Expert Systems with Applications 37 (2010) 1075–1085

Contents lists available at ScienceDirect

Expert Systems with Applications

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

Process control strategies for a steel making furnace using ANN with bayesian regularization and ANFIS

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ARTICLE INFO

Keywords:
Electric Arc Furnace
Artificial Neural Networks
Adaptive Neuro Fuzzy Inference System
Control action
Full sampling
Limited sampling

ABSTRACT

This paper illustrates the control strategies of an Electric Arc Furnace. It involves the prediction of the control action which aids in reduction of carbon, manganese and other impurities from the in-process molten steel. Predictive models using Artificial Neural Networks (ANN) with Bayesian Regularization and Adaptive Neuro Fuzzy Inference System (ANFIS) were developed. The control action is the amount of oxygen to be lanced at different sampling instants. The predictive models were constructed based on the values of the individual chemical constituents of the collected molten samples. Two control strategies were devised: one with full sampling and the other with limited or reduced sampling. For the full sampling case two predictive models were devised separately with ANN with Bayesian Regularization and ANFIS. For the limited sampling strategy a combination of ANN with Bayesian Regularization and ANFIS were employed. For full sampling strategy, ANFIS model performs better than ANN. The application of the limited sampling strategy gave satisfactory Mean Percentage Error (MPE) thereby justifying its practical implementation. The main advantage of reduced or limited sampling is that it helps in the reduction of cost, time and manpower associated the sample collection and its subsequent analysis.

1. Introduction

Proper control of a manufacturing facility is essential for the production of consistent good quality end product. A good control strategy also ensures less wastage, less breakdowns and also do guarantee enhanced safety for the personals involved. The literature on the development and use of control strategies is vast with areas ranging from mathematical model based control techniques (Billings, Boland, & Nicholson, 1979; Ho & Chandratilleke, 1991) to that of intelligent control techniques involving techniques such as fuzzy logic (FL) (Kocaarslan, Cam, & Tiryaki, 2006; Lah, Zupancic, Peternelz, & Krainer, 2006; Shaocheng, Bin, & Yongfu, 2005), Artificial Neural Networks (ANN) (Horng, 2008; Liu, Lian, & Zhao, 2007; Zarate & Bittencout, 2008) and neuro-fuzzy systems, an amalgamation of FL and ANN (Krause, Altrock, Limper, & Schafers, 1994; Rao & Gupta, 1994; Tian & Collins, 2005). The choice of a particular control strategy depends on the process to be controlled, amount of information available pertaining to the process being controlled and also the practical and the economic feasibility of a particular control strategy. The implementation of mathematical model based control techniques requires the complete understanding of the process. A clear understanding of the inputs and outputs behavior and their interactions is imperative and as such one should be able to map the functional relationship between them. However, for most of the processes, a distinct mathematical functional relationship between the inputs and the outputs is hard to establish due to the complexity of the concerned process and incomplete and imprecise information pertaining to the process. In contrast to this, control strategies based on Artificial Intelligence (AI) techniques namely, FL and ANN does not require the in-depth understanding of the microscopic behavior of the concerned process. Hence, AI techniques are the preferred choice for modeling of complex and ill-understood processes. The mathematical details of AI based tools and techniques are given in Rajasekharan and Pai (2003), Hagan, Demuth, and Beale (1996) and Hagan and Menhaj (1994).

Due to the ease with which they can be developed and applied in real life situation, AI based control strategies have found wide range of applications in from aeronautics (Savran, Tasaltin, & Becerikli, 2006) to roller kiln involved in the manufacturing of ceramic tiles (Dinh & Afzulpurkar, 2007). ANN with linear filters and trained with back propagation (BP) algorithm was used for the designing of a controller for an unmanned research aircraft (Suresh & Kannan, 2008). ANN based control strategies have found widespread application in the area of electrical engineering. It has been used for modeling the behavior of an AC servo motor (Horng, 2008). ANN has also been used for development of a controller for controlling the speed of a synchronous motor drive (Elmas, Ustun,

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0957-4174/$ - see front matter © 2009 Published by Elsevier Ltd.
doi:10.1016/j.eswa.2009.06.056

& Sayan, 2008) and induction motor drive (Ren & Chen, 2006). Apart from that ANN was employed for temperature control of a high voltage DC resistive drive (Yilmaz, Dincer, Eksin, & Kalenderli, 2007). Robotics is another field where ANN based control scheme has been widely used (Chatchanayuenyong & Parnichkun, 2006; Huang, Tan, & Lee, 2008; Sato & Ishii, 2006; Thanh & Ahn, 2006). Other usage of ANN based control strategy include prediction of the parameters of gas metal arc welding process (Ates, 2007), development of control system for gun fire (Lee, 2007), development of a controller for an air conditioner (Liu et al., 2007), control of batch reactors in a chemical industry (Mujtaba, Aziz, & Hussain, 2006), and controlling air fuel ratio in a spark ignition engine (Wang, Yu, Gomm, Page, & Douglas, 2006). Control strategies based on the combination of neural network and fuzzy logic or neuro-fuzzy approaches were also cited in the literature (Rao & Gupta, 1994). Application of neuro-fuzzy controller ranges from airbag controller design for automobiles (Mon, 2007) to design of controllers for power plants (Alturki & Abdennour, 1999). Apart from these, neuro-fuzzy controllers have found application in refuse incineration plant, flexible manipulator system and in the field of robotics (Aguilar, Melin, & Castillo, 2003; Naadimuthu, Liu, & Lee, 2007; Rao & Gupta, 1994; Tian & Collins, 2005).

Table 1 lists some of the control strategies adopted in Electric Arc Furnace (EAF) and other steel making furnaces. As evident, majority of those are based on mathematical model developed from first principles. A couple of them dealt with the control strategy of electrode positioning controller (Billings et al., 1979; Nicholson & Roebuck, 1972). Control of EAF off-gas process has also been carried out (Bekker, Craig, & Pistorius, 2000; Kirschen, Velikorodov, & Pfeifer, 2006). Other applications include estimation of tap temperature (Fernandez, Cabal, Montequin, & Balsera, 2008) and designing of set-point controllers for an EAF cooling system (Shinohara & Goodall, 2004). Estimation of the chemical composition of the final steel alloy (Ekmekci, Yetisken, & Camdali, 2007) with the aid of mass balance modeling and estimation of the various output variables of a Basic Oxygen Furnace (BOF) (Kubat, Taskin, Artir, & Yilmaz, 2004) were also carried out.

In this study, a control strategy for the EAF has been attempted with the aid of AI tools such as FL and ANN. ANN model which is an emulation of the biological neuron system and Adaptive Neuro Fuzzy Inference System (ANFIS) (Melin & Castillo, 2005; Mon, 2007; Shing & Jang, 1993), a fusion between ANN and FL were employed for prediction of the control action of the EAF. Following the developed AI tools, several models have been developed for predicting amount of oxygen to be lanced into the EAF. The methodology for the developments is presented in Section 2. Two types of models are developed using full sampling and limited sampling scheme. The application of these models is described in Section 3. The possible implications of the study to the industry have been discussed in Section 4 followed by the conclusions in Section 5.

2. Methodology

2.1. Research setting

The work carried out consists of the prediction of control action in the EAF of a Steel Making Shop (SMS) for an integrated steel plant. An EAF is used for refining the molten metal which is subsequently converted into steel in the form of billets, blooms or slabs Fig. 1 depicts the process flow of the concerned SMS. The EAF under consideration is of 40 ton capacity and uses molten metal, Direct Reduced Iron (DRI) and scrap as the main raw material or charge composition. Along with molten metal, DRI and scrap are fed into the EAF. The entire melting cum refining operation in the EAF on an average takes about 60 min. After that the entire charge mixture is transferred to the Ladle Refining Furnace (LRF) where further refining and alloying additions in case of alloy steels take place. At the culmination of the LRF operation, the molten mixture is transferred to the Continuous Casting Machine (CCM) where it gets converted into billets. The modern steel making process is given in Tupkary and Tupkary (1998).

During the operation in the EAF, molten metal samples are extracted whose chemical composition is checked with the aid of a spectroscope and accordingly the amount of oxygen is being lanced at each sampling instant. The prediction of the accurate amount of oxygen to be lanced at each sampling instant is a key concern as any excess amount of oxygen lanced will reduce the percentage of the individual chemical constituents to a level less than that sought by the specification of the concerned grade of steel being produced. Similarly, a lesser amount of oxygen lanced at each sampling instant will cause an increase in the EAF operational time leading to extra cost and time overrun. Thus to assure the quality of the steel produced, characterized by the percentage content of the individual chemical constituent present in the steel, requires the prediction of the control action, in this case amount of oxygen to be lanced at each sampling instant. The chemical constituents of the molten metal samples are shown in Table 2.

Table 2 provides five chemical constituents which are being measured at the EAF. Out of the five chemical constituents, only C%, and Mn% values are monitored in the EAF. The other important chemical constituent, P% was not measured. The process of silicon removal (disiliconization) takes place before the molten metal charge is being fed into the EAF. Only a trace amount of silicon remains in the molten charge in the EAF and that too largely remains unchanged. Similarly, desulpharization or the removal of sulphur predominantly takes place at the LRF and its value too remains unchanged in the EAF. This implies that the control action, the amount of oxygen to be lanced at each sampling instant at the EAF has minimal or no effect in the reduction of Si% and S% at EAF, respectively, and thus it is deemed prudent to exclude those

Table 1
List of control strategies in EAF and other steel making furnaces.

Serial No.	Techniques employed	Application	Contributors
1	Mathematical model	• Electrode positioning controller • Impedance and current controller • Temperature weighting adaptive controller	Billings et al. (1979)
2	Lyapunov-based robust control approach	Set-point controllers for an EAF cooling system	Shinohara and Goodall (2004)
3	First principles of thermodynamics and reaction kinetics, and well established empirical relationships	Control of an EAF off-gas process	Bekker et al. (2000)
4	Fuzzy neural networks	Estimation of EAF tap temperature	Fernandez et al. (2008)
5	Mass balance modeling	Determination of the chemical composition of the final steel alloy output	Ekmekci et al. (2007)
6	Mathematical model based on mass and energy flow rates	Computation of parameters of off-gas enthalpy and heat transfer in EAF dedusting system	Kirschen et al. (2006)
7	Reduced order linear model	Control of electrode positioning controllers of EAF	Nicholson and Roebuck (1972)
8	Fuzzy logic	Estimation of output variables of a BOF	Kubat et al. (2004)