Expert Systems with Applications 38 (2011) 14786–14798

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Dynamic control model of BOF steelmaking process based on ANFIS and robust relevance vector machine

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ARTICLE INFO

Keywords:
Basic oxygen furnace (BOF) steelmaking
Dynamic control model
Adaptive-network-based fuzzy inference system (ANFIS)
Robust relevance vector machine

ABSTRACT

This study concerns with the control of basic oxygen furnace (BOF) steelmaking process and proposes a dynamic control model based on adaptive-network-based fuzzy inference system (ANFIS) and robust relevance vector machine (RRVM). The model aims to control the second blow period of BOF steelmaking and consists of two parts, the first of which is to calculate the values of control variables, viz., the amounts of oxygen and coolant requirement, and the other is to predict the endpoint carbon content and temperature of molten steel. In the first part, an ANFIS classifier is primarily constructed to determine whether coolant should be added or not, then an ANFIS regression model is utilized to calculate the amounts of oxygen and coolant. In the second part, a novel robust relevance vector machine is presented to predict the endpoint. RRVM solves the problem of sensitivity to outlier characteristic of classical relevance vector machine, thus obtaining higher prediction accuracy. The key idea of the proposed RRVM is to introduce individual noise variance coefficient to each training sample. In the process of training, the noise variance coefficients of outliers gradually decrease so as to reduce the impact of outliers and improve the robustness of the model. Simulations on industrial data show that the proposed dynamic control model yields good results on the oxygen and coolant calculation as well as endpoint prediction. It is promising to be utilized in practical BOF steelmaking process.

1. Introduction

The basic oxygen furnace (BOF) steelmaking is an important metallurgical technology. It is one of the most efficient methods to produce molten steel from hot metal and is also the pre-process of continuous casting and rolling. Because of its high productivity and low cost, until now almost 65% of the total steel in the world are produced by using this method. In general, the aim of controlling BOF steelmaking is to guarantee the proper temperature and element contents of molten steel under the metallurgical standards. In practice, the criterion whether molten steel is acceptable or not mainly depends on the values of endpoint carbon content and temperature (Chou, Pal, & Reddy, 1993). After smelting, carbon content generally decreases from approximate 4% in hot metal to less than 0.08% in molten steel, and temperature increases from about 1250 °C to more than 1650 °C (Han & Huang, 2008). Therefore, it requires some methods to control the decarburization and temperature-rising. In the early years, the process was just controlled according to the experience of operators, which often could not obtain satisfactory result. Thus, some mathematical models were developed to assist the operations. These models were mainly based on material balance and heat balance, which were accountable for their name "static control models". With the development of measuring techniques, a lot of new-style sensors and devices, such as sonic sensors, automatic sub lance and off-gas analysis, have been applied in BOF steelmaking to improve the control effect (Dippenaar, 1999; Iida et al., 1984). Based on these advanced measurements, the process control models are also improved. The models are able to automatically calculate the required amounts of oxygen and auxiliary additions as well as predict the endpoint carbon content and temperature (Birk, Johansson, Medvedev, & Johansson, 2002; Blanco & Diaz, 1993; Chou, Pal & Reddy, 1993; Johansson, Medvedev, & Widlund, 2000). In order to distinguish from the static control models, the improved models are named after "dynamic control models". Notwithstanding the superiority to the static ones, the dynamic models are nevertheless based on physical and chemical laws, which inevitably have some inherent limitations in practical application. That's because BOF steelmaking process is coupled with heat transfer, mass transfer, and a large number of chemical reactions. The complexity of the nature of BOF steelmaking makes its modeling and control extremely difficult and too hard to be reduced to sets of equations.

To overcome the difficulty and establish an exact mathematical relationship between input and output variables of BOF steelmaking, data-driven models such as artificial neural networks (ANNs)

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doi:10.1016/j.eswa.2011.05.071

are adopted. Because of its accurate identification for complex and nonlinear dynamic system (Narendra & Parthasarathy, 1990), ANNs are suitable for both modeling and control purpose in iron and steel making process (Bloch, Sirou, Eustache, & Fatrez, 1997). Radhakrishnan and Mohamed (2000) utilized neural networks as soft sensors to predict silicon and sulfur content of blast furnace hot metal, and created an expert control system to improve the hot metal quality. Pernía-Espinoza, Castejón-Limas, González-Marcos, and Lobato-Rubio (2005) proposed several robust learning algorithms to train neural networks and described the steel annealing process. As for BOF steelmaking, Cox, Lewis, Ransing, Laszczewski, and Berni (2002) used ANNs to predict oxygen and coolant requirements during the second blow period. Fileti, Pacianotto, and Cunha (2006) developed an inverse neural network model to calculate the end-blow process adjustments and the model was successfully implemented on line in a Brazilian steelmaking plant. Das, Maiti, and Banerjee (2009) used ANNs with Bayesian regularization to predict the control action for a steelmaking furnace. Many successful applications of ANNs on steelmaking modeling have been reported in the literature, however ANNs have some limitations. It is difficult to tune the structure parameters, which essentially affect the efficiency and prediction accuracy of ANNs. In addition, the models are sensitive to initialized parameters.

In recent years, statistical learning theory has been rapidly developed. It takes structural risk minimization as its principle and focuses on controlling the generalization ability of learning process (Vapnik, 2000). Based on this theory, the support vector machine (SVM) was invented. It enhances the computational ability by using kernel functions and mapping the data into high-dimensional space. Moreover, a regularization parameter C is defined to control the trade-off between the model complexity and training error (Müller, Mika, Rätsch, Tsuda, & Schölkopf, 2001). Therefore, SVM becomes a powerful tool to identify the nonlinear system and many successful applications have been achieved (Esen, Ozgen, Esen, & Sengur, 2009; Vong, Wong, & Li, 2006; Zhang & Wang, 2008). As in the application of steelmaking process control, SVM has also delivered good performances. Yuan, Mao and Wang (2007b) integrated multiple support vector machines with principle component regression to predict the endpoint parameters of electric arc furnace steelmaking. Valyon and Horváth (2009) proposed a sparse and robust extension of least-square SVM (LS-SVM) to calculate the amount of oxygen blown in BOF steelmaking, and demonstrated that the performance of LS-SVM was better than that of ANNs. However, despite its success, SVM has a number of significant and practical disadvantages. For example, predictions are not probabilistic and the kernel function must satisfy Mercer's condition. The error/margin trade-off parameter C needs to be estimated by using cross validation which consumes a lot of time. Moreover, although SVM is relatively sparse, the number of support vectors still grows linearly with the size of the training sample set (Tipping, 2000). These disadvantages limit the further applications of SVM.

To alleviate the above drawbacks, Tipping (2000, 2001) proposed the relevance vector machine (RVM). RVM is a nonlinear probabilistic model based on Bayesian evidence framework. It uses type-II maximum likelihood method, which is also referred to as "evidence procedure" (Mackay, 1992a, 1992b) to optimize the hyperparameters of the model and obtain a sparse solution. The generalization performance of RVM is comparable to that of SVM, whereas RVM is a higher sparse model (Tipping, 2001). Due to its advantages, RVM has obtained state-of-the-art results in different applications, such as microbiological fermentation (Sun & Sun, 2005), mechanical engineering (Yang, Zhang, & Sun, 2007), medical image processing (Wei, Yang, Nishikawa, Wernick, and Edwards, 2005) and fault diagnosis (Widodo et al., 2009). However, RVM has a serious weakness that it assumes all of the training samples are coupled with independent Gaussian noise: $\varepsilon \sim N(0, \sigma^2)$. A well-known disadvantage with Gaussian noise model is that it is not robust. If the training samples are contaminated by outliers, the accuracy of RVM model will be significantly compromised (Faul & Tipping, 2001). In this paper, a novel robust relevance vector machine (RRVM) is contrived, which assumes that each training sample has its individual coefficient of noise variance. During the model training procedure, the coefficients corresponding to outliers will decrease drastically to detect and eliminate outliers. We utilize the proposed RRVM as an identifier to predict the endpoint carbon content and temperature of molten steel. In BOF steelmaking process, measured data are often interfused with outlying observations, while RRVM can reduce the impact of outliers and has good generalization ability (These will be demonstrated by simulations). Therefore, it is suitable to construct the endpoint prediction model.

On the other hand, the amounts of oxygen and coolant required in the second blow, which are considered as control variables, are critical to achieve the expected endpoint. Based on the control experience of operators and production data of a steel plant, adaptive-network-based fuzzy inference system (ANFIS) is adopted to calculate the values of these control variables. ANFIS can acquire knowledge from a set of input-output data, and has competitive calculation accuracy (Jang, 1993). The proposed dynamic control model is implemented as follows. At first, ANFIS is utilized to calculate the amounts of oxygen and coolant based on metallurgical standards and parameters measured by sublance. Then the calculation results and measured data are used as input variables of RRVM model to predict the endpoint carbon content and temperature. If predicted values are in the expected range, the control variables determined by ANFIS will be accepted. Otherwise, the calculated control variables should be adjusted by operators in order to achieve the optimal values. Combining ANFIS and RRVM, a dynamic control model of BOF steelmaking process is constructed. In order to acquire the expected control effect, the premise is that RRVM model must be well-trained as an identifier to approximate the relationship between input and output, and accurately predict the endpoint carbon content as well as temperature. In the latter part of this paper, simulations will demonstrate that RRVM has good approximation ability and robustness.

The remainder of this paper is organized as follows: In Section 2, the production process of BOF steelmaking is briefly described. Section 3 presents the structure of dynamic control model for the second blow period. Section 4 introduces the methods ANFIS and RRVM utilized in this paper. Some simulations on benchmark data and industrial data are given in Section 5. In Section 6, the conclusions are drawn.

2. Description of BOF steelmaking process

BOF comprises a vertical solid-bottom furnace with a vertical water-cooled oxygen lance entering the furnace from above. The furnace is tilting for charging and tapping. Above the vessel, there are a hood and a duct for exhausted gas. The general view of BOF is shown in Fig. 1(Han & Huang, 2008). The molten steel capacity of a furnace generally ranges from 150 to 180 tons and the whole production process is as follows:

Step 1: Approximately 20–30 tons of scrap and 120–130 tons of molten hot metal are charged into the furnace. The hot metal has been preprocessed for desulfuration.

Step 2: Oxygen is blown into the furnace through the lance at a speed of 500 cubic meters per minute. Meanwhile, burnt lime, dolomite and other auxiliary materials are added. On the