Research on IFHI prediction effect based on grey relational analysis and BP neural network

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Abstract. IFHI (Fire Risk Index) is a key indicator of the fire risk capability of polymer materials.[1] In view of the complexity, uncertainty and nonlinearity of IFHI prediction, this paper adopts the grey relational analysis method proposed by Deng Yulong et al to carry out dimensionality reduction analysis of parameters. Four parameters of SEA, MLR, TTI and CO yield, which are highly correlated with IFHI value, were selected to construct BP neural network prediction model. The predicted value is compared with the actual value, and the mean square error MSE =0.01308. It is proved that this model has a good prediction effect and can provide scientific basis for IFHI prediction.

Keywords: Polymer materials, Grey relational analysis, IFHI, BP neural network.

1. Introduction

The effective prediction of IFHI of different materials is an important means to reduce fire loss of modern materials. In the book Fire Risk of Polymer Materials [2]written by Xu Xiaonan and Shu Zhongjun et al., relevant matrices were constructed by small-scale experiments and analytic hierarchy process to calculate the IFHI value of polymers. The book gives a detailed introduction to the acquisition, meaning and analysis of each parameter of IFHI. The analytic hierarchy process (AHP) is used to compare each parameter to determine the importance of the parameter, and then the judgment matrix is constructed and the weight of each parameter is calculated to obtain IFHI, which leads to the complicated calculation process and tedious procedures of IFHI. BP neural network is a kind of intelligent learning model similar to brain neurons. According to the difference and similarity of input parameters and output parameters, this model uses different data for classification analysis, matrix construction and learning rules as constraints to change the weight and bias value of a single neuron structure. Finally, a nonlinear intelligent learning model that can reflect the relationship between the output layer data and the input layer parameters is constructed. The constructed model can realize the application of probability estimation, data cluster analysis, dynamic network intelligent prediction, function approximation and so on for different situations [4]. Therefore, this paper uses the BP neural network model to predict the IFHI of polymers.

The number of input parameters should be considered when using neural network for data prediction. In the construction of IFHI result model for polymer prediction, the more relevant parameters are used in theory to predict the better results will be obtained. However, in practice, due to the different degree of correlation between different physical parameters and polymer IFHI, excessive
pursuit of parameter types will lead to data overfitting, interfere with the learning rules within the neural network, resulting in data redundancy and complex structure, which is not conducive to the prediction effect of the neural network. The parameters used by polymer to measure IFHI can be divided into thermal risk parameters and flue gas risk parameters. Thermal risk parameters are divided into light time (TTI, from material surface heat to the surface used during combustion in duration), heat release rate (HRR, material is lit, the heat release rate per unit area), effective heat of combustion (EHC, measured by the ratio of the heat release rate and mass loss rate), mass loss rate (MLR, burning sample quality over time and the rate of change in the process of combustion). Smoke hazard parameters include carbon monoxide and carbon dioxide Yield (CO Yield, CO2 Yield) and specific extinction area (SEA, smoke produced by volatile materials per unit mass). Grey relational analysis in grey system theory can be used to solve multi-parameter and multi-dimensional uncertainty problems. Therefore, this paper adopts Deng's correlation degree proposed by Professor Deng Zhulong [5] according to the four axioms of grey correlation to select the number and types of polymer IFHI parameters.

2. Grey correlation analysis of IFHI influencing factors

In the hierarchical analysis of IFHI value, due to the difference of internal and external interference in the evaluation system and the limitation of the artificial cognition of the evaluation algorithm, it is easy to obtain uncertain information, which is deviated from the hard evaluation criteria in the initial evaluation [6]. In order to improve the accuracy of IFHI prediction, grey correlation analysis is used to analyze IFHI parameters in dimension reduction.

2.1. Introduction to grey correlation analysis principle

The grey system is a system with incomplete information. Grey relational analysis is a method to analyze, describe and compare the internal information of a grey system. The idea is to judge whether each sequence is closely related to each other according to the correlation degree of data information curve fluctuation in the sequence, and finally reflect the correlation between the sequences through the numerical value. The larger the correlation coefficient is, the closer the correlation between two sequences is. This method is based on the mathematical basis of space theory and the four axioms of grey relation, namely normality, wholeness, even symmetry and proximity.

When grey correlation degree is used to analyze IFHI parameter sequence and IFHI correlation, it is necessary to determine the correlation degree model to be used. According to each sequence of input parameters of the model, the correlation degree is calculated through the model, and the sequence with large correlation degree is selected as the input parameter sequence of BP neural network model.

2.2. Construction of association degree analysis model

The grey correlation step is generally based on the target output as the parent sequence. In this case, the parent sequence is the fire risk composite index (IFHI), and the factors affecting the fire risk index constitute several sub-sequences, including ignition time (TTI), heat release rate (HRR), effective heat of combustion (EHC), mass loss rate (MLR), specific extinction area (SEA), etc. In the polymer material fire danger", the author through the small size of polymer experiment to obtain the lighting time, heat release rate of the polymer of 8 kinds of parameters, and through the generalized index of nonlinear fitting method for fire danger index of polymer materials, for the nine data, divided into three steps related influence factor correlation analysis.

Step 1 Determine the analysis sequence. The fire risk composite index is used as the parent sequence, $Y = \{Y_0(k) | k = 1,2, ..., n\}$. The ignition time, heat release rate and other 8 parameters are taken as sub-sequences, $X_I$, $X_I = \{X_i(k) | k = 1,2, ..., n\}, i = 1,2, ..., m$. Where $m$ is the number of samples, $n$ is the number of subsequence, and $k$ is the sample of group K.

Step 2 Data dimensionless processing. We removed the unit limits of ignition time, heat release rate, effective heat of combustion and other data, and converted them into dimensionless pure values,
so as to facilitate the comparison and weighted processing of data in the later stage. The concrete implementation method is as follows: divide the data of the sequence uniformly by the value of the first data of the sequence. The formulas are shown in 1 and 2:

\[ Y'_k = \frac{Y_k}{Y_1} \]  
\[ X'_k = \frac{X_k}{X_1} \]  

Where \( 1 \leq i \leq n \), \( k \) is the sample of group \( K \).  

**Step 3 Calculation of correlation coefficient.** \( \xi_i (k) \)

\[ \xi_i = \frac{\min_k \min |Y(k) - X_i(k)| + \rho \cdot \max_k \max |Y(k) - X_i(k)|}{|Y(k) - X_i(k)| + \rho \cdot \max_k \max |Y(k) - X_i(k)|} \]  

In the formula, \( \rho \) is the discrimination coefficient, we generally take \( \rho = 0.5 \) calculate the grey relational value of each impact factor data sequence in the fire Risk Composite Index (IFHI) data sequence.

2.3. Correlation degree calculation and result analysis of IFHI influencing factors  
Factors affecting IFHI include ignition time (TTI), heat release rate (HRR), effective heat of combustion (EHC), mass loss rate (MLR), specific extinction area (SEA), carbon monoxide yield (CO yield), carbon dioxide yield (CO\(_2\) yield), etc. The fire risk composite index (IFHI) in the data is defined as the parent series, and the other indexes are defined as the sub-series. The correlation coefficient between the sequences is calculated and sorted according to the correlation degree value from the largest to the smallest. The results are shown in Table 1.

| Impact factor | MLR   | SEA   | TTI   | CO yield av-HRR | pk-HRR | EHC  | CO\(_2\) yield | correlation |
|---------------|-------|-------|-------|-----------------|--------|------|----------------|-------------|
|               | 0.935 | 0.903 | 0.884 | 0.877           | 0.775  | 0.752| 0.725          | 0.687       |

According to the data in Table 1, the eight factors can be preliminarily divided into three levels. The correlation coefficients of MLR and SEA were both greater than 0.9, with an excellent correlation with the parent sequence. The correlation coefficients of TTI and CO yield were between 0.8-0.9, with a good correlation. The correlation coefficients between AV-HRR, PK-HRR, CO\(_2\) yield, EHC and IFHI were less than 0.8, with a relatively poor correlation. Therefore, four factors (SEA, MLR, TTI, CO yield) with good correlation with the parent sequence were selected as input factors of the BP neural network IFHI prediction model.

3. Prediction by the BP neural network model of IFHI

3.1. Construction of BP neural network model  
The BP neural network uses the input IFHI related parameters as input layer network node, and uses gradients, Jacobian matrix and other algorithms to perform reverse feedback training on each input value. BP neural network is constructed by adjusting the internal bias value, weight value, sensitivity and other numerical values. Then, the prediction effect of the neural network is verified by the input parameters, and the appropriate neural network model is finally obtained to predict the IFHI value.
According to the structure of BP neural network, the structure of BP neural network can be divided into three structures: input layer, hidden layer and output layer. The input layer needs to determine the parameter sequence of network nodes and input the value of each parameter. The hidden layer processes each parameter value input by the input layer, approximates IFHI by the back propagation mechanism according to the learning rules, and finally determines the model to predict IFHI value. The output layer outputs the IFHI value predicted by the neural network model.

When the neural network is constructed, the four parameters with high correlation degree are taken as input variables, and the value of IFHI is taken as output variables for reference to carry out BP neural network training. Therefore, the number of nodes in the input layer and output layer of neurons is 4 and 1 respectively. The structure of BP neural network is shown in Figure 1.

![Figure 1. Topological structure of BP neural network](image)

The empirical formula in literature [7] can be used to determine the optimal number of hidden layers of neurons and the number of layers of BP neural network. The specific formula is shown as:

$$\rho = \sqrt{n + 1} + m$$  \hspace{1cm} (4)

In formula 3.1-1, $\rho$ is the number of hidden nodes; $n$ is the number of parameters in the input layer; $m$ is a constant between 0 and 10. The parameters of the neural network are shown in Table 2.

| Parameter Settings of BP neural network | Maximum number of training | Training target error | Learning rate | Interval number |
|-----------------------------------------|----------------------------|-----------------------|--------------|----------------|
|                                         | 50000                      | 0.0001                | 0.05         | 5              |

When the network meets the established requirements, the training is terminated. Five typical samples are selected as the prediction data input, and the IFHI parameter values of the samples are output as the results. Grey relational analysis optimizes the BP neural network process (as shown in Figure 2).
3.2. Analysis of BP neural network prediction results

71 groups are selected from the sample data as the training data of BP neural network model, and the simulation results are analyzed. IFHI results simulated by BP neural network are shown in Table 3. Where the absolute error value $\varepsilon_i = |\delta_i - \mu_i|$, The relative error $\phi_i = \frac{\varepsilon_i}{\mu_i} \times 100\%$. And draw a histogram according to the predicted results, through which the gap between the predicted value and the actual value of BP neural network can be visually demonstrated (as shown in Figure 3).

| serial number | actual value $\mu_i$ | Predictive value $\delta_i$ | Absolute error $\varepsilon_i$ | relative error $\phi_i$ $\%$ |
|---------------|---------------------|-----------------------------|------------------|------------------|
| 1             | 1.8                 | 1.83                        | 0.03             | 1.6              |
| 2             | 1.8                 | 1.85                        | 0.05             | 2.7              |
| 3             | 1.4                 | 1.55                        | 0.15             | 10               |
| 4             | 1.5                 | 1.31                        | 0.19             | 12               |
| 5             | 1.8                 | 1.82                        | 0.02             | 1.1              |

Figure 2. Flow chart of BP neural network optimized by Grey relational analysis

Figure 3. Comparison of IFHI experimental and predicted values
According to Figure 3 and Table 3, MSE=0.01308 is calculated according to formula 5. The predicted results are close to the actual results, and the model can accurately measure the actual fire hazard degree of the polymer.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} e_i^2$$  \hspace{1cm} (5)

The correlation degree analysis of the aggregated parameter sequence is carried out through the gray correlation degree, and the dimensionality reduction process is performed on the multi-variable and multi-dimensional parameters to highlight the correlation degree between the data. We simplify the relationship between the IFHI that needs to be predicted and the parameters measured in the experiment. In this way, the BP neural network can accelerate the gradient convergence speed through the internal connection between the data when predicting, and avoid the overfitting effect of the model constructed by the data and interfere with the prediction accuracy.

4. Conclusions
In this paper, grey correlation analysis and neural network are combined to reduce the dimensionality of the physical parameters that affect polymer IFHI. Four parameters of SEA, MLR, TTI, CO yield, which are representative and have strong correlation with IFHI value, are selected as the predicted sequence. IFHI is predicted according to the constructed BP neural network model. According to the absolute error between the predicted value of IFHI and the actual value, the mean square error MSE=0.01308 is calculated by formula 3-1. It is proved that it is an effective method to predict IFHI parameters by using BP neural network with grey correlation degree, which has high application value in the actual production process.

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