Implementation of model predictive control in a programmable logic controller

https://doi.org/10.31713/MCIT.2023.078

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Abstract—**The article is aimed at the development of modern automatic control systems, which should provide high-performance indicators in the conditions of variable operating modes of industrial equipment due to effective control structures and algorithms. The purpose of the study is to reduce the cost of the basic oxygen furnace steel, which is a consequence of the increase in the share of scrap metal due to the enhanced post-burning of CO to CO_2 in the cavity, by optimal controlling the duty mode parameters using model-predictive control. The blowing mode of the basic oxygen furnace was considered as a technological object of control, and the problem of controlling blowing parameters in conditions of non-stationarity of the rate of metal decarburization was analyzed. The use of a model-predictive controller made it possible to improve the quality of control for the oxygen flow circuit by 39% and the maximum dynamic deviation of the CO_2 content in the gases was reduced by 16.5% compared to the PID control. The implementation of a software-hardware control system using model-predictive control based on a programmable logic controller is considered.**

Keywords—model-predictive control, basic oxygen furnace, quadratic functional, state space model, control algorithm.

I. Introduction

The modern basic oxygen furnace (BOF) process is a high-tech and automated production equipped with a large amount of measurement and control devices. In the current conditions of metallurgical production development, the tasks of developing resource-saving steel smelting technologies, theoretical and practical aspects of new energy-saving blowing methods, and increasing the efficiency of heat energy utilization are relevant [1]. In manual control, the blowing process often deviates from the optimal, disrupting the slag formation process, resulting in either reversion or foaming of the slag, leading to carryovers and emissions. Only 45-50% of melts, and sometimes even less, are produced successfully on the first attempt under manual control [2]. Important parameters of the blowing mode include blowing intensity, the height of the lance above the level of the calm bath, penetration depth, pressure, and quantity of oxygen jets [3]. The goal of BOF control is to obtain metal with a specific chemical composition and temperature at the end of the blowing process. However, direct measurement of these parameters during blowing is impossible due to the absence of suitable sensors that can operate in BOF conditions [4]. In such case the application of control algorithms that allow the process to be conducted under optimal conditions is relevant.

II. Setting Objectives

The aim of the work is to implement optimal control of the blowing parameters using model predictive control (MPC) based on a programmable logic controller (PLC), which will increase the share of scrap metal by increasing the state of CO combustion to CO_2 in the converter cavity.

III. Controller Design and Implementation

A model-predictive control (MPC) with a quadratic functional was synthesized taking into account the constraints of the BOF smelting mode. The development of the model-predictive controller consists of the following main stages: building a predictive model, determining the performance index characterizing the regulation quality, solving the optimization problem – finding the optimal control strategy that minimizes the performance index. To construct the predictive model of the MPC, we will use the mathematical model of the oxygen converter smelting mode [5]. For the automatic control system of the oxygen converter smelting process the problem of program control and stabilization in the presence of disturbances is considered, so it is necessary to switch to the incremental form (1) of the predictive model in the state space:

$$\begin{aligned}&\Delta u(t)=u(t)-u(t-1)\Rightarrow u(t)=u(t-1)+\Delta u(t)\\&x'(t)=Ax(t)+Bu(t-1)+B\Delta u(t),\end{aligned}\qquad(1)$$

where $u(t)$ – control action; $x(t)$ – process state; A, B – state space matrix.

To do this, we will introduce a new state variable and extend the system (2):

$$\begin{cases}x'(t)=Ax(t)+Bu(t-1)+B\Delta u(t)\\x_u'(t)=x_u(t)+\Delta u(t).\end{cases}\qquad(2)$$

As a result, a predictive model (3) of the oxygen converter smelting process blowing mode was obtained in the form of a controlled canonical state-space model:

$$\begin{cases} \begin{bmatrix} x'(t) \\ x_u'(t) \end{bmatrix} = \begin{bmatrix} A & B \\ 0 & I \end{bmatrix} \begin{bmatrix} x(t) \\ x_u(t) \end{bmatrix} + \begin{bmatrix} B \\ I \end{bmatrix} \Delta u(t) \\ y(t) = \begin{bmatrix} C & 0 \end{bmatrix} \begin{bmatrix} x(t) \\ x_u(t) \end{bmatrix}. \end{cases} \quad (3)$$

The transformation of the continuous model (3) into a discrete model (4) in state space was performed using the Euler method [6]:

$$\begin{cases} \begin{bmatrix} x_1(k+1) \\ x_2(k+1) \\ x_3(k+1) \\ x_4(k+1) \\ x_5(k+1) \\ x_6(k+1) \\ x_u(k+1) \\ x_H(k+1) \end{bmatrix} = \begin{bmatrix} A_d & B_d \\ 0 & I \end{bmatrix} \cdot \begin{bmatrix} x_1(k) \\ x_2(k) \\ x_3(k) \\ x_4(k) \\ x_5(k) \\ x_6(k) \\ x_u(k) \\ x_H(k) \end{bmatrix} + \begin{bmatrix} B_d \\ I \end{bmatrix} \cdot \begin{bmatrix} \Delta u_{vo_2}(k) \\ \Delta H(k) \end{bmatrix} \\ \begin{bmatrix} v(k) \\ \gamma_{CO_2}(k) \end{bmatrix} = \begin{bmatrix} C_d & 0 \end{bmatrix} \cdot \begin{bmatrix} x_1(k) \\ x_2(k) \\ x_3(k) \\ x_4(k) \\ x_5(k) \\ x_6(k) \\ x_u(k) \\ x_H(k) \end{bmatrix}. \end{cases} \quad (4)$$

As a result, new matrices (5) of the controlled canonical discrete state-space model were obtained:

$$\overline{A}_d = \begin{bmatrix} 1-\frac{T_0}{T_v^{u_{O_2}}} & 0 & 0 & 0 & 0 & 0 & \frac{T_0}{T_v^{u_{O_2}}} & 0 \\ 0 & 1 & T_0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & T_0 & 0 & 0 & 0 & 0 \\ 0 & \frac{-T_0}{T_{1\gamma_{CO_2}}^{u_{O_2}}} & \frac{-T_0 T_{3\gamma_{CO_2}}^{u_{O_2}}}{T_{1\gamma_{CO_2}}^{u_{O_2}}} & 1-\frac{T_0 T_{2\gamma_{CO_2}}^{u_{O_2}}}{T_{1\gamma_{CO_2}}^{u_{O_2}}} & 0 & 0 & \frac{T_0}{T_{1\gamma_{CO_2}}^{u_{O_2}}} & 0 \\ 0 & 0 & 0 & 0 & 1 & T_0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{-T_0}{T_{1\gamma_{CO_2}}^{H}} & 1-\frac{T_0 T_{2\gamma_{CO_2}}^{H}}{T_{1\gamma_{CO_2}}^{H}} & 0 & \frac{T_0}{T_{1\gamma_{CO_2}}^{H}} \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}; \quad (5)$$

$$\overline{B}_d = \begin{bmatrix} \frac{T_0}{T_v^{u_{O_2}}} & 0 \\ 0 & 0 \\ 0 & 0 \\ \frac{T_0}{T_{1\gamma_{CO_2}}^{u_{O_2}}} & 0 \\ 0 & 0 \\ 0 & \frac{T_0}{T_{1\gamma_{CO_2}}^{H}} \\ 1 & 0 \\ 0 & 1 \end{bmatrix}; \; \overline{C}_d = \begin{bmatrix} k_v^{u_{O_2}} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & k_{\gamma_{CO_2}}^{u_{O_2}} & 0 & 0 & k_{\gamma_{CO_2}}^{H} & 0 & 0 & 0 \end{bmatrix},$$

where

$$k_{\gamma_{CO_2}}^{H} = 12{,}15 \, \%/m; \; k_v^{u_{O_2}} = 6 \, m^3/(\min \cdot \%);$$

$$k_{\gamma_{CO_2}}^{u_{O_2}} = -0{,}756 \frac{\%_{CO_2}}{\%_{u_{O_2}}};$$

$$T_0 = 0{,}1 s; T_v^{u_{O_2}} = 1{,}2\ s; T_{1\gamma_{CO_2}}^{u_{O_2}} = 9{,}55 s;$$

$$T_{2\gamma_{CO_2}}^{u_{O_2}} = 14{,}98 s; T_{3\gamma_{CO_2}}^{u_{O_2}} = 7{,}05 s;$$

$$T_{1\gamma_{CO_2}}^{H}(\tau) = T_{v_c}^{H} T_{\gamma_{CO_2}}^{v_c} = 15{,}16 \cdot e^{-\left(\frac{\tau-3{,}47}{2{,}9}\right)^2} + 14{,}21 \cdot e^{-\left(\frac{\tau-15{,}57}{2{,}6}\right)^2} + 24{,}68 \cdot e^{-\left(\frac{\tau-9{,}73}{6{,}0}\right)^2} [c];$$

$$T_{2\gamma_{CO_2}}^{H}(\tau) = T_{v_c}^{H} + T_{\gamma_{CO_2}}^{v_c} = 7{,}05 \cdot e^{-\left(\frac{\tau-3{,}47}{2{,}9}\right)^2} + 6{,}61 \cdot e^{-\left(\frac{\tau-15{,}57}{2{,}6}\right)^2} + 11{,}48 \cdot e^{-\left(\frac{\tau-9{,}73}{6{,}0}\right)^2} + 2{,}15 \; [c].$$

τ – time from the start of blowing, min.

To implement the model-predictive controller leading, manufacturer-independent PLC automation software CODESYS V3.5 [7] was chosen, which complies with the requirements of the IEC 61131-3 standard. A functional block of the predictive model for the MPC was developed (see Figure 1). The code for the respective functional block is available at the following link: https://drive.google.com/drive/folders/1jJHXEQJXw38ifcWAnHMWl8oY1_lzmcBM?usp=sharing.

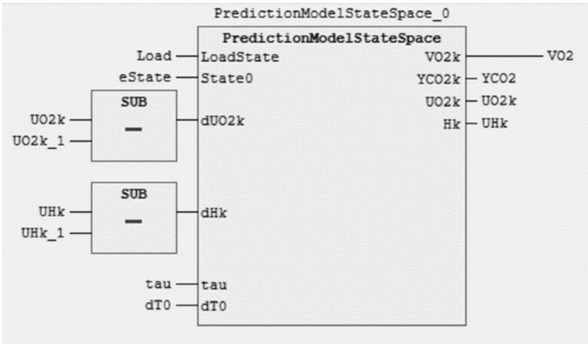

Figure 1. Functional block of the predictive model

The mathematical model for prediction uses the current state of the system as initial conditions. Since measuring the current state of the system is not possible, it is necessary to develop a state observer. For the considered system the Kalman criterion [8] is satisfied regarding observability and controllability, as the rank of the respective matrices equals the number of states of the system, allowing the development of a state observer and a controller. The structural diagram of the state observer for the system is provided in Figure 2, and a Luenberger observer was utilized as the observer.

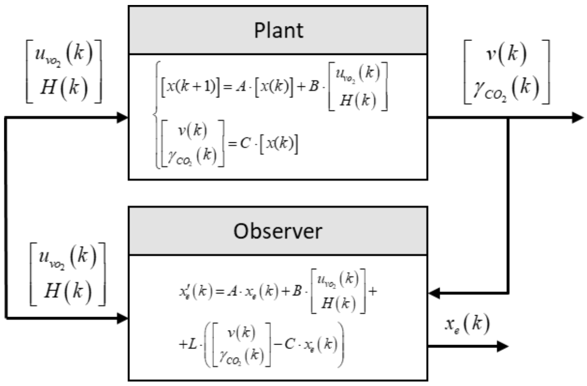

Figure 2. Structural diagram of the state observer for the system

The advantage of using the Luenberger observer is the availability of an additional state correction loop in case of discrepancies between the model and the actual behavior of the system [9]. The mathematical model of the Luenberger observer (6) is presented in the form of the equation:

$$x_e'(k) = A \cdot x_e(k) + B \cdot \begin{bmatrix} u_{vo_2}(k) \\ H(k) \end{bmatrix} + L \cdot \left(\begin{bmatrix} v(k) \\ \gamma_{CO_2}(k) \end{bmatrix} - C \cdot x_e(k) \right), \quad (6)$$

where $L = \begin{bmatrix} l_1 & 0 \\ 0 & l_2 \\ 0 & l_3 \\ 0 & l_4 \\ 0 & l_5 \\ 0 & l_6 \end{bmatrix}$ is the discretized matrix of the observer compensator. The design of the observer compensator depends on the desired characteristic equation: $(s-\beta_1)\cdot(s-\beta_2)\cdots(s-\beta_n)=0$ The observer poles must ensure rapid convergence $\left(\begin{bmatrix} v(k) \\ \gamma_{CO_2}(k) \end{bmatrix} - C \cdot x_e(k) \right)$ of the observation error to 0. This means that the observer's estimation error should decrease 2-5 times faster than the state of the actual system [9]. Let's consider model (6) and find l_1 the observer compensator. Taking into account the dynamic properties of the system for observer synthesis, the eigenvalues of the matrix are $\beta_1 = -2.5$. To find l_1 the Ackermann formula [10] was used $l_1 = 0.023$. Similarly, for $\beta_{2-4} = -0.75$ and $\beta_{5,6} = -1$ were gotten $l_2 = 0.01; l_3 = -0.0019; l_4 = 0.0001; l_5 = 0.0081;$ $l_6 = -0.0017$. A functional block of the Luenberger state observer (see Figure 3) was programmed. The code for the respective functional block is available at the following link:

https://drive.google.com/drive/folders/1jJHXEQJXw38ifcWAnHMWl8oY1_lzmcBM?usp=sharing.

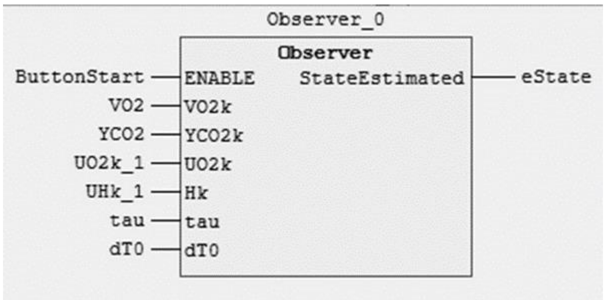

Figure 3. Functional block of the observer

The next crucial element of the MPC is the cost function. To characterize the control quality the quadratic functional (7) was used:

$$J_k(\bar{y}, \Delta\bar{u}) = \sum_{j=1}^{P} \left[\left(y_{k+j} - r_{k+j} \right)^T R \left(y_{k+j} - r_{k+j} \right) + \Delta u_{k+j-1}^T Q \Delta u_{k+j-1} \right], \quad (7)$$

where R and Q are positive definite symmetric matrices; P is the prediction horizon length. The prediction horizon based and the coefficients of matrices R and Q depend on the dynamics of the process and chosen according to the desired quality of the transient process of the control system:

$$R = \begin{bmatrix} 0.2 & 0 \\ 0 & 1.5 \end{bmatrix}; Q = \begin{bmatrix} 0.2 & 0 \\ 0 & 0.03 \end{bmatrix}; P = 35.$$

A functional block for the cost function was developed. The code for the respective functional block is available at the following link:

https://drive.google.com/drive/folders/1jJHXEQJXw38ifcWAnHMWl8oY1_lzmcBM?usp=sharing.

The chosen quadratic functional is a convex function, thus leading to a convex programming problem. The quadratic functional is algorithmically defined, so zeroth-order methods were applied. These are used when, for some reason, calculating the gradient of the objective function is impossible, and also in cases where the function is algorithmically defined. This includes scenarios where conducting a natural or numerical experiment is required to compute the function values for certain argument values. The Hooke-Jeeves method [11] was chosen as an optimization method. It demonstrates an optimal balance between the number of steps and function evaluations when solving the optimization problem, compared to the simplex method and the steepest descent method. The search according to this method consists of a sequence of search steps to explore the function around the base point, from which, in case of success, a search is made in the pattern. A functional block for the Hooke-Jeeves optimization method (see Figure 4) was created. The code for the respective functional block is available at the following link:

https://drive.google.com/drive/folders/1jJHXEQJXw38ifcWAnHMWl8oY1_lzmcBM?usp=sharing.

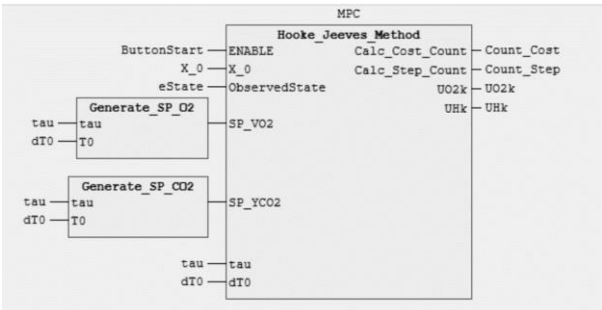

Figure 4. Functional block of the optimization solver

The simulation procedure for the MPC with oxygen converter blowing parameters was performed using Matlab Simulink (process model) and SoftPLC CODESYS V3.5 (MPC). In Matlab Simulink the Euler algorithm with a fixed step size of 0.1s was chosen for solving equations. The absolute and relative calculation accuracy was set to 0.001. In the CODESYS V3.5 programming environment, the execution type of the main task was set as cyclic with a step of 0.1s, which is sufficient for the real process. Communication between Matlab Simulink and CODESYS V3.5 is carried out using the OPC UA protocol. We will perform modeling of the transient characteristics of the automatic control system for the oxygen converter blowing mode using the model-predictive approach. Let's consider the transient characteristic of the control system for the oxygen converter blowing intensity with a predetermined setpoint change (see Figure 5).

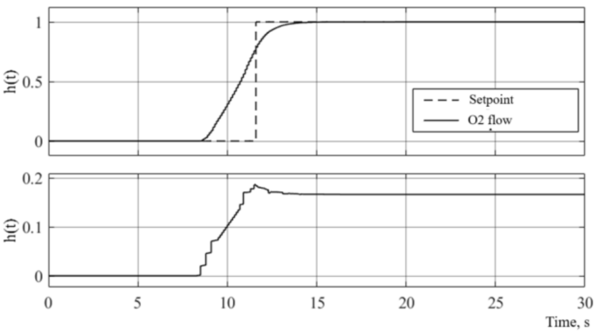

Figure 5. Transient response of the oxygen blowing

For the system regulating the CO_2 content during the oxygen converter process, the task of program control and stabilization is considered in the presence of disturbances: changes in oxygen flow rate for blowing, variation in decarburization speed, introduction of bulk materials, etc. The transient response of the CO_2 content control system with a predetermined setpoint change is shown in Figure 6.

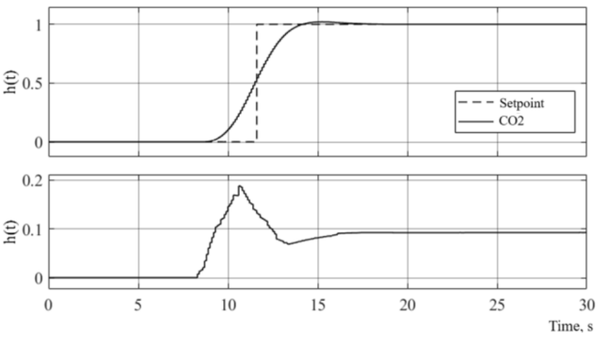

Figure 6. Transient response of the CO_2 content

The transient processes of the blowing mode were simulated for a duration of 20 minutes for a 160-ton converter with model predictive control and a combined control system with PID control for the CO_2 content in the flue gases and oxygen flow rate for the program control task. The obtained transient processes of the automatic control system for the oxygen converter smelting mode using the combined control system provided an Integrated Squared Error (ISE) for the oxygen flow rate loop of 9075 and for the CO_2 content in the converter gases loop of 1397. The maximum dynamic deviation of the CO2 content in the converter gases was 17.5%. Using the model predictive controller achieved an ISE for the oxygen flow rate loop of 5577 and for the CO2 content in the converter gases loop of 43. The maximum dynamic deviation of the CO2 content in the converter gases was 0.95%.

IV. Conclusions

An automatic control system for the oxygen converter blowing mode parameters was developed and analyzed. A Luenberger state observer for the oxygen converter smelting mode was synthesized. Taking into account the dynamic properties of the system, the observer compensator was calculated for the desired characteristic equation using the Ackermann formula. The observability and controllability of the oxygen converter smelting mode model were investigated according to the Kalman criterion. A state observer and a controller were designed to minimize the linear-quadratic functional. Since the quadratic functional was algorithmically defined, a zeroth-order optimization method, the Hooke-Jeeves method, was applied. The application of the model predictive controller improved the regulation quality for the oxygen flow rate loop by 39% (reducing the quadratic deviation from 9075 to 5577) and for the CO_2 content control loop in the converter gases by 97% (reducing the quadratic deviation from 1397 to 43). The maximum dynamic deviation of the CO2 content in the converter gases was reduced by 16.55% (from 17.5% to 0.95%) compared to the combined control system with PID control.

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