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Data-based multiple-model prediction of the production rate for hematite ore beneficiation process

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ABSTRACT

The prediction of the production rate of the hematite ore beneficiation process is important to plant-wide optimization. This paper presents a data-based multi-model approach to predict the production rate with multiple operating modes. The inputs of the predictive model are the performance indices of each unit process, and the output is the global production index (the production rate) of the hematite ore beneficiation process. The multiple models are developed by integrating the fuzzy clustering algorithm and machine learning algorithm. A global model, Takagi–Sugeno–Kang fuzzy model, and multiple neural network model were compared using the data obtained from a practical industrial process, and the effectiveness of the proposed algorithm was proven.

1. Introduction

Iron ore is one of the most important resources of the steel-making industry, but the hematite ore exploited from the earth cannot be directly used to make steel because its grade is low. The hematite ore beneficiation process is to refine the valuable minerals in raw ore via a series of unit processes, where the outputs of each upstream unit process are the inputs of the downstream unit process. Each unit process performs a certain function and uses different performance indices to evaluate the product quality or production efficiency, which are denoted as technical indices. All unit processes work together to produce the final product, and its quality is usually evaluated based on the global production indices, which include the production rate, grade and metal recovery rate of the concentrated ore. In this paper, the relationship between the plant-wide production rate and technical indices is established.

In practice, the technical indices affect the production rate of the concentrated ore. A higher production rate corresponds to a less valuable material that is discharged. However, excessive pursuit of the production rate leads to a low grade of the product, which results in the low efficiency of the downstream smelting process and higher energy consumption. Therefore, the establishment of the predictive model is important in plant-wide optimization. It is known that the optimization of each unit process of a chain of processes cannot lead to the optimal operation of the overall chain because the procedure neglects the interaction among various unit processes. Research has been conducted by coordinating the technical indices of various unit processes to guarantee the plant-wide optimization of the entire production line (Chai and Ding, 2006). The coordination is performed through a hierarchical structure that consists of the process control layer, the optimized layer for the unit process and the coordination layer for the entire mineral beneficiation process. The coordination layer determines the objectives of the layer that is optimized by the process engineers, who adopt technical knowledge and operational experience to make the entire production line run harmoniously. However, many uncertainties, such as the experience-dependent and suboptimal manipulations of the process engineers, make it unavailable for the cooperation of the unit processes. Therefore, many scholars have proposed that model-based plant-wide optimization is successfully applied to paper-making, semiconductor and chemical processes (Madetoja and Tarvainen, 2008; Qin, Cherry, Good, Wang & Harrison 2006; Tosukhowong, Lee, Lee & Lub 2004). In this content, it is essential to establish the model between the global production index and the technical indices (such as particle size in grinding process). It is a challenge to describe the mineral beneficiation process in a first-principle manner because the technical indices of the mineral beneficiation process are extremely complex, where the physical and chemical mechanism is usually difficult to clearly describe (Ding, Chai & Wang 2011). However, the resourceful site data that are sampled in the mineral beneficiation processing plant enables the

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establishment of a data-driven model. Ding et al. proposed a hybrid modeling method, where a linear model is the main function with a nonlinear model that compensates the error between the actual output and the output of the linear model to establish the predictive model of the concentrate grade (Ding et al., 2011). Kong and Cheng adopted least squares support vector machine (LS-SVM) to establish the relationship between the plant-wide production rate and the technical indices (Kong, Cheng, Ding & Chai 2010; Cheng, Ding, Kong, Chai & Qin 2011). However, these studies have not considered the multiple operating regimes of the mineral beneficiation process. And they cannot describe the characteristic of multiple operating regimes (Cheng et al., 2011).

In practice, the mineral beneficiation process is characterized by multiple operating modes, the existence of which lies in the change in physical properties (mainly particle size and grade) of the raw ore from different mines. Clearly, if the particle size of the raw ore increases, the handling capacity of the ball grinding machine decreases, which causes a low production rate of the final product. Similarly, if the grade of the raw ore approaches a proper degree, the production efficiency of the magnetic separation unit process maximizes, and the maximum production rate of the concentrated ore can be obtained. The inverse relationship between grade and throughput is also right. The effect of the raw ore from different mines on the entire production line is represented by the characteristics of the unit processes, and the technical indices of each unit process are used to evaluate these unit processes. It is reasonable to analyze the technical indices to deduce the effect of multiple operating modes on the production rate. For the difficulties discussed above, modeling and system identification of the production rate is expensive and time-consuming. Data-driven modeling has become a potential valuable approach with the development of 'big data', 'data mining', and 'data fusion'. The development of production rate perdition model is driven by the huge amounts of data measured in process control systems, both stored historical data from prior measurements and on-line data available in real time during process runs. Therefore, the challenge of modeling the mineral beneficiation process lies in establishing the data-driven model to represent the mineral beneficiation process with multiple operating regimes.

In recent years, the multi-model strategy has emerged as an efficient tool to identify the multi-operating mode system by decomposing the complex problem into several simple sub-problems (Li, Zhao & Li 2005). In this approach, a set of models is designed to cover the possible system operating regimes or modes, and the overall outputs rely on the teamwork of estimators instead of a single estimator, which contributes to a more accurate output. It has been successfully applied in a wide range of areas, including solution component analysis, reservoir inflowing forecasting, human motion analysis, target tracking, fault detection, etc. (Mazor, Averbuch, Bar-Shalom & Dayan 1998; Nayak and Sudheer 2008; Razavi-Far, Davilua, Paladeb & Lucas 2009; Wang, Chai, Zhao & Qin 2011; Wu and Hong 2005)

Therefore, a data-driven multiple model approach is proposed to establish the predictive model of the plant-wide production rate. The purpose of proposed model is for optimization of the entire production line to provide targeted technical indices of each unit process. The proposed model adopts the technical indices of each unit process as the inputs to predict the production indices.

This paper is organized as follows. Section 2 presents the process description, model inputs and output selection. In Section 3, the multiple model based plant-wide production rate prediction is proposed. A case study of the plant-wide production rate prediction for the hematite ore beneficiation process is provided in Section 4, where the experiment results and comparisons are presented in details. Finally, the paper is concluded in Section 5.

2. Process description, model Inputs and output selection

2.1. Process description of the mineral beneficiation process

In this paper, the mineral beneficiation process for hematite is studied, where the technique of screening-roasting-grinding-magnetic separation-dewatering is adopted. According to Fig. 1, the raw ore is classified into particle ore that is 0–15 mm in size and lump ore larger than 15 mm in size during the screening unit process. Then, these two types of ore are treated using different production lines: a high-intensity magnetic production line (HMPL) and low-intensity magnetic production line (LMPL) (Ding et al., 2011). The −15 mm particle ore is delivered to the cylinder bin I, which feeds the material to the HMPL. Simultaneously, the +15 mm lump ore is conveyed to the stock bin II as the feeding material to the shaft furnace roasting unit process, where the component Fe_2O_3 is transformed into Fe_3O_4. The efficiency of the roasting unit process is represented by the magnetic tube recovery rate, which represents the available metal recovery rate of the roasted ore that is achieved by the separation in the laboratory through a magnetic tube. Next, the roasted ore is separated into valuable ore and waste rock; waste rock is discharged to the waste rock pile, whereas valuable ore is transported to the bin III as the material to the grinding process. The particle ore from bin I (or the roasted ore from bin III) is grinded into pulp slurry with a suitable particle size during the grinding unit process. The particle size of the pulp slurry is defined as the proportion of minerals that are under 200 meshes (less than 0.174 mm) in size, which is considered a key index of the product quality in the grinding unit process. After thickening, the pulp slurry is conveyed to the high-intensity or low-intensity magnetic separation process during which the concentrated ore and tailing are produced and the grade of the concentrated ore and tailing are the technical indices in this unit process. After being dewatered, the concentrated ore and tailing from different production lines are mixed, noted as the concentrated ore and the tailing, and the tailing is sent to the tailing dam. Eventually, the proposed material is obtained through a chain of unit processes, and the plant-wide production rate of the concentrated ore is always considered to be a key index of the entire production line.

2.2. Selection of inputs and output

The proposed model is adopted to link the technical indices of each unit with the global production index in the mineral beneficiation process. According to the previously mentioned modeling objectives, the proposed model is different from the process models in the process control for the controller design, which means that the inputs of the predictive model include the technical indices of each unit process. Simultaneously, the operating condition of the production line should also be considered, such as the variation of the characteristics of raw hematite ore (mainly the grade), and the handling capacity of the production line should also be considered, such as the extra inputs, because these variables affect the selection of the technical indices and are closely related to the production rate of the concentrated ore. The raw ore is screened into powder ore and lump ore; lump ore is roasted in the shaft furnace, where its grade is improved and subsequently divided into the valuable ore and the waste rock. Thus, the grade of the feeding ore of the grinding unit process of HMPL and LMPL and the grade of the waste rock, which represents the grade of the raw ore, are chosen as the inputs, which are denoted as α_{g1}, α_{g2} and α_{g3}. As the bottleneck of the mineral beneficiation process, the handling capacity of the grinding unit process is used to represent the handling capacity of the entire production line. Thus, the input vector X of the model is selected as $X=[\eta, p_1, p_2, \beta_1, \beta_2, \zeta_1,\zeta_2, \alpha_{g1},$