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HYBRID EXPERT SYSTEM-NEURAL NETWORK-FUZZY LOGIC MECHODOLOGY FOR TRANSIENT IDENTIFICATION

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ABSTRACT

A methodology is presented that demonstrates the potential of pretrained artificial neural networks (ANN's) as generators of membership functions for the purpose of transient identification in Nuclear Power Plants (NPP). In order to provide timely concise and task-specific information about the many aspects of the transient and to determine the state of the system based on the interpretation of potentially noisy data, a model-referenced approach is utilized, where pre-trained ANNs provide the model. Membership functions - that condense information about a transient in a form convenient for a rule-based identification system - are produced through ANN's. The results demonstrate the extremely good noise-tolerance of ANN's and suggest a new method for transient identification within the framework of Fuzzy Logic.

INTRODUCTION

Although transient (or accident) identification has been discussed since the construction of the first NPP, it was the Three Mile Island accident in 1979 which dramatically brought this problem to the fore. Identifying a transient under development and taking the necessary actions to prevent catastrophic results is a challenging task confronted by NPP operators around the world. During a transient in a nuclear plant, almost all of the system parameters vary, yet only a small number of them carries the necessary amount of information for deciding the transient identity. It is the fast evolution some transients have, along with the similarity of indicators characterizing different transients which make the transient identification a very difficult task. In order to complement the human expertise, a hybrid ANN-Fuzzy Logic system is proposed, which encodes the knowledge for successful transient identification and executes at the appropriate speed.

The pretrained ANN is the receiver of an on-line time series corresponding to vital NPP's parameters. It essentially acts as a filter, filtering the noise of the time series and it calculates the response of another system parameter, not in the form of time series, but in the form of a membership function of the actual parameter. The membership function encodes only the crucial information for transient identification i.e., the time the peak value is going to be attained and the actual peak value.

In order to demonstrate the proposed methodology we chose two different transients, namely, *Rupture of a Main Steam Line*, and *Major Rupture of a Main Feedwater Line*, for a Westinghouse four-loop PWR NPP, as they have been simulated at the Watts Barr simulator. The data received from the simulator is normalized in the interval 0 to 1 and sampled every 5 seconds with a total time span 210 seconds.

MODEL DESCRIPTION

Three parameters are chosen as the most significant ones for describing the transient identity: **pressurizer pressure, hot leg temperature,** and **steam level indication.** All three, represent average values of the corresponding parameters of a four-loop system. These parameters provide sufficient description of both the primary and secondary systems during the transient development. The time series of these three parameters is used to train an ANN with three inputs and one output, as shown in Figure 1. The output is a membership function which closely follows steam pressure behavior. The reason steam pressure was chosen is that both transients take place in the secondary side of the system and thus it is preferable to use a parameter concerning that part of the NPP. In addition, steam pressure represents the most important parameter of a pressurized system, which is the secondary side of a NPP. The membership function is of the form [1, 2]

$$\mu(SP,t) = SP_{max}(1 - e^{-kt}) \tag{1}$$

where, SP_{max} is the peak steam pressure value attained during each transient, t is the time (sec), and k is a constant characterizing the increase of the membership function up to the maximum value (SP_{max}).

From the above description it is evident that we made use of a membership function in a 3-d space, where the fuzzy variables are **steam pressure** and **time** and the fuzzy values are found in a matrix containing steam pressure - time pairs [3, 4]. This representation offers some unique advantages. It maps a geometrically complicated time series containing peaks and valleys to a conveniently described membership function incorporating only two pieces of information, SP_{max} and $t(SP_{max})$, which are considered to be the most important. The rate at which steam pressure initially increases or later decreases is not a vital piece of information since a number of transients may have these characteristics in common, something which would probably lead the ANN to a false time series representation. In particular, the specific transients under investigation display similar behaviors during the first stages of the transient development. On the other hand, the pair $(SP_{max}, t(SP_{max}))$ is unique and can be distinguished as characteristic of each transient, taking into account an adequate decision window for the fuzzy logic identifier.

The neural network we used was a three-layer network (input, hidden, output layers), and the algorithm for training was Backpropagation as it is supplied by the Parallel Distributing Processing (PDP) ANN software package [4]. The desired output of the network was calculated from the actual time series representing the primary system pressure. The network parameters were:

learning rate = 0.01 momentum = 0.1 w-range = -0.5 to 0.5

In order to test the ability of the ANN to predict the membership function (of the steam pressure) for each transient, we introduced different levels of noise in the input signals. Figure 2 illustrates a typical input time series (as well as the time series with up to 20% random distortion). The results obtained from the ANN concerning the membership function $\mu_{\text{Steam Pressure}}$ are shown in Figures 3 and 4. The network managed to predict, in the MFW transient, the exact time the maximum occurred without any delay, and with 0.48% error in the maximum value of the steam pressure, as shown in Figure 3. In the MSL transient, shown in Figure 4, the network predicted the time the maximum occurred with 5 sec delay and 99.46% accuracy in the desired response.

DISCUSSION AND COMMENTS

A methodology employing artificial neural networks for predicting membership functions has been developed and demonstrated. Two different nuclear power plant transients, *rupture of main steam line* and *major rupture of main feedwater line* were identified with very good accuracy. The value of maximum steam pressure, SP_{max}, and the time, $t(SP_{max})$, at which it occurs, are the two crucial pieces of information encoded in the membership functions.

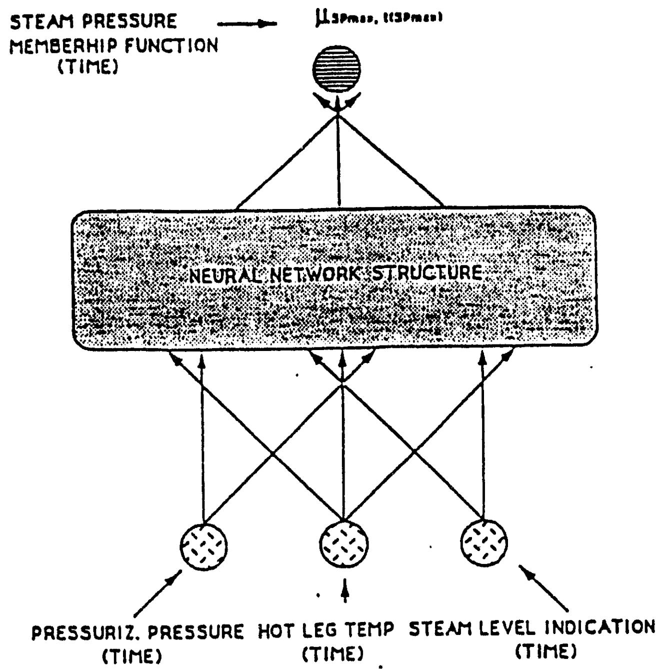

Figure 1. Neural network architecture.

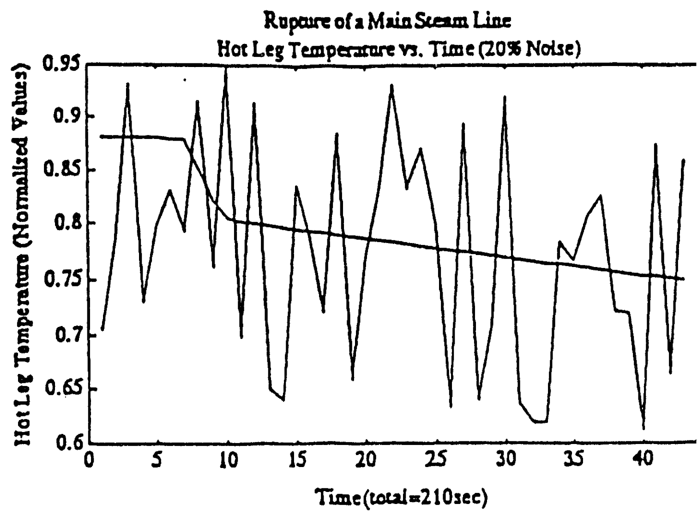

Figure 2. Typical input with 20% noise.

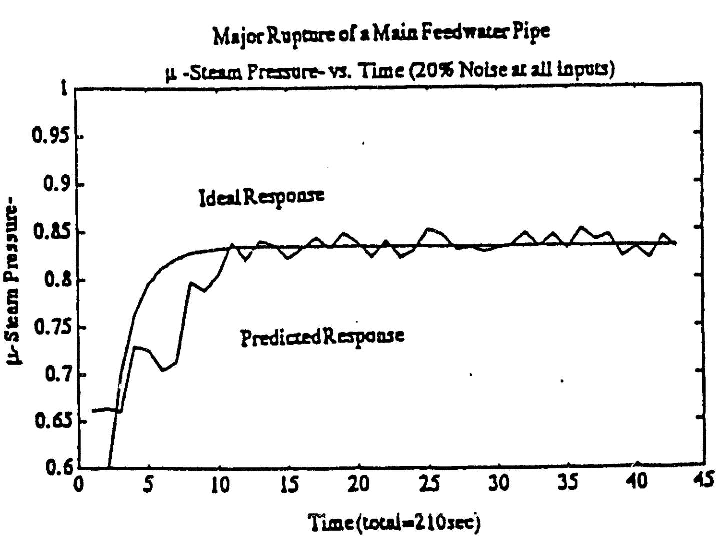

Figure 3. MFW membership function vs. time with 20% noise at all inputs.

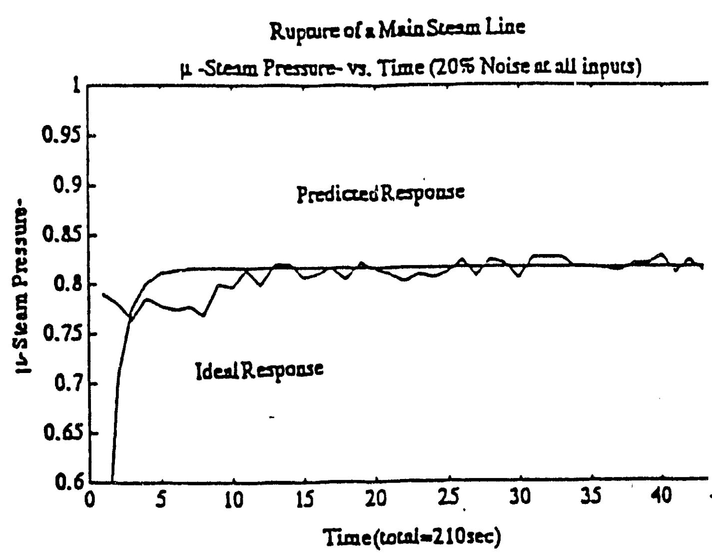

Figure 4. MSL membership function vs. time with 20% noise at all inputs.

The unique pair (SP_{max} , $t(SP_{max})$) was calculated with very small error for each of the two transients under consideration, even under extreme conditions (e.g. up to 20% noise in all three input signals). Therefore the two transients could be adequately distinguished as two separate events very early in the transient development. Introducing membership functions as the output of an ANN, facilitates automated decision-making by a fuzzy logic diagnostic system that determines the status of the transient under consideration. Furthermore, it is not necessary to proceed to full transient development in order to identify the type of the accident, but on the contrary it is adequate to make a decision soon, after the membership function stabilizes around the nominal value.

The results indicate outstanding robustness in the presence of highly noisy environments. Neural networks have been used before for the same purpose in order to reproduce time series. Unfortunately a time series is not always helpful for decision making, since it is highly complicated and its representation often inexact.

The main strength of this methodology rests in coupling the filtering abilities of neural networks with the representational advantages of fuzzy logic. The quality of the information provided by the ANN in this particular application suggests that a fuzzy logic-based monitoring and diagnostic system, with a minimum decision making window would be able to diagnose the exact identity of the transient.

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