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Modeling of contact wire's de-iceing phenomena using artificial neural networks

Modelowanie zjawiska odladzania przewodu jezdnego przy wykorzystaniu sztucznych sieci neuronowych

Abstract

The article presents results of iced wire's temperature approximation during process of heating this wire to melt ice. This approximation was implemented in Matlab using a two-layer feedforward artificial neural network (ANN). The results of the approximation are acceptable, but it is possible to improve them.

Keywords: melting of ice, iced wire, artificial neural network;

Streszczenie

W artykule przedstawiono wyniki aproksymacji temperatury oblodzonego przewodu podczas procesu jego nagrzewania w celu roztopienia osadu. Do aproksymacji wykorzystano sztuczną sieć neuronową (SSN) dwuwarstwową typu feedforward, zaimplementowaną w środowisku Matlab. Uzyskane wyniki aproksymacji są zadowalające, niemniej istnieje możliwość ich polepszenia.

Słowa kluczowe: topienie oblodzenia, oblodzony przewód, sztuczne sieci neuronowe;

1. Introduction

Railway malfunctions causes obstacles for people to reach the workplace which results people's change mean of transport to cars. Finally it increases traffic in cities and leads to traffic jams and wasting of time being inside. The winter is season in which probability of fault on railway is higher than during other seasons. Snow and rain fall in conjunction with gusts of wind can create hoarfrost or ice on the surface of contact wires which is a kind of electrical isolation. This isolation causes problem of electrical locomotive riding.

Exists a lot of methods to get rid of ice or hoarfrost from catenary lines which presents that icing problem is actual and could be solved based on different models of de-icing. Process of melting ice on catenary wires require contact wire – ice system's substitute thermal coefficient changes. During de-icing process coefficient will be decreasing from start value, depended of ice thickness, to value of wire's material thermal coefficient. Authors of this article want to present one of method to model processes of changing temperature according to substitute thermal coefficient value and melting time, during wire's de-icing. At the beginning of de-icing process, it will be heating of ice to temperature of zero degree, and then physical transformation ice into water. It will be the method based on artificial neural network analyzes. Wire's temperature calculations using substitute thermal coefficients let to obtain charts of contact wire's temperature as a function of time.

2. The use of an artificial neural network in the analysis of a selected overload

Artificial neural network (ANN) is a general name for mathematical structures and their software or hardware models, which perform calculations or signal processing by rows of elements called artificial neurons. Artificial neurons realize some basic operations on their input. The original inspiration for ANNs was the structure of natural neurons, synapses connecting the neurons and nervous systems, especially a brain [7, 9]. The neural network algorithms in traction research were used in: [2, 3, 6, 8].

2.1. Introductory information and input data

The calculations were performed using Matlab R2011B version. The input data for the ANN analysis were in this case 2102 pairs of numbers. In each pair one of the numbers (Input) was the time value and the other number (Output) was the temperature corresponding to the time.

Measurement data processing was performed using a two-layer feedforward neural network implemented in Matlab. Fig. 1 shows the neural network block created in the Simulink environment.

Fig. 2 depicts the created neural network structure. This structure had one hidden layer consisting of seven neurons. There were no delays implemented on the input for this layer. The activation function for the hidden layer was tangensoidal (tansig). Fig. 3 presents how the hidden layer looks like. The output layer had a linear activation function.

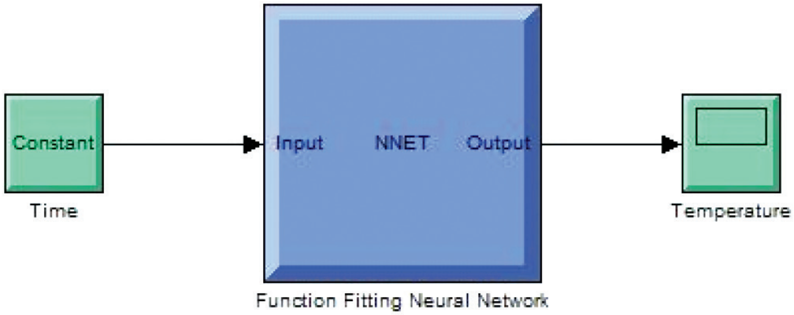

Fig. 1. The neural network block created in the Simulink environment. Own work

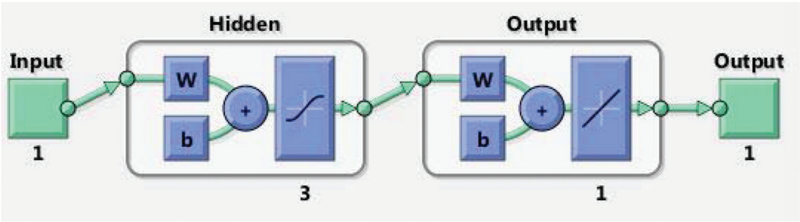

Fig. 2. The created neural network structure. Own work

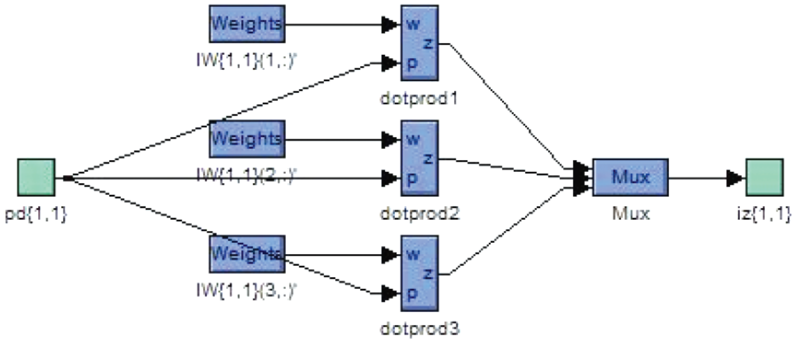

Fig. 3. The hidden layer of created neural network. Own work

The aim of the study was to fit a function between temperature variability phenomena corresponding to melting time.

The results shown below in Subsection 3.2. were obtained for the following ANN training settings [1]:

- maximum number of epochs to train: 10000;
- performance goal: 0;
- learning rate: 0,01;
- maximum validation failures: 12;
- momentum: 0,9;
- minimum performance gradient: 10^{-10};

- epochs between displays: 25;
- maximum time to train in seconds: infinite.

In order to teach the designed artificial neural network, the one-way network (up to 3 layers) training was used according to the Leveneberg-Marquardt algorithm.

2.2. Computation

Fig. 4 depicts results obtained from the training, validation and test of the ANN in the form of an error histogram.

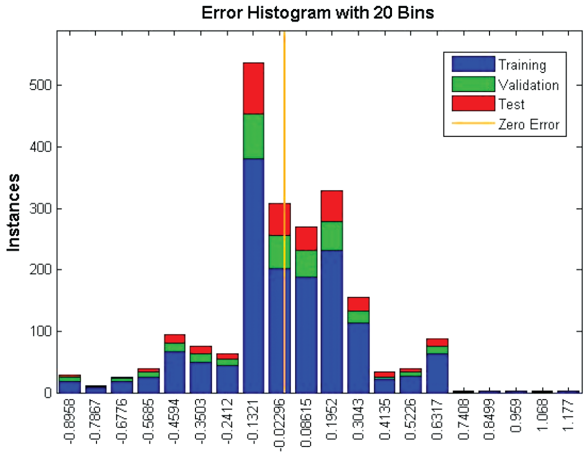

Fig. 4. Error histogram. Own work

Fig. 5 shows the illustration of performance of the ANN for successive learning epochs.

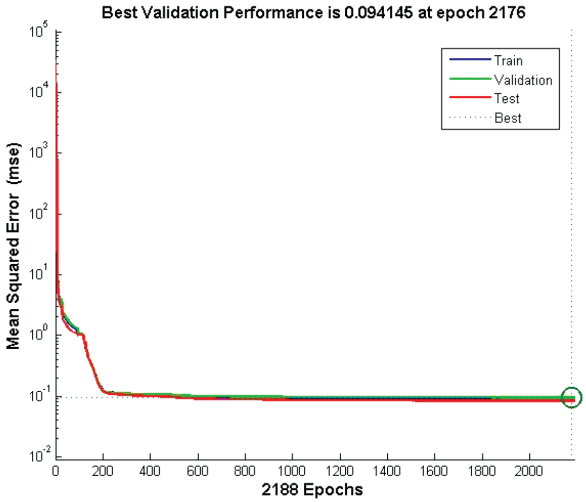

Fig. 5. Performance of the ANN. Own work

Fig. 5 presents the artificial neural network performance graph during its learning. The ordinate axis refers to the ANN performance function values. Mean square error (mse) was chosen as the performance function. The horizontal axis corresponds to learning epochs. The system reached the best neural network validation of the ANN performance for the 2176th epoch and it was equal to 0,094145. One can observe that the neural network system continued the learning algorithm for another 12 epochs in order to confirm the alleged local minimum for the goal set for the created network structure (Fig. 2). From epoch 1 to 2176, a downward trend in validation tests of the ANN learning can be seen.

Fig. 6 depicts the regression results for the training, validation and test and the regression for all data assigned to the ANN learning with a supervisor. Here, the ordinate axis represents the neural network output for the given input data. The abscissa axis shows values from the actual measurements (targets), to which the values returned by the ANN should be convergent.

The $R = 1$ regression result means that there is an unequivocal relation between the actual value (target; from measurement or simulation) and the neural network output value.

The regression results for the discussed case are as follows. The regression for the data assigned to the training reached $R = 0{,}99999$. The data constituted about 70% of all data assigned to the ANN learning with a supervisor. The regression for the validation was equal to $R = 0{,}99999$. The data used for this step were about 15% of all data. Lastly, the regression for the test was $R = 0{,}99999$. Consequently, the data used in this stage was about 15% of all data. One more regression value was calculated, for all data, and it was equal to $R = 0{,}99999$.

The training, validation and test are performed during the procedure of the neural network learning.

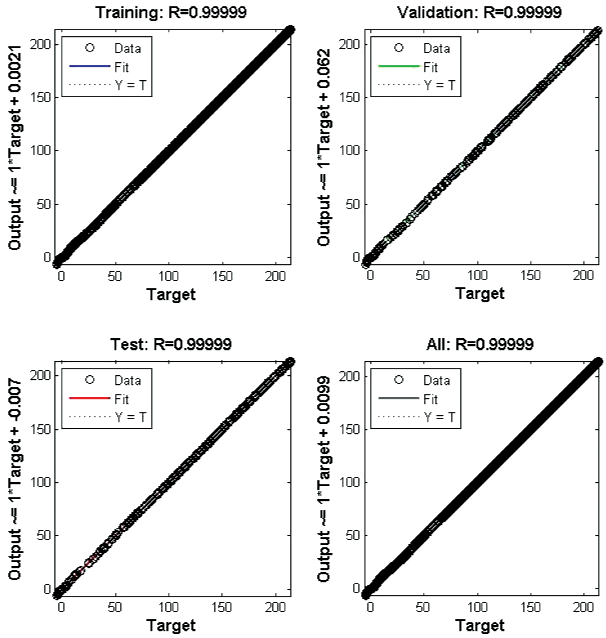

Fig. 6. Regression results for the training, validation and test and the regression for all data assigned to the ANN learning with a teacher. Own work

Figure 7 presents the results obtained from the approximation process (function fitting process) performed by the artificial neural network learning. In this figure, dots represent actual values of the substitute thermal factor obtained from measurements (targets), while cross marks represent results of the approximation. Vertical lines are absolute errors between actual values and the corresponding results obtained by the function fitting process. The solid line is the plot of the resulting approximating function.

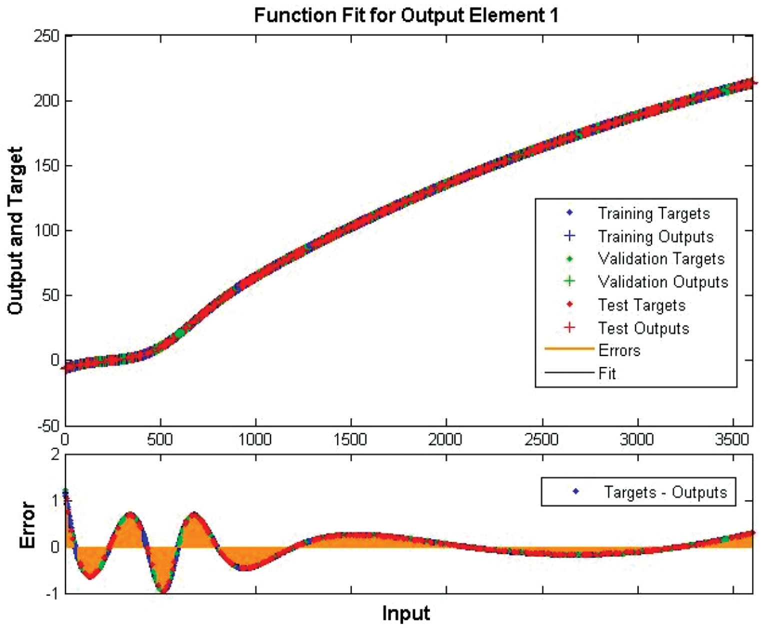

Fig. 7. Results of function fitting with the use of the ANN. Output – temperature, input – time. Own work

3. Conclusions

The calculation results shows that the described phenomena can be modeled with almost 100% precision. Getting to know the possibilities (specificity) of neural networks applied for studies of catenary lines de-icing. Results obtained during analysis presents that data using in calculations are correct. It is really important to confirm regularity of outcome, because it can simplify understanding of melting ice process on catenary lines and it is possible to use this knowledge during power circuits and emergency state protection designing. Authors agrees that it exists the potentiality to improve calculation to exactly 100% precision. Such studies will be continued.

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