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Original Paper

Study on Performance Control of Intercalation Melt-Blown Nonwovens

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Abstract

Intercalation melt-blown nonwovens are made by intercalation process by inserting fibers such as polyester staple fiber into melt-blown nonwovens. They have many excellent properties. However, the preparation process is complicated and the parameters are many, so the control study of the process parameters will help to provide a certain theoretical basis for the establishment of the product property control mechanism.

In this paper, based on data analysis and descriptive statistics, Spearman correlation coefficient, BP neural network, typical correlation analysis, multiple nonlinear regression, genetic algorithm, multiple linear regression, NSGA-II multi-objective optimization model and other algorithms and models are used to solve the performance control problems of interlayer melt-blown nonwovens.

Firstly, the data of structural variables and product performance parameters before and after intercalation were compared by mapping. It was found that the thickness and porosity increased after intercalation, some groups of compression resilience increased, and some groups became smaller, and the overall trend was larger. In addition to the thickness parameter, other parameters became better after intercalation. Finally, the intercalation rate and parameter change rate were analyzed based on Spearman correlation analysis, and it was found that intercalation rate had no effect on the changes of the above 6 parameters.

The BP neural network model between process parameters and structural variables is established. The error of the model is only 0.03, and the goodness of fit is 0.99. Thus, the relationship between process parameters and structural variables is obtained. Using the neural network model, 8 process parameters were substituted to obtain the predicted structural variable data.

Canonical correlation analysis was used to study the relationship between structural variables and product performance, and two pairs of canonical correlation variables were found to be significantly correlated. It was recognized that the greater the thickness, the smaller the filtration resistance and the *lower the filtration efficiency. Then, the relationship between structural variables and product performance was studied based on Spearman correlation analysis, and then the relationship between process parameters and filtration efficiency was studied based on multiple nonlinear regression. It is found that there is a cubic polynomial nonlinear relationship between filtration efficiency and process parameters, and a regression model is obtained. The model has good significance and high fitting degree. Finally, the regression function is taken as the objective function, and the filtering efficiency is optimized based on genetic algorithm.*

Multiple linear regression model was established, and the linear regression model of thickness and receiving distance and hot air speed, compression resilience and receiving distance and hot air speed, filtration efficiency and receiving distance, hot air speed, thickness, compression resilience, filtration resistance and receiving distance, hot air speed, thickness, compression resilience was obtained. Then, the regression model of filtration efficiency and filtration resistance was taken as the objective function, and multi-objective optimization based on NSGA-II model was carried out. The known information was taken as the constraint condition, and the optimal process parameters were obtained to meet the requirement of making filtration efficiency as high as possible and filtration resistance as small as possible.

Keywords

Spearman correlation coefficient, BP neural network, Canonical correlation analysis, Multiple nonlinear regression, Genetic algorithm, Multiple linear regression, NSGA-II multi-objective optimization

1. Problem Restatement

1.1 Question Background

Melt-blown nonwoven material is a good air filtration material with small fiber diameter, large specific surface area and high porosity. Its characteristics of good filtration effect, light weight, environmental protection and moderate price represent the main development direction of filter materials in the future. However, due to the melt-blown nonwovens fiber is very fine, resulting in its performance is often not guaranteed because of poor compression resilience in the process of use. The fiber such as polyester staple fiber and the traditional polypropylene melt-blown nonwoven fiber through intercalation composite, the PET fiber stiffness, good elasticity and other unique advantages into the traditional melt-blown filter material, can be obtained high porosity, fluffy structure, anti-compressibility and high elastic recovery performance of new air filter material. There are many parameters in the preparation process of melt-blown nonwoven materials, and there are interaction effects between the parameters, and it is more complicated after interlacing airflow. Therefore, the control study of the above parameters will help to provide a certain theoretical basis for the establishment of product performance control mechanism.

Second, model hypothesis

(1) Assume that all model prediction results do not consider the impact of sudden human intervention factors;

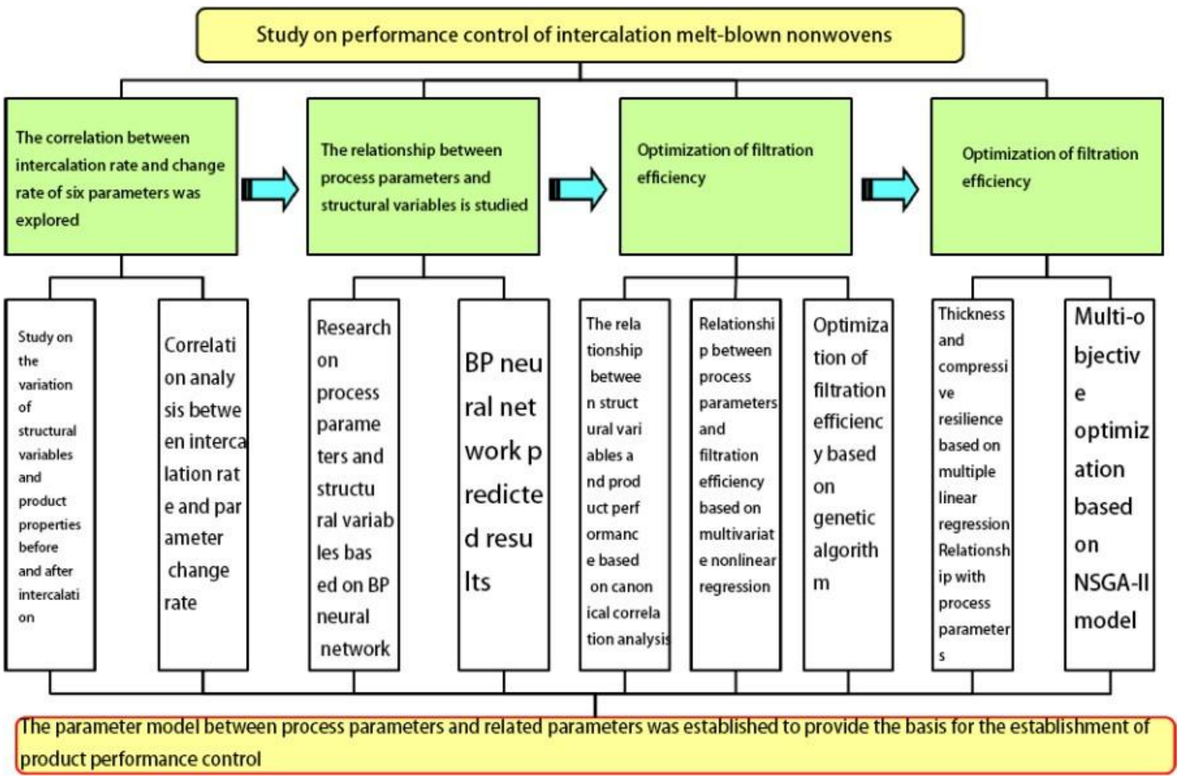
(2) Assume that the device operates normally.

(3) Assume that there are no other influencing factors other than the parameters set.

3. Symbol description

Symbols	Symbol Instructions	Symbols	Symbol Instructions
C_i	Data integrity rate for variable i	Z	Centralized observation data array
σ	Rate of Change	R	Correlation coefficient matrix
p	Number of neurons	N	Maximum number of routes
W_{sp}	Weights	L	Crowding
f	Activation function	f_k^{max}	The maximum value of the KTH objective function
M_i	The threshold of each node of the hidden layer	f_k^{min}	The minimum value of the KTH objective function
eta	Network learning rate	P_c	Cross probability
T_s	Expected output	V_{max}	Maximum comprehensive evaluation value

Four, technical route



Data analysis and preprocessing

In order to make better use of the given data, the established model can better analyze the performance control of intercalation melt-blown nonwovens. Firstly, some descriptive statistics and analysis of the data are carried out, and the data is preprocessed by the corresponding mathematical methods, which will be helpful to the establishment and solution of the model.

The data were 25 groups of controlled experiments, including the data of unintercalated materials (common meltblown materials) and intercalated meltblown materials during the experiment, including process parameters (receiving distance and hot air velocity), structural variables (thickness, porosity, compression resilience), product properties (filtration resistance, filtration efficiency, permeability) and intercalation rate. In addition, the data also included material structure variable data and product performance data of different process parameter combinations under the condition of fixed intercalation rate. Each combination experiment was repeated three times, and a total of 75 experiments were performed.

1.2 Data Integrity Analysis

In this model, the data integrity of each variable is counted and expressed by the data integrity rate, that is, the data integrity of the i variable. The invalid data include missing data, unreasonable data, etc.

(1) $$C_i = \frac{\text{Sum of valid data of the i th}}{\text{i indicator data sum}}$$

As can be seen from this definition, the larger the value, the higher the data integrity and authenticity of variable i, and the stronger the researchability. C_i For the data integrity of the indicators given in the statistical attachment, part of the statistical results are shown in Table 1.

Table 1. Shows the Statistical Results of the Integrity Rate of Some Indicators

Indi cat ors	Thic kn ess mm	Po ros ity (%)	Compr ess ive resilience (%)	Filtr ati on resista nce Pa	Filtr ati on efficien cy (%)	Perme abi lity mm/s
Full rate	1.00	1.0 0	1.00	1.00	1.00	1.00

Parameter data integrity rate = C_i 100%. Therefore, these data should be made full use of when conducting problem analysis.

1.3 Data Processing

1.3.1 Analysis of "Redundant Variables"

Since the given data are all necessary data, therefore, there is no "redundant variable".

1.3.2 Data Outliers Processing

Through careful observation, it is found that the data is reasonable and there are no missing values, so there is no need for outlier processing.

1.4 Descriptive Statistics of the Data

First, data1 and data2 are combined for statistical analysis. The statistical results before intercalation are shown in Table 2, and the statistical results after intercalation are shown in Table 3. The statistical analysis results of data3 data are shown in Table 4.

Table 2. Statistical Results of Data before Intercalation

	Receiving distance (cm)	Hot air speed (r/min)	Thickness before intercalation (mm)	Pre-intercalation porosity (%)	Compressive resilience before intercalation (%)	Filtration resistance before intercalation (Pa)	Filtration efficiency before intercalation (%)	Permeability before intercalation (mm/s)
Average	30	1000	1.519	92.349	79.442	29.784	34.992	347.604
Min.	20	800	0.87	87.23	43.91	8.13	1.733	137.17
Max.	40	1200	2.235	95.03	90.36	65.77	80.033	795.57
Number of observations	25	25	25	25	25	25	25	25

Table 3. Statistical Results of Data after Intercalation

	Receiving distance (cm)	Hot air speed (r/min)	Thickness after intercalation (mm)	Post-intercalation porosity (%)	Compressive resilience after intercalation (%)	Filtration resistance after intercalation (Pa)	Filtration efficiency after intercalation (%)	Permeability after intercalation (mm/s)	Intercalation rate (%)
Average	30	1000	2.6074	95.861	86.622	24.157	49.386	422.134	23.0356
Min.	20	800	1.74	94	75.97	7.2	19.967	156.33	2.5
Maximum	40	1200	3.845	97.3	94.59	62.033	86.967	1019.67	50.87
Observations	25	25	25	25	25	25	25	25	25

Table 4. Data3 Statistical Results

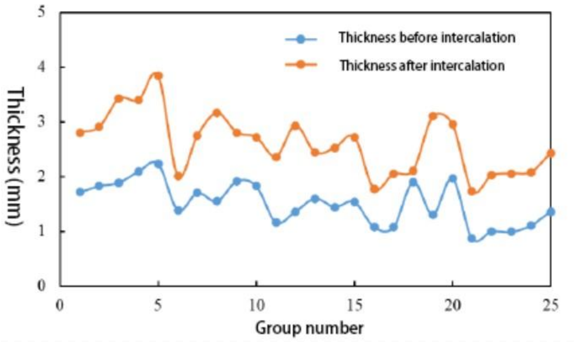
	Re ceiving distanc e (cm)	H ot air spee d (r/mi	Th ickness (mm)	P orosity (%)	Compressiv e resilience (%)	Fi ltration resista nce (Pa)	Fi ltration efficie ncy (%)	Per meabilit y (mm/s)
Average	30	1000	2.607	95.879	86.608	28.900	52.028	433.677
Min.	20	800	1.698	93.739	83.517	18.142	38.145	206.125
Max.	40	1200	3.527	97.284	88.661	40.256	83.201	654.149
Number of observations	75	75	75	75	75	75	75	75

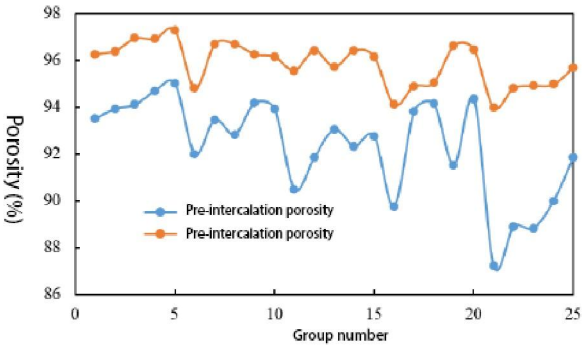
2. Model Building and Solving

2.1 Research on the Variation of Structural Variables and Product Performance before and after Intercalation

2.1.1 Descriptive Statistics

The change curves of six parameters of structural variables and product performance before and after intercalation are made, as shown in Figure 1.





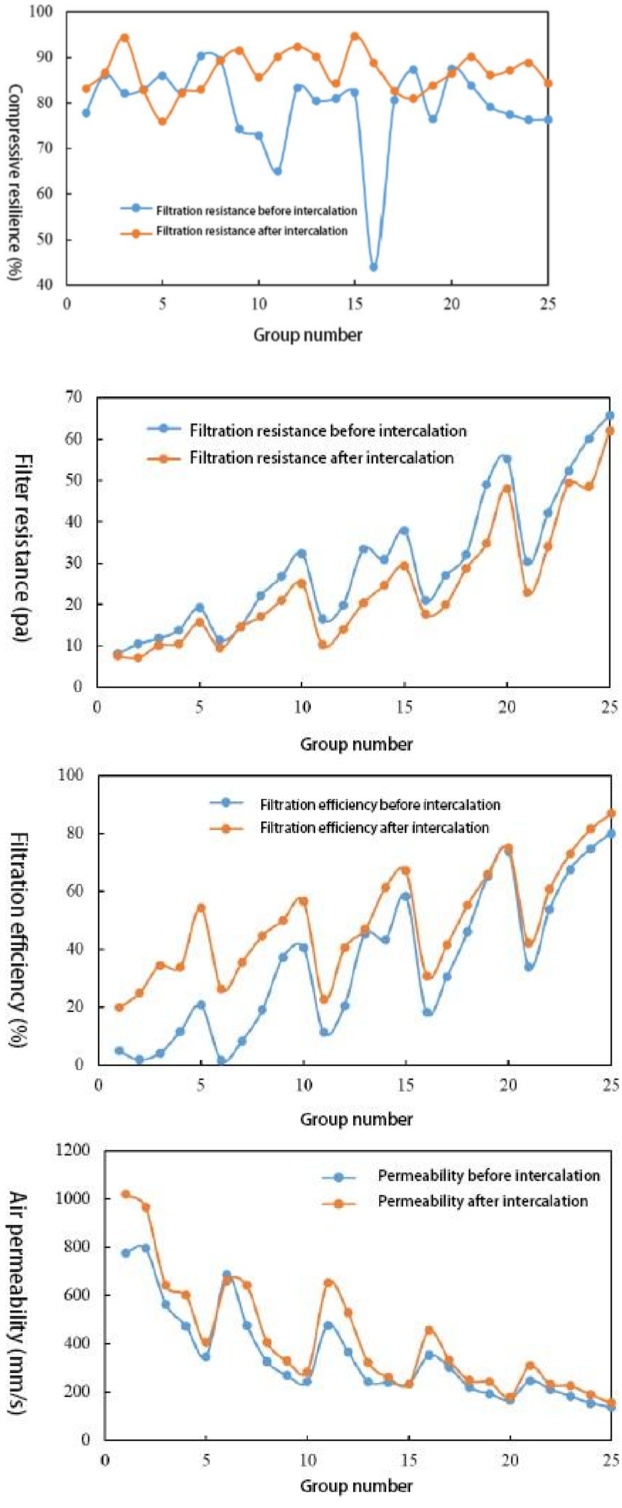


Figure 1. Curves of Structural Variables and Product Performance Parameters before and after Intercalation

It can be seen from the Figure that compared with before intercalation, for structural variables, the thickness and porosity increase after intercalation, and the compressive resilience increase in some groups and decrease in some groups, showing a trend of increasing overall. For product performance, filtration resistance is reduced after intercalation, and filtration efficiency and air permeability are increased. In practice, we want the product to have a smaller thickness, greater porosity, higher compressive resilience, less filtration resistance, higher filtration efficiency and higher permeability, so all parameters except thickness parameters become better after intercalation.

2.1.2 Correlation Analysis

Next, analyze whether the parameters before and after intercalation are correlated, and further analyze the change law of structural variables and product performance after intercalation. Pearson Person correlation coefficient or Spearman Spearman correlation coefficient are commonly used as correlation coefficients. Pearson correlation coefficient requires data to be continuous, normally distributed and linear, while Spearman correlation coefficient has a wider range of applicable conditions. First of all, the normal distribution test of the data is carried out. There are many normal distribution test methods, such as Jacques- Bella test, Shapiro-Wilk Shapiro wilk test, Q-Q graph, etc. This normal distribution test uses Q-Q graph test.

In MATLAB, a total of 12 columns of parameter data were plotted and it was found that the points on the Q-Q diagram of some parameters were not distributed near a straight line, as shown in Figure 6.2, so Pearson correlation coefficient could not be used for correlation analysis, so Spielman correlation coefficient with stronger adaptability was used for solving and analyzing.

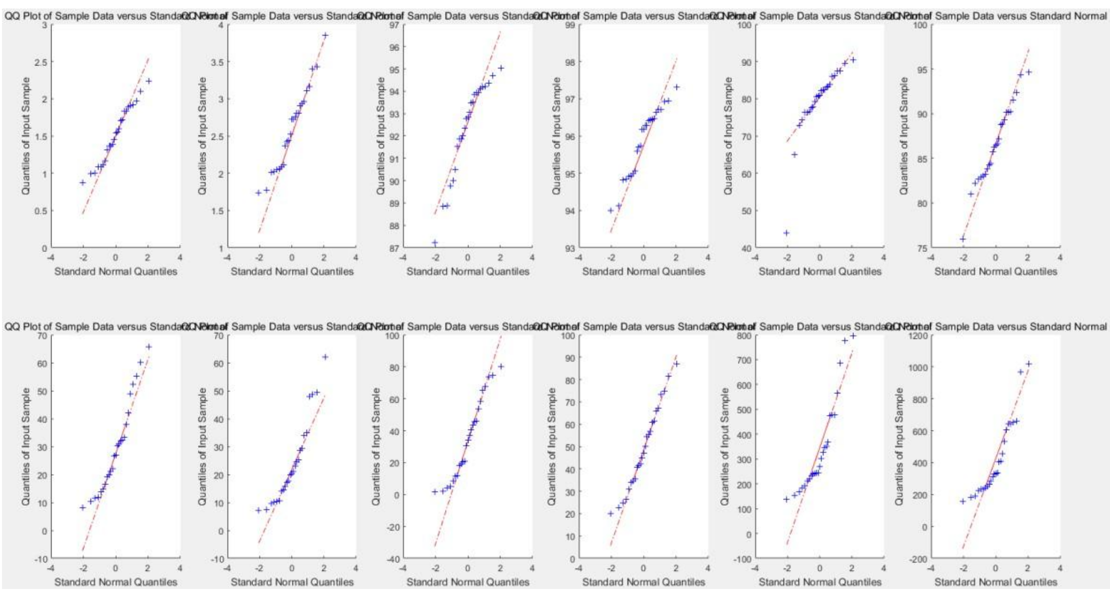


Figure 2. Q-Q Diagram of Each Parameter Data

The correlation coefficient and P value of parameters before and after intercalation were obtained by MATLAB, as shown in Table 5.

Table 5. Correlation of Parameters before and after Intercalation

Parame ters	Thickn ess before and after intercalation	Pre - and post-intercalation porosity	Compr essive resilience before and after intercalation	Filtrati on resistance before and after intercalation	Filtrati on efficiency before and after intercalation	Permea bility before and after intercalation
Correla tion coefficient	0.7 35	0.634	0.221	0.97 7	0.94 6	0.9 91
P value	0	0.001	0.288	0	0	0

It can be seen that the data of the other five parameters before and after intercalation have significant positive correlation, and the correlation coefficient is above 0.6. Among them, the correlation coefficient of filtration resistance before and after intercalation, filtration efficiency before and after intercalation, and air permeability before and after intercalation is above 0.9, showing a strong linear positive correlation. In other words, the thickness, porosity, filtration resistance, filtration efficiency and air permeability after intercalation increase with the increase of the data before and after intercalation.

2.2 Correlation Analysis between Intercalation Rate and Parameter Change Rate

The values of structural variables and product properties before intercalation are defined as x_1, after intercalation as x_2, and the rate of change is, so that the following relationship can be satisfied

$$O=\frac{x_2-x_1}{x_1} \quad (a)$$

2

Correlation analysis was conducted between intercalation rate and change rate of each parameter, and Q-Q chart test was also conducted first, as shown in Figure 3. It can be seen that some parameter data do not meet the normal distribution, so Spearman correlation coefficient is also used for correlation analysis.

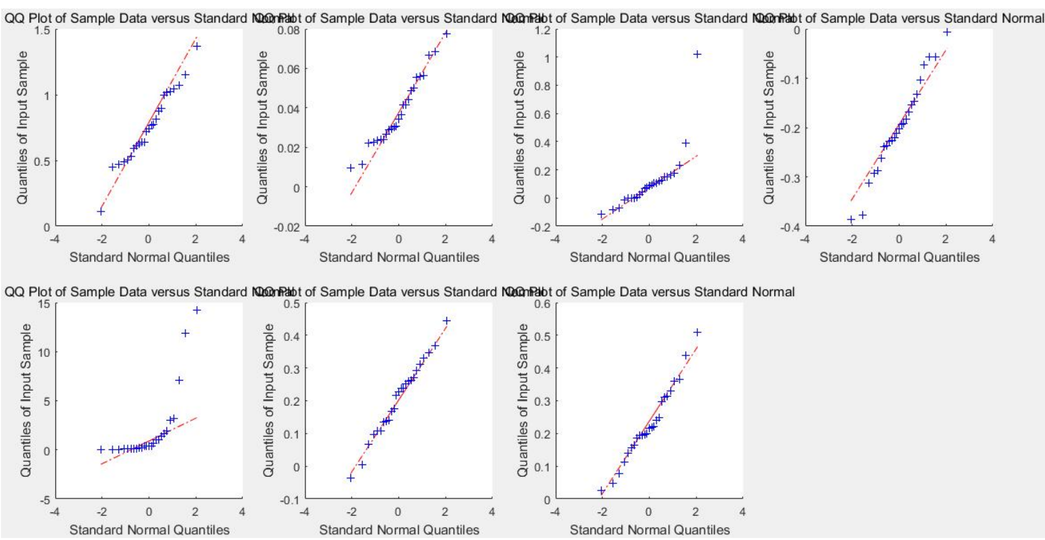


Figure 3. Q-Q Chart of Change Rate and Intercalation Rate of Each Parameter

The correlation coefficient and P value between the rate of change of each parameter and the intercalation rate were obtained by MATLAB, as shown in the table. For the table of phase relations, the darker the color, the stronger the correlation, in which red represents the positive correlation and blue represents the negative correlation; For the P-value table, the darker the color, the larger the value.

Table 6. Phase Relation Table

	Thickness change rate	Rate of por osity change	Compressive res ilience change	Filtratio n re sist ance change rate	Filtrat ion efficie ncy change rate	Permeabi lit change rat	y Intercalatio n e rate
Thickness change rate	1.0000	0.7346	0.2269	-0.2515	-0.2162	0.2746	0.1523
Rate of porosity change	0.7346	1.0000	0.3700	-0.0600	-0.2123	0.3085	-0.1477
Compressive resilie nce change rate	0.2269	0.3700	1.0000	-0.2192	-0.2708	0.2400	-0.3585
Filtration resist ance change rate	-0.2515	-0.0600	-0.2192	1.0000	0.0238	-0.2746	0.3746
Filtration effici ency change rate	-0.2162	-0.2123	-0.2708	0.0238	1.0000	0.1292	-0.0300
Permeability change rate	0.2746	0.3085	0.2400	-0.2746	0.1292	1.0000	-0.1354
Intercalation rate	0.1523	-0.1477	-0.3585	0.3746	-0.0300	-0.1354	1.0000

Table 7. P-value Table

	Thickness	ate of porosity	change				
Thickness change rate	1.0000	0.0000	0.2740	0.2242	0.2980	0.1834	0.4656
Rate of porosity change	0.0000	1.0000	0.0695	0.7754	0.3068	0.1335	0.4794
Compressive resilience change rate	0.2740	0.0695	1.0000	0.2910	0.1899	0.2467	0.0791
Filtration resista nce change rate	0.2242	0.7754	0.2910	1.0000	0.9107	0.1834	0.0659
Filtration effic iency change rate	0.2980	0.3068	0.1899	0.9107	1.0000	0.5365	0.8874
Permeability change rate	0.1834	0.1335	0.2467	0.1834	0.5365	1.0000	0.5171
Intercalation rate	0.4656	0.4794	0.0791	0.0659	0.8874	0.5171	1.0000

It can be seen from the table that the absolute values of the correlation coefficients between the intercalation rate and the change rate of each parameter are less than 0.4, and the P-value is greater than

0.05, indicating that the correlation between the intercalation rate and the change rate of each parameter is low. That is, the intercalation rate has no effect on the changes of the above 6 parameters.

3. Model Establishment and Solution

3.1 Research on Process Parameters and Structural Variables Based on BP Neural Network

3.1.1 Data Collection and Arrangement

75 pieces of data from data3 of the experiment were collected and collated to form a data set of 75×5, including acceptance distance, hot air velocity, thickness, porosity and compressive resilience. The data curve is shown in Figure 4, and some data are shown in Table 7.1.

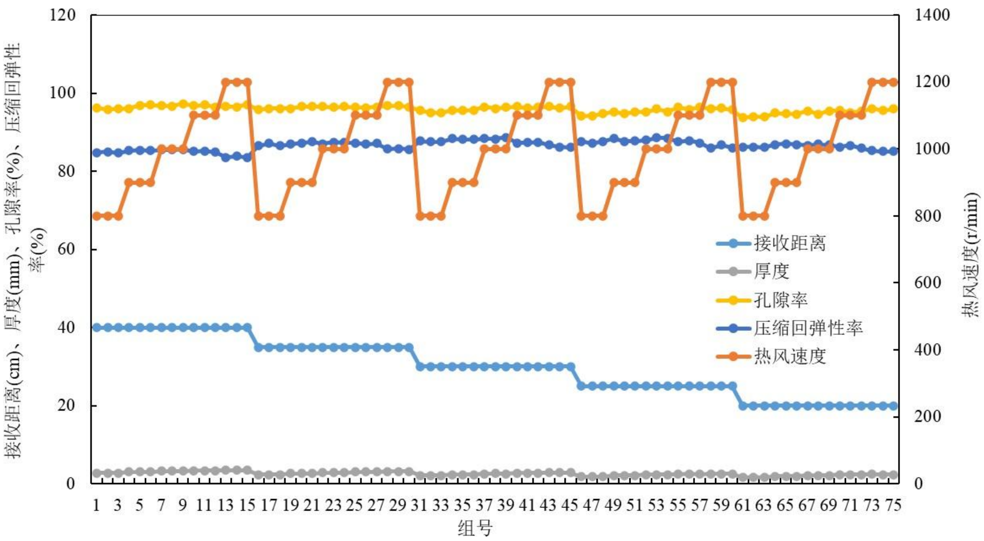


Figure 4. Data Curve of Process Parameters and Structural Variables

Table 8. Partial Data of Process Parameters and Structural Variables

Group No.	Receiving distance (cm)	Hot air speed (r/min)	Thickness (mm)	Porosity (%)	Compress ive resilience (%)
1	40	800	2.766	96.204	84.763
2	40	800	2.755	95.879	84.969
3	40	800	2.757	95.965	84.649
4	40	900	3.051	96.114	85.315
5	40	900	3.051	96.925	85.365
6	40	900	3.045	96.944	85.281
7	40	1000	3.282	96.742	85.526
8	40	1000	3.269	96.703	85.539
9	40	1000	3.287	97.284	85.605
10	40	1100	3.415	96.810	85.073

3.1.2 Establishment of BP Neural Network Model

BP neural network, also known as error backpropagation neural network, is a multi-layer forward neural network (CAI, 2022). It is composed of input layer, hidden layer and output layer. It takes the square of network error as the objective function and adopts gradient descent method to calculate the minimum value of the objective function. The structure is shown in Figure 5.

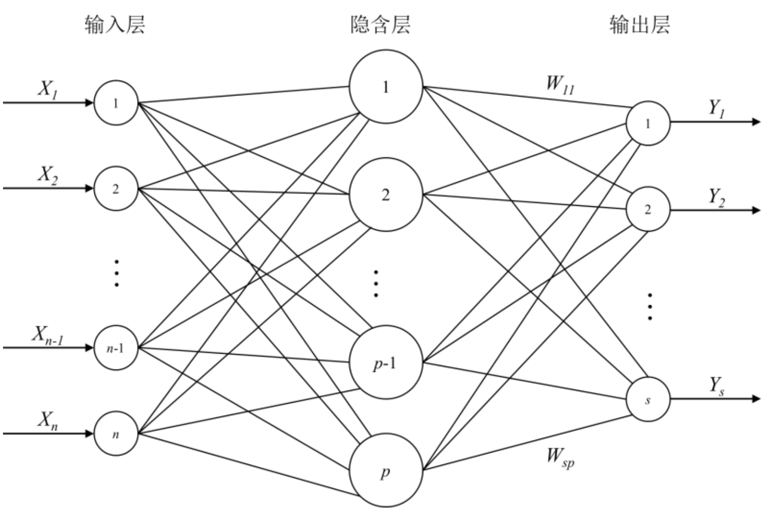


Figure 5. BP Neural Network

In Figure 5, X~X$_1$ represents n inputs of the input$_n$ layer, the hidden layer contains p neurons, W~W$_{11}$ represents the weight between p neurons of the hidden $_{sp}$layer and s neurons of the output layer, and Y~Y 1represents s outputs $_s$of the output layer. The learning process of BP neural network consists of two processes: the forward propagation of signal and the reverse propagation of error. (Tang, Li, Wang,

& Shang, 2022)

(1) Forward propagation of signal

Mark θ for the threshold of each node of the hidden layer, h for the activation function of the hidden layer, a for the threshold of each node of the output layer, and f for the activation function of the output layer.

The input n_n of the NTH node of the hidden layer is:

$$N_n = \sum_{i=1}^{p} W_{ni} x_n + \theta_n \qquad (1)$$

By substituting equation (1) into the activation function h of the hidden layer, the output k of the NTH node of the hidden layer is$_{n]}$

$$N_s = \sum_{i=1}^{p} W_n k_i + a_s = \sum_{i=1}^{p} W_{si} h\left(\sum_{i=1}^{p} W_{mi} x_n + \theta_n \right) + a_s \qquad (2)$$

Then, take k_n as the input node of the output layer and get the input N_s of the output layer as

$$N_s = \sum_{i=1}^{p} W_n k_i + a_s = \sum_{i=1}^{p} W_{si} h\left(\sum_{i=1}^{p} W_{mi} x_n + \theta_n \right) + a_s \qquad (2)$$

Substituting formula (3) to the activation function f of the output layer yields:

$$Y_s = f\left(N_s\right) = f\left[\sum_{i=1}^{p} W_{si} h\left(\sum_{i=1}^{p} W_{ni} x_n + \theta_n \right) + a_s \right] \qquad (3)$$

First calculate the actual output, and then use the error gradient descent method to correct the weights and thresholds of each layer. The error signal generated by the output is defined as

$$e_s = T_s - Y_s \qquad (4)$$

Where: T_s is the expected output. The mean square error function for a single sample is

$$E_1 = \frac{1}{2} \sum_{i=1}^{n} e_i^2 \qquad (5)$$

The total error function for M training samples is

$$E = \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{'} \left(e_j^i \right)^2 \qquad (6)$$

The hidden layer weight correction value ΔW_{np} and threshold correction value Δθ can be obtained by error gradient descent method$_{p.}$, and the output layer weight correction value ΔW_{sp}. And the threshold correction value Δa_s:

$$\Delta W_{np} = -\eta \frac{\partial E}{\partial W_{np}} = \eta \sum_{i=1}^{M} \sum_{j=1}^{s} e_j^i f'(N_s) W_{sp} h'(N_n) X_n \quad (7)$$

$$\Delta a_s = -\eta \frac{\partial E}{\partial a_s} = \eta \sum_{i=1}^{M} \sum_{j=1}^{s} e_j^i f'(N_p) \quad (8)$$

$$\Delta \theta_{pp} = -\eta \frac{\partial E}{\partial \theta_p} = \eta \sum_{i=1}^{M} \sum_{j=1}^{s} e_j^i f'(N_s) W_{sp} h'(N_n) \quad (9)$$

$$\Delta W_{sp} = -\eta \frac{\partial E}{\partial W_{sp}} = \eta \sum_{i=1}^{M} \sum_{j=1}^{s} e_j^i f'(N_p) k_p \quad (10)$$

Where: η is the network learning rate.

The activation function of the hidden layer of BP neural network adopts the Sigmoid tangent function tansig and the activation function of the output layer adopts the linear function purelin. BP neural network has a wide range of adaptability and effectiveness, mainly used in pattern recognition and classification, data compression and function approximation.

The prediction selects the neural network toolbox in MATLAB to train the network. The specific implementation steps of the prediction model are as follows:

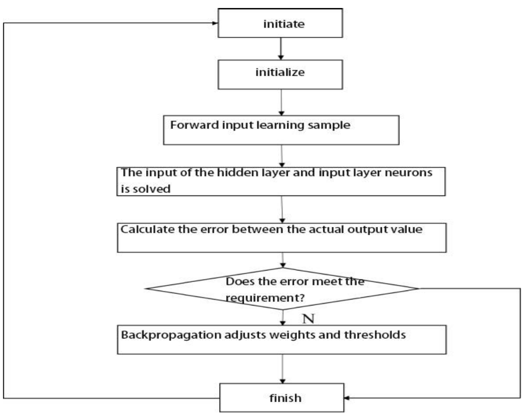


Figure 6. Calculation Flow of BP Neural Network

3.1.3 Prediction Result of BP Neural Network

The training set is 70% of the total samples, the verification set is 15% of the total samples, and the test set is 15% of the total samples. As shown in the figure. Neural network training algorithms include Levenberg-Marquardt method, Bayesian regularization method and quantized conjugate gradient method. After comparison, we choose Levenberg-Marquardt method. The training process took 6 rounds to reach the predetermined accuracy. Figure 7 shows the training error result of BP neural network. It can be seen that by the end of the training, the error is 0.038953, which is small and does not affect the final result.

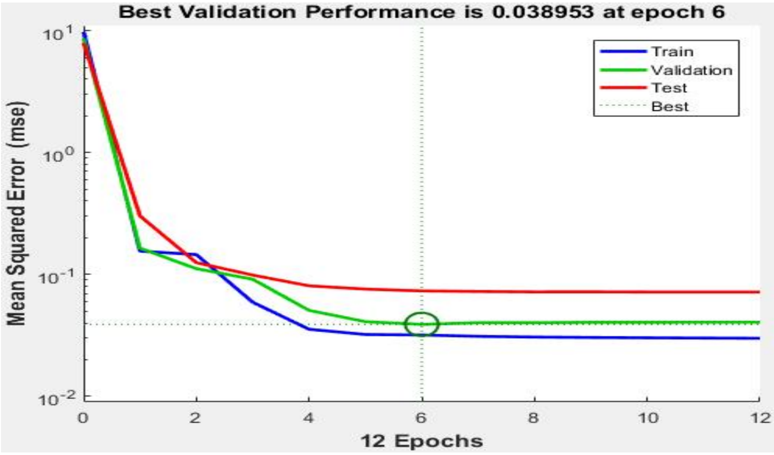


Figure 7. Training Error Result of BP Neural Network

Figure 8 shows the histogram of error distribution, with errors concentrated near 0 and basically normal distribution, which also indicates that the prediction results are good.

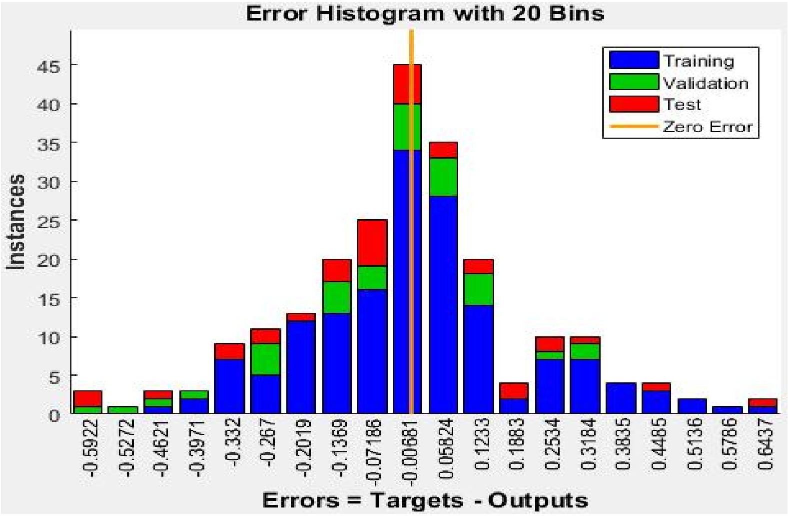


Figure 8. Histogram of Error Distribution

Figure 9 shows the regression results after the training of the neural network using MATLAB. It can be seen that the target value and the output result are basically on the same line, and the fitting result is relatively good.

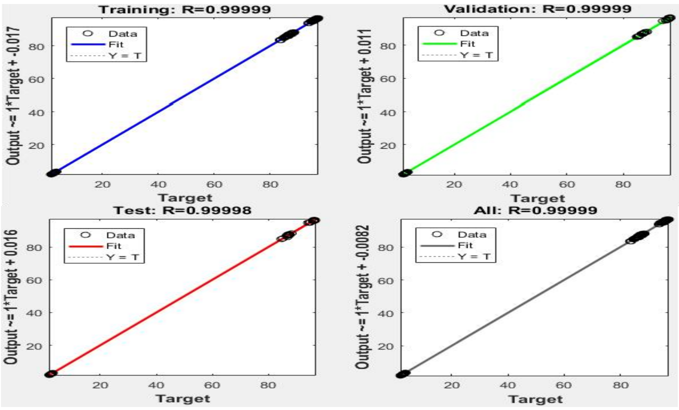


Figure 9. Regression Result of BP Neural Network the Prediction Results of the Neural Network Method are Shown in the Table

Table 9. Results of Question 2

Receiving distance (cm)	Hot air speed (cm)	Thickness (mm)	Porosity (%)	Compressiv e resilience (%)
38	850	2.748	96.305	86.018
33	950	2.724	96.424	87.806
28	1150	2.786	96.567	87.018
23	1250	2.555	95.733	85.674
38	1250	3.416	97.222	84.274
33	1150	2.919	96.224	86.663
28	950	2.398	95.769	88.381
23	850	1.885	94.216	87.245

4. Model Building and Solving

4.1 Relationship between Structural Variables and Product Performance Based on Canonical Correlation Analysis

4.1.1 Establishment of Canonical Correlation Analysis Model

In order to study the correlation between structural variables and product performance, the structural variables are taken as input variables and product performance as output variables, and the canonical correlation analysis method is adopted. It uses the idea of principal component to find out the linear combination of the input variable and the output variable respectively, and then discusses the correlation (KONG, Lu, & WANG, 2022; TANG, LI, WANG & SHANG, 2022) between the linear combination.

The specific steps of establishing the typical correlation analysis model are as follows: Step1. Establish the original matrix;

According to the original data in the table, we assume that the index of structural variables is denoted as, X_1 X_2 X_3 , X the index of product performance is denoted as, Z is the centralized observation data matrix: Y^1, Y^2, Y^3

$$Z = \begin{bmatrix} X_{1,1} & \cdots & X_{1,3} & Y_{1,1} & \cdots & Y_{1,3} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ X_{75,1} & \cdots & X_{75,3} & Y_{75,1} & \cdots & Y_{75,3} \end{bmatrix} = (X_{75\times3}, Y_{75\times3})' \quad (1)$$

Step2. Standardize the original data and calculate the correlation coefficient matrix;

We use formula (1) in question 2 to standardize the index data of structural variables and product performance, and then calculate the correlation coefficient matrix R between the two samples, and divide R into:

$$R = \begin{bmatrix} R_{11} & R_{12} \\ R_{21} & R_{22} \end{bmatrix} \quad (2)$$

Where, R_1 and R_{22} are the correlation coefficient matrix within the structural variable and product performance index respectively, and R_{12} and R_{21} are the correlation coefficient matrix between the structural variable index and product performance index.

Step3. Find the typical correlation coefficient and typical variables;

First, find the eigenroot of $A = R_{11}^{-1} R_{12} R_{22}^{-1} R_{21}$, the eigenvector S1αi,; The eigenroot $B = R_{22}^{-1} R_{21} R_{11}^{-1} R_{12}$ of λ_i^2, the eigenvector S2βi, has:

$$\alpha_i = S_1^{-1}(S_1\alpha_i), \beta_i = S_2^{-1}(S_2\beta_i) \quad (3)$$

Then the typical correlation coefficient of the index X of the random variable structure variable and the index Y of the product performance is λ, and the typical variable is:

$$\begin{bmatrix} V_1 = \alpha_1' X \\ W_1 = \beta_1' Y \end{bmatrix}; \begin{bmatrix} V_2 = \alpha_2' X \\ W_2 = \beta_2' Y \end{bmatrix}; \ldots; \begin{bmatrix} V_t = \alpha_t' X \\ W_t = \beta_t' Y \end{bmatrix} \quad (t \le 75) \quad (4)$$

Step4. Test the significance of each typical correlation coefficient.

Test the significance of the typical correlation coefficient$_i$ λ. Before the typical correlation analysis of the physicochemical index X of the structural variable and the product performance index Y of the two groups of variables, the correlation of the two groups of variables should be tested first; If they are not, that is, cov (X, Y) =0, then the canonical correlation of the two groups of variables discussed is meaningless.

4.1.2 Solving the Typical Correlation Analysis Model Based on SPSS

75 pieces of 6 columns of data, of which the first three are listed as structural variable data (a,$_1$ a,$_2$ a respectively)$_3$, and the last three are listed as product performance index data (b,$_1$ b,$_2$ b respectively)$_3$. SPSS software was used to conduct a typical correlation analysis of structural variables and product performance indicators, and the results were as follows: We can see that at the confidence level of 99%, there are two significant typical correlation coefficients, indicating that there is a correlation between structural variables and product performance, and the first two pairs of typical correlation variables are

significantly correlated.

Table 10. Correlation Analysis

	相关性	特征值	威尔克统计	F	分子自由度	分母自由度	显著性
1	.844	2.483	.194	17.970	9.000	168.078	.000
2	.562	.463	.675	7.590	4.000	140.000	.000
3	.110	.012	.988	.870	1.000	71.000	.354

The correlation variables corresponding to the standardized canonical correlation coefficient are shown in the Table.

Table 11. Linear Combination Coefficients Corresponding to Standardized Canonical Correlation Variables of Set 1 Structural Variables

变量	1	2	3
厚度mm	-1.092	1.642	-1.908
孔隙率（）	.021	-1.216	2.143
压缩回弹性率（）	-.156	1.265	.135

Set 2 Linear combination coefficients corresponding to typical correlated variables of product performance standardization.

变量	1	2	3
过滤阻力Pa	.859	.587	-.361
过滤效率（）	.640	-1.452	-.390
透气性mms	.437	-.847	-1.361

The coefficients of standardized canonical variables are used to establish the canonical correlation model. The first group of canonical correlation models can be seen as equation, and the second pair of canonical correlation models can be seen as equation

$$\begin{cases} U_1 = -1.092a_1 + 0.021a_2 - 0.156a_3 \\ V_1 = 0.859b_1 + 0.64b_2 + 0.437b_3 \end{cases} \quad (1)$$

$$\begin{cases} U_2 = 1.642a_1 - 1.216a_2 + 1.265a_3 \\ V_2 = 0.587b_1 - 1.452b_2 - 0.847b_3 \end{cases} \quad (2)$$

According to the importance degree and coefficient size of typical variables, it can be seen from the established typical correlation model that the degree of effect of product performance on the changes of structural variables can be comprehensively described by two pairs of typical correlation variables.

In the first pair, the absolute value of the coefficient corresponding to the thickness is the largest, indicating that the thickness has a great influence on the structural variables. Similarly, it can be seen that the filtration resistance has a great influence on the yield performance. At the same time, we observe that the thickness and the filtration resistance are different signs, indicating that the larger the thickness, the smaller the filtration resistance.

In the second pair, the absolute value of the coefficient corresponding to the same thickness is the largest, and the filtration efficiency has the greatest impact on the yield performance. At the same time, we observed that the thickness and filtration resistance are different signs, indicating that the greater the thickness, the lower the filtration efficiency.

4.2 Correlation-based Relationship Between Structural Variables and Product Performance

Same principle as 5.2, Spearman correlation coefficient is used to explore the correlation between structural variables and product performance variables. The results of MATLAB calculation are as follows.

4.2.1 Relationship between Structural Variables

For structural variables, the correlation coefficient and P-value are shown in the table. It can be seen that the P-value is less than 0.01, indicating that the correlation between the three variables is significant. The correlation coefficient between thickness and porosity reached 0.92, indicating a strong positive correlation; While thickness and compressive resilience, porosity and compressive resilience showed negative correlation, but the correlation was low, and the correlation coefficient was below 0.5.

Table 12. Correlation Coefficients among Structural Variables

	thickness	porosity	Compressive resilience
thickness	1.00 00	0.0000	0.0000
porosity	0.00 00	1.00 00	0.00 18
Compressive resilience	0.00 00	0.0018	1.00 00

Table 13. P Values Among Structural Variables

	thickness	porosity	Compressive resilience
thickness	1.00 00	0.0000	0.0000
porosity	0.00 00	1.00 00	0.00 18
Compressive resilience	0.00 00	0.0018	1.00 00

4.2.2 Relationship between Product Properties

For product performance, the correlation coefficient and P-value are shown in the table. It can be seen that the P-value is less than 0.01, indicating that the correlation between the three variables is significant. The correlation coefficient between filtration resistance and filtration efficiency is 0.7894, indicating a strong positive correlation, while the correlation between filtration resistance and air permeability, filtration efficiency and air permeability is negative, and the correlation is also high, and the correlation coefficient is

-0.648 and -0.7784 respectively.

Table 14. Correlation Coefficient between Product Performance

	thickness	porosity	Compressive resilience
thickness	1.0000	0.7894	-0.6480
porosity	0.7894	1.0000	-0.7784
Compressive resilience	-0.6480	-0.7784	1.0000

Table 15. P Values between Product Properties

	thickness	porosity	Compressive resilience
thickness	1.0000	0.0000	0.0000
porosity	0.0000	1.0000	0.0000
Compressive resilience	0.0000	0.0000	1.0000

4.3 Relationship between Process Parameters and Filtration Efficiency Based on Multivariate Nonlinear Regression

4.3.1 Multivariate Nonlinear Regression Model

The topic requires the establishment of the relationship between filtration efficiency and process parameters, process parameters include receiving distance and hot air velocity, so we adopt multiple regression to establish a mathematical model of filtration efficiency to guide parameter adjustment. Multiple regression model is a multi-input single-output regression model, which is used to study the response relationship between multiple independent variables and a dependent variable. It is a statistical method based on linear and nonlinear mathematical models between multiple variables (MA, Ma, & HUANG, 2022).

In view of the strong nonlinear characteristics of the data, a cubic polynomial nonlinear regression model in multiple regression is proposed to establish the relationship between process parameters and filtration efficiency. The general formula of the model is shown in equation (7).

$$S = \alpha_0 + \alpha_1 Q_1 + \alpha_2 Q_2 + \alpha_3 Q_1 Q_2 + \alpha_4 Q_1^2 + \alpha_5 Q_2^2 + \alpha_6 Q_1^2 Q_2 + \alpha_7 Q_1 Q_2^2 + \alpha_8 Q_1^3 + \alpha_9 Q_2^3 \qquad \text{(a)}$$

20

Where, denotes filtration efficiency, i denotes coefficient, 0≤i≤9; The model contains two independent variables, Q_1 and Q_2, as well as their cross terms and power terms, as factors affecting the filtration efficiency. The least square method is used to estimate the parameters of 10 coefficients.

4.3.2 Model Evaluation Index

In order to evaluate the performance of the model intuitively, this paper introduces the significance test index (F, P), normalized mean square error (MSE) and correlation coefficient (R^2). F-value is used as a statistic to test whether each item in the model is associated with the response, as shown in equation (8). The larger the F-value, the more significant the statistical significance (Liu, Huo, He , Huo, Jia, & Yang, 2021). P-value is the probability of negating the null hypothesis, and P<0.001 indicates an extremely significant statistical difference; MSE is used as an indicator to measure the degree of dispersion of samples, as shown in equation (9). The closer it is to zero,the higher the accuracy; R2 is the correlation coefficient between the actual value and the predicted value, as shown in Formula (10). The larger R2 is, the higher the correlation between the experimental results and the predicted value of the model. When the R2 of the model is greater than 0.9, it is considered that the model is accurate and conforms to the reality.

$$F = \frac{\left(\sum_{i=1}^{n} y_i^2 - \sum_{i=1}^{n} (y_i - f_i)^2\right) / m}{\sum_{i=1}^{n} (y_i - f_i)^2 / (n-m)} \qquad (1)$$

$$MSE = \frac{1}{n} \sum_{i=1}^{n} [y_i - f_i]^2 \qquad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - f_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \qquad (3)$$

Where y is the true value, the mean of the true value, and f is the predicted value. $\bar{y}$

4.3.3 Model Testing and Evaluation

In order to verify the rationality of establishing a cubic polynomial nonlinear regression model, it can be seen that the filtration efficiency and process parameters present a complex nonlinear relationship, and the interaction between the two is significant, which can reflect the response relationship between process parameters and filtration efficiency. Thus, the cubic polynomial nonlinear regression model is obtained, as shown in equation (11).

$$\begin{aligned}\overline{S} &= 5.28 - 2.609\times10^{-1}Q_1 + 8.197\times10^{-3}Q_2 - 2.12\times10^{-3}Q_1Q_2 \\ &+6.048\times10^{-3}Q_1^2 - 1.491\times10^{-5}Q_2^2 + 1.673\times10^{-3}Q_1^2Q_2 \\ &+1.66\times10^{-5}Q_1Q_2^2 - 4.582\times10^{-3}Q_1^3 + 1.052\times10^{-6}Q_2^3\end{aligned} \quad (1)$$

Table 16 shows the results of ANOVA and significance test of the experimental data. It can be concluded that the significance test of the third-order model has F value =26.62 and P value <0.0001. Compared with other models, the third-order model has the best significance. At the same time, MSE=0.0003721 and R2

=0.9967 are obtained from the original data of this model, which further indicates that this model has a high degree of fit.

Table 16. Analysis of Variance

Models	Sum of squares of error	F	P
Linear	0.04	34.23	< 0.0001
Two factors interact	0.005274	16.46	0.0007
Second order	0.004111	19.86	< 0.0001
Rank 3	0.001489	26.62	< 0.0001
Rank 4	0.0001103	2.69	0.1148
Rank 5	0.00005166	1.49	0.5558

4.4 Optimization of Filtering Efficiency Based on Genetic Algorithm

4.4.1 Introduction to Genetic Algorithm

Genetic Algorithm (GA) originates from the study of computer simulation of biological systems. Following the principle of "survival of the fittest, survival of the fittest" in nature, GA is a kind of randomized search algorithm that draws on the natural selection and natural genetic mechanism in the biological world. The main steps of genetic algorithm are as follows (Figure 8.1):

(1) Coding: The candidate solution of the problem is represented by chromosomes to realize the mapping process from the solution space to the coding space.

(2) Population initialization: An initial population (coding set) is generated that represents the set of possible potential solutions to the problem.

(3) Calculating individual fitness: Using the fitness function to calculate the fitness of each individual.

(4) Evolutionary computation: through selection, crossover, and variation, a population representing a new solution set is generated.

(5) Decoding: the optimal individual in the last generation population is decoded to realize the mapping from the coding space to the solution space, which can be used as the approximate optimal solution of the problem.

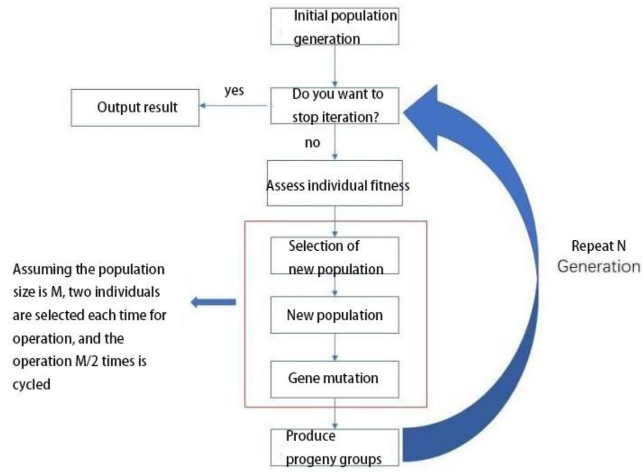


Figure 10. Steps of Genetic Algorithm in This Problem, the Calculation Idea is as Follows

(1) Set the basic parameters of the optimization algorithm, set the maximum number of routes N, and set the penalty coefficient.

(2) Generate initial individuals, each individual length is n (number of locations), set the initial number of vehicles N, randomly assign the route number of each point, and test whether there is no assignment task (the 9th point is excluded when testing), otherwise re-assign the number, and then randomly assign each point an order, so that you can get different paths of different routes.

(3) Calculate the objective function of the initial individual, with the previous distance matrix, you can directly call to calculate the total time (complete route from the starting point to the end point), while calculating the carrying capacity of each route (sum of demand), the overload part multiplied by the penalty factor as an additional cost.

(4) iteration, it is necessary to set the cross variance function of genetic algorithm here. The crossing process is that when rand< cross rate, select the sequence exchange of two points or the route number exchange, and the mutation process will re-use randperm(n) to generate the path order. Then it is asked if there are multiple routes that can be re-numbered with randi ([1,N],1,n), but the crossover and mutation processes must be tested;

(5) The optimal route and path are output at last.

4.4.2 Model Results

In this paper, the genetic algorithm with strong global optimization ability is adopted to optimize the filtering efficiency. It evaluates the fitness of individuals according to the predetermined objective function, continuously obtains better groups according to the evolutionary rule of survival of the fittest, and searches and optimizes the optimal individuals in the group through global parallel search to obtain the optimal solution (Liu, Huang, Wang, Zhou, Liu, Huang, Wang, Zhou et al., 2018; Tu, 2021). In the optimization process, in order to control the maximum filtration efficiency, according to the above established process parameters and filtration efficiency model, the corresponding optimization model is:

$$\begin{cases} \max\ \bar{S} = 5.28 - 2.609\times10^{-1}Q_1 + 8.197\times10^{-3}Q_2 - 2.12\times10^{-3}Q_1Q_2 \\ \quad + 6.048\times10^{-3}Q_1^2 - 1.491\times10^{-5}Q_2^2 + 1.673\times10^{-3}Q_1^2Q_2 \\ \quad + 1.66\times10^{-5}Q_1Q_2^2 - 4.582\times10^{-3}Q_1^3 + 1.052\times10^{-6}Q_2^3 \\ s.t.\ \begin{cases} 20 \le Q_1 \le 40 \\ 800 \le Q_1 \le 1200 \end{cases} \end{cases} \tag{1}$$

In order to obtain the possible optimal solution and reduce the computational amount of genetic algorithm, the maximum genetic algebra was defined as M=100, crossover probability Pc=0.2, and mutation probability Pm=0.05. MATLAB was used to perform GA operation, and the convergence of the optimization process of filtration efficiency was finally obtained after iteration, as shown in Figure 8.2, where the horizontal coordinate is evolutionary algebra, and the vertical coordinate is the objective function value (appropriate value), that is, filtration efficiency. As can be seen from the figure, with the continuous progress of genetic algorithm optimization, the filtration efficiency continues to increase. Finally, the optimal filtration efficiency is obtained as follows: the filtration efficiency is 86.23%, the receiving distance is 24.56cm, and the hot air velocity is 1126.29r/min.

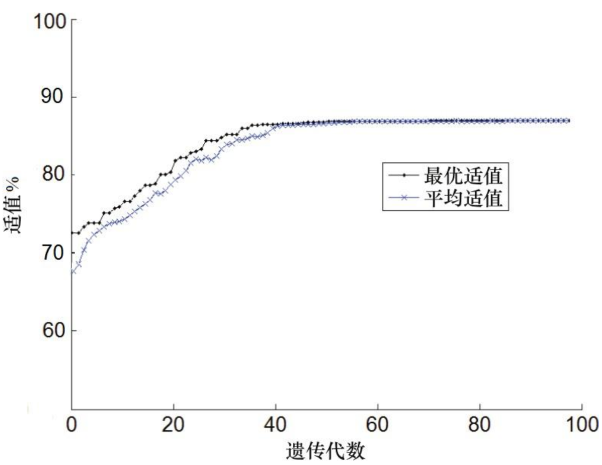


Figure 11. Genetic Algorithm Iteration Results

5. Model Establishment and Solution

5.1 The Relationship between Thickness and Compressive Resilience and Process Parameters Based on Multiple Linear Regression

5.1.1 Establishment of Multiple Linear Regression Model

The principle and calculation process of multiple linear regression model are as follows:

(1) Establish multiple linear regression model

The multiple linear regression model involving p independent variables can be expressed as:

$$\begin{cases} y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p + \varepsilon \\ \varepsilon \sim N\left(0, \sigma^2\right) \end{cases} \quad (1)$$

For convenience, we introduce matrix notation by using n sets of actual observation data:

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix} X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{np} \end{bmatrix} \beta = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_n \end{bmatrix}, \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix} \quad (2)$$

Where ε is an unobservable random error vector, β is a vector composed of regression coefficients, is an unknown and undetermined constant vector.

$$Y \sim N_n\left(X\beta, \sigma^2 I\right), \varepsilon \sim N_n\left(0, \sigma^2 I\right) \text{（I为 n 阶单位阵）} \quad (3)$$

(2) Least squares estimation of regression coefficient β

Choose an estimate of β, denoted as, to minimize the sum of squares of the random error ε, i.e$\hat{\beta}$

$$\begin{aligned} \min_\beta \varepsilon^T \cdot \varepsilon &= \min_\beta (Y - X\beta)^T (Y - X\beta) \\ &= (Y - X\hat{\beta})^T (Y - X\hat{\beta}) \overset{\text{def}}{=} = Q(\hat{\beta}) \end{aligned} \quad (4)$$

By the requirements of least square method, the necessary conditions for obtaining extreme values by multivariate functions can solve the standard equation of regression parameters as follows:

$$\begin{cases} \left.\dfrac{\partial Q}{\partial \beta_0}\right|_{\beta_0 = \hat{\beta}_0} = 0 \\ \left.\dfrac{\partial Q}{\partial \beta_i}\right|_{\beta_i = \hat{\beta}_i} = 0 (j = 1, 2, \cdots, p) \end{cases} \quad (5)$$

(3) Stepwise regression analysis

When establishing the regression model, not every factor has a great influence on y. Therefore, we use the stepwise regression method (elimination of optimal selection method) to screen the factors. The specific process is as follows (FIG. 9.1) :

Step1: Establish multiple linear regression equation

Step$_{max}$2: Test the significance of the regression coefficient, and take t value corresponding to the maximum probability value P;

Step3: Determine whether P $\leq_{max}$0.05, if it is satisfied, enter step5, if not, enter step4;

Step4: Then H is acceptable, that is, the linear relationship between this$_0$ indicator and the dependent variable is not significant, remove the indicator and return to Step1;

Step5: then H_0 can be rejected, then all indicators and the linear relationship between the dependent variable is significant, output the equation, end.

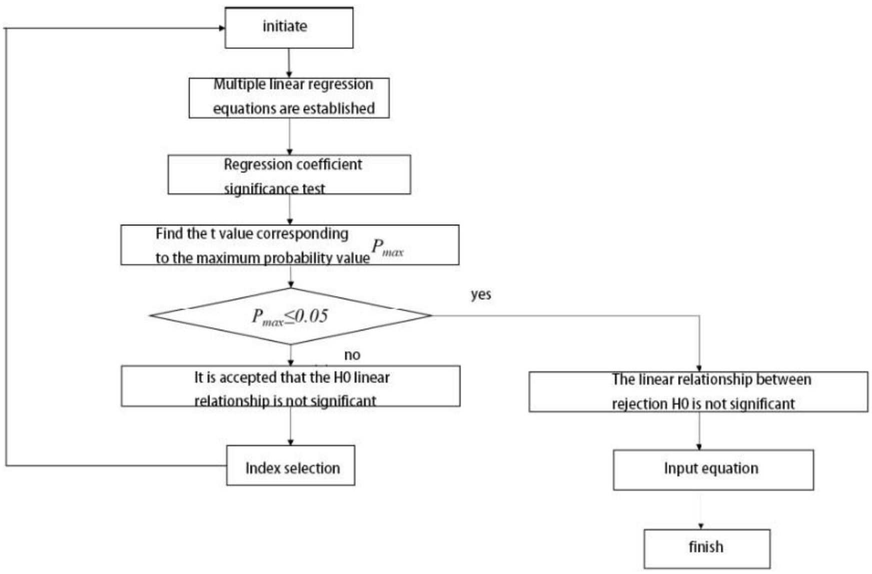


Figure 12. Flow Chart of Stepwise Regression Analysis

(4) Solution of multiple regression model

(5) Significance test of regression model

5.1.2 Model Solving

(1) Thickness and receiving distance and hot air velocity

Multiple linear regression was solved by Stata software. For the relationship between thickness (x_3) and receiving distance (x_1) and hot air velocity (x_2). The joint significance test is shown in the table below.

Table 17. Model Summary

F	Prob>F	R square > f.	Adjust R square	Root MSE
1436.82	0	0.9756	0.9749	0.07485

Table 18. Table of Regression Coefficients

Thickness	Coefficie nt	Standard error	t	P>t	Beta
Receiving distance	0.0542	0.0012	44.34	0	0.8169
Hot air Speed	0.0018	0.0001	30.13	0	0.5552
_cons	0.8602	0.0718	11.98	0	.

It can be seen that the P-value of the joint significance test is 0, indicating that there is an obvious functional relationship between the independent variable and the dependent variable, and the probability p- value is less than the significance level of 0.05. Therefore, it is considered that the partial correlation coefficient is significantly not equal to 0, and each indicator is linearly correlated with the dependent variable. The R square is adjusted to 0.9749, indicating that the fitting effect of the model is good. The regression equation is shown in the equation.

$$x_3 = 0.0542x_1 + 0.0018x_2 - 0.8602 \quad (1)$$

(2) compressive resilience with receiving distance and hot air speed

Similarly, for the relationship between compressive resilience (x_4) and receiving distance (x_1) and hot air velocity (x_2). The joint significance test is shown in Table 19.

Table 19. Model Summary

F	Prob>F	R square > f.	Adjust R square	Root MSE
12.96	0	0.2647	0.2443	1.0577

Table 20. Table of Regression Coefficients

Thickness	Coefficie nt	Standard error	t	P>t	Beta
Receiving distance	0.0688	0.0173	3.98	0	0.4026
Hot air Speed	0.0027	0.0009	3.17	0.002	0.3203
_cons	91.4098	1.0145	90.1	0	.

Similarly, it can be seen that the P-value of the joint significance test is 0, indicating that there is an obvious functional relationship between the independent variable and the dependent variable, and the probability p-value is less than the significance level of 0.05, so it is considered that the partial correlation coefficient is significantly not equal to 0, and each indicator is linearly correlated with the dependent variable. The regression equation is shown as follows.

$$y_1 = -1.9427x_1 - 2.9167x_4 + 353.9574 \quad (3)$$

(3) filtration efficiency and receiving distance, hot air speed, thickness, compression resilience

Similarly, the relationship between filtration efficiency (y_1) and receiving distance (x_1), hot air velocity

(x_2), thickness (x_3), compression resilience (x_4) is discussed. The joint significance test is shown in the table below.

Table 21. Model Summary

F	Prob>F	R square > f.	Adjust R square	Root MSE
22.53	0	0.5628	0.5378	7.3244

Table 22. Table of Regression Coefficients

Thickness	Coefficie nt	Standard error	t	P>t	Beta
Receiving distance	1.9427	0.6375	3.05	0.003	1.2836
Hot air Speed	0.0255	0.0221	1.16	0.252	0.3372
Thickness	13.2245	11.6669	1.13	0.261	0.5797
Compress ive resilience	2.9167	0.8256	3.53	0.001	0.3294
_cons	353.9574	74.9415	4.72	0	.

Similarly, it can be seen that the P-value of the joint significance test is 0, indicating that there is an obvious functional relationship between the independent variable and the dependent variable. The probability P-value receiving distance, compressive resilience rate and constant term are less than 0.05 at the significance level, and the other two are greater than 0.05. Therefore, it is considered that the partial correlation coefficients of the three are significantly different from 0, and each index is linearly correlated with the dependent variable. The regression equation is shown as follows.

$$y_1 = -1.9427x_1 - 2.9167x_4 + 353.9574 \quad (3)$$

(4) filtration resistance and receiving distance, hot air speed, thickness, compression resilience

In the same way, the relationship between filtration resistance ($_1y_2$) and receiving distance (x_2), hot air speed (x_3), thickness (x), compression resilience (x_4). The joint significance test is shown in the table below.

Table 23. Model Summary

F	Prob>F	R square > f.	Adjust R square	Root MSE
22.53	0	0.5628	0.5378	7.3244

Table 24. Regression Coefficient Table

Thickness	Coefficie nt	Standard error	t	P>t	Beta
Receiving distance	1.9427	0.6375	3.05	0.003	1.2836
Hot air Speed	0.0255	0.0221	1.16	0.252	0.3372
Thickness	13.2245	11.6669	1.13	0.261	0.5797
Compress ive resilience	2.9167	0.8256	3.53	0.001	0.3294
_cons	353.9574	74.9415	4.72	0	.

Similarly, it can be seen that the P-value of the joint significance test is 0, indicating that there is an obvious functional relationship between the independent variable and the dependent variable. The probability p-value thickness is less than the significance level 0.05, and the rest are greater than 0.05. Therefore, it is considered that the partial correlation coefficient of thickness is significantly not equal to 0, and the linear correlation with the dependent variable is significant. The regression equation is shown as follows.

$$y_2 = -12.6443x_3 \quad (4)$$

5.2 Multi-Objective Optimization Based on NSGA-II Model

5.2.1 NSGA-II Model

The calculation principle and process of NSGA-II model are[11] as follows:

5 The dominance relationship between any two entities is determined by the fitness function, and the Pareto dominance relationship is defined as follows: For MOP, n objective functions can form $f_i(x) = \left(f_1(x), f_2(x), \cdots f_n(x)\right), \exists X_u, X_V \in U$: if $\forall i \in \{1, \cdots, n\}$, both have $f_i\left(X_U\right) < f_i\left(X_V\right)$, then X_U dominates X_V.

(1) Find out all the non-dominant individuals in the population and define its$_{rank}$ i as 1; Remove the individual whose i_{rank} is 1 and find out the individual whose i_{rank} is 2 in the subpopulation; And so on until all individuals have completed the grading.

(2) The crowding comparison operator is used to sort the chromosomes of the same class. Crowding

$L \quad i$

d refers to the distance between individual i and neighboring individuals of the same rank, and can represent population density, which is defined as follows:

$$L[i]_d = \sum_{k=1}^{n} \left(L[i+1]f_k - L[i-1]f_k \right) \Big/ \left(f_k^{\max} - f_k^{\min} \right) \quad (1)$$

Where L[i] fk , represents the value of the i+1 individual for the KTH objective function, and

f minmaxk represents the maximum and minimum values of the KTH objective function. K

The parent population is fused with the child population to produce a complex population, and the individual order in the population is sorted out by fast non-dominant sequencing to produce a new generation of parent population, so as to preserve the good genes.

(3)Selection operator: the objective function is set as a fitness function, and the expected value method is used for selection. First, for the compound population with 2N individuals, a fast non-dominated sort is carried out to calculate the irank sum of all individuals. L[i]d Secondly, N individuals are selected according to the selection rule. The selection rule is stated as follows:

$$x^i \prec_n x^j$$
$$\text{s.t. } \left(x_{\text{rank}}^i < x_{\text{rank}}^j \right) \cup \left[\left(x_{\text{rank}}^i = x_{\text{rank}}^j \right) \cup \left(L(x^i)_d > L(x^j)_d \right) \right] \quad (2)$$

That is, when the individual x^{ji} is different from the x level, select the small level; When they are of the same rank, choose the one with the highest degree of crowding.

(3) Hybridization operator: using a single point crossing method. First, the individuals in the population are randomly paired and the crossover position is set, and the crossover is judged according to the hybridization probability P_c; If crossover is carried out, the corresponding chromosomes of the two individuals are exchanged at the crossover position; Finally, judge whether the generated individuals meet the range constraints, if not, perform the deletion operator operation and repeat the above steps.

(4) Mutation operator: the basic mutation operation is adopted. First, randomly select the mutation individual and mutation position, according to the mutation probability P_m to determine whether to carry out the mutation operation; If the mutation is carried out, the gene code of the mutation location is changed; Finally, judge whether the generated individual meets the range constraint, if not, perform the deletion operator operation and repeat the above steps.

(5) Deletion operator: Judge whether the individual gene meets the planning scope constraint according to the coding situation of the individual gene. If it does not meet the planning scope constraint, delete the individual. The corresponding judgment rules are as follows:

$$\left| (N_1 + N_4 + N_7) - (N_3 + N_6 + N_9) \right| < GX/2 \quad (3)$$

$$\left| (N_1 + N_2 + N_3) - (N_7 + N_8 + N_9) \right| < GZ/2 \quad (4)$$

Ni (i =1, ...,9) Represents the numberof genes encoded as i in an individual. Formula 7.11 and 7.12 are width range constraints and height range constraints respectively. When the output represented by an individual violates either constraint, the individual is deleted.

5.2.2 Model Establishment and Solution

According to the requirements of the problem and the previous analysis, the objective function and constraint of the model are shown in the following equation.

$$\begin{cases} \begin{cases} \max\ y_1 = -1.9427x_1 - 2.9167x_4 + 353.9574 \\ \min y_2 = -12.6443x_3 \end{cases} \\ s.t. \begin{cases} 0 \le x_1 \le 100 \\ 0 \le x_2 \le 2000 \\ 0 \le x_3 \le 3 \\ 0.85 \le x_4 \le 1 \\ x_3 = 0.0542x_1 + 0.0018x_2 - 0.8602 \\ x_4 = -0.0688x_1 - 0.0027x_2 + 91.4098 \end{cases} \end{cases} \quad (1)$$

In the process of simulation calculation, the relevant parameters of the algorithm are set: initial population size N=200, crossover probability Pc=0.7, mutation probability Pm=0.05, and the maximum number of iterations MG=500. According to the numerical accuracy set by the example, the NSGA-II model is solved and the performance of the model is tested. After the performance meets the requirements, the Pare (YUN, YU, Cheng, Liu, Niu, Hou, LI, LIU, & ZHANG, 2022) to optimal solution set is obtained by running the program.

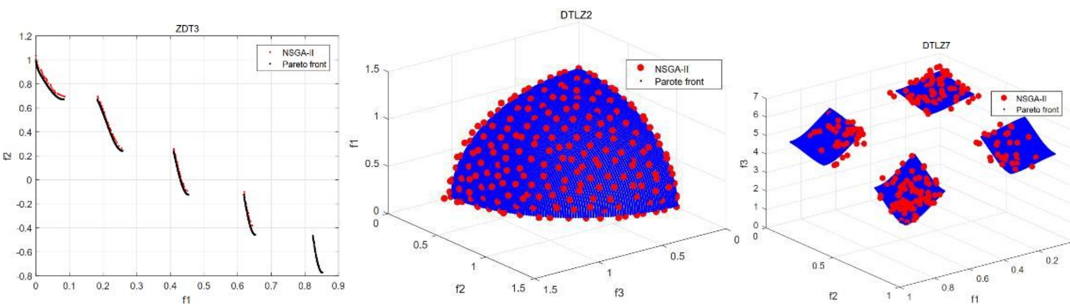
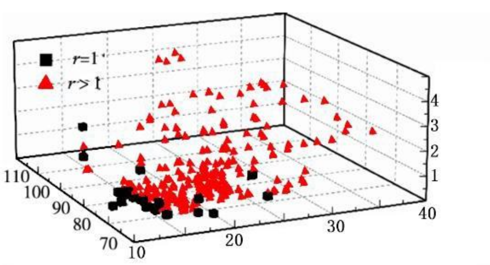


Figure 13. Pareto Frontier Images of DT3, DTLZ2 and DTLZ7 Tests

To illustrate in detail the convergence and diversity of the non-dominated solution sets obtained by each algorithm, Figure 9.3 shows the non-dominated solution sets of NSGA-II algorithm in the ZDT3, DTLZ2 and DTLZ7 test problems and the images of the real Pareto frontier. As can be seen from the above figure, among the three test problems, the NSGA-II model shows good convergence and diversity. At the same time, it can be seen that in the image of the test problem, the non-dominated solution of the Pareto frontier obtained by NSGA-II algorithm not only converges well near the real Pareto frontier, but also has good distribution, and the algorithm performs well.



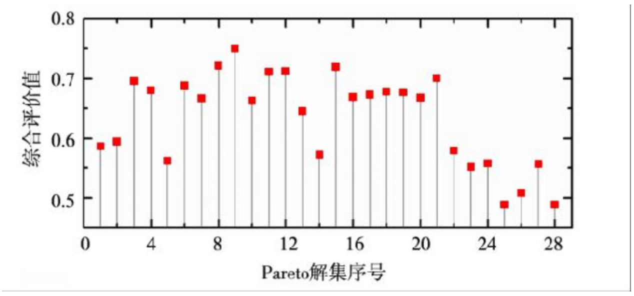


Figure 14. Distribution and Comprehensive Evaluation of Pareto Solution Set

According to the above model, the highest filtration efficiency is finally obtained as 88.95%, while the lowest filtration resistance is 12.34Pa, the receiving distance is 31.58cm, and the hot air speed is 1729.45r/min.

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