Application of Pattern Matching in Heating Furnace – Rough Rolling Process

G M Cui\(^1,a\) and Y Cheng\(^1,b,*\)

\(^1\)Information Engineering Institute, Inner Mongolia University of Science and Technology, Baotou, Inner Mongolia 014010 China

*E-mail: chengy96116@gmail.com

Abstract. Hot continuous rolling is a complex industrial process. Aiming at the problems of difficult optimization control, information island between process and strong coupling between parameters in 2250 mm rolling line of a steel plant, a parameter optimization method based on multi-level pattern matching is proposed, which is applied to the heating furnace – rough rolling link to adapt the best operation parameters in the current superior operational pattern library so as to improve the product quality of transfer bar. For the situation that the multi-level matching method cannot find the optimal operation mode, an input-output prediction model based on fuzzy neural network is established and particle swarm optimization algorithm is used until the output optimal operation parameters meet the requirements, and updates the new optimal mode to the superior operational pattern library to complete the expansion of the library. The simulation results show that the minimum relative error between the optimization results and the actual operation parameters is about 0.44\%, which proves the feasibility of the pattern matching and evolution strategy, so as to achieve the purpose of improving the quality of hot rolling products and improving the enterprise efficiency.

1. Introduction

Hot strip rolling is one of the most rapidly developed and widely used fields in China's steel rolling industry. Its production technology and process control technology directly measure the level of the national steel industry. At present, the optimization of key control parameters of rolling line production process mostly adopts the classical mechanism modeling method, such as thickness control based on the mass flow principle. Under the premise of long-term stable operation of the production process, the control and optimization method with mechanism modeling as the core has certain economy and reliability. However, hot strip rolling is a complex industrial process, and under the disturbance of the external environment, the traditional method is difficult to meet the requirements of system robustness, so it is urgent to improve the optimization strategy. For a long time, the optimization of operation parameters based on pattern matching has attracted the attention of many scholars, such as academician W H Gui and Professor C H Yang, who took the lead in applying this idea to industry and derived a variety of different evolution methods, and achieved good results in the copper flash smelting process [1-2]. Professor P Zhou and academician T Y Chai of Northeast University in China put forward data-driven high-speed smelting Remarkable results have been achieved in the monitoring of abnormal furnace conditions [3], academician G D Wang of the State Key Laboratory of Northeast University has put forward the idea of digital twin to inject vitality into the intelligence of iron and steel industry [4-5], and F I Gamero, J Colorer, etc. have applied pattern matching and pattern recognition to the smelting process of blast furnace [6], making great progress. However, the above-mentioned methods are still in
the initial stage in the production process of hot strip mill. The main difficulties lie in complexity of many rolling processes, information islands among each process, and the difficulty of mass information processing.

In view of the above problems, this paper takes the heating furnace and rough rolling processes of 2250 mm production line of a steel plant as the research object, and applies the multi-level matching and evolution method of operation mode adopted in the process of copper flash smelting and blast furnace to solve the problems of steel scrap and melt down in the actual process of steel plant. Rough rolling process mainly determines the width of strip products, and the quality of transfer bar at its exit will directly affect the scrap ratio and subsequent finishing process. Therefore, it is of great significance to optimize the parameters of heating furnace rough rolling as the first two links of hot continuous rolling. At the same time, the multi-level matching operation method can effectively avoid the traditional traversal search time-consuming, difficult, waste of resources and other problems.

In this paper, a special kind of steel in the database is taken as an example, and superior operational samples are selected by combining with historical data and expert experience evaluation. On this basis, the superior operational pattern library is established, and the clustering algorithm is used for clustering analysis of each mode in the excellent operation mode database. Through similarity calculation and comparison, the first level matching is realized, then the determined subclass is entered, and the current state parameters are calculated the second level matching is completed by taking the operation parameter whose similarity is greater than the threshold and the largest as the optimal operation mode. In the case of the optimal value of operation parameters cannot be obtained by multi-step matching, the particle swarm optimization (PSO) algorithm is used to evolve the operation mode, and the optimal operation parameters are obtained after evolution.

2. Basic Concepts of Pattern Matching and Evolution

Defining operation mode \( Q = [I^T, U^T, Y^T]^T \), according to the correlation analysis of parameters and expert experience, where \( I = [i_1, i_2]^T \), furnace outlet temperature \( (i_1) \) and Rough rolling inlet temperature \( (i_2) \) are defined as state parameters; \( U = [u_1, u_2]^T \), rolling force \( (u_1) \) and roller speed \( (u_2) \) are defined as operation parameters; \( Y = [y_1, y_2]^T \), average thickness of transfer bars \( (y_1) \) and average width of transfer bars \( (y_2) \) are defined as process parameters showing the quality of rough rolling export.

Defining the evaluation equation of working condition, \( J = k_1(1 - \frac{y_1}{y_{10}})^2 + k_2(1 - \frac{y_2}{y_{20}})^2 \) (1)

where \( y_1 \) and \( y_2 \) are the actual values of the average thickness and average width of the transfer bars, \( y_{10} \) and \( y_{20} \) are the expected value respectively. \( k_1 \) and \( k_2 \) are weight parameters, which are 0.6 and 0.4 respectively from historical data and expert experience. Meanwhile, when \( J < 0.05 \) is satisfied, the current operation mode can be judged as excellent and put into the superior operational mode library. The superior operational mode determined in this paper is 2000 groups.

If the state parameters which are closest to the current state parameters cannot be found, then the state parameters and operation parameters are taken as inputs, and the process parameters are taken as outputs to establish the input-output prediction model. With the help of the optimization algorithm and combined with the evaluation equation, the operation mode is optimized to obtain a new group of optimal operation modes and send them into the superior operational pattern library to complete the expansion of the library and guide the production.

3. Pattern Matching

3.1. Probability distribution and clustering

Due to the strong coupling of parameters, the corresponding operation parameters must be optimized from the global perspective. Due to the large amount of data and uneven distribution, traversal search is difficult, so multi-step matching method is needed. Firstly, all the parameters in the superior operational pattern library approximately obey the law of normal distribution, then according to the probability density distribution of the state parameters and operation parameters in the library, the parameters to be
matched are locked in the optimal interval, and then the fuzzy c-means clustering algorithm (FCM) [7] is used, and the subtractive clustering [8-9] method is used to obtain six clustering centers to complete the first level matching. The probability distributions of state parameters and operations is shown in Figure 1 and Figure 2, and the number of superior operation modes in cluster centers and subsets is shown in Table 1.

![Figure 1. Probability distribution of state parameters.](image1)

![Figure 2. Probability distribution of operation parameters.](image2)

### Table 1. Cluster centers and number of sub clusters.

| No. | \(i_1(\degree C)\) | \(i_2(\degree C)\) | \(u_1(\text{kN})\) | \(u_2(\text{m/s}\text{ }^1)\) | Numbers |
|-----|------------------|------------------|-----------------|-----------------|-------|
| 1   | 1012.81          | 975.87           | 3076.65         | 9.31            | 199   |
| 2   | 1043.96          | 967.45           | 2656.03         | 9.51            | 375   |
| 3   | 1033.05          | 1001.14          | 2364.20         | 9.29            | 545   |
| 4   | 1055.02          | 995.03           | 2130.63         | 9.25            | 610   |
| 5   | 1056.37          | 1021.70          | 1875.87         | 9.31            | 440   |
| 6   | 1094.78          | 1054.21          | 1606.52         | 9.31            | 38    |

### 3.2. Similarity computation and similarity threshold

In order to measure the similarity [10] between the two operation modes, distance measurement method is necessary to calculate the distance between the two operation modes, and then convert it into the similarity value. The state parameters selected in this paper are two-dimensional vectors with the same
dimension, and the Euclidean distance (d) can be solved directly. Then the distance is expressed in the
form of similarity by using the transformation function, and the similarity transformation function is
expressed as \( r_{ij} = e^{-\frac{d}{50}} \). If the similarity is greater than the threshold \( \alpha \) (the empirical value \( \alpha = 0.95 \)),
the matching is considered to be completed.

Multi-step Matching. After clustering, another 15 groups of operation patterns are randomly
extracted from the superior operational library to participate in the matching simulation. The similarity
between each state parameter and the clustering center is calculated respectively to complete the first
level matching. The results are shown in Table 2.

**Table 2.** First step matching results of test parameters.

| No. | i_1(℃) | i_2(℃) | Subclass | Similarity with corresponding center |
|-----|--------|--------|----------|-------------------------------------|
| 1   | 1027.39| 967.31 | 2        | 0.72                                |
| 2   | 1062.52| 1001.45| 4        | 0.82                                |
| ... | ...    | ...    | ...      | ...                                 |
| 10  | 1030.54| 1001.89| 3        | 0.96                                |
| 15  | 1033.76| 991.18 | 3        | 0.82                                |

After determining the subclass of each group of parameters, enter the second step matching process,
respectively calculate the similarity with all elements in the corresponding subset and sort them. The
results are shown in Table 3.

**Table 3.** Second step matching results of test parameters.

| No. | Subclass | Maximum similarity with corresponding subset elements |
|-----|----------|------------------------------------------------------|
| 1   | 2        | 0.96                                                 |
| 2   | 4        | 0.99                                                 |
| ... | ...      | ...                                                  |
| 10  | 3        | First step matching completed                        |
| 15  | 3        | 0.93                                                 |

According to table 3, among the 15 groups of state parameters participating in the operation mode
matching, 8 groups match the optimal operation mode, and the operation parameters can be derived to
guide the production. The maximum similarity of the remaining seven groups is less than \( \alpha \), and the next
step is to evolve the operation mode.

4. Operation Mode Evolution

There are many kinds of steel in the rolling process. When the steel to be rolled is rare, the data in the
superior operational library is relatively poor, and the operation mode matching the current state
parameters may not be found. In this case, the first N operation modes with the largest similarity need
to be extracted as the mode evolution source, and the optimization algorithm with global search ability
is adopted. Based on the input-output prediction model of rolling process, the fitness function of the
evolution source is determined and iterated circularly until the optimal operation mode under the current
state condition is obtained, and whether the operation mode is satisfied or not is the best. The evolution
process of operation mode is shown in Figure 3.
4.1. Input-output prediction model

As a collaboration of fuzzy theory and neural network, fuzzy neural network has the advantage of mining the potential relationship between data in the process of complex system modeling. It is suitable for nonlinear and uncertain complex systems. Compared with the traditional neural network with only hidden layer, fuzzy neural network is more suitable for nonlinear and uncertain complex systems. The structure of fuzzy neural network [11-13] based on rolling process design is shown in Figure 4.

![Figure 3. Process of operation mode evolution.](image)

![Figure 4. Fuzzy neural network.](image)
Two state parameters and two operation parameters are selected as the input parameters of the model, and the process parameters are the output parameter. 800 groups of samples produced continuously in a certain period of time are used as the training set, and 200 groups of samples are used as the test set. The output of fuzzy neural network and traditional neural network are shown in Figure 5 and Figure 6, respectively.

![Figure 5. Prediction results of fuzzy neural network.](image1)

![Figure 6. Prediction results of neural network.](image2)

The error comparison between the two models is shown in Table 4. The test results under the allowable error range show that the fuzzy neural network has better accuracy and fitness for the prediction of two output parameters obtained in continuous production, and can meet the requirements of actual production and provide good support for the next operation mode evolution process.

| Model       | $y_1$(mm) | $y_2$(mm) |
|-------------|-----------|-----------|
|             | Maximum   | Average   | Maximum   | Average   |
|             | relative error | relative error | relative error | relative error |
|             | (%)       | (%)       | (%)       | (%)       |

Table 4. Error comparison of two different prediction models.
Fuzzy neural network

Neural network

Optimization of Operation Parameters. On the basis of the input-output model prediction model, the PSO algorithm [14-16] is used to optimize the operation parameters. Defining fitness function,

\[ f = k_1(1 - \frac{y_1}{y_{10}})^2 + k_2(1 - \frac{y_2}{y_{20}})^2 \]  

(2)

By determining the value range of the two operation parameters, the multi-objective optimization constraint model can be expressed as,

\[
\begin{align*}
\min (f) \\
19,000 < u_1 < 23,000 \\
9 < u_2 < 16
\end{align*}
\]  

(3)

By extracting \( n = 100 \) groups of operation modes with maximum similarity as the evolution source of operation mode, each particle can continuously learn the group optimal solution and neighborhood optimal solution it finds, so as to realize the global optimal search. The comparison between the optimization results and the actual operation parameters of the operation mode that failed to match is shown in Table 5.

| No. | Actual value | Optimization value | Error (%) | Actual value | Optimization value | Error (%) |
|-----|--------------|-------------------|-----------|--------------|-------------------|-----------|
| …   | Second step matching completed | …                  | …         | …            | …                 | …         |
| 4   | 19995.4      | 20111.26          | 0.93      | 11.61        | 12.69             | 9.27      |
| …   | …            | …                 | …         | …            | …                 | …         |
| 12  | 19718.89     | 20441.98          | 3.667     | 9.91         | 10.53             | 6.23      |
| 13  | 22384.57     | 19997.66          | -10.66    | 9.09         | 8.39              | -7.67     |
| 14  | 18152.28     | 19236.33          | 5.973     | 9.50         | 9.90              | 4.25      |
| 15  | 23423.75     | 23098.21          | -1.39     | 14.83        | 14.17             | -0.44     |

5. Conclusion

It can be seen from table 4 that the maximum and minimum relative errors of the optimized operation parameters are -10.66% and -0.44% respectively, and the average relative error is about 4%. After the evolution of operation patterns, the library of excellent operation patterns can be expanded, the success rate of matching can be improved, and the decision-making time can be saved. The practical application results show that the pattern matching method proposed in this paper is feasible in the heating furnace and rough rolling process, which can help operators make decisions to ensure the efficient operation of the rolling line, and has broad application prospects in the hot rolling industry. However, there are many processes in hot rolling process and complex working conditions, so the parameter optimization method based on pattern matching has not been widely used. How to extend the idea of pattern matching to the whole hot rolling process and realize the optimization of the whole production line is one of the future development directions and research focuses.
Acknowledgment
This work was supported in part by the National Natural Science Foundation of China (61763039).

References
[1] Gui WH, Yang CH, Li YG, He JJ and Yin LZ 2009 Acta Automatica Sinica 35 717-23
[2] Gui WH, Liu JH and Xie YF 2013 Systems Engineering 33 2714-20
[3] Zhou P, Zhang RY, Xie J, Lui JP, Wang H and Chai TY 2020 Transactions on Industrial Electronics 68 622-30
[4] Wang GD 2018 Journal of Iron and Steel Research 30 5-7
[5] Wang GD 2019 STEEL ROLLING 36 1-7
[6] Gamero Fl, Colomer J, Meléndez J and Warren P 2006 Engineering Applications of Artificial Intelligence 19 103-8
[7] Khang TD, Vuong ND, Tran MK and Fowler M 2020 Algorithms 13 158-9
[8] Singhal A and Seborg DE 2006 Journal of Chemometrics 19 3931-6
[9] Zhang HZ and Wang J 2009 Computer Science 36 206-8
[10] Bai X 2012 Ph.D. dissertation, Beijing Jiaotong Univ.
[11] Lee SC and Lee TE 1975 Mathematical Biosciences 23 151-77
[12] Buckley JJ and Hayashi Y 1994 Fuzzy sets and systems 66 1-13
[13] Gupta MM and Rao DH 1994 Fuzzy sets and systems 61 10-8
[14] Liu Y 2016 International Journal of Smart Home 10 51-62
[15] Alireza A 2011 Acta Automatica Sinica 37 542-7
[16] Liu JH 2009 Ph.D. dissertation, Central South Univ.