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Optimization of Key Process Parameters for Air-Jet Vortex Spun Yarn

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Abstract: As the latest spinning technology in the world at present, air-jet vortex spinning features a short process and high spinning speed by eliminating the two processes of roving and winding. Nevertheless, many problems related to this technology have not been thoroughly solved. To address the difficulty in identifying the key process parameters during yarn formation in air-jet vortex spinning, the input-output relationship of process parameters in the yarn formation process is first analyzed. Based on the collected production process data, a method for screening and optimizing key process parameters is proposed by integrating recursive feature elimination and deep neural network. A deep neural network (DNN) surrogate model is constructed. On the basis of orthogonal experimental design data ($L_{27}(3^{13})$), a high-precision nonlinear mapping between process parameters and quality indices is established. Experimental results show that the average relative error between the predicted values and the measured values of the model is below 3.85%. On this basis, the optimal combination of process parameters (A2B1C3D1E3F1G2H3) that takes into account four quality indices is determined.

Keywords: Process Parameters; Yarn Formation Process; Air-Jet Vortex Spinning; Quality Control

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1. Introduction

1.1 Research Background and Importance

As the most advanced spinning machine in the world today, air-jet vortex spinning features a short process (omitting roving and winding processes), high efficiency (spinning speed of 550–600 m/min, about 20–25 times that of ring spinning and 2–3 times that of rotor spinning), and low energy consumption. Due to the vortex bundling principle, few floating fibers are exposed on the yarn surface, and the yarn smoothness is comparable to compact spinning. However, it suffers from core quality problems such as low tenacity and poor evenness[1]. The fundamental reason is that the air-jet vortex spinning process is an extremely complex nonlinear dynamic coupling system of four bodies: fiber assembly, rigid body, fluid, and elastomer, accompanied by complicated physical and chemical changes. Traditional mechanism modeling methods based on differential equations and empirical trial and error become inadequate when facing such high-dimensional, strongly coupled, and multi-disturbed black-box or gray-box processes, making it difficult to identify key quality-influencing factors and hindering process optimization.

Therefore, the fundamental reasons restricting the accurate prediction of yarn quality are as follows. First, air-jet vortex spinning involves numerous process parameters, such as spinning speed, nozzle pressure, and machine component parameters, for which yarn quality control feature selection algorithms may not be universally applicable[2]. Second, existing models have weak anti-interference ability against outliers in small-sample data, poor generalization ability, and low adaptability to small samples.

Accordingly, this paper holds that data-driven methods are the key to breaking the current deadlock[3]. Instead of completely relying on difficult-to-obtain precise mechanisms, massive data generated in production can be regarded as a new knowledge resource. Advanced learning algorithms can directly mine process rules from data, construct prediction models, and reversely guide optimization.

Taking the difficulty in accurately predicting the yarn quality of air-jet vortex spinning as the entry point[4], a complete data-driven research framework is proposed. Based on recursive feature elimination, deep neural networks, and broad learning system theories, and aiming at improving yarn quality, this paper systematically studies the key process parameter selection and optimization method integrating recursive feature elimination and deep neural networks[5].

1.2 Research Status

Process parameters of air-jet spinning include pre-spinning parameters and post-spinning parameters[6]. Pre-spinning parameters cover raw material specifications, carding speed, drawing speed, number of doublings, sliver linear density, etc. Raw material specifications mainly include fiber length and fineness, raw material moisture regain, and nep content. Post-spinning parameters include directly adjustable parameters such as spinning speed and nozzle pressure, as well as machine component parameters including nozzle orifice diameter, nozzle angle, hollow spindle diameter, and distance from front roller to hollow spindle.

Current research on air-jet vortex spinning parameters is divided into two main aspects. Early studies focused on pre-spinning processes; with technological advancement, the focus shifted to post-spinning processes of air-jet vortex spinning. Rabisankar Chattopadhya et al. discussed the structural characteristics of yarn and their influence on yarn performance, finding that yarns produced by different spinning processes have unique and distinct structural features[7]. Erdumlu et al. showed that the draft ratio has no significant effect on yarn breaking strength, while yarn breaking elongation and breaking work reach the maximum at a middle zone draft ratio of 2.5. When the total draft ratio is maximized, a smaller middle zone draft ratio leads to better evenness[8].

For post-spinning processes, Basal found that lower spinning speed prolongs fiber passage time and strengthens airflow twisting. With increasing pressure, fiber transfer rate gradually rises. A smaller hollow spindle diameter results in a more compact yarn structure, fewer hairiness, and fewer yarn faults[9]. Ortlek et al. conducted spinning experiments with pure cotton as raw material to study the effects of yarn fineness, spinning speed, and nozzle pressure on air-jet vortex yarn quality[10]. Khurshid Alam et al. explored the interactions among fiber composition, spinning process, and yarn performance, and conducted a comparative analysis with conventional ring-spun yarn[11].

Other scholars have focused on key component parameters of air-jet vortex spinning, especially nozzle structure parameter optimization. Pei et al. performed three-dimensional numerical simulations of flow characteristics in a modified vortex spinning nozzle for core-spun yarn, investigating the effects of process and nozzle parameters including inlet, spindle, and filament feed tube protrusion length[12]. Shang et al. established a three-dimensional nozzle model and corresponding airflow domain model for numerical calculation, studying airflow behavior with fiber bundles inside the vortex spinning nozzle[13]. Fang et al. introduced the double-card structure from rotor spinning research into air-jet spinning machines, evaluated the performance of single/double-split jet spinning and nozzle characteristic numbers via simulation, verified the technical advantages of double-split jet spinning, and assessed the influence of nozzle characteristic numbers on the flow field[14]. Chuan et al. numerically simulated airflow inside the nozzle to design an air-saving vortex spinning nozzle, studying the effects of conical chamber length in the middle section of the vortex tube and inlet diameter on internal airflow[15].

Current main limitations lie in two aspects. First, the systematization of post-spinning parameter optimization is insufficient. Most studies on the correlation between process parameters and yarn quality rely on time-consuming and discrete manual test data. Such data acquisition not only has limited sample size and high cost but also fails to dynamically and continuously capture the complete correlation between parameter changes and quality fluctuations, leading to information blind spots in data. Therefore, existing studies are mostly limited to isolated analysis of single or a few post-spinning parameters (e.g., nozzle pressure, draft ratio), lacking the ability to systematically model complex nonlinear interactions among multiple parameters using high-frequency online data. As a result, process optimization schemes are often based on incomplete information, making it difficult to achieve accurate and stable regulation in the global parameter space.

1.3 Research Objectives

Therefore, it is necessary to clarify the yarn formation mechanism of air-jet vortex spinning, investigate and obtain data, screen key process parameters, identify critical factors affecting yarn quality, design orthogonal experiments, construct nonlinear mapping models between process parameters and yarn breaking strength, hairiness H value, and solve the optimal process parameter combination.

2. Material Sources and Quality Index Selection

2.1 Experimental Materials

In this paper, viscose staple fiber is used as the outer fiber, and DTY filament as the core yarn raw material[16]. Viscose fiber exhibits excellent moisture absorption, dyeability and soft hand feel, which can endow the yarn with good serviceability. DTY filament provides necessary structural support and mechanical properties for core-spun yarn due to its high strength and dimensional stability. The detailed specifications and performance indicators of the raw materials are shown in Table 1.

Table 1 Parameters of Raw Materials

Raw Material Type	Raw Material Specification	Breaking Strength / ($cN\cdot dtex^{-1}$)	Breaking Elongation / %	Modulus of Elasticity / ($cN\cdot dtex^{-1}$)
Viscose Staple Fiber	1.44 dtex (38 mm)	1.91	18.09	41.75
DTY Filament	55.5 dtex (36 mm)	3.82	16.69	16.01

2.2 Process Flow

The air-jet vortex spinning process flow and corresponding machines adopted in this paper are as follows[17]:

FA003 Automatic Bale Plucker → MX-6 Multi-bin Blender → CL-C1 Opener → TC10 Carding Machine → TMFD81S Drawing Frame → TMFD81S Drawing Frame → TD8-600 Drawing Frame → VORTEX 870 Air-jet Vortex Spinning Machine. The yarn is packaged according to the winding requirements.

2.3 Experimental Platform and Parameter Selection

The experiments were conducted on a Windows 11 64-bit operating system, with the involved libraries including sklearn (1.3.0), matplotlib (3.3.4), tensorflow (2.10.0), numpy (1.19.5), pandas (0.23.0), pytorch (2.1.2), and keras (2.10.0), and PyCharm was used as the development tool. The data in the research were derived from real production data of multiple branches of a large domestic textile enterprise. The dataset contains a total of 500 samples, each consisting of 16 feature dimensions, including 14 input features (independent variables): {carded sliver linear density, drawn sliver linear density, total draft ratio, main drafting zone gauge, drafting roller pressure, filament feeding tension, nozzle air pressure, yarn drawing speed, winding tension, winding angle, distance from front roller nipper to nozzle inlet, roller gauge, feeding ratio, spinning speed}, and 2 output labels (dependent variables): {breaking strength, hairiness H value}. Data with large-dimensional missing values were eliminated, and those with small-dimensional missing values were filled by the mean value method. The structure of the small-scale and high-dimensional dataset balances multidimensionality and pertinence, aiming to comprehensively capture the key factors affecting the output results[18].

3. Experiments

3.1 Comparison of Feature Selection Algorithms and Experimental Results

In this section, the stability of three feature selection algorithms is evaluated based on the Jaccard[19] similarity coefficient and consistency index[20]. Through multiple random samplings, the Jaccard similarity coefficient and consistency index corresponding to the results of each algorithm are calculated[21], and finally the average values are obtained for comparison. The stability comparison results are shown in Table 2.

Table 2 Stability Comparison of Feature Selection Algorithms

Feature Selection Algorithm	Quality Indicator	Jaccard Similarity Coefficient	Consistency Index
LR-RFE	Breaking Strength	0.6622	0.7900
	Hairiness	0.7597	0.7807
RF-RFE	Breaking Strength	0.8636	0.9220
	Hairiness	0.7714	0.8157
SVR-RFE	Breaking Strength	0.9067	0.9480
	Hairiness	0.8576	0.8868

Figure 1 Feature Subset Scores of Yarn Breaking Strength Analyzed by SVR-RFE

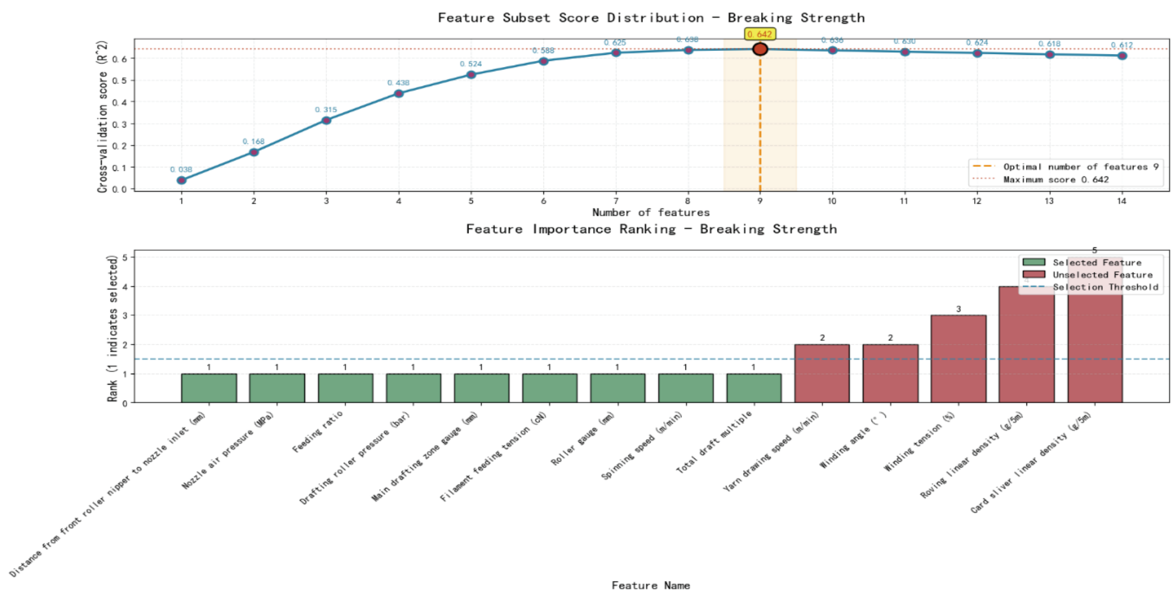
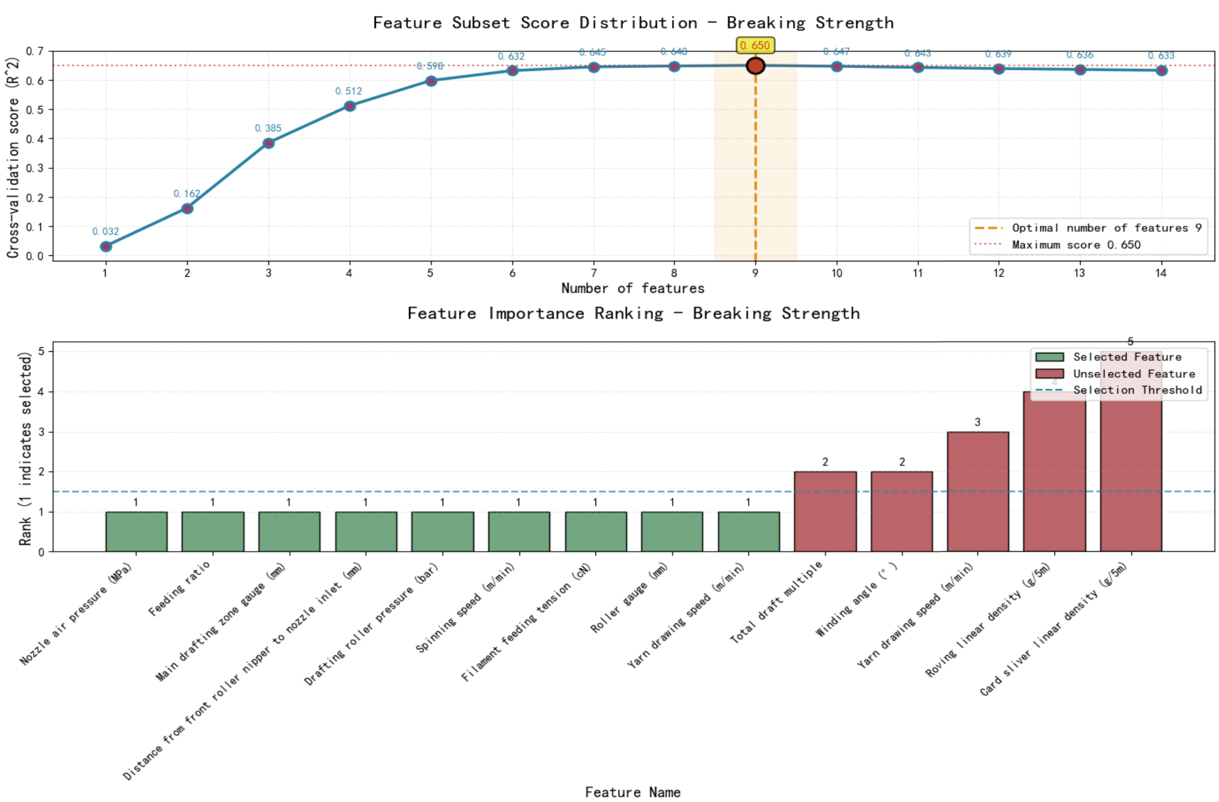


Figure 2 Feature Subset Scores of Hairiness H Value Analyzed by SVR-RFE



It can be seen from Table 2 that under the two yarn quality indicators, the Jaccard similarity coefficient and consistency index of RF-RFE are higher than those of LR-RFE, indicating stronger stability. Meanwhile, the Jaccard similarity coefficient and consistency index of SVR-RFE are both higher than those of the other two algorithms, which means that the feature selection based on the SVR-RFE algorithm is the most stable.

Furthermore, the scores of each feature subset based on yarn breaking strength and hairiness H value were analyzed by the SVR-RFE algorithm, as shown in Figure 1 and Figure 2.

As can be seen from the figures, 9 process parameters affect the two quality indicators during the spinning process, and different process parameters have certain differences in their impacts on different quality indicators. For example, the winding angle parameter of air-jet vortex spinning has a greater impact on yarn breaking strength than on hairiness. The same process parameter has a considerable impact on both indicators, and this study focuses on the process parameters that affect both indicators. Therefore, for subsequent optimization, in terms of selecting key parameters, optimization will be performed on the parameters that have a common impact on the indicators.

3.2 Process Parameter Optimization

Based on the ranking of feature contribution degrees of yarn breaking strength and hairiness H value by the SVR-RFE algorithm, the key process parameters that mainly affect the two indicators can be obtained, namely 8 controllable factors: spinning speed (A), roller gauge (B), nozzle air pressure (C), distance from front roller nipper to nozzle inlet (D), feeding ratio (E), filament feeding tension (F), main drafting zone gauge (G), and drafting roller pressure (H). The specific parameters are shown in Table 3.

Table 3 Process Parameters of Air-Jet Vortex Spun Yarn

Process Parameter	**Level 1**	**Level 2**	**Level 3**
A / (m/min)	360	390	420
B / (mm)	43	44	45
C / (MPa)	0.5	0.6	0.7
D / (mm)	22	26	30
E	1.01	1.02	1.03
F / (cN)	8	14	20
G / (mm)	0.54	0.55	0.56
H / (bar)	0.3	0.35	0.4

Based on the key process parameter information of air-jet vortex spinning obtained by the algorithm, various factors affecting yarn quality in the air-jet vortex spinning process were systematically analyzed. To efficiently study the influence of these factors and determine their significance, the orthogonal experimental design method was adopted. Eight key process parameters were selected as factors, and an $L_{27}(3^{13})$ orthogonal array was designed, which significantly reduced the number of experiments while ensuring the effectiveness of analysis.

A Deep Neural Network (DNN) [22] model was constructed by taking the eight process parameters (A, B, C, D, E, F, G, H) in the orthogonal experiment as input variables and four quality indicators as output variables, so as to search for and verify the optimal configuration of process parameters. The DNN model took the eight process parameters as the input layer, adopted multiple hidden layers, and used the sigmoid activation function in each hidden layer to enhance the nonlinear mapping ability and complex feature extraction capability of the model[23], so as to better capture the complex relationship between process parameters and yarn quality. Finally, the model took yarn breaking strength (maximum), hairiness H value (minimum), breaking elongation (19%), and evenness CV value (minimum) as the output layer, and was trained with optimization algorithms (such as Adam or RMSprop) and loss function (such as Mean Squared Error, MSE) to accurately predict and verify the optimal process combination[24].

After setting the DNN structure and hyperparameters, it was necessary to verify the accuracy and generalization ability of the model. Two groups of experimental data not involved in training were randomly selected to compare the measured values and DNN predicted values of yarn quality indicators. The results are shown in Table 4. It can be seen from Table 4 that the average relative errors between the predicted values and the actual measured values of the DNN model are all less than 3.85%, indicating that the model has high reliability and accuracy, and its prediction results can be used as an effective basis for subsequent process optimization. It can be seen from Figure 3 that the DNN model has gradually learned the relationship between process parameters and quality indicators, and can predict the four quality indicators relatively accurately. The model is fully trained and can be used for parameter optimization[25].

Figure 3 Degree of Difference Between Predicted Values and True Values

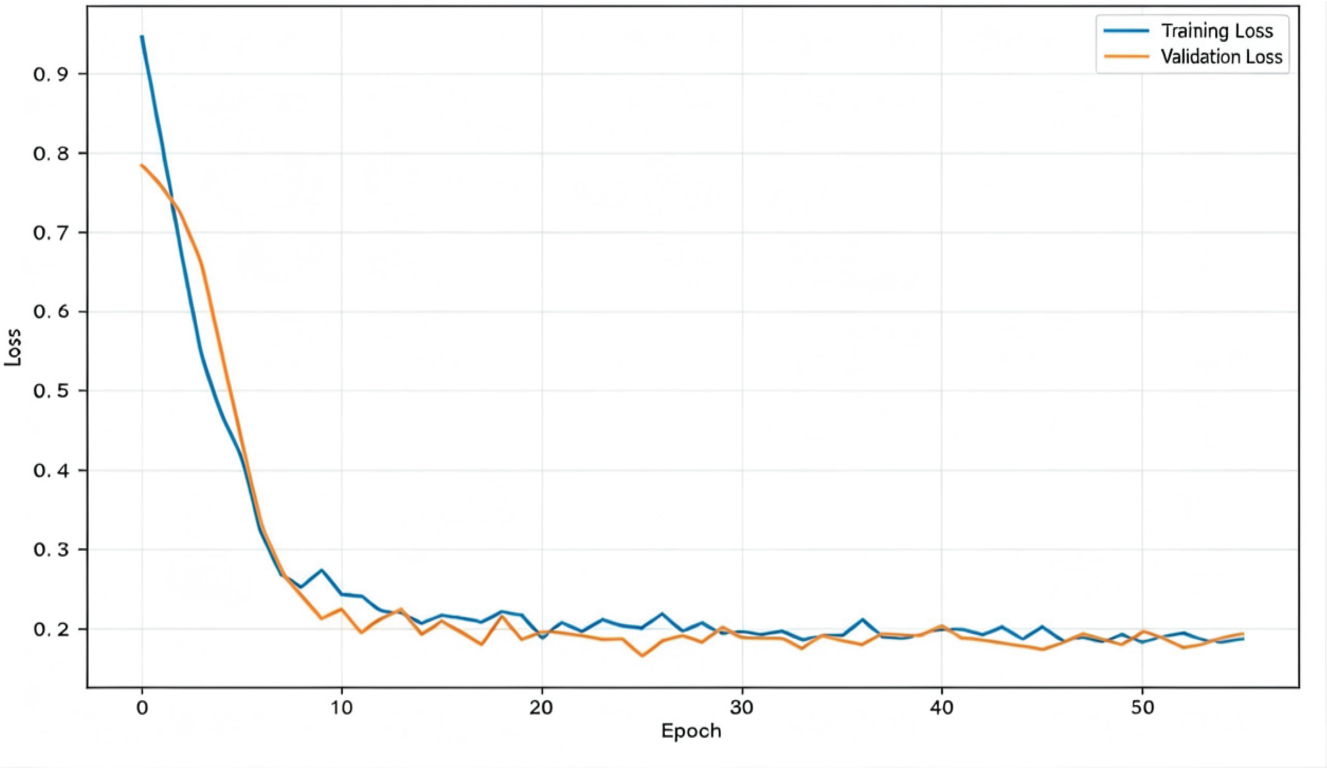


Table 4 Comparative Analysis Results of Measured and Predicted Quality Control Indicators

Quality Control Indicator	Test Batch	Measured Value	Predicted Value	Error / %	Regression Error / %
Breaking Strength	1	20.15	19.72	2.13	2.15
	2	20.45	21.08	3.08	3.10
Hairiness	1	2.45	2.38	2.86	2.90
	2	2.32	2.40	3.45	3.42
Breaking Elongation	1	18.5	19.10	3.24	3.35
	2	19.2	18.60	3.13	3.28
Evenness CV	1	11.35	10.92	3.79	3.82
	2	10.82	11.25	3.97	3.85

To obtain the optimal process parameters and conduct a comprehensive analysis and comparison with the DNN prediction results, an orthogonal experiment was designed to optimize the yarn quality process parameters. The parameter design table is shown in Table 5. The quality indicators of each experiment were measured to evaluate the effects of different yarn forming process parameters on the two quality indicators, and each group of experiments was repeated 10 times.

Table 5 Orthogonal Experiment Parameter Design Table

Test No.	A/(m/min)	B/(mm)	C/(MPa)	D/(mm)	E	F/(cN)	G/(mm)
1	360	43	0.5	22	1.01	8	0.54
2	390	43	0.6	26	1.02	14	0.56
3	420	43	0.7	30	1.03	20	0.55
…	…	…	…	…	…	…	…
26	390	45	0.6	26	1.02	8	0.55
27	420	45	0.7	30	1.03	14	0.54

Based on the validated DNN model, the breaking strength, hairiness H value, breaking elongation and evenness CV value under different yarn forming process parameter combinations were predicted. The optimal process parameter combination was obtained as: spinning speed 390 m/min (A2), roller gauge 43 mm (B1), nozzle air pressure 0.7 MPa (C3), distance from front roller nipper to nozzle inlet 22 mm (D1), feeding ratio 1.03 (E3), filament feeding tension 2 cN (F1), main drafting zone gauge 0.55 mm (G2), drafting roller pressure 0.4 bar (H3), i.e., A2B1C3D1E3F1G2H3.

The visual analysis of the effects of process parameters on breaking strength and hairiness H value is shown in Table 6, where k_1, k_2 and k_3 represent the mean values of quality indicators at level 1, 2 and 3 in the experiments respectively, R is the range, and σ^2 is the variance.

It can be seen from Table 6 that the influence degrees of different process parameters on breaking strength are in descending order: E > H > A > F > B > G > D > C. The most significant factors are E (feeding ratio) and H (drafting roller pressure), with ranges of 1.153 and 0.897, and variances of 0.2218 and 0.1552, respectively.

The influence degrees on hairiness H value are in descending order: C > H > A > F > G > E > D > B. The most significant factors are C (nozzle air pressure) and H (drafting roller pressure), with ranges of 0.397 and 0.343, and variances of 0.0279 and 0.0197, respectively.

The influence degrees on breaking elongation are in descending order: F > E > B > A > D > G > H > C. The more significant factors are F (filament feeding tension) and E (feeding ratio), with ranges of 1.134 and 0.808, and variances of 0.2183 and 0.1212, respectively.

The influence degrees on evenness CV value are in descending order: C > F > H > E > G > B > A > D. The most significant factors are C (nozzle air pressure) and F (filament feeding tension), with ranges of 0.781 and 0.654, and variances of 0.105 and 0.0726, respectively.

The larger the K_n values in Table 6, the larger the breaking strength, hairiness H value, breaking elongation and evenness CV value. It can be further seen from Table 6 that different process parameters have different effects on the four quality indicators. For example, the feeding ratio has the greatest influence on breaking strength but less influence on hairiness and evenness. To obtain the optimal process parameters, combined with the chart analysis, the optimal spinning process parameter configuration is A2B1C3D1E3F1G2H3, which is consistent with the DNN prediction result.

Table 6 Visual Analysis of the Effects of Yarn Forming Process Parameters on Four Quality Indicators

Quality Indicators	Indicator	A	B	C	D	E	F	G	H
Breaking Strength	k_1	19.245	20.057	19.619	19.985	19.172	20.087	19.645	19.051
	k_2	20.084	19.487	19.856	19.522	19.784	19.392	19.887	19.756
	k_3	19.785	19.375	20.071	19.567	20.325	19.484	19.327	19.974
	R	0.839	0.682	0.452	0.463	1.153	0.695	0.56	0.923
	top	3	5	8	7	1	4	6	2
	σ^2	0.1205	0.0892	0.0341	0.0435	0.2218	0.0950	0.0526	0.1552
Hairiness H Value	k_1	2.305	2.448	2.715	2.515	2.472	2.428	2.395	2.618
	k_2	2.438	2.442	2.432	2.51	2.511	2.552	2.342	2.432
	k_3	2.632	2.485	2.318	2.53	2.432	2.585	2.428	2.275
	R	0.327	0.043	0.397	0.02	0.079	0.157	0.086	0.343
	top	3	8	1	7	6	4	5	2
	σ^2	0.0180	0.0004	0.0279	0.0001	0.0010	0.0046	0.0013	0.0197
Breaking Elongation	k_1	18.615	18.211	18.292	18.419	17.827	18.861	18.218	18.279
	k_2	18.422	18.517	18.527	18.227	18.467	18.427	18.156	18.424
	k_3	18.125	18.024	18.528	18.022	18.635	17.727	17.825	18.527
	R	0.49	0.493	0.236	0.397	0.808	1.134	0.393	0.248
	top	4	3	8	5	2	1	6	7
	σ^2	0.0406	0.0413	0.0123	0.0263	0.1212	0.2183	0.0298	0.0103
Evenness	k_1	10.971	11.159	10.573	11.064	10.952	10.902	10.852	11.063
	k_2	11.252	11.052	11.087	10.926	10.825	10.498	11.172	10.722
	k_3	11.093	10.857	11.354	10.974	11.202	11.152	10.932	11.259
	R	0.281	0.302	0.781	0.138	0.377	0.654	0.32	0.537
	top	7	6	1	8	4	2	5	3
	σ^2	0.0132	0.0156	0.1050	0.0033	0.0245	0.0726	0.0185	0.0492

4. Conclusion

Aiming at the problem that yarn quality is affected by multiple process parameters and there are complex interactions between features in the air-jet vortex spinning process, this chapter compared the performance of three estimators—Linear Regression (LR), Random Forest (RF), and Support Vector Regression (SVR)—under the Recursive Feature Elimination (RFE) framework. It was found that SVR-RFE performed the best in both Jaccard similarity coefficient and consistency index (yarn breaking strength: 0.9067 and 0.9480; hairiness H value: 0.8576 and 0.8868), showing the strongest stability, and successfully selected 8 key process parameters from 14 original parameters.

On this basis, the study adopted orthogonal experimental design ($L_{27}(3^{12})$ array) combined with Deep Neural Network (DNN) to construct a nonlinear mapping model between process parameters and yarn breaking strength, hairiness H value, breaking elongation, and evenness CV value. Experimental verification shows that the prediction error of the DNN model is less than

3.85%, demonstrating excellent accuracy and generalization ability.

Through DNN prediction and orthogonal experiment analysis, the optimal process parameter combination considering the four quality indicators was determined as A2 B1 C3 D1 E3 F1 G2 H3, namely spinning speed 390 m/min (A2), roller gauge 43 mm (B1), nozzle air pressure 0.7 MPa (C3), distance from front roller nipper to nozzle inlet 22 mm (D1), feeding ratio 1.03 (E3), filament feeding tension 2 cN (F1), main drafting zone gauge 0.55 mm (G2), and drafting roller pressure 0.4 bar (H3).

Through the systematic method of "feature selection - parameter optimization - model verification", this study provides directly applicable optimal process configuration for textile enterprises, effectively improving yarn quality and production efficiency. It demonstrates the effectiveness and practicality of data-driven algorithms in solving complex industrial optimization problems, and has important theoretical significance for promoting the intelligence of textile production.

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No

Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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