Journal of Computer and Communications, 2023, 11, 146-158
https://www.scirp.org/journal/jcc
ISSN Online: 2327-5227
ISSN Print: 2327-5219

Parameter Optimization of Intercalated Meltblown Nonwovens Based on NSGA-II

Peiyuan Jin[1], Renjie Chu[2], Quanxi Feng[1*]

[1]School of Science, Guilin University of Technology, Guilin, China
[2]Institute of Technology, Guilin University, Guilin, China
Email: *fqx9904@163.com

How to cite this paper: Jin, P.Y., Chu, R.J. and Feng, Q.X. (2023) Parameter Optimization of Intercalated Meltblown Nonwovens Based on NSGA-II. *Journal of Computer and Communications*, **11**, 146-158.
https://doi.org/10.4236/jcc.2023.113011

Received: February 21, 2023
Accepted: March 28, 2023
Published: March 31, 2023

Abstract

The preparation process parameters of intercalated meltblown nonwoven materials are complicated, and the relationship between process parameters, structural variables, and product performance needs to be investigated to establish a good mechanism for product performance regulation. In this study, we first used Wilcoxon test and Pearson correlation analysis to investigate the effect of intercalation rate on structural variables and product performance. Then, regression models were constructed to predict the values of each structural variable under different combinations of process parameters. Finally, we constructed a multi-objective constrained optimization problem based on the stepwise regression model and the product variable conditions. The problem was solved using the NSGA-II algorithm. The optimal was achieved when the acceptance distance was 2.892 cm and the hot air speed was 2000 r/min.

Keywords

Regression Model, NSGA-II Algorithm, Meltblown Nonwovens, Parameter Optimization

1. Introduction

Meltblown nonwoven material [1] is a widely used air filtration material due to its good filtration performance, simple production process, low cost, and light weight. It is an important raw material for mask production for domestic and foreign enterprises. However, the fine fiber of meltblown nonwoven material often results in poor compression and elasticity performance in the final product. To address this issue, scientists have developed the interlayer meltblown method and created "Z-shaped" interlayer meltblown nonwoven material [2] [3]. The intercalated meltblown composite technology is to add a staple fiber carding machine and a blower to the traditional melt-blown equipment. After the intercalated fibers are cleared, they are blown into the melt-blown ultra-fine fiber flow by the blower device. This technology significantly improves the compressive resilience of the product, thereby enhancing its filtration efficiency performance.

The preparation of interlayer meltblown nonwoven materials is a complex process, and the resulting structural variables (such as thickness, porosity, and compressive resilience) of the product can differ under different meltblown process parameters (such as receiving distance and hot air velocity). These variations in structural variables can affect the product properties, such as filtration resistance, filtration efficiency, and gas permeability. Therefore, it is important to investigate the relationship between process parameters and structural variables and product performance to establish a more effective product performance regulation mechanism.

2. Method

2.1. Regression Model

1) Multiple linear regression model [4]

Response variables Y and p the explanatory variables $X_1, X_2, \cdots, X_p$. The relationship between can be portrayed by the following linear model.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + \varepsilon. \tag{1}$$

where β_0 is the constant term, and $\beta_1, \beta_2, \cdots, \beta_p$ is the regression coefficient of the model, and ε is the random error. The regression coefficient represents the contribution of an explanatory variable to the response variable Y of the model.

2) Ridge regression [5]

Ridge regression is an improved least squares estimation method that deals with the problem of covariance among the independent variables of a regression model. In the case of high covariance, perturbations in the data can cause large variations in the regression coefficient estimates, and ridge regression can reveal this phenomenon.

3) Lasso regression [6]

The advantage of Lasso regression is that it is a regression method that avoids overfitting, and while fitting the model the method simultaneously screens the variables, and any type of dependent variable can be modeled using Lasso regression.

4) Polynomial regression [7]

When the linear model cannot fit the target data well, then a polynomial regression model can be considered. The polynomial regression incorporates a higher order of the independent variable, which is equivalent to increasing the degrees of freedom of the model to explore the nonlinear variations in the data.

5) Model evaluation method

Multiple models are compared for their advantages and disadvantages, and the evaluation metrics selected in this paper are residual mean square MSE, information criterion AIC and BIC [8]. When these three metrics are smaller, it means that the model is better and thus the final model is determined.

2.2. Multi-Objective Constrained Optimization Problem

A multi-objective constrained optimization problem [9] [10] is one in which there are multiple conflicting objectives along with constraints that need to be satisfied by multiple equations or inequalities. Its specific definition equation is.

$$\begin{aligned} &\min F(x) = \left(f_1(x), \cdots, f_m(x)\right)^{\mathrm{T}} \\ &\text{s.t. } g_i(x) \le 0, i = 1, \cdots, q \\ &\quad h_j(x) = 0, j = 1, \cdots, p \end{aligned} \tag{2}$$

Among them, the $F(x) = \left(f_1(x), \cdots, f_m(x)\right)^{\mathrm{T}}$ is the m dimensional target vector, $x = [x_1, \cdots, x_n]$ are variables, and n is the dimensional decision space, $g_i(x)$ is the constraint condition of the i-th inequality, and $h_j(x)$ is the constraint condition of the j-th equality.

2.3. Methods for Solving Multi-Objective Constrained Optimization

The main algorithms for solving the problem are mathematical-based planning methods and evolutionary algorithm-based methods. Among them, the core of multi-objective evolutionary algorithms is to coordinate the relationship between each objective function and find the optimal set of solutions that makes each objective function reach the larger (or smaller) function value as much as possible. Among the many evolutionary algorithms for multi-objective optimization, the NSGA-II algorithm is one of the most influential and widely used algorithms [11] [12].

In this paper, we used NSGA-II algorithm to solve the multi-objective constrained problem, which is a multi-objective optimization algorithm based on Pareto optimal solution, that is, on the basis of the basic genetic algorithm, the selection regeneration method is improved: each individual is stratified according to their dominant and non-dominant relationships, and then the selection operation is done, which makes the algorithm obtain very satisfactory results in multi-objective optimization.

3. Data Analysis

3.1. Data Sources

The engineering data in this paper comes from the C question data provided by the third "Huashu Cup" National College Students Mathematical Modeling Competition [13]. The data mainly includes the structural variables and product performance of 25 sets of products generated under different process parameters.

3.2. Relationship between Intercalation Rate and Structural Variables, Product Performance

To study the impact of the intercalation technique on structural variables and product performance, this paper analyzes the presence or absence of intercalation and the intercalation rate. Firstly, 25 groups of control experiments were conducted before and after intercalation, and the change patterns of structural variables and product performance were identified by drawing bar graphs and box plots. Secondly, the Wilcoxon test was used to compare the differences between the three structural variables and the three product performances before and after intercalation. Finally, to investigate the effect of the intercalation rate on the changes in structural variables and product performances, Pearson correlation analysis was used to examine the relationship between the intercalation rate and other variables.

Analysis of Structural Variables and Product Performance Changes before and after Interpolation

In order to study the changes of each variable before and after interpolation, the scatter plot of the distribution density of the variables before and after interpolation is plotted in this section for analysis.

Based on Figure 1, it can be observed that the distribution of post-intercalation sample values for the three structural variables of thickness, porosity, and compression resilience is skewed to the right compared to the pre-intercalation sample. This suggests that the post-intercalation sample generally has larger values for these structural variables than the pre-intercalation sample. Furthermore, the post-intercalation sample exhibits a lower filtration resistance and higher permeability than the pre-intercalation sample at the same filtration efficiency. These results indicate that intercalation technology can effectively enhance the structural variables and product performance of meltblown nonwoven materials.

The effect of interpolation on each variable is further observed by bar and box plots of the changes in structural variables and product performance before and after interpolation.

As can be seen in Figure 2(a) and Figure 2(c), the bars of meltblown nonwoven material thickness and porosity after intercalation are higher than those before intercalation. In Figure 2(b), most of the thicknesses of the materials before intercalation are less than 2 mm, while the average level of the material thickness after intercalation is about 3 mm, which is significantly higher compared with that before intercalation. In Figure 2(d), the dispersion of porosity of the material after intercalation is significantly reduced compared with that before intercalation, and it is found in the experiment that the porosity of the material can be increased by 2 - 3 times by performing the intercalation operation when the receiving distance is small. In Figure 2(e), there are several groups of 25 experiments in which the compressive resilience is unchanged or even decreased before and after intercalation, but the overall compressive resilience is increased.

Through the two subplots of Figure 3(a) and Figure 3(c), it is found that the receiving distance is negatively correlated with both the filtration resistance and the filtration efficiency of the material. The smaller the receiving distance, the greater the filtration resistance and filtration efficiency of the material. In addition,

Figure 1. Distribution density of structural variables and product performance.

the filtration resistance of the material decreases and the filtration efficiency gets increased after the intercalation compared with that before the intercalation. On the contrary, in **Figure 3(e)**, the receiving distance is positively correlated with the permeability of the material, and the smaller the receiving distance, the smaller the permeability of the material. After intercalation, the gas permeability of the material is increased to a small extent compared with that before intercalation.

Table 1 shows that there is a negative correlation between the intercalation rate and compression resilience and gas permeability, and a positive correlation

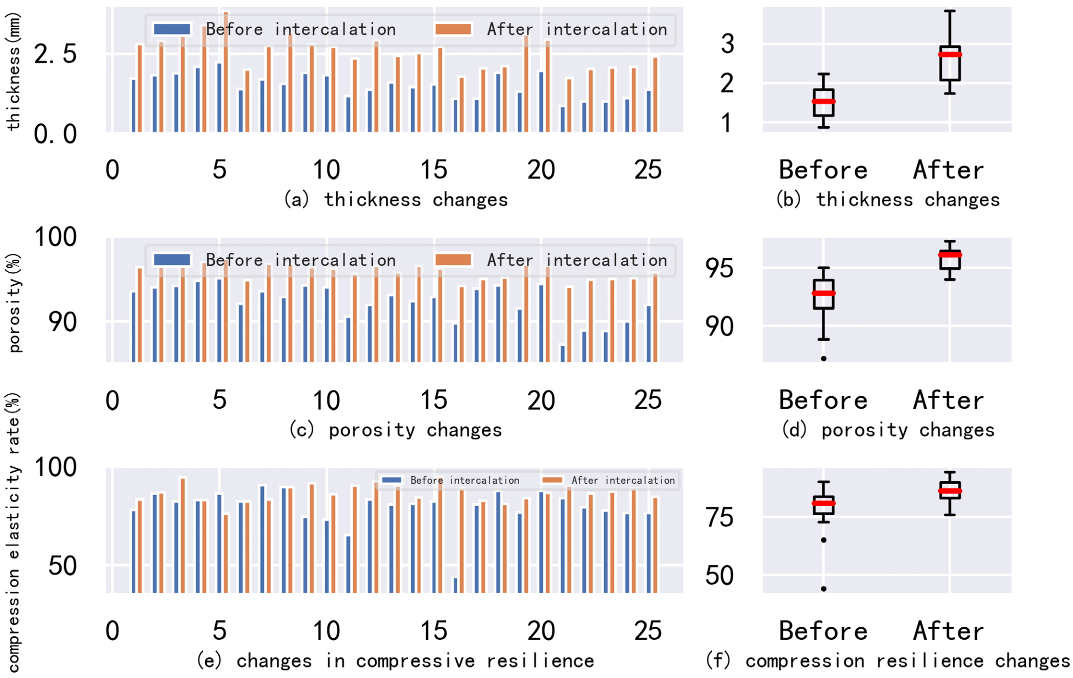

Figure 2. Differences in structural variables before and after interpolation.

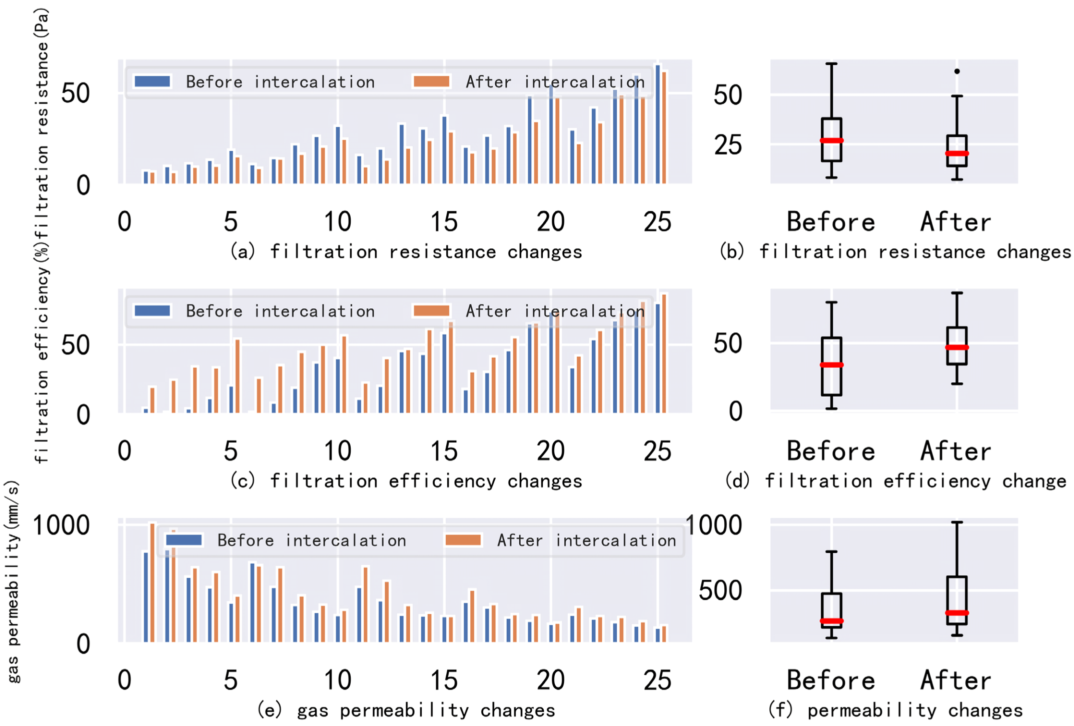

Figure 3. Difference in product performance before and after interpolation.

Table 1. Correlation between intercalation rate, product structure and performance variables.

	Thickness	Porosity	Compression resilience	Filtration resistance	Filtration efficiency	Gas permeability
Interpolation rate	0.15	0.12	−0.5	0.24	0.23	−0.024

with the remaining four variables. The correlation coefficient between the interlayer rate and the compression resilience is −0.5, which indicates that there is a moderate negative correlation between the interlayer rate and the compression resilience, so the interlayer rate should not be set too high when setting the interlayer rate, which makes the compression resilience decrease in the reverse direction.

3.3. Relationship between Process Parameters and Structural Variables

In order to study the relationship between process parameters and structural variables, this paper firstly draws three-dimensional scatter plots of thickness, porosity, and compression resilience of structural variables with process parameters respectively, which are used to observe the distribution of structural variables under different process parameters; secondly, according to the distribution of the three structural variables, different regression models are constructed for fitting, and by comparing the residual mean square MSE and information criterion AIC and BIC to evaluate the effect of the models.

3.3.1. Model Building

The three-dimensional scatter plots between the two process parameters and each structural variable were drawn separately to visually reflect the correlations between the variables. Figure 4(a) and Figure 4(b) show that there is a clear linear correlation between process parameters and thickness and porosity, so this paper integrates three methods of multiple linear regression, ridge regression and Lasso regression [14] to investigate the relationship between process

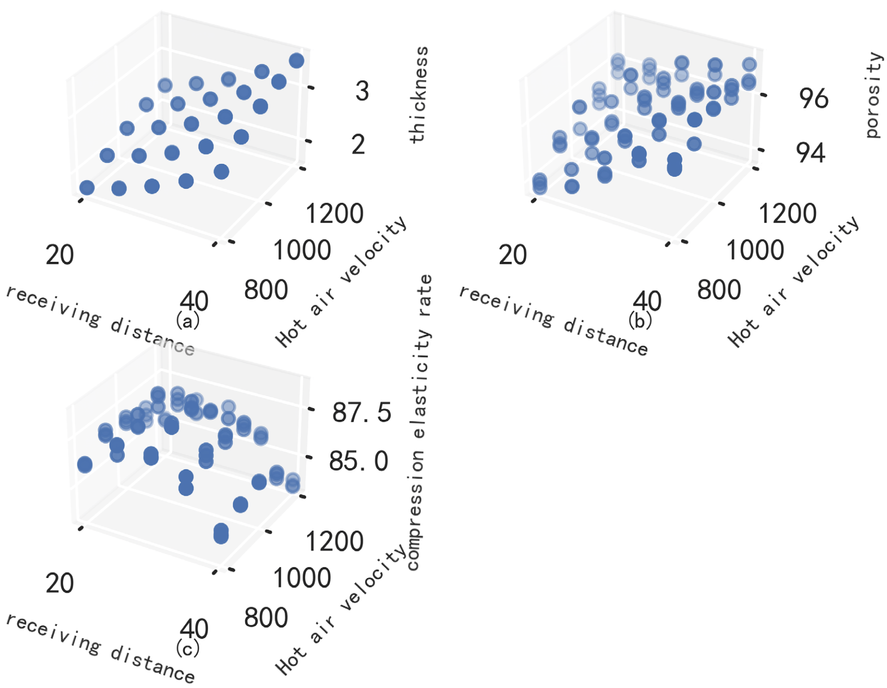

Figure 4. Relationship between process parameters and structural variables.

parameters and thickness and porosity. Figure 4(c) shows the trend of curves, so the polynomial regression method is added to the above three methods to establish the relationship model between process parameters and compression resilience.

3.3.2. Model Building Results

Multiple linear regression, ridge regression and Lasso regression models of process parameters with thickness and porosity were established respectively. The results of model evaluation are shown in Table 2 and Table 3.

The effect of the model is evaluated by the three indicators of residual mean square MSE and information criterion AIC and BIC, the smaller the above three indicators, the better the model, so this paper chooses to establish the relationship between process parameters and thickness and porosity using multiple linear regression model, and the relationship between process parameters and compression resilience using polynomial regression. Among them, the prediction equation of process parameters and thickness is

$$\hat{y}_1' = -0.001 + 0.593x_1' + 0.403x_2'. \tag{3}$$

The prediction equation for the process parameters and porosity is

$$\hat{y}_2' = 0.197 + 0.475x_1' + 0.339x_2'. \tag{4}$$

The prediction equation for the process parameters and the compression resilience rate is

$$\hat{y}_3' = 1.328x_1' + 0.738x_2' - 1.611x_1'^2 + 0.032x_1'x_2' - 0.967x_2'^2. \tag{5}$$

where x_1' is the normalized receiving distance, and x_2' is the normalized hot

Table 2. Regression model results of process parameters with thickness and porosity.

Structure Variables		Multiple linear regression	Ridge regression	Lasso regression
Normalized thickness y_1'	MSE	0.002	0.002	0.002
	AIC	−476.429	−476.096	−476.425
	BIC	−469.476	−469.144	−469.472
Normalized porosity y_2'	MSE	0.010	0.010	0.010
	AIC	−337.319	−337.285	−337.100
	BIC	−330.367	−330.332	−330.148

Table 3. Regression model results of process parameters and compression resilience.

Structure Variables		Multiple linear regression	Ridge regression	Lasso regression	Polynomial regression
Normalized compressional resilience y_3'	MSE	0.041	0.041	0.055	0.002
	AIC	−234.314	−234.064	−211.256	−453.925
	BIC	−227.361	−227.111	−204.303	−437.703

air velocity.

The established model is predicted for the real data and the predicted structural variable values are plotted in **Figure 5**.

The blue points in **Figure 5** are the results of the experimental data, and the brown points are the predicted values of the eight sets of structural variables, from which it can be seen that there are no outlier points in the predicted variable values and the fit is good.

3.4. Multi-Objective Process Parameter Optimization Based on NSGA-II

3.4.1. Stepwise Regression Analysis

In the study of the relationship between the filtration efficiency of the product and the process parameters, this paper uses the stepwise regression method to analyze the specific influence of the relationship and finally find the setting of the process parameters when the filtration efficiency of the product is the highest.

Stepwise regression is a regression method for feature extraction based on the explanatory variables. The basic idea is to introduce independent variables one by one, and the condition of introduction is that their partial regression sum of squares is tested to be significant. At the same time, after each new independent variable is introduced, the old independent variables are tested one by one, and the independent variables with insignificant partial regression sum of squares are eliminated. In this way, new variables are introduced and removed again until no new variables are introduced and no old variables are removed. After stepwise regression, the regression equation with the best results is obtained.

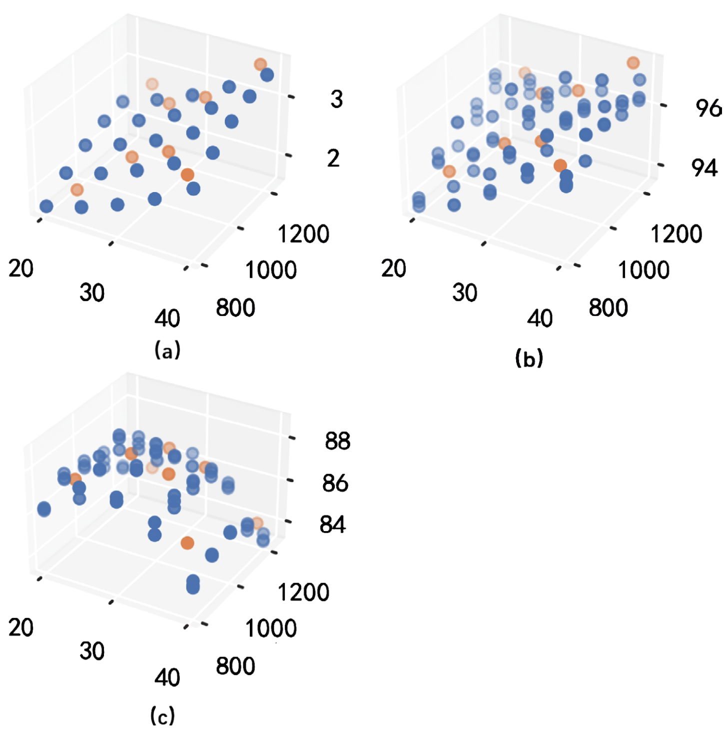

Figure 5. Scatter plot of predicted structural variables.

The relationship between the process parameters and the filtration efficiency of the product is modeled in which the dependent variable is the filtration efficiency and the independent variables are the process parameters (receiving distance and hot air velocity) and the structural variables (thickness, porosity, compressive resilience).

Table 4 shows that the receiving distance and compression resilience rate are significantly correlated with the filtration efficiency of the material, and the model can explain the reason for 55.4% variation in filtration efficiency, and the model F values passed the test and the model was considered valid. And the variance expansion factor of each explanatory variable VIF are less than 10, the model is considered to have no serious covariance, and the model equation is

$$z_2' = 0.786 - 0.546 x_1' - 0.341 y_3'. \tag{6}$$

where z_2' denotes the normalized filtration efficiency.

3.4.2. Building Multi-Objective Constrained Problem

In order to construct a suitable multi-objective constrained optimization model so as to solve for the appropriate values of process parameters. In this paper, the regression model established for the filtration efficiency is firstly used as the first objective, and the model corresponding to the second objective is obtained using the same method.

Stepwise regression analysis was performed on filter resistance and process parameters and structural variables, where the dependent variable was filter resistance and the independent variables were structural variables (thickness, porosity, compression resilience) and process parameters (acceptance distance and hot air velocity).

Table 5 shows that the thickness of the material is significantly correlated with the filtration resistance, and the model can explain 63.2% of the reason for the variation of the filtration resistance, and the model F value passed the test and the model was considered valid. Meanwhile, the variance expansion factor of thickness variable VIF value is equal to 1 and less than 10, then the model is considered to have no covariance, and the model equation is

Table 4. Results of stepwise regression analysis.

	Regression coefficient	p	R^2	VIF	F
Constants	0.786	0.000**	0.554	–	$F(2,72) = 44.794$, $p = 0.000$
x_1'	−0.546	0.000**		1.193	
y_3'	−0.341	0.000**		1.193	

Table 5. Results of stepwise regression analysis.

	Regression coefficient	p	R^2	VIF	F
Constants	0.805	0.000**	0.632	–	$F(1,73) = 125.562$, $p = 0.000$
y_1'	−0.641	0.000**		1.000	

$$z_1' = 0.805 - 0.641 y_1'. \tag{7}$$

Equation (7) is used as the second objective of the multi-objective constrained optimization problem in this paper.

Secondly, the numerical requirements of the structural variables are taken as the constraints for the solution, and the range of values of the decision variables is set according to the constraints of the process parameters. By the above method, a multi-objective constrained optimization model is constructed, in which the objective function and constraint function are respectively expressed by Equations (8) and (9)

$$F(x) = \begin{cases} \max z_2 \\ \min z_1 \end{cases} \tag{8}$$

$$\text{s.t.} \begin{cases} 0 < x_1 < 100 \\ 0 < x_2 < 2000 \\ 0 < y_1 < 3 \\ 85 < y_2 < 100 \end{cases} \tag{9}$$

3.4.3. Optimization Results

The NSGA-II algorithm is used to solve the multi-objective constrained optimization problem constructed in this paper. The population size of the algorithm is set to 10 and the number of iterations is set to 50. 10 approximate solutions are obtained after solving the algorithm, and these solutions are further analyzed.

Considering that parameter optimization of intercalated meltblown nonwovens is a bi-objective constrained optimization problem, the scatter plot of the approximate solution of NSGA-II solving problem model is drawn in this paper

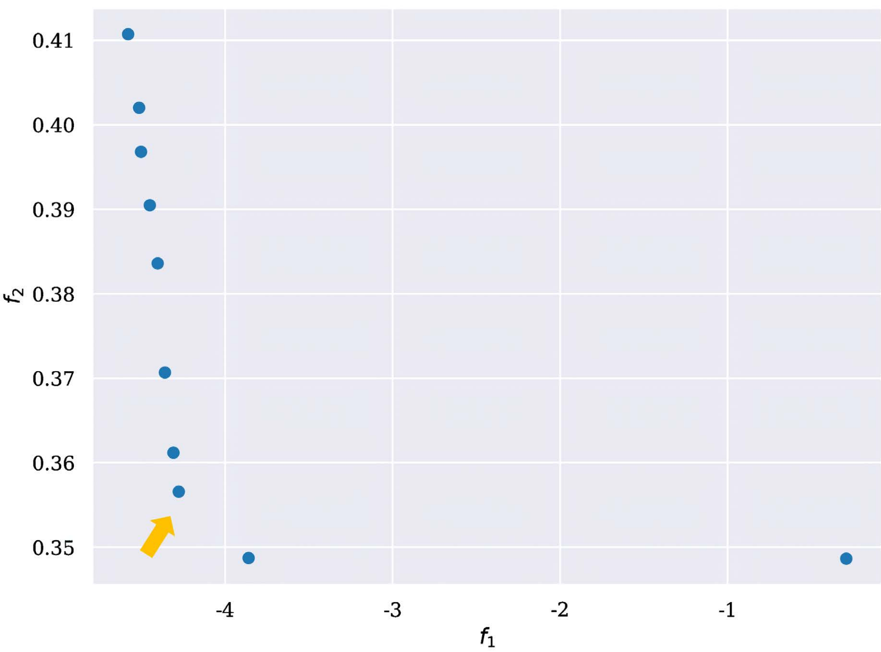

Figure 6. Scatter plot of the approximate solution of NSGA-II solving the parameter optimization.

to determine the optimal solution of the model. The approximate solution indicated by the arrow in Figure 6 is the finalized optimal solution, which takes into account the filtration efficiency and filtration resistance, and tries to reduce the filtration resistance of the product under the premise of ensuring the filtration efficiency. The solution is back-normalized to obtain the final result, which is considered to be optimal when the acceptance distance is 2.892 cm and the hot air speed is 2000 r/min.

4. Conclusion

The intercalation technique helps to improve the product properties of meltblown nonwoven materials. There is a highly significant and moderate negative correlation between the intercalation rate and the compression resilience. By examining the complex relationship between process parameters, structural variables, and product performance, this study provides insights into optimizing the production of interleaved meltblown nonwoven materials for better performance. As a result, the product performance reached the highest when the acceptance distance was 2.892 cm and the hot air speed was 2000 r/min.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Liu, C., Dai, Z., He, B., *et al.* (2020) The Effect of Temperature and Humidity on the Filtration Performance of Electret Melt-Blown Nonwovens. *Materials*, **13**, 4774. https://doi.org/10.3390/ma13214774

[2] Zou, Z.W. (2020) Simulation of the Flow Field of Intercalated Meltblown Gas and Optimization of Production Process Parameters. Tianjin University of Technology, Tianjin. (In Chinese)

[3] Wu, H. (2018) Simulation of the Flow Field of Intercalated Meltblown Gas and Its Filtration Material Performance. Tianjin University of Technology, Tianjin. (In Chinese)

[4] Uyanık, G.K. and Güler, N. (2013) A Study on Multiple Linear Regression Analysis. *Procedia-Social and Behavioral Sciences*, **106**, 234-240. https://doi.org/10.1016/j.sbspro.2013.12.027

[5] Hoerl, A.E. and Kennard, R.W. (1970) Ridge Regression: Applications to Nonorthogonal Problems. *Technometrics*, **12**, 69-82. https://doi.org/10.1080/00401706.1970.10488635

[6] Ranstam, J. and Cook, J.A. (2018) LASSO Regression. *Journal of British Surgery*, **105**, 1348-1348. https://doi.org/10.1002/bjs.10895

[7] Heiberger, R.M., Neuwirth, E., Heiberger, R.M., *et al.* (2009) Polynomial Regression. R Through Excel: A Spreadsheet Interface for Statistics, Data Analysis, and Graphics, 269-284. https://doi.org/10.1007/978-1-4419-0052-4_11

[8] Vrieze, S.I. (2012) Model Selection and Psychological Theory: A Discussion of the Differences between the Akaike Information Criterion (AIC) and the Bayesian In-

formation Criterion (BIC). *Psychological Methods*, **17**, 228-243. https://doi.org/10.1037/a0027127

[9] Li, L., Li, G.-P., Chang, L., *et al.* (2021) Survey of Constraint Evolution Algorithms and Their Applications. *Computer Science*, **48**, 1-13. (In Chinese)

[10] Wang, Y., Cai, Z.X., Zhou, Y.R., *et al.* (2009) Constraint Optimization Evolutionary Algorithms. *Journal of Software*, **20**, 11-29. (In Chinese) https://doi.org/10.3724/SP.J.1001.2009.00011

[11] Deb, K., Pratap, A., Agarwal, S., *et al.* (2002) A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, **6**, 182-197. https://doi.org/10.1109/4235.996017

[12] Zheng, Y.F., Fang, R.C., Zhou, Y.J., *et al.* (2020) Planning of Distribution Network Reliability Optimization Based on NSGA2 Algorithm. *Electrical Automation*, **42**, 70-72+79. (In Chinese)

[13] https://www.saikr.com/vse/chinamcm/2022

[14] Chatterjee, S. and Hadi, A.S. (2006) Regression Analysis by Example. John Wiley & Sons, Hoboken. https://doi.org/10.1002/0470055464