Textile & Leather Review

ISSN 2623-6281 | www.tlr-journal.com | 10.31881/TLR

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How to cite: Wu D, Hu S. Quality Fluctuation Abnormal Source Identification Based on Variable Weighted Reconstruction Analysis in Spinning Process. Textile & Leather Review. 2024; 7:1178-1196. https://doi.org/10.31881/TLR.2024.102

How to link: https://doi.org/10.31881/TLR.2024.102

Published: 8 July 2024

Quality Fluctuation Abnormal Source Identification Based on Variable Weighted Reconstruction Analysis in Spinning Process

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Article
https://doi.org/10.31881/TLR.2024.102
Received 1 May 2024; Accepted 18 June 2024; Published 8 July 2024

ABSTRACT

Due to the numerous and interconnected quality influencing parameters, the production process propagation and evolution of abnormal factors are complex, which can affect the stability of quality characteristics from multiple perspectives. This paper addresses the problem of identifying the quality fluctuations sources and proposes a variable-weighted reconstruction analysis-based method for identifying abnormal sources of quality fluctuations in the spinning process. The method monitors the degree of quality fluctuations by constructing information entropy statistics and reconstructs the weighted parameters of abnormal quality processes. On this basis, abnormal contribution ranking is performed based on the degree of change in quality characteristics before and after weight reconstruction, which achieves the identification of the abnormal source. The proposed method is validated using a spinning process dataset. It reveals that the method could accurately identify the quality fluctuation abnormal source, which indicates its practicability and feasibility and will provide a theoretical basis for the quality stability control.

KEYWORDS

quality fluctuation, abnormal source identification, variable weighted reconstruction, quality, spinning

INTRODUCTION

The traceability of abnormal quality fluctuations is an important basis for evaluating the stability of the production process and making quality optimization decisions. However, in the actual production process, due to the numerous and interconnected quality influencing parameters, the propagation and evolution of abnormal factors become complex, which poses a challenge to the traceability of quality fluctuations. This paper addresses the problem of identifying the quality fluctuations sources and proposes a variable-weighted reconstruction analysis-based method for identifying abnormal sources of quality fluctuations in the spinning process [1-2]. Therefore, it is of great significance to explore the causes of abnormal quality fluctuations in the spinning production process and identify the sources of such fluctuations, to conduct in-depth research on the stability of the spinning production process at the mechanistic level, and achieve optimization decision-making and feedback control of spinning quality.

At present, scholars at home and abroad have conducted extensive research on the problem of identifying abnormal sources in complex product manufacturing processes, mainly including two categories: qualitative analysis-based and data-driven methods for identifying abnormal sources. The main idea of qualitative analysis-based anomaly source identification is to characterize the correlation between manufacturing process quality parameters through methods such as constructing Petri nets, causal relationships, fault trees, and Bayesian networks to determine the generation and propagation mode of anomalies and complete the inference of fault nodes to achieve anomaly source identification [3-6]. However, this method is based on process knowledge and expert experience, making it difficult to determine the strength of causal relationships between variables and unable to cope with dynamic changes in complex industrial processes. With the development of sensor technology and online measurement technology, data-driven anomaly source identification methods have been widely favoured by scholars at home and abroad. Its core is to analyse the correlation between process variables and anomaly fluctuations based on collected historical data and construct a causal relationship-driven fault identification model to identify and locate the source of anomaly fluctuations. Zhang et al. proposed a fault localization and propagation path identification method based on variable causality diagrams, attempting to solve the problems of inaccurate variable localization and difficulty in detecting early faults in traditional fault diagnosis methods [7]. Hu et al. constructed an intelligent ensemble model for quality fluctuation analysis to estimate the variance change point in a multivariable process [8]. Zhang et al. proposed a small fault detection and diagnosis method based on a combination of weighted statistical features and variable contribution graphs. By using KICA to capture independent metadata and residual data from raw data, a fault diagnosis strategy based on variable contribution graphs was designed to achieve small fault localization and recognition [9]. Ma et al. focus on how to fully use those irregular sampling data to realize nonlinear dynamic causality modelling for root cause location and propagation path identification of quality-related faults and propose a practical root cause diagnosis framework developed for manufacturing processes with irregular sampling measurements [10]. Lindner et al. developed a decision-making process to help users decide when to use Granger causality or transfer causality by comparing the applicability of two methods, transfer causality and Granger causality, for different process characteristics, and to help explain the obtained causal relationship diagram [11]. Wu et al. proposed a machining error traceability analysis method based on global sensitivity analysis [12]. In addition, many scholars use machine learning algorithms to study the problem of anomaly source recognition. By mining the patterns and patterns contained in abnormal fluctuations, they construct data-driven supervised learning models to achieve anomaly detection and recognition [13,14]. Hu et al. focused on the impact of parameter correlation in the spinning production process on abnormal quality fluctuations and proposed a method for yarn quality fluctuation prediction in the spinning process based on a multi-correlation parameter feature subspace mechanism [15]. Fu et al. proposed a fault diagnosis method for probe cards based on Bayesian networks, which empowers industrial intelligent production by exploring the potential rules of domain knowledge and manufacturing big data [16]. Li et al. developed a combination of data augmentation techniques and deep learning models for intelligent mechanical fault diagnosis and sample loss issues, for the diagnosis of rotating machinery faults [17]. Xue et al. proposed a quality control chart pattern recognition for imbalanced data based on multi-feature fusion using a convolutional neural network [18]. Yacob proposed a multi-layer shallow neural network regression method that identifies the source of change by best matching the actual surface deviation patterns with the surface deviation patterns generated by the shallow neural network [19].

The above research has found that scholars have paid less attention to the issue of quality fluctuations in the field of spinning production, and there is little literature on the problem of abnormal traceability of spinning quality fluctuations. In the actual spinning production process, there is a complex nonlinear mapping relationship between spinning quality characteristics and process parameters. How to mine quality information that can reflect quality fluctuations and process parameters from high-dimensional spinning process data, and further quantify the contribution of process parameters to abnormal quality characteristics by constructing a nonlinear mapping model is a bottleneck problem that needs to be overcome in the field of textile quality control. Based on team premise research, this article further focuses on the identification of abnormal sources of quality fluctuations in the spinning process. A weighted reconstruction analysis-based method for identifying abnormal sources of quality fluctuations in the spinning process is proposed. By calculating the information on sample quality characteristics and constructing an outlier measurement factor statistic, the spinning quality characteristics are monitored. Based on this, variable weighted reconstruction is performed on samples with abnormal quality characteristics, And based on the degree of change in the predicted values of quality characteristics before and after reconstruction, the abnormal contribution degree is sorted to achieve the identification of abnormal sources of spinning quality fluctuations. Finally, the effectiveness of the proposed method is verified through numerical examples.

THE PROPOSED FRAMEWORK

In the actual spinning quality control process, there is a direct relationship between the fluctuation of spinning quality characteristics and process parameters. When the quality characteristics are abnormal, analysing the impact of process parameters on the contribution of quality characteristics is the key to identifying the source of abnormalities. This article proposes a framework for identifying abnormal sources of quality fluctuations in the spinning process based on weighted reconstruction analysis, as shown in Figure 1. This mainly includes monitoring quality characteristic fluctuations, quantifying the contribution of process variables to anomalies, and identifying anomalous sources. Firstly, based on the concept of information entropy, a quality characteristic outlier measurement factor statistic is constructed for fluctuation monitoring; Then analyses the abnormal contribution of process parameter quantities that cause quality characteristic anomalies, and constructs a quality characteristic prediction model based on a generalized regression neural network. Sort the abnormal contribution degree according to the degree of change in the quality characteristic prediction values before and after variable weighted reconstruction. Based on the sorting results, identify the abnormal sources of spinning quality fluctuations.

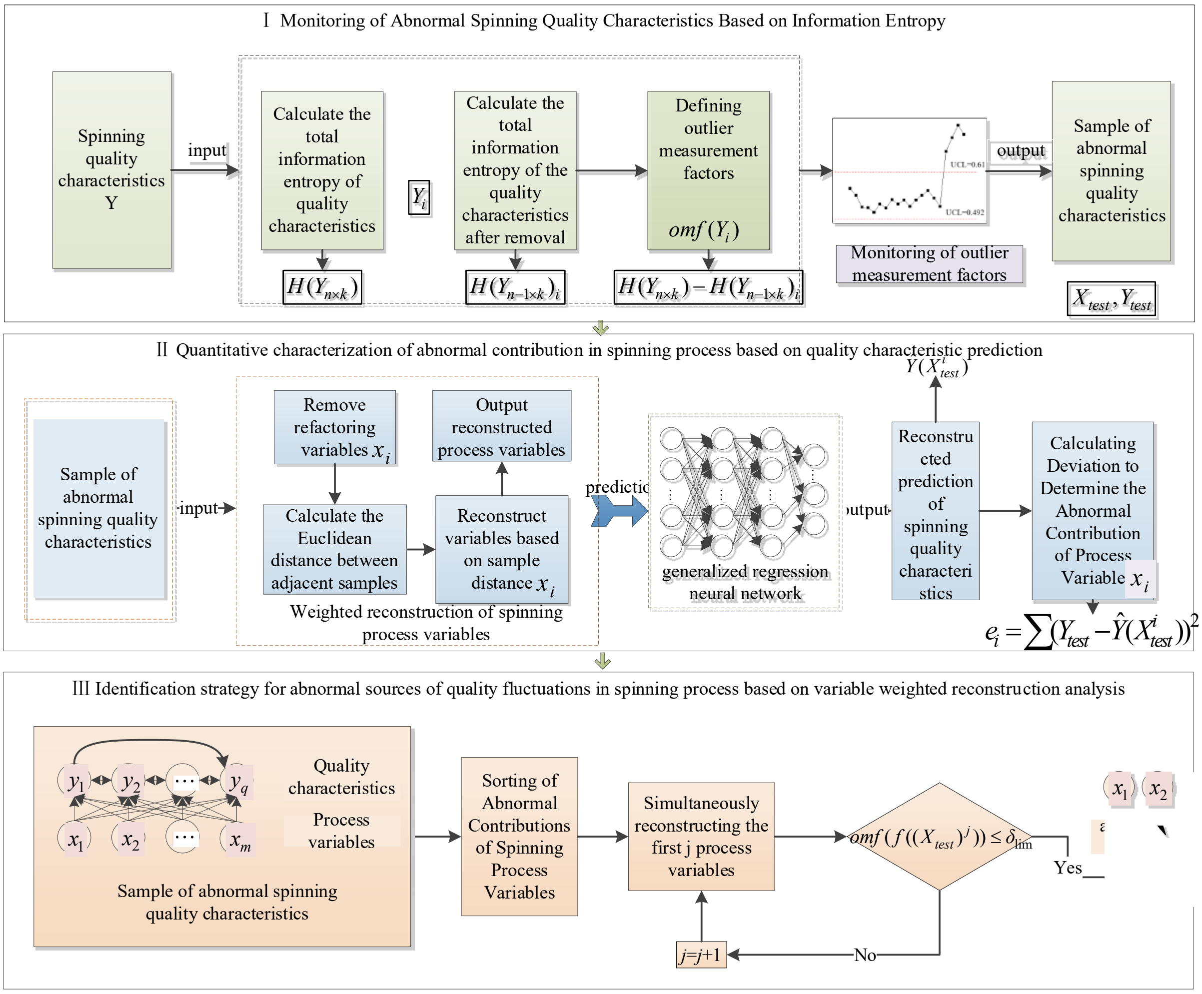


Figure 1. The framework for quality fluctuation abnormal source identification

QUALITY FLUCTUATION MONITORING BASED ON INFORMATION ENTROPY

Information entropy can be used to measure the stability of multivariate process fluctuations. If the quality characteristic monitoring values of the spinning process remain stable, then the information entropy of the quality characteristic of the spinning process should remain stable with the increase of normal data; If abnormal data occurs, the occurrence of such abnormal data will make the system no longer orderly, and the quality characteristic information of the process will experience significant fluctuations. According to the above ideas, information is introduced into the monitoring of abnormal spinning quality characteristics. The spinning process parameter matrix is denoted as $X_{N\times m}$, and the corresponding quality characteristic index matrix is $Y_{N\times k}$. The quality characteristic vector follows a normal distribution. Select the first n groups $Y_{n\times k}$ as historical data for monitoring and modelling the outlier measurement factors of spinning process quality characteristics, and the remaining group $Y_{(N-n)\times k}$ for monitoring and verifying abnormal quality characteristics in stage Ⅱ.

Firstly, calculate the total information entropy $H(Y_{n\times k})$, of the quality characteristic indicators for the first n groups. For a data set $Y_{n\times k} = [Y_1, Y_2, \cdots$ containing k attributes, the information entropy is calculated as equation (1).

$$H(X) = -\sum_{y_1 \in S(Y_1)} \cdots \sum_{y_k \in S(Y_k)} \cdots \cdots \tag{1}$$

If the attributes of the quality feature dataset are independent of each other, equation (1) can be transformed into equation (2)

$$H(X) = H(Y_1) + H(Y_2) + \cdots) \tag{2}$$

Then, after removing the i^th sample Y_i from the data $Y_{n\times k}$, a new data set is obtained and denoted as $(Y_{n-1\times k})_i$. The difference $H(Y_{n\times k}) - H(Y_{n-1\times k})_i$ from the information in the original data set $Y_{n\times k}$ is defined as the outlier measurement factor (outlier measure factor, *omf*) of the sample, and is recorded as $omf(Y_i)$. The degree to which individual samples have an impact on overall information during stable spinning processes.

$$omf(Y_i) = H(Y_{n\times k}) - H(Y_{n-1\times k})_i \tag{3}$$

Based on this, calculate the outlier measurement factors of the quality characteristic data set Y_{N-n} relative to the normal data set $Y_{n\times k}$. Furthermore, based on the distribution of outlier measurement factors in the stable spinning process, control limits are set as shown in equation (4) to monitor anomalies in the outlier measurement factors of data Y_{N-n} .

$$\begin{cases} UCL = u + 3\sigma \\ LCL = u - 3\sigma \end{cases} \tag{4}$$

Where *u* and *σ* are respectively the mean and standard deviation of the outlier measurement factors for the stable spinning process.

The outlier measurement factor $omf(Y_i)$ can quantitatively measure the degree of outlier for each data point, and the larger the value $omf(Y_i)$, the stronger the degree of outlier; On the contrary, the smaller $omf(Y_i)$, the weaker the degree of outlier. Therefore, by introducing outlier measurement factor statistics to monitor the data of spinning quality characteristics, a foundation is laid for the tracing of abnormal fluctuations in spinning quality in the future.

ABNORMAL CONTRIBUTIONS QUANTITATIVE CHARACTERIZATION

Prediction modelling of spinning quality characteristics

The primary task of quantifying the abnormal contribution of spinning quality fluctuations is to establish a predictive model between spinning process parameters and quality characteristics. This article uses a generalized regression neural network for modelling, as shown in Figure 2. Firstly, the first *n* sets of process parameters $X_{n \times m}$ in the spinning process data set are selected as the input matrix for the training set samples of the generalized regression neural network, and the quality characteristic $Y_{n \times k}$ is used as the output matrix to construct a quality characteristic prediction model based on the generalized regression neural network for the spinning process.

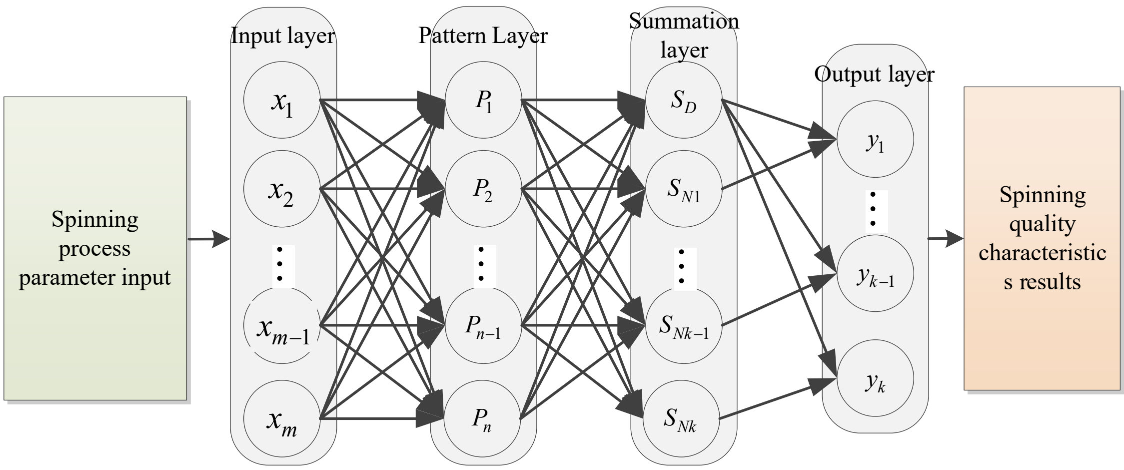


Figure 2. The structure of the yarn quality prediction model

The number of neurons in the input layer of the prediction model is equal to the dimension *m* of the spinning process parameters. The number of neurons in the pattern layer is equal to the number of datasets used for training *n*, and each neuron contains the same dimension m as the input layer. The transfer function of this layer is shown in equation (5):

$$P_i = \exp\left[-\frac{(X-X_i)^T(X-X_i)}{2\sigma^2}\right] \tag{5}$$

Where *X* is the input variable of the prediction model; X_i is the training sample corresponding to the i^{th} neuron; σ and is the smoothing factor.

When σ is very large, the predicted output $\hat{Y}$ approximates the mean of all samples. When σ approaches 0, the predicted output $\hat{Y}$ is very close to the training samples, which may lead to poor generalization ability of the network. Therefore, suitable smoothing factors must be selected during network training.

There are two types of neurons in the summation layer, where the number of neurons 1 S_{Nj} is the dimension k of the output variable, and the connection weight between the i^{th} neuron in the pattern layer and the j^{th} neuron in the summation layer is the corresponding position element y_{ij} of the output variable in the training set; The number of S_D is 1, and their connection weight to the upper-level neurons is 1. The transfer functions of the two types of neurons are respectively $S_{Nj} = \sum_{i=1}^{n} y_{ij} P_i$ and $S_D = \sum_{i=1}^{n} P_i$

The number of neurons in the output layer is equal to the dimension k of the output variable, and the j^{th} neuron corresponds to the j^{th} element of the prediction result $\hat{Y}(X)$, with a transfer function of $\hat{y}_j = S_{Nj}/S_D$. Based on this, a prediction model for the quality characteristics of the spinning process based on a generalized regression neural network is constructed, providing a theoretical basis for quantifying the abnormal contribution of subsequent process variables.

The quantitative contribution of abnormal spinning quality fluctuations based on weighted reconstruction analysis

This section analyzes the dynamic relationship between spinning process variables and quality characteristics based on the constructed quality prediction model and process variable weighted reconstruction method. The process variable with the greatest impact on the output results is the variable with the greatest abnormal contribution, and the abnormal contribution of spinning process variables is quantitatively characterized. The process of quantifying the contribution of abnormal spinning samples to the process parameter vector $X_{test} = [x_{test1}, x_{test2}, \cdots$ and the quality characteristic parameter $Y_{test} = [y_1, y_2, \cdots$ is as follows:

Firstly, reconstruct the first variable, calculate the Euclidean distance between X'_{test} and the first *q* adjacent samples according to equation (6) after removing the reconstructed variable 1, and label the distances $d_1, d_2, \cdots$.

$$d_j = \sum_{i=1}^{m} \quad (6)$$

Where X'_{test} represents the sample X_{test} composed of the remaining variables after removing the variables to be reconstructed, such as after the reconstructed variable 1, $X_{test} = [x_{test1}, x_{test2}, \cdots$; $n_j(X'_{test})$ represents the label of the jth adjacent sample of X'_{test}, where $j = 1, 2, \cdots$ 。

Then, calculate the weight w based on $w_j = (1/d_j) / (\sum_{l=1}^{q} 1/d_l)$, which represents the similarity between the abnormal sample and adjacent samples. The larger the weight, the greater the similarity; On the contrary, the smaller it is. Among them, $\sum_{l=1}^{q} w_j = 1$ further reconstructs the i^{th} variable according to equation (7).

$$x'_{testi} = \sum_{j=1}^{k} w_j (X_{n_j(x'_{test})})_i \quad (7)$$

Where w_j represents the degree of similarity between abnormal samples and adjacent samples. The larger the similarity, the greater the value, and vice versa; $(X_{n_j(x'_{test})})_i$ represents the i^{th} variable value of the j^{th} adjacent sample of x'_{testi} ; x'_{testi} represents the i^{th} variable value in X'_{testi} .

Based on this, each process variable of the abnormal sample $X_{test} = [x_{test1}, x_{test2}, \cdots$ is weighted and reconstructed and X^i_{testi} represents the sample after reconstructing the process variable i . The quality characteristics X^i_{testi} are predicted to obtain the predicted result $\hat{Y}(X^i_{testi})$, and the quality characteristic deviation e_i before and after reconstruction is calculated, as shown in equation (8):

$$e_i = \sum_{j=1}^{k} (Y_{test} - \hat{Y}(X^i_{test}))^2 \quad (8)$$

According to the calculation results, the process variable that causes abnormal quality fluctuations is the variable that contributes the most to the anomaly.

Identification strategy for abnormal sources of quality fluctuations in the spinning process

Based on the above analysis, the proposed strategy for identifying abnormal sources of spinning process quality fluctuations includes monitoring of spinning quality fluctuations, weighted reconstruction of process variables, and identification of abnormal sources, as shown in Figure 3. The specific process is as follows:

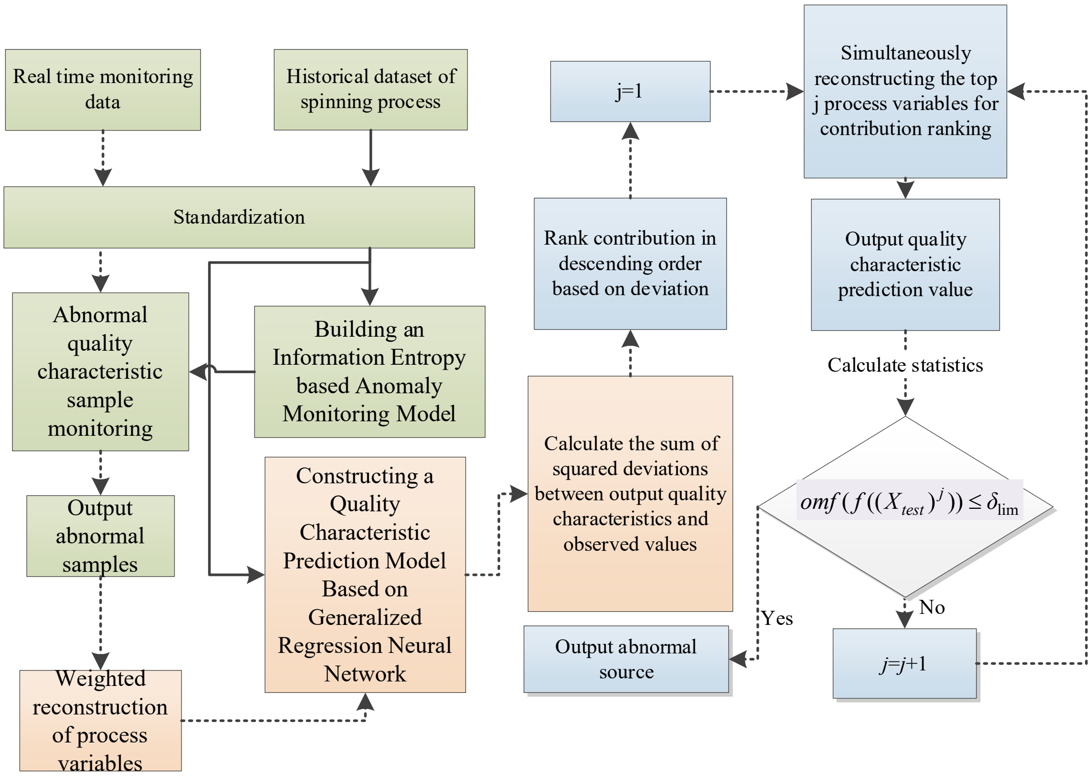


Figure 3. Identification strategy for quality fluctuation abnormal source

1) Standardize the process parameters $X_{N\times m}$ and quality characteristic indexes $Y_{N\times k}$ in the spinning process data, transform them into standard data with mean 0 and standard deviation 1, and construct the quality characteristic monitoring model based on information entropy based on the quality characteristic data of the previous n group, set the quality characteristic control limit $\delta_{\lim}$, and monitor the abnormality of $N-n$ the group to identify the X_{test} of abnormal quality characteristics.

2) Construct a quality characteristic prediction model based on a generalized regression neural network using a spinning data set. The input is the spinning process parameters, and the output is the quality characteristic parameters. Based on the Euclidean distance between abnormal samples and adjacent samples, each process variable is weighted and reconstructed, keeping other variables unchanged to form a reconstructed abnormal sample sequence $\{X_{test}^{i}(i=1,2,\cdots,$.

3) After calculating the deviation of the predicted quality characteristic from the original quality characteristic $e_1, e_2, \cdots$ ..., ranking the deviation of each variable from large to small according to the principle of maximum index reduction, the greater the deviation, the greater the change compared to the reconstruction, the greater the contribution of the reconstructed variable to the anomaly. Assuming that the order of deviations arranged from large to small is $e_1, e_2, \cdots$ ..., first replace the variable x_{test1} that causes the maximum deviation with the reconstructed x'_{test2} to obtain the reconstructed process parameter sample $(x_{test1})^1$. After predicting its quality characteristics, calculate whether the outlier measurement factor $omf(f((x_{test1})^1))$ is within the control limit $\delta_{\lim}$; If it is within the control limit, the output anomaly source is variable 1; If both x'_{test1} x'_{test2} are replaced outside the control limit to obtain a newly reconstructed process parameter sample $(x_{test})^2$ predict its quality characteristics, and calculate whether the outlier measurement factor $omf(f((x_{test1})^2))$ is within the control limit.

4) According to the order of contribution, the above multivariate reconstruction process is carried out in descending order until the deviation is within the control limit $\delta_{\lim}$. The output abnormal source is multiple process parameters reconstructed simultaneously, and the identification of abnormal sources is completed.

CASE STUDY

To verify the effectiveness of the proposed weighted reconstruction analysis method for identifying abnormal sources of spinning quality fluctuations, a case study was conducted using data from the spinning process of coarse and fine yarns [20]. The coarse and fine yarn processes are important in the spinning production process, mainly involving 14 parameters, including 6 fibre indicators (cotton fibre length uniformity base S, fibre length AL, fibre fineness FF, moisture content MRR, micronaire value MV, impurity content MR) There are 4 parameters for the spinning equipment (COS for the output line speed of the carding machine, DOS for the output line speed of the drawing machine, FRS for the front roller of the fine yarn, and SS for the spindle speed) and 4 main yarn quality index (YBS for the breaking strength of the yarn, YSU for the strength of the yarn, SDU for the thousand pieces of yarn, and FL for the elongation at break). The sampled data includes 46 sets of normal fluctuation data and 4 sets of abnormal spinning data with disturbance applied, A total of 50 sets of spinning quality data samples. The abnormal data includes abnormal data with a mean and standard deviation of (-10,0.15) perturbation applied to fibre length, abnormal data with (1000,0.1) perturbation applied to fibre fineness, and corresponding yarn quality index data with significant quality characteristics due to fibre index deviation from normal values.

Table 1. Partial spinning quality data sets

No.	Fibre index						Spinning equipment parameters				Yarn quality index			
	S %	AL mm	FF tex	MRR J/g	MV -	MR %	COS cm/min	DOS m/min	FRS m/min	SS r/min	YBS cN/tex	YSU %	SDU %	FL %
1	33.5	27.7	6365	5.4	3.9	2.3	180	350	19.56	15400	19	7.7	12.6	5.4
2	33.3	27.7	6356	5.2	3.9	2	140	365	19.56	15400	19.2	7.4	12.4	5.2
…	…	…	…	…	…	…	…			…	…	…	…	…
50	32.7	28.1	6140	6.8	4	2.2	180	250	19.56	15400	10.4	7.3	14	6.8

Fluctuation monitoring for quality characteristics

The first 30 sets of data were extracted for quality monitoring modelling of the spinning process. First, the outlier measurement factor statistics of the normalized sample data set were calculated, and the control limit of the outlier factor (UCL = 0.61, LCL = 0.452) was calculated according to Equation (4). The quality monitoring results of the last 20 sets of data were performed as shown in Figure 4. It can be seen that the spinning process is in a stable state at the initial stage, always within the control limit, exceeding the control limit at the 17th sample, and then the statistics are also in an over-limit state, reflecting a significant deviation between the quality characteristic data and historical data at this time, resulting in an increase in the outlier factor. Therefore, it can be concluded that quality characteristic anomaly monitoring based on information entropy can effectively reflect the stability of the spinning process, which can accurately identify samples with abnormal quality characteristics.

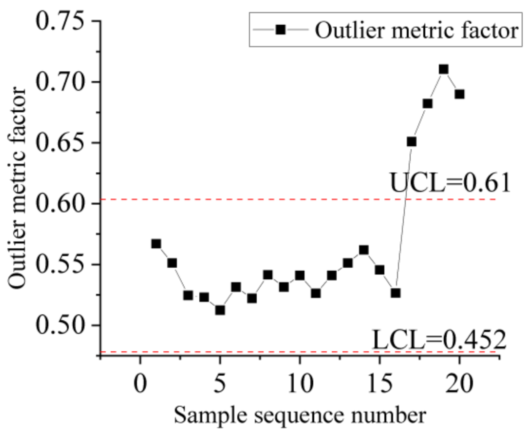


Figure 4. The monitoring results for spinning quality characteristic

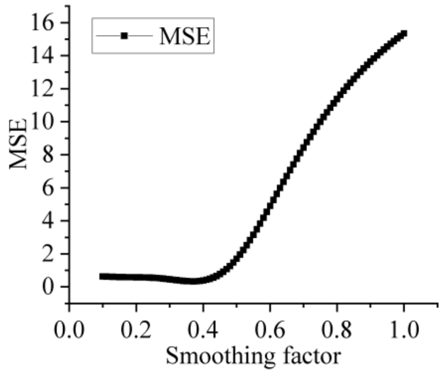


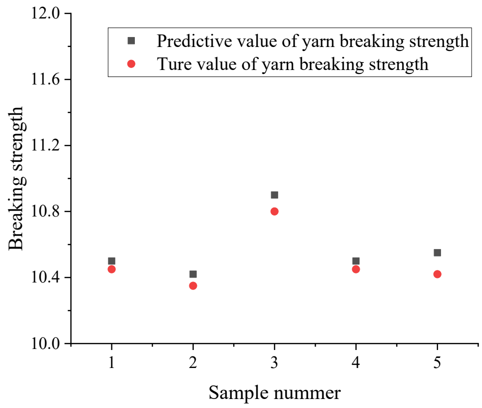
Figure 5. Iteration results in Smooth coefficient

Prediction model construction for spinning quality characteristics

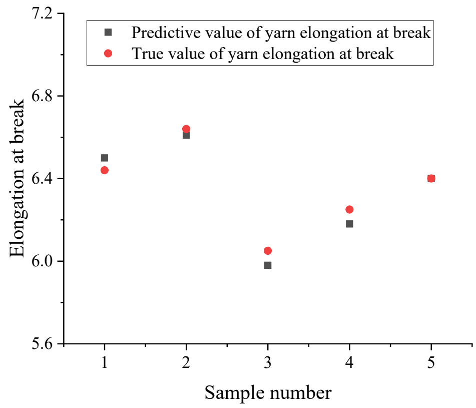
Abnormal fluctuations in the quality characteristics of spinning are generally caused by abnormal process parameters. Therefore, it is necessary to build a prediction model for the quality characteristics of the spinning process and analyze the impact of process parameters on the quality characteristics. A quality characteristic prediction model based on a generalized regression neural network is established using 1-45 sets of spinning data as training set samples and 46-50 sets as testing set samples. The input of the model is 10 process parameters, and the output is the quality characteristics of 4 yarns. The number of training samples is 45. Therefore, the number of neurons in the input layer, pattern layer, summation layer, and output layer of the network is set to 12, 45, 4, and 4, respectively. The activation function is the radial basis function.

Due to the significant impact of smoothing coefficients on prediction accuracy; The smoothing coefficients between (0.1,1) were selected with a step size of 0.01, and the mean square error between the predicted and true values of the model on the test set was used as the objective function for iteration. The results are shown in Figure 5. It can be seen that as the smoothing coefficient increases, the root mean square error of the model on the test set first decreases and then increases. Choosing the smoothing coefficient 0.37 represented by the minimum value of root mean square error as the model parameter, the construction of the spinning process quality characteristic prediction model is achieved.

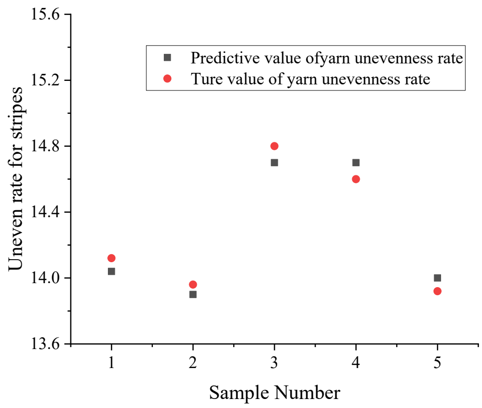
Based on the constructed quality prediction model, quality prediction was performed on the test set samples. The comparison between the predicted values of each quality characteristic and the actual values is shown in Figure 6. It can be seen that the prediction model has high accuracy in predicting indicators such as yarn fracture strength and yarn unevenness, indicating that the constructed model can effectively explore the mapping relationship between spinning process parameters and quality characteristics.



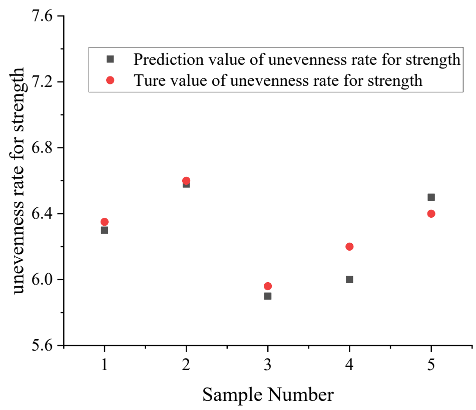
a)



b)



c)



d)

Figure 6. The comparison for spinning quality characteristics between predicted and actual values, a) yarn breaking strength; b) yarn breaking elongation; c) uneven rate for stripes; d) unevenness rate for strength

Performance comparison on different prediction models

To evaluate the effectiveness of constructing quality characteristic prediction models, radial basis function neural networks and BP neural network algorithms were selected in the experiment to compare the prediction performance of 45-50 sets of data. At the same time, indicators such as mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE), and coefficient of determination (R^2) were selected to measure the prediction model effectiveness. After multiple experiments, the parameter settings and predictive performance for different algorithms are shown in Table 2. It can be seen that the parameter settings of the radial basis function neural network and BP neural network are relatively complicated, while the generalized regression neural network only needs to select the smoothing coefficient after determining the data set, which has the characteristics of a simple model and fast modelling. In the same modelling environment, the prediction accuracy of radial basis neural networks is poor, with an R^2 coefficient far below 0.8, indicating that the trained model has very poor performance; The prediction models of the BP neural network and generalized regression neural network both showed high accuracy on the test set, but the generalized regression neural network algorithm used in this article was lower than BP neural network in various quantitative evaluation data, indicating that the established quality characteristic prediction model has better accuracy. In summary, the constructed prediction model can better describe the nonlinear relationship between spinning process parameters and quality characteristics compared to other methods, laying the foundation for accurate identification of abnormal sources of quality characteristics in the spinning process.

Table 2. Model construe and performance comparison

Prediction model category	Parameter settings	MAE	MSE	RMSE	R^2
RBF-NN	The hidden layer is 5, radial basis function is Gaussian function, goal=0.001, smoothing coefficient=0.5	9.0980	25.0702	9.6683	0.2138
BPNN	The hidden layer is 5, the activation function of the hidden layer is sigmoid, and the activation function of the output layer is purelin	2.4810	2.0477	3.0177	0.9266
GRNN	The network structure is 12, 45, 4, and 4, with a smoothing coefficient = 0.37	1.0686	0.3351	1.2859	0.9860

Quantitative characterization of abnormal contribution

Taking the first abnormal sample $X_{test} = [42, 22.5, 6700, 7.4, 4.7, 2.7, 140, 365, 30.16, 950, 19.56, 15300]$ and $Y_{test} = [10.4, 7.4, 14.0, 6.6]$ monitored as an example, a case study is conducted to quantitatively characterize the abnormal contribution of process variables. Firstly, the process parameters of the abnormal sample are weighted and reconstructed. Taking the fibre length parameter as an example, the Euclidean distance between the sample $X_{test}^{'} = [42, 22.5, 6700, 7.4, 4.7, 2.7, 140, 365, 30.16, 950, 19.56, 15300]$ and 15 adjacent samples after removing the fibre length parameter is calculated, and the reconstruction weight w for each sample is determined. After weighted reconstruction according to equation (7), the AL of the sample is 29.3 mm, so the reconstructed abnormal sample is $X_{test}^{2} = [42, 29.3, 6700, 7.4, 4.7, 2.7, 140, 365, 30.16, 950, 19.56, 15300]$. Then, based on the established quality characteristic prediction model, the quality characteristic prediction X_{test}^{2} is carried out to obtain $Y_{test}^{2} = [10.4, 7.4, 14.0, 6.6]$, and the quality characteristic deviation before and after reconstruction is calculated using equation (8) to obtain.

$$e_2 = \sum_{j=1}^{4} (\mathrm{Y}_{test} - \hat{Y}(X_{test}^2))^2 = 3.13 \tag{9}$$

Weighted reconstruction is performed on all variables of X_{test} to predict the quality characteristics after reconstruction, and the abnormal contribution of each variable is calculated. The abnormal contribution degree of process variables is ranked from highest to lowest, as shown in Figure 7. Only the parameters that cause significant deviation are listed in the figure. It can be seen that the fibre length reconstruction has the greatest change in quality characteristics, and it can be inferred that this is the most likely source of anomalies, The subsequent parameter reconstruction will still have a minor impact on the quality characteristics, which may be due to the accuracy deviation of the constructed prediction model.

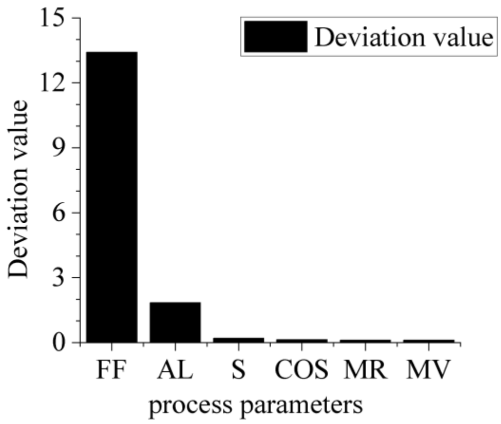


Figure 7. Quantification and characterization for anomalous contribution

Quality fluctuation abnormal source identification

In addition to fibre length, other process parameters also have an impact on quality characteristics. Below, multiple parameters are weighted and reconstructed according to the above sorting, and the quality characteristic deviation before and after weighted reconstruction is calculated. Perform multivariate reconstruction iteration based on the ranking of abnormal contribution, and discriminate the reconstructed outlier measurement factors of multiple parameters through the control limit $\delta_{\lim} = 0.61$ on the outlier measurement factor until they are within the control limit. The iteration process is shown in Figure 8(a), it shows that when the number of simultaneous reconstructions is 2, the quality characteristics after weighted reconstruction are within the control limit, indicating that the reconstructed process parameters have returned to normal and the corresponding quality characteristics are also in a controlled state. Therefore, the identification result of the abnormal source for this abnormal sample is the fibre length and cotton fibre length uniformity cardinality, which is the same as the abnormal source category set in this article, However, as other spinning process parameters remained stable and did not change before and after weighted reconstruction, there was no significant fluctuation in the subsequent outlier measurement factors.

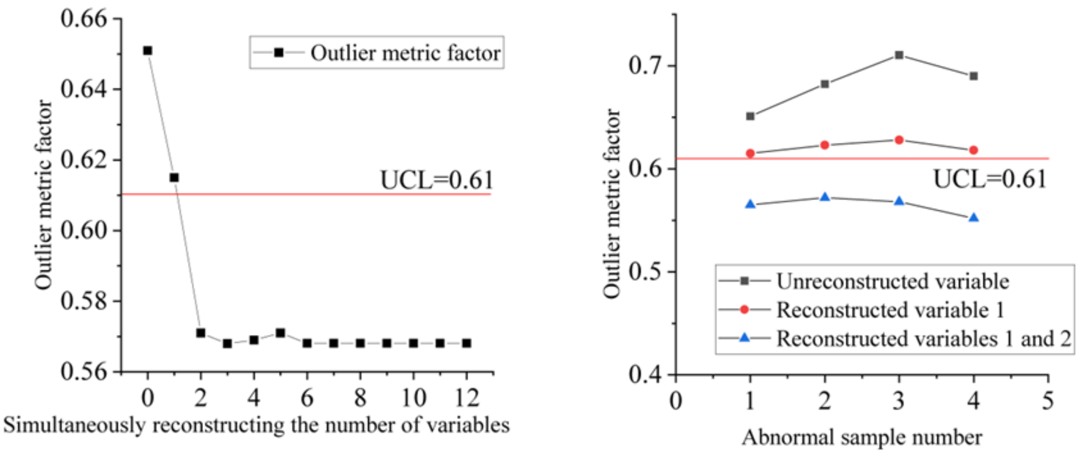


Figure 8. The iterative process and abnormal source identification a) The iteration process; b) The abnormal source identification result

Furthermore, the proposed method is used to identify the source of anomalies in four abnormal samples from the quality characteristic anomaly monitoring results. Figure 8(b) shows the abnormal source identification result. It can be observed that after simultaneously reconstructing variables 1 and 2, the outlier measurement factors of all sample quality characteristics have returned to the control line, indicating that there is no process variable (abnormal source) affecting the quality characteristics at this time, and the quality characteristics have returned to normal. This verifies that the anomaly source identification method proposed in this article can identify the source of abnormal fluctuations and provide a reliable basis for the stability control of spinning quality.

CONCLUSION

This article proposes a method for identifying and locating the source of abnormal quality fluctuations in the spinning process based on variable-weighted reconstruction analysis. By weighted reconstruction of spinning process parameters, the abnormal contribution of process parameters before and after reconstruction is calculated, and the identification of abnormal fluctuation sources is achieved. The following result thus achieved from the study for various perspectives of abnormal quality fluctuations in the spinning process.

- The information entropy-based spinning quality monitoring algorithm can perceive abnormal fluctuations in spinning process parameters in real time, which shows varying degrees of deviation in outlier factor statistics.
- By quantitatively characterising and analysing the abnormal contribution of process parameters on the contribution of quality characteristics, it can be inferred that the fibre length reconstruction has the greatest impact on the quality characteristics, making it the most likely source of anomalies.
- The proposed method monitors the degree of quality fluctuations by constructing information entropy statistics and reconstructs the weighted parameters of abnormal quality processes to identify abnormal sources, which will provide theoretical support for achieving intelligent textile production quality management.

Author Contributions

Conceptualization – Wu D; methodology – Wu D, Hu S; formal analysis – Wu D, Hu S; investigation – Wu D, Hu S; writing-original draft preparation – Wu D; writing-review and editing – Wu D, Hu S. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

Funding

This work is supported by the Natural Science Basic Research Program of Shaanxi Province (Grant No. 2022JQ-721).

Acknowledgements

We thank the editor and referees for the valuable comments.

REFERENCES

[1] Lee M-G, Chechurin L, Lenyashin V. Introduction to cause-effect chain analysis plus with an application in solving manufacturing problems. The International Journal of Advanced Manufacturing Technology. 2018; 99:2159-2169. https://doi.org/10.1007/s00170-018-2217-1

[2] Hu S, Zhao L, Yao Y, Dou R. A variance change point estimation method based on intelligent ensemble model for quality fluctuation analysis. International Journal of Production Research. 2016; 54(19):5783-5797. https://doi.org/10.1080/00207543.2016.1178862

[3] HU Tao, MA Chenhui, ZHOU Xiaoliuting, et al. Fault diagnosis method for complex aerospace systems based on weighted fuzzy Petri net. Computer Integrated Manufacturing Systems. 2019; 25(10):2580-2586.

[4] Liu H, Pi D, Qiu S, Wang X, Guo C. Data-driven identification model for associated fault propagation path. Measurement. 2022; 188:110628. https://doi.org/10.1016/j.measurement.2021.110628

[5] Zhou K, Lu N, Jiang B. Basic Probability Assignment Using Intuitive Fuzzy Cloud Model for Information Fusion and Its Application in Fault Diagnosis. IEEE Transactions on Instrumentation and Measurement. 2023; 73:3504413. https://doi.org/10.1109/tim.2023.3334361

[6] Chen H, Zhao A, Li T, Cai C, Cheng S, Xu C. Fuzzy Bayesian network inference fault diagnosis of complex equipment based on fault tree. Systems Engineering and Electronics. 2021; 43(5):1248-1261. https://doi.org/10.12305/j.issn.1001-506X.2021.05.12

[7] ZHANG Yunfeng, YANG Chunhua, ZHOU Feiyue, et al. Causality diagram based fault isolation and propagation path identification method and application. Systems Engineering and Electronics. 2022; 28(07):2017-2029.

[8] Hu S, Zhao L, Yao Y, Dou R. A variance change-point estimation method based on intelligent ensemble model for quality fluctuation analysis. International Journal of Production Research. 2016; 54(19):5783-5797. https://doi.org/10.1080/00207543.2016.1178862

[9] Zhang C, Pan L, Li Y. Fault detection and diagnosis method based on weighted statistical feature. CIESC Journal. 2022; 73(2):827-837. https://doi.org/10.11949/0438-1157.20211295

[10] Ma L, Dong J, Peng K. A Practical Root Cause Diagnosis Framework for Quality-Related Faults in Manufacturing Processes With Irregular Sampling Measurements. IEEE Transactions on Instrumentation and Measurement. 2022; 71:3511509. https://doi.org/10.1109/tim.2022.3169531

[11] Lindner B, Auret L, Bauer M, Groenewald JWD. Comparative analysis of granger causality and transfer entropy to present a decision flow for the application of oscillation diagnosis. Journal of Process Control. 2019; 79:72-84. https://doi.org/10.1016/j.jprocont.2019.04.005

[12] Wu H, Zheng H, Wang W, Xiang X, Rong M. A method for tracing key geometric errors of vertical machining center based on global sensitivity analysis. The International Journal of Advanced Manufacturing Technology. 2020; 106:3943-3956. https://doi.org/10.1007/s00170-019-04876-8

[13] Kim D-H, Kim TJY, Wang X, Kim M, Quan Y-J, Oh JW, Min S-H, Kim H, Bhandari B, Yang I, Ahn S-H. Smart machining process using machine learning: a review and perspective on machining industry. International Journal of Precision Engineering and Manufacturing-Green Technology. 2018; 5:555-568. https://doi.org/10.1007/s40684-018-0057-y

[14] Fan J, Qi Y, Liu L, Gao X, Li Y. Application of an information fusion scheme for rolling element

bearing fault diagnosis. Measurement Science and Technology. 2021; 32(7):075013. https://doi.org/10.1088/1361-6501/abf9d6

[15] Hu S, Zhang G, Zhao X, Li Z, Li W. A method for yarn quality fluctuation prediction based on multi-correlation parameter feature subspace mechanism in spinning process. Journal of Engineered Fibers and Fabrics. 2023; 18. https://doi.org/10.1177/15589250231208703

[16] Fu W, Chien C-F, Tang L. Bayesian network for integrated circuit testing probe card fault diagnosis and troubleshooting to empower Industry 3.5 smart production and an empirical study. Journal of Intelligent Manufacturing. 2022; 33:785-798. https://doi.org/10.1007/s10845-020-01680-0

[17] Li X, Zhang W, Ding Q, Sun J-Q. Intelligent rotating machinery fault diagnosis based on deep learning using data augmentation. Journal of Intelligent Manufacturing. 2020; 31:433-452. https://doi.org/10.1007/s10845-018-1456-1

[18] Xue L, Wu H, Zheng H, He Z. Control chart pattern recognition for imbalanced data based on multi-feature fusion using convolutional neural network. Computers & Industrial Engineering. 2023; 109410. https://doi.org/10.1016/j.cie.2023.109410

[19] Yacob F, Semere D. A multilayer shallow learning approach to variation prediction and variation source identification in multistage machining processes. Journal of Intelligent Manufacturing. 2021; 32:1173-1187. https://doi.org/10.1007/s10845-020-01649-z

[20] LU Z. Research on intelligent mining and quality control techniques and its application in textile production process. Shanghai: Donghua University, 2007.