Temperature Co-Optimization of Zinc Roasting Process Based on Fuzzy Synthetic Evaluation and Temperature Adjustable Margin

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***Abstract*—The roasting temperature is critical for enhancing product quality, reducing air pollution, and ensuring the long-term operation of the zinc roasting process. However, optimizing the roasting temperature is challenging due to complex reaction mechanisms, feed composition fluctuations, and the coupling relationship with downstream processes. In this article, a two-level decision-making system for co-optimization of the roasting temperature is proposed. In the first level, a fuzzy synthetic evaluation model with a variable-weight degradation degree is established to accurately evaluate the operating performance of the zinc roasting process. The evaluation results are used to design the basic setting rules that provide the basic temperature setting values. In the second level, the concept of a temperature-adjustable margin is introduced via sensitivity analysis of the process model to evaluate the optimality of two roasters in the zinc roasting process. Based on the temperature-adjustable margin, the collaborative setting rules are designed to reasonably allocate the basic setting value to the two zinc roasters for optimizing the operating performance of the zinc roasting process. Finally, an industrial case study is presented to demonstrate the effectiveness of the proposed two-level decision-making system.**

***Index Terms*—Decision-making system, fuzzy synthetic evaluation, temperature optimization, temperature-adjustable margin, zinc roasting process (ZRP).**

I. Introduction

THE zinc roasting process (ZRP) is the upstream process of zinc hydrometallurgy and the acid-making process, which converts the zinc concentrate to zinc calcine and sulfur dioxide flue gas [1]. In the ZRP, the co-optimization of the roasting temperature of two zinc roasters determines the product quality, pollutant discharge, and stable operation [2]. A lower roasting temperature leads to poor product quality, while a higher roasting temperature results in excessive air pollution and roaster sintering.

In recent studies focusing on the temperature optimization of the ZRP, researchers have explored various aspects, including process evaluation [3], [4], optimization [5], [6], [7], and control [8], [9]. Liang et al. [3] introduced an evaluation model of the ZRP that integrates a first principle model with a data-driven approach, dividing operating performance into distinct categories such as over-decomposition, under-oxidation, and fluidized bed deposition conditions. Huang et al. [4] presented a static and dynamic joint analysis method to categorize operating conditions into different grades. However, the evaluation results lacked physical meaning, providing limited guidance for the ZRP process optimization. Abadias Llamas et al. [5] proposed a simulation-based optimization method for the roast-leach-electrowinning process, specifically targeting the reduction of by-products. Sales et al. [6] developed a first principle model to optimize decision variables and the heat transfer area of the ZRP, resulting in increased zinc oxide production, enhanced green steam generation, and reduced CO_2 emissions. Similarly, Liang et al. [7] proposed a first principle model of the ZRP to describe the relationship between the soluble zinc rate and decision variables, thereby realizing a product quality optimization of the ZRP. However, these methods are steady-state optimization methods, mainly used for the process design of the ZRP. Therefore, they are not suitable for solving the dynamic optimization problems considered in this article. Ying et al. [8] introduced an explicit model predictive control algorithm for roasting temperature optimization control, while Liang et al. [9] proposed a transfer predictive control method to ensure stable control of roasting temperature, accommodating the complexities arising from changes in feeding compositions. While these efforts concentrate on optimizing roasting temperature to enhance product quality, it is crucial to note that environmental protection and reaction atmosphere are integral aspects that cannot be ignored in the optimization process. Furthermore, the intricate interplay between two zinc roasters, acid-making, and hydrometallurgy processes poses additional challenges in achieving optimal roasting temperatures.

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In practice, the operators evaluate the operating performance of the ZRP and set the roasting temperature based on individual experience. Due to the complex process characteristics and the coupling relationship between two roasters and downstream processes, manual evaluation and optimization are sometimes untimely and unreasonable, leading to poor operation of the ZRP. It is essential to construct an effective decision-making system for the ZRP to ensure optimal operation. A typical decision-making system consists of two parts: building a model to evaluate the operating performance and extracting optimization rules from the evaluation model for decision-making.

At present, there are relatively few studies about the operating performance evaluation (OPE) of the ZRP [3], [4]. However, many general OPE techniques for complex industrial processes have been proposed, especially the data-driven methods [10]. Data-driven methods do not require precise models and evaluate the operating performance by analyzing and identifying the information within the process data. Hence, they have emerged as the most common OPE approach, mainly including multivariate statistical analysis (MSA) [11], [12], [13], [14], [15], [16], [17], [18] and fuzzy synthetic evaluation (FSE) [19], [20], [21], [22], [23], [24], [25], [26], [27].

The Gaussian mixture model (GMM) is a widely used MSA method to characterize multiple operating modes based on process data. Ye et al. [11]. proposed an online OPE strategy based on safety and optimality indicators. In this strategy, the safety and optimality indicators are calculated and classified into different performance levels under different operating modes that are partitioned by the GMM. In [12], the GMM is employed to deal with the non-Gaussian distribution data, thereby realizing operating optimality assessment under stable and transition modes. Dimensionality reduction methods are a large class of MSA methods to conduct the operating performance evaluation by extracting features from multivariate data. For example, Sedghi and Huang [13] proposed a real-time evaluation strategy for operating performance, in which the mixture probabilistic principal component regression and the dynamic principal component regression are used to tackle the multimodal behavior of steady-state modes and transitions, respectively. Zou and Zhao [15] developed a meticulous evaluation strategy of operating performance for industrial processes. In this strategy, the stationary and nonstationary variables are characterized by the principal component analysis and cointegration analysis, thereby extracting features to online evaluate the process operating performance.

Although the abovementioned MSA methods have achieved good results in the OPE of some industrial processes, they have certain limitations in dealing with the multiscale data and the coexistence of qualitative and quantitative information. The FSE method can solve the limitations by introducing fuzzy techniques and expert experience [21]. Therefore, it is more suitable for realizing the OPE of the complex industrial process. Li et al. [21] proposed a deterioration-degree-based fuzzy synthetic evaluation strategy for a wind turbine generator system. Similarly, Zhu et al. [22] developed a deterioration-degree-based fuzzy synthetic evaluation strategy with a sliding window for an electrocoagulation purification process. Li et al. [23] presented a two-layer fuzzy synthetic strategy for operating performance evaluation of an industrial hydrocracking process, which evaluates operating performance from the perspectives of different products, product properties, and process variables. Previous studies provide an important reference for evaluating the operating performance of the ZRP.

Since OPE models are mostly black-box models, it is essential to effectively extract a set of transparent and interpretable rules, with which the optimization decisions can be made for the next step [28]. To achieve this goal, several techniques have been proposed, such as case-based reasoning [29], [30], classification and regression trees (CART) [31], [32], neural network [33], [34], and fuzzy rules [35], [36], [37], [38], [39], [40]. Among these techniques, the fuzzy rule extraction technique has gained a lot of attention due to its interpretability and comprehensibility. Gao et al. [28] proposed a fuzzy-based support vector machine (SVM) classifier for evaluating hot metal silicon content in the blast furnace and developed a CART-based fuzzy rule extraction strategy to obtain clear and explainable rules for decision-making. Zhang et al. [38] developed a controllable-domain-based fuzzy rule extraction strategy for optimization control of the copper removal process. In [39], an augmented-fuzzy-cognitive-maps-based medical decision support system is designed by combining expert knowledge and data knowledge. These fuzzy rule extraction strategies achieve the goal of deriving transparent and understandable optimization rules from black-box models.

Combining the fuzzy synthetic evaluation and rule extraction strategy holds great promise for deriving transparent and understandable rules to optimize the zinc roasting temperature. However, existing methods for optimizing the roasting temperature of the ZRP have certain limitations. One of the challenges is the dynamic nature of the impact of key performance indicators (KPIs) on operating performance. To address this issue, [21] and [22] introduced the deterioration degree to dynamically update the weight of each KPI in OPE models, thereby dealing with the dynamic nature of the KPIs. While this approach shows potential, it is also important to consider that each KPI may have different priorities in updating the OPE model. Unfortunately, they do not account for this issue and give the same upper and lower bounds on the deterioration degree of each KPI, which can lead to unreasonable evaluation results. Therefore, further research is needed to develop more effective approaches that consider the relative importance of each KPI in the optimization process. On the other hand, most of the existing methods are aimed at building an evaluation model and extracting rules from a global perspective. However, the ZRP studied in this article involves two large-scale roasters operating independently. It is necessary to analyze the operating performance of each roaster from a local perspective and extract additional optimization rules, thereby further improving the effectiveness of decision-making for the ZRP.

To address the above challenges, a decision-making framework for co-optimization of the zinc roasting temperature is proposed. First, the KPIs are defined by analyzing the production process of the ZRP and the coupling relationship with the downstream process. On this basis, a variable-weight degradation-degree-based fuzzy synthetic evaluation (VWDD-FSE) model is built to evaluate the operating performance of the ZRP at a macroscopic level. Then, a dynamic model of the large-scale roaster is introduced and the sensitivity analysis of this model is conducted. Based on the analysis result, the temperature-adjustable margin of the zinc roaster is defined, which can describe the operating performance of each roaster at a microscopic level. Finally, a two-level decision-making system is designed based on the evaluation result and temperature-adjustable margin to realize the co-optimization of the roasting temperature. For the first level, the basic setting rules are designed by analyzing the evaluation result and maximum degradation degree to achieve global optimization of the roasting temperature. For the second level, the collaborative rules are developed according to the difference between the roasting temperature and the temperature-adjustable margin of each roaster to realize the co-optimization of two zinc roasters. The main contributions of this article are summarized as follows.

1) A novel VWDD-FSE model is introduced, which evaluates the operating performance of the ZRP by updating the weights of each KPI based on their priorities. This model provides a comprehensive evaluation of the operating performance from a global perspective.
2) The concept of a temperature-adjustable margin is defined by conducting sensitivity analysis on the process model, which allows for evaluating the optimality of each zinc roaster. This margin allows for an accurate evaluation of the operating performance from a local perspective.
3) A two-level decision-making system is designed, integrating the VWDD-FSE model and the temperature-adjustable margin. This system enables the co-optimization of the roasting temperature by incorporating evaluation results and the temperature-adjustable margin of each roaster. It provides a systematic approach to improve the operating performance of the ZRP.

The rest of this article is organized as follows. Section II details the ZRP and challenges in decision-making. Section III revisits the related methods. Section IV presents the proposed decision-making framework in detail. In Section V, experimental results are presented to illustrate the effectiveness of the proposed method. Finally, Section VI concludes this article.

II. Process Description

The ZRP is the first step in zinc smelting, providing raw materials for subsequent acid-making and hydrometallurgy processes. A schematic diagram of the ZRP and its downstream processes is presented in Fig. 1. In the ZRP, the roasting temperature is the most crucial process variable, typically controlled by adjusting the concentrate feed rate under a fixed blast volume [1]. Increasing the yield through raising the concentrate feed rate can lead to higher roasting temperatures, which can affect the performance of the ZRP and its downstream processes from environmental protection, reaction atmosphere of roasters, and product quality. The detailed analysis is given as follows.

1) Ensuring strict environmental protection is the most crucial consideration in the ZRP. Sulfur dioxide flue gas is a by-product of the ZRP and is used as a raw material for acid-making. However, increasing the roasting temperature to enhance production efficiency can result in higher amounts of flue gas production, potentially exceeding the treatment capacity of the acid-making process. In such cases, excess sulfur dioxide will be released into the atmosphere, leading to severe air pollution and significant fines. Thus, optimizing the roasting temperature to control the sulfur content of the tail gas within the required range ($C_{SO_2} < 100\ \mathrm{mg/m^3}$) is essential for environmental protection in the ZRP.

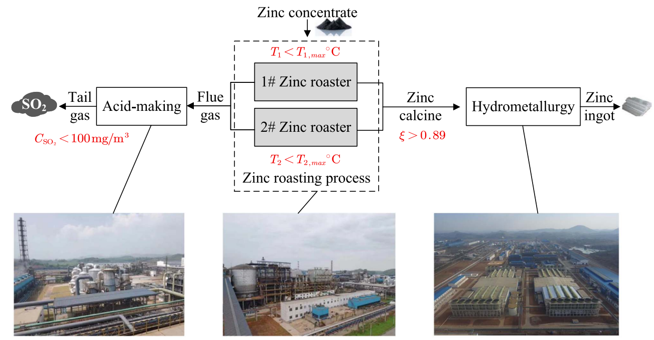


Fig. 1. Schematic diagram of the zinc roasting process and its downstream processes.

TABLE I
Theoretical Upper Limits of Roasting Temperature Under Different Conditions

Working conditions	Pb+SiO_2 (wt.%)		
	$\leq 4\%$	$4\% \sim 5\%$	$\geq 5\%$
Working condition 1	980 °C	965 °C	950 °C
Working condition 2	975 °C	960 °C	950 °C
Working condition 3	970 °C	960 °C	955 °C

2) Maintaining a good reaction atmosphere is the key to ensuring the long-term efficient operation of the ZRP. A good fluidized state improves the quality of the calcine, while low-melting-point substances (such as PbS and SiO_2) in the zinc concentrate can cause sintering at high roasting temperatures, leading to a poor reaction atmosphere or even shutdown of the roaster [2]. It is crucial to control the roasting temperature to avoid exceeding the upper limits ($T_1 < T_{1,\max}$°C and $T_2 < T_{2,\max}$°C). However, the theoretical temperature limits for each roaster differ based on the content of low-melting-point substances in the concentrate and the apparent density. The theoretical upper limits of roasting temperature under different conditions are given in Table I according to expert experience. Therefore, optimizing the reaction atmosphere by limiting the roasting temperature below its upper limit based on practical operating conditions is necessary.
3) Producing a high-quality product is the premise for improving downstream operation efficiency. Over-reaction or under-reaction due to excessively high or low

roasting temperatures can adversely affect the quality of zinc calcine, leading to lower soluble zinc rates ($\xi \leq 0.89$). Although the feeding composition is the same, the optimal roasting temperature for each roaster varies due to differences in long-term operational conditions. Hence, optimizing the roasting temperature of each roaster to ensure it falls within the optimal temperature range is critical in achieving the highest soluble zinc rate.

Among the above indicators, the environmental protection indicator is the most important and cannot exceed its threshold to avoid unnecessary huge fines. The other two indicators can appropriately exceed their thresholds to ensure that the ZRP is relatively optimal.

The analysis highlights the benefits of setting the roasting temperature close to the optimal temperature under actual operating conditions, which can increase the yield and efficiency of the ZRP and its downstream processes. Nevertheless, the complex coupling between the two roasters and the downstream processes poses significant challenges in evaluating the operating performance and optimizing the roasting temperature. Therefore, it is imperative to develop a decision-making system for co-optimization of the roasting temperature for two zinc roasters.

III. Brief Review of Related Methods

A. Deterioration Degree

To assess the degree of deterioration between the current and the optimal conditions for the KPIs, the concept of the deterioration degree is introduced [41]. The traditional deterioration degree can be calculated as

$$d_i = \begin{cases} 0, & u_i \leq a_i \\ \frac{u_i - a_i}{b_i - a_i}, & a_i < u_i < b_i \\ 1, & u_i \geq b_i \end{cases} \tag{1}$$

where d_i is the deterioration degree of the ith KPI; a_i and b_i are the lower and upper limit values, respectively; u_i is the real-time value of the ith KPI. It can be seen that the range of the deterioration degree is [0, 1]. The smaller the deterioration degree, the closer the KPI is to the optimal condition, and vice versa.

B. Fuzzy Synthetic Evaluation

Fuzzy synthetic evaluation is a quantitative approach that leverages fuzzy mathematics to evaluate operating performance comprehensively. This method enables the conversion of qualitative evaluations into quantitative evaluations using the membership degree theory [21]. To improve the evaluation of the operating performance for dynamic industrial processes, the variable weight theory based on the deterioration degree is introduced to update the weight of each KPI dynamically. The specific steps for implementing the deterioration-degree-based FSE are as follows:

1) Determine the KPIs and Operating Performance Grades: According to the analysis of the practical industrial process, m KPIs that are used to evaluate the operating performance can be determined, namely, $F = \{f_1, f_2, \ldots, f_m\}$. Similarly, the operating performance grades can be determined from practical operational conditions and divided into n categories, $G = \{g_1, g_2, \ldots, g_n\}$.

2) Obtain and Update the Weight Set of the KPIs: The initial weight set of the KPIs is $\mathbf{A}^0 = [A_1^0, A_2^0, \ldots, A_m^0]$, where $\mathbf{A}_i^0, (i = 1, \ldots, m)$ is the weight of the ith KPI. The commonly used methods for obtaining the initial weight set include the analytic hierarchy process, gray relational degree, etc. Using a fixed weight set $\mathbf{A}^0$ to evaluate the operating performance of industrial processes may lead to inaccurate evaluation results. Therefore, the degradation degree is introduced to dynamically update the weight set as

$$A_i = A_i^0 (1 - d_i)^{\delta - 1} \Big/ \sum_{j=1}^{m} A_j^0 (1 - d_j)^{\delta - 1} \tag{2}$$

where A_i^0 is the initial weight of the ith KPI; A_i is the weight of the ith KPI after updating; d_i is the current degradation degree of the ith KPI, which can be obtained by (1); δ is the update coefficient of the weight and commonly set as $\delta = -1$.

3) Establish Membership Function Matrix: Determining the membership function is the most important part, which directly impacts the evaluation performance of the FSE model. The semiridge membership function is suitable for practical industrial processes due to its smoothness and ease of parameter determination. The definitions of different semiridge membership functions are given as follows.

The small type

$$v_1(u_i) = \begin{cases} 1, & u_i \leq \alpha_{i,1} \\ \frac{1}{2} - \frac{1}{2}\sin\frac{\pi}{\alpha_{i,2} - \alpha_{i,1}}(u_i - \frac{\alpha_{i,1} + \alpha_{i,2}}{2}), & \alpha_{i,1} < u_i \leq \alpha_{i,2} \\ 0, & u_i > \alpha_{i,2}. \end{cases} \tag{3}$$

The middle type

$$v_2(u_i) = \begin{cases} 0, & u_i \leq \alpha_{i,1} \\ \frac{1}{2} + \frac{1}{2}\sin\frac{\pi}{\alpha_{i,2} - \alpha_{i,1}}(u_i - \frac{\alpha_{i,1} + \alpha_{i,2}}{2}), & \alpha_{i,1} < u_i < \alpha_{i,2} \\ 1, & u_i = \alpha_{i,2} \\ \frac{1}{2} - \frac{1}{2}\sin\frac{\pi}{\alpha_{i,3} - \alpha_{i,2}}(u_i - \frac{\alpha_{i,2} + \alpha_{i,3}}{2}), & \alpha_{i,2} < u_i \leq \alpha_{i,3} \\ 0, & u_i > \alpha_{i,3}. \end{cases} \tag{4}$$

The large type

$$v_3(u_i) = \begin{cases} 0, & u_i \leq \alpha_{i,2} \\ \frac{1}{2} + \frac{1}{2}\sin\frac{\pi}{\alpha_{i,3} - \alpha_{i,2}}(u_i - \frac{\alpha_{i,2} + \alpha_{i,3}}{2}), & \alpha_{i,2} < u_i \leq \alpha_{i,3} \\ 1, & u_i > \alpha_{i,3} \end{cases} \tag{5}$$

where $v_1(\cdot)$, $v_2(\cdot)$, and $v_3(\cdot)$ denote the small, middle, and large type membership function, respectively; $u_i, (i = 1, \ldots, m)$ is the real-time value of the ith KPI; $\alpha_{i,1}$, $\alpha_{i,2}$, and $\alpha_{i,3}$ are the parameters of the semiridge membership functions of the ith KPI.

Substituting the real-time value of each KPI into the above three membership functions, the fuzzy synthetic matrix $\mathbf{V}$ can

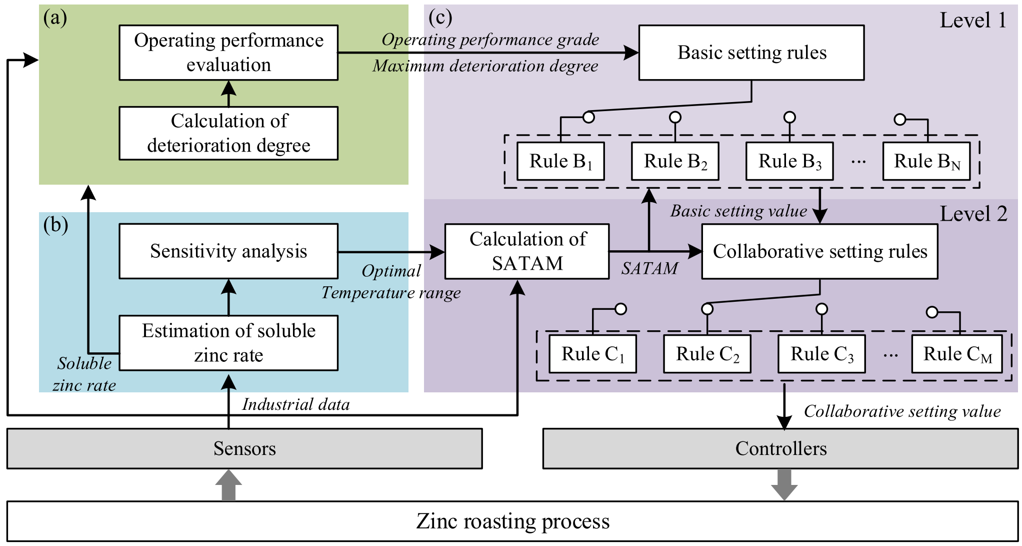


Fig. 2. Framework of the two-level decision-making system for temperature co-optimization. (a) Operating performance evaluation unit. (b) Process model unit. (c) Co-optimization unit.

be obtained as follows:

$$\mathbf{V}=\begin{bmatrix}V_1\\V_2\\\vdots\\V_m\end{bmatrix}=\begin{bmatrix}v_{1,1}&v_{1,2}&\cdots&v_{1,n}\\v_{2,1}&v_{2,2}&\cdots&v_{2,n}\\\vdots&\vdots&\ddots&\vdots\\v_{m,1}&v_{m,2}&\cdots&v_{m,n}\end{bmatrix}\tag{6}$$

where $V_i, (i=1,\ldots,m)$ is the membership degree of the ith KPI; $v_{i,j}, (j=1,\ldots,n)$ is the membership degree of the ith KPI belongs to the jth grade; m and n are the number of the KPIs and operating performance grades, respectively.

4) Obtain the Final Operating Performance Result: The synthetic evaluation matrix $\mathbf{B}$ is calculated as follows:

$$\mathbf{B}=\mathbf{A}*\mathbf{V}=[B_1,B_2,\ldots,B_n]\tag{7}$$

where $\mathbf{A}=[A_1,A_2,\ldots,A_m]$ is the variable weight set of the KPIs. Then, the final evaluation result g can be obtained by the defuzzification of the synthetic evaluation matrix. Generally, the maximum membership principle is used to defuzzify the synthetic evaluation matrix as follows:

$$g=\max_{1\le j\le n}B_j\tag{8}$$

IV. Decision-Making System for Temperature Co-Optimization of the ZRP

The decision-making system for temperature co-optimization of the ZRP is depicted in Fig. 2 and comprises three units: the operating performance evaluation unit, the process model unit, and the co-optimization unit.

The operating performance evaluation unit is responsible for calculating the deterioration degree of each KPI and evaluating the current operating performance grade of the ZRP. The process model unit provides the estimated soluble zinc rate for the operating performance evaluation unit and conducts sensitivity analysis to determine the theoretical optimal temperature range for calculating the temperature-adjustable margin. The co-optimization unit, on the one hand, calculates the basic setting value based on the basic setting rules and evaluation results. On the other hand, it calculates the temperature-adjustable margin by comparing the theoretical optimal temperature range with the current temperature of each roaster. Finally, the basic setting value is allocated to the two roasters according to the collaborative setting rules and temperature-adjustable margin.

A. Variable-Weight Degradation-Degree-Based Fuzzy Synthetic Evaluation (VWDD-FSE)

The first step in VWDD-FSE is to determine the KPIs and operating performance grades. Based on the process analysis in Section II, the KPIs of the ZRP can be determined from three aspects.

1) Sulfur dioxide concentration in tail gas and its changing rate are selected as the KPIs to evaluate the environmental protection level of the ZRP. The sulfur dioxide concentration in tail gas (denoted as f_1) indicates the current processing capacity of the acid production process, and its rate (denoted as f_2) reflects the dynamic change of the processing capacity.
2) The differences between the current roasting temperature and its theoretical upper limit of two roasters are selected as the KPIs to evaluate the reaction atmosphere, calculated as $\Delta T_1=T_1-T_{1,\max}$ and $\Delta T_2=T_2-T_{2,\max}$. When ΔT_1 (denoted as f_3) or ΔT_2 (denoted as f_4) is less than or equal to 0 °C, it indicates a low possibility of sintering in the first or second roaster, and vice versa.
3) The soluble zinc rates of the zinc calcine are selected as the KPIs to evaluate the product quality of the two roasters, denoted as f_5 and f_6. A higher soluble zinc rate means better product quality. Since the soluble zinc rate cannot be measured online during the actual roasting process,

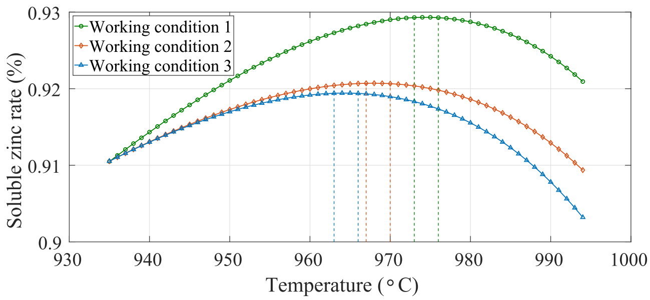


Fig. 3. Sensitivity analysis results under different working conditions.

an estimation model proposed in [42] is introduced to estimate the soluble rate online.

Based on the process knowledge, the operating performance grades are defined as $G = \{\text{optimal, good, poor, unqualified}\} = \{g_1, g_2, g_3, g_4\}$. The grades of optimal, good, and poor are determined using the fuzzy synthetic evaluation method, while the unqualified grade is assigned when the degradation degree is greater than 0.95, indicating the worst operating performance.

The conventional degradation-degree-based fuzzy synthetic evaluation (DD-FSE) has limitations when handling KPIs with varying priorities. When calculating the deterioration degree using (1), each KPI is treated as equally important. However, the ZRP has different priorities for each KPI, with the following ranking of importance: $f_1 > f_2 > f_3 = f_4 > f_5 = f_6$. Additionally, according to (1), all KPIs can deteriorate to 1, resulting in an unqualified grade for the operating performance. However, based on process analysis, the ZRP is only considered unqualified when the concentration of SO_2 in the tail gas exceeds the threshold.

To address these limitations, a variable weight degradation degree approach is proposed. It assigns different ranges of deterioration degrees to each KPI based on their importance and is calculated as follows:

$$D_i = \begin{cases} d_{i,1}, & u_i \le a_i \\ d_{i,1} + (d_{i,2} - d_{i,1})\frac{u_i - a_i}{b_i - a_i}, & a_i < u_i < b_i \\ d_{i,2}, & u_i \ge b_i \end{cases} \tag{9}$$

where $D_i, (i = 1, \ldots, 6)$ is the degradation degree corresponding to the six KPIs of the ZRP; $d_{i,1}$ and $d_{i,2}$ represent the lower and upper limits of the degradation degree of the ith KPI, respectively. By adjusting $d_{i,1}$ and $d_{i,2}$, the influence degree of each KPI on the ZRP can be regulated.

Based on the ranking of importance, the lower and upper limits of the degradation degree are assigned as follows: $d_{i,1} = 0, (i = 1, \ldots, 6)$; $d_{1,2} = 1$; $d_{2,2} = 0.95$; $d_{i,2} = 0.9$, $(i = 3, 4, 5, 6)$. Through these settings, the deterioration degree updates the weight set of the fuzzy synthetic evaluation matrix with different priorities, thereby obtaining a reasonable result of the operating performance.

The proposed VWDD-FSE method is introduced to evaluate the operating performance of the ZRP. The algorithm for VWDD-FSE is presented in Algorithm 1.

Algorithm 1: VWDD-FSE for Evaluating the Operating Performance of the ZRP.

Input: u_i: real-time value; $\mathbf{A}^0$: initial weight set; $\theta_i = \{a_i, b_i, \alpha_{i,1}, \alpha_{i,2}, \alpha_{i,3}, d_{i,1}, d_{i,2}\}$: parameter set
Output: The operating performance grade g and the maximum degradation degree D_{max}

for $i \le 6$ **do**
  Calculate D_i according to Eq. (9)
end for
Calculate the maximum degradation degree $D_{\max} = \max(D_i)$
if $(D_{\max} > 0.95)$**then**
  $g = g_4$
else
  for $i \le 6$ **do**
    Obtain V_i in the fuzzy synthetic matrix $\mathbf{V}$ by substituting u_i into Eqs. (3)–(5)
    Update variable weight A_i according to Eq. (2)
  end for
  Calculate synthetic evaluation matrix $\mathbf{B}$ according to Eq. (7)
  Obtain the operating performance grade g according to Eq. (8)
end if
return g, $D_{\max}$

B. Sensitivity-Analysis-Based Temperature-Adjustable Margin (SATAM)

In the practical ZRP, zinc roasters have their own optimal temperature range, under which they can obtain the best product quality. However, the complex mechanisms and varying feeding compositions result in different working conditions for each zinc roaster, leading to diverse optimal temperature ranges. Besides, the quality of the zinc calcine can only be obtained through low-frequency offline laboratory tests. As a result, it is challenging to obtain the optimal temperature range under different working conditions through data analysis.

In view of the above problems, a sensitivity analysis is conducted on the soluble zinc rate estimation model proposed in [42]. This sensitivity analysis aims to determine the theoretical optimal temperature range of the roaster under different working conditions. The results of the sensitivity analysis are presented in Fig. 3, which show that the soluble zinc rate initially increases and then decreases with the roasting temperature, in line with the findings of the mechanism analysis. Furthermore, the optimal temperature ranges vary significantly under different working conditions, reflecting changes in the roaster characteristics.

In order to leverage the optimal temperature range for co-optimization of the roasting temperature, we introduce the concept of the sensitivity-analysis-based temperature-adjustable margin (SATAM) for the roaster. The SATAM is defined as the allowable deviation from the optimal temperature range, within which the roasting temperature can be adjusted while still maintaining the optimal performance of the roaster. The definition of the SATAM is as follows:

$$\begin{cases} T^{m}_{\max,k} = T^{op}_{\max,k} - T^{sp}_{k} \\ T^{m}_{\min,k} = T^{op}_{\min,k} - T^{sp}_{k} \\ T^{m}_{k} = [T^{m}_{\min,k}, T^{m}_{\max,k}] \end{cases} \tag{10}$$

where the index k refers to the first roaster ($k = 1$) or the second roaster ($k = 2$); $T^{op}_{\max,k}$ and $T^{op}_{\min,k}$ represent the upper and lower limits of the optimal temperature range for the kth roaster; T^{sp}_{k} denotes the setpoint of the roasting temperature for the kth roaster; T^{m}_{k} represents the SATAM, which is the allowable deviation from the optimal temperature range for the kth roaster; and $T^{m}_{\max,k}$ and $T^{m}_{\min,k}$ indicate the upper and lower limits of the SATAM, respectively. The SATAM can have either a positive or negative value, indicating whether the setpoint of the roasting temperature needs to be increased or decreased, respectively.

By utilizing the defined SATAM, it becomes feasible to incorporate an elastic adjustment range during the collaborative setting of the roasting temperature. This adjustment range allows for flexibility in fine-tuning the roasting temperature within the permissible limits. As a result, the system can adapt to variations in the working conditions and optimize the temperature adjustment strategy accordingly.

C. Co-Optimization of the Roasting Temperature Based on VWDD-FSE and SATAM

This section introduces a two-level decision-making system designed to co-optimize the roasting temperature in the ZRP. The system is based on VWDD-FSE and SATAM to achieve the optimal setting of the roasting temperature. At the first level, the basic setting rules are designed according to the VWDD-FSE evaluation results, which focus on determining the roasting temperature's basic setting value. By applying the basic setting rules, the relative optimality of environmental protection, reaction atmosphere, and product quality can be achieved from a global perspective. The second level involves the design of the collaborative setting rules based on the SATAM results, which concentrates on allocating basic setting values to both roasters collaboratively. These collaborative setting rules facilitate the precise adjustment of the two roasters from a local perspective, ultimately achieving the optimal performance of the ZRP and its downstream processes. The specific rules and procedures of the two-level decision-making system are described as follows.

1) VWDD-FSE-Based Basic Setting Rules (First Level): Based on the analysis conducted in Section IV-A, it is evident that different temperature adjustment strategies are required for the ZRP under various operating performance grades and deterioration degrees. When the operating performance grade is optimal, no roasting temperature adjustment is needed. However, for nonoptimal grades, adjustments should be made based on the dominant indicator identified in the deterioration degrees associated with the performance deviation. To address this, a set of basic setting rules is developed to determine the appropriate basic setting value of the roasting temperature for two roasters, taking into account the operating performance grade and the dominant indicator.

When the dominant indicator is f_1, it is necessary to reduce the temperature of both roasters to decrease the deterioration degree of f_1. For operating performance grades of good (g_2), poor (g_3), or unqualified (g_4), the adjustment of the roasting temperature should be based on the deviation of f_1 from its lower limit a_1. Hence, the basic setting rules $\mathbf{R}^b_1$ are as follows:

R^b_1: **IF** argmax $(\mathbf{D}) = f_1$ and $Grade = g_2$ or $Grade = g_3$ or $Grade = g_4$, **THEN** $\Delta T^{sp} = -|(f_1 - a_1)|$°C.

When the dominant indicator is f_2, it is necessary to reduce the temperature of both roasters to decrease the deterioration degree of f_2. For operating performance grades of good (g_2) or poor (g_3), the adjustment of the roasting temperature is a fixed value. The basic setting rules $\mathbf{R}^b_2$ are summarized as follows:

$R^b_{2,1}$: **IF** argmax $(\mathbf{D}) = f_2$ and $Grade = g_2$, **THEN** $\Delta T^{sp} = -10\,°\mathrm{C}$

$R^b_{2,2}$: **IF** argmax $(\mathbf{D}) = f_2$ and $Grade = g_3$, **THEN** $\Delta T^{sp} = -20\,°\mathrm{C}$.

When the dominant indicator is f_3 or f_4, it is necessary to reduce the temperature of the roaster with the highest deterioration degree, thereby achieving a reduction in f_3 or f_4. The basic setting rules $\mathbf{R}^b_3$ are summarized as follows:

$R^b_{3,1}$: **IF** argmax $(\mathbf{D}) = f_3$ and $Grade = g_2$ or $Grade = g_3$, **THEN** $\Delta T^{sp}_1 = -|f_3|$°C

$R^b_{3,2}$: **IF** argmax $(\mathbf{D}) = f_4$ and $Grade = g_2$ or $Grade = g_3$, **THEN** $\Delta T^{sp}_2 = -|f_4|$°C.

When the dominant indicator is f_5 or f_6, it is necessary to consider the relative deterioration degree of $f_1 \sim f4$ about the dominant indicator (f_5 or f_6). If adjusting the roasting temperature with ignoring the relative deterioration degree of $f_1 \sim f4$, it may lead to further deterioration of the operating performance. Therefore, when there is an indicator with a relatively large deterioration degree, it is necessary to adopt this indicator as the leading indicator for adjustment; otherwise, adjust the roasting temperature according to the SATAM, thereby realizing the optimal product quality. Based on the above analysis, the basic setting rules $\mathbf{R}^b_4$ are summarized as follows:

$R^b_{4,1}$: **IF** argmax$(\mathbf{D}) = f_5$ or argmax$(\mathbf{D}) = f_6$ and $Grade = g_2$ or $Grade = g_3$ and F_D(argmax$([D_1, D_2, D_3, D_4])$)$/F_D$ $(f5) \geq 0.8$ or F_D(argmax$([D_1, D_2, D_3, D_4])$)$/F_D(f6) \geq 0.8$, **THEN** using the rule belongs to F_D(argmax $([D_1, D_2, D_3, D_4])$)

$R^b_{4,2}$: **IF** argmax $(\mathbf{D}) = f_5$ and $Grade = g_2$ or $Grade = g_3$ and F_D(argmax$([D_1, D_2, D_3, D_4])$)$/F_D(f6) < 0.8$, **THEN** $\Delta T^{sp}_1 = T^{m}_{\min,1}$°C

$R^b_{4,3}$: **IF** argmax $(\mathbf{D}) = f_6$ and $Grade = g_2$ or $Grade = g_3$ and F_D(argmax$([D_1, D_2, D_3, D_4])$)$/F_D(f6) < 0.8$, **THEN** $\Delta T^{sp}_2 = T^{m}_{\min,2}$°C

where argmax $(\cdot)$ is a function to find the KPI with the maximum deterioration degree; $\mathbf{D} = [D_1, D_2, D_3, D_4, D_5, D_6]$ is the current degradation degree set of all KPIs; $Grade$ is the current operating performance grade; $D_i, (i = 1, 2, 3, 4)$ is the current degradation degree of the i th KPI; ΔT^{sp}_1, ΔT^{sp}_2, and ΔT^{sp} are the adjustment of the temperature setpoint of the first roaster, the second roaster, and overall of the two roasters, respectively; $F_D(\cdot)$ denotes (9), which is used to calculate the degradation degree of the KPI; T_1^m and T_2^m are the SATAMs of the first and second roasters, respectively.

2) SATAM-Based Collaborative Setting Rules (Second Level): The basic setting rules adjust the temperature setpoint of roasters under different operating performance grades and dominant indicators. However, the operator at the industrial site usually allocates the adjustment amount evenly to two roasters or only to a specific roaster. Although this adjustment method can reduce the degradation of environmental protection or reaction-atmosphere indicators, it may cause the roasting temperature to be far away from the optimal temperature range, resulting in a deterioration of product quality. If the adjustment amount is allocated reasonably, the deterioration degree of the product quality indicator can be maintained or reduced without increasing the deterioration degree of the environmental protection and reaction-atmosphere indicators. Based on the above analysis, it is necessary to allocate the basic adjustment amount collaboratively according to the SATAMs of the two roasters.

When using the basic setting rules $\mathbf{R}_1^b$ or $\mathbf{R}_2^b$, it is necessary to allocate the total adjustment amount to the two roasters collaboratively. If the adjustment amount is greater/less than the upper/lower limit of the SATAM, the optimal strategy is to evenly allocate the adjustment amount to the two roasters. If the adjustment amount is within the range of the SATAM, the roaster with the larger lower limit of the SATAM will be adjusted first, and then the remaining adjustment amount will be allocated to the roaster with the smaller lower limit of the SATAM. Based on the above analysis, the basic setting rules $\mathbf{R}_1^b$ and $\mathbf{R}_2^b$ share the same collaborative rules $\mathbf{R}_{12}^c$ as follows:

$R_{12,1}^c$: **IF** $\Delta T^{sp} < T_{\min,1}^m + T_{\min,2}^m$ or $\Delta T^{sp} > T_{\max,1}^m + T_{\max,2}^m$, **THEN** $\Delta T_1^{sp} = \Delta T^{sp}/2$ and $\Delta T_2^{sp} = \Delta T^{sp}/2$

$R_{12,2}^c$: **IF** $T_{\min,1}^m + T_{\min,2}^m \le \Delta T^{sp} \le T_{\max,1}^m + T_{\max,2}^m$ and $T_{\min,1}^m \le T_{\min,2}^m$, **THEN** $\Delta T_2^{sp} = \Delta T^{sp} - T_{\min,1}^m$ and $\Delta T_1^{sp} = T_{\min,1}^m$

$R_{12,3}^c$: **IF** $T_{\min,1}^m + T_{\min,2}^m \le \Delta T^{sp} \le T_{\max,1}^m + T_{\max,2}^m$ and $T_{\min,2}^m < T_{\min,1}^m$, **THEN** $\Delta T_1^{sp} = \Delta T^{sp} - T_{\min,2}^m$ and $\Delta T_2^{sp} = T_{\min,2}^m$.

When using the basic setting rules $\mathbf{R}_3^b$, if the adjustment amount is less than the lower limit of the SATAM, then adjust according to the current adjustment amount, and the adjustment amount of the other roaster is 0. If the adjustment amount is greater than the lower limit of the SATAM, then adjust according to the current lower limit of the SATAM, and provide more adjustment space for the roaster. Based on the above analysis, the collaborative rules $\mathbf{R}_3^c$ is summarized as follows:

$R_{3,1}^c$: **IF** $f_3 > f_4$ and $\Delta T_1^{sp} \ge T_{\min,1}^m$ and $T_{\min,2}^m \ge \Delta T_1^{sp} - T_{\min,1}^m$, **THEN** $\Delta T_2^{sp} = \Delta T_1^{sp} - T_{\min,1}^m$ and $\Delta T_1^{sp} = T_{\min,1}^m$

$R_{3,2}^c$: **IF** $f_3 > f_4$ and $\Delta T_1^{sp} \ge T_{\min,1}^m$ and $T_{\min,2}^m < \Delta T_1^{sp} - T_{\min,1}^m$, **THEN** $\Delta T_2^{sp} = T_{\min,2}^m$ and $\Delta T_1^{sp} = T_{\min,1}^m$

$R_{3,3}^c$: **IF** $f_4 > f_3$ and $\Delta T_2^{sp} \ge T_{\min,2}^m$ and $T_{\min,1}^m \ge \Delta T_2^{sp} - T_{\min,2}^m$, **THEN** $\Delta T_1^{sp} = \Delta T_2^{sp} - T_{\min,2}^m$ and $\Delta T_2^{sp} = T_{\min,2}^m$

$R_{3,4}^c$: **IF** $f_4 > f_3$ and $\Delta T_2^{sp} \ge T_{\min,2}^m$ and $T_{\min,1}^m < \Delta T_2^{sp} - T_{\min,2}^m$, **THEN** $\Delta T_1^{sp} = T_{\min,1}^m$ and $\Delta T_2^{sp} = T_{\min,2}^m$.

When using the basic setting rules $\mathbf{R}_4^b$, the lower limit of the SATAM should be used to adjust the setpoint for the roaster with a higher deterioration degree. Besides, adjust the setpoint of the other roaster under the condition that the overall adjustment amount should be less than 0 as much as possible. Based on the above analysis, the collaborative rules $\mathbf{R}_4^c$ are summarized as follows:

$R_{4,1}^c$: **IF** $T_{\min,1}^m + T_{\min,2}^m \le 0$, **THEN** $\Delta T_1^{sp} = T_{\min,1}^m$ and $\Delta T_2^{sp} = T_{\min,2}^m$

$R_{4,2}^c$: **IF** $f_5 > f_6$ and $T_{\min,1}^m + T_{\min,2}^m > 0$ and $T_{\min,2}^m \le 0$, **THEN** $\Delta T_1^{sp} = T_{\min,1}^m$ and $\Delta T_2^{sp} = T_{\min,2}^m$

$R_{4,3}^c$: **IF** $f_5 > f_6$ and $T_{\min,1}^m + T_{\min,2}^m > 0$ and $T_{\min,2}^m > 0$, **THEN** $\Delta T_1^{sp} = T_{\min,1}^m$ and $\Delta T_2^{sp} = -T_{\min,1}^m$

$R_{4,4}^c$: **IF** $f_6 > f_5$ and $T_{\min,1}^m + T_{\min,2}^m > 0$ and $T_{\min,1}^m \le 0$, **THEN** $\Delta T_2^{sp} = T_{\min,2}^m$ and $\Delta T_1^{sp} = T_{\min,1}^m$

$R_{4,5}^c$: **IF** $f_6 > f_5$ and $T_{\min,1}^m + T_{\min,2}^m > 0$ and $T_{\min,1}^m > 0$, **THEN** $\Delta T_2^{sp} = T_{\min,2}^m$ and $\Delta T_1^{sp} = -T_{\min,2}^m$.

By applying the above collaborative rules, the adjustment amount of the temperature setting value can be reasonably allocated to the two roasters, thereby optimizing the operating performance of the ZRP.

V. Experiment Results

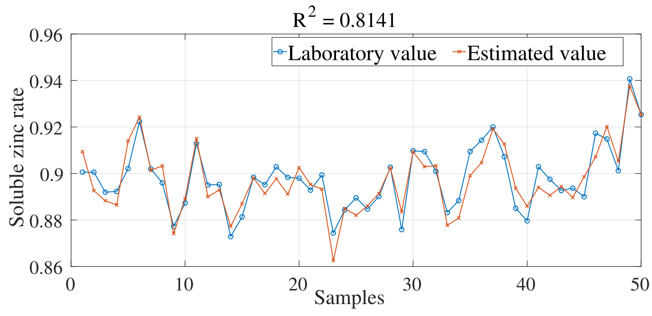
To assess the effectiveness of the proposed two-level decision-making system, a specific ZRP in China is selected for investigation [42]. This ZRP consists of two large-scale roasters that share an acid-making process and a hydrometallurgy process. For the case study, 50 sets of industrial data are collected from the database, including data from the first roaster, the second roaster, and the acid-making process. Each data set comprises 30 sets of real-time operational data and 1 set of laboratory data.

Experiments are conducted on both the VWDD-FSE method and the two-level decision-making system. The evaluation includes a comprehensive analysis of the overall results from all samples, as well as individual case studies. Through these analyses, detailed insights are gained into the performance and effectiveness of the proposed method.

A. Data Preprocessing and Parameter Settings

Since the ZRP is a long-period and large-delay industrial process with a large number of random disturbances, the time window technique is employed to preprocess each set of industrial data. Among the six KPIs, f_1, f_3, and f_4 represent the average values of the real-time data within the time window. The change rate of sulfur dioxide concentration, denoted as f_2, is obtained by fitting the industrial data of f_1 within the time window using a linear function. Additionally, by inputting the industrial data of the first and second roasters into the soluble zinc rate estimation model [42], the estimated values of f_5 and f_6 are obtained as shown in Fig. 4. It can be seen that the estimated value is highly consistent with the laboratory value, so it can be used as the KPIs for evaluating the operating performance of the ZRP. Considering that a higher soluble zinc rate means better product quality, this article takes $1 - f_5$ and $1 - f_6$ as the KPIs of the product quality to be consistent with other indicators.

Based on the analysis of the process mechanism and historical data, the parameter settings of the deterioration degree and fuzzy membership of each KPI are shown in Table II.



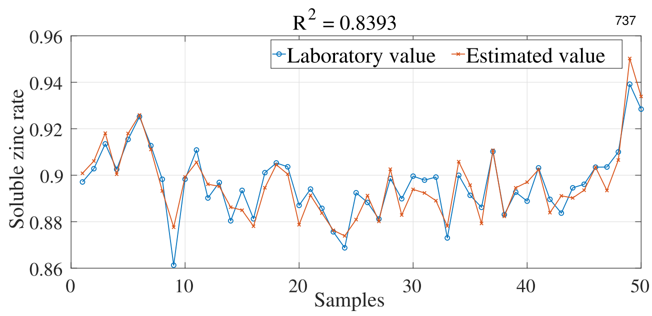


Fig. 4. Performance of the soluble zinc rate estimation model on the samples of the two roasters. (a) The laboratory value and estimated value from the first roaster. (b) The laboratory value and estimated value from the second roaster.

TABLE II
PARAMETER SETTINGS OF THE DETERIORATION DEGREE AND MEMBERSHIP OF EACH KPI

KPIs	a_i	b_i	$\alpha_{i,1}$	$\alpha_{i,2}$	$\alpha_{i,3}$
f_1	70	100	70	80	90
f_2	0	1.5	0	1	1.5
f_3	-20	20	-20	0	20
f_4	-20	20	-20	0	20
f_5	0.0953	0.1117	0.0953	0.1058	0.1117
f_6	0.0965	0.1161	0.0965	0.1057	0.1161

The analytic hierarchy process is used in this article to determine the initial weight set of the KPIs. Based on expert experience, the obtained initial weight set is $\mathbf{A}^0 = [0.34, 0.20, 0.13, 0.13, 0.09, 0.09]$.

B. Results and Performance Analysis of the VWDD-FSE

In this experiment, FSE and DD-FSE are introduced to analyze the effectiveness of the proposed VWDD-FSE. FSE, being the most commonly used performance evaluation method, lacks consideration for the dynamic impact of decision variables on KPIs and the priorities between different KPIs during operating performance evaluation. Hence, FSE is used as the benchmark approach for the comparative validation of the DD-FSE and the proposed VWDD-FSE. The key distinction between DD-FSE and VWDD-FSE lies in the upper limits $d_{i,2}$. In DD-FSE, these upper limits are set to 1, while in VWDD-FSE, they are

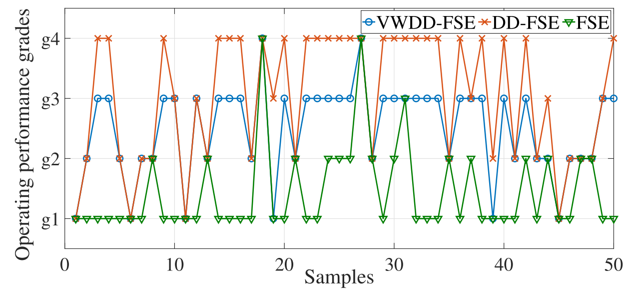


Fig. 5. Evaluation of operating performance grades for different methods.

TABLE III
PROPORTION OF EACH OPERATING PERFORMANCE GRADE UNDER DIFFERENT EVALUATION METHODS

Evaluation methods	Operating grade			
	g_1	g_2	g_3	g_4
FSE	66%	28%	2%	4%
DD-FSE	8%	30%	12%	50%
VWDD-FSE	12%	30%	54%	4%

determined based on the values specified in Table II. The FSE uses the initial weight set $\mathbf{A}^0$ for evaluating the operating performance without weight updates. Besides, in FSE, the operating performance grade is considered unqualified only when $f_1 > 100$ mg/m^3. The evaluation results of the three methods based on 50 sets of industrial data are presented in Fig. 5 and Table III.

The evaluation results of FSE are conservative since most of the operating performance grades are assigned as optimal. This can be attributed to the fact that FSE employs the initial weight set $\mathbf{A}^0$ without any updating, where the proportion of f_1 and f_2 exceeds 50%. Consequently, as long as f_1 and f_2 achieve the optimal grade, the ZRP is considered to be performing well, while overlooking the operating performance of the two roasters. This ultimately leads to a conservative evaluation grade that is inconsistent with practical operating performance.

The evaluation results of DD-FSE are deemed aggressive as half of the operating performance grades are assigned as unqualified. This is due to the fact that the DD-FSE treats the range of deterioration degree for each KPI equally, resulting in an unqualified evaluation if the deterioration degree of the roasting temperature or product quality exceeds a certain threshold. However, it should be noted that while the deterioration of these indicators can impact the operating performance of the ZRP, it does not necessarily lead to severe consequences. Therefore, the aggressive evaluation result of DD-FSE is considered unreasonable.

By appropriately determining the degradation degree ranges for different KPIs, the VWDD-FSE method addresses the need for real-time weight updates and avoids inaccurate evaluations resulting from the deterioration of nondominant indicators. Therefore, the proposed VWDD-FSE can make an accurate evaluation of the operating performance of the ZRP.

C. Results and Performance Analysis of the Two-Level Decision-Making System

In this experiment, the temperature setting values of the two roasters are adjusted using manual optimization (MO), quality-oriented optimization (QO), basic optimization (BO), and co-optimization (CO), respectively. The results of manual optimization are derived from actual industrial data, whereas the results obtained through other methods are based on manual optimization. Since existing studies mainly focus on optimizing roasting temperature to enhance product quality, quality-oriented optimization based on the SATAM is used as the benchmark approach for the comparative validation of the proposed co-optimization. In the quality-oriented optimization method, the lower limit of the SATAM result is used to optimize the roasting temperature, i.e., $\Delta T_1^{sp} = T_{\min,1}^m$ and $\Delta T_2^{sp} = T_{\min,2}^m$. The basic optimization adjusts the roasting temperature according to the basic setting rules derived from VWDD-FSE. The co-optimization adjusts the roasting temperature according to the basic and collaborative setting rules derived from VWDD-FSE and SATAM. Subsequently, the operating performance is reevaluated based on the adjusted temperature setting values to validate the effectiveness of different methods. In this process, according to the analysis of the industrial data, for every 1 °C reduction of the roasting temperature, the SO_2 concentration and its change rate will be reduced by 1 $\mathrm{mg/m^3}$ and 0.1 $\mathrm{mg/(m^3 \cdot min)}$.

The temperature setting values and the evaluated operating performance of the two roasters using the four optimization methods are presented in Fig. 6. In most cases, the temperature after basic optimization or co-optimization is more reasonable. Quality-oriented optimization has the worst effect because this method ignores the impact of the roasting temperature on environmental protection and reaction-atmosphere indicators, and only focuses on improving product quality. When using the quality-oriented optimization method, the roasters are operated at higher roasting temperatures, which leads to the deterioration of environmental protection and reaction-atmosphere indicators. When performing manual optimization, the operators consciously control the roasting temperature at a lower level to avoid the deterioration of environmental protection and reaction-atmosphere indicators.

Compared with manual and quality-oriented optimization, basic optimization generally maintains or achieves better operating performance. When the KPI with the highest deterioration degree is f_1 to f_4, basic optimization successfully improves the operating performance by optimizing the roasting temperature. However, in cases where the KPI with the highest deterioration degree is f_5 or f_6, basic optimization focuses on improving the product quality of a specific roaster by increasing its roasting temperature without adequately considering the impact on other KPIs. From Fig. 6(b) and (c), it can be seen that the roasting temperature of a specific roaster is increased without correspondingly decreasing the roasting temperature of the other roaster in these cases. This leads to excessively high temperatures for both roasters, resulting in an increase in sulfur dioxide concentration in the tail gas. As a consequence, basic optimization leads to unqualified operating performance in some cases.

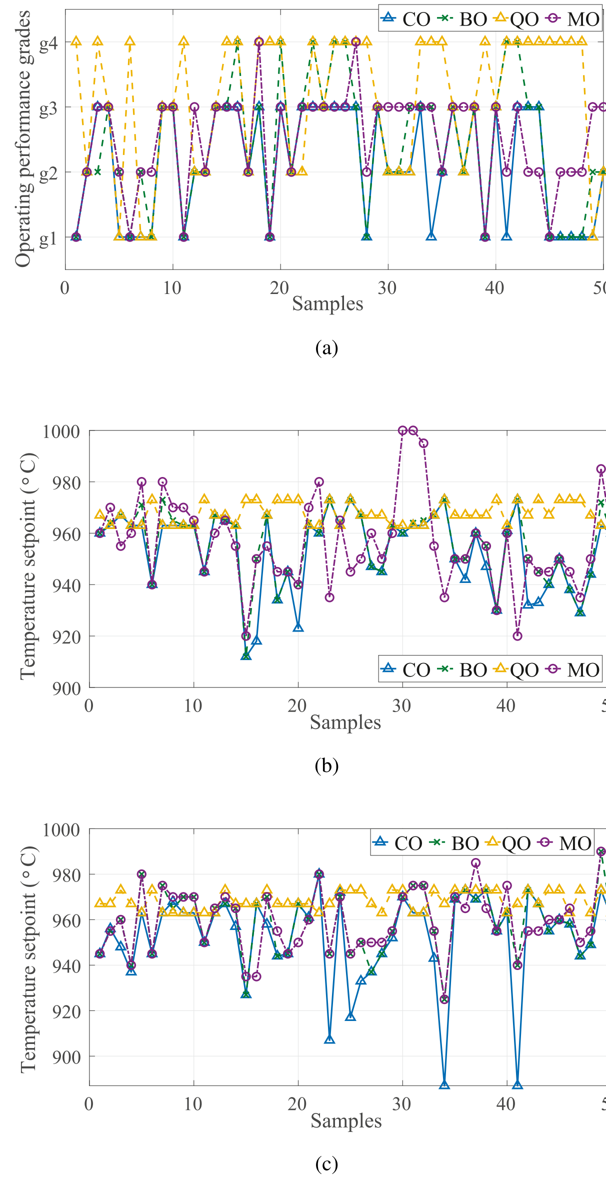


Fig. 6. Performance comparison among MO, QO, BO, and CO methods. (a) The operating performance of the ZRP under four optimization methods. (b) The temperature setpoint of the first roaster. (c) The temperature setpoint of the second roaster.

Similar to basic optimization, co-optimization achieves good performance when the KPI with the highest deterioration degree is f_1 to f_4. In cases where the KPI with the highest deterioration degree is f_5 or f_6, co-optimization intelligently allocates the adjustment amount, avoiding excessively high temperatures for both roasters. As a result, it effectively reduces the deterioration of the evaluation indices f_1 to f_4, leading to an improved level of operating performance. Co-optimization provides a balanced and effective approach for optimizing the roasting temperature in such scenarios.

Table IV illustrates the distribution of operating performance grades obtained through manual optimization, quality-oriented optimization, basic optimization, and co-optimization. In the quality-oriented optimization method, the proportions of

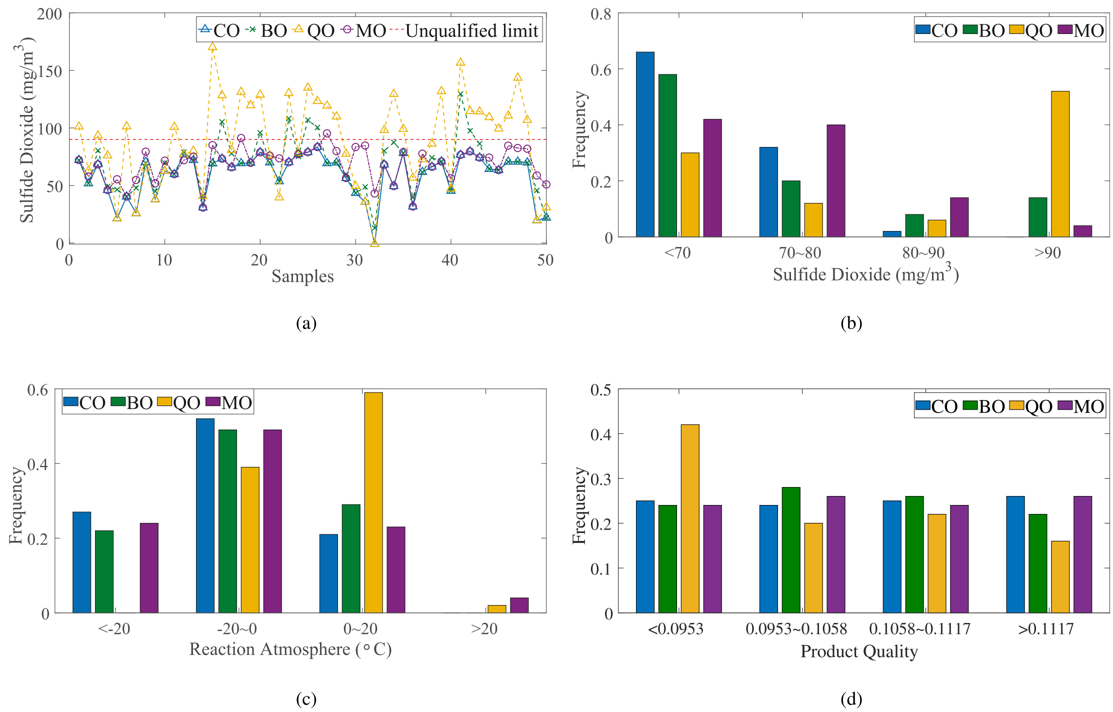


Fig. 7. Optimization results of different KPIs under four optimization methods. (a) The sulfur dioxide concentration in tail gas under four optimization methods. (b) The distributions of the sulfur dioxide concentration. (c) The distributions of the reaction atmosphere for both roasters. (d) The distributions of the product quality for both roasters.

TABLE IV
PROPORTION OF EACH OPERATING PERFORMANCE GRADE UNDER DIFFERENT OPTIMIZATION METHODS

Optimization methods	Operating grade			
	g_1	g_2	g_3	g_4
MO	12%	30%	54%	4%
QO	8%	22%	18%	52%
BO	22%	28%	36%	14%
CO	**32%**	22%	46%	**0%**

optimal grade and unqualified grade were 8% and 54%, respectively. Such poor optimization results indicate that this method cannot meet the needs of production optimization in the actual ZRP. The evaluation results after basic optimization and co-optimization show improvements or maintenance in most cases. The combined proportion of grades g_1 and g_2 increases from 42% in manual optimization to 50% in basic optimization and further to 54% in co-optimization. Additionally, the proportion of grade g_4 decreases from 4% in manual optimization to 0% in co-optimization. However, the proportion of grade g_4 increases by 10% under basic optimization due to its unreasonable adjustment when the KPI with the highest deterioration degree is f_5 or f_6. These results demonstrate the effectiveness of the basic rules for enhancing the overall operating performance of the ZRP. The improvement obtained by co-optimization compared with basic optimization shows that fine-tuning the adjustment amount through collaborative rules can further enhance the operating performance of the ZRP.

Fig. 7 provides a more detailed analysis of the four optimization methods. In Fig. 7(a), the sulfur dioxide concentration in the tail gas is compared with the unqualified threshold under the four methods. Under quality-oriented optimization, the sulfur dioxide concentration exceeded the unqualified threshold in more than half of the samples. During manual optimization, the sulfur dioxide concentration is below the unqualified threshold in most cases. In cases where the sulfur dioxide concentration is close to the unqualified threshold under manual optimization, basic optimization successfully reduces this KPI by lowering the roasting temperature. However, due to the unreasonable adjustment of basic optimization to optimize product quality, some cases that were initially qualified under manual optimization cross over the unqualified threshold, leading to unqualified operating performance. As for co-optimization, the sulfur dioxide concentration is controlled below the unqualified threshold in all cases. This demonstrates the effectiveness of the collaborative rules in allocating the adjustment amount and ensuring that both roasters operate within a reasonable temperature range, thereby maintaining the overall operating performance of the ZRP within the qualified threshold.

Fig. 7(b)–(d) illustrates the distributions of each KPI for different methods. Fig. 7(b) confirms the findings from Fig. 7(a) and provides a more intuitive representation. It clearly shows that under co-optimization, the sulfur dioxide concentration remains below the unqualified threshold in all cases, and most of cases fall within the optimal range. This indicates that the co-optimization method effectively controls and maintains the sulfur dioxide concentration at acceptable levels, ensuring the operating performance of the ZRP stays within the desired parameters.

Additionally, Fig. 7(c) demonstrates that for both basic optimization and co-optimization, the reaction atmosphere of both roasters remains below the unqualified threshold in all cases. Moreover, in 80% of the cases, the reaction atmosphere of both roasters under co-optimization is below 0 °C, indicating that co-optimization offers a more significant temperature-adjustable space for both roasters. This expanded space allows for more flexible and precise adjustments, contributing to better control of the reaction atmosphere and overall operating performance in the ZRP.

Finally, Fig. 7(d) illustrates the distributions of product quality for both roasters under the four optimization methods. Since quality-oriented optimization mainly focuses on improving product quality, this method brings great improvements in product quality at the expense of environmental protection and reactive atmosphere indicators. It can be observed that the distribution of product quality is similar among the other three methods. Compared with manual optimization and collaborative optimization, although basic optimization shows the least distribution in the unqualified range for product quality, it comes at the cost of sacrificing the performance of other KPIs and fails to comprehensively optimize the overall operating performance of the ZRP. On the other hand, co-optimization successfully maintains the product quality within the optimal range while also achieving better performance for other KPIs, leading to a more balanced and improved operating performance.

Based on the above experimental results, the two-level decision-making system proves to be the most effective approach for achieving optimal operating performance in the ZRP. It achieves the trade-offs between different KPIs, allows for flexible temperature adjustments, and ensures environmental protection, reaction atmosphere, and product quality are met. The results highlight the potential of the two-level decision-making system in enhancing the efficiency, sustainability, and overall performance of the ZRP.

VI. Conclusion

This article proposed a two-level decision-making system for the co-optimization of roasting temperature in the ZRP. At the first level, a VWDD-FSE method was proposed to overcome the limitations of fixed weights in the degradation-degree-based update method, thereby realizing the accurate evaluation of the operation performance of the ZRP. It could effectively reduce the conservative evaluation results by updating the weight set of the fuzzy synthetic matrix and the aggressive evaluation results by reasonably assigning different ranges of deterioration degrees to each KPI. Based on the evaluation results of the VWDD-FSE, a set of basic setting rules was designed from a global perspective to optimize the temperature setting values of the two roasters. In the second level, a concept of temperature-adjustable margin based on sensitivity analysis was proposed to evaluate the optimality of the two roasters, within which the roasting temperature could be adjusted while still maintaining the optimal performance of the roaster. According to the SATAM of each roaster, a set of collaborative setting rules was designed from a local perspective to allocate the basic temperature setting values to the two roasters. This ensured that the roasting temperature could be adjusted within a reasonable range while preserving the overall efficiency of the ZRP. The proposed decision-making system offered significant potential for enhancing efficiency, product quality, and overall performance of the ZRP, contributing to the advancement of the ZRP. Besides, considering the current strict requirements for environmental protection, the proposed approach could be extended to the industrial process, where several production processes share the same set of desulfurization and denitrification equipment.

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