Data driven sintering moisture control model based on neural network

Ruijia Shi¹, Mengyao Cui¹, Yufei Wang¹, Jiamin Liu¹ and Zihui Li²

¹School of Mathematics and Statistics, Northeastern University at Qinhuangdao, Qinhuangdao, Hebei, 066000, China
²School of Resources and Materials, Northeastern University at Qinhuangdao, Qinhuangdao, Hebei, 066000, China

Corresponding author’s e-mail: Ruijia Shi, 1000647@neuq.edu.cn

Abstract. Sintering production is an important part of ironmaking industry. The moisture content of sinter material will affect the output and quality of sinter. But at present, most sintering plants still use manual water to control the moisture content of sintering material, which leads to a great fluctuation of moisture content, and it is difficult to improve the sintering efficiency. Only stable control in the best range can stabilize the working condition of sintering machine. Therefore, this paper studies the water control scheme and designs the control system based on the existing data, and uses the established data driven moisture control model to control the appropriate amount of water, and compares and analyzes the advantages of the control ability of different models compared with manual water. Firstly, we eliminated the invalid data, found that five materials were significantly correlated with water content, and then established a multiple linear regression model to further study the influence of the proportion of different materials on water content. Secondly, we established a data-driven sintering moisture automatic control model. The neural network model is used, the input variable is the material usage, water addition and moisture measurement data, and the output variable is water addition. The prediction results obtained by simple BP neural network and NARX neural network with feedback are compared and analyzed. It is found that NARX neural network has smaller prediction mean square error, more stable prediction results. Thirdly, we compared the data-driven NARX model prediction results with the results of manually adding water to control the moisture content of sintering, and made quantitative analysis with standard deviation and coefficient of variation. It was found that the standard deviation and coefficient of variation of NARX model prediction results were smaller, so NARX neural network model was more stable and excellent. If this model can be popularized in industrial production, the output and quality of steel will be improved, the production cost will be reduced, the labor resources will be saved, and the enterprise will get more benefits.

1. Introduction

Sinter is the main raw material for blast furnace iron making. To provide high quality sinter, the moisture content of the mixture in the sintering need to be in the best range [1-3].

However, most of the sintering is still by manual water adding, which leads to a great variation in the moisture content of the mixture. In the sintering process, the raw material after iron ore batching needs to be mixed with water twice to get the final sintering raw material. In Both times, a certain amount of water needs to be added to help the mixing evenly and the granulation. The main task of
moisture control of sintering mixture is to master the amount of water added in the process of first mixing and second mixing, so that the moisture content of the mixture is stable within a certain range (6.8%~7.5% is required by industry)[4-6].

Basic assumptions

- Assuming that various raw materials are mixed according to the ratio of ingredients, and the amount of water added is different with different ratio of ingredients;
- Assuming that there is a close connection between the six steps, and the production is carried out in assembly line production style. Each step is irreversible;
- There is no remedy for the mixture with too little material or adding water, so it can only be adjusted to add water to the mixture behind;
- Assuming that the interval between primary mixing and secondary mixing is very short and the distance is very close. Besides, the absorption or evaporation of water is ignored.

2. Data processing

2.1. Data screening and quantifying indicators
First of all, because some silos are filled with the same material, the amount of the same material can be added to be a variable. After that the main materials are iron concentrate, limestone, dolomite, sintering return, dust, quicklime, coke, pulverized coal and various mixed ore. The amount of water added during the first and second mixing can also be added into the amount of water added at one time. The moisture of the raw material is the change of the moisture after the two addition of moisture minus the two mixing water meter.

2.2. Data preprocessing to delete the data of the stop feeding link
Because there may be stopping of material and unstable working conditions in steel production, the collected data cannot be directly used as the sample basis for establishing the model. Therefore, we need to preprocess these data. The main steps of data preprocessing are as follows. In the actual production, sometimes because of maintenance, adjustment of materials ratio and other situations, there will be stopped and other unstable situations. When the moisture increases or decreases sharply, it can be considered to be stopped, and the data collected during the stop can be deleted. As shown in Figure1, there are three mutation sites of water addition. After finding the corresponding location, the data within this range is deleted.

![Figure 1. Water quantity of two mixtures.](image-url)
3. Model implementation and testing

3.1. Multiple linear regression

In order to further analyze the relationship between various materials in raw materials and moisture content of raw materials, we will take moisture of raw materials as the dependent variable, the mass content of various materials or the mass proportion of each material as the independent variable to carry out regression analysis. The results show that when the mass of each material is the independent variable, \( R^2 = 0.745, \quad F_1 = 9451.7 \) and when the mass proportion of each material is the independent variable, the linear equation \( R^2 = 0.962, \quad F_2 = 81666.6 \). Obviously, \( R^2 \) is closer to 1 than \( R^1 \), and \( F_2 \gg F_1 \). Therefore, when the mass proportion of each material is the independent variable, the linearity of the equation is more significant, the SSR is larger, and the dependent variable is explained more.

Next, we select the mass proportion of each material as the independent variable for multiple linear regression, and the output results are shown in Tables 1.

Table 1. Model Summary of multiple linear regression.

| Model | R   | R Square | Adjusted R Square | Std. Error of the Estimate | R Square Change | F Change | df1 | df2 | Sig. F Change |
|-------|-----|----------|-------------------|---------------------------|-----------------|----------|-----|-----|--------------|
| 1     | .98 | .962     | .962              | 24.43360                  | .962            | 81666.5  | 95  | 3879| .000         |

3.2. BP neural network model

According to the problem of sintering moisture control, we compare and screen the principles and application scenarios of various neural network models, and finally choose BP and NARX neural network models. The input data are the scores of five principal components and the amount of water added, and the output data are the value of water meter after adding water for the second mixing. The training set is 90% of samples, the test set is 5%, the verification set is 5%, and the number of hidden layer is 21. Firstly, the simple BP neural network model is applied to establish the sintering moisture automatic control model, and the output results are shown in Figure 2 and 3.

![Figure 2. MSE of BP neural network.](image)
As can be seen from Figure 2, when the number of training reaches 88, the Mean Square Error (MSE) drops to about 0.0825, and the training stops; as can be seen from Figure 9, when the number of training reaches 94, the gradient and mu reach the preset value, and the training stops.

Figure 3. Gradient, mu, val fail of BP neural network.

Figure 4. BP neural network fitting image.
Figure 4 shows the regression results of BP neural network. It can be seen easily that their correlation coefficients are greater than 0.93, and all are close to 1, indicating that the data fitting effect of training is better, and the model is more effective. However, it can be observed from Figure 4 that the scatters obtained by training distribute relatively concentrated, and they have a gap with the fitting line. Therefore, this model still has some disadvantages and needs to further improve.

3.3. NARX neural network model
Next, we use NARX neural network to establish the automatic control model of sintering moisture content, and the output results are shown in figures 5 and 6. As can be seen from Figure 5, when the training times reach 5 times, the Mean Square Error (MSE) drops to about 0.0361, and the training stops; and as can be seen from Figure 6, when the training times reach 11 times, the gradient and mu reach the preset value, and the training stops.

![Figure 5. MSE of NARX neural network](image)

![Figure 6. Gradient, mu, val of NARX neural.](image)

Figure 7 shows the output value of NARX neural network including the value of training set, validation set, test set and the whole data, and gives the correlation coefficient. Their correlation coefficients are 0.98459, 0.97951, 0.98332 and 0.98427 respectively, which are all greater than 0.97.
and very close to 1, indicating that the fitting effect of training is good, and the model is greatly effective.

![Figure 7. NARX neural network fitting image.](image)

At the same time, the MATLAB software also outputs the simulation image and data. Figure 14 is the image of the original data, output data and error of different sets. It can be seen that the data obtained by neural network training is close to the real value, and the errors distribute around 0. Therefore, it can be concluded that NARX neural network model is highly effective.

![Figure 8. Response of output of NARX.](image)
3.4. Analysis and comparison of two neural network models

In theoretical speaking, BP neural network is a data fitting model, which is trained by a large number of input data and output data to get an "input-output" model, in which the special properties of data are not considered. However, NARX neural network is a nonlinear autoregressive model with external value input, the input and output are time series, and the hysteresis of time series is also considered. Therefore, NARX neural network model is more suitable for the prediction and control of sintering moisture.

Besides, the Mean Square Error (MSE) and R value of the simulation results are shown in Table 2. It can be seen from the Table 2 that the data trained by BP neural network is one order of magnitude larger than the data trained by NARX neural network, and the value of R is also smaller, which indicates that the data trained by NARX neural network model is closer to the original data, so NARX neural network model is better. Therefore, it is an effective method to use NARX neural network model based on historical data in industrial production of sintering water.

![Figure 9. Autocorrelation of error of NARX.](image)

Table 2. Comparison of two neural networks.

|          | BP neural network | NARX neural network |
|----------|-------------------|---------------------|
|          | MSE               | R                   | MSE               | R                   |
| Training | 1.12E-01          | 0.93248             | 2.78E-02          | 0.984791            |
| Validation | 1.25E-01          | 0.94818             | 5.03E-02          | 0.967218            |
| Testing  | 1.18E-01          | 0.96373             | 2.92E-02          | 0.985431            |

According to the survey, the sinter blast furnace ironmaking is the main raw materials, sintering process of the mixture water only control within the scope of the best (generally in the 6.8% to 7.5%) to stabilize sinter machine working condition, the sintering production efficiency is high, also ask that the raw material of sintering moisture fluctuations cannot too big, otherwise result in sintering process is not stable.

For this reason, we calculate the display value of the dimixing water meter of the original sintered water and the mean value, standard deviation and coefficient of variation of the predicted value using NARX neural network, as shown in Table 3, and draw part of the images, as shown in Figure 10.

It can be seen from Table 3 that the mean value of sintering water is almost the same in the case of manual water addition and water addition controlled by NARX neural network. However, the standard deviation of the latter is obviously smaller than that of the former. Therefore, the coefficient of
variation of the latter is also relatively small. This indicates that the water content of sinter is controlled manually by adding water, so that the water content of mixture fluctuates greatly, while the fluctuation degree of sintered water in raw material is small when NARX neural network is used to control the model, which can also be clearly seen from Figure 10.

Table 3. Comparison of NARX and mutual control.

|                  | NARX          | Manual work  |
|------------------|---------------|--------------|
| mean             | 7.511003253   | 7.514504007  |
| standard deviation | 0.086390494  | 0.26038534  |
| Coefficient of variation | 0.011501858 | 0.034651035 |

![Figure 10. NARX prediction and mutual control.](image)

4. Conclusions
From the above analysis, we can assert that the NARX neural network automatic control model is better than the manual water adding method. Through the analysis of the model theory and application, it can get better NARX neural network the main reasons are: (1) The NARX neural network based on a large amount of historical data and judgments, have very strong rationality, the results obtained are often appropriate and credible, but manual water addition only depends on human experience, which is prone to misjudgment; (2) The input variable of NARX neural network is not only the mass of each material, but also the sintered moisture content in the previous moments. With the feature of feedforward, the model can better solve the problem of lag in the production process, while the manual water can only be judged by the current moment, but can not solve the lag problem.
References

[1] Y.X. Duan., Current Situation and Future Development of Sintering Process, Nonferrous Metallurgical Equipment, (2015) 45-48.

[2] X.T. Zhu., Research and design of three-dimensional energy monitoring system for sintering process based on intelligent prediction algorithm, Donghua University, 2017, pp. 84.

[3] S.H. Liu., M.J. Zhou., Review of flue gas circulation sintering process and its application in Baosteel, Baosteel Technology, (2018) 37-44.

[4] H.H. Liu., The study on fabrication of AlN Ceramics by hot-press sintering, Fuzhou University, 2018, pp. 62.

[5] X.X. Gao, Research on Design and Modeling for Sinter Mixture Moisture Control System, Northeastern University, 2015, pp. 71.

[6] H.Y. Cai, Intelligent Control and Research of Self-learning Model in Sinter Mixture Moisture, Northeastern University, 2017, pp. 70.

[7] X.J. Guo, L.L. Z, J.Y. He, R. Liu, Optimization of particle size of sintering mixture based on fuzzy PID control, Sintering and Pelletizing, 44 (2019) 1-6.

[8] W.D. Liu, The application of neural network PID in Moisture control for sinter mixture, Instrumentation-Analys-Monitoring, (2012) 1-3.

[9] J. Chen, Z.K. Chen, L. Wang, Application of Fuzzy-PID Control Strategy in Sintering Ignition Temperature Control, Scientific and Technological Innovation, (2012) 9.

[10] J. Song, B. Li, Nonlinear and additive principal component analysis for functional data, J MULTIVARIATE ANAL, 181 (2021).

[11] Q. Hu., Y. Hu, W.Liu, Principal Component Estimation and Empirical Analysis Based on Logistic Regression, Journal of Quantitative Economics, 37 (2020) 123-129.

[12] K.J. Xia, A Study on Burning State Recognition of Clinker Based on Semi-supervised Independent Component Analysis and Hidden Markov Model, Northeastern University, 2017, pp. 88.

[13] B.X. Su, J.L. Zhang, Evaluation of sintering iron ore fines performance based on principal component analysis, Sintering and Pelletizing, 39 (2014) 1-6.

[14] D.J. Jiang, Research on Main Factors Influencing Sinter Return Fines Rate by Applying Factor Analysis and Countermeasures, Sintering and Pelletizing, 38 (2013) 17-22.

[15] Y. Shi, Realization of Bp Neural Network Based on Matlab, Journal of Xiangnan University, 31 (2010) 86-88.

[16] Z.Y. Fan, BP neural network model and learning algorithm, Software Guide, 10 (2011) 66-68.

[17] F.Q. Xu, Y. Qian, X.G. Liu, GABP Neural Network of the Nonlinear Function Approximating, Microcomputer Information, 28 (2012) 148-149.

[18] L.P. Zhao, K. Wu, L. Zhu, X.M. Chen, X.K. Qin, Prediction model of sinter properties based on BP neural network, Iron & Steel, 52 (2017) 11-15.

[19] S. Li, S.L. Wang, Research of nonlinear filtering algorithm based on BP neural network, Electronic Measurement Technology, 41 (2018) 34-39.