Research on property control of intercalated melt-blown nonwoven materials based on correlation analysis and neural network model

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Abstract. Intercalated melt-blown nonwovens can solve the poor compression resilience caused by melt-blown nonwovens fibers, which is helpful to improve the performance of products, so it is of great significance to study the performance control of intercalated melt-blown nonwovens. In this paper, correlation analysis, BP neural network model and canonical correlation analysis model were constructed to analyze the changes of product performance before and after intercution. Finally, the optimal production process parameters were determined as the acceptance distance of 22.98 cm and the hot air speed of 1790 r/min through the construction of the model, which provided a certain theoretical basis for the product performance control mechanism.

Keywords: intercalation melt-blowout method, multiple linear regression, Spearman correlation coefficient, canonical correlation analysis, neural network.

1. Introduction

With the large-scale production of masks caused by the epidemic, the phenomenon of substandard quality appears frequently. Therefore, melt-blown nonwovens [1] with advantages of better filtration efficiency, light weight, low production process difficulty, environmental protection and low price have become the main development direction of filtration materials. However, because the melt-blown nonwovens fiber is very fine, its resilience against compression (i.e. compression resilience) is poor, which makes its performance difficult to be guaranteed in the process of making masks. Therefore, the intercalated melt-blown nonwoven materials with "Z-type" structure produced by the intercalated melt-blown method came into being. Due to the interaction between the preparation process parameters of intercalated melt-blown nonwoven materials, the performance of masks is affected. Therefore, it is very important to study the performance control of intercalated melt-blown nonwovens, which can provide a theoretical basis for product performance control mechanism.

2. Model Construction

2.1. Correlation analysis

In order to preliminatively explore whether intercalation [2] affects product performance, the change rate of each index before and after intercalation is analyzed first, and the formula to calculate the change rate of performance index is as Eq (1) follows. On this basis, the correlation analysis of intercalation rate and thickness, porosity, compression rebound rate, filtration resistance, filtration efficiency and air permeability was carried out to analyze the influence of intercalation rate on performance.

$$\Delta\bar{k_i} = \frac{\overline{k_i' - \bar{k_i}}}{\bar{k_i}} \tag{1}$$

Where $\overline{k_\iota}$ is the average value of each group of results before intercalation, k_i' is the average value of each group of results after intercalation, so as to obtain the change rate of the average value before and after intercalation, and the result is not affected by the multi-index dimension.
Pearson's correlation model was established by Eq (2):

$$r_s = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)} \tag{2}$$

d_i is the grade difference between two groups of data. A rank is the position in which a set of data is sorted. *n* is the number of samples. Firstly, the correlation coefficient between the intercalation rate and each parameter is solved. It can be seen from the table that when n=25, the correlation coefficient *r* must be greater than 0.337, and the obtained *p* value must be less than 0.1, so that a significant conclusion can be drawn.

2.2. Multiple regression model

The dependent variables thickness, porosity and compressive resilience are y_1, y_2, y_3, respectively, and the independent variables receptive distance and hot air velocity are x_1, x_2, respectively. The equation describing how the dependent variable y depends on the independent variables x_1, x_2 and the error term ε is called the multiple regression model. We established the following multiple regression model (Eq 3):

$$\begin{cases} y_1 = a_1 + b_1x_1 + c_1x_2 + \varepsilon_1 \\ y_2 = a_2 + b_2x_1 + c_2x_2 + \varepsilon_2 \\ y_3 = a_3 + b_3x_1 + c_3x_2 + \varepsilon_3 \end{cases} \tag{3}$$

The model says that *y* is a linear function of x_1 and x_2. The error term ε reflects the random factors other than the linear relationship between the acceptance distance x_1 and the hot air speed x_2 with *y*, that is, the influence of factors on *y* that we have not taken into account, also called unobservable disturbance term[3].

The model parameters were estimated by establishing the estimated multiple regression equations (Eq (4)).

$$\widehat{y_\iota} = \widehat{a_\iota} + \widehat{b_\iota}x_1 + \widehat{c_\iota}x_2 \tag{4}$$

i=1,2,3, $\widehat{y_\iota}$, $\widehat{a_\iota}$, $\widehat{b_\iota}$ and $\widehat{c_\iota}$ are the estimated values of y, a, b, and c. b_1 is the average change in the dependent variable *y* for every unit change in x_1, when x_2 is constant. $\widehat{b_2}$ is the average change in the dependent variable *y* for every unit change in x_2 when x_1 is constant. To obtain the estimated values of the parameters, we use the least square method to minimize the sum of squared residuals Q (Eq (5)).

$$Q = \sum (y_i - \widehat{y_\iota}_i)^2 = \sum (y_i - \widehat{a_\iota} - \widehat{b_\iota}x_1 - \widehat{c_\iota}x_2)^2 \tag{5}$$

The corresponding parameter values can be obtained by solving (Eq (6)):

$$\begin{cases} \dfrac{\partial Q}{\partial a_i}|_{a_i=\widehat{a_\iota}} = 0 \\ \dfrac{\partial Q}{\partial b_i}|_{b_i=\widehat{b_\iota}} = 0 \\ \dfrac{\partial Q}{\partial c_i}|_{c_i=\widehat{c_\iota}} = 0 \end{cases} \tag{6}$$

2.3. Canonical correlation analysis model

Proposed by Hotelling, canonical correlation analysis aims to transform the analysis of the correlation between two groups of variables into the analysis of the correlation between the linear combination of one group of variables and the linear combination of another group of variables. The selected pairs of linear combinations are called canonical variables and their correlation coefficients become canonical correlation coefficients. The canonical correlation coefficient indicates the strength of the relationship between two variables. The larger the canonical correlation coefficient is, the stronger the correlation is.

In the product structure, the thickness, porosity and compressive resilience y_1, y_2, y_3 are set as the first group of variables Y= (y_1, y_2, y_3). Product performance Filtration resistance, filtration efficiency and air permeability z_1, z_2, z_3, set as the second group of variables Z= (z_1, z_2, z_3). Some representative typical variables U_i and V_i are obtained from these two groups of variables, so that these two comprehensive variables are linear combinations of the original variables [4]. The following model was established (Eq (7)):

$$\begin{cases} U_i = e_i y_1 + f_i y_2 + g_i y_3 \\ U_i = h_i z_1 + j_i z_2 + k_i z_3 \end{cases} \tag{7}$$

After combining the two groups of variables, solve the covariance matrix of $(Y, Z)^T$ (Eq (8,9)):

$$\sum = \begin{bmatrix} \sum 11 & \sum 12 \\ \sum 21 & \sum 22 \end{bmatrix} \tag{8}$$

$$\sum\nolimits_{11} = cov(Y), \sum\nolimits_{22} = cov(Z), \sum\nolimits_{12} = \sum\nolimits_{21} T = cov(Y, Z) \tag{9}$$

Since finding the maximum value of $Corr(U_i,\ V_i)$ is equivalent to finding the maximum eigenvalue [5], the following can be obtained (Eq (10)):

$$Corr(U_i, V_i) = \frac{Cov(U_i, V_i)}{\sqrt{D(U_i)}\sqrt{D(V_i)}} \begin{bmatrix} e_i \\ f_i \\ g_i \end{bmatrix} \sum\nolimits_{12} [h_1, j_i, k_i] \tag{10}$$

2.4. BP neural network[6]

In this model, the input layer is the thickness, porosity and compression recovery elasticity y1, y2, y3 in the product structure; the output layer is the filtration efficiency z2 in the product performance; the transmission function of neurons in the hidden layer is tansig function; the transmission function of neurons in the output layer is purelin function; and the training function of back propagation is traingdx function.

At the same time, in order to ensure the prediction accuracy, we determined the best number of hidden layer neurons as 7 by trial and error method through several training sessions. The neural network can not only learn well, but also not easy to overfit. Similarly, in order to ensure the convergence of neural network and obtain good prediction accuracy, we trained for many times, and finally decided to set the training times to 50000, the learning speed to 0.04, the training target to be less than 0.65e-3 to stop training, and 950 times to show the results. The pattern diagram of neural network structure is shown as Fig. 1 follows.

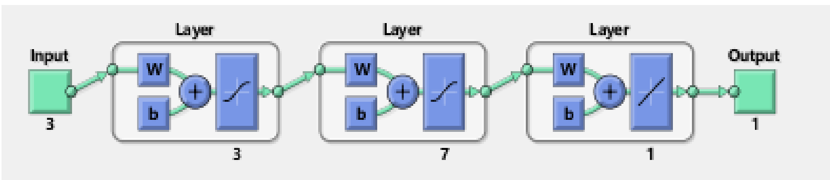

Fig. 1 Structure of neural network

BP neural network [7] model was used twice to train the data of process parameters and structural variables, structural variables and filtration efficiency, so as to get the relationship between process parameters and filtration efficiency. According to the data analysis, it is found that the acceptance distance of the process coefficient is [15,25], and the speed of the hot air is in the interval of [1000,3000], and the possibility of obtaining the highest hot air efficiency is the highest. Then the corresponding structural variables are obtained by using the relationship between the process coefficient and the structural variables in 3.4. Maximum filtration efficiency can be obtained.

3. Result Analysis

3.1. Abbreviations and Acronyms

Firstly, descriptive statistics of each performance index before and after intercalation were carried out, and the results obtained are shown in Table 1.

Table 1. Descriptive statistics of each performance indicator

	before			after		
	Mean	**SD**	**variance**	**Mean**	**SD**	**variance**
Thickness (T, mm)	1.5188	0.3826	0.1460	2.6074	0.5490	0.3010
Porosity (P, %)	92.3492	2.0909	4.3720	95.8612	0.9180	0.8430
Compression resilience rate (C, %)	79.4416	9.3261	86.9750	86.6228	4.4333	19.6540
filtration resistance (FR, Pa)	29.7844	16.4624	271.0120	24.1573	14.7835	218.5520
filter efficiency (FE, %)	34.9920	25.1305	631.5420	49.3867	18.8744	356.2440
Breathability (B, mm/s)	347.6040	189.5751	35938.7280	422.1344	236.8167	56082.1660

Table 2. Change rate of each performance index after intercalation

T	P	C	FR	FE	B
0.7168	0.0380	0.0904	-0.1889	0.4114	0.2144

The results are shown in Table 2. According to the data in Table 2, the thickness, porosity and compressive resilience of the structural variables have all increased after intercalation, among which the thickness has the most significant increase, and the rate of change is above 50%, while the rate of change of porosity is between 0% and 7%. The filtration resistance in the product performance is reduced by about 20%, and the filtration efficiency and air permeability are improved. This means that the overall data after intercalation is better than the data before intercalation, and the product performance is better and the product structure is better.

Table 3. Correlation coefficients between intercalation rate and parameters

	T	P	C	FR	FE	B
Intercalated rate	0.7168	0.0380	0.0904	0.1889	0.4114	0.2144

As shown in Table 3, the absolute value of the correlation coefficient between the change rate of thickness, porosity, filtration efficiency and air permeability and intercalation rate is less than 0.337, so the null hypothesis cannot be rejected, that is, there is no significant correlation. Therefore, the size of intercalation rate does not affect the change rate of thickness, porosity, filtration efficiency and air permeability. The absolute value of the correlation coefficient between the change rate of compression resilience rate and filtration resistance and intercalation rate is greater than 0.337, that is, significant correlation ($p<0.1$). Therefore, the size of intercalation rate will affect the change rate of compression resilience rate and filtration resistance to a certain extent.

3.2. Establishment of multiple regression model

The multiple regression equation obtained is as Eq (11) follows:

$$\begin{cases} y_1 = 0.0542x_1 + 0.0018x_2 - 0.8602 \\ y_2 = 0.0841x_1 + 0.0030x_2 + 90.3488 \\ y_3 = -0.0688x_1 - 0.0027x_2 + 91.4098 \end{cases} \tag{11}$$

P of the three regression equations were all less than 0.05, indicating that the model passed the significance test. The acceptance distance, hot air speed and the corresponding P-value are all close to 0, and the confidence interval does not include zero. Moreover, SSE is close to 0 and goodness-of-fit R^2 is close to 1, indicating that the fitting results are good. To test the existence of heteroscedastic error terms, White test was used. The p value was 0.9741, and the error term ε did not have heteroscedastic.

According to the regression analysis model simulation, we obtained the comparison graph of the predicted value and the actual value (Fig. 2), and found that there was little difference between the actual value and the predicted value of thickness and porosity.

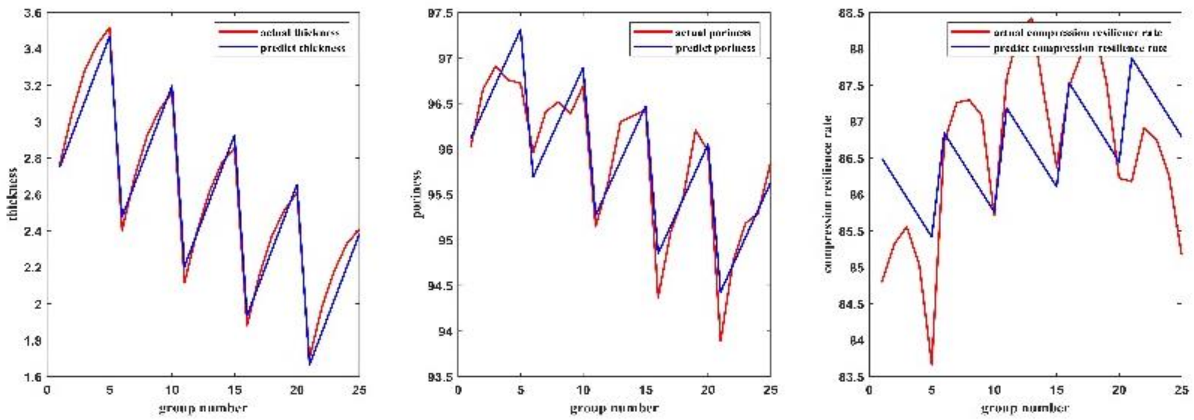

Fig. 2 Comparison of predicted and actual values obtained by multiple regression

However, the actual value of compressive resilience is significantly different from the predicted value, and the predicted value interval is relatively small. Therefore, we decided to use BP neural network to train the data and get the comparison graph of the predicted value and the actual value, and found that the fitting effect of compression resilience rate is better.

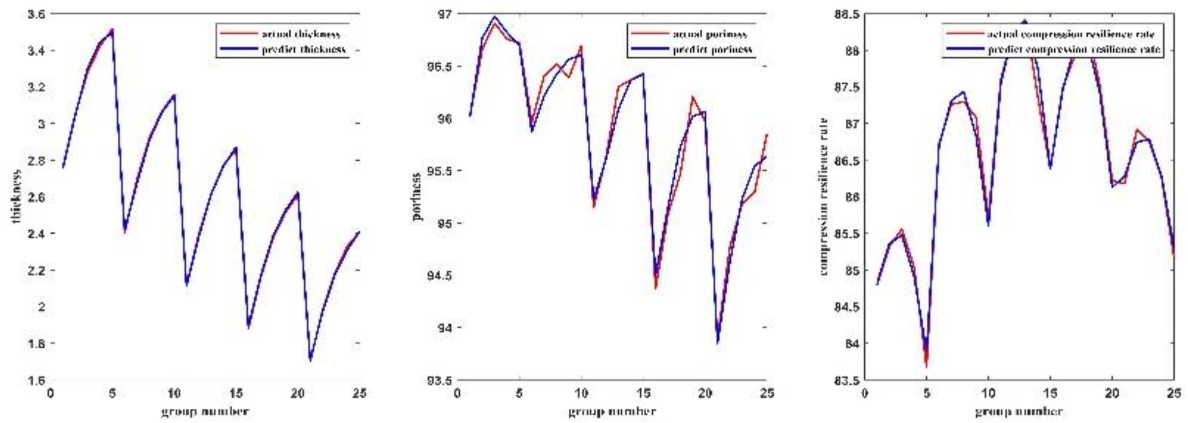

Fig. 3 Comparison of predicted value and actual value obtained by BP neural network

Considering that the sample is small and the data are not divided into training and validation sets, we decide to average the predicted value of the compressive resilience rate obtained by multiple regression and the predicted value obtained by BP neural network, so as to obtain the final predicted value of the compressive resilience rate. However, the regression equations obtained in the multiple regression fit well, and the predicted values of thickness and porosity are not different from the actual values, so the final results of thickness and porosity are obtained by the multiple regression. We get the following results (Table 4):

Table 4. Prediction results

Receiving distance (cm)	Hot wind speed (r/min)	Thickness (mm)	Porosity (%)	Compression resilience rate (%)
38	850	2.7294	96.0946	86.2521
33	950	2.6384	95.9741	87.2742
28	1150	2.7274	96.1536	86.7607
23	1250	2.6364	96.0331	85.7633
38	1250	3.4494	97.2946	84.6961
33	1150	2.9984	96.5741	86.3988
28	950	2.3674	95.5536	87.6983
23	850	1.9164	94.8331	87.4825

3.3. Relationship between structural variables and product performance

We obtained the canonical correlation coefficients of the two groups that passed the significance test, that is, the p value was close to 0, which were 0.844 and 0.562, respectively. Through the significance test, it is preliminarily indicated that there is a strong correlation between structural variables and product performance. According to Table 5, it can be calculated that the contribution rate of the first pair of typical variables is 2.483 / (2.483+0.463+0.012) =0.839419, which has reached 80%. Therefore, the subsequent analysis focuses on the first pair of typical variables.

Table 5. Typical correlation coefficients

	correlation index	eigenvalue	F	*p*
1	0.844	2.483	17.970	0.000
2	0.562	0.463	7.590	0.000
3	0.110	0.012	0.870	0.354

Since the contribution rate of the first pair of typical variables accounted for more than 80% of the total contribution rate, we then explored the relationship between the two variable groups when the correlation coefficient was 0.844. It can be seen from Table 6 that they are linear combination coefficients obtained after standardization of the original variables. According to the typical variable U_1 of the first group of variables Y, the weights of thickness, porosity and resilience of compressibility are -1.092, 0.021 and -0.156, respectively. The greater the absolute value of the weights, the greater the determinacy of the canonical variables. Since the absolute value of the weight of thickness -1.092 is the largest, it indicates that the typical variable U_1 of the variable is mainly determined by the thickness. For the typical variable V of the second group of variables, the weights of filtration resistance, filtration efficiency and air permeability are 0.859, 0.64 and 0.437, respectively. Since the weight of filtration resistance is 0.859, the absolute value is the largest, indicating that the typical variable V_1 of variable V is mainly determined by filtration resistance, but the weight of filtration efficiency and air permeability is close to 0.5, indicating that the typical variable V_1 will also have a relatively obvious influence [8].

Table 6. Corresponding linear combination coefficients of standardized canonical correlation variables

*U*1	weight	*V*1	weight
thickness	-1.092	filtration resistance	0.859
porosity	0.021	filter efficiency	0.640
Compression resilience rate	-0.156	breathability	0.437

The typical load coefficient is the simple correlation coefficient between the typical variable and all the variables in the group. The larger the absolute value of the typical load coefficient is, the stronger the correlation between this variable and the typical variable is. According to Table 7, it can be found that the typical variable U_1 of the first group of variables Y has an obvious strong negative correlation with thickness and porosity, and an insignificant positive correlation with compression and resilience. The typical variable V_1 of the second group of variables Z has a strong positive correlation with filtration resistance, a relatively insignificant positive correlation with filtration efficiency, and a negative correlation with air permeability.

Table 7. Typical load coefficients and cross load coefficients

U_1	Typical load	Cross load
thickness	-0.992	-0.837
porosity	-0.909	-0.767
Compression resilience rate	0.413	0.349
V_1	Typical load	Cross load
filtration resistance	0.919	0.776
filter efficiency	0.616	0.520
breathability	-0.420	-0.355

Finally, we get the expression of a pair of typical variables (Eq (12)):

$$\begin{cases} U_i = -1.092y_1 + 0.021y_2 - 0.156y_3 \\ V_i = 0.859z_1 + 0.640z_2 + 0.437z_3 \end{cases} \tag{12}$$

The contribution rate of these two typical variables accounted for more than 80% of the total contribution rate, and the correlation coefficient was 0.844, indicating that the structural variables of the two variable groups had a strong positive correlation with product performance. And then according to the cross load and typical load, we probably conclude that thickness is negatively correlated with filtration resistance, filtration efficiency, and positively correlated with air permeabilityv [9]; Porosity is negatively correlated with filtration resistance and filtration efficiency, and positively correlated with air permeability. Compression resilience is positively correlated with filtration resistance and filtration efficiency, and negatively correlated with air permeability.

Table 8. Correlation coefficients between structural variables and product performance

	thickness	**porosity**	**compression resilience rate**
thickness	1.0000	0.9785	-0.4785
porosity	0.9785	1.0000	-0.4246
compression resilience rate	-0.4785	-0.4246	1.0000

	filtration resistance	**filter efficiency**	**breathability**
filtration resistance	1.0000	0.8254	-0.6146
filter efficiency	0.8254	1.0000	-0.7731
breathability	-0.6146	-0.7731	1.0000

According to Table 8, the correlation coefficient between thickness and porosity is as high as 0.7, showing a highly positive correlation. However, the correlation coefficient between thickness and compressive resilience as well as between porosity and compressive resilience is negative, about -0.5, showing an insignificant negative correlation.

The correlation coefficient between filtration resistance and filtration efficiency is greater than 0.8, indicating a strong positive correlation. The correlation coefficient between permeability and filtration efficiency is also close to -0.8, indicating a good negative correlation. The correlation coefficient between filtration resistance and permeability is -0.61, not more than -0.7, indicating an insignificant negative correlation, which is also consistent with the typical load coefficient in the canonical correlation analysis [10].

3.4. Filtering efficiency prediction

Firstly, BP neural network was trained between structural variables and filtering efficiency, and the training results of samples were obtained, and the R value was 0.9978, which was very close to 1. MSE is 0.001148, which is close to 0, indicating that the model is good and the prediction accuracy is high (Fig. 4).

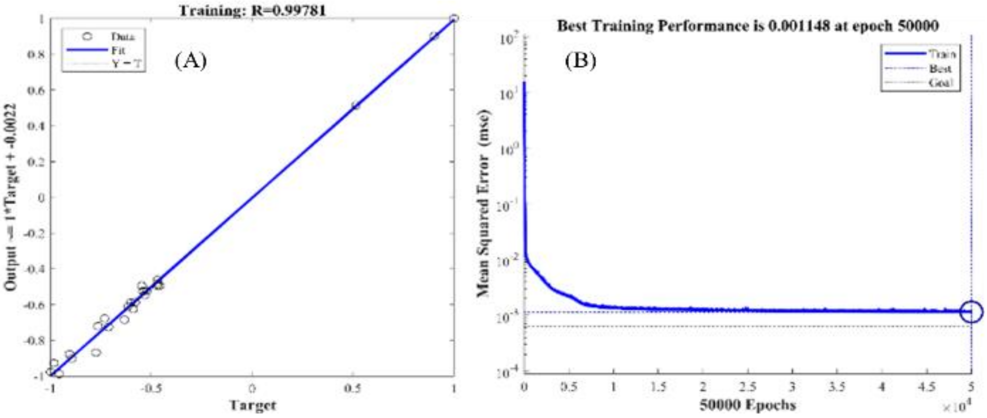

Fig. 4 Curve fitting (A) and MSE (B)

According to the acceptance distance of process coefficient in [15,25] and the speed of hot and hot air in [1000,3000], we obtained 143 groups of acceptance distance and hot air speed. BP neural network training was conducted on these 143 groups to obtain the corresponding thickness, porosity and compressive resilience of each group. Then the BP neural network is trained on the 143 groups of structural variables, and the corresponding filtering efficiency of each group is obtained.

Table 9. Process parameters, structural variables and filtration efficiency values of 143 groups

No.	receiving distance	Hot wind speed	thickness	porosity	Compression resilience rate	filter efficiency
1	15	1000	1.9818	94.7400	85.3528	42.8351
2	15	1025	2.0225	94.8294	85.3061	51.8763
3	15	1050	2.0594	94.9110	85.2081	53.5833
4	15	1075	2.0931	94.9860	85.0625	45.5385
5	15	1100	2.1243	95.0554	84.8771	27.6592
…	…	…	…	…	…	…
71	20	1125	2.3415	95.5177	85.9857	71.6443
72	20	1150	2.3691	95.5918	85.7130	77.7733
73	**20**	**1175**	**2.3970**	**95.6635**	**85.4464**	**88.4996**
74	20	1200	2.4261	95.7323	85.2016	84.4099
75	20	1225	2.4570	95.7975	84.9915	71.4055
…	…	…	…	…	…	…
139	25	1200	2.6271	96.1801	86.1707	47.0916
140	25	1225	2.6575	96.2125	85.9119	67.3016
141	25	1250	2.6894	96.2370	85.6947	70.0832
142	25	1275	2.7231	96.2540	85.5249	66.4884
143	25	1300	2.7583	96.2640	85.4034	62.1693

By finding the maximum filtration efficiency among 143 groups (Table 9), we found that the maximum filtration efficiency of group 73 was 88.50%, the corresponding receiving distance was 20 cm, and the hot air speed was 1175 r/min.

4. Conclusion

In this paper, a variety of models were used to analyze the changes of product performance before and after intercalation and the influence of structural variables. Finally, the optimal production process parameters were determined as the acceptance distance of 22.98cm and the hot air speed of 1790r/min through the construction of the model, which provided a certain theoretical basis for the product performance control mechanism.

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