A STUDY ON INTELLIGENT CONTROL METHOD OF DRYER BASED ON MACHINE LEARNING

Chao YANG[1], Bin YANG[2], Changji ZHANG[3], Wu WEN[4*], Rongya ZHANG[5*], Yu ZHAO[6], Peng KUANG[7], Ruifang GU[8], Min Chang LIU[9], Yaping MA[10], Tingjie BAO[11]

To address the issue of unstable outlet moisture in the tobacco drying process caused by system lag, variable coupling, and nonlinear parameter relationships, this paper constructs a prediction model for the outlet moisture of the dryer using the Random Forest algorithm. Based on this prediction model, a Genetic Algorithm model is employed to dynamically search for the optimal combination of control parameters, thereby achieving predictive control in the drying process. Tests were conducted using the raw material of "Brand A" cigarettes. The results show that after applying the predictive control model based on Random Forest and Genetic Algorithm, compared with the historical manual control results on the same production line, the average deviation of post-drying moisture decreased by 30%, and the Performance Index of Process (PPK) index increased by 38%. The results indicate that the method proposed in this paper not only meets the requirements of product quality and assessment indicators but also performs better in improving the stability of drying control and reducing the deviation of post-drying moisture.

[1] Shifang Cigarette Factory of China Tobacco Sichuan Industrial Co., Ltd., Shifang 618400, Sichuan, China (Co-first author)
[2] Shifang Cigarette Factory of China Tobacco Sichuan Industrial Co., Ltd., Shifang 618400, Sichuan, China (Co-first author)
[3] Shifang Cigarette Factory of China Tobacco Sichuan Industrial Co., Ltd., Shifang 618400, Sichuan, China
[4] Technical Center of China Tobacco Sichuan Industrial Co., Ltd., Chengdu 610100, Sichuan, China (Corresponding author, wenwu@sctobacco.com)
[5] Technical Center of China Tobacco Sichuan Industrial Co., Ltd., Chengdu 610100, Sichuan, China
*(corresponding author) rongyazhang@126.com
[6] Shifang Cigarette Factory of China Tobacco Sichuan Industrial Co., Ltd., Shifang 618400, Sichuan, China
[7] Shifang Cigarette Factory of China Tobacco Sichuan Industrial Co., Ltd., Shifang 618400, Sichuan, China
[8] Technical Center of China Tobacco Sichuan Industrial Co., Ltd., Chengdu 610100, Sichuan, China
[9] Technical Center of China Tobacco Sichuan Industrial Co., Ltd., Chengdu 610100, Sichuan, China
[10] Technical Center of China Tobacco Sichuan Industrial Co., Ltd., Chengdu 610100, Sichuan, China
[11] Technical Center of China Tobacco Sichuan Industrial Co., Ltd., Chengdu 610100, Sichuan, China

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1. Introduction

In the cigarette manufacturing process, drying is one of the most crucial steps. It operates by mixing saturated steam with hot air to precisely control the moisture content of the tobacco shreds, aiming to ensure that the moisture and temperature of the tobacco shreds at the outlet accurately meet the specified process standards for finished tobacco shreds [1]. However, due to the fluctuation of the material properties, the instability of steam and hot air supply, and other factors, it is extremely challenging to control the moisture and temperature of the tobacco shreds at the outlet. This process is highly nonlinear, with various factors being intercoupled and complex. Moreover, the inherent lag of the system further increases the difficulty of control [2]. At present, the control of dryers mainly relies on adjusting control parameters such as the opening degree of the exhaust damper, the frequency of the hot air fan, and the thin plate temperature. However, the drying process is characterized by nonlinearity, coupling, and lag. Traditional control methods, such as PID control, are unable to quickly respond to disturbances (e.g., changes in ambient temperature and humidity) [3]. Lacking the support of intelligent algorithms, these methods are incapable of achieving adaptive optimization and real-time adjustments. Moreover, traditional control methods are highly dependent on the experience of operators, and the control effects are significantly influenced by subjective factors, making it difficult to ensure stability and consistency. As a result, the moisture and temperature of the tobacco shreds at the outlet fluctuate considerably [4] Machine learning is capable of learning complex nonlinear relationships from vast amounts of historical and real-time data and establishing high-precision predictive and optimization models, which have been widely applied in the industrial field [5]. By analyzing the data generated during the drying process, it is possible to identify the key factors that affect the moisture content of tobacco shreds and the outlet temperature, and dynamically adjust process parameters (such as hot air velocity, exhaust damper opening, and thin plate temperature) to achieve precise control. Therefore, accurately predicting the outlet moisture of the dryer based on machine learning and participating in the control of key parameters is of great significance to the production of shredded tobacco [6]-[7]. Scholars and engineers both domestically and internationally have made certain progress in research related to dryers. Fu et al [7] and others proposed a method to control the moisture content of tobacco shreds at the beginning and end of the batch by designing a delayed temperature-increasing program for the thin-plate dryer and optimizing equipment parameters. However, in this control scheme, the exhaust damper opening was set to a fixed value. In actual production, different brands and specifications correspond to different process requirements. Therefore, a fixed exhaust damper opening is obviously not in line with the actual production requirements. Machine learning algorithms, artificial intelligence (AI) modeling, and advanced AI technologies have demonstrated significant advantages in moisture control and process accuracy control[8]-[9].They can effectively enhance the stability of production processes and product quality. By providing precise data analysis and predictive models, these technologies offer strong support for the optimization of complex industrial processes, thereby better meeting the high-precision requirements of industrial production[10].Wang et al [11] and others employed an RBF-ARX model to characterize the dynamic properties of the drying process and proposed a model predictive control method for the outlet moisture content of the dryer. This method achieves better control performance compared to the independent regulation mode of thin plate temperature and exhaust damper opening, meeting the requirements for industrial application. Li et al [12] and others focused on the outlet moisture of the thin-plate dryer, utilizing three machine learning models to conduct modeling, analysis, and prediction of the outlet moisture. They adopted a weighted average model fusion strategy, using the model mean squared error on the validation set as the basis for calculating the fusion weights. This approach provides a novel perspective for predicting the outlet moisture of dryers. However, the model did not take into account the influence of environmental factors such as temperature and humidity, and unfortunately, it did not generate control decisions based on the prediction results. Zhang et al [13] and others proposed a method of predictive control combining Extreme Learning Machine (ELM) with Simulated Annealing algorithm, which preliminarily verified the feasibility of involving model prediction results in the control application of dryers. Bi et al [14] proposed a method based on reinforcement learning to reduce the amount of “dry tips” in tobacco shreds. The study found that the strategy incorporating reinforcement learning significantly improved the stability of the moisture content of the outlet tobacco shreds and achieved joint control of machine learning algorithms and PID.

Although relevant scholars have conducted some research on the control of dryers and achieved certain results, there are still some problems. Since the drying process is a process with large time delay and high coupling, a data processing procedure that meets the business scenario has not been formed in the data processing stage. In addition, many results only studied the factors affecting the outlet moisture and made predictions on the outlet moisture, but did not provide guidance on the control method based on the prediction results. To better address the control issue of the outlet moisture of dryers, this paper proposes a machine learning-based predictive control method for dryers, building on previous research. The main contributions of this paper are summarized as follows. A

Random Forest algorithm-based prediction model for the outlet moisture of the dryer is proposed, transforming the production condition judgment method based on fuzzy experience into a data-driven quantitative analysis, thereby significantly improving the accuracy of tobacco shred moisture prediction. A method of optimizing dryer control by combining prediction results with a Genetic Algorithm is proposed. This algorithm determines whether to participate in control based on the prediction results. If it is to participate in control, it dynamically obtains the optimal control combination according to the Genetic Algorithm to be involved in the actual control parameter control of the dryer. The effectiveness of the proposed optimization control method is verified by comparative experiments with manual intervention control on the actual production line. The experimental results show that the method proposed in this paper is superior to the manual control method in improving control stability and reducing tobacco shred moisture deviation.

2. Materials and Modeling Methods

2.1 Materials and Equipment

The experimental material used in this paper is the tobacco shred formula for “Brand A” cigarettes provided by Shifang Cigarette Factory of Sichuan China National Tobacco Industrial Co., Ltd.The hardware equipment involved in this paper includes a dryer, Huawei IOT Industrial Internet of Things platform, infrared moisture meter, and temperature and humidity sensors.

2.2 Model Establishment

2.2.1 Data Acquisition and Preprocessing

The research data in this paper is based on the existing parameter data of the drying production section equipment of Shifang Cigarette Factory of Sichuan China National Tobacco Industrial Co., Ltd. (with more than 70 process parameters). The data is uploaded to the Industrial Internet of Things platform with a data interval of 1 second. For the convenience of subsequent modeling and analysis, the data used for modeling is sampled at an interval of 10 seconds. In addition to this, historical quality index data extracted from the MES system is also obtained.

This paper selects the historical production data of “Brand A” cigarettes from Line A of the shredded tobacco workshop of Shifang Cigarette Factory from March 2024 to May 2025, which includes a total of 534 batches and over 430,000 rows of data. These data are stored in a MySQL database for subsequent research. Batches with abnormal interruptions in material supply are eliminated, and data from the steady-state phase is retained. Data points that do not conform to the process standards of the brand are removed, and missing values are filled in. Out of a total of 79 fields related to the dryer equipment, 20 fields are retained after removing status variables, duplicate variables, post hoc variables, cumulative quantities, and set variables, which are not relevant to the business context. The detailed indicators are shown in the table 1 below, all the indicators are numeric.

Table 1.

Data indicators related to the dryer equipment

No.	Field Name	Unit
1	Steam Flow Rate	kg/h
2	Inlet Steam Pressure to Thin Plate	bar
3	Thin Plate Temperature	℃
4	Return Water Temperature	℃
5	Inlet Steam Control Valve Opening to Thin Plate	%
6	Total Steam Pressure	bar
7	Outlet Moisture	%
8	Exhaust Damper Opening	%
9	Exhaust Air Volume	m^3
10	Outlet Hood Negative Pressure	bar
11	Outlet Hood Negative Pressure	bar
12	Hot Air Fan Frequency	Hz
13	Inlet Steam Pressure to Heat Exchanger	bar
14	Hot Air Temperature	℃
15	HT Steam Pressure	bar
16	HT Steam Flow Rate	Kg/h
17	HT Outlet Temperature	℃
18	HT Inlet Moisture Content	%
19	Ambient Humidity	%
20	Ambient Temperature	℃

The time-series data from the 20 data acquisition points of the drying process mentioned above are selected to form the data samples, where the target variable is the outlet moisture, and the remaining features are the feature variables.

2.2.2 Feature Selection

Feature selection is a crucial step in data preprocessing, aimed at reducing the risk of overfitting and enhancing model training speed and generalization ability by eliminating irrelevant and redundant features, thereby significantly improving the accuracy and stability of model results. In the initial data processing, constant and duplicate variables have been removed. However, not all remaining variables have a significant impact on the outlet moisture. Therefore, further feature selection is necessary.

In this study, we employ Pearson correlation analysis and Random Forest feature selection methods for feature screening [15-16]. Pearson correlation analysis is a statistical method used to examine the linear correlation between variables. By calculating the correlation coefficient, the strength and direction of the linear relationship between two variables can be measured. A correlation coefficient close to 1 or -1 indicates a strong correlation, while a coefficient close to 0 suggests a weak correlation.

We conducted Pearson correlation analysis between the feature variables and the target variable, and the results are shown in Figure 1. During the feature selection process, we adhere to the following principles:

1. Handling Highly Correlated Variables: For variables with correlation coefficients close to 1 or -1, multicollinearity may exist, which can affect model stability and interpretability. In such cases, we use domain knowledge to select more representative variables, retaining one and discarding the others with high correlation.

2. Handling Weakly Correlated Variables: For variables with correlation coefficients close to 0, their contribution to the model's predictive power may be limited. Therefore, we consider eliminating these variables to reduce model complexity.

Although Pearson correlation analysis can identify linear relationships between variables, it is incapable of capturing nonlinear relationships. Therefore, we further employ the Random Forest feature selection method. Random Forest is a typical nonlinear method that can effectively capture complex relationships in the data, thereby more comprehensively assessing the importance of features.

The Pearson correlation analysis suggests that there may be nonlinear relationships between the target variable and other variables. Therefore, this paper selects the Random Forest feature selection method from machine learning, which is a typical nonlinear approach capable of effectively capturing complex relationships within the data. The feature influence weights calculated using Random Forest are shown in the above Figure 2. From the figure, it can be seen that the feature influence weight of the thin-plate temperature exceeds 23%, occupying a primary influential position. The feature influence weights of steam flow rate, total steam pressure, exhaust damper opening, hot air velocity, hot air fan frequency, and ambient humidity also hold significant influential positions.

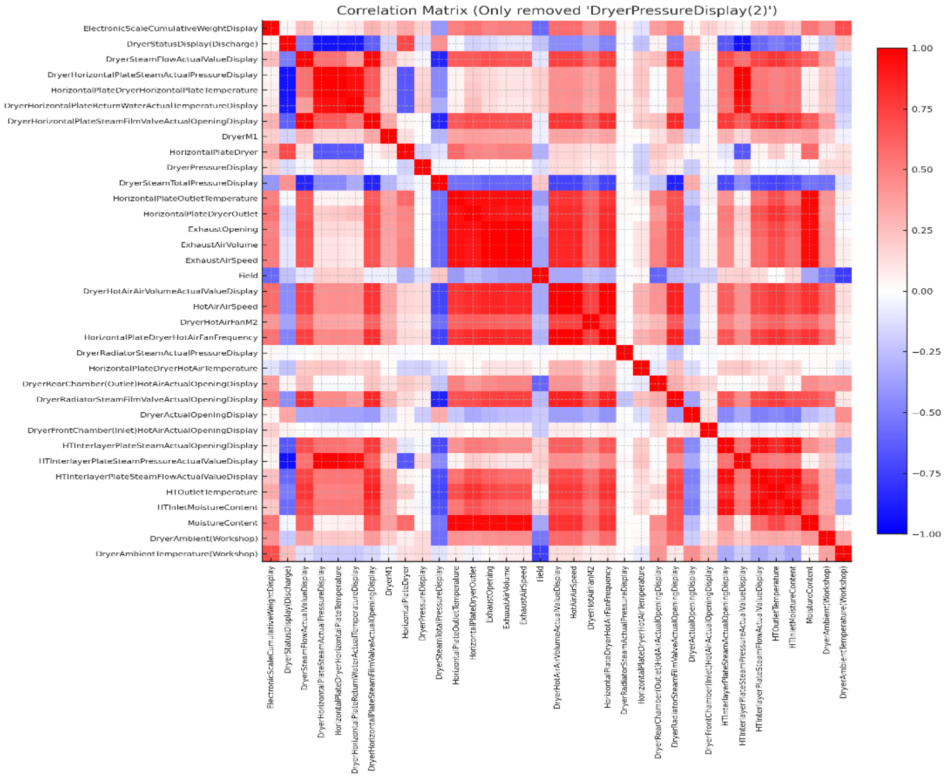

Fig. 1. Pearson Correlation Analysis Between Feature Variables and Target Variable

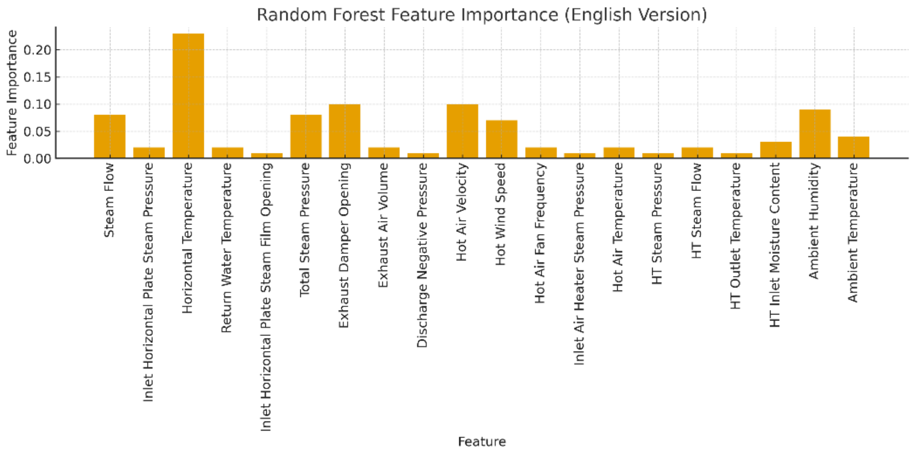

Fig. 2. Feature Importance Weights Calculated by Random Forest

After conducting correlation analysis on the features and performing feature importance screening using Random Forest, the final retained numerical fields are as follows: outlet moisture, steam flow rate, thin-plate temperature, total steam pressure, exhaust damper opening, hot air velocity, hot air fan frequency, HT steam flow rate, HT inlet moisture content, ambient temperature, and ambient humidity.

2.2.3 Data Time Lag Alignment

In the process of shredded tobacco production, it has been observed that the various feature variables of the dryer exhibit certain differences in both temporal progression and spatial distribution. These differences can cause the data relied upon for model training to deviate from the actual situation, thereby reducing its reliability. Taking the inlet scale flow rate as the reference coordinate, and through analysis of historical production batch data, multiple tests were conducted to determine the time intervals from the dryer's inlet scale to subsequent process data collection points. The average values obtained from these tests were used to identify the temporal discrepancies between each process collection point and the reference coordinate. By conducting meticulous process matching and calibration of the time-seriea data corresponding to the feature variables, the training data for the model can more accurately reflect the true production state, thereby enhancing its credibility [17]. Table 2 below shows the data alignment situation:

Table 2.

Data alignment details

Field Name	Time Difference (seconds)
Inlet Scale Flow Rate	**0**
Ambient Temperature	**0**
Ambient Humidity	**0**
HT Inlet Moisture Content	**3**
HT Steam Flow Rate	**35**
Steam Flow Rate	**200**
Thin-Plate Temperature	**200**
Total Steam Pressure	**200**
Hot Air Velocity	**200**
Hot Air Fan Frequency	**200**
Exhaust Damper Opening	**320**
Outlet Moisture	**380**

2.2.4 Construction of Prediction Model Based on Random Forest

The Random Forest algorithm, through ensemble learning and randomization strategies, possesses strong generalization capabilities and is suitable for handling complex data. Additionally, the Random Forest algorithm employs parallelization strategies, enabling the rapid construction of multiple decision trees. During the prediction phase, the predictions of each tree can be executed in parallel, resulting in faster speeds. Therefore, this paper selects the Random Forest algorithm as the model for predicting the outlet moisture of the dryer. The process of predictive modeling is as follows:

(1) Data Processing

The drying process of the dryer can generally be divided into the start-up phase, steady-state phase, and end phase. Since the start-up and end phases of the production line in the shredded tobacco workshop are automatically controlled by the PLC communication device through setting fixed values [18], this paper, in combination with actual business operations, does not participate in the control of delay, start-up, and end phases. Therefore, it is also necessary to screen the data for production status. Usually, the judgment of production status is made by delaying for a period of time after feeding and reaching a certain threshold of outlet moisture, dividing the production status into start-up, steady-state, end, and material breakage, etc. To ensure the consistency of data, the data features in the steady-state are selected for subsequent predictive modeling. The drying production data is time - series data. Therefore, to ensure that the current decision - making can refer to the state of the previous moment during optimization control, it is necessary to preprocess the time - series data when inputting the model. Therefore, before model construction, it is necessary to construct time - series features [19] - [20]. In this paper, the method of time - sliding window is used to intercept the data of outlet moisture. On the basis of the current characteristics, the outlet moisture value of the past one minute is added.

This study aims to use machine learning algorithms to make real - time predictions of the outlet moisture of the shredded tobacco production line. Therefore, the selected algorithm needs to have high accuracy. To improve the generalization ability of the model, reduce the risk of over - fitting, and make the model more stable and adaptive in different data sets, it is necessary to normalize the data. The normalization formula is as follows, where x represents the original data value, $x_{\min}$ is the minimum value in the dataset, $x_{\max}$ is the maximum value, and x_{norm} is the normalized value.

$$x_{norm} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

After the data has been processed through the aforementioned procedures, a new sample dataset is formed. The features include steam flow rate (X1), thin-plate temperature (X2), total steam pressure (X3), exhaust damper opening (X4), hot air velocity (X5), hot air fan frequency (X6), HT steam flow rate (X7), HT inlet moisture content (X8), ambient temperature (X9), and ambient humidity (X10), which together form the input feature vector (X1, X2, …, X10). The label is the outlet moisture (Y), with a total of 330,813 records.

(2) Construction of Random Forest Model

The construction of the Random Forest model in this paper is implemented based on the `RandomForestRegressor` from the Python machine learning library `sklearn`. The input is the feature vector (X1, X2, ..., X10), and the output is the outlet moisture (Y). The model is trained on the training data to determine the settings of the model parameters.

The `n_estimators` parameter represents the number of trees in the model; generally, the more trees, the better the model performance may be. The `max_depth` parameter represents the depth of the trees and is used to control the complexity of the model. The `min_samples_leaf` parameter is the minimum number of samples required at a leaf node; typically, the larger the value, the more conservative the model. The `bootstrap` parameter controls whether bootstrap samples are used when constructing trees. The `random_state` parameter is the seed used by the random number generator; it is usually a fixed value to ensure the reproducibility of the model.

2.2.5 Construction of Control Model Based on Genetic Algorithm

The Genetic Algorithm (GA) is an evolutionary algorithm. The basic principle of this algorithm is based on the evolutionary rule of survival of the fittest. It continuously obtains better populations and searches for the optimal individual in the optimization population in a global and parallel manner to obtain the optimal solution that meets the requirements. The specific optimization method is as follows:

Population: First, define these control variables, and then use the steps of the genetic algorithm to search for the optimal parameter configuration. These control variables include hot air fan frequency, exhaust damper opening, thin - plate temperature, and HT steam pressure.

Fitness Function: The fitness function is used to evaluate the quality of an individual's solution. It needs to accurately assess the deviation of the outlet moisture and outlet temperature from the recommended values. The prediction error of the model can be used as a reverse indicator of fitness, such as Mean Squared Error (MSE) or other statistical error measures. The higher the fitness, the higher the prediction accuracy and the lower the error. It can be represented by the symbol: $f(x)$, where f is the fitness function and x is the individual's solution.

Selection: The selection operation determines which individuals will become parents to participate in crossover and mutation operations. Individuals with the highest fitness are selected from the population, with fitness assessed based on the accuracy of the outlet moisture prediction of the dryer under each parameter configuration. This ensures that parameter configurations with better performance have a greater chance of being retained and used to generate the next generation, thereby continuously improving the control effect of the drying process.

The selection probability represents the likelihood of an individual being chosen as a parent, which is generally proportional to its fitness. The roulette wheel selection method is a common approach that uses the following linear proportion to calculate the selection probability:

$$P_{(x_i)} = \frac{F_{(x_i)}}{\sum_{i=1}^{n} F_{(x_i)}} \tag{2}$$

Let *xi* denote an individual, and $\sum_{i=1}^{n} F_{(x_i)}$ represent the sum of the fitness of all individuals.

Crossover: The crossover operation simulates the recombination process in biological genetics. This step, while maintaining parameter diversity, also helps to combine the advantages of different individuals, potentially discovering new and more effective parameter combinations for the dryer. For instance, a lower hot air fan frequency from one individual combined with a higher exhaust damper opening from another individual may achieve better control of outlet moisture. This operation ensures the stability of the population, guiding it to evolve in the direction of optimization. Two individuals, a_k and a_l, are randomly selected from the previous generation to undergo crossover at position j

$$\begin{aligned} a_{kj} &= a_{kj}(1-\beta) + a_{kj}\beta \\ a_{lj} &= a_{lj}(1-\beta) + a_{lj}\beta \end{aligned} \tag{3}$$

Where β is a random number in the interval(0, 1)

Mutation: The mutation operation is used to introduce random changes in the offspring individuals to increase diversity. Mutation alters certain genes of an individual with a certain probability. A mutation operation is performed on the *j*-th allele of the *i*-th individual, which is randomly selected from the current population:

$$\begin{aligned} a_{ij} &= a_{ij} + (a_{ij} - a_{\min})\gamma, y \le 0.5 \\ a_{ij} &= a_{ij} + (a_{ij} - a_{\max})\gamma, y > 0.5 \end{aligned} \tag{4}$$

During the mutation phase, minor adjustments are made to the values of certain genes, such as fine - tuning the thin - plate temperature or HT steam pressure. This helps to introduce new control schemes, enabling the algorithm to explore a broader parameter space. As a result, it may escape local optima and discover more effective control strategies. Then, iterative evolution is carried out, repeating the aforementioned processes of selection, crossover, and mutation. Through continuous iterations, the individuals in the population gradually adapt to the target outlet moisture and temperature ranges of the dryer. The iterations continue until the preset number of iterations is reached or the improvement in fitness becomes insignificant. Finally, the optimal solution is evaluated. After the iterations are completed, the individual with the highest fitness is selected from the final population as the optimal solution. This parameter configuration represents the best settings under the current operating conditions of the dryer, enabling optimal control and prediction of the outlet moisture and temperature.

By employing this method, the genetic algorithm not only provides a systematic approach to searching for the optimal parameter configuration but also assists the operators of the tobacco dryer in understanding how different parameters interact to influence the outlet moisture of the final tobacco shreds, thereby achieving optimization and control of the production process. This contributes to enhancing the overall efficiency and output quality of the dryer. The optimization process of the aforementioned genetic algorithm is illustrated in Figure 3.

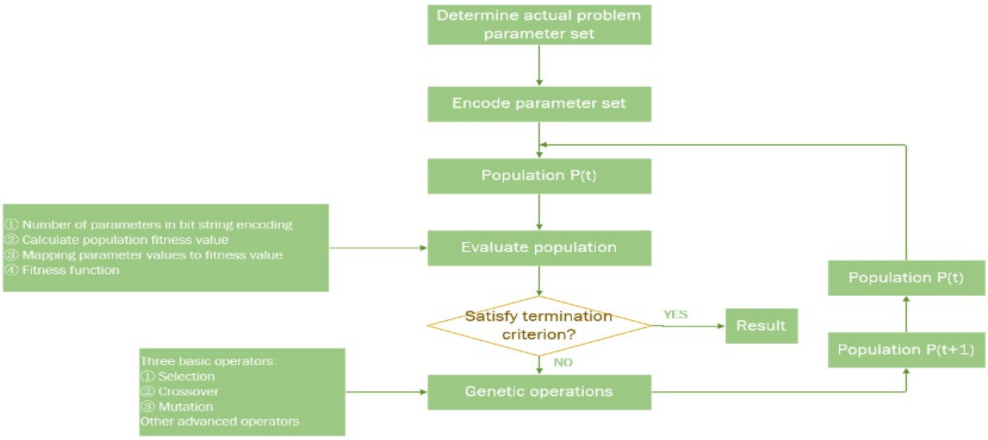

Fig. 3. Optimization Process of Genetic Algorithm

3. Model Prediction and Control Analysis

3.1 Outlet Moisture Prediction Analysis of Dryer Based on Random Forest

Due to the characteristics of batch - to - batch dependence within the data related to the dryer, internal splitting will affect the integrity and validity of the data, and the resulting control strategies may also fail. On the other hand, considering the differences in the set values of outlet moisture between batches, this paper does not shuffle the data when dividing the training set and the test set.

Taking the outlet moisture of the dryer as the target value, the training set and the test set are divided according to the batch number of the existing data and the total production volume in a proportion of 7:3 after the above - mentioned data processing and feature construction. The training set contains 231,569 rows of data, and the test set contains 99,244 rows of data. The training set is used to train the model, and the test set is used to evaluate the trained model. The training set is input into the algorithm for training. Grid search and cross - validation are used to find the optimal parameters of the machine - learning model. Grid search is used to systematically traverse a variety of parameter combinations, with the aim of searching for the optimal hyperparameters in the model, and then cross - validation is used to determine the best parameters.

A batch was randomly selected from the test set for prediction, which contains 853 rows of data. The comparison analysis between the predicted and actual values of outlet moisture under the Random Forest prediction model is shown in Figure 4. The period from 0 to 700 is in a stable operating phase, during which the outlet moisture of the tobacco shreds fluctuates within the range of 13.% ± 0.2%. The MAE is 0.024, the RMSE is 0.028, and the R2 is 0.92. According to the model evaluation index results and the graph, the overall prediction effect is good, which lays the foundation for subsequent parameter optimization.

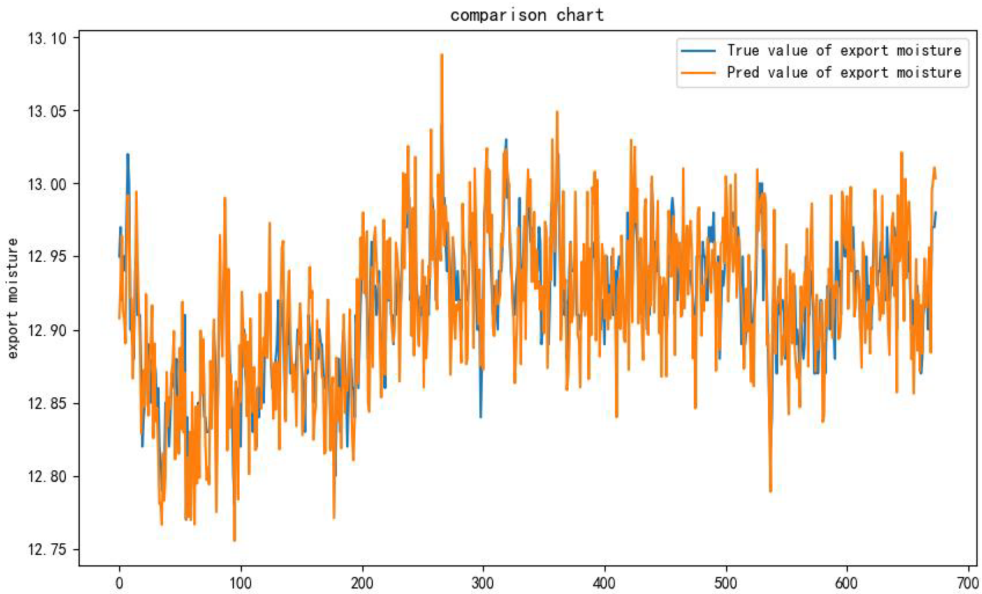

Fig. 4. Comparison of Predicted and Actual Outlet Moisture for Randomly Selected Batch

Five batches were randomly selected from the test set for prediction, and the evaluation indicators of the prediction results are shown in Table 3: It can be seen that the Random Forest model also performed well in predicting the five batches of the test set, which can lay a good foundation for subsequent control based on the prediction results.

Table 3.

Evaluation Indicators of Prediction Results for Five Randomly Selected Batches

Batch Number	MAE	RMSE	R^2
A	0.039	0.045	0.925
B	0.034	0.039	0.933
C	0.036	0.041	0.932
D	0.025	0.0275	0.941
E	0.028	0.033	0.937

3.2 Analysis of Control Process Based on Genetic Algorithm

(1) Single - Batch Control Process Analysis

Taking the drying machine operation data of Line A in the shredded tobacco workshop of Shifang Cigarette Factory on March 3, 2025 as an example, the control method combining Random Forest prediction and Genetic Algorithm proposed in this paper is used for predictive control. As shown in Figure 5, the time at point A is 15:35:03. At this time, the trend of the predicted outlet moisture of the dryer deviates gradually from the set value, and the offset exceeds the threshold of 0.06%. Therefore, this prediction result triggers the Genetic Algorithm to optimize the parameters and intervene in the control. The hot air fan frequency is adjusted from 45 to 47, and the exhaust damper opening is adjusted from 43 to 44, while other control parameters remain unchanged. At point B, the time is 16:41:13. At this moment, the deviation between the predicted outlet moisture of the dryer and the set value is relatively large. However, the predicted trend is decreasing. Therefore, the prediction model did not trigger the Genetic Algorithm to optimize the parameters and participate in the control, and the control parameters remained unchanged. At point C, the time is 17:03:53. At this moment, the deviation between the predicted outlet moisture of the dryer and the set value is also relatively large. However, the predicted trend is moving towards a decrease in the outlet moisture set value. Therefore, this prediction result triggered the Genetic Algorithm to optimize the parameters and intervene in the control. The hot air fan frequency was adjusted from 47 to 49, and the exhaust damper opening was adjusted from 44 to 45, while other control parameters remained unchanged. The final standard deviation of this experiment was 0.038, which met the cigarette factory's requirement of being within 0.045. The assessment result was qualified. The intelligent control method has strong anti - disturbance ability, rapid control response, and short adjustment time, thereby improving the quality of the tobacco shreds.

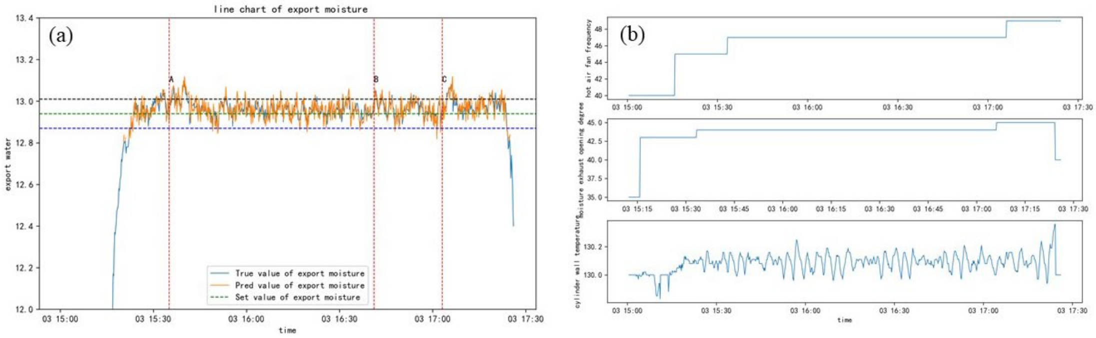

Fig. 5 Moisture Control and Parameter Adjustments in Production：a. Moisture Prediction, Set Value, and Actual Value in Production；b. Parameter Adjustments at Points A, B, and C

(2) Multi-Batch Control Effect Comparison and Analysis

In order to minimize the impact of seasons on the drying process, data were collected from the manual control results of "Brand A" on Line A of Shifang Cigarette Factory from March to May 2024 and the tobacco silk outlet moisture quality index results after automatic control by the algorithm from March to May 2025. The results are shown in Figures 6 and 7. Figure 6 reveals that the algorithm-driven control exhibits a significantly lower average deviation. Specifically, the overall deviation is reduced by 30% compared to manual control. This underscores the superior precision of the predictive control strategy, which integrates random forest and genetic algorithms, in managing multi-batch processes. Figure 7 further illustrates the enhanced stability of the algorithmic control. The Performance Index of Process (PPK) quality evaluation index is notably higher, with an improvement of 38% over manual control. This highlights the robustness and reliability of the predictive control system, powered by random forest and genetic algorithms, in ensuring consistent performance across multiple batches.

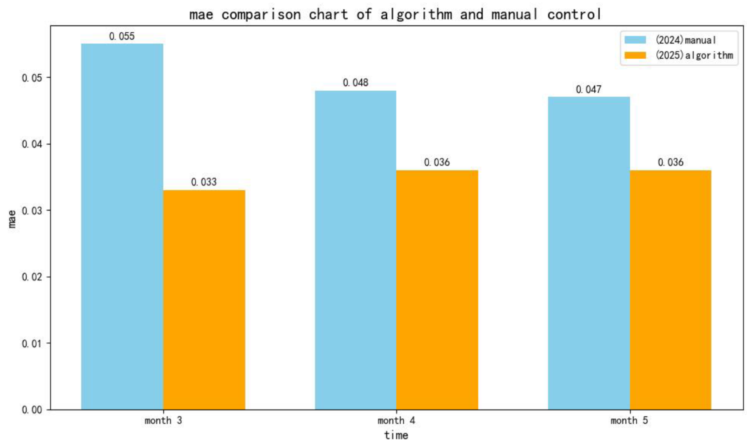

Fig. 6. Comparison of Mean Absolute Error (MAE) Between Algorithm and Manual Control

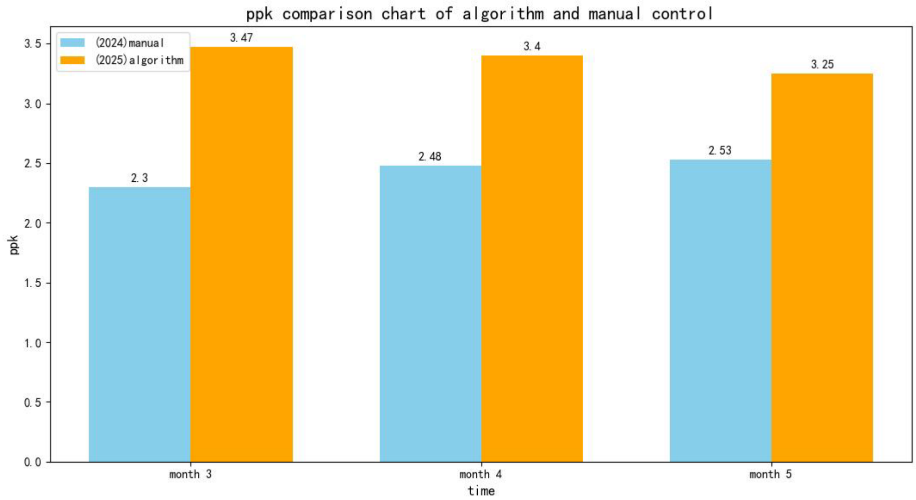

Fig. 7. Comparison of PPK Index Between Algorithm Control and Manual Control

4. Conclusion

To address the issue of unstable outlet moisture in the drying process of a dryer due to system lag, variable coupling, and nonlinear relationships of parameters, this paper employs the random forest algorithm to construct a moisture prediction model for the dryer outlet. Based on this predictive model, a genetic algorithm model is used to dynamically search for the optimal combination of control parameters, thereby achieving predictive control of the drying process. The innovative combination of random forest and genetic algorithms provides a new approach for applying predictive control methods to dryer control. Tests using “Brand A” as the raw material have demonstrated that, compared with the historical manual control results of the same production line, the predictive control model based on random forest and genetic algorithms has reduced the average deviation of post-drying moisture by 30% and increased the Ppk index by 38%. The results show that the method proposed in this paper not only meets the requirements of product quality processes and assessment indicators but also performs better in improving the stability of the drying production control and reducing the deviation of the moisture content of post-drying tobacco silk. During the research process, the production processes of the head and tail of the material were filtered out. In fact, the control processes of the head and tail stages are also very critical. Therefore, future research can start from the predictive control process of the head and tail stages.

R E F E R EN C E S

[1*] Zheng Yinhuan, Sun Xiankui, Wu Fei, et al*. "Research on Moisture Control at the Inlet of Drying Process Based on QGA-XGB Model Prediction." Acta Tabacaria Sinica (2024): 1-11

[2] Zhu, W. K., Wang, Y., Chen, L. Y. , et al. (2016). Effect of two-stage dehydration on retention of characteristic flavor components of flue-cured tobacco in rotary dryer. Drying Technology, 34(13), 1621–1629.

[3] *Wen Guangqiu, Wu Wenqiang, Liu Bin, et al.* Control and Application of Tobacco Shred Moisture Content at the Outlet of Drum Dryer Based on Multi-parameter Feature Collaborative Optimization [J]. Tobacco Science and Technology, 2025, 58(06): 82-91.

[4] *Lin Tianqin, Zhong Wenyuan, Guo Jianhua, et al*. Improvement of the Control System for Tobacco Shred Moisture Content in Drum Dryer. Tobacco Science and Technology, 2013, (12): 14-16.

[5] *Chen Chuantong, Cui Wei, Zhang Chao, et al.* Research on Intelligent Control Method of Outlet Moisture Content of Dryer. Manufacturing Automation, 2016, 38(07): 37-40.

[6] *Martínez-Martínez, Víctor, Carlos Baladrón, et al.* 2012. "Temperature and Relative Humidity Estimation and Prediction in the Tobacco Drying Process Using Artificial Neural Networks" Sensors. 2012; 12(10):14004-14021.

[7] *Fu Laiqiang, GUO Yaqiang, GUO Zhiqiang, et al.* Optimizing equipment parameters of SH626 thin plate cut-tobacco dryer to reduce over-dried cut tobacco. Acta Tabacaria Sinica, 2022,28(1);39-43

[8]. *Morozov MS, Morozov SM, Reut VA*. Automated system for grain moisture control. Bulletin of Science and Education. 2017; 3:1; 47-50

[9] *Kiran, M.S., & Aswin, V.V.* Predictive Irrigation Management Using Deep Learning. International Journal of Research and Peer Review, 5(8), 1-10.

[10] *Kheimi, M., & Zounemat-Kermani, M*. Conventional and advanced AI-based models in soil moisture prediction. Physicochemical Problems of Geology, 52(2), 123-135.

[11] *Fu Laiqiang, Guo Yaqiang, Guo Zhiqiang, et al*. Optimization of SH626 Type Thin Plate Dryer Equipment Parameters to Reduce Dry Head and Tail. Acta Agronomica Sinica, 2022, 28(01): 39-43.

[12] *Wang Xiaofei, Peng Xiaoyan, Yang Yubo, et al*. Optimization and Control Method of Outlet Moisture Content of Dryer Based on RBF-ARX Model. Tobacco Science and Technology, 2014, (01): 26-30.

[13] *Li Zhengkui, Wang Wencai, Niu Wenwei, et al.* Research on Outlet Moisture Prediction of Thin Plate Dryer Based on Model Fusion. Industrial Control Computer, 2024, 37(08): 86-87+90.

[14] *Zhang Fengguang, Zhang Siming, Lin Min, et al.* Research on Intelligent Regulation of Dryer Based on Multi-factor Analysis. Control Engineering, 2024, 31(06): 1138-1145.

[15] *Bi Suhuan, Jiang Yixiang, Yu Shusong, et al*. Method to Reduce the Amount of “Dry Head” in Drying Process Based on Reinforcement Learning. Acta Automatica Sinica, 2023, 49(08): 1679-1687.

[16] *Zhang Xueyan, Li Xiaodong, Sun Jie*. Research on Correlation Analysis of Tobacco Drying Equipment Parameter Data Based on Random Forest. Manufacturing Automation, 2019, 41(08): 145-148.

[17] *Zhao, Xiaolei*. "Process Parameter Optimization of Silk Dryer Based on BP Neural Network and Genetic Algorithm." Mechanical Manufacturing and Automation 2023 (4): 185-189.

[18] *Li Wenqi, Zhang Chao, Li Shanlian, et al*. Calculation Method of Dry Head and Tail Amount of Drum Dryer. Tobacco Science and Technology, 2018, 51(07): 73-78.

[19] *Yu Wenjin, Wang Wenjuan, Ye Zhihui, et al.* Modeling Method of Drying Process Based on State Estimation Deep Time Series Network Model. Manufacturing Automation, 2023, 45(11): 190-194.
[20] *Gu Qian, Qian Jichun*. Research on Real-time Data Application in Shredding Based on Time Series Database and D