

# IDENTIFICATION OF AN ELECTRIC ARC FURNACE MODEL

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Abstract: A nonlinear model of the electric arc furnace (EAF) as developed at the University of Pretoria (UP) is introduced. This work presents the first attempts at applying the model to a real EAF process. Input and output data as well as initial conditions from the plant were used to fit the model to the plant. It is concluded that the model is able to represent, with reasonable accuracy, the behaviour of important furnace variables such as bath temperature and carbon composition.

## 1. INTRODUCTION

The electric arc furnace (EAF) forms an integral part in the manufacture of steel. In the small steel mills, it is the preferred choice for providing molten metal for downstream processes such as casting; this is more so when scrap is used as the main raw material. Its versatility lies in its being amenable for use with various kinds of raw materials, from scrap to DRI (direct reduced iron) to molten metal. For carbon steels, in addition to melting, the furnace is used for primary refining of the molten metal. On the other hand, it is also a highly energy intensive process.

With increasing demands for higher profitability and stringent environmental regulations automation presents ample opportunities to achieve these often conflicting objectives. Poor automation of the EAF process can be attributed to the inferior instrumentation for measurement of important process variables. This is in turn due to the highly corrosive nature of the environment where most of the reliable measurement devices are costly and not reusable.

Accurate control of temperature, yield, pressure, gaseous discharges, and composition of alloys is important for successful operation of the furnace. Despite the benefits of operator experience, the current practice of relying on operator control fails to deliver consistency of process outputs, timely reaction to rapidly changing variables and maintaining outputs within tight margins. A good model will provide an accurate representation of process conditions; and coupled with an appropriate controller will allow for accurate control of the process according to specifications. The model can also be a partial substitute for physical measurement of variables that are too expensive or time consuming.

The focus of the current work is to fit an existing EAF model to input-output data from a real EAF process. The model was initially developed by Bekker *et al.* (1999) and later expanded by Oosthuizen *et al.* (2001) and then Rathaba *et al.* (2003). This modelling forms part of the ongoing project at UP for eventual control of the EAF process. Model parameters that are characteristic of the physics of the elements such as heat capacity and enthalpy of reaction are readily available from

thermo-chemical tables. On the other hand, variables such as melting rates, decarburization and bath temperature are dependent on process inputs and operating conditions which are different from one EAF to the next. These are governed by adjustable parameters whose values will be unique depending on prevailing process conditions. Input and output data along with initial conditions provide valuable process information that can be used to estimate these parameters. This forms the basis for the current work: to use process input-output data and initial conditions to estimate model parameters; this model must then be able to accurately predict process variables of interest.

A short outline of the paper is as follows: Section 2 gives a brief description of the process and modelling. Section 3 presents a brief introduction to parameter estimation. The resulting model and its performance are discussed in section 4. Some final remarks are given in the conclusion.

## 2. MODEL AND PROCESS DESCRIPTION

The EAF is the primary site for melting of scrap, slag formers and DRI. A tap begins with the charging of raw materials into the furnace, the charge is heated to a complete melt which is then refined to a desired composition and temperature; at the end of the tap the steel is poured into a ladle where it will undergo further treatment. In a hot heel practice, some hot metal is left from a previous tap; this provides a pool of hot metal that expedites melting by increasing the rate of heat transfer to the solid scrap. Most of the heat energy is derived from the arc, formed by a three phase electrical supply conducted by three graphite electrodes; these are lowered into the vicinity of the scrap where current flow among the electrodes and the scrap creates a high temperature plasma flow (Billings *et al.*, 1979). A supplementary energy source is the oxyfuel subsystem that plays two roles: to supply high efficiency heat energy by combustion of fuel in the vicinity of the scrap and, to inject oxygen into the bath for refining. Slag, a layer above the molten bath serves as a medium for removal of impurities from the bath. It also improves the energy efficiency of the furnace by preventing heat loss from the bath surface and by confining the high energy arc radiation near the bath. For a detailed process description the reader is referred to Bekker *et al.* (1999), Morales *et al.* (2001) and Taylor (1985). Figure 1 shows a schematic diagram of the furnace.

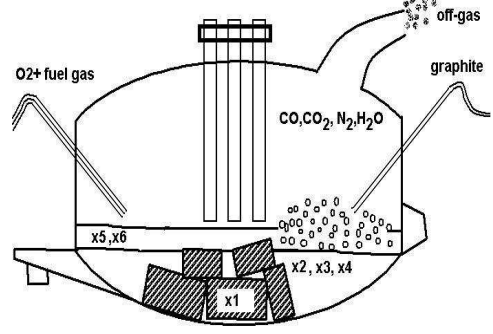


Fig. 1. Schematic of EAF process with important process variables. The oxyfuel lances inject both oxygen and fuel gas simultaneously while during refining, only a supersonic stream of oxygen is injected. A graphite lance is used to control the thickness of the slag by foaming.  $x_1$  and  $x_2$  are the solid and liquid steel;  $x_5$  and  $x_6$  the solid and liquid slag;  $x_3$  and  $x_4$  are the bath carbon and silicon.

In general, the furnace is modelled as

$$\begin{aligned}\dot{x} &= f(x, u, \theta, t) \\ y &= h(x, \theta) \\ x(0) &= x_0\end{aligned}\quad (1)$$

where the state vector  $x \in \mathbb{R}^{17}$ ; the input vector  $u \in \mathbb{R}^7$ ; the parameter vector  $\theta \in \mathbb{R}^5$ ; the carbon and temperature outputs  $y \in \mathbb{R}^2$ ; and the initial conditions  $x_0$ .

The model essentially represents the mass and energy balance of the furnace. In this work only the mass of bath carbon will be considered. The rate of change of carbon in the bath is given by

$$\dot{x}_3 = k_{dC}(X_C - X_C^{eq}), \quad (2)$$

where  $X_C$  is the mass fraction of carbon in the bath and  $X_C^{eq}$  is its equilibrium concentration in the bath. It is assumed that equilibrium is established across the slag-metal interface between the carbon in the bath and the FeO in the slag. From (2) the relationship is that the rate of change of carbon is a function of its current and equilibrium concentrations. It is important to note that  $X_C$  and  $X_C^{eq}$  are dependent on bath mass, silicon and carbon concentrations, slag mass, and  $\text{SiO}_2$  and FeO which are both dissolved in the slag; all change over time. Decarburization is proportional to the decarburization rate constant  $k_{dC}$ .

The rate of change of bath temperature is given by

$$\dot{x}_{12} = \left[ \frac{P_T + \eta_{ARC} d_{ARC} - k_{VT}(x_{12} - T_{air})}{\frac{x_2 C_p(Fe_L)}{M_{Fe}} + \frac{x_3 C_p(C)}{M_C} + \frac{x_4 C_p(Si)}{M_{Si}} + \frac{2x_6 + 2x_7 + 3x_8}{M_{slag}} C_p(Slag(L))} \right]. \quad (3)$$

The numerator sums all the energy sources and sinks (in [kW]);  $P_T$  is the net chemical energy input,  $d_{ARC}$  is the power input from the arc and  $k_{VT}$  controls the rate of heat loss from the furnace to its environment (at  $T = T_{air}$ ). The denominator sums the heat capacities of, respectively, molten steel ( $x_2$ ), bath carbon ( $x_3$ ) and silicon ( $x_4$ ), CaO ( $x_6$ ), FeO ( $x_7$ ) and SiO<sub>2</sub> ( $x_8$ ). Parameters of interest are  $\eta_{ARC}$ ,  $k_{VT}$  and  $\eta_{FeO}$ , the efficiency of bath oxidation. It contributes to chemical energy as  $p_2 = 2\eta_{FeO}\Delta H_{FeO}/M_{O_2}v_1$ , where  $\Delta H_{FeO}$  is the enthalpy of formation of FeO,  $v_1$  and  $M_{O_2}$  are the rate of injection and molar mass of oxygen. The temperature is also a function of the oxy-fuel energy input whose efficiency is controlled by  $\eta_{OXF}$  (Rathaba *et al.*, 2003).

### 3. PARAMETER ESTIMATION

For parameter estimation the popular penalty or cost function minimization procedure will be employed. Inputs and initial conditions measured from the process are applied to the model and the parameters are chosen such that the model output closely follows the measured plant output. That is, given the measured initial conditions, inputs and outputs ( $x_{0m}$ ,  $u_m$  and  $y_m$ ), choose the parameter  $\theta$  from the set  $D$  to minimize the error  $\varepsilon(t) = y_m(t) - y(t)$ , where  $y(t)$  is the model output. Following notation similar to that in Ljung (1999), the problem is then

$$\hat{\theta} = \arg \min_{\theta \in D} V_N(\theta) \quad (4)$$

where

$$\begin{aligned} V_N(\theta) &= \frac{1}{N} \sum_{n=1}^N l(\varepsilon(\theta)) \\ &= \frac{1}{N} \sum_{n=1}^N l(y_{m,n}(t) - y_n(t, \theta)), \end{aligned} \quad (5)$$

$l(\cdot)$  is a scalar-valued function that is applied to the error  $\varepsilon(\theta)$ . A common choice is  $l(\varepsilon) = \frac{1}{2}\varepsilon^2$ , the least squares error. However, the least squares estimate suffers from the drawback that large errors are given more weight such that one large error could be allowed to dominate the resulting estimate. This is severely detrimental when outliers or bad data are present in the measurements - the results could become useless. An alternative is  $l(\varepsilon) = \frac{1}{2}|\varepsilon|^R$ , where  $R$  is chosen

as  $R = 1$  (Bishop, 1995). The resulting output will be the median of the data points instead of the mean which can be dominated by large-error data points.

Many approaches exist for solving (4) and some are built into software packages such as Matlab and Maple. For smooth error functions ( $V_N(\theta)$ ) gradient-based methods can be successfully employed to determine  $\theta$ . With this approach an iterative update of  $\theta$  is carried out in the direction of steepest descent of the error function, i.e.

$$\theta^{\tau+1} = \theta^\tau - \eta \nabla V_N|_{\theta^\tau} \quad (6)$$

where  $\nabla V_N|_{\theta^\tau}$  is the gradient of  $V_N$  evaluated at  $\theta^\tau$  in the iteration step  $\tau$ ;  $\eta$  is the learning rate. The iteration continues until  $\nabla V_N = 0$  or some other stopping criterion is satisfied. A detailed discussion of steepest descent and other optimization methods is given in (Bishop, 1995).

## 4. RESULTS

The EAF process can be separated into two distinct stages: meltdown and refining. In each stage the dynamics of certain variables are most pronounced and so too is the effect of the corresponding parameters on the process. Some parameters whose values affect the meltdown stage have little relevance during refining, and vice versa. This simplifies the parameter estimation in that the problem can be separated into two sub-problems - parameter estimation during meltdown and then refining - each with fewer parameters.

The data used in the current work was obtained from a 50 MVA furnace with an 80 ton capacity. The furnace uses 3 main oxyfuel lances and 3 graphite injection lances. A hot heel practice is followed with a tap to tap time of 57 minutes (Holmes and Memoli, 2001). In the model calculations the hot heel is assumed to be constant at 10 ton and 1550°C. All the necessary raw materials are changed into the furnace using two to three baskets per tap. In the results that follow data from 10 taps was used for fitting the model (test data) and 5 were used for validation.

### 4.1 Meltdown stage

Parameters of interest during meltdown are the heat transfer coefficients, and the transfer efficiencies of electrical and oxyfuel power input. These are responsible for the changes in the mass of steel, slag and most importantly, bath and slag temperature. Parameters for removal (rate constants) of silicon and carbon from the bath play a role during meltdown but their values cannot

be practically verified due to high measurement uncertainties during this stage.

The efficiency parameters  $\eta_{ARC}$ ,  $\eta_{OXF}$ ,  $\eta_{FeO}$  (efficiency of bath oxidation) have a primary effect on bath temperature and indirectly influence the melting rate of the charge materials.  $k_{therea_1}$  and  $k_{therea_5}$  are responsible for the melting rates of the steel and slag, respectively.

No direct method exists for monitoring the progress of melting in the furnace - a measurement of solid and liquid mass phases in the furnace is impractical. At best an educated guess (based on operator experience) is made about when a complete melt has been reached; this is based on visual inspection or noise patterns emanating from the furnace. To determine  $k_{therea_1}$  and  $k_{therea_5}$  it is sufficient to ensure that the model predicts a complete melt at or before some  $t = t_1$  (when a flat bath condition is suspected), i.e.  $m_{scrap} \approx 0$  and  $m_{solidslag} \approx 0$  for all  $t \leq t_1$ . The above parameters have a limited effect on the terminal temperature  $T(t_1)$ ; they are the first to be estimated, then fixed for all subsequent estimation.

Once the melting rates are fixed, the parameters  $\theta = [\eta_{ARC}, \eta_{OXF}, \eta_{FeO}, k_{VT}]$  are determined. Successful adjustment of these parameters will deliver a model for which  $T(\theta, t_1) \approx T_m(t_1)$  over all taps;  $t_1$  is also the time at which the first measurement of temperature  $T_m(t_1)$  is taken and  $T(\theta, t_1)$  is the temperature as reported by the model at the same time. As discussed in section 3 fitting is carried out by minimization of the error function  $V_N(\theta) = \frac{1}{N} \sum_{n=1}^N l(T_n(t_1) - T_{m,n}(t_1))$ , where  $N$  is the total number of taps. The results are given in table 1, the resulting parameter values are  $\theta = [0.370, 0.313, 0.349, 1.059]$ .

Table 1. Results of flat bath temperature fit.

	Test data	Validation data
Average error	33.05	35.07
Std dev	19.02	21.90
Min error	0.17	7.81
Max error	68.67	64.76

## 4.2 Refining stage

Refining is the final stage in the EAF process. Here properties of the molten steel are modified according to requirements of the downstream processes, in the current case the secondary metallurgy in the ladle furnace, and then the continuous caster. Once a laboratory analysis of the bath chemistry is obtained, controlled removal of carbon (and other impurities) commences. At the same time the bath temperature is measured using a disposable thermocouple. With this information available controlled adjustment of temperature

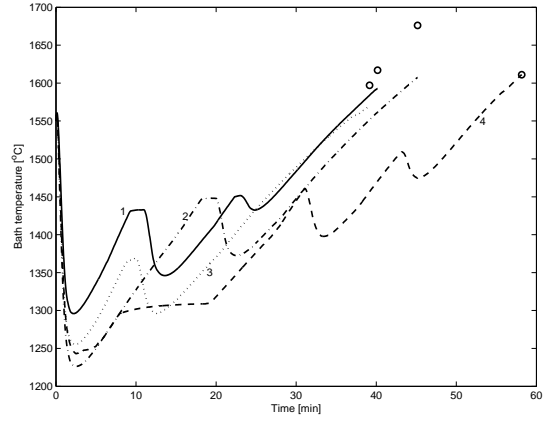


Fig. 2. Model temperature output compared with measured plant outputs (denoted by  $\circ$ ) for 4 taps. Taps 1 and 3 have a smaller error (approximately 25 °C) compared to 2 which is at maximum error, while 4 is at the smallest (see table 1). The troughs in the plots correspond to periods when charging takes place. For tap 4 the error is negligible despite a large disturbance (an idle time  $t = [8, 19]$  minutes) experienced during the tap.

can commence. (Both temperature and carbon composition can only be practically adjusted in one direction: carbon can only undergo a controlled decrease and temperature a controlled increase. On the other hand, decreasing the temperature requires making material additions or leaving the furnace idle to allow the heat losses to cool the bath. The former can also be employed to increase the carbon composition. Both approaches are time consuming and will have a negative impact on furnace productivity; they are best avoided for all practical purposes.)

An analysis of the bath chemistry and a reading of temperature are obtained simultaneously at flat bath  $t = t_1$ ; these measurements will provide initial conditions for the model at refining. Approximately 2 to 10 minutes later at  $t = t_2$  - depending on operating conditions - another measurement of temperature and carbon composition is obtained. Given the above information, the problem then becomes: given the initial conditions  $x(t_1)$  and inputs, the model should be able to predict the terminal point  $y_m(t_2)$  as closely as possible.

The initial conditions in (1)  $x(t_1) = x_1$  are obtained from plant operating conditions. The model output is  $y = h(x) = [\text{temperature, carbon}]^T$ . The optimization problem for refining is then:

$$\begin{aligned} \hat{\theta} &= \arg \min_{\theta \in D} V_N(\theta) \\ &= \arg \min_{\theta \in D} \frac{1}{N} \sum_{n=1}^N l(y_{m,n}(t_2) - y_n(t_2, \theta)), \quad (7) \end{aligned}$$

$y_{m,n}(t_2)$  is the measured output at  $t = t_2$  for tap  $n = 1, \dots, N$  and  $y_n(t_2)$  is the corresponding output as obtained by the model. That is, minimize the model prediction error over a total of  $N$  taps by appropriate choice of  $\theta = [\eta_{ARC}, \eta_{FeO}, k_{dC}]$ .

For the current problem the model fit was carried out using 10 test taps and 5 validation taps. The results are given in tables 2 and 3. The error data refers to the absolute error between the measured and model output per tap. Some model outputs for prediction of temperature and carbon are shown in figures 3 and 4; for clarity only outputs for 4 taps are shown.

Table 2. Results for refining temperature fit.

	Test data	Validation data
Average error [ $^{\circ}\text{C}$ ]	13.23	17.98
Std dev [ $^{\circ}\text{C}$ ]	11.76	13.49
Min error [ $^{\circ}\text{C}$ ]	0.02	3.19
Max error [ $^{\circ}\text{C}$ ]	33.57	39.13

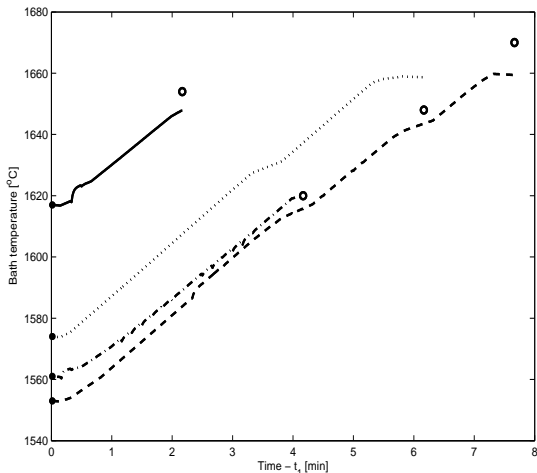


Fig. 3. Model temperature output in relation to measured plant output (denoted by  $\circ$ ) for 4 taps. The plot is shown relative to the first measurement time  $t = t_1$ .

Table 3. Results for refining carbon fit.

	Test data	Validation data
Average error [kg]	3.74	6.05
Std dev [kg]	4.62	7.35
Min error [kg]	0.038	0.16
Max error [kg]	15.0	20.02

The first report of the bath chemistry (along with the bath carbon content) is dependent on operator intervention. There is a finite delay between the time that a bath sample is obtained and when it is actually analyzed in the laboratory: this can vary from 1 to 3 minutes. During the delay, the bath carbon composition will decrease; therefore, the analysis will report a slightly higher reading at the time the data is logged. Offline use of this data will be prone to some error since this delay cannot be taken into account precisely: it can only

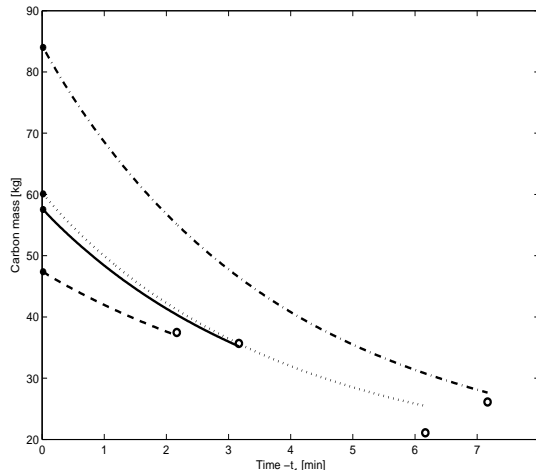


Fig. 4. Model carbon output in relation to measured plant carbon (denoted by  $\circ$ ) for 4 taps.

be estimated to lie in the range specified above. It is important to note that this will introduce error into the estimates, particularly for short estimation periods  $t_2 - t_1 \in [1, 3]$  [minutes]. This may explain the performance results of table 3.

Fitting for refining temperature is also prone to a certain degree of error. The temperature of the bath is strongly influenced by slag foaming - it depends on slag depth. While the model does account for slag depth as a function of graphite injection, the decrease in slag depth by deslagging is neither reliably quantifiable nor practically measured. Deslagging removes excess slag in the bath so that a bath sample or temperature can be obtained. It is carried out by tilting the furnace by  $2^{\circ}$  to  $5^{\circ}$  (from vertical) to allow the slag to flow out. During normal operation, the furnace will be deslagged at least once during refining, thus introducing a significant unmeasured disturbance into the process, especially on the bath temperature.

## 5. CONCLUSION

Model fitting for the meltdown stage shows a better performance compared to the fitting of both carbon and temperature at refining. This is possibly due to the long periods available for meltdown where the effect of disturbances is smoothed out over time. Refining is less immune: the slightest unmodelled disturbance will have a marked effect on the process since it is being controlled within tight margins and over short periods of time. There is little tolerance for error in the raw measurements being taken as well as the times at which they are reported.

The results presented in the current work demonstrate the potential of the EAF model as a predictor of the actual process. Although not conclusive, they are encouraging, and form a foundation for

further work, particularly in modifying the model to accommodate effects such as deslagging.

Work is currently underway for the design of experiments from which more reliable data will be obtained. With this in place, a critical evaluation of the model can be carried out. This, it is expected, will help improve some of the results obtained so far and will inform any new modifications that may be necessary.

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