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A dynamic subspace model for predicting burn-through point in iron sintering process

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ABSTRACT

This paper presents a dynamic modeling method for predicting the exhaust-gas temperature (EGT) of the burn-through point (BTP) in an iron sintering process. First, a subspace modeling method is used to build a steady-state subspace model (SSSM) for the EGT at a steady state. Then, a dynamic subspace model (DSM) that is driven by the errors of the SSSMs is developed to improve the accuracy of the EGT prediction in a continuous process. Finally, a grid search dynamic subspace model (GSDSM) is established to find the best parameters for each SSSM in the DSM. Verification results show that the GSDSM yields a predicted EGT with a high precision, which can be implemented in a predicting controller an actual sintering process.

1. Introduction

A sintering process produces sinters with an appropriate composition and mechanical strength, which directly influence the components of molten iron and thus the quality of the iron product [11]. One of the most important parameters for the sintering process is the burn-through point (BTP), which is the position on a pallet where the sintering process is completed. BTP is essential to evaluate of the sintering process is normal. This parameter also impacts directly the economic efficiency of company. Therefore, predicting the BTP is essential for the control of sintering processes [16].

Since sintering mainly operates at a steady state, many investigations have been focused on developing a steady-state model for the process. For example, Tamura et al. proposed a mathematical model to estimate the thermal state of a material layer based on the pallet velocity, the thickness of the material layer, and other steady-state parameters [20]. This model directly predicts the BTP; however, it is difficult to experimentally obtain all the parameters required for the model. Considering the temperature at the BTP is the highest in a sintering machine, Li and Wang presented a data-driven model using a soft-sensing technique [8]. They built a quadratic function that associated the BTP with three bellows located around the highest temperature but the influence on the temperature caused by the operating conditions of the process was not considered. Moreover, the model did not explicitly show the relationships between the BTP and the steady-state parameters. Based on the above, this model could not easily be used to control the BTP. In general, a steady-state model has poor adaptability to fluctuations caused by the changes on the operating conditions and by disturbances.

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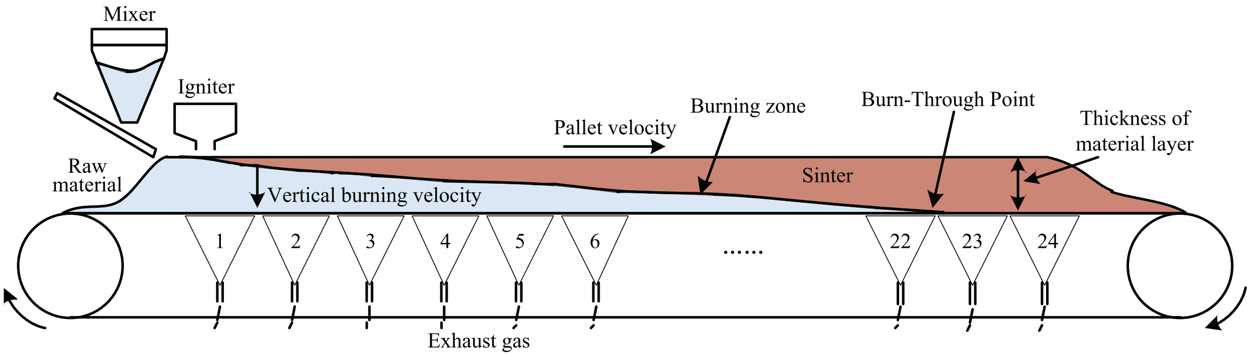

Fig. 1. The working process of a sintering machine.

A sintering process is complex; its parameters are strongly dependent on each other. Changes in operating conditions have a big influence on the BTP. Thus, establishing a dynamic model to ensure real-time tracking is important to improve the quality of sinters [18,25]. Two approaches have been mainly used to build dynamic models: data-driven or mechanism-based methods. For example, Nath and Mitra established a dynamic model for a sintering process based on the mechanism of the process [13], and Shang et al. presented a data-driven dynamic model for the BTP using a new genetic programming method [17]. Since mechanism-based mathematical models often have complicated structures and physical parameters for the formulas are hard to obtain or measure, most dynamic models are based on the data-driven method.

Such models, for example, a fuzzy or a neural-network model, are basically nonlinear [2]. This may result in a complicated control system, making the improvement on control performance difficult [14]. On the other hand, a method called subspace modeling is widely used to build state-space models, which are linear submodels for a specific condition [6,22]. Compared to conventional modeling, this method requires little information. The order of the model can be determined through singular value decomposition (SVD) or QR decomposition. A submodel can perfectly describe the local relationships between the input, the state, and the output. Since the design tools of a linear control system can be easily found and used for the establishment of a submodel, it can be simply applied to a multi-input, multi-output system. Nowadays, this method plays an important role in system analysis [3,19,28], for predictive control [23], and parameter evaluation [1]. For example, Ren and Li proposed an integrated subspace model for a gas mixing process [15], and Houtzager devised an improved real-time subspace method to solve the colored noise problem in industrial data [4,10].

In this paper, a method that combines dynamic algorithm and subspace modeling is presented for predicting the BTP in an iron sintering process. This combination of methods would ease the design of a control system in the sintering process and also allow for the implementation of the system in a real-time manner. The method first considers the sintering mechanism and the analysis of process data to reduce the dimension of the input. Then, it produces a dynamic subspace model (DSM) using the basic subspace modeling method for the reduced input and output.

In Section 2 the sintering process is explained and the relationships between the BTP and the parameters is analyzed. The dynamic subspace modeling method used to build the process model is presented in Section 3. Then in Section 4 results are used to demonstrate the validity of the method. Finally the concluding remarks are stated in Section 5.

2. Analysis of mechanism and data for sintering process

In this section, the mechanism of the sintering process is explained. Then, the characteristics and data collected from an actual production process are analyzed.

2.1. Sintering process

Sintering (Fig. 1) is an important procedure in iron production. The raw material, which contains limestone, ore, coke, and returned sinter is first collected at a given proportion and granulated in a mixer. Then, it is distributed on a sintering pallet and a material layer is set. The surface of the material layer is burned using an igniter at a certain vertical burning velocity. Twenty-four bellows located under the pallet draw air out from the bottom of the layer. The negative pressure helps the material burn from top to bottom and exhaust gas to be extracted. A burning zone is formed in the layer. The exhaust-gas temperature (EGT) of each bellows is measured at their edge.

The bellows number indicates the location of the BTP. Empirically, it has been observed that the best position of the BTP is at the second to last bellows, i.e., bellows 23 (Fig. 1). The sintering area is not effectively utilized if the BTP is located before this position and, if it is located after, the material is not completely sintered and the ratio of returned sintering fines increases. Therefore, the BTP located at the best position not only guarantees the effective use of the sintering area, but also increases sintering productivity.