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The soft sensor of the molten steel temperature using the modified maximum entropy based pruned bootstrap feature subsets ensemble method

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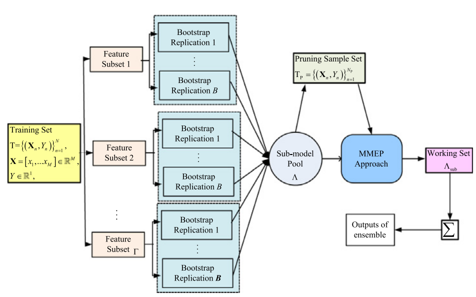
HIGHLIGHTS

- The sort sensor of the molten steel temperature based on the MMEP-BFSE is proposed.
- The BFSE is applied to predict the temperature in ladle furnace on the large-scale and noisy data.
- To reduce number of sub-models in the BFSE, the MMEP approach is presented.
- Introducing a tuning parameter, the MMEP can well trade off the precision and the diversity.
- The proposed soft sensor improves the generalization and is more feasible in applications.

GRAPHICAL ABSTRACT

In this paper, the soft sensor of the molten steel temperature established by the Modified Maximum Entropy based Pruned Bootstrap Feature Subsets Ensemble (MMEP-BFSE) method is proposed. Although the Bootstrap Feature Subsets Ensemble (BFSE) temperature model is prominent in the precision and the forecasting speed on the large-scale and noisy data, its main drawback is too many sub-models required to combine, which is not always feasible for applications. To alleviate this drawback, the Modified Maximum Entropy based Pruning (MMEP) approach is presented, in which a subset of sub-models that better approximates the complete ensemble is find based on the maximum Rényi entropy and the trade-off parameter between the precision and the diversity of sub-models.



The diagram of a MMEP-BFSE model.

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ABSTRACT

The molten steel temperature in ladle furnace is a significant variable, but it is hard to be measured by real-time detection, which has some bad effects on productions. Soft sensors are alternative and effective techniques to solve this issue. In this paper, the soft sensor of the molten steel temperature established by the Modified Maximum Entropy based Pruned Bootstrap Feature Subsets Ensemble (MMEP-BFSE) method is proposed. Although the Bootstrap Feature Subsets Ensemble (BFSE) temperature model is prominent in the precision and the forecasting speed on the large-scale and noisy data, its main drawback is too many sub-models required to combine, which is not always feasible for applications. To alleviate this drawback, the Modified Maximum Entropy based Pruning (MMEP) approach is presented, in which a subset of sub-models that better approximates the complete ensemble is find based on the maximum Rényi entropy and the trade-off parameter between the precision and the diversity of sub-models. Then, the soft sensor of the temperature based on the MMEP-BFSE is established on the practical data. Experiments show that the proposed soft sensor outperforms the others in the precision, and meets

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the precision requirements. Sub-models of the BFSE temperature model are substantially pruned with improved generalization by the MMEP approach.

1. Introduction

In many industrial processes, due to the limitations of techniques, technology and cost, etc., some important variables are difficult to be measured by the real-time detection, which has bad effects on productions. To predict such variables, soft sensors for regression applications are proposed by many experts and scholars, which are inferential mathematics models using measurable (i.e., easy-measuring) variables to predict immeasurable (i.e., hard-measuring) variables that cannot be measured automatically, or can only be measured with long delays, or sporadically, or at high cost (Souza et al., 2016).

By now, soft sensors have been widely used in various industrial fields (Lin et al., 2014; Liu et al., 2015; Jin et al., 2015; Yang et al., 2016; Bidar et al., 2017; Liu, 2017). For example, Jin et al., 2015 developed a soft sensor of online quality prediction in the industrial batch rubber mixing process applying the ensemble just-in-time Gaussian process regression method. Although their soft sensor can well describe the time-varying and nonlinear behavior of the rubber mixing process simultaneously, this method is more suitable for small-scale data, due to the k-nearest neighbors algorithm (used to calculate the partial mutual information core for the input variable selection) and the Euclidean distance (applied to select samples most similar to the query data for the just-in-time learning). Bidar et al., 2017 designed a soft sensor modeling approach for process monitoring, which is based on the state dependent parameter method and can successfully incorporate the state dependency of parameters under the nonlinear relationship between input and output variables.

To precisely measure/predict the molten steel temperature in ladle furnace, ensemble soft sensors have been presented by many scholars to overcome the limitations of the mechanism and the single data-driven soft sensors. As a branch of machine learning and data mining, the ensemble learning generates and combines multiple sub-models (i.e., classifiers/predictors) to solve one prediction problem and obtain an ensemble model with better performance than a single model, such as more accurate, stronger generalization ability, lower computational complexity, and more robustness (Breiman, 2001; Son et al., 2014; Aleksovski et al., 2015). For example, Tian and Mao (2010) proposed a temperature model by using the ensemble extreme learning machines based on the modified AdaBoost. Lv et al. (2014) presented a temperature model by employing the pruned Bagging based on the negative correlation learning. However, it is hard for existing ensemble temperature soft sensors to further improve the precision on the large-scale and noisy data sampled from the industrial process of the ladle furnace system.

To solve the large-scale data, Wang (2017) introduced a temperature model based on the random forest (Breiman, 2001). Aiming at solving the large-scale and the noisy issues simultaneously; the Bootstrap Feature Subsets Ensemble (BFSE) method was proposed by Wang et al. (2016) for improving the precision of the temperature prediction. In a BFSE model, low-dimensional feature subsets are constructed from 1-subdivision to h^*-subdivision of the original feature space, bootstrap replications (i.e., the training subsets) of feature subsets are generated to eliminate noise, and the Regression Tree (RT) algorithm (Breiman et al., 1998) is employed as the base learner. Although the BFSE temperature model is prominent in the precision and the forecasting speed, the main drawback of it is that a large amount of sub-models are required to compute the final ensemble prediction. As a parallel ensemble, a large amount of computers are entailed in a BFSE model, which leads to a drawback to applications.

To alleviate this drawback, the soft sensor of the molten steel temperature using the Modified Maximum Entropy based Pruned Bootstrap Feature Subsets Ensemble (MMEP-BFSE) method is proposed in this paper. Firstly, the BFSE method is applied to solve the large-scale and noisy data. Secondly, to reduce the number of the sub-models in a BFSE model, the Modified Maximum Entropy based Pruning (MMEP) approach is presented. Based on the maximum Rényi entropy criterion, the Maximum Entropy based Pruning (MEP) approach was introduced in paper (Wang et al., Jul. 2017), the purpose of which was to find a sub-ensemble that well approximates the complete ensemble. In the MEP, both the precision of the sub-models and the diversity among the entire selected sub-models are well considered. Nevertheless, the trade-off between the precision and the diversity is an open question, which obviously influences the effectiveness of the MEP. To discuss the open question and to further improve the precision of a sub-ensemble, the trade-off parameter between the precision and the diversity is introduced into the MEP, and then the MMEP approach is presented here. Finally, the MMEP-BFSE method is applied to build the soft sensor of the molten steel temperature on practical data. The proposed soft sensor of the temperature is expect to use fewer sub-models with improved generalization, and to meet the error requirements that the Root Mean Square Error (RMSE) is less than 2.4 °C and the Maximum Error (ME) is less than 6.7 °C.

The remainder of this paper is organized as follows. In Section 2, the background and state of art is introduced, which includes the BFSE method and the review of pruning approaches for parallel ensembles on regression problems. In Section 3, the MMEP approach is proposed. In Section 4, the soft sensor of the molten steel temperature based on the MMEP-BFSE is validated by practical data and compared with other soft sensors of the molten steel temperature, i.e., the MEP-BFSE, the REP-BFSE, the modified AdaBoost, the pruned Bagging, and the single ELM and the single RBF. In Section 5, the conclusions of this paper are summarized. Acronyms and notations are given in Appendix.

2. Background and state of art

2.1. The BFSE method for regression applications

Currently, large-scale data are accumulated from practical processes of ladle furnace. Soft sensors that can successfully mine more beneficial information from large-scale data and can improve the predictive accuracy with reasonable computation burdens are essential. An ensemble model, constructed by a combination of many simple but diverse sub-models, can reduce the computational complexity and simultaneously achieve better performances on the accuracy and generalization than a single model (Breiman, 2001). The random forest and the BFSE are such ensemble methods, and both of them are parallel ensembles with strong learning ability.

The random forest is a sample subset based ensemble method. It is a modified version of Bagging, and sample subsets are constructed based on the bootstrap sampling technique. For regression problems, a RT sub-model is established on each sample subset by