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Neural Network Modelling of Chosen Nonlinearities in Induction Heated Industrial Plants

1. Introduction

Dynamic and static characteristics of induction heated rotating steel cylinder depend among others on heat accumulation and heat losses from its surface. For the closed loop temperature control it is very important to estimate these factors. Heat accumulation, depending on material parameters of the cylinder, can be treated as constant value, whereas value of heat losses can not. It is especially noticeable if cylinder rotation speed changes significantly which results in changing of heat exchange condition. From the entire system point of view these phenomena is another source of nonlinearity which should be compensated within temperature control loop. Therefore the determination of actual value of convection coefficient becomes an important issue if high temperature control accuracy is to be assured. However, there is no good theory which explains phenomena of heat exchanging between surface of the rotating cylinder and environment. Thus for convection coefficient evaluation two methods are proposed in this paper – classic optimization (based on widely used algorithms) and artificial neural network as well accepted tool for nonlinearity modeling.

2. Numerical model of induction heating process of a rotating cylinder

The analyzed heating laboratory system consists of: 1.2 m long steel cylinder, six inductors (nominal power 1.5 kW) and six K-type infrared thermocouples for temperature measurement, giving six heating zones and six measurement channels for temperature control [3, 4]. Properties of such a heating system can be modelled by a numerical model based on adequate thermal laws shown in Figure 1 [1, 2, 5].

The following simplified assumptions in numerical modelling have been made:

- Eddy currents, induced in the cylinder mantle, are replaced by sets of nodes with active power placed near the penetration depth.

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- Values of active power put in nodes were determined by prior inductor-cylinder system electromagnetic calculations and verified by calorimetric method [2].
- Two dimensional model is considered, because the heat conduction along the cylinder axis and through its thickness are the most important factors from system dynamic point of view.

In the paper, the rotating steel cylinder with six heating zones has been taken into consideration. Meshing of the simulated area, heating nodes and boundary conditions are shown in Figure 1.

Such a model can be a very convenient, time-saving tool for analysis of various working conditions of the device. The heat exchange from the cylinder surface can be simulated by total heat transfer coefficient α expressed in [W/(m^2·K)]. The reliable knowledge about value of this coefficient provides good compatibility between the numerical model and the real laboratory system.

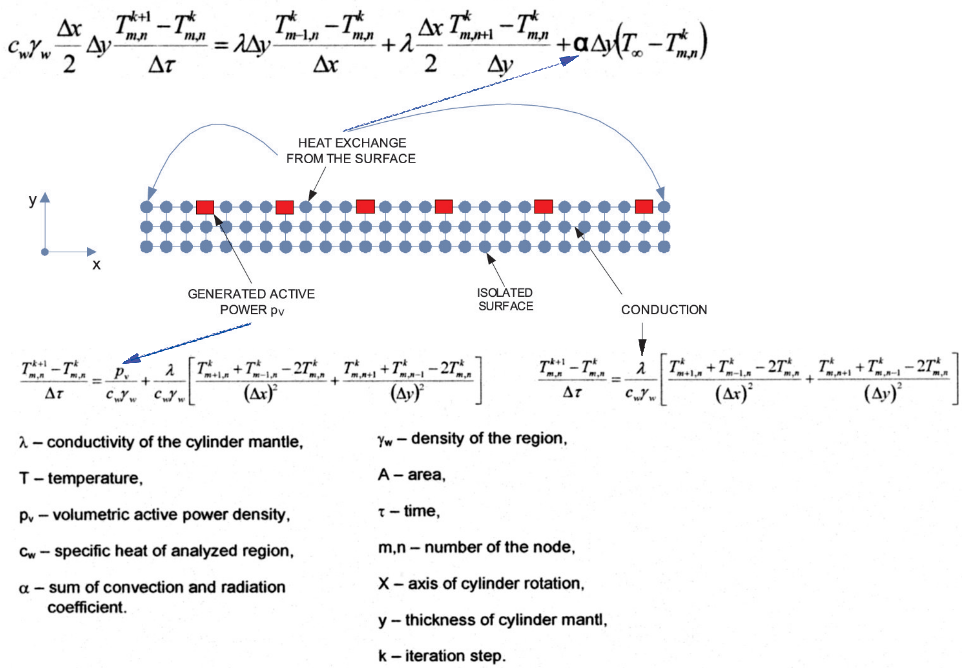

Fig. 1. The outline of numerical model of rotating steel cylinder with thermal boundary conditions. Equations shown in Figure are discrete form of Fourier thermal lows

3. Determination of convection by Nelder–Mead simplex direct search method

It is well known, that intensity of heat losses between the surface of the rotating cylinder and environment depends on its rotation speed. The shape of heating-up curve and steady-state surface temperature also depend on heat exchange coefficient.

First method of determination of the heat exchange coefficient is based on approximation simulated and measured step input temperature response. In this case the classic optimization method (Nelder–Mead simplex direct search method) has been implemented in Matlab optimization toolbox environment [6]. Using this method heat exchange coefficients for four different cylinder's rotation speed have been determined Results are shown in Figure 2.

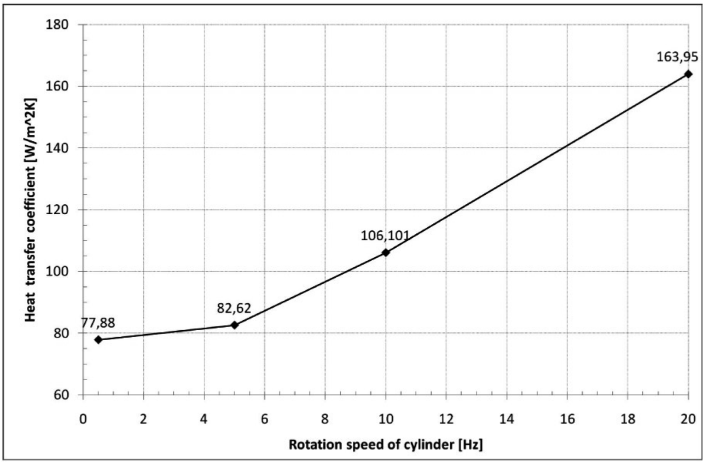

Fig. 2. Dependence of the heat transfer coefficient on the rotation speed of the cylinder

In Figure 3a and 3b it can be seen a very good correlation between measured step-input response of the cylinder and its numerical model, for two exemplary values of cylinder rotation speed – 6 rpm and 120 rpm. On this basis, the heat transfer coefficient can be determined and used for description of heat exchange between rotating cylinder surface and the environment.

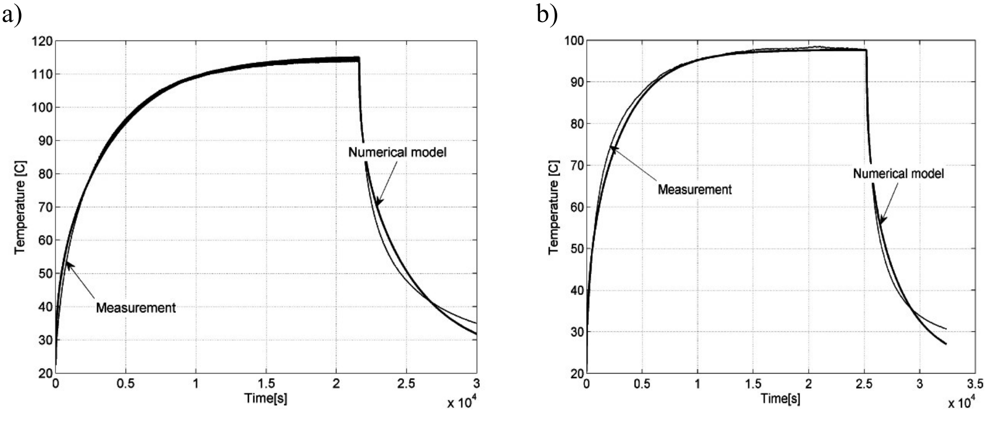

Fig. 3. Comparison of measured temperature step-input response and derived from the numerical model (a) for 6 rpm; b) for 120 rpm of rotation speed)

4. Determination the heat transfer coefficient by artificial neural network

As the second method of determination of the heat transfer coefficient the artificial neural network's algorithm has been proposed. In this case the network structure, number of neurons in hidden layers, and learning algorithm must be predetermine [7]

4.1. Structure of neural network and its learning algorithm

For the determination of heat transfer coefficient a static, double layer artificial neural network with backpropagation learning algorithm has been proposed [7]. This network is shown in Figure 4.

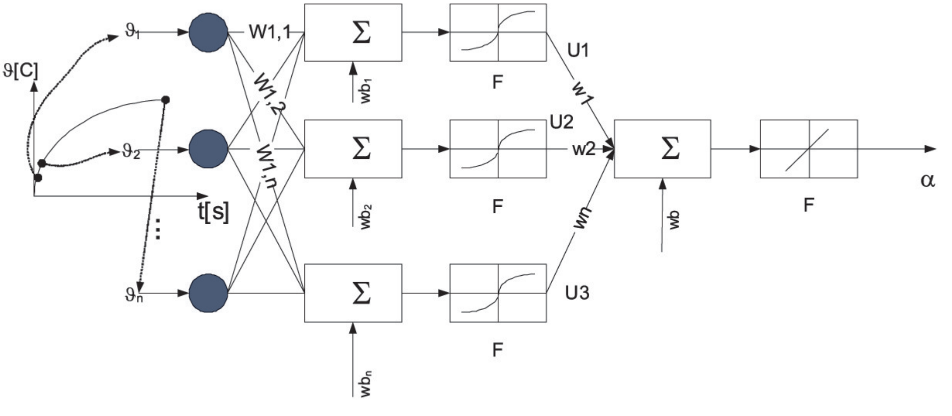

Fig. 4. Static neural network scheme for heat transfer coefficient learning (*n* – number of network inputs determined by number of discrete samples of step-input response)

In such a network the set of temperature patterns (composed of heating-up curves) are fed in parallel mode as an input signal. The targets are the set of convective heat transfer coefficients corresponding to each pattern. The input matrix Θ expressed by equation (1a) contains exemplary input samples while the target matrix A by equation (1b):

$$\Theta = \begin{bmatrix} \vartheta_1^1 & \vartheta_1^2 & \dots & \vartheta_1^m \\ \vartheta_2^1 & \vartheta_2^2 & \dots & \vartheta_2^m \\ \dots & \dots & \dots & \dots \\ \vartheta_n^1 & \vartheta_n^2 & \dots & \vartheta_n^m \end{bmatrix} \tag{1a}$$

$$\mathrm{A} = \begin{bmatrix} \alpha_1 & \alpha_2 & \dots & \alpha_m \end{bmatrix} \tag{1b}$$

where:

υ_i^j – samples of temperature,

$i = 1 \dots n$ – number of samples in one learning pattern,

$j = 1 \dots m$ – number of learning temperature patterns,

α_ι – examples of heat transfer coefficient for j patterns.

The network structure consists of input, hidden and output layer. Quality of network learning depends on a number of neurons in hidden layer and number of input patterns.

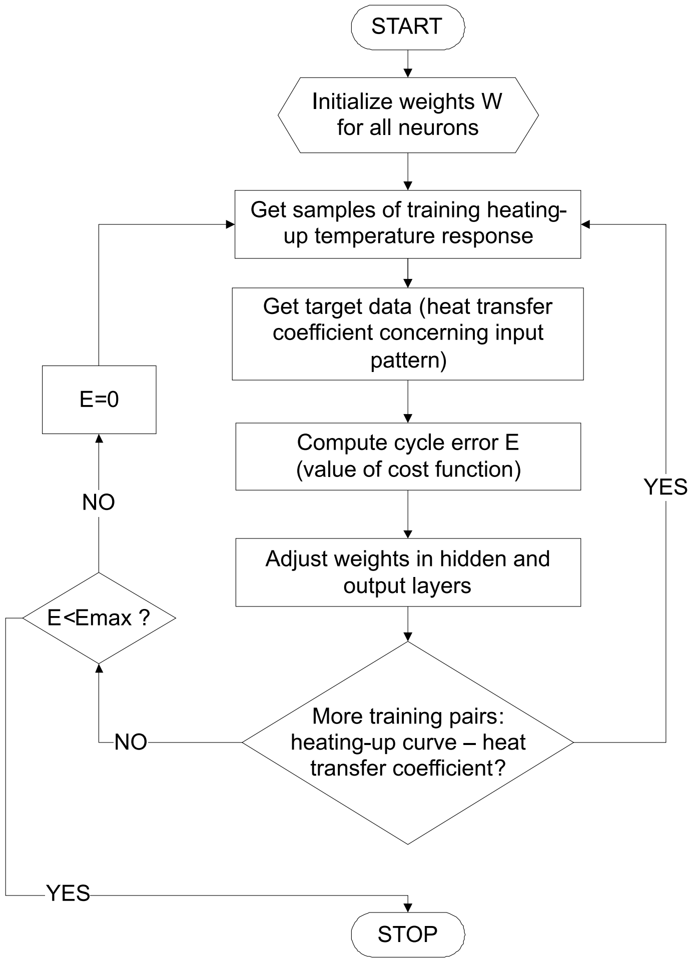

Fig. 5. Diagram of network learning procedure for determination of heat transfer coefficient

Diagram of heat transfer coefficient learning (i.e. changing of network weights) is presented in Figure 5. The learning error (objective function) which should be minimized can be expressed by equation (2) [8].

$$E = \frac{1}{2}\sum_{k=1}^{M}\left[f\left(\sum_{i=0}^{K} W_{ki}^{(2)} U_i\right) - \alpha_k\right]^2 = \frac{1}{2}\sum_{k=1}^{M}\left[f\left(\sum_{i=0}^{K} W_{ki}^{(2)} f\left(\sum_{j=0}^{N} W_{ij}^{(1)} \vartheta_j\right)\right) - \alpha_k\right]^2 \quad (2)$$

where:

l – number of layers,
N – number of network inputs,
K – number of neurons in hidden layers,
M – number of neurons in output layer,
W – weights of neurons,
f – activation function,
U_i – output signal from i^{th} neuron in hidden layer,
ϑ – samples at the network input,
α_κ – target, network output,
j – number of learning samples,
sup(2), sup(1) – hidden layer, input layer.

In order to reach a compromise between reasonable results and calculation time the Levenberg–Marquat's regularization optimization method of error function E has been used [8].

4.2. Generating training data

Training data for teaching of artificial neural network can be obtained from numerical model. It is a very convenient and time saving way of generating training data as it enables to obtain many learning patterns (e.g. step-input response curves) for various sets of model parameters. An example of six heating-up curves for chosen heat transfer coefficient α have been shown in the Figure 6.

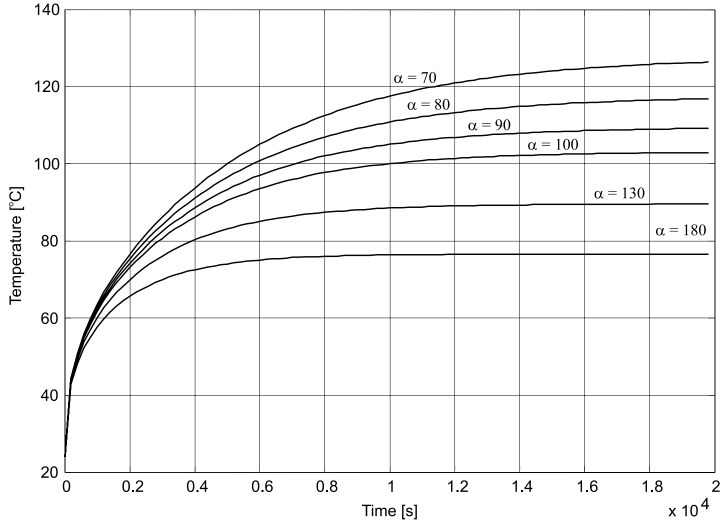

Fig. 6. Exemplary heating-up curves for teaching neural network

The essential questions in learning of artificial neural network are as follows:

- What is the smallest number (*m* in equation (1a) and (1b)) of patterns that should be given to the network input to correctly recognize heat transfer coefficient?
- What is the smallest number of neurons in the hidden layer providing the best quality of learning?

To answer these questions a various number of learning patterns and number of neurons in network hidden layer (10, 13, 15, 17, 25) have been examined. Values of the target matrix A corresponding to number of heating-up curves are presented in Table 1.

Table 1
Values of heat transfer coefficient in target matrix A (eq. 1b)

	Values of heat transfer coefficient W/m/m/K					
No of patterns (heating-up curves)	**α=70**	**α=80**	**α=90**	**α=100**	**α=130**	**α=180**
6	**X**	**x**	**x**	**x**	**x**	**x**
5	**X**		**x**	**x**	**x**	**x**
3	**X**			**x**		**x**
2	**X**					**x**

In order to verify neural network usefulness another patterns (not included in learning set) have been put to the input of the network. These are step-input response curves Θ corresponding to the set $\mathbf{A_{test}}$ = [50, 75, 110, 140, 170]. In Figure 7 errors of network answer for different number of neurons in the hidden layer and different test patterns Θ have been shown. The cost function of learning is defined by the following equation:

$$Mean\ \ error = \sum_{i=1}^{N} \frac{\sqrt{\left(\dfrac{\alpha_{pattern} - \alpha_{determined}}{\alpha_{pattern}}\right)^2} \cdot 100\%}{N} \tag{3}$$

where:

N – number of patterns,

$\alpha_{pattern}$ – heat transfer coefficient for pattern heating-up curve,

$\alpha_{determined}$ – determined heat transfer coefficient.

It can be seen that for fixed number of learning patterns there is an optimal neural network structure which ensures minimal value of the cost function (3). It is also worthwhile to notice that even 3 learning pairs are enough to obtain cost function not exceeded 20%. Of course for 6 and 5 learning patterns the smallest error is less than 3%.

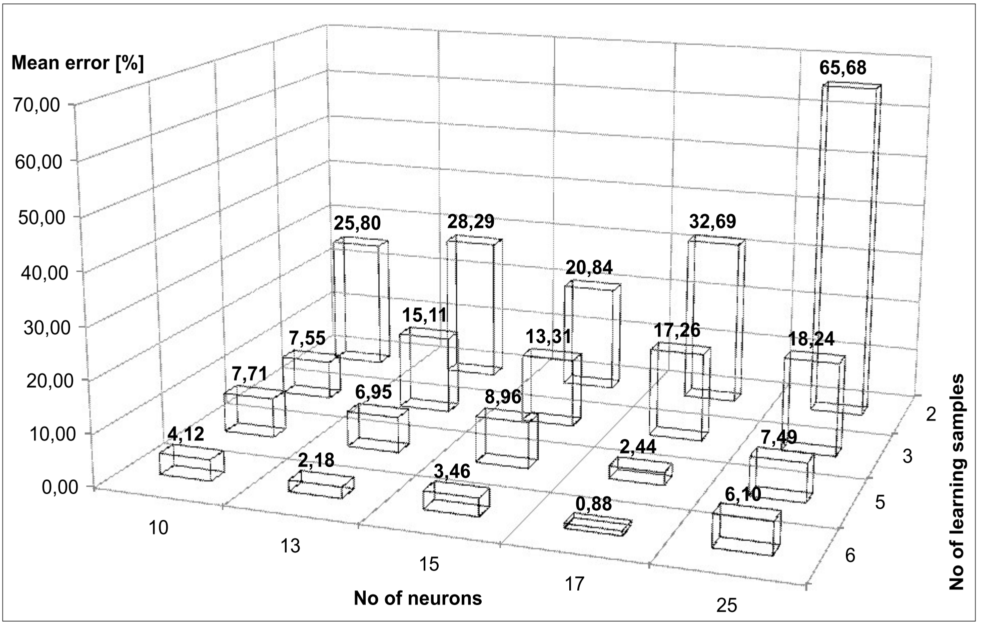

Fig. 7. Error between test patterns of step input response and determined heat transfer coefficient derived from numerical model

4.3. Verification of measurement data

The goal of learning of the described above neural network is to provide system for automatic recognition of heat transfer coefficient basing on heating-up curve measured on the semi-industrial rotating cylinder.

Investigated neural network system have been tested for 4 values of rotation speed of cylinder – 6, 60, 120 and 240 rpm. The aim of the network is to determine the real value of heat transfer coefficient corresponding to each rotation speed of the cylinder. Results are shown in Figure 8.

It can be noticed that for several neurons in hidden layer and at least 5 pattern curves the mean error of recognition of α coefficient not exceeds 20%.

Choosing the network with 17 neurons in hidden layer and 6 learning patterns (coming from numerical model) the heat transfer coefficient was determined for 4 different values of rotation speed. Obtained values of heat transfer coefficient have been compared with those calculated by the gradient descent method described in section 3. Results are shown in Table 2.

Based on the determined values of heat transfer coefficents step-input responses have been numerically calculated and compared with the real measuement data (Fig. 9). Very good compatibility of those characteristics can be noticed, which proves the usefullness of neural network for determination of heat transfer coefficients for temperature control system.

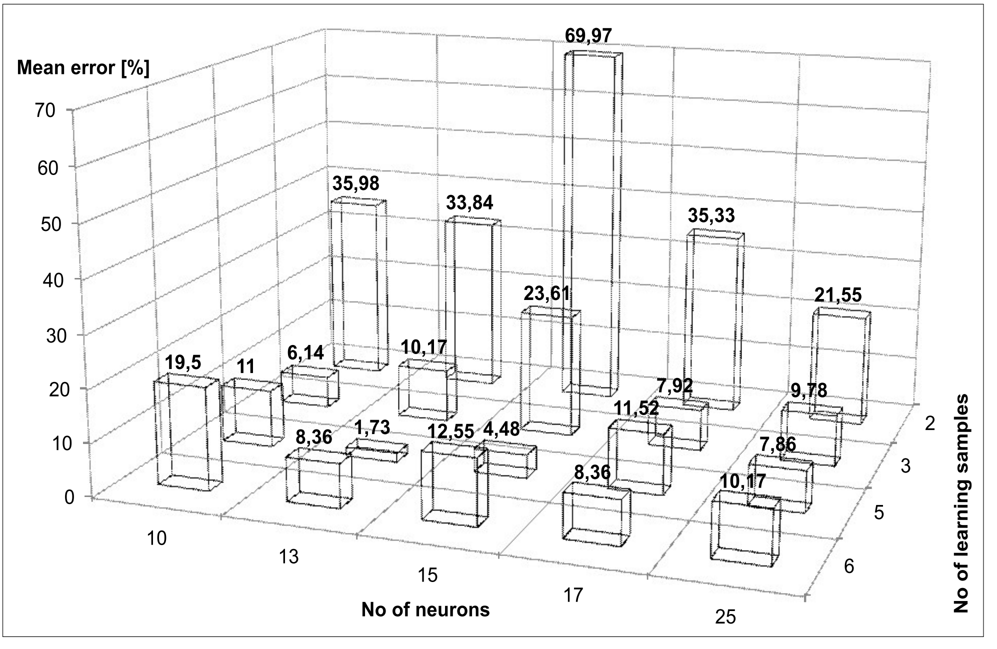

Fig. 8. Errors of heat transfer coefficient determined by the artificial neural network for real measurement data

Table 2
Comparison between calculated and determined by neural network heat transfer coefficient on real rotating cylinder surface

Rotation speed rpm	Calculated α W/m/m/K	Determined α W/m/m/K
6,00	77,90	78,69
60,00	82,60	84,50
120,00	106,10	108,31
240,00	164,00	162,20

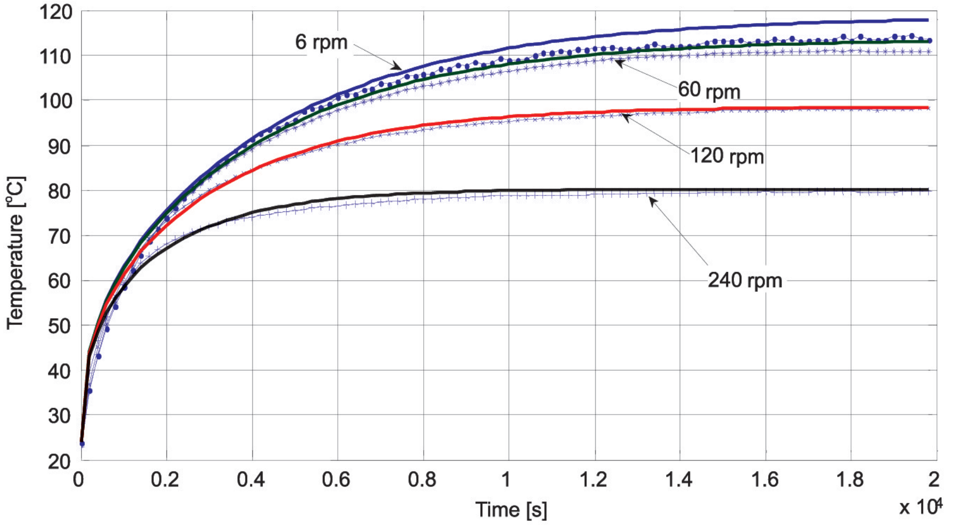

Fig. 9. Step-input response curves determined by neural network (thick lines) and measured (thin lines with markers) transfer factors for 6, 60, 120 and 240 rpm of cylinder

5. Conclusions

In the paper the possibility of application of artificial neural network for determination of the heat transfer coefficient from the surface of rotating cylinder has been presented. Obtained results have been successfully compared with classic method based on compatibility of measured and calculated heating-up temperature response. On the basis of the tests of neural network it was found that it is possible to choose optimal structure and set of example pairs: heating-up curves heat transfer factors. Proposed structure of multi-layer neural network can well recognize highly probable heat transfer coefficient even on the basis of 5 example pairs.

Acknowledgements

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