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RESEARCH ARTICLE

Research on Modeling and Optimization Method of Cement Clinker Calcination Process Based on EGPR Model and Steady State Detection

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ABSTRACT This paper proposes a modeling and optimization method for cement clinker calcination process based on gaussian process regression ensemble (EGPR) model and steady-state detection. Firstly, a modeling strategy based on EGPR model is proposed achieve an accurate description of the dynamic relationship between coal consumption, free calcium oxide (f-CaO) and operation status variables. Secondly, a multivariate steady-state detection method based on trend feature extraction is proposed for the characteristics of mixing steady-state data and dynamic data in the clinker calcination process, which achieves steady-state detection of the process and completes data denoising at the same time.Then, the optimization problem is solved using the bayesian optimization (BO) algorithm Finally, the production data of cement companies are used for validation. The results show that the overall modeling and optimization strategy proposed in this paper provides a feasible solution for achieving the optimization of energy consumption in cement clinker calcination process.

INDEX TERMS Cement clinker calcination, EGPR, MKRVM, VMD, steady-state detection.

I. INTRODUCTION

In recent years, the cement industry has begun to shift from a period of rapid growth to a stage of high-quality development in China, and high energy consumption has become a difficult problem that restricts the development of the cement industry and poses a serious challenge to national energy and resource conservation [1]. Cement clinker calcination is a key part of the cement production process, coal consumption and free calcium oxide (f-CaO) content as two significant production indicators in clinker calcination process [2], which are difficult to be jointly optimized by manual adjustment due to the interconstrained relationship between them, resulting in high energy consumption and serious energy waste in the cement clinker calcination process [3]. Therefore, how to achieve the lowest energy consumption while stabilizing the quality of clinker, so that the key equipment of the cement clinker calcination process can reach the optimal operation has become a pressing problem and focus of attention for the cement industry.

The prerequisite for the optimization of energy consumption is to establish a functional relationship between performance indicators and key process variables. The complications of the clinker calcination process leads to difficulties in establishing an accurate mathematical model for its optimization problem [4], [5]. To address such problems, some scholars have used numerical simulations to reconstruct the combustion field of the cement rotary kiln system as a way to establish a mechanistic model of the cement clinker calcination system [6], [7]. Due to the high number of parameters involved in the mechanistic model, it is not suitable to solve the optimization problem of clinker calcination process. Therefore, the use of data-driven methods to solve modeling problems during optimization has attracted extensive attention from researchers [8], [9]. Shi et al. [10] proposed a data-driven method for simultaneous prediction of coal

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and electricity consumption in cement production process to realize the relationship description between energy consumption and cement production process operation state variables. Zhao et al. [11] analyzed the coupling relationship between process variables and time-varying delay characteristics, on which f-CaO prediction model was developed. Li et al. [12] used flame image features combined with process data to estimate the f-CaO, and improved the performance of the model by fusing multiple sources of information. Furthermore, based on the establishment of predictive models for energy consumption and quality indicators, Hao et al. [13] performed multi-objective optimization of the performance index model based on the Jaya algorithm, but the final optimization result has the problem of finding the pareto-optimal solution. To address this problem, Shi et al. [14] combined electricity consumption and coal consumption into one optimization objective and used f-CaO content as a constraint to avoid the problem of finding the pareto optimal solution.

The above studies are based on a single model to construct the optimization objective model of cement clinker calcination process, which has certain limitations in modeling the clinker calcination process with complex and variable characteristics. Many scholars have conducted related research work to address this type of problem [15], [16]. Zhongda et al. [17] constructed a LSSVM integrated model for soft measurement modeling study of burning zone temperature in rotary kilns, which obtained better modeling results compared with a single model. The prerequisite for integrated modeling is to obtain process characteristics under different operating conditions, which can be solved by clustering the data of process variables with different characteristics. Kmeans++ clustering algorithm avoids the problem of selecting initial clustering centers [18], [19], [20]. Shindler [21] analyzed and compared numerous improved algorithms of k-means, and the results proved that k-means++ is the most successful method for defining k-means initial clustering center is the most successful method. Therefore, the k-means++ was chosen for the study of clustering analysis in the modeling process.

The selection of a suitable machine learning algorithm is also key to the modeling and optimization. GPR is a nonparametric probabilistic model based on a bayesian framework, and compared with machine learning algorithms such as SVM, GPR not only enables adaptive acquisition of hyperparameters, but also gives confidence in the prediction results [22]. Wang et al. [23] compared the predictive modeling effectiveness of six machine learning algorithms, and the results showed that the GPR model exhibits the best predictive performance, which validates the superiority of GPR in regression modeling. The nature of modeling is a black-box function estimation, and bayesian algorithms are very good at dealing with black-box function estimation and global optimization problems [24]. Yamakage and Kaneko [25] analyzed and discussed the effectiveness of bayesian algorithm in the parameter optimization of various soft measurement models, and the results demonstrated the advantages of bayesian optimization algorithm in parameter search and global optimization. Based on the above analysis, GPR and bayesian algorithm were selected for the modeling and optimization study in this paper.

In addition, the actual cement clinker calcination process is in an alternating dynamic and steady-state mode of operation, where steady-state data and dynamic data exist mixed with each other, and modeling with steady-state working condition data can accurately reflect the changing nonlinear relationship between variables. Therefore, steady-state condition detection is of great significance for the optimization of energy consumption in clinker calcination process, which has attracted wide attention from researchers [26]. The essence of the steady state is a signal trend, and the trend feature can be extracted by signal processing to realize the steady state detection of the system [27]. Lu et al. [28] combined empirical modal decomposition (EMD) and least squares method to extract and identify the trend of burning zone temperature, which avoids the problem of selecting the basis function and decomposition layer compared with wavelet transform method. However, the EMD method suffers from the problem of modal mixing when decomposing the signal [29]. Different methods have been developed to avoid this problem, such as integrated EEMD [30] and CEEMD [31]. VMD is a non-recursive variational mode signal decomposition method that can well suppress the modal confounding phenomenon in EMD decomposition [32], [33], [34]. Ren et al. [35] decomposed and reconstructed the original data based on the VMD method to eliminate noise, maximized the retention of the original data features, and performed regression modeling based on the reconstructed data to achieve accurate prediction of key variables. In addition, for the reconstructed signal trend terms, the trend identification results can be given based on the fitting function. For example, Lu et al. [36] characterized the variation of the trend by finding the first-order derivative of the fitting function, and then achieved the steady-state detection of the burning zone temperature.

In this paper, firstly, a multivariate steady-state detection method based on trend feature extraction is proposed for the characteristics of intermixing steady-state and dynamic data in clinker calcination process data. By combining VMD, SE and least squares fitting to achieve trend feature extraction of process variables, the amount of information characterizing trend changes is used to construct steady-state test indexes, and appropriate thresholds are determined for steady-state judgment. Then,a modeling strategy based on EGPR model is proposed to construct an optimization model for coal consumption of cement clinker calcination under quality constraint, which solves the problem that the prediction performance of the traditional single model is not satisfactory under complex working conditions. Eventually, based on the proposed modeling strategy, the BO algorithm was used to solve the optimization problem in this paper, and the minimum coal consumption under steady state conditions and

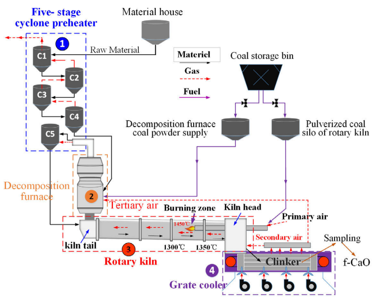


FIGURE 1. Cement clinker calcination process.

the corresponding optimal set value of the decision variable are obtained.

The paper is structured as follows: in Section II, the calcination process of cement clinker is introduced and the clinker calcination process modeling and optimization problem is analyzed, identifying the key variables associated with the optimization objectives and constrained targets. In Section III, a detailed description of the modeling and optimization strategy is presented. In Section IV, the modeling and optimization strategies are validated and evaluated using real data from the cement clinker production process. In Section V, conclusions are drawn and future work is prospected.

II. DESCRIPTION OF CEMENT CLINKER CALCINATION PROCESS

A. PROCESS INTRODUCTION

The raw material of cement enters the raw material mill according to the set raw material ratio, and after drying and grinding, it enters the homogenizing warehouse for homogenization. The homogenized raw meal enters the five-stage suspended air preheater and decomposition furnace for preheating and carbonate decomposition, and then enters the rotary kiln for calcination. Finally, the clinker enters the grate cooler from the kiln head for cooling, and the whole calcination process of clinker is completed. The specific process is shown in Figure 1.

B. VARIABLES SELECTION

The ultimate goal of energy optimization of cement clinker calcination process is to minimize energy consumption while ensuring qualified quality of clinker. Among them, the main source of heat in the clinker calcination process is the exothermic combustion of pulverized coal, the coal consumption is an important parameter to measure the energy consumption of the process, while f-CaO is the key indicator of clinker quality. Therefore, this paper takes coal consumption as the optimization goal and f-CaO as the constraint condition, analyzes and summarizes the relevant variables, and conducts optimization research on the cement clinker calcination process.

As can be seen from the process analysis, the preheater and the decomposer undertake the task of raw material pre-decomposition in the clinker calcination process. The process mainly provides the heat required for raw meal pre-decomposition through the combustion of pulverized coal at the end of the kiln and the hot air entering the decomposer and preheater. Therefore, the C5 outlet temperature, the decomposition furnace outlet temperature and the smoke chamber temperature at the end of the kiln can reflect the coal consumption of the raw meal pre-decomposition process. After the raw meal is pre-decomposed, it enters the rotary kiln for calcination. The burning zone temperature directly reflects the coal consumption in the rotary kiln calcination process. At the same time, the gas generated by the clinker after being cooled by the grate cooler and the heat generated by the combustion of pulverized coal together constitute the high-temperature environment in the kiln. This part of the hot air is called secondary air, and the negative pressure at the kiln head can be characterized by kiln air volume. The load of rotary kiln will change with the change of raw material feed, and the kiln motor current can characterize the change of kiln load. Therefore, the raw material feed rate and kiln motor current can reflect the change of coal consumption. Meanwhile, the stability of raw fuel composition is an important prerequisite for stable cement production, which mainly refers to raw meal and pulverized coal. Cement plants usually judge the ease of burning of raw meal based on the KH, SM and IM, and make the corresponding batching plan. Meanwhile, a reasonable fineness of raw material helps to calcine the reaction completely, increase the burning speed and improve the quality of clinker. Coal powder is obtained by mixing and grinding coals of different coal qualities according to a certain ratio. Under the same temperature requirement, the coal pulverized coal has different calorific value and its coal consumption is also different. Under the same temperature requirement, the coal pulverized coal has different calorific value and its coal consumption is also different.

Based on the above analysis, the variables related to coal consumption and quality are summarized as shown in Table 1. where X1 to X8 are decision variables and X9 to X13 are raw combustion material related variables. Y1 is the optimization objective coal consumption and Y2 is the quality constraint.

TABLE 1. Variable selection.

Serial number	Variable name
X1	Burning zone temperature
X2	kiln motor current
X3	Decomposition furnace outlet temperature
X4	Secondary air temperature
X5	Smoke chamber temperature
X6	C5 outlet temperature
X7	Kiln head negative pressure
X8	Raw material feed rate
X9	KH
X10	SM
X11	IM
X12	Raw material fineness (0.08mm)
X13	Calorific value of pulverized coal
Y1	Coal consumption
Y2	f-CaO

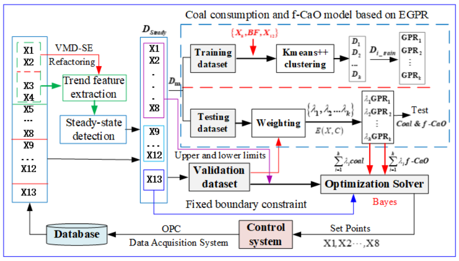


FIGURE 2. Overall framework of the modeling and optimization method for cement clinker calcination process.

III. DESCRIPTION OF MODELING AND OPTIMIZATION METHODS

The overall framework of the modeling and optimization strategy proposed in this paper is shown in Figure 2. It mainly includes data acquisition and processing, steady-state detection, modeling and optimization. In this paper, these four parts will be introduced in detail respectively.

A. DATA ACQUISITION AND PROCESSING

The data of variables used for modeling and optimization in this paper include both DCS online data and offline laboratory data. Among them, the decision variables are collected online through DCS. The DCS systems of cement plants all support OPC standard communication protocol. The data acquisition system collects data of decision variables in the on-site DCS through OPC, and its sampling period is set to 1s. The cement industry generally adopts an offline method to sample and analyze the raw and fuel components. Among them, the sampling period for three-rate value of the raw material (X9, X10, X11), raw meal fineness (X12) and f-CaO (Y2) is 1 hour, the sampling period for pulverized coal (X13) is 4 hours, and the optimization objective (Y1) is the cumulative coal consumption per hour.

In the process of data collection and transmission, due to high-frequency interference between various detection instruments or network anomalies, etc., data is missing in the original data, and it is necessary to fill in the missing data. According to the different ways and types of variable collection, different ways of filling missing data are adopted respectively. The details are as follows.

(a) For online collection variables, in the actual production process, in order to stabilize and secure the calcination system, when data is missing, the time series mean method is used to fill the missing data with the mean value of h seconds before the missing data [37]. The method is calculated on a rolling basis over time. The missing values of the variables at point t are calculated as follows.

$$D_{t\_loss} = S^{-1}\sum_{h=1}^{S} D_{t-h}, \quad h = 1, 2 \ldots S \tag{1}$$

where D_{t-h} is the value at moment D_{t-h}. S is time threshold.

(b) For raw material composition, pulverized coal composition and f-CaO, due to the long sampling period and obtained through artificial sampling and testing, the proportion of missing data in the actual production process is small. Therefore, when there is missing data at a certain moment, we keep the values of the variables at the previous moment unchanged and fill them to the missing position.

B. DESCRIPTION OF STEADY-STATE DETECTION METHOD FOR CEMENT CLINKER CALCINATION PROCESS

1) TREND FEATURE EXTRACTION

In the actual clinker calcination process, the raw data of variables fluctuate greatly and the trend features are not obvious due to the high frequency interference between the equipment itself and various detection instruments. In this paper, we combine VMD, SE and least squares fitting to extract trend features for this type of variable data. The specific steps are described as follows.

(a) VMD signal decomposition. The VMD algorithm is constructed as follows.

$$\begin{cases} \min\limits_{\{u_k\},\{\omega_k\}} \left\{ \sum_k \left\| \delta \frac{\left[\left(\delta\left(\mathrm{t}\right) + \frac{j}{\pi \mathrm{t}}\right) u_k\left(t\right)\right]}{e^{j\omega_k t}} \right\|_2^2 \right\} \\ s.t. \ \sum\limits_k u_k = \mathrm{f} \end{cases} \tag{2}$$

where, u_k is the individual IMF components. ω_k is the center frequency corresponding to each IMF component, and the essence of the VMD algorithm is to find the u_k and ω_k with the smallest sum of the bandwidths of the center frequencies of each modal component. where u_k and ω_k are solved by the following equations.

$$\hat{\mathrm{u}}_k^{n+1}\left(\omega\right) = \frac{\hat{\mathrm{f}}\left(\omega\right) - \sum\limits_{\mathrm{i}\neq\mathrm{k}} \hat{\mathrm{u}}_{\mathrm{i}}\left(\omega\right) + \frac{\hat{\mathrm{u}}(\omega)}{2}}{1 + 2\alpha(\omega - \omega_{\mathrm{k}})^2} \tag{3}$$

$$\omega_k{}^{n+1} = \frac{\int_0^\infty \omega \left|\hat{\mathrm{u}}_k\left(\omega\right)\right|^2 \mathrm{d}\omega}{\int_0^\infty \left|\hat{\mathrm{u}}_k\left(\omega\right)\right|^2 \mathrm{d}\omega} \tag{4}$$

The important parameters involved in the VMD decomposition process are K, α and τ. Where the value of K determines the number of IMF components, α determines the bandwidth of IMF components, and τ is the stopping condition for optimization.

(b) Signal reconstruction. The sample entropy (SE) can measure time series complexity. In this paper, so it was chosen to distinguish the components of the signal. The VMD method realizes the decomposition of the signal from low to high frequencies, and the noise is mostly hidden in the higher-order IMFs. Therefore, this paper adopts the method of VMD local reconstruction (VMD-LR) to discard the high-order IMFs containing noise and reconstruct the remaining low-order IMFs according to the change of the SE value of each IMF, and obtain the reconstructed signal imf_r to characterize the trend of the original signal.

The SE is calculated as follows.

$$SampEn\,(m, r, N) = -ln\frac{B^{m+1}\,(r)}{B^{m}\,(r)} \tag{5}$$

where, r is the threshold value, N is the number of IMF, and m is the dimension.

(c) Trend extraction. The least squares fitting method is used to fit imf_r to obtain a continuous fitting signal f(x). The fitting process is as follows.

Define the data set T, and find the polynomial of order m, such that the regression error $\mathrm{L}\,(u)$ is minimized. Then

$$\begin{cases} f\,(x) = \sum_{\mathrm{j}=0}^{u} \omega_j \mathrm{x}^{\mathrm{j}} \\ \mathrm{L}\,(\omega) = \sum_{i=1}^{n} \left(\sum_{\mathrm{j}=0}^{u} \omega_i \mathrm{x}_i^{\mathrm{j}} - y_i \right)^2 \end{cases} \tag{6}$$

Let $\frac{\partial \mathrm{L}(\omega)}{\partial \omega_k} = 0, , k = 0, 1, \cdots u$, the following relation can be obtained.

$$\begin{cases} \sum_{\mathrm{j}=0}^{u} \omega_j \sum_{i=0}^{n} \mathrm{x}_i^{\mathrm{j}+k} = \sum_{i=1}^{n} \mathrm{f}_i \mathrm{x}_i^{k} \\ \mathrm{f}\,(\mathrm{x}) = \alpha^T \Gamma\,(x) \end{cases} \tag{7}$$

After solving, the optimal estimate of α is as follows.

$$\alpha_{\text{best}} = \left(\Gamma^T \cdot \Gamma\right)^{-1} \cdot \Gamma^T \mathrm{f} \tag{8}$$

The fitted curve f(x) of the reconstructed signal is obtained by the above process, which is used to characterize the trend change of the original data and also to achieve the rejection of the residual noise in the imf_r.

2) MULTIVARIATE STEADY-STATE DETECTION

In the actual cement clinker calcination process, the ideal steady state does not exist. Therefore, a variable is considered to be in a steady state when its trend f(x) has a rate of change less than the threshold θ over the time period Δx and remains constant for N cycles. In addition, whether the cement clinker calcination process is in steady state or not is determined by multiple state variables together. The steps of multivariable-based steady-state detection are as follows.

(a) The principal component analysis (PCA) method was used to determine the contribution rate of each principal component, and the key state variables used for steady-state judgment were determined based on the cumulative contribution rate.

Construct the original data sample matrix $A = \begin{pmatrix} \mathrm{x}_{11} & \cdots & \mathrm{x}_{1n} \\ \vdots & \ddots & \vdots \\ \mathrm{x}_{m1} & \cdots & \mathrm{x}_{mn} \end{pmatrix}$. where m and n denote the number of samples and state variables, respectively.

The covariance matrix R is calculated and its eigenvalues λ and eigenvectors V are obtained. The specific expressions are as follows.

$$R = \frac{\sum_{\mathrm{i}=1}^{\mathrm{m}} \left(\mathrm{x_i} - \frac{1}{\mathrm{m}} \sum_{\mathrm{i}=1}^{\mathrm{m}} \mathrm{x_i}\right)\left(\mathrm{x_i} - \frac{1}{\mathrm{m}} \sum_{\mathrm{i}=1}^{\mathrm{m}} \mathrm{x_i}\right)^T}{\mathrm{m}-1} \tag{9}$$

$$(\lambda \mathrm{E} - R)\, V = 0, \quad \lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_{\mathrm{n}} \geq 0 \tag{10}$$

The new feature matrix $\mathrm{P} = V^T A$ is constructed using V, and the β and ω_{p} of the feature values are calculated separately.

$$\beta_{\mathrm{i}} = \lambda_{\mathrm{i}} \left(\sum_{\mathrm{j}=1}^{\mathrm{n}} \lambda_{\mathrm{j}} \right)^{-1} \tag{11}$$

$$\omega_{\mathrm{p}} = \left(\sum_{\mathrm{j}=1}^{\mathrm{n}} \lambda_{\mathrm{j}} \right)^{-1} \sum_{\mathrm{j}=1}^{\mathrm{p}} \lambda_{\mathrm{j}} \tag{12}$$

The cumulative contribution threshold r_p of the principal components was set, and the top p indicator variables $\mathrm{y}_1, \mathrm{y}_2, \cdots \mathrm{y}_p$ were selected as the key state variables for steady-state judgment.

(b) Calculate the trend change rate φ of key state variables.

$$\varphi\,(\mathrm{x}) = \left| \frac{\mathrm{F}\,(\mathrm{x}) - \mathrm{F}\,(\mathrm{x}_0)}{\Delta \mathrm{x}} \right| \leq \xi \tag{13}$$

(c) Calculation of steady-state indices for individual variables $\phi_{\mathrm{i}}\,(\mathrm{x})$.

$$\phi_{\mathrm{i}}\,(\mathrm{x}) = \begin{cases} 0, & |\varphi_i\,(\mathrm{x})| > T_\varphi \\ 1, & |\varphi_i\,(\mathrm{x})| \leq T_\varphi \end{cases} \tag{14}$$

where T_φ is the trend rate of change threshold of the state variable. In addition, the steady state duration τ for each variable needs to be considered. The state variable is considered to be in a steady state only if it remains steady for the duration.

(d) The steady-state index is weighted according to the contribution of each variable to further obtain the integrated steady-state index S.

$$\mathrm{S} = \sum_{\Gamma=1}^{\mathrm{K}} \gamma_\Gamma \phi_\Gamma\,(\mathrm{x}), \quad \Gamma = 1, 2, \cdots k \tag{15}$$

where, γ_Γ denotes the weight of each state variable. The S satisfies a certain threshold value T_s, then the current working condition is considered as steady state.

C. DESCRIPTION OF THE MODELING STRATEGY BASED ON GPR

The modeling strategy in this paper mainly consists of two parts: raw material working condition division and construction of gaussian process regression ensemble (EGPR) model.

1) CLASSIFICATION OF RAW MATERIAL WORKING CONDITIONS

The raw material condition is a key factor affecting the quality, coal consumption and stability of the production process. Therefore, in this paper, the raw material feed rate (X8), raw

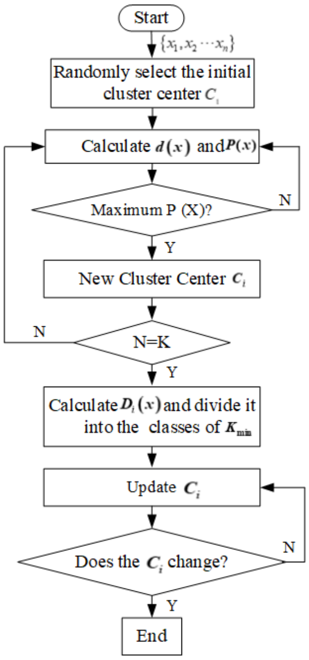


FIGURE 3. The process of dividing raw material conditions based on Kmeans++.

material composition and raw material fineness (X12) are selected as the research variables to classify the raw material working conditions. In the daily control, the characteristics of raw material composition are often characterized by raw material ease of burnability and evaluated quantitatively by using empirical formulae. The specific formulas are as follows.

$$\begin{cases} \mathrm{KH} = \dfrac{\mathrm{CaO} - 1.65 \times \mathrm{Al_2O_3} - 0.35 \times \mathrm{Fe_2O_3}}{2.8 \times \mathrm{SiO_2}} \\ \mathrm{SM} = \dfrac{\mathrm{SiO_2}}{\mathrm{Al_2O_3} + \mathrm{Fe_2O_3}} \\ \mathrm{IM} = \dfrac{\mathrm{Al_2O_3}}{\mathrm{Fe_2O_3}} \\ \mathrm{BF} = \dfrac{((3\mathrm{KH} - 2)\,\mathrm{SM}\,(\mathrm{IM} + 1))}{2\mathrm{IM} + 10} \end{cases} \tag{16}$$

where BF is the raw material burnability index, KH is the lime saturation factor, SM is the silicon-oxygen rate, IM is the aluminum-oxygen rate. CaO, Al_2O_3, Fe_2O_3 and SiO_2 denote the components of the raw material.

The Kmeans++ algorithm is used to cluster X8, X12 and BF to achieve the classification of raw material working conditions. The specific process of raw material working condition classificationby k-means++ is shown in Figure 3.

Where, $P(x) = D^2(x)/\sum_{x \in X} D^2(x)$ is the probability of a sample being selected as a cluster center. N is the number of clustering centers. $D_i(x)$ is the distance between each sample and K clustering centers. K_{min} is the category corresponding to the smallest $D_i(x)$.

2) ESTABLISHMENT OF OPTIMIZATION MODEL FOR CLINKER CALCINATION PROCESS

The modeling process in this paper is as follows.

(a) In this paper, an optimization target model of coal consumption under quality constraint is established based on GPR.

$$\begin{aligned} &\mathrm{minF(x)} = [\mathrm{C}(\mathrm{Y}_1), \mathrm{Q}(\mathrm{Y}_2)]^{\mathrm{T}} \\ &\mathrm{s.t.}\ \mathrm{C}(\mathrm{Y}_1) = \mathrm{f_{Coal}}(\mathrm{X_i}), \quad \mathrm{i} = 1, 2, \cdots, 8 \\ &\quad \mathrm{Q}(\mathrm{Y}_2) = \mathrm{f_{f-CaO}}(\mathrm{X_j}), \quad \mathrm{j} = 1, 2, \cdots, 11 \\ &\quad \mathrm{Q}(\mathrm{Y}_2) \in [\mathrm{Q_{min}}, \mathrm{Q_{max}}] \\ &\quad \mathrm{X_i} \in \left[\mathrm{X_{i\_min}}, \mathrm{X_{i\_max}}\right] \end{aligned} \tag{17}$$

where, $F(x)$ denotes the optimization objective function under the quality constraint. $X_i = (x_1, \cdots x_8)$ denotes the decision variables. $X_{i\_\min}$ and $X_{i\_\max}$ denote the range of values of the decision variables. $X_j = (x_1, \cdots x_{11})$ denotes the variables related to f-CaO. $Q_{\min}$ and $Q_{\max}$ denote the constraints of f-CaO. X_i and X_j are the inputs of the coal consumption and f-CaO prediction models, respectively. $C(Y_1)$ and $Q(Y_2)$ denote the model outputs. The steps for modeling the clinker calcination process based on GPR are as follows.

Define the n-dimensional training sample set as $\{x_i, \mathrm{y}_i\}_{i=1,2\cdots n}^{N}$, then

$$f(x) \sim GP\left(E(x), H + \sigma^2 \xi_{ij}\right) \tag{18}$$

$$\xi_{ij} = \begin{cases} 0, & \mathrm{i} = \mathrm{j} \\ 1, & \mathrm{i} \neq \mathrm{j} \end{cases} \tag{19}$$

where $E(x)$ is mean function, and H is the covariance matrix.

Generally, the initial value of $E(x)$ is set to 0. Let x^* be the input value of the sample to be predicted and f^* be the corresponding value to be predicted, then the joint prior distribution of y and f^* is as follows.

$$\begin{bmatrix} y \\ f^* \end{bmatrix} = N\left(0, \begin{bmatrix} H, H_1{}^T \\ H_1, H_2 \end{bmatrix}\right) \tag{20}$$

According to the above analysis, it can be seen that the choice of covariance function is crucial for GPR modeling. In this paper, the squared exponent is chosen as the covariance function, then

$$H_{SE} = \sigma_h{}^2 \exp\left(-\frac{r^2}{2l^2}\right) + \sigma_m{}^2 \xi_{ij} \tag{21}$$

The maximum likelihood estimation method was used to estimate the hyperparameter ensemble $\theta = (\sigma_h, l, \sigma_m)$ and combined with the conjugate gradient descent method (Dragomiretskiy et al.) to find the hyperparameter optimal solution. The resulting regression prediction equation is as follows.

$$f^* \left| X, y, X^* \sim GP\left[E\left(x^*\right), \mathrm{cov}\left(f^*\right)\right]\right. \tag{22}$$

where $E(x^*)$ is the predicted mean value and cov (f^*) represents the predicted variance.

(b) In this paper, the K and cluster centers are determined according to the Kmeans++ clustering results. The euclidean distance $E(X, C) = \sqrt{\sum_{i=1}^{k} (x_i - c_i)^2}$ between the samples and the cluster centers is calculated to assign different weights λ to the divided working conditions, and the final model prediction output after weighting is as follows.

$$y_i(x_i) = \sum_{k=1}^{k} \tau(x_i) y_{ik}(x_i), \quad i = 1, 2, \ldots N \tag{23}$$

where τ is the weight of the i-th test sample corresponding to each condition category.

D. BAYESIAN OPTIMIZATION

The solution of cement clinker calcination process optimization problem mainly includes the determination of VMD optimal decomposition parameters and finding the minimum value of coal consumption. In view of the advantages of bayesian optimization algorithm in dealing with black-box function estimation and global optimization problems, bayesian optimization algorithm is chosen in this paper for the optimization of VMD decomposition parameters and coal consumption.

Bayesian optimization involves two key processes: the probabilistic agent model and the collection function. Among them, gaussian process has high flexibility and scalability and is theoretically capable of characterizing arbitrary nonlinear functions. Therefore, the gaussian process is chosen as the probabilistic proxy model in this paper. The acquisition function chooses the expectation improvement function (EI), the principle of which is to select the point with the greatest degree of improvement as the next sampling point.

The basic idea of bayesian optimization is that given a set of parameter combinations to be optimized $X = \{x_1, x_2, \cdots x_n\}$. Then, the objective function is evaluated using a continuously updated probabilistic model to update the posterior probabilities of the optimization function and obtain the optimal combination of model parameters.

The choice of parameter combinations for the model is as follows.

$$x^* = \arg\min_{x \in X} f(x) \tag{24}$$

The combination of parameters to be optimized in this study is the coal consumption and VMD decomposition parameter $\theta_{vmd} = (k, \alpha)$. The process of optimizing coal consumption and $\theta_{vmd} = (k, \alpha)$ using bayesian algorithm is shown in Figure 4.

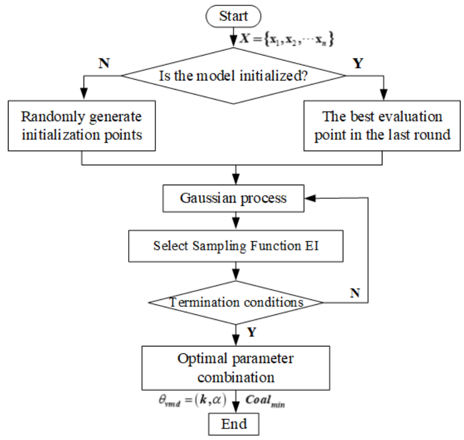


FIGURE 4. Schematic diagram of bayesian optimization process.

TABLE 2. PCA calculation results.

variables	Contribution rate	Cumulative contribution rate
X1	0.3660	0.3660
X2	0.2434	0.6094
X3	0.1319	0.7413
X4	0.1118	0.8531
X5	0.0693	0.9224
X6	0.0377	0.9601
X7	0.0215	0.9816
X8	0.0184	1

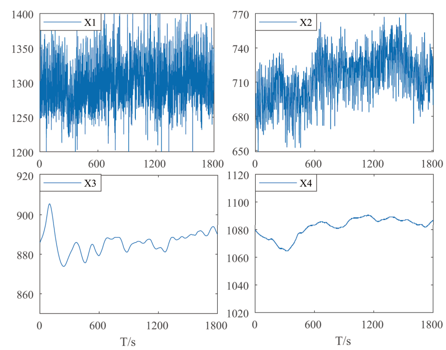


FIGURE 5. Raw data for decision variables X1 to X4.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The historical data from the energy management database of the cement plant are used to screen the steady-state operating condition data for modeling and optimization, and the effects of their application are analyzed and discussed.

A. ANALYSIS OF STEADY-STATE DETECTION RESULTS

In order to have an intuitive and clear representation, 1800 sampling points in continuous time were selected for the experimental results presentation. First, PCA was used to calculate the contribution rates of the eight decision variables (see Table 2).

By setting the cumulative contribution threshold r_p to 0.85, the variables X1 to X4 are selected as principal components and their trend features are extracted for the steady-state judgment. The raw data of variables X1 to X4 are shown in Figure 5.

In Figure 5, the raw data trend characteristics of X1 and X2 are not obvious. Therefore, the raw signals of burning zone temperature and kiln motor current are decomposed and reconstructed by VMD. where the convergence threshold is set to $\tau = 10^{-6}$, the bayesian algorithm is used to optimize the K and α. The process of bayesian optimization of VMD

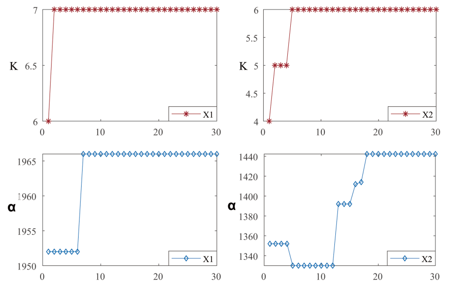


FIGURE 6. **VMD parameter optimization based on bayesian algorithm.**

TABLE 3. **VMD parameter settings.**

Variables	K	α
Burning zone temperature(X1)	7	1966
Kiln motor current(X2)	6	1442.3

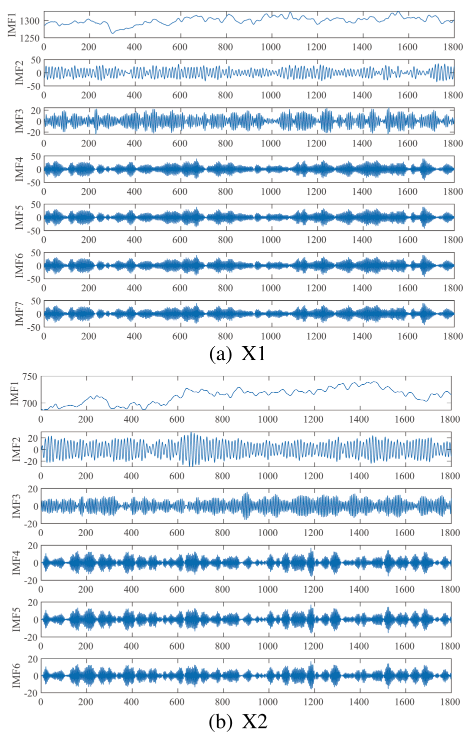


FIGURE 7. **Results of VMD decomposition.**

parameters and the results of parameter optimization are shown in Figure 6 and Table 3 respectively.

The results of VMD decomposition sequence based on the parameters in Table 3 are shown in Figure 7. According to Figure 7, it can be seen that the original signal is decomposed into modal components IMFs with different frequency characteristics. Then the SE value of each IMF is calculated separately. Among them, the m=2 and r=0.2, then the calculation results of the sample entropy value are shown in Figure 8.

The characteristic inflection points of the relevant trend terms can be clearly distinguished based on the trend of the sample entropy values in Figure 8. Among them, for the

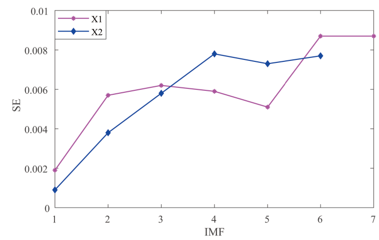


FIGURE 8. **Trend of sample entropy value.**

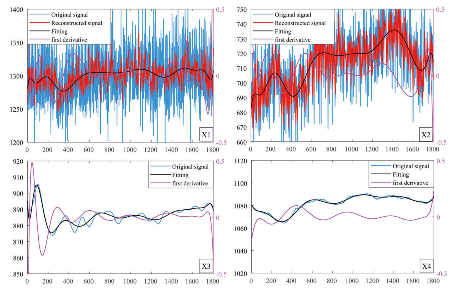


FIGURE 9. **Trend extraction results.**

TABLE 4. **Steady-state detection parameter settings.**

Parameter	X1	X2	X3	X4
T_φ	0.05	0.05	0.05	0.05
τ	120s	60s	60s	60s
γ	0.4	0.3	0.2	0.1

burning zone temperature, IMF6 and IMF7 have similar and relatively highest SE values, so IMF6 and IMF7 are defined as high-frequency noise components to eliminate them. Similarly, the modal components of the kiln motor current, IMF4, IMF5, and IMF6, are eliminated as high-frequency noise components. The residual IMFs were reconstructed by superimposing them as effective trend characteristic signals to obtain the reconstructed signals imf_{r_x1} and imf_{r_x2} for burning zone temperature and kiln motor current. Least-squares fits were performed for imf_{r_x1}, imf_{r_x2}, X3 and X4, respectively, and the steady-state index was calculated. Where the maximum fitting order threshold is set to 20, the trend extraction results of variables X1 to X4 are shown in Figure 9.

It can be seen from Figure 9 that the reconstructed signal curves of variables X1 and X2 can well filter out the high-frequency noise in the original signal. The fitted function curves and the first-order derivative curves can accurately reflect the trend change characteristics of the variable data. Then, the steady-state index ϕ_i (x) and the integrated steady-state index S for each variable are calculated using eqs.(11) and eqs.(12). Based on the field operation experience and the contribution of each variable, the relevant parameters are set as shown in Table 4.

According to the parameters in Table 4, set the steady-state threshold T_s is 0.7, and obtain the final steady-state detection result as shown in Figure 10. Where 0 represents

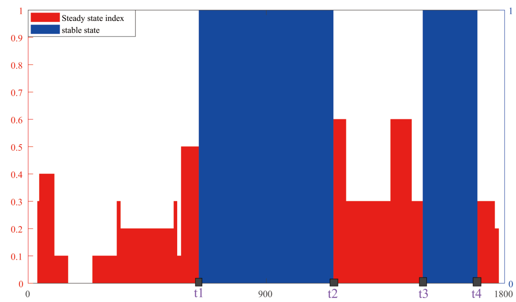
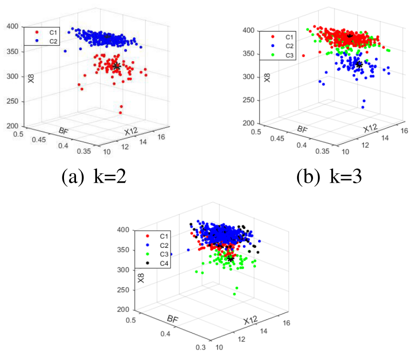


FIGURE 10. Steady state detection results.



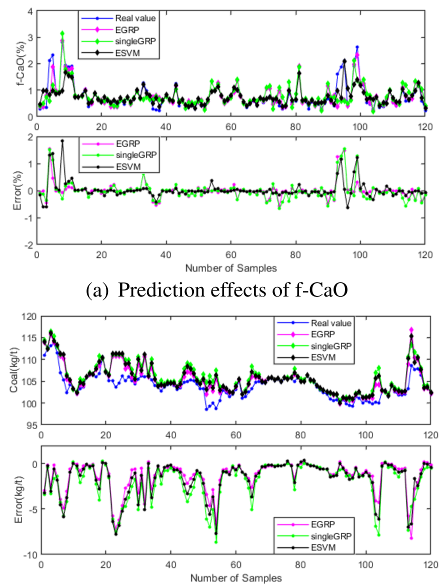
(a) k=2 (b) k=3

(c) k=4

FIGURE 11. Kmeans++ clustering effects.

TABLE 5. kmeans++ clustering results.

Clustering Center	Raw material fineness	BF	Raw material feed rate
C1	14.60	0.42	350.69
C2	15.10	0.41	316.44



(a) Prediction effects of f-CaO

(b) Prediction effects of coal consumption

FIGURE 12. Comparison of model results.

non-steady state and 1 represents steady state, then in the time periods of [t1,t2] and [t3,t4], it means that the process is a steady-state working condition. The steady-state detection results in Figure 10 show that the steady-state detection method proposed in this paper can be well used for the steady-state detection of the cement clinker calcination process.

B. ANALYSIS AND DISCUSSION OF MODELING RESULTS

The steady-state detection method described above was used to perform steady-state detection on historical data in database over a continuous period of time. First, the historical data were filled with missing values, and time series analysis and matching were performed according to the method in the literature [38], and then steady-state testing was performed to finally obtain 820 sets of steady-state sample data. Among them, 600 sets are used for model training, 120 sets are used as test samples to test the performance of the model, and the remaining 100 sets are used as a validation sample set for coal consumption optimization.

Before constructing the optimization model, the Kmeans++ algorithm is used to perform clustering to classify the raw material working conditions. Among them, the K is crucial to model prediction results. We selected different values of K (K = 2,3,4) for clustering experiments. The results are shown in Figure 11.

According to Figure 11, it can be seen that when K = 2, the sample data are obviously divided into 2 classes with the best clustering effect. The training sample data at other K values are mixed with each other, and the classification of raw material conditions cannot be achieved. Therefore, in this paper, we choose K = 2 to perform kmeans++ clustering on the raw material-related variable data. The clustering results are shown in Table 5.

Based on the clustering results, a subset of training samples for the optimized model is determined as follows.

$$\begin{cases} \mathrm{D}_{k\_coal} = [x_1, x_2 \cdots, x_7, C(Y_1)] \\ \mathrm{D}_{k\_f-cao} = [x_1, x_2 \cdots, x_{11}, Q(Y_2)] \end{cases} \tag{25}$$

For the new test samples, the prediction results are weighted and combined by calculating the membership degree with each subclass to obtain the final prediction output. In addition, a single GPR model and an SVM ensemble (ESVM) model were established using the same sample data for comparison with the text model (EGPR), and the comparison results are shown in Figure 12.

To better evaluate the modeling effect, root mean square error (RMSE), coefficient of determination (R^2), and Theil's inequality coefficient (TIC) were chosen to evaluate the model performance, and the results are shown in Table 6 and Table 7.

According to the data comparison in Table 6 and Table 7, compared with the traditional single work condition modeling and SVM model, the RMSE of the coal consumption EGPR model is reduced by 24% and 14%, R^2 is improved by 62%

TABLE 6. Performance comparison of different models.

Modeling methods	RMSE(Y1)	R^2(Y1)	TIC(Y1)
EGPR	2.1541	0.7306	0.0103
Single-GPR	2.8497	0.6515	0.0136
ESVM	2.5188	0.6854	0.0120

TABLE 7. Performance comparison of different models.

Modeling methods	RMSE(Y2)	R^2(Y2)	TIC(Y2)
EGPR	0.3067	0.6665	0.1695
Single-GPR	0.3579	0.5649	0.1975
ESVM	0.3350	0.5740	0.1934

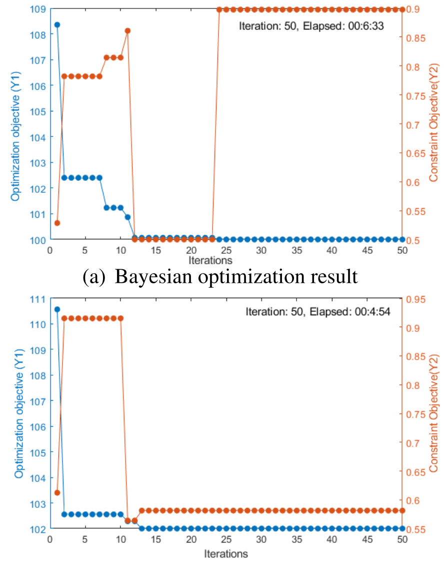
TABLE 8. Range of variable constraints.

Variables	lower limit	upper limit
X1(°C)	1250	1400
X2(A)	650	750
X3(°C)	880	895
X4(°C)	1050	1150
X5(°C)	1150	1200
X6(°C)	840	860
X7(Pa)	-140	-100
X8(t/h)	360	380
Y2(%)	0.5	1.5
X13(kcal/kg)	6400	6600

and 7%, and TIC is reduced by 24% and 14%, respectively. Similarly, the EGPR model of f-CaO has 14% and 8% lower RMSE, 18% and 16 higher R^2, and 14% and 12% lower TIC, respectively. In addition, the calculation time of the model in this paper is 2.38 seconds. For the optimization of the clinker calcination process, the calculation time in this paper is sufficient to meet the actual production needs. The above results show that the EGRP has better prediction accuracy and generalization ability, and can adapt to the changing clinker calcination working conditions. The modeling results demonstrate the feasibility of the modeling method proposed in this paper, which can provide dependable data support for the optimal control of the clinker calcination process.

C. ANALYSIS AND DISCUSSION OF STEADY-STATE OPTIMIZATION RESULTS

Based on the above modeling strategy, the constraint range of each variable is determined as shown in Table 8. where X1 to X8 are decision variables, f-CaO is the constraint index, and the calorific value of pulverized coal is a fixed boundary condition. Based on the EGPR model developed in Section IV-B of this paper, the bayesian optimization (BO) algorithm was used to optimize 100 sets of validation set sample data according to the constraint ranges of each variable in Table 8. In addition, to better illustrate the feasibility of the bayesian algorithm in the study, it was compared with the particle swarm optimization (PSO) algorithm under the same hardware equipment conditions. In this case, the number of optimization iterations was chosen as 50. The optimization results are shown in Figure 13, and the comparison results are shown in Table 9.



(a) Bayesian optimization result
(b) PSO optimization result

FIGURE 13. Optimization results of different algorithms.

TABLE 9. Comparison of optimization results.

Algorithm	time	speed	Y1	Y2
BO	393s	24	100.42	0.897
PSO	294s	13	102.24	0.58

According to Figure 13, You can see that the decrease of coal consumption is accompanied by the increase of f-CaO, implying that the decrease of temperature leads to the increase of f-CaO. The optimization direction is in line with the process requirements. Combined with the data comparison in Table 9, you can see that the BO algorithm can obtain lower coal consumption compared with the PSO, and the calculation time and convergence speed can meet the actual production requirements. Although the PSO optimization algorithm performs well in the field of convergence speed and computation time, the target value is easy to fall into local optimum and the f-CaO value is closer to the constrained lower limit, which can easily lead to over-burning of clinker quality. A comprehensive comparison of the above results shows that, compared with the PSO, the BO algorithm has better advantages in solving the optimization problem in this paper, and can meet the demand for coal consumption optimization of the clinker calcination process.

V. CONCLUSION

This paper proposes a modeling and optimization method for cement clinker calcination process based on EGPR model and steady-state detection to reduce coal consumption in the cement clinker calcination process. Firstly, a modeling strategy based on GPR integrated model was proposed, and a coal consumption optimization model for cement clinker calcination under quality constraints was constructed. Then, a steady-state detection method based on trend feature extraction is proposed to achieve steady-state detection of the clinker calcination process. On this basis, the optimization problem is solved using steady-state operating data and Bayesian optimization algorithm to obtain the minimum coal consumption and corresponding decision variable settings under steady-state operating conditions.

The actual production data from cement plants were used for verification. Among them, the steady-state detection method proposed in this paper can effectively screen the steady-state data of the clinker calcination process, and in addition, the modeling results show that compared with the traditional single work condition modeling and SVM model, the RMSE of the coal consumption EGPR model proposed in this paper is reduced by 24% and 14%, R^2 is improved by 62% and 7%, and TIC is reduced by 24% and 14%, respectively. Similarly, the EGPR model of f-CaO has 14% and 8% lower RMSE, 18% and 16 higher R^2, and 14% and 12% lower TIC, respectively, which provides an effective method for modeling coal consumption and f-CaO content under complex and multi-working conditions. Optimization experiments were conducted using steady-state operating conditions data combined with Bayesian optimization algorithm, and compared with PSO algorithm. The results show that the BO algorithm used in this paper can achieve lower coal consumption, and the calculation time and convergence speed can meet actual production requirements. The above experimental comparison results show that the modeling and optimization strategy proposed in this paper provides an effective and feasible solution for achieving energy consumption optimization in the cement clinker calcination process under steady-state conditions, which can effectively reduce the coal consumption in the clinker calcination process while ensuring qualified quality.

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