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Modeling and optimization method featuring multiple operating modes for improving carbon efficiency of iron ore sintering process

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ABSTRACT

Iron ore sintering is one of the most energy-consuming processes in steelmaking. Since its main source of energy is the combustion of carbon, it is important to improve the carbon efficiency to save energy and to reduce undesired emissions. A modeling and optimization method based on the characteristics of the sintering process has been developed to do that. It features multiple operating modes and employs the comprehensive carbon ratio (CCR) as a measure of carbon efficiency. The method has two parts. The first part is the modeling of multiple operating modes of the sintering process. *K*-means clustering is used to identify the operating modes; and for each mode, a predictive model is built that contains two submodels, one for predicting the state parameters and one for predicting the CCR. The submodels are built using back-propagation neural networks (BPNNs). An analysis of material and energy flow, and correlation analyses of process data and the CCR, are used to determine the most appropriate inputs for the submodels. The second part of the method is optimization based on a determination of the optimal operating mode. The problem of how to reduce the CCR is formulated as a two-step optimization problem, and particle swarm optimization is used to solve it. Finally, verification of the modeling and optimization method based on actual process data shows that it improves the carbon efficiency of iron ore sintering.

1. Introduction

Iron ore sintering is the process of heating iron ore fines, coke fines, and other materials to produce a semi-molten mass that solidifies into porous pieces of sinter with a size and strength suitable for a blast furnace. It is the second most energy-consuming process in steelmaking. Its main source of energy is the combustion of coke, which consists primarily of carbon.

The carbon efficiency of an industrial process quantifies how much of the energy from carbonaceous fuel is used productively and how much is wasted. It is often expressed as the ratio of the amount of carbon consumed to the amount of some substance that is used as an activity indicator. Improving it involves increasing the amount of energy released by the fuel and making better use of that energy. Increasing the carbon efficiency of sintering reduces the amount of coke needed, thereby reducing costs, energy requirements, and harmful emissions.

Different industries employ different definitions of carbon efficiency. For example, Constable, Curzons, and Cunningham (2002) gave a definition for a commercial pharmaceutical process. It is the ratio of the amount of carbon remaining in the product to the amount of carbon used. Cao et al. (2012) proposed three types of carbon efficiency for machine tools related to different services. In sintering, the proportion of coke in the raw mix and the quantity of sinter produced are the two most important parameters related to carbon efficiency; and both are measurable. So, Chen, Wen, Wu, and Cao (2013) defined the comprehensive carbon ratio (CCR) to be the amount of coke per ton of sinter and proposed its use as a metric for a sintering process. This is the metric employed in this study.

Our approach to improving the carbon efficiency of sintering involves first building a predictive model for the CCR that takes raw-material parameters, operating parameters, and state parameters as inputs, and then optimizing those parameters.

There are two main types of predictive models for industrial processes: mathematical models and data-driven models. Mathematical models (Zhang et al., 2015; Zhao, Loo, & Dukino, 2015) are built based on an analysis of the conservation of energy and mass. Since they tend not to be very precise due to differences between

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experiments and an actual industrial environment, they are not used very often for practical applications. Data-driven models, on the other hand, take process data as inputs; and they are widely used in practice. This study employed a data-driven model to describe an iron ore sintering process. To build such a model, it is necessary (1) to determine the inputs and (2) to choose a modeling method that is suited to the characteristics of the data.

Iron ore sintering is a complex process with a large number of raw-material parameters, operating parameters, and state parameters. These parameters are coupled to each other, and the distributions of the values of the parameters do not follow the same pattern. So, we immediately encounter the problem of how to determine which parameters are most suitable for the inputs of a predictive model. Mechanism and data analyses were carried out to determine the relationships between the inputs and the outputs and the relationships among the inputs themselves. Partial correlation coefficients (PCCs) are widely used to investigate the relationships between variables. One example is Yang, Farid, and Thornhill (2014), in which the PCCs between input parameters and the overall unexpected product mass loss were calculated, taking the coupling between the inputs into account. Moreover, Spearman (1987) used a Spearman's rank correlation coefficient (SRCC) analysis to examine relationships between data because it does not impose restrictions on the type of data distribution. In this study, a mechanism analysis was first used to make a preliminary selection of potential inputs so as to simplify the correlation analysis of the inputs. Then, PCC and SRCC analyses were carried out to examine the relationships among the potential inputs, taking parameter coupling into account. The features and characteristics of the process were considered, and these three methods were used to determine the most appropriate parameters to be used as inputs for the predictive model.

An operating mode is defined in terms of the raw-material, operating, and state parameters that describe the state of the process. A sintering process has multiple operating modes. So, using a single model to describe it does not yield very accurate results. Building a model for each mode enhances prediction accuracy. But first, the modes must be identified, and one way of doing that is by clustering (see, for example, Havens, Bezdek, Leckie, & Hall, 2012; Lee, Min, Han, Chang, & Choi, 2004; Luengo & Sepúlveda, 2012). Since *K*-means clustering is scalable and efficiently handles large amounts of data, this study used an improved *K*-means clustering algorithm to identify the operating modes of the sintering process.

Regarding modeling, a neural network (NN) is often used to build a predictive model when the amount of data is large (Iliyas, Elshafei, Habib, & Adeniran, 2013; Wu, Xu, She, & Yokoyama, 2009). The salient features are that (1) it has a good ability to fit nonlinear data, (2) it can learn from known data and use the results to make predictions with a given accuracy, and (3) it does not require knowledge of the process because it is based on a black-box modeling theory. One of the most widely used types of NNs is a back-propagation NN (BPNN). It has been used to model many industrial processes (Wang, Wang, Zhang, & Guo, 2011; Wu, Chen, Cao, She, & Wang, 2014), and was also used in this study.

Regarding optimization, genetic algorithms (Reynoso-Meza, Blasco, Sanchis, & Martinez, 2014), particle swarm optimization (PSO) (Lu, Li, & Yuan, 2010), differential evolution (Yüzgec, 2010), ant colony algorithms (Leung, Wang, Mark, & Fung, 2010), and other intelligent optimization methods are commonly used to solve industrial optimization problems. They are robust with regard to the modeling method and are easy to implement. This study employed PSO because it has few parameters that need to be adjusted, it converges quickly, and it has a global search ability.

This paper describes a modeling and optimization method that improves the carbon efficiency of an iron ore sintering process. Section 2 describes the process and its characteristics. Section 3 gives a precise definition of the CCR and outlines a modeling and optimization method that takes the characteristics of the process into account. The method has two parts: the establishment of predictive models for the CCR for multiple operating modes (Sections 4 and 5) and parameter optimization for the optimal operating mode (Section 6). Section 4 analyzes the mechanism, explains the preparation of the data sets and the analysis of the data, and explains how appropriate inputs for the predictive model of the CCR are selected. Section 5 describes the use of *K*-means clustering to identify the operating modes and the use of a BPNN to build a model for each one. Section 6 describes an optimization problem and how a PSO is used to solve it. Section 7 presents verification results based on actual process data. They show that the model is effective in reducing the CCR of an iron ore sintering process. And Section 8 presents some concluding remarks.

2. Sintering process and its characteristics

This section first briefly describes the sintering process, and then explains the characteristics of the process that are important for the modeling and optimization of the process.

2.1. Sintering process

This study concerns a downdraft sintering machine. The main steps in the sintering process are proportioning, mixing, and sintering. The proportioning step produces a raw mix, which is mixed with water in the mixing step to form granules of different sizes. Then, a roller feeder pours the granules onto a moving grate to form a sintering bed. Igniters in the ignition hood ignite the surface of the bed to start the sintering process. As the coke in the bed burns, it creates a high-temperature combustion zone. The heat produced induces chemical reactions and physical changes in the bed. Wind boxes under the grate draw in air, promoting combustion. As the process continues, various zones are successively formed: a wet zone, a preheating and drying zone, a combustion zone, a melting zone, and a product zone (Fig. 1). This process produces sinter with a certain chemical composition, permeability, and strength.

The combustion zone is the most important zone in the process. It is the region with the highest temperature and the most intense reactions. As it propagates downward toward the grate, the temperature of the material above it decreases, and the melting zone forms. As the cold air being drawn down by the wind boxes further reduces the temperature, the binding-phase liquid cools to form sinter in the product zone.

The hot gas being drawn downward from the combustion zone by the wind boxes causes the water in the region below the combustion zone to evaporate; this is the preheating and drying zone. The water vapor moves downward with the gas and condenses when it meets the cooler layer under the preheating and drying zone. This forms the wet zone.

Thus, the heat from the combustion of coke is necessary to induce the physical and chemical changes that result in the formation of sinter.

2.2. Characteristics of sintering process

The characteristics of the process related to the modeling and optimization of the CCR are described below.

(1) *Multiple types of parameters*: There are three types of parameters involved in the sintering process:
Raw-material parameters: The raw-material parameters