Study on Intercalated Melt-blown Nonwovens Based on Product Performance Control Mechanism

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Abstract. There are many factors affecting the preparation of intercalation melt-blown nonwovens, and scientists are committed to studying the conditions required for optimal product performance. Therefore, in order to study the optimal conditions, this paper first uses multiple linear regression to explore the correlation between intercalation rate and the change rule. It is found that intercalation rate is related to the change rule of thickness and filtration resistance, but has nothing to do with other indicators. In order to explore the relationship between process parameters and structure variables, a multi-layer perceptron (BP neural network) model with process parameters as input and structure variables as output is established. The relationship between input and output is obtained by using the trained network and the functional relationship is calculated. By analyzing the function, it is found that the correlation between the receiving distance and thickness and porosity is stronger than the positive correlation between the hot air speed and the compression resilience is stronger than the negative correlation between the hot air speed. The correlation between hot air velocity and thickness and porosity is weaker than that of receiving distance, and the correlation between hot air velocity and compressive resilience is weaker than that of receiving distance.

Keywords: Intercalated Melt-blown Nonwovens, Technological Parameter, Multiple Linear Regression, Multilayer Perceptron Model

1. Introduction

Industrial textile is an indispensable key material in the global strategic emerging industry, with an annual output value of 30 dollars. Due to its advantages of high technology content, wide application range and large market potential, its development become one of the important symbols to measure the comprehensive strength of a country's textile industry. Melt-blown non technology is an important means of efficient production and processing of industrial textiles, with short process flow and high production efficiency. Its products have the characteristics of ultra-fine fiber, large specific surface area and high porosity, and have unique advantages in the fields of medical and health protection (haze, avian flu etc.), thermal insulation (high cold protection, high temperature insulation etc.) sound absorption and noise reduction[1].Because the fiber of melt-blown nonwovens material is very fine, the material properties are often damaged due to poor compression resilience during use. Therefore, this paper studied the variation law of structural variables and product properties after intercalation, analyzed whether intercalation rate has an impact on the variation law, also studied the relationship between process parameters and structural variables, and analyzed the data of structural variables by establishing a prediction model.

2. Establishment of multiple linear

2.1. Preparation of the model

Set random variable

If the intrinsic relationship between variable y and six other variables 1, 2, 3, ... 6 is linear, its first data is:

$$(y_\alpha; x_{\alpha,} x_{\alpha 2}, ...x_{\alpha 6}), \alpha = 1, 2, ..., 6 \quad (1)$$

The linear regression model (1) can be expressed as:

$$\begin{cases} y_1 = \beta_0 + \beta_1 x_{11} + \beta_{12} x_{12} + \ldots + \beta_6 x_{16} + \varepsilon_1 \\ y_2 = \beta_0 + \beta_1 x_{21} + \beta_2 x_{22} + \ldots + \beta_6 x_{26} + \varepsilon_2 \\ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \\ y_{23} = \beta_0 + \beta_1 x_{231} + \beta_2 x_{232} + \ldots + \beta_6 x_{236} + \varepsilon_{23} \end{cases} \tag{2}$$

Among them $\beta_0, \beta_1, .., \beta_6$ are 7 estimated yield parameters, $x_1, x_2, x_3, \ldots x_6$ are 6 general variables that can be accurately measured, and are 23 the random variables that are mutually independent and subject to the same normal distribution $N(0,\sigma)$ are the mathematical model of multiple linear regression[2].

$$Y = X\beta + \varepsilon \tag{3}$$

Among them:

$$Y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_{23} \end{pmatrix}, \quad X = \begin{pmatrix} 1 & x_{11} & x_{12} & \cdots & x_{16} \\ 1 & x_{21} & x_{22} & \cdots & x_{26} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ 1 & x_{231} & x_{232} & \cdots & x_{236} \end{pmatrix} \tag{4}$$

$$\beta = \begin{pmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_6 \end{pmatrix}, \quad \varepsilon = \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_{23} \end{pmatrix} \tag{5}$$

Least square method

In this paper, the least square method is used to find $\beta_0, \beta_1, \ldots \beta_p$ that estimate of $\hat{\beta}_0, \hat{\beta}_1, \ldots \hat{\beta}_p$ is satisfied:

$$\begin{aligned} Q\left(\hat{\beta}_0, \hat{\beta}_1, \hat{\beta}_2, \ldots, \hat{\beta}_p\right) &= \sum_{i=1}^{n} (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_{i1} - \hat{\beta}_2 x_{i2} - \ldots - \hat{\beta}_p x_{ip})^2 \\ &= \min \sum_{i=1}^{n} (y_i - \beta_0 - \beta_1 x_{i1} - \beta_2 x_{i2} - \ldots - \beta_p x_{ip})^2 \end{aligned} \tag{6}$$

By using equation and determining $\hat{\beta}_0, \hat{\beta}_1, \ldots, \hat{\beta}_p$ is called the least squares estimate of the regression parameter $\beta_0, \beta_1, \ldots \beta_p$. According to the extreme value theorem in calculus, make its partial derivative zero, and then we can get the normal equations of the estimated value of the parameter to be estimated:

$$\begin{cases} \sum(\hat{\beta}_0 + \hat{\beta}_1 x_{i1} + \hat{\beta}_2 x_{i2} + \ldots + \hat{\beta}_p x_{ip}) = \sum y_1 \\ \sum(\hat{\beta}_0 + \hat{\beta}_1 x_{i1} + \hat{\beta}_2 x_{i2} + \ldots + \hat{\beta}_p x_{ip}) x_{i1} = \sum y_i x_{i1} \\ \sum(\hat{\beta}_0 + \hat{\beta}_1 x_{i1} + \hat{\beta}_2 x_{i2} + \ldots + \hat{\beta}_p x_{ip}) x_{i2} = \sum y_i x_{i2} \\ \vdots \\ \sum(\hat{\beta}_0 + \hat{\beta}_1 x_{i1} + \hat{\beta}_2 x_{i2} + \ldots + \hat{\beta}_p x_{ip}) x_{ip} = \sum y_i x_{ip} \end{cases} \tag{7}$$

Obviously, if the coefficient matrix of a normal system of equations is a symmetric matrix, the matrix form is:

$$(X'X)\hat{\beta} = X'Y \tag{8}$$

When $X'X$ exists, the regression coefficient of the regression equation is obtained:

$$\hat{\beta} = (X'X)^{-1} X'Y \tag{9}$$

Heteroscedasticity test:

Assuming a regression model, test the following original hypothesis:

$$H_0 : E(\varepsilon_1^2 \mid x_2, \ldots, x_k) = \sigma^2 \tag{10}$$

If H_0 does not hold, the function of the conditional variance $E(\varepsilon_1^2 \mid x_2, \ldots, x_k)$ is called the conditional variance function. BP test assumes that the sub conditional variance function is a linear function:

$$\varepsilon_i^2 = \delta_1 + \delta_2 x_i + \ldots + \delta_k x_{ik} + u_i \tag{11}$$

Due to unpredictability, residual squared e_i^2 was used to regress the explanatory variable:

$$\varepsilon_i^2 = \delta_1 + \delta_2 x_i + \ldots + \delta_k x_{ik} + u_i \tag{12}$$

The R^2 statistic is still used:

$$nR^2 \xrightarrow{d} \chi^2(K-1) \tag{13}$$

Multicollinearity test

Assuming there are k independent variables, then the $VIF_n = \dfrac{1}{1-R^2_{1-k\backslash n}}$ of the nth variable. $R^2_{1-k\backslash n}$ is taking the nth independent variable as the dependent variables, Goodness of fit obtained by regression of the remaining k-1 independent variables.

a) Establishment of the model

According to multiple linear regression, thickness (mm), porosity (%), compression resilience (%), filtration resistance (Pa), filtration efficiency (%), permeability (mm/s) and intercalation rate were used as six sets of related variables to establish a multiple linear regression model, as shown in Fig 1:

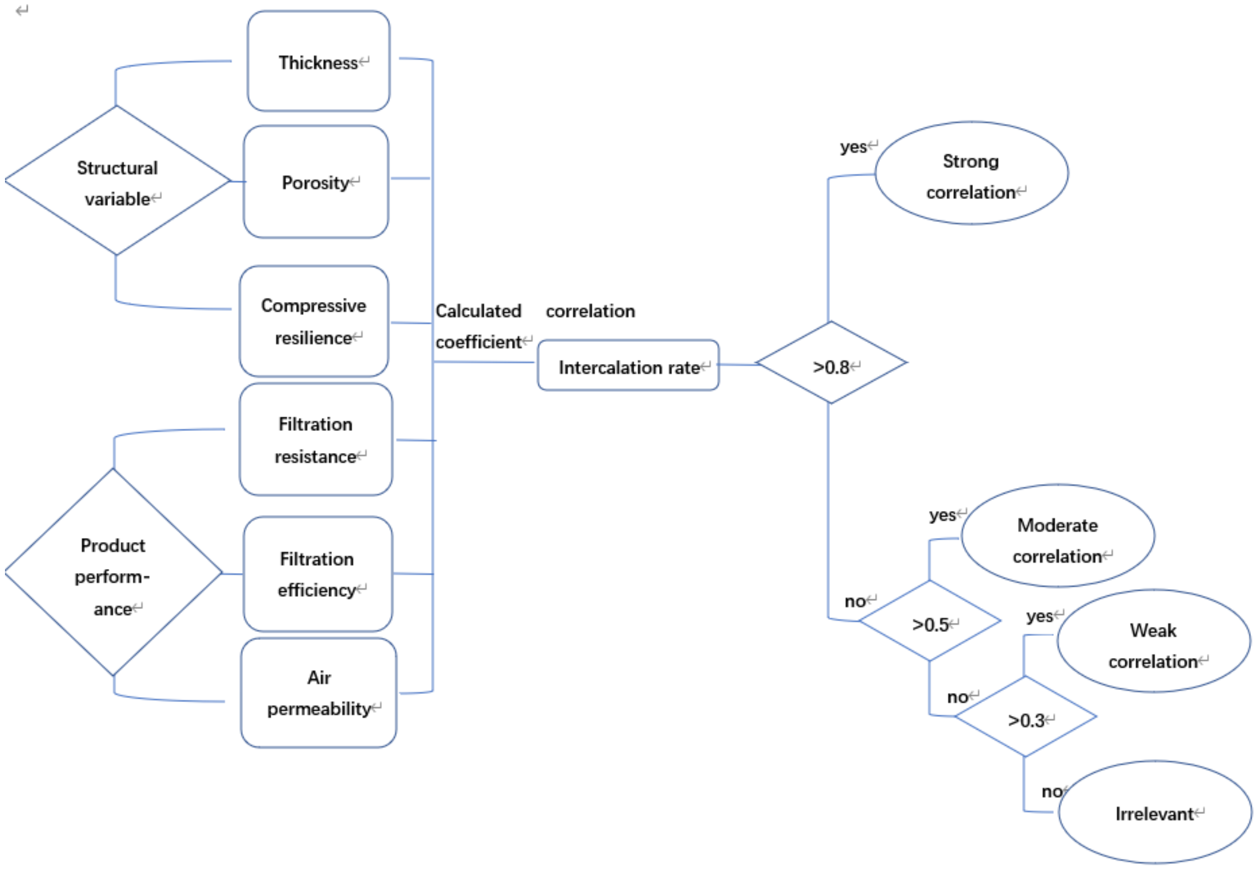

Fig. 1 Multiple linear regression model

From the above figure, it can be seen that the corresponding relationship between each indicator and the insertion rate is the standard correlation coefficient calculated by multiple linear regression[3] to judge. The larger the correlation coefficient, the higher the degree of correlation between the indicator and the insertion rate. The determination of the coefficient size needs to be based on the data provided by the question. The solving process and results will be provided in the subsequent model solving.

Linear correlation analysis: Study the degree of linear relationship between two variables. Represented by the correlation coefficient r. Table e describes the degree of correlation between r and various indicators[4]. As shown in table 1:

Table 1. Significance of correlation coefficient r and correlation degree

Correlation coefficient	Degree of correlation
0.0 ≤|r|≤0.3	Irrelevant
0.3 ≤|r|≤0.5	Weak correlation
0.5 ≤|r|≤0.8	Moderate correlation
0.8 ≤|r|≤1.0	Strong correlation

Equation solving

Draw visualization, observe structural variables, and observe changes in product performance

Analyze the six indicator data in this article, including thickness (mm), porosity (%), compression resilience (%), filtration resistance (Pa), filtration efficiency (%), and permeability (mm/s), to obtain 25 sets of structural variables and product performance change rate data after intercalation. Plot the trend of 6 sets of data as shown in Figure 2. By analyzing the figure below, it was found that except for the two peaks in filtration efficiency, there was no significant change in the rate of change of other variables, and it was not possible to determine whether the intercalation rate had an impact on these changes. Therefore, this article continues to study the relationship between intercalation rate and variation rule through multiple linear regression analysis.

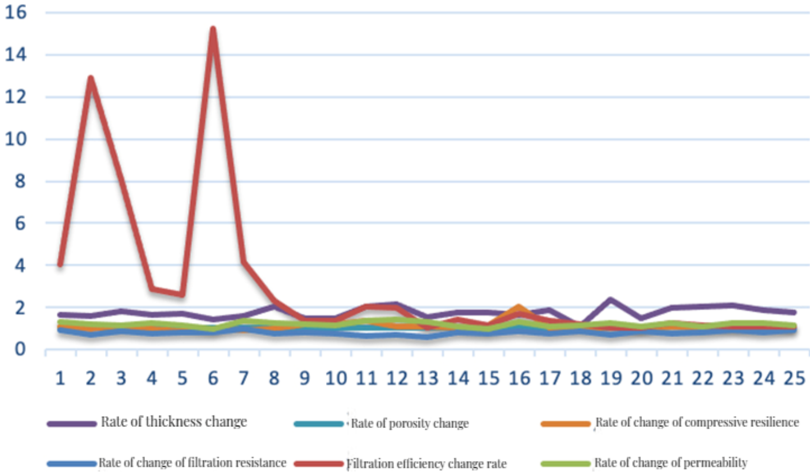

Fig. 2 Plot the trend of 6 sets of data

Solving Regression Equations

The data used in this article is quantitative data, and using Stata software to perform multiple linear regression on the corrected data is mainly to determine whether it is correlated. This study found that the values of P were all greater than the significance level of 0.05, indicating the presence of heteroscedasticity[5]. Therefore, BP test will used to study the heteroscedasticity among the six groups of indicators.

Bp teste

According to the results of the BP test, when the significance is greater than 0.05, it indicates the presence of heteroscedasticity in multiple regression.

Heteroscedasticity Robust Standard Error

Heteroscedasticity -- robust standard error refers to the fact that its standard deviation is not sensitive to possible heteroscedasticity or autocorrelation issues in the model, and the robust t-statistic calculated based on the robust standard deviation still approximately follows a t-distribution. This article found that even with the addition of robust standard errors, most p-values are greater than significance 0.05, porosity change rate, filtration resistance change rate, and thickness value of P are less than significance 0.05, indicating that the four sets of indicators are not related to the intercalation rate, but rather to the thickness change rate, porosity change rate, and filtration resistance change rate. Finally, we use the test of multicollinearity to see whether there will be multicollinearity. As shown in table 2

Table 2. Robust Standard Error Regression

Intercalation rate	Coef.	Std.Err	t	p>|t|	95% Conf.	Interval
Rate of thickness change	35.72	10.97	3.26	0.005	12.47	58.97
Rate of porosity change	-459.94	150.68	-3.05	0.008	-779.37	-140.51
Rate of resilience change	-0.06	4.86	-0.01	0.990	-10.37	10.25
Rate of filtration resistance	59.53	18.19	3.27	0.005	20.96	98.09
Rate of filtration efficiency change	0.36	0.41	0.89	0.385	-0.50	1.23
Rate of change of permeability	2.45	23.57	0.10	0.918	-47.52	52.42

Multicollinearity test

According to the results shown in Table 3, the VIF is less than 10, indicating that there is no multicollinearity, which means that the above the conclusion is valid.

Table 3. Multicollinearity test

Variable	VIF	1/VIF
Rate of thickness change	1.98	0.504954
Rate of porosity change	1.86	0.537737
Rate of compression rebound	1.17	0.856691
Rate of change of permeability	1.22	0.819015
Filter efficiency	1.13	0.886516
Rate of filtration resistance	1.10	0.907910

Pearson correlation analysis

The correlation between changes in six indicators and intercalation rate was obtained using SPSS[6]. As shown in Table 4. From the result data in the table, it can be seen that only the change in thickness is weakly correlated with the intercalation rate, while other indicator changes are not related to the intercalation rate. This result are mutually confirmed with those of multiple linear regression analysis. Therefore, this article believes that the rate of change in compression resilience and filtration resistance is related to the intercalation rate.

Table 4. Pearson correlation analysis

	Rate of thickness change	Rate of porosity change	Rate of compressive resilience change	Rate of filtration resistance	Rate of filtration efficiency change	Rate of change of permeability	Intercalation rate (%)
Rate of thickness change	1.000	.676**	.145	-.132	-.174	.224	.226
Rate of porosity change	.676**	1.000	.311	.080	-.195	.262	-.168
Rate of compressive resilience change	.145	.311	1.000	-.158	-.327	.208	-.324
Rate of filtration resistance	-.132	.080	-.158	1.000	-.010	-.239	.375
Rate of filtration efficiency change	-.174	-.195	-.327	-.010	1.000	.142	.139
Rate of change of permeability	.224	.262	.208	-.239	.142	1.000	-.160
Intercalation rate (%)	.226	-.168	-.342	.375	.139	-.160	1.000

**** At level 0.01(two-tailed),the correlation was significant**

3. Multilayer perceptron model

This article studies the relationship between process parameters and structural variables, and predicts structural variable data based on this. A multi-layer perceptron model with excellent input-output mapping function was established to fit the relationship between process parameters and structural variables, and the model with good prediction effect was obtained by training the network passion several times, and the functional relationship between the process parameters and the structural variables was obtained, and the trained multi-layer perceptron model was used to predict the structural variable data.

3.1. Establishing a model

Multilayer perceptron (MLP), also known as artificial neural network (ANN) [7], is composed of three types of layers, namely input layer, hidden layer and output layer. The hidden layer of the multi-layer perceptron can contain multiple hidden layers, and the simplest multi-layer perceptron only contains one hidden layer. Building a network.

The input layer of this article should be the process parameters (receiving distance and hot air velocity), and the output layer should be the structural variables (thickness, porosity, compression resilience).

In the process of network design, the determination of the number of hidden layer neurons is very important. If there are too many neurons in the hidden layer, it will increase the computational complexity of the network and easily lead to overfitting problems; If the number of neurons is too small, it will affect network performance and fail to achieve the expected effect. The number of hidden layer neurons in a network is directly related to the complexity of the actual problem, the number of neurons in the input and output layers, and the setting of expected errors. According to data review, there is no clear formula for determining the number of neurons in the hidden layer, only some empirical formulas. The final determination of the number of neurons still needs to be based on experience and multiple experiments. This article refers to the following empirical formula when selecting the number of hidden layer neurons[8]:

$$\begin{aligned} &l < n-1 \\ &l < \sqrt{(m+n)} + a \\ &l = \log_2 n \end{aligned} \tag{14}$$

This article selects the number of hidden layers as 2, and based on empirical formulas, the number of neurons in each hidden layer can be determined to be 10.

Activation function

The elu function can effectively solve the problem of gradient dispersion and the inability to solve negative values. The $sigmoid$ function can control the output value within [0,1] and obtain probability judgment parameters to assist in model interpretation[9].

Loss function

In backpropagation, Adam gradient descent algorithm is used to minimize the cross-entropy loss function:

$$J(\theta) = -\frac{1}{m}\sum_{i=0}^{m}[(y^{(i)}\log(h^{[2](i)}) + (1-y^{(i)})\log(1-h^{[2](i)}))] \tag{15}$$

Neuron weight

When determining the initial weight, the parameters should be cancelled as much as possible to avoid the complexity of the network, which may cause the calculation amount to exceed the operation capacity of the computer. Therefore, random values between zero and zero should be taken to update the parameters by gradient descent method[10], where the updated formula is:

$$\theta = \theta - \alpha\frac{\partial J}{\partial \theta} \tag{16}$$

Thereinto, α is the update rate

b) Predictive structural variable

After the training of the neural network built in MATLAB, the training of each structural variable and the comparison between the prediction and the actual figure can be obtained. It can be found that the predicted value and the real value basically coincide, so it is preliminarily believed that the model has a good prediction effect. As shown in fig 3.

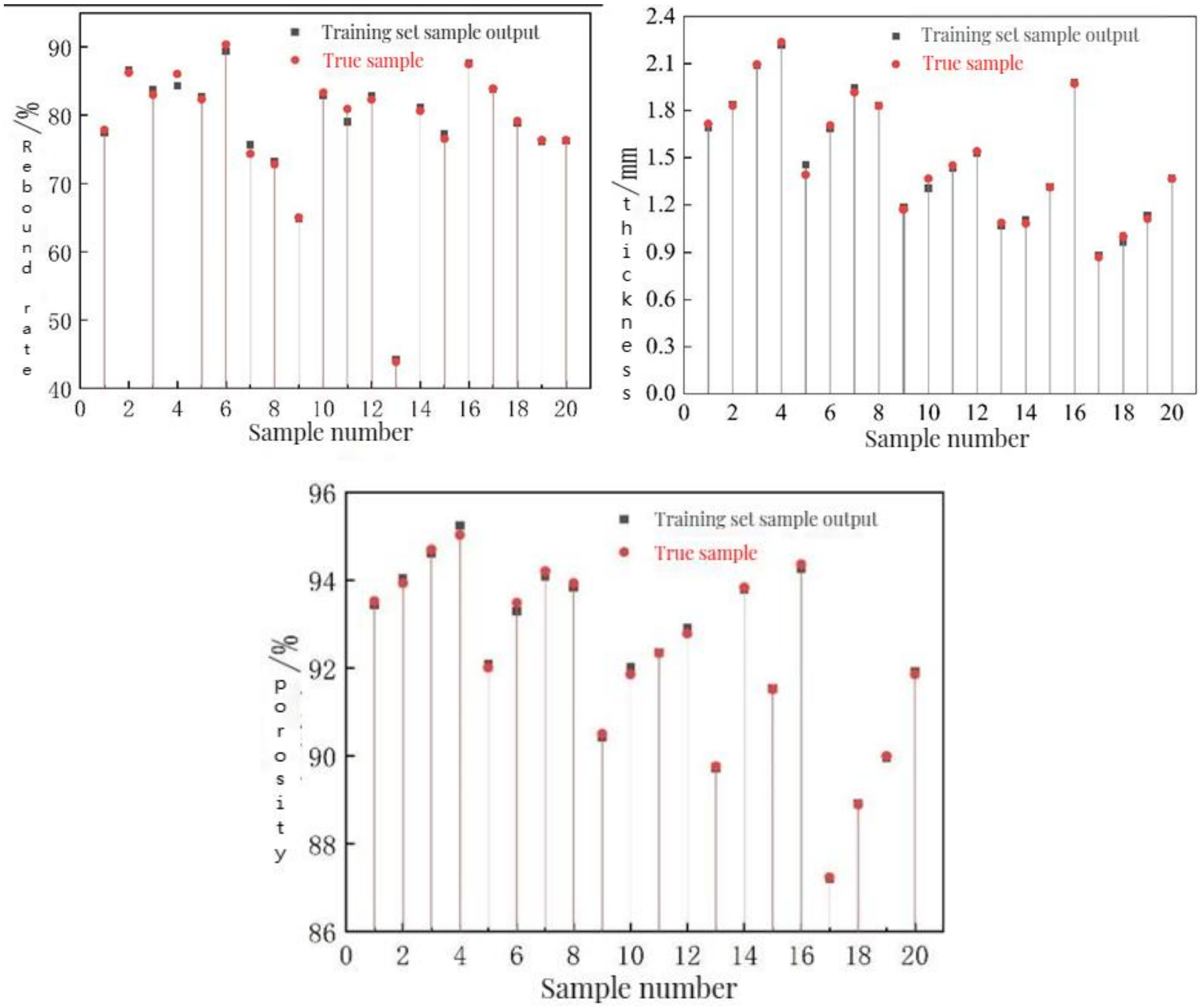

Fig. 3 Training set prediction versus actual values

The relative error of each structural variable can be obtained by visualization of the error value (as shown in Fig 4). It can be found that the error of other samples is relatively low except for the error of individual test samples. Therefore, in general, the trained neural network still has a good fitting effect.

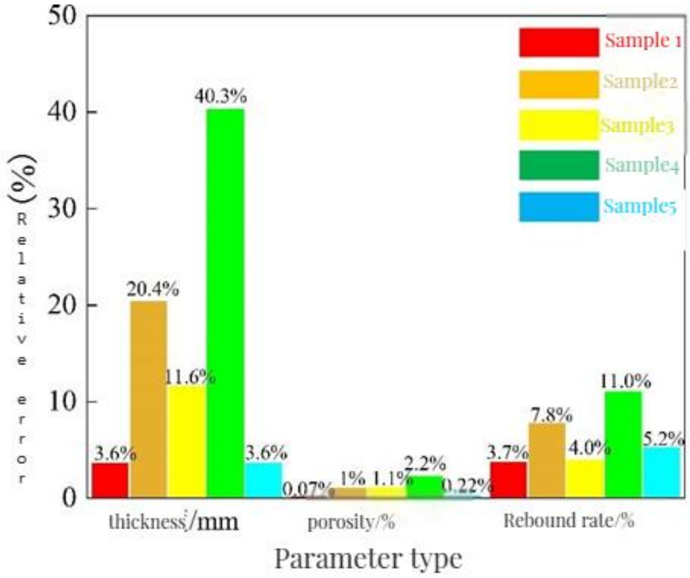

Fig. 4 Relative error value of each structural variable

The functional relation between process parameters and structural variables can be obtained. The following functional relation can be obtained according to the trained network:

$$\begin{cases} O_1 = X \\ I_2 = w_{ij} \times O_i + B_{ij} \times ones \\ O_2 = \dfrac{1}{1+e^{-I_2}} \\ I_3 = w_{jk} \times O_2 + B_{jk} \times ones \\ O_3 = \dfrac{1}{1+e^{-I_3}} \\ I_4 = w_{kl} \times O_3 + B_{kl} \times ones \\ O_4 = I_4 \end{cases} \tag{17}$$

Among them, the receiving distance (x_1), hot air velocity (x_2)are input X ($X = [x_1, x_2]T$), thickness (y_1), porosity (y_2), and compression resilience (y_3) are output O_4 ($O_4 = [y_1, y_2, y_3]T$). w_{ij}, w_{jk}, w_{kl} are the weight matrix. and B_{ij}, B_{jk}, B_{kl} are threshold matrices.

Normalize the coefficients between the obtained process parameters and structural variables based on the relationship obtained in this article, and draw their thermal matrix diagram (As shown in Table 5)

Table 5. Coefficient thermodynamic matrix

	Reception distance	Hot air velocity
Thickness	0.967143	0.032857
Porosity	0.965483	0.034517
Compression resilience	-0.961751	-0.038249

As can be seen from the figure, the correlation between the thickness of receiving distance and porosity is stronger than the positive correlation between hot air velocity and the negative correlation between hot air velocity and compression resilience. The correlation between hot air velocity and thickness and porosity is weaker than the positive correlation between receiving distance and compression resilience is weaker than the negative correlation between receiving distance.

4. Conclusion

This article first studies the changes in structural variables and product performance after intercalation. By establishing a multiple linear regression model, it is found that the change rate of compression resilience and filtration resistance is related to the intercalation rate, while other indicators are independent of the intercalation rate. After that, this paper studies the relationship between process parameters and structural variables. Through the establishment of a multi-layer perceptron model, it is concluded that the correlation between receiving distance and thickness and porosity is stronger than the positive correlation of hot air velocity, and the correlation with compression resilience is stronger than the negative correlation of hot air velocity; The correlation between hot air velocity and thickness and porosity is weaker than the positive correlation of receiving distance, and the correlation with compression resilience is weaker than the negative correlation of receiving distance.

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