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Research Article

Corrosion Control by Impressed Cathodic Protection Using Intelligent Systems

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Abstract: The aim of this study is to adopt the Artificial Neural Network (ANN) to Model the Cathodic Protection system (CPS) and evaluation the potential required to protect the coated and bared pipeline as well as to the prediction of corrosion rate. On the other hand, the experimental work was carried out to collect the required data to be used for training and testing the neural network. The objective of this research paper is to corrosion control in the pipeline with different potential values. The proposed structure of ANN for potential and corrosion is an input layer, two hidden layers and one output layer and this structure is arbitrarily selected. The transfer function that has been used in the first hidden layer for each network is the Tan-Sigmoid function and for the second layer is the pure line. The back propagation training algorithm with one variable learning rate is used to train these neural networks. For the potential assessment; the ANN input data includes the distance between anodes and cathodes (D), Current Density (CD), length of pipe from end to the drain point (L), resistivity of solution (ρ) and the voltage of power stations, while the potential is the network output. For the corrosion rate prediction, the network input information is only time, surface area and resistivity of the soil (solution) (ρ), while the corrosion rate is the network output. Many networks are constructed by changing the number of neurons for the hidden layers. This has been simulated by using the MATLAB R2009a software. The optimum network for coated pipe was (13) neurons in the first hidden layer and (8) neurons in the second hidden layer which is tested and trained by using (120 data sample). This network has proved to be reliable and can be used to assess the potential required for CPS. Concerning the bared pipe-lines, the collected experimental data is not stable and the fluctuation of the data occurs due to the interference between the corroded part of the pipe and the protected parts, which causes the un-stability of potential. The optimum network for coated pipe was (15) neurons in the first hidden layer and (4) neurons in the second hidden layer) which is tested and trained by using (250 data sample). This network demonstrates to be reliable and capable of predicting the corrosion rate.

Keywords: Corrosion control, cathodic protection, intelligent systems, neural network

INTRODUCTION

The methods used for the identification of the polarization parameters of cathodic protection systems are the statistical methods (e.g., fractional design and Fractional factorial design). In the present time, the creative techniques are used successfully in a broad band of applications; one of these applications is the cathodic protection. Examples of these techniques that are employed in CP are fuzzy logic and genetic algorithms. Intelligent control is now becoming a standard tool in many engineering and industrial applications (Elaibi, 2014; Corr-Rad, 2000). It can comprehend and learn about plants, disturbances, environment and operating conditions (Dayhoff, 1990; Wegener, 2004). Some examples of the factors to be determined are plant characteristics such as its static and dynamic behaviors (Elaibi, 2014; Corr-Rad, 2000).

Artificial neural networks, with their self-organizing and learning ability, are now used as promising tools for such purposes. The architecture and functions of the artificial neural network are based on the biological brain. Neural network provides a different computing architecture compared with the Von Neumann computers. The main characteristics of the neural network are parallel and distributed in nature as well as self-organization, however, conventional computers have series, local and algorithmic properties (Dayhoff, 1990; Wegener, 2004).

Work on artificial neural networks, commonly referred to as neural networks have been motivated right from its inspection by the recognition that the brain computes in an entirely different way from the conventional digital computer. The struggle is to understand the brain operation philosophy. The favor is to the pioneering work of Fausett (Mil-HDBK, 1984), who introduced the idea of neurons as structural of the brain. Typically, neurons are five to six orders of magnitude slower than silicon logical gates; events in silicon chip happen in the nanosecond range, whereas neural events occur in the millisecond range. However, the brain compensates for the relatively slow rate of operation of a neuron by having a truly staggering number of neurons (nerve cells) with massive interconnections between them. Fundament, it is estimated that there must be on the order of 10 billion neurons in the human cortex and 60 trillion synapses or connections (Frank, 1999). The net result is that the brain is an enormously efficient structure.

In its most general form, a neural network is a machine that designs a model in the same way when the brain performs a particular task or function of interest (Mil-HDBK, 1984). It resembles the brain in two respects:

- Knowledge is acquired by the network through the learning process.
- Inter- neurons connections strength known as synaptic weights are used to store the knowledge.

In this study, ANN has been used to model a Cathodic Protection system for evaluation of the potential required to protect the coated and bared pipe-line.

EXPERIMENTAL WORK

Experimental work has been carried out to determine the modeling of cathodic protection for bare and coated pipe (with different coats), current demand and resistivity of ground bed, the proper distance between the cathodic pipe and anode and finally the attenuation potential of the pipes.

Electrochemical polarization method was used for six solution resistivity (4934.579, 1044.139, 538.785, 62.856, 34.322 and 24.5 Ohm.cm) which represent moderate to severe conditions of a large extent of land in north Iraq-Turkey pipeline in Nineveh to Um-Qaser in Basrah-Iraq. The details of experimental setup are explained in (Al-Shareefi, 2009).

RESULTS AND DISCUSSION

Neural networks for coated pipe: The tested network's output was compared with tests samples to find the optimum neural network. The best parameters values of for the neural network that has been selected are shown below:

- One Input layer (Receiving Five parameters)
- Two Hidden layer:
  - 13 neurons in the 1st hidden layer
  - -8 neurons in 2nd hidden layer
- One output layer (give one output)

Figure 1 shows the comparison between the optimum neural network outputs with experimental data for the same conditions (Length, Current Density, Resistivity, Distance and Voltage of Power station) for each point for the optimum network and Fig. 2 shows the regression for this network.

Figure 3 to 12 show the comparison between the other neural networks outputs with experimental data and their regression curves for coated pipe.

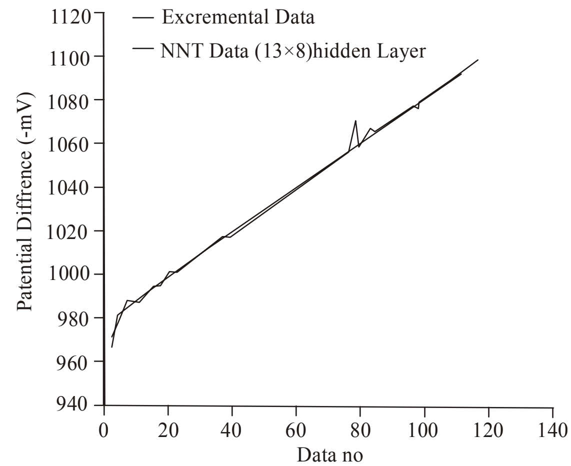

Fig. 1: Comparison between experimental data and NNT data of potential difference for coated pipe of the optimum NNT which has two hidden layers (13) neurons 1st hidden layer and 8 neurons in 2nd hidden layer).

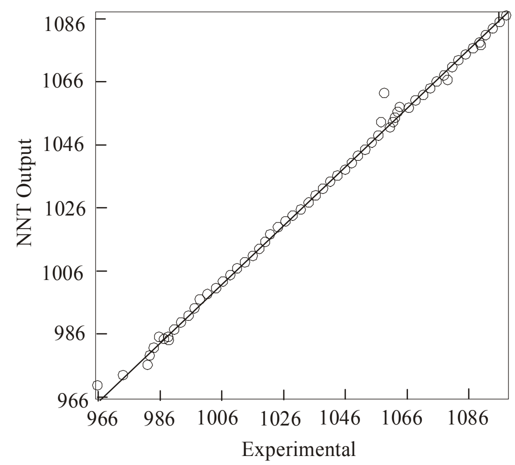

Fig. 2: Regression for the optimum NNT which has two hidden layers (13 neurons 1st hidden layer and 8 neurons in 2nd hidden layer) for coated pipe

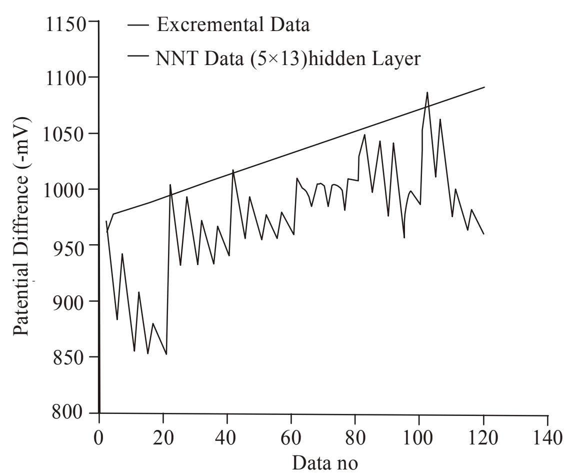

Fig. 3: Comparison between experimental data and NNT data of potential difference for coated pipe of NNT which has two hidden layers (5 neurons 1st hidden layer and 13 neurons in 2nd hidden layer)

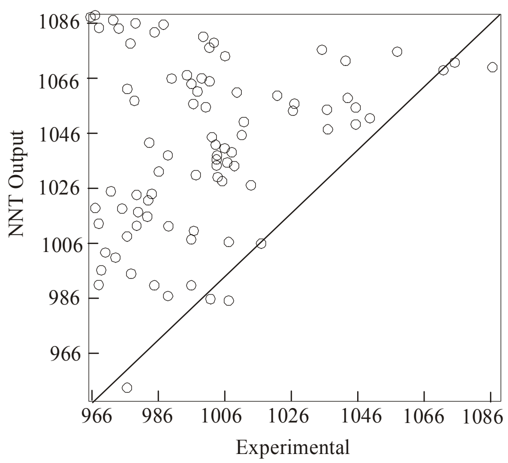

Fig. 4: Regression for the optimum NNT which has two hidden layers (5 neurons 1st hidden layer and 13 neurons in 2nd hidden layer) for coated pipe

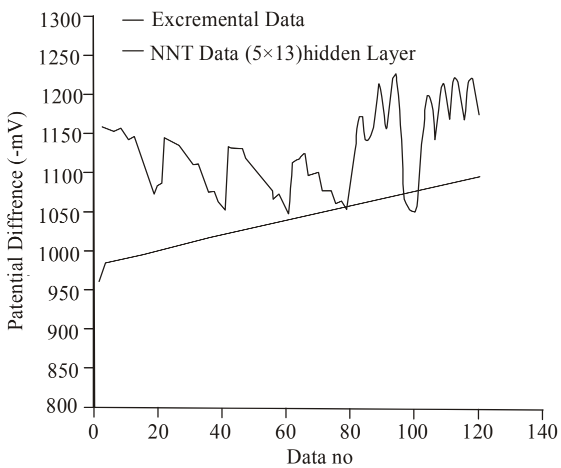

Fig. 5: Comparison between experimental data and NNT data of potential difference for coated pipe of NNT which has two hidden layers (8 neurons 1st hidden layer and 6 neurons in 2nd hidden layer)

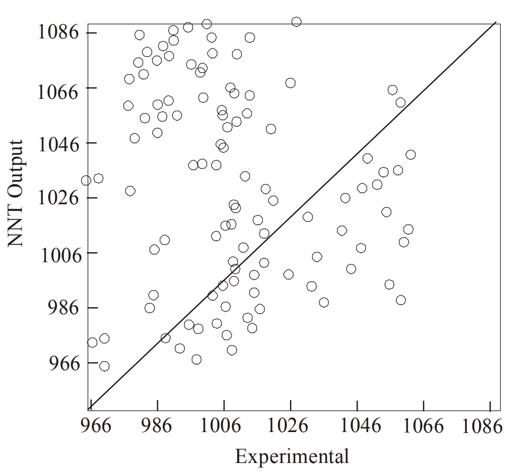

Fig. 6: Regression for the optimum NNT which has two hidden layers (8 neurons 1st hidden layer and 6 neurons in 2nd hidden layer) for coated pipe

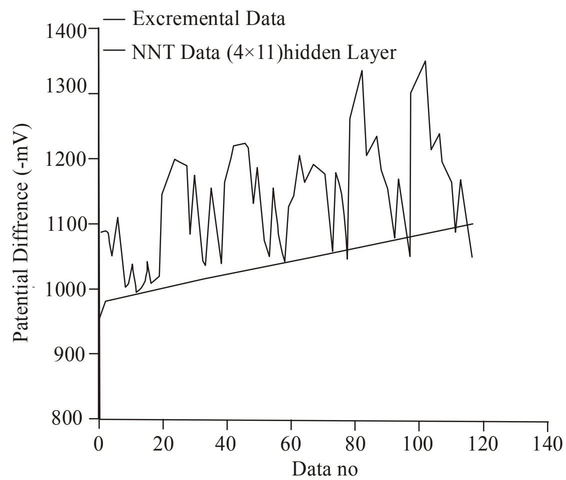

Fig. 7: Comparison between experimental data and NNT data of potential difference for coated pipe of NNT which has two hidden layers (4 neurons 1st hidden layer and 11 neurons in 2nd hidden layer)

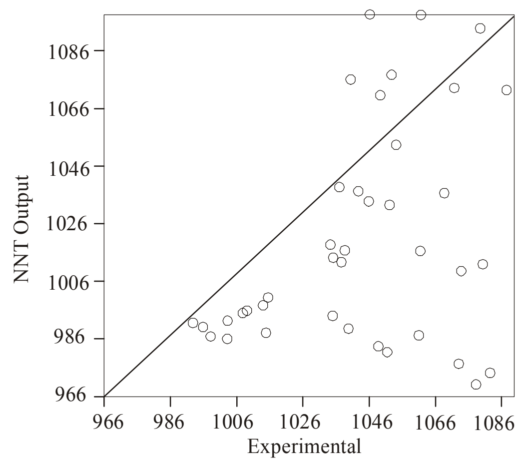

Fig. 8: Regression for the optimum NNT which has two hidden layers (4 neurons 1st hidden layer and 11 neurons in 2nd hidden layer) for coated pipe

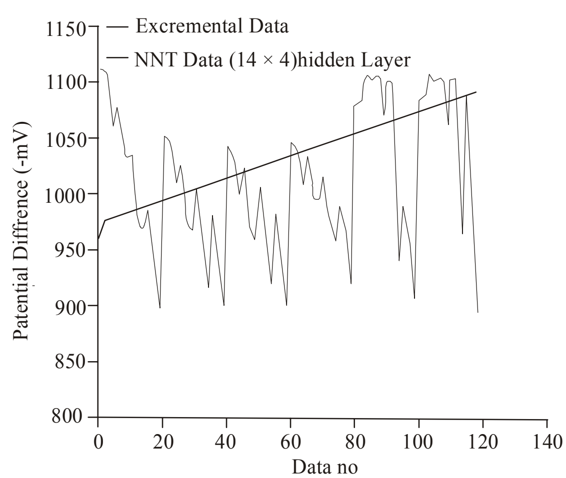

Fig. 9: Comparison between experimental data and NNT data of potential difference for coated pipe of NNT which has two hidden layers (14 neurons 1st hidden layer and 4 neurons in 2nd hidden layer)

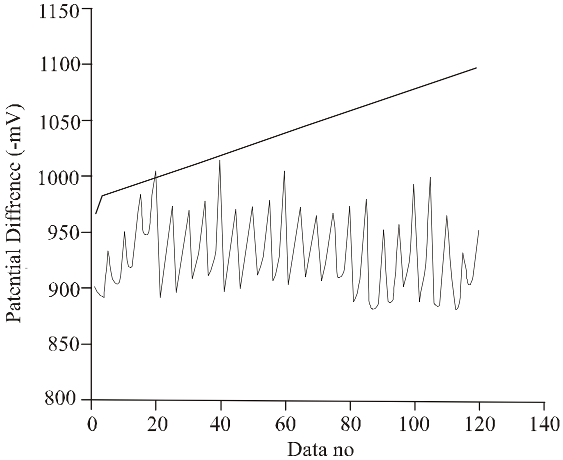

Fig. 10: Regression for the optimum NNT which has two hidden layers (14 neurons 1st hidden layer and 4 neurons in 2nd hidden layer) for coated pipe

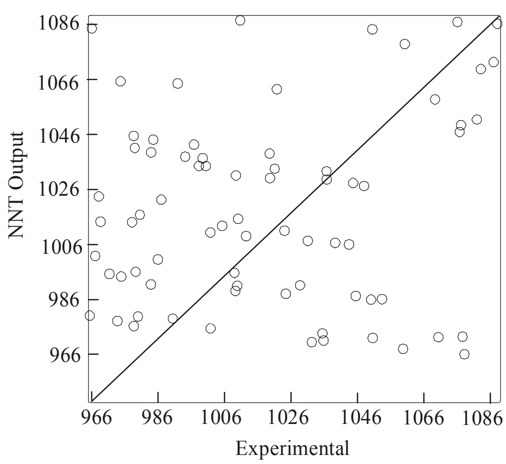

Fig. 11: Comparison between experimental data and NNT data of potential difference for coated pipe of NNT which has two hidden layers (13 neurons 1st hidden layer and 6 neurons in 2nd hidden layer)

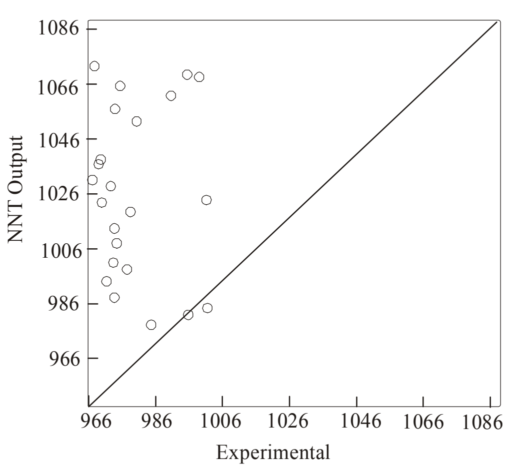

Fig. 12: Regression for the optimum NNT which has two hidden layers (13 neurons 1st hidden layer and 6 neurons in 2nd hidden layer) for coated pipe

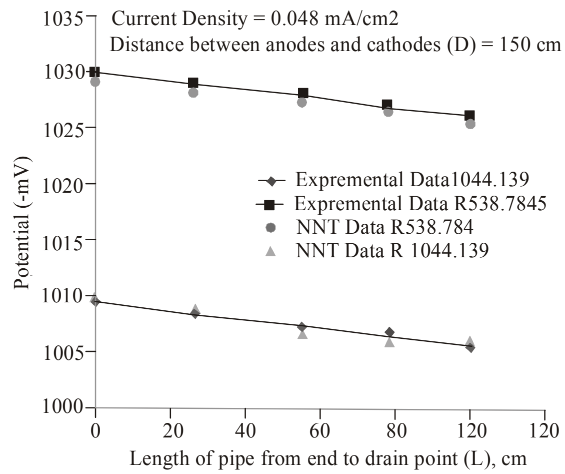

Fig. 13: Comparison between the data predicted by NNT with experimental data of the distribution of potential along length of pipe from the end to the drain point

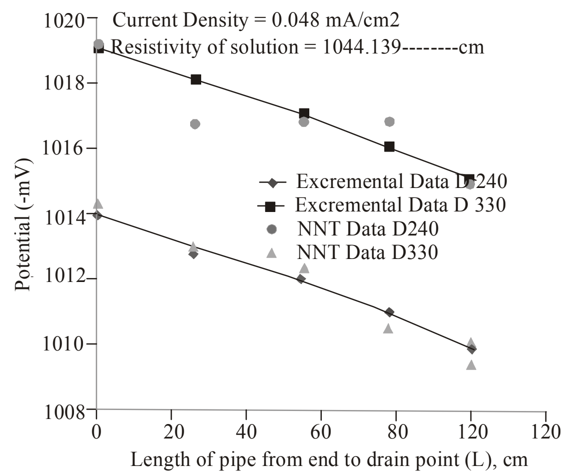

Fig. 14: Comparison between the data predicted by NNT with experimental data of the distribution of potential along length of pipe from the end to the drain point

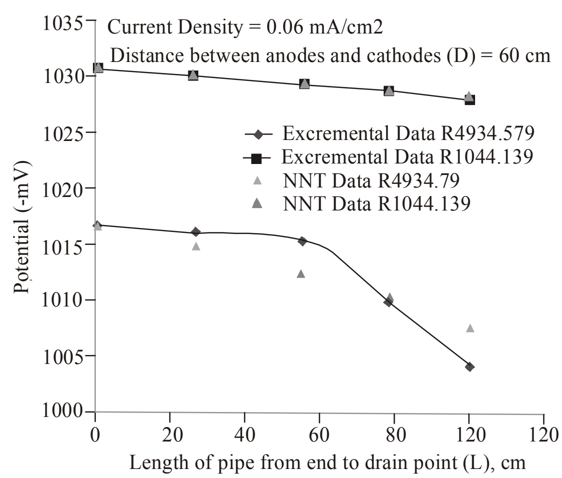

Fig. 15: Comparison between the data predicted by NNT with experimental data of the distribution of potential along length of pipe from the end to the drain point

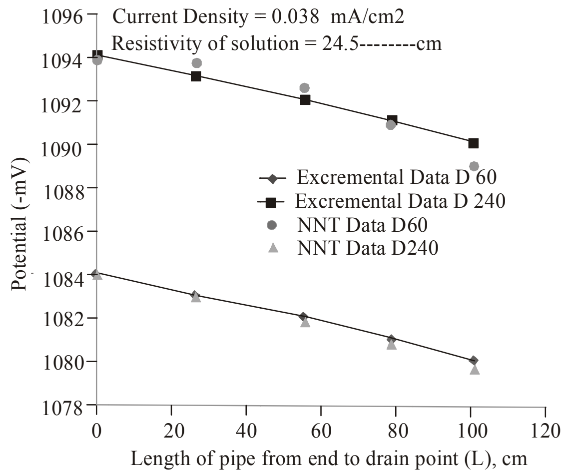

Fig. 16: Comparison between the data predicted by NNT with experimental data of the distribution of potential along length of pipe from the end to the drain point

Table 1: Special features of Error! no text of specified style in document

Experimental data	Length of pipe	Potential value
R4934.579	0	985
	20	983
	60	981
	80	974
	100	967
R1004.139	0	1004
	20	1003
	60	1002
	80	1001
	100	100

Figure 13 to 16 show the comparison between the distribution of potential along length of pipe from the end to the drain point from experimental data and the distribution of potential along length of pipe from the end to the drain point from NNT output.

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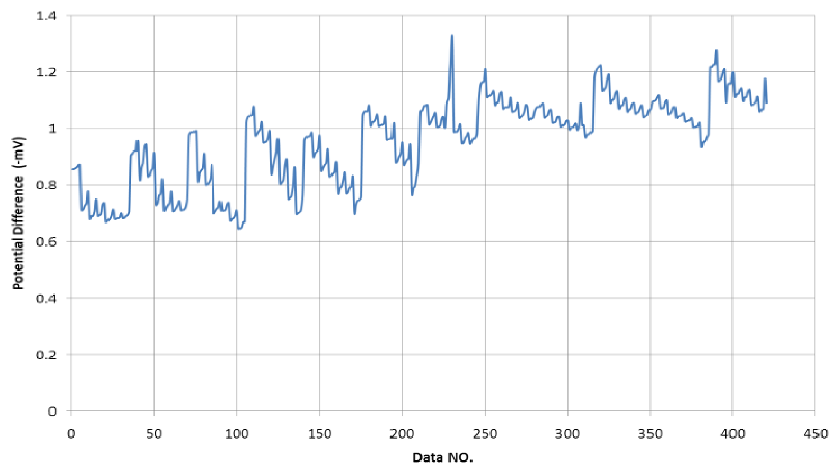

Fig. 17: The fluctuation of potential for bared pipe

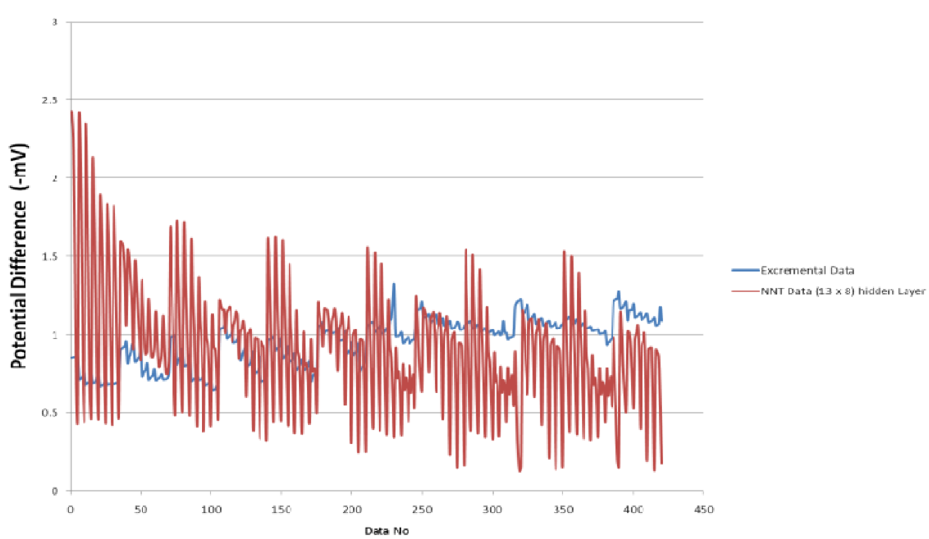

Fig. 18: Comparison between experimental data and NNT data of potential difference for bared pipe of NNT which has two hidden layers (13 neurons 1st hidden layer and 8 neurons in 2nd hidden layer)

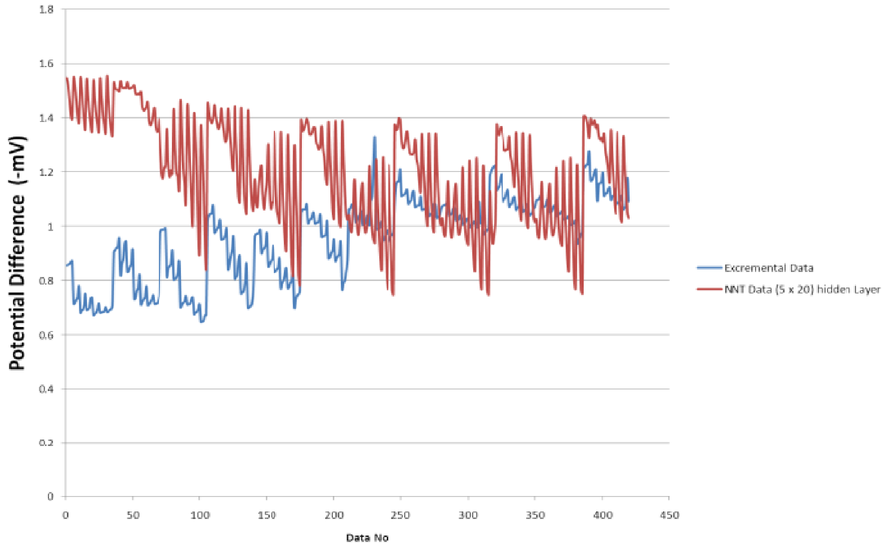

Fig. 19: Comparison between experimental data and NNT data of potential difference for bared pipe of NNT which has two hidden layers (5 neurons 1st hidden layer and 20 neurons in 2nd hidden layer)

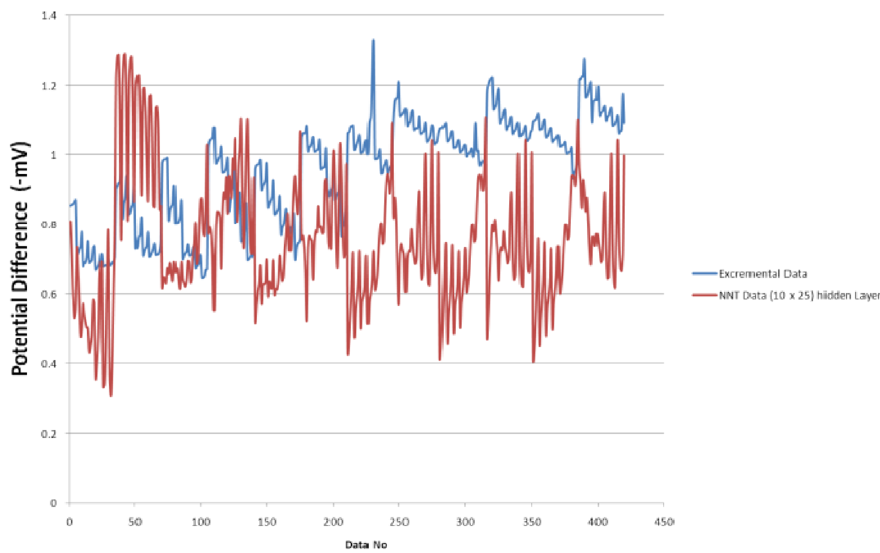

Fig. 20: Comparison between experimental data and NNT data of potential difference for bared pipe of NNT which has two hidden layers (10 neurons 1st hidden layer and 25 neurons in 2nd hidden layer)

Neural networks for bared pipe: For this type of pipe, the collected experimental data are not stable as shown in Fig. 17 to 22. The fluctuation of the data occurs due to the interference between the bare part of pipes and the protected parts; this will cause the un-stability of potential. This un-stability of potential was not happened in the coated pipe because the coated pipe has a uniform structure due to the isolation of coated layers which gives uniform polarization. This fluctuation is affecting on the training process of neural networks. For that reason, all proposed networks will not give good results as shown in Fig. 18 to 22.

The significant of this study it is predictive route for protection for pipeline methods (Al-Shareefi, 2009).

CONCLUSION

This study introduces a new topology to determine the performance of neural network corrosion control by the impressed cathodic protection which was used in petroleum and gas pipeline protection. The following conclusions can be deduced:

- The neural network control protects the pipeline from the corrosion. The controller is flexible and the curve mode corresponds well with the changing of the environment resistivity.
- The controller produces good results, compensating for changes in environment

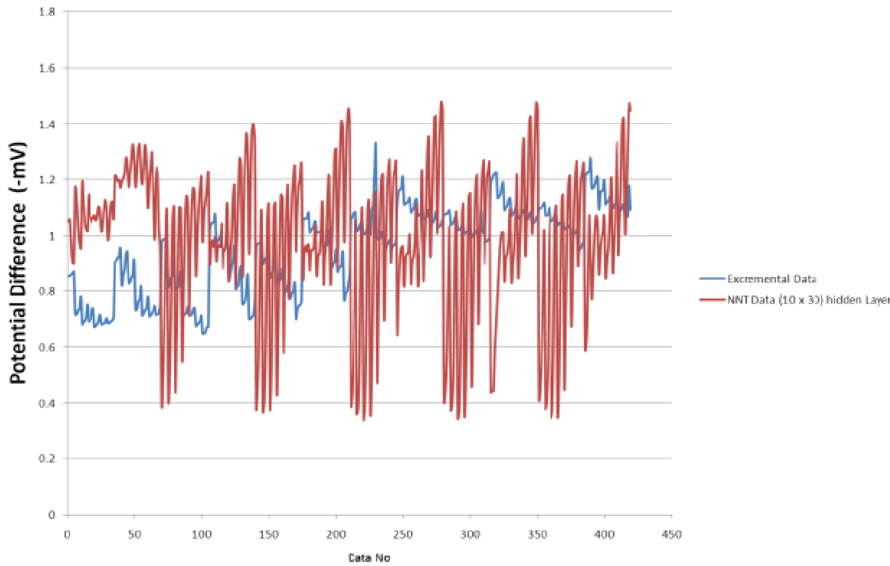

Fig. 21: Comparison between experimental data and NNT data of potential difference for bared pipe of NNT which has two hidden layers (10 neurons 1st hidden layer and 30 neurons in 2nd hidden layer)

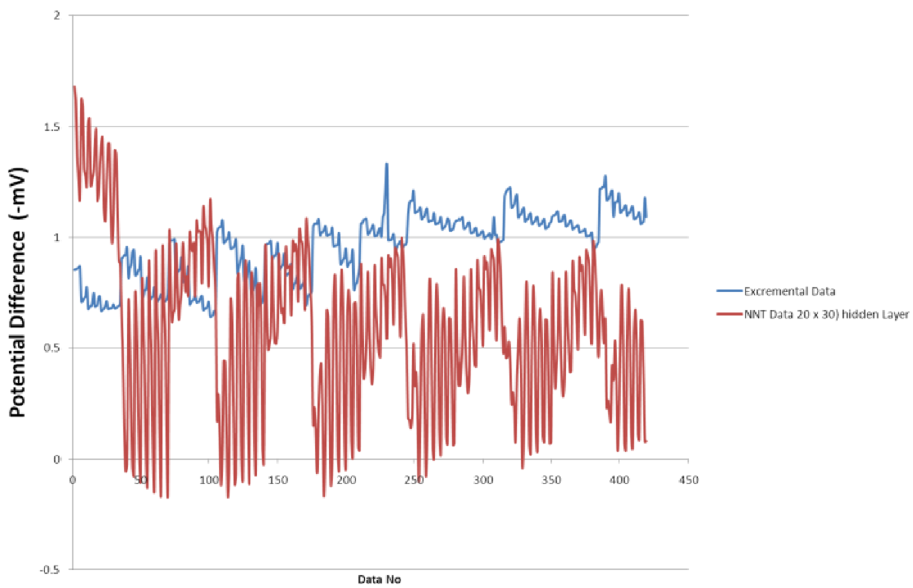

Fig. 22: Comparison between experimental data and NNT data of potential difference for bared pipe of NNT which has two hidden layers (20 neurons 1st hidden layer and 30 neurons in 2nd hidden layer)

resistivity, the distance between cathode and anode and protection voltage on a pipeline.

- The obtained results from the physical experimental works match the field results.
- The neural networks have manifested exceptional performance in predicting the corrosion protection for the current cathodic system.
- The neural networks are utilized as regression tool, especially when used for pattern recognition and function.
- The neural networks mimic the protection pipeline and operation of protection neurons and they have a unique quality of self-learning, mapping and functional approximation as shown in this study.
- The model that has been developed can be useful for planning, monitoring and design of remedial works as well as improvement of their cathodic protection.

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