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Heat Transfer in Steel Ladles: Models and Applications ⋆

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Abstract: This work presents a summary of the main tools and contributions, since the 2000s, to solve temperature control problems and predict thermal temperatures in steel ladles. We discuss different modeling strategies implemented to several applications related to heat transfer in steel ladles and their most relevant contributions, as well we show some of the main process parameters. Finally, future perspectives are described, mainly the advantages of the implementations based on machine learning.

Keywords: Steel Ladle; Thermal Control; Thermal Loss; Modeling; Machine Learning.

1. INTRODUCTION

With the development of steel technologies and the search for energy efficiency, characterizing and minimizing thermal losses of steel during production have become essential. Due to the complexity, and the non-linear and time-varying relationship among the process parameters, monitoring the variables for precise temperature control has been a major research problem over the past two decades (Fredman, 2000; Gupta and Chandra, 2004; Laha et al., 2015; Cavalcante, 2019).

Lower steel temperatures along the continuous casting process may promote the interruption of production or the need for greater demand for aluminum to reheat the bath, i.e., liquid steel. Aluminum still contributes to occur an event called clogging in the submerged entry nozzle (Ferreira et al., 2002). Clogging is defined as a material obstruction in the flux of steel during continuous casting, which can interfere in the production quality and control (Thomas and Bai, 2001). On the other hand, high temperatures of liquid steel imply a greater loss of energy, more fluxes for dephosphorization and greater degradation in the refractory wear of both converter and ladle. In addition, high temperatures can also reduce the casting speed, thus reducing the productive capacity of the system.

In order to establish the factors that most impact the thermal losses in the ladles, part of the literature that deals with the control of the thermal status of liquid steel was reviewed, not only in the ladles, but also in all the stages between tapping and casting. Until the end of the 20th century, most contributions were limited to articles from conferences and experimental studies on plants (Fredman, 2000). However, since the beginning of the 21st century, this scenario has changed, reflecting an increase in the number of scientific works and publications in journals.

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In order to define the main factors that most impact heat losses from ladles, Fredman (2000) reviewed part of the literature, starting in 1956, which deals with the control of the thermal status of liquid steel, not only in ladles, but also in all stages between the tapping of the converter and the continuous casting. From the beginning of the 21st century, the works found in the literature began to apply different types of models, especially physical, mathematical, empirical and statistical ones (Gupta and Chandra, 2004; Jormalainen and Louhenkilpi, 2006; Tian et al., 2008; Wu et al., 2012; Ahmad et al., 2014; He et al., 2014; Laha et al., 2015; Wang et al., 2018; Hou et al., 2019).

The objective of this paper is to present a summary of the main contributions developed after the synthesis carried out by Fredman (2000), in an attempt to understand thermal losses, as well as in order to identify the main process parameters that influence them.

This paper is organized as follows: In Section 2, a description of the steelmaking process is made and the effects of temperature control in this process are discussed; Section 3 presents the main models used in the literature since the 2000s; Section 4 mentions the main applications in the industry and their results; future prospects are discussed in Section 5; and, finally, the conclusions are presented in Section 6.

2. THERMAL CONTROL OF LIQUID STEEL

The basic raw materials for the steelmaking process include iron ore, mineral coal and limestone. The first stage of the process consists of the preparation of raw materials, which transforms iron ore into sinter and mineral coal into coke. These materials are sent to silos that have systems responsible for forming the load used in the next stage of the process, the reduction. This stage occurs in the blast furnace, using the countercurrent principle (Geerdes et al., 2015). Ferrous raw materials and fuel are loaded through

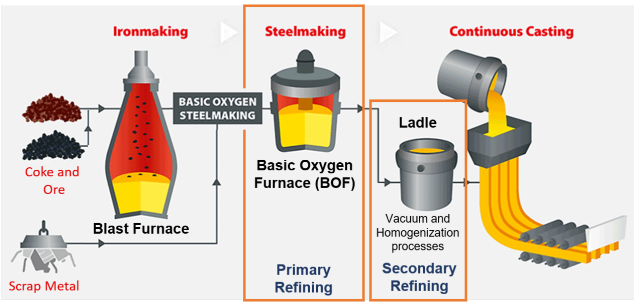

Figure 1. Schematic flowchart of the steel refining steps in steelmaking.

the upper part of the blast furnace. At the bottom, hot air is blown through the nozzles, and auxiliary fuel injections can also be made, in order to generate heat to the process through the combustion of carbon (Mourão et al., 2011). This part of the process is shown on the left side of Figure 1.

The final product of this phase is a hot metal, produced at a temperature of approximately 1500°C, in a liquid state, composed of iron, carbon and other alloying elements such as silicon, manganese, phosphorus and sulfur. Slag and blast furnace gas are also generated as by-products. The slag is directed to a granulation system through the slag channel, while the hot metal is transported, using torpedo cars (equipment made of structural steel and coated with refractories), to be transformed into steel, through the oxidation of impurities and alloy additions (Geerdes et al., 2015).

During steelmaking process, the hot metal passes through the refining stages, where it is transformed into steel. Refining can be divided into three stages: primary refining, secondary refining and casting, as shown in Figure 1 (Rizzo, 2005).

The primary refining occurs mainly in Basic Oxygen Furnace (BOF), which has a cylindrical shape, composed of heat resistant steel, internally coated with refractory materials. The primary refining process is fundamentally based on the oxidation reactions of the impurities found in the hot metal, through the blowing of oxygen. Thus, the need to add immiscible ingredients to the liquid metal is justified, so that impurities are removed from the metal with the aid of these ingredients. As a result, slag is produced, which, due to the difference in density, separates from the metal and carries the impurities (Rizzo, 2005; Mourão et al., 2011).

In general, although slag is important for the steelmaking process, protecting it against oxidation by air and controlling thermal losses, its improper passage from the converter to the ladle can cause some inconvenience to the subsequent processes. The passage of slag to the steel ladle can not only affect the product's quality, but also enhance the wear of refractories and decrease the efficiency of steel deoxidation and desulfurization. For these reasons, the slag must be discarded at each stage of production (Rizzo, 2005; Mourão et al., 2011).

After processing in the primary refining, the liquid steel is transferred to the ladle steel, which fulfills not only the transport role for subsequent equipment, but also the metallurgical reactor in the secondary refining operations. At this time, the steel temperature abruptly decreases, mainly due to exposure of the liquid steel to the environment, when passing from the converter to the ladle. This process is called tapping. Thus, the tapping time has a strong influence on the thermal loss of the liquid steel, which in general occur by convection and radiation (Rizzo, 2005).

The secondary refining of liquid steel, which is also called Ladle Metallurgy, constitutes the fine adjustment of the chemical composition of the steel, usually in a reducing atmosphere (absence of oxygen) and temperature adjustment. During this stage, some factors contribute to the reduction of the thermal input of the bath, such as the addition of materials to adjust the chemical composition, injection of inert gas to homogenize the metal and the contact of the steel with the walls and bottom of ladle refractories (Mourão et al., 2011).

Throughout the secondary refining stages, although the thermal losses become smaller, those that occur through the slag remain, becoming more important than the losses by the refractories. This happens since the heat lost to the refractory is reduced over time, due to the increasing difficulty of heat entering the refractory layers. However, the greatest reduction in the temperature of the steel can occur in the vacuum and homogenization processes due to the agitation of the bath, as well as by the specific treatment for the injection of calcium. In these stages, radiation losses mainly occur at the top of the ladle (Ferreira, 2000; Ferreira et al., 2002).

After refining is complete, the steel is sent to the continuous casting process. This is the last stage in steelmaking where the metal is liquid. The main objective of casting is the solidification of liquid steel, in such a way that it can be used in the subsequent stages of the production chain (Mourão et al., 2011). The basic principle of this process is the vertical casting of liquid steel from a ladle positioned over the tundish, which is a mechanism for feeding the molds using dip tubes.

In continuous casting, high temperature losses occur due to the action of steel passing through the long valve. The temperature of the liquid steel depends fundamentally on its residence time inside the tundish. In this way, the speed of the casting and the level of the steel in the tundish have a strong influence on the temperature of the process. According to Ferreira (2000), the actual temperature of the continuous casting, also called stabilized temperature, is calculated by averaging the three temperatures measured within the tundish throughout the process (beginning, middle and end of the casting).

In general, the operational performance of steelmaking can be assessed from four parameters: productivity, yield, correct chemical composition and, fundamentally, temperature of the liquid steel at the end of the blow. Thus, the need to cool or heat the liquid steel to reach the casting temperature, the increase in the frequency of new blows in the converter and the formation of the skull in the ladle (formed by solidified metal) are relevant factors in the loss of productivity. In addition, the efficiency of continuous casting is closely related to the temperature of arrival of the steel. In this sense, temperature control is essential throughout the process, making it necessary to estimate thermal losses during all the steps that compose it, as well as defining the optimal release temperatures for each of the process equipment.

3. TYPES OF MODELING

In general, the works developed since the 2000s can be divided into three major categories. Initially, the works were still based on numerical and heat transfer equations (Xia and Ahokainen, 2001; Ferreira et al., 2002; Gupta and Chandra, 2004; Samuelsson and Sohlberg, 2009; Wu et al., 2012). These models represent the phenomena by theoretical means, considering the basic laws of physics and chemistry that characterize the process, or phenomenological, which are also based on the process, but apply parameters whose values must be obtained in the process itself (Dym, 2004).

Heat can be transferred by three different mechanisms. This characterization is based on models based on Fourier's laws, Newton's cooling and Stefan-Boltzmann's; that deal with conduction, convection and radiation, respectively. In real physical systems, the three mechanisms of heat transfer are present, consequently, the heat transferred is the set of contributions corresponding to each of them. In some situations, the predominance of one of the mechanisms makes it possible to ignore the contributions of the others. However, the adoption of this practice must be done carefully, under condition of distancing the model too much from the real situation (Bejan and Kraus, 2003; Dym, 2004).

With the development of new computational tools, researchers started to apply techniques such as Computational Fluid Dynamics (CFD). As presented in the works of Pan et al. (2003), Jormalainen and Louhenkilpi (2006) and Tripathi et al. (2012), the use of these tools is a very common practice in the literature. In general, Fortuna (2000) defines CFD as an area that studies computational methods for simulating phenomena involving fluid flow with and without heat transfer and chemical reactions. The tool starts from the premise that fluids are governed by Partial Differential Equations (PDE) that represent, for example, the laws of conservation of mass, amount of movement and conservation of energy. The goal of CFD then is to promote the solution of these PDE systems using numerical methods, such as, for example, Finite Differences and Finite Elements. Thus, using these techniques, it is possible to numerically evaluate different parameters relevant to the problem.

Further on, with the increase in the volume of data and access to information due to the advent of Industry 4.0, as well as the need for solutions applied in real time and more robust to noise, models based on machine learning started to be used for the solution of practical problems. In particular, this type of modeling can be divided into two classes: hybrids, also known as gray-box modeling, which start from the premise that information inherent to the process derived from physical modeling can provide important gains to the model and, therefore, should be used to compose the solution to the problem (Tian et al., 2008; Ahmad et al., 2014; He et al., 2014; Botnikov et al., 2019; Song et al., 2019); and non-hybrids, called black-box modeling, in which little or no prior knowledge of the system is needed. In general, this type of modeling is composed of algorithms based purely on machine learning, capable of identifying patterns between information and then predicting and executing tasks (Laha et al., 2015; Klanke et al., 2017; Wang et al., 2018; Hou et al., 2019; Jo et al., 2019).

4. APPLICATIONS AND RESULTS

4.1 Physical models based on heat transfer

The transient flow and heat transfer in a ladle during the waiting period was investigated by Xia and Ahokainen (2001), who proposed a simplified physical model for heat losses for the refractory. Based on numerical predictions, the thermal stratification, steel temperature and heat loss rates were obtained. As a result, the authors concluded the importance of considering the influence of the ladle walls to obtain reasonable flow and thermal stratification predictions during the holding period, that is, the period when the empty ladle waiting for the liquid steel.

In order to reduce the consumption of aluminum in the heating process in the secondary refining, Ferreira et al. (2002) present a project developed in a real plant. The methodology applied a two-dimensional model with axial symmetry in finite elements, using the commercial software Algor, elaborated in order to establish the thermal state of the ladles through a parameter called Soak Index, in different set points. As a result, in the comparison between the temperatures measured by the instrumentation and those calculated by the model, there was a certain discrecy between the values of the first two heats for the refractories of both the wall and the bottom of the ladle. Applying fixed values of density and the specific heat of the materials, the developed model converted the temperatures of the elements into stored heat, allowing simulation of five thermal categories of the ladles, to mention: drying and heating; cooling the empty ladle with lid; cooling the empty ladle without a lid; ladle with steel; and ladle during casting. However, the model did not consider the thermal losses due to radiation, slag and dissolution of alloys, which are fundamental for the evaluation of the refractory degradation, in addition to not adapting to the dynamism of the process conditions. The simulations demonstrated that the use of the cover is capable of promoting a reduction of approximately 50% of the thermal losses of liquid steel.

Gupta and Chandra (2004) proposed a combination of a simple regression model and one-dimensional heat transfer for controlling the casting temperature. The methodology calculates forward and backward direction temperatures. In this way, for a desired casting temperature, the temperature of the liquid steel before casting is predicted by forward modeling, through the heat transfer model. On the other hand, during all stages of the steelmaking process, the model receives information about the events that have occurred. In this sense, a developed statistical model can be used to update the process, resulting in temperature control during all stages of the refining process (these steps are also called heat or race), using the previous model. Although the pre-processing of the data is not well described, the model was tested with the actual observations of the plant. The prediction of the temperature of the steel in the bubbling station presented an error within 5°C, from the actual value for 66% of the heats and within 7°C for 97% of the heats. A comparison of the predicted with the actual casting temperature shows that 75%, 88% and 95% of the predicted value showed an error around 5°C, 7°C and 10°C, respectively.

Using gray-box modeling, Samuelsson and Sohlberg (2009) use a model of Ordinary Differential Equations (ODE), derived from physical relationships, for modeling the temperatures of steel and ladle walls. The model provided promising performance in estimating steel temperature, but the predicted temperatures for the ladle walls showed a bias. The reason for this was not found, but the possible causes may be a difference in the characteristics of the material or in the assembly of the ladle. Another point observed was that, for some heats, the estimate of the steel temperature showed a very large deviation from the measured values. Although they do not justify precisely, the authors point out as possible causes some systematic measurement error or even the influence of thermal stratification due to insufficient agitation. In particular, the absence of temperature measurements at different positions on the wall and bottom of the ladle, as well as a possible deterioration in the refractory layers, should have been evaluated by the proposed model. Possibly these factors were determinant for the limitations of the presented model.

In order to establish an online multi-factor temperature compensation model in a steel industry, Wu et al. (2012) apply a numerical simulation method based on finite element analysis to quantitatively calculate the effects of the ladle thermal state in the temperature of the steel, throughout the various stages of its operating cycle, and use the actual data to verify the calculation results. When performing a regression analysis of the thermal losses of steel caused by the ladle for different process conditions using the software SPSS (Verma, 2012), they establish a nonlinear regression model for temperature compensation on different circumstances, as a way of guiding the control of plant operations. Data analysis showed that the errors between the measured value and the estimated temperature were within a range around ±6°C, with values measured in the range of 1551 °C at 1571°C. According to the authors, the application of this model would be able to meet the production requirements.

4.2 Models Based on Fluid Dynamics

Pan et al. (2003) discuss the heat transfer and liquid steel flow in the ladles, using one-dimensional CFD numerical models (predict heat conduction fluxes through the ladle wall, bottom and slag layer), two-dimensional (to simulate the natural convection in the ladles during the holding period before casting) and three-dimensional (for the simulation of fluid dynamics in the ladles and drainage flows during casting). Although the 1D and 2D models showed sufficiently faster results, 3D simulations of the fluid dynamics in the ladles during casting were shown to be inefficient and can only be used offline. Even so, the authors make many observations regarding the ladle thermal losses and note a strong impact of the evaluated parameters on the temperature of the steel during the casting, with a difference between real and estimated temperature of up to 20°C.

Mathematical models to predict steel temperatures in the ladle and in the tundish in continuous casting were also developed in CFD by Jormalainen and Louhenkilpi (2006). These models were, at first, developed to simulate the influence of the control parameters on the ladle during its cycle. Subsequently, models were developed to simulate the fluxes of molten steel from the ladle and the evolution of the temperature in the tundish during the ladle change period and during the casting. Finally, a final predictive model was tested with data collected from a real plant, being found, through statistical tests, the correlation coefficients of the temperature at the start, in the middle, and at the end of casting, respectively equal to 0.9, 0.92 and 0.87. The authors discussed a possible increase in the performance of the model at the beginning of the casting if any type of parameter related to the final ladle exchange period had been used. Anyway, although the model needs adjustments, the tool can be applied offline to assist in scheduling process operations.

Later, a mathematical model based on the CFD was also developed by Tripathi et al. (2012) predict the temperature of the liquid steel and the thermal profile of the steel ladles. For this purpose, the authors considered that the heat losses due to conduction and radiation during the heat are much more dominant than convection and, therefore, the convective effect was limited to the homogenization of the bath. Constant values were also applied to the calculations regarding the physical and thermal properties of molten steel, slag, smudge and ladles refractories. Through the model, it was possible to analyze the thermal profile of liquid steel throughout the process, to study the role played by the slag layer and the useful life of the ladles. The model was validated with data collected from the plant, with a maximum deviation of 4% between the predicted and measured data.

4.3 Gray-Box Modeling

Tian et al. (2008) combined the conventional methodology for thermodynamic calculation with a machine learning algorithm to predict the temperature of molten steel in a ladle furnace of a real plant. The strategy was to analyze, through thermodynamic equations, the energy input and output of liquid steel during the refining process in the ladle furnace, being proposed the application of Extreme Learning Machine (ELM) together with AdaBoost.RT for to increase the performance of calculation of the heat exchange coefficients used by these equations. Thereafter, the error between the actual temperature and the predicted temperature was used to modify the hybrid model to obtain better performance. In addition, they compare the performance of the proposed model with a standard ELM for temperature prediction. The results of this experiment demonstrated that the performance of the black box model was lower than that of the hybrid model.

Tian et al. (2008) also comparing the proposed model with a hybrid applying a Back-Propagation Neural Network (BPNN), and a higher speed and precision of the hybrid model was verified using ELM. Although the performance metrics of the compared models are not presented in the work, neither do they provide more information about the topologies used, the experiment demonstrates that the proposed hybrid model can improve the generalization performance and the prediction quality. According to the results presented, about 87.5% of the predictions presented errors below 5°C. Another point that must be taken into account is that, although there was a certain concern with the dynamism of the coefficients, some simplifications were imposed on the model. For example, liquid steel was considered homogeneous in terms of temperature and composition throughout the process, as well as a one-dimensional variation of the temperature profile was assumed in the refractory ladle.

Ahmad et al. (2014) also provides a general gray box modeling framework to predict and control the temperature of steel in a tundish. The parameters of the physical model were estimated from process variables using a non-linear statistical model. However, as this modeling is not able to accurately describe the uncertainties of the process, such as the degradation of ladle refractories and their respective heat transfer coefficient, another statistical model, based on Random Florests (RF) was developed to compensate the prediction errors caused by such disturbances in the process. Two types of gray box structure (series and parallel) were developed and their applicability and limitations were discussed. In parallel mode, a statistical model to compensate for the prediction error of the physical model was developed using 53 process variables, not described in the work, measured in the processes from the converter to the tundish. Although some parameters depend on the operating conditions, other parameters in the parallel gray-box model are constant, consequently, these simplifications could decrease the performance of the physical model. In order to circumvent these issues, the gray-box serial model was proposed, used to estimate the parameters as functions of the input variables. As a result, there was a reduction of about 36% in the value of the Root Mean Square Error (RMSE) of the combined gray-box model compared to the physical model.

A hybrid modeling based on the thermal state of the ladle furnace and on Artificial Neural Networks (ANN) was proposed by He et al. (2014), in order predict the temperature of the liquid steel. They developed a ladle thermal classification scheme based on a coding of their state. Following this logic, forward and backward prediction models were implemented that act simultaneously. Thus, for each output of the model, a set of input variables was selected, although the authors do not elaborate on how the selection was made, nor the pre-processing applied to these data. After the simulations, there was be observed that the hit rate of prediction for the initial temperature in the ladle furnace is 88.2%, in the error range of ±15°C, and the hit hate of prediction for the final temperature of this step is 96% for error range of ±10°C. The prediction hit rate for the tundish temperature in the first casting and in the casting of the sequence was 95.8% and 97.9% with an error range of ±10°C, respectively. The results of the application revealed that the models presented considerable precision in the prediction and are satisfactory for the practical production process.

Hou et al. (2019) applied a BPNN to predict the thermal and thermomechanical responses of a steel ladle, considering variables related to the properties of refractory linings and ladle geometry. To this end, five orthogonal matrices were used for finite element simulations and training of the neural model, with the aim of organizing the combination of ten characteristics in the variables space. First, a test was carried out to explore the ideal number of nodes in the hidden layer, with 7 neurons being proposed, although this configuration did not result in the lowest Maximum Relative Error (REMAX). The objective of the second test was to identify the minimum sample size for the study of the lining configurations, with a minimum sample size of 160, that is, 16 times the number of entries. Eight learning algorithms were used individually in the third test to detect the one that best fits the model to the data. Although four learning techniques showed the most acceptable coefficients of determination, i.e., Conjugate Gradient with Fletcher-Reeves updates (CGF), Scaled Conjugate Gradient (SCG), One-Step Secant (OSS) and Bayesian Regularization (BR), the SCG and OSS algorithms needed a longer time to converge. When analyzing the performance of the CGF and BR prediction in the thermal and thermomechanical responses, the superiority of the BR over the CGF was verified. Thus, the BPNN model with BR was chosen, resulting in a REMAX of 7.15% and a Mean Square Error (MSE) of 1.76%.

Song et al. (2019) demonstrate the ability to generalize a model involving the use of Convolutional Neural Networks (CNN) and Deep Neural Network (DNN) to predict cooling parameters demanded during continuous casting. As CNN input, the temperature data obtained from the simulation based on the Finite Difference Method (FDM) were used, while the DNN has some process condition parameters, such as the environment temperature and the initial temperature of process, as well as the shape of the steel (thickness and width), in addition to the amount of carbon contained in steel, which was defined as the main variable in steel production. The final nodes of the models of the two architectures were concatenated using a fully connected layer to predict a total of 11 cooling temperature zones. The proposed model was not only able to overcome the limitations of traditional ANNs, but also to reasonably reduce computational time and prediction error.

4.4 Black Box Models based on Machine Learning

A comparison between RF algorithms, ANN, Dynamic Evolution Neuro-Fuzzy Inference System (DENFIS) and Support Vector Regression (SVR) for modeling and predicting steel characteristics at the output of the steelmaking process, using 10 input variables selected by prior knowledge, was carried out by Laha et al. (2015). Based on the results, DENFIS and SVR outperformed RF and ANN. The authors attribute the best performance of the SVR due to the fact that it is a global optimization method, which can map a low dimension input space to a high dimension characteristics space for regression tasks. In addition, although it took a longer processing time, the high performance of DENFIS was justified because it combines the generalization capacity of the fuzzy system with the training capacity of an ANN. In terms of computational time, DENFIS and RNA were the slowest algorithms due to the training procedure. In contrast, RF is the fastest because its training does not require much parameter tuning.

In this sense, the authors conclude that the SVR was the algorithm that presented the best performance for the task of forecasting steel production among the four evaluated methods. However, due to the limitations imposed on data collection and treatment, it was not possible to obtain better predictions on large real data sets.

Klanke et al. (2017) present a detailed study for the prediction of the carbon content and temperature of the steel produced in a converter. For that, different pre-processing and validation strategies were used in combination with several supervised machine learning approaches, such as Bayesian Regression, SVR and DNN. The attributes were classified into two groups, in relation to the availability of this information before and during the blowing process or after the end of the blowing and, based on a joint discussion with the specialist engineers, rules were determined to deal with missing data. The selection of characteristics was done manually and automatically, applying algorithms such as Backward Selection and Forward Selection, however the attributes selected in the final model are not mentioned. Among the machine learning approaches suggested, the authors decided to use Bayesian regression with Automatic Relevance Determination (ARD), according to them, for exercising a certain complexity control and selection of integrated resources, however, no comparative test between the performances of other techniques were presented in the work. As a measure of the quality of the predictions, RMSE was applied, with an improvement in the prediction about 9% compared to the physical model used by plant operators (no information was given regarding these data). Although the authors emphasize the advantages of applying a data-driven forecasting model for a future online application, they suggest combining the proposed modeling with approaches that use metallurgical and thermodynamic equations.

On the other hand, Wang et al. (2018) propose a more comprehensive strategy, integrating the prediction of liquid steel temperature with the detection of outliers. The model developed consists of three levels based on the Gaussian Process (GP), with three types of detectors being applied to each division of the data set. After evaluating the process data, the outliers were categorized into two groups. The first are the outliers contained in the model's training set, where detection can be implemented offline. The other group consists of the outliers of the input variables applied to the model's test set. The detection of this type of outlier must be implemented online. Three of the input variables were selected a priori based on the knowledge of the process and the others were processed by the Kernel Principal Component Analysis (KPCA) algorithm, with the first nine components being chosen. The experimental results showed the capacity of the method to achieve a better generalization in comparison with other proposed methodologies, resulting in an RMSE of 3.3807, reaching an hit rate of 86% for the liquid steel in the ladle furnace, for error range of 5°C. The authors attribute this improvement in performance due to the implementation of the outlier detection procedure.

Botnikov et al. (2019) propose a prediction model for the median of the steel temperature in a specific time interval during continuous casting. The model was a kind of combination containing elements of statistics, analytical calculations, and experience of the process operators, which took into account the history and treatment of the ladle during the secondary metallurgical processes. The modeling was based on two stages. The first stage integrated an RF-based machine learning algorithm with a Probabilistic Graphical Model with a Bayesian Network; and the second stage used a method to assess probability distributions. Three nonlinear algorithms were also tested for the construction of regression equations, based on decision tree, RF and gradient descent on decision trees, however, no further information is presented regarding the configuration of the techniques used or how the results were generated. The precision of the developed models reached 5.4°C for non-degassed steel and 5.9°C for vacuum degassed steel. According to the characteristics of the plant, as the error remained within the range of ±7.5°C, the quality of the models obtained is very promising. In the second stage, the integration of the model in the plant's process control system improved the prediction, resulting approximately 4.6 times fewer occurrences of temperatures outside the range targeted for casting, in addition to energy savings (up to 0.75 kWh) and reduced consumption of graphite electrode (up to 1%) in the ladle furnace.

Jo et al. (2019) develop a machine learning algorithm to predict the end point temperature of liquid steel in a converter and compare the results of the simulation with the actual operating temperatures. Searching for an efficient way to understand and analyze the data, Exploratory Data Analysis (EDA) was used, but the authors do not give details on how the input variables were determined. The missing values and outliers were replaced by the mean or median, depending on the asymmetry of the distribution of each variable. Some variables were manipulated in order to create new variables or transform them into other types of data, generating artificial resources, however, it is not taken into account that the use of this resource without a certain caution can lead to redundancy in the information.

In particular, Jo et al. (2019) define a decision tree algorithm based on gradient descent and combine the predictions made by several estimators in order to improve the predictive performance in relation to a single estimator. A steel industry evaluated this new proposed model for three months and, during this period, the model showed an absolute error (i.e., absolute error less than 10°C) around 9% less than the conventional model. However, the authors conclude that the performance of the proposed model may be compromised if the number of samples is reduced, which may happen if specific cases of the primary refining process are evaluated.

5. FUTURE PERSPECTIVES

Based on the developed analysis, the revised works arouse some reflections on the modeling of this type of system. The studies show that the experimental study of these systems played an important role in understanding the mechanisms involved in heat transfer, as well as in formulating theoretical models that describe the thermal state of the system.

With regard to theoretical modeling, the focus has not been on considering the real complexity and dynamism of plants, but on ensuring a simpler model whose results reflect a certain agreement with the measurements through calibrations. Considering these aspects, some authors limit themselves to the development of more complex dynamic models only for design purposes, while, for real time simulations, they use simpler models.

In fact, the implementation of a modeling that contemplates the non-linearities inherent to the process and variations over time, as well as the validation with large-scale experimental data obtained in different circumstances, is not a trivial task. In contrast to what happens with traditional metallurgical models, statistical or data-oriented models are based on partially hidden relationships that are systematically determined by the application of certain algorithms to a data set. These characteristics made it possible to apply variables that, although influencing the process itself, are often not present in physical equations.

The research also reveals that, due to the data-oriented nature, models based on machine learning are able to adapt to different process conditions during training, unlike what occurs with traditional metallurgical models. This fact justifies its wide application in the modeling of thermal losses in real time, with precision of forecast within the criteria established by the Industry 4.0 (Ferreira et al., 2002; Klanke et al., 2017; Cavalcante, 2019).

With the aim of providing not only realism to the model, but also computing speed, the researchers are looking for new solutions based on machine learning. In view of the performance of these models in industrial applications, the study and exploration of machine learning has been continuously deepened, in order to guarantee the viability of applications in real time.

6. CONCLUSION

Several works were evaluated, including solutions for the monitoring, modeling and control of thermal losses in steelmaking process. Usually the method of control have a direct impact on the thermal control and ladles can be combined with the geometry and composition of the refractory layers for reducing the prediction error of the thermal losses.

Although the results described here are, in general, relevant and promising for the Industry 4.0 demands, most of the solutions presented in the bibliography have no direct application in any real plant, due to the particularities of each steel industry. Some reasons for this are: the capacity differences of ladle and tundish, different qualities of steel produced, variations in raw materials and characteristics of primary and secondary refining, as well as the steelmaking layout. Being aware of the complexity involved and adding technical knowledge of the particularities of each specific plant, it is possible to develop an effective methodology for solving the problem.

In general, the modeling methods are based on metallurgical and thermodynamic rules for idealized systems. In contrast, statistical or data-driven models are based on partially hidden relationships that are systematically determined by applying certain algorithms to a data set. These characteristics allow the application of variables that, although they influence the metallurgical process, are not present in the metallurgical equations. In addition, the data-oriented models based on machine learning can be easily adapted to the current process conditions during training, unlike what occurs with traditional metallurgical models. Therefore, due to the ability to generalize of the models based on machine learning, this type of modeling should be better explored in order to guarantee the viability of real-time applications, according to the demands especially of industry 4.0.

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