    # Model predictive control for the blowing regime of the steelmaking process

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Abstract

The study sought to lower the production costs of basic oxygen furnace steel by increasing the amount of scrap metal used. This was accomplished by improving the conversion of CO to CO_2 during afterburning in the furnace chamber through optimal model predictive control of the blowing regime parameters. This system enabled simultaneous control of the blowing intensity and the lance position while dynamically adjusting the oxygen consumption and CO_2 content setpoint. The result was improved control quality and energy savings during the melting process, driven by the increased afterburn degree during the CO to CO_2 conversion. The proposed solution improves the quality of process control within the technological constraints of the plant compared to the combined control system using PID controllers. Simulation of the transient processes of a 20-minute blowing mode for BOF with model predictive control and a combined control system with a PID controller of CO2 content was conducted. Application of the proposed a model predictive controller result: the integral squared error was reduced, a 1.63-fold for the oxygen consumption loop and a 32.5-fold in the converter gas CO_2 content control loop. Additionally, the maximum dynamic deviation of the CO_2 content in the converter gases was reduced by 16.55% compared to the combined control system utilizing PID controllers.

Keywords

Prediction model, control, steelmaking

1. Introduction

Steel production is a complex process that requires the use of a combination of technological, energy, and transport equipment, each necessitating appropriate automation. Today, the basic oxygen furnace (BOF) is the most popular steelmaking process in the world and is becoming increasingly widespread. According to the World Steel Association Sustainability Indicators 2023 report [1], the global share of BOF was 72%. Ukrainian metallurgical production is extremely energy-intensive due to the wear and tear of fixed assets and outdated technological processes. When steel is produced in BOF, up to 30% of the metal content is scrap. The rest is liquid pig iron, which is more expensive than scrap and requires blast furnace production. Therefore, the current problem of the BOF process is to increase the amount of scrap in the converter steel melt. In today's metallurgical landscape, the modern basic oxygen furnace (BOF) process stands as a pinnacle of technological advancement, boasting automation and an array of measurement and control devices.

With ongoing developments in metallurgical production, the pursuit of resource-efficient steelmaking technologies, innovative energy-saving blowing methods, and heightened heat energy utilization efficiency remains paramount [2]. Under manual control, the blowing process often deviates from the optimal trajectory, disrupting slag formation and leading to undesirable outcomes such as slag reversion or foaming, which can result in carryovers and emissions. Only 45-50% of melts, and sometimes even fewer, are successfully produced on the first attempt when relying on manual control. Key parameters governing the blowing regime encompass blowing intensity, lance height above the calm bath level, penetration depth, pressure, and oxygen jet quantity [3]. The primary objective of BOF control is to achieve metal with precise chemical composition and

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temperature by the end of the blowing process. However, direct measurement of these parameters during blowing proves challenging due to the lack of sensors capable of operating effectively in BOF conditions [4]. Consequently, the application of control algorithms capable of steering the process toward optimal conditions emerges as a pertinent solution. At present, there are several known methods for increasing the proportion of scrap metal in the charge: preheating the scrap metal outside the converter and converting carbon monoxide to carbon dioxide inside the converter [2]. The gases exiting the converter are predominantly CO, making the conversion of CO to CO_2 an effective method that doesn't need extra equipment. Controlling blowing mode parameters like lance position and oxygen flow rates adequately achieves the desired outcomes. Model Predictive Control (MPC) is a modern approach for analyzing and synthesizing control systems using mathematical optimization methods. The ideology of the Model Predictive (MP) approach is based on the following scheme of feedback control [5]: a mathematical model of the plant is considered, with its current state serving as initial conditions; with a given control, a forecast of the plant movement is made over a certain finite time (prediction horizon); optimization of control is performed, aiming to approximate the forecast of the predictive model to the corresponding desired value (setpoint) at the control horizon; the found optimal control is implemented, and a measurement (or estimation based on measured variables) of the actual state of the object is performed at the end of the step; the prediction horizon is shifted forward by one step, and this algorithm is repeated. Although the majority of controllers (about 90%) utilize Proportional-Integral-Derivative (PID) laws [6, 7] and Fuzzy logic (FL) [8], an increasing number of researchers are implementing MPC to achieve higher control quality. Some researchers combine MPC with other approaches to generate setpoints for local controllers, such as fuzzy logic, artificial neural networks [9], and others. This is why Model Predictive Control is gaining popularity in the industries due to a clear algorithm and the use of model-based state-space and transfer function approaches.

2. Objective

The aim of this work is to increase the scrap content by improving the degree of CO to CO_2 conversion in the converter cavity through optimal control of the blowing mode parameters. In order to achieve this objective, the following research tasks have been undertaken:

- explore the intricacies of the technological process during the melting blowing regime;
- examination of approaches for synthesizing control systems and developing a mathematical model of the control system;
- synthesizing a model predictive controller and carrying out simulations of the control system for blowing regime.

3. Development of the control system

Steelmaking is an intensive process, so the converter operator physically cannot process a large volume of information, select the best mode, and intervene promptly in the course of the smelting process.

Key parameters of the blowing mode include the blowing intensity, lance height above the bath level, depth of penetration, pressure, and the quantity of oxygen streams [2]. Various approaches are used for building an automated control system for the BOF blowing mode: the use of static and dynamic predictive models (recommendations for refining smelting based on intermediate measurements and the history of "successful" smelts); control of the output parameters of smelting; dynamic control of blowing.

For example, in the article [3], the use of neural networks with backpropagation allows for the analysis of large datasets to optimize the smelting process.

Optimal dynamic control of the blowing mode using predictive models [4] enabled the authors to improve the metal output with specific substance and temperature, contributing to enhanced steel quality.

However, increasing the metal temperature leads to overheating of water-cooling structures and reduces the productivity of the unit. The use of a portion of the generated converter gas as fuel in the converter cavity for melting scrap metal will increase the scrap content, resulting in a reduction in the cost of BOF steel.

Considering that the gases exiting the converter consist of approximately 90% CO and <10% CO_2, there is significant potential for increasing the scrap ratio by enhancing the degree of CO combustion in the converter cavity. The dynamic relationship of the change in the degree of CO to CO_2 as the lance distance from the bath level varies can be described as a controllable canonical form model in state space (1):

$$\begin{cases} \begin{bmatrix} x_1'(t) \\ x_2'(t) \end{bmatrix} = \begin{bmatrix} 0, & 1 \\ -\dfrac{1}{T^H_{1\gamma_{CO_2}}(\tau)}, & -\dfrac{T^H_{2\gamma_{CO_2}}(\tau)}{T^H_{1\gamma_{CO_2}}(\tau)} \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix} + \begin{bmatrix} 0 \\ \dfrac{1}{T^H_{1\gamma_{CO_2}}(\tau)} \end{bmatrix} H(t), \\ \gamma_{CO_2}(t) = \begin{bmatrix} k^H_{\gamma_{CO_2}} & 0 \end{bmatrix} \begin{bmatrix} x_1(t) \\ x_2(t) \end{bmatrix}, \end{cases} \qquad (1)$$

where $x_{1,2}$ - system states of relationship of the change in the degree of CO to CO_2 as the lance distance from the bath level varies; $k^H_{\gamma_{CO_2}} = 12{,}15 \%/m$ - gain factor through the channel of decarbonization rate - the degree of oxidation of carbon to CO_2; $T^H_{1\gamma_{CO_2}}(\tau) = 15{,}16 \cdot e^{-\left(\frac{\tau-3{,}47}{2{,}9}\right)^2} + 14{,}21 \cdot e^{-\left(\frac{\tau-15{,}57}{2{,}6}\right)^2} + 24{,}68 \cdot e^{-\left(\frac{\tau-9{,}73}{6{,}0}\right)^2}$ - first time constant, s; $T^H_{2\gamma_{CO_2}}(\tau) = 7{,}05 \cdot e^{-\left(\frac{\tau-3{,}47}{2{,}9}\right)^2} + 6{,}61 \cdot e^{-\left(\frac{\tau-15{,}57}{2{,}6}\right)^2} + 11{,}48 \cdot e^{-\left(\frac{\tau-9{,}73}{6{,}0}\right)^2} + 2{,}15$ - second time constant, s; τ - time from the start of blowing, min; H - lance distance from the bath level, m; γ_{CO_2} - the degree of oxidation of carbon to CO_2, %.

The change in the degree of CO to CO_2, depending on the position of the oxygen blowing pneumatic valve, can be represented as a controllable canonical form model in state space (2):

$$\begin{cases} \begin{bmatrix} x_3'(t) \\ x_4'(t) \\ x_5'(t) \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ -\dfrac{1}{T^{u_{O_2}}_{1\gamma_{CO_2}}(\tau)} & -\dfrac{T^{u_{O_2}}_{3\gamma_{CO_2}}(\tau)}{T^{u_{O_2}}_{1\gamma_{CO_2}}(\tau)} & -\dfrac{T^{u_{O_2}}_{2\gamma_{CO_2}}(\tau)}{T^{u_{O_2}}_{1\gamma_{CO_2}}(\tau)} \end{bmatrix} \begin{bmatrix} x_3(t) \\ x_4(t) \\ x_5(t) \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \dfrac{1}{T^{u_{O_2}}_{1\gamma_{CO_2}}(\tau)} \end{bmatrix} u_{vO_2}(t), \\ \gamma_{CO_2}(t) = \begin{bmatrix} k^{u_{O_2}}_{\gamma_{CO_2}} & 0 & 0 \end{bmatrix} \begin{bmatrix} x_3(t) \\ x_4(t) \\ x_5(t) \end{bmatrix}. \end{cases} \qquad (2)$$

where x_{3-5} - system states of relationship of the change in the degree of CO to CO_2, depending on the position of the oxygen blowing pneumatic valve; $k^H_{\gamma_{CO_2}} = -0{,}756 \dfrac{\%_{CO_2}}{\%_{u_{O_2}}}$ - gain factor through the channel of position of the oxygen blowing pneumatic valve - the degree of oxidation of carbon to CO_2; $T^{u_{O_2}}_{1\gamma_{CO_2}} = 9{,}55$ - first time constant, s; $T^{u_{O_2}}_{2\gamma_{CO_2}} = 14{,}98$ - second time constant, s; $T^{u_{O_2}}_{3\gamma_{CO_2}} = 7{,}05$ - second time constant, s; τ - time from the start of blowing, min; u_{vO_2} - position of the oxygen blowing pneumatic valve, %; γ_{CO_2} - the degree of oxidation of carbon to CO_2, %.

The synthesis of a model predictive controller using a quadratic functional was conducted, taking into account the constraints of the BOF blowing regime.

The development of the model predictive controller includes the following primary components: constructing the predictive model, defining the functional that describes the control quality, and solving the optimization problem to determine the optimal control strategy that minimizes the functional.

The structural diagram of the system state observer is depicted in Fig. 1. A Luenberger observer was employed as the state observer (Fig. 2). One advantage of using the Luenberger observer is its capability to incorporate an additional state correction loop to address discrepancies between the model and the actual behavior of the system.

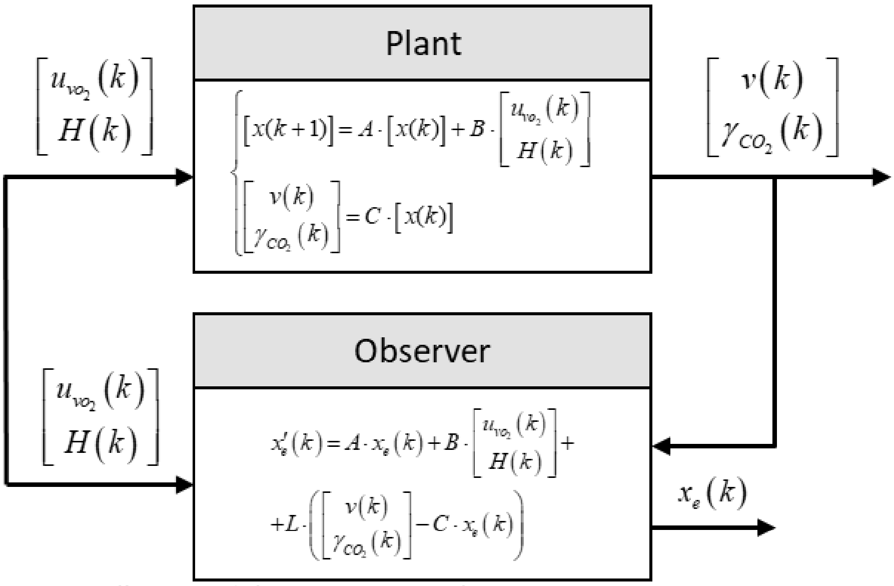

Figure 1: Structural diagram of the system state observer

The benefit of utilizing the Luenberger observer lies in its provision of an additional state correction loop for addressing discrepancies between the model and the actual behavior of the system [10]. The mathematical model of the Luenberger observer (3) is presented in equation form as follows:

$$x_e'(k) = A \cdot x_e(k) + B \cdot \begin{bmatrix} u_{vo_2}(k) \\ H(k) \end{bmatrix} + L \cdot \left(\begin{bmatrix} v(k) \\ \gamma_{CO_2}(k) \end{bmatrix} - C \cdot x_e(k) \right), \tag{3}$$

where x_e - estimated system states of relationship of the change in the degree of CO to CO_2; A, B, C - state space model matrix; $L = \begin{bmatrix} l_1 & 0 \\ 0 & l_2 \\ 0 & l_3 \\ 0 & l_4 \\ 0 & l_5 \\ 0 & l_6 \end{bmatrix}$ 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 [10].

The quality of control is cost function using the linear-quadratic functional (4):

$$J_k(\bar{y}, \Delta\bar{u}) = \sum_{j=1}^{P}\left[\left(y_{k+j} - r_{k+j}\right)^T R\left(y_{k+j} - r_{k+j}\right) + \Delta u_{k+j-1}^T Q \Delta u_{k+j-1}\right], \quad (4)$$

where $\bar{y}$ - sensors value; r - setpoint value; $\Delta\bar{u}$ - change in control action; R and Q are positive definite symmetric matrices, and P represents the number of prediction horizon steps. The choice of the prediction horizon will be determined based on the process dynamics and the coefficients of matrices R and Q, aligning with the desired quality of the system's transient response: $R = \begin{bmatrix} 0{,}2 & 0 \\ 0 & 1{,}5 \end{bmatrix}$; $Q = \begin{bmatrix} 0{,}2 & 0 \\ 0 & 0{,}03 \end{bmatrix}$; P = 35.

As a result, a control system for the blowing regime was synthesized using a model predictive approach.

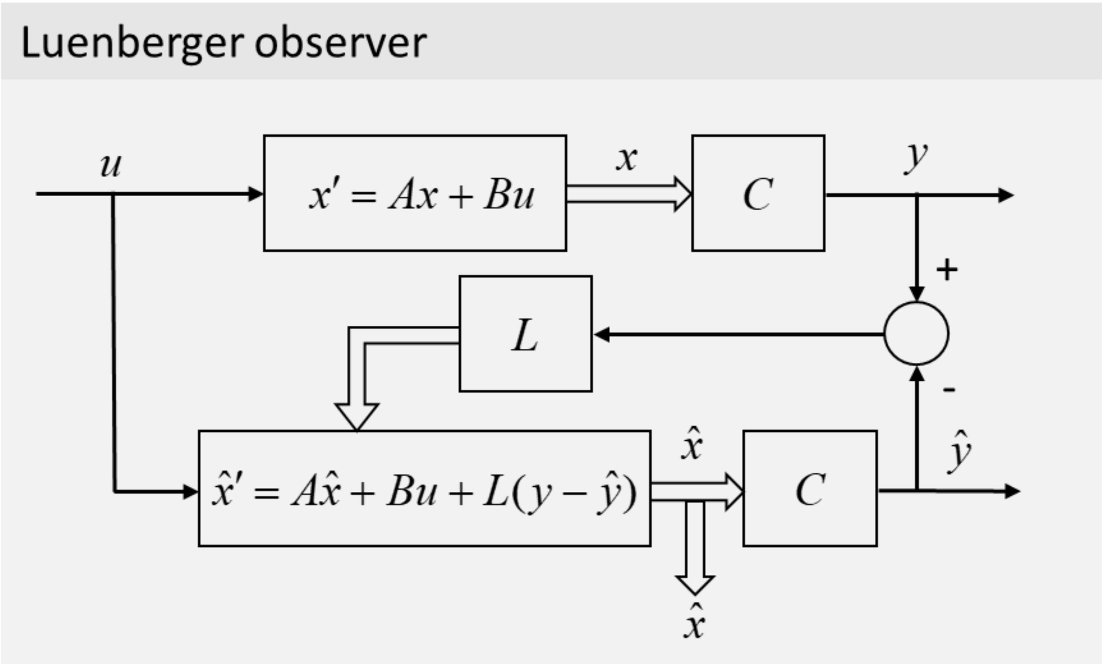

Figure 2: Luenberger state observer model

The simulation procedure was conducted using Matlab Simulink for the plant and SoftPLC CODESYS V3.5 for the controller. In Matlab Simulink, the Euler algorithm with a fixed step size of 0.1s was selected for solving equations, with absolute and relative calculation accuracies set to 0.001. In the CODESYS V3.5 programming environment, the main task execution type was set as cyclic with a step of 0.1s, which is suitable for the real-time process. Communication between Matlab Simulink and CODESYS V3.5 is established through the OPC UA protocol. The transient characteristics of the automatic control system for the blowing regime will be modeled using the model-predictive approach.

The transient response of the model-predictive control system for oxygen flow with and without a predefined setpoint change is depicted in Figure 3, 4.

In systems controlling CO_2 content during the BOF process, challenges include program control and stabilization amidst disturbances such as changes in oxygen flow rate, variations in decarburization speed, and the introduction of bulk materials. Figure 5 and 6 illustrates the transient response of the CO_2 content with the model-predictive control system with and without predefined setpoint change.

Block diagrams of the developed model predictive and combined PID – based control system are shown in Figure 7 and 8.

Also, simulation of the transient processes (Fig. 9) of a 20-minute blowing mode for BOF with model predictive control and a combined control system (Fig. 10) with a PID controller of CO_2

content. The transient processes obtained from the automatic control system of the basic oxygen furnace blowing mode using model predictive control yielded an Integrated Squared Error (ISE) of 5577 for the oxygen flow rate loop and 43 for the CO2 content in the converter gases.

Additionally, the maximum dynamic deviation of the CO2 content in the converter gases was 0.95%.

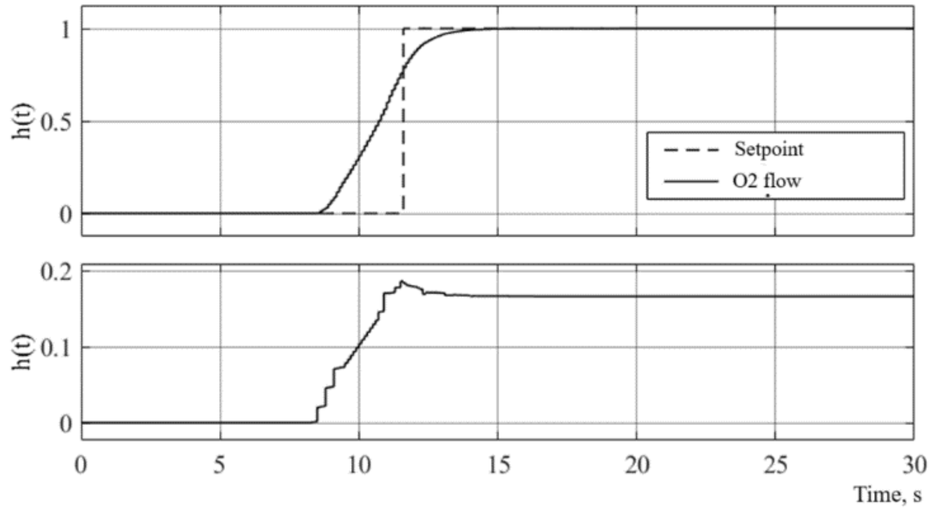

Figure 3: Transient response of the oxygen flow using MPC with a predefined setpoint

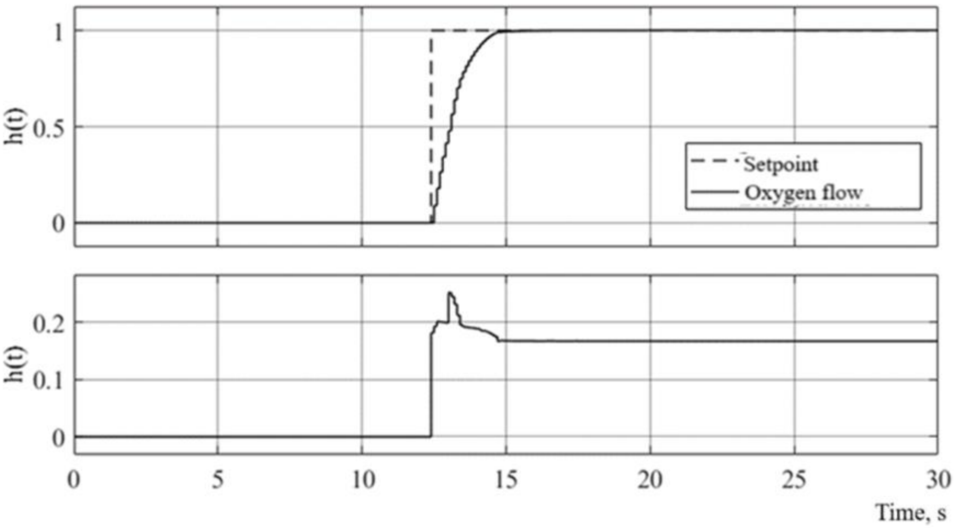

Figure 4: Transient response of the oxygen flow using MPC without a predefined setpoint

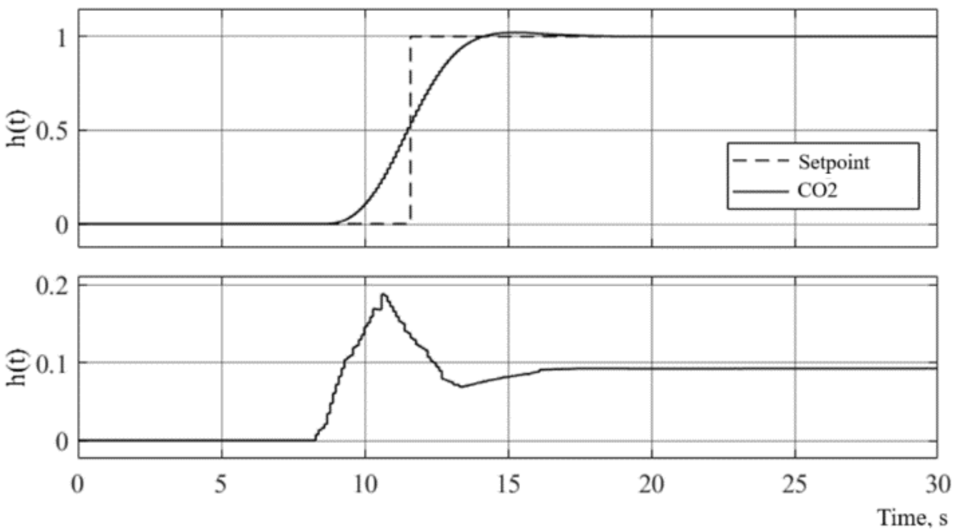

Figure 5: Transient response of the CO_2 content using MPC with a predefined setpoint

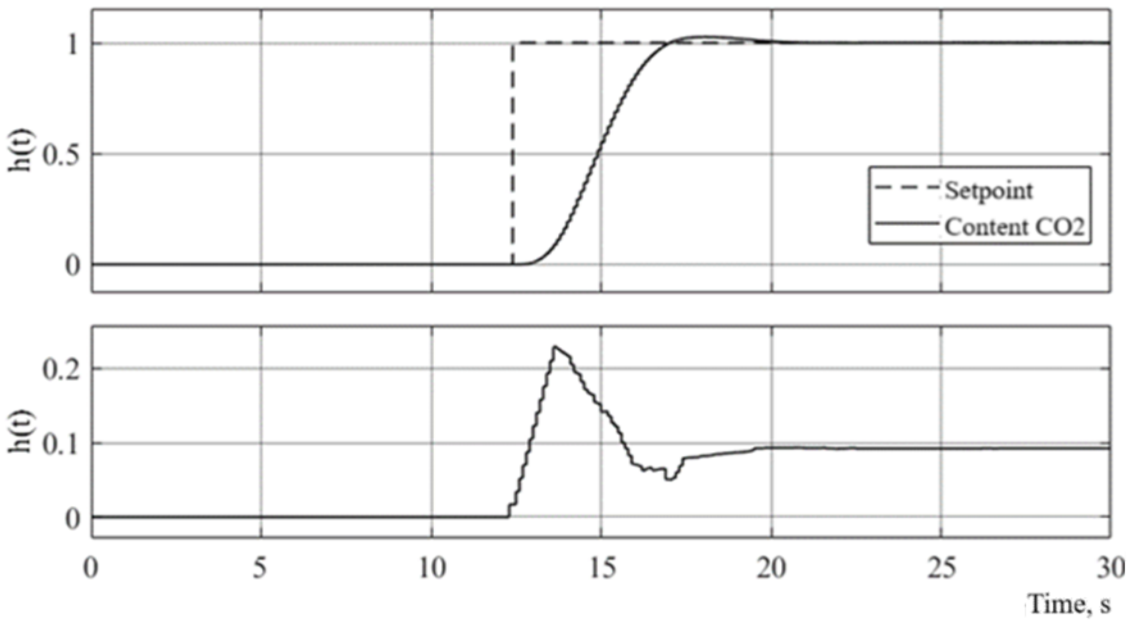

Figure 6: Transient response of the CO_2 content using MPC without a predefined setpoint

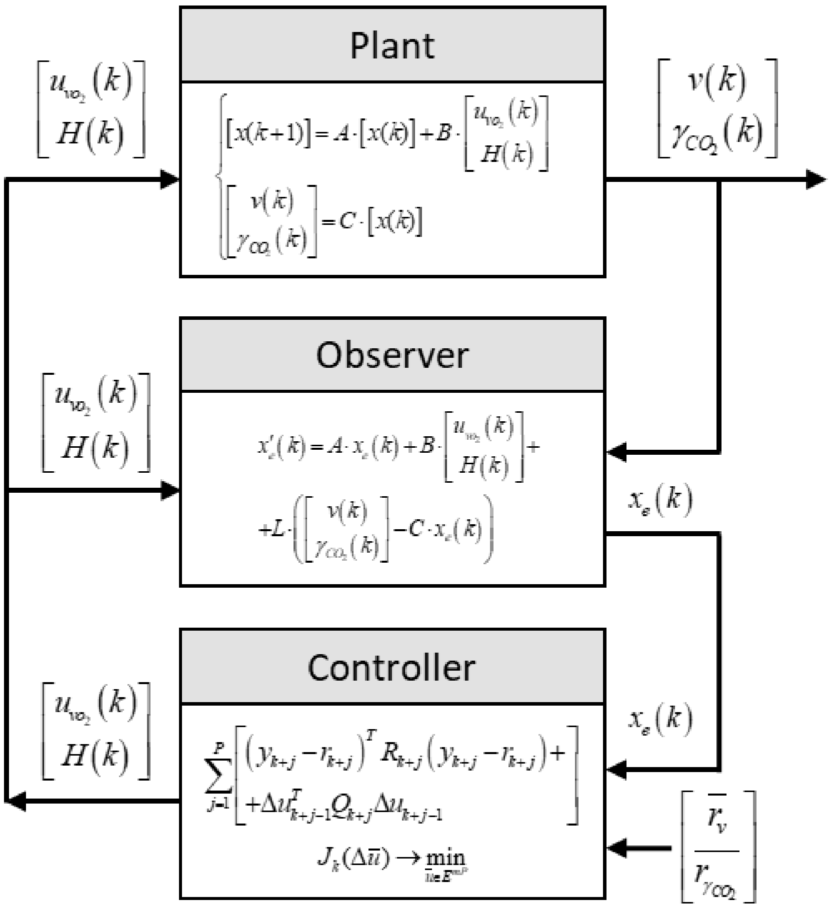

Figure 7: Block diagrams of the model predictive control system

The transient processes of the automatic control system for the basic oxygen furnace blowing regime, using a combination of a PID controller and model predictive control, resulted in an Integrated Squared Error (ISE) of 9075 for the oxygen flow rate loop and 1397 for the CO2 content in the converter gases. Additionally, the maximum dynamic deviation of the CO2 content in the converter gases was 17.5%.

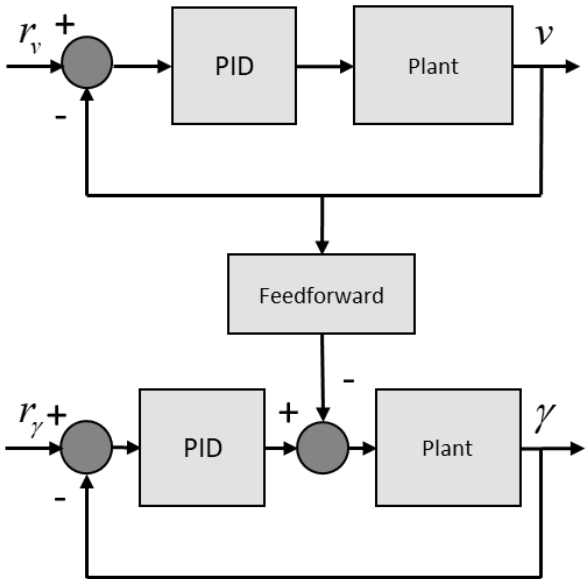

Figure 8: Block diagrams of the combined PID – based control system

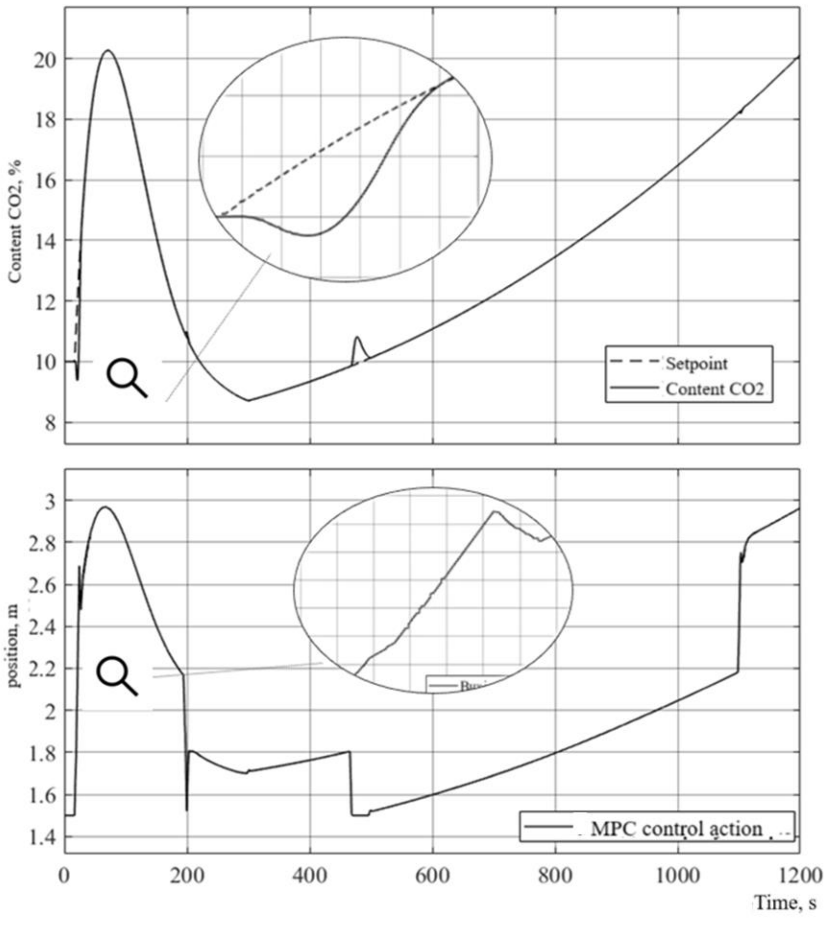

Figure 9: Transient processes of the automatic control system of the BOF blowing mode using model predictive control

The application of the model predictive controller led to an improvement in control quality for the oxygen flow rate loop by a factor of 1.6 (9075/5577) and for the CO2 content control loop in the converter gases by a factor of 32.5 (1397/43). Additionally, the maximum dynamic deviation of the CO2 content in the converter gases was reduced by 17% compared to the combined control system. These performance indicators of the automatic control system meet the specified requirements, demonstrating the effectiveness of implementing an enhanced automatic control system using model predictive control.

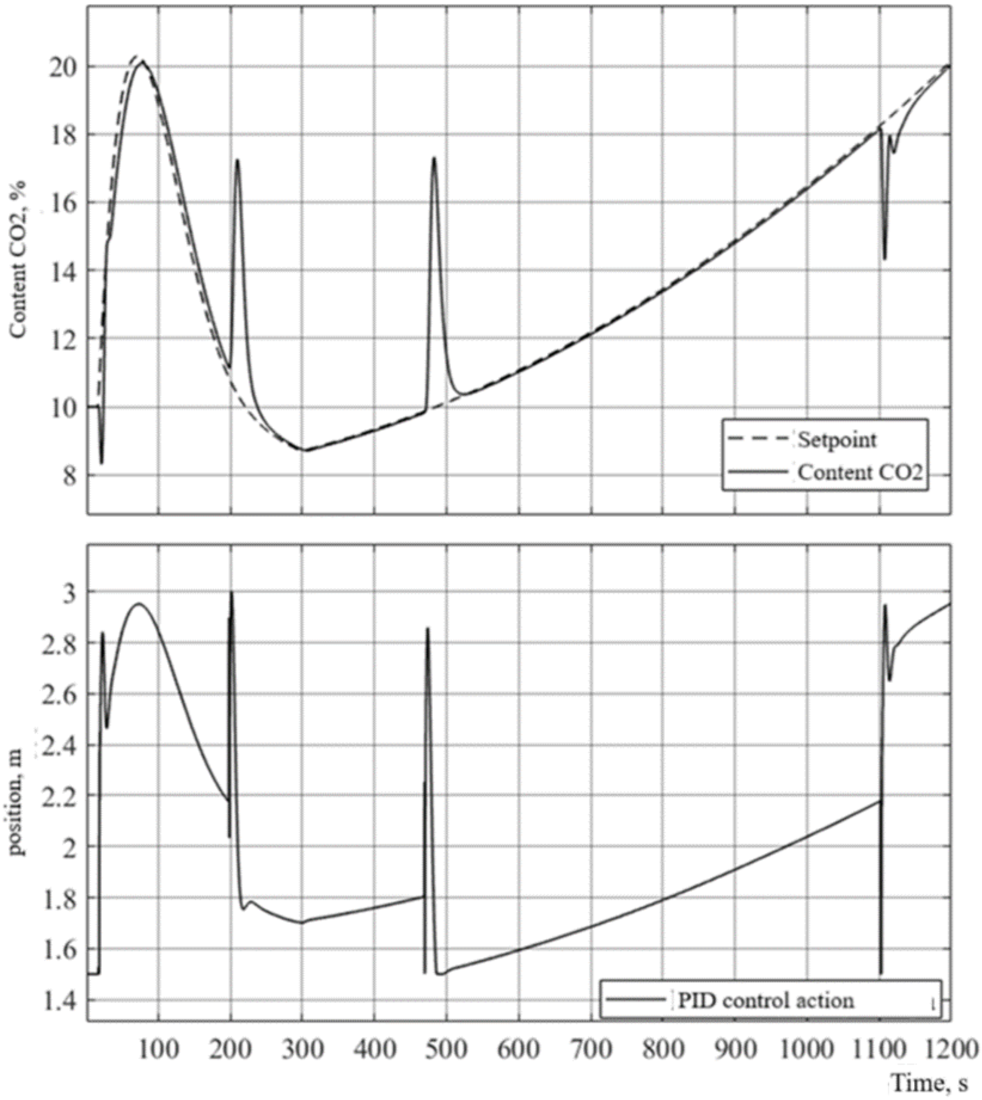

Figure 10: Transient processes of the automatic control system of the BOF blowing mode using combined control system with a PID controller

4. Conclusion

The purpose of the study is to reduce the cost of oxygen-converter steel, which is a consequence of the increase in the share of scrap metal due to the increase in the degree of post-burning of CO to CO_2 in the converter cavity, by optimal control of the parameters of the duty mode using model predictive control. In the study, the mathematical model of the blowing regime of basic oxygen furnace process was improved, taking into account the influence of the intensity of blasting on the process of decarburization of the bath, which made it possible to increase the accuracy and quality of blasting control in the conditions of changes in the oxygen consumption during purging. For the first time, an optimal control system for the parameters of blowing regime during basic oxygen furnace process was synthesized based on the principle of feedback with model-predictive control using a linear-quadratic functional, which allowed simultaneous control of the blowing intensity and the position of the lance, as well as to improve the quality of control and energy saving during melting, due to the increase in the degree of post-burning of CO to CO_2, which is a consequence of the increase in the proportion of scrap metal.

A model predictive controller has been synthesized for the blowing mode of the basic oxygen furnace smelting process. It includes a Luenberger state observer, an algorithmically defined linear-quadratic functional, and a zero-order optimization method to solve the problem of finding optimal control strategies. Simulation results demonstrated that the developed model predictive controller achieved an Integrated Squared Error (ISE) of 5577 for the oxygen flow rate loop and 43 for the CO_2 content in the converter gases. Furthermore, the maximum dynamic deviation of the CO2 content in the converter gases was reduced to 0.95%.

The implementation of the model predictive controller resulted in enhancing the control quality for the oxygen flow rate loop by a factor of 1.6 and for the CO_2 content regulation loop in the converter gases by a factor of 32.5. Additionally, the maximum dynamic deviation of the CO_2 content in the converter gases was reduced by 17% compared to the combined control system. The application of the model predictive control system, focused on enhancing energy-efficient heat utilization, improves the accuracy and quality of control.

This approach ensures increased combustion of CO to CO_2 within the BOF cavity by optimizing the position of the lance above the calm bath level and adjusting the oxygen flow pneumatic valve. This will lead to an increase in the proportion of scrap metal in the charge by 2.7%, potentially resulting in a reduction in the cost of BOF steel.

Further development is associated with the use of closed control systems for the degree of post-burning of CO to CO_2 and improvement of the predictive model of the blowing regime through the synthesis of a model predictive controller taking into account the technological saturation of the speed of movement of regulatory bodies, which allowed to improve the quality of process control in the presence of saturation.

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