Attainment of more precise parameters of a mathematical model for cooling flat and cylindrical hot surfaces by nozzles

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Abstract

The paper describes a method of improving parameters of an experimental data based mathematical model of cooling by water-nozzles using a neural network. Experiments are carried out using hot flat and cylindrical moving objects. These experiments simulate industrial applications such as cooling in continuous casting, cooling of products in hot rolling, and cooling of rolls in rolling technology. The measurements are evaluated using the inverse 3D task. The inverse task computes the surface temperature history and heat transfer coefficients. Using the heat transfer coefficients, the parameters for the mathematical model of cooling are obtained for a specific nozzle. Their correctness is verified using the computer simulation of the experiment. It has been found that for high temperatures the simulation based on experimentally obtained parameters is less precise than that for low temperatures. The analysis of the experimentally obtained data has shown that for high temperatures a much smaller set of data is available than for low ones. On the basis of comparison of the experimental data and the data obtained by computer simulation of the experiment, the correction for parameters is made, and more precise results of the mathematical model are obtained. The paper also describes the experimental methods used, the main characteristics of the inverse 3D task computing boundary conditions from the temperature history measured inside objects, and the method for correction of data obtained in the area sparsely described by the experiment.
1 Introduction

Thermal numerical models used for design and control purposes in metallurgical industry require a precise description of the heat transfer phenomena. Attention is focused on the search for boundary conditions describing the heat transfer in engineering applications of spray cooling of hot steel surfaces (up to 1200 °C). The cooling in continuous casting, cooling of products in hot rolling, and cooling of rolls in rolling technology are the typical industrial applications. Comprehensive quantitative information regarding the heat transfer conditions is not available for the quenching of hot moving surfaces.

The previous tests carried out in the Heat Transfer and Fluid Flow Laboratory of the Technical University of Brno were designed to simulate hot rolling [1] and [2], and continuous casting [3] applications. They were followed by the building of a laboratory stand for the study of cooling of products in hot rolling [4]. These measurements provide data used in the inverse 3D task that computes the major thermal parameters: surface temperature, heat flux, and heat transfer coefficients (HTC). It has been found that the relative movement of the nozzle and the cooled surface plays an important role.

All the above experiments are based on the same principles. This can be described as the measurement of the temperature histories in selected points of a test plate that is cooled downward from an initial temperature. The temperature measurements (and additional information obtained using the inverse 3D task) contain an enormous amount of data but only a few data corresponding to the high surface temperatures. The data reduction described by Raudenský [5] works well but may fail if there is a lack of data, especially for the high surface temperatures. This paper describes an approach to solving this problem by applying a feed-forward neural network.

2 Experimental apparatus and obtained temperature history

The stand simulating continuous casting (Figure 1) was designed for obtaining HTC. An austenitic steel plate (210*320*25 mm) is heated up to a required temperature (usually 1200 °C) and then cooled downward to the coolant temperature by fluid flat jet nozzles. The plate is equipped with 21 thermocouples that are arranged 2.5 mm under the cooled surface, in three rows. The other sides of the plate are insulated. During the cooling process, the nozzles move under the cooled surface from the left to the right, and backward, with the deflector open and closed, respectively. Signals of the thermocouples and information on the nozzle position, in relation to the plate, are recorded continuously in digital form. After the test, the temperature history with the time step of one second allows computing of the HTC and a heat flux. The tests were carried out for different nozzles and nozzle configurations, for different spray heights, water pressures, and movement speeds.
3 Inverse 3D task

The measured temperature history is the input into the 3D inverse heat conduction task and the outputs are the surface temperature, heat flux, and HTC. The inverse task uses the minimisation approach. In the case of a fast change of the HTC, especially with fast moving surface tests, the inverse method uses the classical Beck's approach [6] with several forward time steps. The inverse task is based on a mathematical model of the temperature fields in the tested body. The initial temperature field is known from the temperature measurements before spraying. The control volume method is used for a 3D thermal model.

An example of obtained results is presented in Figure 2. It demonstrates the linearly moving flat plate. The peaks of the HTC curve represent the instants at
which the sensor passes under the spraying nozzle. The time interval between two peaks represents the total time for one spraying cycle. The peaks are deformed. On the right, they are wider due to the relative movement of the nozzles and cooled surface.

4 Mathematical model of the HTC and data reduction

An enormous amount of computed data is approximated by the function $HTC = f(x, T)$. The eqns (1), (2), and (3) are used to express the dependence of HTC on a surface point position and surface temperature [5].

\[
HTC(x, T) = \delta(T)e^{-(x-\mu)^2/2\sigma^2(T)} \quad (1)
\]

\[
\delta(T) = \frac{a-b}{\pi} \arctg(c(T-d)) + \frac{a+b}{2} + k_1e^{-k_2T} \quad (2)
\]

\[
\sigma(T) = \begin{cases} 
\sigma_L(T) = q_LT + p_L & \text{for } x < \mu \\
\sigma_R(T) = q_RT + p_R & \text{for } x \geq \mu 
\end{cases} \quad (3)
\]

Here the functions $\delta(T)$ and $\sigma(T)$ represent the maximum value of the HTC in the dependence on the surface temperature and the parameter that describes the shape in the x direction, respectively. The shape in the $x<\mu$, where $\mu$ represents the nozzle position, is different from $x\geq\mu$. Hence the $\sigma(T)$ parameter is divided into the two parameters $\sigma_L(T)$ and $\sigma_R(T)$ for the left and right sides, respectively.

To find parameters of the mathematical model, it is not possible to use the classical square method. Owing to the dependence of the HTC on the surface temperature, the method [5] splits the HTC into several temperature intervals and evaluates the $\delta$, $\sigma_L$, and $\sigma_R$ for each interval. After finding these parameters it computes the temperature dependent parameters ($a$, $b$, $c$, $d$, $q_L$, $p_L$, $q_R$, $p_R$, $k_1$, $k_2$).

![Figure 3: Comparison of measured and computed temperatures](image-url)
The method computing parameters $\delta, \sigma_L,$ and $\sigma_R$ is very stiff and finds the parameters for a sparse-described temperature interval but the computed values are different from the real ones (Figure 3). The lack of data is, especially in the highest temperature intervals, due to the fast decrease in the surface temperature that occurs at the beginning of the experiment. To solve this problem, the temperature interval of usability of the parameters was defined, but now using the method described in this paper a wider temperature interval can be used.

5 Application of the feed-forward neural network for the highest temperature interval

It has been found that the parameters $\delta, \sigma_L,$ and $\sigma_R$ can be obtained directly from the measured temperature history using a feed-forward neural network, and this method enables automatic evaluating of the corresponding surface temperature.

The neural network can serve as a black box with some input and output

![Diagram of a feed-forward neural network](image)

Figure 4: Feed-forward neural network

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INPUT | OUTPUT
---|---
$T(1)$ | $\delta$
$T(2)$ | $\sigma_L$
$T(3)$ | $\sigma_R$
$T(n)$ | $\cdot$ 

- $T(1) ... T(n)$ - temperature history
- $W_1, W_2$ - weight matrixes
- $b_1, b_2$ - bias vectors
vectors. The input and output vectors represent the temperature history and the desired parameters ($\delta, \sigma_L, \sigma_R$), respectively.

5.1 The structure of the feed-forward neural network

A two-layer network [7] is used as the main model (Figure 4). The number of neurons in the output layer is equal to the number of the requested parameters ($\delta, \sigma_L, \sigma_R$). The number of hidden neurons should reflect the complexity of the problem under solution. A computation experiment has shown that three neurons are a minimum. The hyperbolic tangent sigmoid and linear transfer functions are used for hidden and output layers, respectively.

5.2 Training of the feed-forward neural network

The training data must be available before the start of the training. The experiment is simulated on a computer for several different parameters ($\delta, \sigma_L, \sigma_R$), which are used as constants in this case, and the computed temperature history together with $\delta, \sigma_L, \sigma_R$ represents the requested training data. A computation experiment has shown that it is enough to perform three simulations for each parameter, $\delta, \sigma_L$, and $\sigma_R$. After obtaining the training data, the data must be standardised (in the range from 0 to 1).

The feed-forward neural network is trained using fast back-propagation, i.e. the Levenberg-Marquardt functions. The neural network reaches the sum-squared error goal (0.002) usually in less than 50 training epochs.

Computation using the learned neural networks has proved that not all of them can be used. Some of them return confused results. A computation experiment has shown that the learned neural networks should fulfil the condition that the maximal absolute value of the element of the matrixes $W_1$, $b_1$, $W_2$, and $b_2$ is less than 1.7 (eqn (4)). The neural network with the lowest maximum, within the group with equal sum-squared error goals, represents the best one. In the case presented in this paper the maximal value was 1.19.

\[
\begin{align*}
\max & \left( W_{1,\text{max}}, W_{2,\text{max}}, b_{1,\text{max}}, b_{2,\text{max}} \right) < 1.7 \\
W_{1,\text{max}} &= \max_{i,j} |w_{ij}|, W_1 = (w_{ij})_{i=1..n, j=1..3} \\
W_{2,\text{max}} &= \max_{k,l} |w_{kl}|, W_2 = (w_{kl})_{k=1..3, l=1..3} \\
b_{1,\text{max}} &= \max_m |b_m|, b_1 = (b_m)_{m=1..3} \\
b_{2,\text{max}} &= \max_n |b_n|, b_2 = (b_n)_{n=1..3}
\end{align*}
\]
5.3 Obtaining requested parameters and their scope

After training neural networks with the fulfilled condition in eqn (4), the requested parameters \( (\delta, \sigma_L, \sigma_R) \) are computed. The measured temperature history is set as the input vector of the neural network.

Owing to the dependence of the HTC on the surface temperature it is necessary to specify the temperature interval for each parameter, \( \delta, \sigma_L, \) and \( \sigma_R \). First a new simulation is executed using the parameters \( (\delta, \sigma_L, \sigma_R) \) obtained from the neural network. The computed surface temperature history and HTC are shown in Figure 5. The width of the area affected by the nozzle is equal to the sum of \( 2\sigma_L \) and \( 2\sigma_R \). The parameters \( \sigma_L \) and \( \sigma_R \) hold in temperature intervals \( T_1 \) and \( T_2 \), respectively. The scope of the parameter \( \delta \) holds in the both temperature intervals \( T_1 \) and \( T_2 \).

6 Computing temperature dependent parameters

The parameters \( q_L, p_L, q_R, \) and \( p_R \) in eqn (3), and the parameters \( a, b, c, d, k_1, \) and \( k_2 \) are computed by means of the least square method [5]. The values of the parameters \( \delta, \sigma_L, \) and \( \sigma_R \) computed by the feed-forward neural network and by the method described in [5] are used as the input data for the highest temperature interval and low temperature intervals, respectively. A comparison of the measured and computed temperature histories using the old and new approaches is illustrated in Figure 6.
7 Conclusion

The paper shows experimental methods used for obtaining boundary conditions (HTC, surface temperature) describing the heat transfer in engineering applications. A laboratory test replaces the difficult and expensive measurements in the mill or in continuous casting. An enormous amount of data obtained from the measurement can be simplified by a set of functions. These functions take into account the dependence of HTC on the surface temperature and the surface point position. Precision and relevance of these functions can be enhanced using the described feed-forward neural network.

The experimental and computational parts allow the design of cooling sections according to customer requirements regarding the temperature field history or the final material structure and parameters.

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Nomenclature

\(a, b, p, p_s, k_1\) parameters of the mathematical model \([W/(m^2\cdot K)]\)

\(c, q, q_s, k, k_2\) parameters of the mathematical model

\(d\) parameter of the mathematical model \(\left[\degree C\right]\)

HTC heat transfer coefficient \([W/(m^2\cdot K)]\)

\(\mu\) nozzle position [mm]

\(x\) surface point position [mm]

\(t\) time [s]

\(T\) temperature \(\left[\degree C\right]\)
$b_1, b_2, \ldots$ bias vectors of the feed-forward neural network

$W_1, W_2, \ldots$ weight matrixes of the feed-forward neural network

References


