Use of Advanced Analytics to Forecast Low Efficiency Pots

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Abstract

CBA is a Brazilian aluminum company with VSS Søderberg technology and is moving towards Industry 4.0 to improve potroom operations and make more consistent and predictable performance. One of several initiatives is the use of advanced data analytics in a cloud environment to forecast pot conditions in advance to avoid pot problems and maintain high productivity. The project started in 2020 and after several attempts with different numbers of variables the neural networking configuration was selected as the best candidate. The training data set has two years of history and has more than ten variables in a weekly average to check pot conditions as a supporting tool for the technical team. The test was conducted in our six potrooms with two groups: the control group and the test group (calculated by the neural network). The algorithm forecasts one week ahead the probability to lose production by pot. After one year of test the results showed 12 % decrease in production loss due to early diagnosis and action. The results were only achieved through combined software and human effort. This work changes the potroom operation from a reactive and manual interference in low production pots to a proactive and automated early detection.

Keywords: Aluminum production, Advanced data analytics, Neural networks, Industry 4.0.

1. Introduction

CBA is a Brazilian aluminum company with vertical stud Søderberg (VSS) technology and is moving towards the 4.0 industry to improve potroom operations making it with more consistent and predictable performance. From Cyber-Physical Systems, Internet of Things and Internet of Services, production and processes tend to become more efficient, autonomous and customizable. The CBA Industry 4.0 program focuses on several initiatives such as: artificial intelligence (AI), business intelligence and others, as well as a pipeline of R&D projects, which are expected to enhance the sustainability of processes and products.

This paper explores one of the fields of Industry 4.0 Big Data Analytics. These are very extensive and complex data structures that use new approaches to collect, analyze and manage information. Applied to Industry 4.0, Big Data technology consists in handling relevant information: Connection (to industrial network, sensors and PLCs), Cloud (cloud/data on demand), Cyber (model and memory), Content, Community (sharing of information) and Customization

(customization and values). From Big Data technology emerges the Advanced Analytics that is a methodology of data analysis that uses predictive modeling, machine and deep learning algorithms, process automation and other statistical methods to analyze information from a different data source.

Nowadays one of the best performance algorithms that ensemble classifiers/predictors is the extreme gradient boosting (XGBoost). It is an optimized distributed gradient boosting algorithm designed to be highly efficient, flexible and portable. It implements machine learning algorithms under the Gradient Boosting framework. The algorithm category is based on Decision Trees with Gradient Boosting. Gradient means that the algorithm uses the Gradient Descent algorithm to minimize loss. It has many hyperparameters that can be tuned to adjust the algorithm to best suit to the scenario. Decision Trees are methods where there is a function that takes a value as a vector of attributes as input and returns a decision (output). For a decision tree to arrive at the output value, it performs a series of steps, creating various branches throughout the process. Each node in this tree represents a single decision. The more times an attribute is used for decision making, the greater its relative importance in the model. Gradient boosting is a machine learning technique, which produces a prediction model in the form of an ensemble prediction models, typically decision trees [1, 2]. When a decision tree is the weak learner, the resulting algorithm is called gradient boosted trees, which usually outperforms random forest [2, 3].

2. Experimental

The first step was to build the data architecture that consists in the acquisition of data from our source of historic process data (PIMS), where the tags are sequenced and queued for consumption based on the frequency of capture by the sensors. The Data Ingestion process uses the extraction, transformation and loading (ETL) resources combined between the Data Factory and the Event Hub, forming the first stage, where the data presents a raw and semi-structured format.

In the next step, we internalize the information in our Data Lake, producing an accurate version, enriched with other information from auxiliary and complementary spreadsheets, as well as a source that is fed back by Tableau's own visualization, which allows an evaluation of the actions taken later.

In the intelligence stage, we apply machine learning algorithms in order to obtain the evaluated insights from the period in question, acting in the prescriptive way of analyzing the acquired variables.

Some of the parameters used in the algorithm were: DEPTH, SHRINKAGE, SUBSAMPLE, COLSAMPLE_BYTREE, GAMMA, MIN_CHILD_WEIGHT. Where DEPTH means maximum depth of a tree. Increasing this value will make the model more complex and more likely to overfit. SHRINKAGE which means in modifying the update rule. It can increase the computational time both during training and querying. SUBSAMPLE is the ratio of the training instances. COLSAMPLE_BYTREE is the subsample ratio of columns when constructing each tree. GAMMA is the minimum loss reduction required to make a further partition on a leaf node of the tree. MIN_CHILD_WEIGHT is the minimum sum of instance weight needed in a child. If the tree partition step results in a leaf node with the sum of instance weight less than min_child_weight, then the building process will give up further partitioning.

The general objective function of the gradient tree boosting is presented by Equation (1)

$$\gamma_{jm} = \arg min_{\gamma} \sum_{x_i \epsilon R_{jm}} L(y_i, F_{m-1}(x_i) + \gamma) \tag{1}$$

The steps to lead used in the prediction model were:

a. Data pre-treatment: Construction of derivatives and means of variables in different time windows;
b. Training based on training from 2019-03-01 to date with calculated targets (considering the solution, it would be the date 14 days ago);
c. Last month of data is used to calculate the thresholds applied in the model's probability cut (calculated by quantiles using the number of occurrences of the target's positive classification in this period);
d. The algorithm used optimized fixed values;
e. Thresholds are applied per potroom (each potroom has its own) and the classification in Alarm, Alert and Good performance is generated.

There were more than ten input variables such as: Bath Temperature, %AlF_3, Instability (low frequency), Instability (high frequency), Average Pot Voltage, Anode Problems, Silicon and Iron content, Age, DB (slope resistance) and as an output the metal pad level. Through the visualization panel, all necessary alarms and actions are returned to the model based on the decisions of the tool operators, Figure 1.

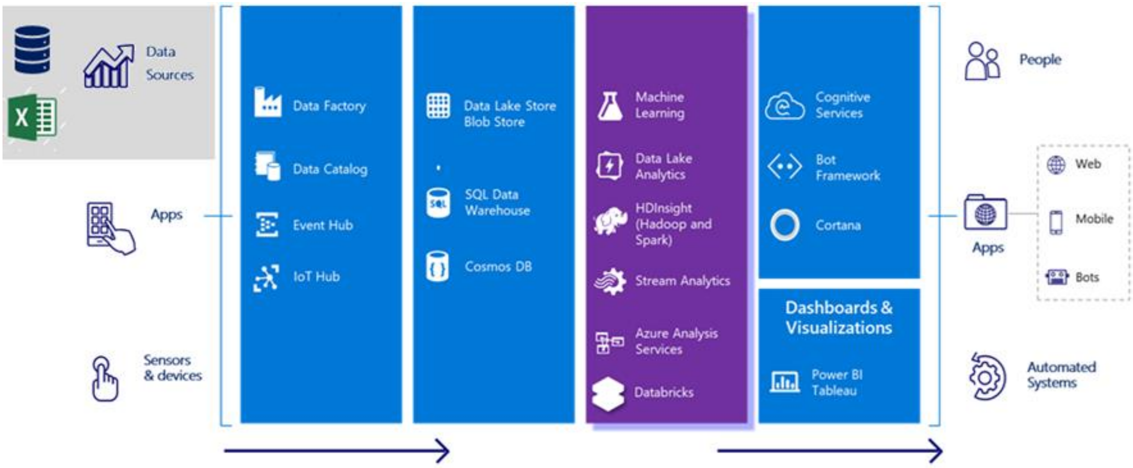

Figure 1. Data flow for the models and use in the shopfloor.

The test was conducted in our six potrooms with two groups one was the control group and the other was the test group. The algorithm forecast with two weeks of advanced the probability to lose production by pot. After the alarm the operator had to check the pot and justify the actions to avoid the loss of production.

3. Results

The evaluation of the algorithm prediction is based on four categories precision, sensitivity, effectiveness and actuation gain for each reduction, Table 1. Data was collected from 01/01/2020 until 15/08/2021.

For potroom decision tool there were a few other screens to support the decision making. In Figure 2 there was a screen that shows the distribution of pots from one line e.g., Line 6, red - activated alarm, orange – alert, blue – good performance. In the Figure 3 there was a single pot alarm.

Table 1. Categories for algorithm prediction.

LINE	PRECISION (%)	SENSITIVITY (%)	EFECTIVENESS (%)	ACTUATION GAIN (%)
2	25.6	6.4	96.7	3.9
4	25.5	10.5	99.3	5.4
5A	33.6	25.8	71.2	4.8
5B	29.9	40,5	71.4	1.0
6	34.6	49.6	72.8	1.5
7	30.5	51.9	78.5	3.5
TOTAL	**31.3**	**33.6**	**76.7**	**3.2**

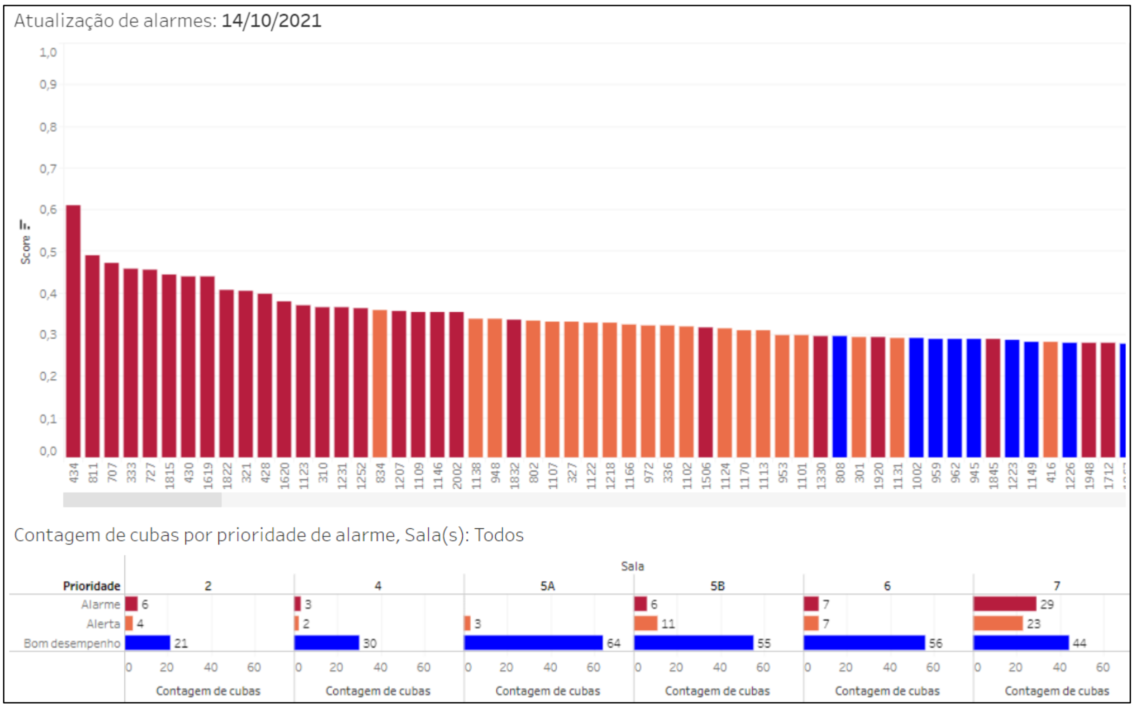

Figure 2. Screens to support potroom - line behavior.

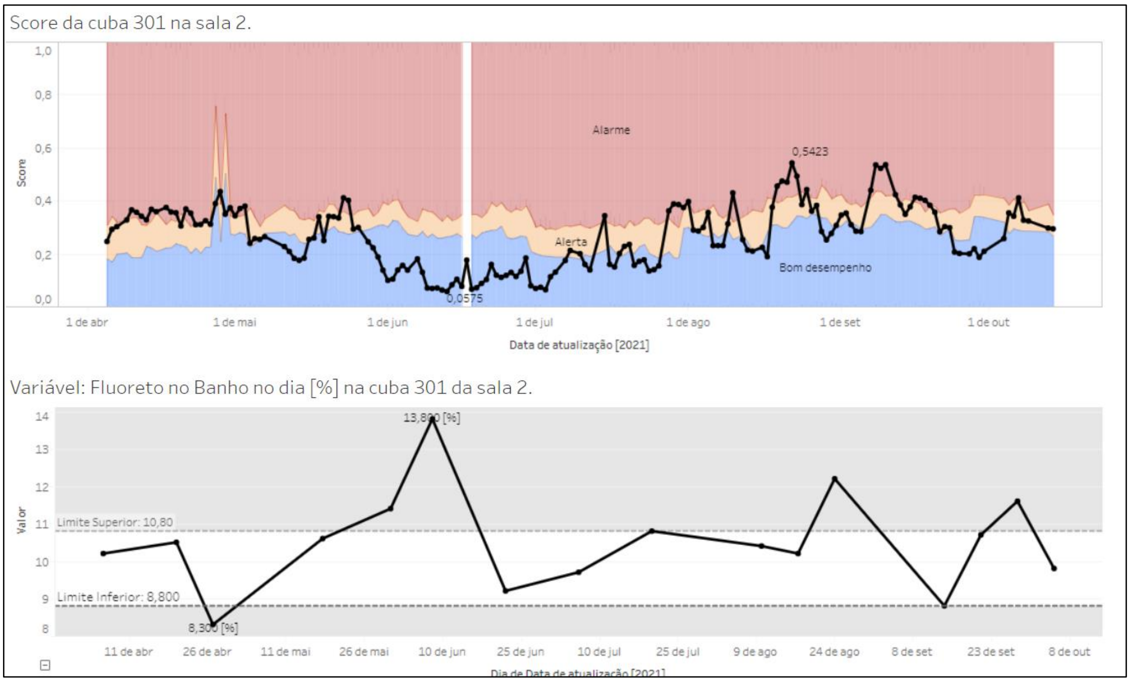

Figure 3. Screens to support potroom – single pot behavior.

Once the alarm is activated the operator should check the pot and take actions to stop it. Then in the office the information had to be inserted in the analysis screen. The analysis screen is presented in Figure 4, the finds, the actions and the potential root cause analyses.

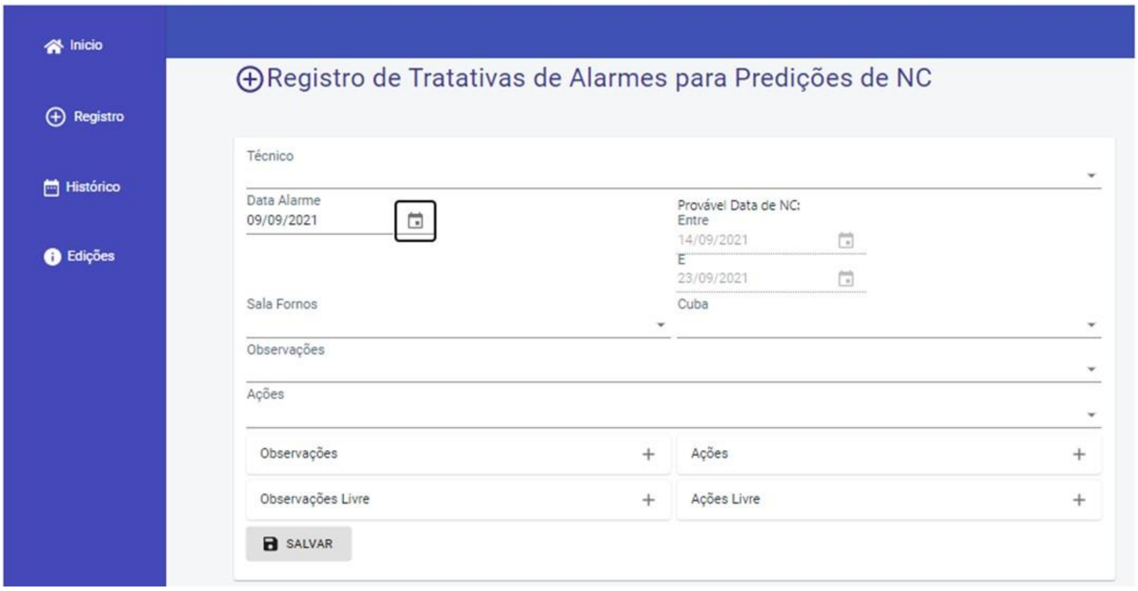

Figure 4. Input screen for low efficiency pots.

The overall behavior between the test group and reference is presented in Figure 5.

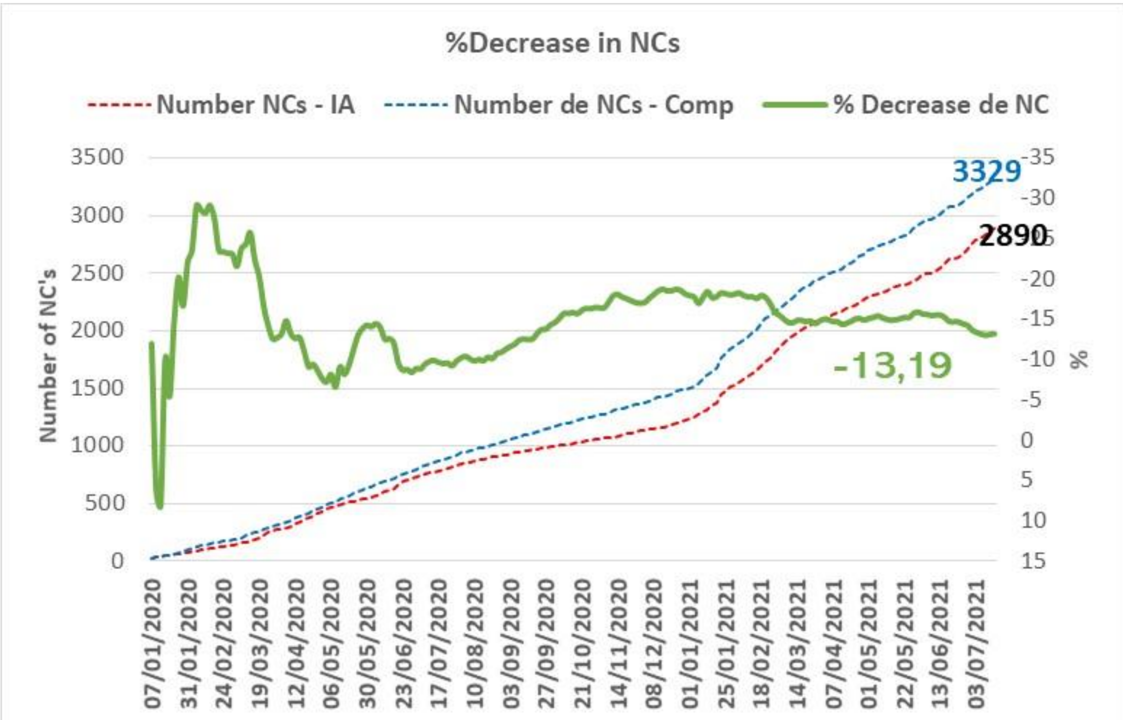

Figure 5. Number of incidents in the test group and reference.

Also, the overall improvement on metal production of the test group is presented in Figure 6.

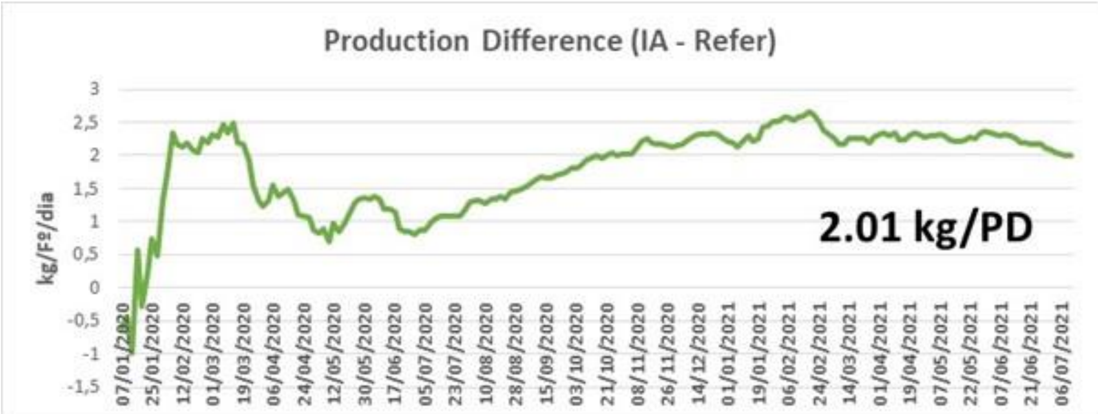

Figure 6. Difference between test and reference group. Vertical scale: kg/pot-day.

4. Discussion

At the beginning, there were some difficulties in implementing the tool in the routine basis of process technicians, as in addition to a technological evolution, there was also a behavioral barrier and the fear of being replaced. After rounds of training, conversations and joint use, the tool was inserted into the operational routine of the Process Engineering team.

The tool was calibrated by two inversely proportional pillars: Sensitivity and Precision. The first, sensitivity, concerns how sensitive the model is in relation to process variation, the greater, the greater the number of alarms generated. The former concerns the accuracy of the model and is inversely linked to sensitivity, that is, the more alarms are generated, the less accurate is the model.

After the modeling phase, we were presented with a table with results of effectiveness based on sensitivity and precision. Based on these data, a decision was made as to the best parameterization, seeking an optimal point between gain and capacity of service and treatment of generated alarms.

Table 1 shows the overall test results, there were around 76 % of effectiveness that means an agreement by model assumptions and potroom findings. The sensitivity of the model was impacted by potroom 2 and 4 restart.

For comparison, the decision was made to hide part of the alarms and show only 50 % of the line monitored by the tool. This allowed to compare how effective technicians could be when they had the information in advance, against the old methodology of work (hidden group). At the beginning of use, there was a significant reduction in production losses in the control groups compared to the hidden group, Figure 4. This was due to the fact of greater attention was given to the control group and the learning curve. Right after the peak there was a drop due to adherence to the use of the tool by the end user.

After engagement actions, such as linking the use to the users' individual goals and a better understanding of the global intention and trend towards similar initiatives in line with the industry 4.0 movement, an evolution and consequent stabilization was achieved. With the control group showing a gain around 0.3 % in current efficiency compared to the hidden group, Figure 5. For the evolution and maintenance of the result, a biweekly follow-up is carried out with the technicians to understand the difficulties and perceptions of using the tool on a daily basis. The increase in the metal output of the test group was higher by 2.01 kg/per po-day.

5. Conclusion

Data analytics became a new reality as a tool for potroom decisions. This project is still improving the results as the overall knowledge increases. Several optimization algorithms are planned to be tested to improve the results. The current project decreases the loss of production by early pot diagnosis but it requires the potroom engagement not only by using the tool but by putting in the system the correct root cause to support the weights of the model.

6. References

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