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Tree-Structure Ensemble General Regression Neural Networks applied to predict the molten steel temperature in Ladle Furnace

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ABSTRACT

To control the molten steel temperature in a Ladle Furnace accurately, it is necessary to build a precise (i.e. accurate and good generalized) temperature prediction model. To solve this problem, ensemble modeling methods have been applied to predict the temperature. Now, in the production process, large-scale data with more helpful information are sampled, which provides possibilities to improve the precision of the temperature prediction. Although most of the existing ensemble temperature models have strong learning ability, they are not suitable for the large-scale data. In this paper, to solve the large-scale issue, the Tree-Structure Ensemble General Regression Neural Networks (TSE-GRNNs) method is proposed. Firstly, small-scale sample subsets are constructed based on the regression tree algorithm. Secondly, GRNN sub-models are built on sample subsets, which can be designed very quickly and cannot converge to poor solutions according to local minima of the error criterion. Then, the TSE-GRNNs method is applied to establish a temperature model. Experiments show that the TSE-GRNNs temperature model is more precise than the other existing temperature models, and meets the requirements of the RMSE and the maximum error of the molten steel temperature prediction in Ladle Furnace.

1. Introduction

With the rapid development of the steelmaking industry, the molten steel temperature adjustment or control becomes one of the hot topics [1,2]. The efficiency of the energy transformation has a strong influence on the Ladle Furnace control system, which directly affects the consumption of the electrode, the consumption of the additions, and the efficiency of the production [1]. However, in the production process, the molten steel temperature cannot be measured continuously, which brings much burden to control the temperature accurately [3–5]. Consequently, it is necessary to build a precise (i.e. accurate and good generalized) temperature prediction model.

In the past decades, some molten steel temperature prediction models have been reported, and these models can be roughly arranged in mechanism temperature models and data-driven temperature models. Most of the mechanism temperature models are based on thermodynamics and conservation of energy [6,7]. However, since the parameters are hard to obtain, mechanism temperature models cannot be used efficiently for online precise prediction [3].

To improve the precision of mechanism temperature models, single data-driven models have been applied to predict the molten steel temperature. For example, Sun et al. [1] use neural network to estimate the temperature. Wang [8] presents a PLS-SVM (Partial Least Squares-Support Vector Machine) temperature prediction model. However, single data-driven temperature prediction models only learn from a single predictor, and their precision is hard to improve when the data is badly polluted or the object is complicated.

Compared with a single data-driven predictor, ensemble data-driven modeling methods have stronger learning ability [9,10], and have been successfully applied to establish the model steel temperature prediction models in Ladle Furnace. For example, in paper [3], the ensemble Extreme Learning Machines [11] model combined the AdaBoost.RT with the extreme learning machine is established by Tian and Mao to predict the molten steel temperature. In paper [12], a hybrid ensemble temperature model is proposed by Lv et al. in which a negative correlation learning based pruned Bagging method is used to estimate the unknown parameters, simultaneously to predict the undefined function of the thermal model.

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Now, with the development of the computer and the information techniques, large-scale data containing more helpful information are sampled from the practical production process in Ladle Furnace. The large-scale data provide possibilities to improve the precision (the accuracy and the generalization) of the molten steel temperature prediction. Furthermore, a high precise temperature prediction model can reduce the consumption of the energy and boost the efficiency of the production in Ladle Furnace.

Unfortunately, large-scale data impose strong restrictions on modeling [13,14], and most of the existing ensemble temperature models are not suitable for large-scale data. In paper [3], Tian and Mao use the modified AdaBoost.RT as the ensemble method, and the extreme learning machine is the "weak learner" (i.e. base learner) of AdaBoost.RT. Although the extreme learning machine can be designed very quickly, the AdaBoost.RT is a serial ensemble method in which a new sub-model relies on the old one. Generally, a serial ensemble model is more complex than a single model in the phases of training and actual using [15,14]. In paper [12], although the presented pruned Bagging can boost the precision of the temperature prediction, an obvious shortcoming is the loss of computational efficiency with respect to the original Bagging, especially on large-scale data.

To solve large-scale issue, the Tree-Structure Ensemble General Regression Neural Networks (TSE-GRNNs) method is proposed in this paper. Firstly, small-scale sample subsets are constructed based on the regression tree algorithm [16]. Secondly, GRNN [17,18] sub-models are built on sample subsets, which can be designed very quickly and cannot converge to poor solutions according to local minima of the error criterion. Even with sparse data in a multidimensional measurement space, the GRNN forms very reasonable regression surfaces.

The TSE-GRNNs method is expected to utilize the large-scale data sampled from the production process of Ladle Furnace effectively, to improve the precision of the temperature prediction, and to meet the requirements that the RMSE of the temperature is less than 3 °C and the maximum error is less than 5 °C.

The remainder of this paper is organized as follows. In Section 2, the main factors in the temperature prediction model of Ladle Furnace are present. In Section 3, the TSE-GRNNs method is proposed. In Section 4, experimental investigations of the TSE-GRNNs temperature model are brought out. In Section 5, the conclusion of this paper is summarized.

2. The main factors in the temperature prediction model of Ladle Furnace

In Ladle Furnace, the power supply system transforms the high voltage and small current power into the low voltage and large current electric arc, and generates the thermal energy to heat the molten steel [1]. To establish the data-driven based model of the molten steel temperature, the entire refining process of Ladle Furnace is considered as an energy conservation system. The main factors in the molten steel temperature prediction model are obtained from the refining process.

The diagram of the LF refining process is shown in Fig. 1. This process is the same as that in Tian and Mao's pp. 76–77 [3]. Thus, we do not introduce the mechanism of the production process.

The main factors used here are the weight of molten steel, the temperature of the empty ladle, the number of the ladle, the ladle states, the initial temperature, the refining power consumption, the refining time, the time interval of temperature measure, the volume of argon purging, and the heat effects of additions. More factors are considered in this paper than those in Tian and Mao's paper [3].

The molten steel temperature prediction in the process of practical producing must satisfy that:

(1) The Root Mean Square Error (RMSE) of the temperature prediction must be less than 3 °C.
(2) The maximum error of the temperature prediction must be less than 5 °C.

3. The tree-structure ensemble GRNNs method

Currently, ensemble prediction models have been paid attention to for their better performance [19–22]. In an ensemble model/predictor, a set of sub-models are generated by means of applying a base learner (i.e. learning algorithm of sub-models) to different distributions of the training data, and then to predict a new sample, the outputs/predictions from sub-models are aggregated suitably by a combination method.

With many simple but diverse sub-models, an ensemble model can reduce the complexity and achieve a higher precision compared to a single model [10]. The Random Forests [10] method proposed by Breiman is such an ensemble model. To deal with a regression problem, in the random forest, a regression tree [16] sub-model is built on a bootstrap sample subset and uses a set of randomly selected features to determine the split of the root node and the internal nodes.

The random forest method is suitable for a large-scale regression problem. However, the molten steel temperature model estimated with the random forest cannot meet the strict precision requirements of the production process in Ladle Furnace. In fact, the random forest bases on the piecewise linearization to fit a nonlinear function, which is the same as the regression tree. And the predictions of a random forest model are finite, discrete, constant and linear. With more input features considered, the random forest cannot well describe the nonlinear characteristic of the molten steel temperature. In this paper, the TSE-GRNNs method is proposed to predict the temperature on large-scale data.

There are two main steps to build a TSE-GRNNs model. Firstly, small-scale sample subsets are constructed based on the regression tree algorithm. Secondly, a GRNN sub-model is estimated on each sample subset.

3.1. The small-scale sample subsets based on the regression tree algorithm

In a TSE-GRNNs model, leaf-nodes of a regression tree [16] are used as small-scale sample subsets. The splitting algorithm and the stopping criterion are key to construct sample subsets in a TSE-GRNNs model.

① The splitting algorithm

The purpose of a splitting algorithm in the regression tree is to achieve the recursive partition of the training set. All samples in the training set start at the root node. A piecewise function to one of the input features x_i is applied to divide the samples on the root node or interior nodes into two parts: if $x_i < \hbar_i$, where $\hbar_i$ is the threshold of x_i, the sample will go to the left sub-branch; else, to the right one. At the en of the recursive partition, a training set is divided into smaller sample subsets [16,23].

To achieve the splitting, two issues need to be considered [16,24]: which is the best input feature x_i; and how to determine the valve of its threshold $\hbar_i$; The splitting algorithm is the minimum of, after splitting, the sum of mean square errors of the outputs in the two sample subsets [23]: