Control of Heat Transfer in Continuous Casting Process Using Neural Networks

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Abstract In continuous casting, the cooling-solidification process must be based on the adaptation of heat transfer, which is directly connected to casting conditions such as casting speed, casting temperature, and cooling parameters. Most control schemes are based on the static relation between casting speed and water flow rate in each cooling zone; this constitutes an open loop that does not consider the dynamic surface temperature, which is an important parameter for the final slab quality. In steelmaking, the casting-speed changes affect the global heat transfer. An optimal operation requires an adjustment of the process control variables, i.e., global heat transfer. A learning neural network (NN) allows the identification and the control of a nonlinear heat transfer model in the continuous casting process. A heat transfer model was developed using the dynamic heat balance. A comparison between the experimental open loop results and those of the model simulation is considered. Following adaptation, the model is used for controlling the slab surface temperature in closed loop, using NN technology and PID controllers. The NN identification and control strategy gives a stable temperature closed loop control comparatively to the conventional PID.

Key words Neural networks, identification, control, heat transfer, continuous casting

In the steel industry, the continuous casting process permits the formation of ingots of solidified metal called slabs that are obtained by the passage of liquid steel through several cooling zones. In the first phase, the liquid steel is poured in the mould, cooled by water, after getting cold enough penetrates the cooling zones at constant casting speed and receiving optimal flow water quantity. The final solidified ingot quality depends on its thermal history during its stay in the different cooling zones. Therefore, it is necessary to lead the cooling according to the casting events, variations of thermal loss, casting speed, and different heat and mass dissipations. In most industrial applications, the correction of cooling flows is made only according to the casting speed, by linear correlation, anticipating the casting speed effect on the temperature in the considered cooling zones[1−3]. This control approach is inefficient in transient response as the thermal diffusion and the relation between water flow rate and casting speed are nonlinear and unsteady state functions[4−7]. At present, this control approach is only an open-loop linear static compensation.

During the cooling phase, slabs maintained at high temperature are in direct contact with the cooling water provoking the formation of oxides called calamine that involves some important variations in heat exchange and affects the surface temperature stability[8−10]. According to results of metallurgical studies, surface defects such as cracks and

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segregation are the result of the deviation from the target temperature in different cooling zones, so the control of temperatures is necessary in these points[11−13]. An appropriate application of water cooling is of significant importance because it significantly affects the casting quality. Temperature stability is very important, especially for casting crack sensitive steel grades. Such performance cannot be achieved without the NN technology because the process has an important nonlinearity and disturbances in casting speed, water temperature, and specific heat coefficients.

The temperature at the embedding point must be out of low ductility range[8−9, 14] that is characterised by a high level of surface oxidation, which generates a disturbance of the (measured) surface temperature.

The aim of the present study is to develop a closed-loop control scheme of temperature in every cooling zone. This control approach considers the global heat transfer changes. Such control scheme is based on NN identification and control. Due to their exceptional ability in approximating an arbitrary nonlinear function, neural networks have become an attractive means for modelling complex nonlinear processes such as slabs cooling in continuous casting. Numerous neural network models and their corresponding learning strategies, particularly multilayered feed forward neural networks with back propagation (BP) learning algorithm[15−16], will be proposed. An on-line adaptive neural network scheme is applied in this study to compute an optimal iterative control law.

This study is organized as follows.

1) As the first step, a heat-transfer model based on heat balance is developed. Interactions between slab surface temperature, casting speed, water flow rate, and other physical and thermal parameters are obtained. Model is fitted using measurement. Water flow rates and slab surface temperatures are considered as the input and the output of the model respectively, and other variables are considered as perturbations.

2) A closed-loop control scheme is designed and simulated based on the developed model. A comparative study between the conventional PID control and the NN control scheme is presented.

1 Heat transfer model

Fig. 1 illustrates the structure of cooling-solidification scheme in a continuous casting.

Every cooling zone i is characterised by its temperature $T_i(t)$, its water flow rate $q_i(t)$, and its length (l_i).

Steel flows into the mould at a temperature $T_0(t)$, called casting temperature, and at a casting speed $v(t)$.

The solidified slab is characterized by slab density ρ, specific heat C_{pi}, geometrical characteristics L, h. The cooling changes is characterized by water specific heat C_{Pe} and water temperature T_e.

We suppose that the outlet water temperature is equal to the slab surface temperature T_i, the slab is in direct contact with the water stream, the dynamic of slab surface temperature is controlled by the boundary conditions[12, 14] defined by the term $q_i(t)C_{pe}(T_i(t) - T_e)$.

The thermal balance in dynamic regine, for every zone is given as

$$m_i C_{Pi}\frac{\mathrm{d}T_i(t)}{\mathrm{d}t} = q_m(t)C_{Pi}(T_{i-1}(t) - T_i(t)) - q_i(t)C_{Pe}(T_i(t) - T_e) \tag{1}$$

where $m_i = \rho L h l_i$, $q_m(t) = \rho L h v(t)$.

We consider C_{pi}, C_{pe}, m_i, ρ, and T_e as constants. The second order variation of (1) is written as

$$\frac{\mathrm{d}^2T_i(t)}{\mathrm{d}t^2} = \frac{C_{Pi}}{m_iC_{Pi}}(T_{i-1}(t) - T_i(t))\rho Lh\frac{\mathrm{d}v(t)}{\mathrm{d}t} + \frac{C_{Pi}\rho Lhv(t)}{m_iC_{Pi}}\left(\frac{\mathrm{d}T_{i-1}(t)}{\mathrm{d}t} - \frac{\mathrm{d}T_i(t)}{\mathrm{d}t}\right) - \frac{C_{Pe}}{m_iC_{Pi}}(T_i(t) - T_e)\frac{\mathrm{d}q_i(t)}{\mathrm{d}t} - \frac{q_i(t)C_{Pe}}{m_iC_{Pi}}\frac{\mathrm{d}T_i(t)}{\mathrm{d}t} \tag{2}$$

$$\frac{\mathrm{d}T_i(t)}{\mathrm{d}t} \approx \frac{T_i(t) - T_i(t-\Delta t)}{\Delta t} \tag{3}$$

where Δt is the sampling time (the sampling number is a multiple of the sampling time).

After transformation, we obtain

$$T_i(k) = A^{-1}(BT_i(k-1) + CT_i(k-2) + DT_{i-1}(k) + ET_{i-1}(k-1) + F) \tag{4}$$

where

$$A = \Delta t^{-2} + \Delta q_m(k)a_1\Delta t^{-1} + a_2q_m(k)\Delta t^{-1} + a_3\Delta t^{-1}\Delta q_i(k) + a_3\Delta t^{-1}q_i(k)$$

$$B = 2\Delta t^{-2} + q_m(k)a_2\Delta t^{-1} + a_3\Delta t^{-1}q_i(k)$$

$$C = \Delta t^{-2}; D = a_1\Delta t^{-1}\Delta q_m(k) + a_2q_m(k)\Delta t^{-1}$$

$$E = -a_2q_m(k)\Delta t^{-1}; \quad F = -a_3\Delta q_i(k)T_e\Delta t^{-1}$$

$$a_1 = C_{Pi}m_i^{-1}; \quad a_2 = C_{Pi}m_i^{-1}; \quad a_3 = C_{Pe}m_i^{-1}C_{Pi}^{-1}$$

$$\Delta q_i(k) = q_i(k) - q_i(k-1); \quad \Delta q_m(k) = q_m(k) - q_m(k-1)$$

(2) is a nonlinear relation, describing temperature variations in zones (i) and $(i-1)$ and the casting speed and flow rate of cooling water in the zones (i) and $(i-1)$. It also considers the coupling due to zone interactions. The main influences on the strand surface temperature are the water flow rate, the strand specific heat coefficient C_{Pi}, the specific heat coefficient of water C_{Pe}, the water temperature T_e, and the casting speed $v(k)$. Other variables are not crucial in casting operation.

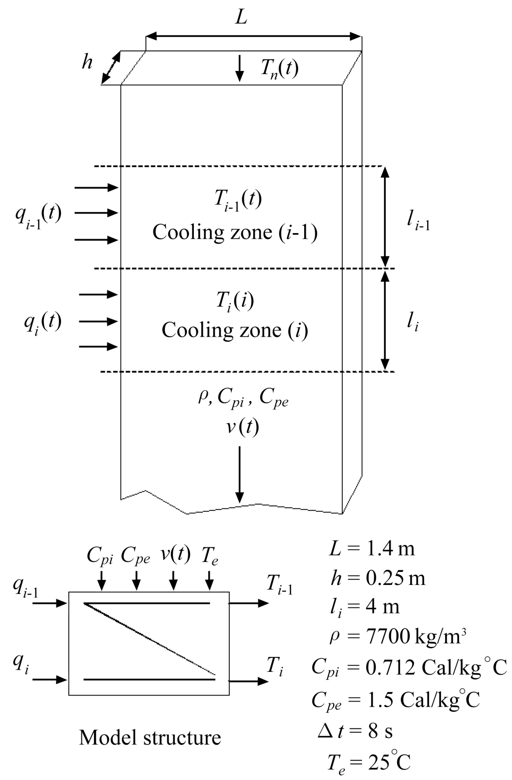


Fig. 1 Principle of cooling-solidification scheme in continuous casting process

2 Measurement and model validation

The simulation results obtained from the model described by (2) have been compared with measured results on the continuous casting process computer. The measurement principle is illustrated in Fig. 2 and achieved in the steel work.

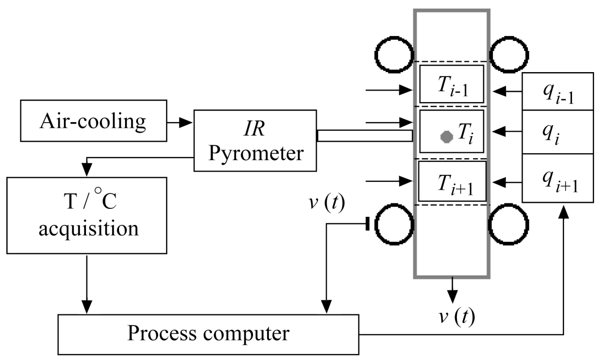


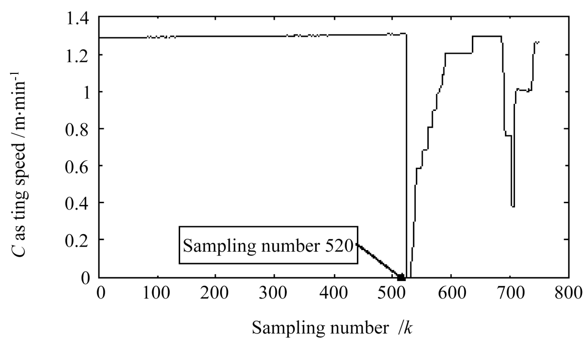
Fig. 2 Principle of temperature measurement and closed loop control

An infrared pyrometer was installed in the cooling zone at 2.5 m below the level of the mould bath, which is supplied with compressed air for its own cooling.

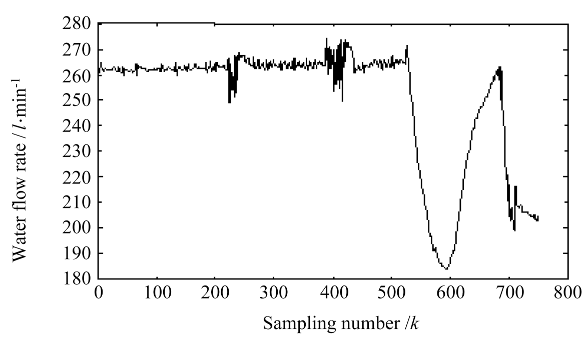
The measured signals of the pyrometer range from 4 to 20 mA corresponding to a temperature range of 900 ∼ 1 300° C. The sampling time for all process variables is equal to 8 s; this time has been recommended and fixed in the engineering step by the process computer management. The constants and structure of the model are shown in Fig. 1.

The calculated and measured temperatures obtained by the model are shown in Fig. 3. Process dynamics described in Fig. 3 have been used for testing the model temperature response. It has been noticed that an adequate choice of initial conditions for the model described by (2) results in a static error approximately equal to zero. In the present study, the initial value of the casting temperature was equivalent to 1 532°C. The complex metallurgical reactions such as strand surface oxidation disturb the temperature measurement due to the variation of the specific heat coefficient C_{Pi} of the steel. The change in water quality affects the specific heat coefficient C_{Pe} of the water. The casting temperature variation $T_0(t)$ has a considerable effect on the internal stress and defects of the solidified strand, but it has negligible influence on the strand surface temperature[3, 9]. As shown in Fig. 3, temperature variation of the sampling number 520 approximately is generated by a reduction of casting speed according to a casting incident.

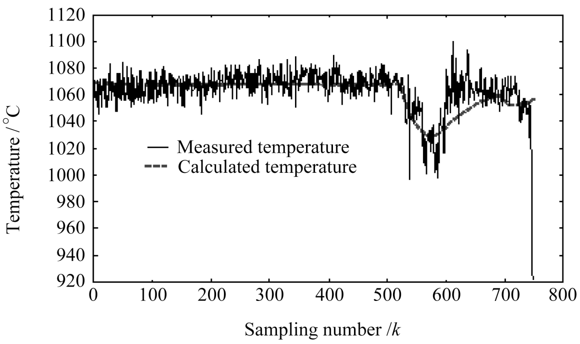
As shown in Fig. 3 (c), the measured and computed temperatures are appreciatively equal, and there is a static error of 5°C (Relative error ≈ 5/1070 ≈ 0.5%). This value is sufficiently acceptable for this type of process. The computed temperature is obtained using parameter values given in Fig. 1; the initial temperature is equal to casting temperature with the value of 1 532°C. The measured temperature presents a normal distributed noise, this can easily be filtered. The used modern infrared pyrometer is equipped by a tuning system for reducing the noise considerably, in this situation, the filtering system is used to know the maximum range of noise variations.



(a) Dynamics of casting speed



(b) Water flow rate dynamics



(c) Measured and calculated temperatures

Fig. 3 Measurement of process variables

3 Conventional control

Fig. 4 gives the closed loop structure using a PID controller. The tracking error for each cooling zone (i) is defined by the following equation.

$$e_i(k) = Tg_i(k) - T_i(k) \tag{5}$$

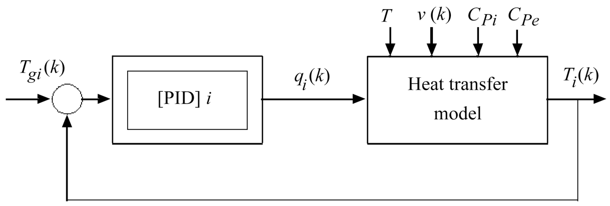


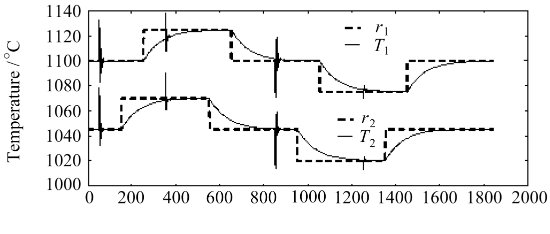
Fig. 4 Structure of PID control

where $Tg_i(k)$ is the set point of each temperature cooling zone (i). The PID digital control attains a stable closed loop by an optimal tuning of PID actions.

$$q_i(k) = q_i(k-1) + K_{Ri}\left[(1 + \frac{T_{Vi}}{\Delta t})e_i(k) - (1 - \frac{\Delta t}{T_{Ni}} + \frac{2T_{Vi}}{\Delta t})e_i(k-1) + \frac{T_{Vi}}{\Delta t}e_i(k-2)\right] \tag{6}$$

where K_{Ri} is the proportional action, T_{Ni} is the integral action, and T_{Vi} is the derivative action.

After several trials, the optimal values of controller actions (K_{Ri}, T_{Ni}, and T_{Vi}) are chosen through the simulation. Optimal values of PID actions for the casting speed variations result in a closed-loop stability limit for the heat transfer characterized by the variations of C_{Pi}, C_{Pe}, and T_e. Fig. 5 shows the closed loop control performance for the variations of casting speed and specific heat coefficients.



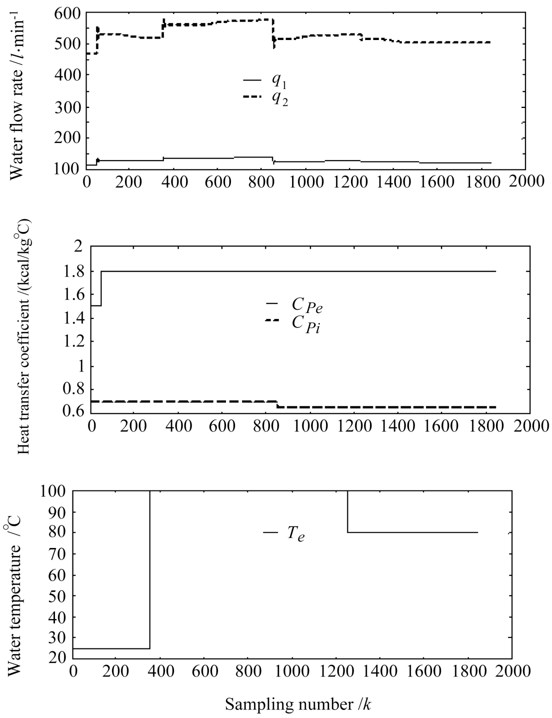


Fig. 5 PID closed loop control according to variations of C_{Pi}, C_{Pe}, and T_e

4 Neural network control

4.1 Overall structure of the neural identification and control

In this section, iterative online adaptive weights of the NN are considered. The control input is estimated to achieve a process output according to the track of a given reference signal. The neural network is used for controlling the heat transfer model, i.e., strand surface temperature is described by (2). The overall structure of the identification and control is given in Fig. 6. In a widely used multilayer feed-forward network, the past process output, the measured perturbations, control input, and the past control input are introduced. The network is trained to generate appropriate weights to reduce the error. After convergence the obtained NN weights are used to compute the control law.

The NN structure of the controller is chosen basically on the model structure.

1) Heat transfer model is highly nonlinear, this is considered in the controller by a choice of a sigmoid function as a NN outputs;

2) The number of the inputs/outputs of the controller is equivalent the model inputs/outputs;

3) It has been chosen two hidden layers to overcome the heat transfer model complexity, i.e., nonlinearity and other eventual changes.

It is clear that the computing time to achieve iterations can be important.

1) In this study, the sampling time is equal to 8 s, which is sufficient to achieve the required control law; this is verified in simulation.

2) If the computing time exceeds 8 s, the control inputs used in the past sampling time ($t-1$) can be used in the actual instant. The sampling time can be extended; the surface temperature closed loop is actually a slow loop be-

cause it is used only to adjust the flow water rate set points, and this is localized in the level two of the automation architecture system.

3) In continuous casting, the main problem is to obtain an optimal stability of the temperature closed loop according to different changes in physical and operating parameters such as casting speed and cooling water properties (C_{Pe}, T_e). The measured noise can be easily cancelled by an optimal adjustment of the hardware filtering system incorporated on the infrared pyrometer. In our experiment, this system voluntarily takes off. It is known that a feedback combined to a feed-forward (Fig. 6) also reduces the measured noise effects in the closed loop.

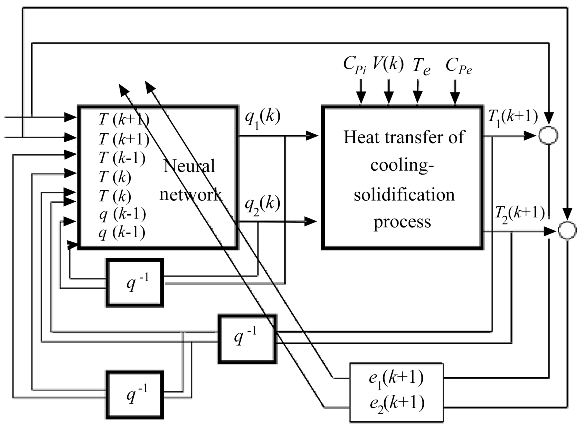


Fig. 6 Overall structure of the control using NN of temperature

4.2 Control using neural networks

The control scheme (Fig. 6) is used to compute the control law using the weights from the identification process. For each controlled temperature zone, the control law minimizes the tracking error. To ensure that the error signal is equal to zero, the control inputs are inversely estimated by trained NN as

$$q_i(k) = NN[Tg_{i-1}(k+1), Tg_i(k+1), T_{i-1}(k), T_i(k), T_{i-1}(k-1), T_i(k-1), q_i(k-1), q_{i-1}(k-1)] \tag{7}$$

Fig. 7 shows the NN closed loop performance for the variation of casting speed, water temperature T_e, and specific heat coefficients C_{Pi}, C_{Pe}. The on-line control algorithm can be summarized as follows.

Step 0. Initialize the network weights (−0.5 to +0.5);

Step 1. Identification

1) Acquisition of inputs/outputs;

2) For each cooling zone (i), calculate the tracking error $e_i^{(k)} = Tg_i(k) - T_i(k)$

a) If $e_i(k) \cong 0$, $W_{ij}^{new} = W_{ij}^{old}$;

b) Else, adjust NN weights using the BP algorithm;

Step 2. Control

1) Using W_{ij}^{new}, compute the new control inputs $q_i(k)$, using (7);

2) Next time Step $k = k + 1$;

3) Go to Step 1.

Stability plays a very important role in the control theory. It is a necessary condition for feasibility on the control system in the closed loop. Additionally, the controller must of course be designed in such a way that the behavior of the closed-loop system satisfies various requirements such as the tracking of a reference model[16−18]. The process output T_i follows the reference signal Tg_i, for a bounded output the input must be also bounded.

Define $e_i(k) = Tg_i(k) - T_i(k)$. The stability is defined by $\lim_{k\to\infty} \|e_i(k)\| \to 0$. If $k \to \infty$, this is easily verified by different simulation results. According to different perturbations on the model parameters, the NN control is stable and robust than the PID (see Figs. 5 and 7)

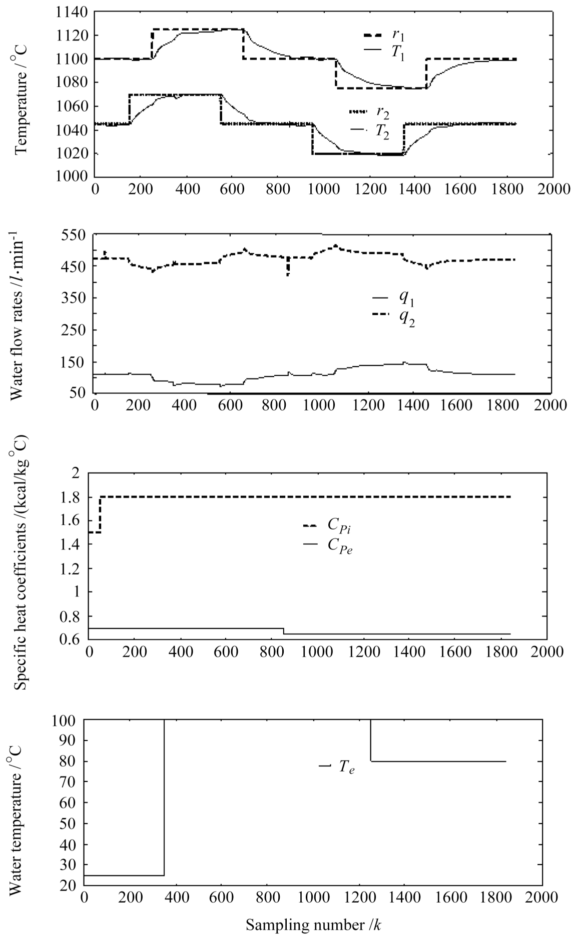


Fig. 7 NN control according to variations of C_{Pi}, C_{Pe}, and T_e

5 Results of simulation

The analysis of the heat transfer dynamic model shows the existence of coupling between cooling zones (i) and ($i-1$). A multivariable structure with two inputs and two outputs has been selected. The set points $r_1(k)$ and $r_2(k)$ are filtered by a second-order model that defines stable closed-loop dynamics, which reduces the output temperature oscillations $T_i(k)$ and limits the control saturation of water flow rate $q_i(k)$. In the present NN controller, there are eight input nodes, $Tg_1(k+1)$, $Tg_2(k+1)$, $T_1(k)$, $T_2(k)$, $T_1(k-1)$, $T_2(k-1)$, $q_1(k-1)$, and $q_2(k-1)$, in the input layer. In addition to nine nodes in the first hidden layer, five in the second hidden layer, and two NN outputs $q_1(k)$ and $q_2(k)$.

The closed-loop dynamics must track the target values, Tg_1 and Tg_2. For the same variations of casting speed, water temperature and specific heat coefficients, the closed loop performance for the PID and the NN controllers were different. The NN control gave an improvement of the surface temperature dynamics compared with PID with reduced tracking error. After several simulations, an optimally tuned PID controller based on the variations of the casting speed has been found, whereas for the other variables T_e, C_{Pi}, and C_{Pe}, the surface temperature behavior is yet to be improved. This was expected due to the large variations of process parameters and the model nonlinearities with some oscillations mainly due to the variations of T_e, C_{Pi}, and C_{Pe}. In practice, at normal operating conditions, the maximum variation of casting speed $|v(k) - v(k-1)|$ is limited to 0.3 m/min, which does not affects the surface temperature stability and reduces the input oscillations for NN and PID control. The present performance was obtained by iterative adaptation of NN weights using the tracking error.

A closed-loop control model has been developed. As shown in the different figures (Figs. 5 and 7), the closed loop is stable. The NN identification and control strategy achieve a robust and stable temperature closed-loop control compared with the conventional PID.

6 Conclusion

An NN closed-loop control scheme of heat transfer in the continuous casting process was designed and tested through simulation. The neural controller based on the inverse model seems to have good control performance for heat transfer parameters changes, casting speed variations, and set point changes. The temperature changes of slab surface are smaller than in conventional control, where there is an important tracking error. Coupling effects are also cancelled. The implementation on continuous casting process for on-line control is currently being investigated.

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