Machine Learning–Based On-Line Model for Slag Conditioning in Ladle Furnaces at Ternium Mexico

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The importance of slag has been very well understood by the steelmaking industry to cut the cost of producing quality steel. In a general sense, the primary purpose of the slag is to absorb metallic impurities, as well as cover the arc produced by electrodes to protect the refractory from arc flare; protect the metal from oxidation; control the steel oxygen levels and chemistry of the steel; avoid oxygen and nitrogen pickup; reduce temperature loss; and help in dephosphorization and desulfurization.[1]

Works that lead to the design and test of models to calculate with precision the required alloy and additions for electric arc furnace (EAF) and ladle furnace (LF) slag target chemical composition are of interest for steelmakers and have been reported in the literature.[2–6] These models for slag conditioning in LFs encounter a major drawback that compromises the precision in the calculation of the slag chemical composition, affecting the performance of the model at the end: the uncertainties associated with the EAF's slag carryover weight; inhomogeneous distribution of slag and/or the steel; increase of MgO content in the slag due to refractories wear; and the process parameter dispersion of the current heat being treated at the LF during the EAF operation.

The current work shows the implementation of a machine learning–based on-line model for slag conditioning in ladle furnaces. The model calculates the lime and aluminum additions in order to achieve a slag target chemical composition and is based on a weighted k-Nearest Neighbor (wKNN) algorithm to calculate an initial approximation of additions, and then a mass balance within an optimization algorithm to adjust the final additions. This approach addresses the drawbacks described in the previous paragraph. The developed model was validated with process data from two ladle furnaces and the results demonstrate that a better control of the final slag chemical composition from heat to heat can be achieved.

Slag Conditioning During Refining

The EAF's carryover slag composition and weight, the tapping additions performed at the EAF, and the additions at the LF are important factors that constitute the slag in the LF.

EAF Slag and Tapping Additions — The melting process in the EAF is followed by an oxidation stage where the formation of liquid slag is crucial. Liquid slag formation is facilitated by the oxidation of silicon in the bath. The primary sources of slag formation are oxidation of metallic elements in the base metal such as manganese, silicon and aluminum, non-metallic elements such as sulfur and phosphorous, and minerals such as lime, spar and dolomite. Also, oxygen blown into the melt promotes the oxidation stage. During this stage, excessive carbon, phosphorus, silicon and manganese oxidize to form magnesium oxide, carbon monoxide, silicon dioxide and diphosphorus pentoxide.

$$(FeO) = [Fe] + [O]\ ;\ [C] + [O] = \{CO\}\ ;\ [Si] + \{O_2\} = (SiO_2) \quad \text{(Eq. 1)}$$

$$[Mn] + {}^{1}/_{2}\{O_2\} = (MnO) \; ; \; 2[P] + {}^{5}/_{2}\{O_2\} = (P_2O_5)$$

(Eq. 2)

Slag absorbs these oxides and carries them as waste. CO bubbles floating up in the melt help the process and refine the steel. Slag collected on the top surface of the molten steel in the furnace, enriched with oxides, is removed in a process known as de-slagging.

During EAF tapping, lime, aluminum and ferroalloys are added. These additions promote the formation of slag in the LF and serve as alloy elements of the steel; each has a chemical composition and known yields that are described in Table 1.

LF Additions for Slag Conditioning — A general overview of the secondary refining practice is shown in Fig. 1. After the reception of the heat coming from the EAF, the slag conditioning stage begins. A slag sample is prepared and sent to the laboratory, which delivers the results of the chemical composition and sends it to the level 2 system in the automation platform of the meltshop. The results are displayed to the operators and then they make the decision about the weight of aluminum and lime that will be added in order to adjust the slag chemical composition to the desired target values. In addition, if there are delays on the laboratory, the operators perform a visual inspection of a slag sample after cooling it in advance.

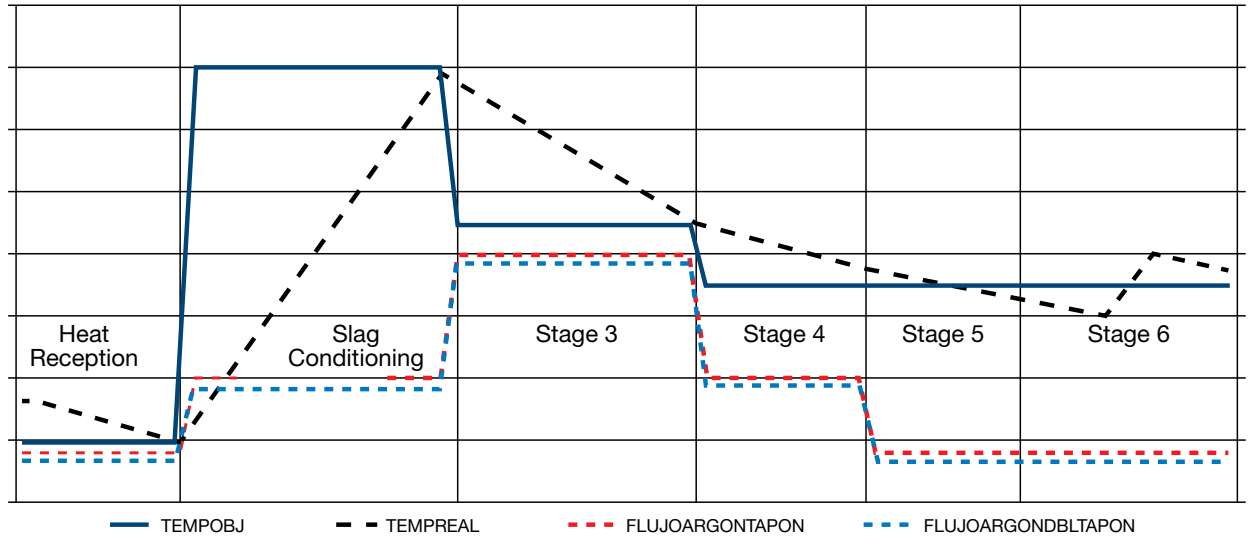
The additions used for slag conditioning are aluminum and dolomite, from Table 1, and the target values for the slag chemical composition are Al_2O_3 = 30%, CaO = 54% and BA4 = 1.8. After operators make the additions for slag conditioning, the process

Table 1

Chemical Compositions of Tapping Additions

Tapping additions	%CaO	%MgO	%MnO	%Al_2O_3	%P_2O_5	%SiO_2	%FeO	%Al	%Mn	%Si
Aluminum	0	0	0	0	0	0	0	98.5	0.7	0
Dolomite	54.0	32.0	0	3.0	0	3.0	0.9	0	0	0
Limestone	90.0	1.7	0	0.3	0	1.3	0.3	0	0	0
Desulfurizing slag (RSR)	54.6	6.6	0	15.5	0	3.4	0	18.8	0	0
FeMn MC	0	0	0	0	0	0	0	0	74.5	0.4
FeMn STD	0	0	0	0	0	0	0	0	74.5	0
FeSi Mn	0	0	0	0	0	0	0	0	77.0	18.0

Figure 1



Secondary refining practice at ladle furnaces (LFs).

of verifying the slag condition by visual inspection and chemical analysis is repeated. After slag condition is OK, the secondary refining process at the LF continues. Hence, the aim of the present work is the design of an on-line model that can help operators calculate the amount of aluminum and dolomite that must be added to the heat being processed at the LF in the time frame of the slag conditioning stage in order to achieve the target chemical composition of the slag.

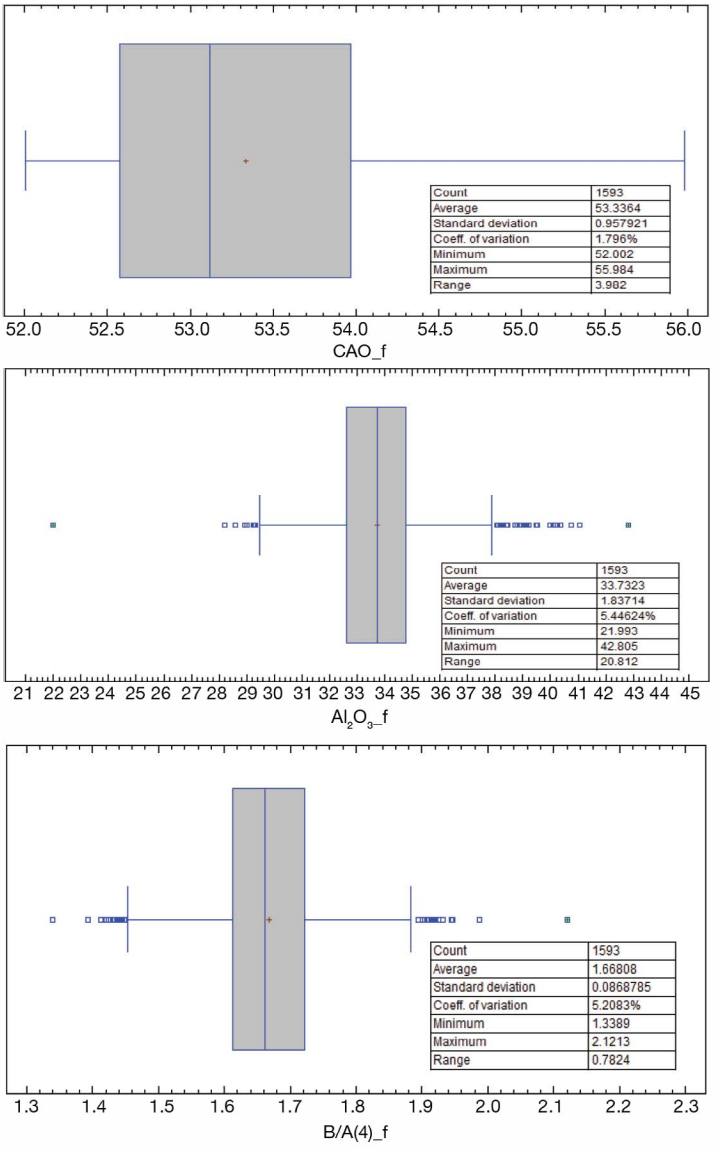
Machine-Learning Approach

The proposed approach to solve the aforementioned problem is to combine a machine-learning algorithm, the wKNN, to compute what is called the "initial approximation" of the aluminum and dolomite additions for the slag conditioning at the LF, with a mass balance that allows the calculation of the slag chemical composition and an optimization algorithm that recalculates the slag chemical composition after changing the aluminum addition, always checking the BA4. Finally, the approach should calculate the amount of dolomite that constitutes the best solution in terms of adjustment of the slag chemical composition target values.

Dealing With Uncertainties: Heat Data as Training and Test Set — The essence of implementing a model using machine learning is that a pattern exists. Such technology is useful for selection from a hypothesis set of candidate formulas, the best one that represents the pattern in terms of inputs and outputs. This hypothesis selection is based on data and computer algorithms that relies on probability concepts. Therefore, it makes sense to apply a machine-learning approach to find the patterns that conventionally the operator follows for estimation of aluminum and dolomite weights to be added during the slag conditioning stage at the LF. Fig. 2 shows the box and whisker plots of the BA4, Al_2O_3 and CaO of the heats that were selected to constitute the training and test set.

To build the model, 140 variables were considered, including process variables and chemical composition variables for both steel and slag from the two EAFs and two LFs at Ternium Mexico. Through several runs of the wKNN using design of experiments, changing the size of the input vector and the selected variables on each run, it was determined that 24 variables are relevant to model the aluminum and dolomite addition at LFs, shown in Table 2.

Figure 2



Box and whiskers plot of the slag CaO content, slag Al_2O_3 content and slag BA4 at LF from heats data considered training and test sets.

The Model: Blending the Weighted K-Nearest Neighbors, the Metallurgical Model and the Optimization Algorithm — The block diagram shown in Fig. 3 highlights the core building blocks of the proposed on-line model. The on-line model will be executed on a level 2 computer in the LF control room, and will query information from the DAT DB for reading the chemical composition of each addition and target values of the slag chemical composition according to the context information, i.e., the steel grade. In addition, the model

Table 2

Variables That Constitute the Input Vector for the wKNN

Group	Variable
EAF/LF process variables	EAF No.
	EAF tapped weight (t)
	EAF final oxygen activity (ppm)
	LF initial temperature (C)
LF slag target values	Target % CaO
	Target % Al_2O_3
	Target BA4
EAF tapping additions	Aluminum (kg)
	Dolomite (kg)
	Limestone (kg)
	De-sulfurizing slag (kg)
	FeMn MC (kg)
	FeMn STD (kg)
	FeSi Mn (kg)
LF slag chemical composition, first sample	%MgO
	%CaO
	%Al_2O_3
	%SiO_2
	%MnO
	%Fe_T
	%P_2O_5
	%S
	%FeO+MnO
	BA4

will query information from the Laboratory DB in order to obtain the initial slag chemical composition analysis. The final chemical composition analysis of slag and steel are used for adaption. From the Model DB, the model also accesses configuration parameters of the application itself such as input and output tags, training set, coefficients and reports. One human-machine interface (HMI) allows the tuning and configuration of the model, while another one allows the operator see the results of the model and select between manual or automatic setup of aluminum and dolomite addition to the LF. In the model application, an acquisition submodule gather all the input information, and transfer it to the calculation submodules wKNN, Mass Balance + Optimization and Adaption.

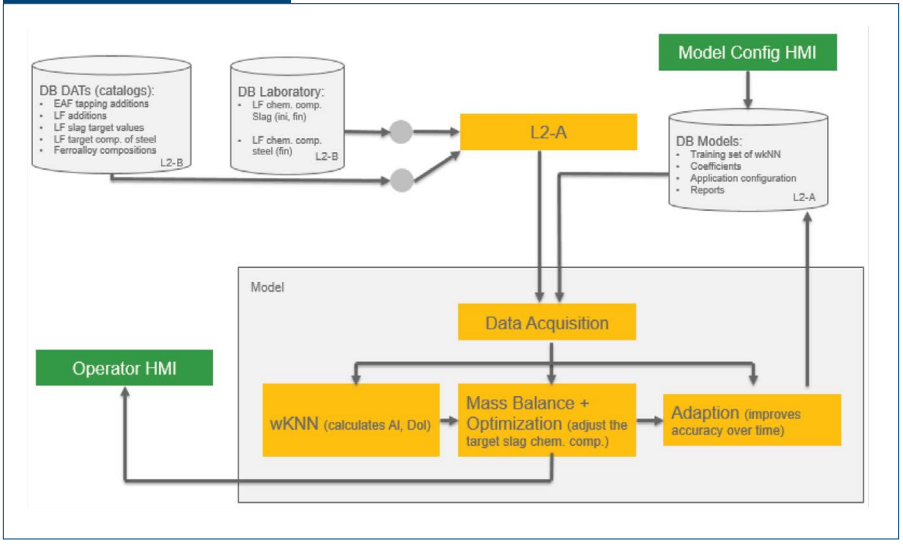
Regarding the model calculations, the sequence of calculation for the formula explanation will be followed. Let L be the number of labeled examples and $k \leq L$ be a fixed positive integer, and consider a feature vector x. A simple algorithm to estimate its corresponding outcome y consists of two steps:[7]

1. Find within the training set the k indices i_1, …, i_k are nearest, according to a given feature-space metric, to the given x vector.
2. Calculate the estimated outcome y by the following average, weighted with the inverse of the distance between x and the stored feature vectors:

$$y = \frac{\sum_{j=1}^{k} \frac{y_{i_j}}{d\left(x_{i_j}, x\right) + d_0}}{\sum_{j=1}^{k} \frac{1}{d\left(x_{i_j}, x\right) + d_0}} \qquad \text{(Eq. 3)}$$

where $d(x_i,x)$ is the distance between the two vectors in the feature space (for example the Euclidean distance), and d_0 is a small constant offset used to avoid division by zero. The larger the d_0, the larger the relative contribution of faraway points to the estimated output. If d_0 goes to infinity, the predicted output tends to the mean output over all training examples. In this work, $d_0 = 1$ and $k = 7$. The outcome y is a vector of two components: aluminum and dolomite initial approximations and the

Figure 3



Block diagram of the proposed on-line model.

feature vector x is constituted by the 24 components listed in Table 2.

The tapping additions are responsible for the initial slag formation in the LF. The proportion of oxides will depend on both the chemical composition of such tapping additions and the amount of it. The chemical composition of these additions and their yield are known. However, there are elements such as aluminum and manganese whose yields do not remain constant during the refining process, and for that reason it is necessary to calculate the yield to have a better accuracy of the slag oxides.

The Al_2O_3 mass produced by the aluminum addition is calculated as:

$$Al\_Al_2O_{3Mass} = \frac{\left(Al_{addition} * Al_{chemical}\right) * \left(100 - Al_{yield}\right) * Al_{Al_2O_3}}{10{,}000}$$

(Eq. 4)

Dolomite and limestone have the ability to promote CaO, Al_2O_3, SiO_2 and FeO oxides to the slag given its chemical composition. The following equation can be applied for the calculation of the MgO weight contribution by the addition of dolomite, and can be extended to the other elements weight contributions due to the oxides.

$$Dolomite_{MgO_{Mass}} = \frac{Dolomite_{addition} * Dolomite_{chemical_{MgO}}}{100}$$

(Eq. 5)

The synthetic slag used counts with the following oxides and elements within its chemical composition: CaO, MgO, SiO_2, Al_2O_3 and Al. The weights of the oxides can be calculated using the following equation, which is expressed for the MgO mass calculation, and in the case of aluminum it must be multiplied by the aluminum capacity of become Al_2O_3, which usually uses 1.89 as a factor.

$$RSR_{MgO_{Mass}} = \frac{RSR_{addition} * RSR_{chemical_{MgO}}}{100}$$

(Eq. 6)

FeMn MC, FeMn STD and FeSi Mn have in their chemical composition Mn and Si. The estimation of the mass of oxide produced by both elements is influenced by the yield and the ability to become oxides. The weight is generally estimated using the following equation:

$$FeMn_{MnO_{Mass}} = FeMn_{addition} * \frac{FeMn_{chemical_{MnO}}}{10{,}000} * \left(100 - Yield\right) * Mn\_to_{MnO}$$

(Eq. 7)

Slag mass of each oxide, due to the tapping additions, can be calculated as extension of the following formula for MgO mass:

$$MgO_{Mass_{total}} = Dolomite + Limestone_{MgO_{Mass}} + RSR_{MgO_{Mass}} + FeMn_{MgO_{Mass}} + FeMnSTD_{MgO_{Mass}} + FeSi_{MgO_{Mass}}$$

(Eq. 8)

The total slag mass is the sum of the mass of all the oxides produced by the tapping additions:

$$Slag_{Mass_{total}} = CaO_{Mass_{total}} + MgO_{Mass_{total}} + MnO_{Mass_{total}} + Al_2O_{3Mass_{total}} + SiO_{Mass_{total}} + FeO_{Mass_{total}}$$

(Eq. 9)

However, these percentages will differ somewhat with respect to the initial chemical analyzes of the slag. This is because the exact amount of eccentric bottom tapping (EBT) sand pass and EAF carryover slag to the LF are not known. This difference in mass will cause a difference in the percentages of estimated oxides.

The EBT sand pass will initially be set at 70 kg, and knowing the chemical composition will serve later as a learning factor or model adjustment factor.

There are several ways to estimate the theoretical carryover slag by means of the oxides (Al_2O_3, SiO_2, P_2O_5 and CaO). The calculations and tests performed showed that the balance with the amount of phosphorus pentoxide (P_2O_5) that existed showed the most consistent results. The tapping additions do not promote the formation of P_2O_5 in the LF and for this reason the mass of P_2O_5 present in the slag of the LF corresponds to P_2O_5 remaining from the EAF. Therefore, the P_2O_5 content in the EAF slag is known and, consequently, the P_2O_5 in the first sample of the LF's slag. Additionally, the slag mass can be estimated based on the tapping additions, so it is possible calculate the P_2O_5 present in the LF slag and the theoretical carryover slag based on the P_2O_5.

$$Mass_{P_2O_5} = \frac{-\left(Slag_{Mass_{total}} + Slag_{Mass_{EBT}}\right)}{\left(\frac{1}{\%P_2O_{5_{LF}}}\right) - \left(\frac{1}{\%P_2O_{5_{EAF}}}\right)} * 100$$

(Eq. 10)

$$Slag_{carryover_{EAF_{to_{LF}}}} = \frac{Mass_{P_2O_5} * 100}{P_2O_{5_{EAF}}}$$

(Eq. 11)

The total slag mass is calculated as:

$$Slag_{total} = Slag_{Mass_{total}} + Slag_{carryover_{EAF_{to_{LF}}}}$$

(Eq. 12)

Using the aluminum initial addition calculated by the wKNN through Eq. 3, Al_2O_3 mass contribution to the LF slag is:

$$Al\_Al_2O_{3_{Mass}} = \frac{\left(Al_{addition} * Al_{chemical}\right) * \left(100 - Al_{yield}\right) * Al_{Al_2O_3}}{10{,}000}$$

(Eq. 13)

Using the dolomite initial addition calculated by the wKNN through Eq. 3, CaO, MgO, SiO_2, MnO and Al_2O_3 mass contributions to the LF slag can be Al_2O_3 with the following equation, extended to the mentioned oxides:

$$Dolomite\_CaO_{Mass} = \frac{Dolomite\_Chemical_{CaO}}{100}$$

(Eq. 14)

The weight of LF slag due to the wKNN initial additions is:

$$WeightSlag_{addition} = Al_{Al_2O_{3_{Mass}}} + Dolomite_{CaO_{Mass}} + Dolomite_{MgO_{Mass}} + Dolomite_{SiO_{2_{Mass}}} + Dolomite_{MnO_{Mass}} + Dolomite_{Al_2O_{3_{Mass}}}$$

(Eq. 15)

The calculated chemical composition of the LF slag can be calculated using the following expression for the CaO, extended to the MgO, Al_2O_3, SiO_2, MnO and FeO, as:

$$CaO_{porc_{addition}} = \frac{CaO_{Mass_{total}}}{WeightSlag_{addition}} * 100$$

(Eq. 16)

The quaternary basicity, BA4, is used as condition in the optimization algorithm of the model, and is calculated as:

$$B4_{addition} = \frac{\left(CaO_{porc_{addition}} + MgO_{porc_{addition}}\right)}{\left(Al_2O_{3\,porc_{addition}} + SiO_{2\,porc_{addition}}\right)}$$

(Eq. 17)

The optimization algorithm recalculates the slag chemical composition after changing the aluminum addition by a delta_Aluminum configurable in the Model DB. On each iteration, always check the BA4. Finally, this algorithm calculates the amount of dolomite that constitutes the best solution in terms of adjustment of the slag chemical composition target values.

Results

Training, Test and Validation Sets — The data set consists of information from 1,593 heats produced in two EAFs at Ternium Planta Guerrero. The distribution of the data is shown in Table 3.

Results of the off-line evaluation of 30 heats from the validation set are presented in this paper (* indicates this is a portion of the total validation set). The BA4, Al_2O_3 and CaO contents in the LF slags and the comparison between the target value, the real value and the model calculation are presented in Figs. 4–6.

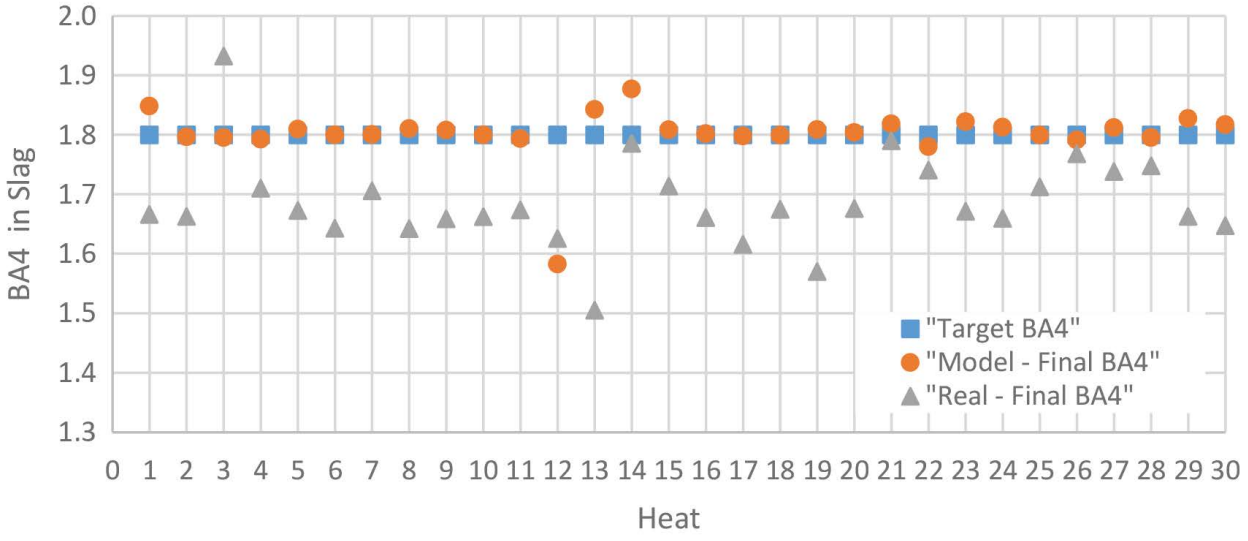
In the previous three plots, the displayed Real data shows more dispersion from heat to heat than the Model data, because the additions were set by operational practice, without a model or an automated system. The Target data remains constant for the selected heats, and in the case of BA4 and Al_2O_3, Model data has less dispersion than Real data. In the

Table 3

Data Set Distribution

Set	EAF 1 # heats	EAF 2 # heats	Variables
Complete	776	817	140
Training	465	490	24
Test	311	327	24
Validation*	30	30	24

Figure 4

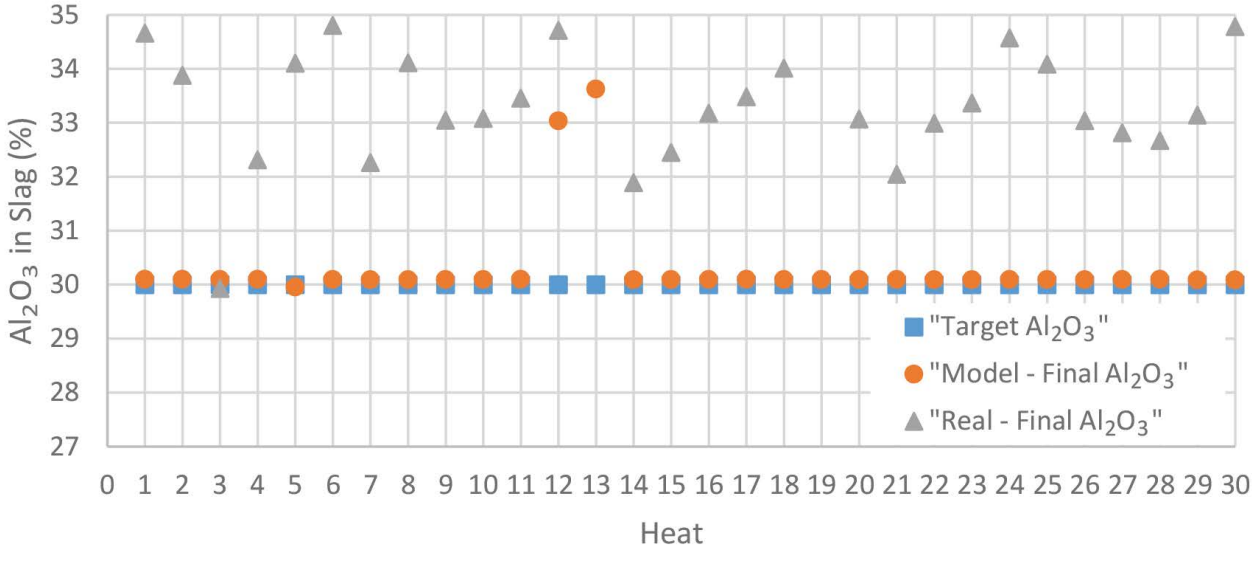


Results of BA4 in the LF slag.

case of the CaO, the Model data has more dispersion than Real data. This can be explained as follows: the optimization algorithm in the model adjusts the BA4 changing the aluminum addition, so prioritize the BA4 and Al_2O_3 adjustment. Then, the calculation of dolomite addition to achieve the best result in terms of CaO, keeping BA4 tied to the target, through recalculation of slag chemical composition is carried out.

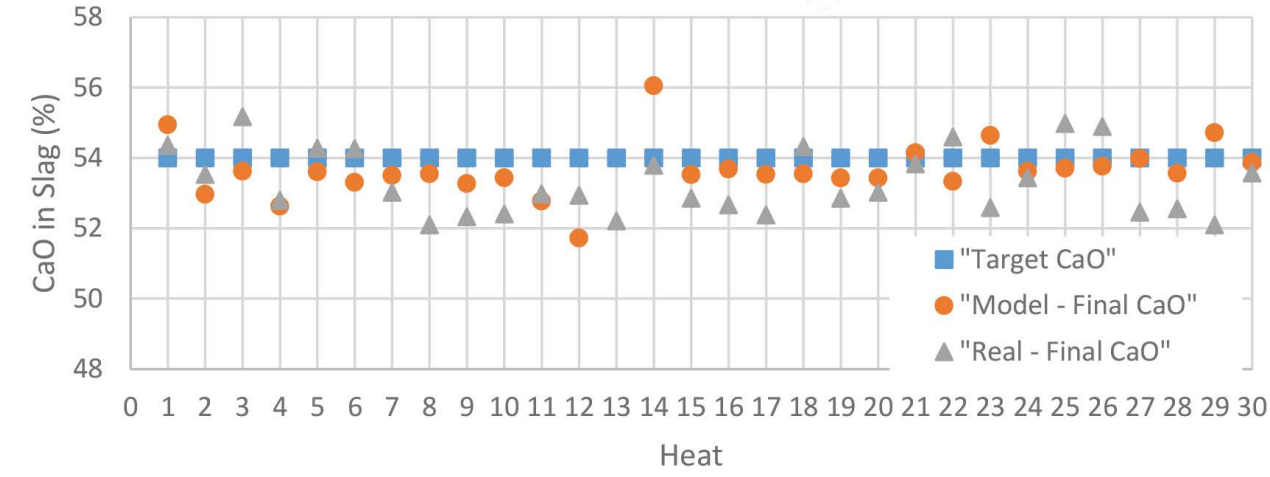
Table 4 shows a summary of results and expected benefits of the model for the validation set. Dispersion in Al_2O_3 is potentially improved by 46% while BA4 can be improved by 39%. Dispersion in CaO is worst, by 92%. The total amount of aluminum proposed by the model for the 30 heats is less than the total amount of aluminum applied for those heats, and this can potentially lead to an improvement of 49% in consumption. In the case of dolomite, the model proposes major total addition than the applied, with a potential impact of –85% in the dolomite consumption. Regarding costs, there is a potential saving of

Figure 5



Results of Al_2O_3 content in the LF slag.

Figure 6



Results of CaO content in the LF slag.

US$0.41/ton if the model is used to set the aluminum and dolomite additions at the LFs, at the period of evaluation.

Table 4

Results Summary

Item	Model	Real	Improvement (%)	Model costs	Real costs
Total added Al (kg)	1,423.3	2,798.3	49	US$2,295.79	US$4,513.70
Total added lime (kg)	8,379.5	4,519.4	–85	US$921.32	US$496.90
STDV - Al_2O_3	0.826	1.520	46		
STDV - CaO	1.786	0.931	–92		
STDV - BA4	0.046	0.075	39		
Total				US$ 3,217.11	US$5,010.60
Expected total savings					US$1,793.49
Expected savings				US$0.41/ton	
Expected savings @1 heat, 140 t				US$57.86	

Conclusions

The wKNN algorithm is a robust machine-learning technique for solving problems with several uncertainties, as is the case of the meltshop. The proposed model, in simulations, performs better than the manual operation, adjusting the BA4 and Al_2O_3 of the LF slag to the target values, with a low standard deviation. The CaO presents the worst dispersion, but the BA4 is not compromised and in the worst case of the validation set, CaO was 2% lower than the target value, which is inside the plant tolerances. The proposed model can lead to a reasonable cost saving per ton of steel, due to the fact that helps reduce the aluminum additions during the slag conditioning stage. Future work includes the on-line test of the model with the adaption schema.

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