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INTELLIGENT CONTROL OF THE ELECTRIC – ARC STEELMAKING PROCESS USING ARTIFICIAL NEURAL NETWORKS

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Abstract

Development of computational intelligence allows to combine some conventional approaches with artificial intelligence modules, like Artificial Neural Networks (ANNs). The combination leads to so-called Intelligent Systems which potential is practically unlimited. ANNs based models for electrodes positioning, prediction of the electric energy consumption and end-of-heat in electric arc furnaces were implemented by number of authors and they have obtained applicable practical results. The present paper describes methods of intelligent control of the EAF steelmaking process, particularly neural control. The elaborated neural network models for smelting control in the EAF are discussed. The goal is to provide a compact review of neural modeling and control methods and their capabilities for the EAF steelmaking process.

Key words: Electric Arc Furnace, steelmaking, neural networks, intelligent control

1. INTRODUCTION

Electric arc furnaces (EAFs) are widely used in steelmaking and in smelting of nonferrous metals. The EAF is the central process of the so-called minimills, which produce steel mainly from scrap. Typical EAFs operate at power levels from 10MVA to 130MVA, which is directly related to production throughput. It is very important to control the EAF at the highest possible power with a low variance. For efficient power control, adaptive, dynamic models of EAFs are required (Baumert et al., 2002).

The production of steel by EAFs has steadily expanded during the past few decades as well as furnace capacity and power level. The basic operating principle of this furnace, whether of the AC or the DC type, is that an electric arc is struck from one or more electrodes to a metallic charge, usually steel scrap. With this type of charge, the operation of the furnace is unstable, especially during the initial meltdown period, that can result in significant electrical disturbances. Due to stochastic behavior of the EAF load and severity of the disturbances, there has been an ongoing need for accurate and reliable characteristic predictors. The prediction problem is further complicated by the facts that the EAF characteristics are essentially nonlinear, and the fluctuations of the voltage amplitude, are not only random, but depend on the wearing of the furnace and its mode of operation. The known conventional control and optimization methods are not able to solve this task. The amount of electrical energy transferred to the steel melt should be optimally maintained during the entire melting and refining process, with the optimal distribution of radiated heat within the furnace.

Control of the EAF process is carried out by determination of electrical working points (set points). It takes place through step-wise adjustment of the

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output voltage of the furnace transformer and through an adjustment of the control value. The determination of the set points are based on experience with modeling of the EAF processes. This method of determining the set points is never completely accurate and has got a static character. A number of nonlinear influences and the temporary change in the process must be taken into account. Due to the variability and complexity of the EAF process, accurate optimization must be based on actual operating data, which are often noisy, and requiring significant preprocessing. The steelmaking process is continually changing, as the furnace wears, procedures change, and raw materials change. This requires such a data-based optimization system which is adaptive. Neural networks can take over both tasks, modeling and adaptation at the same time and that is why neural networks are used for solving this kind of control problem.

This paper will provide a literary review of the publications on the problem of ANNs application to the control of the steelmaking electric-arc furnaces. We also will discus a worldwide solution IAF™ and consider suiting the EAF process to a neural network application.

2. NEURAL CONTROL OF THE ELECTRIC ARC FURNACE PROCESS

The literature on the modeling and control of EAF processes is very rich due to both the commercial value of obtained practical results and the variety of engineering applications of electric arc energy (Baumert et al., 2002; Bekker, 2000; Boulet et al., 2003; Jang et al., 2000; (Wieczorek and Pyka, 2005). Early papers discuss simple models involving only some chosen groups of phenomena connected with EAF, e.g. electric equivalent circuits, heat and mass transfer, chemical reactions. Some papers discuss the same methods but for the purposes of dynamic control (Boulet et al., 2003).

But classical modeling based on differential or integral equations, equilibrium chemistry, and material and energy balances does not lead to required results. Precise modeling of three, asymmetrical arcs with process-dependent, nonlinear characteristics (such as highly variable reactances) is not possible, because number of nonlinear influences and temporary changes in the process must be taken into account. Therefore has grown interest in artificial intelligence methods.

W.E. Staib (1992) first applied the methods, developing so-called “Intelligent Arc Furnace (IAF™)”. Staib assumed that control over arc electric electrodes is essential for proper furnace operation, therefore he researched the application of Artificial Neural Networks (ANN) to closed-loop control of an electrode positioning subsystem (Staib, 1993). Results of applications of the IAF™ systems in American steelworks were very positive (Bliss et al., 1995), therefore European companies intensified research on AI methods for the EAF process (Simens, 2003). There were published many papers on optimization of EAFs with use of neural networks, e.g. Sesselmann et al. (1995). Those researchers developed a system that constantly optimizes the set point for the electrode control so that the three-phase EAF can operate with the maximum constant energy consumption. The developed optimization method was based on an adaptive neural network. The system provided an adaptive control which learned the characteristics of the furnace as it operated, allowing it to optimize the power and provide for maximum arc power by maintaining a stable long arc. Pappe et.al. described a system in which an analytical model was combined with a neural network to form a hybrid model. Implementation of the system at Krupp’s EAF plant reduced energy and raw materials requirements (Pappe et al., 1995).

An intelligent optimal control system used in the steelmaking process of the EAF is presented by Gao et al (1997). A hybrid real-time intelligent control strategy was set up to realize the close-loop control of the arc furnace (Gao et al., 1997). First the systems based on expert knowledge were proposed in China by Shanghai University, in 1992 as well as an intelligent control of electrode and adaptive predictive control were presented by Beijing University, in 1994. All the solutions were invented for AC EAF. In the Gao’s paper there is presented a set-point intelligent control system for UHP DC EAF. Electric energy had been reduced by 10%, electrode consumption by 28%, tap-to-tap time reduced by 10 min.

The neural network supported system for optimal control of energy input into the EAF has been described by (Gerling et al., 1997). The system developed by Siemens AG is based on neural electrode and energy control. It has been installed in Stahlwerk Bous GmbH (Germany), in Benteler AG, Stahlwerk Lingen (Germany), Krupp Nirosta Bochum (Germany). The neural network based control system, called SIMELT®NEC (Simens, 2003) brings reduction of costs and increasing of production. The key of the solution is a complete electrical three-phase model of the furnace supported by neural networks. The existing electrode control system is extended by a neural optimization control system, that provides the dynamic corrections for the set point of the electrode control system. When the optimization system is activated, instead of the set points being taken from a table as a function of the given transformer tap, they are transmitted from the model in real time. Siemens solution utilizes a hybrid model in the optimization concept. This intelligent approach has the advantage of combining a physical model of the three-phase AC electric-arc furnace with a neural network capable of learning.

ANNs based models for prediction of the electric energy consumption and end-of-heat in electric arc furnaces were implemented by Baumert et al., 2002. Besides the approach using a time-series model, a new dynamic process model based on series of interconnected ANNs has been developed. A new method, called by authors, "error-feed-through" technique has been used. Improving process control and gains in energy, time and productivity have been obtained for the arc furnace in ProfilARBED-Esch-Belval.

Sadeghian and Lavers (2000) propose and apply feedforward neuro-fuzzy multi-step predictors. Based on the principles of neural networks and fuzzy logic inference mechanism, the proposed feedforward predictor implements the fuzzy rule-base using data clustering techniques, and adjusts the parameters of the rules using neural network adaptive capabilities. The network learns to predict the *v-i* characteristics of the particular EAF, whose measurements have been used to build the neuro-fuzzy network. Attempts are also made to show how accurate and fast EAF prediction can be accomplished using adaptive fuzzy logic techniques. The underlying idea is that by identifying the proper input/output structure, and using a suitable learning algorithm, a well-structured feedforward neuro-fuzzy system has the capability of predicting the dynamics of the electric arc furnace. The implementation of the feedforward neuro-fuzzy network together with its training and validation using the actual recorded data are highlighted (Sadeghian and Lavers, 2000).

Bekker et.al. (2000) describe predictive control of an electric arc furnace off-gas process. They state that there are only limited references to dynamic EAF models in the literature, and many such models tend to be proprietary. For example Petersohn et al. (1992) derived a dynamic EAF model based on mass and energy balances. Since no suitable plant model was available in the literature, an extensive modelling effort was conducted (Bekker, 2000). This model, which consists of 17 non-linear ordinary differential equations, was approximated by a linear time invariant state space system for controller design purposes. Projects on EAF control have focused mainly on electrode control. There is discussed the impedance-based electrode control of submerged arc furnaces and how neural networks can be used to control the electrode voltages and currents of a single-phase arc furnace.

Jang et.al. (2000) discuss a chaotic EAF model to represent the low and high frequency variations of the arc current respectively and a chain-shaped chaotic EAF model to characterize the current variation. The concept of chaotic parameters, such as chaotic resistance, inductance or admittance has been also proposed for the characterization of arc furnace operation and the highly nonlinear physical processes.

Basing on the presented state of the art we conclude, that intelligent control using ANNs seems to be an ideal solution for complex and non-linearly related EAF process. The EAF requires a controlling, electrical model of the furnace that is continuously adapted to the changing conditions. Adaptive control is the only way for this class of nonlinear, dynamic systems, for which determination of the uncertainty in the dynamics is either unknown or impossible.

3. ARC FURNACE ELECTRODES CONTROL

Control of electric arc furnace electrodes is crucial for effective furnace operation. Existing electrode regulators are based on an impedance-model and enable many facets of furnace to be controlled. Some rule-based systems have been developed to establish optimum set points during a heat. The set points are given to the existing regulator of the furnace, tracing its operating program. Effective set-point control has enabled plants to achieve cost savings.

Application of Artificial Neural Networks to closed-loop control of an electric arc furnace could overcome all the limitations of traditional regulators. But practical implementation of neural arc furnace regulation system was possible after solving metering and data acquisition problems. For proper learning of a neural system, large amounts of accurate data are necessary. In the analyzed case the following furnace-state variables were used as inputs for neural networks (for all variables all 3 phases were sampled) (Staib, 1992; Staib, 1993):

- Primary phase-to-phase voltage.
- Primary phase current.
- Secondary phase-to-phase current.
- Secondary phase voltage.
- Secondary phase current
- Existing regulator output signals.
- Operating sounds (by microphone)
- Instantaneous primary phase power.
- Total (3 phase) instantaneous primary power
- Instantaneous phase voltage.
- Average primary apparent power over a specified sampling period (1 to 60 cycles).
- Average power factor.
- Phase shift (voltage to current).
- Instantaneous secondary power.
- Total (3 phase) instantaneous secondary power
- Instantaneous phase voltage.
- Average secondary apparent power over a specified sampling period (1 to 60 cycles).
- Distortion percentage from a true sine wave.
- Persson factor of arc stability
- Hydraulic system pressure for each phase.

The data collection system was connected to the electric arc furnace and the gathered data were analyzed off-line.

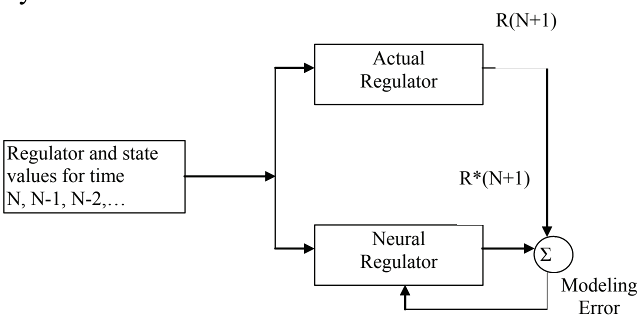

Fig. 1. The Neural Regulator Emulator, according to Staib (1992)

The Intelligent Arc Furnace (IAF™) (Bliss et al., 1995) uses three neural models, these are: the Regulator Emulator, the Furnace Emulator and the Neural Furnace Controller. The Regulator Emulator (Fig. 1) has been trained to match the responses of a traditional electric arc furnace controller. It was emulating the existing furnace regulator. This was to ensure that the neural network would initially output reasonable signals. The ANN, obtaining as inputs a time history of the real regulator outputs and corresponding furnace state conditions (primary phase-to-phase voltage, primary phase current, secondary phase-to-phase current, secondary phase voltage, secondary phase current, hydraulic system pressure for each phase), has learnt to predict real regulator outputs for the next time period (for this kind of regulator the outputs could be "lower" or "upper" the electrode). A multilayer feedforward perceptron, trained with a supervised learning method, with weight correction by the delta-bar-delta back-propagation algorithm, has been chosen as the model of the Regulator Emulator (the same algorithm was used for training the Furnace Emulator and Neural Controller). The architecture of the network was three-layered: input, hidden and the output layer with three outputs, one for each electrode. After processing about 1 min. of real-time data this model was 95% correct in emulating the regulator. The furnace metering was handled by a 16-channel analogue input subsystem capable of sampling at 400 000 samples a second at 12-bit accuracy. For instance, the neural network utilized 5000 samples per second to predict and correct furnace flicker problem.

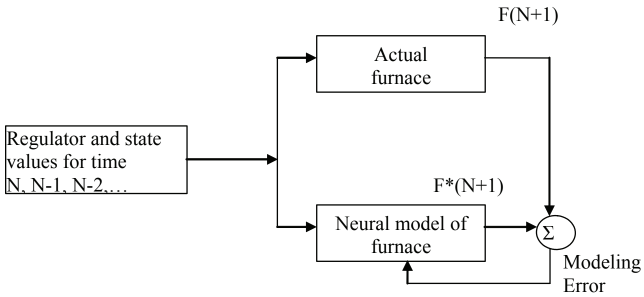

Fig. 2. The Neural Furnace Emulator, according to Staib (1992)

Next, the furnace-emulating ANN was built (Fig. 2). The Furnace Emulator is trained to predict furnace operation one-tenth to three-tenth of a second ahead of it. It makes possible to identify unwanted trends. Inputs of the network were: a time history of regulator outputs and corresponding furnace-state conditions (there was a group of furnace control set points: arc current, power factor, flicker percentage, arc stability factor) and regulator outputs for N+1 moment of time. The network was trained to predict furnace-state conditions for the moment N+1.

Finally, the furnace and regulator emulators were combined to form a Neural Furnace Controller (Fig. 3). The network was learned how to regulate the electrodes to achieve a set of furnace control set points: arc current, power factor, flicker percentage, arc stability factor.

Used ANNs are able to be continuously adapted to operating conditions. Both, the Furnace Emulator weights and the Neural Furnace Controller weights are updated every 15s., according to the set point deviation and the furnace state prediction error. Such an automatic compensation can be made for changes in furnace impedances. The methods permits furnace prediction to improve continually. Because of changes in scrap charge, voltage, electrode length and other system parameters, some adoption of ANNs weights is absolutely significant, but last years have been developed new methods for updating of ANNs without necessity their re-training.

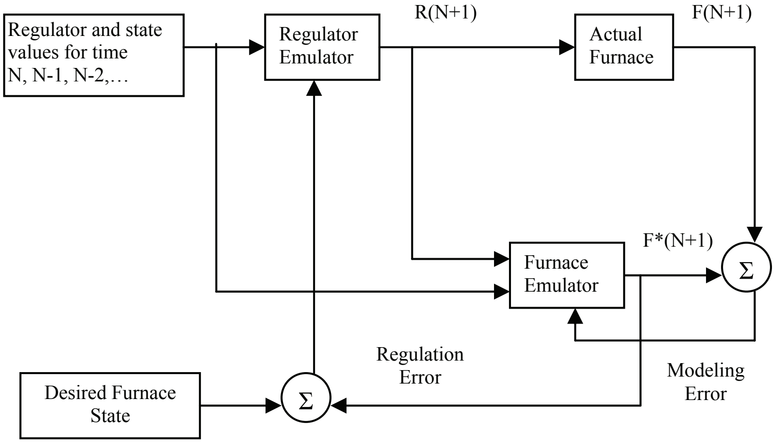

Fig. 3. The Neural Furnace Controller, according to Staib, 1992)

Despite many advantages of ANNs we cannot assume that they will always produce a reasonable output, when a new situation arises. Therefore the IAF™ was designed with an expert system which monitors furnace conditions and only allows ANN control during "normal" operation. When furnace operation is not normal, a rule-based regulator is invoked. The IAF™ consists of the neural networks and an expert system which is a set points generation system.

With the Intelligent Arc Furnace™ (IAF®) controller, Neural Applications Corporation has already applied neural-network technology to optimize the electrical input for an EAF at more than 40 installations worldwide (Bliss et al., 1995). The IAF uses a patented neural-network-based electric power regulator to continually adapt to changing operating conditions in order to optimize electric power input. It provides supervisory closed-loop control and regulation of the arc furnace melting and refining process.

By applying artificial intelligence technologies such as Artificial Neural Networks to electrodes control for the EAF, authors (Neural Application Corp.) has achieved significant improvements in electrode consumption, electrical energy efficiency, and productivity.

4. CONCLUSIONS

Control and optimization of complex modern industrial processes, as EAF steelmaking process, often exceeds the capabilities of conventional control technologies. Intelligent systems are the most important solution in modern control and optimization technologies (Wieczorek and Pyka, 2004). Nonlinear transformations, parallel processing and adaptive capabilities make the ANNs the most promising for control applications. With a well designed topology and learning algorithms the ANNs are capable of approximating complicated multi-input to multi-output mappings.

Analyzing IAF™, the most worldwide spread solution for intelligent control of electric-arc steelmaking process we can find many advantages, pointed out by the authors, like: three-phase aware control, decreasing of electrical flicker, better operation with too short electrode, and cost benefits. The advantages and benefits encourage development of the technology. But in the papers there is no information regarding the architecture of the ANNs, activation functions, sizes of training and validation sets, parameters of learning, methods of set points generation, updating of weights and other important data for evaluating of the solution, obviously due to commercial value of the obtained results. It makes us find all the significant information by complex research.

Practical application of neural networks for control and modeling of EAF processes is determined by evaluation of costs and benefits. Making decision about control system we have to take into considerations the facts, that furnace equipment, metallurgical `procedures, scrap and other charge materials characteristics as well as personnel change over time. Every heat is different from another. Therefore the control system should be very flexible and adaptive. Effective application of an intelligent system demands understanding of the steelmaker's needs, analysis of the noise level present in the data transferred from the EAF furnace, and implementation and evaluation of several process models and optimization approaches. That's why, the intelligent systems are often difficult to apply. However strengths of ANNs like nonlinearity, online adaptability, generality and distributed parallel processing ability make the technology most developmental.

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INTELIGENTNE STEROWANIE PROCESEM WYTWARZANIA STALI W PIECACH ŁUKOWYCH

Streszczenie

Rozwój metod tzw. inteligencji obliczeniowej pozwała na łączenie tradycyjnego modelowania z modułami sztucznej inteligencji, jak np. Sztuczne Sieci Neuronowe (SSN). Prowadzi to do budowy tzw. Inteligentnych Systemów Informatycznych, których możliwości są praktycznie nieograniczone. Oparte na SSN modele pozycjonowania elektrod pieca, przewidywania zużycia energii elektrycznej i czasu końca wytopu w elektrycznych piecach łukowych, zostały wykorzystane przez wielu autorów w konkretnych, praktycznych zastosowaniach. W pracy opisano metody inteligentnego sterowania procesem wytwarzania stali w piecach łukowych, w szczególności metody neuronowe. Przedyskutowano neuronowy model sterowania roztapianiem wsadu w piecu. Celem pracy jest przeprowadzenie przeglądu metod modelowania i sterowania neuronowego i możliwości ich wykorzystania w badanym procesie stalowniczym.

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