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# STUDY ON NEURAL NETWORK PROPORTIONAL-INTEGRATION-DIFFERENTIAL(PID) CONTROL STRATEGY OF THE MOLTEN METAL POOL LEVEL IN THE TWIN ROLL CASTING PROCESS

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In the twin-roll casting process, how to accurately control the molten metal pool level is a key problem to produce high quality strip. In this paper, the mathematical model about the pool level control is set up based on the process characteristics. Meanwhile, the limitations of the traditional PID control strategy are analyzed owing to the real-time change of the roll gap and roll speed. Furthermore, the neural network is applied to adaptively optimize the PID control parameters and the simulations show the neural network PID strategy can precisely control the molten metal pool level in twin-roll casting process under the condition of multiple factors interfering.

*Key words:* magnesium strips, twin-roll casting process, molten metal level, PID control, neural network(NN)

## INTRODUCTION

In the twin-roll casting process, the molten metal is poured into the pool formed by two rollers rotating in opposite direction and two side dams, then is solidified in a short time and is rolled into thin strip [1-3]. This technology greatly shortens the metal strip production process because a series of the conventional strip production procedures are eliminated, such as continuous casting and hot rolling. In the process, the molten metal pool level is an important factor affecting the thickness uniformity and surface quality of the strip, while the pool level is influenced by many process parameters, such as the stopper height, roll gap and casting speed, and there are time-varying, nonlinear and hysteretic characteristics among these parameters, therefore, it is difficult to precisely control the molten metal pool level. Recently, many scholars have made many efforts to solve the problem. In [4], a fuzzy PID controller was used to control the pool level, but the control parameters need to be determined according to the expert experience, which means the control accuracy and instantaneity cannot be guaranteed. In [5], a fuzzy neural network was applied to solve the problem, while the fuzzy network structure is so complex that it cannot mostly be used in the actual industrial production. In this paper, a molten metal pool level control strategy is presented by using neural network and PID control, which is self-adapted under multi-factor disturbances. Simulations show the control preciseness, robustness and the response time of the pool level are greatly improved compared with the traditional PID control method.

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## MODELING AND PARAMETER DECOUPING ANALYSIS

In the Magnesium Alloy Cast-rolling Engineering Research Center of University of Science and Technology Liaoning of China, a pilot twin-roll caster has been established to produce strip continuously at thickness from 1 to 4 mm at casting speed from 5 to 60 m/min, which schematic diagram is shown in Figure 1. The shadow part $S$ is the area of the molten metal pool, $Q_{in}$ and $Q_{out}$ are the input/ output flow of the metal pool, the metal pool height($H$), the roll gap($X_g$), the roll radius($R$) and the roll rotating angular speed($\omega$), respectively. Assuming the density change of the casting metal is little and can be neglected, the following mathematical model can be established.

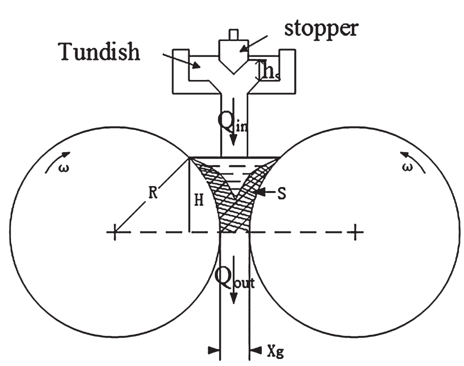


**Figure 1** Schematic diagram of the twin-roll casting process system

According to the principle of flow balance, the molten metal volume change in the pool is described as

$$L\frac{dS}{dt} = Q_{in} - Q_{out} \tag{1}$$

where $L$ is the width of the roller.

According to the geometry shape of $S$, the volume change is also presented as

$$L\frac{dS}{dt} = L\left[H\frac{dX_g}{dt} + (X_g + 2 - 2\sqrt{R^2 - H^2})\right]\frac{dH}{dt} \tag{2}$$

Assuming there is no displacement between the solidification metal shell and the casting roll, the output flow $Q_{out}$ is calculated by $Q_{out} = LX_gR\omega$ . In the casting process, the input flow $Q_{in}$ is adjusted by the height of the stopper $h_s$ in the tundish, which is controlled by a micro-servo motor. On this condition, $Q_{in}$ is simplified as a proportion loop of the stopper height, that is described as $Q_{in} \approx Kh_S$, where $K$ can be determined empirically. Based on this analysis, synthesizing (1) and (2), the final mathematical model of the molten metal pool level is gotten as

$$\frac{dH}{dt} = \frac{Kh_s - LX_gR\omega - LH\dfrac{dX_g}{dt}}{L(X_g + 2R - 2\sqrt{R^2 - H^2})} \tag{3}$$

In (3), there are three process parameters directly affecting the pool level, which are the casting speed, the roll gap and the height of the stopper. The simulation influence results of one parameter on the pool level is shown as Figure 2 when the other two parameters keep constant. In the simulation, the initial set-values of the main parameters are as follows, $X_g$ = 0,003 m, $v = R\omega$ = 0,3 m/s, $h_s$ = 0,0234 m, $H$ = 0,08 m, $K$ = 1 000.The caster roll width $L$ is 0,26 m and the roll radius $R$ is 0,15 m.

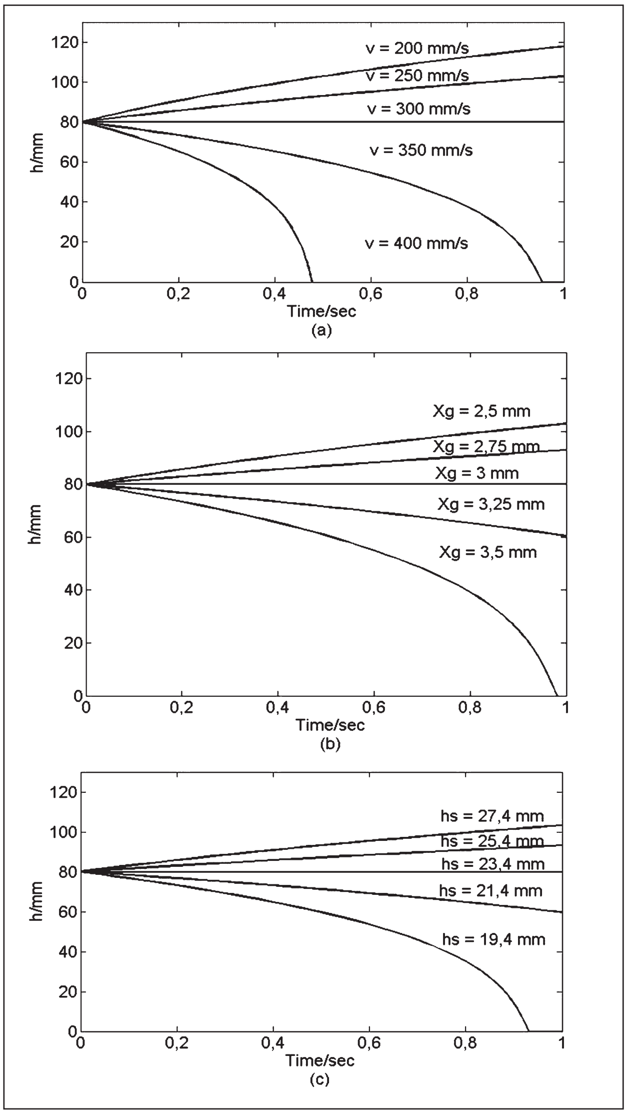


**Figure 2** Simulation about influence effect of three parameters on the pool level

Figure 2(a) shows that the pool level keeps stable on $v$ = 0,3 m/s when the roll gap and the stopper height keep set-values. While the pool level rises synchronously when the casting speed is less than 0,3 m/s, which leads to the time lengthening of the molten metal solidification and rolling, meanwhile the casting rolling force increases, which results in the strip break, even causes the molten metal leakage from the side dams. When the casting speed is higher than 0,3 m/s, the pool level decreases sharply because the volume of the lower part of the pool decreases gradually. Under such conditions, the metal solidification and rolling are insufficient, which will seriously affect the surface quality of the sheet.

In Figure 2(b), when the roll gap is 0,003 m, the pool level remains stable and casting process is completed in the normal way. Once the roll gap rises due to the metal dendrite growth during the metal solidification, the level decreases sharply and the casting process is out of control, and vice versa.

In Figure 2(c), it can be seen that when the stopper height is 0,00234 m, the amount of the molten metal flowing into and out of the pool is equal and the pool level remains stable. Once the stopper height changes, the molten metal amount balance in the pool will be destroyed, which will inevitably cause the level fluctuation, and that leads to the corresponding fluctuation of the metal solidification and rolling process. The whole casting process cannot maintain stable, which will affect the strip quality seriously.

Obviously, the stopper height, the casting speed and roll gap have strong influence on the pool level, and the fluctuation of anyone among the three parameters results in the instability of the casting process, so the pool level control is essentially a complex problem with three variables input and single variable output.

## DISADVANTAGES OF THE PID CONTROL FOR THE POOL LEVEL

Since the traditional PID controller only solves the problem of single-input/ single-output, in this section, the stopper height is used as the main control variable while the casting speed and the roll gap are viewed as disturbances. If the PID control parameters ( $K_p$, $K_i$, $K_d$ ) are set felicitously, the molten metal inflows properly and the pool level may be adjusted to the set-value.

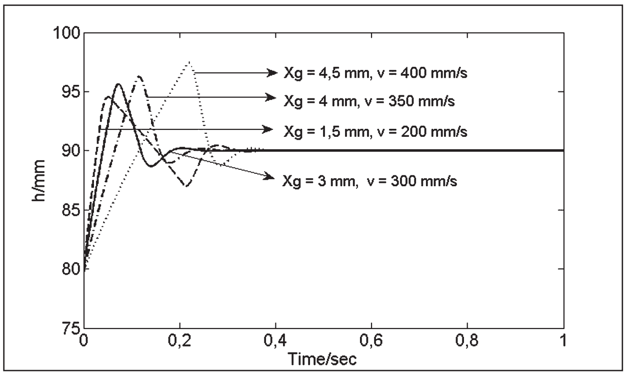


**Figure 3** Traditional PID control curve about the pool level

When the controlled object is described as the mathematical model in (3) and the level initial/target value is respectively set at 0,08/0,09 m, a series of simulations are run to get the best value of the control parameters according to the simulation curve. Under the condition of $X_g$ = 0,003 m, $v$ = 0,3 m/s, and both the parameters are supposed not to be changed in the casting process, when $K_p$ = 8,5, $K_i$ = 0,4, $K_d$ = 0,5, which are got by multiple manual adjustment, a good control curve is shown in Figure 3, in which the overshoot is below 60 % and the adjusted time is less than 0,2 s, which meet the control performance requirements. But in practice, the requirement is impossible that the casting speed and roll gap should keep constant, while these two parameters fluctuate. If the PID control parameters are still invariant, the control results will get bad, which is also shown in Figure 3. So the problem must be solved as to how to self-adaptively adjust three control parameters ($K_p$,$K_i$,$K_d$) with the unavoidable fluctuation of the main process parameters.

## MOLTEN POOL LEVEL CONTROL STRATEGY BASED ON NEURAL NETWORK PID(NN-PID)

According to the above simulations and analysis, in order to achieve good control effect, the PID controller parameters have to be adjusted repeatedly and manually with the fluctuation of the casting speed and roll gap, which is not a realistic way in the practical application, so the traditional PID controller structure should be modified to improve the self-adaptive ability.

Because the neural network has strong ability of self-learning and self-adaptation, it has been widely used in approximation, classification, recognition and control fields [6,7].The Back-Propagation(BP) neural network uses the error back propagation algorithm to solve the self-learning problem of multilayer neural unit, and lots of productive practice has proven that the BP neural network is a mature method which is easy to implement [8,9]. So in the paper, a PID control method based on BP neural network is used to realize precise control of the molten pool level under the condition of multi-factor interferences.

The BP neural network is a multi-layer structure, in which the input layer, the hidden layer and the output layer are all connected and each layer can be composed of many neurons. The input layer is linear connected with the hidden layer by the connection weights, while the transfer function is nonlinear between the hidden layer and the output layer to enhance the ability of the system nonlinear optimization, which is generally the Sigmoid function. The trained set is composed of a group of given input data and output data, and the input data is linearly and nonlinearly transferred through the connection weights to form the intermediate output; the error between the intermediate and given output is back propagated by the gradient descent method to modify the connection weights among the neurons. Through several iterations, an optimized neural network structure is got when the error is within the allowable range. A schematic diagram of the molten pool level controlled by NN-PID is shown in Figure 4, in which the roll gap and casting speed are taken as input data, and the appropriate PID control parameters are self-adaptive output through the optimized neural network model.

When the roll gap is discretized in the scope [1,5] mm and step is 0,2 mm, the roll gap is discretized in the scope [200,600] mm/s and step is 20 mm/s, an input data set including 400 pair data groups are got. To every input data group, according to the simulation results, the PID parameters are adjusted manually until the best control effect is achieved, and then the corresponding best PID parameters can be got as the output data. Finally, 400 groups input/output data are collected as the trained set of the neural network. Analyzing the experimental data, it is shown that the influence of differential coefficient ($K_d$) on the control of molten pool level can be neglected, so in the trained set, the input data includes the roll gap and roll speed, and the output data includes proportional coefficient ($K_p$) and differential coefficient *($K_i$)*.

In the paper, a three-layer structure of the neural network model is chosen with 2 input nodes and 2 output nodes, while the number of the hidden layer nodes is determined empirically. Observing lots of simulation results, when the number of the hidden layer nodes is 6, the model training time and control performance are

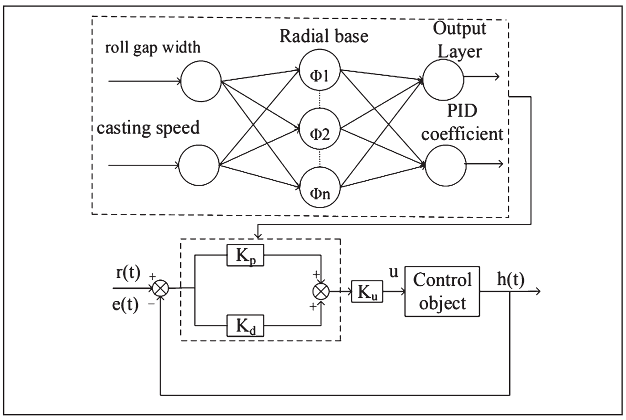


**Figure 4** Schematic diagram of NN-PID control strategy for the molten pool level

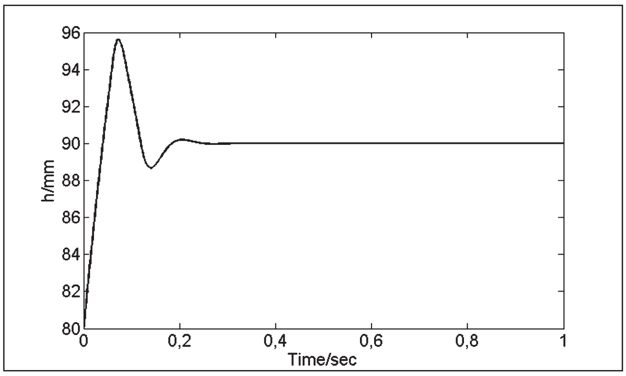


**Figure 5** Simulation curve of NN-PID control for the molten pool level

satisfactory. In the MATLAB simulation environment, BP neural network is created by the function newff, the learning rate is 0,1. The neural network model is trained until the iteration time reaches 500 or all of 5 times successive error are less than $e^{-2}$, lastly the optimized model has self-adaptive ability, it means that the model can adaptively supply better control parameters($K_p$,$K_i$) according to the change of the roll gap and the cast speed in the pool level control problem. For example, under the condition of $X_g$ = 0,004 m and v = 0,35 m/s, the output of the optimized neural network is $K_p$ = 8,1397, $K_i$ = 0,4876, and the pool level control curve is shown in Figure 5, in which the system response is 0,2 s and the overshoot is 50 %. When the control curves in Figure 5 and Figure 3 are compared, it is obvious that the neural network PID control method shows better self-adaptability and the control performance is satisfactory. Of course, owing to the inevitable difference between the theory model and the practice object, it is difficult that a good control result is expected when the neural network model optimized by simulation is applied in practice. In the practical application, the neural network model got by simulation can be regarded as the optimizing initial-point, the random offset in the proper range can be superimposed on the output of the neural network, the system ITAE (Integral of Time-weighted Absolute Error) is real-timely calculated, and then the control parameters corresponding to the best ITAE can be enriched into the trained set. Lastly, through the iterative learning and training, the neural network model will get better and can be put into the application.

## CONCLUSIONS

In this paper, a neural network PID control strategy is presented to realize the self-adaptive precise control of the molten metal pool level in the twin-roll casting process under the multi-interferences of the roll gap and casting speed. Compared with the traditional PID control method, in the strategy, the trained neural network model can supple proper control parameters that according to the interferences in order to get a satisfactory control performance. Meanwhile a self-study improvement clue is given to solve the problem as to how to apply the model got by simulation to the actual production.

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**Note:** The responsible translators for English language is Lihua Cai—University of Science and Technology Liaoning, China