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POINT REACTOR SIMULATION FOR THE PURPOSE OF KNOWLEDGE BASED
CONTROLLER DESIGN

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INTRODUCTION

As man made systems get more and more complex it becomes increasingly
difficult for men to maintain and operate them. Especially, in nuclear
power plants with a great number of interacting units and almost innumerable
sources of disturbances coupled with the fact that operational
errors can lead to disastrous consequences such as Three Mile Island and
Chernobyl, makes control and regulation of such systems as important part
of the field.

Every branch of science is, in the broadest sense, an attempt to model
aspects of the real world and it provides a conceptual structure intended
to reflect certain aspects of reality. And every model is necessarily an
abstraction of the reality if it is to be useful. But the level of
abstraction must be appropriate for the given task.

In analytical control system design, the elementary object or source
of information is the continuous, real valued function. Here lies the
merits of analytical approach in that it provides a unique solution
allowing precise optimization of the dynamic response. The continuous
real valued function of time corresponds to the observable behavior of
the actual system. However, this correspondence depends on the precision
and completeness of the model predicting the actual response with different
levels of faithfulness. Also, if the model is incomplete in the sense
that a subsystem or parameter relationship is missing then the analytical
methods become inapplicable since no line of reasoning can be pursued
with a default value for the missing subsystem. Such models in real time
applications suffer also from the problems of system dynamism meaning
a changing system and environment, time limitations, and uncertainties
in sensor readings needed for control purposes. Analytical representation
schemes are most helpful in predicting behavior but otherwise, they are
quite inflexible. What is expected of an analytical model is not only
its faithful reproduction of real behavior but also its efficient
countactization of essential events explaining the patterns of interest
in terms of an easily understood set of elements.

Problems of control arise when the system at hand is either ill defined
or there is a lack of access to some of the internal variables of the
system. This lack of complete information about the underlying physical
system can be remedied by having access to as many variables as possible
and by designing a tight feedback system. This approach is most promising
for regulation problems. Lack of information being more crucial for
servomechanisms, use of an explicit model to generate behavior estimates
which are then used to modify the closed-loop time response in order to
satisfy the performance specification becomes the feasible approach for
such systems.

The central idea of cybernetics is systems which can observe their
present state and from the knowledge of the desired state generate the
difference between the two states as feedback to move the system towards
the desired state. In the analytical approach the system and the desired
state are represented as points in a vector space constituting the state
space. Furthermore, a relationship, usually linear, between this difference
and the appropriate control action or variable is presumed. It was at this
point that cybernetics bifurcated into analytical approach of established
control theory and the empirical approach of the knowledge-based control
systems. The essential difference between the two approaches is in the
definition of the fundamental unit of knowledge representation; analytic
control theory takes the continuous real valued function as its unit while
the knowledge based systems employ the symbol. The adoption of the real
valued function inevitably led to a sophisticated and comprehensive
mathematical theory of feedback control. Differential or difference equations
are used to model continuous-time or discrete-time dynamic systems and
powerful synthesis methods have been developed. However, a strict association
between the actual physical variables and the predicted real continuous
variables has led to a confusion between the actual physical system and
its mathematical model. At times modelling assumptions necessary for the
analytical method are first made and then neglected at the design and
verification stage. This can result in significant differences between the actual and designed behaviors in which case empirical methods are used to restore the performance to satify the original specifications. For sophisticated processes the range of satisfactory operation can be extended through the use of adaptive controllers which attempt to identify and modify the model in real time so as to update the control law. A priori assumptions and the significant amounts of heuristic logic required by these controllers ensure proper functioning but tend to negate the advantages of analytic methods.

In recent years qualitative simulation methods along the lines of Artificial intelligence have been developed for deriving a qualitative behaviour of a system from the description of its structure and an initial state. A significant advantage of qualitative descriptions is that the qualitative variables can be given semantic interpretation such as positive, zero, negative or increasing, steady, deGreasing, fast, slow which are more easily understood by the operating personnel and allow a reliable machine interaction since the method is already mimicking the decision making processes of an operator. Thus one of the aims of Artificial intelligence is to replace human beings with precise tasks by machines and in order to design more sophisticated controllers it is necessary to understand and utilize more aspects of human intelligence. Clearly human powers of reasoning have a lot to offer in the design of such controllers. Human beings, when making decisions, tends to work with imprecise concepts which can often be expressed linguistically such as slow, fast etc. Certain classes of such linguistic statements can be treated mathematically in the form of fuzzy set theory. The element of imprecision in human decision making is considered as the important factor contributing to powers of human intelligence. The linkage between the real imprecise world outside expressed linguistically and the mathematical representation inside the controller is provided by the fuzzy set theory.

The scope of this study is the design of a regulator, namely an automatic unit replacing the human operator as the means of coping with normal operating transients. This unit with its limited capability is actually a part of of a larger control unit that has other subunits to
deal with more serious disturbances. And this unit will be of the knowledge based control type in contrast with an analytical controller.

The nuclear power plant being a complicated time dependent physical system, no unique mathematical model can be devised to represent it. Instead, short term response in the face of changes in input parameters and long term behavior due to fuel depletion and deteriorating component performance are studied with different models used alternatively in an interactive fashion. It was pointed out that such analytical models suffer not only from a limited scope in power of representation due to simplifications in modeling but also due to uncertainties in determination of model parameters. This is where the advantages of knowledge based control become apparent because such techniques of control do not require an accurate model of the system. In fact, in some cases model of the process to be controlled can be dispensed with altogether.

There are two ways of building the knowledge based controller

a) Providing an initial set of heuristic rules and a mechanism for the controller to learn the appropriate action to take,

b) Incorporating deep models, i.e., a model of the system to be controlled to the knowledge base and provide meta-rules to find the control rule to be used. In the latter case, however, a sequential processor might require a prohibitive amount of time to sift through the available knowledge thus making the controller practically useless. Neural nets, building and incorporating the knowledge into hardware may remedy this situation but such new areas of research are beyond the scope of this study. Hence, the more promising approach is the use of heuristics and a learning strategy. At this point, in the absence of operational experience an analytical model of the system is still helpful to run various scenarios contingent upon changes in control variables so as to develop a sound set of heuristics to work with. Another advantage of the knowledge based controller then becomes the possibility of building the knowledge base incrementally and allowance for learning.

Now, let us examine the model to be used in deriving a set of heuristics.
POWER PLANT MODEL

Due to a lack of access to operational power plant data on one hand and the need for model validation on the other hand, a well established PWR power plant model has been chosen along the lines of H.B. Robinson model of Kerlin et al. This model being a linear one would be sufficient to meet the needs of a regulator design. A nonlinear model valid over a wider range of system parameters, especially power, would be necessary for the design of a controller with general control capability. Such a nonlinear model could then be linearized pointwise in order to employ the same numerical techniques as here so as to guide the control action in different parameter ranges. This extension of scope to a controller more general than the regulator under consideration could be the next aim of this study. Returning back to the model, each one of the components making up the system is described by an appropriate set of ordinary differential equations.

a) Core: The reactor power is modeled using the point kinetics equations with six groups of delayed neutrons and reactivity feedbacks due to changes in fuel temperature, moderator temperature and primary loop coolant pressure. The linearized equations are:

\[
\frac{dSP}{dt} = -\frac{\beta}{\Lambda} SP + \sum_{i} \lambda_{i} \delta C_{i} + \frac{\alpha_{p} P_{o}}{\Lambda} \sum_{\text{nodes}} \delta T_{fi} i, \delta T_{fi} + \frac{\alpha_{p} \rho_{o}}{\Lambda} (\delta p_{i} + \frac{\rho_{o}}{\Lambda} \sum_{\text{coolant nodes}} \delta C_{i} )
\]

\[
\frac{d\delta C_{i}}{dt} = \delta \frac{\delta P - \lambda_{i} \delta C_{i}}{\Lambda}, \quad i = 1, 2, \ldots, 6
\]

The core heat transfer model uses a nodal approximation for fuel and coolant temperatures. Each axial section includes a fuel temperature node and two coolant temperature nodes which are used to obtain a good approximation to the average coolant temperature.

\[
\frac{d\delta T_{fi}}{dt} = \frac{Q_{fi}}{(MC_{p})_{f}} \delta P - \left( \frac{UA}{MC_{p}} \right)_{f} \left( \delta T_{fi} - \delta T_{oi} \right)
\]
\[
\frac{d\delta T_{ci}}{dt} = \left(\frac{UA}{MC_p}\right)_i \left(\delta T_{fi} - \delta T_{ci}\right) - \frac{2}{c} \left(\delta T_{ci} - \delta T_{cin}\right)
\]

\[
\frac{d\delta T_{ci}}{dt} = \left(\frac{UA}{MC_p}\right)_i \left(\delta T_{fi} - \delta T_{ci}\right) - \frac{2}{c} \left(\delta T_{ci} - \delta T_{cin}\right)
\]

b) Pressurizer: The pressurizer model is based on mass, energy and volume balances and the assumption that saturation conditions apply for the steam water mixture in the pressurizer.

The pressurizer has a controller of its own which uses a heater to compensate for steady state heat losses from the pressurizer. It is also used for pressure control for normal pressure variations. Heat input increases for low pressure and decreases for high pressure.

\[
\frac{d\delta P}{dt} = B_1 \delta P + B_2 \delta W_N + B_3 \delta q
\]

\[
\delta W_N = \sum_{i} N_i v_i C_i \frac{d\delta T_{ci}}{dt}
\]

\[
\frac{d\delta X}{dt} = B_A \delta P
\]

c) Steam Generator: The steam generator model uses three regions to represent the whole steam generator: primary fluid, tube metal, and secondary fluid. The model includes no control action. This is equivalent to assuming that the model applies for small upsets in which controller dead bands or long time constants prevent significant changes in feedwater flow.

\[
\frac{d\delta T_p}{dt} = \frac{1}{\varepsilon_s a} \delta T_{ip} - \frac{(hA)_p}{H_p C_p} \left(\delta T_p - \delta T_m\right) - \frac{1}{\varepsilon_s q} \delta T_p
\]
\[
\frac{d\delta T_m}{dt} = \frac{(h_A)_{m}}{M_m C_m} (\delta T_p - \delta T_m) - \left[ \delta T_m - \left( \frac{\delta T_{sat}}{\delta P_s} \right) \delta P_s \right] \frac{(h_A)_{ns}}{M_m C_m}
\]

\[
\frac{d\delta P_s}{dt} = D_1 \delta P_s + D_2 \delta T_m + D_3 \delta W_{so}
\]

d) Piping and Plenums: All piping sections and plenums are modeled as well-mixed volumes.

\[
\frac{d\delta T}{dt} = \frac{1}{\varepsilon} \delta T_{in} - \frac{1}{\varepsilon} \delta T
\]

Fig. 1. Schematic of the H.B. Robinson Nuclear Plant
The model thus obtained consists of a set of ordinary linear differential equations and has two inputs corresponding to the control variables:
1) reactivity due to control rod movement
2) steam flow rate to the turbine

The mathematical method used in the numerical solution for the state trajectory is considered next.

**MATHEMATICAL METHOD OF SIMULATION**

Considering a system of equations:

\[
\frac{d\mathbf{x}}{dt} = \mathbf{A} \mathbf{x} + \mathbf{g}(\mathbf{x}, t) + \mathbf{f}(t)
\]

where
- \(\mathbf{x}\) the solution vector
- \(\mathbf{A}\) Matrix of constant coefficients corresponding to linear terms
- \(\mathbf{g}(\mathbf{x}, t)\) the vector of nonlinear and variable coefficients
- \(\mathbf{f}(t)\) vector of forcing terms, namely inputs

The output at time \((t+\Delta t)\) is given by

\[
\mathbf{x}(t+\Delta t) = \exp(\mathbf{A} \Delta t) \mathbf{x}(t) + \int_t^{t+\Delta t} \exp(\mathbf{A} (t-t'))\left[\mathbf{g}(\mathbf{x}(t'), t') + \mathbf{f}(t')\right] dt'
\]

If \(\mathbf{g}(\mathbf{x}, t)\) and \(\mathbf{f}(t)\) can be assumed to be piecewise constant, the integral can be evaluated, and

\[
\mathbf{x}(t+\Delta t) = \exp(\mathbf{A} \Delta t) \mathbf{x}(t) + \left[\exp(\mathbf{A} \Delta t) - \mathbf{I}\right] \mathbf{A}^{-1}\left[\mathbf{g}(\mathbf{x}(t), t) + \mathbf{f}(t)\right].
\]

The terms involving matrix exponentials are evaluated as follows:

\[
\exp(\mathbf{A} \Delta t) = \mathbf{I} + \mathbf{A} \Delta t + \frac{1}{2!} (\mathbf{A} \Delta t)^2 + \frac{1}{3!} (\mathbf{A} \Delta t)^3 + \ldots
\]

\[
[\exp(\mathbf{A} \Delta t) - \mathbf{I}] \mathbf{A}^{-1} = \Delta t \left[\mathbf{I} + \frac{1}{2!} \mathbf{A} \Delta t + \frac{1}{3!} (\mathbf{A} \Delta t)^2 + \frac{1}{4!} (\mathbf{A} \Delta t)^3 + \ldots \right]
\]

where \(\mathbf{I}\) is the unit diagonal matrix.
COMPUTER PROGRAM

The equations given above describing the time dependence of variations of the state variables around an equilibrium are solved by the above method to trace out the paths followed by the system. Initial disturbances may be fluctuations in power or stepwise changes in any one of the state variables.

An interactive software has been developed to perform the simulation and generate or test control rules which can be implemented on a microcomputer due to the recent developments in such hardware and software. An IBM-compatible Olivetti M-24 computer with an Intel 8086 CPU and an additional Intel 8087-2 floating point co-processor having a clock speed of 8 MHz each, 640 KB RAM and two 360 KB floppy disk drives is used for this purpose. The software written is in Turbo Pascal 4.0 because of its good graphics capability, compact and fast code generation characteristics. A 100 sec simulation takes about 50 minutes to run. Obviously, using this program with no modifications on Intel 80386 based machines will greatly improve the running time. On the other hand, use of solution techniques based on stiff systems rather than the above matrix calculations could relax the upper limit on the step length used so as to decrease the number of steps required for a 100 sec simulation thereby reducing the overall computing time.

Features of The Program:

A) Initialization: As the rest of the program, initialization is menu driven, allowing the user to access the options easily by just using the arrow keys on the keyboard. It is possible to select the time step, and stopping time for the simulation. It is also possible to change their values at any time during the simulation.

All the variables in the model can be initialized, and changed during the simulation. This feature is the most important one since it allows the application of control through external means, i.e., by the user or the knowledge based control module.

B) Plotting: It is possible to select up to 10 variables for plotting which can be examined on the screen through the use of another menu at any time during the simulation.

Simulation can be interrupted and restarted at any moment, and a report of values of the selected variables can be saved in a disk file
or printed.

The graphs are interactive with a movable cursor. The numerical values of the dependent and independent variables of the point where the cursor rests is displayed at the bottom of the graph, which relieves the burden of examining both a graph and a printout to see the exact values of the point.

c) Simulation: During the simulation a schematic layout of the power plant is displayed on the screen and numerical values of some of the values are shown as the simulation progresses.

DISCUSSIONS FOR FURTHER WORK

In the design of a regulator the system behavior examined by the computer code developed can be used to form heuristics to be devised as part of the control process. In order to clarify the intended procedure some notions of fuzzy logic need to be introduced.

Suppose that the rate of change of reactor power and reactivity insertion can be considered as being positive or negative fast or slow or effectively zero. And also suppose that an operator observing the state trajectory of the system would consider the present rate of change of reactor power as positive fast with 70% probability, as positive slow with 20% probability and effectively zero with 10% probability. Note also that such imprecision is innate in human reasoning and these probabilities can be established either by asking the same operator a number of times his/her opinion about the classification of a given state trajectory within a time interval or by asking the same question to a number of different operators. Hence, the system state ends up belonging to positive fast increasing power category with 70% probability, positive slow increasing category with 20% probability, etc. In conventional set theory, an object is either a member of a category or not corresponding to membership values of either zero or one. But this is not so in fuzzy logic and this ability to deal with a continuous range of values rather than just true and false is exactly what is needed in the real world.
On the other hand, the heuristics arrived at through the use of our simulation model might be of the form:

\[
\text{IF THE POWER IS INCREASING POSITIVE FAST BUT THE DEVIATION FROM THE DESIRED POWER LEVEL IS EFFECTIVELY ZERO AND THE COOLANT TEMPERATURE IS NOT HIGH THEN WITHDRAW THE CONTROL ROD ASSEMBLY SLOWLY.}
\]

And such heuristics are formulated by using the reasoning of the human operator reasoning. Fuzzy logic is used to ascertain the compliance of the state being examined with this or any other heuristic with a value above a certain specified threshold in which case the control action specified will be undertaken. The truth values of the preconditions for any heuristic is evaluated as a result of application of fuzzy logic rules.

Thereby at each time step a system state assessment is made and consequently a control action is chosen inorder to restore the desired state.

After the successful application of this regulator program an extension to control capability between widely different states could be achieved through the use of the nonlinear version of our mathematical model and by pointwise linearization along the system trajectory.

NOMENCLATURE

- \( \Delta P \): deviation of reactor power from initial steady-state value
- \( P_0 \): initial power level
- \( \lambda_i \): delayed neutron decay constant for \( i \) th delayed neutron group
- \( \Delta C_i \): deviation of normalized precursor concentration from its steady state value
- \( P_r \): primary system pressure
- \( \alpha_f \): fuel temperature coefficient of reactivity
- \( \alpha_{C} \): coolant temperature coefficient of reactivity
- \( \alpha_P \): coolant pressure coefficient of reactivity
(12)

\( \delta T_{fi} \): deviation of fuel temperature in the i th fuel node from its initial steady state value

\( \delta T_{ci} \): deviation of coolant temperature in the i th coolant node from its initial steady-state value

\( \delta P_{roa} \): reactivity due to control rod movement

\( \beta_i \): delayed neutron fraction for the i th delayed neutron group

\( \beta \): total delayed neutron fraction

\( \Lambda \): neutron generation time

\( F_{Ti} \): reactivity importance for temperature changes in the i th fuel node

\( F_{Ci} \): reactivity importance for temperature changes in the i th coolant node

\( \delta T_{av} \): average fuel temperature

\( \delta T_{ci} \): average coolant temperature in i th fuel node

\( \delta T_{oi} \): outlet coolant temperature in the i th fuel node

\( \Phi_i \): fraction of total reactor power generated in fuel node i

\( (MC_f)i \): total heat capacity for the i th fuel node

\( (MC_c)i \): total heat capacity of both coolant nodes associated with the i th fuel node

\( U \): overall fuel-to-coolant heat transfer coefficient (includes resistance in fuel as well as film resistance)

\( A_f \): heat transfer area

\( \tau \): résidence time (both coolant nodes)

\( \delta T_{cin} \): deviation in inlet temperature of the first coolant node from its initial steady state value

\( \delta M_{win} \): mass flow of water into(or out of) the pressurizer

\( \delta q \): rate of heat addition to the pressurizer fluid with electric heater

\( B_1, B_2, B_3, B_4 \): numerical constants obtained after linearization

\( V_i \): volume of the i th coolant node

\( \gamma_i \): slope of coolant density versus temperature curve

\( T_{ci} \): temperature of the i th coolant node

\( X \): integral control action variable

\( \delta T_{sm} \): steam generator tube metal temperature

\( \delta T_{Pr} \): primary coolant temperature in the steam generator

\( \tau_{sm} \): residence time of coolant in the steam generator

\( \delta T_{ip} \): primary coolant temperature in the steam generator inlet plenum

\( h_{pm} \): heat transfer coefficient for primary coolant to metal (includes a portion of the metal resistance as well the film resistance)
A : heat transfer area
M_P : mass of primary coolant in the steam generator
C_P : specific heat of primary coolant
h_{ms} : heat transfer coefficient for metal to secondary coolant (includes a portion of the metal resistance as well as the film resistance)
M_m : mass of tube metal
C_m : specific heat of tube metal
\frac{\partial T_m}{\partial P_s} : slope of saturation temperature versus saturation pressure curve
P_s : steam pressure
W_{so} : steam flow rate to turbine
T : temperature of fluid in the section (equal to outlet temperature)
T_{im} : fluid temperature at entrance
\tau : fluid residence time

REFERENCES:

Fig. 2.4 Outlet Temperature

Fig. 2.5 Primary coolant pressure

Fig. 2.6 Steam pressure