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TIME RESPONSE PREDICTION OF BRAZILIAN NUCLEAR POWER PLANT TEMPERATURE SENSORS USING NEURAL NETWORKS

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ABSTRACT

This work presents the results of the time constants values predicted from ANN using Angra I Brazilian nuclear power plant data. The signals obtained from LCSR Loop Current Step Response test sensors installed in the process presents noise end fluctuations that are inherent of operational conditions. Angra I nuclear power plant has 20 RTDs as part of the Protection Reactor System. The results were compared with those obtained from traditional way. Primary coolant RTDs (Resistance Temperature Detector) typically feed the plant's control and safety systems and must, therefore, be very accurate and have good dynamic performance. An in-situ test method called LCSR - Loop Current Step Response test was developed to measure remotely the response time of RTDs. In the LCSR method, the response time of the sensor is identified by means of the LCSR transformation that involves the dynamic response modal time constants determination using a nodal heat-transfer model. For this reason, this calculation is not simple and requires specialized personnel. This work combines the two methodologies, Plunge test and LCSR test, using Neural Networks. With the use of Neural Networks it will not be necessary to use the LCSR transformation to determine sensor's time constant and this leads to more robust results.

1. INTRODUCTION

Most critical process temperatures in nuclear power plants are measured using RTDs (Resistance Temperature Detector) and thermocouples. In a PWR (Pressure Water Reactor) plant, the primary coolant temperature and feedwater temperature are measured using RTDs, and the temperature of the water that exits the reactor core is measured using thermocouples. These thermocouples are mainly used for temperature monitoring purposes and are therefore not generally subject to very stringent requirements for accuracy and response-time performance. In contrast, primary coolant RTDs typically feed the plant's control and safety systems and must, therefore, be very accurate and have good dynamic performance. [1]

The response time of RTDs and thermocouples has been characterized by a single parameter called the Plunge Time Constant. This is defined as the time it takes the sensor output to achieve 63.2 percent of its final value after a step change in temperature is impressed on its surface. This step change is typically achieved by suddenly immersing the sensor in a rotating tank of water, called Plunge Test. In nuclear reactors, however, plunge testing is inconvenient because the sensor must be removed from the reactor coolant piping and taken to a laboratory for testing. Nuclear reactor service conditions of 150 bar and 300°C are difficult to reproduce in the laboratory. Therefore, all laboratory tests are performed at much milder conditions, and the results are extrapolated to service conditions. This leads to significant errors in the measurement of sensor response times and an in-situ test method called LCSR - Loop Current Step Response test was developed to measure remotely the response time of RTDs.

In the LCSR method, the sensing element is heated by an electric current; the current causes Joule heating in the sensor and results in a temperature transient inside the sensor. The temperature transient in the element is recorded, and from this transient, the response time of the sensor to changes in external temperature is identified by means of the LCSR transformation. This transformation involves the dynamic response modal time constants determination using a nodal heat-transfer model. For this reason, this calculation is not simple and requires specialized personnel.

This work presents the results of the time constants values predicted from ANN using Angra I Brazilian nuclear power plant data. The signals obtained from LCSR Loop Current Step Response test sensors installed in the process presents noise end fluctuations that are inherent of operational conditions. Angra I nuclear power plant has 20 RTDs as part of the Protection Reactor System.

2. PLUNGE TEST

Plunge Test is a laboratory test that simulates a temperature step change in the fluid temperature where the sensor is immersed. The test consists in a sensor that is suddenly immersed in a fluid maintained in a constant temperature and to monitor its output until it reaches the steady state temperature. In such a way, the sensor quickly passes from a room temperature T_a to a fluid temperature T_1, that is, it suffers a temperature step change. The Time constant value is obtained directly from the Plunge Test and consists in the time necessary to the sensor reach 63.2% of its final value [3]. Figure 1 shows a Plunge Test and a plot of the temperature step change and the corresponding RTD output.

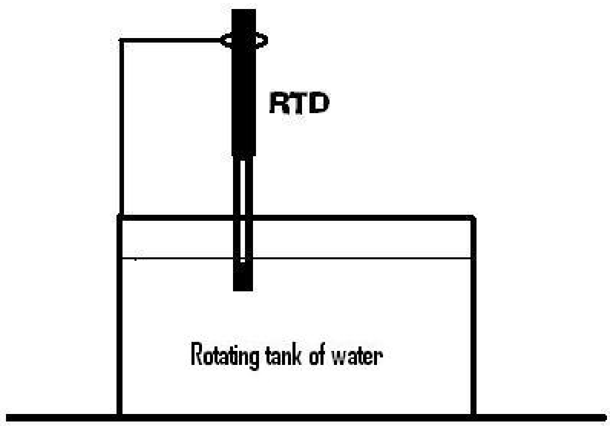

Figure 1.a) Plunge Test;

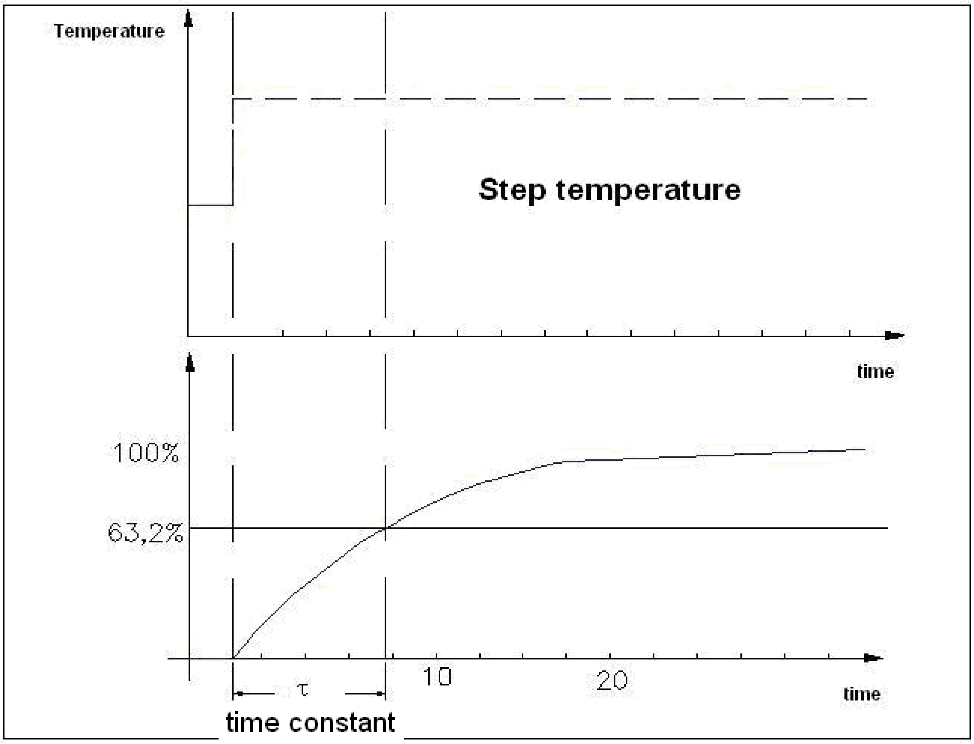

Figure 1.b) Temperature step change

3. LOOP CURRENT STEP RESPONSE TEST

The Loop Current Step Response methodology was developed to remotely measure RTDs time response while the sensor is installed in the process. The test consists in applying a small current to the RTD leads that heats the sensor filament and the temperature transient due to a step change is analyzed to determine the response time that would have followed a fluid temperature change. The LCSR data gives the sensor response of an internal heating perturbation, but the response of interest is the one that results from a fluid temperature perturbation. The time plot, of either the heating while the current is applied, or the cooling after the current is discontinued, is recorded during the LCSR test. From this plot, the sensor response time is obtained by means of the LCSR transformation [1].

The LCSR test accounts for all the effects of installation and process conditions on response time and thereby provides a sensor's actual "in-service" response time.

The LCSR test equipment consists in a Wheatstone bridge with current switching capability (Figure 2). The switch can be opened or closed to decrease or increase the current. The LCSR test is made by connecting a test instrument at the point where the sensor leads are normally connected to their in-plant transmitter (Figure 2).

First, the bridge is balanced with 1 to 2 mA of DC current running through the RTD (switch open). Then, the current is switched "high" to about 30 to 50 mA (switch closed). This causes the RTD sensing element to heat up gradually and settle a few degrees above the ambient temperature. The amount by which the temperature rises in the RTD depends on the magnitude of the heating current used and on the rate of heat transfer between the RTD and its surrounding medium. Typically, the RTD heats up about 5 to 15 ºC during the LCSR test.

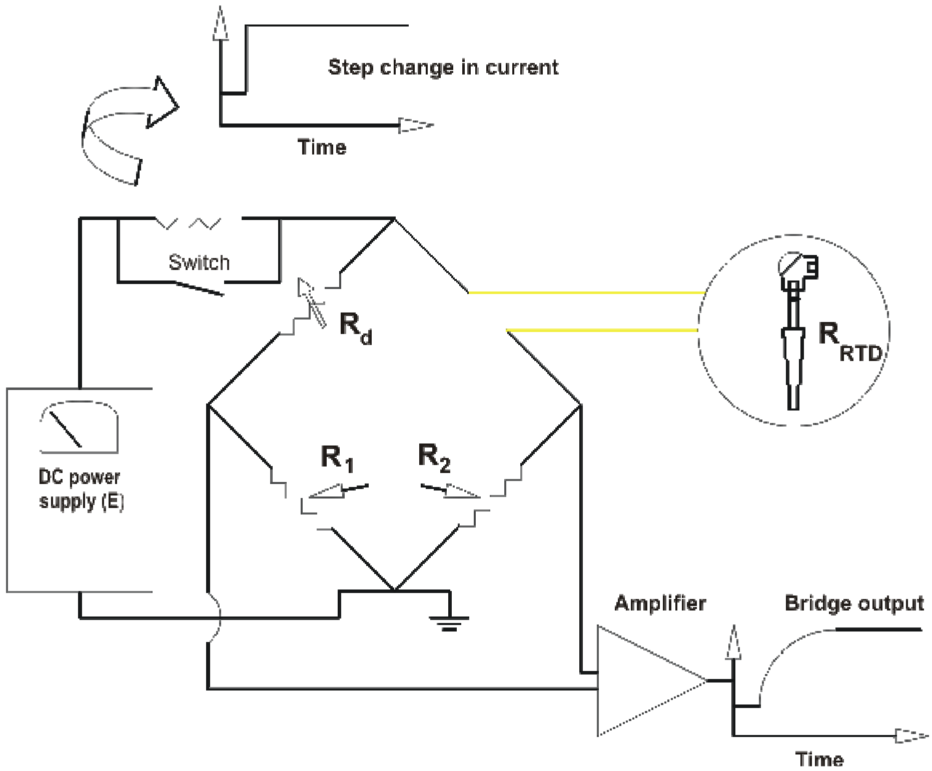

Figure 2 - Wheatstone bridge used in RTDs LCSR tests.

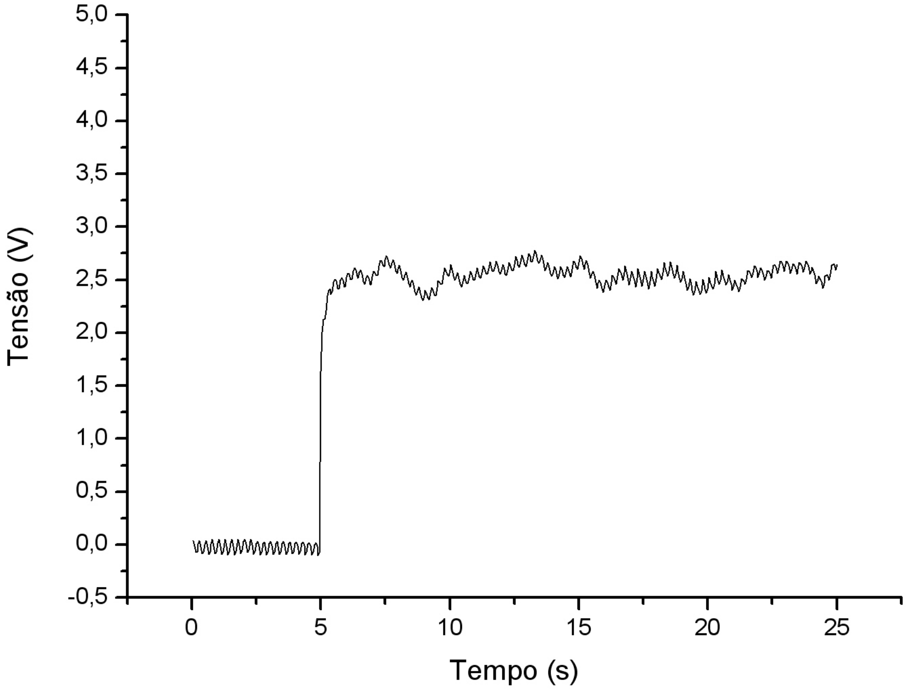

Figure 3 – A typical in-plant LCSR test.

Figure 3 shows a typical LCSR test result performed in a nuclear power plant using a heat current of about 40 mA. Figure 4 shows a typical LCSR test performed in the laboratory also using a 40 mA heat current.

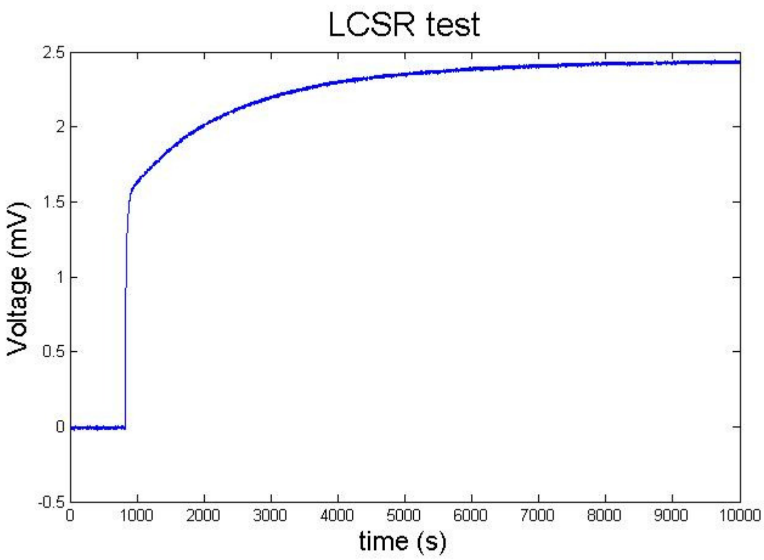

Figure 4 - A typical laboratory LCSR test.

4. NEURAL NETWORKS

An ANN is a massively parallel distributed processor made up of simple processing units, which has a natural propensity for storing experiential knowledge and making it available for use. The knowledge is acquired by the networks from its environment through a learning process which is basically responsible to adapt the synaptic weights to the stimulus received by the environment. The fundamental element of a neural network is a neuron, which has multiple inputs and a single output, as we can se in Figure 2. It is possible to identify three basic elements in a neuron: a set of synapses, where a signal x_j at the input of synapse j connected to the neuron k is multiplied by the synaptic weight w_{kj}, an adder for summing the input signals, weighted by the respective synapses of the neuron; and an activation function for limiting the amplitude of the output of a neuron. The neuron also includes an externally applied *bias*, denoted by b_k, which has the effect of increasing or lowering the net input of the activation function, depending on whether it is positive or negative, respectively [8].

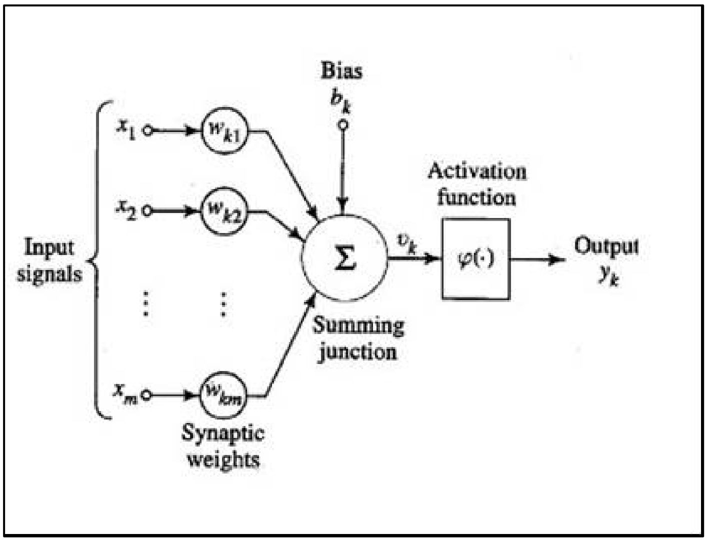

Figure 5. Neuron Model

In this work, it was used the MLP (Multilayer Perceptron Neural Network). In this kind of architecture, all neural signals propagate in the forward direction through each network layer from the input to the output layer. Every neuron in a layer receives its inputs from the neurons in its precedent layer and sends its output to the neurons in its subsequent layer. The training is performed using an error backpropagation algorithm, which involves a set of connecting weights, which are modified on the basis of a Gradient Descent Method to minimize the difference between the desired output values and the output signals produced by the network, as show the equation (4):

$$E = \frac{1}{2}\sum_{m=1}^{m}\left(y_{dj}(n) - y_j(n)\right)^2 \qquad (4)$$

Where:

E: mean squared error
m: number of neurons in the output layer
y_{dj}: target output
y_j: actual output
n: number of interactions

5. RESULTS

In this work the input data are the LCSR test results and the output data are the sensor time constant obtained from previous LCSR measurements. Data was acquired from ten different RTD temperature sensors from Angra I nuclear power plant Reactor Safety System. Figures 6 and 7 show the Neural Network input and output.

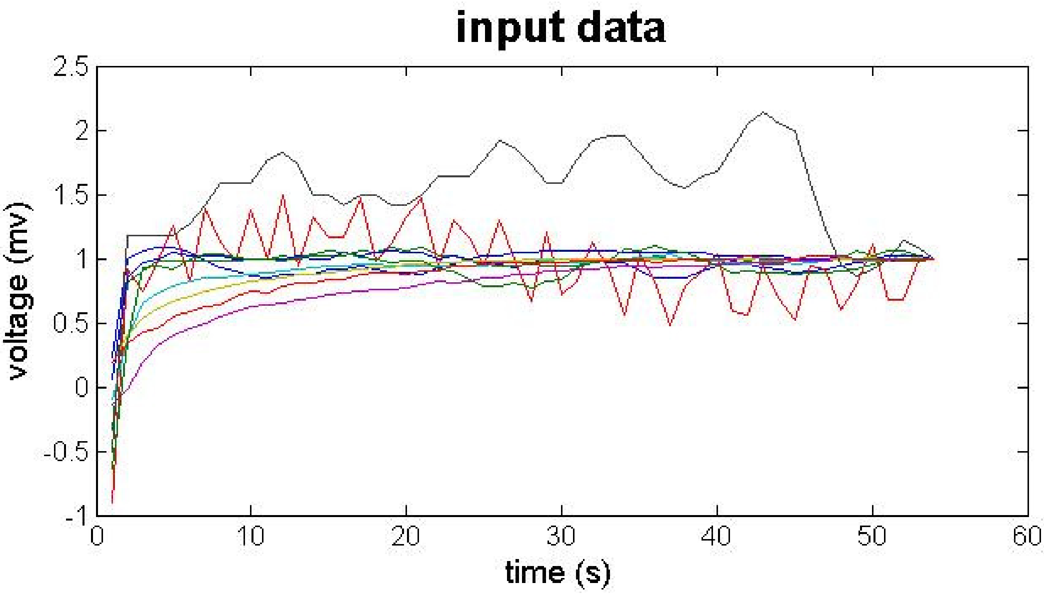

Figure 6. Input data set – LCSR tests.

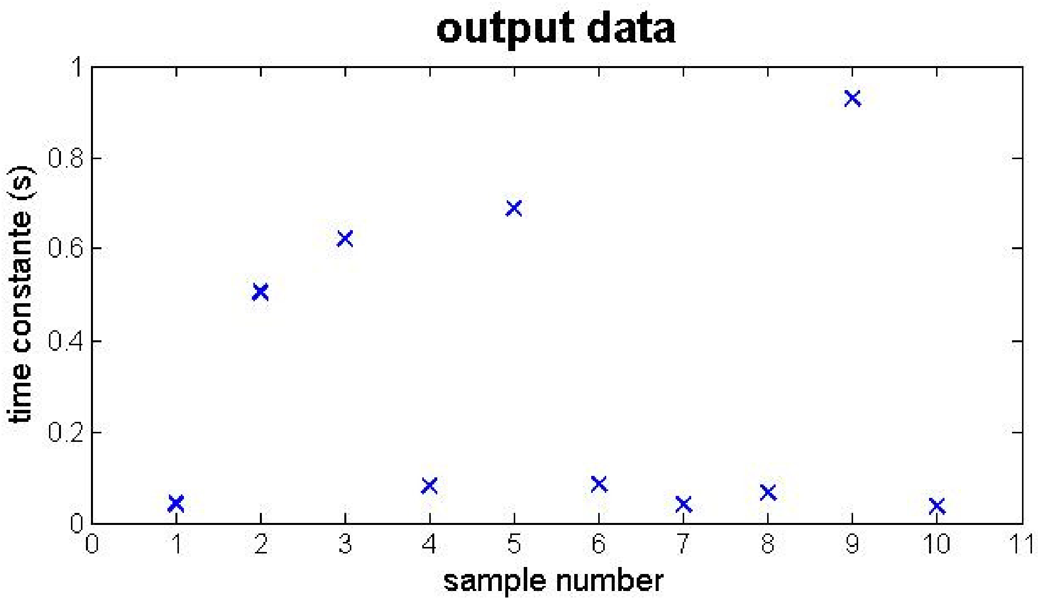

Figure 7. Output data – time constants.

It was developed a Neural Network using the Neural Network Toolbox from Matlab software. The NN type used was the backpropagation network, with 3 layers (1 input, 1 hidden and 1 output layer) 100 epochs training or an error criterion of 0.001 as shown in Figures 8 to 11.

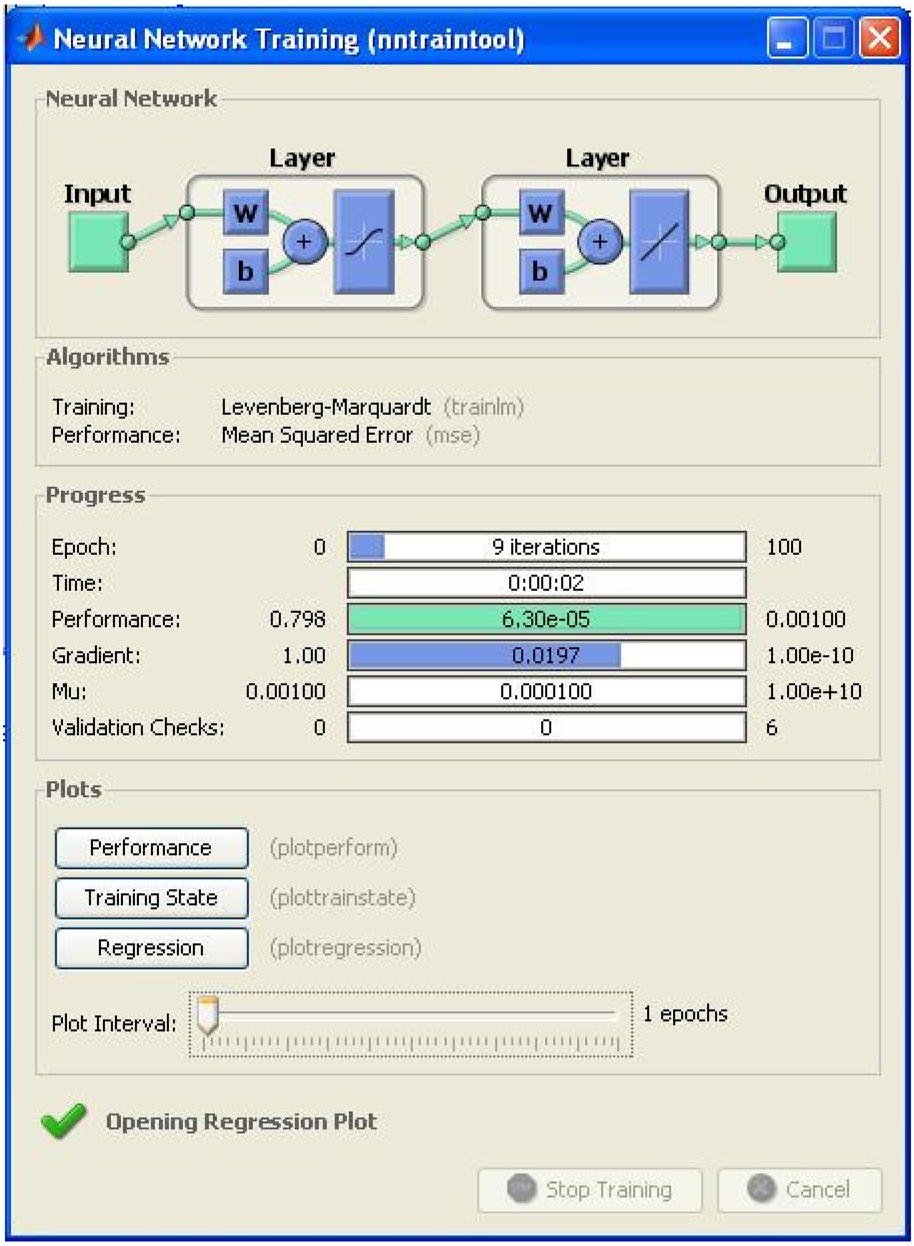

Figure 8. Neural Network training.

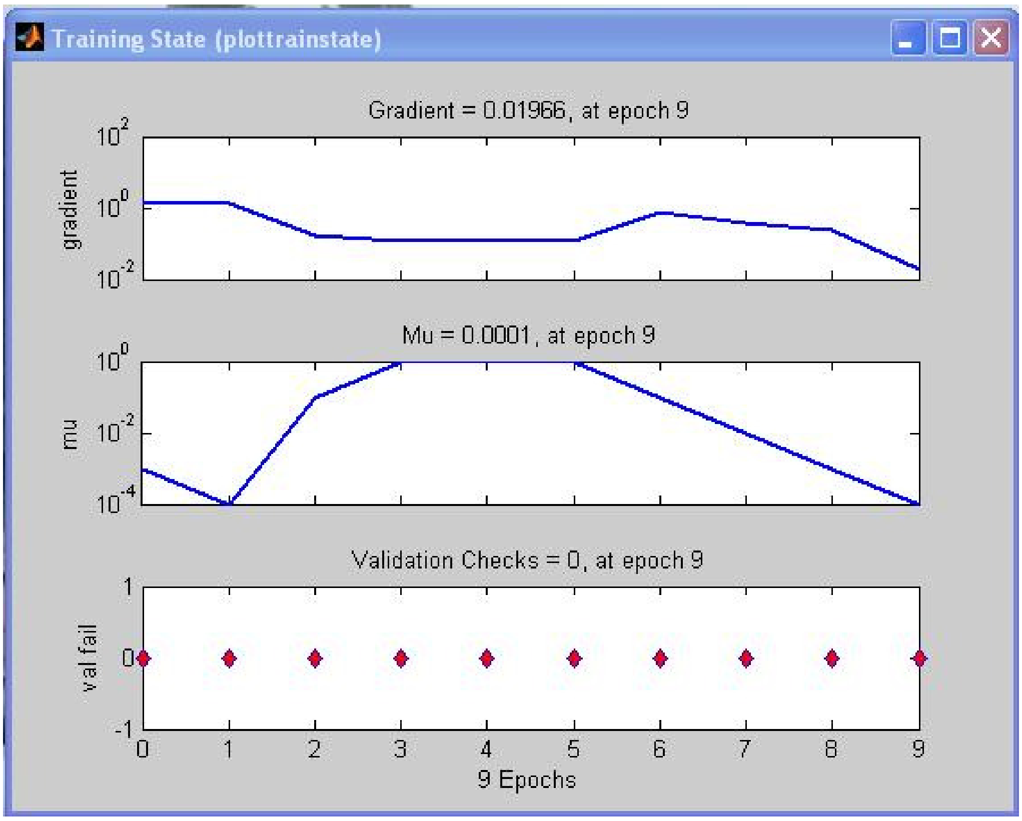

Figure 9. Training State.

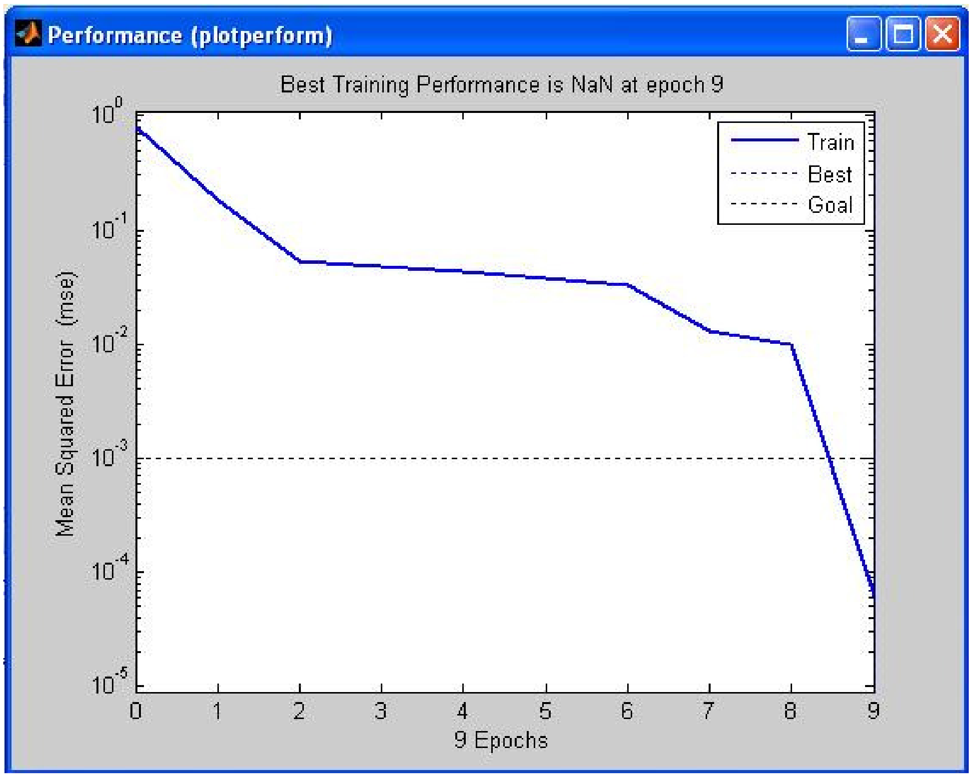

Figure 10. Performance.

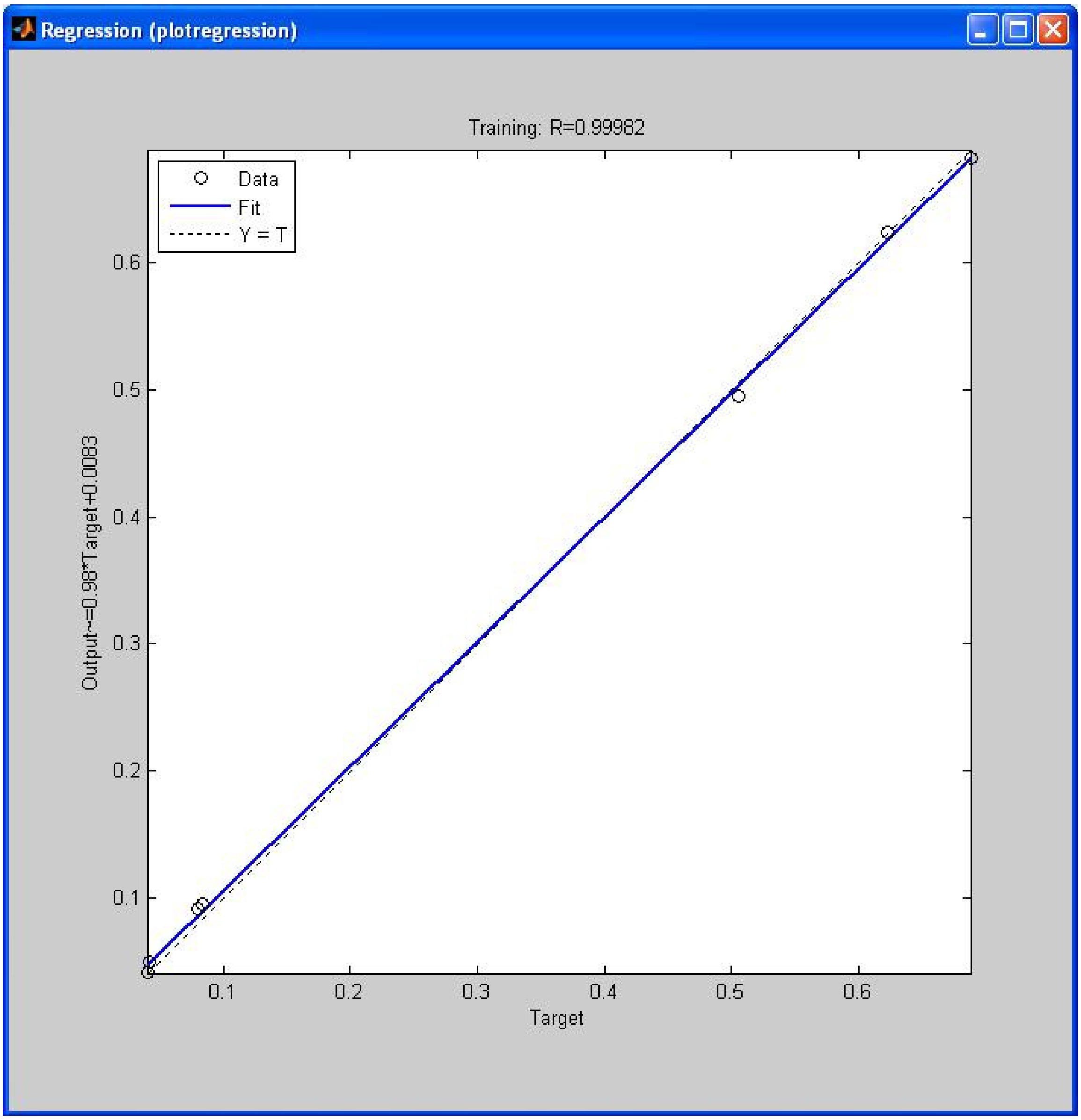

Figure 11. Regression.

Figure 12 shows a plot comparing the neural network output and the target (training process). As it can be seen, the neural network training presented a good result as expected. The same behavior was verified during the test process as shown in Figure 13.

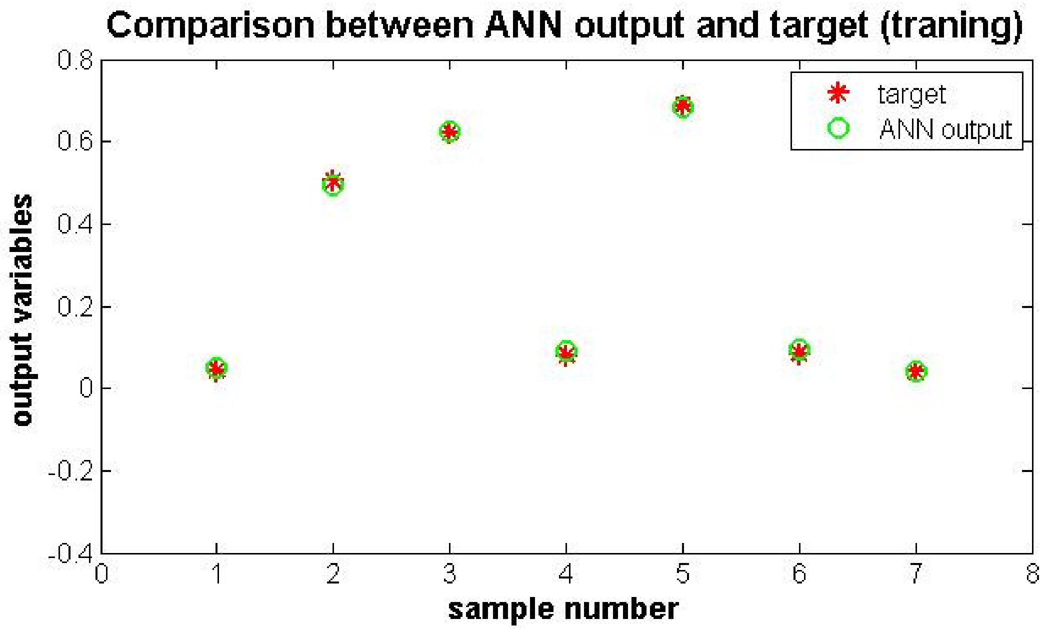

Figure 12. Neural Network Training Results.

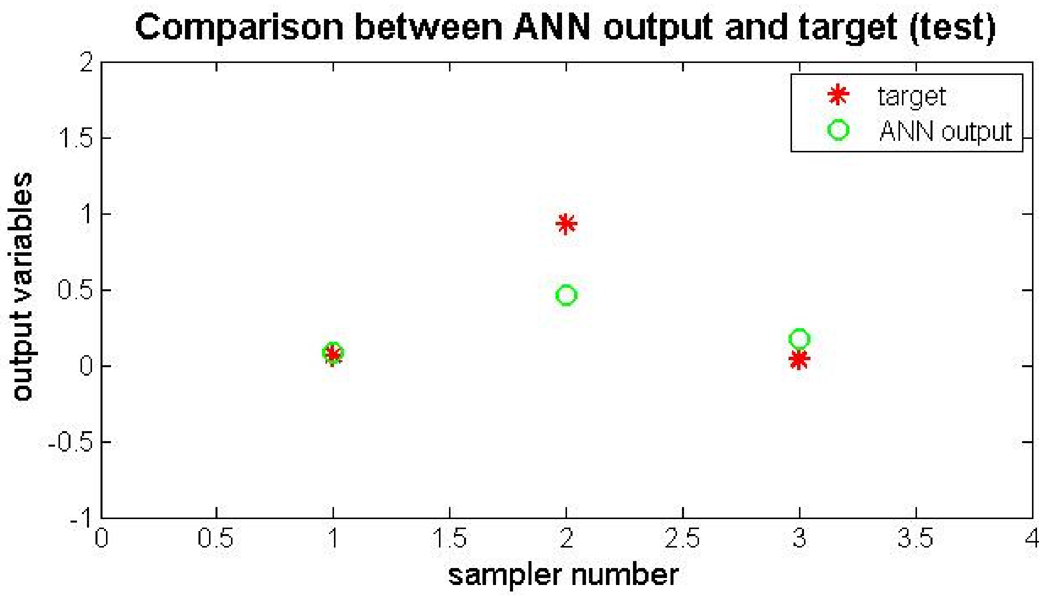

Figure 13. Neural Network Test Results.

5. CONCLUSIONS

A methodology using Neural Networks for RTD temperature sensor time response is presented. A set of 10 LCSR test results from Angra I nuclear Power Plant were used as ANNs input parameters. The ANNs outputs were the time constant obtained from previous measurements obtained from LCSR tests. The mean squared error obtained in the training process is about 6.3 e-3 % and the error obtained in the test process was 8 %. This work combines the two methodologies, Plunge test and LCSR test, using Neural Networks. With the use of Neural Networks it will not be necessary to use the LCSR transformation to determine sensor's time constant and this leads to more robust results.

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