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Optimizing integrated steelworks process off-gas distribution through Economic Hybrid Model Predictive Control and Echo State Networks

S. Dettori*, I. Matino*, V. Colla*, A. Wolff, M. Neuer**, V. Baric***, D. Schroeder***, V. Utkin*** F. Schaub***.**

**Scuola Superiore Sant'Anna, TeCIP Institute, 56124, Italy, (e-mail: {s.dettori, i.matino, v.colla}@santannapisa.it).*

*** VDEh-Betriebsforschungsinstitut GmbH, 40237, Düsseldorf, Germany (e-mail: {andreas.wolff, marcus.neuer}@BFI.de)*

**** ArcelorMittal Bremen, 28237, Bremen, Germany, (e-mail: {valentin.baric, dustin.schroeder}@arcelormittal.com)*

Abstract: Steel production in integrated steelworks involves the simultaneous production of various by-products, including process off-gases that are usually exploited for generating electricity in the internal power plant, heat and steam. Their discontinuous production is managed through complex network, gasholders and torches, which must be managed with stringent operational constraints. In this paper we present a supervision and control system designed to optimize the economic management of the distribution of process off-gases that also allows minimizing the environmental impact. The system implements a digital twin based mainly on machine learning techniques, including Echo State Networks, and a hierarchical optimization system, which first level is based on an economic model predictive approach and the second level is based on the economic hybrid model predictive control. This system allows to effectively maximize the use of off-gases while minimizing the environmental impact of their use up to 97%.

Keywords: Economic Hybrid Model Predictive Control, Artificial Intelligence, Machine Learning, Process off-gas distribution, Integrated Steelworks, Reservoir computing

1. INTRODUCTION

In the race to reduce greenhouse gas emissions, the steel industry is making intense efforts and important investments, to improve the efficiency and reduce the impact of production processes, by also exploiting at best its own by-products in a circular economy perspective. Optimizing consumption and production of energy distributed through the process gas networks is part of this improvement, as it plays a key role in the company's economic balance, and can also reduce the environmental impact. Process off-gases (POGs) are a valuable energy source produced in the three main integrated steelworks processes: coke ovens (COG), blast furnaces (BFG) and basic oxygen furnaces (BOFG). They can satisfy a large portion of energy demands of the steelworks from power plants, furnaces and steam production. However, their production and their distribution to consumers is a complex issue. Firstly, some of these gases (e.g. BOFG) are produced in a discontinuous way, thus excesses and shortage must be managed through gasholders and torches, respectively, (and flaring implies waste of valuable energy resources and also environmental impact), and through natural gas (NG) purchase. Therefore, POGs distribution must be planned over time and must consider future trends of production and demand, constraints of networks, transformation equipment and consumers. Such task also involves production planning to some extent, as it affects POGs production and consumption. The problem of POGs optimal distribution has typically been tackled through real-time optimization systems that allow modelling the main energy and material flows, dynamics of plants, and equipment from a mathematical point of view, through the solution of Mixed Integer Linear (MILP) or nonlinear (MINLP) Programming formulations (Zhao et al., 2017a; Zeng et al., 2018; Pena et al., 2019; Qiu et al., 2022). However, literature has often focused on POG distribution control system design, neglecting systems for predicting energy flows, which allow to enhance their usefulness and effectiveness. Although several works concern predictive models of POG (Zhao et al., 2016; Zhao et al., 2017b; Zhang et al., 2019), such models are not integrated into control systems, but rather used to give indications to operators, who make decisions based on experience.

The previous analysis shows the difficulty of planning the distribution of process off-gases through the mentioned methodologies for an interval longer than 1 h, mainly due to the difficulty of predicting future production and consumption of energy within integrated steelworks. In this sense, advanced digital twins aimed at describing energy media flows can be a turning point on improving the current methodologies.

In this work we overcome the mentioned limitations in two ways: (i) a detailed digital twin of energy flows has been developed, incorporating all equipment, plants and processes that contribute to POG consumption and transformation. This digital twin predicts the future POG internal production and consumption and simulates the behavior of networks and equipment according to calculated control trends. Among

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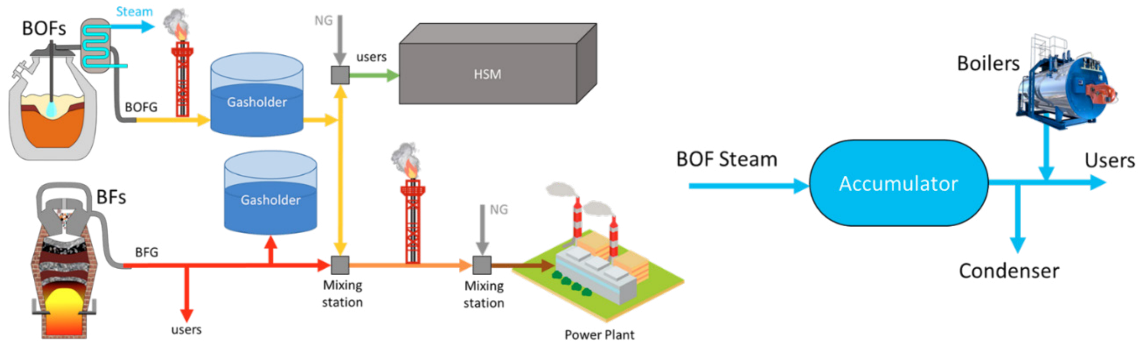

Figure 1: POG distribution and steam network schemes at AMB

different methodologies exploited, Echo State Networks (ESN) have proved to be particularly effective in predicting the quantities involved; (ii) a multi-period hierarchical supervision and control system that allows optimizing the distribution of POGs, the environmental and economic impact of the use of energy within the integrated steelworks. This system exploits all the information provided by the digital twin, through an enhanced mutual interaction.

The paper is organized as follows: Section 2 describes the energy flows in integrated steelworks, by reporting the specific study case; Section 3 presents the digital twins that aims at describing the integrated steelworks behavior from an energy point of view, and the formulation and design of the optimization strategy. In Section 4 the main results are reported. Finally, Section 5 provides some concluding remarks and hints for future work.

2. ENERGY FLOWS IN INTEGRATED STEELWORKS

In this paper we present the case study related to the ArcelorMittal Bremen (AMB) integrated steelworks, in which the main process off-gases are BOFG and BFG, since the plant exploit externally produced coke. The structure of the POG networks is schematically reported in Figure 1. The BOFG network is feed by two BOFs, and the off-gas excess is managed through a gasholder and torches. The Hot Strip Mill (HSM) is the main BOFG consumer, exploited within Walking Beam Furnaces (WBFs) that re-heat billets, blooms, and slabs before the rolling mill. Here, the available off-gas can be mixed with NG and burned in specific WBF zones. BOFG can also be transferred to the BFG network and mixed with BFG for electricity production in the power plant. The BFG is produced in two BFs and its excess is managed through torches and gasholder. The main BFG consumer are the power plant, the hot blast stoves and steam boilers.

In this specific case study, it is possible to minimize both environmental impact by scheduling and then manipulating POG volume flow to WBFs, power plant, and steam boilers. The main objective is to avoid the use of torches, and keeping the level of gasholder between minimum and maximum range, finding the best POG distribution solution between the internal users in order to balance economic and environmental objectives. As secondary objective, a stable and smooth POG exploitation is needed, avoiding as much as possible abrupt changes of the setpoints for each subnetwork and equipment.

3. OFF-GAS OPTIMIZATION SYSTEM

The developed DSS core is a complex hierarchical supervision and control system composed of three main functional blocks: (i) a database exploited for collecting plant data and as a foundation for the communication between the several parts of the software and operators; (ii) a digital twin that models and predicts the energy flows within the integrated steelworks; (iii) an optimization system that optimizes the POG distribution for helping process operator in the management of each energy subnetwork (POG, NG, steam and electricity).

3.1 The Integrated Steelworks Digital Twin

Digital Twins have a key role in the industry digitalization, as they can virtually represent a physical plant which characterization can be adapted and constantly updated through its data (VanDerHorn et al., 2021).
In this work, different methodologies have been used for reproducing the behavior and dynamics of energy flows and equipment, in function of the specific task that here, for the sake of synthesis, can be classified in (i) system simulation and (ii) energy forecasting. System simulations allow to study how controllable equipment and processes react to control strategies. The models used within optimization problems are essentially linear, mainly based on state space representations or simple linear regressions, in order to simplify as much as possible the control strategy and calculating it in real-time. The modelling errors in terms of normalized mean absolute error in this case are below 4%, that justifies the linear control approach in this case study.
Forecasting models predict the energy production and consumption in the main energy-intensive processes of the plant. Those predictions are exploited by the optimization system for compensating the strong effects of disturbances on off-gas, steam and electricity networks. These models exploit the current and past data of each process and its production scheduling. Most of the predictions are calculated through various machine learning methodologies, including Deep Echo State Networks (Gallicchio et al., 2017), Gaussian Mixture Regressions and Feed Forward Neural Networks that allow to have an insight into the future behavior of energy flows for horizons from 2 to 24 hours. In some previous works of the authors of this paper, some of the most remarkable results are here reported (Colla et al., 2019; Dettori et al., 2019; Dettori et al., 2022a; Matino et al., 2019a; Matino et al., 2019b).

3.2 The hierarchical supervision and control system

Maximizing POG usage, selecting the most convenient routes is a task that can be framed in the solution of constrained nonlinear optimization problems, as the behavior of energy networks and equipment behave in a substantially non-linear manner. Their optimal distribution in real-time requires a synergistic and coordinated action of different processes and equipment, a task that by nature is particularly complex to solve only through the sole experience of the operators of the various processes involved. Furthermore, due to the strong mutual interactions between energy networks, resulted from the continuous exchanges and transformations of energy, an effective optimization of their flows is possible only through a supervision and control system that can be designed to have a global point of view. For these reasons, we developed a hierarchical multiperiod real-time optimization system that helps process operator in taking global decision for minimizing the overall energy costs and environmental impact.
The developed control system is divided into two layers: the first, solves a Linear Programming (LP) formulation for a prediction interval up to one day ahead, which has the main purpose of planning the electricity production in the internal power plant. This layer, from now on High-Level (HL) Optimization system, calculates the main setpoints for the distribution of energy flows and POGs for each energy subnetwork. These setpoints are used by the Low-Level (LL) Optimization System which implements an Economic Hybrid Model Predictive Control strategy (Dettori et al., 2022b) that allows optimizing the control actions on all the POG networks, of the electricity production and of the steam networks, for a prediction interval of 2 hours ahead. The LL Optimization System solves in real-time, every minute, a MILP that describes all the main dynamics of the users and equipment involved and all the main operational constraints, through the well-known Mixed Logical Dynamical System framework.

More in details, the HL optimizer solves in real time, every 15 minutes, a LP formulation where the objective is minimizing the economic cost function $J_{HL}(t, N_{HL}, \boldsymbol{u_{HL}})$, calculated from the current time t for a prediction/control horizon of N_{HL} samples, through the manipulable variables $\boldsymbol{u_{HL}}$:

$$J_{HL}(t, N_{HL}, \boldsymbol{u_{HL}}) = \sum_{k=t}^{t+N_{HL}} \gamma^k \big(c_{NG}E_{NG}(k) + c_{EP}(k)E_{EP}(k) + \\ -c_{PP}(k)E_{PP}(k) + c_T E_T(k) + c_{cs}M_{cs}(k) + \boldsymbol{c}_s^T \boldsymbol{s}(k)\big) \quad (1)$$

where $\gamma \in (0,\ \ 1]$ is a parameter that de-penalizes the modelling error in predicting the future processes behaviors, k is the discretized time along the prediction horizon, c_{NG} and E_{NG} are respectively the prize and NG energy consumption considering only the manipulable portion, c_{EP} and E_{EP} are the prize and electric energy purchased from external sources, c_{PP} and E_{PP} are the prize and the electric energy production in the internal power plant, c_T and E_T are the prize and the POG energy waste in the torches, c_{cs} and M_{cs} are the prize and the mass of steam condensed, $\boldsymbol{c_s}$ and $\boldsymbol{s}$ are the prize and soft variables, useful to soften the most difficult constraints of the optimization problem.

The LP formulation includes a set of constraints that describe the behavior of gasholders, power plant, steam boilers, and steam and POG networks, and their main operative limits. The sampling time and control period of each energy sub-network in this layer is set to 15 minutes, which allows to neglect the dynamics of gas and steam flows in the networks, and the steam boiler and power plant dynamics. Furthermore, the following hypotheses have been made: in each point of POG pipelines the gas mixture is constant; POG and steam pressure and temperature are constant along the pipelines; gas and steam flows are instantly transmitted from producers to consumers through the pipelines. With these assumptions, the steam mass flow production in the j-th boiler M_{S_j} is calculated with (2), the electric energy generated in the power plant is calculated with (3), the dynamics of gasholder level of the l-th POG L_{GH_l} can be predicted with (4):

$$M_{S_j}(k) = k_{B_j} \sum_{i=1}^{g_{S_j}} NCV_i(k) V_i^B(k) + b_{B_j} \quad (2)$$

$$M_{S_j}^{\min} \leq M_{S_j}(k) \leq M_{S_j}^{\max} \quad (3)$$

$$E_{PP}(k) = k_{PP} \sum_{i=1}^{g_{PP}} NCV_i(k) V_i^{PP}(k) + b_{PP} \quad (4)$$

$$E_{PP}^{\min} \leq E_{PP}(k) \leq E_{PP}^{\max} \quad (5)$$

$$\Delta E_{PP}^{\min} \leq E_{PP}(k+1) - E_{PP}(k) \leq \Delta E_{PP}^{\max} \quad (6)$$

$$L_l^{GH}(k+1) = L_l^{GH}(k) + k_{GH_l} V_l^{GH}(k) \quad (7)$$

$$L_l^{GH\min} \leq L_l^{GH}(k) \leq L_l^{GH\max} \quad (8)$$

where NCV_i and V_i^B are the net calorific value and the volume of the i-th gas burned in the boilers, V_i^{PP} is the volume of the i-th gas burned in the power plant, V_l^{GH} and L_l^{GH} are the excess volume of l-th POG filling the gasholder and the its level, k_{B_j}, b_{B_j}, k_{PP}, b_{PP}, and k_{GH_l} are the identified models parameters.

POG distribution in the pipelines is calculated in two different ways. When there is no mixture between different gases, the balance of the l-th POG network is calculated as follows:

$$V_l^p(k) - V_l^c(k) - V_l^{PP}(k) - V_l^T(k) - V_l^{GH}(k) = 0 \quad (9)$$

otherwise, the energy balance E_h at the h-th mixing station outlet is calculated as:

$$\sum_{i=1}^{g_h} NCV_i^h(k) V_i^h(k) = E_h(k) \quad (10)$$

where V_l^p and V_l^c are respectively the POG production and consumption volumes, V_l^{PP} is the POG volume consumption in the power plant, $V_l^T \in \left[0 \quad V_l^{T\max}\right]$ is the volume of POG waste in the torch, and $V_i^h \in \left[0 \quad V_i^{h\max}\right]$ is the volume of the i-th gas at the mixing station inlet.

The steam network behavior is modelled by considering only the steam mass flow balances:

$$M_{ncs}(k) + \sum_{j=1}^{n_b} M_{S_j} - M_{acc}(k) - M_{cs}(k) = 0 \quad (11)$$

$$M_{SN}(k+1) = M_{SN}(k) + \frac{15}{60}M_{acc}(k) \quad (12)$$

$$0 \le M_{SN}(k) \le M_{SN}^{max} \quad (13)$$

Where M_{ncs} it is a disturbance due to the excess of steam calculated between the producers of non-controllable steam (the BOF boilers) and the consumer plants, M_{acc} and M_{SN} are respectively the steam mass flow accumulated in the steam network and accumulators and the total accumulated steam.

For the electric network, the energy conservation is calculated:

$$E_{PP}(k) + E_{nce}(k) - E_{ncu}(k) + E_{EP}(k) - E_{ES}(k) = 0 \quad (14)$$

$$E_{EP} \ge 0, E_{ES} \ge 0 \quad (15)$$

Where E_{nce} and E_{ncu} are respectively the non-controllable electric energy production and consumption (disturbances acting on the electric system), E_{EP} is the electric energy purchased and E_{ES} is the electricity sold to external grid (if power plant is allowed to feed the external grid).

Since the LP formulation of the HL optimizer is substantially "simple" to solve, and the time interval of its predictive horizon is not large (up to 1 day with a 15 minute sampling time), the computational cost is not excessive. For this reason, no blocking strategy has been adopted for manipulable variables. This layer calculates three sets of setpoint that are transmitted to the LL optimizer, each set calculated for the specific POG/steam network: (i) The reference for BFG volume available for steam boilers; (ii) BOFG volume available for WBFs and volume transferable to the BFG network, BOFG burnable volume in the torches; (iii) Electric Energy production scheduling for the Power Plant, BFG volume burnable in the torches.

The LL optimizer has been developed following a Distributed Sequential hybrid economic MPC approach. Since in AMB case study the mutual interactions between the networks are essentially the transfer of BOFG to the BFG network and the use of BFG in the steam boilers, it is possible, through the setpoints calculated by the HL optimizer, to divide the global optimization problem through a distributed control approach in which three different MPCs deal with their own specific network, and sequentially solve the optimization problem in real-time: First, the BOFG network MPC solves its own optimization problem, calculating BOFG transferred to the BFG network ($\boldsymbol{v}_{\mathrm{BOFG}\rightarrow\mathrm{BF_n}}^{\mathrm{pred}}$) for the overall prediction horizon. Secondly, the steam network controller solves its distribution problem by calculating the BFG volume flow consumed in the boilers ($\boldsymbol{v}_{\mathrm{BFGcons}}^{\mathrm{pred}}$). These two setpoints are exploited by the BFG controller that finally calculates the POG amount to be sent to the power plant. In integrated steelworks where the mutual interactions between networks are of greater entity, an approach different than sequential should be used. In this case, in order to obtain an overall optimal solution, different methods can be used (Trodden et al., 2017).

More in details the LL optimizer calculates, for a prediction horizon of N_{LL} samples, a control strategy characterized by a 1 minute sampling time. The chosen sampling time allows considering the main dynamics of each equipment and network, and a more detailed and stringent set of constraints. As mentioned before, each network controller has its specific formulation. The main objective of the steam controller is keeping the pressure of steam accumulator p_a within the safety limits $[p_a^{min} \quad p_a^{max}]$ while satisfying the steam needs of the users connected to the network. In particular, the steam network controller minimizes the economic objective function $J_{LL}^{S}(t, N_{\mathrm{LL}}, \boldsymbol{u}_{\mathrm{LL}}^{S})$ at control instant t, by manipulating $\boldsymbol{u}_{\mathrm{LLS}} = [\boldsymbol{m}_{\mathbf{cs}} \quad \boldsymbol{\delta}_B \quad \boldsymbol{v}_{\mathrm{NG}_i} \quad \boldsymbol{v}_{\mathrm{BFG}_i}]^{\boldsymbol{T}}$ without a blocking strategy (and a prediction horizon equal to the control horizon):

$$J_{LL}^{S}(t, N_{LL}, \boldsymbol{u}_{\mathrm{LL}}^{S}) = \sum_{k=t}^{t+N_{LL}} \gamma^k \big(c_{NG} E_{NG}^{SN}(k) + c_{cs} m_{cs}(k) + \\ -c_p C_{p_a}(k) + C_{\Delta\delta_B}(k) + \boldsymbol{c}_s^{SN} \boldsymbol{s}^{SN}(k)\big) \quad (16)$$

Where E_{NG}^{SN} is the total NG consumption in the steam boilers, m_{cs} is the condensed steam mass flow, c_p is a fictious cost that penalizes the accumulator pressure for pressure outside the range $[\check{p}_a \quad \hat{p}_a]$:

$$C_{p_a}(k) = \max([0, \check{p}_a - p_a(k)]) + \max([0, p_a(k) - \hat{p}_a]) \quad (17)$$

$C_{\Delta\delta_B}$ is a fictious cost that penalizes (by a factor c_{off}) the switching of each i-th boilers δ_{off_i}:

$$C_{\Delta\delta_B}(k) = c_{\mathrm{off}} \sum_{i=1}^{n_b} \left|\delta_{\mathrm{off}_i}(k) - \delta_{\mathrm{off}_i}(k-1)\right| \quad (18)$$

Each boiler can be operated in different Boolean modalities δ: δ_{off_i} when it is off, δ_{BFG_i} when it exploits only BFG, and δ_{MG_i} when it exploits a mixture of BFG and NG. Each z-th modality δ_{z_i} is exclusive and is characterized by different limits on the heating power $[HJ_{iz}^{\min} \quad HJ_{iz}^{\max}]$:

$$\boldsymbol{\delta}_B = [\boldsymbol{\delta}_{\boldsymbol{B}_1} \quad \cdots \quad \boldsymbol{\delta}_{\boldsymbol{B}_{n_b}}], \delta_{B_i} = [\delta_{\mathrm{off}_i} \quad \delta_{\mathrm{BFG}_i} \quad \delta_{\mathrm{MG}_i}] \quad (19)$$

$$\delta_{\mathrm{off}_i} + \delta_{\mathrm{BFG}_i} + \delta_{\mathrm{MG}_i} = 1 \quad (20)$$

$$\delta_{iz} \rightarrow \left(HJ_{iz}^{\min} \le \sum_{l=1}^{gs_j} NCV_l(k) v_l^{B_i}(k) \le HJ_{ij}^{\max} \right) \quad (21)$$

Bold characters refer to vector of variables that takes into account the overall control horizon.

The problem formulation includes the steam mass conservation in the network calculated by (22) and the dynamic of the steam mass stored in the accumulator and network M_a:

$$m_{nc}(k) + \sum_{i=1}^{n_b} m_{B_i}(k) - m_{CS}(k) - m_a(k) = 0 \quad (22)$$

$$M_a(k+1) = M_a(k) - \frac{1}{60} m_a(k) \quad (23)$$

Where m_{nc} is the excess of steam mass flow between non-controllable producers (the BOF boilers) and the users that acts on the steam network as a disturbance, m_{B_i} is the steam mass flow produced by boilers and m_a is the mass flow stored in the accumulator and network. The boiler can exploit an amount of BFG that can exceed the BFG setpoint reserved for them by a quantity s_{BFG}, penalized in the cost function:

$$\sum_{i=1}^{n_b} v_{\mathrm{BFG}_i}(k) \le \boldsymbol{v}_{\mathrm{BFGcons}}^{\mathrm{pred}}(k) + s_{\mathrm{BFG}}(k) \quad (24)$$

The dynamics of the produced steam mass flow m_{B_i} is modelled by a state space model, whose parameter are identified through real field data. In the same way, the dynamics of the accumulator pressure is modelled through a specific state space model excited by the excess of steam mass flow that is stored within.

The BOFG and BFG controllers minimize their specific economic cost functions. BOFG controller implementation is widely described in the work (Wolff et al., 2019), where all the technical details and some simulation results are reported. For the AMB case study, the BFG controller implements a simpler formulation, in which the optimization routines minimize the following cost function:

$$J_{\mathrm{LL}}^{\mathrm{BFG}}(t, N_{\mathrm{LL}}, \boldsymbol{u}_{\mathrm{LL}}^{\mathrm{BFG}}) = \sum_{k=t}^{t+N_{\mathrm{LL}}} \gamma^k \big(c_{EP}(k)E_{EP}(k) - c_{PP}(k)E_{PP}(k)$$

$$+C_{\mathrm{BFG}}^{\mathrm{GH}}(k) + c_T E_{BFG}^T(k) + C_{\Delta E_{PP}}(k) + \boldsymbol{c}_s^{BFG}\boldsymbol{s}^{BFG}(k)\big) \quad (25)$$

Where the term $C_{\mathrm{BFG}}^{\mathrm{GH}}$ penalizes the level of gasholder when it is outside the range $[\check{L} \quad \hat{L}]$, E_{BFG}^T is the BFG waste in the torches, $C_{\Delta E_{PP}}$ penalizes the variation of produced electric energy in the power plant, $\boldsymbol{s}^{BFG}$ and $\boldsymbol{c}_s^{BFG}$ are respectively the soften variables of the most difficult constraints and their penalization price.

$$C_{\mathrm{BFG}}^{\mathrm{GH}}(k) = \max([0, \check{L} - L_{BFG}^{GH}(k)]) + \max([0, L_{BFG}^{GH}(k) - \hat{L}]) \quad (26)$$

$$C_{\Delta E_{PP}}(k) = c_{\Delta E}|E_{PP}(k+1) - E_{PP}(k)| \quad (27)$$

The electric network balance is calculated with equation (14), enhanced with three indicator constraints, where δ_S and δ_P are Boolean variables that respectively indicates when the electric energy is sold to the external grid or is purchased:

$$0 \le E_{EP}(k) \le \delta_P(k)E_{EP}^{max} \quad (28)$$

$$0 \le E_{ES}(k) \le \delta_S(k)E_{sold}^{max} \quad (29)$$

$$\delta_S(k) + \delta_P(k) = 1 \quad (30)$$

The BFG flows are modelled through:

$$v_{BFG}^p(k) - v_{BFG}^c(k) - v_{BFG}^{PP}(k) - v_{BFG}^T(k) - v_{BFG}^{GH_{in}}(k) = 0 \quad (31)$$

where v_{BFG}^p and v_{BFG}^c are respectively the BFG production and consumption (disturbances acting on the system), v_{BFG}^{PP} is the BFG consumption in the power plant, v_{BFG}^T is the BFG volume flow waste in the torches, $v_{BFG}^{GH_{in}}$ is the BFG excess accumulated in the gasholder. In particular, $v_{BFG}^{GH_{in}}(k)$ excites the level dynamics of the gasholder, simulated through an ad-hoc identified state space model.

The described supervision and control system has been prototyped in Matlab environment, through YALMIP (Lofberg, 2004) and GUROBI, respectively an optimization language and an optimization library, and the translated in C++ through Google Or-Tools and the optimization library SCIP. Each MPC solves in real-time the MILP formulation. The optimization routines must find a solution within a dedicated time slot in order to deliver the control trends to the operators that apply them through dedicated Human Machine Interfaces.

4. NUMERICAL RESULTS

The validity of the control approach has been assessed through a wide test campaign, by exploiting real past field data of the AMB integrated steelworks. Several scenarios have been simulated, which take into account both periods of more continuous steel production and periods of discontinuous production, during which POGs are produced in strictly proportional quantities. Here we summarized and reported the main achieved results. With the aim of verifying the behavior of each steam, POG and electricity network and assessing the achievable performances, and the gains in terms of economic costs and environmental impact, the supervision and control system was tested in closed loop through accurate models of each plant, equipment and network. Closing the loop through the models allows us to estimate the improvements that can be obtained if operators promptly applied the calculated control trends. Figures 2-3 summarize the results. All the figures and performances are normalized with respect to the maximum values for confidentiality reasons. More in details, figure 2 in blue and yellow respectively shows the economic costs for the optimized simulation (CTRL) and the real non-optimized data (Real). In particular, the figure presents only the fraction of energy costs that can be controlled through a proper POG distribution, and they do not take into account the overall energy expense of the integrated steelworks. The costs presented are the Total energy costs (including electricity, NG, and environmental impact). Figure 3 shows some results related to the energy distribution in the integrated steelworks: the BOFG distribution to the main users in the optimized and real cases (BOFG volumes are normalized with respect to its total produced volume); the environmental impact in terms of the total POG wasted in the torches; the amount of condensed steam in the condenser, exploited to control accumulator and network pressures.

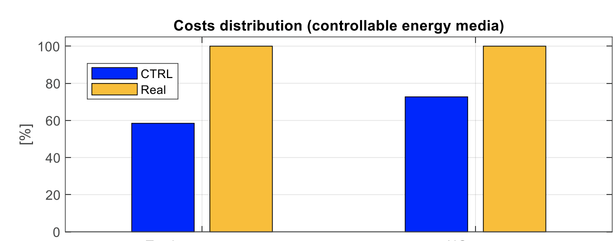

Figure 2: Costs distribution of the controllable fraction of energy media.

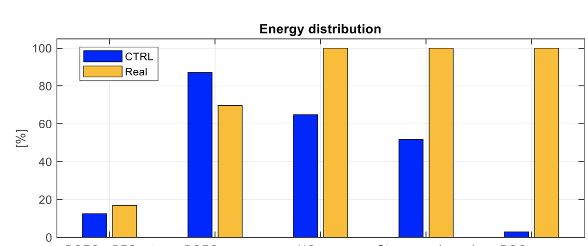

Figure 3: Energy distribution.

In general, the optimization system allows to synchronize all the energy flows, minimizing the exploitation of external resources such as natural gas and electricity. The controllers, thanks through the prediction calculated by the digital twin, maximize the electricity production through POGs, and distribute the POG flows to the plants, ensuring their energy needs but also considering economic aspects in function of the prices of natural gas and electricity. For the steam network, condenser and steam boilers are better synchronized with respect to the real case, allowing from a hand to decrease the energy losses in the condensed steam and decreasing the steam production in the boilers, with an improvement in the efficiency of the steam network management.

5. CONCLUSIONS

This paper presents a supervision and control system aimed at optimizing process off-gas distribution to satisfy the energy needs of integrated steelworks. The implemented system is the core of a Decision Support System that is going to be installed and tested by ArcelorMittal Bremen in their plant, improving the current energy management system. The control system takes advantage of an ad-hoc developed digital twin that models the integrated steelworks from and energy point of view, through standard linear modelling techniques and advanced machine learning methodologies. All the models have been developed and validated through real field data, and the optimization and control system has been extensively tested through simulation campaigns to verify its effectiveness and validate the approach followed. The system allows reducing the process off-gases flaring in the torches by up to 97% and significantly the purchase of electricity and natural gas from external sources, with a considerable reduction on the economic costs but also environmental impact. Future works will investigate mixed integer quadratic programming formulations for the low level controller, in order to implement a tracking MPC and study the possible improvements.

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