Prediction of Yarn Quality Based on Actual Production

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Abstract

In recent decades, the neural network approach to predicting yarn quality indicators has been recognized for its high accuracy. Although using neural networks to predict yarn quality indicators has a high accuracy advantage, its relationship understanding between each input parameter and yarn quality indicators may need to be corrected, i.e., increasing the raw cotton strength, the final yarn strength remains the same or decreases. Although this is normal for prediction algorithms, actual production need is more of a trend for individual parameter changes to predict a correct yarn, i.e., raw cotton strength increase should correspond to yarn strength increase. This study proposes a yarn quality prediction method based on actual production by combining nearest neighbor, particle swarm optimization, and expert experience to address the problem. We Use expert experience to determine the upper and lower limits of parameter weights, the particle swarm optimization finds the optimal weights, and then the nearest neighbor algorithm is used to calculate the predicted values of yarn indexes. Finally, the current problems and the rationality of the method proposed in this paper are verified by experiments.

Keywords: Accuracy, Actual production, Nearest neighbor, Expert experience, Yarn quality prediction

1 Introduction

With the consumption level improvement and life quality, people are paying more and more attention to whether clothes fabric is comfortable and whether clothes fabric is clean, and the main factor affecting these is the yarn quality. Yarn quality prediction can predict final yarn quality based on raw cotton quality, which can significantly reduce production experiments number and reduce costs. Therefore, predicting yarn quality is the key to solving this problem for many researchers.

Yarn quality prediction is always one indicator in the textile field. Yarn strength affects whether the yarn has process properties and determines the final use of the yarn. D. L. Adams and L. Cheng first attempted to use neural networks to resolve inaccurate strength prediction problems in yarn quality prediction [1]. A. Guha et al. used neural networks, machinery, and statistics to predict yarn strength [2]. A. Majumdar et al. added fuzzy logic advances to artificial neural networks [3]. Üreyen and Gürkan used artificial neural networks to predict several blended yarns' strengths [4]. Rocco and Maurizio proposed a model based on a feedforward back propagation artificial neural network to predict yarn strength [5]. Z. Hu et al. used the role of feature extraction presence in convolutional neural networks (CNN) to propose a CNN-BP neural network for yarn strength prediction [6]. Z. Hu et al. proposed an artificial recurrent neural network (RNN) based yarn strength quality prediction model [7]. B. Zhang et al. offered an expert weight neural network for yarn strength quality prediction model by combining expert experience and neural network [8].

However, Yarn unevenness is also one of the indicators. Ureyen and Gurkan used an artificial neural network to predict yarn unevenness and compared the obtained results with the linear regression model [9]. Üte and Kadoğlu proposed a new model to estimate ring-spun yarn uniformity from cotton fiber properties using multiple linear regression [10]. Z. G. Wu et al. proposed a method to predict yarn uniformity using the evolutionary thinking algorithm (MEA) to accomplish the weights optimization and BP network thresholds for the complex optimization problem of weights and thresholds in neural networks [11]. H. Ghanmi et al. proposed a fuzzy artificial neural network prediction model incorporating expert experience and high accuracy by combining artificial neural networks with fuzzy experts [12]. H. Jiang et al.) arranged a Broad Multilayer Neural Network for predicting yarn unevenness by combining a comprehensive learning system with a multi-layer neural network [13].

In like manner, the strength coefficient of variation (CV) is also a significant index to measure yarn quality. Yarn strength CV can be used to reflect the yarn strength dispersion. Chaudhari et al. studied the speed drafting system's effect on yarn strength CV [14]; Rutkowski studied the yarn treated by yarn purification technology and yarn strength CV changes [15]. B. Zhang et al. proposed a P-ARD algorithm for yarn strength CV prediction by combining principal component analysis (PCA) with automatic relevance determination (ARD) [16].

Although there are many methods for predicting yarn quality indicators, most are based on the final prediction accuracy, which means the higher accuracy, the better model. However, practice need is more of a trend that can predict a correct yarn for individual parameter changes. Due to the neural network uncertainty, the final neural

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network prediction may result in a decrease, no change, or an increase. Such results could be more practical for guiding yarn production, even though the overall accuracy is high.

We address this problem with a yarn quality prediction method based on the nearest neighbor idea, particle swarm optimization idea, and expert experience proposed in this paper. The algorithm determines the upper and parameter weights lower limits by expert experience, finds the optimal weights by particle swarm algorithm, and finally predicts yarn quality indexes using the nearest neighbor algorithm. The specific work done in this paper is as follows:

(1) A weight determination method on account of the Particle Swarm Optimization (PSO) algorithm and expert experience is proposed. The expert experience is transformed into a range of weights, and the particle swarm algorithm is used to find the optimal weights as the parameter weights.

(2) A yarn quality prediction method based on actual production is proposed, and experiments verify its effectiveness and rationality.

(3) Validated the current problem. Specific experiments are used to verify that the current problem of considering only the prediction accuracy without considering its prediction rationality does exist.

2 Principle and Method

2.1 Normalization and Inverse-normalization

The same species data normalization prevents the different units' effect of each parameter on the results, which is suitable for comprehensive comparative evaluation, where the normalizing data common way is 0-1 standardization, calculated as shown in formula (1).

$$x_i^* = \frac{x_i - x_{i-min}}{x_{i-max} - x_{i-min}}. \tag{1}$$

Where x_i denotes the data before a specific ith attribute processing, $x_i - min$ denotes the minimum value in the $i - th$ attribute, $x_i - max$ denotes the maximum value in the $i - th$ attribute, and x_i^* denotes the data after the $i - th$ attribute processing.

The normalized data needs to be reversely normalized to get the original data, and the calculation of reverse normalization is shown in the formula (2).

$$x_i = x_i^* * (x_{i-max} - x_{i-min}) + x_{i-min}. \tag{2}$$

2.2 Nearest Neighbor

The nearest neighbor prediction algorithm is the current input variable averaged over the nearest point in the sample range to the input variable, which is the predicted value. For finding the most similar historical data with the current input variables, the Euclidean distance is generally used to determine whether the input variables are similar to the data in the historical data. The Euclidean distance between X and Y is calculated by the formula (3).

$$d(X,Y) = \sqrt{\sum_{i=1}^{n} (x_i - \mathrm{y}_i)^2}. \tag{3}$$

Where $d(X, Y)$ denotes the Euclidean distance between X and Y, n denotes the number of attributes of data X (Y), x_i denotes the value of the i-th attribute of data X, and y_i denotes the i-th attribute value of data Y.

2.3 Particle Swarm Optimization

The particle swarm optimization (PSO) algorithm was first proposed in 1995 when Kennedy and Eberhart established a simplified algorithm model inspired by birds' foraging behavior regularity [17]. Particle swarm optimization algorithm is also through the different particles in the population between the cooperation and competition to achieve in the search space for finding the problem optimal location. In the particle swarm optimization algorithm, the particle attributes only have velocity and position, and each particle changes its direction and position through velocity in the solution space. In the algorithm, particles always track two extreme values: the historical individual optimal position and the population's historical optimal position. In the continuous iteration process, the particle flight velocity is dynamically adjusted according to the particle's historical optimal position, and the population's historical optimal position and the optimal value satisfying the conditions are finally obtained. Each particle velocity update formula is shown in (4), and each particle position update formula is shown in (5).

$$\begin{aligned} V_{id} &= \omega V_{id} + C_1 random(0,1)(P_{id} - X_{id}) + \\ & C_2 random(0,1)(P_{gd} - X_{id}). \end{aligned} \tag{4}$$

$$x_{id} = x_{id} + V_{id}. \tag{5}$$

Where ω is the inertia factor and its value is negative. When ω is large, the global optimization ability is strong, but the local optimization ability is weak. When ω is small, the global optimization ability is weak, but the local optimization ability is strong. V_{id} is the $i - th$ particle velocity in d dimensions. X_{id} is the $i - th$ particle position in D dimension. C_1 and C_2 are acceleration constants, C_1 is each particle's learning factor, and C_2 is each particle's sociological factor. Usually set $C_1 = C_2 \in [0, 4]$, random (0, 1) denotes a random number on the interval [0, 1], P_{id} denotes the d-th dimension of the $i - th$ variable individual extreme value, and P_{gd} denotes the global optimal solution d-th dimension.

2.4 Yarn Quality Prediction Method Based on Actual Production

The yarn quality prediction method based on actual production is implemented based on the expert experience ideas, particle swarm optimization, and nearest neighbor, and its main algorithm flow chart is shown in Figure 1.

(1) Expert judging. Expert experience is transformed into upper and lower limits for the parameter

weights, and multiple experts jointly determine their transformed weights;

(2) Determine the parameter weights range. Suppose the input parameters are positively correlated with the output parameters. In that case, the plurality given by each expert is taken as the final parameter weights upper limit, and the lower limit is 0. Suppose the input parameters are negatively correlated with the output parameters. In that case, the plurality given by each expert is taken as the final parameter weight lower limit, and the upper limit is 0. If all experts give different parameters, the value with the most significant absolute value is chosen as the parameter weight upper (lower) limit.

(3) Initialization. Initialize the parameters and PSO algorithm parameter weights, and the PSO algorithm randomly generates the parameter weights within the parameter weight range.

(4) Fitness calculation. First, the predicted value is calculated using formula (6), and then the mean square error (MSE) is calculated using formula (7), and the evaluation index value reciprocal is used as the algorithm fitness. Among them, formulas (6) and formulas (7) are shown below, respectively.

$$predicted_j^* = \sum_{i=1}^{n} w_i x_{ji}^{\ *}. \quad \textbf{(6)}$$

$$\mathrm{MSE} = \frac{1}{N}\sum_{j=1}^{N}(actual_j - predicted_j)^2. \quad \textbf{(7)}$$

Where $predicted_j^*$ denotes the normalized value of the $j-th$ data predicted value, w_i denotes the $i-th$ parameter weight, x_{ji}^* denotes the $i-th$ parameter normalized value of the $j-th$ number; N denotes test data total number, $actual_j$ denotes the $j-th$ data actual value, and $predicted_j$ denotes the $j-th$ data predicted value.

(5) Update the optimal solution. Select this iteration's global optimal solution and let it compare with the historical optimal and take both better values as the optimal solution.

(6) Update the velocity and position. The particle's velocity and position are updated according to the current fitness. The updated formulas are shown in (4) and (5).

(7) Determine if the termination condition is met. Determine whether the maximum iteration number is reached, and end the loop if the maximum iteration number is reached; otherwise, skip to step D and start the loop next round.

(8) Obtain the best matching data. The optimal random weights are selected as the weights of the final parameters and substituted into formula (8) to calculate the distance between the historical data and the predicted data, and the data with the smallest distance is selected as the best-matched data (the smaller the distance is, the more similar the two data are).

$$S_j = \sum_{i=1}^{n} w_i\left(x_{ji}^* - x_i^*\right). \quad \textbf{(8)}$$

S_j denotes the distance between the j-th historical data and the predicted data, and x_i^* denotes the predicted data ith parameter normalized value.

(9) Calculate the predicted value. Calculate the predicted value according to formula (9).

$$y_{pre} = \hat{y} + f\,'(S_{\min}). \quad \textbf{(9)}$$

Where y_{pre} denotes the predicted value, $\hat{y}$ denotes the yarn indicator value corresponding to the best-matched data, $f\,'$ denotes the inverse normalization function, and S_{min} denotes the distance between the best-matched data and the predicted data.

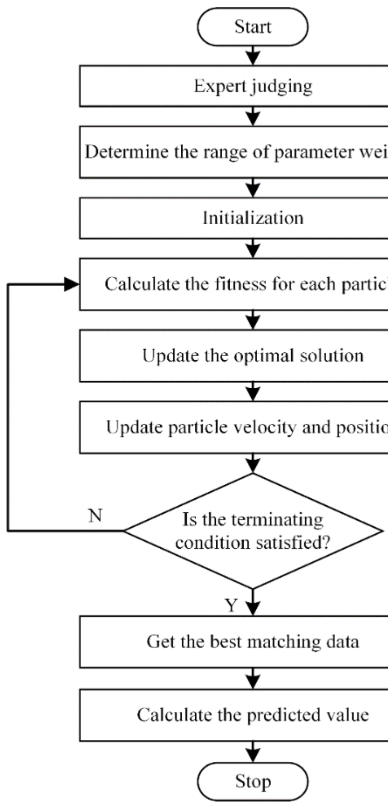

Figure 1. The flowchart of yarn quality prediction algorithm on account of expert experience

3 Data Collection and Preparation Before the Experiment

The experimental data used in the paper experiment part are from a textile factory's actual production data in Anhui, China. The yarn produced in this experiment belongs to combed compact spinning (5.9 Tex)

3.1 Parameter Setting

The parameters in this research data mainly included input parameters and output parameters. The input parameters were divided into basic cotton parameters (data before production), raw cotton parameters (data detected during production), and parameters during machine operation. Each part's parameters and their corresponding units and abbreviations are exhibited in Table 1 to Table 3. The output parameters include yarn strength (cN/tex) (y_1), unevenness (%) (y_2), and strength CV (%) (y_3).

Table 1. Raw cotton parameters (before production)

Parameter	Symbol
Percentage of staple fiber (%)	x_1
Neps per-gram	x_2
Micronaire value	x_3
Strength (cN/tex)	x_4
The quality length (mm)	x_5
Length uniformity (%)	x_6
Impurities rate (%)	x_7

3.2 Parameter Setting
Division of Training Set and Test Set

There are 98 pieces of data collected from textile mills. The data set used in the experiment is divided by the train_test_split function in the sklearn library package in Python language. This function can divide the dataset into training and test sets with different sizes and sample distributions depending on random_seed and test_size. We utilize train_test_split function such that test_size = 0.1 and random_seed = 1 to divide the data into 88 training data and 10 testing data.

Table 2. Raw cotton parameters (during production)

Parameter	Symbol
AFIS detects the neps of cotton before it is treated by carding machine (Neps/g)	x_8
AFIS detects the neps of cotton after it is treated by carding machine (Neps/g)	x_9
AFIS detects the short fiber percentage of cotton before it is treated by carding machine (%)	x_{10}
AFIS detects the short fiber percentage of cotton after it is treated by carding machine (%)	x_{11}
The percentage of the quality of cotton lost during the process of the cotton passing Carding machine is used to ensure the quality of the input cotton (%)	x_{12}
AFIS detects the neps of cotton before it is treated by comber (Neps/g)	x_{13}
AFIS detects the neps of cotton after it is treated by comber (Neps/g)	x_{14}
AFIS detects the short fiber percentage of cotton before it is treated by comber (%)	x_{15}
AFIS detects the short fiber percentage of cotton after it is treated by comber (%)	x_{16}
The cotton quality lost during the process of passing through the carding machine as a percentage of the input cotton quality (%)	x_{17}

Table 3. Machine operating parameters

Parameter	Symbol
Carding linear speed (m/min)	x_{18}
Pre-drawing linear speed in the drawing process (m/min)	x_{19}
The working speed of the combing machine (nips/min)	x_{20}
Roving twist rate (%)	x_{21}
Spun yarn twist rate (%)	x_{22}
The spindle speed of the spinning frame (r/min)	x_{23}
Spinning stretch ratio	x_{24}

4 Case Study

Based on TensorFlow (2.1.0), Python (2.8.1), NumPy (1.18.0), Pandas (1.0.1), Keras (2.3.1), matplot (0.1.9), sklearn (0.0), and sko (0.5.9) environments, the following experiments were conducted.

(1) To verify the current problems. Yarn strength prediction after parameter changes using three-layer and four-layer neural networks to investigate whether the trend changes are reasonable.
(2) Obtain the parameter weights by comparing multiple algorithms. Obtain the optimal parameter weights using multiple algorithm comparisons.
(3) Predict the yarn quality index and compare it with the actual yarn index changes.

4.1 Neural Network

In this section, the experiment verifies that although the artificial neural network model has high precision, it guides the demanding production needs.

The experiments are conducted to predict the yarn strength using a three-layer neural network (29*10*1, 29, 10, 1 for the neurons number in the input layer, the hidden layer, and the output layer, respectively) and a four-layer neural network (29*10*8*1, 29, 10, 8, 1 for the neurons number in the input layer, the first hidden layer, the second hidden layer, and the output layer, respectively). Prediction data, including base data and test data (test data for the base data only changes the raw cotton strength index data). The model evaluation index is the MSE index. The model training process is shown below.

(1) Select the base data and test data. The specific values are shown in Table 4 and Table 5.
(2) Train the other data to get the trained neural network.
(3) Use the trained model to predict the test data and the base data.
(4) Cycle steps B and C and records representative cases of them in Table 6.

As shown in Table 6, Three - layer neural network and four - layer neural network are used to predict yarn strength. Although the prediction results are highly accurate, the change in the test data predicted values relative to the underlying data predicted values might be reduced, constant, and increasing. Since the raw cotton strength becomes more prominent in the test data compared to the base data, the correct trend is that the yarn strength becomes more prominent as the raw cotton strength increases and decreases as the raw cotton strength decreases. Therefore, it is concluded that in the neural network model, the change in yarn strength does not converge to the actual change as the MSE index becomes smaller.

Therefore, it can be concluded that although the neural network can obtain high accuracy in predicting yarn strength, it cannot guide production.

Table 4. The first half of the first five data bars parameters

x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}	x_{13}	x_{14}
5.3	165	4.18	39.5	35.24	85.9	2.42	298	38.5	8.18	7.51	8.5	31.17	7.2
5.3	165	4.18	39.7	35.24	85.9	2.42	298	38.5	8.18	7.51	8.5	31.17	7.2

Table 5. The second half of the first five data bars parameters

x_{15}	x_{16}	x_{17}	x_{18}	x_{19}	x_{20}	x_{21}	x_{22}	x_{23}	x_{24}	y
6.78	3	20	100.2	450	397	92	380.62	19000	106.9	144.3
6.78	3	20	100.2	450	397	92	380.62	19000	106.9	145.1

Table 6. Representative examples of neural network prediction

Index	Three-layer neural network			Four-layer neural network		
	1	2	3	1	2	3
MSE	5.4197	4.8596	6.3276	6.29427	5.03532	5.62145
The true value of base data	144.3	144.3	144.3	144.3	144.3	144.3
True value of test data	145.1	145.1	145.1	145.1	145.1	145.1
The predicted value of the base data	139.341	140.408	139.448	140.911	138.987	140.742
The predicted value of the test data	139.316	140.408	139.466	140.869	138.987	140.757

4.2 Determining Parameter Weights

Determining parameter weights is the key to the yarn quality prediction model based on actual production. In this section, Pearson coefficients, linear regression, and linear regression based on expert experience to determine parameter weights are presented, respectively.

4.2.1 Pearson Correlation Coefficient

The calculated Pearson correlation coefficients are shown in Figure 2. Only some of the relationships between the parameters are shown here, and specific Pearson correlation coefficients are presented in the Appendix.

It can be seen from Figure 2 that there is a strong correlation between raw cotton parameters. For example, the correlation coefficient between short fiber percentage and neps is 0.94. There is also a strong correlation between process parameters and raw cotton parameters. For example, the correlation coefficient between spun yarn draw ratio and the micronaire value is -0.61. However, the obtained Pearson correlation coefficient for the strength index is negatively correlated with the strength, which is the actual situation opposite. Therefore, the obtained Pearson correlation coefficients cannot be used as actual parameter weights to guide production.

4.2.2 Linear Regression

The linear regression model's primary purpose is to find a series of weights to make the calculated prediction data as close as possible to the actual data. The experimental content uses the linear regression method to get the weights with MSE as the evaluation index, and the results of the obtained weight are shown in Table 7 and Table 8.

Table 7. The weights of the first half obtained by linear regression

	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}
y_1	0.38	0.20	0.07	0.11	0.39	0.05	0.05	-0.13	0.02	-0.13	0.18	0.10
y_2	-0.30	-0.18	-0.09	-0.13	-0.35	0.07	-0.08	0.11	0.01	0.15	-0.14	-0.05
y_3	-0.08	-0.11	0.05	0.29	-0.37	-0.01	-0.07	0.09	0.01	0.04	0.02	-0.05

Table 8. The weights of the second half obtained by linear regression

	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	x_{18}	x_{19}	x_{20}	x_{21}	x_{22}	x_{23}	x_{24}
y_1	0.01	0.08	-0.13	0.10	0.12	-0.05	0.09	-0.02	0.33	-0.05	0.13	-0.99
y_2	-0.04	-0.13	0.03	-0.01	-0.09	0.00	-0.10	0.00	-0.23	0.14	-0.14	0.84
y_3	-0.07	0.00	-0.06	-0.01	-0.05	-0.03	-0.06	0.01	-0.23	0.10	-0.18	0.56

Figure 2. Heat map of partial Pearson correlation coefficients

Table 7 and Table 8 show that the short fiber percentage weight coefficients, neps, quality length, roving twist rate, and spun yarn draw ratio are larger than the strength and unevenness indexes. Compared to the strength CV index, the strength, quality length, roving twist rate, and spun yarn draw ratio have a larger weighting factor.

However, these weights need to be more reasonable. The spun yarn draw ratio is negatively correlated with the strength of the yarn strength index, but it is not the main factor. In addition, the neps effect on the strength is small and almost negligible. For the yarn unevenness index, the weight of short fiber percentage and neps should be positive, not negative. The quality length should be positively correlated instead of negatively correlated for the yarn strength CV indicator, and the roving twist rate should be negative instead of positive.

4.2.3 Linear Regression Based on Expert Experience

We address the linear regression problems with the linear regression method based on expert experience used for improvement. The experiment is to use the linear regression method based on expert experience to find the weights with MSE as the evaluation index. The method transforms the expert experience into upper and parameter weights lower limits, and the optimal values are obtained as parameter weights by the PSO algorithm. The PSO algorithm initialization includes making the population number 20 and the maximum iteration number 50. Meanwhile, selecting the velocity coefficient ($C_1 = C_2 = 0.5$) and choosing the inertia coefficient ($\omega = 0.8$). The obtained parameter weights are shown in Table 9.

Table 9 shows that the weights obtained using the linear regression method based on expert experience are consistent with expert experience. Therefore, these weights are taken as the parameter weights.

4.3 Yarn Quality Prediction

The parameter weights obtained in section 4.2.3 are used to predict yarn strength, unevenness, and strength CV. Predicted results are shown in Figure 3, Figure 4, and Figure 5, respectively.

Table 9. The weights obtained from linear regression are based on expert experience

Index	Weight range-strength	Weight-strength	Weight range-unevenness	Weight-unevenness	Weight range-strength CV	Weight-strength CV
x_1	-0.7 0	0	0 0.9	0.194	-0.1 0	0
x_2	0 0.1	0.1	0 0.1	0	-0.1 0	-0.020
x_3	-0.8 0	0	0 0.9	0.875	-0.7 0	0
x_4	0 0.9	0.236	0 0.9	0	0 0.6	0
x_5	0 1	0	-0.9 0	0	0 0.8	0
x_6	0 0.1	0.1	-0.9 0	-0.033	0 0.9	0.291
x_7	-0.1 0	-0.1	0 0.1	0.087	-0.1 0	-0.1
x_8	0 0.1	0	0 0.1	0.068	-0.1 0	0
x_9	0 0.1	0.1	0 0.1	0.099	-0.1 0	-0.1
x_{10}	-0.1 0	0	0 0.1	0	-0.1 0	-0.026
x_{11}	-0.1 0	0	0 0.1	0.099	-0.1 0	0
x_{12}	0 0.5	0.343	-0.4 0	-0.167	0 0.5	0.5
x_{13}	0 0.1	0	0 0.1	0.052	-0.8 0	0
x_{14}	0 0.1	0.072	0 0.1	0.1	-0.8 0	0
x_{15}	-0.3 0	0	0 0.1	0.002	-0.1 0	-0.031
x_{16}	-0.3 0	0	0 0.1	0.007	-0.1 0	-0.1
x_{17}	0 0.4	0	-0.5 0	0	0 0.5	0.5
x_{18}	-0.1 0	-0.1	0 0.2	0	-0.1 0	0
x_{19}	-0.1 0	0	0 0.6	0	-0.1 0	-0.013
x_{20}	-0.1 0	0	0 0.5	0	-0.1 0	0
x_{21}	0 0.1	0.1	-0.6 0	-0.340	0 0.1	0.1
x_{22}	0 0.2	0	-0.6 0	-0.566	0 0.9	0.317
x_{23}	-0.1 0	0	0 0.8	0.300	-0.1 0	0
x_{24}	-0.2 0	-0.2	0 0.8	0	-0.7 0	-0.7

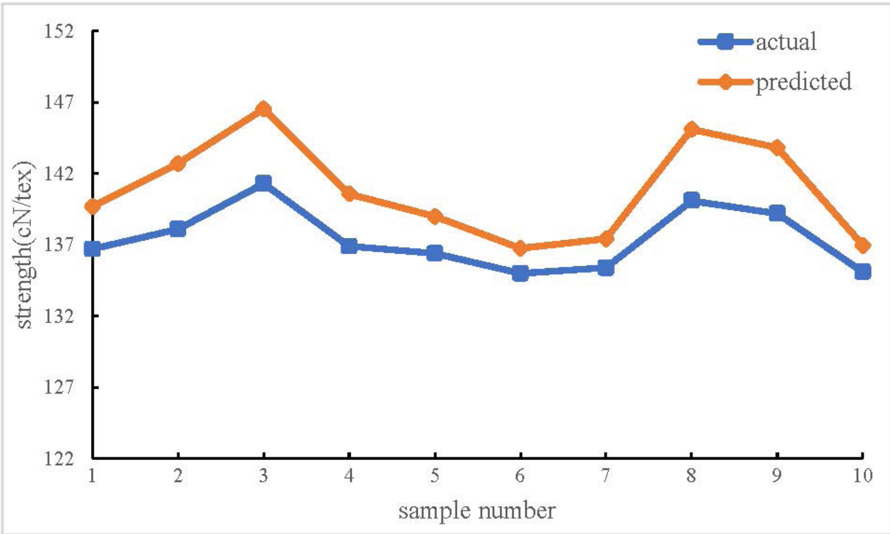

Figure 3. Comparison chart of predicted value and true value-strength

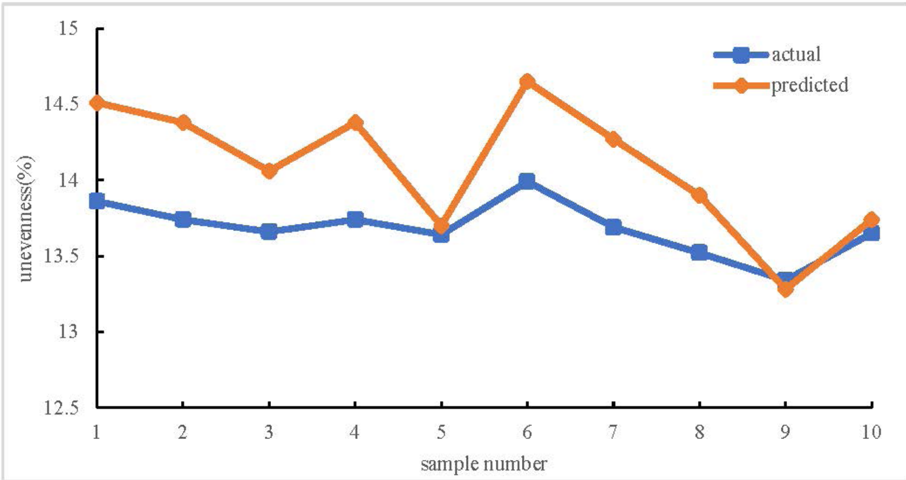

Figure 4. Comparison chart of predicted value and true value-unevenness

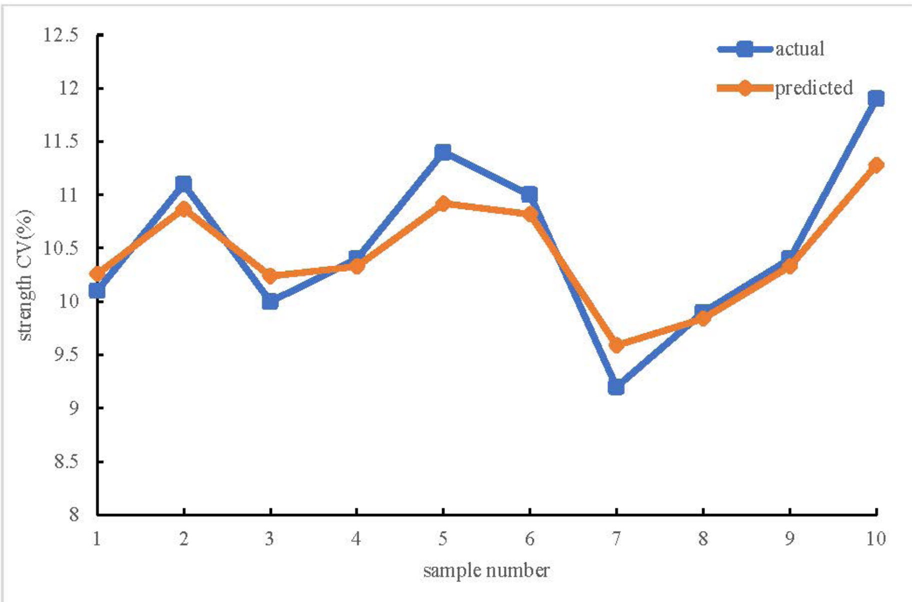

Figure 5. Comparison chart of predicted value and actual value-strength CV

From Figure 3, Figure 4, and Figure 5, it can be seen that predicted values trends of yarn strength, unevenness, and strength CV are the same as the trends of the actual values. Therefore, it can be concluded that the trend of yarn strength, unevenness, and strength CV can be predicted using the yarn quality prediction method based on actual production.

5 Conclusion

This paper's main objective is to propose a yarn quality prediction model based on actual production. The model's main advantage over the traditional yarn quality prediction model is that it no longer aims at the final prediction accuracy but at the correct trend. In this study, firstly, the principal and the yarn quality prediction model method based on actual production are presented. Secondly, it is demonstrated experimentally that the current problem is that only the final prediction accuracy is considered and does not guide the production process. Finally, it is presented why using linear regression based on actual production is considered to obtain parameter weights, and the goodness of the yarn quality prediction model based on expert experience is verified experimentally. The experimental results show that the yarn quality prediction model based on the actual product has a stable prediction advantage of model variation trends.

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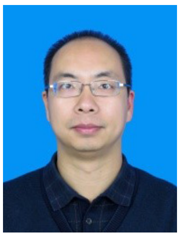
Biographies



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