Optimization of sintering machine parameters using simulated annealing metaheuristic

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Abstract

The sintering process consists of agglomerating fine iron ore with other materials and additives to form a porous agglomerate called sinter. The sinter is used as feedstock for blast furnaces, where it is converted into pig iron, which is the basis for steel production. One of the major challenges of the sintering process is the degradation of the chemical quality of the iron ores, which can affect the quality of the sinter produced. Therefore, this work proposes an approach to optimize the parameters for sintering machines. This approach uses machine learning and computational optimization techniques based on the simulated annealing algorithm by analyzing production history data with the aim of maximizing sinter productivity and yield while ensuring that product quality requirements are met. As a result, the quantity of pellets used in pig iron production was reduced by replacing part of this material with additional sinter produced according to the recommendations of the mathematical model for the sintering machine parameters.

Keywords: Sintering machine; Parameters optimization; Machine learning; Product quality.

1 Introduction

The sintering process is fundamental to the steel industry because it produces an intermediate product for steel production. This transformation of iron ore into a material optimally suited for blast furnaces has several advantages. It allows adequate charging of the blast furnaces, reduces heat loss, improves efficiency, and allows the use of fine ores. The composition of the blast furnace mix has been thoroughly researched, and this mix consists of sinter, pellets, and lump ore. Sinter has physical and chemical properties ideal for blast furnaces and is also less expensive to produce than pellets, making it an excellent choice for steelmakers.

The sinter is a porous and resistant material formed in the sintering process by partial melting of fine iron ores, coke, sinter feed (the ore most used in sinter production, with particle sizes ranging from 0.15 mm to 6.3 mm) and fluxes [1]. One of the major challenges in this process is the chemical quality of iron ores, such as an increase in the content of impurities, changes in mineralogical composition, variations in particle size, and a decrease in iron content. In an analogous case, an increase in the content of impurities can lead to a decrease in the chemical quality of the sinter, since the impurities can affect the physical structure of the sinter, which directly affects the yield of this product. The yield is the percentage of the starting material that is converted into sinter after the sintering process. Although investments are made today in monitoring the chemical quality of iron ores, it is often not possible to guarantee the quality because the iron ores are purchased from external sources.

After investigating possible initiatives to improve sintering quality and productivity, three main levers were identified to explain fluctuating sintering productivity: raw material composition, sintering machine process parameters, and blast furnace constraints. Although the chemical quality of the raw material is an important factor in producing high quality sinter, optimizing the parameters of the sintering machine can help improve productivity even when the chemical quality of the raw material is poor [2,3]. To achieve these goals, mathematical modeling and computer-aided optimization techniques have been used to understand system behavior and determine the best parameter settings based on historical process data. This approach makes it possible to increase the productivity of the sintering process and obtain a greater quantity of high-quality sinter. With the increase in sinter production, it is possible to reduce the quantity of pellets used to produce pig iron, as some of this material can be replaced by the sinter produced.

Thus, the objective of this paper is to present an approach for parameter optimization of sintering machines using machine learning and computational optimization models. In addition, computational results obtained with these models are presented, demonstrating the improvements achieved in terms of cost reduction and increased quality of the sinter produced for the blast furnaces. Finally, a front-end tool was developed to make the results easily accessible to business experts.

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2 Development

Machine learning algorithms can efficiently analyze large amounts of data generated by the sintering machine and identify the most important parameters affecting sintering performance. Therefore, the project consisted in developing a tool capable of providing recommendations for the parameterization of the sintering machine to ensure optimal performance and productivity based on the chemical composition of the raw materials.

The diagram in Figure 1 illustrates the blueprint consisting of a metaheuristic capable of providing recommendations for the parameterization of the variables associated with the sintering machine based on the input data (1) and (2) of Figure 1.

A metaheuristic is an optimization technique that attempts to find solutions to complex problems through an iterative search process. One of the most important steps of a metaheuristic is to define a cost function that measures the quality of a candidate solution with respect to the objective of the problem. The modeled cost function for this problem was obtained from the product of the outputs of two machine learning models: Yield Prediction and Sinter Productivity, as shown in Figure 1 (3). This was done because productivity and sintering yield are important metrics for the steel industry as they directly affect the efficiency, quality, and cost of the process.

Therefore, the tool performs a local search [4] based on the simulated annealing metaheuristic [5], as shown in the flowchart in Figure 2, and iteratively improves the candidate solution with the goal of maximizing the yield and productivity of the sintering process. Each candidate solution represents a possible configuration of the sintering machine.

To build a predictive model as a cost function in a metaheuristic algorithm, it is necessary to collect relevant historical data and apply machine learning techniques to build this model. Therefore, the first step was to understand and collect the main variables of the sintering machine that are controllable by the operation during the sintering manufacturing process (Table 1) and recommended by the optimizer. In addition, the data shown in Figure 1 (1, 2) were also collected to understand the other data since they are the input data for the predictive model.

Table 1. Identified parameters of the sintering machine

| Controllable	Non-controllable
Information on the composition and granulometry of the fuel	Raw material quality
Homogeneous pile composition	Fuel quality
Layer height	Sintering speed
Loading density	Crusher speed
Burning-through point (BTP)	Ignition gases quality
Limestone percentage	Seasonality
Ignition parameters	
Burden humidity	
Gases temperature average	
Exhaust fan temperature	
Sinter temperature	
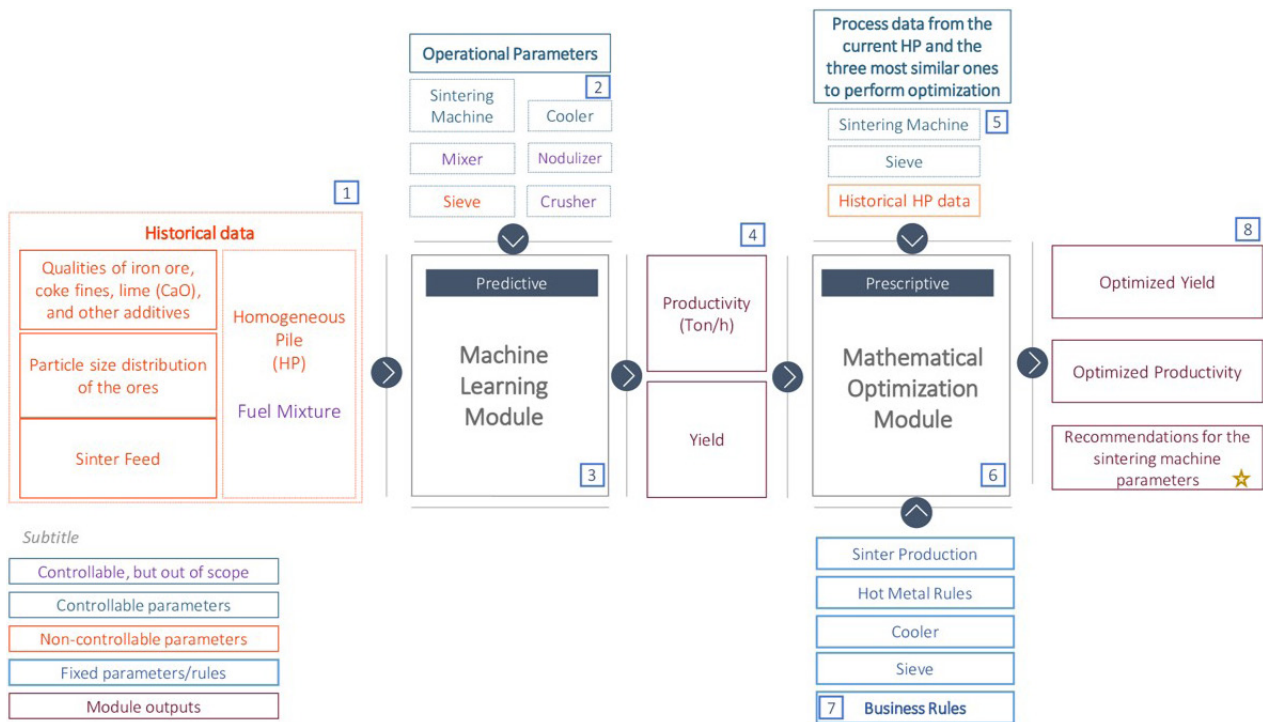
Figure 1. Blueprint of the proposed macro-level solution.

The data sources are different, some are stored in a database, others are from Excel spreadsheets.

Therefore, it was necessary to aggregate and process the data, including handling missing data, outliers, and other necessary manipulations to the data of interest. Once this phase was completed, the next step was to identify and understand the correlations between the input and output variables of the machine learning models (sinter yield and productivity). This step is critical to the development of predictive models because it can significantly improve the performance of the final model by excluding unnecessary information. To understand this information, methods such as the Spearman test [6], a non-parametric test to evaluate the correlation between two variables, were used. In addition, graphical analysis and descriptive statistics were used. The mutual information method [7] was also used as several non-linear or complex relationships were identified. Following this process, the permutation-importance method [8] was used to reduce the size of the problem by considering only the input variables that have the greatest impact on the outputs. In this way, predictive models were developed, trained with sufficiently representative data, and validated on an independent data set before being used in metaheuristics. A tree-based algorithm [9] was chosen to develop these machine learning models due to its advantageous properties such as scalability, flexibility, and robustness. This algorithm can efficiently process large amounts of data, adapt to a variety of problem types, and handle missing or anomalous data without compromising accuracy or reliability.

After developing the predictive models, the cost function was integrated into the optimizer. The assumptions and constraints shown in Figure 1, item 6, and explained in Table 2 were also considered to ensure the accuracy and effectiveness of the optimization process. The approach chosen to implement the constraints in the simulated annealing algorithm was "penalization". In this approach, solutions that violate a constraint are penalized with a high value in the objective function, preventing the algorithm from exploring infeasible solutions. Another approach was to restrict the search space of feasible solutions. For example, if the algorithm violates a quality objective, the cost function, which is the product of sintering productivity and yield, is penalized by a predetermined value to prevent the algorithm from searching for a solution with that parameter. It is worth noting that these approaches were chosen with the goal of ensuring that all generated solutions are viable and meet the imposed constraints.
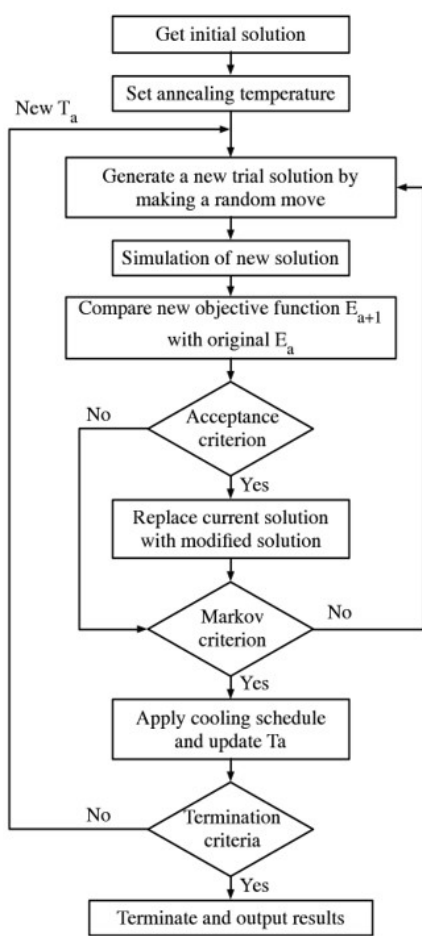
3 Results and discussion

After studying the correlations between the variables shown in the diagram in Figure 1 (items 1 and 2) and the outputs (item 4), the most important information that has predictive power in terms of yield and productivity were identified, as shown in Figure 3 and 4, respectively.

Figure 2. Flowchart for the simulated annealing algorithm.

Table 2. Constraints implemented in the optimization module

Type of constraint	Information source	Implementation
Minimum and maximum constraints	Sintering machine parameters	Linear constraint
Shatter	Results of laboratory	Predictive model
Granulometry of sinter greater than 5	Results of laboratory	Predictive model
Sinter temperature	Results of laboratory	Predictive model
Correlation coefficient between variables	Sintering machine parameters	Correlation coefficient
Composition of blast furnace burden*	Results of laboratory	Linear constraint

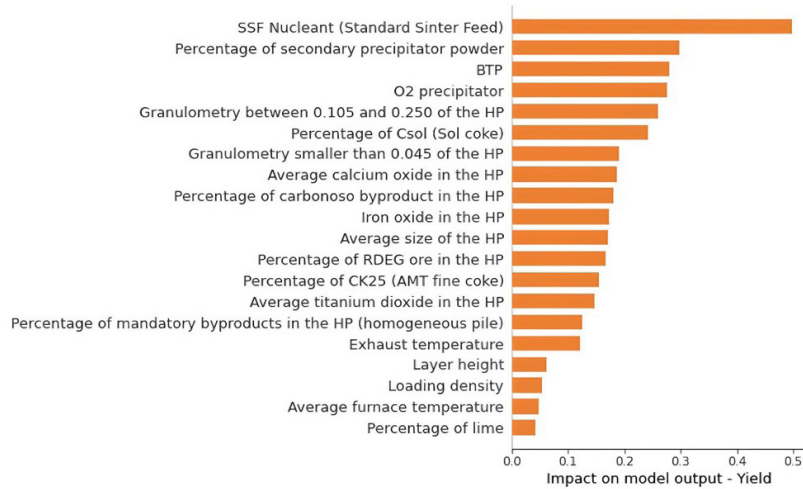Load composition constraints have been mapped but will be implemented and detailed in a future work.

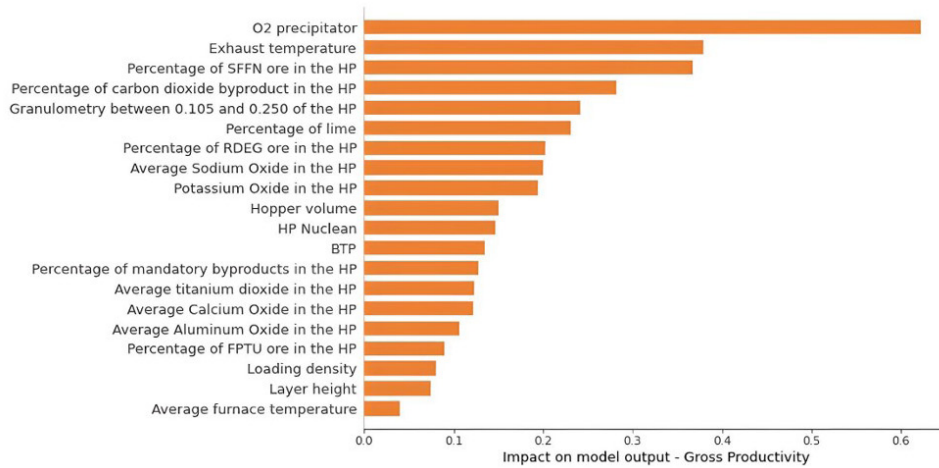**Figure 3.** Process variables that most impact sinter yield.

Figure 4. Process variables that most impact sinter productivity.

It is necessary to carry out this study because this information allows a more accurate prediction of the targets and helps to avoid overfitting, which occurs when a model is overfitted to the training data, resulting in less accurate predictions with new data. To understand these key predictive insights, a Random Forest model was employed with the parameters set as follows: max_depth configured as 15 (the square root of the number of features), n_estimators set to 100, min_samples_split of 2, min_samples_leaf of 1, and bootstrap set to True for sampling with replacement.

Business experts had already anticipated that some variables would have these predictive capabilities, while for others there was no prior understanding due to the amount of data and lack of information needed to perform this analysis. This opened new perspectives for the business unit.

The data used to develop the models were obtained from all the data shown in Figure 1 (3), which were collected from the year 2019 to the end of the year 2021. To evaluate

the performance of the developed models, more than two metrics were used.

Equation 1 shows the main metric chosen, namely the root mean square error (RMSE), as it is a robust and sensitive error measure that accounts for both positive and negative errors, while larger errors are penalized proportionally. In this equation, the difference between the predicted value $\hat{y}$ and the actual value y is performed, which is then squared. However, to keep the result on the same scale as the data, the square root is applied to the result.

$$\text{RMSE}(y,\hat{y}) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (1)$$

To evaluate the effectiveness of the predictive models implemented as constraints, the recall metric was primarily used. This was done because false negatives are more

important in the context of the quality issues observed in this study. For instance, if the model predicts that there will be no problem when there is one (false negative), this may be more detrimental in the context of a particular solution proposed for the parameterization of the sintering machine than predicting a quality problem that does not ultimately occur. It should be noted that while the implementation of these constraints is relevant to this topic, the main objective of this paper is to study in more detail the results obtained by the optimization module. This aspect has been less addressed in the literature so far.

Figures 5 and 6 show the scatter plot between the values predicted by the model compared to the actual values in the data set reserved for testing, i.e., the model did not have prior access to these data. The results in terms of the RMSE metric are shown in Table 3. They show that the models obtained satisfactory results that can be implemented as a cost function of the optimization algorithm. In developing the models, the cross-validation method was used, which consists of dividing the data set into smaller subsets (folds) so that the model can be trained on one part of the data and tested on another, ensuring accurate evaluation and more robust model performance. The cross-validation method was also used to fit the hyperparameters of the models. Therefore, the standard deviation shown in Table 3 represents the variation in the RMSE metric for each fold in this cross-validation process.

After evaluating and implementing the cost function and the constraints described in the methodology, the optimization algorithm was run to explore the solution space in search of the best possible solution. The experiment was conducted using sintering process data from the past, i.e., the optimization algorithm was run on a test data set from 2021 to verify that the resulting recommendations offered an increase in productivity and throughput, as well as a better understanding of the characteristics of this material compared to the process performed during this period. For this test, it was necessary to remove data from the models, so there was no prior knowledge of this test set.

The optimization module was tested in practice. For each raw material (i.e., each HP), 50% of the sintering process was carried out with the usual parameterization, while for the other 50% the recommendations of the model developed in this work were used.

This process was performed on 5 homogeneous piles. After the test period, an average percentage increase in liquid sinter (product between gross productivity and yield) of 3.42% was observed, as shown in Figure 7.

Finally, a web platform was successfully developed (Figure 8) to provide sintering process specialists with a

Table 3. RMSE metric result for the training and testing datasets after developing the models.

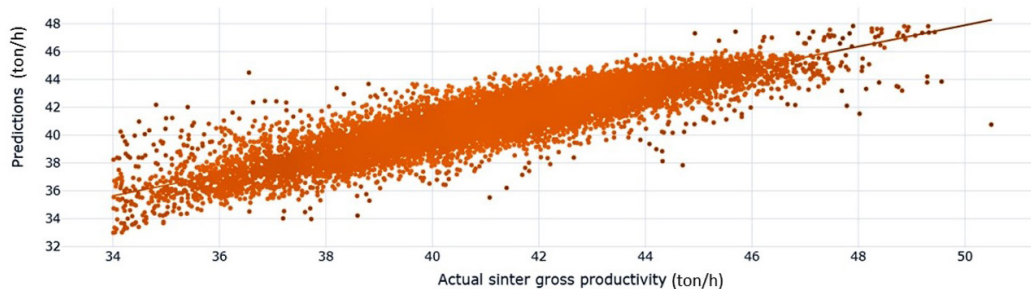| Model	Data Set	RMSE	Standard Deviation
Productivity (ton/h)	Train	1.549	0.022
Yield (%)	Train	2.383	0.012
Productivity (ton/h)	Test	2.147	0.037
Yield (%)	Test	3.214	0.002

Figure 5. Comparison between values predicted by the gross productivity model and actual values using a data set not observed by the model.
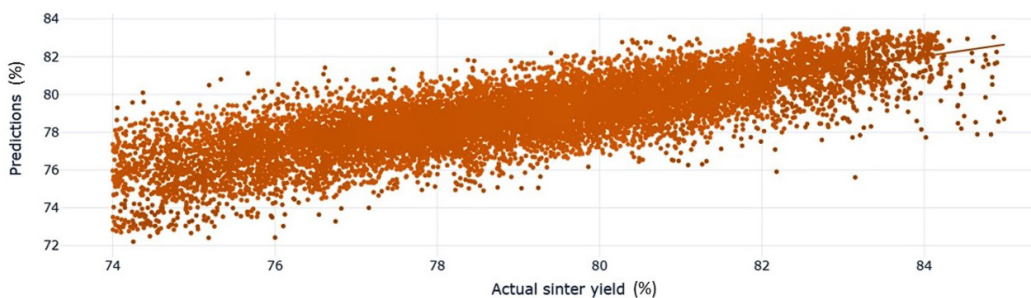

Figure 6. Comparison between values predicted by the yield model and actual values using a data set not observed by the model.

front-end tool to monitor parameters and key KPIs resulting from this work. By implementing this tool, users can access an integrated solution that enables a more comprehensive analysis of the sintering process and provides valuable insights to improve production quality and efficiency.
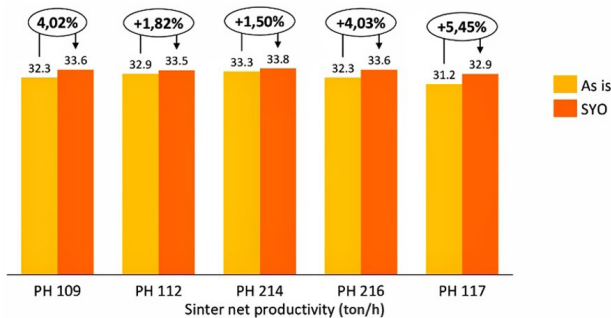

Figure 7. Test results of the SYO (Sinter Yield Optimization) tool.

Figure 9 shows the parameter simulation function, which is useful when the optimization model solution cannot be implemented due to external or unmonitored factors. This function allows fine tuning of the parameters. The platform shows the impact on the monitored KPIs, providing valuable information to adjust improve the sintering process.

The platform is a significant step forward in the digitalization of the sintering process and demonstrates the potential of digital technologies to improve production results and increase efficiency. In addition, other processes were improved during the development phase of this project, such as automating data collection for granulometric analysis of fuels.

Previously, this information was stored in Excel spreadsheets. Now this automated process is expected to save costs and time while improving production efficiency and quality.

Reference has been made to several articles [2,3,9-11] to illustrate various approaches to optimizing sintering.

Figure 8. Web platform developed and made available for specialists in the sintering process.
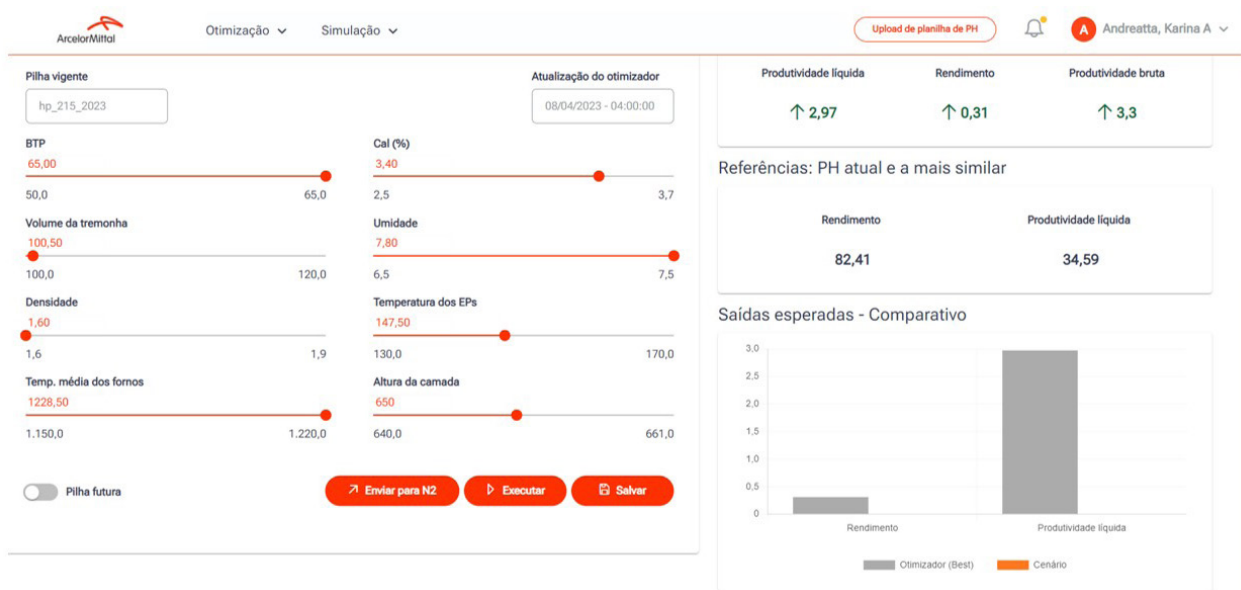

Figure 9. Parameter simulation module parameter simulation.

While these articles discuss increases in process efficiency and improvements in productivity, the present work also stands out for its significant enhancement in productivity through computational optimization of sintering machine parameters.

4 Conclusion

One of the ways to optimize sintering production is to optimize the parameters of the sintering machines, which can contribute to higher productivity, regardless of the quality of the raw material. The study proposes the use of mathematical modeling and computational optimization techniques using machine learning and the simulated annealing algorithm to analyze historical production data and determine the best parameter settings to maximize productivity and quality of the sinter produced. The use of the optimization module for the sintering process showed positive results in practice. The test performed on 5 homogeneous ore piles showed an average increase in liquid sinter of 3.42% when comparing the usual parameterization with the recommendations of the model developed in this work. These results show the importance of using optimization tools in the industry to improve the efficiency of production processes, reduce costs and increase product quality. In summary, the intuitive and user-friendly front-end platform was developed to encapsulate an optimization model and provide business specialist with results that enable more accurate and strategic decisions. It is hoped that these results can be replicated in other areas of activity to promote the use of optimization techniques in various industries.

Acknowledgments

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