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Estimation of finish cooling temperature by artificial neural networks of backpropagation during accelerated control cooling process

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ABSTRACT

Artificial Neuron Networks (ANN) is considered one of the most practical technologies in the fields of intelligent manufacturing. In this study, the conventional heat transfer model and multilayer ANN analysis are compared to analyze the accelerated control cooling process, and the accuracy improvement of finish cooling temperature prediction by the ANN is evaluated. The temperature prediction error from the heat transfer model tends to increase with increasing the start cooling temperature in Curie temperature. It is found that the specific heat for low carbon steel shows a nonlinear tendency in Curie temperature. The ANN of backpropagation is applied to solve the nonlinear tendency of the specific heat. In the ANN analysis, the key parameters such as dimensions of plate, chemistry, start cooling temperature, air cooling time, water cooling time are selected as the input values. The hyperbolic tangent, sigmoid and linear functions are applied for the activation functions. The weights training was conducted 100,000 times, the weights were trained to satisfy the standard deviation of finish cooling temperature within 10.56 K. It was found that the accuracy from the ANN analysis was improved 2.74 times than the heat transfer model with least square method. It was concluded that the ANN with multilayer type could train the weights by the effect of the nonlinear trend of specific heat according to temperature. It is recommended that the heat transfer model should be replaced by the neural networks method of 3 layers (one input-layer, one hidden-layer, one output-layer) with the trained weights for the precise control cooling.

1. Introduction

Nowadays, high quality plate from the viewpoints of toughness, strength and yield ratio is demanded in the ship building industry. The demand for a high quality of plate has made engineers aware of the precise cooling for finish cooling temperature and cooling rate. And many steel-making companies have developed more precise cooling model than the previous one by adapting a special logic with the site effects for the precise plate cooling. The manufacturing process of thermal mechanical control cooling plate called “accelerated control cooling” is one of the typical cases. One important issue is to get more fine grain size with hot rolling in two-phase region and water cooling [1,2]. The other is to control the steel strength, yield ratio and toughness [3–5]. Many researchers have modeled the cooling condition of a material for more efficient usage and more precise cooling with the finite element method (FEM) and the finite difference method (FDM). The researchers have studied on the appropriate start cooling temperature, finish cooling temperature, cooling rate and phase transformation for steel properties. The temperature prediction error about finish cooling temperature occurs in actual cooling processes in plant industry. The main causes are the specific heat deviation according to temperature, components of chemistry and heat transfer coefficient deviation of air and the plate flatness. To reduce the temperature prediction error, most of cooling machines have an adaptation model by using the least square method for long-term compensation and by applying amplification factors for short-term compensation about the target temperature. However, the adaptation model cannot include the compensation of temperature error without the precise specific heat data about infinite cases.

For calculating accurate specific heat and strength, many engineer had been used avrami equation [6–8]. Serajzadeh [9,10] studied the modelling of temperature history and phase transformations for an distribution of ferrite, pearlite, austenite according to temperature and time. The results from Denis et al. [11] were applied for the prediction model of average of specific heats, strength according to the phase distribution. In addition, a product for the control cooling is grouped by the influence factors for accurate cooling.

Zheng et al. [12] studied the locally-linear-reconstruction based instance-based-learning (LLR-IBL) to calculate the heat transfer coefficient more accurately. Wang et al. [13] and Nobari et al. [14]

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Nomenclature

C_p	specific heat, J/kg · K
e_j	temperature error of output layer, K
E	sum squared temperature error, K
g	gravitational acceleration, m/s^2
Gr	Grashof number
h_C	convective heat transfer coefficient of air, W/m^2 · K
h_R	radiative heat transfer coefficient of air, W/m^2 · K
h_{Air}	total heat transfer coefficient of air, W/m^2 · K
L	characteristic length, m
Nu	Nusselt number
O_j	output value of layer, K
Pr	Prandtl number
Ra	Rayleigh number
t	time, s
T_j	target value of layer, K
T	temperature, K
X	measurement value
$\bar{X}$	measurement mean value

Greek symbol

α	thermal diffusivity, m^2/s
φ	thermal expansion coefficient, K^{-1}
β	Stephan Boltzmann constant, W/m^2 · K^4
λ	thermal conductivity, W/m · K
ε	emissivity, –
ρ	density, kg/m^3
ν	kinematic viscosity, m^2/s
η	learning constant, –
ϕ	activation function
ϕ'	derivative of activation function

Subscripts

j	node of current layer
k	node of next layer
X_t	transformed ratio of austenite in steel
W	weights

measured the heat transfer coefficient on hot steel by experiments. Ma et al. [15] studied the heat transfer coefficient for supercritical water based on neural network in nuclear reactor. Olivia and Sousa [16] studied the air/water spray cooling to predict the heat transfer coefficient and air/water pressure ratio with the neural network analysis in forging process. They found that a non-mathematically formulated model could be used as a useful tool for integrated design and manufacturing without the heat transfer model. Although the control cooling and prediction accuracy of the finish cooling temperature were improved by these studies, the prediction error was still remained involving the nonlinear compensation in wide temperature change, especially around the curie point.

The artificial neural networks model includes the concepts about not only the process of heat transfer coefficient calculation, but also the initial temperature distribution because the multilayer can include each calculation process with neurons. It is also well known that the backpropagation of artificial neural networks can separate the linear condition like AND, OR logic functions as well as the nonlinear condition like exclusive or (XOR) logic. Wang et al. [17] studied the neural network to predict the plate cooling temperature, which was an useful approach about the finish cooling temperature. However, they did not consider the effects of chemistry of slab and air cooling time before and after the water cooling. The artificial neural network has been applied to an artificial intelligent manufacturing such as optimization of process parameters in feed manufacturing [18], distinguishing letters, analyzing microstructures [19] and flow stress for rolling force [20] in material process engineering, calculating heat flux in nuclear engineering [21], determining the effects of cooling water flow rate on heat pump performance [22] and heat transfer prediction of supercritical water [23] and so on. In this study, the backpropagation of artificial neural network is applied to control the cooling process to obtain more accurate temperature prediction. The prediction accuracy of the finish cooling temperature is estimated by the artificial neural networks, and the results are compared with those from the heat transfer model and the experimental results.

2. Experiments

2.1. Plate cooling system

Fig. 1 shows the schematic of the plate cooling system in steel industry. In the plate cooling system, it is very important to predict the finish cooling temperature of plate and the water cooling time with primary data such as thickness, start cooling temperature, and components of chemistry. Generally, the heat transfer model is used to predict the finish cooling temperature and the water cooling time. In this study, both the artificial neural network model based on the backpropagation algorithm and the typical heat transfer model are developed and the prediction accuracies of the finish cooling temperature are compared for both models.

2.2. Heat transfer model

The principle of energy conversation, Fourier's law, Newton's law of cooling and Stefan-Boltzmann's law are applied for the heat transfer model in the plate cooling system. Fig. 2 shows the control volume for the heat transfer model. It is assumed one dimension in the thickness direction because the width and length are very large compared to the thickness of the plate. The governing equation for the energy balance is expressed as in Eq. (1) [24,25].

$$\frac{\partial}{\partial x}\left(\lambda\frac{\partial T}{\partial x}\right)+q=\rho\cdot Cp\frac{\partial T}{\partial t} \tag{1}$$

The implicit equations of numerical analysis for finite difference method could be derived by Eq. (1). To solve the implicit governing equation, tri-diagonal matrix algorithm is programed. With this basic model, the heat transfer coefficient of water cooling can be plotted as a function of the top surface temperature based on the experimental data [16]. Fig. 3 shows the heat transfer coefficient versus the top surface temperature for each cooling efficiency. The cooling efficiency depends on the cooling rate, the finish cooling temperature, and the equipment capacity. The heat transfer coefficient of cooling air is expressed by Nusselt number with Rayleigh number (Ra). It is expressed as Eqs. (2)–(4).

$$h_C=\frac{\lambda}{L}Nu=\frac{\lambda}{L}f(Ra) \tag{2}$$

$$h_R=\varepsilon\cdot\beta\cdot(T_S+T_A)\cdot(T_S^2+T_A^2) \tag{3}$$

$$h_{Air}=h_C+h_R \tag{4}$$

where h_C is the convective heat transfer coefficient of air, h_R is the radiative heat transfer coefficient of air and h_{Air} is the total heat transfer coefficient of air, which is defined as the summation of convection and radiation effects. Fig. 4 shows the total theoretical