Intelligent breakout prediction method based on support vector machine

Yuanpeng Tian 1, Yu Liu 1*

1School of Mechanical Engineering, Northeast Electric Power University, No. 169 Changchun Road, Chuanying District, Jilin, CN 132012
E-mail address: yuliu@neepu.edu.cn

Abstract. Breakout is a serious accident during continuous casting. In order to reduce breakout accident, a breakout prediction method was proposed based on support vector machine model. The typical characteristics of continuous casting breakout were reconstructed by thermocouple temperature signals. The temperature data of three adjacent thermocouples in the first row were added and then connected with the temperature data of the middle second row, which was used to capture the typical spatial characteristics of breakout. The 80% of true and false breakout samples were used to train the support vector machine model and 20% samples were used to test the model. The results show that this method can predict all breakouts, which has a true-sticker alarm rate of 100%. There is one false alarm and the accuracy rate is 95.8%.

1. Introduction
Slab continuous casting is an important process in the iron and steel plant [1]. In order to produce high quality slabs, the continuous casting process must be smooth and subject to disruptions as few as possible. While sticker breakout in mould is the main cause of disruptions to production and can result in serious damage to the slab caster and to the secondary cooling rollers. Therefore, an effective and intelligent breakout prediction system is required, with no missed alarms and the minimum number of false alarms [2].

Breakout detection systems were the first practical examples of an intelligent mould and are now in widespread use in slab casters [3]. In the past 20 years, a series of methods for predicting breakout have been developed based on logical judgement [4, 5] and artificial intelligence [6, 7]. In these methods, the mould copper temperature is commonly used in the breakout prediction system (BOPS) and the mould monitoring system [8, 9]. However, frequent sticker breakouts are still common in practice, especially at high casting speeds and with wide slabs. False alarms from the BOPS are considered to be another serious problem in continuous casting production. The casting speed is decreased in a controlled and abrupt manner to avoid breakout whenever the BOPS sends an alarm, regardless of whether this is a true or false alarm. Although false alarms are less costly than sticker breakouts, there are still too many of them than might be hoped. Both the production process and the quality of the slab surface and interior are adversely affected by the reduction of casting speed[10], which compromises the ability to produce a high-quality product, as well as leading to a lack of confidence in the BOPS on the part of the operator. Therefore, sticker breakout and false alarms are two key problems for mould monitoring in continuous casting production.

In this work, a "T" type construction method of breakout feature was proposed, which captures the horizontal and vertical spatial characteristics of sticker breakout formation and development process.
Then the support vector machine model optimized by grid search was trained and tested with the true and false breakout samples, which provides a new method for continuous casting breakout prediction.

2. Experiment

2.1. Caster
The radius of the arc continuous caster was 10.75m, whose metallurgical length was 28.8m. The mould length was 0.9m and standard mould level was 0.8m. The slab thicknesses were 0.22m, 0.26m and 0.32m and width was 1.8 to 2.7m. The maximum and minimum casting speeds were 1.2 and 0.75 min/m. The main parameters are shown in Table 1.

| Item                | Parameters     |
|---------------------|----------------|
| Strand              | 1              |
| Slab Width          | 1.8-2.7m       |
| Slab thickness      | 0.22, 0.26, 0.32m |
| Radius              | 10.75m         |
| Metallurgical length| 28.8m          |
| Mould length        | 0.9m           |
| Mould level         | 0.8±0.003m     |
| Drive               | Hydraulic drive|
| Oscillation frequency| 40-400 times/min |
| Casting speed       | 0.75-1.2m/min  |

2.2. Temperature and temperature velocity
Figure 1 and figure 2 are the temperature and temperature velocity of single column thermocouples, respectively. It can be seen that the temperature and its velocity have similar change patterns when the breakout happens. The maximum temperature of sticker breakout in the first row appears in the 64th second, and the maximum temperature in the second row appears in the 80th second, as shown in figure 1. The maximum temperature velocity of sticker breakout in the first row appears in the 58th second and the maximum temperature rate in the second row appears in the 75th second as shown in figure 2. It can be seen that when the sticker breakout happens, the typical characteristics of sticker can be captured more quickly by the temperature velocity. Therefore, temperature velocity is more suitable than temperature for sticker breakout detection.

Fig.1 Typical breakout single column thermocouple temperature
3. Reconstruction of spatial characteristics of sticker breakout

3.1. Spatial characteristics of sticker breakout

Figure 3 is the temperature velocity of sticker breakout in three columns adjacent thermocouples. In figure 3(a), the temperature velocity of the upper thermocouple (1, 1) starts to rise in the 2\textsuperscript{nd} second, and reaches the maximum value in the 6\textsuperscript{th} second, while the temperature velocity of the lower thermocouple (2, 1) gradually rises in the 11\textsuperscript{th} second and reaches the maximum value in the 29\textsuperscript{th} second. The temperature velocities of the upper and lower thermocouples have the same temperature change pattern, and the second row is later than the first row, which shows the longitudinal "time lag" phenomenon of sticker breakout. Figure 3(b) and 3(c) have similar phenomena. As shown in figure 3(b), the temperature velocity of the upper thermocouples (1, 2) begins to rise in the 2\textsuperscript{nd} second, and the temperature velocity rate reaches the maximum in the 7\textsuperscript{th} second. The maximum temperature velocity value of the upper thermocouple (1, 1) appears earlier than that of the upper thermocouple (1, 2) and (1, 3). It shows that the sticker breakout first occurs at the first column (1, 1) and has a transverse propagation phenomenon, which is the transverse "time lag". In figure 3(a)-(c), at the 29\textsuperscript{th}, 24\textsuperscript{th} and 30\textsuperscript{th} seconds, the temperature velocities of the second row (2, 1), (2, 2) and (2, 3) are greater than zero, and the temperature velocities of the first row (1, 1), (1, 2) and (1, 3) are less than zero, which shows the phenomenon of temperature inversion.
Fig. 3 The temperature velocity of three adjacent thermocouples of typical breakout

3.2. Reconstruction of temperature velocity spatial characteristics of breakout

In order to reduce the input characteristic data of the model, the temperature data of adjacent three columns of thermocouples are reconstructed. The temperature velocity of adjacent three columns in the first row for 30 seconds are added and connected with the 22 seconds temperature velocity of the middle second row. The reconstructed result is shown in figure 4. It can be seen that the temperature velocity reaches the first peak at the 6th second which is $0.98\, ^\circ\text{C}/\text{s}$, and the second peak at the 19th second, which is $0.38\, ^\circ\text{C}/\text{s}$. These peaks capture the transverse "time lag" characteristic of sticker breakout. At the 46th temperature characteristic point, it reaches the third peak, and the temperature velocity is $1.1\, ^\circ\text{C}/\text{s}$, which captures the longitudinal "time lag" characteristic of sticker breakout. The
temperature velocity at the trough point is -1.56℃/s. The overall trend of temperature velocity declines in the first row and forms "inversion" characteristic together with the rising temperature velocity in the second row. Typical transverse "time lag", longitudinal "time lag" and longitudinal "inversion" phenomena can be captured by reconstructed temperature velocity data of sticker breakout, which demonstrates that the reconstructed data is feasible for breakout prediction.

Fig.4 Reconstructed temperature velocity of the spatial characteristics of the breakout

4. Prediction model based on support vector machine

4.1. support vector machine
Support vector machine (SVM) model establishes a classification hyperplane as a decision surface, so as to maximize margin between positive and negative support vector as shown in figure 5. The theoretical basis of SVM is statistical learning theory. The principle is based on the fact that the error rate of the learning machine on the test data is bounded by the sum of the training error rate and a term that depends on VC dimension. In the case of separable mode, the value of the former term of the SVM is zero, and the second term is minimized. Therefore, SVM can provide its unique generalization performance in pattern classification.

Fig.5 Schematic diagram of optimal classification hyperplane
The training sample is \((x_i, y_i), (i=1, 2, \ldots, n)\), where \(x_i\) is the training sample input and \(y_i\) is the training sample output. In the sample space, the hyperplane can be described by the following linear equation:

\[
\omega^T x + b = 0
\]

where \(\omega=(\omega_1; \omega_2; \cdots; \omega_d)\) is the normal vector, which determines the direction of hyperplane; \(b\) is the displacement term, which determines the distance between hyperplane and origin.

Because most of the problems in the real world are nonlinear, strict linear classification can’t meet the actual needs. Therefore, relaxation variables are used to relax constraints.

\[
\min_{\omega, b} \frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^{N} \xi_i
\]

s.t. \(y_i \left[ \omega^T x_i + b \right] \geq 1 - \xi_i, \quad \xi_i \geq 0, \quad i = 1, 2, \cdots, n.\)

where \(C\) is the penalty parameter; \(\xi\) is the non-negative relaxation factor.

In order to solve this constrained optimization problem more efficiently, Lagrange multiplier method can be used to get its "dual problem", because the above process satisfies Karush Kuhn Tucker (KKT) condition, and the optimal classification function of this problem can be written as:

\[
f(x) = \text{sgn}( \sum_{i=1}^{N} a_i^* y_i K(x_i, x_j) + b^* )
\]

where \(a_i^*\) is the optimal Lagrangian multiplier; \(b^*\) is the classification threshold; \(K(x_i, y_j)\) is the kernel function.

Kernel function can solve nonlinear problems and overcome dimension disaster for SVM, and replace inner product operation in optimal classification function. Radial basis function (RBF) kernel function has a good ability to classify all kinds of data. By comparing and analyzing the performance of several kernel functions, this paper finally chooses RBF kernel function, and its function is as follows.

\[
K(x_i, x_j) = \exp\left(-\frac{\|x_i - x_j\|^2}{2g^2}\right)
\]

where \(g\) is the kernel function parameter.

4.2. Grid search optimization for parameters

The variation range of parameter \(C\) is [0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0] and the variation range of parameter \(g\) is [0.001, 0.01, 0.1, 1.0, 10].

4.3. Model training and testing

All 119 samples are selected from sticker breakout, false alarms and normal casting in a steel plant from 2015 to 2017 years. True stickers and false stickers are 47 and 72, respectively. In order to reduce human interface, random samples are selected as training and testing samples, which accounted for 80% and 20%, respectively. So the testing samples are 10 sticker breakout and 14 false sticker breakout. If the sample is true sticker, the output value of SVM model is 1, otherwise the value is 0.

Grid search is used to explore 10*5=50 combinations of SVM hyperparameters, and each model training uses 5-fold cross-validation. The optimal parameters \(C\) and \(g\) are obtained by calculating the best average accuracy of each group. After the SVM model is trained with input training temperature samples, the penalty factor \(C\) is 0.8, and the kernel function parameter \(g\) is 0.1. The testing result is shown in table 2. All 10 sticker breakouts can be predicted by SVM and optimized SVM model. The true sticker alarm rate is 100%. But the SVM model has 2 false alarms. The optimized SVM model has only 1 sticker breakout, which is better than SVM model. The accuracy rate is 95.8%.
Table 2 Test result of SVM and optimized SVM

| Model        | True sticker breakout | False sticker breakout | False sticker breakout alarm | True-sticker alarm rate | False sticker breakout alarm | Accuracy rate |
|--------------|------------------------|-------------------------|-----------------------------|------------------------|-------------------------------|---------------|
| SVM          | 10                     | 14                      | 10                          | 100%                   | 2                             | 91.7%         |
| Optimized SVM| 10                     | 14                      | 10                          | 100%                   | 1                             | 95.8%         |

5. Conclusion
1. The temperature velocity of sticker breakout has the same pattern as the temperature. And the maximum value is earlier than that of temperature. So temperature velocity is more suitable for breakout prediction than thermocouple temperature.
2. By accumulating the thermocouple temperature velocity in the first row and connecting the thermocouple temperature in the second row of middle column, the typical temperature characteristics of sticker breakout are reconstructed, and the typical transverse and longitudinal propagation characteristics of breakout are captured.
3. With the reconstructed "T" type temperature velocity as input, the SVM model is established and optimized by grid search algorithm, which can achieve 100% true-sticker alarm rate and 95.8% accuracy rate is.

Acknowledgements
"We would like to acknowledge financial support from the National Natural Science Foundation of China (51704073), Science and Technology Development of Jilin Province (20180520065JH), “13th Five-Year Plan” Science and Technology Research Project of Jilin Provincial Education Department (JJKH20180419KJ), and Technology Innovation Development Project of Jilin City (20166013).

References
[1] Lukyanov SI, Suspitsyn ES, Krasilnikov SS, Shvidchenko DV (2015) Intelligent system for prediction of liquid metal breakouts under a mold of slab continuous casting machines. Int J Adv Manuf Technol 79(9): 1861-1868
[2] Moon CH, Lee D, Moon SC, Park HD (2008) Re-start technology for reducing sticking-type breakout in thin slab caster. ISIJ Int 48(1): 48-57
[3] Thomas BG (2002) Modeling of the continuous casting of steel – past, present, and future. MMTB 33B: 795-812
[4] Watzinger J, Pesek A, Huebner N, Pillwax M, Lang O (2004) MoldExpert – operational experience and future development. Ironmaking & Steelmaking 32(3): 208-212
[5] Qin X, Zhu CF, Yin YR, Dong XR (2010) Forecasting of molten steel breakouts for the slab continuous casters with hydraulic servo oscillation systems. Iron and Steel 45(11): 97-100
[6] Wang XD, Yao M, Chen XF (2006) Development of prediction method for abnormalities in slab continuous casting using artificial neural network models. ISIJ Int 46(7): 1047-1053
[7] Ji C, Cai ZZ, Tao NB, Yang JL, Zhu MY (2012) Molten steel breakout prediction based on genetic algorithm and BP neural network in continuous casting process. In: Proceedings of 31st Chinese Control Conference (CCC), 25–27 July 2012, Hefei. IEEE, New York, pp 3402-3406
[8] Normanton AS, Hewitt PN, Hunter NS, Scoones D, Harris B (2004) Mould thermal monitoring: a window on the mould. Ironmaking & Steelmaking 31(5): 357-363.
[9] Yazid LDL, Salah B, Seghir BM, Jurgen B (2013) Adaptive support vector machine-based surface quality evaluation and temperature monitoring. Application to billet continuous casting process. Int J Adv Manuf Technol 67(9): 2063-2073
[10] Zhou J, Peng X, Qin Y (2009) A coupled thermal-mechanical analysis of a mold-billet system during continuous casting. Int J Adv Manuf Technol 42(5): 421-428