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A hybrid just-in-time soft sensor for carbon efficiency of iron ore sintering process based on feature extraction of cross-sectional frames at discharge end

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ABSTRACT

Iron ore sintering is the second-most energy-consuming process in steelmaking. The main source of energy for it is the combustion of carbon. In order to reduce energy consumptions and improve industrial competitiveness, it is important to improve carbon efficiency. Reliable online prediction of the carbon efficiency would be extremely beneficial for making timely adjustments to the process to improve it. In this study, the comprehensive carbon ratio (CCR) was taken to be a measure of the carbon efficiency; and a soft sensing system was built to make an online estimation of the CCR. First, the sintering process was analyzed, and the key characteristics of the process parameters were extracted. Then, the configuration of the soft sensing system was devised based on the characteristics of the process. The system consists of three parts: an image selection, an image segmentation, and a hybrid just-in-time learning soft sensor (HJITL-SS). First, an image selection method was devised to automatically select the key frames (KFs) from the video taken at the discharge end of the sintering machine. Then, a genetic-algorithm-based fuzzy c-means clustering method was devised to extract feature parameters from the KFs. Finally, an HJITL-SS, which consists of online and offline submodels, was devised to estimate the CCR using the extracted feature parameters as inputs. Actual run data were used to verify the validity of our system. Accuracy, overfitness, and error distribution of the HJITL-SS, offline, and JITL-based soft sensing methods were compared, which show the validity of the HJITL-SS. The actual run results also show the validity of the soft sensing system with 97% of the actual runs are in an acceptable range.

1. Introduction

A typical iron ore sintering process mainly consists of proportioning, ignition, sintering, screening, and weighting. Iron ores and coke fines are heated in this process to produce sinter with a certain chemical composition and strength for feeding into the blast furnace [1]. It is the secondary most energy consuming procedure in steel making industry. Its main energy is from the combustion of coke, which consists primarily of carbon. In order to reduce the energy consumptions and improve the competitiveness of an enterprise, it is necessary to improve the carbon efficiency.

Before any improvement can be made, a metric of the carbon efficiency must first be specified. There have been various attempts to do that for different industrial processes, such as a commercial pharmaceutical process [2], and a manufacturing process [3]. And for iron ore sintering, Chen et al. suggested the comprehensive carbon ratio (CCR), which is the amount of coke used per ton of sinter [4,5]. This is the metric employed in this study, and its value should be as small as possible.

Lab measurements to obtain information for calculating the CCR are possible. However, they are done long after the process is finished. So, they cannot provide real time information for optimizing the process. Reliable online prediction of the CCR would be beneficial, as it would allow control room personnel to make timely adjustments to the process to improve the carbon efficiency.

A soft sensor is an inferential model based on software technique to estimate the value of a process variable [6]. This is in contrast to a physical sensor that directly measures the value of the process

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variable. The values of process variables can be obtained through lab measurement. However, the measurement results are available after significant delays. This can be prevented through soft sensors as they are able to predict the process variables online [7,8]. In this paper, a soft sensor is build to predict the CCR online. As the process is very complex, the mechanism of which is not well understood, data-driven modeling methods are often used to build such soft sensors [9]. There are two key problems involved in building a data-driven soft sensor: determine the input parameters, and devise an appropriate soft sensing method.

The first is the determination of input parameters. In a sintering process, cross-sectional images of the sinter bed is taken by a CCD camera located at the discharge end of the sintering machine. It consists of three zones: a background zone, a flame front zone, and a hot zone. It is observed from actual run sintering process that the CCR is the lowest when the image has the following features:

1) it has a relatively high average grayscale value,
2) the flame front zone occupies about 30% of the area of the sinter bed,
3) the ratio of the area of the hot zone and the area of the flame front zone is around 0.4, and
4) there is a relatively big difference between the grayscale value of the flame front zone and the grayscale value of the hot zone.

So, the features of the images, which can be characterized by some feature parameters extracted from three zones, are strongly correlated with the CCR. These parameters are used as inputs of a soft sensor to estimate the CCR.

The second is to devise an appropriate soft sensing method. Conventional offline soft sensing methods, such as a back-propagation neural network (BPNN), a support vector machine (SVM), and an extreme learning machine (ELM), are widely employed in industrial processes [6,9]. A BPNN has been proven to have the mapping ability of any nonlinear characteristics, and it is the most widely used offline soft sensing method [8,10,11]. So, the BPNN method was chosen to build a soft sensor in this study.

Since a sintering process is very complex, a single BPNN model is not efficient enough to describe the whole. If a single BPNN model is trained only to predict the current CCR without reference to the past and future values of the CCR, it easily leads to low prediction precision and bad generalization performance. A multi-task learning is an effective way to solve these problems. It aims at improving the generalization performance and prediction precision by training a BPNN to predict the CCR at different time points in parallel using a shared representation. It can exploit the intrinsic relatedness among the time series, and has been widely used in the time series prediction problems [12]. In this study, an integrated model that combines a multi-task learning and a BPNN was devised to model the sintering process.

The parameters in the offline soft sensing method are trained in advance and cannot be changed online. So, although they are quick in prediction, they cannot update online. The just-in-time learning (JITL) is currently an attractive way to compensate for the disadvantages [13,14]. In a JITL structure, a local model is built using nearest neighbours (the most relevant samples from the historical dataset) around a query sample when a prediction is required. The JITL-based method uses a local model structure, and is different from global models, such as the offline and recursive soft sensors. It is built online in a lazy learning manner [15–17]. Thus, the most relevant samples from the historical dataset are tracked by the JITL model, and then the samples are used to train the online soft sensor.

In order to improve the online estimation precision of a soft sensor, a hybrid JITL soft sensor (HJITL-SS) was devised. It takes into account the time series information from offline model and the information of the nearest neighbours from online model. The hybrid sensor combined the very best of the offline and online models to estimate the carbon efficiency in an iron ore sintering process.

As the best of our knowledge, this is the first time to build a data-driven soft sensor for the carbon efficiency of an iron ore sintering process by using the feature parameters extracted from the cross-sectional images of the sinter bed as inputs. Although there have been several studies on the application of a BPNN, a SVM, and an ELM for modeling of different complex processes, using these techniques especially for the online estimation of the carbon efficiency of an iron ore sintering process has not been reported in the literature.

This study also provides a comprehensive comparison of the HJITL-SS with commonly used soft sensing methods for the estimation of the CCR. The actual iron ore sintering process have a strict requirement on the sensor. The effectiveness of the sensor is evaluated in terms of three metrics: (1) Accurracy. The accuracy is thoroughly evaluated through the mean square error (MSE), the mean absolute percentage error (MAPE), and the coefficient of determination (R^2) of the testing dataset. (2) Overfitness. As a common problem of data-driven modeling methods, the overfitness of these methods was evaluated. And (3) error distribution. If the prediction error is beyond an acceptable range, the estimation is failed. It is necessary to reduce the number of failures as much as possible.

The remaining of this paper is organized as follows. Section 2 explains the basic principles of the BPNN, the SVM, and the ELM methods. Section 3 briefly describes an iron ore sintering process, analyzes its main characteristics, and defines the CCR as the metric for the carbon efficiency. Section 4 describes the design of the HJITL-SS based on the characteristics of the process. Section 5 explains a genetic-algorithm-based fuzzy C-means (GA-FCM) clustering algorithm for the extraction of the features of the cross-sectional image of the sinter bed. Section 6 describes the development of the HJITL-SS soft sensing method. Section 7 uses the data collected from actual runs to verify the validity of our method, and shows the results of actual runs. The validity is studied by comparing the HJITL-SS with commonly used soft sensing algorithms in terms of accuracy, overfitness, and error distribution.

2. Basic principals of data-driven soft sensing methods

This section describes the basic principle of a BPNN, a SVM, and an ELM for the soft sensing of the CCR. Suppose that there are l training samples taking as $(X_1, y_1), (X_2, y_2), \ldots, (X_l, y_l)$, $X_i = [x_{i1}, x_{i2}, \ldots, x_{id}]^T \in \mathbb{R}^d$ is the ith input. $y_i \in \mathbb{R}$ is the corresponding output.

2.1. BPNN

The input of the BPNN model is $X_i = [x_{i1}, x_{i2}, \ldots, x_{id}]^T$. And the output is

$$\hat{y}_i = BPNN(X_i) = \sum_{j=1}^{n_h} w_{jo} \operatorname{logsig}\left(\sum_{d=1}^{6} w_{ij} x_{id} + \theta_j\right) + \theta_o, \quad (1)$$

where n_h is the number of neurons in the hidden layer; w_{ij} is the weight connecting the ith input neuron to the jth hidden neuron; w_{jo} is the weight connecting the jth hidden neuron to the output neuron; and θ_j and θ_o are the thresholds for the hidden and output layers, respectively.

The variables w_{ij}, w_{jo}, θ_j, and θ_o are determined by training the BPNN. n_h is one of the important parameter in BPNN, and