İSTANBUL TEKNİK ÜNİVERSİTESİ ★ FEN BİLİMLERİ ENSTİTÜSÜ

ÖZAYARLAMALI KONTROL EDİCİLERİN HASSAS AYAR PARAMETRELERİNİN SEÇİMİ ÜZERİNE BİR ÇALIŞMA

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CONTENTS

İSTANBUL TEKNİK ÜNİVERSİTESİ ★ FEN BİLİMLERİ ENSTİTÜSÜ

ÖZAYARLAMALI KONTROL EDİCİLERİN HASSAS AYAR PARAMETRELERİNİN SEÇİMİ ÜZERİNE BİR ÇALIŞMA

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NOMENCLATURE

A	Polynomial
AD	Analog to Digital Convertor
AR	Auto Regressive
ARMA	Auto Regressive Moving Average
ARMAX	Auto Regressive Moving Average eXogeneous
ASL	Asymptotic Sample Length
B	Polynomial
C	Polynomial
c	Controlled Signal
CARMA	Controlled Auto Regressive Moving Average
CR	Covariance Resetting
CRT	Covariance Resetting Techniques
d	Constant
DA	Digital to Analog Convertor
DE	Differential Equation
E	Polynomial
E{...}	Expectation Factor
e_t	Disturbance Signal
E_a	Sum of Error Squares of A Parameters
E_b	Sum of Error Squares of B Parameters
E_c	Sum of Error Squares of C Parameters
E_e	Sum of Error Squares E Parameters
ELS	Extended Least Squares
ERRSQ	Estimation Error Squares
G	Polynomial
GLS	Generalised Least Squares
GMV	Generalised Minimum Variance
GMVC	Generalised Minimum Variance Controller
GMVSTC	Generalised Minimum Variance Self Tuning Controller
GMVSTR	Generalised Minimum Variance Self Tuning Regulator
GPC	Generalised Predictive Controller
H	Level
H_0	Transfer Function of ZOH
I	Unit Matrice
IAE	Integral Error of Absolute Error
ITAE	Integral of Time Absolute Error
I/O	Input/Output
IV	Instrumentation Variable
J	Cost Function
k	Time Delay

K	Gain
K_f	Kalman Filter
LQG	Linear Quadratic Gaussian
LS	Least Squares
MA	Moving Average
MIMO	Multi-Input-Multi-Output
ML	Maximum Likelihood
MLE	Maximum Likelihood Estimate
MRAC	Model Reference Adaptive Control
MRAS	Model Reference Adaptive System
MV	Minimum Variance
MVSTC	Minimum Variance Self Tuning Controller
MVSTR	Minimum Variance Self Tuning Regulator
n	Order of the System
NMP	Non-Minimum Phase
ODE	Ordinary Differential Equation
ORLS	Ordinary Recursive Least Squares
P	The Weighting on the Output 'y'
PAC	Parametric Adaptive Control
PC	Proportional Controller
PI	Proportional-Integral
PIC	Proportional-Integral Controller
PID	Proportional-Integral-Derivative
PIDC	Proportional-Integral-Derivative Controller
PPC	Pole Placement Control
PPSTC	Pole Placing Self Tuning Controller
Q	The Weighting on the Input 'u'
Q'	Polynomial
q	Flowrate
R	The Weighting on the Setpoint 'w'
RALS	Recursive Approximate Least Squares
RELS	Recursive Extended Least Squares
RGLS	Recursive Generalised Least Squares
RIV	Recursive Instrumental Variable
RKF	Recursive Kalman Filtering
RLM	Recursive Learning Method
RLS	Recursive Least Squares
RML	Recursive Maximum Likelihood
RMRA	Recursive Model Reference Approach
RSA	Recursive Stochastic Approximation
RSR	Recursive Square Root
RUD	Recursive Upper Diagonal
S	Estimator Covariance Matrix
SAA	Stochastic Approximation Approach
SAM	Stochastic Approximation Method

SISO	Single-Input-Single-Output
STC	Self Tuning Control
STDU	Standard Deviation of Input Signal
STDV	Standard Deviation of Noise Signal
STMVC	Self Tuning Minimum Variance Control
STR	Self Tuning Regulator
STUPID	Self Tuning PID
t_d	Dead Time
Δt	Sampling Time
u	Controller Output/Process Input
UD	Upper Diagonal
V_t	Disturbance Signal (Coloured Noise)
w	Process Setpoint
ϖ	Mean Value of Process Setpoint
$\underline{W}$	Weighting Matrix
WLS	Weighted Least Squares
$\underline{x}$	Data Vector
Y	Polynomial
y	Process Output
y	Mean Value of Process Output
z	Shift Operator
z^{-1}	Back-Shift Operator
ZOH	Zero Order Hold
ξ	Random Sequence Disturbing the System
$\wedge$	Denotes Estimate Values
$\underline{\theta}$	Parameter Vector
ε	Equation Error
ρ	Forgetting Factor
σ_e	Standard Deviation of Estimation Error
σ_n	Standard Deviation of Disturbance (Noise)
ϕ	Weighted Process Output
ϕ^*	Prediction of Weighted Process Output
λ	Tuning Parameter of the Q filter
α	Tuning Parameter of the Q filter
τ	Time Constant

FIGURE LIST

TABLE LIST

ABSTRACT

Last couple of decades, there has been great interest on adaptive control schemes and automatic control. Many researchers put many specific methods to overcome control problems in industrial chemical processes. Automatic control of industrial processes is a challenging task due to the presence of large time-delays, non-linearities, complex process dynamics, interactions from other control loops, corruption of data by noise, unmeasurable load disturbances, etc.

Using a conventional control scheme such as PID scheme is often not very satisfactory depending on the characteristics mentioned above. In spite of having large usage in the industry, fixed parameter PID control algorithm suffers from many draw backs:

- Time delays cannot be handled properly, this results to get sluggish response from the process.

- Physical constraints of a process cannot be incorporated in the control algorithm.

- Tuning of a conventional controller loop is usually time consuming operation. The tuning of a multiloop PID controller is at best if it is not an important process. In the absence of a mathematical model, it is performed on-line by an iterative experimental approximation like trial and error. The mathematical modelling of a process accounting for all the non-linearities in the process is a problem. The linear model of a process can help in selecting initial tuning constants but is not good enough to give the best performance along the complete period of operation.

- Because of the changes in process dynamics (catalyst decay, change in production levels, fouling of heat exchangers or variation in raw material quality and quantity etc.) controller has to be retuned and this leads to a degraded performance until it has been done.

These problems can be overcome by using a control strategy first proposed by Kalman (1958). Adaptive controllers and self-tuning controllers are capable of identifying the model of the process on-line and are able to compensate for the variations in the characteristics of a process.

Using self-tuning controller gives us better and faster controller commissioning, furthermore gives us the ability of expert tuning of the controller by non-expert personnel.

In this study and work, it is shown and explained how to select the necessary elements of the self tuning control schemes and how to employ appropriate methods by choosing fine tuning parameters for the some type of self-tuning controllers.

ÖZET

Yaklaşık son yirmi yıldır adaptive kontrol stratejileri ve otomatik kontrol büyük ilgi kazanmıştır. Bir çok araştırmacı yeni bir çok özel metotlar geliştirerek kimya endüstrisinde var olan kontrol problemlerini çözmeye çalışmaktadırlar. Endüstriyel proseslerde otomatik kontrol kullanımı büyük zaman gecikmeleri, non-lineerlik, karmaşık proses dinamikleri ve diğer kontrol çevrimleri arasındaki etkileşimden ve ölçülemeyen yüklenme değerleri yüzünden zor bir olaydır. Klasik kontrol metotları kullanımı genellikle bu yukarıda belirtilen sorunlardan dolayı memnuniyet verici değildir. Günümüzde sanayiide geniş kullanım alanı olan PID kontrol ediciler aşağıda verilen türde birçok sorun ile karşılaşmaktadırlar.

- Zaman gecikmelerinin etkileri ortadan kaldırılamaz, kontrol sistemini yavaş davranmak zorunda bırakır.
- Fiziksel sınırlamalar kontrol algoritması içinde temsil edilemezler.
- Klasik bir kontrol ediciyi ayarlamak zaman alan bir operasyondur. Çok çevrimli bir PID tipi kontrol edici ancak önemli olmayan basit proseslerde iyi bir şekilde ayarlanabilir.Bu da deneme ve yanılma yoluyla olur. Kimyasal reaksiyon içeren prosslerde ise deneme - yanılma yöntemini kullanmak kesinlikle söz konusu değildir.
- Katalizör bozunması, üretim hattındaki değişiklikler, ısı değiştiricilerindeki kirlenmeler, debi ve basınç değişimleri gibi proses dinamiğini etkileyen değişiklikler algılanamadığından kontrol performansı zamanla düşer. Bu yüzden kontrol edici tekrarlı olarak ayar edilmelidir.

Bu tip problemler ilk defa Kalman (1958) tarafından düşünülen kontrol stratejisi ile çözülmeye başlamıştır. Adaptive kontrol ediciler ve kendinden ayarlı kontrol ediciler prosesin modelini direkt olarak tanımlayabilirler ve proses özelliklerindeki değişimleri algılayarak kendilerini düzeltebilirler.

Kendinden ayarlı kontrol edicilerin (STC) kullanımı daha hızlı ve güvenli olmasının yanında uzman olmayan personelin gelişmiş bir kontrol edicinin yardımı ile proses üzerinde sağlam bir hakimiyet kurmasını sağlar.

Bu çalışmada kendinden ayarlı kontrol edicilerin ana elemanlarının nasıl düzenlenebileceği ve belirli kontrol edici tipleri için hassas ayar değerlerinin nasıl seçilebileceği gösterilmiştir.

Bu çalışmada kullanılan kendiliğinden ayarlı kontrol ediciler üç ana bileşenden oluşmaktadır. İlk olarak bir parametre tahmin edici (Parameter Estimator), ikinci olarak bir kontrol edici (Controller) ve son olarak da tahmin edilmiş proses parametrelerinden kontrol edici parametrelerini hesaplayan bir parametre hesaplayıcısı (Parameter Calculation) bulunmaktadır.

Bu çalışmada tekli giriş tekli çıkış sistemler incelenmiştir. Kendiliğinden ayarlanan kontrol edicilerin amacı sabit fakat bilinmeyen parametrelere sahip prosesleri kontrol etmektir. Ayrıca ısı değiştiricileri gibi parametreleri zamanla yavaşça değişen sistemlere de uygulanabilirler. Kendiliğinden ayarlanan kontrol ediciler başlangıçta bilinen bir sistem ve tasarım yöntemi ile oluşturulabilirler. Kontrol algoritması ardışık parametre tahmin ediciler kullanılarak bulunabilirler. Parametre tahmin ediciler proses girdi ve çıktılarına göre hesap yaparlar. Bir çok parametre tahmin yöntemi ve kontrol edici parametreleri hesap yöntemi olduğundan çeşitli tiplerde kontrol ediciler mevcuttur.

Bu tezdeki çalışmada kullanılan kontrol edici bir ön tahminli model üzerine kurulu ardışık parametre hesaplayıcıdan oluşmaktadır. Kendiliğinden ayarlanan kontrol edicinin, aynı zamanda bilinen girdi değerlerine karşılık sistemin verdiği çıktıları belirli bir zaman aralığında ölçerek her hangi bir sistemin transfer fonksiyonunu elde edebilmesi de mümkündür. Gerçek zaman uygulamalarında her numunelendirme periyodunda yeni dataya ihtiyaç vardır. Böylelikle, sistemin transfer fonksiyonu her zaman için izlenebilir ve bunun içinde geliştirilmiş teknikler mevcuttur. Bu tezdeki çalışmada 'unutma faktörü' olarak adlandırabileceğimiz bir faktör kullanılmıştır (Forgetting faktör), bu geçmişteki bazı verilerin unutma faktörüne bağlı olarak silinmesi anlamındadır. Sayısal değer olarak unutma faktörü bir'den küçük 'sıfır'dan büyük olarak seçilmelidir. Unutma faktörü numunelendirme zamanına da bağlı olarak 0.95 ile 0.999 arasında bir değer olarak seçilebilir, bu da 20 ile 1000 numunelendirme aralığına eşittir.

Kendiliğinden ayarlanan kontrol edicilerin minimum değişimli kontrol algoritmasını kullanmaları son kontrol elemanlarının aşırı şiddetli davranmalarına yol açabilir. Pratikte kabul edilemeyecek aşırı kontrol hareketlerinin optimize edilmesi için bazı sınırlandırmalar getirilebilir. Kendiliğinden ayaralanan kontrol algoritmaları başlıca iki ana grupta incelenebilir. Doğrudan yöntemler ve dolaylı yöntemler olarak adlandırılabilecek bu yöntemlerin arasındaki en önemli fark birincisinde parametre tahmin edicinin kontrol edici parametrelerini doğrudan vermesi, diğerinde ise tahmin edicinin sistem parametrelerini üreterek kontrol edici parametrelerini hesaplamasıdır.

Herhangi bir prosesin modelinin bilinmesi kontrol sistemlerinin tasarımı ve analizi için bir avantajdır. Böyle bir sistem modeli sistem dinamiğini olabildiğince tanımlamalıdır. Bir prosesin modelinin sağlanması için iki temel yaklaşım vardır, bunlar fiziksel kanunlardan elde edilen modeller ve deneysel yollardan elde edilen modellerdir. Genellikle sadece fiziksel kanunlardan yararlanarak yeterince hassas bir model elde etmek mümkün değildir, bazı sistem parametreleri deneysel olarak saptanmalıdır. Bu iki yaklaşımın birlikte değerlendirilmesi iyi bir model elde etmemizi sağlar. Model ne kadar iyi olursa uygulanan kontrolün de o kadar iyi olacağı düşüncesinden hareketle sistem tanımlanmasının (parametre tahmininin) önemi ortaya çıkmaktadır.

Uyarlamalı kontrolde kontrol kanununun tesbiti parametre tahmininden (sistem tanımlanmasından) sonra ikinci temel aşamadır. Uyarlamalı kontrol mekanizmalarının tasarımıda iki kademe vardır. Bunlardan ilki, sistem üzerinde olabildiğince deney yaparak eksik bilgileri tamamlamaktır (off-line). İkincisi proses parametrelerinin tahminlerine bağlı olarak kontrol edici parametrelerinin sürekli olarak ayarlandığı mekanizmadır (on-line).

Bu çalışmada öncelikle hızlı cevap veren bir sistem fiziksel kanunlar ve deneyler yardımı ile modellenerek iyi tanımlanmış birinci derece bir sistem örneği elde edilmiştir. Kendiliğinden ayarlanan kontrol edicinin algoritması Genelleştirilmiş Minimum Değişimli olarak tasarlandığından kontrol girişini düzenleyen çeşitli filtrelerin bu model üzerinde denenmesi ile kontrol edicinin temel yapısı belirlenmiştir. Modelin birinci mertebe olup parametrelerinin iyi biliniyor olması kontrol edicinin sağlıklı bir şekilde geliştirilebilmesi ve bütün filtrelerle tatminkar sonuçlar vermesini sağlamıştır.

Birinci mertebeden sistem modeli üzerinde gerçekleştirilen benzetim çalışmalarından elde edilen bilgiler yardımı ile ikinci mertebe bir proses üzerinde gerçek zaman (on-line) kontrol çalışmalarına geçilmiştir. İkinci mertebe proses örneği olarak bir elektrikli ısıtma sistemi kullanılmıştır. Bu sistem 4.5 kW gücünde, boşluk hacmi küçük olan (yaklaşık 0.5 l) tüp rezistanslı bir ısıtıcı ile bunun çıkış hattına yerleştirilmiş plastik kılıflı bir yarı iletken sıcaklık algılayıcısından (LM 335) oluşmaktadır. Bu sıcaklık algılayıcısı 0-100 °C aralığında çalışan 4-20 mA lik bir sıcaklık ileticisine bağlıdır. Sıcaklık algılayıcısının plastik kılıflı olması zaman sabitinin elektrikli ısıtıcının zaman sabiti yanında ihmal edilemeyecek bir büyüklükte olmasına, sonuç olarak da sistemin belirgin ikinci mertebe davranış göstermesine yolaçmaktadır.

Yapılan deneyler sonucunda çeşitli kontrol edici filtrelerinin davranışları incelenmiş, gerekli filtre parametreleri (hassas ayar parametreleri) tesbit edilmiş sisteme çeşitli bozan etkenler yüklenerek ikinci mertebeden bir sistemin

Kendiliğinden Ayarlı Genelleştirilmiş Minimum Değişimli Kontrol Edicilere verdiği cevaplar elde edilmiş Kimya Mühendisliği'nde karmaşık bir yapıya sahip olan Reaksiyonlu Distilasyon Kolonu'nun sıcaklık kontrolü için kullanılabilecek filtre ayar değerleri belirlenmeye çalışılmıştır. İkinci mertebeden sıcaklık sisteminin servo kontrolü ve regülasyon kontrolü incelenmiş, bütün bu deneyler sistemde son kontrol elemanının zaman-oransal kontaktör modülü ve triak modülü kullanılması halleri için ayrı ayrı gerçekleştirilmiştir. Zaman-oransal kontaktör modülünün kullanıldığı deneylerde sistem gürültülerinin daha fazla olduğu buna rağmen ulaşılması istenen ayar değerlerine (set point) kabul edilebilir hatalar ile yaklaşıldığı, kontrol girişlerinin proses çıktıları ile uyumlu olduğu gözlemlenmiştir. Triak modülü kullanılmasının temel nedeni bir sonraki çalışmamızda sıcaklığı daha hassas olarak kontrol edilecek olan Reaksiyonlu Distilasyon Kolonu'nda da buna benzer bir modülün bulunmasıdır. Triak modülünün kullanıldığı ısıtma sistemi deneylerinde gürültülerin daha aza indirgendiği ve kontrol girişlerinin proses çıktıları ile çok daha uyumlu hale geldikleri gözlemlenmiştir.

Reaksiyonlu Distilasyon Kolonu'nun ısıtıcı elemanı 2.5 kW gücünde olup deneylerde kullanılan alkol karışımlarının esterleşmesinde yeterli gücü sağlayabilecek düzeydedir. Kullanılan kolon dolgulu tip olup 8 cm çapında ve 40 cm uzunluğunda cam boruların 4 adetinin birbirlerine eklenmesi ile elde edilmiş, dolgu malzemesi olarak 5 mm çaplı Rasching halkaları kullanılmıştır. Kolonun üstündeki yoğunlaştırıcı bir U dönüşü ile sabitlenmiştir. Yoğunlaştırıcının altında kolon baş ürününü toplayan ve faz ayrılması ile baş ürünün sudan ayrılmasını sağlayan bir depo mevcuttur. Ester fazı yanal yüzeyden alınarak bir geri besleme bölücüsüne gönderilmektedir. İstenmeyen su fazı deponun altından çekilmektedir. Kolon 20 l hacminde bir cam reboyler tarafından ısıtılmaktadır. Önceki çalışmalardan elde edilmiş sonuçlar ve literatür bilgileri değerlendirilerek kolonun besleme debileri ayarlanmış, kolon rejimine uygun şekilde etil ester üretimi için gerekli alkol karışımı ve asetik asit beslemesi yapılmış, düzenli baş ürün yaklaşık 75 min sonra çekilmeye başlanmıştır. Yukarıda açıklanan ön çalışmalardan elde edilen bilgiler ile kolonun sıcaklığını en iyi şekilde kontrol edebilecek filtre parametrelerinin seçilmesiyle reboyler buhar faz sıcaklığı kontrol edilmiş buna bağlı olarak kolon tepe sıcaklığının davranışı gözlemlenmiştir.

Literatürden elde edilen modifiye edilmiş PID kontrol edici sonuçları ile kendiliğinden Ayarlanan Genelleştirilmiş Minimum Değişimli Kontrol Edici'nin sonuçları karşılaştırılmış, klasik PID tipi bir kontrol edici ile kontrolünün mümkün olmadığı bilinen bu karmaşık sistemin modifiye edilmiş PID tipi kontrol edici ile belli toleranslara kadar kontrol edilebildiği fakat bozan etken yüklenmesi durumunda kolon tepe sıcaklığının kritik bir değer olan 79 °C ın altına düştüğü ve bu durumun baş ürün ile gelmesi beklenen su çıkışını engellediği, bunun da kolon rejiminin bozulmasına yol açtığı belirlenmiştir. Benzer şartlarda aynı besleme debileri ile Kendiliğinden Ayarlı Kontrol Edici'nin kullanılması durumunda kolon yatışkın duruma getirildikten sonra besleme debileri iki katına çıkarılarak bir Reaksiyonlu Distilasyon Kolonun'nda verilebilecek en yüksek bozan etken denenmiş ve kolon tepe sıcaklığının kritik sıcaklığın altına düşmediği, reboylerin sıvı ve buhar faz sıcaklıklarının birbirleri ile ve kontrol girişi ile uyumlu davrandıkları gözlenmiştir.

Bu çalışmanın sonunda daha az uzman kişilerin çok daha karmaşık ve sorunlu sistemlerin kontrolünde kullanılabileceği ve parametre tahmini sayesinde prosesin daha iyi tanımlanabileceği, elde edilen modele bilinen bozan etkenler göz önüne alınarak ileri beslemeli kontrol adımlarının da eklenmesi ile klasik kontrol edicilerden cok daha iyi bir kontrol sağlama imkanı olduğu görülmüştür.

CHAPTER 1. INTRODUCTION

1.1. HISTORY OF THE CONTROL STRATEGIES

The control term can be described as the problem of achieving desired behavioural characteristics from a system by on-line collection of data and the systematic processing of the data as a decision making tool. The problems of control occur in almost all branches of engineering, economics, bio-technology and medical sciences. Closed-loop proportional-integral and derivative control (**PID**) have been most popular control strategy in the chemical industry.

Process control and automatic control applications in the chemical and petro-chemical industries owe much of their current status to early developments in the field achieved in the military and allied industries. In 1955, it was first suggested that military computer control systems could be applied to the control of chemical processes. At that time, the obvious applications were in data acquisition, alarm systems, management calculations and set-point control. Digital computer process control was first applied by Texaco to a refinery process in 1958 (Farrar, 1959). After that, increasing numbers of computers installed on process plants in the United States of America and in the United Kingdom, they are documented in some reviews (Williams, 1963 and Russell, 1967). At that time computer technology was not very advanced and usage of these bulky control systems was limited. The total cost of the system was that of the computer and of the conventional equipment. These controllers were in fact simple special purpose analogue computers executing the standard three-term control algorithm.

In the last two decades both the computer technology and the control theory advanced very fast and made it possible to the usage of advanced computer control applications to many dynamic systems.

These technological developments provide better facilities for the applications of the classical control techniques and also put forward the advanced modern control methods to handle complex processes which are difficult to control .

Early classical feedback control methods have been progressively supplemented by other advanced predictive and adaptive control strategies since the landmark papers by Åström and Wittenmark (1973), Clarke and Gawthrop (1975), Wittenmark (1975), Kam (1985), Clarke (1986), Morris (1987), Warwick et. al. (1987), Goodwin et. al. (1988), Masten (1988), etc. Recently the successful applications of adaptive control techniques received widespread acceptance among chemical industries (Seborg et. al., 1986; Lambert, 1987) and in other areas such as mining, metallurgical industries. One of the most interesting area is the control of bio-medical systems (Linkens, 1984; Linkens and Hacisalihzade, 1990). The human body can be taken as a chemical plant producing numerous chemicals and making different reactions at certain temperature and pressure conditions, heat and mass transfer operations also take part in these reactions.

Historically, self-tuning control has been concerned with the sub-optimal control of noisy linear time invariant systems of known order and delay but with unknown parameters. After three decades of the first work of Kalman (1958) and over a decade since the original designs of Peterka (1970) and Åström and Wittenmark (1973), self-tuning or adaptive control is widely referred to as almost any form of automatic regulator tuning and is finding a better place among the industrial controllers, Morris et. al. (1977), Wellstead et. al. (1979), Morris et. al. (1981), Dexter (1983), Wittenmark (1984), Farsi (1986), Peel (1986), Song et. al. (1986), Tham (1986), Peel et. al. (1987).

Self-tuning controllers can be useful in the areas of ; automatic tuning of PID regulators (Gawthrop, 1986; Warwick, 1987), control of time-delay systems with predictor based designs, control of multivariable systems with interactions and delays (Morris et. al., 1982), design of standalone controllers for specific high-performance loops, tuning of dynamic feedforward compensators and tuning of general feedback controllers continuously or on demand.

Self-tuning and in general adaptive control theory has made an outstanding mark on the development of control theory and practice since 1959. The number of publications and conferences on adaptive control strategies and related subjects such as estimation methods and identification techniques have been increasing and still keep increasing.

1.2 OBJECTIVE OF THE STUDY

This thesis reports on the results of an investigation of the fine tuning parameters of self-tuning controller of single-input single-output **(SISO)** systems. The project studies one of the three sections of adaptive controllers; control algorithm. Although the algorithm used is based on the Generalised Minimum Variance control law, the implementation considerations are applicable to other self tuning strategies. This study shows the advantage of applying adaptive control to chemical process elements and systems by using predicted feedbacks and provides dead-time compensation as well as the ability of adaptive control algorithms to tune feedforward load compensation terms.

As Generalised Minimum Variance (GMV) control algorithm includes a number of parameters which can be chosen by the user to generate different control philosophies, different filters used to obtain better results and compared respectively.

In this work, the important decisions had to be made before implementations of the GMV control law, such as the model order, the model type, choice of the sample time, determination of the process delay and the choice of Q' filter. Some of these parameters set by using experimental results obtained from the pilot plant and by using Recursive Least Square Parameter Estimation method to identify to the controlled system. On the other hand, choosing some vital estimation parameters had been done by both from the literature and from the simulation experiments on trial basis.

1.3 STRUCTURE AND LAYOUT OF THE THESIS

The first part of this thesis from Chapters 2 to 4 concentrates on the basic elements of the Self Tuning Regulator and the literature review. The second part deals with the controller algorithm and its applications on the controlled system. The structure and the layout of the thesis are as follows:

Chapter 2 provides a brief account of the advances in adaptive controllers and in particular, Self Tuning Controllers.

Chapter 3 describes the parameter estimation methods and the system identification techniques. Recursive Least Squares Parameter Estimation method is described in details and shown how to be derived. The other form of estimation variations is also discussed in short.

In Chapter 4, the self-tuning controllers are described and derived, special cases of the STC control law are discussed and time delay compensation is explained.

Chapter 5 shows the experimental implementation of the STC, experimental conditions and results.

Chapter 6 summarises the results of the project and provides further suggestions for the direction of future work.

CHAPTER 2. LITERATURE SURVEY

2.1. INTRODUCTION

A brief survey of the developments of adaptive control and its applications is presented in this chapter. As covering the whole range of adaptive control schemes is beyond the scope of this thesis, this chapter reviews the class of stochastic adaptive control schemes known as 'Self Tuning Control'.

2.2. ADAPTIVE PROCESS CONTROL

In spite of the good performance of classical controllers (**PID**) due to the requirements for the high performance control systems, even when the dynamic characteristics of the plants are not known or poorly known and when they are time varying, a new class of control algorithms called '**Adaptive Controllers**' were developed.

It was not a new idea to develop a controller that continuously learns about the process it is controlling, then controller's parameters could be adjusted accordingly to satisfy a specified optimal objective. The origin of such idea goes back to Kalman (1958) and his studies on a '**self-optimising**' control algorithm. The scheme firstly involved with the on-line determination of the parameters of a model which is assumed to describe the process.

The latest estimates of the parameters of the process model are then employed to calculate a control signal based on a control law.

The strategy hence conforms to the conventional design practice of process modelling followed by controller synthesis. The advantage over classical off-line design is the ability of the algorithm to automatically adjust the controller's parameters to account for slowly time varying process characteristics, at every sample interval if it is desired. At that time lack of computational efforts and expensive computer powers made Kalman's idea to be frozen about 12 years.

In 1970, Peterka (1970) and, later Åström and Wittenmark (1973) succeeded Kalman and revived his idea. Peterka's algorithm can be considered to be the first recognisable modern self-tuning control scheme. The self-tuning regulator of Åström and Wittenmark differs from the original scheme of Kalman's in that controller parameters, rather than process model parameters, are directly estimated on-line.

In order to design an adaptive controller, an on-line process identification technique is used to estimate the parameters of a model of the process and this information is used to obtain an appropriate control law. Although an effective adaptive control algorithm requires a good parameter estimation law and a good control law , the parameter estimation forms the main part of an adaptive controller (Shah, 1986). Figure 2.1 shows the block diagram of the estimation law.

Figure 2.1 Block Diagram of the Estimation Law.

According to Tsypkin (1966), the term '**adaptation**' means "**the process of changing parameters, structure and possibly the controls of a system on the basis of information obtained during the control period, so as to optimise the state of system, when operating conditions are either incompletely defined initially, or changed**". This means that a fixed gain feedback is not considered to be part of an adaptive system (Åström, 1983).

According to Goodwin and Sin (1984), an adaptive controller is actually nothing more than a special nonlinear control algorithm which is motivated by combining on-line parameter estimation with on-line control.

The principal reason for suggesting adaptive schemes in practical applications is to compensate the large variations in plant parameters over time (Lee and Narendra, 1988). Typically, the parameters of the plant change slowly. However, when such changes take place over a long period, the total variation in the values may be substantial.

There are three schemes for parameter adaptive control strategy; **Gain Scheduling**; **Model Reference Control (MRC)** and **Self Tuning Controllers (STC)** (Åström, 1983 and Landau, 1982). In this thesis only **Self Tuning Controllers** will be examined.

2.3. SELF-TUNING REGULATOR (STR)

An ideal regulator should have an adaptive mechanism able to distinguish between noise, drifts or deterministic changes and at the same time use moderate control action to prevent overshoot and instability. In order to make it acceptable by the industry it should suit to a broad class of processes, consists of simple algorithm and performance requirements and also must be dependent upon as few as possible parameters, and all these should have simple initiative base (Hiram and Kershenbaum, 1985).

In 1973, Åström and Wittenmark proposed the '**self tuning regulator**' (**STR**). The purpose of this regulator is to control systems with unknown but constant parameters. The regulators can also be applied to the systems with slowly varying parameters. The STR is also known as the **Minimum Variance Self Tuning Regulator (MVSTR)**.

The analysis has been restricted to single-input single-output **(SISO)** systems. It has been assumed that the disturbances could be characterised as filtered white noise, with zero mean and finite variance. The criterion considered is the minimisation of the variance of the output. The algorithms analysed are those obtained on the basis of a separation of identification and control. To obtain a simple algorithm, the identification is simply achieved by a least squares parameter estimator.

The self tuning regulator is in essence, the same as Peterka's (1970) algorithm. The major contributions of their publication were the results of the analysis of the closed-loop properties of self-tuning algorithm. These may be summarised by two theorems. The first one states that if the parameters of the self -tuning regulator converge, then certain covariances of the output and certain covariances of the control variable and the output will vanish under weak assumptions on the system to be controlled.

These assumptions are that the model representing the process is of sufficient order and that process time-delay is known. This theorem implies that if the process being controlled is stable, then the self-tuned closed-loop will also be stable. In the second theorem, it is assumed that the system to be controlled is a general linear n^{th} order system. If the parameters estimated converge such that the controller polynomials do not have common factors, then the self tuning regulator will converge to the '**optimal**' minimum variance regulator.

The control law obtained is in fact the minimum variance control law that could be computed if the parameters of the system were known. This theorem implies that if the model is of sufficient order, then even if the converged estimated parameters are biased, the control signal will still approach that calculated from knowledge of the true characteristics of the process. It means that the self tuning regulator has the desired asymptotic properties.

The regulator can be thought of as being composed of three parts; **a parameter estimator** that estimates the process parameters, **a controller** and a third part, **a controller designer** which relates the controller parameters to the process estimator.

Åström and Wittenmark (1973) has defined the concepts of self-tuning in their work. That was the beginning of much research interest into the self-tuning technique. Since then it has drawn much attention to this method of adaptive control which is still very much in interest. The good transient and asymptotic properties and computational simplicity of the self-tuning regulators made the method attractive for industrial applications (Tham, Montague and Morris, 1987).

Using STR in industrial environments were very encouraging, there were some points that were not in favour of the STR. Firstly, the demands on final control elements made by minimum variance control law were too severe. In order to maintain optimality of control, minimum variance control signals tend to exhibit large magnitude changes, resulting in excessive wear and tear of instrumentations. Secondly, the applicability of the minimum variance control law was also limited to minimum phase processes. Control of **non-minimum**

phase (NMP) system could however be affected by scaling the controller parameters or even and by increasing sampling intervals.

Self-Tuning Regulators are able to control uncertain systems and have been used in a number of experimental facilities and industrial plants. However, potential practical problems have prevented the full acceptance of these controllers in industry; this includes difficulties in choice of parameters, method of start-up, long-term operation, variable and uncertain time-delays, valve saturation and sudden changes in the system (Hiram and Kershenbaum, 1985).

2.4. SELF TUNING CONTROLLER (STC)

Clarke and Gawthrop (1975) proposed an extension to the **Minimum Variance Self-Tuning Regulator (MVSTR)** of Åström and Wittenmark(1973). This extension was that the excessive control effort was penalised by introduction of a weighting on control signals.

Suitable choice of control weighting is also enabled to control non minimum phase (NMP) systems. The resulting algorithm was called as the Generalised Self-Tuning Regulator, and was later named **'Self-Tuning Controller'** **(STC)** by Clarke and Gawthrop (1975).

The STC not only penalises excessive control, but also had included in its cost function, the set-point ($\mathbf{w}_t$). It could therefore accomplish regulation as well as set-point tracking of both minimum phase and non minimum phase systems. Gawthrop (1977) pointed out the similarities between the STC and the classical Smith Prediction and also between the STC and Model Reference Adaptive Control (MRAC). Later, Clarke and Gawthrop (1979) put forward a refined version of their STC algorithm.

Although the differences between these algorithms by Clarke and Gawthrop (1975, 1979) were slight, the latter version was more useful to on-line implementation. The method of (1975) and a subsequent refinement of structure (1979) is now commonly known as the '**Generalised Minimum Variance (GMV)**' self-tuning strategy.

The STC schemes fall into the class of adaptive scheme known as non-dual certainty equivalence stochastic adaptive systems. If the cost function only takes into account the previous measurements and does not assume that further information will be available, then the resulting controller is called as '**non-dual**' controller, otherwise the result would be a '**dual**' controller.

The certainty equivalence principle assumes that the estimated parameters are the true parameters. In other words, the control signal is calculated as if the controller had been designed from known plant parameters.

In adaptive control, there are very few cases where the certainty equivalence principle is applicable. One exception is when the unknown parameters are stochastic variables that are independent between different sampling intervals.

This is the assumption made in the design of self-tuning algorithms. The cautious controller is made aware that parameter estimates may not be correct and will therefore take a more '**cautious**' control action.

Self-tuning control algorithms may be divided into two groups (Åström, 1983; Gawthrop, 1987); **implicit** (direct) methods where the estimator directly produces controller coefficients and **explicit** (indirect) methods where the estimator generates system coefficients which then can be used to calculate controller coefficients. Figure 2.2 shows the block diagram of an implicit controller coefficients. Figure 2.2 shows the block diagram of an implicit (direct) STC while Figure 2.3 shows the block diagram of an explicit (indirect) STC.

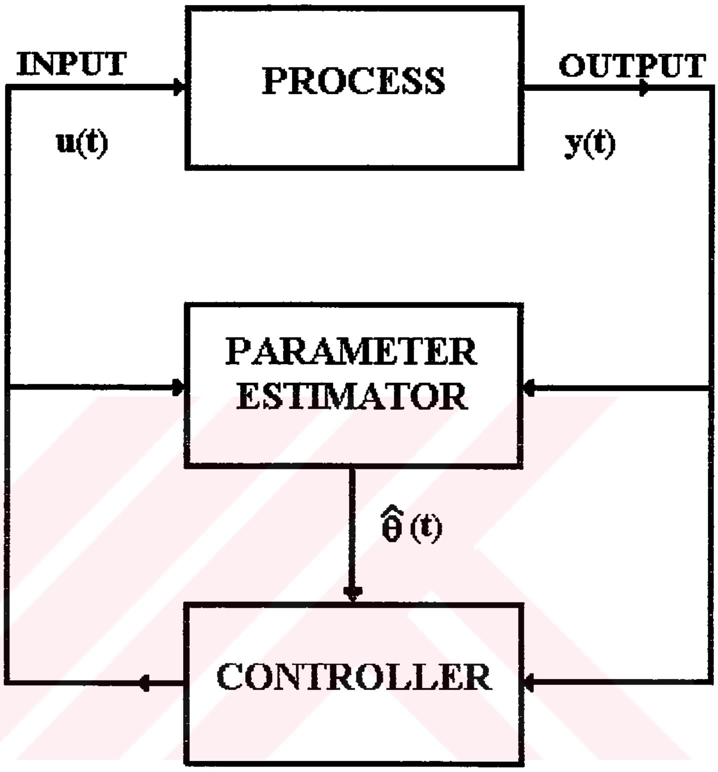

Figure 2.2 Block Diagram of Implicit (Direct) STC.

Explicit self-tuning controllers are known to have a robustness defect; if the plant is not adequately excited, then even small disturbances can result in drifting parameter estimates and instability. However, if the plant is being persistently excited, then the adaptive system is locally exponentially convergent and stable (Åström, 1983). The self-tuning controller will be described in more detail in Chapter 4.

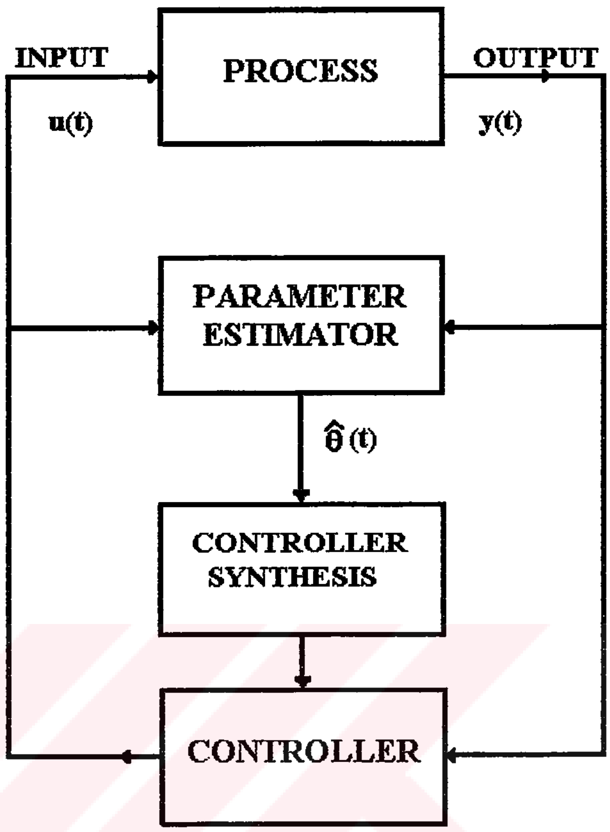

Figure 2.3 Block Diagram of Explicit (Indirect) STC.

2.5. SYSTEM IDENTIFICATION

Having a mathematical model of any process which is to be controlled is an advantage for analysing and designing control systems. Such a model should describe the system dynamics as completely as possible. There are two basic approaches to obtain a model of the process (Ogata, 1987). First one is to obtain a model based on physical laws, the other is to use experimentation. The experiments must be performed on the system or the process, in order to obtain lacking knowledge of the system or the process. In general, it might not be possible to obtain an accurate model by applying physical laws only. Some of the plant parameters must be determined by experiments.

Thus the two approaches need to be combined to get a reasonably good mathematical model, and not forgetting perfect model gives perfect control. The process of constructing model and estimating the best values of unknown parameters from experimental data is called '**system identification**'.

System identification or parameter estimation is one of the two main parts of the adaptive control scheme. The other is the '**control law**'. There are two stages involved in the design of adaptive control schemes; firstly, it is often possible to perform experiments on the system in order to obtain lacking knowledge. Secondly, based upon the estimates of process parameters, controller parameters could be adjusted constantly (Åström and Eykhoff, 1971).

System identification could be categorised into two different groups:

- OFF-LINE method of identification.
- ON-LINE method of identification.

The field of identification and process parameter estimation has developed rapidly during the last two decades and it is still developing. There are countless number of publications on system identification (see Åström and Eykhoff, 1971; Furth, 1973; Galier, 1974; Gertler, 1974; Eykhoff, 1974; Ljung and Sodestrom, 1975; Landau, 1976; Wittenmark, 1979; Dugard and Landau, 1980; Isermann, 1980; Strejc, 1980; Kumar et. al., 1981; Wong and Bayoumi, 1983; Ljung and Soderstrom, 1983; Farsi et. al., 1984; Dumortier, 1985; Warwick, 1986; Ljung, 1987; Ljung and Gunnarson, 1990). In spite of the differences between different methods of identification the underlying principles are almost the same. The basic method of off-line and on-line method of identification will be discussed in Chapter 3.

CHAPTER 3. INTRODUCTION TO PARAMETER ESTIMATION

3.1. INTRODUCTION

The first step in designing Self-Tuning Controller scheme is the determination of the process model. This process model can be in many forms depending on the system and the usage. It might be linear or non-linear; might have lumped or distributed parameters; might have time varying parameters and most important it may be represented in continuous or discrete time. While the mechanistic model development is fundamental, knowledge obtained from such an exercise may be discredited due to lack of reliable data. This is especially true for the chemical reaction systems that process behaviour is non-stationary and ill-defined. In this circumstances, using a second modelling approach to obtain dynamic information about the process in the region of interest by designed experiments is essential. The general philosophy of obtaining the 'best' values of otherwise unknown process parameters by experiment is known as '**System Parameter Estimation** (or as it is called System Identification)'.

As this philosophy forms the main part of all self-tuning/adaptive control schemes, parameter estimation (**system identification**) is discussed in this chapter.

The literature devoted to identification is voluminous (see Wong et. al., 1967; Kailath, 1968; Panuska, 1968; Young, 1970; Åström and Eykhoff, 1971; Wieslander et. al., 1971; Eykhoff, 1974; Sinha, 1975; Gustavsson et. al., 1977;

Moore, 1978; Isermann, 1980; Mayne et. al., 1982; Sin et. al., 1982; Ljung and Soderstrom, 1983; Lozano, 1983; Farsi et. al., 1984; Isermann, 1985; Warwick, 1986; Ljung, 1987; Norton, 1987; Sripada, 1987; Ljung and Gunnarson, 1990).

The system identification literature contains hundreds of technical papers on many different approaches to the subject. Therefore, it is very difficult for the engineers who are not familiar with the adaptive control theory, to select the appropriate approach to use for any given problem. Thus, it is a good idea to remember the comment by Åström and Eykhoff (1971) ; ''**A typical example is the discussion whether the accuracy of an identification should be judged on the basis of derivations in model parameters or in the time response. However, if the ultimate purpose is to design control systems, then it seems logical that the accuracy of an identification should be judged on the basis of the performance of the control systems designed from the results of identification**''.

Identification means that a batch of data is collected from the system and subsequently as a separate procedure this batch of data is used to construct a model, such a procedure is called as '**Off-Line Identification**'. In general, the methods which are used for off-line system identification are based on information obtained from the system previously. This is usually a set of data observation of system input-output after statistical tests have been applied to the system in order to make an estimation of the model order and subsequently the parameter values of the process.

The purpose of this chapter is to provide an insight into parameter estimation techniques and emphasis is placed on the mechanism of the particular algorithm used in this work; **Recursive Least Squares (RLS)**. This technique is based on the minimisation of some squared error function.

3.2. LEAST SQUARES PARAMETER ESTIMATION

The history of least squares started with Karl Gauss (Bodewig, 1956). Amongst the many other estimation schemes, the **least squares (LS)** method is one of the most popular and useful techniques for the system identification. It is based on the principle that the most probable values of the unknown quantities will be those for which the sums of squares of the differences between the actually observed and computed values, multiplied by numbers that measure the degree of precision, is minimised. Consider the following model;

$$A(z^{-1})\, y_t = B(z^{-1})\, u_{t-k} + e_t \qquad (3.1)$$

where '**y**' and '**u**' are the sequences of output and input signals respectively; '**e**' is a disturbance signal and assumed to be a random sequence with zero mean and variance σ^2 and is uncorrelated with 'y' and 'u'; 't' is the time index and '**k**' is the total time delay or dead time that is an integer multiple of the sampling time.

Equation (3.1) is a special case of the model:

$$A(z^{-1})\, y_t = B(z^{-1})\, u_{t-k} + C(z^{-1})\, \xi_t + d \qquad (3.2)$$

with d=0, C=1 and e=ξ

Polynomials $A(z^{-1})$ and $B(z^{-1})$ are defined as:

$$A(z^{-1}) = 1 + a_1 z^{-1} + a_2 z^{-2} + \dots + a_{nA} z^{-nA} \qquad (3.3\ a)$$

$$B(z^{-1}) = b_0 + b_1 z^{-1} + b_2 z^{-2} + \dots + b_{nB} z^{-nB} \qquad (3.3\ b)$$

Expansion of equation (3.1) at time t=1 will yield:

$$\begin{aligned} \underline{y}_1 = -a_1\, y_0 - a_2\, y_{-1} - \ldots - a_{nA}\, y_{1-nA} \\ + b_0\, u_{1-k} + b_1\, u_{1-k-1} + \ldots + b_{nB}\, u_{1-kn-B} + e_1 \end{aligned} \tag{3.4}$$

where a_i (i=1,2,3,...,nA) and b_j (j=0,1,2,3,...,nB) are unknown parameters, '**nA**' and '**nB**' are degrees of the polynomials '**A**' and '**B**' respectively. The total number of parameters which must be estimated is:

$$\deg(A) + \deg(B) + 1$$

or;

$$nA + nB + 1 \tag{3.5}$$

Equation (3.4) can be written in following form:

$$\underline{y}_t = \underline{x}^T{}_t\underline{\theta} + e_t \tag{3.6}$$

The parameter vector '$\underline{\theta}$ ' is defined as:

$$\underline{\theta}^T = (\, a_1, a_2, \ldots, a_{nA}; b_0, b_1, \ldots, b_{nB}\,) \tag{3.7}$$

and '$\underline{\mathbf{x}}$' the regressor or data vector is defined as:

$$\begin{aligned} \underline{x}^T{}_t = (-y_{t-1}, -y_{t-2}, \ldots, -y_{t-nA}; \\ u_{t-k}, u_{t-k-1}, \ldots, u_{t-k-nB}) \end{aligned} \tag{3.8}$$

Equation (3.6) with t=1 can be written as:

$$\underline{y}_1 = \underline{x}^T{}_1\underline{\theta} + e_1 \tag{3.9}$$

Suppose 'N' observations of the output and input have been made, resulting in 'N' equations such as given by equation (3.9):

$$\underline{y} = \underline{x}\,\underline{\theta} + \underline{\varepsilon} \qquad (3.10)$$

where:

$$\underline{y}^T = (y_1, y_2, \ldots, y_N) \qquad (3.11)$$

$$\underline{\varepsilon}^T = (\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_N) \qquad (3.12)$$

$$\underline{x}^T = (\underline{x}_1, \underline{x}_2, \ldots, \underline{x}_N) \qquad (3.13)$$

The objective is to determine the elements of '$\underline{\theta}$'. From the principle of Least Squares algorithm, it is known that this result can be obtained by the minimisation of some error squared function with respect to '$\underline{\theta}$'. Such a function will have the general form that is given by:

$$J_S = \sum_{t=1}^{N} W_t\, \varepsilon^2_t = \underline{\varepsilon}^T\, \underline{W}\, \underline{\varepsilon} \qquad (3.14)$$

where ε_t is the residual and it is defined as:

$$\varepsilon_t = y_t - \underline{x}^T_t\, \underline{\hat{\theta}}_{t-1} \qquad (3.15)$$

It is noted that; $t = 1, 2, 3, \ldots, N$ and '$\wedge$' denotes the estimated value.

'**W**' is a weighting matrix of appropriate dimensions and three major forms may be encountered:

(1) If the matrix '**W**' is chosen equal to the identity matrix, **W=I**, the procedure of minimisation of the equation (3.14) is simply called the procedure of '**Least Squares (LS)**' parameter estimation.

(2) If the matrix '**W**' is a general positive definitive matrix, the method is called ' **Weighted Least Squares (WLS)** ' parameter estimation.

(3) If the characteristics of the noise effecting the system is known, then by choosing '$\mathbf{W}^{-1}$' equal to the noise covariance matrix, the minimisation results in the ' **Generalised Least Squares (GLS)** ' parameter estimation.

Proceeding with the minimisation, rewrite equation (3.14) as;

$$J_S = (\underline{y}-\underline{x}\underline{\theta})^T \underline{W} (\underline{y}-\underline{x}\underline{\theta}) \tag{3.16}$$

Expansion of equation (3.16) yields:

$$J_S = \underline{y}^T \underline{W}\,\underline{y} - \underline{y}^T \underline{W}\,\underline{x}\,\underline{\theta} - \underline{\theta}^T \underline{x}^T \underline{W}\,\underline{y} + \underline{\theta}^T \underline{x}^T \underline{W}\,\underline{x}\,\underline{\theta} \tag{3.17}$$

Differentiation of equation (3.17) with respect to '$\underline{\theta}$' leads to the well known result in system identification;

$$(\partial J_S/\partial\theta) = -2\,\underline{x}^T \underline{W}\,\underline{y} + 2\underline{x}^T \underline{W}\,\underline{x}\,\underline{\theta} \tag{3.18}$$

The vector '$\underline{\theta}_{\mathbf{WLS}}$' that sets the equation (3.18) to zero is therefore;

$$\hat{\underline{\theta}}_{WLS} = (\underline{x}^T \underline{W}\,\underline{x})^{-1} \underline{x}^T \underline{W}\,\underline{y} \tag{3.19}$$

By setting W=I the Least Squares estimator of '$\underline{\theta}$' is obtained as;

$$\hat{\underline{\theta}}_{LS} = (\underline{x}^T \underline{x})^{-1} \underline{x}^T \underline{y} \tag{3.20}$$

Equations (3.19) and (3.20) are known as the '**normal**' equations of the respective estimators.

As was mentioned earlier, the procedures described here are '**Off-Line**' (**Batch**) methods. In other words, a set of 'N' observations of the system inputs and outputs are collected and stored before processing. However, in self-tuning control, or generally speaking in adaptive control schemes, identification may be required to be performed at every sampling interval. When the model is updated periodically with reference to its past values, this is called '**Recursive Least Square Parameter Estimation (RLS)**' or '**Recursive Identification**'.

There are some other terms used for recursive identification such as '**On-Line Identification**'; '**Real-Time Identification**'; '**Adaptive Algorithm**'; '**Sequential Estimator**' (Wieslander et. al., 1971; Ljung, 1987; Mansoori, 1987a; Mansoori, 1987b).

There is an important reason to use adaptive methods and recursive identifications in practice as the properties of the system may be time varying and it is desired that the identification algorithm should track system variations.

3.3. RECURSIVE PARAMETER ESTIMATIONS

For on-line parameter estimation, the ordinary or batch least squares algorithm may be unsuitable. This is a consequence of the large number of arithmetic operations and calculations involved, that are caused by the matrix inversion. Therefore, it may be better to make computations in recursive form, ie. the algorithm is formulated as the results obtained at the previous time step may be used to compute the estimates at current time, '**t**'. Re-evaluating the parameters in the model makes the recursive estimation techniques very desirable.

Some '**Recursive**' or '**On-Line**' identification algorithms described by Åström and Eykhoff (1971); Eykhoff (1974); Graupe et. al. (1980); Isermann (1980); Kurtz et. al. (1980); Ljung (1987); Olcer et. al. (1986); Soderstrom et. al. (1978); Soderstrom and Ljung (1983); Warwick (1986); Wong et. al. (1983). Most common types of recursive algorithms are as follows;

Recursive Least Squares (RLS), Recursive Generalised Least Squares (RGLS), Recursive Extended Least Squares (RELS), Recursive Maximum Likelihood (RML); Recursive Upper Diagonal (RUD); Recursive Square Root (RSR); Recursive Instrumental Variable (RIV); Recursive Learning Method (RLM); Recursive Stochastic Approximation (RSA); Recursive Approximate Least Squares (RALS); Recursive Model Reference Approach (RMRA); Recursive Kalman Filtering (RKF). Most of these methods have great similarities and their algorithms have almost the same structure.

These methods have been used in many experimental work and discussed in many papers and publications. In this section some recursive identification methods will be explained and discussed.

3.3.1. Recursive Least Squares (RLS) Parameter Estimation:

RLS algorithm is one of the most popular and well known estimation methods to be used an on-line identification. Having less computational requirements and being straightforward to be understood makes this method very popular.

Rewriting equation (3.20) that gives Least Squares (LS) algorithm;

$$\underline{\hat{\theta}}_t = (\underline{x}^T \underline{x})_t^{-1} (\underline{x}^T \underline{y})_t \qquad (3.21)$$

The vector ($\underline{x}^T \underline{y}$) and matrix ($\underline{x}^T \underline{x}$) in equation (3.21) contains data from time (t-N+1) to time (t), which has been collected from 'N' observations.

The matrix $(\underline{x}^T \underline{x})_t$ can be expressed as the sum of two terms;

$$(\underline{x}^T \underline{x})_t = \sum_{i=t-N}^{t-1} (\underline{x}\,\underline{x}^T)_i + (\underline{x}\,\underline{x}^T)_t \qquad (3.22)$$

or ;

$$(\underline{x}^T \underline{x})_t = (\underline{x}^T \underline{x})_{t-1} + (\underline{x}\,\underline{x}^T)_t \qquad (3.23)$$

Let $\underline{S}_t = (\underline{x}^T \underline{x})_t^{-1}$, Equation (3.23) becomes;

$$\underline{S}^{-1}{}_t = (\underline{S}_{t-1})^{-1} + (\underline{x}\,\underline{x}^T)_t \qquad (3.24)$$

or ;

$$\underline{S}_t = \{(\underline{S}_{t-1})^{-1} + (\underline{x}\,\underline{x}^T)_t\}^{-1} \qquad (3.25)$$

by using the '**Matrix Inversion Lemma**' ;

$$(\underline{A} + \underline{B}\,\underline{C}\,\underline{D})^{-1} = \underline{A}^{-1} - \underline{A}^{-1}\underline{B}\,(\underline{C}^{-1} + \underline{D}\,\underline{A}^{-1}\underline{B})^{-1}\,\underline{D}\,\underline{A}^{-1} \qquad (3.26)$$

Where $\underline{\mathbf{A}}$, $\underline{\mathbf{B}}$, $\underline{\mathbf{C}}$ and $\underline{\mathbf{D}}$ are general matrices with appropriate dimensions, equation (3.25) can be written as:

$$\underline{S}_t = \underline{S}_{t-1} - \underline{S}_{t-1}\,\underline{x}_t\,\underline{x}_t^T\,\underline{S}_{t-1}\,(1 + \underline{x}_t^T \underline{S}_{t-1}\,\underline{x}_t)^{-1} \qquad (3.27)$$

where;

$$\underline{A} = (\underline{S}_{t-1})^{-1} \;;\; \underline{B} = x_t \;;\; \underline{C} = 1 \text{ (scalar) and } \underline{D} = \underline{x}_t^T \qquad (3.28)$$

In equation (3.27), the only scalar inversion required is $(1 + \underline{x}_t^T \underline{S}_{t-1}\,\underline{x}_t)^{-1}$. In equation (3.21), apart from the term $(\underline{x}^T \underline{x})_t$, there is another term, $(\underline{x}^T \underline{y})_t$, and this can be written as;

$$(\underline{x}^T \underline{y})_t = (\underline{x}^T \underline{y})_{t-1} + x_t\,y_t \qquad (3.29)$$

Substitution of equations (3.27) and (3.29) into equation (3.21) yields;

$$\hat{\underline{\theta}}_t = \{\underline{S}_{t-1} - \underline{S}_{t-1}\, \underline{x}_t\, \underline{x}_t^T \underline{S}_{t-1}\, (1 + \underline{x}_t^T \underline{S}_{t-1} \underline{x}_t)^{-1}\}\{(\underline{x}^T \underline{y})_{t-1} + \underline{x}_t \underline{y}_t\} \qquad (3.30)$$

Multiplying equation (3.21) by backshift operator z^{-1} yields;

$$\hat{\underline{\theta}}_{t-1} = (\underline{x}_t^T \underline{x})^{-1}_{t-1}\, (\underline{x}^T \underline{y})_{t-1} \qquad (3.31)$$

Expansion of the equation (3.30) and recalling that $(1 + \underline{x}_t^T \underline{S}_{t-1}\, \underline{x}_t)^{-1}$ is a scalar results in;

$$\hat{\underline{\theta}}_t = \hat{\underline{\theta}}_{t-1} + \underline{K}_t\, \varepsilon_t \qquad (3.32)$$

[New Estimate] = [Old Estimate] + Gain * [Prediction Error of Old Model]

Where the estimation feedback correction gain '$\mathbf{K_t}$' is calculated as;

$$\underline{K}_t = \underline{S}_{t-1}\, \underline{x}_t\, (1 + \underline{x}_t^T \underline{S}_{t-1}\, \underline{x}_t)^{-1} \qquad (3.33)$$

The equation error 'ε' is defined by ;

$$\varepsilon_t = y_t - \hat{\underline{y}}_t \qquad (3.34)$$

where '$\hat{\underline{\mathbf{y}}}_t$' is the estimate of the output signal '$\underline{\mathbf{y}}_t$' and is given by;

$$\hat{\underline{y}}_t = \underline{x}_t^T\, \hat{\underline{\theta}}_{t-1} \qquad (3.35)$$

'$\mathbf{K_t}$' is the estimator's feedback correction gain. For a particular 'K_t', if ε_t is small, very little change is made in the estimates. However, for a large 'ε_t' the estimates change significantly.

We can identify the transfer function of any system off-line, all we need is just to apply known random values of inputs and measure the output values for a period of time. Then the data obtained can be inserted into the summations and the equations subsequently solved to give best estimates for the system parameters for that given number of samples.

For the real-time applications and adaptive controllers a new estimate of 'θ' is required at each sample interval, therefore system transfer function is tracked at all times. In order to achieve this, updated formulas are required particularly for 'θ'.

As there are several solutions for the tracking of time varying parameters, in this thesis forgetting factor is used to forget data of the past, ie some data will be discounted relatively by the value of the forgetting factor. In that case Kalman gain 'K' can be written in the following way,

$$\underline{K}_t = \underline{S}_{t-1}\, \underline{x}_t\, (\rho + \underline{x}_t^T \underline{S}_{t-1}\, \underline{x}_t)^{-1} \qquad (3.36)$$

'ρ' is the forgetting factor ($0<\rho\leq 1$). A simple guide to the choice of a value for forgetting factor is the concept of "Asymptotic Sample Length" (ASL) or "Memory Time Constant", which can be defined as,

$$ASL = 1/(1-\rho) \quad \text{or} \quad \rho = (ASL - 1)/ASL \qquad (3.37)$$

Typical values of 'ρ' are in the range of 0.95 to 0.999, corresponding to 'ASL' values of 20 and 1000 sample steps respectively. Lower values of ρ should result in faster tracking of time varying parameters.

The implementation of the RLS Algorithm is as follows:

1. Sample and update the data vector '$\underline{x}_t$'
2. Calculate the prediction error 'ε_t' from equation (3.34)
3. Calculate the gain $\underline{K}_t$
4. Calculate 'new' estimates from equation (3.32)
5. Update $\underline{S}_t$
6. Wait for sample then go to step 1

As mentioned earlier in this section, RLS estimation algorithm does not require complex and time consuming matrix inversion. It also has the ability to remember what has happened in the past through the input-output information is contained in the matrix $\underline{S}$, which is generally known as the estimator '**Covariance**' matrix.

A slight disadvantage of the technique is that unlike the batch (**off-line**) least squares approach, certain parameters must be specified prior to implementation. For example, $\underline{S}_t$ '**Covariance Matrix**' must be initialised at a non zero value or estimated parameter values must be equal to the previous ones; in contrast, estimation will not proceed.

3.3.2. Recursive Generalised Least Squares (RGLS):

The off-line method of generalised least squares identification was developed by Clarke (1967), while the recursive generalised least squares method was proposed by Hastings-James and Sage (1969). It consists of two RLS estimator working together via filtering. First one estimates the coefficients of '**A**' and '**B**' polynomials while the second one estimates the coefficients of '**C**' polynomial. The derivation of the RGLS algorithm is as follows:

Recalling the equation (3.1), in the case of RGLS is;

$$A\,y_t = B\,u_{t-k} + v_t \qquad (3.38)$$

Supposing the coloured noise '$\mathbf{v_t}$' is equal to '$\mathbf{e_t/C}$', so;

$$v_t = e_t/C \qquad (3.39)$$

and

$$Cv_t = e_t \qquad (3.40)$$

can be written.

Then the equation (3.38) could be rewritten as :

$$A\ y_t = B\ u_{t-k} + e_t/C \qquad (3.41)$$

Multiplying equation (3.41) by '**C**' yields:

$$A\ C\ y_t = B\ C\ u_{t-k} + e_t \qquad (3.42)$$

by defining; $y_t^F = C\ y_t$ and $u_t^F = C\ u_t$ (3.43)

the equation (3.42) can be rewritten as:

$$A\ y_t^F = B\ u^F_{t-k} + e_t \qquad (3.44)$$

The equation (3.44) is in the form that is suitable for LS estimation. The new data vector $\underline{x}^F$ must be defined by replacing all 'y' and 'u' terms by 'y^F' and 'u^F' respectively in the data vector '$\underline{x}$'. The equivalent matrix vector representation is therefore :

$$\underline{y}^F = \underline{x}^F\ \underline{\theta} + \underline{e} \qquad (3.45)$$

By application of least squares minimisation on the equation (3.45), the unbiased estimates are then obtained from;

$$\theta = (x^{FT}\, x^{F})^{-1} x^{FT}\, y^{F} \tag{3.46}$$

The problem with this method is that 'C' is unknown. Clarke (1967) proposed a method to determine the coefficients of 'C'. He suggested the use of the least squares method to obtain a first approximation for '$\underline{\theta}$'.

$$\hat{\underline{\theta}}_1 = (\underline{x}^T \underline{x})^{-1} \underline{x}^T \underline{y} \tag{3.47}$$

then the residual is calculated from ;

$$\varepsilon = y - \underline{x}\, \underline{\theta}_1 \tag{3.48}$$

Now replacing 'v' by 'ε' in the equation (3.40), gives the following;

$$\varepsilon_t = -C_1\varepsilon_{t-1} - C_2\varepsilon_{t-2} - \ldots - C_{nC}\varepsilon_{t-nC} + e_t \tag{3.49}$$

Putting sequential sets of equation (3.49), results in;

$$\underline{\varepsilon} = \underline{E}\, \underline{c} + \underline{e} \tag{3.50}$$

'**c**' is a vector containing the coefficient of (1-C), while 'E' is a matrix containing the calculated values of the residuals. Here again, the least squares estimation procedures is used to obtain the values of 'c' from;

$$\underline{c} = (\underline{E}^T \underline{E})^{-1} \underline{E}^T \underline{\varepsilon} \tag{3.51}$$

When 'c' is estimated then the filtered values of 'y^F' can be obtained from equation (3.43) and so '$\hat{\underline{\theta}}$' from equation (3.46) and '$\hat{\underline{\theta}}_1$' from equation (3.47). '$\hat{\underline{\theta}}_1$' is then replaced by '$\hat{\underline{\theta}}$' and the calculations repeated from equation (3.48). This procedure is stopped when no further improvement is observed in going from $\hat{\underline{\theta}}_1$ to $\hat{\underline{\theta}}$.

As there are always initial uncertainties in estimating the parameters of the noise filter 'C', the convergence rate of the RGLS is slow. If the noise level is high, it is possible that the RGLS estimator can converge to false parameter values (Soderstrom et. al., 1978). The main disadvantage of this method is the high computational load even in its recursive form (Tham, 1985).

3.3.3. Recursive Extended Least Squares (RELS):

This method of identification is an extension to the **RLS** method and first it was proposed by Panuska (1969). In this technique the past values of residuals are included in the regression vector;

$$\underline{x}^T_t = (-y_{t-1}, -y_{t-2}, \ldots, -y_{t-nA};\ u_{t-k}, u_{t-k-1}, \ldots, u_{t-k-nB};\ e_{t-1}, e_{t-2}, \ldots, e_{t-nC}) \quad (3.52)$$

The system equation remains as ;

$$A\, y_t = B\, u_{t-k} + C\, e_t \quad (3.53)$$

where,

$$C = 1 + c_1 z^{-1} + c_2 z^{-2} + \ldots + c_{nc} z^{-nc} \quad (3.54)$$

Equation (3.53) could be expressed in matrix vector form as;

$$\underline{y}_t = \underline{x}_t^T \hat{\underline{\theta}}_{t-1} + \underline{e}_t \tag{3.55}$$

where the data vector is given by equation (3.52) whilst parameter vector is;

$$\underline{\theta}^T = (a_1, a_2, \ldots , a_{nA}; b_o, b_1, \ldots , b_{nB}; c_1, c_2, \ldots ,c_{nC}) \tag{3.56}$$

Note that both data and parameter vectors have been '**extended**' to include noise terms. '$\mathbf{e_t}$' is an uncorrelated sequence but since it is unknown, it must therefore be estimated. The approximation of 'e_t' is:

$$e_t = \varepsilon_t = \underline{y}_t - \underline{x}_t^T \hat{\underline{\theta}}_{t-1} \tag{3.57}$$

resulting in an '**a priori**' error algorithm.

If '$\underline{\theta}_t$' is used for the estimation instead of '$\underline{\theta}_{t-1}$' in the equation (3.57), the result would be ' **a posteriori**' error algorithm (Strejc, 1980).

3.3.4. U-D Factorised Recursive Least Squares (RUD):

The covariance update equation in the method of RLS is numerically unstable due to computing the difference of two positive semi-definite matrices. In order to overcome this problem, a very well known factorisation method known as **Upper-Diagonal (U-D)** factorisation was introduced by Bierman (1976). Using this factorisation for computing the covariance matrix $\underline{\mathbf{S}}_t$ quarantees that $\underline{S}_t$ remains positive definite (Bierman, 1977; Ljung and Sodestrom, 1983; Thornton and Bierman, 1980).

The U-D factorisation of $\underline{S}_t$ is defined as :

$$\underline{S}_t = U_t D_t U_t^T \tag{3.58}$$

where '**U**' is upper triangular matrix with all diagonal elements equal to 1, and '**D**' is a diagonal matrix.

The recursive U-D factorisation method further reduces the significant round-off error caused by taking square roots. Therefore, it is the most robust method and also has shown the best performance of those recursive estimation schemes considered in this chapter. Derivation of the RUD algorithm and details can be obtained from Thornton and Bierman (1978).

3.4. PROPERTIES OF THE ESTIMATES:

3.4.1. Consistency and Unbiasedness of the Estimator:

Consider the estimate given by the equation (3.20) and assume that the data has been generated by the process model as shown in equation (3.1) where $\{\mathbf{e}_t, \mathbf{t} = \mathbf{1}, \mathbf{2}, \ldots\}$ is a sequence of independent randomly distributed variables with zero mean and finite variance (σ^2), ie. non-deterministic and unmeasurable.

As a result of the random effect, to enable the evaluation of the estimator performance relationships allowing the quality of the estimates to be assessed are desirable. Two such measures are consistency and bias.

If the following condition is satisfied, then the estimator is said to be '**consistent**':

$$\lim_{t \to \infty} E \; \{ (\underline{\hat{\theta}}_t - \underline{\theta})^T (\underline{\hat{\theta}}_t - \underline{\theta}) \} = 0 \tag{3.59}$$

Consistency is an asymptotic property of the estimators. Although it is a desirable characteristic, it also has a limiting behaviour and holds only for an unrealisable infinite number of observations. However, it does not give any indication of whether '$\hat{\underline{\theta}}$' is close to the unknown '$\underline{\theta}$' for any finite sample size. A condition which does it, is given below; If,

$$E\{\hat{\underline{\theta}}\} - \underline{\theta} = b = 0 \tag{3.60}$$

is satisfied, then the estimates are said to be '**unbiased**'.

Bias and consistency are closely related. It can be shown that an estimator must be at least unbiased in the limit for the consistency condition to be satisfied. While a consistent estimator can be biased in a sampled population of finite size, an unbiased estimator is a sufficient condition for consistency. Therefore, if the estimator is '**unbiased**' or '**unbiased in the limit**', the estimator is also consistent; viz is not true.

3.4.2. Analysis of the Recursive Identification Convergence:

Accuracy of the estimates and the convergence questions such as how fast it is or if the estimator is really converging are very difficult to be answered analytically. Many of the identification methods use the following algorithm;

$$\hat{\underline{\theta}}_t = \hat{\underline{\theta}}_{t-1} + \underline{K}_t \underline{\varepsilon}_t \tag{3.61}$$

which is a non-linear, time varying stochastic difference equation. Apart from that, the residual 'ε_t' in the equation (3.61) implicitly depends on all previous parameter estimates '$\underline{\theta}$', which makes it fairly difficult to carry on analytically treatment. The most common way of studying and comparing different identification techniques is through simulation, which indeed is a natural and valuable tool. Soderstrom et. al. (1978) suggested that it should be analysed under the following general assumptions:

1. The system is identifiable in the sense that it can be found in the considered model structure.

2. The order of the model polynomials coincides with the respective polynomials in the system description (ie., the order of the model is equal to the order of the true system).

3.4.3. Limitations of the Least Squares Approach:

In this chapter, the properties of the off-line estimates were discussed. The concepts of '**consistency**' and '**unbiasedness**' have been used as measures of the quality of estimates. These are in the main formulated for the limiting condition that an infinite number of observations will be available. Since this situation can never be realised, the estimated parameters of stochastic models can never approach to their true values under practical conditions. Even though the RLS algorithm is efficient, its disadvantage lies in the assumption that the noise affecting the process is an uncorrelated sequence and also uncorrelated with the data vector. This is a weak assumption, because, in fact non-deterministic disturbances affecting real process are correlated sequences and also correlated with the data vector and have non zero mean levels.

The problem of having non-zero mean levels could easily be overcome. But the problem of correlated data, which is very common in the feedback systems has to be resolved. Consider the simple feedback block diagram in Figure 3.1 where all the variables are scalar. It can be seen that noise '**e**' is carried out through the feedback, and hence the process input '**u**' will be contaminated by '**e**'. Therefore, when identification of the process takes place by the RLS identification method, using the measurements of '**u**' and '**y**', due to '**u**' not being independent of '**e**', the resulting estimates will be biased. The Equation;

$$E\ \{ (\hat{\underline{\theta}}) \} - \underline{\theta} = E\ \{ (\underline{x}^T\underline{x})^{-1}\underline{x}^T(\underline{x}\,\underline{\theta} + \underline{e}) \} - \underline{\theta} \qquad (3.62)$$

must be written in the form;

$$E\ \{ \hat{\underline{\theta}} \} - \underline{\theta} = E\ \{ (\underline{x}^T\underline{x})^{-1}\ \underline{x}\,\underline{e}) \} \qquad (3.63)$$

This equation will not be equal to zero, even if '**e**' has zero mean. So the estimation performance is biased. Some of the RLS based algorithm (ie. RGLS, RELS) have been modified in order to overcome this kind of problem.

It must be noted that RLS should be used with caution in identification and generally in adaptive control, especially when the value of forgetting factor is less than one (Wong, Bayoumi and Nuyan, 1983).

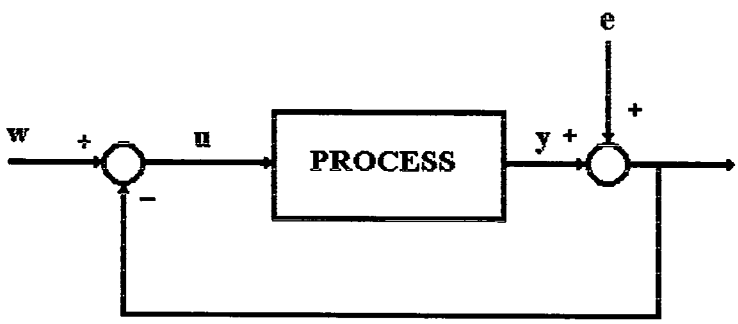

Figure 3.1 A simple Feedback Loop

CHAPTER 4. SELF-TUNING CONTROL (STC)

4.1. INTRODUCTION

Åström and Wittenmark (1973) developed an important class of controller called **'Self-Tuning Regulator'** for the control of systems with constant, but unknown parameters. The regulator is based on a recursive least squares estimation of the parameters of a feedback control law, followed by the use of the estimated parameters in the control law itself and is the self-tuning version of the Minimum Variance Controller. The self-tuning regulator attempts to minimise the fluctuations of the system's output when the loop is randomly disturbed. However, it makes no attempt to ensure that the set-point are followed optimally nor does it try to penalise excessive control action (Åström et. al., 1977).

In 1975, Clarke and Gawthrop proposed an extension to the Minimum Variance Self-Tuning Regulator of Åström and Wittenmark. The resulting algorithm was called the '**Self Tuning Controller (STC)**' which minimises a cost function that incorporates weighting of inputs, outputs and set points, whilst retaining the main concepts of the basic algorithm. There are numerous work on STR and STC (see Wellstead et. al., 1979; Clarke, 1980; Nazer, 1981; Clary and Franklin, 1985; Tuffs et. al., 1985; Warwick et. al., 1985; Lelic et. al., 1987a; Lelic et. al., 1987b; Tham et. al., 1986; Tham et. al., 1988; Mansoori, 1990).

4.2. SINGLE-INPUT SINGLE-OUTPUT (SISO) STC

The system considered is a single-input single-output process that is randomly distributed and which can be described by the following discrete difference equation:

$$\sum_{i=0}^{n} a_i y_{t-i} = \sum_{i=0}^{n} b_i u_{t-i-k} + \sum_{i=0}^{n} c_i \xi_{t-i} + d \qquad (4.1)$$

where;

u_t = system manipulative input at time '**t**', which is measurable.

y_t = system controlled output at time '**t**', which is measurable.

ξ_t = random sequence disturbing the system, N $(0,\sigma^2)$

d = constant that takes into account the case of non-zero steady state output for a zero steady-state input.

n = order of the system.

k = time delay of the system, expressed as an integer multiple of the sampling interval.

The terms in equation (4.1) can be represented as polynomials in the back-shift operator (z^{-1}) in the form $(\mathbf{z^{-1}y_t = y_{t-1}})$ and equation (4.1) becomes as;

$$A(z^{-1})\, y_t = z^{-k} B(z^{-1})\, u_t + C(z^{-1})\, \xi_t + d \qquad (4.2)$$

or simply as;

$$A\, y_t = z^{-k} B\, u_t + C\, \xi_t + d \qquad (4.3)$$

where :

$$A = A(z^{-1}) = 1 + a_1 z^{-1} + a_2 z^{-2} + \dots + a_{nA} z^{-nA} \qquad (4.4a)$$

$$B = B(z^{-1}) = b_0 + b_1 z^{-1} + b_2 z^{-2} + \dots + b_{nB} z^{-nB} \qquad (4.4b)$$

$$C = C(z^{-1}) = 1 + c_1 z^{-1} + c_2 z^{-2} + \dots + c_{nC} z^{-nC} \qquad (4.4c)$$

It is assumed that the random sequence (noise) filter '**C**' is strictly stable, ie. the roots of '**C**' must lie within the unit circle. Figure (4.1) shows the block diagram of the system given by the equation (4.3).

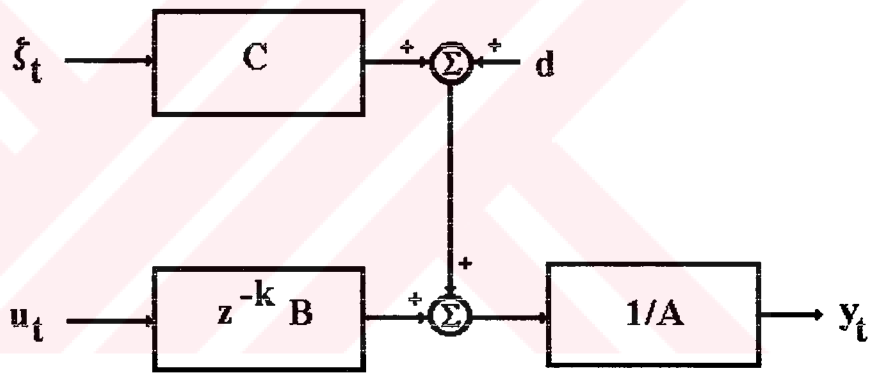

Figure 4.1 Block Diagram Representation of Process.

The aim is to design a controller that minimises a quadratic cost function of the form;

$$I = E\{ (\sum_{i=0}^{m} p_i y_{t+k-i} - \sum_{i=0}^{n} r_i w_{t-i})^2 + (\sum_{i=0}^{1} q_i u_{t-i})^2 \qquad (4.5)$$

or alternatively, if '**P**', '**Q**'' and '**R**' are the polynomials in the back-shift operator, equation (4.5) could be written as:

$$I = E\{((P\,y_{t+k} - R\,w_t)^2 + (Q'\,u_t)^2)\,|_t\} \qquad (4.6)$$

where :

'$\mathbf{E}\{\ldots|_t\}$' is the expectation operator.

'$\mathbf{w_t}$' is the set-point or desired point of the system output.

'**P**' is the weighting (filter) on output ($\mathbf{y_{t+k}}$), that is monic (ie. the leading coefficient of 'P' is equal to one).

'**R**' is the weighting (filter) on the set-point '$\mathbf{w_t}$'.

'**Q′** ' is the weighting (filter) on the input '$\mathbf{u_t}$'.

In Clarke and Gawthrop (1975), incorporation of the weighting polynomials '**P**' and '**R**' in '**I**' was for the 'sake of completeness'. The main emphasis was on the control input weighting polynomial ' **Q′** '. If ' **Q′** ' is set to zero, equation (4.6) becomes as;

$$I = E\{(P\,y_{t+k} - R\,w_t)^2\,|_t\} \qquad (4.7)$$

and with P=1, R=1 yields ;

$$I = E\{(y_{t+k} - w_t)^2\,|_t\} \qquad (4.8)$$

which $\qquad I = E\{(\text{error})^2\,|_t\}$ and $\qquad I = \text{Variance (error)}$

Minimisation of the equation (4.8) with respect to u_t leads to a '**Minimum Variance (MV)**' control law.

A non-zero (Q′) includes the two important cases:

1. Recall equation (4.6) and replacing Q′ by λ′ ;

$$I_1 = E\,\{(\,(P\,y_{t+k} - R\,w_t\,)^2 + (\,\lambda'\,u_t)^2\,)\,|_t\,\} \qquad (4.9)$$

Minimisation of 'I_1' with respect to 'u_t' yields a control which penalises both output deviations from setpoint and excessive control effort. However, if the setpoint 'w_t' has a non-zero mean, ie. $\bar{\mathbf{w}} \neq 0$, then unless $\lambda' = 0$, the system output will not be able to track the set-point exactly. In other words, offset will result.

2. Recall equation (4.6) and replacing Q′ by λ′ and 'u_t' by '$u_t - u_{t-1}$';

$$I_2 = E\,\{(\,(P\,y_{t+k} - R\,w_t\,)^2 + (\,\lambda'\,(1\text{-}z^{-1})\,u_t)^2\,)\,|_t\,\} \qquad (4.10)$$

Minimising 'I_2' again penalises output deviations from set-point, but now, instead of penalising absolute control output, changes in control are penalised. The resulting control quarantees that the mean value of system-output , ' $\bar{\mathbf{y}}$ ', equals the mean value of the set-point ' $\bar{\mathbf{w}}$ '. This is however achieved at the expense of possible degradation of dynamic performance as a result of the inclusion of an integrating term $(1\text{-}z^{-1})^{-1}$ into the controller. The control law resulting from the general cost function 'I' (eq. 4.6) will now be derived.

The '$\mathbf{y_{t+k}}$' term in equation (4.6) represents a future value; as it is unknown, $\partial I/\partial u_t$ is not achievable. However 'y_{t+k}' can be replaced by its prediction '$\mathbf{y^*_{t+k/t}}$' with :

$$y_{t+k} = y^*_{t+k\,/\,t} + e_{t+k} \qquad (4.11)$$

The relationship between '$\mathbf{y^*}$' and process parameters can be obtained by rewriting equation (4.3) as :

$$y_{t+k} = B/A\ u_t + z^k\ C/A\ \xi_t + d/A \tag{4.12}$$

Use of the '**separation identity**';

$$z^k\ C/A = z^k\ E' + F'/A \tag{4.13}$$

allows the stochastic term in Equation (4.12) to be regarded as a combination of future sequences and sequences which have occurred up to and including present time 't', ie.

$$z^k\ C/A\ \xi_t = z^k\ E'\ \xi_t + F'/A\ \xi_t \tag{4.14}$$

where;

'$\mathbf{z^k\ E'\ \xi_t}$' is the future sequence.

'$\mathbf{F'/A\ \xi_t}$' is the past and present sequence.

(**E' and F'**) are polynomials in the back-shift operator z^{-1}.

deg (E') = k-1 and the leading coefficient of 'E'' is unity, ie. $\mathbf{e_0=1}$

Substitution of equation (4.14) into equation (4.12) yields;

$$y_{t+k} - E'\ \xi_{t+k} = B/A\ u_t + F'/A\ \xi_t + d/A = y^*_{t+k/t} \tag{4.15}$$

From equation (4.11) it follows that $e_{t+k} = E'\ \xi_{t+k}$. The random disturbance 'ξ' can be eliminated from equation (4.15) by using the system description of equation (4.3). Equation (4.15) then becomes :

$$y^*_{t+k/t} = B/A\ u_t + (F'/AC)\ (Ay_t - z^{-k}B\ u_t - d) + d/A \tag{4.16}$$

This could be simplified as;

$$y^*_{t+k/t} = (1/A - F' z^{-k}/AC)\,Bu_t + (F'/C)y_t + ((1/A)-(F'/AC))d \quad (4.17)$$

or;

$$y^*_{t+k/t} = (E' B\, u_t + F'\, y_t + E'(1)d\,)\,/\,C \quad (4.18)$$

where;

$$E'(1) = \sum_{i=0}^{k-1} e_i \quad (4.18a)$$

Defining; $G \cong E'B$ and $\delta' \cong E'(1)\,d$, equation (4.18) could be rewritten as;

$$y^*_{t+k/t} = (G\, u_t + F'\, y_t + \delta'\,)\,/\,C \quad (4.19)$$

Using equations (4.11) and (4.19) in the cost function given by the equation (4.6) yields;

$$I_3 = E\,\{(\,P(\,y^*_{t+k/t} + e_{t+k}) - R\,w_t\,)^2 + (\,Q'\,u_t)^2\,)\,|_t\,\} \quad (4.20)$$

'I_3' can be minimised with respect to 'u_t' to obtain the '**Generalised Minimum Variance (GMV)**' control law. Using the assumption that 'e_{t+k}' is an uncorrelated sequence with zero mean, ie. ;

$$E\,\{e\} = E\,\{ey\} = E\,\{eu\} = E\,\{ew\} = 0 \quad (4.21)$$

and

$$E\,\{\,(Pe)^2\,\} = \sigma^2 + E\,\{Pe\}^2 = \sigma^2 \quad (4.22)$$

where 'σ^2' is the variance of (Pe). 'I_3' thus simplifies to;

$$I_3 = E\,\{(\,(P\,y^*_{t+k/t} - R\,w_t\,)^2 + (\,Q'\,u_t)^2\,)\,|_t\,\} + \sigma^2 \quad (4.23)$$

The objective is to minimise 'I_3' with respect to 'u_t', ie. ;

$$\partial I_3 / \partial u_t = 0 \qquad ; \qquad \partial E\{....\}/\partial u_t = 0$$

Then the new cost function will be ;

$$J = E\{((P\, y^*_{t+k/t} - R\, w_t)^2 + (Q'\, u_t)^2)\,|_t\} + \sigma^2 \tag{4.24}$$

From the equation (4.19),

$$P\, y^*_{t+k/t} = (G\, u_t + F'\, y_t + \delta')\, P / C \tag{4.25}$$

Substituting equation (4.25) into equation (4.24) yields;

$$J = E\{(((P\, F'/C)\, y_t + (PG/C)\, u_t + (P\delta'/C) - R\, w_t)^2 + (Q'\, u_t)^2)\,|_t\} + \sigma^2 \tag{4.26}$$

Minimisation of the cost function with respect to 'u_t' yields;

$$\partial J/\partial u_t = 2\,(P\, y^*_{t+k/t} - R\, w_t)\, p_0 g_0/c_0 + 2\,(Q'\, u_t)\, q'_0 = 0 \tag{4.27}$$

after simplification, it can be written as;

$$\partial J/\partial u_t = P\, y^*_{t+k/t} - R\, w_t + (c_0 q'_0/p_0 g_0)\, Q'\, u_t = 0 \tag{4.27a}$$

Since $c_0=1$, $p_0=1$ and defining $Q \cong q_0 Q'/g_0$, equation (4.27a) can be rewritten as;

$$P\, y^*_{t+k/t} - R\, w_t + Q\, u_t = 0 \tag{4.28}$$

The result is a control law that provides instantaneous optimal control action, ie. it does not take into account the effect that the present control action

'u_t' will have on future outputs at load times greater than the process time delay '**k**'. In figure 4.2 the block diagram that represents the control law given by equation (4.28) and in figure 4.3 the block diagram of a feed-back system with self -tuning controller can be seen. Figure 4.4 is a simplified form of figure 4.3.

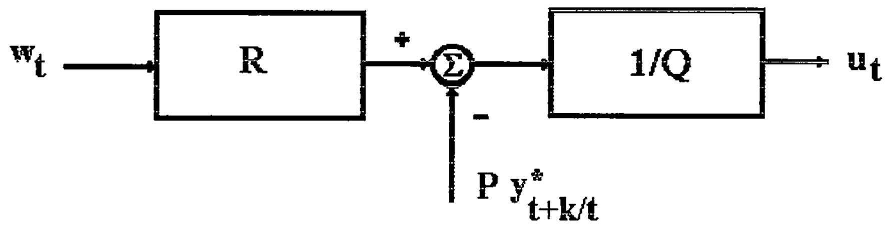

Figure 4.2 Control Law Representation.

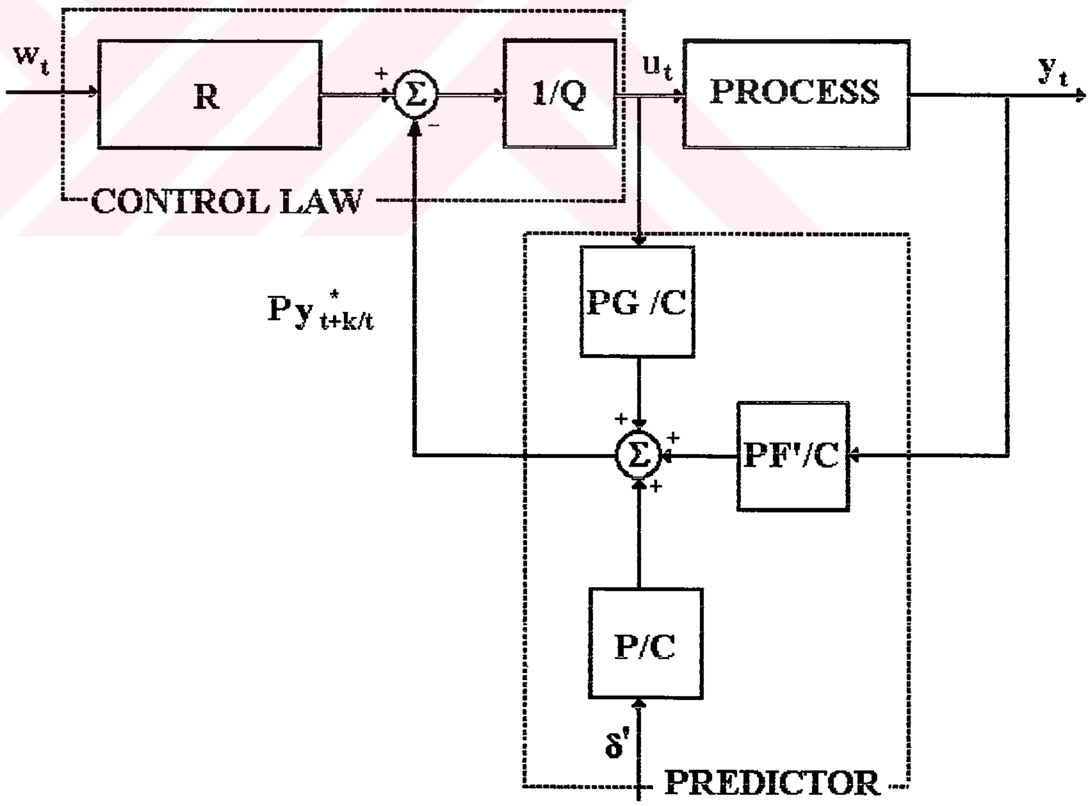

Figure 4.3 A Feed-back System with STC .

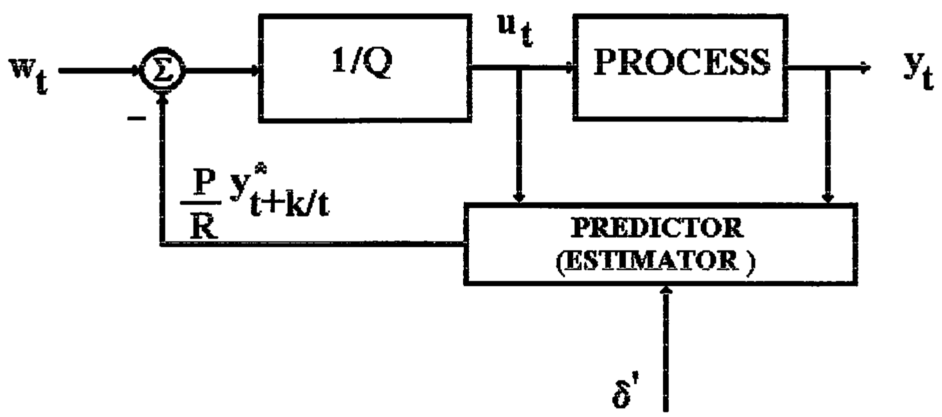

Figure 4.4 A Simplified Feed-back System with STC .

4.3. SPECIAL CASES OF THE STC CONTROL LAW

Self Tuning Control law can be set up to get different control strategies, by considering the equation (4.28) a few cases will be discussed in this section. By setting '**Q**', '**P**' and '**R**' weighting functions to specific values as mentioned below, results in different type of control actions:

1. If it is assumed that **P=1**, **R=0** and **Q=0** then the control law becomes the '**Minimum Variance Self Tuning Regulator**' (**MVSTR**) form.

2. If it is assumed that **P=1**, **R=1** and **Q=0**, then the control law results in the '**Minimum Variance Self Tuning Controller**' (**MVSTC**) form.

3. If it is assumed that **P≠0**, **R≠0** and **Q≠0** then the control law converts to a '**Generalised Minimum Variance Self Tuning Controller**' form.

These special cases of the Self Tuning Control algorithms mentioned above, especially '**Generalised Minimum Variance (GMV)**' type controller properties discussed in the chapter 5 as experimental implementation.

CHAPTER 5. EXPERIMENTAL IMPLEMENTATION OF STC

5.1. INTRODUCTION

Application of Self-Tuning Controller to first order processes including time delay and selecting appropriate tuning parameters for the STC control law will be explained and discussed here. As there are several algorithms for self-tuning controllers, a '**Minimum Variance Control (MVC)**' algorithm and a '**Generalised Minimum Variance Control (GMVC)**' algorithm applied to a **SISO** process will be considered.

Self-Tuning regulators can be obtained by starting with a known system and a design method. The control algorithm can be obtained by introducing a recursive parameter estimator into the closed loop. The parameter estimator acts on the process inputs and outputs, and produces estimates of certain process parameters. Then the true parameter values are replaced by their estimated values when determining the control law using the design method. As there are several ways to do parameter estimation and calculation of the regulator parameters, this leads to different types of regulators.

The regulator described in this work is based on recursive scheme of estimating the parameters of a prediction model, and it is in implicit (direct) controller form. Figure 5.1 shows the type of the regulator used in this work.

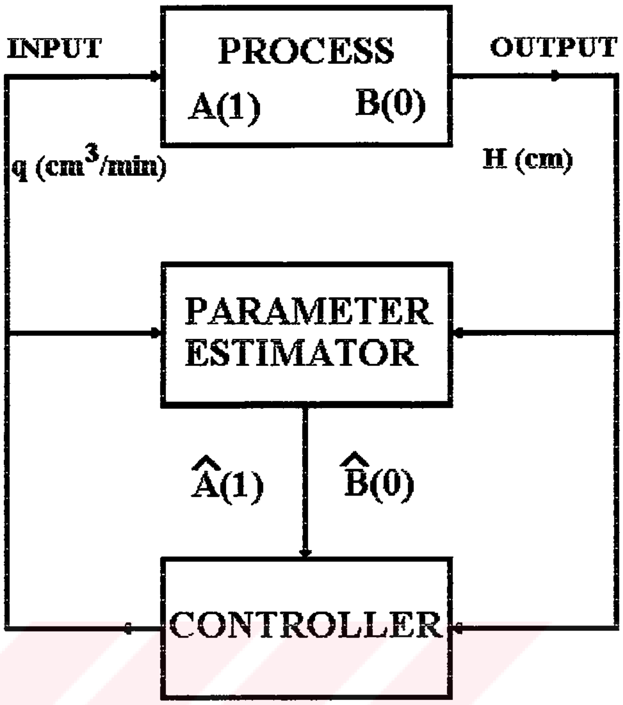

Figure 5.1 Block Diagram of STR used in this thesis.

5.2. DETERMINATION OF THE FIRST ORDER SYSTEM PARAMETERS

The plant which has been chosen for the experimental studies is an experimental rig in the control laboratory. The system consisted of two tanks, pump, valves and pipings. Figure 5.2 shows the arrangement of tanks, piping, pump and valves of the real plant. To maintain simplicity the figure does not include the control instruments as they were not used during the experiments. The diameter of tanks were 14.7 cm at the cylindrical end and the valve orifice sizings for the valve 1, valve 2, valve 3 and the valve 4 were 4.0 mm, 2.5 mm, 4.5 mm and 5.0 mm respectively. It must be noted that only a single tank (Tank No.1) is used in this study.

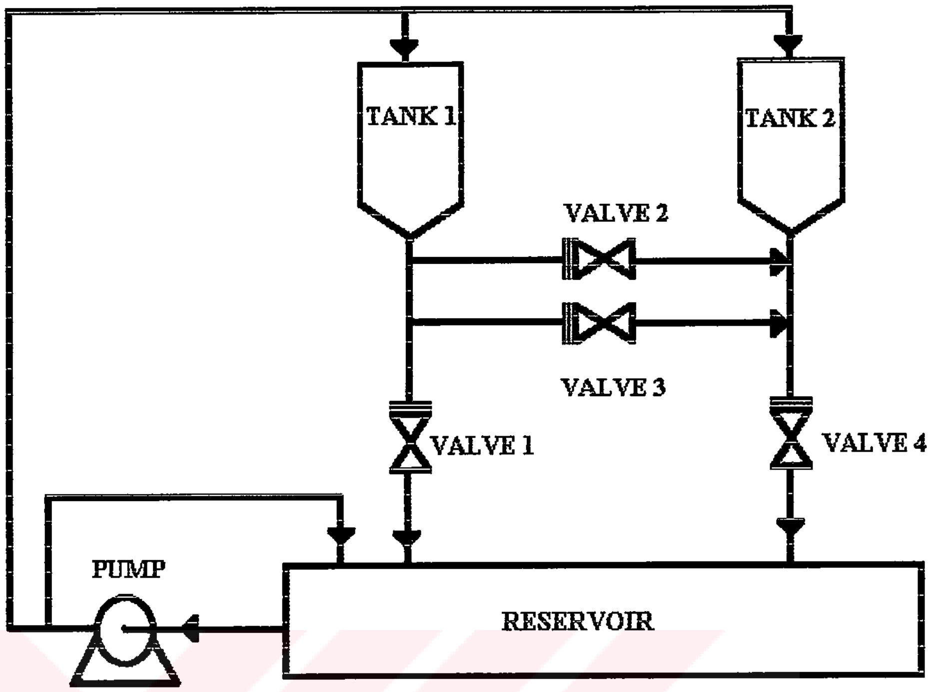

Figure 5.2 Tank System used for the Experiments.

The process parameters such as process gain '$\mathbf{K_p}$' and time-constant '$\boldsymbol{\tau}$' for the tank system shown in figure 5.2 are obtained via series of experiments. The object of the our control system is to control the level of the liquid in the tank, and this is achieved by controlling the flow of the liquid into the tank via a control valve. When a time-delay ($\mathbf{t_d}$) is included into the process we can rewrite process transfer function as;

$$G_p(s) = (K_p e^{-t_d s}) / (\tau s + 1) \qquad (5.1)$$

As the controller output signals must be converted from digital to analog form, a zero order hold '**ZOH**' device used to obtain signal reconstruction:

$$H_0(s) = (1 - e^{-s\Delta t}) / s \qquad (5.2)$$

where '$\mathbf{\Delta t}$' is the '**sample time**'. Forming new transfer function gives;

$$G_p(s)\,H_0(s) = (K_p\, e^{-t_d S})\,(1 - e^{-S\Delta t}) / s\,(\tau s + 1) \qquad (5.3)$$

where , $t_d = k\Delta t$.

To convert this expression to its z-transform equivalent, partial fraction expansion technique is used, result can be written as;

$$Y(z) / X(z) = H_0\, G_p(z) = K_p\,(1 - \gamma)\, z^{-k-1} / (1 - \gamma z^{-1}) \qquad (5.4)$$

where, $\gamma = e^{-\Delta t/\tau}$.

In difference equation form, equation (5.4) becomes;

$$y_n = \gamma\, y_{n-1} + K_p\,(1 - \gamma)\, x_{n-k-1} \qquad (5.5)$$

By recalling ARMA model from equation (3.1), we can get the system parameters from equation (5.5) for the first order single-tank system, ie. ;

$$a_1 = -e^{-\Delta t/\tau} \quad , \quad b_0 = K_p\,(1 - e^{-\Delta t/\tau}) \quad \text{and} \quad k = t_d / \Delta t$$

As the control algorithm based on a least squares estimation and a generalised minimum variance controller will be simulated, the following prediction model is used for the estimation;

$$y(t) = -a_1\, y(t-1) + b_0\, u(t-k-1) \qquad (5.6)$$

The objective function of the Generalised Minimum Variance Controller contains 'y (t + k)' values that is k step ahead into the future at time 't', the minimisation is not realisable . This problem is overcome by replacing the unknown y (t + k) with its prediction y*(t + k / t) obtained from only the current and past data. In order to obtain k-step ahead prediction y*(t + k / t) values '**Diophantine Equation (Separation Identity)**' used as it is mentioned earlier in chapter 4.

5.3. EXPERIMENTAL WORK FOR THE FIRST ORDER SYSTEM

The object of these experiments were to investigate the Control System as shown in Figure 5.2, the valve characteristics and the resistance of the valve were also found. The time constant 'τ' and the process gain '$\mathbf{K_p}$' were found experimentally by using a simple step-up and a step-down techniques in set-point. Firstly, the characteristics of the control valve that controls the flowrate into the tank was found; this was done by measuring the time taken for a certain volume of liquid to pass through the valve. The tank was assumed to be cylindrical, and so volume was proportional to the height of liquid in the tank. After each run the tank was emptied, and the procedure repeated for various values of valve % from fully open to fully closed. This allowed a calibration curve to be plotted for valve % openings against flowrate (q).

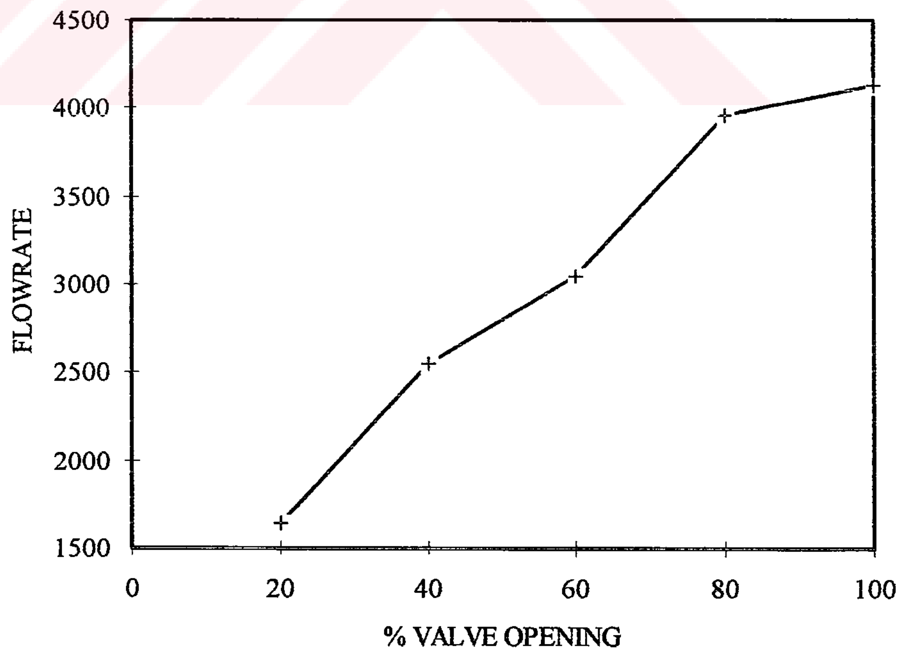

Figure 5.3 Valve % Openings vs Flowrate '$q(cm^3/min)$'.

Latter, the tank was allowed to reach equilibrium for various valve positions, and the height of the liquid in the tank noted. From these results a plot of height versus flowrate could be made, and the resistance of the valve found.

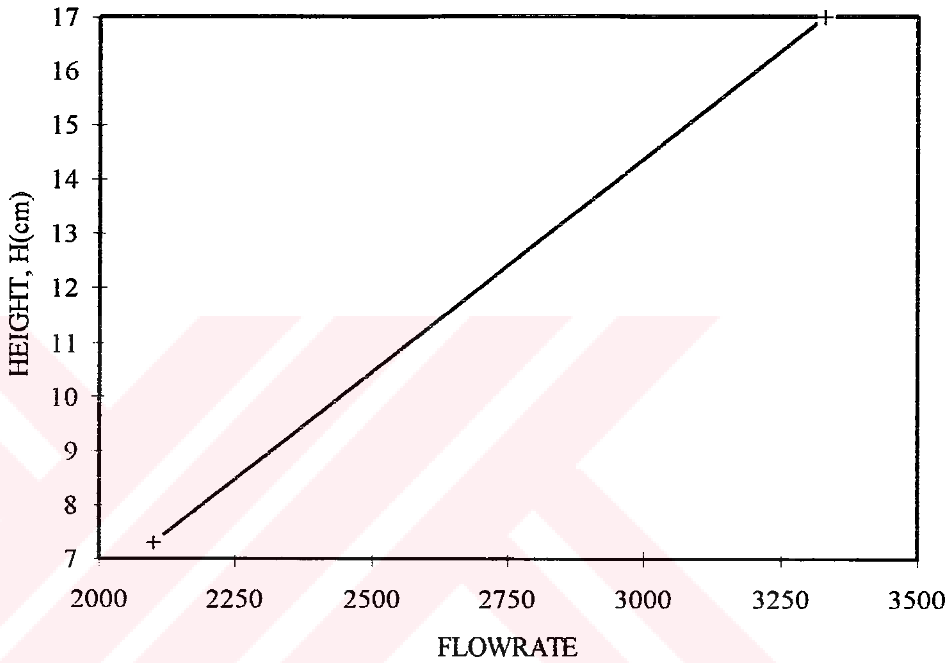

Figure 5.4 Tank level vs Flowrate 'q(cm^3/min)'.

Finally, the open-loop response of a single tank was found by allowing the system firstly to reach equilibrium at a certain valve position. A load change was then imposed by changing the valve % opening. The change in height was monitored against time for a step-up and a step-down response, and these curves compared with mathematical model of first order single tank system. Table 5.1 below shows the time taken for a certain volume interval to pass through the control valve.

Table 5.1 The Relation Between Valve % Openings and Flowrate.

VALVE (%) OPENINGS	TIME TAKEN (min)				q (cm³/min)
	1	2	3	AVERAGE	
20	0.92	0.95	0.95	0.94	1644
40	0.59	0.63	0.62	0.61	2550
60	0.51	0.50	0.50	0.50	3048
80	0.38	0.38	0.41	0.39	3960
~100	0.36	0.38	0.38	0.37	4134

The equilibrium heights for various valve positions and corresponding flowrates are given in Table 5.2 .

Table 5.2 Equilibrium Heights for the Valve Positions and Flowrates.

VALVE POSITION (% OPENINGS)	HEIGHT OF THE LIQUID (cm)	FLOWRATE (cm^3/min)
64.0	17.0	3330
32.2	7.3	2100

The valve positions in Table 5.1, the flowrate values through the valve is found as given in Table 5.2. Using this data in the mathematical model of the system, the process gain 'K_p' and the time constant 'τ' were found as **0.0078 (min/cm²)** and **1.217 (min)** respectively.

5.3.1. Initial Conditions for the First Order System Simulation Studies :

The conditions for the simulation studies were as follows:

Initial value of the covariance matrix	1000.0 I
Initial value of the parameter 'a_1'	0.0
Initial value of the parameter 'b_0'	0.0
Identification method	UD factorised RLS
Forgetting factor value	0.98
Single Tank System Gain (K_p)	0.0078 (min/cm²)

Time Constant of the System (τ)	1.217 (min)
System parameter 'a_1'	0.439
System parameter 'b_0'	0.0043
Type of simulation	Closed-Loop
Sampling Period (Δt)	0.4 (min)

5.3.2. Parameter Variations and Fine Tuning of an STC

The important decisions to be made before implementation of the 'Generalised Minimum Variance (GMV)' control law are as follows;

- the model order,
- the model type,
- choice of the sample time,
- determination of the process delay,
- choice of the Q filter

Earlier chapters we have seen almost all important parts of a Self-Tuning Controller (GMV) except the choice of the filter '**Q**'. The heart of this thesis is to implement different types of the filter '**Q**' and to show their applications to the real plant.

In chapter 4, by using different weighting functions P,R and Q is shown to reach different types of controller schemes such as MVSTR, MVSTC and GMVSTC. Recalling the equation (4.28), and definition '**Q**' which is equal to '$\mathbf{q_0 Q'/g_0}$';

$$P\, y^*_{t+k/t} - R\, w_t + Q\, u_t = 0 \tag{5.7}$$

This equation can be rewritten as;

$$R\, w_t - P\, y^*_{t+k/t} = Q\, u_t \tag{5.8}$$

In the case of R=1 and P=1, equation (5.8) becomes;

$$w_t - y^*_{t+k/t} = Q\, u_t \tag{5.9}$$

Now, as it can be seen from the equation (5.9) all the controller action is depended on the definition of the weighting function '**Q**'. Recalling the equation (4.19) and substituting into equation (5.9) yields;

$$w_t - F'\, y_t - G\, u_t = Q\, u_t \tag{5.10}$$

By using equation (5.10) and substituting different 'Q' implementations into this equation gives the following results:

1) If $Q = \lambda$, rewriting the equation (5.10) yields;

$$w_t - F'\, y_t - G\, u_t = \lambda\, u_t \tag{5.11}$$

then,

$$u_t\,(G + \lambda) = w_t - F'\, y_t \tag{5.12}$$

$$\boxed{\mathbf{u_t = w_t - F'\, y_t / (G + \lambda)}} \tag{5.13}$$

For λ=0 the controller tries to cancel the plant resulting in an unstable system if the open-loop system is NMP 'Non-Minimum Phase'. However, if open-loop system is stable (ie. roots of the polynomial A are inside the unit circle) then by tuning an appropriate 'λ' value can cause the closed-loop poles to move arbitrarily close to those of the open-loop system. Note that, the large values of 'λ' weight the control at the expense of large offsets in the set-point tracking .

Figure 5.5, Figure 5.6, Figure 5.7 and Figure 5.8 show the closed loop behaviours for 'λ=0' and the stability of the estimated parameters respectively.

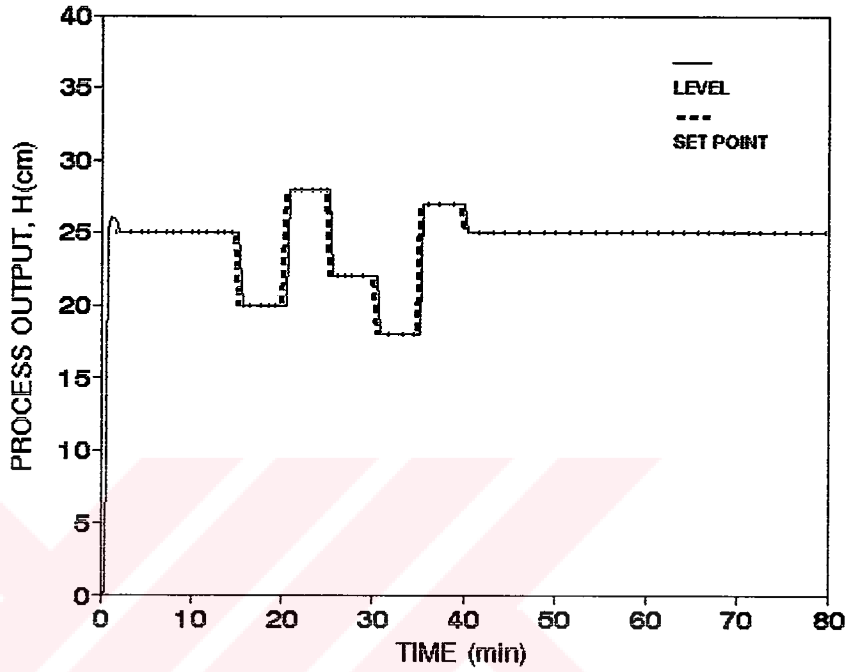

Figure 5.5 Process Output vs Time for weight function 'λ=0'.

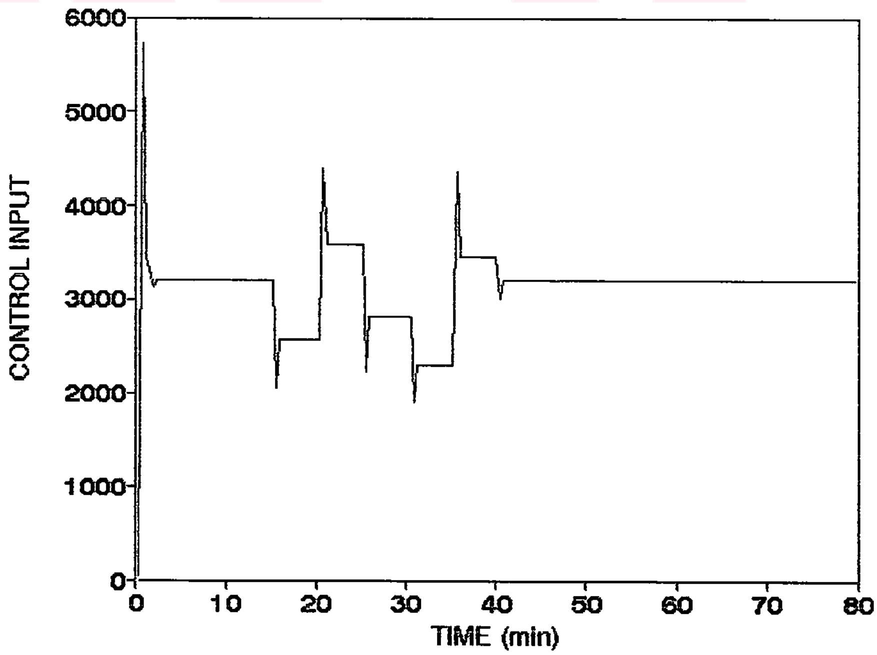

Figure 5.6 Control Input vs Time for weight function 'λ=0'.

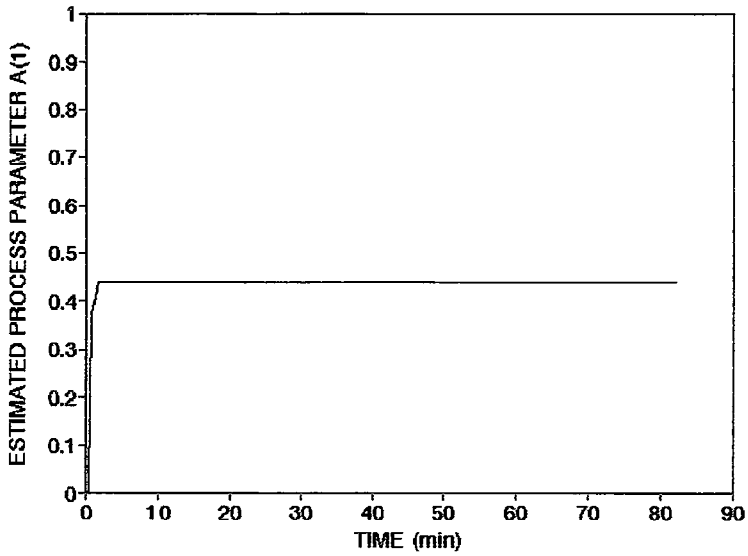

Figure 5.7 Parameter A(1) vs Time for weight function 'λ=0'.

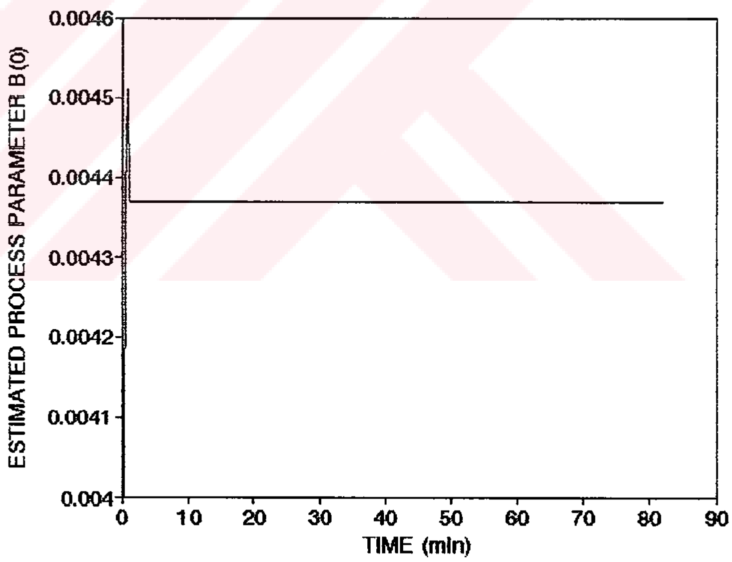

Figure 5.8 Parameter B(0) vs Time for weight function 'λ=0'.

Figure 5.9, Figure 5.10, Figure 5.11 and Figure 5.12 show the controller behaviours in the case of 'λ= **0.025**' and the stability of the estimated parameters respectively. As it can be seen easily from these figures tuning 'λ' is a very fine operation and in most cases it results with unstable control action or at least with an off-set.

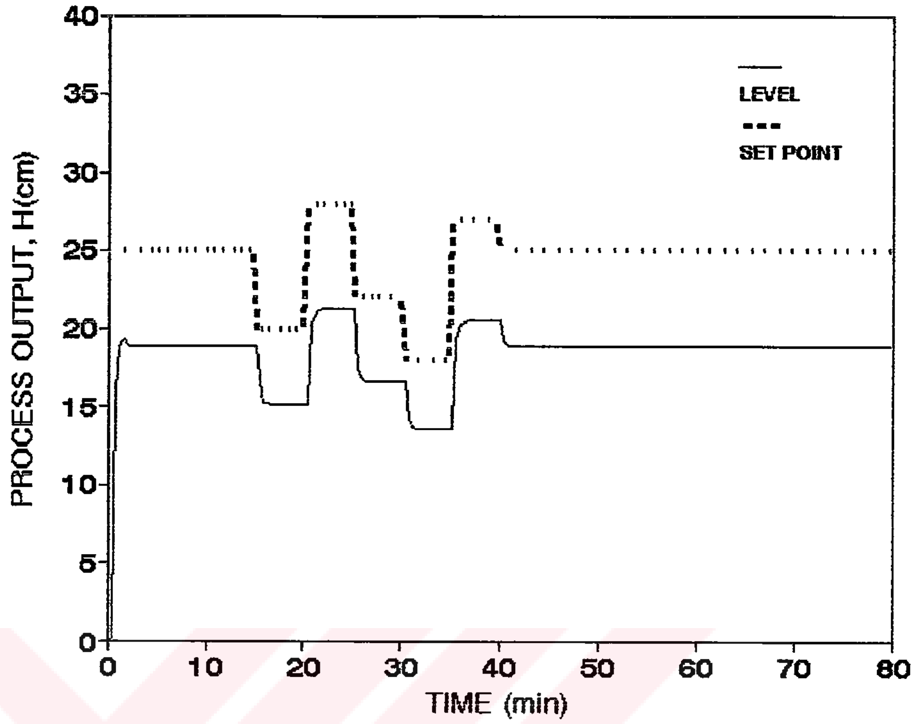

Figure 5.9 Process Output vs Time for weight function 'λ=0.025'.

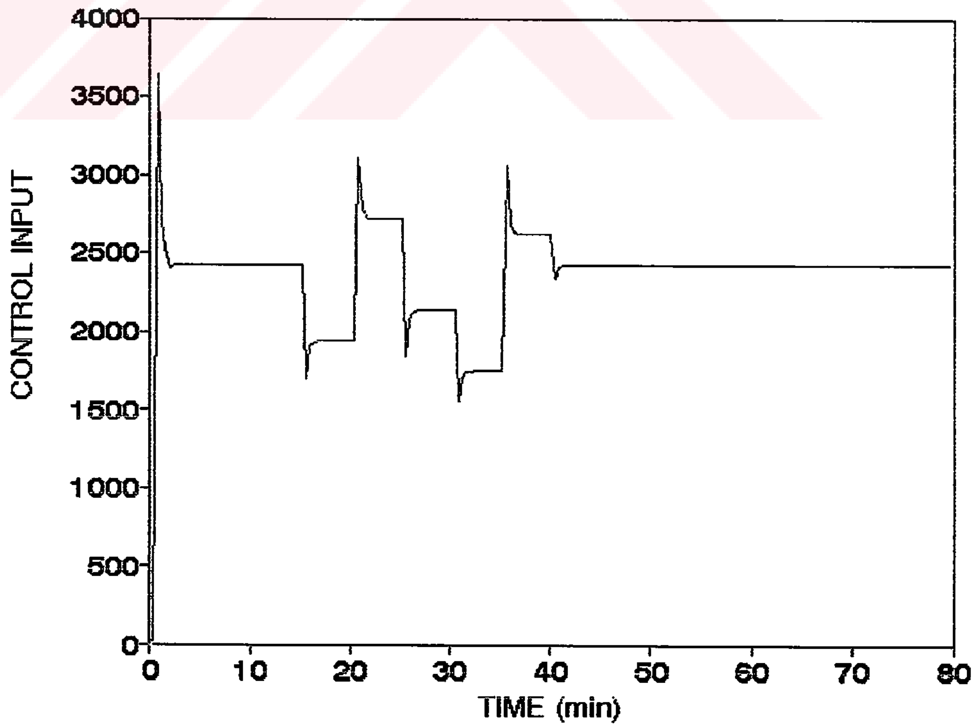

Figure 5.10 Control Input vs Time for weight function 'λ=0.025'.

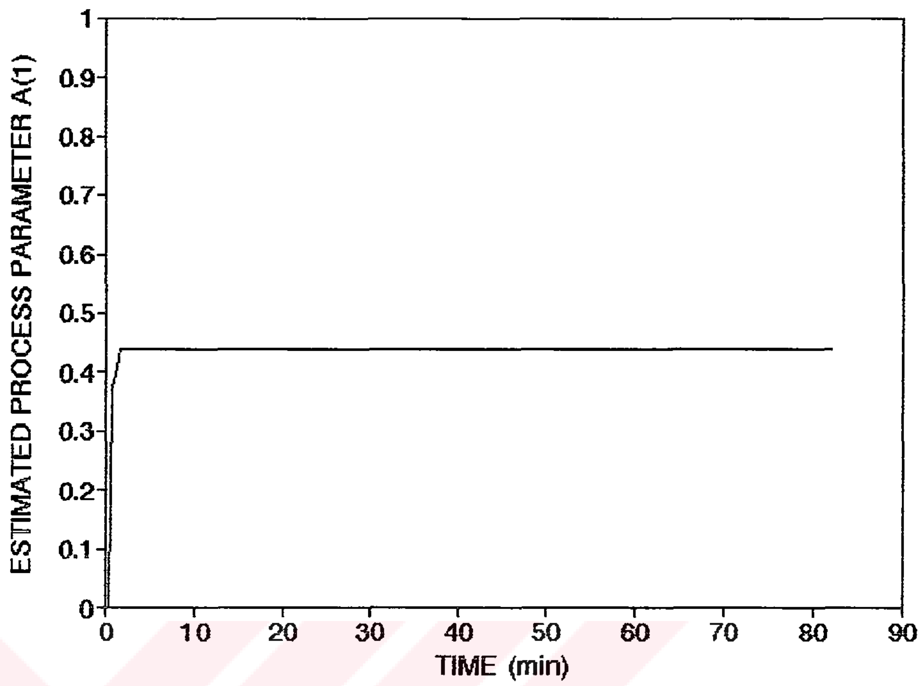

Figure 5.11 Parameter A(1) vs Time for weight function 'λ=0.025'.

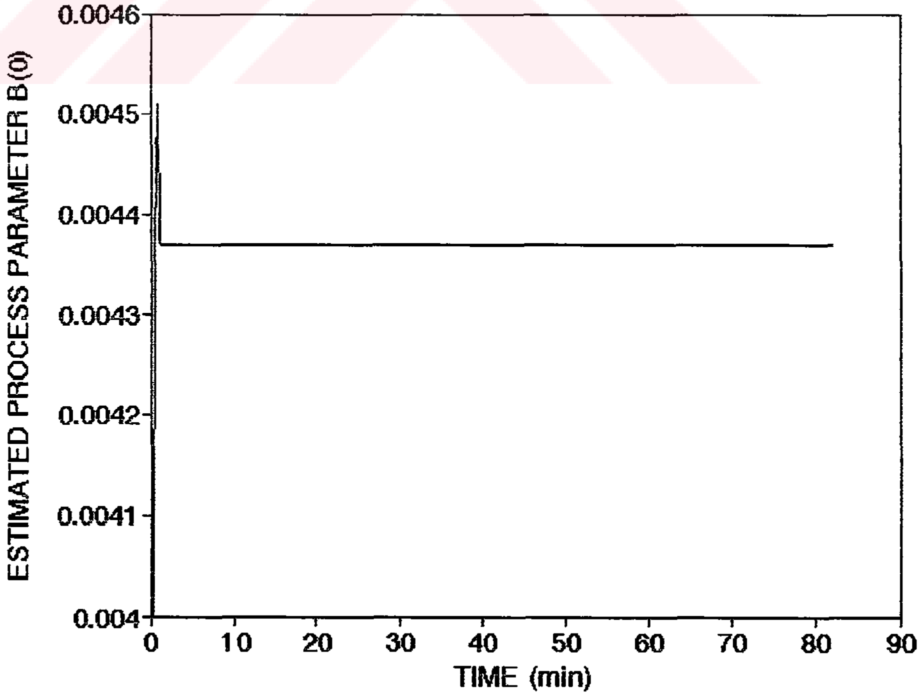

Figure 5.12 Parameter B(0) vs Time for weight function 'λ=0.025'.

2) If $Q = \Delta\lambda = \lambda\,(1\text{-}z^{-1})$, rewriting the equation (5.10) yields;

$$w_t - F' y_t - G u_t = \lambda\,(1\text{-}z^{-1})\,u_t \tag{5.14}$$

then,

$$w_t - F' y_t - G u_t = \lambda\,(u_t - u_{t-1}) \tag{5.15}$$

and,

$$w_t - F' y_t - \lambda u_{t-1} = (G + \lambda)\,u_t \tag{5.16}$$

$$\boxed{\mathbf{u_t = w_t - F' y_t + \lambda u_{t-1} / (G + \lambda)}} \tag{5.17}$$

Figure 5.13, Figure 5.14, Figure 5.15, Figure 5.16, Figure 5.17 and Figure 5.18 show the controller behaviours in the case of '**Q=Δλ**' and the robustness of the estimated parameters respectively.

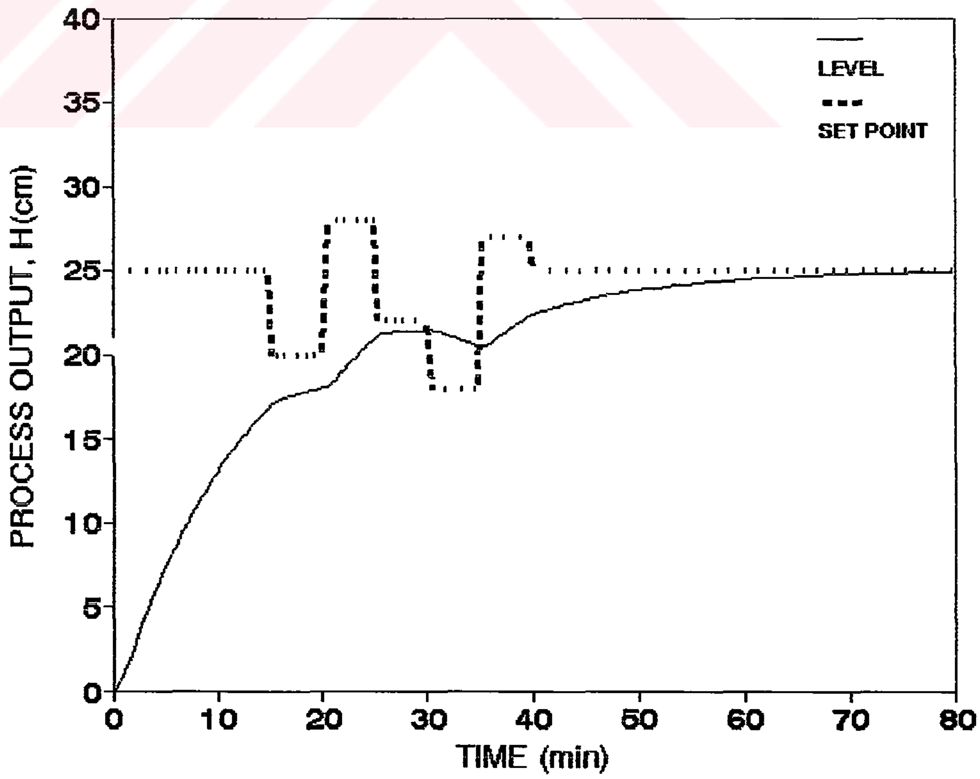

Figure 5.13 Process Output vs Time for 'Q=Δλ' and λ=0.25

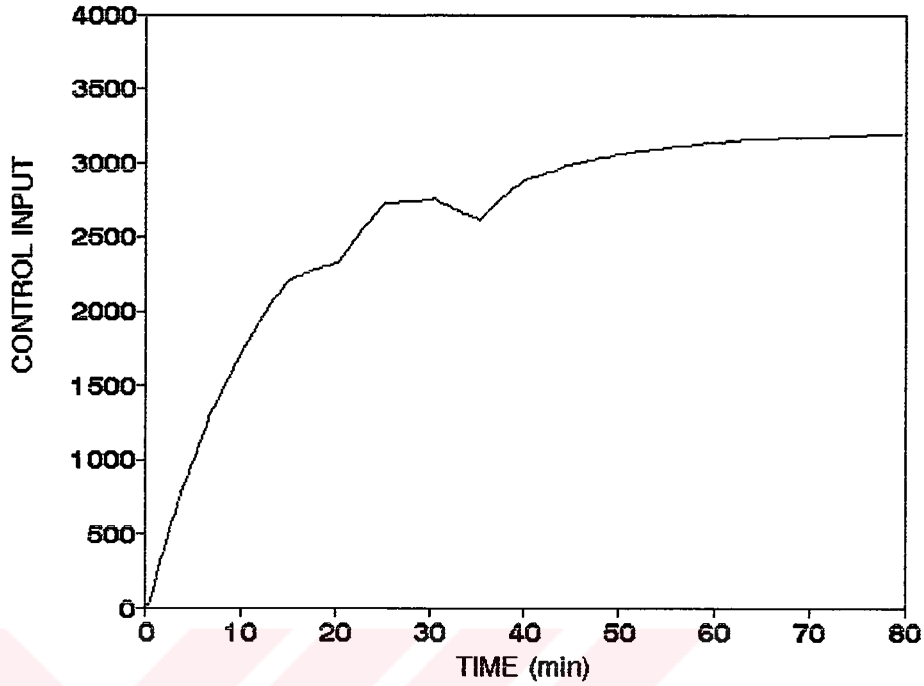

Figure 5.14 Control Input vs Time for 'Q=Δλ'and λ=0.25

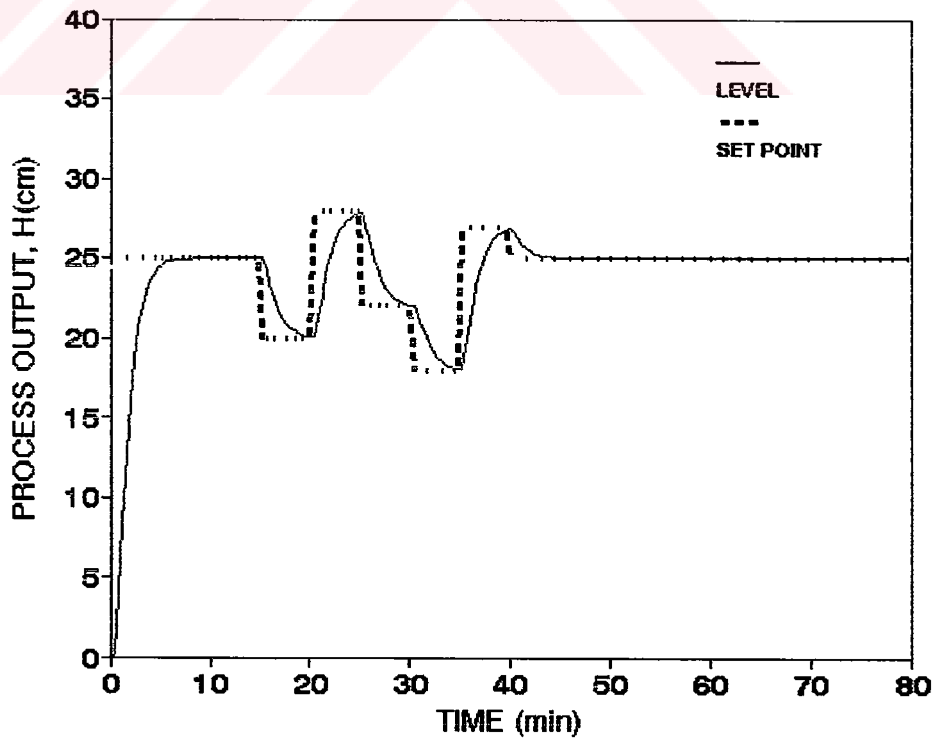

Figure 5.15 Process Output vs Time for 'Q=Δλ' and λ=0.025

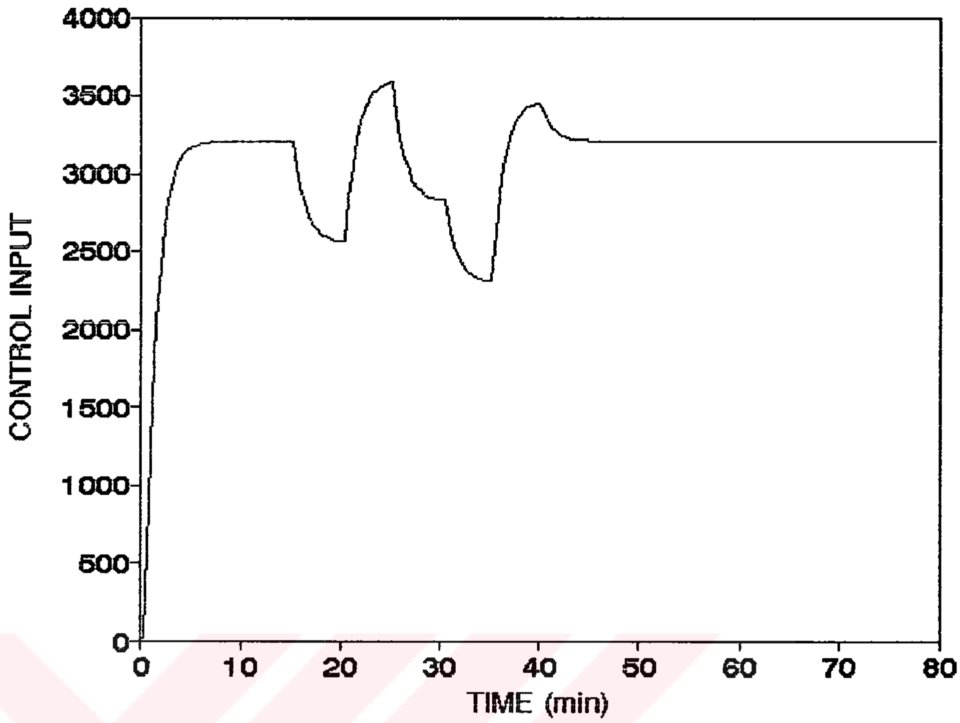

Figure 5.16 Control Input vs Time for 'Q=Δλ'and λ=0.025

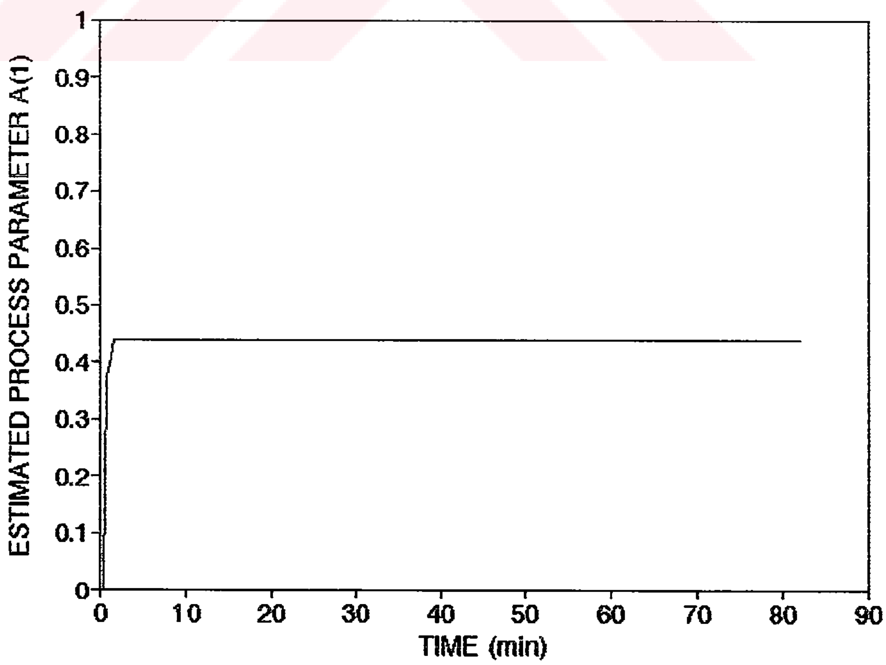

Figure 5.17 Parameter A(1) vs Time for weight function 'Q=Δλ'.

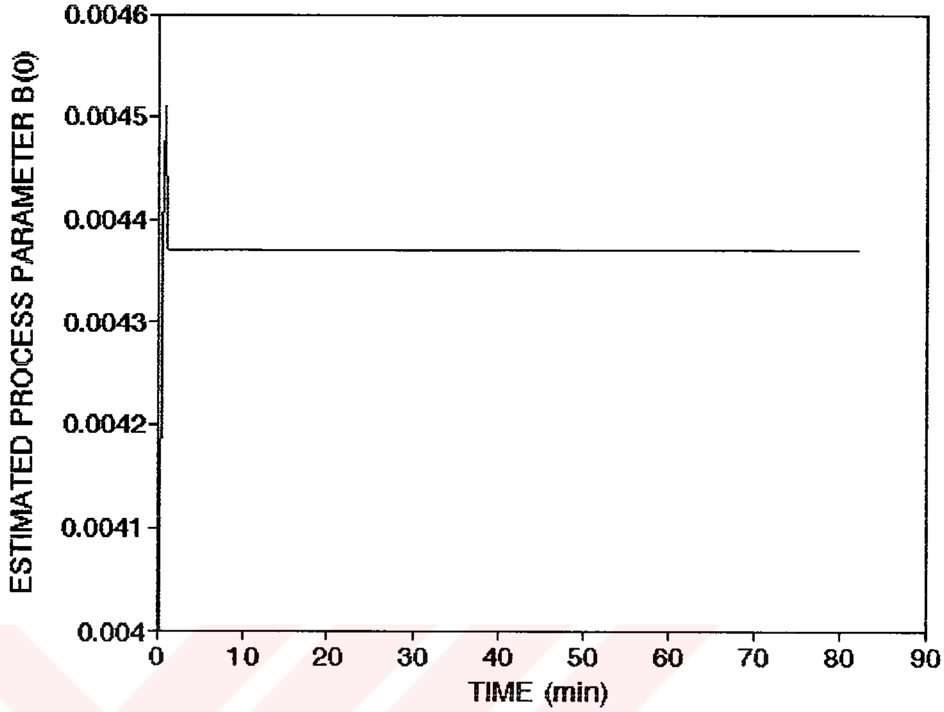

Figure 5.18 Parameter B(0) vs Time for weight function '$Q=\Delta\lambda$'.

3) If $Q = \lambda (1\text{-}z^{-1}) / (1- \alpha z^{-1})$, rewriting the equation (5.10) yields;

$$w_t - F' y_t - G u_t = \lambda \{(1-z^{-1}) / (1- \alpha z^{-1})\}u_t \quad (5.18)$$

assigning the left hand side of the equation (5.18) as 'φ_t' yields,

$$\varphi_t = w_t - F' y_t - G u_t \tag{5.19}$$

and,

$$\varphi_t = \lambda \{(1-z^{-1}) / (1- \alpha z^{-1})\} u_t \tag{5.20}$$

$$\varphi_t = \lambda (u_t - u_{t-1}) / (1- \alpha z^{-1}) \tag{5.21}$$

$$\varphi_t (1- \alpha z^{-1}) = \lambda u_t - \lambda u_{t-1} \tag{5.22}$$

$$\varphi_t - \alpha \varphi_{t-1} = \lambda u_t - \lambda u_{t-1} \tag{5.23}$$

by recalling equation (5.19) and substituting into the equation (5.23) yields,

$$w_t - F' y_t - G u_t - \alpha \varphi_{t-1} + \lambda u_{t-1} = \lambda u_t \tag{5.24}$$

and,

$$w_t - F' y_t - \alpha \varphi_{t-1} + \lambda u_{t-1} = (G + \lambda) u_t \tag{5.25}$$

as a result;

$$\boxed{\mathbf{u_t = (w_t - F' y_t - \alpha \varphi_{t-1} + \lambda u_{t-1}) / (G + \lambda)}} \tag{5.26}$$

Figure 5.19, Figure 5.20, Figure 5.21 and Figure 5.22 shows the controller behaviour in the case of **'Q= λ (1-z^{-1}) / (1- α z^{-1})'** and the stability of the estimated parameters respectively. **λ=0.01** and **α =0.01** specified as the fine tuning parameters in these figures.

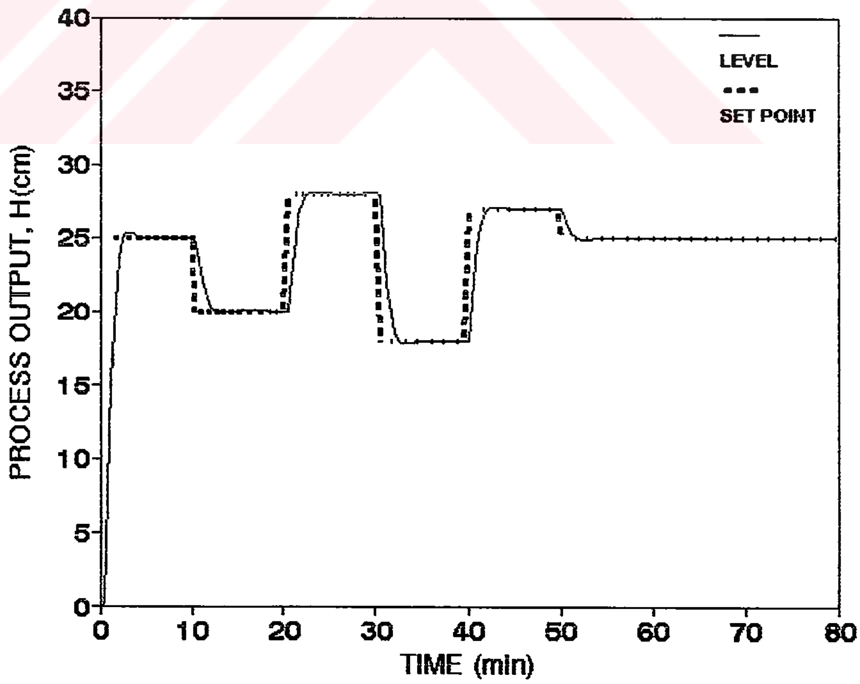

Figure 5.19 Process Output vs Time for weight function 'Q = λ (1-z^{-1}) / (1- α z^{-1})'; λ=0.01 and α=0.01

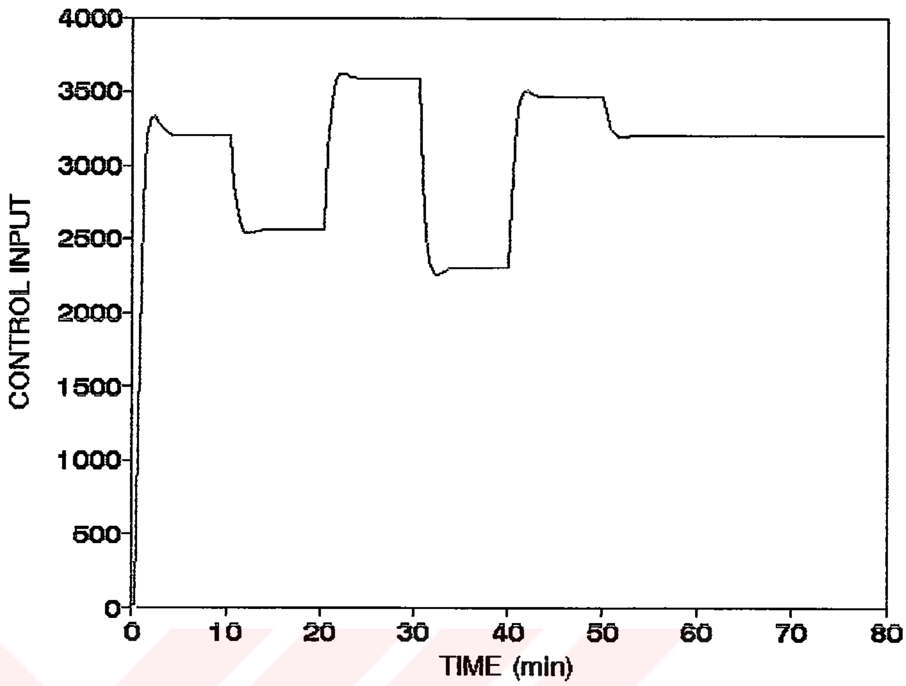

Figure 5.20 Control Input vs Time for weight function

'Q = λ (1-z^{-1}) / (1- α z^{-1})'; λ=0.01 and α=0.01

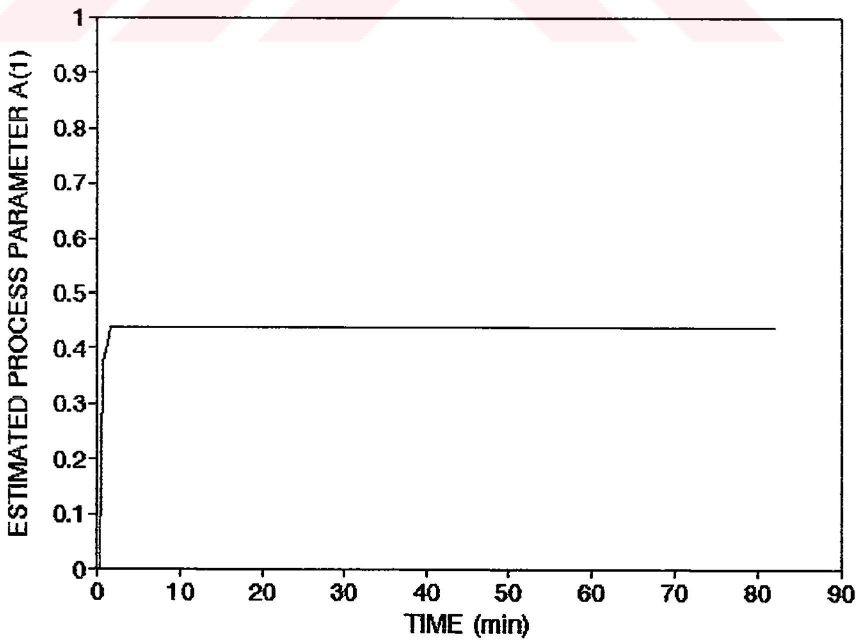

Figure 5.21 Parameter A(1) vs Time for weight function

'Q = λ (1-z^{-1}) / (1- α z^{-1})'; λ=0.01 and α=0.01

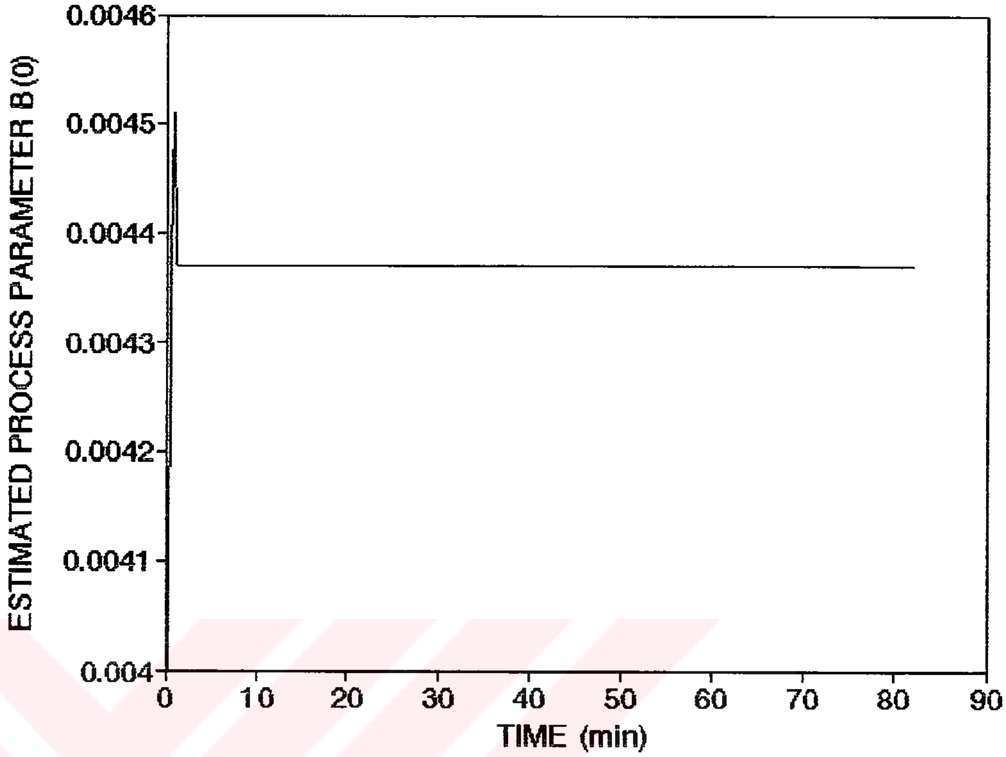

Figure 5.22 Parameter B(0) vs Time for weight function '$Q = \lambda (1\text{-}z^{-1}) / (1\text{-} \alpha z^{-1})$', λ=0.01 and α=0.01

Figure 5.23, Figure 5.24 and Figure 5.27 and Figure 5.28 shows the setpoint tracking ability of the controller in the case of Ramp input and Sine wave input respectively for the Generalised Minimum Variance Controller employing '**$Q= \lambda (1\text{-}z^{-1}) / (1\text{-} \alpha z^{-1})$**'. Figure 5.25, Figure 5.26, Figure 5.29 and Figure 5.30 show the stability of the estimated parameters respectively. **λ=0.01** and **α =0.01** specified as the fine tuning parameters in these figures.

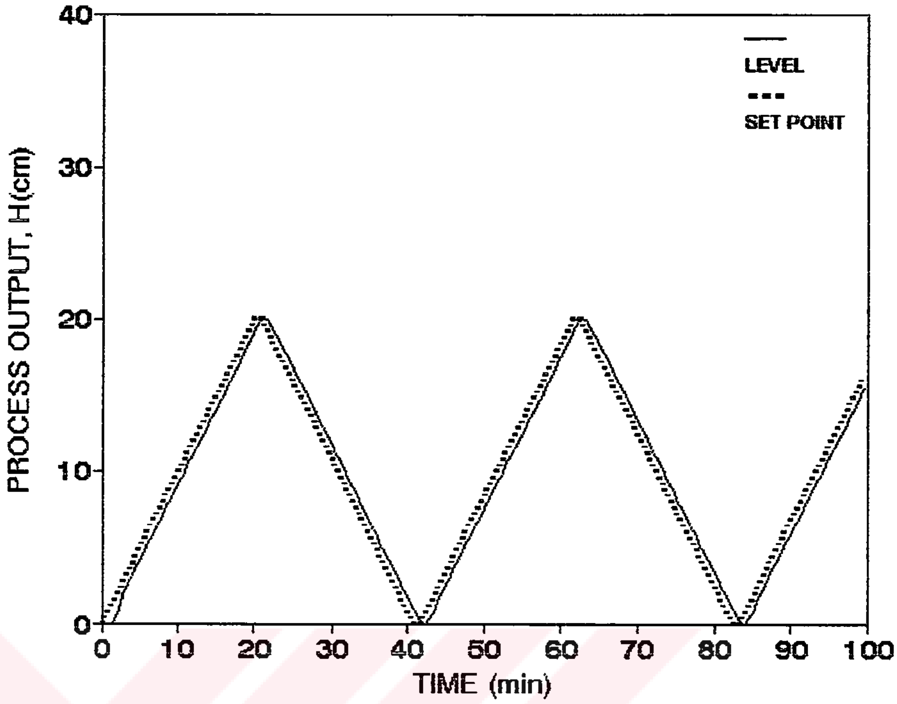

Figure 5.23 Process Output vs Time for the Ramp input

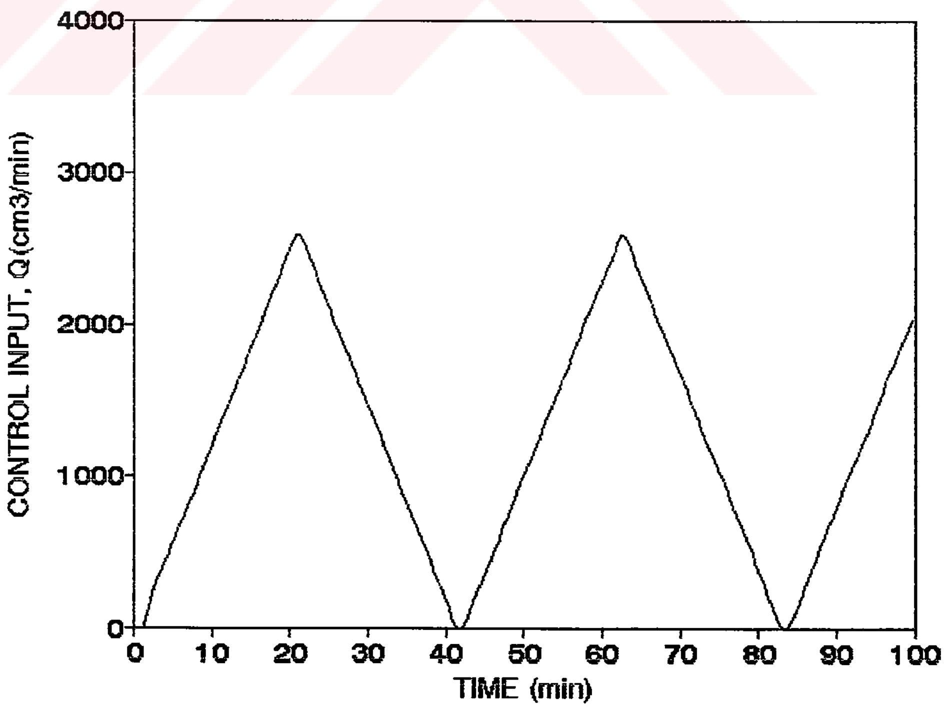

Figure 5.24 Control Input vs Time for the Ramp input

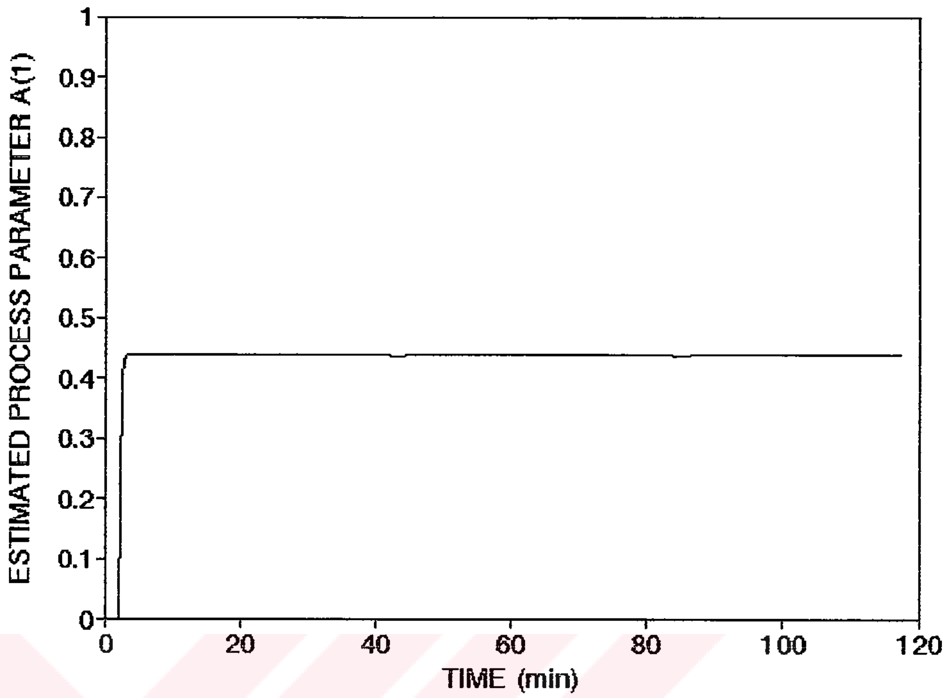

Figure 5.25 Parameter A(1) vs Time for the Ramp input

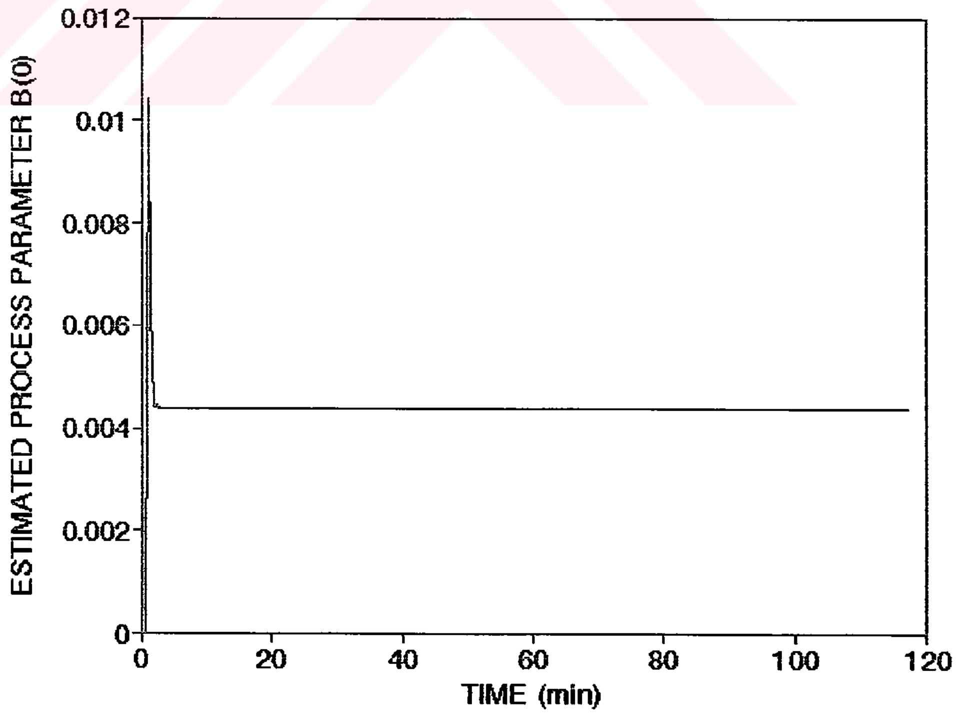

Figure 5.26 Parameter B(0) vs Time for the Ramp input

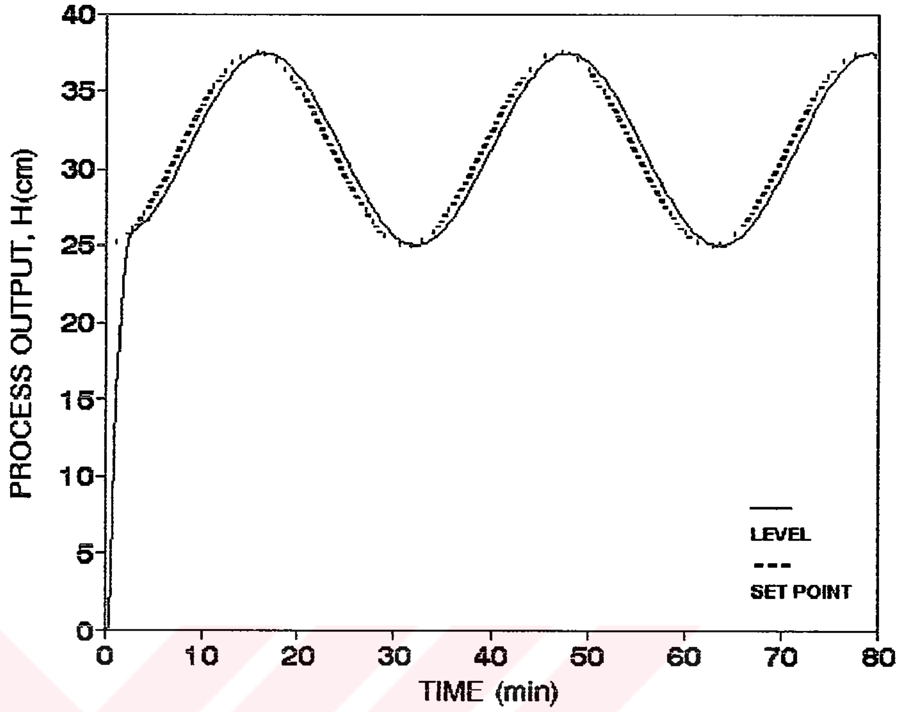

Figure 5.27 Process Output vs Time for the Sine wave input

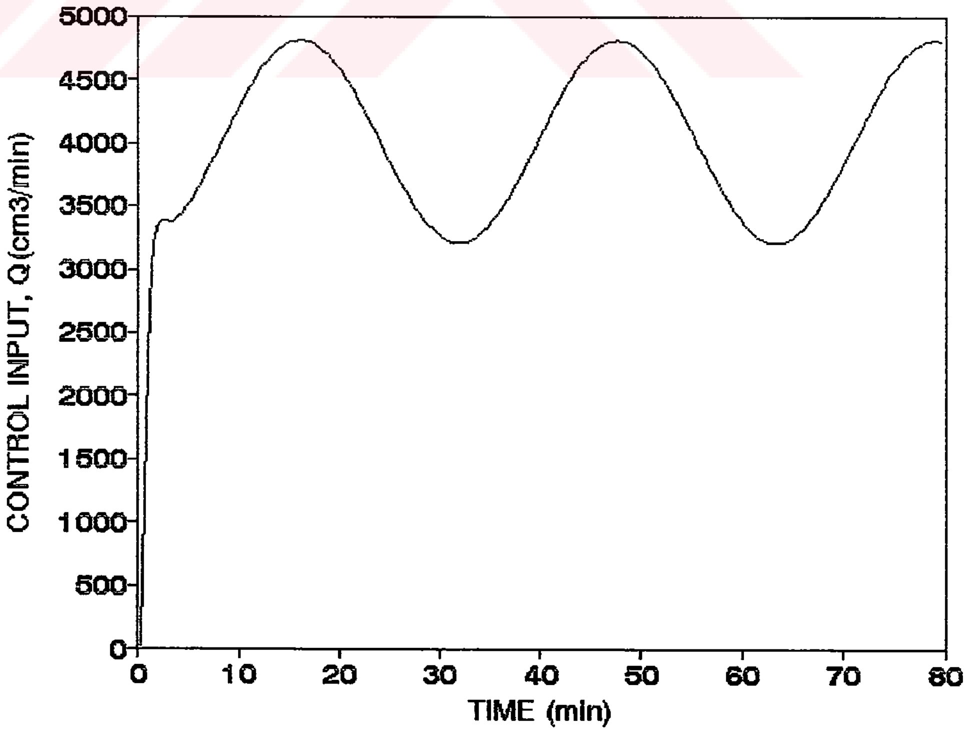

Figure 5.28 Control Input vs Time for the Sine Wave input

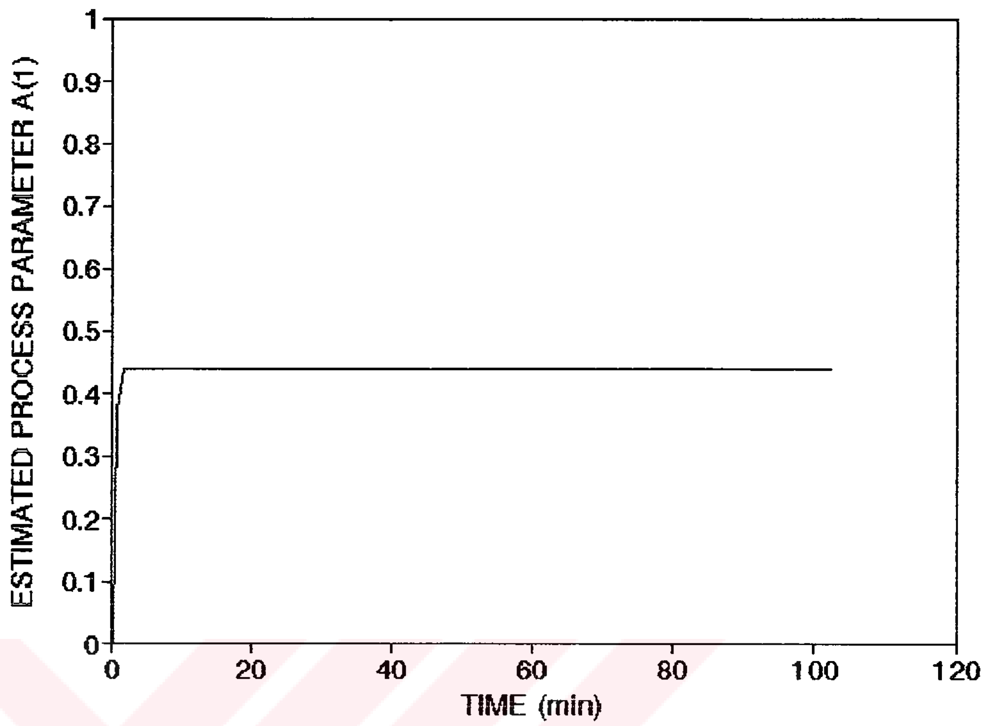

Figure 5.29 Parameter A(1) vs Time for the Sine Wave input

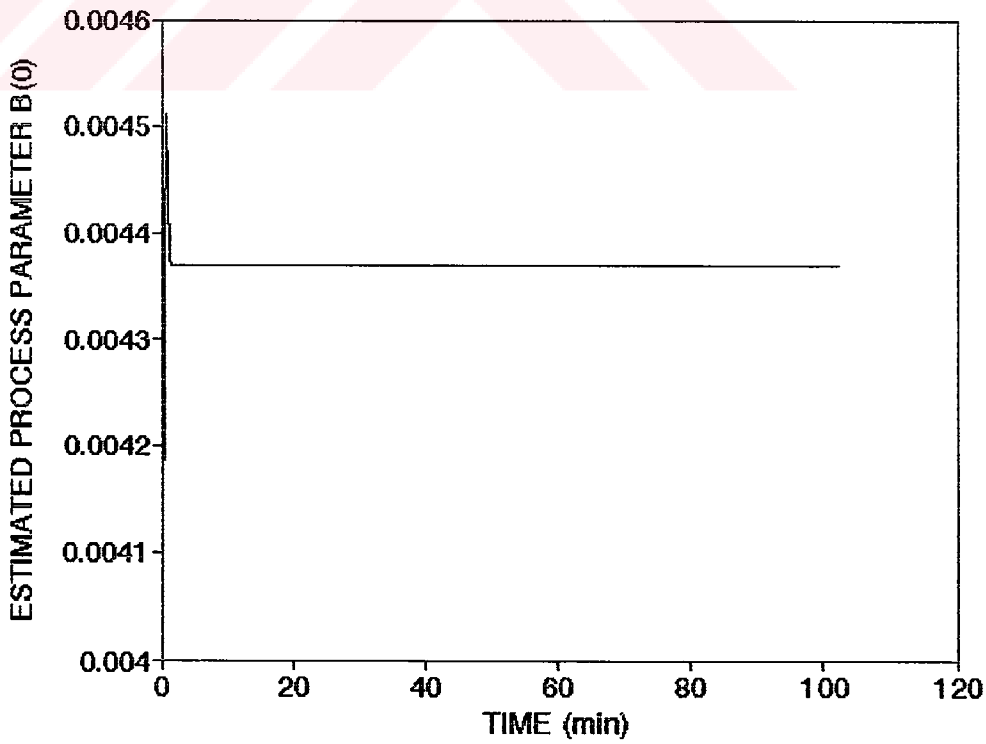

Figure 5.30 Parameter B(0) vs Time for the Sine Wave input

5.3.3. Simulation Results and Discussions

The algorithms mentioned in earlier sections, evaluated on the real plant and the results are presented by the figures in section 5.3.1. These simulation results can be summarised as follows:

1. The first control scheme ($Q=\lambda$ and $\lambda=0$), which is reduced to Self Tuning Minimum Variance Controller (STMVC) by setting the parameter λ is equal zero gave us good results by means of process output and the estimated parameters but excited control action that can be seen from Fig.5.6 . This control action cannot be realistic for the complex systems and can cause wear and tear problem for the final control elements, ie. control valve. As this algorithm was one of the first steps in Self Tuning technology, it had to be included in the simulation study as base case.

2. As mentioned above, choosing a large value for λ will cause some stability problems and at least it will result in off-set from optimistic point of view. It easily can be seen that the estimated parameters are not very stable and in long run of the process estimator can burst (blowing-up) and become unreliable. There are overshoots as well as excited control action.

3. Assigning Q as $\Delta\lambda$ (ie. $\lambda(1-z^{-1})$) results in better control action in control input and yields better estimates of parameters. There is not any overshoot on the process output and responses almost perfect but with slight delay. Using same λ value (0.025) in this technique gave us far better control than the previous one as it removes off-sets which would have occurred due to a scalar λ . The integrating term ($1-z^{-1}$) impairs loop stability and deteriorates the transient response.

4. The third and last procedure is the one that Q has the form of a discrete inverse PI regulator. In this case, the control signal can be interpreted as being calculated according to a conventional control law acting on a k-step ahead prediction of the process output. The disadvantage of this scheme is that the coefficients of Q (λ and α) must be supplied a-priori.

5. Effectiveness of the GMV controller by using the last and the best procedure can be seen from Figure 5.23, Figure 5.24 , Figure 5.25 and Figure 5.26 showing the implementation of the Ramp input and Sine wave input in order to push the controller to work in servo mode.

5.4. ON-LINE IMPLEMENTATION OF STC ON HIGHER ORDER SYSTEMS

5.4.1. On-line STC Experiments on the Second Order Heater System

In this part of study, basically a second order heater system consisting **a heater, a controller** and **a final control element** shown in Figure 5.31 is used. The **heater** has a nominal heating power of 2.5 (kw) and the temperature is measured by J-type thermocouples in the flow circuit; the one in the water leaving the end of the heater is used for the following experiments. The **controller** is based on a computer control system with 8 channel input and 3 channel output and the details of the 8 bits controller card used for the data acquisition are given in Figure 5.32. The **final control** element used in this study comes in two types; a triac module and a time-proportional contactor. Both of these elements have the capacity of 35 (A) driving powers for the heater and are used to show the difference between their precision.

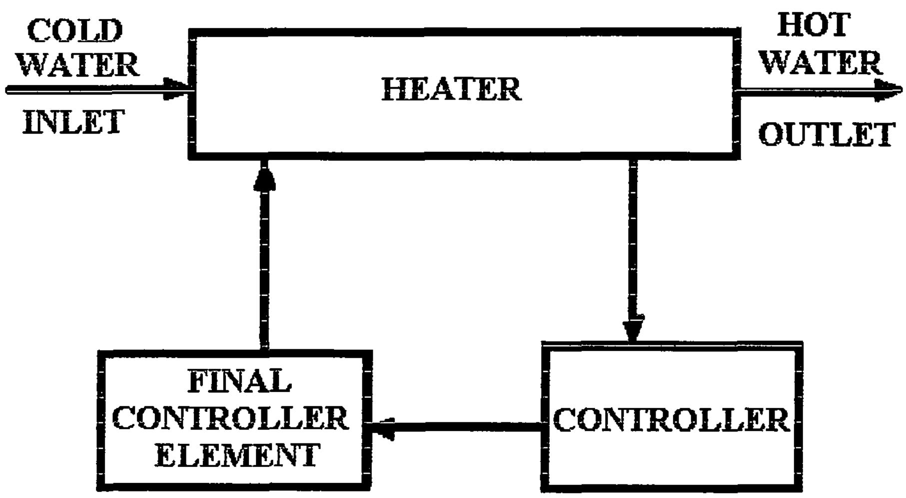

Figure 5.31 Heater System Used for the Experiments.

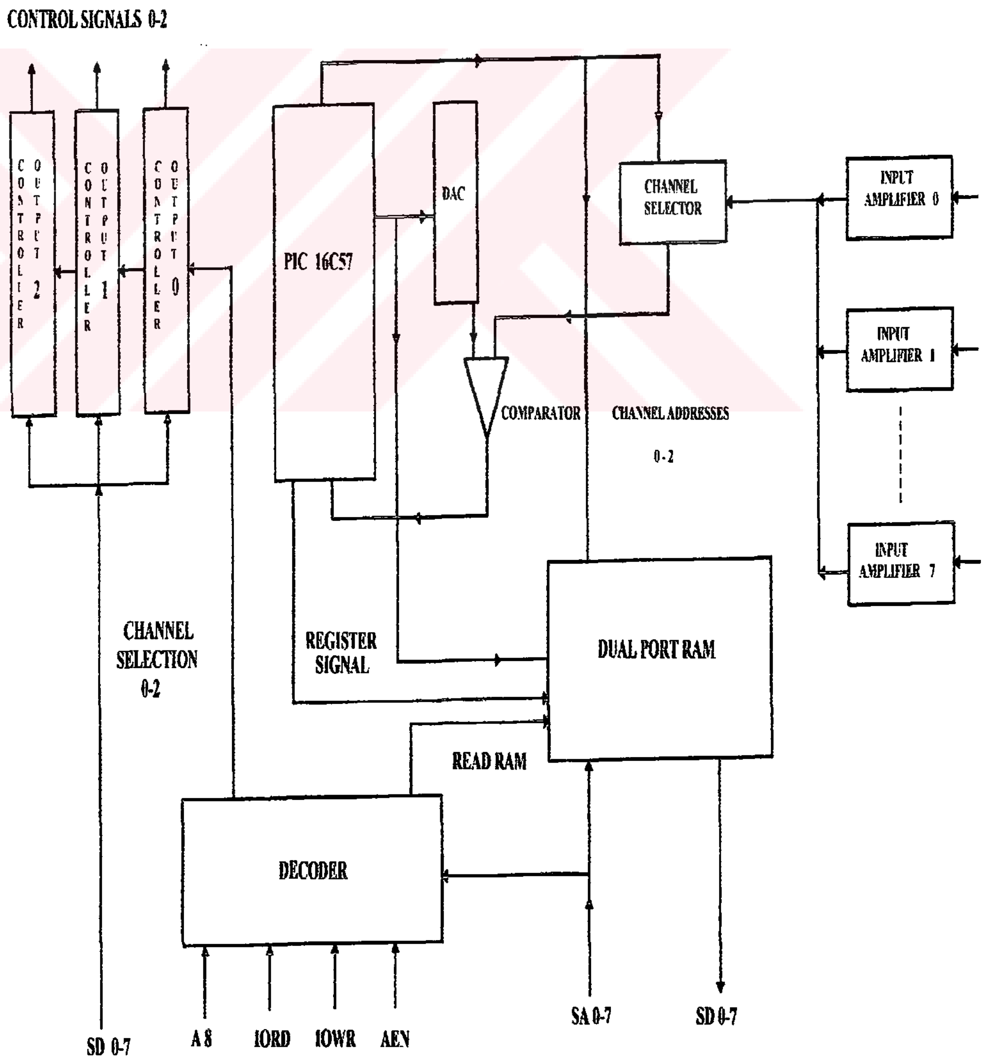

Figure 5.32 Data Acquisition Board Used for the Controller

In the first group of experiments, a time-proportional actuator was used. Figure 5.33, Figure 5.34 and Figure 5.35 show the controller behaviours in the case of '**λ=0.8**' and the stability of the estimated parameters respectively. The water inlet has a value of 8 (l/min) and the heater has the maximum power of 4.5 (kw) for this set of experiments resulting in great offset.

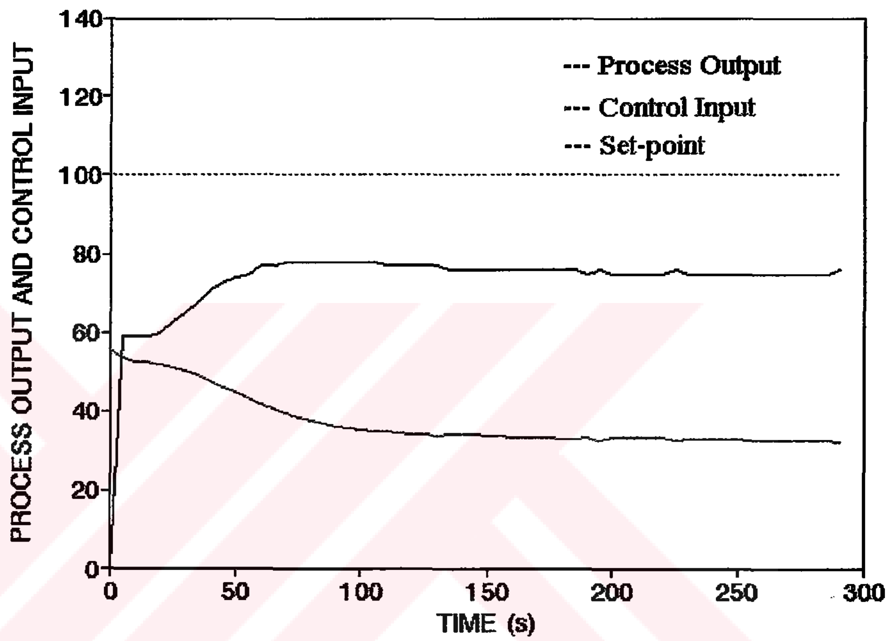

Figure 5.33 Process Output and Control Input vs Time for Weight Function'λ=0.8'.

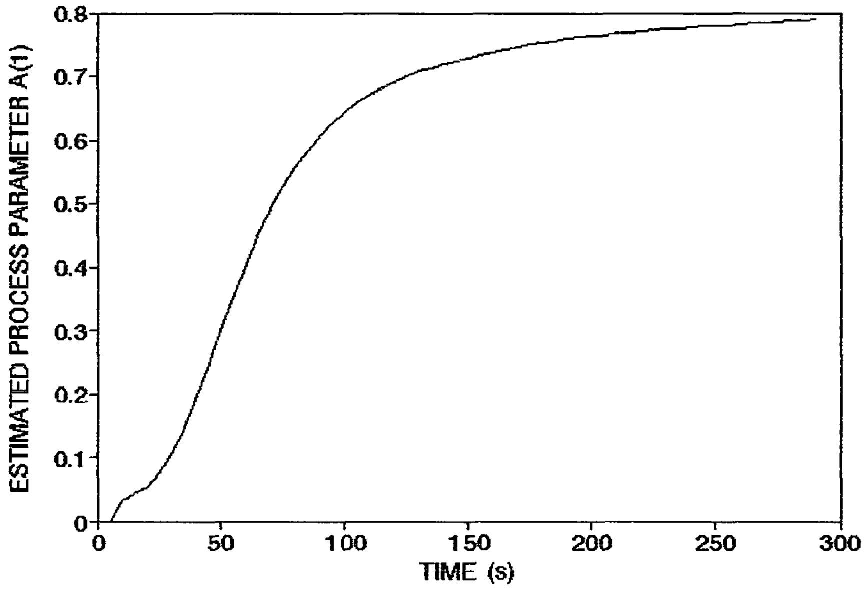

Figure 5.34 Estimated Process Parameter A(1) vs Time for Weight Function'λ=0.8'

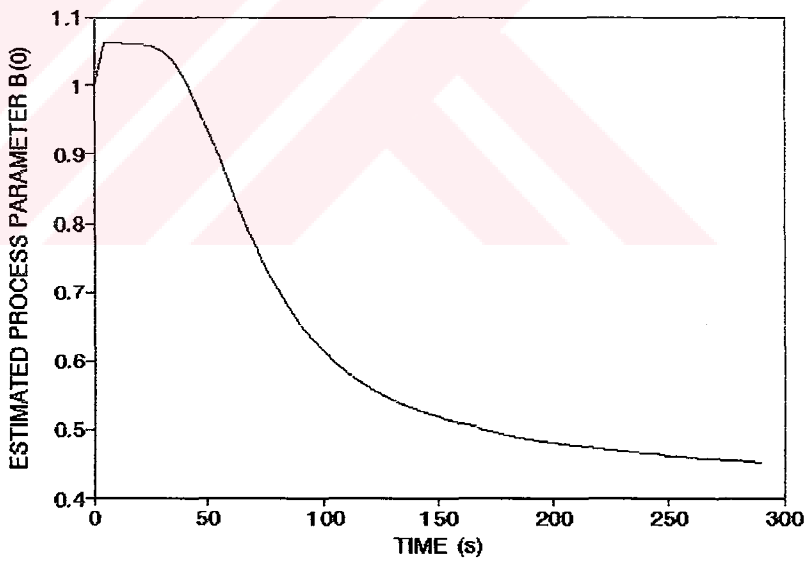

Figure 5.35 Estimated Process Parameter B(0) vs Time for Weight Function'λ=0.8'.

Figure 5.36, Figure 5.37 and Figure 5.38 show the controller behaviours in the case of **'λ=0.05'** and the stability of the estimated parameters respectively. With this λ value, resulting control action resembled on-off behaviour.

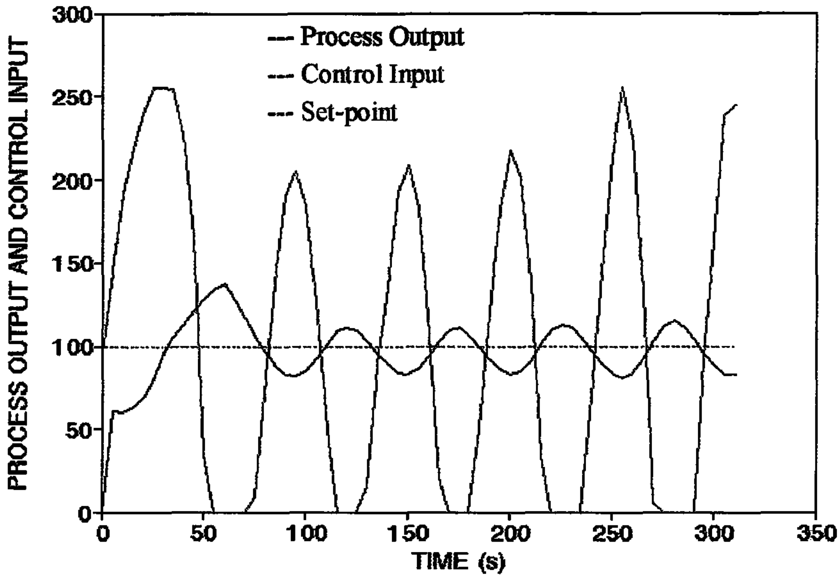

Figure 5.36 Process Output and Control Input vs Time for Weight Function'λ=0.05'.

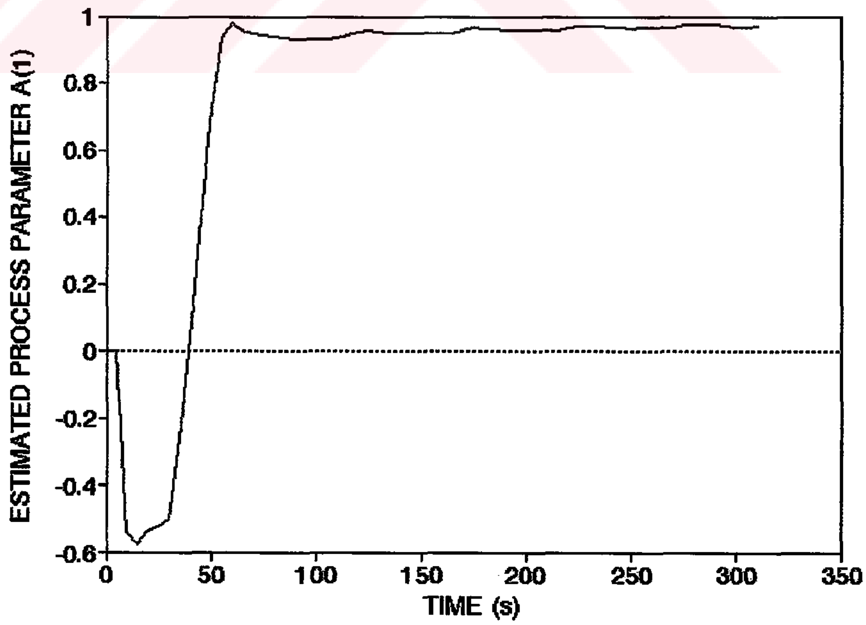

Figure 5.37 Estimated Process Parameter A(1) vs Time for Weight Function'λ=0.05'.

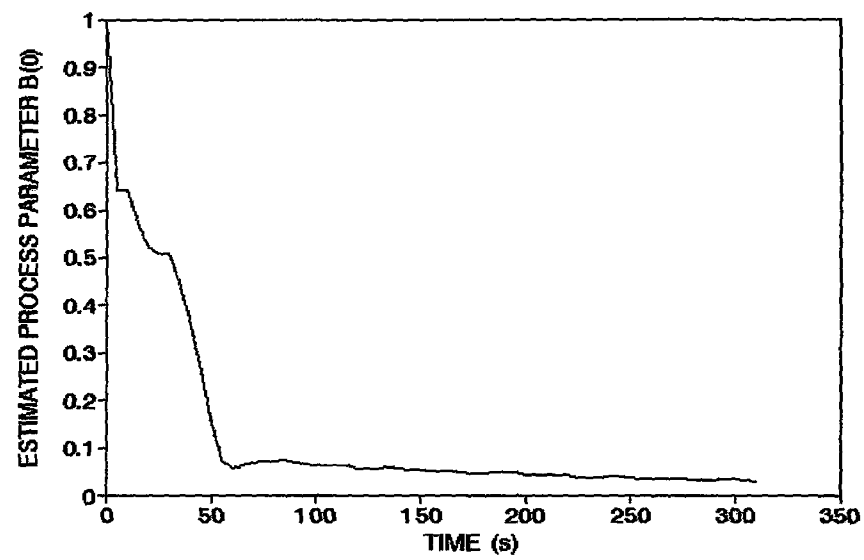

Figure 5.38 Estimated Process Parameter B(0) vs Time for Weight Function'λ=0.05'.

Figure 5.39, Figure 5.40 and Figure 5.41 show the controller behaviours in the case of **'λ=0.2'** and the stability of the estimated parameters respectively. This adjustment resulted in lesser offset.

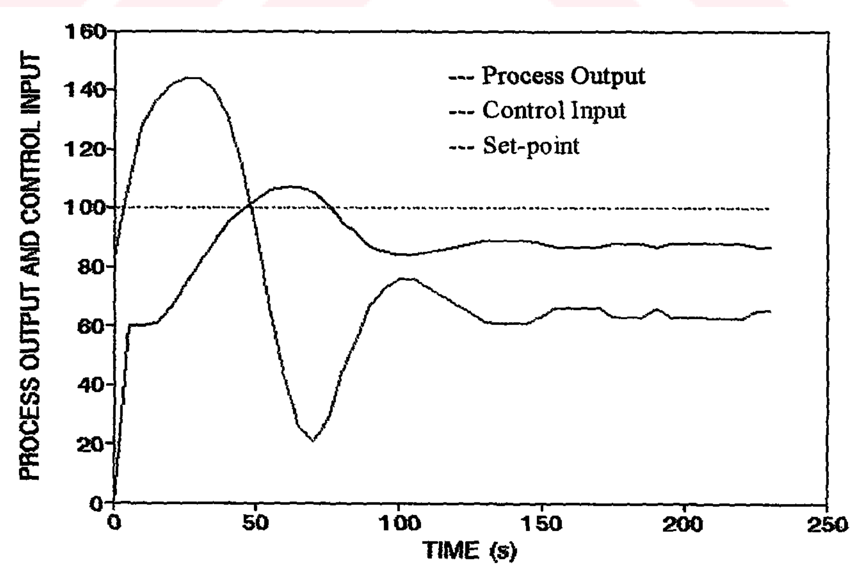

Figure 5.39 Process Output and Control Input vs Time for Weight Function'λ=0.2'.

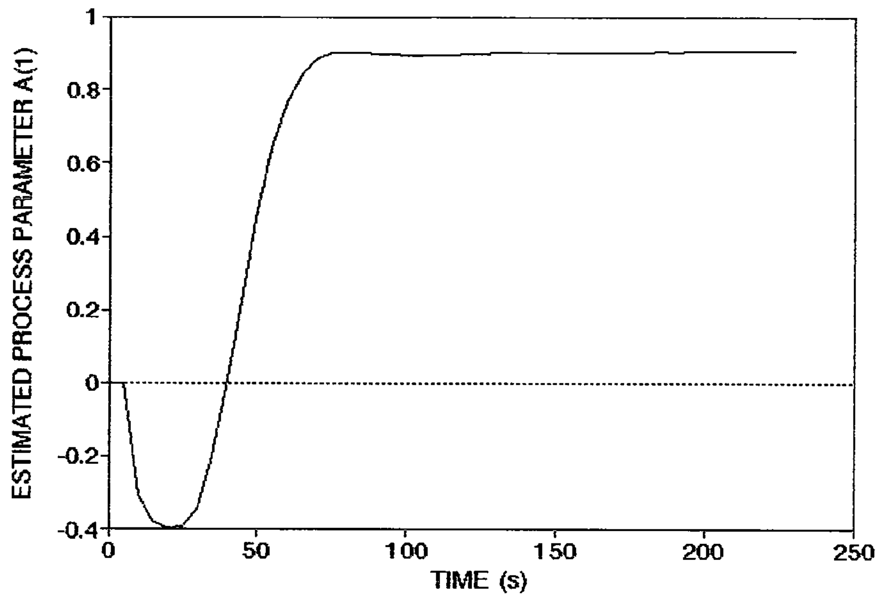

Figure 5.40 Estimated Process Parameter A(1) vs Time for Weight Function'λ=0.2'.

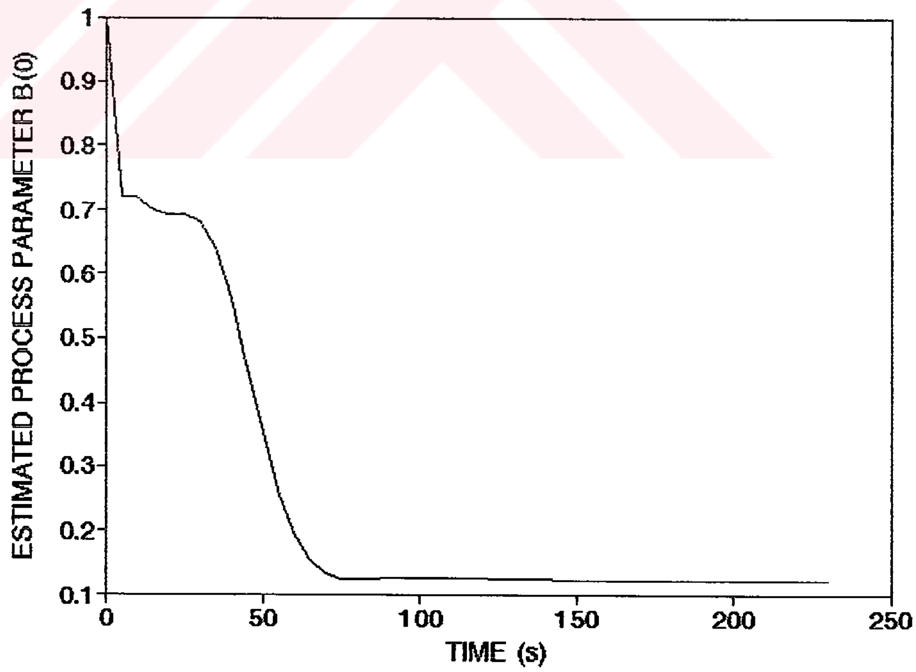

Figure 5.41 Estimated Process Parameter B(0) vs Time for Weight Function'λ=0.2'.

Figure 5.42, Figure 5.43 and Figure 5.44 show the controller behaviours in the case of **'Q=Δλ'** (where **λ=1**) and the stability of the estimated parameters respectively. The water inlet has a value of **8 (l/min)** and the heater has the maximum power of **4.5 (kw)** for this set of experiments. Regulatory behaviours of the system were studied by using step-down and step-up responses beginning at the period of time and for $t_{s\text{-}down}$**=300 (s)**, $t_{s\text{-}up}$**=785 (s)** respectively. Firstly, the flowrate of the water was dropped to the value of **7 (l/min)** for the examining step-down response of the system and latter raised to the original value of **8 (l/min)** to get the step-up response. After introducing step-down input an oscillatory but damping-by-time control action was observed, and step-up response of the controller was lesser oscillatory and quick damping.

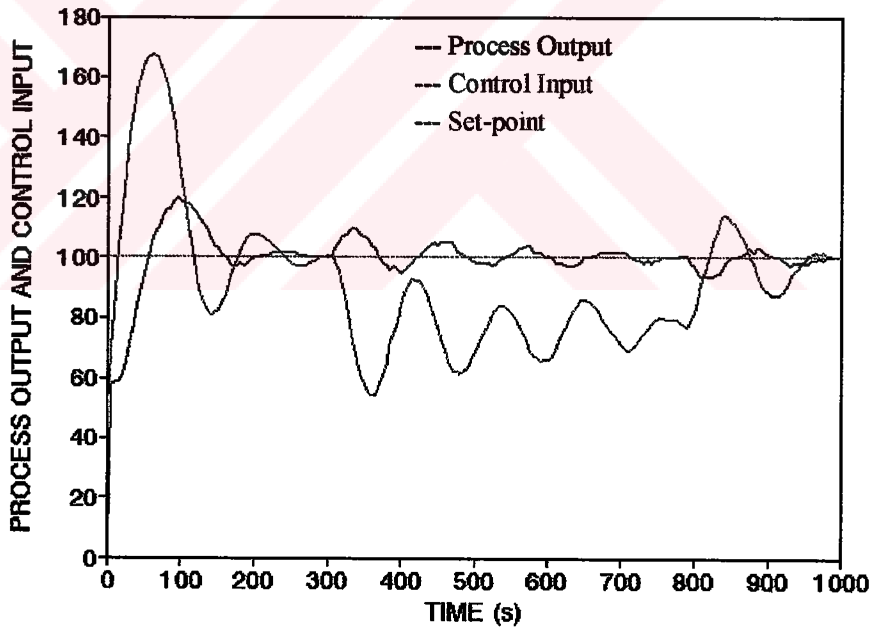

Figure 5.42 Process Output and Control Input vs Time for 'Q=Δλ' and 'λ=1' (For Regulatory Response).

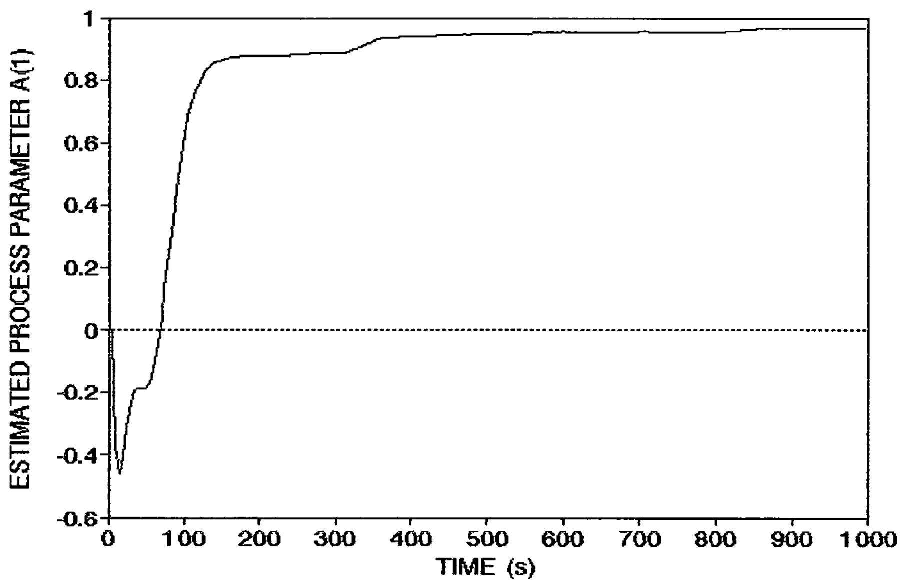

Figure 5.43 Estimated Process Parameter A(1) vs Time for 'Q=Δλ' and 'λ=1'(For Regulatory Response).

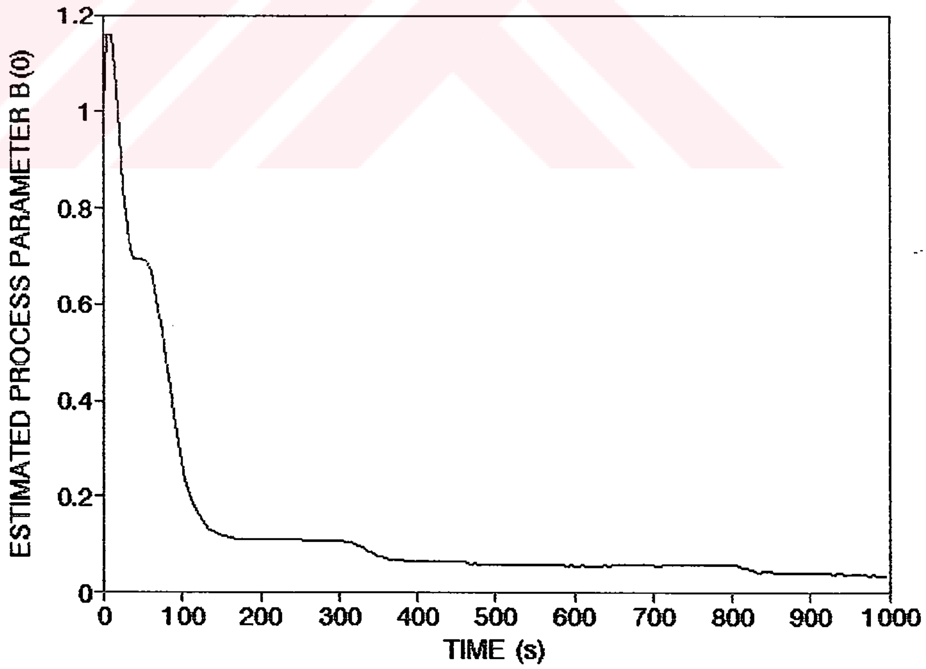

Figure 5.44 Estimated Process Parameter B(0) vs Time for 'Q=Δλ' and 'λ=1'(For Regulatory Response).

Figure 5.45, Figure 5.46 and Figure 5.47 show the controller behaviours in the case of '$Q=\Delta\lambda$' (where $\lambda=1$) and the stability of the estimated parameters respectively. The **Servo** responses of the system were also examined by employing set values of T_1=**100 °C**, T_2=**80 °C** and T_3=**100 °C** for the periods of time t_1=**0 (s)**, t_2=**300 (s)** and t_3=**600 (s)** respectively. As in the preceeding cases, an oscillatory behaviour was observed.

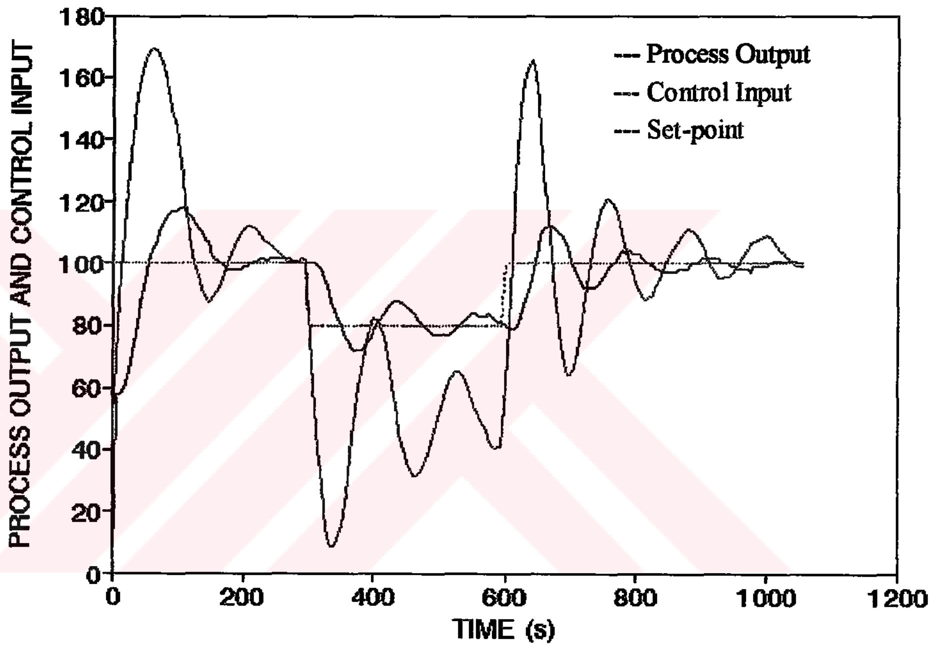

Figure 5.45 Process Output and Control Input vs Time for '$Q=\Delta\lambda$' and '$\lambda=1$'(For Servo Response).

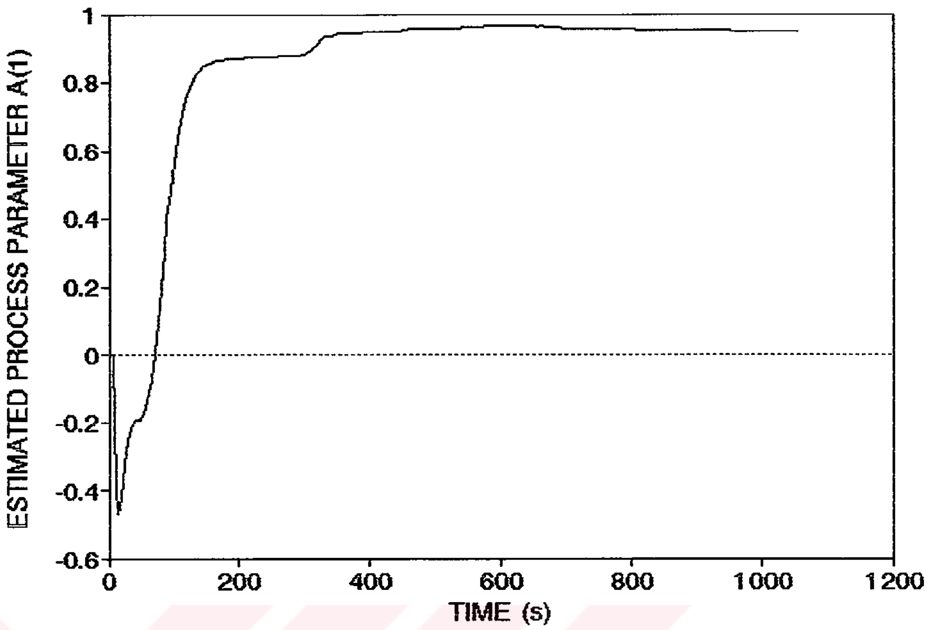

Figure 5.46 Estimated Process Parameter A(1) vs Time for '$Q=\Delta\lambda$' and '$\lambda=1$'(For Servo Response).

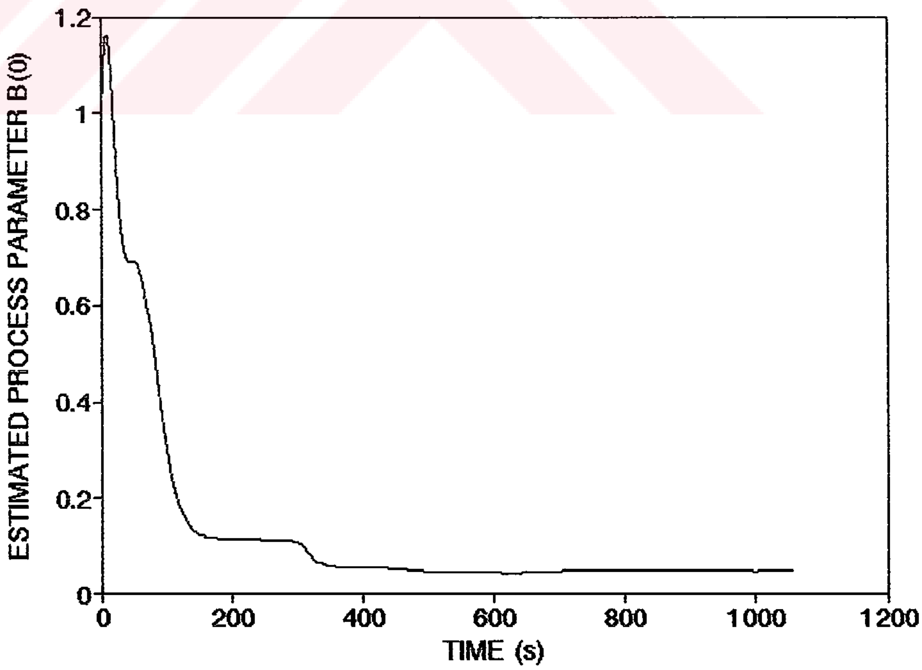

Figure 5.47 Estimated Process Parameter B(0) vs Time for '$Q=\Delta\lambda$' and '$\lambda=1$'(For Servo Response).

Figure 5.48, Figure 5.49 and Figure 5.50 show the controller behaviours in the case of '$Q=(1-z^{-1})\lambda/(1-\alpha z^{-1})$' (where λ=0.5 and α=0.5) and the stability of the estimated parameters respectively. The water inlet has a value of **8 (l/min)** and the heater has the maximum power of **4.5 (kw)** for this set of experiments. Regulatory behaviours of the system were studied by using step-down and step-up responses beginning at the period of time and for $t_{s\text{-}down}$**=455 (s)**, $t_{s\text{-}up}$**=700 (s)** respectively. Firstly, the flowrate of the water was dropped to the value of **7 (l/min)** for the examining step-down response of the system and latter raised to the original value of **8 (l/min)** to get the step-up response. This new controller performed apparently better action causing no excessive changes in the manipulated variable.

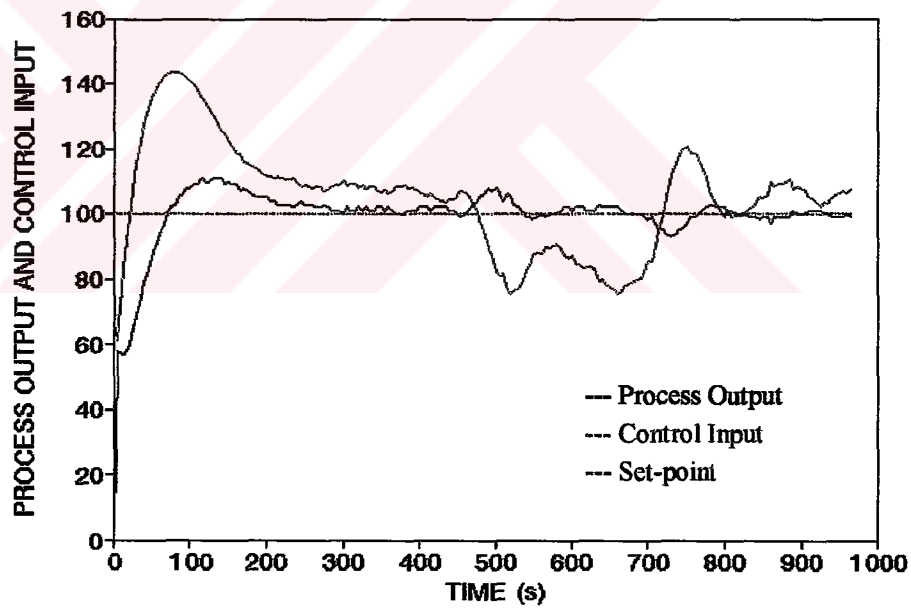

Figure 5.48 Process Output and Control Input vs Time for '$Q=(1-z^{-1})\lambda/(1-\alpha z^{-1})$', ($\lambda$=0.5 and α=0.5) (For Regulatory Response).

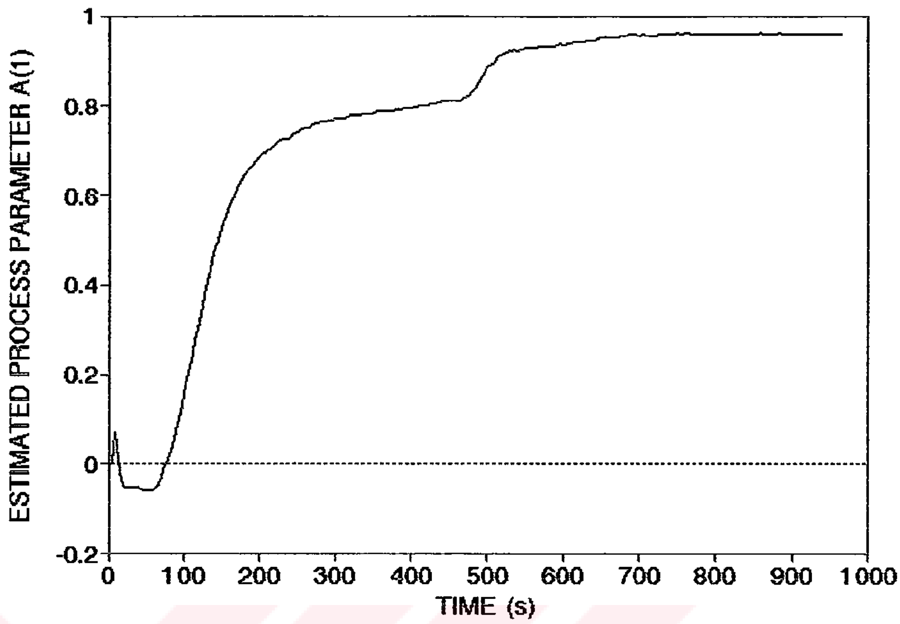

Figure 5.49 Estimated Process Parameter A(1) vs Time for '$Q=(1-z^{-1})\lambda/(1-\alpha z^{-1})$', ($\lambda$=0.5 and α=0.5) (For Regulatory Response).

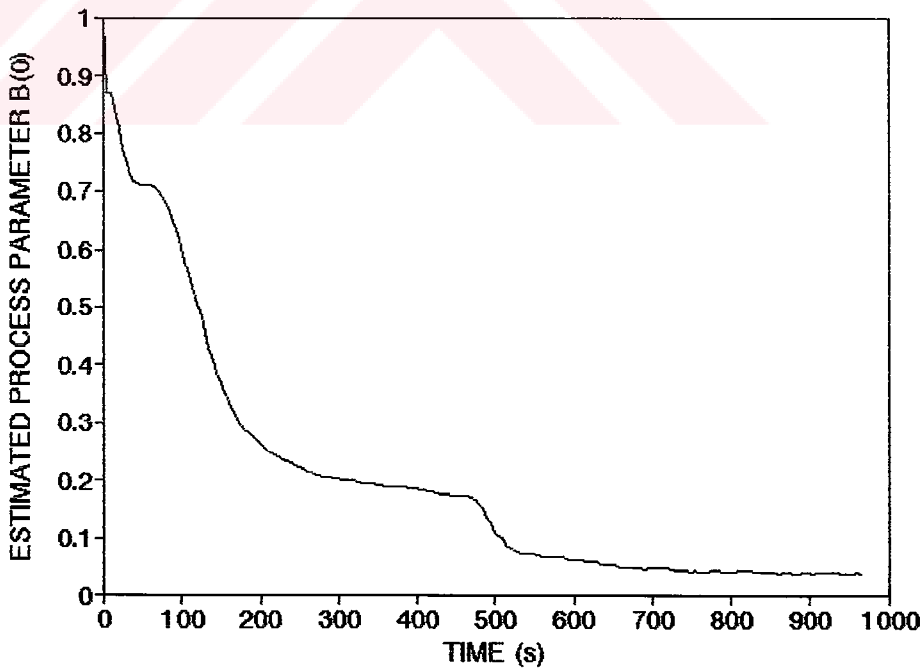

Figure 5.50 Estimated Process Parameter B(0) vs Time for '$Q=(1-z^{-1})\lambda/(1-\alpha z^{-1})$', ($\lambda$=0.5 and α=0.5) (For Regulatory Response).

Figure 5.51, Figure 5.52 and Figure 5.53 show the controller behaviours in the case of **'$Q=(1-z^{-1})\lambda/(1-\alpha z^{-1})$'** (where **$\lambda$=0.5** and **$\alpha$=0.5**) and the stability of the estimated parameters respectively. The **Servo** responses of the system were also examined by employing set values of **T_1=100 °C**, **T_2=80 °C** and **T_3=100 °C** for the periods of time **t_1=0 (s)**, **t_2=300 (s)** and **t_3=600 (s)** respectively. Because of the pulsative operation nature of actuator used, a noisy process output was obtained. In the following experiments, a triac module was used as the actuator to improve this situation.

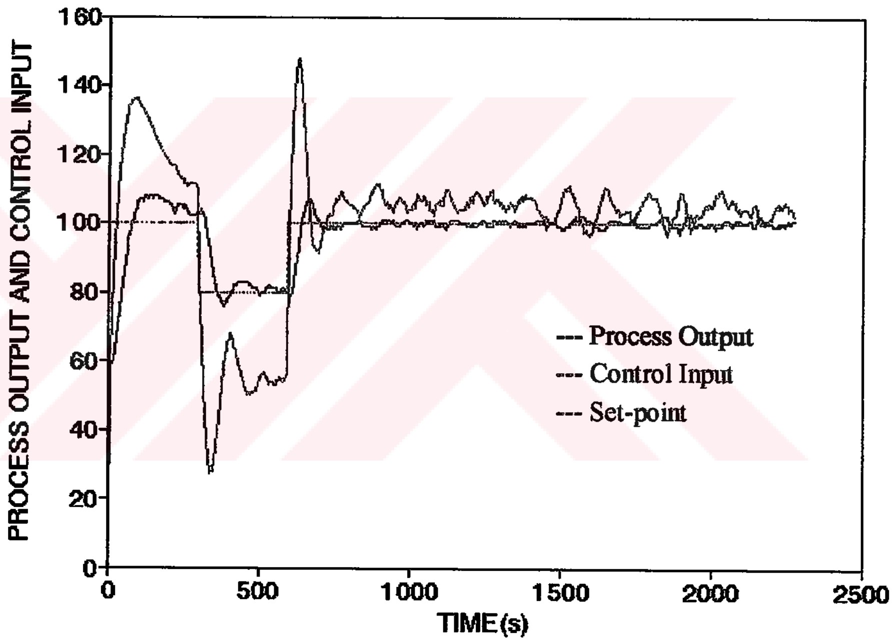

Figure 5.51 Process Output and Control Input vs Time for '$Q=(1-z^{-1})\lambda/(1-\alpha z^{-1})$', ($\lambda$=0.5 and α=0.5) (For Servo Response).

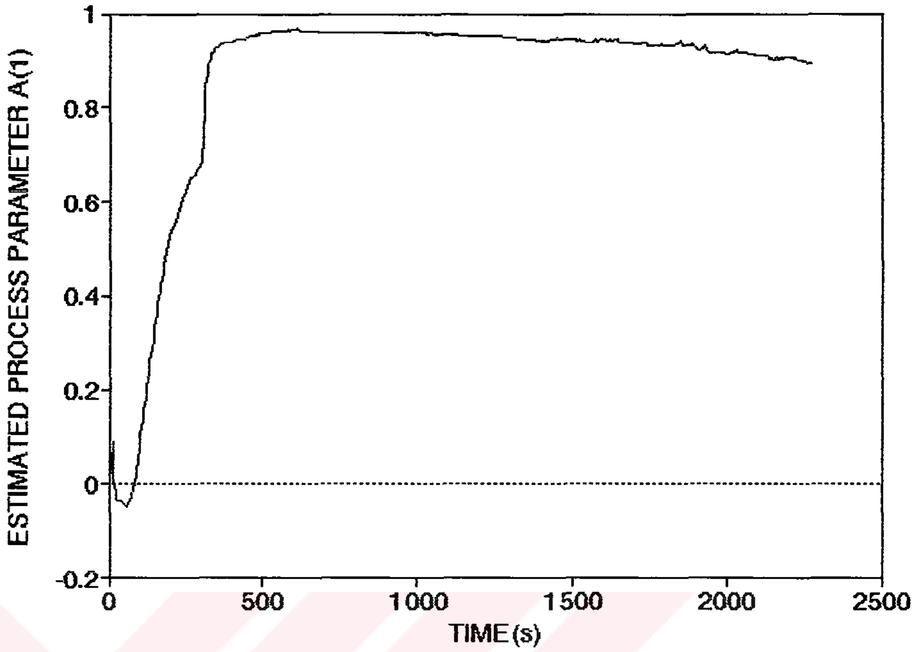

Figure 5.52 Estimated Process Parameter A(1) vs Time for '$Q=(1-z^{-1})\lambda/(1-\alpha z^{-1})$', ($\lambda=0.5$ and $\alpha=0.5$) (For Servo Response).

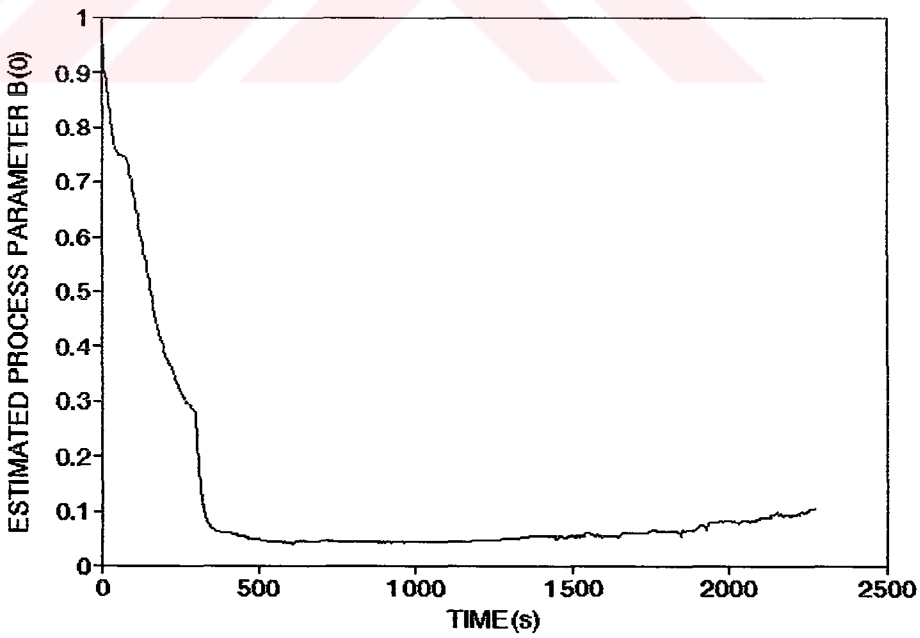

Figure 5.53 Estimated Process Parameter B(0) vs Time for '$Q=(1-z^{-1})\lambda/(1-\alpha z^{-1})$', ($\lambda=0.5$ and $\alpha=0.5$) (For Servo Response).

Figure 5.54 shows the controller behaviour in the case of **'PID'** controller used for the Regulation. Parameters of the PID controller were found by using Cohen-Coon method, and adjusted finely as $\mathbf{K_C=3}$, $\mathbf{\tau_I=10(s)}$ and $\mathbf{\tau_D=2(s)}$ by setting up several experiments. The water inlet has a value of **8 (l/min)** and the heater has the maximum power of **4.5 (kw)** for this set of experiments. Regulatory behaviours of the system were studied by using step-down and step-up responses beginning at the period of time and for $\mathbf{t_{s\text{-}down}=300}$ **(s)**, $\mathbf{t_{s\text{-}up}=600}$ **(s)** respectively. Firstly, the flowrate of the water was dropped to the value of **7 (l/min)** for the examining step-down response of the system and latter raised to the original value of **8 (l/min)** to get the step-up response.

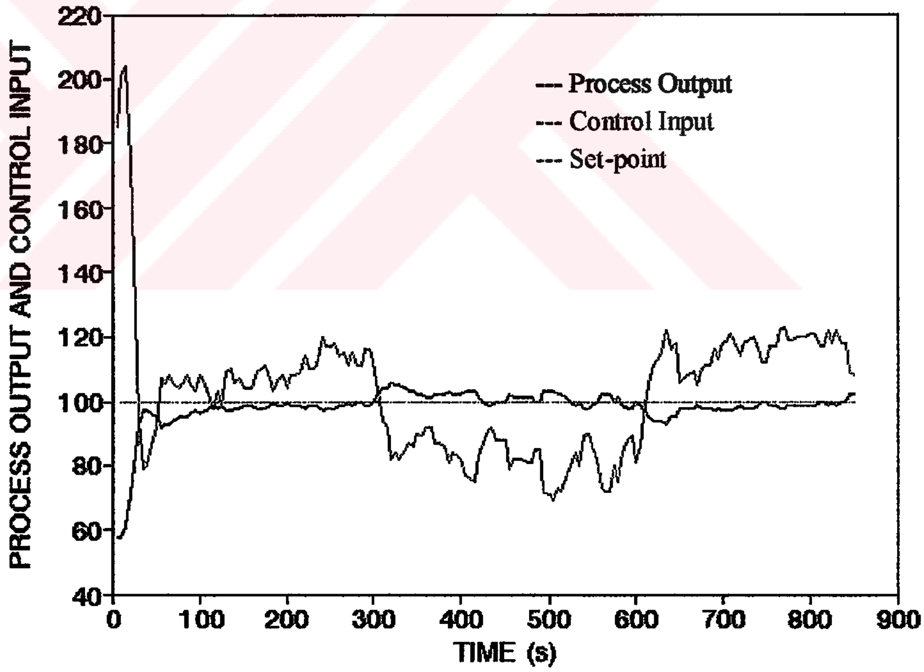

Figure 5.54 Process Output and Control Input vs Time for 'PID', (For Regulatory Response).

Figure 5.55, Figure 5.56 and Figure 5.57 show the **Triac Module** fitted GMV controller behaviours in the case of **'$Q=(1-z^{-1})\lambda/(1-\alpha z^{-1})$'** (where **$\lambda=0.7$** and **$\alpha=0.7$**) and the stability of the estimated parameters respectively.

The **Servo** responses of the system were also examined by employing set values of **$T_1=100$ °C**, **$T_2=80$ °C** and **$T_3=100$ °C** for the periods of time **$t_1=0$ (s)**, **$t_2=400$ (s)** and **$t_3=800$ (s)** respectively.

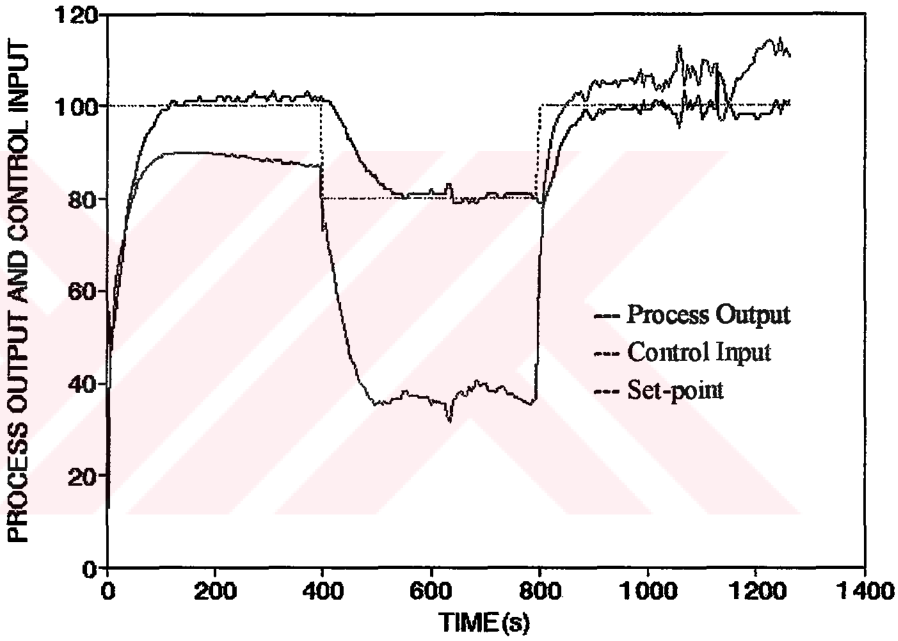

Figure 5.55 Process Output and Control Input vs Time for '$Q=(1-z^{-1})\lambda/(1-\alpha z^{-1})$', ($\lambda=0.7$ and $\alpha=0.7$) (For Servo Response).

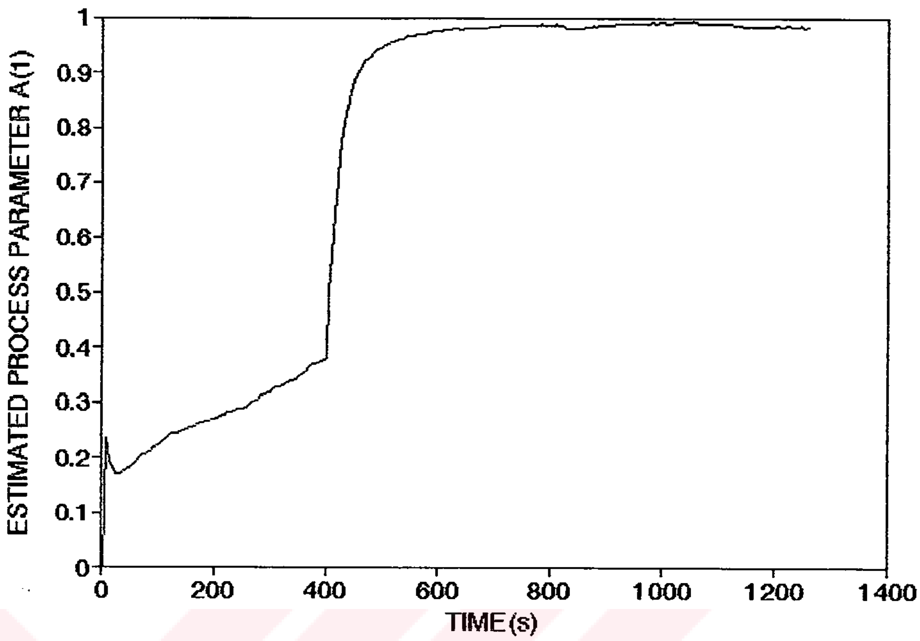

Figure 5.56 Estimated Process Parameter A(1) vs Time for '$Q=(1-z^{-1})\lambda/(1-\alpha z^{-1})$', ($\lambda$=0.7 and α=0.7) (For Servo Response).

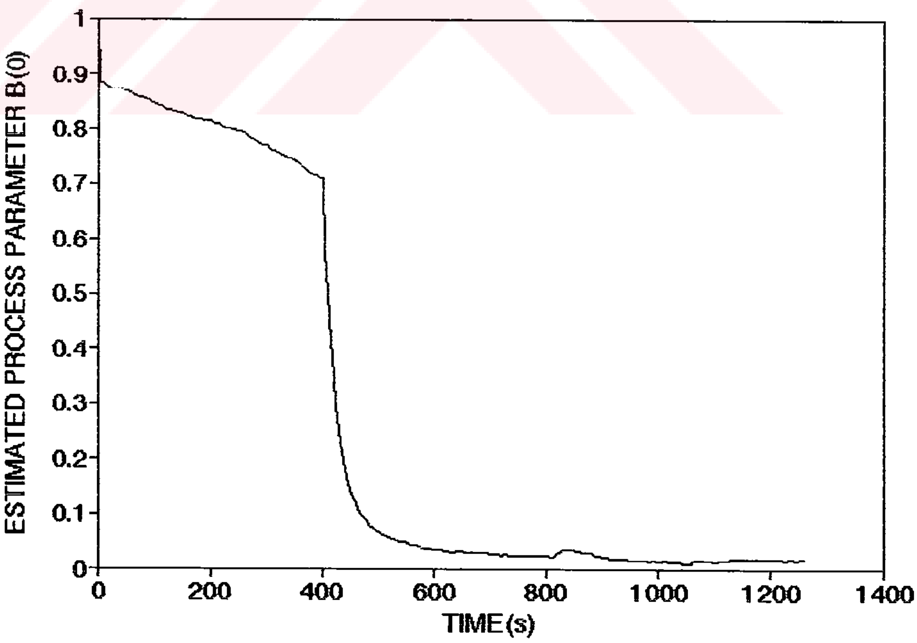

Figure 5.57 Estimated Process Parameter B(0) vs Time for '$Q=(1-z^{-1})\lambda/(1-\alpha z^{-1})$', ($\lambda$=0.7 and α=0.7) (For Servo Response).

Figure 5.58, Figure 5.59 and Figure 5.60 show the **Triac Module** fitted GMV controller behaviours in the case of **'$Q=(1-z^{-1})\lambda/(1-\alpha z^{-1})$'** (where **$\lambda$=0.7** and **$\alpha$=0.7**) and the stability of the estimated parameters respectively.

In this set of experiments water inlet has an initial value of **8.8 (l/min)** and the heater has the maximum power of **4.5 (kw)**. Regulatory behaviour of the system was studied by using step-down response beginning at the period of time **$t_{s\text{-}down}$=630 (s)**. The flowrate of water was dropped to the value of **7 (l/min)** to introduce a big disturbance.

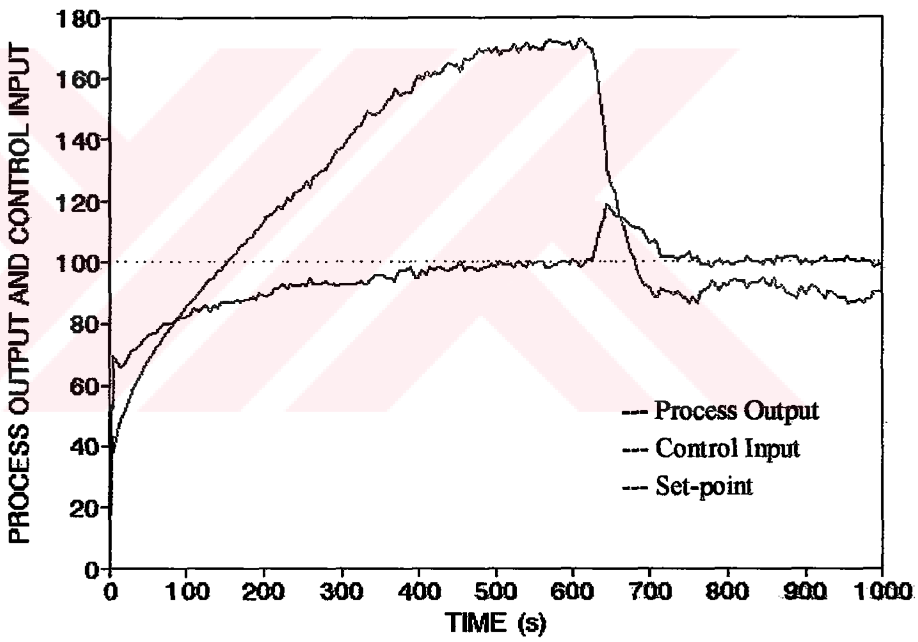

Figure 5.58 Process Output and Control Input vs Time for '$Q=(1-z^{-1})\lambda/(1-\alpha z^{-1})$', ($\lambda$=0.7 and α=0.7) (For Step-Down Response).

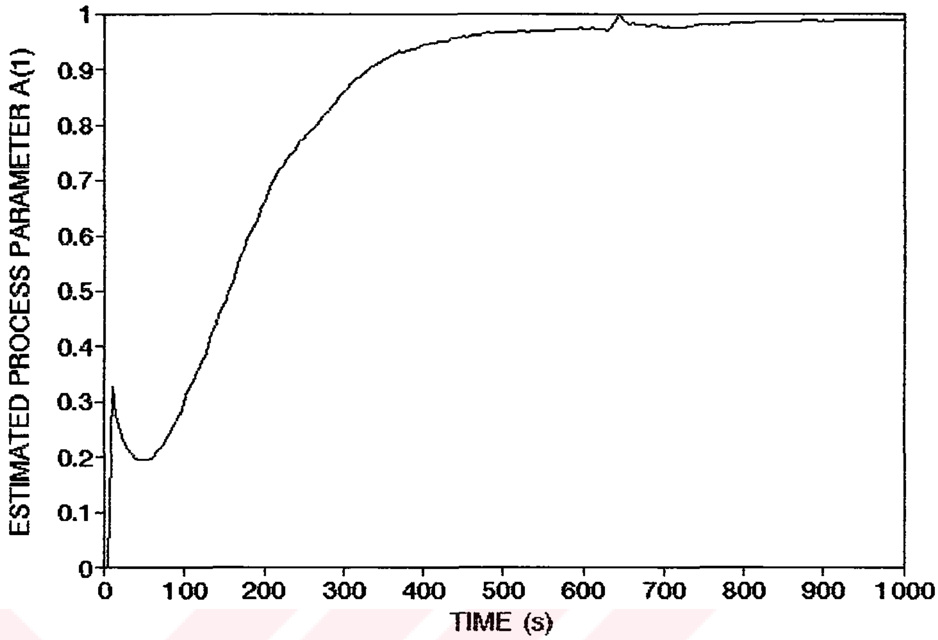

Figure 5.59 Estimated Process Parameter A(1) vs Time for '$Q=(1-z^{-1})\lambda/(1-\alpha z^{-1})$', ($\lambda$=0.7 and α=0.7) (For Step-Down Response).

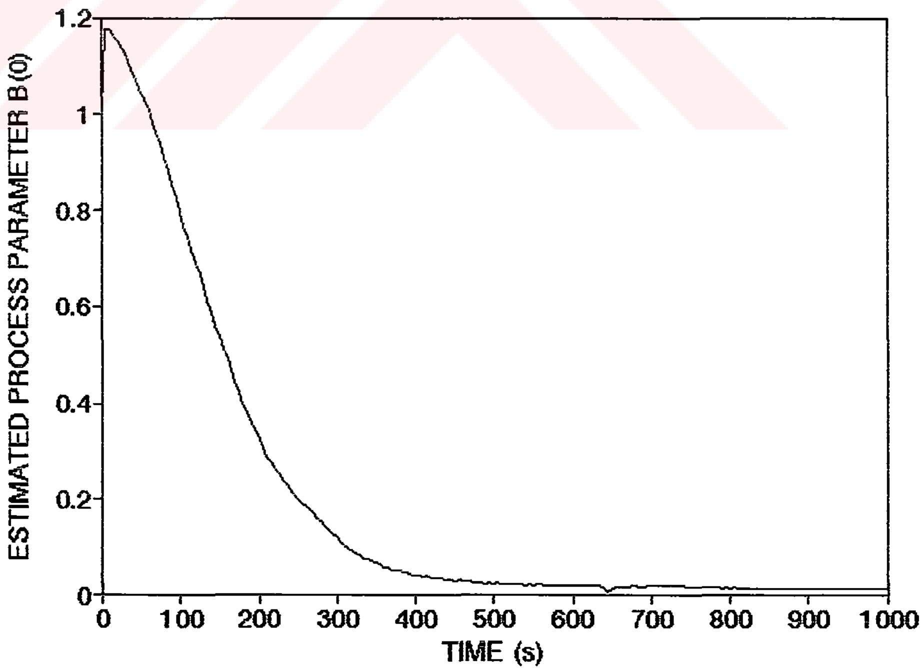

Figure 5.60 Estimated Process Parameter B(0) vs Time for '$Q=(1-z^{-1})\lambda/(1-\alpha z^{-1})$', ($\lambda$=0.7 and α=0.7) (For Step-Down Response).

Figure 5.61, Figure 5.62 and Figure 5.63 show the **Triac Module** fitted controller behaviours in the case of **'$Q=(1-z^{-1})\lambda/(1-\alpha z^{-1})$'** (where **$\lambda$=0.7** and **$\alpha$=0.7**) and the stability of the estimated parameters respectively. Water inlet has an initial value of **7 (l/min)** and the heater has the maximum power of **4.5 (kw)** for this set of experiments. Regulatory behaviour of the system was studied by using step-up response beginning at the period of time **$t_{s\text{-}up}$=400 (s)**. The flowrate of water was raised to the value of **8.8 (l/min)**.

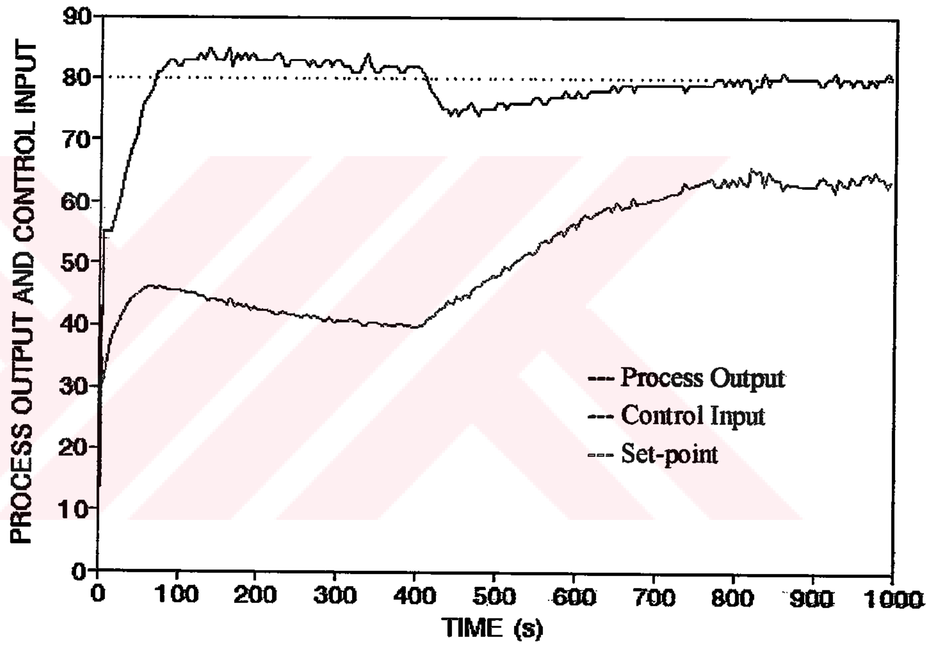

Figure 5.61 Process Output and Control Input vs Time for '$Q=(1-z^{-1})\lambda/(1-\alpha z^{-1})$', ($\lambda$=0.7 and α=0.7) (For Step-Up Response).

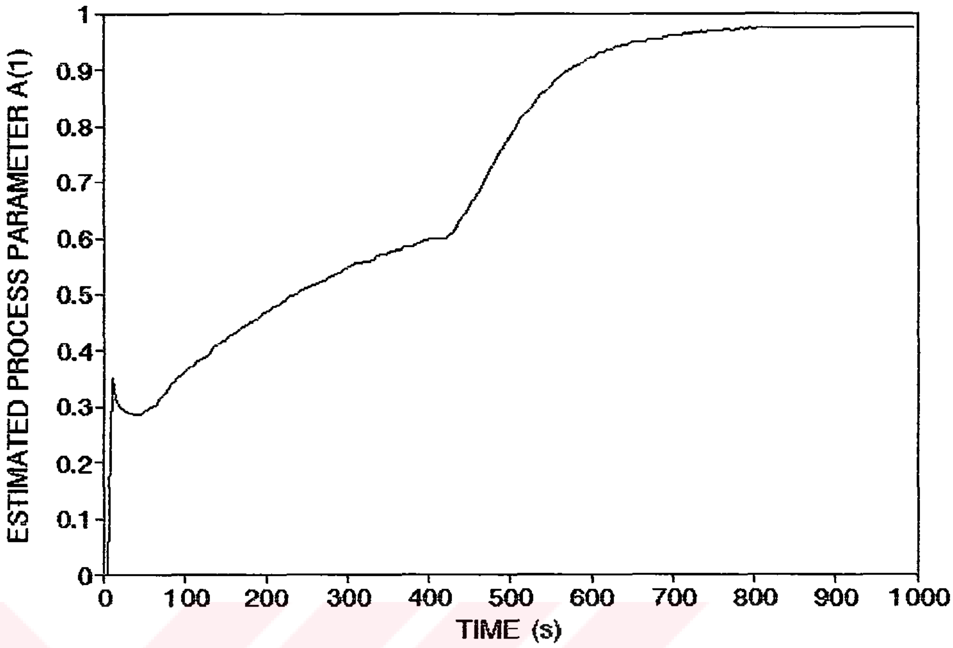

Figure 5.62 Estimated Process Parameter A(1) vs Time for '$Q=(1-z^{-1})\lambda/(1-\alpha z^{-1})$', ($\lambda$=0.7 and α=0.7) (For Step-Up Response).

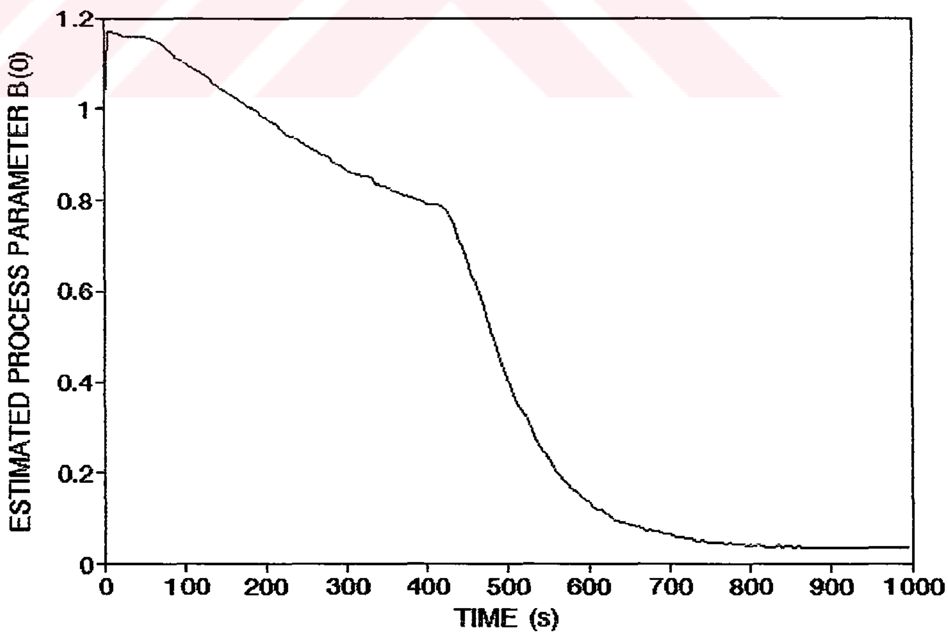

Figure 5.63 Estimated Process Parameter B(0) vs Time for '$Q=(1-z^{-1})\lambda/(1-\alpha z^{-1})$', ($\lambda$=0.7 and α=0.7) (For Step-Up Response).

5.4.2 On-line STC Experiments on the Reacting Distillation Column

Reacting distillation is a new and attractive alternative way to produce light esters because it provides ease of production and purification progress in one step. As esterification is an equilibrium process, it is necessary to take out one of its products either water or ester. In the case of producing fusel alcohol acetates, it is convenient to draw out reaction water and water coming from feedstock as the top product along with light esters that is ethyl acetate and propyl acetate. In this case, the top product will be separated into two phases and lower water phase can easily be discarded. Normally, the bottom product consists of heavy esters namely i-butyl and i-amyl acetates.

In the experiments realised a heavy alcohols fraction obtained by preprocessing of fusel oil with the composition given in Table 5.3 and glacial acetic acid were used as feed stocks.

Table 5.3 Composition of Stock Alcohol Mixture

COMPONENT	% AMOUNT
Water	16
Ethyl Alcohol	17.12
n-Propyl Alcohol	1.86
i-Butyl Alcohol	4.04
i-Amyl Alcohol	60.99

5.4.3 Experimental Rig

The distillation column reactor used in this part of studies is a packed type distillation column having four glass packing compartments. Each packing is 40 cm long and 8 cm in diameter and full of Rasching rings of 5 mm in diameter. The reboiler of the column is a 20 liter glass flask equipped with a 2.5 kW heat mantle. At the top a total condenser was fitted after a U turn in order to faciliate both refluxing and water removing. The total length of the apparatus reaches 5.7 meters including alcohol and acid storages. Figure 5.64 gives the illustration of the system used in the experiments.

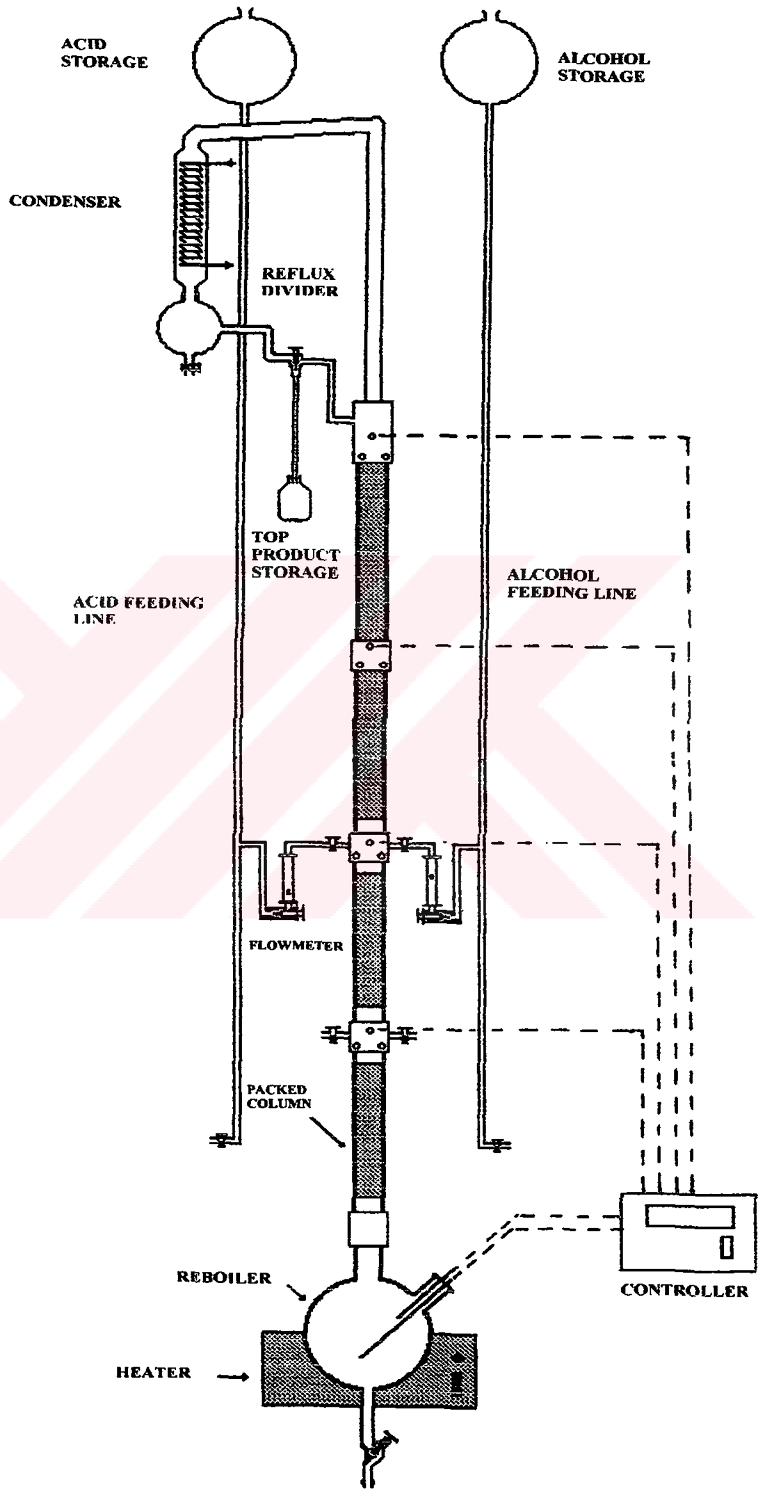

Figure 5.64 Distillation Column Reactor used in the Experiments

5.4.4 Application of Modified PID Controller

The standart form of PID controller was found not applicable to the system. This is because, the controlled parameter, temperature of the gas phase leaving reboiler is ten times sensitive than liquid phase temperature to the variations in the heat input and responses to the step-up and step-down at the heat input are quite different. This can be easily seen from Figure 5.65 , Tanriverdi (1996).

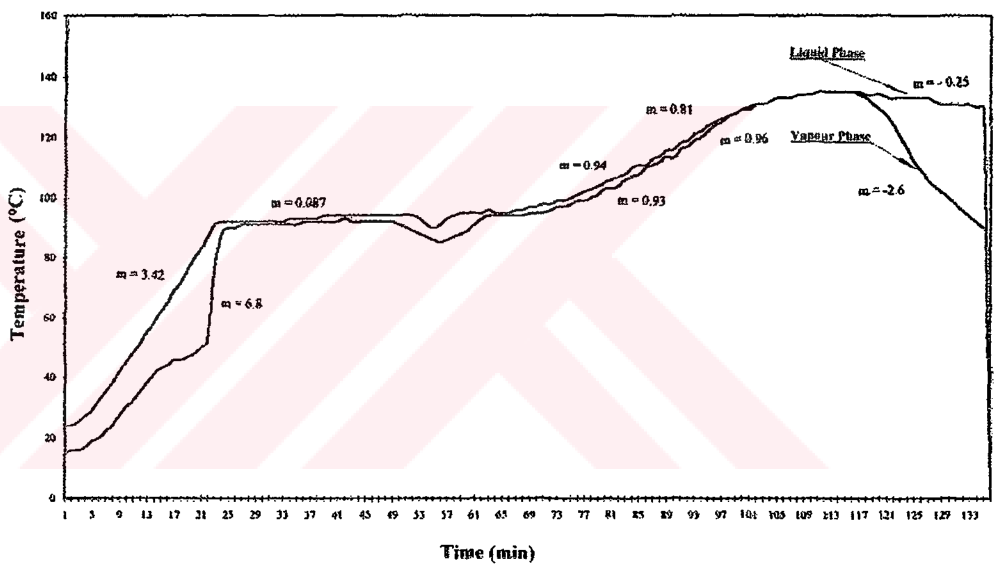

Figure 5.65 Step-up and Step-down Responses of the System

As it can be seen from the Figure 5.65, step-up and step-down responses are quite different, this is why a dual slope PID controller was used. This controller was obtained by introducing an error polarity detector at the input. The controller parameters were set as K_{p+}=7.5, K_{I+}=0.025, K_{D+}=10 and K_{p-}=4.6, K_{I-}=0.05, K_{D-}=5 by using an approximation idea closely similar to that of Cohen-Coon method, Tanriverdi (1996). This controller put in the progress with %30 controller output when the reboiler temperature reached 135 ^{o}C.

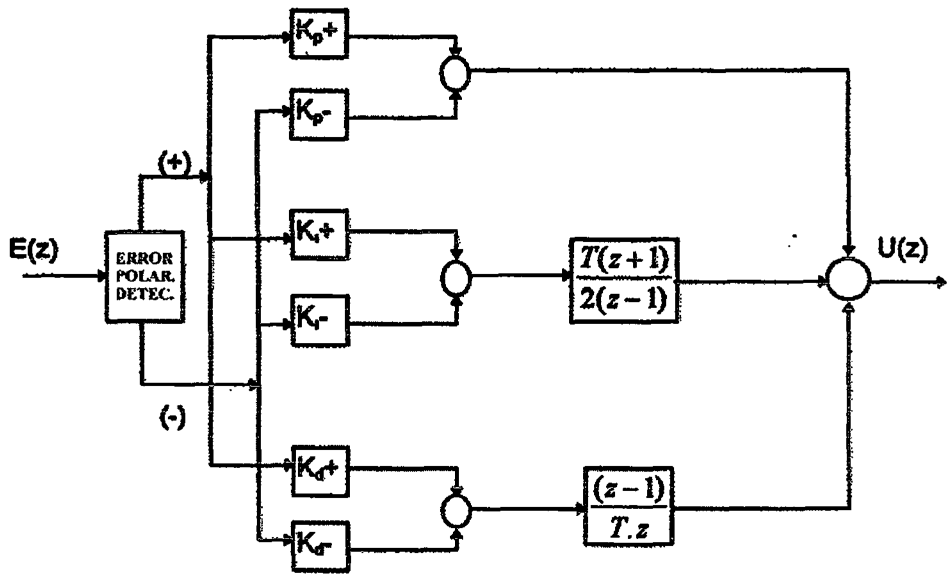

Figure 5.66 Dual Slope PID Controller, Tanriverdi (1996).

In the application, this controller caught the set-point after both start up and after doubling the feed rates without oscillation, but it could not prevent the head temperature to drop below the critical value of 79 °C though driving its output near saturation point. This event can be seen in Figure 5.67 and Figure 5.68 properly.

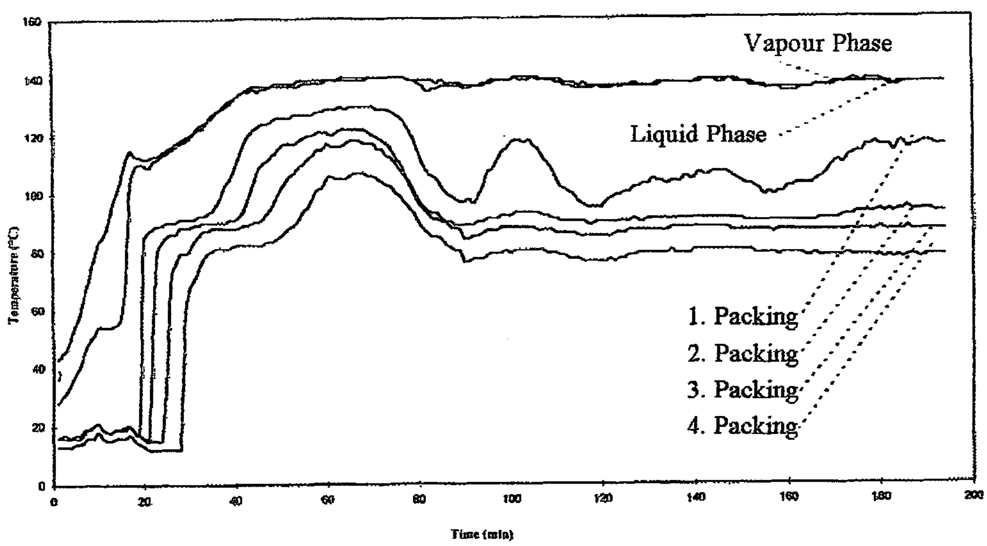

Figure 5.67 Results Obtained from the Modified PID Controller, Tanriverdi (1996).

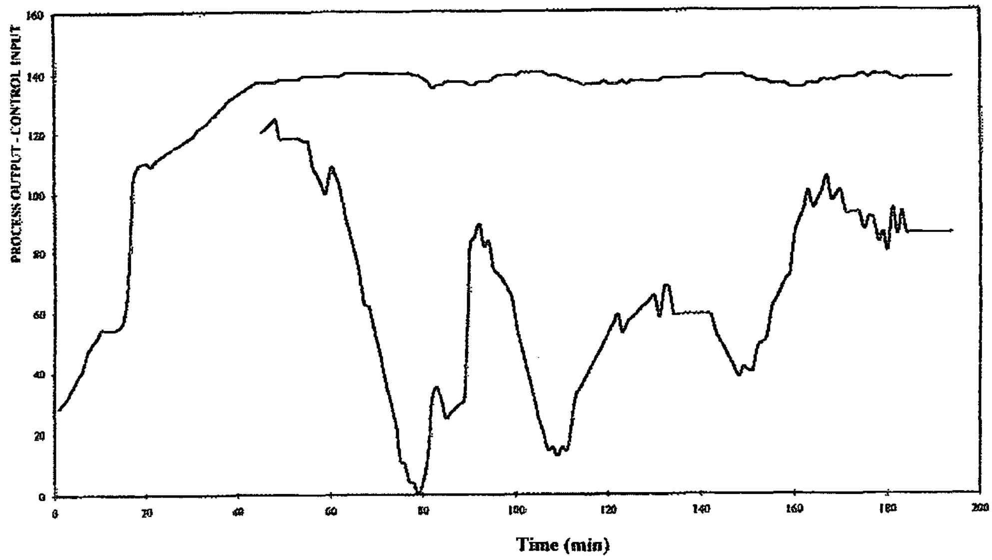

Figure 5.68 Process Output vs Control Input of the Modified PID Controller, Tanriverdi (1996).

5.4.5 Application of STC

Figure 5.69, Figure 5.70, Figure 5.71 and Figure 5.72 show the controller behaviours in the case of '$Q=(1-z^{-1})\lambda/(1-\alpha z^{-1})$' (where λ=0.7 and α=0.7) and the stability of the estimated parameters respectively. The alcohol feed has a value of **1.17 (l/h)**, the acid feed has a value of **0.66 (l/h)** and the heater has the maximum power of **2.5 (kw)** for this set of experiments. Regulatory behaviour of the system was studied by using step-up response beginning at time $t_{s\text{-}up}$=**6600 (s)**, the flowrates of feeds were doubled to their values of **2.34 (l/h)** and **1.32 (l/h)** for the examining step-up response of the system. The setpoint for the vapour phase was **135 (°C)**.

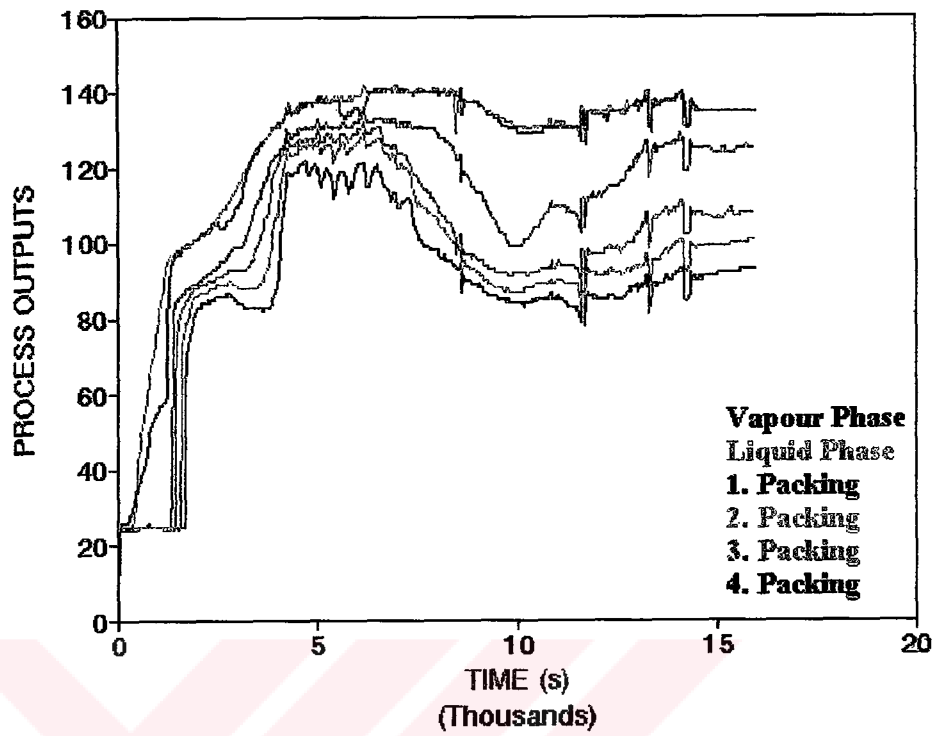

Figure 5.69 Process Outputs and Control Input vs Time for '$Q=(1-z^{-1})\lambda/(1-\alpha z^{-1})$', ($\lambda$=0.7 and α=0.7)(For Step-Up Response).

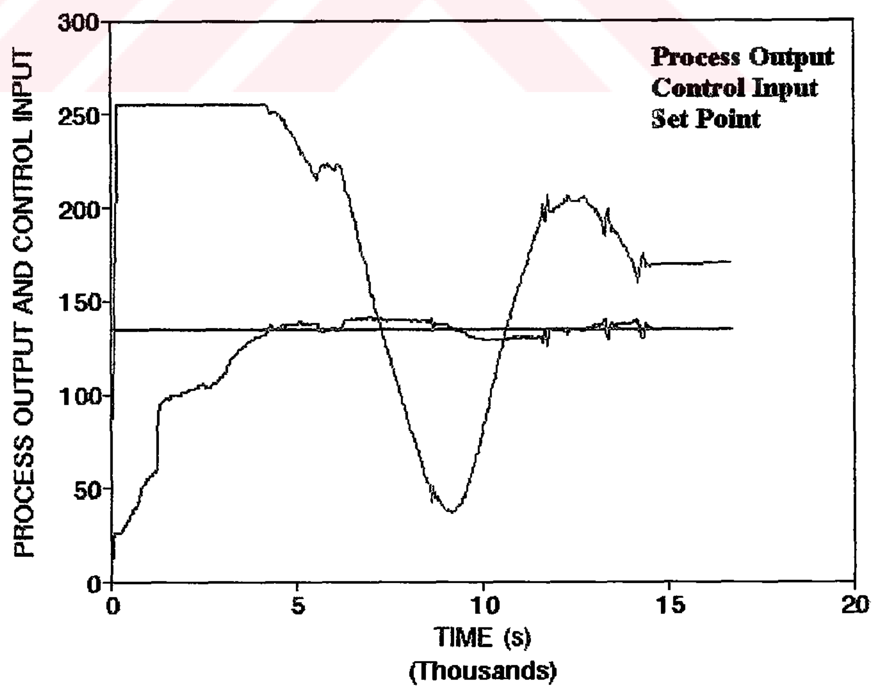

Figure 5.70 Process Output and Control Input vs Time for '$Q=(1-z^{-1})\lambda/(1-\alpha z^{-1})$', ($\lambda$=0.7 and α=0.7) (For Step-Up Response).

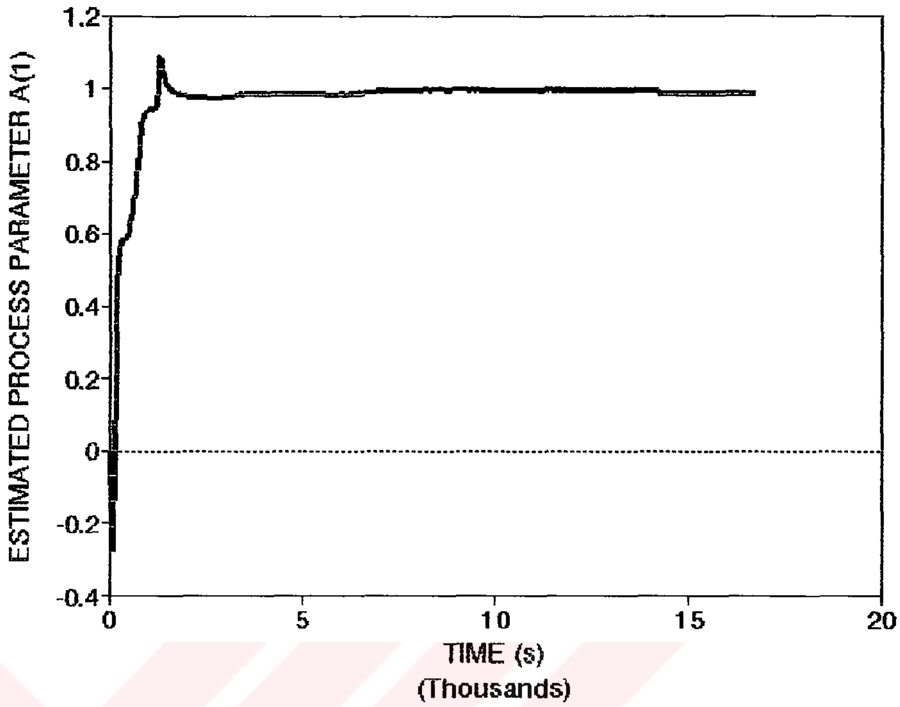

Figure 5.71 Estimated Process Parameter A(1) for '$Q=(1-z^{-1})\lambda/(1-\alpha z^{-1})$', ($\lambda$=0.7 and α=0.7) (For Step-Up Response).

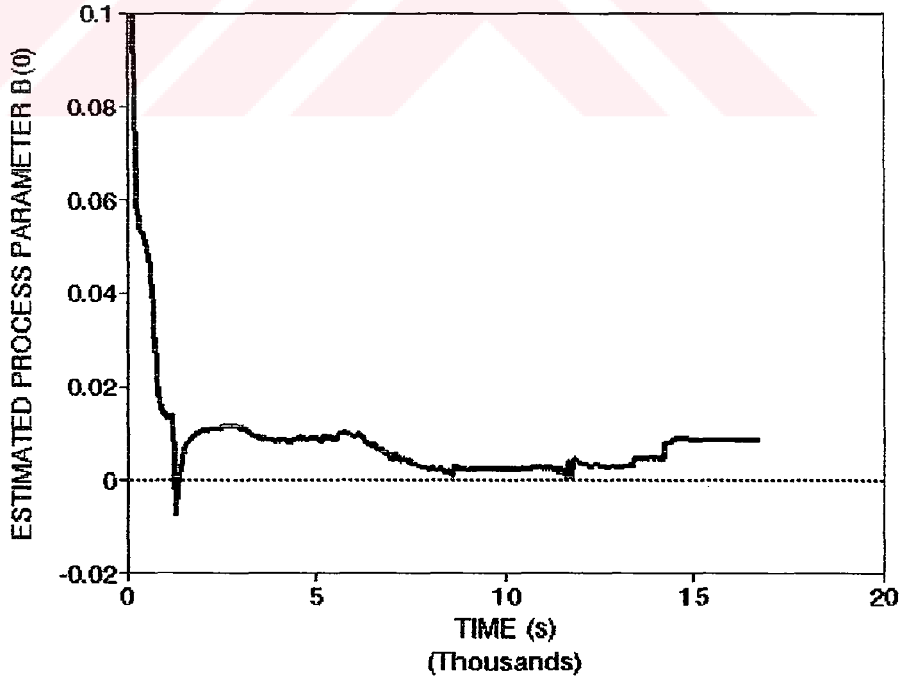

Figure 5.72 Estimated Process Parameter B(0) for '$Q=(1-z^{-1})\lambda/(1-\alpha z^{-1})$', ($\lambda$=0.7 and α=0.7) (For Step-Up Response).

5.4.6 Experimental Results and Discussions

From the control point of view, modified PID controller caused excessive control action to keep vapour phase temperature at the given setpoint but this affected the column regime and the head temperature of the distillation column reactor went down to 79°C that is critical value for the esterification process. Below or around at this critical temperature value water stop coming out from the top of the column resulting spoilage in the process regime.

Employing GMV Self Tuning Controller provides better performance and control action than the Modified PID by introducing more smooth control input therefore causing no spoilage in the column regime. The key point here is to remove the effect of disturbances without excessive changes in the control input. This is absolutely necessary to protect the sensitive column regime in order to get desired top and bottom product compositions.

Examining the experimental results we get a point that GMVSTC is quite succesful in estimation of the process parameters (Figure 5.73 and Figure 5.74). Doubling the feed streams is very strong disturbance even on a simple distillation process. When considering there is also a chemical reaction in the distillation column it might easily be seen that this would cause much more strong disturbing effect.

From the given figures above, it is clear that having good estimation of the process parameters can remove the effects of such a big disturbance by smart changes in the control input carefully avoiding excessive changes. The succes of the controller can also be proved by that top product reached almost 94% of Ethyl Acetate purific which is above the typical value of the commercial technical grade Ethyl Acetate.

CHAPTER 6. CONCLUSIONS

6.1. GENERAL DISCUSSIONS AND CONCLUSIONS

Self -Tuning Controllers fall into the class known as stochastic adaptive systems. The design of this class of adaptive controllers is based on processes whose parameters have been described by stochastic models. Controller design is based on the assumption that the unknown process can be described by a stochastic model, generally an input-output or transfer function model. The estimator attempts to find the coefficients of this model based on past values of input and output data. These coefficients provide the information that is required to calculate the parameters of the controller. Finally the controller determines the input signal to the process usually after the minimisation of a cost function. Self-Tuning control has a very large interest through the years. Although self-tuning techniques have not been successful at the beginning in the 1970's, self-tuning control schemes always had heavy demand by researchers. With the advantage of micro-computer developments it always had strong driving force behind it. Self-tuning controllers have gained popularity because, they could be used with a little a-priori knowledge about the process. Learning about the process dynamics on-line, they could solve many practical problems in industry. Even though there are some differences between academic and industrial practices over self-tuning control schemes, many people from industries shown great interest on such a controller. The appearance of commercial self-tuning controllers is a success and a very good indication of acceptance by the world.

Parameter estimation (system identification) is one of the main part of any adaptive control scheme. The second one is the 'Control Law' strategy. Designing any self-tuning controller begins with the determination of the model.

There is one important golden rule in adaptive control schemes that 'perfect model gives perfect controller'. Therefore, it is necessary to have a mathematical model of any processes to be controlled. This model should describe the system dynamics as much complete as possible. There are two types of approaches to obtain a model of a process. One is to obtain model by physical laws, the other one is to use experimentation. Combining these two approaches makes it better and gives more reliable models. The process of constructing a model and estimating the best values of unknown parameters from experimental data is called 'system identification'. Identification can be done by two methods; on-line or off-line (batch). The RLS estimator is a well known and a very popular method of on-line identification. It not only has the advantage of low computational requirements, it is also a simple algorithm that can be applied straightforward and understood. The disadvantage of the RLS estimator is that whenever there are changes in the process dynamics, parameter tracking capability is slow and poor. To overcome this problem, least squares based algorithms can be modified to have more or better weighting functions. This can be done by weighting forgetting factor or introducing some resetting techniques to the estimator.

Understanding the control scheme and using different type of weighting functions (ie filters) as they can be changed from process to process is essential to employ fine tuning parameters of the STC which is trying to be developed to control systems with a little knowledge. By using experimental techniques we can get much knowledge about the system and when we know the system dynamics properly it could be easier for us to employ a trouble-free STC with low maintenance.

In this study, many simulation and experimental studies are done and some hints about the self-tuning controllers are revealed. This thesis just described the necessary and more important methods for the self-tuning control schemes and there are still many efforts to improve this class of controllers if they can be accepted as promising signals for their future.

6.2. SUGGESTIONS FOR FUTURE WORK

A self-tuning controller, as generally reminding better control with less effort thoughts, must be employed by using only a few parameters and its performance must be as independent as possible from a-priori knowledge without losing its reliability and robustness. And much important it must have an economical value to be widespreaded in all type of industries to be used by non-expert personnel.

The identified models are usually assumed to be linear in the parameters. It would be an advantage if a recursive identification method for estimating the parameters of non-linear models could also be developed.

Any unknown disturbances entering system always makes a 'bang' effect on the process parameters resulting biased parameters as long as the disturbance continues. Therefore, a class of compensation methods can be searched and some type of feedforward compensation algorithms can be developed. Including the necessary control weighting term in the cost function will overcome the effects of expected or unexpected disturbances and will make the controlled system more flexible and robust .

BIBLIOGRAPHY

Åström, K. J.; Eykhoff, P. (1971), 'System Identification - A Survey', Automatica, Vol.7, pp123-162

Åström, K. J.; Wittenmark, B. (1973), 'On Self-Tuning Regulators', Automatica, Vol.9, pp185-189

Åström, K. J.; Borisson, U.; Ljung, L.; Wittenmark, B. (1977), 'Theory and Applications of Self-Tuning Regulators', Automatica, Vol.13, pp457-476

Åström, K. J. (1983), 'Theory and Applications of Adaptive Control - A Survey', Automatica, Vol.19, No.5, pp471-486

Åström, K. J.; Wittenmark, B. (1984), 'Computer Controlled Systems; Theory and Design', Englewood Cliffs, N.J., Prentice Hall

Åström, K. J.; Ostberg, A. B. (1985), 'A Teaching Laboratory for Process Control', ACC-85, pp-1380-1385, Boston, MA, USA, June

Bierman, G. J. (1976), 'Measurement Updating Using the U-D Factorization', Automatica, Vol.12, pp375-382

Bierman, G. J. (1977), 'Factorization Methods For Discrete Sequential Estimation', Academic Press, New York, U.S.A.

Bodewig, E. (1956), 'Matrix Calculus', North Holland Pub. Co., Amsterdam, Holland

Bristol, E. H. (1985), 'Control Teaching and Theory; An Industrial Point of View', ACC-85, pp1376-1379, Boston, MA, U.S.A.

Clarke, D. W. (1967), 'Generalised Least Squares Estimation of the Parameters of a Dynamic Model', Proc. IFAC. Symp. on Identification in Automatic Control Systems, Prague

Clarke, D. W.; Gawthrop, P. J. (1975), 'Self-Tuning Controller', Proc. IEE, Vol.122, No.9, pp929-934, September

Clarke, D. W.; Gawthrop, P. J. (1979), 'Self-Tuning Control', Proc. IEE, Vol.126, No.6, pp633-640, June

Clarke, D. W. (1980), 'Some Implementation Considerations of Self-Tuning Controllers', Numerical Techniques for Stochastic Systems, North Holland Publishing Company, pp81-101

Clarke, D. W. (1986), 'Adaptive Control', Industrial Digital Control Systems, IEE Control Engineering Series 29, Peter Peregrinus

Clary, J. P.; Franklin, G. F. (1985), 'A Variable Dimension Self-Tuning Controller', ACC-85, pp973-979, Boston, MA, U.S.A., June

Dexter, A. L. (1983), 'Self-Tuning Algorithm for Single-Chip Microcomputer Implementation', Proc. IEE, Vol. 130, Pt D, No.5, pp255-260, September

Dugard, L.; Landau, I. D. (1980), 'Recursive Output Error Identification Algorithms Theory and Evaluation', Automatica, Vol.16, pp-443-462

Dumortier, F. A. G. (1985), 'Book Review; Theory and Practice of Recursive Identification, L. Ljung and T. Soderstrom', Automatica, Vol.21, No.4, pp499-504

Eykhoff, P. (1974), 'System Identification', John Wiley, Great Britain

Farrar, G. L. (1959), 'Digital Computers-key to plant automation', Oil Gas Journal, Vol. 57, No.41

Farsi, M.; Karam, K. Z.; Warwick, K. (1984), 'A Simplified Recursive Identifier for ARMA Process', Electronic Letter, Vol.20, pp913-915

Farsi, M. (1986), 'Simplified Self-Tuning Algorithm and Model Reduction for Robot Control', PhD Thesis, Department of Electrical&Electronic Engineering, University of Newcastle upon Tyne, U.K.

Franklin, G. F.; Powell, J. D. (1980), 'Digital Control of Dynamic Systems' Addison-Wesley Publishing Co. Inc., Philippines

Furth, B. P. (1973), 'New Estimator for Identification of Dynamic Processes' IBK Report, Inst. Boris Kidric Vinca, Belgrade, Yugoslavia

Gallier, P. W. (1974), 'Process Identification for Control; A Review', ISA Transaction, Vol.13, No.1, pp50-58

Gawthrop, P. J. (1977), 'Some Interpretations of the STC', Proc. IEE, Vol.124, No.10, October

Gawthrop, P. J. (1986), 'STPID Controllers; Algorithms and Implementation' IEEE Transactions on Automatic Control, Vol.AC-31, No.3, pp201-209, March

Gawthrop, P. J. (1987), 'Adaptive Systems in Control and Signal Processing' Fourth workshop on 'Self Tuning and Adaptive Control', Oxford University, U.K.

Gertler, J.; Banyasz, C. (1974), 'A Recursive (on-line) Maximum Likelihood Identification Method', IEEE Transaction, AC-19, pp816-820

Goodwin, G. C.; Hill, D. J.; Palaniswami, M. (1984), 'A Perspective on Convergence of Adaptive Control Algorithms', Automatica, Vol.20, No.5, pp519-533

Goodwin, G. C.; Sin, K. S. (1984), 'Adaptive Filtering Prediction and Control' Prentice-Hall, U.S.A.

Goodwin, G. C.; Salgado, M. E.; Middleton, R. H. (1988), 'Indirect Adaptive Control; An Integrated Approach', ACC-88, Vol.3, pp2440-2445, Atlanta, Georgia, U.S.A.

Graupe, D.; Jain, V. K.; Salahi, J. (1980), 'A Comparative Analysis of Various Least-Squares Identification Algorithms', Automatica, Vol.16, pp663-681

Gustavsson, I.; Ljung, L.; Soderstrom, T. (1977), 'Identification of Processes in Closed Loop Identifiability and Accuracy Aspects', Automatica, Vol.13, pp59-75

Hasting-James, R.; Sage, M. W. (1969), 'Recursive Generalised Least Squares Procedure for On-Line Identification of Process Parameters', Proc. IEE, Vol.116, No.12, pp2057-2062, December

Higham, E. H. (1986), 'An Expert System for Process Control', Industrial Digital Control Systems, IEE Control Engineering Series 29, Peter Pereginus

Higham, E. H. (1987), 'Application of an Expert System in a Process Controller', Fourth Workshop on Self-Tuning and Adaptive Control Oxford University, Oxford, U.K., March

Hiram, Y.; Kershenbaum, L. (1985), 'Overcoming Difficulties in the Application of STC', ACC-85, pp1507-1513, Boston, MA, U.S.A., June

Isermann, R. (1980), 'Practical Aspects of Process Identification' Automatica, Vol.16, pp575-587

Isermann, R. (1982), 'Parameter Adaptive Control Algorithms; A Tutorial' Automatica, Vol.18, pp513-528

Isermann, R. (1985), 'Parameter Adaptive Control Systems; A Review on Methods and Application', IFAC Identification and System Parameter Estimation, pp373-378,York, U.K.

Kailath, T. (1968), 'An Innovation Approach to LS Estimations', IEEE Transactions on Automatic Control, Vol.AC-13, pp646-655, December

Kam, W. Y. (1985), 'Investigations into the performances of several adaptive control scheme'PhD thesis, Dept. of Chem. Eng., Newcastle University, U.K.

Kalman, R. E. (1958), 'Design of self-optimising control system', Transactions of the ASME, February, pp468-478

Kumar, R.; Moore, J. B. (1981), 'Detection Techniques in LS Identification' Automatica, Vol.17, No.6, pp805-819

Kurz, H.; Isermann, R.; Schumann, R. (1980), 'Experimental comparison and application of various parameter-adaptive control algorithms.', Automatica, Vol.16, pp117-133

Lambert, E. P. (1987), 'Process Control Applications of LRP', Ph D Thesis, University of Oxford, Oxford, U.K.

Landau, I. D. (1976), 'Unbiased Recursive Identification using Model Reference Techniques', IEEE Transactions on Automatic Control, Vol.AC-21, pp194-202

Landau, I. D. (1982), 'Combining Model Reference Adaptive Controllers and Stochastic STR', Automatica, Vol. 18,No.1, pp77-84

Lee, T. H.; Narendra, K. S. (1988), 'Stable direct adaptive control of time-varying discrete time system', ACC88, pp1995-1999, Georgia,U.S.A.

Lelic, M. A.; Wellstead, P. E. (1987),'Generalised Pole-placement STC' Int. J. Cont., Vol. 46, No.2, pp569-601

Lelic, M. A.; Zarrop, M. B. (1987), 'Generalised Pole-placement STC' Int. J. Cont., Vol. 46, No.2, pp547-568

Linkens, D. A. (1984), 'Computer control in bio-medicine', Real-time Computer Cont., ed. by S. Bennett and D. A. Linkens, Chapter 14., P. Peregrinis

Linkens, D. A.; Hacisalihzade, S. S. (1990), 'Computer control systems and pharmacological drug administration: A survey', Jour. of Med. Eng. & Tech., Vol.14, No.2, pp41-54

Ljung, L.; Soderstrom, T.; Gustavsson, I. (1975), 'Counterexamples to general convergence of a commonly used recursive identification method', IEEE Trans. on Automatic Cont., Vol.AC20, No.5, pp643-652

Ljung, L.; Soderstrom, T. (1983), 'Theory and Practice of Recursive Identification', MIT Press, U.S.A.

Ljung, L.; Gunnarsson, N. (1990), 'Adaptation and tracking in system identification: A survey', Automatica, Vol.26, No.1, pp7-21

Lozano, R. (1981), 'Adaptive Control with Forgetting Factor' Proc. 8th IFAC Triennial World Cong., Kyoto, Augustus

Lozano, R. (1983), 'Convergence analysis of recursive identification algorithms with forgetting factor', Automatica, Vol. 19, No.1, pp95-97

Luenberger, D. G. (1979), 'Introduction to dynamic systems, theory, models& applications', John Wiley & Sons Inc., London

Mansoori, S. N. (1987), 'Recursive Extended LS with Covariance Resetting Techniques', Internal Reports No. 4/87 & 5/87, Process Control Research Group, Dept. of Chem. Eng., Newcastle University, U.K.

Mansoori, S. N. (1987), 'Recursive Extended LS with Variable Forgetting Factors', Internal Report No. 6/87, Process Control Research Group, Dept. of Chem. Eng., Newcastle University, U.K.

Mansoori, S. N. (1990), 'Tracking of time varying parameters in STC' PhD Thesis, Dept. of Chem. Eng., Newcastle University, U.K.

Masten, M. K.; Cohen, H. E. (1988), 'Introduction to a showcase of adaptive Controller Design', ACC88, Vol.3, pp2418-2422, Atlanta, Georgia, U.S.A.

Mayne, D. Q.; Firoozan, F. (1982), 'Linear identification of ARMA processes' Automatica, Vol. 18, No. 4, pp461-466

Minter, B.J.; Fisher, D. G. (1988), 'A comparison of adaptive controllers: Academic vs Industrial', ACC88, Vol.2, pp1653-1658, Atlanta, Georgia, U.S.A.

Moore, J. B. (1978), 'On strong Consistency of Least Squares Identification Algorithms', Automatica, Vol. 14, pp505-509

Morris, A.J.; Fentton, T. P.; Nazer, Y. (1977), 'Application of STR to the control of chemical processes', Digital Comp. Appl. to Process Cont., ed. Van Nanta Lemke, North Holland

Morris, A. J.; Nazer, Y.; Wood, R. K.; Lieuson, H. (1981), 'Evaluation of STC for Distillation Column Control', Digital Comp. Appl. to Process Cont., ed. R. Isermann and H. Kaltenecker, Pergamon Press, Oxford, U.K.

Morris, A. J.; Nazer, Y.; Wood, R. K.; (1982), 'Multivariable Self Tuning Process Control', Optimal Cont. Appl. and Methods, Vol.13, No.4, pp363-387

Morris, H. M. (1987), 'How adaptive are adaptive process controllers', Control Eng., pp96-100, March

Nazer, Y. (1981), 'Singlevariable and Multivariable STC', PhD thesis, Dept. of Chem. Eng., Newcastle Uni., U.K.

Norton, J. P. (1987), 'Identification of parameter bounds for ARMAX models from record with bounded noise', Int. J. Cont., Vol.45. No.2, pp375-390

Ogata, K. (1987), 'Discrete Time Control Systems', Prentice-Hall, U.S.A.

Olcer, S.; Egardt, B.; Mors, M. (1986), 'Convergence Analysis of Ladder algorithms for AR and ARMA models', Automatica, Vol. 22, No.3, pp345-354

Panuska, V. (1968), 'A stochastic Approximation method for identification of linear system using adaptive filtering', Proc. JACC Uni. of Michigan, Michigan, U.S.A.

Panuska, V. (1969), 'An adaptive RLS identification algorithm', 8th IEEE Symp. on Adaptive Process on Design and Control, Pennsylvania State Uni., U.S.A., November

Patrick, D. R.; Fardo, S. W. (1979), 'Industrial Process Control Systems' Prentice-Hall Inc., Englewood Cliffs, N.J., U.S.A.

Payne, A. N. (1987), 'Stability Result with Application to Adaptive Control' Int. j. Control, Vol. 46, No.1, pp249-261

Peel, D. (1986), 'Self-Tuning Process Control with Application to an Industrial Dryer', PhD Thesis, Newcastle University, U.K.

Peel, D.; Lambert, E. P.; Lambert, M. R. (1987), 'Industrial Self-Tuning Control ', Fourth workshop on Self-Tuning and adaptive Cont., Oxford Uni., Oxford, U.K., March

Peterka, V. (1970), 'Adaptive digital regulation of noisy system', Proc. of 2nd IFAC Symp.on identification and process estimation, Prague

Peterka, V. (1975), 'A square root filter for real time multivariable regression' Kybenetika, Vol. 11, pp53-67

Russel, J.L. (1967), 'Computer Control applications in industry', Instrumental Pract., Vol.21

Seborg, D. E.; Edgar, T. F.; Shah, S. L. (1986), 'Adaptive Control Strategies for Process Control: A survey', AIChe Jour., Vol. 32, No. 6, pp881-913, June

Shah, S. L. (1986), 'Parameter estimation techniques for STC', 25th IEEE conference on decision and cont., Athens,Greece, December

Sin, K. S.; Goodwin, G. C. (1982), 'Stochastic adaptive control using a modified LS algorithm', Automatica, Vol. 18, N0.3, pp315-321

Sinha, N. K.; Sen, A.; Sen, M. S. (1975), 'Critical evaluation of on-line identification method', Proc. IEE, Vol.122, No.10, pp1153-1161, October

Soderstrom, T.; Ljung, L.; Gustavsson, I. (1978), 'A theorical analysis of recursive identification methods', Automatica, Vol. 14, pp231-244

Soderstrom, T.; Ljung, L. (1983), 'User choices for recursive identification methods', ACI'83, Denmark

Soderstrom, T.; Stoica, P. (1989), 'System Identification', Prentice-Hall

Song, H. K.; Shah, S. L.; Fisher, D.G. (1986), 'A self-tuning Robust Controller', Automatica, Vol.22, No.5, pp521-531

Sripada, N. R.; Fisher, G. (1987), 'Improved LS identification for adaptive controllers', ACC'87, Minneapolis, U.S.A., June

Stephanopoulos, G. (1984), 'Chemical Process Control', Prentice-Hall International Editions

Strejc, V. (1980), 'LS parameter estimation', Automatica, Vol.16, pp535-550

Tanriverdi, H. I. (1996), 'Investigation and Control of the Reacting Distillation Process Producing Acetate Esters from the Fusel Alcohols', PhD Thesis, Dept. of Chem. Eng., ITU, Istanbul, Turkey

Tham, M. T. (1985), 'Some aspects of multivariable STC', PhD Thesis, Dept. of Chem. Eng., Newcastle Uni., U.K.

Tham, M. T.; Morris, A. J.; (1986), 'Data Conditioning for Robust Parameter Estimation and Adaptive Control', IEE Colloquium on ' System Identification for Control', Durham Uni., U.K., September.

Tham, M. T.; Morris, A. J. (1986), 'An Introduction to STC', Fourth workshop on 'self-tuning and adaptive control', Oxford Uni.,U.K.

Tham, M. T.; Morris, A: J.; Montague, G. A. (1987), ' Self-tuning process control; a review of some algorithms and their applications'ACC87, pp996-1001, Minneapolis, MN, U.S.A., June

Tham, M. T.; Mansoori, S. N. (1988), 'Covariance Resetting Techniques' IEE Int. Conference Cont. '88, Oxford Uni., Oxford, U.K.

Thornton, C. L.; Bierman, G. J. (1978), 'Filtering and error analysis via the UDU^T covariance factorisation', IEE Transaction on Automatic Control, Vol. AC-23, N0.5, pp901-907, October

Thornton, C. L.; Biermann, G. J. (1980), 'UDU^T Covariance factorisation' Control and Dynamic Systems, Academic Press, Vol.16, Ed. C. T. Leondes

Tsypkin, Y.Z. (1966), 'Adaptation, training and self-organisation in automatic systems', Automation and remote Control, Vol. 27, pp16-51

Tuffs, P. S.; Clarke, D. W. (1985), 'STC of off-set; A unified Approach' IEE Proc. D Cont. Theory and Appl., No.132, pp100-110

Warwick, K.; Farsi, M.; Karam, K.Z. (1985), 'A simplified pole-placement Self-Tuner', Proc. Int. Conference, Control '85, Cambridge Uni., U.K.

Warwick, K. (1986), 'Recursive Techniques in Identification', IEE Colloquium on 'System Identification for Control', Durham Uni., U.K., September

Warwick, K. (1987), 'PID Methods in STC',Fourth Workshop on Self-tuning and Adaptive Control, Oxford Uni., Oxford, U.K., March

Warwick, K.; Karam, K.Z.; Tham, M. T. (1987), 'Simplified Parameter Adaptive Control', Optimal Control Applications and methods, Vol.8, pp37-48

Wellstead, P. E.; Prager, D.; Zanker, P. (1979), 'Pole-assignment STR' Proc. IEE, Vol.126, No.8, pp781-789

Wellstead, P. E.; Zanker, P. (1979), 'Servo self-tuners', Int. J. Control, Vol.30, N0.1, pp27-36

Wieslander, J.; Wittenmark, B. (1971), 'An approach to adaptive control using real time identification', Automatica, Vol. 7, pp211-217

Williams, T. J. (1963), 'Progress in Chemical Process Control in America' Trans. IChemE, Vol.41, No. 11

Wittenmark, B. (1975), 'Stochastic Adaptive Control Methods: A Survey' Int. Jour. Cont., Vol. 21, No.5, pp705-730

Wittenmark, B. (1979), 'A two-level estimator for time varying parameters' Automatica, Vol.15, pp85-89

Wittenmark, B.; Åström, K. J. (1984), 'Practical issues in the implementation of STC', Automatica, Vol.20, No.5, pp595-605

Wong, K. Y.; Polka, E. (1967), 'Identification of linear discrete time systems using the instrumental variable method' IEEE Trans. on Automatic Control,Vol.AC-12, No.6, pp707 718 , December

Wong, K. Y.; Bayoumi, N. M; Nuyan, S. (1983), 'Comparative study of some estimation algorithms for the STC of time varying systems', ACI '83, Denmark, June

Young, P. C. (1970), 'An instrumental variable method for real-time Identification of noisy process', Automatica, Vol.6, pp271-287

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