MPC CONTROL OF THE REFINING STAGE OF AN ELECTRIC ARC FURNACE

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Abstract: The aim of this article was to design a MPC controller for the refining stage of an electric arc furnace. A reduced version of the generic EAF model will be used - it simplifies the controller. The carbon content is controllable only in one direction - it can only decrease asymptotically. The goal of the MPC controller will be to steer the temperature to the desired value before the carbon content reaches its target value. A controller design was done with this goal in mind and verified through simulation. The controller was found to be sensitive to plant parameter variations due to its open-loop nature, but can be improved if timely measurements are taken of required variables such as temperature and carbon.

Keywords: Model predictive control, MPC, electric arc furnace, EAF, reduced model

1. INTRODUCTION

Electric arc furnaces (EAFs) are used to convert scrap iron to steel. The refining of steel in an electric arc furnace is still a process that depends on manual control by an operator in order to get the desired steel grade. This article investigates the automation of the refining stage in order to control the variables of steel temperature and carbon content. Control of these variables will have an effect on the economics of the process. This is accomplished by reducing the amount the corrective runs in order to meet the specification on temperature and carbon content.

Previous work on modelling and control of electric arc furnaces by Bekker *et al.* [2000], Oosthuizen *et al.* [2001] focused on the control of the off-gas system, where relative furnace pressure, CO emissions and off-gas temperature were controlled. Oosthuizen *et al.* [2004] expanded on this controller by adding economic objectives to the controller in order to optimize the economic operation of the electric arc furnace. In order to conduct the controller design and simulations, a suitable EAF model was required. There are only limited references to dynamic EAF models in the literature and many tend to be proprietary [Morales *et al.*, 1997].

Since no suitable model was available, an extensive modeling effort was conducted by Bekker *et al.* [1999]. This effort resulted in a generic model that consists of 17 non-linear ordinary differential equations (ODEs). This generic model was further fitted to measured values to closer resemble a real

EAF plant [Rathaba, 2004]. At the refining stage of the tap, the off-gas system does not have a big influence on the temperature and the carbon content of the steel. The assumption was made that the amount of metal is constant as well as the amount of slag. Based on these assumptions, the model was reduced to 5 non-linear ordinary differential equations (ODEs) [Rathaba, 2004]. In this study, parameter estimation was done, which resulted in model parameters and regions of parameter uncertainty.

The control method selected for this article is that of model predictive control (MPC). MPC is based on the concept of predictive control, which was pioneered by Richalet *et al.* [1978] and Cutler and Ramaker [1980]. The MPC control strategy is computed from predictions of the output signals based on a linear internal model that resulted from optimization of a performance index with respect to a future control sequence. MPC displays its strengths when applied to problems with [Morari and Ricker, 1995]:

- A large number of manipulated and controlled variables;
- Constraints imposed on the manipulated variables;
- Changing control objectives or equipment failures.

These properties make MPC well suited for the control of the refining stage of a tap.

2. EAF REDUCED MODEL

The MPC controller uses an optimization algorithm to calculate the future control sequence. This requires a number of iterations to be done on the internal model. If the model is complex, as is the case with the generic EAF model, this will result in long computation time. The reduced model relieves the computation burden in the refining stage where certain assumptions can be made to simplify the model.

The generic model was reduced by Rathaba [2004]. Over an entire tap, the process is very unpredictable due to delays, breakdowns and maintenance that invalidate the assumption of process continuity. The advantage of the refining stage is that after the initial measurement, except for deslagging, the process is mostly uninterrupted until the final measurement is made. This is typically a flat bath stage when all melting has occurred; the modeling assumption of homogeneity is also valid. The bath temperature and carbon content become important during the refining stage just before tapping.

Process variables that undergo significant change during refining are bath temperature, carbon and silicon concentrations (masses), masses of SiO_2 and FeO in slag and all free-board gases. Under the above assumptions, all masses of the bath and composite slag are at steady state - they can be treated as constants. Oxygen injection is the only mechanism by which the furnace heat balance (and hence the bath temperature) can be affected by the free-board gases.

The reduced model is given by

$$\dot{x_3} = -k_{dC}\left(X_C - X_C^{eq}\right) \tag{1}$$

$$\dot{x_4} = -k_{dSi}\left(X_{Si} - X_{Si}^{eq}\right) \tag{2}$$

$$\dot{x_7} = \frac{2M_{FeO}d_1}{M_{O_2}} - \frac{x_7 k_{gr} M_{Fe} d_5}{\left(m_{T(slag)} + x_7 + x_8\right) M_C} + 0.13 d_2 \tag{3}$$

$$\dot{x_8} = \frac{M_{SiO_2}}{M_{Si}} k_{dSi}\left(X_{Si} - X_{Si}^{eq}\right) + 0.045 d_2 \tag{4}$$

$$\dot{x_{12}} = \left(p_t + \eta_{ARC} d_4 - k_{VT}\left(x_{12} - T_{air}\right)\right) / \left[\frac{m_{T(Fe)} C_{p(FeL)}}{M_{Fe}} + \frac{2m_{T(slag)} + 2x_7 + 3x_8}{M_{slag}} C_{p(slag_{(L)})}\right] \tag{5}$$

where the molar concentrations are given by

$$X_c = \frac{x_3/M_C}{m_{T(Fe)}/M_{Fe} + x_3/M_C + x_4/M_{Si}} \tag{6}$$

$$X_{FeO} = \frac{x_7/M_{FeO}}{m_{T(slag)}/M_{slag} + x_7/M_{FeO} + x_8/M_{SiO_2}} \tag{7}$$

$$X_C^{eq} = k_{XC}\left(\frac{m_{T(slag)} M_{FeO}}{x_7 M_{slag}} + \frac{x_8 M_{FeO}}{x_7 M_{SiO_2}} + 1\right) \tag{8}$$

$$X_{Si} = \frac{x_4/M_{Si}}{m_{T(Fe)}/M_{Fe} + x_3/M_{Si} + x_4/M_{Si}} \tag{9}$$

$$X_{Si}^{eq} = k_{XSi}\left(\frac{m_{T(slag)} M_{FeO}}{x_7 M_{slag}} + \frac{x_8 M_{FeO}}{x_7 M_{SiO_2}} + 1\right)^2 \tag{10}$$

The reduced equations for the heat balance are:

$$p_2 = \left(-2H_{FeO} d_1 / M_{O_2}\right)\eta_{FeO} \tag{11}$$

$$p_5 = \frac{d_1}{M_{O_2}}\left(x_{12} - T_{O_2}\right) C_{P(O_2)} \tag{12}$$

$$p_{11} = \frac{x_7 k_{gr} d_5 \left(\Delta H_{FeO} - \Delta H_{CO}\right)}{\left(m_{T(slag)} + x_7 + x_8\right) M_C} \tag{13}$$

$$p_t = p_2 + p_5 + p_{11} \tag{14}$$

where k_{dC} and k_{dSi} are the constants for removal of carbon and silicon from the bath; k_{gr} is the graphite reactivity constant; η_{ARC} and η_{FeO} are the efficiencies of arc energy input and bath oxidation; $m_{T(Fe)}$ and $m_{T(slag)}$ are the total masses of the slag formers and bath - both are assumed constant; M_C, M_{Fe}, M_{FeO}, M_{Si}, M_{SiO_2} and M_{slag} are the molar masses of the different elements. The states and inputs are described in table 1.

3. LINEARIZED MODEL

For MPC controller design, it is customary to use a linear internal model. The reduced model of

Table 1. States and inputs.

State	State Description	Input	Input Description
x_3	Dissolved Carbon	d_1	Oxygen injection rate
x_4	Dissolved Silicon	d_2	DRI addition rate
x_7	FeO in bath	d_3	Slag addition rate
x_8	SiO_2 in bath	d_4	Arc power
x_{12}	Bath temperature	d_5	Graphite injection rate

section 2 was linearized in order to be used in the MPC controller. The operating point around which the linearization will take place is the average values from measured tap data summarized in table 2.

The reduced model was linearized [Goodwin *et al.*, 2001] and produced the following matrices:

$$A = \begin{bmatrix} -3.116e-3 & -4.477e-6 & 4.188e-6 & 0 \\ 0 & -3.168e-5 & 2.94e-5 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & -7.959e-6 & -1.084e-5 & 9.154e-6 \end{bmatrix}$$

$$B = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 12 & 0.13 & 0 & -9.433e-5 \\ 0 & 0.045 & 0 & 0 \\ 0.424 & 0 & 6.197e-6 & -1.351e-6 \end{bmatrix}$$

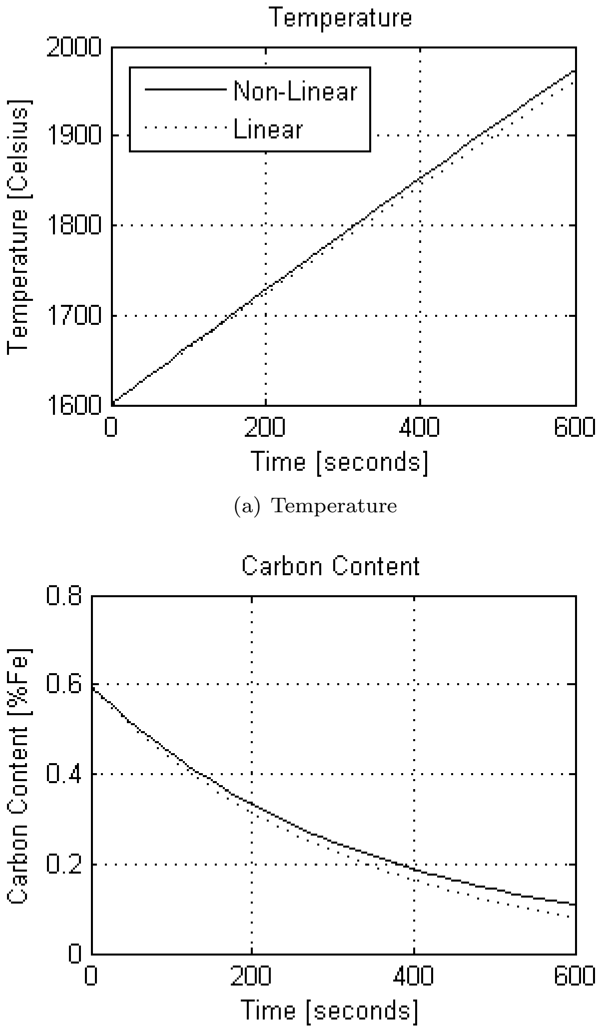
$$C = \begin{bmatrix} 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 \\ 1.25e-3 & 0 & 0 & 0 \end{bmatrix}$$

$$D = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \tag{15}$$

The linear model has only four states, in comparison to the non-linear model with five states. This is the result of a minimum realization, that removed a redundant state. The comparison of the linearized model with the non-linear model is shown in figure 1 with respect to temperature and carbon content. The system controllability is calculated as follow: $\mathrm{rank}(\Gamma_C) = \mathrm{rank}\left([B, AB, A^2B, A^3B]\right) = 4$. The controllability matrix has full row rank and the system is thus completely controllable. The system observability is calculated as follow: $\mathrm{rank}(\Gamma_O) = \mathrm{rank}\left(\begin{bmatrix} C \\ CA \\ CA^2 \\ CA^3 \end{bmatrix}\right) = 4$. The observability matrix has full column rank and the system is thus completely observable.

4. CONTROL STRATEGY

In general, the steel grade is determined by the carbon content. It is also desired that the temperature be at a certain value when the target carbon content is reached. This should be accomplished without increasing the FeO content to more than 40% of the total slag mass. The FeO content is



(a) Temperature

(b) Carbon Content

Fig. 1. Linear and Non-linear model comparison

controllable though the oxygen injection rate. The oxygen injection rate will have a variable influence on the decarburization rate depending on the level of the bath carbon. Under high bath carbon levels, oxygen injection leads to high decarburization, while only a limited influence is observed in the late stages of refining. The speed of the reaction cannot be accelerated through control, because of the weak controllability of the carbon content. The aim of the controller would be to steer the temperature to the desired value before the carbon is at its target level.

This work forms part of futher study, where other control strategies, that incorporate the variable nature of the model parameters, e.g. Robust MPC by Kothare *et al.* [1996], are being considered.

5. MPC CONTROLLER DESIGN

The MPC controller have a few design parameters [Maciejowski, 2002] in the form of prediction horizon length, control horizon, sampling time,

Table 2. Operating point.

State	State value	Input	Input Value	Misc	Misc value
x_3	480 kg	d_1	1 kg/s	$m_{T(Fe)}$	80 000 kg
x_4	24 kg	d_2	0 kg/s	$m_{T(slag)}$	6 917.8 kg
x_7	4250.6 kg	d_3	0 kg/s		
x_8	1405 kg	d_4	40 000 kW		
x_{12}	1400 ^0C	d_5	0.5 kg/s		

input and output weights and input and output constraints.

5.1 Prediction and control horizons

A sampling rate of 10 times the closed loop bandwidth is considered normal. With model time constants being above 10s, because the off-gas subsystem was removed from the model, a sampling interval of 1s was chosen. For the prediction horizon it is recommended to have the product of the prediction horizon and sampling interval at least 2.5 times longer than the longest time constant. A prediction horizon of 25 was chosen because $T_s = 1s$. The accuracy of the model should also be considered, because a shorter prediction horizon can accommodate a more inaccurate model, will hence result in a more robust controller. For inaccurate models a small control horizon is recommended by Seborg *et al.* [1989]. Blocking, that is the amount of samples that the input is kept constant, can also be used to get a smoother response according to Morari and Ricker [1995].

5.2 Weights

The weights specifies the severity of the penalty that a violation of a certain goal will produce. The cost function (with constraints on the manipulated and controlled variables) is shown in eq. 16-19 from Maciejowski [2002]. The weights on the controlled variables are indicated by μ_j and the weights on the manipulated variables are indicated by λ_j. The weights μ_j are used to attain the goals set on the temperature, while the λ_j parameters increases stability.

$$V = \sum_{j=H_w}^{Hp} \mu_j ||\hat{z}(k+i|k) - r(k+i|k)||^2 + \sum_{j=0}^{H_u-1} \lambda_j ||\Delta\hat{u}(k+i|k)||^2 \quad (16)$$

$$y_{min} \leq \hat{y} \leq y_{max} \quad (17)$$

$$u_{min} \leq u \leq u_{max} \quad (18)$$

$$|\Delta u| \leq \Delta u_{max} \quad (19)$$

The predicted output is $\hat{z}(k+i|k)$, the reference trajectory is $r(k+i|k)$ and the predicted change in control action is $\Delta\hat{u}(k+i|k)$. The prediction horizon has length H_p. In the case of time delay in the system, deviations of z from r are not immediately penalized by setting $H_w > 1$. The control horizon has length H_u, where in general $H_u < H_p$.

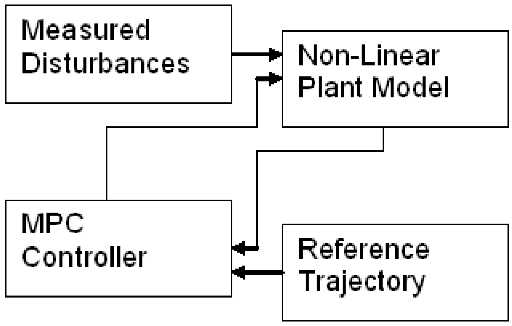


Fig. 2. System block diagram.

As the carbon content is weakly controllable, it is eliminated from the cost function by setting its weight to 0. The FeO content is only constrained to be less than 40% of the total slag mass. Temperature is the only remaining goal. The reference trajectory will be calculated as a linear reference from the initial temperature to the desired temperature, because temperature increase is generally linear.

5.3 Constraints on controlled and manipulated variables

The manipulated variables only have a range of practical values [Rathaba, 2004]. The controller must be aware of these constraints in order to ensure that the desired output can be obtained. There is also a constraint on the FeO content to prevent the controller from producing unrealistic amounts of FeO. The constraints on the manipulated and controlled variables are shown in table 3.

6. SIMULATION

The designed MPC controller is simulated on the non-linear plant to verify that the controller achieves its objectives. The non-linear model parameters are then changed to test the sensitivity of the controller to the plant uncertainties.

The system block diagram is shown in figure 2, where the measured outputs are temperature and carbon content and an estimated value of FeO. The reference trajectory is the desired trajectory

Table 3. Constraints on manipulated and controlled variables.

Variable	Minimum	Maximum	Variable	Minimum	Maximum
Oxygen injection rate	0 kg/s	1 kg/s	Power	0 kW	40 000 kW
DRI addition rate	0 kg/s	0 kg/s	Graphite injection rate	0 kg/s	1 kg/s
Slag addition rate	0 kg/s	0 kg/s	FeO amount	0% of Iron	40% of Slag

we wish the output to follow and the measured disturbances are the DRI addition rate and slag formers addition rate. These last two inputs are set as measured disturbance in the MPC toolbox of MATLAB to ensure correct operation, but in reality are not used and have no effect on the system, because they are set to 0. The manipulated variables are oxygen injection rate, electric power and graphite injection rate.

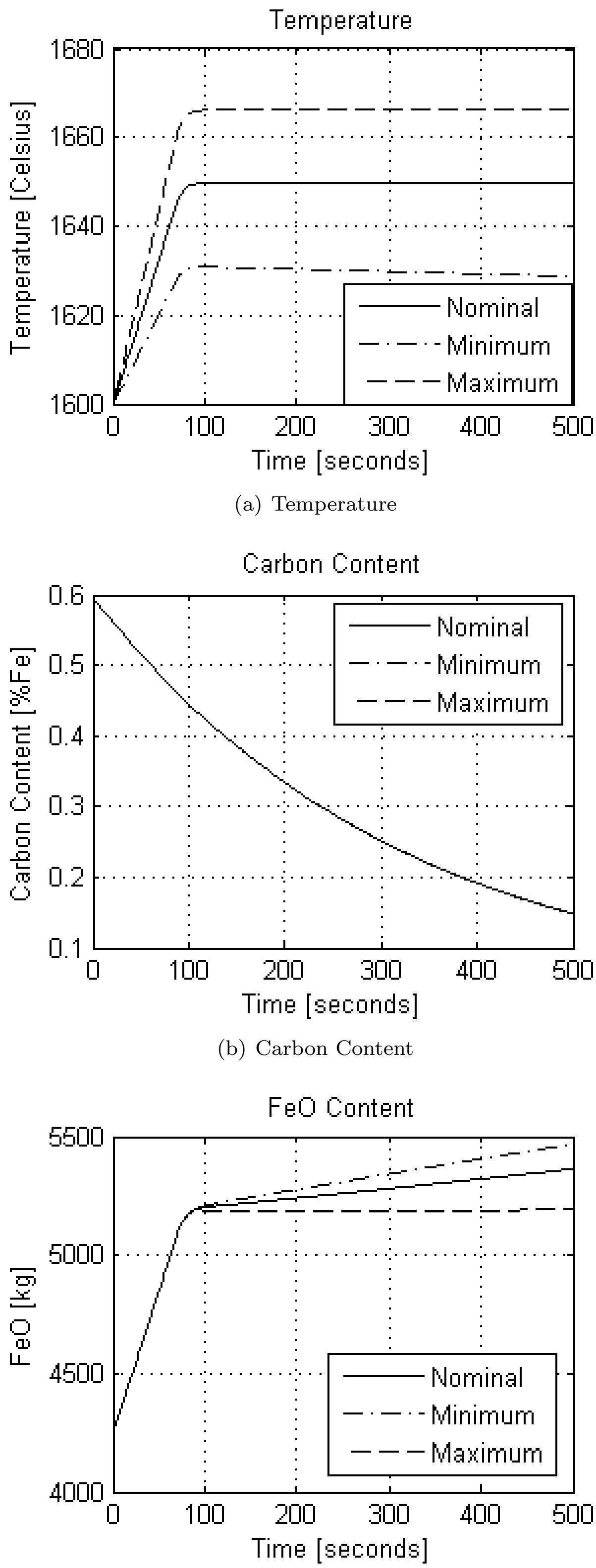
The system was simulated with the MPC toolbox of MATLAB [Bemporad *et al.*, 2004]. The designed controller response on the nominal plant model and the worst-case scenarios are shown in figure 3. The nominal response is the expected response in the figures. For these simulations, a temperature set-point of 1650 Celsius was chosen, with a constraint on the FeO content of 10000 kg. The initial conditions are the same as the operating point as summarized in table 2.

To test the sensitivity of the controller to the uncertainties of the plant, the parameters were varied between their minimum and maximum values in order to analyze their effect on the system [Rathaba, 2004]. The plant parameters are summarized in table 4. The results of the worst case scenarios are shown in figure 4. From these results it is clear that the parameter uncertainties have substantial effect on the temperature. This is the worst case scenario and the assumption is that the plant parameters will be close to nominal in most cases as shown in figure 3. The system was simulated while assuming that a measurement is take in the middle of the process to correct for model inaccuracies. The result for the model parameters in worst case is shown in figure 4.

7. CONCLUSION

There is promise in developing a MPC controller for the refining stage of an electric arc furnace. The aim of the controller would be to ensure the correct temperature of the molten metal at the time the that the carbon content reaches its target value. This will reduce the amount of unscheduled delays and will result in increased throughput.

The system would largely be implemented in open-loop, since only a few measurements are taken during the refining stage. This would require proper initial measurements to determine the initial conditions, otherwise this could result in a incorrect control sequence. The open-loop nature of the system makes the controller sensitive to



(a) Temperature

(b) Carbon Content

(c) FeO Content

Fig. 3. Nominal and worst-case plant response.

plant parameter variations. This sensitivity can be reduced by taking timely measurements of required variables such as temperature and carbon.

8. ACKNOWLEDGEMENTS

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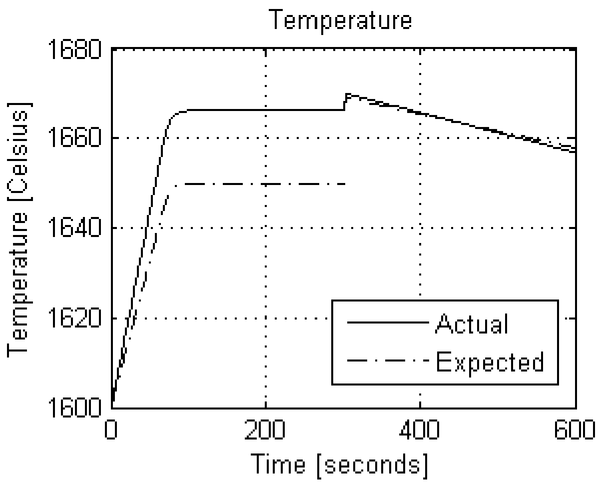
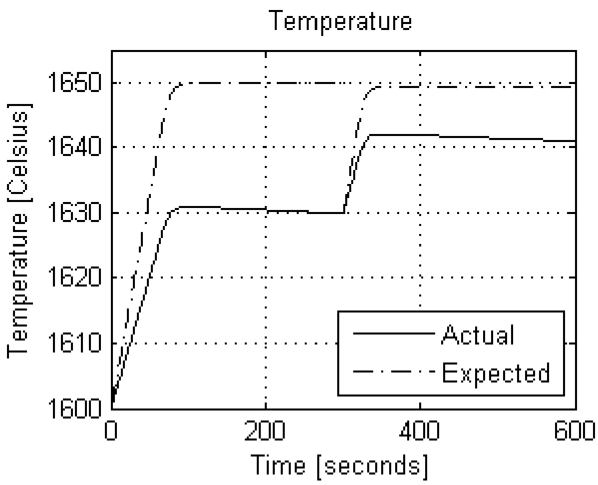
Table 4. Plant parameters.

Parameter	Lower bound	Nominal	Upper bound
k_{VT}	1.73	2.08	2.42
η_{ARC}	0.29	0.51	0.73
η_{FeO}	0.54	0.75	0.96
k_{dC}	54.74	54.90	55.05
k_{gr}	0.08	0.42	0.76



(a) Temperature - Maximum response



(b) Temperature - Minimum response

Fig. 4. Simulation with plant parameter values at worst case and with one feedback point.

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