TP VI-A

Dynamic Load Flow by J. A. Bubenko and I. E. Nordanlycke.

This paper presents the Dynamic Load Flow (DLF), which is a digital method for simulation of power system state variables as explicit functions of time. The time dependent state variable solution obtained by the DLF is the simultaneous solution to the load flow problem when the state of the system is time dependent. The general approach of the DLF simulation technique can easily be adjusted to fit to different requirements for the simulation of power system dynamics.

TP VI-B

A Simplex-Like Method for Solving the Optimum Power Flow Problem by H. Duran.

A new method for solving the optimum power flow problem, similar to the simplex-method, is presented. The method approaches the optimal solution by solving a sequence of equality constrained problems. These equality constrained problems are essentially power flow problems, but generalized in two ways: 1) it is not required that exactly two variables be given at every node, thus allowing for a more flexible problem specification, and, 2) the problem is allowed to have more than zero degrees of freedom. The generalized power flows are effectively solved using Newton's method. The underlying mechanisms of the method are: 1) a simplex-like test for verifying the optimality of a generalized power flow solution, and 2) a procedure that takes the place of the simplex pivoting operation for finding an improved gpf. The main advantages over other methods are: 1) a more reliable convergence for finding those variables which should be a their bounds, and 2) having quadratic convergence towards the optimal solution. The method has been successfully tested for systems of up to 60 buses under a variety of constraint situations.

TP VII-A

Adaptive Coordinated Control for Nuclear Plant Load Changes by R. L. Moore, F. C. Schweppe, E. P. Gyftopoulos, and L. S. Gould.

The problem considered is providing control for large, fast load changes in a pressurized water nuclear power plant. Fast load change control is feasible if the movements of the reactor control rods and the turbine throttle valves are coordinated to avoid serious transients in the plant.

The coordinated control is based on a dynamic model identified from plant data. The model is adapted after each load change to cope with plant variations. The model includes a stochastic representation of disturbances and measurement noise. The results are experimentally tested using digital computer control of an analog plant simulation. A predictive display is used as an aid in monitoring the load change.

TP VIII-A

Reliable Loading of Generating Units for System Operation by A. V. Jain and R. Billinton.

System spinning reserve must be able to satisfy system loss of generation within the available margin time to bring about an orderly change of generation. Two types of margin time are important; one minute, in order to satisfy the system frequency and dynamic stability requirement; five minutes, in order to satisfy a loss of generation. A quantitative reliability index designated as response risk indicates the capability of the system backed by all the standby resources, to react to a loss of generation within the required margin time. This paper presents the quantitative effect of the system standby resources such as rapid-start gas turbine generation and units in the hot reserve mode on system response risks. Effect of interruptible loads and time to interrupt these loads is also incorporated into the analysis. A system can sometimes be operated in a more reliable mode by adjusting the unit loadings within the system. Modification of unit loadings is accompanied by a change in system operating costs per hour. A marginal shift from system optimum economic operation to bring about satisfactory system response risks can be accomplished. The effect of interchange assistance on response risks is also illustrated in this paper.

TP VIII-B

A Program for Calculating Optimal Maintenance Schedules Recognizing Constraints by W.R. Christiaanse

The paper describes a computer program for generating annual overhaul schedules for generating facilities. Starting dates are set by the program so that generating reserves and manpower resources are equalized over the year. Generally speaking, this criterion tends to minimize the need for purchased capacity, maximize reliability and minimize production cost. To keep the schedules realistic and feasible, the program recognizes a comprehensive set of timing constraints on the starting dates of each outage. The program also allocates the necessary manpower and equipment resources for each outage from pools which are shared between outages. The schedule is composed so that the given supplies of these resources are not exceeded at any time during the year. The program, which has been used successfully at a major utility for the last nine months, is designed for continuous application throughout the year. It makes optimal revisions in the schedule in response to forced outages, strikes and other unexpected contingencies. The output includes a variety of reports and graphic plots drawn from the maintenance schedule. The reports eliminate the bulk of the manual effort necessary to tabulate and sketch plots of outage dates, manpower requirements and reserve requirements. The paper includes a summary of the optimization algorithm, which is based on previous work, and a description of the input and output for the program.

TP VIII-C

Probabilistic Evaluation of the Operation Reserve in a Power System by J.A. Bubenko and M. Anderson.

A computation method for probabilistic evaluation of the operation reserve in a power system is presented.

The probabilistic behaviour of the components in the system originates different system states. The probabilities of those states existing combined with the uncertainly predicted load give the probability for loss of load, which is used as a reliability index.

The immediateness of the investigated time period requires computation of time dependent state probabilities. When calculating those it is assumed that any kind of probability distribution function can rule the stochastic behaviour of the components in the system.

Calculations on a simulated system are performed varying the parameters that can influence the reliability of the system. The effect of using a maximum probability for loss of load as a constraint in the daily operation is also demonstrated.

TP VIII-D

Simultaneous Interchange Optimization by Means of the Z Matrix by H.E. Brown.

A Z Matrix algorithm is described, which enables the maximum permissible interchange between several companies of an interconnection to be determined without using linear programming. This multi-area algorithm is an extension of Commonwealth Edison's interchange capability program for the evaluation of the allowable interchange with a single neighboring company. The single interchange program has been used for several years with good success. (1.2)

TP VIII-E

Differential Injections Method—A General Method for Secure and Optimal Load Flows by J.L. Carpentier.

The "Differential Injections Method" solves the optimal load flow problem including constraints which guarantee that the solution will not only be feasible, but also secure, meeting first contingency requirements. Voltage optimization and spinning reserve localization analysis are included in the process, which is based upon the Generalized Reduced Gradient method, Matrix Sparsity, decomposition and expression of the problem in terms of the physical control variables of the system. As yet, the program has been applied to networks up to 100 nodes with short computation durations. The method is very flexible; extensions are mentioned, particulary concerning real time applications, to give a "Secure Economic Dispatch".

TP VIII-Eb

Total Injections Method — A Method for the Solution of the Unit Commitment Problem Including Secure And Optimal Load Flow by J. L. Carpentier.

The Total Injections Method solves at a time the unit commitment and the secure and optimal load flow problems. It provides the most

ADAPTIVE COORDINATED CONTROL FOR NUCLEAR POWER PLANT LOAD CHANGES

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ABSTRACT

The problem considered is providing control for large, fast load changes in a pressurized water nuclear power plant. Fast load change control is feasible if the movements of the reactor control rods and the turbine throttle valves are coordinated to avoid serious transients in the plant.

The coordinated control is based on a dynamic model identified from plant data. The model is adapted after each load change to cope with plant variations. The model includes a stochastic representation of disturbances and measurement noise. The results are experimentally tested using digital computer control of an analog plant simulation. A predictive display is used as an aid in monitoring the load change.

INTRODUCTION

Nuclear power plants are rapidly becoming a major source of the nation's power supply. As this happens, it will be necessary to provide improved load change control, so that they can be easily used to balance the power load of a network.

The balance of power in a network can be upset by customer load changes, by plant failures and by other causes. The restoration of balance in the power network may depend on the ability of nuclear power plants to undergo large, fast changes in the power which they produce.

Before discussing the load change problem, the basic elements of a pressurized water nuclear power plant are briefly summarized here. About half of the commercial nuclear power plants in the United States are of the pressurized water type. Figure 1 illustrates the plant structure. The plant includes a reactor which generates thermal power, circulating water and steam loops to transfer the heat, and a turbine to transform the thermal power into mechanical power to drive the generators.

A power load change involves changing the power produced in the reactor and the power delivered by the turbine. This must not seriously disturb the plant operation. Large and fast load changes require a control which provides simultaneous coordinated control for both the reactor and the turbine. This is necessary to avoid large deviations in plant variables. Any residual deviations can then be corrected by feedback control. If a load change is made without close coordination of the reactor and the turbine controls, then a large, fast power load change can cause serious deviations in important plant variables. These deviations, in turn, can trigger an automatic emergency plant shutdown.

The design of a control to coordinate the reactor and turbine during power changes must consider variation and uncertainty in plant behavior. These effects cause the plant to respond differently to the same inputs at different times. Therefore, fixed control systems such as conventional analog control systems cannot consistently handle large and fast load changes.

Techniques from control and estimation theory are applied in this study to overcome the problems of variations and uncertainty. Techniques of identification, prediction, control, and adaptation are used in a set of computer programs for load change control. These programs are experimentally tested on a detailed simulation of a nuclear power plant, which includes the effects of variation, disturbance noise, and measurement noise. The simulation is run on an analog computer. The estimation and control programs are run on a digital computer which treats the analog simulation as if it were a plant.

Table 1 illustrates the experimental part of this study. The plant inputs which are controlled by the digital computer are the reactor control rods and the turbine load set point. The plant measurements which are used by the digital computer are the reactor power, primary loop average temperature, turbine power, rod group position measurement, and turbine load set-point measurement. The measurements and control actions are implemented on a one-second time period. The period was chosen to be fast relative to the dynamic phenomena which dominate the response of the plant. The details of the study are described by Moore[1]. The prior studies, which considered applications of modern system theory to nuclear plant load change control, have generally explicitly or implicitly considered low power operation, where the plant-reactor interaction can be neglected. There are several studies of the control of the reactor alone under these conditions, including Duncombe and Rathbone[2], Monta[3], Marciniak[4], and Weaver[5].

At high power operation, the plant-reactor interactions have a major influence on the reactor operation. The limiting constraints for high power load changes are state constraints in the plant external to the reactor. This study differs from the previous control studies in that it considers the load change problem for the entire plant at high power operation.

In addition to control strategy development, this investigation brings together techniques to provide control in the presence of variation and uncertainty. This means improved control of the nuclear power plant during load changes under more realistic conditions than in prior studies.

The Simulated Plant

Figure 1 shows the major nuclear power plant parts which are simulated. These include the reactor, the primary loop, the pressurizer, the heat exchanger, the secondary loop, the throttle valves, and the turbine-generator unit. The simulation also includes disturbance noise and measurement noise. The structure of the simulation is shown in Figure 2. The analog controls for the pressurizer, the turbine, and the reactor are part of the simulation.

The simulation is constructed on an analog computer. There are 64 amplifiers included, of which 23 are integrators. The nonlinearities are produced by 2 dividers, a function generator, and 4 limiters. The disturbance and measurement noise originate from a noise diode. The simulation is connected to a digital computer, which treats the simulation as an actual plant. The digital computer is used for the prediction, adaptation, and control tasks. The data from the simulated plant are acquired by analog to digital conversion at one second intervals.

The simulation presented here is not an exact representation of a nuclear plant. The simulation does, however, experience some of the transients similar to actual plant behavior, and is treated as an actual plant to demonstrate the application of the control techniques.

The behavior of the plant for different moderator temperature coefficients and for different Xenon concentrations was considered. The concentration of Xe^{135}, a fission product, has an effect on the dynamic behavior of the reactor at high power operations.

Figure 3 shows a load change experiment performed under analog control. For 10 percent step load changes, the analog control system performs acceptably. A number of variables are disturbed during the load change, particularly the primary loop pressure, but the deviations are within acceptable bounds. However, the undesirable deviations in pressure and other variables get worse as larger load change steps are attempted with the analog control system. Therefore, the analog control system is limited to small step load changes. In contrast, the computer control developed in this study is capable of large, fast load changes, with less deviation in the primary loop pressure and temperature than is produced by the analog control for these small load change experiments.

The Model Identification

In this study a load change control is developed for the nuclear power plant. The control is based on a model of the plant. However, the nuclear plant (or the simulated plant) is a complex process. The types of simple low order models which are required for control purposes can only approximate the actual plant. Several methods used in this study compensate for part of the approximation and allow a low order model to be useful. The methods used include deterministic modeling of the major physical phenomena, modeling disturbance and measurement noise effects, and identification of the overall model parameters.

The model can be understood in terms of reactor power, turbine power, and energy storage. There are dynamics associated with both the reactor power and the turbine power. If these two powers are somehow maintained equal, then the stored energy in the plant is not seriously disturbed even if the power is rapidly changing. If the reactor power and the turbine are mismatched, then the plant energy is changing. Figure 4 shows the structure of the deterministic part of the model. This part of the model contains approximations of the major plant phenomena, including six states and twelve parameters.

The model considered in this study is a stochastic model, containing a deterministic part and a representation of disturbance noise and measurement noise. The use of a stochastic model provides the means to cope with random process behavior. In addition, the stochastic model compensates for some model errors. A model error causes the model to behave somewhat differently from the plant. This is the same effect which disturbance noise produces. Therefore, the disturbance noise portion of the model represents random disturbances and also model errors.

The noise portion of the model includes both disturbances to the states of the deterministic model, and noise added to the measurements. The parameters of the deterministic and the noise parts of the model are considered initially unknown. The overall stochastic model has a specified structure. However, the parameters are identified to match the model to the measured plant performance.

Values of stochastic model parameters are based on simulated plant data records taken during load change. Maximum likelihood is the criterion for choosing the parameter values. The model identification technique used in this study is Schweppe's[6]. A separate hypothesis test technique is used to see if the maximum likelihood identification is successfully producing a stochastic model consistent with the plant data records.

The identification technique requires a search over the parameters to determine, at least locally, the maximum likelihood estimates. This search is expedited by making some reasonable initial guesses on the parameters. The search technique was a modified Fletcher-Powell[7].

Figure 5 shows a data record taken from the simulated plant. The deterministic predictions of the model are superposed on this figure to illustrate the model fit. The data was taken at one second intervals. The length of the data records varied from 100 to 300 seconds. During this time the plant was in a transient load change condition. The reactor power measurement was noisy with standard deviation of 2 to 3 percent of the total signal. The other measurements were less noisy. This was intended to match actual plant measurement conditions.

With reasonable initial guesses, the time required for a maximum likelihood identification was about 10 minutes of IBM 360-50 computer time per 100 seconds of data for 10 undetermined parameters. In practice, this identification time could be improved by orders of magnitude. This depends on program efficiency, approximation in the calculations, and the speed of the computer. There was no effort to minimize computer time in this study. The acceptability of the identification is judged using a hypothesis test.

After the stochastic model has been identified, it is used in a number of separate applications. One application is a state estimator design. The type of state estimator used in this study is a Kalman filter. This state estimator is designed automatically by the computer once the stochastic model parameters are known[1]. The state estimator gives estimated values for important unmeasured states. For example, fission product isotope concentrations in the reactor are estimated in this way for use in the control strategy. Other stochastic model uses are discussed shortly, after a presentation of control strategy.

The Control

A goal of this study is to provide a control scheme which makes large and fast load changes without serious disturbances to the nuclear plant. This control must operate in the presence of variation and uncertainty. The problem is attacked in two parts. The first part deals with the deterministic control problem, which involves the control using the deterministic model alone with no consideration of variation or uncertainty. The second part presents the modifications which are made to cope with plant variation and uncertainty.

The goal of the control strategy developed here is to provide rapid load changes which keep the plant within specified constraints. The operator can choose some of these constraints to ensure smooth plant operation. Other constraints are calculated based on plant hardware capabilities and on the initial plant state. The constraints define operating regions where a load change can be made without serious plant upset.

The input constraints are the rate and extent of rod movement and the turbine and reactor power rate of change. The state constraints include primary loop pressure deviations, pressurizer level deviations, and primary loop average temperature deviations. The deterministic part of the control problem is to take the plant through a rapid specified load change subject to the input and state constraints.

The stochastic model is used to determine adjustments in the control constraints to cope with uncertainty. The nominal state behavior is predicted for the load change, together with the state covariance of the system linearized about the nominal trajectory. This covariance is used as a measure of the variation which might be expected in performance, considering the process is stochastic rather than deterministic A band of uncertainty about the nominal trajectory is calculated from this covariance representing a specified probability, a priori, that the state will be within the band at a given time. This calculated band is used to make the state constraints more restrictive (Figure 6). Therefore, control calculations consider uncertainty effects even though the control equations are based on the deterministic portion of the model.

Figure 7 shows a 40 percent load change made by the computer. The load change limiting constraint was the primary loop temperature state constraint. The model-based control allows the reactor and the turbine to be coordinated, and the load change is made without violating the constraint.

A special case, where the constraint on the primary loop average temperature is reduced to zero deviation, is also considered. This corresponds to balancing reactor power and turbine power throughout the load change. This procedure avoids disturbances to the stored energy or the average temperature in the primary loop. This strategy produces a slower power change, but eliminates the undesirable plant variations in primary loop pressure and in pressurizer level (Figure 8).

This control strategy could also be modified to give a steady programmed change in primary loop temperature as the load changes. The transient deviations are greatly reduced by the model-based coordinated control scheme.

The control strategies were tested under a variety of reactor conditions. The load increase problem was considered for two values of moderator temperature coefficient, and for high and low Xenon poisoning. The details are described by Moore[1].

The Predictive Display

The stochastic model is used to predict the plant performance prior to each load change. Both a nominal plant state trajectory and the covariance of the states about the trajectory are predicted. The predictions have two uses. One use is to modify the state constraints. This makes these constraints conservative, so that the stochastic model predicts a very low probability of violating the original constraints. This use was discussed previously.

The second use is to predict measurement bands. The plant measurements are expected to lie inside these bands with high probability. These measurement bands are displayed before the load change begins (Figure 9a), and the actual measurements are superposed on the display during the load change (Figure 9b). This display should reassure the plant operator during normal load changes, and supply a visual warning of any unexpected behavior. The same data is used by the computer to monitor the load change. If an unacceptable plant variation occurs, as detected by a hypothesis test or by the measurement bands test, the load change can be stopped.

The plant performance during the load change is automatically monitored by the computer using two distinct criteria. The first criterion uses the predicted measurement performance bands. The load change can be aborted if these bands are violated. (However, since an occasional noise spike on the measurements can cause a bounds violation, it is desirable to abort only if several points are outside the bounds.) The other criterion uses a statistical test, called a "hypothesis test." For the test used in this study[8], when the plant behavior is different from that predicted by the stochastic model, the hypothesis test quickly detects this error.

The Model Adaptation

The plant performance during the load change can be automatically monitored by the computer. The load change can be aborted if the predicted measurement performance bands are violated. Figure 10a shows a violation of the measurement performance predictions. This was produced by altering the moderator feedback parameter in the simulation. The model of the plant used by the digital computer was adapted from the data acquired during the abortive load change. Figure 10b shows the predictions and the realized performance for the load change following adaptation. A partial adaptation of only the deterministic parameters was made using a least-squares technique on the on-line computer. The stochastic model identification was only done off-line in this study, due to the computational time.

Model adaptation is an essential element in the overall control scheme. If the process never changed its behavior, a fixed analog control system could be tuned to provide coordinated ramp inputs to the control rods and the turbine load set point. A similar performance is shown in Figure 8. However, in reality, the plant behavior varies significantly due to several factors. The Xe^{135} and I^{135} isotope concentrations in the reactor can cause significant day-to-day variations under some high power operating conditions. The reactor moderator reactivity coefficient changes dramatically over the fuel cycle — about one year — as the Boron concentration in the water is adjusted. Other plant behavior changes also occur. In conclusion, a fixed control system is not a practical solution to the problem of large and fast load changes. Adaptive control is essential to solve this problem.

CONCLUSIONS

These experiments demonstrate the feasibility of smooth control for large and fast load changes on a nuclear power plant. The experiments also demonstrate the feasibility of detecting and adapting to plant variation, and the feasibility of control in the presence of uncertainty.

These techniques could be extended to other types of plants. In general, the important requirements are:

1. The desirability of large and fast changes without violating some input and state constraints.

2. The presence of disturbances and measurement noise.

3. The possibility of plant variations.

Extensions of this study could take many forms. The separate results of stochastic model parameter identification and the uses of such models for prediction and control could find application in other processes as well as for nuclear power plants. The inclusion of constraints on local reactor conditions would also be a useful extension.

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TABLE 1

The Experimental Procedure of the Study

1. Analog Computer: used to simulate the plant.
   - A. Coupled nonlinear simulations of the physical processes, including the reactor, heat exchanger, pressurizer, turbine, and analog controllers.
   - B. Disturbance noise and measurement noise added to enhance realism.
2. Analog to Digital Interface: one second scan intervals.
   - A. Measurements:
     - -reactor power
     - -primary loop average temperature
     - -turbine load
     - -rod group position
     - -turbine load set point
   - B. Manipulated control inputs:
     - -rod group speed
     - -turbine load set point
3. Digital Computer: used for calculations and control.
   - A. Stochastic model parameter identification.
   - B. Kalman Filtering to give estimates of measured and unmeasured states.
   - C. Prediction of bands of uncertainty.
   - D. Calculation of control inputs.
   - E. Display of predicted plant performance prior to the load change.
   - F. Display of realized vs predicted performance during the load change.
   - G. On-line hypothesis testing to detect plant variation.
   - H. Adaptation of model.

APPENDIX A: THE CONTROL MODEL

The structure of the model used for computer control is determined by physical laws, but the parameters of the model are assumed to be varying or unknown. In the noise part of the model, the parameters of the disturbance noise and measurement noise are also assumed to be unknown.

Values of the parameters of the model are identified from data records from the simulated plant taken during load change. The criterion for choosing the parameter values is maximum likelihood. The details of the model parameter identification technique are discussed in references (1) and (8).

The deterministic model developed in this study can be expressed as:

$$\frac{dx}{dt} = \underline{f}(\underline{x},\underline{u},\underline{b}) \tag{A-1}$$

where:
- $\underline{x}$ is a six dimensional vector of plant states
- $\underline{u}$ is a two dimensional vector of plant inputs
- $\underline{b}$ is a twelve dimensional vector of parameters

where:
- x_1 is delayed neutron precursor concentration
- x_2 is primary loop average water temperature
- x_3 is turbine power
- x_4 is reactor control rod group position
- x_5 is Xe^{135} concentration
- x_6 is I^{135} concentration
- u_1 is reactor control rod group velocity
- u_2 is turbine load set point

The measurements are considered as:

$$\underline{y} = \underline{h}(\underline{x},\underline{u},\underline{b}) \tag{A-2}$$

where:
- $\underline{y}$ is a five dimensional vector of measurements
- y_1 is reactor power
- y_2 is primary loop average water temperature
- y_3 is turbine power
- y_4 is reactor rod group position
- y_5 is turbine power set point

The derivation of this nonlinear deterministic model is discussed by Moore[1].

The basic procedure for constructing the model was to represent the major energy storage, generation, and energy output phenomena in terms of simple lumped models. Thus the known plant structure was used in defining the model structure. The alternative procedure, to consider the plant unknown except for model order, was rejected due to the large number of unknown parameters which would result.

A stochastic model of the plant is defined using disturbance and measurement noise models in addition to the deterministic model. The data from the plant consist of samples which are corrupted by noise. The noise is assumed to be added to the nominal measurements, equation A-2 to give

$$\underline{z}_K = \underline{h}(\underline{x}_K, \underline{u}_K, \underline{b}) + \underline{w}_K \qquad \text{(A-3)}$$

where the subscripts K refer to the sampled values at a time labeled K. $\underline{w}_K$, the measurement sensor noise, is assumed to be zero mean white Gaussian noise with covariance W.

$$E(\underline{w}_K \underline{w}_{K'}) = W \qquad \text{(A-4)}$$

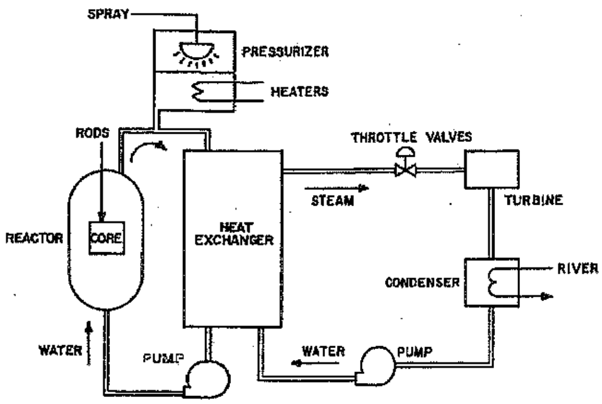

Figure 1 - A Pressurized Water Nuclear Power Plant

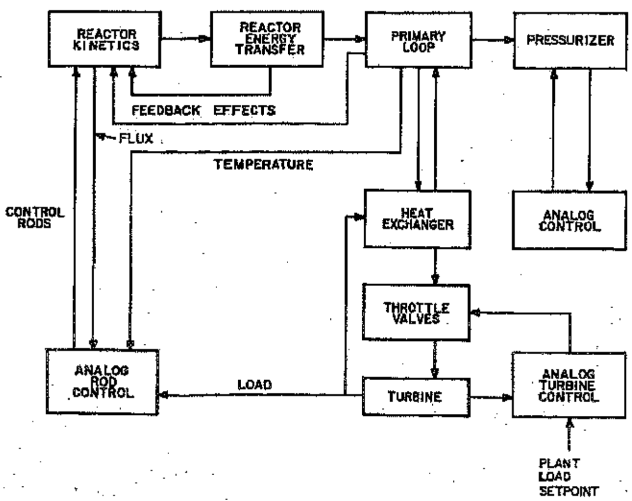

Figure 2 - The Plant Simulation Structure

The covariance matrix W is assumed to be unknown, to be identified from the data records.

The stochastic model allows for disturbance noise driving the model states. This noise represents random plant disturbances and model errors, which appear as disturbances. The result of allowing for disturbance inputs to the model is that the model states are described by probability distributions at a particular time. These distributions evolve through time. Small deviations from the expected state propagate approximately according to a model linearized about the nominal expected state. It is assumed that the probability distribution about the nominal state evolves according to this model also.

This model is used for a variety of purposes in the study. The model, in summary, consists of a nonlinear deterministic model which converted to discrete time form and is augmented with additive measurement and disturbance noise models. The parameters in the model are identified from data records.

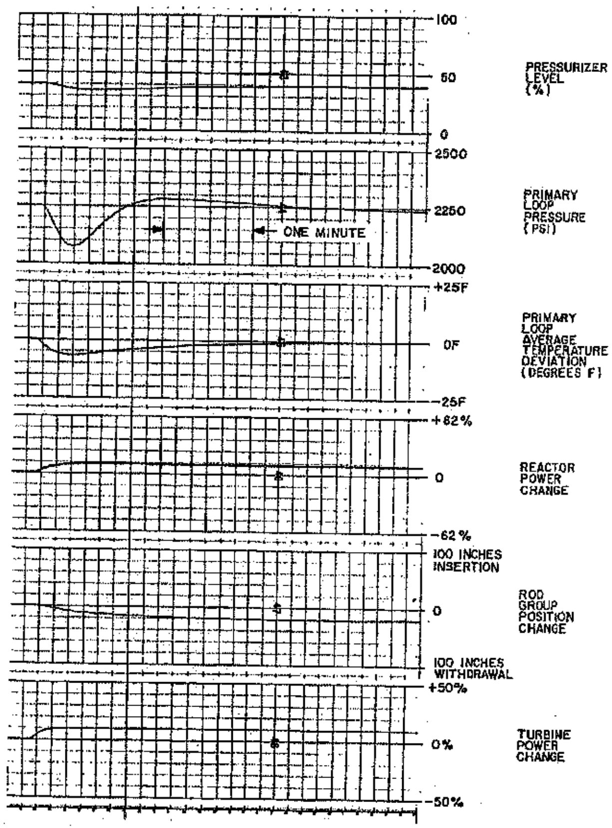

Figure 3 - A 10% Load Increase Under Analog Control

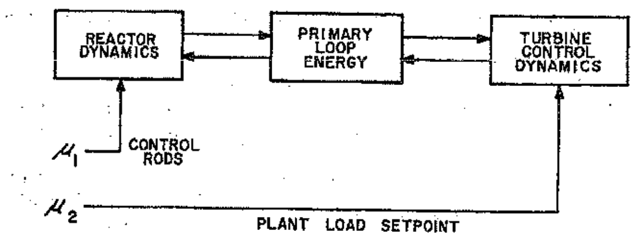

Figure 4 - The Model Structure

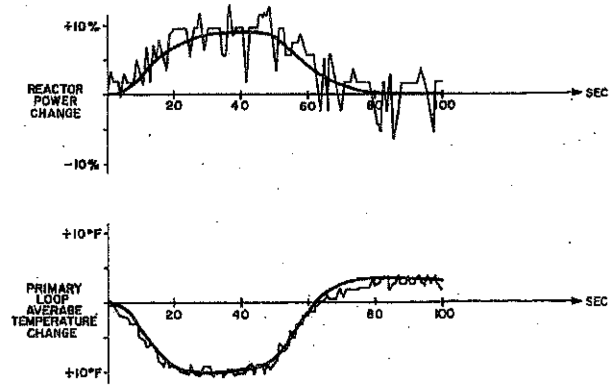

Figure 5 - A Data Record Used for Model Parameter Identification

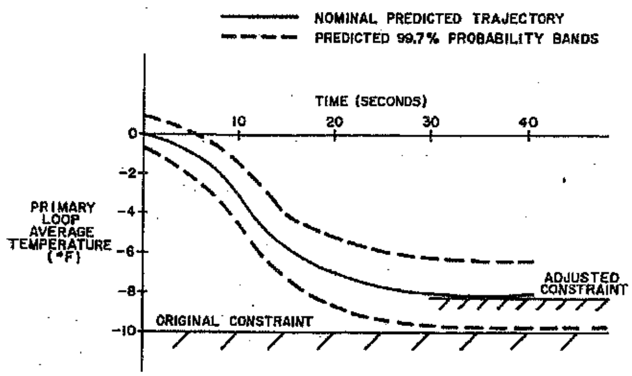

Figure 6 - Adjustment of the Constraints

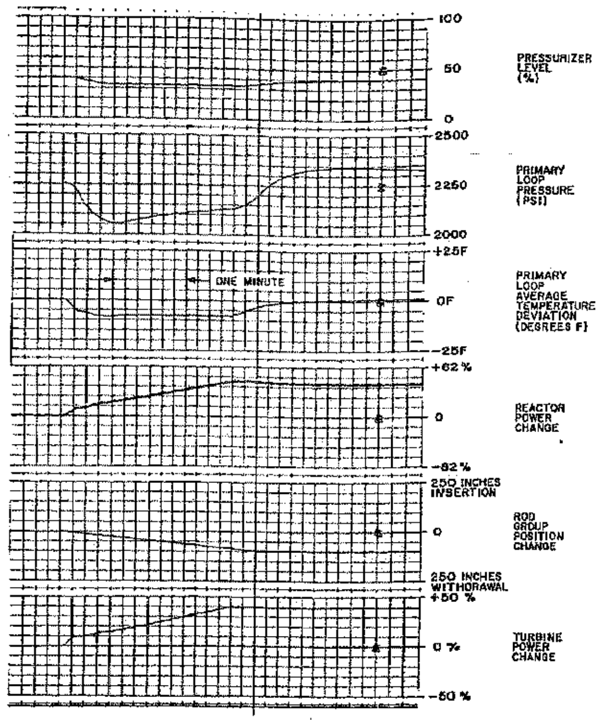

Figure 7 - A 40% Load Change Under Computer Control, With Primary Loop Average Temperature As The Limiting Constraint

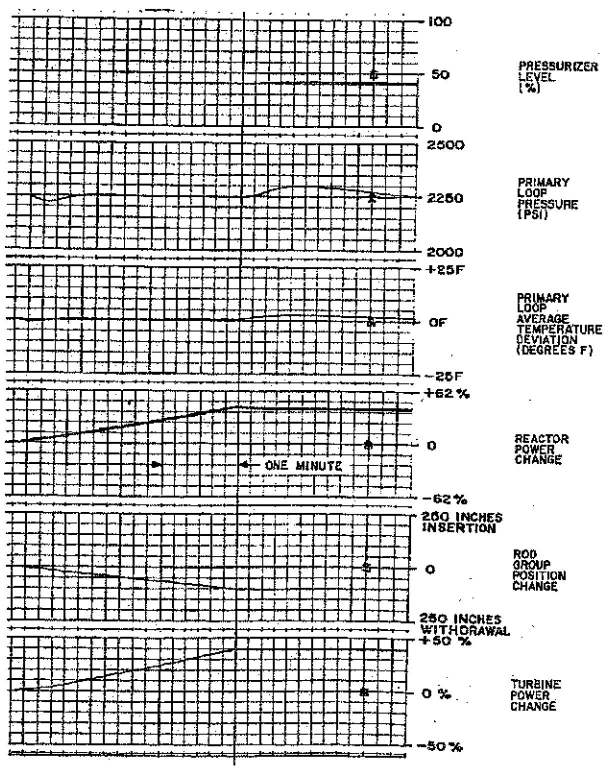

Figure 8 - A 40% Load Change Under Computer Control, Zero Desired Primary Loop Average Temperature Deviation

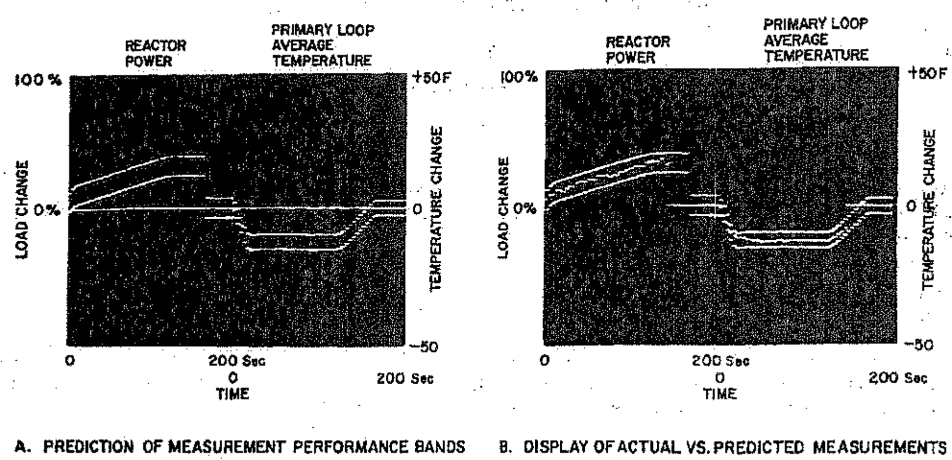

Figure 9 - The Load Change

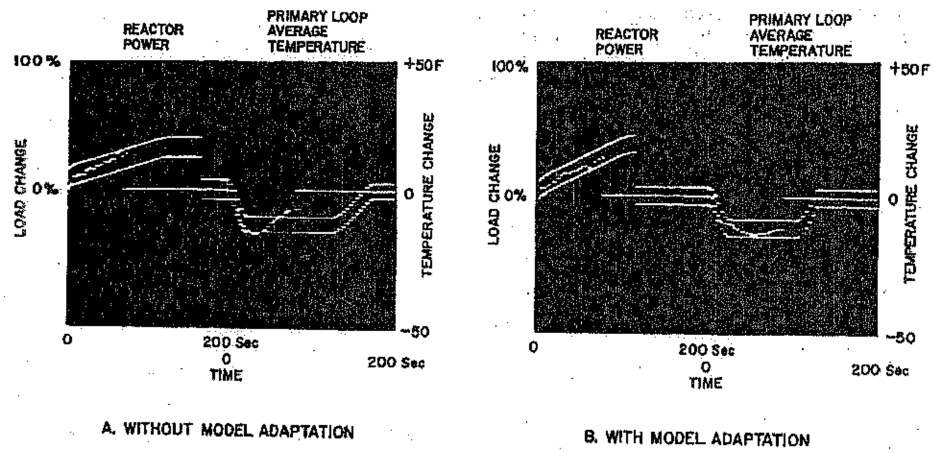

Figure 10 - Model Adaptation