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Continuous Bayesian Network in Intelligent Analysis and Early Warning Platform of Silk Making Process

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Abstract: With the development of cigarette technology in tobacco industry, more and more cigarette enterprises pay attention to Bayesian network aided cigarette product design. This study mainly discusses the application of continuous Bayesian network in the intelligent analysis and early warning platform of silk making process. This system designs the module of quality abnormal management and warning, which can monitor the whole process of silk production automatically. At the beginning of the system, the built-in discrimination criterion is used as the condition of pre alarm, and the system carries out real-time calculation according to Bayesian network. The module collects all the abnormal information in the process of silk production, including the batch and occurrence time of process quality parameters. The quality analyst can directly view the details of the abnormalities in the production process and the processing status. Cigarette formula maintenance module is based on clustering and Bayesian network. The individual cigarettes are divided into several categories according to the attribute characteristics by clustering method, and the individual cigarettes under each category have similarities under the selected attribute characteristics. When one individual cigarette is missing, other individual cigarettes under the category that the individual cigarette belongs to are found out as the initial candidate set of individual cigarette replacement. In order to verify whether the new formula belongs to the same brand as the original formula, the complete attribute information of the formula is put into the Bayesian network classifier for prediction. The correlation coefficient between predicted value and actual value of hot air temperature is 0.9703, and the root mean square error is 0.3074, which can meet the application demand of moisture content of cut tobacco at dryer outlet. The scheme designed in this study can predict the change of moisture in the process of processing in time, and has high practical value.

1. Introduction

The moisture content of cut tobacco has a very important impact on the internal quality of cigarette products. With the continuous progress of tobacco processing technology, tobacco enterprises have more stringent requirements on the process indicators of each link. If the moisture content of cut tobacco is too high, it is easy to cause mildew. If the moisture content is too low, it will increase the crushing rate of cut tobacco processing, and the moisture content of cut tobacco affects the moisture content of finished tobacco, it directly affects the taste of cigarette products. Therefore, in order to produce a cigarette product that meets the sensory and smoking quality of consumers, it is necessary to strictly control the moisture content of cut tobacco in the production process. At present, there is no relevant accurate parameter prediction model.

Tobacco processing process is extremely complex, each link in the production process will affect the quality of cigarette products and cause different degrees of consumption of raw materials. In the whole process of cigarette processing, the silk processing technology is an important guarantee for the internal quality of cigarette products. Its process flow is the longest, and the processing equipment is the most complex and diverse. Loose moisture regain is the first process, and the key assessment index of this process is moisture content. The outlet moisture of this process point has a great impact on the quality of the whole production line, It is the key quality index of product quality.

Bayesian networks (BNs) are widely used in predicting software defects and software reliability. Fenton N enables analysts to combine causal process factors and qualitative and quantitative methods to overcome some of the well-known limitations of traditional software measurement methods. He pre-defined discrete intervals and led to inaccurate predictions, such as a large range of defect counts. Fortunately, the latest developments in the BN algorithm now make it possible to perform inferences in BN with continuous nodes. Although his research does not need to specify the discretization level in advance, there is still a lack of comparative experiments [1]. Duan Z proposed the key role of prior knowledge, and he discussed the important concept of input-dependent regularization. He assumed many benchmark methods, which are algorithms or algorithmic solutions that can be applied more or less directly to problems without the need for a truly new concept. Although some of his research may become the basis of real methods, the research ideas are not clear enough [2]. Doguc O proposed an overall method to build a Bayesian network (BN) model to estimate the reliability of the system. He has designed a pre-built BN to represent the system. His task of establishing BN is usually left to a group of experts composed of BN and domain experts. BN experts should understand the domain before building BN, which is usually very time-consuming and may lead to wrong inferences. Although he uses historical data about the system to model BN and provides an effective automatic method, there is no existing research that can eliminate the need for experts in the system reliability evaluation process [3]. Mcnally R J believes that background obsessive-compulsive disorder (OCD) usually coexists with depression. Using network analysis methods, he calculated two networks. He examines the relationship between the symptoms that constitute these syndromes by calculating a (regular) partial correlation network through the graphical LASSO program and calculating the directed acyclic graph (DAG) through the Bayesian hill climbing algorithm. Although Bayesian analysis can expand the scope of network analysis methods, there are too few research process data [4].

The system is designed with quality abnormality management and pre-alarm modules to automatically monitor the whole process of silk production. When the system just started running, the built-in discriminant criterion was used as the pre-alarm condition, and the system performed real-time calculation based on the Bayesian network. This module summarizes all abnormal information in the silk production process, including the batch of process quality parameters and the occurrence time. Quality analysts can directly view the detailed information and processing status of abnormalities in the silk production process. The cigarette formula maintenance module is based on the relevant knowledge of clustering and Bayesian networks. The clustering method of single-material cigarettes is divided into multiple categories according to the attribute characteristics. The single-material cigarettes under each category have similarities under the selected attribute characteristics. When a single-material cigarette is missing, find the other single cigarettes in the category to which the single cigarette belongs are used as the candidate set for the initial single-load cigarette replacement.

2. Intelligent Silk Making Process

2.1. Continuous Bayesian Network

Bayesian theory is a very effective modeling method for assessing low probability and high risk chemical abnormal events [5-6]. The directional energy is defined as:

$$OE_{\theta,s} = \left(I * f_{\theta,s}^{e}\right)^2 + \left(I * f_{\theta,s}^{o}\right)^2 \tag{1}$$

Among them, $f_{\theta,s}^{e}$ is an orthogonal filter bank [7]. The expression of the likelihood function is as follows:

$$p(\theta \mid X) = \prod_{i=1}^{n} p(\theta \mid x_i) \tag{2}$$

According to the nature of exchangeability and conditional probability:

$$p(y,\varphi) = p(y)p(\varphi \mid y) \tag{3}$$

$$p(\varphi, y) = p(\varphi)p(y \mid \varphi) \tag{4}$$

$$p(\varphi \mid y) = \frac{p(\varphi)p(y \mid \varphi)}{p(y)} \propto p(\varphi)p(y \mid \varphi) \tag{5}$$

The prior information is updated through historical data, and the posterior probability density function $f(x \mid data)$ is obtained. Its expression is as follows:

$$f(x \mid data) = \frac{g(x \mid data) f(x)}{\int g(x \mid data) f(x)dx} \propto g(x \mid data) f(x) \tag{6}$$

The probability density function of Beta(a,b) prior distribution is as follows:

$$f(x) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} x^{a-1}(1-x)^{b-1} \propto x^{a-1}(1-x)^{b-1}, a>0, b>0 \tag{7}$$

The expectation and variance of Beta(a,b) are:

$$E(x) = \frac{a}{a+b} \tag{8}$$

$$V(x) = \frac{ab}{(a+b)^2(a+b+1)} \tag{9}$$

Use the sample reflected by the probability density function to estimate the expected value of the distribution:

$$E(x) = \lim_{N\to\infty} \frac{\sum_{i=1}^{N} x_i f(x_i)}{\sum_{i=1}^{N} f(x_i)} \tag{10}$$

Among them, N is the number of iterations [8-9].

The silk quality management system includes five main functional modules: quality basic data management module, quality standard module, quality statistical analysis module, quality statistical report module, quality exception management and pre-alarm module, and cigarette formula maintenance module. These six functional modules are divided according to the characteristics of SPC statistical technology and the integration of computer programs, as well as the actual needs of the tobacco factory. Each module is independent and interrelated [10].

2.2. Silk Making Process

The silk-making process design is to blend the alcoholized tobacco leaves, recycled tobacco shreds, flakes, and various sugar flavors according to the formula requirements of the formulator. Based on the existing process routes and production equipment of the cigarette enterprises, the model calculations and Knowledge reasoning and other means help to formulate the process control parameters of each process of the cigarette production process, and form the process of related process documents. The main task of the silk making process is to reprocess the leaves and tobacco stems after the initial processing of the threshing and redrying plant. By heating and humidifying the leaves and tobacco stems, the processing resistance of the raw materials is improved, and the process transportation and processing are reduced. The production of shredded materials can realize the maximum use of raw materials [11-12]. The second is to apply a certain proportion of flavors and fragrances to the leaves and tobacco stems to compensate or improve the aroma of the tobacco leaf raw materials. After drying, they are uniformly mixed with other formula components according to the design ratio, and then enter the silk storage cabinet to balance, and finally form a supply Rolled finished shredded tobacco of a specific brand [13]. Therefore, the silk-making process level of a cigarette company is often a concentrated expression of the company's core competitiveness. The most important business of silk making process design mainly includes three parts: process plan design and process plan maintenance. The silk making process is shown in Figure 1.

(1) Process plan design

For a new silk-making task, the process design process is as follows:

1) The technologist combines the process flow of each process section of the silk process, the production equipment of each process, the process control parameters of each equipment, the adjustable range of each parameter and other information to configure the silk process route [14-15];

2) Describe the special processing requirements of raw materials (tobacco leaves, sugar flavors) in each process of silk making (process control parameter constraints);

3) Preliminary selection of process control parameters based on previous processing history records (case library);

4) Combining the research results of the parameter index relationship, propose an alternative plan for optimizing process control parameters, and the technologist selects the best plan from them;

5) Carry out experimental realism and verify the optimized process parameters through production [16];

6) Inspect realistic production data, if the process quality requirements are met, save the current process parameter scheme in the instance library; otherwise, further adjust the process parameters, re-experiment and verify, and repeat until you are satisfied [17-18].

Figure 1. Silk making process (From http://alturl.com/febvz)

(2) Process plan maintenance

When there are quality problems in the production site where the silk-making process is in progress, the silk-making process quality requirements cannot be met, or the process quality fluctuations detected in the production exceed the allowable range, or the process quality indicators are found to exceed the design requirements by analyzing the production test data , You need to maintain the current process plan [19]. The process of process plan maintenance is:

1) Carry out an analysis of the original process plan, understand the causes of quality problems, and determine the process parameters to be adjusted;

2) Adjust the values of related process parameters to form a new process plan until the requirements are met [20-21].

Define the texture gradient as the distance between these two histograms χ^2:

$$\chi^2(g,h) = \frac{1}{2}\sum \frac{(g_i - h_i)^2}{g_i + h_i} \tag{11}$$

In order to ensure stability, the improved characteristics are defined as:

$$\hat{f}(x) = f(x) \cdot \left(\frac{-f''(x)}{|f'(x) + \lambda|} \right) \tag{12}$$

Among them, λ is a parameter used to optimize features. BN is a probabilistic method used to model and predict the behavior of the system based on observed random events [22]. The BN model is a directed acyclic graph (DAG), where nodes represent system components, and arcs represent the relationship between them [23-24].

$$f(sal \mid I) = \frac{f(sal)f(I \mid sal)}{f(sal)f(I \mid sal) + f(b)f(I \mid b)} \tag{13}$$

$$f(b) = 1 - f(sal) \tag{14}$$

2.3. Continuous Bayesian Network Training Model

(1) Determination of training times

The shredded process in the cigarette production process is the process of reprocessing the fermented tobacco leaf raw materials to make it into the shredded tobacco required by the brand style [25]. It is an important link in the process of cigarette production. Its technological level has a decisive influence on the internal quality and external style of cigarette products, and also plays a vital role in controlling the energy consumption in the process of cigarette production.

Generally, the pre-given network accuracy restricts the number of trainings. However, in the actual operation process, there will often be a situation where the model output will have a small error in the learning sample and fast convergence, but it will have the opposite effect on the test sample, and the error will increase instead. For this reason, when determining the number of network training times, it is necessary to study their changing laws to achieve simultaneous control of training error (E) and prediction error (EC). The number of trainings determined in this study is 50,000.

(2) Selection of learning rate

In order to make the system in a stable state, we will prefer to choose a smaller learning rate. The learning rate generally fluctuates between 0.01-0.7 [26-27].

3. Intelligent Platform Experiment of Silk Making Process

3.1. Quality Control Module Design

(1) Quality basic data management module

The production data of each process section of the silk production process is the basis for the realization of the entire analysis system, and the data management module obtains the production data from the bottom silk control system. The data collection of this system is to collect the data in the underlying control system in real time through SIMATIC IT RTDS, and store the collected data in the SQL Server 2005 database through a series of configuration of SIMAITIC IT PPA.

The real-time data source of the silk production process: quality indicators refer to the material flow, temperature, moisture content, and liquid temperature in the silk production. These quality indicators directly affect the quality of tobacco; important process parameters refer to the important parameters in each process the setting amount of the material, such as the setting amount of the material flow, the setting amount of the moisture content, the setting amount of the feeding ratio, etc.; the general process parameters are mainly some control parameters in the production process, such as the fan speed and the opening degree of the exhaust air door Wait.

(2) Quality standard module

The quality standard is the process quality standard, which is an important factor throughout the silk quality management system. The collection, calculation and analysis of quality data all require process quality standards as a reference. Its role is to formulate process quality standards in the silk production process. Quality analysts can add, delete and update the process quality standards of certain process sections in the silk production process after obtaining the advanced authority. These include the standard value, upper and lower limits of quality indicators, etc. The functions of the quality standard module designed by this system according to the actual needs of the cigarette factory and the characteristics of the SPC technology are as follows:

1) Establish a standard database of process quality parameters;

2) The historical data of the quality standards are backed up at any time to ensure that the quality analysts have historical data to query after updating the quality standards;

3) The quality parameter standards should be consistent with the production batches to ensure that a production batch uses the same quality standard.

(3) Quality statistical analysis module

The main function of the quality statistical analysis module is to perform statistical analysis on the process indicators in the silk production process, and use the SPC control chart to control the quality of the silk production process. Quality statistics is mainly to count the process indicators in a certain period of time in the silk production process, that is, the minimum, maximum, and average values of the quality indicators, important process parameters and general process parameters in the silk production process Statistical calculation of value, standard deviation, overrun rate, CPK, range. The silk production process index is the key data used by the tobacco factory to investigate the production situation of the silk production stage, and then help the manager to grasp the production performance, find the problems in the production, and take necessary measures. The configuration of the silk production process indicators includes the configuration of the real-time data collection frequency of the process indicators and the configuration of the trigger conditions and trigger modes of the process indicators.

Quality analysis is to conduct in-depth mining and analysis of process quality data in the silk production process, to determine whether the production process is in a controlled state, to find the cause of abnormality, and to provide a decision-making basis for process quality control management. Quality analysis includes control chart analysis and histogram analysis of key process parameter points, and quantitative analysis of the influence law between process indicators and process parameters with mathematical models, so as to provide data analysis support for process quality analysis and process quality improvement. In response to the actual needs of tobacco factories, this system provides histogram analysis, mean-range control chart, and mean-standard deviation control chart analysis of key art parameters. It also supports the combination of these analysis tools. Quality analysts can use multiple analysis tools on the same interface. A control chart analyzes the process quality data. After the quality analyst selects the type of control chart and imports the process quality parameters to be analyzed, the system will automatically draw the analysis result chart.

(4) Quality statistical report module

The quality statistical report is a module for the digital display of the quality characteristics and process capability evaluation of each process parameter in the silk production process. It can not only help the quality analyst to fully understand the process quality information of a specific process section, but also help Quality analysts correctly understand the conditions of each process and find a breakthrough in process improvement. The quality statistical report module of this system includes two parts: multi-dimensional reports and customized reports. The multi-dimensional report is mainly to compare the process quality parameters and indicators according to the parameters, grades and batch information. Its function is to count the comprehensive process capability of each process parameter. Customized reports are personalized reports customized by the system according to the needs of quality analysts. All reports can be exported in Excel text format.

3.2. Quality Exception Management and Pre-Alarm Module

The quality statistical analysis part can intuitively monitor the quality status of each process section in the silk production process, and discover quality problems in the silk production process in time, but it requires quality analysts to run the system at all times and can only monitor the selected process circumstances, it is impossible to monitor the quality of the whole process of silk production at the same time. Therefore, this system has designed a quality abnormality management and pre-alarm module to automatically monitor the whole process of silk production, and automatically capture and alarm the abnormal processes that occur. When the system just started running, the built-in discriminant criterion was used as the pre-alarm condition, and the system performed real-time calculation based on the Bayesian network. When the judgment is consistent with the pre-set alarm conditions, the system will automatically generate the corresponding pre-alarm information. At this time, relevant quality analysts should take corresponding measures to eliminate abnormalities and achieve the purpose of real-time control of the quality of the silk production process. This module summarizes all abnormal information in the silk production process, including the batch of process quality parameters and the occurrence time. Quality analysts can directly view the detailed information and processing status of abnormalities in the silk production process. The status of abnormal information includes pending, pending, confirmed, etc. The quality analyst can visually monitor the process of abnormal handling.

Use the ISC algorithm to learn the Bayesian structure of the process parameters of the clinker heat exchange system of the silk making system, combine the MLE algorithm to learn the parameters of the model, and use the joint tree inference algorithm to diagnose the model and establish the fault diagnosis model of the silk machine. Finally, use the fault diagnosis model of the silk making machine to diagnose the pressure of the silk system, and give a comparative analysis of the accuracy of the fault diagnosis. Taking 8000 sets of data as an example, ISC algorithm and classic HC algorithm are trained to learn the Bayesian network structure. The diagnosis model obtained by HC learning has large deviations. For example, the model constructed by HC mistakenly adds the influence of the two-chamber fan speed on the amount of raw meal entering the kiln, which reverses the effect of the amount of raw meal entering the kiln on the pressure of the silk making machine, and increases The influence of the secondary air temperature on the negative pressure of the kiln head is analyzed, and the diagnostic model obtained by ISC is closer to expert knowledge.

3.3. Cigarette Formula Maintenance Module

Based on the relevant knowledge of clustering and Bayesian network, the idea of maintaining cigarette formula is proposed. First, the clustering method of single-material cigarettes is divided into multiple categories according to the attribute characteristics. The single-material cigarettes under each category have similarities under the selected attribute characteristics. When a single-material cigarette is missing, find other single cigarettes under the category to which the single cigarette belongs are selected as the candidate set of the original single cigarette replacement. Secondly, the amount of substitute cigarettes is sequentially traversed to take the historical amount, and then replace the missing single-material cigarette to supplement the missing formula, and recalculate the characteristic attributes of the formula. Finally, put the supplemented formula attribute information into the Bayesian network classifier for prediction, and verify whether the new formula belongs to the same brand as the original formula.

3.4. Level of Key Process Parameters

The feeding strength test is carried out in a feeding process (feeder 30kg/h), and the feeding ratio is 0.5% functional material + 3.0% brand material. Set high, medium and low strength levels for the selected parameter processing time, hot air temperature, process flow rate, and compensation steam flow rate. Combining the actual situation and other research papers, determine the test value range of each process parameter level as shown in the table 1 shown. After treatment, the tobacco leaves are packed in boxes according to batches and stored on site after being clearly marked. The storage time is 6-24h, and the discharge temperature is controlled at 50℃-70℃.

Table 1. Test value range of each process parameter level

Process parameters	Processing time	Hot air temperature	Process flow	Compensation steam flow
Horizontal range	0-300	Unheated wind -1000	0-15	0-70

4. Intelligent Silk Making Process

4.1. Comparative Analysis of Bayesian Networks

The data collected from the secondary leaf conditioning experiment of the characteristic craft of the Cigarette Factory Technological Research Laboratory is selected for research, and there are 100 sets of samples. Each group of samples is an 8-dimensional target feature vector obtained from process experiments under different process conditions. The first 80 groups are used as training sets, and the last 20 groups are used as test sets. For the convenience of comparison, the comparison results of the three groups of methods are shown in Table 2. The comparison between the temperature of the exit blade and the moisture of the exit blade is shown in Figure 2. Table 3 shows the moisture statistics of some exported leaves. The outlet blade temperature is shown in Table 4. The results show that the prediction effect of the continuous Bayesian network is significantly better than that of the general Bayesian network: (1) From the absolute error distribution, the absolute error of the prediction value of the continuous Bayesian network is mostly smaller than that of the general Bayesian network. The absolute error of the predicted value of the network; (2) The maximum absolute error of the continuous Bayesian network (temperature: 4.492, moisture: 2.716) <the maximum absolute error of the general Bayesian network (temperature: 7.736, moisture: 5. 870) (3) The relative error of the prediction value of the continuous Bayesian network, except that the outlet leaf moisture of sample 8 and sample 16 reach: +10. 35% and +15. 30%, and the rest of the samples are in -10%-10 %, and the relative error of the prediction value of the general Bayesian network is more than 10%. For example, the moisture of the exit leaf of sample 16 even exceeds 30%. Similarly, the prediction effect of the continuous Bayesian network is also better than the multiple linear regression method, which is mainly reflected in the prediction of the exit leaf temperature. The two methods have little difference in the prediction effect of the exit leaf moisture. But it needs to be pointed out that if the neural network structure used by the continuous Bayesian

network can be further improved, the prediction effect will be greatly improved. Only then can it be shown that the neural network method is compared with the multiple linear regression method. The superior type.

Table 2. Comparison results of three groups of methods

Tolerance scope		0-1	1-2	2-3	3-4	4-5	Maximum absolute error
Outlet blade temperature (℃)	Multiple linear regression	6	4	2	4	2	5.762
	General BN	4	4	2	6	1	7.736
	Continuous BN	7	4	5	2	2	4.492
Export leaf moisture (%)	Multiple linear regression	10	7	3	0	0	2.558
	General BN	7	7	4	1	1	5.870
	Continuous BN	12	6	2	0	0	2.716

Table 3. Moisture statistics of some exported leaves

Actual value	General BN	Continuous BN
20.85	23.62	20.833
22.97	22.515	23.149
21.62	21.919	21.711
20.7	19.652	21.747
20.15	19.242	21.206
18.97	16.705	20.188
23.1	21.255	21.385
20.01	22.624	22.081
21.5	21.401	22.303

Table 4. Outlet blade temperature

Multiple linear regression	General BN	Continuous BN
43	49.779	41.178
55	50.395	53.46
60	60.812	59.162
59	65.929	61.997
79	69.332	68.995
44	42.944	41.746
52	54.989	55.584
58	61.107	57.506
61	61.136	60.091

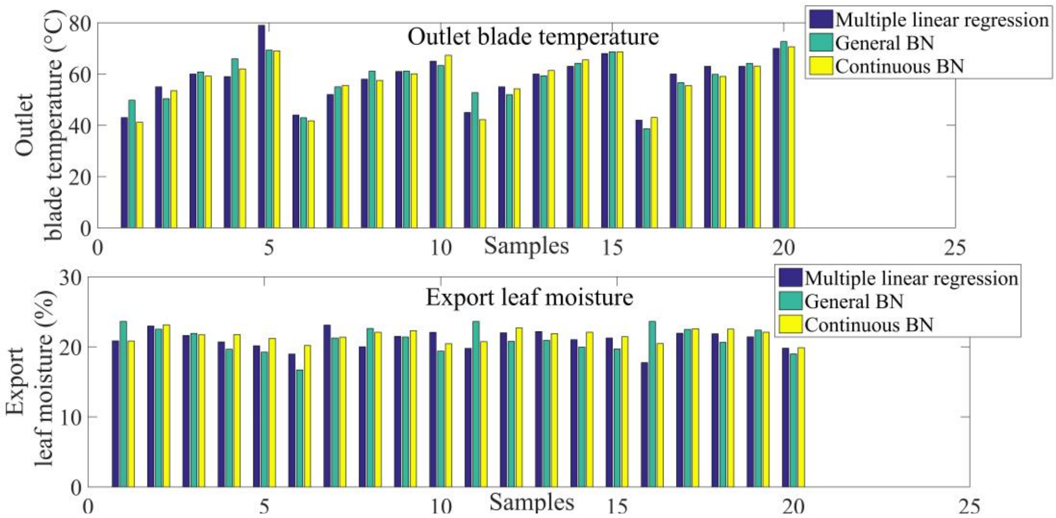

Figure 2. Comparison of outlet leaf temperature and outlet leaf moisture

4.2. BN Model Application Effect Analysis

The continuous Bayesian network model is applied to the online parameter control of the silk dryer. It can be seen from Figure 3 that the moisture content of the cut tobacco in the export has a relatively small fluctuation compared with that before the improvement, which indicates that the qualification rate of the moisture content of the cut tobacco in the export has been qualitatively improved. This method can be better applied in the dryer. The test parameters and levels are shown in Table 5. The comparison before and after the study is shown in Figure 3.

Table 5. Test parameters and levels

Key parameters/gradient	Gradient 1	Gradient 2	Gradient 3	Gradient 4
Processing time/s	-	180	210	240
Hot air temperature/℃	No heating wind	90	100	110
Process flow/kg	-	9	10	11
Compensation steam flow/kg/h	10	20	30	40

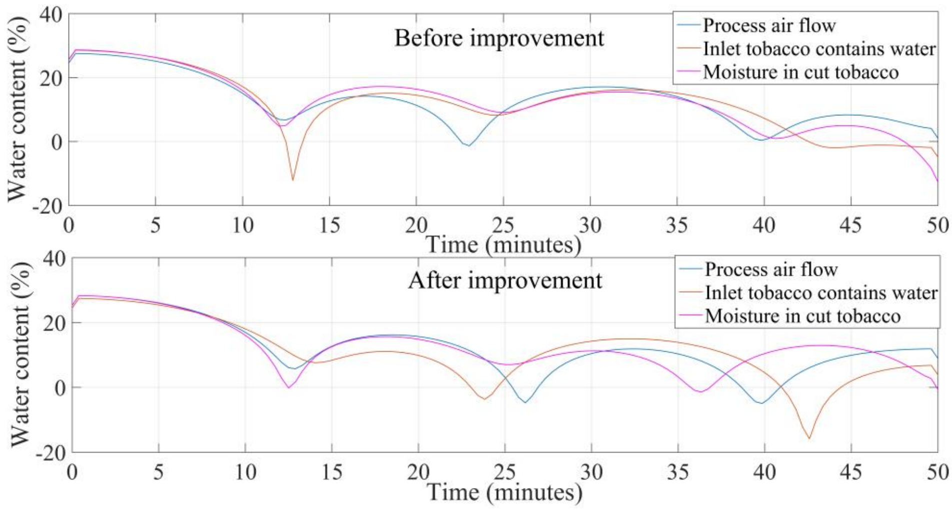

Figure 3. Comparison before and after the study

The simple wall temperature prediction of the BN network is shown in Figure 4. From Figure 4, it can be seen that the correlation coefficient between the predicted value of the barrel wall temperature and the actual value is 0.9672, and the root mean square error is 0.3557 demand.

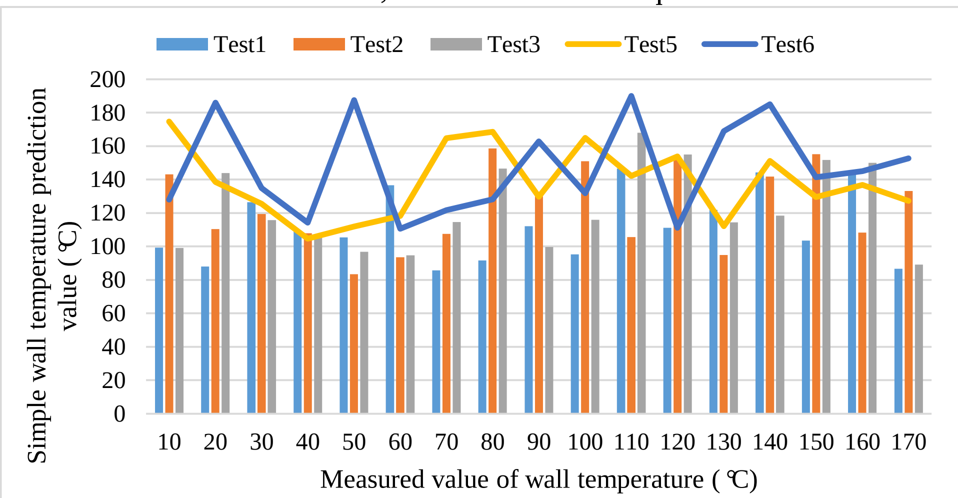

Figure 4. Simple wall temperature prediction of BN network

The continuous BN network model hot air temperature prediction is shown in Figure 5. From Figure 5, it can be seen that the correlation coefficient between the predicted value of the hot air temperature and the actual value is 0.9703, and the root mean square error is 0.3074, which can meet the application of the moisture content of tobacco at the outlet of the dryer demand. In the process of cigarette processing, a brand of tobacco leaf material is composed of multiple tobacco leaf varieties and tobacco leaf grades. Therefore, certain kinds of raw materials are often insufficient in the production process, so that the phenomenon of raw material replacement is carried out due to the different grades and varieties. Its physical and chemical properties will also be different. During the processing, the operator cannot predict the change of the incoming moisture, which will cause the moisture content of the tobacco at the outlet of the dryer to deviate from the process requirements. The continuous Bayesian network can better solve this problem, predict its parameters, and make its control system intelligent.

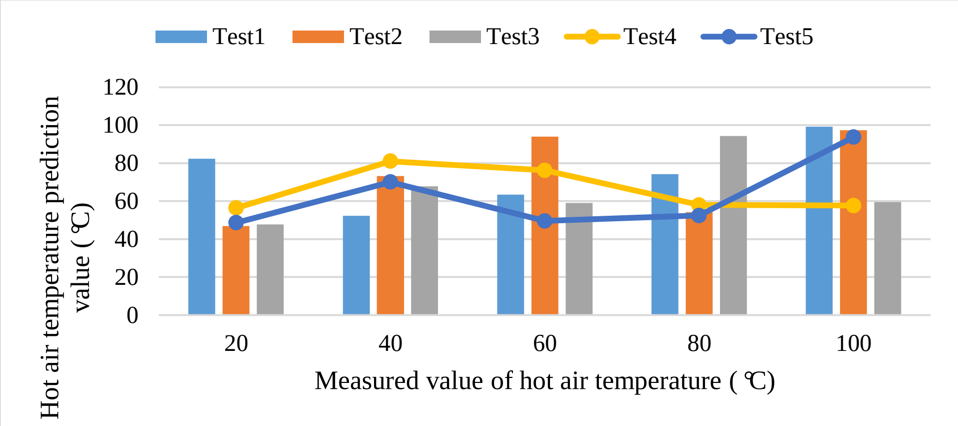

Figure 5. Hot air temperature prediction of continuous BN network model

4.3. Impact of Tobacco Sensory Quality Evaluation Indicators

Through the BN evaluation method, the comprehensive score of the sensory quality of cut tobacco under different processing intensities can be obtained, so as to select the appropriate processing intensity. The overall score of the sensory quality of shredded tobacco given by the comprehensive score cannot clearly reflect the degree of change of each evaluation index. Using the index evaluation set scale and evaluation matrix in the BN evaluation method, the degree of change of the sensory quality evaluation index of cut tobacco under each processing intensity is obtained.

The effect of different processing intensities on the aroma characteristics of cut tobacco The aroma characteristics of cut tobacco include aroma quality, aroma volume, and odor. The four different processing intensities of 2#, 4#, 6#, and 7# all improve the aroma quality of tobacco, including 7 #Processing strength improves the tobacco aroma quality the most, with an improvement degree of 0.86; followed by 2# and 6# with an improvement degree of 0.57 and 0.43, respectively; 4# processing intensity has the smallest improvement effect on aroma quality, with an improvement degree of 0.14. 4# , 6# processing intensity reduces the tobacco aroma, the reduction degree is 0.71, 1.14 respectively, that is, the 6# processing intensity reduces the tobacco aroma most significantly, while the 2# and 7# processing intensity does not significantly change the tobacco aroma,2#, 6#, 7# processing intensity has the effect of improving the quality of tobacco impurity index, 2# processing intensity has the most obvious improvement effect on tobacco impurity index quality, followed by 7#, 6#, 4# processing intensity impact of tobacco impurities is not obvious. The sensory quality changes of cut tobacco with different processing strengths are shown in Table 6. The test results of different groups of samples are shown in Figure 6.

Table 6. Sensory quality changes of cut tobacco with different processing strengths

Test number	Aroma characteristics		
	Aroma	Aroma amount	Miscellaneous
2#	0.57	0.00	1.29
4#	0.14	-0.71	0.00
6#	0.43	-1.14	0.14
7#	0.86	0.00	0.86

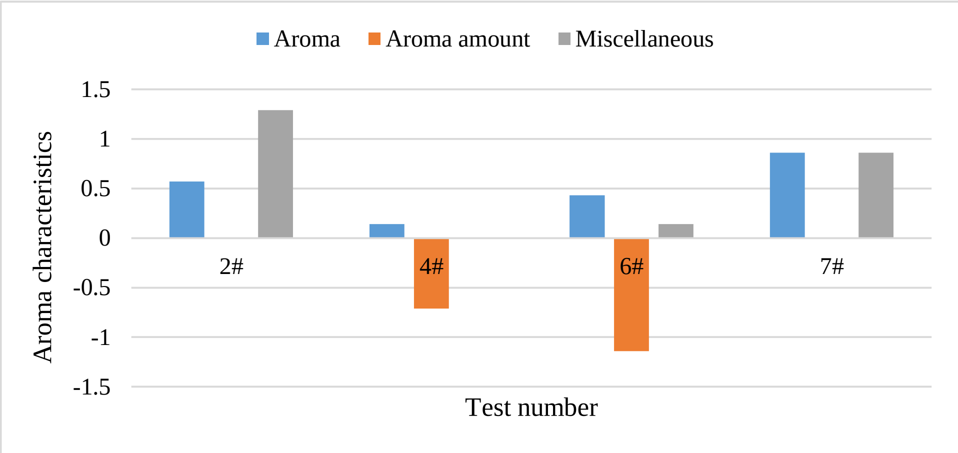

Figure 6. Test results of different groups of samples

The taste characteristics of cut tobacco include irritation, dryness, sweetness, and cleanliness. The degree of change in the irritation of cut tobacco under 2# processing intensity is 1.29; the degree of change in irritation of cut tobacco under 4# processing intensity is 0.57; under 6# processing intensity The degree of change in the irritation of cut tobacco is -0.43; the degree of change in the irritation of cut tobacco under 7# processing intensity is 1.57, that is, the processing strength of 2#, 4#, 7# can reduce the irritation of tobacco, and the processing intensity of 7# can reduce the irritation of tobacco. The effect is most obvious, but the processing strength of 6# increases the irritation of cut tobacco. Among the influences of these four processing strengths on the dryness of cut tobacco, the processing strength of 2#, 4#, and 7# improves the dryness quality of tobacco, and the processing strength of 6# reduces the dryness quality of tobacco. The dryness index quality improvement effect of cut tobacco is the most obvious. The degree of change of 2#, 4#, 6#, and 7# processing strength tobacco sweetness index is 1.14, 0.43, 0.29, 0.71 respectively, that is, the four processing intensities have an effect on improving the quality of tobacco sweetness index, and 2# processing strength improves The degree of improvement is the largest, and the improvement degree of 6# is the smallest. The 2# processing strength can improve the cleanliness of the cut tobacco most, the 6# processing strength reduces the degree of appreciation of the cut tobacco, and the 7# processing strength has an effect on the cleanliness of the tobacco is 0.29, that is, it has the effect of improving the cleanliness of the tobacco. The effect of cleanliness is not obvious. The influence of different processing intensities on the mouthfeel characteristics of cut tobacco is shown in Table 7. The taste analysis of different groups of cut tobacco is shown in Figure 7.

Table 7. The influence of different processing intensities on the taste characteristics of cut tobacco

Test number	Taste characteristics		
	Dryness	Sweet back	Cleanliness
2#	1.43	1.14	1.29
4#	0.14	0.43	0.00
6#	-0.14	0.29	-0.14
7#	1.00	0.71	0.29

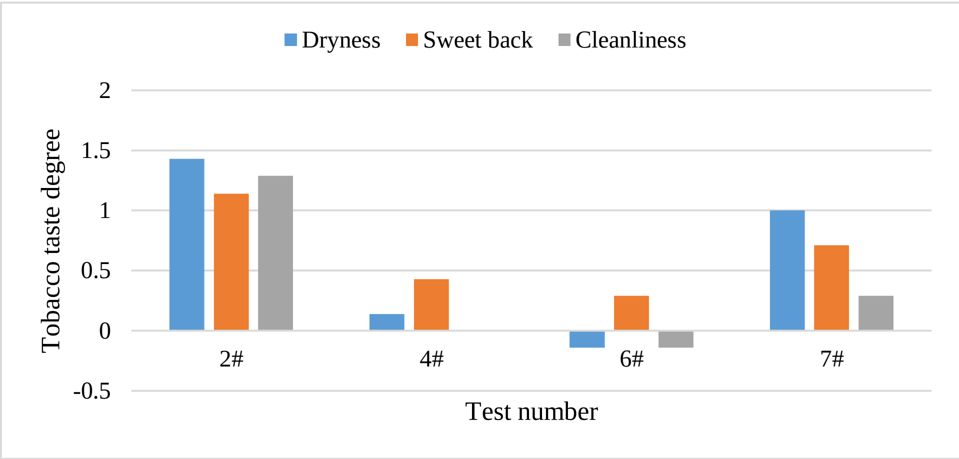

Figure 7. Taste analysis of different groups of cut tobacco

5. Conclusion

The main function of the quality statistical analysis module is to perform statistical analysis on the process indicators in the silk production process, and use the SPC control chart to control the quality of the silk production process. Quality statistics is mainly to count the process indicators in a certain period of time during the silk production process. The silk production process index is the key data used by the tobacco factory to investigate the production situation of the silk production stage, and then help the manager to grasp the production performance, find the problems in the production, and take necessary measures. The configuration of the silk production process indicators includes the configuration of the real-time data collection frequency of the process indicators and the configuration of the trigger conditions and trigger modes of the process indicators.

Quality analysis is to conduct in-depth mining and analysis of process quality data in the silk production process, to determine whether the production process is in a controlled state, to find the cause of abnormality, and to provide a decision-making basis for process quality control management. Quality analysis includes control chart analysis and histogram analysis of key process parameter points, and quantitative analysis of the influence law between process indicators and process parameters with mathematical models, so as to provide data analysis support for process quality analysis and process quality improvement. After the quality analyst selects the type of control chart and imports the process quality parameters to be analyzed, the system will automatically draw the analysis result chart.

The quality statistical report module of this system includes two parts: multi-dimensional reports and customized reports. The multi-dimensional report is mainly to compare the process quality parameters and indicators according to the parameters, grades and batch information. Its function is to count the comprehensive process capability of each process parameter. Customized reports are personalized reports customized by the system according to the needs of quality analysts. All reports can be exported in Excel text format. The scheme designed in this study can predict the moisture changes of incoming materials in time during processing, and has high practical value.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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