

# Performance control study of interleaved meltblown nonwoven materials

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**Abstract.** Meltblown nonwoven material is an important raw material for mask production, and in order to optimize the product performance, this paper conducts a relevant study on its performance control. A typical correlation analysis model is constructed to study the effect of interpolation on structural variables and product performance variation, and a four-layer BP neural network model is constructed for predictive analysis to study the relationship between process parameters and structural variables. This paper maximizes the filtration efficiency and minimizes the filtration resistance while taking into account all conditions and requirements

**Keywords:** Typical correlation analysis, Neural Networks Bayesian regularization, Multiple regression model, Multi-objective planning model.

## 1. Questions to ask

**In question 1**, based on the study of the changes in structural variables and product properties after intercalation, we analyze whether the intercalation rate has any effect on the first question is to study the relationship between process parameters and structural variables.

**In question 2**, the relationship between process parameters and structural variables was investigated and the structural variables were predicted by combining the process parameter combinations given in Table 1. The structural variables are predicted with the combination of process parameters given in Table 1.

**In question 3**, the relationship between structural variables and product performance is investigated, and the relationship between structural variables and product performance is studied separately. The relationship between the structural variables and the product performance is studied separately. In conjunction with the second question, analyze what the highest filtration efficiency of the product is when the process parameters are set.

**In Question 4:** In order to achieve the goal of high filtration efficiency and low filtration resistance, the value of the process parameters should be found when the filtration efficiency is as high as possible and the filtration resistance is as low as possible, taking into account the conditions and requirements of the product production and the emergent factors.

## 2. Problem analysis

### 2.1 Analysis of Question 1

In order to investigate the effect of intercalation rate on structural variables and product performance, we construct a typical correlation analysis model to investigate the effect of interpolation rate on structural variables and product performance. The typical correlation coefficients are obtained to reflect the effect of intercalation rate on structural variables and product performance. We constructed a typical correlation analysis model to obtain the typical correlation coefficients between the interpolation rate and structural variables and product performance.

### 2.2 Analysis of Question 2

A four-layer BP neural network model is constructed to achieve the prediction purpose, and the output layer is set in matrix format to achieve the effect that the BP neural network can predict multiple values. At the same time, to prevent the overfitting problem of the BP neural network model

during the training process, we introduce Bayesian regularization to prevent the overfitting of the model and realize the correction of the overfitting phenomenon of the neural network model. Finally, the trained model is used to predict the structural variables under different process parameters.

### 2.3 Analysis of Question 3

Using SPSS software, typical correlation analysis was performed. Further, to construct the Multiple regression models were developed, and in building the regression models, in order to prevent the influence of heteroskedasticity and interference terms on the models, we In order to prevent the influence of heteroskedasticity and interfering terms on the model, we performed the consistency test and White's test to reduce the error of the model and improve the significant nature of the model. We then used Stata software to solve the multivariate regression model to find the equation parameters between process parameters and filtration efficiency. The optimal solution was found.

### 2.4 Analysis of Question 4

A multi-objective planning model was established to obtain the universal form of the multi-objective planning model regarding the filtration resistance and filtration efficiency. Using STATE software, the multiple regressions of filtration efficiency and filtration resistance models were derived separately, and the process parameters under the optimal values were finally solved.

## 3. Model building and solving

### 3.1 Creation and solution of Problem 1

#### 3.1.1 Modeling of a typical correlation analysis

To investigate the effect of interpolation rate on structural variables and product performance changes, a typical correlation analysis model was developed for the two two variables.

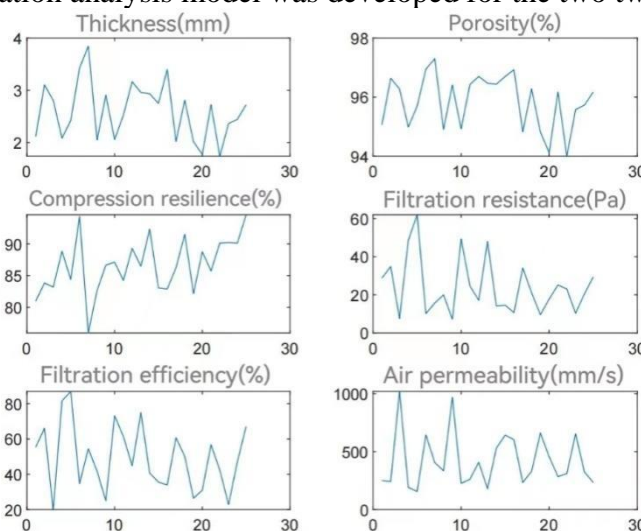


Figure 1 Structural variables and product performance

Assume that the two sets of variables are:  $X^{(1)} = (X_1^{(1)}, X_2^{(1)}, \dots, X_p^{(1)})$ ,  $X^{(2)} = (X_1^{(2)}, X_2^{(2)}, \dots, X_p^{(2)})$ , The subgroup selects a number of representative composite variables in both groups  $U_i, V_i$ , such that each composite variable is a linear combination of the original variables the linear combination of

$$U_i = a_1^{(i)} X_1^{(1)} + a_2^{(i)} X_2^{(1)} + \dots + a_p^{(i)} X_p^{(1)} = a^{(i)'} X_1$$

$$V_i = a_1^{(i)} X_1^{(2)} + a_2^{(i)} X_2^{(2)} + \dots + a_p^{(i)} X_p^{(2)} = a^{(i)'} X_2$$

Under the condition that  $var(U_i) = var(V_i) = 1$  is satisfied, find the two sets of coefficients  $a^{(1)}$  and  $b^{(1)}$  that maximize  $\rho(U_1, V_1)$ . Following that, for each group of variables, their typical correlation coefficients were obtained according to the above method.

### 3.1.2 Solution of a typical correlation analysis model

The model is solved using SPSS software, and the interpolation rate is set to set 1, and the structural variables and product performance are set to set 2. as set 2, and their typical correlations are obtained as follows.

Table 1 Typical correlations

Relevance	Wilke Statistics	F	Molecular degrees of freedom	Denominator degrees of freedom	Significance
0.633	0.600	2.003	6.000	18.000	0.118

Their variance ratios were obtained as follows.

Table 2 Explained proportion of variance

Typical Variables	Set 1* Self	Set 1* Set 2	Set 2* Self	Set 2* Set 1
1	1.000	0.400	0.166	0.067

Their typical loads are obtained as follows.

Table 3 Typical load

Collection 2	Typical load
Variables	1
Thickness(mm)	0.239
Porosity(%)	0.192
Compression resilience(%)	-0.794
Filtration resistance(Pa)	0.379
Filtration efficiency(%)	0.358
Air permeability(mms)	-0.037

Their standardized typical correlation coefficients and unstandardized typical correlation coefficients are obtained as follows.

Table 4 Standardized Typical Correlation Coefficient

Collection 2	Standardized Typical Correlation Coefficient
Variables	1
Thickness(mm)	0.865
Porosity(%)	-0.793
Compression resilience(%)	-0.712
Filtration resistance(Pa)	0.402
Filtration efficiency(%)	0.725
Air permeability(mms)	0.837

Table 5 Non-standardized typical correlation coefficient

Collection 2	Non-standardized typical correlation coefficient
Variables	1
Thickness(mm)	1.575
Porosity(%)	-0.864
Compression resilience(%)	-0.161
Filtration resistance(Pa)	0.027
Filtration efficiency(%)	0.038
Air permeability(mms)	0.004

The typical correlation coefficients after normalization were visualized to obtain the correlation coefficient heat map as shown in Figure 2. We generally specify that there is no significant effect when the significance is greater than 0.05, i.e., above the 5% level, and a more significant effect when the significance is less than 0.05. After analyzing and processing the data by SPSS software, the significance value is 0.118. Therefore, from Figure 2, it can be seen that although the interpolation rate has an effect on the performance of structural variables and product performance, but since the significance is only 0.118, it indicates that the effect of interpolation rate on structural variables and product performance is minimal.



Figure 2 Typical correlation coefficient heat map

### 3.2 Creation and solution of Problem 2

#### 3.2.1 BP neural network modeling

##### 1. BP Neural Network Training

In order to stabilize the error between the actual and desired outputs of the structural variables (thickness, porosity, compressive resilience) the connection weights and node thresholds between the layers must be adjusted in order to keep the error between the actual and desired outputs of the structural variables (thickness, porosity, compressive resilience) within a small value. In general, we can describe the learning algorithm of BP nerve network as follows warp network learning algorithm as the following steps.

##### (1) Network initialization

Determine the number of nodes in the input layer, the number of nodes in the hidden layer, the number of nodes in the output layer, the initialized weights, the threshold, the learning rate and neuron excitation function.

(2) Implicit layer output calculation

$$H_j = f \left( \sum_{i=1}^n \omega_{ij} x_i - a_j \right), j = 1, 2, \dots, l$$

(3) Output layer output calculation

Calculate the predicted output O.

$$O_k = \sum_{j=1}^l H_j \omega_{jk} - b_k, k = 1, 2, \dots, m$$

(4) Error calculation

The error e is calculated from O and the desired output Y.

$$e_k = Y_k - O_k, k = 1, 2, \dots, m$$

(5) Weight update

$\eta$  is the learning rate.

$$\omega_{ij} = \omega_{ij} + \eta H_j (1 - H_j) x(i) \sum_{k=1}^m \omega_{jk} e_k, i = 1, 2, \dots, n; j = 1, 2, \dots, l$$

$$\omega_{ij} = \omega_{ij} + \eta H_j e_k, j = 1, 2, \dots, l; k = 1, 2, \dots, m$$

(6) Threshold update

$$a_j = a_j + \eta H_j (1 - H_j) \sum_{k=1}^m \omega_{jk} e_k, j = 1, 2, \dots, l$$

$$b_k = b_k + e_k, k = 1, 2, \dots, m$$

(7) Determine if the iteration of the algorithm is finished, and if not, return to step 2.

3. Bayesian regularization to prevent overfitting

Let the vector of ownership and bias values of the BP neural network be  $x$ , the training data set be  $D$ , the parameters related to the density function be set to  $\alpha$  and  $\beta$ , and the selected network structure be  $M$ . Then we have.

$$P(x|D, \alpha, \beta, M) = \frac{P(D|\alpha, \beta, M)P(x|\alpha, \beta, M)}{P(D|x, \beta, M)}$$

where  $P(D|\alpha, \beta, M)$  denotes the case where the weights  $x$  obtained from the previous training, the parameters  $\beta$ , and the network model  $M$  are known  $P(x|\alpha, \beta, M)$  is the prior term in the model, i.e., the canonical term, characterizing the probability density of the weights  $x$   $P(D|x, \beta, M)$  denotes the marginal probability of the training data  $D$  and is a normalization factor. There is also that

$$P(D|\alpha, \beta, M) = \frac{1}{Z_D(\beta)} e^{-\beta E_D}$$

This term, which can be called the likelihood function, is a function of the network weights  $x$  and expresses the probability density  $P(D|\alpha, \beta, M)$  of the training data  $D$  when the network weights  $x$  of the training data  $D$ , the probability density  $P(D|x, \beta, M)$  can be maximized when the network weights  $x$  are combined in the same way. Here we assume that the weights are smaller values centered at 0-centered smaller values, so a Gaussian prior density with zero mean is chosen.

To obtain the maximum network weight  $x$  for  $P(D|\alpha, \beta, M)$ , we propose here the maximum likelihood rule. If this likelihood function is a Gaussian function,  $P(D|x, \beta, M)$  obtains the maximum value when  $E_D$  obtains the minimum value. Therefore It can be assumed that the training set  $D$  contains Gaussian noise, so that a statistical approach (maximum likelihood estimation) can be used to introduce standard error-squared and performance metrics. That is.

$$P(x|\alpha, M) = \frac{1}{Z_W(\alpha)} e^{-\alpha E_W}$$

where,  $\alpha = \frac{1}{2\delta_\omega^2}$ ,  $\delta_\omega^2$  is the variance of each weight and  $Z_W(\alpha) = 2\pi\delta_\omega^2$ , and n is the number of weights in the network and the number of bias values.

In summary, the Bayesian framework can be written in the following form.

$$P(x|D, \alpha, \beta, M) = \frac{1}{Z_F(\alpha, \beta)} e^{-F(x)}$$

Where  $F(x) = \beta E_D + \alpha E_W$ ,  $Z_F(\alpha, \beta) = Z_D(\beta)Z_W(\alpha)$  is a function of  $\alpha$  and  $\beta$ .

### 3.2.2 Solving the BP neural network model

The structure of the obtained BP neural network is illustrated as follows.

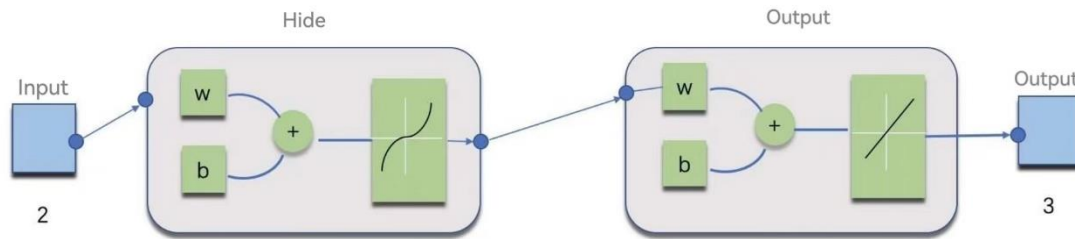


Figure 3 BP neural network structure diagram

The model has been trained 1000 times and the objective function has started to converge with a convergence value of 0.030066, indicating that the training of the neural network model is completed.

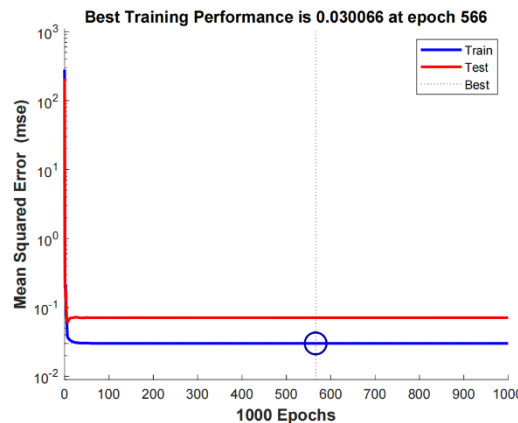


Figure 4 BP Neural Network Convergence

The training results of the final neural network are shown below, and the accuracy of the model from the training set, test set, and overall The accuracy of the model is 99.99%.

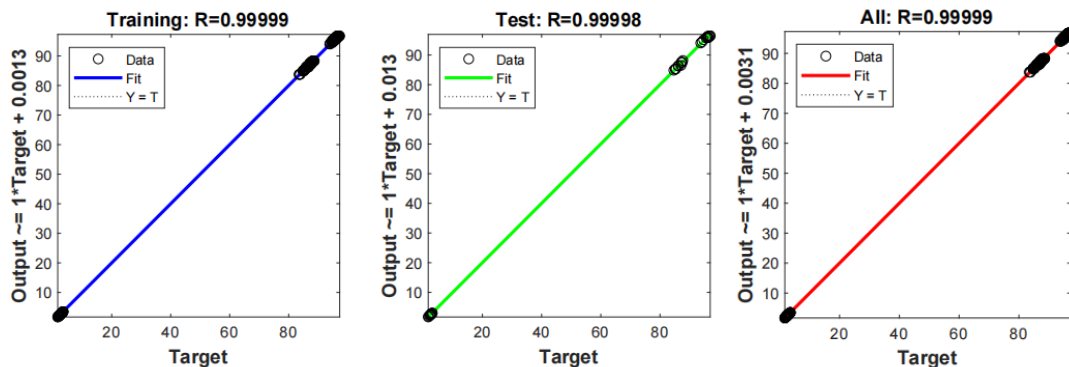


Figure 5 Effectiveness of BP neural network training

Bringing the receiving distance and hot air velocity into the model, the predicted structural variables are shown in the following table.

Table 6 Results for Question 2

Receiving distance	Hot air speed	Thickness	Porosity	Compression resilience
38	850	2.7758	96.2425	85.7596
33	950	2.6829	96.3064	87.9771
28	1150	2.7086	96.3672	87.0302
23	1250	2.6047	95.9575	85.3259
38	1250	3.0703	96.7274	85.6758
33	1150	2.9943	96.5597	86.8455
28	950	2.4131	95.6476	88.4502
23	850	1.9430	94.3708	87.1705

### 3.3 Creation and solution of Problem 3

#### 3.3.1 CCA solves for the relationship between structural variables and product performance

In order to investigate the relationship between structural variables and product performance, we set thickness, porosity, and compression rebound rate as Set 1, set the filtration resistance, filtration efficiency, and air permeability as Set 2, and use SPSS software to conduct typical correlation analysis. The typical correlation coefficients between them were obtained as follows.

Table 7 Set 1 Standardized Typical Correlation Coefficient

Variables	1	2	3
Thickness(mm)	-1.092	1.642	-1.908
Porosity(%)	0.021	-1.216	2.143
Compression resilience(%)	-0.156	1.265	0.135

Table 8 Set 2 Standardized typical correlation coefficients

Variables	1	2	3
Filtration resistance (Pa)	0.859	0.587	-0.361
Filtration efficiency (%)	0.640	-1.452	-0.390
Air permeability (mms)	0.437	-0.847	-1.361

The unstandardized typical correlation coefficient data between them are as follows.

Table 9 Set 1 Unstandardized typical correlation coefficient

Variables	1	2	3
Thickness(mm)	-2.313	3.476	-4.040
Porosity(%)	0.025	-1.483	2.613
Compression resilience(%)	-0.128	1.040	0.111

Table 10 Set 2 Unstandardized typical correlation coefficients

Variables	1	2	3
Filtration resistance (Pa)	0.187	0.127	-0.078

Filtration efficiency (%)	0.059	-0.135	-0.036
Air permeability (mms)	0.005	-0.010	-0.016

In turn, their typical correlation values were obtained as shown in the following table.

Table 11 Typical correlation

Relevance	Eigenvalue	Wilco statistic Statistic	F	Molecular freedom degree	Denominator degrees of freedom	Significance	
1	0.844	2.483	0.194	17.970	9.000	168.087	0.000
2	0.562	0.463	0.675	7.590	4.000	140.000	0.000
3	0.110	0.012	0.988	0.870	1.000	71.000	0.354

It indicates that there is a correlation between structural variables and product performance at a confidence interval of 95% and the first pair of variables and the second pair of variables are significantly correlated.

Next, use STATE software to continue to find their typical loading data as well as the variance ratio data.

Table 12 Set 1 Typical load

Variables	1	2	3
Thickness(mm)	-0.992	-0.116	-0.056
Porosity(%)	-0.909	-0.153	0.388
Compression resilience(%)	0.413	0.794	0.447

Table 13 Set 2 Typical load

Variables	1	2	3
Filtration resistance (Pa)	0.919	0.391	0.052
Filtration efficiency (%)	0.616	-0.564	0.549
Air permeability (mms)	-0.420	0.058	-0.906

The obtained variance proportion data are as follows.

Table 14 Explained proportion of variance

Typical Variables	Set 1* Self	Set 1* Set 2	Set 2* Self	Set 2* Set 1
1	0.660	0.470	0.467	0.333
2	0.222	0.070	0.158	0.050
3	0.118	0.001	0.375	0.005

In summary, it can be concluded that there is a typical correlation between structural variables and product performance, and the correlation reaches 0.844.

### 3.3.2 Multiple regression modeling equation

#### 1. Multiple regression modeling

In the multiple regression model, let the variables we enter  $x$  have  $d$  attributes.

$$X_i = [X_i^{(1)}, X_i^{(2)}, \dots, X_i^{(d)}]^T$$

The equation needs to be solved.

$$f(x_i) = \omega^T x_i + b$$

Putting the constant  $b$  into the weight vector  $\omega$  yields a  $(d+1)$ -dimensional weight vector  $\hat{\omega} = (\omega; b)$ ,  $\hat{\omega} = [\omega_1, \omega_2, \dots, \omega_d, b]$ . Correspondingly, we represent the input as a matrix  $X$ , where each row corresponds to a sample, and the first  $d$  elements of that row correspond to We assume that there are  $m$  samples, and  $X$  can be expressed as

$$X = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1d} & 1 \\ x_{21} & x_{22} & \cdots & x_{2d} & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{md} & 1 \end{pmatrix} = \begin{pmatrix} x_1^T & 1 \\ x_2^T & 1 \\ \vdots & \vdots \\ x_m^T & 1 \end{pmatrix}$$

$$X\hat{\omega} = \begin{pmatrix} x_{11}\omega_1 + x_{12}\omega_2 + \cdots + x_{1d}\omega_d + b \\ x_{21}\omega_1 + x_{22}\omega_2 + \cdots + x_{2d}\omega_d + b \\ \vdots \\ x_{m1}\omega_1 + x_{m2}\omega_2 + \cdots + x_{md}\omega_d + b \end{pmatrix}$$

$$\Leftrightarrow f(x_i) = \omega^T x_i + b$$

Need to solve for the minimum of the following functions

$$L = \frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2$$

For computational purposes, we use a column vector transpose multiplied by a column vector form  $\omega^* = \arg_{\hat{\omega}} \min (y - X\hat{\omega})^T (y - X\hat{\omega})$  the following is the derivative of

$$\frac{\partial h(\hat{\omega})}{\partial \hat{\omega}} = \frac{\partial [(y - X\hat{\omega})^T (y - X\hat{\omega})]}{\partial \hat{\omega}}$$

$$= 2 \frac{\partial y^T}{\partial \hat{\omega}} (y - X\hat{\omega})$$

Based on the formula for the derivative of row vectors with respect to column vectors, we can introduce.

$$\frac{d(Ax)^T}{dx} = \frac{d(\sum_{i=1}^n a_{1i} x_i, \sum_{i=1}^n a_{2i} x_i, \dots, \sum_{i=1}^n a_{mi} x_i)}{dx}$$

$$= \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{pmatrix} = A^T$$

The final result is

$$2x^T(x\hat{\omega} - y)$$

Let this equation be 0. The transpose of  $X$  is invertible when the multiplication by  $X$  is a full rank matrix, so that  $\omega$  can be solved for.

$$\begin{aligned} \because 2x^T(x\hat{\omega} - y) &= 2x^T x\hat{\omega} - 2x^T y = 0 \\ \because x^T x\hat{\omega} &= x^T y \\ \because \hat{\omega} &= (x^T x)^{-1} x^T y \\ \because \omega^* &= (x^T x)^{-1} x^T y \end{aligned}$$

Finally, let  $\hat{x}_i = (x_i, 1)$ , to obtain the expression of the multiple regression model.

$$f(\hat{x}_i) = \hat{x}_i^T (x^T x)^{-1} x^T y$$

## 2. Solving the multiple regression model

Using Stata software to perform multiple regression models solving, the multiple regression equation is obtained

$$y = -0.0849776 x_1 - 0.2459132 x_2 - 3.564837 x_3 + 5.12051 x_4 + 5.37696 x_5 - 0.0473448 x_6 - 1.441785 x_7 - 9.6394$$

Where  $y$  represents the filtration efficiency,  $x_1, x_2, x_3, x_4, x_5, x_6$  and  $x_7$  represent the permeability, filtration resistance, compression resilience, porosity, thickness, hot air velocity and receiving distance, respectively.

### 3.3.3 Finding the optimal filtration efficiency

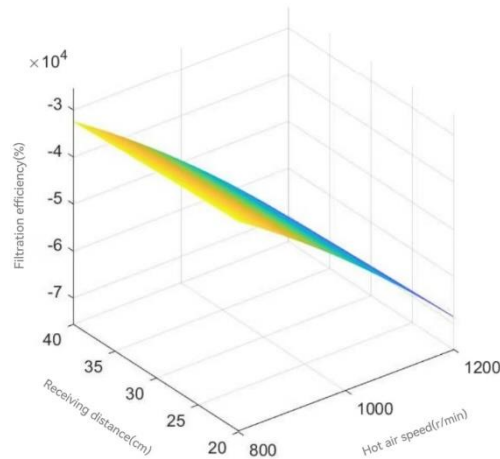


Figure 6 Filter efficiency function image

The obtained multiple regression equation was reduced dimensional processing, replacing the variables except process parameters with mean values to obtain the equation between process parameters and filtration efficiency equation.

$$y = -0.0473448 x_1 - 1.441785 x_2 + 142.6246$$

The function image of the objective function is shown in Figure 6 Filter efficiency function image. When the hot air speed is 1150r/min and the receiving distance is 20cm, the filtration efficiency is the highest and can reach 83.20%. The maximum filtration efficiency can reach 83.20% when the receiving distance is 20cm.

### 3.4 Creation and solution of Problem 4

#### 3.4.1 Multi-objective planning modeling

In order to make the product meet the goal of high filtration efficiency and low filtration resistance at the same time, and to prevent the meltblown nonwoven filter material from The filtering resistance of meltblown nonwoven filter material makes a large number of particles block the pores and cause a rapid decline in filtration efficiency, so to establish a multi-objective To prevent the rapid decline of filtration efficiency due to the large number of particles clogging the pores due to the high filtration resistance of meltblown nonwoven filter materials, a multi-objective planning model is established.

$$Z = F(x) = \begin{pmatrix} \max(y_1) \\ \min(y_2) \end{pmatrix}$$

$$st. \Phi(x) = \begin{cases} \varphi(x_1) \leq 100 \\ \varphi(x_2) \leq 2000 \\ \varphi(x_3) \leq 3 \\ \varphi(x_4) \geq 85\% \end{cases}$$

#### 3.4.2 Establishment of the objective function

To obtain the functional relationship between  $y_1$ ,  $y_2$  and  $x_1$ ,  $x_2$ ,  $x_3$ ,  $x_4$ , we use STATE software and adopt multiple regression model to establish the equations, and the parameters of the multiple regression equation for  $y_1$  are obtained as follows.

Table 15 Multiple regression results

Filtration efficiency	Coef.	Std. Err.	t	P> t	Beta
Receiving distance	-1.942698	0.6374805	-3.05	0.003	-1.283595
Hot air speed	-0.0255186	0.0220857	-1.16	0.252	0.3372177
Thickness	13.22452	11.66694	1.13	0.261	0.5796503

Compression resilience	-2.916677	0.8256154	-3.53	0.001	-
Cons	353.9574	74.94147	4.72	0.000	0.3293821

The multiple regression equation for  $y_1$  is obtained as follows.

$$y_1 = -1.942698 x_1 - 0.0255186 x_2 + 13.22452 x_3 - 2.916677 x_4 + 353.9574$$

The parameters of the multiple regression equation for  $y_2$  are as follows.

Table 16 Multiple regression results

Filtration efficiency	Coef.	Std. Err.	t	P> t	Beta
Receiving distance	0.3162948	0.2434788	1.30	0.198	0.489243
Hot air speed	0.0090524	0.0084354	1.07	0.287	0.2800439
Thickness	-12.64434	4.456063	-2.84	0.006	-1.297453
Compression resilience	0.3798627	0.315335	1.20	0.232	0.1004264
Cons	10.42427	28.62309	0.36	0.717	

The multiple regression equation for  $y_2$  is obtained as follows.

$$y_2 = 0.3162948 x_1 + 0.0090524 x_2 - 12.64434 x_3 + 0.3798627 x_4 + 10.42427$$

Bringing in the relevant equations for  $y_1$  and  $y_2$ , the resulting mathematical model expression is

$$Z = F(x) = \begin{pmatrix} \max(-1.942698 x_1 - 0.0255186 x_2 + 13.22452 x_3 - 2.916677 x_4 + 353.9574) \\ \min(0.3162948 x_1 + 0.0090524 x_2 - 12.64434 x_3 + 0.3798627 x_4 + 10.42427) \end{pmatrix}$$

The constraints of the model are.

$$\Phi(x) = \begin{cases} \varphi(x_1) \leq 100 \\ \varphi(x_2) \leq 2000 \\ \varphi(x_3) \leq 3 \\ \varphi(x_4) \geq 85\% \end{cases}$$

### 3.4.3 Solving multi-objective planning models

By solving the above mathematical model, the following conclusions were obtained.

In the case that the receiving distance is not greater than 100 cm, the hot air speed is not greater than 2000 r/min, the thickness is as less than grade 3 mm as possible, and the compression resilience is as much as possible not less than 85%, when the receiving distance is 25 cm and the hot air speed is 1250 r/min. When the receiving distance is 25cm and the hot air speed is 1250 r/min, it can make the filtration efficiency as high as possible and the filtration resistance as small as possible, the filtration efficiency is 83.26% and the filtration resistance is 27.50 Pa. The filtration efficiency is 83.26% and the filtration resistance is 27.50 Pa.

## 4. Conclusion

The model describes the problem accurately and skillfully to a certain extent, and it is quite simplified and easy to understand the operation. When building the BP neural network model, Bayesian regularization is introduced to prevent the model from overfitting, which effectively improves the accuracy of the model. When constructing the multi-objective planning model, a multiple regression model is introduced for interpretation, which makes the accuracy of the model greatly the accuracy of the model is greatly enhanced.

## References

- [1] Liu Yan. Mathematical model of multiple linear regression [J]. Journal of Shenyang Engineering College (Natural Science Edition) 2005(Z1):128-129.

- [2] Liu Yujun,Hou MUYI,Xiao Xiaoxiong. Meltblown nonwovens technology progress and the use of meltblown fabrics [J].Textile Herald, 2006(08):7980+83+95.
- [3] Zhou Pengfei,Lu Zeyu. Prediction of urban water consumption based on SPSS multiple linear regression model [J]. Water Science and Technology and Economy,2018,24(05):6-10.
- [4] Sun Quansen,Zeng Shenggen,Wang Pingan,Xia Deshen. The theory of typical correlation analysis and its application to feature fusion [J]. Journal of Computer Science ,2005(09):1524-1533.
- [5] Qi Dehu,Kang Jichang. Design of BP Neural Networks [J]. Computer Engineering and Design ,1998(02):47-49.
- [6] Wen Jiqin. Study on the factors influencing the filtration performance of polypropylene meltblown cloth [J]. Guangdong Chemical ,2021,48(21):85-87+92.
- [7] Su GaoLi,Deng Fangping. On the improvement algorithm of BP neural network based on MATLAB language [J]. Science and Technology Journal ,2003(02):130-135. DOI:10.13774/j.cnki.kjtb.2003.02.012.