ANTICIPATORY MONITORING AND CONTROL IN A PROCESS ENVIRONMENT

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ABSTRACT

A methodology for the synthesis of engineering Anticipatory Systems is presented. It accounts for both random and fuzzy aspects of uncertainty introduced in process control, and develops mathematical measures of *performance*. The random, probabilistic component quantifies the uncertainty of occurrence of an event. The fuzzy, possibilistic component quantifies the imprecision in the meaning of an event. Facts about the system are represented as fuzzy information granules of the form: g = **(number of carts carrying parts)** is **(small)** is **(likely)**.

The performance measures are used as an input to the diagnostic and control functions which are assumed by a Production-Rule System. Using a fuzzified Bayes formula as the link between present and future states, a model-based system estimates at any time t, *current performance* as well as *anticipated performance* at time $t + \Delta t$. A control action can be taken at time t, based on both *current* and *anticipated performance* . Accordingly, the system can change its current state on the basis of both the current and the anticipated future state. The agency for the prediction is a model of the system and/or its environment which is internal to the system.

The synthesis of such system is demonstrated using a model of a nuclear reactor. The model of the reactor is constructed using procedural programming methods and is coupled to a symbolic program which assumes the overall control function.

Introduction

An Anticipatory System is a system containing a predictive model of itself and/or its environment, which allows it to change state at an instant in accordance with the model's predictions pertaining to a latter instant. Although the impetus for the development of a theory for Anticipatory Systems has come from the field of theoretical biology in an attempt to explain the behavior of organisms[1], the present research suggests that it can provide a useful metaphor for the monitoring and control of engineering systems as well[2-4].

The basic premise of anticipatory control is that both current and anticipated (future) performance are the basis of diagnostic/control decisions i.e., they are incorporated in the control strategy. Constructing a Model-Based System or an Expert System in a process environment with monitoring and control functions in the context of the anticipatory paradigm requires that it performs two main functions at any time t. *First* , it must calculate current performance levels. This is done after it has obtained: (a) information from the external world, in the form of sensor readings, and their associated probability distributions, and (b) a set of criteria about how things ought to be, which are embodied quantitatively in a set of membership functions. These comprise the biggest part of its Knowledge Base, in the form of rules, constraints, heuristics, etc. *Second,* it must estimate the performance in the near future, that is, some time Δt later. To achieve this goal, it requires: (a) an estimate of current performance, (b) membership functions for the anticipated values of the state variables -- obtained through the employment of a predictive model -- and, (c) a memory of its past experience, concerning the effectiveness of earlier predictions. The methodology presented here allows for estimating present as well as future performance on the basis of probabilistic and possibilistic information and is demonstrated with the simulation of an anticipatory model-based system in a process environment.

Combining Probabilistic and Possibilistic Information in Anticipatory Systems

The basis for the calculation of the current and anticipated performance of a system are the notions of the probability of a fuzzy event and the fuzzyfied Bayes formula. Let $X = \{x_1, x_2, .. , x_n\}$ and $Y = \{y_1, y_2, ... , y_m\}$ be sets of basic events with probabilities $p(x_i)$ and $p(x_j)$ respectively. Let $p(x_i, y_j)$ be the joint probability of x_i and y_j. A fuzzy event A on X is characterized by a membership function μ_A: X--> [0,1], and similarly a fuzzy event A' on Y is characterized by a membership function $\mu_{A'}$:Y-->[0,1] . The probability of the fuzzy events A and A' are given by [5-7]:

$$P(A) = \sum_{i=1}^{n} \mu_A(x_i)\, p(x_i) \, , \quad \text{and}$$

$$P(A') = \sum_{j=1}^{m} \mu_{A'}(y_j)\, p(y_j) \qquad (1)$$

The conditional probability of the fuzzy event A' given the occurrence of A is[1]:

$$P(A' \mid A) = \frac{\sum_i \sum_j \mu_A(x_i)\, \mu_{A'}(y_j)\, p(y_j \mid x_i)\, p(x_i)}{\sum_i \mu_A(x_i)\, p(x_i)} \qquad (2)$$

where $p(y_j \mid x_i)$ is the conditional probability of the basic event y_j conditional on the occurrence of the event x_i . Equation (2) is a fuzzified version of Baeys formula. For the logical operators AND, OR, and NOT there exist equivalent expressions in probability and possibility theory. In the fuzzy set (or possibility) theory, AND corresponds to a MAX and OR to a MIN operator respectively.

An integral part of the anticipatory systems contemplated in this research, is a symbolic processor, an Expert System (or a Model-based System) using *productions* (rules) for inferencing. In the Rule-Based Paradigm of Artificial Intelligence the typical structure of a production in a production-rule system is "If A then B," where A is the antecedent (or condition) and B is the consequent. The case of Anticipatory Systems requires a structure that can account for phenomenological data in which there might be both probabilistic and possibilistic knowledge. To account for such a combination, the generalized description of an event X as a Fuzzy Granule[12] is adopted. A fuzzy granule in this context is a proposition having the canonical form:

$$g = X \text{ is } G \text{ is } \lambda \tag{3}$$

Where X is a random variable whose values represent *measured data,* G is a fuzzy qualification on X, whose values represent *calculated data* (which is the output of some model M) and λ is a fuzzy qualification on the proposition "X is G". For example, we may have: g = (device-A-output) is (adequate) is (likely). Here X is "device-A-output", G is the fuzzy subset "adequate" with membership function $\mu_{adequate}$ and λ is the fuzzy probability "likely", which denotes the certainty of g, with membership function μ_{likely}. For instance, in the case of of the proposition above we get:

$$\begin{aligned}&\text{(device-A-output) is (adequate) is (likely)} \rightarrow \\ &\pi(p_X) = \mu_{likely}\left(\int p_X(u)\, \mu_{adequate}(u)\, du\right) \\ &\qquad = \mu_{likely}\left(\rho(p_X)\right).\end{aligned} \tag{4}$$

The use of the enunciated theory for combining environmental probabilistic data to possibilistic modelling data in Anticipatory Systems can be demonstrated by considering an engineering system with two production lines operating in parallel, each line having three componenets in series: A, B, C in one line and H, I, J in the other[1]. The components A, B, C, H, I, J are connected in a series-parallel configuration. Let D be on of the parallel branches, E the other branch and F the total system. We can generate a Model-Based system describing the functioning of the system. The functioning of the individual components is described through the Information Granule of Eqn. (3), and the functioning of the system is described through the following rules:

Rule 1: **If** (1) A is G_A is λ_A, **AND**
(2) B is G_B is λ_B, **AND** (5)
(3) C is G_C is λ_C,
Then D

Rule 2: **If** (1) H is G_H is λ_H, **AND**
(2) I is G_I is λ_I, **AND** (6)
(3) J is G_J is λ_J
Then E

Rule 3: **If** (1) D , **OR**
(2) E (7)
Then F

With each component, branch and the total system we associate a possibility which is called the *performance* of the component, branch or system:

Rule 1: $\pi_D = \text{Min}\,[\,\pi(p_A), \pi(p_B), \pi(p_C)\,]$ (8)
Rule 2: $\pi_E = \text{Min}\,[\,\pi(p_H), \pi(p_I), \pi(p_J)\,]$ (9)
Rule 3: $\pi_F = \text{Max}\,[\pi_D, \pi_E\,]$ (10)

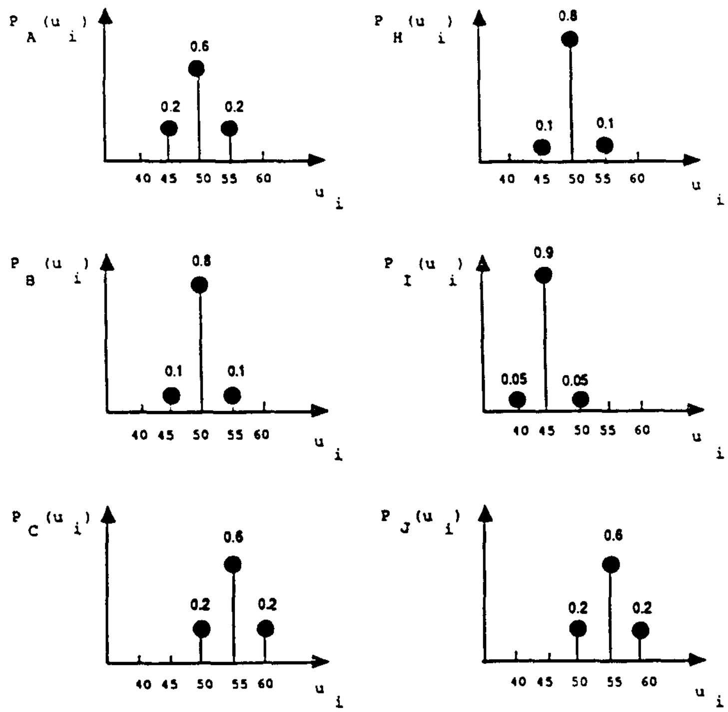
The form of representation, according to the proposed approach considers both the probabilistic aspects of the data through the probability density functions $p_X(u)$ and the possibilistic aspects through the membership functions $\mu_G(u)$ and $\mu_\lambda(\rho(p_X))$. The quantities π_D, π_E, and π_F constitute a measure of how well the expectations or predictions which are generated by the model M and take the form of membership functions, "match" the actual environmental inputs in the form of probability density functions. Accordingly the quantities π_D, π_E and π_F are recognized as *performance measures* for the system's components and parameters.

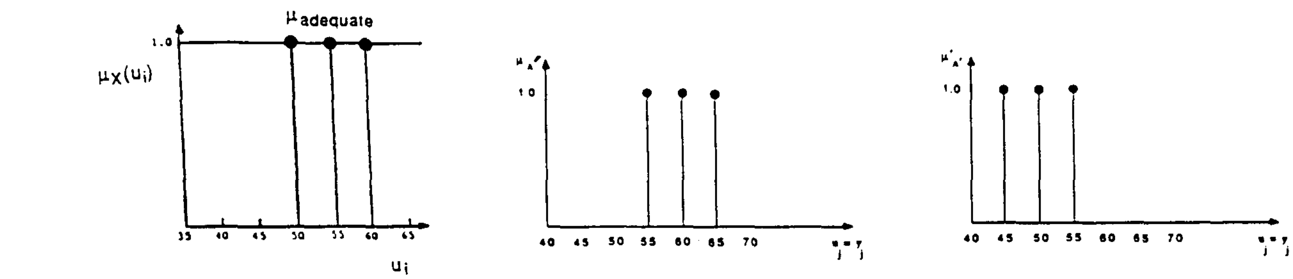
An application of the theory developed in the last section is here demonstrated with a numerical case. We choose discrete triplex arithmetic density functions for the components as shown in Fig. 1. Notice that the component I appears as functioning at a lower performance level than the other components. Let us further choose the membership functions $\mu_G(u_i)$ and $\mu_\lambda(\rho(p_{Xi}))$, to be as shown in Fig. 1, where the former corresponds to $\mu_{adequate}$, and the latter to μ_{likely}. Application of Eqn. (4) for each component in Fig. 1 yields: $\rho(p_A) = 1.0\ (0.6 + 0.2) = 0.8$, $\rho(p_B) = 1.0\ (0.8 + 0.1) = 0.9$, $\rho(p_C) = 1.0\ (0.2 + 0.6 + 0.2) = 1.0$, $\rho(p_H) = 1.0\ (0.8 + 0.1) = 0.9$, $\rho(p_I) = 1.0\ (0.05) = 0.05$, $\rho(p_J) = 1.0\ (0.2 + 0.6 + 0.2) = 1.0$. Notice that the component I yields a low probability compared to the others. Let us apply Eqn. (4) to get from Fig. 1 for the different components: $\pi(p_A) = 0.8$, $\pi(p_B) = 0.9$, $\pi(p_C) = 1.0$, $\pi(p_H) = 0.9$, $\pi(p_I) = 0.05$, $\pi(p_J) = 1.0$.Now applying Eqns. (8), (9) and (10) we get as a measure of the performance of D, E, and F: $\pi_D =$ Min (0.8, 0.9, 1.0) = 0.8, $\pi_E =$ Min (0.9, 0.05, 1.0) = 0.05 and $\pi_F =$ Max (0.8, 0.1) = 0.8 ,which suggests that the global performance is $\pi_F = 0.8$.

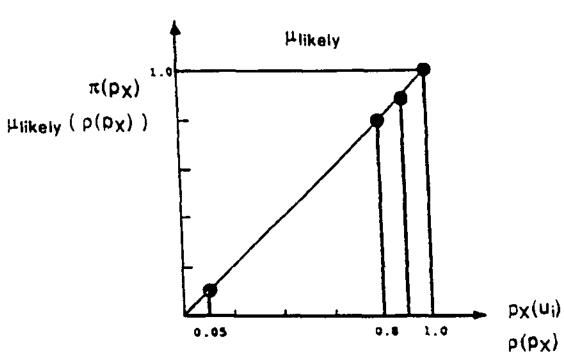
Estimation of Anticipated Performance

Consider component A in the example above. At a particular time, t, the fuzzy event "X is G_A" is a description of the component's state. After the probability of the fuzzy event "X is G_A" is calculated through Eqn. (1), we can proceed with estimating the uncertainty of the fuzzy granule, $g = X$ is G_A is λ, which provides us with a measure of the performance of component A. Next the Anticipatory System can estimate the performance of component A at some latter time, $t + \Delta t$, before it actually occurs (in real time). In other words, provided it has a complete knowledge of g it can estimate the uncertainty in the anticipated - fuzzy granule: $g' = X$ will-be $G_{A'}$ will-be λ, and take this to be a measure of the future or anticipated performance for component A. In order to calculate *anticipated performance* let us use Eqn. (2). If the fuzzy events "X is G_A" and "X is $G_{A'}$" are denoted by A and A' respectively, Eqn.(2) allows us to calculate the probability of occurrence of A' given that the of A is known. The membership function, $\mu_{A'}$, represents the anticipated criterion for what "will-be-adequate."

Let us consider the anticipated performance of a component A, when the criterion for what will constitute "adequate" at $t = t+\Delta t$, is as shown in Fig. 1. Also shown in Fig. 1 are the conditional probabilities $p(y_j \mid x_i)$. (We have set here $x_i = u_i$ and $y_j = u_j$) They form a symmetric matrix, capturing the past experience with the sensor data and its variation. The present distributions and membership functions are assumed to be the same as before, i.e., linear. The membership function for the qualification of the anticipated fuzzy event, μ_{likely} is considered to be linear also. Using Eqn. (1) the probability of the fuzzy event "X will-be $G_{A'}$" given the probability of the fuzzy event "X is G_A" is: $P(A' \mid A) = 0.3$. Thus $P(A') = P(A' \mid A)\ P(A)$ or $P(A') = (0.3)\ (0.8) = 0.24$. The anticipated performance will be $\pi_{A'} = 0.24$. Since the criterion for what will be "adequate" becomes so "hard" at $t + \Delta t$ the anticipated performance for component A is predicted to be quite low. If, on the other hand, the anticipated membership function is







x_i \ y_j	45	50	55
45	0.9	0.1	0.0
50	0.1	0.8	0.1
55	0.0	0.1	0.9

Fig. 1 Discrete probability density functions, membership functions and conditional probabilities.

comparable to $\mu'_{A'}$ in Fig. 1, the anticipated performance decreases only slightly: $\pi_{A'} = 1.0$ (0.8), which corresponds to a higher level of anticipated performance than the previous case. On the basis of current and anticipated performance the rule-based system is able to identify troubled components, thus performing a diagnostic function.

Simulating an Anticipatory System

A program which uses the performance measures developed in the last section to aid an idealized reactor operator/observer move the values of the state variables of the system in a desired region of the state space is developed. A point kinetics model of the reactor is used as the source of knowledge about anticipated states and external files provide the current value of reactor parameters as well as their history. A schematic view of the system is given in Fig 2. The central control of the program is through the symbolic program TELIC.OPS. It accepts environmental data from the CURRENT.DAT file. It also accepts possibilistic data (fuzzy) from the predictive model via the procedural program KS.FOR, in the form of membership functions. The current and anticipated performance calculations are carried out by the PSP.FOR and PST.FOR programs. They have access to the historical profile of the data which is stored in files HTEMP.DAT and HPOWER.DAT. An interface is built for coupling OPS5 to FORTRAN. Special utilities are included in the file TU.FOR and there is an interactive user interface. The role of the operator is mimicked by the expert system TELIC (purpose-driven) which is the main program.

The predictive model used by TELIC, program KS.FOR in Fig. 2 , uses a point reactor kinetics formulation, i.e., it ignores the spatial distribution of the reactor flux. It is however a time and temperature dependent model since it includes a coupling between the flux and the energy content of the system and essentially provides a model for the temperature and power evolution of the reactor. In this model the control parameter is δk_0 (DELK0 in the program), which is a step change in k, the neutron multiplication factor, applied to the reactor at the initial time $t = 0$. If a the volumetric heat source $q'''(t)$, is of the type $q'''(t) = P_0 \exp[\,v(t)]$ after a step multiplication input at $t = 0$, it follows:

$$\ddot{v}(t) + \beta\, l^{-1}\, \dot{v}(t) + (\gamma P_0 / l\, C)\, v(t) = 0 \qquad (11)$$

with initial conditions $v(0) = 0$ and $v(0) = dk_0 / l$, where $v(t)$ is the *power function*, C is the heat capacity of the system, l the average neutron lifetime,γ is the temperature coefficient of reactivity and β the delayed neutron fraction. The equation for the power function $v(t)$ above is analogous to the equation of harmonic oscillations in mechanical systems including viscous damping. It is observed that the term β / l is analogous to the "damping coefficient," and the term $\gamma P_0 / l\, C$ is analogous to the "spring constant." In this sense the temperature coefficient of reactivity, γ, is a measure of the "stiffness" of the reactor. This means that a large temperature coefficient implies a rapidly responding system and higher frequencies of oscillations following a disturbance. Systems with large heat capacities on the other hand, respond slowly to excitation and experience power oscillations at lower frequencies. By the same analogy , the presence of delayed neutrons, i.e., the term β / l, damps the oscillations resulting from disturbances.

TELIC Architecture and Example

TELIC is the part of the simulation that mimics the role of an idealized reactor "controller." At the software level it also functions as the controlling or "main" program (Fig. 2). It is written in OPS5 and uses the performance measures developed earlier in order to assess the system's present state through current performance, and to estimate the system's anticipated

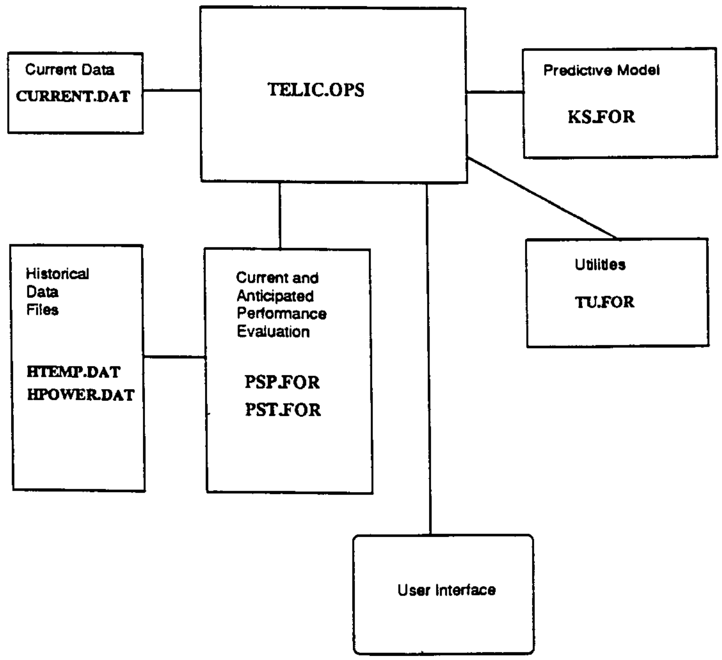


Fig. 2 TELIC architecture and associated routines.

state through anticipated performance. On the basis of the current and anticipated performance it selects the optimum value for the control parameter.

TELIC is an interactive system. During the input phase of a case, the user can choose the look-ahead time for the system anticipation. This is the time used by the predictive model to calculate the anticipated values of the power function v(t), and hence the power P(t) and the temperature variation T(t). On the basis of these values the upper limit of the anticipated membership functions are set. The lower limit is taken to be the current value. Additionally the upper and lower limits as well as some starting value for the control parameter DELK0 are chosen. The program will search through this range first through clusters of rules and select the best anticipated temperature and power. These values should be near the values of the desired ones entered by the user. Finally the user enters the P_0/C value (P0C) which is a way of choosing between a damped, a critically-damped or an over-damped reactor.

The input for a typical case is shown in Fig. 3. The conditional probabilities matrix has been chosen to be a unit matrix, i.e. the predictions of the system have been perfectly consistent with the sensor values during the past history of the problem. This is the case of a

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Anticipatory System TELIC -- Input Phase
=====================================

--> Please enter 'Look-Ahead time"(sec)......>1.0

--> Please enter DELKO min value.............>0.0001

--> Please enter DELKO max value.............>0.004

--> Please enter DELKO value.................>0.0007

--> Please enter DELKO step..................>0.0002

--  Please enter the desired TEMPERATURE(C)..>370.0

--> Please enter the desired POWER(MW).......>1180.0

--> Please enter POC value...................>100.0
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Anticipatory System TELIC -- Control Mode (^Y to exit)
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Current Temperature(C):                      361.0
Current Power(MW):                           1120.0
Current Performance for TEMP:                1.0
Current Performance for POWER:               1.0

TEMP Max Anticipated Performance:            1.0
-->Achieved by setting DELKO at:             0.1100000E-02


POWER Max Anticipated Performance:           1.0
-- Achieved by setting DELKO at:             0.1100000E-02

Anticipated TEMP [C]:
[Look-Ahead Time[sec] =  1.0 ]               369.2064
Anticipated Power [MW]:
[Look-Ahead Time[sec] =  1.0 ]               1174.263

Look-Ahead Time[sec]:                        1.0
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Fig. 3 Input and output for the simulation of a reactor as an anticipatory control system.

over-damped reactor. The value of POC for a critically-damped reactor is 142.0 for this calculation. The minimum and maximum values of DELKO define a range for the search that the system would conduct for identifying a value of DELKO which would lead to maximum performance, while DELKO is a starting point for the search. In this case POC = 100.0 < 142.0, hence this a system that responds slowly to the DELKO perturbation chosen. The output is shown in Fig. 3. This figure reports the current values of the temperature and power state variables. The programs PSP.FOR and PST.FOR access the historical data fits HTEMP.DAT and HPOWER.DAT. They accept earlier values in the memory of temperature and power then classify them statistically. This random probabilistic data is used to construct probability density functions for the temperature and power. The membership functions for "adequate" or "acceptable" levels of power and temperature are next accessed. This is chosen as the interval defined as:

$$\mu_{adequate} = [\, 0.95\, S_{current} \;,\; 1.05\, S_{current} \,] \;,$$

where $S_{current}$ is the current value of the state variable.

Other membership functions can be chosen by the user. The "likely" membership function is chosen to be a straight line as done earlier. At this stage the fuzzified Baye's formula, Eq. (2), is used to estimate the anticipated performances of temperature and power. An optimization is carried within the already specified range of DELKO, and the maximum performance values are reported. In this calculation the anticipated membership function of "will-be-adequate" or "will-be-acceptable" is defined as the interval: $\mu_{will\text{-}be\text{-}adequate} = [\, S_{current}, \; S_{max.performance} \,]$, where $S_{max.performance}$ is the value of the state variable corresponding to max.performance $S_{max.performance} > S_{current}$. According to these estimates the anticipatory simulation recommends to the operator the use DELKO of 0.11 x 10-2 for attaining a maximum anticipated performance. If a user or an operator would be replaced by a feedback signal to the system, and the process repeated for anticipation for regular intervals into the future.

Conclusions

A methodology for the realization of the anticipatory paradigm in the diagnosis and control of complex systems, such as nuclear power plants and process control systems has been developed. The basic premise underlying this project is that a complex system can modify its behavior on the basis of present as well as anticipated future states. To succeed in this it must contain a predictive model of itself and/or its environment, a method for representing the functionaly significant part of its world at the appropriate level of detail, and the capability of making decisions concerning its change of state. The systems contemplated in this research use measures of performance to represent the current as well as anticipated states in such a manner that decisions about changing state are related to a search for maximizing the performance associated with a state variable. Mathematically, the measures of performance used in this research are developed through a formulation coupling probabilistic(random) data and possibilistic(fuzzy) data in the form of an Information Granule. Random data represents environmental inputs (*measured* data). Fuzzy data is based on epistemic information (calculated data), such as criteria or constraints qualifying the environmental inputs. Anticipated performance is generated through the employment of a fuzzified Baye's formula. The possibility of constructing such a system is demonstrated through a simulation of an anticipatory system that models a nuclear reactor controlled by a reactor operator. The role of the operator is mimicked by an Expert System called TELIC. The software implementation of the system involves the coupling between symbolic and procedural programming. Two major characteristics of anticipatory modeling are nonlinearity and complexity. This research suggests that they can be alleviated in part through the use of symbolic computations and techniques from the field of Artificial Intelligence. For more realistic problems different search techniques may be necessary to explore, based on the time constraints and the representation of knowledge.

REFERENCES

[1] Rosen, R., Anticipatory Systems, Pergamon Press, New York, 1985.

[2] Trakhtenbrot B. A. and Barzdin Y. M., Finite Automata Behavior and Synthesis, North-Holland Publishing Co., Amsterdam, 1973.

[3] Tsoukalas, L., and Ragheb, M., "Performance Monitoring and Diagnosis in a Process Environment Using a Probability-Possibility Approach," in Manufacturing International '88: Symposium on Manufacturing Systems - Design, Integration, and Control, G. Chryssolouris, B. Von Turkovich, and P, Francis, Eds., American Society of Mechanical Engineers, 1988.

[4] Ragheb, M. and Tsoukalas, L., "A Coupled Probability-Possibility Method for Decision-Making in Knowledge-Based Systems," Knowledge-Based Expert Systems for Manufacturing, S. C-Y. Lu, R. Commanduri, Eds., ASME, New York, 1986.

[5] Zadeh, L. A., "Fuzzy Sets as a Basis for Theory of Possibility," Fuzzy Sets and Systems, 1978, pp. 3-28.

[6] Zadeh, L. A., "Fuzzy Sets and Information Granularity," Advances in Fuzzy Set Theory and Applications, M. M. Gupta, R. K. Ragade, and R. R. Yager, Eds., North-Holland Publishing Company, 1979, pp. 3-18.

[7] Zadeh , L. A., "Probability Measure of Fuzzy events," Journal of Mathematical Analysis and Applications, 23, pp. 421-427, 1968.

[8] Ragheb, M. and Tsoukalas, L., "Monitoring Performance of Devices Using a Coupled Probability-Possibility Method", in International Journal of Expert Systems, Research and Applications, 1988.

[[9] Ragheb, M., Tsoukalas, L., McDonough, T., and Parker, M., "A Production-Rule Analysis System for Nuclear Plant Monitoring and Emergency Response Applications," in Artificial Intelligence and other Innovative Computer Applications in the Nuclear Industry, M. C. Majumdar, D. Majumdar and J. I. Sackett, Eds., Plenum Press, New York, pp. 231-238, 1988.