Study on the adaptability of cellulose diacetate tow for tobacco to the type of curling machine

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ABSTRACT – REZUMAT

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The raw material of cigarette filters is cellulose diacetate slurry, and potentially harmful substances such as acetone are used during production. To improve cigarette filters' filtering effectiveness, increase cellulose diacetate filaments' utilisation rate, and reduce environmental pollution during production, this study aims to investigate the effects of cellulose diacetate tow specifications and crimping machine models on tow formation quality. In this paper, the correlation between the specification of cellulose acetate tow, crimping machine models, and the resulting tow quality is determined to guide the selection of crimping machines for practical production. To tackle the challenges of large sample sizes and high experimental costs, a multidimensional sampling method is developed. Utilizing a learning-based approach, we identify a robust nonlinear relationship among these three factors and validate the relationship by using historical production data. Our findings reveal a significant nonlinear correlation between the crimping machine model and both single and total deniers. Through two regression adjustments, a reasonable degree of regression fitting for the relationships among the three factors is achieved. The experimental results indicate that the selection of the crimping machine is positively correlated with the number of filaments in the bundle and the pressure on the rollers, while it is negatively correlated with the cross-sectional area of the filaments. Additionally, a production guidance model, which relates the crimping machine model to the specifications of cellulose acetate tow, is established.

Keywords: *curling machine, cellulose diacetate, orthogonal experimental design, Latin hypercube sampling, logistic regression*

Studiu privind adaptabilitatea filamentului din diacetat de celuloză pentru tutun la tipul de mașină de sertizare

Materia primă a filtrelor pentru țigări este suspensia de diacetat de celuloză, iar în timpul procesului de producție sunt utilizate substanțe potențial nocive, cum ar fi acetona. Pentru a îmbunătăți eficiența de filtrare a filtrelor de țigări, pentru a crește rata de utilizare a filamentelor de acetat de celuloză și a reduce poluarea mediului în timpul producției, acest studiu urmărește să investigheze efectele specificațiilor filamentelor de acetat de celuloză și ale modelelor de mașini de sertizare asupra calității formării filamentelor. În această lucrare, se determină corelația dintre specificațiile filamentelor de acetat de celuloză, modelele de mașini de sertizare și calitatea filamentelor rezultate pentru a ghida selecția mașinilor de sertizare pentru producția practică. Pentru a face față provocărilor legate de dimensiunea mare a eșantioanelor și de costurile experimentale ridicate, este dezvoltată o metodă de eșantionare multidimensională. Utilizând o abordare bazată pe învățare, identificăm o relație neliniară robustă între acești trei factori și validăm relația prin utilizarea datelor istorice de producție. Constatările noastre relevă o corelație neliniară semnificativă între modelul mașinii de sertizare și denierul unic și cel total. Prin două ajustări ale regresiei, se obține un grad rezonabil de ajustare a regresiei pentru relațiile dintre cei trei factori. Rezultatele experimentale indică faptul că selectarea mașinii de sertizare este corelată pozitiv cu numărul de filamente din fascicul și cu presiunea exercitată asupra rolelor, în timp ce este corelată negativ cu aria secțiunii transversale a filamentelor. În plus, este stabilit un model de ghidare pentru producție, care leagă modelul mașinii de sertizare cu specificațiile filamentului de acetat de celuloză.

Cuvinte-cheie*: mașină de sertizare, diacetat de celuloză, design experimental ortogonal, prelevare de probe cu hipercub latin, regresie logistică*

INTRODUCTION

Cellulose acetate fibres, known for their excellent adsorption properties [1] and substantial surface area, can effectively capture harmful substances in cigarette smoke. These fibres are primarily derived from cellulose acetate, which is the main component of cigarette filters [2, 3]. The preparation of cellulose acetate fibres involves the production of cellulose acetate slurry, which is then extruded through a spinneret with a defined cross-sectional shape and directed into a duct. After exposure to heated air within the duct, the slurry transforms into filaments with specific plasticity. The preparation process involves the use of hazardous chemicals, such as acetone. In the long-term production processes, leaks and other issues can arise, potentially impacting the environment and posing health risks to those involved. Additionally, cellulose diacetate can take several years or even decades to degrade in natural environments [4, 5]. Therefore, improving the quality of filament formation and increasing product utilization can reduce the environmental impact indirectly.

In the production of cellulose acetate fibre tows, the filaments exiting the duct are treated with oil on oiling wheels. This process helps protect the filaments in subsequent stages by reducing friction, providing lubrication, cleaning, and cooling. When the slurry is sprayed through nozzles of varying diameters, it creates filaments with different cross-sections, resulting in different single-fibre specifications, commonly referred to as 'single denier' in practical production. Different specifications of the total filament bundle, depending on the number of converging ducts and variations in spray nozzle models, combine to form different total fibre specifications, known as 'total denier' in practical production.

Once the specifications for single and total fibres are established, physical processes such as stretching and squeezing occur through a crimping machine. This results in the formation of large and small curling waves, which shape the filament tows and determine their overall quality. Extensive experimental research has been conducted on the compatibility between cellulose acetate tows for smoking and crimping machines, as well as on the width of the filaments before they enter the crimping machine [6].

To improve the curling process of cellulose acetate fibres for smoking [7], we established the relationship between the specifications of filament curling and different types of crimping machines. A guiding model has been developed to assist in selecting crimping machines based on the specifications of single and total denier. Under optimal conditions for filament quality, this model establishes the relationship between single and total deniers, and crimping machine types. In other words, for specific specifications and types of single and total deniers, the regression model developed in this study provides recommendations for suitable crimping machine models, offering significant reference value.

Experimental considerations

Cigarette filters are typically manufactured from cellulose acetate tows [8], which undergo a series of processing steps. The crimping process of the filament bundle is a central and crucial technology in the production of cigarette filters. This process often employs a crimping machine to process the preliminarily formed filament tow [9]. Horizontal stuffing box curling machines consist of upper and lower pressure rollers and a stuffing box [10]. The rotating rollers are responsible for both stretching and rolling the filament bundle, while in the stuffing box, the fibres deform and curl due to mutual compression and the pressure applied by the stuffing box plate. The rollers of the crimping machine play a significant role in determining the final shaping pattern of cellulose acetate tows through their effects on the rolling and stretching of the filaments.

This study aims to achieve optimal matching between cigarette cellulose acetate tow specifications and crimping machine models. It develops a robust nonlinear model to relate fibre specifications to crimping machine types. Given the extensive range of fibre specifications, a full-sample experiment would be cost-prohibitive. Therefore, an orthogonal experimental design and a Latin hypercube sampling scheme are employed to select representative samples from the experimental population, thereby reducing both the complexity and cost of the experiment. Additionally, to better align with practical production and avoid sampling in areas irrelevant to actual production, commonly used fibre specifications are employed as the base library for experimental selection. Biased treatments are applied to the specimens within this base library to enrich the sample space and enhance the trend data of model variations at the sampling points. In the experiment, sampling models are established using production data from a real company. 70% of the randomly extracted data from the constructed dataset is used for model training, while the remaining 30% is allocated to validate the accuracy of the trained model.

The quality of cellulose acetate tows can be assessed from several perspectives, including the stability of curling for fibres with the same specifications, the amount of fibre fly produced during subsequent processing, the tensile strength of the fibres, and the size and distribution of the curling waves. However, these evaluation metrics are influenced by factors such as the fibre tow specifications and the oiling process, making it challenging to normalize them under varying conditions and isolate the impact of a single variable on fibre tow quality. Therefore, considering the combined influence of these factors, we use a weighted comprehensive evaluation score as the final criterion for selecting curling machines.

The final evaluation criteria for the fibre tows can be obtained from the relevant data in table 1.

Finally, the original data model is processed using logistic regression to build an initial adaptation model. By evaluating different specifications, scores for the crimping machines are generated, and the model with the highest score is selected. The training data is then updated, and the model is retrained and reevaluated. The model's fitting accuracy is validated using the test set. This comprehensive approach aims to account for various influencing factors, incorporate bias treatment, and iteratively refine the model to ensure the accurate evaluation and selection of crimping machines under different conditions.

PRELIMINARIES

In this section, we will introduce several key methods, including Latin hypercube sampling (LHS) [11], orthogonal experimental design, and logistic regression modelling.

Table 1

SPINNING PRODUCTION QUALITY INSPECTION INFORMATION			
Indicators	**Equipment**	**Control range**	**Common methods**
Beating evaluation	Beating machine	Individual item < 3 Total score < 5	Beating
Fly test	Fly machine	< 90 mg/30 min	Weighing method
Line density test for crimped fibre tows	Total denier testing station	Target value: ± 0.1 ktex	Weighing method
Fibre bundle moisture test	Rapid moisture meter	5.7 ± 1.0%	Moisture meter method
Crimping energy test	Tensile tester	Target value: ± 35.0 g cm/cm	Tensile tester method
Break strength test	Tensile tester	≥ 18 N/ktex	Tensile tester method
Whiteness	Whiteness meter	≤ 8.0 B	Instrumental method
Fibre bundle crimp count measurement	Single fibre denier meter	Target value: ± 4	Instrumental method

Latin hypercube sampling

LHS is a method based on the principles of mathematical random theory, notable for its features of stratification, randomness, and disorder, which has been widely used in practical engineering. This sampling technique effectively mitigates the collapse of sample points [12]. These characteristics ensure that, while covering the entire feasible space through random sampling, the collected sample space avoids excessive clustering. Additionally, it guarantees edge sampling within the total space, thus preventing distortion of the sample space.

To investigate this, we compared Monte Carlo random sampling and Latin hypercube sampling for sampling from a standard normal distribution, as shown in figure 1, *a*. Both methods maintain the distribution pattern of the original data, with denser sampling in areas of higher probability density and sparser sampling in areas of lower probability density. However, Monte Carlo random sampling tends to lose samples at the distribution edges (as indicated by the sparse red points in the intervals [–4, –2] and [2, 4] in figure 1, which diminishes the representativeness of the overall distribution. In contrast, Latin hypercube sampling effectively avoids this issue.

In the present experimental data, the results of Latin hypercube sampling for the distribution of single denier are depicted in figure 1, *b* and *c*.

Orthogonal experimental

Orthogonal experimental design [13] is a method used to study the effects of multiple factors at different levels. Based on Galois theory [14], it selects representative combinations of factor levels from a fully matched set of experiments to identify the optimal level combinations. Typically, high-order interactions between factors are minimal, with first-order interactions (interactions between two factors) being the primary focus. The orthogonal design ensures that all possible two-factor combinations at different levels are represented in the orthogonal table, addressing first-order interactions. This approach maintains experimental representativeness while reducing complexity.

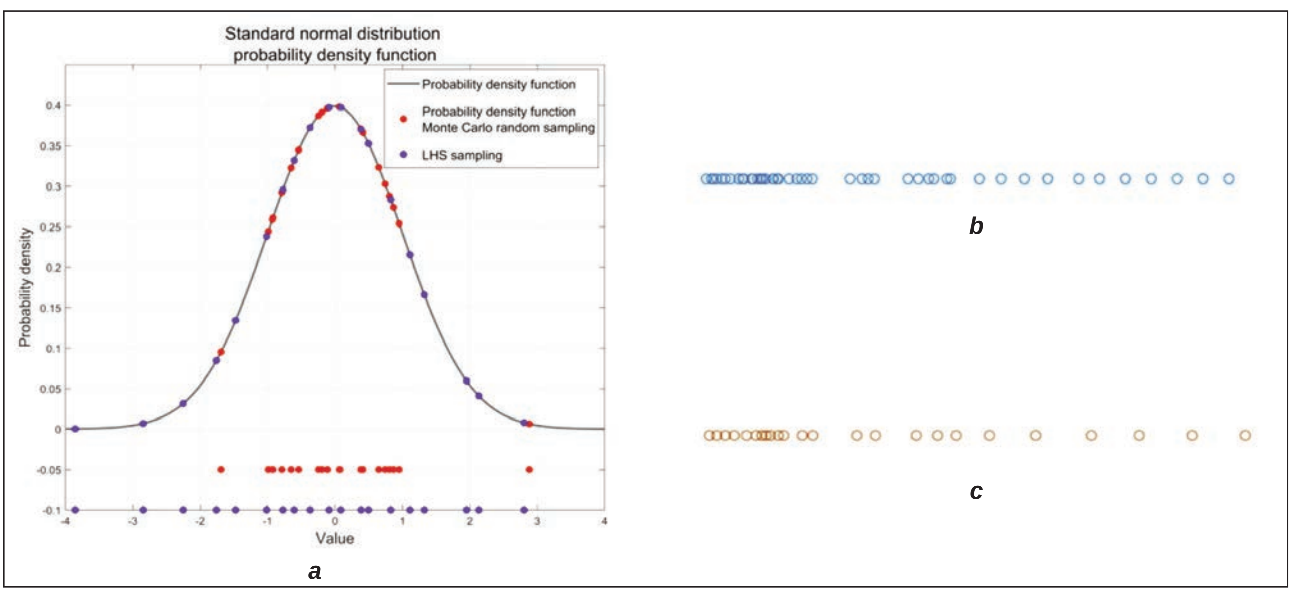

Fig. 1. Image of: *a* – the comparative schematic diagram between Monte Carlo sampling and LHS under the standard normal distribution; *b* and *c* – the demonstration of the LHS on the original data and sampled data

The fundamental requirement of orthogonal experimental design is to maintain orthogonality among various factors. Hence, it is necessary to ensure:

1. For any pair of distinct factors (A,B), it is essential to fulfil the requirement of interaction

$$AB = 0 \tag{1}$$

2. The sum across different levels of the same factor should meet the requirement

$$A_1 + A_2 + A_3 + \ldots A_k = 0 \tag{2}$$

Thus, ensuring the independence of mutual influences among different factors.

Logistic regression

Logistic regression [15–18] is a widely used algorithm in machine learning. It starts with the assumption that the data follows a logistic distribution. Using maximum likelihood estimation, the algorithm determines the error values of the parameters.

Optimization methods such as gradient descent, Newton's method [19], and others are employed to minimize the loss function by identifying the parameter values that yield the smallest error.

Logistic regression can be viewed as a classification method. The associated logistic distribution is a continuous probability distribution, characterized by its probability distribution function (CDF) and probability density function (PDF), defined as follows,

$$\begin{aligned} F(x) &= P(X \le x) = \frac{1}{1 + e^{-(x-\mu)/\gamma}} \\ f(x) &= F(X \le x) = \frac{e^{-(x-\mu)/\gamma}}{\gamma(1 + e^{-(x-\mu)/2})^2} \end{aligned} \tag{3}$$

When the probability corresponding to an event exceeds a specific threshold, the event is classified as one type; otherwise, it is classified as another type. The logistic distribution is a continuous probability distribution characterized by its location and scale parameters. The shape of the logistic distribution is similar to that of the normal distribution, but features longer tails. This characteristic makes the logistic distribution suitable for modelling data distributions with longer tails and higher peaks compared to the normal distribution. The sigmoid function commonly used in deep learning is a special case of the logistic distribution function, mapping any real-valued number into a value between 0 and 1.

EXPERIMENTAL DESIGN

Theoretical analysis

In the experimental study conducted in this research, the matching between the specifications of cellulose acetate fibre tows and the crimping machine is primarily influenced by both the single denier and the total number of fibres. The specification of a total deniers is determined by the combined effects of the spinneret and the number of spinneret holes, as described by the following formula:

$$N = \alpha(k,n) \cdot n \tag{4}$$

where, N represents the total denier, $\alpha(\cdot)$ is the constraint function, k, m, and n denote the type of spray, positions, and single denier in the spinneret, respectively.

The selection of the spinneret model is constrained by the limitation, which can only correspond to a specific range of single denier specifications. The three factors of single denier, spinneret, and the number of positions cannot form a completely orthogonal design. To address this, we map the spinneret to the single filament, taking the mapping results $\mathcal{S}$ and the number of positions $\mathcal{T}$ as the factors for orthogonal experimental design. Consequently, design a two-factor $(\mathcal{S},\mathcal{T})$ orthogonal experimental table with 35 levels and 27 levels, respectively.

However, since this experiment involves only two factors, each with numerous levels, using a single orthogonal experimental table for modelling would still require a lot of experiments, failing to demonstrate the advantages of orthogonal experimental design in reducing experimental complexity. To achieve a better design for the experimental setup with two factors and multiple levels in this study, we adopted the concept of "blocking". Utilizing LHS, extracted samples with lower levels from factors $\mathcal{S}$ and $\mathcal{T}$, resulting in an orthogonal experimental table $L64$ with 2 factors and 8 levels. This process was repeated three times, excluding duplicated sampling points. The resulting baseline orthogonal experimental table is shown in figure 2, *a*, where the horizontal axis $\mathcal{S}$ represents the full mapping combination of single denier and total deniers after applying the constraint function $\alpha(\cdot)$, the vertical axis $\mathcal{T}$ represents the part number. In figure 2, *b*, X_i represents the designed fibre specifications, Y_i represents the curling machine model, $Y_{i,j}$ represents the curling machine model library obtained after bias processing by the preliminary model, $Q_{i,j}$ represents the quality score of the corresponding fibre after passing through the corresponding curling machine, R_L represents the logistic regression model, M represents the final 'fibre tows-curling machine' matching model obtained.

Taking the obtained data from the orthogonal experimental table, reverse mapping it to the set of positions $(\mathcal{T})$ and mapping set $(\mathcal{T})$ to single denier specifications, we form the training set X, which includes the number of positions m and single denier specifications n.

Using the existing pairing relationship between single denier, total deniers, and curling machine in Nanxian Company's current production, we establish a logistic regression model R_L. The model takes single denier and total deniers as inputs X_0, and predicts the type of curling machine used in actual production as the output Y_0. We have modelled the existing data to develop a preliminary model M_0 for pairing single filament specifications, total denier, and curling machine types.

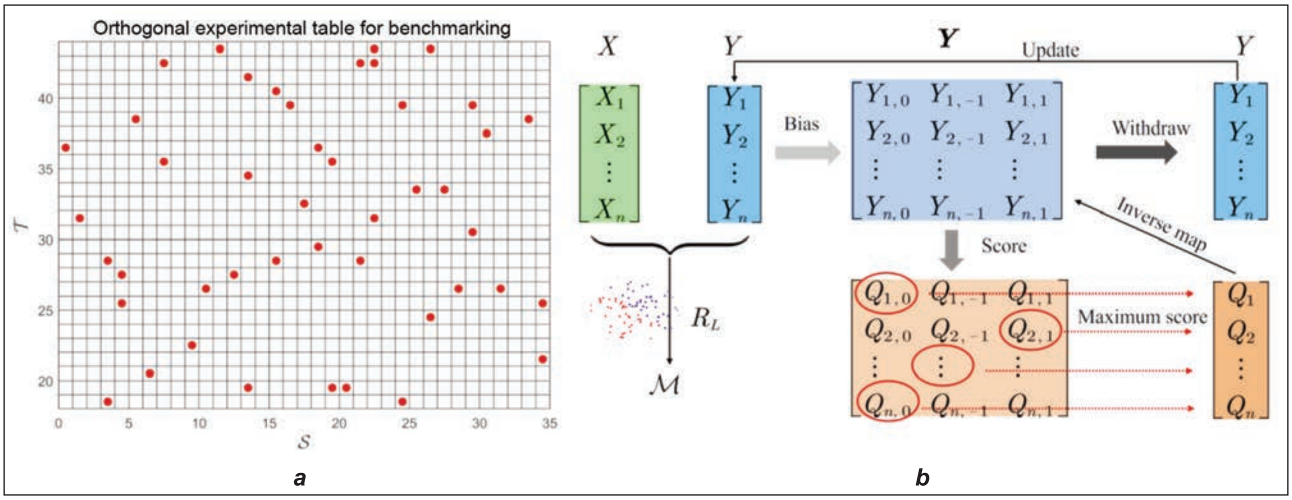

Fig. 2. Images of: *a* – orthogonal experimental table for benchmarking; *b* – update of the Logistic Regression Model

For the obtained training set X, apply the model M_0 to find the matching curling machine model in the training set Y. For each training input X_i and training output Y_i, a bias is applied to Y_i as follows:

$$Y_i \leftarrow [Y_{i,0}, Y_{i,-1}, Y_{i,1}] \quad (5)$$

Through the obtained relationship (X, Y), i.e., the experimental matching relationship between single denier, total denier X_i and curling machine Y_i, physical experiments are conducted by the technical department of NanXian Company. This resulted in semi-finished filament tows after curling, and the quality of the filament tows was evaluated and scored as $Q_{i,*}$.

For each training input X_i, a set of curling machine types Y_i and the corresponding fibre quality scores $Q_{i,*}$ can be obtained. By searching for the highest fibre quality score and its corresponding curling machine type Y_i, the original logistic regression model can be updated. Subsequently, the updated single denier, total deniers and curling machine matching model M is retrained. The flowchart is illustrated in figure 2, *b*.

Design of evaluation indicators

Through testing and analysis of the final selected experimental fibre tows in terms of curl stability, filter rod stability, flying ashes, number of curls in the fibre, breaking strength, etc., an evaluation of the final quality of fibre curling is conducted. This evaluation aims to refine the initial curling machine model, M_0.

The scoring will primarily consider suction resistance stability (suction resistance CV), accounting for 80%, curling stability accounting for 10%, fibre fly and number of curls, each contributing 5% to the overall evaluation. The final fibre curling score, denoted as Q, will be generated based on these factors.

The design flow chart of the overall experiment is shown in figure 3, *a*.

Table 2

SPECIFICATION FOR SUCTION RESISTANCE STABILITY TESTING

Norm	Value	Unit
Conventional Filter Rod Circumference	24.2	mm
Circumference of small and medium branch filter rods	19.9	mm
Circumference of large and medium branch filter rods	22.0	mm
Fine branch filter rod circumference	16.9	mm

EXPERIMENT AND THEORETICAL ANALYSIS

Experiment result

According to the experimental design, the data was modelled using the proposed approach, and the classification performance on the test set is illustrated in figure 3, *b*. The characteristics of single denier, total deniers, etc., in the figure have been subjected to biasing for confidentiality reasons.

The scatter plot displays the specifications of single denier and total deniers in production. The colour of the scatter points indicates the corresponding curling machine. Curling machine F covers a relatively extensive region across the phase plane. Curling machine E is primarily located in areas with low single denier characteristics and high total deniers characteristics, forming the boundary between machines E and F. Curling machine B, in comparison to machine F, shows a slightly lower ratio of total deniers characteristics to single denier characteristics. Curling machine H is predominantly found in regions with higher single denier characteristics.

In the test set, the comparison between predicted models for the curling machine types and the actual true values is presented in table 3. And the accuracy of the testing reached a precision of 88.889%.

Theoretical analysis

The physical characteristics of the fibres are essentially consistent. Therefore, it can be inferred that the

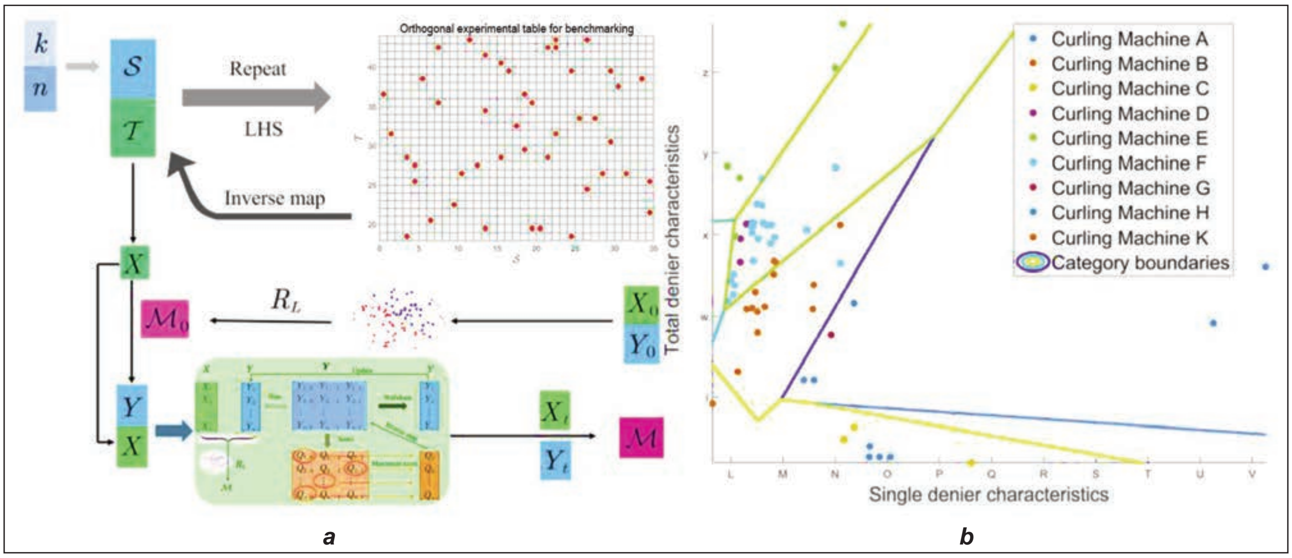

Fig. 3. Images of: *a* – Comprehensive flowchart of experimental design; *b* – Regression and classification model diagram

Table 3

MODEL TEST SET COMPARISON																		
Predict	F	B	F	**D**	F	F	B	F	F	F	B	**C**	E	**G**	B	H	A	K
True	F	B	F	**F**	F	F	B	F	F	F	B	**H**	E	**A**	B	H	A	K

pressure exerted on the unit pressed surface (line) of a single denier, when it undergoes curling due to the rolling and pressing of the crimping machine, should be approximately the same. In other words, there should be a linear relationship between the roller pressure and the roller wheel width. The ratio of the roller pressure to the roller wheel width, and similarly, the ratio of the roller pressure to the cross-sectional area of a single denier, should be constant for the single denier pressure.

Through analysis and verification of experimental data, the relationship between roller pressure and roller wheel width of the curling machine is shown in figure 4, *a*, and the variation of single denier pressure obtained from data of each fibre tow is shown in figure 4, *b*.

It can be observed that the single denier pressure does not remain constant but instead exhibits a certain trend of change, contrary to our initial speculation. However, the specifications of the denier tows entering the crimping machine are also influenced by the number of fibres. Therefore, we infer that there is a functional relationship between the roller pressure and the number of fibres.

The force on the plastic deformation of a single denier is consistent, and there are gaps between single denier and total deniers as they enter the curling machine, there should be a corresponding functional relationship between the force and the number of fibres. This function is directly affected by the specifications and quantity of tows. That is, there is a strong coupling relationship between roller pressure and the tows. Based on this, we analyse and verify the relationship, as shown in figure 4, *c*.

There is a strong linear coupling relationship between the single denier pressure and the quantity

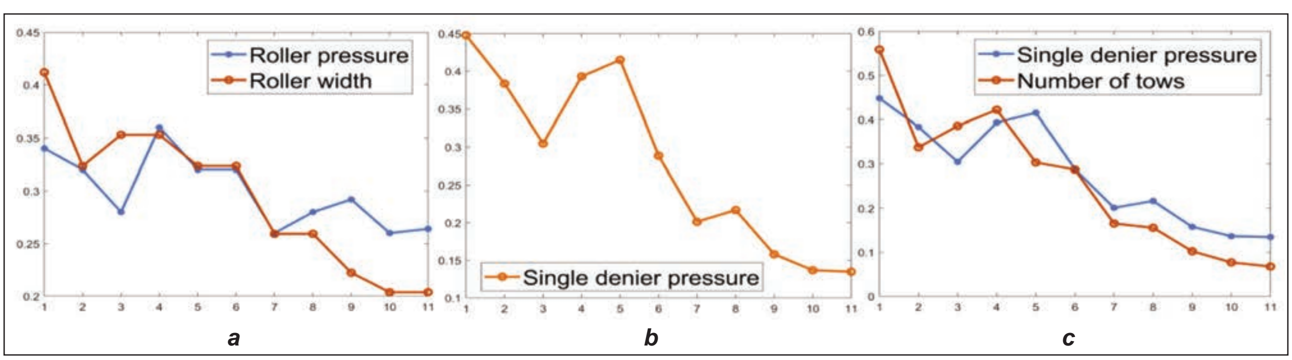

Fig. 4. Graphs of: *a* – the relationship between the curling machine roller pressure and the roller width, with the fibres number on the horizontal axis and the normalized data value on the vertical axis; *b* – the ratio of roller pressure to the cross-sectional area of a single denier-the variation of single-strand pressure with fibre specifications; *c* – the relationship between single-denier pressure and the specifications of the number of tows

of fibre tows. Considering the impact of measurement errors and random factors, it can be approximated that there is a positive correlation between them. Based on this observation, we can proceed with theoretical analysis and modelling of the relationship between fibre specifications and the type of crimping machine.

Definition 1. (*Roll pressure P_{roll}*). *The ratio between the rolling force F_{roll} and the width of the rolling element W_{roll} is defined as the rolling pressure*

$$P_{roll} = \frac{F_{roll}}{W_{roll}}.$$

Definition 2. (*Fibre pressure P_s*). *The ratio between the rolling pressure P_{roll} and the cross-sectional area of a single denier S_a is denoted as the fibre pressure*

$$P_s = \frac{F_{roll}}{S_a}.$$

The selection of the curling machine is denoted as M, the rolling force as F_{roll}, the cross-sectional area of a single denier as S_a, and the number of tows as N. The relationship among these variables can be expressed as follows:

$$\frac{\frac{F_{roll}}{M}}{S_a} \cdot N = C \tag{6}$$

where, C is a constant coefficient.

The selection of the curling machine corresponds to the choice of the rolling element width model, and there exists a proportional relationship between the cross-sectional area of a single denier S_a and the diameter of the single denier D_s expressed as:

$$S_a = C_1 D_s \tag{7}$$

where, C_1 represents the linear coefficient between the cross-section area of the denier per fibre.

The relationship between the total deniers D_t and the cross-sectional area S_a can be expressed as:

$$D_t = C_2 C_1 S_a N \tag{8}$$

Therefore, the relationship between the curling machine M and the diameter of a single denier D_s, as well as the total deniers D_t can be expressed as:

$$M = \frac{C C_1^3 D_s^2}{\frac{D_t}{C_2} F_{roll}} \tag{9}$$

The relationship between the curling machine, the width of the rolling element, the number of tows, the rolling force, and the cross-sectional area of a single denier can be expressed as:

$$M \propto W_{roll} \propto N \frac{F_{roll}}{CS_a} \tag{10}$$

DISCUSSION AND CONCLUSION

In this study, we developed a matching model by analysing the relationships between single denier, total denier, and crimping machines in practical production. Building on this model, we refined it by adjusting the selection criteria and validating these adjustments through experimentation. The updated training model improved upon the original, leading to the final matching model, with regression results shown in figure 3, *b*. The experimental design revealed a significant nonlinear relationship between the type of crimping machine and the specifications of both single and total deniers. Figure 3, *b* illustrates the fundamental distribution, with axes representing inputs (single denier and total deniers) and colours representing outputs (the type of crimping machine). After two rounds of training corrections, the classification relationships for the original data are depicted by the enclosed data points in figure 3, *b*. And the final model's performance on the test set is summarized in table 3.

The basic relationships between the data revealed significant non-linearity and instances where input data were closely situated at extreme operating points. Despite the proximity of the input data, variations in the selected crimping machine were observed. This is illustrated in the dense enclosure region in the top-left corner of figure 3, *b*, which includes two additional crimping machine types within the region for crimping machine F. Both the training data and actual production data indicated that crimping machine F was the predominant choice, covering nearly the entire range of single and total deniers. In contrast, the other five crimping machine types were distributed sporadically, with significantly lower occurrences and probabilities compared to crimping machine F. This uneven distribution presented considerable challenges for modelling and regression of these less common crimping machine types.

In this study, we developed a theoretical reference model based on experimental data to link fibre tows with crimping machines. We constructed a matching model to guide the selection of crimping machines based on fibre specifications. This model helps identify suitable crimping machine specifications within a narrower range, enhances the quality of fibre crimping, significantly reduces the number of required experiments, and lowers production costs.

Additionally, it provides preliminary guidance for further exploration of the fibre crimping mechanism. Future experimental improvements will focus on expanding the model's adaptability to less common crimping machine types, enabling it to better accommodate a broader range of single denier, total deniers, and crimping machine types.

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