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ORIGINAL ARTICLE

Online prediction of work roll thermal expansion in a hot rolling process by a neural network

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Abstract Profile and shape control is utilized to maintain the dimensional quality of a rolled strip. Prediction of work roll thermal expansion is an important element in controlling the strip profile and flatness in a modern, high-speed rolling mill. In this study, a full three-dimensional analytical model "based on the finite difference method under transient condition" that already was developed is used to calculate the temperature and the thermal crown of a work roll. The work roll temperature field and thermal expansion were obtained at any instance during the process. The results were verified against the actual work roll temperature data measured in Mobarakeh Steel Co. as a real model of a hot rolling process. The computation time of this model using a quad-core 2.8-GHz computer was more than 15 s. Due to the long computation time of the accurate analytical model, the online application of this model was unfeasible. Hence, the results of the analytical model were used to train a neural network. The developed artificial neural network (ANN) model was used to predict the thermal crown expansion of the work roll. The developed model is realized to be accurate enough while its computation time for rolling of each slab is measured to be less than 0.1 s, making it possible for online application.

Keywords Hot rolling · Thermal expansion · Work roll · Flatness control

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List of symbols

C	Specific heat (J/kg K)
h	Heat transfer coefficient (W/m^2 K)
K	Thermal conductivity (W/m K)
$\dot{q}''$	Heat flux (W/m^2)
$\dot{q}'''$	Heat generation (W/m^3)
r	Radial coordinate (m)
R	Radius (mm)
T	Temperature (°C)
t	Time (s)
V	Speed (m/s)
Z	Axial coordinate (m)
α	Thermal diffusion coefficient (m^2/s)
Δ	Difference
θ	Angle (°)
ρ	Density (kg/m^3)
ω	Work roll rotational speed (rad/s)

Subscripts

b	Backup roll
c	Circumference
cool	Cooling zone
def	Deformation
fr	Friction
jet	Spraying zone
RB	Roll bite zone
r	Radial
w	Work roll
wb	Interface between work and backup roll
z	Axial
θ	Circumference

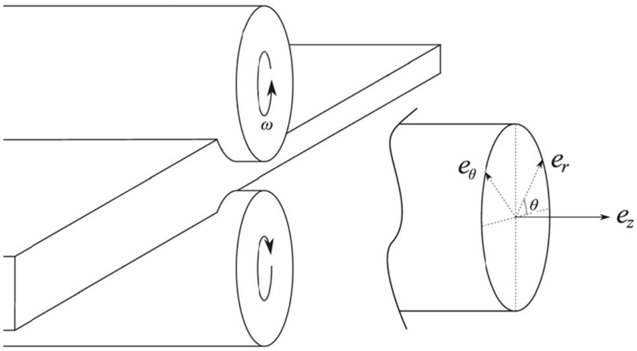


Fig. 1 The cylindrical coordinate and axes

1 Introduction

The quality of flat rolled strips is defined based on uniformity in surface finish, mechanical properties, and dimensions along the length as well as the width of the product. The strip profile is defined as the thickness variations along the width while the strip crown is characterized as the thickness difference at the center and edges along the width of the strip. It can be assumed that the strip profile is identical to the loaded roll gap profile. Variations in the strip profile in any stand should be within an acceptable range to maintain flatness quality. Flatness and thickness profile are directly related to the shape of the work roll during the rolling process. The loaded work roll shape is affected by the following parameters:

- Thermal crown
- Wear crown
- Primary crown
- Roll flattening

Since accurate prediction of the work roll temperature is an important issue in predicting the thermal crown, providing a good thermal model to obtain the temperature distribution of

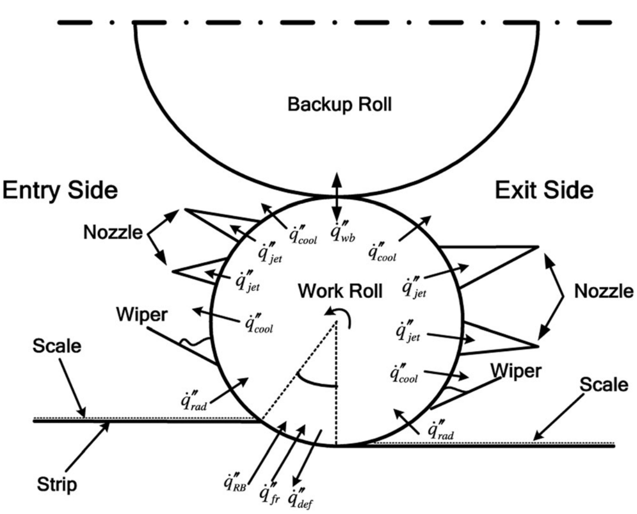


Fig. 2 Effective boundary conditions around the roll

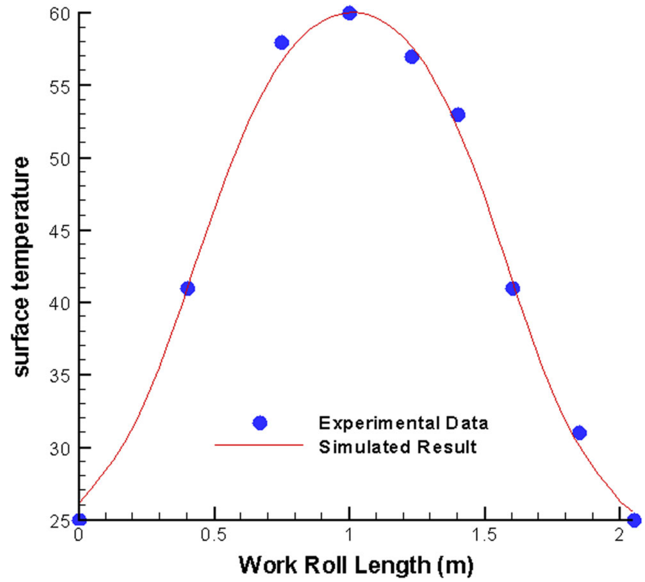


Fig. 3 Comparison of the mathematical model with experimental data [7]

the rolls has been the main objective of several researchers. Different methods were used to solve this problem. These methods are categorized as the following four methods or a combination of these methods:

1. Temperature prediction based on simplified formulas
2. Finite difference method
3. Finite element method
4. Data mining method such as artificial neural network (ANN)

Simplified formulas are extracted from heat transfer equations based on different boundary conditions. Easy implementation is the main advantage of this method. Due to limitations in geometry, heat load and cooling condition simplified formulas are not applicable in most cases. Hence, numerical methods such as finite difference and finite element methods are employed to consider complicated geometry and boundary conditions. By employing such approaches in general, the accuracy and the computation time are increased simultaneously.

Data mining can be combined with other methods and optimization algorithms to decrease the computation time while

Table 1 ANN input parameters and correlations

	Gap time	*T* strip	Length of slab	Reduction	Width
Gap time	1	0.01	0.01	0.03	−0.01
T strip	0.01	1	0.11	−0.01	0.01
Length of slab	0.01	0.11	1	0.03	−0.22
Reduction	0.03	−0.01	0.03	1	0.01
Strip width	−0.01	0.01	−0.22	0.01	1

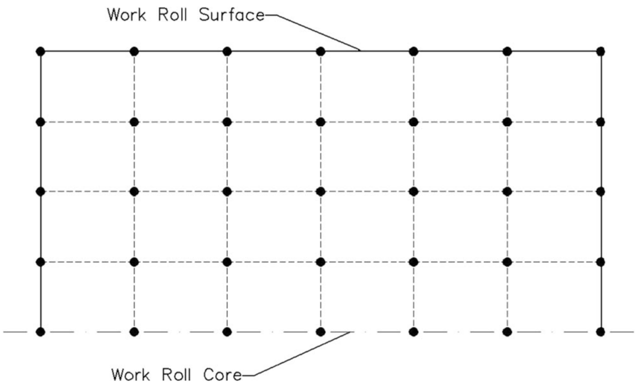
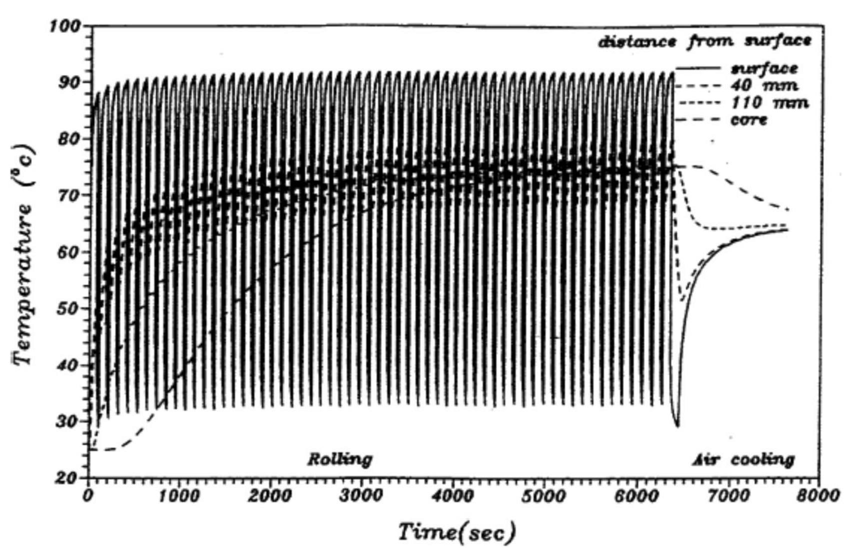


Fig. 4 Discredited work roll in radial and axial directions

maintaining the accuracy. Another way to deal with this problem is the experimental method which is a direct method as a replacement of modeling of the system, but sometimes it is very hard to implement. For example, the thermal crown of a work roll cannot be measured during rolling, but an inverse analytical method uses real experimental data to model the work roll thermal condition. Some attempts were made to give solution to the heat transfer equation in radial direction under transient conditions using the finite difference method (FDM), and some of them use the finite element method (FEM) to model the temperature of a work roll during rolling. Montmitonnet et al. [1] gave a comprehensive review of three-dimensional models (by FEM and FDM) of the rolling process. Ginzburg [2] analyzed the transverse temperature distribution in a hot strip mill of a compact strip production plant. A solution to the work roll heat transfer equations in circumferential and axial directions is also given by Van Steden and Tellman [3]. The main objective of their study was to improve productivity and strip quality. The actual heat transfer coefficients for spraying based on the experimental data were found and used for numerical simulations. Ginzburg et al. [4, 5] applied the cool flex model using the finite difference method under spray boundary conditions explained by Van Steden and Tellman [3] to obtain the best cooling conditions. They finally proposed a new roll thermal crown (RTC) cooling system for thermal crown control. Crisa et al. [6] also solved differential equations and applied the new RTC cooling system to obtain the best cooling conditions. Abbaspour and Saboonchi [7] developed a finite difference model under transient conditions to calculate the temperature and thermal crown profile of the work roll. Their model has the ability to cover different boundary conditions in both circumferential and axial directions. Thermal crown was investigated by Zhang et al. [8] using a two-dimensional FEM for an online control model. The circumferential direction was neglected for reducing the computation time. Three-dimensional predictive models based on the finite difference model have also been proposed by Zone-Ching and Chang-Cheng [9]. The heat source of the contact region of the work roll was calculated by a two-dimensional model to simplify the problem and save CPU time. Serajzadeh et al. [10] solved unsteady-state heat transfer equations with time-dependent boundary conditions and combined them with a two-dimensional finite element model to predict the work roll temperature distribution. Guerrero et al. [11] developed a four-heat flux model including two finite difference models: one integrated the heat flow to the roll and the fourth was based on the heat flow integration to compute the temperature distribution at steady-state conditions. Since the accurate analytical models are complex and time consuming, they are not used in online applications. Therefore, artificial intelligence methods including neural networks were employed in hot and cold steel rolling. For example, Gunasekera et al. [12] developed a neural network model for the flat rolling process. They used a nonlinear mathematical model based on the slab method to guide and supervise the learning procedures. Laurinen and Roning [13] used

Fig. 5 Average temperature variations at the surface and different layers of the work roll [23]



neural networks to predict the roughing mill temperatures. Similarly, prediction of post roughing mill temperature of a steel slab [14] and prediction of post run-out table strip temperature [15] have been performed using ANNs.

A significant number of studies were conducted to predict the rolling force in hot strip mills. Some examples are the research by Son et al. [16] and Sikdar and Kumari [17] where the strip crown was predicted during rolling in the finishing stands of a HSM using an ANN. The operational parameters such as width, thickness, speed, and roll bending were taken into account in their studies. Also, Mohanty et al. used an ANN to develop a system for online prediction of the mechanical properties in hot-rolled IF steel [18]. Furthermore, Zarate and Bittencout [19] used an ANN to control the cold rolling process using sensitivity factors, while Gudur and Dixit [20] proposed an ANN developed by FE analysis of cold flat rolling. This

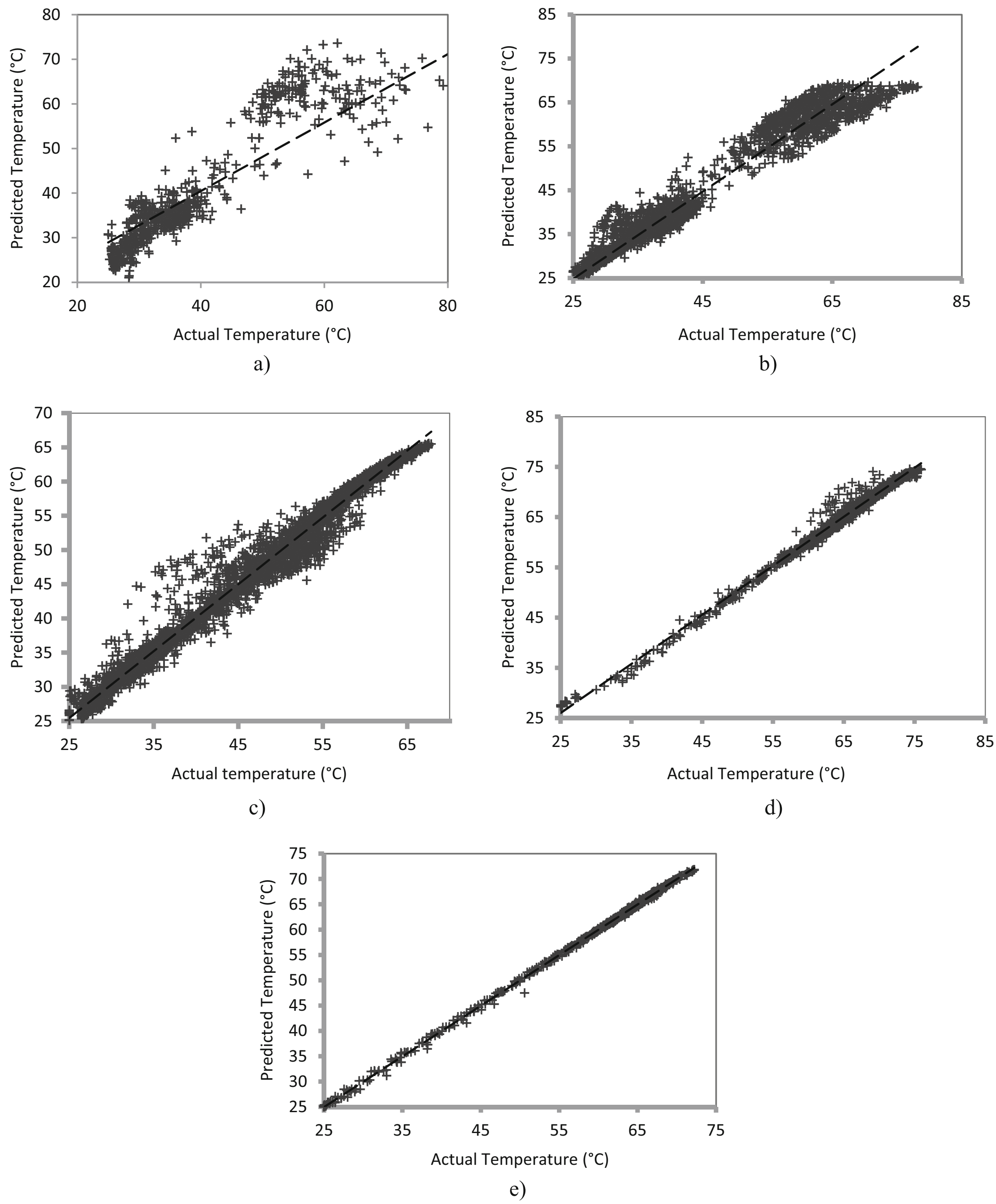


Fig. 6 Comparison of temperature prediction by ANNs and actual temperature at different distances from the surface: **a** at the surface of the work roll, **b** at 0.09 m from the surface, **c** at 0.18 m from the surface, **d** at 0.27 m from the surface, and **e** at 0.36 m from the surface (center of the work roll)

neural network was used to predict the velocity field and location of a neural point. The training data were obtained from a rigid-plastic finite element code. It was claimed that this procedure provided a highly accurate solution with reduced computational time and was suitable for online control or optimization. Weisz-Patrault et al. [21, 22] also developed a three-dimensional inverse analytical model to determine the temperature field and heat fluxes using the temperatures measured by thermocouples fully embedded in the roll body. They used this model for online interpretation and designed as a tool for adapting the rolling parameters during the rolling process. Simple two-dimensional models ignore some of the boundary conditions that are assumed less effective. This work considers the development of a fast model with high accuracy to predict the thermal expansion of work rolls during the rolling process.

In this study, using the Saboonchi and Abbaspour [7, 23] model, a three-dimensional finite difference model under transient conditions was developed. This model took variable boundary conditions into account in both circumferential and axial directions for different cooling configurations. At the hot rolling mill in Mobarakeh Steel Co., the rolling program was selected and rolling parameters, cooling conditions, and work roll temperatures were recorded. The model was run for the real rolling program with real rolling operational parameters. The results of the model were verified against the measured roll surface temperature in Mobarakeh Steel Co. Since the computation time of the model was so high and could not be used in online application, an ANN was developed. The analytical model was used to supervise the learning procedure of the neural network. The main advantage of this method was the high accuracy as well as a very low computation time. In fact, a fast accurate model can be used to control the rolling condition and optimization algorithms. For example, level 2 automation systems need a fast estimation of the main rolling parameters, such as roll force, cooling condition, reduction in each stand, and thermal condition of the work roll, to pre-set them for a level 1 automation system. Model predictive control also uses fast models to control complicated systems. The ANN can predict the thermal expansion of a work roll at any instance during rolling in less than 0.1 s. It should be mentioned that this time for an analytical model was more than 15 s with the same processor.

2 Analytical model

2.1 Energy equation for the work roll

The thermal crown of the work rolls is calculated by solving the energy equation with variable boundary conditions [7]. The method used in this analysis is the finite difference method. The general energy equation is expressed below:

$$\nabla.(k_{\mathrm{w}}\nabla T_{\mathrm{w}}) + \dot{q}'' = \rho_{\mathrm{w}} C_{\mathrm{w}} \frac{DT_{\mathrm{w}}}{Dt} \tag{1}$$

where T is the temperature and C and ρ are the specific heat (J/kg K) and density (kg/m^3), respectively; the subscript w is the work roll representation. The cylindrical axes are shown in Fig. 1. The term $\nabla.(k_{\mathrm{w}}\nabla T_{\mathrm{w}})$ in the cylindrical coordinate is considered as follows:

$$\nabla.\ (k_{\mathrm{w}}\nabla T_{\mathrm{w}}) = \frac{1}{r}.\frac{\partial}{\partial r}\left(k_{\mathrm{w}} r.\frac{\partial T_{\mathrm{w}}}{\partial \mathrm{r}}\right) + \frac{1}{r^2}.\frac{\partial}{\partial \theta}\left(k_{\mathrm{w}}\frac{\partial T_{\mathrm{w}}}{\partial \theta}\right) + \frac{\partial}{\partial z}\left(k_{\mathrm{w}}\frac{\partial T_{\mathrm{w}}}{\partial z}\right) \tag{2}$$

Assuming constant roll thermal conductivity (k_{w}) and thermal diffusion coefficient, $\alpha_{\mathrm{w}} = \frac{k_{\mathrm{w}}}{\rho_{\mathrm{w}} C_{\mathrm{w}}}$, the following equation is obtained:

$$\frac{\partial T_{\mathrm{w}}}{\partial t} + v_{\mathrm{r}}\frac{\partial T_{\mathrm{w}}}{\partial r} + \frac{v_\theta}{r}\frac{\partial T_{\mathrm{w}}}{\partial \theta} + v_{\mathrm{z}}\frac{\partial T_{\mathrm{w}}}{\partial z} = \alpha_{\mathrm{w}}\left[\frac{1}{r}.\frac{\partial}{\partial r}\left(r.\frac{\partial T_{\mathrm{w}}}{\partial r}\right) + \frac{1}{r^2}.\left(\frac{\partial^2 T_{\mathrm{w}}}{\partial \theta^2}\right) + \left(\frac{\partial^2 T_{\mathrm{w}}}{\partial z^2}\right)\right] + \frac{\dot{q}''}{\rho_{\mathrm{w}} C_{\mathrm{w}}} \tag{3}$$

2.2 Boundary condition

In simplifying Eq. 3, the following assumptions were made [7]:

a) An unsteady-state condition is considered $\frac{\partial T_{\mathrm{w}}}{\partial t} \neq 0$
b) Due to the high rotational speed of the rolls, the heat conduction in the circumferential direction $\frac{1}{r^2}.\left(\frac{\partial^2 T_{\mathrm{w}}}{\partial \theta^2}\right)$ is ignored. The most important energy transport in this

Table 2 Correlation coefficient between the desired and output temperature of the ANN

Radial direction (m)	*Z* direction (mm)						
	0	350	700	1050	1400	1750	2100
R=0.36 (surface)	0.993479	0.856654	0.808939	0.809314	0.809113	0.826698	0.993259
R=0.27	0.988018	0.980167	0.9768525	0.9744864	0.9767365	0.973538	0.990192
R=0.18	0.994391	0.991044	0.927653	0.919923	0.923198	0.983519	0.994356
R=0.9	0.998593	0.998815	0.995701	0.99534	0.99568	0.998441	0.998571
R=0 (center)	0.999855	0.999748	0.999764	0.999715	0.999755	0.999781	0.99984

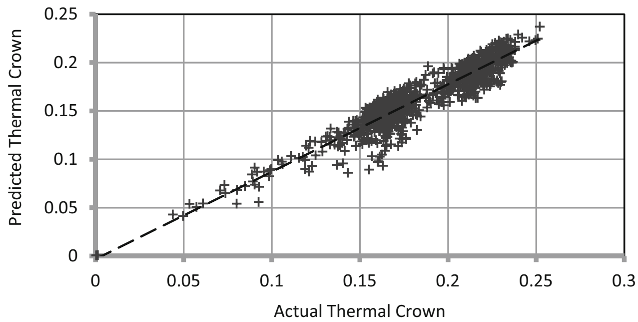


Fig. 7 Comparison of the predicted thermal crown with the actual thermal crown for all test data sets

direction is the heat convection. In the differential equation, this is specified by the expression $\frac{v_\theta}{r}\frac{\partial T_w}{\partial \theta}$.

c) The work roll movement in radial direction is negligible so that $v_{r=0}$. Thus, $v_r \frac{\partial T_w}{\partial r} = 0$.

d) As the axial displacement of the rolls has no effect on thermal energy transport, the present model may include the roll shifting and hence $v_z \frac{\partial T_w}{\partial z} = 0$

e) No energy inside the roll is produced.

So, the final equation is simplified as

$$\frac{\partial T_w}{\partial t} + \frac{v_\theta}{r}\frac{\partial T_w}{\partial \theta} = \alpha_w \left[\frac{1}{r} \cdot \frac{\partial}{\partial r}\left(r. \frac{\partial T_w}{\partial r} \right) + \left(\frac{\partial^2 T_w}{\partial z^2} \right) \right] \quad (4)$$

As shown in Fig. 2, boundary conditions effective around the roll could be considered as follows [7]:

q''_{rad} Radiation from strip to roll
q''_{cool} Convection through environment and cooling water
q''_{jet} Convection with nozzle spray
q''_{wb} Heat conduction between backup and work rolls
q''_{fr} Heat generation of friction
q''_{RB} Conducting heat transmission from sheet to roll
q''_{def} Energy production of plastic work

By applying the above boundary conditions to Eq. 4, the temperature distribution of the roll is obtained. Basically, due to combination of roll thermal, wear, bending, and initial crowns, online measurement of the thermal crown is not directly possible. In addition, the predicted thermal crown is related to boundary conditions, geometrical dimensions, the contact area between roll and strip, the water cooling effect, etc. To validate the model, the following experiment was performed for a number of times. The rolls were removed from the stand and left at room temperature for 15 min. Then, the temperature was measured over the length of the roll surface by a direct contact thermometer (accuracy ±1 °C). As seen in Fig. 3, there was a good agreement between the results of the model and those of the experiments.

3 Neural network model

The results of the verified analytical model were used to supervise and train the ANN. For data acquisition, at first, the process variables of 70,000 sheets in 530 schedules at Mobarakeh Steel Co. were collected. The next step was to analyze and eliminate the roll schedules that were similar in process variables in the rolling process such as width, target thickness, initial temperature of the slab. Seven thousand slabs were selected in 61 rolling schedules. These schedules were simulated using the analytical thermal model to calculate the temperature at four points over the length of the slab.

Since considering all the parameters as the inputs of the neural network makes the network too complicated, only uncorrelated critical parameters were taken into account to design the network. For network architecture, the effects of rolling parameters on the work rolls were evaluated and consequently the parameters listed in Table 1 are selected as the inputs of the ANN. The correlations between the selected parameters show the independency of these parameters. The parameters have low correlation with each other, as shown in the table.

To predict the roll temperature distribution, the work rolls are discredited in radial and axial directions as shown in Fig. 4. The work roll temperature field was predicted at nodes in radial and axial directions by the ANN. The critical parameters in Table 1, the node temperature at the current time, and a number allocating the part of the slab, which enters the bite region, were the inputs of the ANN, and consequently the node temperatures at the next time step are calculated by the ANN.

As shown in Fig. 5, the rate of temperature changes increases from the work roll core to the surface. The layers close to the surface are highly affected by the cooling system while they are simultaneously in contact with the hot sheets [23]. So, using different ANNs with appropriate structures for different layers seems necessary for an accurate modeling. Another advantage of applying different ANNs is that each layer of

Table 3 Correlation coefficient between the ANN output and desired thermal crown in the length of the work roll

	Z direction (mm)						
	0	350	700	1050	1400	1750	2100
Correlation coefficient of thermal expansion	0.995879	0.992093	0.965939	0.964092	0.964418	0.986747	0.996132
Maximum error (μm)	0.37	3.99	4.95	5.33	5.09	4.19	0.37

work roll was affected by the temperature of side layers. Therefore, for any specific layer of work roll, only the temperature of the side layers was taken into account and the effect of the temperature of other layers was ignored.

4 Results and discussion

The work roll was divided into five layers, while for every single layer, a different ANN was designed and trained. The optimal structure of each ANN was determined by the change rate of temperature at that layer. The work roll surface layer had the greatest complexity, and consequently its ANN had the most neurons in hidden layers.

After determining the network structure, learning method, and network training, the network integrity was verified by the test data set. In all networks, 70 % of data were used as the training set, 15 % for the verification set, and 15 % as the test set. The test data and the network output results were compared with the target values as shown in Fig. 6.

There were differences between network output and actual temperature at some data shown in Fig. 6a because the surface of the work roll was subjected to complex boundary conditions and it has a maximum rate of temperature change, but this error did not affect the thermal expansion of the work roll significantly and the thermal crown was mainly determined by the body temperature field and not the surface temperature. The accuracy of the predicted temperatures increases when approaching the center of the work roll. The correlation between desired and output temperature of ANNs for the test data set is listed in Table 2. The high correlation values in the table show that the ANNs can predict the work roll temperature accurately.

Figure 7 shows the comparison of the predicted thermal crown with the actual thermal crown for all the test data. As shown, there is a good agreement between the two data sets. The correlation between the ANN output and the desired thermal crown of the work roll was 0.962. This correlation coefficient indicates a satisfactory response of the neural network. The correlation coefficient for thermal expansion in the length of the work roll is listed in Table 3.

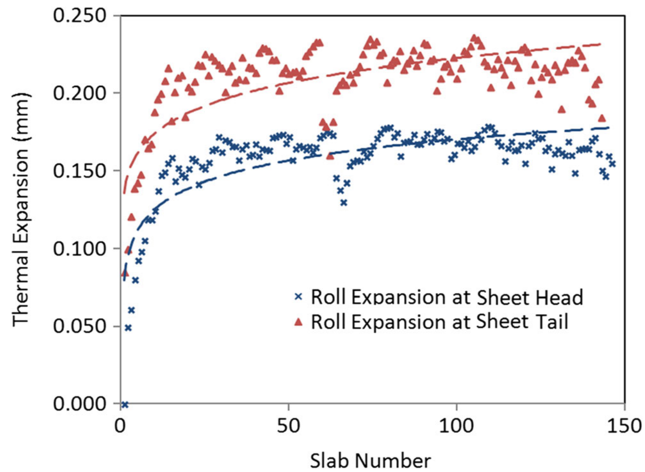


Fig. 9 Change in the thermal crown for a rolling schedule

A hot rolling schedule in the Mobarakeh steel complex was simulated, and the result of the ANN model was compared with a verified analytical model [7]. In Fig. 8, the thermal expansion profile, which was calculated by the analytical model, was compared with the predicted one for a sheet in a rolling schedule. Good accuracy was observed between results in this figure.

Figure 9 shows the change of the thermal crown within a rolling schedule at the head and tail of the sheet. As it can be seen, when the rolling process continues, the thermal crown increases while the rate of variation in the thermal crown decreases. The correlations between the ANN output and the desired thermal crown at the head and tail sheets in a rolling schedule were 0.921 and 0.966, respectively. This reasonable result shows the capability of the ANN in time series prediction during a rolling schedule.

Thermal expansion of side of the work roll was shown in Fig. 10. The maximum value in this figure related to the coffin

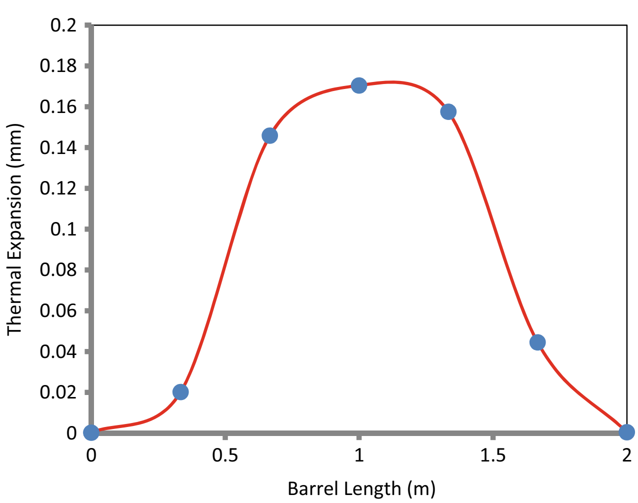


Fig. 8 Comparison of the predicted thermal crown with the actual one

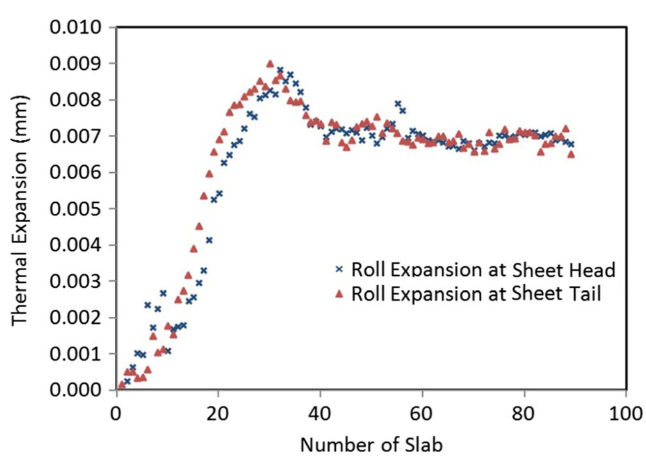


Fig. 10 Average thermal expansion of the two sides of the work roll at the head and tail of the sheets

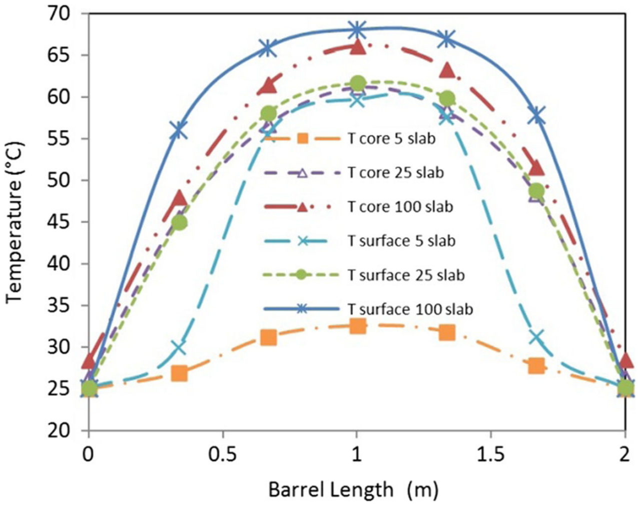


Fig. 11 Surface and core temperatures after rolling of 5, 25, and 100 sheets

shape rolling schedule. Indeed, the side expansion was related to width of the sheet and wider sheets increase the side expansion of the work rolls. The correlation coefficients of side expansion were 0.990 and 0.995 for head and tail of the sheet.

In Fig. 11, the predicted surface and core temperatures of the work roll are shown after rolling of 5, 25, and 100 slabs in the schedule. Heat is gradually transferred from the roll surface to the core, and the difference between the surface and core temperatures decreases with time.

5 Conclusions

A neural network was developed to predict the thermal expansion of a work roll during a rolling process. A verified three-dimensional analytical model was used to guide and supervise the learning procedure. The accurate analytical model was based on FDM and variable boundary conditions were taken into account. The iterative method was not developed to avoid long computation time. Hence, the simplified model is less accurate but its accuracy is within the acceptable range. A neural network model based on an accurate mathematical model was developed for online prediction of thermal expansion of a work roll. The following are some of the concluding remarks of this study:

- Temperature predictions at the core of the work roll are more accurate than the points close to the surface as the outer layers close to the surface are subjected to rapid temperature changes. This error did not affect the thermal expansion of the work roll significantly, and the thermal crown was mainly determined by the body temperature field and not the surface temperature.
- Good agreement between the data sets of the predicted thermal crown and that of the actual thermal crown is found which shows that the ANNs can predict the work roll expansion accurately.
- High correlation coefficients between the output value and data obtained from the analytical model show the capability of the neural network to predict thermal expansion accurately and rapidly. The computation time of thermal expansion calculation of the ANN model compared to that of the FDM was significantly decreased from more than 15 s to less than 0.1 s for a slab in a rolling schedule. The ANN model can be used in online application and optimization of a rolling process.

The results of this work have to be combined with wear and elastic deformation online models to effectively control flatness and crown during a rolling process.

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