Using GA-BP Neural Network for Sticking Breakout Prediction in Continuous Slab Casting

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***Abstract* — Breakout is a hazardous accident in continuous casting process. Losses caused by a typical breakout accident can be as high as hundreds of thousands of dollars. Breakout prediction technique is playing an important role in reducing the occurrence of breakout events. Back propagation (BP) neural network based forecast method as an important breakout prediction technique which can be applied in continuous casting. Due to the error function of BP neural network not being a strictly convex function, when training BP neural network it is easy to fall into a local extreme point. In this paper, single thermocouple time sequence network and "T" shaped four thermocouples space network are constructed for sticking breakout prediction. A genetic algorithm (GA) is used to determine the initial values of network weights to make BP neural network converge to global optimum more quickly and not to plunge into a local extreme. Compared to previous breakout prediction methods our results show it is more accurate.**

Keywords - breakout prediction; continuous casting; neural network; genetic algorithm.

I. INTRODUCTION

Continuous casting (CC) is the main method of casting steel billet in modern steel making enterprises. It has the advantages of simple production process, high utilization rate of molten steel, low energy consumption, high automation of the production process [1]. The application of continuous casting technology has greatly improve the production efficiency. The stable running of continuous casting and the quality of the steel billet are two important tasks of continuous casting. In continuous casting process, if solidified shell formed in mold was fracture due to some reason, the non-solidified molten steel will leak out, this type of accident is called breakout [2]. Breakout will cause the casting interruption, which will affect the continuity of the continuous casting production. Serious cases, the leakage of molten steel will burn out some equipment of production line, thus cause huge economic losses. A calculation in paper [3] shows that the losses caused by a typical breakout accident can be as high as hundreds of thousands of dollars. Breakout has become the main obstacle to the efficient continuous casting production, which seriously affects the operation rate of the continuous casting machine. The practice of continuous casting at home and abroad shows that the breakout prediction system can effectively prevent the occurrence of breakout, it not only can reduces the damage of equipment and personal injury, but also can improve the operation rate. At present, breakout prediction technology has become a main component of high efficient continuous casting, so the research of breakout prediction system is of great significance.

The occurrence of breakout in continuous casting is often caused by different kinds of reasons [4]. There are many factors that may cause solidified shell fracture, such as the heat transfer ability of mold and so on. Breakout form is varied, which can be roughly divided into the following kinds: (1) cast-start breakout. (2) suspended breakout. (3) crack breakout. (4) slag breakout. (5) cut off breakout. (6) sticking breakout. The proportion of various types of breakout is shown in figure 1 [5], it can be seen the sticking breakout is the main form of the breakout. So, it is important to accurately predict the sticking breakout.

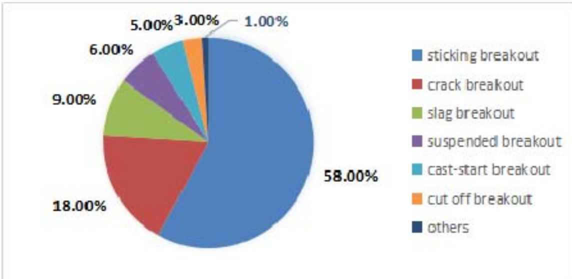

Figure. 1 The proportion of various types of breakout.

The research of breakout prediction system began in 1960s. Based on different theories, a number of breakout prediction systems have been developed in different periods. At the present, the prediction method of the breakout is mainly in the following five:

(1) Prediction method based on thermocouple temperature measurement.

This method is based on the temperature change of the thermocouple installed on the mold copper plate to make a recognition of the occurrence of breakout. This method has high feasibility and low cost, it has been widely used in breakout prediction system [6]. In 1990, japan eight iron works and Fujitsu developed a neural network breakout prediction system based on thermocouple temperature measurement. The false alarm is only 1/8 of the original logical judgment system, and the forecast alarm time is 3 - 6s ahead of the original system [7].

(2) Prediction method based on the friction between the billet shell and the mould plate.

When a breakout accident occurs, the molten steel enters into the air gap between the mould plate and the billet shell, which will increases the friction [8]. So breakout accident can be predicted by using this theory. Because the change of the friction is restricted by many factors (cleanliness of molten steel, casting speed, mould vibration etc) [9], the prediction accuracy of this method is low.

(3) Prediction method based on analysis of mold heat exchange.

When the breakout occur inside the mold, the mold's heat exchange rate will change [10,11]. Select the heat flux value based on the minimum shell thickness of the billet shell which does not occur breakout in the historical data. When the heat flux is lower than the threshold value, the breakout can be determined [12]. This method have good performance in the prediction of small square billet and medium slab [13]. But the accuracy of this prediction method is relatively low, now it is mainly used as an auxiliary criterion.

(4) Prediction method based on vibration waveform analysis.

The vibration waveform of the mould will be changed when the breakout occurs. A phase difference will be produced between the actual vibration waveform and the reference vibration waveform. According to this phase difference breakout accident can be predicted. However, this method is complex, so it is difficult to applied in breakout prediction.

(5) Prediction method based on ultrasonic detection.

Ultrasonic probe is arranged on the two narrow side copper plate of the mould. Through auto correlation analysis of the received ultrasonic wave, this method can make a recognition of the occurrence of dilatancy breakout. So this method has limitation of only can predict the breakout caused by dilatancy.

BP neural network forecast model is an important prediction method based on thermocouple temperature measurement, which has excellent performance in sticking breakout prediction. However, the error function of BP neural network is not a strictly convex function, so when training BP neural network it is easy to fall into local extreme point. Genetic algorithm (GA) is a search heuristic that mimics the process of natural selection, first proposed by Holland [14]. This heuristic is routinely used to generate useful solutions to optimization problems. In this paper, a BP neural network based prediction model is proposed. This model are combine single thermocouple time sequence network and "T" shaped four thermocouple space network, which use genetic algorithm to initial value of network weights and use L-BFGS algorithm to training BP neural network. By using GA and L-BFGS, it can make BP neural network to converge to global optimum more quickly and not to plunge a local extreme. By combine time sequence network and space network, it can increase the forecast precision and reduce false alarm. The results show that this model can effectively predict the breakout of steel, it has lower false alarm rate compared to existing known methods.

The remainder of this paper is organized as follows. In the next section, prediction principle of sticking breakout is described in detail. In section 3, the GA which we adopted is described in detail. In section 4, structures of single thermocouple time sequence network and "T" shaped four thermocouple space network are given. In section 5, some results are shown. Finally, paper conclusion are given in section 6.

II. PREDICTION PRINCIPLE OF STICKING BREAKOUT

Stick type of breakout is the major type of breakout during the continuous casting operations. The mainly reasons of the sticking breakout is the poor lubricating of meniscus. When meniscus and solidified steel shell are stick together, the casting friction force increases. Along with the slab downward movement, the sticking portion's solidified shell will ruptures, and the liquid steel flows out of the ruptured portion immediately under the CC mould.

The task of prevention of breakouts during the continuous casting operation is as old as the continuous casting technology itself. Several methods have been developed and used. Out of these methods, thermocouple temperature measurement based method is the most reliable and the preferred method. The essence of sticking breakout prediction based on thermocouple temperature measurement is a pattern recognition problem of temperature waveform. As shown in figure 2, two rows thermocouples are installed on the mold copper plate. Under normal circumstances, the growth of solidified shell is uniform. So, the upper row thermocouples's temperature are higher than the lower row thermocouples's temperature, and the temperature of each thermocouple will fluctuate within a small range [15] (see figure 3 in the first 14 moments). When sticking breakout occurs, the molten steel contact the mould copper plate directly, the gap extensions to horizontal and vertical in "V" shape. At first, the upper row thermocouples's temperature rise sharply. As the gap continues to move down, the lower thermocouples's temperature start rising, the temperature difference between the upper row thermocouples and the lower row thermocouples gradually decrease [16] (see figure 3 in the last 14 moments).

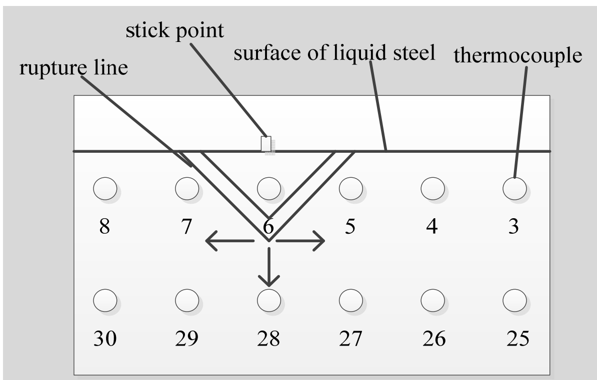

Figure. 2 The model of sticking breakout.

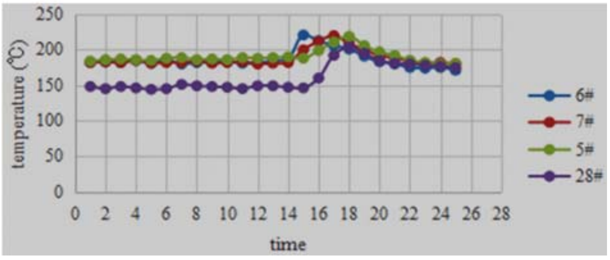

Figure. 3 6#, 7#, 5#, 28# Thermos-Couples' Temperature.

III. Genetic Algorithm

Genetic algorithm is first put forward by Professor J. Holland of the University of Michigan in 1975. It is a random search algorithm that simulates the biological evolution of nature. Genetic algorithm is a general algorithm to solve the optimization problem, it has the advantage of require no derivative information. It has the good performance on global optimization [17]. So far, genetic algorithm has been developing for nearly 50 years. Now genetic algorithm as a rapid development of optimization technology, get the high attention of scholars at home and abroad [18]. Genetic algorithm can be defined as an eight tuple *GA* [19], *GA* is define as follow:

$$GA = (D, F, P_0, N, S, M, C, T) \tag{1}$$

where D is the individual coding mode, F is the individual fitness function, P_0 is the initial population, N is the population size, S is the selection operator, M is the mutation operation, C is crossover operation, T is the termination condition. Figure 4 shows the detail process of GA. From figure 4, we know if we want to use GA to optimize the neural network, first we need to select an individual coding scheme. Paper [20] shows that for the global optimization problem of multi extremum function, using decimal float-encoding GA can make iterative process converges to the global optimum more quickly and hardly gets stuck at an local optimum. So we select decimal float-encoding method as D. The fitness function we used is the BP neural network's error function, and the greater the value of error function on behalf of the individual's fitness is lower. The selection operator we used is ranking selection [21], the selection probability $P(x)$ can be calculate as follow:

$$P(x) = \frac{rank(x)}{0.5 * N * (N+1)} \tag{2}$$

where $rank(x)$ represent individual x's fitness, $1 \le rank(x) \le N$. The greater the value of $rank(x)$ on behalf of the individual x's fitness is higher. For example, $rank(x)=N$ represents individual x have the highest fitness in the population. We do the selection operator according to the roulette method. The crossover operation can be done using the follow formulas:

$$new\_x1 = lambda*x1 + (1-lambda)*x2 \tag{3}$$

$$new\_x2 = x1 + lambda*(x1-x2) \tag{4}$$

where lambda is a random number between 0-1. The mutation operation we used is Gauss Mutation. And when the number of iterations reaches the preset value, the algorithm terminates.

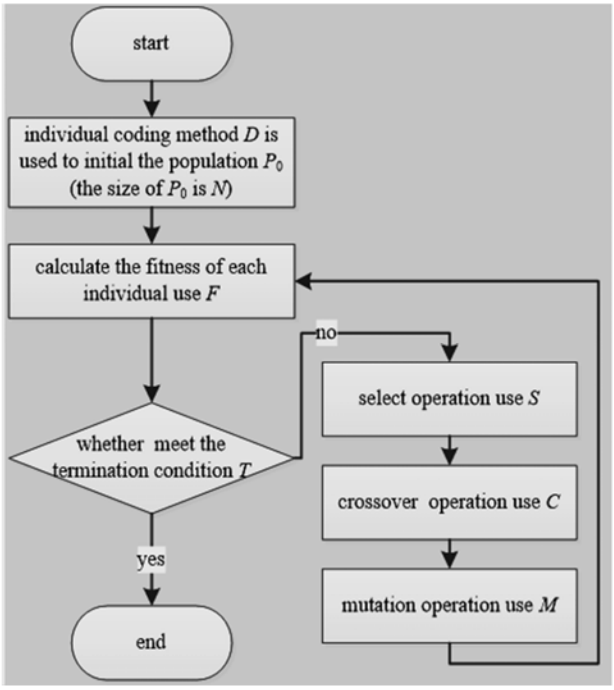

Figure. 4 Genetic algorithm's work flow.

IV. Network Structures

In the practical application of artificial neural network, the ratio of BP neural network or it's variants is 80% ~ 90% [15] . Therefore, BP neural network is the most widely used neural network. Robert Hecht Niel-son proves that a continuous function in any closed interval can be approximated by a BP network with one hidden layer. Thus, a three layers BP network can complete the arbitrary n-dimensional mapping to m-dimension. In this paper, two BP neural networks of three layers are constructed for sticking breakout prediction.

Single thermocouple time sequence network is constructed for each upper row's thermocouples, this network has three layers. Input layer has 15 neurons, because 15 consecutive sampling periods of each thermocouple can accurately present the characteristics of the temperature pattern in the occurrence of the breakout. Output layer has 1 neuron, the value of output neuron is between 0 and 1, and the greater the value of output neuron represents the greater the possibility of breakout. The number of hidden layer

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neurons can calculate according to empirical formula $n_1 = \sqrt{n+m} + a$ [22], where n is the number of input layer neurons, m is the number of output layer neurons, a define as the constant between 1 and 10. Through experiments, the number of hidden layer neurons is finally determined as 14, i.e., a=10.

”T” shaped four thermocouple space network is constructed use three upper row thermocouples and one lower row thermocouple, such as 7#, 6#, 5#, 28# (see figure 2). Space network also has three layers. The input layer has 4 input neurons, used to input the temperature values of four thermocouples at every moment. Output layer has 1 neuron, represents the possibility of the breakout. For the hidden layer, the number of hidden layer neurons is finally determined as 12, i.e., a=10.

For both time sequence network and space network, the activation function is sigmoid function, and the error function is *CostFun.*

$$CostFun = \frac{1}{2} * \sum_{i=1}^{n} \sum_{j=1}^{len\text{-}out} (y_{ij} - \overline{y}_{ij})^2 \tag{5}$$

where n is the data set size, *len-out* is the neuron numbers of the output layer, y_{ij} is the actual output of neuron, and $\overline{y}_{ij}$ the ideal output of neuron. And we set vigilance parameter = 0.8, that is to say when the value of output neuron is greater than 0.8, then breakout is determined by this network. In order to further reduce the false alarm, only both output neuron’s value of time sequence network and space network are greater than 0.8, then the breakout is determined.

V. Evaluation

In order to verify the performance of the proposed breakout prediction method, we used MATLAB to implement the proposed neural network. And evaluated it by using historical data which collected by a certain steel mill over a period of two months. After analyzing and dealing the historical data, 1000 normal samples and 300 breakout samples are selected to verify the performance of the proposed breakout prediction method, and 60% of samples are used to train the time sequence network and space network, 40% of samples are used to test the performance of the proposed breakout prediction method. And prediction rate η_1 and report rate η_2 are use to evaluate the proposed method, η_1 and η_2 are defined as follows:

$$\eta_1 = \eta_r / (\eta_r + \eta_f + \eta_0) \tag{6}$$

$$\eta_2 = \eta_r / (\eta_r + \eta_0) \tag{7}$$

where η_r is the number of true alarms, η_f is the number of false alarms, η_0 is the number of failing report.

For training the proposed BP network, GA and L-BFGS algorithms are used, GA algorithm is used to initializing the weights of the BP network, L-BFGS algorithm is used to training BP network. For the GA, we set initPopSize = 20, pc = 0.9, pm = 0.02 and maxIter = 1000. For the L-BFGS we set m = 7, epsilon = 1E-5, max_iterations = 200, max_linesearch = 10. In training process, the above parameters are use to training both BP and proposed GA-BP, and the error curves of BP and proposed GA-BP are shown in figures 5 and 6. The results show that the proposed GA-BP neural network can converge to global optimum more quickly.

Figure. 5 Error curves of BP.

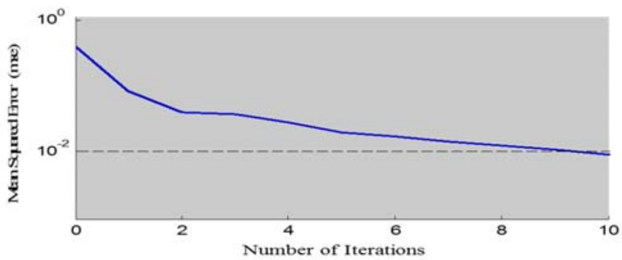

Figure. 6 Error curves of proposed GA-BP.

In the testing process, the proposed breakout prediction method gives 122 alarms, which contains 2 false alarms, 120 correct alarms. And the number of failing report is 0. The BP neural network gives 129 alarms, which contains 9 false alarms and 120 correct alarms, the number of failing report is 0. The prediction rate and report rate can be calculated by using formulas 6 and 7. As shown in table 1, the proposed prediction method has good performance than BP.

TABLE 1 PREDICTION RESULTS

prediction model	prediction rate	report rate
proposed model	98.36%	100%
BP	93.02%	100%

VI. Conclusions

In this paper, a GA-BP neural network based sticking breakout prediction method is proposed. Which use GA and

L-BFGS algorithms training the network, thus it overcomes BP neural network's limitation of easy to fall into local extreme point. By using both time sequence network and space network, the proposed method can effective reduce the number of false alarms. Experimental results show that the new method has better identification capability than BP neural network, the number of false alarm was significantly reduced.

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