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An Interval Type-2 Fuzzy Controller Based on Data-Driven Parameters Extraction for Cement Calciner Process

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ABSTRACT The stable control of the calciner plant is vital for the clinker quality and energy consumption in the cement calcination process. However, traditional calciner control strategies cannot efficiently deal with complicated characteristics, such as the changes in the material component, process disturbances and uncertainty, and meanwhile cannot obtain knowledge from data. For these challenges, an intelligent control strategy based on an interval type-2 fuzzy logic controller (IT2FLC) is proposed by making full use of process data in this work. The feedback IT2FLC combines with feedforward IT2FLC, taking into account various disturbances. An improved interval type-2 fuzzy C-means (IT2FCM) clustering algorithm is used to extract membership functions and rules, taking into account process uncertainty. Finally, the proposed control strategy is applied to control a calciner simulation process with practical data. The results show that the proposed strategy has better performance than the type-1 fuzzy logic controller (T1FLC) and can better meet the demand for real-life applications.

INDEX TERMS Calciner process control, interval type-2 fuzzy C-means cluster, interval type-2 fuzzy controller.

I. INTRODUCTION

A calciner is a complicated system that is employed in the cement calcination process. The stable control of the calciner device is vital because it is associated with fuel consumption, pollutant emission, and clinker quality [1]. The applications of the commercial software systems show that the advanced control of the calciner is beneficial for energy savings and quality improvements [2]. However, the stable control of the calciner process has proved to be a challenging task due to the complexity of the process characteristics, uncertainties in coal kinetics, and inherent process uncertainties. For this challenging task, the traditional strategy based on a single controller, such as a proportional-integral-derivative (PID) controller, cannot cope with the complicated process control, and therefore their performance may be sub-optimal. For this problem, this study proposes an intelligent control strategy by making full use of process data information for the cement calciner device, considering the complicated characteristics.

The existed researches related to the calciner process control are focused on fuzzy control, model prediction control (MPC), and model reference adaptive control (MRAC) with similar variables. For the applications of fuzzy control, Qiao and Chai [3] proposed an intelligent temperature switching control strategy, which consists of three parts, namely, a regular fuzzy-based controller, an abnormal controller, and a switching method to adjust abnormal conditions and increase the decomposition rate. Lu *et al.* [4] used a fuzzy-PI controller combined with expert operation experience, which has a high dynamic response and accuracy for process control. For the application of MPC, Feng *et al.* [5] designed a controller combined with the model prediction method and fuzzy control for the lime kiln. Moreover, a sliding mode control method using a regression model is utilized to achieve control over the calciner outlet temperature [6]. However, the cited control researches using a linear controller did not

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efficiently consider the influence of process disturbances and uncertainty. Meanwhile, the MPC and MRAC controllers cannot make full use of process data information and simulate the operator rules. The fuzzy control is an efficient method with rules-based regulation, which comes from expert knowledge or process data. However, the traditional fuzzy strategy with crisp fuzzy has limitations when handling systems under uncertainty, especially for the calciner plant. To overcome this problem, more attention has been given to the improved fuzzy control strategy [7], [8], such as the adaptive fuzzy tolerant control [9], [10] and interval type-2 fuzzy logic controller (IT2FLC) with interval membership functions [11], [12]. The researches show that the IT2FLC with the upper membership functions (UMFs) and lower membership functions (LMFs) has more robustness in terms of uncertainties than the previous strategies, such as type-1 fuzzy logic controller (T1FLC) [13]–[16]. In the real-world applications of IT2FLC, Tan [17] proposed an improved type-2 fuzzy logic controller for liquid level control with less computational cost. Lin *et al.* [18] used an adaptive IT2FLC for a planar two-link manipulator. The IT2FLC is used to attain the desired position and direction for a mobile two-wheeled inverted pendulum [19]. Dirik used IT2FLC system to plan robot path under the uncertain environment [20]. Moreover, IT2FLC was used to control a reverse flow reactor considering process high nonlinearity and uncertainty [21]. In these applications, IT2FLC can efficiently overcome the process uncertainty and achieve accurate decisions with better performance.

The design of a suitable IT2FLC is critical and contains many aspects, including the shape of membership functions (MFs), the number of MFs, the type of rules, and the type-reduction algorithms [22], [23]. For these aspects, MFs and fuzzy rules are vital for the performance and structure of the controller. The design methods of the fuzzy-rule-based system are composed of two parts, the expert-driven and data-driven approaches, which obtain controller parameters from expert knowledge and process data, respectively. Importantly, with the advances in data storage technology, increasing data for different variables are stored in the real-time database of the distributed control system (DCS) in many factories. Therefore, to make full use of process data, further research may focus more on the data-driven approach due to the accurate and robust performance. Meanwhile, knowledge discovery with data-driven clustering methods can help engineers find various states with little detailed knowledge of the process [24]. The controller formation methods existed in recent reaesrches are used to extract fuzzy rules and MFs with uncertainty. To obtain the fuzzy rules, balancing the tradeoff between model accuracy and model complexity is an important step to maintain the overall performance. Setnes [25] used the orthogonal least squares method to remove clusters. Meanwhile, the Gustafson-Kessel (GK) algorithm with an adaptive distance measure is used to extract rules. A strategy called precise and fast fuzzy modeling method was proposed to obtain the process rule bases [26]. To obtain the MFs, Cao proposed the MFs formation method based on an improved density clustering algorithm [27]. To extract the uncertain information from data, a clustering method with the type-2 fuzzy criterion is used to get uncertain cluster bounds, which can improve robustness and promote enhanced model performance [28], [29]. Moreover, other fuzzy parameters with dynamic adaptation are essential for algorithm performance. Many optimization algorithms are proposed to adjust parameters, such as bee colony optimization [30] and gravitational search algorithm [31]. Therefore, considering process uncertainty, the data clustering is a useful method to extract fuzzy rules and obtain MFs based on the above-mentioned researches, and the advantage is that it can extract more information from practical data and improve the reliability.

The primary objective of this study is to design a new control strategy for the complicated characteristics by using process data. For the cement calcination process, this study proposes an intelligent control structure based on IT2FLC that is able to deal with process uncertainty, disturbances, and achieve precise control. The main contributions of the proposed works involve three parts, including the control strategy design and controller formation. In terms of control strategy design, an intelligent control strategy including a feedback IT2FLC and a feedforward IT2FLC is developed to control the C1 outlet temperature inside the calciner. The feedback controller is the primary adjuster for precise temperature control, and the feedforward controller is to overcome process disturbances caused by tertiary, tail, and inlet raw meal temperature. In terms of controller formation, the IT2FLC has better robustness with interval MFs. In order to obtain the MFs and fuzzy rules for IT2FLC, an improved IT2FCM algorithm is used to extract the critical parameters by making full use of process data. Finally, the proposed control strategy is tested on a calciner mechanism model with real cement data, which can simulate the real-world application scenario. The control results show that the proposed strategy has better control performances than T1FLC, and the general control framework, considering process uncertainty and disturbances, can meet the demand for practical applications not only for the calciner but also for other complicated processes.

The rest of this paper is structured as follows. Section II describes the calcination process and analyzes the calciner process characteristics. IT2FLC and IT2FCM are introduced in Section III. Section VI proposes an intelligent control strategy based on the IT2FLC and IT2FCM, While section V provides the results and discussions of the proposed control strategies. Finally, conclusions and future works are presented in Section IV.

II. ANALYSIS OF CEMENT CALCINER PROCESS

A. DESCRIPTION OF CALCINATION PROCESS

Fig.1 depicts the primary process of the clinker calcination, which is composed of four main parts: cyclone preheater, calciner, rotary kiln, and grate cooler. In the whole process, material and gas move in opposite directions to achieve full heat exchange. The solid and dotted lines shown in Fig.1

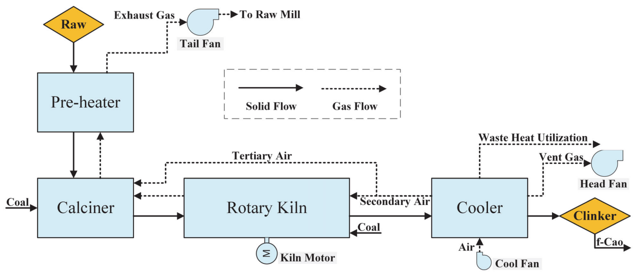

FIGURE 1. Schematics of the clinker calcination process.

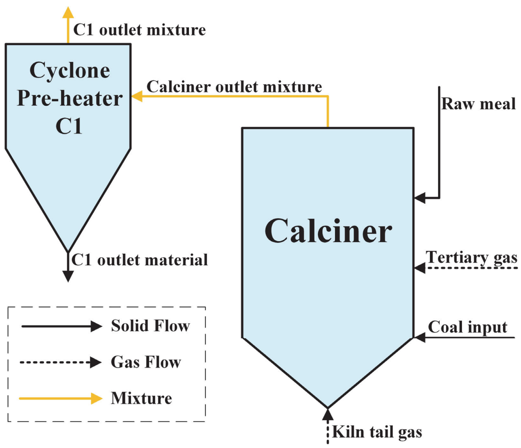

FIGURE 2. Schematics of cyclone pre-heater and calciner.

represent the moving directions of different materials. First, the raw meal enters the cyclone from the material bank. The primary function of the cyclone preheater is to achieve gas-solid heat exchange and gas-solid separation. The raw meal in cyclone preheater is heated to approximately 800°C before placing it in the calciner by high-temperature exhaust gas. The role of the calciner involves fuel combustion and the CaCO3 decomposition. Therefore, the main reactions that are taking place in the calciner are pulverized coal combustion and decomposition of CaCO3. The material in calciner is then heated to approximately 870°C before placing inside the rotary kiln, and it moves slowly during the time the clinker reaction occurs. The main products in the kiln are 2CaO·SiO2 (C2S) and 3CaO·SiO2 (C3S), which are the main components of cement clinker. The stability of the burning zone temperature is vital for the improved calcination working conditions and the clinker quality indicators, such as free calcium oxide (f-CaO) [32]. As the last step, the grate cooler recycles the heat from the high-temperature clinker to improve energy efficiency, since the heat prepares the calciner and kiln for the coal combustion and heat exchange between the material and gas.

Fig.2 displays the political process, including the cyclone preheater C1 and the calciner. The different flows include the solid flow, gas flow, and mixture flow. In terms of solid flow, the primary inputs include the raw meal and coal, whereas the main output is the C1 outlet material. In terms of gas flow, the primary inputs involve tertiary gas and kiln gas, whereas the main output is the C1 outlet gas. As the solid input flow, the raw meal is heated to approximately 800°C before placing it inside the calciner. The primary reaction in calciner is described as follows.

$$CaCO_3 \rightarrow CaO + CO_2, C + O_2 \rightarrow CO_2 \tag{1}$$

The main reactions inside the calciner are CaCO3 decomposition and coal combustion listed as Equation (1). Meanwhile, the oxygen for coal combustion is mainly derived from the tertiary, and the component is equal to air. The reaction time and residence time in the calciner are short because the velocity of the gas flow is very rapid, and the coal in calciner is pulverized. The material and gas mixture then enters cyclone preheater C1, which is used to separate the gas and solid mixture. Then, the solid flow enters the rotary kiln with a decomposition rate of approximately 90%, and the exhaust gas exits from the top of the cyclone preheater. Importantly, the decomposition rate mainly determined by the C1 outlet solid temperature is the key indicator, which directly affects the working conditions in the calcination process. Therefore, the C1 outlet solid temperature is the key controlled variable, and the flow of the coal is the primary manipulated variable for the design of the controller. Based on the above analysis, the process characteristics are analyzed to design the control strategy in the next part.

B. ANALYSIS OF PROCESS CHARACTERISTICS

The calciner process has complicated material transportation and reaction that is nonlinear and uncertain. From the above process descriptions and analysis, the main characteristics of the calciner can be summarized as follows.

1) NONLINEAR AND RAPID REACTION

The complicated gas-solid mixture reaction that takes place in the calciner is fast with a time constant of several seconds. Therefore, the main reactions in calciner have nonlinear and no time-delay characteristics.

2) SIGNIFICANT UNCERTAINTY AND VARIOUS DISTURBANCES

The cement calciner suffers from uncertainty and disturbances caused by the gas-solid environment, large noise, and instrument failure, including high temperature, as well as the tertiary, tail, and inlet raw meal temperature.

3) PRECISE CONTROL REQUIREMENT

The control requirement for the calciner outlet temperature is that the controller achieves stable operation with minimal errors, so it will be able to maintain the decomposition rate of the raw material. Therefore, the stable and precise control of the outlet temperature is the basis of the excellent working conditions in the calcination process, especially for rotary kiln.

Therefore, the control of the calciner device proves to be a challenging task with the above-mentioned characteristics. Importantly, the calciner problems with these characteristics

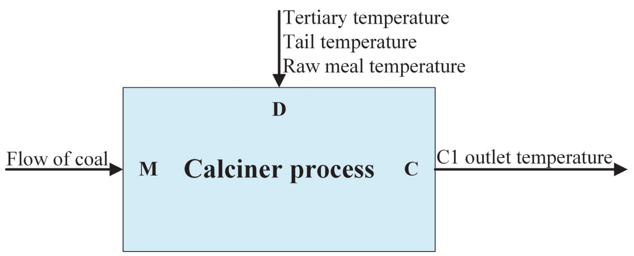

FIGURE 3. Control design of main process variables (C: Controlled variable, M: Manipulated variable, D: Disturbance variables).

can be treated as a general control problem compared with different transfer functions and state-space models. To deal with this problem, an intelligent control strategy based on the above characteristics is designed. Firstly, the feedback controller, combined with a feedforward controller, can achieve precise control and deal with the disturbance. Meanwhile, the IT2FLC can efficiently handle the uncertainty based on the interval MFs and nonlinearity based on the complicated MFs and rules. The first step in designing the intelligent control strategy is choosing the proper process variables, including the controlled variables, manipulated variables, and disturbance variables.

C. DESIGN OF PROCESS VARIABLES

From the analysis of the calcination process, the variables are separated from the controlled, manipulated, and disturbance variables based on the requirements of the control strategy. The primary variable is the controlled variables corresponding to the critical process parameters. Meanwhile, the manipulated variables represent the actuators in the control loops to control the critical process parameters. Fig.3 depicts the principal process variables for the control design of the calciner process in this study. For the controlled variable, the C1 outlet temperature (°C) has a direct impact on the decomposition rate of $CaCO3$ and product quality. The precise control of the C1 outlet is also vital in ensuring stable working conditions in the rotary kiln. Corresponding to the controlled variable, the manipulated variable for this process is the flow of coal (t/h) in the calciner. As depicted in Fig.3, the control strategy will deal with three kinds of disturbances, including tertiary temperature (°C), tail temperature (°C), and raw meal temperature (°C).

III. PRELIMINARIES

The interval type-2 fuzzy logic control and interval type-2 fuzzy cluster fuzzy C-means clustering algorithm will be introduced in this section.

A. INTERVAL TYPE-2 FUZZY CONTROLLER

Fuzzy set theory has been used in many fields, such as automatic control, signal processing, and decision making. Furthermore, the application of fuzzy control based on fuzzy set theory has been implemented and tested in many complex dynamic systems. The advantage of fuzzy control is that it does not require a complex mathematical model, and the fuzzy rules can be formulated from expert experience.

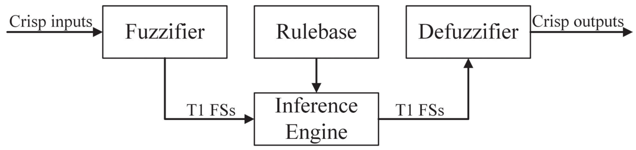

FIGURE 4. Structure of the type-1 fuzzy logic system.

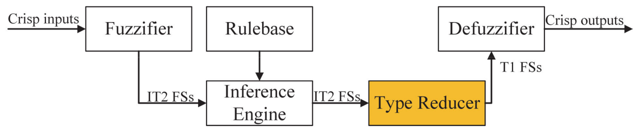

FIGURE 5. Structure of interval type-2 fuzzy logic system.

Fig.4 depicts a traditional structure of a type-1 fuzzy logic system, and the main components include the fuzzification, inference, rule base, and defuzzification modules. Importantly, the values of input and output variables for traditional fuzzy logic are crisp. Many practical applications with Mamdani fuzzy controllers, Takagi-Sugeno fuzzy controllers, and adaptive and predictive control system can be found in [33], for further reference. However, the T1FLC with crisp logic cannot efficiently cope with the uncertain process.

To deal with uncertainty, the interval type-2 fuzzy set (IT2FS) theory is proposed. In the last couple of years, there have been many types of research focused on IT2FLC. The schematics of the IT2FLC is presented in Fig.5. Moreover, Fig.4 and Fig.5 reveal that the main differences in IT2FLC compared with the traditional T1FLC is the MFs and type-reducer, which occur before the defuzzification module. The MFs of an IT2FLS is considered an interval, which includes upper membership function (UMF) and lower membership function (LMF). Meanwhile, the type-reducer is an essential part of converting IT2FLS to T1FLS to obtain the optimal output, which directly affects the performance of the control algorithm. An IT2FLC can effectively cope with process uncertainties compared with T1FLC [34]. Furthermore, since IT2FLC can include more information, it will be able to reduce the number of rules because the footprint of uncertainty (FOU) can present uncertainties. The experimental result shows that IT2FLC obtains a smoother control surface than that of T1FLC is highly adaptable and can design a complicated input-output relationship [35].

A T1FS X, as given in Equation (2), comprises a domain D_X together with MF $\mu_X : D_X \to [0, 1]$.

$$X = \int_{D_X} \frac{\mu_X}{x} \tag{2}$$

where $\int$ represents the collection of all points $x \in D_X$ with associated MF $\mu_X(x)$.

An IT2FS $\bar{X}$, as given in Equation (3), is defined by its MF $\mu_{\bar{X}}(x, u)$.

$$\bar{X} = \int_{x\in D_{\bar{X}}} \int_{u\in J_x \subseteq [0,1]} \frac{\mu_{\bar{X}}(x, u)}{x, u} = \int_{x\in D_{\bar{X}}} [\int_{u\in J_x \subseteq [0,1]} 1/u] \tag{3}$$

where x is the primary variable. $u \in [0, 1]$, is the secondary variable and has the domain $J_x \in [0, 1]$ at all $x \in D_{\tilde{X}}$. J_x is the support of secondary MF. For IT2FS, the value of $\mu_{\tilde{X}}(x, u)$, which represents the second grade of $\tilde{X}$, is 1.

The control logic for IT2FLC is proposed as follows after considering that the rule base of an IT2FLC is composed of N rules.

$$\bar{R}^n : IF\ x_1\ is\ \bar{X}_1^n\ and \ldots and\ x_i\ is\ \bar{X}_i^n, \quad THEN\ y\ is\ Y^n n = 1 \sim N$$

where $\bar{X}_i^n (i = 1 \sim I; n = 1 \sim N)$ and I is the number of input variables. $Y^n = [\underline{y}^n, \bar{y}^n]$ is an interval output, and N is the number of interval output. For an input vector $x' = (x_1', x_2', \ldots, x_I')$, typical calculations in an IT2FLC based on Fig.5 involve the four steps.

(1) Compute the membership interval of x_i' on each X_i^n, $[\mu_{\underline{X}_i^n}(x_i'), \mu_{\bar{X}_i^n}(x_i')]$, $i = 1 \sim I; n = 1 \sim N$, where I and N are the number of input variables and output variables, respectively.

(2) Calculate the interval of the n th rule using a product $F^n(x')$

$$\begin{aligned} F^n(x') &= \left[\mu_{\underline{X}_1^n}(x_1') \times \ldots \times \mu_{\underline{X}_I^n}(x_I'), \mu_{\bar{X}_1^n}(x_1') \times \ldots \times \mu_{\bar{X}_I^n}(x_I')\right] \\ &= \left[\underline{f}^n, \bar{f}^n\right] \end{aligned} \tag{4}$$

(3) Based on the results, execute a type-reducer algorithm to convert IT2FLS to T1FLS.

$$\begin{aligned} y_l &= min \frac{\sum_{n=1}^{k} \bar{f}^n \underline{y}^n + \sum_{n=k+1}^{k} \underline{f}^n \underline{y}^n}{\sum_{n=1}^{k} \bar{f}^n + \sum_{n=k+1}^{k} \underline{f}^n} \\ &= \frac{\sum_{n=1}^{L} \bar{f}^n \underline{y}^n + \sum_{n=L+1}^{N} \underline{f}^n \underline{y}^n}{\sum_{n=1}^{L} \bar{f}^n + \sum_{n=L+1}^{N} \underline{f}^n} \end{aligned} \tag{5}$$

$$\begin{aligned} y_r &= max \frac{\sum_{n=1}^{k} \underline{f}^n \bar{y}^n + \sum_{n=k+1}^{k} \bar{f}^n \bar{y}^n}{\sum_{n=1}^{k} \underline{f}^n + \sum_{n=k+1}^{k} \bar{f}^n} \\ &= \frac{\sum_{n=1}^{R} \underline{f}^n \bar{y}^n + \sum_{n=R+1}^{N} \bar{f}^n \bar{y}^n}{\sum_{n=1}^{R} \underline{f}^n + \sum_{n=R+1}^{N} \bar{f}^n} \end{aligned} \tag{6}$$

where L and R are the switched points of the type-reducer algorithm. The result of y_l and y_r is vital for control performance and computing resources. In this study, several types of reducer algorithms are selected according to the performances of the control results. The details about different type-reducer algorithms are presented in the next sections.

(4) Compute the defuzzified output, the average of y_l and y_r is used to obtain the final crisp output in this study.

$$y = \frac{y_l + y_r}{2} \tag{7}$$

where y is the final output of the IT2FLC.

From every step, the main components of IT2FLC are MFs, rules, and type-reducer algorithm. Therefore, the design of the IT2FLC, including the above-mentioned component for the calcination process, is the core of this study. In the next part, the extraction of MFs and rules, different types of type-reducer algorithms would be introduced.

B. INTERVAL TYPE-2 FUZZY C-MEANS CLUSTERING ALGORITHM

The primary purpose of the clustering algorithm is to extract the key parameters form the process data using unsupervised learning. Compared with the traditional fuzzy C-means (FCM) cluster, the IT2FCM algorithm has more robustness for practical data based on the interval MFs. This proves to be necessary, primarily when representing uncertainty, IT2FCM is suitable to extract FOU, including UMFs and LMFs. Similar to the conventional cluster algorithms, the optimization problem for IT2FCM is as follows.

$$minObj\,(X, U, V) = \sum_{j=1}^{n} \sum_{i=1}^{c} (u_{ij})^m \left\| x_j - v_i \right\|^2 \tag{8}$$

where u_{ij} is the membership of input x_j and cluster center $v_i = [\underline{v}_i, \bar{v}_i]$. c is the number of cluster centers, and m is the fuzzy factor, which represents the fuzzy degree of the clustering result.

The main steps of IT2FCM are presented as follows [28].

(1) Select the clustering numbers c, the value of fuzzy factors m_1, m_2, m, a maximum number of iterations, and threshold ε. Meanwhile, initialize the clustering centers v_i.

(2) Calculate the membership u_{ij} consisted of $\bar{u}_{ij}$ and $\underline{u}_{ij}$ by the distance between the input x_j and the cluster center v_i representing d_{ij}.

$$\bar{u}_{ij} = \max\left(\frac{1}{\sum_{l=1}^{c} (d_{ij}/d_{lj})^{\frac{2}{(m_1-1)}}}, \frac{1}{\sum_{l=1}^{c} (d_{ij}/d_{lj})^{\frac{2}{(m_2-1)}}}\right) \tag{9}$$

$$\underline{u}_{ij} = \min\left(\frac{1}{\sum_{l=1}^{c} (d_{ij}/d_{lj})^{\frac{2}{(m_1-1)}}}, \frac{1}{\sum_{l=1}^{c} (d_{ij}/d_{lj})^{\frac{2}{(m_2-1)}}}\right) \tag{10}$$

where m_1 and m_2 represent the different fuzzy factors, which represent the fuzzy degree of the clustering result.

(3) Calculate the clustering center.

$$\tilde{v}_i = \frac{\sum_{j=1}^{n} (\tilde{u}_{ij})^m x_j}{\sum_{j=1}^{n} (\tilde{u}_{ij})^m} \tag{11}$$

where $\tilde{u}_{ij} = (\bar{u}_{ij} + \underline{u}_{ij})/2$. The lower value $\underline{v}_i$ and upper value $\bar{v}_i$ about centers are obtained by the iteration of the KM algorithm.

(4) Calculate the distance of the previous centers $\left\| \boldsymbol{v}' - \boldsymbol{v} \right\|$, where $\boldsymbol{v}'$ and $\boldsymbol{v}$ are the previous and current centers. If $\left\| \boldsymbol{v}' - \boldsymbol{v} \right\| \leq \varepsilon$ or a maximum number of iterations, then stop the iteration. Otherwise, return to step (2) and go on.

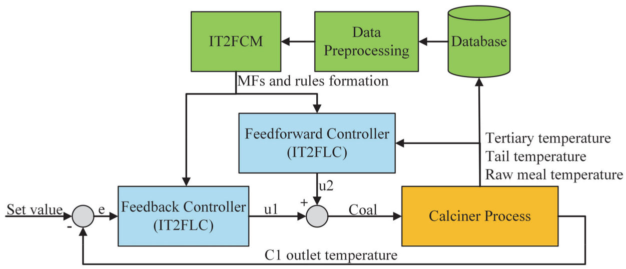

FIGURE 6. Structure of the intelligent control strategy.

(5) Calculate the width of the cluster v_i using the K-nearest neighbor, which is used to determine the MFs parameter.

$$\sigma_i = \sqrt{\left(\frac{1}{K}\right)\sum_{j=1}^{K}\left\|v_i - d_j\right\|^2} \tag{12}$$

where d_j is the jth neighbor of centers v_i. The value of K determines the size of the neighbors.

Based on the above-mentioned clustering method, the process data is divided into several classes representing the different conditions. For the single part, the UMF and LMF can be obtained by projecting the single class result. Similarly, the relationships of different classes can represent the fuzzy rules. Based on the MFs and the fuzzy rules, an intelligent IT2FLC controller can be designed to control the process.

IV. INTELLIGENT CONTROL STRATEGY FOR CALCINER

A. CONTROL STRATEGY DESIGN

Based on the above-mentioned process characteristics, an intelligent control strategy based on data-driven MFs and rules extraction is proposed in this study. Fig.6 depicts the structure of the intelligent control strategy, including controllers (blue part), data cluster analysis (green part), and the calciner process (yellow part). For the first part, a feedback controller and a feedforward controller based on IT2FLC are designed to control the calciner process with uncertainty and various disturbances. Importantly, the MFs and fuzzy rules of IT2FLC are extracted using IT2FCM combined with expert experience. The data-driven parameter extraction is a crucial part of controller formation in the proposed control strategy. For this study, the calciner process (yellow part) uses the calciner simulation model based on the mechanism with real data collected from the cement factory in this study. The details about the calciner process mechanism, which is composed of mass and energy balance equations, are presented in Section 4.3.

For the controller (blue part in Fig.6), the first part is the feedback controller, which is based on the error of the C1 outlet temperature, representing the controlled variable. The second part is the feedforward controller based on the process disturbance variables, which include the tertiary, tail, and the inlet raw meal temperatures. The error of the feedback value and the set value of C1 outlet temperature is used as feedback to the controller. Meanwhile, the disturbance variables will be treated as inputs to the feedforward controller. The manipulated variable is the flow of coal, which is added by the feedback controller and the feedforward controller output. Based on these controllers, the C1 outlet temperature can be controlled precisely to ensure the working conditions in the whole calcination process. The critical step is the designs of the IT2FLC, including MFs and fuzzy rules formation, are presented in the next part.

B. DESIGN OF IT2FLC FOR CALCINER

The design of IT2FLC (green part in Fig.6) mainly includes MFs, rules, and the type-reducer algorithm. In this work, the designs of IT2FLC focus on MFs and fuzzy rules formation using the IT2FCM algorithm. The design of IT2FLC based on the process data for calciner control is the main novelty. Meanwhile, data preprocessing is an essential step in obtaining efficient training data and is performed before the data analysis.

1) DATA PREPROCESSING

Useful data is the basis of data clustering analysis. Therefore, data preprocessing is vital for the real data collected from the factory. In this study, a three-sigmoid (3σ) method is used to delete outlier points. However, due to the time-varying characteristic, the absolute value of variables cannot reflect the actual conditions that are taking into account the influence of different working conditions. Therefore, the time difference is an efficient method for time-varying conditions, which can efficiently address the effects of drift and gradual changes [36]. Meanwhile, the control problems are focused on the relative value, not the absolute value. In this study, the time difference strategy for all variables is used to obtain the training data for the clustering operation. Moreover, the influence of different variables has an accumulated relationship. Therefore, to obtain the relationship between variables, such as the coal flow and the temperature, different variables will be accumulated by period based on the response time.

2) DESIGN OF MFS

The shape of MFs and fuzzy rules are extracted using process data clustering. In terms of data analysis method, the interval type-2 Fuzzy C-mean (IT2FCM) clustering algorithm is an efficient approach for uncertain data analysis, which can obtain interval MFs of IT2FLC. In the control strategy, the coal feeder and C1 outlet temperature are used to design the MFs of the feedback controller. Meanwhile, the tertiary, tail, and inlet raw meal temperatures are used to establish the MFs of the feedforward controller to overcome disturbances.

According to the clustering results with the centers and boundary, the MFs for IT2FLC can be developed. In this study, the functions of upper and lower MFs use the Gaussian function, which is determined by two parameters (v, σ). The standard deviation σ is fixed, and the mean value v is varied. The membership functions, including UMFs and LMFs, are

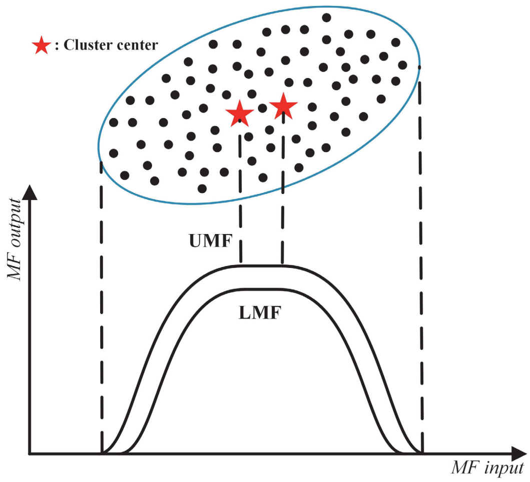

FIGURE 7. MFs formation based on the clustering results.

listed as follows.

$$UMF(x) = \begin{cases} e^{-\frac{(x-\underline{v}_i)^2}{\sigma^2}}, & x < \underline{v}_i \\ 1 & \underline{v}_i \le x \le \bar{v}_i \\ e^{-\frac{(x-\bar{v}_i)^2}{\sigma^2}}, & x > \bar{v}_i \end{cases} \tag{13}$$

$$LMF(x) = k * UMF(x) \tag{14}$$

where $k \in (0, 1]$ is a parameter of LMF, representing the degree of MFs. The different values of parameters k are used to test the control performance (tested in Section V.C). The Gaussian parameters including v_i and σ are developed by using the IT2FCM algorithm. Fig.7 depicts the design of MFs according to the one class. The centers v for UMF and LMF can be extracted for different centers. The UMF value between different centers is 1 representing the importance of centers range. For the range of class, the bounds for UMF and LMF can be obtained. For the different classes, the other MFs can be represented by using similar methods.

3) DESIGN OF RULES

The different classes based on the clustering results from real data can represent different operating habits. For the corresponding relationship, several fuzzy rules can be extracted from the different classes by obtaining the value ranges. In this control strategy, the outputs of rules are interval values representing the flow of coal (manipulated variable) in the calciner. Meanwhile, to improve the response rate of automatic control, the inputs of rules include the error and the error derivative. Therefore, the feedback controller has two inputs and one output.

4) DESIGN OF TYPE-REDUCER ALGORITHMS

The purpose of the type-reducer step is to obtain crisp results from the interval MFs. Type-reducer algorithms are vital for the performance and computational costs of IT2FLC. In the various type-reducer algorithms, the Karnik-Mendel (KM) algorithm is the most widely used algorithm [37]. Considering the computational cost and performance of KM, many type-reducer algorithms are proposed, such as Wu-Mendel Uncertainty Bound (WM) and Begain-Melek-Mendel (BMM) [38], which can improve the performance and reduce the computational costs. In this study, several type-reducer algorithms are utilized to test the performance IT2FLC in the next section.

C. DYNAMIC MECHANISM MODEL OF CALCINER PROCESS

The primary purpose of the dynamic mechanism model (yellow part in Fig.6) is to test the proposed control strategy. The efficient mechanism model combined with real data can represent the practical process for the simulation and optimization. In terms of dynamic modeling, many researchers have focused on process simulation and device design, such as the mechanism and data-driven models. In mechanism modeling, the endothermic calcination reaction mechanism was proposed to investigate the effect of temperature, decomposition pressure, and diffusion [39]. Mujumdar *et al.* [40] presented an integrated model of a cyclone preheater, calciner, rotary kiln, and grate cooler in the cement industry. The integrated simulator is converted into a software named RoCKs. Qiao and Chai [41] presented a mechanism model of a calcination process for control. Meanwhile, a parameter identification strategy based on radial basis function is applied to obtain capacities. Moreover, the process modeling software, such as ASPEN HYSYS, was used to simulate a cement plant for energy simulation [42].

Given the complexity of the real process, the following assumptions about the mechanism model are considered. Firstly, the particles of the raw meal and coal have uniform particle sizes. The gas and solid in calciner are thoroughly mixed, and the surrounding temperature is fixed in the calciner. Then, reaction, such as coal combustion and decomposition of CaCO3 cannot occur inside the cyclone preheater. Meanwhile, the gas and solid are subject to constant separation rate in the cyclone preheater.

Fig.8 provides a description of the calciner and cyclone preheater variables. The main reactions in calciner include $CaCO_3$ decomposition and coal combustion listed as Equation (1). The reaction kinetics of $CaCO_3$ decomposition (R_{raw}) and coal combustion (R_{coal}) are given in Equation (15) and (16), and the descriptions of all variables used in the mechanism model are listed in the Appendix.

$$R_{raw} = k_r exp\left(-\frac{E_r}{R\,(T_{cal}+273.15)}\right) A_{p,r} \left(\frac{P_{CO2} - P_{eq}}{P_{eq}}\right) \tag{15}$$

$$R_{coal} = k_c exp\left(-\frac{E_c}{R\,(T_{cal}+273.15)}\right) A_{p,c} P_{O2} \tag{16}$$

The CO_2 pressure (P_{CO2}) and the equal pressure (P_{eq}) inside the calciner affect the reaction rate of $CaCO_3$. From

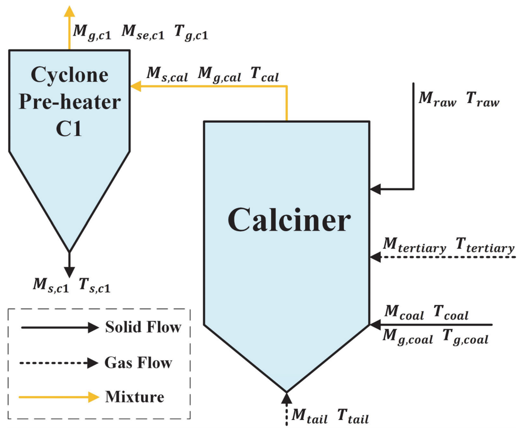

FIGURE 8. Primary variables of calciner and cyclone preheater.

reference [43], the P_{eq} is given as follow.

$$P_{eq} = 1.826 \times 10^7 exp\left(-\frac{19680}{T_{cal}}\right) \quad (17)$$

Based on the reference [40], an improved model of calciner is shown below. The mass balance of gas-solid is given in Equation (18).

$$\frac{dM_{cal}}{dt} = M_{tail} + M_{tertiary} + M_{g,coal} + M_{raw} + M_{coal} - M_{g,cal} - M_{s,cal} \quad (18)$$

where M_{Cal} is the cumulative gas-solid mixture in the calciner. The mass of tail (M_{tail}), tertiary ($M_{tertiary}$), and coal gas ($M_{g,coal}$) are the gas substance of entering calciner. M_{raw} and M_{coal} are the mass of raw meal and coal, respectively. $M_{g,cal}$ and $M_{s,cal}$ are the masses of gas and solid leaving the calciner.

Based on the mass balance, the energy balance equation for the gas-solid mixture is given as follows:

$$\frac{dQ_{cal}}{dt} = Q_{g,in} + Q_{s,in} + Q_{gcomb} + Q_{ccomb} - Q_{raw} - Q_{s,cal} - Q_{g,cal} - LOSS_{cal} \quad (19)$$

where Q_c is the energy of the cumulative gas-solid mixture. $Q_{g,in}$ and $Q_{g,cal}$ are the gas energy of entering the calciner and leaving the calciner. $Q_{s,in}$ and $Q_{s,cal}$ are the solid energy entering the calciner and leaving the calciner. The energy of coal volatile combustion (Q_{gcomb}), coal char combustion (Q_{ccomb}), and $CaCO_3$ decomposition (Q_{raw}) are given as Equation (20-22).

$$Q_{gcomb} = R_{gcomb}H_{gcomb} \quad (20)$$

$$Q_{ccomb} = R_{coal}H_{ccomb} \quad (21)$$

$$Q_{raw} = R_{raw}H_{raw} \quad (22)$$

The heat value of coal (H_{ccomb}) and $CaCO_3$ (H_{raw}) determined by material quality are fundamental parameters for calcination, which have a direct influence on the energy balance. $LOSS_{cal}$ given in Equation (23) refers to the surface heat dissipation of the calciner.

TABLE 1. Input variables of calciner mechanism model.

Variable name	Unit	Variable Type
Tertiary temperature	°C	Disturbance variable
Tail temperature	°C	Disturbance variable
Raw meal temperature	°C	Disturbance variable
C1 gas temperature	°C	Input variable
Fan speed	Rpm	Input variable
Coal flow	t/h	Manipulated variable
Raw meal flow	t/h	Input variable

$$LOSS_{cal} = \frac{2\pi H_{cal}k_L\left(T_{cal} - T_{ex}\right)}{\ln\left[\frac{R_{cal}+e}{R_{cal}}\right]} \quad (23)$$

The masses of the gas and solid are balanced in the preheater based on the assumptions. The energy balance of gas and solid substance for the cyclone can be expressed as follows.

$$\frac{dT_{g,c1}}{dt}\left[C_gM_{g,c1} + C_s\left(1-\eta\right)M_{s,c1}\right] = C_gM_{g,c1}T_{g,cal} - \left[C_gM_{g,c1} + C_s\left(1-\eta\right)M_{s,c1}\right]T_{g,c1} \quad (24)$$

$$\frac{dT_{s,c1}}{dt}C_s\eta M_{s,c1} = C_sM_{s,c1}T_{s,cal} - C_s\eta M_{s,c1}T_{s,c1} \quad (25)$$

where C_s and C_g are the capacity of the solid and gas, respectively. η is the fixed separation rate of the cyclone based on assumption. The descriptions of all variables used in the mechanism model are listed in the Appendix. Table.1 provides the input variables for the calciner mechanism model. Compared with the variables used in the control strategy, the new input variables are the fan speed and raw meal flow. The fan sped represents the air volume, and the raw meal flow reflects the load in the calcination process. Generally, the fan speed and raw meal flow are stable in general to ensure the working conditions.

V. RESULTS AND DISCUSSIONS

A. RESULTS OF THE CALCINER MODEL

In this study, process data were collected from a cement plant located in Anhui, China. Data of the input-output variables listed in Table.1 are stored in the real-time database of the DCS. The sampling time is 10s to meet the time demand for control, and the data was collected over three months to develop the controller. In order to verify the model effectiveness, the mechanism model is tested for step response as well as for a long period. The purpose of the step response is to verify the gain and correlation between the manipulated variables and the controlled variable. Meanwhile, the test performed for a long period can prove whether the dynamic model can meet the demand for real conditions, which is vital to represent the practical process.

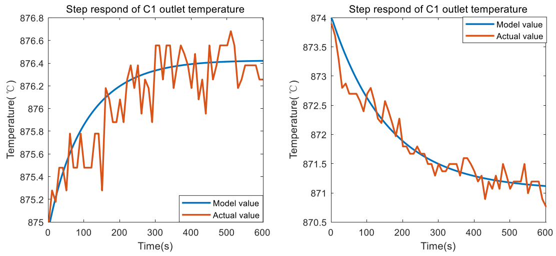

FIGURE 9. Simulation of step response in coal feeder (Coal feeder, left: +0.2 t/h, right: −0.3 t/h).

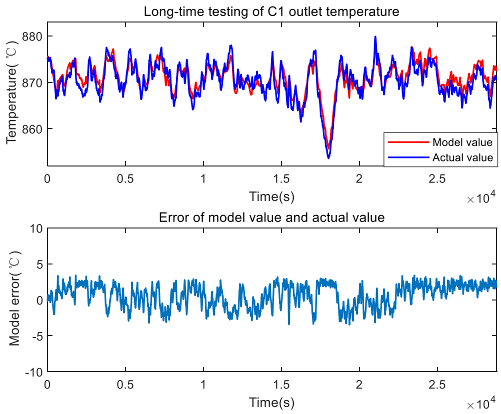

FIGURE 10. Long time result of the calciner dynamic model.

During calcination, the manipulated and controlled variables are the coal feeder and C1 outlet temperature. For the step response, we have an increase of 0.2 t/h and a decrease of 0.3 t/h for the coal feeder to obtain the variations in C1 outlet temperature, as shown in Fig.9. The other variables listed in Table.1, especially disturbance variables, stay relatively stable in the step response. From Fig.9, the stabilization time is about 600s, which is in accordance with the response time of the calciner process. Compared with the model and actual outputs, the step response reveals that the dynamic model can accurately describe the relationship between the manipulated and controlled variables.

Fig.10 presents the testing of the dynamic model over a long period (about 8 hours) considering input variables listed in Table.1. From the figure, the calciner suffers different working conditions, especially the temperature fall sharply. However, the model output (red line) is shown in the upper part of the figure compared with the actual output (blue line). The lower part of the figure shows the model error keeping in plus or minus three degrees. From the results of the step response and long period testing, it can be shown that the mechanism model with real cement data can meet the demand of representing the practical process and be used as the calciner process to test the proposed intelligent control strategy.

B. CONTROLLER DESIGN FOR CALCINER

First, a data preprocessing method is used to delete the outlier data because failure samples typically exist in the cement plant with complicated reactions. Meanwhile, to obtain the MFs and the corresponding rules from the process, it is essential to identify the relationships between variables by using data clustering methods. The data clustering method uses IT2FCM that can extract the process uncertainty of IT2FLC in this study. According to the proposed control strategy, the types of variables include two aspects: (1) the corresponding relationship between the manipulated and controlled variables for the feedback controller. (2) the corresponding relationship between the disturbance and controlled variables for the feedforward controller. The clustering results of different controllers are shown in the next section.

1) FEEDBACK CONTROLLER DESIGN

The manipulated and controlled variables are the flow of coal and C1 outlet temperature, respectively. The number of IT2FCM centers is set to four, which represent the four working cases. In the aspects of parameters selection, the fuzzy factors m, m_1, m_2 of IT2FCM are selected as 2, 2, and 3. The maximum number of iterations is 100, and the threshold ε, 10e-5.

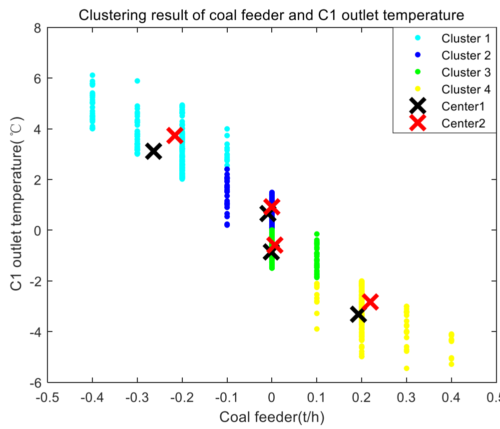

FIGURE 11. Clustering result of coal feeder and C1 outlet temperature.

Fig.11 presents the IT2FCM clustering result about the feedback controller, including four clustering classes. It can be observed that the controlled variable has a negative correlation with the manipulated variable, and the correlativity is right based on the process analysis. For instance, when the C1 outlet temperature is low, the coal feeder is added. According to the corresponding relationship shown in Fig.11, MFs and fuzzy rules can be developed. The main information about the clustering result is the centers and the bound of the different classes.

Table.2 presents the values of the two clustering centers. According to the clustering center and bounds, the UMFs and LMFs for the feedback controller can be developed based on Equation (13) and (14).

Fig.12, based on Fig.11 and Table.2, reveals the MFs of the error (upper figure) and error rate (lower figure). For the MFs of error, clustering centers 1 and 2 with clustering bounds are used to determine UMFs and LMFs based on Equation (13) and (14), respectively. The gain k of the lower MFs is set to

TABLE 2. Clustering centers of coal feeder and C1 outlet temperature.

Cluster	Center1	Center2
Cluster1	(-0.2164,3.7344)	(-0.2638,3.1151)
Cluster2	(0.0065,0.5879)	(-0.0015,0.8574)
Cluster3	(0.0001,-0.9218)	(-0.0090,-0.6564)
Cluster4	(0.2191,-2.8314)	(0.1927,-3.3161)

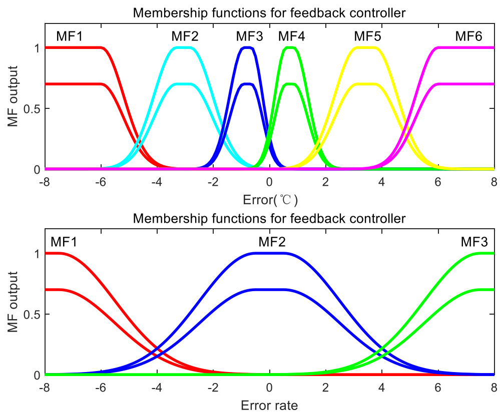

FIGURE 12. Membership functions for the feedback controller.

TABLE 3. Fuzzy rules of feedback controller.

Rule	MF1	MF2	MF3
MF1	[3, 4]	[2.4, 3.6]	[0.8, 2.4]
MF2	[2.4, 3.6]	[0.8, 2.4]	[0, 1]
MF3	[0.8, 2.4]	[0, 1]	[-1, 0]
MF4	[0, 1]	[-1, 0]	[-2.4, -0.8]
MF5	[-1, 0]	[-2.4, -0.8]	[-3.6, -2.4]
MF6	[-2.4, -0.8]	[-3.6, -2.4]	[-4, -3]

0.7 in this section, which can represent the uncertainty, and the different values of gain k are selected to test the controller performance. The MF2-MF4 are determined from the clustering results with eight centers. MF1 and MF6 with large MFs output are used to address abnormal conditions with a massive error of temperature. Table.3 lists the fuzzy rules for the feedback controller. The first line represents the error rate, and the first column represents the error. To improve the speed of controller response, the controller rules are determined by the clustering result combined with expert experience to improve the output. Following the fuzzy rules, when the error or error rate is high, the controller can increase the output. The surface of IT2FLC combined with MFs and fuzzy rules is presented in Fig.13, and it can be observed that the controller output with error and error rate corresponds with the actual analysis results.

2) FEEDFORWARD CONTROLLER DESIGN

The disturbance variables are the tertiary, tail, and raw meal temperatures. Compared with the controlled variable, the disturbance variables with leading time may cause the fluctuation of working conditions. Therefore, the feedforward controller can compensate for the impact of the disturbance

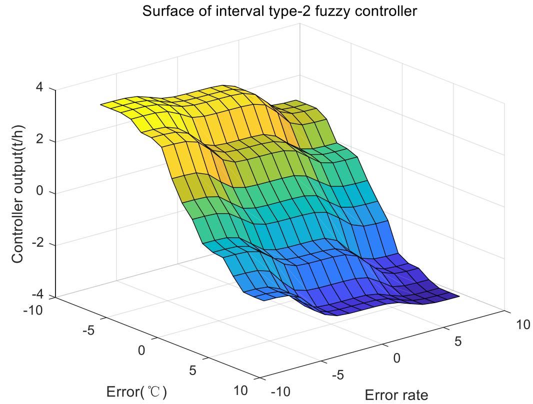

FIGURE 13. Surface of interval type-2 fuzzy logic controller.

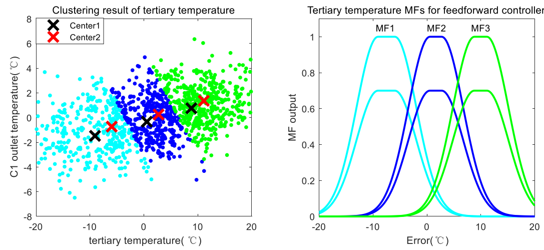

FIGURE 14. Clustering result and MFs of tertiary temperature.

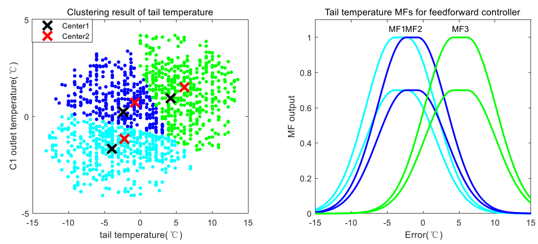

FIGURE 15. Clustering result and MFs of tail temperature.

variables in advance. The number of IT2FCM centers is set to three, which represents the three working cases. In the aspects of parameters selection, the fuzzy factor m, m_1, m_2 of IT2FCM are set as 2, 2, and 3. The maximum number of iterations is selected to be 100, and the threshold ε is 10e-5.

Fig.14-Fig.16 illustrate the clustering results and MFs for the disturbance variables. The gain k of the lower MFs is set to 0.7, which can represent the uncertainty. These disturbance variables are positively correlated with the controlled variable. According to the clustering result, the UMFs and LMFs are developed by clustering centers. Centers 1 and 2 with clustering ranges are used to establish lower and upper MFs, respectively. The number of fuzzy rules for the feedforward controller is 27. The influence between the disturbance and controlled variables is converted to the coal feeder, and the correspondence is derived from the relationship between the manipulated and controlled variables.

C. CONTROL RESULT OF IT2FLC

1) IT2FLC RESULT FOR CALCINER CONTROL

Based on the above MFs and fuzzy rules, Fig.17 depicts the result of IT2FLC for the calciner control. The set value has

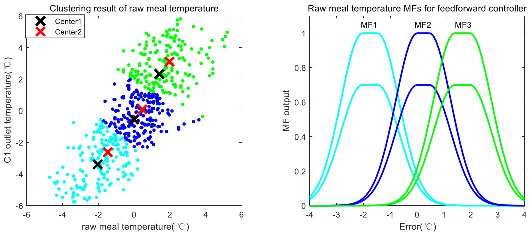

FIGURE 16. **Clustering result and MFs of raw meal temperature.**

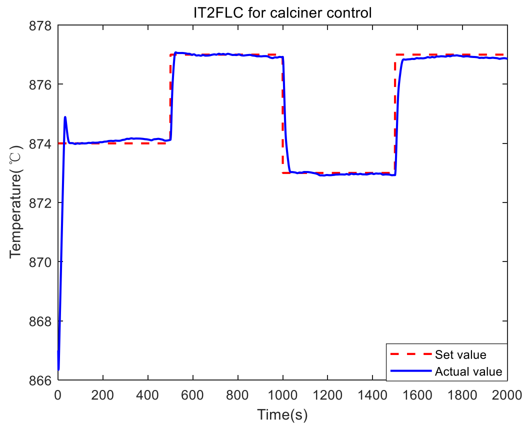

FIGURE 17. **Result of IT2FLC for calciner control.**

been set different values over a long period to test the controller performance. The changes in the set value are based on a relatively stable state. The result shows that the actual value (blue line Fig.17) can rapidly track the set value, and the controller can efficiently handle the real-world conditions. The stable control of C1 outlet temperature is the basis of ensuring the quality and working conditions.

The controller output corresponds to the coal feeder for the calciner and is presented in Fig.18. The output includes the feedback controller output (upper Fig.18) and feedforward controller output (lower Fig.18). For different set-points, the feedback controller output with a large amount of coal can rapidly respond to meet the set-points demand, and the feedforward controller output with a small amount of coal efficiently overcomes local disturbances from the changes of gas temperature. Compared with manual control, the proposed control strategy can deal with more disturbances and achieve precise control. The stable control of the calciner device is vital because it is associated with fuel consumption, pollutant emission, and clinker quality.

2) COMPARISON OF IT2FLC AND T1FLC RESULT

To compare the performance of the proposed control strategy, the T1FLC method is used to test the same calciner process. Similarly, the MFs of TIFLC are extracted by the traditional FCM cluster. Meanwhile, fuzzy rules are obtained by clustering results and expert experience. Fig.19 illustrates the surface of T1FLC. Compared with T1FLC (Fig.19), IT2FLC has a smoother response surface (Fig.13).

Fig.20 and Fig.21 provide a control comparison between IT2FLC and T1FLC in the local part. The set value of the

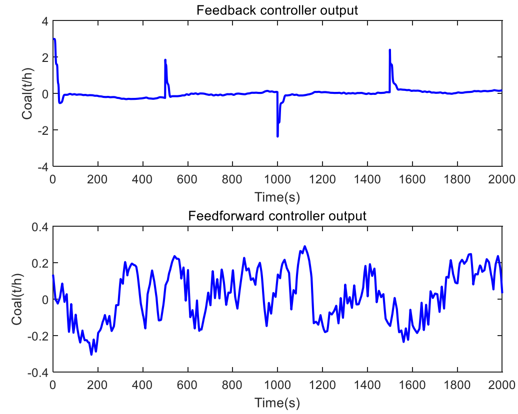

FIGURE 18. **IT2FLC output for calciner control.**

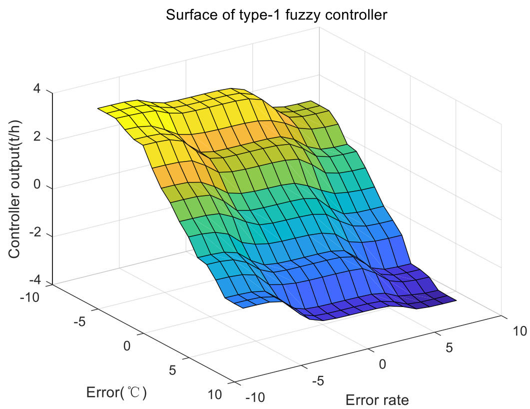

FIGURE 19. **Surface of type-1 fuzzy logic controller.**

C1 outlet temperature is set from 874 °C to 877 °C. The result shows IT2FLC has better performance with minimum deviation and rapid response, and the comparison of the two methods shows that the IT2FLC has better performance.

Fig.22 presents the result of T1FLC, whereas Fig.23 provides the controller output of T1FLC in the same condition compared with IT2FLC. IT2FLC (Fig.17), with the smoother surface, has better control results compared with those of T1FLC (Fig.22). The main reason for the smoother surface is that IT2FLC with UMFs and LMFs can consider the process uncertainty and more conditions.

To compare the control performance, two measurement indicators are employed using integral of the square of errors (ISE), as given in Equation (26), and the root mean square error (RMSE), as given in Equation (27). The smaller value of these indicators represents better control performances with a smaller error.

$$ISE = \int_0^{\infty} e^2 dt \tag{26}$$

$$RMSE = \sqrt{(1/N) \sum_{i=1}^{N} e^2} \tag{27}$$

where $\boldsymbol{e}$ is the error of set value and actual value. Table.4 provides a list of performance indicators. Based on the above-mentioned performance indicators and controller results, IT2FLC has a better performance compared with T1FLC in

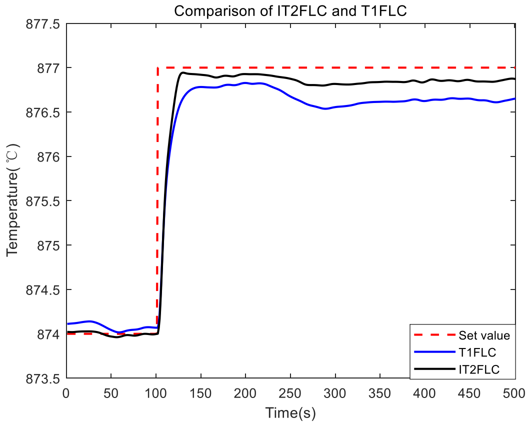

FIGURE 20. Comparison of IT2FLC and T1FLC.

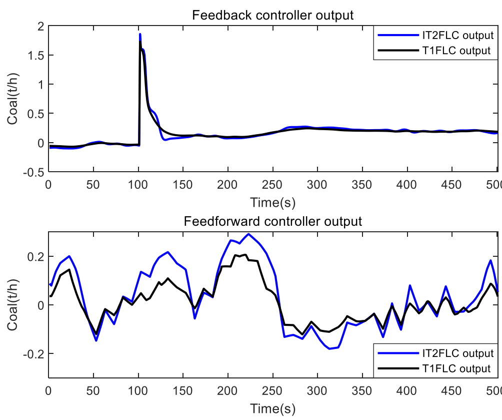

FIGURE 21. Comparison of IT2FLC and T1FLC outputs.

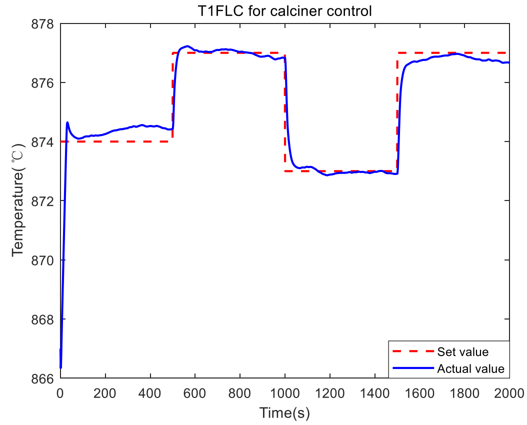

FIGURE 22. Result of type-1 fuzzy logic controller.

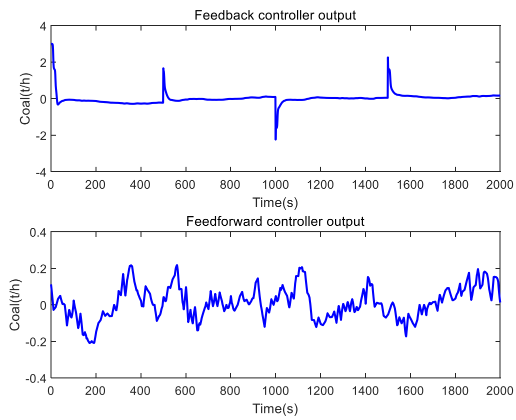

FIGURE 23. T1FLC output for calciner control.

the calciner process control. The main reason for this control result is that IT2FLC can efficiently cope with the process of uncertainty and various disturbances. Therefore, IT2FLC achieves stable operation with minimal errors to maintain the decomposition rate of the raw meal. Meanwhile, the different gain parameters of LMFs are listed in Table.4, and the results show that parameter $\boldsymbol{k} = \mathbf{0.9}$ has better performance with the minimum error.

TABLE 4. Performance indicators for different control methods.

Method	ISE	RMSE
T1FLC	991.9129	0.7041
IT2FLC($k = 0.7$)	905.9332	0.6729
IT2FLC($k = 0.8$)	903.6405	0.6720
IT2FLC($\boldsymbol{k = 0.9}$)	**902.0139**	**0.6714**

TABLE 5. Performance indicators for different type-reducer algorithms.

Method	ISE	RMSE
IT2FLC_KM	141.2297	0.5058
IT2FLC_WM	154.1139	0.5284
IT2FLC_BMM	**133.2814**	**0.4914**

D. INFLUENCE OF TYPE-REDUCER ALGORITHMS

The various type-reducer algorithms determine different computational complexities and control performances on the control result. In this work, three type-reducer algorithms, namely KM, WM, and BMM, are used to test the control performance of the calciner process. The set value of the C1 outlet temperature is set from 873 °C to 877 °C. Fig.24 presents the results, and Table.5 lists the performance indicators. According to the results, IT2FLC using the BMM algorithm shows slight performance improvement with smaller error compared with other algorithms.

E. DISCUSSIONS

The experiments are three parts, including mechanism model verification, controller formation, and IT2FLC results. The mechanism model with practical data proposes a simulation environment, which is similar to real-world devices. The data-driven clustering results are introduced to the method of controller formation. Importantly, the IT2FLC is the crucial part of the experiments, which includes the comparisons of TIFLC and different parameters. From the results presented in this work, the proposed control strategy based on IT2FLC shows better performance than T1FLC in calciner process control. The main factors affecting IT2FLC performance are summarized as follows.

(1) The key IT2FLC parameters are extracted by the IT2FCM clustering algorithm. Therefore, the process

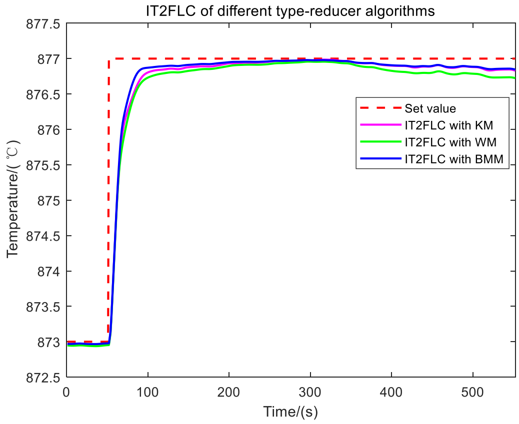

FIGURE 24. **IT2FLC of different type-reducer algorithms.**

data collected from real-world devices can be effectively used to generate MFs and fuzzy rules by using data-driven parameters extraction. According to the different working conditions, the clustering number is four, and the clustering number of feedforward controllers is three in this study. Meanwhile, different values for the gain $\boldsymbol{k}$ will represent the intensity of uncertainty, and the results show that the larger gain has better performance.

(2) To precise control, the feedforward controller plays a significant role by overcoming the disturbances in advance. In a relatively stable state, the feedback controller is the main output to regulate the set values. The strategy, combined with feedback and feedforward controllers, can be treated as a general framework for complex processes.

(3) The IT2FCM algorithm is used to develop controllers by extracting knowledge from process data, and the fuzzy factors $\boldsymbol{m}$, $\boldsymbol{m_1}$, $\boldsymbol{m_2}$ have an impact on the clustering results, including the centers and the bounds. Therefore, the proper parameters for the clustering algorithm are essential to ensure the quality of controller formation.

(4) Moreover, different type-reducer algorithms are used to test IT2FLC performances. The type-reducer algorithm determines the performance and complexity of the IT2FLC. The results show that IT2FLC with the BMM algorithm has better performances than the other type-reducer algorithms.

However, there are other challenges in industrial applications with various working conditions. It is vital to maintain the performance of the controller during abnormal operating conditions, such as plant failures. Therefore, the switching controllers, including normal and abnormal controllers, have an efficient performance on the calciner device. Meanwhile, to deal with time-varying characteristic, the on-line controller parameter extraction is essential to update the controller.

VI. CONCLUSION

This work proposes an intelligent control strategy for cement calciner process, including a feedback controller IT2FLC and a feedforward controller IT2FLC for the calciner process, considering the uncertainty and disturbances. The MFs and fuzzy rules in the IT2FLC are extracted by making full use of process data. A calciner mechanism model with real data from a cement manufacturing plant is used to test the control strategy, and the results show that the proposed IT2FLC has more robustness and better performance than T1FLC. The developed control strategy in this paper may serve as a general strategy to control the complex process with various disturbances and uncertainty. Moreover, controller formation with data-driven clustering methods can find various states and improve performance with little detailed knowledge of the process.

Future researches on the IT2FLC will continually focus on the design of MFs and fuzzy rules and efficient type-reducer algorithms. Moreover, the time-varying characteristic caused by different working conditions may be concerned. Considering the time-varying characteristic, an online data analysis strategy of designing the controller is an efficient approach to apply on the actual plants, and more data-driven methods are used to controller formation. Meanwhile, to reduce the computational resources, new type-reducer algorithms will be further studied.

APPENDIX

Symbol	**Description**
η	Cyclone separation efficiency (%)
$A_{p,c}$	Coal surface area (m^2)
$A_{p,r}$	$CaCO_3$ surface area (m^2)
C_g	Gas capacity (kJ/(kg·°C))
C_s	Solid capacity (kJ/(kg·°C))
E_c	Coal activation energy (kJ/mol)
E_r	$CaCO_3$ activation energy (kJ/mol)
e	Device thickness (m)
H_{cal}	Length of calciner (m)
H_{gcomb}	Heat value of volatile (kJ/kg)
H_{ccomb}	Heat value of coal (kJ/kg)
H_{raw}	Heat value of $CaCO_3$ (kJ/kg)
k_c	Reaction rate constant of coal (kg/(h · m^2 · Pa))
k_r	Reaction rate constant of $CaCO_3$(kg/(h·m^2))
k_L	Thermal conductivity (W/(m·°C))
$LOSS_{cal}$	Loss heat of calciner surface (kJ/h)
M_{cal}	Solid and gas mixture flow in calciner (kg/h)
$M_{g,cal}$	Leaving calciner gas flow (kg/h)
$M_{s,cal}$	Leaving calciner solid flow of (kg/h)
M_{tail}	Tail gas flow (kg/h)
$M_{tertiary}$	Tertiary gas flow (kg/h)
$M_{g,coal}$	Coal gas flow of entering calciner (kg/h)
M_{coal}	Coal flow of entering calciner (kg/h)
M_{raw}	Raw meal flow of entering calciner (kg/h)
$M_{g,c1}$	C1 cyclone gas flow (kg/h)
$M_{s,c1}$	C1 cyclone solid flow (kg/h)
P_{CO2}	CO_2 pressure in calciner (Pa)
P_{O2}	O_2 pressure in calciner (Pa)
P_{eq}	Equal pressure in calciner (Pa)

Q_{cal}	Solid and gas heat in calciner (kJ/h)
$Q_{g,in}$	Gas heat of entering calciner (kJ/h)
$Q_{s,in}$	Solid heat of entering calciner (kJ/h)
$Q_{g,cal}$	Gas heat of leaving calciner (kJ/h)
$Q_{s,cal}$	Solid heat of leaving calciner (kJ/h)
Q_{gcomb}	Coal volatile combustion heat (kJ/h)
Q_{ccomb}	Coal char combustion heat (kJ/h)
Q_{raw}	Calcium $CaCO_3$ heat (kJ/h)
R_{gcomb}	Volatile combustion reaction rate (kg/h)
R_{coal}	Coal reaction rate (kg/h)
R_{raw}	$CaCO_3$ reaction rate of (kg/h)
R	Molar gas constant (J/mol·K)
R_{cal}	Calciner diameter (m)
$T_{g,c1}$	Gas temperature in C1 cyclone (°C)
$T_{s,c1}$	Solid temperature in C1 cyclone (°C)
T_{cal}	Calciner outlet temperature (°C)
T_{ex}	Environment temperature (°C)

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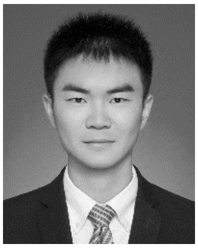

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