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Optimization of coke ratio for the second proportioning phase in a sintering process base on a model of temperature field of material layer

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ABSTRACT

Coke ratio for a sintering process is often determined by experience because models of calculating a coke ratio are very complicated, and are hard to be used in practice. This paper presents a three-step optimization method to find a coke ratio that meets the requirements for commercial operations. First, a back-propagation neural network (BPNN) for temperature field of the material layer (TFML) is built to calculate a mass of sinter cake of a sintering process. Then, the energy flow in a sintering process is analyzed, and a theoretical value of the coke ratio is calculated. Finally, the optimization problem for the second portioning phase is formulated that takes into consideration of the conventional constraints, such as material balance, chemical composition, required quality, etc., and a coke ratio constraint based on the theoretical value. This benefits the reduction of CO_2 for the sintering process. Numerical verification has shown the validity of the method.

1. Introduction

A sintering process not only consumes a large amount of fossil fuels, but also releases a great number of contaminants [1]. Coke, as one of a raw material, is added into the raw mixture in the second proportioning phase of a sintering process so as to provide energy for burning to cause physical changes and chemical reactions. Coke ratio is the ratio of the mass of coke powder to that of the raw mixture. If the coke ratio is too low, the raw mixture cannot be transformed into sinter. This phenomenon is called a less burning. It leads to a big deterioration in the strength and the amount of the production of sinter [2]. On the other hand, if the coke ratio is too high, it results in a waste of fuel and an increase in the emission of CO_2 and SO_2. This leads to the early arrival of the burn through point (BTP) and causes the loss of productivity. Due to the change of prices of raw materials on the resource market and the change of types of stocked ores, new types of iron ore are often required to be used for sintering production. This increases the difficulty in the arrangement of the proportioning of coke [3,4]. To avoid a less burning, the coke ratio in operation is usually set to a relatively large value. So, finding an accurate coke ratio not only in ensuring the quality and quantity of sintering production, but also in energy saving and emission reduction.

Many studies have been made on the proportioning of a sintering process. Pownceby and Clout analyzed the chemical reactions in a sintering process and proved that the sintering temperature in [1250,1300] °C is suitable for producing qualified sinter ore [5]. Yang et al. proposed a mathematical model based on sintering pot experiments to predict the temperature and the combustion zone of a sintering bed [6]. They also showed the relationships between a combustion zone, the burning time, and the production of sinters for some typical coke ratios. Based on their results, Giri and Roy presented a method of modeling the temperature field using a genetic algorithm [7], and simulated the temperature profile on one side of sintering bed at different time. These modeling methods are based on experiments with sintering pots but not on a working DL-type sintering machine. So, they do not take the effect of the change of BTP on temperature into consideration, and are difficult to be directly used to calculate a coke ratio in the production practice.

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Computational intelligence, that is, a neural network, fuzzy logic, adaptive dynamic programming, particle swarm optimization (PSO), etc., is now widely used to model and control complex industrial systems [8–10]. A back-propagation neural network (BPNN) is a kind of feedforward neural network. It has an input layer, an output layer, and one or two hidden layers. Each layer has a group of neurons in which the connected weights and thresholds are stored. The weights are adjusted by the back-propagation algorithm [11]. While some issues of a BPNN, such as overfitting, generalization, and local minimums, are needed to be improved [13], it is widely used in system and control engineering. For example, since a BPNN is able to approximate a nonlinear function at a prescribed precision based only on the data collected from experiments, it is used to build a model for an industrial process. Compared with other methods, such as recurrent neural network [14], a BPNN has a simple structure and low computational expense. This makes it easy to be applied in an industrial process.

Recently, BPNN is widely used in complex industrial systems modeling. For example, Wu et al. presented an integrated neural-network-based model for predicting the BTP in lead-zinc sintering process [12]. In order to improve the estimation precision, they built a time-sequence-based model to predict the BTP using grey system theory. Xu et al. provided an improved BPNN to model coal pyrolysis characteristics [13]. Momentum term and adaptive learning rate were introduced to a BPNN to increase the convergent speed and accuracy. Zhang et al. used a BPNN to build a multi-objective optimization model for a sintering process. They considered only the relationships between the ratio of each raw material, the production cost, and energy consumption [15]; but not the constraints in the proportioning phase. So, it is hard to produce a practical scheme for a working sintering machine.

In iron sintering process, Wu et al. combined a two-step method and the simplex method to build a sintering proportioning optimization model [16]. The optimization was carried out based on the analysis of the characteristics of the material compositions under the proportioning constraints. But they just focused on cost reduction and did not consider energy saving. Since the price of coke powder is usually lower than that of iron ore mix, the cost optimization usually yields a relatively large coke ratio. This results in a waste of fuel and a large emission of CO_2. Li et al. optimized the average cost of the sintering production by adding the cost of returned fines in the performance index and regarding the tumbler strength and average granular size as constraints [17]. Wu et al. presented an integrated intelligent optimization system for the sintering proportioning that optimized proportioning schemes of the first and the second proportioning phases by converting SO_2 emission into the production cost [18]. However, these optimization methods took the coke ratio as a fixed parameter and did not optimize it.

This paper presents a three-step optimization method that takes the coke ratio into consideration for the second proportioning phase in a sintering process. First, a practical model based on BPNN is built to describe the temperature field of the material layer (TFML). This is the key to the calculation of the sinter cake for the next step. Then, the theoretical coke ratio is calculated based on the analysis of energy flow. Finally, the optimization problem is solved using the PSO algorithm. It finds a solution that has the coke ratio close to the theoretical one for the actual use. This method is effective to reduce the cost and the CO_2 emission. The rest of the paper is organized as follows.

Section 2 builds a BPNN model for the TFML, which is used to calculate a mass of sinter. In Section 3, we analyze the energy flow in the sintering process based on the material properties, and calculate a theoretical value of the coke ratio by incorporating the analysis result, the mass of sinter, and the physical characteristics of the raw materials. In Section 4, we formulate the optimization problem that takes material balance, chemical composition, and required quality as constraints. Then, we perform a fine adjustment of the practical range of the coke ratio in the second proportioning phase for optimization so as to ensure that the produced coke ratio is practical. Section 5 presents some simulation results. We solve the optimization problem by using PSO algorithm. The comparisons between the theoretical value, the optimal result, and the actual production data of the coke ratio demonstrate the validity of the optimization method.

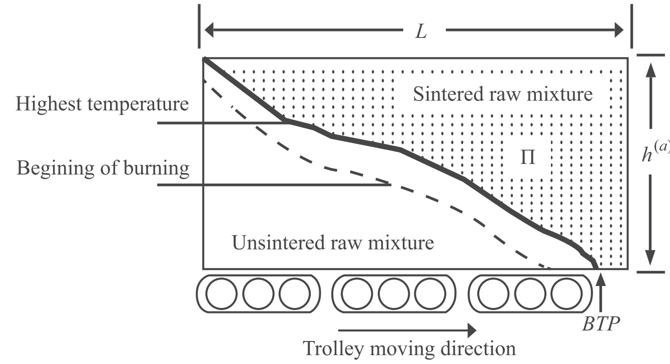

Fig. 1. Typical TFML in a sintering machine.

In this paper, the superscript "(G)" stands for a value related to Giri et al.'s temperature curve in [19], "(L)" for a value given by Li et al. in [20], "(t)" for a theoretical value, "(a)" for an actual value, and "(o)" for the optimized value.

2. Model of temperature field of material layer

In this section, we build a BPNN model of the TFML so as to simulate the distribution of temperature in the combustion zone for different BTPs. This model gives a way to calculate the mass of a sintered raw mixture by simulation. We use this model to calculate a theoretical value of the coke ratio.

A typical TFML in a sintering machine is shown in Fig. 1. Different materials are mixed in the sintering machine into raw materials, which are discharged into the sintering machine to from a bed on a moving trolley. The surface of the bed is ignited by a stationary burner that is installed at the top left of the machine. The sintering progresses downward through the bed as the trolley moves forward. This process continues until the sintering front reaches the BTP [18]. So, the curve of the highest temperature separates the raw mixture into two parts: sintered raw mixture (sinter cake) and unsintered raw mixture. The sinter cake is the shadowed part in Fig. 1.

The relationship between the temperature of the material layer and different BTPs is

$$T = F(h, l, BTP), \tag{1}$$

where T is the temperature at the position of height h and length l; and BTP means the BTP position, which is in the term of the number of the bellows.

The distribution of temperature of (1) over the whole trolley is hard to be detected directly. Giri et al. showed the relationship of (1) for $BTP = 23$ through numerical simulations [7]. BTP causes a big change in the temperature distribution. In details, an early arrival of the BTP increases the inclination of an isothermal line. And on the other hand, a late arrival of the BTP decreases it. To build an actual TFML, we extend Giri et al.'s result [19] by incorporating the following height–length–temperature relationship

$$\frac{BTP}{BTP^{(G)}} = \frac{v}{v^{(G)}} = \frac{h(T_g, l)}{h^{(G)}(T_g, l)} \tag{2}$$