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Soft-sensing method for optimizing combustion efficiency of reheating furnaces

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ABSTRACT

Rolling mill reheating furnaces are widely used in large-scale iron and steel plants, the efficient operation of which has been hampered by the complexity of the combustion mechanism. In this paper, a soft-sensing method is developed for modeling and predicting combustion efficiency since it cannot be measured directly. Statistical methods are utilized to ascertain the significance of the proposed derived variables for the combustion efficiency modeling. By employing the nonnegative garrote variable selection procedure, an adaptive scheme for combustion efficiency modeling and adjustment is proposed and virtually implemented on a rolling mill reheating furnace. The results show that significant energy saving can be achieved when the furnace is operated with the proposed model-based optimization strategy.

1. Introduction

The reheating furnace for a rolling mill is the most energy consumption equipment in a large-scale iron and steel plant, thus it is of great significance to improve the combustion efficiency and reduce gas consumption [1,2]. Since combustion efficiency cannot be measured directly, the adjustment of oxygen content in the exhaust gas is often used to indirectly control the efficiency. Another method is to estimate combustion efficiency based on oxygen content in the exhaust gas and then implement control actions [3]. However, the performance of these methods depends on the precision and stability of oxygen analyzers, which are susceptible to corrosion and wear of high-temperature gases and difficult to maintain in full operational status for a long period of time.

When quality variables cannot be easily obtained, a soft sensor model that can predict these quality characteristics (as response variables) using readily available sensor variables (as candidate predictors) will be most desirable. A variety of soft sensor methods and applications have been studied in different fields [4–7].

For a reheating furnace, a number of soft sensors have been investigated. The feature of continuous prediction of temperature and composition of the combustion atmosphere has the potential of acting as a soft sensor, thereby leading to a reduced number of temperature measurements and sampling for chemical analysis [8]. The secure, economic, and stable control of the combustion process is realized by the cooperation work of a cascade fuzzy control system for furnace temperature, a ratio control system for air flow with a soft-sensing model, plus a fault diagnosis model [9]. A data-driven soft sensor modeling technique for furnace temperature of the Opposition Multi-Burner (OMB) gasifier is proposed and the selection of secondary variables and model structure of a back propagation (BP) neural network is studied, which indicates that the furnace temperature predictive model integrating the principal component analysis (PCA) and the BP neural network has a promising performance with good predictive precision [10]. A soft sensor modeling method is proposed to predict the billet temperature of the reheating furnace based on a relevance vector machine (RVM), which has a higher prediction accuracy and a certain practical significance to the on-site production of a reheating furnace [11]. The least square support vector machine (LSSVM) inductance

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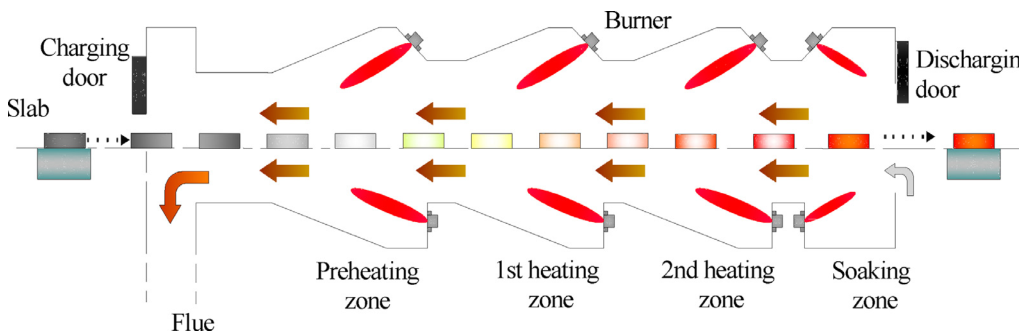

Fig. 1. The schematic of the heating process in the reheating furnace.

model optimized by the particle swarm optimization method with a compression factor (PSO-CF) algorithm is presented for the difficulty of time prediction, which can improve PSO convergence accuracy and effectively avoid falling into a local optimum [12]. However, the soft sensor developed for combustion efficiency was not investigated in these research efforts, which is significant for energy conservation.

On the premise of the model prediction accuracy, the model-based control makes optimal operation feasible, which can then be successfully employed to operate a reheating furnace in an efficient way. The potential of the nonlinear model predictive control techniques is explored to improve the temperature control for the metal slabs in a hot mill reheating furnace, and particularly whether or not these control techniques can be exploited to reduce energy consumption [13]. Steinboeck et al. developed a mathematical model of the reheating process of steel slabs in industrial fuel-fired furnaces in 2010. They exploited a dynamic optimization method for temperature control of the steel slabs in a continuous reheating furnace and a temperature control method for reheating steel slabs in an industrial furnace in 2011. They also designed a nonlinear model predictive controller for a reheating furnace for steel slabs in 2013 [2,14,15].

Obviously, the research on the numerical model for the heating performance of reheating furnace can be done based on basic combustion theory and heat transmission characteristics. Many scholars devote themselves to the simulations of the heat flow phenomenon in the reheating furnace. Zhang et al. attempted to apply a computational fluid dynamic (CFD) simulation to predict the combustion performance for a reheating furnace by simplifying the furnace to a cuboid and assuming that the slab possesses infinite length and enters the reheating furnace at a fixed speed [16]. The CFD method has been applied to the study of reaction turbulence, radiation heat transmission and the calculation for the steady state heat transmission rate of the slab under the given temperature [17]. In the works of references [16–20], the authors used the given temperature data of slabs to compute the steady flow and temperature field. However, owing to the changing operating conditions, the actual implementation of these numerical model methods still bristle with difficulties, although the methods mentioned above are feasible for the prediction. Thus, for an online application, it is necessary to adopt a real time, data-driven model to resolve the time varying characteristics.

Proper variable selection is an important step in model building for a large-scale combustion system. A well-trimmed variable dimension ensures the acquired model is transparent, comprehensible, and robust. Some studies reported that the combustion model built by a selected subset of input variables provide more accurate predictions of combustion efficiency than the entire set of variables [21–23]. Recently, shrinkage methods, which conduct variable selection by shrinking or setting some coefficients of a “greedy” model to zero, have received significant attention. A popular form of these methods is the non-negative garrote (NNG) [23,24].

Table 1
Variables and descriptions in the soaking zone.

Variable	Description	Unit
$A_{S\text{-}u}$	Air flow in the ‘up’ area	Nm^3/h
$A_{S\text{-}d}$	Air flow in the ‘down’ area	Nm^3/h
$G_{S\text{-}u}$	Gas flow in the ‘up’ area	Nm^3/h
$G_{S\text{-}d}$	Gas flow in the ‘down’ area	Nm^3/h
$T_{S\text{-}ul}$	Temperature in the left part of the ‘up’ area	°C
$T_{S\text{-}uc}$	Temperature in the center part of the ‘up’ area	°C
$T_{S\text{-}ur}$	Temperature in the right part of the ‘up’ area	°C
$T_{S\text{-}dl}$	Temperature in the left part of the ‘down’ area	°C
$T_{S\text{-}dc}$	Temperature in the center part of the ‘down’ area	°C
$T_{S\text{-}dr}$	Temperature in the right part of the ‘down’ area	°C

Against this background, this paper aims to propose a combustion efficiency index for the reheating furnace and investigate for room in improvement regarding energy conservation. The primary contribution is a practical combustion efficiency index, the incorporation of the derived variables and soft-sensing method for the optimization of combustion efficiency of reheating furnaces. The derived variables are found more physically meaningful than the plain variables when constructing the model of combustion efficiency. By employing a NNG variable selection procedure, an adaptive scheme for combustion efficiency modeling and adjustment is proposed and virtually implemented for a rolling reheating furnace. The results show that there is significant room for energy conservation.

The remainder of the paper is organized as follows. In the next section (Section 2), the reheating furnace and the data preprocessing is described. In Section 3, the statistics analysis for different variables and the formation of derived variables are presented. In Section 4, the framework of an adaptive model based on NNG variable selection is presented and two models developed for the temperature and temperature–gas (T/G) ratio are compared according to the model prediction precision. A model-based optimization scheme is provided and applied to the combustion efficiency improvement for an actual case of a reheating furnace presented in Section 5. Several remarks and a summary conclude the last section (Section 6).

2. Plant description and data preprocessing

The schematic of the heating process in the rolling mill reheating furnace is shown in Fig. 1. There are four zones in the reheating furnace, including the preheating zone (P), the first heating zone (1), the second heating zone (2) and the soaking zone (S). The steel slab moves through the four zones in turn and is heated to the demanded state using a specific temperature increase curve. As is shown in Table 1, the soaking zone has two areas that are defined as up and down, and both of the areas possess the same five variables including two manipulated variables: the air flow (A) and the gas flow (G), and three temperatures in left, center and right