ARCHIVES

of

FOUNDRY ENGINEERING

Artificial Neural Network to the Control of the Parameters of the Heat Treatment Process of Casting

J. Wróbel*, A. Kulawik, A. Bokota

Institute of Computer and Information Sciences, Czestochowa University of Technology,
Dąbrowskiego 73, 42-200 Częstochowa, Poland
*Corresponding author. E-mail address: joanna.wrobel@icis.pcz.pl

Abstract

In the paper the use of the artificial neural network to the control of the work of heat treating equipment for the long axisymmetric steel elements with variable diameters is presented. It is assumed that the velocity of the heat source is modified in the process and is in real time updated according to the current diameter. The measurement of the diameter is performed at a constant distance from the heat source ($\Delta z = 0$). The main task of the model is control the assumed values of temperature at constant parameters of the heat source such as radius and power. Therefore the parameter of the process controlled by the artificial neural network is the velocity of the heat source. The input data of the network are the values of temperature and the radius of the heated element. The learning, testing and validation sets were determined by using the equation of steady heat transfer process with a convective term. To verify the possibilities of the presented algorithm, based on the solve of the unsteady heat conduction with finite element method, a numerical simulation is performed. The calculations confirm the effectiveness of use of the presented solution, in order to obtain for example the constant depth of the heat affected zone for the geometrically variable hardened axisymmetric objects.

Keywords: Heat treatment, Moving heat source, Artificial neural network, Numerical modelling, System of the control of the heating process

1. Introduction

Modern control systems of the equipments used in the heat treatment process allows for the significant automation in the production process. Using the temperature or thickness sensors gives the possibility to perform the heat treatment process for the small series production. The devices equipped with measuring systems significantly reduces the costs associated with the use of the production line. The possibility of the supervision of the process in the modern equipments significantly improve the quality of the heat treatment [1]. The work station with movable heat source which moving not only along the path but also having the possibility to determine the distance and angle to the heating surface are quite often used. Using these type of equipments in the heat treatment for the axisymmetric elements with variable radius facilitates the production line service and reduces the number of treatments required from the user [2].

The control elements in such equipment are the system described by the analytical functions connected with conditional statement. Determination the coefficients for these empirical functions require large financial outlays. A significant disadvantages of such solutions is the lack of system control reaction for the cases which the system designer didn't provide.

Most of the drawbacks can avoid by using a control system with artificial intelligence. The one of the best, especially in the terms of speed, are artificial neural networks (ANN). The important advantage is that neural networks can react correctly on the situation close to the learning patterns [3, 4].

2. Fundamental assumptions of the model

In the paper the artificial neural network to the control the velocity of the heat source in the heat treatment process for the axisymmetric elements with variable values of radius is used. It was assumed that heating steel elements rotate to provide uniform distribution of the temperature on the perimeter of the element. This type of the approach is required by used the superficial heat source. It allows for the constant distance to the heating element in the case of the parts with variable diameters.

The design of control system which based on the artificial neural network require perform the following steps:

- determine the learning and testing sets on the basis of data from numerical simulations,
- define the number of the network layers and neurons in these layers,
- select the appropriate learning algorithm and specify the weights of the interneural connections,
- validation of the ANN.

The numerical models of the steady and unsteady heat transfer are used to determine the learning and testing set or to verify the ANN.

3. The numerical models of the heating process

In the paper the two heat transfer models are used. To determine the learning and testing sets, the application to calculate the temperature fields is developed. This values on the basis of solution of the heat transfer equation with convection term in the axisymmetric coordinates (stationary task) are obtained

$$\frac{\lambda}{r}\frac{\partial T}{\partial r} + \frac{\partial}{\partial r}\left(\lambda\frac{\partial T}{\partial r}\right) + \frac{\partial}{\partial z}\left(\lambda\frac{\partial T}{\partial z}\right) - \rho C\left(V_z\frac{\partial T}{\partial z}\right) = 0 \quad (1)$$

where: T [K] – temperature, $\lambda = \lambda(T)$ [W/mK] – the thermal conductivity coefficient, ρ [kg/m3] – the density, C [J/kgK] – the thermal capacity, V_z [m/s] – the velocity of the heat source, r – is a distance from the symmetry axis.

The equation (1) is complemented by the appropriate boundary conditions. To solve this equation the finite element method in Petrov-Galerkin formulation is used. Finite element method in the PG formulation allows to obtain the correct solutions for the cases where Péclet number is greater than 2 [5]. System of equation after aggregation is in the form

$$K_{ij}T_j = -B_{ij}q_j \quad (2)$$

where element matrix: conductivity (K_{ij}^e), boundary condition (B_{ij}^e) are described as [6]

$$K_{ij}^e = \int_{\Omega^e} r\lambda w_{i,\alpha}\phi_{j,\alpha}drdz + \rho C\int_{\Omega^e} rw_i\phi_{j,\alpha}V_{k\alpha}\phi_k drdz$$

$$B_{ij}^e = \int_{\Gamma_Q^e} rw_i\phi_j d\Gamma \quad (3)$$

where: w_i are the weight functions, ϕ_j are the shape functions.

The second numerical model is used to verify the trained artificial neural network. In order to the numerical model of unsteady heat transfer for axially symmetric space is applied

$$\frac{\lambda}{r}\frac{\partial T}{\partial r} + \frac{\partial}{\partial r}\left(\lambda\frac{\partial T}{\partial r}\right) + \frac{\partial}{\partial z}\left(\lambda\frac{\partial T}{\partial z}\right) - \rho C\frac{\partial T}{\partial t} = 0 \quad (4)$$

where: t [s] - time.

The above equation by finite element method in Bubnov-Galerkin formulation is solved. For this task and for different time scheme the solution take the following form

$$\left(\gamma K_{ij} + M_{ij}\right)T_j^{(s+1)} = \left(M_{ij} - \left(1-\gamma\right)K_{ij}\right)T_j^{(s)} + $$
$$- \gamma B_{ij}q_j^{*(s+1)} - \left(1-\gamma\right)B_{ij}q_j^{*(s)} \quad (5)$$

where element matrix: conductivity (K_{ij}^e), heat capacity (M_{ij}^e), boundary condition (B_{ij}^e) are described by the integrals

$$K_{ij}^e = \int_{\Omega^e} r\lambda\phi_{i,\alpha}\phi_{j,\alpha}drdz$$

$$M_{ij}^e = \frac{\rho C}{\Delta t}\int_{\Omega^e} r\phi_i\phi_j drdz \quad (6)$$

$$B_{ij}^e = \int_{\Gamma_Q^e} r\phi_i\phi_j d\Gamma$$

In the presented model which verifying the control system built on the basis of artificial neural network, is assumed that the location of the heat source is incrementally changing according to the velocity calculated by ANN.

The superficial heat source (Neumann boundary condition) in the simulation of the heating process is determined by the function [5]

$$q = \frac{Q}{2\pi R^2}\exp\left(-\frac{(z-z_0)^2}{2R^2}\right) \quad (7)$$

where: Q [W] power of the heat source , R [m] radius of the heat source, z_0 [m] is the coordinate of the centre of the heat source.

4. Calculation example

To determination of the input and output data to the learning process of the artificial neural network the 2000 numerical simulation were performed. This data were obtained for the steel elements with constant diameters (Fig. 1). The appropriate boundary conditions were assumed:

- the velocity of the heat source was taken the random value from 0,005 to 0,03 m/s,
- the radius of the steel element was selected randomly in the range 0,006 – 0,014 m,
- Dirichlet condition on boundary Γ_D with $T = 293$ K,
- the power of the heat source Q was equal 500 W,
- the radius of the heat source $R = 0,0015$ m.

The material properties were assumed like for the medium carbon steel [9]. From the obtained results the values of temperature for the 25 sensors located on the boundary of considered element (Fig. 1) and the radius of element were selected. This values were the input data to the ANN. The output parameter of the network was the velocity of the heat source.

The ANN requires to the learning process the right number of diversified data in the learning set (Fig. 2 and 3)
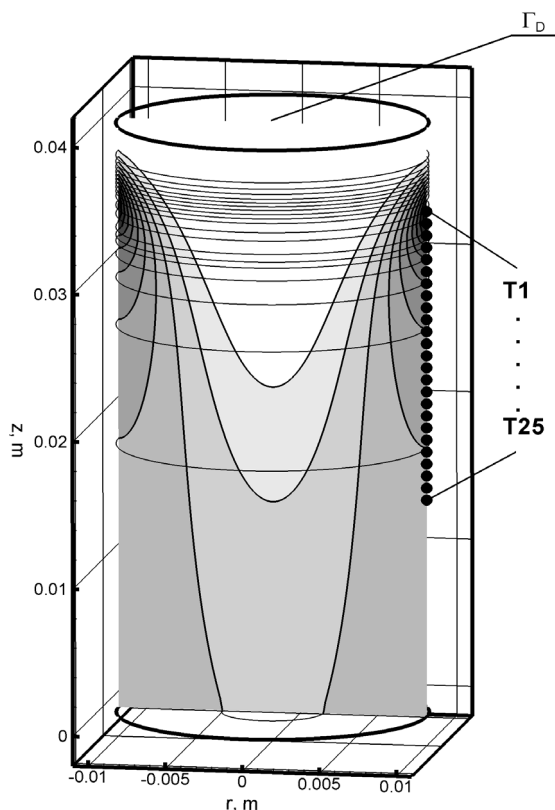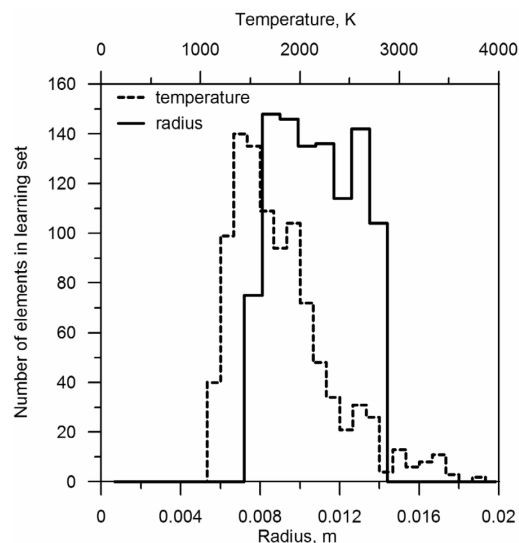

Fig. 2. The number of considered radius for the steel elements ($\Delta r = 0,0009$ m) and maximum value of the temperature ($\Delta T = 133$ K) in the learning set, input data
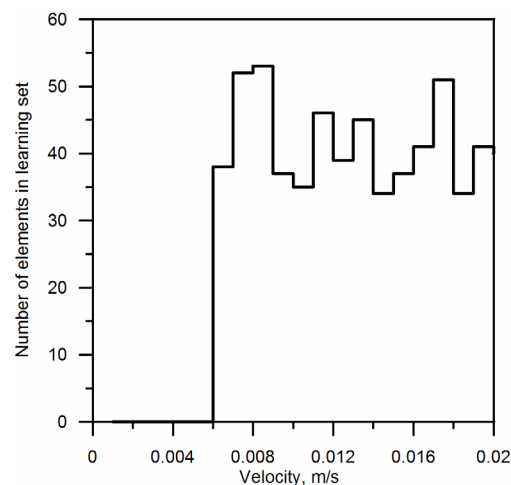

Fig. 3. The number of velocities of the heat source ($\Delta V_z = 0,001$ m/s) in the learning set, output data

The ranges of the values of velocity and radius of the elements allowed for obtain the appropriate maximum value of the temperature for heat treatment process (Fig. 2 and 4).

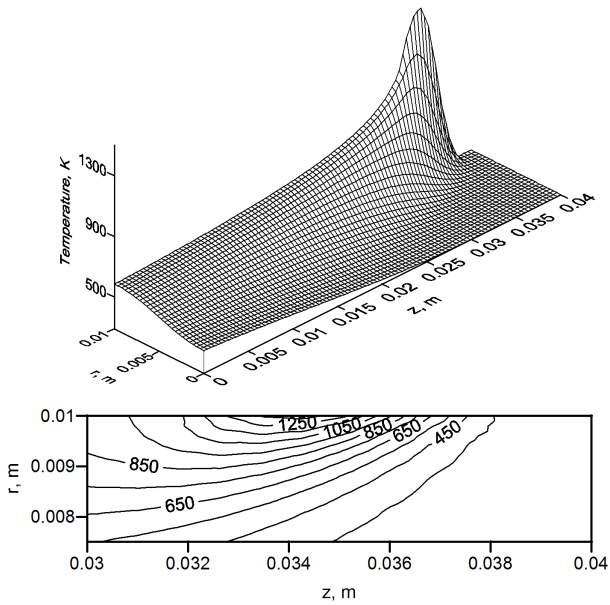Fig. 1. The geometry of the presented steel element with the sensors

Fig. 4. The example of the distribution of the temperature for
$r = 0.01$ m, $V_z = -0.02$ m/s

For the above assumptions the artificial neural network was designed. The one–way multilayer perceptron with sigmoidal neurons was used. The network was create using a one input layer (26 neurons), two hidden layers (20 and 10 neurons) and one output layer (1 neuron).
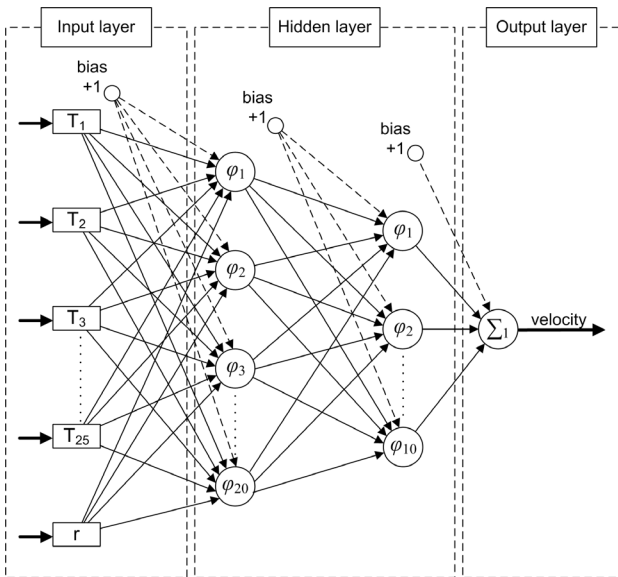

Fig. 5. The diagram of the applied multi-layer neural network

To train the network the backpropagation algorithm was used. To increase the speed of the learning neural network the backpropagation with momentum was applied [3]. The momentum coefficient was equal $\alpha = 0,7$, and the learning coefficient was $\eta = 0,03$. During the learning process made an analysis depending the number of epochs on the value of root mean square error

(RMSE) and percentage error (Fig. 6) for the testing set. The number of elements in the learning and testing sets for each epochs was 1000.
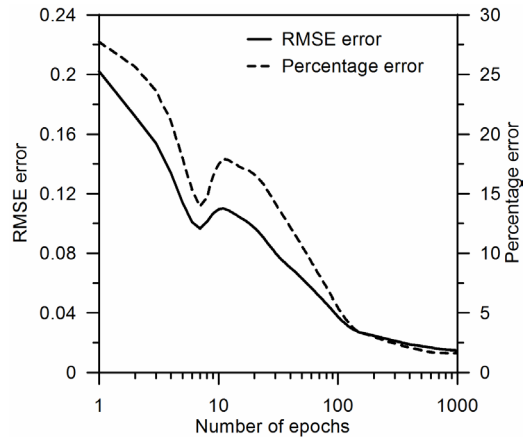

Fig. 6. The values of RMSE and percentage errors in the learning process for the testing set

5. The testing of the artificial neural network

To verify the correctness of the implemented algorithm a numerical test was conducted. The test was performed for axisymmetric element with variable diameter (Fig. 8). The required distribution of temperature on the boundary of the element was assumed. On the basis of the distribution of temperature the values of velocity of the heat source was computed by the artificial neural network (Fig. 7). The initial position of the heat source was situated below the heated element and the start velocity was equal 0,02 m/s.
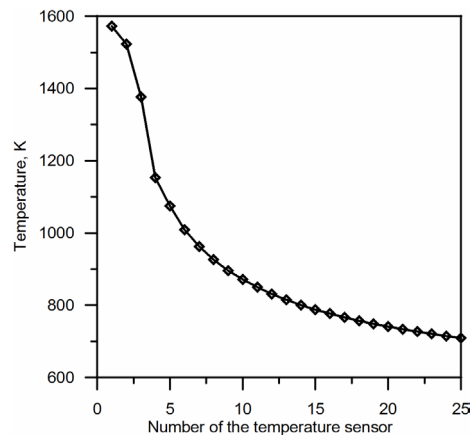

Fig. 7. The input data for the neural network - the required distribution of the temperature
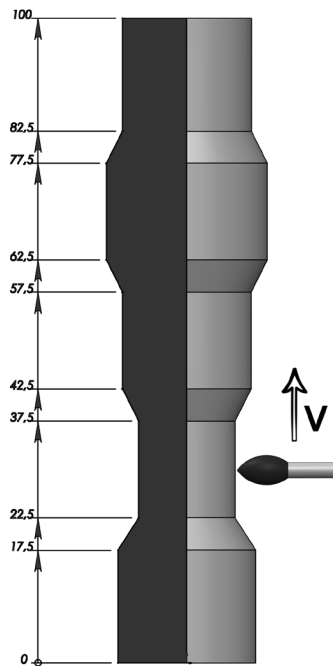
Fig. 8. The geometry of the considered example test

The responsible sensor for the read the current radius of the element was located on the same coordinates (z) as the heat source. The initial value of temperature of the steel element the was equal $T_0 = 293$ K. On the basis of temporary value of radius the neural network updating the velocity of the heat source, what caused the changes of temperature (Fig. 9). In the figures 9 and 10 the value of temperature for the measuring point of the radius was presented. To determine the effectiveness of used ANN the test was performed. This test was consisted in the verification the distribution of the value of temperature in case when artificial neural network wasn't work and the velocity of the heat source is constant (Fig. 10). The size of the heat affected zone was determined by A_{C3} curve on the level 1058 K (Fig. 11).
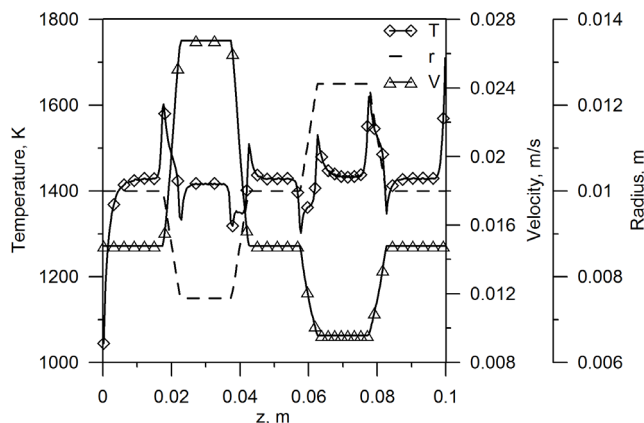

Fig. 9. The changes of the temperature in the case of variable velocity of the heat source determined by artificial neural network
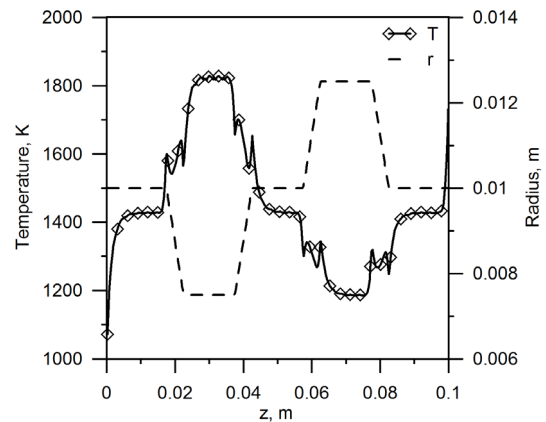

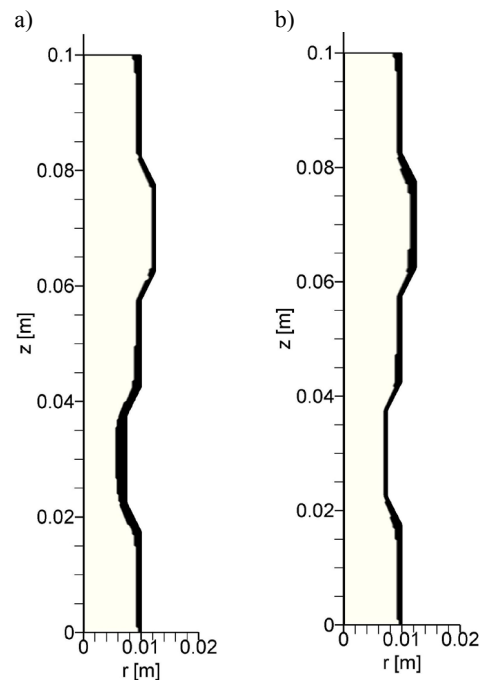Fig. 10. The changes of temperature for the constant velocity of the heat source ($Vz = 0,148$ m/s)

Fig. 11. The comparison of the heat affected zone for: a) constant velocity of the heat source, b) velocity of the heat source controlled by ANN

6. Conclusions

Using the artificial neural network in the control elements of the equipment in the heat treatment allows for effective control the parameters of these process. In the paper this parameter was the velocity of the heat source. The effects of changes of the velocity of the heat source was the maintenance of the established maximum temperature on the surface of heated element. The artificial neural network correctly reacted on the changes of the radius of the steel element. The presented method of steering of parameter for the

heating process can be also using to control the depth of the heat affected zone. The instability of the maximum temperature on the boundary of areas with different radius were the result from assumed position of the radius sensor. The maximum value of the temperature wasn't exceed the melt temperature.

References

[1] Canale, L.C.F., Mesquita, R.A., Totten, G.E. (2008). *Failure Analysis of Heat Treated Steel Components*. United States of America: ASM International.

[2] Totten, G.E. (2006). *Steel Heat Treatment: Equipment and Process Design*. United States of America: CRC Press.

[3] Rutkowski, L. (2005). *Computational Intelligence: Methods and Techniques*. Berlin: Springer.

[4] Yegnanarayana, B. (2006). *Artificial neural networks*. New Delhi: Prentice-Hall of India Learning.

[5] Bokota, A. (2012). *Modelling of hardening tool steels. Thermal phenomena, phase transformations, mechanical phenomena*. Częstochowa: Wydawnictwo Politechniki Czestochowskiej. (in Polish).

[6] Wait, R., Mitchell, A.R. (1985). *Finite Element Analysis and Applications*. Chichester: John Wiley & Sons.

[7] Zienkiewicz, O.C., Taylor, R.L. (2000). *The finite element method*. Butterworth-Heinemann: Oxword.

[8] Mochnacki, B., Nowak, A., Pocica, A. (2002). Numerical model of superficial layer heat treatment using the TIG method. In K. Świątkowski (Eds.), *Polska metalurgia w latach 1998-200, Tom 2* (pp. 229-235). Kraków: WN Akapit.

[9] Kulawik, A. (2012). Modeling of thermomechnical phenomena of welding process of steel pipe. *Archives of Metallurgy and Materials*. 57 (4), 1229-1238.