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Prediction of Energy Losses through Thermal Lines Using Artificial Neural Networks

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Abstract: ***The energy losses through thermal pipes is determined today by a series of formulas that take into consideration very few standard variables. Therefore, a rough value is usually used by engineers to compensate for any rogue factor they haven't predict. This paper presents a method for predicting the specific heat loss through transport and distribution pipes taking into consideration the nonlinearity problems of different physical, thermic and climatic variables. This method can be used with great ease in any application that is designed to optimize the heat loss through the transport and distribution system of heat and hot water. To this end, several artificial neural networks were built, trained and tested, generating a computer software that can be used for future determinations.***

Keywords: energy, dynamic variable, residential thermal systems, artificial neural networks

1. Introduction

The problem of determining the specific heat loss through transport and distribution water pipes is extremely difficult by conventional methodology because of the nonlinear relationship between the input parameters and output, the large number of physical, thermal and climatic variables needed and the interdependence between them. Another problem is the need to repeat the calculations for any modification of these values, which implies the lack of appreciation for previously obtained data. Solving this problem by using artificial neural networks will allow to accurately determine the results almost instantly, without the need to use mathematical modeling of the process and repeating these calculations for new situations [1].

In order to determine the specific heat loss, one must take into consideration the outside temperature variation throughout the cold season, thus necessitating multiple climate data. Also, the thermal characteristics of the pipe insulation must be taken into account in order to determine the thermal resistance or transmittance. Another factor that the determination of heat losses depends upon in a nonlinear form is the material of the pipe and its characteristics. These can be seen as just a few of the reasons why artificial neural networks method could be used successfully in operating with these parameters [6].

2. Theoretical considerations on Artificial Neural Networks (ANN)

An artificial neural network is defined as an evenly distributed information processor with the ability of experimental data storage and prediction on new input cases. The information processing module mimics the human brain activity forming patterns by studying the existing situations and applying the knowledge to generate predictions about new situations.

ANN's are used in the engineering field as an alternative method of analysis and prediction. Neural networks operate successfully in most cases where conventional methods fail, data analysis being applied at present to solve a variety of nonlinear problems such as pattern recognition. [3]

Instead of using complex rules and mathematical routines, ANN's are able to learn the key information patterns within a multidimensional information domain. In addition, neural networks successfully eliminate data entry errors and supplementary information irrelevant to the processes, becoming robust tools for data modeling and prediction [4].

3. The database construction for the ANN's training

The database that will be used to train the neural network must contain a sufficient number of cases in order for the method to have a general application. Also, the cases should be evenly distributed over the length of analyzed interval, in order for the level of accuracy in predicting future cases to be as high as possible.

3.1 Initial hypothesis

The first step in building the neural network is to establish the most important thermal characteristics of the pipes. In this regard steel was chosen for the construction of the pipes having the following characteristics:

- Density of δ= 7850 [kg/m^3];
- Specific heat c= 465 [J/kgK];
- Thermal conductivity λ=45[W/mK]

The fluid within the pipe is water having:

- Density of δ_{water} = 983,2 [kg/m3];
- Specific heat c_{water} = 4185 [J/kgK];

3.2 Selecting the input and output parameters

Given the data available, the following variables are chosen to represent the input parameters of neural network, being the input neurons of the network as well:

- Dn the nominal diameter of the pipe [mm];
- $\Delta\theta$ the temperature difference between the water temperature θ_{hw} and the environment θ_{amb}[°K];

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- D_{iz} the thickness of the insulation[mm];

The variable chosen to represent the output parameter of the neural network and also the output neuron is:

- q_{spec} the specific energy loss [W/m].

3.3 Construction of the ANN's training file

For constructing the database iterative calculations were made for 12 different dimensions of the pipes diameter, 10 values for the insulation thickness and 7 values for the temperature difference:

- D_n : 8, 10, 15, 20, 25, 32, 40, 50, 65, 80, 90, 100 [mm];
- $\Delta\theta$: 40, 50, 60, 70, 80, 90, 100, 110 [°C];
- D_{iz} : 6, 9, 13, 19, 32, 40, 50, 65, 80, 90, 100 [mm].

In the end, 580 sets of values were obtained, being organized on spreadsheets and stored in the ANN's training file.

4. The construction and the training of the ANN

The program Tiberius Data Mining, version 7.0.4, was used for the construction of the neural networks, for which an academic license was obtained.

In order to determine the right architecture of the network, a series of trials were made. The final architecture is composed of 4 neurons on the input layer (3 corresponding to the input parameters and one to the Bias), and one neuron on the output layer corresponding to the output parameter.

Regarding the neurons on the hidden layer a series of configurations were examined in order to reduce the errors, arriving at a number of 6 neurons.

The final architecture of the neural network created is being presented in Figure 1.

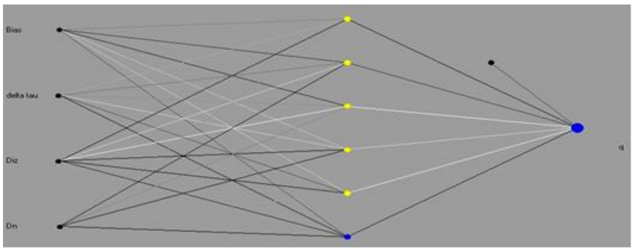

Figure 1: The architecture of the neural network

The training process was conducted at a rate of 0.4 and the number of epochs was originally established at 5000. The last adjustment for the synaptic weights occurred after 2591 epochs.

The specific heat loss targeted values for the network's testing; the modeled values and the errors between the two of them for 15 of the 60 test cases contained in the test file are shown in Table 1. Differences between the targeted values introduced and the model output of the neural network do not exceed 1 [%] which allows for the next step to occur, which is the validation of the method for determining the specific energy loss.

Table 1: The testing results of the ANN

Case number	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Targeted q_{spec} value	9,35	12,06	14,45	15,07	21,07	25,64	30,05	32,05	43,60	44,88	53,25	60,35	73,59	89,00
Modeled q_{spec} value	9,3188	12,4881	14,1067	15,0186	21,7010	25,2621	29,6643	31,5860	43,5584	44,1757	53,6882	60,4023	73,8663	89,5949
Error	-0,03121	0,42808	-0,34331	-0,05136	0,63097	-0,3779	-0,38571	-0,464	-0,04162	-0,70429	0,43815	0,05228	0,27883	0,5949

The chart for the targeted values and the modeled values of the specific heat loss and the error between them for 70 out of 580 cases on which the neural network gets validated are shown in Fig. 3. It can be seen an almost perfect overlap between the two graphs, which demonstrates the networks capability to determine the required value with sufficient accuracy.

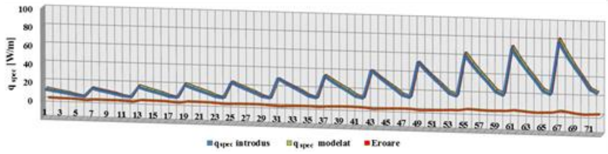

Figure 2: The chart for the targeted, the modeled values and the error for the ANN

Once trained for these cases, the neural network can predict the specific heat losses through the external pipe wall structure for new cases, by modifying any of the input neurons values. The new values must not exceed the trained interval by a large amount; otherwise the possibility of error will increase.

Table 2 contains the relative contribution of the neurons in the hidden layer which help to determine the final result for the 580 cases used. It can be seen that each neuron of the hidden layer contributes at some point to the correct solving of the non-linearity between the input parameters and the output result.

Neuron Number	Neuron's Name	Relative Importance	Level of Importance
1	Dn	1,000	
2	Diz	0,652	
3	delta tau	0,470	

Table 2: The testing results of the ANN for determining the specific heat loss

In the end a software program was generated by the networks that can determine the specific heat losses for the transport and distribution steel pipes in the conditions mentioned above. The last two columns of the program are showing the minimum and maximum values experimented by the neural network in the training process. The software's interface generated with the neural networks is shown in Figure 3.

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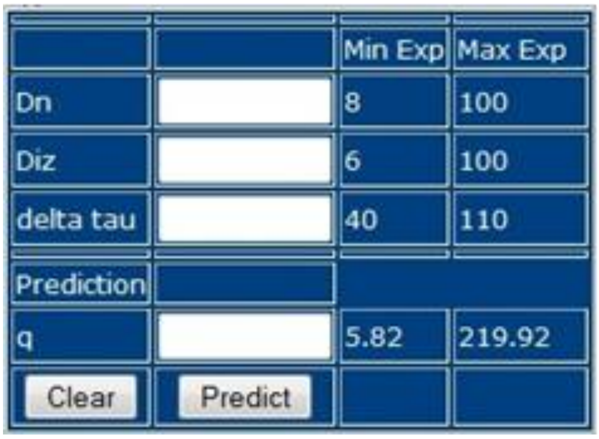

Figure 3: The interface of the software program created with the neural network

5. Conclusions

The application of the neural network to determine the energy losses through different transport and distribution pipes can be done successfully due to their ability to overcome the problems of non-linearity between the input parameters and the values to be calculated.

The software program generated by using neural networks allows the determination of accurate values in a very short period for any input values that don't exceed the intervals that the networks experienced during training. To extend these intervals one must increase the number of cases used to train the networks to include the new values in the process of modifying the synaptic weights.

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Author Profile

Rusu Daniel Sorin received his Phd. Diploma in Civil Engineering from Techincal University of Cluj-Napoca in 2012. Currently he is a lector at the Faculty of Building Services, specialized in Computer Aided Engineering. He is also a consultant and a designer in energy efficiency systems for residential and industrial sectors.

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