

Nonlinear Predictive Control of Steel Slab Reheating Furnace

L. Balbis, J. Balderud and M. J. Grimble

Abstract— In a steel plant, reheating furnaces are used for heating the steel slabs to a temperature of approximately 1200 C before rolling. Reheating furnaces consumes a lot of energy in steel plants. For competitive advantage it is important to improve the heating quality of slab and reduce the energy consumption as much as possible. This paper explores the potential of nonlinear model predictive control techniques to improve the temperature control of the metal slabs in a hot mill reheat furnace, and particularly whether or not these control techniques can be exploited to reduce the energy consumption. An example of actual furnace operation is presented to show the effectiveness of the proposed scheme.

I. INTRODUCTION

In a steel manufacturing process, metal sheet is produced through rolling process of steel blocks (slabs). The slabs are obtained from continuous casting of refined steel and stored for later use. The slabs are then reheated by the furnace to a temperature of approximately 1200 C before entering the rolling section, otherwise a product with unacceptable metallurgical properties could result [12]. Usually the required drop-out temperature at the end of such process must belong to a range determined by the following treatment process.

Normally, a reheat furnace is divided into three burner zones: preheating, heating and soaking chambers. The slabs are heated approximately to the desired temperature in the preheating and heating zones. The temperature uniformity through the slabs is achieved in the soaking zone. There can be in the order of 30 slabs in the furnace at one time. At discrete-time intervals, a 'cold' slab is charged in the furnace and a hot slab is pushed out. The hot slab then is transported to the mill to be rolled. The temperature of the slabs is controlled by varying the zones temperatures and the furnace temperature is controlled by varying the gas flow of the burners of the chamber.

Traditionally the speed of the slabs through the furnace and the temperature levels in the furnace are regulated

manually, so that each slab being discharged from the furnace comes as close as possible to its target temperature [1]. Although manual control gives satisfactory performances when the furnace operates in steady state, a typical reheating furnace does not operate in such a consistent manner. Slabs vary greatly in composition, dimension, and in processing requirements and mill delays, whether planned or unplanned, also influence the travel of the slabs through the furnace. All these events produce divergence from nominal operating conditions and generate variations in the slabs mean temperatures. This means that the heating capabilities of the furnace must be adjusted as accurately as possible and therefore manual control is not the most efficient way to operate such furnaces.

In current systems, the emphasis is often put on the heating quality while the energy saving is seldom taken into account [2][7][8][9]. Today's steel industry presents significant challenges to keep operations competitive and it is of increasing concern that much fuel may be wasted in the operation of a reheat furnace due to improper control.

In this paper, the problem of guarantee temperature requirements as well as minimizing fuel consumption for the reheating furnace is tackled employing a nonlinear model based predictive controller. This paper is organized as follows: In section 2 a dynamic model of the reheating furnace using energy balances is presented. Section 3 then describes the nonlinear predictive control algorithm employed. Finally, some simulation results and concluding remarks are given in sections 4 and 5.

II. MODEL OF THE FURNACE

A mathematical model representing the dynamic behaviour of the reheat furnace process can be obtained by considering the heat and mass balance conditions within the reheat furnace. In line with previous results, [2][3][4][10][11][13], it is assumed that heat and mass is convectively transported along the length direction (x -direction) of the furnace by the steel slabs and the exhaust gasses, respectively. It is also assumed that heat is continuously exchanged along the x -direction between the exhaust gasses and the steel slabs and between the exhaust gasses and the furnace walls, and that the heat and mass continuously produced by the gas burners mounted along

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J. Balderud is Research Fellow at the Industrial Control Centre, University of Strathclyde, Glasgow, U.K. (tel: +44 141 548 2245; fax: +44 141 548 4203; e-mail: j.balderud@eee.strath.ac.uk).

L. Balbis is Ph. D. student at the Industrial Control Centre, University of Strathclyde, Glasgow, U.K. (e-mail: lbalbis@eee.strath.ac.uk).

M. J. Grimble is Director of the Industrial Control Centre, University of Strathclyde, Glasgow, U.K. (e-mail: m.grimble@eee.strath.ac.uk).

the length direction of the furnace is mixed homogeneously, and instantaneously, with the existing exhaust gas. It is further assumed that the heat and mass produced by the gas burners in each of the furnace heating zones is equally distributed along the length of the zone and that the exhaust gas can be considered incompressible. It is finally assumed that a small amount of heat escapes through the furnace walls to the outside environment. The heat balance conditions that results from these assumptions are depicted in Figure 1.

The steady state heat flow conditions within the furnace can be obtained by considering a small section, with length Δx , of the furnace. Within this section of the furnace the steady state heat flow conditions are given by,

$$Q_w(x, \Delta x)\Delta x - Q_o(x, \Delta x)\Delta x = 0 \quad (1)$$

$$Q_s(x, \Delta x)\Delta x - \left(\frac{\partial Q_s(x)}{\partial x} \Delta x + Q_s(x) \right) + Q_s(x) = Q_w(x, \Delta x)\Delta x - \frac{\partial Q_s(x)}{\partial x} \Delta x = 0 \quad (2)$$

$$\begin{aligned} & \left(\frac{\partial Q_g(x)}{\partial x} \Delta x + Q_g(x) \right) - Q_g(x) \\ & + \Delta x (Q_a(x, \Delta x) + Q_c(x, \Delta x) + Q_f(x, \Delta x)) \\ & - \Delta x (Q_w(x, \Delta x) - Q_o(x, \Delta x)) \\ & = \frac{\partial Q_g(x)}{\partial x} + Q_a(x, \Delta x) + Q_c(x, \Delta x) + Q_f(x, \Delta x) \\ & - Q_w(x, \Delta x) - \frac{\partial Q_s(x)}{\partial x} = 0 \end{aligned} \quad (3)$$

where $Q_g(x)$ denote the heat flow carried by the exhaust gas, $Q_s(x)$ denote the heat flow carried by the steel slabs, $Q_s(x, \Delta x)$ denote the average heat flow per unit of length, from x to $x+\Delta x$, absorbed by the steel slabs, $Q_a(x, \Delta x)$ denote the average heat flow per unit of length, valid from x to $x+\Delta x$, brought into the furnace by air (consumed by the gas burners), $Q_f(x, \Delta x)$ denote the average heat flow per unit of length, from x to $x+\Delta x$, brought into the furnace by the gas burner fuel, $Q_c(x, \Delta x)$ denote the average heat flow per unit of length, from x to $x+\Delta x$, produced by combustion of the air and the gas burner fuel, $Q_w(x, \Delta x)$ denote the average heat flow per unit of length, from x to $x+\Delta x$ absorbed by the furnace walls, $Q_o(x, \Delta x)$ denote the average heat flow per unit of length, from x to $x+\Delta x$, that escapes through the furnace walls to the outside environment and where the variable x denote the position in the length direction of the furnace. Equation (1), from above, states that under steady state conditions the heat transported to the furnace walls by the exhaust

gasses is equal to the amount of heat escaping to the outside environment. Equation (2) states that the amount of heat added to the steel slabs in a small section of the furnace is equal to the difference in heat flow at the boundaries of the section. Equation (3) finally states that the amount of heat added to the exhaust gasses in a small section of the furnace is equal to the amount of heat produced by the gas burners and the amount of heat absorbed by the furnace walls and steel slabs.

In order to determine the heat flows in (1)-(3), the temperatures of the steel slabs, the furnace wall and the exhaust gasses must first be established. Expressions that relate the heat flows to the furnace wall temperature, the slab temperature and the exhaust gas temperature can be found in [14].

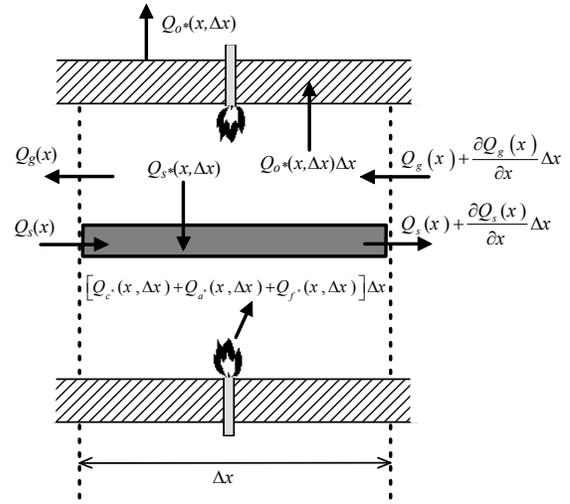


Figure 1 Energy balance in a generic section of the furnace

III. MODEL PREDICTIVE CONTROLLER SCHEME

The proposed control scheme splits the control calculation into a steady-state optimization followed by a dynamic optimization as shown in Figure 3. A similar scheme is adopted in many industrial model predictive control technologies such as Dynamic Matrix Control, SMC-Idcom, and RMPCT, in which optimal steady-state targets are computed for each input and output and then passed to a dynamic optimization to compute the optimal input vector [5]. In these technologies, the local steady-state optimization uses a linear steady-state model that may be obtained by linearizing a nonlinear model of the plant at each control execution or may simply be the steady-state version of the linear dynamic model used in the dynamic optimization.

On the contrary, in the control scheme here proposed the

local steady-state optimization is carried out employing a nonlinear process model. The control law is computed in two steps. First, a steady state operating point that is optimal with respect to fuel-consumption versus furnace throughput is chosen, having information on the current economic value of final product and on the current cost of input variables (fuel flows). The cost function is nonlinear, because of the use of a nonlinear model. The optimization is carried out subject to input and output constraints. These are in the form of nonlinear inequality and equality constraints, so that the optimal set-points are computed by solving a nonlinear programming problem.

In the second step, a control trajectory is chosen over a control horizon which is predicted to bring the plant to the desired steady state computed by the nonlinear optimization. A linear model derived linearizing the nonlinear process model around the current operating point is used in the dynamic optimization step. Again, constraints on the drop-out temperature and inputs are imposed. The problem is formulated in terms of a quadratic problem and solved using a quadratic programming approach.

For control purposes the furnace process can be viewed as having four inputs; the furnace speed, $u_v(t)$, and three gas-flow inputs, $u_1(t)$, $u_2(t)$, $u_3(t)$, corresponding to the fuel flow in the pre-heating zone, the fuel flow in the heating zone and the fuel flow in the soaking zone, respectively. The measurable outputs from the furnace process are the slab temperatures, the gas temperatures and furnace wall temperatures at various locations along the length of the furnace. The most important of these temperature outputs is the slab temperature at the end of the soaking zone; the drop-out temperature, $T_d(t)$.

In order to meet the desired quality targets the drop-out temperature, $T_d(t)$, should remain in the range from 1200 degree Celsius to 1250 degree Celsius. In order to prevent damage to the furnace the gas-temperatures must never increase beyond 1300 degree Celsius. The manipulated variables are finally constrained by the following physical constraints:

$$\begin{aligned} 0 \leq u_1(t) &\leq 4 \text{ [m}^3/\text{s]} \\ 0 \leq u_2(t) &\leq 2 \text{ [m}^3/\text{s]} \\ 0 \leq u_3(t) &\leq 1.5 \text{ [m}^3/\text{s]} \\ 0 \leq u_v(t) &\text{ [m/s]} \end{aligned} \quad (4)$$

IV. CONTROL OBJECTIVE

The objective in this paper is to maximize the profit of the furnace operations whilst ensuring that the product quality remains within acceptable limits. These objectives can be expressed in terms of constrained optimization problem that employs a linear costing term,

$$\begin{aligned} \max_{u_v(t), u_1(t), u_2(t), u_3(t)} & \sum c_{prod} u_v(t) - c_{fuel} (u_1(t) + u_2(t) + u_3(t)) \\ \text{s.t.} & \\ u_v(t) \in \Omega_v, & u_1(t) \in \Omega_1, u_2(t) \in \Omega_2, u_3(t) \in \Omega_3 \end{aligned} \quad (5)$$

where the term $c_{prod} u_v(t)$ represents the income derived from the furnace operations and where the term $c_{fuel}(u_1(t)+u_2(t)+u_3(t))$ represents the cost associated with the furnace operations. The parameters c_{prod} and c_{fuel} are constants that relate the furnace speed to product income and fuel flows to fuel costs. The constraints in the above optimization problem ensure that the product quality is maintained within acceptable levels and that physical constraints are satisfied.

A. Static Optimization

The following nonlinear discrete time model structure can be used to characterize the dynamic behaviour of the rehear furnace:

$$\begin{aligned} x(t+1) &= f(x(t), u(t)) \\ T_d(t) &= Cx(t) \end{aligned} \quad (6)$$

where the states $x(t)$, corresponds to temperatures of the gas, steel slabs and the furnace wall at different locations in the furnace, the output $T_d(t)$ corresponds to the drop-out temperature at discrete time intervals and input $u(t)=[u_v(t), u_1(t), u_2(t), u_3(t)]^T$ corresponds to the furnace speed and the fuel flows.

At steady state conditions, (x_{ss}, u_{ss}) , a process exhibits only negligible change over an arbitrarily long period when undisturbed, and therefore,

$$x_{ss} = f(x_{ss}, u_{ss}) \quad (7)$$

The objective of the static optimization problem is to find steady state operating conditions, (x_{ss}, u_{ss}) , that maximize the production profit. By taking into account the quality targets, formulated as constraints, this leads to the following constrained nonlinear optimization problem:

$$\begin{aligned} \max_{u_v(t), u_1(t), u_2(t), u_3(t)} & c_{prod} u_v(t) - c_{fuel} (u_1(t) + u_2(t) + u_3(t)) \\ \text{s.t.} & \\ 0 \leq u_{v_{ss}} \leq u_{v_{max}}, & 0 \leq u_{1_{ss}} \leq 4, 0 \leq u_{2_{ss}} \leq 2, 0 \leq u_{3_{ss}} \leq 1.5 \\ x_{ss} &= f(x_{ss}, u_{ss}) \\ T_{d_{ss}} &= Cx_{ss} = 1200 \end{aligned} \quad (8)$$

where $u_{v_{max}}$ is a constant parameter. By solving the above nonlinear optimization problem, one obtains a steady state operating condition that maximizes the production profit

whilst ensuring that the product quality targets are met (this is enforced by the bottom equality constraint).

B. Dynamic Optimization

The predictive control problem is formulated here as a regulatory problem that may be stated as follows:

At each time instant, t , find an optimal control sequence, $U(t)=[u(t)^T, u(t+1)^T, \dots, u(t+N_u-1)^T]^T$, over a control horizon N_u , such that optimal steady state operating conditions are reached in the shortest possible time and as efficiently as possible.

The optimization problem is reduced to the minimization problem

$$\min_{U(t)} J(U(t)) \quad (9)$$

The cost function $J(U(t))$ is expressed as sum of three terms:

$$J(U(t)) = J_1(U(t)) + J_2(U(t)) + J_3(U(t)) \quad (10)$$

where

$$\begin{aligned} J_1(U(t)) &= \left(q_1 \sum_{i=0}^{N_u-1} J(u_{ss}) - \left(c_1 u_v(t+i) - c_2 (u_1(t+i) + u_2(t+i) + u_3(t+i)) \right) \right)^2 \\ J_2(U(t)) &= q_2 \sum_{i=0}^{N_u-1} (u_{v,ss} - u_v(t+i))^2 \\ J_3(U(t)) &= \sum_{i=0}^{N_u-1} (u(t-i-1) - u(t-i))^T \\ &\quad Q_3(u(t-i-1) - u(t-i)) \end{aligned} \quad (11)$$

The first term ensures that the system is driven toward the optimal steady state operating conditions. The second term ensures that the furnace speed quickly approaches its steady state optimum whilst the third term penalizes excessive actuator adjustments.

The optimization problem must satisfy constraints on both inputs and outputs. The input constraints are formulated as hard constraints, whereas the output constraints are soft constraints in order to avoid infeasibility of the solution. This is due to the fact that when the furnace starts up cold there is an initial time in which the furnace is warming up and the slabs temperatures are outside the boundary conditions. In the optimisation problem, this leads to infeasibility of the solution. A straightforward way to deal with infeasibility is to soften the output constraints, so that the hard bounds can be crossed occasionally in order to avoid infeasibility [6].

Constraints are softened introducing slack variables which are additional optimization variables defined such that they are non-zero only if the corresponding constraints are violated. With the addition of slack variables w the optimization problem (9) becomes:

$$\min_{U(t), w} J(U(t)) + w^T Q_4 w \quad (12)$$

Subject to:

$$\begin{aligned} AU(t) &\leq b \\ T_{d_{\min}} &\leq T_d(t+i) + w \leq T_{d_{\max}} \quad i = 1, \dots, N_p \\ w &\geq 0 \\ x(t+i+1) &= f(x(t+i), u(t+i)) \quad i = 1, \dots, N_p - 1 \\ T_d(t+i) &= Cx(t+i) \quad i = 1, \dots, N_p \end{aligned} \quad (13)$$

where N_p is the output prediction horizon. The weight, Q_4 , in the cost function (12) have to be chosen large enough such that the optimiser tries to keep the slack variables at zero if the original, hard constrained solution is feasible.

So far, the optimisation problem (12) is non-convex due to the nonlinearity of the system dynamic (6). In order to recover the convexity of the optimisation problem the nonlinear model is replaced by linear model, which can be obtained by linearising the system (6) around an operating point (x_0, u_0) :

$$\begin{aligned} \Delta x(t+1) &= \mathcal{A}x(t) + \mathcal{B}u(t) \\ \Delta T_d(t) &= \mathcal{C}x(t) + \mathcal{D}u(t) \end{aligned} \quad (14)$$

The matrices \mathcal{A} , \mathcal{B} , \mathcal{C} and \mathcal{D} are the Jacobian matrices of the nonlinear model (28).

$$\begin{aligned} \mathcal{A} &= \left. \frac{\partial f(x(t), u(t))}{\partial x} \right|_{u_0, x_0}, \quad \mathcal{B} = \left. \frac{\partial f(x(t), u(t))}{\partial u} \right|_{u_0, x_0} \\ \mathcal{C} &= \left. \frac{\partial h(x(t), u(t))}{\partial x} \right|_{u_0, x_0}, \quad \mathcal{D} = \left. \frac{\partial h(x(t), u(t))}{\partial u} \right|_{u_0, x_0} \end{aligned} \quad (15)$$

The states, inputs and outputs of the nonlinear system are related to the states, inputs and outputs of the current LTV system by the relationship

$$\begin{aligned} \Delta x(t) &= x(t) - x_0 \\ \Delta u(t) &= u(t) - u_0 \\ \Delta T_d(t) &= T_d(t) - y_0 \end{aligned} \quad (16)$$

The dynamic optimization problem (12) subject to the

linear system dynamics (15) is reduced to a “standard” Linear MPC, formulated in terms of a quadratic problem and solved using a quadratic programming approach.

V. SIMULATION RESULTS

In the first case, we study a realistic, industrial scenario that has been supplied by an actual steel production company. The furnace speed maximum values changes in time and a series of both expected and unexpected halts takes place. From $t=0$ to $t=5$ hours v_{max} is limited to 0.002 m/s, then at $t=5$ hours, there is an unexpected problem in the finishing mill and the furnace must stop production. Immediately after that, the finishing mill announces that the problem will be solved within 15 minutes. At $t=5.25$ the furnace is asked to produce maximally after $t=8$ hours and v_{max} is increased to 0.005 m/s. At $t=10$ hours a scheduled delay occurs, which lasts one hour, and is announced one hour in advance. This simulation scenario is shown in Figure 2.

The corresponding plots of drop-out temperature, gas temperature in each section of the furnace and input variables are shown in Figure 4. The output response plots show that the controller is able to maintain the drop-out temperature within the specified limits, despite the continuous changes in the speed constraints. No constraint violation was detected in the manipulated variables responses. The fluctuation of the fuel flux has significant impact on the energy saving. Because the controller can regulate the fuel flux in the on-line optimization, it is also an ideal energy saving technique. Taking the fuel flux change into account in the performance index is useful to make the fuel flux changes smoother, for large fluctuation of fuel flux is harmful to the combustion in the furnace. The profit over the simulation horizon is $7.7217e+005$ euro.

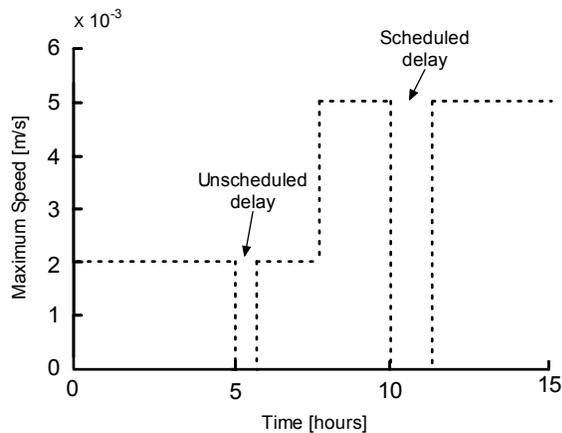


Figure 2 Maximum Speed Variation

VI. CONCLUSIONS

In this paper, we have presented a model predictive control design procedure for the reheating furnace. Simulations illustrate that the proposed control strategy provides significant advantages in the operation of reheat furnaces, including:

- Reduced fuel consumption. This benefit arises from the ability to control the slab heating at all time.
- Increased furnace capacity. This is because the control system can respond quickly to changes in material flow and various delays.

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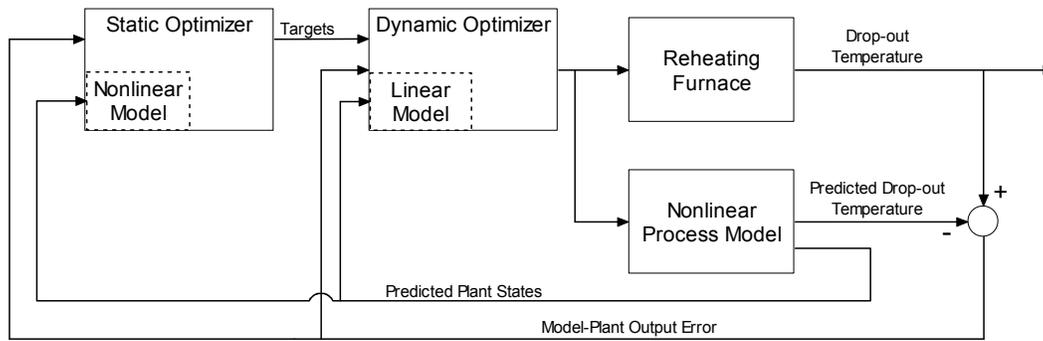


Figure 3 Feedback control scheme

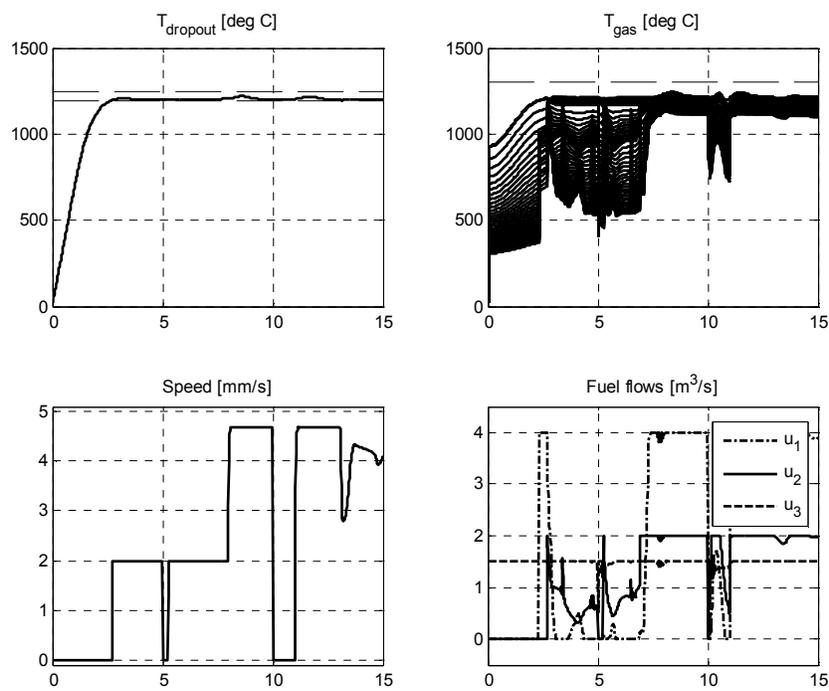


Figure 4 Simulation Results