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A prediction and outlier detection scheme of molten steel temperature in ladle furnace

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ABSTRACT

Molten steel temperature prediction is a crucial step in ladle furnaces (LFs). Due to the complicated working conditions, process data usually suffers from various types of outliers. However, most of existing temperature models have not taken robustness to outliers into account. Hence, their accuracies usually cannot satisfy the industrial production. In this paper, we propose a comprehensive scheme that integrates temperature prediction with outlier detection. Of this scheme, we develop a three-level ensemble model where Gaussian process (GP) is used as the base learner, to accomplish the prediction task. Motivation for GP base leaner is two-fold. One is that GP models perform well on the nonlinear regression problem. The other is that GP is a Bayesian method and its output can be used in the outlier detection step. Motivation for our ensemble model is also two-fold. First two problems regarding GP, i.e. high computational complexity and model selection, can be alleviated. Second, the predictive accuracy can be further improved. As for the outlier detection task, we develop two types of detectors implemented for both training and testing data points. We proposed a novel detector based on one-class classification (OCC) and use it for training samples and inputs of testing data. And the detector for the output values of testing data is constructed from outputs of the prediction model. Finally, we verify the prediction performance on several real-world data sets and compare their performance with several competitors. The significance of the proposed outlier detection step is also validated. Experimental results approve the potential of our scheme.

1. Introduction

The control of molten steel temperature in ladle furnaces is one of the most important operations for the sake of stable and high-quality production in steel industry. While in practice, successive measuring of molten steel temperature is prohibitive limited by current measurement technology. This has led to a great challenge for precise process control. As a result, developing a forecasting model either from the first-principle or aided by process data have drawn much attention from researchers.

In the context of mechanism models, most are constructed based on thermodynamics and conservation of energy law (Camdali et al., 2001; Zabadal et al., 2004; Jormalainen and Louhenkilpi, 2006; Camdali and Tunc, 2006; Austin et al., 2007). This type of model is usually extracted from the original process, which is very complicated in essence. Accordingly, some simplified procedures are inevitable. In addition, several hard-determined parameters are usually estimated by experience of engineers. As a result, the predictive accuracy can hardly be guaranteed.

Recently, many data-driven prediction models based on artificial intelligence (AI) technology and machine learning (ML) technology were proposed for chemical processes (Ge, 2017; Ge et al., 2017; Lu et al., 2017; Qin, 2014). It is observed that these models usually outperform the mechanism model provided sufficient and effective process data was available. According to the model structure, we categorize these methods into three groups.

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- Single data model. In general, a black-box model is constructed through input-output measurements. Neural Network (NN), as a popular AI algorithm, has been developed for forecasting molten steel temperature (Sun et al., 2000; Tian et al., 2006; Bouhouche et al., 2004). Then support vector machine (SVM), as a successful ML algorithm, has also been proposed to predict molten steel temperature (Yang et al., 2012; Wang, 2007).
- Hybrid model. Hybrid models are also referred to as gray-box models, which can be categorized into three types: (1) parallel gray-box model, in which a statistical model is constructed so as to compensate the error of the mechanism model (Johansen and Foss, 1992); (2) serial gray-box model, where parameters of the mechanism model are deemed as functions of input variables and optimized by a statistical model (Lv et al., 2012; Psichogios and Ungar, 1992); and (3) combined gray-box model that combines the above-mentioned two models. In combined gray-box models, parameters of the mechanism model are estimated by the inner statistical model and predictive errors are compensated by the outer statistical model (Ahmad et al., 2014).
- Ensemble data model. An aggregation of many simple but different models can reduce the complexity and achieve better performance which cannot be achieved by a single model. Ensemble extreme learning machine (ELM) (Tian and Mao, 2010) and ensemble regression tree (Wang et al., 2016) have been proposed and been verified to outperform single data model.

1.1. Motivation

In this paper, we propose a comprehensive scheme that integrates temperature prediction with outlier detection. The motivation is two-fold.

Firstly, due to the complicated working conditions of LFs, process data can easily suffer from outliers resulting from various aspects, such as process faults, sensor faults, and artificial faults. These outliers could negatively influence any data-driven model. In the context of molten temperature prediction in LFs, we categorize outliers into two groups. One is outliers in the training set of the temperature model. Detecting this type of outliers can be implemented off-line. The other is outliers in the inputs and outputs of the temperature model. Suppose the input value is an outlier when predicting the temperature, the output value can hardly be credible. Outliers in the outputs indicate the faulty measurements resulting from the instrument. Detecting this type of outliers should be implemented online.

Secondly, we aim to efficiently improve the predictive accuracy. Note that factors effecting the final temperature are various and their relationship with the temperature is very complicated. Traditional temperature models may not satisfy the industrial production. Therefore, we propose an ensemble temperature model where base learner is GP. Motivation for GP base leaner is two-fold. One is that GP models perform well on the complicated regression problems. The other is that GP is a Bayesian method and its outputs can be used for validating the real outputs. Motivation for our ensemble model is also two-fold. First, two problems regarding GP, i.e. high computational complexity and model selection, can be alleviated in the ensemble model. Second, predictive accuracy can be further improved compared with the original GP models.

1.2. Outline

Although several outlier detection methods have been proposed for chemical processes, the combination with temperature prediction is rare (Liu et al., 2004; Li et al., 2015; Xu et al., 2015, 2017). In this paper, for the detection method dedicating to the training set and testing input measurements, we propose a novel unsupervised detection algorithm since prior information regarding outlier class is difficult to obtain. The proposed method is based on algorithm SVDD (support vector data description) but is more robust than SVDD. Via gradually refining the training set, three SVDD models are constructed successively. Thus, we name our method triSVDD. For the detector tailored for testing output measurements, we can use results provided by the prediction model this will be described below.

With regard to the prediction model, we use a nonparametric Bayesian method, Gaussian process (GP). It is observed that high computational complexity and selection of covariance function are two main obstacles preventing GP models developing in practical applications. To mitigate these two problems, in this paper, we develop a three-level ensemble GP (TLEGP) model. At the first level, several feature subspaces (lower dimension) are constructed by a hybrid method, where domain knowledge and data-driven technique are combined together. At the second level, bootstrap sampling procedure is used to build more subsets (fewer samples). At the third level, several sub-ensemble models, in which base learners are specified with different covariance functions, are trained on subsets derived from the former level. Note that outputs of any Bayesian model are distributions, the predictive variances can not only used for flagging outliers for testing outputs but also aggregating outputs of base learners in TLEGP.

1.3. Contributions

We summary our contributions as follows.

(1) We integrate outlier detection with temperature prediction. This is of much significance in practical applications. To our best of knowledge, none of the existing temperature models has the function of detecting outliers in testing input measurements, let alone output measurements.
(2) We propose a novel ensemble temperature model, where Gaussian process models are used as base learners. Since Gaussian process belongs to the Bayesian paradigm, we can utilize its outputs to validate the real measurements. In addition, our ensemble model could achieve better generalization performance, as well as solve the problems of high computational complexity and model selection.
(3) We propose a novel outlier detection method based on a one-class classifier, i.e. SVDD. Our method is more robust to outliers in the training set and is more appropriate for practical applications.

The rest of this paper is organized as follows. We briefly introduce the analysis of energy budget in LF in Section 2. Details of the proposed prediction and outlier detection scheme are presented in Section 3. Experiments are carried out in Section 4. Finally, Section 5 draws some conclusions.

2. Energy budget in LF

By analyzing the energy budget in LF, main factors affecting the end temperature of molten steel can be concluded.

2.1. Energy gain

The heating supply of LF is constituted by secondary transformer, short net, hydraulic system, and graphite electrode. In order to reduce the radiant heat loss and protect the furnace liner, the graphite electrode is submerged within the slag that lies upon the molten steel. Then electric energy is converted to heat energy via the electric arc generated between electrode and molten steel. Consequently, the energy gain of LF is determined by the consumed electric energy (E) and the energy loss from short net (E_{sn}) and electric arc (E_{ea}).

2.2. Energy consumption

Heat energy absorbed into the molten bath is consumed by five sectors: (1) most energy is used to heat the molten slag and steel (E_{ss}); (2) energy consumed by the ladle refractory wall (E_{rw}); (3) energy consumed through the radiation loss from molten slag surface and bare liquid steel surface (E_{lss}); (4)