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TIME RESPONSE OF TEMPERATURE SENSORS USING NEURAL NETWORKS

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ABSTRACT

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. The response time of RTDs has been characterized by a single parameter called the Time Constant defined as the time it takes for the sensor output to achieve 63.2 percent of its final value after a step change in temperature. 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 nuclear reactor service conditions are difficult to reproduce in the laboratory. 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.

The objective of this work is to combine the two methodologies, Plunge test and LCSR test, using Neural Networks. Neural Networks, or artificial neural networks, represent a technology that is rooted in many disciplines: neurosciences, mathematics, statistics, physics, computer science, and engineering. Neural networks find applications in such diverse field as modeling, time series analysis, pattern recognition, signal processing, and control by virtue of an important property: the ability to learn from input data with or without a teacher [2]. 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.

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.

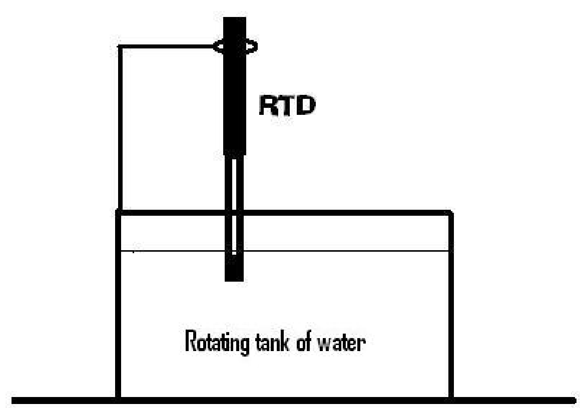

Figure 1.a) Plunge Test;

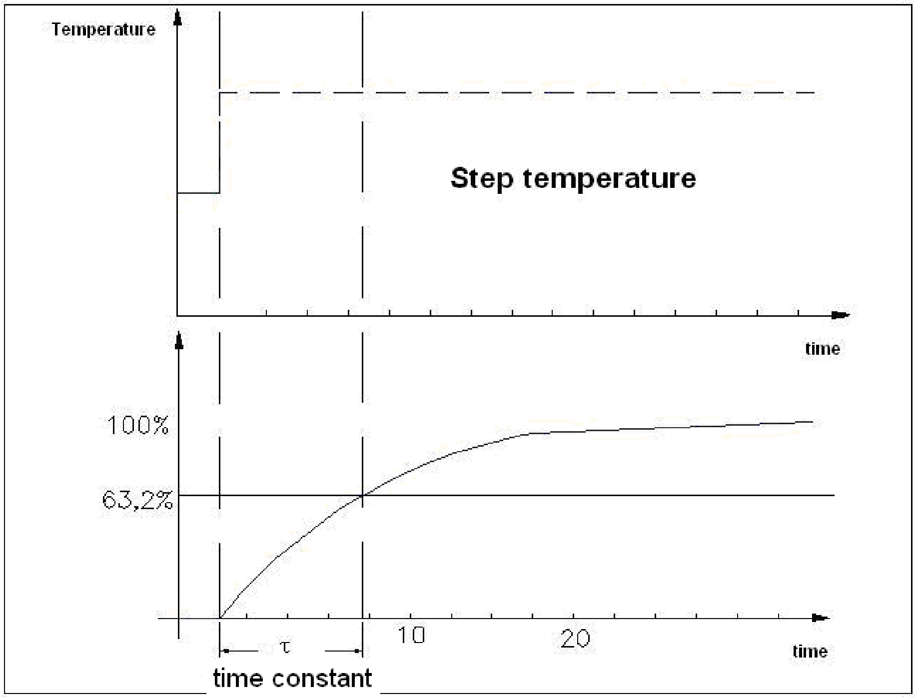

Figure 1.b) Temperature step change

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.

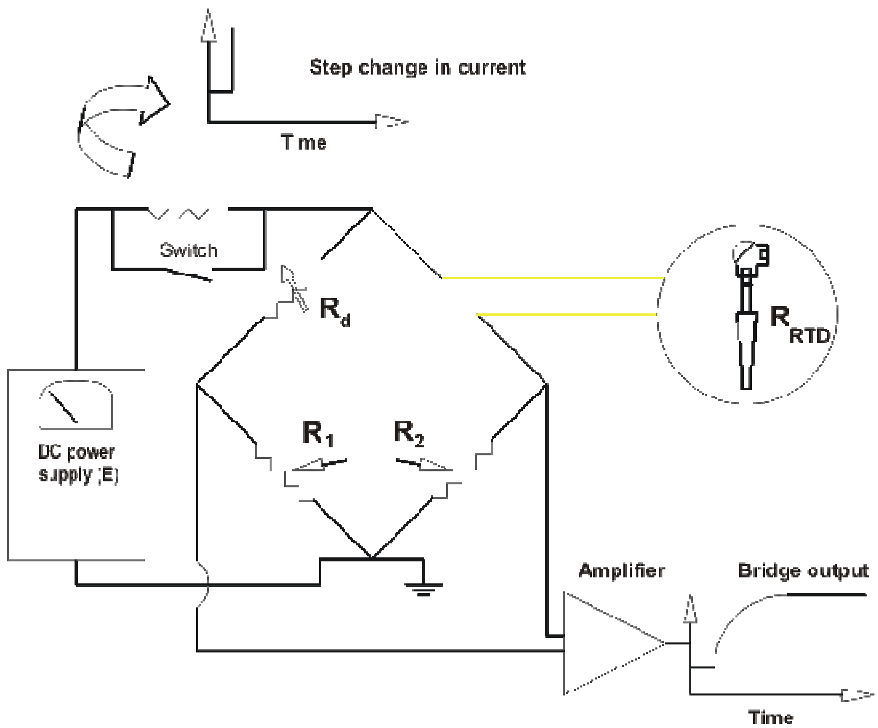

Figure 2 - Wheatstone bridge used in RTDs LCSR tests.

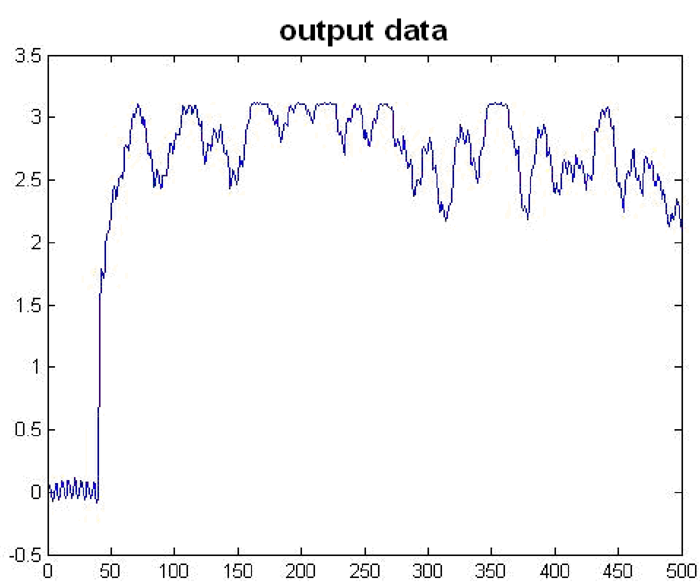

Figure 3 – A typical in-plant LCSR test.

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.

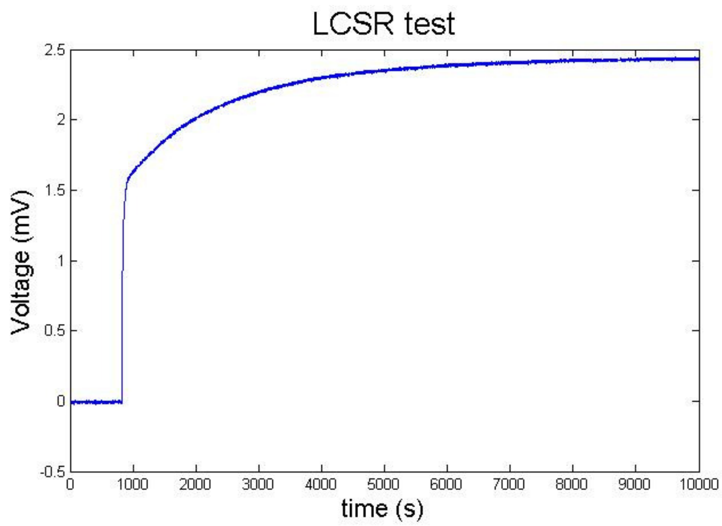

Figure 4 - A typical laboratory LCSR test.

4. NEURAL NETWORKS

A Neural Network (NN) 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. [2].

In this work the input data are the LCSR test results and the output data are the sensor time constant obtained from the Plunge Test. Data was acquired in controlled laboratory conditions that means no noise data different from a nuclear power plant conditions. For this work, 20 LCSR measurements and 20 Plunge Test measurements were used.

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) 10 epochs training or an error criterion of 0.01.

The 20 set of input data were adjusted in order to all start at the same point, with 34 data points (Figure 5). Figure 6 shows sensor time constant values (output data).

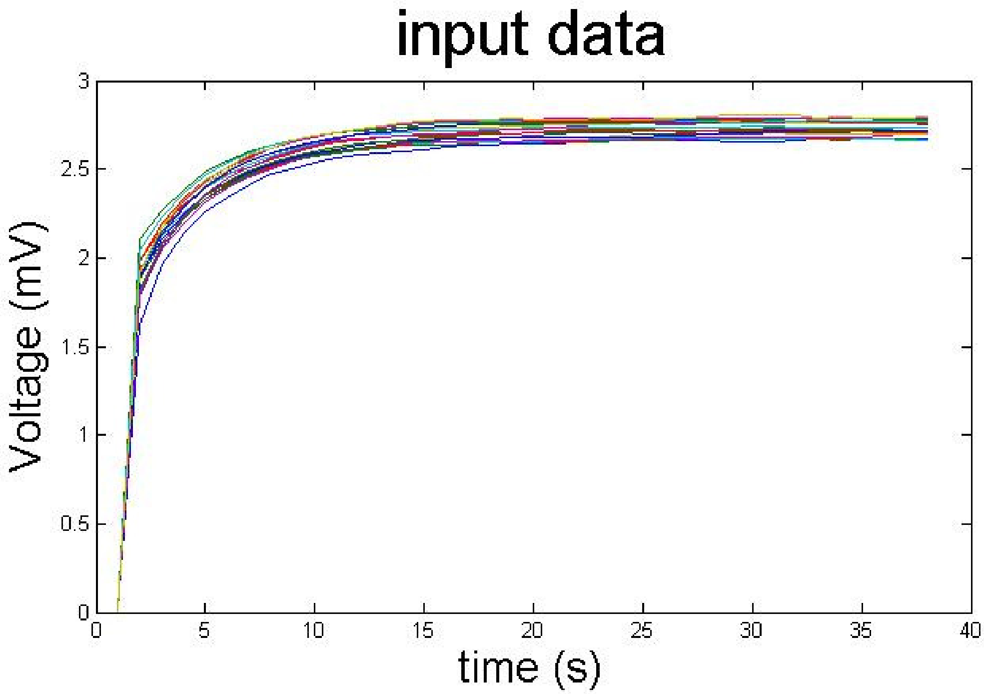

Figure 5 –Input data set – LCSR tests.

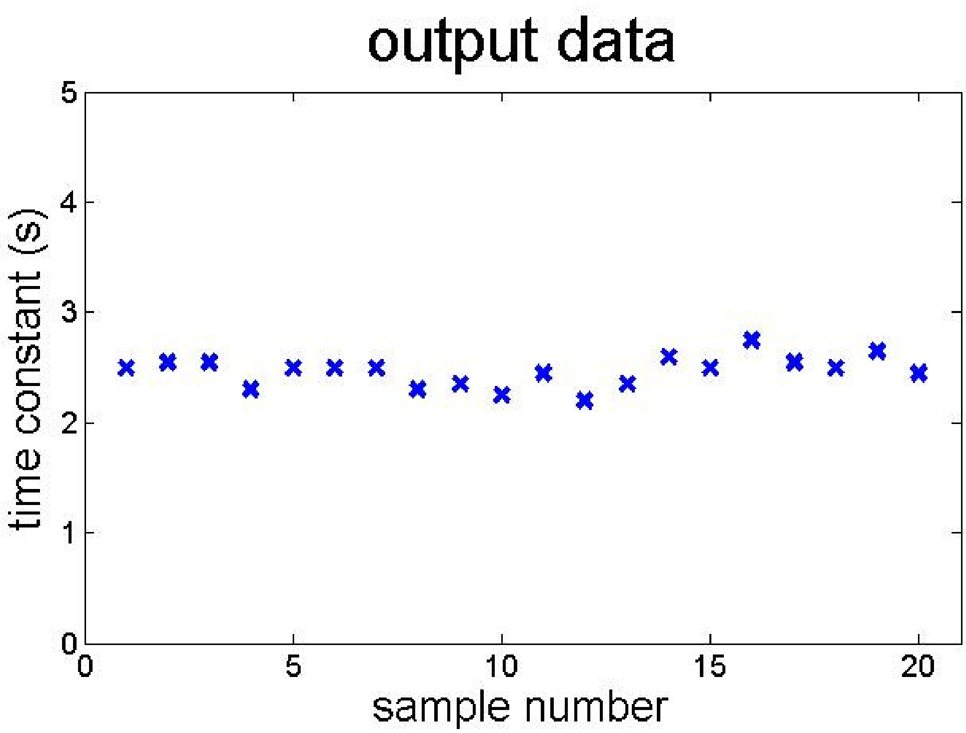

Figure 6 – Output data - Plunge Test.

Data was divided in two sets of 10 elements for training and 10 elements to test. Matlab functions used were TANSIG used for the hidden layer and PURELIN for used output layer. Figure 7 shows a plot of the training process.

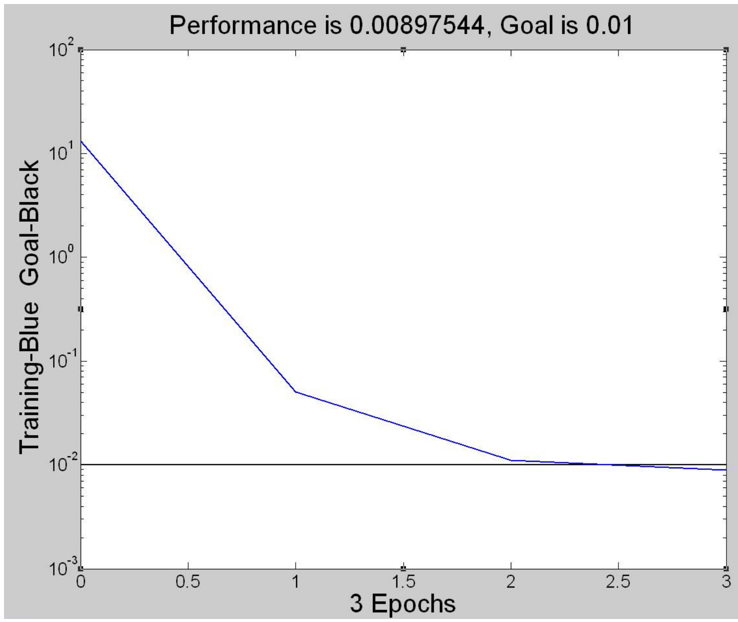

Figure 7 – Neural network training plot, relative error vs epochs.

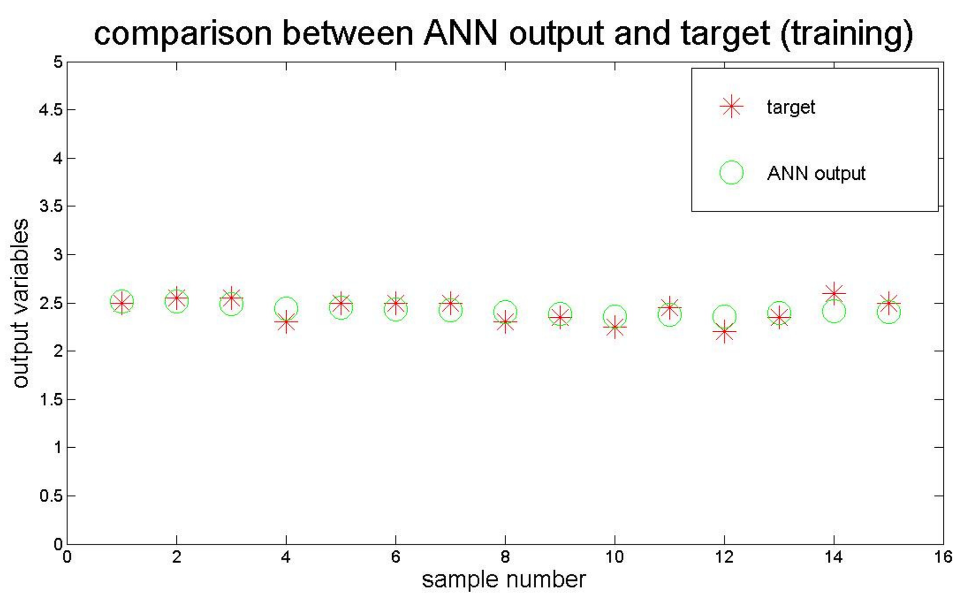

Figure 8 – Comparison between training results and target.

Figure 8 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 9.

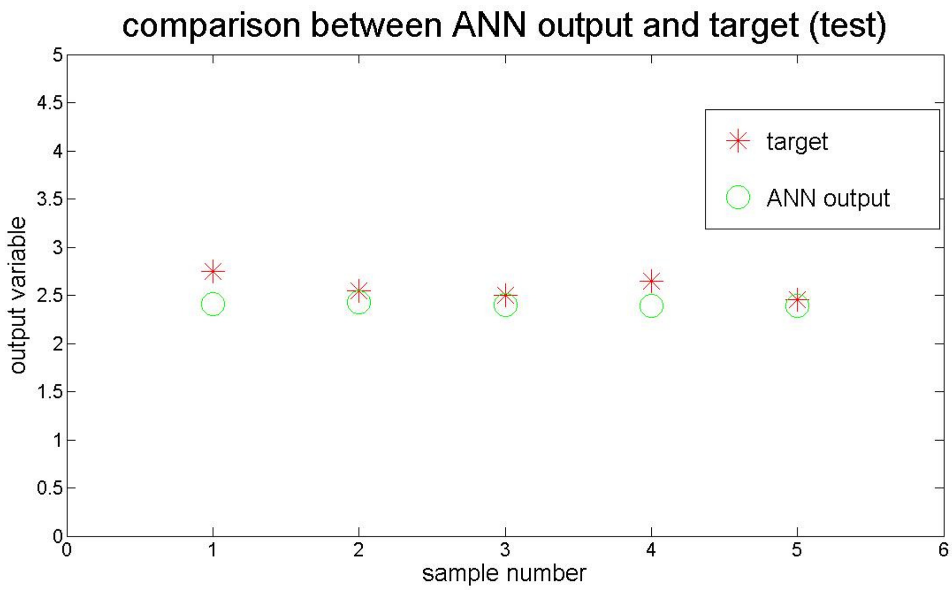

Figure 9 – Test output neural network values.

5. CONCLUSIONS

A methodology using Neural Networks for RTD temperature sensor time response is presented. A set of 20 LCSR test results were used as ANNs input parameters. The ANNs outputs were the time constant obtained from Plunge Test. The error obtained in the training process is about 1 % and the error obtained in the test process was 10 %. The RTD time response obtained using neural networks eliminates the use of the LCSR transformation. This work is a first step towards a more complex methodology for RTD time constant prediction using neural networks. A new data set of laboratory LCSR tests from different RTDs can be easily obtained in order to generate a more robust time constant prediction value. Data from in-plant LCSR tests can also be used to implement a neural network.

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