Research on performance control of intercalated meltblown nonwovens based on neural network and grey relational analysis

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Abstract. In this paper, aiming at the performance of intercalated meltblown nonwoven materials, the relationship between its process parameters, structural variables and product performance is explored, and the product performance can be optimized by changing the process parameters through regression, planning and other methods. The results of grey correlation analysis showed that the intercalation rate had a significant effect on both structural variables and product properties. According to the results of the multivariate nonlinear regression model, the ideal maximum cleaning efficiency can reach 99.7%. Finally, in order to explore when the influencing factors such as acceptance distance, hot air speed, thickness, and compression rebound rate are limited, to achieve the goal of achieving the highest filtering efficiency and the smallest filtering resistance as possible, the machine learning method is used, and random forest is selected as the regression model, build samples and make predictions, and finally get the optimal value of the acceptance distance of 21 cm and the hot air speed of 1580 r/min.

Keywords: Neural network, grey relational analysis, spearman correlation coefficient, machine learning, product performance.

1. Introduction

In recent years, the epidemic has been rampant, and masks have almost become a necessity. Therefore, their production level and processing technology have attracted widespread attention world-wide. The pursuit of excellent filtration performance, simple production process, low cost, and light and thin quality is increasing day by day. However, because the melt blown nonwovens woven by the original melt blown method are very slender and have a low compression rebound rate, so scientists created a new melt-blown method-intercalation melt-blown method to produce a new “Z-shaped” structure of intercalated melt-blown nonwoven materials [1].

There are many process parameters in the production process of intercalated melt blown nonwoven materials, and each process parameter affects each other (mainly the receiving distance and hot air speed), which in turn affects the structural variables (mainly based on thickness, porosity, compression resilience), and structural variables will affect product performance (mainly filtration resistance, filtration efficiency, and air permeability), so the research content and production process are extremely complex. By establishing the correlation between process parameters, structural variables, and product performance, it helps to reduce the complexity of the manufacturing process to a certain extent, improve the ratio of resources, and improve product performance [2].

2. Model building

2.1. Grey relational model

According to the grey theory system, the intercalation rate and the other six indexes are regarded as a gray system, the intercalation rate y is the reference sequence, and the other indexes are the comparison sequence x_i (thickness x_1, porosity x_2, compression resilience x_3, filtration resistance x_4, filtration efficiency x_5, air permeability x_6), the correlation coefficient between the valuation level and each indicator is calculated by the formula [3-4].

$$\xi i(k) = \frac{min_i\, min_k|y(k)-x(k)|+\rho max_i max_k|y(k)-x_i(k)|}{|y(k)-x(k)|+\rho max_i max_k|y(k)-x_i(k)|} \tag{1}$$

Among them, $\xi i(k)$ in Eq (1) is the coefficient of x_i to y(k) at point k, $|y(k)-x_i(k)|$ is the absolute difference between y and x_i at point k, $\boldsymbol{min_i\, min_k|y(k)-x(k)|}$ is the absolute value of the second-level minimum difference between the y sequence and the xi sequence at the point of view, $\boldsymbol{max_i max_k|y(k)-x_i(k)}$ is the absolute value of the second-level maximum difference between the y sequence and the xi sequence at the point of view, ρ is the gray discriminant coefficient, the value is between 0 and 1, and the value here is 0.5. Bring the correlation coefficient of each index into the formula (Eq (2)) to get the correlation r_i between x_i and y(k)

$$r_i = \frac{1}{n}\sum_{k=1}^{n} \xi i(k) \tag{2}$$

2.1.1. Normality test

Since the sample size is greater than 75, the Kolmogorov Smirnov test is used. In order to explore the relationship between process parameters and structural variables, the process variable should be a factor and the structural variable should be a dependent variable, and a normality test is performed. The p-values of the test results are all greater than 0.05, which can be seen to obey the normal distribution, and then the analysis of variance is performed.

Table 1. Tests for between-subject effects.

		F	p
Receiving distance (cm)	Thickness (mm)	61388.155	.000
	Porosity (%)	88.361	.000
	Compression rebound rate (%)	338.437	.000
Hot air speed (r/min)	Thickness (mm)	529215.158	.000
	Porosity (%)	50.168	.000
	Compression rebound rate (%)	144.175	.000
Receiving distance (cm) * hot air speed (r/min)	Thickness (mm)	5.403	.000
	Porosity (%)	2.947	.002
	Compression rebound rate (%)	1.177	.318

As can be seen from the results in Table 1, when the receiving distance changes, the significance levels of thickness, porosity, and compression resilience are far less than 0.05, and there is no significant difference. It can be seen that there is a certain relationship between the thickness and the three. Similarly, it can be seen that when the hot air velocity changes, the thickness, porosity and resilience are also less than 0.05, and there is no significant difference.

2.1.2. The construction of BP neural network

The working method of BP neural network is mainly divided into three processes (Figure. 1). The first is the forward direction of the signal, the signal is transmitted from the input layer weighted calculation to the hidden layer, and then the new weight is output through the calculation of the hidden layer, and so on, and finally to the output layer. The second is the back propagation of the error. The BP neural network model calculates the error between the predicted data and the actual data according to the output result of the output layer, then adjust the weight and bias from the hidden layer to the output layer and the weight and bias from the input layer to the hidden layer according to the error. Finally, the accuracy is calculated, and the model test is performed, the process is repeated until the mean square error between the output result and the expected output result reaches a reasonable range, and then the training ends [5-6].

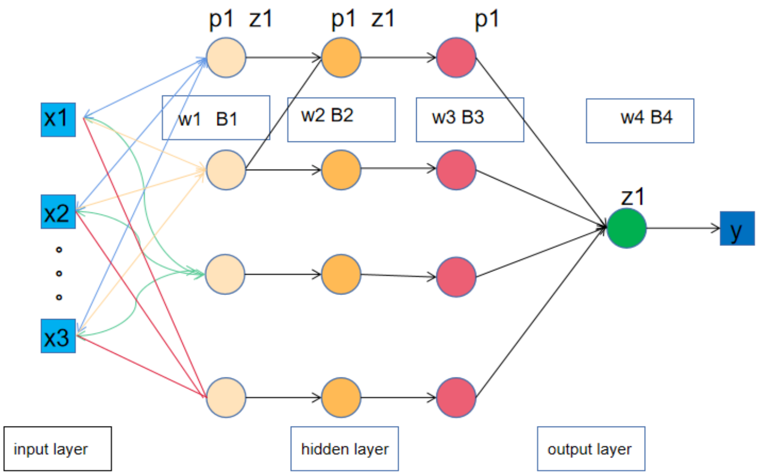

Figure 1. Schematic diagram of BP neural network algorithm.

In this paper, the hot air velocity [X1] and the receiving distance [X2] are used as the input, the thickness [Y1], the porosity [Y2] and the compression spring rate [Y3] are the output of the complex function mapping problem, and the hidden layer is five layers, the sigmod function is the activation function for BP neural network simulation.

After outlier removal and normalization, there are 75 data of acceptance distance, hot air velocity, thickness, porosity, compression resilience, filtration resistance and filtration efficiency of meltblown nonwovens. Randomly select five data as validation samples, and the remaining seventy data as training set.

The BP neural network includes an input layer, five hidden layers and an output layer, with two neurons and three output nodes. From the output layer to the hidden layer and between the hidden layers, the sigmoid function is used as the activation function, the perelin function from the last hidden layer to the output layer is used, the expression between the network input data and the output data is obtained as shown in Eq 3.

$$y_k' = \sum_{j=1}^{r} v_j \cdot \mathrm{f}[\sum_{\mathrm{i}=1}^{\mathrm{m}} \mathrm{w_{ij}} \cdot \mathrm{p_i} + \theta_\mathrm{j} \tag{3}$$

k=1, 2…N, $\mathrm{w_{ij}}$is link weight, θ_j is the threshold, y_k is the expected output value, $y_k{}'$ is the actual output value of the network. The schematic diagram of the neural network structure is shown in Figure. 2.

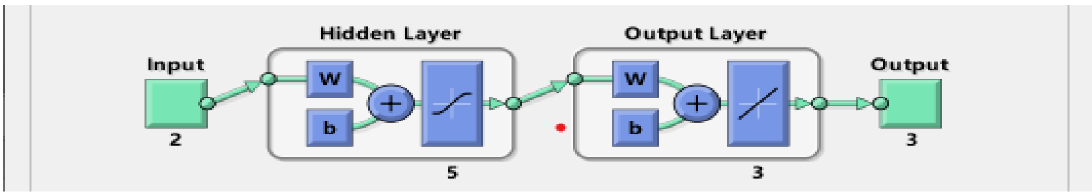

Figure 2. Schematic diagram of the neural network structure.

The main parameters included in the prediction of BP neural network are: max training step, snet. tranParam. epoch; interval steps for training results, net.trainParam.show; learning rate, net.trainParam.1r; training target error, net.trainParam.goal. The parameters set in this model are shown in Table 2:

Table 2. Parameter values of BP neural network.

max training step	interval steps for training results	learning rate	training target error	training times
1000	1	0.0000001	0.000001	1000

2.1.3. Solution of the model

Since the raw data of thickness, porosity, compression resilience, filtration resistance, filtration efficiency, and air permeability have different dimensions, the size of the data is very different, and the range is also different, excessive differences will seriously affect the subsequent correlation analysis, and at the same time will weaken the influence of some variables on the program, it is necessary to normalize the thickness, porosity, compression rebound rate, filtration resistance, filtration efficiency, and air permeability after removing outliers, and convert all data into data between [0, 1] to eliminate the impact of data size varies.

In this paper, the same-division synthesis method is used for normalization. The normalization formula (Eq4) for thickness, porosity, compression resilience, filtration resistance, filtration efficiency, and air permeability is as follows:

$$x_i{}' = \frac{x_i}{\sum_{i=1}^{n} x_i} \tag{4}$$

$\sum_{i=1}^{n} x_i$ is the sum of the column where x_i is located, $x_i{}'$ is the value of x_i after normalization

2.2. Correlation model

2.2.1. Normality test

Since the number of samples is 75, which is much larger than 30, it belongs to a large sample, and the JB test is used. The steps are as follows:

First, construct the JB statistic. For a random variable xi, assuming that its skewness is s and its kurtosis is k, the JB statistic is constructed as follows (Eq 5):

$$JB = \frac{N}{6}[S^2 + \frac{(K-3)^2}{4}] \tag{5}$$

If xi is a normal distribution, then in the case of large samples, JB follows a chi-square distribution with 2 degrees of freedom (the skewness of the Chint distribution is 0, and the kurtosis is 3). From table 3, Only the filter resistance follows a normal distribution, using the spearman correlation coefficient.

Table 3. Normal distribution hypothesis test.

Thickness	Porosity	Compression rebound rate	Filter resistance	Filtration efficiency	Breathability
0.31714325	0.031056414	0.121906413	0.5	0.001	0.002752462
NO	NO	NO	YES	NO	NO

2.2.2. Spearman correlation coefficient

Spearman's rank correlation coefficient, also known as rank correlation, does not require the distribution of the original variable [7-8]. It is suitable for data that does not obey the normal distribution and data whose overall distribution state is unknown. It is suitable for the correlation coefficient between ordinal variables and ordinal variables. The calculation formula is Eq 6:

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

Where $d_i = (x_i - y_i)$, x_i and y_i are the ranks of the two variables sorted by size or pros and cons, respectively, n is the sample size, the value range of the spearman correlation coefficient is [-1, 1], and the larger the absolute value, the stronger the correlation. If r_s is an integer, it is a positive correlation, and if r_s is a negative number, it is a negative correlation. If the absolute value is equal to 1, it is a perfect positive correlation or a perfect negative correlation.

2.3. Multiple regression model

Multivariate nonlinear regression is used to build the model, the independent variables are the hot air speed and the receiving distance, and the dependent variable is the filtration efficiency, and the nonlinear relationship between the dependent variable and the independent variable is obtained [9].

In order to study the influence of hot air speed and receiving distance on filtration efficiency, it is assumed that the combined effect of process parameters on filtration efficiency is additive, and the independent variables are hot air speed and receiving distance, and the dependent variable is filtration efficiency. A regression fitting model is built (Eq 7):

$$y = a \cdot x_1^2 + b \cdot x_2^2 + c \cdot x_1 + d \cdot x_2 + e. x_1 \cdot x_2 + f \tag{7}$$

x_1 indicates acceptance distance, x_2 indicates hot air speed, a, b, c, d, e, f are parameters respectively. Taking this as the objective function, the regression equation was solved by SPSS.

3. Model solving and results analysis

3.1. The effect of intercalation on product performance

It can be seen from Figure 3 that after intercalation, the thickness, porosity, compression resilience, filtration resistance, filtration efficiency, and air permeability all decreased slightly. In terms of overall volatility, the standard deviation and variance of the data decreased. Porosity, compression resilience, filtration resistance, filtration efficiency, and air permeability have improved stability.

It can be seen from table 4 that the intercalation rate has a certain influence on thickness, porosity, compression resilience, filtration resistance, filtration efficiency, and breathability, and has the greatest influence on thickness. Overall, the intercalation rate has a greater impact on the structural variables.

3.2. BP neural network model

Table 5 shows the prediction results of the neural network. It is not difficult to see that the prediction results are good from the following goodness of fit and norm. From the regression effect (Figure. 4), it can be seen that the correlation coefficient R values are all as high as 0.97 or more, indicating that the BP neural network is more accurate for the prediction of thickness [Y1], porosity [Y2], and compression spring rate [Y3]. And the norm is 0.7, the accuracy is above 90%. It can be seen that the prediction performance is good and the results are accurate.

It can be seen from Figure. 5 that in the relationship between structural variables and product performance, filtration resistance and filtration efficiency have a strong negative correlation with thickness and porosity, and the correlation coefficients are all above 0.77. The correlations of other indicators are weak. Within the structural variables, the porosity and thickness have a strong positive correlation, and the correlation degree reaches 0.92. The correlation degrees of the other indicators are relatively general. It can be seen from the inside of the product performance that the filtration efficiency has a strong positive correlation with the filtration resistance, and the correlation coefficient reaches 0.79, while the air permeability has a strong negative correlation with the filtration efficiency and filtration resistance, and the negative correlation reaches more than 0.64.

In this paper, the sensitivity analysis of BP neural network prediction is carried out [10-11], and the input data: receiving distance and hot air speed × 10 times, the result is as table 7 follows. It can be seen from the returned results that the corresponding pre-data increase is greater than 10 times after the input variable receiving distance and hot air speed are increased by 10 times, which shows that the sensitivity of the model is good.

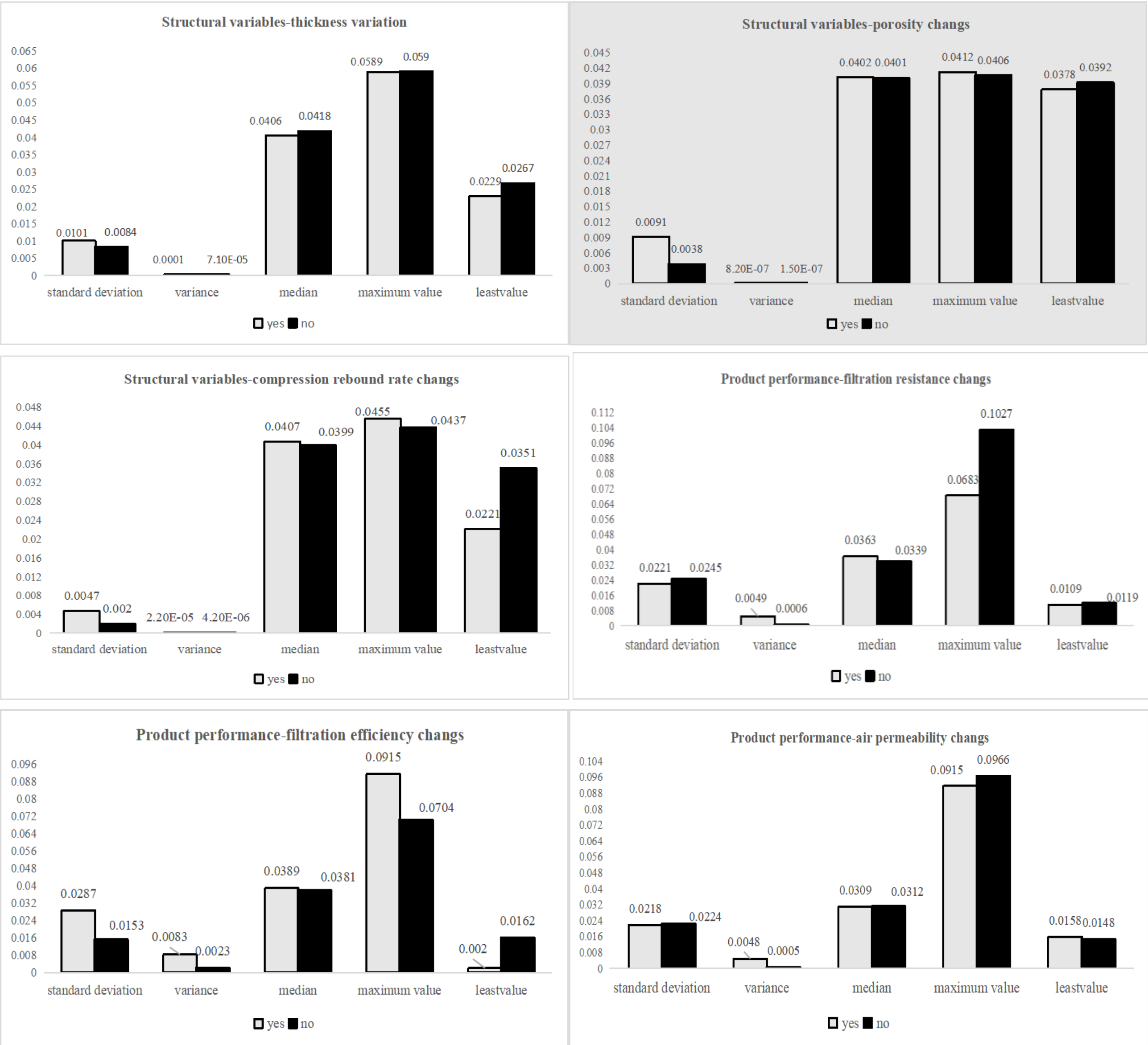

Figure 3. Comparative analysis of structural parameters and product performance data.

Table 4. Correlation coefficients.

Thickness	Porosity	Compression rebound rate	Filter resistance	Filtration efficiency	Breathability
0.727467	0.718281	0.713482	0.630428	0.697838	0.619105

Table 5. BP neural network prediction results.

Receiving distance (cm)	Hot air speed (r/min)	Thickness (mm)	Porosity (%)	Compression rebound rate (%)
38	850	2.8044	96.2449	84.6934
33	950	2.5615	96.0928	87.7469
28	1150	2.5911	96.1860	87.5895
23	1250	2.3932	95.8179	85.1191
38	1250	3.4366	96.7624	83.7734
33	1150	2.9657	96.5570	84.3172
28	950	2.2212	95.3950	88.1711
23	850	1.6978	93.9765	86.3594

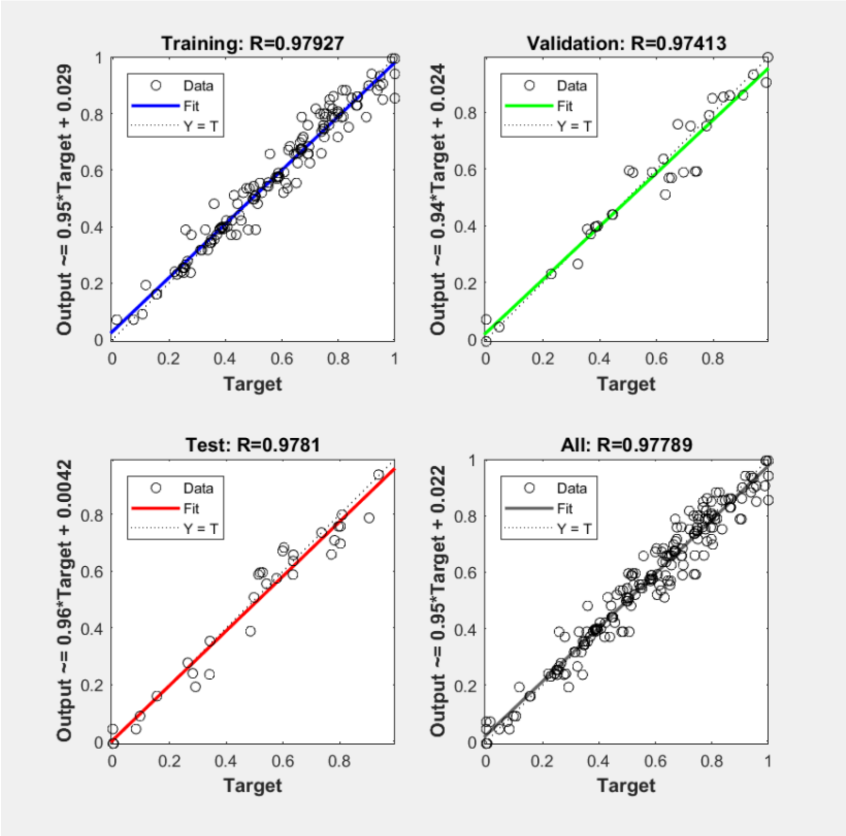

Figure 4. The regression effect of the BP neural network prediction model.

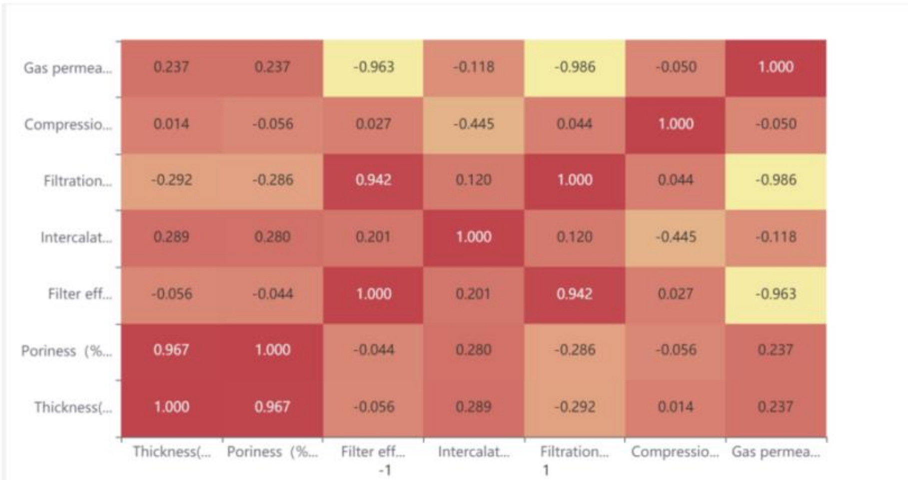

Figure 5. Spearman correlation coefficient heatmap.

Table 6. BP neural network prediction sensitivity test values.

Receiving distance (cm)	Hot air speed (r/min)	Thickness (mm)	Porosity (%)	Compression rebound rate (%)
380	8500	27.70	960.36	850.13
continued				
330	9500	26.18	960.65	877.05
280	11500	25.92	961.15	877.57
230	12500	24.51	956.89	852.09
380	12500	35.31	967.32	837.42
330	11500	29.13	965.24	873.15
280	9500	22.72	954.50	882.65
230	8500	16.75	940.40	866.94

3.3. Multiple regression model

The nonlinear regression equation obtained by calculation is as Eq 8 follows, and R^2 is 0.77:

$$y = 0.087 \cdot x_1^2 - 1.878 \cdot x_1 + 0.076 \cdot x_2 - 0.004.x_1 \cdot x_2 + 50.4 \quad (8)$$

It is obtained by finding the extreme value of the multivariate function. When x1=20, x2=120, the maximum filtering efficiency is 0.997.

4. Conclusion

This paper analyzes the relationship between process parameters, structural variables and product performance in the production process of intercalated meltblown nonwovens by using grey relational analysis, BP neural network and random forest models. The results show that the intercalation rate has a significant impact on the structural variables and product performance. In addition, under ideal conditions, the maximum filtration efficiency is 99.7%. When the practical indicators are limited, the optimal value of the receiving distance is 21cm and the hot air speed is 1580r/min. Our results provide a certain research basis for the fabrication process parameters of intercalated meltblown nonwovens.

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