Dynamic Optimization, Estimation and Control of Electric Arc Furnace Operation

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1. Introduction

Electric arc furnaces (EAFs) are widely used in the steel industry to produce steel by melting scrap metal and adjusting the composition through the addition of oxygen, carbon and fluxes. They are highly energy intensive operations, and due to the harsh operating conditions, have limited measurements.

This paper presents an overview of advances toward economic optimization of EAF operations, focusing on approaches followed within our research group. The remainder of the paper is organized into four sections covering the key components of a real-time optimization-based decision support system: a dynamic model, dynamic optimization, state estimation, and real-time implementation frameworks. This is followed by concluding remarks.

2. Dynamic Model Development

Various modeling paradigms have been applied to EAFs, ranging from very detailed models involving computational fluid dynamics, to purely empirical models. In order to be used in a real-time setting, key considerations are computational speed and reliability. The model should also be dynamic in order to capture the transient nature of a heat (batch), and capture the relationship between the process inputs, response variables, constraints and a suitably defined objective function.

First-principles based dynamic models have been proposed by several workers. Cameron et al. [1] present an EAF model for dynamic simulation in which the EAF contents are considered as four phases, with mass transfer between phases and chemical equilibrium at phase interfaces. Matson and Ramirez [2] consider two control volumes in which chemical equilibrium is assumed. The scrap is modeled as spheres. Optimal carbon and oxygen additions are determined using iterative dynamic programming. Bekker et al. [3], on the other hand, utilize kinetic relationships in a dynamic EAF model developed for closed-loop simulation. MacRosty and Swartz [4] present a dynamic EAF model comprising four zones, illustrated in Fig. 1, with

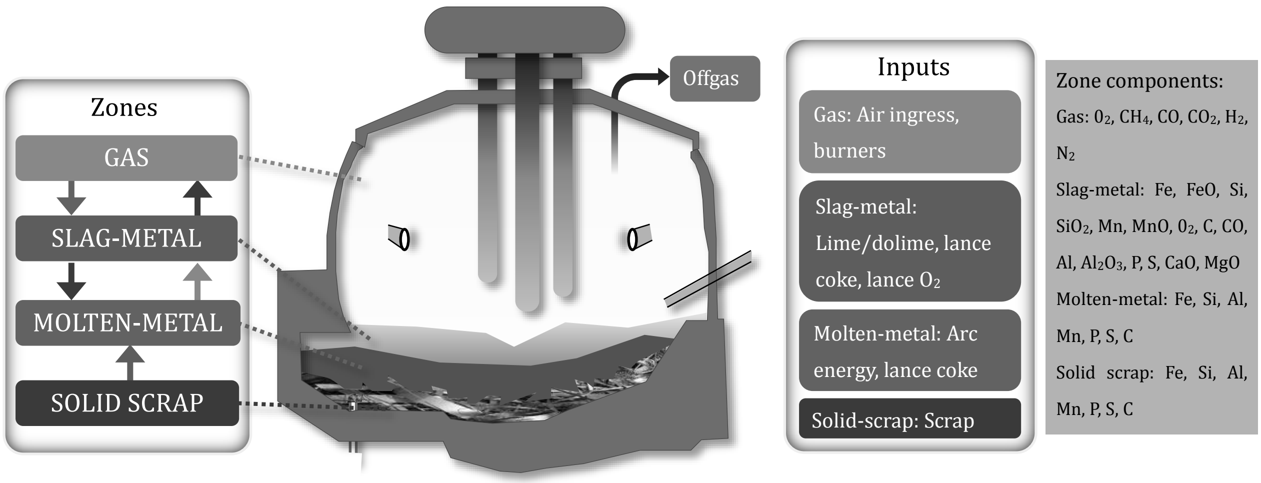

Fig.1 Schematic of EAF model with zones, inputs and components within zones indicated

chemical equilibrium considered in the gas and slag-metal zones, and mass transfer across zone interfaces determined by concentration gradients. The model includes material and energy balances, accounts for the addition of a second scrap charge as well as oxygen, carbon and fluxes, includes radiative heat transfer between the arc and exposed surfaces, and accounts for slag depth through empirical relationships. The model takes the form of a differential-algebraic equation (DAE) system with 85 differential and 1050 algebraic state variables. Six parameters are chosen for rigorous parameter estimation based on a sensitivity analysis in which the model response trajectories are matched to industrial data in a weighted least-squares sense, with the model subsequently validated against batch data not used in the estimation.

3. Dynamic Optimization

A dynamic optimization problem that maximizes a performance criterion over the duration of the heat can be formulated as

$$\begin{aligned} \max_{u(t)} \quad & \phi\left(x(t), z(t), u(t), t_f\right) \\ s.t. \quad & f(\dot{x}(t), x(t), z(t), u(t), t) = 0 \\ & g(x(t), z(t), u(t), t) \geq 0 \\ & g_s(x(t_s), z(t_s), u(t_s), t_s) \geq 0 \end{aligned}$$

where ϕ represents a suitable objective function such as profit, f represents a set of differential and algebraic equations describing the process, and g and g_s represent path and point constraints respectively. x, z and u represent differential state, algebraic state and input variables. MacRosty and Swartz [5] use a profit based objective function given by

$$\phi = c_0 M_{steel}\left(t_f\right) - \left(c_1 \int_0^{t_f} P\, dt + c_2 \int_0^{t_f} \left(F_{O_2,brnr} + F_{O_2,Inc}\right) dt + c_3 \int_0^{t_f} F_{CH_4,brnr}\, dt \right.$$
$$\left. + c_4 \int_0^{t_f} F_{C,inj}\, dt + c_5 \int_0^{t_f} F_{C,chg}\, dt + c_6 \int_0^{t_f} F_{flux}\, dt + c_7 \int_0^{t_f} \left(F_{scrap,1} + F_{scrap,2}\right) dt\right)$$

where P represents the electrical power, the F_i are the inputs and the c_i are revenue/cost coefficients.

Parameterization of the inputs by a finite set of parameters, such as through piecewise constant inputs, allows the dynamic optimization problem to be cast as a nonlinear programming (NLP) problem. In a sequential solution approach [6], the optimization and integration of the dynamic equations occur sequentially, with updated input trajectories provided to the DAE integration at each optimization iteration. A simultaneous solution or direct transcription approach [7], on the other hand, involves discretization of the dynamic system over the time horizon under consideration, and inclusion of the resulting algebraic equations as equality constraints in a single, large-scale optimization problem. MacRosty and Swartz [5] apply a sequential optimization strategy implemented in gPROMS/gOPT to determine the optimal operation of an EAF under various conditions. Fig. 2 shows the economically optimal solution profiles of the power and oxygen inputs to an EAF for using the EAF model as adapted in Shyamal and Swartz [8]. Two optimal profiles for each

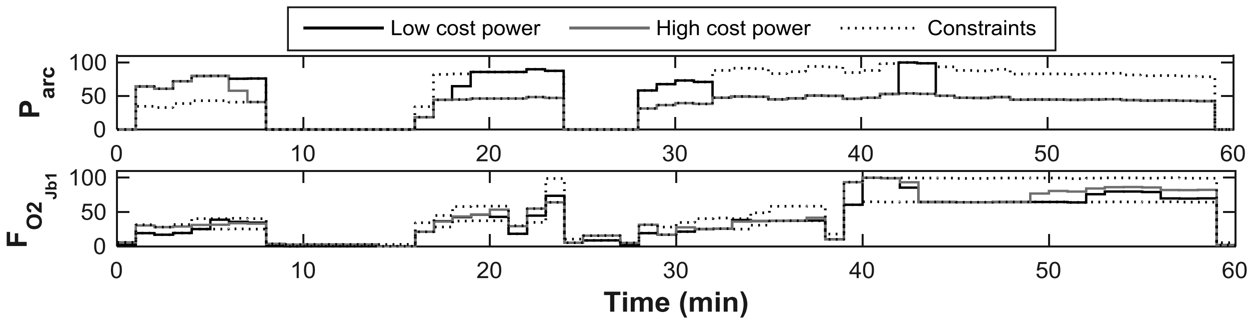

Fig.2 Optimal power and oxygen input trajectories for different electricity prices

variable are shown, corresponding to high and low electricity prices respectively. When the electricity cost is high, less power is used over the duration of the heat, with the product end-point and operational constraints enforced over the heat. The complexity of the relationships and interactions between the variables and constraints prohibits the generation of high quality solutions based on operator experience and judgement alone.

4. State Estimation

In order for EAF optimization to be applied in real-time, it is important that accurate estimates of the system states are available as initial conditions for the optimization. Two popular state estimation algorithms for nonlinear dynamic systems are the extended Kalman filter (EKF) [9] and moving horizon estimation (MHE) [10] strategies. MHE accounts for process constraints directly through a dynamic optimization problem formulation, which for a discretized dynamic system takes the form

$$\begin{aligned}
&\min_{x_{i-N},w_k} \sum_{k=i-N}^{i-1} ||w_k||^2_{Q^{-1}} + \sum_{k=i-N}^{i} ||v_k||^2_{R^{-1}} + ||x_{i-N} - \hat{x}_{i-N}||^2_{S_i^{-1}} \\
&s.t. \quad x_{k+1} = f(x_k, u_k) + w_k, \qquad k = i-N, \dots i-1 \\
&\qquad\;\; y_k = h(x_k) + v_k, \\
&\qquad\;\; x^{LB} \le x_k \le x^{UB},
\end{aligned}$$

where w_k is a piecewise constant noise term introduced to model the process noise (i.e. the model uncertainty), $\hat{x}_{i-N}$ is an estimate for the state at the beginning of the horizon, f integrates the model, given the system state vector x_k, the control input u_k and the process noise w_k, over one sampling interval, and h is the measurement function that maps the system state to measurement y_k. v_k is the measurement noise term. x^{LB} and x^{UB} represent lower and upper bounds respectively on the state variables.

Shyamal and Swartz [11] apply a multi-rate MHE formulation to an EAF system using a sequential solution strategy. The multirate formulation accounts for the commonly occurring situation in EAF operation where some measurements (such as offgas composition) are available at a regular frequency, while others (such as slag composition) are less frequent or intermittent. In Swartz and Shyamal [12], a simultaneous solution strategy is applied to the MHE optimization problem, with significantly reduced solution times achieved over the sequential approach due in part to the elimination of optimization variables through equality constraints, and a novel initialization scheme that can be applied in the background between sample times.

5. Real-Time Decision Support and Control

Shyamal and Swartz [12] present a real-time decision support framework for EAF operation in which a dynamic model coupled with an MHE algorithm, runs in parallel with the plant, with plant inputs and outputs provided to the MHE (see Fig. 3). At any point in time during the heat, the operator can initiate dynamic optimization, with the dynamic optimization plant model using as initial states estimated states from the MHE. A natural extension is to execute dynamic optimization at a regular frequency, with the computed process inputs applied to the EAF process, yielding a shrinking horizon economic model predictive control (EMPC) strategy. MacRosty and Swartz [13] propose a strategy of this type, with the nonlinear MPC optimization problems solved via a sequential solution approach. The EMPC approach of Shyamal and Swartz [8] includes state estimation via MHE, and use of a simultaneous solution strategy which significantly reduces the computation time. The control strategy is posed as a real-time energy management system for optimal EAF operation within a time-varying electricity market.

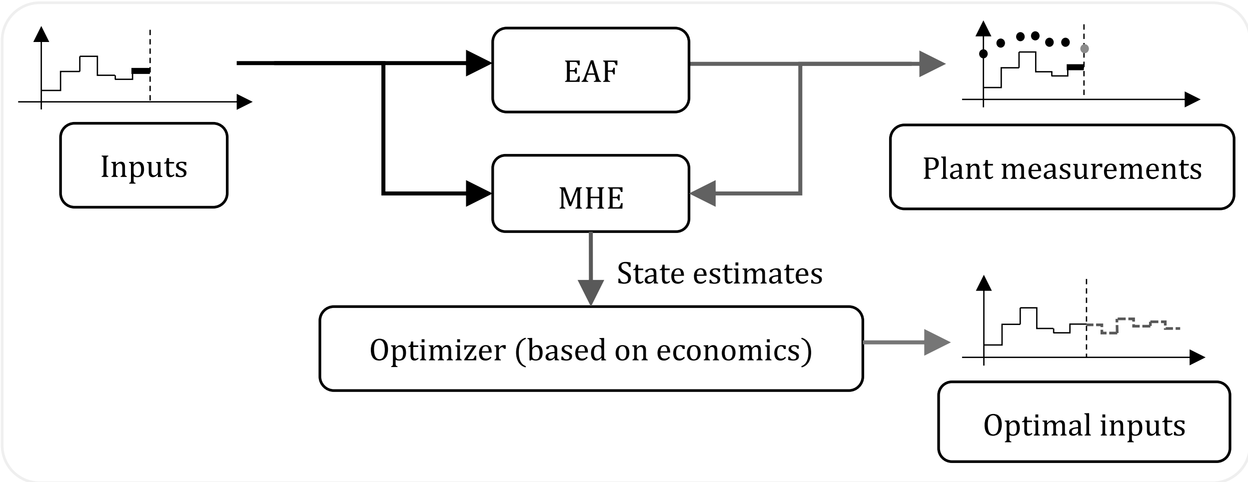

Fig.3 Optimization-based decision support framework

6. Conclusion

The high energy consumption of EAFs make them prime candidates for real-time economic optimization. The complexity of the EAF process, multiple constraints, and limited process measurements pose significant challenges for operator-based optimization. In this paper, the components of a real-time EAF optimization strategy are described, as well as their utilization within EAF real-time decision support and EMPC frameworks. The potential economic benefit of these approaches has been demonstrated through simulation studies, with plant trials constituting a useful next step.

Acknowledgements

Support from the McMaster Steel Research Centre and the McMaster Advanced Control Consortium is gratefully acknowledged.

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