A hybrid soft sensor for measuring hot-rolled strip temperature in the laminar cooling process

Jinxiang Pian, Yunlong Zhu

Abstract

To overcome the difficulties associated with the frequently varying operating conditions of the laminar cooling process and measuring the strip temperature in the cooling process online, a soft sensor model of the hot-rolled strip is proposed which combines mathematical and hybrid intelligent methods. The proposed approach is based on computational intelligence techniques, where RBF neural networks, CBR and fuzzy logic reasoning are employed to estimate process parameters for predicting the cooling temperature of the strips. A number of simulation tests using industrial data are conducted where the desired numerical results are obtained. It has been shown that the proposed soft sensor has a high potential for being used to effectively measure the strip temperature in the laminar cooling process.

Keywords:
Soft sensors
Laminar cooling systems
Case-based reasoning (CBR)
Radial basis function (RBF) neural networks

1. Introduction

The laminar cooling system is used to cool the strips from the austenitic finishing temperature (820–900 °C) down to the ferrite cooling temperature (500–700 °C) which can improve the metallurgical properties of the hot rolled strip [1,2]. Strips enter the laminar cooling zone after the finishing mill, they are then cooled in the water cooling section, and finally they are coiled by coilers. The strips’ mechanical properties are determined by the strip temperature which is controlled in the laminar cooling zone. Therefore, effective control of the cooling system is extremely important for strip quality. However, the temperature of the water vapor in the cooling process is generally very high, so it is difficult to measure the strip temperature continuously in the cooling zone. Indeed, only the strip surface temperature before it enters the cooling zone can be measured, but the strip temperature cannot be obtained due to a lack of suitable instruments. Only when the strip has been coiled by the coilers can the strip coiling temperature be measured, by which time the cooling operation is complete. So, the closed loop control cannot be effectively conducted. For this reason, a soft sensor is needed to measure the strip temperature in the cooling zone which will be a basis of implementing effective closed-loop control.

Earlier work on modeling the laminar cooling process goes to mathematical equations [3,4]. In order to enlarge the scope of strip specifications, Xie et al. [5] and Chai and Wang [6] developed an error compensation model based on neural networks to improve the precision of the prediction model. However, these models are static and cannot be used to predict the temperature dynamically for the hot rolling strip in the laminar cooling process. In [7], a mathematical model was proposed by using the heat transfer mechanism and a differential equation. The output of the equation actually gives an average temperature along the strip thickness. For thick strips, the temperature difference in the thickness direction cannot be ignored [8]. To reduce the model bias caused by the temperature difference in the thickness direction, Uetz et al. [9] assumed that the temperature density function follows the parabola distribution in the strip thickness direction and established a one-dimensional differential equation system for problem solving. Indeed, some researchers have taken the temperature difference along with time and the thickness direction into account and established two-dimensional dynamic strip temperature models [10–13]. However, the two-dimensional dynamic models cannot be solved effectively and it is hard to apply them for process industries.

The heat transfer mechanism of hot rolling strips in the laminar cooling process is complex, and the heat exchange process parameters are difficult to be estimated by simple regression models. Most of heat exchange process parameters are provided by domain workers based on their working experience. In [6], the strips were classified into several categories according to the product specifications, and the corresponding heat transfer coefficient, heat conductivity coefficient and temperature conductivity coefficient for each category were set accordingly. As we know that the heat transfer process is associated with many factors including the strip specification, cooling water temperature, the environment temperature, and the strip running speed. These factors are varying in the laminar cooling process, and make the improvement on the strip temperature...
model to be limited. Over the past years, many efforts have been made on the model improvement through advanced parameter identification techniques along with the changing boundary conditions. In the petrochemical industry, a cost function for the parameter identification is defined as deviation between the model output and actual output, and the traditional least squares techniques have been employed for the parameter optimization [14,15]. Although quadratic (nonlinear) programming techniques and genetic algorithms can be used for the unknown parameter estimation of dynamic models in the laminar cooling process, online solutions cannot be achieved due to the real-time constraint.

This paper is built on our previous work on modeling the laminar cooling process [16,17], where a two-dimensional parameterized model, the case-based reasoning (CBR) and GA-based optimization techniques have been used. In [16], we considered the influence of changing conditions on the model parameters, but did not address how to set up the initial case base of the case-based reasoning system. Also, the retrieval weight, an important parameter in the case-based reasoning system, was determined subjectively. In [17], a hybrid parameter identification method was proposed to deal with uncertainties caused by the strip specification.

This paper aims to improve the soft sensor model performance in terms of the prediction accuracy of the strip temperature in the cooling process. A mathematical model is firstly developed for predicting the strip temperature, followed by a dynamical tuning of the model's parameters according to varying operating conditions. In this work, RBF neural networks are employed to adjust the weight parameter of the CBR system to improve the system performance. Simulations were carried out on real data from an industrial process. Results indicate that the proposed soft sensor model has good potential to favorably estimate hot strip temperature in the cooling process.

2. Laminar cooling process

The general layout of the laminar cooling process is shown in Fig. 1 with top headers and bottom water sprays. During this process, first the strip will be sent into the run-out table (ROT) after being exported from the finishing mill, then it will be water-cooling in a long cooling zone and finally rolled by the coilers. The cooling water is pumped into the two main water pipes from the water head tank and then distributed by the water dividing pipes. The motors mounted under the ROT are used to control the rolling speed of the ROT. The main function of the laminar cooling system is to regulate the quantity of the cooling water in order to control the cooling temperature of the strip.

In the cooling zone, it is difficult to measure the strip temperature because of two factors: one is that the strip steel produces a lot of high temperature gas during the cooling process. In this situation, it is unavailable for instruments to measure the strip temperature accurately. The other one is that the strip moves quickly in the cooling zone, making the instruments unable to sample accurately in a short time. Therefore, there are only two temperature measuring points mounted at the entry and exit of the cooling zone. In the cooling process, the open loop control cannot guarantee the cooling temperature to meet the technological requirements which are related to product quality. However, in the absence of continuously measured data of the strip temperature, it is difficult to implement conventional closed loop control because the controlled cooling process has already finished before the cooling temperature is sampled. Therefore, in order to implement a real-time control in the cooling process, it is vital to design an online soft sensor model to estimate the values of the strip temperature.

3. Mathematical model of strip temperature

In order to reduce the negative effect on the strip temperature caused by strip thickness and speed, we define a strip segment with one meter length. At the same time, the strip thickness is divided into several layers. In addition, a pair of vertically symmetrical spray header is defined as a cooling unit. Only three kinds of cooling ways can work in the defined cooling unit, described as follows: (1) If the pair of spray headers are all open, the strips are cooled by water both on the top and bottom surface; (2) If the top spray header is open and bottom header is closed, the strips are cooled by water on the top of the strip surface and cooled by air on the bottom; (3) If the pair of spray headers are all closed, the strip is cooled by air on both the top and bottom of strip surface. These variants imply a need to establish three kinds of heat exchanging models according to the three cooling ways.

As shown in Fig. 2, a small section of the strip in the cooling zone is selected at time $\tau$, where $x$ is the strip direction, $y$ denotes the direction of the thickness, and $z$ denotes the transverse direction. For the non-homogeneous temperature distribution inside the selected strip section, a small element is defined as its volume given by $(dx\,dy\,dz)$. During the unit time, the quantity of the heat entering this element is defined by $R_{in}$, whilst the heat out of this element is denoted by $R_{out}$. The heat produced inside this element is denoted by $R_{e}$ and the energy variation is given by $R_{e}$. Ignoring the thermal distortion and expansion, by using the law of conservation of energy and the Fourier theory, the heat exchanging model can be described in (1) as follows:

$$R_{in} - R_{out} + R_{e} = R_{de}$$

(1)

According to physics, the generalized heat transfer equation of the selected element can be established as follows:

$$\frac{\partial}{\partial x} \left( \lambda \frac{\partial T}{\partial x} \right) + \frac{\partial}{\partial y} \left( \lambda \frac{\partial T}{\partial y} \right) + \frac{\partial}{\partial z} \left( \lambda \frac{\partial T}{\partial z} \right) + Q = \rho c_{v} \frac{\partial T}{\partial \tau}$$

(2)
where $T$ is the strip temperature, $\lambda$ is the thermal conductivity, $Q^*$ is the latent heat that generated by the phase change, $\rho$ is the strip density, and $c_p$ is the specific heat. For as a strip segment, we can ignore the temperature difference in the $x$ direction. The design of the cooling equipment can guarantee the generalized temperature distribution in the strip width direction. Also, we can ignore the temperature difference in the $z$ direction. Because this study focuses on the mild-carbon steel strip with limited latent heat, so $Q^*$ could be ignored as well. In the end, (2) can be simplified as follows:

$$\frac{\partial T(y,t)}{\partial t} = \frac{\partial^2 T(y,t)}{\partial y^2}$$

where the initial condition is given as follows:

$$T(y,t) = X_T$$

The boundary conditions are described as follows:

$$\frac{\partial T(y,t)}{\partial y} |_{y = -z} = -h_0 \frac{d}{2} T \left( \frac{d}{2} t \right)$$

$$\frac{\partial T(y,t)}{\partial y} |_{y = z} = -h_0 \frac{d}{2} T \left( \frac{d}{2} t \right)$$

$$\frac{\partial T(y,t)}{\partial y} |_{y = 0} = 0$$

where $s$ is the thermal diffusivity, $\lambda$ is the thermal conductivities, $h_0$ and $h_{wa}$ are the heat transfer parameters of the top surfaces and the bottom surface respectively, $T(y,t)$ is the temperature of the strip segment at time $t$, $d$ is the strip thickness, and $X_T$ is the strip temperature measured at the entry of the cooling zone.

We divide the strip segment into mesh nodes in the thickness direction and time, and apply the finite difference method to solve (3). The different nodes' temperature models are proposed as follows:

(M1) Inner node temperature model:

$$\left[ 2 + 2 \frac{\Delta \tau}{\Delta d} \gamma_j \right] T_j(k) - \frac{\Delta \tau}{\Delta d} \gamma_j T_{j-1}(k) - \frac{\Delta \tau}{\Delta d} \gamma_j T_{j+1}(k)$$

$$= \frac{\Delta \tau}{\Delta d} \gamma_j \left[ 2 \Delta \tau S_j T_{j-1}(k-1) + \Delta \tau S_j T_{j+1}(k-1) \right]$$

(M2) Strip top surface temperature model:

$$\left[ 1 - \frac{\Delta \tau S_0}{\Delta d} \gamma_0 \right] T_0(k) - \frac{\Delta \tau S_0}{\Delta d} \gamma_0 T_1(k)$$

where $T_j(k)$ is the strip temperature, $j$ is the thickness node index, $k$ is the iterative time, and $\Delta \tau$ and $\Delta d$ are the finite difference units of the time and strip thickness.

(M3) Strip bottom surface temperature model:

$$\left[ 1 + \frac{\Delta \tau S_j}{\Delta d} + \frac{\Delta \tau S_j}{\Delta d} \gamma_j \right] T_j(k) - \frac{\Delta \tau S_j}{\Delta d} \gamma_j T_{j-1}(k)$$

$$= \frac{\Delta \tau S_j}{\Delta d} T_{j-1}(k-1) + \left[ 1 - \frac{\Delta \tau S_j}{\Delta d} \gamma_j \right] T_j(k-1) + \frac{\Delta \tau S_j}{\Delta d} \gamma_j T_j$$

where $H_0$ is the medium temperature of the strip top surface.

The model parameters in (8)–(10) take different values according to the cooling ways. As the strip segment is cooled by water both on the top and bottom strip surface (water-cooling mode), the heat transfer parameters are given as follows:

$$h_0(t) = 2 - \frac{(r + 1 - N_{top})}{11} \frac{\gamma_k \gamma_v r \gamma_j T_0(t)}{F_v}$$

$$h_j(t) = 2 - \frac{(r + 1 - N_{top})}{11} \frac{\gamma_k \gamma_v r \gamma_j T_0(t)}{F_v}$$

$$H_0 = H_f = H_w$$

where $H_w$ is cooling water temperature; $r$ is the cooling unit index determined by the strip segment's location; $v$ is the running velocity when the strip segment enters the cooling unit and $N_{top}$ is the location of first spraying water unit.

As the strip segment is cooled by water on the top of the strip surface and cooled by air on the bottom, the heat transfer parameters are

$$h_0(t) = 2 - \frac{(r + 1 - N_{top})}{11} \frac{\gamma_k \gamma_v r \gamma_j T_0(t)}{F_v}$$

$$h_j(t) = 2 - \frac{(r + 1 - N_{top})}{11} \frac{\gamma_k \gamma_v r \gamma_j T_0(t)}{F_v}$$

where $H_e$ is the environment temperature; $\gamma$ is the Boltzmann constant $5.67 \times 10^{-8}$[W/m²K⁴], and $\epsilon = 0.82$ is the thermal emissivity.

As the strip segment is cooled by air on both top and bottom strip surfaces (air-cooling mode), the heat transfer parameters are given as follows:

$$h_0 = \sigma \epsilon \times \frac{|T_0(t)|^4 - (H_e)^4}{(T_0(t) - H_e)} + 6.5 + 5.5 \times (v_r - \gamma)$$

$$h_j = 2 - \frac{(r + 1 - N_{top})}{11} \frac{\gamma_k \gamma_v r \gamma_j T_0(t)}{F_v}$$

$$H_0 = H_f = H_w$$

The thermal conductivity parameters are defined as follows:

$$\lambda_0(t) = 56.43 - 0.0186 \times (v_r - \gamma) \times T_0(t)$$

$$\lambda_j(t) = 56.43 - 0.0186 \times (v_r - \gamma) \times T_j(t)$$

The thermal diffusivity parameters are defined as follows:

$$s_j(t) = \begin{cases} 8.65 + (5.0 - 8.65) |T_j(t) - 400|/250, & T_j(t) \in [400, 650] \\ 5.0 + (2.75 - 5.0) |T_j(t) - 650|/50, & T_j(t) \in [650, 700] \\ 2.75 + (2.75 - 2.75) |T_j(t) - 700|/100, & T_j(t) \in [700, 800] \\ 5.25 + 0.00225 |T_j(t) - 800|, & T_j(t) \in [800, 1000] \end{cases}$$

where the key parameters $c$, $\Delta v$, $\gamma$, $\gamma_v$, $\gamma_d$ and $\gamma_r$ are unknown in (11)–(19).
4. Hybrid intelligent parameter identification

Sensitivity analysis of the unknown parameters \((c, \Delta v, \gamma_v, \gamma_d, \gamma_i)\) is helpful to determine the structure of the parameter identification. A first order sensitivity index is defined to perform single factor analysis, which is defined as follows:

\[
\zeta_\theta = \frac{[Y(\theta + \Delta \theta) - Y(\theta)]/Y(\theta)}{\Delta \theta/\theta}
\]

where \(\zeta_\theta\) is the sensitivity of the system output with respect to the parameter \(\theta\), \(Y\) is the strip coiling temperature and \(\theta\) represents the unknown parameters \((c, \Delta v, \gamma_v, \gamma_d, \gamma_i)\). By adding the varying \(\Delta \theta\) to \(\theta\) and computing the coiling temperature \(Y(\Delta \theta + \theta)\), we can obtain the sensitivity of the parameters in (20). Table 1 illustrates that the sensitivity of the parameter \(\gamma_v\) is much higher than others. This means that \(\gamma_v\) is the key parameter which affects the system output.

Even for the same strip, the running speed, the initial temperature, and the thickness after finishing mill vary within a limited range. As for the parameter \(\gamma_v\), this change should not be ignored, and parameters \(c, \Delta v, \gamma_v, \gamma_d\) and \(\gamma_i\) can be assumed to be constant around the operating point. Due to the various characteristics of these parameters, we adopt different methods to identify them, as outlined below.

(a) Two-step identification of parameter \(\gamma_v\):

According to the different change cycle of operating conditions, we can identify \(\gamma_v\) using the following two steps. The first step is to identify the normal value, denoted by \(\gamma_{kw}\), and the second step is to adjust \(\gamma_{kw}\) with \(\Delta \gamma_v(i)\) at every sampling point (denoted by \(i\)). Summing up \(\gamma_{kw}\) and \(\Delta \gamma_v(i)\) gives the parameter \(\gamma_v(i)\). As \(\gamma_{kw}\) represents the most characteristics, the correction term \(\Delta \gamma_v(i)\) will not be too large. Even if \(\Delta \gamma_v(i)\) is not very accurate, \(\gamma_v\) will be a good estimate as well.

(b) Parameter identification based on RBF neural networks:

To identify the parameter \(\gamma_{kw}, \gamma_v\) and \(c\), we employ the well-known radial basis function (RBF) neural networks through learning from some collected data.

(c) Parameter identification based on case-based reasoning (CBR):

Notice that the parameter \(\Delta \gamma_v(i)\) can be easily obtained from the first step, however, the calculation of \(\Delta \gamma_v(i)\) takes time and hardly meets the real-time requirement for online application. To overcome this difficulty, case-based reasoning (CBR) techniques can be applied to solve this problem by reasoning a solution from the existing cases.

(d) Parameter identification based on the adaptive neural fuzzy inference system (ANFIS):

Some prior knowledge on the parameters \(\gamma_v, \gamma_d\) and \(\Delta v\) are available in practice. For example, \(\gamma_v\) increases if the strip becomes thicker. Similarly, the \(\gamma_v\) and \(\Delta v\) will increase if the speed is higher. In such a circumstance, ANFIS is a better candidate to be employed for parameter identification.

The flow chart of our proposed hybrid parameter identification system is depicted in Fig. 3.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Sensitivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\gamma_v)</td>
<td>0.0589</td>
</tr>
<tr>
<td>(\gamma_v)</td>
<td>0.1253</td>
</tr>
<tr>
<td>(\gamma_d)</td>
<td>0.1324</td>
</tr>
<tr>
<td>(\gamma_i)</td>
<td>0.1118</td>
</tr>
<tr>
<td>(\Delta v)</td>
<td>0.1015</td>
</tr>
<tr>
<td>(c)</td>
<td>0.0820</td>
</tr>
</tbody>
</table>

4.1. Identification of parameter \(\gamma_v\)

4.1.1. Identification of \(\gamma_{kw}\) at the operating point

In this paper, a RBF network with five nodes connecting with the operation conditions is employed. The five input signals are the strip grade \((G)\), the finishing speed \((F_v)\), the finishing thickness \((F_d)\), the finishing temperature \((F_T)\), and the cooling water temperature \((H_w)\). The basis function used in the hidden layer is the Gaussian type function:

\[
O_i = R_i(X) = \exp \left[ -\frac{||X - C_i||^2}{(0.5r_0)^2} \right]
\]

\[T(i) \rightarrow v(i) \rightarrow \text{CBR identification method} \rightarrow \gamma_{kw} \rightarrow \Delta \gamma_v(i) \rightarrow \gamma_v(i) \rightarrow \gamma_v \rightarrow \gamma_d \rightarrow \gamma_y \rightarrow \Delta v \]

Fig. 3. Hybrid intelligent parameter identification method.
The output is evaluated by using a weighted linear summation of the functions:
\[ y = \sum_{i=1}^{k} O_i w_i \]  
(23)

where \( y \) is the output; \( w_i \) is the weight connected with the \( i \)th node of the hidden layer, and \( k \) is the total number of nodes in the hidden layer.

The number of nodes in the hidden layer directly affects the modeling performance. In order to implement a self-adaptation neural network to the different strips, the dynamic near-neighbor clustering algorithm [18] is adopted online to determine the number of the nodes. Because the initial center points of the basis functions are randomly selected, we need to use a subtractive clustering algorithm [19] to locate a set of suitable initial center points before switching on the dynamic clustering algorithm for online updating.

4.1.1.1. Online determination of the number of the nodes in hidden layer

Step 1: A suitable width (\( r \)) for the Gaussian function is firstly defined according to the real process data. \( A(h) \) is defined as the output of RBF network and \( B(h) \) is defined as the number of nodes of the different cluster.

Step 2: \( X_i \) is denoted as the first center point of the first cluster when the first sample \((X_1, y_1)\) is given. Furthermore, let \( A(1) = y_1 \) and \( B(1) = 1 \). Consequently, the number of the nodes in hidden layer is one, and the first connective weight \( (w_1) \) is assigned as \( w_1 = A(1)/B(1) \).

Step 3: The sample with the highest potential \( P_i \) is picked out, and we update the following function:
\[ P_i = P_i - r_1 \exp \left[ -\frac{||X_i - X_j||^2}{(0.5r_a)^2} \right], \quad r_b = 1.5r_a \]  
(26)

For each potential value \((P_i)\), if \( P_i/P_j > \eta_1 \), \( P_i \) is accepted as a new class, and the number of nodes is increases by one. If \( P_i/P_j < \eta_2 \), then only when it has reasonable potential value and the corresponding \( X_i \) is far away from the other clustering centers, it will be accepted as a new center point. Otherwise, it will be rejected.

Step 4: If \( X_i \) has been accepted as a new center point, the corresponding potential value should be reduced. Then, the next sample with the highest potential is selected and Step 3 will be repeated.

4.1.2. Identification of parameter \( \Delta y_k(i) \) at the sample points

CBR is used to update parameter \( \gamma_k \) at every sampling point by adding the correction term \( \Delta y_k(i) \). As shown in Fig. 4, the CBR used here has a problem-solving life cycle and consists of four parts: retrieving, reusing, revising and retaining of a new solution.

The cases are stored in case pool with the format shown in Table 2, consisting of two index features, and one key feature. The index features include the deviations of the temperature \( \Delta T(i) \), and the moving speed \( \Delta v(i) \) of the ith sample point. The key feature is the \( \Delta y_k \).

Case retrieving is a process of searching cases that are close to the current case to be inferred. As all the features are of numerical type, a similarity measure based on the weighted Euclidean distance is used:

\[ d_{P}^{w} = \left[ \sum_{j=1}^{n} \left( \frac{\Delta \gamma_j(i)}{\eta_j} \right)^2 \right]^{1/2} \]  
(27)

where \( \Delta \gamma_j(i) \) and \( \Delta \gamma_j \) are the features of the initial strip temperature; \( \Delta \gamma_j \) and \( \Delta \gamma_j \) are the features of the strip running speed; and the \( w_i \) is assigned to the jth feature to indicate the importance weight. As a result, a similarity metric for measuring the closeness between two cases is defined as follows:

\[ SM_{P,i} = \frac{1}{1 + \mu d_{P}^{w}} \]  

where \( \mu = 0.05 \). If all the feature weights are equal to 1, we denote this metric as \( SM_{P,i} \). The feature weight indicates the degree of importance of a feature to the solution. Thus, these weights are crucial in
computing the similarity. A gradient-based optimization technique and neural networks are used to learn the feature weights [20]. As shown in Fig. 5, there are four nodes in the input layer, two nodes in the hidden layer and the output layer, respectively.

The evaluation function of the feature is defined as follows:

$$E(w) = \sum_i \sum_j \left[ SM_i^w (1 - SM_j^o) + SM_j^o (1 - SM_i^w) \right]$$

(29)

The feature evaluation function decreases if the similarity measure between the $p$th and $q$th cases tends to be either 0 (when $SM_{pq}^1 < 0.5$) or 1 (when $SM_{pq}^1 > 0.5$). Our objective is to obtain those feature weights which minimize the evaluation function (28). The gradient-based optimization technique can be employed to find a solution, that is

$$\Delta w_j = -\lambda \frac{\partial E}{\partial w_j}$$

(30)

where $\lambda$ is a learning rate, taken as 0.01 in this work. The trained neural network is utilized to compute the similarity measure between the problem and the cases in the case base. Those cases with similarity measures above 0.85 are retrieved.

The following formula describes the process of case reusing. Suppose that we have $n$ retrieved cases ($c_1$, $c_2$, ..., $c_n$) with the corresponding keys ($\Delta \gamma_{i1}$, $\Delta \gamma_{i2}$, ..., $\Delta \gamma_{i6}$), and the similarity measures are given by $SM_{pq1}$, $SM_{pq2}$, ..., $SM_{pqn}$. The reused case is defined as

$$\Delta \gamma_i(i) = \sum_{i=1}^{n} SM_{pqi} \times \Delta \gamma_i(i)$$

(31)

Once the reused case has been generated, an estimated value of $\Delta \gamma_i(i)$ can be obtained. Then, $\gamma_i(i)$ of the current strip segment can be calculated by adding this $\Delta \gamma_i(i)$ to $\gamma_{i\text{prev}}$. When the strip segment arrives at the pyrometer before the coolers, the cooling temperature is obtained. At the same time, the case revising process begins with an error analysis. The mathematical model results are obtained by using the identified coefficients ($\gamma_i(i)$, $\gamma_c$, $\gamma_v$, $\gamma_d$ and $\Delta \nu$). If the error between the calculated temperature and the measured cooling temperature is above $5^\circ\text{C}$, $\Delta \gamma_i(i)$ should be adjusted until the error is controlled in the range of $5^\circ\text{C}$. Then, the adjusted $\Delta \gamma_i(i)$ is stored to refresh the old cases.

### 4.2. Identification of parameters $\gamma_c$ and $c$

The RBF networks are used to identify the parameters $\gamma_c$ and $c$. The structure of the RBF network for the parameter $\gamma_c$ is $2-m-1$, that is, two nodes in the first layer, $m$ nodes in the hidden layer and one node in the output layer. The first layer with two nodes is connected to the strip gauge and the temperature of the finishing mill. The output layer with one node computes the parameter $\gamma_c$. Similarly, the structure of the RBF network for the parameter $c$ is $3-n-1$, that is, three nodes in the first input layer with the strip grade, the temperature and the thickness of the finishing mill. The output layer computes the parameter $c$.

### 4.3. Identification of parameters $\gamma_v$, $\gamma_d$, $\Delta \nu$

ANFIS, as a powerful tool to deal with uncertain data modeling, has been widely applied in process industries. The main merits of such a leaner model come from the use of a prior knowledge and effective model optimization through parameter tuning. In this work, we employ three ANFIS models to estimate the parameters $\gamma_v$, $\gamma_d$, $\Delta \nu$, respectively. A fuzzy rule base can be described as

If $\gamma_i$ is $A_i$, then $\gamma_i' = k_i \gamma_i + b_i$, $i = 1, \ldots, r$

where $r$ is the number of rules, $\gamma_i$ is the moving speed of ROT, $A_i$ is a fuzzy subset sets in the space of the input, and $k_i$ and $b_i$ are two adjustable parameters. The effective partitioning of the input space can reduce the number of fuzzy rules. For details of the ANFIS, one may refer to [21].

### 5. Experimental results

In our experiments, some industrial operating data are used with strip thickness ranged from 10.2 mm to 12.9 mm. The initial structure of the RBF network is set as 5-4-1 and the radius ($r_a$) as 0.2, acceptance ($\eta_1$) as 0.5 and the rejection ($\eta_2$) as 0.15, respectively. Then, the dynamic near-neighbor clustering method is used online by taking the width ($r$) as 0.2. The center nodes’ positions and the number of nodes are varying dynamically with the training data. Meanwhile, the input spaces of the ANFIS models for $\gamma_v$, $\gamma_d$, and $\Delta \nu$ are divided by using the subtractive clustering method. It is shown in Table 3 that the number of the rules varies with different radius. Considering the accuracy and the convergence of model implementation, the radius of $\gamma_v$, $\gamma_d$, and $\Delta \nu$ are assigned as 0.05, 0.5 and 0.7, respectively. So, three ANFIS systems are built with the following architectures: 1-3-3-3-1, 1-3-3-3-1 and 1-2-2-2-1, where the acceptance rate and rejection rate are taken as $\eta_1=0.5$ and $\eta_2=0.15$, respectively. First, all of the condition parameters are fixed, and the least squares algorithm is applied to identify the conclusion parameters. Second, the obtained conclusion parameters are fixed, and the back propagation (BP) algorithm is used to update the condition parameters.

### Table 2

<table>
<thead>
<tr>
<th>Index features</th>
<th>Key feature</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x_1$</td>
<td>$x_2$</td>
</tr>
<tr>
<td>$\Delta \gamma_c(i)$</td>
<td>$\Delta \gamma_v(i)$</td>
</tr>
</tbody>
</table>

![Fig. 5. Architecture of neural networks.](image)

### Table 3

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Radius</th>
<th>Rule number</th>
<th>Training times</th>
<th>Error</th>
<th>Structure</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma_d$</td>
<td>0.05</td>
<td>3</td>
<td>200</td>
<td>0.0155</td>
<td>1-3-3-3-1</td>
</tr>
<tr>
<td></td>
<td>0.05</td>
<td>4</td>
<td>200</td>
<td>0.0153</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.01</td>
<td>6</td>
<td>200</td>
<td>0.0112</td>
<td></td>
</tr>
<tr>
<td>$\gamma_v$</td>
<td>0.5</td>
<td>3</td>
<td>200</td>
<td>0.0145</td>
<td>1-3-3-3-1</td>
</tr>
<tr>
<td></td>
<td>0.2</td>
<td>5</td>
<td>200</td>
<td>0.0141</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.1</td>
<td>9</td>
<td>200</td>
<td>0.0114</td>
<td></td>
</tr>
<tr>
<td>$\Delta \nu$</td>
<td>0.7</td>
<td>2</td>
<td>200</td>
<td>0.0115</td>
<td>1-2-2-2-1</td>
</tr>
<tr>
<td></td>
<td>0.5</td>
<td>3</td>
<td>200</td>
<td>0.0082</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.1</td>
<td>6</td>
<td>200</td>
<td>0.0082</td>
<td></td>
</tr>
</tbody>
</table>
As shown in Table 4, if the initial weights were set at 0.7 and 0.3, according to the temperature and strip speed, the initial evaluation index $E(w_j)$ is 0.1268. After 860 times of training, $E(w_j)$ becomes 0.1, whilst the weights of the temperature and strip speed are 0.7676 and 0.2324, respectively.

5.1. The coiling temperature forecasting experiment

Two strips with grade (G) 130 and 131 are considered in this experiment. The segment numbers are 59 and 47 according to strip grade 130 and 131, respectively. The identified parameters at the operating points are shown in Table 5. Then, further identification on the parameter $\gamma_n(i)$ was done at every sampling point. The obtained results are shown in Fig. 6.

Fig. 7 shows a comparison of the precision of the coiling temperature between the method in [5] and our proposed one in this paper. As shown in Table 6, for strip grade 130, the average error from [5] is 8.81°C, and 34 segments are controlled in the range of $\pm 10^\circ\text{C}$ with the hit rate 57.6%; 19 segments are controlled in the range of $\pm 5^\circ\text{C}$ with the hit rate 32.2%. However, using the hybrid identification method proposed in this paper, the average temperature error becomes 2.67°C, and 50 segments are controlled in the range of $\pm 5^\circ\text{C}$ with the hit rate 86.4%; 33 segments are controlled in the range of $\pm 3^\circ\text{C}$ with the hit rate 55.9%. For strip grade 131, the average error from [5] is 13.18°C, and 15 segments are controlled in the range of $\pm 10^\circ\text{C}$ with the hit rate 46.6%; 17 segments are controlled in the range of $\pm 5^\circ\text{C}$ with the hit rate 31.5%. Corresponding results with our method are that the average temperature error becomes 2.67°C, and all the segments are controlled in the range of $\pm 10^\circ\text{C}$; 35 segments are controlled in the range of $\pm 3^\circ\text{C}$ with the hit rate 74.5%, respectively.

To see the effectiveness of our proposed identification method, we carried out an analysis of auto-correlation for the coiling temperature error of the sampling points. As shown in Fig. 8, the curve approximately meets Gaussian distribution, validating the proposed identification techniques.

The identification of $\gamma_n$ is critical to improve the model’s precision. In [5], the identified parameters are the average values of the same strip, and they cannot adapt to the fluctuations around the operating point. However, a two-step identification of the parameter $\gamma_n$ can adjust well online according to the varying operating point. Even when the strip grades are changed, the identifier still works properly to produce suitable estimate values.

### Table 4

<table>
<thead>
<tr>
<th>$w_1$</th>
<th>$w_2$</th>
<th>$E_x(w_j)$</th>
<th>$n$</th>
<th>$wa(n)$</th>
<th>$wb(n)$</th>
<th>$E(w_j)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.5</td>
<td>0.5</td>
<td>0.1408</td>
<td>1320</td>
<td>0.7582</td>
<td>0.2433</td>
<td>0.1</td>
</tr>
<tr>
<td>0.3</td>
<td>0.7</td>
<td>0.1669</td>
<td>2130</td>
<td>0.7401</td>
<td>0.2510</td>
<td>0.1</td>
</tr>
<tr>
<td>0.7</td>
<td>0.3</td>
<td>0.1268</td>
<td>860</td>
<td>0.7676</td>
<td>0.2324</td>
<td>0.1</td>
</tr>
</tbody>
</table>

Where $w_1$ and $w_2$ are the initial weight for the temperature, $w_3$ is the initial weight for the moving speed, $n$ is training times, $E_x(w_j)$ is the initial index, $wa(n)$ is trained $w_1$, $wb(n)$ is trained $w_2$, $E(w_j)$ is the index after training.

5.2. Soft measuring strip temperature in the cooling process

When a steel segment reaches the coiler, the control of the segment has already been completed. This simulation is to test the ability of the system to provide the strip temperature in the cooling process. The 13th strip element was chosen as a tracking segment in this study, where eleven nodes were assigned along the thickness direction. The strip grade is 320, the measured temperature is 856.6°C, and strip running speed at the entrance is 2.97 m/s. In addition, the total number of active headers related to the segment is 61. The estimated parameters values at the operating point are $1230, 1.34, 0.022, 2.7, 0.5, 0.48$ assigned to $\gamma_{air}, \gamma_n, c, r_w, r_w, \Delta$, respectively. After the second identification of $\gamma_n(13)$ with the measured sampling data, the $\Delta \gamma_n(13)$ is 190. So, the $\gamma_n(13)$ becomes 2420 by adding $\Delta \gamma_n(13)$ to $\gamma_{air}$ making an output of the mathematical model 562.71°C, and the error of the coiling temperature is 2.11°C.

The corresponding control array of this element is shown in Fig. 9, where “0” indicates a closed valve and “1” indicates an active valve. As shown in Fig. 10, the segment that arrives in the first air-cooling zone is marked as stage “1”, where the distance is from the cooling entrance to the valve #16. In this cooling zone, the heat exchange parameters belong to the air-cooling mode and Eqs. (16) and (17) are applied, where the temperature is dropping slower. When the segment runs into the section of valve #17, the strip segment is cooled by water on the top of the strip surface and cooled by air on the bottom, and Eqs. (14) and (15) are applied. Then the segment runs into the water-cooling zone marked as stage “2”, where the range is from the first top active valve #17 to valve position #43. The heat exchange parameters in this zone belong to the water-cooling mode and Eqs. (11) and (12) are applied, where the temperature drop is the greatest in the main forced water-cooling zone. When the segment runs into the section of valve #44, the strip segment is cooled by water on the top of the strip surface and cooled by air on the bottom, and Eqs. (14) and (15) are applied. Then, the segment runs into the second air-cooling zone marked as stage “3” and “4”, where the distance is from valve #45 to valve #76. The heat exchange parameters in this zone belong to the air-cooling mode, where the temperature increases about 50 degrees due to the phase transition denoted as stage “3”. Subsequently, the segment runs in the water-cooling zone marked as stage “5”, where the range is from the active valve #77 to the last valve #80. The heat exchange parameters in this zone belong to the water-cooling mode, where the temperature is dropping fast again. Finally, the segment runs into the last air-cooling zone after the cooling zone marked as stage “6”, and then it is cooled by the coolers.

Fig. 10 shows the temperature distribution of the eleventh node along the thickness direction. The top line describes the strip temperature changing in the cooling zone of middle node. The middle line describes the temperature changing in the cooling zone of the strip bottom surface, and bottom line describes the temperature changing in the cooling zone of the strip top surface. It can be seen that the biggest temperature difference is about 50°C, which should be controlled in a limited range and cannot be ignored. If first-order dimensional temperature model is applied,

### Table 5

<table>
<thead>
<tr>
<th>Strip index</th>
<th>Finishing data</th>
<th>Parameters of the operating point</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strip</td>
<td>$H_{cm}$ (°C)</td>
<td>$F_1$ (°C)</td>
</tr>
<tr>
<td>1</td>
<td>130</td>
<td>29</td>
</tr>
<tr>
<td>2</td>
<td>131</td>
<td>31</td>
</tr>
</tbody>
</table>

$r_w = 2400, r_s = 1.2, r_w = 0.52, r_s = 2.1, c = 0.02, \Delta v = 0.6$

$r_w = 1700, r_s = 1.46, r_w = 0.63, \Delta v = 2.7c = 0.03, \Delta \nu = 0.51$
the obtained result is the average temperature along the direction of the thickness and cannot tell the temperature difference. In Fig. 11, the coiling temperature distribution along the direction of the thickness is shown, and the temperature distribution profile is similar to a parabola curve because of the thermal conductivity.

Thus, the mathematical model with the hybrid parameter identification techniques proposed here not only has the ability to forecast the coiling temperature, but can forecast any segment’s

---

**Table 6**

The comparison results of the two methods.

<table>
<thead>
<tr>
<th>Strip grade</th>
<th>Average error</th>
<th>Hit rate of error varying in the range of</th>
<th>Hit rate of error varying in the range of</th>
</tr>
</thead>
<tbody>
<tr>
<td>[5]</td>
<td></td>
<td>±10°C</td>
<td>±5°C</td>
</tr>
<tr>
<td>130</td>
<td>8.81</td>
<td>57.6%</td>
<td>32.2%</td>
</tr>
<tr>
<td>131</td>
<td>13.18</td>
<td>42.6%</td>
<td>31.9%</td>
</tr>
<tr>
<td>This paper</td>
<td></td>
<td>±5°C</td>
<td>±3°C</td>
</tr>
<tr>
<td>130</td>
<td>2.67</td>
<td>86.4%</td>
<td>55.9%</td>
</tr>
<tr>
<td>131</td>
<td>2.0</td>
<td>100%</td>
<td>74.5%</td>
</tr>
</tbody>
</table>

---

**Fig. 6.** The identification of \( r_k \) (i) for different strip segment.

**Fig. 7.** The comparison between the models in [5] and our proposed one in this paper.

**Fig. 8.** Auto-correlation results of the coiling temperature errors.

**Fig. 9.** The control valve array for the 13th strip segment.
temperature distribution along the direction of the thickness during the cooling zone as well.

6. Conclusions

Accurate estimation of the strip temperature in the cooling zone is important and essential to implement closed-loop control schemes for a class of process industry. This paper, based on computational intelligence techniques, proposes a soft sensor model for effectively measuring the hot-rolled strip temperature in real time and with wider strip specifications. Empirical studies on industrial data are carried out with promising results. This research provides a technical support to further develop intelligent control techniques for improving steel product quality.

There are so many parameters involved in the soft sensor model. It is necessary and interesting to see how these parameters will impact on the system performance, that is, a comprehensive robustness analysis should be done in the further work.

Acknowledgment

This work is supported by the National Natural Science Foundation of China under Grants 61174164 and 61440004.

References


