Application of different tools to improve process control in the electric arc furnace

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Tenaris Siderca produces seamless pipes mainly for the oil and gas industry as well as other segments, such as mechanical applications or automotive components. The steelmaking shop is equipped with two Electric Arc Furnaces (EAFs) of 100 tons which are fed with a mix of scrap and Direct Reduced Iron produced on site. In the present work, different tools to control the temperature and bath oxidation during the operation of the two furnaces are described.

In order to predict the evolution of steel temperature during the process, a large database containing steel temperature measurements and relevant process variables was compiled. A multilinear analysis was performed, and an algorithm was developed to estimate the temperature as a function of the last measurement and the additions of materials and energy carried out in the interval considered. Calculated values can reproduce in a reasonable way the measurements, especially towards the end of the heats when the process conditions become more stable. Using this approach, a reliable tapping temperature can be predicted after the last temperature measurement.

The temperature drop between EAF and Ladle Furnace (LF) depends on several factors, like: the weight and type of materials added during tapping, the elapsed time of the ladle in the car and the thermal status of the ladle. Based on statistical data collected from a large number of heats, an equation was developed to estimate this temperature drop. This equation was incorporated at the Level-2 automation system to set the tapping temperature in each heat. While the weight and type of materials added for each steel grade is known in advance, the waiting time of the ladle before entering the LF and its thermal regime change heat-to-heat. So, different tools were implemented to estimate on-line these parameters in daily operation. The implementation of the whole package was helpful for the operators to make the necessary adjustments along the heat. After the deployment of the system, a reduction in the average steel temperature at the beginning of the refining stage as well as its dispersion was verified.

A similar approach to that developed for the evolution of steel temperature was implemented to estimate the oxygen activity of the bath. Based on the last measurement, the algorithm can predict the next oxygen activity value with a reasonable precision. The implementation of this module allowed a reduction in the number of measurements carried out in each heat without affecting the dispersion of the results.

KEYWORDS: ELECTRIC ARC FURNACE, PROCESS CONTROL, MODELS, TEMPERATURE, OXYGEN ACTIVITY

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INTRODUCTION

The technical developments introduced in the operation of Electric Arc Furnaces (EAFs) during the last decades have significantly improved their efficiency, achieving many advantages over the traditional route of steel production via Blast Furnace and Oxygen Converter [1]. The higher flexibility to accommodate changes in the production rate makes the EAF process suitable for an always changing industrial scenario. Moreover, it is also much better positioned to face the challenges imposed by a reduction in the CO2 emissions in the coming years.

Despite these clear advantages, the uncertainties introduced by the varying characteristics of the loaded materials and the different complexities of the process require a deeper understanding of the phenomena involved. In this sense, several statistical and physical models have been developed to estimate key aspects of the EAF operation, such as the specific electrical energy consumed to melt and heat the metallic charge. The characteristics and applicability of these models have been exhaustively reviewed in recent publications [2-4].

The control of steel temperature and bath oxidation along the process are key aspects to ensure a stable and repeatable production, reducing the dispersions of the main operating variables. Keeping these variables within limited ranges not only impacts the quality of the steels produced but also helps to optimize the energy consumption and reduce operating costs. The use of on-line models has proven to be an effective tool to achieve these goals [5]. In the present paper, the deployment of different models to improve the process control in Tenaris Siderca's EAFs are discussed.

PLANT DESCRIPTION

Tenaris Siderca produces seamless pipes mainly for the oil and gas industry as well as other segments, such as mechanical applications or automotive components. The steelmaking shop is equipped with two Electric Arc Furnaces of 100 tons, two Ladle Furnaces and two Continuous Casting Machines of round bars. Main steel grades produced include medium carbon steels (0.10-0.40 %C) with different alloying elements (like Cr, Mo, Ti, Nb, etc). All the heats produced are fully aluminum killed during tapping and calcium treated at the end of the refining stage.

Both furnaces can be fed with a mixture of local and external scrap, pig iron and Direct Reduced Iron (DRI), the latter being produced on site in a facility that has a production rate of 125 tons/h. Scrap is normally charged in one or two buckets and DRI is continuously fed from the upper part of the furnace. Slag formers, like lime and dolomitic lime, are also charged continuously during the process. The furnaces are equipped with different configurations of burners and carbon injectors. Further details are presented in Table 1.

Since a large proportion of the steels produced are intended for products with high quality requirements, a tight control of bath oxidation and temperature is mandatory in the EAF process. Hence, several samples are taken to monitor the evolution of steel temperature and oxygen activity in every heat. With the aim of improving the stability of the process and reducing the number of samples taken in each heat, different tools were developed to predict the evolution of temperature and oxygen activity along the process. Once correctly calibrated, these modules can be used to more accurately predict the values expected at the time of steel tapping.

Tab.1 - Main characteristics of both furnaces.

FEATURES	EAF4	EAF5
Ladle Capacity (tons)	80	80
Transformer Power (MVA)	75	90
Current (kA) / Voltage (V)	60 / 750	60 / 840
Tap to tap (min)	50	44
Metallic charge	Scrap + DRI	Scrap + DRI
Tapping	EBT	EBT
Chemical Energy	CH_4, O_2	CH_4, O_2

PREDICTION AND CONTROL OF STEEL TEMPERATURE

Temperature estimation along the process

In order to predict the evolution of steel temperature during the EAF process, a statistical model was developed. As a first step, a large database was created compiling the information of more than 3 years of operation. For all the heats, the time at which each temperature measurement was carried out and the value obtained were recorded. Additionally, the average values of relevant process parameters between two consecutive temperature measurements were also recorded. A preliminary analysis was carried out to identify which of these variables had a significant contribution to the temperature change. As a result of this assessment, it was concluded that for the operating conditions of these furnaces the most relevant variables were: the electrical energy consumption (ΔEE), the weights of DRI (ΔW_{DRI}), fluxes (ΔW_{Flux}) and carbon injected (ΔW_C), as well as the volume of oxygen blown (ΔVO_2) and the elapsed time between both measurements (Δt). Therefore, the following equation was proposed to estimate the steel temperature as a function of the last measurement (T_{Last}) and the indicated variables:

$$T_t(t) = T_{Last} + C_1 \cdot \Delta EE + C_2 \cdot \Delta W_{DRI} + C_3 \cdot \Delta W_C + C_4 \cdot \Delta W_{Flux} + C_5 \cdot \Delta V_{O2} + C_6 \cdot \Delta t \qquad \text{(eq.1)}$$

A total of 20000 intervals corresponding to 12300 heats from both furnaces were initially evaluated to estimate the parameters (C_i) of the previous equation through Multiple Linear Regression, see Fig. 1. The results were assessed by calculating the Mean Absolute Error (MAE), which is defined as:

$$MAE(°C) = \frac{\sum_{i=1}^{N} |T_{Meas} - T_{Calc}|}{N} \qquad \text{(eq.2)}$$

The prediction capability of the model increased when the elapsed time between two consecutive measurements was relatively short (< 10 minutes) or when the heat was closer to its end, reaching a MAE below 19 °C, see Table 2. Since these conditions are usually met after the last temperature reading, the calculation is reliable to estimate the actual tapping temperature. The obtained equation was then tested with a new set of intervals that had not been used in the original fitting, obtaining similar results, see Fig. 2.

Therefore, an application was implemented in the Level 2 automation system of both furnaces to calculate on-line the expected temperature from the previous measurement. As an example, Fig. 3 shows the evolution of measured and calculated temperature in one of the heats, together with the weight of DRI added and the electrical energy input. As these magnitudes have an opposite effect, the evolution of temperature will depend on the net contribution of both, being the model useful to quantify these situations. The application is currently being used by the operators to make the necessary adjustments along the heats.

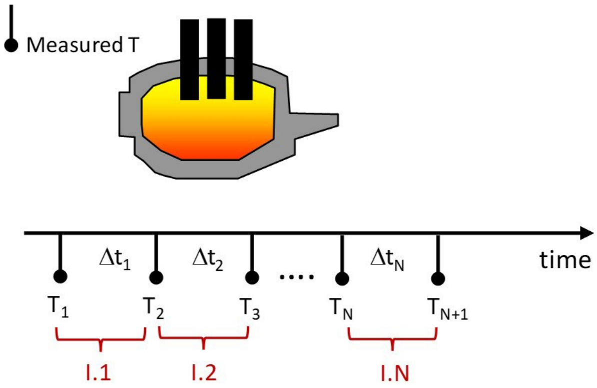


Fig.1 - Different temperature readings considered in each heat.

Tab.2 - Mean Absolute Error of the model for different intervals and times between two consecutive temperature readings.

Interval	Time between measurements (min)			
	0-5	5-10	10-15	15-20
I.1	20.0	23.6	24.6	27.0
I.2	17.9	19.3	20.6	21.3
I.3	15.0	17.7	19.4	20.5
I.4	15.8	16.4		
I.5	12.7	14.4		

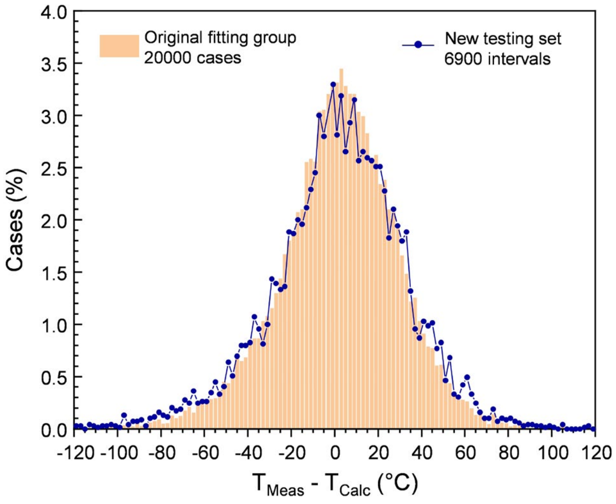


Fig.2 - Distribution of model errors. Comparison with a new data set

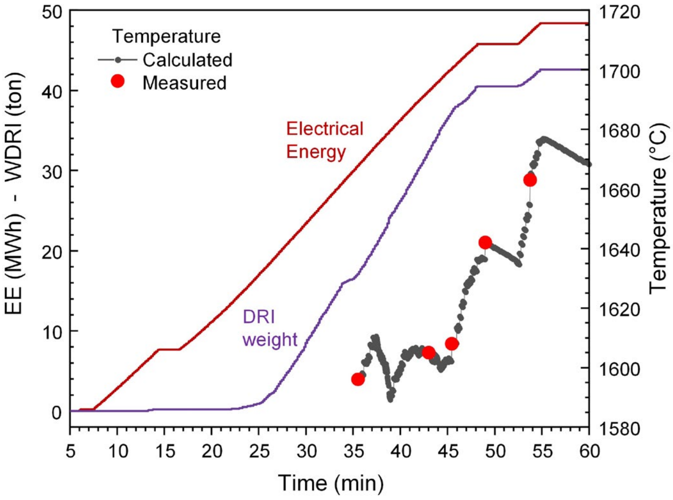


Fig.3 - Evolution of calculated and measured temperature in one heat.

Target tapping temperature

To obtain a repeatable steel temperature at the start of the Ladle Furnace (LF) process, the EAF tapping temperature must be properly set. This value will depend on several factors, like the weight of alloys and fluxes added at tapping, the time that the ladle must wait in the car before entering the LF and the thermal regime of the ladle refractory lining. In order to quantify the contribution of each factor, the temperature drop between EAF and LF as well as the relevant process parameters were collected for a large number of heats. In each case, the tapping temperature was estimated by taking the last measurement and applying the equation described in the previous section, see Fig. 4.

As expected, the temperature change between EAF and LF increases with the amount of ferroalloys added at tapping (Fig. 5-a). Furthermore, for the same steel grade, the temperature drop also increases for longer ladle waiting times in the car (t_{Car}), as shown in Fig. 5-b. Due to the specific lay-out and operating conditions of this plant, the waiting time in the car can be long and variable from heat to heat, so an algorithm was developed to estimate it by combining the plant's scheduling module and statistical information collected from historical data.

The thermal status of the ladle is characterized in each heat by means of a mathematical model that calculates the temperature distribution of the refractory wall during the whole thermal cycle of the ladle. The model receives on-line information of relevant events and updates the temperature distribution in the ladle wall. A Thermal Regime Index (TRI) is defined, which indicates the relationship between the total thermal energy stored in the refractories at each moment and that obtained when the steady state is reached. Further details of this application have been described elsewhere [6].

So, with the information collected, an algorithm was developed to estimate the temperature drop between EAF and LF as a function of the materials added, the ladle thermal status and the waiting time. As the materials added at tapping have different chilling effects [7-8], four categories were considered: ferroalloys (W_{FeX}), carbon (W_C), fluxes (W_{Flux}) and aluminum (W_{Al}). Although each ferroalloy may also have a slightly different behavior [7-8], for the sake of simplicity they were initially grouped in a single category. Aluminum was considered separately because, due to the exothermic reaction that occurs during steel deoxidation, an increase in temperature rather than a drop is expected. Thus, the temperature drop is estimated as:

$$\Delta T_{EAF-LF}(^\circ C) = f(W_{FeX}, W_C, W_{Flux}, W_{Al}, TRI, t_{Car}) \quad \text{(eq.3)}$$

By setting the target LF start temperature, the above procedure can be used to define the EAF tapping temperature in all the heats. For each steel grade, the weight of the materials added at tapping are known in advance and the expected waiting time of the ladle is defined by the algorithm that combines plant's scheduling and historical data. The thermal status of the ladle is obtained in real time by the mathematical model already described.

The whole package that sets the target tapping temperature was implemented in both furnaces and has been operative for several months. Since its implementation some improvements were observed, such as a reduction in the steel temperature at the beginning of the LF process as well as in its dispersion, see Fig. 6.

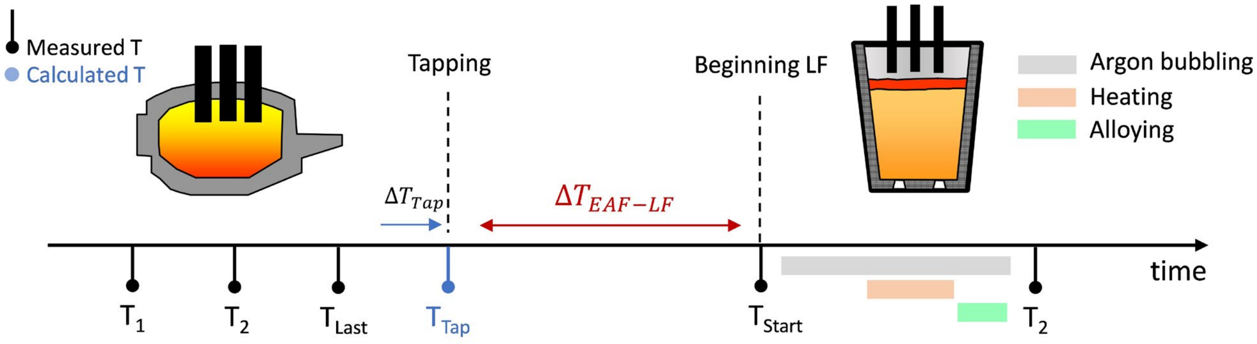
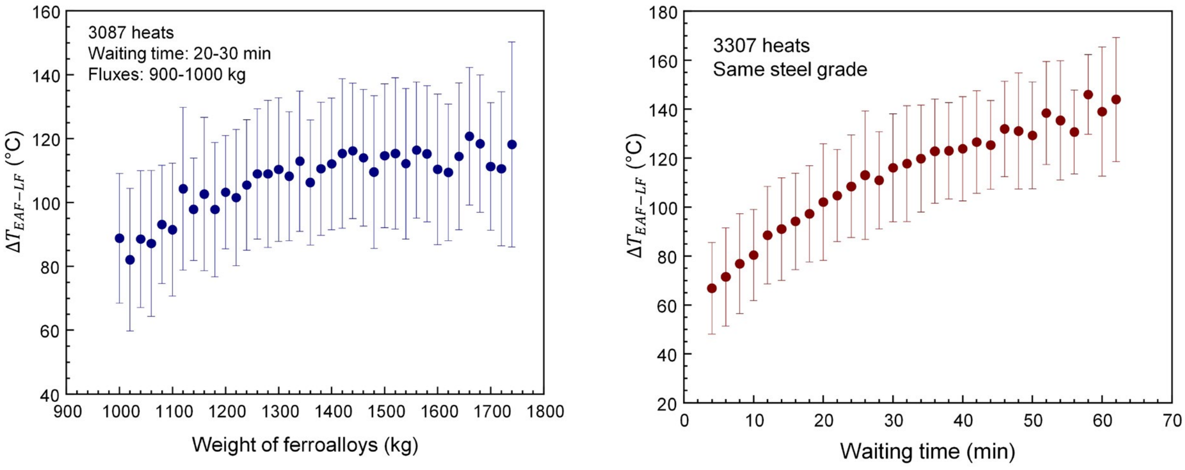


Fig.4 - Temperature drop between EAF and LF.



(a) (b)

Fig.5 - Temperature drop between EAF and LF
a) Effect of ferroalloys addition b) Influence of the waiting time in the car

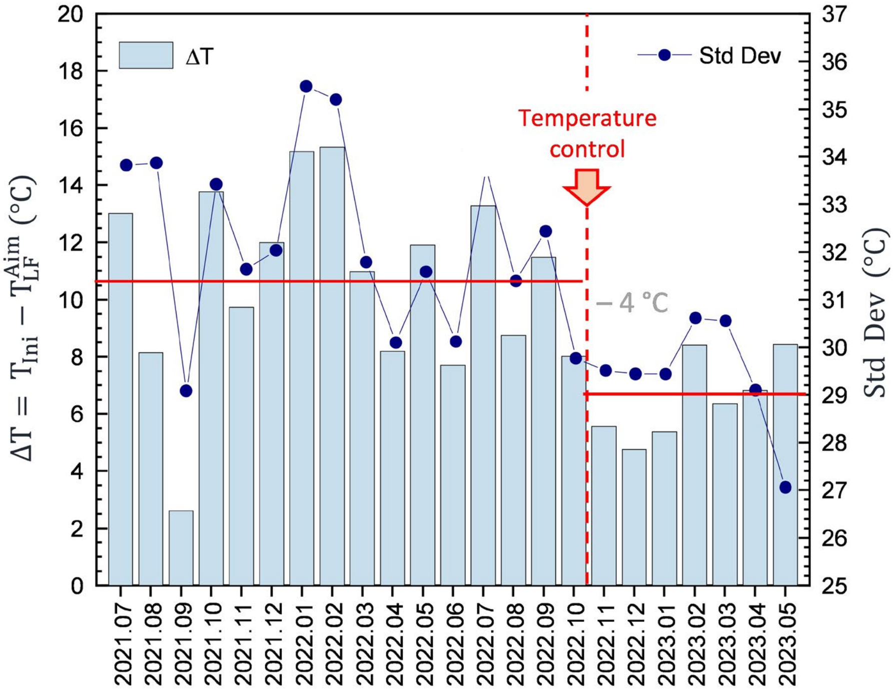


Fig.6 - Reduction of average temperature and its dispersion at the beginning of LF process.

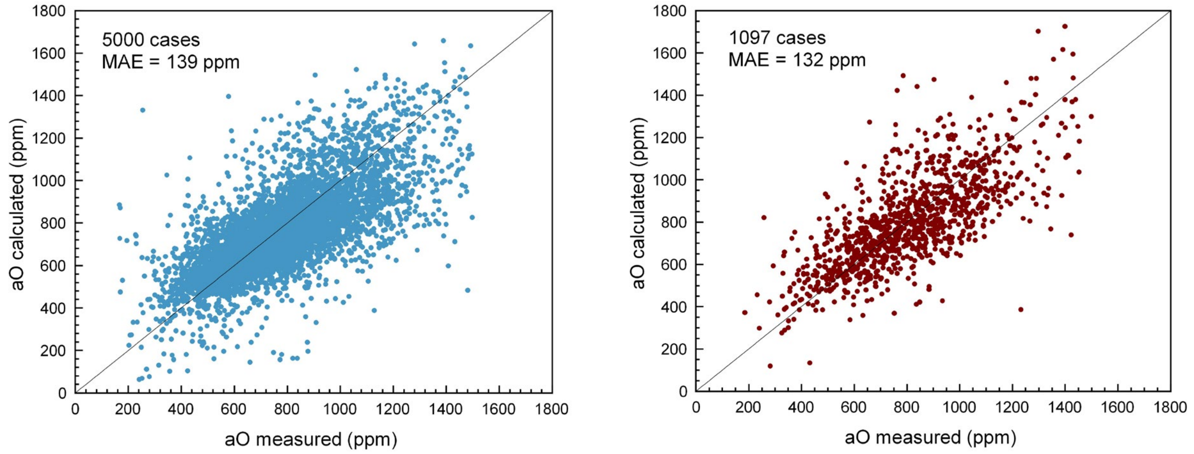
ESTIMATION OF OXYGEN ACTIVITY

Model development

As mentioned before, a large proportion of the heats produced in this plant have stringent cleanliness requirements, so a tight control of the bath oxidation is mandatory. To achieve this goal, several oxygen activity measurements are normally carried out during the elaboration of the heats in the furnace. This frequent sampling can promote delays in the process and increase the operating costs, so a predictive tool was developed to reduce the number of measurements while keeping the oxidation values within the expected control range.

A similar approach to that developed to predict the steel temperature was implemented to estimate the oxygen activity of the bath. After a first analysis, it was concluded that the same group of variables selected to estimate the steel temperature was also appropriate for the prediction of oxygen activity. From the collected historical data, a total of 5000 intervals with oxygen activity measurements and process variables could be recovered. Using multilinear analysis, an expression similar to (eq. 1) was developed to predict oxygen activity. As shown in Fig. 7-a, a reasonable agreement between calculated and measured values was obtained. The developed equation was then tested for a different group of heats that had not been used to fit the parameters and the results were still acceptable, see Fig. 7-b.

Owing to the good results observed, a calculation module was implemented in the Level 2 of both furnaces. As the system gained reliability, it was possible to reduce the number of measurements carried out during the process by 13 % without affecting the dispersion in the results obtained.



(a) (b)

Fig.7 - Comparison between measured and calculated oxygen activity.
a) Data set used to fit the model b) Testing with a new data set

IMPACT OF OXYGEN ACTIVITY ON STEEL DEOXIDATION

It is a common practice in Al-killed steels to adjust the amount of aluminum added at tapping with the oxygen activity measured at the EAF to obtain a similar Al content at the beginning of the LF process [9]. Hence, as the oxygen activity at the EAF increases, a higher amount of Al is consumed at tapping which can be estimated as follows:

$$Al_{Fade}(kg/ton) = \frac{W_{Al}(kg)}{W_S(ton)} - 10 \cdot [Al] \tag{eq.4}$$

Where W_S is the steel weight, [Al] the Al content measured in the ladle and W_{Al} the amount of Al added, which is a function of the oxygen activity. So, for similar Al contents in the ladle, the Al consumption increases with the oxygen activity measured at the EAF. However, the actual oxygen activity at tapping may differ from the last measurement carried out if some late adjustments are made in the furnace. The developed algorithm was used to evaluate the impact of these differences, comparing the Al fade in heats with the same oxygen activity measured but different values calculated at tapping. As can be seen in Fig 10, when the calculated oxygen activity at tapping is greater than the last measurement, a higher consumption is verified. Conversely, Al consumption decreases when the calculated activity is lower than the last measurement. These results indicate that an accurate estimation of the oxygen activity at tapping can provide a better control of the amount of Al added for steel deoxidation.

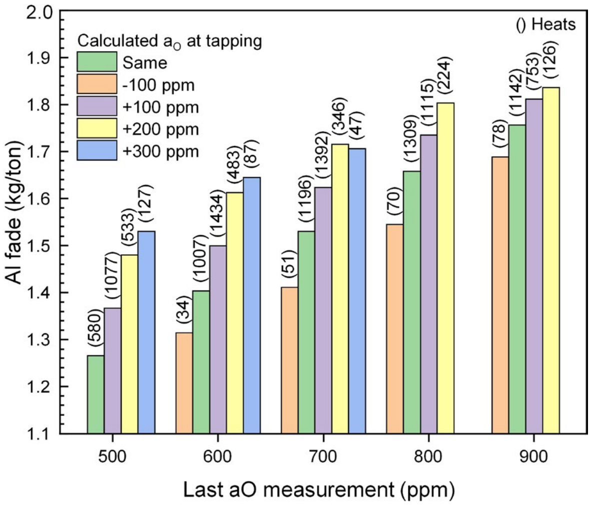


Fig.8 - Change of Al fade when calculated oxygen activity at tapping differs from the last measurement.

CONCLUSIONS

In the present work, different algorithms were implemented to estimate the evolution of steel temperature and oxygen activity along the process. After tunning these tools, they prove to reproduce with a reasonable precision the measured values. Therefore, these equations were implemented in the Level 2 system of both furnaces to help the operators to make the necessary adjustments during the process. Furthermore, after the installation of these algorithms some improvements were observed in the daily operation, like a reduction in the number of oxygen activity measurements and a narrower dispersion of steel temperature at the beginning of the refining process.

REFERENCES

[1] J. Madias, Electric Furnace Steelmaking, in Treatise in Process Metallurgy, Vol. 3: Industrial Processes, Vol. 1.5, 2014, p. 271-300.

[2] H. Odenthal, A. Kemminger, F. Krause, L. Sankowski, N. Uebber, N. Vogl, Review on modeling and simulation of the Electric Arc Furnace, Steel Research International, 2018, Vol. 89, 1700098.

[3] L. Carlsson, P. Samuelsson, P. Jönsson, Predicting the Electrical Energy consumption of Electric Arc Furnaces using statistical modeling, Metals, 2019, Vol. 9, 959.

[4] T. Hay, V. Visuri, M. Aula, T. Echterhof, A review of mathematical process models for the Electric Arc Furnace process, Steel Research International, 2021, Vol. 92, 2000395

[5] B. Kleimt, W. Krieger, D. Vasallo, A. Ayarza, I. Iriondo, Model-based decision support system for Electric Arc Furnace online monitoring and control, Metals 2023, Vol. 13, 1332.

[6] S. Ferro, C. Cicutti, P. Galliano, Thermal Tracking of Ladles, 8th International Conference on Modeling and Simulation of Metallurgical Processes in Steelmaking, STEELSIM, 2019, p. 241-249.

[7] G. Kor, P. Glaws, Ladle Refining and Vacuum Degassing, AISE The Making Shaping and Treating of Steel, Chapter 11: Steelmaking and Refining, 1998, p. 661-713.

[8] H. Tian, Z. Mao, Y. Wang, Hybrid modeling of molten steel temperature prediction in LF, ISIJ International, 2008, Vol. 48, N° 1, p. 58-62.

[9] A. Conejo, D. Hernández, Optimization of Aluminum deoxidation practice in the Ladle Furnace, Materials and Manufacturing Processes, 2006, Vol. 21, p 796–803.

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