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MONITORING NUCLEAR REACTOR SYSTEMS USING NEURAL NETWORKS AND FUZZY LOGIC

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ABSTRACT

A new approach is presented that demonstrates the potential of trained artificial neural networks (ANNs) as generators of membership functions for the purpose of monitoring nuclear reactor systems. ANN's provide a complex-to-simple mapping of reactor parameters in a process analogous to that of measurement. Through such "virtual measurements" the value of parameters with operational significance, e.g., *control-valve-disk-position*, *valve-line-up* or *performance* can be determined. In the methodology presented the output of a virtual measuring device is a set of membership functions which independently represent different states of the system. Utilizing a fuzzy logic representation offers the advantage of describing the state of the system in a condensed form, developed through linguistic descriptions and convenient for application in monitoring, diagnostics and generally control algorithms. The developed methodology is applied to the problem of measuring the disk position of the secondary flow control valve of an experimental reactor using data obtained during a start-up. The enhanced noise tolerance of the methodology is clearly demonstrated as well as a method for selecting the actual output. The results suggest that it is possible to construct virtual measuring devices through artificial neural networks mapping dynamic time series to a set of membership functions and thus enhance the capability of monitoring systems.

INTRODUCTION

Monitoring the performance of equipment and systems in a nuclear facility requires a program for recognizing whether the values of various parameters are within expected, normal, off-normal and in general desirable or undesirable ranges. The parameters to be monitored are typically specific to a particular system, often the outputs of sensors and meters. Thus for general plant equipment *voltage*, *current*, *winding temperature*, *oil* or *water temperature* and *pressure* are monitored. For the power supply of a typical motor operated valve, for example, one needs to monitor the *voltage*, *current* and *breaker position*, while monitoring the performance of a steam turbine driven pump requires attention to the indications of *speed*, *pressure* and *stop valve position*. Generally, the notions of *performance*, *normal*, *undesirable*, are quantified in technical specifications and operating procedures, in terms of set-points and ranges. Yet, in the course of operations they are imputed with meanings that vary not only with the history of a particular system or equipment but also with different operators and the state of the plant as a whole.

A *virtual measuring device* is a software-based instrument for the "measurement" of user-specified dynamic variables with operational significance. Usually these variables cannot be measured directly, or the failure of a sensor requires that a variable be inferred from other measurements. A promising feature of virtual instruments is that their function may be modified by changing their software, not hardware. Generally, *measurement* involves a mapping of complex input patterns to simple output patterns. Neural networks can map a complex input pattern of variables to a simplified set of membership functions representing the values of a fuzzy variable[1]. They produce membership functions that uniquely and unambiguously represent the values of variables that are fuzzy, such as performance, risk, operability, and availability.

The only fundamental requirements for useful measurements are the *precision* and *reproducibility* of the input-output relation and the functional value of the entire operation of the system doing the measuring. The requirement of reproducibility means that the measuring device must be *isolatable* from the system being measured and *resettable* so that the measurements can be repeated an arbitrary number of times to give the same output for the same input pattern. Both requirements are met by the artificial neural networks contemplated here.

A major problem in the utilization of fuzzy logic for monitoring purposes is the difficulty in generating membership functions[1]. In the proposed approach neural networks are used to map a set of time signals representing the state of a nuclear system to a set of membership functions that describe the values of a fuzzy variable, called in this study VALVE_POSITION. As can be seen in the general schematic shown in Figure 1, a set of pre-trained neural networks are the receivers of several on-line time-series corresponding to vital nuclear system parameters. They filter the noise of the time-series and calculate other system parameters not in the form of time-series but in the form of a membership function. Each membership function corresponds to a different value of the monitored variable and has a unique shape.

NEURAL NETWORK - FUZZY LOGIC METHODOLOGY

Fuzzy logic is a convenient tool for describing a system whose behavior can be articulated in fuzzy "IF-THEN" rules[1]. For example, fuzzy rules utilized by fuzzy controllers, describe the relation between state variables and action or control variables, e.g.,

IF **flow** is *high* AND **pressure** is *low* THEN **control-valve-position** is *open*.

where, **pressure** is a fuzzy variable describing the state of the system and *high* is one of its fuzzy values, **control-valve-position** is a control variable and *open* is one of its fuzzy values. The above rule is an association between flow, pressure and control-valve-position. Fuzzy logic algorithms have been demonstrated to be reliable and superior in performance to conventional systems[1,2,5]. One of the main issues in the development of these systems, however, is determining the membership functions that represent fuzzy values. In this approach we present a methodology for producing such membership functions via mappings employing neural networks.

The neural networks contemplated in this research are three-layer networks, as illustrated in Figure 2, (input, hidden, output layers). A number of input-output pairs, called examples, are presented to the network and the connection weights are adjusted until the network has "learned" the underlying relationship that the examples represent. This is called supervised learning and the process of weight adjustment is called training. The algorithm for training in the methodology presented is backpropagation with generalized delta rule and momentum term, as supplied by the Plexi software package. The change in weight w_{ji}, due to pattern p, on each connection is proportional to the product of the error signal δ[6,7] e.g.,

$$\Delta_p w_{ji} = \eta \, \delta_{pj} \, o_{pi} \tag{1}$$

where, o_{pi} is the ith component of the actual output pattern, and η is called the "learning rate."

The error signal for output neurons is computed as:

$$\delta_{pj} = (t_{pj} - o_{pj}) f_j'(net_{pj}) \tag{2}$$

where, t_{pj} is the jth component of the output produced by the network, and $f_j'(net_{pj})$ is semilinear activation function of the net total output.

The error signal for hidden units -- for which there is no specified target -- is calculated recursively in terms of those of the units to which it directly connects and the weights of those connections, that is:

$$\delta_{pj} = f_j'(net_{pj}) \sum_k \delta_{pk} w_{kj} \tag{3}$$

A linear threshold function cannot be applied in this case, as in the perceptron, because it is discontinuous and its derivative does not exist. Instead we may use the logistic activation function:

$$o_{pj} = \frac{1}{1 + \exp(-\sum_i (w_{ji} o_{pi} - \theta_j))} \tag{4}$$

where, θ_j is called "bias." In order to incorporate a term that gives importance to previous weight changes on the current weight change, a "*momentum*" term is employed:

$$\Delta w_{ji}(t+1) = \eta\,(\delta_{pj} o_{pi}) + \alpha\,\Delta w_{ji}(t) \tag{5}$$

where, t is the iteration number, and α is a constant that characterizes the effect of previous weight changes on the current weight change.

In the application through which we examine the presented methodology the input layer of the network consists of five nodes, each one receiving input from a particular time series, i.e., simultaneous values of five variables. The output consists of four (three) nodes corresponding to the peaks of the trapezoidal (triangular) membership function describing the position of the Secondary Flow Control Valve. Typically 50 learning cycles will produce a sum of square error of 0.02 when 10 nodes are used in the hidden layer.

After the networks are trained they receive on-line time signals as inputs and produce a set of membership functions as outputs. Generally the outputs will be somewhat different than the membership functions the networks were trained for and moreover one or at most two (if we allow overlap of membership functions) will represent correct values while the rest need to be ignored. It is thus important to identify the correct output. We consider the neural network outputs to be fuzzy numbers and use a *dissemblance index*[2] to estimate the distance between two fuzzy numbers. In this manner we estimate the outputs that are closest to the set of prototype membership functions we trained the network with and select them as the actual output of the monitoring virtual device at any given time.

Suppose, for example, that the network that recognizes the disk position value *closed* has been trained on the output membership function μ_{closed}, and after training it produces an actual output membership function μ^*_{closed}. We consider the two membership functions as two fuzzy numbers, call them C and C^*, each with a trapezoidal shape and support on the universe of discourse [0,1]. The support of each function is an interval, i.e.,

$$C = [\,c_1, c_2\,]$$
$$C^* = [\,c_1^*, c_2^*\,]$$

We can compute a numerical function $\delta(C, C^*) \in [0,1]$ which is the distance between C and C^*. The α-cuts for the two membership functions are denoted by, C_α, C^*_α, respectively. The *dissemblance index* of the prototype output, C and the actual output, C^*, is defined as:

$$\delta(C, C^*) = \int_{\alpha=0}^{1} \delta(C_\alpha, C^*_\alpha)\; d\alpha \tag{6}$$

When the universe of discourse is [0,1], we can easily derive from Equation 6 a value for the *dissemblance index* in terms of the support of each fuzzy value and the α cuts, $\alpha \in [0,1]$:

$$\delta(C, C^*) = \frac{1}{2} \int_{\alpha=0}^{1} \left(\left| c_1^{(\alpha)} - c_1^{*(\alpha)} \right| + \left| c_2^{(\alpha)} - c_2^{*(\alpha)} \right| \right)\; d\alpha \tag{7}$$

The *dissemblance index* is a number ranging from 0 to 1, representing the distance between two fuzzy numbers. If $\delta(C, C^*) = 0$ then C and C^* are almost identical, on the other hand, if $\delta(C, C^*) = 1$, then C and

C^* are totally different. For a virtual gauge with three outputs, i.e., three trained networks, the output with the lowest *dissemblance index* is chosen as the actual output at any given time, with two outputs (overlapping membership functions) being given by the pair of values with the two lowest *dissemblance indices.*

MODEL DESCRIPTION AND RESULTS

In order to demonstrate the proposed methodology we utilized actual data obtained during a start-up of the High Flux Isotope Reactor (HFIR), three-loop pressurized water reactor, operated at the Oak Ridge National Laboratory. The parameter which is to be simulated is the position of the Secondary Flow Control Valve. This particular valve controls the flow of water in the secondary side of the system and is considered as a vital system component. The data used is normalized in the interval 0.1 to 0.9 and sampled every 16 seconds, with a total of 1000 samples available for network training.

Five parameters were chosen for describing the Secondary Flow Control Valve position: **neutron flux, primary flow pressure variation (DP), core inlet temperature, core outlet temperature** and **secondary flow** (Figures 3, 4, 5, and 6). All but the last one of the above mentioned time series contain average values of the corresponding parameters of the three loop system. These parameters are selected in order to provide sufficient description of both the primary and secondary sides of HFIR during start-up. The time series of these five parameters are used to train three neural networks where each one of them has five nodes at the input layer and four nodes at the output layer (Figure 2). The output is a membership function uniquely labeling a particular position of the Secondary Flow Control Valve.

The behavior of the Secondary Flow Control Valve is represented in the space of alternatives (universe of discourse)[1-3] with the fuzzy variable **VALVE_POSITION**, which may take three fuzzy values, namely, **closed, medium_open**, and **open**. Each one of these fuzzy values is represented with a membership function, $\mu_{\mathbf{closed}}$, $\mu_{\mathbf{medium\_open}}$, and $\mu_{\mathbf{open}}$. These three membership functions describe the position of the valve at every instant during the start-up period. A schematic of the membership functions[3,4] representing the values of the fuzzy variable **VALVE_POSITION**, is shown in Figure 7.

The area occupied by every membership function in the universe of discourse depicts the uncertainty associated with that particular class[1]. The fuzzy set (or class) **open** in the space of alternatives is characterized by a membership function $\mu_{\mathbf{open}}$ which associates each point in the universe of discourse with the value of $\mu_{\mathbf{open}}$ at this point, representing the grade of membership of that point in the class **open**. It is apparent that such a framework provides a natural way of dealing with problems in which the source of imprecision is the absence of sharply defined boundaries of class membership rather than the presence of random variables[1]. In the case under consideration the vagueness in the definition of the exact position of the valve disc introduces the fuzziness of the valve position and hence is the reason for the absence of sharply defined criteria. This means that although we deal with a deterministic system, the constraints and the goals set are fuzzy in nature. The decision-making process takes place in a fuzzy environment where only the fuzzy goals and the fuzzy constraints can be defined as fuzzy sets (classes) in the space of alternatives. The fuzzy decision will be the intersection of the given goals and constraints[2]. In our case both goals and constraints are defined by the same set of classes.

The membership functions utilized in this particular study have trapezoidal shape or the degenerated (triangular) form of it, which is very useful for computations in the fuzzy control area[2-4]. The membership function $\mu_{\mathbf{closed}}$ (Figure 7) is defined by a trapezoid with peak coordinates {(0.09, 0), (0.1, 1), (0.3, 1), (0.5, 0)}, where $\mu_{\mathbf{medium\_open}}$ (Figure 7) is represented by the triangle with coordinates {(0.3, 0), (0.5, 1), (0.7, 0)}, and $\mu_{\mathbf{open}}$ is depicted by the coordinates {(0.5, 0), (0.7, 1), (0.9, 1), (0.91, 0)}. It is obvious from the above geometrical schemes that there is an overlap between the membership functions used. The reason for the overlap is the fuzziness of the definition of the different states of the valve position. It is characteristic of fuzzy logic to assume, that at a particular moment the valve may be described as **closed** and/or **partially open**. Therefore, the uncertainty associated with instrument measurements is reflected on the position of the membership functions in the universe of discourse[2]. Henceforth whenever the valve position is between 0.5 and 0.7 it could be characterized as **medium_open** as well as **open** (Figure 7). If the position is above 0.7 then it is definitely **open**. This representation offers some unique advantages. It maps a set of complicated time series to the universe of discourse of human linguistics, through a neural network which acts as an interpreter of vital information supplied from the nuclear system. The information encoded in a time series is in the form of rate of increase/decrease, and maximum/minimum values attained over a period of time. The ANN is trained to represent this kind of "hidden" information in the form of membership functions which can be used by a rule-based diagnostician. The shape of the membership function which has been assigned to each valve position is unique and therefore there is a sharp distinction between different states. The membership function provides sufficient information to describe the valve position at a particular time but also to predict the actual valve position in the near future. Furthermore, an ANN trained to recognize a specific complicated time pattern will lose much of its ability to deal with noisy input signals since it will tend, for distorted inputs, to produce averaged forms of the desired output, missing therefore vital pieces of information[5]. This handicap can be overcome by the proposed technique which has an output that is a simple membership function[8].

As was pointed out, the position of the valve at a particular time step may be characterized by two membership functions instead of only one. The purpose of the pre-trained neural networks is to calculate both membership functions leaving the task of decision making to the fuzzy controller. Considering therefore the position of the different membership functions in the universe of discourse (Figure 7), the 1000 time steps (input vectors) used as input to the networks should be classified as listed in Table 1. It is apparent from Table 1, that although the neural network responsible for detecting the open position of the valve has to fire all the time steps between 228 and 805, the medium_open neural network is expected to fire also at the time step intervals 228 - 248, 358 - 504, and 612 - 805. This comes as a result of the particular design imposed on the membership functions.

In order to test the ability of each ANN to predict the valve position by calculating the right membership function at any particular time step, different levels of noise were introduced in the input signals. Initially up to 10% noise was introduced to all five input signals and the set of networks was tested with the "noisy" vectors. The appropriate networks fired at the corresponding time steps calculating the coordinates of the peaks of the corresponding membership functions with 98% accuracy. Henceforth there was an excellent prediction of the position of the disc valve during the whole time interval under consideration. Going one step further, 20% noise was introduced to all five input signals and the networks were tested again. The response of the system was the same as in the previous case, but this time the accuracy of the coordinate prediction dropped to 95%. Once again the accuracy of the network response was adequate to define the boundaries of the membership function responsible for firing. It is worthwhile to mention that the effect of noise at the input signals to the system response was expected to be minimum. The reasoning of that statement lays in Figures 3-6 where it is obvious that the initial signals contain a significant amount of noise. Therefore the set of pre-trained networks has already been exposed to noise during the training process. As a result the extra noise added to the input vectors during the testing process tends to distort the information contained in the original signal in a small degree. Certainly the effects of noise would be more pronounced if the original signals were noise free. This does not apply in this study, since the data have been obtained from actual reactor operation and not from simulation.

The response of the system during testing may be shown in Figures 8-11 where the results have been summarized for both cases of noise addition. During the first 208 time steps (Figure 8) the neural network responsible for recognizing the closed condition fired throughout the testing interval. For the next 18 time steps (209-227) (Figure 9) both the closed and medium_open networks fired since the condition of the valve could be characterized as closed as well as medium_open. The ambiguity existing in the response of the system is to be resolve by the fuzzy controller. When the data corresponding to time steps 228-805 were tested (Figure 10), the closed network did not fire at all, and this time the medium_open and open networks were active. The prediction of the valve position remained to be open throughout this time interval as well as medium_open at particular time periods. During time steps 228-248, 358-504, and 612-805 the position of the valve disc was predicted as being medium_open, since the valve was not sufficiently open to be classified as strictly open. At the final testing period (806-1000) (Figure 11), the closed network was activated again. During time steps 806-899 the valve position was calculated as both closed and medium_open. This appears plausible since there should be a smooth transition between different states of the valve.

It is obvious from the previous description that the valve position was never calculated as medium_open alone. This is a direct consequence of the artificial separation of the universe of discourse. All points in the interval [0.3, 0.5] in the universe of discourse, are considered as belonging to membership function closed also. The rest of the $\mu_{\mathbf{medium\_open}}$ space (0.5, 0.7], is occupied by the $\mu_{\mathbf{open}}$ also. Hence whatever value calculated from the network in the range [0.3, 0.7] is going to be classified not only as medium_open but either open or closed as well. It should be stressed that this particular division of the space of alternatives is widely suggested in the bibliography by different authors[2,5]. A more articulate segmentation of the universe of discourse would offer the advantages of more meticulous representation of the state of the valve, but on the other hand it would greatly complicate the system since a greater number of neural networks would be required. Furthermore, characterizations as **almost_open, very_closed**, etc., do not seem appropriate in this particular application. Membership function modifiers like "almost" and "very" are mostly used in classification problems dealing with more complex categorizations than the one used here[2].

CONCLUSIONS

A methodology for monitoring nuclear reactor systems employing neural networks and fuzzy logic has been developed. It employes the notion of *virtual device*, i.e., a software-based instrument for the "measurement" of user-specified dynamic variables with operational significance. The function of such devices may be modified by changing their software, not hardware, a promising feature for application-specific monitoring tasks. Neural networks are employed to map a complex input pattern of variables to a simplified set of membership functions. The produced membership functions uniquely and unambiguously represent the values of variables that are fuzzy, such as performance, risk, operability, and availability.

One of the very first points to be made on the basis of the results discussed in the earlier section is the noise tolerance demonstrated by the ANNs. The ability of the neural network to pick up the necessary information from a signal embedded in 20% noise is unique. Neural networks have been widely used before[8] in order to reproduce time patterns. Unfortunately a time series is not always helpful for decision making, since it is highly complicated and its representation hardly exact[5]. In this study ANNs have been integrated with the representational advantages of fuzzy logic in order to produce fuzzy membership functions.

The representation of the form of the membership functions is sufficient for preserving the necessary information in order to distinguish between different states of the valve. It is apparent that, with the demonstrated methodology, the valve position could be adequately classified as belonging to one (or two adjacent) class(es) as soon as the information "hidden" in the time series is supplied to the neural networks. This offer the advantage of predicting the position of the valve for the next few time steps. Introducing membership functions as the output of the ANNs, facilitates automated decision-making by a fuzzy logic diagnostic system that determines the condition of the valve. Furthermore it is not necessary to proceed to full time series analysis in order to infer the valve position, but on the contrary, it is adequate to make a decision after the ANN gives the same response for a number of consecutive time steps[8]. The quality of the information provided by the ANN suggests that a fuzzy logic identifier - with a minimum decision making window - would be able to diagnose the exact state of the system.

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TABLE 1: TIME STEP CLASSIFICATION

Time Step Number	μ_{closed}	μ_{medium_open}	μ_{open}
001 - 208	*		
209 - 227	*	*	
228 - 248		*	*
249 - 357			*
358 - 504		*	*
505 - 611			*
612 - 805		*	*
806 - 899	*	*	
900 - 1000	*		

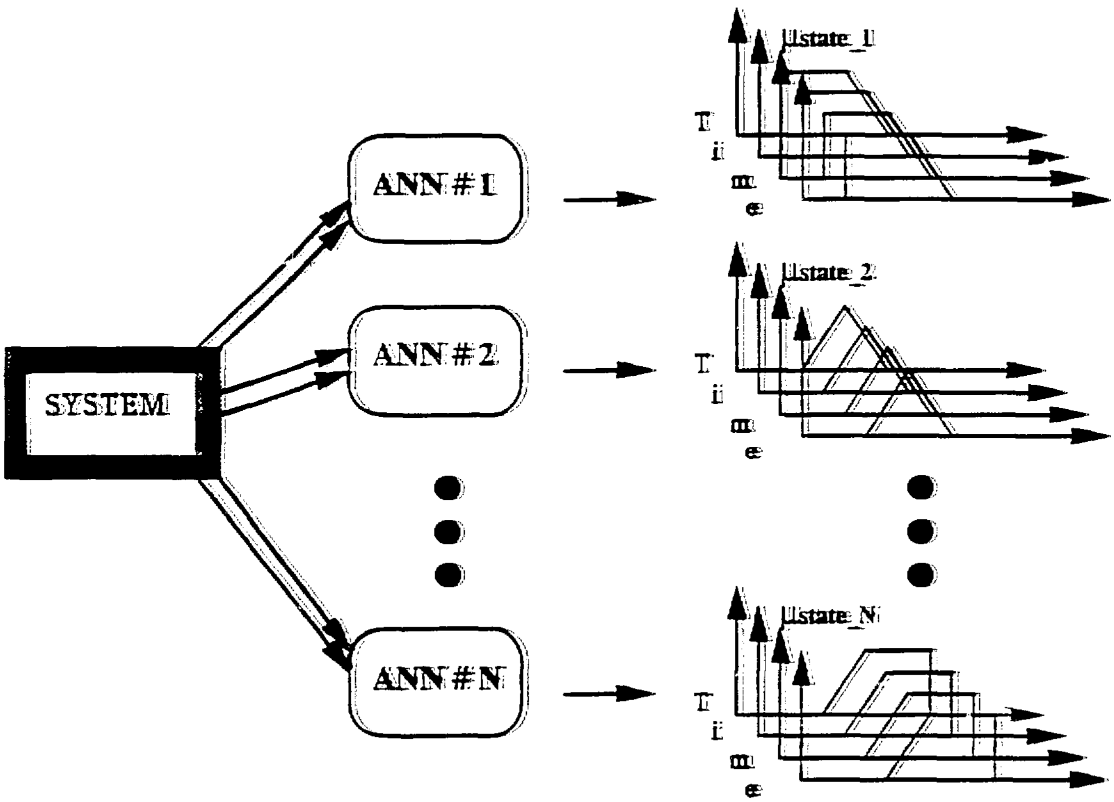

Figure 1. A hybrid neural network - fuzzy logic monitoring system.

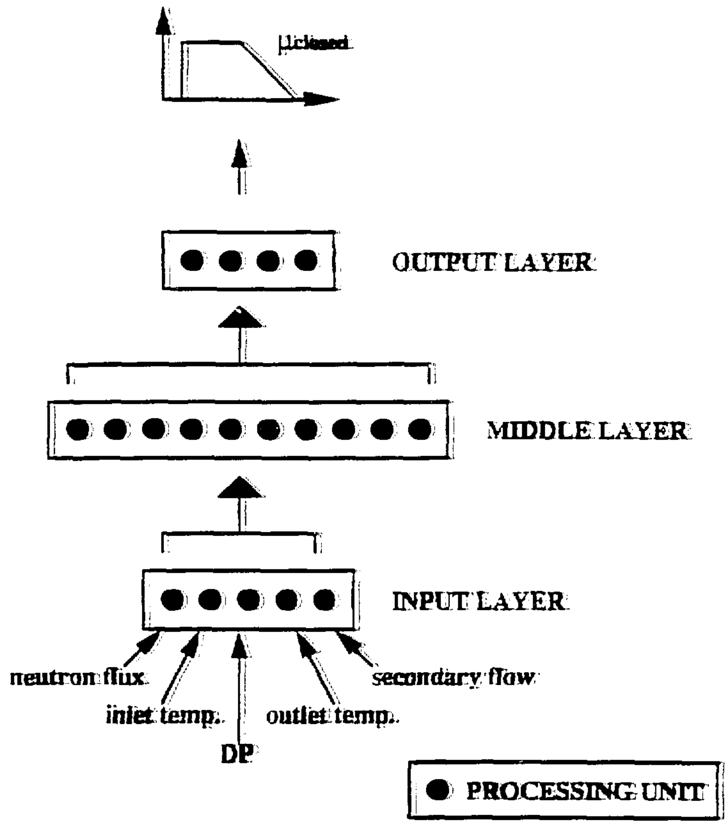

Figure 2. Neural network architecture.

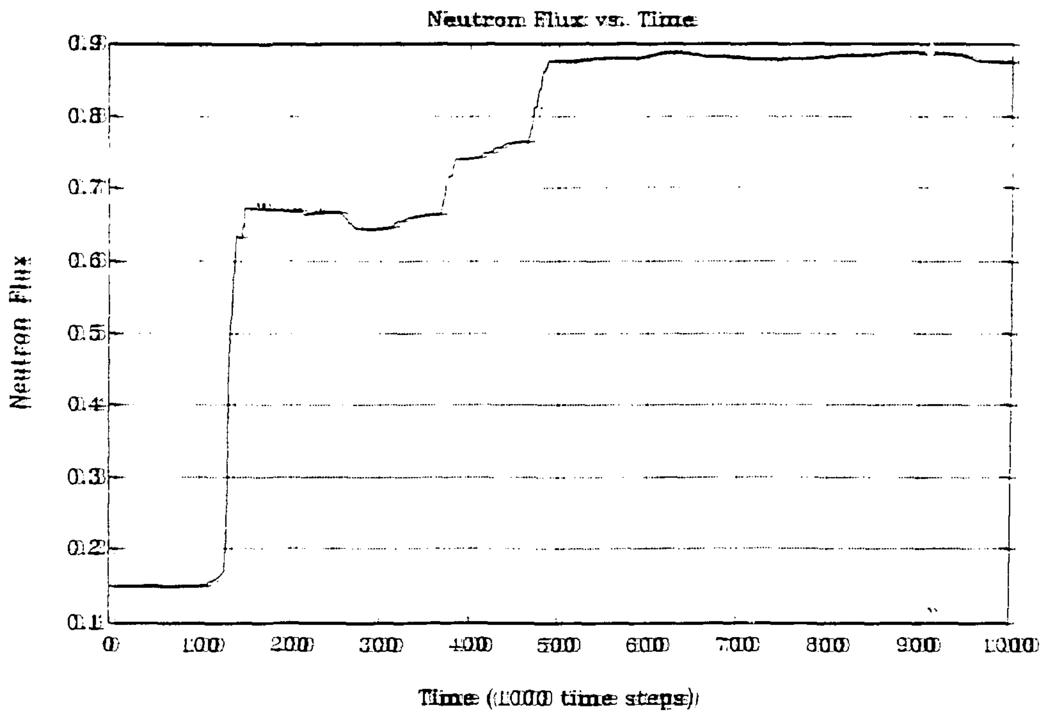

Figure 3. Neutron flux during startup of the reactor (normalized).

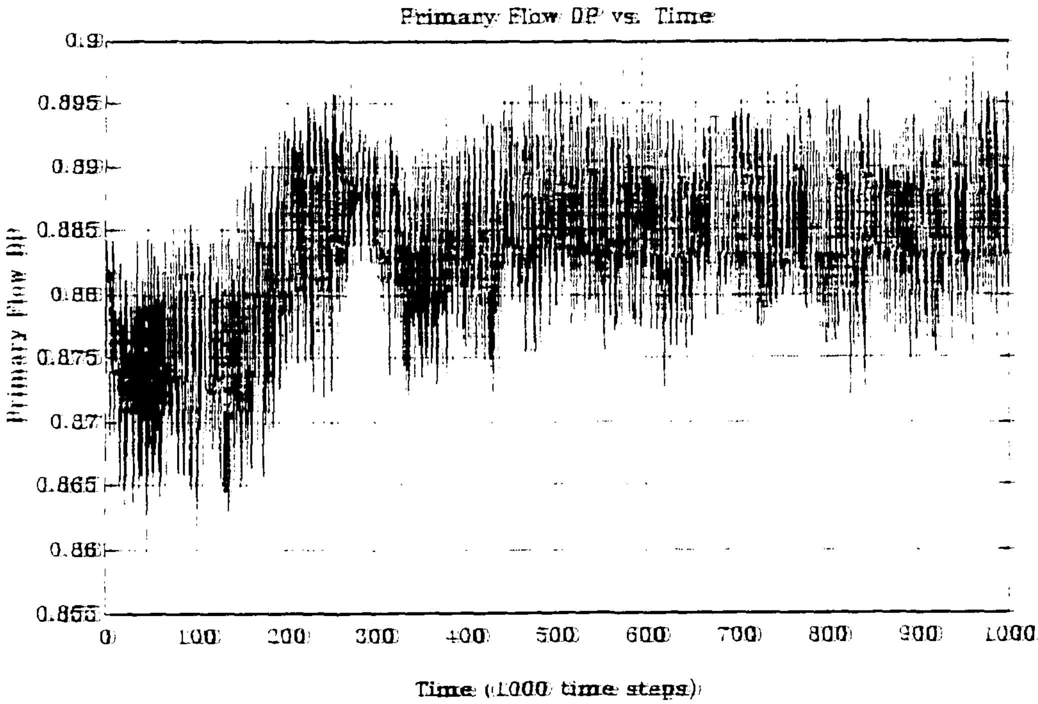

Figure 4. Primary flow ΔP during startup of the reactor (normalized).

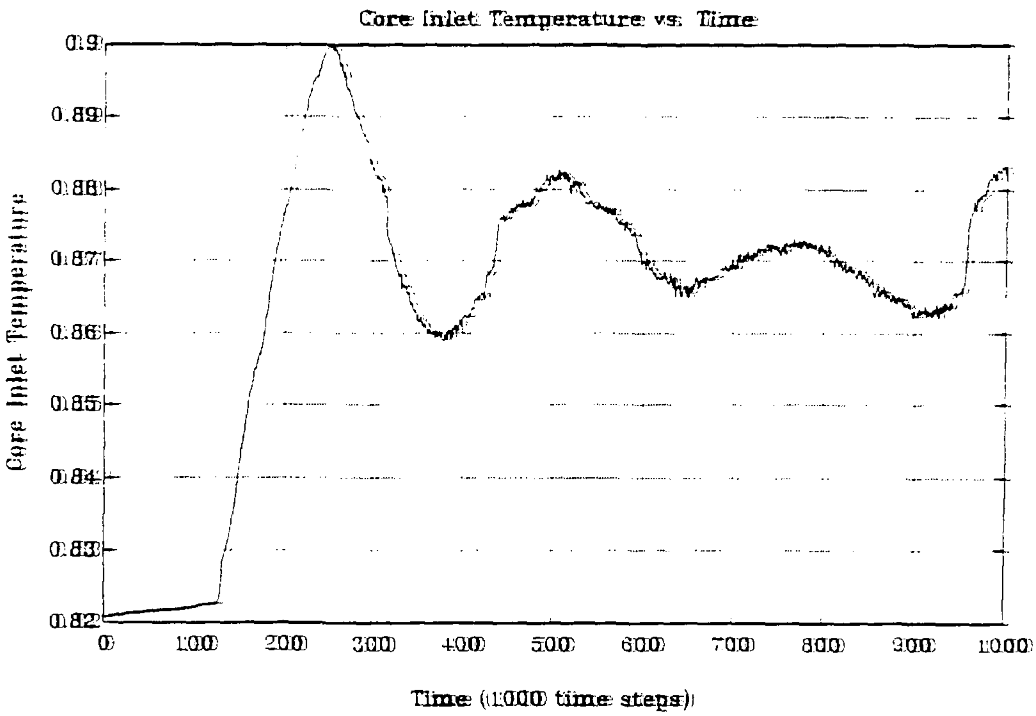

Figure 5. Core inlet temperature during startup of the reactor (normalized).

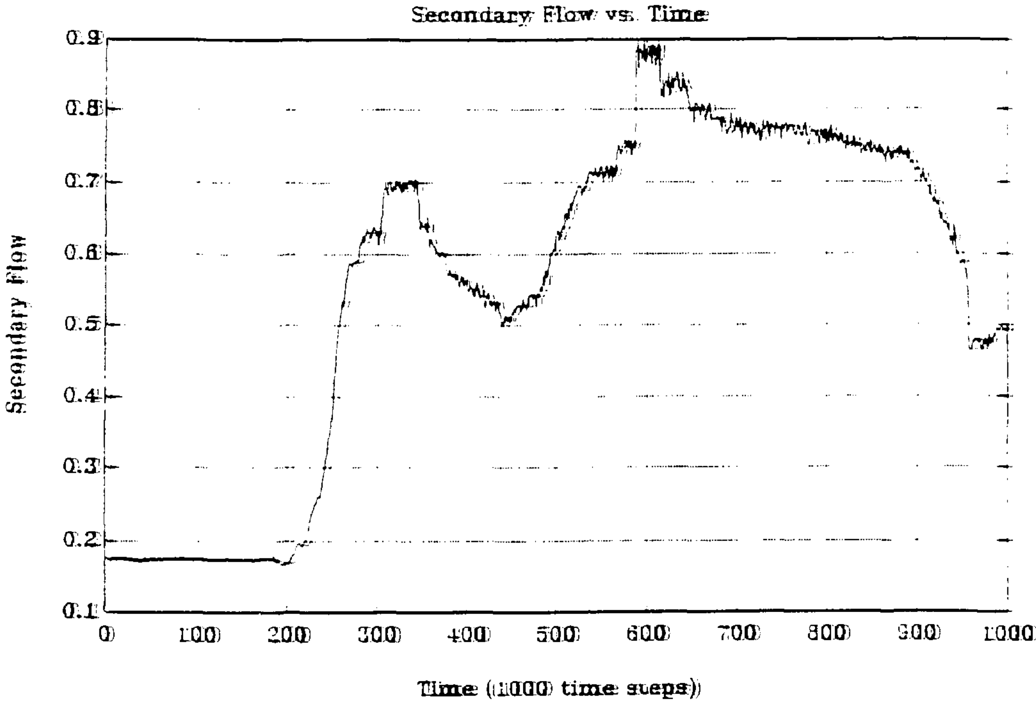

Figure 6. Secondary flow during startup (normalized).

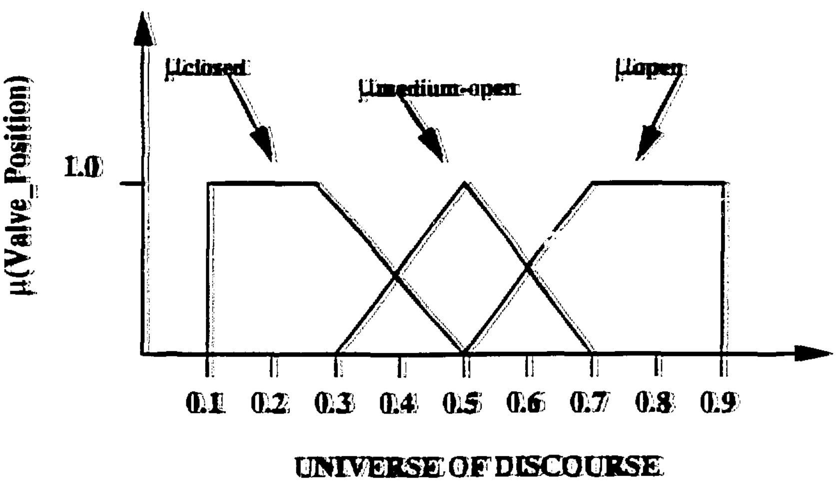

Figure 7. Fuzzy values for the monitored variable VALVE_POSITION.

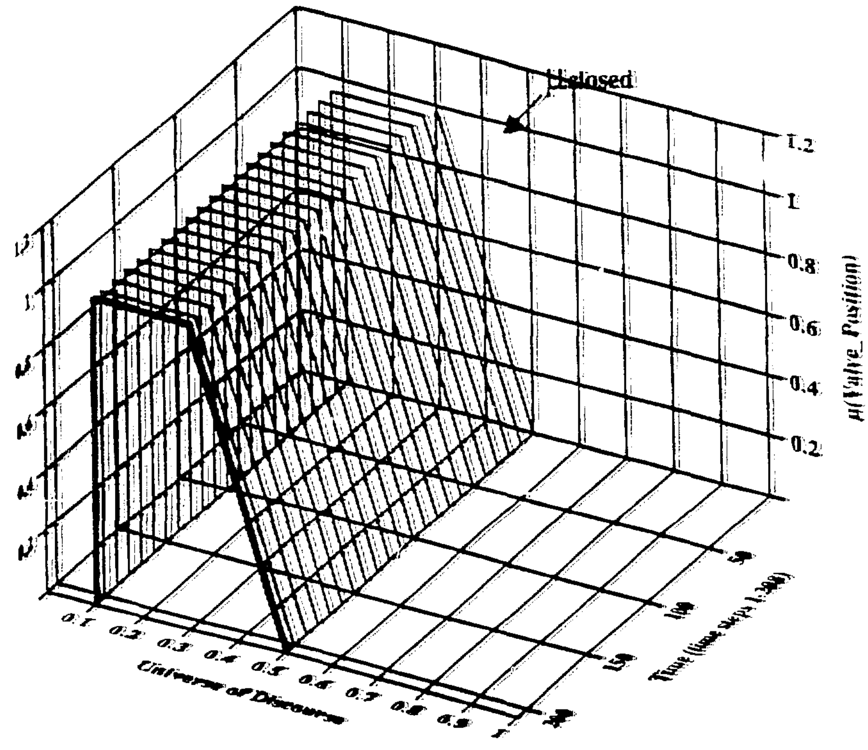

Figure 8. The membership function for the value of VALVE_POSITION during time steps 1-208.

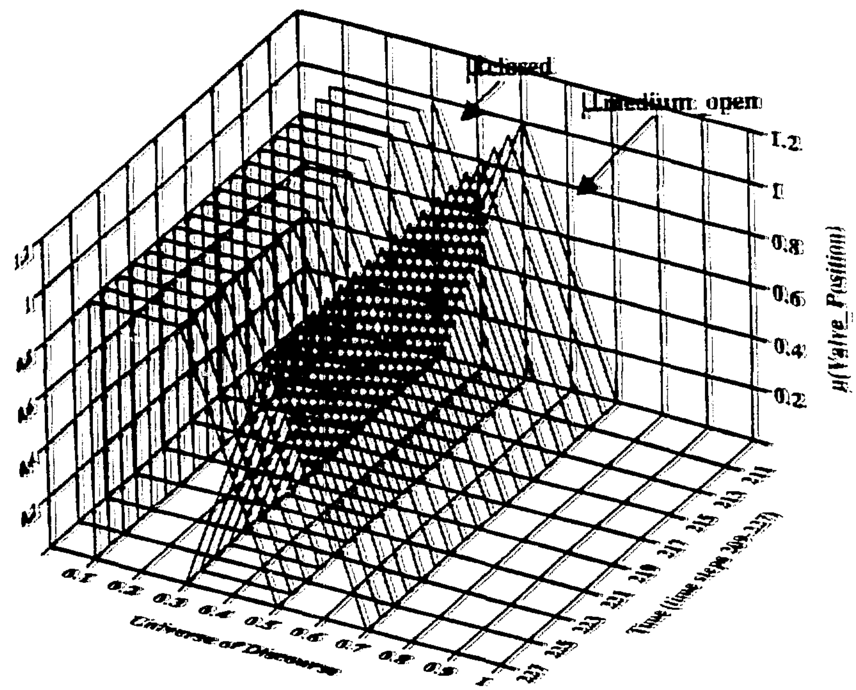

Figure 9. The membership function for the value of VALVE_POSITION during time steps 209-227.

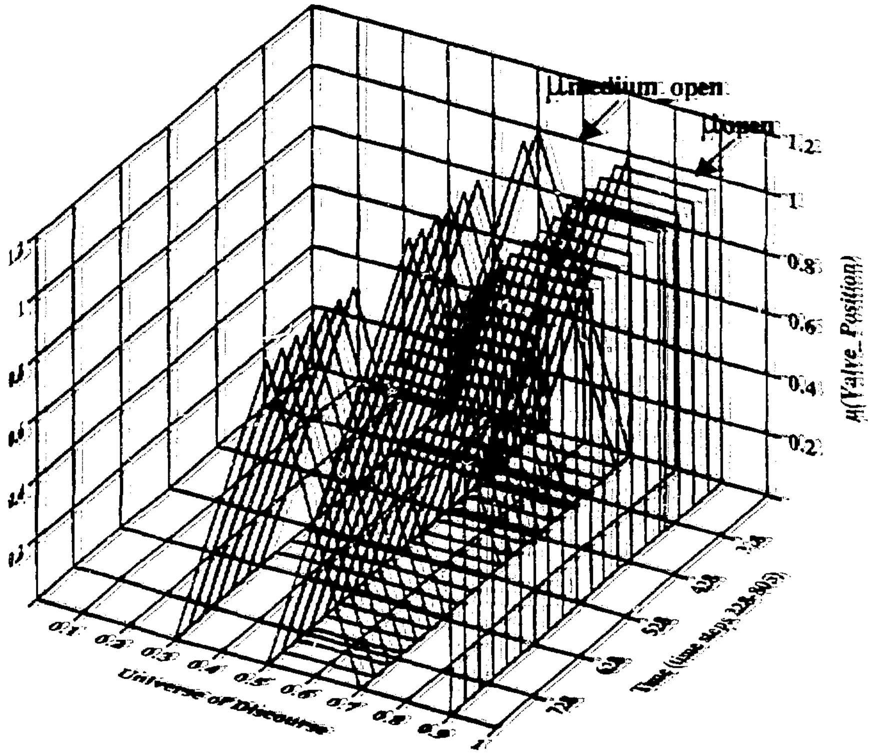

Figure 10. The membership function for the value of VALVE_POSITION during time steps 228-805.

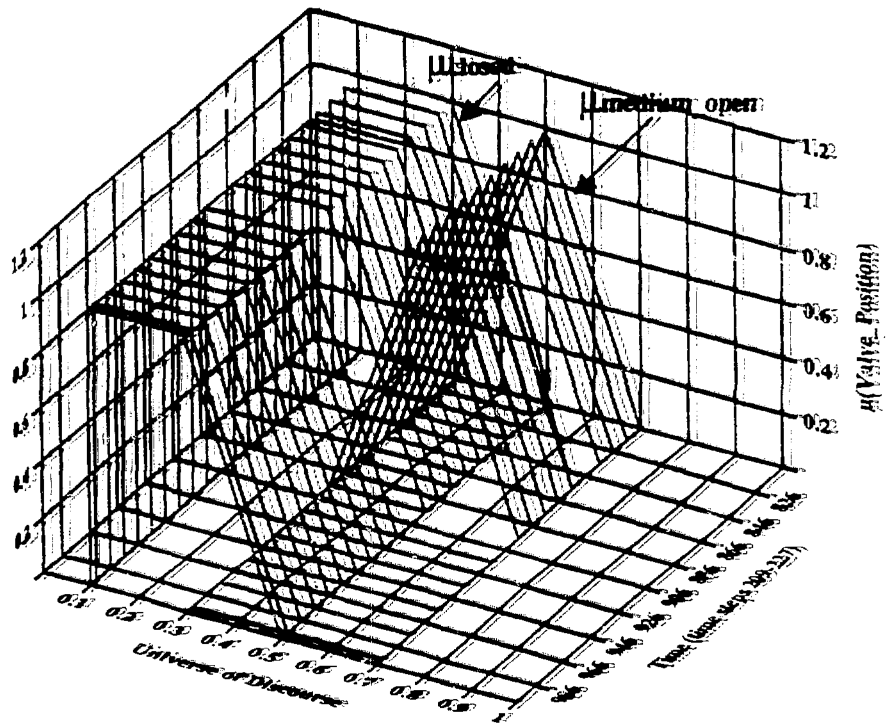

Figure 11. The membership function for the value of VALVE_POSITION during time steps 806-1000.