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Gray-box modeling for prediction and control of molten steel temperature in tundish

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ABSTRACT

To realize stable production in the steel industry, it is important to control molten steel temperature in a continuous casting process. The present work aims to provide a general framework of gray-box modeling and to develop a gray-box model that predicts and controls molten steel temperature in a tundish (TD temp) with high accuracy. Since the adopted first-principle model (physical model) cannot accurately describe uncertainties such as degradation of ladles, their overall heat transfer coefficient, which is a parameter in the first-principle model, is optimized for each past batch separately, then the parameter is modeled as a function of process variables through a statistical modeling method, random forests. Such a model is termed as a serial gray-box model. Prediction errors of the first-principle model or the serial gray-box model can be compensated by using another statistical model; this approach derives a parallel gray-box model or a combined gray-box model. In addition, the developed gray-box models are used to determine the optimal molten steel temperature in the Ruhrstahl–Heraeus degassing process from the target TD temp, since the continuous casting process has no manipulated variable to directly control TD temp. The proposed modeling and control strategy is validated through its application to real operation data at a steel work. The results show that the combined gray-box model achieves the best performance in prediction and control of TD temp and satisfies the requirement for its industrial application.

1. Introduction

The steel industry faces stiff competition in the global market, and each steel company has to realize stable and efficient operation and produce high quality products satisfying various customer demand [1]. The process diagram of the steel making process is shown in Fig. 1. The tundish is a vessel used for delivering molten steel from a ladle to a mold in the continuous casting process. In steel making, control of the molten steel temperature in the tundish (TD temp) is one of the key factors to realizing stable operation. If TD temp is too high, breakouts may occur and cause tremendous increase in maintenance cost and productivity loss. When the temperature is too low, clogging in the tundish nozzle occurs, which causes disruptions in the casting process. However, no effective manipulated variable is available after the secondary refining process to control TD temp. To realize the target TD temp, therefore, it is necessary to adjust the molten steel temperature in the secondary refining process (Ruhrstahl–Heraeus degassing process). The molten steel temperature at the end of secondary refining operation is hereafter called RH temp. To control TD temp by manipulating RH temp, a model relating TD temp and RH temp needs to be constructed. In the past, various models such as first-principle models [2–7], statistical models [8], and gray-box models [9–12] have been proposed.

The gray-box model, which integrates a first-principle model and a statistical model, has attracted researchers' attention by its capability: known linear/nonlinear phenomena can be embedded in the first-principle model, and an unknown relationship among variables can be embedded in the statistical model by extracting such a relationship from the data. In general, gray-box models are more accurate than simplified first-principle models, less complicated than computational fluid dynamics (CFD) models, and more easily interpreted than statistical models. Although a gray-box model aims to improve the prediction performance by combining a first-principle model and a statistical model, the accuracy of the first-principle model is still important. In general, first-principle models have various parameters which need to be determined by using data. Even when some parameters depend on the operating

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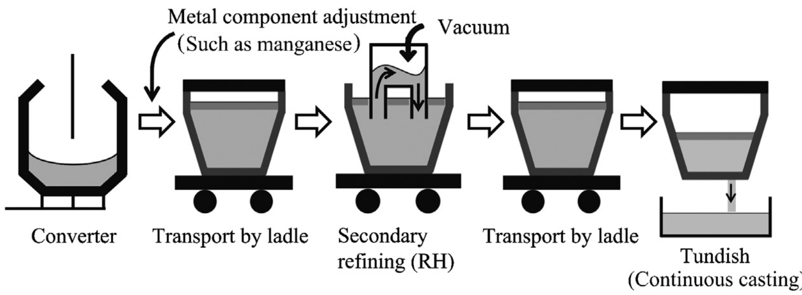

Fig. 1. Schematic diagram of the steel making process.

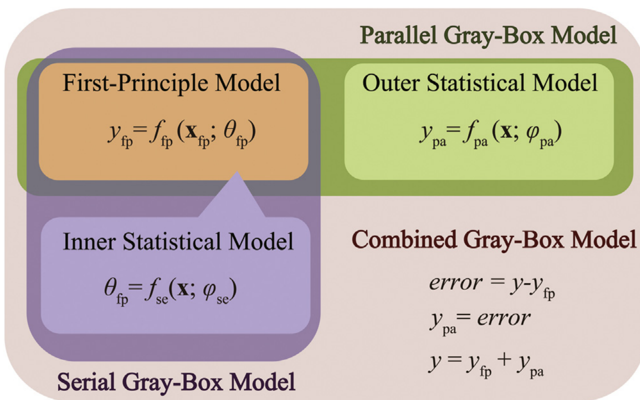

Fig. 2. Generalized framework of gray-box modeling.

conditions, they are kept constant if it is difficult to identify the relationship between the parameters and the operating conditions. In such a case, large prediction error might be caused.

The present work aims to develop a new gray-box model that can overcome such deficiency and can predict molten steel temperature with high accuracy. To achieve this goal, a parameter in the first-principle model is estimated from process variables with a nonlinear statistical model. In addition, process disturbances such as uncertainties in temperature measurements, composition and weight of added alloys and the extent of oxidation reactions for removal of impurities are also taken into account. Ideally, such disturbances should be modeled by adding certain mathematical expressions to the first-principle model. However, due to lack of process information, realizing such mathematical expressions is difficult and therefore another statistical model is developed to compensate prediction errors caused by such process disturbances. Random forests (RF) is adopted in this work to build statistical models.

In Section 2, three types of gray-box models are explained in general. Then, the first-principle model of the steel making process is described in Section 3, and the statistical models integrated with the first-principle model to build the gray-box models are described in Section 4. In Section 5, the proposed method is applied to the problems of predicting and controlling molten steel temperature in a real steel making process. Finally, the contents are summarized in the conclusion section.

2. Gray-box models

A general framework of the gray-box modeling is shown in Fig. 2, where gray-box models are categorized into three types, i.e., parallel gray-box models [9], serial gray-box models [10], and combined gray-box models. In this section, modeling methods of these gray-box models are explained.

2.1. Parallel gray-box model

A typical gray-box model is constructed by combining a first-principle model and a statistical model sequentially; the statistical model is built so as to compensate the error of the first-principle model. This type of gray-box model, hereafter called the parallel gray-box model, is developed through the following steps.

i. Build a first-principle model f_{fp} to predict an output variable y from input variables $\boldsymbol{x}_{fp}$.

$$\hat{y}_{fp} = f_{fp}(\boldsymbol{x}_{fp}, \boldsymbol{\theta}) \quad (1)$$

where $\hat{y}_{fp}$ is the prediction of y and $\boldsymbol{\theta}$ is a parameter vector. The first-principle model can be of any form including differential algebraic equations. Eq. (1) can be derived from such a first-principle model as shown in the next section.

ii. Estimate $\boldsymbol{\theta}$ by minimizing the sum of squared errors.

$$\tilde{\boldsymbol{\theta}} = \arg\min_{\boldsymbol{\theta}} \sum_{n=1}^{N_d} e_{fp,n}^2 \quad (2)$$

$$e_{fp,n} = y_n - f_{fp}(\boldsymbol{x}_{fp,n}, \boldsymbol{\theta}) \quad (3)$$

$$\boldsymbol{\theta}_L \leq \boldsymbol{\theta} \leq \boldsymbol{\theta}_U \quad (4)$$

where $\boldsymbol{x}_{fp,n}$ and y_n are the nth sample of input and output variables, respectively. N_d is the number of samples used for developing the model. $\boldsymbol{\theta}_L$ and $\boldsymbol{\theta}_U$ are lower and upper bound vectors of parameters which are determined in advance.

iii. Build a statistical model f_{pa} to predict the output error e_{fp} from input variables $\boldsymbol{x}$.

$$\tilde{\boldsymbol{\varphi}}_{pa} = \arg\min_{\boldsymbol{\varphi}_{pa}} \sum_{n=1}^{N_d} (e_{fp,n} - f_{pa}(\boldsymbol{x}_n, \boldsymbol{\varphi}_{pa}))^2 \quad (5)$$

$$\hat{e}_{fp,n} = f_{pa}(\boldsymbol{x}_n, \boldsymbol{\varphi}_{pa}) \quad (6)$$

where $\boldsymbol{\varphi}_{pa}$ is a vector of parameters in the outer statistical model. In general, $\boldsymbol{x}_{fp}$ is a subset of $\boldsymbol{x}$.

iv. Build a gray-box model by combining the first-principle model and the outer statistical model.

$$\hat{y}_{pa} = f_{fp}(\boldsymbol{x}_{fp}, \tilde{\boldsymbol{\theta}}) + f_{pa}(\boldsymbol{x}, \tilde{\boldsymbol{\varphi}}_{pa}) \quad (7)$$

where $\hat{y}_{pa}$ is the prediction of y by using the parallel gray-box model.

The parallel gray-box model is the simple sum of the first-principle model and the statistical model. This statistical model is referred to as the outer statistical model because it is used on the outside of the first-principle model. In general, the parallel gray-box model can significantly improve the prediction performance because it can extract information from data that is not used in the first-principle model and also it can overcome the limitations imposed by the structure of the first-principle model.