IMPROVED QUALITY OF CONTINUOUS FLOW MAN-

UFACTURING THROUGH THE COMBINATION OF

STATISTICAL PROCESS CONTROL AND

CONVENTIONAL COMPUTER

PROCESS CONTROL

By

JOHN ROY ENGLISH
II

Bachelor of Science in Electrical Engineering
University of Arkansas
Fayetteville, Arkansas
1981

Master of Science
University of Arkansas
Fayetteville, Arkansas
1982

Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
DOCTOR OF PHILOSOPHY
December, 1988

IMPROVED QUALITY OF CONTINUOUS FLOW MAN-

UFACTURING THROUGH THE COMBINATION OF

STATISTICAL PROCESS CONTROL AND

CONVENTIONAL COMPUTER

PROCESS CONTROL

Thesis Approved:

K. E. Case
Thesis Adviser

Allen C. Schuermann

Michael H Branson

M. Palmer Terrell

David F. Keeler

Norman N. Durham
Dean of the Graduate College

ACKNOWLEDGMENTS

I wish to express my sincere gratitude to the faculty
and staff of the Industrial Engineering and Management
Department for making our stay at Oklahoma State University
a rewarding and enjoyable experience. I wish to take a
special moment to thank my major advisor Dr. Kenneth Case
for his advice and guidance as I progressed through this
portion of my career. He is gentlemen who brings into his
research and classroom a level of excellence for which few
individuals will ever achieve.

Additionally, I would like to take this opportunity to
thank my committee members for their direction and
assistance during the past three years. Specifically, I
would like to thank Dr. Allen Schuermann, Dr. Mike Branson,
Dr. Palmer Terrell, and Dr. David Weeks, each of which
deserve many thanks.

I would like to offer special thanks to Dr. Marvin
Stone and Ronald Delahoussaye for their guidance in several
phases of this project.

My parents, Roy and Carolyn, have always supported me
in any endeavor. This accomplishment would not have been
achieved without their incredible support. The rest of our
family and our dear friends deserve many thanks.

Of foremost attention is my wife Elizabeth. She has been the essence of loving support and encouragement throughout this and all other endeavors. She has believed in me and my goals without reservation, and has been the basis of any success achieved.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

THE RESEARCH PROBLEM

Introduction

Virtually everyone in American Industry today agrees
that consistent high quality is an essential ingredient, and
possibly the single most important performance measure
associated with manufacturing.

Manufacturing processes may be split into two distinct
categories. The first is production of discrete components
such as electronic parts, automobiles, bolts and in general,
things which may be counted. Statistical process control
(SPC) is now being used extensively throughout these
industries extensively. Research results spanning
approximately 60 years support this effort.

The second category, quite different from the first, is
continuous flow processing (production of chemicals,
petroleum products, synthetic rubber, etc.). Product from
such a process is observed as a continuous stream measured
on a continuous scale such as pounds, gallons, tank cars,
and so on. The application of SPC in the continuous flow
processes is relatively new. This effort has been seriously
pursued for only about five years. The SPC tools used so

frequently for discrete processes are virtually useless or misleading for continuous processes.

In continuous flow processes, conventional computer process control (CCPC) is used extensively. With CCPC, sensors are used to monitor inputs and outputs, supplying data to a process control computer at short intervals of time. Virtually all such data is autocorrelated; that is, the time series of data sampled has a high correlation from one data value to the next. Every minor shift in a process output measure is treated as having intrinsic value, resulting in shifts being made to process inputs as directed through the use of a complex control model. A common result of CCPC has been trending or cycling and overcontrol (overcompensation), resulting in a product that is inconsistent.

On the contrary, SPC requires that independent data be used. As long as sample results are within prescribed statistical bands, called control limits, process variations are observed only as noise, and only when non-random patterns are witnessed on a control chart, is action taken. Therefore, there exists a serious incompatibility between CCPC and SPC. Specifically, this is due to the emergence of overcontrol of a process as a result of using CCPC and the lack of independence between sample observations, or the existence of autocorrelated data.

This research presents the first application of statistical process control within the realm of control

systems. Additionally, an evaluation of the quality (a
measure of the size of variation around a target value) of a
control scheme utilizing various filtering methods is
presented.

Conventional Computer Process Control

Feedback Control is an important technique used in
process control. It involves measuring a response
associated with the process output, comparing it to a target
value (set point), and adjusting a final control element
(e.g. - control valve) in an attempt to keep the output
variable equal to a given target value. The implementation
requires that the process output be sampled at discrete
points in time and the data collected be transmitted to the
computer for the appropriate action of the final control
element. Thus, the computer provides the decision making
for the control loop.

Proportional/Integral/Derivative Control

The difference between the observed process output over
time (c(t)) and the desired target value (r(t)) is known as
the error signal, e(t); therefore, the equation that
describes the error signal is as follows:

$$e(t) = r(t) - c(t)$$

It is the objective of any manufacturing process to
maintain this error signal at zero. This objective is
achieved by implementing a control scheme which algorith-

mically evaluates the error of the process and sends a

message/decision to the final control element. Consider the

following block diagram:
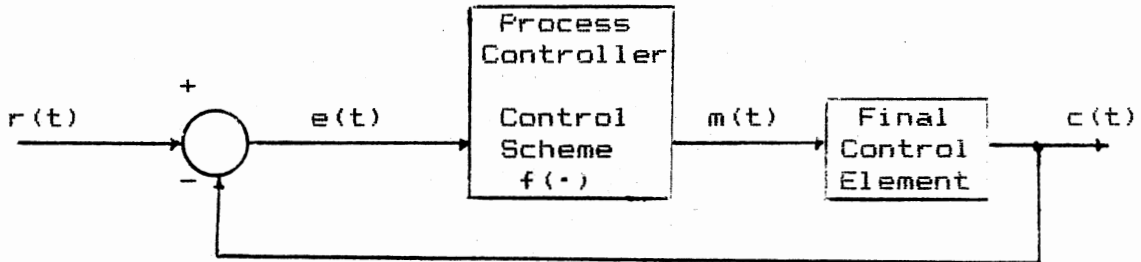
where: r(t) = Process Setpoint
        e(t) = Error Signal
        m(t) = Output of process
               controller or input to
               the final control element
        c(t) = Process Output

Figure 1-1.   Block Diagram of an Automatically Controlled
               Process

From Figure 1-1 above, we see that the relationship between

m(t), the output of the controller, and the error signal is

as follows:

$$m(t) = f(r(t) - c(t))$$

$$= f(e(t))$$

This function $f(\cdot)$ can take on a variety of forms depending

on the response desired to a given process output

disturbance.   There are three fundamental forms for $f(\cdot)$,

commonly known as controller actions, that are utilized

within industry.   They are referred to as: (see Coughanowr

and Koppel, 1965; Smith and Corripio, 1985)

(1)   Proportional Controller (P)

(2)   Proportional-Integral Controller (PI)

(3)   Proportional-Integral-Derivative Controller (PID)

The first controller action, Proportional Controller, is

described by the following equation:

$$m(t) = m + K_c(r(t) - c(t))$$

$$= m + K_c e(t)$$

where: K_c = Controller Gain, Constant

m = Bias Value, the output from the
controller when the error is zero.

The primary disadvantage of the Proportional Controller

is that once the system has reached steady state following a

disturbance to the system, an offset or steady state error

will exist.

In order to combat the existence of the steady state

offset, a second action is introduced.   Specifically, the

integral action is combined with the proportional action to

eliminate the steady state offset.   The mathematical

relationship between the controller output and the error

signal for the PI controller is as follows:

$$m(t) = m + K_c[r(t) - c(t)] + \frac{K_c}{\tau_I} \int [r(t) - c(t)]dt$$

$$= m + K_c e(t) + \frac{K_c}{\tau_I} \int e(t)dt$$

where: τ_I = parameter associated with the integral action of the controller (preset and constant)

In so far as there exists a non-zero error signal, the output of the controller will continue to change until the steady state error is zero. The primary weakness of the PI controller is that the combined proportional and integral actions have no ability to anticipate where the process is heading since the time rate of change of the error is not known. Hence, the derivative action is added to the mathematical relationship describing the output of the controller. This relationship, constituting the PID controller is shown below:

$$m(t) = m + K_c e(t) + \frac{K_c}{\tau_I} \int e(t)dt + K_c \tau_D \frac{de(t)}{dt}$$

where: τ_D = parameter associated with the derivative action of the controller (preset and constant)

Filtering Algorithms

Within the control loop of a given process, transient variations may arise. These variations may be caused by noisy transmitters/receivers, unstable movement of the output variable being monitored, noisy transmission (i.e. - interference), etc. These variations are typically at a much higher frequency than the variation of the process itself. This high frequency variation is called noise.

Filters are introduced into the control loop in an attempt to reject the noise component of the process output

signal; therefore, the objective of a filter is to accept the "true" process signal and reject the noise. Noise rejection requires the additional expense of signal distortion (i.e. - Phase Lag). If the noise component is not rejected, excessive final control element activity will result.

The three standard types of filters that will be utilized in this research will be: (1) The Exponential Filter, (2) The Least Squares Filter, and (3) The Non-Linear Exponential Filter.

Cascaded Control

In many control loops, the phase lag between an input change and the corrected process output is too long. The reasons for this excessive lag or sluggish operation of the primary control loop is due to the large number of components (each with their own lag) placed in series. Consider the block diagram shown in Figure 1-2.

The objective of the control loop is to maintain T_o at a given set point. In Figure 1-2, many components are placed serially; therefore, the phase lag may be excessive. T_H is the variable used to control T_o. If an additional controller is placed in the loop to compare T_H to a set point as determined by the primary control loop, we would reduce the phase lag. Consider the modified block diagram shown below in Figure 1-3.
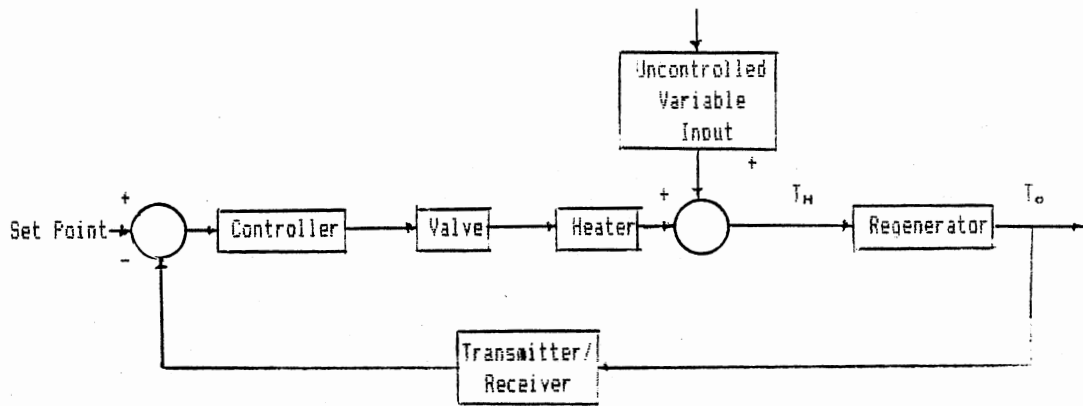
Figure 1-2.   Block Diagram of a Typical Feedback Control
              Loop
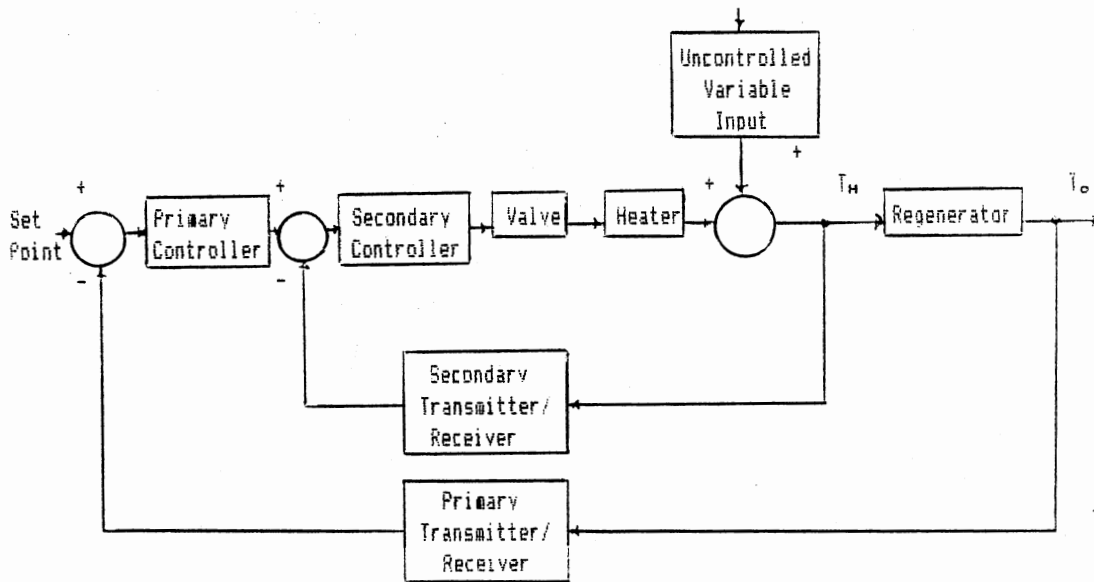
Figure 1-3.   Cascaded Control Scheme

It was shown by Smith and Corripio (1985) that the

cascaded control scheme, as shown above in Figure 1-3, can dramatically reduce process phase lag. Although this type of control appears to be appealing, the secondary loop must be faster than the primary loop (Smith and Corripio, 1985).

Control Charts for Continuous Processes

The samples collected from a continuous type process must be based on a single observation, and the time between successive observations/samples must be large enough to support the assumption of independence between samples. The techniques developed to control such processes are as follows:

(1) Exponentially Weighted Moving Average Charts

(2) Moving Average and Moving Range Charts

(3) Individual and Moving Range Charts

The objective of the control chart as applied to a continuous (or discrete) type process, is to statistically evaluate the presently observed noise by making inference about the process from a sample collected at a specific point in time.

Exponentially Weighted Moving Average

The Exponentially Weighted Moving Average (EWMA) has

been classified as a method for establishing real time
dynamic control (Hunter, 1986). When the EWMA is employed
as a control chart technique, it is assumed that the
individual observations are independent and normally
distributed.

The EWMA is a statistic with the characteristic that it
gives less weight to individual data as they get older. A
plotted point on an EWMA chart can be given a long memory or
a short memory (depending on the age of the observations
included in the EWMA).

The EWMA may be viewed as a way to forecast the next
observation and may be graphed simultaneously with data
appearing on an individuals chart. The EWMA equals the
present predicted value plus α times the present observed
error (observed value minus the previous forecasted value)
where $\alpha=[0,1]$. The smaller the value of α the greater the
influence of the historical data.

The control limits of the EWMA charts are based on the
same premise as other control charts. That is, the upper
and lower control limits are placed at $\pm 3\sigma_{EWMA}$ from the
process average. As in the application of the moving
average chart, if the current EWMA is greater than the UCL
or lower than the LCL, it is usually concluded that the
process is not in a state of statistical control and an
assignable cause exists.

Moving Average and Moving Range

Moving averages are formed from a time series of individual measurements by finding the arithmetic mean of the first n consecutive values and subsequently dropping the oldest value and adding the newest value to form each successive mean. Once a moving average is determined, it is plotted and compared to predetermined control limits. The control limits are placed at $\pm 3\sigma_{xBAR}$ from the process average. If the presently observed moving average is less than the lower control limit (LCL) or greater than the upper control limit (UCL), it is usually concluded that the process is not in a state of statistical control, and a special cause exists. The moving average chart provides the user with the ability to draw inference regarding the present process average.

The moving range chart is utilized concurrently with the moving average chart. The moving range is determined by calculating the range of the first n consecutive values from a time series of individual measurements. The moving range, like the moving average, is determined each time a new observation is collected by including the newest observation and dropping the oldest. The moving range is an estimate of present process variation, and as new moving ranges are determined, the user determines if there has been a significant change in the process variation by comparing each moving range to the predetermined upper and lower control limits.

Individuals and Moving Range

Individuals charts are based on the same principle as most all other control charts. Individual measurements are plotted and compared to predetermined control limits. The UCL and LCL are placed at $\pm 3\sigma$ from the process average. The moving range chart is employed as previously described. Additionally, the sensitivity of the Individuals chart to shifts in the process average is improved by utilizing various runs rules (AT&T Technologies, 1985).

Summary of Research Objectives

Based on the preceding discussion, the objective of this research is as follows:

Objective

To apply statistical process control within the realm of control systems and to evaluate the quality of a control scheme when utilizing various SPC and conventional filtering methods.

This objective above is reached by achieving the following subobjectives:

Subobjectives

1. By designing a set of statistical process control tools and procedures that are applicable as filtering devices within a control loop.

2. By establishing a single loop control scheme (PID) with known parameters which represents a real application. The use of a secondary loop or cascaded scheme is considered and evaluated in the research.

3. By developing analytic and simulation models for the control scheme discussed in 2. with no process noise included. The simulation is developed on the main frame computer utilizing FORTRAN.

4. By evaluating the quality of the output of the control system, discussed above in 2. and 3., utilizing the following conventional filtering methods when noise is added to the system:

    a. Exponential Filter

    b. Least Squares Filter

    c. Non-Linear Exponential Filter

The measure of performance that is used in the evaluation of quality is proportional to the amount of variation of the output about a target value.

5. By evaluating the quality of the output of the control system, discussed above in 2. and 3., utilizing the previously described set of statistical process control tools and procedures as statistically based filtering methods when noise is added to the system. The following list

represents the techniques from which the set
evolved:

    a.   Exponentially Weighted Moving Average
        Charts

    b.   Moving Average/Moving Range Charts

    c.   Individuals/Moving Range Charts

The measure of performance that is used in the
evaluation of quality will be proportional to the
amount of variation of the output about a target
value.

6.   Based on the analyses in 4. and 5. above,
comparisons of the six filtering methods were
made.

Contribution

The combination of statistical process control
techniques and classical control systems theory represents
the foundation on which many years of research may result.
This study will be the first of its kind. Successful
completion will not only meet the objectives described in
the preceding section, but it will also provide an excellent
indicator of the future direction. Additionally, the
evaluation of the improvement of quality as a function of
the filtering methods deployed is of primary interest to
American manufacturing.

In many respects, this research provides a starting
point from which Industrial Engineers may become
fundamentally involved in control systems theory.

CHAPTER II

LITERATURE REVIEW

Introduction

This chapter provides a review of the development of
research relevant to the objectives of this research.
Statistical Process Control (SPC) and Conventional Computer
Process Control (CCPC) have evolved as integral parts of
manufacturing. These two tools have evolved separately,
with little, or no interaction. Due to the independent
development of these fields of research, little literature
exists which utilize SPC within CCPC or visa versa.
Therefore, this chapter is divided into three main sections.

(1) Statistical Process Control

(2) Statistical Process Control of Continuous Processes

(3) Digital Signal Processing/Filtering

Included in the first section will be a brief overview
of the history of statistical process control techniques.
Following that discussion, SPC techniques utilized in
continuous processes will be highlighted. The concluding
section will provide a brief overview of the more common
filtering techniques utilized in the continuous process
industry.

Statistical Process Control

Statistical Process Control as used in this discussic
refers to the use of statistical techniques as tools to
monitor the performance/variability given process. The
primary resource used today is the control chart. Walter .
Shewart introduced the concept of quality control charts :
1924 (Shewart, 1926). Over the past sixty years many
advances have evolved. Statistical process control provic s
manufacturing with the ability to anticipate and/or ident: v
process changes before adverse effects results (Bingham,
1957).

Control charts are based on the premise that regardl: s
of how well a process designed or maintained, a certain
amount of inherent or natural variability will always exi:
(Montgomery, 1985). As discussed in the preceding chapter
the limits of a control chart are based on this natural
variability of a given process. Additionally, runs rules
have been developed or recommended to improve the control
charts ability to detect small shifts in the process aver: s
(see, Weiler, 1953).

The primary performance measure of the control chart·
ability to detect changes in a process is called the Aver: s
Run Length (ARL) or Mean Action Time (MAT). The ARL or Mr
is the average number of samples required to detect a giv:
shift in a process. In Page (1955) and Page (1962), ARL's
were considered for control charts utilizing one of four
rules. Roberts (1958) proposes that if standard control

chart tests are supplemented with another zone test, the
sensitivity to process changes is improved while the number
of type I errors increase. Weindling, Littauer, and Tiago
de Ouveria (1970) determined the MAT for XBAR charts using
runs rule and one point beyond control limits for out of
control conditions. Wheeler (1983) attempted to determine
the power function (inverse of the ARL) for the XBAR chart
using AT&T rules while Champ and Woodall (1987) developed a
method to determine exact ARL's for Shewart control charts
using many different runs rules. It is shown that
supplementary runs rules cause the Shewart charts (xbar
charts) to be more sensitive to small shifts in the mean,
but they are not as sensitive as cumulative sum charts
(Champ and Woodall, 1987).

In a survey of 173 firms (Saniga and Shirland, 1977) it
is shown that Shewhart's original control charts (the Xbar,
R, Sigma, p, c, and u charts), see Shewart (1931), are most
frequently used by industry. The moving average chart is
the second most frequently used in industry, while the
individuals chart is one of the more frequently used control
chart techniques other than those originally listed in the
questionnaire.

Statistical Process Control of

Continuous Processes

The data obtained from well mixed vessels in a continu-

ous flow process is different than data collected from discrete manufacturing processes. The data from continuous flow processes are often interdependent resulting in autocorrelated date (Brooks and Case,1987). Statistical process control emerged as useful tools in the petroleum industry (Walter, 1955), the chemical industry (Bingham, 1957; Bingham, 1958), and the steel industry (Occcasione, 1956). As SFC progressed in its application to the continuous flow process additional tools were utilized/developed.

Correlation analysis was used in a chemical process for changeover efficiency (Hinchen, 1956). Freund (1960) recommended the use of acceptance control charts in continuous flow processes. The use of exponentially smoothed data in control charts is recommended by Wortham (1972). Individuals and moving range charts are often used in continuous flow processes (Montgomery, 1985). Juran (1974) recommends the use of moving average and ranges for continuous processes.

The assumption of each control chart technique is that each sampled value is statistically independent. Unfortunately, statistical independence between sample data points may or may not be valid. Vasilopoulos and Stambouils (1978) modify existing control limits to account for the interdependence of sampled values. They assumed an autoregressive process (AR(2)) and determine appropriate limits. Additionally, samples can be spread far enough

apart in time such that one can reasonably assume independence. Brooks and Case (1987) provide a procedure for checking data independence and three methods for dealing with autocorrelated data (specifically, avoidance, compensation, and control limit adjustment).

It is shown in Neuhardt (1987) that the effect of correlated measurements within the subgroups of an XBAR chart cause an increase the Type I error rate.

Exponentially Weighted Moving Average
Control Charts

Exponentially Weighted Moving Average (EWMA) Control charts or geometrically moving average control charts have emerged since the late fifties (see, Roberts, 1959; Muth, 1960; Freund, 1962; Roberts, 1966). Robinson and Ho (1978) present a numerical procedure for the tabulation of ARL's for the geometric moving average chart. Hunter (1986) points out that the EWMA can be thought of as a compromise between the Shewhart XBAR chart and the cumulative sum chart. Runs rules are not utilized since the EWMA provides a formal use of historical data.

Crowder (1987) proposed the exact average run lengths and the standard deviation of the run lengths for the EWMA chart assuming normal observations. The value obtained were consistent with those obtained by Roberts (1959) and Robinson and Ho (1978). Ng (1987) develops the control limits and necessary factors for four control charts for

EWMA's. Specifically, control charts for sample means, sample ranges, individual measurements, and moving ranges were developed. MAT's for each chart are determined for each chart through the use of computer simulations. Each are compared to the appropriate XBAR, R, Individuals, or Moving Range Chart. It is concluded in Ng (1987) that the MAT for the EWMA for individuals is better than the individuals chart and the EWMA for moving ranges is better than the moving range chart. Sweet (1986) presents equations governing the construction of control charts for both the mean and the standard deviation or variance of a process using exponentially weighted averages.

Moving Average and Moving Range Charts

Gibra (1975) states that the moving average and moving range charts are useful in situations where the time required to measure a certain quality characteristic is so great that repeated observations cannot be considered or the observations become available at a rate so slow that is may not be feasible or possible to form a rational subgroup. The plotted points are not independent. The use of the moving average has the effect of reducing the noise of the system. Successive moving averages of n values have n-1 values in common. Nelson (1983) concludes that the moving averages are therefore positively correlated and the correlation increases with n. A sequence of moving averages

will form an oscillatory series. Roberts (1959) generated tabulated ARL's for the moving average chart.

Individuals and Moving Range Charts

Individuals charts are useful when it is neither easy nor desirable to form rational subgroups (Grant and Leavenworth, 1980; Montgomery, 1985). In Nelson (1982), it is stated that the moving range of two minimizes the inflationary effects on the variability caused by trends and oscillations that may be present, since it measures variations from point to point irrespective of their average level. The control chart for individuals provides the fastest feedback of information and the assumption of normality is most critical.

Crowder (1987) provides a numerical procedure for the tabulation of the ARL for an individuals chart in combination with a moving range chart. Ng (1987), provides simulated data to determine the MAT. In both cases, runs rules were not included. Champ and Woodall (1987) provide ARL's for the XBAR chart including runs rules.

Digital Signal Processing

Digital computers are increasingly being used to perform varied signal processing functions originally achieved with analog equipment. These applications vary from the simplest control systems (as shown in Chapter 1) and filtering techniques (as shown in the following

discussion) to complex control algorithms (i.e.-Adaptive

Control) or complex filtering (i.e.-Kalman Filters), see

Aström and Wittenmark (1984). The following discussion

provides a review of the basic principles in digital signal

processing.

Today the trend in industry is toward the implemen-

tation of control functions using digital computers. A

common characteristic of these installation is that the

control calculations are performed at regular intervals of

time T, the sample time. A recommended rule of thumb, Smith

and Corripio (1985), is that the sample time should be from

one-tenth to one-twentieth of the effective process time

constant. When the sample time is of this order, its effect

can be taken into consideration by adding one-half of the

sample time to the process dead time.

The presence of disturbance in a process is the

principle reason for using control. Aström and Wittenmark

(1984) categorize disturbances into two types: Deterministic

and Stochastic. Disturbances may convey important

information about the process or may be the result of random

or deterministic noise introduced at some point within a

given system. It is the purpose of the digital filter to

eliminate the noise. Exxon (1977) classifies noise into

three types: (1) random (2) exponentially correlated (3)

periodic noise. It is recommended that the sampling period

be approximately one-half the period of the noise. There

are three basic filters as recommended by Exxon (1977) in

aiding in the attenuation of noise. Specifically, these digital filters are the exponential filters, linear least squares filters, and non-linear least squares.

The exponential filter (Exxon, 1977; Stephanopoulos, 1984) is expressed by the following recursive relationship:

$$Y_n = PY_{n-1} + (1-P)X_n$$

where: Y_n = Filtered Output at Sample n

Y_n = Unfiltered Output at Sample n

P = Filter Constant.

Essentially, the exponential filter is a first order lag process. As P increases, more attenuation results at the expense of increased lag (Takahashi, Rabins, and Auslander (1972)).

The least squares filter (Exxon, 1977) is expressed by the following recursive relationship:

$$Y_n = \sum_{i=1}^{N} B_1 X_{n-i+1}$$

where: Y_n = Filtered Output

X_{n-i+1} = Raw Data Point

B_1 = Constant Coefficients

N = Number of Raw Values Used

The least squares filter has very good noise reduction at high frequencies but can result in overshooting and undershooting the true process signal at low frequencies, (Exxon, 1977).

The nonlinear exponential filter is expressed by the following recursive relationship:

$$Y_n = Y_{n-1} + [\min (1, \left|\frac{\Delta X_n}{R\sigma}\right|)] \Delta X_n$$

where: Y_n = Filtered Value at time n

$\Delta X_n = X_n - Y_{n-1}$

R = Filter Parameter

σ = Standard Deviations of Sampled Noise Signal

The nonlinear exponential filter works well in situations where the noise is predictable and works poorly in conditions where noise is erratic (Exxon, 1977).

In addition to the previously described standard filters, common filters such as low-pass, high-pass, band-rejection filters described in textbooks (i.e.-Stanley, 1975) can be used to attenuate periodic noise.

Even with the filtering methods employed above, classical process control (i.e.-PID) assumes that the incoming information contains intrinsic information. That is, action is taken on every point (filtered or unfiltered) which deviates from a target (Brooks, 1986). At Proctor and Gamble, classical controllers are used when noise is not a problem or can be adequately filtered (Maurath, 198X).

Summary

This chapter presents a survey of the literature on problems, contributions, and needs relative to the objectives of this research. This survey demonstrates that research interests exist in the fields of Statistical Process Control and Conventional Computer Process Control. Many SPC techniques have been developed for continuous flow

processes, but none have been applied within the framework of a feedback control system in an attempt to reject the natural variation existing in a continuous flow process.

This survey indicates a need for the following:

1. To evaluate the applicability of control charts for continuous flow type processes within a feedback control loop in an attempt to reject the natural variation of a process.

2. To compare the performance of the control charts with the performance of standard filtering techniques.

3. To hypothesize the potential usefulness of SPC techniques within the entire realm of control systems theory.

CHAPTER III

THE DETERMINATION OF THE

AVERAGE RUN LENGTHS

Introduction

The primary performance measure of a control chart's
ability to detect changes in a process is the Average Run
Length (ARL) or Mean Action Time (MAT). The ARL or MAT is
the average number of subgroups required to detect a given
change in a process. In Page (1955) and Page (1962), ARL's
are considered for control charts utilizing one of four
rules. Roberts (1958) proposes that if standard control
chart tests are supplemented with another zone test, the
sensitivity to process changes is improved while the number
of type I errors increase. Weindling, Littauer, and Tiago
de Oliveira (1970) determine the MAT for XBAR charts using a
runs rule and one point beyond control limits for out of
control conditions. Wheeler (1983) attempts to determine
the power function (inverse of the ARL) for the XBAR chart
using AT&T rules, while Champ and Woodall (1987) develop a
method to determine exact ARL's for Shewhart control charts
using many different runs rules. It is shown that
supplementary runs rules cause the Shewhart charts (XBAR
charts) to be more sensitive to small shifts in the mean.

The data obtained from well mixed vessels in a continuous flow process is different than data collected from discrete manufacturing. The data from continuous flow processes are often interdependent, resulting in autocorrelated data (Brooks and Case, 1987). The use of exponentially smoothed data in control charts is recommended by Wortham (1972); therefore the exponentially weighted moving average (EWMA) chart is often found applied to continuous processes. Individuals and moving range (IMR) charts are often used in continuous flow processes (Montgomery, 1985). Juran (1974) recommends the use of moving average and moving range (MAMR) charts for continuous processes.

The assumption of each control chart technique is that each sampled value is statistically independent. Unfortunately, statistical independence between all sampled data points may or may not be valid for a given continuous type process. For the purposes of the research to follow, independence of sampled data points is assumed.

In statistical process control, the premise on which the control charts are developed is the same for all charts. Specifically, as long as subgroup results are random and within prescribed statistical bands, called control limits, process variations are assumed to be noise or the natural variation of the process, and only when non-random patterns are witnessed or a point falls outside control limits, is action taken. Conventional computer process control (CCPC)

on the other hand assumes that all data points have intrinsic value. That is, every minor shift in a process output measure is treated as having value which often results in trending or over control. Therefore, there exists a serious incompatibility between CCPC and SPC.

The following discussion represents the evaluation of control charts commonly utilized in the statistical control of continuous processes when subjected to various disturbances in the process mean. The process disturbances that will be considered are unit step and linear trend disturbances; both of these disturbances are common in continuous type processes. The ARL is determined for different charts (or chart combinations) for given disturbances using a computer simulation.

Process Disturbance

Unit Step Disturbances

It is assumed that the process variation is normally distributed with mean, μ, and standard deviation, σ. At time 0, the process is subjected to a shift in the process mean, and the magnitude of this shift is $k\sigma$. Therefore, the model describing the process at time t is:

$$Y(t) = (\mu + k\sigma) + \epsilon,$$

where: 1. $(\mu + k\sigma)$ = New process mean
2. $\epsilon \sim N(0, \sigma^2)$

The ARL (to be determined later) represents the average number of subgroups required to detect a shift in the process average of magnitude $k\sigma$.

Linear Trend Disturbances

As stated previously, it is assumed that the process variation is normally distributed with mean, μ, and standard deviation, σ. At time 0, the process average begins to increase in magnitude of kσ units every sampling period. Therefore, the model that describes the process after time zero is as follows:

$$Y(t) = (\mu + kT\sigma) + \epsilon$$

where: 1. $(\mu + kT\sigma)$ = New process mean
at the Tth sample
2. $\epsilon \sim N(0, \sigma^2)$

Exponentially Weighted Moving
Average Charts

The exponentially weighted moving average (EWMA) has been classified as a method for establishing real time dynamic control (Hunter, 1986). Like the previously discussed charts, it is assumed that the individual observations are independent and normally distributed. The EWMA may be viewed as a way to forecast the next observation. The EWMA equals the present predicted value plus α times the present observed error (observed value minus the previous forecasted value) where α=[0,1]. The smaller the value of α the greater the influence of the historical data.

The control limits of the EWMA charts are based on the same premise as other control charts. The upper and lower control limits are placed as follows:

$$\text{Upper Control Limit} = \mu + 3\sigma \sqrt{(\alpha/(2-\alpha))}$$
$$\text{Center Line} = \mu$$
$$\text{Lower Control Limit} = \mu - 3\sigma \sqrt{(\alpha/(2-\alpha))}$$

As is the case for the MA and MR charts, it is usually concluded the the process is not in a state of statistical control if the current EWMA is greater than the upper control limit or less than the lower control limit. Runs rules are not applicable since the current EWMA takes into account historical information, thereby rendering each plotted point not independent from other plotted points.

Moving Average and Moving Range Charts

Moving averages are formed from a time series of individual measurements by finding the arithmetic mean of the first n consecutive values and subsequently dropping the oldest value and adding the newest value to form each successive man. Once a moving average is determined, it is plotted and compared to predetermined control limits. The control limits are placed as follows:

$$\text{Upper Control Limit} = \mu + 3\sigma/\sqrt{n}$$
$$\text{Center Line} = \mu$$
$$\text{Lower Control Limit} = \mu - 3\sigma/\sqrt{n}$$

where: n is the number of samples in a subgroup

If the presently observed moving average (MA) is less than the lower control limit or greater than the upper control limit, it is usually concluded that the process is not in a state of statistical control, and a special cause exists. The moving range chart is utilized concurrently

with the moving average chart. The moving range is determined by calculating the range of the first n consecutive values from a time series of individual measurements. The moving range (MR), like the moving average, is determined each time a new observation is collected by including the newest observation and dropping the oldest. The upper and lower control limits for the moving range chart are placed at $\pm 3\sigma_{MR}$ from the average MR. In Nelson (1982), it is stated that the moving range of two minimized the inflationary effects on the variability caused by trends and oscillations that may be present, and in Nelson (1983), it is concluded that the moving averages are positively correlated and the correlation increases as n increases. Therefore, for the purposes of this research, subgroups of size two (n=2) will be used for the determination of the MA and MR.

Individuals and Moving Range Charts

Individuals charts are based on the same principle as most all other control charts. Individual measurements are plotted and compared to predetermined control limits. The upper and lower control limits are places as follows:

$$\text{Upper Control Limit} = \mu + 3\sigma$$
$$\text{Center Line} = \mu$$
$$\text{Lower Control Limit} = \mu - 3\sigma$$

The sensitivity of the Individuals chart to changes in the process is improved by utilizing various runs rules for the determination of out of control conditions. One of the

most common set of runs rules are those recommended by AT&T

Technologies (1985). These are as follows:

(1) A single point falls outside of the 3σ limits.
(2) Two out of three successive points fall between
    $+2\sigma$ and beyond from the process average or
    between -2σ and beyond from the process average
(3) Four out of five successive points fall between
    $+1\sigma$ and beyond from the process average or
    between -1σ and beyond from the process average
(4) Eight successive points fall on a given side of
    the center line

The simulation to follow utilizes the above described

rules for the individuals chart. The moving range chart of

subgroup size two is utilized as previously described.

Results

The ARLs were determined for each control chart or

control chart combination for a given change in the process

average (shift or linear trend) for different values of k.

With the exception of the EWMA chart subjected to unit step

increase in the process average, all ARLs were determined by

a computer simulation. Each simulation is the result of

10,000 trials, where each trial represents the number of

samples collected until a process change is detected with a

given control chart. Tables 3-1, 3-2, and 3-3 below provide

the ARLs for the EWMA chart, MAMR combination and the IMR

combination, respectively, when the process mean is

subjected to a unit step increase (of magnitude $k\sigma$). The

ARLs listed in Table 3-1 for the EWMA chart are

representative of the theoretical results as presented in

Crowder (1987).

Tables 3-4, 3-5, and 3-6 present the ARLs when the process average is subjected to a linear trend. These results are based on the same type of simulation as previously described for the EWMA chart, the MAMR combination and the IMR combination, respectively. As described previously, the increase in the process average between successive samples is constant at $k\sigma$ each sample. The listings of the programs used to determine the ARLs in Tables 3-2, 3-3, 3-4, 3-5, and 3-6 are included in Appendix A.

TABLE 3-1

ARLs FOR EXPONENTIALLY WEIGHTED MOVING AVERAGE CHART
– UNIT STEP DISTURBANCE (FROM CROWDER (1987))

	----------k – Number of σ increase in process mean----------						
α	0.00	0.25	0.50	1.00	2.00	3.00	4.00
0.10	842.15	144.74	37.41	11.38	4.67	3.05	2.30
0.25	502.90	171.09	48.45	11.15	3.62	2.26	1.73
0.50	397.56	208.54	75.35	15.74	3.47	1.87	1.31
0.75	374.50	245.76	110.95	25.64	4.15	1.79	1.20
1.00	370.40	281.15	155.22	43.89	6.30	2.00	1.19

TABLE 3-2

ARLs FOR MOVING AVERAGE AND MOVING RANGE CHART COMBINATION
– UNIT STEP DISTURBANCE (BASED ON COMPUTER SIMULATIONS)

–––––––––k – Number of σ increase in process mean––––––––––

0.0	0.1	0.2	0.3	0.4	0.5	1.00	2.00	3.00	4.00

Resulting ARLs,

99.27	96.17	90.25	82.27	71.95	60.74	20.70	3.77	1.91	1.37

TABLE 3-3

ARLs FOR INDIVIDUALS USING AT&T RUNS RULES AND MOVING RANGE
CHART COMBINATION – UNIT STEP DISTURBANCE
(BASED ON COMPUTER SIMULATIONS)

–––––––––k – Number of σ increase in process mean––––––––––

0.0	0.1	0.2	0.3	0.4	0.5	1.00	2.00	3.00	4.00

Resulting ARLs,

59.26	55.34	47.85	38.78	30.64	24.05	9.17	3.18	1.75	1.22

TABLE 3-4

ARLs FOR EXPONENTIALLY WEIGHTED MOVING AVERAGE CHART —
LINEAR TREND DISTURBANCE (BASED ON
COMPUTER SIMULATIONS)

------k - Number or σ increase/sample in process mean-------

α	0.0	0.1	0.2	0.3	0.4	0.5	1.00	2.00	3.00	4.00
0.20	567.37	13.23	8.63	6.76	5.72	5.03	3.40	2.31	1.98	1.84
0.40	415.96	13.78	8.61	6.58	5.43	4.73	3.09	2.07	1.77	1.41
0.60	380.93	14.94	9.11	6.84	5.61	4.80	3.03	1.97	1.62	1.24
0.80	370.71	16.45	9.89	7.34	5.95	5.07	3.10	1.95	1.53	1.18
1.00	368.42	18.40	11.64	8.11	6.53	5.53	3.28	1.96	1.50	1.16

TABLE 3-5

ARLs FOR MOVING AVERAGE AND MOVING RANGE CHART COMBINATION
— LINEAR TREND DISTURBANCE (BASED ON COMPUTER SIMULATIONS)

------k - Number of σ increase/sample in process mean-------

0.0	0.1	0.2	0.3	0.4	0.5	1.00	2.00	3.00	4.00
Resulting ARLs,									
99.27	14.89	9.32	6.99	5.72	4.89	3.06	2.05	1.75	1.38

TABLE 3-6

ARLs FOR INDIVIDUALS USING AT&T RUNS RULES AND MOVING RANGE
CHART COMBINATION – LINEAR TREND DISTURBANCE (BASED ON
COMPUTER SIMULATIONS)

------k – Number of σ increase/sample in process mean-------

0.0	0.1	0.2	0.3	0.4	0.5	1.00	2.00	3.00	4.00

Resulting ARLs,

59.26	11.77	7.93	6.30	5.34	4.68	3.27	3.09	2.58	1.43

Summary

As indicated in the tables for ARLs for different control charts subjected to various disturbances in the process average, the ARL is dependent upon the type and magnitude of disturbance. It is noted that the IMR combination provides the greatest amount of strength in detecting both unit step disturbances and linear trend disturbances. But it is essential that the AT&T runs rules be utilized in order that this strength might be utilized.

It is observed that in the situation where no change in the process average has occurred, the IMR combination will result in the largest number of false alarms. Furthermore, the performance of the MAMR combination is better than its EWMA counterpart for small unit step disturbances in the process average regardless of the value of α. Once larger unit step shifts are encountered, the EWMA chart is preferred if small α values are utilized.

If linear trends are encountered, the EWMA chart would be preferred over its MAMR combination counterpart as long as small α values are used.

CHAPTER IV

THE MODEL

Introduction

If a chemical reaction occurs in a system, the number
of moles of an individual component will increase if it is a
product of the reaction or decrease if it is a reactant.
The component continuity equation for the jth chemical
species of the system says

$$\begin{pmatrix} \text{Flow of moles of jth} \\ \text{component into system} \end{pmatrix} - \begin{pmatrix} \text{flow of moles of jth} \\ \text{component out of system} \end{pmatrix}$$

$$+ \begin{pmatrix} \text{rate of formation of moles of jth} \\ \text{component from chemical reaction} \end{pmatrix} = \begin{pmatrix} \text{time rate of change} \\ \text{of jth component} \\ \text{inside system} \end{pmatrix}$$

The units of this equation are moles of j per unit time.

One component continuity equation for each component
can be written for each component in the system. If there
are J components there are J component continuity equations
for any one system. However, there is one total mass-
balance equation, and these J component balances are not all
independent, since the sum of all the moles times their
respective molecular weights equals the total mass.

In the model developed in the following discussion,
there is a component A that reacts irreversibly and at a
specific reaction rate k to form a product, component B.

This reaction occurs in a continuous stirred-tank reactor (CSTR).

Physical Description of the Model

Consider a tank of a perfectly mixed liquid in which a chemical reaction takes place in the liquid in the tank. This system is a CSTR (continuous stirred-tank reactor) as shown in Figure 4-1.
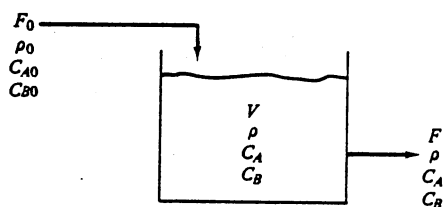
Figure 4-1.   CSTR

A component A reacts irreversibly and at a specific reaction rate k to form a product, component B.

$$A \xrightarrow{\quad k \quad} B$$
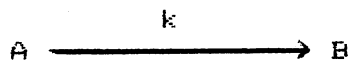
Let the concentration of component A in the inflowing or feed stream be C_{AO} (moles of A/ft^3) and in the reactor C_A. Assuming a simple first-order reaction, the rate of consumption of reactant A per unit volume will be directly

proportional to the instantaneous concentration of A in the
tank. Filling in the terms of the previously described
continuity equation for a component balance on reactant A.

Flow of A into system   = F_oC_{AO} (ft³/sec)(moles A/ft³)
Flow of A out of system = FC_A (ft³/sec)(moles A/ft³)
Rate of formation of A from reaction = $-VkC_A$
                                        (ft³)(1/sec)(moles A/ft³)
Time rate of change of A inside tank = $\frac{d\ (VC_A)}{dt}$

Combining,

$$\frac{d\ (VC_A)}{dt} = F_oC_{AO} - FC_A - VkC_A$$

The units of this component continuity equation are
moles of A/sec. The left-hand side of the equation is the
dynamic term. The first two terms on the right-hand side
are known as the convective (due to bulk flow) terms. The
last term is the generation (due to diffusion) term. Since
the system is a mixture of two components, A and B, another
component continuity equation for component B could be
written as,

$$\frac{d\ (VC_B)}{dt} = F_oC_{BO} - FC_B + VkC_B$$

The system sketched below in Figure 4-2 is a simple
extension of the CSTR considered previously. Product B is
produced and reactant A is consumed in each of the three
perfectly mixed reactors by a first-order reaction occurring
in the liquid. The temperatures and volumes of the three
tanks can be different, but both the temperatures and the
liquid volumes are assumed to be constant (isothermal and

constant holdup). Density is assumed constant throughout

the system.
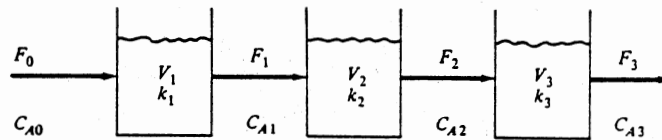
Figure 4-2. Series of CSTR's

If the volume and density (p) of each tank are con-

stant, the total mass in each tank is constant. Thus the

total mass balance equation for the first reactor is,

$$\frac{d(pV_1)}{dt} = pF_0 - pF_1 = 0$$

or

$F_1 = F_0$

Likewise total mass balances on tanks 2 and 3 give

$F_3 = F_2 = F_1 = F_0 = F$

where F is defined as the throughput (ft^3/sec). For a more

in-depth discussion of mass balance equations, see either

Coughanowr and Koppel (1965) or Luyben (1973).

The amounts of reactant A and product B in each tank

are to be monitored, so component continuity equations are

needed. However, since the system is binary (only two

components, A and B) and the total mass of material in each
tank is known, only one component continuity equation is
required. Either B or A can be used. If A is arbitrarily
chosen, the equations describing the dynamic changes in the
amounts of reactant A in each tank are (with units moles of
A/sec):

$$\frac{d\ (VC_{A1})}{dt} = F(C_{A0} - C_{A1}) - V_1 k_1 C_{A1}$$

$$\frac{d\ (VC_{A2})}{dt} = F(C_{A1} - C_{A2}) - V_2 k_2 C_{A2} \qquad (4-1)$$

$$\frac{d\ (VC_{A3})}{dt} = F(C_{A2} - C_{A3}) - V_3 k_3 C_{A3}$$

The specific reaction rates k_n are given by the
Arrhenius equation (see Luyben, 1973) below.

$$k_n = \alpha e^{-E/RT_n} \qquad n=1,2,3$$

where: n = Stage Number

If the temperatures in the reactors are different, the k's
are different.

The volumes V_n can be pulled out of the time derivative
because they are constant. The flows are all equal to F but
can vary with time. An energy equation is not required
because an isothermal operation has been assumed.

The three first-order, nonlinear, ordinary differential
equations given above are the mathematical model of the
system. The parameters that must be known are V_1, V_2, V_3,
k_1, k_2, and k_3. The variables that must be specified before
these equations can be solved are F and C_{A0}. "Specified"
does not mean that they must be constant. They can be time-

variable, but they must be known or given functions of time. The initial conditions of the three concentrations must also be known.

The system as defined by the differential equations above represent the model upon which the research to follow is based. If the throughput, F, is constant and the volumes and temperatures are the same in all three tanks, equations (4-1) can be written as,

$$\frac{dC_{A1}}{dt} + (k + 1/\tau) \, C_{A1} = (1/\tau) \, C_{AO}$$

$$\frac{dC_{A2}}{dt} + (k + 1/\tau) \, C_{A2} = (1/\tau) \, C_{A1} \qquad (4-2)$$

$$\frac{dC_{A3}}{dt} + (k + 1/\tau) \, C_{A3} = (1/\tau) \, C_{A2}$$

where $\tau = V/F$

There is only one forcing function or input variable into the system, C_{AO}. The differential equations in (4-2) above can be rewritten as,

$$\frac{dC_{A1}}{dt} = (1/\tau) \, (C_{AO} - C_{A1}) - kC_{A1}$$

$$\frac{dC_{A2}}{dt} = (1/\tau) \, (C_{A1} - C_{A2}) - kC_{A2} \qquad (4-3)$$

$$\frac{dC_{A3}}{dt} = (1/\tau) \, (C_{A2} - C_{A3}) - kC_{A3}$$

The above described system is controlled by a conventional feedback control system utilizing proportional/integral/ derivative (PID) control. PID controllers are used in processes with long time constants. Typical of these processes are temperature and concentration loops (see Smith

and Corripio, 1985). The specific tuning criterion will be based on a decay ratio of one-fourth where the decay ratio is the ratio of the amplitudes of two successive oscillations. Ziegler and Nichols (1942) provide formulas for the determination of the tuning parameters of the PID controller once the ultimate gain and frequency are known. The block diagram of the system is shown below in Figure 4-3. The feedback controller and the system are incorporated into the block diagram.
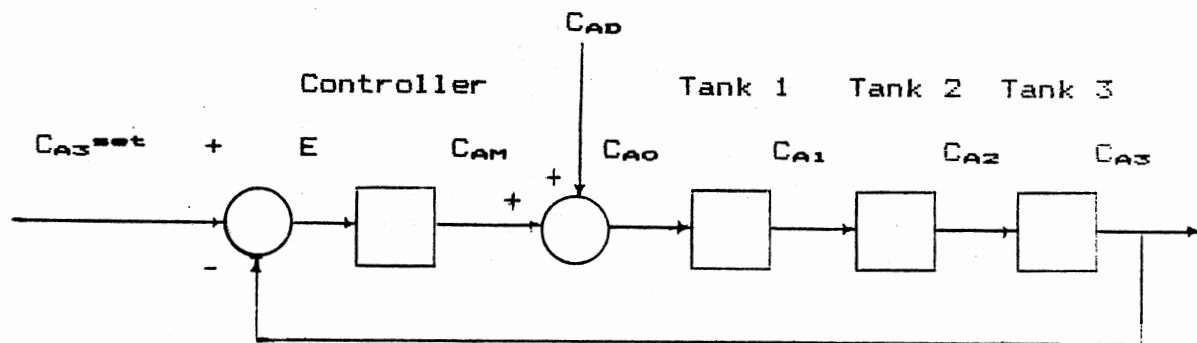
Figure 4-3. Block Diagram Representation of Model

The set of equations that define the process are as follows,

$$\frac{dC_{A1}}{dt} = (1/\tau)(C_{AO} - C_{A1}) - kC_{A1}$$

$$\frac{dC_{A2}}{dt} = (1/\tau)(C_{A1} - C_{A2}) - kC_{A2}$$

$$\frac{dC_{A3}}{dt} = (1/\tau)(C_{A2} - C_{A3}) - kC_{A3}$$

$$C_{AO} = C_{AD} + C_{AM}$$

$$C_{AM} = 0.8 + K_c(E + \frac{1}{\tau_I}\int Edt + \tau_D\frac{dE}{dt})$$

$$E = C_{A3}^{set} - C_{A3}$$

(4-4)

Determination of Tuning Parameters

From the equations in (4-4) and known parameters of the process, the required tuning parameters for the PID controller may be determined utilizing the ultimate gain and frequency and the Ziegler and Nichols tuning formulas (see Ziegler and Nichols, 1942). Taking the Laplace transformation of each of the equations, the block diagram and transfer functions are determined and are shown in Figure 4-4 and equations (4-5) below, respectively.
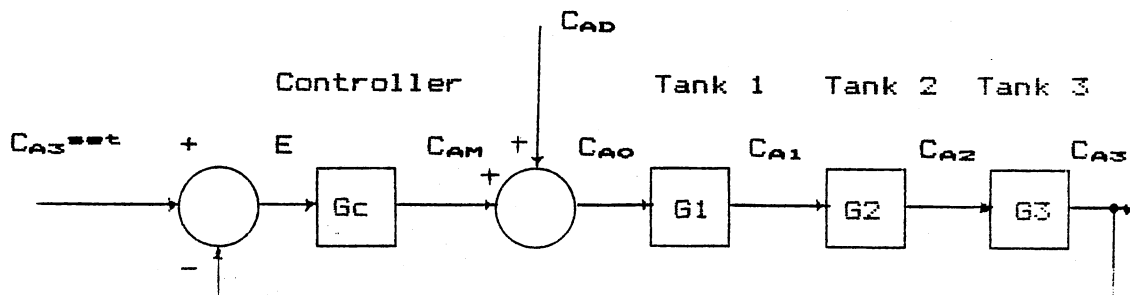
Figure 4-4. Block Diagram Representation of Model, Laplace Domain

where,

$$G_c(s) = K_c(1 + 1/(\tau_I s) + \tau_D s)$$

(4-5)

$$G_1(s) = G_2(s) = G_3(s) = \frac{1/\tau}{s + 1/\tau + k}$$

Utilizing Block Diagram Algebra,

$$\frac{C_{AS}(s)}{C_{AD}(s)} = \frac{\left(\frac{1/\tau}{s+1/\tau+k}\right)^3}{1 + K_c(1+1/(\tau_I s)+\tau_D s)\left(\frac{1/\tau}{s+1/\tau+k}\right)^3}$$

The resulting characteristic equation is,

$$1 + K_c(1+1/(\tau_I s)+\tau_D s)\left(\frac{1/\tau}{s+1/\tau+k}\right)^3 \quad (4-6)$$

To determine the ultimate gain and frequency, the characteristic equation (4-6) is set equal to zero, the derivative and integral actions are removed, and direct substitution ($s=jw_u$, $K_c=K_{cu}$) is used. The resulting equation is as follows,

$$= -jw_u^3\tau^3 -w_u^2(3\tau^2+3k\tau^3) + jw_u(3\tau+6k\tau^2+3k^2\tau^3) + 1 + 3k\tau + 3k^2\tau^2 + k^3\tau^3 + K_{cu} = 0$$

Combining the imaginary parts

$$-w_u^3\tau^3 + w_u(3\tau + 6k\tau^2 + 3k^2\tau^3) = 0$$

Combining the real parts

$$-w_u^2(3\tau^2 + 3k\tau^3) + 1 + 3k\tau + 3k^2\tau^2 + k^3\tau^3 + K_{cu} = 0$$

Assuming $\tau=2$ min and $k=0.5$ min^{-1} and solving,

$$w_u = \sqrt{3} \text{ Rad/min}$$

$$K_{cu} = 64$$

The ultimate period (as required by the Ziegler-Nichols tuning formulas) is,

$$T_u = 2\pi/w_u = 3.627598728 \text{ min}$$

The tuning parameters are set by the formulas described by
Ziegler and Nichols (see Ziegler and Nichols, 1942). The
following calculations provide the values at which the
controller will be set for this model,

Controller Gain = K_c = $K_{cu}/1.7$ = 37.647

Integral Time   = τ_I = $T_u/2$ = 1.814 min/repeat

Derivative Time = τ_D = $T_u/8$ = 0.453 min

Analytical Solution to a
Unit Step Disturbance

With the known parameters of the controller and the
system itself and the type of disturbance applied to the
process, it is possible to determine the analytical solution
to the problem. For the problem, the following values are
assumed,

τ_I = 1.814

τ_D = 0.453

K_c = 37.647

τ = 2.0

k   = 0.5

C_{AD} = 0.6u(t)   where u(t) = $\begin{cases} 1 & \text{for } t \geq 0 \\ 0 & \text{for } t < 0 \end{cases}$

Utilizing the block diagram of Figure 4-4 and block diagram
algebra, the resulting process transfer function is

$$\frac{C_{AS}(s)}{C_{AD}(s)} = \frac{0.125s}{s^4 + 3s^3 + 5.131761357s^2 + 5.705875s + 2.59419705}$$

Given that the Laplace transformation of C_{AD} is 0.6/s, the response in the Laplace domain is,

$$C_{A3}(s) = \frac{0.075}{s^4 + 3s^3 + 5.131761375s^2 + 5.705875s + 2.59419705}$$

The roots of the denominator are,

$r_1 = -1.0694687$

$r_2 = -1.1228866$

$r_3 = -0.40382239 + j1.4132065$

$r_4 = -0.40382239 - j1.4132065$

Thus using partial fraction expansion, the equivalent expression for C_{A3} in the Laplace domain is,

$$C_{A3}(s) = \frac{0.575363535}{s + 1.0694687} - \frac{0.558436251}{s + 1.1228866} -$$

$$- \left(\frac{0.008463642 - j0.006567656}{s + 0.40382239 - j1.4132065} + \frac{0.008463642 + j0.006567656}{s + 0.40382239 + j1.4132065} \right)$$

Taking the inverse Laplace transformation,

$$C_{A3}(t) - C_{A3,ss} =$$

$$0.575363535e^{-1.0694687t} - 0.558436251e^{-1.1228866t} -$$

$$-e^{-0.40382239t}(2(0.008463642)\cos(1.4132065t) -$$

$$2(-0.006567656)\sin(1.4132065t))$$

where: $C_{A3,ss}$ is the steady state response of $C_{A3}(t)$

This function is plotted over time in Figure 4-5 below.
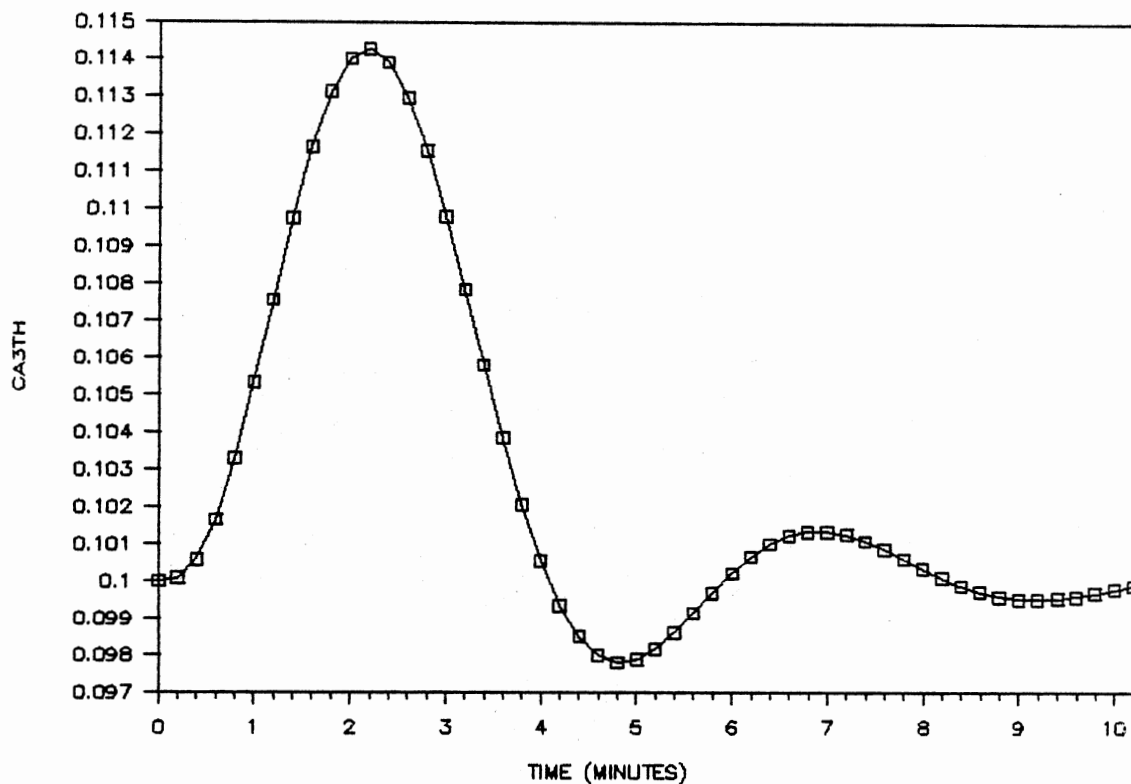
Figure 4-5.   Response of Three Serial CSTR's, Unit Step
              Disturbance

Numerical Model

In this research, the analysis is not based on a system

in which it is reasonable to assume that all signals/

measurements are collected with no error.   Therefore, it is

necessary to construct a simulation of the entire process.

The simulation of the differential equations is performed

using fourth order Runga Kutta integration (for a complete

explanation of Runga Kutta see Hultquist (1988) or Jaluria

(1988)).   The validation of the numerical simulation is

based on the comparison of the analytical solution

determined in the previous section and the results of the numerical simulation.

Prior to the comparison, it is important to recognize the analytical solution presented in the previous section is based upon the use of perturbation variables. That is, the resulting solution is the departure from the steady-state values over time. It is necessary to determine the appropriate steady state condition so that the appropriate initial conditions are determined. The steady state conditions are determined by starting the numerical simulation with no input disturbance and allowing the entire process to stabilize. These resulting values are best presented by viewing each of the dynamic variables over time. These plots are shown below in Figure 4.6. From Figure 4-6 it is easy to recognize the steady state conditions for each of the dynamic variables. Specifically,

$C_{AM,ss} = 0.8$

$C_{A1,ss} = 0.4$

$C_{A2,ss} = 0.2$

$C_{A3,ss} = 0.1$
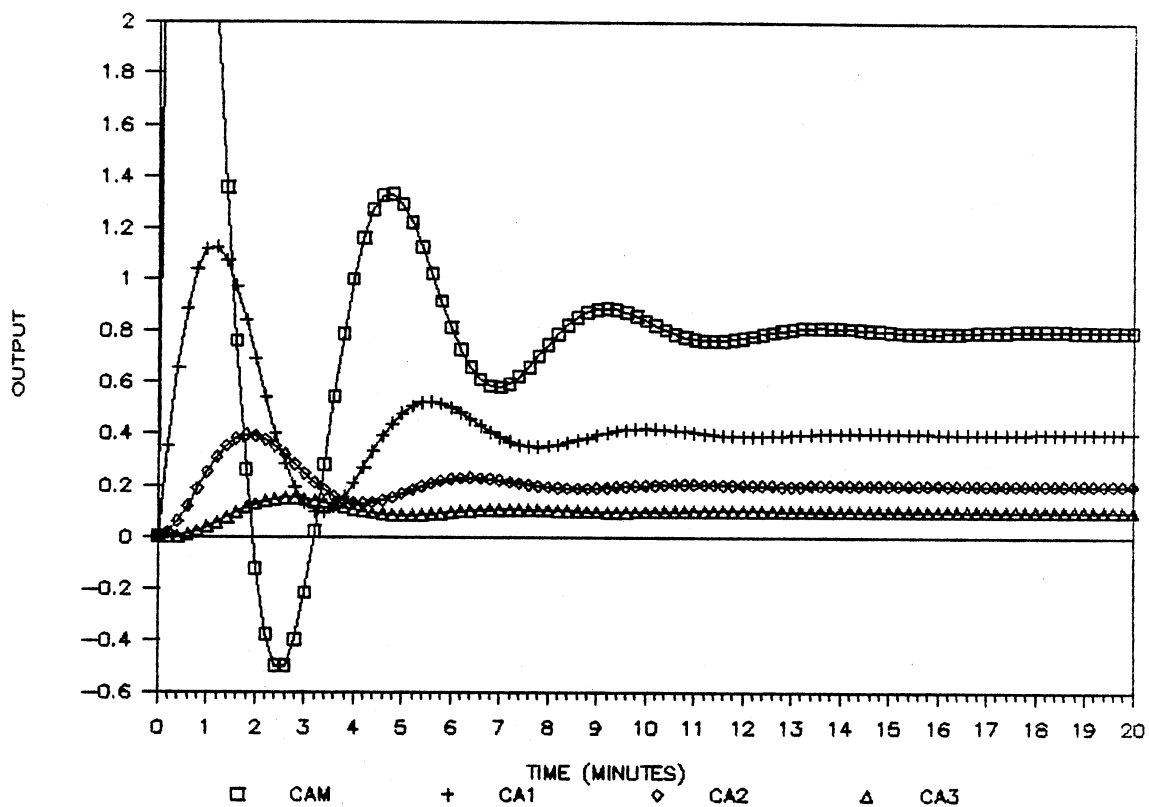
Figure 4-6. Determination of Steady State Conditions

Utilizing the steady state values of the dynamic variables as determined above as initial conditions, the numerical simulation will provide a response identical to that of the analytical solution. The results are plotted with the analytical solution in Figure 4-7 below.
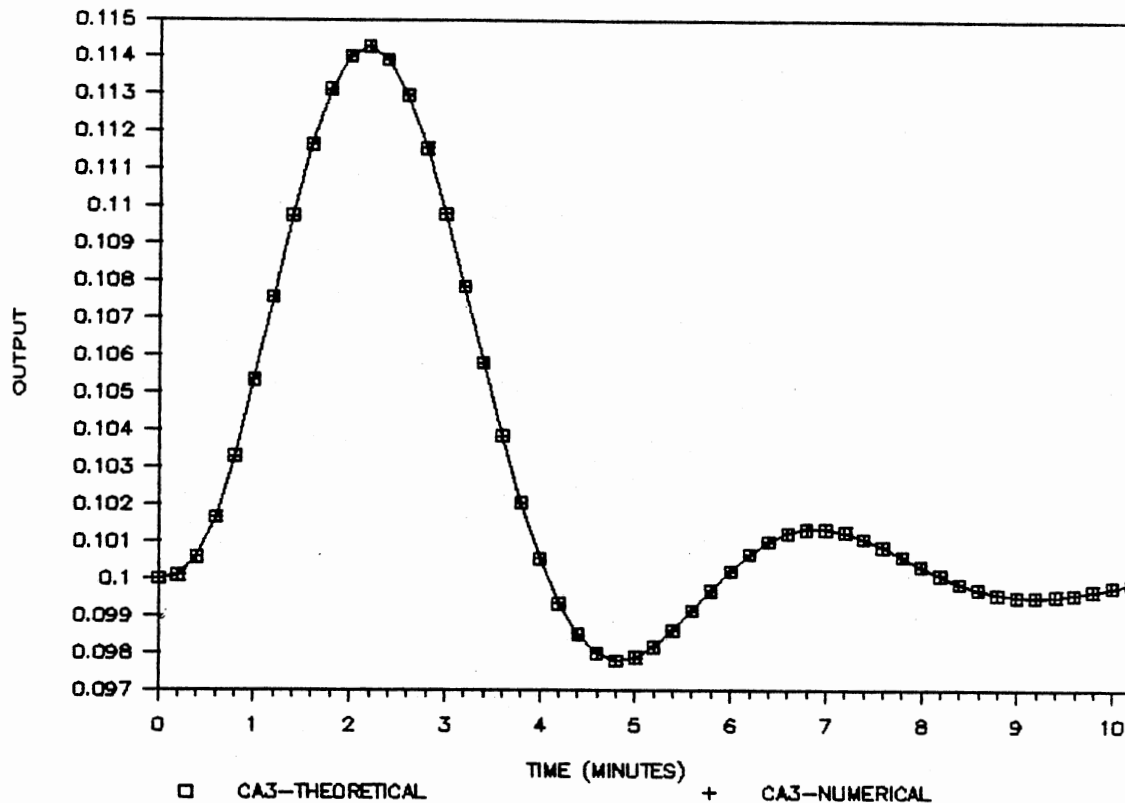
Figure 4-7.   Analytical Response and Numerical Simulation of
the Output of Three Serial CSTR's

Summary

Based on these results, it was determined that the
numerical solution was correctly modeling the process. The
intent of this part of the work is not to provide numerical
results for a problem that can be solved analytically, but
to provide a benchmark on which the following research may
be based.   At this point, it is no longer assumed that a
perfect signal is available for monitoring the process.
Specifically, noisy conditions will exist henceforth, and
various filtering devices will be utilized in an attempt to

reject/attenuate the noise component of the input signal to
the controller.

CHAPTER V

THE SYSTEM

Introduction

The following discussion presents the implementation of
the model as discussed in the preceding chapter. The
numerical system previously developed is utilized and is
augmented by adding features such as 1) uncertainty in the
feedback loop, 2) various filtering algorithms, and
3) various process input disturbances of various magnitudes.
This chapter provides insight regarding the type of the
noise found in the control loop, the filtering algorithms
used (which attempt to reject or attenuate the noise
component of the signal), the type of the input disturbance
found in the process, the measures of performance to be used
in the analysis, the construction of the computer system
used to model the plant, and a brief description of the
validation of the computer system.

The Noise

The noise in the plant is assumed to be found in the
feedback control loop. This assumption is based on the fact
that in many of the noisy conditions existing in feedback

control schemes, the existence of uncertainty in the signal

stem from a noisy transmitter or measurement error (see

Exxon 1977). The noise, N, is assumed to be normally

distributed with mean zero and variance, σ^2 or represented

symbolically as shown below in (5-1).

Noise of the
Feedback   = $N_{\bullet} \sim N(0, \sigma^2)$ (5-1)
Control Loop

It is further assumed that the variance of the noise is

known and is used to implement the random component of the

signal in the feedback control loop.

Filtering Algorithms

The filtering algorithms used in this research are the

exponential (EXP) filter, least squares (LS) filter,

nonlinear exponential (NL) filter, moving average and moving

range (MAMR) filter, individuals and moving range (IMR)

filter, and exponentially weighted moving average (EWMA)

filter. Each of the filtering algorithms are described

below along with any special requirements for their

implementation in a filtering application.

The Exponential Filter

The exponential filter (Exxon, 1977; Stephanopoulos,

1984) is expressed by the following recursive relationship:

$$Y_n = PY_{n-1} + (1-P)X_n \qquad (5-2)$$

where: Y_n = Filtered Output at Sample n

X_n = Unfiltered Output at Sample n

P = Filter Constant, [0,1]

The exponential filter is a first order lag process. As P increases, more attenuation results at the expense of increased lag. For the purposes of this research, the values of P will be 0.0 and 0.8. This range between the P values will provide a sufficient range such that the difference due to different P values will be observed if it exists at all.

The Least Squares Filter

The least squares filter (Exxon, 1977) as expressed by the following relationship:

$$Y_n = \sum_{i=1}^{N} B_i \, X_{n-i+1} \qquad (5-3)$$

where: Y_n = Filtered Output

X_{n-i+1} = Raw Data Point

B_i = Constant Coefficients (Exxon, 1977)

N = Number of Raw Values Used

The least squares filter has very good noise reduction at high frequencies but can result in overshooting and undershooting the true process signal at low frequencies.

The values of N that are used for this research are 3 and 19. This range between the N values will provide a sufficient range such that the difference due to different N values will be observed if it exists at all.

The Nonlinear Exponential Filter

The nonlinear exponential filter is expressed by the following recursive relationship:

$$Y_n = Y_{n-1} + [min (1, \left|\frac{\Delta X_n}{R\sigma}\right|)] \Delta X_n \qquad (5-4)$$

where: Y_n = Filtered Value at time n

$\Delta X_n = X_n - Y_{n-1}$

R = Filter Parameter

σ = Standard Deviation of the Noise Signal

The nonlinear exponential filter works well in situations where the noise is predictable and works poorly in conditions where noise is erratic (Exxon, 1977). The values of R that are used for this research are 4 and 7. This range between the R values will provide a sufficient range such that the difference due to different R values will be observed if it exists at all.

Statistical Process Control Filters

The assumption of each of the statistical process control (SPC) filters, the EWMA, MAMR, and IMR filters, is

that each sampled value is statistically independent.
Unfortunately, statistical independence between sampled data
points will not be valid unless sufficient time has passed
such that independence can be reasonably assumed. In Brooks
and Case (1987), it is noted that a good general rule is to
ensure sampling intervals of at least twice the response
time of the process. The response time of the process is
the sum of the effective time constant and dead time of the
process.

The plant to be modeled is a fourth order system. In
Smith and Corripio (1985), it is shown that a higher order
system may be approximated by a first order process plus
dead time (FOPDT). Their procedure requires that we
determine the point in time at which the open loop response
meets 28.3 and 63.2 per cent of the final steady state
response. The times are known as t_1 and t_2, respectively.
The values of t_1 and t_2 are 1.85075 and 3.2577 minutes,
respectively. Figure 5-1 shows the relationship between
t_1 and t_2 and the open loop response of the process.

Figure 5-1. Three Serial CSTR's, Open Loop System
             Determination of the Response Time

Following the procedure as outline in Smith and

Corripio (1985), the following relationships are known:

Effective Time Constant = $\tau \approx 3/2 \ (t_2 - t_1)$ = 2.11 minutes

Dead Time $= t_o \approx t_2 - \tau$ = 1.15 minutes

The resulting FOPDT approximation in the Laplace domain is,

$$G(s) \approx .125e^{-1.15s}/(2.11s + 1).$$

Applying a unit step forcing function to the open loop plant, the resulting output in the Laplace domain is,

$$C_{A3,open}(s) \approx .125e^{-1.15s}(1/s - 1/(s + 1/2.11)).$$

Taking the inverse Laplace transformation,

$$C_{A3,open}(t) \approx .125u(t-1.15)[1 - e^{-(t-1.15)/2.11}]$$

where: $u(x) = \begin{cases} 1 & \text{for } x \geq 0 \\ 0 & \text{else.} \end{cases}$

The theoretical response of the open loop system to the same unit step forcing function is,

$$C_{A3,open}(t) \equiv .125(u(t) - (t^2/2 + t + 1)e^{-t}).$$

The approximate FOPDT and theoretical responses are shown below in Figure (5-2).
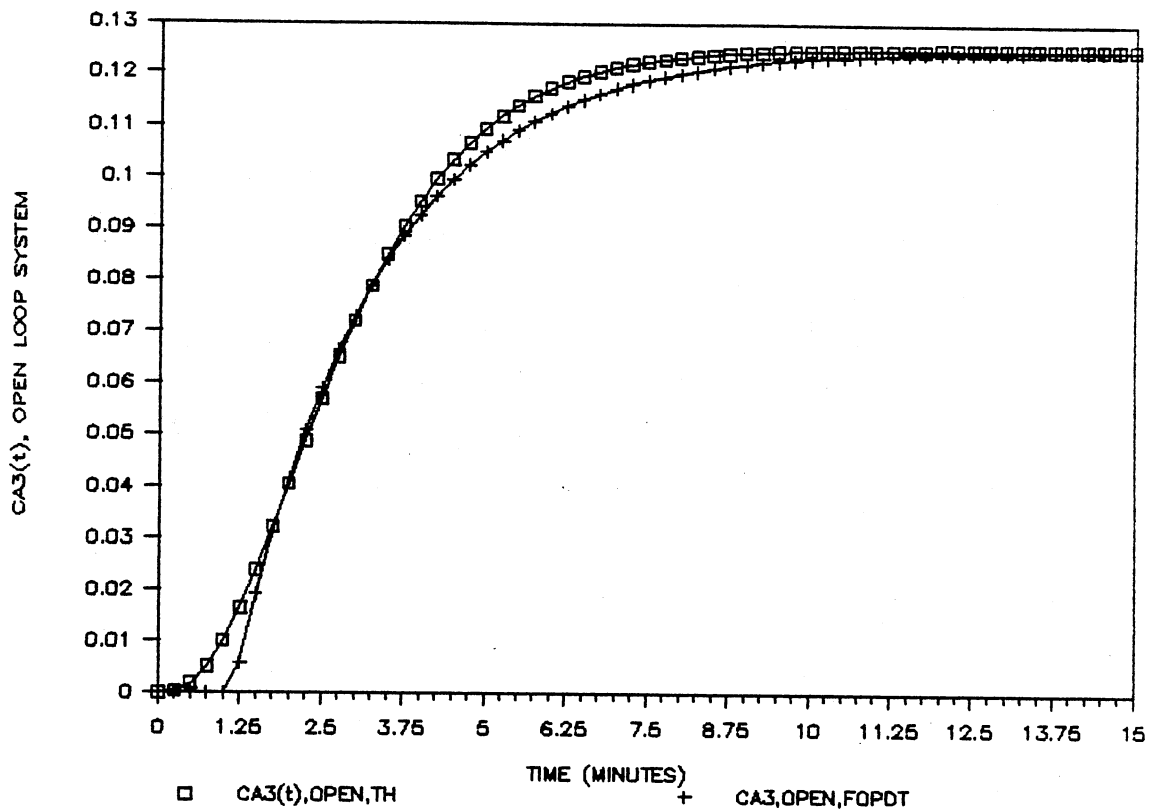
Figure 5-2. Three Serial CSTR's, Open Loop System
Theoretical Solution verses FOPDT

With the above determined analysis, it was assumed that

the sampling interval between two independent samples was

6.5 minutes. This is derived from the fact that $2(\tau + t_o)$

is approximately 6.5 minutes.

The statistically based filters used were the EWMA

filter, MAMR filter, and the IMR filter. Their applications

are similar to their application as control charts when used

to control a process. The primary difference in their
applications is the determination as to when the process has
returned to a state of statistical control following an out
of control condition. The statistically based filters
behave as follows:

(1)   Collect the sampled output every 6.5 minutes

(2)   Determine if an out of control condition is
       indicated.

(3)   If an out of control condition is identified, the
       current measured output of the process is fed to
       the controller.

(4)   If the current data indicate that the process is
       in a state of statistical control, the current set
       point of the plant is returned to the controller.

These four rules are used for all three statistically based
filters.

The Exponentially Weighted Moving Average Filter. The
exponentially weighted moving average (EWMA) filter is
similar to the application of the EWMA control chart to a
process. The EWMA is a statistic with the characteristic
that it gives less weight to individual data as they get
older. A plotted point of the output of an EWMA filter can
be given a long memory or a short memory. Each EWMA is the
present predicted value plus α times the present observed
error (observed value minus the previous forecasted value)
where $\alpha=[0,1]$. The smaller the value of α the greater the
influence of the historical data. The values of α that are
used for this research are 0.2 and 1.0. As was the case for
the exponential filter, the wide selection of α will provide

sufficient range for which results will be observed. Additionally, it is interesting to note that the EWMA filter with α set equal to one is equivalent to an individuals filter with only rule one of the AT&T rules employed.

The control limits of the EWMA filter are based on the same premise as control charts. That is, the upper and lower control limits (UCL and LCL, respectively) are placed at $\pm 3\sigma_{EWMA}$ from the process average. The resulting formulas are as shown in Ng (1987) and below.

$$UCL_{EWMA} = SET\ POINT + 3\sigma\sqrt{\alpha/(2-\alpha)}$$
$$LCL_{EWMA} = SET\ POINT - 3\sigma\sqrt{\alpha/(2-\alpha)}$$

$$(5-5)$$

where: SET POINT = 0.1

σ = Standard Deviation of the noise introduced in the feedback control loop

α = Weighting factor for the EWMA filter

The desired process average is the set point of the process, which is assumed to be 0.1 for the process used in this research. If the current EWMA is greater than the UCL or less than the LCL, it is concluded the the process is not in a state of statistical control (SOSC) and the current unfiltered output of the plant should be fed to the controller (which includes the noise encountered in the feedback loop). As discussed in rule (4) above, if the current EWMA is within the control limits, the current set point for the process output is sent to the controller for a duration of 6.5 minutes (as determined above).

The Moving Average and Moving Range Filter. The moving
average and moving range (MAMR) filter is implemented
precisely as the moving average and moving range control
chart as discussed in Chapter I. The control limits are
placed at $\pm 3\sigma_{xBAR}$ from the process set point for the moving
average (MA) portion of the filter. The moving range (MR)
is an estimate of the process variation; therefore, its
control limits are a function of the process variation.
Since the process variation is known (simply the variation
implemented in the feedback loop) and sample sizes of two
have been recommended for moving range charts, (Nelson,
1982), the control limits can be predetermined for the
moving average and moving range portions of the MAMR filter.
The calculations are precisely those given in Montgomery
(1985) and are shown below.

$$UCL_{MA} = SET\ POINT + 3\sigma/\sqrt{2}$$

$$LCL_{MA} = SET\ POINT - 3\sigma/\sqrt{2}$$

$$(5-6)$$

$$UCL_{MR} = (d_2 + 3d_3)\sigma$$

$$LCL_{MR} = 0$$

where: SET POINT = 0.1

σ = Standard Deviation of the noise
introduced in the feedback control loop

d_2, d_3 = Constants (see Montgomery, 1985)

If the current MA or MR are greater than the
appropriate UCL or lower than the appropriate LCL, it is
concluded the the process is not in a state of statistical
control and the current unfiltered output of the plant

should be fed to the controller (which includes the noise encountered in the feedback loop). As discussed in rule (4) above, if the current MA or MR are within their respective control limits, the current set point for the process output is sent to the controller for a duration of 6.5 minutes (as determined above).

The Individuals and Moving Range Filter. Individuals and moving range filters (IMR) are based on the same principle as the individuals and moving range charts for statistical process control. The UCL and LCL are placed at $\pm 3\sigma$ from the process set point for the individuals (I) portion of the IMR filter, and the UCL and LCL for the moving range (MR) portion of the IMR filter are placed as described in the control limit calculations for the MR portion of MAMR filter. The resulting formulas are shown in Montgomery (1985) and below.

$$UCL_I = SET\ POINT + 3\sigma$$

$$LCL_I = SET\ POINT - 3\sigma$$

$$UCL_{MR} = (d_2 + 3d_3)\sigma$$

$$(5-7)$$

$$LCL_{MR} = 0$$

where: SET POINT = 0.1

σ = Standard Deviation of the noise introduced in the feedback control loop

d_2, d_3 = Constants (see Montgomery, 1985)

The out of control and in control conditions for the MR portion of the IMR filter are interpreted as the MA or MR

portions of the MAMR filter. The sensitivity of the
individuals portion of the IMR filter is improved by
utilizing the AT&T runs rules. These rules are listed in
Western Electric Co. Inc. (1985) and below.

   (1) A single point falls outside of the 3σ limits.

   (2) Two out of three successive points fall between
        $+2\sigma$ and beyond from the process average or
        between -2σ and beyond from the process average

   (3) Four out of five successive points fall between
        $+1\sigma$ and beyond from the process average or
        between -1σ and beyond from the process average

   (4) Eight successive points fall on a given side of
        the center line

   As described above, if at any sample an out of control
(OOC) condition is signaled, the current unfiltered output
is sent to the controller.

Prefiltering

   Due to the time required to reasonably assume indepen-
dence between samples for each of the statistically based
filters, prefiltering is employed in an attempt to reduce
the time lag required to detect a change in the process
using the statistically based filters. Data is sampled at
each instant in time, and the technique employed is simply
an individuals chart with control limits placed at $\pm$ four
process standard deviations. The control limits are placed
at four standard deviations so that the number of false
alarms will not be excessive. Rule number one of the AT&T
rules is utilized to estimate the present state of the

process. The stream of data collected is autocorrelated,
but it is known that the presence of autocorrelation in data
requires that the spread of the control limits of the
control chart being used to control the process be reduced
(Brooks and Case, 1987). Additionally, larger changes in
the process are required to have the same probability of
being detected as the situations where only independent data
are being detected.

The only random variation in the process is the noise
that is encountered in the feedback control loop; therefore,
the control limits are determined as follows:

$$UCL_x = SET\ POINT + 3\sigma$$

$$(5-8)$$

$$LCL_x = SET\ POINT - 3\sigma$$

where: SET POINT = 0.1
σ = Standard Deviation of the noise
introduced in the feedback control loop.

The research in the following chapters include the
analysis for the situations in which the statistical process
control filters are used alone and the situation in which
the prefiltering precedes the use of the statistical
filters. The information shown in Table 5-1 below
represents the logic used to determine the filtered output
when both the prefilter and the statistical filters are
used.

TABLE 5-1

FILTERING LOGIC EMPLOYED WHEN BOTH PREFILTERING AND
STATISTICAL PROCESS CONTROL FILTERING ARE USED

Device Individuals Prefilter	Statistical Filter	Filtered Output
SOSC	SOSC	Set Point
SOSC	OOC	Random Signal
OOC	SOSC	Random Signal
OOC	OOC	Random Signal

Additionally, once an OOC condition is detected for the individual prefilter, the process is not sampled until ten minutes later. This amount of time allows enough time for the PID control to react to a large change in the process.

The Input Disturbance

The input disturbances common to continuous type processes are varied in nature. Some of the more common types of disturbances are unit steps of various magnitudes, unlimited ramp functions of various slopes, and sinusoidal functions. Additionally, the set point can be changed during the operation of a control loop, and these set point changes are typically a unit step function.

The research that follows considers only input disturbances and does not investigate the impact of set point changes. This is based on the fact that the tuning criteria used in setting the constants on the controller

action are based on the quarter decay ratio and are not recommended for processes that are subjected to changes in set point (see Smith and Corripio, 1985). Additionally, the analysis in the following chapters is based on unit step and unlimited ramp function disturbances to the process. The computer system can be modified to offer other types of disturbances, but due to the great amounts of computer time to run the simulations, an exhaustive analysis can not be reasonably obtained. Furthermore, it is recognized that the intent of this research is to evaluate the potential applicability of the new statistically based filtering devices.

Measures of Performance

In addition to the tuning criterion based on the quarter decay ratio, some researchers have used another performance criterion which results in optimum solutions which are unique. One of the more popular relationships in the Integral of the Absolute Value of the Error (IAE), see Smith and Corripio (1985), and this formula is shown below.

$$\int_0^\infty |e(t)|dt \qquad (5-9)$$

where: $e(t)$ = SET POINT – THE CONTROLLER FROM
CURRENT INPUT TO
THE FEEDBACK LOOP

It is this relationship that will become the measure of performance in the analysis of the use of the various

filtering devices within the control scheme as outlined in Chapter IV. Since the system to be modeled in this research is stochastic, multiple runs must be made to evaluate the performance of a given filter. Additionally, it is desired to know the area of error over time, but in the context of this problem error must be redefined. It is known how the plant will respond to a given disturbance if the output of the plant is fed back to the controller with no randomness employed (see the theoretical or numerical results described in Chapter 4). But, the ability of the plant to meet the theoretical results when randomness is employed is not known. Therefore, the error of interest is the absolute difference between the observed output and the theoretical output, and since the analysis must be based on multiple observations, an average of this error is of interest. Integrating this new absolute average error over time results in the following relationship,

$$\int_0^{\infty} \left[\sum_{i=1}^{n} |(\text{Observed Output})_i - (\text{Theoretical Output})| / n \right] dt \quad (5\text{-}10)$$

where: i = The ith Observation

         n = The Number of Observations/Runs

Using the variables as illustrated in Chapter IV, equation
(5-10) results in the following relationship,

$$\text{Integral of the Average Absolute Error} = \text{IAAE} = \int_0^{-} [\Sigma_{i=1}^{n} |C_{A3}(t)_i - C_{A3TH}(t)|/n] dt \quad (5-11)$$

where: i   = The ith Observation

        n   = The Number of Observations/Runs

    C_{A3TH} = The Theoretical Response

The final IAAE is dependent upon the magnitude of the
errors and the length of time for which the plant was run.
Since the integral is dynamic with time, the integral will
be determined for a finite time period for multiple runs in
an attempt to determine the performance of the plant when
subjected to various filtering devices with respect to the
error seen for different runs.

Additionally, plots of the average output of the plant
under known conditions when a given filtering device is used
will be made to provide additional information regarding the
performance of the plant.

The Computer System

The computer system is described in the flow chart
shown below in Figure 5-3.
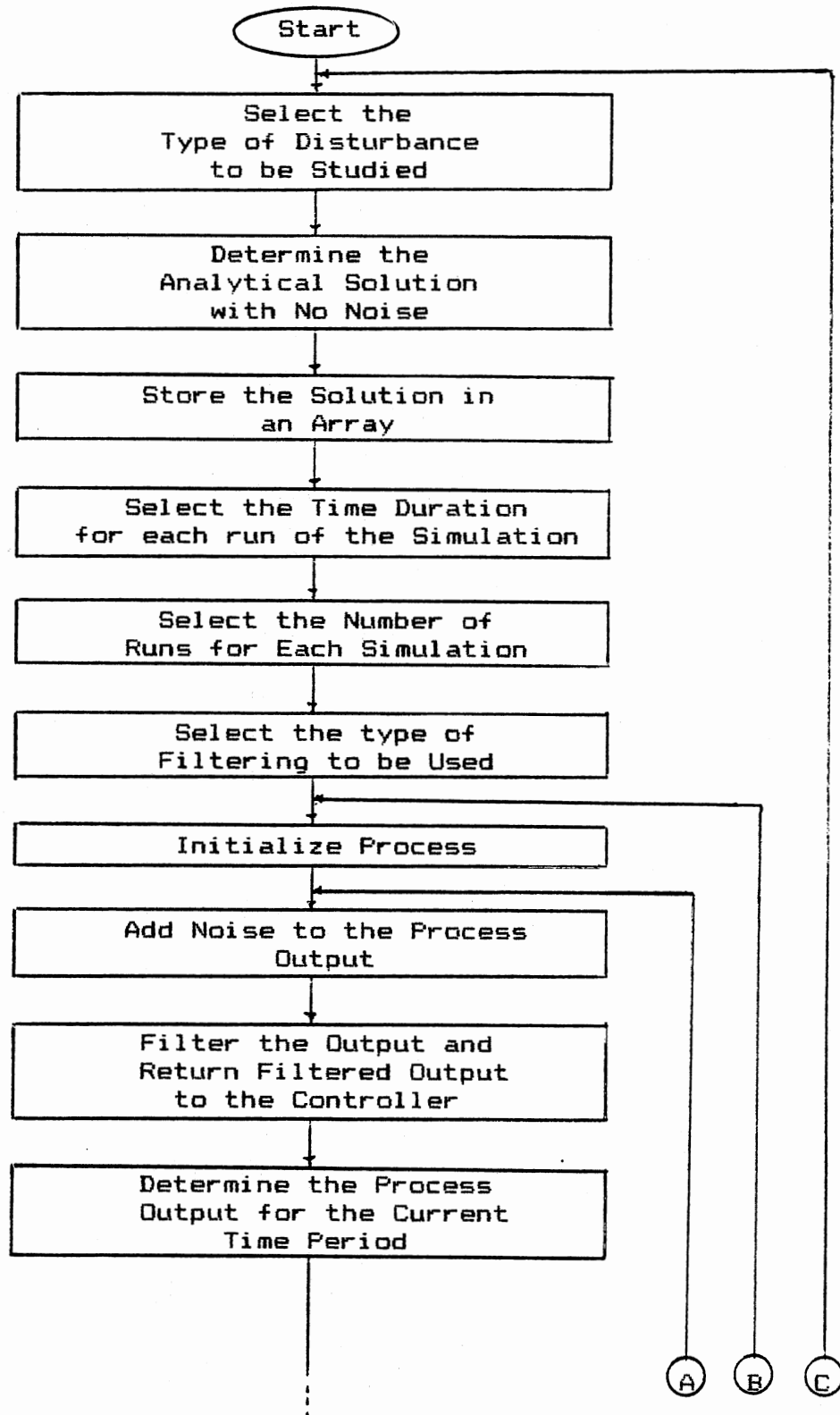
Figure 5-3.   The Flow Chart of the Computer System
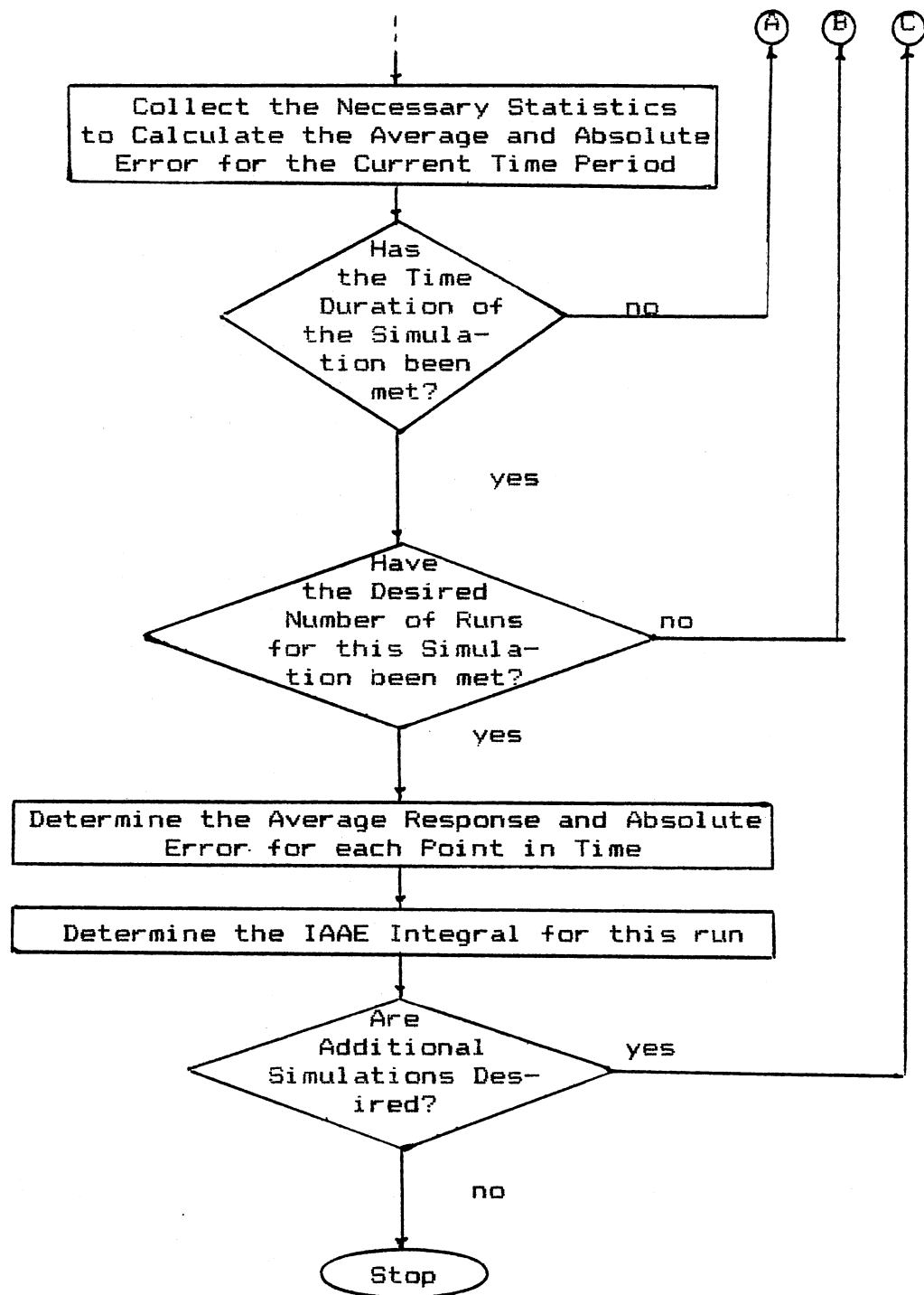
Figure 5-3 (continued). The Flow Chart of the Computer
System

As discussed in Chapter 4, the simulation of the differential equation that describe the completed process is made using forth order Runga Kutta techniques (for a complete explanation of Runga Kutta see Hultquist (1988) or Jaluria (1988)). Additionally, since the Runga Kutta techniques are simply an integration routine, the techniques are applicable to the determination of the IAAE. The choices of filters employed are based on the filters discussed throughout this work. The filtering and Runga Kutta algorithms are placed in subroutines following the main program.

The listing of the program developed for the unit step disturbance is included in Appendix B. The program was developed in FORTRAN and implemented on the IBM 360. The use of the main frame was required due to the amount of time required to run the dynamic simulation of the process previously described. For example, approximately three and one-half minutes of central processing unit time were required to simulate the process for 60 minutes for 100 replications. The system is simply modified to change the type of input disturbance.

Validation of the Computer System

This section represents a brief description of the process by which the computer system was validated. A discussion is presented for some of major validation steps employed.

The first validation step was to validate the numerical results (with no noise implemented) with the known analytical response of the system. This is discussed in its entirety in Chapter IV. Additionally, each filtering device was run twice using the same random number stream. This measure insures that all variables were being reset between subsequent runs. Furthermore, all flags and process signals were listed for each filtering devices during a short simulation of one run for each filtering device. Some of the process signals are shown below in Figure 5-4.
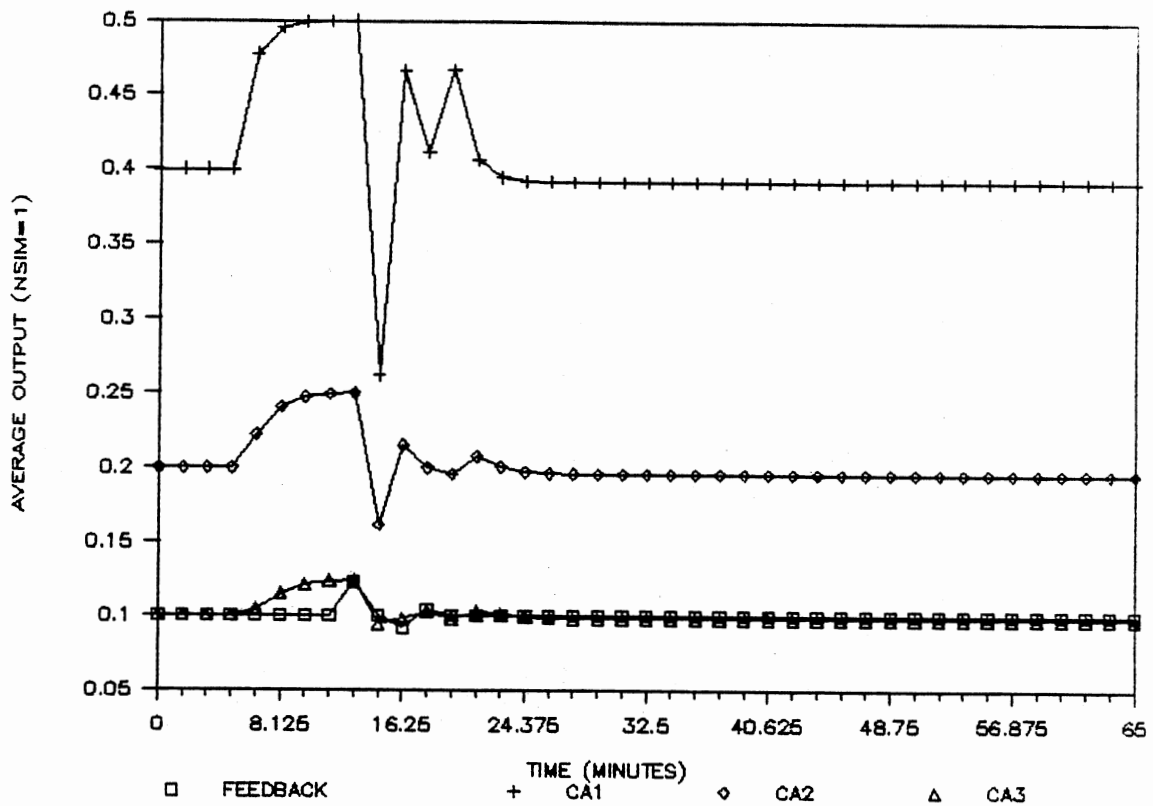
Figure 5-4. Example of a Validation Run

Looking at all of the variables in the process insures that the logic designed in the system was being correctly employed and that the responses (with noise included) appeared reasonable when compared to the noiseless system response. Figure 5-4 represents the process response when subjected to a unit step disturbance of magnitude 0.2 and EWMA filtering. Throughout the development of the system, data were maintained for validation runs so that each augmented system could be validated to its predecessor.

Since the response of the system is not known when noise is induced in the feedback control loop, validation could not be made with certainty. However, the final results (as shown in the following chapters) appear reasonable for each of the filtering devices employed. Multiple runs were made to estimate the amount of variability between runs.

CHAPTER VI

RESULTS

Introduction

The results collected of the simulation of the chemical reactor described in Chapter IV using the computer system described in Chapter V follow. The chemical reactor is simulated using a given filtering device. Specifically, the filtering devices modeled are the exponential filter with parameter P, the least squares filter with parameter N, the nonlinear exponential filter with parameter R, the exponentially weighted moving average filter with parameter α, the moving average and moving range filter, the individuals and moving range filter, the exponentially weighted moving average filter with parameter α and the individuals prefilter, the moving average and moving range filter with the individuals prefilter, and the individuals and moving range filter with the individuals prefilter. In what follows, the results of simulations of the chemical reactor utilizing each of the filtering devices when the chemical reactor is subjected to various input disturbances are given. In all Tables and Figures, CAD is the same as C_{AD} as previously described.

Conventional Filters

The conventional filters are the exponential filter
with parameter P, EXP(P), the least squares filter with
parameter N, LS(N), and the nonlinear exponential filter
with parameter R, NL(R). As discussed in Chapter V, this
research uses values of 0.0 and 0.8 for P, 3 and 19 for N,
and 4 and 7 for R. The chemical reactor is simulated with
a given filtering device (with a known parameter value) and
type of disturbance for 100 replications of sixty minutes of
plant operation time. The types of input disturbances for
CAD utilized in the research were the unit step of
magnitudes 0.0, 0.12, and 0.2 for the values of CAD, and
ramp functions with the slope of 0.12 and 0.2 for the values
of CAD. The disturbance is not introduced until five minutes
have elapsed allowing the process sufficient time to reach a
stable condition. The standard deviation of the noise
introduced in the feedback control loop is 0.005, and the
parameters of the reactor and PID controller are as
described in Chapter IV.

Table 6-1 below presents the integral of the average
absolute error (IAAE) of two runs of the simulation
described above for the situation in which there is no input
disturbance introduced to the system. Two runs were made
utilizing each of the conventional filters described above.

TABLE 6-1

IAAE; UNIT STEP DISTURBANCE; CAD=0.0, t≥5.0

Filtering Device

	EXP(0.0)	EXP(0.8)	LS(3)	LS(19)	NL(4)	NL(7)
Run 1	0.01936	0.02017	0.01924	0.01926	0.02083	0.02179
Run 2	0.01947	0.01963	0.01902	0.01923	0.02125	0.02158
AVG	0.01942	0.01990	0.01913	0.01925	0.02104	0.02168

The average outputs of the chemical reactor using the EXP(0.0), EXP(0.8), LS(3), LS(19), NL(4), and the NL(7) filters are shown below in Figures 6-1A, 6-1B, 6-1C, 6-1D, 6-1E, and 6-1F, respectively.

Figure 6-1A. Average Output; CAD=0.00, t≥5; Filter=EXP(0.0)

Figure 6-1B.   Average Output; CAD=0.00, t≥5; Filter=EXP(0.8)

Figure 6-1C.   Average Output; CAD=0.00, t≥5; Filter=LS(3)

Figure 6-1D.   Average Output; CAD=0.00, t≥5; Filter=LS(19)

Figure 6-1E.   Average Output; CAD=0.00, t≥5; Filter=NL(4)
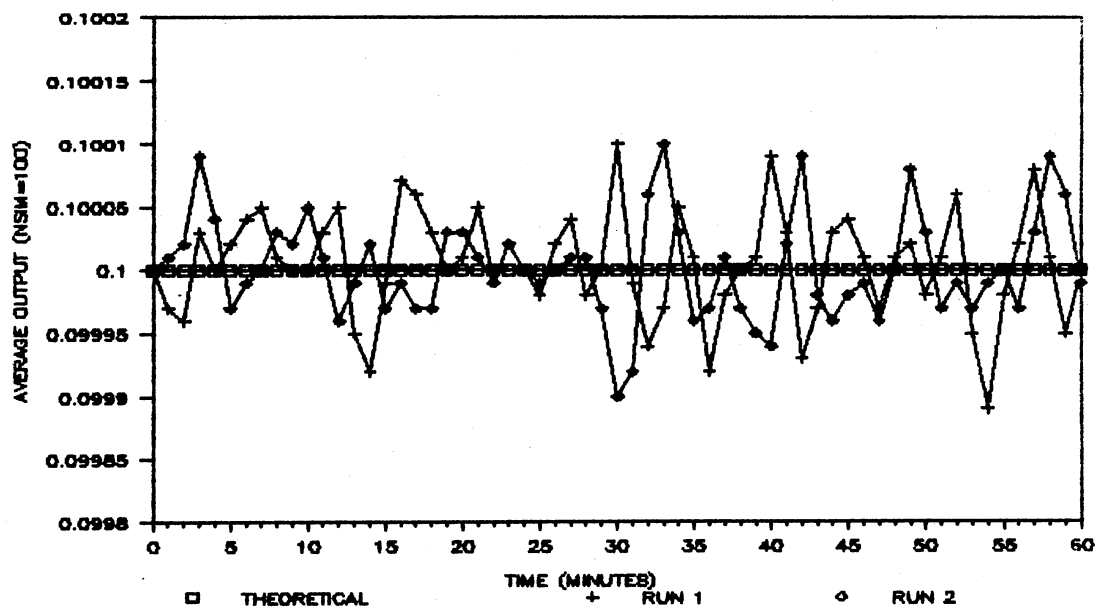
Figure 6-1F.   Average Output; CAD=0.00, t≥5; Filter=NL(7)

Table 6-2 below presents the integral of the average absolute error (IAAE) of two runs of the simulation described above for the unit step input disturbance of magnitude 0.12.   Two runs were made utilizing each of the conventional filters described above.

TABLE 6-2

IAAE; UNIT STEP DISTURBANCE; CAD=0.12, T≥5.0

Filtering Device

	EXP(0.0)	EXP(0.8)	LS(3)	LS(19)	NL(4)	NL(7)
Run 1	0.01952	0.01976	0.01909	0.01944	0.02099	0.02161
Run 2	0.01938	0.01959	0.01880	0.01961	0.02086	0.02154
AVG	0.01945	0.01968	0.01895	0.01953	0.02092	0.02157

The average outputs of the chemical reactor using the EXP(0.0), EXP(0.8), LS(3), LS(19), NL(4), and the NL(7) filters are shown below in Figures 6-2A, 6-2B, 6-2C, 6-2D, 6-2E, and 6-2F, respectively.

Figure 6-2A. Average Output; CAD=0.12, t≥5; Filter=EXP(0.0)

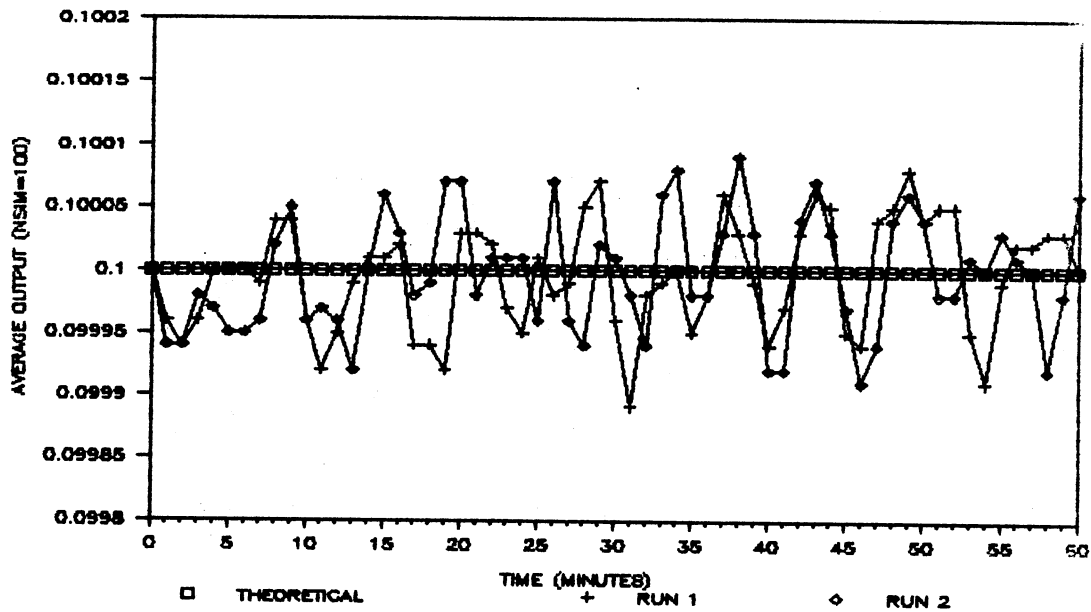Figure 6-2B.   Average Output; CAD=0.12, t≥5; Filter=EXP(0.8)
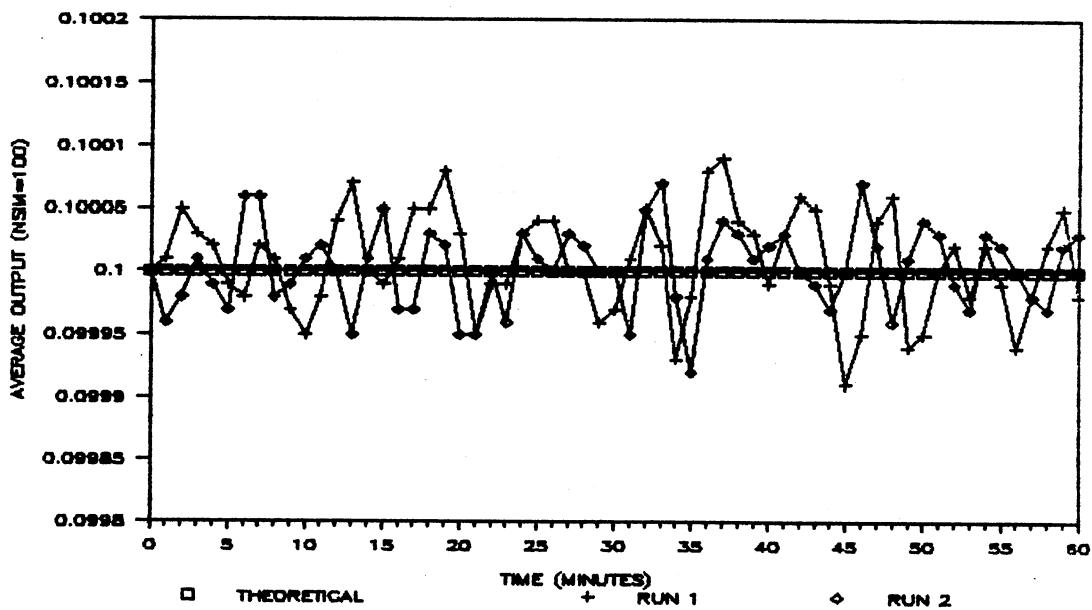

Figure 6-2C.   Average Output; CAD=0.12, t≥5; Filter=LS(3)

Figure 6-2D. Average Output; CAD=0.12, t≥5; Filter=LS(19)

Figure 6-2E. Average Output; CAD=0.12, t≥5; Filter=NL(4)

Figure 6-2F.   Average Output; CAD=0.12, t≥5; Filter=NL(7)

     Table 6-3 below presents the integral of the average

absolute error (IAAE) of two runs of the simulation

described above for the unit step input disturbance of

magnitude 0.20.   Two runs were made utilizing each of the

conventional filters described above.

TABLE 6-3

IAAE; UNIT STEP DISTURBANCE; CAD=0.20, T≥5.0

Filtering Device

	EXP(0.0)	EXP(0.8)	LS(3)	LS(19)	NL(4)	NL(7)
Run 1	0.01927	0.01991	0.01955	0.01907	0.02098	0.02163
Run 2	0.01905	0.02005	0.01903	0.01949	0.02124	0.02147
AVG	0.01916	0.01998	0.01929	0.01928	0.02111	0.02155

The average outputs of the chemical reactor using the
EXP(0.0), EXP(0.8), LS(3), LS(19), NL(4), and the NL(7)
filters are shown below in Figures 6-3A, 6-3B, 6-3C, 6-3D,
6-3E, and 6-3F, respectively.

Figure 6-3A. Average Output; CAD=0.20, t≥5; Filter=EXP(0.0)

Figure 6-3B.   Average Output; CAD=0.20, t≥5; Filter=EXP(0.8)

Figure 6-3C.   Average Output; CAD=0.20, t≥5; Filter=LS(3)
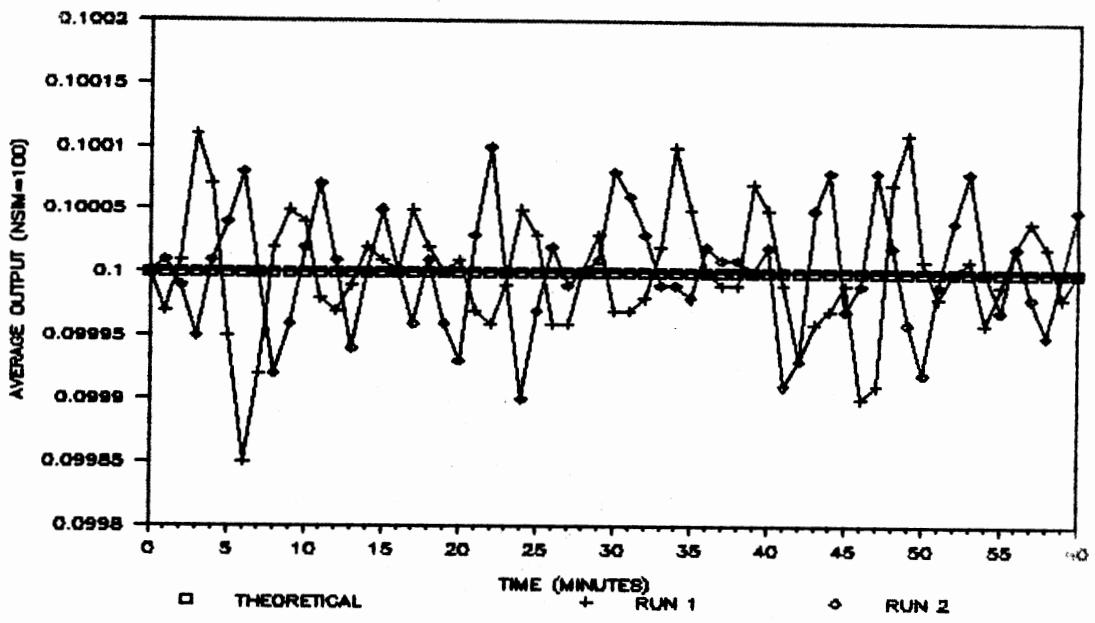
Figure 6-3D.   Average Output; CAD=0.20, t≥5; Filter=LS(19)
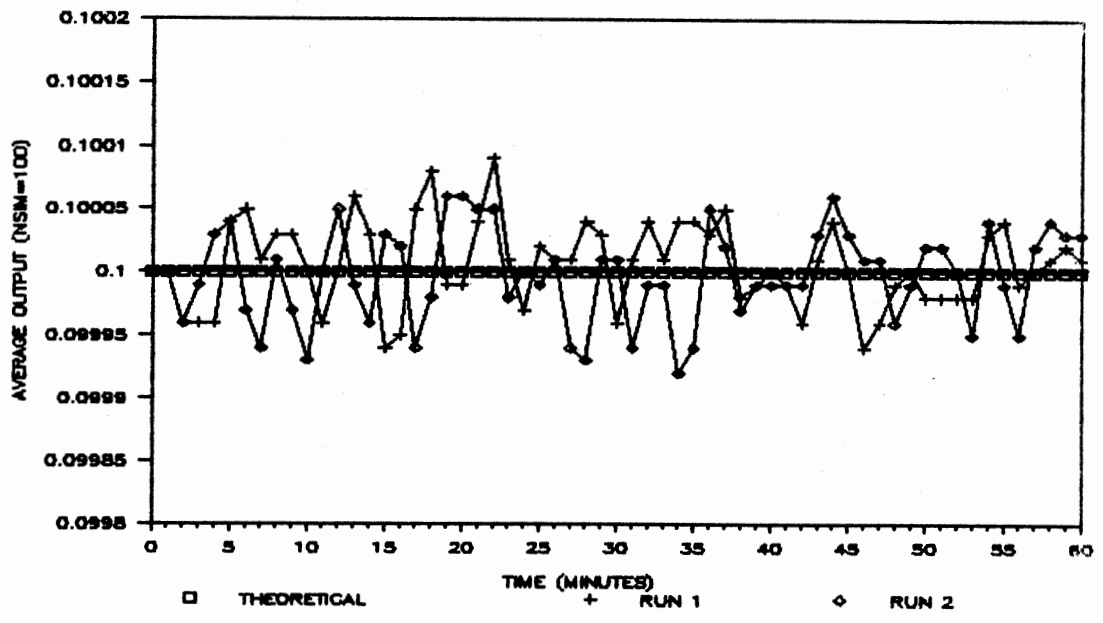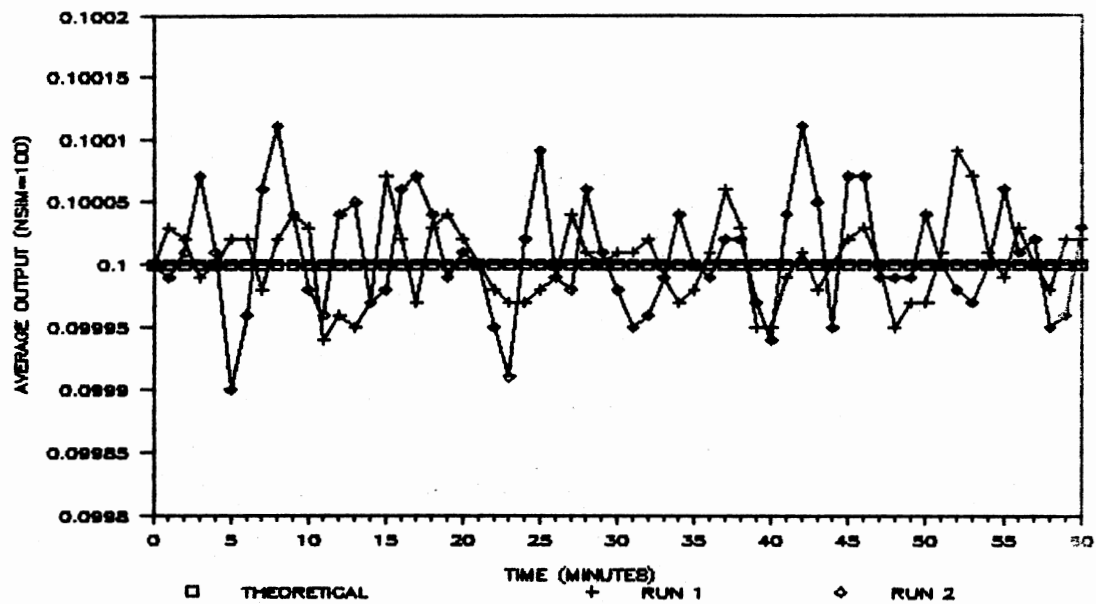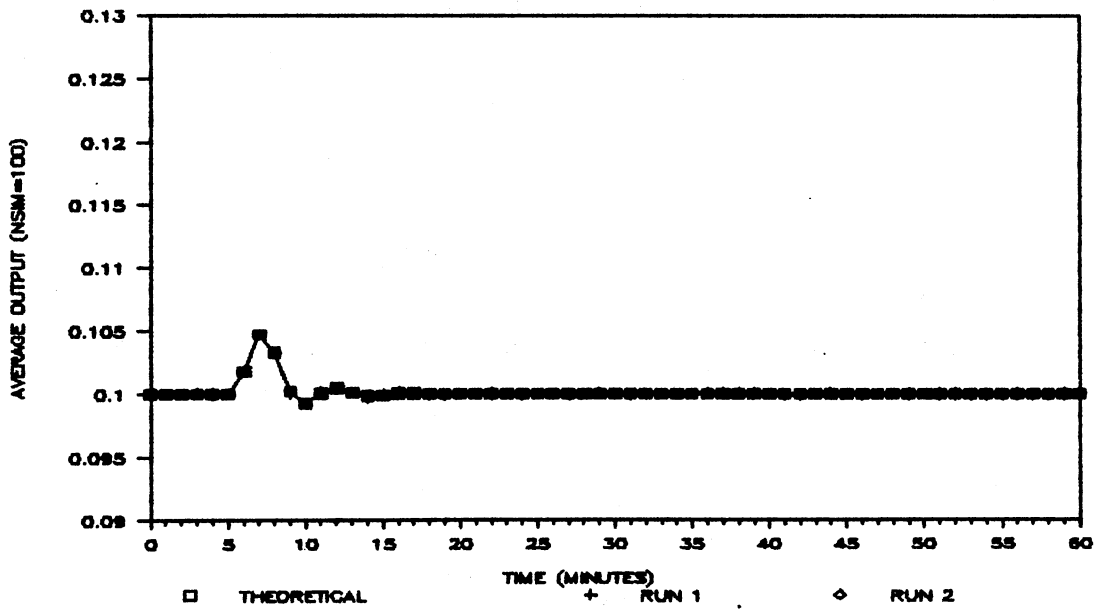

Figure 6-3E.   Average Output; CAD=0.20, t≥5; Filter=NL(4)
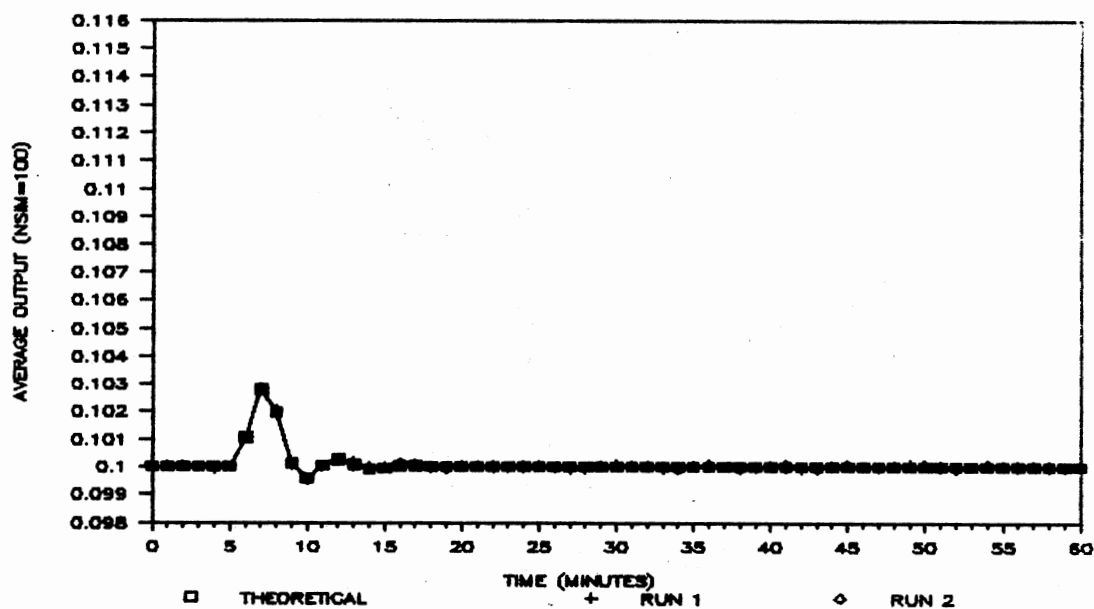
Figure 6-3F.   Average Output; CAD=0.20, t≥5; Filter=NL(7)

Table 6-4 below presents the integral of the average absolute error (IAAE) of two runs of the simulation described above for the ramp input disturbance of slope 0.12.   Two runs were made utilizing each of the conventional filters described above.

TABLE 6-4

IAAE; RAMP DISTURBANCE; CAD=0.12(T-5.0), T≥5.0

Filtering Device

	EXP(0.0)	EXP(0.8)	LS(3)	LS(19)	NL(4)	NL(7)
Run 1	0.01938	0.01975	0.01953	0.01972	0.02099	0.02176
Run 2	0.01918	0.01993	0.01925	0.01928	0.02104	0.02159
AVG	0.01928	0.01984	0.01939	0.01950	0.02101	0.02167

The average outputs of the chemical reactor using the
EXP(0.0), EXP(0.8), LS(3), LS(19), NL(4), and the NL(7)
filters are shown below in Figures 6-4A, 6-4B, 6-4C, 6-4D,
6-4E, and 6-4F, respectively.
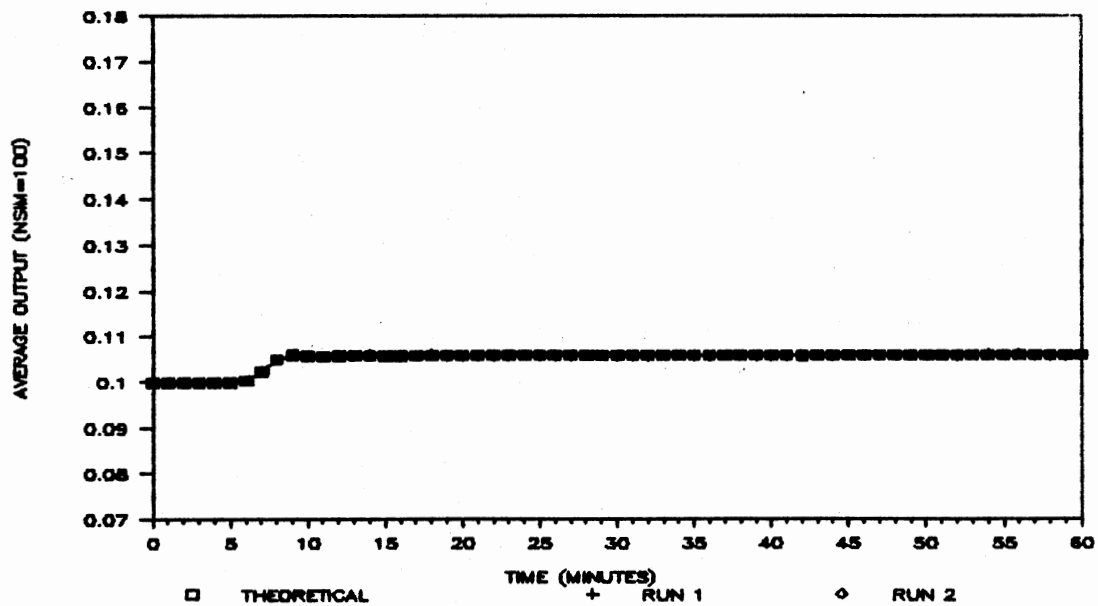
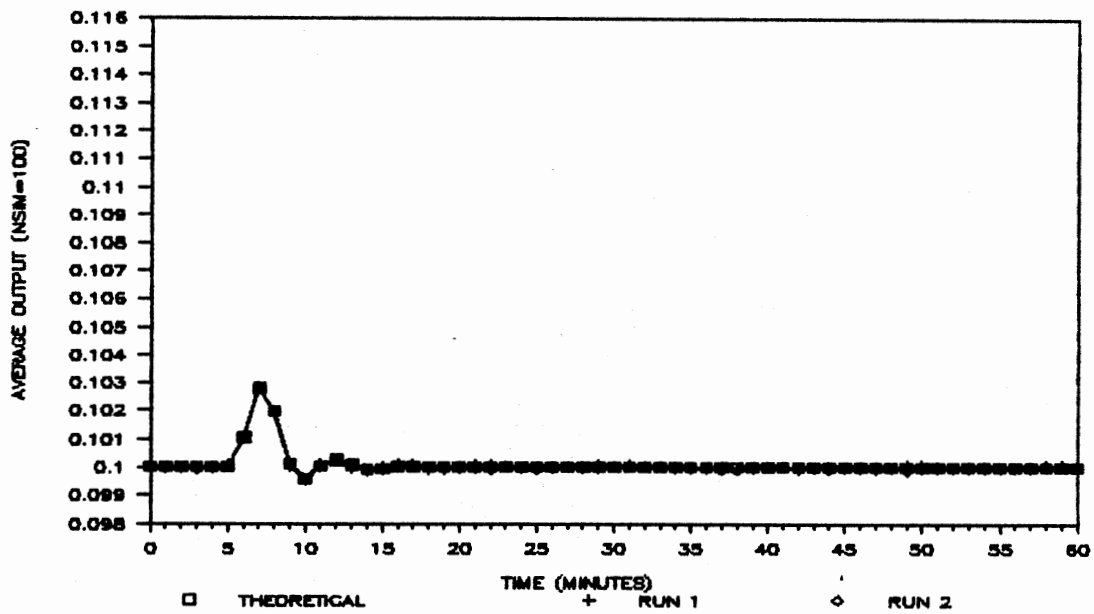Figure 6-4A.   Average Output; CAD=0.12(t-5.0), t≥5;
Filter=EXP(0.0)
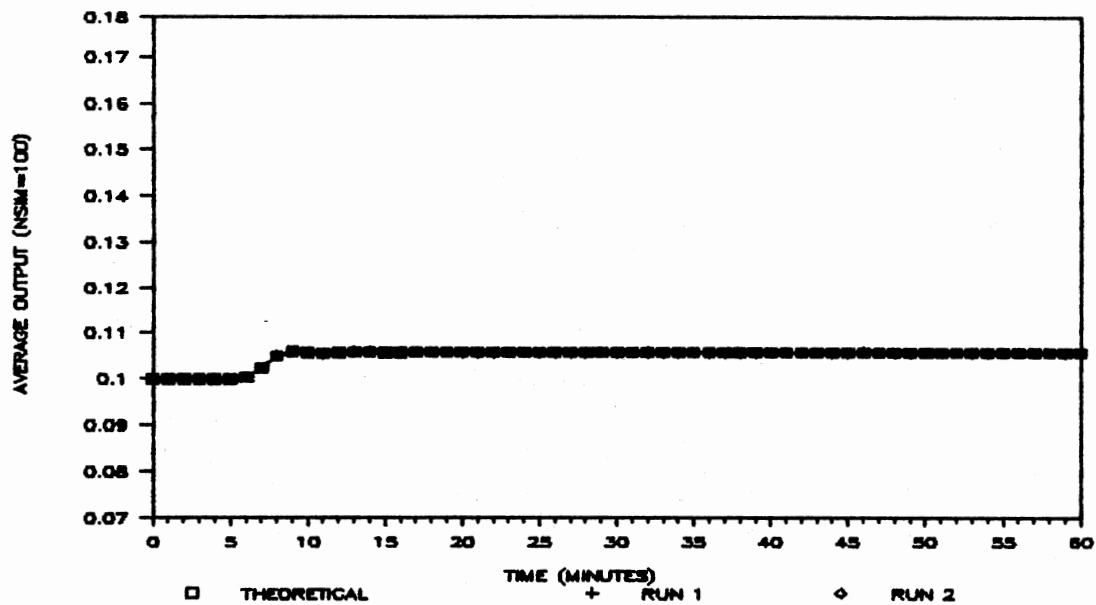
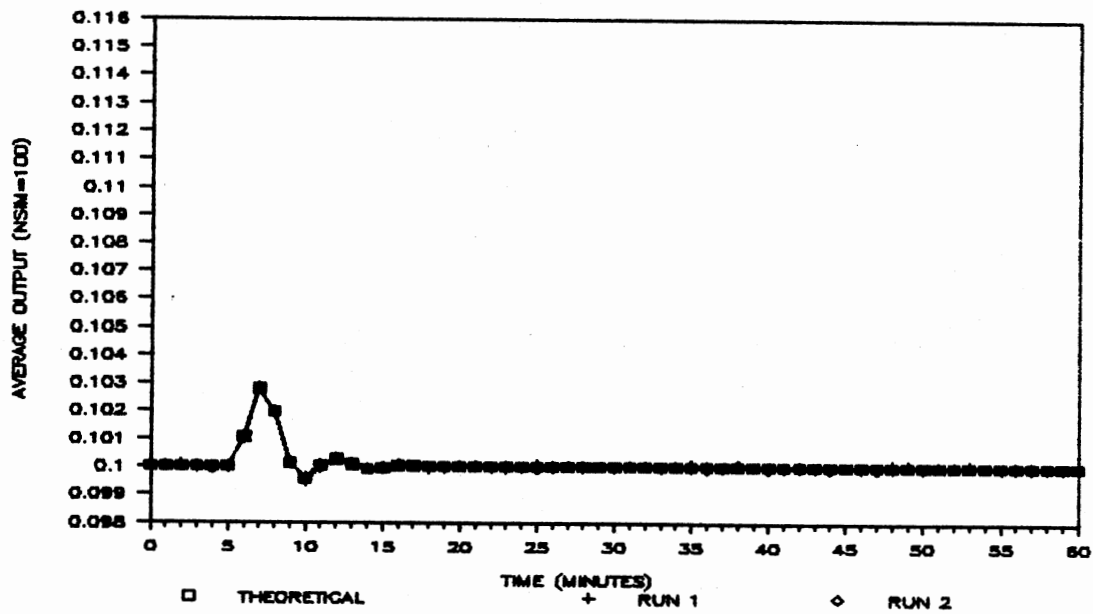Figure 6-4B.   Average Output; CAD=0.12(t-5.0), t≥5;
Filter=EXP(0.8)
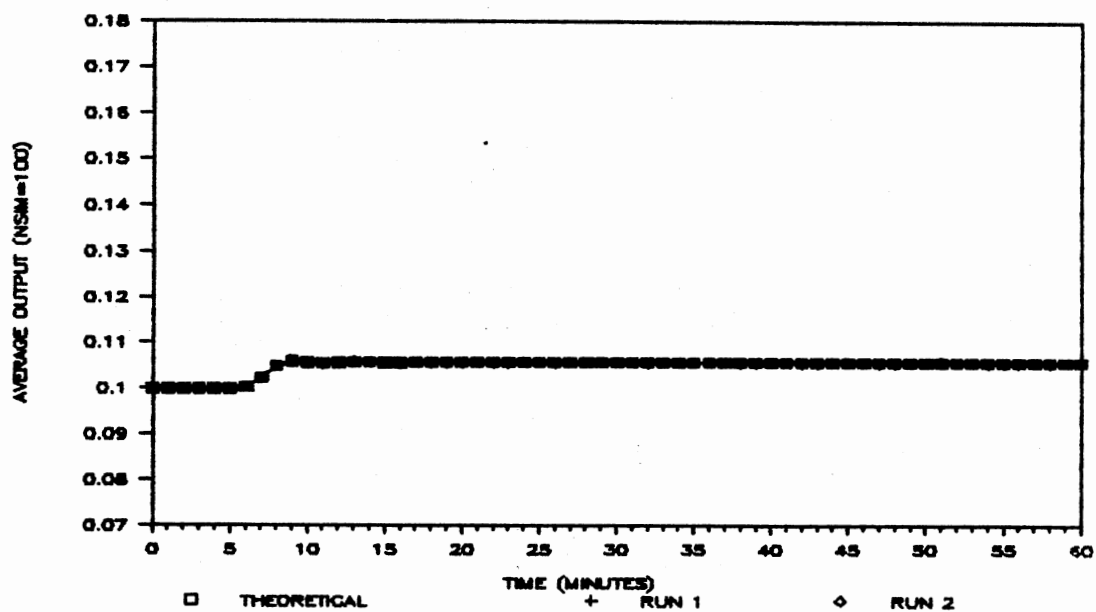
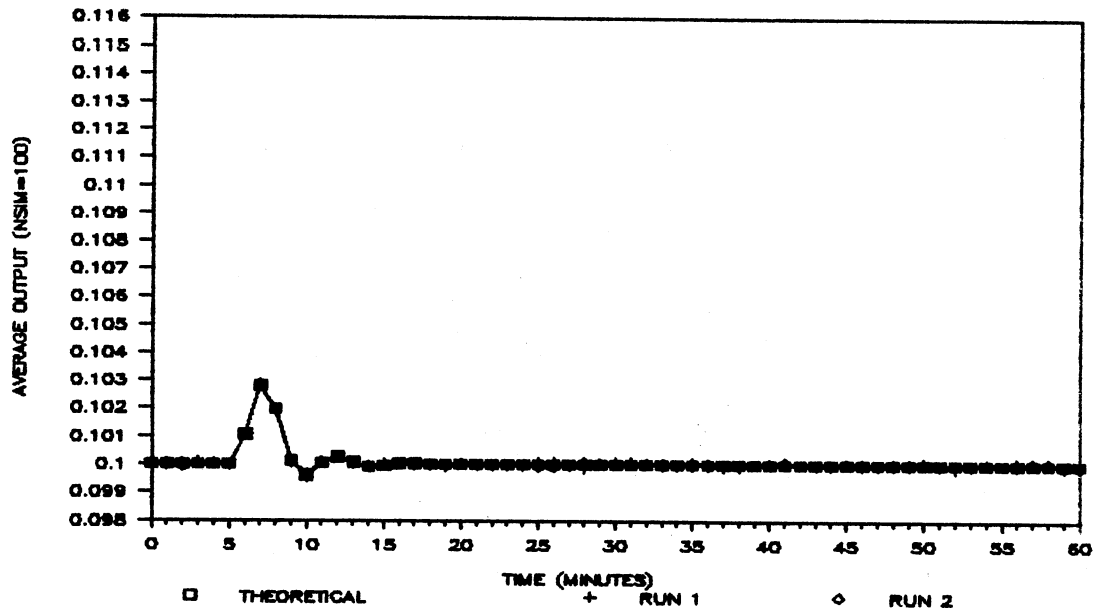Figure 6-4C.   Average Output; CAD=0.12(t-5.0), t≥5;
Filter=LS(3)
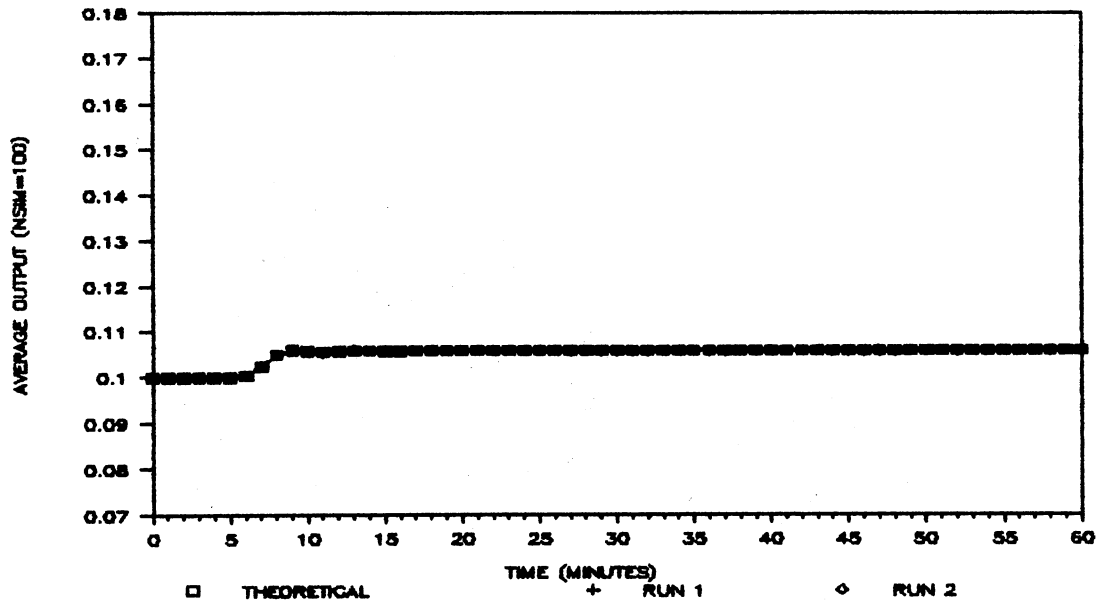
Figure 6-4D.   Average Output; CAD=0.12(t-5.0), t≥5;
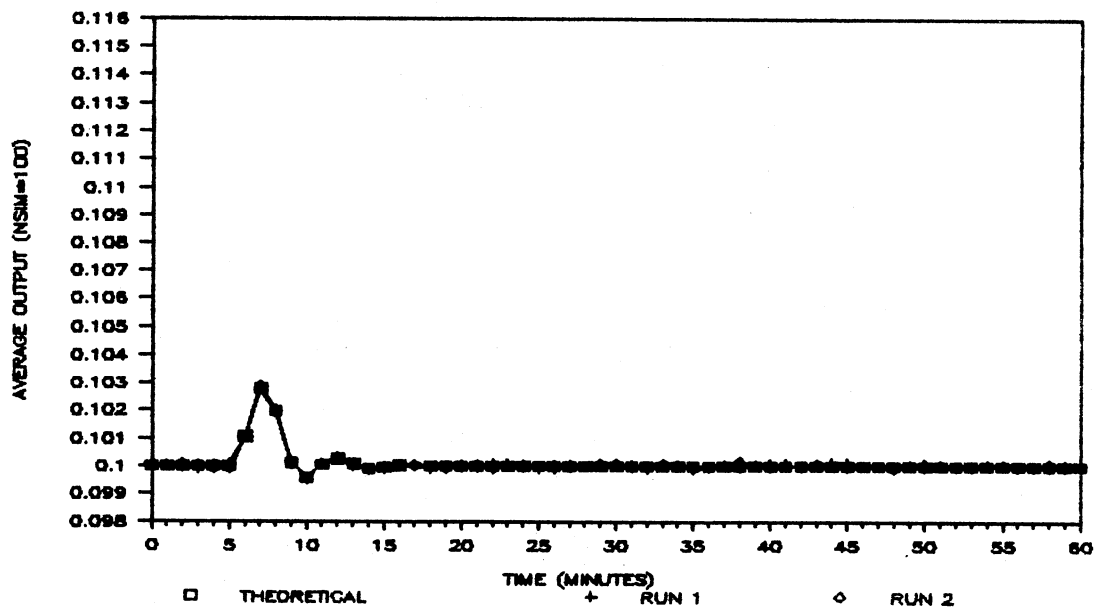   Filter=LS(19)
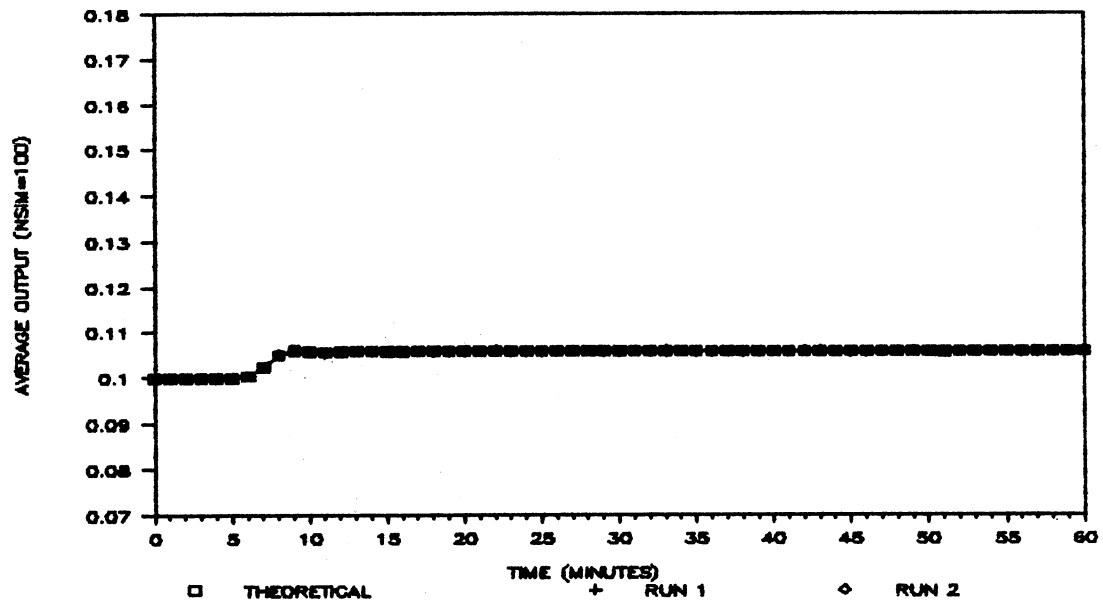
Figure 6-4E.   Average Output; CAD=0.12(t-5.0), t≥5;
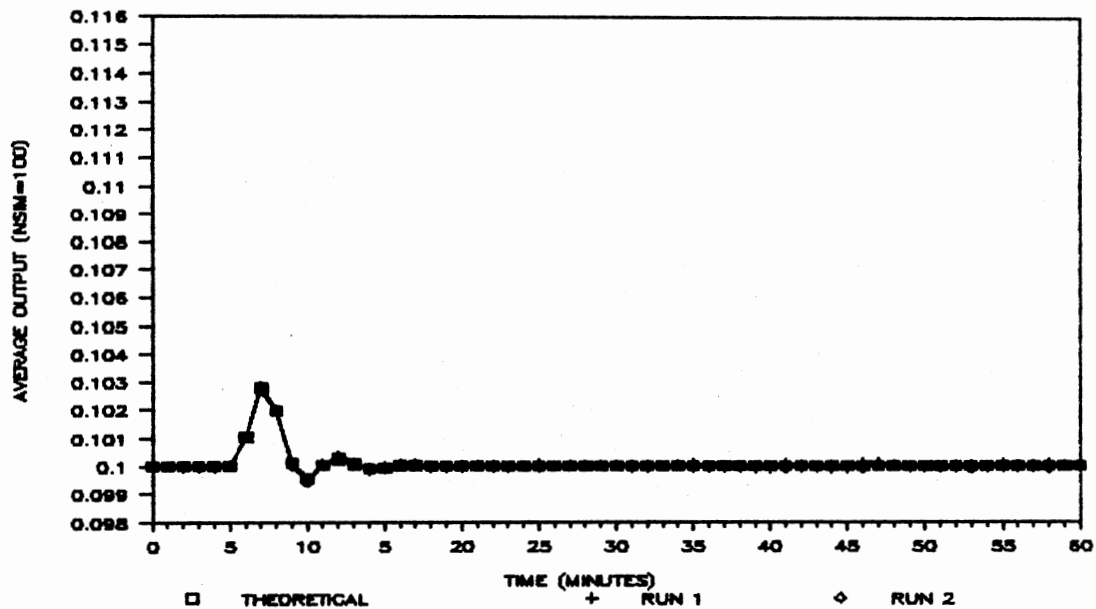   Filter=NL(4)

Figure 6-4F.   Average Output; CAD=0.12(t-5.0), t≥5;
Filter=NL(7)
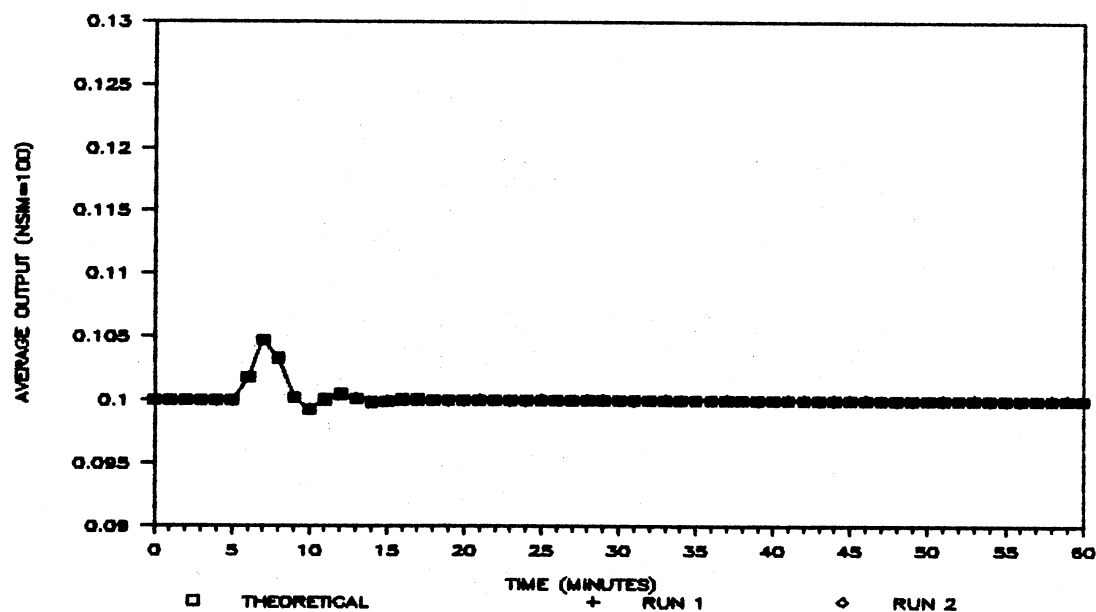
Table 6-5 below presents the integral of the average

absolute error (IAAE) of two runs of the simulation

described above for the ramp input disturbance of slope

0.20.   Two runs were made utilizing each of the conventional

filters described above.

TABLE 6-5

IAAE; RAMP DISTURBANCE; CAD=0.20(T-5.0), T≥5.0

Filtering Device

	EXP(0.0)	EXP(0.8)	LS(3)	LS(19)	NL(4)	NL(7)
Run 1	0.01926	0.01988	0.01927	0.01965	0.02133	0.02133
Run 2	0.01983	0.01990	0.01909	0.01946	0.02154	0.02191
AVG	0.01955	0.01989	0.01918	0.01956	0.02143	0.02162

The average output of the chemical reactor using the EXP(0.0), EXP(0.8), LS(3), LS(19), NL(4), and the NL(7) filters are shown below in Figures 6-5A, 6-5B, 6-5C, 6-5D, 6-5E, and 6-5F, respectively.
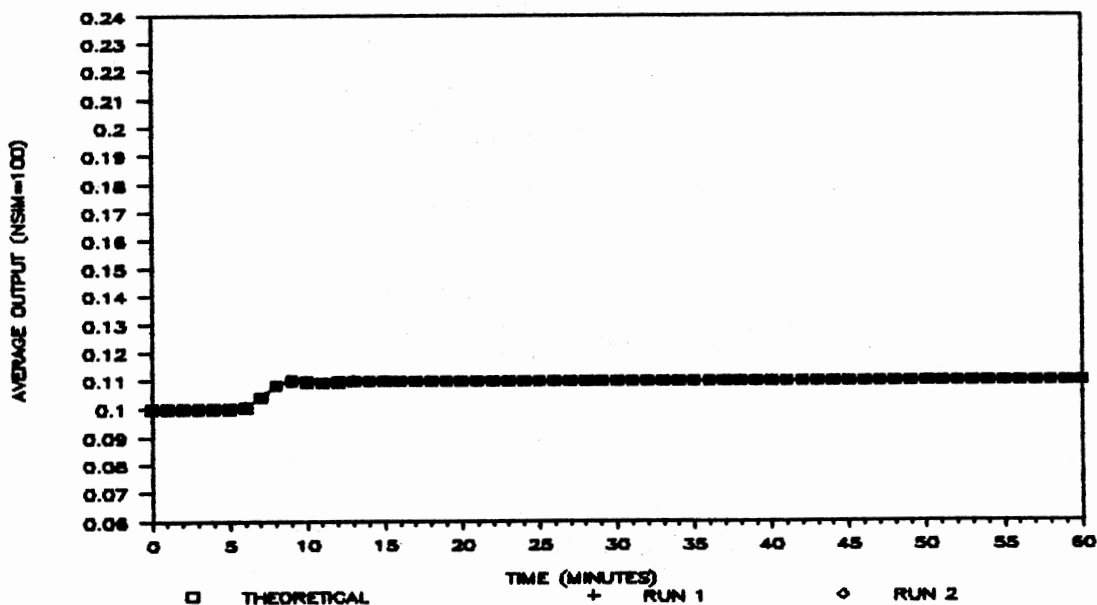
Figure 6-5A. Average Output; CAD=0.20(t-5.0), t≥5; Filter=EXP(0.0)
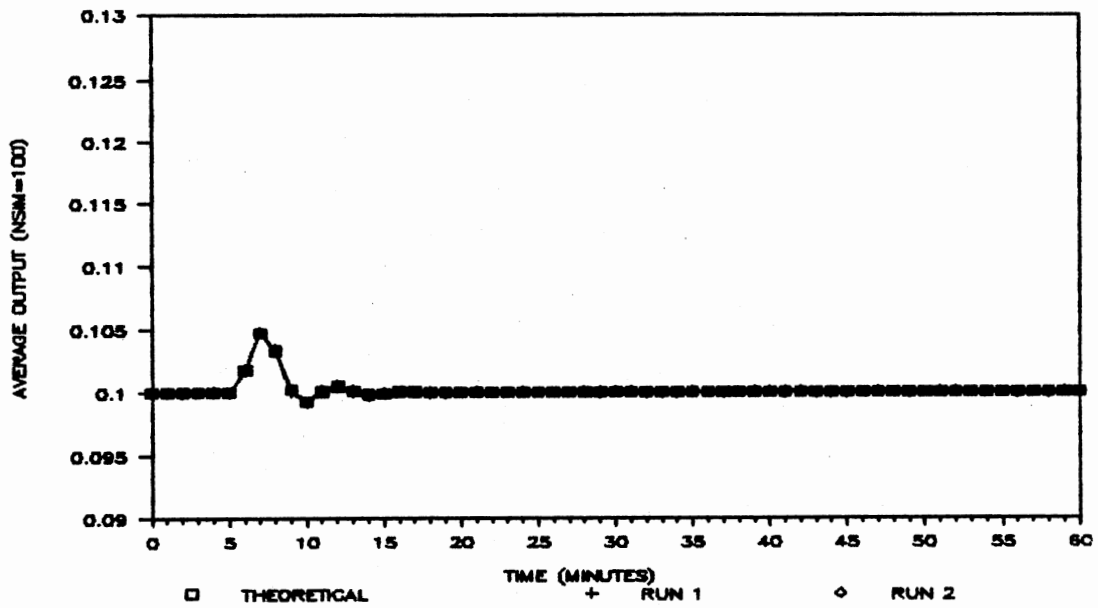
Figure 6-5B.   Average Output; CAD=0.20(t-5.0), t≥5;
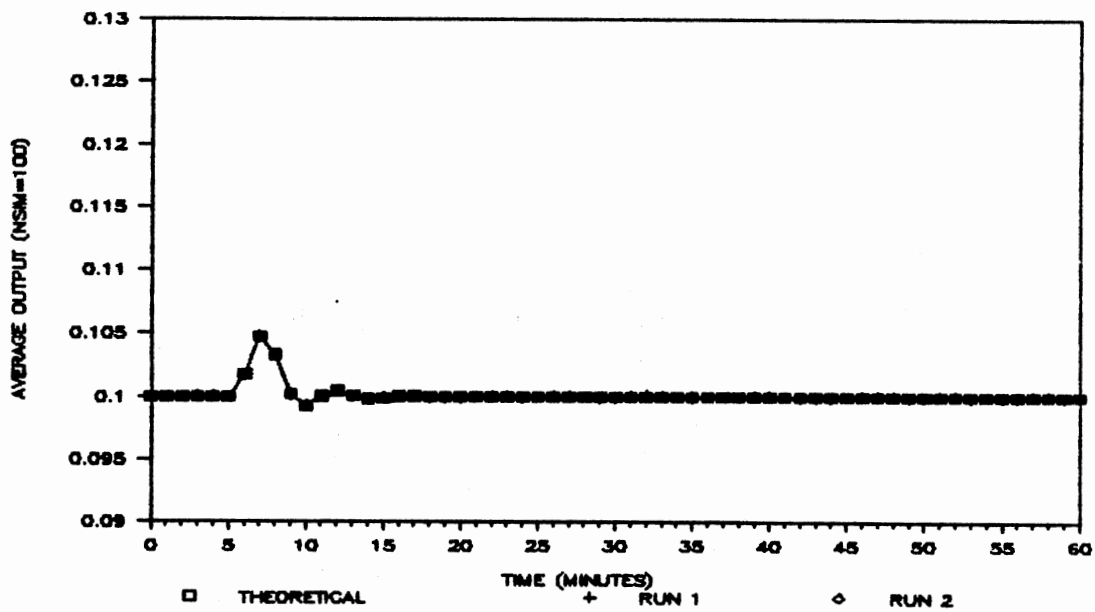Filter=EXP(0.8)

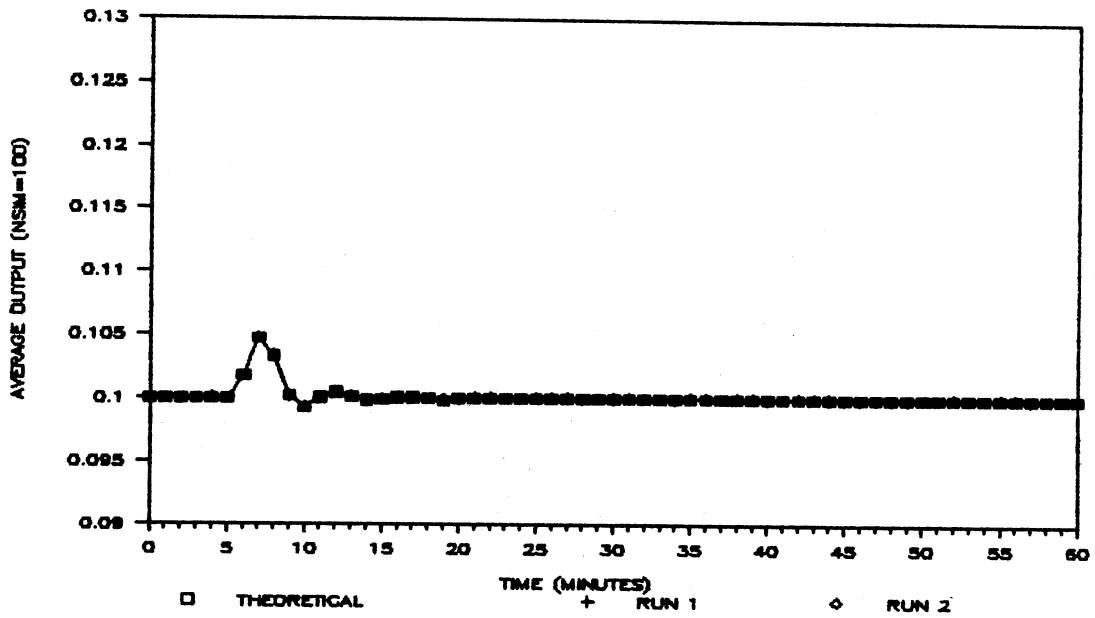Figure 6-5C.   Average Output; CAD=0.20(t-5.0), t≥5;
Filter=LS(3)
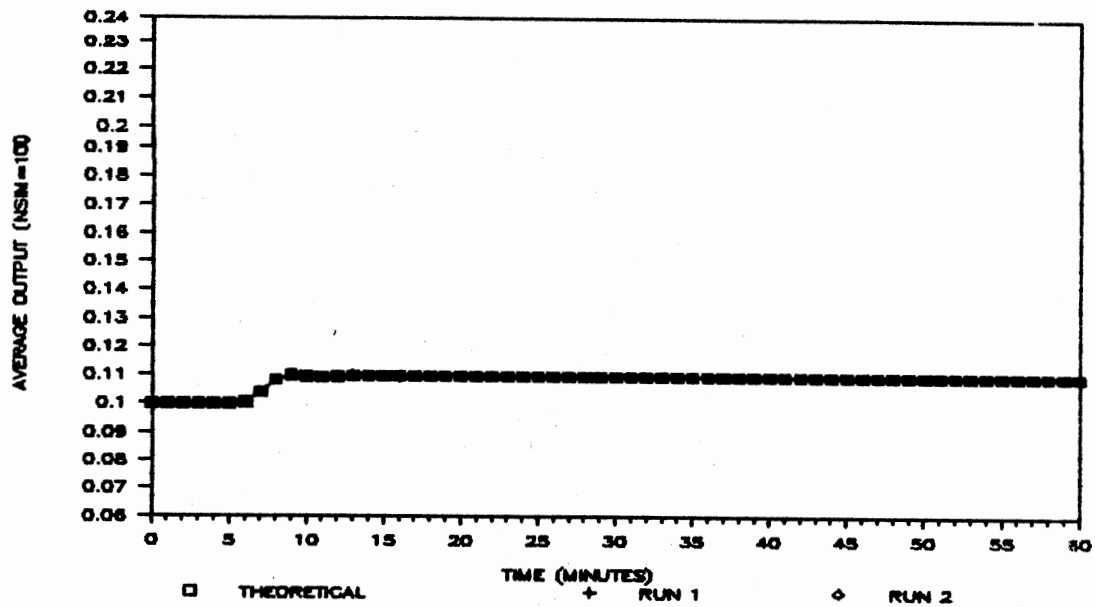
Figure 6-5D.   Average Output; CAD=0.20(t-5.0), t≥5;
Filter=LS(19)
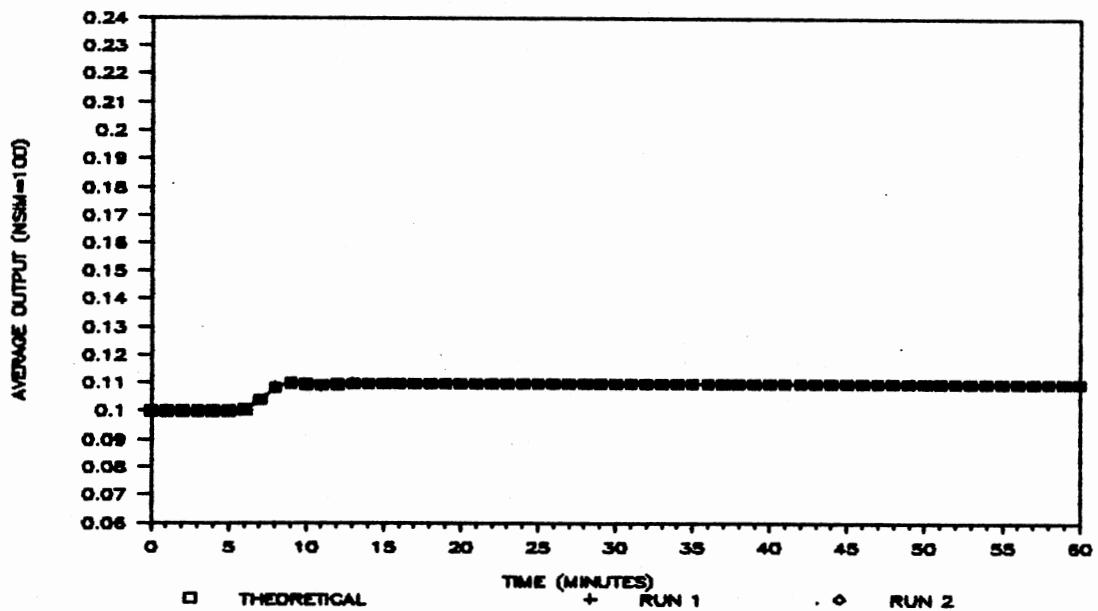
Figure 6-5E.   Average Output; CAD=0.20(t-5.0), t≥5;
Filter=NL(4)
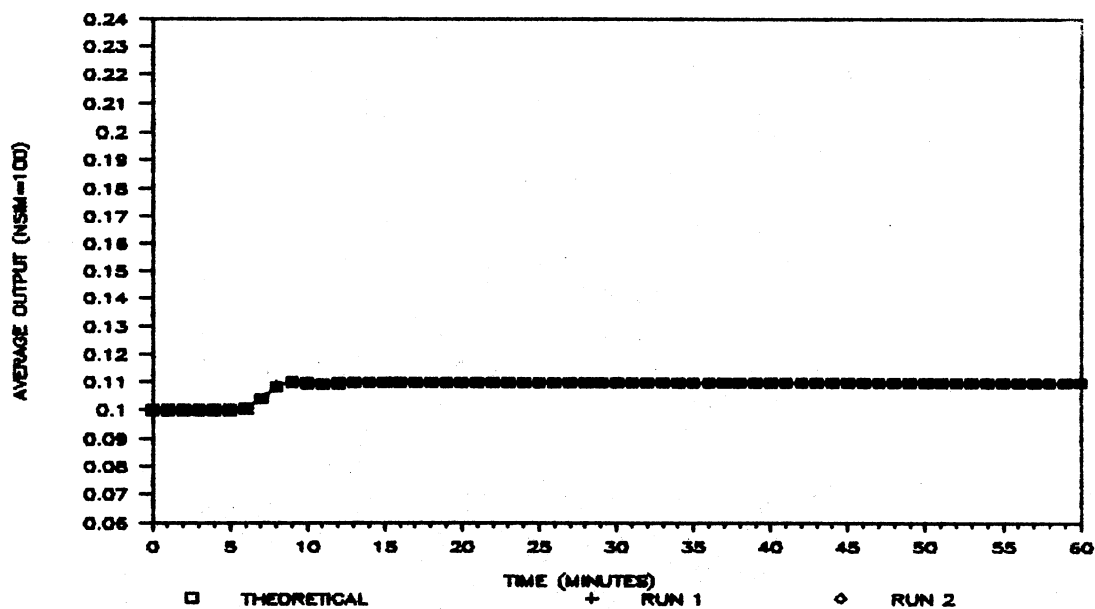
Figure 6-5F.   Average Output; CAD=0.20(t-5.0), t≥5;
              Filter=NL(7)

Statistical Process Control Filters

The statistical process control (SPC) filters are the

exponentially weighted moving average filter with parameter

α, EWMA(α), the moving average and moving range filter,

MAMR, and the individuals and moving range filter, IMR.   As

discussed in Chapter V, this research uses values of 0.2 and

1.0 for α.   The chemical reactor is simulated with a given

filtering device (with a known parameter value) and type of

disturbance for 100 replications of sixty minutes of plant

operation time.   The types of input disturbances for CAD

utilized in the research were the unit step of magnitudes

0.0, 0.12, and 0.2 for the values of CAD, and ramp functions

with the slope of 0.12 and 0.2 for the values of CAD. The

disturbance is not introduced until five minutes have elapsed allowing the reactor sufficient time to reach a stable condition. The standard deviation of the noise introduced in the feedback control loop is 0.005, and the parameters of the reactor and PID controller are as described in Chapter IV.

Table 6-6 below presents the integral of the average absolute error (IAAE) of two runs of the simulation described above for the situation in which there is no disturbance introduced to the system. Two runs were made utilizing each of the statistical filters described above.

TABLE 6-6

IAAE; UNIT STEP DISTURBANCE; CAD=0.0, T≥5.0

	Filtering Device			
	EWMA(0.2)	EWMA(1.0)	MAMR	IMR
Run 1	0.0	0.00032	0.00281	0.00093
Run 2	0.0	0.00039	0.00310	0.00108
AVG	0.0	0.00036	0.00295	0.00100

The average output of the chemical reactor using the EWMA(0.2), EWMA(1.0), MAMR, and IMR filters are shown below in Figures 6-6A, 6-6B, 6-6C, and 6-6D, respectively.
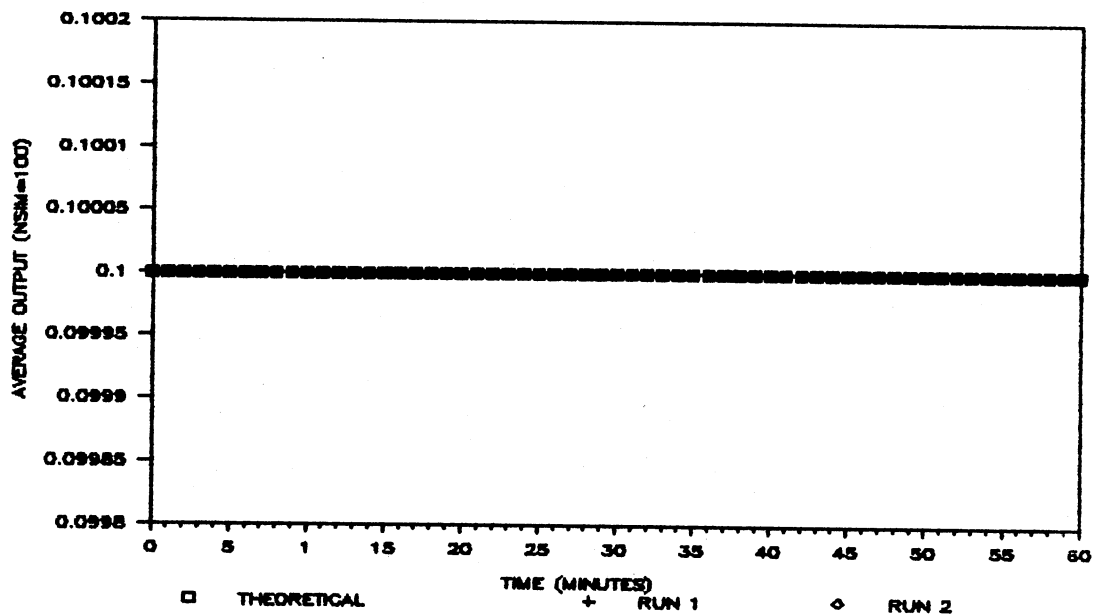
Figure 6-6A.   Average Output; CAD=0.00 ,t≥5;
Filter=EWMA(0.2)

Figure 6-6B.   Average Output; CAD=0.00, t≥5;
Filter=EWMA(1.0)
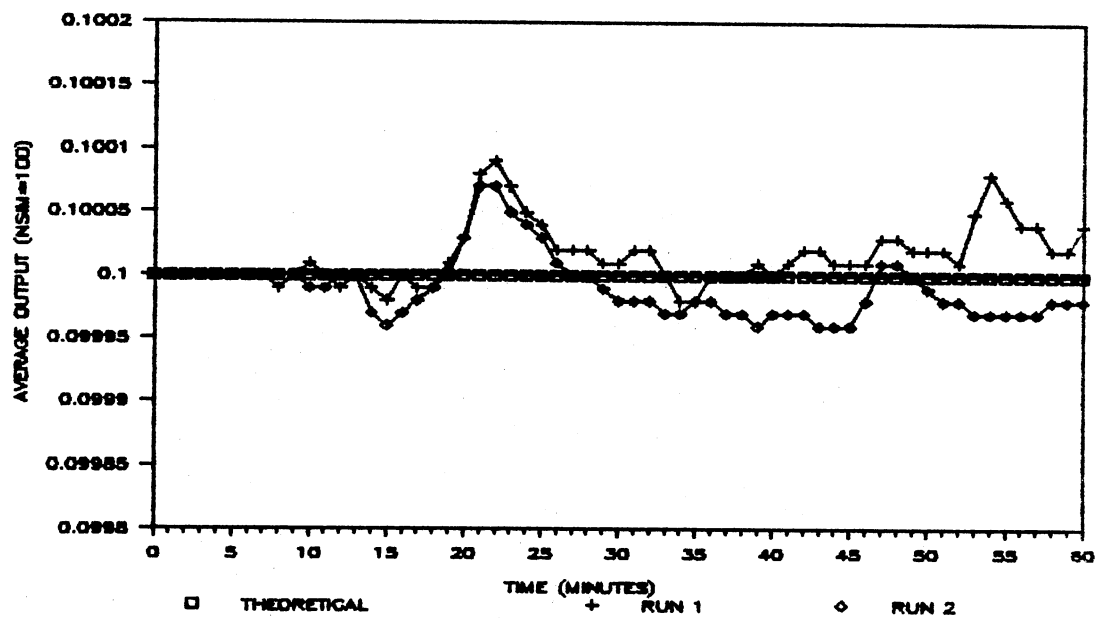
Figure 6-6C.   Average Output; CAD=0.00, t≥5;
Filter=MAMR

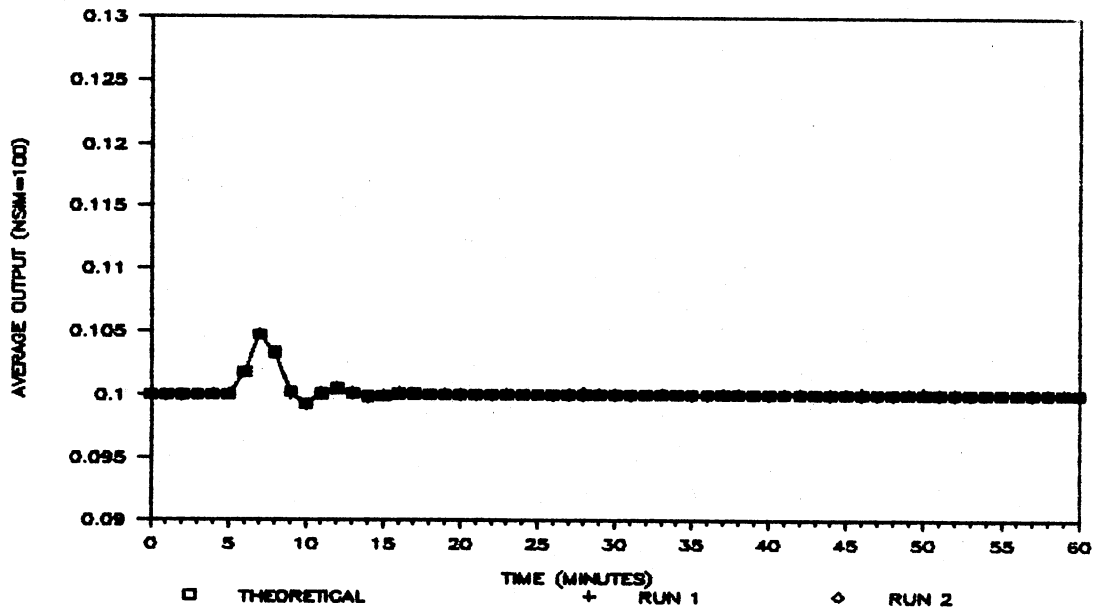Figure 6-6D.   Average Output; CAD=0.00, t≥5;
Filter=IMR

Table 6-7 below presents the integral of the average
absolute error (IAAE) of two runs of the simulation
described above for the unit step input disturbance of
magnitude 0.12. Two runs were made utilizing each of the
statistical filters described above.

TABLE 6-7

IAAE; UNIT STEP DISTURBANCE; CAD=0.12, T≥5.0

	Filtering Device			
	EWMA(0.2)	EWMA(1.0)	MAMR	IMR
Run 1	0.25884	0.25878	0.20287	0.17397
Run 2	0.25519	0.25952	0.19288	0.15121
AVG	0.25702	0.25915	0.19787	0.16259

The average output of the chemical reactor using the
EWMA(0.2), EWMA(1.0), MAMR, and IMR filters are shown below
in Figures 6-7A, 6-7B, 6-7C, and 6-7D, respectively.
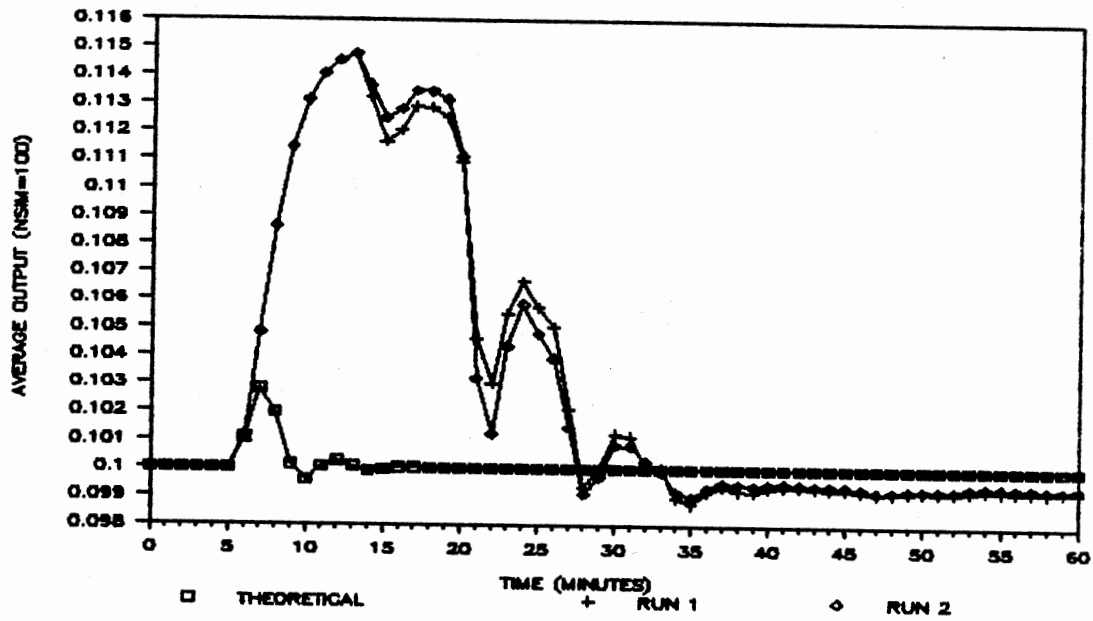
Figure 6-7A.   Average Output; CAD=0.12 ,t≥5;
Filter=EWMA(0.2)

Figure 6-7B.   Average Output; CAD=0.12, t≥5;
Filter=EWMA(1.0)

Figure 6-7C.   Average Output; CAD=0.12, t≥5;
              Filter=MAMR

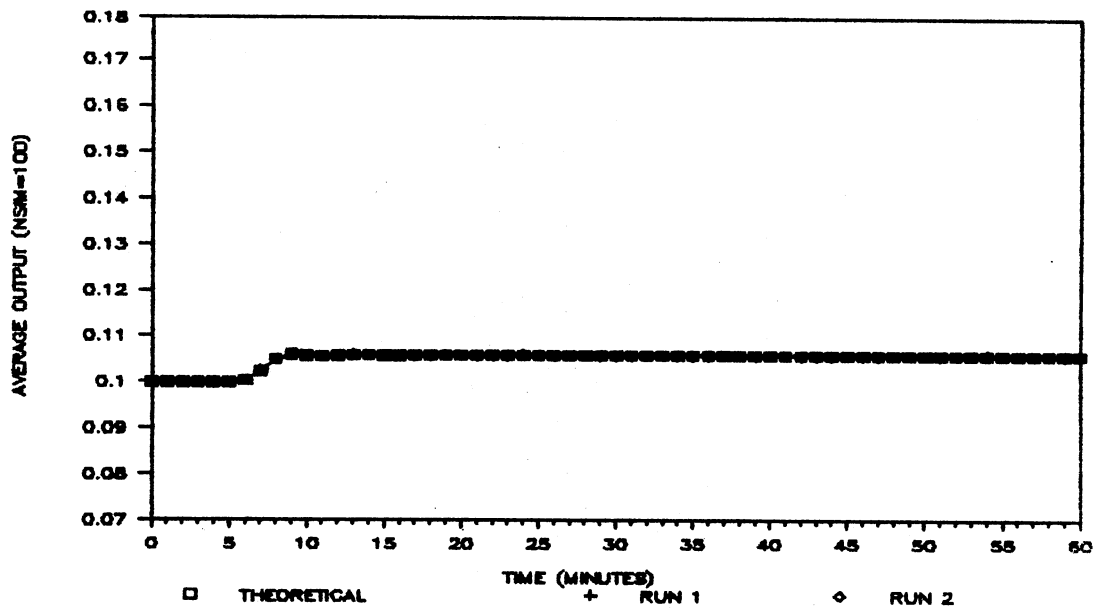Figure 6-7D.   Average Output; CAD=0.12, t≥5;
              Filter=IMR

Table 6-8 below presents the integral of the average absolute error (IAAE) of two runs of the simulation described above for the unit step input disturbance of magnitude 0.20. Two runs were made utilizing each of the statistical filters described above.

TABLE 6-8

IAAE; UNIT STEP DISTURBANCE; CAD=0.20, T≥5.0

	Filtering Device			
	EWMA(0.2)	EWMA(1.0)	MAMR	IMR
Run 1	0.26171	0.25196	0.19054	0.17097
Run 2	0.26882	0.25292	0.18761	0.16330
AVG	0.26527	0.25244	0.18907	0.16713

The average output of the chemical reactor is using the EWMA(0.2), EWMA(1.0), MAMR, and IMR filters are shown below in Figures 6-8A, 6-8B, 6-8C, and 6-8D, respectively.

Figure 6-8A.   Average Output; CAD=0.20 ,t≥5;
Filter=EWMA(0.2)

Figure 6-8B.   Average Output; CAD=0.20, t≥5;
Filter=EWMA(1.0)

Figure 6-8C.   Average Output; CAD=0.20, t≥5;
Filter=MAMR

Figure 6-8D.   Average Output; CAD=0.20, t≥5;
Filter=IMR

Table 6-9 below presents the integral of the average absolute error (IAAE) of two runs of the simulation described above for the ramp input disturbance of slope 0.12. Two runs were made utilizing each of the statistical filters described above.

TABLE 6-9

IAAE; RAMP DISTURBANCE; CAD=0.12(T-5.0), T≥5.0

	Filtering Device			
	EWMA(0.2)	EWMA(1.0)	MAMR	IMR
Run 1	0.32838	1.21752	0.99529	0.30085
Run 2	0.33589	1.21351	0.98680	0.31617
AVG	0.33214	1.21552	0.99104	0.30851

The average output of the chemical reactor using the EWMA(0.2), EWMA(1.0), MAMR, and IMR filters are shown below in Figures 6-9A, 6-9B, 6-9C, and 6-9D, respectively.

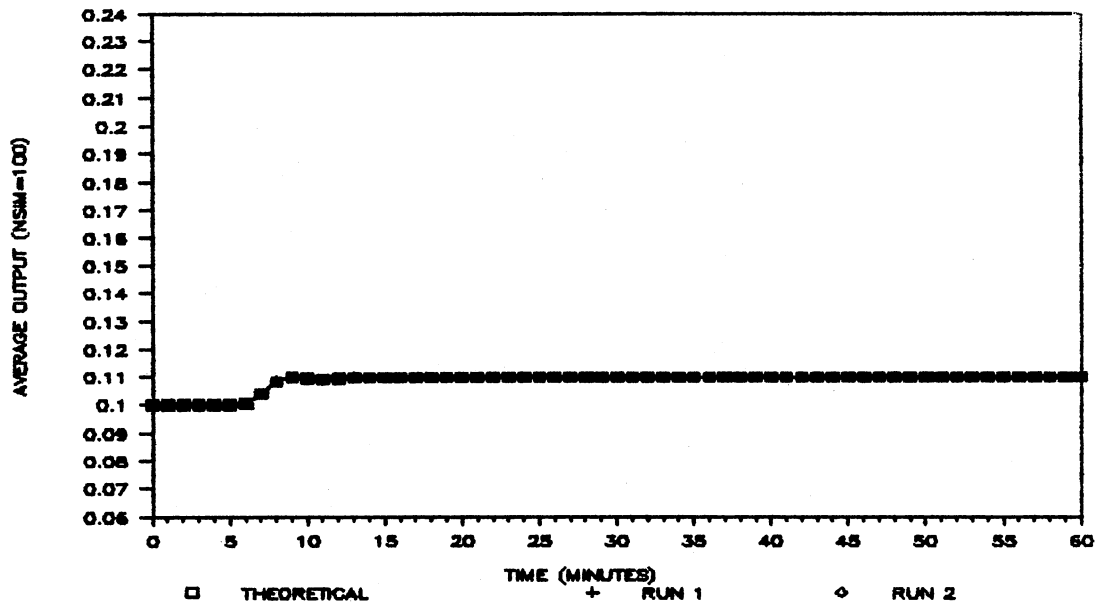Figure 6-9A.   Average Output; CAD=0.12(t-5.0) ,t≥5;
Filter=EWMA(0.2)

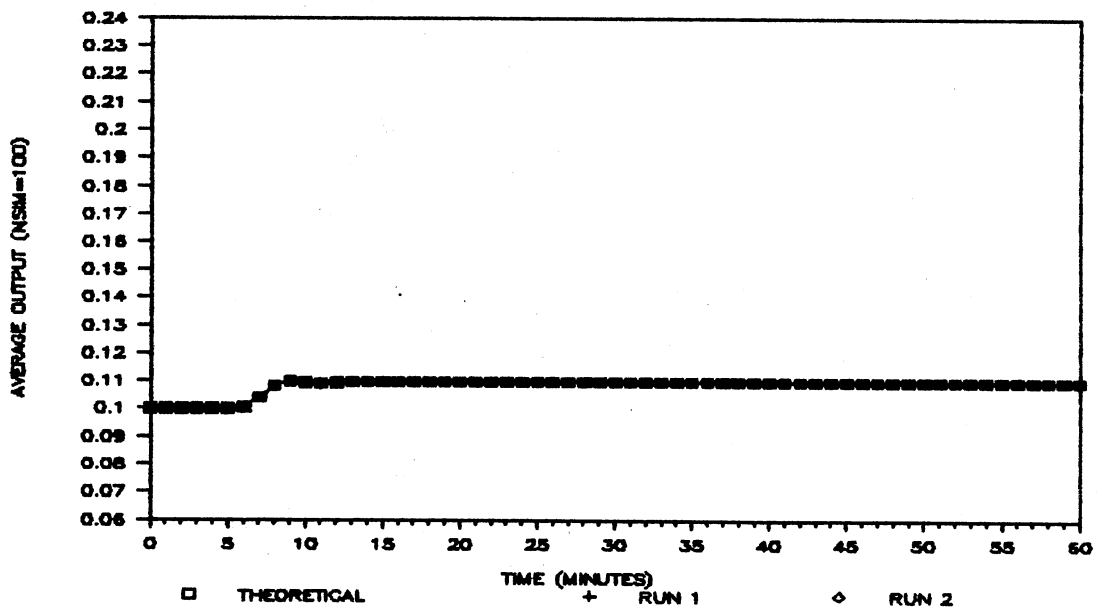Figure 6-9B.   Average Output; CAD=0.12(t-5.0), t≥5;
Filter=EWMA(1.0)
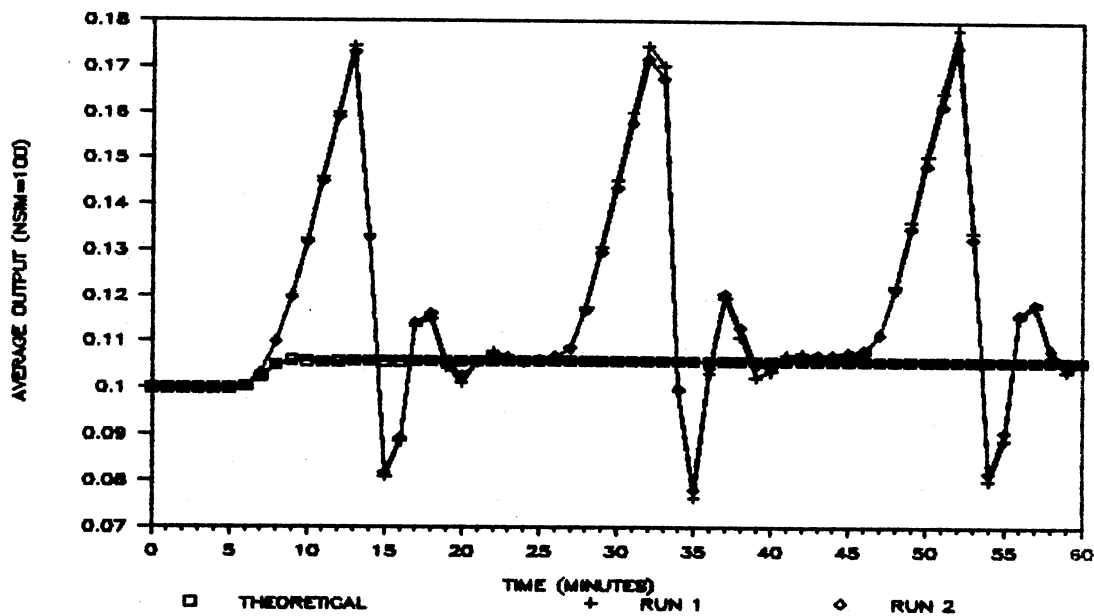
Figure 6-9C.   Average Output; CAD=0.12(t-5.0), t≥5;
              Filter=MAMR

Figure 6-9D.   Average Output; CAD=0.12(t-5.0), t≥5;
              Filter=IMR

Table 6-10 below presents the integral of the average absolute error (IAAE) of two runs of the simulation described above for the ramp input disturbance of slope 0.20. Two runs were made utilizing each of the statistical filters described above.

TABLE 6-10

IAAE; RAMP DISTURBANCE; CAD=0.20(T-5.0), T≥5.0

| | Filtering Device | | | |
	EWMA(0.2)	EWMA(1.0)	MAMR	IMR
Run 1	0.51867	2.02332	1.50764	0.50349
Run 2	0.51876	2.02108	1.53169	0.51889
AVG	0.51872	2.02220	1.51966	0.51119

The average output of the chemical reactor using the EWMA(0.2), EWMA(1.0), MAMR, and IMR filters are shown below in Figures 6-10A, 6-10B, 6-10C, and 6-10D, respectively.

Figure 6-10A.   Average Output; CAD=0.20(t-5.0) ,t≥5;
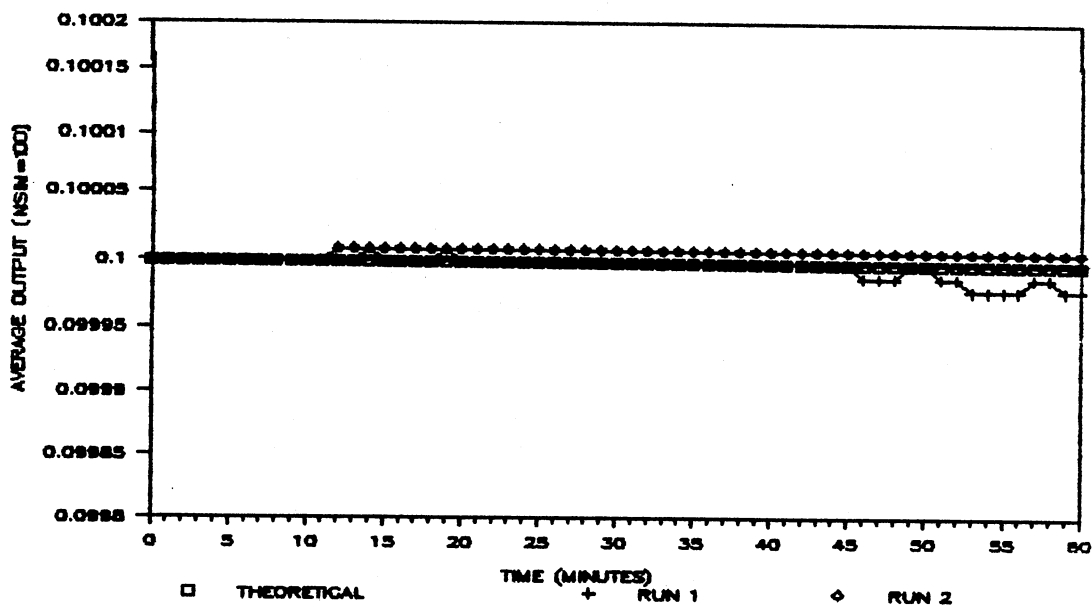Filter=EWMA(0.2)

Figure 6-10B.   Average Output; CAD=0.20(t-5.0), t≥5;
Filter=EWMA(1.0)

Figure 6-10C.   Average Output; CAD=0.20(t-5.0), t≥5;
Filter=MAMR

Figure 6-10D.   Average Output; CAD=0.20(t-5.0), t≥5;
Filter=IMR

Statistical Process Control Filters with

Individuals Prefiltering

The statistical process control (SPC) filters are the
exponentially weighted moving average filter with parameter
α, EWMA(α), the moving average and moving range filter with
parameter, MAMR, and the individuals and moving range
filter, IMR, and in each case the individuals prefilter,
IPRE, is employed. As discussed in Chapter V, this research
uses values of 0.2 and 1.0 for α for the EWMA(α) filter.
The chemical reactor is simulated utilizing a given
filtering device (with a known parameter value) and type of
disturbance for 100 replications of sixty minutes of plant
operation time. The types of input disturbances for CAD
utilized in the research were the unit step of magnitudes
0.0, 0.12, and 0.2 for the values of CAD, and ramp functions
with the slope of 0.12 and 0.2 for the values of CAD. The
disturbance is not introduced until five minutes have
elapsed allowing the reactor sufficient time to reach a
stable condition. The standard deviation of the noise
introduced in the feedback control loop is 0.005, and the
parameters of the reactor and PID controller are as
described in Chapter IV.

Table 6-11 below presents the integral of the average
absolute error (IAAE) of two runs of the simulation
described above for the situation in which there is no input

disturbance. Two runs were made utilizing each of the statistical filters and prefilter combinations as described above.

TABLE 6-11

IAAE; UNIT STEP DISTURBANCE; CAD=0.0, T≥5.0

	Filtering Combination			
	EWMA(0.2) IPRE	EWMA(1.0) IPRE	MAMR IPRE	IMR IPRE
Run 1	0.01140	0.01241	0.01251	0.00891
Run 2	0.01287	0.01228	0.01231	0.00872
AVG	0.01214	0.01235	0.01241	0.00882

The average output of the chemical reactor using the EWMA(0.2)/IPRE, EWMA(1.0)/IPRE, MAMR/IPRE, and IMR/IPRE filters/prefilter combinations are shown below in Figures 6-11A, 6-11B, 6-11C, and 6-11D, respectively.
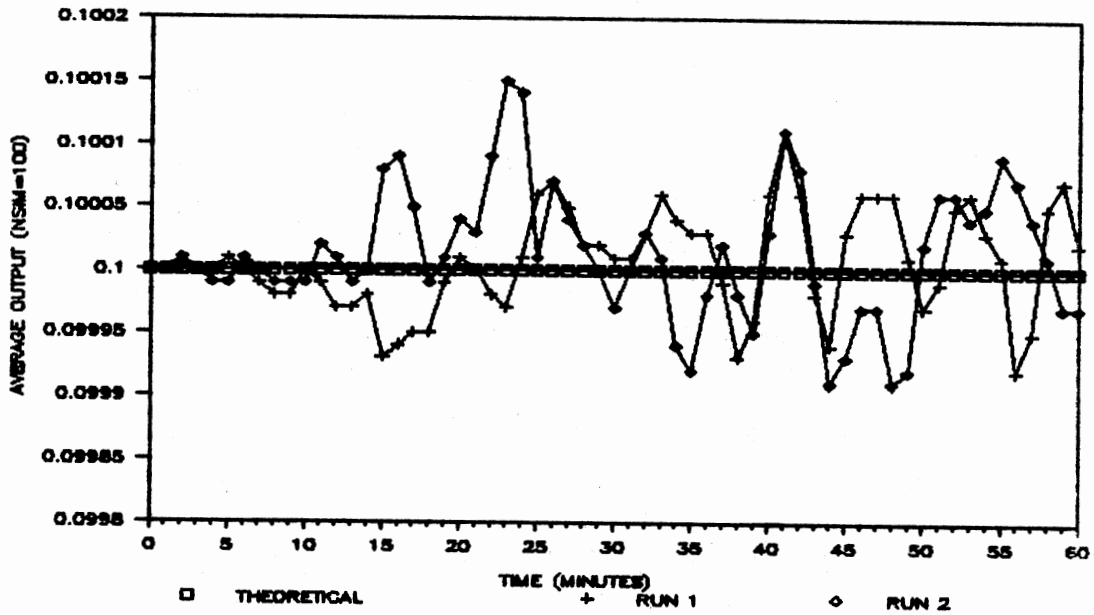
Figure 6-11A. Average Output; CAD=0.00 ,t≥5;
Filter=EWMA(0.2)/IPRE
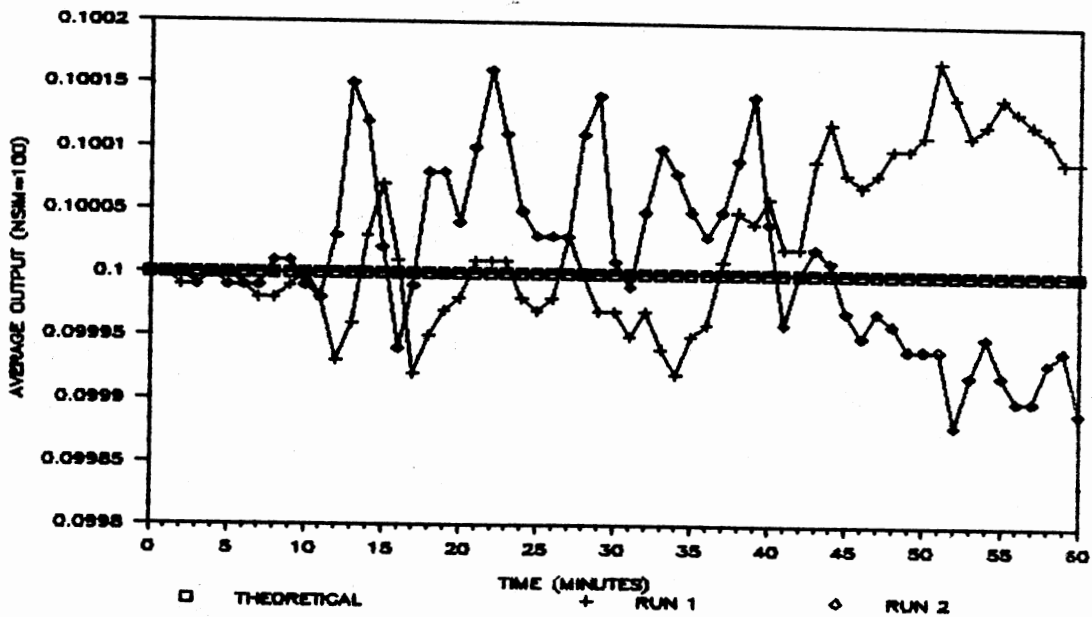
Figure 6-11B. Average Output; CAD=0.00, t≥5;
Filter=EWMA(1.0)/IPRE
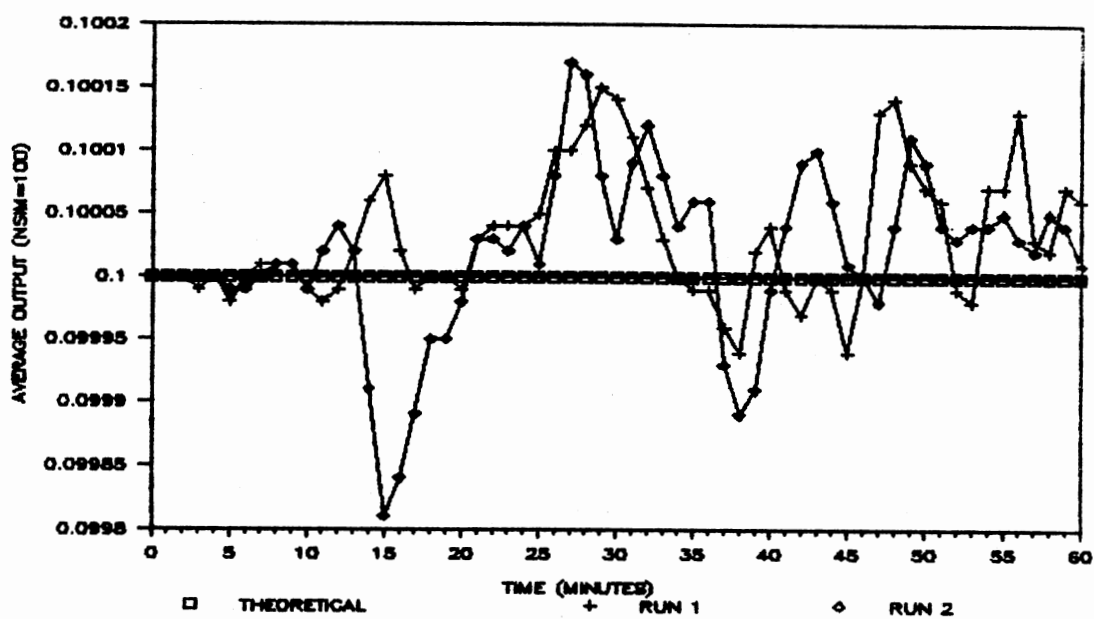
Figure 6-11C.   Average Output; CAD=0.00, t≥5;
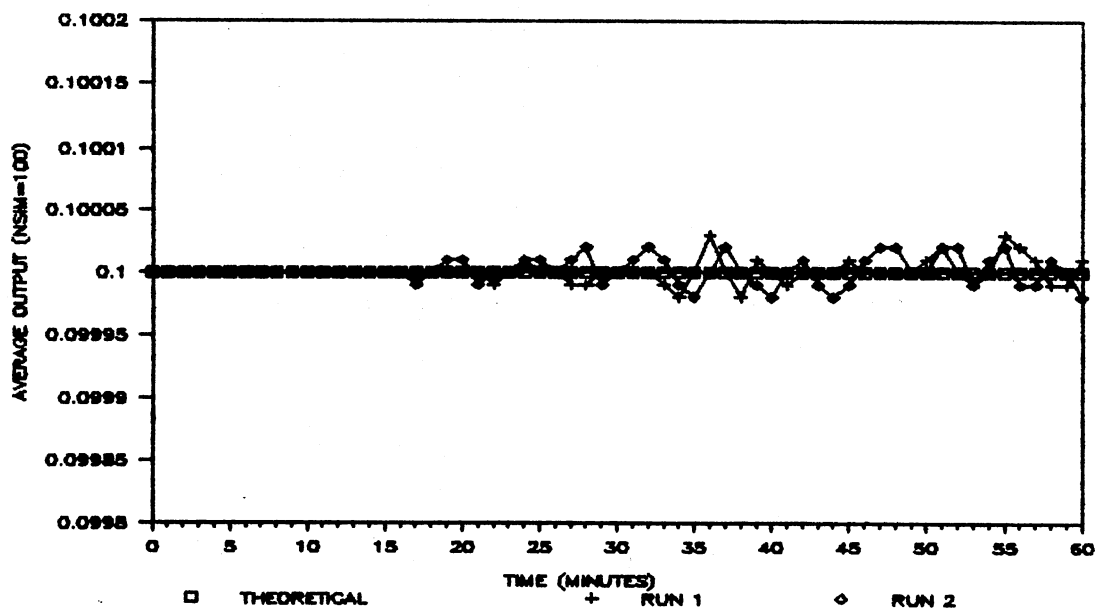Filter=MAMR/IPRE
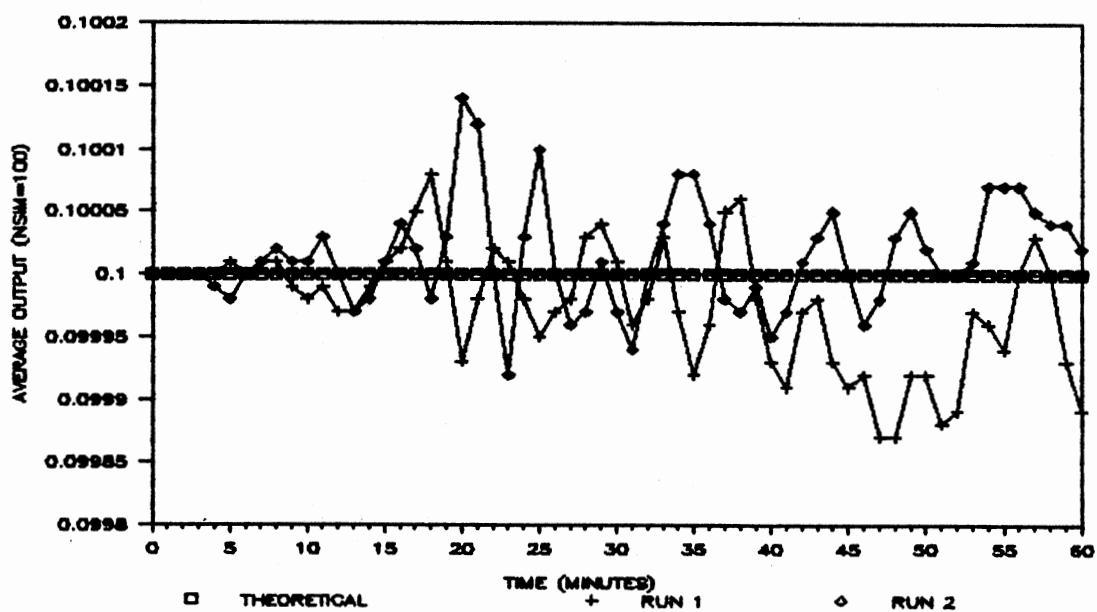
Figure 6-11D.   Average Output; CAD=0.00, t≥5;
Filter=IMR/IPRE

Table 6-12 below presents the integral of the average absolute error (IAAE) of two runs of the simulation described above for the unit step input disturbance of magnitude 0.12. Two runs were made utilizing each of the statistical filters and prefilter combinations as described above.

TABLE 6-12

IAAE; UNIT STEP DISTURBANCE; CAD=0.12, T≥5.0

	Filtering Combination			
	EWMA(0.2) IPRE	EWMA(1.0) IPRE	MAMR IPRE	IMR IPRE
Run 1	0.04845	0.05002	0.05030	0.04973
Run 2	0.05071	0.04938	0.04793	0.04744
AVG	0.04958	0.04970	0.04912	0.04859

The average output of the chemical reactor using the EWMA(0.2)/IPRE, EWMA(1.0)/IPRE, MAMR/IPRE, and IMR/IPRE filters/prefilter combinations are shown below in Figures 6-12A, 6-12B, 6-12C, and 6-12D, respectively.
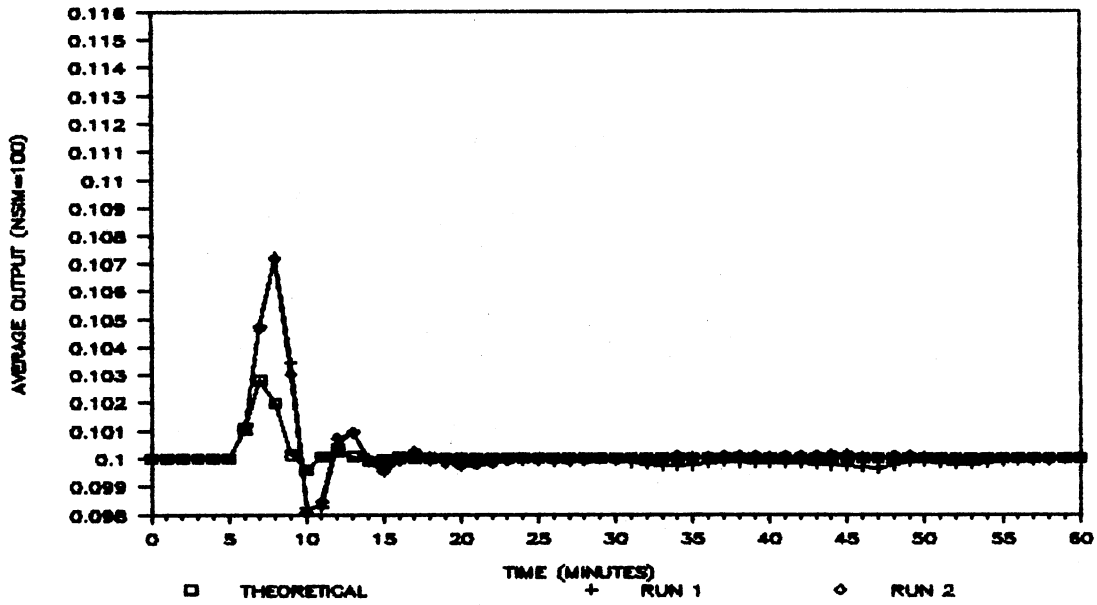
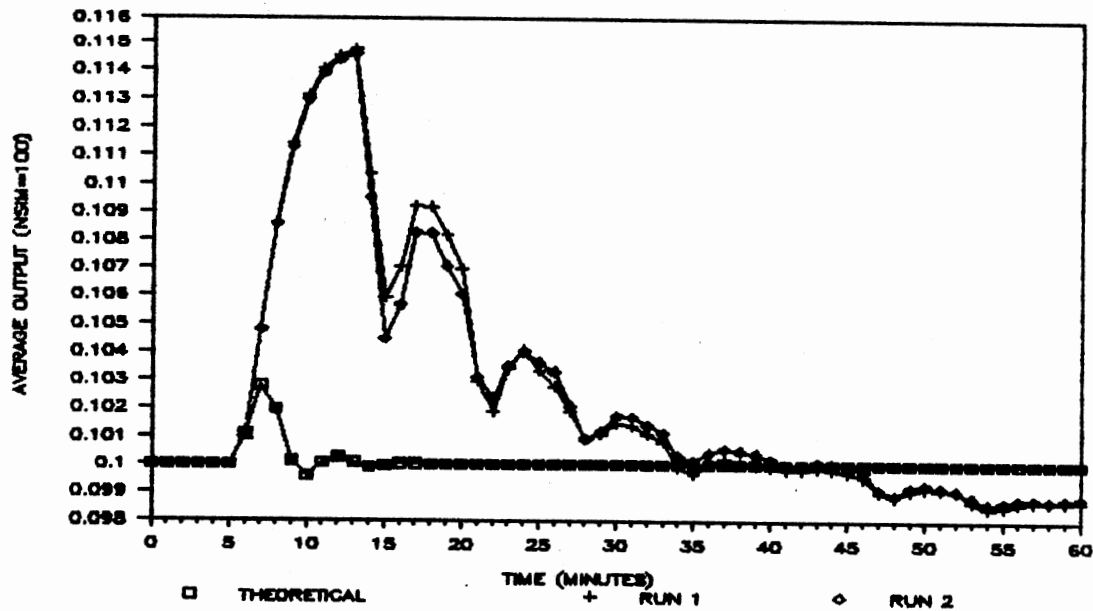Figure 6-12A.   Average Output; CAD=0.12 ,t≥5;
Filter=EWMA(0.2)/IPRE
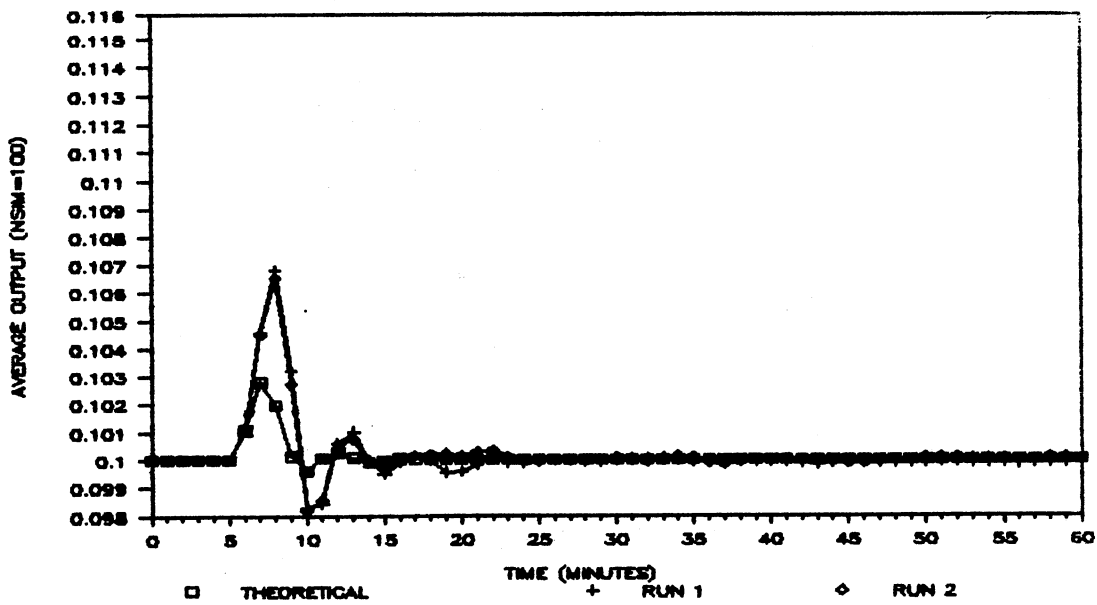
Figure 6-12B.   Average Output; CAD=0.12, t≥5;
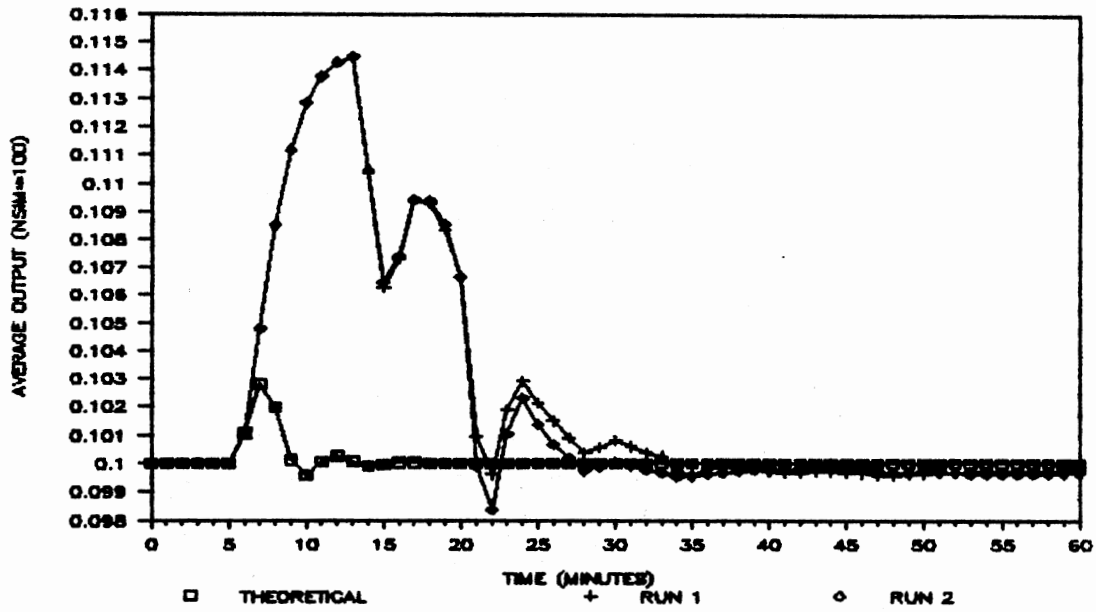Filter=EWMA(1.0)/IPRE
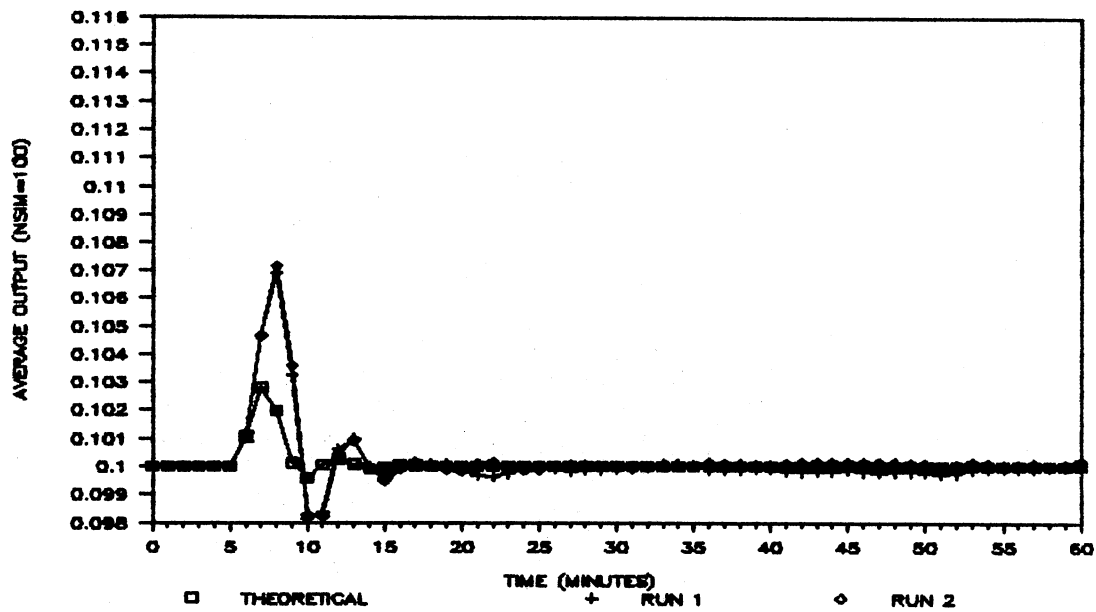
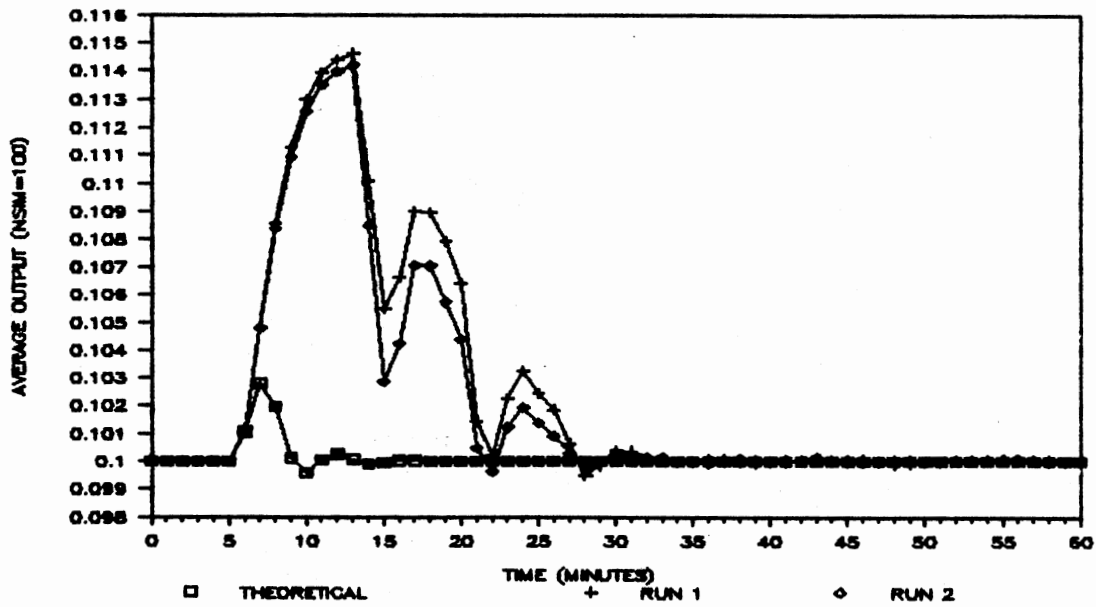Figure 6-12C.   Average Output; CAD=0.12, t≥5;
Filter=MAMR/IPRE
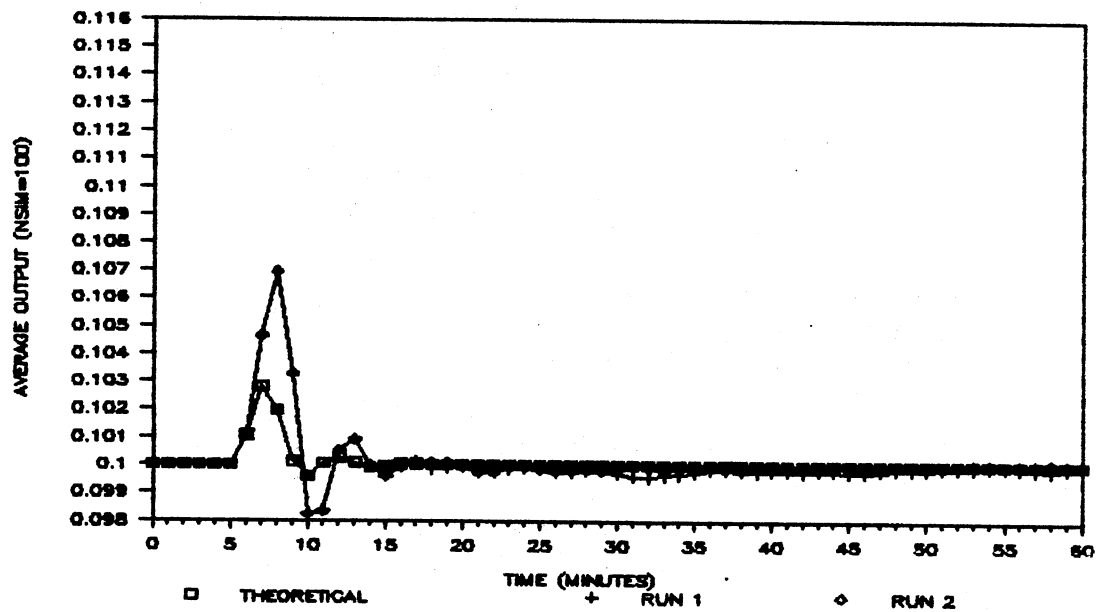
Figure 6-12D.   Average Output; CAD=0.12, t≥5;
Filter=IMR/IPRE

Table 6-13 below presents the integral of the average absolute error (IAAE) of two runs of the simulation described above for the unit step input disturbance of magnitude 0.20. Two runs were made utilizing each of the statistical filters and prefilter combinations as described above.

TABLE 6-13

IAAE; UNIT STEP DISTURBANCE; CAD=0.20, T≥5.0

	Filtering Combination			
	EWMA(0.2) IPRE	EWMA(1.0) IPRE	MAMR IPRE	IMR IPRE
Run 1	0.04570	0.04519	0.04587	0.04388
Run 2	0.04695	0.04863	0.04782	0.04473
AVG	0.04633	0.04691	0.04685	0.04431

The average output of the chemical reactor using the EWMA(0.2)/IPRE, EWMA(1.0)/IPRE, MAMR/IPRE, and IMR/IPRE filters/prefilter combinations are shown below in Figures 6-13A, 6-13B, 6-13C, and 6-13D, respectively.
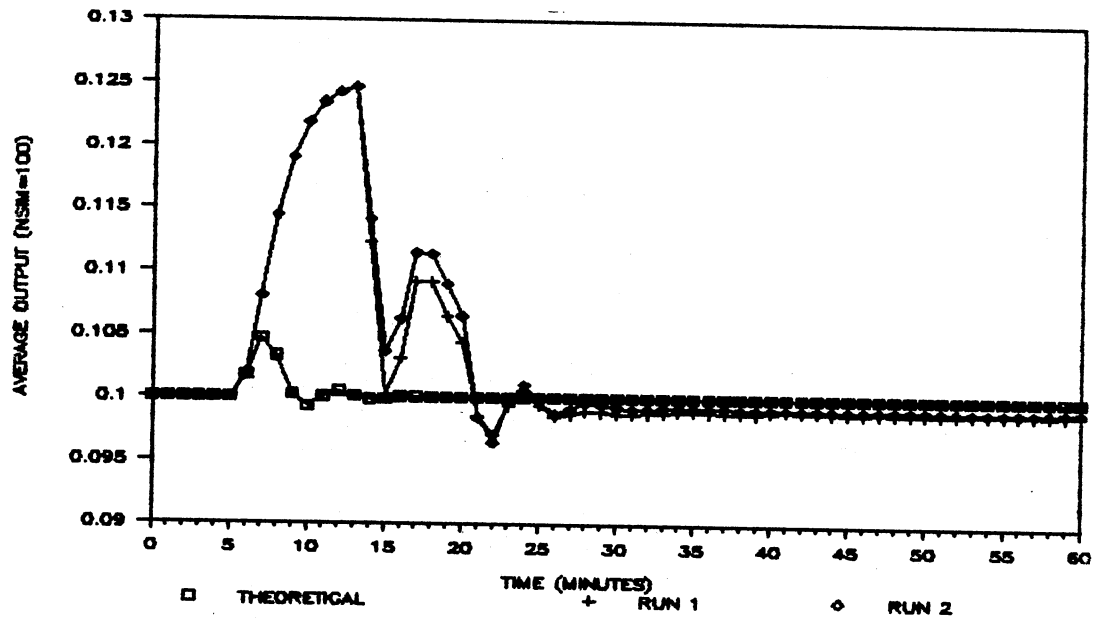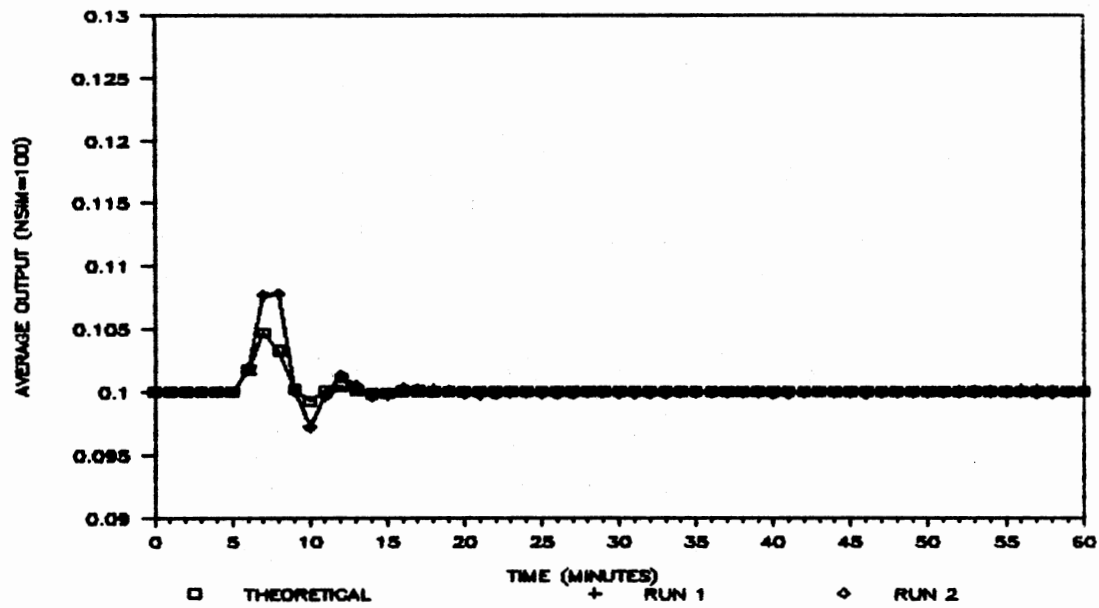
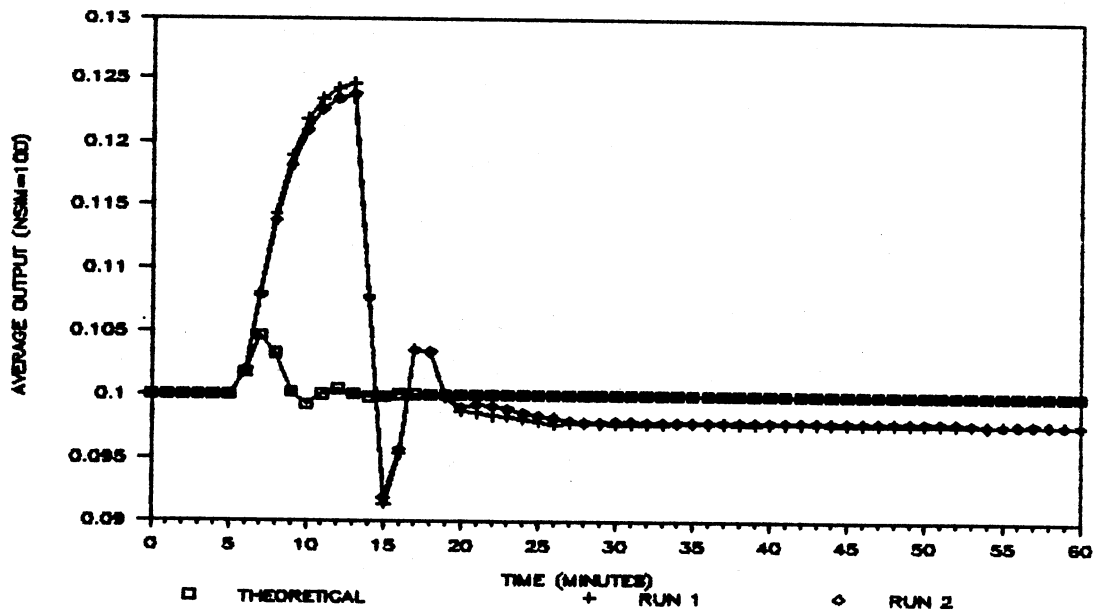Figure 6-13A.   Average Output; CAD=0.20 ,t≥5;
Filter=EWMA(0.2)/IPRE
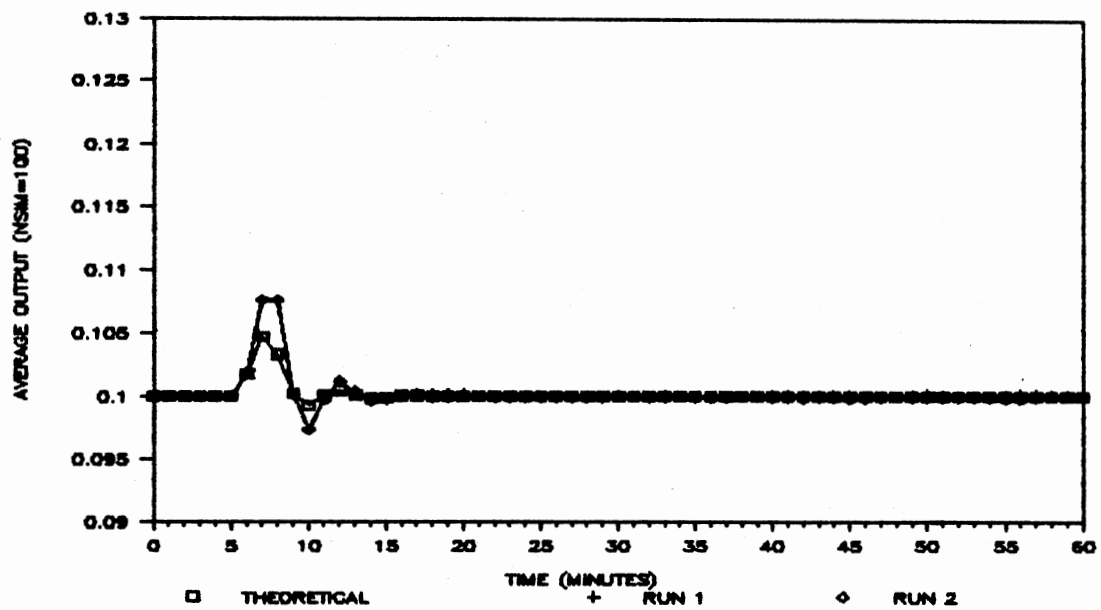
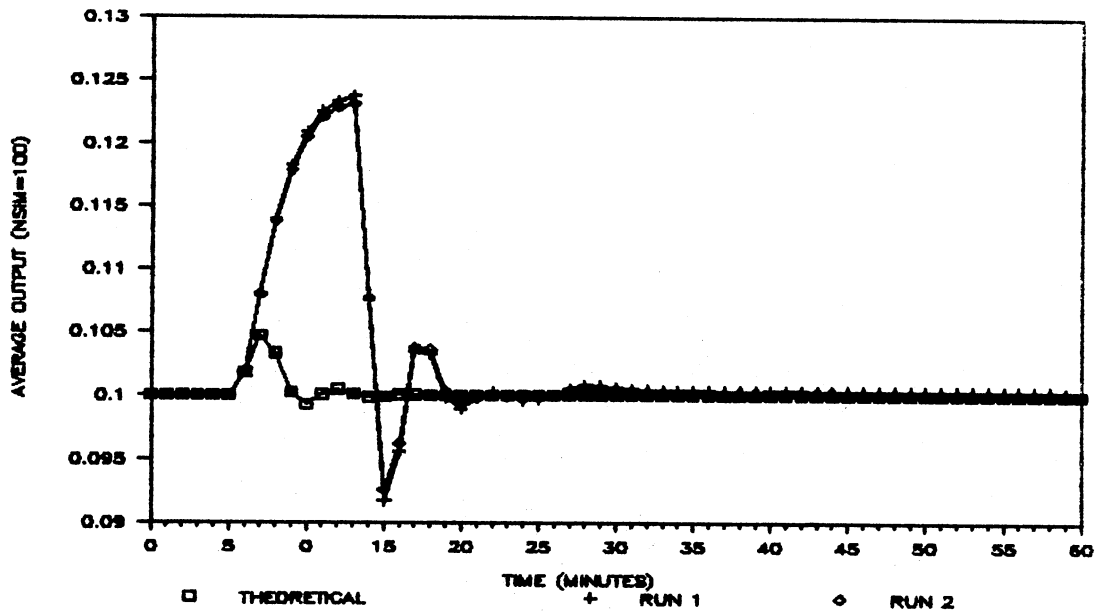Figure 6-13B.   Average Output; CAD=0.20, t≥5;
Filter=EWMA(1.0)/IPRE
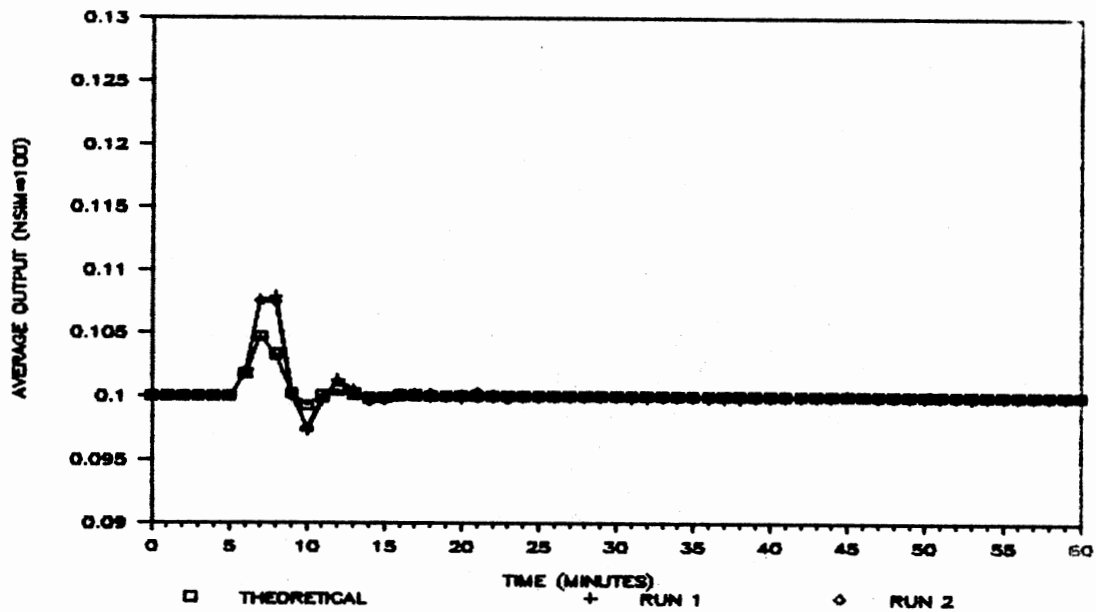
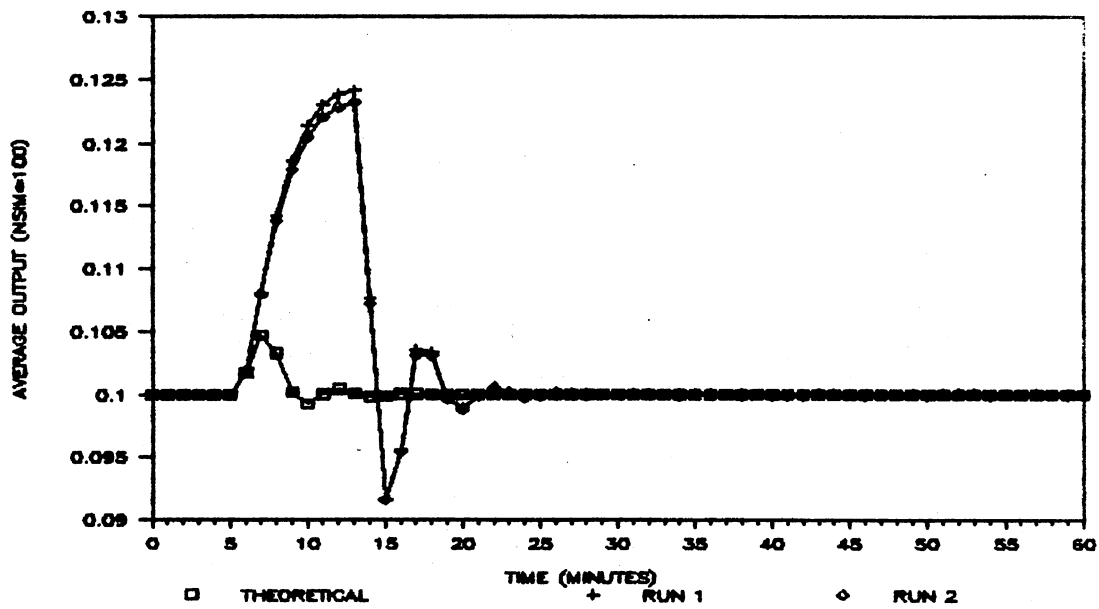Figure 6-13C. Average Output; CAD=0.20, t≥5;
Filter=MAMR/IPRE
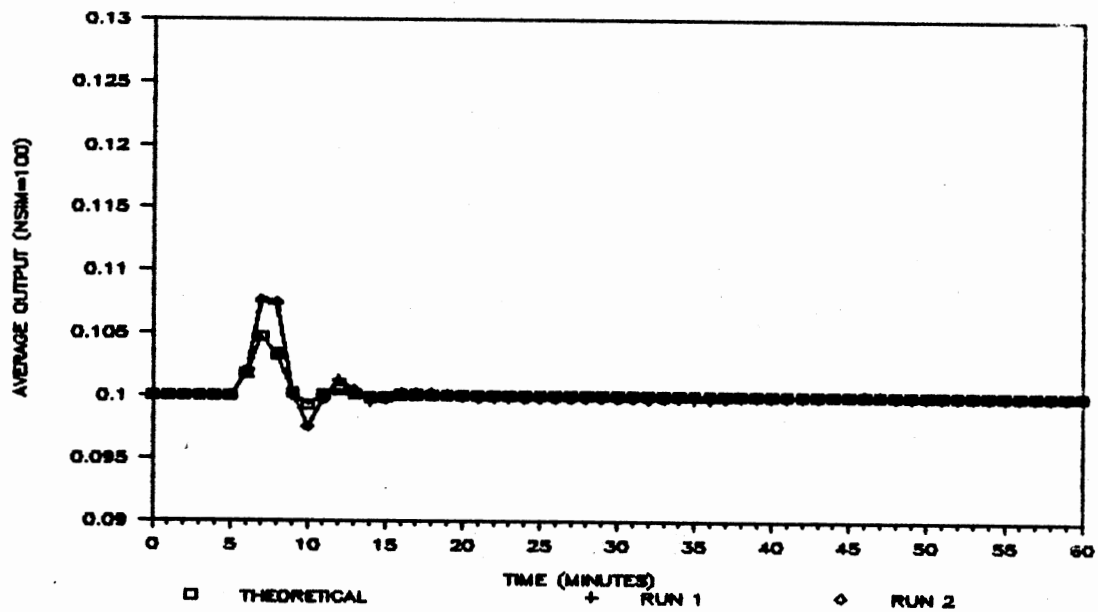
Figure 6-13D. Average Output; CAD=0.20, t≥5;
Filter=IMR/IPRE

Table 6-14 below presents the integral of the average absolute error (IAAE) of two runs of the simulation described above for a ramp input disturbance of slope 0.12. Two runs were made utilizing each of the statistical filters and prefilter combinations as described above.

TABLE 6-14

IAAE; RAMP DISTURBANCE; CAD=0.12(T-5.0), T≥5.0

	Filtering Combination			
	EWMA(0.2) IPRE	EWMA(1.0) IPRE	MAMR IPRE	IMR IPRE
Run 1	0.05497	0.06060	0.06117	0.04731
Run 2	0.05528	0.06253	0.05954	0.04773
AVG	0.05513	0.06157	0.06036	0.04752

The average output of the chemical reactor is using the EWMA(0.2)/IPRE, EWMA(1.0)/IPRE, MAMR/IPRE, and IMR/IPRE filters/prefilter combinations are shown below in Figures 6-14A, 6-14B, 6-14C, and 6-14D, respectively.
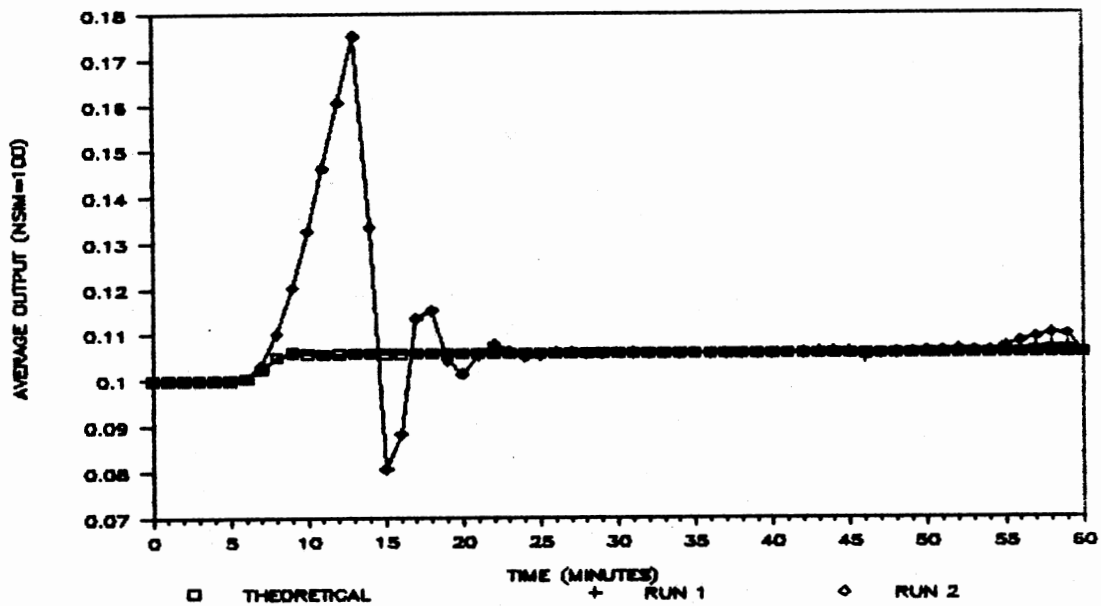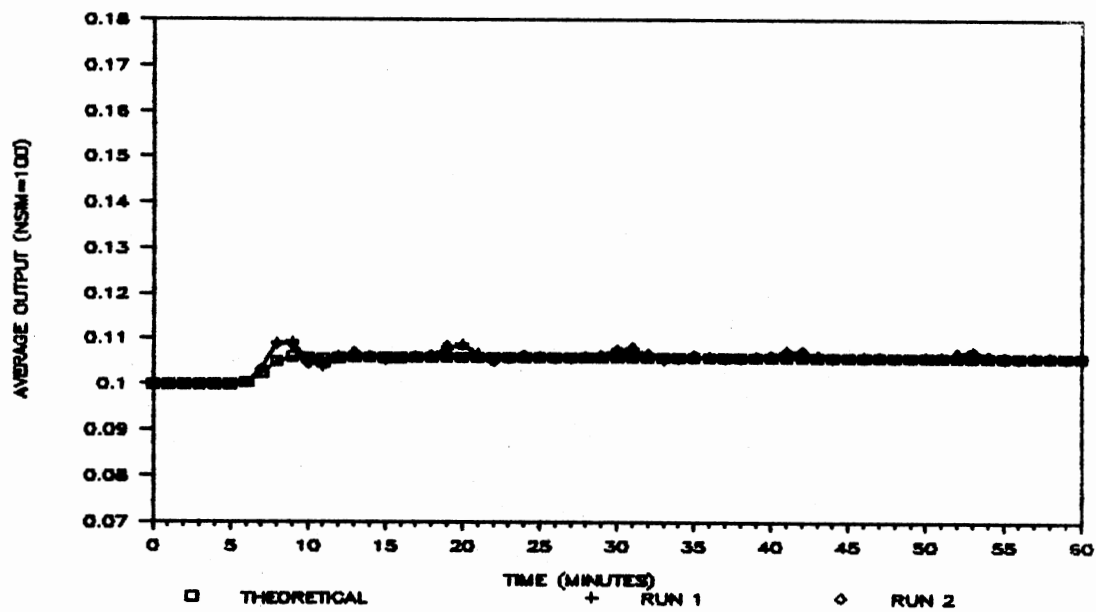
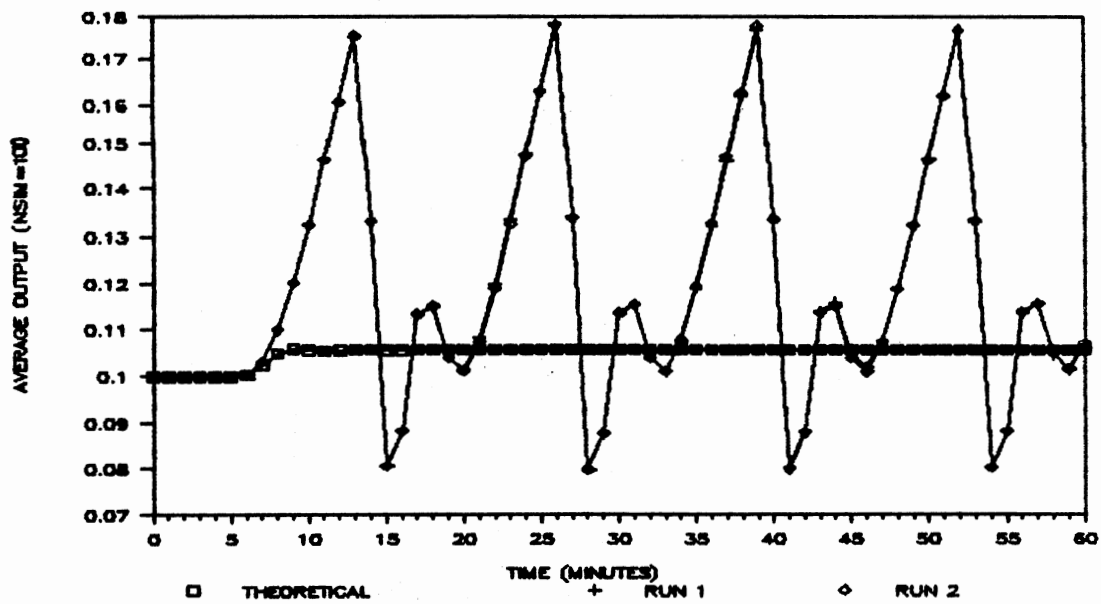Figure 6-14A.   Average Output; CAD=0.12(t-5.0) ,t≥5;
Filter=EWMA(0.2)/IPRE
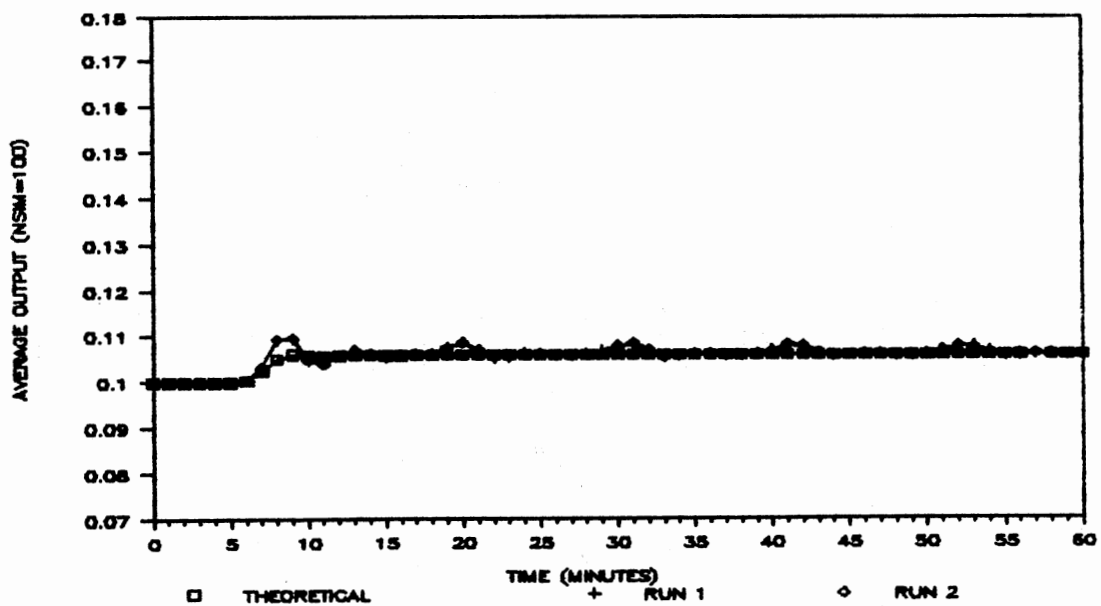
Figure 6-14B.   Average Output; CAD=0.12(t-5.0), t≥5;
Filter=EWMA(1.0)/IPRE
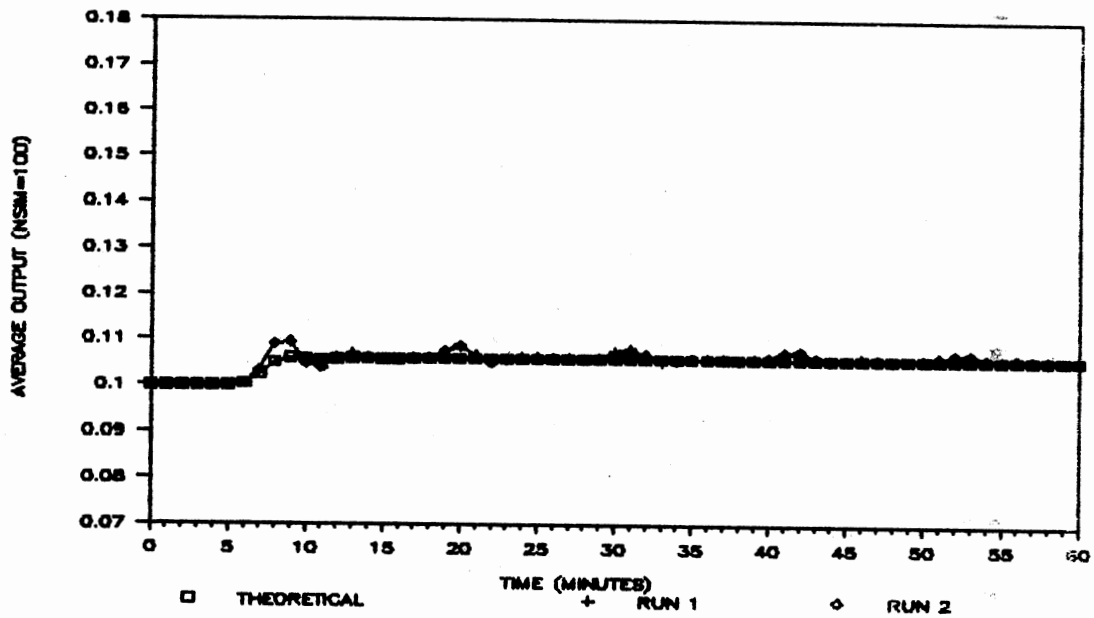
Figure 6-14C. Average Output; CAD=0.12(t-5.0), t≥5;
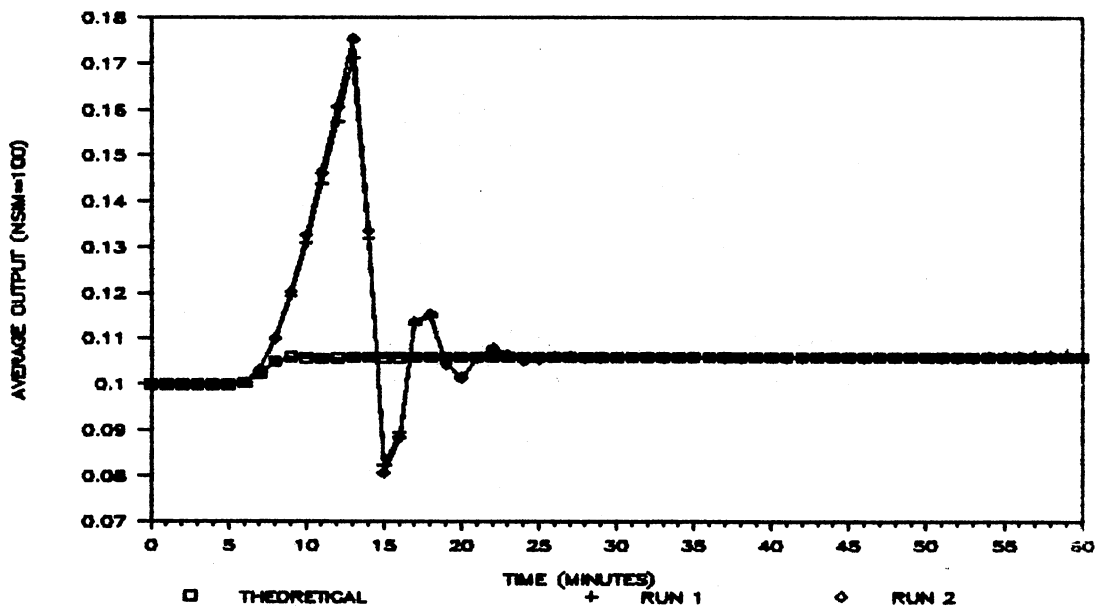Filter=MAMR/IPRE
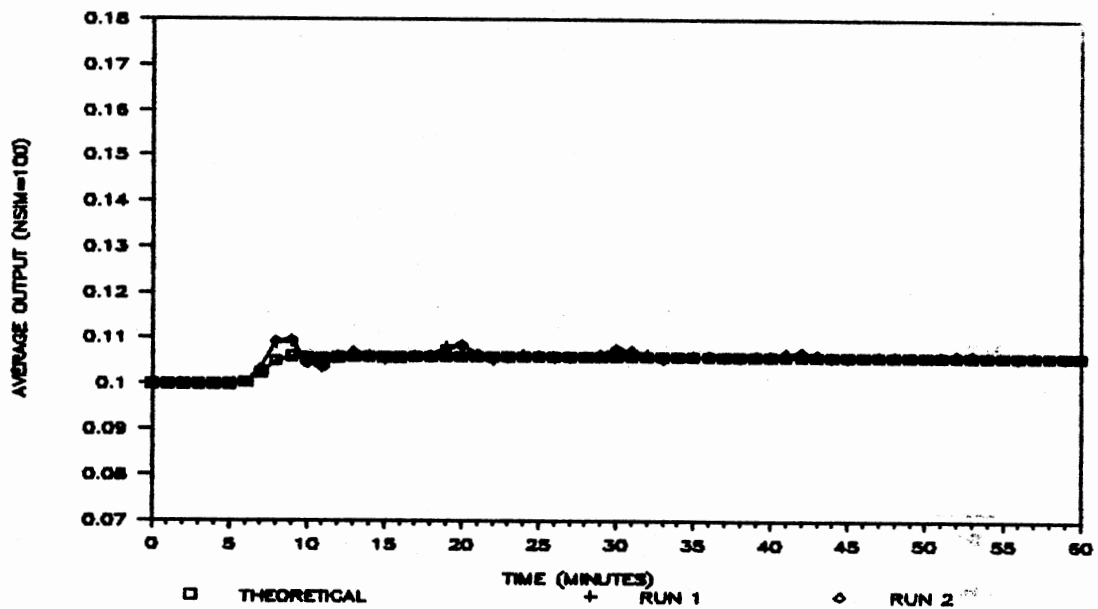
Figure 6-14D. Average Output; CAD=0.12(t-5.0), t≥5;
Filter=IMR/IPRE

Table 6-15 below presents the integral of the average absolute error (IAAE) of two runs of the simulations described above for a ramp input disturbance of slope 0.20. Two runs were made utilizing each of the statistical filters and prefilter combinations as described above.

TABLE 6-15

IAAE; RAMP DISTURBANCE; CAD=0.20(T-5.0), T≥5.0

| | Filtering Combination | | | |
	EWMA(0.2) IPRE	EWMA(1.0) IPRE	MAMR IPRE	IMR IPRE
Run 1	0.03704	0.04639	0.04195	0.03495
Run 2	0.03718	0.04771	0.04241	0.03200
AVG	0.03711	0.04705	0.04218	0.03348

The average output of the chemical reactor using the EWMA(0.2)/IPRE, EWMA(1.0)/IPRE, MAMR/IPRE, and IMR/IPRE filters/prefilter combinations are shown below in Figures 6-15A, 6-15B, 6-15C, and 6-15D, respectively.
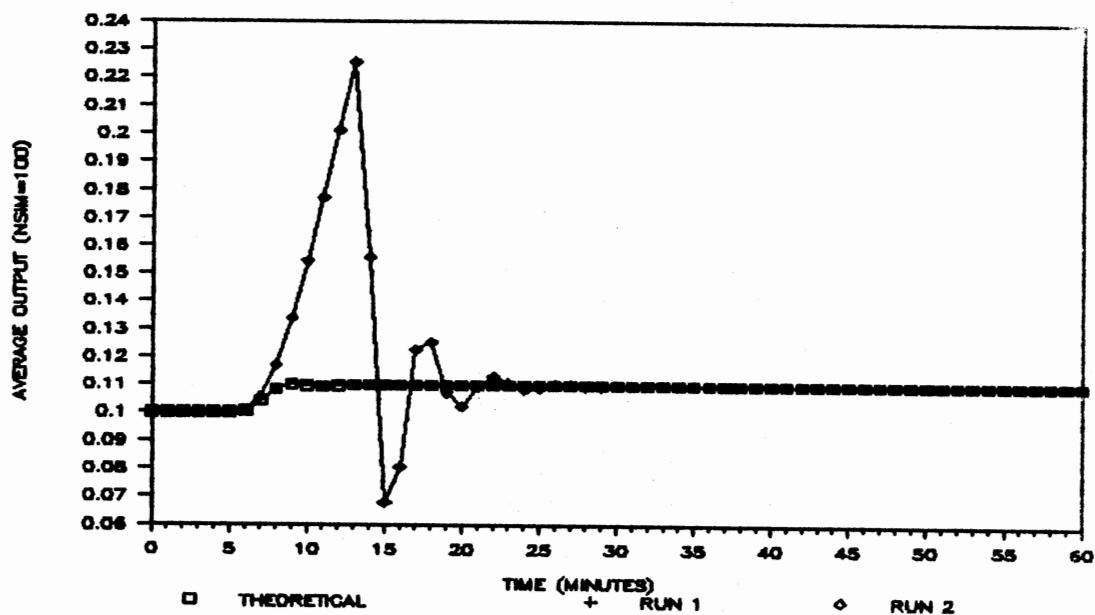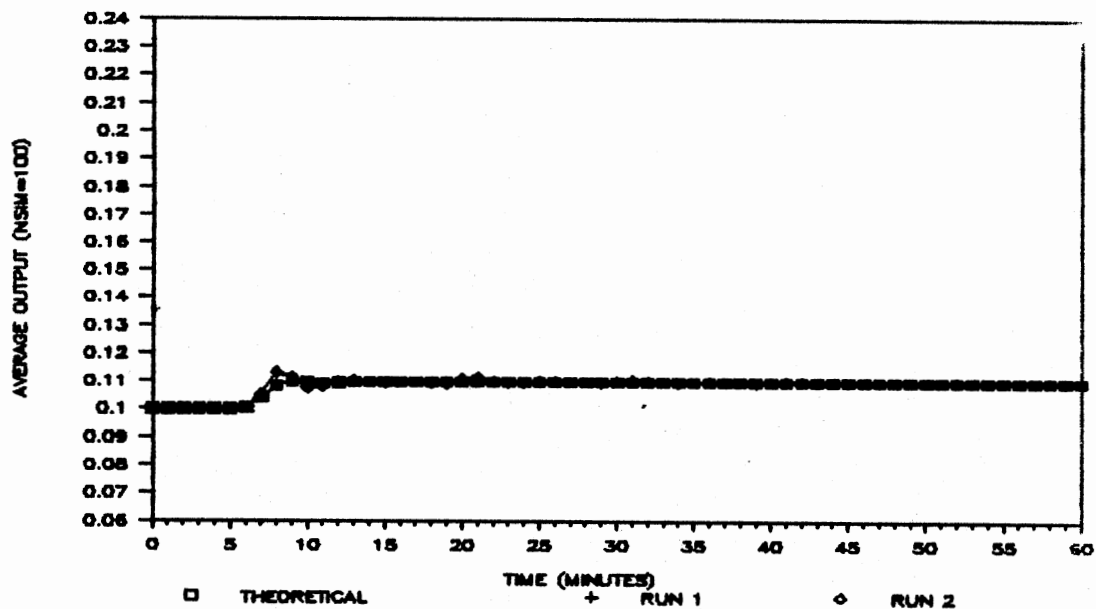
Figure 6-15A.   Average Output; CAD=0.20(t-5.0) ,t≥5;
Filter=EWMA(0.2)/IPRE
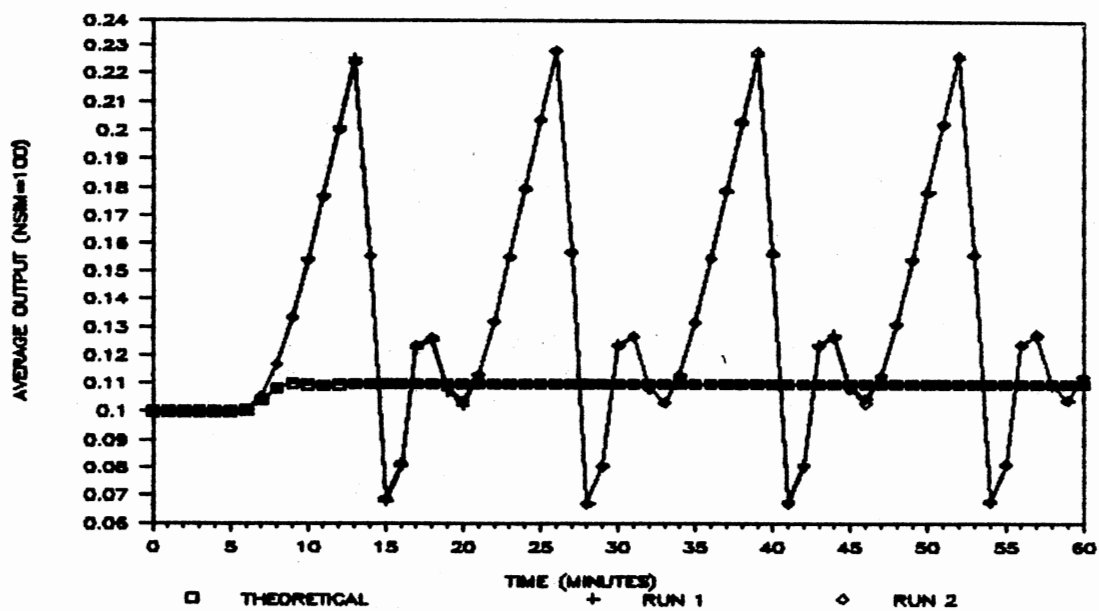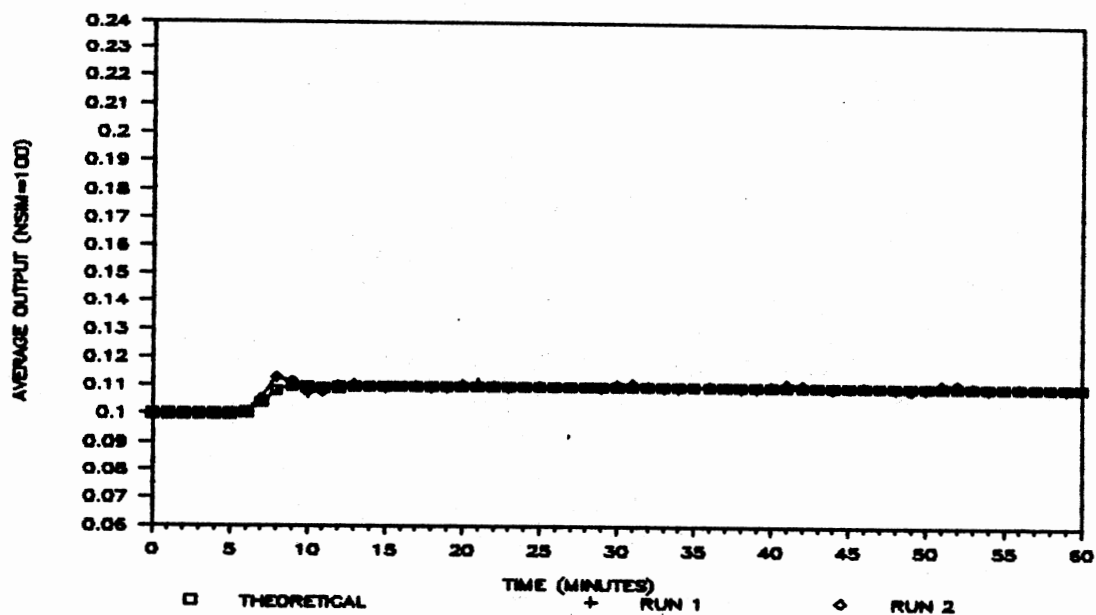

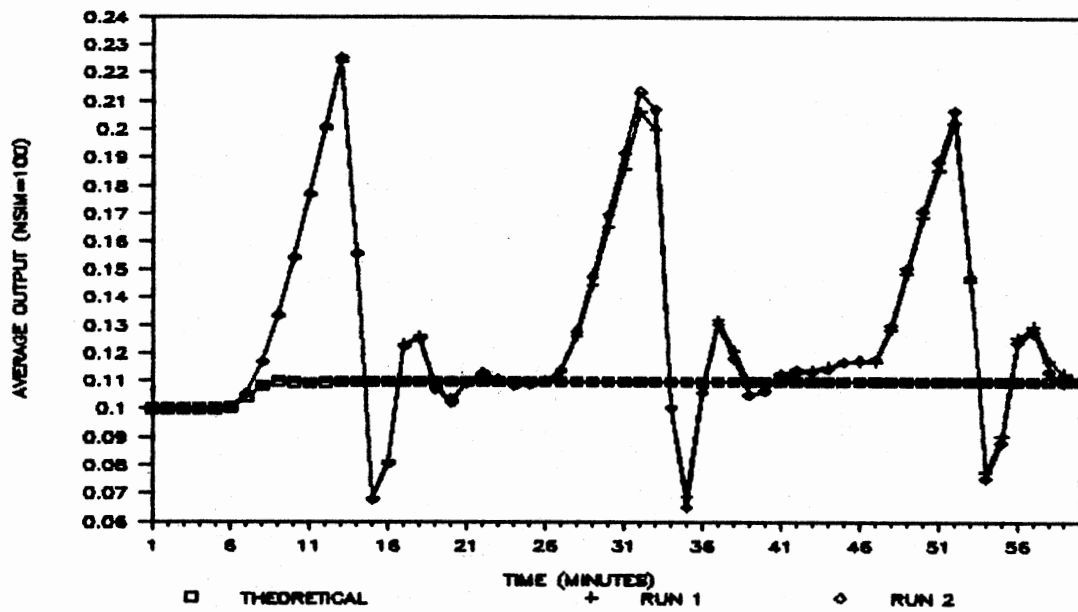Figure 6-15B.   Average Output; CAD=0.20(t-5.0), t≥5;
Filter=EWMA(1.0)/IPRE
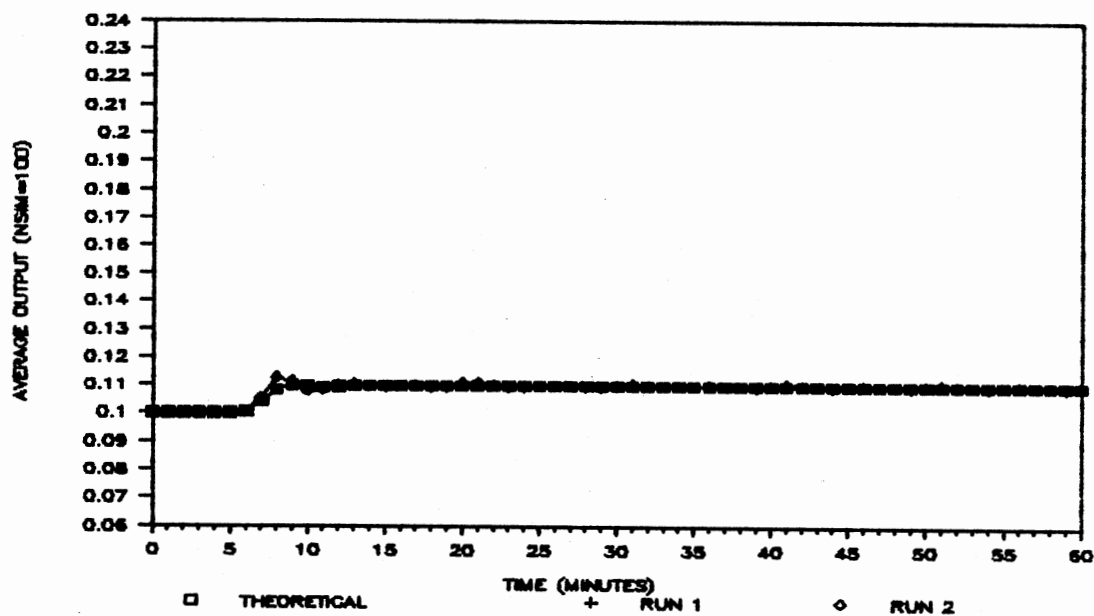
Figure 6-15C.   Average Output; CAD=0.20(t-5.0), t≥5;
Filter=MAMR/IPRE
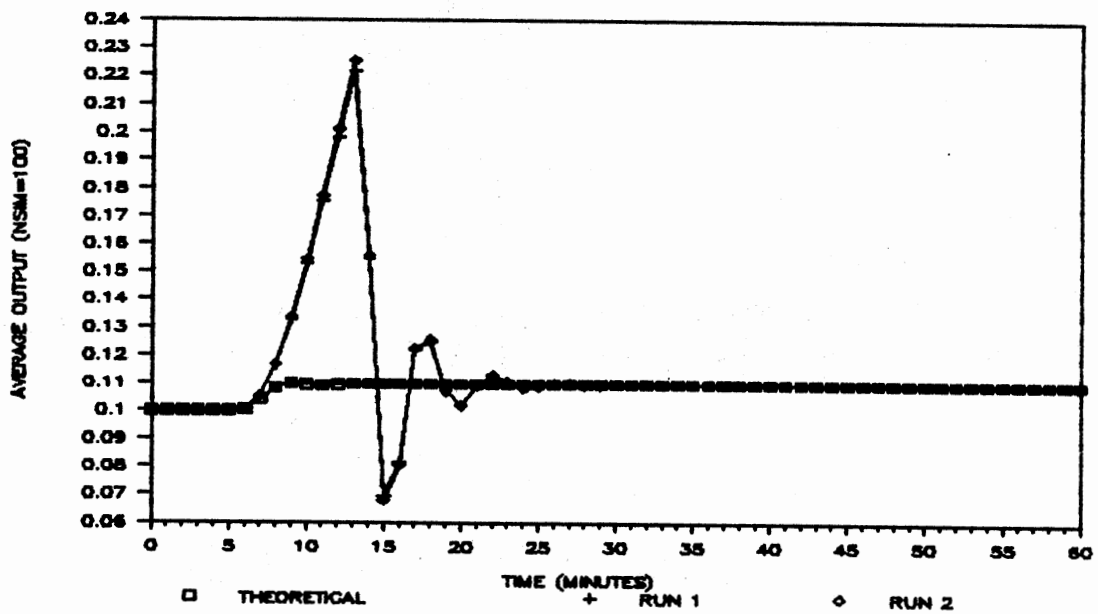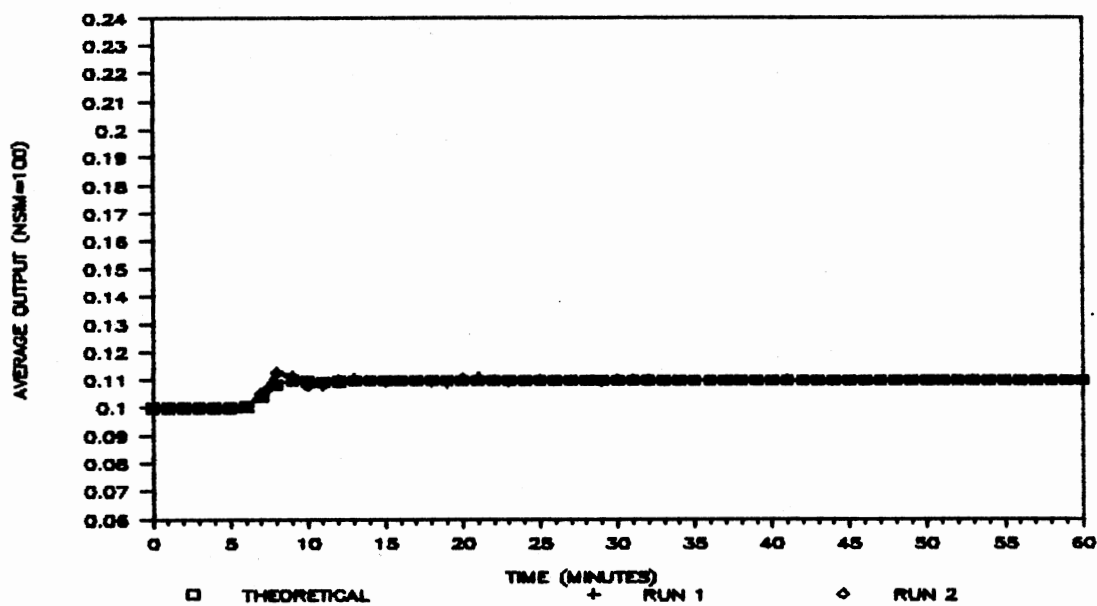

Figure 6-15D.   Average Output; CAD=0.20(t-5.0), t≥5;
Filter=IMR/IPRE

CHAPTER VII

SUMMARY

Introduction

This Chapter represents the discussion of the results

presented in the Chapter VI and the direction of future

research in this field. This research has provided an

indication of the compatibility between statistical process

control and classical control systems techniques and their

potential to complement each other when used in the same

control situation. Even though the preceding research is

based on an unique process, general conclusions can be made

regarding the combination of the two fields.

Conclusions

Chapter VI presents the information around which the

following discussion is based. The objective of this

research is to apply statistical process control (SPC)

within the realm of control systems and to evaluate the

quality of a control scheme utilizing various statistical

process control and conventional filtering methods. The

application of statistical process control within the realm

of control systems is achieved by applying SPC as filtering

devices within the feedback control loop as demonstrated in Chapter V and VI.

The conventional filters used are the exponential filter, the least squares filter, and the non-linear exponential filter, and the SPC filtering techniques are the exponentially weighted moving average filter, the moving average and moving range filter, and the individuals and moving range filter. Additionally, individuals prefiltering is used in conjunction with the SPC filtering techniques in an attempt to reduce the time lag required to detect a change in the process when using only SPC filtering techniques.

A computer system is developed which models three serial continuous stirred-tank reactors (CSTRs) where conventional proportional/integral/derivative (PID) control is employed utilizing the Ziegler and Nichols (1942) tuning formulas based on a decay ratio of one fourth. Random noise is introduced within the feedback control loop, and it is the goal of the filtering device employed within the feedback control loop to remove or attenuate the noise. The ideal output of the filter would be the true output of the process. The desired theoretical response of the system or the desired targeted output of the system is the response of the system to a known input disturbance in which no noise is introduced within the feedback control loop.

The amount of variation of the output about the target value is measured by observing the average output of the

process over time. Plots for each filtering device are shown in Chapter 6. Additionally, a measure of performance is developed in Chapter 5 which is similar to the Integral of the Absolute Value of the Error (IAE) used in control theory research (Smith and Corripio (1985)). The measure of performance developed is the Integral of the Average Absolute Error (IAAE), and this value is shown in Chapter 6 for each filtering device employed.

Conventional Filters

Figures 6-1(A-F), 6-2(A-F), 6-3(A-F), 6-4(A-F), and 6-5(A-F) represent the average response of the system using the conventional filters when a unit step disturbance of magnitude 0.0, unit step disturbance of magnitude 0.12, unit step disturbance of magnitude 0.20, ramp disturbance of slope 0.12, and ramp disturbance of slope 0.20 are applied to the system, respectively. Tables 6-1, 6-2, 6-3, 6-4, and 6-5 provide the IAAE for a unit step disturbance of magnitude 0.0, unit step disturbance of magnitude 0.12, unit step disturbance of magnitude 0.20, ramp disturbance of slope 0.12, and ramp disturbance of slope 0.20, respectively, when conventional filtering devices are used.

As shown in Table 6-1, the performance of the conventional filtering devices is close to the same for the conventional filters when no disturbance is applied to the system. It is interesting to note that the exponential filter with parameter P set equal to zero is equivalent to

doing no filtering to the signal being transmitted through the feedback control loop. A slight improvement in performance may be achieved by utilizing the least squares filter, with the exponential filter following closely behind. The non-linear exponential filter provides the poorest performance of the conventional filters when no disturbance is applied to the process. As the parameters of the conventional filtering devices change, there is only a small change in the resulting IAAEs. This result is due to the fact that the system modeled is slow. If the process was faster, the resulting differences would be more pronounced.

The plots of the average outputs while utilizing various filtering devices when no disturbance is applied to the system (see Figures 6-1(A-F)) indicate that little observable difference can be distinguished as the parameters of a given filter are changed or the type filtering is changed. This result is indicative of the fact that this process is very slow to changes in the system.

As medium to large unit step disturbances are introduced to the system when conventional filtering devices are used, the resulting randomness of the output system is hidden by the change of output due to the disturbance. By observing the resulting IAAEs (see Tables 6-2 and 6-3), the improvement of the least squares filter over the exponential filter becomes less pronounced due to the tendency of the least squares filter to overshoot the true process signal

(Exxon, 1977). The non-linear exponential filter provides the poorest performance. As is the case when no disturbance is introduced to the system, the effect of changing the parameters of a given filtering device appear to have little impact on the resulting IAAEs. The plots of the average output while utilizing various filtering devices when medium to large disturbances are applied to the system (see Figures 6-2(A-F) and 6-3(A-F)) indicate that little observable difference can be distinguished as the parameters of a given filter are changed or the type filtering is changed. The resulting randomness of the average output of the system is hidden by the change of output due to the magnitude of the disturbance.

The tables of 6-4 and 6-5 provide an indication that there exists no measurable difference in the calculated IAAEs when either the exponential filter or the least square filter is used, and the process is disturbed with a ramp disturbance. The non-linear exponential filter offers the poorest performance of the conventional filters.

Figures 6-4(A-F) and 6-5(A-F) indicate that little observable difference can be distinguished as the parameter of a given filter is changed or the type filtering is changed. The resulting randomness of the average output of the system is hidden by the change of output due to the ramp disturbance. The PID control of the system appears to be close to the desired theoretical response which results in a slight offset of the output.

Statistical Process Control Filters

Figures 6-6(A-F), 6-7(A-F), 6-8(A-F), 6-9(A-F), and
6-10(A-F) represent the average response of the process when
utilizing the statistical process control (SPC) filters when
a unit step disturbance of magnitude 0.0, unit step
disturbance of magnitude 0.12, unit step disturbance of
magnitude 0.20, ramp disturbance of slope 0.12, and ramp
disturbance of slope 0.20, respectively. Tables 6-6, 6-7,
6-8, 6-9, and 6-10 provide the IAAE for a unit step
disturbance of magnitude 0.0, unit step disturbance of
magnitude 0.12, unit step disturbance of magnitude 0.20,
ramp disturbance of slope 0.12, and ramp disturbance of
slope 0.20, respectively, when SPC filters are employed.

As observed in Table 6-6, the IAAEs for the SPC filters
are improved over conventional filters of Table 6-1. This
result is as expected due to the design of statistical
process control. Statistical process control is designed
such that the Type I errors are controlled. Therefore, when
the process is running in a SOSC, the controller input is
zero, since there is no random error passed to the process.
When random error is passed to the controller, additional
variation of the process output will result. The EWMA chart
with $\alpha=0.25$ has an average run length (ARL) of 502.9
(Crowder, 1987) when the process average is unchanged which
indicates that very few false alarms, if any at all, would
be expected for these simulations. Therefore, the average

response is very near the set point, and this is the case as shown in Figure 6-6A.

The ARL for the MAMR chart is 99.27 (see Table 3-2), and the ARL for IMR chart is 59.26 (see Table 3-3). Therefore, an increasing number of false alarms would result from the change from an EWMA filter with $\alpha=0.2$ to an MAMR filter or an IMR filter. This observation would result in the random signal being fed to the controller more often resulting in a more variable average output. This can be seen in either Figure 6-6C or 6-6D. When $\alpha=1.0$ for the EWMA filter, the resulting filter is simply an individuals filter with rule 1 of the AT&T rules (see Chapter 3 or Chapter 5) employed. The ARL for the individuals chart when the process average is left unchanged is 370.40 (Crowder, 1987). Therefore, the number of false alarms is more than the EWMA chart with $\alpha=0.2$ and less than the MAMR or IMR chart. Therefore, the average output of a process using EWMA filtering with $\alpha=1.0$ would appear smoother than the average output of a system using either MAMR or IMR filtering. This is shown in Figure 6-6B.

Based on the observations above, the SPC filters would be preferred over the conventional filters. This statement assumes that no disturbance has been introduced to the process.

Once the process is subjected to a disturbance, the conventional filters perform better than the SPC filters, as shown by comparing the resulting IAAEs from Tables 6-7,

6-8, 6-9, and 6-10 to 6-2, 6-3, 6-4, and 6-5, respectively.
This is due to the time lag required by the SPC filters to
detect a process change. The conventional filters respond
quicker since all changes (random or deterministic process
disturbances) are reacted upon immediately. Therefore, if
given the situation that a process disturbance has occurred,
the conventional filters would be preferred over the SPC
filters based on the value of the IAAEs. These results can
be verified by viewing figures 6-7(A-D), 6-8(A-D), 6-9(A-D),
and 6-10(A-D) by noting the deviation from the average
output to the theoretical output (or target). This large
difference stems from the time required for the SPC filter
to detect the process disturbance. The input disturbance is
passed through three first order lags before it can be
detected at the output of the process, which results in a
large time delay before the disturbance is detected by the
SPC filters. Additionally, if the disturbance is not
detected at the first sample, it is 6.5 minutes until the
next sample will be collected. This results in additional
time delay in the detection of the process disturbance.

The EWMA filter with $\alpha=1$ results with an average offset
in the average output (see Figure 6-7B). The offset is
reduced when α is reduced to 0.2 (Figure 6-7A) and
practically eliminated when the IMR filter is employed
(Figure 6-7D). Since additional historical information is
being included at each sample (i.e., as α is reduced, more
historical information is included; or as runs rules are

employed, more historical information is included), the probability of detecting small shifts is improved (see Tables 3-1, 3-2, and 3-3).

It is interesting to note that in the application of SPC filters alone the resulting response of the process behaves much like an open loop system due to the time required to detect the disturbance immediately following the disturbance. The average output of the process is approaching the steady state, open loop response when subjected to an unit step disturbance for all four SPC filters (see Figures 6-7(A-D) and 6-8(A-D)) by the time that the second sample is collected (t=13.0 minutes).

When the process disturbance is a ramp disturbance, the resulting IAAEs show that the conventional filters are preferred over the SPC filters (see Tables 6-9 and 6-10). The average outputs of the EWMA filter with $\alpha=1.0$ and the MAMR filter are cyclic (see Figures 6-9B, 6-9C, 6-10B, and 6-10C). This result stems from the inability of either the EWMA filter with $\alpha=1$ (which is an individuals filter with only rule 1 of the AT&T rules employed) or the MAMR chart to detect trends in the process output. On the other hand, both the EWMA filter with $\alpha=0.2$ and the IMR filter can more quickly detect trends (see Figures 6-9A, 6-9D, 6-10A, and 6-10D). Therefore, if an SPC filter is used, the EWMA filter with a small α or the IMR filter will provide protection against offsets or cyclic behavior of the average output of the process.

Statistical Process Control Filters with

Individuals Prefilter

Figures 6-11(A-F), 6-12(A-F), 6-13(A-F), 6-14(A-F), and 6-15(A-F) represent the average response of the process utilizing the SPC filters in conjunction with the individuals prefiltering when the process is disturbed with a unit step disturbance of magnitude 0.0, a unit step disturbance of magnitude 0.12, a unit step disturbance of magnitude 0.20, a ramp disturbance of slope 0.12, and a ramp disturbance of slope 0.20, respectively. Tables 6-11, 6-12, 6-13, 6-14, and 6-15 provide the IAAE for a unit step disturbance of magnitude 0.0, unit step disturbance of magnitude 0.12, unit step disturbance of magnitude 0.20, ramp disturbance of slope 0.12, and ramp disturbance of slope 0.20, respectively, when SPC filters are used in conjunction with individuals prefiltering.

When the process utilizing SPC filtering and individuals prefiltering is subjected to no input disturbance, the resulting IAAEs are less than the IAAEs obtained while using conventional filtering (contrast Tables 6-1 and 6-11) and greater than the resulting IAAEs when using SPC filters alone (contrast Tables 6-6 and 6-11). These results are based on the fact that an increased number of false alarms are made when the individuals prefiltering is added to the SPC filters which results in a more variable average output than the average output observed when SPC filters are used alone (compare Figures 6-11(A-D) to Figures

6-6(A-D)). The resulting output, however, is not as variable as the average output when conventional filtering is used (compare Figures 6-11(A-D) to Figures 6-1(A-D)).

Once an input disturbance is introduced to the system, the individuals prefiltering provides a quicker response to the disturbance than when SPC filters are used alone, since the data are collected more often. The resulting IAAEs listed in Tables 6-12, 6-13, 6-14, and 6-15 indicate an improvement over the situations in which SPC filtering is used alone (see Tables 6-7, 6-8, 6-9, and 6-10). The improvement made, however, does not make the results better than the results collected when conventional filtering techniques are used (see Tables 6-2, 6-3, 6-4, and 6-5). When SPC filtering techniques are used in conjunction with individuals prefiltering, the resulting IAAE is on the order of 1.75 to 2.5 times as large (based on best and worse case results of IMR filtering with individuals prefiltering). Therefore, when SPC filters are used in conjunction with individuals prefiltering, the resulting Iaaes are more competitive but not better than the resulting IAAEs achieved when conventional filtering is used.

The average output of the process using SPC filtering with individuals prefiltering is similar to the results achieved with SPC filtering alone. By comparing Figures 6-12(A-D) and 6-13(A-D) to 6-7(A-D) and 6-8(A-D), respectively, it is easily recognized that the improvement in the IAAEs is due to the improved response time to

detecting the process disturbance. Additionally, the offset behavior of the EWMA filter with large alphas and MAMR filters is eliminated due to the use of the individuals prefilter, since the data are more often collected and the number of opportunities to detect slight changes in the process are increased.

When SPC filters are used in conjunction with individuals prefiltering and the process input is subjected to a ramp disturbance, a cyclic behavior results (see Figures 6-14(A-D) and 6-15(A-D)). This result is based on the overpowering impact of the individuals prefilter, since data are collected so often. The disturbance is detected quickly, and once the disturbance is detected, the logic of the individuals prefilter requires that 10 minutes must pass before the process will be sampled again. At that point, the PID control has returned the process output close to desired set point, and the individuals prefilter does not immediately detect the continued ramp disturbance. This condition continues until sufficient time has passed such that the change in the process input is large enough to be detected. The overall impact of these filtering combinations is a cyclic behavior which has a period of 10 minutes plus the incremental amount of time required to make subsequent detections of the process disturbance.

In conclusion, when SPC filters are used in combination with individuals prefiltering, the resulting IAAEs are larger than the IAAEs that would have been achieved if

conventional filtering had been utilized. This statement is based on assumption that the process is disturbed. If no disturbance is in the process, smaller IAAEs are achieved when either SPC filtering is used alone or SPC filtering is used in conjunction with individuals prefiltering.

Future Research

Even though the results of this research are not completely in favor of SPC filtering over the conventional filtering techniques, the potential for research in the field is very good. For example, all of the parameters of the SPC filtering techniques have been set at single values. Improved performance may be achieved if the control limits of the SPC filters are reduced to values less than three standard deviations. Additionally, the use of SPC filters in conjunction with conventional filters could be evaluated.

The measures of performance used in this research are based on the amount of variability of the average response about the response of the system when no noise is introduced into the feedback control loop. There is the potential of considering economic tradeoffs between false alarms and the time lag required to detect and correct a process change.

Additionally, future work should include the analysis of results utilizing optimal control type designs. One of the more popular optimal design methods is the use of the Kalman Filter (see Astrom and Wittenmark, 1984). The Kalman filter minimizes the variance of the estimation error

assuming the noise is Gaussian. Successful application of SPC filters implies that they must perform as well as or better than conventional filtering devices and the optimal design techniques.

The clearest problem of the SPC filters is their inability to respond quickly. In general, when correctly applied, a cascaded system makes the overall loop more stable and faster responding (see Smith and Corripio, 1985). The cascaded system has been introduced in Chapter 1 but not fully developed within the realm of this research. It is strongly indicated through this research that if the response time of the SPC filters could be improved, the resulting IAAEs would also improve. A cascaded control scheme would appear to achieve favorable results. A possible implementation of cascaded control is shown in Figure 7-1 below.
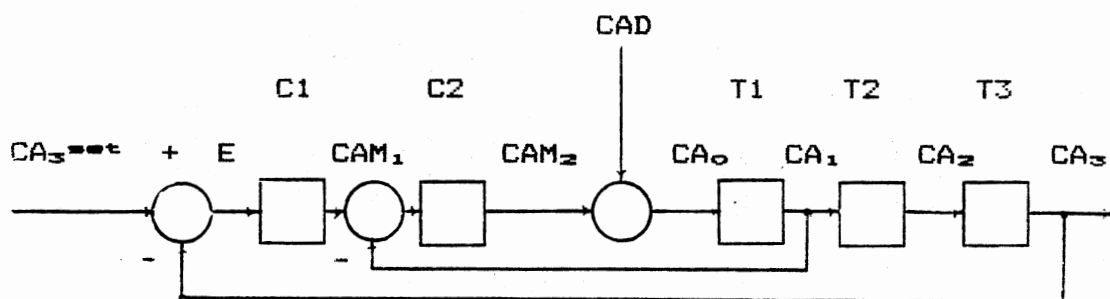
where: T1 = Tank 1
         T2 = Tank 2
         T3 = Tank 3
         C1 = Primary Controller
         C2 = Secondary Controller

Figure 7-1.   Potential Implementation of Cascaded Control

For the implementation of cascaded control both controllers would need to be tuned based on the analytical characteristics of the system, and the research to study the performance of the system would require that a new computer system be developed. SPC filters could be employed on both the primary and secondary loops.

Additional work could be completed using other types of disturbances such as limited ramps, sinusoids, triangular, and other periodic functions. Additionally, the performance of the control loop is dependent upon the magnitude of the noise. Research relating the magnitude of the noise to the control scheme's ability to correct the process could be achieved.

REFERENCES

Aström, K.J. and Wittenmark, B. (1984). <u>Computer Controlled Systems, Theory and Design</u>. In T. Kailath (Ed.), Prentice-Hall, Inc., Englewood Cliffs, N.J.

AT&T Technologies (1985). <u>Statistical Quality Control Handbook</u>, Delmar Printing Company, Charlotte, North Carolina.

Bingham, R.S., Jr. (1958). "A Guide to the Use of Statistics in the Chemical Insustry." <u>Industrial Quality Control</u> 15, pp. 14-18.

Bingham, R.S., Jr. (1957). "Control Charts in Multi-Stage Batch Processes." <u>Industrial Quality Control</u> 13, pp. 21-26.

Bingham, R.S., Jr. (1957). "Practical Chemical Process Control." <u>Industrial Quality Control</u> 13, pp. 46-56.

Brooks, D.H. "From Shewhart to PID - The Quality Control Continuum." Unpublished Lecture Notes, 1986.

Brooks, D.H. and Case, K.E. "The Application of Statistical Process Control to the Continuous Flow Process: The Effects of Autocorrelated Data." Unpublished Paper, 1987.

Champ, C.W. and Woodall, W.H. (1987). "Exact Results for Shewhart Control Charts with Supplementary Runs Rules." <u>Technometrics</u> 29, pp. 393-399.

Coughanowr, D.R. and Koppel, L.B. (1965). <u>Process Systems Analysis and Control</u>, McGraw-Hill Book Company, New York, N.Y.

Crowder, S.V. (1987). "A Program for the Computation of ARL for Combined Individual Measurement and Moving Range Charts." <u>Journal of Quality Technology</u> 19, pp. 103-106.

Crowder, S.V. (1987). "A Simple Method for Studying Run-Length Distributions of Exponentially Weighted Moving Average Charts." <u>Technometrics</u> 29, pp. 401-407.

Crowder, S.V. (1987). "Average Run Lengths of
    Exponentially Weighted Moving Average Control Charts."
    Journal of Quality Technology 19, pp. 161-164.

Crowder, S.V. (1987). "Computation of ARL for Combined
    Individual Measurement and Moving Range Charts."
    Journal of Quality Technology 19, pp. 98-102.

Duncan, A.J. (1986). Quality Control and Industrial
    Statistics. Fifth Edition. Homewood, IL: Richard D.
    Irwin.

Exxon Computer Control Practices. (1977). Volume 2,
    Computer Control Fundamentals.

Exxon Computer Control Practices. (1984). Volume 3,
    Controls for Specific Processes.

Freund, R.A. (1960). "A Reconsideration of the Variables
    Control Charts." Industrial Quality Control 16, pp.
    35-41.

Freund, R.A. (1962). "Graphical Process Control."
    Industrial Quality Control 18, pp. 15-22.

Gibra, I.N. (1975). "Recent Developmants in Control Chart
    Techniques." Journal of Quality Technology 7, pp. 183-
    192.

Grant, G.E. and Leavenworth, R.S. (1980). Statistical
    Quality Control. Fifth Edition. McGraw-Hill Book
    Company, New York, N.Y.

Harrison, H. and Bollinger, J.G. (1969). Introduction to
    Automatic Controls. Harper & Row, New York, N.Y.

Hinchen, J.D. (1956). "Correlation Analysis in Batch
    Process Control." Industrial Quality Control 11, pp.
    54-59.

Hultquist, P.F. (1988). Numerical Methods for Engineers
    and Computer Scientists. The Benjamin/Cummings
    Publishing Company, Inc., Menlo Park, CA.

Hunter, J.S. (1986). "The Exponentially Weighted Moving
    Average." Journal of Quality Technology 18, pp. 203-
    210.

Jaluria, Y. (1988). Computer Methods for Engineering.
    Allyn and Bacon, Inc., Needham Heights, MA.

Juran, J.M. and Gryna, F.M., Jr. (1980). Quality Planning
    and Analysis. Second Edition. McGraw-Hill, New York,
    N.Y.

Juran, J.M. (1988). Juran on Planning for Quality. The Free Press, A Division of Macmillan, Inc., New York, N.Y.

Juran, J.M. (1974). Quality Control Handbook. 3rd Ed. McGraw-Hill, New York, N.Y.

Luyben, W.L. (1973). Process Modeling, Simulation, and Control for Chemical Engineers. NcGraw-Hill Book Company, New York, N.Y.

Maurath, P.R. "Process Control and Statistical Quality Control at Procter & Gamble or SQC and the PID -- War in the Control Room?" Unpublished Lecture Notes, 198X.

McCabe, W.L.; Smith, J.C.; and Harriott, P. (1985). Unit Operations of Chemical Engineering. McGraw-Hill Book Company, New York, N.Y.

Montgomery, D.C. (1985). Introduction to Statistical Quality Control. John Wiley & Sons, New York, N.Y.

Muth, J.F. (1960). "Optimal Properties of Exponentially Weighted Forecasts." Journal of the American Statistical Association 55, pp. 299-306.

Nelson, L.S. (1987). "Comparing Averages of Moving Ranges of Two." Journal of Quality Technology 19, pp. 55-56.

Nelson, L.S. (1982). "Control Charts for Individual Measurements." Journal of Quality Technology 14, pp. 172-173.

Nelson, L.S. (1983). "The Deceptiveness of Moving Averages." Journal of Quality Technology 15, pp. 99-100.

Neuhardt, J.B. (1987). "Effects of Correlated Sub-Samples in Statistical Process Control." IIE Transactions 19, pp. 208-214.

Ng, C.H. (1987). "Development and Evaluation of Exponentially Weighted Moving Average Control Charts." Unpublished Master's Thesis.

Occasione, J.F. (1956). "Quality Control as Applied to Continuous Processes." Industrial Quality Control 13, pp. 9-13.

Page, E.S. (1962). "A Modified Control Chart with Warning Limits." Bimetrica 49, pp. 171-176.

Page, E.S. (1955). "Control Charts with Warning Lines." Biometrica 42 pp. 243-257.

Roberts, S.W. (1966). "A Comparison of Some Control Chart Procedures." Technometrics 8, pp. 411-430.

Roberts, S.W. (1959). "Control Charts Based on Geometric Moving Averages." Technometrics 1, pp. 239-250.

Roberts, S.W. (1958). "Properties of Control Chart Zone Tests." The Bell System Technical Journal 37, pp. 83-114.

Robinson, D.B. and Ho, T.Y. (1978). "Average Run Lengths of Geometric Moving Average Charts by Numerical Methods." Technometrics 20, pp. 85-93.

Saniga, E.M. and Shirland, L.E. "Quality Control in Practice--A Survey." Quality Progress 10, pp. 30-33.

Shewhart, W.A. (1926). "Quality Control Charts." Bell System Technical Journal 5, pp. 593-603.

Shewhart, W.A. (1927). "Quality Control." Bell System Technical Journal 6, pp. 722-735.

Shewhart, W.A. (1931). Economic Control of Quality of Manufactured Product. D. Van Nostrand Co., Inc., New York, N.Y.

Smith, C.A. and Corripio, A.B. (1985). Principles and Practice of Automatic Process Control. John Wiley & Sons, New York, N.Y.

Stanley, W.D. (1975). Digital Signal Processing. Reston Publishing Company, Inc., Reston, Virginia.

Stephanopoulos, G. (1984). Chemical Process Control. Prentice-Hall, Inc., Englewood Cliffs, N.J.

Sweet, A.L. (1986). "Control Charts Using Coupled Exponentially Weighted Moving Averages." IIE Transactions 18, pp. 26-33.

Takahashi, Y.; Rabins, M.J.; and Auslander, D.M. (1972). Control and Dynamic Systems, Addison-Wesley Publishing Company, Reading, Massachusetts.

Valdeman, S. and Cornell, J.A. (1987). "A Partial Inventory of Statistical Literature on Quality and Productivity Through 1985." Journal of Quality Technology 19, pp. 90-97.

Vance, L.C.   (1983).   "A Bibliography of Statistical Quality
     Control Chart Techniques, 1970-1980."   Journal of
     Quality Technology 15, pp. 59-62.

Vasilopoulos, A.V. and Stamboulis, A.P.   (1978).
     "Modification of Control Chart Limits in the Presence
     of Data Correlation."   Journal of Quality Technology,
     10, pp. 20-30.

Walter, J.T.   (1955).   "Continuous Process Control in a
     Petroleum Refinery."   Industrial Quality Control 12,
     pp. 5-7.

Ward, R.V.   (1963).   "SQC Applications in the Chemical
     Industries."   Industrial Quality Control 20, pp. 4-8.

Weiler, H.   (1953).   "The Use of Runs to Control the Mean in
     Quality Control."   Journal of American Statistical
     Association 48, pp. 816-825.

Weindling, J.L.; Littauer, S.B.; and Tiago de Oliveria,J.
     (1970).   "Mean Action Time of the X-Control Chart with
     Warning Limits."   Journal of Quality Technology 2,   pp.
     79-85.

Wheeler, D.J.   (1983).   "Detecting a Shift in Process
     Average: Tables of the Power Function for X Charts."
     Journal of Quality Technology 15, pp. 155-170.

Wortham, A.W.   (1972).   "The Use of Exponentially Smoothed
     Data in Continuous Process Control."   International
     Journal of Production Research 10, pp. 393-400.

Ziegler, J.G. and Nichols, N.B.   (1942).   "Optimum Settings
     for Automatic Controllers."   Transactions ASME 64, p.
     759.

APPENDIXES

APPENDIX A

LISTING OF PROGRAMS USED TO DETERMINE

AVERAGE RUN LENGTHS

```
//U11226A JOB (11226,123-12-3123),'JRE',CLASS=4,TIME=(59,0),
// MSGCLASS=X,NOTIFY=*
/*PASSWORD ????
/*JOBPARM ROOM=N
/*ROUTE PRINT LOCAL
// EXEC FORTVCLG
//FORT.SYSIN DD *
C
C   THIS PROGRAM IS DESIGNED TO DETERMINE THE ARL/MAT
C   FOR THE EWMA CHART WHEN THE PROCESS IS DISTURBED WITH
C   EITHER A UNIT STEP DISTURBANCE OR LINEAR TREND
C
      DOUBLE PRECISION DSEED,SUM,MAT
      REAL NUM,LCL,NMEAN,MEAN,K
      READ *,MEAN,STD,N
      PRINT *,'ORIGINAL PROCESS MEAN                 ',MEAN
      PRINT *,'ORIGINAL PROCESS STANDARD DEVIATION  ',STD
      PRINT *,'THE # OF TRIALS                       ',N
C
C   THE ALPHA VALUE
C
      ALPHA=0.0
      DSEED=8064697.
      PRINT *
C
C   LOOP TO RUN SIMULATIONS FOR
C   VARIOUS ALPHAS
C
      DO 400 I1=1,5
            K=-0.1
            ALPHA=ALPHA+0.2
C
C   THE DETERMINATION OF CONTROL LIMITS
C
      C=ALPHA/(2.-ALPHA)
      D=SQRT(C)
      E=3*STD*D
      UCL=MEAN+E
      LCL=MEAN-E
      DO 500 I2=1,14
C
C   DIFFERENT SHIFTS IN THE MEAN
C
            IF (K.GE.1.0)  K=K+0.5
            IF ((K.LT.1.0).AND.(K.GE.0.5))  K=K+0.25
            IF (K.LT.0.5)  K=K+0.1
      SUM=0.0
C
C   LOOP FOR EACH RUN OF A SIMULATION
C
      DO 200 I=1,N
          EWMA=MEAN
          SHIFT=K*STD
          NUM=0
```

```
  50         Z=GGNQF(DSEED)*STD+MEAN+SHIFT
C
C                                   = K*STD FOR UNIT STEP
C
           SHIFT=SHIFT+K*STD
           EWMA=ALPHA*Z+(1-ALPHA)*EWMA
C
C   TEST FOR STATISTICAL CONTROL
C
           IF ((EWMA.GE.LCL).AND.(EWMA.LE.UCL)) THEN
C
C   COUNT OF SAMPLES
C
               NUM=NUM+1
                 GO TO 50
               ELSE
                 NUM=NUM+1
C
C    SUM TOTAL OF ALARMS
C
                 SUM=SUM+NUM
           ENDIF
 200    CONTINUE
        X=N
C
C   CALCULATION OF THE ARL/MAT
C
        MAT=SUM/N
        WRITE (6,300) ALPHA,K,MAT
 300    FORMAT (1X,'THE WEIGHTING FACTOR = ',F10.2/
       $         1X,'K STD DEV INC IN MEAN EA SAMPLE = ',F10.2/
       $         1X,'MAT = ',F10.4//)
 500    CONTINUE
 400    CONTINUE
        STOP
        END
//GO.SYS        STOP
        END
//GO.SYN DD *
50,10,10000
//
```

```
//U11226A JOB (11226,123-12-3123),'JRE',CLASS=4,TIME=(30,0),
// MSGCLASS=X,NOTIFY=*
/*PASSWORD ????
/*JOBPARM ROOM=N
/*ROUTE PRINT LOCAL
// EXEC FORTVCLG
//FORT.SYSIN DD *
C
C   THIS PROGRAM IS DESIGNED TO DETERMINE THE ARL/MAT
C   FOR THE MAMR CHART COMBINATION WHEN THE PROCESS IS
C   DISTURBED WITH EITHER A UNIT STEP OR LINEAR TREND
C   DISTURBANCE
C
      DOUBLE PRECISION DSEED,SUM,MAT
      REAL NUM,LCLX,MEAN,K
      READ *,MEAN,STD,N
      PRINT *,'ORIGINAL PROCESS MEAN                  ',MEAN
      PRINT *,'ORIGINAL PROCESS STANDARD DEVIATION  ',STD
      PRINT *,'THE # OF TRIALS                      ',N
      PRINT *
      DSEED=8064697.
C
C   DETERMINE THE CONTROL LIMITS
C
      E=(3*STD)/SQRT(2.0)
      UCLX=MEAN+E
      LCLX=MEAN-E
      UCLR=(1.128+3*(.853))*STD
      K=-0.1
C
C   LOOP FOR DIFFERENT SIZE SHIFTS
C
      DO 500 I2=1,14
         IF (K.GE.1.0)   K=K+0.5
         IF ((K.LT.1.0).AND.(K.GE.0.5))   K=K+0.25
         IF (K.LT.0.5)   K=K+0.1
      SUM=0.0
      DO 200 I=1,N
         X=MEAN
         SHIFT=K*STD
         NUM=0
 50      Z=GGNQF(DSEED)*STD+MEAN+SHIFT
C
C                                       = K*STD FOR UNIT STEP
C
C
C   DETERMINATION OF CURRENT MA AND R
C
         XBAR=(Z+X)/2
         R=ABS(Z-X)
      X=Z
         SHIFT=SHIFT+K*STD
C
C   DETERMINE IF PROCESS IS IN CONTROL
```

```
C
          IF ((XBAR.GE.LCLX).AND.(XBAR.LE.UCLX).AND.(R.LE.UCLR))
         $THEN
                 NUM=NUM+1
                 GO TO 50
              ELSE
                 NUM=NUM+1
C
C   COUNT OF TOTAL ALARMS
C
                 SUM=SUM+NUM
           ENDIF
  200   CONTINUE
        X=N
C
C DETERMINE THE MAT/ARL
C
        MAT=SUM/X
        WRITE (6,300) K,MAT
  300   FORMAT (1X,'K STD DEV INC IN MEAN EA SAMPLE = ',F10.2/
        $          1X,'MAT = ',F10.4//)
  500   CONTINUE
        STOP
        END
//GO.SYSIN DD *
50,10,10000
//
```

```
//U11226A JOB (11226,123-12-3123),'JRE',CLASS=4,TIME=(59,0),
// MSGCLASS=X,NOTIFY=*
/*PASSWORD ????
/*JOBPARM ROOM=N
/*ROUTE PRINT LOCAL
// EXEC FORTVCLG
//FORT.SYSIN DD *
C
C    THIS PROGRAM IS DESIGNED TO DETERMINE THE ARL/MAT
C    FOR THE IMR CONTROL CHART COMBINATION WHEN THE PROCESS
C    IS SUBJECTED TO A UNIT STEP OR LINEAR TREND DISTURBANCE
C
       DIMENSION XBAR(8)
       INTEGER UPRUN(8),DNRUN(8)
       INTEGER
      $RUNL,TOTRUN,TUPRUN,TDNRUN,RULE,ABOVE,BELOW,COUNT
       INTEGER FLAG1,FLAG2,FLAG3,FLAG4,FLAGC
       REAL MEAN,K
       DOUBLE PRECISION DSEED,MAT
       DSEED=8064697.
       READ *,MEAN,STD,N
       PRINT *,'ORIGINAL PROCESS MEAN                    ',MEAN
       PRINT *,'ORIGINAL PROCESS STANDARD DEVIATION  ',STD
       PRINT *,'THE NUMBER OF TRIALS                     ',N
C
C    DETERMINE THE APPROPRIATE ZONES FOR THE I CHART WHEN
C    THE AT&T RUNS RULES ARE USED
C
       UP1SIG=MEAN+STD
       UP2SIG=MEAN+2*STD
       UP3SIG=MEAN+3*STD
       DN1SIG=MEAN-STD
       DN2SIG=MEAN-2*STD
       DN3SIG=MEAN-3*STD
C
C    DETERMINE THE CONTROL LIMITS FOR THE MR CHART
C
        UCLR=(1.128+3*.853)*STD
       NSIMS=0
       TOTRUN=0
        K=-0.1
        DO 1   I1=1,14
C
C    LOOP TO DETERMINE THE SHIFT TO BE STUDIED
C
          IF(K.GE.1.0)    K=K+0.5
          IF((K.LT.1.0).AND.(K.GE.0.5))   K=K+0.25
          IF(K.LT.0.5)   K=K+0.1
        NSIMS=0
        TOTRUN=0
 1000 SHIFT=K*STD
       COUNT= 1000 SHIFT=K*STD
       FLAG1=0
       FLAG2=0
```

```
        FLAG3=0
        FLAG4=0
        FLAGC=0
 2000 DO 2050   I=1,7
           XBAR(I)=GGNQF(DSEED)*STD+MEAN+SHIFT
C
C                                            = K*STD FOR UNIT STEP
C
        IF(I.LE.1)   R=ABS(XBAR(I)-MEAN)
        IF(I.GT.1)   R=ABS(XBAR(I)-XBAR(I-1))
C
C  CHECK MR CHART FOR CONTROL STATUS
C
        IF(R.GT.UCLR) THEN
            COUNT=COUNT+I-1
            GOTO 7000
          ENDIF
          SHIFT=SHIFT+K*STD
          UPRUN(I)=0
C
C   THE FOLLOWING LOGIC IS THE CODING NECESSARY TO EMPLOY
C   THE AT&T RUNS RULES.  IT IS THE SAME AS THE CODING
C   INCLUDED IN APPENDIX B FOR THE SUBROUTINE FOR IMR
C   FILTERING
C
            DNRUN(I)=0
            IF(XBAR(I).GT.UP1SIG)   UPRUN(I)=1
            IF(XBAR(I).LT.DN1SIG)   DNRUN(I)=1
  2050 CONTINUE
        IF(XBAR(1).GT.UP3SIG.OR.XBAR(1).LT.DN3SIG)    THEN
          FLAG1=1
          GOTO 7000
        ENDIF
        COUNT=COUNT+1
        IF(XBAR(2).GT.UP3SIG.OR.XBAR(2).LT.DN3SIG)   FLAG1=1
        IF(XBAR(2).GT.UP2SIG.AND.XBAR(1).GT.UP2SIG)   FLAG2=1
        IF(XBAR(2).LT.DN2SIG.AND.XBAR(1).LT.DN2SIG)   FLAG2=1
        IF(FLAG1.EQ.1.OR.FLAG2.EQ.1)   GOTO 7000
        COUNT=COUNT+1
        IF(XBAR(3).GT.UP3SIG.OR.XBAR(3).LT.DN3SIG)   FLAG1=1
        IF(XBAR(3).GT.UP2SIG.AND.XBAR(2).GT.UP2SIG)   FLAG2=1
        IF(XBAR(3).LT.DN2SIG.AND.XBAR(2).LT.DN2SIG)   FLAG2=1
        IF(XBAR(3).GT.UP2SIG.AND.XBAR(1).GT.UP2SIG)   FLAG2=1
        IF(XBAR(3).LT.DN2SIG.AND.XBAR(1).LT.DN2SIG)   FLAG2=1
        IF(FLAG1.EQ.1.OR.FLAG2.EQ.1)   GOTO 7000
        COUNT=COUNT+1
        IF(XBAR(4).GT.UP3SIG.OR.XBAR(4).LT.DN3SIG)   FLAG1=1
        IF(XBAR(4).GT.UP2SIG.AND.XBAR(3).GT.UP2SIG)   FLAG2=1
        IF(XBAR(4).LT.DN2SIG.AND.XBAR(3).LT.DN2SIG)   FLAG2=1
        IF(XBAR(4).GT.UP2SIG.AND.XBAR(2).GT.UP2SIG)   FLAG2=1
        IF(XBAR(4).LT.DN2SIG.AND.XBAR(2).LT.DN2SIG)   FLAG2=1
        TUPRUN=UPRUN(1)+UPRUN(2)+UPRUN(3)+UPRUN(4)
        TDNRUN=DNRUN(1)+DNRUN(2)+DNRUN(3)+DNRUN(4)
        IF(TUPRUN.GE.4.OR.TDNRUN.GE.4)   FLAG3=1
```

```
      FLAGC=FLAG1+FLAG2+FLAG3
      IF(FLAGC.GT.O)   GOTO 7000
      COUNT=COUNT+1
      IF(XBAR(5).GT.UP3SIG.OR.XBAR(5).LT.DN3SIG)   FLAG1=1
      IF(XBAR(5).GT.UP2SIG.AND.XBAR(4).GT.UP2SIG)   FLAG2=1
      IF(XBAR(5).LT.DN2SIG.AND.XBAR(4).LT.DN2SIG)   FLAG2=1
      IF(XBAR(5).GT.UP2SIG.AND.XBAR(3).GT.UP2SIG)   FLAG2=1
      IF(XBAR(5).LT.DN2SIG.AND.XBAR(3).LT.DN2SIG)   FLAG2=1
      TUPRUN=UPRUN(1)+UPRUN(2)+UPRUN(3)+UPRUN(4)+UPRUN(5)
      TDNRUN=DNRUN(1)+DNRUN(2)+DNRUN(3)+DNRUN(4)+DNRUN(5)
      IF(TUPRUN.GE.4.OR.TDNRUN.GE.4)   FLAG3=1
      FLAGC=FLAG1+FLAG2+FLAG3
      IF(FLAGC.GT.O)   GOTO 7000
      COUNT=COUNT+1
      IF(XBAR(6).GT.UP3SIG.OR.XBAR(6).LT.DN3SIG)   FLAG1=1
      IF(XBAR(6).GT.UP2SIG.AND.XBAR(5).GT.UP2SIG)   FLAG2=1
      IF(XBAR(6).LT.DN2SIG.AND.XBAR(5).LT.DN2SIG)   FLAG2=1
      IF(XBAR(6).GT.UP2SIG.AND.XBAR(4).GT.UP2SIG)   FLAG2=1
      IF(XBAR(6).LT.DN2SIG.AND.XBAR(4).LT.DN2SIG)   FLAG2=1
      TUPRUN=UPRUN(2)+UPRUN(3)+UPRUN(4)+UPRUN(5)+UPRUN(6)
      TDNRUN=DNRUN(2)+DNRUN(3)+DNRUN(4)+DNRUN(5)+DNRUN(6)
      IF(TUPRUN.GE.4.OR.TDNRUN.GE.4)   FLAG3=1
      FLAGC=FLAG1+FLAG2+FLAG3
      IF(FLAGC.GT.O)   GOTO 7000
      COUNT=COUNT+1
      IF(XBAR(7).GT.UP3SIG.OR.XBAR(7).LT.DN3SIG)   FLAG1=1
      IF(XBAR(7).GT.UP2SIG.AND.XBAR(6).GT.UP2SIG)   FLAG2=1
      IF(XBAR(7).LT.DN2SIG.AND.XBAR(6).LT.DN2SIG)   FLAG2=1
      IF(XBAR(7).GT.UP2SIG.AND.XBAR(5).GT.UP2SIG)   FLAG2=1
      IF(XBAR(7).LT.DN2SIG.AND.XBAR(5).LT.DN2SIG)   FLAG2=1
      TUPRUN=UPRUN(3)+UPRUN(4)+UPRUN(5)+UPRUN(6)+UPRUN(7)
      TDNRUN=DNRUN(3)+DNRUN(4)+DNRUN(5)+DNRUN(6)+DNRUN(7)
      IF(TUPRUN.GE.4.OR.TDNRUN.GE.4)   FLAG3=1
      FLAGC=FLAG1+FLAG2+FLAG3
      IF(FLAGC.GT.O)   GOTO 7000
      COUNT=COUNT+1
 3000 XBAR(8)=GGNQF(DSEED)*STD+MEAN+SHIFT
C
C                                         =K*STD FOR UNIT STEP
C
      SHIFT=SHIFT+K*STD
C
C   CHECK CURRENT DATA POINT FOR CONTROL STATUS
C
      R=ABS(XBAR(8)-XBAR(7))
      IF(R.GT.UCLR)   GOTO 7000
      UPRUN(8)=0
      DNRUN(8)=0
      IF(XBAR(8).GT.UP1SIG)   UPRUN(8)=1
      IF(XBAR(8).LT.DN1SIG)   DNRUN(8)=1
      IF(XBAR(8).GT.UP3SIG.OR.XBAR(8).LT.DN3SIG)   FLAG1=1
      IF(XBAR(8).GT.UP2SIG.AND.XBAR(7).GT.UP2SIG)   FLAG2=1
      IF(XBAR(8).LT.DN2SIG.AND.XBAR(7).LT.DN2SIG)   FLAG2=1
      IF(XBAR(8).GT.UP2SIG.AND.XBAR(6).GT.UP2SIG)   FLAG2=1
```

```
        IF(XBAR(8).LT.DN2SIG.AND.XBAR(6).LT.DN2SIG)    FLAG2=1
        TUPRUN=UPRUN(4)+UPRUN(5)+UPRUN(6)+UPRUN(7)+UPRUN(8)
        TDNRUN=DNRUN(4)+DNRUN(5)+DNRUN(6)+DNRUN(7)+DNRUN(8)
        IF(TUPRUN.GE.4.OR.TDNRUN.GE.4)    FLAG3=1
        ABOVE=0
        BELOW=0
        DO 4000 K1=1,8
            IF(XBAR(K1).GT.MEAN)    ABOVE=ABOVE+1
            IF(XBAR(K1).LT.MEAN)    BELOW=BELOW+1
 4000 CONTINUE
        IF(ABOVE.EQ.8.OR.BELOW.EQ.8)    FLAG4=1
        FLAGC=FLAG1+FLAG2+FLAG3+FLAG4
        IF(FLAGC.GT.0)    GOTO 7000
 5000 COUNT=COUNT+1
        DO 6000   L=1,7
          M=L+1
          XBAR(L)=XBAR(M)
          UPRUN(L)=UPRUN(M)
          DNRUN(L)=DNRUN(M)
 6000 CONTINUE
        GOTO 3000
C
C
C   COUNT THE TOTAL OF ALARMS
C
 7000 RUNL=COUNT+1
        TOTRUN=TOTRUN+RUNL
        NSIMS=NSIMS+1
        IF(NSIMS.LT.N)    GOTO 1000
C
C   DETERMINE THE MAT/ARL
C
 8000 MAT=FLOAT(TOTRUN)/FLOAT(NSIMS)
C
C   PRINT RESULTS
C
        WRITE (6,9000) K,MAT
 9000 FORMAT (1X,'K STD DEV INC IN MEAN EA SAMPLE = ',F10.2/
      $            1X,'MAT = ',F10.4//)
    1   CONTINUE
        STOP
        END
//GO.SYSIN DD *
50,10,10000
//
```

APPENDIX B

LISTING OF PROGRAM USED TO IMPLEMENT

AN UNIT STEP DISTURBANCE

```
//U12522A JOB (12522,123-12-3123),'JRE',CLASS=4,TIME=(120,0),
// MSGCLASS=X,MSGLEVEL=(1,1),NOTIFY=*
/*PASSWORD ????
/*JOBPARM ROOM=N,FORMS=2972,COPIES=001,LINECT=88
/*ROUTE PRINT LOCAL
// EXEC FORTVCLG,GOREGN=5000K
//FORT.SYSIN DD *
C
C  MAIN PROGRAM
C
C    THIS PROGRAM IS DESIGNED TO MODEL THE DYNAMICS OF
C    THREE SERIAL CSTR'S.  THE PROGRAM IS DEVELOPED SO THAT
C    VARIOUS TYPES OF NOISE, INPUT DISTURBANCES, AND FILTERING
C    TECHNIQUES CAN BE MODELLED
C
C  DESCRIPTION OF VARIABLES
C
C    A1        ARRAY OF ALPHAS FOR EWMA FILTERING
C    ALPHA     CURRENT ALPHA BEING USED IN THE EWMA FILTERING
C    B         BETA ARRAY FOR LS FILTERING
C    CA1       OUTPUT OF TANK 1
C    CA2       OUTPUT OF TANK 2
C    CA3       OUTPUT OF TANK 3
C    CA3A      ACTUAL OUTPUT OF THE PROCESS
C    CA3S      SUM OF THE OUTPUTS AT A GIVEN POINT IN TIME
C    CA3SET    SETPOINT OF THE OUPUT OF THE PLANT
C    CA3SQD    SUM OF THE SQUARED OUTPUTS AT A GIVEN POINT IN TIME
C    CA3T      ANALYTICAL OUTPUT, NO NOISE
C    CAD       INPUT DISTURBANCE
C    CADD      INPUT DISTURBANCE, THE ARRAY OF POSSIBLE DISTURBANCES
C    CAM       OUPUT OF THE CONTROLLER
C    CAMO      CONTROLLER OUTPUT + INPUT DISTURBANCE
C    DELTA     TIME INCREMENT
C    DSEED     SEED OF THE RANDOM NUMBER GENERATOR
C    ERINT     INTEGRAL OF (OUTPUT-SETPOINT) OVER TIME
C    ERR1      AVERAGE ABSOLUTE ERROR AT A GIVEN POINT IN TIME
C    ERR2      ABSOLUTE AVERAGE ERROR AT A GIVEN POINT IN TIME
C    FCA3      CURRENT FILTERED OUTPUT OF THE PLANT
C    I1        COUNTER OF DELTA TIME INCREMENTS
C    IEXPFG    FLAG DESIGNATING WHETHER OR NOT THIS IS THE FIRST PASS
C                 TO THE EWMA FILTER
C    IFIL      FLAG DESIGNATING THE TYPE OF FILTERING TO BE USED
C    IFLG      FLAG DESIGNATING THE CURRENT STATISTICAL CONTROL OF THE
C                 STATISTICAL FILTER TO BE USED
C    IMRFLG    FLAG DESIGNATING WHETHER OR NOT THIS IS THE FIRST PASS
C                 TO THE IMR FILTER
C    IOCC      FLAG DESIGNATING THE CURRENT STATISTICAL CONTROL OF THE
C                 I CHART PREFILTER
C    IPFIL     FLAG DESIGNATING WHETHER OR NOT THIS IS THE FIRST PASS
C                 TO THE ICHART PREFILTER
C    IPFIL     FLAG DESIGNATING WHETHER OR NOT I CHART PREFILTERING IS
C                 TO BE USED
C    LSFLAG    FLAG DESIGNATING WHETHER THIS IS THE FIRST PASS OF THE
C                 LS FILTER
C    MAFLG     FLAG DESIGNATING WHETHER OR NOT THIS IS THE FIRST PASS
```

```
C                   TO THE MAMR FILTER
C     N           CURRENT N OF THE LS FILTERING
C     N1          ARRAY OF N'S FOR LS FILTERING
C     NCOUNT      NUMBER OF DELTA TIMES IN EACH TSTOP
C     NSIM        NUMBER OF SIMULATIONS OF THE PLANT OF LENGTH TSTOP
C     P           CURRENT P OF THE EXPONENTIAL FILTERING
C     P1          ARRAY OF P'S FOR EXPONENTIAL FILTERING
C     R           CURRENT R OF THE NL EXP FILTERING
C     R1          ARRAY OF R'S FOR NL EXPONENTIAL FILTERING
C     RCA3        CURRENT OUTPUT OF PLANT WITH NOISE INCLUDED
C     SDEST       ESTIMATE OF THE STD DEV OF THE OUTPUT OF THE PLANT AT
C                   A GIVEN POINT IN TIME
C     STD         ESTIMATED STANDARD DEVIATION OF THE NOISE INDUCED IN THE
C                   FEEDBACK LOOP
C     STDCA3      STANDARD DEVIATION OF THE OUPUT OF THE PLANT
C     TAU         TIME CONSTANT OF ONE TANK
C     TAUD        DERIVATIVE TIME
C     TAUI        INTEGRAL TIME
C     TCONST      EFFECTIVE PROCESS REACTION TIME OF THE PLANT
C     TIME        TIME
C     TRESP       ESTIMATED RESPONSE TIME OF THE PLANT ASSUMING A VERY
C                   LARGE INPUT DISTURBANCE
C     TSTOP       DURATION OF A SINGEL SIMULATION
C     XK          GAIN OF ONE TANK
C     XKC         CONTROLLER GAIN
C     XKIJ        COEFFICIENTS OF THE RUNGA KUTTA INTEGRATION
C     Z           CURRENT DISTANCE OF CLS USED IN THE ICHART PREFILTERING
C     Z2          ARRAY OF CL DISTANCES FOR I CHART PREFILTERING
C
C
C   **********MAIN ROUTINE*********
C
C
      IMPLICIT DOUBLEPRECISION(A-H,O-Z)
      DIMENSION CA3T(50000),CA3S(50000),CA3SQD(50000),
     $B(19,19),ERR1(50000),ERR2(50000),CA3A(50000),CADD(10),
     $P1(5),N1(3),R1(2),A1(5),Z2(3)
      COMMON XKC,TAUI,CAD,TAU,XK,CAM,TAUD,CAMO,B,IOCC,IFLG,FCA3
      DATA P1/0.0,0.2,0.4,0.6,0.8/
      DATA N1/3,11,19/
      DATA R1/4.0,7.0/
      DATA A1/0.2,0.4,0.6,0.8,1.0/
      DATA Z2/3.0,3.5,4.0/
C
C SET THE INCREMENTS OF TIME IN WHICH OUTPUT IS DESIRED
C
      ITIME=200
C
C
C SET FILTERING TYPES
C IFIL=0,NO FILT;1,EXP;2,LS;3,NLEXP;4,EWMA;5,MAMR;6,IMR
C
      IFIL=0
C
C TOGGLE PREFILTERING; IPFIL=0,NO;1,YES
```

```
C
      IPFIL=0
      READ *,TAUI,TAU,XK,XKC,TSTOP,TAUD,NSIM
      READ *,((B(I,J),I=1,19),J=1,19)
      DSEED=8064697.
      CADD(1)=0.0000
      CADD(2)=0.0037
      CADD(3)=0.0111
      CADD(4)=0.0185
      CADD(5)=0.0
      CADD(6)=0.12
      CADD(7)=0.2
      CADD(8)=1.2
C
C    VALIDATION SUBROUTINE
C
C         DO 2002   IF=1,7
C         IFIL=IF-1
C
C
C    SET DO LOOPS FOR VARIOUS FILTERING PARAMETERS
C
          DO 2001   J14=1,28
C
C    SET DO LOOPS FOR VARIOUS INPUT DISTURBANCES
C
          READ *,IFIL,IPFIL,J1
          J=5
          P=0.0
          N=0
          R=0.0
          ALPHA=0.0
          CAD=0.0
C
C    ANALYTICAL SOLUTION WITH NO NOISE USING RUNGA KUTTA
C
          IFLG=7
          I1=1
          LSFLAG=0
          DELTA=0.005
          NCOUNT=TSTOP/DELTA + 1
          CA1=0.4
          CA2=0.2
          CA3=0.1
          FC=CA3
          TIME=0.0
          ERINT=0.0
          CAM0=0.8
          CA3T(I1)=CA3
  100  IF(TIME.GE.5.0)   CAD=CADD(J)
C
C    CALL THE INTEGRATING SUBROUTINE
C
          CALL F(TIME,CA1,CA2,CA3,ERINT,XK11,XK12,XK13,XK14)
          CALL F(TIME+DELTA/2,CA1+DELTA/2*XK11,CA2+DELTA/2*XK12,
```

```
      $C3+DELTA/2*XK13,ERINT+DELTA/2*XK14,XK21,XK22,XK23,XK24)
       CALL F(TIME+DELTA/2,CA1+DELTA/2*XK21,CA2+DELTA/2*XK22,
      $CA3+DELTA/2*XK23,ERINT+DELTA/2*XK24,XK31,XK32,XK33,XK34)
       CALL F(TIME+DELTA,CA1+DELTA*XK31,CA2+DELTA*XK32,
      $CA3+DELTA*XK33,ERINT+DELTA*XK34,XK41,XK42,XK43,XK44)
       TIME=TIME+DELTA
C
C   DETERMINE THE CURRENT PROCESS RESPONSES
C
       CA1=CA1+DELTA/6.0*(XK11+2*XK21+2*XK31+XK41)
       CA2=CA2+DELTA/6.0*(XK12+2*XK22+2*XK32+XK42)
       CA3=CA3+DELTA/6.0*(XK13+2*XK23+2*XK33+XK43)
       ERINT=ERINT+DELTA/6.0*(XK14+2*XK24+2*XK34+XK44)
       I1=I1+1
       CA3T(I1)=CA3
       IF(TIME.GE.TSTOP)  GO TO 1000
       GO TO 100
 1000 CONINUE
C
C   REAL SYSTEM SIMULATION WITH NOISE USING RUNGA KUTTA
C
       X=NSIM
C
C   SET GENERAL VARIABLES
C
       STD=0.005
       STDCA3=STD
       CA3SET=0.1
       TCONST=6.5
       WRITE(6,0)
  0    FORMAT(1X,'UNIT STEP DISTURBANCE')
       IF(IFIL.EQ.0)   THEN
           WRITE(6,1)
  1        FORMAT(1X,'NO FILTERING')
       ELSE
       ENDIF
C
C   SET CONSTANTS FOR EXPONENTIAL FILTERING
C
       IF(IFIL.EQ.1)   THEN
           P=P1(J1)
           WRITE(6,2)   P
  2        FORMAT(1X,'EXPONENTIAL FILTERING',1X,'P=',F4.2)
       ELSE
       ENDIF
C
C   SET CONSTANTS FOR LEAST SQUARES FILTERING
C
       LSFLAG=0
       IF(IFIL.EQ.2)   THEN
           N=N1(J1)
           WRITE(6,3)   N
  3        FORMAT(1X,'LEAST SQUARES FILTERING',1X,'N=',I4)
       ELSE
       ENDIF
```

```
C
C   SET CONSTANTS FOR NONLINEAR EXPONENTIAL FILTERING
C
        IF(IFIL.EQ.3)   THEN
            R=R1(J1)
            WRITE(6,4)   R
  4         FORMAT(1X,'NL EXPONENTIAL FILTERING',1X,'R=',F4.2)
        ELSE
        ENDIF
C
C   SET CONSTANTS FOR PREFILTERING
C
        IOCC=0
        J2=3
        Z=Z2(J2)
        IPRE=0
        TRESP=10.0
        IF(IPFIL.EQ.1)   THEN
            WRITE(6,5)   Z
  5         FORMAT(1X,'I CHART PREFILTERING',1X'Z=',F4.2)
        ELSE
        ENDIF
C
C   SET CONSTANTS FOR EWMA FILTERING
C
        IEXPFG=0
        IF(IFIL.EQ.4)   THEN
            ALPHA=A1(J1)
            WRITE(6,6)   ALPHA
  6         FORMAT(1X,'EWMA FILTERING',1X,'ALPHA=',F4.2)
        ELSE
        ENDIF
C
C   SET CONSTANTS FOR MAMR FILTERING
C
        MAFLG=0
        IF(IFIL.EQ.5)   THEN
            WRITE(6,7)
  7         FORMAT(1X,'MAMR FILTERING')
        ELSE
        ENDIF
C
C   SET CONSTANTS FOR IMR FILTERING
C
        IMRFLG=0
        IF(IFIL.EQ.6)   THEN
            WRITE(6,8)
  8         FORMAT(1X,'IMR FILTERING')
        ELSE
        ENDIF
       WRIT(6,200) STD,TAU,XK,TAUI,XKC,TAUD
 200   FORMAT(1X,'STD=',F6.3,' TAU=',F4.1,' XK=',F4.1,' TAUI=',
      $F7.3,' XKC=',F7.3,' TAUD=',F7.3)
C
C   DO LOOP FOR DIFFERENT SETUPS
```

```
C   INTIALIZE SUMS FOR ESTIMATED AVERAGES, STANDARD
C   DEVIATIONS AND ERROR TERMS FOR EACH SIMULATION
C   GIVEN STD OF THE NOISE IS KNOWN
C
      DO 800 I4=1,NCOUNT
      ERR1(I4)=0.0
      ERR2(I4)=0.0
      CA3S(I4)=0.0
  800 CA3SQD(I4)=0.0
      DO 3000 N2=1,NSIM
      LSFLAG=0
      IOCC=0
      IEXPFG=0
      IPRE=0
      MAFLG=0
      IMRFLG=0
      CAD=0.0
      I1=1
      I=-1
      CA1=0.4
      CA2=0.2
      CA3=0.1
      FCA3=A3
      FC=CA3
      IFLG=7
      ERR1(I1)=ERR1(I1)+DABS((CA3-CA3T(I1))/X)
      CA3S(I1)=CA3S(I1)+CA3
      CA3SQD(I1)=CA3SQD(I1)+CA3**2.0
      TIME=0.0
      ERINT=0.0
      CAMO=0.8
C
C   ADD NOISE
C
  400 RCA3=GGNQF(DSEED)*STD
      RCA3=RCA3+CA3
      IF(TIME.GE.5.0)   CAD=CADD(J)
C
C   FILTER THE OUTPUT
C
C
C   NO FILTERING
C
      IF(IFIL.EQ.0)   FCA3=RCA3
C
C   PREFILTER
C
      IF(IPFIL.EQ.1) THEN
        CALL PREFIL(TIME,IPRE,IOCC,STDCA3,CA3SET,TRESP,RCA3,Z)
      ELSE
      ENDIF
C
C   EXP FILTERING
C
      IF(IFIL.EQ.1) THEN
```

```fortran
          CALL EXP(P,RCA3,FCA3)
        ELSE
        ENDIF
C
C   LS FILTERING
C
        IF(IFIL.EQ.2)   THEN
          CALL LS(N,LSFLAG,RCA3)
        ELSE
        ENDIF
C
C   NL FILTERING
C
        IF(IFIL.EQ.3) THEN
           CALL NLEXP(R,STDCA3,RCA3,FCA3)
        ELSE
        ENDIF
C
C   EWMA FILTERING
C
        IF(IFIL.EQ.4)   THEN
          CALL EWMA(TIME,TCONST,ALPHA,STDCA3,IOCC,IFLG,IEXPFG,
     $CA3SET,RCA3,FCA3)
        ELSE
        ENDIF
C
C   MAMR FILTERING
C
        IF(IFIL.EQ.5)   THEN
          CALL MAMR(TIME,TCONST,STDCA3,IOCC,IFLG,MAFLG,CA3SET,RCA3,FCA3)
        ELSE
        ENDIF
C
C   IMR FILTERING
C
        IF(IFIL.EQ.6)   THEN
         CALL IMR(TIME,TCONST,STDCA3,IOCC,IFLG,IMRFLG,CA3SET,RCA3,FCA3)
        ELSE
        ENDIF
        DER=(FCA3-FC)/DELTA
        IF(IFLGEQ.0.AND.IOCC.EQ.0)   DER=0
        FC=FCA3
C
C   CALL THE INTEGRATING SUBROUTINE
C
        CALL F2(TIME,CA1,CA2,CA3,ERINT,XK11,XK12,XK13,XK14,DER)
        CALL F2(TIME+DELTA/2,CA1+DELTA/2*XK11,CA2+DELTA/2*XK12,
     $CA3+DELTA/2*XK13,ERINT+DELTA/2*XK14,XK21,XK22,XK23,XK24,DER)
        CALL F2(TIME+DELTA/2,CA1+DELTA/2*XK21,CA2+DELTA/2*XK22,
     $CA3+DELTA/2*XK23,ERINT+DELTA/2*XK24,XK31,XK32,XK33,XK34,DER)
        CALL F2(TIME+DELTA,CA1+DELTA*XK31,CA2+DELTA*XK32,
     $CA3+DELTA*XK33,ERINT+DELTA*XK34,XK41,XK42,XK43,XK44,DER)
C
C   INCREMENT TIME
C
```

```
      TIME=TIME+DELTA
C
C   DETERMINE THE INTEGRALS
C
      CA1=CA1+ELTA/6.0*(XK11+2*XK21+2*XK31+XK41)
      CA2=CA2+DELTA/6.0*(XK12+2*XK22+2*XK32+XK42)
      CA3=CA3+DELTA/6.0*(XK13+2*XK23+2*XK33+XK43)
      ERINT=ERINT+DELTA/6.0*(XK14+2*XK24+2*XK34+XK44)
      I1=I1+1
C
C   TOTAL STATISTICS (FOR ERRORS, AVERAGES, AND STD DEV OF CA3
C   AT EACH TIME T)
C
      ERR1(I1)=ERR1(I1)+DABS((CA3-CA3T(I1))/X)
      CA3S(I1)=CA3S(I1)+CA3
      CA3SQD(I1)=CA3SQD(I1)+CA3**2
      IF(TIME.GE.TSTOP)  GO TO 3000
      GO TO 400
 3000 CONTINUE
      SDEST=0.0
      WRITE(6,300) CAD,NSIM
  300 FORMAT(1X,'**** CAD = ',F8.5,' NSIM =',I6)
      PRINT *,'   TIME      CA3T      CA3A      SDE      ERR1
     $ERR2'
C
C   DETERMINE AVERAGE CA3 AND THE ABSOLUTE VALUE OF THE
C   AVERAGE ERROR AT EACH TIME T
C
      DO 550  I3=1,NCOUNT
      CA3A(I3)=CA3S(I3)/X
  550 ERR2(I3)=DABS(CA3A(I3)-CA3T(I3))
      DO 500  I3=1,NCOUNT,ITIME
      TIME=(I3-1)*DELTA
      IF(NSIM.LE.1) GO TO 900
       ZD=CA3SQD(I3)-CA3S(I3)**2/X
       IF(ZD.LE.0.0)  GO TO 900
       SDEST=(ZD/(X-1))**0.5
  900 WRITE(6,600) TIME,CA3T(I3),CA3A(I3),SDEST,ERR1(I3),ERR2(I3)
  600 FORMAT(1X,F5.1,5X,5F10.5)
  500 CONTINUE
      TIME=0.0
      ERR1IN=0.0
      ERR2IN=0.0
      I5=1
  650 CALL F1(TIME,ERR1(I5),ERR2(I5),XK11,XK12)
      CALL F1(TIME+DELTA/2,ERR1(I5)+DELTA/2*XK11,ERR2(I5)+
     $DELTA/2*XK12,XK21,XK22)
      CALL F1(TIME+DELTA/2,ERR1(I5)+DELTA/2*XK21,ERR2(I5)+
     $DELTA/2*XK22,XK31,XK32)
      CALL F1(TIME+DELTA,ERR1(I5)+DELTA*XK31,ERR2(I5)+DELTA*XK32,
     $XK41,XK42)
      TIME=TIME+DELTA
      I5=I5+1
      ERR1IN=ERR1IN+DELTA/6.0*(XK11+2*XK21+2*XK31+XK41)
      ERR2IN=ERR2IN+DELTA/6.0*(XK12+2*XK22+2*XK32+XK42)
```

```
       I13=I13+1
       IF(TIME.GE.TSTOP)  GO TO 675
       GO TO 650
 675   WRITE(6,680) ERR1IN
 680   FORMAT(1X,'THE INTEGRAL OF THE AVERAGE OF ABS ERROR =',
      $F10.5)
2000 CONTINUE
2001     CONTINUE
2002         CONTINUE
       STOP
       END
C
C SUBROUTINE FOR RUNGA KUTTA INTEGRATION
C
       SUBROUTINE F(X,CA1,CA2,CA3,ERINT,XK1,XK2,XK3,XK4)
       IMPLICIT DOUBLEPRECISIO(A-H,O-Z)
       DIMENSION B(19,19)
       COMMON XKC,TAUI,CAD,TAU,XK,CAM,TAUD,CAMO,B,IOCC,IFLG,FCA3
       DER=CA2/TAU-(1/TAU+XK)*CA3
       CAM=CAMO+XKC*(0.1-CA3+ERINT/TAUI-DER*TAUD)
       CAO=CAD+CAM
       XK1=CAO/TAU-(1/TAU+XK)*CA1
       XK2=CA1/TAU-(1/TAU+XK)*CA2
       XK3=DER
       XK4=0.1-CA3
       END
C
C SUBROUTINE FOR EXPONENTIAL FILTERING
C
       SUBROUTINE EXP(P,RCA3,FCA3)
       IMPLICIT DOUBLEPRECISION(A-H,O-Z)
       FCA3=P*FCA3+(1.0-P)*RCA3
       END
C
C SUBROUTINE FOR LEAST SQUARES FILTERING
C
       SUBROUTINE LS(N,LSFLAG,RCA3)
       IMPLICIT DOUBLEPRECISION(A-H,O-Z)
       DIMENSION B(1919),CA3(50)
       COMMON XKC,TAUI,CAD,TAU,XK,CAM,TAUD,CAMO,B,IOCC,IFLG,FCA3
       IF(LSFLAG.GE.1)  GO TO 2001
       DO 2002  I10=1,N
 2002 CA3(I10)=FCA3
       LSFLAG=1
 2001 DO 2003  I11=1,N-1
 2003 CA3(I11)=CA3(I11+1)
       CA3(N)=RCA3
       FCA3=0.0
       DO 2004  I12=1,N
 2004 FCA3=FCA3+B(I12,N)*CA3(N-I12+1)
       END
C
C SUBROUTINE FOR NONLINEAR EXPONENTIAL FILTERING
C
       SUBROUTINE NLEXP(R,STDCA3,RCA3,FCA3)
```

```
      FCA3=FCA3+MIN(1.0,ABS((RCA3-FCA3)/(R*STDCA3)))*(RCA3-FCA3)
      END
C
C SUBROUTINE FOR EWMA FILTERING
C
      SUBROUTINE EWMA(TIME,TCONST,ALHA,STDCA3,IOCC,IFLG,IEXPFG,CA3SET,
     *RCA3,FCA3)
      IMPLICIT DOUBLEPRECISION(A-H,O-Z)
      DOUBLE PRECISION LCL
C
C  DETERMINE IF THIS IS THE FIRST TIME TO FILTER.  IF SO, DETERMINE
C  CONTROL LIMITS FOR THE EWMA CHART
C
      IF (IEXPFG.GE.1)  GOTO 4000
      IFLG=0
      IEXPFG=1
      C=ALPHA/(2.0-ALPHA)
      D=DSQRT(C)
      E=3*STDCA3*D
      UCL=CA3SET+E
      LCL=CA3SET-E
      EWMA2=CA3SET
      GOTO 4020
C
C  DETERMINE IF SUFFICIENT TIME HAS PASSED SUCH THAT IT IS REASONABLE
C  TO ASSUME INDEPENDENCE BETWEEN SAMPLED DATA POINTS
C
 4000 IF(TIME.LT.TSET-0.00)  GOTO 4010
 4020 EWMA2=ALPHA*RCA3+(1-ALPHA)*EWMA2
      TSET=TIME+TCONST
      IF((EWMA2.GE.LCL).AND.(EWMA2.LE.UCL))  THEN
C
C  EWMA CHART IS IN CONTROL; THEREFORE, THE FILTERED OUTPUT WILL BE
C  THE CENTER LINE OF THE EWMA CHART (OR CA3SET)
C
      IFLG=0
         GOTO 4010
       ELSE
C
C  EWMA CHART IS OUT OF CONTROL;  THEREFORE, THE FILTERED OUTPUT WILL
C  BE THE CURRENT RCA3
C
      IFLG=1
      ENDIF
 4010 IF(IOCC.EQ.1.AND.IFLG.EQ.1)  FCA3=RCA3
      IF(IOCC.EQ.0.AND.IFLG.EQ.1)  FCA3=RCA3
      IF(IOCC.EQ.1.AND.IFLG.EQ.0)  FCA3=RCA3
      IF(IOCC.EQ.0.AND.IFLG.EQ.0)  FCA3=CA3SET
      END
C
C   SUBROUTINE FOR MAMR FILTERING
C
      SUBROUTINE MAMR(TIME,TCONST,STDCA3,IOCC,IFLG,MAFLG,CA3SET,
     *RCA3,FCA3)
      IMPLICIT DOUBLEPRECISION(A-H,O-Z)
```

```
      DOUBLE PRECISION LCLX
C
C  DETERMINE IF THIS WILL BE THE FIRST FILTERED OUTPUT.  IF SO, THE
C  CONTROL LIMITS FOR THE MA AND MR CHARTS MUST BE DETERMINED
C
      IF(MAFLG.GE.1)  GOTO 5000
      IFLG=0
      MAFLG=1
      E=(3*STDCA3)/SQRT(2.0)
      UCLX=CA3SET+E
      LCLX=CA3SET-E
      UCLR=(1.128+3*0.853)*STDCA3
      X1=CA3SET
      GOTO 5020
 5000 IF(TIME.LT.TSET-0.001)  GOTO 5010
 5020 TSET=TIME+TCONST
      Z1=RCA3
      XB=(Z1+X1)/2.0
      R=DABS(Z1-X1)
      X1=Z1
      IF((XB.GE.LCLX).AND.(XB.LE.UCLX).AND.(R.LE.UCLR))  THEN
C
C  THE MAMR CHARTS ARE IN CONTROL;  THEREFORE THE FILTERED OUTPUT
C  IS THE CENTER LINE OF THE MA CHART (CA3SET)
C
         IFLG=0
         GOTO 5010
      ELSE
C
C  THE MAMR CHARTS ARE NOT IN CONTROL;  THEREFORE THE FILTERED OUTPUT
C  IS THE CURRENT RCA3
C
      IFLG=1
      ENDIF
 5010 IF(IOCC.EQ.1.AND.IFLG.EQ.1)  FCA3=RCA3
      IF(IOCC.EQ.0.AND.IFLG.EQ.1)  FCA3=RCA3
      IF(IOCC.EQ.1.AND.IFLG.EQ.0)  FCA3=RCA3
      IF(IOCC.EQ.0.AND.IFLG.EQ.0)  FCA3=CA3SET
      END
C
C  SUBOUTINE FOR IMR FILTERING USING AT&T RULES FOR OCC CONDITIONS
C
      SUBROUTINE IMR(TIME,TCONST,STDCA3,IOCC,IFLG,IMRFLG,CA3SET,
     #RCA3,FCA3)
      DIMENSION XBAR(8)
      INTEGER UPRUN(8),DNRUN(8)
      INTEGER RUNL,TOTRUN,TUPRUN,TDNRUN,ABOVE,BELOW
      INTEGER FLAG1,FLAG2,FLAG3,FLAG4,FLAGC
C
C  DETERMINE IF THIS IS FIRST TIME TO FILTER.  IF SO, DETERMINE UCL
C  AND LCL FOR ICHART AND UCL FOR MR CHART BASED ON KNOWN PARAMETERS
C
      IF(IMRFLG.GE.1)  GO TO 6000
      IFLG=0
      IMRFLG=1
```

```
      UP1SIG=CA3SET+STDCA3
      UP2SIG=CA3SET+2*STDCA3
      UP3SIG=CA3SET+3*STDCA3
      DN1SIG=CA3SET-STDA3
      DN2SIG=CA3SET-2*STDCA3
      DN3SIG=CA3SET-3*STDCA3
      UCLR=(1.128+3*0.853)*STDCA3
      X=CA3SET
      DO 6010  I10=1,8
      UPRUN(I10)=0.0
      DNRUN(I10)=0.0
C
C  CHECK MOST CURRENT 8 POINTS FOR STATISTICAL CONTROL
C
 6010 XBAR(I10)=CA3SET
      GOTO 6020
C
C  DO NOT ATTEMPT TO FILTER IF DATA INDEPENDENCE CANNOT BE
C  REASONBLY ASSUMED
C
 6000 IF(TIME.LT.TSET-0.001)  GOTO 6030
C
C  DETERMINE NEXT SAMPLE POINT FOR FILTERING
C
 6020 TSET=TCONST+TIME
C
C  DO THE IMR FILTERING USING AT&T RUNS RULE
C
      XBAR(8)=RCA3
      FLAG1=0
      FLAG2=0
      FLAG3=0
      FLAG3=0
      FLAG4=0
      FLAGC=0
C
C CHECK RANGES AND DETERMINE THE NUMBER OF POINTS QUALIFYING IN THE
C COUNT FOR 4/5 RULE
C.
 2000 DO 2050  I11=1,8
          IF(I11.LE.1)  R=ABS(XBAR(I11)-X)
          IF(I11.GT.1)  R=ABS(XBAR(I11)-XBAR(I11-1))
          UPRUN(I11)=0
          DNRUN(I11)=0
          IF(R.GT.UCLR)  GOTO 7000
          IF(XBAR(I11).GT.UP1SIG)  UPRUN(I11)=1
          IF(XBAR(I11).LT.DN1SIG)  DNRUN(I11)=1
 2050 CONTINUE
C
C   CHECK RULE 1, OLDEST DATA POINT
C
      IF(XBAR(1).GT.UP3SIG.OR.XBAR(1).LT.DN3SIG)  THEN
        FLAG1=1
        GOTO 7000
      ENDIF
```

```
C
C    CHECK RULE 1 FOR XBAR(2) AND RULE 2 FOR BARS(1,2)
C
      IF(XBAR(2).GT.UP3SIG.OR.XBAR(2).LT.DN3SIG)  FLAG1=1
      IF(XBAR(2).GT.UP2SIG.AND.XBAR(1).GT.UP2SIG)  FLAG2=1
      IF(XBAR(2).LT.DN2SIG.AND.XBAR(1).LT.DN2SIG)  FLAG2=1
      IF(FLAG1.EQ.1.OR.FLAG2.EQ.1)  GOTO 7000
C
C    CHECK RULE 1 FOR XBAR(3) AND RULE 2 FOR XBARS(1,3;2,3)
C
      IF(XBAR(3).GT.UP3SIG.OR.XBAR(3).LT.DN3SIG)  FLAG1=1
      IF(XBAR(3).GT.UP2SIG.AND.XBAR(2).GT.UP2SIG)  FLAG2=1
      IF(XBAR(3).LT.DN2SIG.AND.XBAR(2).LT.DN2SIG)  FLAG2=1
      IF(XBAR(3).GT.UP2SIG.AND.XBAR(1).GT.UP2SIG)  FLAG2=1
      IF(XBAR(3).LT.D2SIG.AND.XBAR(1).LT.DN2SIG)  FLAG2=1
      IF(FLAG1.EQ.1.OR.FLAG2.EQ.1)  GOTO 7000
C
C    CHECK RULE 1 FOR XBAR(4), RULE 2 FOR XBARS(2,4;3,4) AND RULE 3 FOR
C    XBARS(1,2,3,&4)
C
      IF(XBAR(4).GT.UP3SIG.OR.XBAR(4).LT.DN3SIG)  FLAG1=1
      IF(XBAR(4).GT.UP2SIG.AND.XBAR(3).GT.UP2SIG)  FLAG2=1
      IF(XBAR(4).LT.DN2SIG.AND.XBAR(3).LT.DN2SIG)  FLAG2=1
      IF(XBAR(4).GT.UP2SIG.AND.XBAR(2).GT.UP2SIG)  FLAG2=1
      IF(XBAR(4).LT.DN2SIG.AND.XBAR(2).LT.DN2SIG)  FLAG2=1
      TUPRUN=UPRUN(1)+UPRUN(2)+UPRUN(3)+UPRUN(4)
      TDNRUN=DNRUN(1)+DNRUN(2)+DNRUN(3)+DNRUN(4)
      IF(TUPRUN.GE.4.OR.TDNRUN.GE.4)  FLAG3=1
      FLAGC=FLAG1+FLAG2+FLAG3
      IF(FLAGC.GT.0)  GOTO 7000
C
C    CHECK RULE 1 FOR XBAR(5), RULE 2 FOR XBARS(3,5;4,5) AND RULE 3 FOR
C    XBARS(1,2,3,4,&5)
C
      IF(XBAR(5).GT.UP3SIG.OR.XBAR(5).LT.DN3SIG)  FLAG1=1
      IF(XBAR(5).GT.UP2SIG.AND.XBAR(4).GT.UP2SIG)  FLAG2=1
      IF(XBAR(5).LT.DN2SIG.AND.XBAR(4).LT.DN2SIG)  FLAG2=1
      IF(XBAR(5).GT.UP2SIG.AND.XBAR(3).GT.UP2SIG)  FLAG2=1
      IF(XBAR(5).LT.DN2SIG.AND.XBAR(3).LT.DN2SIG)  FLAG2=1
      TUPRUN=UPRUN(1)+UPRUN(2)+UPRUN(3)+UPRUN(4)+UPRUN(5)
      TDNRUN=DNRUN(1)+DNRUN(2)+DNRUN(3)+DNRUN(4)+DNRUN(5)
      IF(TUPRUN.GE.4.OR.TDNRUN.GE.4)  FLAG3=1
      FLAGC=FLAG1+FLAG2+FLAG3
      IF(FLAGC.GT.0)  GOTO 7000
C
C    CHECK RULE 1 FOR XBAR(6), RULE 2 FOR XBARS(4,6;5,6) AND RULE 3 FOR
C    XBARS(2,3,4,5,&6)
C
      IF(XBAR(6).GT.UP3SIG.OR.XBAR(6).LT.DN3SIG)  FLAG1=1
      IF(XBAR(6).GT.UP2SIG.AND.XBAR(5).GT.UP2SIG)  FLAG2=1
      IF(XBAR(6).LT.DN2SIG.AND.XBAR(5).LT.DN2SIG)  FLAG2=1
      IF(XBAR(6).GT.UP2SIG.AND.XBAR(4).GT.UP2SIG)  FLAG2=1
      IF(XBAR(6).LT.DN2SIG.AND.XBAR(4).LT.DN2SIG)  FLAG2=1
      TUPRUN=UPRUN(2)+UPRUN(3)+UPRUN(4)+UPRUN(5)+UPRUN(6)
      TDNRUN=DNRUN(2)+DNRUN(3)+DNRUN(4)+DNRUN(5)+DNRUN(6)
```

```
      IF(TUPRUN.GE.4.OR.TDNRUN.GE.4)   FLAG3=1
      FLAGC=FLAG1+FLAG2+FLAG3
      IF(FLAGC.GT.0)   GOTO 7000
C
C  CHECK RULE 1 FOR XBAR(7), RULE 2 FOR XBARS(5,7;6,7) AND RULE 3 FOR
C  XBARS(3,4,5,6,&7)
C
      IF(XBAR(7).GT.UP3SIG.OR.XBAR(7).LT.DN3SIG)   FLAG1=1
      IF(XBAR(7).GT.UP2SIG.AND.XBAR(6).GT.UP2SIG)   FLAG2=1
      IF(XBAR(7).LT.DN2SIG.AND.XBAR(6).LT.DN2SIG)   FLAG2=1
      IF(XBAR(7).GT.UP2SIG.AND.XBAR(5).GT.UP2SIG)   FLAG2=1
      IF(XBAR(7).LT.DN2SIG.AND.XBAR(5).LT.DN2SIG)   FLAG2=1
      TUPRUN=UPRUN(3)+UPRUN(4)+UPRUN(5)+UPRUN(6)+UPRUN(7)
      TDNRUN=DNRUN(3)+DNRUN(4)+DNRUN(5)+DNRUN(6)+DNRUN(7)
      IF(TUPRUN.GE.4.OR.TDNRUN.GE.4)   FLAG3=1
      FLAGC=FLAG1+FLAG2+FLAG3
      IF(FLAGC.GT.0)   GOTO 7000
C
C  CHECK RULE 1 FOR XBAR(8), RULE 2 FOR XBARS(6,8;7,8), RULE 3 FOR
C  XBARS(3,4,5,6,7,&8) AND RULE 4 FOR ALL XBARS
C
      IF(XBAR(8).GT.UP3SIG.OR.XBAR(8).LT.DN3SIG)   FLAG1=1
      IF(XBAR(8).GT.UP2SIG.AND.XBAR(7).GT.UP2SIG)   FLAG2=1
      IF(XBAR(8).LT.DN2SIG.AND.XBAR(7).LT.DN2SIG)   FLAG2=1
      IF(XBAR(8).GT.UP2SIG.AND.XBAR(6).GT.UP2SIG)   FLAG2=1
      IF(XBAR(8).LT.DN2SIG.AND.XBAR(6).LT.DN2SIG)   FLAG2=1
      TUPRUN=UPRUN(4)+UPRUN(5)+UPRUN(6)+UPRUN(7)+UPRUN(8)
      TDNRUN=DNRUN(4)+DNRUN(5)+DNRUN(6)+DNRUN(7)+DNRUN(8)
      IF(TUPRUN.GE.4.OR.TDNUN.GE.4)   FLAG3=1
C
C CHECKING FOR RULE 4
C
      ABOVE=0
      BELOW=0
      DO 4000 K1=1,8
      IF(XBAR(K1).GT.CA3SET)   ABOVE=ABOVE+1
 4000 IF(XBAR(K1).LT.CA3SET)   BELOW=BELOW+1
      IF(ABOVE.GE.8.OR.BELOW.GE.8)   FLAG4=1
      FLAGC=FLAG1+FLAG2+FLAG3+FLAG4
      IF(FLAGC.GT.0)   GOTO 7000
C
C  AT THIS POINT, NO OCC CONDITION IS FOUND; THEREFORE,THE FILTERED
C  OUTPUT IS SIMPLY THE CENTER LINE OF THE I CHART (OR CA3SET)
C
      IFLG=0
      X=XBAR(1)
      DO 6001 L=1,7
C
C  SHIFT THE STACK OF XBARS TO PREPARE FOR NEXT ANALYSIS
C
      XBAR(L)=XBAR(L+1)
 6001 CONTINUE
      GOTO 6030
C
C  OOC CONDITION WAS FOUND; THEREFORE, THE FILTERED OUTPUT WILL BE
```

```
C   THE AVERAGE OF THE XBAR'S HELD IN THE XBAR ARRAY
C
 7000 ZBAR=0.0
      IFLG=1
      DO 7001 K2=1,8
 7001 ZBAR=XBAR(K2)+ZBAR
      ZBAR=ZBAR/8
      X=XBAR(1)
C
C   SHIFT THE STACK OF XBARS TO PREPARE FOR NEXT ANALYSIS
C
      DO 7002 L1=1,7
      XBAR(L1)=XBAR(L1+1)
 7002 CONTINUE
 6030 IF(IOCC.EQ.1.AND.IFLG.EQ.1)    FCA3=RCA3
      IF(IOCC.EQ.0.AND.IFLG.EQ.1)    FCA3=RCA3
      IF(IOCC.EQ.1.AND.IFLG.EQ.0)    FCA3=RCA3
      IF(IOCC.EQ.0.AND.IFLG.EQ.0)    FCA3=CA3SET
      END
C
C SECOND RUNGA KUTTA INTEGRATION ROUTINE
C
      SUBROUTINE F1(X,ERR1,ERR2,XK1,XK2)
      IMPLICIT DOUBLEPRECISION(A-H,O-Z)
      XK1=ERR1
      XK2=ERR2
      END
C
C   SUBROUTINE FOR ICHART PREFILTERING
C
      SUBROUTINE PREFIL(TIME,IPRE,IOCC,STDCA3,CA3SET,TRESP,
     $RCA3,Z)
      IMPLICIT DOUBLEPRECISION(A-H,O-Z)
      DOUBLE PRECISION LCLI
      IF(IPRE.EQ.0)   THEN
         IOCC=0
         IPRE=1
         T=0.0
         UCLI=CA3SET+Z*STDCA3
         LCLI=CA3SET-Z*STDCA3
      ELSE
      ENDIF
      IF(TIME.LT.T-0.001)   GO TO 15
      IF(RCA3.GT.UCLI.OR.RCA3.LT.LCLI)   THEN
           IOCC=1
           T=TIME+TRESP
        ELSE
           IOCC=0
      ENDIF
 15   END
C
C   THIRD RUNGA KUTTA ROUTINE FOR SYSTEM WHEN USING
C   FILTERED FEEDBACK
C
      SUBROUTINE F2(X,CA1,CA2,CA3,ERINT,XK1,XK2,XK3,XK4,DER)
```

```
      IMPLICIT DOUBLEPRECISION(A-H,O-Z)
      DIMENSION B(19,19)
      COMMON XKC,TAUI,CAD,TAU,XK,CAM,TAUD,CAMO,B,IOCC,IFLG,FCA3
      CAM=CAMO+XKC*(0.1-FCA3+ERINT/TAUI-DER*TAUD)
      CAO=CAD+CAM
      XK1=CAO/TAU-(1/TAU+XK)*CA1
      XK2=CA1/TAU-(1/TAU+XK)*CA2
      XK3=CA2/TAU-(1/TAU+XK)*CA3
      XK4=0.1-FCA3
      END
C
C     END OF SYSTEM
C
//*O.FT06F001 DD DSN=U1222A.FINAL1.OUTLIST,DISP=(OLD,KEEP),
//GO.FT06F001 DD DSN=U12522A.CD00.OUTLIST,DISP=(NEW,CATLG),
//      UNIT=STORAGE,SPACE=(9044,(60,60),RLSE),
//      DCB=(RECFM=FBA,LRECL=133,BLKSIZE=9044)
//GO.SYSIN DD *
1.814,2.0,0.5,37.647,60.0,0.453,100
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0
0.83333,0.3333,-0.16666,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0
0.6,0.4,0.2,0.0,-0.2,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0
0.46428,0.35714,0.25,0.14285,0.03571,-0.07142,-0.17857
0,0,0,0,0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,,0
0.37777,0.31111,0.24444,0.17777,0.11111,0.04444,-0.02222
-0.08888,-0.15555,0,0,0,0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0
0.31818,0.27272,0.22727,0.18181,0.13636,0.0909,0.04545,0.0
-0.04545,-0.0909,-0.13636,0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0
0.24166,0.21666,0.19166,0.16666,0.14166,0.11666,0.09166,0.0666
0.04166,0.01666,-0.00833,-0.03333,-0.05833,-0.08333,-0.10833
0,0,0,0
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0
0.19473,0.17894,.16315,0.14736,0.13157,0.11578,0.1,0.08421
0.06842,0.05263,0.03684,0.02105,0.00526,-0.01052,-0.02631
-0.04210,-0.05789,-0.07368,-0.08947
1,0,1
1,0,1
1,0,5
1,0,5
2,0,1
2,0,1
2,0,3
2,0,3
3,0,1
3,0,1
```

```
3,0,1
3,0,2
3,0,2
4,0,1
4,0,1
4,0,5
4,0,5
5,0,1
5,0,1
6,0,1
6,0,1
4,1,1
4,1,1
4,1,5
4,1,5
5,1,1
5,1,1
6,1,1
6,1,1
//
```

VITA

John Roy English

Candidate for the Degree of

Doctor of Philosophy

Thesis: IMPROVED QUALITY OF CONTINUOUS FLOW MANUFACTURING
           THROUGH THE COMBINATION OF STATISTICAL PROCESS
           CONTROL AND CONVENTIONAL COMPUTER PROCESS CONTROL

Major Field: Industrial Engineering

Biographical:

    Personal Data: Born in Tulsa, Oklahoma, March 12,
        1958, the son of Roy L. and Carolyn English.

    Education: Graduated from Prairie Grove High School,
        Prairie Grove, Arkansas in May 1976; received
        Bachelor of Science Degree in Electrical
        Engineering from University of Arkansas in
        January 1981; received Master of Science Degree
        in Operations Research from University of Arkansas
        in August 1982; completed the requirements for the
        Doctor of Philosophy in Industrial Engineering at
        Oklahoma State University in December 1988.

    Professional Experience: Graduate Assistant,
        Department of Industrial Engineering and
        Management, Oklahoma State University, September,
        1985, to August, 1988; Manager, AT&T-
        Communications, August, 1982, to August, 1985;
        Graduate Assistant, Department of Industrial
        Engineering, University of Arkansas, January,
        1981, to August, 1982.