İSTANBUL TECHNICAL UNIVERSITY ★ SCIENCE AND TECHNOLOGY INSTITUTE

ONLINE PROCESS IDENTIFICATION OF A HEATING SYSTEM

M. Sc THESIS

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NOMENCLATURE

A	Polynomial
AR	Auto Regressive
ASL	Asymptotic Sample Length
B	Polynomial
C	Polynomial
CR	Covariance Resetting
d	Constant
e_t	Disturbance Signal
E{...}	Expectation Factor
E_a	Sum of Error Squares of A Paraameters
E_b	Sum of Error Squares of B Paraameters
E_c	Sum of Error Squares of CParaameters
E_e	Sum of Error Squares of E Paraameters
ELS	Extended Least Squares
G	Polynomial
GLS	Generalized Least Squares
GMV	Generalized Minimum Variance
GMVC	Generalized Minimum Variance Controller
GMVSTC	Generalized Minimum Variance Self–Tuning Controller
GMVSTR	Generalized Minimum Variance Self–Tuning Regulator
GPC	Generalized Predictive Control
T	Temperature
H_o	Transfer Function of ZOH
I	Unity Matrix

I/O	Input/Output
k	Time delay
J	cost Function
K	Gain
K_f	Kalman Filter
LS	Least Squares
MA	Moving Average
MIMO	Multi –Input-Multi-Output
MRAC	Model Reference Adaptive Control
MRAS	Model Reference Adaptive System
MV	Minimum Variance
MVC	Minimum Variance Controller
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
Q	The Weighting on the Input 'u'
R	The Weighting on the Set point 'w'

RLS	Recursive Least Squares
S	Diagonal matrix
s	Element of the Diagonal Matrix
SISO	Single-Input-Single-Output
STC	Self-Tuning Control
STMVC	Self-Tuning Minimum Variance Controller
STR	Self-Tuning Regulator
STPID	Self-Tuning PID
SVD	Singular Value Decomposition
t_d	Dead Time
Δt	Sampling Time
U	Orthogonal Matrix
u	Controller Output
w	Process Output
ϖ	Mean Value of Process Set point
$\underline{W}$	Weighting Matrix
WLS	Weight Least Squares
$\underline{x}$	Data Vector
Y	Polynomial
y	Process Output
$\ddot{y}$	Mean Value Process Output
z	Shift Operator
z^{-1}	Back-Shift Operator
ZOH	Zero Order Hold
ξ	Random Sequence Disturbing the System
$\wedge$	Denotes Estimate value
ρ	Forgetting Factor

ϕ	Weighted Process Output
ϕ^*	Prediction of Weighted Process Output
λ	Tuning Parameter of Q Filter
τ	Time Constant
γ	Tuning Parameter of Q Filter
$\underline{\theta}$	Parameter Vector
ε	Equation Error

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ABSTRACT

In recent years there has been extensive interest on feedback control systems that automatically adjust their controller settings to compensate for changes in the process or the environment. Such systems are referred to adaptive controllers.

Using a conventional control scheme is often not very satisfactory. In spite of having large usage in the industry, fixed parameter PID control algorithm suffers from many draw backs such as the ones listed below.

- Time delays cannot be handled properly.
- Physical constraints of a process cannot be incorporated in the control algorithm.
- Tuning of a conventional controller loop is usually time consuming operation. In the absence of a mathematical model, tuning of a PID controller is performed on-line by an iterative experimental approximation like trial and error. The mathematical modeling 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.

In this thesis a PID and a self-tuning control scheme are used (and at the same time compared) to control the temperature of a heating system by choosing fine-tuning elements. Using self-tuning controller gives better and faster controller together with the ability of expert tuning of the controller by non-experts.

ÖZET

1970'lerden beri adaptive kontrol stratejileri ve otomatik kontrol büyük ilgi kazanmıştır. Bir çok araştırmacı kimya endüstrisinde var olan kontrol problemlerini çözmek için yeni bir çok özel metotlar geliştirmeye çalışmaktadır. Endüstriyel proseslerde otomatk 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 belirtilen bu sorunlardan dolayı memnuniyet verici değildir. Günümüzde sanayiide kullanım alanı geniş olan PID kontrol ediciler iyi sonuç vermesinin yanında aşağıda da belirtildiği gibi bazı sorunlarla karşılaşmaktadır.

- Zaman gecikmelerinin etkilerini ortadan kaldıramadığı için kontrol sistemi yavaş davranır.
- Klasik bir PID tipi kontrol ediciyi ayarlamak zaman alan bir operasyondur. Deneme yanılma yolu ile yapılır, bu da kimyasal reaksiyon içeren proseslerde istenmeyen bir durumdur.
- Katalizör bozunması, üretim hattındaki değişiklikler, ısı değiştiricilerindeki kirlenmeler, sıcaklık algılayıcısındaki gecikmeler, debi ve basınç değişimleri gibi proses dinamiğini etkileyen değişiklikler kontrol edicilerde yeni ayarlamalara neden olur.

Kontrol ettiği prosesin dinamiklerindeki değişikliği fark edip, kendi parametrelerini buna göre ayarlayan, ve bu anlamda prosesi tanıyan bir kontrol edici klasik sabit parametreli bir kontrol ediciden daha iyidir. Bu tip bir bakış açısını ilk defa Kalman (1958) çalışmalarında kullanmıştır. Adaptive kontrol edicilerin temelini oluşturan bu çalışmalar sonunda, kullanılan kontrol

ediciye, Kalman 'Kendi Kendini Optimize Eden Kontrol Sistemleri adını vermiştir.

Sunduğu basit kullanım avantajıyla uzman olmayanlarında rahatça kontrol hakimiyeti kurduğu kendinden ayarlı kontrol ediciler (STC), aynı zamanda daha hızlı ve güvenlidir de.

Bu çalışmada klasik PID ve Kendinden Ayarlı Genelleştirilmiş Minimum Değişimi Kontrol Edicilerin ana elemanlarının nasıl düzenlenebileceği gösterilmiştir. Ayrıca bu iki ayrı tipteki kontrol edicilerin servo ve regülator çalışmalarındaki karşılaştırmaları yapılmıştır.

Bu çalışmada kullanılan kendiliğinden ayarlı kontrol ediciler üç ana bileşenden oluşmaktadır. Ilk 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.

Kendiliğinden ayarlanan kontrol ediciler başlangıçta bilinen bir sistem ve tasarım yöntemi ile oluşturulabilirler. Burada bilinen girdi değerlerine karşılık sistemin verdiği çıktılar belirli bir zaman aralığında ölçülerek sistemin transfer fonksiyonu elde edilmiştir.

Kontrol algoritmaları parametre tahmin ediciler kullanılarak bulunabilirler. Parametre tahmin ediciler proses girdi ve çıktısına göre besap yaparlar. Burada tekli giriş tekli çıkış (SISO) sistemleri kendiliğinden ayarlanan ve PID kontrol ediciler kullanılarak incelenmiştir. Gerçek zaman uygulamalarında her yeni data alınışında sistemin transfer fonksiyonu izlenebilir ve bunun içinde geliştirilmiş teknikler mevcuttur. Numunelendirme sırasında data yüklenmesini azaltmak ve sistemi son alınan numunelere daha ağırlık vererek dağerlendirmek için 'unutma faktörü' (Forgetting factor) kullanılmıştır. Bu 0 ile 1 arasında değerlerden oluşmalıdır. Bu sistemdeki unutma faktörü 0.95 ile 0.999 arasında bir değer olarak seçilmiştir. Bu da 20 ila 1000 numunelendirme aralığına eşittir.

Kendiliğinden ayarlanan kontrol edicilerin minimum değişimli kontrol algoritmasını kullanmaları son kontrol elemanlarının aşırı şiddetli davranmalarına yol açabilir. Sistemdeki bu elemanlarda aşınma yıpranma ve doygunluk oluşabilir. Kontrol ediciler bazi sınırlandırmalar getirilerek optimize edilebilir.

Kendiliginden 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.

Bir prosesin modelinin bilinmesi o sistem için tasarlanacak kontrol edicinin analizi için bir avantajdır. Herhangi bir proses için de model ya fiziksel ya da deneysel yollarla bulunur. Bunlardan ilki ile elde edileni bazı durumlarda mümkün değildir, ya da yeterince hassas değildir, bu nedenle deneysel veriler kullanılarak sistem parametreleri belirlenmelidir.

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

Bu çalışmada yavaş cevap veren bir sistem deneysel yollarla tanımılanmış ve birinci derece bir sistem elde edilmiştir. Elde edilen sistemin parametreleri hem Cohen ve Coon hem de numerik hesaplama yöntemi ile iki ayrı şekilde bulunmuştur. Bunlardan ilki PID kontrol edicisinin parametrelerinin belirlenmesinde diğerleri de uyarlamalı kontrolde kullanımıştır. PID kontrol edicisi için kullanılan parametreler sistem için uygun cevabı verememiştir, ama bunlar iyi başlangıç değerleri olmuştur.

Bu deneyde kullanılan sistem, 4.0 kW gücünde, boşluk hacmi küçük olan (yaklaşık 0.4 l) tüp rezistanslı bir ısıtıcı ile bunun giriş ve çıkış hattına yerleştirilmiş bir yarı iletken sıcaklık algılayıcısından oluşmaktadır. Bu sıcaklık algılayıcısı 0-100 °C aralığında çalışan 4-20 mA lik bir sicaklık ileticisine bağlıdır.

Yapılan deneylerde çeşitli kontrol edici filtreleri incelenmiş, gerekli filtre parametreleri tesbit edilmiş sisteme çeşitli bozan etkenler yüklenerek birinci mertebeden bir sistemin kendiliğinden ayarlı Genelleştirilmiş minimum değişimli kontrol edicilere verdiği cevaplar elde edilmiş ve bir sıcaklık kontrolü için kullanılabilecek filtre ayar değerleri belirlenmeye çalışılmıştır. Kontrol edici filtre değerinin istenen ayar değerine bağlı olarak değişken halde olması sistem için en uygun cevabı vermiştir. Sistemin servo ve regülasyon kontrolü zaman-oransal kondaktör modülü ile gerçekleştirilmiştir. Bu durum sistemde gürültülerin daha fazla olmasına yol açmış, buna rağmen istenen ayar değerine kabul edilebilir hatalarla yaklaşıldığı, kontrol edici girişlerinin proses çıktıları ile uyumlu olduğu gözlemlenmiştir.

Elde edilen PID kontrol edici sonuçları ile Kendiliğinden Ayarlanan Genelleştirilmiş Minimum Değişimli Kontrol Edici'nin sonuçları karşılaştırılmış, klasik PID tipi bir kontrol edicinin parametre ayarlamasından sonra daha hızlı ve kabul edilebilir sonuçlar verdiği gözlemlenmiştir. Ancak bu durum deneylerin sistem dinamiğinde değişimlere neden olacak kadar uzun sürmemesi, ve böylece PID kontrol edicisinin parametrelerinde ayarlamaya gidilmemesi durumunda söz konusu olmuştur. Herhangi bir değişim durumunda Kendiliğinden Ayarlanan Genelleştirilmiş Minimum Değişimli Kontrol Edici'nin avantajları kendini açıkça gösterecektir. Kendiliğinden Ayarlanan Genelleştirilmiş Minimum Değişimli Kontrol Edici'nin regülator çalışma sırasında bozan etkendeki %60'lık değişimlerde bile sistemi kararlı halde tuttuğu gözlemlenmiştir.

Bu çalışma sonunda uzman olmayanların da çok daha karmaşık ve sorunlu sistemlerin kontrolünde kullanabileceği ve parametre tahmini sayesinde prosesin daha iyi tanınabileceği 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

Chapter 1.1 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 self-tuning adaptive controllers' control algorithm and PID control algorithm. The adaptive algorithm used is based on the Generalized Minimum Variance control law, but its implementation considerations are applicable to other self-tuning strategies. This study shows the result of updating PID controller parameters from reaction curve compared with the tuned ones. And it also 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 Generalized 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 good results. At the end variable weight function is used to obtain satisfactory results.

In this study, the model order, the type of the model, choice of sample type, determination of the process delay and the choice of Q filter were made before implementations of the GMV control law. Some of these parameters set obtained by using process reaction curve from the pilot plan and some are by using Recursive Least Square Parameter Estimation method with SVD to identify to the controlled system.

Chapter 1.2 STRUCTURE AND LAYOUT OF THE THESIS

The first part of this thesis gives a general definition about terms used in this thesis, then from Chapters 2 to 4, it concentrates on the basic elements of the Self Tuning Regulator, PID Controller 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 Singular Value Decomposition is also discussed in short.

In Chapter 4, the self-tuning controllers and PID 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 two controllers experimental conditions and results.

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

Chapter 1.3 DYNAMICAL SYSTEMS

In loose terms a system is an object in which variables of different kinds interact and produce observable signals and dynamic, which means that the output value depends not only on the current external stimuli but also on their earlier values. The observable signals that are of interest to us are usually called outputs. The system is also affected by external stimuli. External signals that can be manipulated by the observer are called inputs. Others are called disturbances and can be divided into those that are directly measured and those that are only observed through their influence on the output.

Chapter 1.4 PROCESS IDENTIFICATION

In practice many of the industrial processes to be controlled are too complex to be described by the application of fundamental principles. Either the task requires too much time and effort or the fundamentals of the process are not understood. By means of experimental tests, one can identify the dynamic nature of such processes and from the results obtain a process model, which is at least satisfactory for use in designing control systems. The experimental determination of the dynamic behaviour of a process is called process identification.

The need for process models arises in many control applications, as we have seen in the use of tuning methods. Process models are also needed in developing feed-forward control algorithms, self-tuning algorithms, and internal model control algorithms.

Process identification provides several forms that are useful in process control; some of these forms are:

Process reaction curve (obtained by step input)
Frequency response diagram (obtained by sinusoidal input)
Pulse response (obtained by pulse input)

In the case of the Z-N method, the procedure obtained one point on the open-loop frequency response diagram when the ultimate gain was found. (This point corresponds to a phase angle of -180° and a process gain of I/K_{cu} at the crossover frequency w_{co}). In the case of the C-C method, the process identification took the form of the process reaction curve.

Chapter 1.4.1 Step Testing

A step change in the input to a process produces a response, which is called the process reaction curve. For many processes in the chemical industry, the process reaction curve is an S-shaped curve as shown in Fig. 1.1

It is important that no disturbances other than the test step enter the system during the test, otherwise the transient will be corrupted by these uncontrolled disturbances and will be unsuitable for use in deriving a process model. For systems that produce an S-shaped process reaction curve, a general model that can be fitted to the transient is the following second-order with transport lag model.

$$G_p(s) = Y(s)/X(s) = K_p e^{-T_d s} / (T_1 s+1)(T_2 s+1) \qquad (1.1)$$

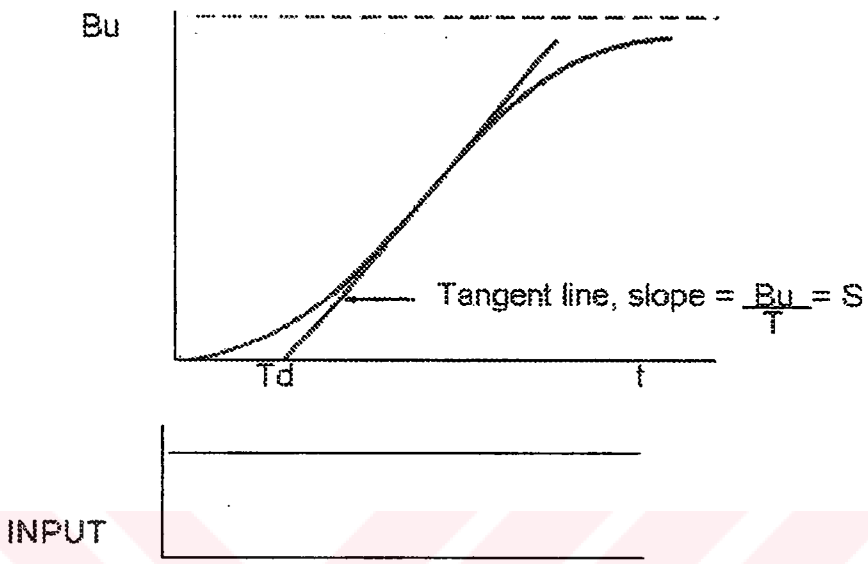

Figure 1.1 Typical process reaction curve showing graphical construction to determine first-order with transport lag model.

Chapter 1.4.2 Frequency Testing

A process having a transfer function G(s) can be represented by a frequency response diagram (or Bode plot) by taking the magnitude and phase angle of G(jw). This can be reversed to obtain G(s) from an experimentally determined frequency response diagram. The procedure requires that a device be available to produce a sinusoidal signal over a range of frequencies. We describe such a device as a sine wave generator. In frequency testing of an industrial process, a sinusoidal variation in pressure is applied to the top of the control valve so that manipulated variable can be varied sinusoidal over a range of frequencies. The block diagram that applies during frequency testing is the same as the one in Figure 1.2 with the step input (M/s) replaced by a sinusoidal signal. The sine wave generator used to test electronic devices operates at frequencies that are too high for many slow moving chemical processes. For frequency testing of chemical processes, special low-frequency generators must be built that can produce sinusoidal variation in pressure to a control valve. To preserve the sinusoidal signal in the flow of manipulated variable through the valve, the valve must be linear.

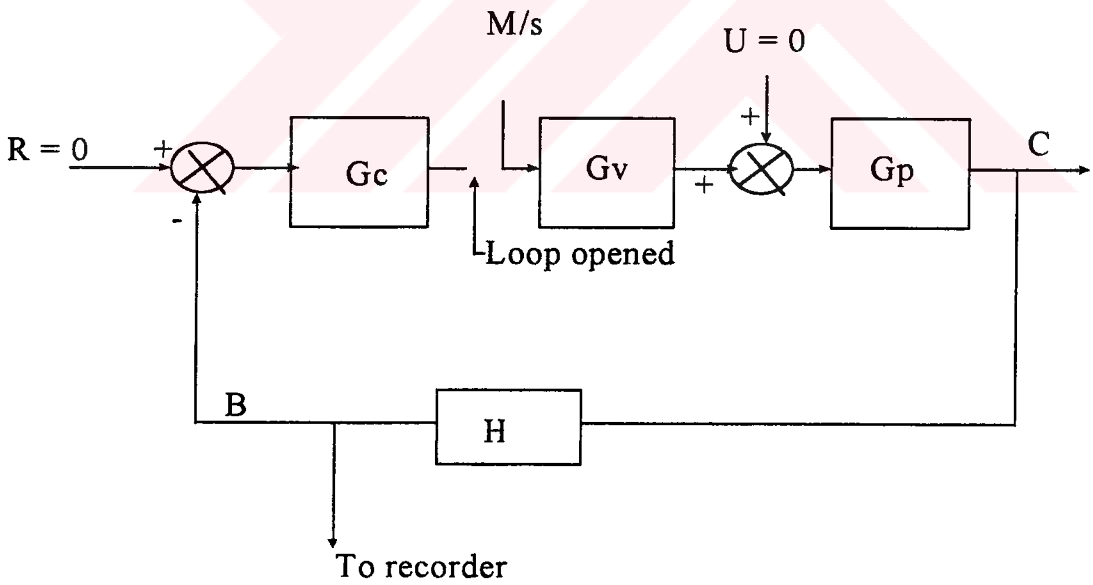

Figure 1.2 Block diagram of a control loop for measurement of the process reaction curve.

Chapter 1.4.3 Pulse Testing

Pulse testing is similar to step testing; the only difference in the experimental procedure is that a pulse disturbance is used in place of a step disturbance. The pulse is introduced as a variation in valve top pressure as was done for step and frequency testing (see fig. 1.2). In applying the pulse, the open-loop system is allowed to reach steady state, after which the valve top pressure is displaced from its steady state for a short time and then returned to its original value. The response is recorded at the output of the measuring element. An arbitrary pulse and a typical response are shown in Fig. 1.3. Usually the pulse shape is rectangular in experimental work, but other well-defined shapes are also used. The input-output data obtained in a pulse test are converted to a frequency response diagram, which can be used to tune a controller. The transfer function of the valve, process, and measuring element (referred to as the process transfer function, for convenience) is given by:

$$G_p(s)=Y(s)/X(s) \qquad (1.2)$$

where Y(s) = Laplace transform of the function representing the recorded output response

X(s) = Laplace transform of the function representing the pulse input

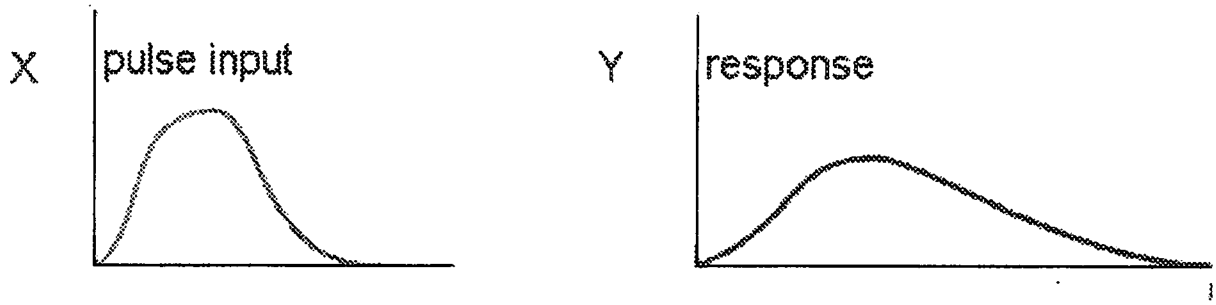

Figure 1.3Typical process response to a pulse input.

Chapter 1.4.4 The System Identification Procedure

The construction of a model from data involves three basic entities:

1. The data,
2. A set of candidate models,
3. A rule by which candidate models can be assessed using the data.

1. The data record. The input – output data are sometimes recorded during specifically designed identification experiment, where one may determine which signals to measure and when to measure them and may also choose the input signals. The object with experiment design is thus to make these choices so that the data become maximally informative subject to constraints at hand. In other cases the user may not have the

possibility to affect the experiment, but must use data from the normal operation of the system.

2. The set of models. A set of candidate models is obtained by specifying within which collection of models we are going to look for a suitable one. This is no doubt the most important and, at the same time, the most difficult choice of the system identification procedure. It is here that a priori knowledge and engineering intuition and insight have to be combined with formal properties of models. Sometimes the model set is obtained after careful modeling. Then a model with some unknown physical parameters is constructed from basic physical laws and other well-established relationships. In other cases standard linear models may be employed, without reference to the physical background. Such a model set whose, parameters are basically viewed as vehicles for adjusting the fit to the data and do not reflect physical considerations in the system, is called a black box. Model sets with adjustable parameters with physical interpretation may, accordingly, be called gray boxes.

3. Determining the "best" model in the set, guided by the data. This is the identification method. The assessment of model quality is typically based on how the models perform when they attempt to reproduce the measured data.

Chapter 1.5 HISTORY OF THE ADAPTIVE CONTROL STRATEGIES

Most chemical processing plants were run essentially manually prior to 1940s. Only the most elementary types of controllers were used. Many operators were needed to keep watch on the many variables in the plant. Large tanks were employed to act as buffers or surge capacities between various units in the plant. These tanks, although sometimes quite expensive, served the function of filtering out some of the dynamic disturbances by isolating one part of the process from upsets occurring in another part.

With increasing Labor and equipment costs and with the development of more severe, higher-capacity, higher-performance equipment and process in the 1940s and early 1950s, it became uneconomical and often impossible to run plants without automatic control devices. At this stage feedback controllers were added to the plants with little real consideration of or appreciation for the dynamics of the process itself. Rule-of-thumb guides and experience design techniques. Closed-loop proportional integral and derivative control (PID) have been most popular control strategy in the chemical industry.

In the 1960's chemical engineers began to apply dynamics analysis and control theory to chemical engineering processes. Most of the were adapted from the work in the aerospace and electrical engineering fields, In addition to designing better control systems, processes and plants were developed or modified so that they were easier to control. The concept of automatic and adaptive control became more important. They owe much of their current status to the 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 the time, the obvious applications were in data acquisition, alarm systems, management calculations and set-point control. Digital computer process control was first applied in 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 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 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 Kam (1985), Clarke (1986), Morris (1987), Warwick 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 Hacısalihzade, 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.

Self-tuning controllers can be useful in the area 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 compensator 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.

Chapter 1.6 SAMPLED-DATA SYSTEMS

Sampled-data systems are systems in which signals are discontinuous or discrete. Every T, minutes the sampler closes for a brief instant. The output of the sampler $f_{s(t)}$ is, therefore, an intermittent series of pulses. Between sampling times, the sampler output is zero. At the instant of sampling the output of the sampler is equal to the input function.

A typical input signal is represented by the continuous function f(t). When the duration is much shorter then the system time constants, the output of the sampler may be approximated by the train of impulses f*(t). The term f*(t) is read "f star of t."

The area of each impulse is equal to the value of the input signal at the time t = nT of the particular impulse. Thus, the area of the nth impulse which occurs at time t = nT is f(nT). The equation for the entire train of impulses is

$$F^*(t) = f(0)\delta(t) + f(T)\,\delta(t-T) + f(2T)\,\delta(t-2T) +$$

$$= \sum_{0}^{\infty} f(nT)\,\delta(t-nT) \qquad (1.3)$$

where $\delta(t)$ is a unit impulse at t = 0 and $\delta(t - nT)$ is a unit impulse at t = nT

The Laplace transform of the sampled signal is

$$F^*(s) = L[f^*(t)] = f(0) + f(T)e^{-Ts} + f(2T)e^{-Ts} +$$

$$=\sum_{0}^{\infty} f(nT)e^{-nTs} \qquad (1.4)$$

To illustrate the preceding concept, consider the continuous input

$$f(t) = e^{-as}$$

The corresponding sampled signal f*(t) is

$$f^*(t) = \delta(t) + e^{-aT}\,\delta(t-T) + e^{-2aT}\,\delta(t-2T) + \ldots = e^{-anT}\,\delta(t-nT)$$

The Laplace transform of the continuous input f(t) is

1

$$F(s) = L[\,f(t)] = 1/(s+a)$$

The Laplace transform of the sampled signal f*(t) is

$$F^*(s) = L[f^*(t)) = 1 + e^{-aT}e^{-sT} + e^{-2aT}\,e^{-2sT} + \ldots$$

$$= 1 + e^{-(s+a)T} + e^{-2(s+a)T} + \ldots$$

$$= \sum_{0}^{\infty} e^{-n(s+a)T}$$

The Laplace transform of a sampled signal is an infinite series.

A very important theorem of sampled-data systems is:

To obtain dynamic information about a plant from a signal that contains components out to a frequency w_{max}, the sampling frequency w_s, must be set at a rate greater than twice w_{max} .

$$w_s > 2w_{max}$$

This basic sampling theorem has profound implications. It says that any frequency components in the signal (for example, 60-cycle-per-second electrical noise) can necessitate very fast sampling, even if the basic process is quite slow. It is, therefore, always recommended that signals be analog-filtered before they are sampled. This eliminates the unimportant high-frequency components.

Chapter 1.7 THE z TRANSFORM

The simple substitution

$$z = e^{Ts}$$

converts the Laplace transform to the z transform. Making this substitution in Eq.1.4 gives

$$Z[f^*(t)] = F(z) = f(0) + f(T)/z + f(2T)/z^2 + \ldots$$

$$=\sum_{0}^{\infty} f(nT)z^{-n} \qquad (1.5)$$

Where F(z) designates the z transform of f*(t). Because only values of the signal at the sampling instants are considered, the z transform of *f*(t) is the same as that of f*(t).

Chapter 2. CHAPTER 2 LITERATURE SURVEY

Chapter 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".

Chapter 2.2 ADAPTIVE PROCESS CONTROL

The basic idea of a self-tuning system is to construct an algorithm that will automatically change its parameters to meet a particular requirement or situation. This is done by the addition of an adjustment mechanism which monitors the system (in a control setting) or the signal (in a signal processing setting) and adjusts the coefficients of: the corresponding controller or signal processor to maintain a required performance.

The origin of such idea goes back to Kalman (1958) and his studies on a "self-optimizing" 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 modeling followed by controller synthesis. The advantage over classical off-line design is the ability of the algorithm to automatically adjust (self-tune) the controller's parameters to account for slowly time varying process characteristics, at every sample interval if it is desired. At that time idea was 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 recognizable modern self-tuning control scheme. The self-tuning regulator of Åström and Wittenmark differs from the original scheme of Kalman's in that controller process, rather than process model parameters, which are directly estimated on-line.

In order to design as adaptive controller, an on-line process identification technique is used to estimate the process parameters of a model of the process and this information is used to obtain an appropriate 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).

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 optimize 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 process 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 along 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.

Chapter 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 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 characterized as filtered white noise, with zero mean and finite variance. The criterion considered is the minimization of the variance of the output. The algorithms analyzed 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 summarized by two theorems. The first one states that if the parameters of the self-tuning regulator converge, then certain covariance's of the output and certain covariance's 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 bet 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 the 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 favor 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 instrumentation. 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 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).

Chapter 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 penalized 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 Generalized Self-Tuning Regulator, and was later named **'Self-Tuning Controller'** **(STC)** by Larke and Gawthrop (1975).

The STC not only penalises excessive control, but also had included in its cost function, the set-point (w_t). It could therefore accomplish regulation as well as set-point tracking of both minimum phase and non-minimum phase systems.

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, than the resulting controller is called as '**non-dual**' controller, otherwise the result would be a '**dual**' controller.

Self-tuning control algorithms may be divided into two groups ; **implicit** (direct) methods were 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.

Chapter 3. INTRODUCTION TO PARAMETERS ESTIMATION

Chapter 3.1 INTRODUCTION

System identification is a prerequisite to adaptive prediction and control; it concerns the generation (for example through specific experimentation) and collection of information, revealing the characteristic behavior of the process, and development of a mathematical representation of the process. Thus while **parameter estimation** concerns the determination of the numerical values of the parameters of the process model which best describe the dynamics of the process, identification involves model structure selection, collection of relevant information, parameter estimation, and model validation. The nature of the model is very much process and problem dependent.

There are different methods of parameter estimation. The suitability of a method depends on the quality of information contained in the data, the conceptual structure and the application concerned. The quality of the estimates are shown to depend on the nature of the noise, and the richness of the information contained in the data.

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, 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 o f 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 minimization of some squared error function.

Chapter 3.2 THE LEAST SQUARES PARAMETER ESTIMATION

The history of least squares started with Karl Gauss (Bodewig, 1956) and it 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 sum of squares of the differences between the actually observed and computed values (ie. error), multiplied by numbers that measure the degree of precision is minimized. Consider the following model;

$$A(z^{-1})y_t = B(z^{-1})u_t + C(z^{-1})\xi_t + d \qquad (3.1)$$

where 'y' and '**u**' are the sequences of output and input signals respectively; 'ξ' 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 time delay or dead time that is an integer multiple of the sampling time.

A special case of the model equation (3.1) is:

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

with d= 0, C = 1 and e = ξ

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

$$A(z^{-1}) = 1 + a_1z^{-1} + a_2z^{-2} + \dots + a_{nA}z^{-nA} \qquad (3.3a)$$

$$B(z^{-1})=b_0 + b_1z^{-1} + b_2z^{-2} + \ldots + b_{nB}z^{-nB} \qquad (3.3b)$$

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

$$\underline{y}_t + a_1y_{t-1} +\ldots+ a_{nA}y_{t-nA} = b_1u_{t-k-1} +\ldots+ b_{nB}u_{t-k-nB} + e_t \qquad (3.4)$$

where ai (i= 1,2,3,…,nA) and bj (j = 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;

$$nA + nB+1$$

Equation (3.4) could be written in the following form:

$$\underline{y}_t = \underline{x}^T_t\underline{\theta} + e_t \qquad (3..5)$$

The regressor or data vector 'x' is defined as:

$$\underline{x}^T_t = (-y_{t-1},\ - y_{t-2},\ \ldots\ ,-y_{t-nA}\ ;\ u_{t-k},\ u_{t-k-1},\ \ldots\ ,u_{t-k-nB}) \qquad (2.6)$$

and the parameter vector is 'θ' is defined as:

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

For N equations that means N observations the following equations results:

$$\underline{y} = \underline{x}^T \underline{\theta} + \underline{\varepsilon} \tag{3.8}$$

where

$$\underline{y} = (y_1, y_2, \ldots, y_N) \tag{3.9}$$

$$\underline{x} = (x_1, x_2, \ldots, x_N) \tag{3.10}$$

$$\underline{\varepsilon} = (\underline{\varepsilon}_1, \underline{\varepsilon}_2, \ldots, \underline{\varepsilon}_N) \tag{3.11}$$

The objective is to determine the elements of '$\underline{\theta}$' by minimization of some error squared function with respect to '$\underline{\theta}$'. Such a function is given by:

$$J_s = \sum_{1}^{N} \Sigma W_t \varepsilon^2_t = \underline{\varepsilon}^T \underline{W} \, \underline{\varepsilon} \tag{3.12}$$

where ε_t is the residual and it is defined as:

$$\varepsilon_t = yt - x^T_t \hat{\theta}_{t-1} \tag{3.13}$$

It is noted that; t =1,2,3,…,N and '∧' denotes the estimated value.
'W' is a weighting matrix of appropriate dimensions and three major forms may be encountered.

If **W = I**

Least Squares (LS)

2. If **W** is a general positive definitive matrix

Weighted Least Squares (WLS)

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 minimization results in the **'Generalized Least Squares (GLS)'** parameter estimation.

Proceeding with the minimization , rewrite equation (3.12) as;

$$J_s = (\underline{y} - \underline{x}\,\underline{\theta})^T \underline{W} (\underline{y} - \underline{x}\,\underline{\theta}) \qquad (3.14)$$

Expansion of the equation yields:

$$J_s = \underline{y}^T \underline{W}\,\underline{y} - \underline{y}^T \underline{W}\,\underline{x}\,\underline{\theta} - \underline{\theta}^T \underline{x}^T \underline{W}\,\underline{y} + \underline{\theta}^T \underline{x}^T \underline{W}\,\underline{x}\,\underline{\theta} \qquad (3.15)$$

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

$$\partial J_s/\partial\theta = -2\underline{x}^T \underline{W}\,\underline{y} + 2\underline{x}^T \underline{W}\,\underline{x}\,\underline{\theta} \qquad (3.16)$$

For W = I the Least Square estimator of '$\underline{\theta}$' is obtained as;

$$\hat{\underline{\theta}}_{LS} = (\underline{x}^T\underline{x})^{-1}\underline{x}^T\underline{y} \qquad 3.17)$$

The procedures described here are '**Off-line**' (**Batch**) methods. When the model is updated periodically with reference to its past values, this is called **'Recursive Square Parameter Estimation (RLS)'** or **'Recursive Identification'.**

Chapter 3.3 RECURSIVE LEAST SQUARES METHOD

For on-line parameter estimation it is 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.

Chapter 3.3.1 Recursive Least Squares (RLS) Parameter Estimation:

RLS algorithm is one the most popular and well known estimation methods to be used an on-line identification. Having less computational requirements and being straight forward to be understood makes this method very popular. In a general way it can be expressed as following equations:

$$\underline{\hat{\theta}}_t = \underline{\hat{\theta}}_{t-1} + K_t\varepsilon_t \quad (3.18)$$

(New Estimate) = (Old Estimate) + (Correction Factor)*(Prediction Error)

Where the gain (correction factor) '$\mathbf{K_t}$' is calculated as;

$$K_t = P_{t-1}x_t(1 + x_t^T P_{t-1}x_t)^{-1} \quad (3.19)$$

$$P_t = (I - K_t x_t^T)P_{t-1} \quad (3.20)$$

P : Covariance of the parameter-estimation error.

And the equation error 'ε' is defined by;

$$\varepsilon_t = (y_t - x_t\underline{\hat{\theta}}_{t-1}) \quad (3.21)$$

For a particular 'K', if ε_t is small, very little change is made in the estimates. However, for a large 'ε_t' the estimates change significantly.

Since new estimates of 'Θ' is required at each sample interval, to avoid computing load and put much stress on new data, a forgetting is used.

$$K_t = P_{t-1}x_t(\rho + x_t^T P_{t-1}x_t)^{-1} \quad (3.22)$$

where ρ is the forgetting factor.

$1 \geq \rho > 0$

A simple guide to the choice of a value for forgetting factor is the concept of " Asymptotic Sample Length" (ASL) or the way we can call it " Memory Time Constant", which can be defined as,

$ASL = 1/(1-\rho)$

Typical values of 'ρ' are in the range of .95 to .999, corresponding to 'ASL' values of 20 and 100 sample steps respectively.

The implementation of the Recursive Least Square Algorithm is as follows:

Sample and update the data vector '$\underline{x}_t$
Calculate the prediction error 'ε_t' from equation (3.21)
Calculate the gain $\underline{K}_t$
Calculate 'new' estimates from equation (3.19)
Update P_t
Wait for sample then go to step 1.

Chapter 3.4 SINGULAR VALUE DECOMPOSITION (SVD)

Singular value decomposition is an optimal orthogonal decomposition which finds wide applications in rank determination and inversion of matrices, as well as in the modeling prediction, filtering and information compression of data sequences. From a numerical point of view, SVD is extremely robust, and the singular values in SVD can computed with greater computational accuracy than eigenvalues.

SVD is popularly used for the solution of least squares problems; it offers an unambiguous way of handling rank deficient or nearly rank deficient least squares problems.

Given any m×n real matrix **A,** there exist two real orthogonal matrixes **U** and **V** and a diagonal matrix **S** where;

$$A = USV^T \qquad (3.23)$$

and

A is m×n , U is m×n , V is n×n , S is m×n

The orthogonal property is as follow:

$UU^T = U^TU = I$, $VV^T = V^TV = I$

For nonsingular **A**,

$S = U^T A V = \text{diag.}\{s_1, s_2, \ldots, s_p\}$ $\qquad p = \min(m,n)$

For **A** of rank r

$s_1 \geq s_2 \geq \ldots \geq s_r > 0$ $\qquad$ and $s_{r+1} = s_{r+2} = \ldots = s_p = 0$

The solution according to this property can be get as in the following:

$$\mathbf{A^T A}\hat{\underline{\theta}} = \mathbf{A^t y} \tag{3.24}$$

Writing A in SVD and putting it in equation (3.24)

$$\mathbf{VSU^T USV^T}\hat{\underline{\theta}} = \mathbf{VSU^T y} \tag{3.25}$$

And putting S on the left side

$$\mathbf{VT}\hat{\underline{\theta}} = \mathbf{S^{-1}U^T y} \tag{3.26}$$

The final form which is a solution for $\underline{\theta}$ can get.

$$\hat{\underline{\theta}} = \mathbf{VS^{-1}U^T y} \tag{3.27}$$

Chapter 4. SELF-TUNING CONTROL (STC)

Chapter 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 in the control law itself. The self-tuning regulator, as its name implies, attempts to minimize the fluctuations of the system's output when the loop is randomly distributed. However, it makes no attempt to ensure that the set-point are followed optimally nor does it try to penalize 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 minimizes a cost of 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.

Chapter 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 equation:

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

$$A(z^{-1})y_t = z^{-k}B(z^{-1})u_t + C(z^{-1})\xi_t + d \qquad (4.1)$$

or simply as;

$$Ay_t = z^{-k}Bu_t + C\xi_t + d \qquad (4.2)$$

where:

$$A = A(z^{-1}) = 1 + a_1z^{-1} + a_2z^{-2} + \ldots + a_{nA}z^{-nA} \qquad (4.3a)$$

$$B = B(z^{-1})=b0 + b_1z^{-1} + b_2z^{-2} + \ldots + b_{nB}z^{-nB} \qquad (4.3b)$$

$$C = C(z^{-1}) = 1 + c_1z^{-1} + c_2z^{-2} + \ldots + b_{nC}z^{-nC} \qquad (4.3c)$$

It is assumed that the random sequence (noise) filter 'C' is strictly stable, ie. The roots of 'C' must lie with in the unit circle. Figure (4.1) shows the block diagram of the system given by the equation (4.2)

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

$$\text{“}I = E\{(Py_{t+k} - Rw_t)^2 + (Q'u_t)^2 \,|\, _t\} \qquad (4.4)$$

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

'wt' set-point.

'P,R,Q'' are the weiting filters.

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 (4.4) becomes as;

$$I = E\{(Py_{t+k} - Rw_t)^2 \,|\, _t\} \qquad (4.5)$$

And with P=1,R=1 yields;

$$I = E\{(y_{t+k} - w_t)^2 \,|\, _t\} \qquad (4.6)$$

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

Minimization of the equation (4.6) with respect to u_t leads to a 'Minimum Variance (MV) ' control law.

A non zero (Q') includes the important cases:

Recall equation (4.6) and replacing Q' by λ';

$$I = E\{(P\,y_{t+k} - R\,w_t)^2 + (\lambda' u_t)^2 \,|\, _t\} \qquad (4.7)$$

Minimization of 'I_1' with respect to 'u_t' yields a control, which penalizes both output deviations from set-point and excessive control effort. However, if the set point w_t has a non-zero mean, ie. $\varpi \neq 0$, then unless $\lambda' = 0$, the system output will not be able to track the set-point exactly. In other words, offset will result.
Recall equation (4.4) and replacing Q' by λ' and 'u_t' by '$u_t - u_{t-1}$';

$$I_2 = E\{ ((P\, y_{t+k} - R\, w_t)^2 + (\lambda'(1-z^{-1})u_t)^2) \mid_t \} \qquad (4.8)$$

Minimizing 'I_2' again penalizes output deviations from set-point, but now, instead of penalizing absolute control output, changes in control are penalized. The resulting control guarantees that the mean value of the system output, 'y' equals the mean value of the set-point 'w'.

This is however achieved at the expense of possible degradation of dynamic performance as a result of the inclusion of an integrating term $(1-z^{-1})^{-1}$ into the closed loop. The control law resulting from the general cost function 'I' will now be derived .

The 'y_{t+k}' term in equation (4.4) 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 '$y^*_{t+k/t}$' with,

$$y_{t+k} = y^*_{t+k/t} + e_{t+k} \qquad (4.9)$$

The relationship between 'y^*' and process parameters can be obtained by rewriting equation () as;

$$y_{t+k} = B/A u_t + z^k C/A \xi_t + d/A \qquad (4.10)$$

Use of the 'separation identity'.

$$z^kC/A = z^kE + F/A \quad (4.11)$$

allows the stochastic term in Equation (4.10) to be regarded as a combination of future sequences and sequences which have occurred up to and including present time 't' ie.

$$z^kC/A\xi_t = z^kE\xi_t + F/A\xi_t \quad (4.12)$$

where

'$z^kE\xi$' is the future sequence.
'$F/A\xi_t$' 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. $e_0 = 1$
Substitution of equation (4.6) into (4.4)

$$y_{t+k} - E\xi_{t+k} = B/Au_t + F/A\xi_t + d/A\xi_t = y^*_{t+k/t} \quad (4.13)$$

$$e_{t+k} = E\xi_{t+k} \quad (4.14)$$

$$y^*_{t+k/t} = B/Au_t + (F/AC)(Ay_t - z^{-k}Bu_t - d) + d/A \quad (4.15)$$

$$y^*_{t+k/t} = Ebu_t + Fy_t + E(1)d)/C \quad (4.16)$$

where ;

$$E'(1) = \sum_{i=1}^{k-1} ei \qquad (4.16a)$$

Defining; $G \cong EB$ and $\delta' \cong E(1)d$, equation (4.16) can rewritten as;

$$y^*_{t+k/t} = (Gut + Fyt + \delta')/C \qquad (4.17)$$

Using equations (4.4) and (4.17) in the cost function given by the equation (4.3) yields.

$$I_2 = E\{((Py^*_{t+k/t} + e_{t+k}) - Rw_t)^2 + (Q'u_t)^2) \mid_t\} \qquad (4.18)$$

'I_2' can be minimized with respect to 'u_t' to obtain the 'Generalized Minimum Variance (GMV)' control law. Using the assumption that 'e_{t+k}' is an uncorrelated sequence with zero mean, ie.;

$$E\{e\} = E\{ey\} = E\{eu\} = E\{ew\} = 0 \qquad (4.19)$$

and

$$E\{(Pe)^2\} = \sigma^2 + E\{Pe\}^2 = \sigma^2 \qquad (4.20)$$

where 'σ^2' is the variance of (Pe). 'I_2' thus simplifies to;

$$I_2 = E\{((Py^*_{t+k/t} - Rw_t)^2 + (Q'u_t)^2) \mid_{t\}} + \sigma^2 \qquad (4.21$$

the objective is to minimize 'I_2' with respect to 'u_t', ie.;

$\partial I_2/\partial u_t = 0 \quad ; \quad \partial E\{\ldots\}/\partial u_t = 0$

The new cost function will be ;

$$J = E\{((Py^*_{t+k/t} - Rw_t)^2 + (Q'u_t)^2) \mid_t\} + \sigma^2 \qquad (4.22)$$

From the equation (4.17),

$$Py^*_{t+k/t} = (Gut + Fyt + \delta')P/C \qquad (4.23)$$

Substituting equation (4.23) into equation (4.22) yields;

$$J = E\{(((PE/C)y_t + (PG/C)u_t + (P\delta'/C) - Rwt)^2 + (Q'u_t)^2) \mid_t\} \quad (4.24)$$

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

$$\partial J/\partial u_t = 2(Py^*_{t+k/t} - Rw_t)p_0g_0/c_0 + 2(Q'u_t)q'_0 = 0 \qquad (4.25)$$

After simplification, it can written as;

$$\partial J/\partial u_t = Py^*_{t+k/t} - Rw_t + (c_0\, q'_0/p_0g_0)Q'u_t = 0 \qquad (4.25a)$$

Since $c_0 = 1$, $p_0 = 1$ and defining $Q = q'_0\, Q'/g_0$, equation (4.25a) can be written as;

$$Py^*_{t+k/t} - Rw_t + Qu_t = 0 \qquad (4.26)$$

The result 's a control law that provides instantaneous optimal control action, ie. it does not take into account the effect that the present control action will have on future outputs at load timers greater than the process time delay . In figure 4.2 the block diagram that represents the control law given by equation (4.26) 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

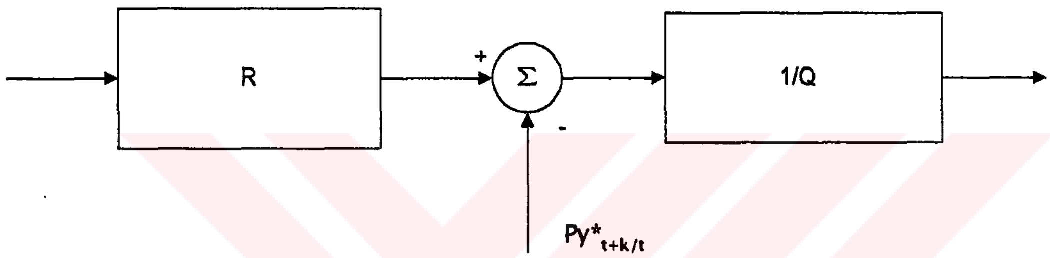

Figure 4.1 The block diagram that represents the control law given by equation (4.25)

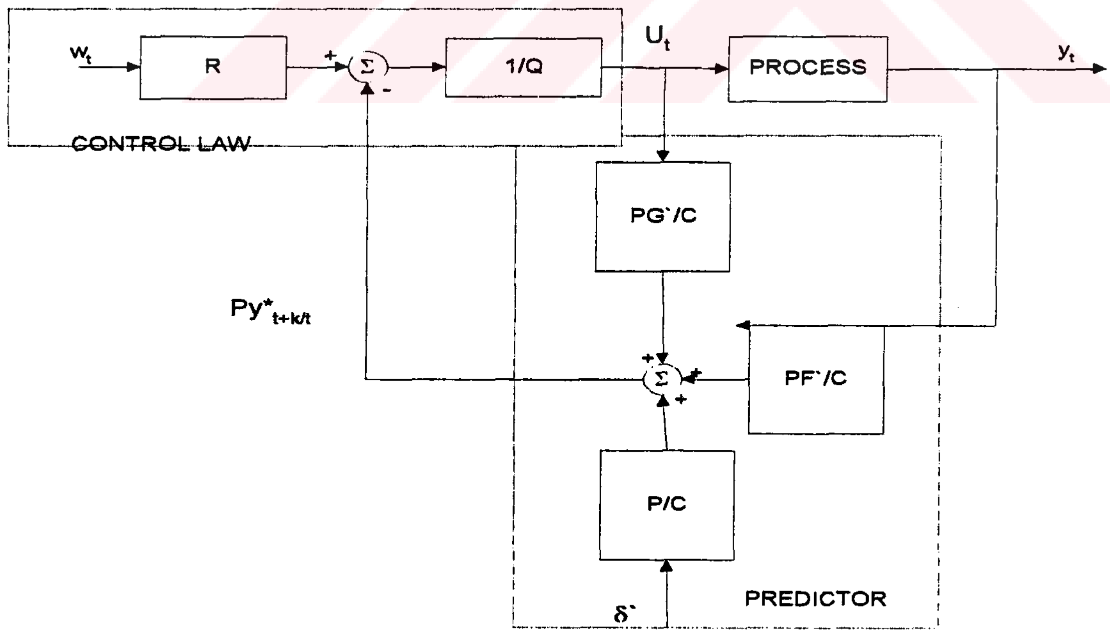

Figure 4.2 Block diagram of a feed-back systems with self-tuning controller.

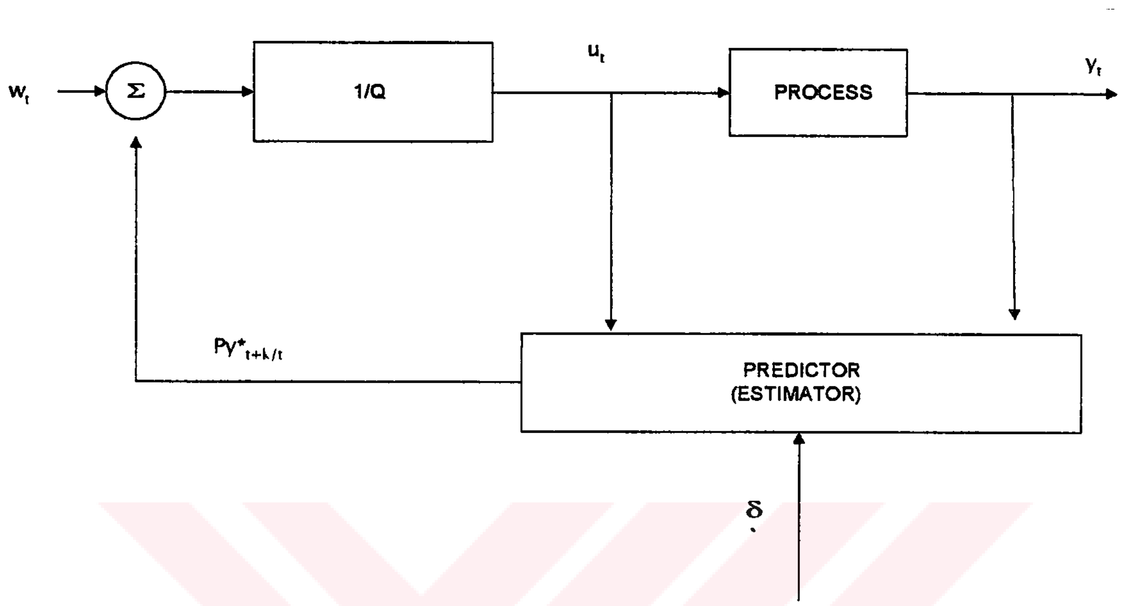

Figure 4.3 is simplified form of figure 4.2.

Chapter 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 (4.26) 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:

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.

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

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

Chapter 4.4 PID CONTROLLERS

In this study first process parameters are obtained by Cohen-Coon method based on tangent line through point of inflection then the controllers parameters are tuned by Zeigler-Nichols methods. A general description of the new trends in PID control theory is given below.

Although the history of adaptive control has been around for four decades; it was only during the last fifteen years that the theory could actually be realized in practice. In recent years, the availability of powerful digital computers and the very idea of potentials of adaptive control has motivated considerable amount of work being done on this subject. These works have refined or extended the original theory and brought about new ideas, such as self-tuning control, to the extent that there is now a solid theory backed by a large body of literature on this area of research.

As a result, many new control algorithms have emerged which are superior to traditional PID controllers. However, it seems that the process control industry is a bit cautious if not suspicious about this huge development.

The possible reasons for this attitude include:

1. PID controllers are regarded as "jack of all trades" in the process control industry.

2. Developments in classical control and especially tuning PID controllers were largely due to close co-operation between universities and engineers in industry whereas, in general, adaptive control was born in academic world and brought up there. It was considered more an academic topic than a practical solution to difficult actual processes up to a few ago.

3. Adaptive control is based on advanced control theory, which is not appreciated by many plant operators.

4. For sometime, there was a misunderstanding that self tuning controllers would substitute the existing PID controllers, this, of course, can not be justified. Andreiev (Andreiev 1981) makes a conservative guess that in a typical plant, about fifty percent of all process control loops are being run in manual (open loop) rather auto (closed loop) mode. In practice this figure would be much lower; therefore more than fifty percent of all process control loops can be adequately controlled by PID controllers.

Many years of experience have proved that PID controllers are versatile enough to control a wide variety of processes, however even if a nearly optimal set of parameters are selected, the process operating points will certainly change due to many variables acting on the system. In order to return to optimum performance, the controller parameters should be readjusted. That is the selection of the appropriate gain, integral and derivative time constants so-called tuning for better performance. This procedure is still very much a manual operation performed by a skilled operator.

In view of the causes mentioned above and since the tuning procedure is mathematically defined, there has been a strong tendency towards automating the tuning process, thus a new chapter in adaptive control has been opened; that is PID adaptive controllers. Names such as PID self tuners, PID auto tuners and intelligent PID controllers are all attributed to a class of adaptive controllers which are essentially PID controllers but tuned automatically.

Chapter 4.4.1 State of Art

There have been different approaches to the problem of deriving a PID like adaptive controller. However, all of these can be classified under two broad classifications; namely *Model Based (Parameter Estimation)* Or *Expert systems (Pattern recognition).*

The model-based approach is a special case of self-tuning control where the structure of the controller is pre-fixed to that of the PID algorithm. The parameters of the model of the system are continually updated to match the input output behavior of the actual process. The PID controller is then tuned based on the estimated system parameters.

The so called pattern recognition approach is basically automating the manual process of tuning a PID controller. The theme of most of these "packaged" designs is an intelligent PID controller that can reason logically within some defined context. The process recovery curve (reaction curve) is observed after a disturbance or a set point upset or whenever tuning is required; the appropriate PID adjustments are then made to produce the desired damping and overshoot.

Chapter 4.4.2 Model based PID self tuners

One of the early model based implementations was a model reference PID self-tuner by Hawk et al (Hawk, 1982). The system model was recursively updated by an Instrumental variable algorithm. The PID parameters were then selected through interactive communication of operator and controller,

Nishikawa et al (Nishikawa, 1984) proposed an alternative algorithm for auto tuning PID controllers. When running is required an intentional disturbance is applied to estimate the process parameters. The authors acknowledge that use of perturbation signal is not desirable. However, they argue that the signal is a small pulse, which does not disturb the normal operation of the plant significantly. After estimating the system parameters, the PID parameters are chosen so as to minimize the weighted ISE (Integral Of Square Error). This method -like previous method- is essentially a man-machine interactive tuning procedure. The authors have tested this algorithm in real processes and have reported that sufficiently good settings of PID parameters is obtained.

Other alternative designs have been pole-placement PID self tuners (Warwick, 1988), (Banyasz., 1982), and (Ortega, 1984). All these approaches share the following: they are based on discrete time self-tuning control, and the parameters of the system are identical by massive least squares estimation. The difference between them is how the PID parameters are updated. Warwick and Ortega adopt a pole placement design control law but fit a PID algorithm to control structure. Banyasz et al derive an explicit formula ensuring prescribed overshoot of the process to update PID parameters.

Chapter 4.4.3 Pattern Recognition PID self tuners

Taylor's "Micro-Scan 1300 (Andreiev, 1977) controller was one of the early PID adaptive controllers. The distinct feature of this model was that it was one of the first PID auto-tuners supplied as a "packaged product". Before that, self-tuning control was in use in large computer installations based on direct digital control in which the self-tuning algorithm was in the form of software resided an a main frame or minicomputer. Basically, this is an adaptive gain controller where the gain is varied according to a preprogrammed gain schedule. When there is no upset to the plant, it performs exactly like an ordinary PID controller tuned for fastest response with low gain. As the error exceeds a preset value, the gain increases dynamically with the error.

Leeds & Northtop's "Electromax V" single loop controller (Andreiev, 1981) was introduced in 1981. It was the first generation of PID adaptive controllers on pattern recognition. During the tuning, the plant is upset by a signal -as large as the plant can handle- to determine the reaction curve of the process. The controller watches the recovery curve and corrective resetting of the original PID parameters are initiated.

One of the interesting auto tuning techniques is reported by Åström (Aström, 1984). The method is essentially based on the Ziegler and Nichols closed loop formula suggested in a classical paper (Ziegler, 1942). In this method, a relay is implemented in parallel with the PID controller. The system actually operates as a relay controller in the tuning mode and as an ordinary PID controller in normal operation. The aim of the relay in the loop is to find critical gain and period which is needed in order to apply the Zeigler and Nichols tuning rules. When the system is under relay control, it drives the system into a limit cycle with frequency equal to that at which the plant phase is -180 degrees. The gain at this frequency is estimated from the limit cycle amplitude. This information is used to calculate the PID parameters. The relay auto-tuner concept has been implemented in products from Satt Control and Fisher.

Chapter 4.4.4 PID PARAMETERS UPDATE

The PID parameters are updated at each sample intervals based the information obtained from the identification part. Either Haalman or Pemberton tuning rules will be used for this purpose. It is possible to update the PID parameters using the open loop Zeigler and Nichols for those systems that can be modelled by a time delay, a time constant and a gain; i.e:

$$y(s) / u(s) = K_p e^{-st_d}/(\tau s+1) \qquad (4.27)$$

Z-N rules for a PID controller for the above model are as follows:

$$Kc = 1.2\tau/(K_p t_d), \qquad \tau_I = 2t_d, \qquad \tau_d = .5t_d \qquad (4.28)$$

Chapter 5. EXPERIMENTAL IMPLEMENTATION of SELF-TUNING CONTROLLER and PID CONTROLLER

Chapter 5.1 INTRODUCTION

Application of Self-Tuning Controller to first order processes with time delay and selecting appropriate tuning parameters for the STC control law together with a PID controller will be explained and discussed here. As there were several algorithms for self- tuning controllers, a '**Minimum Variance Control (MVC)**'algorithm and a '**Generalized Minimum Variance Control (GMVC)**' algorithm applied to a **SISO** process will be considered. For PID controller the parameters obtained from Cohen-Coon method that are tuned by Zeigler-Nichols method will also be discussed.

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. The parameter estimator acts on the process inputs and outputs, and produces estimates of certain process parameters. Then 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 controller form. Figure 5.1 (from Dr. Hikmet İSKENDER) shows the type of the regulator used in this work.

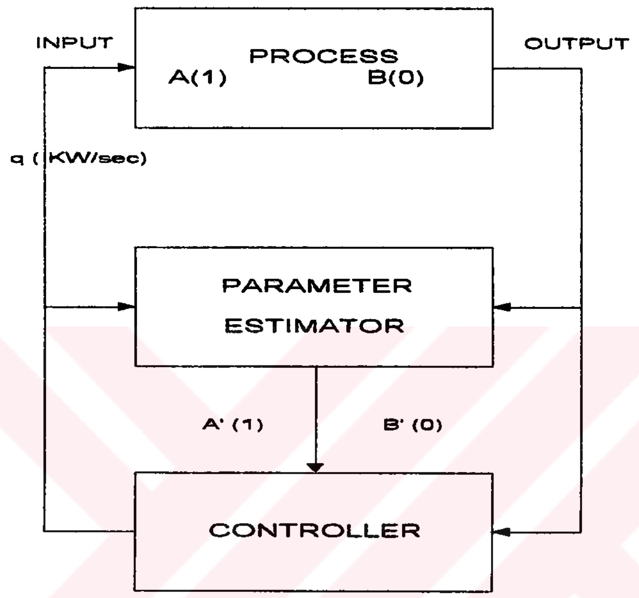

Figure 5.1 Block Diagram of the STR used in this System.

Chapter 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 a tank, pump, valves piping, a computer and a heating system. Figure 5.2 shows the arrangements pump and valves of the real plant. To maintain simplicity the figure does not include the control instruments. The tank was 0.5 m^3, the heater was 4 KW.

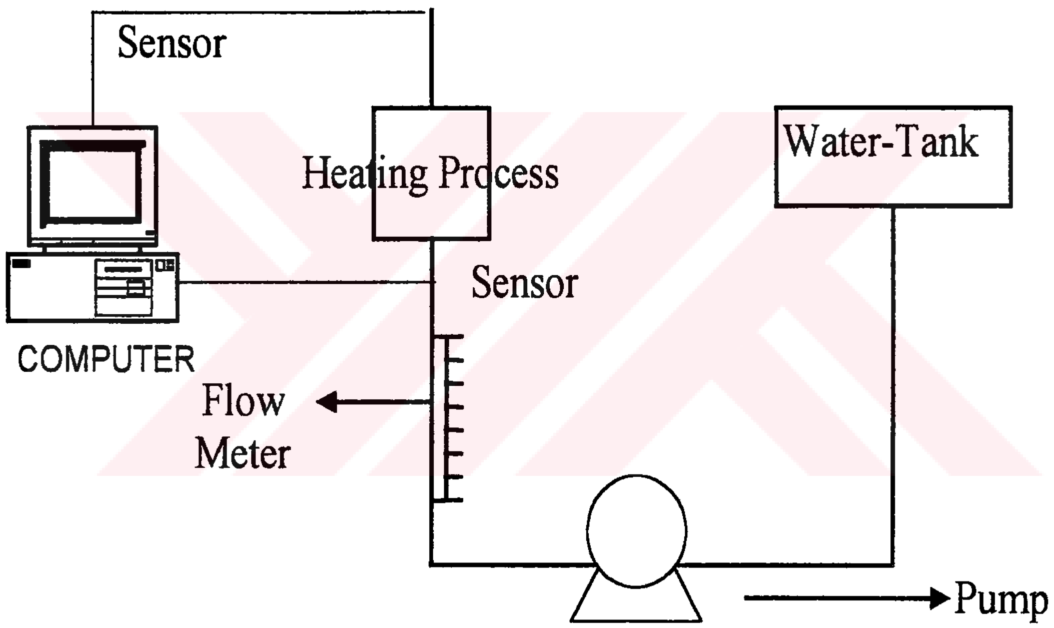

Figure 5.2 The System Used for the Experiment

The process parameters such as process gain '$\mathbf{K_p}$' and time-constant 'τ' are obtained by two ways. First way is by Cohen-Coon method from which the parameters are used for PID parameters tuning. The second way is through numerical method (SVD) which are used for adaptive controller. The object of the control system is to control the output temperature of the liquid. The process transfer function with time delay is as follows.

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

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 'Δ**t**' is the '**sample time**'. Forming new transfer function gives;

$$G_p(s)H_0(s) = (Kpe^{-tds})\ (1 - e^{-s\Delta t})/(\tau s +1)s \qquad (5.3)$$

Where, $t_d = k\Delta t$

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

$$Y(z)/X(Z) = G_pH_0(z) = K_p(1-\gamma)z^{-k-1}/(1-\gamma z^{-1}) \qquad (5.4)$$

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

In difference equation form, potion (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 heating system, ie.

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

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

$$y(t) = - a_1y(t-1) + b_0u(t-k-1) \qquad (5.6)$$

The objective function of the Generalized Minimum Variance Controller contains y(t+k) values that is k step ahead into the feature at time 't', the minimization is not realizable . 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 (Seperation Identity)'** used.

Chapter 5.3 EXPERIMENTAL WORK FOR THE FIRST ORDER SYSTEM

The object of these experiments were to investigate the Control System as shown in Figure 5.1. The time constant 'τ' and the process gain '**Kp**' were found experimentally by using a simple step-up techniques in set-point. After the step- up the system parameter's were obtained by Cohen and Coon rule.

Using the data for the process reaction curve as ca be seen from figure 5.3 mathematical model of the system, the process gain '**Kp**' and the time constant ' τ' were found as 1.53(kw) and 19(sec) respectively. They're used in PID control. For the adaptive control Kp and τ are found from the simulation by SVD. They're 1.63 and 1.2 respectively.

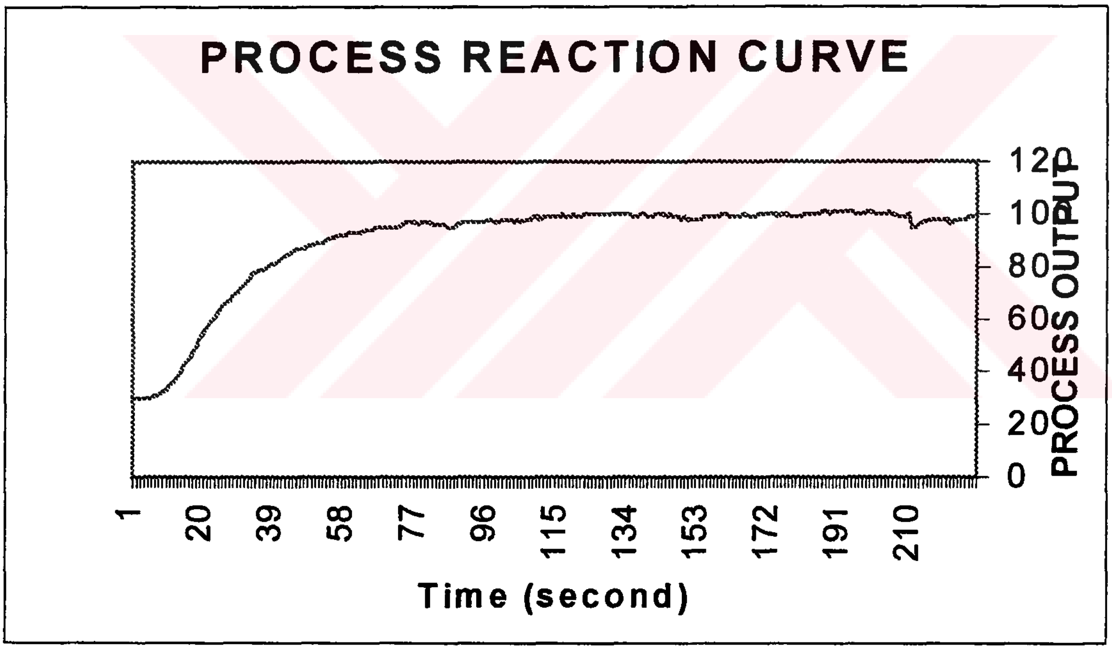

Figure 5.3 Process Reaction Curve Obtained from the input-output data for this System.

Chapter 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	I
Initial value of the parameter 'a_1'	0.0
Initial value of the parameter 'b_0'	0.0
Identification method	SVD
Forgetting factor value	0.98
System Gain (K_p)	1.63(sec/KW)
Time Constant of the System (τ)	1.2 (sec)
System parameter 'a_1'	0.433
System parameter 'b_0'	0.923
Type of simulation	Closed-Loop
Sampling Period (Δt)	1(sec)

Chapter 5.3.2 Parameter Variations and Fine Tuning of an STC

The important decisions to be made before implementation of the 'Generalized 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

The weighting functions P,R and Q are used to obtain different types of controller schemes such as MVSTR, MVSTC and GMVSTC. Recalling the equation (4.25), and definition '**Q**' which is equal to '$\mathbf{q_0Q/g_0}$';

$$Py^*_{t+k/t} - Rw_t + Qu_t = 0 \tag{5.7}$$

This equation can be rewritten as;

$$Rw_t - Py^*_{t+k/t} = Qu_t \tag{5.8}$$

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

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

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 (4.16) and substituting into equation (5.9) yields;

$$w_t - Fy_t - Gu_t = Qu_t \tag{5.10}$$

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

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

$$w_t - Fy_t - Gu_t = \lambda u_t \tag{5.11}$$

then,

$$u_t(G + \lambda) = w_t - Fy_t \tag{5.12}$$

$$\mathbf{ut = (wt - Fyt)/(G + \lambda)} \tag{5.13}$$

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 the set-point tracking (ie. offset problem).

Figure 5.4, Figure 5.5, Figure 5.6 and Figure 5.7 show the controller behavior for 'λ=0' and the stability of the estimated parameters respectively.

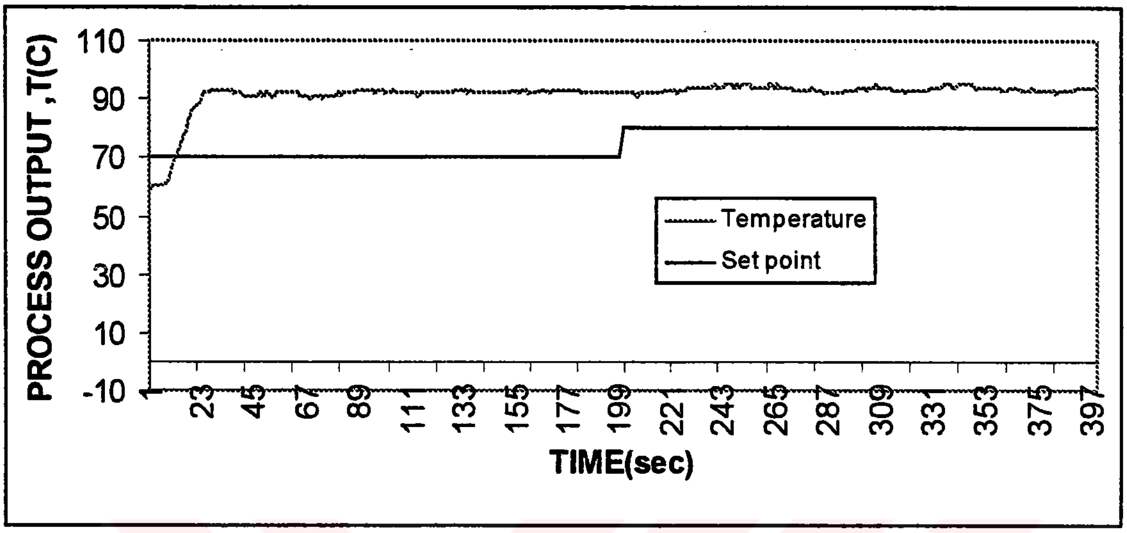

Figure 5.4 Process Output vs Time for weight function 'λ=0'

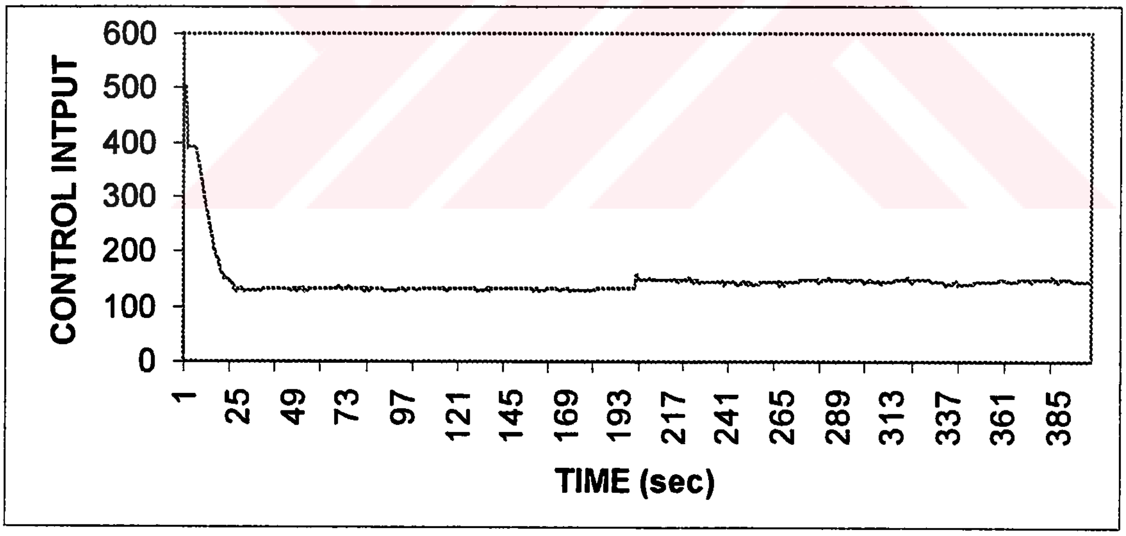

Figure 5.5 Control Output vs Time for weight function 'λ=0'

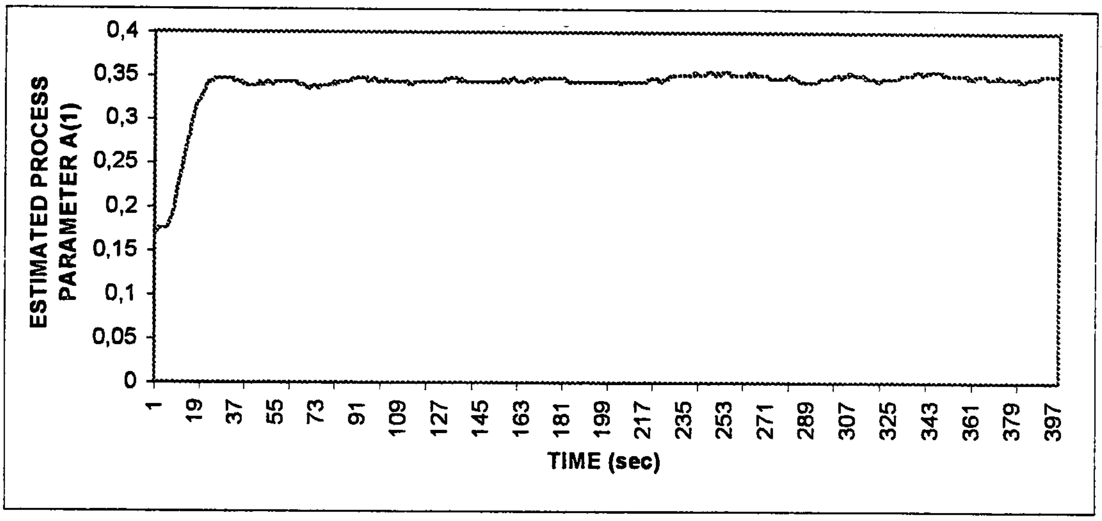

Figure 5.6 Parameter A(1) vs Time for weight function 'λ=0'

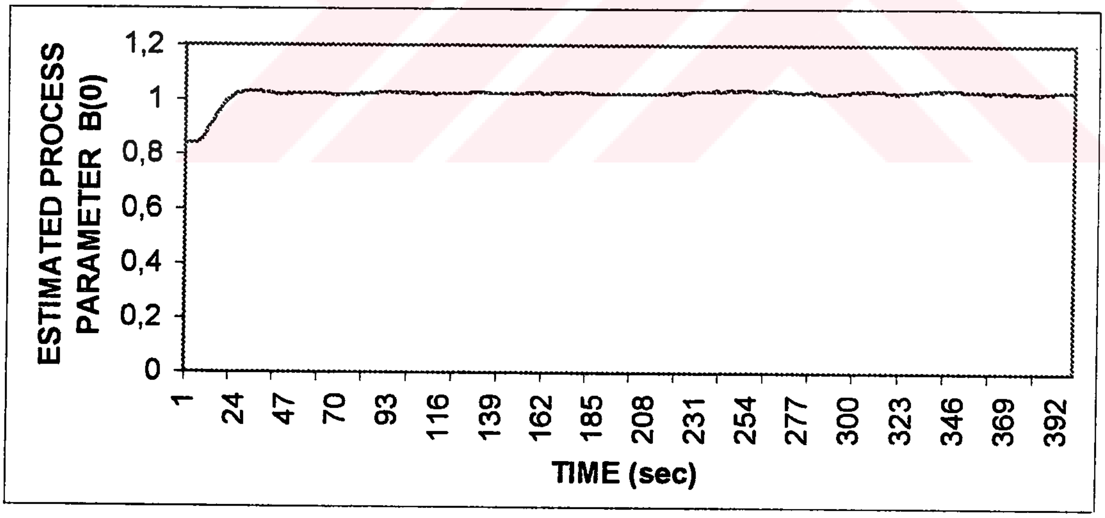

Figure 5.7 Parameter B(1) vs Time for weight function 'λ=0'

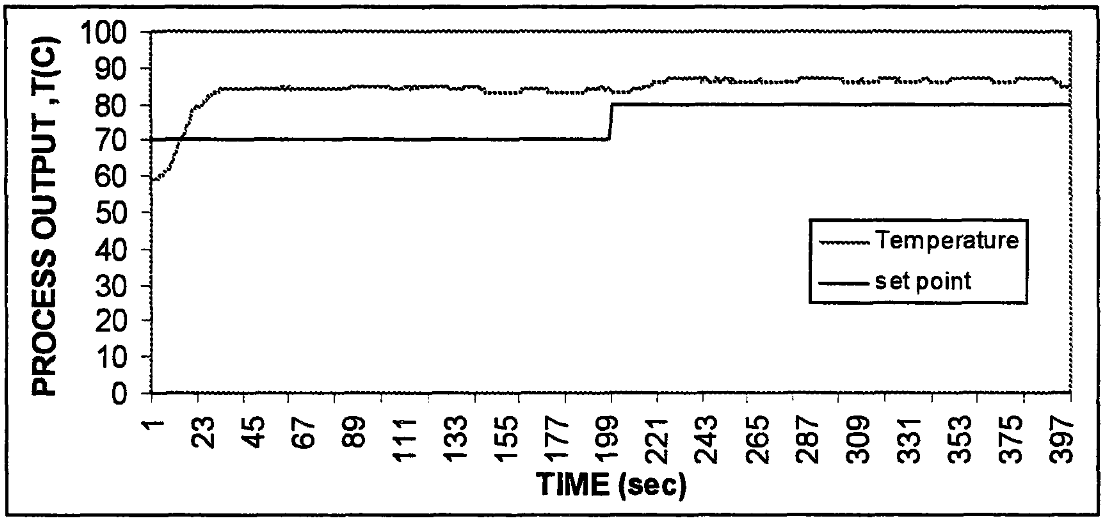

Figure 5.8 Process Output vs Time for weight function 'λ=0.25'

Figure 5.8, Figure 5.9, and Figure 5.10 show the controller behaviors in the case of 'λ =0.25', 'λ =0.5', and 'λ =0.75' respectively. As it can be seen from the graphs in order to have zero offset for each value of the set point a different value of λ is needed.

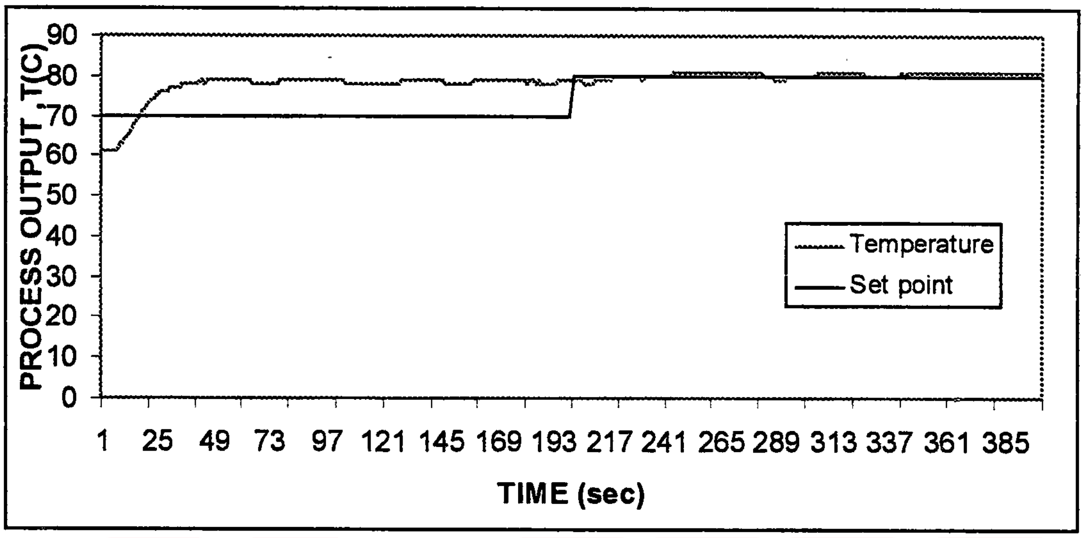

Figure 5.9 Process Output vs Time for weight function 'λ=0.5'

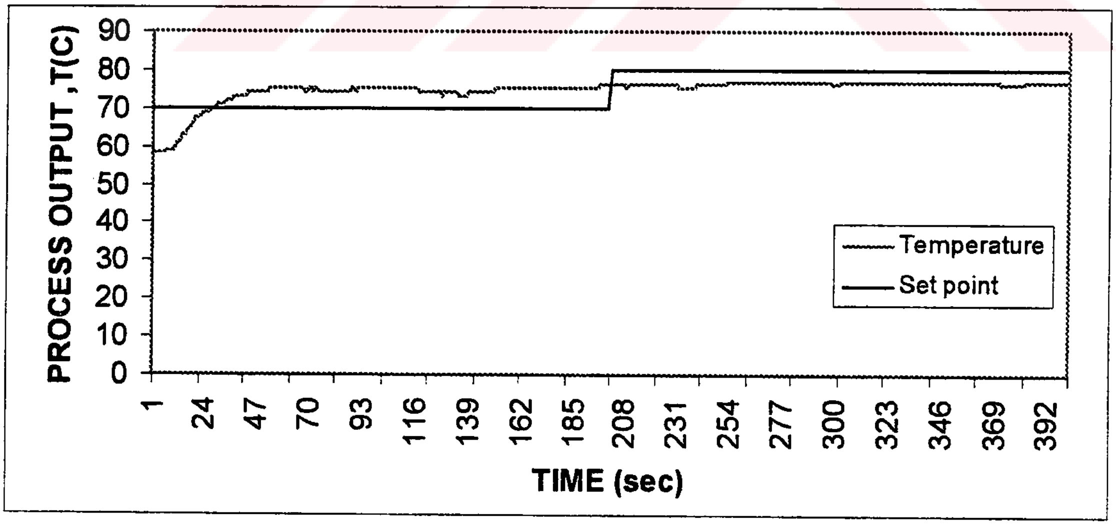

Figure 5.10 Process Output vs Time for weight function 'λ=0.75'

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

$$w_t-Fy_t-Gu_t=\lambda\ (1-z^{-1}) \qquad (5.14)$$

then,

$$w_t-Fy_t-Gu_t=\lambda\ (u_t-u_{t-1}) \qquad (5.15)$$

and

$$w_t-Fy_t-\lambda u_{t-1}=(G+\lambda)u_t \qquad (5.16)$$

$$\mathbf{u_t = (w_t-Fy_t+\lambda u_{t-1})/(G+\lambda)} \qquad \mathbf{(5.17)}$$

Figure 5.11, Figure5.12, Figure 5.13 and Figure 5.14 show the controller behaviors in the case of '$Q=\Delta\lambda$' and the robustness of the estimated parameters respectively.

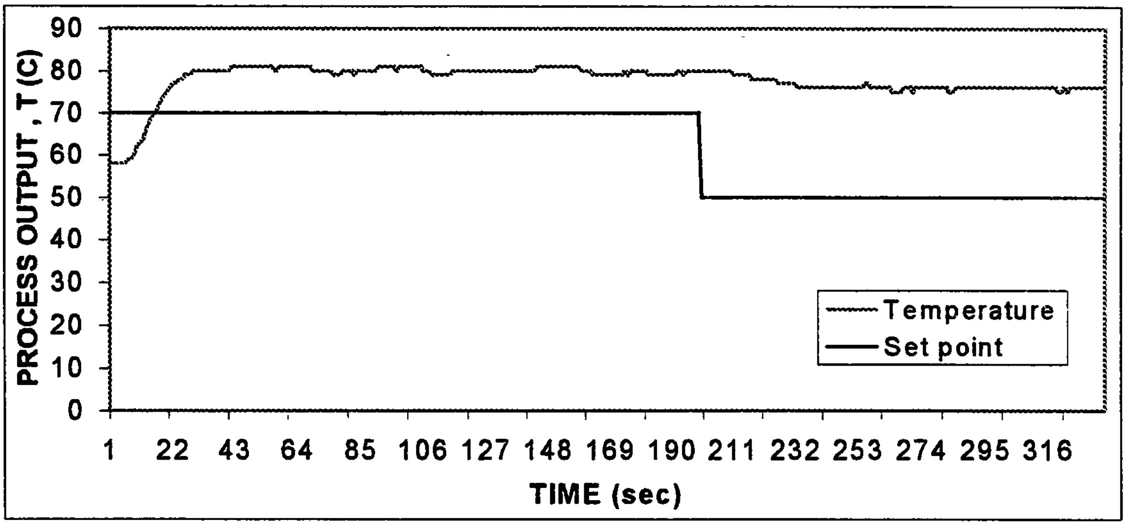

Figure 5.11 Process Output vs Time for weight function 'λ=Δλ'

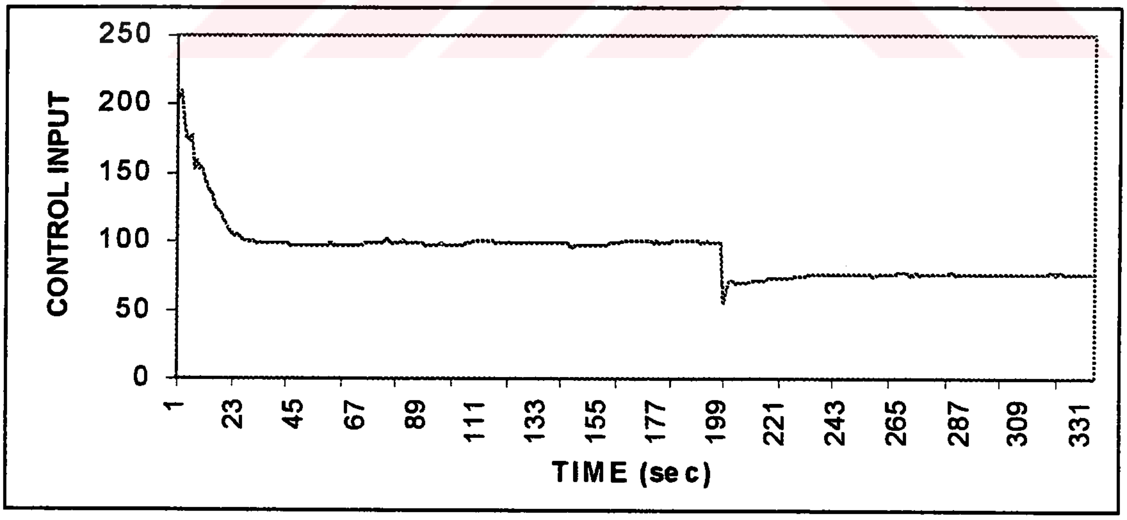

Figure 5.12 Control Output vs Time for weight function 'λ=' Δλ

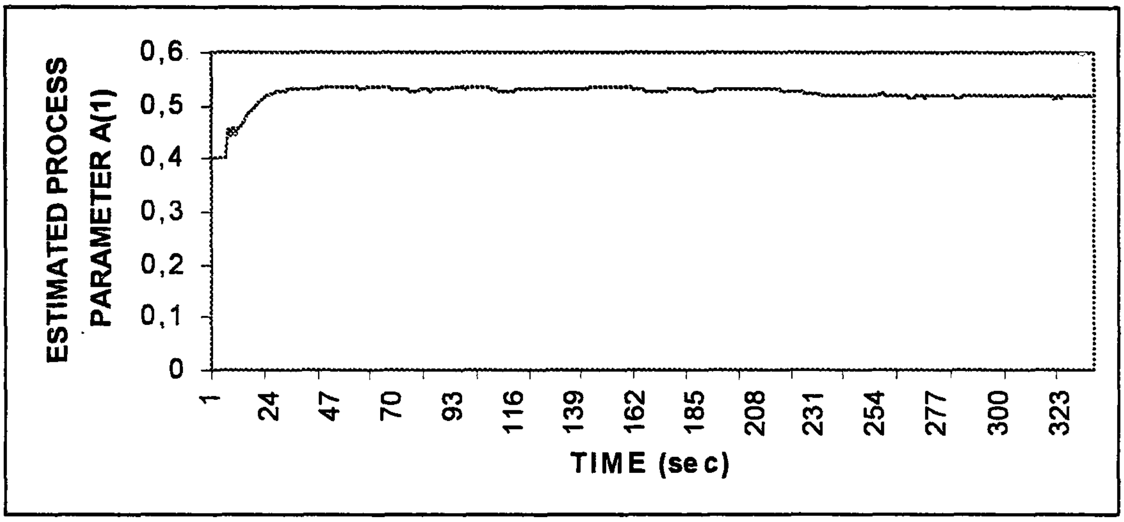

Figure 5.13 Parameter A(1) vs Time for weight function 'λ=Δλ

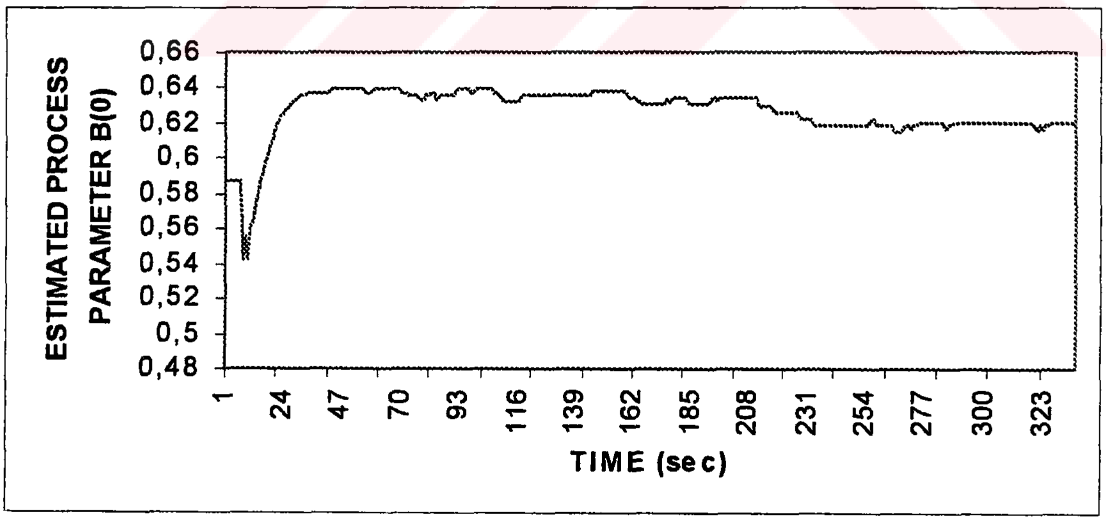

Figure 5.14 Parameter B(1) vs Time for weight function 'λ=Δλ

In this study a variable λ is used which is changed according to the set point values. Figure 5.15, Figure5.16, Figure 5.17 and Figure 5.18 show the controller behaviors in the case of varying λ and the robustness of the estimated parameters respectively.

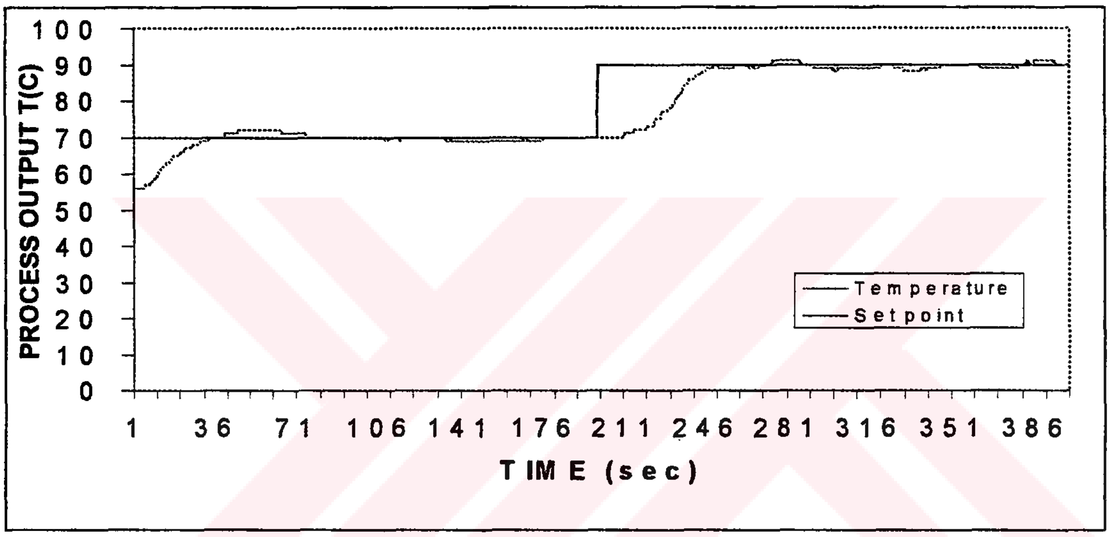

Figure 5.15 Process Output vs Time for variable weight function 'λ'

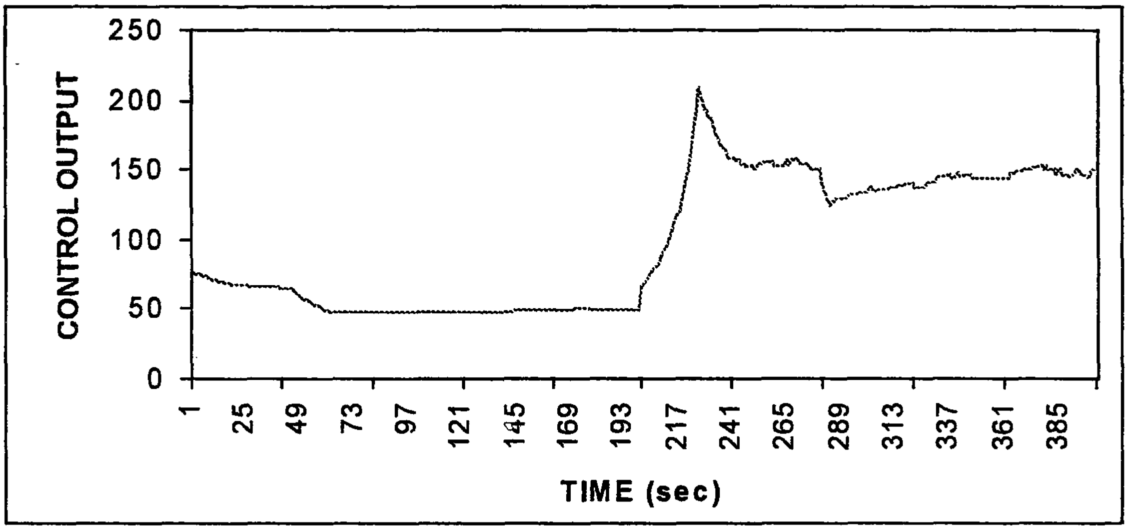

Figure 5.16 Control Output vs Time for variable weight function 'λ'

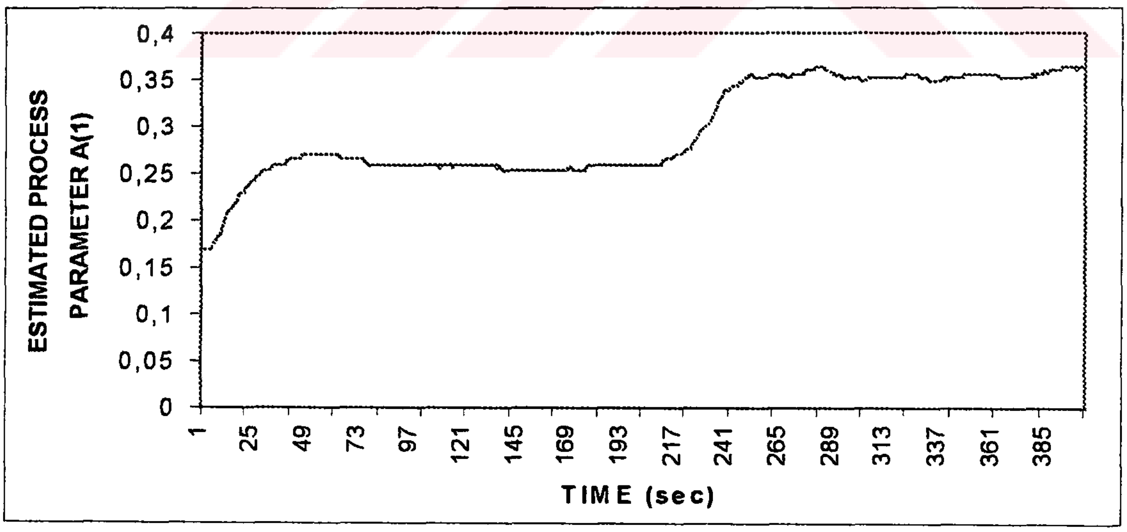

Figure 5.17 Parameter A(1) vs Time for variable weight function 'λ'

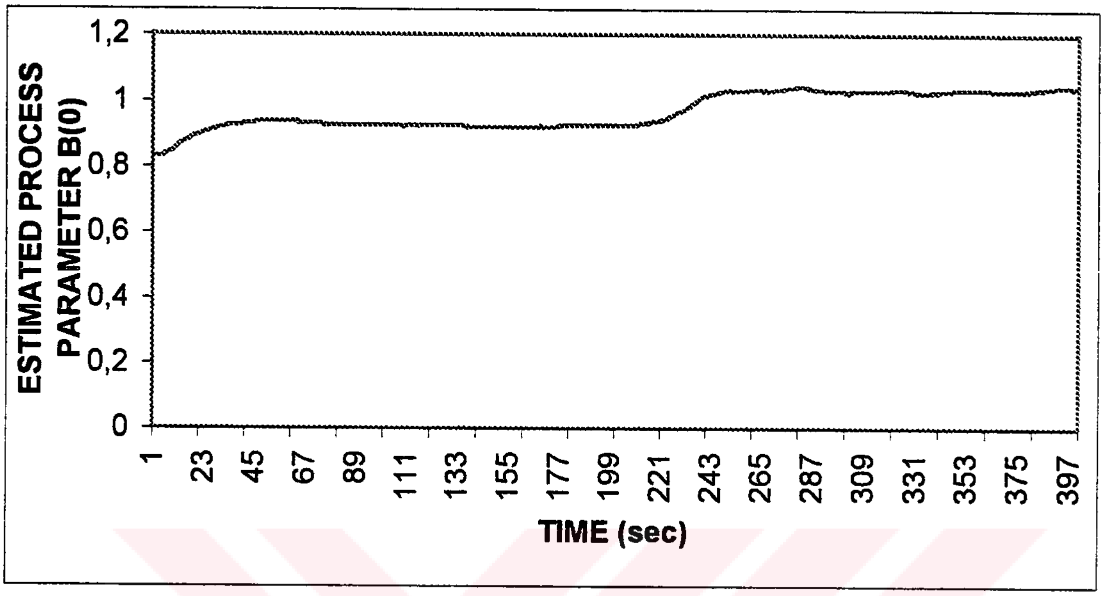

Figure 5.18 Parameter B(0) vs Time for variable weight function 'λ'

Figure 5.19, Figure5.20, Figure 5.21 and Figure 5.22 show the controller behaviors in the case of variable 'λ' and the robustness of the estimated parameters in regulatory step changes. At first a %25 step-down change is inserted in the system then a %20 step-up is applied.

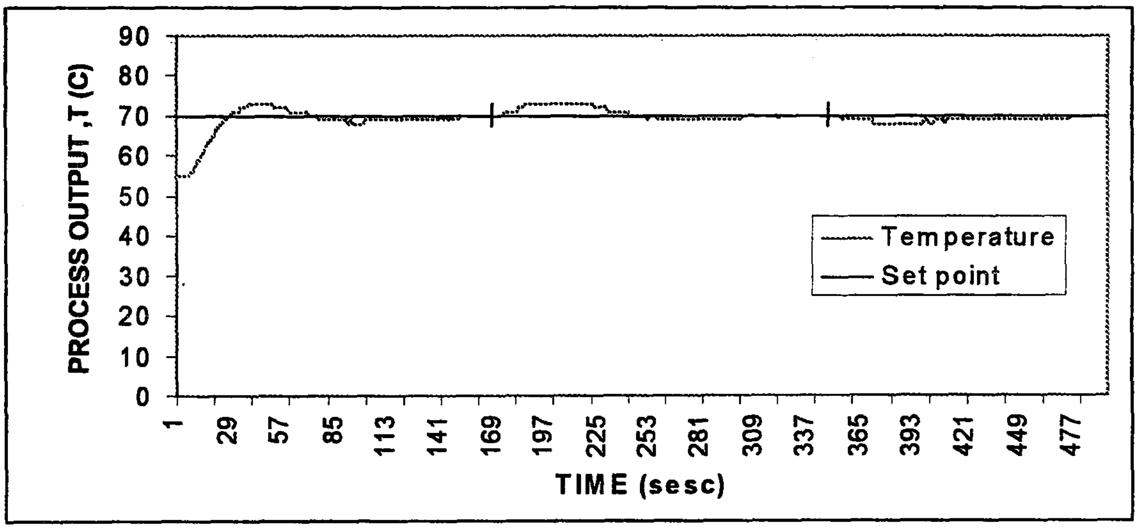

Figure 5.19 Process Output vs Time for variable weight function 'λ',

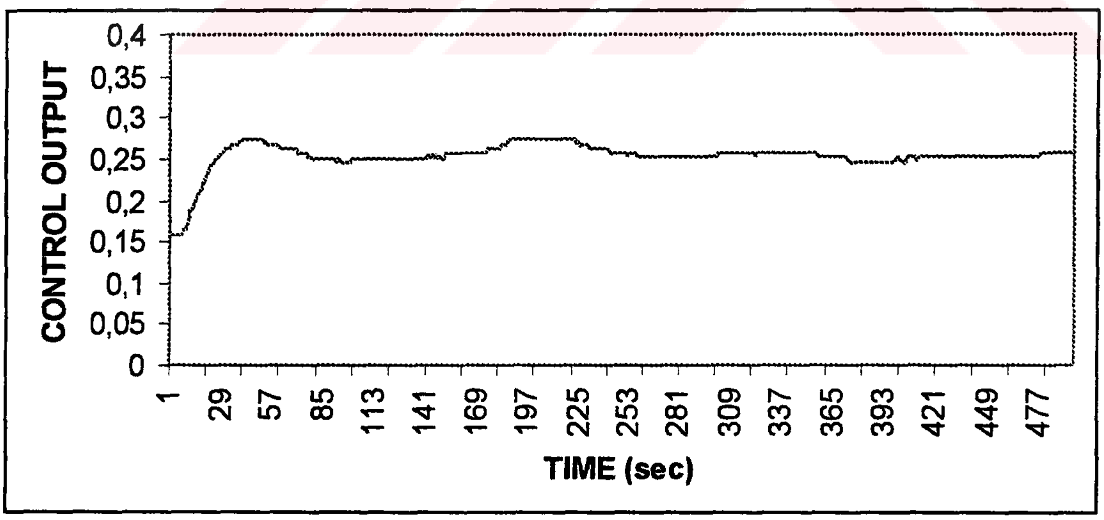

Figure 5.20 Control Output vs Time for variable weight function 'λ'

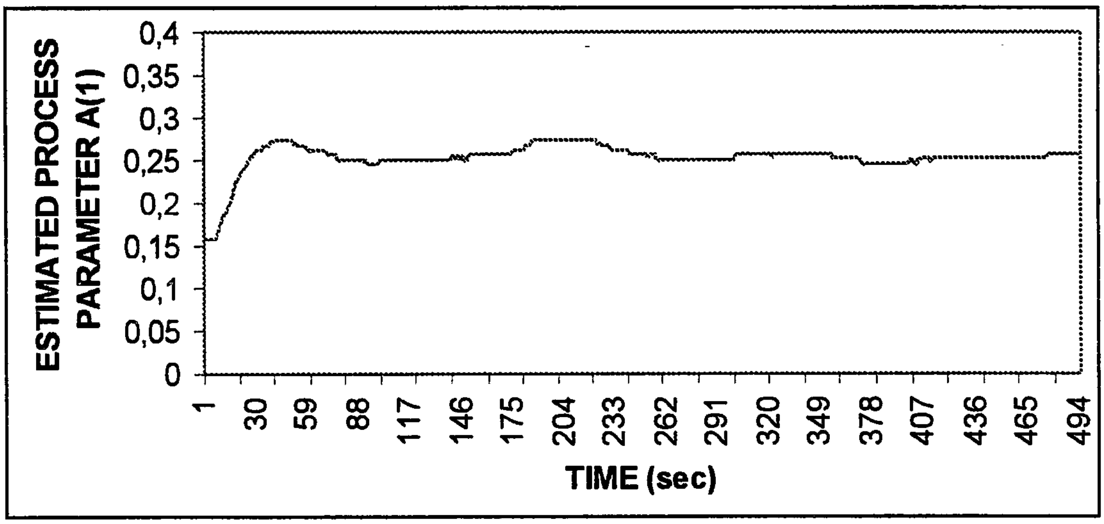

Figure 5.21 Parameter A(1) vs Time for variable weight function 'λ'

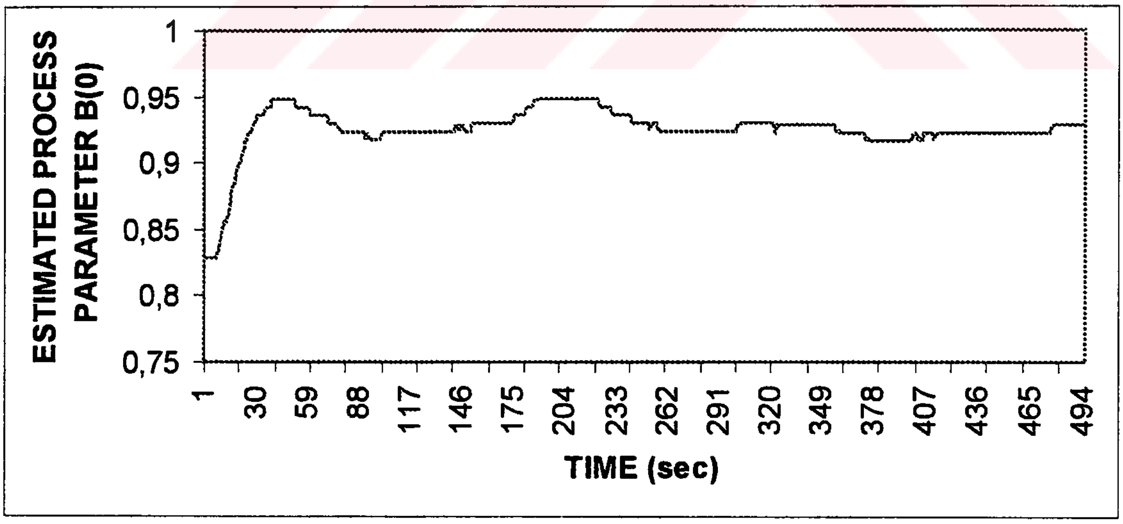

Figure 5.22 Parameter B(0) vs Time for variable weight function 'λ'

Figure 5.23 and Figure5.24, show the behaviors of PID controller for changes in set point. Figure 5.25 and Figure 5.26 show the behaviors of PID controller for changes in load of the process.

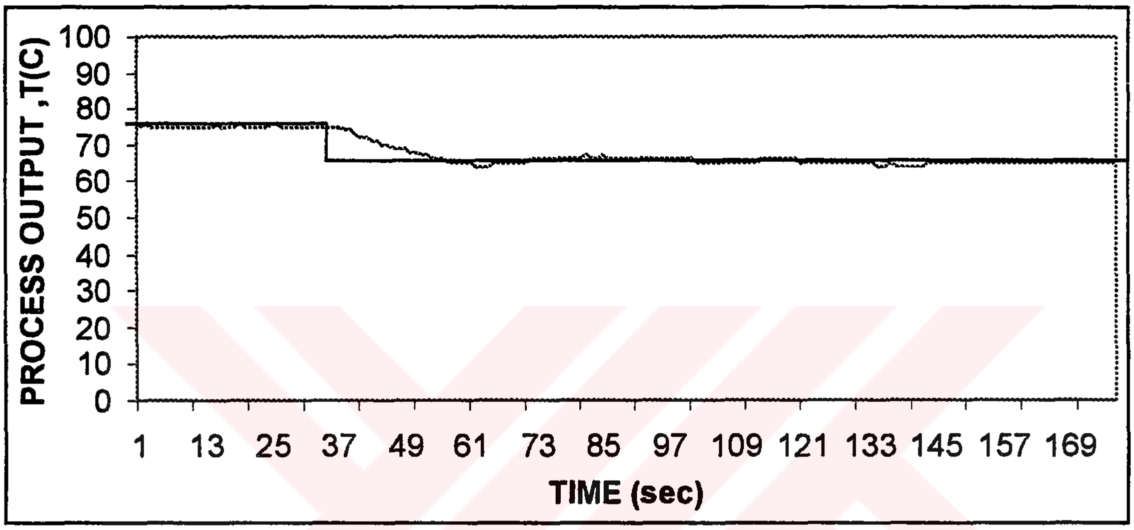

Figure 5.23 Process Output vs Time for PID controller

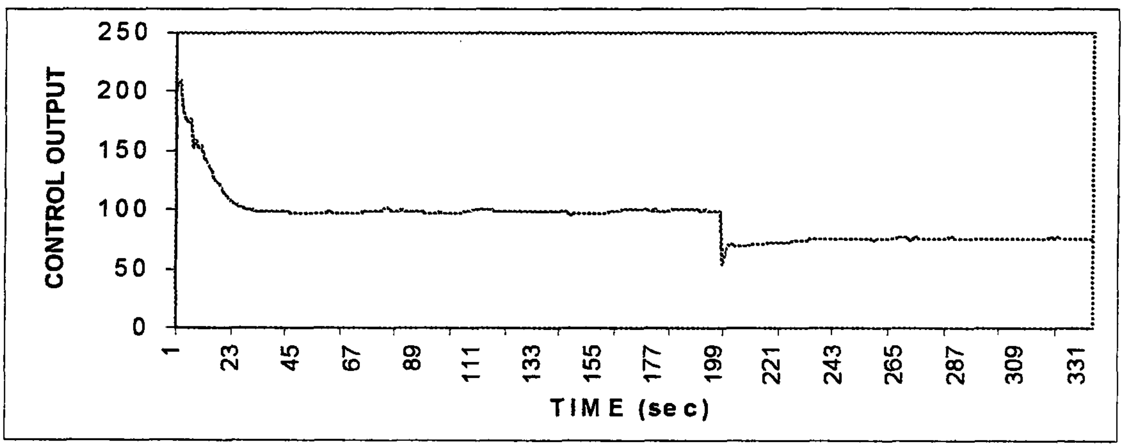

Figure 5.24 Controller Output vs Time for PID controller

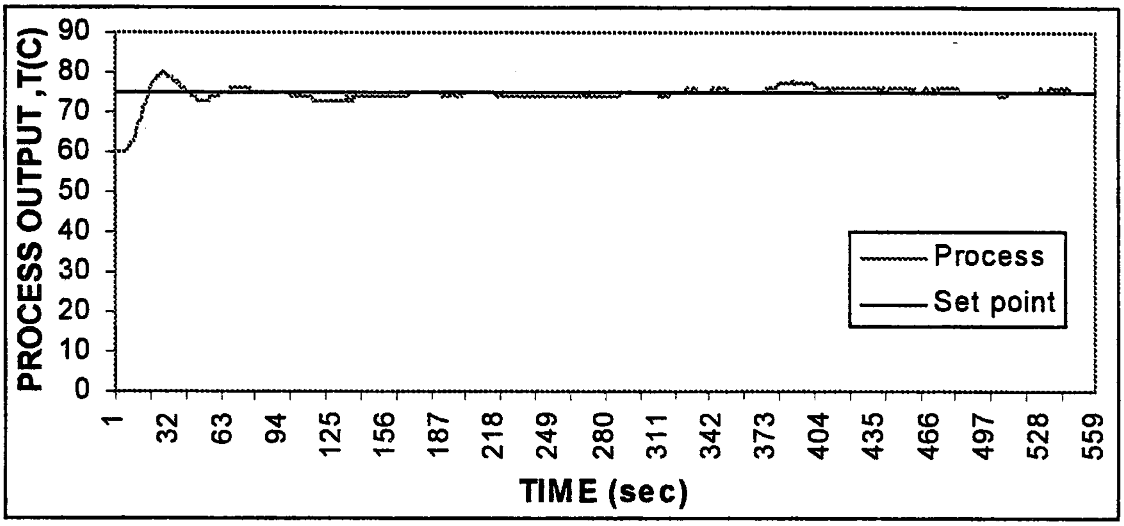

Figure 5.25 Process Output vs Time for PID controller

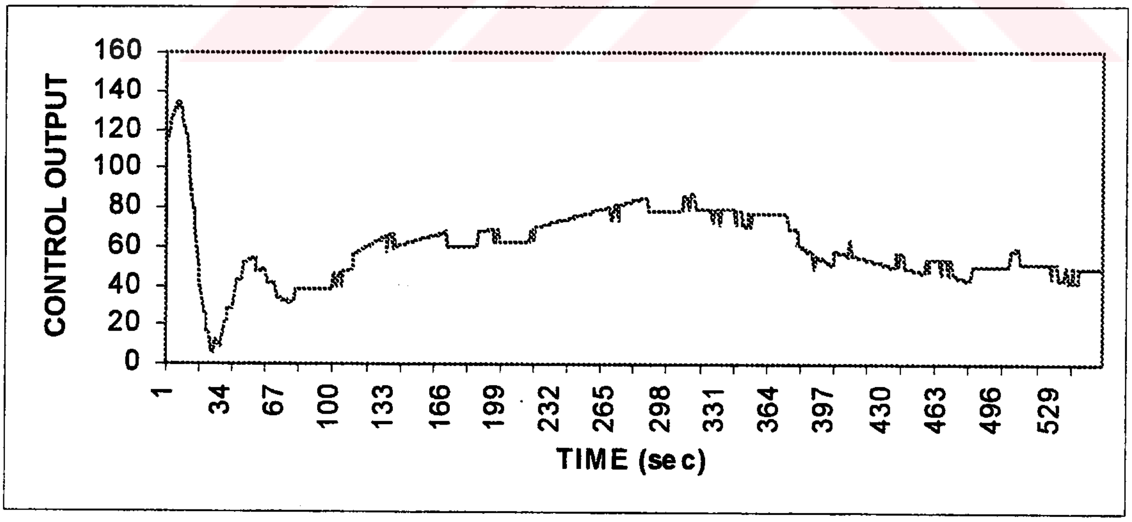

Figure 5.26 Controller Output vs Time for PID controller

Figure 5.27 shows the effect of setting the integral error to 0 after the set point is reached.

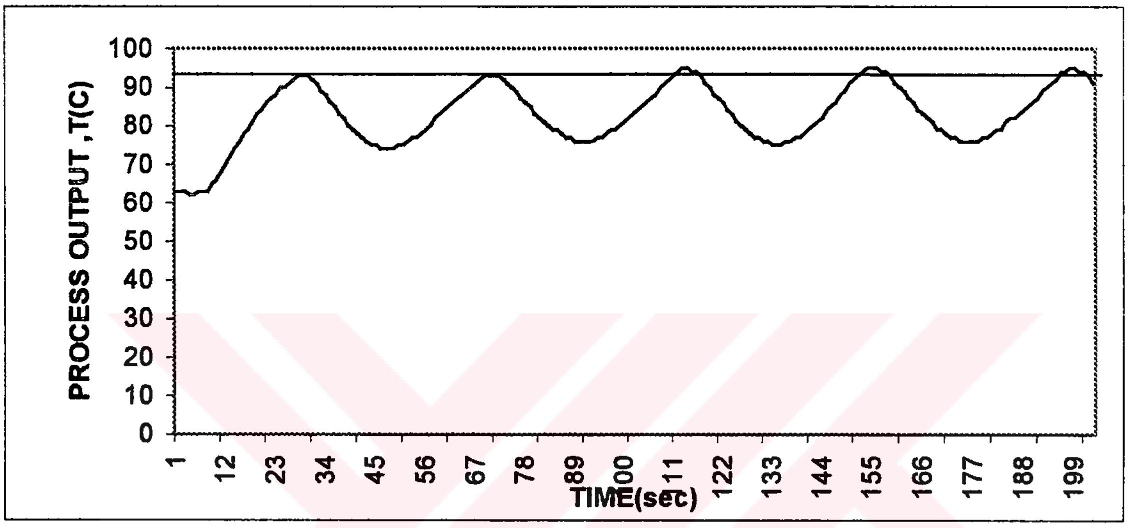

Figure 5.27 Process Output vs Time for PID controller (int=0)

Chapter 5.4 Experimental Results and Discussions

The set point and the load are changed up to %70 to test the performance of the controller. At different operating ranges PID controller shows sharp variations for small changes in error still tracks the set point properly.

Figure 25 shows the variation of process output with time for PID controller. This process was well controlled, despite the wide changes in the operating range; Figure 26 shows the variation of process inputs, that is heating water, with time.

Same changes are also applied in the GMV Self-Tuning controller, this time the controller provided better performance and control action than the classical PID controller. The key point here is to remove the effect of the disturbances without excessive controller changes in the control output. This aim is quite important in sensitive processes. It is clear that having good estimation of the process parameters can remove big disturbances by smooth changes in control output.

Figure 19 shows the variation of process output with time for GMV Self-Tuning Controller. It can be seen that the process output was kept at its set point under GMV control despite the changes in the operating range. Figure 20 shows the variation of process input.

From the results it is clear that both GMV Self-Tuning Controller and PID controller can provide satisfactory control for this heating process.

However, the GMV had an advantage in this case since, it shows a smooth control action, it is much better for the final control element of the process.

Chapter 6. CONCLUSION

Chapter 6.1 GENERAL DISCUSSION AND CONCLUSIONS

It is generally acknowledged that the problem of designing a good control system is basically that of matching the dynamic characteristics of a process by those of the controller. In other words, if the dynamic behavior of process is known, then the characteristics of a controller, necessary to give a desired performance, can be designed.

In this paper servo and regulatory control of a heating process around the certain set points using the GMV Self-Tuning Controller and a classical PID Controller is carried out. The process which is found out to be first order is determined by Cohen and Coon method. This method calls for only a single step testing under open-loop system without any trial and error procedure.

The parameters of the first order process formed a good basis for the starting values in tuning PID Controller. Then Zeigler and Nichols method is used for fine-tuning of the controller's parameters. This tuning procedure is one of the main disadvantage of PID Controllers because of its duration of the experimentation level.

The STC, in the form as we know it today, fall into the class known as stochastic adaptive systems. The design procedure which is almost identical to the approach outlined by Kalman realized entirely in the discrete time domain. A design procedure for unknown process is based on the assumption that it can be described by a stochastic model. The coefficients of this model based on the past input and output data. The estimator calculates the coefficients of this model. The controller parameters are obtained on these coefficients. After minimizing the prespecified cost function, the controller determines the process input signal.

The success of the self-tuning controllers in industrial environment were very encouraging; the demands on final control element made by the minimum variance control law were too exacting. In order to maintain optimality of control performance and also to have smooth changes in control signal, the self-tuning controller not only penalize control effort, but also changes in control are penalized.

The two important parts of adaptive systems are parameter estimation and "Control Law" strategy. If the second one is perfect then it means there is a chance of perfect control.

The model of a process to be controlled can be obtained by two ways. One is by physical laws, the other is by experiments. In practice many of the industrial processes to be controlled are too complex to be described by the application of fundamental principles. Either the task requires too much time and effort or the fundamentals of the process are not understood. By means of experimental tests, one can identify the dynamic nature of such processes and from the results obtain a process model which is at least satisfactory for use in designing control systems. The experimental determination of the dynamic behavior of a process is called process identification.

The RLS estimator is a well-known on-line identification method. It is a simple algorithm that can be applied and has the advantage of low computational requirements. It's disadvantage which is poor tracking capability of changes in process dynamics, can be overcame by introducing weighting forgetting factor or some resetting techniques to the estimator.

Tuning STC with a little knowledge needs using different type of weighting functions. By using experimental techniques we can get much knowledge about the system thus we can employ trouble-free STC with low maintenance.

In this system a variable weighting function is used depending on the set points which gave a better controller performance. In this thesis experimental studies with some hints about the self-tuning are displayed and the important methods for the self-tuning control algorithms are explained.

SUGGESTIONS FOR FUTURE WORK

A self-tuning controller must be economical in order to be used in all around the world and it should be simple enough for non-expert persons. Beside this the self-tuning controller should have a good control performance and robustness.

The unexpected disturbances should be compensated by including necessary control weighting term in the cost function. This weighting term has to be proper enough to overcome the 'bang' effect and also it should smoothen the control output variation to prevent the final control element of the process from tear and wear.

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