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An application of adaptive techniques in the control of a class of manufacturing processes

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AN APPLICATION OF ADAPTIVE TECHNIQUES IN THE CONTROL OF A CLASS OF MANUFACTURING PROCESSES

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ABSTRACT

The application of adaptive, steady-state control to batch type manufacturing processes is addressed. An empirical modeling technique based on steepest ascent is developed and the performance of an optimal control system is compared with that of an adaptive control system.

A Tantalum Nitride Sputtering Process is simulated and the empirical modeling procedure is used to obtain a process model. The model thus derived is used in both a model based optimal control system and a model referenced adaptive control system, both of which are implemented on the simulated batch process.

The investigation indicated that the empirical modeling technique to be effective in the case tested. The index of performance of the optimal control system was found to be a critical factor in control system operation. The results also indicated that the model based optimal control system performed considerably better than the model referenced adaptive control system under all conditions of drift and measurement error tested.

1.0 INTRODUCTION

The subject of this thesis is the application of adaptive control to a class of manufacturing processes. Adaptive control is a new and powerful concept in the field of automatic control. An adaptive control system reacts to its environment. It automatically measures the characteristics of its outputs and the process being controlled, and, on the basis of these measurements, adjusts the over-all system to better suit prevailing conditions. Important attributes of adaptive control are performance consistency, the ability to improve system performance, and the ability to cope with unknown elements of a process or its environment.

In the past, one approach to automatic process control has been to apply the techniques of linear control theory. Although most real processes are definitely non-linear, many display what may be considered to be linear characteristics over some portion of their operating region. Linear control theory is used to derive a fixed relationship (transfer function) between the process inputs and the process outputs. Control of the process is maintained through a feedforward, feedback, or combined feedforward-feedback configuration of the system.

The simple single loop feedback control system shown diagrammatically in Figure 1 illustrates the conventional linear control theory approach to process control. The basic concept of automatic control is embodied in such a system. The control system consists of

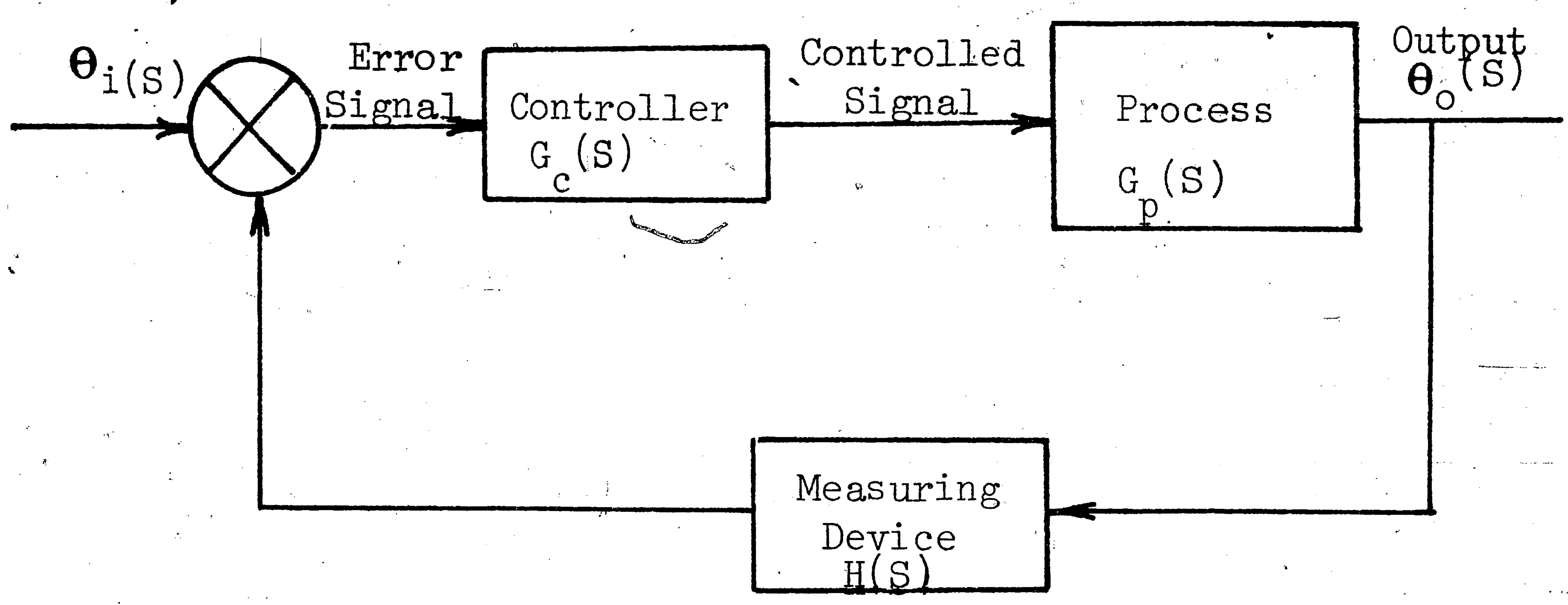

Figure 1. A Simple Single Loop Feedback Control System

a process to be controlled, a device for measuring the value of the system output, a comparator for generating an error signal measuring the deviation of the output signal from the desired value, and a controller which modifies the error signal and generates a manipulating signal for correcting the state of the system in such a way as to drive the error toward zero. The transfer function for the system is derived by expressing the system input and output, together with the characteristic equations of the controller, process, and measuring device, as the Laplace Transforms of the time varying functions. Then the ratio of the system input, $\theta_i(S)$, to system output, $\theta_o(S)$, is found to be:

$$T(S) = \frac{\theta_i(S)}{\theta_o(S)} = \frac{G_c(S)\, G_p(S)}{1 - H(S)\, G_c(S)\, G_p(S)}$$

1.1 CONCEPTS OF ADAPTIVE CONTROL

Although there exists a substantial amount of literature in the area, there is not general agreement on how one would formulate the definition of adaptive control. Definitions given by the experts in the field range from broad to specific. As an example of the broader definitions, Truxal[27], in his general discussion on the subject, describes an adaptive control system as any control system which has been designed with an adaptive viewpoint. A more precise definition which in essence encompasses the definitions given by a number of experts is given by Gibson[19] who defines an adaptive control system as a control system which provides a means for monitoring its own performance in relation to a given figure of merit or optimum condition and a means of automatically modifying the systems parameters, by closed loop action, to approach this optimum.

Adaptive control consists of three basic functions -- identification, decision, and modification[21]. Although some experts[26] lump the decision and modification functions into a single control function, there is general agreement that these functions are characteristics of an adaptive system. These functions are defined as follows:

(1) Identification function -- the adaptive controller must evaluate the state of the process on either a continuous or a periodic basis. This means that the performance quality of the

process is evaluated. This requires that the performance quality be characterized by some index of performance (also referred to as the figure of merit). The identification function thus involves the computation of this index of performance based on measurements of the important process variables.

The identification function is required since there is some aspect of the process which is changing with time. Control systems would not need to be adaptive if operating conditions remained constant. Unfortunately, most processes are operated where conditions are quite unpredictable. There are many sources of these changes in operating conditions. The relationships which define the process and its environment may change according to some unknown influence. There may also be random (stochastic) disturbances to the process and/or its environment which may be time-varying in nature. These changes affect the performance of the control system, whatever the source. Hence, the system must monitor its own performance to maintain effectual operation.

(2) Decision Function -- once the process performance has been identified, a decision must be made as to how the system should be altered (adapted) so as to improve the performance. If the performance is not adequate, it is the objective of the adaptive controller to decide according to some predetermined strategy how to best improve the index of performance. The decision function thus determines the course of action to be followed in order to move the index of performance toward an optimal value. The decision

may be to change one or more internal control parameters or to adjust the process variables, depending upon the adaptive strategy employed.

(3) Modification function -- The modification function is the means of implementing the decision made in the decision function. This involves the changing of system parameters or the adjustment of process variables as required to force improvement in system performance.

A simplified block diagram of an adaptive control system is shown in Figure 2. Note that while the identification computer and the control computer are shown as separate entities, in actuallity

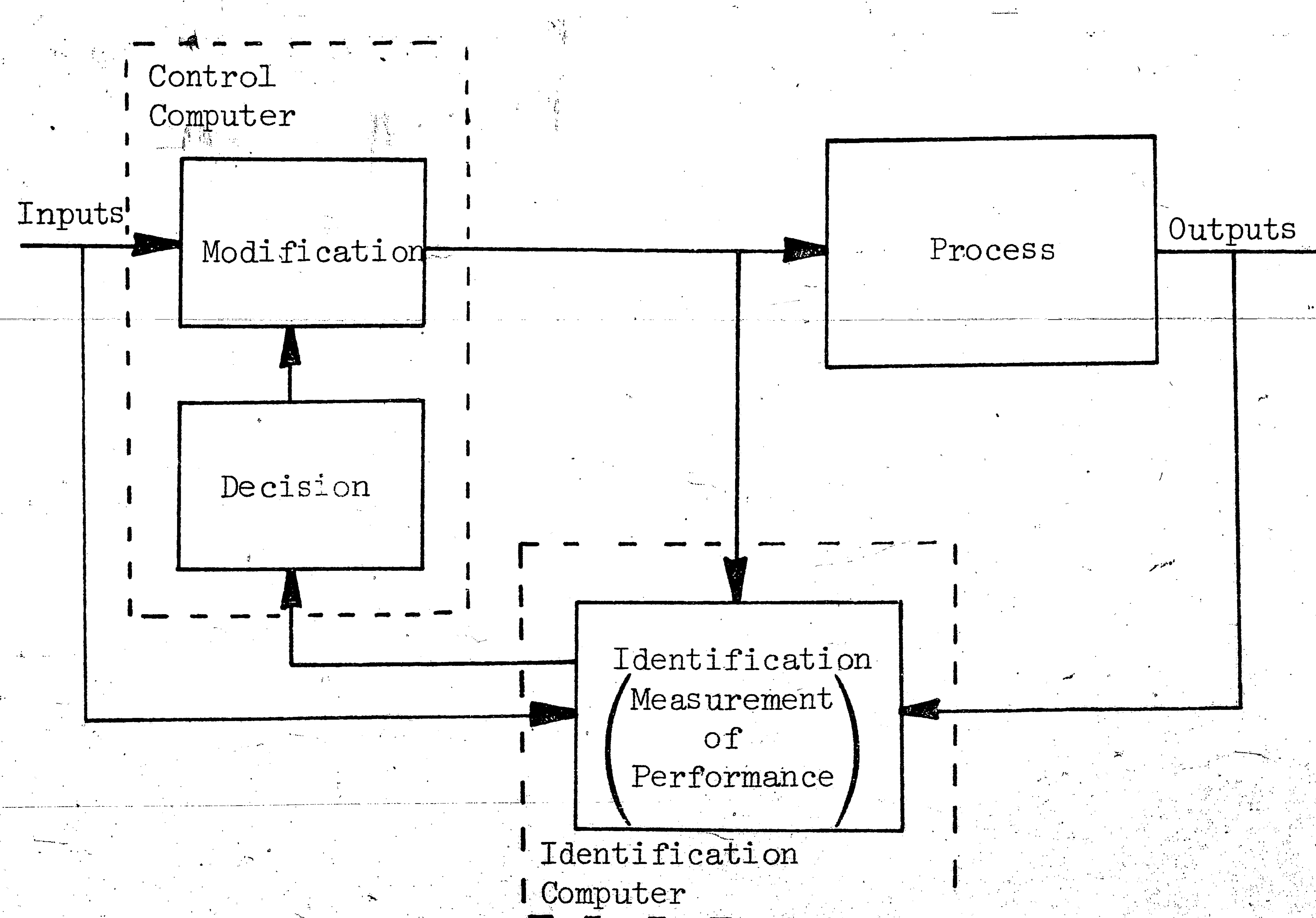

Figure 2. A Generalized Adaptive Control System

both functions are performed by the same computer. The figure shows the three functions performed by the adaptive system. The identification function compares the process outputs (performance) to the desired process performance (inputs), a decision is made concerning improvement of performance which is in turn carried out by the modification function.

Special note should be made at this point concerning the importance of the index of performance in an adaptive control system. This is probably the most important aspect of the adaptive system since it is against this figure of merit that the process measures its own performance. The index of performance may be a directly measurable quantity or a calculated quantity. The final system response can be no better than this criterion, whatever its derivation.

Although adaptive control systems may take many diverse forms, this thesis will focus its attention on the type of adaptive systems classed as model referenced adaptive control systems. As the name implies, the model referenced system employs a reference model which is a simulation of the system's overall response (index of performance) as its identification function. The model referenced adaptive control system is explained in detail in the next section.

1.2 MODEL REFERENCED ADAPTIVE CONTROL

Model referenced adaptive control may best be explained in terms of the block diagram shown in Figure 3. The control system operates in the following way.

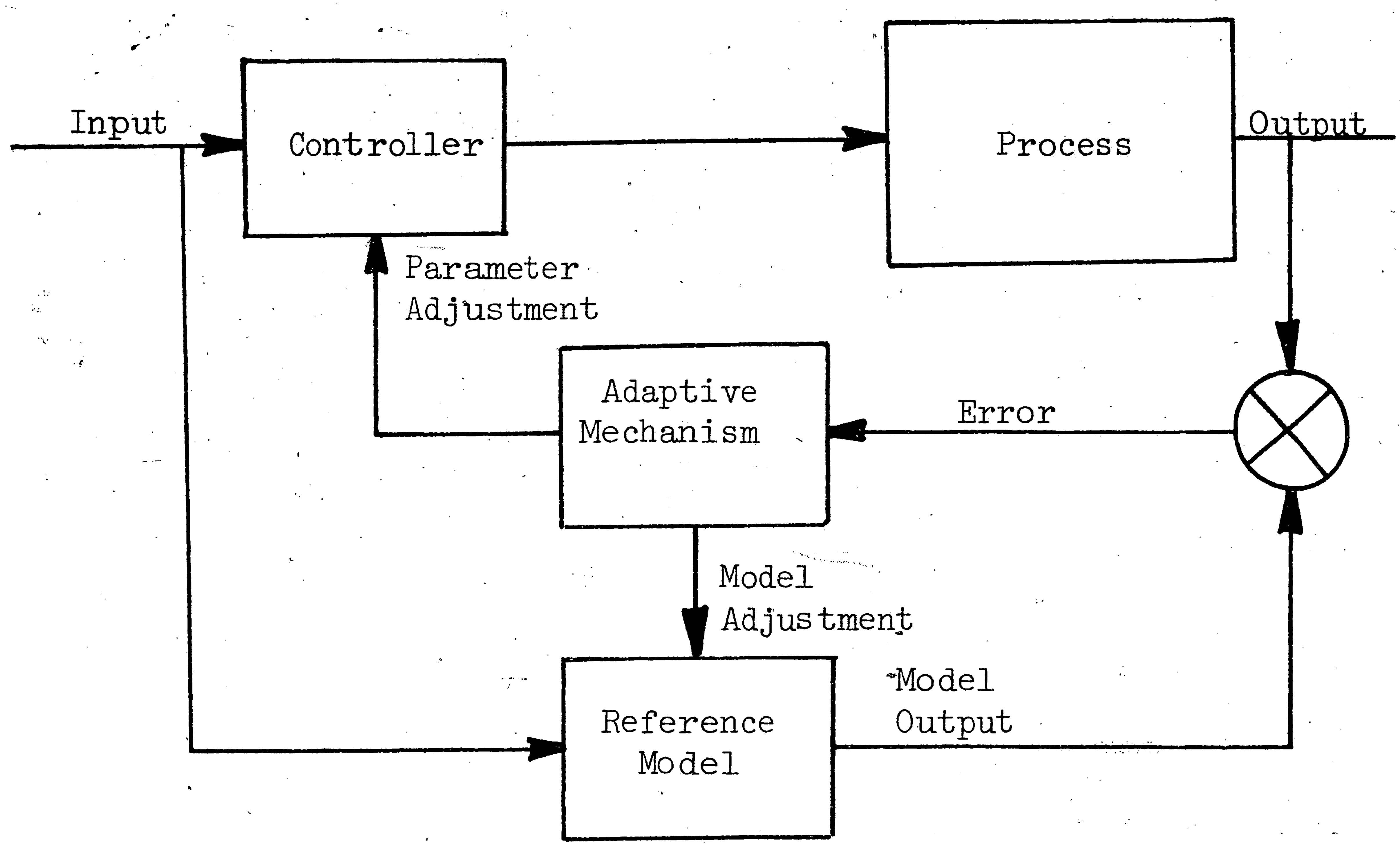

Figure 3. A Model Referenced Adaptive Control System

The same input signals are applied to both the reference model and the process and the output signals of each are compared. If the process response differs from the response of the reference model, then it is the objective of the adaptive strategy (mechanism) to determine how the process should be modified and implement the modification so that the system output closely matches that of the reference model. In this system, the identification function is performed by the reference model, while the decision function is performed by the adaptive mechanism and the modification function is performed by the controller.

It is evident that the model referenced system requires for its effective operation mathematical model of the process which relates the independent variables of the process to the dependent variables contained in the index of performance. The derivation of such a model could be approached in two ways:

(1) Analytically - through the application of the laws of physics and/or chemistry. If, however, the process is extremely complex or if the process is not fully understood, a satisfactory model would be extremely difficult to obtain analytically.

(2) Empirically - through controller experimentation on the process and statistical analyses performed on the experimental data.

The derivation of an adequate model of a process usually requires a combination of the two modeling techniques: the analytical to set up the basic model and the empirical to refine the model and "fill in the gaps". The modeling task can range in difficulty from trivial to impossible. Often the amount of empirical data required in the modeling task is tremendous and the cost of the sequential experimentation necessary is not insignificant. The large cost of process characterization has been a factor which has hampered the application of adaptive control to manufacturing processes.

Basically, however, there are two types of control strategies: steady state control and dynamic optimization and control.

(1) Steady state control. Steady state optimization is in the absence of transient effects. Time is not considered to be a continuous variable in this case. Steady state optimization is applicable in cases where external disturbances to the process are relatively infrequent as compared to the time required for the system to reach equilibrium after the occurrence of such a disturbance. This means that steady state control is suitable for processes in which the index of performance criterion is not significantly affected by transient behavior between control setting adjustments. Various optimizing machines may be used as the adaptive strategies when steady state control is employed -- gradient search, sequential search, mathematical programming, etc..

(2) Dynamic optimization and control. In cases where transient and nonequilibrium conditions are prevalent and have a significant effect on the index of performance during processing operations, dynamic optimizing control should be considered. This form of control is a more advanced control than steady state optimization. The control objective is to determine the optimal time dependent control function to optimize an index of performance subject to operational constraints and to

time and state dependent equations describing the rate of change of process state variables. It is desirable that the index of performance be completely observable during the continuous processing operation when dynamic control is employed. Where this is possible, continuous control procedures may be applied directly. Continuous control procedures such as model search or the variational approaches, which utilize dynamic programming or the maximum principle in their computational scheme, are usually extremely difficult to apply. For this reason, dynamic control is usually resorted to only if the projected performance improvement over steady state control is thought to justify the additional effort and expense.

Adaptive control systems have been used widely in the aero-space industry. In the control of industrial and manufacturing processes, however, the use of the adaptive concept has been somewhat restricted. The next section describes some current applications of adaptive control to manufacturing processes.

1.3 CURRENT APPLICATIONS OF ADAPTIVE PROCESS CONTROL

The literature of the past decade contains many diverse applications of adaptive control. The aero-space industry, especially, has applied adaptive techniques extensively in the area of automatic flight controllers for both supersonic aircraft and space vehicles.

In the area of manufacturing process control, adaptive techniques have been applied to both continuous and discrete (batch) processes. It would not be feasible to summarize here all significant applications of adaptive control. The applications to be described, however, are representative of the applications of adaptive techniques in the control of batch manufacturing processes.

Batch manufacturing processes represent a fertile area for the application of adaptive control. Processes of this type are subject to a number of sources of variation. Raw materials at the process input usually varies from batch to batch; tool and machine wear may cause variation within a batch; environmental conditions may affect both raw materials and machine performance. There have, however, been relatively few applications of adaptive control in this area.

Some of the strongest efforts to perfect adaptive control have been exerted in the machine tool industry. An adaptive control system, as applied to a machining process, would attempt to respond to the unpredictable changes in the process and at the same time attempt to optimize some relevant index of performance[21]. There are several sources of unpredictable change in machining processes. Variations in work price material (eg. hardness, strength, composition, etc.) affect tool wear. Tool wear then in turn affects the amount of metal which could be cut with the tool. Variations in width of cut and depth of cut due to variations in raw stock size and/or intentional variations as in profile milling operations must also be accounted for.

The Bendix Research Laboratories[10] has developed an adaptive milling machine controller to optimize operating profits. The milling process is a complex operation, many aspects of which are understood only through empirical data tables relating to such factors as tool wear rate, tool life, surface finish, and milling accuracy. These factors depend on characteristics such as hardness and temperature of the part being processed. Ideally, it is desirable to feed as rapidly as possible thereby maximizing machine output. Feed rate, however, is limited by available power, and increased feed rate often results in poor machining accuracy and vibration, which in turn results in excessive tool wear. In any practical system a compromose between feed rate, surface quality, final milling accuracy, and tool life would be required.

Bendix developed an index of performance to be optimized by the adaptive system which accomplishes the required compromise. The index of performance as given in reference 10 is

$$P = \left[\frac{MRR}{K_1 + \left(\frac{K_1 \Upsilon + K_2 B}{W_o} \right) \cdot TWR} \right]$$

Where

MRR = metal-removal rate in cubic inches per minute

TWR = tool wear rate in inches per minute

W_o = maximum allowable tool wear in inches

K_1 = direct labor plus overhead in dollars per minute

K_2 = cost per regrind + $\frac{\text{initial tool cost}}{\text{maximum number of regrinds}}$ in dollars

τ = tool change time in minutes

B = constant

The value of B is chosen relative to the emphasis placed on production rate and total cost. When B is one, cost is emphasized; when B is zero, production rate is emphasized; intermediate values of B provide a compromise between the two extremes. Control of the operation is maintained by a combined feedback-adaptive system. The conventional feedback system maintains control continuously while the adaptive control loop periodically computes values of the performance variable. The values of the performance variable are used to determine what modifications are to be made on the feedback controller to improve process performance .

Another area in which adaptive control is being applied is batch chemical processing. A process control system representative of the work being done in this area was developed by the B. F. Goodrich Company for a batch catalytic polymerization process[2]. The process studied was highly exothermic with a reaction rate which doubled with each ten degree centigrade increase in temperature. Close temperature control tolerances were required since the process tended to be unstable and explosive if temperature limits were exceeded. If, however, the processing temperature was too low unacceptable batch usually resulted. The problem, then, was to produce a batch of rubber within a narrow span of reaction temperature so as to minimize batch to batch variation while producing acceptable product.

The control system developed for the process was a model referenced system having two modes of operation -- an adaptive mode and a predictive mode. When in the adaptive mode, a real time model, derived analytically from the chemical kinetics of the process, operates in parallel with the process. Outputs from the model and the process are compared, and the model parameters are adjusted until the error is zero, at which time the model "fits" the process.

In the predictive mode, the model, updated by the adaptive mode, again runs in parallel with the process, but the model now runs in a fast time, repetitive-operation mode. The current status of the real system provides the initial conditions for the model. The model input is a control set point which is compared to the models predicted output. The difference (error) signal is then used to modify the input to the process thus providing a form of feedforward control.

The two systems described here are by no means all inclusive of all the applications of adaptive control. Adaptive control system, similar to the Bendix system, have been applied to grinding machines and automatic welding machines[24] and injection molding machines as well. The systems thus described, however, are representative of the applications of adaptive control in batch processing operations.

1.4 OBJECTIVES

The main objectives of this thesis are:

(1) To present a unified procedure for the development of a general model referenced adaptive control system for batch type manufacturing processes.

(2) To compare the operation of a batch process when controlled by a model referenced adaptive control system with the operation of the same process when controlled by a non-adaptive, model based, optimal control system.

1.5 PROCEDURAL OUTLINE

The procedure to be followed in the realization of the stated objectives is as follows:

1. The development of a general empirical modeling procedure for batch processes based on response surface methodology.
2. The development of an optimal, non-adaptive control system and an adaptive control system which could be used as alternative systems to control a batch process.
3. The application of the empirical modeling technique to a simulation of an actual batch process to obtain a process model.
4. The simulation of a process control system for the batch process.
5. The evaluation of the two control strategies using the simulated process control system.

2.0 MODEL DEVELOPMENT

2.1 THE PURPOSE OF THE PROCESS MODEL

The ability to control requires the ability to predict. Effective control action may be taken only if the effects of the control action can be foreseen. A predictive mathematical model is therefore crucial to the development of a model referenced adaptive control system. This type model relates the dependent process variables to the independent process variables thus enabling one to predict process response to changes in the independent variables.

Predictive models are either steady-state or dynamic. The steady-state model describes the relationship between the dependent and independent process variables when the system is under static conditions. A dynamic model is somewhat more general in that it describes the relationship between the dependent and independent process variables during transient periods. As time approaches infinity, however, the dynamic model reduces to the steady state model.

In practice, when applying steady-state control to complex, multivariable processes, formal dynamic models and extensive studies of process dynamics are generally bypassed. Judgement and experience determine the frequency and magnitude of control changes which can be tolerated[28].

Basically, there are two approaches to the modeling of a process -- analytical and empirical. Analytical process modeling involves the investigation of the physical laws governing the underlying mechanism of the process. From these laws, a more or less exact set of relationships between the dependent and independent variables can be developed. The phrase "more or less exact" implies that no matter how well known or well defined a process may be, there are still parameters or constants which cannot be derived via strict theoretical analysis. Thus even for processes which lend themselves to a strict analytical approach to model development, the model developed in this manner must be verified empirically and the "gaps" filled in via empirical means.

There are several problems which arise in the development of strictly theoretical process models. First, a theoretical model may be extremely complex from a computational standpoint and therefore of limited use in a control scheme. Secondly, there are many processes for which there is not a sufficient amount of theory developed to allow one to derive the necessary theoretical equations describing the relationships between the dependent and independent variables. For processes of this nature an empirical approach is the only feasible method of model derivation.

A certain amount of empirical work is required for any process model. Even if a process is well defined and well known, the analytical model must still be verified empirically to establish that the model does indeed describe the actual behavior of the process. In cases where the process is highly complex or one for which a fully developed body of theory is lacking, an empirical model is probably the only attainable process model. One may conclude then that the empirical approach to the development of a process model for use in process control is probably the more feasible approach to model development.

The empirical approach to model development covers a broad range of applications. This range extends from the "gray area" between the analytical and empirical approaches, where the analytical model is verified and/or augmented by experimental means, to the totally empirical "black box" model.

The empirical approach is not without its problems. The empirical model is valid only within the range of observation. Therefore any extrapolation beyond the area of observation must be verified experimentally, otherwise no confidence may be placed in such predictions. Experimental data used in development of the empirical model must also be collected with discrimination, and statistical analysis must be applied critically[28] if a meaningful model is to be obtained. This approach requires that all available knowledge and understanding of the process being studied be applied during the modeling process.

The subsequent sections of this chapter will explain a technique of applying the empirical approach to process modeling based on response surface methodology.

2.2 EMPIRICAL PROCESS MODELING

The intent of an adaptive control system is to maintain process performance at its optimum level in the face of disturbances to the process and/or its environment. A model referenced adaptive control system utilizes a mathematical model of the process it controls in order to predict the state of the process for a given set of input variable settings. If the model used in this control system is empirically derived, then, in order to predict accurately, the model must have been derived from experimental observations collected in the vicinity of the optimum level of process performance. This requirement is made due to the fact that, as previously stated, an empirical model is valid only within the circumscribed range of experimentation[12]. This being the case, in the derivation of the model by empirical means, the optimum combination of factor levels, with respect to an index of performance, must be determined experimentally. The process model is then developed from this configuration of dependent/independent process variables.

Since, generally, the cost of experimentation on a process is not insignificant, it is highly desirable to use an experimental technique which would "locate" the vicinity of the optimum operating level of the process most economically. One such technique is the method of steepest ascent as applied to the exploration of response surfaces.

The exploration of response surfaces via the method of steepest ascent was developed by G.E.P. Box and his co-workers in the early 1950's. Since this method is well documented[20,8,22,7,6,12], only a brief description will be given here. The basic idea is that a response is considered to be influenced by a number of independent variables. The response, which may be an actual amount of product yielded by the process or some other measure of process performance, may be considered to represent a surface in the space of the independent variables. Starting at a given "set point" of the independent variables, the gradient of the response surface is estimated by a carefully selected experimental design, chosen specifically for its "clean" statistical properties and efficiency in detecting significant effects. Usually all independent variables thought to have significant influence on the process are combined into two level factorial or fractional factorial design combinations. The gradient is estimated by least squares regression on the experimental data and a direction of steepest ascent determined from the regression equation of the "local" response surface. The independent process variables are then adjusted a given amount in the direction of steepest ascent. Observations are then made to determine if improvement in the response is obtained at the "new" operating point. If so, a second step is taken in the direction of the gradient. This procedure continues until the response begins to decrease, at which time the independent variables are adjusted back to the highest level of response and a new experimental design is centered at this point. A new estimate of the gradient is then calculated and the procedure repeated until no further improvement in response can be obtained[20].

The response as a function of the independent process variables defines the response surface. Since the process model derived as a result of the experimentation will be used as the reference model in an adaptive control system, the response being optimized via this experimentation is necessarily the response which will be optimized by the control system. It is therefore crucial that the response chosen be some single, unambiguous, and objective measure of process performance.

The process under study may have several dependent variables thereby requiring that the process model contain a number of equations equal to the number of dependent variables. The chances of optimizing each dependent variable separately and finding that each such response has the same set point of the independent variables are, needless to say, extremely small. Thus the need for a single index of performance, whether it be a composite of the dependent process variables or a contrived function of the dependent variables, is an absolute necessity. The next section introduces one possible index of performance for a process having a multi-equation model and develops an automated steepest ascent modeling procedure.

2.3 AN AUTOMATED MODELING PROCEDURE

The task of determining the equations of a process model which relates the dependent to the independent process variables in the vicinity of the optimum level of process performance (as measured by the process index of performance) is by no means trivial. Most processes for which a control system is to be developed possess a large number of independent variables and, usually, more than one dependent variable. Although the set of independent variables may be reduced in number through preliminary experimentation and/or knowledge of the process, there are usually more than two elements in the subset of the independent process variables which can be termed the control variables of the process. Thus the problem is one of searching hypersurface formed by the index of performance of the process expressed as a function of the control variables of the process.

The problem in the search of the index of performance hypersurface is to find, in as few experiments as possible, a set of operating conditions for the control variables yielding a value of the performance criterion which is close to the best obtainable. The method of steepest ascent has been shown to be most effective among empirical optimization techniques at locating the vicinity of the optimum of a response surface most quickly[20]. As described by Cochran and Cox[12]: "The method of steepest ascent probes more thoroughly and is safer and more informative. It should frequently reach the optimum with less total experimentation ...".

The implementation of a steepest ascent strategy in the exploration of a response surface involves a great deal of computational effort. An efficient modeling procedure utilizing this method should be as automated as possible to take advantage of the speed and accuracy of the digital computer. An automated steepest ascent computational procedure involves:

1. Obtaining a mathematical model of the system from experimental data.
2. Determination of the gradient of the index of performance function.
3. Making corrective adjustments in the control variables proportional to the gradient of the performance function.
4. A condition for stopping, usually when the magnitude of the gradient vector is less than a predetermined constant.
5. Printing out of the values of the control variables at the optimum level of the index of performance, or the values of the control variables at which the next experiment in the sequence is to be centered.

There are several steps in the development of an automated steepest ascent computational procedure. These steps are defined as follows:

1. Determination of the process model -- The form of the process must be determined at the outset. The model may be expressed as:

$$Y_i = Q_i\ (X_1, X_2, \ldots, X_n)\ ,\ i = 1,2, \ldots$$

where

Y_i is the i^{th} dependent variable in the process model.

$Q_i (X_1, X_2, \ldots, X_n)$ is a polynomial equation of first or second order in the n control variables.

2. Choice of the index of performance -- The index of performance is a difficult function to choose; yet its selection is crucial. The performance function selected must have the quality of being easily calculable from the process model.

The index of performance used in the automated steepest ascent computational procedure is residual error. This function is described as follows:

For a process with K dependent variables and n independent variables:

$$Y_1 = Q_1 (X_1, X_2, \ldots, X_n)$$
$$Y_2 = Q_1 (X_1, X_2, \ldots, X_n)$$
$$\vdots \quad \vdots$$
$$Y_k = Q_k (X_1, X_2, \ldots, X_n)$$

Let $Y_1^*, Y_2^*, \ldots, Y_k^*$ be the values of the dependent variables of the process model which have been established as being the desired characteristics of the process output. Define the index of performance to be the residual error

$$E = \sum_{i=1}^{k} (Y_i^* - Y_i)^2 .$$

Hence the objective is the minimization of the residual error E. This minimization presents no problem, since the method of steepest ascent is converted to the method of steepest ascent simply by changing the sign of the objective function or by moving the control variables in the direction of the negative gradient.

3. Definition of all constraints which must be satisfied. -- Ordinarily it may be assumed that the optimum level of the performance function will be located well within the boundaries of the established limits of the control variables. This assumption is not as "wild" as it may at first appear. Processes and their models tend to be well behaved, based as they are on natural laws, and their performance functions usually do not demonstrate the irregularities of some artificially contrived response surface[29]. Therefore, an unconstrained approach to the search for the optimum should usually yield the optimum level of performance without violating set point limits, which are in many cases not what may be considered absolute constraints. If, however, it is found that one of the set point limits is violated,

the simplest remedy is to fix the value of the violating variable at its limiting value, as long as its value is beyond its limit in the search procedure, and continue the search.

4. Choose and/or develop the computational algorithms to be used. -- Basically there are three major algorithms which are used in the automated search procedure. First, the algorithm to perform the least squares fit of polynomial equations to the experimental data. This fitting is accomplished most efficiently by means of multiple linear regression. Therefore, a currently available multiple linear regression program[30] was incorporated as the model generating algorithm in tbe automated procedure.

The second major algorithm required for an automated search procedure is a program to compute and evaluate the gradient of the performance function at different operating points. The gradient of the residual error performance function is computed as follows:

For the process model

$$Y_1 = Q_1 (X_1, X_2, \ldots, X_n)$$
$$Y_2 = Q_2 (X_1, X_2, \ldots, X_n)$$
$$\vdots$$
$$Y_k = Q_k (X_1, X_2, \ldots, X_n)$$

Form the performance function

$$E = \sum_{i=1}^{k} (Y_i^* - Y_i)^2$$

Where the Y_i^*'s are given constants. Then

$$\text{grad } E = \begin{bmatrix} \frac{\partial E}{\partial X_1} \\ \frac{\partial E}{\partial X_2} \\ \cdot \\ \cdot \\ \cdot \\ \frac{\partial E}{\partial X_n} \end{bmatrix}$$

$$\text{grad } E = \begin{bmatrix} \frac{\partial E}{\partial Y_1} \cdot \frac{\partial Y_1}{\partial X_1} + \frac{\partial E}{\partial Y_2} \cdot \frac{\partial Y_2}{\partial X_1} + \cdots + \frac{\partial E}{\partial Y_k} \cdot \frac{\partial Y_k}{\partial X_1} \\ \frac{\partial E}{\partial Y_1} \cdot \frac{\partial Y_1}{\partial X_2} + \frac{\partial E}{\partial Y_2} \cdot \frac{\partial Y_2}{\partial X_2} + \cdots + \frac{\partial E}{\partial Y_k} \cdot \frac{\partial Y_k}{\partial X_2} \\ \cdot \\ \cdot \\ \cdot \\ \frac{\partial E}{\partial Y_1} \cdot \frac{\partial Y_1}{\partial X_n} + \frac{\partial E}{\partial Y_2} \cdot \frac{\partial Y_2}{\partial X_n} + \cdots + \frac{\partial E}{\partial Y_k} \cdot \frac{\partial Y_k}{\partial X_n} \end{bmatrix}$$

$$\text{grad } E = \begin{bmatrix} \frac{\partial Y_1}{\partial X_1} & \frac{\partial Y_2}{\partial X_1} & \cdots & \frac{\partial Y_k}{\partial X_1} \\ \frac{\partial Y_1}{\partial X_2} & \frac{\partial Y_2}{\partial X_2} & & \frac{\partial Y_k}{\partial X_2} \\ \vdots & \vdots & & \vdots \\ \frac{\partial Y_1}{\partial X_n} & \frac{\partial Y_2}{\partial X_n} & \cdot & \frac{\partial Y_k}{\partial X_n} \end{bmatrix} \cdot \begin{bmatrix} -2\,(Y_1^* - Y_1) \\ -2\,(Y_2^* - Y_2) \\ \vdots \\ -2\,(Y_k^* - Y_k) \end{bmatrix}$$

The third algorithm must provide a method for determining the size of the "step" to move the control variables in the direction of the gradient of the performance function. This step size is determined as follows:

Let

$$\bar{U}_o = \cos_o \theta_1 \cdot \hat{x}_1 + \cos_o \theta_2 \cdot \hat{x}_2 + \ldots + \cos_o \theta_n \cdot \hat{x}_n$$

be the unit vector of grad E evaluated at the current experimental design center.

Where

$$\cos_o \theta_i = \frac{\left(\frac{\partial E}{\partial X_i}\right)_o}{\sqrt{\sum_{L=1}^{n} \left(\frac{\partial E}{\partial X_i}\right)_o^2}}$$

Let ρ be the computational gain factor, $0 \leq \rho \leq 1$. Then a new set point, a candidate configuration for the next experimental design, is calculated as follows:

$$X_i' = X_{io} - \rho\,(X_i^h - X_i^L) \cos_o \theta_i$$

where

X_i' = a new value of the i^{th} control variable in the direction of − grad E.

X_{io} = the current value of the i^{th} control variable at the present experimental design center.

X_i^h = the upper operating limit on the i^{th} control variable.

X_i^L = the lower operating limit on the i^{th} control variable.

With new values for the control variables thus obtained, there now is a need to test the "new" operating point to insure that the step length was neither too long nor too short. This is done by evaluating grad E at the new operating point testing to see if grad E at this control variable setting still points in the same general direction as grad E evaluated at the experimental design center. If grad E at $\overline{X}'$ shows little or no divergence from grad E at $\overline{X}$ then the gain factor is increased. If grad E at $\overline{X}'$ indicates a large amount of divergence in direction from grad E at $\overline{X}$, then the gain factor is reduced. The procedure is outlined as follows:

a. The value of the gain factor is set at a low value, say $\rho = 0.1$.

b. A new set point is determined

$$X_i' = X_i - \rho\,(X_i^h - X_i^L)\ \cos_o\ \theta_i, \quad i - 1, 2, \ldots, n$$

c. Grad E is evaluated at $\overline{X}'$ and the unit vector in the direction of grad E at $\overline{X}'$,

$$\overline{U}_1 = \cos_1 \theta_1 \cdot \hat{X}_1 + \cos_1 \theta_2 \cdot \hat{X}_2 + \ldots + \cos_1 \theta_n \cdot \hat{X}_n$$

is computed.

d. The dot product of the unit vectors of grad E, evaluated at $\overline{X}$ and $\overline{X}'$ respectively, is computed:

$$\overline{U}_o \cdot \overline{U}_1 = \left|\overline{U}_o\right| \cdot \left|\overline{U}_1\right|\ \cos\ \theta_E$$

Since $\overline{U}_o$ and $\overline{U}_1$ are unit vectors,

$$\overline{U}_o \cdot \overline{U}_1 = \cos\ \theta_E$$

e. Since θ_E represents the angle between grad E evaluated at $\overline{X}'$ and grad E evaluated at $\overline{X}$, the following tests and corresponding alternative may be applied:

(i) If $0.8 \leq \cos \theta_E \leq 1.0$, increase the gain factor to, say, $1.5\,\rho$ and recompute $\overline{X}'$.

(ii) If $\cos \theta_E \leq 0.1$, decrease the gain factor ρ to, say, $0.5\,\rho$ and recompute $\overline{X}'$.

(iii) If $0.1 \leq \cos \theta_E \leq 0.8$, then $\bar{X}'$ is the center for the next experiment.

Throughout the previous development, many references were made to designed experiments performed in the area of and centered at a particular level of control variable settings. These experimental designs may be either of two types, according to the fit of the polynomial equations of the process model. At the initial configuration of control variable settings, for reasons of ignorance about the response surface in that area, a linear relationship between the dependent and control variables is assumed. The experimental design best suited for generating data on which to fit linear polynomial equation is a two level factorial or fractional factorial design.

Should it be found that there is a significant "lack of fit" of the linear regression equations to the experimental data from the two level factorial design, then a non-linear surface must be assumed and a second order polynomial fit attempted. In order to generate the extra data required for a second order fit in the most economical and efficient manner, the two level factorial design used initially may be very simply transformed into a Box-Wilson central composite experimental design[12]. This alteration amounts to the addition of "star" points and center point replications to the original two level design. A good indication of the polynomial fit to the experimental data is the multiple correlation coefficient[14], obtained readily from the multiple regression program.

A flow chart of the procedure for locating the vicinity of the optimum of the performance function and the determination of the process

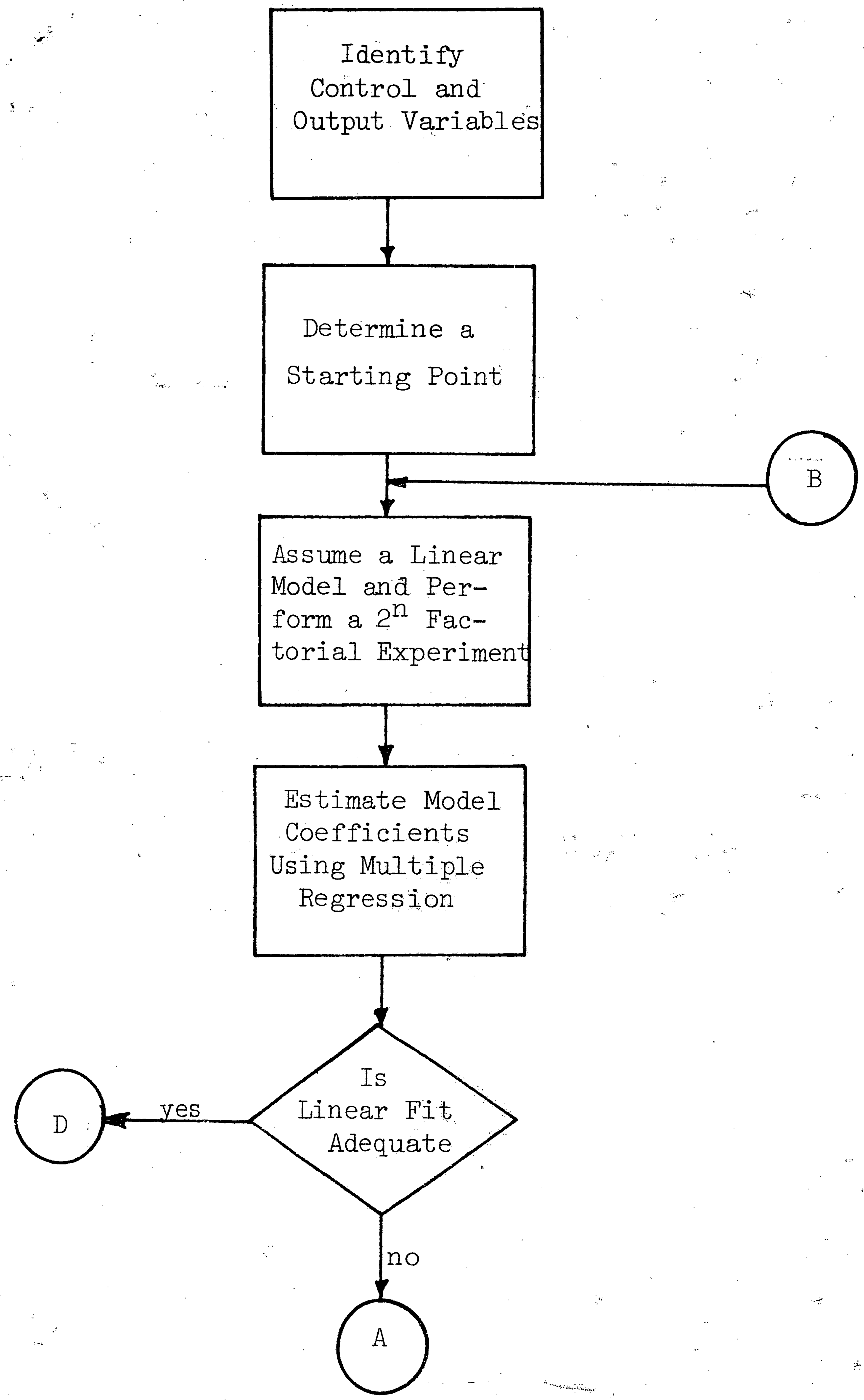

Figure 4. Flow Chart of Modeling Procedure

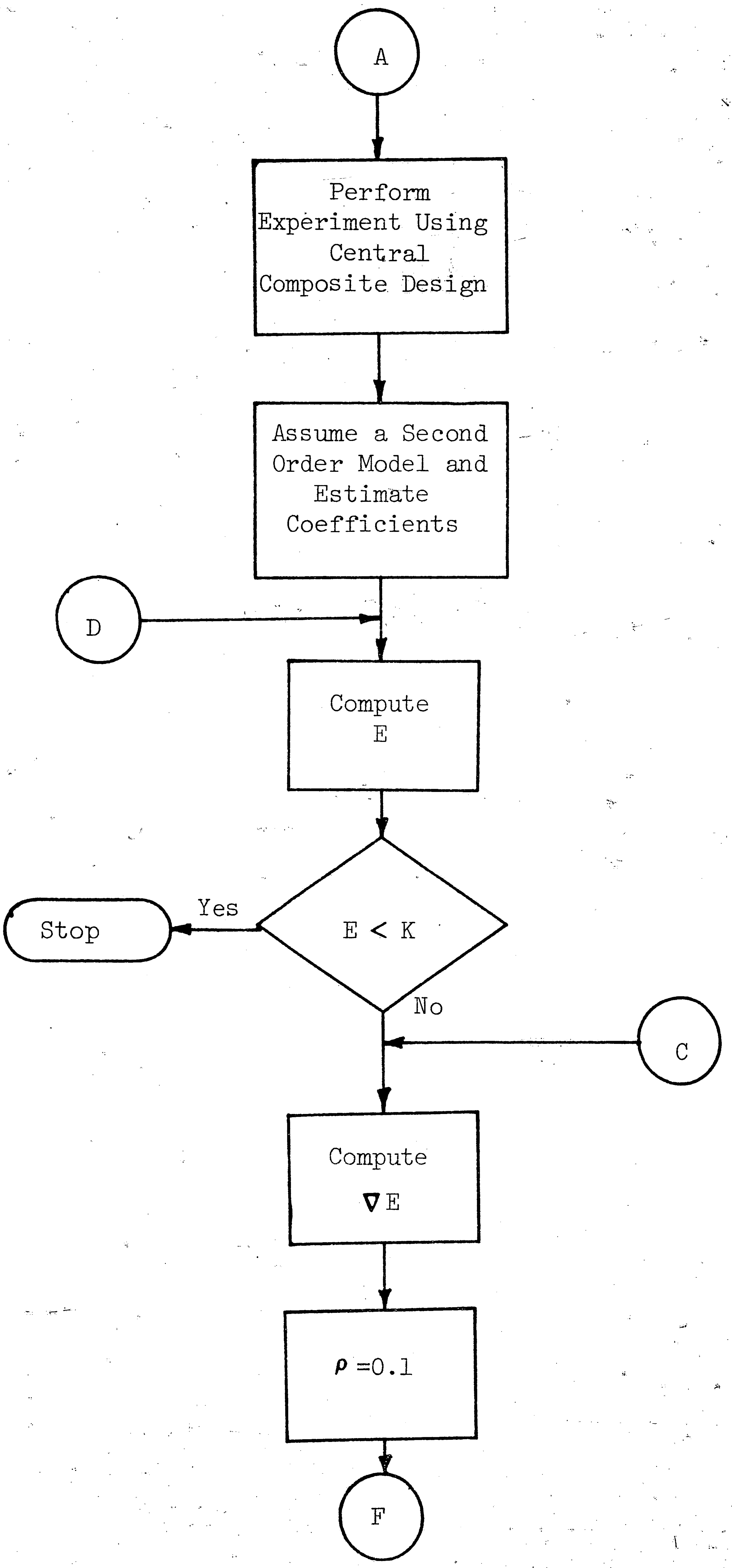

Figure 4. (Continued)

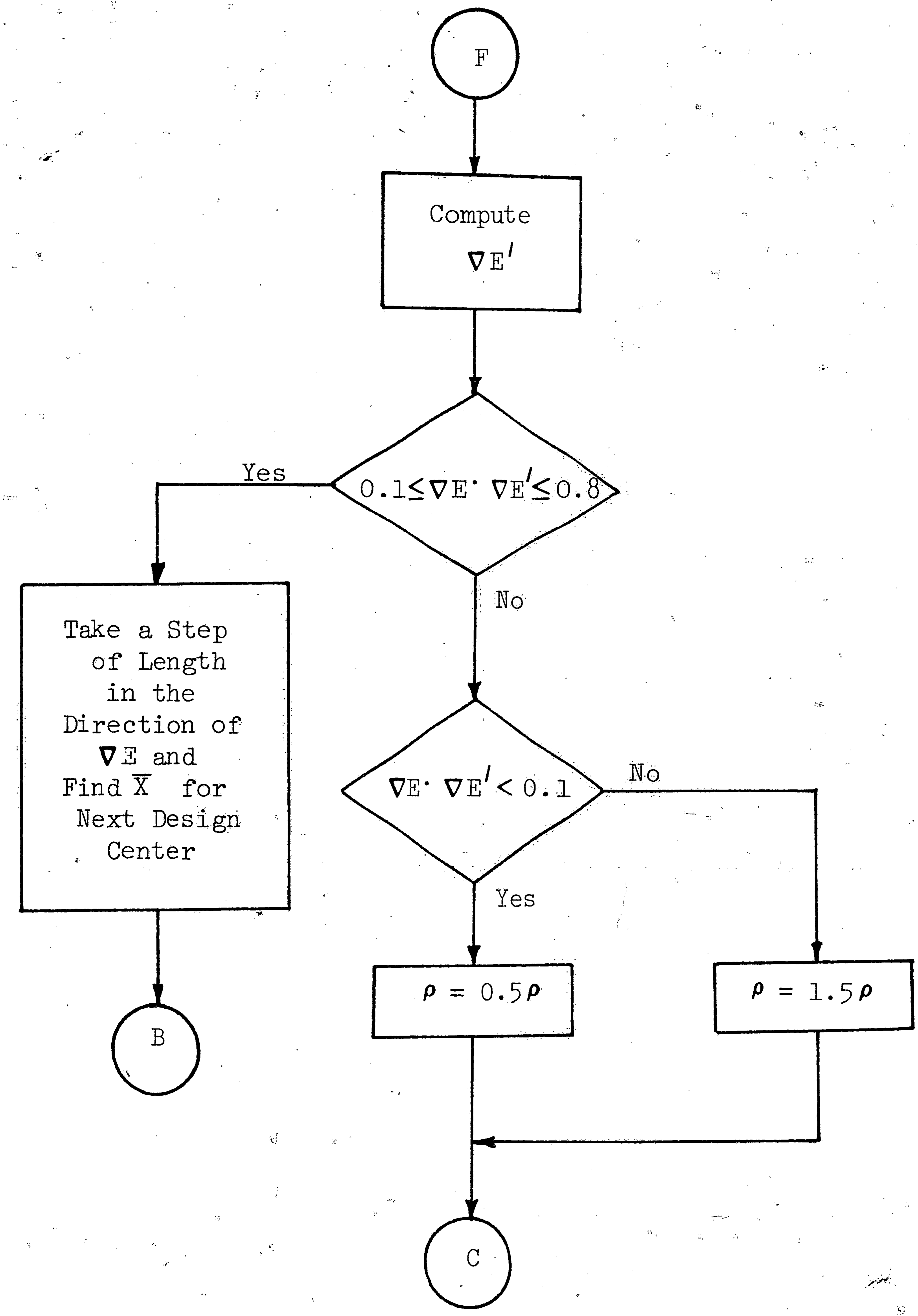

Figure 4. (Continued)

model equations from the response surface in htis vicinity is given in Figure 4. The procedure is outlined as follows:

1. Determine, from prior knowledge of the process under study or from preliminary experimentation, the input (control) and output (dependent) variables to be included in the process model.
2. Choose the most "likely" configuration of input variables as the design center for the initial experiment. These settings should be those which are intuitively determined, through prior knowledge of the process, to be the closest approximation to the optimal settings.
3. Perform experiments on the process and collect experimental data. Initially, assume a linear relationship between the input and output variables and use a 2^n factorial or fractional experimental design.
4. Estimate the coefficients of the polynomial equations using multiple regression. If the linear "fit" for any equation in the model is inadequate, as indicated by the multiple correlation coefficient value for that equation, then star points and center point replications must be added to the 2^n factorial design. A second order fit of each model equation is then established via multiple regression.

5. Form the process index of performance,

$$E = \sum_{i=1}^{K} (Y_i^* - Y_i)^2 .$$

If E is less than a predetermined constant, then optimality is assumed at the current operating point. If not proceed to step 6.

6. Compute grad E and evaluate at the current design center. From these calculations, determine the unit vector in the direction of grad E at the current design center -- $\overline{U}_o$.

7. Establish an initial value for the computational gain factor -- ρ .

8. Determine new settings for the control variables:

$X_i = X_i' - \rho (X_i^h - X_i^L) \cos_o \theta_i$, i=1, ..., n

Evaluate grad E at $\overline{X}$ and determine $\overline{U}_1$, the unit vector in the direction of grad E at $\overline{X}$.

9. Compute

$$\cos \theta_E = \overline{U}_o \cdot \overline{U}_1$$

10. Test $\cos \theta_E$ as follows:

 (i) If $\cos \theta_E \leq 0.1$, set the value of the computational gain constant equal to one half the present value and return to step 8.

 (ii) If $1.0 \leq \cos \theta_E \leq 0.8$, set the value of the computational gain constant to one and one half its present value and return to step 8.

(iii) If $0.8 < \cos \theta_E \leq 0.1$, then center the next experimental design at X and repeat the sequence from step 1.

The automated process modeling procedure outlined above is one approach to the rapid development of an empirical, steady-state process model via the method of steepest ascent. The method used here yields rapid feedback of the next experimental design center in the sequence, based on data collected about the current design center. Other steepest ascent methods are suggested in the statistical literature[12,13,15,31]. However, the method suggested here seems better suited to an automated, interactive model development procedure.

Once a process model has been obtained, the next step in the implementation of a model referenced adaptive process control system is to establish the control strategy. The next chapter develops an optimal control strategy which could be used in either an adaptive or a non-adaptive control system.

3.0 BATCH PROCESS CONTROL SCHEMES

This chapter deals with the development of two control schemes which could be used in a control system for batch processes. The first of these schemes is a non adaptive, optimal control strategy. The second is an adaptive control scheme which utilizes the optimal control strategy of the first as its control function.

3.1 AN OPTIMAL CONTROL STRATEGY

This control scheme, developed by Bhattacharyya[32] for a steady state control system, may be explained in terms of the simple single input single output process shown in Figure 5.

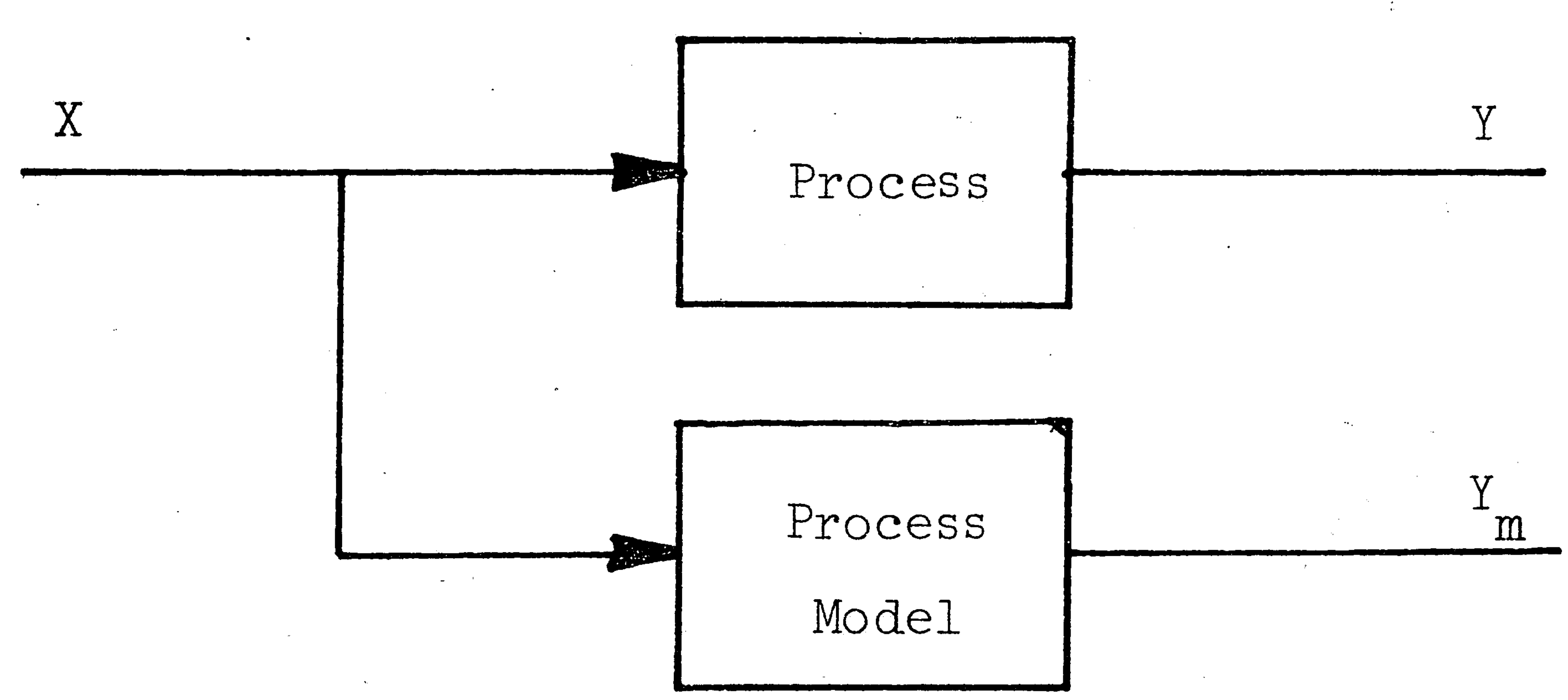

Figure 5. A process with one control and one state variable.

Assume that the process model is a second order polynomial, empirically derived by the method discussed in chapter two. Let the following symbol definitions be assigned:

X = Control variable

Y = State variable

f = Process model function

Y_m = $f(\bar{x})$ = the value of the state variable predicted by the process model $Y_m = A_o + A_1 X + A_2 X^2$

A_o, A_1, A_2 = Coefficients of the process model

Since the process model was empirically derived, and therefore only an approximate representation of the process, Y will generally be different from Y_m. The least squares estimation of the model coefficients, however, guarantees that Y_m "fits" Y in a minimum least squares sense[11].

Suppose the process drifts from its original characteristics so that Y takes on a new value, say $Y+\epsilon$, while the output of the process model remains at Y_m. The process control scheme should then make adjustments to the process such that the desired output, Y, is once again obtained.

For the case at hand, assume that the model is constant and that it is required to compute a new setting for the control variable which will yield a model output of, say Y_m', which is a least squares fit of $Y-\epsilon$. The argument here is based on an implied assumption of linearity. Since a given input X no longer yields an output Y but rather $Y+\epsilon$, a new input, say X', is applied which originally have yielded a value of $Y-\epsilon$. Hence the process output is restored to the desired value of Y. This assumption of linearity, obviously, does not hold over a very wide range, since the process is not linear. Linearity may, however, be assumed to hold over a limited range in a piece wise linear manner. The range over which linearity holds actually depends on which coefficients of the process are varying[32].

The control scheme may be generalized and represented mathematically as follows: Assume that the process under study is modeled in n control variables and K state variables. The model may be represented symbolically as follows:

$$Y_1 = Q_1 (X_1, X_2, \ldots, X_n)$$

$$Y_2 = Q_2 (X_1, X_2, \ldots, X_n)$$

$$\vdots$$

$$Y_k = Q_k (X_1, X_2 \ldots, X_n)$$

Where the $Q_1(X_1, X_2, \ldots, X_n)$ are assumed to be second order polynomial equations. Then it follows that,

$$\frac{\partial Y_i}{\partial X_1} = \frac{\partial Q_i (X_1, X_2, \ldots, X_n)}{\partial X_1}$$

$$\frac{\partial Y_i}{\partial X_2} = \frac{\partial Q_i}{\partial X_2} (X_1, X_2, \ldots, X_n)$$

$$\vdots$$

$$\frac{\partial Y_i}{\partial X_n} = \frac{\partial Q_i}{\partial X_n} (X_1, X_2, \ldots, X_n)$$

Where i goes from 1 to K.

Let the observed changes in the state variables be defined as Y_1. Then, under the assumption of linearity, the following equation can be written:

$$\begin{bmatrix} \frac{\partial Y_1}{\partial X_1} & \frac{\partial Y_1}{\partial X_2} & \cdots & \frac{\partial Y_1}{\partial X_n} \\ \frac{\partial Y_2}{\partial X_1} & \frac{\partial Y_2}{\partial X_2} & & \frac{\partial Y_2}{\partial X_n} \\ \vdots & \vdots & & \vdots \\ \frac{\partial Y_K}{\partial X_1} & \frac{\partial Y_K}{\partial X_2} & & \frac{\partial Y_K}{\partial X_n} \end{bmatrix} \cdot \begin{bmatrix} \Delta X_1 \\ \Delta X_2 \\ \vdots \\ \Delta X_n \end{bmatrix} = \begin{bmatrix} \Delta Y_1 \\ \Delta Y_2 \\ \vdots \\ \Delta Y_K \end{bmatrix}$$

This equation can be rewritten as follows:

$$\begin{bmatrix} \Delta X_1 \\ \Delta X_2 \\ \vdots \\ \Delta X_n \end{bmatrix} = \begin{bmatrix} \frac{\partial Y_1}{\partial X_1} & \frac{\partial Y_1}{\partial X_2} & \cdots & \frac{\partial Y_1}{\partial X_n} \\ \frac{\partial Y_2}{\partial X_1} & \frac{\partial Y_2}{\partial X_2} & & \frac{\partial Y_2}{\partial X_n} \\ \vdots & & & \\ \frac{\partial Y_K}{\partial X_1} & \frac{\partial Y_K}{\partial X_2} & & \frac{\partial Y_K}{\partial X_n} \end{bmatrix}^{-1} \cdot \begin{bmatrix} \Delta Y_1 \\ \Delta Y_2 \\ \vdots \\ \Delta Y_K \end{bmatrix}$$

This equation can now be solved for the changes in the control variables required to yield the desired values of the state variables. Thus, the new values of the control variables are:

$$X_1' = X_1 - \Delta X_1$$

$$X_2' = X_2 - \Delta X_2$$

$$\vdots$$

$$X_n' = X_n - \Delta X_n$$

So far, linearity has been assumed. The process, however, is non-linear. Thus the procedure is modified to take this non-linearity into account as follows:

Let Y_1' , Y_2', ..., Y_k' be the values of the output variables obtained by inserting the values X_1', X_2', ..., X_n' into the model equations. Now let the desired values of the state variables be Y_1^*, Y_2^*, ... Y_k^*. Thus,

$$Y_i^* = Y_i - \Delta Y_i$$

where i goes from 1 to K. Define the residual error, E, to be

$$E = \sum_{i=1}^{K} (Y_i^* - Y_i)^2.$$

Then the objective is to minimize the value of the residual error. One method of minimization is the use of gradiant (steepest descent) search.

The direction cosines of the gradient of E are found from

$$\cos \theta_i = \frac{\frac{\partial E}{\partial X_i}}{\sqrt{\sum_{i=1}^{n} \left(\frac{\partial E}{\partial X_i}\right)^2}}$$

where i goes from 1 to n. Let the magnitude of the descending step be ΔE. Then, the corresponding variations in the control variables will be $\Delta E \cdot \cos \theta_i$, where i goes from 1 to n. The new values of the control variables will be:

$$X_1'' = X_1' - \Delta E \cdot \cos \theta_1$$

$$X_2'' = X_2' - \Delta E \cdot \cos \theta_2$$

$$\vdots$$

$$X_n'' = X_n' - \Delta E \cdot \cos \theta_n$$

The search routine is repeated until the control variables converge to a set of values which makes the residual error small enough to be within an acceptable bound. Ideally, E should identically equal zero. This however is usually not a feasible goal in the real world. The next section discusses the inclusion of this scheme into an adaptive control system.

3.2 AN ADAPTIVE CONTROL SCHEME

The optimal control scheme discussed in the previous section assumed that the process model was accurate and would never be changed. This is an unrealistic assumption in all but theoretical situations. With an empirically derived process model, imperfections are always present due to inherent errors in using regression techniques to derive the model coefficients from experimental data. Model imperfections may also be caused by physical wear and tear on the process equipment and/or variations in raw materials. The control scheme to be developed in this section is basically a continuation of the optimal control scheme of the previous section except that a provision will be made to update the process model in order to adapt to changes in the process coefficients.

The development of the adaptive control scheme proceeds as follows: A process model is obtained as before and the process is operated under the control of the optimal control scheme based on this model. As the process operates, data, consisting of values of the control and state variables, is sampled at the end of each batch cycle and stored in a table of Φ entries. When the number of process cycles exceeds the value of Φ, entry $\Phi+1$ is entered as the most recent entry and the first (oldest) entry is dropped from consideration. In this manner, the table of process data forms what is known as a "push-down" list of the Φ most recent observations. Thus the table is continually updated by dropping the oldest entry each time a new entry is added.

An indication of how well the process model is performing during the process operation must be determined so that a decision can be made as to when to use the collection of process data to reestimate the model coefficients. This is done as follows: Let $Y^*_1, Y^*_2, \ldots Y^*_K$ be the desired values of the state variables of the process. Let $Y_1, Y_2, \ldots Y_K$ and $Y^M_1, Y^M_2, \ldots Y^M_K$ be the values of the state variables from the process and process model respectively.

Let

$$E_p = \sum_{i=1}^{K} (Y^*_i - Y_i)^2$$

be the actual value of current residual error and let

$$E_M = \sum_{i=1}^{K} (Y_i^* - Y_i^M)^2$$

be the value of the current residual error function as predicted by the process model. Let Ω be a positive constant which is the maximum allowable error between the actual and predicted values of the objective function. Then, if

$$\Omega \geq \left| E - E_M \right|$$

the process is considered to be adequately controlled and there is no need to update the model. If, however,

$$\Omega < \left| E - E_M \right|$$

the process is considered to be poorly controlled and the process model coefficients must be reestimated from the sets of data collected during the operation of the process.

The number Φ , the number of data points in set of historical data, is a function of the number of coefficients to be estimated from this data. As a minimum, there should be a ratio of at least three entries in the data list for each coefficient to be estimated. For example, if the process model consists of K first order polynomial equations in n control variables, the number of coefficients which must be estimated is K(n+1).

A flow chart of the adaptive control procedure is shown in Figure 6. The steps of the procedure are summarized briefly as follows:

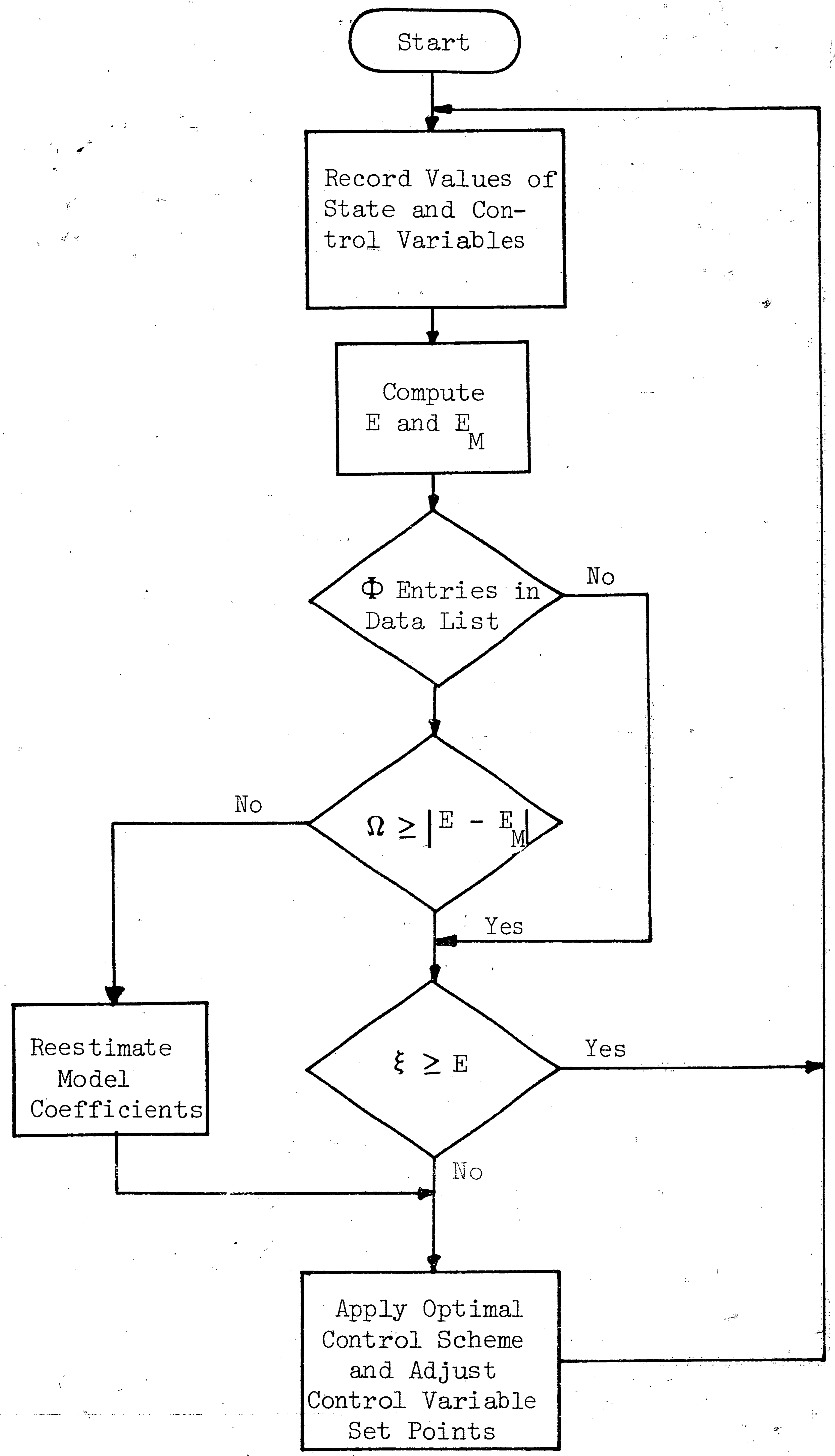

Figure 6. Flow Chart of Adaptive Control Scheme

1. Start the process.
2. At the end of the batch cycle, record the values of the control and state variables in the push-down list.
3. Compute the actual value of the objective function E and the value of the objective function E_M as predicted by the current process model.
4. Define Ω as the maximum allowable error between the actual and the predicted values of the objective function. Then, if $\Omega < |E - E_M|$, reestimate the coefficients of the process model and go to step 6. If $\Omega \geq |E - E_M|$ go to step 5.
5. Define ξ as the maximum allowable value of the actual residual error. Then if $\xi \geq E$, go to step 2, since the process is operating within limits and requires no control adjustments. If $\xi < E$, go to step 6.
6. Apply the optimal control scheme to determine the new set points for the control variables. Return to step 1.

It should be noted here that prior to the first reestimation, and any subsequent reestimation of the model coefficients there must be Φ entries in the push-down list. This amounts to inserting a delay of Φ process batch cycles between any reestimation attempts and the initial process cycle.

The next chapter discusses a batch process on which these two control schemes might be applied. Simulations of a control system for the process using first the optimal control, then the adaptive control scheme will be developed.

4.0 Control System Implementation and Evaluation

The effectiveness of an automatic process control system can usually be measured by the improvement in process operation when controlled by an automatic control system when compared to process operation when the process is manually controlled. The objective of an automatic process control system is to increase process productivity.[25] There are many ways this increase, or improvement in process productivity, can be measured. From a pragmatic viewpoint, however, a reduction in the variance of the process response variables from the desired mean would be the most obvious measurement of effectiveness. Such a reduction would increase the process yield through the reduction of scrap due to process output excursions into the range of rejection for some output variables.

The proof of the effectiveness of an automatic process control scheme, then, resides in the actual implementation of the control system on a physical process. Thus, in order to validate the empirical modeling procedure described in Chapter 2 and to evaluate the effectiveness of the control schemes discussed in Chapter 3, a suitable process must be selected and simulated as a test vehicle for the procedures and control schemes developed herein.

In this study only one case will be investigated. This makes the selection of a representative example all the more difficult. The concern here is not only on the physical nature of process being representative, but also that the outward process characteristics should be representative of batch manufacturing operations. There are two alternative means of obtaining such a model. The first would be to fabricate a process model based on the desired representative characteristics and the second would be to select an actual case study from the manufacturing floor. Since the objective of this study is concerned with practical application, the latter alternative was employed. The actual process can thus be used to provide realistic estimates for errors of measure and control, data structures, and process mechanisms to be incorporated in the process simulation model. Such a specific case obviously cannot be construed as a general representation of all batch processes. It is not intended to be such a representation. Its only purpose is to provide a study model with which to make initial assessments, specific though they may be, of the modeling procedure and the two alternate control schemes. It is felt that the generality lost by not employing a "representative model" (if such a model exists) is incidental to the gains afforded by an actual case.[20]

4.1 Selected Process

The model process chosen for this investigation was a continuous vacuum thin films deposition (sputtering) process.[11] The product output of the process is tantalum nitride thin film circuits for use in telephone switching equipment. This process is of a complex multivariate nature and one for which an analytical model would be extremely difficult to derive. The process may be simply described as follows:

The deposition process begins with the selection of a suitable substrate, usually a glass or ceramic material, on which the tantalum metal film is to be deposited. The substrate is cleaned according to a specified cleaning procedure and then placed in a vacuum system where the tantalum metal film is deposited over the entire substrate by the cathodic sputtering process.

In the cathodic sputtering process, a plate of the metal to be deposited, tantalum in this process, is used as an electrical cathode. The substrate is placed at a distance of about two to three inches from this plate. After the sputtering chamber has been completely evacuated, an ionizable, inert gas such as argon is introduced into the chamber. When a high voltage is applied to the cathode, the argon ionizes and the positive argon ions bombard the cathode. Many of these ions are accelerated to a sufficient velocity such that they possess enough energy when they strike the cathode to dislodge atoms or clusters of atoms of the cathode material. These dislodged atoms then diffuse away through the ionized argon and deposit on any surface nearby. In the tantalum sputtering operation, nitrogen gas is introduced into the sputtering chamber. The presence of the nitrogen allows some of the free metallic atoms to entrap or combine with, according to the amount of nitrogen present, the nitrogen atoms as they deposit on nearby surfaces thus yielding a tantalum nitride film on the nearby substrate. This doping with nitrogen provides a deposited film with more desirable properties than with tantalum metal alone.

In the continuous vacuum sputtering process, cleaned substrates are loaded individually onto carriers mounted on a continuous track which travels through the continuous vacuum machine. As the substrate on its carrier travels through the machine it is exposed to a series of vacuum chambers of successively higher vacuum. During this phase, also, the substrate is preheated to a predetermined temperature. The substrate then passes through the sputtering chamber where the tantalum nitride film is deposited, then through a series of vacuum chambers of successively lower vacuum where substrate cool-down is accomplished before the substrate exits the machine and is once again exposed to the atmosphere. A simplified schematic of the sputtering process is shown in Figure 7.

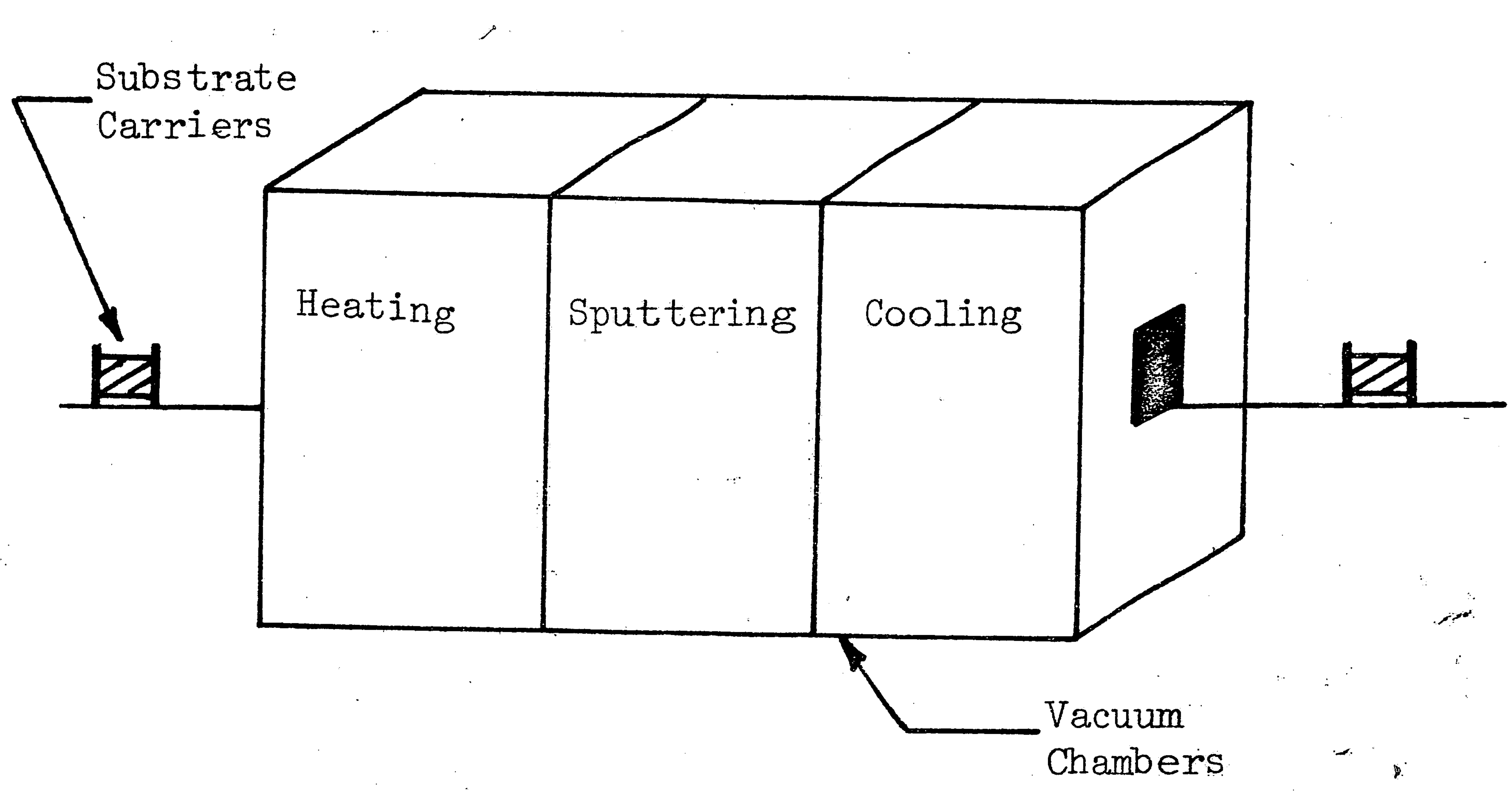

Figure 7. A Simplified Schematic of the Sputtering Process

The deposition process is essentially the most important single process in thin films circuit fabrication during which the film properties are determined by the deposition process variables. Some of the important process variables are sputtering voltage, current, nitrogen gas flow rate, carrier track speed, preheat temperature, substrate geometry, etc. The tantalum films are evaluated based on various electrical characteristics which could be used as indicators of the stability of the circuits during subsequent processing.[32] These characteristics are sheet resistance, film thickness, specific resistivity, temperature coefficient of resistivity and crystaline structure.

This process was an ideal candidate for the implementation of an automatic process control system, since some difficulty had been experienced in the development of a simple method of setting up the machine for each production run and in predicting the corrections in machine settings based on samples of process output.[23] Fortunately, this difficulty had prompted an extensive characterization study[23] of the process which resulted in the development of an empirical process model relating the significant process variables to the desired qualities of the product output. The important process variables considered in the statistical study of the process are listed as follows:

1. Input Variables
    a. Manipulated Variables:
        1. Sputtering Voltage
        2. Current

3. Dopant (nitrogen)

4. Carrier track speed

b. Associated variables: These variables can be adjusted only through adjustment of the manipulated variables.

1. Temperature

2. Pressure

2. Output on response variables: These variables indicate the process operating level.

a. Film thickness

b. Sheet resistance

c. Temperature coefficient of resistance (TCR)

d. Specific resistance

e. Crystalline structure

The results of the process characterization study determined the control variables of the process to be:

(1) X_1 = Sputtering voltage in volts

(2) X_2 = Sputtering current in milliamperes

(3) X_3 = Nitrogen flow rate in cubic centimeters per minute

and the response variables to be:

(1) Y_1 = Deposition Rate in angstroms/minute

(2) Y_2 = Sheet resistance in ohms per square

(3) Y_3 = Temperature coefficient of resistance (TCR) in parts per million per degree centigrade.

The relationships between the input variables and the output variables were found to be of the form:

$$Y = b_o + b_1X_1 + b_2X_2 + b_3X_3 + b_{11}X_1^2 + b_{22}X_2^2$$
$$+ b_{33}X_3^2 + b_{12}X_1X_2 + b_{13}X_1X_3 + b_{23}X_1X_2$$

where the values for the model coefficients for each of the three equations of the process model are given in Table 1.

With a validated empirical model thus available, the development of a simulator for the process and process control systems was undertaken. The next section describes this development.

4.2 Simulation of the Process and Control Systems

The development of a simulator for the process, the optimal process control system, and the adaptive process control system was basically a three-phased operation. The phases of the simulator development are shown in Figure 8. Figure 8a shows the basic simulator for the process. The variables captioned in this diagram are as follows:

1. $\overline{X}$ = the vector of input or control variables, where:

   X_1 = sputtering voltage in volts

   X_2 = sputtering current in milliamperes

   X_3 = nitrogen flow rate in cubic centimeters per minute

2. $\overline{Y}$ = the vector of output or response variables, where:

   $Y_1 = f_1(X_1,X_2,X_3)$ = deposition rate of the deposited film in angstroms/minute

   $Y_2 = f_2(X_1,X_2,X_3)$ = sheet resistance in ohms per square

   $Y_3 = f_3(X_1,X_2,X_3)$ = the temperature coefficient of

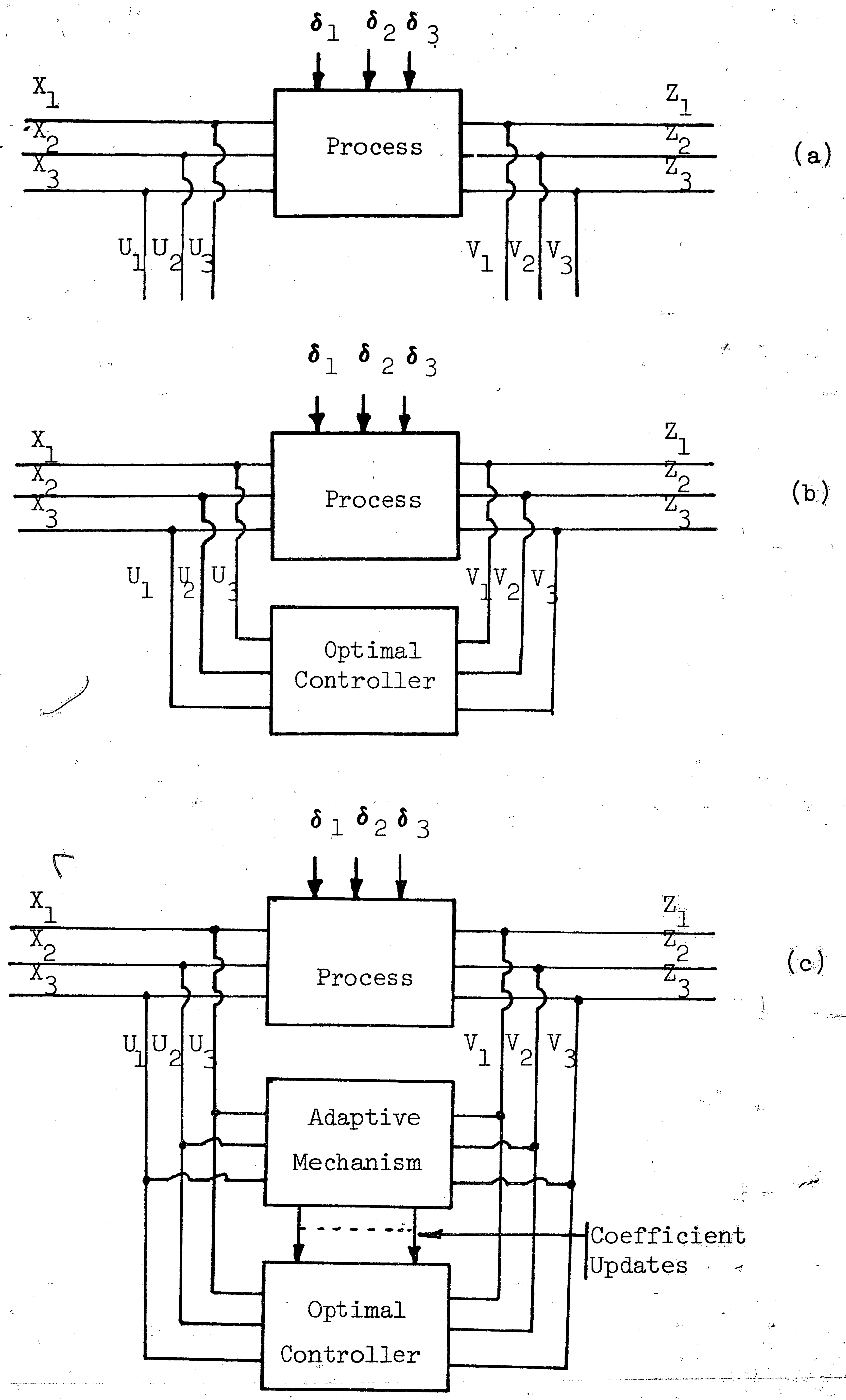

Figure 8. Simulator Development Stages

(a) The Process Simulator
(b) The Optimal Control System Simulator
(c) The Adaptive Control System Simulator

resistance (TCR) in parts per million per degree centigrade

3. $\overline{Z} = \overline{Y} + \overline{\partial}$ = the vector of actual process responses. is the vector of drift components for each response variable. Since processes do, in reality, drift from their original output points, it seems logical to include this drift in a simulation of the process. The drift $\overline{\partial}$ may be cyclic or linear in nature.

4. $\overline{U} = \overline{X} + \overline{\theta}$ = the vector of the measured values of the input variables. $\overline{\theta}$ is the vector of measurement error components for each of the input variables. Since measurements made on any variables are generally made through some intermediate system -- electrical or mechanical transducers, meters, probes, etc. -- each of which contains its own inherent error, the errors of observation must be included in the simulation model. These errors are assumed to occur randomly and, for this study, are assumed to be distributed N(0,1).

5. $\overline{V} = \overline{Z} + \overline{\xi}$ = the vector of the measured values of response variables. $\overline{\xi}$ is the vector of measurement error components for the actual process output responses. These errors are included for the same reason as the measurement errors, $\overline{\theta}$, on the input variables. $\overline{\xi}$ is also assumed to be distributed N(0,1).

1. Coding Scheme

$$X_1 = \frac{\text{Voltage} - 5000}{1000}$$

$$X_2 = \frac{\text{Current} - 530}{130}$$

$$X_3 = \frac{\text{Nitrogen Flow} - 3.0}{0.6}$$

2. Mathematical Equations

$$Y = b_1 + b_1X_1 + b_2X_2 + b_3X_3 + b_{11}X_1^2 + b_{22}X_2^2 + b_{33}X_3^2 +$$

$$b_{12}X_1X_2 + b_{13}X_1X_3 + b_{22}X_2X_3$$

Variable	Coefficient	Deposition Rate	Sheet Resistance	TCR
Constant	b_0	379.73	30.77	-82.92
Voltage	b_1	18.39	-24.91	69.18
Current	b_2	96.47	-15.73	64.22
Nitrogen	b_3	-25.02	10.77	-56.22
$(\text{Voltage})^2$	b_{11}	-1.59	10.80	-12.68
$(\text{Current})^2$	b_{22}	-4.90	2.97	6.04
$(\text{Nitrogen})^2$	b_{33}	-9.13	2.30	-5.43
(Voltage Current)	b_{12}	3.00	9.14	-20.50
(Voltage Nitrogen)	b_{13}	8.50	-6.17	21.75
(Current Nitrogen)	b_{23}	-5.50	-1.30	16.00

Table 1. Model for Tantalum Nitride Sputtering Process Simulator[32]

4.3 Simulated Process Conditions

Simulation study is an extremely useful technique in the development of automatic control systems. The operation of a process control system when the system is subjected to a variety of input and environmental conditions by using this technique. Thus a good indication of the performance of the process control system under actual operating conditions can be gained by applying various sets of operating conditions to the process control system simulator and observing the simulated system operation. The point of the simulation study of the tantalum nitride sputtering process in this study, then, is to determine the validity and/or applicability of the modeling procedure of Chapter 2 and the control schemes of Chapter 3. Hence the simulator is approached as if it were the process in operation.

The first phase of the implementation of a process control system for the process under study is to obtain an empirical model of the process. For this phase of the development it was assumed that the following conditions would prevail:

1. The measurement errors on both the control and the response variables were assumed to have values equal to one percent of the measured variable.

2. The process output variables were assumed to drift from their initial values according to a sinusoidal drift function of amplitute equal to 10 percent of the measured response and of periodicity equal to twenty machine cycles.

The normal operating ranges of the input (control) variables for the process are as follows:

	X_1	X_2	X_3		
1	-1	-1	-1	(a)	(b)
2	1	-1	-1		
3	-1	1	-1		
4	1	1	-1		
5	-1	-1	1		
6	1	-1	1		
7	-1	1	1		
8	1	1	1		
9	-1.682	0	0		
10	1.682	0	0		
11	0	-1.682	0		
12	0	1.682	0		
13	0	0	-1.682		
14	0	0	1.682		
15	0	0	0		
16	0	0	0		
17	0	0	0		
18	0	0	0		
19	0	0	0		
20	0	0	0		

Table 2. Experimental Design for Empirical Modeling:
(a) 2^3 factorial design for linear model
(b) central composite rotatable design for second order model

Variable	Description	Range
X_1	Sputtering Voltage	0 to 10,000 volts
X_2	Sputtering Current	0 to 1,000 milliamps
X_3	Nitrogen Flow Rate	0 to 5.0 atm. C.C./min.

The experimental designs for the modeling procedure are given in Table 2. Prior experience on the process indicated that an area of the input variable space which would produce acceptable thin films was as follows:

X_1 = 3,000 volts to 6,300 volts

X_2 = 363 milliamps to 697 milliamps

X_3 = 2.0 atm. C.C./min. to 3.8 atm. C.C./min.

Thus, as a starting point, the initial experimental design was centered at:

X_1 = 3,000 volts

X_2 = 300 milliamps

X_3 = 2.0 atm. C.C./min.

An initial step size in the direction of each variable was arbitrarily chosen as follows:

ΔX_1 = 500 volts

ΔX_2 = 50 milliamps

ΔX_3 = 0.5 atm. C.C./min.

After a model of the process is determined as the result of phase one, the second phase of the control system development is begun. This phase consists of the implementation of each of the two control schemes as the controller for the process. Then, to compare, the operation of the process when controlled first, by the optimal control scheme and second, by the adaptive control scheme. The comparisons being made on the basis of operations when the two systems are exposed to similar sets of operating conditions.

The operating conditions to which each of the control systems was simulated to form the basis for comparison are given as follows:

1. Process drift -- process is assumed to drift from its initial response according to a sinusoidal drift function of period **T** process cycles and amplitude ρ . One drift period, **T** = 40 cycles, will be simulated. The amplitude of the drift will be 0, 2, 5, 10, 15 and 20 percent of the measured value of the response variable with which it is associated.

2. Measurement error -- values of the input and output variables of the process as measured by the controller are subject to measurement error. The measurement error for all input and output variables is assumed to have a magnitude equal to a given percentage of the variable measured. Thus if k is this percentage, then:

$$\overline{U} = \overline{X} + \overline{\theta}$$

$$\overline{V} = \overline{Z} + \overline{\xi}$$

Where $\overline{\theta}$ and $\overline{\xi}$ are random variables of magnitude $k\overline{X}$ and $k\overline{Z}$, respectively.

In the study of the process control systems, for each amplitude the measurement error will take on values of 0, 0.5, 1.0, 3.0, 5.0, 7.0, 9.0, and 11.0 percent of the values of the measured variables.

3. Process set points -- In each simulation run, the initial settings of the process input will be set at those values determined

in the modeling procedure to yield minimum residual error between the desired and actual values of the response variables.

When the simulator is run in the optimal control mode, the control algorithm will be applied whenever the residual error function, E, is greater than 50. When the simulator is operating as an adaptive control system, the control algorithm will be applied whenever the residual error is greater than 50; the adaptive mechanism will reestimate the coefficients of the process model whenever the absolute difference between the actual residual error, E, and the model residual error, E_M, exceeds 150. The length of the push-down list in the adaptive mode will be 60 entries, with a delay of thirty entries between any two consecutive adaptations. Each simulation run will be 300 machine cycles in duration.

The primary basis for comparison of the operation of the two process control systems will be the standard deviation of the responses from the desired mean value of each. This basis for comparison is both pragmatic and realistic since, in general, the intent of a process control system is to reduce the variance of the process responses about a desired mean value. The next chapter will discuss the results of the empirical modeling procedures on the simulated process and compare the operation of the two process control systems under the specified operating conditions.

5.0 RESULTS AND ANALYSIS

The process and control system simulators described in Chapter 4 were programmed and executed on a PDP-10 timesharing computer. The results of the application of the empirical modeling technique developed in Chapter 2 and the control schemes developed in Chapter 3 to the simulated batch process are discussed in this chapter. These results will be presented in two phases. The first phase will discuss the results of the modeling technique, while the second phase will discuss and compare the results of the applications of the control schemes.

5.1 PROCESS MODELING

The empirical modeling techniques performed extremely well under the conditions specified in Chapter 5. At the outset of the experimentation, a cutoff value for the residual error function, E, was set arbitrarily at 150. That is, the experimentation would cease and the current experimental model would be accepted as the process model for use in the control system when:

$$150 \geq E = \sum_{=1}^{3} (Y_i^* - Y_i)^2.$$

From the initial experimental design center, this cutoff value was realized in a sequence of sixteen experiments, the results of which are summarized in Tables 3 and 4.

EXPERIMENT		DESIGN CENTER			Y VALUES AT PRESENT CENTER			Y VALUES PREDICTED AT NEXT CENTER			RESIDUAL ERROR VALUE
Number	Order	X_1	X_2	X_3	Y_1	Y_2	Y_3	Y_1	Y_2	Y_3	
1	First	3000.0	300.0	2.0	187.17	164.01	164.00	353.19	36.88	-36.87	116660.9
2	First	4795.9	465.7	1.79	336.93	34.89	-26.36	372.84	42.21	-62.21	5077.9
3	First	4301.2	503.9	2.14	369.01	46.58	-68.16	374.81	47.73	-74.34	582.28
4	First	4219.6	513.7	2.2	375.73	48.75	-75.58	378.01	47.72	-74.20	388.26
5	Second	4219.6	513.7	2.2	380.84	43.14	-65.82	376.02	45.92	-73.63	443.1
6	Second	4174.3	510.5	2.25	375.95	46.21	-74.60	381.18	45.32	-77.58	318.47
7	Second	4196.7	517.86	2.33	382.20	45.20	-76.80	380.06	45.65	-79.21	244.89
8	Second	4198.8	517.0	2.35	380.76	45.66	-79.29	381.54	44.03	-76.76	228.87
9	Second	4241.0	518.7	2.36	382.41	44.04	-76.74	381.21	44.39	-78.18	214.94
10	Second	4236.8	518.8	2.37	382.53	44.35	-79.00	380.35	44.53	-79.79	209.10
11	Second	4246.4	517.8	2.39	381.37	44.50	-79.87	381.62	42.98	-77.47	193.63
12	Second	4289.9	518.9	2.39	382.51	42.96	-77.40	381.32	43.32	-78.81	180.99
13	Second	4285.1	519.1	2.41	382.31	43.36	-79.21	380.53	43.12	-79.96	172.49
14	Second	4305.3	518.19	2.43	380.52	43.99	-85.14	382.14	42.60	-81.73	180.19
15	Second	4331.6	520.94	2.47	382.99	42.60	-81.85	382.62	41.29	-79.40	151.65
16	Second	4372.2	521.45	2.48	383.63	41.17	-78.88	382.32	41.49	-80.12	139.56

Table 3. Modeling Experimental Results

Table 3 shows the results of the sixteen experiments. The first four experiments utilized a first order 2^3 experimental design since the purpose in the initial steps was to get to a region of curvature as rapidly as possible. The fourth experiment indicated that a region of curvature had been reached. At this point, using the same design center as with experiment four, the initial second order design was implemented. The succeeding eleven experiments yielded a residual error value which was less than the cutoff value set prior to initiation of the experiments. Hence, the sequence of experiments was terminated and the process model was assumed to be the model containing the three equations yielded by the sixteenth experiment.

From the residual error column of Table 3, the residual error is seen to have an extremely large value on the first experiment and then shows a significant reduction with each of the next three experiments. A slight rise in the residual error is noticed with the initial second order experiment which was not an unexpected occurrence since the cross terms were incorporated at this point. Through the sequence of second order experiments, the residual error is seen to decrease in smaller steps with each succeeding experiment. This indicates that the response surface for this particular performance index is more on the order of a plateau than peaked in the vicinity of the optimum value.

The value of 150 chosen initially as an experimentation cutoff value appeared to have been a proper choice. From the thirteenth experiment to the sixteenth, the values of the response variables at the next design center as predicted by the current set of model equations were almost exact. The shortening steps of decrease in the value of the residual error function, coupled with only minor changes in the model coefficients over the course of the last four experiments, also validate this choice.

It is conceivable that the sequence of experiments could have continued until the value of the residual error approached zero. This, however, is not acceptable in practice since experimentation on a process is generally a costly endeavor. Thus, to obtain only minor improvements in the empirical model may prove to be an extremely costly venture.

Table 4 shows the model derived by the empirical modeling technique together with the actual process model. The experimentally derived equation for sheet resistance and the TCR are extremely close to the actual model equations. The equation derived for deposition rate, however, differs from the actual equation in the coefficients for voltage, nitrogen, and $(\text{current})^2$. These coefficients may have been brought closer to those of the actual model if further experimentation had been done. Overall, however, the actual process model and the experimentally derived

ACTUAL MODEL:

Variable	Coefficient	Deposition Rate	Sheet Resistance	TCR
Mean	b_0	379.73	30.77	-82.92
Voltage	b_1	18.39	-24.91	69.18
Current	b_2	96.47	-15.73	64.22
Nitrogen	b_3	-25.02	10.77	-56.22
$(\text{Voltage})^2$	b_{11}	- 1.59	10.80	-12.68
$(\text{Current})^2$	b_{22}	- 4.90	2.97	- 6.04
$(\text{Nitrogen})^2$	b_{33}	- 9.13	2.30	- 5.43
(Voltage·Current)	b_{12}	3.00	9.14	-20.50
(Voltage·Nitrogen)	b_{13}	8.50	- 6.17	21.75
(Current·Nitrogen)	b_{23}	- 5.50	- 1.30	16.00

EMPIRICALLY DETERMINED MODEL:

Variable	Coefficient	Deposition Rate	Sheet Resistance	TCR
Mean	b_0	389.72	31.34	-83.89
Voltage	b_1	28.70	-24.50	68.41
Current	b_2	100.25	-15.83	63.74
Nitrogen	b_3	-18.72	11.44	-56.88
$(\text{Voltage})^2$	b_{11}	2.12	10.82	-14.14
$(\text{Current})^2$	b_{22}	0.20	2.45	- 6.71
$(\text{Nitrogen})^2$	b_{33}	- 6.85	2.50	- 5.69
(Voltage·Current)	b_{12}	5.73	10.33	-21.25
(Voltage·Nitrogen)	b_{13}	10.10	- 5.67	22.71
(Current·Nitrogen)	b_{23}	- 4.54	- 1.74	16.09
Multiple Correlation Coefficient	R^2	0.99	0.99	0.99

Table 4. Comparison of Actual Process Model with Empricially Derived Model.

process model are in close agreement. The next section discusses the results of the application of the two control schemes, based on this model, in simulated control systems for the process.

5.2 COMPARISON OF CONTROL SYSTEM SIMULATIONS

The process simulator was run under control of the optimal controller, then under the control of the adaptive controller under identical conditions as specified in Chapter 4. A run of the process simulator operating as an uncontrolled process was made for each test condition prior to the control system runs to provide a basis of comparison for control system effectiveness in reducing the standard deviations of the process responses about their desired means. The results of these simulations will be discussed in the remainder of this chapter. First, the operation of the optimal control system will be compared to the operation of the uncontrolled process. Next, the operation of the adaptive control system will be compared to the operation of the uncontrolled process. Finally, the operations of the two control systems will be compared.

The first sequence of process and control system simulations were run at a drift period of forty cycles. The results of the simulations of 300 process cycles at this drift period for each process configuration at each of the fifty-six drift amplitude-measurement error combinations and for each dependent process variables are given in Tables 5 through 10. Tables 5 through 7 show the actual (without measurement error) values of the process dependent variables while Tables 8 through 10 show the values of these variables with measurement error - as those values would be recorded or monitored through electrical or mechanical transducers. The actual values of the process output variables show how the process is actually performing. These values may be somewhat misleading, especially for those actual values of the output variables in cases where the process is being controlled. In these cases, although these values are the actual values of the output variables of the process, the process controller actually "sees" the values of the output variables with measurement error included. Thus the analysis of the process performance will be based on Tables 8 through 10 more heavily than on Tables 5 through 7, since these are the values which would actually be recorded or monitored by a controller in an actual situation.

Tables 8 through 10 yield, for each variable, the following process performance information:

(1) Deposition Rate -- Table 8 contains mean and standard deviation values of the deposition rate output variable for each process configuration. The desired mean value for this variable is 379.73 Angstrom units per minute.

When no drift is present, the mean of the uncontrolled process is seen to increase as the measurement error increases.

Table 5

Deposition Rate (Actual)
Desired Value = 379.73 Angstroms/Minute
Drift Period = 40 Cycles

Percent Drift	Percent Meas. Err.	Uncontrolled		Optimally Controlled		Adaptively Controlled	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
0.0	0.5	379.73	0.0	379.73	0.0	379.73	0.0
	1.0	379.73	0.0	379.32	3.48	380.88	67.21
	3.0	379.73	0.0	378.02	19.10	353.91	151.47
	5.0	379.73	0.0	378.61	30.85	383.12	116.92
	7.0	379.73	0.0	378.42	46.24	367.12	97.52
	9.0	379.73	0.0	376.71	57.42	375.03	92.62
	11.0	379.73	0.0	373.71	75.96	394.52	154.81
2.0	0.5	380.05	5.36	379.68	3.70	376.67	152.38
	1.0	380.05	5.36	379.60	4.36	367.20	86.51
	3.0	380.05	5.36	378.26	16.16	409.16	151.55
	5.0	380.05	5.36	378.11	33.02	384.19	101.61
	7.0	380.05	5.36	376.30	46.03	384.04	104.35
	9.0	380.05	5.36	377.91	62.18	382.35	147.78
	11.0	380.05	5.36	372.85	81.68	398.65	210.65
5.0	0.5	380.53	13.40	379.14	4.72	344.68	142.68
	1.0	380.53	13.40	379.31	5.68	358.76	127.73
	3.0	380.53	13.40	378.85	16.69	341.75	146.08
	5.0	380.53	13.40	378.53	32.96	392.11	128.48
	7.0	380.53	13.40	377.56	44.77	350.88	141.08
	9.0	380.53	13.40	377.79	59.78	373.73	141.26
	11.0	380.53	13.40	376.23	75.09	371.41	152.83

Table 5 (Continued)

Percent Drift	Percent Meas. Err.	Uncontrolled Mean	Uncontrolled S.D.	Optimally Controlled Mean	Optimally Controlled S.D.	Adaptively Controlled Mean	Adaptively Controlled S.D.
10.0	0.5	381.34	26.80	379.35	6.73	305.20	149.90
	1.0	381.34	26.80	379.43	9.20	374.26	126.21
	3.0	381.34	26.80	378.02	19.56	384.33	169.12
	5.0	381.34	26.80	377.66	33.66	387.38	109.68
	7.0	381.34	26.80	376.74	46.36	422.63	167.70
	9.0	381.34	26.80	376.77	62.39	394.73	131.91
	11.0	381.34	26.80	377.23	78.57	406.98	170.76
15.0	0.5	382.14	40.21	379.84	31.24	378.73	134.43
	1.0	382.12	40.21	378.06	24.85	399.74	160.43
	3.0	382.14	40.21	377.81	31.12	427.15	173.05
	5.0	382.14	40.21	378.96	35.36	379.50	123.66
	7.0	382.14	40.21	378.79	47.55	402.17	153.34
	9.0	382.14	40.12	374.70	62.48	394.61	149.66
	11.0	382.14	40.21	377.76	86.84	408.98	174.27
20.0	0.5	382.95	53.61	379.83	52.20	417.20	172.24
	1.0	382.95	53.61	377.84	34.53	415.11	157.00
	3.0	382.95	53.61	377.29	40.17	372.03	139.05
	5.0	382.95	53.61	378.63	35.51	439.55	195.58
	7.0	382.95	53.61	382.02	56.48	381.37	162.70
	9.0	382.95	53.61	383.39	69.60	406.43	177.09
	11.0	382.95	53.61	376.21	81.06	408.98	176.13

Table 5 (Continued)

Percent Drift	Percent Meas. Err.	Uncontrolled		Optimally Controlled		Adaptively Controlled	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
25.0	0.5	383.75	67.01	377.71	62.80	401.47	154.26
	1.0	383.75	67.01	380.57	61.47	422.43	177.27
	3.0	383.75	67.01	380.81	52.52	405.89	169.38
	5.0	383.75	67.01	381.46	39.72	403.92	167.52
	7.0	383.75	67.01	382.09	69.29	409.25	180.21
	9.0	383.75	67.01	385.24	73.88	365.98	211.53
	11.0	383.75	67.01	382.51	94.78	412.99	175.62
30.0	0.5	384.56	80.41	381.79	67.76	448.32	243.98
	1.0	384.56	80.41	382.31	48.27	413.27	188.98
	3.0	384.56	80.41	378.83	38.67	440.49	176.98
	5.0	384.56	80.41	377.44	45.53	389.57	211.44
	7.0	384.56	80.41	385.43	62.02	432.05	199.39
	9.0	384.56	80.41	382.06	73.76	416.64	189.19
	11.0	384.56	80.41	385.46	98.61	330.90	239.10

Table 6

Sheet Resistance (Actual)
Desired Value = 30.77 Ohms/Square
Drift Period = 40 Cycles

Percent Drift	Percent Meas. Err.	Uncontrolled		Optimally Controlled		Adaptively Controlled	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
0.0	0.5	30.77	0.0	30.77	0.0	30.77	0.0
	1.0	30.77	0.0	30.74	1.09	50.19	68.05
	3.0	30.77	0.0	31.60	4.70	52.75	78.71
	5.0	30.77	0.0	33.01	8.41	39.86	30.47
	7.0	30.77	0.0	35.51	12.41	39.69	21.56
	9.0	30.77	0.0	37.80	15.97	40.85	23.61
	11.0	30.77	0.0	42.55	23.65	53.40	37.62
2.0	0.5	30.80	0.43	30.73	0.82	70.06	114.09
	1.0	30.80	0.43	30.92	1.20	34.92	26.90
	3.0	30.80	0.43	31.34	4.95	46.55	48.77
	5.0	30.80	0.43	33.12	8.21	39.44	25.60
	7.0	30.80	0.43	36.06	13.32	38.67	23.71
	9.0	30.80	0.43	38.44	16.15	50.72	50.74
	11.0	30.80	0.43	42.28	23.19	109.26	135.18
5.0	0.5	30.84	1.09	30.94	0.93	62.63	91.58
	1.0	30.84	1.09	30.81	1.35	50.09	74.78
	3.0	30.84	1.09	30.11	4.37	50.44	67.15
	5.0	30.84	1.09	33.23	8.36	53.77	78.50
	7.0	30.84	1.09	35.06	11.61	110.89	252.78
	9.0	30.84	1.09	39.18	21.05	49.04	35.20
	11.0	30.84	1.09	41.98	24.48	52.29	57.84

Table 6 (Continued)

Percent Drift	Percent Meas. Err.	Uncontrolled		Optimally Controlled		Adaptively Controlled	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
10.0	0.5	30.90	2.17	31.28	1.93	102.49	149.15
	1.0	30.90	2.17	31.44	2.56	54.15	100.02
	3.0	30.90	2.17	32.27	5.64	41.25	42.80
	5.0	30.90	2.17	34.08	8.70	40.68	21.44
	7.0	30.90	2.17	36.81	13.46	37.25	24.90
	9.0	30.90	2.17	40.54	21.41	43.75	24.31
	11.0	30.90	2.17	42.03	23.12	51.88	46.34
15.0	0.5	30.97	3.26	33.52	5.68	44.49	49.33
	1.0	30.97	3.26	33.49	5.57	41.27	48.63
	3.0	30.97	3.26	34.48	8.56	38.60	19.38
	5.0	30.97	3.26	36.10	13.74	43.34	42.98
	7.0	30.97	3.26	37.39	13.70	42.35	33.97
	9.0	30.97	3.26	40.14	17.98	43.93	25.42
	11.0	30.97	3.26	46.84	30.44	48.32	61.74
20.0	0.5	31.03	4.34	40.67	42.06	42.45	41.74
	1.0	31.03	4.34	36.67	21.64	34.66	18.50
	3.0	31.03	4.34	37.57	29.44	70.87	183.54
	5.0	31.03	4.34	36.57	10.53	45.13	40.17
	7.0	31.03	4.34	39.55	20.97	49.61	34.58
	9.0	31.03	4.34	41.02	23.25	47.45	35.63
	11.0	31.03	4.34	45.97	26.53	53.98	44.13

Table 6 (Continued)

Percent Drift	Percent Meas. Err.	Uncontrolled		Optimally Controlled		Adaptively Controlled	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
25.0	0.5	31.10	5.43	49.12	46.87	48.75	59.47
	1.0	31.10	5.43	45.26	41.80	44.83	53.57
	3.0	31.10	5.43	41.30	33.41	45.73	36.53
	5.0	31.10	5.43	39.18	18.63	42.87	37.21
	7.0	31.10	5.43	40.14	19.26	53.99	59.36
	9.0	31.10	5.43	42.99	22.12	52.53	34.62
	11.0	31.10	5.43	44.98	28.65	53.12	36.01
30.0	0.5	31.16	6.52	47.81	49.17	41.26	36.65
	1.0	31.16	6.52	43.31	36.94	44.16	53.87
	3.0	31.16	6.52	41.93	35.99	36.72	21.01
	5.0	31.16	6.52	41.41	21.94	47.40	32.05
	7.0	31.16	6.52	38.36	28.82	42.77	27.20
	9.0	31.16	6.52	42.10	21.67	52.43	48.87
	11.0	31.16	6.52	45.77	35.07	169.85	200.59

Table 7

TCR (Actual)
Desired Value -82.92 PPM/Degree Centigrade
Drift Period 40 Cycles

Percent Drift	Percent Meas. Err.	Uncontrolled Mean	Uncontrolled S.D.	Optimally Controlled Mean	Optimally Controlled S.D.	Adaptively Controlled Mean	Adaptively Controlled S.D.
0.0	0.5	-82.92	0.0	-82.92	0.0	-82.92	0.0
	1.0	-82.92	0.0	-82.97	3.19	-72.52	68.76
	3.0	-82.92	0.0	-83.93	16.33	-112.76	231.60
	5.0	-82.92	0.0	-83.58	28.99	-83.54	85.63
	7.0	-82.92	0.0	-84.96	40.87	-87.49	66.99
	9.0	-82.92	0.0	-86.28	53.77	-81.90	79.81
	11.0	-82.92	0.0	-90.94	67.49	-89.65	108.95
2.0	0.5	-82.99	1.17	-82.77	2.56	-129.88	222.11
	1.0	-82.99	1.17	-83.56	3.73	-79.67	49.44
	3.0	-82.99	1.17	-83.42	15.56	-92.44	116.56
	5.0	-82.99	1.17	-84.12	29.58	-81.48	73.35
	7.0	-82.99	1.17	-86.51	42.70	-76.12	87.60
	9.0	-82.92	1.17	-86.17	53.92	-103 21	135.97
	11.0	-82.92	1.17	-89.61	69.24	-148.67	209.14
5.0	0.5	-83.10	2.93	-83.33	2.74	-120.64	127.25
	1.0	-83.10	2.93	-82.95	4.35	-100.15	150.29
	3.0	-83.10	2.93	-82.95	15.48	-103.97	113.20
	5.0	-83.10	2.93	-84.39	30.38	-99.41	111.82
	7.0	-83.10	2.93	-85.53	41.50	-272.27	719.86
	9.0	-83.10	2.93	-86.62	54.22	-99.22	131.22
	11.0	-83.10	2.93	-87.65	66.99	-82.11	136.46

Table 7 (Continued)

Percent Drift	Percent Meas. Err.	Uncontrolled Mean	Uncontrolled S.D.	Optimally Controlled Mean	Optimally Controlled S.D.	Adaptively Controlled Mean	Adaptively Controlled S.D.
10.0	0.5	-83.27	5.85	-82.64	3.85	-134.16	138.50
	1.0	-83.27	5.85	-82.24	7.13	-112.47	271.99
	3.0	-83.27	5.85	-83.42	17.04	-65.56	78.82
	5.0	-83.27	5.85	-83.91	31.24	-82.21	60.60
	7.0	-83.27	5.85	-84.94	41.77	-67.40	81.71
	9.0	-83.27	5.85	-86.81	54.15	-73.82	95.40
	11.0	-83.27	5.85	-89.43	67.50	-58.15	124.68
15.0	0.5	-83.44	8.78	-80.72	20.50	-76.87	88.32
	1.0	-83.44	8.78	-81.80	13.12	-73.33	93.55
	3.0	-83.44	8.78	-81.92	21.53	-49.06	91.82
	5.0	-83.44	8.78	-82.02	31.26	-80.80	85.15
	7.0	-83.44	8.78	-82.47	42.75	-71.48	111.57
	9.0	-83.44	8.78	-86.70	54.66	-72.58	92.73
	11.0	-83.44	8.78	-89.56	72.71	-79.67	146.64
20.0	0.5	-83.63	11.71	-80.67	46.61	-59.41	80.49
	1.0	-83.62	11.71	-80.84	30.11	-64.17	80.13
	3.0	-83.62	11.71	-80.79	34.70	-151.08	514.68
	5.0	-83.62	11.71	-80.09	31.78	-69.07	87.96
	7.0	-83.62	11.71	-80.64	42.98	-75.06	95.42
	9.0	-83.62	11.71	-79.25	52.37	-60.57	112.97
	11.0	-83.62	11.71	-86.55	67.38	-67.44	126.21

Table 7 (Continued)

Percent Drift	Percent Meas. Err.	Uncontrolled Mean	Uncontrolled S.D.	Optimally Controlled Mean	Optimally Controlled S.D.	Adaptively Controlled Mean	Adaptively Controlled S.D.
25.0	0.5	-83.80	14.63	-80.97	48.25	-76.15	107.83
	1.0	-83.80	14.63	-79.01	40.38	-60.17	95.28
	3.0	-83.80	14.63	-77.60	40.67	-61.75	94.50
	5.0	-83.80	14.63	-76.14	31.96	-62.10	86.32
	7.0	-83.80	14.63	-76.89	51.94	-59.71	115.34
	9.0	-83.80	14.63	-73.84	53.35	-83.17	129.62
	11.0	-83.80	14.63	-83.27	70.73	-67.36	113.35
30.0	0.5	-83.97	17.56	-77.98	54.54	-34.90	105.50
	1.0	-83.97	17.56	-74.38	38.47	-52.02	97.75
	3.0	-83.97	17.56	-75.65	35.99	-54.07	98.49
	5.0	-83.97	17.56	-75.10	33.00	-63.72	104.53
	7.0	-83.97	17.56	-72.08	50.28	-37.86	104.52
	9.0	-83.97	17.56	-74.47	53.26	-65.05	123.44
	11.0	-83.97	17.56	-77.56	71.48	-192.62	307.18

Table 8

Deposition Rate (Measured)
Desired Value = 379.73 Angstroms/Minute
Drift Period = 40 Cycles

Percent Drift	Percent Meas. Err.	Uncontrolled		Optimally Controlled		Adaptively Controlled	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
0.0	0.5	379.91	1.77	379.91	1.77	379.91	1.77
	1.0	380.10	3.54	379.70	5.27	381.25	68.21
	3.0	380.82	10.63	379.16	22.81	354.57	151.31
	5.0	381.56	17.72	380.55	37.16	384.52	118.60
	7.0	382.30	24.80	381.24	54.75	369.36	101.05
	9.0	383.03	31.89	380.56	69.70	378.14	100.26
	11.0	383.76	38.97	378.60	90.89	399.26	161.20
2.0	0.5	380.24	5.77	379.86	4.16	376.81	152.35
	1.0	380.42	6.65	379.97	6.05	367.59	86.68
	3.0	381.16	12.29	379.40	20.30	410.26	152.59
	5.0	381.90	18.94	380.13	39.61	386.09	106.02
	7.0	382.65	25.83	379.22	55.51	386.86	110.18
	9.0	383.39	32.82	381.72	73.63	385.35	152.35
	11.0	384.13	39.84	378.14	98.36	402.21	215.14
5.0	0.5	380.72	13.66	379.33	5.13	344.82	142.68
	1.0	380.91	14.13	379.68	6.92	359.20	128.13
	3.0	381.66	17.79	380.01	20.94	342.95	146.83
	5.0	382.42	23.13	380.46	38.77	393.98	130.06
	7.0	383.17	29.25	380.38	53.58	353.20	144.47
	9.0	383.92	35.75	381.53	70.88	378.40	150.09
	11.0	384.68	42.45	381.19	90.59	376.55	165.33

Table 8 (Continued)

Percent Drift	Percent Meas. Err.	Uncontrolled		Optimally Controlled		Adaptively Controlled	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
10.0	0.5	381.53	27.01	379.54	6.93	305.32	150.02
	1.0	381.73	27.33	379.80	10.02	374.72	126.78
	3.0	382.50	29.70	379.18	23.23	384.95	168.41
	5.0	383.27	33.47	379.53	39.87	389.12	110.46
	7.0	384.04	38.24	379.62	55.19	425.62	172.52
	9.0	384.81	43.68	380.68	73.99	398.98	139.29
	11.0	385.59	46.60	381.91	91.88	412.36	179.23
15.0	0.5	382.34	40.40	380.04	31.52	379.93	134.44
	1.0	382.54	40.68	378.46	25.33	400.17	160.44
	3.0	383.33	42.54	378.96	34.01	428.15	173.27
	5.0	384.13	45.50	380.88	40.43	381.19	125.24
	7.0	384.92	49.36	381.60	55.93	405.49	157.31
	9.0	385.71	53.92	378.55	73.48	399.52	159.38
	11.0	386.51	59.03	382.81	101.20	413.55	183.65
20.0	0.5	383.15	53.80	380.03	52.24	417.41	172.42
	1.0	383.35	54.05	378.19	34.85	415.50	156.80
	3.0	384.17	55.67	378.38	41.99	373.44	141.82
	5.0	384.98	58.17	380.57	40.85	440.93	196.12
	7.0	385.80	61.45	384.93	64.03	383.09	164.55
	9.0	386.61	65.39	387.30	79.73	409.79	180.13
	11.0	387.42	69.89	380.76	93.22	413.27	181.75

Table 8 (Continued)

Percent Drift	Percent Meas. Err.	Uncontrolled Mean	Uncontrolled S.D.	Optimally Controlled Mean	Optimally Controlled S.D.	Adaptively Controlled Mean	Adaptively Controlled S.D.
25.0	0.5	383.96	67.20	377.92	62.84	401.66	154.19
	1.0	384.17	67.45	380.91	61.31	422.95	177.52
	3.0	385.00	68.92	382.01	54.30	406.91	169.45
	5.0	385.83	71.14	383.51	45.49	405.63	168.98
	7.0	386.67	74.05	385.19	77.79	412.73	185.65
	9.0	387.50	77.55	389.23	83.74	369.34	218.73
	11.0	388.33	81.59	387.40	107.60	417.38	184.14
30.0	0.5	384.77	80.61	381.96	67.75	448.43	243.86
	1.0	384.98	80.85	382.68	48.24	414.28	189.06
	3.0	385.84	82.24	380.12	41.31	441.58	177.19
	5.0	386.69	84.28	379.52	50.79	392.67	215.73
	7.0	387.54	86.93	388.17	67.57	435.23	204.17
	9.0	388.40	90.12	386.34	86.37	421.34	201.06
	11.0	389.24	93.81	391.06	112.37	333.17	240.36

Table 9

Sheet Resistance (Measured)
Desired Value = 30.77 Ohms/Square
Drift Period = 40 Cycles

Percent Drift	Percent Meas. Err.	Uncontrolled		Optimally Controlled		Adaptively Controlled	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
0.0	0.5	30.77	0.15	30.97	0.15	30.77	0.15
	1.0	30.77	0.30	30.74	1.14	50.23	67.34
	3.0	30.78	0.90	31.60	4.76	52.69	78.55
	5.0	30.78	1.50	33.01	8.55	39.92	30.65
	7.0	30.79	2.10	35.52	12.76	39.74	21.78
	9.0	30.79	2.70	37.81	16.53	40.66	23.01
	11.0	30.79	3.30	42.62	24.30	53.17	38.12
2.0	0.5	30.80	0.44	30.73	0.81	70.09	114.19
	1.0	30.80	0.50	30.92	1.24	34.94	27.03
	3.0	30.80	0.95	31.34	5.03	46.52	48.77
	5.0	30.81	1.51	33.11	8.25	39.43	25.30
	7.0	30.81	2.09	36.09	13.74	38.73	24.32
	9.0	30.81	2.68	38.51	16.85	50.35	48.55
	11.0	30.82	3.27	42.28	23.78	109.52	136.90
5.0	0.5	30.84	1.08	30.94	0.94	62.68	91.70
	1.0	30.84	1.09	30.81	1.37	50.11	75.01
	3.0	30.84	1.39	31.11	4.45	50.64	68.91
	5.0	30.84	1.74	33.24	8.58	53.42	77.16
	7.0	30.84	2.24	35.07	11.98	109.29	247.09
	9.0	30.84	2.78	39.11	20.73	48.92	34.99
	11.0	30.85	3.34	42.08	26.17	53.31	58.59

Table 9 (Continued)

Percent Drift	Percent Meas. Err.	Uncontrolled		Optimally Controlled		Adaptively Controlled	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
10.0	0.5	30.90	2.16	31.28	1.94	102.41	148.01
	1.0	30.90	2.15	31.44	2.57	54.15	100.10
	3.0	30.90	2.24	32.28	5.76	41.30	43.27
	5.0	30.90	2.47	34.11	8.99	40.70	21.34
	7.0	30.90	2.82	36.85	13.86	37.19	25.10
	9.0	30.90	3.24	40.47	21.40	43.53	24.01
	11.0	30.90	3.71	42.03	23.12	52.07	50.47
15.0	0.5	30.97	3.24	33.52	5.67	44.50	49.37
	1.0	30.93	3.23	33.50	5.60	41.27	48.96
	3.0	30.96	3.27	34.49	8.62	38.63	19.57
	5.0	30.96	3.41	36.13	13.78	43.28	42.42
	7.0	30.95	3.65	37.41	14.13	42.34	33.01
	9.0	30.95	3.96	40.15	18.70	43.73	25.21
	11.0	30.95	4.33	47.03	31.47	47.97	60.37
20.0	0.5	31.03	4.23	40.67	42.03	42.43	41.58
	1.0	31.03	4.32	36.66	21.43	34.68	18.62
	3.0	31.02	4.32	37.54	27.84	70.63	182.35
	5.0	31.02	4.41	36.59	10.73	45.23	40.99
	7.0	31.01	4.58	39.56	21.02	49.53	34.65
	9.0	31.00	4.82	40.98	23.21	47.17	33.72
	11.0	31.00	5.12	45.98	27.12	53.85	45.96

Table 9 (Continued)

Percent Drift	Percent Meas. Err.	Uncontrolled		Optimally Controlled		Adaptively Controlled	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
25.0	0.5	31.09	5.41	49.12	46.92	48.73	59.24
	1.0	31.09	5.40	45.31	42.18	44.84	53.72
	3.0	31.08	5.39	41.35	33.94	45.73	36.48
	5.0	31.07	5.45	39.19	18.74	42.78	36.09
	7.0	31.07	5.57	40.21	19.76	53.80	58.14
	9.0	31.06	5.76	42.93	21.97	52.09	32.89
	11.0	31.04	6.00	44.67	27.16	52.92	36.64
30.0	0.5	31.16	6.50	47.83	49.20	41.27	36.71
	1.0	31.16	6.48	43.30	36.88	44.19	54.15
	3.0	31.14	6.46	41.99	37.04	36.71	20.99
	5.0	31.13	6.50	41.48	22.29	47.36	32.07
	7.0	31.12	6.60	38.46	29.78	42.63	27.03
	9.0	31.11	6.74	42.17	22.68	52.12	48.29
	11.0	31.10	6.94	45.99	36.42	169.20	200.86

Table 10

TCR (Measured)
Desired Value -82.92 PPM/Degree Centigrade
Drift Period 40 Cycles

Percent Drift	Percent Meas. Err.	Uncontrolled		Optimally Controlled		Adaptively Controlled	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
0.0	0.5	-82.92	0.39	-82.92	0.39	-82.92	0.39
	1.0	-82.92	0.78	-82.96	3.26	-73.53	69.19
	3.0	-82.92	2.35	-83.93	16.58	-112.84	231.51
	5.0	-82.91	3.91	-83.71	29.57	-83.63	89.93
	7.0	-82.91	5.47	-85.21	41.60	-87.46	67.39
	9.0	-82.91	7.03	-86.64	54.37	-82.88	80.31
	11.0	-82.91	8.60	-91.31	67.72	-89.94	111.49
2.0	0.5	-82.99	1.21	-82.77	2.56	-129.80	221.59
	1.0	-82.99	1.36	-82.56	3.80	-79.69	49.61
	3.0	-82.98	2.55	-83.45	15.86	-92.77	118.40
	5.0	-82.98	4.01	-84.27	30.21	-81.31	73.83
	7.0	-82.98	5.52	-86.78	43.37	-76.29	89.66
	9.0	-82.98	7.06	-86.60	54.82	-104.21	139.25
	11.0	-82.97	8.61	-89.77	69.26	-147.76	210.45
5.0	0.5	-83.09	2.93	-83.03	2.75	-102.67	127.39
	1.0	-83.09	2.98	-82.95	4.41	-99.95	148.80
	3.0	-83.09	3.63	-82.99	15.87	-103.85	112.66
	5.0	-83.08	4.73	-84.49	30.73	-99.35	112.21
	7.0	-83.07	6.04	-85.75	42.01	-269.89	709.38
	9.0	-83.07	7.45	-86.89	54.58	-99.12	129 93
	11.0	-83.06	8.92	-88.04	67.12	-82.44	140.30

Table 10 (Continued)

Percent Drift	Percent Meas. Err.	Uncontrolled		Optimally Controlled		Adaptively Controlled	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
10.0	0.5	-83.27	5.84	-82.64	3.84	-134.20	138.62
	1.0	-83.27	5.85	-82.24	7.15	-112.52	272.25
	3.0	-83.26	6.16	-83.45	17.33	-65.57	79.08
	5.0	-83.25	6.83	-83.91	31.24	-82.29	60.88
	7.0	-83.24	7.76	-85.09	42.08	-67.37	82.30
	9.0	-83.23	8.88	-87.19	54.74	-74.02	94.73
	11.0	-83.22	10.12	-89.43	67.50	-58.15	124.68
15.0	0.5	-83.44	8.76	-80.72	20.45	-76.89	88.28
	1.0	-83.44	8.78	-81.80	13.10	-73.26	93.42
	3.0	-83.43	8.94	-81.95	21.83	-49.17	91.97
	5.0	-83.41	99.38	-82.03	31.43	-79.75	84.39
	7.0	-83.40	10.06	-82.50	42.93	-71.37	111.14
	9.0	-83.39	10.92	-86.99	55.01	-72.74	93.85
	11.0	-83.37	11.94	-86.90	74.00	-78.23	136.21
20.0	0.5	-83.62	11.69	-80.66	46.63	-59.41	80.29
	1.0	-83.62	11.68	-80.86	30.29	-64.17	80.13
	3.0	-83.60	11.78	-80.78	35.11	-151.59	517.23
	5.0	-83.58	12.10	-80.18	32.10	-68.71	87.36
	7.0	-83.56	12.62	-80.66	43.21	-75.53	96.13
	9.0	-83.54	13.30	-79.15	51.94	-61.43	112.50
	11.0	-83.53	14.14	-86.62	67.76	-68.29	125.64

Table 10 (Continued)

Percent Drift	Percent Meas. Err.	Uncontrolled		Optimally Controlled		Adaptively Controlled	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
25.0	0.5	-83.79	14.61	-80.97	48.21	-76.13	107.99
	1.0	-83.79	14.60	-78.99	40.60	-60.21	95.19
	3.0	-83.77	14.67	-77.59	41.14	-62.07	94.50
	5.0	-83.75	14.90	-76.24	32.34	-61.71	86.78
	7.0	-83.72	15.30	-76.91	53.29	-59.40	113.16
	9.0	-83.70	15.87	-74.12	54.33	-82.88	129.21
	11.0	-83.68	16.57	-83.78	71.09	-67.71	114.20
30.0	0.5	-83.97	17.50	-78.00	54.64	-34.94	105.52
	1.0	-83.96	17.52	-74.39	38.32	-52.07	97.56
	3.0	-83.94	17.56	-75.64	35.21	-54.19	98.64
	5.0	-83.91	17.75	-75.21	33.47	-63.98	104.52
	7.0	-83.89	18.08	-72.34	51.11	-37.68	105.12
	9.0	-83.86	18.55	-74.57	53.38	-64.58	122.72
	11.0	-83.84	19.14	-77.44	71.11	-193.23	307.53

The standard deviation also increases, as would be expected, as measurement error is increased. In comparison to corresponding values for the optimally controlled process, it is seen that the controlled process tends to hold closer to the desired mean than the uncontrolled process. A comparison in standard deviations for these two configurations, however, shows that the optimal controller does not hold the variations about the mean as well as the uncontrolled process when the measurement error exceeds about one percent.

Under the same no drift conditions, the adaptive controller performs erratically, allowing the mean value to swing widely about the desired mean value. The standard deviations of corresponding levels of measurement error for all three configurations who that the adaptive controlled process to yield a significantly higher standard deviation for all levels of measurement error than either the optimally controlled or the uncontrolled process.

When the drift amplitude takes on values of 2, 5, 10, and 15 percent, it is seen that once again the optimally controlled process holds closer to the desired mean than the uncontrolled process. Under these conditions the optimal controller holds the standard deviation to values less than those at corresponding levels of the uncontrolled process for measurement error up to one percent for two percent drift; up to three percent, at five percent drift; and up to approximately seven percent at 15 percent drift. For drift values of 20, 25, and 30 percent, the optimally controlled process means and standard deviations are held better than the uncontrolled process only up to the five percent level of measurement error. Above this measurement error level, the optimal controller loses its ability to hold either the mean or standard deviation better than the uncontrolled process for each of these higher drift levels.

For all drift and measurement error levels at this drift period, the adaptively controlled process means and standard deviations of the deposition rate are erratic. The adaptive controller appears unable to hold the mean value near that desired. The standard deviations are also seen to fluctuate wildly at large values.

(2) Sheet Resistance -- Tables 6 and 9 contain the measured and actual values, respectively, of the sheet resistance means and standard deviations for each of the process configurations. Table 9 shows that for all levels of drift amplitude and for measurement error at levels greater than 0.5 percent, the uncontrolled process holds closer to the desired mean value than either the optimal or the adaptive control system configurations of the process. In these cases, also, the standard deviations of the controlled versions are seen to be greater than with the uncontrolled process.

In comparing the points at which the standard deviations for the deposition rate became larger than the standard deviations for the uncontrolled process to like levels of drift and measurement error for the sheet resistance, there appears to be no indication of correlation between the action of the optimal controller on the two variables. The action of the adaptive controller configuration for this variable is, however, similar to that for the deposition rate in that the same erratic action is observed.

(3) TCR -- Tables 7 and 10 contain the actual and measured values, respectively, of the means and standard deviations of the thermal coefficient of resistivity (TCR) output variable for each of the three process configurations. Table 10 shows that, basically, everything said about the systems effects on the sheet resistance holds for TCR. Once again, the uncontrolled process mean value is closer to the desired mean than either the optimally controlled or the adaptively controlled configurations for all levels of drift and for measurement error levels of more than 0.5 percent. The standard deviations of the controlled versions also show little or no indication of control.

The adaptively controlled configuration once again displays erratic action in comparison with the other two configurations.

Tables 5 through 10 reveal several interesting facts about the operation of the simulator when it is operated in the optimally controlled and adaptively controlled configurations. First, when the simulator is operated in the optimally controlled mode, only one output variable - the deposition rate - exhibits the effects of the actions of the controller. The means and standard deviations for the other two output variables, sheet resistance and TCR, appear to be adversely affected by the actions of the controller. This phenomenon can most probably be attributed to the index of performance function which the controller seeks to minimize on each control action performed. This index of performance was defined in Chapter 3 as the sum of the squared deviations of the output variables about specified desired values. The steepest descent search procedure utilized by the optimal controller than attempts to minimize this function by changing the values of the independent values in such a way that this sum of squares is reduced most rapidly. Now if the deviations from their desired values of the output variables are of approximately the same magnitude, the search procedure should perform properly. For the situation at hand, however, this is not the case. In these simulations, the drift amplitude was assumed to be a percentage of the output variable value which was impressed on that variable's value. The measurement error was also treated in this manner. Thus, since percentages of the output variable values were used, the values of these variables become critical. The desired values for each of the output variables show that the deposition rate (379.73) is much larger than the values of either sheet resistance (30.77) or TCR (82.92). Thus on a percentage drift and measurement error basis, the deposition rate variable would generate substantially larger error values than the other two variables. Hence, the dominance of the deposition rate in the control function.

The second fact exhibited by the data in Tables 5 through 10 is that the adaptively controlled process simulator appears not to operate in a successful manner at any drift-measurement error level combination. Although the adaptive controller uses the optimal controller as part of its control function, the problem here lies deeper than single variable dominance. The major problem with the adaptive controller when a short drift period is encountered (forty cycles in this case) lies in the re-estimation of the model coefficients. As the adaptive mechanism was set up for the simulation of the adaptively controlled process, each adaptation performed was accomplished by re-estimating the coefficients of the process model based on the sixty most recent observations of the process dependent and independent variables. To further complicate matters, a thirty cycle delay was required between any two consecutive adaptations. Some reflection on these conditions raises the question: to what is the adaptive mechanism adapting the process model equations? The answer to this is that although adaptation was being performed by the adaptive mechanism, these adaptations were not adapting the process model equations to the process drift. That this is true can be seen from the fact that while the drift period of the process was forty cycles, the adaptation was performed with data from sixty cycles. Thus, the adaptation in this case was attempted over one and one-half drift periods instead of a fraction of a drift period. In this situation, if one considers the drift sinusoid to be represented by a linearization, the process output would have, at best, been subject to three linear equations. Therefore, the performance of the adaptively controlled process in Tables 5 through 10 is not a valid indication of the adaptive control scheme's capability.

In order to better present the operation of the adaptive controller, the entire sequence of process simulations was rerun at a drift period of 160 machine cycles. The adaptive mechanism of the adaptive controller was modified for this sequence in such a way that any re-estimation of model coefficients (adaptation) required would be based on the forty most recent observations of the process input and output variables. As an additional modification to the original scheme, the delay between adaptations was eliminated thus allowing re-estimation of model coefficients on consecutive machine cycles if called for. Tables 11 through 16 contain the results of the 160 cycle drift period runs, presented in the same format as Tables 5 through 10.

Table 11

Deposition Rate (Actual)
Desired Value = 379.73 Angstroms/Minute
Drift Period = 160 Cycles

Percent Drift	Percent Meas. Err.	Uncontrolled		Optimally Controlled		Adaptively Controlled	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
0.0	0.5	379.73	0.0	379.73	0.0	379.73	0.0
	1.0	379.73	0.0	379.32	3.48	374.52	42.39
	3.0	379.73	0.0	378.36	17.16	376.51	50.52
	5.0	379.73	0.0	377.01	37.23	385.78	88.02
	7.0	379.73	0.0	376.45	56.79	380.95	98.60
	9.0	379.73	0.0	377.01	60.48	383.89	131.99
	11.0	379.73	0.0	382.19	82.85	369.20	125.65
2.0	0.5	379.91	5.48	379.28	2.56	379.92	47.92
	1.0	379.91	5.48	378.84	3.30	376.13	41.87
	3.0	379.91	5.48	380.30	32.02	378.55	87.52
	5.0	379.91	5.48	377.77	57.27	385.99	76.76
	7.0	379.91	5.48	377.30	46.00	388.33	112.71
	9.0	379.91	5.48	377.51	60.57	392.42	124.47
	11.0	379.91	5.48	374.71	80.15	377.02	111.26
5.0	0.5	380.18	13.71	379.27	3.17	377.79	40.57
	1.0	380.18	13.71	379.45	4.24	373.21	69.82
	3.0	380.18	13.71	377.15	27.80	366.54	78.28
	5.0	380.18	13.71	377.84	29.74	381.51	94.89
	7.0	380.18	13.71	378.57	43.05	372.22	119.61
	9.0	380.18	13.71	374.04	62.17	376.15	112.97
	11.0	380.18	13.71	378.83	82.85	377.79	115.21

Table 11 (Continued)

Percent Drift	Percent Meas. Err.	Uncontrolled Mean	Uncontrolled S.D.	Optimally Controlled Mean	Optimally Controlled S.D.	Adaptively Controlled Mean	Adaptively Controlled S.D.
10.0	0.5	380.63	27.42	381.05	2.38	374.34	70.44
	1.0	380.63	27.42	379.05	5.58	372.61	88.49
	3.0	380.63	27.42	377.28	28.88	387.31	82.01
	5.0	380.63	27.42	376.52	39.27	362.63	83.13
	7.0	380.63	27.42	374.77	50.81	380.41	88.19
	9.0	380.63	27.42	376.19	71.82	385.07	123.11
	11.0	380.63	27.42	378.38	79.09	369.41	137.72
15.0	0.5	381.08	41.13	379.37	10.19	382.80	100.81
	1.0	381.08	41.13	380.24	29.73	368.71	83.59
	3.0	381.08	41.13	378.39	19.33	385.92	97.13
	5.0	381.08	41.13	377.42	40.42	377.43	117.27
	7.0	381.08	41.13	376.41	55.55	386.11	90.08
	9.0	381.08	41.13	375.79	62.54	376.99	104.21
	11.0	381.08	41.13	377.59	88.79	387.92	125.57
20.0	0.5	381.53	51.84	378.13	52.32	377.38	90.90
	1.0	381.53	51.84	377.55	44.71	382.67	132.09
	3.0	381.53	51.84	380.46	34.34	380.21	109.52
	5.0	381 53	51.84	381.94	43.06	372.83	123.59
	7.0	381.53	51.84	379.64	53.35	382.22	128.68
	9.0	381.53	51.84	378.94	66.11	374.38	116.78
	11.0	381.53	51.84	375.23	86.32	390.09	153.05

Table 11 (Continued)

Percent Drift	Percent Meas. Err.	Uncontrolled Mean	Uncontrolled S.D.	Optimally Controlled Mean	Optimally Controlled S.D.	Adaptively Controlled Mean	Adaptively Controlled S.D.
25.0	0.5	381.98	68.55	380.96	36.48	369.31	85.56
	1.0	381.98	68.55	376.18	48.78	382.39	109.14
	3.0	381.98	68.55	377.90	48.34	405.51	123.92
	5.0	381.98	68.55	379.08	40.47	395.08	126.71
	7.0	381.98	68.55	382.30	62.98	402.13	117.28
	9.0	381.98	68.55	378.44	67.13	365.65	135.08
	11.0	381.98	68.55	377.54	86.53	368.92	139.91
30.0	0.5	382.43	82.27	384.20	32.67	385.27	112.77
	1.0	382.43	82.27	381.93	49.61	389.98	112.64
	3.0	382.43	82.27	385.67	39.35	409.76	122.28
	5.0	382.43	82.27	381.25	66.55	394.19	127.15
	7.0	382.43	82.27	379.57	60.47	388.22	128.47
	9.0	382.43	82.27	371.07	74.43	381.01	117.99
	11.0	382.43	82.27	381.00	93.14	383.79	130.08

Table 12

Sheet Resistance (Actual)
Desired Value = 30.77 Ohms/Square
Drift Period = 160 Cycles

Percent Drift	Percent Meas. Err.	Uncontrolled		Optimally Controlled		Adaptively Controlled	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
0.0	0.5	30.77	0.0	30.77	0.0	30.77	0.0
	1.0	30.77	0.0	30.74	1.09	38.78	80.52
	3.0	30.77	0.0	31.28	4.45	35.34	29.06
	5.0	30.77	0.0	33.49	9.65	35.51	19.16
	7.0	30.77	0.0	36.18	14.26	39.04	26.56
	9.0	30.77	0.0	38.99	17.54	45.89	35.66
	11.0	30.77	0.0	40.83	20.17	51.38	44.66
2.0	0.5	30.78	0.44	30.72	0.38	33.83	26.12
	1.0	30.78	0.44	30.70	0.97	34.17	25.93
	3.0	30.78	0.44	31.88	7.67	36.04	29.05
	5.0	30.78	0.44	35.11	19.29	35.37	15.17
	7.0	30.78	0.44	35.34	11.93	46.63	56.47
	9.0	30.78	0.44	38.94	16.74	42.91	31.58
	11.0	30.78	0.44	42.44	22.17	53.26	63.53
5.0	0.5	30.81	1.11	30.81	0.62	33.35	16.99
	1.0	30.81	1.11	30.83	1.07	34.12	25.74
	3.0	30.81	1.11	31.70	6.06	36.80	33.10
	5.0	30.81	1.11	33.09	8.61	37.91	29.65
	7.0	30.81	1.11	34.98	11.49	40.66	30.74
	9.0	30.81	1.11	37.96	16.27	57.84	111.70
	11.0	30.81	1.11	42.80	23.75	49.93	39.22

Table 12 (Continued)

Percent Drift	Percent Meas. Err.	Uncontrolled Mean	Uncontrolled S.D.	Optimally Controlled Mean	Optimally Controlled S.D.	Adaptively Controlled Mean	Adaptively Controlled S.D.
10.0	0.5	30.84	2.22	31.49	3.59	35.44	20.45
	1.0	30.84	2.22	31.22	1.56	38.80	49.08
	3.0	30.84	2.22	32.61	6.73	32.94	11.33
	5.0	30.84	2.22	33.99	9.36	46.54	85.50
	7.0	30.84	2.22	36.52	12.99	38.06	21.96
	9.0	30.84	2.22	40.27	19.68	47.09	47.49
	11.0	30.84	2.22	43.38	22.92	48.11	28.56
15.0	0.5	30.88	3.33	30.04	4.87	39.17	47.99
	1.0	30.88	3.33	34.08	9.92	36.64	27.94
	3.0	30.88	3.33	33.94	7.50	38.56	30.15
	5.0	30.88	3.33	35.78	10.47	39.90	27.70
	7.0	30.88	3.33	38.88	36.06	41.92	30.95
	9.0	30.88	3.33	40.92	22.82	42.44	31.25
	11.0	30.88	3.33	43.47	22.48	46.35	28.32
20.0	0.5	30.92	4.44	44.81	53.47	35.94	24.41
	1.0	30.92	4.44	35.82	12.33	40.10	45.64
	3.0	30.92	4.44	36.25	13.10	42.43	66.52
	5.0	30.92	4.44	36.24	11.08	43.22	40.47
	7.0	30.92	4.44	38.62	15.98	42.55	31.14
	9.0	30.92	4.44	40.99	17.60	49.52	58.97
	11.0	30.92	4.44	48.37	48.27	51.90	61.79

Table 12 (Continued)

Percent Drift	Percent Meas. Err.	Uncontrolled		Optimally Controlled		Adaptively Controlled	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
25.0	0.5	30.95	5.56	37.73	14.43	43.95	55.11
	1.0	30.95	5.56	41.39	35.42	35.37	19.85
	3.0	30.95	5.56	40.28	32.87	34.70	18.47
	5.0	30.95	5.56	38.48	15.97	37.98	21.30
	7.0	30.95	5.56	38.43	14.40	39.31	20.68
	9.0	30.95	5.56	42.61	20.01	56.26	63.85
	11.0	30.95	5.56	44.68	23.94	58.42	48.28
30.0	0.5	30.99	6.67	38.72	25.60	35.91	36.08
	1.0	30.99	6.67	41.88	40.97	37.86	32.13
	3.0	30.99	6.67	35.55	17.66	36.33	37.92
	5.0	30.99	6.67	40.00	22.19	38.51	38.80
	7.0	30.99	6.67	40.00	19.42	44.04	46.86
	9.0	30.99	6.67	46.93	36.51	46.56	44.08
	11.0	30.99	6.67	44.73	23.55	52.93	80.87

Table 13

TCR (Actual)
Desired Value -82.92 PPM/Degree Centigrade
Drift Period 160 Cycles

Percent Drift	Percent Meas. Err.	Uncontrolled		Optimally Controlled		Adaptively Controlled	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
0.0	0.5	-82.92	0.0	-82.92	0.0	-82.92	0.0
	1.0	-82.92	0.0	-82.97	3.19	-105.05	229.80
	3.0	-82.92	0.0	-83.66	15.33	-89.15	83.31
	5.0	-82.92	0.0	-85.22	31.71	-77.57	64.69
	7.0	-82.92	0.0	-86.41	46.21	-83.48	78.9
	9.0	-82.92	0.0	-86.84	54.93	-81.59	108.74
	11.0	-82.92	0.0	-85.96	65.69	-96.41	154.08
2.0	0.5	-82.96	1.20	-82.78	1.32	-91.43	99.07
	1.0	-82.96	1.20	-82.03	2.94	-83.98	49.12
	3.0	-82.96	1.20	-82.25	23.49	-78.41	60.10
	5.0	-82.96	1.20	-85.14	42.85	-77.20	67.01
	7.0	-82.96	1.20	-85.10	41.02	-87.84	123.62
	9.0	-82.92	1.20	-86.72	53.75	-79.88	96.96
	11.0	-82.96	1.20	-88.87	70.05	-93.96	118.46
5.0	0.5	-83.02	2.99	-82.86	2.13	-84.12	26.49
	1.0	-83.02	2.99	-83.04	3.42	-82.60	39.81
	3.0	-83.02	2.99	-83.89	19.13	-93.30	104.73
	5.0	-83.02	2.99	-84.38	28.89	-79.44	57.65
	7.0	-83.02	2.99	-83.39	40.08	-82.96	88.17
	9.0	-83.02	2.99	-87.55	55.85	-111.35	303.75
	11.0	-83.02	2.99	-88.75	70.69	-89.83	137.53

Table 13 (Continued)

Percent Drift	Percent Meas. Err.	Uncontrolled		Optimally Controlled		Adaptively Controlled	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
10.0	0.5	-83.12	5.99	-81.21	1.72	-86.48	65.95
	1.0	-83.12	5.99	-82.71	4.02	-83.72	68.37
	3.0	-83.12	5.99	-82.57	19.76	-72.77	56.18
	5.0	-83.12	5.99	-85.19	32.10	-107.83	232.80
	7.0	-83.12	5.99	-86.93	44.14	-78.33	66.49
	9.0	-83.12	5.99	-87.34	63.94	-90.30	121.91
	11.0	-83.12	5.99	-89.42	69.21	-88.76	100.94
15.0	0.5	-83.21	8.98	-80.92	7.04	-82.29	103.12
	1.0	-83.21	8.98	-79.57	19.53	-78.05	45.89
	3.0	-83.21	8.98	-81.94	17.65	-76.15	81.70
	5.0	-83.21	8.98	-83.09	33.30	-79.27	82.03
	7.0	-83.21	8.98	-84.80	55.49	-76.46	69.73
	9.0	-83.21	8.98	-84.27	56.03	-79.25	87.36
	11.0	-83.21	8.98	-84.86	72.92	-70.70	97.84
20.0	0.5	-83.31	11.98	-82.22	51.79	-69.35	54.98
	1.0	-83.31	11.98	-78.73	26.89	-66.60	82.22
	3.0	-83.31	11.98	-77.26	27.37	-76.78	91.88
	5.0	-83.31	11.98	-77.51	37.13	-81.27	84.60
	7.0	-83.31	11.98	-79.29	43.86	-71.96	88.21
	9.0	-83.31	11.98	-81.65	56.16	-86.34	129.88
	11.0	-83.31	11.98	-87.04	79.28	-79.16	127.75

Table 13 (Continued)

Percent Drift	Percent Meas. Err.	Uncontrolled Mean	Uncontrolled S.D.	Optimally Controlled Mean	Optimally Controlled S.D.	Adaptively Controlled Mean	Adaptively Controlled S.D.
25.0	0.5	-83.41	14.97	-70.79	30.49	-70.80	67.04
	1.0	-83.41	14.97	-79.36	35.69	-68.47	57.73
	3.0	-83.41	14.97	-77.97	39.75	-61.88	73.30
	5.0	-83.41	14.97	-76.62	33.84	-62.47	94.63
	7.0	-83.41	14.97	-76.62	46.34	-62.99	81.65
	9.0	-83.41	14.97	-79.23	50.83	-84.48	126.01
	11.0	-83.41	14.97	-83.24	75.06	-83.94	113.59
30.0	0.5	-83.51	17.96	-70.72	32.72	-69.23	78.91
	1.0	-83.51	17.96	-75.67	49.19	-57.16	70.58
	3.0	-83.51	17.96	-70.59	29.31	-56.47	86.78
	5.0	-83.51	17.96	-73.79	44.24	-62.13	75.07
	7.0	-83.51	17.96	-77.05	45.80	-61.89	96.54
	9.0	-83.51	17.96	-85.14	69.75	-69.88	89.68
	11.0	-83.51	17.96	-82.04	70.84	-89.52	224.61

Table 14

Deposition Rate (Measured)
Desired Value = 379.73 Angstroms/Minute
Drift Period = 160 Cycles

Percent Drift	Percent Meas. Err.	Uncontrolled		Optimally Controlled		Adaptively Controlled	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
0.0	0.5	379.91	1.77	379.91	1.77	379.91	1.77
	1.0	380.10	3.54	379.69	5.27	374.85	42.45
	3.0	380.83	10.63	379.51	21.11	377.65	51.57
	5.0	381.56	17.71	378.93	42.70	387.49	89.13
	7.0	382.30	24.80	379.31	64.88	383.99	103.47
	9.0	383.03	31.88	380.75	71.73	387.85	140.26
	11.0	383.76	38.97	387.43	98.68	374.18	135.07
2.0	0.5	380.09	5.74	379.47	3.11	379.37	47.89
	1.0	380.28	6.50	379.21	5.09	376.48	41.99
	3.0	381.01	11.92	381.48	35.13	379.58	88.16
	5.0	381.74	18.51	379.70	60.45	387.74	77.50
	7.0	382.47	25.37	380.19	55.30	390.89	115.83
	9.0	383.20	32.34	381.37	72.48	397.00	134.88
	11.0	383.94	39.35	380.26	94.62	381.87	122.94
5.0	0.5	380.36	13.80	379.45	3.68	377.98	40.57
	1.0	380.55	14.13	379.82	5.80	373.60	70.07
	3.0	381.28	17.28	378.25	30.52	367.55	78.74
	5.0	382.01	22.34	379.82	36.51	383.54	97.65
	7.0	382.74	28.30	381.44	52.21	374.99	123.49
	9.0	383.47	34.70	377.88	73.07	380.28	119.89
	11.0	384.18	41.33	383.99	97.08	381.88	122.34

Table 14 (Continued)

Percent Drift	Percent Meas. Err.	Uncontrolled		Optimally Controlled		Adaptively Controlled	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
10.0	0.5	380.81	27.46	381.24	2.47	374.49	70.34
	1.0	380.99	27.62	379.42	6.65	373.02	88.68
	3.0	381.72	29.35	378.40	31.33	388.39	82.48
	5.0	382.45	32.60	378.62	45.05	364.27	84.47
	7.0	383.18	36.97	377.54	59.35	383.75	96.39
	9.0	383.95	42.11	380.03	80.58	388.85	129.16
	11.0	384.63	47.11	383.48	93.18	373.73	148.08
15.0	0.5	381.26	41.16	379.55	10.31	382.95	100.79
	1.0	381.44	41.26	380.59	29.87	369.04	83.57
	3.0	382.17	42.45	379.53	22.77	387.04	97.57
	5.0	382.89	44.78	379.57	46.63	379.52	120.87
	7.0	383.61	48.09	378.91	58.67	389.33	100.83
	9.0	384.34	52.19	379.81	74.05	380.59	111.62
	11.0	385.07	56.91	382.69	104.21	392.62	134.04
20.0	0.5	381.71	54.86	378.30	52.25	377.59	91.03
	1.0	381.89	54.94	377.88	44.76	382.96	131.80
	3.0	382.61	55.85	381.69	37.37	381.57	110.66
	5.0	383.34	57.67	383.94	48.29	374.98	126.98
	7.0	384.06	60.32	382.31	59.13	385.94	135.95
	9.0	384.78	63.69	382.99	77.97	378.17	123.45
	11.0	385.51	67.67	379.88	98.45	394.95	162.75

Table 14 (Continued)

Percent Drift	Percent Meas. Err.	Uncontrolled		Optimally Controlled		Adaptively Controlled	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
25.0	0.5	382.16	68.57	381.14	36.50	369.49	85.62
	1.0	382.34	68.64	376.52	48.86	382.64	108.97
	3.0	383.06	69.39	379.14	50.02	406.45	123.54
	5.0	383.78	70.89	381.15	45.45	397.12	130.96
	7.0	384.50	73.10	385.34	69.44	404.66	118.74
	9.0	385.22	75.96	382.37	77.58	368.16	138.33
	11.0	385.94	79.39	381.97	99.39	373.56	149.03
30.0	0.5	382.61	82.28	384.39	32.72	385.47	113.00
	1.0	382.79	82.34	382.28	49.86	390.26	113.00
	3.0	383.51	82.98	386.85	41.13	410.91	123.33
	5.0	384.22	84.28	383.31	70.89	396.08	128.24
	7.0	384.90	86.19	382.33	66.76	390.93	133.55
	9.0	385.56	88.68	375.20	84.04	384.96	124.98
	11.0	386.38	91.71	385.95	106.35	387.88	134.64

Table 15

Sheet Resistance (Measured)
Desired Value = 30.77 Ohms/Square
Drift Period = 160 Cycles

Percent Drift	Percent Meas. Err.	Uncontrolled		Optimally Controlled		Adaptively Controlled	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
0.0	0.5	30.77	0.15	30.77	0.15	30.77	0.15
	1.0	30.77	0.30	30.74	1.14	38.84	81.32
	3.0	30.78	0.90	31.28	4.53	35.35	29.21
	5.0	30.78	1.50	33.48	9.73	35.43	18.81
	7.0	30.78	2.10	36.17	14.29	39.07	27.35
	9.0	30.79	2.70	38.88	17.82	46.06	36.74
	11.0	30.80	3.30	40.88	20.92	51.38	44.82
2.0	0.5	30.78	0.49	30.72	0.41	33.83	26.08
	1.0	30.79	0.58	30.71	1.03	34.17	25.81
	3.0	30.79	1.07	31.89	7.68	36.03	28.74
	5.0	30.80	1.64	35.19	19.91	35.30	14.98
	7.0	30.81	2.22	35.45	12.37	46.32	55.02
	9.0	30.81	2.81	39.06	17.54	42.81	31.45
	11.0	30.82	3.41	42.47	23.56	52.99	62.82
5.0	0.5	30.81	1.15	30.81	0.65	33.35	16.96
	1.0	30.81	1.20	30.84	1.11	34.12	25.75
	3.0	30.82	1.55	31.70	6.08	36.78	34.04
	5.0	30.83	2.02	33.10	8.85	37.99	30.58
	7.0	30.84	2.55	35.00	11.89	40.74	30.87
	9.0	30.85	3.10	37.99	16.74	56.87	105.08
	11.0	30.85	3.67	42.86	24.24	49.89	39.02

Table 15 (Continued)

Percent Drift	Percent Meas. Err.	Uncontrolled		Optimally Controlled		Adaptively Controlled	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
10.0	0.5	30.85	2.25	31.49	3.58	35.44	20.42
	1.0	30.85	2.30	31.22	1.56	38.81	49.16
	3.0	30.86	2.54	32.61	6.75	32.93	11.33
	5.0	30.87	2.90	33.96	9.27	46.44	84.69
	7.0	30.89	3.33	36.56	13.41	38.03	21.85
	9.0	30.90	3.80	40.32	20.17	46.54	46.47
	11.0	30.91	4.31	43.57	24.24	48.28	29.67
15.0	0.5	30.88	3.36	33.04	4.85	39.15	47.88
	1.0	30.89	3.40	34.07	9.91	36.64	28.05
	3.0	30.90	3.61	33.93	7.36	38.54	29.95
	5.0	30.92	3.90	35.77	10.57	39.68	26.68
	7.0	30.94	4.25	38.87	35.85	41.78	29.93
	9.0	30.95	4.66	40.87	22.23	42.39	30.59
	11.0	30.97	5.11	43.65	23.57	46.37	28.33
20.0	0.5	30.92	4.47	44.79	53.28	35.95	24.44
	1.0	30.93	4.51	35.82	12.39	40.09	45.38
	3.0	30.95	4.69	36.23	12.96	42.31	65.50
	5.0	30.97	4.94	36.20	11.00	43.15	39.39
	7.0	30.99	5.25	38.59	15.90	46.68	32.43
	9.0	31.01	5.61	40.99	17.98	49.64	60.99
	11.0	31.03	6.01	48.65	49.72	51.49	61.02

Table 15 (Continued)

Percent Drift	Percent Meas. Err.	Uncontrolled Mean	Uncontrolled S.D.	Optimally Controlled Mean	Optimally Controlled S.D.	Adaptively Controlled Mean	Adaptively Controlled S.D.
25.0	0.5	30.96	5.58	37.73	14.43	43.95	55.10
	1.0	30.96	5.62	41.37	35.24	35.36	19.89
	3.0	30.99	5.79	40.26	33.17	34.73	18.47
	5.0	31.01	6.01	38.43	15.86	37.97	21.23
	7.0	31.04	6.29	38.42	14.47	39.46	21.17
	9.0	31.06	6.62	42.70	20.64	56.33	65.15
	11.0	31.09	6.98	45.02	25.80	58.60	49.86
30.0	0.5	30.99	6.69	38.72	25.58	35.89	35.86
	1.0	31.00	6.73	41.88	40.92	37.83	31.93
	3.0	31.03	6.89	35.56	17.71	36.32	37.56
	5.0	31.06	7.10	39.98	22.12	38.42	38.48
	7.0	31.09	7.35	40.10	19.68	44.17	47.74
	9.0	31.12	7.65	46.81	35.00	46.71	46.10
	11.0	31.15	7.98	44.97	24.74	52.14	72.83

Table 16

TCR (Measured)
Desired Value -82.92 PPM/Degree Centigrade
Drift Period 160 Cycles

Percent Drift	Percent Meas. Err.	Uncontrolled		Optimally Controlled		Adaptively Controlled	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
0.0	0.5	-82.92	0.39	-82.92	0.39	-82.92	0.39
	1.0	-82.78	0.78	-82.96	3.26	-105.06	229.85
	3.0	-82.92	2.34	-83.68	15.59	-89.18	83.34
	5.0	-82.91	3.91	-83.41	32.38	-77.52	64.77
	7.0	-82.91	5.47	-86.52	46.53	-83.54	78.05
	9.0	-82.91	7.03	-87.23	55.16	-82.35	108.22
	11.0	-82.91	8.60	-86.23	66.12	-94.98	147.11
2.0	0.5	-82.96	1.29	-82.78	1.39	-91.44	99.34
	1.0	-82.96	1.48	-83.03	3.04	-83.93	48.81
	3.0	-82.96	2.71	-82.31	23.36	-78.28	59.46
	5.0	-82.96	4.18	-85.34	43.03	-77.54	68.28
	7.0	-82.96	5.70	-85.34	41.78	-88.36	125.78
	9.0	-82.96	7.24	-86.92	53.81	-80.01	101.11
	11.0	-82.96	8.79	-89.40	70.71	-93.22	113.86
5.0	0.5	-83.02	3.05	-82.86	2.16	-84.14	27.00
	1.0	-83.02	3.15	-83.04	3.56	-82.60	39.96
	3.0	-83.02	3.94	-83.93	19.52	-93.54	106.30
	5.0	-83.02	5.11	-84.50	29.43	-79.49	57.08
	7.0	-83.02	6.46	-83.65	40.90	-82.39	87.37
	9.0	-83.03	7.89	-87.82	56.13	-109.36	284.39
	11.0	-83.03	9.36	-89.19	71.24	-90.33	141.10

Table 16 (Continued)

Percent Drift	Percent Meas. Err.	Uncontrolled Mean	Uncontrolled S.D.	Optimally Controlled Mean	Optimally Controlled S.D.	Adaptively Controlled Mean	Adaptively Controlled S.D.
10.0	0.5	-83.12	6.03	-81.20	1.37	-86.48	65.94
	1.0	-83.12	6.10	-82.71	4.13	-83.69	68.15
	3.0	-83.13	6.60	-83.65	20.41	-72.92	56.18
	5.0	-83.13	7.41	-85.29	32.28	-108.16	234.18
	7.0	-83.14	8.45	-87.38	45.19	-78.31	65.96
	9.0	-83.14	9.64	-87.73	65.43	-90.72	125.34
	11.0	-83.15	10.93	-89.81	68.64	-89.27	99.76
15.0	0.5	-83.22	9.01	-80.92	7.06	-82.29	103.21
	1.0	-83.22	9.07	-79.53	19.56	-78.08	45.92
	3.0	-83.23	9.46	-81.99	18.00	-75.96	78.83
	5.0	-83.24	10.08	-83.30	34.08	-79.26	81.53
	7.0	-83.25	10.91	-83.34	57.58	-76.22	69.36
	9.0	-83.26	11.90	-84.57	56.46	-79.59	89.27
	11.0	-83.27	13.01	-84.99	72.99	-71.88	99.79
20.0	0.5	-83.32	12.01	-82.23	51.90	-69.37	54.98
	1.0	-83.32	12.06	-78.72	26.86	-66.65	82.26
	3.0	-83.33	12.38	-77.30	27.13	-76.72	91.42
	5.0	-83.35	12.90	-77.70	37.61	-81.06	83.91
	7.0	-83.36	13.59	-79.48	44.00	-71.72	87.08
	9.0	-83.38	14.44	-32.06	56.82	-87.19	133.81
	11.0	-83.39	15.40	-87.73	80.50	-78.40	127.24

Table 16 (Continued)

Percent Drift	Percent Meas. Err.	Uncontrolled Mean	Uncontrolled S.D.	Optimally Controlled Mean	Optimally Controlled S.D.	Adaptively Controlled Mean	Adaptively Controlled S.D.
25.0	0.5	-83.42	15.00	-70.80	30.50	-70.79	66.94
	1.0	-83.42	15.05	-79.37	35.73	-68.51	57.54
	3.0	-83.44	15.33	-77.97	39.57	-62.01	73.52
	5.0	-83.46	15.78	-76.72	34.19	-62.52	98.25
	7.0	-83.47	16.38	-76.84	46.68	-62.54	82.30
	9.0	-83.49	17.12	-79.63	51.57	-84.72	124.70
	11.0	-83.51	17.98	-83.78	74.50	-82.83	113.44
30.0	0.5	-83.51	18.00	-70.83	25.68	-69.21	78.59
	1.0	-83.52	18.04	-75.69	49.23	-57.16	70.59
	3.0	-83.54	18.29	-70.67	29.52	-56.37	85.99
	5.0	-83.56	18.70	-73.94	44.51	-62.26	76.16
	7.0	-83.57	19.23	-77.32	46.02	-61.95	96.07
	9.0	-83.61	19.90	-85.65	70.89	-69.74	91.11
	11.0	-83.63	20.67	-82.61	71.29	-90.42	234.34

Table 14 contains the means and standard deviations for the deposition rate output variable for each of the three process simulator configurations. In comparison to Table 8, Tabel 14 reveals that the optimal controller is little affected by the drift period increase from 40 to 160 machine cycles. There is a minor tendency for the mean values of the deposition to hold closer to the desired mean with the optimal controller configuration at the longer drift period. The standard deviations also show a slight reduction in value, but no significant difference is noted at any drift-measurement level combination at the increased drift period.

Basically, the same control pattern for the sheet resistance TCR output variables for the optimal controller configuration are noted at both 40 and 160 machine cycle drift periods. Tables 15 and 16 contain the means and stand deviations for each of the three process simulator configurations at a drift period of 160 cycles for the sheet resistance and TCR output variables respectively. When Table 15 is compared to Table 9 and Table 16 is compared to Table 10, it is seen that there is no significant difference in the operation of the optimal controller, with respect to these output variables, at the longer drift periods. The dominance of the deposition rate of the control function is, as expected, still evident for the reasons already noted. In general then, one may surmize that the operation of the optimal controller is not dependent on the period of a periodic process drift.

For all three output variables, the operation of the adaptive controller at the 160 cycles drift period was still not as "good" as that of the optimal controller, as is evident from Tables 14 through 16. The operation of the adaptive controller at the longer drift period, however, does show a significant improvement over its operation at the 40 cycle drift periods. A comparison, for example, of the "adaptively controlled" columns of Tables 8 and 14, indicates that the mean value of the deposition rate is held somewhat more consistently closer to the desired mean value for this variable when the longer drift period is in effect. A significant reduction in the standard deviations of the deposition rate under adaptive control at the increased drift period is also noted.

For the sheet resistance and TCR variables with the adaptively controlled process simulator configuration, less erratic operation is noted at the longer drift period than at the 40 cycle drift period. When the "adaptively controlled" columns of Table 9 and 10 are compared to the corresponding columns of Tables 15 and 16, respectively, it is seen that for both the sheet resistance and TCR output variables, respectively, that the control action of the adaptive controller on these variables is improved and less erratic at the longer drift period. This is evident mainly from the tendency for the mean values of these variables, as was the case with the deposition rate output variable, to be held with somewhat more consistency near their desired values. Reductions in the standard deviations at most of the drift-measurement amplitude levels is also noted.

The improvement gained in the operation of the adaptively controlled configuration with the extended drift is not conclusive enough to allow one to make any estimate as to the operation of this control scheme if the drift period were made longer while holding the process data over which the re-estimation of the process model coefficients is to be made to the forty most recent observations at the input and output variables. Although intuitively, it seems that the adaptive mechanism would better adapt if the drift period were long in comparison to the portion of the drift period stored in the push down (adaptation) list of the most recent observations of process operations. This assumption, however, is not borne out to any great extent from the action of the adaptive controller with a 160 cycle drift period. In this case, the number of observations in the push down was equal to one quarter of a drift period. To make any statement on operational improvement which might be gained by extending the drift period such that re-estimation would be based on a smaller fraction of the drift period would be mere conjecture, based on the data presented here. The next chapter presents some conclusions drawn as a result of the process and control system simulations.

6.0 CONCLUSIONS

The results of the application of the modeling and control techniques developed herein to a simulated batch process provide a basis from which several conclusions concerning the effectiveness of these techniques for this type of application may be drawn. The conclusions concerning the empirical modeling technique will be discussed, then those concerning the optimal control scheme, and finally those which concern the adaptive control scheme.

The empirical modeling procedure performed extremely well in determining an "adequate" process model in a small number of experiments. The term "adequate" in this context indicates that the model determined by the procedure met the accuracy standards established prior to the experimentation. Based on the performance of this technique in this investigation, this modeling procedure could be used to great advantage in the modeling of multivariate processes whose outputs possess multiple characteristics, each having a known desired value.

Several observations can be made concerning the operation of the optimal control scheme. First, as indicated in Chapter 5, the action of the optimal controller was dominated by the output variable having the greatest magnitude. Secondly, based on the dominant output variables, the optimal control scheme demonstrates a limited ability to cope with measurement error at low levels of drift amplitudes. As the amplitude of the drift increases, however, higher levels of measurement error are tolerated. A third observation which can be made is that the operation of the optimal control scheme is relatively independent of the period of a sinusoidal process drift.

The operation of the adaptive control scheme did not live up to expectations. At no drift-measurement error combination did the adaptive control scheme perform an adequate control function on any output variable.

When comparing the effectiveness of the adaptive control scheme with the optimal control scheme, one is hard pressed to say that either performs an adequate control function based on the results of this investigation. The performance of the optimal control scheme, however, does demonstrate good control of the dominant output variable at given drift-measurement error combinations. The operations of the adaptive control scheme, on the other does not indicate adequate control of any of the output variables under any of the conditions of this investigation.

7.0 RECOMMENDATIONS FOR FURTHER STUDY

Several areas which may prove fruitful for further study have been opened as a result of this investigation. The first of these areas concerns the empirical modeling procedure. The response surface associated with the process simulated in this study was very well behaved. It would be most interesting to see the results of the application of this procedure to processes, either simulated or actual, where the response surface was not so well behaved.

In the area of the optimal control scheme, the action of the controller appeared to be dominated by the output variable having the greatest magnitude. It would be worthwhile to develop a weighting scheme for the index of performance such that each output variable receives the desired emphasis.

A third area which may be of interest would be to develop a scheme which would enable the optimal controller to better cope with measurement error. It has been suggested [25] that perhaps an averaging of the index of performance be used for this purpose. Another alternative might be exponential smoothing of the index of performance.

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Educational Background

Lanier Senior High School Macon, Georgia	Graduated - 1957
Southern Technical Institute Marrietta, Georgia	Attended - 1958
Mercer University Macon, Georgia Bachelor of Science in Physics	1961-1965
Georgia Institute of Technology Atlanta, Georgia Bachelor of Electrical Engineering	1966-1969
Lehigh University Bethlehem, Pennsylvania Candidate for Master of Science in Industrial Engineering	1970-1972

Professional Experience

Western Electric Company, Inc. Atlanta, Georgia	1965-1967
Staff Associate	
Western Electric Company, Inc. Burlington, North Carolina	1969-1970
Engineer (Planning)	
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