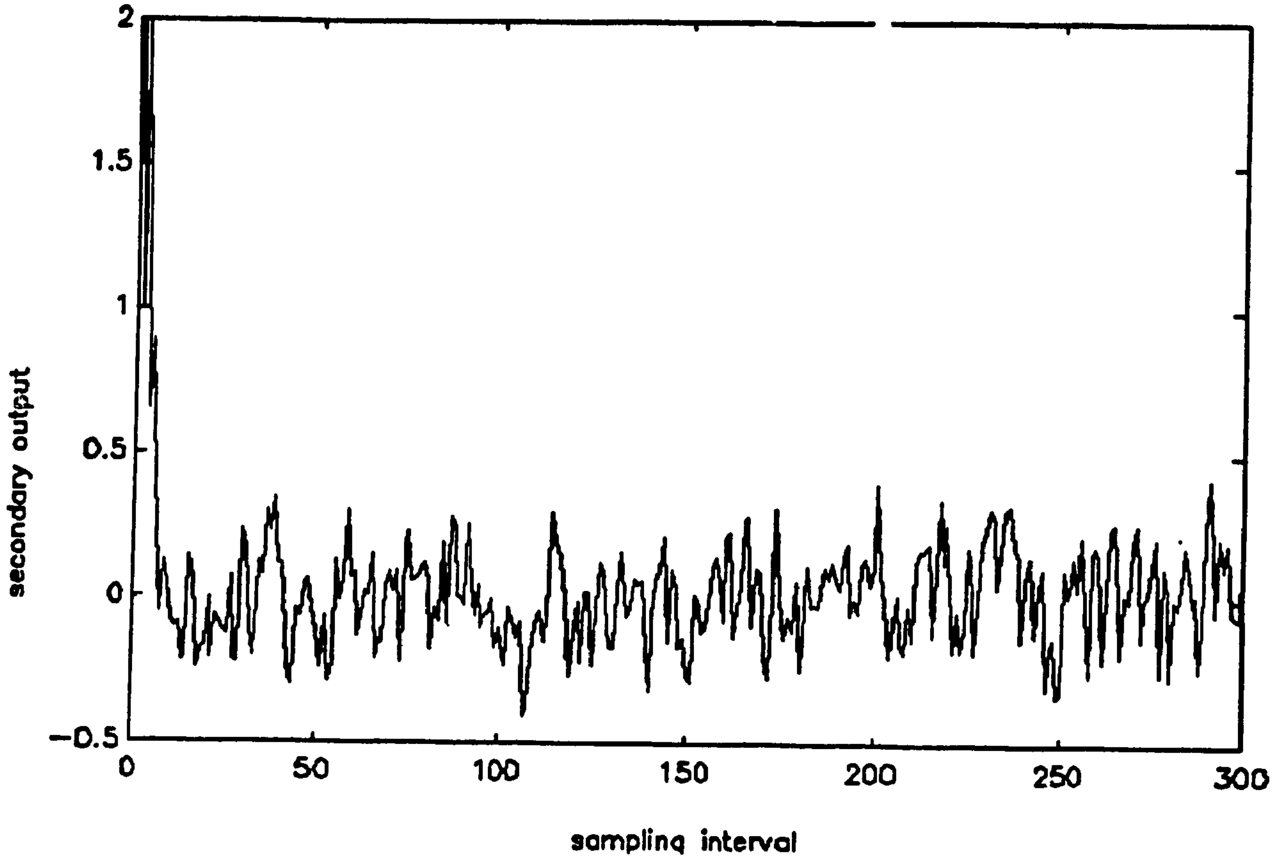


Figure 4.4 Secondary Output for Regulatory Control

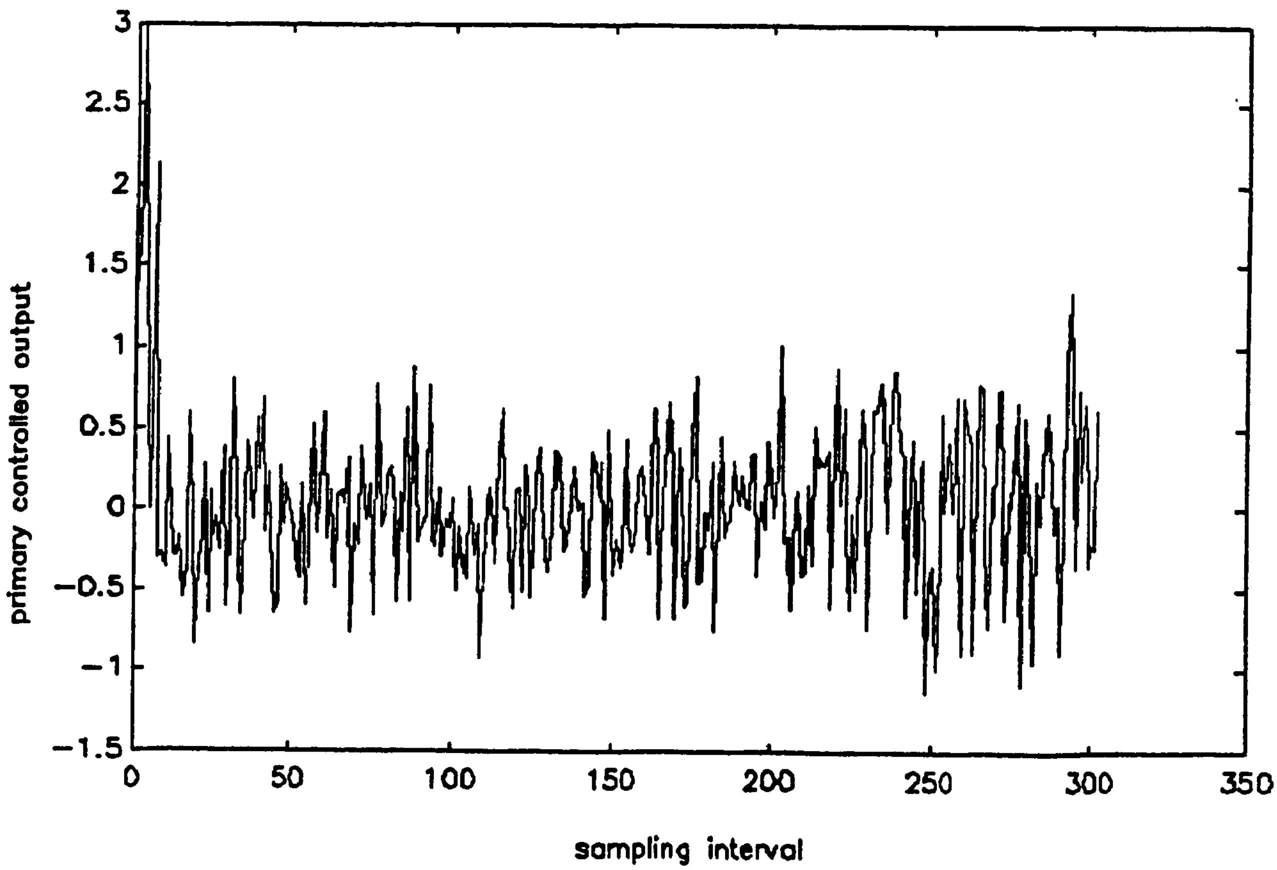


Figure 4.5 Primary Controlled Output for Regulatory Control

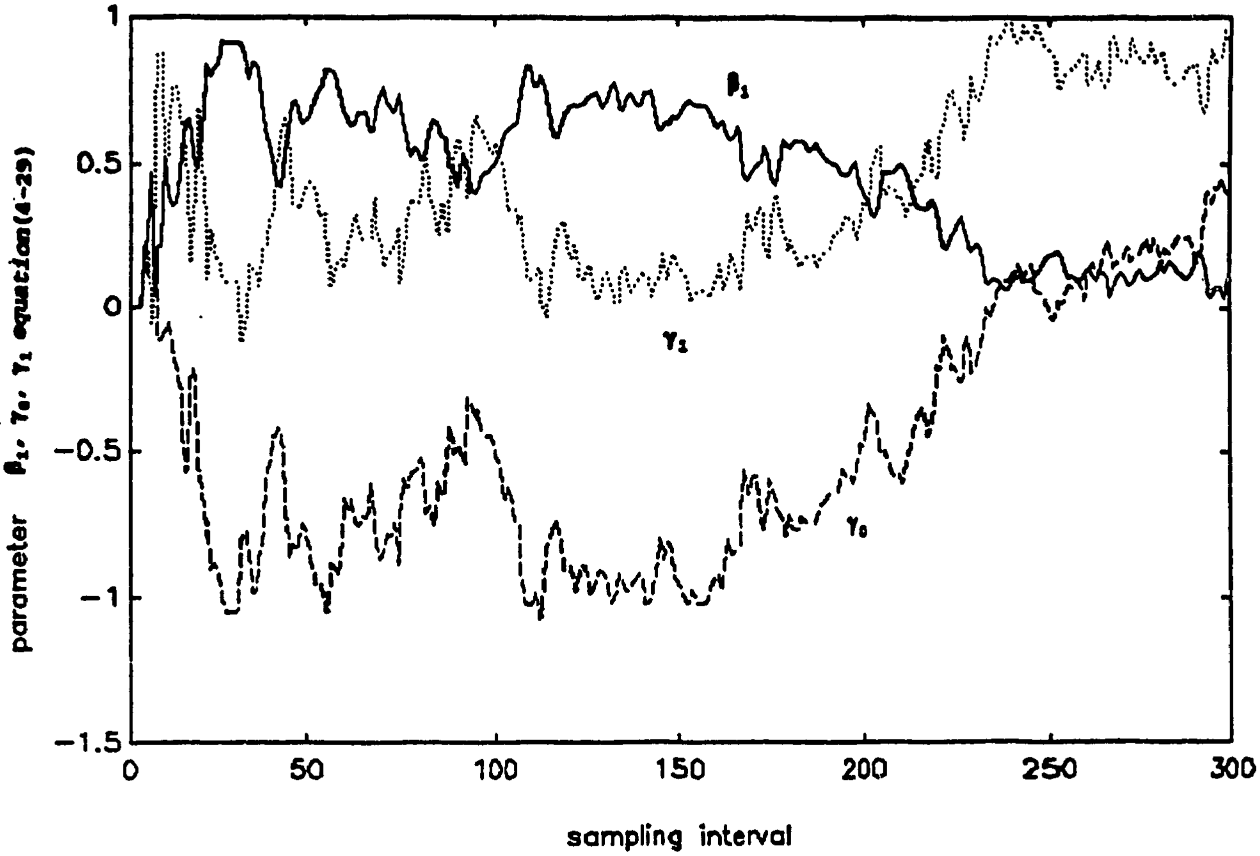


Figure 4.6 Identification of Parameter in Inferential Equation (4-29)

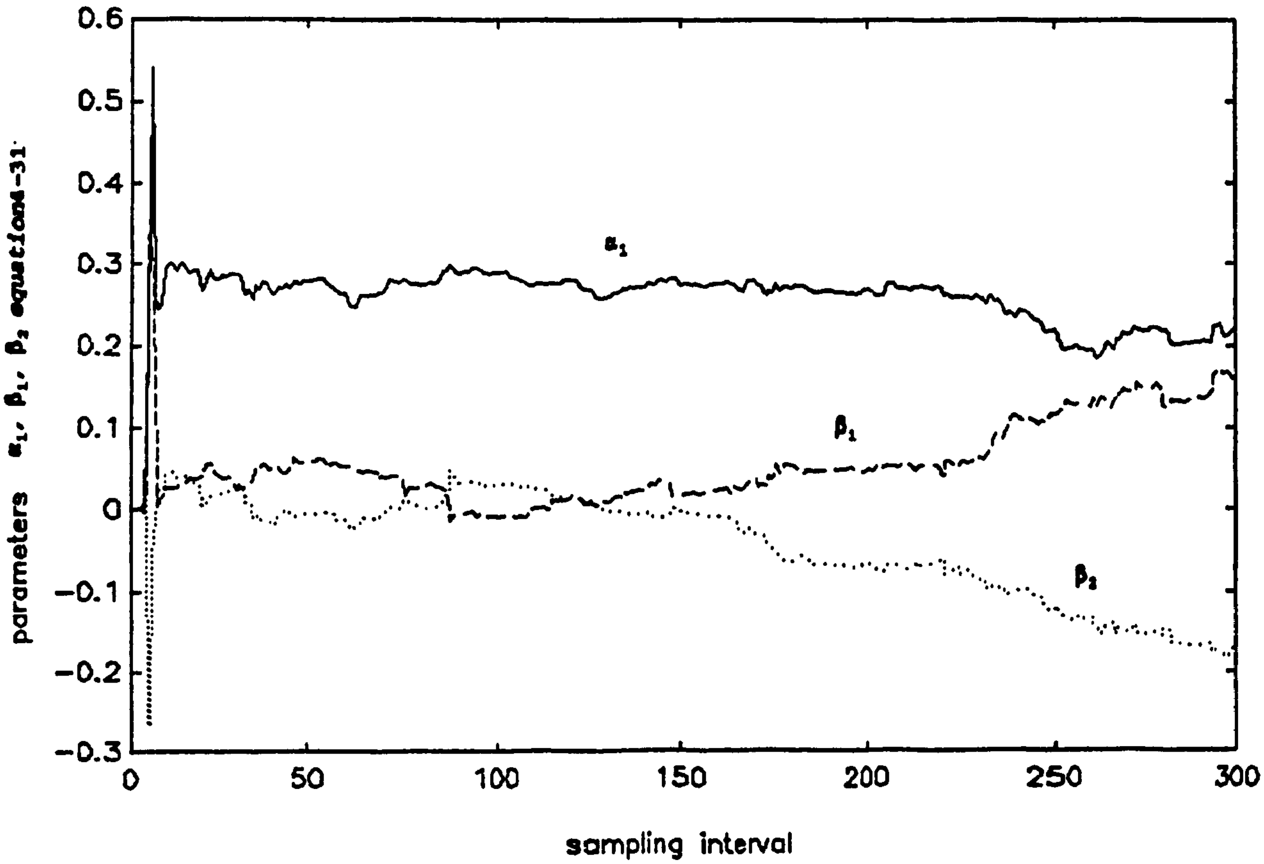


Figure 4.7 Parameter Estimation for STR in Regulator Control

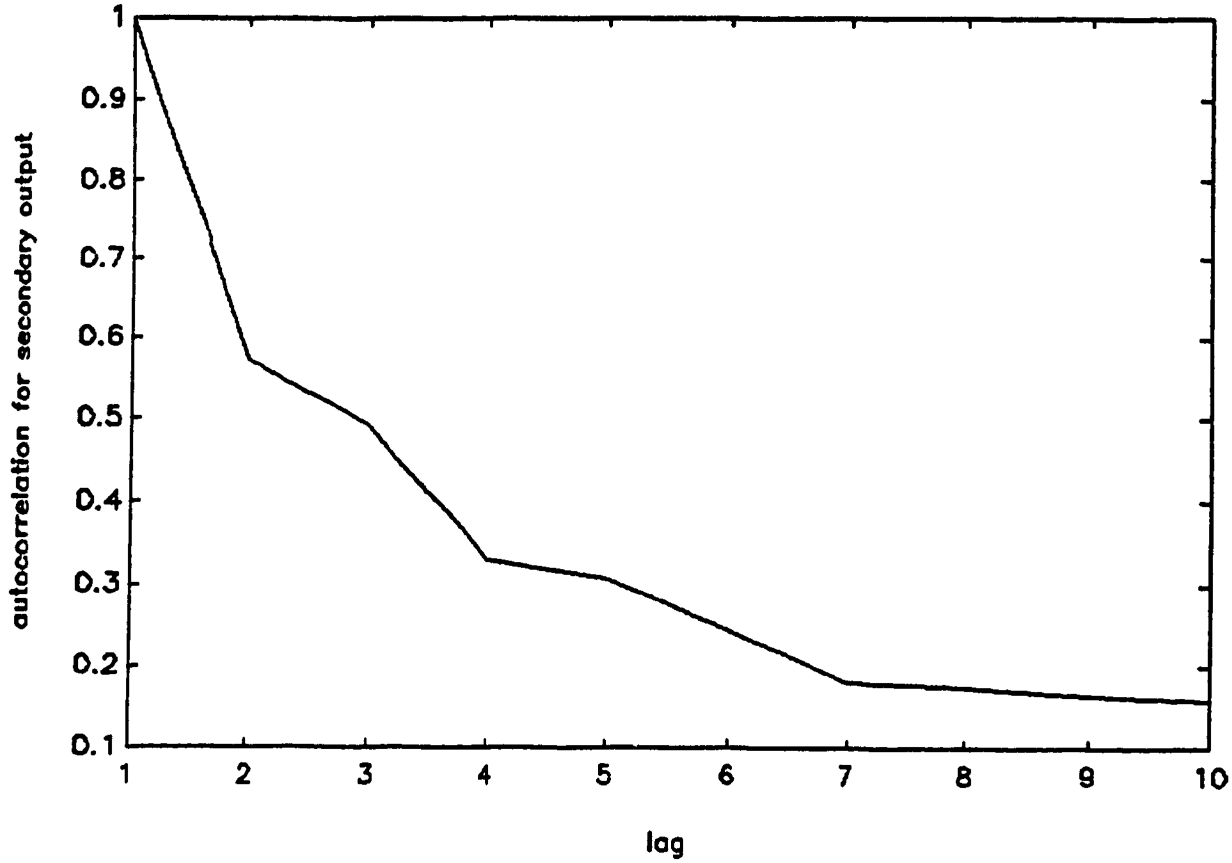


Figure 4.8 Autocorrelation plot for Secondary Output in Regulatory Control for Fixed Forgetting Factor ,d=2

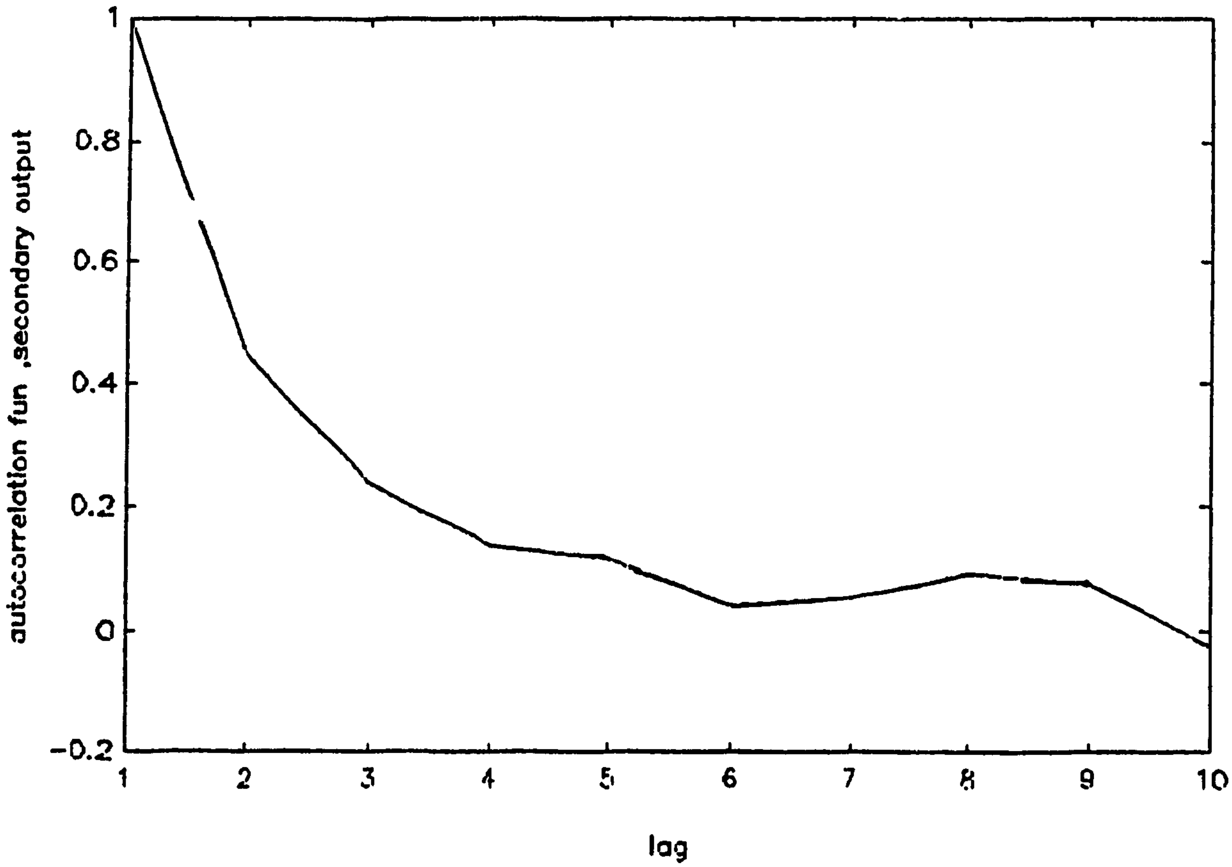


Figure 4.9 Autocorrelation Function for Secondary Output in Regulatory Control for Variable Forgetting Factor, d=2.0

Set point change on freeness is often encountered in refiner plant when there is a requirement of new product specification. Present method of open loop manual control is not capable of providing a satisfactory control in a relatively short time period.

Simulation is carried out for time varying chip refiner as described before using STR with integral action. First order exponential disturbance is used in the process model. Figure (4-10) shows the closed loop response to a new set point change in freeness. The time varying parameter estimation for the control law is carried out using RLS with fixed forgetting factor λ-0.98, β_0 -1. Figure (4-11) shows the parameter estimation for closed loop control of freeness; from 150 to 350 sampling intervals parameters (β_1, β_2) diverges, and finally converge to steady values after 350 sampling interval.

A variable forgetting factor improves the sentivity of parameter estimation by adjusting the λ ; for slow parameter variation, λ varies from 1 to 0.999. However, for a fast variation in parameter λ is raset to 0.95 and then followed by exponential increase to 0.999. Figure (4-12) shows the response of freeness to a set point change, and Figure (4-13) shows the improvement of tracking during the parameter estimation using the variable forgetting factor.

Example (4-3) Load Change

For testing the proposed adaptive inferential control strategy for the rejection of disturbance, the process is simulated with load disturbance introduced to the process, such as the change in chip density, etc. The refiner used in the simulation is slowly time variant using the similar modelling conditions as described before. The stochastic disturbance in the system is assumed first order exponential disturbance. The implicit self tuning regulator has incorporated the integral action using $\Delta u(n) = u(n) - u(n-1)$ for eliminating the offset. Figure (4-14) shows that the controller is capable to reject the load disturbance and bring the freeness back to the steady state in a relatively short time period.

Fixed forgetting factor of $\lambda = 0.98$, is used both in the parameter estimation for inferential equation identification and control design. Figure (4-15) shows the change of control signal , u(t) in response to load disturbance introduced in order to bring the freeness back to steady state as before.

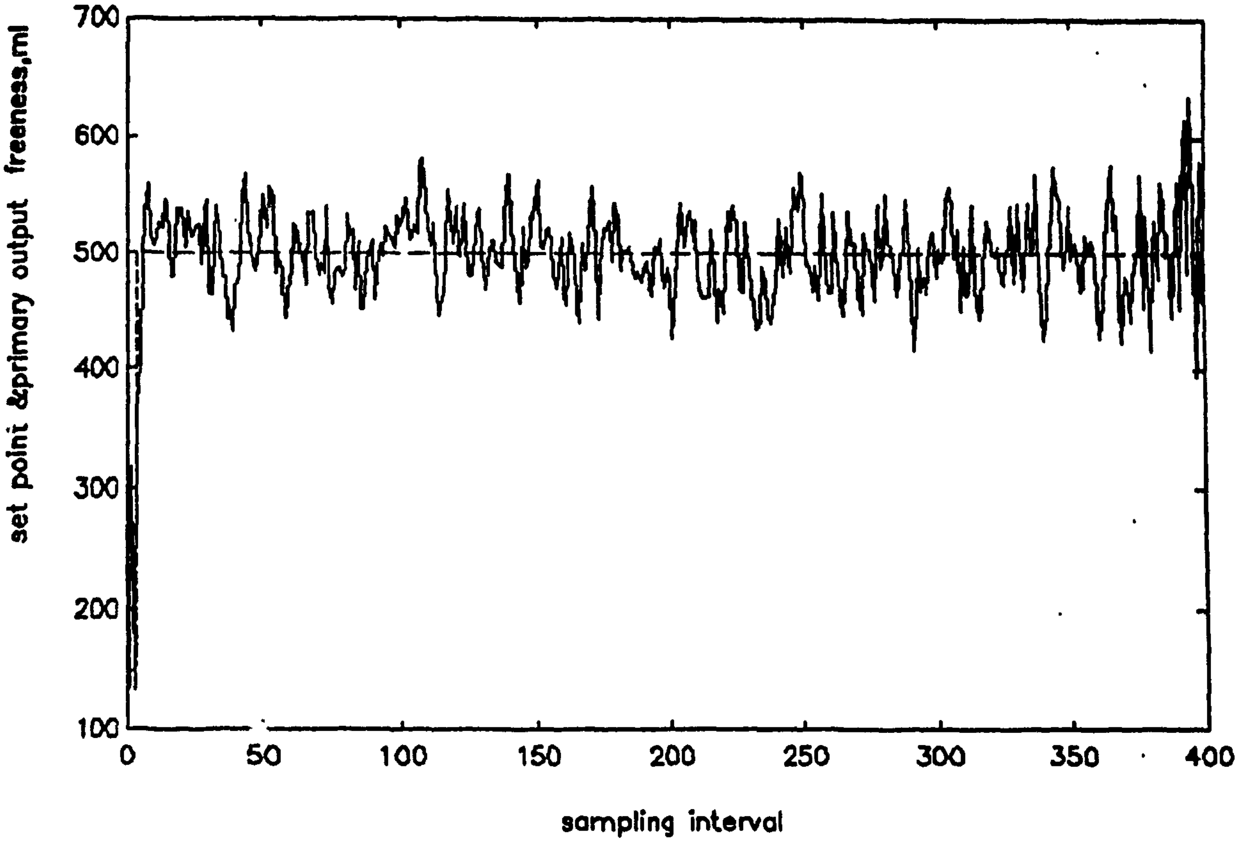


Figure 4.10 Set Point Change for Freeness Using Fixed Forgetting Factor in RLS

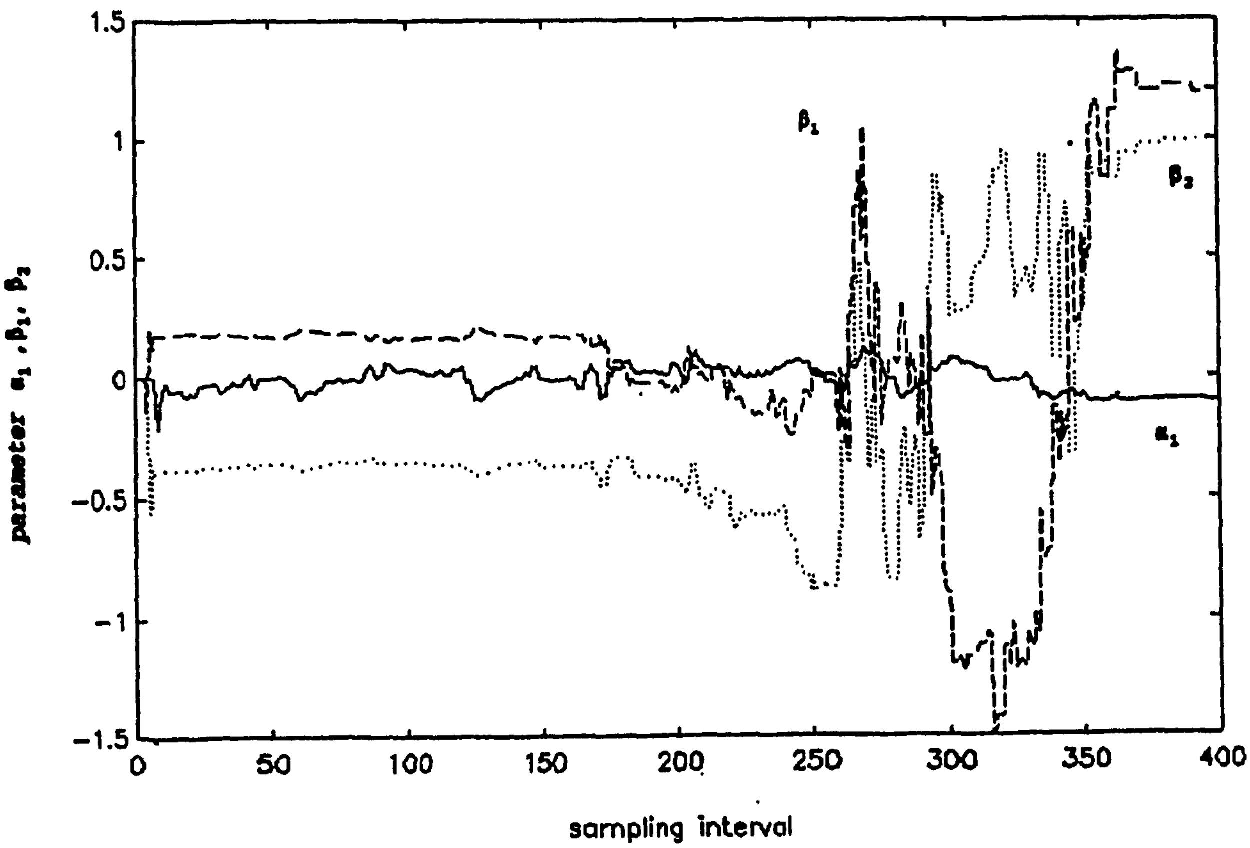


Figure 4.11 Parameter Estimation for Set Point Change Using Fixed Forgetting Factor(λ=0.98)

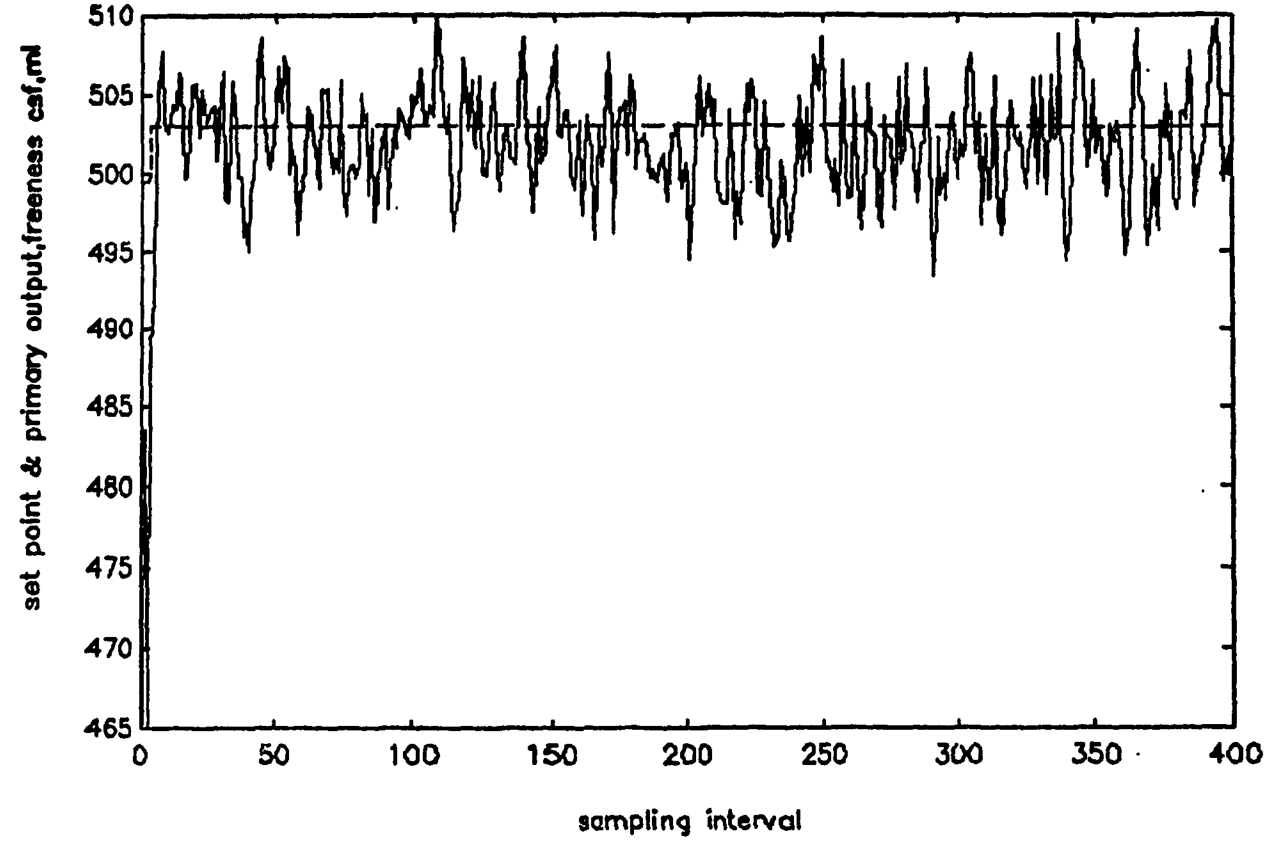


Figure 4.12 Set Point Change for Freeness, Variable Forgetting Factor Used in RLS

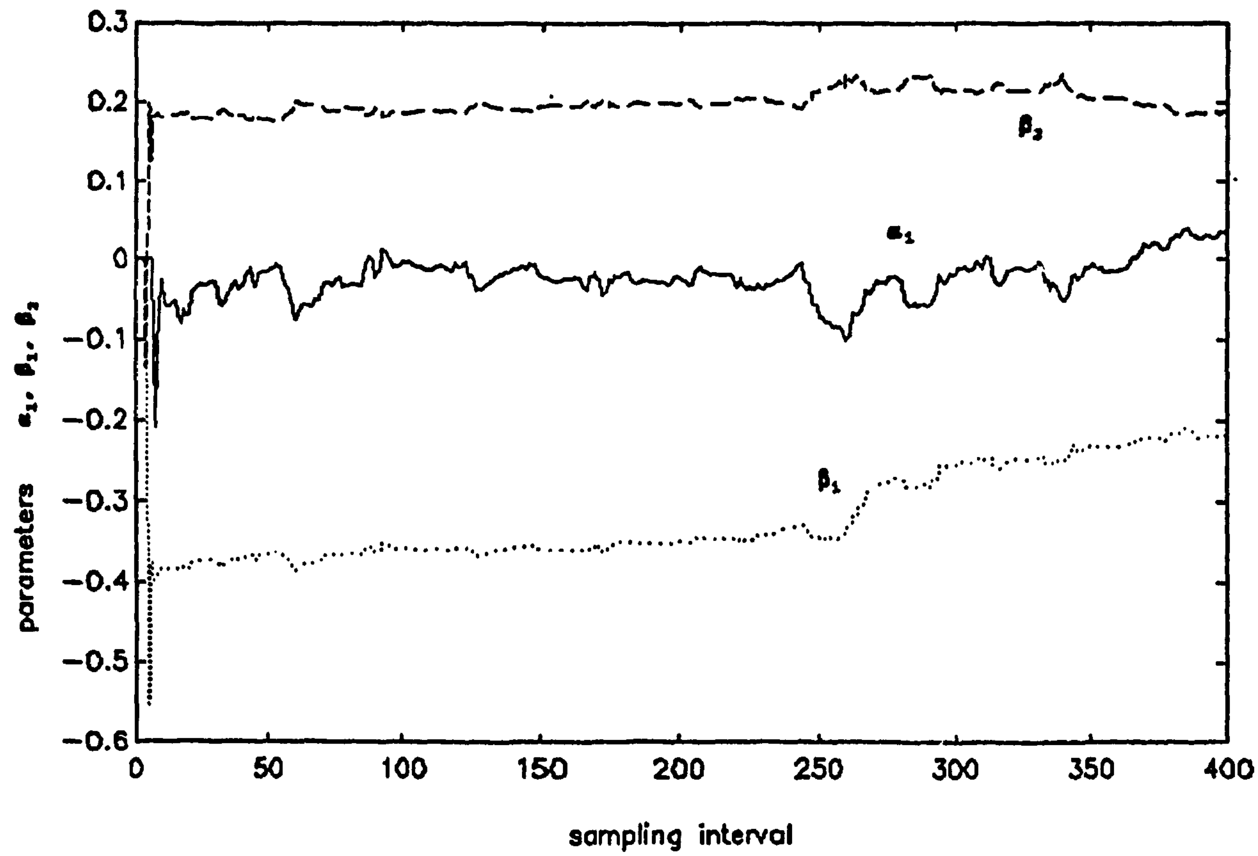


Figure 4.13 Parameter Estimation for Set Point Change Using Variable Forgetting Factor

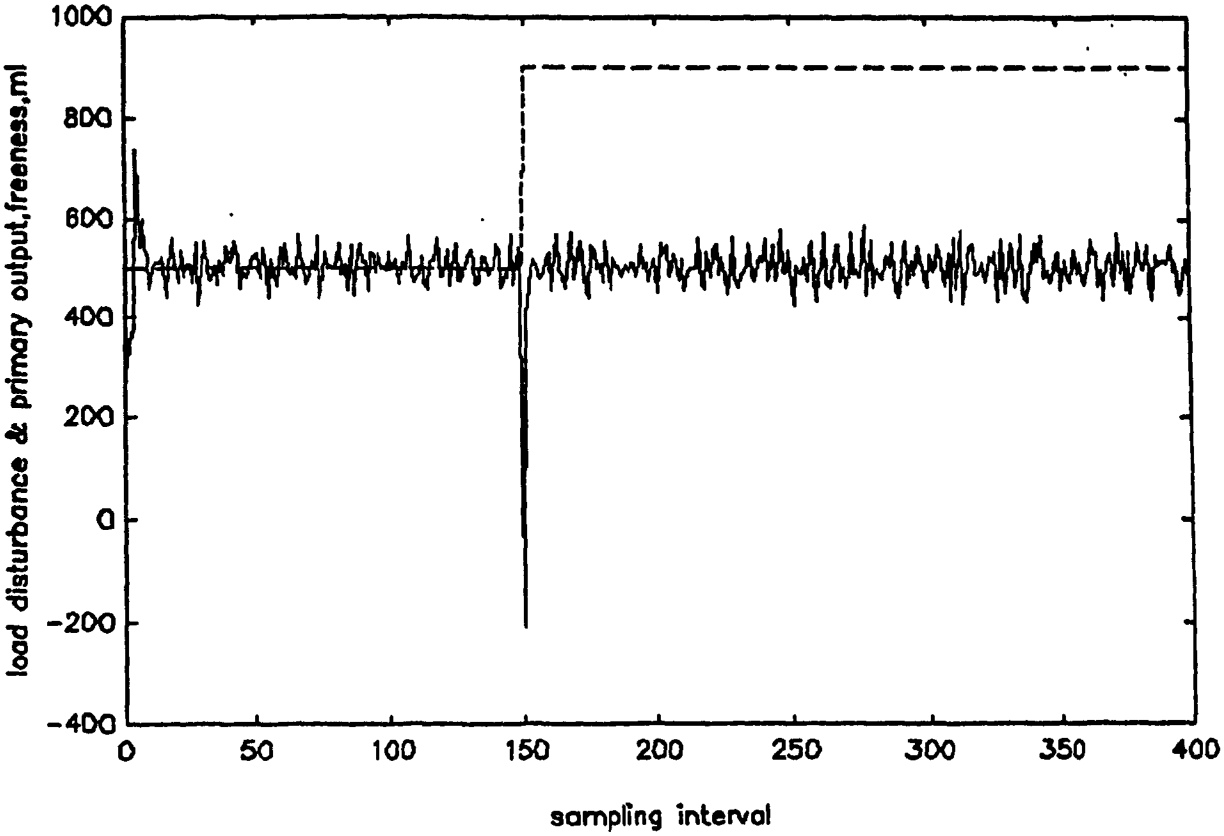


Figure 4.14 Response of Freeness to Load Disturbance in Tine Varying Refining Process

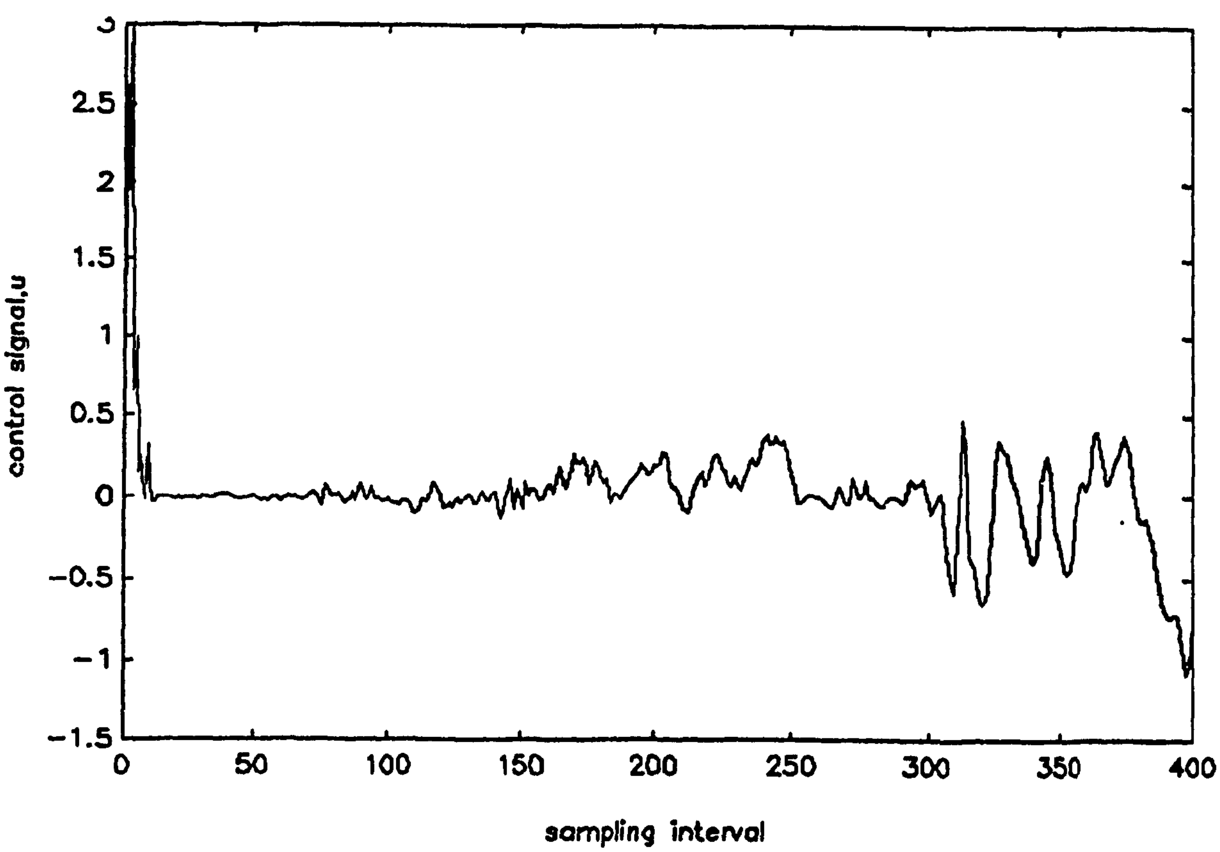


Figure 4.15 Control Signal Response to Load Disturbance

4.5 Conclusions of Simulation Results

Simulation results are compared for regulatory control, set point change and load change for refiner exhibiting slowly time varying dynamics and operating under different wood species. The control scheme is implemented using two stage parameter estimation namely in the primary output estimation and in the control design.

In Example 4-1, the study is made to compare the time variant system operating under white noise versus non stationary noise and STR design incorporating with and without integral action. Effect of fixed and variable forgetting factor used in the parameter estimation is also studied.

Using white noise, and controlling with STR having integral action and fixed forgetting factor, non optimal solution is obtained as shown in autocorrelation plot given in Figure 4.8. When variable forgetting is used together with integral action included in the control design, sub-optimal solution is obtained as shown in autocorrelation plot given in Figure 4.9.

Example 4-2 simulates set point change of freeness commonly encountered in the TMP mill operation. Comparison of closed-loop freeness control indicates that the variable forgetting factor used in the parameter estimation gives a better response to set point change as shown in Figure 4.2 as compared to Figure 4.10.

The simulation result of load change indicates that using only fixed forgetting factor in the parameter estimation is capable of rejecting short term disturbance. STR design in the example is incorporated with integral action.

4.6 Summary

This chapter describes the theory and application of the adaptive inferential control method for closed loop control of freeness. The inferential relationship between primary and secondary output are represented by pseudo ARMAX model. Identification of the parameters of the model is carried out using recursive least square. The estimated primary output is used directly in the design of self tuning regulator to provide a closed loop control of freeness.

The adaptive inferential control strategy has demonstrated the ability to provide a satisfactory closed loop freeness control for set point as well as manitaining the steady state operation in rejecting the load disturbance such as chip quality fluctuation. The results shows that the adaptive inferential control method had its potential application to the thermomechanical pulping industry.

CHAPTER V

CONCLUSIONS

This thesis has provided an extensive study of process modelling, identification and control of chip refining process for thermomechanical pulping plant in the pulp and paper industry.

The important contribution of this thesis had been the demonstraction of the use of adaptive inferential control strategy to provide a closed-loop control of freeness. To the best knowledge of the author, no mill has attempted to close the loop for freeness control. It is hoped that the study of this thesis will initiate some co-operation between the industry and academic institution to implement the proposed control strategy. In chapter II, the refining process is modelled as first order with time delay and the model is represented by input output form. The process modell selection has been verified by using the technique of open loop identification method.

Two different methods of control strategy are proposed, a constant inferential scheme namely implicit self tuning regulator applicable to a constant wood species; and dynamic adaptive inferential control scheme applicable to mix wood species and refiner using different wood species. In chapter III it has been shown that for a constant wood species, an implicit self tuning regulator is used to provide a closed loop control of freeness. The freeness would be inferred from the specific energy easily because of its unique relationship for the same wood species. Minimum variance control for freeness can be achieved if the controller is designed for time invariant system. For treating the time variant system with slowly changing of parameters, it was shown that the forgetting factor is capable of tracking the change of parameters and sub-optimal solution is obtained.

In controlling refiner running a different wood species, the implicit self tuning regulator based on constant wood species has a limitation and it is not capable of providing a good control. This leads to the concept of on line adaptation of identifying the dynamic relationship between the primary and secondary output. A pseudo ARMAX model describing the relationship between primary and secondary output allows on-line estimation of their dynamic parameters. The estimated primary output variable , the freeness can be used for control design. Closed-loop control of freeness using adaptive inferential approach has shown that the control strategy is capable for controlling a change of new set point as well as rejection of load disturbance. The results show that the closed-loop control of freeness is an improvement over the present method of open loop control operation.

5.1 Potential Industrial Application

The adaptive control strategy outlined in this thesis can be easily implemented to the industrial refiner. The refiner should be equipped with sensing device giving the continuous information of plate gap position and specific energy. Most of the refiner is equipped with the plate protection logic which ensures the refiner plate will back up when come close to the tolerance gap limit. The objective of the closed loop control will generate the optimal plate gap set point signal thus replacing the operator intuitive law as shown in Figure 1.6. In the implementation of the proposed control strategy, there will be no production and process upset.

5.2 Recommendations for Future Works

Throughout the study and simulation in this thesis, the control design considered is based on single input and single output system. The extend of this thesis would be the inclusion of multi input-multi output (MIMO) of the refiner process. Dilution water flow and one of the pulp physical property such as tear, shive etc could be considered as an extra input and output respectively.

Another extension of the study and control of the refiner could be the inclusion of quality optimisation. Freeness control is a fast loop in the refining process, an outer loop based on measurement of the fibre property would be included as a cascade control in providing the set point for inner freeness control for quality optimisation.

In the thermomechanical pulping plant, the refiner process consists of two stage refiners, a primary refining followed by secondary refining in series. Finally, the extension of the refiner control could include the two stage refiners in series.

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