The Research on Improving the Precision of The Polymer IFHI By BP Neural Network of The Method Data Normalization

Dingran Zhang*, Lei Chen, Yiqi Wang, Huiya Wang
School of China People's Police University, Langfang 065000, China

*Corresponding author: dingranzhang@cppu.edu.cn

Abstract. BP neural network has a good effect on data prediction. Using BP neural network to predict polymer fire risk index (IFHI) is a cross research method based on computer intelligent learning model and traditional fire risk assessment. In order to solve the defect of low precision of BP neural network in IFHI prediction, a solution to standardize the initial data processing is proposed to optimize the BP neural network simulation model. In the construction of BP neural network model, the range, threshold, and weight of the initial data need to be processed globally, and then the BP neural network is simulated and trained. Finally, the data is simulated and predicted by using MATLAB. The output results of the neural network with different data standardization processing methods are compared to verify the simulation accuracy. The results show that the input node parameters of BP neural network are processed by Z-score normalization method, which improves the learning ability of the model, improves the accuracy of the prediction effect, and reduces the IFHI error of prediction.

Keywords: Polymer materials, data normalization, BP neural network, IFHI.

1. Introduction
The fire risk index of polymer (IFHI) is closely related to ignition time (TTI), heat release rate (HRR), effective heat of combustion (EHC) and mass loss rate (MLR) [1-3]. The IFHI of traditional polymers is usually determined by small-scale experiments with cone calorimeter, and then IFHI is obtained by analytic hierarchy process (AHP). However, the operation of this method is complex, and there are errors in the experiment. There are many factors affecting polymer IFHI, so it is difficult to use a traditional mathematical model to predict IFHI. In order to obtain more accurate IFHI, intelligent prediction model is needed. The artificial neural network can process the multi-factor and multidimensional data through the application of the synaptic structure similar to the brain neurons, and realize the simulation and prediction of polymer IFHI [4-6].

In this paper, in order to explore the influence of the standardized processing method of the initial data of neural network on the learning efficiency and simulation results of the neural network, we first set the blank comparison group (i.e., do not process the initial data), and take two standardized processing methods to process and optimize the data, and then use the BP neural network for training. By comparing the output results (IFHI prediction value) between the control group and the experimental group, the original data processing method suitable for a neural network model is determined.
2. Modelling of BP neural network optimized by data standardization

When using BP neural network to predict IFHI value, it is necessary to determine the required parameters according to the structure of BP neural network. IFHI is not only related to thermal risk parameters (ignition time, heat release rate, effective heat of combustion, etc.) but also to non-thermal risk parameters (such as smoke risk). According to the literature investigation [3,5], the main factors affecting the IFHI parameters of materials are ignition time (TTI), heat release rate (HRR), effective heat of combustion (EHC), mass loss rate (MLR), production of carbon monoxide and carbon dioxide (CO yield, CO$_2$ yield) and specific extinction area (SEA, smoke produced by a volatile unit mass of materials). Therefore, these parameters are selected as the input nodes of the neural network to participate in the construction of the model and the simulation of the results.

2.1. The Topological structure of neural networks

BP neural network is widely used because of its simple structure, adjustable parameters and more training algorithms [6]. According to the topological structure of BP neural network, it can be divided into three or more layers of a neural network. The best number of hidden layers is determined by the calculation formula of hidden layer (as shown in Formula1).

$$l = \sqrt{m + n + a}$$ (1)

In the above formula, l is the number of nodes in the hidden layer, n is the number of nodes in the input layer, m is the number of nodes in the output layer, and a is an integer between 0 and 10. Through error comparison of training results (As shown in Table 1), considering that too many hidden layers will greatly increase the complexity of network structure, the optimal number of hidden layer neurons is determined to be 10.

| Hidden layer number | Network error | Hidden layer number | Network error | Hidden layer number | Network error | Hidden layer number | Network error |
|---------------------|---------------|---------------------|---------------|---------------------|---------------|---------------------|---------------|
| 3                   | 0.0758        | 8                   | 0.0764        | 13                  | 0.1222        | 18                  | 0.1024        |
| 4                   | 0.1043        | 9                   | 0.0739        | 14                  | 0.0956        | 19                  | 0.1270        |
| 5                   | 0.1270        | 10                  | 0.0526        | 15                  | 0.3073        | 20                  | 0.0791        |
| 6                   | 0.1361        | 11                  | 0.0671        | 16                  | 0.1385        | 21                  | 0.0458        |
| 7                   | 0.0743        | 12                  | 0.1081        | 17                  | 0.1024        | 22                  | 0.0690        |

Because there are many factors that affect IFHI, these factors are mainly related to smoke risk and four combustion performance. Therefore, the structure of BP neural network is designed as a topology structure of eight nodes and ten hidden layers, as shown in figure 1.
2.2. Data standardization optimization of initial weights

In the BP artificial neural network system, different feature vectors describe different evaluation indexes, and different units of evaluation index dimensions will also affect the simulation results. Therefore, dimensionless processing is often used in metrology to reduce or even eliminate the influence between dimensions. The data standardization processing in BP neural network is based on this idea to reduce the impact of various index units on the simulation results.

2.2.1. Data min-max normalization. The input parameters of BP neural network generally need to be standardized, and the common initial data standardization processing is the minimum-maximum normalization processing [7]. In data processing, the minimum-maximum normalization of data is the discrete standardization of data. The initial data value of BP neural network after linear processing by this method will be mapped between [0,1]. The mathematical formula is 2:

$$y_i = \frac{x_i - \min_{1 \leq i \leq n} \{x_j\}}{\max_{1 \leq i \leq n} \{x_j\} - \min_{1 \leq i \leq n} \{x_j\}}$$  \hspace{1cm} (2)$$

Because this method preserves the original size relation in the data, it is the simplest method to eliminate the influence of the data dimension. However, if the fluctuation of data is large (there is a maximum or minimum), the data will be close to 0, which will lead to the distortion of input data and lack of representativeness.

2.2.2. Data Z-score normalization. In the BP neural network, data Z-score normalization is also a method of initial data mapping. Data Z-score normalization is also known as standard deviation standardization, that is, the mean value of the original input data is fixed to 0, and the standard deviation is 1. The mathematical formula is 3.

$$y_i = \frac{x_i - \bar{x}}{s}$$  \hspace{1cm} (3)$$

In the above formula, $\bar{x}$ is the average value of this group of data, and the calculation method is formula 4:

$$\bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i$$  \hspace{1cm} (4)$$

Figure 1. The topological structure of BP neural network
σ is the standard deviation of the original data, and the calculation formula is 5:

\[
s = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2}
\]  

In this standardized way, the main purpose is to deal with the standard deviation of the initial data according to its mean value. There will be positive and negative in the data mapping value.

2.2.3. Neural network modelling process. After data standardization and optimization, the preprocessing data is obtained and applied to BP neural network training. At the same time, set the training index parameters: MSE is 0.001, the learning rate is 0.01, and the maximum training times is 1000. When the network meets the established requirements, the training is terminated. Six typical samples are selected as the prediction data input, and the IFHI parameter values of the samples are output as the results. Data standardization optimizes the BP neural network process (as shown in figure 2).

![Figure 2. Flow chart of BP neural network optimized by data standardization](image)

3. Result analysis of IFHI simulation effect

The characteristic combustion parameters of different materials are input into the BP neural network as initial data, and different data normalization methods are used to process the initial data, and the neural network is trained. In order to analyze the accuracy of the simulation effect, a group of blank control group neural network models were constructed by not processing the initial data. At the same time, the minimum-maximum method and Z-score normalization method were used to build two groups of experimental group neural network models. Using MATLAB software, according to the established three groups of models, IFHI results were predicted six times. The IFHI prediction results are compared with the original data, and the prediction effects of different data processing methods on BP neural network are compared. The prediction results are shown in Table 2.

|       | 1   | 2   | 3   | 4   | 5   | 6   |
|-------|-----|-----|-----|-----|-----|-----|
| Original Data | 2.10 | 2.10 | 2.10 | 2.20 | 2.10 | 2.10 |
| Untreated     | 2.16 | 2.00 | 1.83 | 1.81 | 1.93 | 1.98 |
| Mapminmax     | 2.29 | 2.04 | 1.91 | 1.97 | 1.96 | 2.04 |
| Z-score       | 2.26 | 2.11 | 2.03 | 2.07 | 2.09 | 1.82 |
At the same time, in order to intuitively see the error value between the prediction results of the neural network model and the actual data, the histogram of statistical error is drawn, as shown in Figure 3.

![Figure 3. Statistical Discrepancy](image)

The data in figure x is calculated using formula $\varepsilon_i = |\delta_i - \mu_i|$. $\varepsilon_i$ represents the absolute value of the difference between the actual data of group I and the predicted data, $\delta_i$ represents the actual data of group I, and $\mu_i$ represents the value of IFHI obtained from group I by using different neural networks. In order to measure the dispersion between the prediction effect and the actual effect, show the accurate effect of BP neural network model on IFHI, calculate the mean square error of each group of data, and show the IFHI prediction effect of the model according to the mean square error of a group of data, and the formula of prediction mean square error is 5:

$$MES = \frac{1}{n} \sum_{k=0}^{n} \varepsilon_i^2$$ (6)

The variance results are shown in Table 2.

| Model     | Untreated | Mapminmax | Z-score |
|-----------|-----------|-----------|---------|
| Variance  | 0.0465    | 0.0244    | 0.0202  |

It can be seen from the table that the errors obtained by the two methods are 0.0244 and 0.0202, respectively; the MES of the data without any processing is 0.0465. It can be seen from the MES results of the three models that the BP neural network with Z-score standardized data processing has high precision in predicting IFHI. According to the actual MSE value, it can be seen that when using BP neural network to predict IFHI of different polymers, the accuracy of the neural network can be improved by processing the initial experimental parameters, and the prediction effect can be more in line with the IFHI calculated manually. From the prediction essence of BP neural network model, the normalization of data processing can reduce the dimensional influence of data, facilitate the weighting of different parameters or node data, and map the input parameters to the range of digital signal processing faster; on the other hand, different normalization methods map the initial data to different intervals, which is helpful for the learning of BP neural network. The prediction effect of the neural network is disturbed by certain influence.
4. Conclusions
In this paper, the input node parameters of BP neural network are normalized to explore the influence of data normalization on the accuracy of the neural network to predict polymer IFHI. At the same time, we are looking for a relatively high-precision BP neural network prediction model and apply this model to predict the IFHI value of polymer materials. The results show that after the data is normalized by Z-score, BP neural network model can predict the IFHI value of the polymer relatively accurately, and the constructed model has a better simulation effect. Therefore, z-Score normalized processing can not only accelerate the gradient convergence of data in the process of prediction but also improve the prediction accuracy of the neural network. However, according to the initial data situation, appropriate data normalization methods should be used in the actual construction of a neural network.

Acknowledgements
This work was financially supported by Synthesis of a novel phosphorus nitrogen intumescent flame retardant based on "three sources" and its flame-retardant polystyrene (16211248) fund.

References
[1] Shu Zhongjun, Xu Xiaonan, Yang Shousheng, et al. Fire risk assessment of polymer materials based on cone calorimeter test, J. Polymer Bulletin, 2006 (5): 37-44, 78
[2] Shu Zhongjun, Xu Xiaonan, Li Xiang. Test method of cone calorimeter for evaluation of flammability of polymer materials in fire, M. Beijing, 2007.
[3] Chen Yuming. Fire risk assessment of polymer materials based on analytic hierarchy process, J.Fire protection technology and product information, 2006 (03): 13-16
[4] Liu Jianwei, Zhao Huidan, Luo xionglin, Xu Xu. Research progress of deep learning batch normalization and related algorithms, J. Acta Automatica Sinica, 2020,46 (06): 1090-1120
[5] Wu Yun. Discussion on polymer fire risk test and evaluation method, J. Fire protection technology and product information, 2013 (06): 45-47
[6] Ge Zhexue, Sun Zhiqiang, Neural network theory and MATLAB7 implementation, M. Beijing, 2005.
[7] Tang Rongzhi. Research on improving SVM training efficiency by data normalization method, D. Shandong Normal University, 2017