Tail Deviation's Predictive Control of the Tandem Rolling Strip based on Manifold Learning

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Abstract. In the rolling process, serious deviation will cause product quality drop and rolling equipment fault. This reserch propose tail deviation's predictive control method of the tandem rolling strip based on manifold learning. Based on real deviation data in the rolling production site,tail deviation patterns are divided according to deviation's value. Using manifold learning method to deviation data in middle rolling stage, tail deviation pattern and scope are obtained. According to regression model between the control variable and deviation, predictive control strategy of the tandem rolling strip may be implemented. Experiment shows this method may control tail deviation in preconcerted permission range.

Intorduction

In the rolling process, deviation is the phenomenon that the strap width direction's centerline deviates from rolling system setting centerline. when strap withdraws each planish rolling stand constantly in the tail rolling stage, deviation becomes serious because speed accelerates, strap thickness and system control ability reduces, which will cause product quality drop and rolling equipment fault.

This reserch propose tail deviation's predictive control method of the tandem rolling strip based on manifold learning. Based on real deviation data in the rolling production site, tail deviation patterns are divided according to deviation's value. Faced on various rolling parameters, using manifold learning method, the low dimension main characteristic parameters in different deviation pattern and linear mapping function is obtained. Based on variables sensitivity to inhibit the tail deviation, the control variable can be found and the relation function between the control variable and deviation may be established. At last, paper propose tail deviation's predictive control strategy of the tandem rolling strip. Experiment shows this method may control tail deviation in preconcerted permission range.

1. Tail deviation patterns of the tandem rolling strip

The tandem rolling line include mainly such equipment as Furnace, Rough mill(RM), Finishing (F1~F4), Edger, 150mm shear, Tension reel, Coiler. Frame distribution is shown in Fig.1. Firstly the heating strip is taken from furnace, the head and tail are cut after roughing mill, and then start the continuous finishing mill irreversibly, finally the profile parameters is detected by FDP and strip is coiled by coiler. If the strip before the finishing have these status of bigger lateral difference in thick, temperature or position, bigger deviation will occurred. Especially when the strap withdraws from each finish rolling stands constantly, deviation becomes more and more serious and must be controlled timely.

We define that finishing process have three stages, the rolling head stage, the rolling tail stage and the middle rolling stage. The rolling head stage is the time from the 8 seconds before strip tail withdraws F1 to strip tail arrives to FDP.

Fig.2 is the curve of a set of the tail deviation data. We can see from this figure, the tail deviation process have

RM F F F F F FDP

Fig.1 The schematic drawing of stands' distribution

four local extremum, A,B,C,D extremum are respectively the time when the strip tail withdraws

F1,F2,F3,F4. Each strip's tail deviation has this characteristics, every local extremum has a certain deviation range. $A \in [-15\text{mm},15\text{mm}], B \in [-20\text{mm},15\text{mm}], C \in [-15\text{mm},75\text{mm}], D \in [-102\text{mm},15\text{mm}].$

At the production site, deviation range of \pm 15mm to \pm 20mm is consider as normal. Baecause the values of A and B are in the normal range, deviation is classified as three patterns in this paper. Pattern 1 is normal, Pattern 2 is that only the value of C is over standard, Pattern 3 is that the values of C and D are over standard.

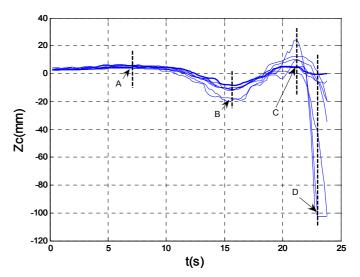


Fig.2 The curve of a set of tail deviation data

2. Tail deviation patterns' prediction base on Local Preserving Projection

In 2000, Roweis etc. and Seung etc.simultaneously had published the research papers about the manifold learning in Science [1-2], proposed Isometric feature Mapping (ISOMAP) [1] and Locally Linear Embedding (LLE) [2] algorithm, and successfully applied them to recognition in the graph and characters. As a starting point, the researchers had launched a variety of algorithms, such as Laplace feature Mapping (LE) [3], Local Tangent Space Alignment (LTSA) [4], Locality Preserving Projection (LPP)[5] and other algorithms [6-7].

Local Preserving Projection (LPP) belongs to unsupervised manifold learning algorithm to preserve local neighbors information in the dimension reduction process. Given data set X, $Y = [y_1, y_2, \cdots y_d] \in R^{l \times d}$ are the mapping result by $Y = A^T X$, A is the transformation matrix, $A = [a_0, a_1, \cdots a_{l-1}] \in R^{n \times l}$ may be solved by the optimization problem as followed

min
$$A^{T}XLX^{T}A$$

subject to $A^{T}XDX^{T}A = I$ (1)

Where, L is laplacian matrix, L = D - S, D is the diagonal matrix $D_{ij} = \sum_{j} S_{ij}$, S_{ij} is the neighbor weight matrix,

$$S_{ij} = \begin{cases} \exp(-\|x_i - x_j\|^2 / \sigma) & x_i, x_j \text{ are nearest neighbour} \\ 0 & \text{others} \end{cases}$$
 (2)

The basic way of the tail deviation patterns' prediction base on LPP is, to extract the high dimension characteristic value of deviation in the middle rolling stage, and then find the intrinsic manifold by LPP which can make effectively pattern recognition, finally predict tail deviation value scope.

In order to accurately describe the deviation feature of the middle rolling condition, the mean, variance, the absolute mean, the peak-peak value, the root-mean-square value, the waveform index, the peak value index, the pulse index the allowanceindex, the kurtosis index, the skewness index, these 11 time-domain characteristics are extracted. Take 24 pieces of tandem rolling straps' deviation as the training data, each deviation pattern have 8 set of data and onstitutes 24×11 train sample matrices. Take 6 pieces of straps' deviation as the test data, each pattern have 2 set of data and onstitutes 26×11 test sample matrices.

The process of the tail deviation patterns' prediction is as followed.

- 1) Select the neighbor number k and the kernel parameter σ , construct high dimensional local manifold space.
- 2) Run LPP algorithm to train sample and obtain the low-dimensional main characteristics and linear mapping matrix. adjust the parameters k and σ , obtain the optimal projection matrix A.
- 3) Make use of projection matrix A, obtain the low-dimensional main characteristics of test sample. By observing the projection value falls in sample's deviation

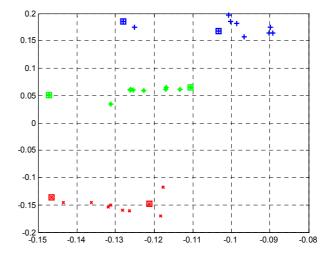


Fig.3 The sample's the low-dimensional mapping

pattern area, we may get the predictions' result of the tail deviation pattern.

Fig.3 is the sample's the low-dimensional mapping ,here k=10 and $\sigma=0.2$.the train samples' low dimension mapping in three kind of pattern respectively express with the symbol "*", "X", "+", the test samples' low dimension mapping expresse with the symbol "\subseteq" outside from symbol "*", "X", "+" .we can see from Fig.3, the low dimension mapping to training sample have very good classification, with optimal projection matrix A, these to test sample fall into correct deviation patterns' scope. Finally the method achieves prediction of the tail deviation patterns according to the deviation data of the middle rolling stage.

3. Regression model of controlling parameter and deviation

After predicting deviation pattern, we can obtain the scope of the tail deviation, and then based on the data we may control deviation by adjusting rolling parameters. From the actualdeviation data, it can be found that the effect leads to tail deviation is mainly concentrated in rolling system F4, the change of rolling parameters in F4 rolling system, often has a decisive impact on the final deviation of the strip. The most influential parameters on tail deviation in F4 are roll gap difference (OS-DS) and rolling force difference (OS-DS), because correlation exists between these two variables by the mill stiffness,in this paper, rolling force difference is used as the main control parameters, establish regression model of rolling force difference and deviation in F4.

Regression analysis is commonly used in mathematical modeling, which widely used in rolling production. Regression analysis is used to determine the function expression of a set of observations (x_i, y_i) , $i = 1, 2, 3, \dots m$ of f(x), f(x) can be linear or nonlinear. Function relation between the rolling force differenceand the deviation was established by regression analysis in this paper, the basic expression of simple linear regression model is:

$$y = ax + b \tag{4}$$

HPC

Through linear regression, model of rolling force difference (set x) and tail deviation(set y) in three kinds of deviation model can be obtain as follows (the confidence level is 95%)

 ΔS_{ds}

 $\varepsilon\alpha$

K

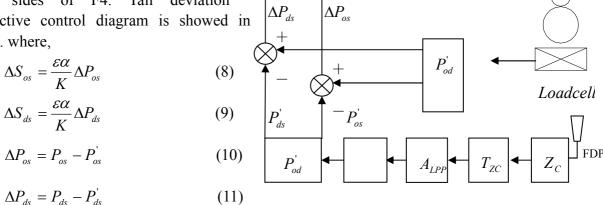
P1
$$y = 0.1692x + 9.7518$$
 (5)

P2
$$y = 0.2544x + 17.5063$$
 (6)

P3
$$y = 0.1536x - 8.7940$$
 (7)

4. Realization of tail deviation predictive control

Patterns' prediction of the tail deviation and deviation regression model above paragraphs are established on the basis of statistical data, but the deviation control need to adjust the pressure on both sides of F4. Tail deviation predictive control diagram is showed in Fig. 6. where,



 ΔS_{os}

εα

K

Fig.4 Tail deviation predictive control diagram

 ΔP_{os} , ΔP_{ds} are respectively rolling force variable quantity (KN) in Operate Side(OS) and Drive Side(DS).

 ΔS_{os} , ΔS_{ds} are respectively press quantity variable value (mm) in Operate Side(OS) and Drive Side(DS).

 $P_{os}^{'}$, $P_{ds}^{'}$, P_{os} , P_{ds} are respectively predictive value and measured value of the adjustment (KN) of the rolling force in Operate Side(OS) and Drive Side(DS).

 $P_{od}^{'}$ is difference of the predictive value between Operate Side(OS) and Drive Side(DS).

 α is mill bounce coefficient, \mathcal{E} is influence coefficient, K is stiffness of mill stand, Z_{C} is deviation, T_{ZC} is deviation characteristic value, A_{LPP} is LPP mapping matrix, W_{ZC} is the tail deviation predictive value.

Next, we analyse to the actual rolling production deviation data in one aluminum company. This aluminum had been rolled at 12:35:34 on June 25^{th} , the average wedge of the product is 3.12mm, average wedge is 5μ m, belt speed is 5.16m / s, rolling length is 764m. Because thick jump exist in tail, adjusting deviation's method is carried out by increase the rolling force in one side constantly. Thus, when we complete the correction of the tail deviation, he tail thick jump is also eliminated.

The basic steps for deviation control are, when aluminum roll into the middle stage, 100s deviation signal Z_C is collected, and then deviation pattern is obtained as P2 by manifold learning, this is to say, the point D in tail deviation exceeds 200mm to get correction target curve. Secondly, according to regression model in formula 6, rolling force adjust curve is obtained, and then we can

find P_{os} , P_{ds} , ΔP_{os} , ΔP_{ds} , by means of formula 8 and 9 ΔS_{os} , ΔS_{ds} are also solved. Lastly, the deviation is rectified by hydraulic position control system HPC.

Fig.5 is the the result of deviation control, solid line is deviation curve after correction, X line is correction target curve, dot-line is original deviation curve. Fig.5 shows that deviation is controlled in an ideal range. Where, Comprehensive delay time such as time delay of deviation measure point, operating time of hydraulic system, calculation and analysis time is taken as 0.2s.

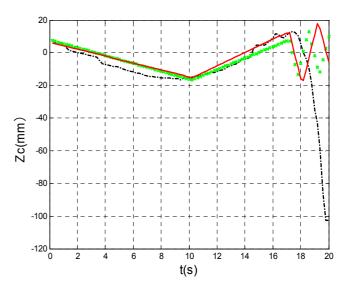


Fig.5 The result of deviation control

5. Conclusion

A new tail deviation's predictive control method of the tandem rolling strip was proposed in this paper. On basis of distribution rule of actual rolling data, tail deviation was divided into three pattern, obtained characteristic parameters and mapping matrix by LPP manifold learning algorithm to predict tail deviation pattern. This reserch has establishes the function between the control variable and deviation and tail deviation's predictive control strategy. Experiment shows this method can effectively control the deviation range. In fact, if pattern was more meticulous and control compensation system was more perfect, the correction effect will be more satisfactory.

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