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An improved multi-source based soft sensor for measuring cement free lime content

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ABSTRACT

The excess free lime (f-CaO) content in clinker is the main cause of cement instability. Thus, it is crucial to effectively measure f-CaO content in real time for implementing a closed-loop control. To improve the estimation accuracy and sensor's reliability, improved multi-source modeling techniques are developed in this paper. In this work, fuzzy entropy is employed to compress the feature vectors of a segmental point dataset to enhance the sensor model's generalization power, and a decorrelated neural-net ensemble (DNNE) with random weights is employed to build the soft sensor. In this way, experiments with comprehensive comparisons can be carried out. Experimental results indicate that the improved soft sensor performs favorably in terms of both prediction accuracy and model reliability, compared with other soft sensor models.

1. Introduction

Rotary kiln is widely used in metallurgical, cement, chemical, and environment protection industries. Clinker, as its output, occupies 85% cement component. Therefore, the excess f-CaO content in clinker is the main cause of cement instability [21]. A major issue in the cement rotary kiln sintering process is the online f-CaO content measurement. Unfortunately, due to the special structure of rotary kiln, there has been no analyzer instrument available for f-CaO content estimation, which renders f-CaO content-based closed-loop control infeasible. Some relevant works based on statistical approaches utilizing either process variables or flame images could be found in [10,14,17]. Burning state directly determines the f-CaO content in the clinker. From operators' point of view, flame image region of interest (ROI) could be used to recognize the burning state to indirectly estimate the f-CaO content [16]. In [8], a multi-source data-driven based burning state recognition system was developed for the first time to establish the basis of f-CaO content online estimation, where ROI features were extracted by using a segmentation-free approach.

Due to significant sampling delay between the manipulated variables and the f-CaO content, methods for online f-CaO content estimation as feedback have been envisioned to greatly help in reducing the amount of clinker rejections and applying closed-loop control strategies. According to the development of computational intelligence techniques, data-driven based soft sensor modeling techniques have received considerable attention [5,6,11], where input variable selection and estimator design are two key underlying issues [4,15].

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Our recent work reported in [9] developed a random vector functional-link (RVFL) nets ensemble based f-CaO content soft sensor model, where flame images and simultaneous process variables were utilized to estimate the f-CaO content. However, it is observed that such a point-to-point mapping bears certain inherent irrationality, i.e., the f-CaO content is resulted from an accumulative effect of operations over a period of time. In order to improve the accuracy and reliability of the sensor model, multi-source data should be collected for a time interval used to estimate the f-CaO content. However, the relationship between the length of the segmental dataset and the f-CaO content remains unknown. Practically, clinker could only be manually sampled at the kiln outlet at one hour intervals, and its f-CaO content is measured offline using a mixed solution of clinker and ethanediol or anhydrous glycerin–ethanol for 5–20 min [21]. Therefore, all flame images and simultaneous process variables in one hour will contribute to model the f-CaO content. As the employment of a segmental point dataset, the direct concatenation for the extracted features of the segment will be destined to deteriorate the soft sensor model's reliability. Therefore, dimensionality reduction of the extracted feature vectors should be taken into account for achieving better reliability of the resulting sensor model.

This research extends our previous work in [9] with the aim to improve the soft sensor's performance. Our technical contributions in this paper could be summarized as follows: (i) proposing a multi-source segment-to-point ensemble learning-based f-CaO content soft sensor model to improve the accuracy of existing point-to-point estimator; (ii) applying fuzzy entropy [2] to reduce the feature dimension of a segmental multi-source dataset to enhance the model's reliability; (iii) employing DNNE algorithm [1] in estimator design to build a faster and more stable sensor model. Our proposed framework is composed of several modules, including data pre-processing, feature extraction and estimator design. In the data pre-processing phase, a compact Gabor filter bank [7] and modified median filter are employed to distinguish a flame image ROI and remove the process variables outlier. At the feature extraction step, the features of a flame image ROI are firstly computed, and concatenated with simultaneous filtered process variables as the feature vector. In addition, fuzzy entropy is used to generate a compressed feature vector for a multi-source segmental dataset. For the estimator design, features of all multi-source segmental dataset are fed into the DNNE-based estimator to construct reliable mapping between the segmental dataset feature inputs and their f-CaO content outputs.

The remainder of the paper is organized as follows. Section 2 details the cement producing process and our multi-source segment-to-point ensemble modeling approach. Section 3 describes the feature extraction methods. Section 4 gives the details of the DNNE-based estimator design. Section 5 reports our experimental results with comparisons. Section 6 concludes this work.

2. Process description and multi-source ensemble modeling framework

2.1. Brief description of cement production process

The raw materials for cement production are limestone, clay, laterite, and red ochre. These materials with the required proportions and sizes are fed into a rotary kiln. At the rotary kiln burning zone with temperature up to 1300 °C, the molten tetracalcium aluminoferrite, tricalcium aluminate, and dicalcium silicate absorb f-CaO to produce the main product in the clinker, i.e., tricalcium silicate. The residual f-CaO content in the cement is targeted at 0.5–2.0% by national standards. However, due to the special rotary kiln structure, the significant measurement delay for the f-CaO content makes real-time f-CaO content-based control impossible, which leads to the rejection or recycling of the substandard clinker.

As an alternative, the f-CaO content open-loop control mode is adopted. By observing the burning zone over a period of time, operators combine visual image features with process variables (kiln operation variables, manipulated variables, and raw material quality) to recognize the current burning state to estimate the f-CaO content. Nevertheless, the accuracy of the estimated f-CaO content could be affected by the operator's mental state, work experience, and attitude, and lab analysis values could only be a reference and guide for operators in subsequent operations. Therefore, any soft sensor will greatly help in reducing the amount of clinker rejections and implementing closed-loop control strategies. With the aim of imitating operators' operation mode, the selected inputs and outputs for soft sensor model are given in Table 1.

2.2. Multi-source ensemble modeling framework

This subsection introduces our proposed multi-source ensemble modeling framework (see Fig. 1) for f-CaO content estimation, where four modules and their functions are briefly described as follows.

- *Feature extraction:* A training flame image is pre-processed. Color feature f_a, global configuration feature $\boldsymbol{f}_b$, and local configuration feature $\boldsymbol{f}_c$ of ROI are extracted, and then are concatenated with the simultaneous filtered process variables $\boldsymbol{f}_d$ to form the feature vector $\boldsymbol{F}^{tr} = [f_a, \boldsymbol{f}_b, \boldsymbol{f}_c, \boldsymbol{f}_d]$ for this multi-source point dataset.
- *Feature compression:* For each point dataset of a segmental dataset, feature vectors $\{\boldsymbol{F}_1^{tr}, \ldots, \boldsymbol{F}_{n_{seq}}^{tr}\}$ are extracted similarly for $\boldsymbol{F}^{tr}$, where n_{seq} is the segmental length. Then, fuzzy entropy F_E is calculated for this segment $\{\boldsymbol{F}_1^{tr}, \ldots, \boldsymbol{F}_{n_{seq}}^{tr}\}$ to generate a compact vector $\mathbf{x}^{tr} = [\boldsymbol{F}_1^{tr}, F_E]$ to correspond a f-CaO content.
- *DNNE-based sensor design:* For all training f-CaO contents, their multi-source segmental dataset features $\{\mathbf{x}_1^{tr}, \ldots, \mathbf{x}_{n_{tn}}^{tr}\}$ are used as the inputs of the soft sensor model, and DNNE-based estimator is to build the mapping between the segmental dataset feature inputs and their f-CaO content outputs.