EVALUATION OF CAS-OB PROCESS CONDITIONS IN THE OCCURRENCE OF LADLE NOZZLE CLOGGING THROUGH MACHINE LEARNING*

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Abstract

Ladle nozzle clogging is a recurring problem in steel shops worldwide. This event may cause heat return to BOF, interruptions in the continuous casting sequence, decrease continuous casting speed, and remove the ladle from the production cycle, leading to productivity losses. The causes of clogging are generally associated with the deposition of non-metallic inclusions (NMI) on valve walls or the solidification of steel by low temperature. Several factors can affect the behavior of NMI during the process, from slag chemical composition, deoxidation, calcium treatment, and flotation time. Thus, based on an exploratory analysis of a database of industrial heats, this study aimed to determine which process parameters have the highest correlation with clogging events in steels treated in the CAS-OB route. Machine learning algorithms were used to select important variables and develop a model to classify clogging events. The model achieved a classification performance of 66% and was explained using the Shapley values method, which considered the influence of calcium content, valve life, desulfurizer weight and NMI removal mechanisms such as the use of argon lance and porous plug. Based on these results, it was possible to propose actions to reduce the incidence of ladle nozzle clogging.

Keywords: Ladle nozzle clogging; Non-metallic inclusions; Secondary refining, Machine learning.

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1 INTRODUCTION

One of the main problems during continuous casting is the clogging events. This abnormality can lead to a decrease in the casting speed, quality deviations and even interruptions in the casting sequence, which are extremely harmful to the manufacturing process. Clogging is more likely to occur in refractory devices responsible for controlling the transfer of the metal bath, such as ladle and tundish slide gate valves, ladle shroud, stopper rod and submerged entry nozzle (SEN) [1-4].
The slide gate valve is the most widespread system for transferring liquid steel between the ladle and tundish, as it allows excellent flow control, can be used in several heats and is easy to change. The ladle nozzle system comprises well block, upper nozzle, upper plate, lower plate, and lower nozzle, as shown in figure 1. The upper and lower plates contain holes, and the upper nozzle is fixed, while the lower nozzle can move. The nozzle opens when the lower plate moves, the holes coincide, allowing the steel to flow. The nozzle can work fully open, closed, or semi-open, depending on the continuous casting conditions [5,6].

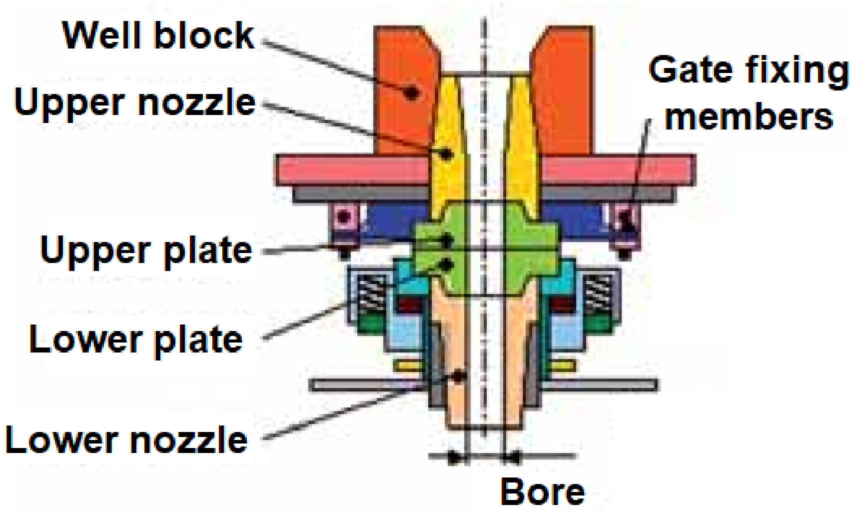

Figure 1. Schematic draw of ladle nozzle [7].

The clogging during continuous casting has the main causes associated with the deposition of non-metallic inclusions (NMI) on the nozzle walls, or the steel solidification by low temperature. Particles adhesion is mainly governed by surface tension between inclusion, liquid steel and refractory. In this sense, aluminas, products of deoxidation and eventually reoxidation, are inclusions with a strong adherence tendency. In addition, factors such as nozzle roughness, number and size of NMI can influence clogging. Thus, the inclusions' layers are formed to reduce/block the steel flow between the ladle and tundish [8,9].
There is no consensus on a single solution to clogging among steel shop workers because it is a complex mechanism, which depends on steel chemical composition, process route and characteristics of the reactors involved. Thus, the presented countermeasures can be adapted to each steel shop [9]. According to Pawełek and Czechowski [10], each measure presents a type of limitation, which may increase costs, require investments, adaptations and exchange of materials.
Aiming to reduce NMI adherence to the nozzle and avoid clogging, it's possible to: modify the deoxidation products, either by calcium addition [8-11], or replacing the deoxidizing agent, with the aim of generating less deleterious inclusions [6]. Nozzles

with argon injection and made of material with lower wettability by the liquid steel, such as alumina graphite, can be used. Also, it is possible to reduce the roughness of the valves and even increase the temperature of the liquid steel, considering the casting limitations of each type of steel [10].
With the big volume of data generated and the evolution of computational resources, machine learning (ML) techniques have been gaining strength in the understanding, prediction, and solution of the most diverse problems. Thus, algorithms such as decision trees have been used to classify samples, such as process abnormalities [12,13]. Another tendency for ML models is the explanation through the SHAP values method, which can extract information on the performance and behavior of the variables on the algorithm, as determining the magnitude and how each variable contributes to the model [14].
Thus, this work aimed to identify the main parameters correlated with ladle nozzle clogging events, in steels treated in the CAS-OB route, based on the analysis of process data from Steel Shop 2 of Usiminas. From the identification, it was possible to propose actions to reduce the occurrence of clogging in the process.

2 DEVELOPMENT

Aiming to identify which parameters most influence nozzle clogging in steel ladles at Steel Shop 2, the work was carried out in the following stages: database construction, variables exploratory analysis, variables selection, application of models to classify the clogging events and explanation of the models. Heats on route BOF -> CAS-OB -> continuous casting were studied, as illustrated in figure 2.

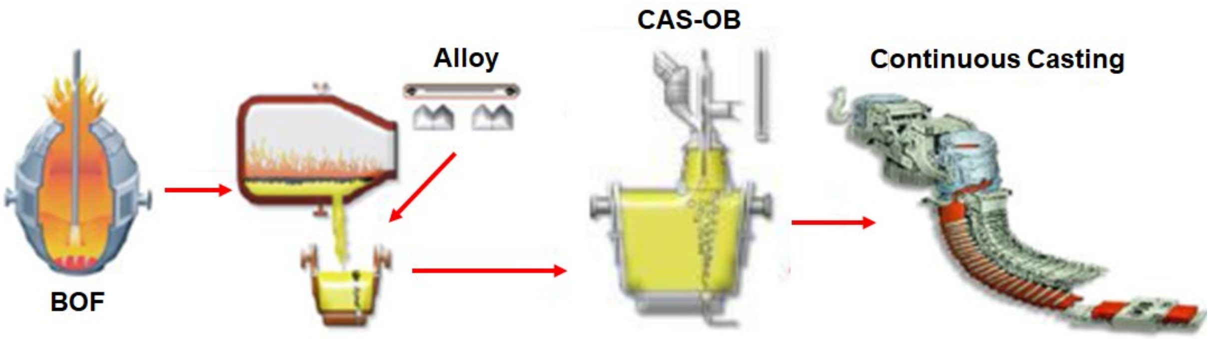

Figure 2. CAS-OB route.

2.1 Database

The database was built with industrial heats from January 1, 2016 to May 31, 2022. The heats were raised according to parameters that may be related to nozzle clogging events. Variables were selected on general heat data, BOF and tapping, ladle preparation, CAS-OB processing and continuous casting, as listed in figure 3. After data cleaning, the base had 5365 heats.

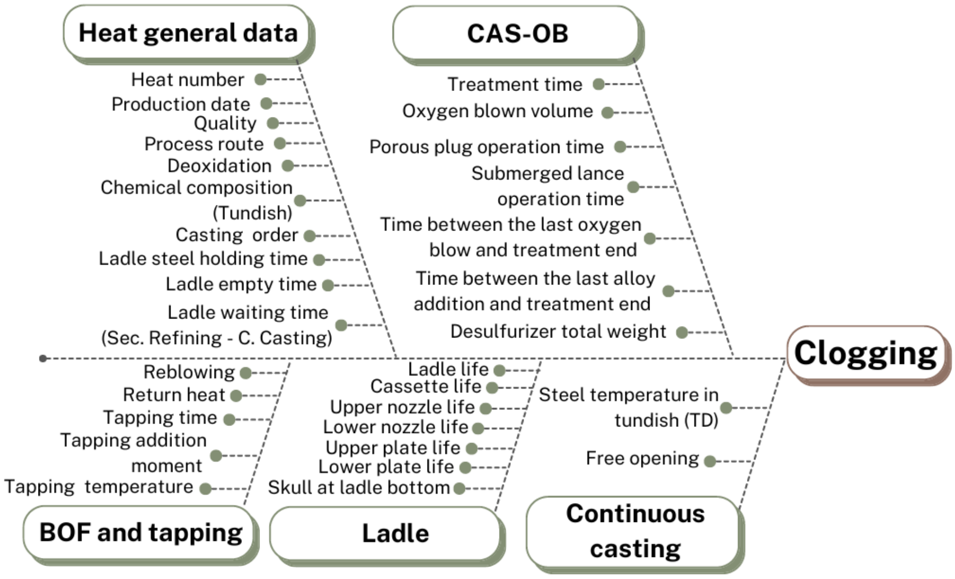

Figure 3. Parameters analyzed for clogging database.

2.2 Clogging Evaluation

To evaluate the clogging events, Python language was used. The code was structured as follows: importing the database and libraries, database exploratory analysis, variables selection with the greatest impact, training and testing of classification models, and results explanation.

2.2.1 Selection of Important Variables

To select the most important variables for clogging events, at first, the data were divided into: 70% for training and 30% for testing. The training data are the ones presented to the machine learning algorithms for model creation, while the test data are used for validation, as suggested by Nguyen *et al*. [15]. After separation, the XGBoost classification model (xgb.XGBClassifier) was applied, used to select heats with clogging, or not (regular heats). Subsequently, the Recursive Feature Elimination with Cross Validation (RFECV) algorithm was applied to select the most important variables in the model for identifying cases of clogging, in order to improve its accuracy, as well as Sevastianov and Shchetinin [16].

2.2.2 Algorithm Training and Test

The clogging events occur in a much smaller number than the total number of heats (374 cloggings for 4991 regular heats), resulting in an unbalanced database. Thus, the under-sampling technique (imblearn.under_sampling.RandomUnderSampler) was used to balance the class distribution, as proposed by Singh *et al*. [17]. After rebalancing the database, the Extra Trees Classifier classification algorithm (sklearn.ensemble.ExtraTreesClassifier) was applied to predict heats with clogging and the regular ones.

2.2.3 Explanation

At the code end, to explain how the variables affected the classification models, the SHAP values method (shap.Explainer) was used, as proposed by Scavuzzo *et al*. [14]. This feature has stood out in studies involving machine learning, especially “black box” algorithms, to facilitate the interpretations of the results.

2.3 Results

The Extra Trees Classifier (ET) model was trained and tested to classify the ladle nozzle clogging occurrence in CAS-OB route. One way to evaluate the performance of a classification model is via the confusion matrix [18].
Figure 4(a) shows the confusion matrix of the ET model. The confusion matrix should be read as follows. The actual data are presented on the Y axis, while on the X axis are the data predicted by the model for the “regular” and “clogging” classes. The matrix is composed of four squares, in which the first presents heats that truly had no abnormalities and the model was correct in the prediction (true negative). The second frame configures cases in which there was regular heats, but the model predicted clogging (false positive). In the third, they are real cases of clogging and that the model pointed out as “regular” (false negative). In the latter, they are true cases of clogging convergent with the model prediction (true positive). Thus, on the main diagonal, signaled by the red arrow in Figure 4(a), the heats in which the model got the classification right are indicated.
Therefore, in the confusion matrix of Figure 4(a), it can be seen that, out of 112 clogged heats, the ET model correctly classified 91 (81.25%). For regular heats, the model was right 1264 out of 1498, that is, 84.38%. The distribution of model performance is presented in Figure 4(b). The accuracy (ACC) of the model was 84.16%. However, as clogging events have a small incidence in the total number of heats, there is a case of unbalanced data, that is, there is a lot of information about heats without abnormality and less about the minority category (clogging), which provides high ACC values. For an unbalanced database, the use of the macro metric F1-score [19] is suggested, which gives equal importance to each class. Thus, the macro F1-score of the model was 66.24%. Compared to the accuracy value, the low value is mainly due to cases in which the heats were regular and classified as clogged (second quadrant). Even so, it is considered the model with a good performance for event classification.

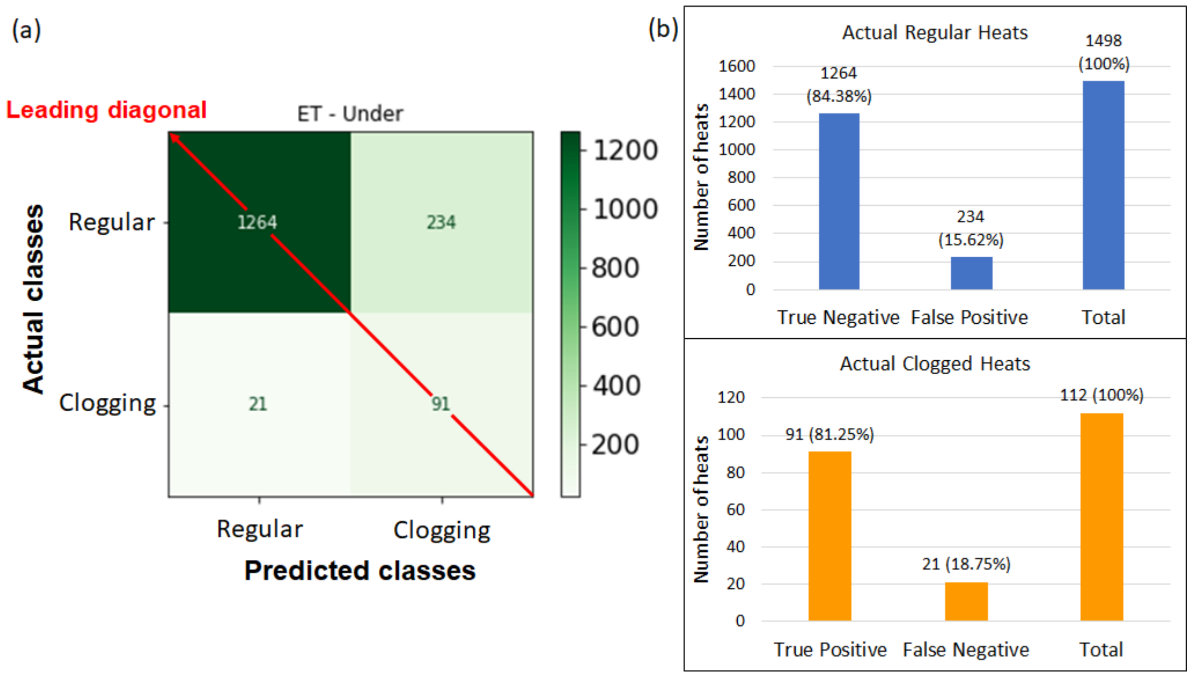

Figure 4. (a)Confusion matrix of predicted and actual data, according to classification in “clogging” and “regular" (b) model performance distribution for actual heats.

One of the strengths of Python language is its data visualization capability. The summary plot (shap.summary_plot) presents the contribution of each variable to the model [14]. Reading this type of chart should be done as follows. Parameters are listed in order of importance on the y-axis from top to bottom. Each point on the graph represents a sample from the database. The colors indicate the magnitude of each variable, where the red color corresponds to higher values of the parameter and the blue color corresponds to lower levels. The horizontal axis represents the Shapley values of each parameter on the response variable (clogging). That is, the more to the right, the greater the probability of the clogging happening. If the point is positioned to the left, less chance of clogging occurring.
Interpreting the results of the Extra Trees Classifier (ET) model, in Figure 5, the calcium content in the tundish sample can be seen as the main parameter of impact on clogging, followed by the life of lower plate, total desulfurizer weight and submerged lance operation time. For the case of Ca, higher levels correlated with regular heats, while cases of clogging tend to heats with lower levels of the element. This makes sense, since one of the purposes of adding the alloy is to modify non-metallic alumina inclusions in order to reduce clogging in liquid steel transfer systems, as widely discussed in the literature [8,9,20,21].
As for the life of the lower plate, a trend of clogging in smaller lives can be observed, as shown in figure 5. The clogged heats were concentrated in plates with up to 3 heats of use, while the regular ones had an average life of 3 heats. As liquid steel flows through the refractory surface, wear of the lining layer occurs [22]. Therefore, valves with a longer use time tend to have a larger internal diameter. The internal diameter, in turn, is directly associated with the flow of liquid steel, in which larger dimensions imply greater flows [11]. The speed at which the liquid steel passes through the valve is directly related to the inclusions drag force, associated with the detachment of the refractory surface [8].
The third parameter with the greatest influence on clogging was the total weight of desulfurizer, in which higher amounts correlated with the process abnormality. Regarding the total time of argon injection in the lance, higher values were associated with the clogging occurrence, as shown in figure 5.

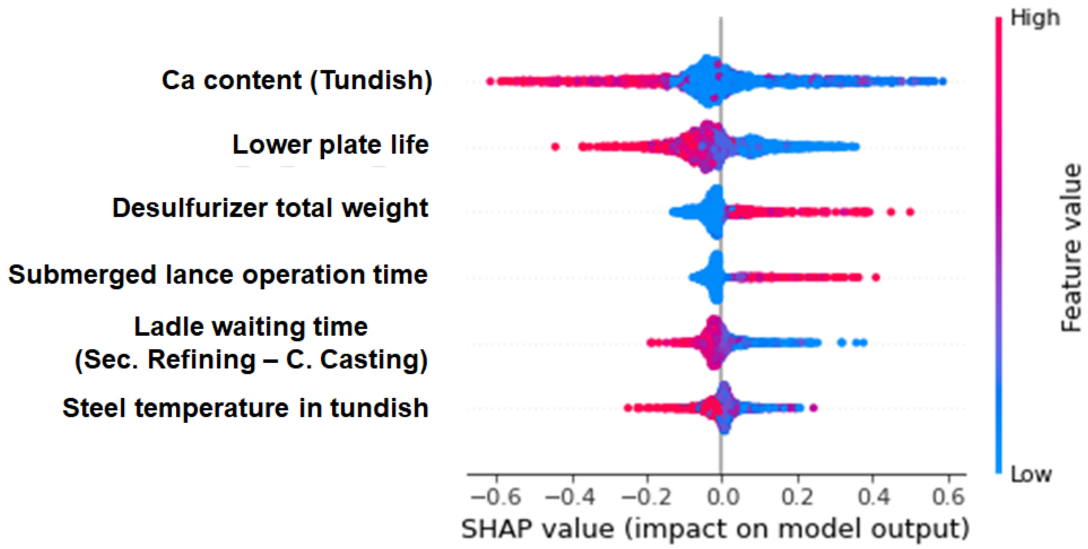

Figure 5. Summary plot for explain ET model trained for heats in CAS-OB route.

SHAP also provides individual interpretation, which is interesting to evaluate a specific sample, such as a clogging event. One of the ways to do this is by creating a

Waterfall plot (shap.plots.waterfall), as shown in Figure 6. To interpret this plot, start with the lower x-expectation axis, (E[f(x)]), towards the top, where we have the result in probability f(x). If f(x) = 0, the heat had a regular process during casting, if f(x) is equal to 1, a case of clogging is indicated. Each variable contributes either positively (red color) or negatively (blue color). The arrows' values, sizes and directions also indicate each parameter's contribution to the response variable. It is important to point out that, in this type of graph, how the variable impacted the model is not addressed, but its weight in the response variable, since they were standardized for application of the classification models.
As an example, a heat sample with clogging was selected, as shown in figure 6. From a base value E[f(x)]=0.24, all parameters contributed positively until the nozzle clogging (f(x)=1), with the exception of the ladle waiting time. Note the Ca content in the tundish sample as the main contributing factor to the abnormality of the process (with a weight of 36% in the response variable), following the overall result of the summary chart (figure 5). In this heat, there was no significant effect of lower plate life, argon time in the lance and use of desulphurizing material. A regular condition was also explored, shown in Figure 7. For this sample, the calcium content was the parameter with the greatest influence on the model, followed by the lower plate life, however, acting in favor of process stability. The other parameters did not present a significant contribution in the clogging classification.

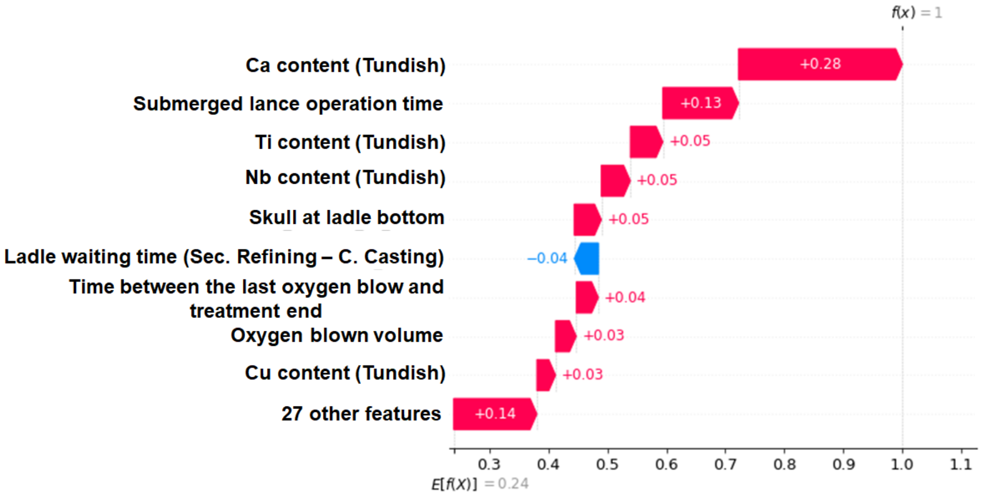

Figure 6. Waterfall plot for a clogged heat on CAS-OB route.

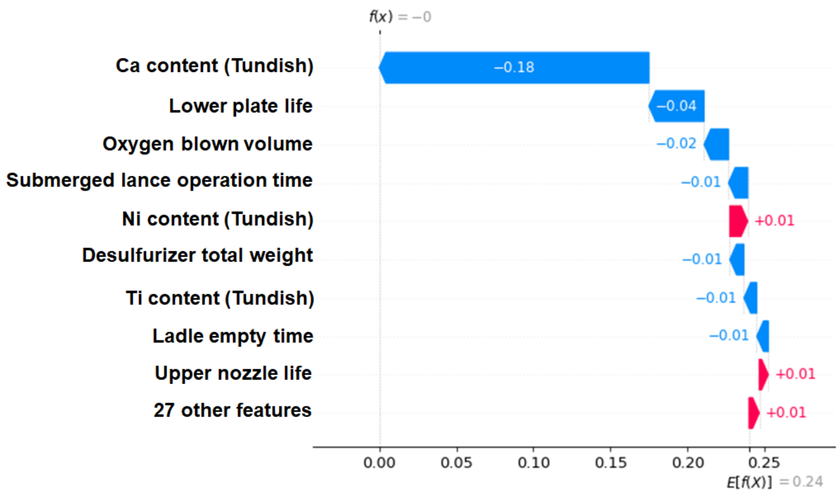

Figure 7. Waterfall plot for a regular heat on CAS-OB route.

2.4 Discussion

The calcium content was the parameter that stood out most concerning the occurrence of ladle nozzle clogging. Certainly, one of the purposes of adding the alloy to the bath is to improve its castability, namely the ease of flowing through liquid steel transfer valves. However, it is known that the amount of calcium added cannot be random. According to Leão *et al*. [21], Holappa *et al*. [23] and Devi *et al*. [24], the amount of calcium must be added in order to reach the "lingotability window". In this field, the inclusions of calcium aluminates are in a liquid state, at ladle temperatures, favoring non-deposition on the valve walls. Excessive additions can lead to the formation of calcium sulfides (CaS), harmful to the process. Also, insufficient additions lead to the formation of solid calcium aluminates, which are also deleterious. One way to calculate the castability window is via thermodynamic software, for example Thermo-Calc®. Thus, it is suggested to verify the feasibility of using calcium alloys to attenuate clogging, especially in steels with a high history of process abnormality.
Another highlighted parameter was the life of the nozzle system, in which higher lives, that is, valves with a larger internal diameter, presented less tendency to clog. The possibility arises that the valve is undersized, however, this is a complex issue, since changing the dimensions does not only have an effect on clogging, but on casting speed, reuse of valves, costs, among others. Thus, further investigations on the subject are suggested.
The use of the argon lance, associated with the non-functioning of the porous plug, also proved to be a relevant factor for the occurrence of clogging. Therefore, improving the performance of the plug is of paramount importance.

3 CONCLUSION

A database of Usiminas Steel Shop 2 heats, collected from January 2016 to May 2022, was built to investigate the influence of process parameters on the occurrence of ladle nozzle clogging in heats processed on the CAS-OB route.
Models were applied to select the most important variables and to classify heats with clogging and regular ones, in which a satisfactory performance of 66% was obtained. The explanation of the models highlighted the importance of calcium content, valve life, amount of desulfurizer used, as well as how the argon lance works.
Identifying the most critical variables made it possible to propose countermeasures to attenuate the occurrence of nozzle clogging in steel ladles at Usiminas Steel Shop 2.

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