**EEE** Access

Received 6 July 2024, accepted 21 July 2024, date of publication 31 July 2024, date of current version 9 August 2024. Digital Object Identifier 10.1109/ACCESS.2024.3436043

# **RESEARCH ARTICLE**

# **Digital Evaluation of Cigarette Smoke Clumping Based on Aerosol Particle Analysis**

LEI JIAO<sup>1</sup>, SHISHUAN GUAN<sup>1</sup>, KEZHI WU<sup>1</sup>, XIAOFEI JI<sup>2</sup>, CUNFENG YU<sup>1</sup>, XINLONG ZHANG<sup>1</sup>, ZENGYU WANG<sup>1</sup>, SHUAISHUAI SUN<sup>1</sup>, HONGTAO LI<sup>1</sup>, LIWEN ZHENG<sup>1</sup>, JUN LI<sup>1</sup>, GUANGWEI JIANG<sup>1</sup>, QIANG SUN<sup>1</sup>, ERGE LIN<sup>1</sup>, AND HONGWEI ZHENG<sup>1</sup> <sup>1</sup>Shandong Qingdao Tobacco Company Ltd., Qingdao 266101, China <sup>2</sup>Qingdao University, Qingdao 266071, China

Corresponding author: Hongwei Zheng (15064659103@163.com)

**ABSTRACT** Cigarette smoke clumping, an important indicator of smoke status, draws consumer attention due to its correlation with smoke concentration, thickness, fullness, and the clumping index, which significantly affects the sensory quality of cigarettes. Due to the difference of individuals and the influence of environment, the current manual evaluation method is greatly influenced by subjectivity, and the consistency and reproducibility of the evaluation results are poor. In order to solve this problem, this study takes clusteriness as a breakthrough point in the digital research of sensory evaluation. Firstly, the best-selling cigarettes are selected as the research object to form a consistent evaluation of clusteriness through expert evaluation. Then, from the microscopic point of view, that is, the particle size distribution of flue gas, the influence degree of flue gas clumping is explored. In the experiment, the diameter particle spectrometer was used to detect the aerosol diameter particles, and the characteristics of the diameter particle distribution curve, including the spectral shape area, the spectral peak intensity and the mean width, were further verified, and the correlation was proved. Finally, a model of granularity distribution and cluster relationship is constructed based on the feature engineering method, and the expert evaluation score is used as the expected value of the model for training, and finally the cluster digital evaluation system is realized.

**INDEX TERMS** Cigarette smoke clumping, size distribution, characteristic correlation, digital evaluation.

# I. INTRODUCTION

Smoke clumping, as defined in the industry standard "Sensory Evaluation Methods for Tobacco Products in Process", is an important indicator of smoke characteristics, which is significantly correlated with the sensory quality of cigarettes. The concentration, thickness and fullness of smoke concerned by consumers are all related to the clumping index [1].However, as an important sensory index, clusteriness is rarely studied in the industry. This study takes clusteriness as a breakthrough point in the digital research of sensory evaluation to accurately grasp the true level of sensory quality of cigarettes, which is of great significance [2]. Of course, a number of studies have also been conducted on sensory evaluation of tobacco products. Researchers apply absorbent liquid on the inner wall of the bionic device of the mouth

The associate editor coordinating the review of this manuscript and approving it for publication was Haidong Shao<sup>10</sup>.

and nose and analyze the chemical composition by gas chromatograph, but the effect is not good and there are no relevant studies on the formation of smoke [3]. In addition, CFD numerical simulation of upper respiratory tract has been studied, which uses simulation software to simulate the status of smoke to observe the deposition of particulate matter [4]. Moreover, although the study on flue gas aerosols did not specifically evaluate the clumping property of flue gas, the instruments used in the experiment, such as fast particle size spectrometer and laser particle size analyzer, have shown good results in the detection of flue gas particle size distribution [5]. So far, as an important sensory index, there are few targeted studies, and a technical method is urgently needed to improve the accuracy of its evaluation. In the current research on fluid mechanics, turbulent agglomeration is mainly in the direction of aerosol dynamics.For example, the agglomeration efficiency of sub-micron particles with smaller particle size is significantly higher than that of larger

particle size [6]. It can be seen that there is a strong correlation between the clumping property and the motion characteristics of flue gas particles, and the main starting point of the study is to study the clumping property index from the microscopic point of view by using the particle size spectrometer [7].

Our research on flue gas clumping is pioneering and can help the country to promote the formation and formulation of evaluation standards on flue gas clumping. Therefore, for the purpose of research, we established cigarette smoke cluster scoring data set SClusterS under the guidance of cigarette smoking evaluation experts from China Tobacco Shandong Industry Co., LTD.

In this study, in order to realize the visualization of the final analysis of flue gas clumping data, a flue gas simulation experiment platform was established to construct the relationship model between flue gas particle size change curve and flue gas clumping score. Among them, the smoke simulation experiment platform device creates the oral and nasal model according to the 3D reconstruction method, and uses industrial equipment to detect the clumping characteristics of the smoke produced after the combustion of different brands of cigarettes. That is, the gas particle size change curve is detected by the diameter particle spectrometer. Feature engineering and support vector regression methods in machine learning were used to establish a relationship model between gas clumping score and gas particle size change curve, and the model was continuously trained and verified [8]. After fitting the training data, the relationship model between the smoke clumping score and the gas particle size change curve was deployed on the experimental platform to realize the automatic detection and analysis of the smoke clumping after burning different brands of cigarettes. The final evaluation system of flue gas clumping is formed by the relationship model between flue gas particle size change curve and flue gas clumping score.

Finally, our contribution can be summarized as follows: (1)Through the smoke simulation simulation experiment platform, we obtained the gas particle size change curves of different brands of cigarettes from a microscopic perspective. And a dataset SClusterS for cigarette smoke clusteriness score evaluation was made based on the clusteriness score of smoking experts. (2) We used support vector regression method to establish a good relationship model between gas clumping score and gas particle size curve. (3) We used the trained relationship model to establish a complete evaluation system for smoke clumping [9]. We believe that our research will greatly promote the formation and formulation of evaluation criteria for flue gas clumping.

## **II. EVALUATION INDEX AND METHOD**

# A. CLUMPING INDEX

Smoke clumping refers to the degree to which the smoke produced by cigarettes gathers into clumps, and its clumping index has been mentioned and studied many times in industry standards [10]. In addition, in upper respiratory tract fluid simulation studies and aerosol studies of cigarette smoke, relevant factors such as deposition particles and smoke particle size distribution have been paid attention to. Although these experiments and studies have not specifically explored and verified the clumping of smoke, based on this, in order to improve the accuracy and reliability of the research, during the formation and movement of smoke, It provides support and basis for us to explore the evaluation index from the micro Angle.

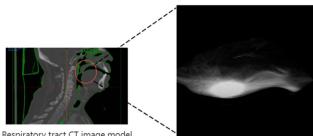
To sum up, in order to form the final evaluation criteria for cluster indicators and combine the current application status of computer machine learning, on this basis, the production of upper respiratory tract simulation device and the configuration of particle size spectrometer for detecting flue gas particle size data can be carried out. Finally, the particle size distribution of flue gas is taken as an evaluation index from a microscopic perspective for evaluation and verification [11].

### **B. SMOKE DATA ACQUISITION**

#### 1) SMOKE SIMULATION EXPERIMENTAL EQUIPMENT

In order to achieve the determination of cluster evaluation indicators and the establishment of subsequent cluster digital and standardized evaluation platform, the experiment was established on the smoke simulation device, which mainly consists of a transparent upper respiratory tract simulation model with good sealing and pressure resistance (-3000pa~3000pa).

It also includes an industrial camera (specification MV-CH250-90GC), a lens (specification MVL-KF1224M-25MP) and a light source (specification MVL-KF1224M-25MP) for capturing the overall motion pattern of the smoke. As well as gas mass flow controller (specification AST10-HLCMX-002L-040-A2B2-48VY), industrial computer (specification HD-510), vacuum pump (specification WT-230 primary 65L), and universal scanning electromobility particle spectrometer. The structure diagram of the experimental device is shown in Figure 1.



Respiratory tract CT image model

Cigarette smoke status

FIGURE 1. The smoke of the cigarette after combustion surrounds the human mouth, and the composition of the microscopic particles forms a different taste

#### DATA ACQUISITION

The device uses MV-CH250-90GC's 25 million pixel network port array camera for image acquisition, with a resolution of 5120  $\times$  5120, and is equipped with

MVL-KF1224M-25MP light source to shoot inside the oral and nasal model during smoke test to obtain image data. In addition, the flue gas is input to the rapid particle size spectrometer through the standard suction unit to detect the flue gas aerosol particles, and the flue gas particle size distribution curve is obtained. The particle size and particle size distribution of flue gas at different concentrations were investigated.

Among them, the diameter particle spectrometer is an instrument used for the detection of flue gas particles, which can generate the diameter particle distribution curve by measuring the diameter of particles. The specific detection and generation process is as follows:

Sampling: The diameter spectrometer first needs to collect a sample of particulate matter in the flue gas. A sampling head is usually used to introduce the flue gas into the instrument, and then the particles are separated by a filter or condenser. Dispersion: After the particle sample enters the instrument, it needs to be dispersed by the dispersion device. This is to avoid the phenomenon of aggregation between particles, so that each particle can be detected and measured independently. Measurement: The dispersed particle sample will enter the measurement area, and the diameter particle spectrometer usually uses the principle of laser scattering for measurement. The laser beam shines on the particles, and the scattered light is picked up by the detector and converted into an electrical signal. Based on information such as the intensity and Angle of the scattered light, the diameter of the particle can be calculated. Data processing: The measured particle diameter data is transmitted to the data processing system for processing. The data processing system will classify and count particles according to different diameter ranges according to the measurement results, and generate a diameter particle distribution curve, that is, draw a curve of the quantity or quality of particles changing with the diameter.

## C. DATA VISUALIZATION ANALYSIS

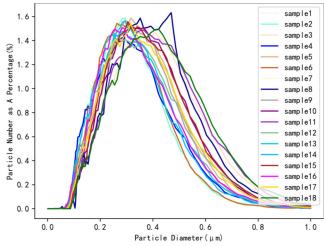
The smoke particle size distribution curves of some samples after smoke detection by particle size spectrometer were analyzed, as shown in Figure 3. The above three rows of images show the sampling data of coarse, medium and fine-branched cigarette samples successively from top to bottom. All of them are collected by the particle size detection instrument deployed in the equipment from the relevant data in the flue gas experiment to draw charts, intuitively display the change curve of the particle size and the total proportion, and directly calculate the output concentration and the area and average width of the curve.

In the traditional classification of curves, feature engineering can be used to extract some features that are helpful for classification. Here are some common curve features and what they do:

Average: The average of the curve can reflect the overall trend or the central position; Variance: The variance of the curve can reflect the degree of dispersion of the data;



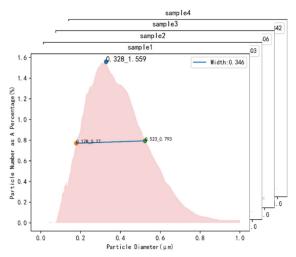
FIGURE 2. Smoke simulation device structure diagram, which marked: 01. Light source 02. Industrial camera 03. Smoke inlet 04. Touch screen 05. Relay 06. Smoke outlet 07. Simulated nasal 08. Simulated oral 09. Particle size spectrometer 10. Pump 11. Gas flowmeter.



**FIGURE 3.** Data collection diagram of diameter distribution curve. The figure shows the gas particle size change curve of 18 different brands of cigarette samples during combustion, where the horizontal coordinate is the particle diameter and the vertical coordinate is the proportion.

Kurtosis and skewness: Kurtosis can reflect the sharpness of the curve, and skewness can reflect the skewness of the curve; Maximum and minimum values: The maximum and minimum values of the curve can provide information about the extreme values of the curve; Periodic features: For periodic curves, features such as period and frequency can be extracted; Frequency domain characteristics: The energy distribution of the curve at different frequencies can be extracted by means of Fourier transform and other methods.

Among them, the frequency domain features focus on the energy distribution at different frequencies of the curve, which is applicable to the dimensional transformation processing of music signals, but not to the single dimensional curve in this study. Periodicity does not appear in the above curve. In addition, kurtosis and maximum value characteristics were evaluated by fusion of spectral peak intensity, and



**FIGURE 4.** Sample of flue gas particle size distribution curve.The characteristics of gas particle size change curves of a single sample are analyzed in detail, including mean value, variance, spectral peak intensity, spectral peak average width, etc.

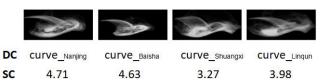


FIGURE 5. The above picture shows the smoke produced by the combustion of four brands of cigarette samples, and the corresponding smoke particle size distribution curve names and scores.

mean and variance characteristics were evaluated by fusion of spectral peak mean width [12].

The relevant data collected in the smoke experiment were sorted out, and the correlation analysis of each index and score data was carried out, and the following laws were initially found.

Analysis of the three key parameters-spectral area, mean width, and spectral peak intensity-revealed a 'V' shaped relationship for spectral area with scores, where the spectral area decreases towards the center of a given range and increases towards the edges. The influence of the mean width on the score showed a "W-shaped" relationship, that is, the mean width gradually decreased toward the middle of the two intervals and increased on both sides. The influence of spectral peak intensity on the score showed a V-shaped relationship, that is, the spectral peak intensity gradually decreased towards the middle of a certain range and increased on both sides. In summary, the three dimensions of spectral shape area, mean width and spectral peak intensity showed strong correlation with the score of crude cigarettes. And each dimension can be judged by the range of its value. In addition, the three dimension parameters and scores of the middle branch generally showed a "W" shape relationship, that is, the two intervals gradually decreased toward the middle. In summary, the three dimensions of spectral shape area, mean width and spectral peak intensity also showed a strong correlation with the middle branch score. Finally, thin branches are weakly correlated or irrelevant in the three dimensions of spectral shape area, mean width and spectral peak intensity (the actual points are mostly offset by the trend line). The spectral shape area and mean width are weakly correlated, but the spectral peak intensity is irrelevant. It is not possible to obtain a score by analyzing a single dimension of a single cigarette. Although a single dimension cannot distinguish different scores, by combining 3-dimensional features, it is possible to classify small cigarettes with different scores from a specific point of view. This indicates that a high-dimensional model can be used to fit the score estimation of a fine cigarette [13].

## D. CLUSTER EVALUATION METHOD

According to the smoke particle size distribution curve obtained by the smoke particle size distribution detection method in the upper respiratory tract, we have evaluated and analyzed from multiple feature angles. In order to further verify the correlation between particle size distribution and the evaluation results of flue gas clumping, a relationship model between particle size distribution curve and clumping score was established by using characteristic engineering method. Build a machine learning environment, train the model, input the verification set into the machine learning model, verify the model accuracy, and optimize the model parameters. Feature engineering is an important step in machine learning, which extracts useful information from data by selecting, constructing, and transforming features in order to better train models. In the process of establishing the model, the characteristics of the curve such as spectral area, spectral peak intensity and mean width will be used to classify the curve.

In short, we obtained particle size distribution data of different grades of flue gas by experimental means, studied the correlation between particle size distribution and clusterability evaluation, and finally established the relationship model between particle size distribution curve and clusteriness score. It not only further verifies the feasibility and correctness of particle size distribution as the evaluation of flue gas clumping, but also promotes the establishment of the final digital and standardized evaluation platform for flue gas clumping.

#### **III. METHOD IMPLEMENTATION**

#### A. DATASETS

Our cigarette smoke cluster score dataset, SClusterS, contains smoke particle size distribution curves and corresponding scores for 51 different brands of cigarettes. The average scores of 10 cigarette evaluation experts from China Tobacco Shandong Industrial Co., Ltd. on different brands of cigarettes are taken as the final score results. In addition, we used the smoke simulation experiment platform to obtain 9 flue gas particle size distribution curves for each brand of cigarettes. At each test, we adjusted the air pump flow rate and controlled the smoke lighting time to improve the generalization ability of subsequent models. Therefore, our cigarette smoke cluster scoring dataset, SClusterS, contains a total of 459 smoke particle size distribution curves and corresponding scoring results.

# **B. LINEAR FOUNDATION MODEL**

Based on the above evaluation methods, a relationship model between the particle size curve and the smoke cluster scoring is established by using the feature engineering method. The steps include data acquisition and preprocessing, feature extraction, feature selection, data division, model selection and training, and model evaluation.

Among them, the data acquisition process is to input the flue gas into the rapid particle size spectrometer through the standard suction unit, detect the flue gas aerosol particles, and obtain the flue gas particle size distribution curve. For the data preprocessing stage of flue gas particle size distribution curve, it is necessary to carry out operations including removing noise, smoothing processing or filling missing values. The feature extraction stage, informed by our data visualization analysis, involves isolating key characteristics from each curve, specifically the spectral shape area, peak intensity, and mean width.For the spectral shape area, it represents the total area under the particle size distribution curve, which can reflect the number and distribution range of particle concentration, and can be obtained by calculating the area under the curve. Spectral peak intensity is the intensity of the highest peak in the curve, indicating the relative number of the most common or significant particle sizes in the particle size distribution; The mean width is the average width of the curve and provides information about the uniformity of the particle size distribution and the clustering trend. Subsequently, in the data division phase, we conduct rigorous testing, training, and validation of cigarette samples. Detailed discussions on feature selection, model training, and selection follow below.

In this study, we first developed a linear prediction model based on particle size distribution and established the theoretical basis of the model [14].

The particle size distribution data was recorded by using a rapid particle size spectrometer under controlled environmental conditions. At least ten independent samples were taken for each sample, and the average was taken for analysis. The data was de-noised by Butterworth low-pass filter and normalized by max-min normalization method.

In the feature engineering stage, the key features are extracted: spectral area, spectral mean width and spectral peak intensity. These features are independent variables of the linear model, and the model equation is

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \epsilon$$
 (1)

where X represents the above characteristic spectral shape area, spectral shape mean width and spectral peak intensity respectively,  $\beta$  coefficient represents the characteristic weight, and  $\epsilon$  is the error term.

K-fold cross-validation ensures the generalization ability of the model, and the detailed steps of model training and validation are strictly implemented. The model performance was evaluated by mean square error (MSE) and coefficient of determination ( $\mathbb{R}^2$ ), the results of which support the prediction accuracy of the model. The linear model effectively predicts smoke clumping and provides a practical tool for cigarette production and quality control, but the actual results show that the model still has room for improvement.

## C. SVR OPTIMIZATION MODEL

Support Vector Regression (SVR) is a regression algorithm of support vector machine (SVM) [15], [16], [17]. Compared with the ordinary linear model, the following advantages of the SVR model should be absorbed to optimize the linear base model: One is the nonlinear fitting capability, which SVR can achieve by using kernel functions to map data into high-dimensional Spaces. This makes SVR more flexible and accurate in dealing with nonlinear problems; The other is robustness, SVR has little effect on outliers. Because SVR uses support vectors to fit data, it focuses primarily on the data points closest to the decision boundary and ignores other data points [18]. This makes SVR less powerful to outliers and more robust.

$$\mathbf{X} = \mathbf{Y} \tag{2}$$

$$X' = \frac{X - Min(X)}{Max(X) - Min(X)}$$
(3)

Feature scaling and Max-Min normalization based on features (1) of the basic linear model (3) :Max (x) and Min (x) are the minimum and maximum values of the feature feature X in the entire dataset, respectively. The established SVR model uses the kernel function as the radial basis function (RBF) to effectively handle the non-linear relationship between the input features. The kernel function transforms the input vector into a high-dimensional space with the following formula:

$$K(X_{i}, X_{j}) = \exp(-\gamma(||X_{i}, X_{j}||)^{2})$$
(4)

Here,  $X_i$  and  $X_j$  are the two eigenvectors generated by the underlying linear model, and  $\gamma$  is the parameter of the kernel function of the SVR model [19].

In SVR, the predictive output of the model is achieved by linearly combining the transformed features of the support vectors, plus a bias term b. The prediction function f(x) can be expressed as:

$$f(X) = \sum_{i=1}^{n} \left( \alpha_i - \alpha_i^* \right) \mathbf{K}(\mathbf{X}_i, \mathbf{X}) + b$$
 (5)

where,  $\alpha_i$  and  $\alpha_i^*$  are Lagrange multipliers solved during training; n is the number of support vectors; X<sub>i</sub> is the support vector;

K is the kernel function applied between the input data and the support vector; b is the offset term.

Finally, the model output f(x) is the prediction score of the flue gas agglomeration, and this value is continuous and reflects the agglomeration characteristics implied in the flue gas particle size data. The above steps outlined how

the raw input data can be transformed by preprocessing and kernel function, with the resulting model parameters learned to predict the output values. The power of SVR lies in the treatment of nonlinear problems through kernel techniques and the precise control of the balance between model complexity and prediction error through optimization algorithms [20]. This makes SVR particularly suitable for complex regression problems, such as smoke formation evaluation [21].

TABLE 1. Model cross-validation results.

Fold	MSE	R <sup>2</sup>
Fold 1	0.0400	0.960
Fold 2	0.0380	0.962
Fold 3	0.0420	0.958
Fold 4	0.0360	0.964
Fold 5	0.0390	0.961
Average	0.0390	0.9610

The table above is to perform a 5-fold cross-validation and record the performance of the SVR regression model, which is evaluated by the mean square error (MSE) and the coefficient of determination ( $\mathbb{R}^2$ ). These two indicators provide a measure of the model prediction error and the degree of correlation between the model prediction value and the actual value, respectively. It can be seen that the effect of the established SVR regression model is very ideal.

## **IV. CONCLUSION**

In this study, with the help of cigarette smoking evaluation experts from China Tobacco Shandong Industry Co., LTD., an innovative smoke cluster scoring dataset SClusterS was successfully developed, and a smoke simulation experiment platform was constructed. The platform can not only accurately simulate the dynamic environment in the mouth and nose through 3D reconstruction technology, but also detect the smoke particle size after burning different brands of cigarettes by using diameter spectrometer. By collecting this data, we were able to reveal the changing characteristics of smoke particle size and correlate these characteristics with smoke clumping scores.

By using support vector regression method, we analyzed the collected data deeply, and successfully established a quantitative relationship model between gas clumping score and gas particle size curve. After several rounds of training and verification, the accuracy and stability of the model have been proved. Finally, the relationship model was integrated into our experimental platform to realize the automatic detection and scoring analysis of smoke clumping after combustion of different brands of cigarettes. Some sample results are shown in Table 2.

The results of this study have many contributions. First of all, the development of the smoke simulation simulation experiment platform provides us with the ability to observe

#### TABLE 2. Sample rating sheet.

sample	area	mean width	intensity	comprehensive score
Sample0	0.00680	0.413	0.422	4.52
Sample1	0.00575	0.346	0.316	4.14
Sample2	0.00570	0.379	0.274	3.56
Sample3	0.00606	0.390	0.340	4.92
Sample4	0.00535	0.305	0.284	3.32
Sample5	0.00476	0.276	0.229	2.68
Sample6	0.00500	0.288	0.229	2.67

and analyze the smoke particle size changes of different brands of cigarettes from a microscopic perspective [22]. Secondly, through the established data set and relationship model, we not only improve the understanding of the nature of smoke clumping, but also provide a quantitative method for the scientific evaluation of smoke clumping. Finally, these research results will greatly promote the formulation and optimization of national evaluation standards on smoke cluster, and improve the scientific and effective public health protection.

We believe that the methods and findings of this study will provide an important scientific basis for the evaluation of flue gas clumping, and provide technical support and theoretical guidance for the formulation of related policies in the future. Going forward, we plan to further optimize the model's algorithms and expand the size of the dataset to enhance the model's versatility and scope of application. In addition, we will also explore the application of this technique to other types of flue gas cluster studies to broaden the impact and practicality of our research.

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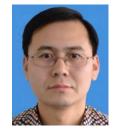
**KEZHI WU** was born in 1970. He received the bachelor's degree in equipment engineering and management and the master's degree in project management engineering from Harbin Institute of Electrical Engineering, in 1995. He is engaged in equipment management and cigarette technology research for 29 years, undertook the process optimization research of Shandong Zhongyan Baxi series and several Taishan brand key specifications of cigarettes, and has rich experience in equipment

management and cigarette technology research.



**XIAOFEI JI** is currently pursuing the Ph.D. degree. He is an Associate Professor, the Director of the Industrial Internet Platform Application Innovation Promotion Center, Ministry of Industry and Information Technology, an Executive Member of the CCF Information System Special Committee, a Special Committee Member of China Entrepreneur Federation Smart Enterprise Promotion Committee, the Deputy Director of Qingdao Artificial Intelligence Expert Committee,

a Qingdao Science and Technology Bureau Storage Expert, Haier Group, a Shandong Industrial Technology Research Institute Special Expert, and National Judge of Internet + Competition.



**CUNFENG YU** was born in 1975. He received the bachelor's degree in tobacco engineering and the master's degree in food engineering from Zhengzhou University of Light Industry, in 1998. He is engaged in cigarette product development for 25 years, responsible for the design and maintenance of Shandong ZhongTobacco Rufeng series Taishan brand high-end specifications of cigarettes, and has rich experience in cigarette product development.



**LEI JIAO** was born in 1988. He received the Master of Engineering degree in chemical process machinery from Qingdao University of Science and Technology, in 2012. He is engaged in cigarette equipment and technology research for 12 years and has rich experience in cigarette intelligent manufacturing and cigarette technology research.



**SHISHUAN GUAN** was born in 1969. He received the bachelor's degree in industrial analysis from the Department of Processing Technology, Hefei University of Economics and Technology. He has published six core journal articles and one SCI article and more than ten national invention and utility model patents were authorized. He is mainly engaged in tobacco processing technology and cigarette product development and other technical research work. In recent years, he presided over

or participated in the completion of a number of company's major science and technology projects, key points, industry standards, and other projects. He won one first prize, one second prize, and two third prizes of Shandong Tobacco Science and Technology Progress. As the main draftsman, he developed an industry standard. He has won the title of Technical Expert of Qingdao Cigarette Factory, Shandong Zhongyan Taishan Craftsman, Shandong Zhongyan Model Worker, and Shandong May 1st Labor Medal.

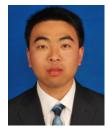


**XINLONG ZHANG** was born in 1976. He received the Bachelor of Engineering degree in tobacco engineering and the Master of Engineering degree in food engineering from Zhengzhou Institute of Light Industry, in 1998. He is engaged in cigarette product development for 25 years, undertook the development and maintenance of key specifications of Shandong Tobacco Taishan Brand Yue series, and has rich experience in cigarette product development and raw material research.



**ZENGYU WANG** was born in 1976. He received the bachelor's degree in industrial analysis and the master's degree in food engineering from Hefei University of Economics and Technology, in 1998. He is engaged in cigarette product development for 25 years, undertook the development and design of Shandong Zhongtobacco Baxi series and several Taishan brand key specifications of cigarettes, and has rich experience in cigarette product development.

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**SHUAISHUAI SUN** was born in 1987. He received the master's degree in agronomy and majoring in agricultural product quality and food safety from Chinese Academy of Agricultural Sciences, in 2012. He is engaged in cigarette product development and maintenance and material research for 11 years and has rich experience in cigarette product development and material design.



**GUANGWEI JIANG** was born in 1980. He received the bachelor's degree in food science and engineering and the master's degree in agricultural extension from the School of Economics and Technology, University of Science and Technology of China, in 2002. He is engaged in cigarette technology research for 15 years, undertook the process research work of Shandong Zhongyan, and has rich experience in cigarette technology improvement.



**HONGTAO LI** was born in 1982. He received the master's degree in food science from Zhengzhou Tobacco Research Institute, China National Tobacco Corporation, in 2008. He is engaged in cigarette technology research for 16 years, undertook more than 30 science and technology projects of China National Tobacco Corporation and Shandong Tobacco Industry Company Ltd., and has rich experience in the field of cigarette technology.



**QIANG SUN** was born in 1976. He received the bachelor degree in tobacco engineering from Zhengzhou Institute of Light Industry, in 1998. He is engaged in cigarette product development for 25 years, undertook the development and design of Shandong Zhongyan Taishan (Fuguang) series and several Taishan brand key specifications of cigarettes, and has rich experience in cigarette product development.



**LIWEN ZHENG** was born in 1992. He received the master's degree in food science and engineering from Zhengzhou University of Light Industry, in 2017. He is currently an Engineer. He is engaged in tobacco technology research.



**ERGE LIN** was born in 1991. He received the master's in tobacco engineering from Henan Agricultural University, in 2018. He is engaged in tobacco technology research and has rich experience in cigarette technology research.



**JUN LI** was born in 1986. He received the master's degree in agronomy and a major in plant nutrition from the Tobacco Research Institute, Chinese Academy of Agricultural Sciences, in 2012. He is engaged in cigarette product development for 12 years, undertook the development and design of Shandong Zhongtobacco Rufeng series and several Taishan brand key specifications of cigarettes, and has rich experience in cigarette product development.



**HONGWEI ZHENG** was born in 1974. He received the bachelor's degree in tobacco engineering and the master's degree in project management from Hefei University of Economics and Technology, in 1996. He is engaged in cigarette product development for 27 years, undertook the development and design of Shandong Zhongyan General series and several Taishan brand key specifications of cigarettes, and has rich experience in cigarette product development.

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