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Prediction Method of SO2 in Desulfurization System based on Neural Network

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Abstract

There are many influencing factors on desulfurization efficiency of desulfurization system. Firstly, the key influencing factors are determined through theoretical analysis; Secondly, taking the key influencing factors as the input of desulfurization efficiency model, combined with the fast Self-learning Model of limit learning machine, a data-driven prediction model of desulfurization efficiency is established; The results show that the prediction model can accurately predict the desulfurization efficiency of wet desulfurization system.

Keywords

SO2, Extreme Learning Machine, Prediction Model.

1. Stacked Automatic Encoder

SAE uses multiple automatic encoders as building blocks for building DNN. Therefore, before introducing SAE, the automatic encoder is first described [1-3].

1.1 Automatic Encoder

Automatic encoder is an unsupervised neural network, which is composed of three layers: input layer, hidden layer and output layer [4]. It attempts to mine a limited number of representations to reconstruct its input, that is, the target output is equal to the input of the model. Figure 1 shows the structure of an automatic encoder with L hidden nodes.

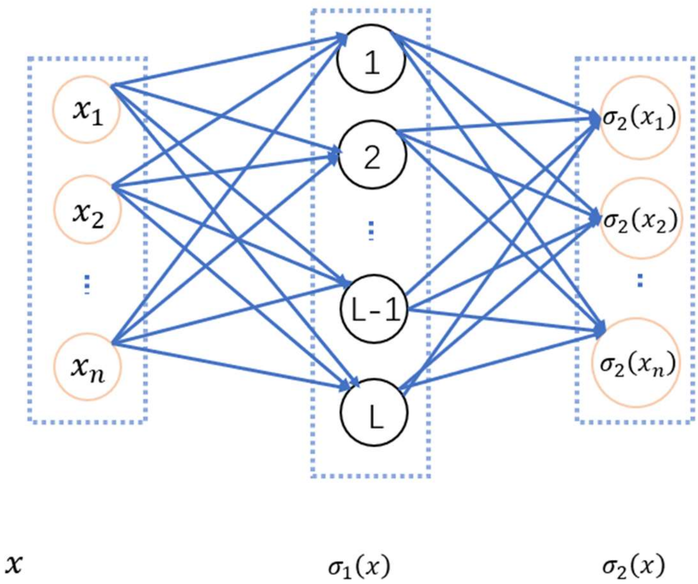

Figure 1. automatic encoder

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In the automatic encoder, there are two processes - encoding process and decoding process. During encoding, the automatic encoder attempts to mine hidden representations $\sigma_1(x)$, It can be calculated as:

$$\sigma_1(x) = f(\omega_1 x + b_1) \tag{1}$$

1.2 Limit Stack Automatic Encoder and its Training Algorithm

In order to predict building energy consumption, we propose a deep learning method called limit SAE [5-7], which combines SAE and elm. The structure of the proposed extreme SAE is shown in Figure 2. In this method, the input is input into the SAE part, and then the fully connected layer is trained by elm. The SAE part is used to extract the characteristics of building energy consumption, while the elm part is used as a predictor to obtain accurate prediction results.

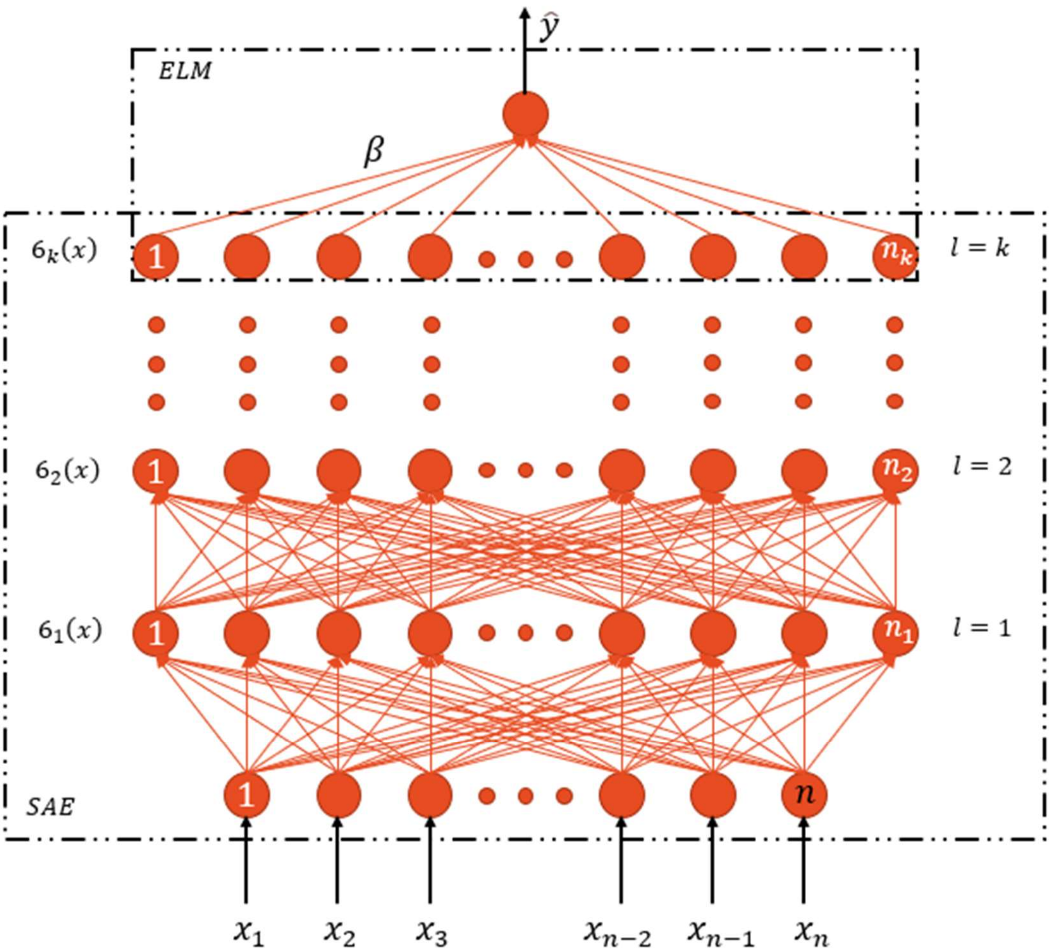

Figure 2. A structure with K hidden layers.

To design a limit SAE with good performance, select the best parameters, including first determining the parameters in the SAE part and elm part. In this study, we used two steps to determine these parameters. In the first step, we pre train the parameters in the SAE section [8-9].

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2. Data Analysis

Compared with LSTM model and traditional BP neural network, LSTM2 - BP model can improve the prediction accuracy by 39%, , That is, the prediction error of LSTM2 - BP model is smaller than that of single LSTM model and BP neural network, with higher prediction accuracy and better prediction effect. At the same time, the RMSE of slurry density predicted 8 times of the generalization error predicted by cascade model. Similarly, the generalization error of LSTM prediction in the slurry feed flow is about twice that of the cascade model. This is because the BP neural network part of the cascade model has good generalization ability, which further improves the overall prediction accuracy of the cascade model. In order to intuitively see the prediction effect of the cascade model, the comparison between the predicted values and the real values of the cascade model in the test set. It can be seen that the LSTM2 - BP model can reflect the change trend of the real data. To sum up, from the comparison between the prediction results of LSTM - BP cascade model and other traditional models, it can be seen that the cascade model has better prediction effect and high reliability. At the same time, when LSTM has two hidden layers, the prediction accuracy of cascade model is the highest.

3. Conclusion

Combined with the characteristics of desulfurization system in thermal power plant, in order to build the environmental model of desulfurization system, a prediction method of slurry density and slurry flow predicted by LSTM - BP cascade model is proposed. The training result is accurate, high precision and fast calculation speed. The desulfurization efficiency is predicted by using the trained model. The validation data show that the prediction results of the model are basically consistent with the actual samples. Although there are some errors, the error value is small.

References

[1] Zheng Mingyou, Wang Wei, Zhao Wenjie, Wang Jianfeng, Ying Jie Outlet so of wet desulfurization in power plant based on PSO lasso algorithm_ (2) Concentration prediction [J / OL] Journal of North China Electric Power University (NATURAL SCIENCE EDITION): 1-7 [2021-12-15] http://kns.cnki.net/ kcm s/detail/13.1212.TM.20210412.0910.002.html.

[2] Fan Zheng, Tian Runzhi, Lin Liang, Han Yanzhong, Guo Yang, Dou longlong, Jing Genhui, tyoor AgI Damian Optimization of heavy catalytic dry gas desulfurization by radial basis function artificial neural network based on PSO algorithm [J] Progress in chemical industry, 2021,40 (06): 3107-3118 DOI: 10. 160 85/j.issn. 1000-6613.2020-1426.

[3] Song Xiuchen Research on photovoltaic energy saving transformation of grain depot under contract energy management mode [D] Shandong University of architecture, 2020 DOI:10.27273/d.cnki. gsajc. 2020.000631.

[4] Zhang Yating Bearing fault diagnosis of desulfurization booster fan based on VMD and convolution neural network [J] Inner Mongolia Science, technology and economy, 2019 (10): 79-81.

[5] Liu Pan BP neural network decoupling and improved genetic algorithm control of CFBB main steam pressure and bed temperature [D] Changsha University of technology, 2019 DOI:10.26985/d.cnki. gcsjc. 2019.000648.

[6] Qi Xiaobin Research on parallel fast learning network algorithm and its application in circulating fluidized bed boiler [D] Yanshan University, 2018.

[7] Wang Qi, fan Changhao, Bai Jianyun, Li Yongmao, Li Jinxia So based on the combination of variable selection and support vector machine_ 2 emission characteristic modeling [J] Thermal power generation, 2018,47 (03): 68-75 DOI:10.19666/j.rlfd. two hundred and one million seven hundred and ten thousand one hundred and thirty-five.

[8] Liu Bin PH value optimization control of flue gas desulfurization process [D] Shanghai Jiaotong University, 2018 DOI:10.27307/d.cnki. gsjtu. 2018.003007.

[9] Wang Jie, Zou Ping, sun Peishi, Li Chuankuan Simulation and prediction of biological flue gas NOx purification based on BP neural network [J] Resource conservation and environmental protection, 2015 (11): 30-31 DOI:10.16317/j.cnki. 12-1377/x.2015. 11.020.