Neural network modeling of surface heat transfer intensifiers in the form of segment recesses

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Abstract. The results of neural network modeling of surface heat transfer intensifiers in the form of spherical recesses are presented, based on experimental data. The possibility and prospects of building artificial neural networks for modeling the characteristics of heat exchange surfaces are shown.

Introduction
Currently, all the generated thermal energy before its use is repeatedly converted into various heat exchangers. Therefore, the efficiency of the entire production depends on the efficiency of heat exchangers. Intensification of heat exchange and increase of energy efficiency of heat exchangers are of great interest and are of great importance for many industries.

Surface heat transfer intensifiers in the form of hemispherical (segmental) recesses and projections are widely used in heat exchange equipment. Interest in this type of intensifiers has increased after the appearance of messages on increasing the heat transfer coefficient while reducing the hydraulic resistance. [1-3] and others. They can significantly improve the efficiency of heat exchangers. It is particularly advantageous to use such heat exchangers in high-energy installations.

The design of intensified heat exchangers with optimal characteristics is complicated by the problem of generalization of research results. The analysis of literature sources shows that it is impossible to generalize the characteristics of surface heat transfer intensifiers by conventional conservation equations due to the complexity of thermal and hydro-mechanical processes. The latter is also due to the large number of design parameters of intensifiers in the form of hemispherical (segment) recesses. If it is possible to generalize the results of the research in the form of empirical formulas of the dependence of the Nusselt numbers on the Reynolds and Prandtl numbers with the involvement of the determining dimensions, then, as a rule, for a narrow class of single recesses or systems of recesses in the range of parameters of the experiments [4].

A certain way out of the situation is offered by artificial intelligence systems capable of learning or self-learning. These are artificial neural networks. Neural network modeling allows to generalize the results of the experiments of complex multiparameter processes, “looking” beyond the range of parameters in which the experiments were conducted. In neural networks, knowledge is contained in the States of many neurons and connections between them. A neural network with a certain number of inputs and outputs is constructed from neurons (nodes) connected in a certain way.

The neural network operation consists of two stages: training the network to "correct" or adequate response to the input information (input vector) and using the trained network to recognize input vectors. The last stage is often called testing. In other words, the network learns to recognize input
vectors, i.e. to form output vectors corresponding to the recognized class of input vectors.

When testing (using) a trained neural network, the process of finding the nearest minimum of the objective function occurs. This restores the distorted bits of the input vector or “remembering” the unknown bits associated with the given (known) bits.

**Neural network modeling**

Artificial neural network is implemented using neurospace ”NeuroSolutions”. It contains a master of neural network architectures (“NeuralWizard”), which is used to set the architecture, select the training sample, the training criteria. When solving the task we used a version of the program with full functionality.

Experimental material was used as a “teacher” [5]. Table 1 presents the relative geometric parameters of the channels and spherical recesses.

**Table 1.** The relative geometric parameters of the investigated channels and spherical recesses.

| №  | h     | D     | H      | h/D   | H/D   | h/H   |
|----|-------|-------|--------|-------|-------|-------|
| 1  | 0.00071 | 0.00514 | 0.012  | 0.138 | 2.334 | 0.059 |
| 2  | 0.0015  | 0.00714 | 0.012  | 0.21  | 1.68  | 0.125 |
| 3  | 0.003   | 0.00916 | 0.012  | 0.327 | 1.31  | 0.25  |
| 4  | 0.005   | 0.01   | 0.012  | 0.5   | 1.2   | 0.416 |
| 5  | 0.00071 | 0.00514 | 0.01   | 0.138 | 1.945 | 0.071 |
| 6  | 0.0015  | 0.00714 | 0.01   | 0.21  | 1.44  | 0.15  |
| 7  | 0.003   | 0.00916 | 0.01   | 0.327 | 1.091 | 0.3   |
| 8  | 0.005   | 0.01   | 0.01   | 0.5   | 1     | 0.5   |
| 9  | 0.00071 | 0.00514 | 0.008  | 0.138 | 1.556 | 0.088 |
| 10 | 0.0015  | 0.00714 | 0.008  | 0.21  | 1.12  | 0.187 |
| 11 | 0.003   | 0.00916 | 0.008  | 0.327 | 0.873 | 0.375 |
| 12 | 0.005   | 0.01   | 0.008  | 0.5   | 0.8   | 0.625 |
| 13 | 0.00071 | 0.00514 | 0.005  | 0.138 | 0.972 | 0.142 |
| 14 | 0.0015  | 0.00714 | 0.005  | 0.21  | 0.7   | 0.3   |
| 15 | 0.003   | 0.00916 | 0.005  | 0.327 | 0.545 | 0.6   |
| 16 | 0.005   | 0.01   | 0.005  | 0.5   | 0.5   | 1     |
| 17 | 0.00071 | 0.00514 | 0.002  | 0.138 | 0.389 | 0.355 |
| 18 | 0.0015  | 0.00714 | 0.002  | 0.21  | 0.28  | 0.75  |
| 19 | 0.003   | 0.00916 | 0.002  | 0.327 | 0.218 | 1.5   |
| 20 | 0.005   | 0.01   | 0.002  | 0.5   | 0.2   | 2.5   |

Here h is the depth or height of the notch or protrusion, m; D is the diameter of the notch, ledge, m; H is the height of the channel, m.

**Figure 1.** Setting parameters of artificial neural network
The synthesis and analysis of data on hydraulic resistance and heat transfer carried out in [5] allowed to make a sample of data for neural network modeling presented in Table 2.

**Table 2. Sampling data for training.**

| №  | ReD | Nu/Nu0 | ReD | Nu/Nu0 | ReD | Nu/Nu0 | ReD | Nu/Nu0 |
|----|-----|--------|-----|--------|-----|--------|-----|--------|
| 1  | 5400| 1      | 7800| 1.03   | 9200| 1.06   | 11000| 1.05   |
| 2  | 7000| 1.07   | 7000| 1.1    | 12000| 1.25   | 16500| 1.27   |
| 3  | 6500| 1.8    | 9000| 1.47   | 12000| 1.75   | 13400| 1.67   |
| 4  | 6200| 1.44   | 9000| 1.76   | 11800| 2.1    | 13000| 2.05   |
| 5  | 3800| 0.93   | 7800| 1      | 9700 | 1.06   | 12100| 1.07   |
| 6  | 3500| 0.93   | 5400| 1      | 7000 | 1.07   | 9000 | 1.18   |
| 7  | 9000| 1.7    | 12000|1.75   | 13000| 1.8    | 16000| 1.76   |
| 8  | 6200| 1.92   | 9500| 2.2    | 11400| 2.25   | 17000| 1.71   |
| 9  | 5500| 0.95   | 8000| 1.04   | 9700 | 1.26   | 14000| 1.3    |
| 10 | 6600| 1.6    | 5400| 1.05   | 7000 | 1.27   | 12000| 1.8    |
| 11 | 1900| 1      | 5000| 1.5    | 9000 | 1.83   | 12000| 1.75   |
| 12 | 5200| 2.1    | 6600| 2.24   | 9200 | 2.05   | 17000| 2.7    |
| 13 | 2500| 0.7    | 4300| 0.7    | 6000 | 0.83   | 8500 | 1      |
| 14 | 4700| 1.3    | 7000| 1.28   | 10000| 1.3    | 14000| 1.3    |
| 15 | 5900| 1.67   | 7100| 1.84   | 10000| 1.95   | 19000| 2.23   |
| 16 | 4800| 2.9    | 6600| 3      | 9900 | 3.14   | 13600| 3.3    |
| 17 | 4300| 0.7    | 5900| 0.8    | 8800 | 0.93   | 10200| 1      |
| 18 | 4700| 1.6    | 7400| 1.21   | 10800| 1.41   | 12200| 1.36   |
| 19 | 5500| 2.2    | 7200| 2.5    | 10000| 2.94   | 12400| 3.18   |
| 20 | 4400| 5      | 7200| 4.6    | 10800| 5.3    | 13000| 5      |

In accordance with tables 1 and 2 is a matrix that perceived neuropace "NeuroSolutions". Next comes the process of setting up the parameters of the artificial neural network, which is shown in figure 1.

After setting up the parameters, specifying the inputs and outputs of the network and the parameters of building the network, the program completes the work by creating a network (not yet trained, just structure). The network structure is shown in figure 2.
Next, go directly to the learning process, figure 3. In the learning process, you can observe a reduction in error, which depends on the number of lessons. This can be clearly seen in figure 4 a. Also in figure 4 b are graphs showing what values gives our history network in the learning process, and what there were values actually. Thus, according to the graphs it is seen that the learning error is small and the results of the network based on the training data are practically the same as the actual values of the sample. This allows us to conclude that the network training was successful, and we can start testing i.e. calculation of the probability with which the neural network will predict the results of the experiment.

As a test matrix, we use a matrix with unknown data that needs to be predicted, these are the data of \( \frac{Nu}{Nu_0} \) given in table 3.
Table 3. Sampling data for testing

| ReD | Nu/Nu0 | ReD | Nu/Nu0 | ReD | Nu/Nu0 | ReD | Nu/Nu0 |
|-----|--------|-----|--------|-----|--------|-----|--------|
| 3400 | 0.7    | 5150 | 0.765  | 7250 | 0.915  | 10000 | 1.01  |
| 5850 | 1.29   | 8500 | 1.29   | 12000 | 1.3    | 17500 | 1.3   |
| 6500 | 1.755  | 8550 | 1.895  | 14500 | 2.09   | 20000 | 2.19  |
| 5700 | 2.95   | 8250 | 3.07   | 11750 | 3.22   | 17050 | 3.21  |
| 5100 | 0.75   | 7350 | 0.865  | 9500  | 0.965  | 15400 | 1.01  |
| 6050 | 1.405  | 9100 | 1.31   | 11500 | 1.385  | 16100 | 1.43  |
| 6350 | 2.35   | 8600 | 2.72   | 11200 | 3.06   | 16500 | 3.36  |
| 5800 | 4.8    | 9000 | 4.95   | 11900 | 5.15   | 16850 | 4.92  |

After testing, the trained network showed the accuracy with which the data was predicted. This can be seen in figure 5, which shows the actual values (Des) and figure 6, which shows the values predicted by our network (Out).

Figure 5. Real values of the experimental matrix

| Cut (In/10) 1 | Out (In/10) 1 | Cut (In/10) 2 | Out (In/10) 2 | Cut (In/10) 3 | Out (In/10) 3 | Cut (In/10) 4 | Out (In/10) 4 | Cut (In/10) 5 |
|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| 0.820304297262  | 0.79000455921 | 0.897206329306 | 0.912779425242 | 0.8786667382542 |
| 1.0815675706444 | 1.149655962430 | 1.208916495947 | 1.153932961306 | 1.257582059310 |
| 1.665784803076 | 1.84619586214 | 1.941538783829 | 2.037423345181 | 2.105651486605 |
| 2.023159228982 | 2.775390383768 | 2.946733366088 | 2.988167473126 | 3.141591027704 |
| 0.891020362566 | 0.852899736836 | 0.968565772626 | 1.035620594839 | 0.96516719955 |
| 1.542118597050 | 1.65327301569 | 1.667093030003 | 1.59401254399 | 1.782034064606 |
| 3.05947648152 | 3.0729306591 | 3.36392411228 | 3.41030637966 | 3.45536102140 |
| 4.798449575329 | 4.385944985267 | 5.13682058267 | 4.783576601381 | 4.747279581283 |

Figure 6. The result of the test network (the Predicted value) Thus, we can see that the error is about 0.2 %.

Figure 7. Network prediction error

Conclusion

Thus, the possibility of constructing artificial neural networks for modeling surface heat transfer intensifiers in the form of spherical recesses is presented. Testing of the neural network has shown an error of modeling of 0.2 %, which can be considered satisfactory, given the spread in the sample of
data related to the error of the experiments. It should also be noted that for the practical use of the simulation results it is necessary to expand the range of data on the surface heat transfer intensifiers.

References
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