IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received February 24, 2020, accepted March 20, 2020, date of publication March 24, 2020, date of current version April 8, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.2983134

An Approach for in-Line Control of Moisture Content During Green Tea Processing

ZHANGFENG ZHAO, LUN CHEN, GUODA CHEN, WEIYUE XIE, AND JIYU PENG

Key Laboratory of E&M, Ministry of Education and Zhejiang Province, Zhejiang University of Technology, Hangzhou 310014, China

Corresponding author: Jiyu Peng (jypeng@zjut.edu.cn)

This work was supported in part by the National Key Research and Development Program of China under Grant 2018YFD0700502, in part by the Zhejiang Provincial Key Research and Development Program under Grant 2017C02027, and in part by the Talent Project of Zhejiang Association for Science and Technology under Grant 2018YCGC016.

ABSTRACT During preliminary tea processing, moisture content is an important consideration affecting the tea quality. Traditionally, the moisture content of tea leaves was manually controlled by the joint action of multiple processing units, and maintaining stability was difficult. In this paper, a multi-unit collaborative strategy was proposed for controlling moisture content in preliminary tea processing. Multivariate methods including polynomial regression, radical basis function neural network (RBFNN), and least squares support vector machine (LSSVM) were used to establish models for moisture content prediction in the first fixation, second fixation, and drying units, with minimal root mean square errors (RMSEs) of 1.34%, 0.86%, and 0.13%, respectively. The combination of RBFNN and LSSVM, with a RMSE of 0.03%, was used to model the preliminary processing of whole tea. Rough set data mining technology was used to obtain the optimum ranges of moisture content and critical process parameters. Finally, a Monte Carlo simulation experiment was carried out within the optimum range, and moisture content design spaces for the single unit and the whole processing line were obtained. With the proposed approach, the stability of the final moisture content of tea can be improved, which is of great significance for improving tea quality and accelerating the automation of tea production.

INDEX TERMS Critical process parameter, design space, moisture content, multivariate method, rough set, tea.

I. INTRODUCTION

Tea is the second most consumed beverage (other than water) worldwide and is widely cultivated in China, India, and other areas. Green tea has been demonstrated to lower the incidence of chronic pathologies, such as cancer [1] and cardiovascular diseases [2]. Moisture content is an important consideration affecting the tea quality. Excessive moisture content will accelerate the aging and mildew growth of tea [3]. Currently, the control of tea moisture content relies on the experiences of workers, which are very subjective. Furthermore, guaranteeing the stability of the final tea moisture content is difficult.

Some research concerning the relationship between the tea moisture content and tea quality has been proposed, which has mainly focused on the single processing unit. Botheju *et al.* [4] investigated the relationship between the withering process and the rate of water loss in fresh leaves. Vargas and Vecchietti [5] found that the withering time and temperature in black tea processing should be adjusted according to the moisture content of the harvested leaves; it also showed that this adjustment caused a drop in fabric productivity when the humidity of the shoots exceeded a critical value. Ullah *et al.* [6] indicated that excessive withering led to a significant decrease in tea moisture content and the inhibition of polyphenol oxidase (PPO) activity. Wang *et al.* [7] found that a decrease in water content led to significant changes in gene transcription and concentration of tea flavor compounds, which promoted the special flavor of various teas. Hence, the precise control of moisture content in tea is strongly related to the tea quality, which is of great importance in tea production. However, the final moisture content of tea is produced through the interaction of multiple processing units. It is difficult to optimize the final quality of tea by simply analyzing the relationship between tea quality and the moisture content of a single unit.

The associate editor coordinating the review of this manuscript and approving it for publication was Azwirman Gusrialdi.

Mathematical methods, including theoretical models and multivariate methods, have been utilized to predict some important features in tea. Panchariya *et al.* [8] fitted the production data of the drying process to different semi-theoretical models. The Lewis model could best describe the thin-layer drying characteristics of black tea particles. Zhu *et al.* [9] established a discriminant mode of the degree of fermentation with multi-layer perceptron, random forest, and support vector machine methods and developed a rapid method for detecting the degree of black tea fermentation based on the electrical properties of tea. Hyperspectral imaging technology was also used to predict tea moisture content. Sun *et al.* [10] determined characteristic wavelengths for moisture content prediction using the successive projections algorithm and competitive adaptive reweighted sampling method and visualized the moisture content distribution in tea leaves. Wei *et al.* [11] established a least squares support vector machine (LSSVM) model for moisture content prediction based on hyperspectral images of the front and back of tea and obtained the distribution map. Deng *et al.* [12] proposed an excellent 3D image filter to represent textural information; this was used to improve the prediction accuracy of moisture content in the partial least squares model. Taheri-Garavand *et al.* [13] presented an approach for predicting the moisture content of dried savory leaves using the combination of an artificial neural network and genetic algorithm. However, most studies ignored the relationship between tea moisture content and critical process parameters (CPPs), and few studies have examined the selection of CPPs in each unit with the final moisture content as a target.

In addition, some studies for tea processing control has been reported. Huang *et al.* [14], Ma *et al.* [15] studied the automatic control process of Pu'er tea fermentation; programmable logic controller (PLC) was used for in-line control of the temperature and humidity during the fermentation process. Gong *et al.* [16] designed an automatic white tea dryer including machinery and control systems to control white tea drying conditions. Zheng *et al.* [17] used varied smart meters and centralized controllers to construct a control system, and designed a novel interface software for the automatic control of tea baking. Javanmard *et al.* [18] proposed an automatic tea dryer system based on a programmable controller for controlling the moisture content and temperature at different stages of drying; the moisture content of tea leaves declined from 68% to 3%, and the temperature increased from 30 °C to 80 °C. However, most of these studies focused on the automatic control of a single unit, while ignoring that tea processing is an organic whole where multiple processing units are coupled to each other.

In this study, a whole-process optimization method for the synergistic control of moisture content in preliminary tea processing is proposed. The specific objectives of this study were (a) to establish models for predicting the moisture content in each processing unit and the whole production line, (b) to determine the CPPs of each unit to synergistically control moisture content in preliminary tea processing, and (c) to verify the proposed methods with practical application.

II. MATERIALS AND METHODS

A. SAMPLE PREPARATION

Green tea samples of one bud with two leaves were harvested from the Mingchun tea base in Lichuan City, Hubei Province. A conventional green tea processing method was employed in this experiment (Fig. 1), the details of which are as follows:

(1) Withering: harvested tea samples were spread out in a withering room for 16-27 h at 25-30 °C until the moisture content was around 75%.

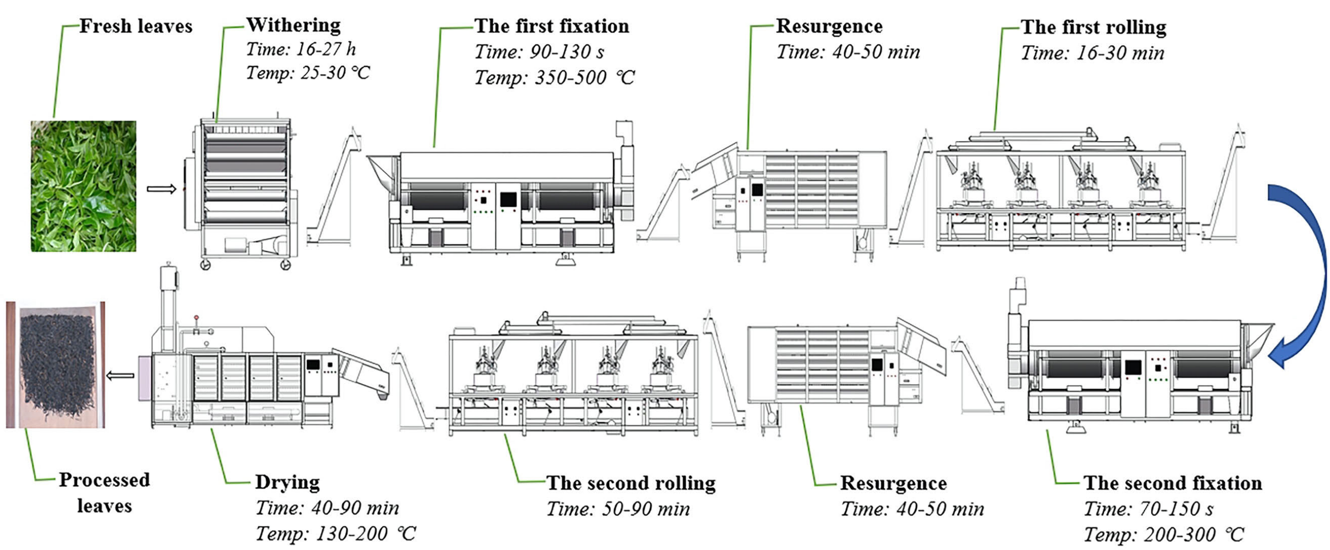


FIGURE 1. The production process of green tea.

(2) First fixation: withered tea samples were stir-fried at 350-500 °C for 90-130 s until the moisture content was around 60%. The fixation temperature was obtained by a sensor attached to the first fixation machine (6CSF-100, Sunyoung Machinery Co. Ltd., China). The fixation time was recorded by a timer.

(3) First rolling: after 40-50 min of resurgence, the tea leaves were transferred into a rolling machine (6CR-55, Sunyoung Machinery Co. Ltd., China) for 16-30 min until the leaves were tightly tied and scented.

(4) Second fixation: rolled tea samples were stir-fried again at 200-300 °C for 70-150 s until the moisture content was around 45%. The time and temperature of the second fixation were obtained in the same way as the first fixation.

(5) Second rolling: after 40-50 min of resurgence, the tea leaves were transferred into a rolling machine (6CR-55, Sunyoung Machinery Co. Ltd., China) for 50-90 min until the leaves were tightly tied again and scented.

(6) Drying: rolled tea samples were transferred into a drying machine (6CCP-60, Sunyoung Machinery Co. Ltd., China) for dehydration by roasting until the moisture content was around 6%. The time and temperature of the drying were obtained in the same way as the first fixation.

An automatic moisture analyzer (MA-150, Sartorius, Germany) was used to measure the moisture content of tea leaves. Tea samples (6 g) were uniformly laid on a sample pan and then dried in the analyzer at 100 °C until no changes in weight were observed. The moisture content was calculated with (1), where y is the moisture content, w is the sample weight before drying, and w' is the sample weight after drying.

$$y = (w - w') \big/ w. \tag{1}$$

All processes were performed in triplicate. The temperature and time of each unit and the moisture content after each unit were collected for each batch. In total, 60 batches were performed with the above-mentioned processing methods, and all CPPs and moisture contents were measured. To establish and test the models, 50 batches were randomly assigned to a training set, and the rest were assigned to the testing set.

Ten extra sample batches were used to verify the established control strategy. The initial conditions for these 10 sample batches are shown in Table 6. The batches of samples were divided into two groups, A and B. The CPPs of group A were specified according to the experiences of workers. The CPPs of group B were specified according to the guidance of the established design space. CPPs and moisture contents were measured by the same methods used in training samples.

B. SENSORY EVALUATION

Sensory evaluation was performed for groups A and B during experimental verification according to tea sensory evaluation method (GB/T 23776-2009). Group A was produced according to traditional craftsmanship, and Group B was produced according to the design space. Then, the color, aroma, shape, and overall quality of the tea were scored by an experienced tea taster on a 10-point scale and rounded to one decimal place.

C. DATA ANALYSIS

To establish the moisture content design space, it is necessary to identify the relationship among the CPPs, unit moisture content, and final moisture content and to determine the optimum ranges of the CPPs and unit moisture content. The unit model was used to determine the relationship between the CPPs and unit moisture content. The overall model was used to determine the relationship between the unit and final moisture contents. Rough set theory was used to determine the optimum ranges of CPPs and the unit moisture content.

1) MULTIVARIATE METHODS

a: POLYNOMIAL REGRESSION

Regression analysis is a commonly used statistical analysis method to determine the interdependence between two or more variables [19]. It can accurately measure the correlation between the various factors and the degree of regression fitting and obtain the most comprehensible mathematical model. In this case, a quadratic polynomial was used for regression, the significance level was 0.05, and the confidence of the estimated value of the coefficient was 95%.

b: RADICAL BASIS FUNCTION NEURAL NETWORK (RBFNN)

RBFNN is a typical feedforward neural network. The basic principle is to convert the input data of the low-dimensional mode into high-dimensional space, making the linearly indivisible problem in low-dimensional space linearly separable in high-dimensional space [20]. RBFNN has a good nonlinear fitting ability, which can map arbitrarily complex nonlinear relationships and has the best unique approximation. In this case, the input layer and hidden layer of the neural network were fully connected, the number of samples was used as the number of hidden layer nodes, and the Gaussian radial basis function was selected as the function of hidden layer activation.

c: LSSVM

Support vector machine (SVM) is a method based on VC (Vapnik-Chervonenkis) dimension theory and structural risk minimization principles. To obtain the best generalization ability, SVM seeks the best compromise between model complexity and learning ability based on limited sample information. LSSVM transforms the inequality constraint in the SVM optimization problem into an equality constraint, which is more computationally efficient and has a complete mathematical and theoretical basis [21]. In this case, the grid search method was used to optimize the penalty coefficient γ and the kernel parameter σ, and radial basis function (RBF) was utilized as kernel function.

TABLE 1. The results of models for moisture content prediction in the three units.

Unit	Model	Training set		Testing set	
		RMSE (%)	R^2	RMSE (%)	R^2
The first fixation	Polynomial regression	1.13	0.9147	1.70	0.8580
	RBFNN	1.19	0.9058	1.36	0.9043
	LSSVM	**1.19**	**0.9069**	**1.34**	**0.9078**
The second fixation	Polynomial regression	0.66	0.9326	1.00	0.8804
	RBFNN	0.70	0.9228	0.88	0.8951
	LSSVM	**0.69**	**0.9260**	**0.86**	**0.8963**
Drying	Polynomial regression	0.10	0.9799	0.16	0.9491
	RBFNN	0.15	0.9592	0.16	0.9655
	LSSVM	**0.12**	**0.9743**	**0.13**	**0.9659**

RBFNN: radical basis function neural network; LSSVM: least squares support vector machine; RMSE: root mean square error; R^2: coefficient of determination.

d: HYBRID MODEL

Because the relationship between the input and output of the overall model is complex, it is difficult to meet the accuracy requirements with a single model. In this case, a hybrid modeling strategy with RBFNN and LSSVM as the main model and error compensation model, respectively, was used for overall modeling. Firstly, RBFNN was used to establish a prediction model for the final moisture content, and the difference (ΔE) between the final moisture content prediction value $\hat{y}$ and the actual value y^* could be obtained. Then, the LSSVM model was used to predict ΔE. Next, the grid search method was used to optimize the hyperparameters of RBFNN and LSSVM. Finally, the predicted values of RBFNN and LSSVM were added together to obtain the predicted value $\hat{Y}$ of the final moisture content, as shown in (2).

$$\hat{Y} = \hat{y} + \widehat{\Delta E}. \tag{2}$$

In this experiment, the models for the prediction of moisture content in each unit were established with polynomial regression, RBFNN, and LSSVM. Because the product quality of the upstream unit directly affects the tea quality of the downstream unit during the tea production process, and the time and temperature are the CPPs that have the greatest impact on the tea moisture content, the moisture content of the previous unit and the CPPs of the current unit were used as inputs, and the moisture content of the current unit was used as the output. In addition, 10-fold cross-validation was used to optimize parameters and prevent overfitting. All models were performed in MATLAB (v2018a, MathWorks, USA).

2) ROUGH SET ERROR FEEDBACK RULE MINING

To establish the unit and final moisture content design spaces, it was necessary to obtain the optimum ranges of CPPs and moisture content in each unit; in this case, these ranges were determined by rough set.

The expression of knowledge in rough set theory generally adopts the form of information table or information system. The information system can be represented by a quaternion ordered array K $= \langle U, A, V, \rho \rangle$, where U is the whole object, that is, the domain; A is the total attribute, $A = C \cup D$, where C is the conditional attribute set, D is the decision attribute set; $V = \bigcup_{a \epsilon A} V_a$, V_a is the value range of the attribute a; $\rho{:}U \times A \rightarrow V$ is an information function, $\rho_x{:}A \rightarrow V, x \in U$ reflects the complete information of the object x in K [22]. In this case, rule mining with rough sets is subject to initial data discretization, attribute reduction, attribute value reduction, and extraction rules, etc. [23], [24].

In the practical production process, experienced workers adjust the target value of the moisture content of each unit according to the difference between the actual and target values of the final moisture content; then, they adjust the CPPs of each unit. Manual adjustments can be converted to automatic adjustments by rough set theory.

Let the final moisture content in any two adjacent samples have the following relationship:

$$y(i) = f(y1\,(i)\,, y2\,(i)\,, y3\,(i)\,, y4(i)), \tag{3}$$

$$y(i{+}1) = f(y1\,(i{+}1)\,, y2\,(i{+}1)\,, y3\,(i{+}1)\,, y4(i{+}1)), \tag{4}$$

where $y(i)$ is the final moisture content, $y1\,(i)$ is the moisture content of the withered leaf, $y2\,(i)$ is the moisture content after the first fixation, $y3\,(i)$ is the moisture content after the second fixation, and $y4(i)$ is the moisture content after drying.

The difference in the final moisture content between two adjacent samples was:

$$\Delta y = y(i{+}1){-}y(i). \tag{5}$$

The difference in the unit moisture content between two adjacent samples was:

$$\begin{aligned} &\{\Delta y1\,(i)\,, \Delta y2\,(i)\,, \Delta y3\,(i)\,, \Delta y4\,(i)\} \\ &\quad = \{y1\,(i+1) - y1\,(i)\,, y2\,(i+1) - y2\,(i)\,, y3\,(i+1) \\ &\qquad - y3\,(i)\,, y4(i+1) - y4(i)\}. \end{aligned} \tag{6}$$

In this case, Δy, $y1\,(i)$, $y2\,(i)$, $y3\,(i)$, and $y4(i)$ were considered as the condition attributes, and $\Delta y1\,(i)$, $\Delta y2\,(i)$, $\Delta y3\,(i)$, and $\Delta y4\,(i)$ were considered as the decision attributes. The attributes were used to construct the decision information

TABLE 2. Comparison of overall model performance.

Model	Training set		Testing set	
	RMSE (%)	R^2	RMSE (%)	R^2
RBFNN	0.34	0.8132	0.17	0.7461
LSSVM	0.15	0.8045	0.16	0.7656
RBFNN-LSSVM	**0.04**	**0.8723**	**0.03**	**0.9025**

RBFNN: radical basis function neural network; LSSVM: least squares support vector machine; RMSE: root mean square error; R^2: coefficient of determination.

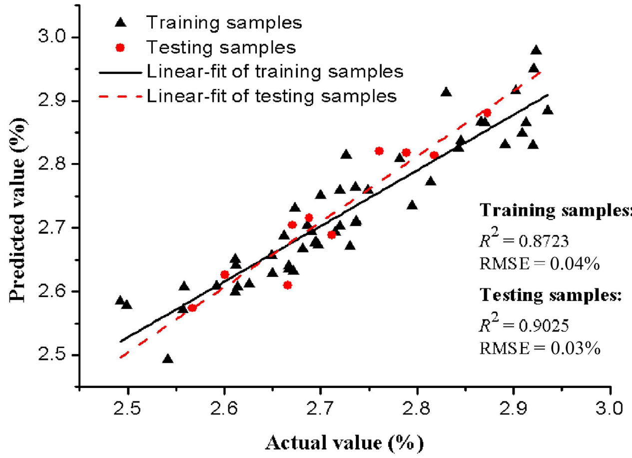


FIGURE 2. Relationship between the predicted moisture content and actual value in the hybrid model.

tables. And the change rules of the final and unit moisture contents could be determined with following steps: (a) The decision information table was split into a single decision attribute decision table; (b) The data discretization method based on information entropy was used to discretize the data; (c) The attribute reduction algorithm based on positive domain changes was used to implement attribute reduction; (d) Then each attribute value was reduced one by one to obtain a final simplified decision table, which could be regarded as an error feedback rule table. The difference between the actual and target values of the final moisture content was considered as a condition attribute to query the rule base, and the difference between the actual and optimum values of the moisture content of each unit of each sample could be obtained. Then, the actual value and the difference were added to obtain the optimum value of the moisture content of each unit of each sample, and the maximal and minimal values of the optimum values in all samples were identified to obtain the best moisture content range in each unit.

By replacing the condition attributes with the differences in the final moisture content between two adjacent samples and the CPPs in each unit and replacing the decision attributes with the differences in CPPs between two adjacent samples in each unit, the optimum range of CPPs per unit could also be determined.

D. DESIGN SPACE THEORY

Quality by design (QbD) is a systematic approach that emphasizes process control, which is commonly used in aviation, electronics, chemical, and drug development [25], [26]. The design space is defined as the multidimensional combination and interaction between input variables and process parameters that ensures product quality. As mentioned above, the optimum ranges of the moisture content and CPPs of each unit were obtained via the rough set. In this case, the final moisture content was considered as nonadjustable when the moisture content of a certain unit exceeded the optimum range.

TABLE 3. Error feedback rules for the moisture content of withered leaves and the temperature of the first fixation.

No.	Moisture content of withered leaves	Temperature of the first fixation
1	IF $\Delta y(3)$ and $y1(8)$ and $y2(6)$ and $y3(4)$ THEN $\Delta y1(5)$	IF $y1(7)$ and $r1(3)$ THEN $\Delta r1(5)$
2	IF $\Delta y(4)$ and $y1(6)$ and $y2(8)$ and $y3(5)$ THEN $\Delta y1(4)$	IF $\Delta y(4)$ and $y1(5)$ and $r1(1)$ THEN $\Delta r1(1)$
3	IF $\Delta y(6)$ and $y1(4)$ and $y2(8)$ and $y3(7)$ THEN $\Delta y1(2)$	IF $\Delta y(6)$ and $y1(3)$ and $r1(2)$ THEN $\Delta r1(7)$
4	IF $\Delta y(1)$ and $y1(1)$ and $y2(1)$ and $y3(3)$ THEN $\Delta y1(3)$	IF $\Delta y(4)$ and $y1(3)$ THEN $\Delta r1(7)$
5	IF $\Delta y(4)$ and $y1(4)$ and $y2(1)$ and $y3(1)$ THEN $\Delta y1(7)$	IF $\Delta y(7)$ and $y1(1)$ and $r1(8)$ THEN $\Delta r1(4)$
6	IF $\Delta y(7)$ and $y1(1)$ and $y2(1)$ and $y3(1)$ THEN $\Delta y1(4)$	IF $\Delta y(7)$ THEN $\Delta r1(1)$
7	IF $\Delta y(7)$ and $y1(4)$ and $y2(6)$ and $y3(6)$ THEN $\Delta y1(6)$	IF $\Delta y(4)$ and $r1(4)$ THEN $\Delta r1(7)$
8	IF $\Delta y(4)$ and $y1(1)$ and $y2(4)$ and $y3(6)$ THEN $\Delta y1(3)$	IF $\Delta y(8)$ and $y1(3)$ and $r1(1)$ THEN $\Delta r1(2)$
…	…	…
59	IF $\Delta y(6)$ and $y1(2)$ and $y2(5)$ and $y3(6)$ THEN $\Delta y1(5)$	IF $\Delta y(5)$ and $r1(2)$ THEN $\Delta r1(5)$

Δy: the difference in final moisture content between two adjacent samples; $y1$: the moisture content of withered leaves; $y2$: the moisture content after the first fixation; $y3$: the moisture content after the second fixation; $\Delta y1$: the difference in moisture content between two adjacent samples of leaves after withering; $r1$: the first fixation temperature; $\Delta r1$: the difference in the first fixation temperature between two samples.

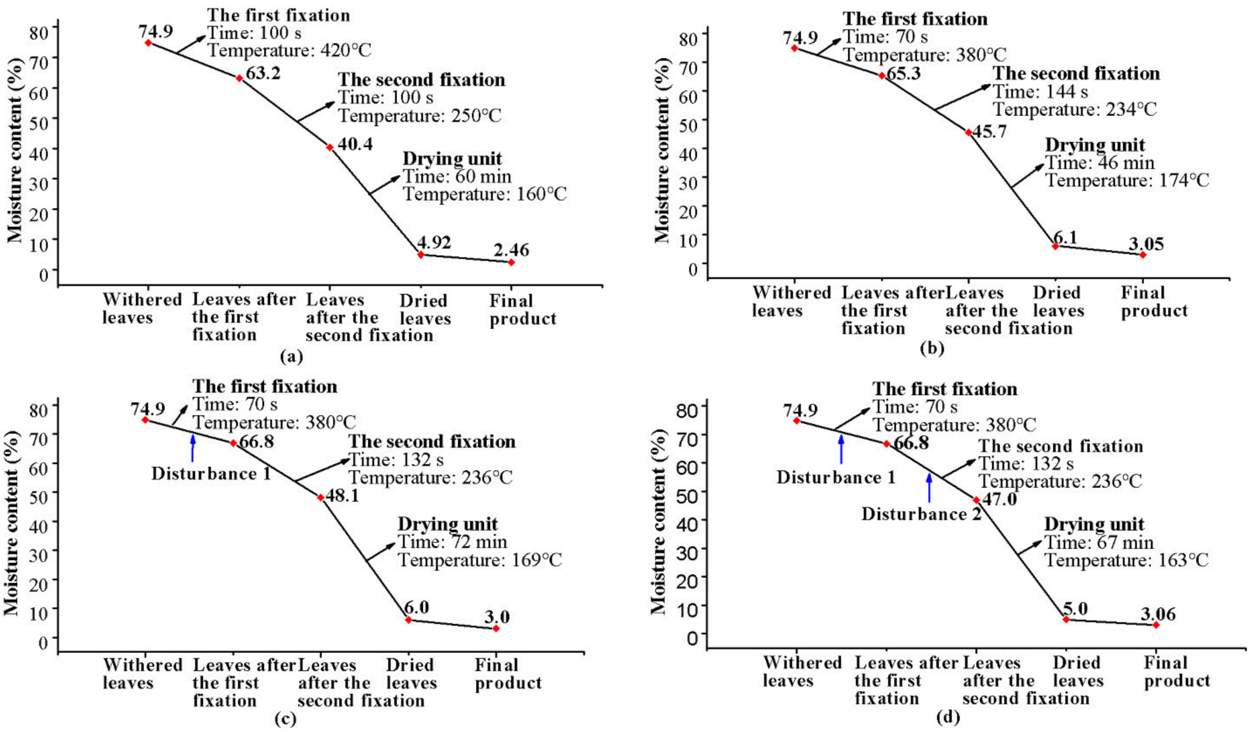


FIGURE 3. Changes in moisture content in group A (a), changes in moisture content in group B (b), changes in moisture content in group B (with disturbance added to the first fixation) (c), changes in moisture content in group B (with disturbance added to the second fixation) (d).

According to the principle of Monte Carlo simulation, many sampling results can be randomly generated by computer simulation, and the value of the statistic or parameter can be calculated [27]. Within the optimum range of CPPs per unit, 10,000 sets of CPP combinations in each unit were generated by a random sampling method. The predicted moisture content values of each unit could be obtained based on the unit model. The combinations of the CPPs whose predicted values were beyond the optimum range were removed, and the retained CPP combinations served as the design space of the unit moisture content. Hence, the initial CPPs in each unit could be determined by querying the unit moisture content design space.

The design space for the final moisture content was established in the same manner. Firstly, 10,000 sets of moisture content combinations within the optimum range were generated by a random sampling method. Then, the predicted values of the final moisture content were obtained based on the whole model. The combinations of the unit moisture content with predicted values beyond the optimum range were removed, and the retained combinations of the unit moisture content served as the design space of the final moisture content. When there was a deviation in the upstream unit, the CPPs of the downstream unit could be adjusted depending on the final moisture content design space.

E. PERFORMANCE EVALUATION

In order to evaluate the performance of the moisture content prediction model, some figures of merits were used.

TABLE 4. The optimum ranges of the moisture content and CPPs per unit.

	$y1^*$ (%)	$y2^*$ (%)	$y3^*$ (%)	$r1^*$ (°C)	$r2^*$ (s)	$r3^*$ (°C)	$r4^*$ (s)	$r5^*$ (°C)	$r6^*$ (*min*)
Min	56.0	40.0	4.5	270	50	190	44	135	40
Max	70.0	49.0	7.0	500	120	290	146	180	90

$y1^*$: the optimum range of the moisture content after the first fixation; $y2^*$: the optimum range of the moisture content after the second fixation; $y3^*$: the optimum range of the moisture content after the drying unit; $r1^*$: the optimum range of the first fixation temperature, $r2^*$: the optimum range of the first fixation time; $r3^*$: the optimum range of the second fixation temperature; $r4^*$: the optimum range of the second fixation time; $r5^*$: the optimum range of the drying temperature; $r6^*$: the optimum range of the drying time.

Root mean square error (RMSE) measures model accuracy. Smaller RMSE value indicate higher model accuracy. The coefficient of determination (R^2) measures the relationship between the predicted and actual values; higher R^2 indicates better prediction performance. The values of RMSE and R^2 could be deduced with the following equations:

$$\mathrm{RMSE} = \sqrt{(1/n)\sum_{i=1}^{n}(y_i - \tilde{y}_i)^2}, \quad (7)$$

$$R^2 = 1 - \sum_{i=1}^{n}(y_i - \tilde{y}_i)^2 \Big/ \sum_{i=1}^{n}(y_i - \tilde{y}_i)^2, \quad (8)$$

where n is the sample number, y_i is the actual value, and $\tilde{y}_i$ is the predicted value.

TABLE 5. Sensory evaluation and moisture content of 10 batches in groups A and B.

	Group A					Group B				
	Color	Shape	Aroma	Overall quality	Moisture content (%)	Color	Shape	Aroma	Overall quality	Moisture content (%)
Batch 1	7.5	7.5	7.0	7.1	2.46	8.0	7.5	8.0	8.2	3.06
Batch 2	7.0	7.0	8.0	7.6	2.51	8.0	8.0	8.5	8.5	3.02
Batch 3	7.5	6.5	7.0	7.1	3.65	8.0	7.5	8.5	8.2	2.94
Batch 4	6.5	7.0	7.0	7.1	2.54	8.5	8.5	8.0	8.2	3.11
Batch 5	7.0	7.5	8.0	7.9	3.52	8.5	8.0	8.0	8.4	3.03
Batch 6	8.0	8.5	7.5	8.0	2.61	9.0	8.5	8.5	8.7	2.95
Batch 7	8.0	7.5	7.5	7.6	2.21	8.5	9.0	8.5	8.8	3.02
Batch 8	7.0	7.0	7.5	7.4	2.67	9.0	8.5	9.0	9.0	3.03
Batch 9	8.0	8.5	8.0	8.4	2.42	9.5	9.0	9.0	9.2	2.95
Batch 10	7.0	7.5	7.0	7.0	2.49	8.0	8.0	7.5	8.1	2.99
Comprehensive evaluation	Average score for sensory evaluation Color: 7.35 Shape: 7.45 Aroma: 7.45 Overall quality: 7.52 Variance of moisture content: 0.2294 RMSE of moisture content: 0.54%					Average score for sensory evaluation Color: 8.50 Shape: 8.25 Aroma: 8.35 Overall quality: 8.53 Variance of moisture content: 0.0029 RMSE of moisture content: 0.05%				

III. RESULTS AND DISCUSSION

A. MOISTURE CONTENT PREDICTION FOR A SINGLE UNIT

To simplify the research, multivariate methods were carried out for the fixation and drying units, which were closely related to the change in moisture content. The polynomial regression model, RBFNN, and LSSVM were used to predict the moisture content of each unit. The model with the best prediction performance would be selected as the unit model.

The results of models for moisture content prediction of the three units are shown in Table 1. In the first fixation unit, the moisture content of withered leaves, fixation temperature, and fixation time were utilized as inputs, and the moisture content after the first fixation was utilized as the output. The spread factor of RBFNN was optimized by the grid search method with a search range of 0-3000. The spread factor was 1350 in this case. The penalty coefficient (γ) and the kernel parameter (σ) of LSSVM were optimized by the grid search method with search ranges of 1-200 and 1-500, respectively. The optimized γ and σ values were 90 and 100, respectively. As shown in Table 1, the polynomial model performed poorly on the testing set; this might be due to its poorer generalization ability [28]. In general, LSSVM performed best on the testing set, the RMSE and R^2 of which were 1.34% and 0.9078, respectively. Compared with RBFNN, LSSVM had a unique solution and a lower tendency toward overfitting. LSSVM was used as the unit model for moisture content prediction in the first fixation.

In the second fixation unit, the moisture content after the first fixation, fixation temperature, and fixation time were used as inputs, and the moisture content after the second fixation was used as the output. The spread factor, γ, and σ were optimized in the same way as described for the first fixation unit. In this case, the spread factor, γ, and σ were 2000, 91, and 101, respectively. As shown in Table 1, LSSVM performed best in moisture content prediction in the second fixation unit, with an RMSE and R^2 of 0.86% and 0.8963 on the testing set, respectively. Hence, LSSVM was chosen as the unit model for the second fixation unit.

TABLE 6. Initial conditions of the 10 Tea leaf batches.

	Ambient temperature (°C)	Ambient humidity (%)	Moisture content of withering leaves (%)
Batch 1	27.1	76	74.9
Batch 2	25.3	76	75.1
Batch 3	26.7	72	75.4
Batch 4	24.4	85	74.3
Batch 5	25.9	64	73.5
Batch 6	28.2	82	76.7
Batch 7	24.8	68	77.1
Batch 8	26.2	84	74.7
Batch 9	27.7	88	76.2
Batch 10	29.4	77	76.0

In the drying unit, the moisture content after the second fixation, drying temperature, and drying time were used as inputs, and the moisture content after the drying unit was used as the output. The spread factor of RBFNN, penalty coefficient, and kernel parameter of LSSVM were optimized in the same way as described for the first fixation unit. The optimized spread factor, γ, and σ were 2000, 70, and 45, respectively. As shown in Table 1, LSSVM also performed best in the drying unit, with an RMSE and R^2 of 0.13% and 0.9659, respectively.

TABLE 7. Decision information table of the error feedback for moisture content.

Conditional attribute					Decision attribute			
Δy	$y1$	$y2$	$y3$	$y4$	$\Delta y1$	$\Delta y2$	$\Delta y3$	$\Delta y4$
-0.32	76.58	65.08	43.31	5.12	0.02	2.75	-3.00	-0.54
-0.06	75.75	67.63	43.79	5.14	-0.83	2.55	0.48	0.02
0.32	74.30	67.24	45.14	6.03	-1.45	-0.39	1.35	0.89
-0.49	73.21	54.70	41.67	4.91	-1.09	-12.54	-3.47	-1.12
-0.11	74.46	51.08	38.13	4.34	1.25	-3.62	-3.54	-0.57
0.51	73.47	57.63	40.34	4.97	-0.99	6.55	2.21	0.63
0.45	74.31	65.08	44.11	5.62	0.84	7.45	3.77	0.65
-0.12	73.10	61.05	45.02	5.56	-1.21	-4.03	0.91	-0.06
0.81	74.78	69.55	47.11	7.12	1.68	8.50	2.09	1.56
-1.32	78.58	59.46	44.93	5.83	3.80	-10.09	-2.18	-1.29
-0.06	76.32	60.88	42.16	4.84	-2.26	1.42	-2.77	-0.99
-0.36	74.21	64.11	41.77	4.83	-2.11	3.23	-0.39	-0.01
0.02	75.83	64.05	41.02	4.79	1.62	-0.06	-0.75	-0.04
0.17	76.22	62.11	40.06	4.65	0.39	-1.94	-0.96	-0.14
0.58	74.12	66.46	47.12	6.28	-2.10	4.35	7.06	1.63
-0.48	75.16	54.63	40.88	4.65	1.04	-11.83	-6.24	-1.63
0.02	73.89	57.74	40.52	4.68	-1.27	3.11	-0.36	0.03
-0.44	74.98	52.84	38.32	4.17	1.09	-4.90	-2.20	-0.51
0.43	76.13	60.02	40.93	4.92	1.15	7.18	2.61	0.75
1.14	77.53	69.85	48.43	7.35	1.40	9.83	7.50	2.43
-1.21	76.32	61.69	41.65	5.03	-1.21	-8.16	-6.78	-2.32
0.6	73.29	65.65	45.33	6.53	-3.03	3.96	3.68	1.5
0.11	75.12	65.76	46.83	6.28	1.83	0.11	1.50	-0.25
-0.54	73.88	60.63	41.08	4.82	-1.24	-5.13	-5.75	-1.46
-0.01	76.45	56.35	39.23	4.62	2.57	-4.28	-1.85	-0.2
0.75	75.32	65.35	48.69	7.51	-1.13	9.00	9.46	2.89
-0.44	75.11	60.60	43.86	5.71	-0.21	-4.75	-4.83	-1.8
-0.06	74.90	66.83	44.94	5.58	-0.21	6.23	1.08	-0.13
-0.04	73.33	68.01	45.87	5.84	-1.57	1.18	0.93	0.26
0.06	74.23	65.77	45.76	5.73	0.90	-2.24	-0.11	-0.11
-0.2	73.98	59.34	43.37	5.48	-0.25	-6.43	-2.39	-0.25
0.15	76.56	62.02	43.11	5.41	2.58	2.68	-0.26	-0.07
-0.29	76.17	62.46	42.13	4.98	-0.39	0.44	-0.98	-0.43
0.56	74.22	67.43	48.35	6.66	-1.95	4.97	6.22	1.68
-0.2	76.45	65.48	44.02	5.55	2.23	-1.95	-4.33	-1.11
-0.43	75.31	59.04	41.33	4.75	-1.14	-6.44	-2.69	-0.8
0.23	73.99	60.25	43.55	5.31	-1.32	1.21	2.22	0.56
-0.13	75.26	60.95	41.12	4.95	1.27	0.70	-2.43	-0.36
0.23	76.41	63.67	43.01	5.02	1.15	2.72	1.89	0.07
0.45	76.12	66.98	46.03	5.94	-0.29	3.31	3.02	0.92
-0.64	74.35	62.36	42.74	4.96	-1.77	-4.62	-3.29	-0.98
-0.15	74.11	63.22	41.98	4.93	-0.24	0.86	-0.76	-0.03
-0.18	75.03	60.56	41.44	4.78	0.92	-2.66	-0.54	-0.15
0.31	74.98	59.01	43.03	5.46	-0.05	-1.55	1.59	0.68
0.36	77.52	64.12	46.02	6.12	2.54	5.11	2.99	0.66
-0.38	76.38	59.02	43.27	5.08	-1.14	-5.10	-2.75	-1.04

TABLE 7. ***(Continued.)*** **Decision information table of the error feedback for moisture content.**

0.2	77.11	63.99	43.88	5.48	0.73	4.97	0.61	0.4
0.19	75.21	63.69	46.24	6.04	-1.90	-0.30	2.36	0.56
-0.25	74.08	63.21	45.14	5.61	-1.13	-0.48	-1.10	-0.43
0.24	73.21	63.82	43.87	5.55	-0.87	0.61	-1.27	-0.06
-0.07	74.33	58.98	42.61	5.35	1.12	-4.84	-1.26	-0.2
-0.37	74.85	61.77	43.44	5.28	0.52	2.79	0.83	-0.07
0.65	76.04	67.00	47.43	6.42	1.19	5.23	3.99	1.14
-0.64	73.85	60.86	43.02	5.32	-2.19	-6.14	-4.41	-1.1
0.65	77.06	66.02	48.48	6.71	3.21	5.16	5.46	1.39
-0.78	76.82	61.34	40.92	4.88	-0.24	-4.68	-7.56	-1.83
-0.17	74.17	57.67	39.21	4.52	-2.65	-3.67	-1.71	-0.36
0.46	74.11	62.16	43.54	5.12	-0.06	4.49	4.33	0.6
0.2	73.88	63.73	43.89	5.42	-0.23	1.57	0.35	0.3
-0.32	76.58	65.08	43.31	5.12	0.02	2.75	-3.00	-0.54

Δy: the difference in final moisture content between two adjacent samples; $y1$: the moisture content of withered leaves; $y2$: the moisture content after the first fixation; $y3$: the moisture content after the second fixation; $y4$: the moisture content after the drying unit; $\Delta y1$: the difference in moisture content between two adjacent samples of leaves after withering; $\Delta y2$: the difference in moisture content between two adjacent samples of leaves after the first fixation; $\Delta y3$: the difference in moisture content between two adjacent samples of leaves after the second fixation; $\Delta y4$: the difference in moisture content between two adjacent samples of leaves after the drying unit.

B. OVERALL MODEL BUILDING

Compared with the unit model, the correlation between the unit and final moisture contents was more complicated. It is difficult to predict the moisture content accurately with a single model. Hence, a hybrid model (RBFNN-LSSVM) was used in this case; results for the hybrid and single models are shown in Table 2. In the hybrid model, the moisture contents of each unit were used as inputs and the final moisture content was used as the output. RBFNN was used to fit the final moisture content, LSSVM was used to fit the residual, and the final prediction was the sum of the results of these two models.

As shown in Table 2, the performance of the hybrid model was better than that of the single model. Previous study has shown that a single model has worse performance in a complex situation [29]. A single model only focuses on a certain aspect, and it is easy to ignore some information in complex data; however, a hybrid model can combine the advantages of different single models to achieve complementary effects. The correlation between the predicted and actual values is shown in Fig. 2.

C. OPTIMIZATION OF RANGES OF CPPS AND UNIT MOISTURE CONTENT

The rough set theory was utilized to determine the optimum ranges of unit moisture content and CPPs, which were used to establish the design space. The difference in final moisture content between two adjacent samples (Δy) and the moisture contents after withering, first fixation, second fixation, and drying ($y1$, y2, y3, and y4, respectively) were taken as the condition attributes. The differences in moisture contents between two adjacent samples of leaves after the processes of withering (Δy1), first fixation ($\Delta y2$), second fixation ($\Delta y3$), and the drying unit ($\Delta y4$) were taken as the decision attributes. The decision information table of the error feedback for moisture content is shown in Table 7.

The difference in final moisture content between two adjacent samples (Δy), the moisture content of withered leaves ($y1$), first fixation temperature ($r1$), first fixation time ($r2$), second fixation temperature ($r3$), second fixation time ($r4$), drying unit temperature ($r5$), and drying unit time ($r6$) were taken as the condition attributes. The differences in the first fixation temperature ($\Delta r1$), first fixation time ($\Delta r2$), second fixation temperature ($\Delta r3$), second fixation time (Δr4), drying unit temperature ($\Delta r5$), and drying unit time ($\Delta r6$) between two samples were taken as the decision attributes. The decision information table of the error feedback for CPPs is shown in Table 8.

Because the decision information tables of the error feedback for the unit moisture content and CPPs were multi-decision attribute decision tables, Table 7 was divided into four decision tables of single decision attributes, and Table 8 was divided into six decision tables of single decision attributes. Taking Δy1 and Δr1 as examples, the data discretization method based on information entropy and the attribute reduction algorithm based on positive domain change were used to discretize data and reduce the attributes of the two decision tables [23], [24]. Then, each attribute value was reduced individually. If a conflict occurred, the attribute value was not deleted; the lack of a conflict indicated that the attribute value should be deleted. Finally, the simplified decision table is shown in Table 9; according to this table, 59 error feedback rules each could be generated for

TABLE 8. Decision information table of the error feedback for critical process parameters.

Conditional attribute								Decision attribute					
Δy	$y1$	$r1$	$r2$	$r3$	$r4$	$r5$	$r6$	$\Delta r1$	$\Delta r2$	$\Delta r3$	$\Delta r4$	$\Delta r5$	$\Delta r6$
-0.32	76.58	400	101	305	118	171	67	10	5	100	45	-15	-15
-0.06	75.75	335	103	278	147	195	63	-65	2	-27	29	24	-4
0.32	74.30	380	93	272	87	157	50	45	-10	-6	-60	-38	-13
-0.49	73.21	450	110	240	59	179	61	70	17	-32	-28	22	11
-0.11	74.46	495	129	250	98	155	65	45	19	10	39	-24	4
0.51	73.47	485	90	260	82	119	65	-10	-39	10	-16	-36	0
0.45	74.31	370	104	252	127	176	47	-115	14	-8	45	57	-18
-0.12	73.10	420	80	190	148	156	72	50	-24	-62	21	-20	25
0.81	74.78	360	72	230	131	156	47	-60	-8	40	-17	0	-25
-1.32	78.58	450	150	230	98	151	63	90	78	0	-33	-5	16
-0.06	76.32	448	98	280	76	145	80	-2	-52	50	-22	-6	17
-0.36	74.21	390	87	280	123	132	77	-58	-11	0	47	-13	-3
0.02	75.83	430	88	310	110	156	68	40	1	30	-13	24	-9
0.17	76.22	450	75	290	117	185	60	20	-13	-20	7	29	-8
0.58	74.12	340	100	240	88	150	86	-110	25	-50	-29	-35	26
-0.48	75.16	400	163	210	80	165	73	60	63	-30	-8	15	-13
0.02	73.89	480	96	250	92	166	55	80	-67	40	12	1	-18
-0.44	74.98	422	174	265	98	169	80	-58	78	15	6	3	25
0.43	76.13	480	104	280	78	138	78	58	-70	15	-20	-31	-2
1.14	77.53	405	78	255	100	134	72	-75	-26	-25	22	-4	-6
-1.21	76.32	490	80	260	120	157	50	85	2	5	20	23	-22
0.6	73.29	370	94	200	144	137	45	-120	14	-60	24	-20	-5
0.11	75.12	400	99	210	98	149	70	30	5	10	-46	12	25
-0.54	73.88	475	64	290	88	165	60	75	-35	80	-10	16	-10
-0.01	76.45	480	103	245	110	158	65	5	39	-45	22	-7	5
0.75	75.32	420	78	195	92	144	52	-60	-25	-50	-18	-14	-13
-0.44	75.11	445	96	210	96	138	55	25	18	15	4	-6	3
-0.06	74.90	400	71	268	134	162	72	-45	-25	58	38	24	17
-0.04	73.33	370	79	280	120	180	60	-30	8	12	-14	18	-12
0.06	74.23	400	76	250	105	165	75	30	-3	-30	-15	-15	15
-0.2	73.98	470	79	200	104	160	65	70	3	-50	-1	-5	-10
0.15	76.56	460	101	275	95	155	68	-10	22	75	-9	-5	3
-0.29	76.17	470	73	295	102	178	54	10	-28	20	7	23	-14
0.56	74.22	340	90	230	96	134	78	-130	17	-65	-6	-44	24
-0.2	76.45	470	60	270	105	154	62	130	-30	40	9	20	-16
-0.43	75.31	470	108	205	125	177	68	0	48	-65	20	23	6
0.23	73.99	450	92	240	87	186	66	-20	-16	35	-38	9	-2
-0.13	75.26	460	94	290	98	155	53	10	2	50	11	-31	-13
0.23	76.41	435	96	280	112	154	82	-25	2	-10	14	-1	29
0.45	76.12	420	84	250	104	158	65	-15	-12	-30	-8	4	-17
-0.64	74.35	390	105	290	88	180	66	-30	21	40	-16	22	1
-0.15	74.11	405	98	275	108	144	72	15	-7	-15	20	-36	6
-0.18	75.03	480	76	248	121	157	85	75	-22	-27	13	13	13
0.31	74.98	455	124	210	94	134	65	-25	48	-38	-27	-23	-20
0.36	77.52	430	96	195	120	148	64	-25	-28	-15	26	14	-1

TABLE 8. ***(Continued.)*** **Decision information table of the error feedback for critical process parameters.**

-0.38	76.38	480	105	260	85	176	80	50	9	65	-35	28	16
0.2	77.11	440	94	265	98	189	55	-40	-11	5	13	13	-25
0.19	75.21	450	80	238	82	166	64	10	-14	-27	-16	-23	9
-0.25	74.08	390	110	220	97	192	54	-60	30	-18	15	26	-10
0.24	73.21	410	88	255	103	160	65	20	-22	35	6	-32	11
-0.07	74.33	470	105	270	78	158	54	60	17	15	-25	-2	-11
-0.37	74.85	455	92	215	136	168	78	-15	-13	-55	58	10	24
0.65	76.04	400	85	220	105	184	56	-55	-7	5	-31	16	-22
-0.64	73.85	385	128	225	128	134	77	-15	43	5	23	-50	21
0.65	77.06	450	78	260	76	150	67	65	-50	35	-52	16	-10
-0.78	76.82	480	86	285	106	162	54	30	8	25	30	12	-13
-0.17	74.17	475	102	290	94	177	62	-5	16	5	-12	15	8
0.46	74.11	375	124	238	106	196	54	-100	22	-52	12	19	-8
0.2	73.88	380	98	240	110	153	84	5	-26	2	4	-43	30

Δy: the difference in final moisture content between two adjacent samples; *y1*: the moisture content of withered leaves; *r1*: the first fixation temperature; *r2*: the first fixation time; *r3*: the second fixation temperature; *r4*: the second fixation time; *r5*: the drying temperature; *r6*: the drying time; $\Delta r1$: the difference in the first fixation temperature between two samples; $\Delta r2$: the difference in the first fixation time between two samples; $\Delta r3$: the difference in the second fixation temperature between two samples; $\Delta r4$: the difference in the second fixation time between two samples; $\Delta r5$: the difference in the drying temperature between two samples; $\Delta r6$: the difference in the drying time between two samples.

the moisture content of withered leaves and the first fixation temperature (Table 3).

The optimum ranges of the moisture content of the tea leaves after each unit and the CPPs in each unit are shown in Table 4. The optimum ranges of moisture content, temperature, and time in the first fixation were 56.0-70.0%, 270-500 °C, and 50-120 s, respectively; those in the second fixation were 40.0-49.0%, 190-290 °C, and 44-146 s, respectively; and those in the drying unit were 4.5-7.0%, 135-180 °C, and 40-90 min, respectively.

D. MOISTURE CONTENT DESIGN SPACE FOR THE PRELIMINARY PROCESSING OF GREEN TEA

Ten thousand sets of CPP combinations in each unit were randomly selected within the optimum CPP range. Using the moisture content predicted by the unit model, combinations beyond the optimum range of the moisture content of each unit were discarded. Hence, the remaining combinations were selected as the unit moisture content design space.

In the same manner, ten thousand sets of combinations of the unit moisture content were randomly selected within the optimum range of the unit moisture content. Using the final predicted moisture content, combinations beyond the optimum range of the final moisture content were discarded, and the remaining combinations were selected as the final moisture content design space.

The unit moisture content design space was used to guide the selection of initial CPPs of each unit. When there was an interference or operational deviation in the upstream unit, the target value of the moisture content of the downstream unit could be adjusted according to the final moisture content design space. The CPPs of the downstream unit could be guided by the unit design space according to the new target value of the moisture content of the downstream unit. In this case, the final moisture content could remain stable.

E. EXPERIMENTAL VERIFICATION

To verify the guiding role of the moisture content design space for whole-process optimization and collaborative control, experiments were carried out on the tea production line of Hubei Mingchun Tea Company. Ten batches of withered leaves with different environmental temperature, humidity, and moisture content were divided into two groups (A and B). Group A was processed according to the general processing method, and group B was processed according to the design space. The initial conditions of the 10 tea leaf batches are shown in Table 6.

Fig. 3 (a) and (b) show the changes in moisture contents in the first batches of groups A and B. The CPPs of group A were set according to the specified empirical values. The target value of the unit moisture content of group B was first specified according to the final moisture content design space, and then the initial value of CPPs per unit was designated according to the unit moisture content design space. The final moisture content from group B was 3.05%, which was close to the target value (see Fig. 3 (b)). To test the stability of the proposed control strategy, a disturbance was added manually in the first and second fixation units. As shown in Fig. 3 (c) and (d), the moisture content after adding disturbances diverged from the target values, and the new CPP values were adjusted accordingly to achieve the final moisture content. The new target value of the moisture content of the subsequent units could be specified according to the final moisture content design space, and then the new

TABLE 9. Compensation decision table for moisture content of withered leaves and the temperature of the first fixation.

No.	Condition Attribute				Decision Attribute	No.	Condition Attribute			Decision Attribute
	Δy	$y1$	$y2$	$y3$	$\Delta y1$		Δy	$y1$	$r1$	$\Delta r1$
1	3	8	6	4	5	1	*	7	3	5
2	4	6	8	5	4	2	4	5	1	1
3	6	4	8	7	2	3	6	3	2	7
4	1	1	1	3	3	4	*	*	*	8
5	4	4	1	1	7	5	4	3	*	7
6	7	1	1	1	4	6	7	1	8	4
7	7	4	6	6	6	7	7	*	*	1
8	4	1	4	6	3	8	4	*	4	7
9	8	4	8	8	7	9	8	3	1	2
10	1	8	2	6	8	10	1	*	6	8
11	4	7	3	3	1	11	4	6	5	4
12	2	3	5	3	1	12	2	3	*	2
13	5	6	5	2	7	13	*	5	5	6
14	5	7	4	1	5	14	5	6	*	6
15	7	3	7	8	1	15	7	*	*	1
16	2	5	1	2	6	16	2	4	3	7
17	5	2	2	2	2	17	*	1	7	8
18	2	5	1	1	6	18	2	4	4	2
19	6	7	3	2	7	19	7	6	7	7
20	8	8	8	8	7	20	*	8	4	1
21	1	7	4	3	3	21	1	6	8	8
22	8	1	6	7	1	22	8	1	2	1
23	5	5	7	8	8	23	5	*	3	6
24	1	2	3	2	2	24	*	1	*	8
25	5	7	1	1	8	25	5	7	7	5
26	8	6	6	8	3	26	8	5	4	2
27	2	5	3	6	5	27	2	4	5	6
28	4	5	7	6	5	28	4	4	3	2
29	5	1	8	7	2	29	4	*	2	3
30	5	3	7	7	6	30	5	*	3	6
31	3	2	2	4	4	31	*	*	6	8
32	5	8	4	4	8	32	5	7	6	4
33	3	7	4	3	4	33	3	*	6	5
34	7	3	8	8	1	34	7	*	*	1
35	3	7	6	6	8	35	3	*	6	8
36	2	6	2	3	3	36	2	*	6	4
37	6	2	3	5	2	37	6	*	6	3
38	4	6	3	2	7	38	*	*	6	5
39	6	7	4	4	7	39	6	*	5	3
40	7	6	7	7	4	40	7	6	4	4
41	1	4	4	4	2	41	1	3	*	3
42	4	3	4	3	4	42	3	2	4	5
43	3	5	3	3	6	43	3	4	7	8
44	6	5	2	4	5	44	6	*	6	3
45	6	8	6	7	8	45	6	*	5	3

TABLE 9. ***(Continued.)*** **Compensation decision table for moisture content of withered leaves and the temperature of the first fixation.**

46	2	7	2	4	3	46	2	7	7	7
47	6	8	5	6	6	47	5	8	*	2
48	5	6	5	7	2	48	*	5	6	5
49	3	2	4	7	3	49	*	2	3	2
50	6	1	5	6	4	50	6	1	4	6
51	4	4	2	4	6	51	4	3	*	7
52	2	4	4	5	5	52	2	*	6	4
53	8	6	8	8	7	53	8	6	3	2
54	1	2	3	4	1	54	1	1	3	4
55	8	8	7	8	8	55	8	*	6	7
56	1	8	4	2	4	56	*	8	7	6
57	3	3	1	1	1	57	*	2	7	4
58	7	3	4	5	5	58	7	*	*	1
59	6	2	5	6	5	59	5	*	2	5

Δy: the difference in final moisture content between two adjacent samples; $y1$: the moisture content of withered leaves; $y2$: the moisture content after the first fixation; $y3$: the moisture content after the second fixation; $\Delta y1$: the difference in moisture content between two adjacent samples of leaves after withering; $r1$: the first fixation temperature; $\Delta r1$: the difference in the first fixation temperature between two samples.

value of CPPs of the subsequent units could be designated according to the unit moisture content design space. The final moisture content fluctuated around the target value (3%), which indicated that the control strategy was stable.

The sensory evaluation and moisture content of 10 batches in groups A and B are shown in Table 5. According to the production standard of Mingchun Tea Company, better tea quality can be achieved when the final moisture content is closer to 3%. As shown in Table 5, the average scores for the color (8.50), shape (8.25), aroma (8.35), and overall quality (8.53) of group B were higher than those of group A. In addition, the final moisture content of group B fluctuated around the target values. The RMSE and variance of the final moisture content of group A were 0.54% and 0.2294, respectively; in group B, they were 0.05% and 0.0029, respectively. The final moisture content of group B was more stable and was closer to the target value. The results indicated that in-line and precise control of moisture content during tea processing could be achieved, and the tea quality could be more stable and improved with the proposed method.

IV. CONCLUSION

In this work, a novel approach was established for in-line and precise control of moisture content in green tea processing. Multivariate models for predicting moisture content in a single unit and the whole production line of tea processing were established. LSSVM performed best in the first fixation, second fixation, and drying units, with RMSEs of 1.34%, 0.86%, and 0.13%, respectively. Moreover, RBFNN-LSSVM performed best in the whole production line, with an RMSE of 0.03%. The guidance of CPPs was determined with rough set and design space methods. In addition, the proposed approach was verified in a practical tea production line. For the final moisture content of tea, an RMSE of 0.05% and a variance of 0.0029 were achieved with specified CPPs, which are significantly better than those of the conventional method. This work provided the first proof-of-principal data for in-line and precise control of moisture content in a tea production line. These data may provide an approach for accelerating the automation of preliminary processing of green tea.

APPENDIX

Table 6, Table 7, Table 8 and Table 9 are shown in the submitted appendix table.

ACKNOWLEDGMENT

The authors thank Hubei Mingchun Tea Company for providing tea samples and experimental equipment, and related senior tea tasters in Mingchun Tea Company for their sensory evaluation.

REFERENCES

[1] M. S. Butt and M. T. Sultan, "Green tea: Nature's defense against malignancies," *Crit. Rev. Food Sci. Nutrition*, vol. 49, no. 5, pp. 463–473, May 2009.

[2] V. Stangl, H. Dreger, K. Stangl, and M. Lorenz, "Molecular targets of tea polyphenols in the cardiovascular system," *Cardiovascular Res.*, vol. 73, no. 2, pp. 348–358, Jan. 2007.

[3] M. Hall, "Near-infrared reflectance prediction of quality, theaflavin content and moisture content of black tea," *Food Chem.*, vol. 27, no. 1, pp. 61–75, 1988.

[4] W. S. Botheju, K. S. P. Amarathunge, and I. S. B. Abeysinghe, "Thin layer drying characteristics of fresh tea leaves," *J. Nat. Sci. Found. Sri Lanka*, vol. 39, no. 1, p. 61, 2011.

[5] R. Vargas and A. Vecchietti, "Influence of raw material moisture on the synthesis of black tea production process," *J. Food Eng.*, vol. 173, pp. 76–84, Mar. 2016.

[6] M. R. Ullah, N. Gogoi, and D. Baruah, "The effect of withering on fermentation of tea leaf and development of liquor characters of black teas," *J. Sci. Food Agricult.*, vol. 35, no. 10, pp. 1142–1147, Oct. 1984.

[7] Y. Wang, P.-C. Zheng, P.-P. Liu, X.-W. Song, F. Guo, Y.-Y. Li, D.-J. Ni, and C.-J. Jiang, "Novel insight into the role of withering process in characteristic flavor formation of teas using transcriptome analysis and metabolite profiling," *Food Chem.*, vol. 272, pp. 313–322, Jan. 2019.

[8] P. C. Panchariya, D. Popovic, and A. L. Sharma, "Thin-layer modelling of black tea drying process," *J. Food Eng.*, vol. 52, no. 4, pp. 349–357, May 2002.

[9] H. Zhu, F. Liu, Y. Ye, L. Chen, J. Liu, A. Gui, J. Zhang, and C. Dong, "Application of machine learning algorithms in quality assurance of fermentation process of black tea- based on electrical properties," *J. Food Eng.*, vol. 263, pp. 165–172, Dec. 2019.

[10] J. Sun, X. Zhou, Y. Hu, X. Wu, X. Zhang, and P. Wang, "Visualizing distribution of moisture content in tea leaves using optimization algorithms and NIR hyperspectral imaging," *Comput. Electron. Agricult.*, vol. 160, pp. 153–159, May 2019.

[11] Y. Wei, F. Wu, J. Xu, J. Sha, Z. Zhao, Y. He, and X. Li, "Visual detection of the moisture content of tea leaves with hyperspectral imaging technology," *J. Food Eng.*, vol. 248, pp. 89–96, May 2019.

[12] S. Deng, Y. Xu, X. Li, and Y. He, "Moisture content prediction in tealeaf with near infrared hyperspectral imaging," *Comput. Electron. Agricult.*, vol. 118, pp. 38–46, Oct. 2015.

[13] A. Taheri-Garavand, V. Meda, and L. Naderloo, "Artificial neural Network–Genetic algorithm modeling for moisture content prediction of savory leaves drying process in different drying conditions," *Eng. Agricult., Environ. Food*, vol. 11, no. 4, pp. 232–238, Oct. 2018.

[14] Y. Huang, H. Zhou, T. Xiong, and Y. Zhao, "The research and development on Pu'er tea fermentation automatic control technology and key equipment," in *Proc. 3rd Int. Conf. Comput. Sci. Inf. Technol.*, Jul. 2010, pp. 555–559.

[15] Z.-G. Ma, Y.-Z. Huang, D.-P. Liu, H.-J. Zhou, and T.-Q. Xiong, "Lift-off type Pu'er tea fermentation pot's design and automatic control research," in *Proc. 3rd Int. Conf. Adv. Comput. Theory Eng. (ICACTE)*, Aug. 2010, pp. 566–570.

[16] D. Gong, Y. Zhou, F. Xu, Q. Ling, and L. Rong, "Design of automatic drying machine for white tea based on ADAMS," in *Proc. Int. Conf. Sens., Diagnostics, Prognostics, Control (SDPC)*, Aug. 2018, pp. 380–382.

[17] Z. Zheng, J. Dong, and Z. Chen, "Process control for the tea baking," in *Proc. 14th Int. Conf. Mechatronics Mach. Vis. Pract.*, Dec. 2007, pp. 18–22.

[18] M. Javanmard, K. A. Abbas, and F. Arvin, "A microcontroller-based monitoring system for batch tea dryer," *J. Agricult. Sci.*, vol. 1, no. 2, p. 101, 2009.

[19] G. Bel and X. Fageda, "Factors explaining local privatization: A meta-regression analysis," *Public Choice*, vol. 139, nos. 1–2, pp. 105–119, Apr. 2009.

[20] J. Moody and C. J. Darken, "Fast learning in networks of locally-tuned processing units," *Neural Comput.*, vol. 1, no. 2, pp. 281–294, Jun. 1989.

[21] V. Vapnik, "Pattern recognition using generalized portrait method," *Automat. Remote Control*, vol. 24, no. 6, pp. 774–780, Jan. 1963.

[22] Z. Pawlak, "Rough sets," *Int. J. Comput. Inf. Sci.*, vol. 11, no. 5, pp. 341–356, 1982.

[23] Q. Hu, L. Zhang, D. Zhang, W. Pan, S. An, and W. Pedrycz, "Measuring relevance between discrete and continuous features based on neighborhood mutual information," *Expert Syst. Appl.*, vol. 38, no. 9, pp. 10737–10750, Sep. 2011.

[24] J. Ji and Z. Dongjian, "An information-based rough set approach to critical engineering factor identification," *Water Sci. Eng.*, vol. 1, no. 3, pp. 73–82, Sep. 2008.

[25] L. Cavin, U. Fischer, A. Mošať, and K. Hungerbühler, "Batch process optimization in a multipurpose plant using Tabu Search with a design-space diversification," *Comput. Chem. Eng.*, vol. 29, no. 8, pp. 1770–1786, Jul. 2005.

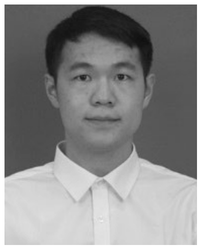
[26] M. Gries, "Methods for evaluating and covering the design space during early design development," *Integr., VLSI J.*, vol. 38, no. 2, pp. 131–183, Dec. 2004.

[27] Y.-K. Hong, L. Huang, W. B. Yoon, F. Liu, and J. Tang, "Mathematical modeling and Monte Carlo simulation of thermal inactivation of non-proteolytic clostridium botulinum spores during continuous microwave-assisted pasteurization," *J. Food Eng.*, vol. 190, pp. 61–71, Dec. 2016.

[28] D. E. Bruno, E. Barca, R. M. Goncalves, H. A. de Araujo Queiroz, L. Berardi, and G. Passarella, "Linear and evolutionary polynomial regression models to forecast coastal dynamics: Comparison and reliability assessment," *Geomorphology*, vol. 300, pp. 128–140, Jan. 2018.

[29] Y. Meng, S. Yu, J. Zhang, J. Qin, Z. Dong, G. Lu, and H. Pang, "Hybrid modeling based on mechanistic and data-driven approaches for cane sugar crystallization," *J. Food Eng.*, vol. 257, pp. 44–55, Sep. 2019.

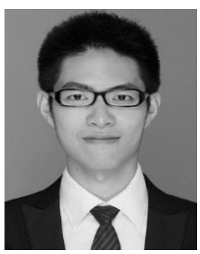
ZHANGFENG ZHAO received the B.S. and M.S. degrees from Huazhong Agricultural University, in 1995 and 1998, respectively, and the Ph.D. degree from the Zhejiang University of Technology, in 2011. He is currently an Associate Professor with the Zhejiang University of Technology and the Deputy Director of the Institute of Mechatronic Engineering. He has participated in several national and provincial research and development programs. He has published three books and more than 30 articles. His main research directions are in mechatronics and computer advanced control technology. He received the National Science and Technology Progress Award, in 2004.



LUN CHEN was born in Hubei, China, in 1995. He received the B.S. degree from Zhejiang Sci-Tech University, in 2017. He is currently pursuing the B.S. degree with the Zhejiang University of Technology. His main research interest includes electromechanical control of agricultural machinery.

GUODA CHEN received the Ph.D. degree from the Harbin Institute of Technology, in 2015. From 2012 to 2013, he was a Visiting Ph.D. Student with the Department of Mechanical Engineering, Northwestern University, and a Visiting Scholar with the Department of Mechanical Engineering, National University of Singapore, in 2018. He is currently a Lecturer with the Zhejiang University of Technology, China, where he joined as the Faculty, in 2015. His research interests include intelligent control, precision manufacturing, robotics, and engineering optimization. He was the winner of the Talent Project of Zhejiang Association for Science and Technology, in 2018.

WEIYUE XIE was born in Zhejiang, China, in 1996. She received the B.S. degree from the Zhejiang University of Technology, in 2019, where she is currently pursuing the B.S. degree. Her research interest includes the application of optical detection technology in agriculture.



JIYU PENG received the B.S. degree from the Zhejiang University of Technology, in 2013, and the Ph.D. degree from Zhejiang University, in 2018. He is currently a Research Assistant Professor with the Zhejiang University of Technology. He has published more than ten SCI/EI articles in international authoritative journals by first or correspondent authors. His main research interests are in optical detection technology and data processing.