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by

DANIEL S. MAN

A THESIS

SUBMITTED TO THE FACULTY OF GRADUATE STUDIES AND RESEARCH

IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE

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IN

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To my parents,

who have given so much and asked for so little.

Abstract

Single series forecasting (SSF) is the forecasting of a single time series based on the current and past values of the series only. It is implemented for process control using a process model, a forecaster and a controller. The difference, or residual $r(k)$, between the actual process output $y(k)$ and the model output $\hat{y}(k)$ is fed back through the forecaster to the controller. Based on the present and past values of $r(k)$ only, the forecaster generates forecasts $\hat{r}(k+\lambda)$, where λ is not less than the process plus sampling delays. Any controller may be used. However, since the process model is already available, a predictive controller is recommended because it generates the appropriate control action at time k to compensate for the forecasted error at time $k+\lambda$.

SSF was investigated as a means:

1) to improve the performance of both conventional and modern control techniques, and
2) to provide insight into the structure and performance of techniques such as Internal Model Control (IMC) as proposed by Garcia and Morari.

It has been shown that, given perfect forecasting, SSF can result in perfect control even with the presence of unmeasured disturbances. If the available process model is not perfect, then SSF helps to compensate for both unmeasured disturbances and modelling errors.

The quality of control using SSF depends on the quality of the forecast and hence deteriorates in the presence of large amounts of random noise and/or strong nonlinearities. Furthermore, a perfect predictive controller will compensate for the effect of a disturbance in λ time intervals when λ equals the sampling plus process delays. Thus, the best that SSF can do when combined with a perfect predictive controller is to achieve compensation at time k rather than $k+\lambda$. The practical justification for actual SSF applications is therefore limited.

Comparison of the SSF approach with other classical and modern control techniques does, however, provide some important insights.

1) Classical proportional plus derivative feedback control can be interpreted as proportional control based on SSF of the control error or process output.
2) IMC can be interpreted as an SSF system that uses the current value of the residual r(k) as an estimate of the future value $r(k+\lambda)$. Futhermore, the design rule that the IMC controller should approach the inverse of the process model is readily seen as being equivalent to the classical design observation that perfect control is approached as the feedback gain approaches infinity. (There are of course stability and performance limitations with most practical systems.)
3) IMC can be interpreted as a classical feedforward scheme based on the forecasted (estimated) disturbance rather

than the actual measured value.

Simulations results also showed that SSF could improve the performance of adaptive control techniques, such as the Adaptive Predictive Control System (APCS), which use the magnitude of the estimation error as a criterion for switching identification on and off and have no explicit identification of the noise term. During the periods that the adaptive parameter estimation is turned off, SSF is used to model the structure of the residual (disturbances plus modelling error) and augment the predictive control action. This second level of control can be justified on the basis that it prevents unnecessary corruption of the process I/O model by unmeasured disturbances and can reduce the control error.

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Table of Contents

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Nomenclature

Alphabetic

a	ARMA model parameters
b	ARMA model parameters
C	Feedback controller
d	Disturbances
$\hat{d}$	Residual or estimated disturbances
F	Filter
Gc	Controller
Gd	Disturbance transfer function
Gm	Process model
Gp	Process transfer function
Gx	Feedforward controller
k	Sampling instant
Kc	Proportional constant
r	Residual
$\hat{r}$	Estimated residual
R	Reference model
u	Process input
x	Process input/output vector
y	Output
$\hat{y}$	Estimated output
y_d	Desired output
y_m	Estimated output
y_s	Setpoint
y_x	Disturbance effect on the output

Greek

α	Coefficient of AR forecaster
Δ_d	Upper bound on the absolute value of $\Delta(k)$
Δ_m	Minimum upper bound of Δ_d
ϵ	Control error
θ	Process parameters
$\hat{\theta}$	Model parameters
λ	Process time delay plus sampling delay
ξ	Disturbances
τ_d	Derivative time constant
τ_i	Integral time constant
Φ	Process input/output vector
ω	Switching factor

1. Introduction

1.1 Introduction

In chemical process control, process lags and time delays present a challenging problem to most control techniques. Conventional feedback control is still the most popular control technique despite the vast development in modern control techniques, but it performs poorly for systems with large time delays.

Predictive control techniques have been developed to address this probelm. An example of an early development is the Smith Predictor. Modern control techniques such as the Self Tuning Regulator (STR), Adaptive Predictive Control System (APCS) and Internal Model Control (IMC) are all predictive in nature. Control action is determined based on the prediction of the process output by an input/output (I/O) model.

It is obvious that the use of a perfect I/O model for prediction can improve control in the presence of process lags and time delays. However, non-idealities such as modelling errors and unmeasured disturbances generally degrade the performance. Unmeasured disturbances cannot be detected until their effects appear in the output of the process. In order to compensate for unmeasured disturbances before they affect the process output, some form of forecasting of their effects on the output is necessary. An estimate of the current disturbance effect can be obtained from the difference between the measured process output and the predicted output from the I/O model. Based on the current and past values of this estimate, future values of the disturbance can be obtained using single series forecasting (SSF). The work in this thesis is devoted to investigating this use of SSF for compensating unmeasured disturbances.

1.2 Objectives of the Thesis

The overall objective of the thesis is to investigate the use of SSF in process control. The original interest of this project was to improve the control performance of adaptive control techniques by SSF. The scope was later expanded to include Internal Model Control (IMC) and conventional feedback and feedforward control. Conventional control techniques have been included because some of their fundamental principles can be used to interpret IMC and to introduce the use of SSF for process control.

The specific objectives of this thesis are:

1) to investigate the use of SSF as a means to improve the performance of both conventional and modern control techniques, and
2) to gain insight into the structure and performance of techniques such as Internal Modern Control (IMC) as proposed by Garcia and Morari (1982).

Since time series forecasting is a fairly well established area, the primary concern in the first objective is the viability of using SSF with existing control techniques rather than the relative merits of different forecasting methods. Perfect forecasting is assumed in many cases to establish the best improvement obtainable from SSF. Then a linear forecaster or an autoregressive forecaster is used to establish a more realistic case.

1.3 Structure of the Thesis

The contents of the seven chapters of this thesis have been arranged to give the readers a logical view of the development of the work on SSF. Following the introduction of the objectives of the thesis in Chapter One, Chapter Two explains the concept of SSF and presents some common forecasting methods. Readers who have prior exposure to SSF will be able to omit Chapter Two or use it as a review.

The main results of the thesis are presented in Chapters Three to Five according to the various control techniques which have been studied. For each control technique, a description of the technique is given followed by an analysis or an interpretation of the technique. Then the use of SSF with the control technique or the relation of SSF with it is examined. Finally, some numerical examples are given to illustrate the ideas presented.

The control structure for implementing SSF is introduced from a feedforward control point of view in Chapter Three. This structure serves as a reference for the use of SSF with IMC and APCS in Chapters Four and Five respectively. Also in Chapter Three, some fundamental principles of conventional feedback and feedforward control are presented explicitly as concepts for the purpose of easy reference by Chapter Four in the interpretation of the IMC structure. The thesis is deliberately structured to emphasize that many of the features of "advanced" control schemes such as IMC follow directly from a sound understanding of classical feedback and feedforward control.

Chapter Six contains an application of SSF on a simulated double effect evporator as a realistic evaluation of SSF. Chapter Seven presents conclusions from the results in the previous chapters and recommends ideas for future work.

2. Single Series Forecasting (SSF)

2.1 Introduction

The technique of single series forecasting (SSF) has been used extensively in economics, business, engineering and many other areas. The purpose of this chapter is to explain briefly the concept of SSF and present some simple forecasting methods. Special emphasis has been placed on the differences between SSF and prediction using an input/output (I/O) model. This chapter is intended for readers with no prior knowledge of SSF.

2.2 Concept of SSF

SSF is the forecasting of a single time series based on knowledge of the current and past values of the series only. To illustrate the idea of SSF, consider a measured discrete time variable $r(k)$ as plotted in Figure 2.1. At a certain sampling instant k, it is required to forecast the future values $\hat{r}$ of r. Assuming the factors affecting r are either unknown or unmeasured, the only information available for the forecast are the current and past values of r. Therefore, estimates of the future values, $\hat{r}$, have to be generated by SSF.

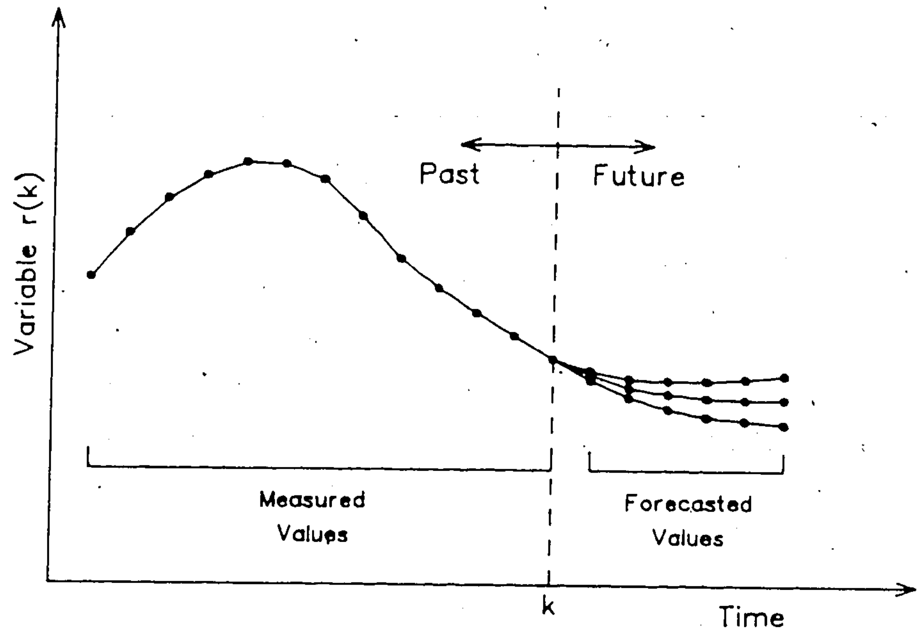

Figure 2.1 Illustration of Single Series Forecasting

The term "forecasting" is used here to distinguish SSF from "prediction" using an I/O model. An I/O model represents a functional relationship between two variables - the input and the output. If the model is accurate and there is no other factor affecting the output, perfect prediction can be obtained knowing the current and past input and output values. Therefore, SSF and I/O model prediction are different in terms of the information they use for prediction.

To use SSF, it is obvious that the time series must have some deterministic structure since it is impossible to accurately forecast a random variable. The quality of the forecast depends on the dynamics of the time series, the lead time of the forecast, and the type of forecasting method used. The type of forecasting method used will be determined by the requirements of the individual application. Some common forecasting methods will be presented in the following section.

2.3 Forecasting Methods

The problem to be solved here is to forecast future values of a time series using the current and past values of the series only. Many methods based on different approaches are available. Three commonly used methods will be presented in the this section.

1) Forecasting using current value

There is actually no real forecasting done in this method because it uses the current measured value as the forecasted value. For a one-step ahead forecast,

$$\hat{r}(k+1) = r(k) \tag{2.1}$$

This method is satisfactory if the time series changes slowly. It can also be used as a conservative approach for time series containing a large amount of noise.

2) Linear extrapolation

This method makes use of the first derivative of the time series at the current value to calculate the future values. The equation for a one-step ahead forecast is

$$\hat{r}(k+1) = r(k) + \frac{dr}{dt}\Delta t \qquad (2.2)$$

where Δt = sampling time

The derivative can be calculated by the Newton's backward difference formula. For example, the two-point formula and the three-point formula are given as follows.

$$\text{Two points: } \frac{dr}{dt} = \frac{r(k) - r(k-1)}{\Delta t} \qquad (2.3a)$$

$$\text{Three points: } \frac{dr}{dt} = \frac{3r(k) - 4r(k-1) + r(k-2)}{2\Delta t} \qquad (2.3b)$$

In general, the use of two or three points is sufficient for calculating the first derivative.

The advantage of this method is that the computation is simple and the extrapolation is accurate for time series without sharp changes in the values. The disadvantage is that it is easily confused by noise. It is also not good for long term forecasting. In general, only forecasts for one or two sampling periods ahead are reliable.

3) Forecasting using an auto-regressive equation

In this method, a general λ-step ahead forecast is given by the auto-regressive (AR) equation.

$$\hat{r}(k+\lambda) = \alpha_1 r(k) + \alpha_2 r(k-1) + \ldots + \alpha_n r(k-n+1) \qquad (2.4)$$

The coefficients α_1, α_2, ..., α_n may or may not be known. If they are unknown, they have to be identified either off-line or on-line. Then the equation can be used to calculate the forecasted values.

To use the AR equation for disturbances whose nature generally changes with time, the coefficients have to be identified on-line by a parameter identification algorithm. If the time series has a structure, the AR equation can be interpreted as a model for the series. The coefficients will get closer to the true values as the identification process continues. If the coefficients converge to the correct values, the forecast will be perfect. However, it is possible to obtain accurate forecast without using accurate coefficients. The primary objective is to have accurate forecasting rather than accurate coefficients.

There are many on-line parameter identification algorithms available. Two of them will be described here becau of their simplicity and fast convergence.

a. Recursive least square algorithm

The time series of the variable r is assumed to be described by the equation

$$r(k) = \Phi(k-1)\ \theta \tag{2.5}$$

where

$$\theta^t = [\ \alpha_1\ \alpha_2\ \dots\ \alpha_n\ ]$$

$$\Phi(k-1) = [\ r(k-1)\ r(k-2)\ \dots\ r(k-n)\ ]$$

The recursive least square algorithm, e.g. Astrom and Eykhoff (1971), is given by

$$\theta(k) = \theta(k-1) + K(k-1)[r(k)-\Phi(k-1)\theta(k-1)] \tag{2.6}$$

$$K(k-1) = P(k-1)\Phi^t(k-1)[1+\Phi(k-1)P(k-1)\Phi^t(k-1)]^{-1} \tag{2.7}$$

$$P(k) = \frac{1}{\beta}\{P(k-1)-K(k-1)[1+\Phi(k-1)P(k-1)\Phi^t(k-1)]K^t(k-1)\} \tag{2.8}$$

β is the exponential forgetting factor whose value is chosen as $0.9 < \beta \leq 1$. P(k) is the covariance matrix.

b. APCS projection algorithm

The Adaptive Predictive Control System (APCS) was proposed by Martin-Sanchez (1976). The recursive identification algorithm, also known as a projection or a gradient search algorithm, used by APCS is

$$\theta(k) = \theta(k-1) + \frac{\psi^2(k)\Phi(k-1)[r(k)-\Phi(k-1)\theta(k-1)]}{1+\psi^2(k)\Phi(k-1)\Phi^t(k-1)} \quad (2.9)$$

$\psi(k)$ is a scalar which is used for turning identification on and off. A more detailed definition of $\psi(k)$ will be given in Chapter Five.

Forecasting with an AR equation requires much more computation effort than linear extrapolation. However, it has the advantage that if the time series has a slowly time varying structure, the AR equation can model it and provide accurate forecasts.

3. SSF and Conventional Feedback and Feedforward Control

3.1 Introduction

The conventional feedback and feedforward control systems are the oldest and still the most common control systems used in chemical process control. Their structures are very simple and the theories behind them are well understood. The purpose of this chapter is not to propose any new theory about these conventional control systems, but rather to identify some of the concepts used by them. These concepts will be shown to be intrinsic in more advanced control systems such as the Internal Model Control discussed in later chapters. The presentation is based on an intuitive, practical approach such as would be obtained by experience with these control systems. Another purpose of this chapter is to explore the relationship of SSF with these traditional control systems. It will be shown that the proportional-derivative feedback controller can be interpreted as a proportional controller with a linear forecaster. In addition, the feedforward control concept has been extended in a scheme which uses SSF for compensating unmeasured disturbances.

3.2 SSF and Conventional Feedback Control

3.2.1 Description of the Feedback Control System

The block diagram of a conventional PID feedback control system is shown in Figure 3.1. The block diagram has been simplified by omitting the measurement device and the final control element since their dynamics are typically negligible and/or incorporated in the process model.

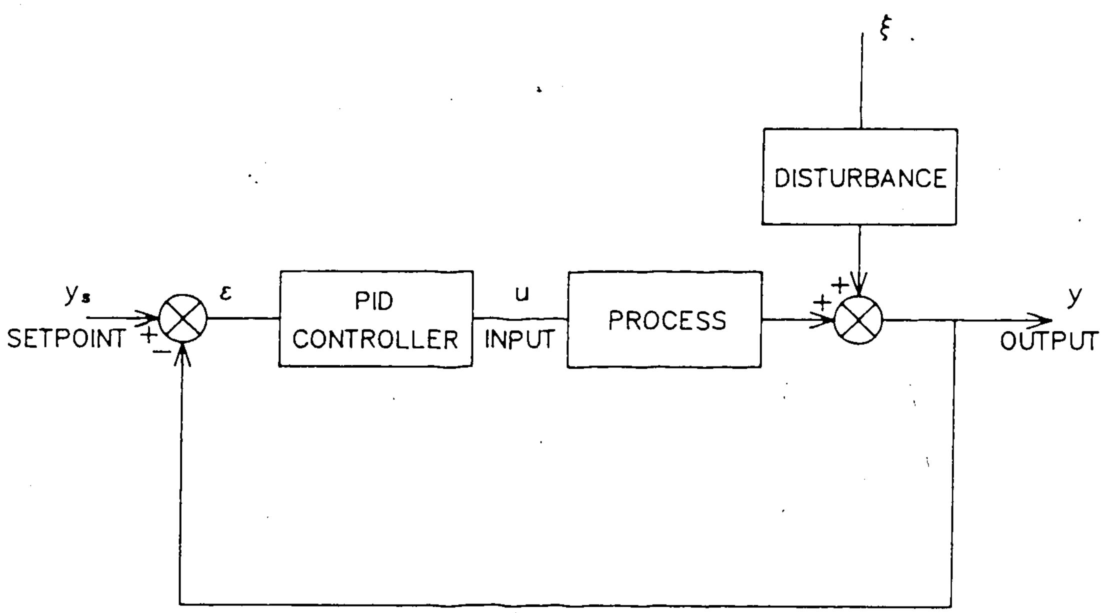

Figure 3.1 Block Diagram of a Conventional Feedback Control System

The principle of feedback control is the feedback of the output variable to calculate the control error, ϵ, which forms the input to an "error driven" controller.

$$\epsilon = y_s - y \tag{3.1}$$

The control error can arise from two sources: setpoint changes and disturbances. Servo control refers to eliminating the control error arising from setpoint changes. Regulatory control refers to eliminating the control error arising from disturbances. Since the error-driven feedback controller does not distinguish the source that gives rise to the control error, it cannot distinguish between servo and regulatory control.

CONTROLLER MODES

The conventional PID feedback controller has three modes of control action: proportional, integral and derivative. Mathematically, the controller output in the continuous time domain is given by:

$$u(t) = Kc\ [\epsilon(t) + \frac{1}{\tau_i}\int \epsilon(t)dt + \tau_d\frac{d}{dt}\epsilon(t)] \tag{3.2}$$

The simplest feedback controller has only the proportional mode. The problem with it is that it leaves offset in the output. The integral mode is added primarily to eliminate this offset. However, it also makes the response more oscillatory. The derivative mode is added to speed up the response of the system.

Equation (3.2) represents the theoretical PID feedback controller. In practice, there are many variations. One variation which is of interest to this study is where the derivative mode acts on the process output instead of the control error. In practice, this is done to avoid a "derivative kick" which is a sudden change in the controller output when there is a sudden change in the setpoint. The equation is

$$u(t) = Kc \left[\epsilon(t) + \frac{1}{\tau_i}\int\epsilon(t)dt + \tau_d\frac{d}{dt}y(t)\right] \qquad (3.3)$$

CLOSED LOOP TRANSFER FUNCTION

The closed loop transfer function of the system in Figure 3.1 is given by:

$$y = \frac{Gc\ Gp}{1 + Gc\ Gp}\, y_s + \frac{Gd}{1 + Gc\ Gp}\,\xi \qquad (3.4)$$

The setpoint y_s and disturbance ξ are the two inputs to the closed-loop system. The transfer function between y and y_s determines the dynamics of servo control while the transfer function between y and ξ determines the dynamics of regulatory control. Since the two transfer functions are different, the dynamics in servo and regulatory control are different. Therefore, the use of a single controller in the feedback control system may not guarantee good performance in both cases. There may be advantage in separating the two controllers.

CONCEPT 3.1 Servo control and regulatory control generally have different closed loop dynamics, it would be better to have separate servo and regulatory controllers.

From equation (3.4), perfect control can be defined as requiring

$$\frac{Gc\ Gp}{1 + Gc\ Gp} = 1 \tag{3.5a}$$

and

$$\frac{Gd}{1 + Gc\ Gp} = 0 \tag{3.5b}$$

This is possible when the gain of the controller is very high or infinite. Hence, perfect feedback control can be obtained with an infinite gain controller.

However, the gain of a feedback controller is usually limited by stability constraints. According to the Bode criterion, a stable loop requires that $|GcGp| \leq 1$ at the crossover frequency i.e. when the phase angle is -180°. Therefore, the controller gain is constrained and perfect control in the sense of equation (3.5) is not always possible.

CONCEPT 3.2 Perfect feedback servo and regulatory control can be approached by using a high gain controller provided that the high gain is within the stability constraints.

3.2.2 Interpreting Proportional-Derivative Control as SSF

One characteristic of feedback control is that it is remedial i.e. it corrects for error which is already present in the output. For systems which contain time delay or measurement lag, feedback control is not very good because the control action always lags behind the disturbance and tends to overcompensate. All discrete digital control systems have at least one period of inherent time delay due to sampling. The approach used to control time-delayed system is to have some form of prediction. In this section, it will be shown that the proportional-derivative controller contains a form of forecasting.

Consider the structure of a proportional-derivative controller in a discrete system (Figure 3.2). The controller can be considered as composed of two parts: a forecaster and a controller. The forecaster is given by

$$\left(1 + \tau_d \frac{d}{dt}\right) \epsilon(t) \tag{3.6}$$

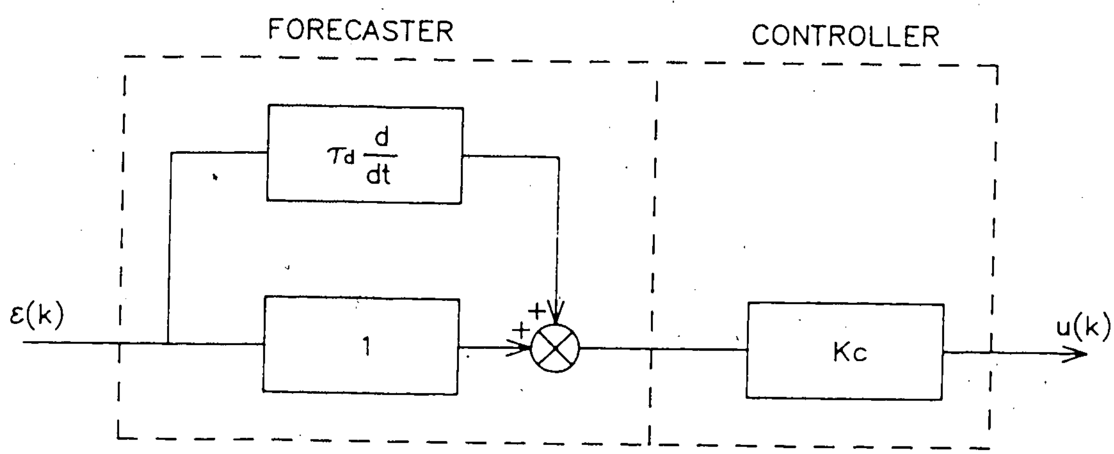

Figure 3.2 Structure of a Proportional-Derivative Controller

For the special case where $\tau_d = n*\Delta t$, the expression forecasts $\epsilon(k)$ exactly n sampling intervals ahead using the slope of $\epsilon(k)$.

$$\left(1 + n*\Delta t \frac{d}{dt}\right) \epsilon(k) = \hat{\epsilon}(k+n) \tag{3.7}$$

The controller is a proportional controller with gain Kc which acts on the forecasted error $\hat{\epsilon}(k+n)$ and equation (3.7) is equivalent to the equation of a linear forecaster as given by equation (2.2). Therefore, the proportional-derivative controller can be interpreted as containing a linear forecaster of the *control error*. A one-step ahead forecaster is needed to compensate for the inherent sampling delay in discrete control system (Jacobson (1970) and Moore (1969)). Forecasting ahead for more than one step can be used to compensate for delays and/or process lags.

CONCEPT 3.3 The proportional-derivative controller in Figure 3.2 can be interpreted as a proportional controller with a linear forecaster on the control error.

Consider now the feedback controller described by equation (3.3) where the derivative mode acts on the process output rather than the control error. A block diagram of the control system with a proportional-derivative controller is shown in Figure 3.3.

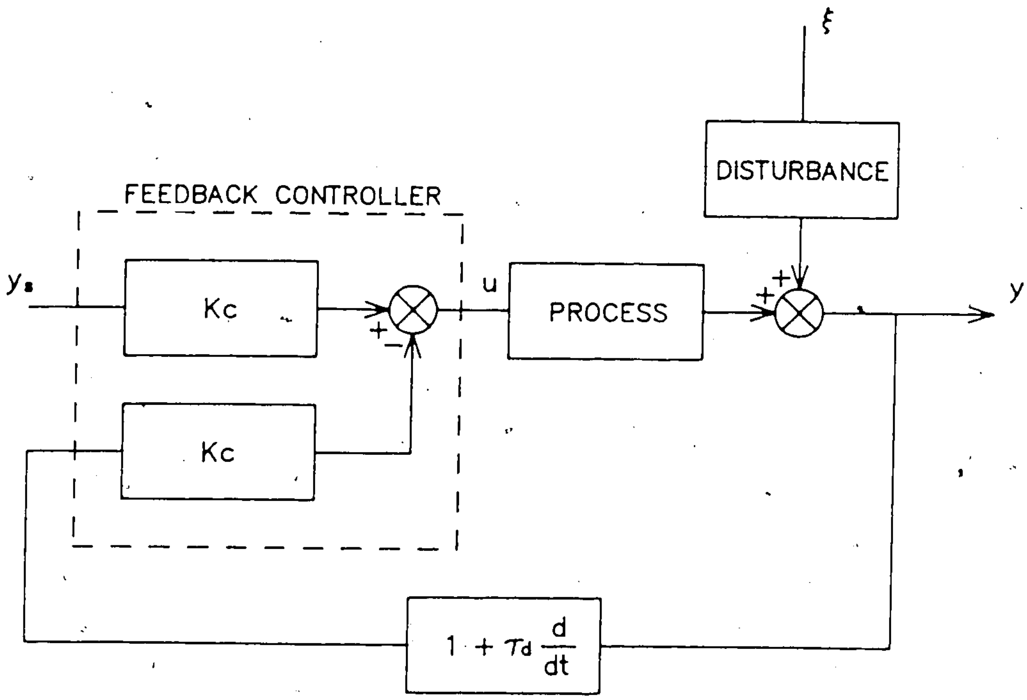

Figure 3.3 A Re-structuring of the PD Feedback Control System

The controller in the feedback path is the same PD feedback controller as that in Figure 3.2. The only difference is that the input to the controller is the process output y. Therefore, following the same argument for the feedback controller in Figure 3.2, it can be shown that the feedback controller in Figure 3.3 can be interpreted as containing a linear forecaster on the *output* since

$$(1 + \tau_d \frac{d}{dt})\ y(k) = \hat{y}(k+1) \quad \text{for } \tau_d = \Delta t \tag{3.8}$$

The controller gain Kc acts on the forecasted process output $\hat{y}(k+1)$.

CONCEPT 3.4 The proportional-derivative controller in Figure 3.3 can be interpreted as a proportional controller with linear forecasting of the process output.

Another feature in Figure 3.3 is that there are two controllers in the system. The one in the "setpoint path" can be regarded as the servo controller and the one in the "feedback path" can be regarded as the regulatory controller. As mentioned previously, the dynamics in servo control can be quite different from that in regulatory control. Therefore, with this separation, it is possible to design different servo and regulatory controllers if justified by improved performance. The implementation of two controllers is easily done in computer control system since all that is required is software.

3.3 SSF and Feedforward Control

3.3.1 Description of Feedforward Control

Feedforward control is used primarily to compensate for a disturbance before it upsets the process. The block diagram of a conventional feedforward control system is shown in Figure 3.4.

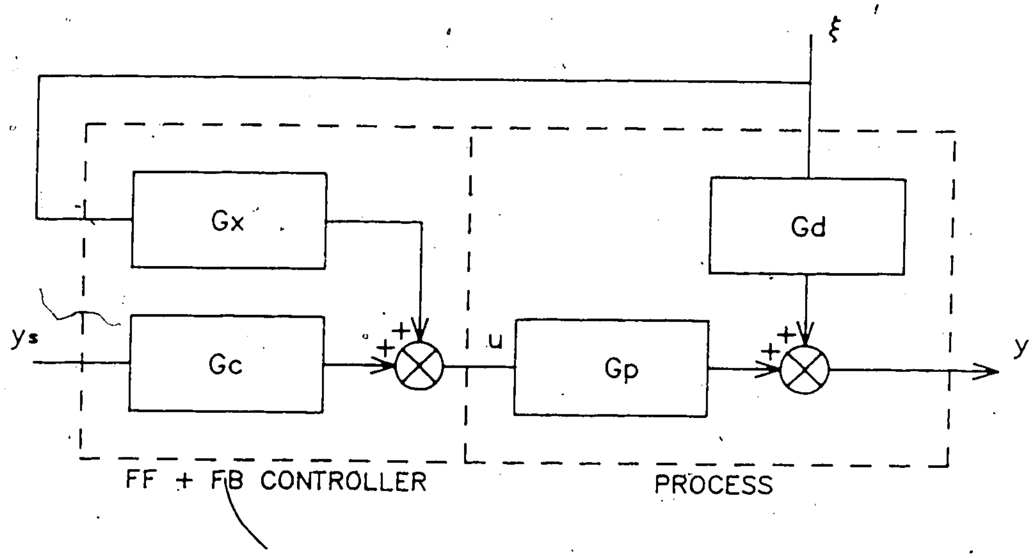

Figure 3.4 Block Diagram of a Feedforward Control System

The disturbance that affects the process is measured as it enters the process. Based on this measurement, the feedforward controller generates appropriate control action to compensate for the effect of the disturbance so that the output is not affected. Note that a key feature of feedforward control is derived from the fact that the disturbance is known and corrective action is taken *before* its effect propagates through the process to affect the output. This time advantage gives the controller time to take action to compensate for the effect of the disturbance.

CONCEPT 3.5 Feedforward control makes use of the time advantage from knowing the disturbance and taking corrective action before its effect propagates through the process.

The objective of the feedforward controller can be described by the following equation.

$$\xi\ Gd + \xi\ Gx\ Gp = 0 \qquad (3.9)$$

From equation (3.9), the structure of the perfect feedforward controller is obviously

$$Gx = -\frac{Gd}{Gp} \qquad (3.10)$$

The controller works on the principle of cancellation of transfer functions. For perfect control, i.e. exact cancellation, the disturbance and process transfer functions must be known exactly.

CONCEPT 3.6 In conventional feedforward control, the perfect controller transfer function is a product of the load transfer function and the inverse of the process transfer function.

The combination of Gd and Gp to form Gx often results in simplification in the structure of the feedforward controller. For example, consider a first order process with a first order disturbance tranfer function.

$$Gp = \frac{Kp}{\tau_1 s + 1} \qquad (3.11a)$$

$$Gd = \frac{Kd}{\tau_2 s + 1} \qquad (3.11b)$$

If $\tau_1 = \tau_2$, then

$$Gx = - \frac{Kd}{Kp} = - Kx \qquad (3.12)$$

The feedforward controller is simplified to a proportional controller.

Note that the perfect feedforward controller requires the inversion of the process transfer function. This could be a problem if the process transfer function contains some non-invertible parts such as a time delay or unstable zeros. One solution is to find an approximate inverse for the process which neglects these non-invertible parts. In practice, most feedforward controllers are proportional controllers or have simple "lead-lag" type dynamic compensation.

3.3.2 Feedforward Control Using SSF

The disadvantage of conventional feedforward control is that it is designed only to compensate for *measured* disturbances. However, some of its principles can be applied to compensate for *unmeasured* disturbances if estimates of these disturbances can be obtained. It will be shown in the following how SSF can be used as part of a scheme to compensate for unmeasured disturbances in a feedforward manner.

Figure 3.5 shows a block diagram of the control system to be described. The first step in the control scheme is to obtain an estimate of the effect of the unknown disturbance on the current output. This is achieved by introducing a process model which estimates the process output at every sampling instant. Not much will be said about the process model at this point except that its function is, given values of the process input variables, to estimate the process output as accurately as possible. The type of model used is not of concern here.

The difference between the actual output and the estimated output is the estimation error or residual r(k).

$$r(k) = y(k) - \hat{y}(k) \qquad (3.13)$$

If the model is exact, the residual is equal to the effect of the unknown disturbances $y_x(k)$. If the model is not exact, the estimation error will contain some modelling

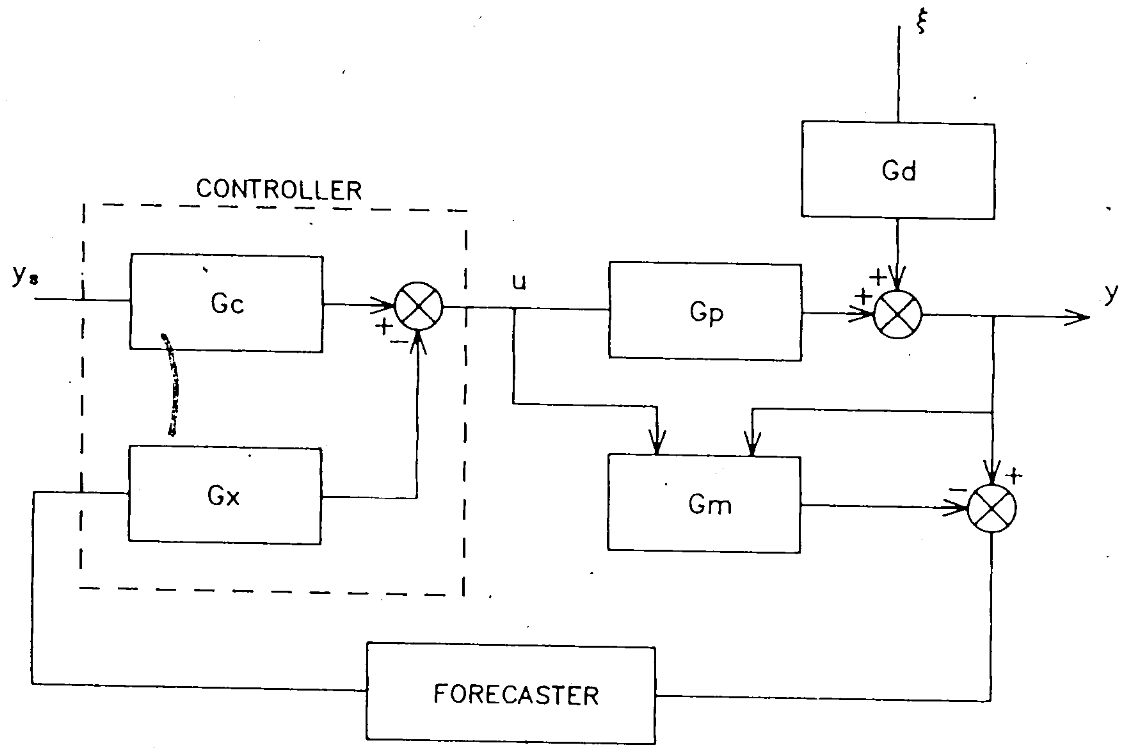

Figure 3.5 System for Feedforward Compensation of Unmeasured Disturbance Using SSF

error as well as the disturbance. Note that in the ideal case, the residual is an estimate of the unmeasured disturbances.

CONCEPT 3.7 A residual can be generated by subtracting the predicted output from the measured output. This residual is an estimate of disturbances and/or modelling error.

In order not to complicate the discussion for the time being, it will be assumed that the model is exact and $r(k) = y_x(k)$.

It is not sufficient just to know the effect of the unknown disturbances in the current output. For feedforward control, the time advantage in knowing the future disturbances (CONCEPT 3.5) must be provided. This is achieved by introducing a forecaster which forecasts the future residual $r(k+\lambda)$ based on the past values $r(k)$, $r(k-1)$, ... The type of forecasting technique used is also not of concern here. It may be any one of those mentioned in Chapter Two. The main criteria for the choice of the forecaster are accuracy and computational effort.

CONCEPT 3.8 The time advantage required for feedforward control can be generated by forecasting the estimated disturbances.

The controller design is analogous to the feedforward controller described in the previous section. Given the estimated disturbances, the controller that will generate the exact compensatory action is a predictive controller. Its form is

$$Gx = \frac{1}{Gp} \qquad (3.14)$$

Since the input to this controller is y_x rather than ξ, Gd is not present in equation (3.14). The minus sign which was in equation (3.10) but not in (3.14) has been incorporated in the summing junction in Figure 3.5.

This controller also works on the principle of cancellation of transfer functions. For perfect control, the process transfer function must be known exactly i.e. Gm = Gp.

CONCEPT 3.9 Perfect feedforward control based on estimated disturbances requires the use of an exact process model for prediction of the process output and an exact inverse for the controller.

The controller design determines how far ahead the forecaster has to estimate. This is actually related to the time delay of the process. Assume that the process contains a time delay of λ sampling periods including the unit delay due to sampling. When the process transfer function is inverted to form the controller, the delay becomes a prediction. Therefore, the forecaster has to estimate λ sampling periods ahead to provide the disturbance estimate for the controller.

In the inversion of the process transfer function, a problem is encountered if the process transfer function contains unstable zeros. The controller will be unstable if the inversion is done. Therefore, the above controller design is restricted to stable-inverse processes only. For process with unstable zeros, an approximate inverse may be used by inverting only the stable and invertible part of the process. This problem will be addressed again in Chapter Four in the discussion of IMC.

A simulation example will be given in the following as an illustration for the system in Figure 3.5. Consider a first order process described by the discrete ARMA equation.

$$y(k) = 0.8y(k-1) + 0.6u(k-1) + \xi(k) + 0.5\xi(k-1) \quad (3.15)$$

The effect of the disturbance on the output is $y_x(k)$ and is assumed to be

$$y_x(k) = \xi(k) + 0.5\xi(k-1) \quad (3.16)$$

Assuming the disturbance is unknown, the best I/O process model is

$$y(k) = 0.8y(k-1) + 0.6u(k-1) \tag{3.17}$$

Two forms of one-step ahead forecasters are considered here. The first one is a linear forecaster described by the following equation

$$\hat{r}(k+1) = r(k) + (r(k) - r(k-1)) \tag{3.18}$$

The second one is an adaptive autoregressive forecaster of the form

$$\hat{r}(k+1) = \alpha_1 r(k) + \alpha_2 r(k-1) + \alpha_3 r(k-2) \tag{3.19}$$

The parameters α_1, α_2 and α_3 are identified on-line by a parameter estimation scheme.

The same process model (equation (3.17)) has been used to design both Gc and Gx as per Figure 3.5. The controller output is derived from equation (3.7) by replacing y(k) with $y_s(k+1)-\hat{r}(k+1)$.

$$u(k) = [y_s(k+1) - \hat{r}(k+1) - 0.8y(k)] / 0.6 \tag{3.20}$$

In the simulations (Figure 3.6 to 3.11), the process was initially at steady state and an arbitrary disturbance sequence was introduced. The process was first simulated under feedback control using well-tuned controllers in Figure 3.6 and 3.7. In Figure 3.6, a proportional controller was used with a gain of 1.7. In Figure 3.7, a proportional-derivative controller of the type shown in Figure 3.2 was used and an improvement in control performance was obtained. This improvement can be attributed to the inherent forecasting of the proportional-derivative controller which tends to offset the process lag.

In Figure 3.8 to 3.11, the process was under the control of the proposed feedforward control system in Figure 3.5. The process model was perfect as given by equation (3.17) while the controller was an inverse model controller as given by equation (3.20). Figure 3.8 shows the system response for the case of perfect forecasting of the disturbance effect, the process output is not affected at all. This is the best and ideal case. No forecaster was used in Figure 3.9 and there was no compensation for the disturbances. This is the worst case for the system which is under inverse model control.

Figure 3.10 and 3.11 show the response of the system under more realistic conditions. The linear forecaster of equation (3.18) was used in Figure 3.10. An adaptive autoregressive forecaster (equation (3.19)) was used in Figure 3.11. The parameters in the adaptive forecaster were identified by the projection algorithm used in the Adaptive Predictive Control System. In this simple example, the linear and adaptive forecasters appear to give similar control performance which is better than that given by the proportional feedback controller in Figure 3.6. However, the input sequence for the adaptive forecaster is smoother than that of the linear one.

The response of the proportional-derivative controller (Figure 3.7) is different from that of the SSF system with a linear forecaster. The reason is that the proportional-derivative controller uses a proportional controller whereas the SSF system uses a predictive controller.

This simulation example shows that the use of SSF can improve control performance with respect to disturbance compensation.

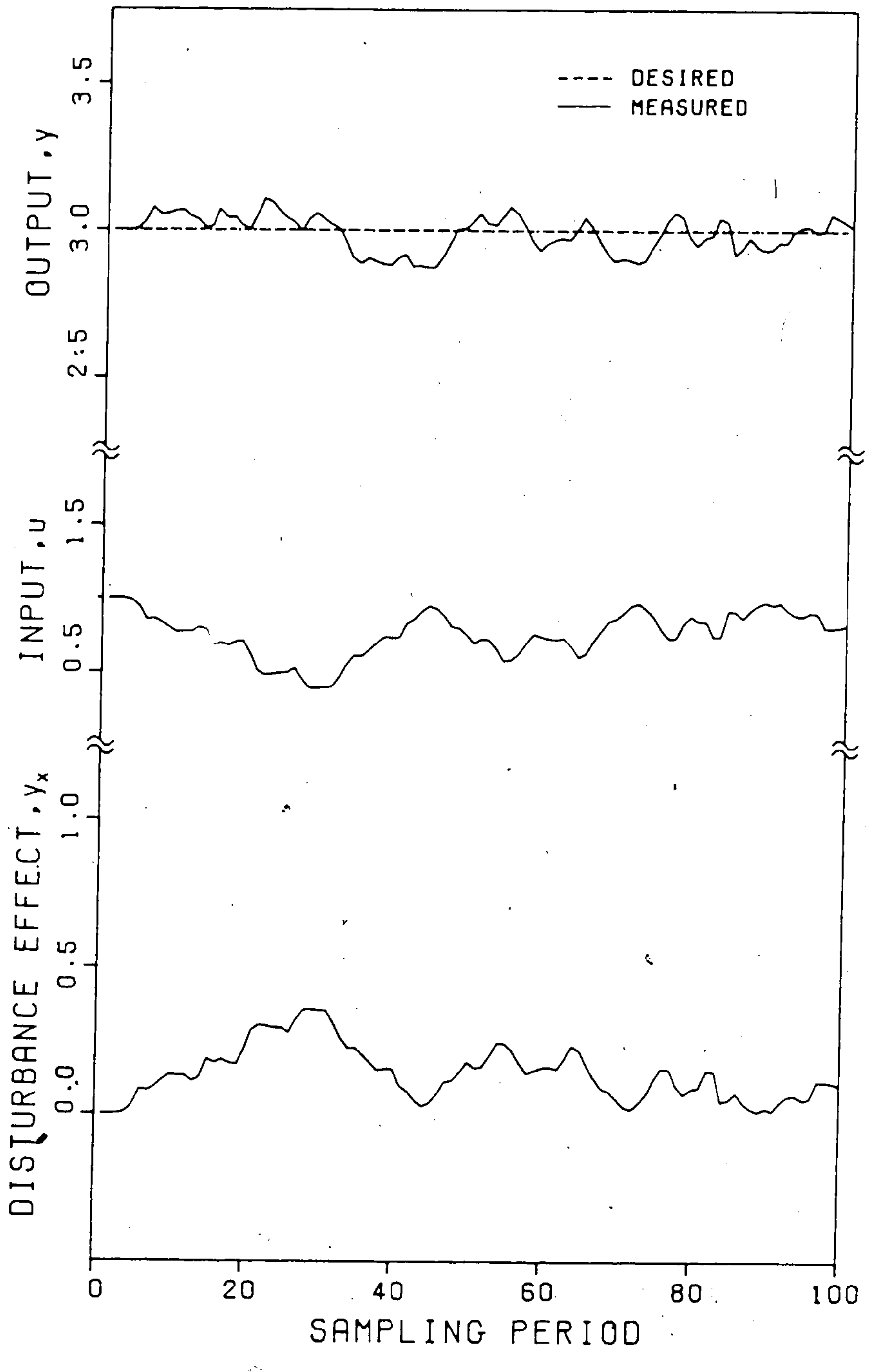

Figure 3.6 Disturbance Compensation by a Proportional Controller (Kc=1.7)

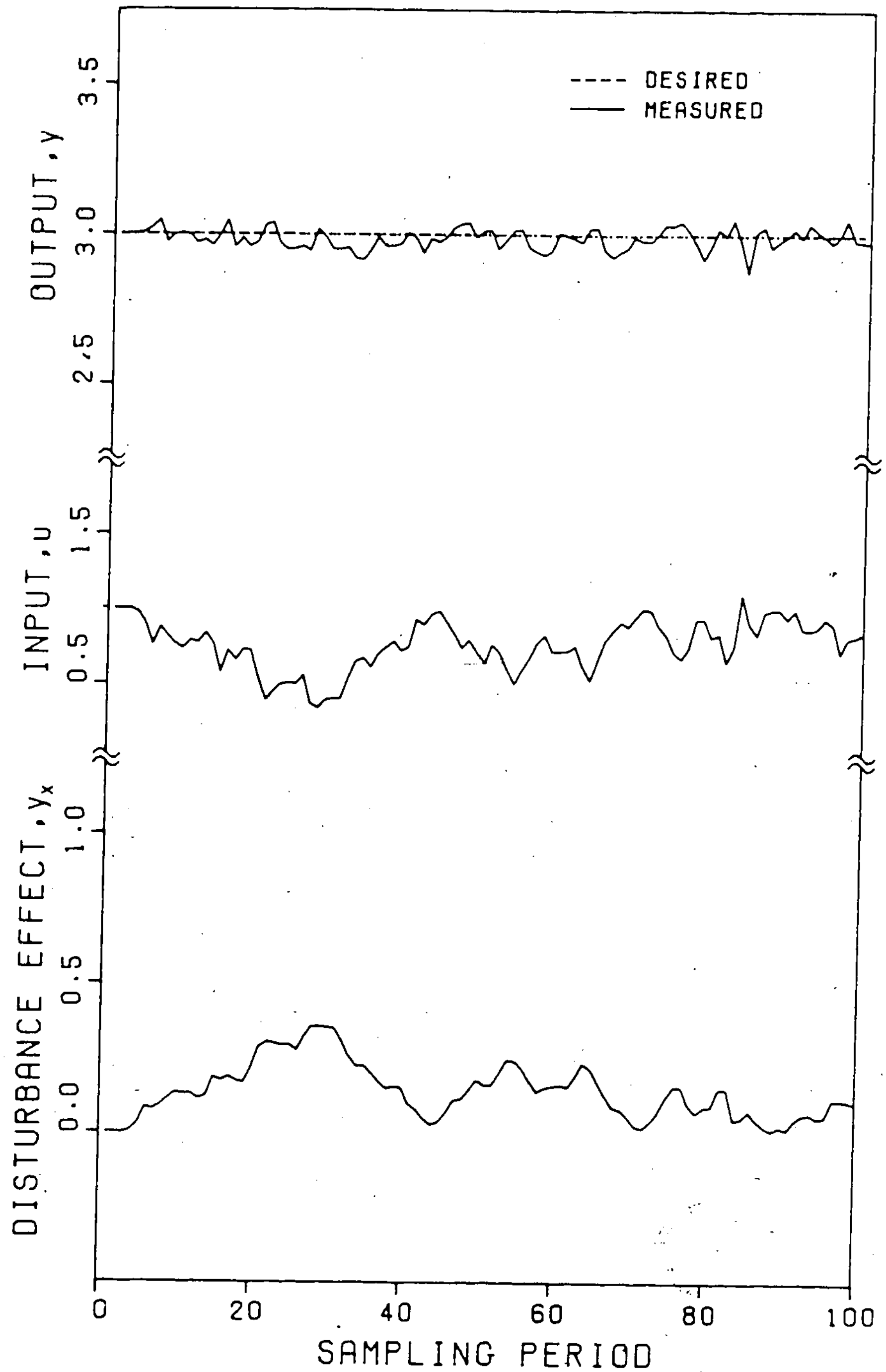

Figure 3.7 Disturbance Compensation by a Proportional-Derivative Controller (K_c=1.7, K_d=1.0)

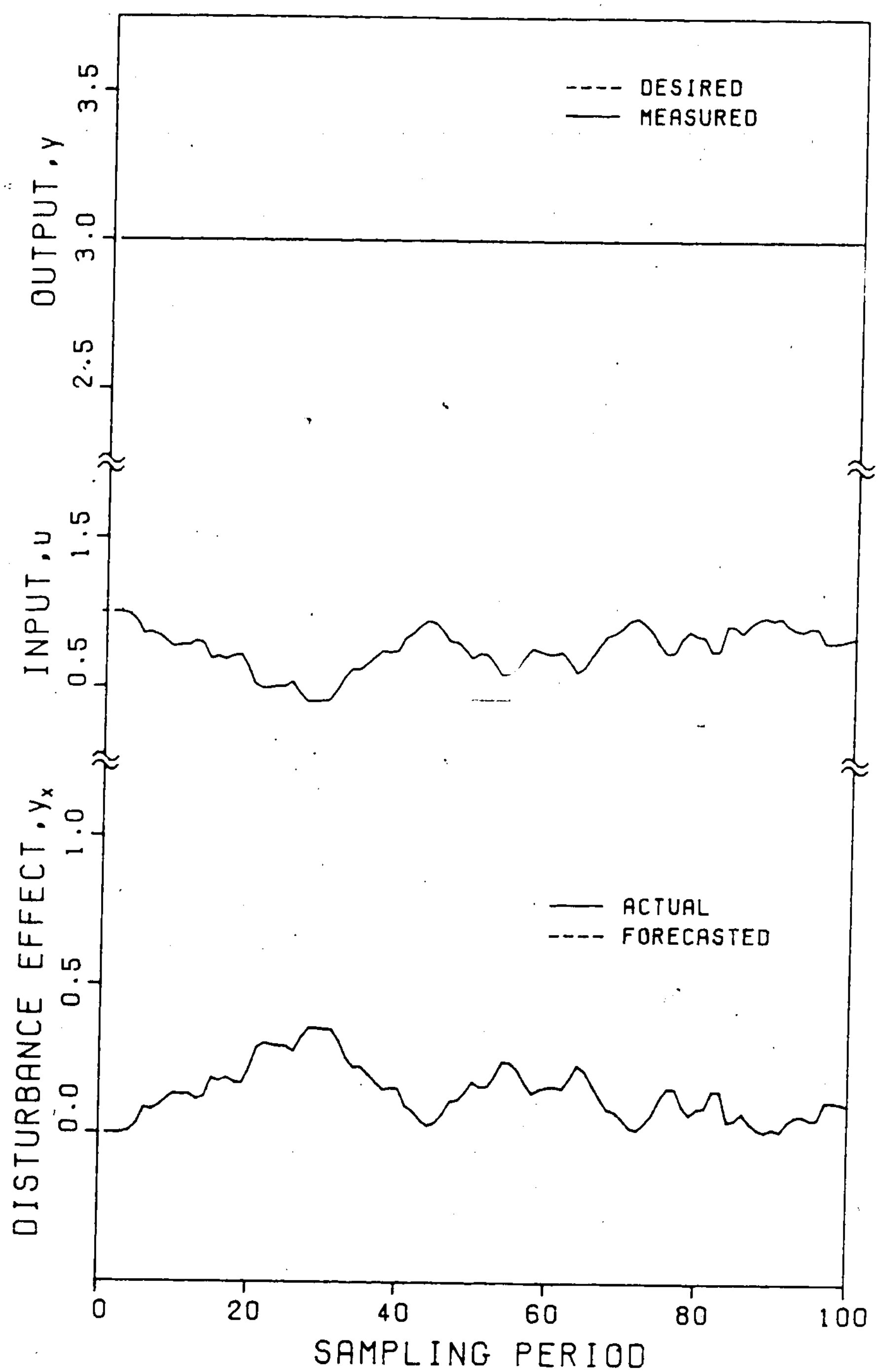

Figure 3.8 Disturbance Compensation by a Predictive Controller with Perfect SSF

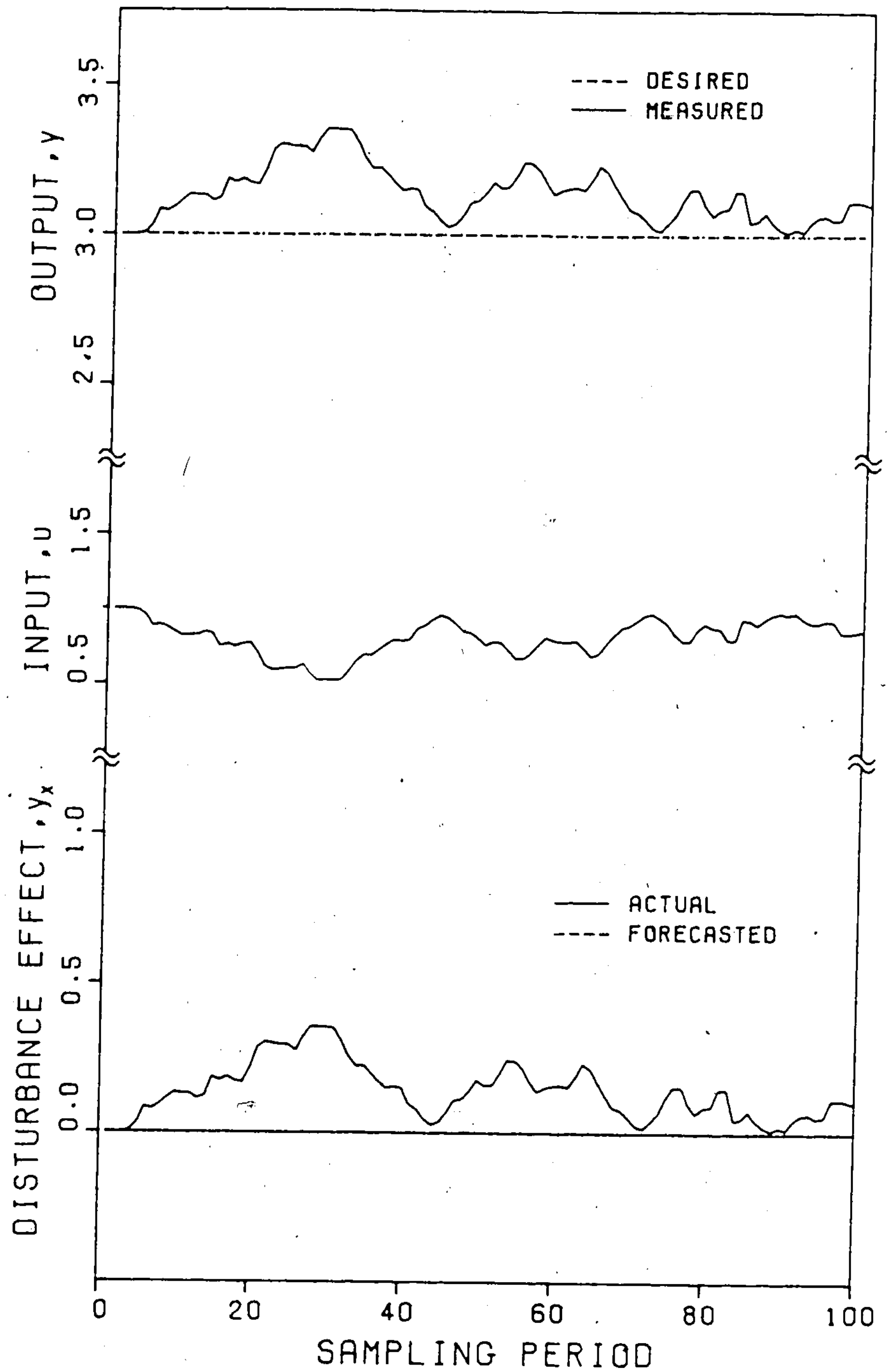

Figure 3.9 Disturbance Compensation by a Predictive Controller with No SSF

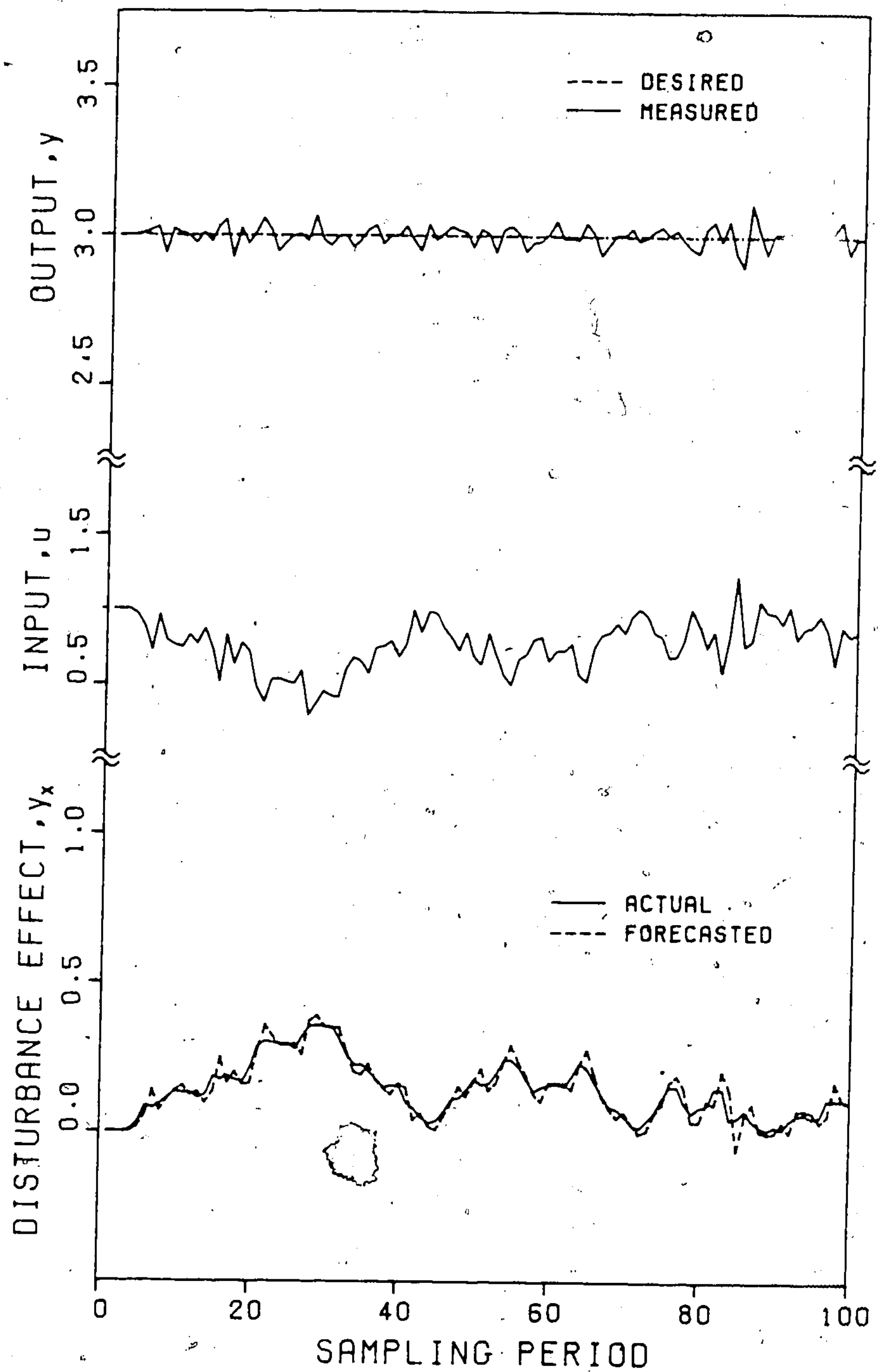

Figure 3.10 Disturbance Compensation by a Predictive Controller with Linear SSF

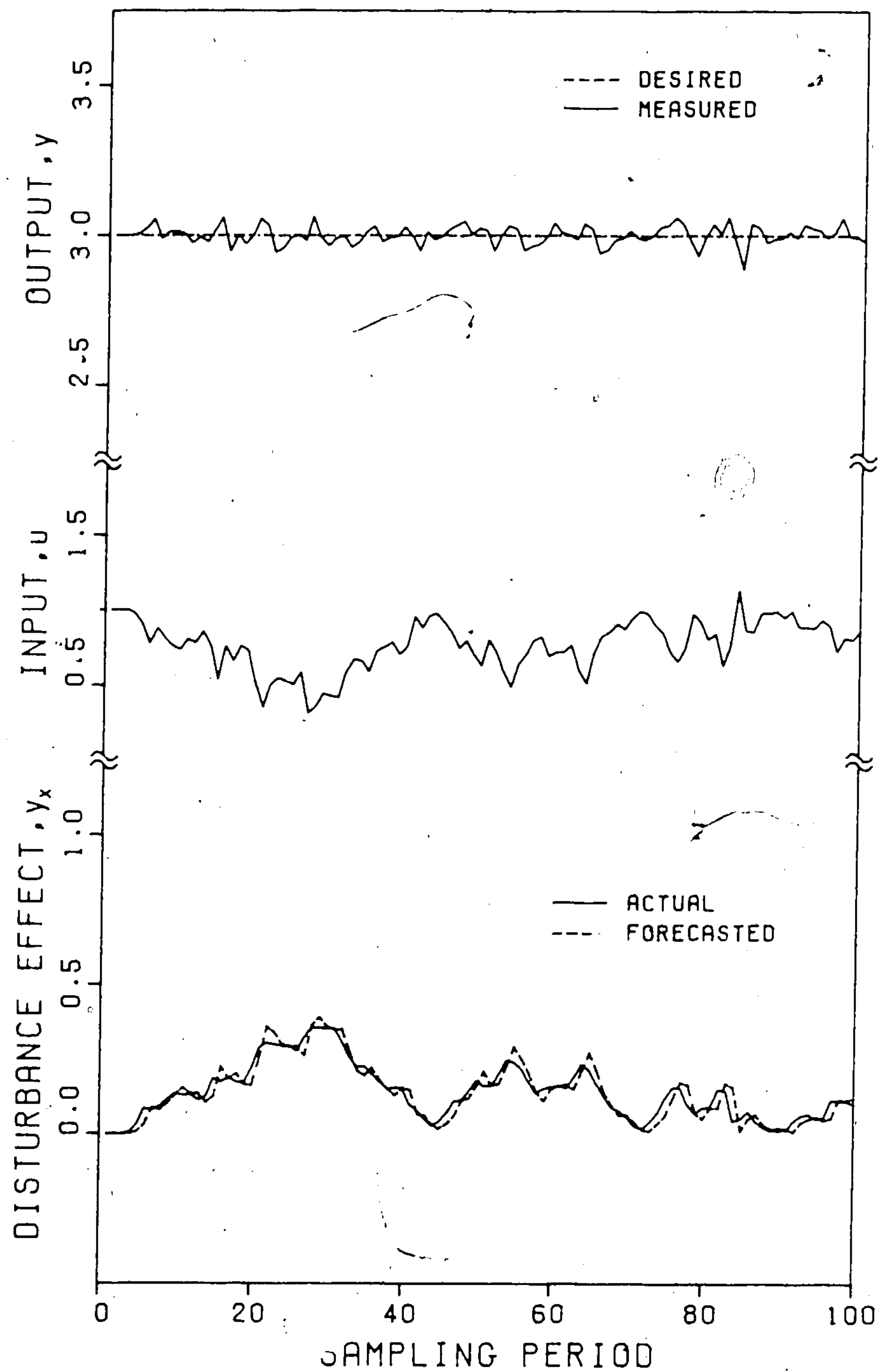

Figure 3.11 Disturbance Compensation by a Predictive Controller with AR SSF

3.3.3 Comparison of Conventional FF and SSF FF Control

SSF has been proposed for the compensation of unmeasured disturbances. It is a modification of the idea of conventional feedforward control. The differences between conventional FF control and SSF FF control are summarized in the following table.

Conventional FF	FF using SSF
1. compensates for measured disturbances only	1. compensates for estimated residuals, e.g. unmeasured disturbances and modelling errors
2. measures disturbances directly as they enter process	2. estimates disturbances based on measured process output and estimated output generated from a process model
3. has an inherent time advantage by measuring disturbances as they enter the process	3. needs to extrapolate so control action u(k) can compensate for $y_x(k)$
4. perfect controller is Gx = - Gd / Gp	4. perfect controller is Gx = 1 / Gp (note minus sign in summing junction in Figure 3.5)

The implementation of conventional FF control requires hardware for the measurement of the disturbances. On the other hand, the implementation of SSF FF control in a computer control system requires computer software only. Therefore, any computer control system can add feedforward control using SSF instead of measurement hardware. However, the performance of SSF FF depends on the quality of the process model and the forecast. The availability of a good process model and forecaster is, therefore, a major consideration in using SSF FF.

3.4 Conclusions

CONVENTIONAL FEEDBACK CONTROL

1) Proportional-derivative control can be interpreted as proportional control with a linear forecaster.
2) Forecasting of the output signal can improve control performance when a system contains time delay due to sampling and/or process lags.
3) Perfect control in feedback systems can, in theory, be achieved by an infinte gain controller. However, this is impractical because the gain is limited by contraints imposed by stability requirements and physical realizability.
4) Separation of servo and regulatory control functions may lead to better control.

FEEDFORWARD CONTROL BASED ON ESTIMATED DISTURBANCES

1) A control structure which consists of a process model, a forecaster and an inverse model controller has been shown to be capable of compensating unmeasured disturbances in a feedforward manner. Simulation results show improvement in performance of the SSF system over conventional feedback control.

2) Perfect feedforward control is achieved by the use of an exact model inverse controller. The principle behind it is the cancellation of process transfer function i.e. $Gc\ Gp = 1$ and hence $Gc = Gp^{-1}$.

3) Feedforward control using SSF can be implemented as part of the control calculation in any computer control system. It does not require the addition of hardware to measure the disturbances. All that is required for implementation is computer software.

4. SSF and Internal Model Control (IMC)

4.1 Introduction

Internal Model Control (IMC) was proposed by Garcia and Morari (1982) as an attempt to unify several different control schemes (Smith Predictor, Inferential Control, Model Algorithmic Control, Dynamic Matrix Control, etc.). The interest in formulating IMC is partly aroused by the success of the two control schemes developed in industry: Model Algorithmic Control (MAC) and Dynamic Matrix Control (DMC). They were developed on a heuristic basis and have shown excellent performance in industrial applications.

MAC was developed in France by Richalet et al (1978) and its theory was extended by Mehra et al (1980). DMC was presented by Cutler and Ramaker (1980) of Shell Oil in the United States. A constrained multivariable version of DMC was applied to a catalytic cracking unit by Prett and Gillete (1980).

The other work which stimulated the proposal of IMC is the inferential control structure proposed by Brosilow (1979). In a study of the classical Smith Predictor and inferential control, Brosilow proposed the Inferential Smith Predictor structure together with a set of controller design procedures. The IMC structure can be considered as an extension of this Inferential Smith Predictor structure which can also be shown to include MAC and DMC as particular cases.

The purpose of this chapter is two fold. The first one is to interpret the IMC structure according to the concepts of feedback and feedforward control as summarized in Chapter Three. The second one is to investigate the incorporation of SSF in the IMC structure. Simulation examples are presented to illustrate the properties of the modified system.

4.2 Description of Internal Model Control (IMC)

BASIC IMC STRUCTURE

According to Garcia and Morari (1982), the IMC structure can be described in three levels of complexity. The first level is the basic IMC structure which is shown in Figure 4.1.

The basic IMC structure is obtained from a conventional feedback control structure by adding and subtracting an output, y_m, as shown in Figure 4.1. It is equivalent to a conventional feedback structure since the two paths incorporating Gm cancel out. Theoretically, the IMC structure does not impose any restriction on the type of process model used. In practice, an impulse response model is often used.

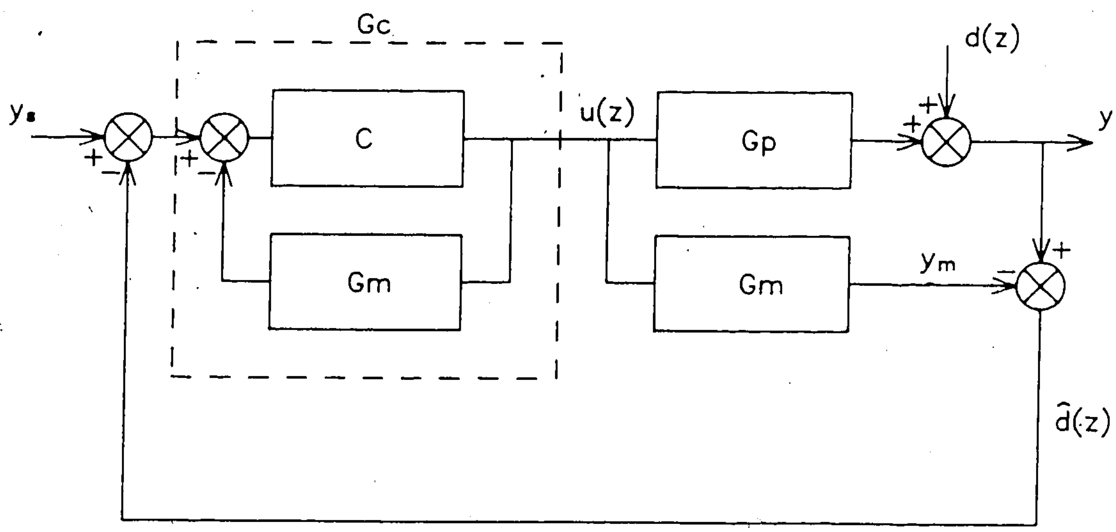

Figure 4.1 Basic IMC Structure

In Figure 4.1, Gc(z) is the IMC controller. It is related to the conventional feedback controller C(z) by the following equation.

$$Gc(z) = \frac{C(z)}{1 + Gm(z)C(z)} \qquad (4.1)$$

The claimed advantage of the IMC structure over the conventional feedback control structure is that Gc(z) is easier to design than C(z). This is because the design procedure for Gc(z) can be easily established from the IMC structure. Moreover, robustness can be included as a design objective in a very explicit manner. This is partly due to the special form of the feedback signal $\hat{d}(z)$.

$$\hat{d}(z) = [\ 1 + (Gp(z)-Gm(z))Gc(z)\ ]^{-1}d(z) \tag{4.2}$$

If the model is perfect, the feedback signal $\hat{d}(z)$ is equal to the disturbance d(z). If the model is not perfect, $\hat{d}(z)$ will contain some information about the model-process mismatch. By modifying $\hat{d}(z)$ appropriately, robustness can be obtained.

The following transfer functions can be obtained for the structure in Figure 4.1.

$$u(z) = \frac{Gc(z)}{1 + Gc(z)[Gp(z)-Gm(z)]}\,(y_s(z)-\hat{d}(z)) \tag{4.3}$$

$$y(z) = d(z)+\frac{Gp(z)Gc(z)}{1 + Gc(z)[Gp(z)-Gm(z)]}\,(y_s(z)-d(z)) \tag{4.4}$$

Equation (4.4) indicates that perfect control requires

$$Gc(z) = \frac{1}{Gm(z)} \tag{4.5}$$

Because Gc(z) has to be stable, Gm(z) is factorized into two parts.

$$Gm(z) = Gm_+(z)\ Gm_-(z) \tag{4.6}$$

$Gm_+(z)$ contains the non-invertible part (time delay and unstable zeros) and $Gm_-(z)$ contains the invertible part. According to Garcia and Morari (1982), from optimal control theory and assuming $Gm(z) = Gp(z)$ and $Gp(z)$ is stable, the controller that minimizes the sum of the square of control errors is

$$Gc(z) = \frac{1}{Gm_-(z)} \tag{4.7}$$

COMPLETE IMC STRUCTURE

It has been shown in equation (4.5) that the IMC controller is an inverse model controller. If the inverse is exact, the controller gives perfect control. However, very often the exact inverse cannot be obtained and an approximate inverse has to be used. This brings up the need for additional features for the IMC structure which corresponds to the second level of complexity in the IMC structure. Figure 4.2 shows the complete IMC structure.

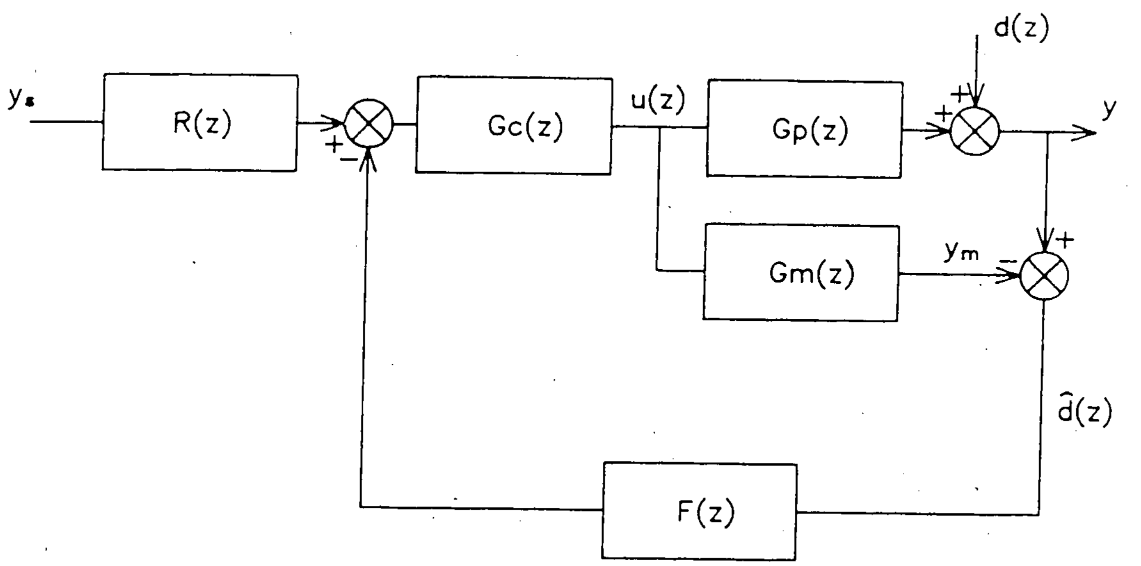

Figure 4.2 Complete IMC Structure

A filter has been added in the feedback path. Its function is to account for the model-process mismatch reflected in the feedback signal $\hat{d}(z)$. It can also compensate for certain types of disturbance dynamics. The characteristic equation with reference to equation (4.4) is changed to

$$Gc^{-1}(z) + F(z)[Gp(z)-Gm(z)] = 0 \qquad (4.8)$$

For a given model-process mismatch, F(z) can be designed to ensure stability i.e. equation (4.8) has stable roots.

Another feature in the complete IMC structure is the reference model R(z) for the setpoint. It provides a reference trajectory which has certain desired dynamics. It can also desensitize the process with respect to modelling inaccuracies by "shaping" the desired value, y_d, seen by the controller, Gc.

In summary, the IMC controller design procedure for the ideal case involves selecting an inverse controller which gives perfect control. However, if an inverse controller is not feasible, an approximate inverse model controller is used and a filter is added to improve robustness. Finally, a reference model can be added to reduce sensitivity to modelling inaccuracies.

IMC WITH PREDICTIVE CONTROLLER

The third level of complexity in the IMC structure involves the design of a predictive controller. This is one of the ways of obtaining an approximate inverse of the model. This approach has been found to possess many desirable properties. The formulation of the predictive controller is given as follows.

The predictive control strategy considers a desired output trajectory $y_d(k)$ over a horizon of P sampling times into the future. Then the sequence of control actions $u(\underline{k})$, $u(\underline{k}+1)$, ..., $u(\underline{k}+P-1)$, where $\underline{k}$ is the current sampling instant, is calculated so that the predicted output $y(\underline{k}+i|\underline{k})$, i=1, ..., P, follows $y_d(\underline{k}+i)$, i=1, ..., P, as closely as possible. The prediction is calculated by the model using the inputs up to $\underline{k}+i-\tau-1$, where τ is the pure time delay, and output up to $\underline{k}$. If the process model, whic is used for the prediction and the control calculation, is not exact, the process output will deviate from the desired trajectory. Therefore, it is preferable to implement only the present input $u(\underline{k})$ and to resolve the problem again at $\underline{k}+1$ with the measured output $y(\underline{k}+1)$ as the new starting point. Figure 4.3 illustrates one step in this moving horizon problem.

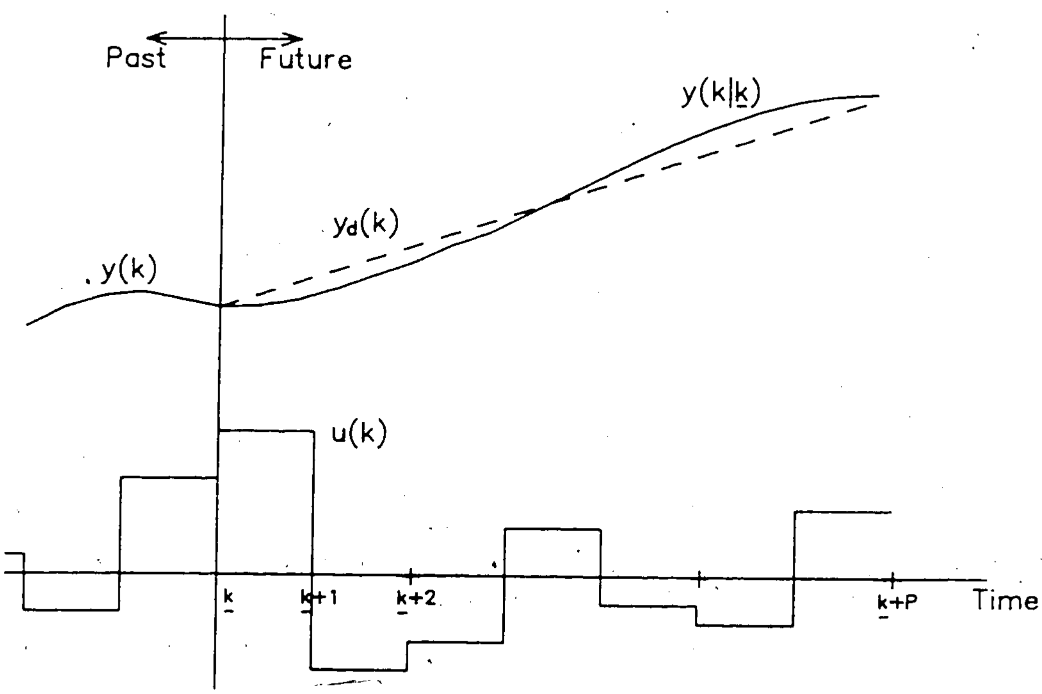

Figure 4.3 One Step in the Predictive Control Problem

At each sampling instant $\underline{k}$, the following general problem is solved.

$$\min_{u(\underline{k}),\, u(\underline{k}+1),\, \ldots,\, u(\underline{k}+M-1)} \sum_{i=1}^{P} \gamma_i^2 \, [y_d(\underline{k}+\tau+i)-\hat{y}(\underline{k}+\tau+i\,|\,\underline{k})]^2 + \beta_i^2 u(\underline{k}+i-1)^2 \qquad (4.9)$$

subject to

$$\hat{y}(k+\tau\,|\,\underline{k}) = y_m(k+\tau) + \hat{d}(k+\tau\,|\,\underline{k})$$

$$= h_1 u(k-1)+h_2 u(k-2) + \ldots + h_n u(k-n)+\hat{d}(k+\tau\,|\,\underline{k})$$

$$u(\underline{k}+M-1) = u(\underline{k}+M) = \ldots = u(\underline{k}+P-1)$$

$$\beta_i^2 = 0 \quad \text{for } i > M$$

where P is the horizon ($P \geq 1$)

$y_d(\underline{k}+\tau+i)$ is the desired trajectory

γ_i^2 are time varying weights on the output error

β_i^2 are time varying weights on the input

M is the input suppression parameter which specifies the number of intervals into the future during which u(k) is allowed to vary

$\hat{y}(k+\tau\,|\,\underline{k})$ is the predicted output

$y_m(k+\tau)$ is the output of the internal model

$\hat{d}(k+\tau\,|\,\underline{k})$ is the predicted disturbance.

The simplest prediction of the disturbance is to set it equal to the residual at the present time.

$$\hat{d}(k+\tau|\underline{k}) = \hat{d}(\underline{k}) \quad \text{for all } k > \underline{k} \tag{4.10a}$$

$$\hat{d}(\underline{k}) = y(\underline{k}) - y_m(\underline{k}) \tag{4.10b}$$

M, P, γ_i, β_i are the tuning parameters of the algorithm. They have a direct influence on stability and dynamic response.

The complete IMC structure with predictive controller is shown in Figure 4.4. Details on the computation of the control law were presented by Garcia and Morari (1982).

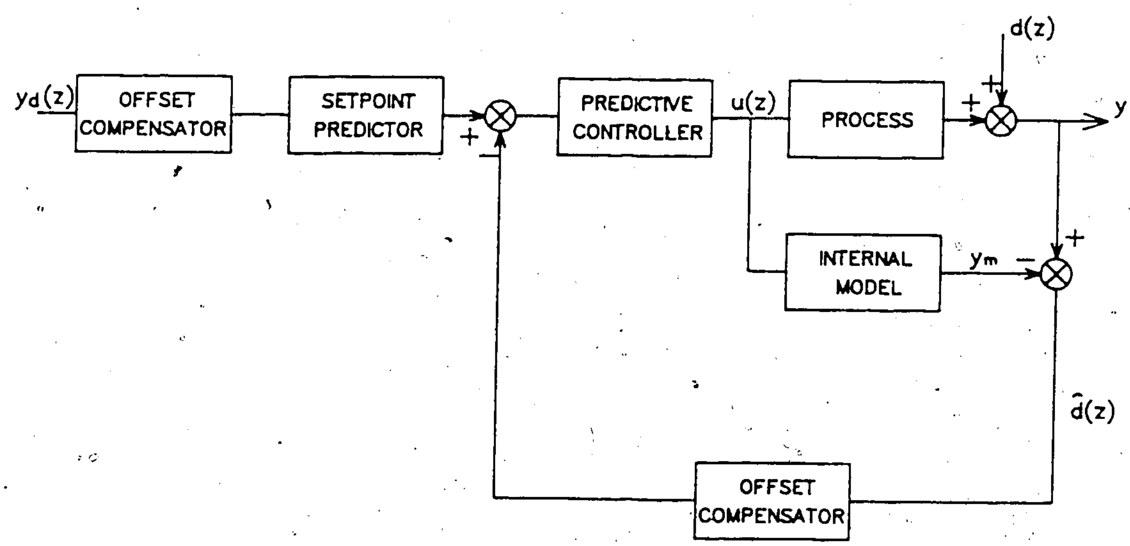

Figure 4.4 IMC Structure with Predictive Controller

4.3 Discussion of IMC

Garcia and Morari (1982) showed that the IMC structure is related to Optimal Control, the Smith Predictor, Inferential Control, Model Algorithmic Control and Dynamic Matrix Control. In this section, the IMC structure will be interpreted according to the concepts of feedback and feedforward control as summarized in Chapter Three. The issues of accuracy and invertibility of the process model will also be explored by examining the filter, reference model and predictive controller in the IMC structure.

4.3.1 Feedback Interpretation of IMC

The first step in the IMC controller design is to select a controller which gives perfect control. It has been determined from equation (4.4) that the perfect IMC controller is the inverse of the process model. In order to understand how the inverse model controller achieves perfect control, the equivalence of the relationship between the feedback control system and the IMC structure will be examined.

Equation (4.1) gives the relationship between the feedback controller C(z) and the IMC controller Gc(z). The equation can be re-arranged into the following form.

$$C(z) = \frac{Gc(z)}{1 - Gm(z)Gc(z)} \qquad (4.11)$$

Substituting the perfect IMC controller, $Gc(z) = Gm^{-1}(z)$, into the equation, the denominator of the expression becomes zero and $C(z)$ becomes infinite. Therefore, the IMC inverse model controller is equivalent to an infinite gain feedback controller. Perfect control in IMC, as in feedback control, is achieved on the basis of infinite gain (Concept 3.2).

An alternate way of obtaining the same result is through the block diagram. Figure 4.5 shows an equivalent IMC structure which is drawn differently from Figure 4.1.

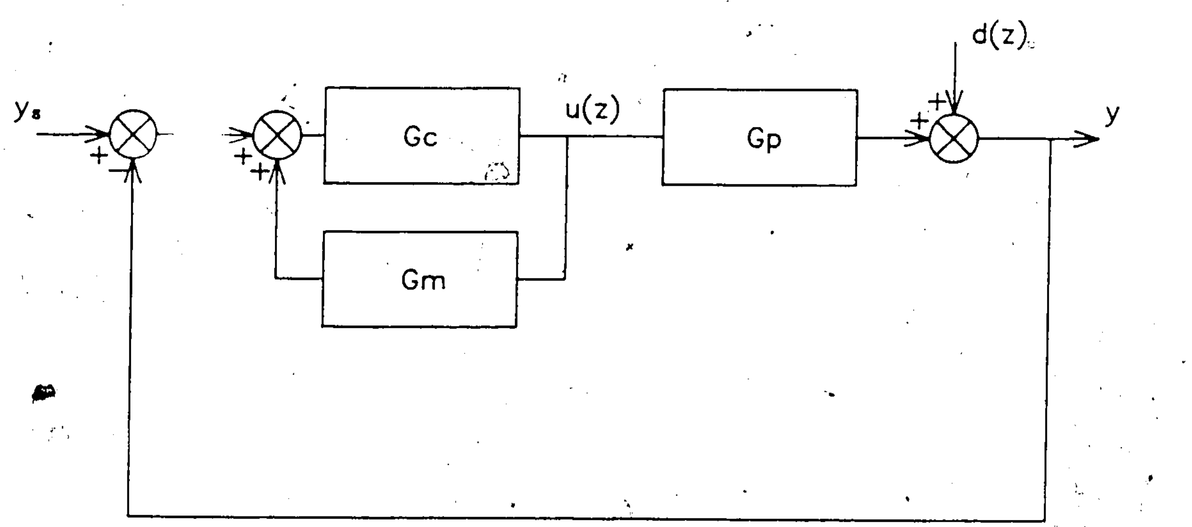

Figure 4.5 An Equivalent Form of the IMC Controller

The IMC structure of Figure 4.5 becomes a conventional feedback control structure if the positive feedback loop is included in the controller block. Using the perfect IMC controller, $Gc = Gm^{-1}$, the positive feedback loop becomes an infinite gain controller in a feedback control structure. Therefore, from a structural point of view, IMC is equivalent to feedback control and perfect control is achieved through the principle of infinite gain.

In a feedback system, the use of high gain is limited by stability and performance considerations and perfect control may not be attained under such restrictions. Similarly, the IMC inverse model controller can only attain perfect control when the model is perfect and the inverse model controller is realizable. The reason for this is as follows.

For discrete systems, there is at least one sampling period of time delay. Therefore, the IMC inverse model controller will contain at least one period of prediction. This means that the controller input, $y_d - \hat{d}$, must be known at least one period of time ahead. The setpoint y_d can be specified ahead of time. However, if the model is imperfect, the feedback signal $\hat{d}$ will contain model-process mismatch and disturbances. Future values of $\hat{d}$ cannot be known since the model-process mismatch is dependent on the current process input which needs to be calculated using future values of $\hat{d}$. Therefore, perfect control is impossible with an imperfect model. In addition, realizability of the perfect controller requires that the process be minimum phase.

Since future values of $\hat{d}$ are required in the control calculations, they are approximated by the current value of $\hat{d}$ in the IMC structure. This approximation represents a deviation from the ideal condition of perfect control. The extent of this deviation depends on the model-process mismatch contribution to the feedback signal. The contribution of the mismatch decreases as the process model becomes more accurate. When the process model is perfect, the feedback signal $\hat{d}$ contains disturbances only. For the case of no disturbance, the controller input is equal to the setpoint which is known exactly and perfect servo control can be obtained. When disturbances are present, perfect regulatory control can only be obtained if the disturbances can be forecasted accurately. Hence the interest in combining SSF with IMC.

4.3.2 Feedforward Interpretation of IMC

An alternate interpretation of IMC is based on the feedforward control structure using SSF (Figure 3.5). This interpretation is appropriate for explaining the need for a perfect process model and more accurately reflects the design philosophy of IMC.

The IMC structure (Figure 4.1) is similar to the estimated feedforward control structure (Figure 3.5). Both of them make use of a process model to generate a residual signal which is sent to the controller. For perfect control, the controller has to be equal to the inverse of a perfect process model. It has been shown that perfect control in feedforward control is achieved through cancellation of transfer functions (Concept 3.9). Because of the similarity in structure between IMC and feedforward control, perfect control in IMC can also be interpreted as being achieved through cancellation. This is a more appropriate interpretation than the feedback interpretation when the process model is perfect *since the feedback signal is equal to the disturbance and the system is effectively open loop.* It should be noted that the forecaster present in the feedforward control structure is not obvious in the IMC structure. However, some form of prediction is implicit in the inverse model controller.

The IMC structure can be interpreted as being designed for open loop feedforward control using the inverse of a perfect process model as the controller and an estimated disturbance $\hat{d}(z)$ (which is equal to d(z) when the process model is perfect). *A perfect model removes the problem of instability arising from the feedback control structure.* The perfect process model is also used to generate the residual signal which is used for regulatory control in a feedforward manner. This is the ideal IMC design philosophy. When the model is imperfect and/or non-invertible, then feedback is present, instability could result and other features such as the filter, reference model and predictive controller are necessary.

4.3.3 Filter and Reference Model

The filter and the reference model can be considered as part of the controller in IMC. When the filter and the reference model have the same transfer function, they can be combined with the controller to form an equivalent system with only one control block. The advantage of separating part of the controller out to form the reference model in the setpoint path and the filter in the feedback path is to provide a means to have different servo and regulatory controllers. The reason for it has been discussed in Chapter Three (Concept 3.1).

The function of the reference model is to generate a reference trajectory from a given setpoint for the system to track. A reference trajectory can often be made more appropriate than an external setpoint because it usually requires less extreme control effort to track and it may possess certain optimal characteristics. In addition, it can desensitize a system i.e. make the system respond slower.

The filter, on the other hand, can be used in a number of ways. The first use of the filter proposed in the IMC is to compensate for the model-process mismatch. From equation (4.8), it can be seen that the filter can be designed to ensure stability and shape the dynamic response of the system for a given model process mismatch. Brosilow (1979) has discussed the use of a filter to compensate for modelling errors in time delay, process gain and process time constant using the example of a first order process. He showed that a first order lag filter with an appropriately chosen time constant will provide satisfactory compensation in most cases.

The filter can also be used to compensate for certain classes of disturbances. A typical example is that of a low-pass filter which is used to filter out high frequency disturbances or noise. This use is very important in providing smooth measurement data to the predictive controller.

The filter can also be interpreted as generating a reference trajectory for the disturbance signal in the feedback path for regulatory control. This helps to reduce extreme excursions in the process input. It slows down the response of the system and improves robustness.

4.3.4 IMC Predictive Controller

The perfect IMC controller is an inverse model controller. Therefore, the invertibility of the model is very important in the controller design. For models which contain non-invertible parts, an approximate inverse has to be used. There are two ways of obtaining an approximate inverse of the model. The first one is to invert the invertible part and approximate the non-invertible part. The second one is to approximate the inverse of the whole model. The predictive controller in IMC inverts the process model using the second method. With appropriate choice of the tuning parameters, the inverse can be made exact or approximate. The objective in the controller design is to find a stable inverse of the model which gives good control performance. The physical significance of the tuning parameters and their effects on the controller characteristics have been discussed by Garcia and Morari (1982).

4.4 SSF and IMC

4.4.1 Description and Interpretation

The IMC structure requires the use of an inverse model controller. In discrete control systems, an inverse model controller implies that some form of prediction is inherent. In the IMC structure, this prediction requirement means that future values of the controller input, i.e. setpoint and feedback signal, are required for the control calculations. To simplify the discussion, the model is assumed to be perfect so that the feedback signal is equal to the disturbance.

Consider the IMC structure with predictive controller in Figure 4.4. The need for future setpoints does not present any problem since they are simply assumed to be specified by the operator. However, values of future disturbances have to be generated by some means. The predictive controller proposed by Garcia and Morari (1982) uses the present disturbance in the place of the future disturbance (Equation (4.10)). There is no forecasting done to obtain the future disturbances.

From another point of view, this can be interpreted as being equivalent to the first forecasting method described in Section 2.3. It uses the current value as the forecast. This is justified if the disturbance is stochastic and therefore difficult to forecast. However, in cases where the disturbance has some structure, it is often possible to forecast future values with a reasonable degree of accuracy by using information from the past values. This is exactly the idea of the SSF. It fits in the IMC structure and is used to forecast future disturbance values based on the past values. Figure 4.6 shows a schematic diagram of an IMC structure with SSF.

The forecaster can be interpreted as part of the inverse model controller in this context. It is added to make the inverse model closer to the exact inverse. The inverse model controller is then made up of three blocks: controller, filter and forecaster. Conceptually, the functions of the three blocks can be separated. The control block contains the inverse of the invertible part of the model. The forecaster contains the inverse of the time delay of the model. The filter contains a reference model which generates a reference trajectory for better control.

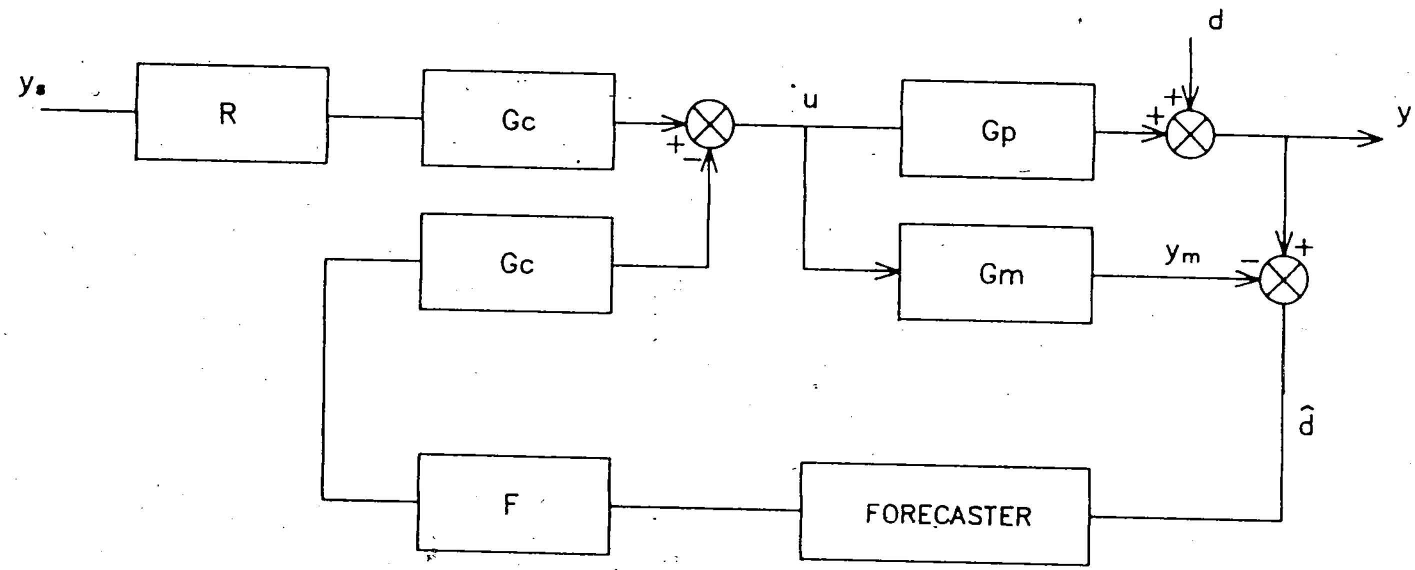

Figure 4.6 IMC Structure with SSF

Another interpretation of the forecaster is that it is a model of the unknown disturbances since it generates forecasts of future disturbances. This is particularly appropriate if an adaptive AR forecaster is used. The accuracy of the forecasts depends on the forecaster structure and parameters. When there is doubt about the forecasted disturbance, the controller may want to compensate for only part of the disturbance. This idea is similar to the concept of "relaxation factor" in numerical methods. In this case, the filter, which contains a reference model, can function as the "relaxation factor". By proper choice of the filter, good control can be obtained even if the forecaster does not forecast very accurately.

Intuitively, the forecaster will forecast well when the disturbance is well structured and has slow dynamics relative to those of the process. It will forecast poorly when the disturbance has fast dynamics and no structure. In view of this, another use of the filter block will be to filter out the fast and random disturbances or noise. A low pass filter is well suited for this function. Then the forecaster can work on the slow filtered disturbances. In cases where the process model is a low order approximation of the high order process, the modelling errors which are the fast modes of the process will be part of the feedback signal. Since the important process dynamics are generally slow, the low pass filter can also filter out errors due to these fast modes. When the filter block is a low pass filter, then for purposes of interpretation, the order of the forecaster and the filter should be reversed in Figure 4.6.

4.4.2 Illustrative Examples

A simulation example will be given to illustrate the use of SSF in IMC and to explore some of the properties of the system. A second order process without a process delay is used in the example. The discrete transfer function of the process is

$$\frac{y(z)}{u(z)} = \frac{0.158z^{-1} + 0.101z^{-2}}{1 - 1.03z^{-1} + 0.289z^{-2}} \qquad (4.12)$$

The 8th order impulse response truncated model is

$$\begin{aligned} y(k) = \; & 0.158u(k-1) + 0.264u(k-2) + 0.226u(k-3) \\ & + 0.156u(k-4) + 0.096u(k-5) + 0.053u(k-6) \\ & + 0.027u(k-7) + 0.013u(k-8) \end{aligned} \qquad (4.13)$$

The following set of parameters are used for the IMC predictive controller in all the cases and the input suppression parameter M is set individually in each case.

$$P = N = 8 \qquad (4.14a)$$

$$\gamma_1 = \gamma_2 = \ldots = \gamma_8 = 1 \qquad (4.14b)$$

$$\beta_1 = \beta_2 = \ldots = \beta_8 = 0 \qquad (4.14c)$$

Two forecasting techniques are studied. The linear forecaster as given by the equation

$$\hat{r}(k+1) = r(k) + (r(k) - r(k-1)) \tag{4.15}$$

and the AR forecaster:

$$\hat{r}(k+1) = \alpha_1 r(k) + \alpha_2 r(k-1) + \alpha_3 r(k-2) \tag{4.16}$$

where α_1, α_2 and α_3 are identified on-line by the APCS projection algorithm (Equation (2.9)). For the simulations in Figures 4.7 to 4.10, the process is subject to a disturbance sequence which consists of four types of disturbances: ramp, exponential decay, sinusoid and step. A perfect process model is used for prediction and control calculations. The input suppression parameter M for the controller is set to be equal to N. For this particular case where P=M=N, the number of unknowns is equal to the number of equations. An exact solution, rather than a least square solution, is obtained and the controller is an exact inverse of the process. Control action is calculated at every sampling instant. In cases where SSF is used, a one-step ahead forecast of the residual is calculated and used as the value for all the future residuals. The reason for this will be explained later.

Figure 4.7 shows the process response under IMC control with no SSF. A constant offset is present during the ramp disturbance. This indicates that IMC contains some form of integral control action. Figure 4.8 shows the response of perfect control as a result of using a perfect forecaster. Note that the forecast need only be perfect for the one-step ahead residual and not for the future ones. In the control calculation, an exact solution is obtained due to P=M=N. With control action being unconstrained, any setpoint change can be accomplished in one step. Since the calculation is done at every sampling instant, only the one-step ahead forecast of the residual is important. The future values has no effect on the *implemented* control action. This is why only a one-step ahead forecast is calculated.

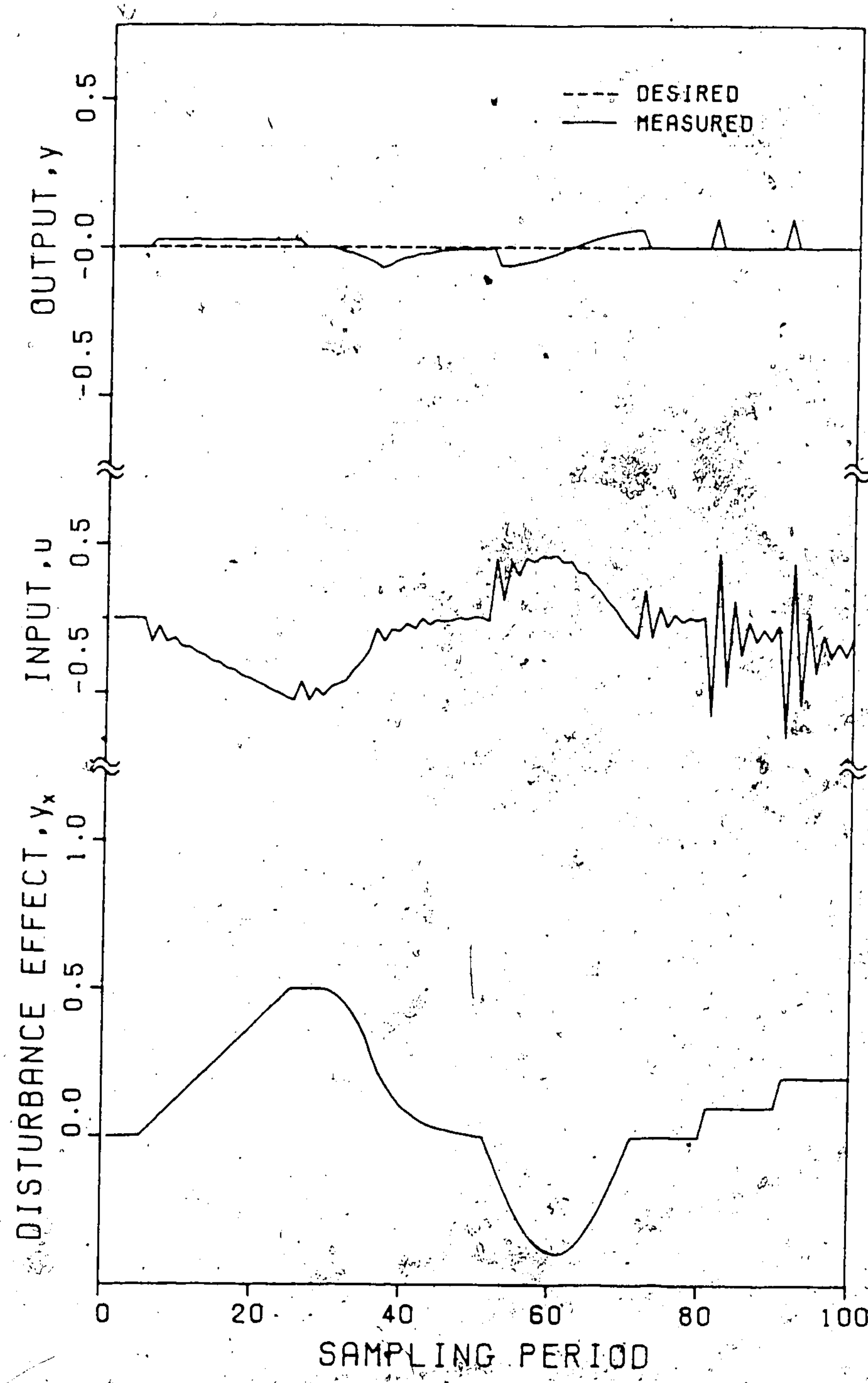

Figure 4.7 Compensation of Noise-free Disturb[illegible]ce Using IMC

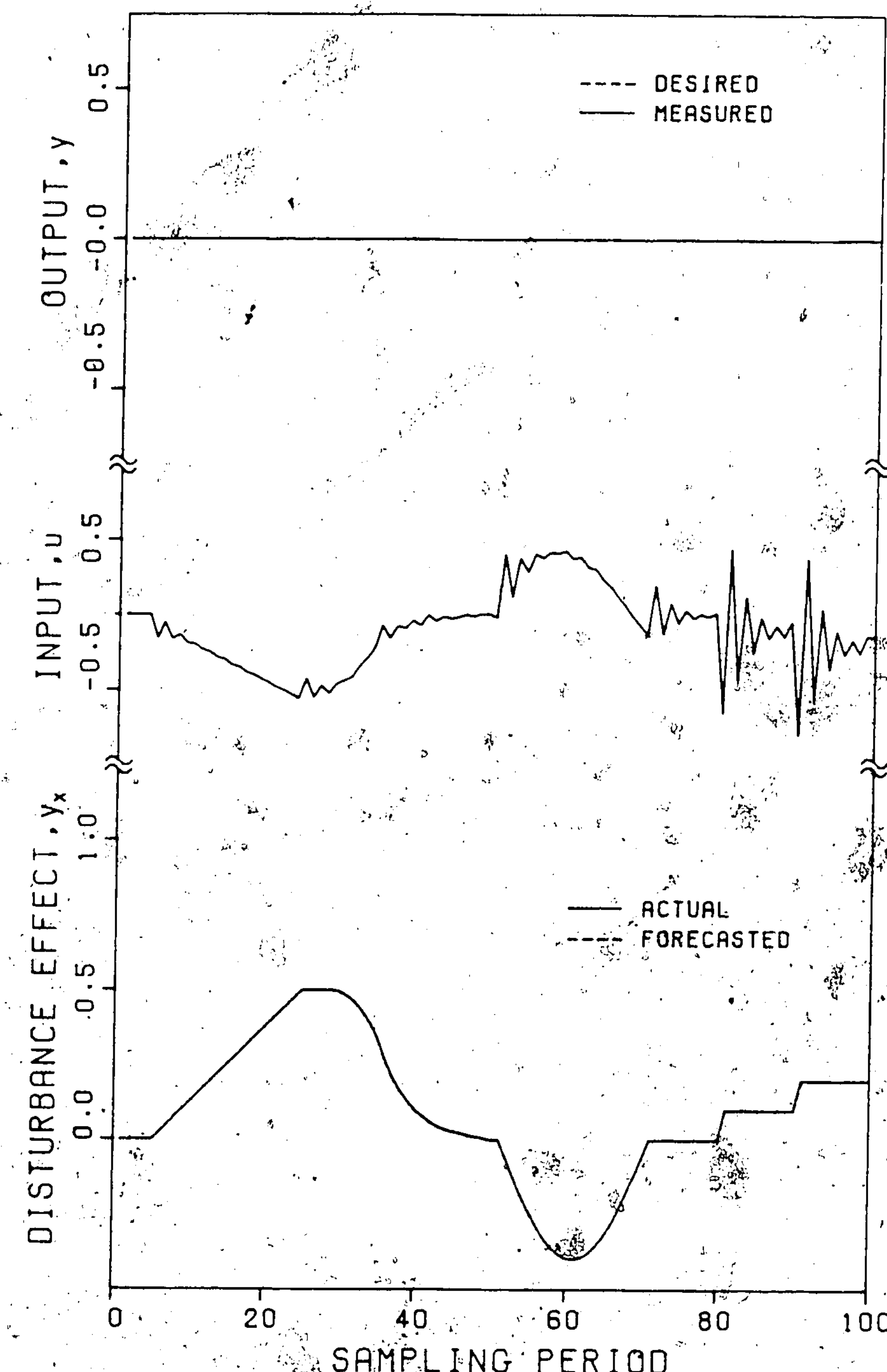

Figure 4.8 Compensation of Noise-free Disturbance Using IMC with Perfect SSF

The linear forecaster of equation (4.15) is used in Figure 4.9 and the AR forecaster of equation (4.16) is used in Figure 4.10. Comparing Figure 4.7 with Figures 4.9 and 4.10 shows that the addition of SSF in IMC does improve regulatory control performance for smooth disturbances. SSF helps to eliminate the offset during the ramp disturbance and the non-linear disturbances. However, as expected, the forecasters do not help in the case of the step disturbances. Comparing the linear forecaster and the AR forecaster, the linear forecaster seems to be superior in performance for the smooth disturbance in this example. However, it gives rise to a more oscillatory input sequence and is very poor for step disturbances.

Since noise is an integral part of most measurement signals, the following simulations will help to explore the effect of noise on the functionality of SSF. A noisy disturbance sequence is generated by adding random noise to the smooth disturbance sequence used previously. The conditions for the process model, controller and forecaster are all the same as the previous cases. Figure 4.11 shows the process response under IMC with no SSF. Figures 4.12 and 4.13 show the cases where the linear forecaster and the AR forecaster are used respectively. A quick comparison of the three figures seems to show that there is no obvious advantage in using SSF for noisy signals and that the input sequence has become more oscillatory in cases with SSF. However, a careful comparison of the output signal in

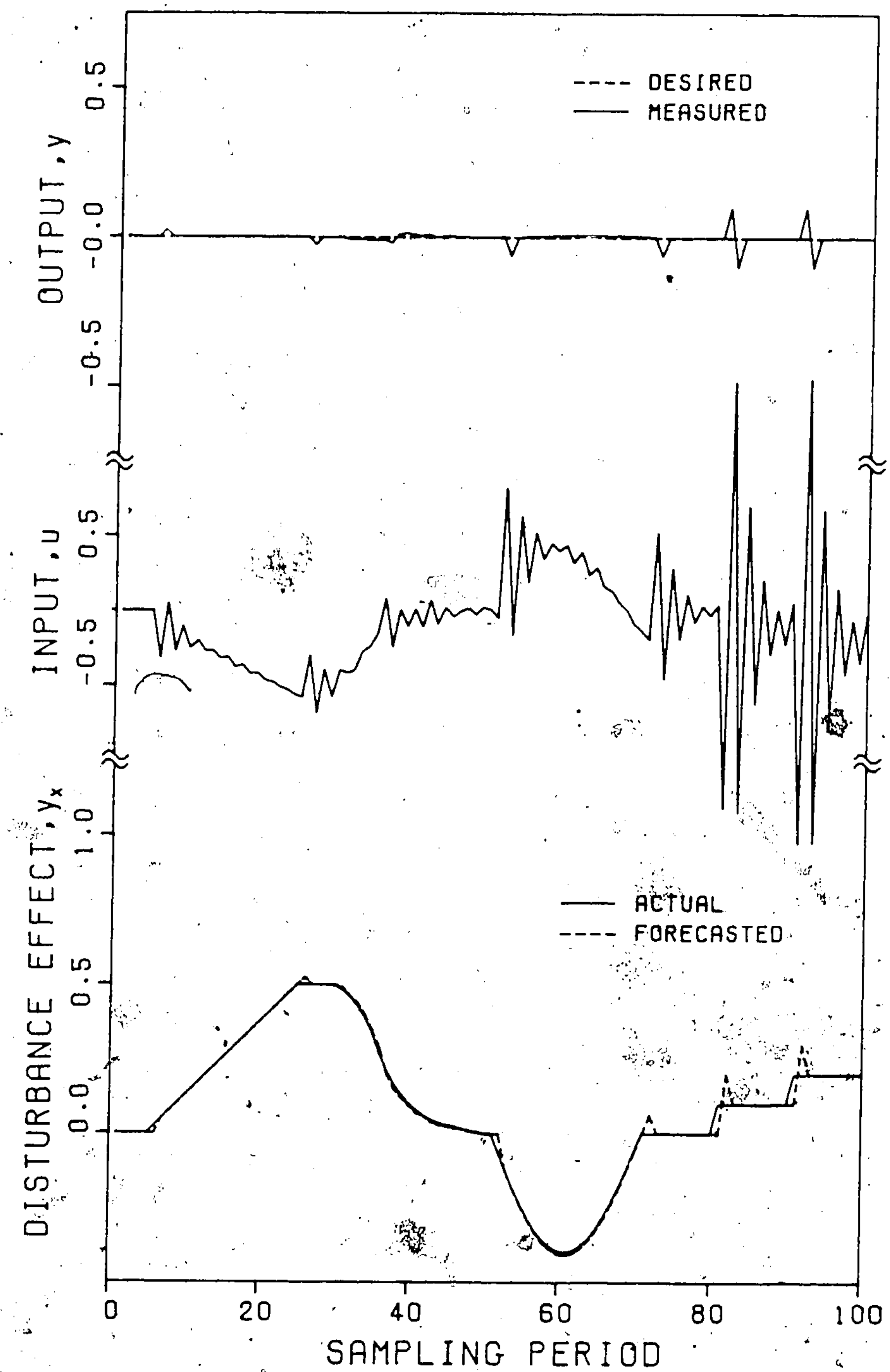

Figure 4.9 Compensation of Noise-free Disturbance Using IMC with Linear SSF

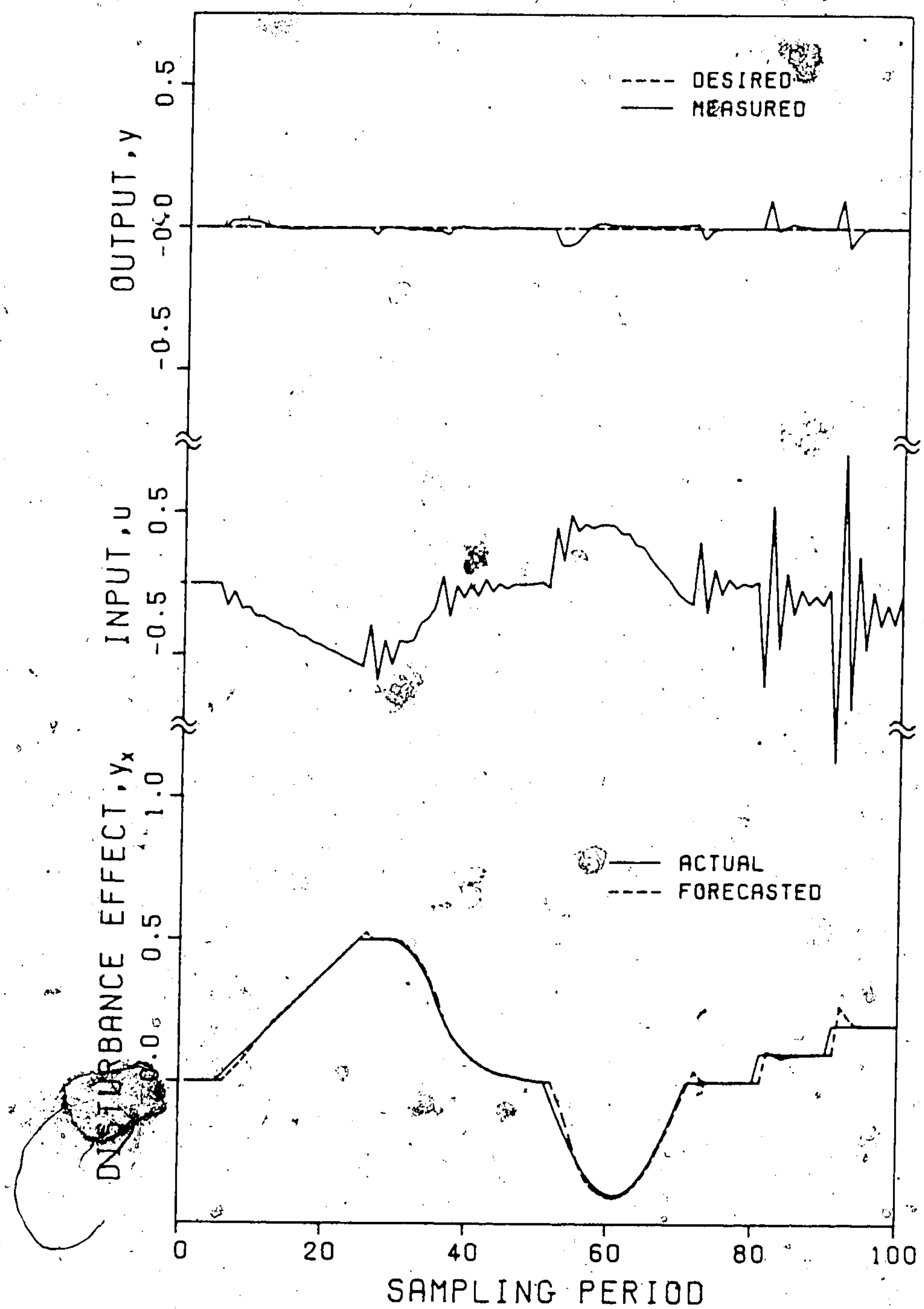

Figure 4.10 Compensation of Noise-free Disturbance Using IMC with AR SSF

Figures 4.11 and 4.13 shows that the output in Figure 4.13 is randomly distributed around zero whereas the output in Figure 4.11 has certain trends possibly caused by the disturbances. Therefore, the use of SSF helps the process to compensate for disturbance which has a trend even though it may be noisy.

A common solution to the noisy measurement signals is to use a low pass filter. The equation is

$$F(z) = \frac{1 - \alpha}{1 - \alpha z^{-1}} \tag{4.17}$$

Simulation for the previous three cases are repeated with the addition of a low pass filter ($\alpha = 0.3$) in the system. The results are shown in Figures 4.14 to 4.16. The filter seems to do very little in improving the control performance but it does help to reduce the oscillation in the input sequence considerably. No attempt was made to optimize the value of the filter constant α.

In summary, it has been demonstrated through simulation examples that SSF can be used to improve disturbance compensaton for IMC. The AR forecaster is better than the linear forecaster in an environment with noisy signals. A low pass filter should be used to filter the noisy signal before is is used by the forecaster.

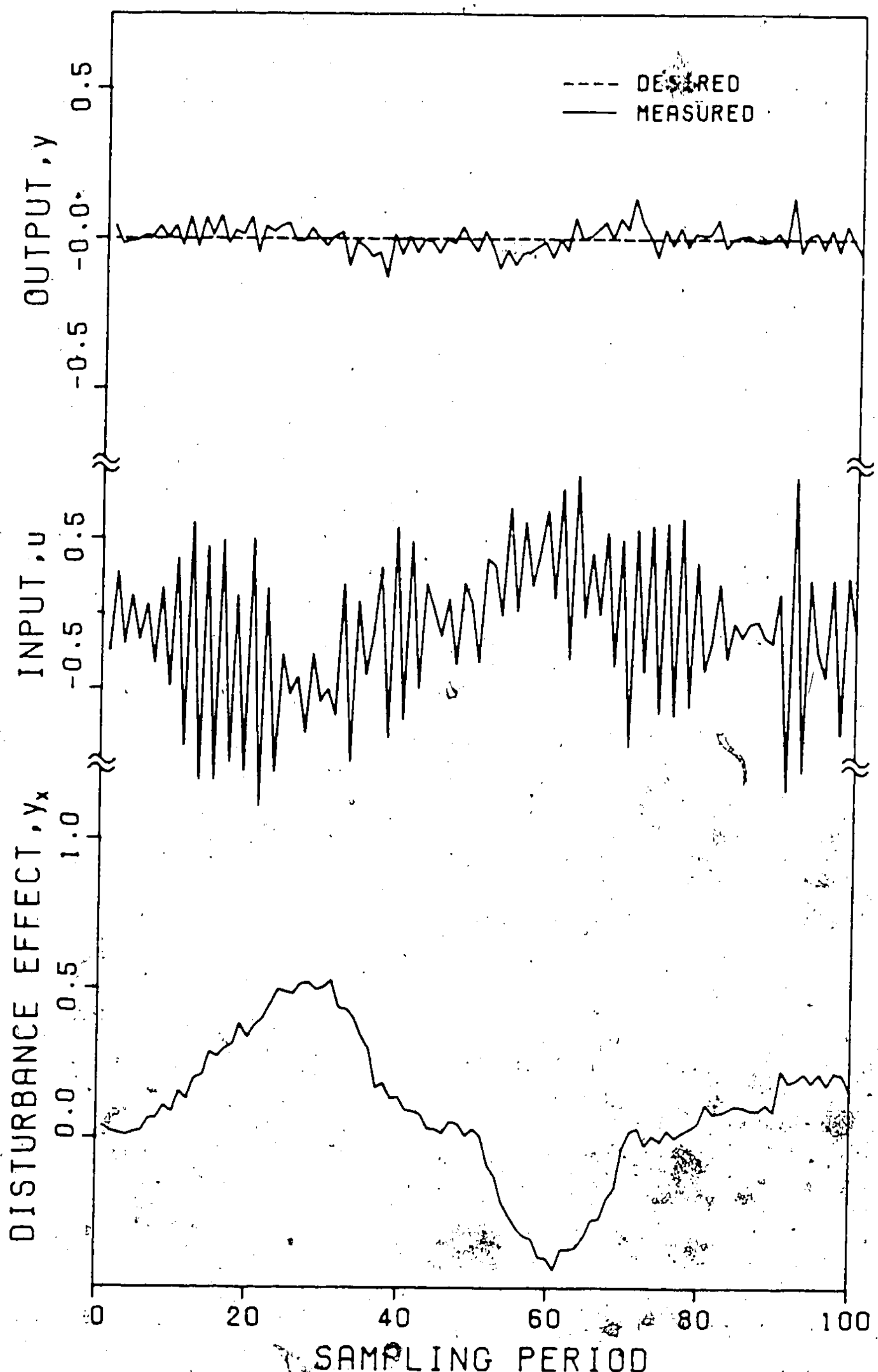

Figure 4.11 Compensation of Noisy Disturbance Using IMC

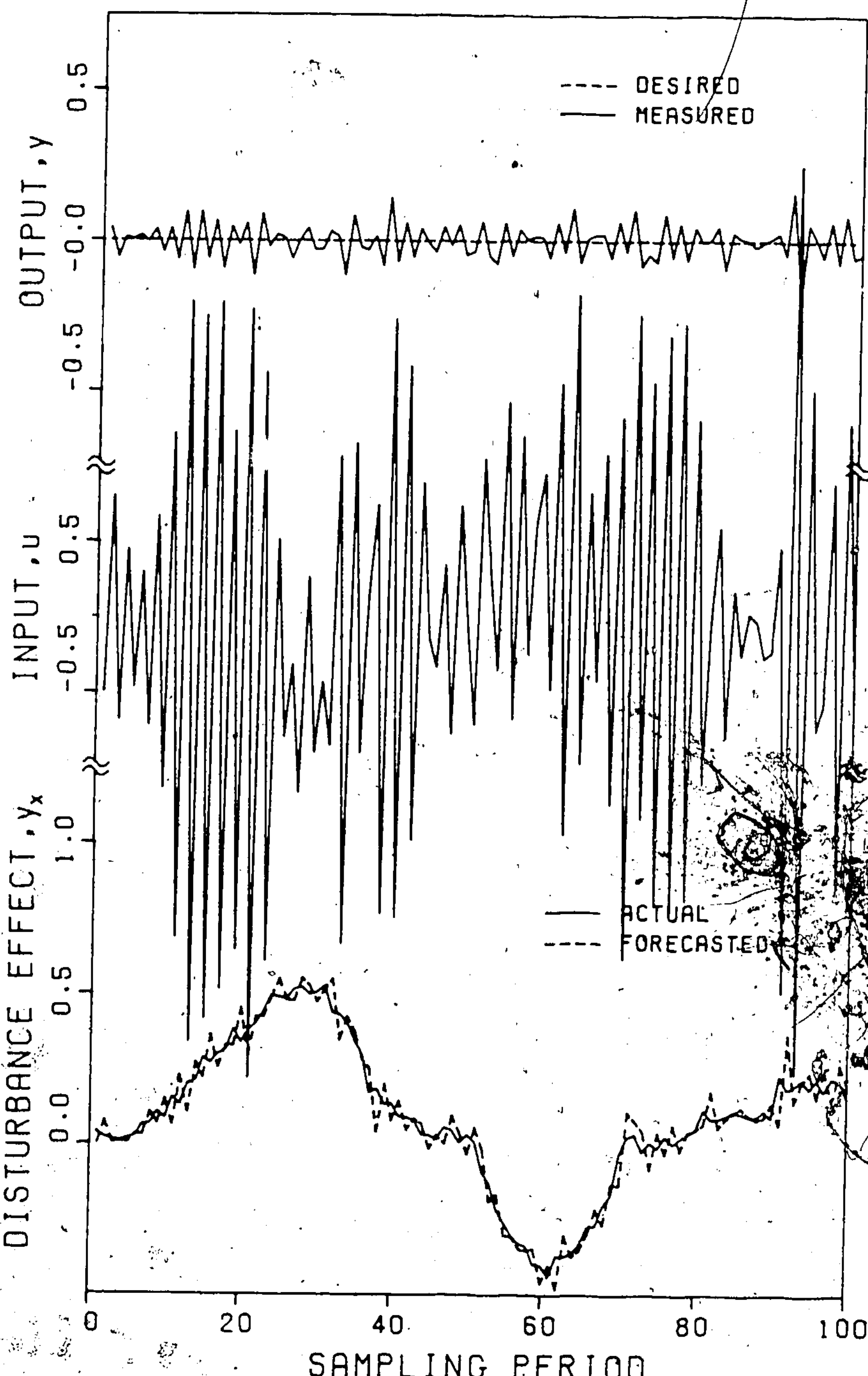

Figure 4.12 Compensation of Noisy Disturbance Using IMC with Linear SSF

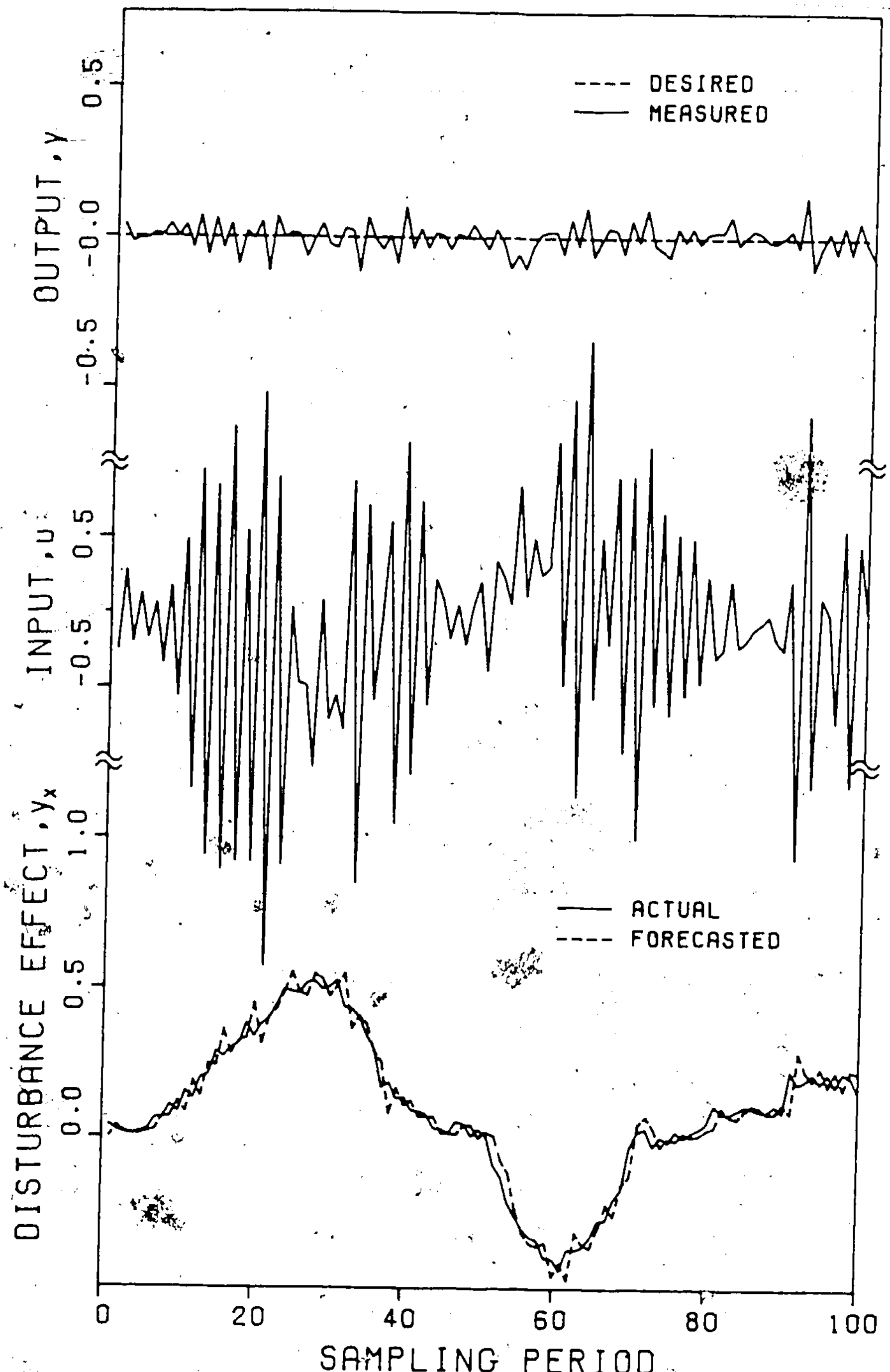

Figure 4.13 Compensation of Noisy Disturbance Using IMC with AR SSF

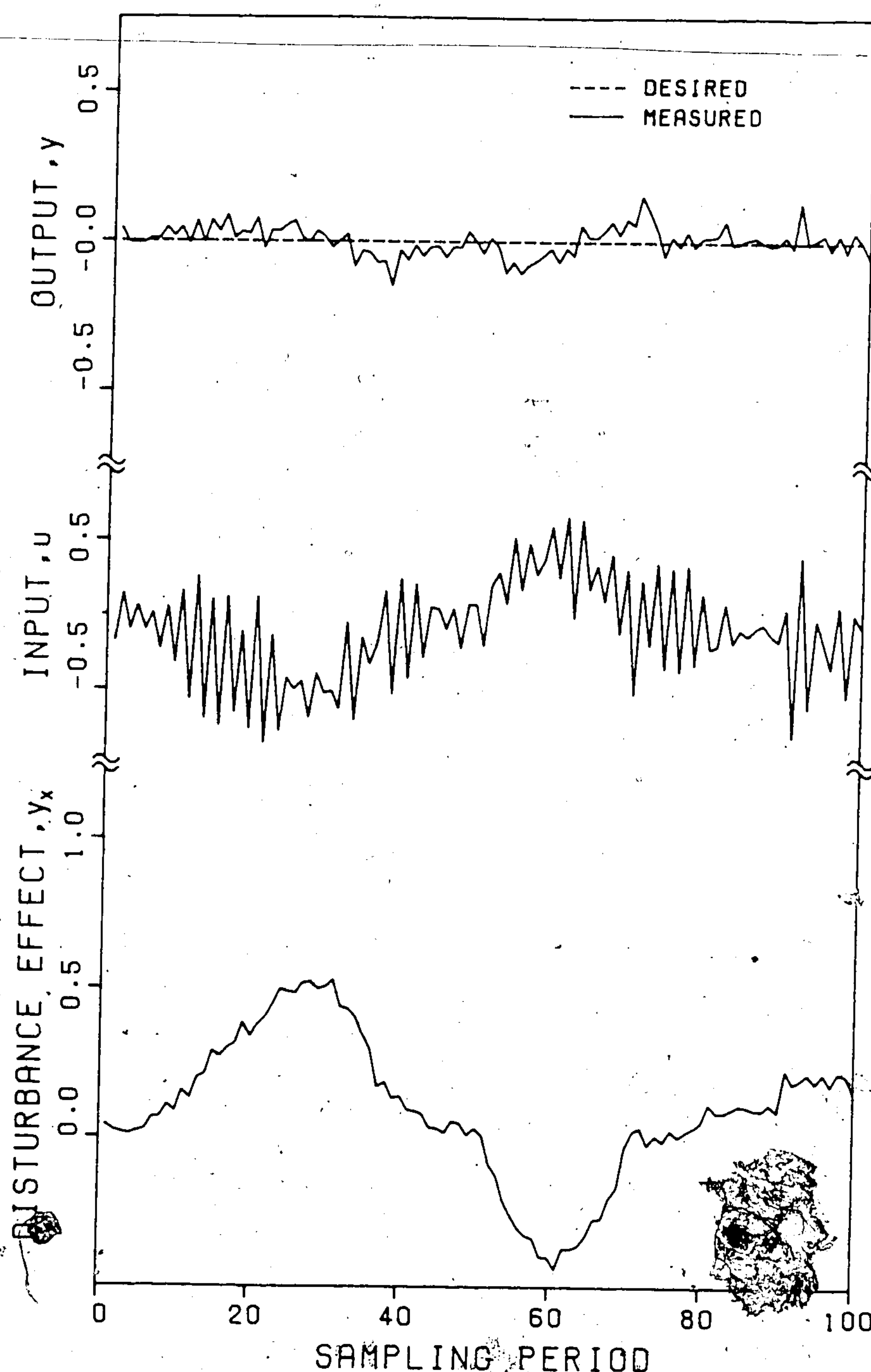

Figure 4.14 Compensation of Noisy Disturbance Using IMC with Filter (α=0.3)

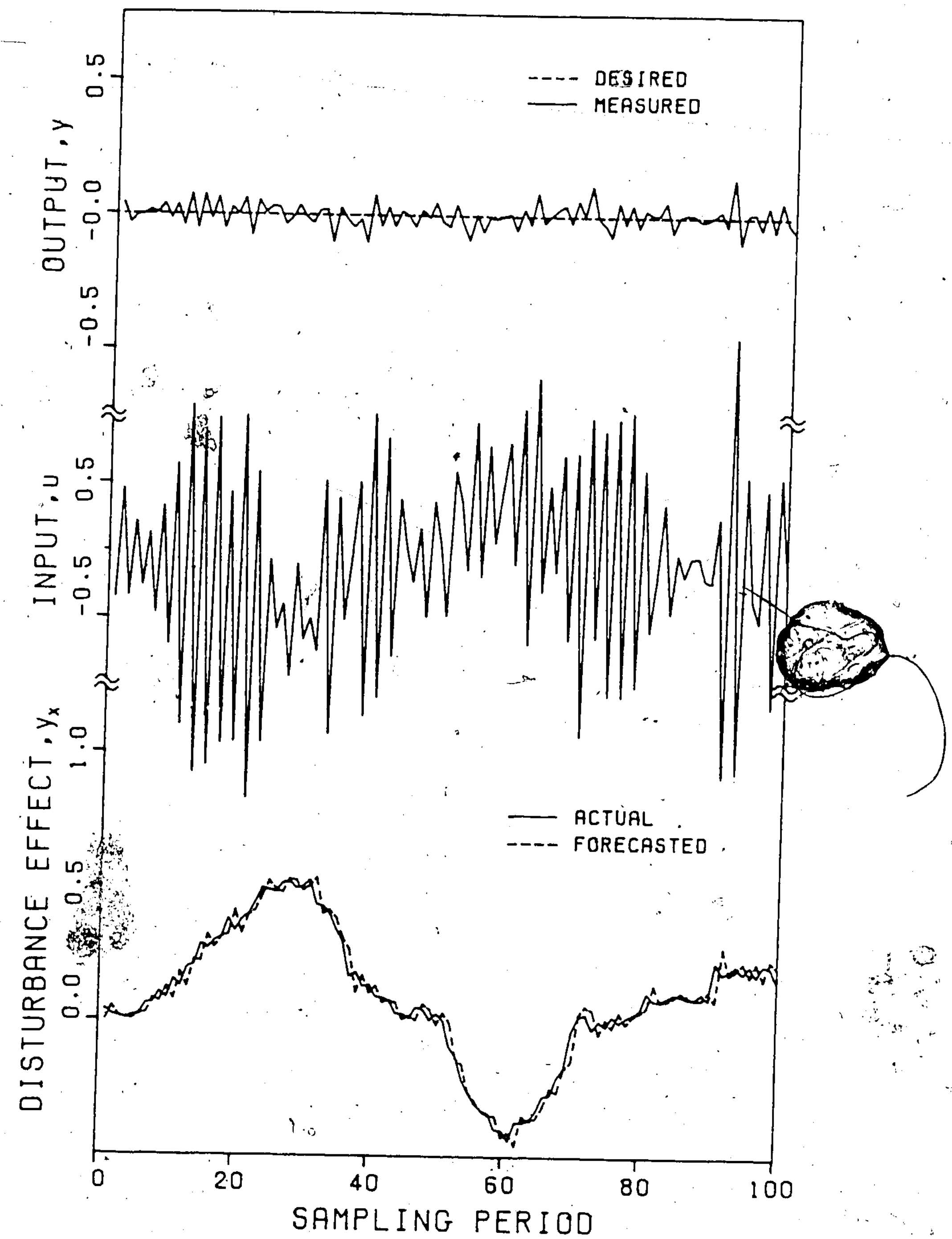

Figure 4.15 Compensation of Noisy Disturbance Using IMC with Filter (α=0.3) and Linear SSF

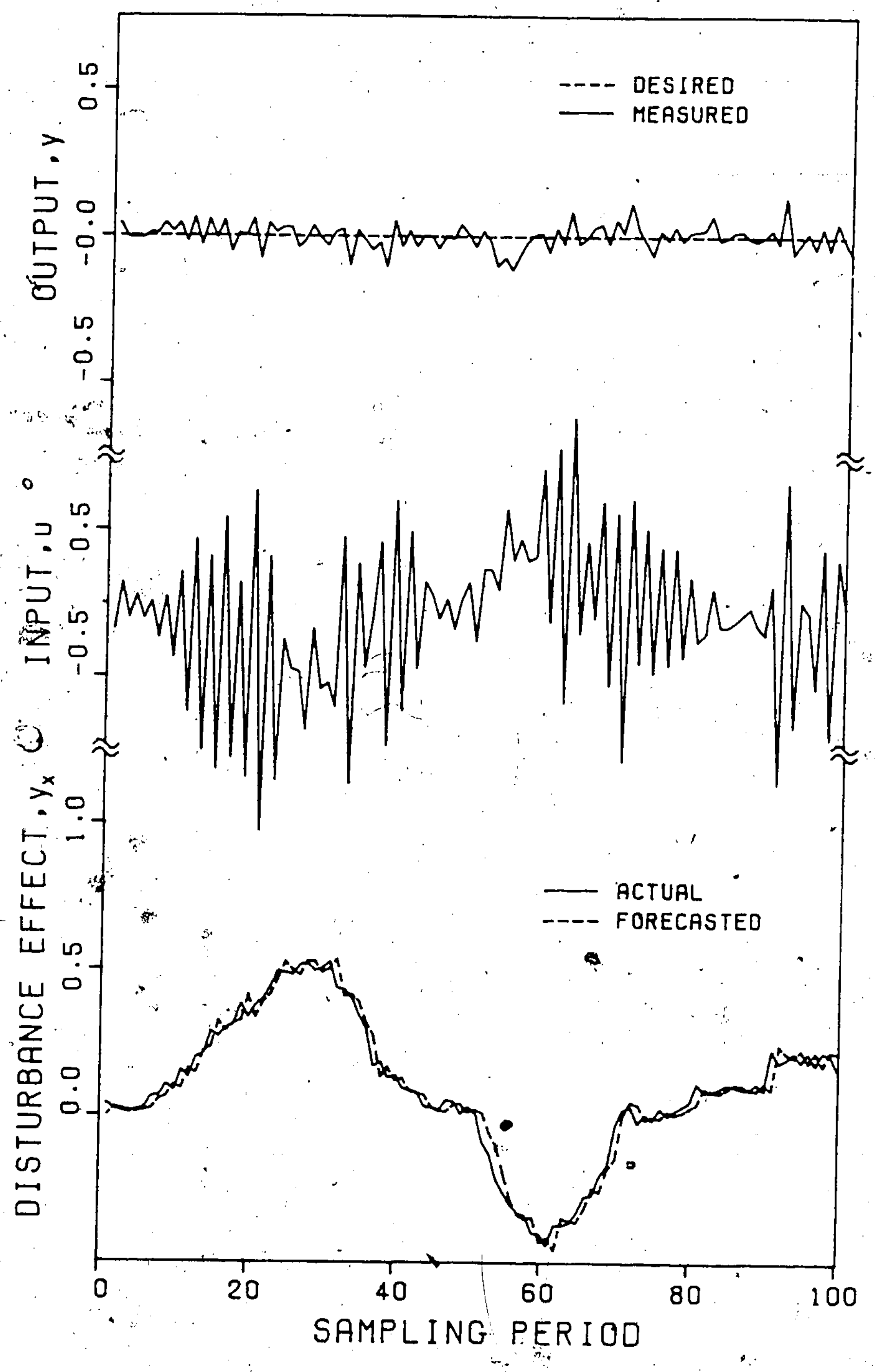

Figure 4.16 Compensation of Noisy Disturbance Using IMC with Filter (α=0.3) and AR SSF

4.5 Conclusions

1) In the feedback interpretation of the IMC structure, the design rule that the IMC controller should ...oach the inverse of the process model is readi... s being equivalent to the classical design o... on that perfect control is approached as the feedback gain approaches infinity. The use of high gain for perfect control in feedback control is restricted by stability and performance considerations. Similarly, the inverse model controller in IMC has the additional requirement of a perfect model in order to provide perfect control.

2) IMC can be interpreted as a classical feedforward control scheme based on the forecasted disturbance rather than the actual measured value. This interpretation helps to explain the function and form of the controller, the filter and the reference model.

3) IMC can be interpreted as an SSF system that uses the current value of the residual as an estimate of the future value. The use of other forecasting methods can therefore be seen as an attempt to provide more accurate forecasts.

4) Simulation examples show that the addition of linear or AR SSF to IMC improves its ability to compensate for unmeasured disturbances. However, the advantage gained is that the disturbances will be compensated λ sampling periods earlier where λ equals the sampling plus process delays. Moreover, the improvement is easily destroyed

by stochastic noise which introduces uncertainty into the forecasting. Therefore, the practical justification of using SSF with IMC is limited.

5. SSF and the Adaptive Predictive Control System (APCS)

5.1 Introduction

The APCS is a multivariable adaptive control system for the control of linear, time-invariant processes with unknown parameters and subject to "bounded" stochastic noise and unmeasured disturbances. The basic theory of APCS was published by Martin-Sanchez in 1976 based on the work of his doctoral thesis in 1974. An extension of the results to handle multivariable processes with time-delays was included in an US patent on APCS filed by Martin-Sanchez in 1977. In these early works, the stability of APCS was based on Popov's hyperstability criterion (1963). A new proof of convergence and global stability for APCS was reported by Martin-Sanchez, Shah and Fisher (1984). The new result involves the modification of the original adaptive mechanism to include a criterion for turning parameter identification on and off. This result has been further extended to cover time-delayed systems by Martin-Sanchez (1984).

The strength of an adaptive controller comes from its ability to adapt its parameters continuously so as to improve control performance. The feature of stopping identification in APCS, though providing some distinct advantages, does raise doubts since the advantages of adaption are absent when the identification is off. This will be of particular concern if the criterion of stopping identification is not chosen appropriately. The incentive to improve the control performance of APCS was the original motivation for the work of this thesis. The solution is to make use of the estimation error or residual in the control calculation.

The purpose of this chapter is to investigate the use of SSF on the estimation error in APCS for compensating unmeasured disturbances and/or modelling error during the period when APCS parameter identification is off. Simulation examples will be used as illustrations for the ideas presented in this chapter.

5.2 Description of APCS

The Adaptive Predictive Control System is a globally stable control system for multivariable, stable-inverse, time-invariant processes with pure time delays and in the presence of bounded unmeasured disturbances plus process and measurement noise. The following is a brief description of the control system for the case of single-input single-output processes. Fig. 5.1 shows a schematic diagram of the system to be described.

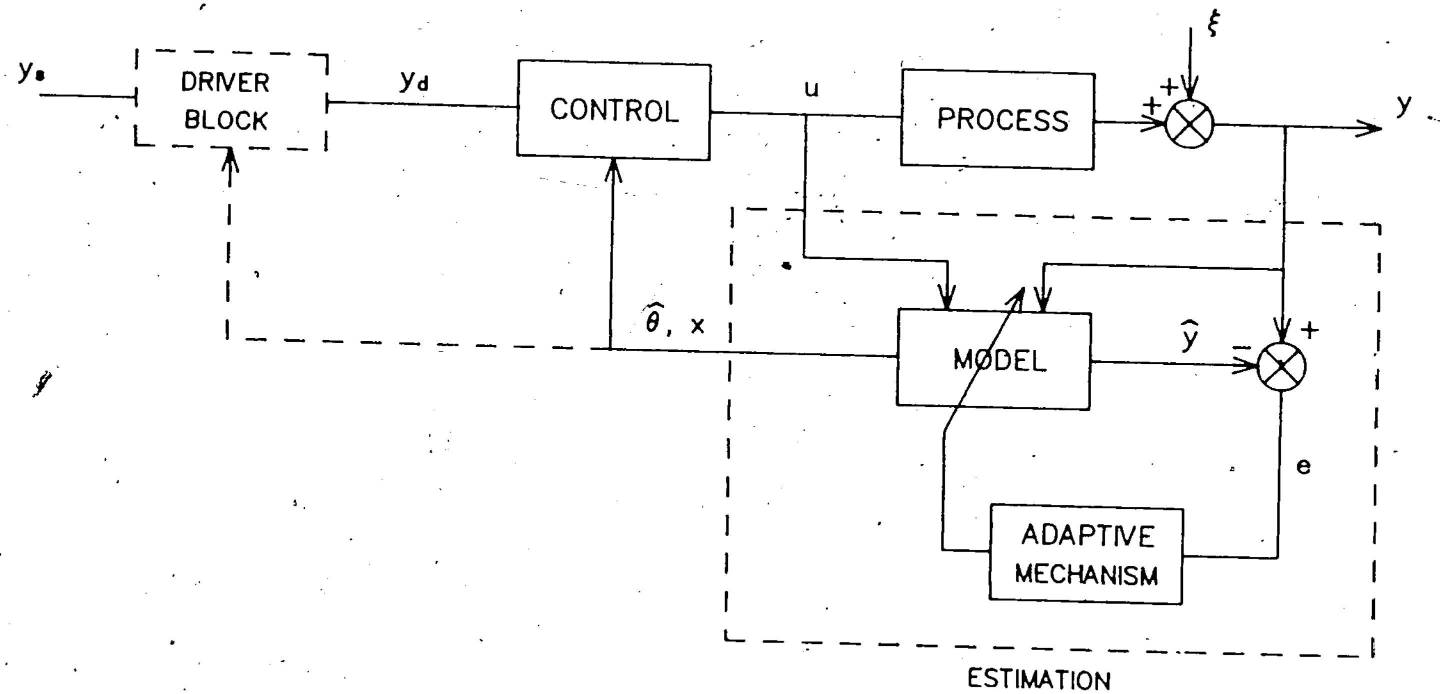

Figure 5.1 Schematic Diagram of APCS

Consider the single-input single-output process in Figure 5.1. Assuming there is no measured disturbances, the process can be represented by a discrete ARMA model

$$y_t(k) = \theta_0 \Phi_t(k-d-1) + \theta_1 u_t(k-d-1) + \xi(k) \tag{5.1}$$

where

$$\Phi_t{}'(k-d-1) = [\ y_t(k-d-1)\ y_t(k-d-2)\ \ldots \\ u_t(k-d-2)\ u_t(k-d-3)\ \ldots\ ] \tag{5.2}$$

$\Phi_t(k-d-1)$ is a vector of past actual values of the process output, y_t, and the control inputs, u_t. The dimension of Φ_t depends on the assumed process model order. d is an integer which represents the pure time delay of the process. $\xi(k)$ represents the effect of unmeasured disturbances on the process output at the kth sampling instant. θ_0 and θ_1 are unknown vectors of process parameters of appropriate dimension.

Because of measurement errors and noise, the measured process variables are different from the actual values. Therefore,

$$y(k) = y_t(k) + n_y(k) \tag{5.3}$$

$$u(k) = u_t(k) + n_u(k) \tag{5.4}$$

The corresponding measured Φ vector becomes

$$\Phi(k) = \Phi_t(k) + n_\Phi(k) \quad (5.5)$$

Substitution of equations (5.3) to (5.5) into equation (5.1) gives the final form of the process model.

$$y(k) = \theta\ x(k-d-1) + \Delta(k) \quad (5.6)$$

where

$\theta = [\ \theta_0\ \theta_1\ ]$ = process parameter vector

$x^t(k-d-1) = [\ \Phi^t(k-d-1)\ u(k-d-1)\ ]$ = process I/O vector

$n_x{}^t(k-d-1) = [\ n_\Phi{}^t(k-d-1)\ n_u{}^t(k-d-1)\ ]$ = noise vector

$\Delta(k) = n_y(k) - \theta\ n_x(k-d-1) + \xi(k)$ = perturbation term

The one step ahead prediction of the process output $\hat{y}(k|k-1)$, based on the estimation at time k-1 of the process parameters vector $\theta(k-1)$, is given by

$$\hat{y}(k|k-1) = \theta(k-1)\ x(k-d-1) \quad (5.7)$$

The corresponding prediction error or estimation error is

$$e(k|k-1) = y(k) - \hat{y}(k|k-1) \quad (5.8)$$

The estimated parameter vector is updated by the following recursive algorithm at every sampling instant depending on the value of $\psi(k)$.

$$\theta(k) = \theta(k-1) + \frac{\psi^2(k)x(k-d-1)e(k|k-1)}{1+\psi^2(k)x^t(k-d-1)x(k-d-1)} \qquad (5.9)$$

The scalar $\psi(k)$ provides a basis for turning parameter adaption on and off. The definition of $\psi(k)$ is given as follows.

a) $\psi^2(k) = 0$ if and only if

$$|e(k|k-1)| \le \Delta_d'(\psi_1,\Delta_d,k) \le 2\Delta_d < \infty \qquad (5.10)$$

where

$$\Delta_d'(\psi_1,\Delta_d,k) = \frac{2+2\psi_1^2x^t(k-d-1)x(k-d-1)}{2+\psi_1^2x^t(k-d-1)x(k-d-1)}\Delta_d \qquad (5.11)$$

with $0 < \psi_1^2 < \infty$, $\Delta_d \ge \Delta_m = \max_{0<k\le\infty} |\Delta(k)|$

Δ_d is an estimate of a constant upper bound on the absolute value of the perturbation term $\Delta(k)$ for all k. Δ_m is the minimum value of this upper bound.

b) $\psi_1^2 < \psi^2(k) \le \psi_d^2(k) \le \psi_m^2 < \infty$ if and only if

$$|e(k|k-1)| > \Delta_d'(\psi_1,\Delta_d,k) \ge \Delta_d \qquad (5.12)$$

where $\psi_d(k)$ is defined as follows:

i) $\psi_d^2(k) = \psi_m^2$ if $|e(k|k-1)| > \Delta_d'(\psi_m,\Delta_d,k)$ (5.13)

where

$$\Delta_d'(\psi_m,\Delta_d,k) = \frac{2+2\psi_m^2 x'(k-d-1)x(k-d-1)}{2+\psi_m^2 x'(k-d-1)x(k-d-1)} \Delta_d \qquad (5.14)$$

ii)

$$\psi_d^2(k) = \frac{2(|e(k|k-1)|-\Delta_d)}{(2\Delta_d-|e(k|k-1)|)\; x'(k-d-1)x(k-d-1)} \qquad (5.15)$$

$$\text{if } \Delta_d'(\psi_1,\Delta_d,k) < |e(k|k-1)| < \Delta_d'(\psi_m,\Delta_d,k)$$

The calculation of $\psi(k)$ requires an operator-specified parameter Δ_d which is defined above. The definition of $\psi(k)$ is closely related to the proof of stability which is given by Martin-Sanchez et al (1984).

The prediction at time k of the process output at time k+d+1, $\hat{y}(k+d+1|k)$, is given by

$$\hat{y}(k+d+1|k) = \theta(k)x(k) = \theta_0(k)\Phi(k) + \theta_1(k)u(k) \qquad (5.16)$$

The control input u(k) is computed to make the predicted output $\hat{y}(k+d+1|k)$ equal to the desired output $y_d(k+d+1)$. Therefore,

$$u(k) = \theta_1^{-1}(k)\,[\, y_d(k+d+1) - \theta_0(k)\Phi(k)\,] \qquad (5.17)$$

In order to guarantee a finite control input u(k), $\theta_1(k)$ must be non-zero. Martin-Sanchez et al (1984) have shown that $\theta_1(k)$ can be made non-zero by an appropriate choice of $\psi(k)$.

The control error is defined as

$$\epsilon(k) = y(k) - y_d(k) \tag{5.18}$$

Equations (5.1) to (5.18) describe a basic APCS algorithm. In Fig. 5.1, the general formulation of APCS also includes a "driver block". It can be interpreted as an extension to the traditional concept of the "reference model". At each sampling instant, the driver block generates from the operator-specified setpoint y_s a desired process output y_d for a future sampling instant. This desired process output y_d belongs to a desired process output trajectory that satisfies a specified performance criterion. The driver block provides a means to enable the control algorithm to handle non-minimum phase systems and variable time-delayed process.

As a summary, the characteristics of the APCS are listed as follows.

1) It uses an ARMA process model which is identified on-line.
2) It makes use of an I/O process model to calculate control action such that the predicted output is equal to the desired output.
3) It has a criterion for stopping parameter adaption. This requires an operator-specified parameter which is an estimate of the upper bound of the perturbation term.
4) Global stability is established for multivariable,

stable-inverse, time-invariant processes with pure time delays and subject to bounded disturbances.

5) It contains a driver block which generates a desired output from an operator-specified setpoint, the current parameter estimates, and in some cases an objective function and/or design method.

5.3 Discussion of APCS

The basic control algorithm of APCS is quite similar to the Self Tuning Regulator (STR) proposed by Astrom et al (1973). However, it possesses several advantages over the STR. The first advantage of APCS is the guarantee of global stability. Since the identification algorithm in most adaptive control systems is a highly nonlinear algorithm, the proof of stability is very difficult. For STR, it can only be shown that the algorithm will converge in most cases. In contrast, global stability has been proved for APCS.

The second advantage of APCS is the criterion for turning parameter identification on and off. This not only saves computation time, but also avoids problem like estimator windup which is common in STR. The third advantage of APCS is that the assumption it makes about the unknown disturbances is very general. Most of the other adaptive control algorithms impose more restrictive assumptions on the disturbance or noise dynamics.

The APCS also has some weaknesses. The following discussion will focus on two problems associated with the APCS adaptive algorithm and the feature of stopping parameter identification. Implications from these problems and solutions to them will also be discussed.

5.3.1 APCS Adaptive Algorithm

The APCS adaptive algorithm is a fairly simple algorithm to implement and the prediction $\hat{y}(k+\lambda|k)$ calculated using the estimated model converges rapidly to the true value. However, the convergence of the model parameters can be quite slow. This is due to the form of the adaptive algorithm (equation (5.9)) as explained by Song (1983). All the parameters adapt with the same gain which is the estimation error. The direction for adaption for each parameter depends on the sign of the elements in the vector $x(k-d-1)$. This is different from the recursive least square algorithm which allows the parameters to adapt in different directions and with different gains because of the covariance matrix. This slow parameter convergence is not a problem if the model is used for prediction since accurate prediction does not require accurate parameters. However, it becomes a problem when the process model is used to calculate control action. In equation (5.11), the parameter θ_1 acts like an overall gain and affects directly the value of the control action calculated. If θ_1 is small and close to zero, even a slight change in its value will affect the control action significantly. This may lead to erratic control action which is undesirable in most cases. Therefore, the accuracy of θ_1 is very important. One solution to resolve this practical problem is to first identify θ_1 accurately off-line and then use it as a known parameter in the process model.

5.3.2 On/Off Feature for Identification

An adaptive control algorithm works by constantly adapting the parameters of the system so as to minimize the error between the output and the setpoint. When the parameters are not being adapted, the controller is fixed and it loses its ability to improve its performance at a certain operating condition or to maintain the level of performance when the operating condition changes.

In APCS, the parameters of the process model are being adapted until the estimation error is smaller than Δ_d'. Δ_d' is a function of Δ_d, which is an estimate of the upper bound of the absolute value of the perturbation term. In essence, APCS will stop parameter identification when it is not sure whether the estimation error is due to modelling error or disturbances. This feature provides the advantage that the model parameters will not be corrupted by the disturbances and the model will represent the true input-output relationship of the process.

However, since the control error is equal to the estimation error, it means that APCS will only try to bring the output to within Δ_d' of the setpoint. Therefore, the choice of Δ_d dictates the ultimate performance level of the control algorithm. In practice, since the magnitude of the disturbances is unknown, Δ_d has to be estimated. In order to guarantee stability, the choice of Δ_d has to be lenient. This results in degradation of the control performance.

The estimation error contains information about the unmeasured disturbances and modelling error. When the identification is on, this information is utilized since the estimation error is used in the adaptive algorithm to update the I/O model parameters. When identification is off, the estimation error is not used and the information it contains is wasted. Therefore, an obvious improvement to APCS is to make use of the estimation error for control when the identification is off. Two cases will be described in the following paragraghs to show potential improvement through using the estimation error for control when the identification is off.

Consider the first case where a process is subject to some unmeasured disturbances and a non-zero Δ_d is chosen for the identification algorithm. Assume that when the identification stops, the model is perfect and the estimation error is equal to the disturbances. Since the estimation error is not used when the identification is off, information about the disturbances is only fed back to the controller through the use of *measured* process output values. Compensation of the disturbances is slow and requires that the controller contains inherent integral action. Alternately, by feeding the estimation error back to the controller, more direct control action can be generated and the disturbances can be compensated faster.

Consider the second case where a non-zero Δ_d is used but for a while there is no disturbance affecting the system. Identification stops when the estimation error is smaller than Δ_d' but the process model is not perfect. Theoretically, identification should be allowed to continue. However, Δ_d cannot be made zero because the disturbance is unknown. Therefore, the modelling error is left uncorrected. An offset will be present in the output. By making use of the estimation error or residual in the control algorithm to adjust the control action, the offset can be eliminated even though the modelling error is not corrected.

5.4 SSF and APCS

5.4.1 Description

It has been explained in the previous section that the control performance of APCS can be improved, when the identification is off, by making use of the estimation error. This section will describe how the estimation error can be used and how SSF fits in this additional feature for APCS.

Depending on the accuracy of the process model, the estimation error contains unmeasured disturbances and/or modelling error. This error is already present in the process output. If the value of the error is used directly by the controller, the control action, whose effect will be felt some time in the future, will be correcting the current error at a future time. What is really needed is the value of the future error so that the effect of the current control action can be chosen to minimize with the future error. Therefore, instead of feeding the estimation error directly back to the controller, its present and past values are used in SSF to forecast a future error for the controller.

Recalling the feedforward control system based on estimated disturbance in Chapter Three, the situation is similar here for APCS. SSF can be used to forecast future values of the estimation error based on the current and past values. The general form of the forecasting equation is

$$\hat{e}(k+d+1) = f(e(k), e(k-1), \ldots) \tag{5.19}$$

The forecasted value can be used by the APCS controller which is already an inverse model controller. Therefore, equation (5.17) is modified to

$$u(k) = \theta_1^{-1}(k)\,[y_d(k+d+1) - \hat{e}(k+d+1) - \theta_0(k)\Phi(k)] \tag{5.20}$$

The modified APCS structure with SSF is shown in Figure 5.2. The forecaster is designed to be used when the APCS identification is off. When the APCS identification is on, the forecaster has to be turned off so that it will not affect the identification. In order to provide a "bumpless" on/off switching of the forecaster, the forecasted value is multiplied by a switching factor to switch the forecaster on and off gradually. The switching factor ω which lies in the range of 0 to 1, is defined by the following equations.

Switching on : $\omega = \omega + \gamma(1-\omega)$ (5.21a)

Switching off : $\omega = (1-\gamma)\omega$ (5.21b)

where γ is a parameter which determines the rate of switching and $0 \leq \gamma \leq 1$

$\gamma = 0$ means no switching action

$\gamma = 1$ means bang-bang switching

With the switching feature for SSF, the identification and control action of the basic APCS is not affected. Therefore, the stability proof of APCS is maintained and the modified APCS (with SSF) is also stable.

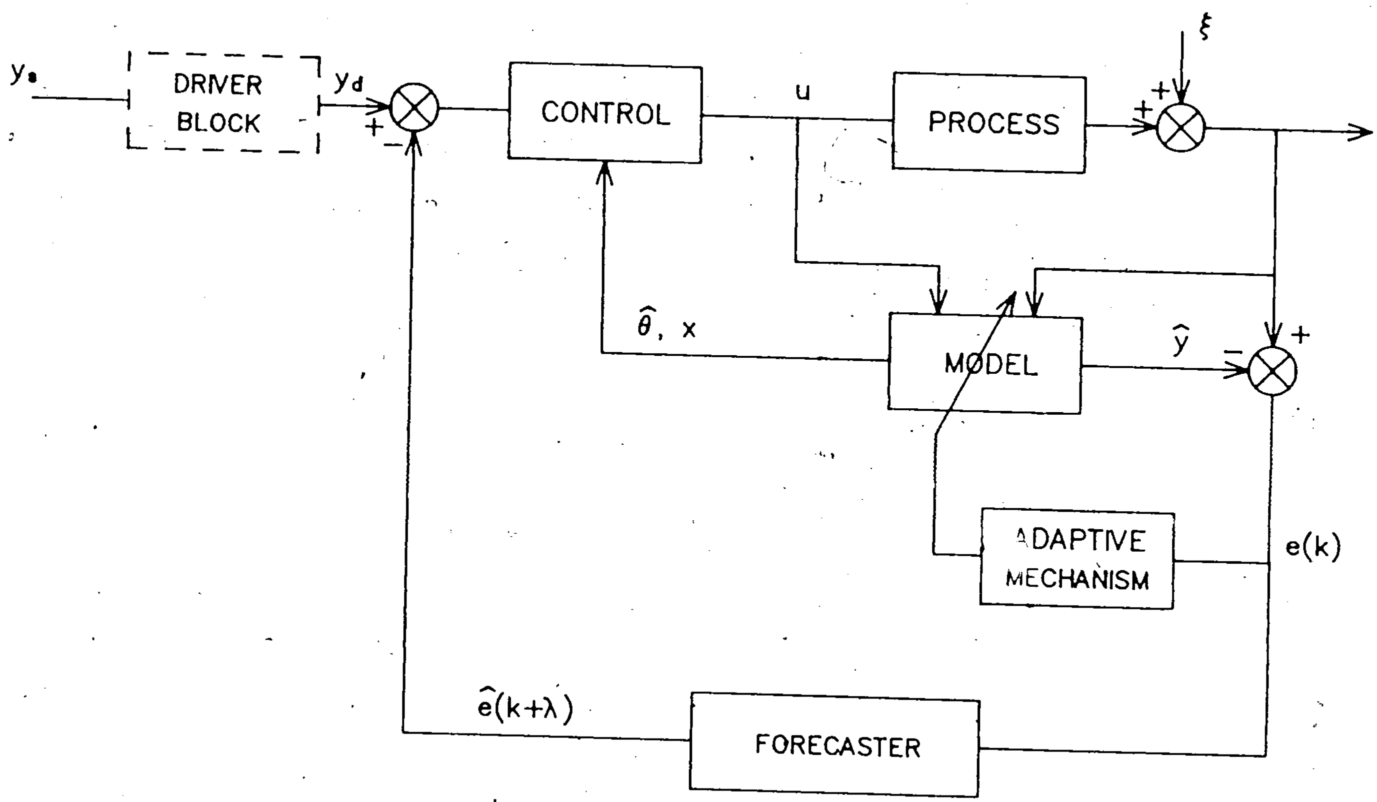

Figure 5.2 Schematic Diagram of APCS with SSF

Before proceeding with some simulation examples of SSF, an alternative to the second level of control by SSF will be discussed. The alternative is to allow parameter identification to run at all time. This approach is found in most adaptive control schemes which do not have on/off switching for parameter identification.

The disadvantage of this alternative is that the process model parameters could be corrupted if the residual error is due mainly to disturbances. Consider the situation where an accurate set of model parameters have been obtained. If identification is allowed to continue and some new disturbances come in, the parameters will be corrupted while the disturbances are being compensated for. If a setpoint change is required at this point, the response will be poorer with the corrupted set of parameters. Moreover, if this alternative is adopted for APCS, the conditions required for the stability proof will not be met and stability is not guaranteed.

Therefore, the use of SSF to provide a second level of control can reduce the control error and prevent unnecessary corruption of the process I/O model by unmeasured disturbances.

5.4.2 Illustrative Examples

Some simulation examples will be given to illustrate the use of SSF in APCS and to explore some of the properties of the system. The second order process which has been used in Chapter Four will be used again. The process can be described by the following ARMA equation.

$$y(k) = 1.030\ y(k-1) - 0.289\ y(k-2) + 0.158\ u(k-1) + 0.101\ u(k-2) \quad (5.22)$$

A second order ARMA model as described by the following equation is used by APCS.

$$y(k) = a_1 y(k-1)+a_2 y(k-2)+b_1 u(k-1)+b_2 u(k-2) \quad (5.23)$$

The following cases have been examined via simulation studies.

1) In the first case, the AP model has perfect parameters and no identification takes place. The process is subject to a noise-free disturbance sequence. This is the first case described in Section 5.3.2. Figure 5.3 shows the response of the system under APCS control. In Figures 5.4 and 5.5, a linear forecaster and an AR forecaster were added respectively. The figures show that APCS performs poorly in compensating for unmeasured disturbances and the addition of SSF improves the control performance significantly.
2) In the second case, the AP model parameters are considered to have converged under certain operati... conditions but they are not equal to the ... parameters. A setpoint change is introduced. The Δ_d is

non-zero but there is no unmeasured disturbance. Figure 5.6 shows the response of the system under APCS control. A steady state offset is present because of the imperfect parameters and a non-zero Δ_d. Figure 5.7 shows the addition of SSF helps to remove the steady state offset.

3) In real applications, the model parameters are generally not equal to the true parameters and there are unmeasured disturbances. In this case, the simulation was done with an imperfect AP model to compare the performance of APCS with and without SSF for regulatory control. A noise-free disturbance sequence is used for Figures 5.8 and 5.9 while a noisy disturbance sequence is used for Figures 5.10 and 5.11. The results show that the modelling error does degrade the control performance of APCS. The addition of AR SSF helps to compensate for both disturbance and modelling error. Moreover, the noise has no significant effect on the performance of the AR SSF.

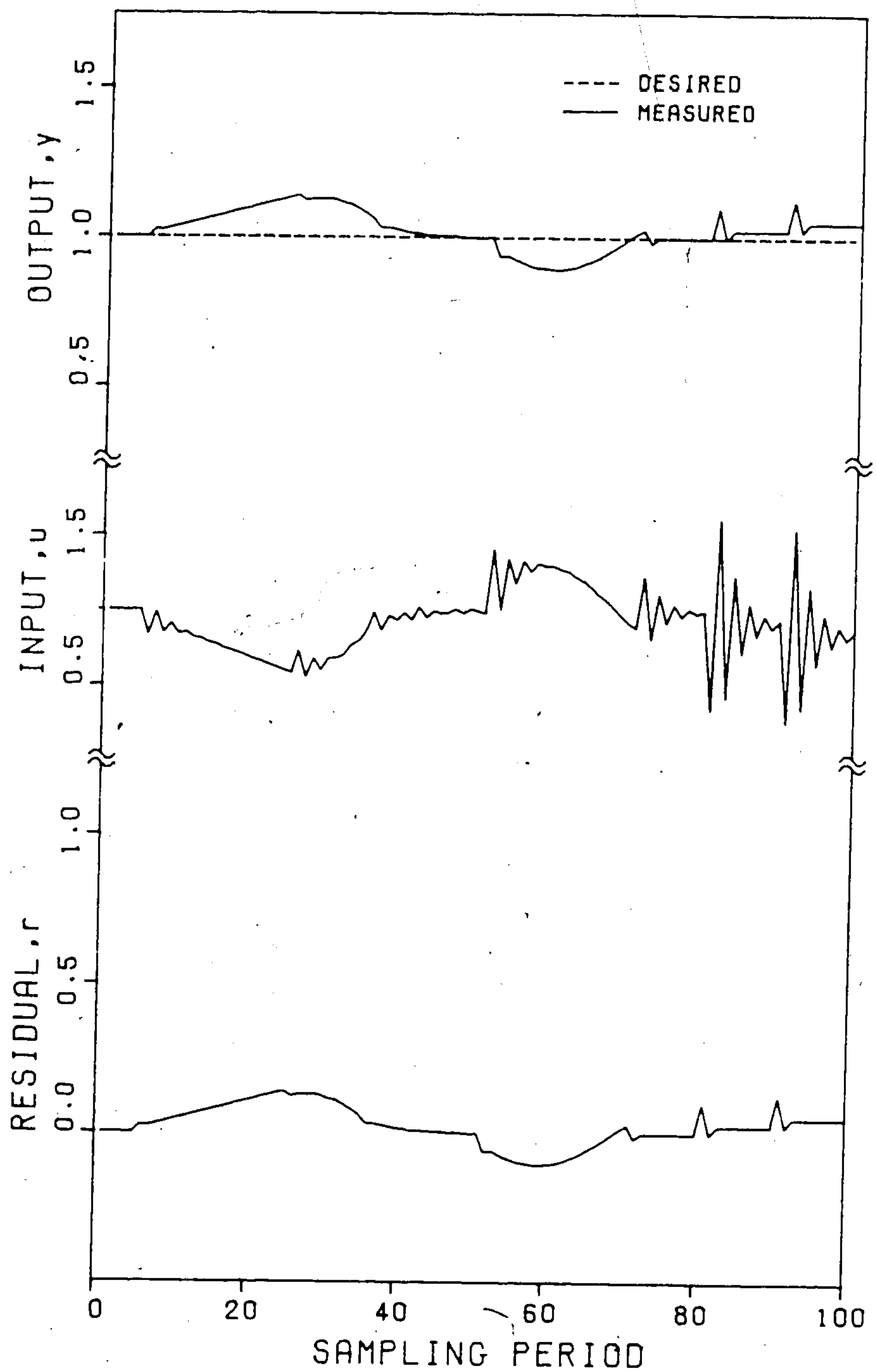

Figure 5.3 Compensation of Noise-free Disturbance Using APCS (Perfect Model)

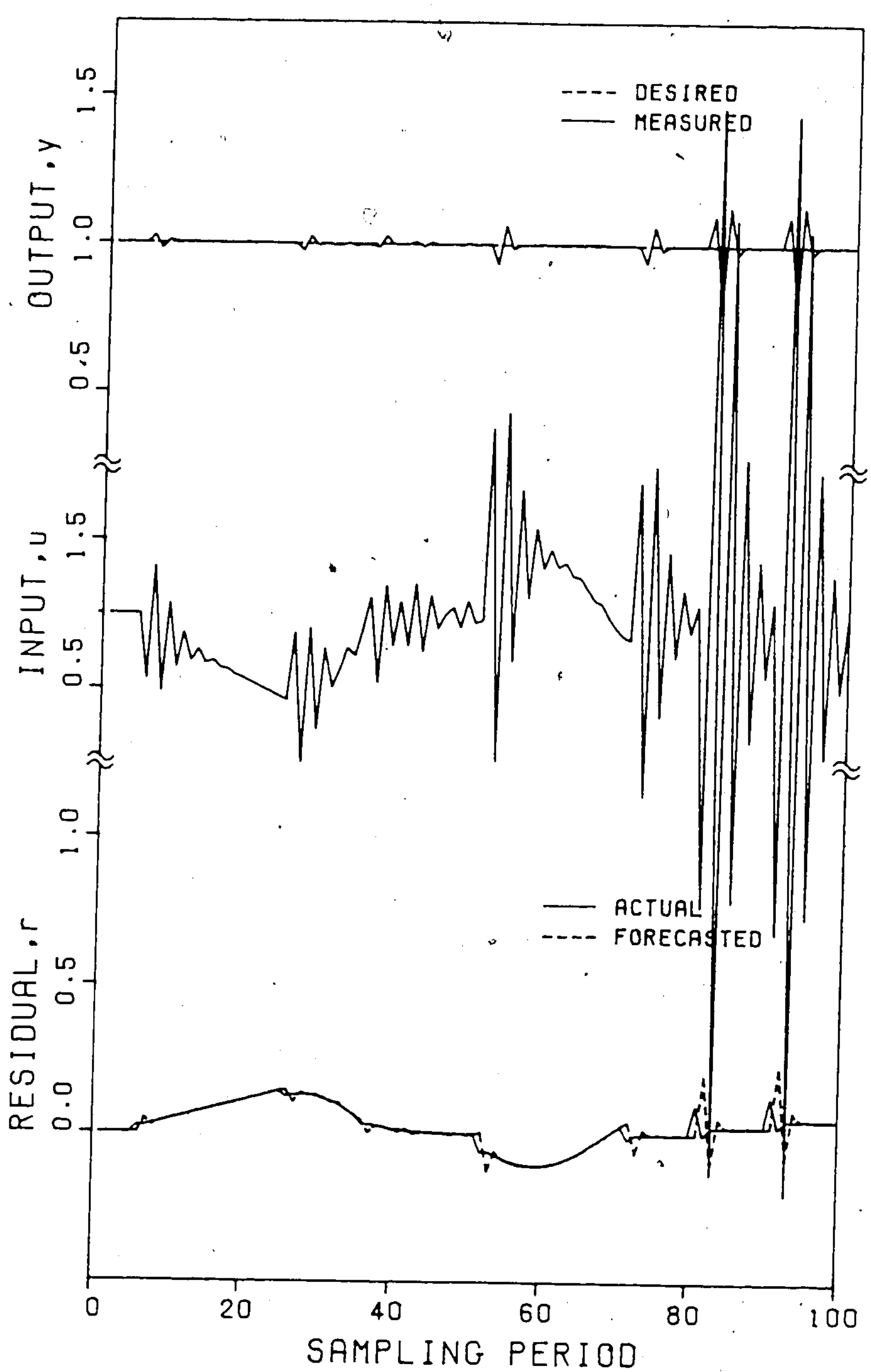

Figure 5.4 Compensation of Noise-free Disturbance Using APCS (Perfect Model) with Linear SSF

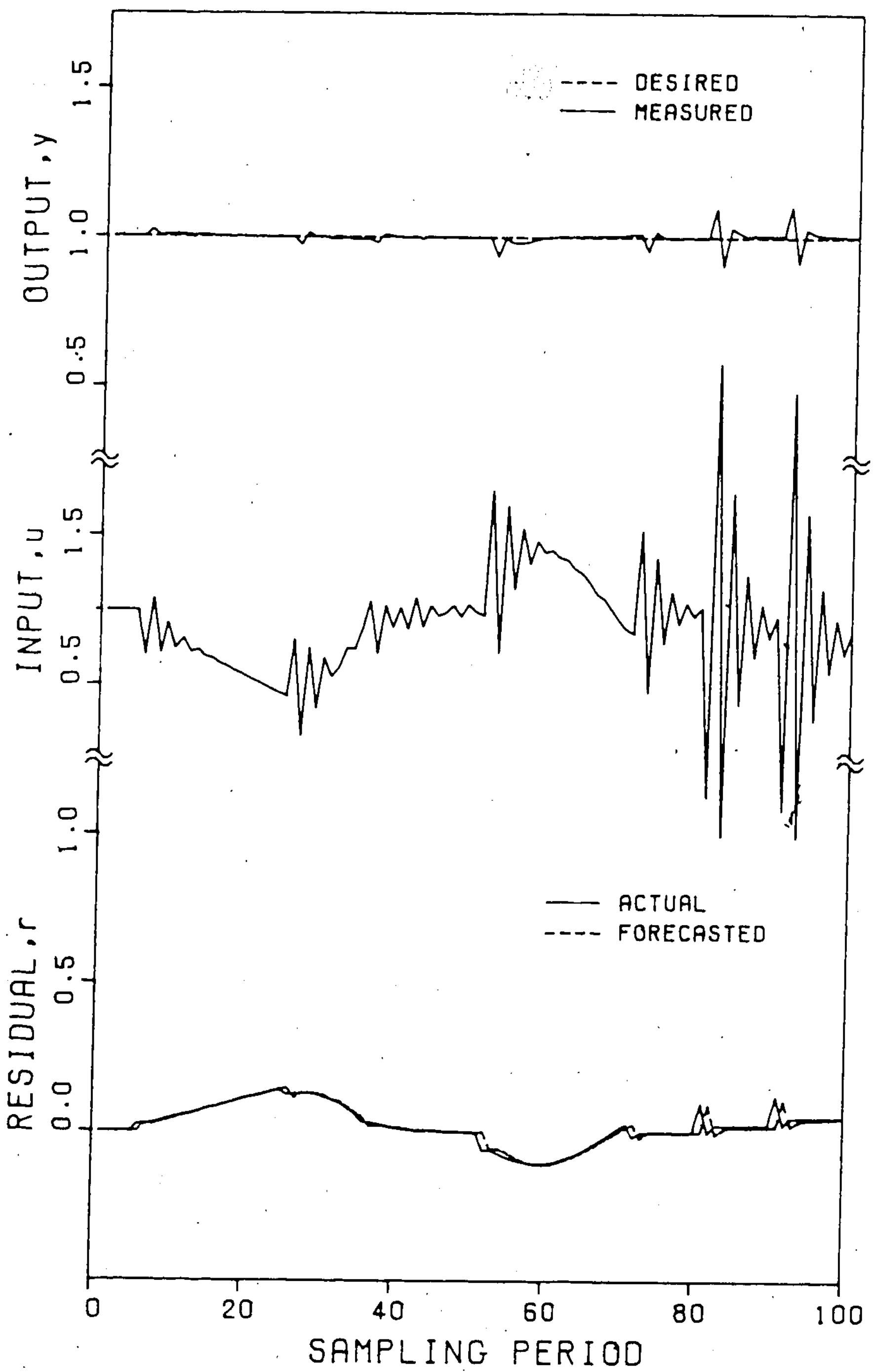

Figure 5.5 Compensation of Noise-free Disturbance Using APCS (Perfect Model) with AR SSF

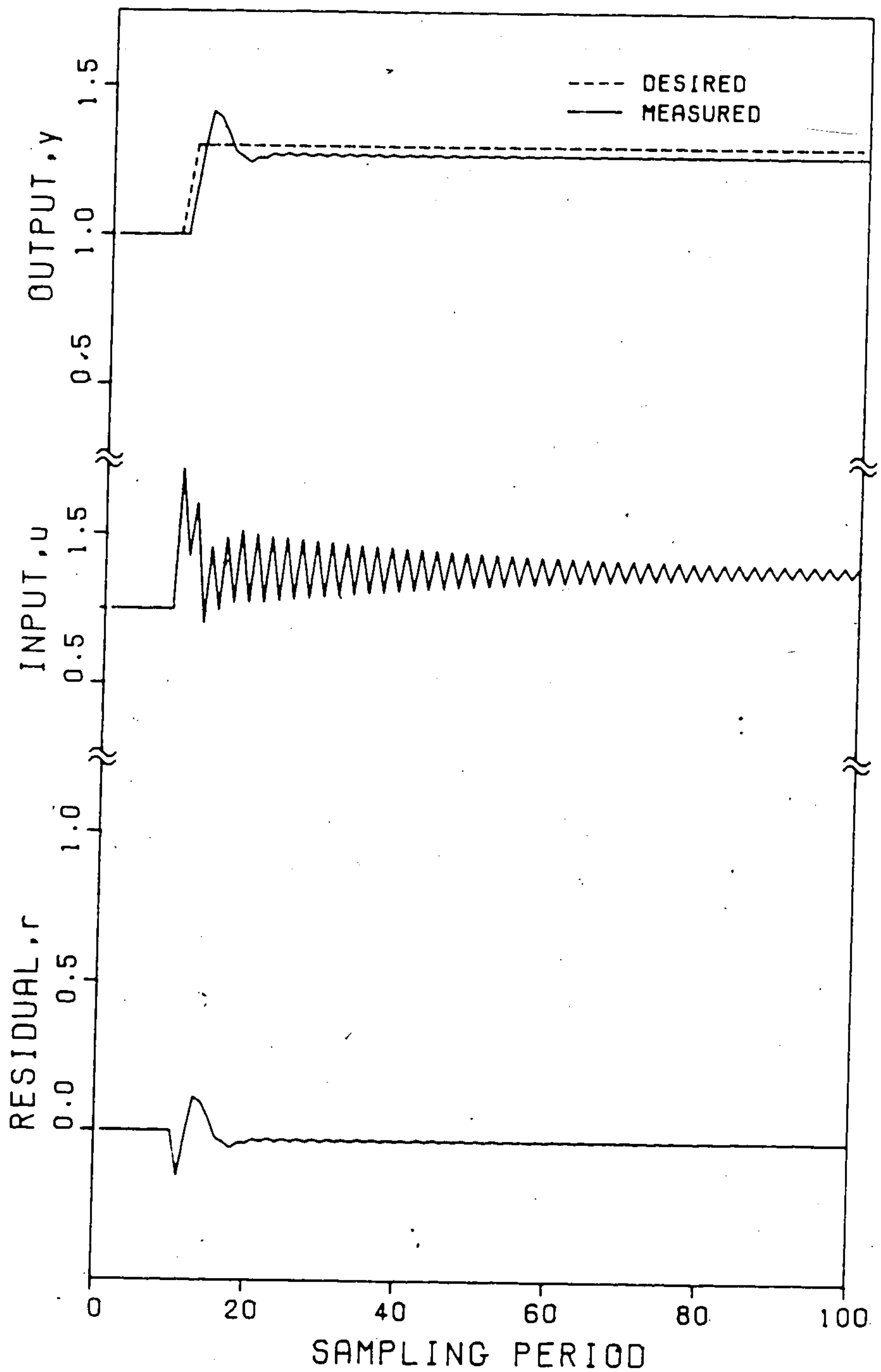

Figure 5.6 Setpoint Tracking Using APCS (with Modelling Error)

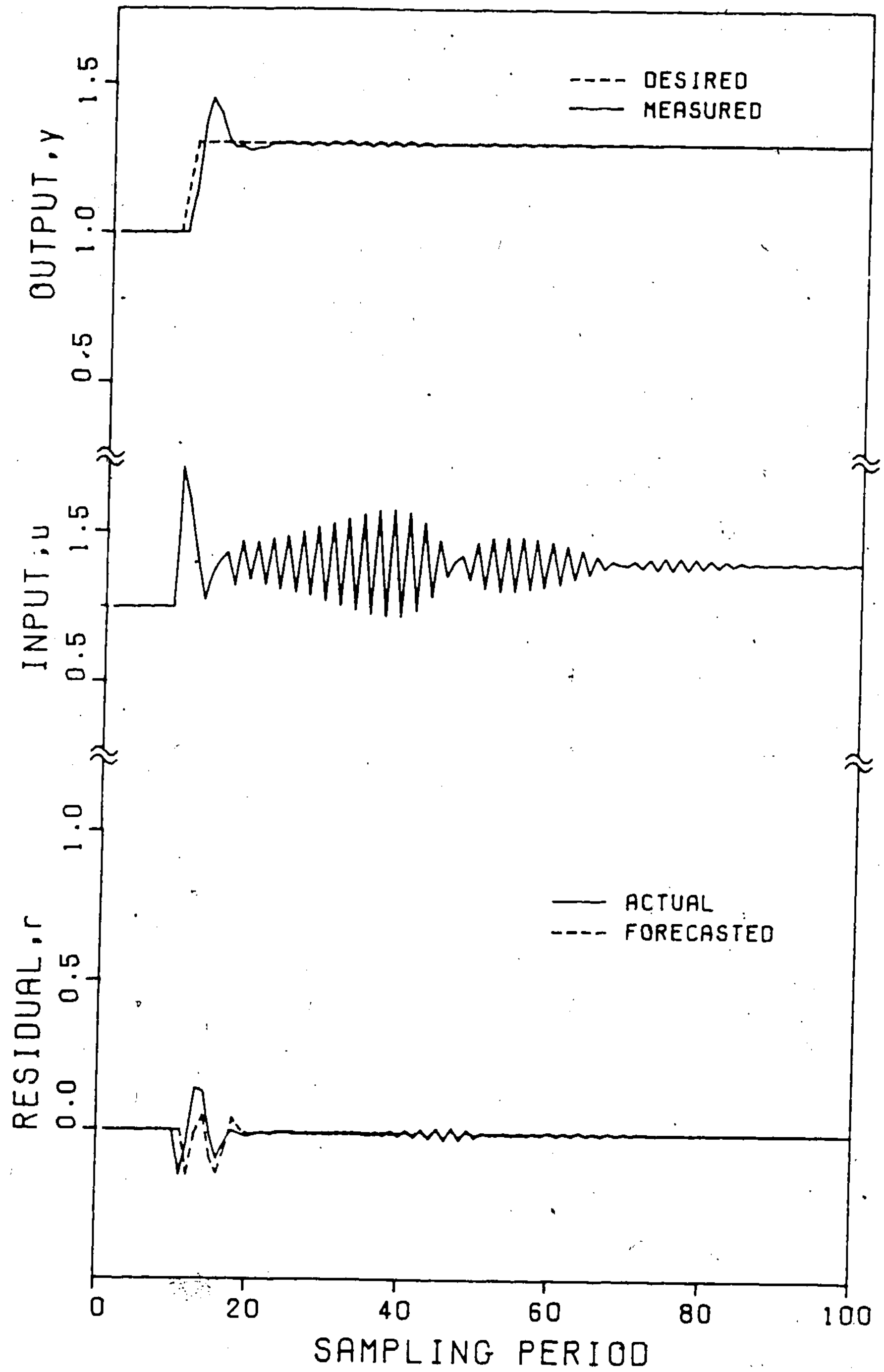

Figure 5.7 Setpoint Tracking Using APCS (with Modelling Error) with AR SSF

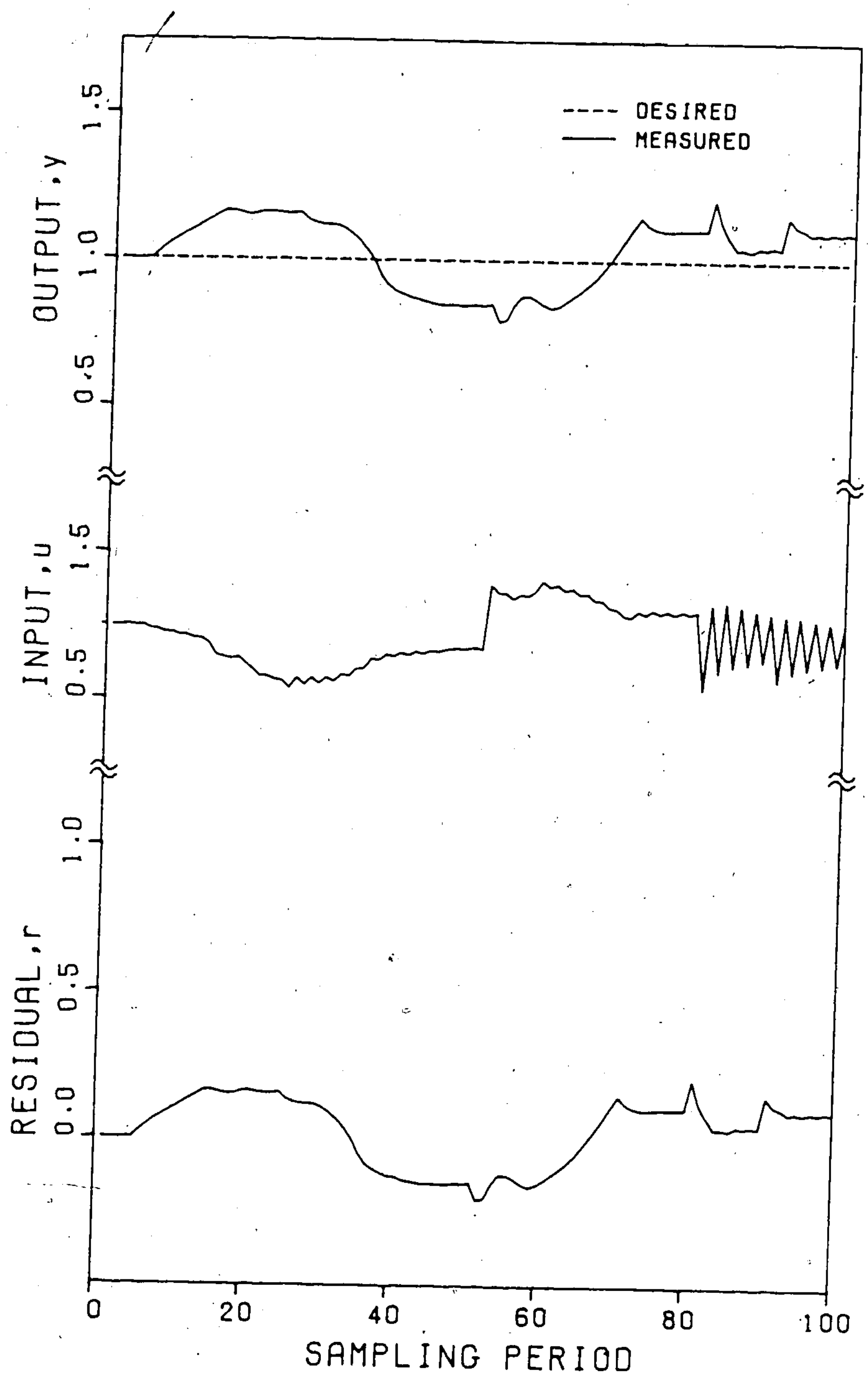

Figure 5.8 Compensation of Noise-free Disturbance Using APCS (with Modelling Error)

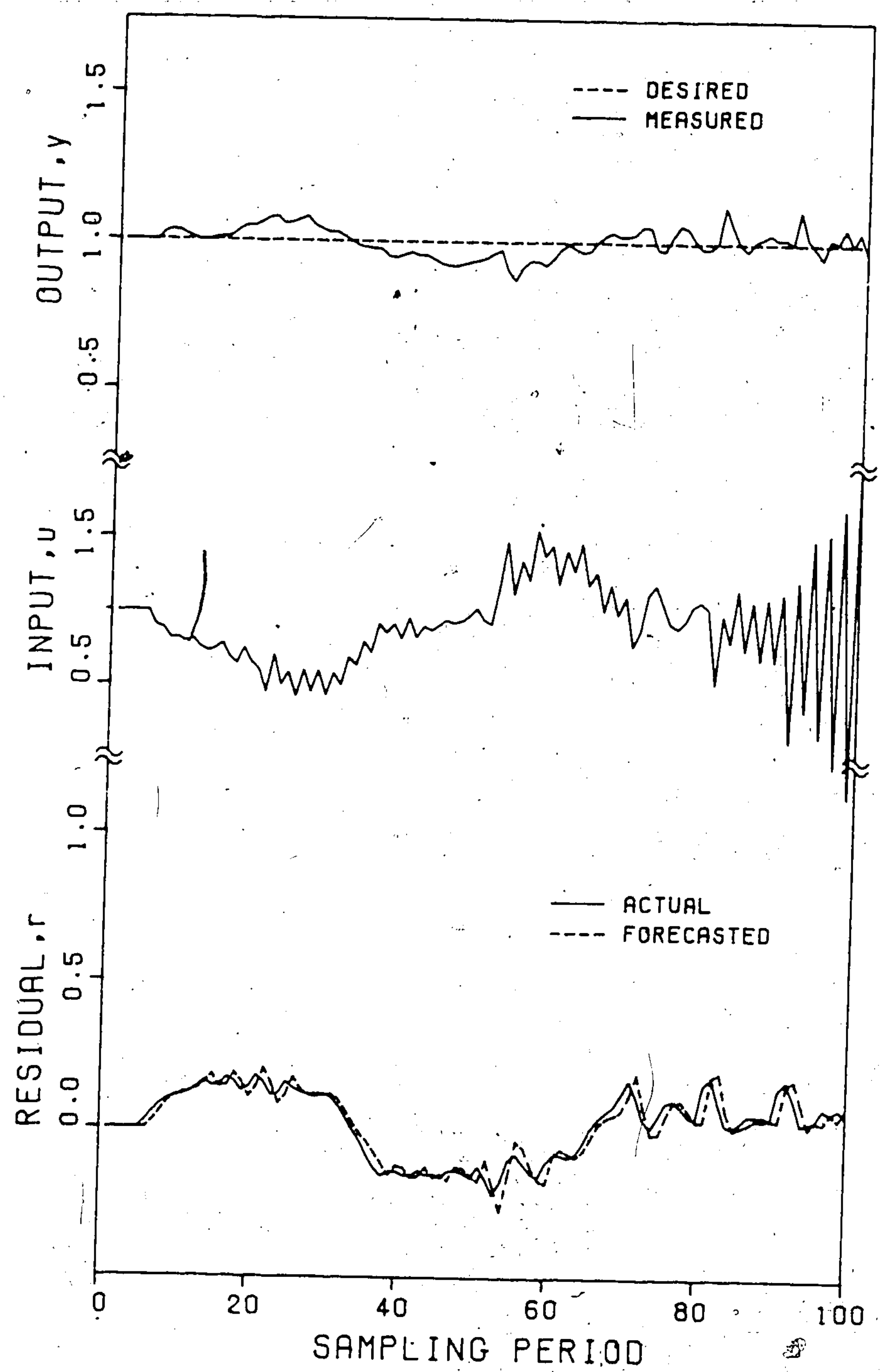

Figure 5.9 Compensation of Noise-free Disturbance APCS (with Modelling Error) with AR SSF

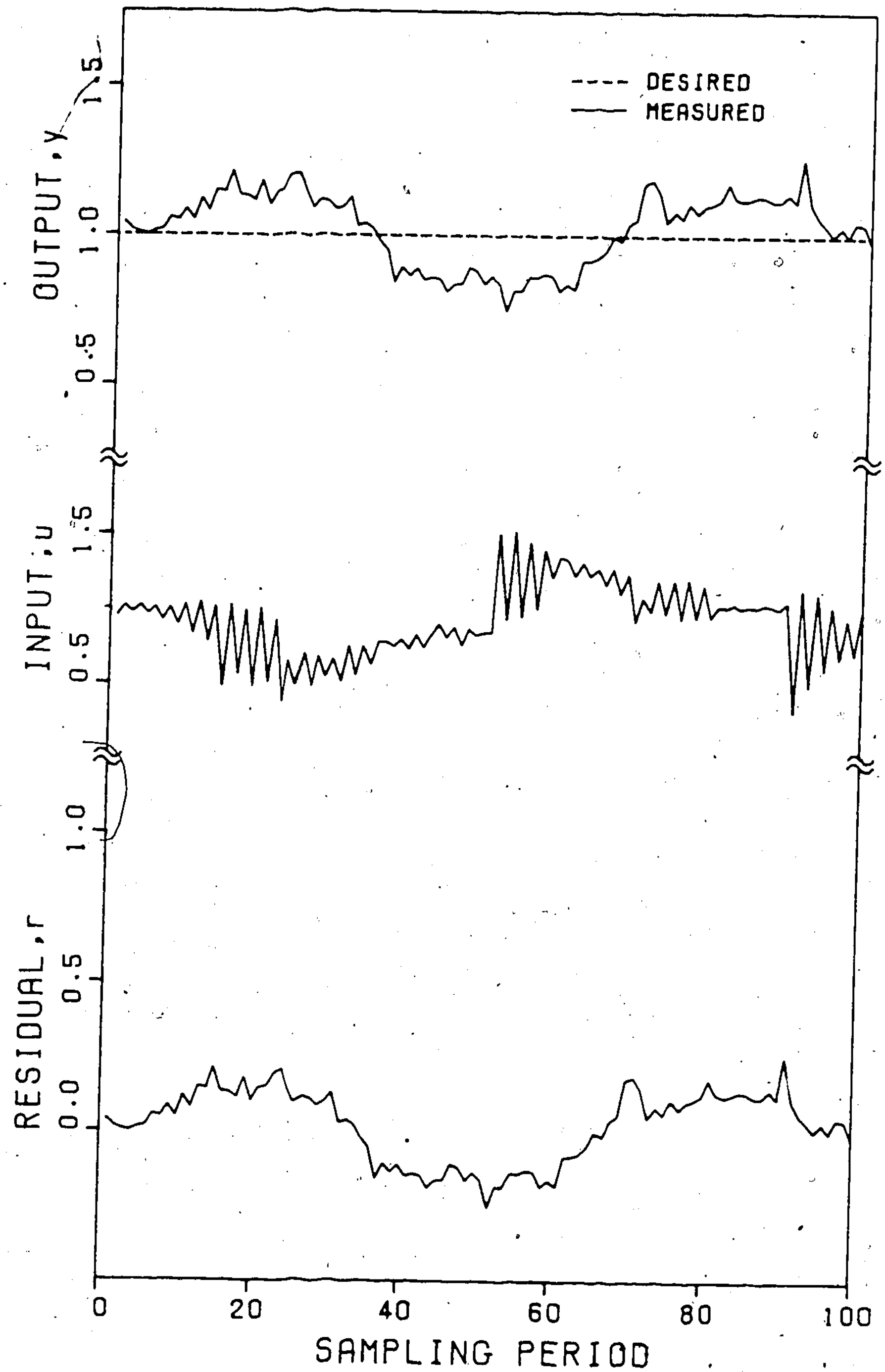

Figure 5.10 Compensation of Noisy Disturbance Using APCS (with Modelling Error)

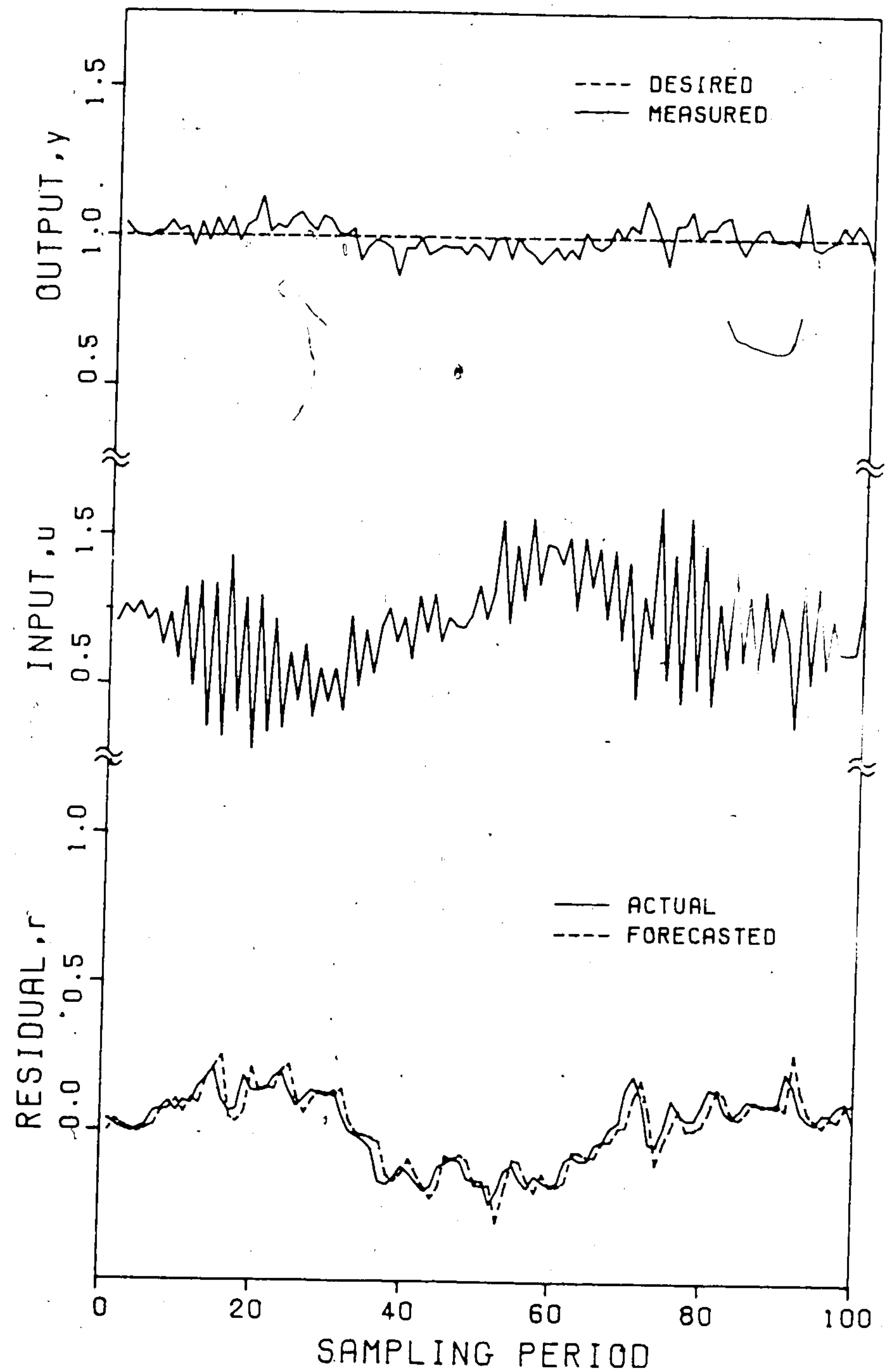

Figure 5.11 Compensation of Noisy Disturbance Using APCS (with Modelling Error) with AR SSF

5.5 Conclusions

1) Adaptive control systems, such as APCS, use the magnitude of the estimation error as a criterion for switching identification on and off to prevent the disturbances from corrupting the identificaton of the true input-output relationship of the process. However, this criterion also has the disadvantage of not utilizing the information in the estimation error when the identification is off.

2) The addition of SSF to adaptive control systems such as APCS provides a second level of control when identification is suspended. SSF generates future values of the residual for the controller to provide additional control action to compensate for unmeasured disturbances and/or modelling errors. The second level of control also helps to prevent unnecessary corruption of the process I/O model.

3) When SSF is used with APCS, it provides the advantage that the stability proof of APCS is maintained since the forecasting is done when APCS identification is off.

4) Simulation results confirm the improvement expected from the second level of control based on SSF. Modelling errors degrade the performance of APCS but can be compensated for by SSF. The performance of the AR forecaster is not significantly affected by the presence of noise and is therefore recommended for use over other forecasters.

6. Application of SSF

6.1 Introduction

In the previous chapters, the idea of using SSF as a means to compensate for unmeasured disturbances has been introduced. Numerical examples were used to illustrate the concepts presented. In this chapter, SSF is applied to a simulated double effect evaporator in order to study its practical usefullness in a more realistic application. SSF is applied as an improvement to APCS for the compensation of unmeasured disturbances. The performance is compared to that of the conventional feedback control and the basic APCS.

6.2 The Evaporator

6.2.1 Description of the Equipment

The evaporator whose model is used in the simulation studies is the double effect pilot plant evaporator in the Department of Chemical Engineering, University of Alberta. The evporator has been described in detail by Fisher and Seborg (1976) and its schematic diagram is shown in Figure 6.1.

The first effect of the evaporator is a natural circulation calandria type unit with thirty-two 18 inch

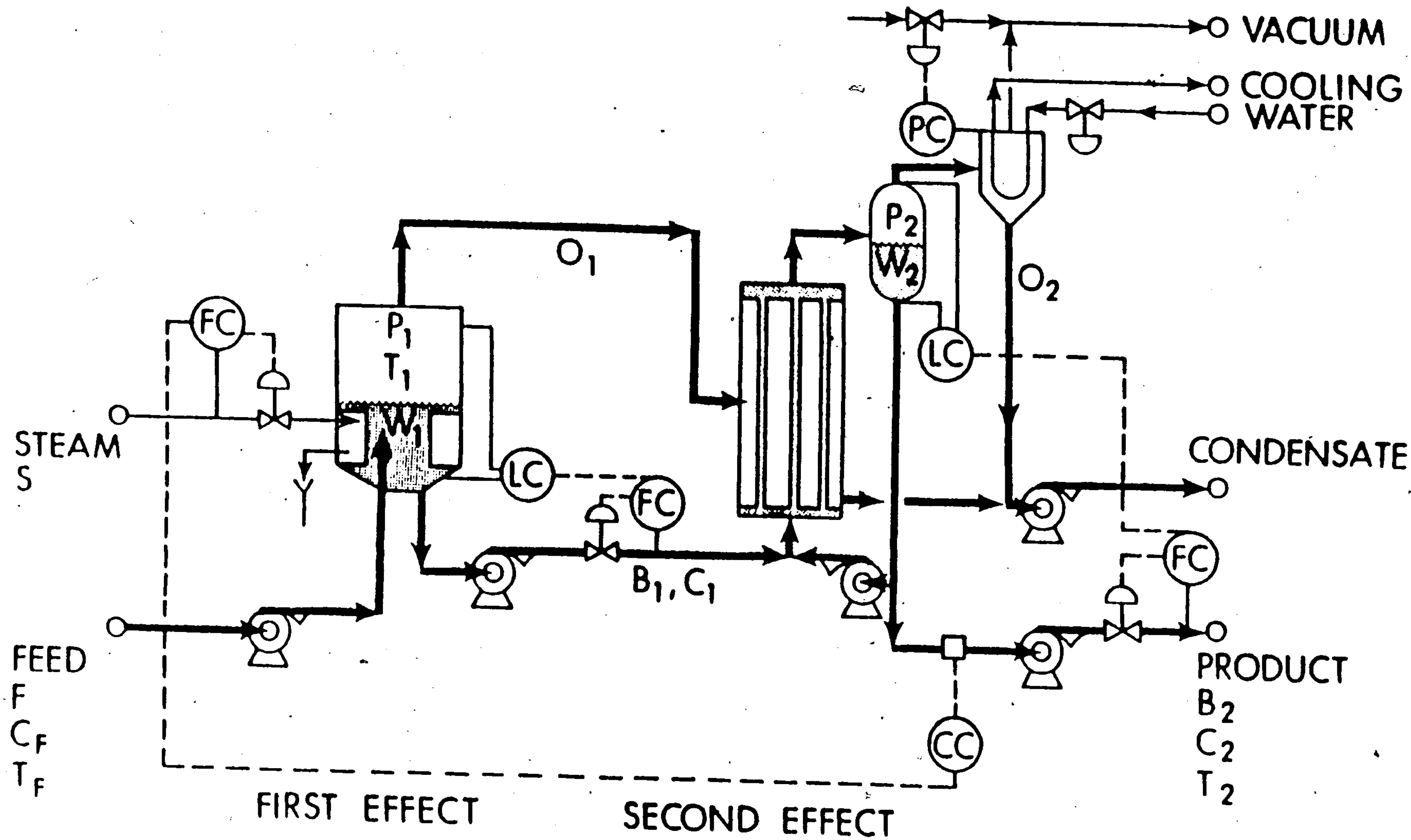

Figure 6.1 Schematic Diagram of the Double Effect Evaporator

long, 3/4 inch OD tubes. It is heated by process steam. The second effect is a forced circulation long tube unit with three 6 feet long, 1 inch OD tubes. It is operated under vacuum and is heated by the overhead vapor from the first effect.

The evaporator is fully equipped with industrial electronic instrumentation and is interfaced to an HP/1000 computer via a LSI-11 microcomputer in the Data Acquisition, Control and Simulation (DACS) Centre of the Department of Chemical Engineering at the University of Alberta. Therefore, evaluation of advanced control techniques can be easily carried out on the evaporator.

The primary controlled variable of the evaporator is the product concentration, C_2, from the second effect. It is controlled by manipulating the steam flow rate, S. Other important controlled variables are the first effect holdup, W_1, and the second effect holdup, W_2. They are controlled by manipulating the first effect bottom flow rate, B_1, and the second effect bottom flow rate, B_2, respectively. When the evaporator is used as a single-input-single-output system, the C_2/S loop is used and the other loops are closed by conventional feedback control.

6.2.2 Evaporator Model

Several models have been developed for the double effect evporator in previous studies Newell (1971); Wilson

(1974). They range from a tenth-order nonlinear model to a first order transfer function model. The evporator model used in this work is the fifth order nonlinear model developed by Newell (1971). The model consists of five ordinary differential equations and a set of algebraic equations. The equations are given as follows.

Steam chest :

$$S\,\lambda_s = U_1A_2\,(T_s-T_1) \qquad (6.1)$$

First effect :

$$\frac{dW_1}{dt} = F - B_1 - O_1 \qquad (6.2)$$

$$W_1\,\frac{dC_1}{dt} = F\,(C_0-C_1) + O_1C_1 \qquad (6.3)$$

$$W_1\,\frac{dh_1}{dt} = F\,(h_0-h_1) - O_1(Hv_1-h_1) + Q_1 - L_1 \qquad (6.4)$$

where

$$Q_1 = U_1A_1\,(T_s-T_1) \qquad (6.5)$$

$$O_1 = (Q_2+L_2)\,/\,(Hv_1-hc_2) \qquad (6.6)$$

$$Q_2 = U_2A_2\,(T_1-T_2) \qquad (6.7)$$

Second effect :

$$\frac{dW_2}{dt} = B_1 - B_2 - O_2 \tag{6.8}$$

$$W_2 \frac{dC_2}{dt} = B_1(C_1 - C_2) + O_2 C_2 \tag{6.9}$$

where

$$O_2 \left(Hv_2 - h_2 + \frac{\partial h_2}{\partial C_2} C_2\right) = Q_2 - L_2 + B_1(h_1 - h_2) + \frac{\partial h_2}{\partial C_2} B_1 (C_2 - C_1) \tag{6.10}$$

Some property relations are :

$$Hv = 0.4Tv + 1066.0 \tag{6.11}$$

$$hc = Tv - 32.0 \tag{6.12}$$

$$hsol = Tsol\ (1 - 0.16Csol) - 32.1 \tag{6.13}$$

A FORTRAN evaporator simulation program was written based on the above equations. The differential equations were solved by the Fourth order Runge-Kutta Method with a simulation interval of 0.1 minute. Steady state operating data for the evaporator were obtained from Wilson's thesis (1974) and are tabulated in Appendix A.

3 Practical Considerations

In applying APCS with SSF to a real process or a model one, there are many practical considerations in the implementation. The following discussion will address these considerations in the application of APCS with SSF to the double effect evaporator model.

1) Process model order

APCS requires an ARMA process model whose parameters are identified on-line. The order of the model should theoretically match the order of the process. However, in practice, a low order model is usually sufficient as an approximation. For the evaporator, a second order model is used. The equation of the model is

$$y(k) = a_1 y(k-1) + a_2 y(k-2) + b_1 u(k-1) + b_2 u(k-2) \quad (6.14)$$

There is considerable modelling error as can be seen by comparing equation (6.14) versus equations (6.1) through (6.13). Note that one of the purposes for using SSF is to help compensate for modelling errors.

2) Initial parameters

The choice of the initial parameters for the model is critical to the performance of the control algorithm. A discussion on the choice of initial parameters for APCS has been given by Song (1983). In the following application, a set of identified parameters from Song's doctoral thesis (1983) were chosen. They were used as starting values in a period of parameter identification which yielded a more accurate set of parameters for use as initial parameters in the simulation studies.

3) Scaling of variables

The evaporator model generates values in absolute engineering units. If the variables used in the process model are in engineering units, the magnitude of the model parameters may vary greatly and computational problems may result. Therefore, the input and output variables have to be normalized. In this case, the normalization is based on the steady state values.

4) Sampling interval

The choice of sampling interval for adaptive control systems should relate to the time constant of the process. For the evaporator, the sampling interval should be about 3 to 4 minutes. However, the actual evaporator is usually run with a sampling interval of 64 seconds. Therefore, a sampling interval of 1 minute is used for the simulation studies.

5) AR forecaster order

Theoretically, the order of the AR forecaster should match the order of the residual series. However, since only short term forecasts are made, a third order AR forecaster is used to reduce the computational effort. The form of the AR forecaster is

$$\hat{r}(k+1) = \alpha_1 r(k) + \alpha_2 r(k-1) + \alpha_3 r(k-2) \qquad (6.15)$$

6) Initial parameters for the AR forecaster

The choice of the initial parameters for the AR forecaster affects the accuracy of the forecast. Using engineering judgment, the initial parameters have been chosen so that the AR forecaster is initialized to use the current value as its forecast. This is a good approximation and provides reliability for the SSF. The parameters are

$$\alpha_1 = 1$$

$$\alpha_2 = \alpha_3 = 0$$

7) Identificaton algorithm for the AR forecaster

Many parameter identification algorithms are available for on-line identification. The APCS projection algorithm (equation (2.9)) has been chosen because of its simplicity and the author's familiarity with it.

6.4 Simulation Results

The performance of conventional feedback control, APCS and APCS with SSF was studied. The evaporator was subject to a noisy disturbance sequence in the feed flow rate. The control objective for the system was to maintain the product concentration at the setpoint value.

Figure 6.2 shows the case for a well tuned feedback PI controller (K_c = 200, K_i = 0.1). The control action is not sufficient to keep the output at the setpoint. The product concentration deviates from the setpoint due to the feed disturbance. Figure 6.3 shows the performance of a well tuned feedback PID controller (K_c = 300, K_i = 0.15, K_d = 0.3). The addition of the derivative mode improves control since it provides anticipatory action (c.f. Chapter Three). However, the product concentration still deviates from the setpoint slightly.

Figure 6.4 shows the performance of APCS. Since the identification is off, the controller parameters are fixed and the controller cannot compensate for the varying disturbances. Figure 6.5 shows the case where SSF has been added to APCS. SSF provides additional control action when APCS identification is off. The disturbances were compensated and there is significant improvement in the output response.

Comparing the four cases in Figures 6.2 to 6.5, it can be concluded that the concept of SSF, whether applied in conjunction with a predictive controller (APCS) or a

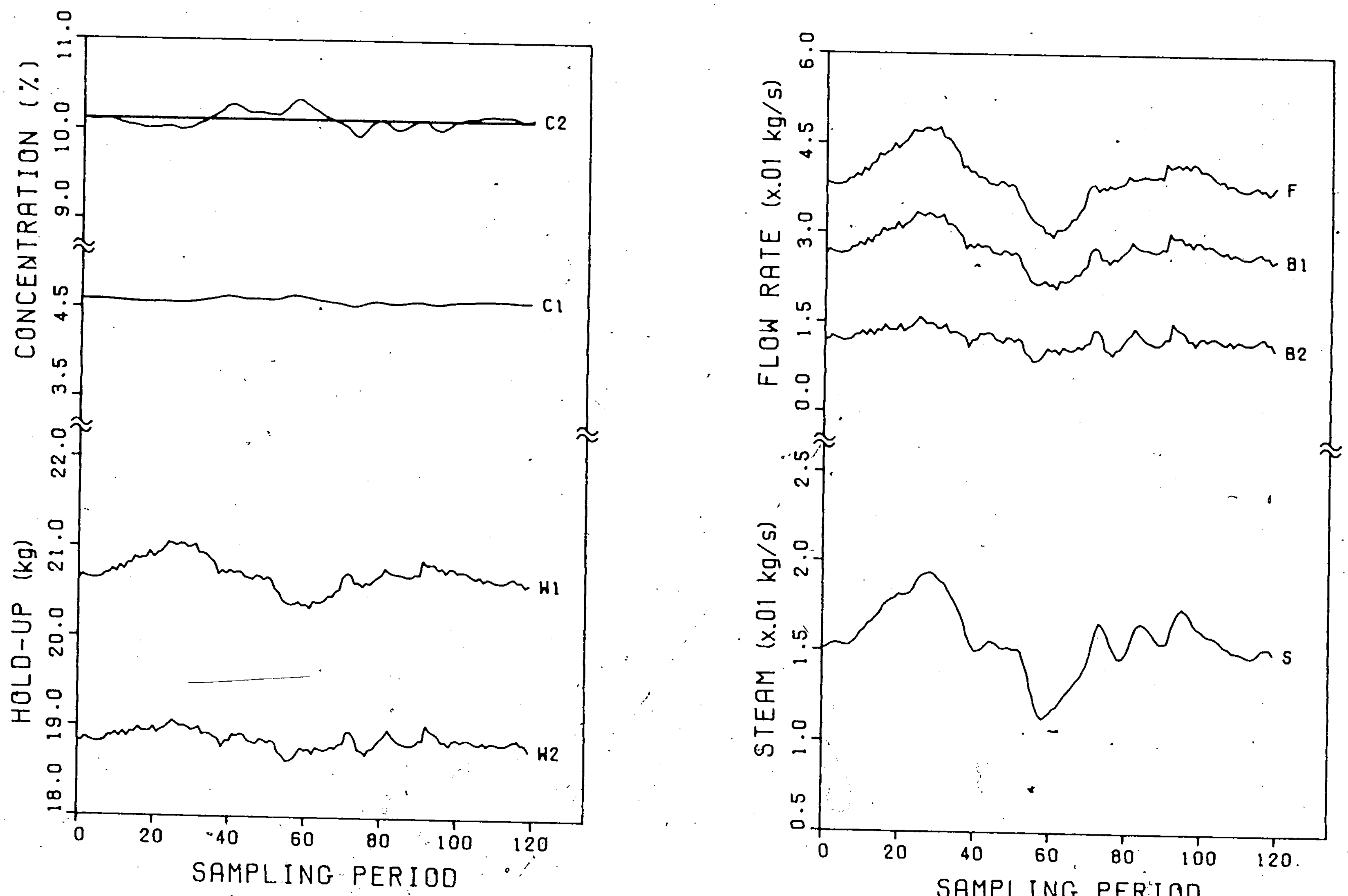

Figure 6.2 Evaporator Response to Feed Disturbances Using PI Controller (Kc=200, K_I=0.1)

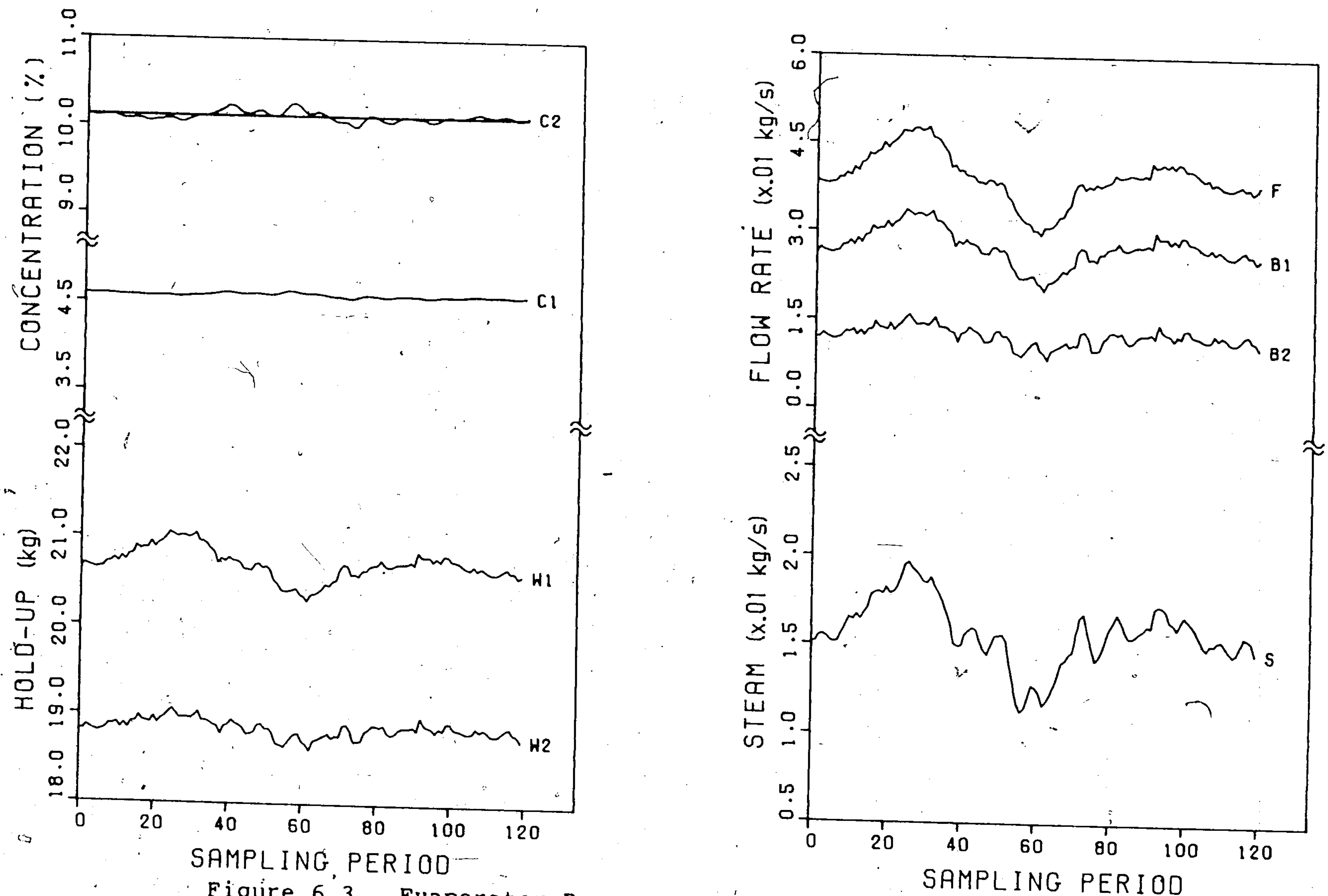

Figure 6.3 Evaporator Response to Feed Disturbances Using PID Controller (Kc=300, K_I=0.15, K_d=0.3)

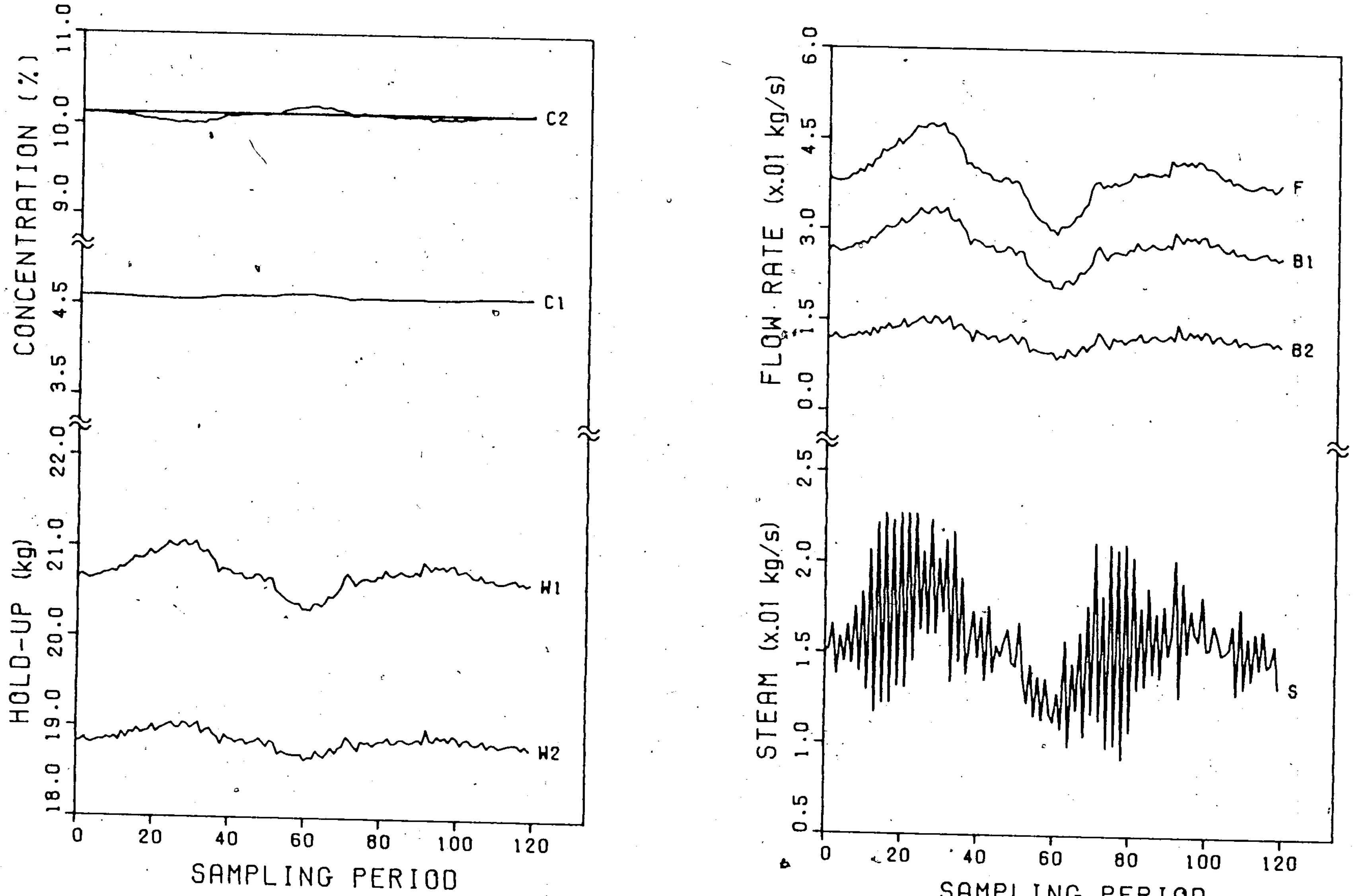

Figure 6.4 Evaporator Response to Feed Disturbances Using APCS

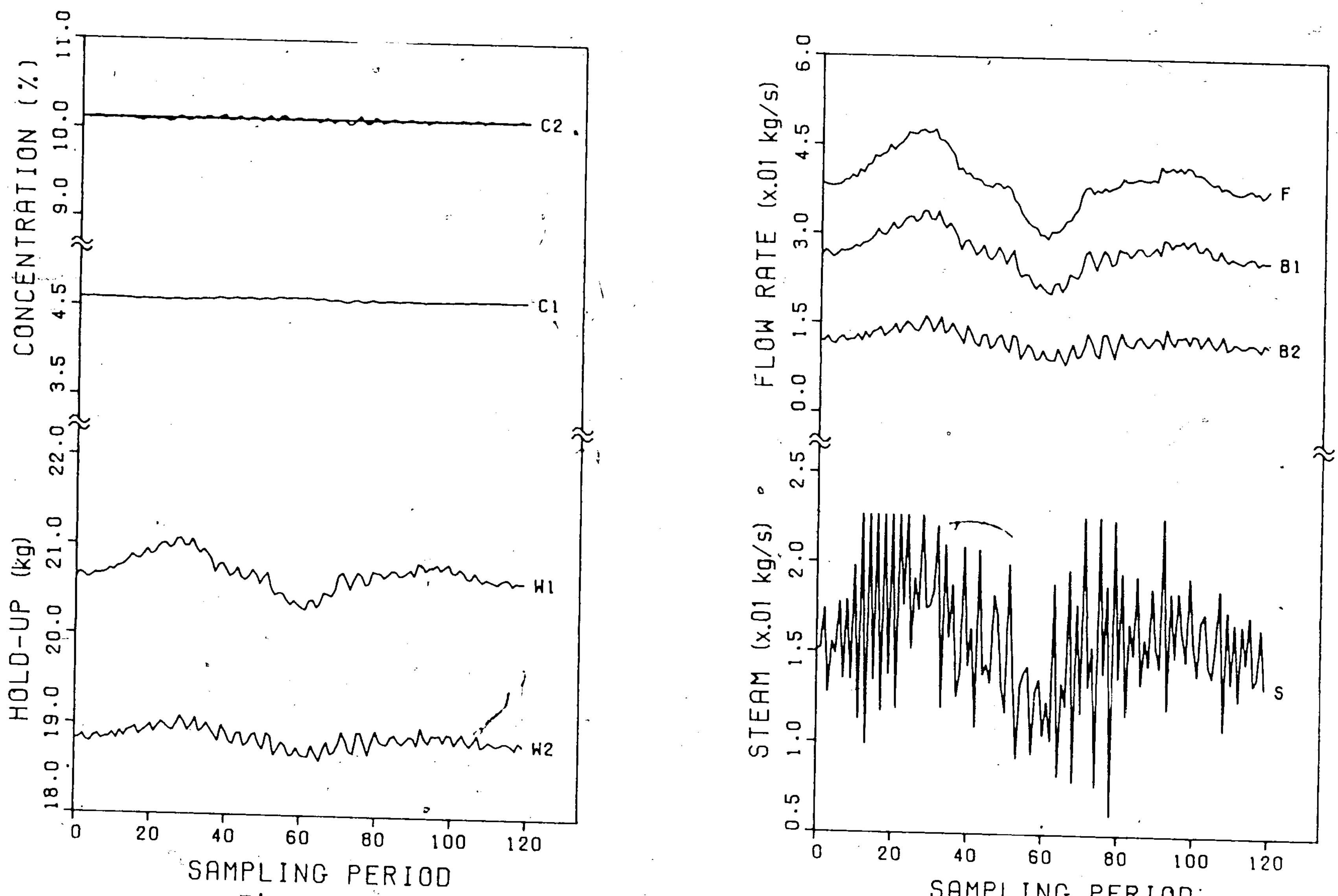

Figure 6.5 Evaporator Response to Feed Disturbances Using APCS with AR SSF

non-predictive controller (feedback control), can be used to improve a control system's performance in disturbance compensation and/or in accommodating modelling errors. However, the practical justification will vary in individual cases and the advantages gained will have to be evaluated relative to cost and overall system performance.

7. Conclusions

7.1 Conclusions

The conclusions resulting from this study can be divided into two categories:

A) those relating to the performance of SSF, and

B) insights gained by comparing other classical and modern control techniques with SSF.

A1) SSF can result in perfect control if the process I/O model and the forecast are perfect. However, the quality of control deteriorates due to factors such as large amounts of random noise, strong nonlinearities, which make forecasting difficult.

A2) The forecaster should be able to predict the future values of the residual time series λ sampling periods into the future where λ is the sum of the sampling plus process delays. Autoregressive forecasters of moderate order provided better performance in the simulated studies than simple linear extrapolation or the assumption that $r(k+\lambda) = r(k)$.

A3) Since a process I/O model is required for the implementation of SSF and since a model based (e.g. predictive) controller gives, in general, better performance than, say, a PID controller, the base case for comparing the advantages of SSF should assume the use of a predictive controller.

A4) Several simulated runs showed that SSF helped to compensate for unmeasured disturbances and/or modelling errors. However, when used with a perfect predictive controller, the best that SSF can do is provide compensation for the effect of a disturbance at time k rather than λ periods later. Thus its practical usefulness is limited.

A5) The addition of SSF to adaptive control systems such as APCS, which uses the magnitude of the estimation error as a criterion for switching identification on and off, provides a second level of control. When identification is stopped to prevent the I/O model from being corrupted by the disturbances, the second level of control comes in to provide short term compensation for unmeasured disturbances and/or modelling errors based on information of the residual.

A6) When SSF is used with APCS, it provides the advantage that the stability proof of APCS is maintained since the forecasting is done when APCS identification is off.

B1) Classical proportional plus derivative feedback control can be interpreted as SSF of y(k) in conjunction with a proportional controller.

B2) From the equivalence relationship of the feedback control structure and the IMC structure, the design rule that the IMC controller should approach the inverse of the process model is readily seen as being equivalent to the classical design observation that perfect control is approached as the feedback gain approaches infinity. (There are of course stability and performance limitations with most practical systems.)

B3) IMC can be interpreted as an SSF system that uses the current value of the residual r(k) as an estimate of the future value r(k+λ). This implies that IMC can also be interpreted as a classical feedforward scheme based on the forecasted (estimated) disturbance rather than the actual measured value.

7.2 Recommendations

1) The primary concern in this thesis is to investigate the idea of using SSF to improve control. The issues involved in the implementation of SSF, such as the choice of process model, forecaster and controller, have not been addressed in detail and are proposed for future work.

2) Extension of the use of SSF in multi-input multi-output (MIMO) systems is recommended for investigation.

3) Experimental evaluation of SSF should provide results for verification of the conclusions drawn from simulations in this thesis.

4) The interpretation of the forecaster as a disturbance model suggests a possible relationship with the Internal Model Principle by Wonham. Future work can also be done in this area.

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Appendix A : Steady State Operating Data for the Evaporator

The following steady state operating data for the double effect evaporator were taken from Wilson's thesis (1974) and listed in SI units.

Ts	steam temperature	177.8 C
Tw1	First effect tube wall temperature	108.3 C
W1	First effect holdup	20.64 kg
C1	First effect concentration	4.59 % glycol
H1	First effect enthalpy	440.1 kJ/kg
Tw2	Second effect tube wall temperature	82.8 C
W2	Second effect holdup	18.82 kg
C2	Second effect concentration	10.11 % glycol
H2	Second effect enthalpy	311.9 kJ/kg
Tw3	Condenser tube wall temperature	42.2 C
S	Steam flow	0.0151 kg/s
B1	First effect bottom flow	0.0263 kg/s
B2	Second effect bottom flow	0.0120 kg/s
F	Feed flow	0.0378 kg/s
CF	Feed concentration	3.2 % glycol
HF	Feed enthalpy	364.9 kJ/kg

Appendix B : Data for simulation examples of Chapter 3

General data :

Process : $y(k) = 0.8y(k-1) + 0.6u(k-1) + \xi(k) + 0.5\xi(k-1)$

Constant setpoint : $y_s = 3.0$

Simulation time : 100 sampling periods

Process subject to random disturbances

Predictive controller : $u(k) = [y_s(k+1) - \hat{r}(k+1) - 0.8y(k)]/0.6$

Linear SSF : $\hat{r}(k+1) = r(k) + (r(k) - r(k-1))$

AR SSF : $\hat{r}(k+1) = \alpha_1 r(k) + \alpha_2 r(k-1) + \alpha_3 r(k-2)$

Initial values : $\alpha_1 = 1.0$

$\alpha_2 = 0.0$

$\alpha_3 = 0.0$

Identification : APCS adaptive algorithm

Cases and specific data :

1. Feedback controller

   Figure 3.6 Proportional controller

   $Kc = 1.7$

   Figure 3.7 Proportional-derivative controller

   $Kc = 1.7$ $K_d = 1.0$

2. Predictive controller with and without SSF

   Figure 3.8 Perfect SSF

   Figure 3.9 No SSF

   Figure 3.10 Linear SSF

   Figure 3.11 AR SSF

Appendix C : Data for simulation examples of Chapter 4

General data :

Process : $y(k) = 0.158u(k-1) + 0.264u(k-2) + 0.226u(k-3) + 0.156u(k-4) + 0.096u(k-5) + 0.053u(k-6) + 0.027u(k-7) + 0.013u(k-8)$

Constant setpoint : $y_s = 0.0$

Tuning parameters : $P = M = 8$

$\gamma_1 = \gamma_2 = \ldots = \gamma_8 = 1$

$\beta_1 = \beta_2 = \ldots = \beta_8 = 0$

Simulation time : 100 sampling periods

Linear SSF : $\hat{r}(k+1) = r(k) + (r(k) - r(k-1))$

AR SSF : $\hat{r}(k+1) = \alpha_1 r(k) + \alpha_2 r(k-1) + \alpha_3 r(k-2)$

Initial values : $\alpha_1 = 1.0$

$\alpha_2 = 0.0$

$\alpha_3 = 0.0$

Identification : APCS adaptive algorithm

Cases and specific data :

1. Compensation of noise-free disturbances

Figure 4.7 IMC

Figure 4.8 IMC with Perfect SSF

Figure 4.9 IMC with Linear SSF

Figure 4.10 IMC with AR SSF

2. Compensation of noisy disturbances

   Figure 4.11 IMC

   Figure 4.12 IMC with Linear SSF

   Figure 13 IMC with AR SSF

3. Compensation of noisy disturbances with filter

   Filter : $F(z) = \dfrac{1 - \alpha}{1 - \alpha z^{-1}}$

   $\alpha = 0.3$

   Figure 4.14 IMC

   Figure 4.15 IMC with Linear SSF

   Figure 4.16 IMC with AR SSF

Appendix D : Data for simulation examples of Chapter 5

General data :

Process : $y(k) = 1.030\ y(k-1) - 0.289\ y(k-2) + 0.158\ u(k-1) + 0.101\ u(k-2)$

Constant setpoint : $y_s = 1.0$

Simulation time : 100 sampling periods

Linear SSF : $\hat{r}(k+1) = r(k) + (r(k) - r(k-1))$

AR SSF : $\hat{r}(k+1) = \alpha_1 r(k) + \alpha_2 r(k-1) + \alpha_3 r(k-2)$

Initial values : $\alpha_1 = 1.0$

$\alpha_2 = 0.0$

$\alpha_3 = 0.0$

Identification : APCS adaptive algorithm

Cases and specific data :

1. Compensation of noise-free disturbances with perfect model

   Figure 5.3 APCS

   Figure 5.4 APCS with Linear SSF

   Figure 5.5 APCS with AR SSF

2. Setpoint tracking with imperfect model

   Setpoint change : 1.0 to 1.3

   Figure 5.6 APCS

   Figure 5.7 APCS with AR SSF

3. Compensation of noise-free disturbances with imperfect model

Figure 5.8 APCS

Figure 5.9 APCS with AR SSF

4. Compensation of noisy disturbances with imperfect model

Figure 5.10 APCS

Figure 5.11 APCS with AR SSF

Appendix E : Data for simulation examples of Chapter 6

General data :

Process : 5th order nonlinear evporator model

Simulation time : 120 minutes

Process subject to feed disturbances

AR SSF : $\hat{r}(k+1) = \alpha_1 r(k) + \alpha_2 r(k-1) + \alpha_3 r(k-2)$

Initial values : $\alpha_1 = 1.0$

$\alpha_2 = 0.0$

$\alpha_3 = 0.0$

Identification : APCS adaptive algorithm

Cases and specific data :

1. Feedback control

Figure 6.2 Proportional-integral controller

Kc=200 K_i=0.1

Figure 6.3 Proportional-integral-derivative controller

Kc=300 K_i=0.15 K_d=0.3

2. APCS with and without SSF

Figure 6.4 APCS

Figure 6.5 APCS with AR SSF