ISSN: 2664-9640

# Prediction Model of Rolling Force based on DBN

Baoshen Zhang [a, *], Hua Huo and Yafei Zhi

School of Information Engineering, Henan University of Science and Technology, Luoyang 471023, China;

[a] baoshen515@foxmail.com

* Corresponding Author

## Abstract

**In the rolling process of copper alloy, the rolling force directly affects the quality of the product. In order to predict the rolling force of hot rolling mill, a deep belief network (DBN) prediction model was established. The rolling force prediction model based on deep belief network does not consider the complex relationship among the parameters. By analyzing the construction of a hot rolling force model, the correlation between parameters of rolling mill and rolling force, the stochastic gradient descent method is adopted to fine-tune connection weights, to improve the stability of the hot rolling force model to use Adam optimization algorithm optimize the hot rolling force network model, and compares them in the SVM and BP algorithm.**

## Keywords

**Rolling force prediction, Deep belief network, Optimization algorithm.**

## 1. Introduction

Copper alloy material has many excellent comprehensive properties, but the production process of copper alloy material is very complex, which is affected by many factors such as material composition, rolling power, deformation resistance and other complicated factors in the rolling process of copper alloy [1]. In order to accurately predict the copper alloy process, many researchers have carried out analytical studies [2-3].

Jia Weitao et al. [4] proposed a method to determine the friction coefficient and established a mathematical model to solve the friction coefficient. Considering the normal pressure and friction stress, the rolling force prediction model was optimized and reconstructed, and the contact friction stress and its influence on the rolling force were defined, and the influence ratio was about 4.36%. He Weijun et al. [5] established a 3D finite element model to simulate ABAQUS/Standard Pilger rolling, and simulated the whole process of Pilger rolling of ZR-4 alloy tube. Sang-Min BYON et al. [6] used the flow stress equation to calculate the rolling force, and combined the improved model with the finite element method to calculate the rolling force in the finishing mill stand of the actual bar rolling mill. Shuai Meirong et al. [7] modified the mathematical formula of the rolling force model on the basis of the analysis of the mathematical model of rolling force and the rolling deformation zone. Peng Wen et al. [8] proposed a self-learning model to predict the rolling force deviation in the unsteady process of hot rolling force, and optimized the learning coefficient of the model. Dong Zhikui et al. [9] established the rolling force mechanics model to solve the taper problem existing in conical barrel joints, and the error was less than 20%. Wei Lixin et al. [10] proposed a rolling force prediction model based on deep BP neural network, which predicted the rolling force in the process of aluminum hot rolling with an error of 3%. Hou Dongxiao et al. [11] established a nonlinear dynamic model of four-high rolling mill on the basis of dynamic rolling force and dynamic rolling moment mold, which provides a reference for solving the vibration problems of vertical and torsional rolls of the rolling mill.

However, modern production line is equipped with a large number of sensors, detectors and instrument, real time, power, temperature, rolling force is vertical roll rolling force and roll gap mass containing hidden rule of the production process data [12], high redundancy and the strong correlation, but the valuable information submerged and need effective mining [13]. Based on the actual rolling mill data, the influences of track number m, power P, rolling speed V, temperature T, east (west) vertical roll rolling force $F_w$, $F_e$ and roll gap G on the rolling force prediction of rolling mill are analyzed.

The materials in this paper are organized in the following order: Section 2 introduces the deep network model. In the third section, the rolling force prediction model based on deep belief network is introduced and the experimental results are analyzed. The fourth part draws the conclusion.

## 2. Deep network model

### 2.1. Restricted Boltzmann Machine (RBM)

Constrained Boltzmann Machine [14] (RBM) is a model of two-layer network structure, which can be divided into Visible layer and Hidden layer. Visible layer and Hidden layer are fully connected. Random combination of different RBMs constitutes a deep belief network (DBN). The structure of RBM is shown in Figure 2-1.

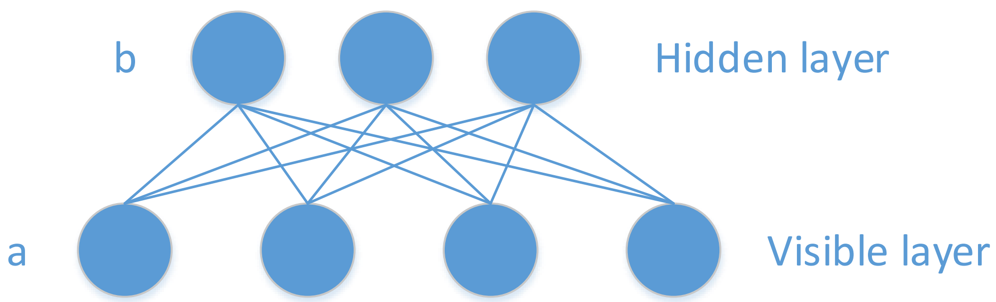



Figure 1: RBM network structure diagram

The constrained Boltzmann machine model is a probabilistic model that analyzes the energy function between the data by analyzing the existing data sets. The energy function is the basis of the constrained Boltzmann machine, and the probability distribution function is also affected by the energy function. For the state vectors H of the hidden layer and V of the visible layer that can be determined, the energy function of RBM is as follows [15].

$$E(v,h) = -\sum_i a_i v_i - \sum_j b_j h_j - \sum_i \sum_j h_j w_{i,j} v_i \tag{1}$$

Where $v=(v_1,v_2,\ldots,v_i,\ldots,v_m)$ is the state vector of Visible layer, $h=(h_1,h_2,\ldots,h_j,\ldots,h_n)$ is the state vector of Hidden layer, $a_i$ is the bias of Visible layer $v_i$, $b_j$ is the bias of Hidden layer $h_j$, $w_{i,j}$ is between neurons of Visible layer and Hidden layer.

The joint probability distribution function between layers of restricted Boltzmann machine based on energy function can be defined as.

ISSN: 2664-9640

$$P(v,h)=\frac{1}{Z}e^{-E(v,h)} \tag{2}$$

Where, Z is the normalized factor, defined as the sum of $e^{-E(v,h)}$ under all possible values of the node.

## 2.2. Deep Confidence Network (DBN)

Deep belief network [16] (DBN) consists of a random combination of different constrained Boltzmann machines (RBM).In the process of data processing, the deep belief network uses algorithms to optimize the network model and weight.The training process of DBN model is a combination of unsupervised training and supervised training mode. The unsupervised part completes the extraction of input data features, while the supervised part completes the classification or prediction. Its structure is shown in Figure 2.

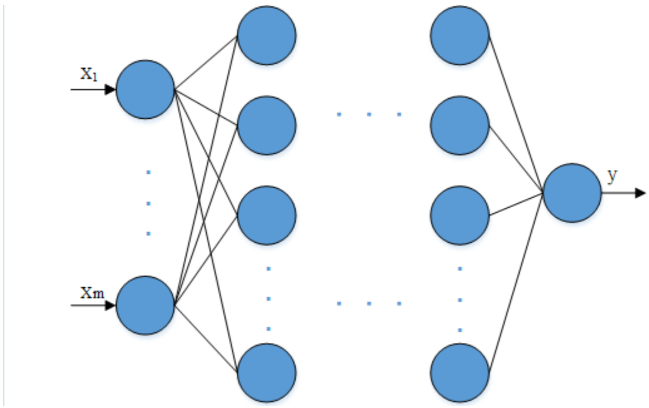



Figure 2: DBN structure diagram

The training of deep belief network is divided into pre-training and fine-tuning. Pre-training is to train the network by using the data set on the basis of the existing network model. According to the training results of the network on the data set, the parameters are adjusted until the model reaches the expected standard. Fine tuning refers to the debugging of the pre-trained model so that it can better adapt to the model, often using Contrastive Divergence [17] to update the parameters. The process of deep belief network training model can be analogous to the optimization of a BP neural network with multiple hidden layers. The optimization of its network weight overcomes the shortcomings of deep belief neural network, such as the long process of model training data set, which is easy to fall into the situation of local optimal data prediction.

## 2.3. Adam stochastic optimization algorithm

Adam algorithm [10] was proposed by Diederik Kingma and Jimmy Ba. It also obtained the advantages of AdaGrad and RMSProp algorithm and can replace the traditional gradient descend algorithm. Adam algorithm dynamically adjusts the learning rate according to the loss function. In each iteration of the algorithm, the learning step size of the parameters can be directly selected within a certain range.

The parameters of Adam algorithm include learning rate $\alpha$, exponential decay rate $\beta_1$ and $\beta_2$, $\varepsilon$, where $\alpha$ is the gradient learning rate of weight update, which is generally set as 1/1000.$\beta_1$ and $\beta_2$ are the exponential decay rates of the first and second order moment estimation in the process of data training, respectively. Combining with the practical application, the value range of $\beta_1$ and $\beta_2$ is defined as a number close to 1.$\varepsilon$ is to prevent the denominator of the algorithm to appear zero, often set $\varepsilon$ to a very small number.

ISSN: 2664-9640

# 3. Rolling force model based on deep belief network

## 3.1. Prediction model of rolling force

This article USES the deep belief network (DBN) to prediction of rolling force, through the building of hot rolling force model, analysis the correlation between parameters of rolling mill and rolling force, the stochastic gradient descent method is adopted to fine-tune connection weights, using Adam algorithm optimize the network model structure, constantly optimize the hidden layer of the number of neurons in hidden layer and each layer.

For deep belief networks rolling force prediction model, the selected number m, V power P, rolling speed, temperature T, east (west) vertical roll rolling force Fw, Fe, roll gap G as the input of the model, such as rolling force F as output, rolling force network forecast model with five hidden layer, 8 unit of input layer, an output; When training limited Boltzmann machine, the number of iterations is 200,1000; In order to predict rolling force better, penalty factor was introduced. In the process of network propagation, data were standardized before activation function of each layer was activated, and ADAM algorithm was used to optimize DBN network. The DBN algorithm flow chart is shown in Figure 3.

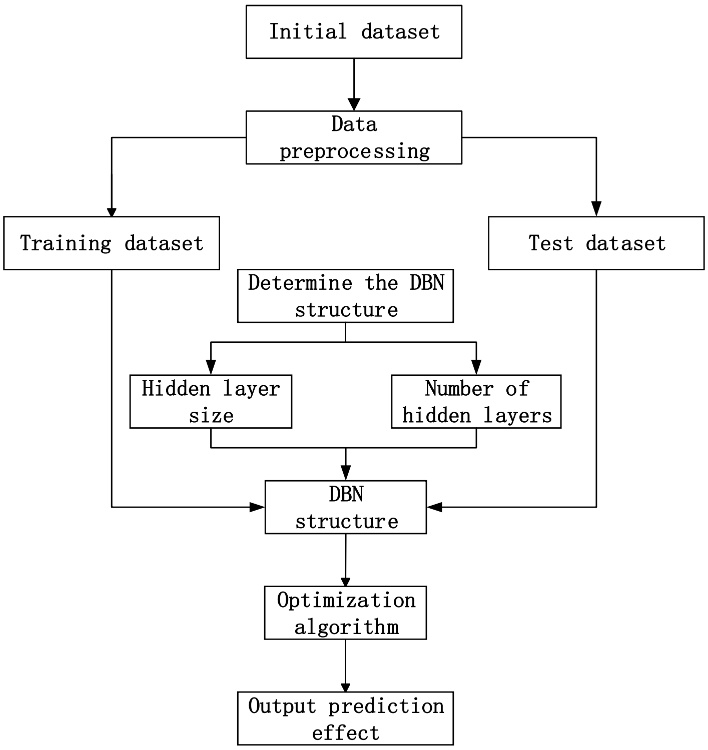



Figure 3: DBN algorithm flow chart

## 3.2. Selection of sample data

The mathematical model of rolling force selection of sample data is basically based on Karman equation or Orowan equation, and Bland-Ford[18] rolling force calculation formula is commonly used. The formula is as follows:

$$P = Bl_c Q_p K_T K \tag{3}$$

Where, P is the rolling force (KN);B is the average width of rolled piece (mm); $L_c$ is the projection length of contact arc (mm); $Q_p$ is the coefficient of friction stress state; K is deformation resistance; $K_T$ is the influence coefficient of tension on rolling force, which is related to the tension before and after rolling [18].

ISSN: 2664-9640

Due to deep learning is an experience ahead of theory analysis, can't write with precise theory formula, but the adaptive neural network, combined with neural network to the internal rules, not as the input node [19], so consider the traditional rolling force model, will be collected the parameters of the Pearson correlation coefficient analysis, finally selected number m and V power P, rolling speed, temperature T, east (west) vertical roll rolling force $F_w$, $F_e$, roll gap G for the depth of the neural network input. The rolling force data are shown in Table 1.

Table 1: Partial rolling data sheet

| Pass-Number | Force（T） | Speed（mpm） | Power（KW） | Mech.Screw (mm) | Strip-Length（mm） |
|---|---|---|---|---|---|
| 1 | 63.22 | 60 | 62.9 | 201.875 | 105.4 |
| 1 | 64.37 | 60 | 54.8 | 202.06 | 109.5 |
| 1 | 67.25 | 60 | 51 | 202.85 | 110 |
| 2 | 407.15 | -60.1 | 1111 | 169.64 | 5.3 |
| 2 | 415.79 | -57.3 | 1226.5 | 169.695 | 0.8 |
| 2 | 424.43 | -56 | 739.2 | 169.545 | 0 |
| 3 | 435.38 | 59.8 | 1065.5 | 138.815 | 3.2 |
| 3 | 431.34 | 59.7 | 1087.9 | 138.145 | 5.8 |
| 3 | 385.83 | 60.5 | 894.2 | 138.365 | 8.3 |

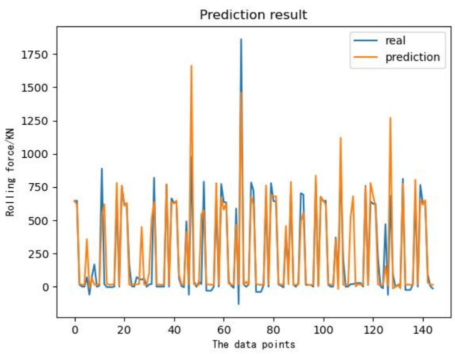
## 3.3. Experimental results and analysis

The rolling force in hot rolling process is predicted by deep confidence network model. Its loss function is:

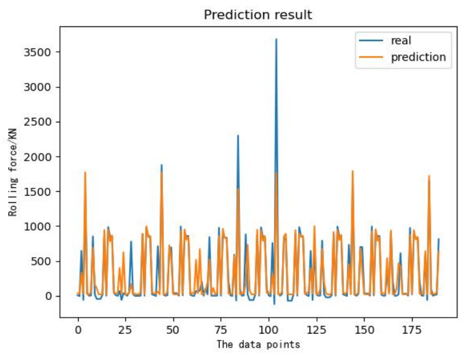
$$MSE = \frac{1}{m}\left(\sum_{i=1}^{n}(y_i - y_i^{'})^2\right) \quad (4)$$

The model was trained by using the actual production data of a hot bonding production line on a frame in a domestic copper sheet and strip processing plant. 10,000 pieces of data were selected to train the model, and the rolling force of 1000 pieces of hot rolling that were not in the training sample was predicted.

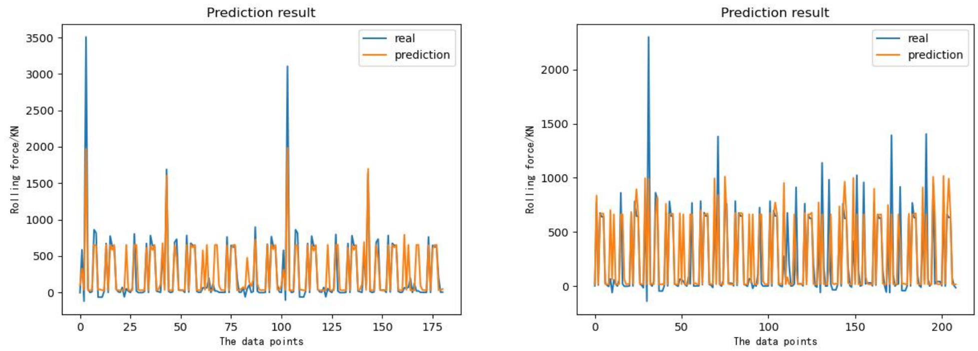
Based on the deep belief network model, the rolling force in hot rolling line was predicted. The predicted value of the algorithm was compared with the actual value, and then it was compared with other models. The rolling force prediction results of the model are shown in Figure 4, and the comparison of the rolling force prediction results of different models is shown in Table 2.



(a) C1020



(b) C1100




(c) C1921 (d) C1940

Figure 4: predicted value and actual comparison diagram

In Figure 4(a)-(d), curves of predicted and actual rolling force of DBN model under different data sets of the same stand are presented. In figure a and b can see there are three obvious outlier points, figure c the forecast effect of a total of two best outlier points, good for hot rolling force prediction, the prediction effect of figure d the worst, there are more abnormal value, cannot be good for hot rolling force prediction, the abnormal values between predicted values and the actual value, need further optimization of the model, make its can better predict the rolling force; At the same time, considering the particularity of data set, the use of the rolling force prediction model based on the depth of the belief network fitting the real rolling force data trends, analysis of abnormal value of rolling force prediction is the connection between the actual data, the solution enterprise under the same process in production of different product performance problems, is the focus of the next step work.

Table 2: Comparison of model prediction results

| Model | Modeling time | Relative error | Absolute error |
|---|---|---|---|
| SVM | 875s | 0.089 | 271.4 |
| BP | 815s | 0.046 | 263.7 |
| Deep BP | 652s | 0.022 | 140.5 |
| DBN | 550s | 0.013 | 43.6 |

Table 2 shows the comparison of prediction results of different models, in which the error of the model is the data obtained after removing obvious outliers. It can be seen from the table that the modeling time of the Deep belief network model is 550s, significantly higher than that of SVM, BP, Deep BP and other models. The average relative error of the Deep belief network model is 1.3%. Compared with the Deep BP model, the convergence speed of the Deep belief network model is improved by nearly half, which is further higher than other intelligent models. Deep belief network model of the absolute error is 43.6, Deep BP's absolute error is 140.5, far lower than the other two model, can be found by the data in the table, the rolling force prediction model based on belief network depth relative to other prediction model has better generalization ability, can better for hot rolling process of rolling force prediction.

## 4. Conclusion

1) In the prediction of rolling force of hot rolling mill, the parameters of each rolling mill are strongly correlated with the rolling force. The deep belief network is used to establish the prediction model of rolling force. Based on this idea, the internal relationship between the data is found and the variation trend of rolling force is counted, which effectively improves the prediction accuracy of rolling force. The experimental results show that DBN prediction model

has better generalization ability compared with other prediction models, and has great potential in predicting rolling force based on hot mill data.

2) The average relative error of rolling force prediction based on Deep belief network is 1.3%, and the absolute error is 43.6. Compared with SVM, BP and Deep BP models, the prediction speed and accuracy of rolling force prediction are higher. It has great potential in practical production.

## Acknowledgements

National Key R&D Program of China (2017YFB030640).

## References

[1] Ding-fei ZHANG,Qing-wei DAI,Lin FANG,Xing-xing XU. Prediction of edge cracks and plastic-damage analysis of Mg alloy sheet in rolling[J]. Transactions of Nonferrous Metals Society of China,2011,21(5).

[2] ZHANG Shunhu, WANG Xiaonan, ZHAO Dewen, et al.Analysis of Widening Rolling Force of Hot Rolling Thick Plate Based on Angular Bisection Yield Criterion [J].Journal of University of Science and Technology Liaoning, 2016,39 (6) :418-423.

[3] Li Weigang, Chen Shuixuan, Liu Xianghua.Rolling Force Model Considering Phase Change in Hot Strip Finishing Rolling Process [J].Journal of Northeastern University (Natural Science), 2013,34 (10) :1425-1429.

[4] Jia Weitao, Ma Lifeng,Tang Yan, et al. Prediction for Magnesium Alloy Rolling Force Based on Quantitative Study of Contact Friction[J]. 2017, 46(10):2763-2769.

[5] He Weijun, Yuan Gaihuan, Luan Baifeng, et al. On the Pilger Rolling of Zr-4 Alloy: Finite Element Modeling and Plastic Deformation Behavior[J]. 2018, 47(1):82-88.

[6] Sang-min BYON, Doo-hyun NA, Young-seog LEE. Flow stress equation in range of intermediate strain rates and high temperatures to predict roll force in four-pass continuous rod rolling[J]. 2013, 23(3):742-748.

[7] Meirong Shuai, Qingxue Huang, Jianping Qin, et al. Analysis of Mechanical Parameters during Hot Continuous Rolling Process of Titanium Alloy TC11 Rod[J]. 2012, 41(6):952-957.

[8] Peng Wen, Ji Yafeng, Chen Xiaorui, Zhang Dianhua.Journal of Northeastern University (Natural Science Edition),2019,40(10):1408-1412.

[9] Dong Zhikui, Peng Liwei, Jiao Yunjing.A model for calculating rolling force of large conical barrel considering conical flow to metal[J].China Mechanical Engineering,2019,30(19):2385-2393.

[10] Wei Lixin, Wei Xinyu, Sun Hao, Wang Heng.Rolling Force Prediction Based on Deep Network Training [J]. The Chinese Journal of Nonferrous Metals,2018,28(10):2070-2076.

[11] HOU Dongxiao, GUO Dawu, CHEN Xiaohui.Research on Vertical-torsional Coupling Nonlinear Vibration Characteristics of Four-high Rolling Mill Based on Dynamic Rolling Force [J].Journal of Vibration and Shock,2020,39(20):106-112.

[12] XU Jiwei, MA Xin.Research on the construction of big data platform based on the background of industrial Internet [J]. Software Engineering,2019,22(12) : 41.

[13] Chen Dan, Shao Jian, Yin Shi, Zhang Yaqian, Zhang Wei, Hu Tao.Optimization of Rolling Force Self-learning Model for Tandem Cold Rolling Based on Big Data Platform [J]. Metallurgical Automation,2020,44(06):25-29+61.

[14] Zhou Zhijie, Cao You, Hu Changhua, Tang Shuaiwen, Zhang Chunchao, Wang Jie.The interpretability of rule-based modeling method and its development [J/OL]. Acta automatica: 1-19 [2020-12-17]. https://doi.org/10.16383/j.aas.c200402.

ISSN: 2664-9640

[15] Shang C, Yang F, Huang DX, Lyu WX. Data-driven soft sensor development based on deep learning technique. J Process Control 2014;24:223–33.

[16] HINTON G E, OSINDERO S, TEH Y-W. A fast learning algorithm for deep belief nets [J]. Neural computation, 2006, 18(7): 1527-1554.

[17] Hinton GE. Training products of experts by minimizing contrastive divergence. Neural Comput 2002;14:1771–800.

[18] SUN Yikang. Computer Control of Strip Tanned Cold Rolling [M]. Beijing: Metallurgical Industry Press,2002. 50.

[19] YANG Jingming, SUN Xiaona, CHE Haijun, LIU Chang. Neural Network Rolling Force Prediction Based on Ant Colony Algorithm [J].Iron and Steel, 2009, 44(3): 52-55.