Real Case of Optimization in the Recovery and Use of Steelmaking Gases Through an Artificial Intelligence Tool Leading to CO_2 Reduction







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Digital technologies are transforming industry at all levels. Steel has the opportunity to lead all heavy industries as an early adopter of specific digital technologies to improve our sustainability and competitiveness. This column is part of AIST's strategy to become the epicenter for steel's digital transformation, by providing a variety of platforms to showcase and disseminate Industry 4.0 knowledge specific for steel manufacturing, from big-picture concepts to specific processes.

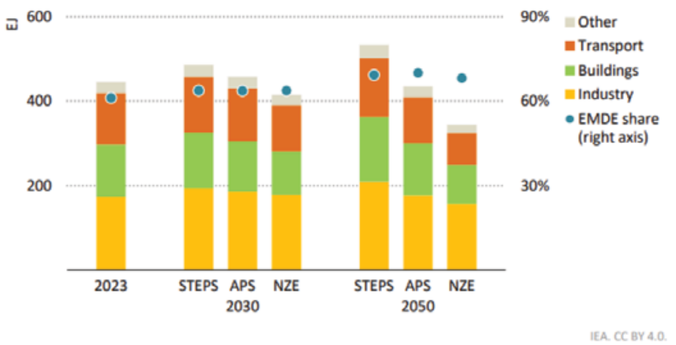
Environmental concerns and legislation are driving the steel industry to seek sophisticated tools for more efficient and cleaner processes. Digital tools based on data learning and optimization techniques show great potential in gas dispatch optimization. This study presents the use of the Viridis Dispatch tool to enhance gas recovery from the basic oxygen furnace process and optimize the distribution of residual gases in an integrated steel mill located in Brazil. The optimization led to a reduction in CO_2 emissions and operational costs, achieving a 17% reduction in CO_2 emissions when burning mixed fuel that supplies the blast furnaces.

Introduction

Global energy demand continues to grow, driven by industrial development and population increase. In 2023, this growth reached 1.7%, totaling 445 exajoules

Figure 1

Total final consumption by end-use sector and scenario, 2023, 2030 and 2050.[1]

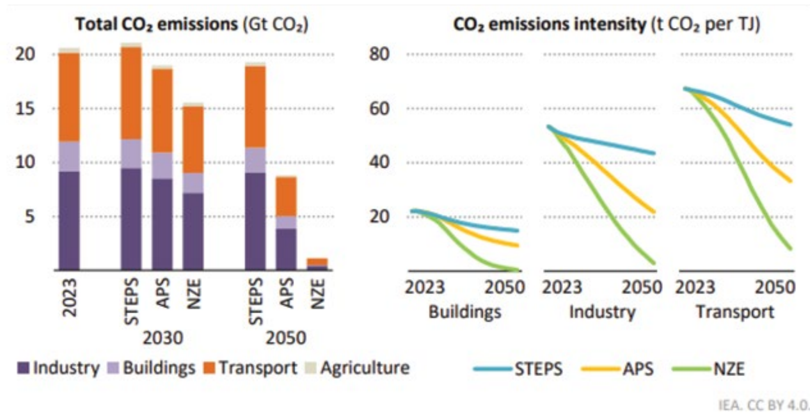


Final consumption increases to 2050 in the STEPS, declines in the APS and falls faster in the NZE Scenario; the difficulty of applying efficient technologies in industry increases its share

Note: EJ = exajoules; EMDE = emerging market and developing economies; NZE = Net Zero Emissions by 2050 Scenario.

Figure 2

CO_2 emissions and emissions intensity by end-use sector and scenario, 2023, 2030 and 2050.[1]



Industry and transport contribute most of the total emissions from final consumption, but transport sees the biggest drop in emissions intensity thanks to rising electrification

Note: Gt CO_2 = gigatonnes of carbon dioxide; t CO_2 per TJ = tonnes of carbon dioxide per terajoule.

(EJ). This rising demand is accompanied by significant environmental challenges, particularly concerning carbon dioxide (CO_2) emissions. Forecasts based on the latest market data, technology costs and an in-depth analysis of the prevailing policy frameworks across countries worldwide indicate that energy consumption will continue to grow steadily throughout the decade, with an average annual rate of 1.3% until 2030, in line with the pace observed over the past 10 years.[1] After that, growth will slow down, with the annual rate dropping to an average of just 0.5% between 2030 and 2050, as shown in Fig. 1 (STEP scenario).

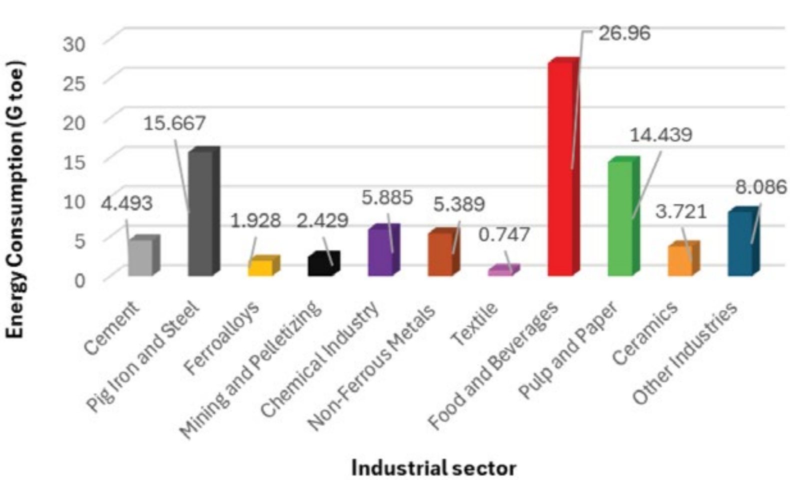
Forecasts indicate that this growth will occur exclusively in emerging and developing economies, driven by the growth of the industrial sector, contributing nearly 20 EJ of additional demand by 2030. According to the International Energy Agency, the industrial sector is responsible for approximately 39% of global energy consumption, with its emissions close to 10 GT CO_2, representing about 40% of total emissions by end-use sector. As shown in Fig. 2, this percentage remains consistent in the predicted scenarios until 2050.[1] Among industrial segments, steelmaking stands out as one of the largest emitters. Since its manufacturing processes are predominantly coal-based and highly dependent on fossil fuels such as oil and diesel, significant amounts of fossil CO_2 emissions are released, representing approximately 6% of global CO_2 emissions.[2]

In Brazil, which ranks as the ninth-largest steel producer,[3] the situation follows a similar trend. The industrial sector accounted for 28.6% of Brazil's energy consumption in 2023. The steel sector, which consumed 15.7 gigatonne of oil equivalent (Gtoe) in 2023 (Fig. 3), is one of the country's largest energy consumers, representing approximately 18% of the total consumption in the manufacturing industry and 5.5% of Brazil's total energy consumption.[4] The CO_2 emissions from this sector are also significant, given the intensive use of fossil fuels in blast furnaces and steel refining processes. Considering the international commitments made by Brazil under the Paris Agreement and the increasing pressure from regulators and consumers, it is essential to adopt strategies aimed at reducing energy consumption and greenhouse gas (GHG) emissions in steelmaking.

Steel production primarily occurs through two methods: the reduction of iron ore to obtain primary iron or the recycling of steel scrap through a melting process. Steel production from raw iron ore is preceded by iron production, whose main refining process occurs through the blast furnace (BF) followed by the basic oxygen furnace (BOF) converter, responsible for 71.1% of global steel production in 2023. The electric arc furnace (EAF) predominantly

Figure 3

Energy consumption by industrial sector in Brazil 2023.



operates with recycled steel scrap but can also use solid iron derived from direct reduced iron (DRI) processes (DRI or hot briquetted iron, HBI), which is melted using electricity. In the same year, 28.6% of global steel production was achieved by this method.[5]

The BF+BOF route, while predominant, is the most CO_2-intensive, with an average intensity of 2.33 tCO_2 per ton of crude steel. In comparison, production via the electric arc furnace (EAF) using scrap emits only 0.68 tCO_2 per ton of crude steel, while the DRI-EAF route has an intermediate intensity of 1.3 tCO_2 per ton of crude steel. The steel industry faces increasing pressure to reduce its environmental impact while maintaining efficiency and competitiveness. Stricter environmental regulations and growing concerns about climate change have driven the sector to seek advanced technologies that optimize processes and minimize GHG emissions.

To address this challenge, several initiatives have been implemented globally, promoting increased energy efficiency in steelmaking processes,[6] the use of hydrogen as a reductant in blast furnaces,[7,8] the electrification of processes,[9] the enhancement of metal scrap recycling,[10] and carbon capture and storage (CCS).[11,12] Among these solutions, the reuse of steel gases has proven to be an effective approach to reduce reliance on fossil fuels and, consequently, CO_2 emissions.

The residual gases generated during steel production, such as blast furnace gas (BFG), oxygen steelmaking gas (basic oxygen furnace gas, BOFG) and coke oven gas (COG), can be repurposed for energy generation, combustion in furnaces and heating internal processes. However, the efficient distribution of these gases presents a complex challenge, as it involves many dynamic variables; the interplay with other energy resources such as petroleum derivatives, steam and electricity; as well as the intricate gas distribution networks that span large areas and the number of consuming equipment.[13]

In this context, tools based on artificial intelligence (AI) have proven highly effective in optimizing the dispatch of steel gases. Studies show that AI-based systems can enhance energy efficiency and reduce emissions by automating the allocation of gases based on predictive analysis and optimization algorithms.[13–15] Successful applications include the use of artificial neural networks to predict gas availability,[16] smart control systems for optimized distribution,[17] and machine learning tools aimed at optimizing EAF processes by automatically defining input energy.[18]

This study aims to present the real-world application of the Viridis Dispatch tool in an integrated steel plant in Brazil. The implementation of this AI-based optimization system focused on improving the recovery of BOF gases and efficiently distributing the residual gases within the plant. By demonstrating the impact of gas dispatch optimization through AI in a real industrial environment, this study highlights the potential of digital transformation in steelmaking, paving the way for more sustainable and economically viable operations.

Methodology

Real Case Implementation

This section presents the real case of the implementation of Viridis Dispatch to enhance gas recovery from the basic oxygen furnace process and optimize the distribution of residual gases in an integrated steel plant in Rio de Janeiro. The facility in question, whose production flowchart is shown in Fig. 4, has two blast furnaces, a steel shop with two converters, continuous casting with two machines, a heat recovery coke oven and a sintering plant. Additionally, it has its own port for receiving raw materials and exporting steel slabs, its final product.

When analyzing the plant's energy flow, the integration of the steelmaking processes within the complex becomes evident. The combustion processes are interconnected and contribute to energy self-sufficiency, enabled by the reuse of process gases generated during the physicochemical transformation of reducing agents (BFG and BOFG). These gases are reused to meet energy demands in the blast furnace hot-blast stoves, in the heating of steel shop ladles, and in the burners of the sinter ignition furnace, as well as to help maintain the doors of the coke

Figure 4

Plant production flowchart.[19]

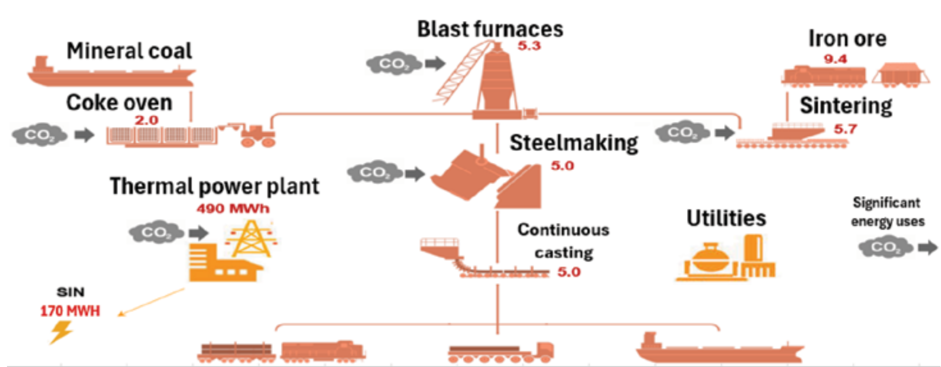
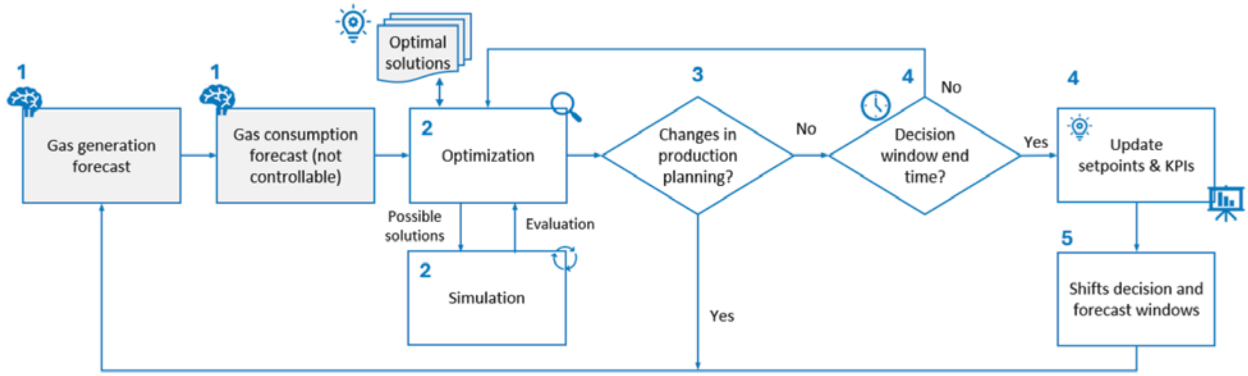


Figure 5

Strategy implemented by Viridis Dispatch to find optimized decisions.



ovens. Fossil natural gas is used to supplement the energy demand required to produce hot metal and steel.

Self-sufficient in electric power, the company operates two gas turbines equipped with heat recovery boilers that utilize residual gases from the blast furnaces and the steel shop, as well as a steam turbine that generates electricity from the high-pressure steam produced in the coking process. With this infrastructure, the plant generates an average of 360 MWh, meeting its own demand and supplying approximately 170 MWh to the Brazilian National Interconnected System.

Optimized management of gas and steam distribution in steel plants requires a holistic view of production, integrating functions such as forecasting the generation and consumption of inputs, simulating process variables, and employing real-time optimization algorithms to dynamically support decision-making as production conditions change. To achieve optimal operational decisions, it is essential to adopt a rolling horizon planning approach, ensuring that production order updates and uncertainties related to process variables are dynamically adjusted. A cyclic procedure for determining the best decisions regarding gas and steam recovery and utilization is demonstrated in Fig. 5, following the strategy implemented by Viridis Dispatch.

This procedure follows these steps:

1. Updating forecasts for the generation and consumption of energy inputs in each process area, based on production planning and parameters, historical time-series data, and predictive models defined for each area.
2. Executing a stochastic search procedure to identify decisions that optimize the economic performance of operations (or other objectives, such as emission reduction). Each potential solution requires scenario simulations to assess its impact and ensure operational constraints are not violated within a future time window (forecast horizon).
3. Revising forecasts to see if there are updates in production planning or key variables affecting the accuracy of the procedure.
4. Updating decision setups for operations if the decision window is exceeded (according to a user-defined update frequency). Performance indicators are also calculated to evaluate operational performance since the last decision window.
5. Shifting the forecast window, updating predictions and restarting the search process.

The adoption of this strategy involves developing three different types of modeling: consumption and generation forecasting models, simulation models, and the optimization model. To ensure development aligns with the plant's reality and specific process needs, these models were detailed based on information gathered during the basic engineering phase, site visits and workshops conducted with stakeholders from various process areas at different stages of development. The planning and preliminary results of these models are presented in the following sections.

Gas Generation and Consumption Forecast Models

The models were designed based on the interactions between different process areas, as summarized in Table 1, where the letters G and C indicate, respectively, the areas where a given input is generated or consumed. The forecasting models are summarized in Table 2. The relationship between these models is represented in Fig. 6, which illustrates how each process area (gray rectangles) consumes or generates energy inputs (gases and/or steam), as indicated by the circles in the upper-left (consumption) and upper-right (generation) corners.

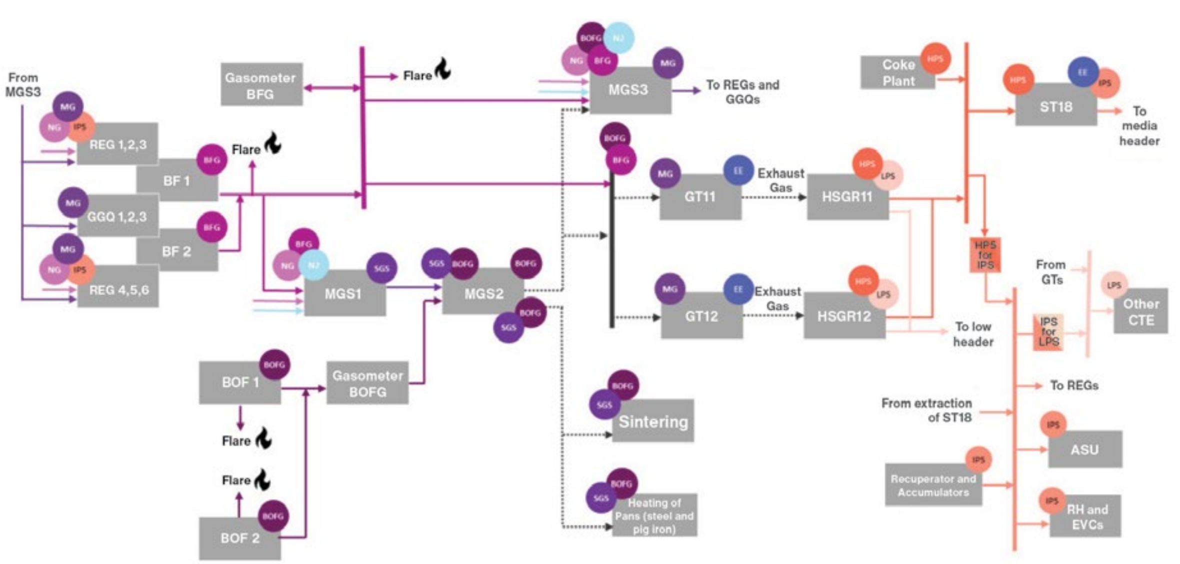
Table 1

Consumption and Generation Ratio of Steelmaking Gases by Process Area

Area	Mixed gas (MG) (BFG + BOFG + GN)	BFG	BOFG	Natural gas (NG)	N_2	Substitute gas (SGS) (BFG + NG)	Synthetic gas (SYG) (NG + N_2)
Blast furnaces		G					
Ladle heating station			C			C	C
Air separation unit							
Basic oxygen furnaces (BOFs)			G				
Coke oven							
Desulfurization				C			
Gas turbine 11 (GT11)		C	C	C			
Gas turbine 12 (GT12)		C	C	C			
Mixing gas station 1 (MGS1)		C		C	C	G	G
Mixing gas station 3 (MGS3)	G	C	C	C	C		
Pulverized coal injection and hot gas generators (HGG)	C						
Hot-blast stoves	C			C			
Sintering			C			C	C

Figure 6

Consumption and generation ratio of steelmaking gases by process area.[19]



To achieve accurate time-series forecasting, the predictive models were built using machine learning techniques capable of capturing the relationships between different production system variables (related to planning or production context) to predict gas generation or consumption behavior in each process area. The development of the model followed four key steps. Relevant data for each model were gathered from automation and information systems, with 6 months of historical data collected or the maximum available when 6 months were not feasible. Data preprocessing was then performed, including the removal of spurious (anomalous) data, followed by mathematical transformations and auxiliary data manipulations to create new features and maximize the extracted information. The data set was randomly split into different subsets, with the larger portion used to train models through various machine learning techniques applicable to the studied case, while a separate portion was reserved to assess model performance and ensure reliability before deployment.

Thus, each modeling possibility was evaluated using error metrics that allowed for comparison of the prediction of response $\hat{y}_i$, against the observations y_i associated with the attributes x_i from the evaluation data set, with a limited number of samples, n. This project used two different metrics: Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE), as shown in Eqs. 1 and 2. Finally, the model with the lowest error is selected for system representation and used for evaluating new data to predict responses. The performance of these models should be continuously monitored by Viridis Dispatch, as temporal degradation of predictions (i.e., an increase in forecast error relative to the actual observation) is naturally expected. In this case, the model is retrained to adjust the technique or parameterization used in its learning process.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}$$

(Eq. 1)

Table 2

Summary of Gas Generation and Consumption Forecasting Models

Forecast type	Process area	Forecast inputs	Units
Gas generation	Blast furnaces	BFG	Nm^3/hour
Gas generation	BOFs	BOFG	Nm^3/hour
Gas consumption	Hot-blast stoves	MG	Nm^3/hour
Gas consumption	HGGs	MG	Nm^3/hour
Gas consumption	Ladle heating station	BOFG/SGS	Nm^3/hour
Gas consumption	Sintering	BOFG/SGS	Nm^3/hour

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|y_i - \hat{y}_i\right|}{y_i}\cdot 100\%$$

(Eq. 2)

Forecasted Models for the Generation of BFG and BOFG: To perform the time-series forecasting of BFG generation from the reduction process in the blast furnaces, a data analysis was conducted to correlate this information with the following planned and/or actual variables: hot metal production rate, blast air flow, metallic charge consumption, coke and coke fines consumption, as well as the blend and moisture characteristics of the ores and coke used, and the composition of the hot metal in production. Learning from historical data and using different techniques resulted in average errors

Figure 7

Blast furnace gas (BFG) generation forecast.

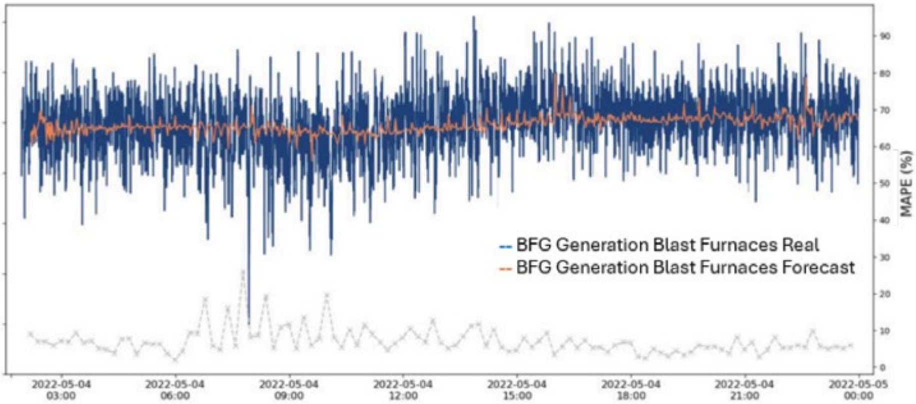
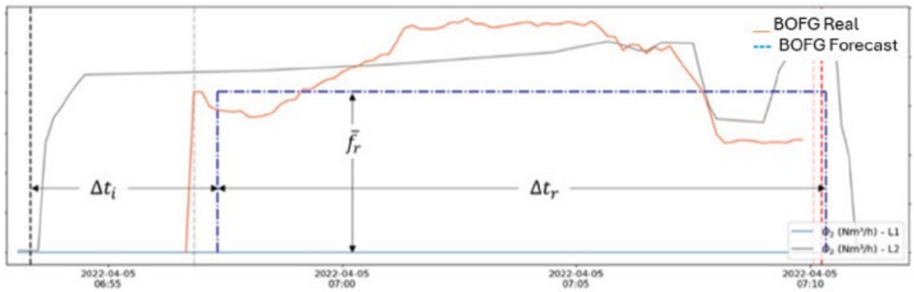


Figure 8

Basic oxygen furnace gas (BOFG) generation forecast.



of RMSE and MAPE equal to 35 kNm^3/hour and 5.2%, respectively.

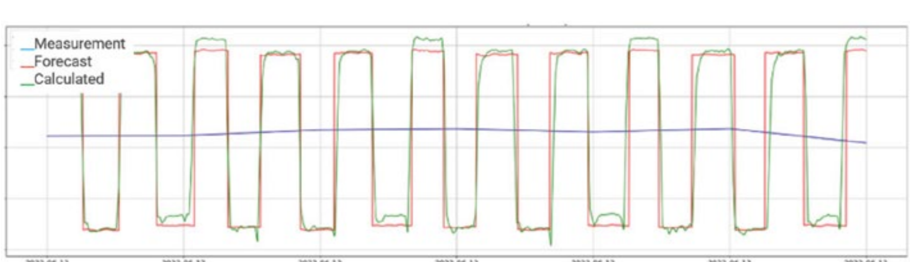
Fig. 7 shows a moment when the model with the lowest error is used to forecast a 12-hour operating period of the blast furnace, where the blue, red, and gray lines represent, respectively, the actual measurement, the forecast, and the mean error (MAPE) at each moment.

The forecast of the temporal generation of BOFG recovered in the converters during the steel heat is performed based on the start and end times of oxygen blowing and on the production planning data. To constitute the forecast model, the correlations with the amount of pig iron and scrap, the volume of oxygen blown, predicted and/or realized, the slag rate, the blowing pattern, the temperature of the pig iron, and the percentage of silicon in the pig iron, quantity of fluxes, as well as the composition of the scrap and steel to be produced were analyzed.

Fig. 8 illustrates the approximation performed, where the solid red line represents the actual BOFG flowrate, and the dotted blue line represents the prediction, according to the learning of the mentioned parameters. The learning of these parameters is conducted for each steel grade, and different techniques were analyzed. The average errors obtained in the evaluation of historical data are 125 kNm^3/hour and 3.8% for RMSE and MAPE, respectively.

Figure 9

Forecast of total MG consumption by blast furnace 1.



Forecasting Models for the Consumption of BFG and BOFG: To perform the time-series forecasting of MG consumption from the MGS3 mixing station, intended for air heating in the hot-blast stoves, a correlation analysis was conducted using the following information: blast air flowrate, blast air inlet and outlet temperatures, events and time windows for the start and end of the blow, both planned and/or actual, as well as the low heating values (LHV) of the combustion gases (NG and MG, mixed at the hot-blast stove inlet to form enriched mixed gas (EMG). Fig. 9 illustrates the forecasted MG flowrate from MGS3 to meet the demand of blast furnace 1, based on the calculation of partial flowrates (green line) and based on the learned MG flowrate directly from MGS3 (red line), using the same learning technique. The real flowrate measurement in the provided data is updated only once per hour, representing the average flowrate over that period, which shows good adherence to MG consumption forecasting approaches), with the lowest RMSE and MAPE errors obtained being 171 kNm^3/hour and 5.8%, respectively.

The time-series forecasting of MG consumption from the MGS3 mixing station for use in the hot gas generators was based on the analysis of pulverized coal injection (PCI) flowrates, both planned and actual, as well as the LHV value and composition of MG. Due to the low number of process variables involved, historical data learning yielded good results using autoregressive techniques. The average errors, RMSE and MAPE, were 234 kNm^3/hour and 4.6%, respectively. Fig. 10 presents a one-day forecast of the hot gas generator operation, showing good adherence to the prediction in capturing the consumption levels.

To perform the time-series forecasting of BOFG or SGS (i.e., substitute gas or synthetic gas) consumption in the sintering furnace, sourced from the MGS1 and MGS2 mixing stations, correlations were analyzed with combustion air flowrate, production rate, type and moisture content of the ore blend for the produced sinter, as well as the LHV of the combustion gas. No significant correlations were found with any process or production variables. Consequently, consumption forecasting based on historical data could only apply autoregressive techniques for model training. The average errors, RMSE and MAPE, were 111 kNm^3/hour and 1.7%, respectively. Fig. 11 presents a one-day forecast for the sintering furnace operation using the model with the lowest average error. The forecast demonstrates good adherence, with a tendency for continuous operation at specific consumption levels over extended periods, this is a typical operational behavior.

The time-series forecasting of BOFG or SGS consumption for ladle heating in the steelmaking plant could not be approached on a per-heater basis due to the lack of individualized consumption measurements. For this reason, historical data learning was also conducted using autoregressive techniques for training the consumption model. The average errors, RMSE and MAPE, were 112 kNm^3/hour and 1.1%, respectively. Fig. 12 presents the forecast for a given consumption period. Once again, the forecast shows good adherence, reflecting the tendency of operation at specific consumption levels over extended periods.

Simulation Models for Process Variables of the System

To provide an optimized dispatch decision, in addition to accurate predictions of gas and vapor generation and consumption behavior, it is important to forecast, within a future time window, how other process variables, related to the performance and safety of operations, will behave in response to the set of actions taken. It is also important to predict, based on

Figure 10

Forecast of MG consumption in hot gas generators.

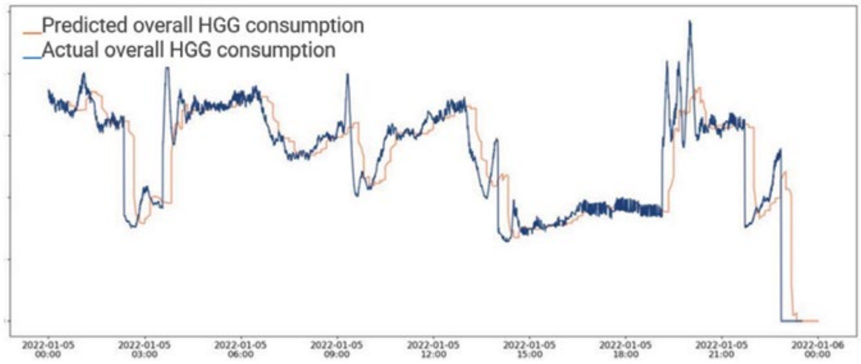


Figure 11

Gas consumption forecast for sintering.

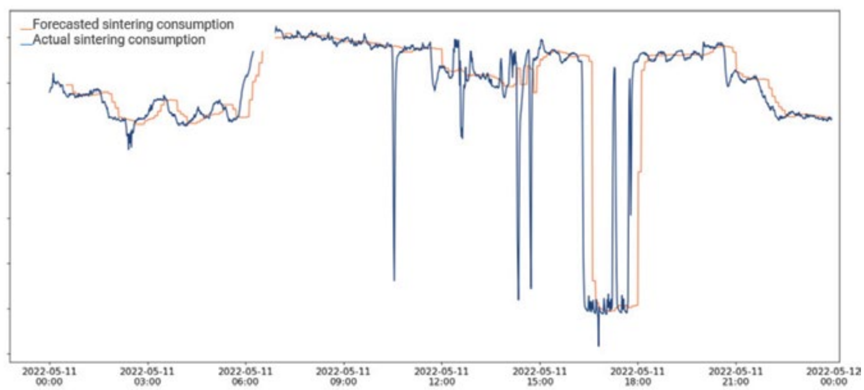
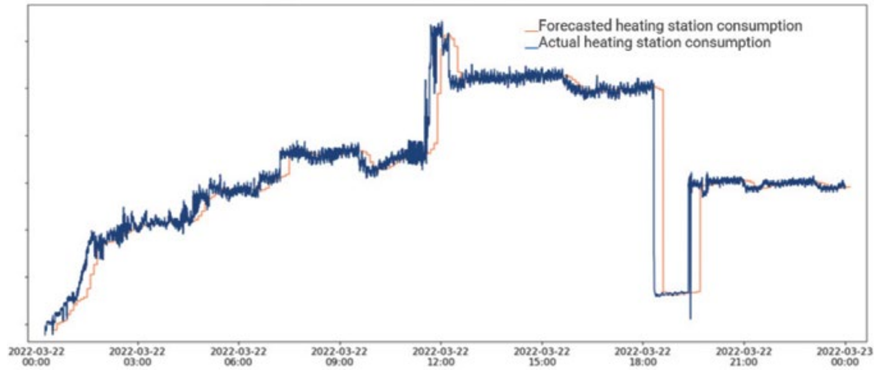


Figure 12

Gas consumption forecast for ladle heating station.



different decision contexts, how other correlated variables behave, as they are closely linked to the optimized gas dispatch. In the following subsections, the simulation models summarized in Table 3 are presented.

Table 3

Summary of Process Variable Simulation Models

Forecast type	Process area	Process variable	Units
Gasometer	Blast furnaces	Gasometer level	%
Gasometer	BOFs	Gasometer level	%
Gas consumption	MGS 1	Flowrate of BFG, NG and SGS	Nm^3/hour
Gas consumption	MGS 3	Flowrate of BFG and BOFG or SGS	Nm^3/hour
Gas consumption	GTs	Electrical output power	MW

Simulation Models for Gasometer Levels: The BFG gasometer level is estimated through the mass balance between the BFG generated in the blast furnaces (and not burned in flare) and the flowrates consumed in MGS1 (for SGS production), MGS3 (for MG production), and the thermal power plant, for electricity generation through GT11 and GT12. Since the BFG consumption in these various destinations depends on the decision of the Optimizer system, each possible decision must be simulated to ensure that the minimum and maximum gasometer limits are not exceeded during system operation. It is important to clarify that there is a single flow measurement for the BFG produced in both blast furnaces. The average RMSE and MAPE errors found for the application of this methodology to the studied historical base were 4.5% and 2.1%, respectively, while Fig. 13 shows the forecast for an operation period, where a good adherence to the inferred level behavior was observed.

The BOFG gasometer level is estimated through the mass balance between the BOFG recovered from the converters (not burned in flare) and the flowrates consumed in MGS3 (for MG production), in the GTs (for electricity generation), in sintering, and in the heating of pig iron and steel ladles in the steelmaking area. Again, since these consumptions depend on the decision of the Optimizer system, each possible decision must be simulated, ensuring that the operational constraints are respected (maintaining the level between the minimum/maximum gasometer limits). The average RMSE and MAPE errors found in the evaluation of the obtained historical data were 5.8% and 2.4%, respectively. Fig. 14 shows the forecast for an operation period, with good adherence to the inferred level behavior.

Simulation Models for Gas Consumption: The temporal forecast for the consumption of BFG, NG and N_2 for SGS production in MGS1 is based on the flowrates requested by their consumers (currently, sintering and ladle heaters), considering the forecast of unavailability (low gasometer level) or low LHV of BOFG, and the decision for gas management through the directional valves in MGS2. Therefore, the decision to provide SGS to some consumers will be related to the Optimizer system, requiring simulations in different scenarios to assess how this decision affects the availability and economic value of the operations. For this, the temporal flowrates of each gas involved in SGS generation were simulated through mass and energy balances, taking into account the average LHVs of the involved gases (BFG and NG) and the total BOFG flowrate required by consumers, along with the target LHV of SGS. The average RMSE and MAPE errors found in the evaluation of historical data for SGS production simulation were 4.8 kJ/hour and 6.4%, respectively.

Figure 13

BFG gasometer level simulation.

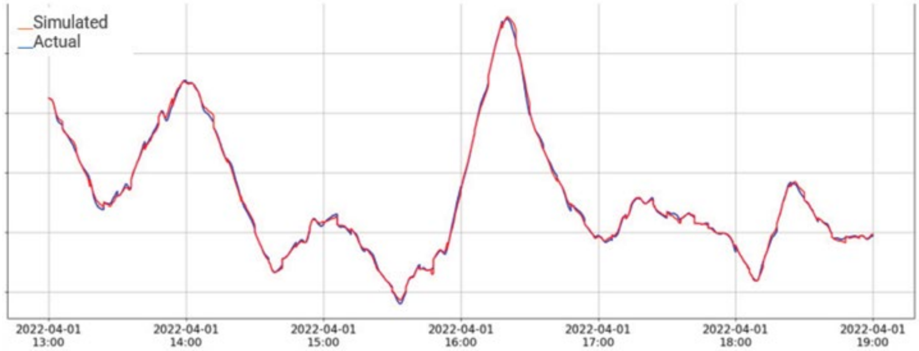
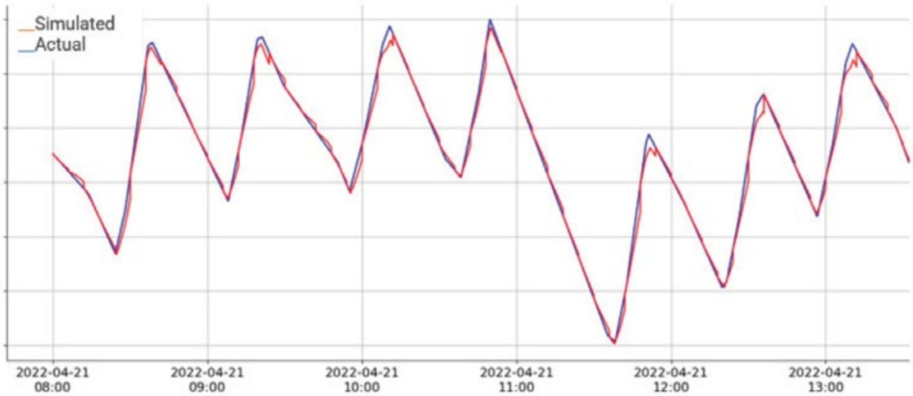


Figure 14

BOFG gasometer level simulation.



The temporal forecast for the consumption of BFG, BOFG and NG used for MG production in MGS3 is based on the flowrates requested by their consumers (hot-blast stoves and hot gas generators) and the LHV of these gases (BFG, BOFG, NG), according to the intended mixture type (BOFG + BFG + NG) as well as the limitation imposed for BOFG injection, to be simulated through Viridis Dispatch when seeking optimized decisions for the use of steelmaking gases. Again, the simulation of the temporal flowrates of each of the gases involved in MG generation is carried out through mass and energy balances of the gases, considering the average LHVs of the involved gases (BFG, BOFG, NG), the total MG flowrate required by hot-blast stoves and HGGs, and the target LHV of MG. The average RMSE and MAPE errors found in the evaluation of historical data for the MG production simulation were 6.8 kJ/hour and 8.5%, respectively.

The operating level of the gas turbines (output load, in MW) depends on the decision of the Optimizer system. Therefore, each possible decision must be made to evaluate how the consumption of input gases can impact on the availability of gases, as well as the economic value of the operations. This is not a simple relationship due to the high interdependence with other process variables, which significantly alters the performance of these thermal machines. A forecasting model was employed to predict the temporal consumption of gases by the gas turbines, based on the output power decision of these machines. The average RMSE and MAPE errors found in the historical evaluation were 12 MW and 5.2%, respectively.

Optimization Model and Decision-Making

In addition to making accurate forecasts of consumption and generation time series, the strategic planning of gas and vapor dispatch also requires a thorough understanding of the business, area by area, translating the existing objectives and constraints (technical, economic, physical, environmental and safety) into plausible metrics that are easy to calculate and understand. Furthermore, all decision variables must be identified — those variables that can be controlled/acted upon and that, in some way, influence the objectives and/or constraints of the business. The following subsections clarify each of these aspects — decision variables, objectives and constraints — based on the analysis of the gas and vapor dispatch problem of the plant. These aspects are mathematically represented through Viridis Dispatch to evaluate and simulate the best possible decisions for gas dispatch.

Decision Variables: The decision variables related to the dispatch of gases and vapors are presented below. The values of these variables are dynamically defined to fully meet all operational constraints and, at the same time, optimize (maximize or minimize) the process objectives (detailed in the following subsections), within a future forecast window:

- Decision of the timing for the recovery of BOFG produced, for storage in the gasometer, through the LHV setup (or equivalently, the %CO) for the start/end of recovery in each of the converters.
- Injection limit of BOFG in MGS3, to meet the MG flow in the blast furnace (hot-blast stoves and hot gas generators), indirectly controlling the proportion of mixed gases, as well as the injection of natural gas.
- Power generation level.

Objectives: Below are the objectives related to the dispatch of gases and vapors at the steel plant:

- Minimize the burning of BFG in the flare, by better management of the gasometer (avoiding high levels).
- Minimize the burning of BOFG in the flare, through better management of the gasometer and improved recovery of generated gases: that is, recover a higher volume in each campaign, according to the available gasometer space; and recover the higher quality gas portion, based on the gas LHV.
- Minimize the use of natural gas (NG) in MGS3, reducing operational costs and associated CO_2 emissions.

- Maximize electricity generation in GT11 and GT12, by better availability of steelmaking gases, and a better understanding of the operational efficiency of these thermal machines, according to dynamic field conditions.

Constraints: The constraints related to the dispatch of gases and vapors at the steel plant are presented below. These constraints must be strictly adhered to in every future forecast window, for any action or modification of the decision variables:

- Maintain the BFG and BOFG gasometer levels within the minimum and maximum safety thresholds.
- Keep gas flowrates within the maximum specified limits for each section of the pipelines.
- Maintain the calorific values (LHV) of gas mixtures (SGS or MG) within the specifications for each process area (MGS3, GTs and sintering).
- Ensure operational stability in the operation of the GTs (i.e., no abrupt and/or frequent changes in the operation of these machines).
- Ensure operational stability in the operation of MGS3 (no abrupt changes in the injection of BOFG), avoiding sudden variations in the LHV of the mixed gas sent to the blast furnaces.
- Ensure that electricity generation at the thermal power plant meets the nominal values for the thermal machines.

Search Heuristic: Once the decision variables, objectives, and constraints of the gas and steam dispatch problem in the integrated steel plant are defined, the Viridis Dispatch heuristics can be used to search for optimal decisions.[20] To achieve this, the Optimizer performs searches within a given forecasting window, where the evaluation of objectives and constraints depends not only on the decision variables but also on the predicted generation and consumption of gases and steam (updated periodically according to the forecasting/decision horizon), the current process states, and the dynamic simulations performed.

Results and Discussion

The implementation of Viridis Dispatch at the integrated steel plant followed a structured six-phase schedule: engineering, procurement, development, commissioning, go-live and assisted operation. During the engineering phase, a site survey was conducted to assess the plant's current state. This survey considered aspects related to automation and IT systems interacting with the software, the company's operational processes, the personnel groups involved, and the tools or controls currently in use. Additionally, the collection of available historical data was requested.

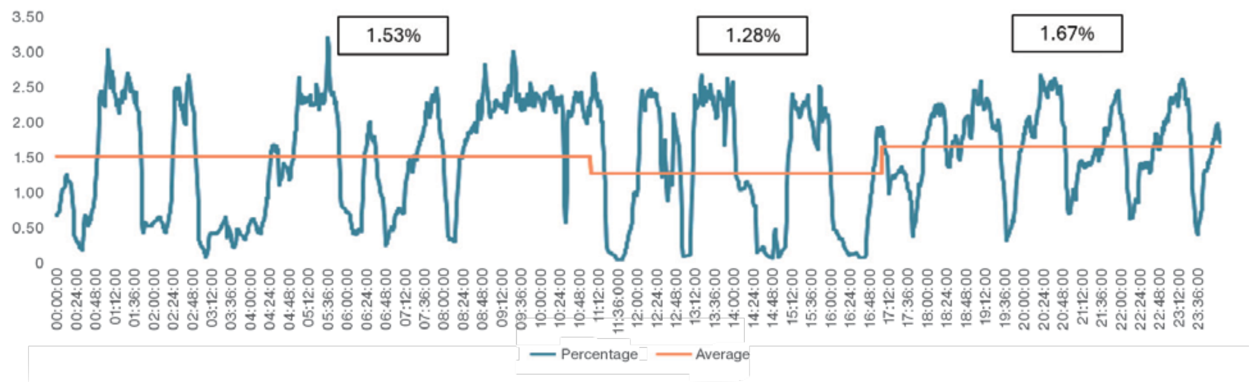
The procurement phase aimed to acquire the necessary hardware and software to ensure the full operationalization of the Viridis system. During the development phase, predictive, simulation and optimization models were designed according to the defined methodology. This stage also involved model validation and refinement. In parallel, the installation of Viridis product components

Figure 15

Dashboard developed for BOFG-related models.

Figure 16

Percentage of natural gas in mixed gas.



was carried out, along with their integration into the plant's automation and information systems.

The commissioning phase focused on configuring the Viridis Dispatch system, including the definition of equipment, metrics, key performance indicators (KPIs), users, permissions and models, among other parameters. Customized dashboards were developed to visualize models related to BFG, BOFG (Fig. 15) and MG gases, as well as panels designed to assist in the operation of each production area and the monitoring of KPIs. Additionally, this phase included an intensive period of training and operational support, essential for ensuring that users became familiar with the tool and could use it effectively. During the training sessions, operators and other stakeholders had the opportunity to clarify doubts, understand the logic behind the models, and deepen their knowledge of the system's functionalities. In parallel, the implementation team closely monitored operations, gathering feedback and identifying potential improvements and adjustments to enhance the user experience.

Another essential aspect was the off-line monitoring of model behavior, allowing for an assessment of their alignment with real plant scenarios before full integration into production processes. This monitoring enabled the identification of potential deviations, validation of assumptions, and ensured that the predictive, simulation and optimization models were properly calibrated to meet operational requirements.

To evaluate the effectiveness of the recommendations generated by Viridis Dispatch in determining the optimal timing for BOFG recovery and the injection limit of this gas into gas mixing station 3, a controlled test was conducted. For 6 consecutive hours, operators from the utilities and steelmaking areas strictly followed the system's recommendations. The results indicated a 17% reduction in natural gas consumption in the mixer compared to the consumption profile observed in the period adjacent to the test. This reduction also led to lower CO_2 emissions associated with natural gas combustion, as illustrated in Fig. 16. These findings highlight the positive impact of digitalization and the application of machine learning models in industrial process management, demonstrating how intelligent automation can contribute to energy consumption optimization and environmental emissions reduction.

Table 4 presents the RMSE and MAPE error metrics for the period in which the test was conducted. The results indicate that the models demonstrated good adherence in online operation. For all models, the RMSE error during the test was lower than that observed during the modeling, training and validation phase with historical data. However, the BOFG generation forecasting model for converters and the BOFG gasholder level simulation model exhibited MAPE error values higher than those recorded in the development phase, reaching 10.7% and 9.6%, respectively. This performance is directly linked to the critical dependence of these models on the steelmaking heat synchronization system, which experienced instabilities during the test, justifying the higher-than-expected error.

The mixed gas consumption forecasting model for hot-blast stoves also recorded a MAPE higher than that observed in the development phase. During that phase, it was identified that the accuracy of consumption profile predictions is strongly correlated with the regularity of the hot-blast stoves' blowing and combustion cycles. Therefore, during periods of increased variability in these cycles, the model is expected to show lower adherence, resulting in a higher absolute percentage error — a behavior that was confirmed during the test.

In addition to quantitative benefits, such as the reduction in natural gas consumption in the mixing gas station — responsible for producing mixed gas used in the blast furnace area — and the decrease in CO_2 emissions associated with its combustion, the implementation of Viridis Dispatch brought significant qualitative improvements.

Table 4

Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) for Forecasting and Simulation Models

Forecast type	Process area	Forecast Inputs	Units	RMSE	MAPE
Gas generation	Blast furnaces	BFG	Nm^3/hour	6,850 Nm^3/hour	1.1%
Gas generation	BOFs	BOFG	Nm^3/hour	73,055 Nm^3/hour	10.7%
Gas consumption	Hot-blast stoves	MG	Nm^3/hour	24,201 Nm^3/hour	12.4%
Gas consumption	HGGs	MG	Nm^3/hour	134 Nm^3/hour	2.8%
Gas consumption	Ladle heating station	BOFG/SGS	Nm^3/hour	23 Nm^3/hour	0.08%
Gas consumption	Sintering	BOFG/SGS	Nm^3/hour	260 Nm^3/hour	0.98%
Forecast type	**Process area**	**Process variable**	**Units**	**RMSE**	**MAPE**
Gasometer	Blast furnaces	Gasometer level	%	1.8%	1.4%
Gasometer	BOFs	Gasometer level	%	3.4%	9.6%
Gas consumption	MGS 1	BFG Flowrate	Nm^3/hour	1,099 Nm^3/hour	4.4%
Gas consumption	MGS 3	MG flowrate	Nm^3/hour	2,2694 Nm^3/hour	1.8%
Gas consumption	GT 11	Electrical output power	MW	2.9 MW	2.4%

The intuitive interface and centralized information facilitated user adoption, reducing time spent on operational tasks and optimizing decision-making. Moreover, the system enabled more efficient tracking of key managerial KPIs by the plant's technical staff. Teams reported increased data reliability, greater accessibility to information and improved integration between operational departments, resulting in a more streamlined and efficient workflow.

Another significant impact was the standardization of operational decision-making, now based on machine learning models. Before implementation, many decisions were made based on the individual experience and perception of operators, which led to distinct approaches for similar operational situations. This, in turn, did not always ensure the most effective and optimized choice. With the new solution, decisions became more consistent, data-driven and aligned with best operational practices. This set of improvements reinforces the value of the implemented solution, not only from a technical perspective but also in the perception and acceptance of the professionals involved in the process.

Conclusions

This study presented a real-world application of Viridis Dispatch in an integrated steel plant in Brazil, demonstrating its effectiveness in optimizing steel gas dispatch and delivering significant environmental and operational benefits. The 17% reduction in natural gas consumption in the mixing gas station not only lowered energy costs but also contributed to CO_2 emissions reduction, aligning with global decarbonization efforts in the steel industry. Beyond quantitative gains, the tool provided essential qualitative improvements, such as enhanced data reliability, integration across departments and optimized decision-making. The digitalization of this process enabled the standardization of operational decisions, reducing reliance on individual judgment and ensuring greater predictability and efficiency in energy management. The success of this initiative highlights the strategic role of AI in the digital transformation of the steel industry, demonstrating that the adoption of machine learning–based solutions can make the sector more sustainable and competitive. Based on these results, new opportunities emerge to expand the use of this technology in optimizing other production processes, solidifying intelligent automation as a key pillar for the industry's future.

References

1. "World Energy Outlook 2024," International Energy Agency, accessed 4 February 2025, https://www.iea.org/reports/world-energy-outlook-2024#overview.
2. Quader, M.A. et al., "Present Needs, Recent Progress and Future Trends of Energy-Efficient Ultra-Low Carbon Dioxide (CO_2) Steelmaking (ULCOS) Program," *Renewable and Sustainable Energy Reviews*, Vol. 55, 2016, pp. 537–549.
3. "Major Steel-Producing Countries 2022 and 2023," World Steel Association, accessed 4 February 2025, https://worldsteel.org/data/world-steel-in-figures-2024.
4. "Brazilian Energy Balance, Year 2023," Empresa de Pesquisa Energética Nacional, accessed 4 February 2025, https://www.epe.gov.br/pt/publicacoes-dados-abertos/publicacoes/balanco-energetico-nacional-2024.
5. "Crude Steel Production by Process," World Steel Association, accessed 4 February 2025, https://worldsteel.org/data/world-steel-in-figures-2024.
6. Landim de Carvalho, P.S.; Dias Mesquita, P.P.; and Araújo, Gonçalves de Elizio, D., "Sustainability of the Brazilian Steel Industry: Energy Efficiency, Emissions and Competitiveness," (in Portuguese) *BNDES Setorial,* No. 41, 2015, pp. 181–236.
7. Patisson, F.; Mirgaux, O.; and Birat, J-P., "Hydrogen Steelmaking. Part 1: Physical Chemistry and Process Metallurgy," *Matériaux & Techniques,* Vol. 109, No. 3–4, 2021, p. 303.
8. Birat, J-P.; Patisson, F.; and Mirgaux, O., "Hydrogen Steelmaking, Part 2: Competition With Other Net-Zero Steelmaking Solutions–Geopolitical Issues," *Matériaux & Techniques,* Vol. 109, No. 3–4, 2021, p. 307.
9. Wei, M.; McMillan, C.A.; and de la Rue du Can, S., "Electrification of Industry: Potential, Challenges and Outlook," *Current Sustainable/Renewable Energy Reports,* Vol. 6, 2019, pp. 140–148.
10. Hao, H. et al., "Scrap Steel Recycling: A Carbon Emission Reduction Index for China," *Sustainability,* Vol. 16, No. 10, 2024, 4250.
11. Lee, H.; Lee, J.; and Koo, Y., "Economic Impacts of Carbon Capture and Storage on the Steel Industry — A Hybrid Energy System Model Incorporating Technological Change," *Applied Energy,* Vol. 317, 2022, 119208.
12. Birat, J.P., "Carbon Dioxide (CO_2) Capture and Storage Technology in the Iron and Steel Industry," *Developments and Innovation in Carbon Dioxide (CO_2) Capture and Storage Technology,* Woodhead Publishing, 2010, pp. 492–521.
13. Zhao, J. et al., "Data-Based Predictive Optimization for Byproduct Gas System in Steel Industry," *IEEE Transactions on Automation Science and Engineering,* Vol. 14, No. 4, 2016, pp. 1761–1770.
14. Zhang, X. et al., "An Optimal Method for Prediction and Adjustment on Byproduct Gas Holder in Steel Industry," *Expert Systems With Applications,* Vol. 38, No. 4, 2011, pp. 4588–4599.
15. Yang, J-H. et al., "Optimization and Scheduling of Byproduct Gas System in Steel Plant," *Journal of Iron and Steel Research International,* Vol. 22, No. 5, 2015, pp. 408–413.
16. Matino, I. et al., "Forecasting Blast Furnace Gas Production and Demand Through Echo State Neural Network-Based Models: Pave the Way to Off-Gas Optimized Management," *Applied Energy,* Vol. 253, 2019, 113578.
17. Jiang, S-L.; Wang, M.; and Bogle, I.D.L., "Plant-Wide Byproduct Gas Distribution Under Uncertainty in Iron and Steel Industry via Quantile Forecasting and Robust Optimization," *Applied Energy,* Vol. 350, 2023, 121603.
18. Choi, S-W.; Seo, B-G.; and Lee, E-B., "Machine Learning-Based Tap Temperature Prediction and Control for Optimized Power Consumption in Stainless Electric Arc Furnaces (EAF) of Steel Plants," *Sustainability,* Vol. 15, No. 8, 2023, 6393.
19. Rodrigues, M.A.; Machado De Rezende, L.; Anunciação, V.J.; Machado Da Silva, A.; Da Silva Do Carmo, E.; Farah, A.A.M.; and Da Silva Machado, F., "Automation of the Recovery and Distribution of Steelmaking Gases and Vapors" (in Portuguese), *43º Seminário De Energia, Utilidades E Transição Energética*, São Paulo, Brasil, 2024, pp. 294–306.
20. Farah, A.; Drumond, F.; Cançado, K.; Soares, L.; Giacomin, R.; and Maia, T., "Optimization of Steelmaking Gas Distribution Using an Artificial Intelligence Tool" *AISTech 2023 Conference Proceedings*, 2023.

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