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Signal Prediction in the LOCA Using Elman Recurrent Neural Networks

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Abstract- In a reactor accident like a loss of coolant accident (LOCA), one or some signals can not be monitored by control panel for some reasons such as interruptions and so on. Therefore a fast alternative method could guarantee the safe and reliable exploration of nuclear power planets. In this study, an artificial neural network (ANN) with Elman recurrent structure is used to predict five thermal hydraulic signals in a LOCA after the upper plenum break. In the prediction procedure, a few previous samples are fed to the ANN and the output value of the next time step is estimated by the network output. The Elman recurrent network is trained with data obtained from the benchmark simulation of a LOCA in VVER. The results reveal that the predicted values follow the real trends well and ANNs can be used as a fast alternative prediction tool in LOCA.

Keywords- *Nuclear Safity; LOCA; ANN.*

I. INTRODUCTION

In the operation of a nuclear power planet (NPP), the operators should always observe to what condition the planet is going. However there are so many parameters that the operator can not watch all of the signals. This is especially happening in the accidents like a loss of coolant accident (LOCA). For this reason, the need to develop computerized signal prediction systems becomes significant. The computerized signal prediction can be applied to generate warning messages to the planet operators, calling their attention to the problems that are likely to occur. Also it can be used as the alternative method to signal prediction in the accident.

An artificial neural network (ANN) is an attempt to simulate the human brain. In the application of ANNs to data processing system, one can predict one or more process variables with a set of other related variables. The use of this method for signal prediction has several advantages. It is not necessary to define an exact functional form relating a set of process variables. Once the network is fully trained, the prediction of variables is efficiently interpolated during both steady-state and transient operation. Also, this is less sensitive to measurement noise and fault signals.

The research of signal prediction in the nuclear power planet with ANN has been done since 1989. Robert E. Uhring [1] has proposed neural network ability to identify causes of perturbations in steam generator. Roh *et al.* [2] used ANN to thermal power prediction. Ayaz *et al.* [3] showed that Elman network has better performance against back propagation (BP) structure in typical signal prediction in NPP's. Also there are some other study about signal prediction in NPP's using ANN [4],[5].

In this study, an artificial neural network with the Elman recurrent structure is utilized to predict six thermal hydraulic signals in a LOCA after upper plenum break. In the prediction procedure, a few previous samples are fed to the ANN and the output value of next time step is estimated by the network output. The Elman recurrent network is trained with data obtained from the benchmark simulation of LOCA in VVER [6].

II. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks attempt to mimic some or all of the characteristics of biological neurons that form the structural constituents of the brain. Recently, artificial neural networks (ANNs) have been applied to a wide variety of different areas such as prediction, approximation, modeling, classification and etc. Artificial neural networks consist of great number neurons which are connected to each other. A neuron is an information-processing unit that is fundamental to the operation of a neural network. Figure 1 shows the model for a neuron. In mathematical terms, a neuron is described by the following equation:

$$output = F(\sum_{k=1}^{p} w_k . x_k - \theta) \quad (1)$$

Where x_1, x_2, …, x_p are the input signals; w_1,w_2, …, w_p are the synaptic weights of neuron; θ is neuron bios and $F()$ is the activation function which could have several forms, regarding the problem.

Neural network architecture can be divided into two main types: recurrent and non-recurrent networks. For the non-recurrent architecture well known multi-layer perceptron

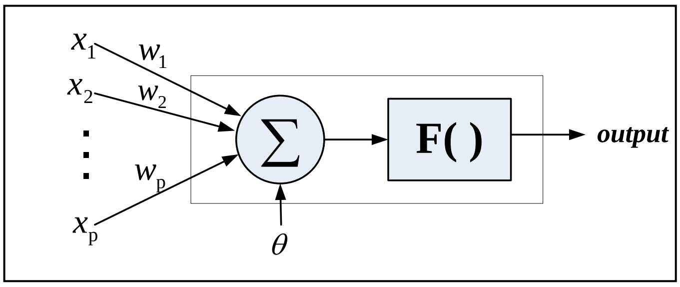

Figure 1. Neuron Model

(MLP) architecture could be addressed. The MLP has a fully connected structure where each neuron is connected to all neurons in the next layer and neurons are grouped in layers which are connected to the direction of the passing signal. There are no lateral connections within each layer and also no feedback connections within the network. On the other hand, recurrent neural networks are characterized by both feed forward and feedback paths between the layers. The feedback paths enable the activation at any layer to either be used as an input to a previous layer or be returned to that layer after one or more time steps.

From the point of view of system theory, MLPs can approximate the relationship between the inputs and outputs of a system. In a linear system, this would be described as the transfer function of the system. These networks can approximate non-linear stationary systems, while recurrent topologies can fit dynamic non-linear systems. Several topologies of recurrent neural networks are found in the literature for the identification of dynamic non-linear models.

In the present work, we used the Elman recurrent neural network to model and predict thermal hydraulic parameters in nuclear reactor. The Elman recurrent network is chosen because it is simple in structure and simple in training procedure, and because it has been shown to perform well in comparison to other recurrent architectures. This type of neural network is a partially recurrent network, where the feed-forward connections are modifiable and the recurrent connections are fixed. Additionally to the input and the output units, the Elman network has a hidden unit and a context unit. Theoretically, an Elman network with n hidden units is able to represent a nth order dynamic system. Figure 2 shows an Elman neural network with one input and one output The main difficulty related to the recursive training of recurrent networks arises from the fact that the output of the network and its partial derivatives with respect to the weights depend on the inputs since the beginning of the training process and on the initial state of the network. Therefore, a rigorous computation of the gradient, which implies taking into account all the past history, is not practical [7].

III. SIMULATION AND DISCUSSION

After a break it is very important to monitor the thermo hydraulic signals by control panel but sometimes it is difficult to detect accurately for some reasons like interruptions and so on. Therefore the fast alternative method could be guaranteeing the safe and reliable exploration of NPPs.

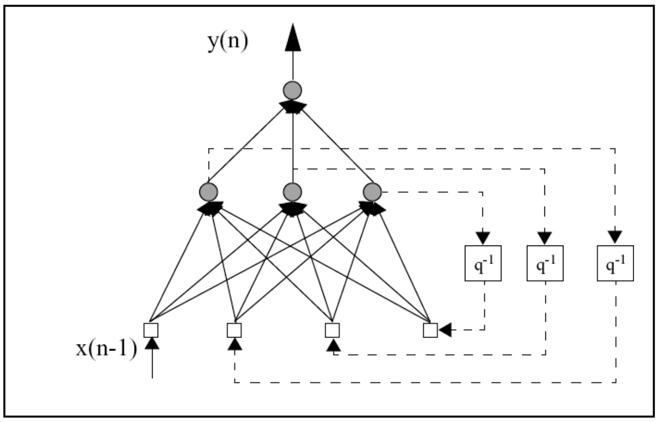

Figure 2. Example of a Elman recurrent neural network

The network can be trained by data obtained from experiments or computer code simulations. In the present work, data obtained from the numerical simulations of VVER that have been performed with RELAP5/MOD 3.2 code is used to train ANNs. In that simulation, RELAP5/MOD 3.2 was being investigated to determine its applicability for modeling 11% break in the upper plenum of a VVER.

This model has all of the major features of the PSB test facility at the Electrogorsk Research and Engineering Center for Nuclear Planets Safety (EREC). The PSB-VVER facility (Figure 3) is a full-height scale model of a VVER-1000 reactor that is approximately 1/300 scale in volume and power. The break was located in a special pipe connected to the upper plenum. An insert with an inner diameter of 16 mm and a length-to-diameter ratio of 10 was installed in the 45-mm diameter break piping. This model can simulate the thermo hydraulic parameters in different places of reactor with reasonable accuracy [6].

Signal prediction is the estimation of the signal value to be detected in the near future using the last available measurement data. The signals are:

- Liquid Temperature (K)
- Liquid Internal Energy (J/kg)
- Liquid Void Fraction (-)
- Mass Flow Rate (kg/s)
- Pressure (Pa)

Networks are trained with samples belong to only first 300 second of each signal. The training process is stopped when the prediction mean square error is acceptable minimal. In the test phase and for the evaluation of prediction performance all samples of signals, until about 800 second, are used. Overall procedure for the data prediction in this study is depicted in Figure 4.

The prediction performance, in general, depends on the structure, number of layers, nodes and learning patterns.

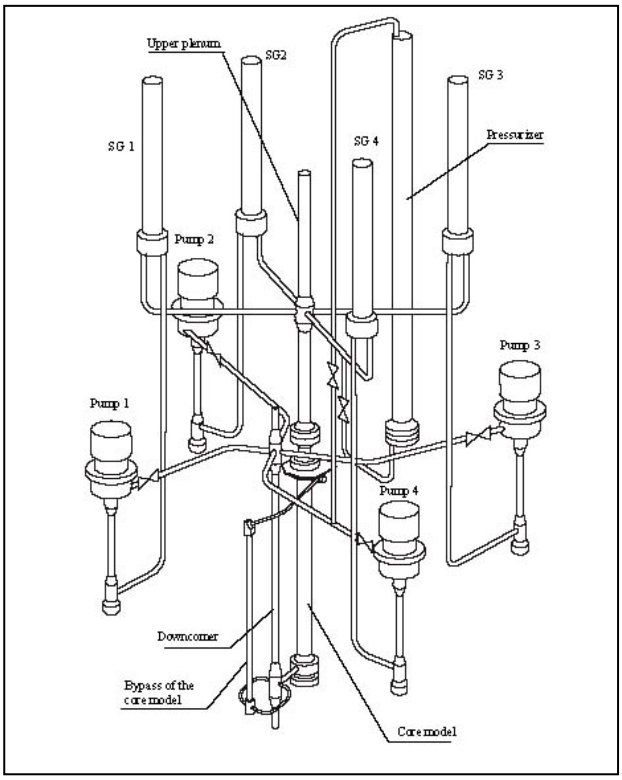

Figure 3. General view of the PSB facility

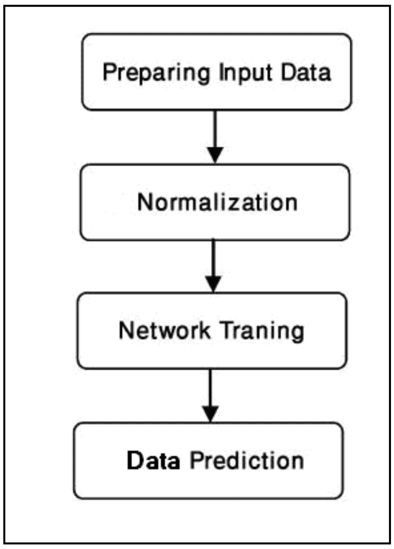

Figure 4. Overall procedure of a signal prediction

Connections are fixed at 1.0 and are not subject to adjust. The context units are initially set to 0.5 and regarding the neural network, the number of hidden units is set to seven and number of delay is set to one. Figures 5 to 9 show the results of simulation. They show that predicted values follow real values trend very well. Figures 5 and 6 show that liquid temperature and liquid internal energy can be predict very well. After about 130 second the prediction values are very similar to real ones.

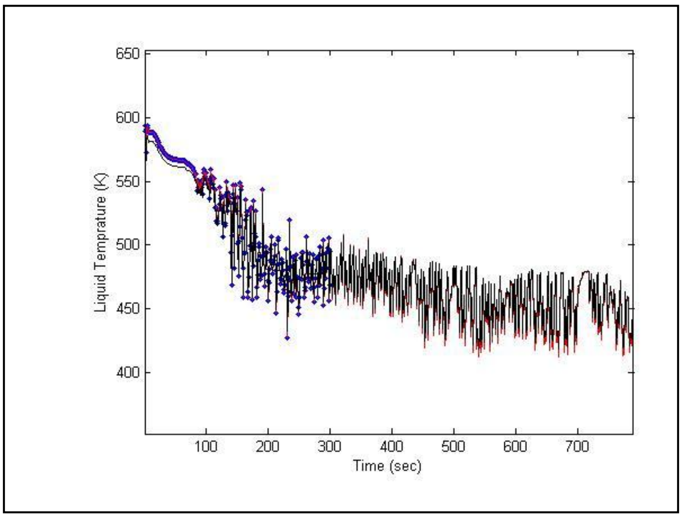

Figure 5. Liquid temperature

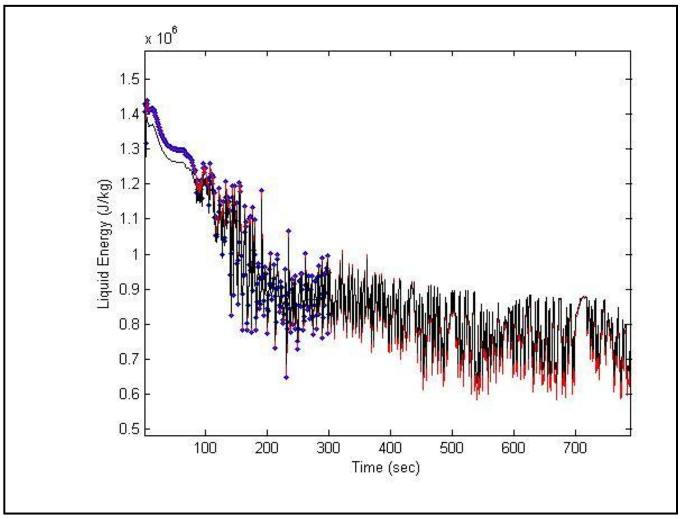

Figure 6. Liquid internal energy

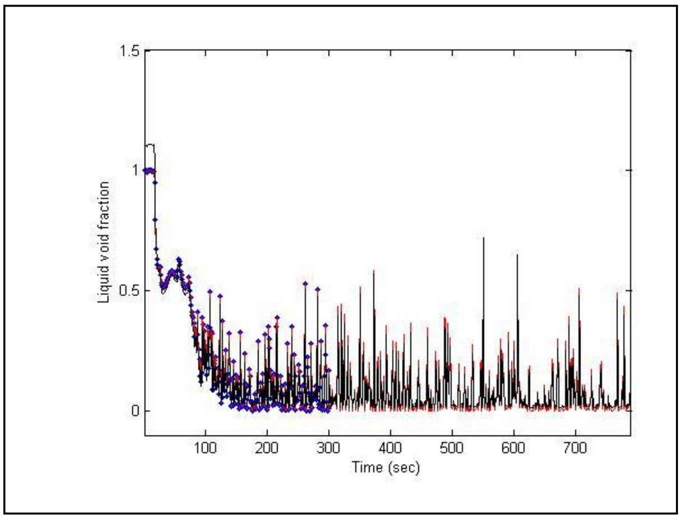

Figure 7. Liquid void fraction

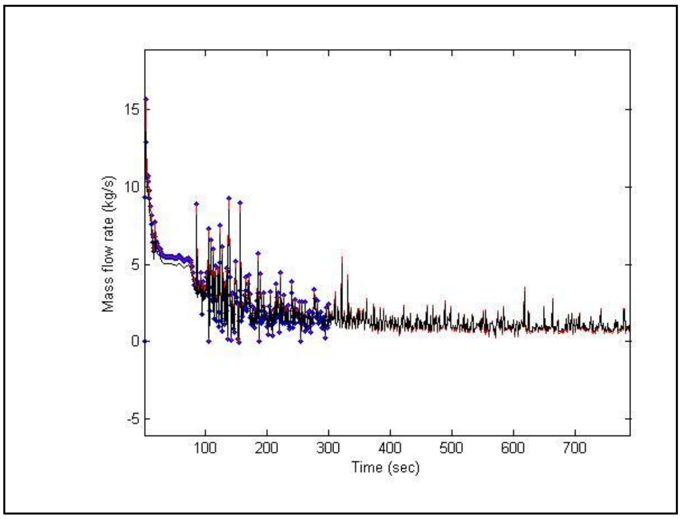

Figure 8. Msaa flow rate

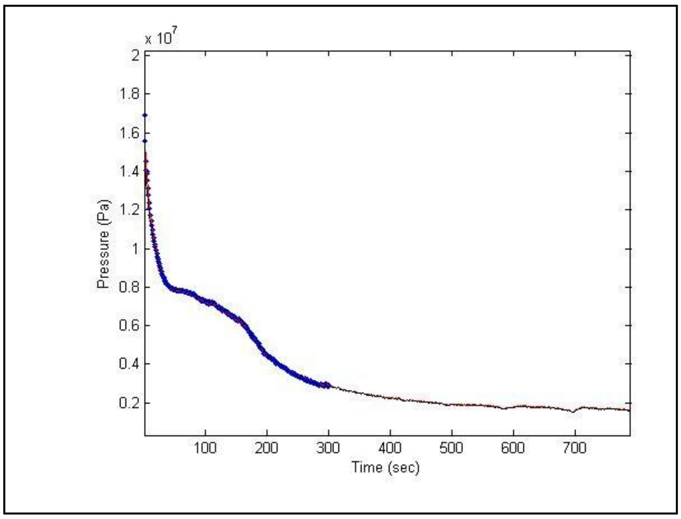

Figure 9. Pressure

Only there are some differences between them in the beginning however the prediction result is relatively good at that area. Liquid void fraction and density (Figures 7 and 9) also are predicted well and differences are at the top and down of signals. In mass flow rate signal (Figure 8) errors are a few noticeable. After training times approximately all predict values are less than real values. Pressure (Figure 9) is very simple signal and predict very well.

IV. CONCLUSIONS

Elman recurrent artificial Neural Network for signal prediction are developed and applied to five thermo hydraulic parameters in the LOCA of VVER. The following conclusions can be drowning from this study:

- This study showed that the Elman recurrent neural network could elegantly learn temporal structure of Pressure
- Five thermal hydraulic signals and their dynamic behavior.
- Network structure and the number of training samples are very important to gain a good performance. An acceptable prediction result of these parameters is obtained by 300 second.

By the prediction like this, the plant operator can predict the next state of the planet in the accidents like LOCA and it can help the determination of the operation strategy and the prohibition of an undesirable Situation.

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