The International Journal of Advanced Manufacturing Technology (2018) 95:4081–4089
https://doi.org/10.1007/s00170-017-1517-1

ORIGINAL ARTICLE

Mold breakout prediction in slab continuous casting based on combined method of GA-BP neural network and logic rules

Fei He [1] · Lingying Zhang [1]

Received: 19 July 2017 / Accepted: 18 December 2017 / Published online: 4 January 2018

Abstract

Given advantages of artificial intelligent technology, the genetic algorithm (GA) and back propagation (BP) neural network is used to construct time series model for recognizing temperature change waveform of single thermocouple in mold breakout process. Based on breakout mechanism, the logic rules are used to construct spatial model of multi-thermocouples for identifying two-dimensional (2D) propagation behavior of the sticker. Time series model based on GA-BP neural network and spatial model based on logic rules form a new breakout prediction method. And the simulation and field test of this method are carried out for validating its performance. Simulation results of time series model show that the GA-BP neural network has better recognition precision than BP neural network for sticking temperature pattern of single thermocouple. And simulation results of spatial model show that it can predict all stickers accurately and timely, with no missed alarm and false alarm. Furthermore, field test results show that this breakout prediction method has detection ratio of 100% and a lower false alarm frequency (0.1365% times/heat), which is better than actual breakout prediction system used in continuous casting production. So the combined method of GA-BP neural network and logic rules is feasible and effective in breakout prediction and can be used in more intelligently industrial process.

Keywords Continuous casting · Breakout prediction · Mold · Neural network · Genetic algorithm · Logic rule

1 Introduction

The continuous casting breakout is a most hazardous quality accident, which is caused when mold surface quality defects such as the stickers or cracks evolve to a certain extent. Such accidents will lead to interruption of continuous casting, affect whole molten steel production plan, damage relevant equipments, affect operating rate and output of the caster, reduce metal yield, and thus lead to huge economic losses. A key reason for liquid metal breakout is the sticker or slab shell sticking [1]. One main breakout form is the sticker breakout, which frequently happens during actual production and accounts for about 70–80% of all breakout accidents. Especially with development of modern high-efficient continuous casting technologies, higher casting speed will lead to more complicated mold heat transfer, friction and lubrication problems, significantly reducing uniformity of the cooling and solidification of primary shell, flow-in stability and uniformity of mold flux, increasing the possibility of shell sticking inside the mold, and thus greatly increasing the risk of the sticker breakout. So studying and solving the sticker breakout are significant for ensuring smooth production and high-quality slabs, optimizing continuous casting process.

Since the 1970s, many detection methods for symptoms of the sticker breakout have been developed at home and abroad. The most effective method is the breakout prediction system based on measuring temperature with thermocouples in the mold. The basic principle of this method is that some thermocouples are laid on the mold copper plates to detect temperature change of different locations, and then local heat transfer conditions inside the mold can be monitored in real time via the temperature change of the cooper plates, and the position and movement of the sticker's V-shaped rupture can be identified. Now, the breakout prediction method based on measuring temperature with thermocouples can be divided into two types: logic judgment method [2–4] and artificial intelligent method [5–8]

✉ Fei He
hf2573546@sina.com

1 School of Metallurgical Engineering, Anhui University of Technology, Ma'anshan, Anhui 243002, China

The logic judgment method is based on the qualitative and quantitative analyses of breakout mechanism and actual breakout data and then predicts the breakout by extracting appropriate logic rules. In essence, this method is to compare temperature variation amplitude and velocity of each thermocouple, temperature difference of up and down thermocouples, and temperature variation time-delay with defined threshold for breakout alarm. The logic judgment method mainly depends on specific process and equipment parameters. The selection of model parameters is very sensitive to the prediction performance and needs massive manpower and time for testing. Especially in some complicated casting process, some problems such as thermocouple failure, non-uniform heat transfer and slab shell growth, big fluctuation of thermocouples' temperature, unstable casting, the casting of crack-sensitive and diversified steels, and thickness change of mold cooper plates may occur, making it highly difficult to find appropriate model parameters. So there are a lot of false alarms. Frequent false alarms will also affect slab quality and high-efficient production of slab caster. It is very important to reduce false alarms.

The artificial intelligent method can predict the sticker breakout by using pattern recognition algorithms such as BP neural network and support vector machine, which features stronger adaptation, self-learning capabilities, fault tolerance, and robustness and better handles complicated non-linear problems to further improve breakout prediction accuracy; thus, it has been a current research hotspot in this field. But breakout prediction model based on artificial intelligent method belongs to a black box model, lacking guidance of process mechanism, and is largely dependent on data. For example, the training of neural network model must rely on enough and effective samples. If samples are not complete or accurate, generalization capability of the model will be affected.

Based on characteristics of logic judgment method and artificial intelligent method, with time-space change rule of thermocouples' temperature inside the mold in case of slab shell sticking as the basis, this paper proposes a breakout prediction method by combining GA-BP neural network with logic rules in order to solve the technical difficulty of sticker breakout in slab continuous casting. Firstly, considering advantages of artificial intelligent technology in waveform pattern recognition, this paper establishes a time series model of single thermocouple by using GA-BP neural network to recognize whether the time series change of single thermocouple's temperature is consistent with temperature change waveform of the sticker, which belongs to a dynamic waveform pattern recognition problem. Here, GA is used to optimize BP neural network. The optimal weight and threshold of BP neural network can be obtained via global search capability of GA, and recognition precision of time series model of single thermocouple for temperature change waveform of the sticker can thus be improved. Then, based on time series model of single thermocouple, considering 2D propagation behavior of V-shaped rupture of the sticker [9], this paper establishes a spatial model of multi-thermocouples via effective logic rules to determine whether the adjacent thermocouples involve sticker propagation. This method can effectively combine the intelligent method with the logic rules to make them complement each other's advantages, overcome determination difficulty or inaccuracy of pure logic judgment model parameters and lack of process guidance of pure intelligent model, and further improve recognition precision of the sticker breakout.

2 Experimental conditions

This experiment is carried out in two straight-curved slab casters of a steel plant in China. Each caster has two strands, an arc radius of 9.5 m, and the casting slab section size is $230 \times (900\sim2150)$ mm^2. The operation casting speed is 0.80~2.03 m/min. The casting steel grades in the caster are various and complex, such as ultra-low-carbon steel, low-carbon steel, medium carbon steel, and peritectic steel. So the casting is usually difficult and the sticker breakouts occur frequently.

The corresponding mold in the caster is a combined straight mold, which is comprised of four copper plates: broad face fixed side, broad face loose side, narrow face left, and narrow face right. The mold width can be adjusted according to slab width. The mold length is 900 mm. The mold level standard is 100 mm. In order to detect the propagation behavior of the sticker breakout, more rows of thermocouples in high density are embedded in mold copper plates for monitoring local temperature variation at different locations. Six rows of 12 columns, a total of 72 thermocouples are embedded in each broad face. Six rows of two columns, a total of 12 thermocouples are embedded in each narrow face. In total, 168 thermocouples are installed in the four copper plates. Horizontal spacing and vertical spacing of thermocouples are 185 and 111 mm, respectively. The first row of thermocouples is located 172.5 mm below the mold top.

Measured data from the slab caster are collected and saved for duration of each heat. The data includes all thermocouples' temperature, alarm record of breakout prediction system, casting speed, and mold level change. From the data, sticker samples and normal samples could be obtained.

3 Combined method of GA-BP neural network and logic rules

Intelligent algorithm has been widely applied in breakout prediction field due to its advantages. The most typical application is the breakout prediction method based on neural network, which is composed of time series model of single thermocouple and spatial model of multi-thermocouples [7, 10, 11]. Now, these breakout prediction methods based on neural network fully depend on the neural network technology from construction of time series model of single thermocouple to construction of spatial model of multi-thermocouples. The intelligent technologies such as neural network have significant advantages in dynamic waveform pattern recognition but are not suitable to establish the spatial model of multi-thermocouples and recognize the 2D propagation behavior because they do not reflect sticker propagation mechanism. If the outputs of multiple neural network models of single thermocouple are used as the input variables of multi-thermocouple neural network model for prediction, it will increase the training time and reduce generalization capability. This paper establishes a new breakout prediction method, as shown in Fig. 1. Different from previous breakout prediction method based on pure neural network model or logic judgment model, it firstly recognizes temperature change waveform of single thermocouple in case of shell sticking via GA-BP neural network (namely time series model of single thermocouple based on GA-BP neural network) and then identifies the 2D propagation behavior by the logic rules for lateral and vertical detection according to time-delay change law of adjacent thermocouple temperature in space in case of sticker's V-shaped rupture propagation (namely spatial model of multi-thermocouples based on logic rules).

3.1 Time series model of single thermocouple based on GA-BP neural network

Construction of time series model of single thermocouple includes determination of model input and output variables, data preparation and pre-processing, and establishment of GA-BP neural network.

(1) Selection and determination of the input and output variables

It is very critical to select suitable input and output variables for the model, which will directly affect prediction results of the time series model of single thermocouple. Based on the practical measured sticker or sticker breakout samples, the abnormal temperature change of single thermocouple in time axis is about 30 s in sticking. And the acquisition cycle of temperature data is 1 s. Therefore, if 30 continuous temperature sampling points of single thermocouple in time axis are selected as the model input variables, they can fully represent typical waveform pattern of temperature change of single thermocouple in sticking (called as sticking temperature pattern), as shown in Fig. 2. The output variable of the model is sticking alarm signal of single thermocouple and depends on approximation degree between temperature change waveform pattern of 30 sampling points and sticking temperature pattern. When the temperature waveform pattern of the 30 sampling points is completely same as the sticking temperature pattern, the model's output variable is equal to 1. When the temperature change curve of 30 sampling points keeps stable or fluctuates little, the model's output variable is approximately equal to 0. And the model's output variable is between − 1 and 2.

(2) Data preparation and pre-processing

Extract samples from field data in sticker and normal cases according to model input and output variables remove incomplete and incorrect temperature data and get 611 groups of valid samples, including 161 groups of samples for sticking temperature pattern. Normalize the above 611 groups of valid samples into the range [− 1, 1] by using the Formula (1), and randomly select 502 groups of samples from normalized samples to train the model which include 131 groups of samples for sticking temperature pattern. Test the model with residual 109 groups of samples, among which there are 30 groups of samples for sticking temperature pattern.

$$x' = \frac{2(x - x_{\min})}{x_{\max} - x_{\min}} - 1 \tag{1}$$

Where x' is the normalized value of each variable x; $x_{\max}$ and $x_{\min}$ are the maximum and minimum of each variable x.

(3) Establishment of GA-BP neural network

From the above analysis, BP neural network's input variables are 30 continuous temperature sampling points of single thermocouple in time axis, and BP neural network's output variable is the sticking alarm signal of single thermocouple. Since there are 30 input variables and 1 output variable, the input layer of the network contains 30 neurons and the output layer contains 1 neuron. Here, of concern is output result of the network. In practical test, a recognition threshold interval $[\theta_{\min}, \theta_{\max}]$ is obtained according to test results of the network. And when the output result of the network does not exceed the defined threshold interval, it indicates that the sticking temperature pattern is detected.

Three-layer BP neural network is used in network training. The sigmoid tangent function is used as the transfer function of hidden layer. The linear transfer function is used as the transfer function of output layer. The LM (Levenberg-Marquardt) optimization algorithm is used for training the network. After many attempts, the selected BP neural network model includes 12 neurons at the hidden layer and is designed as 30 × 12 × 1 structure, as shown in Fig. 3. The learning process of the BP neural network includes the information forward transmission and error back propagation. The connection weights and thresholds among neurons are continuously learnt and adjusted according to the input and output vector of training samples to make the neural network continuously

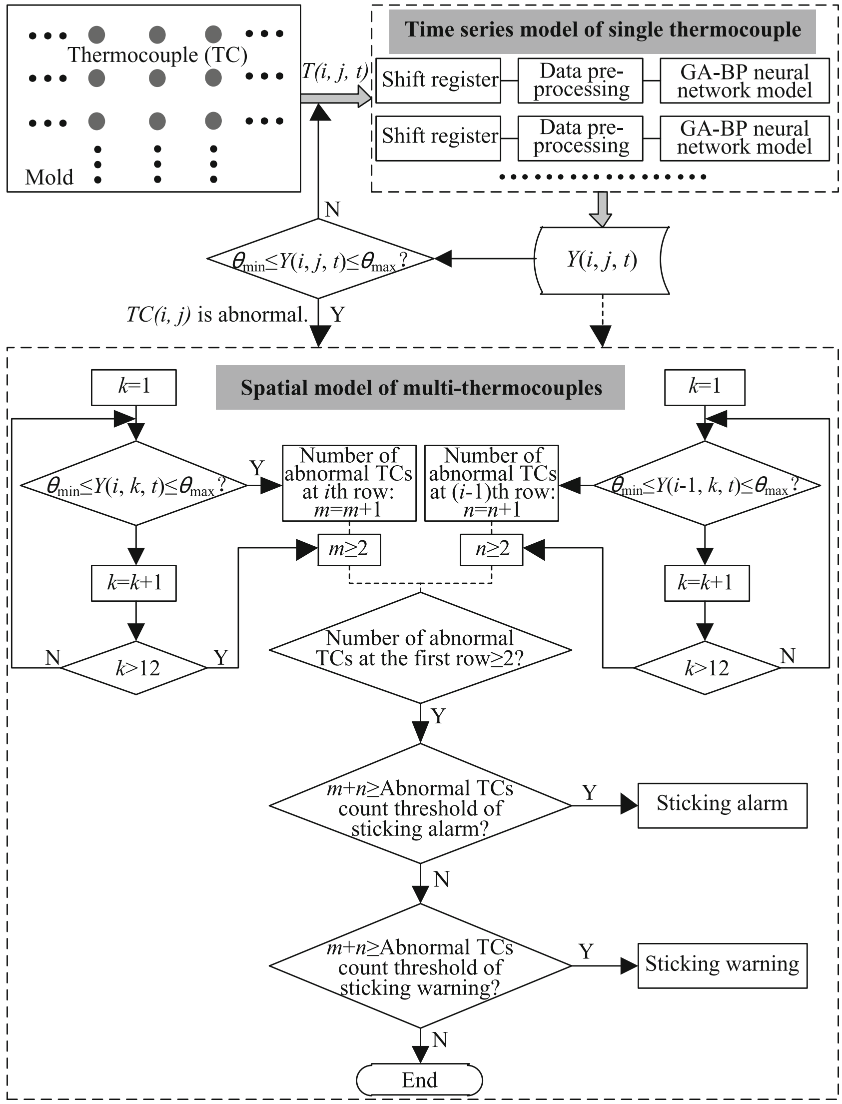

Fig. 1 Flow chart of new breakout prediction method proposed in this study

approximate to the actual mapping relation between input and output vector. The maximal training time of the BP neural network is set as 2000, the learning ratio is set as 0.05, and the performance error is set as 0.0001.

To improve generalization capabilities of BP neural network, the GA is used to optimize the BP neural network. The basic steps are described as follows: (1) initialize population, code all weights and thresholds of neural network with real numbers, generate individuals, set the population scale, and evolutional generations; (2) compute an individual fitness function $f(x)$, as shown in Formula (2). The minimum is optimal; (3) perform selection, crossover, and mutation operator and generate a new generation of individual populations; (4) evaluate new generation of population and determine whether the evolutional generations satisfy requirement or the network error satisfies the preset condition. If satisfied, the individual with the optimal fitness can be obtained in current population, namely the corresponding optimal BP neural network weights and thresholds. The population scale of the GA is set as 50, the crossover probability is set as 0.7, the mutation probability is set as 0.06, and evolutional generation is set as 200. The GA is used to optimize BP neural network. After effective sample training and

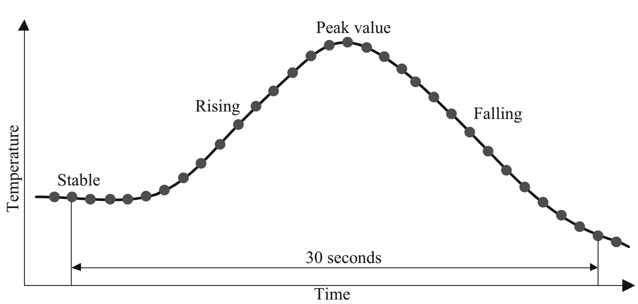

Fig. 2 Typical sample of sticking temperature pattern for single thermocouple

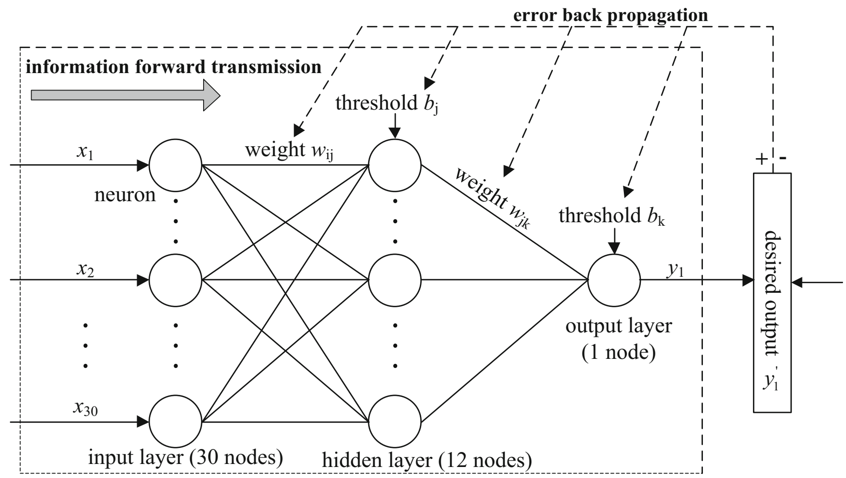

Fig. 3 Topology structure and learning process diagram of BP neural network model

testing, the optimal neural network structure can be obtained, which is used by time series model of single thermocouple to recognize the sticking temperature pattern.

$$f(x) = \sum_{i=1}^{N} \left| y_i - y_i' \right| \tag{2}$$

Where N is the number of nodes of the output layer of the BP neural network; y_i and y_i' are the predicted output and desired output of the ith node of the network, respectively.

3.2 Spatial model of multi-thermocouples based on logic rules

As shown in Fig. 1, by the time series model, the temperature change pattern of each thermocouple with time is identified, and the output result will be stored to the three-dimensional array $Y(i, j, t)$, which represents the recognition result of time series model for the thermocouple at the ith row and jth column at the time t (namely sticking alarm signal). When $Y(i, j, t)$ is within the pre-defined threshold interval $[\theta_{\min}, \theta_{\max}]$, it indicates that the temperature change of the thermocouple $TC(i, j)$ at the ith row and jth column complies with the sticking temperature pattern and the thermocouple is marked as abnormal. The next step is to enter the judgment of spatial model of multi-thermocouples and compute the number of abnormal thermocouples at the row and previous row of current thermocouple. The details are as follows: (1) check $Y(i, j, t)$ of all thermocouples at the ith row and count the number of abnormal thermocouples within the threshold interval $[\theta_{\min}, \theta_{\max}]$ as m. And meanwhile, check $Y(i\text{-}1, j, t)$ of all thermocouples at previous row of the ith row and count the number of abnormal thermocouples within the threshold interval $[\theta_{\min}, \theta_{\max}]$ as n. Here, i is more than 1. (2) If m and n are bigger than or equal to 2, check whether the number of abnormal thermocouples at the first row in the past 10 s is bigger than or equal to 2. If satisfied, compare the total number of abnormal thermocouples (namely $m + n$) with abnormal thermocouples' count thresholds of sticking warning and alarm, respectively. If $m + n \geq$ abnormal thermocouples count threshold of sticking alarm, a sticking alarm is released. Otherwise, if $m + n \geq$ abnormal thermocouples count threshold of sticking warning, a sticking warning is released.

From the above, the spatial model of multi-thermocouples in this paper is based on the time series model of single thermocouple and then uses logic rules to determine whether the adjacent thermocouples have space propagation of the sticker.

4 Experimental results and discussion

4.1 Simulation of time series model of single thermocouple

BP neural network and GA-BP neural network are used to establish time series model of single thermocouple, respectively. BP and GA-BP models are trained by the same 502 groups of samples and are tested by the same 109 groups of samples which obtained in Section 3.1. The test results in Fig. 4 show that proximity degree of predicted output and desired output for GA-BP model is higher than that for BP model. It demonstrates that GA can improve generalization performance of the BP neural network model. Meanwhile, from the recognition results of 30 sticker samples for GA-BP model, appropriate recognition threshold interval $[\theta_{\min}, \theta_{\max}]$ should be [0.6, 1.3].

Table 1 shows the hit rate of prediction with BP and GA-BP models. It can be observed that the hit rates of BP and GA-BP model are 81.7 and 84.4% in the deviation range [− 0.1, 0.1], respectively. The hit rates of BP and GA-BP model are same in the deviation range [− 0.2, 0.2]. The hit rates of BP and GA-BP model are 93.6 and 98.2% in the deviation range [− 0.3, 0.3], respectively. The hit rates of BP and GA-BP model are 96.3 and 100.0% in the deviation range [− 0.4,

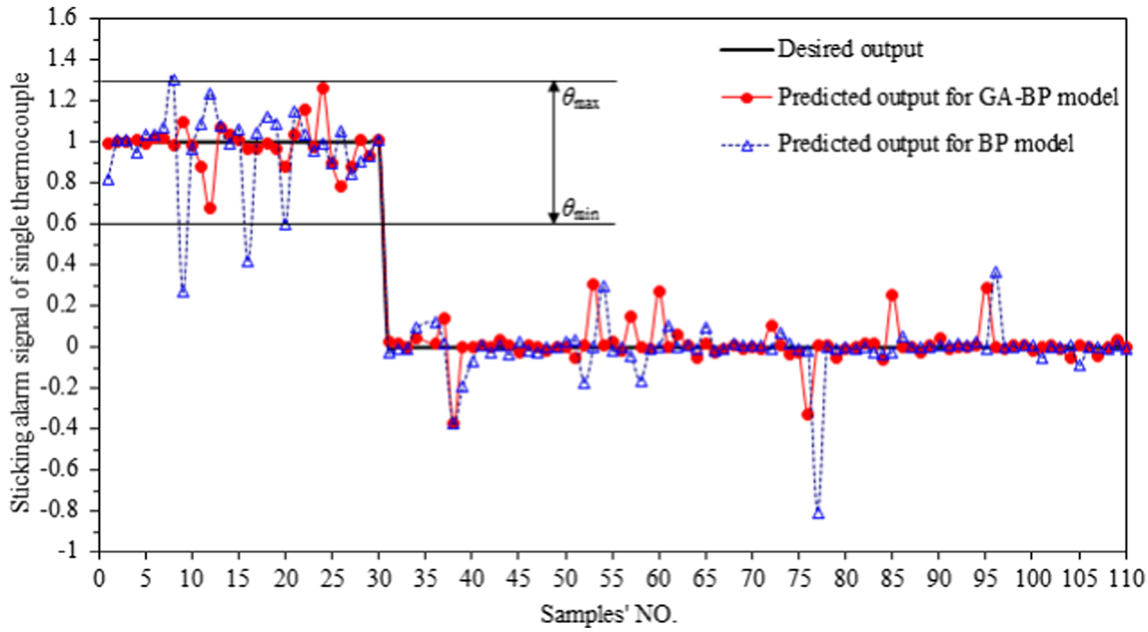

Fig. 4 Comparison of desired output and predicted output by BP and GA-BP models

0.4], respectively. Obviously, GA-BP model has better recognition precision than the BP model for the temperature change waveform pattern of single thermocouple. Here, the hit rate of prediction is the ratio of hit samples in all calculated samples, which can be calculated as Formula (3).

$$\theta_p = \frac{N_{hit}}{N_{all}} \tag{3}$$

Where θ_p is the hit rate of prediction, N_{hit} is the number of samples that hit the target, and N_{all} is the number of all calculated heats.

4.2 Simulation of spatial model of multi-thermocouples

The data of 97 heats are used for simulation experiment of the spatial model of multi-thermocouples. There are 14 stickers in these data. Simulation results indicate that the optimal count thresholds of abnormal thermocouples for sticking alarm and sticking warning are 6 and 3, respectively. And the results are compared with actual breakout prediction system (BOPS) in prediction performance and alarm time, as shown in Tables 2 and 3. The actual BOPS is mold breakout prevention system of Danieli and uses a logic judgment method which relies on the rate of temperature changes of thermocouples in the row near the meniscus and temperature inversion characteristic [2, 12, 13]. Here, detection ratio = true alarm times/(missed alarm times + true alarm times), and prediction accuracy ratio = correct alarm times/(missed alarm times + true alarm times + false alarm times).

Table 1 Hit rate of prediction for BP and GA-BP models

Model	Deviation range of predicted output and desired output			
	[− 0.1, 0.1]	[− 0.2, 0.2]	[− 0.3, 0.3]	[− 0.4, 0.4]
BP neural network (%)	81.7	91.7	93.6	96.3
GA-BP neural network (%)	84.4	91.7	98.2	100.0

The results in Table 2 show that actual BOPS has eight missed alarms and its prediction precision is very low. In contrast, spatial model of multi-thermocouples can predict all stickers, and the missed alarm times and false alarm times are zero, and the prediction accuracy rate has reached 100%. So the spatial model is significantly better than the actual BOPS. At the same time, as shown in Table 3, for sticker samples 1–8, the sticking alarm time of the spatial model is over 10 s earlier than actual breakout time, so it can provide enough time for subsequent breakout recovery. For sticker samples 9–14, the sticking alarm time of the spatial model is earlier than actual BOPS in most cases. The later alarm will increase the risk of the breakout. So the breakout prediction method proposed in this paper is better than the actual BOPS in prediction precision and alarm time, which can not only accurately predict all stickers in time, but also avoid missed alarms and false alarms.

At the same time, a particular example is given here to demonstrate the analysis process of new method in detail

Table 2 Prediction results for spatial model and actual BOPS

	Spatial model	Actual BOPS
Total number of heats	97	97
True alarm times	14	6
Missed alarm times	0	8
False alarm times	0	4
Detection ratio (%)	100	42.86
Prediction accuracy ratio (%)	100	33.33

and quantitatively. This example is a sticking-type breakout incident which is sticker sample 5 in Table 3. The example is simulated by new method and the sticking alarm is released in 05:04:31. The alarm analysis process is presented as follows. According to the flow chart of new method, firstly, the temperature change pattern of each thermocouple with time is recognized by time series model based on GA-BP neural network, and the recognition result $Y(i, j, t)$ is shown in Table 4. The next step is to enter the judgment of spatial model of multi-thermocouples. From Table 4, $Y(2, 7, 05{:}04{:}31)$ is within recognition threshold interval [0.6, 1.3], and at the second row, the number of abnormal thermocouples within the threshold interval, $m = 2$, and at the first row, the number of abnormal thermocouples within the threshold interval: $n = 4$. m. Here, m and n are bigger than 2. Meanwhile the number of abnormal thermocouples at the first row in the past 10 s is bigger than or equal to 2. Then, the total number of abnormal thermocouples (namely $m + n$) could be obtained and is equal to 6, which has reached abnormal thermocouples count threshold of sticking alarm.

4.3 Field test

To further validate accuracy and performance, the above presented method for mold breakout prediction is carried out field test. Test results of two consecutive months are collected and compared with actual BOPS. In the 2 months, there are 2930 casting heats and 19 stickers. For the above presented method, all stickers have been detected in time and there are only four false alarms. In other words, detection ratio for stickers and frequency of false alarm for the presented method are 100 and 0.1365% times/heat, respectively. In contrast, the actual BOPS has released 17 true alarms and 65 false alarms for stickers. The actual BOPS not only has a lot of false alarms, but the worst is that two stickers were not detected and thus the breakouts happened. Therefore, it can be concluded that the combined method of GA-BP neural network and logic rules is feasible for prediction of the sticker breakout.

5 Conclusions

Sticker breakout is one of the key factors which restrict the development of high-speed continuous casting and wide and heavy plate continuous casting technology. Solving the sticker breakout is of great significance for ensuring smooth production and high-quality slabs. In this study, given advantages of artificial intelligent technology in waveform pattern

Table 3 Alarm response time for spatial model and actual BOPS

Sticker sample	Slab section size	Casting speed	Sticking alarm time		Actual breakout time
			Spatial model	Actual BOPS	
1	1500 × 230	1.10	00:22:35	Missed alarm	00:22:46
2	1554 × 230	1.20	05:04:31	Missed alarm	05:04:44
3	1554 × 230	1.20	04:59:25	Missed alarm	04:59:37
4	2006 × 230	0.90	06:17:59	Missed alarm	06:18:31
5	1502 × 230	1.10	21:20:40	Missed alarm	21:20:55
6	1502 × 230	1.00	00:53:05	Missed alarm	00:53:16
7	1802 × 230	0.90	00:54:52	Missed alarm	00:55:03
8	1802 × 230	0.90	23:43:41	Missed alarm	23:43:55
9	1502 × 230	0.90	12:34:02	12:33:58	–
10	1802 × 230	0.90	00:10:36	00:10:40	–
11	1802 × 230	0.90	01:01:04	01:01:06	–
12	1802 × 230	0.90	01:08:22	01:08:23	–
13	1802 × 230	0.90	18:23:21	18:23:22	–
14	1802 × 230	0.90	23:46:14	23:46:16	–

Table 4 Alarm analysis of new method

Time	Sticking alarm signal of each thermocouple in a broad face copper plate											
t	*Y*(1,1,t)	*Y*(1,2,t)	*Y*(1,3,t)	*Y*(1,4,t)	*Y*(1,5,t)	*Y*(1,6,t)	*Y*(1,7,t)	*Y*(1,8,t)	*Y*(1,9,t)	*Y*(1,10,t)	*Y*(1,11,t)	*Y*(1,12,t)
	Y(2,1,t)	*Y*(2,2,t)	*Y*(2,3,t)	*Y*(2,4,t)	*Y*(2,5,t)	*Y*(2,6,t)	*Y*(2,7,t)	*Y*(2,8,t)	*Y*(2,9,t)	*Y*(2,10,t)	*Y*(2,11,t)	*Y*(2,12,t)
	Y(3,1,t)	*Y*(3,2,t)	*Y*(3,3,t)	*Y*(3,4,t)	*Y*(3,5,t)	*Y*(3,6,t)	*Y*(3,7,t)	*Y*(3,8,t)	*Y*(3,9,t)	*Y*(3,10,t)	*Y*(3,11,t)	*Y*(3,12,t)
	Y(4,1,t)	*Y*(4,2,t)	*Y*(4,3,t)	*Y*(4,4,t)	*Y*(4,5,t)	*Y*(4,6,t)	*Y*(4,7,t)	*Y*(4,8,t)	*Y*(4,9,t)	*Y*(4,10,t)	*Y*(4,11,t)	*Y*(4,12,t)
	Y(5,1,t)	*Y*(5,2,t)	*Y*(5,3,t)	*Y*(5,4,t)	*Y*(5,5,t)	*Y*(5,6,t)	*Y*(5,7,t)	*Y*(5,8,t)	*Y*(5,9,t)	*Y*(5,10,t)	*Y*(5,11,t)	*Y*(5,12,t)
	Y(6,1,t)	*Y*(6,2,t)	*Y*(6,3,t)	*Y*(6,4,t)	*Y*(6,5,t)	*Y*(6,6,t)	*Y*(6,7,t)	*Y*(6,8,t)	*Y*(6,9,t)	*Y*(6,10,t)	*Y*(6,11,t)	*Y*(6,12,t)
05:04:28	0.0000	0.0000	− 0.0247	− 0.032	0.5326	1.0662	0.1365	0.006	1.0178	− 0.0209	0.0000	0.0000
	0.0000	0.0000	− 0.0021	0.0025	− 0.0504	− 0.0197	0.5902	0.2531	0.0292	0.0040	0.0000	0.0000
	0.0000	0.0000	− 0.0004	− 0.0005	− 0.0030	− 0.0514	0.0299	− 0.0079	0.0512	0.0027	0.0000	0.0000
	0.0000	0.0000	0.9992	0.0000	0.0007	0.0119	0.0364	0.0369	0.0009	0.0056	0.0000	0.0000
	0.0000	0.0000	0.0036	0.0040	1.099	− 0.0060	0.0280	− 0.0041	0.0018	− 0.0022	0.0000	0.0000
	0.0000	0.0000	− 0.0046	0.0054	0.0007	0.0005	0.0029	0.0014	− 0.0174	0.0044	0.0000	0.0000
05:04:29	0.0000	0.0000	− 0.0366	− 0.0298	0.7861	1.0078	0.1737	− 0.0067	0.9846	− 0.0044	0.0000	0.0000
	0.0000	0.0000	− 0.0004	0.0012	− 0.0502	− 0.0318	1.1342	0.4578	− 0.0058	− 0.0093	0.0000	0.0000
	0.0000	0.0000	− 0.0026	0.0016	− 0.0085	− 0.0309	0.2107	0.0503	0.0739	0.0009	0.0000	0.0000
	0.0000	0.0000	− 0.8034	0.0000	− 0.008	− 0.0047	0.0823	0.0528	− 0.0061	0.0020	0.0000	0.0000
	0.0000	0.0000	0.0219	− 0.0084	− 3.8346	0.0272	0.0080	− 0.0096	0.0026	− 0.0033	0.0000	0.0000
	0.0000	0.0000	− 0.0106	0.0038	0.0048	− 0.0130	0.0194	− 0.0155	− 0.0128	− 0.0101	0.0000	0.0000
05:04:30	0.0000	0.0000	− 0.0444	− 0.0269	1.1959	1.0043	− 0.2032	− 0.0128	0.9579	0.0162	0.0000	0.0000
	0.0000	0.0000	0.0018	− 0.0020	− 0.0502	− 0.0185	0.956	0.8904	− 0.0102	− 0.0347	0.0000	0.0000
	0.0000	0.0000	− 0.0013	0.0006	− 0.0089	− 0.0410	0.5314	0.0327	− 0.0081	0.0039	0.0000	0.0000
	0.0000	0.0000	0.7297	0.0000	0.0096	− 0.0140	0.0417	0.0944	0.0144	− 0.0051	0.0000	0.0000
	0.0000	0.0000	0.0101	0.0050	0.7493	0.1271	0.0836	− 0.0246	− 0.0036	− 0.0039	0.0000	0.0000
	0.0000	0.0000	−0.0134	−0.0071	−0.0016	−0.0077	0.0116	−0.0081	−0.0146	−0.0027	0.0000	0.0000
05:04:31	0.0000	0.0000	−0.0952	−0.0318	0.9782	0.9876	−0.0650	−0.0246	0.9602	1.0062	0.0000	0.0000
	0.0000	0.0000	0.0019	0.0004	−0.0398	−0.0114	1.0689	0.8934	−0.0364	−0.0555	0.0000	0.0000
	0.0000	0.0000	−0.0001	−0.0012	−0.0328	−0.0104	0.7049	0.0201	0.0383	0.0016	0.0000	0.0000
	0.0000	0.0000	−0.6747	0.0000	−0.0040	0.0035	0.0842	0.1263	−0.0064	−0.0011	0.0000	0.0000
	0.0000	0.0000	−0.0205	0.0036	2.0737	0.1872	0.0852	0.0197	0.0060	0.0027	0.0000	0.0000
	0.0000	0.0000	−0.0053	−0.0001	0.0024	−0.0040	−0.0100	−0.0162	−0.0021	−0.0181	0.0000	0.0000

recognition and spatial propagation mechanism of slab shell sticking, a combined method of GA-BP neural network and logic rules has been proposed for mold breakout prediction in slab continuous casting. Different from previous breakout prediction method based on pure neural network model or logic judgment model, it firstly recognizes temperature change waveform of single thermocouple in case of shell sticking via GA-BP neural network (namely time series model of single thermocouple) and then identifies the 2D propagation behavior of the sticker by appropriate logic rules (namely spatial model of multi-thermocouples). This breakout prediction method effectively combines advantages of neural network technology with spatial propagation mechanism of shell sticking.

To validate accuracy and performance of breakout prediction, the presented method is simulated by historical data with real stickers. Simulation results of time series model of single thermocouple show that the GA-BP neural network has better recognition precision than the BP neural network for the sticking temperature pattern of single thermocouple. So the time series model of single thermocouple is constructed by GA-BP neural network. Simulation results of spatial model of multi-thermocouples show that it can timely detect all 14 stickers on the simulated 97 heats, with a detection ratio of 100% and with no false alarms. At the same time, the presented method for breakout prediction has been carried out field test of 2 months and compared with actual BOPS used in continuous casting production. On the tested 2930 heats with 19 real stickers, the actual BOPS has 2 missed alarms and 65 false alarms. In contrast, the presented method can timely detect all stickers and has only four false alarms, with a detection ratio of 100% and false alarm frequency of 0.1365% times/heat.

Therefore, it can be concluded that the combined method of GA-BP neural network and logic rules could achieve better performance for prediction of the sticker breakout.

Funding information The authors are grateful to the financial support for this project from the National Natural Science Foundation of China (Grant No. 51504002).

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