Forecasting of refractory wall thickness in an electric arc furnace used in ferro-nickel production

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ABSTRACT

The mining industry has encountered numerous challenges in recent years, and it has surmounted these obstacles by embracing cutting-edge technologies such as intelligent sensors, structural monitoring and control systems, and artificial intelligence. These innovations have entirely transformed data management, enabling the automation and real-time surveillance of critical infrastructure, such as electric arc metal smelting furnaces, which are indispensable for extracting vital metals like ferronickel, iron, copper, and aluminum. Nevertheless, these furnaces operate under extreme conditions, posing difficulties in terms of monitoring and safety. To tackle this issue head-on, a predictive model for refractory wall thickness has been meticulously developed and rigorously validated using historical data and machine learning techniques, thereby facilitating precise monitoring for up to 11 days from the initial operating conditions. This substantial enhancement significantly extends the safe operational window of the furnace while yielding invaluable insights. This pioneering approach has been effectively applied at Cerromatoso S.A., a leading ferronickel producer located in northern Colombia, cementing its position as one of the world's foremost ferronickel producers. Furthermore, this initiative represents a pivotal advancement in enhancing the mining industry's safety and efficiency, simultaneously establishing a precedent for managing critical infrastructure within harsh environments. This article elucidates the theoretical foundations underpinning the development of the predictive model, the essential components for its implementation, and the achieved results in refractory wall thickness prediction, underscoring its potential impact on pivotal sectors such as automotive and electronics. These efforts collectively point towards a future characterized by enhanced safety and productivity in mining and analogous domains, owing to the symbiotic interplay between technology and expertise.

1 Introduction

Structural Health Monitoring (SHM) is critical in ensuring the safety and durability of buildings, bridges, and other civil and military infrastructure. Through the application of cutting-edge sensors and technologies, it becomes possible to monitor the status of these structures in real time, anticipating potential problems before they endanger their integrity. This proactive approach enables timely repairs and maintenance, reducing the risk of catastrophic failures and, consequently, strengthening the overall security of the infrastructure. Likewise, monitoring the structural condition contributes to prolonging the useful life of these buildings, translating into long-term financial and resource savings. In short, investing in structural health monitoring presents itself as a wise choice for any organization or government entity that prioritizes safety and sustainability.

Structural Control and Structural Health Monitoring represent two vital domains that enable the assessment of a structure's condition and the formulation of preventative measures against accidents arising from environmental and operational factors [1]. Their application to structures subject to diverse alterations in operational conditions over their service life yields enhanced longevity and improvements in maintenance procedures [2]. In the case of structures utilized in mineral extraction processes, such as electric arc smelting furnaces, variations in the chemical composition of the mined material being processed can lead to shifts in the operating parameters and potential wear on the furnace wall [3]. To preempt such issues, the utilization of historical operational data emerges as a viable solution for monitoring processes and regulating the structural elements involved throughout operations.

The furnaces are constructed from refractory materials designed to withstand the extremely high temperatures necessary for the casting process, often exceeding 1200 °C. Typically, These types of furnaces operate in most cases 24 hours a day, seven days a week. In the existing literature, several studies have delved into data analysis for smelting furnaces, as seen in works like [4] and [5], where various modeling techniques, including artificial neural network (ANN) models, multiple linear regression (MLR), and integrated moving average, have been explored. The Autoregressive Integrated Moving Average (ARIMA) model is also employed to predict furnace flame temperatures, emphasizing selecting the model that most significantly influences this crucial process parameter. Computational results have yielded satisfactory outcomes regarding selected performance metrics, encompassing regression coefficients and mean square error. Notably, the RNA models exhibit superior performance compared to the RLM and ARIMA models.

On the other hand, in 2004, Jiménez et al. [6] developed a prediction of hot metal temperature in a blast furnace through models based on neural networks, considering dynamic modeling purposes. However, because the value of the variable to be forecast cannot be measured with a sampling frequency equal to that of the input variables, it is necessary to pre-process it before introducing it into the model to obtain a regular distribution of the values. It can be done by interpolating the available data, or another possibility is to include time in the model explicitly. In this sense, the work presented at [3] develops a temperature prediction model in an electric smelting furnace using *deep learning* techniques in sequential models based on GNU networks and Dense networks. In 2017, Hafid and Lacroix [7] presented a reverse heat transfer method to predict the state of the refractory brick sidewall of a melting furnace. By collecting temperature data with a thermocouple embedded in the brick wall, the reverse method can predict The time-varying thickness of the protective bank that covers the inner lining of the furnace wall, The thermal contact resistance between the inner lining and the protective bench, and Possible erosion of the firebrick wall. The reverse procedure is based on the Levenberg Marquardt algorithm combined with the Broyden method. This work investigates the effect of noise on the collected temperature data of the thermal diffusivity of the brick wall, the location of the built-in temperature sensor, and of the Biot number in the inverse predictions is investigated. Recommendations are made for the optimal position of the built-in sensor and its operation. In 2014, LeBreux et al. [8], developed a virtual sensor to predict the variable thickness of the crust on the inner surface of a wall of a high-temperature metallurgical reactor. The virtual sensor senses the position of the solid-liquid phase front using thermal measurements taken from a heat flux sensor embedded in the reactor wall. The virtual sensor comprises a state observer coupled to a reduced reactor model. It also explains the thermal contact resistance of the wall structure. The results indicate that the virtual sensor becomes more accurate as the magnitude of the thermal contact resistance increases. In [9] thermography techniques are used to calculate figures of merit that evaluate the level of wear on the refractory walls of an electric smelting furnace for the ferronickel extraction.

The work described in this article presents a methodology to predict the thickness of the refractory wall of an electric arc furnace (EAF), using historical values of operational variables such as temperatures on the wall, composition of the material to be merged, power in the electrodes, among others. This methodology is validated using operating data from a smelting furnace for ferronickel extraction from Cerro Matoso S.A. with excellent results. This article is organized as follows: First, a theoretical foundation shows some concepts about the methods included in the methodology in section 2. The third section presents a general schema of the elements considered in the methodology. The fourth section consists of the experimental setup and the experimental results, and finally, the conclusions are in the last section.

2 Theoretical Background

This section describes the main processes involved in ferronickel production in Cerro Matoso S.A. (CMSA), emphasizing the recognition of variables found in the information provided by CMSA and their contribution to each process.

2.1 Ferro-nickel production and Cerro Matoso S.A.

Figure 1 shows a simplified block diagram of the processes present in the ferronickel plant at CMSA. Before the mineral enters the stack, the nickel concentration is analyzed. If it is less than 0.8%, the mineral will not deposit in this. The process is detailed below.

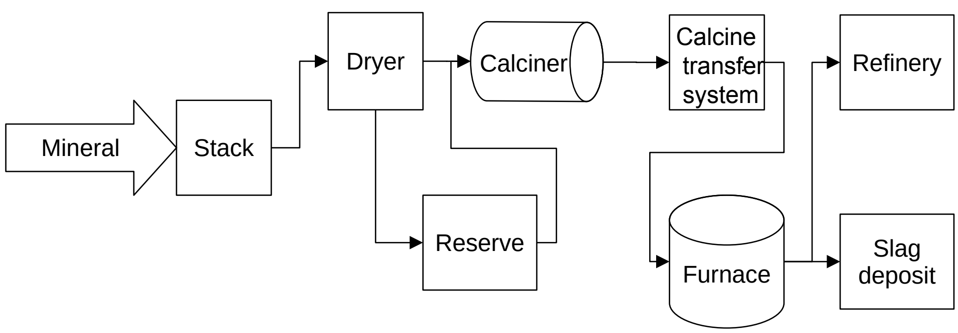
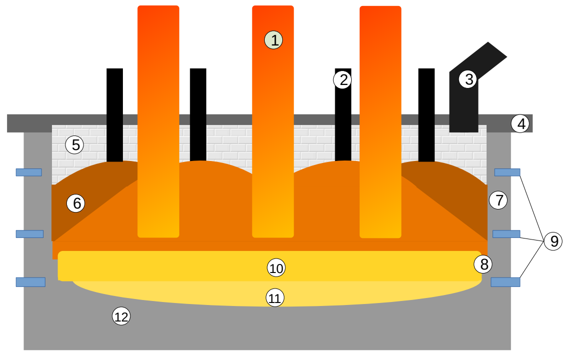


Figure 1: Sub processes in the ferronickel production CMSA

Figure 2 shows an interior view detailing the furnace's parts. The furnace walls are segmented into three sections based on their height, and for this study, the middle wall was examined. This particular wall contains the ferronickel and slag extraction zones and the cooling elements consisting of plate and waffle coolers. The main function is to preserve the structural stability of the furnace. The arrangement of the cooling elements is shown in Figure 3a, and in figure 3b there is a detail of the hydraulic circuits used for dissipation, in which we can identify the different existing measurements tags, water temperatures, water flows and wall temperatures.



1. Electrodes
2. Load feed pipe
3. Chimney
4. Refractory roof
5. Gas chamber
6. Calcine
7. Refractory brick wall
8. Slag crust
9. Thermocuples
10. Slag
11. Ferronickel
12. Furnace bottom

Figure 2: Furnace parts.

2.2 Wall thickness model

There are two groups of thermal models to use for this development. The first corresponds to the refractories in front of the coolers (grouped in arrows in figure 3a) and the second to the refractories between them. This work presents the development and validation of the first developed models. Integration strategies of the defined models were defined for temperature estimation [10] and wall thickness estimation using the thermal dissipation expressions for cylindrical elements consistent with the shape of the furnace. The proposed mathematical model, defined under the equation 1, for this the values of r_n represent the radius of the walls, in our case thickness of the wall components, bricks, and refrigerators, K_a represents the thermal conductivity provided by the brick manufacturer, q_{WC} the energy flow in the Waffer coolers and h_B is the heat passed through the brick by conduction and through the waffle cooler.

$$\frac{1}{UA} = \frac{72}{2\pi L}\left(\frac{Ln\frac{r_0}{r_1}}{K_a} + \left(\frac{1}{r_2 h_B}\right)\right) \tag{1}$$

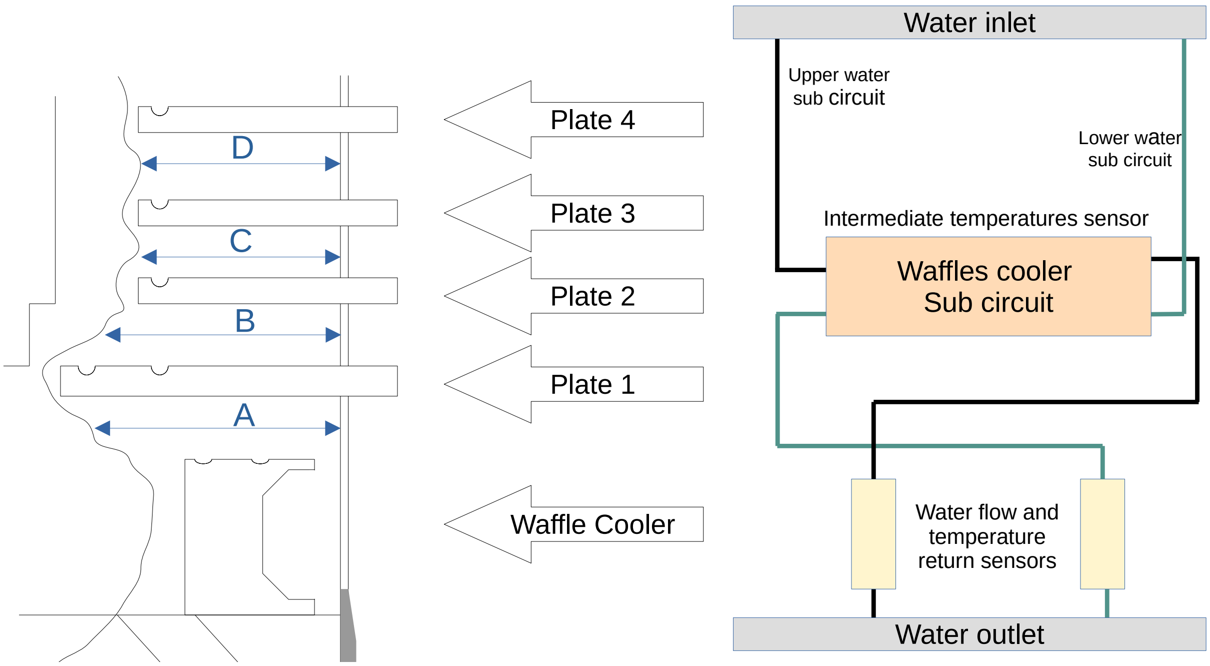
with:

$$q_{WC} = UA\left(T_0 - T_2\right) \tag{2}$$

3 Experimental setup and results

Taking into account the requirements of wall thickness estimation, the following configuration of the temperature estimation model was determined: GRU plus Dense neural network, 100 cells in the GRU network, RMSprop optimization method, learning rate 0.001, seven epochs training, 90% of the data set for training, 10% of the dataset for testing, 270 estimation steps (equivalent to 11 days), 63 input variables and error determination using RMSE. The variables used as input correspond to the currents, voltages, powers, positions and electric arc in the electrodes, the inlet and outlet flows of water in the cooling circuits, lower and upper temperatures of the water supply, and the temperature in the Waffles cooler and material chemistry composition. This configuration is shown in figures 3b and 4 .

About obtaining and guaranteeing the quality of the data to be used, the process shown in figure 5 is proposed, which is proposed to be executed at a high level and is composed of four steps: Obtaining the captured records from the Data Lake by the furnace sensors; Preparation of the data, selecting only



(a) Middle wall components (b) Refrigeration Circuits

Figure 3: Middle wall detail

the fields necessary for the model and transforming them to the format that is required for its execution; Execution of the model prediction process with the prepared data; And Persistence of the predictions delivered by the model, saving the corresponding data in the final information system.

3.1 Experimental results

For the validation of this model, six refrigeration circuits were used. These are distributed as shown in figure 6. The circuit consists of the waffle coolers WC08 to WC11 and plate coolers PC08 to PC11; these are used as a training segment. Test circuits include the ones surrounding it (04-07; 12-15) and refrigeration circuits at approximately 90 degrees (28-31; 46-49; 68-71). The test procedure was carried out by training the model and its subsequent use in the estimation of the output variables in the selected refrigeration circuits; the training was carried out using segments of 2160 historical data with sampling periods of one hour, and the tests They estimate 240 values that are compared with the historical information of the furnace.

To validate the possibilities of using the trained model, two types of validations were carried out; the first focused on the estimation of variables using the same time windows in different time-spaces between July 1, 2020, and December 18, 2020. Then, in September 2021, as a second approach, the operation of the trained model was tested in different time windows; this second test gave us information about the temporal behavior of the model and possible retraining requirements. The results of the training sessions are presented in the figure 7.

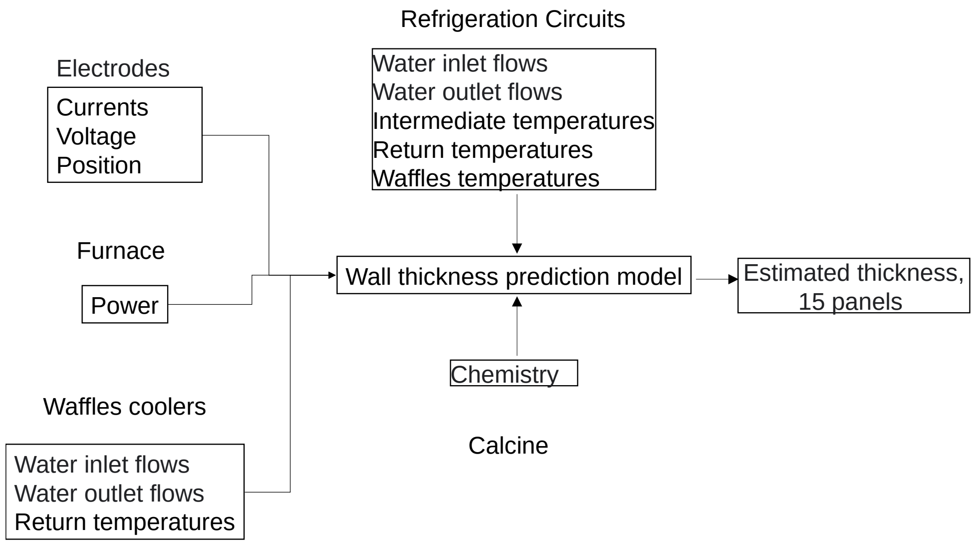


Figure 4: Model Setup.

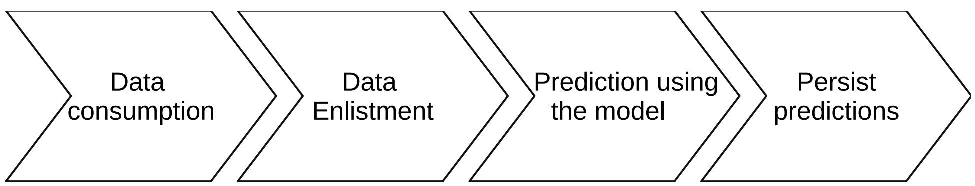


Figure 5: High-level process steps.

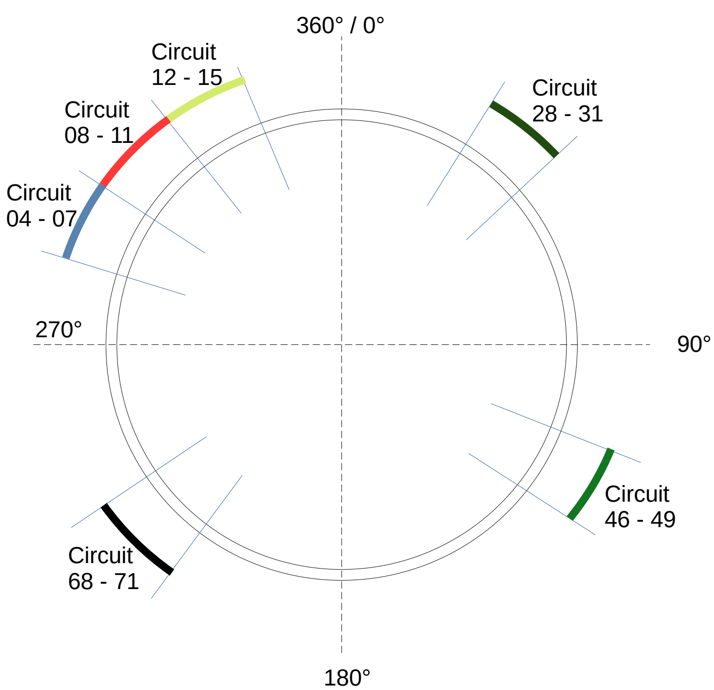
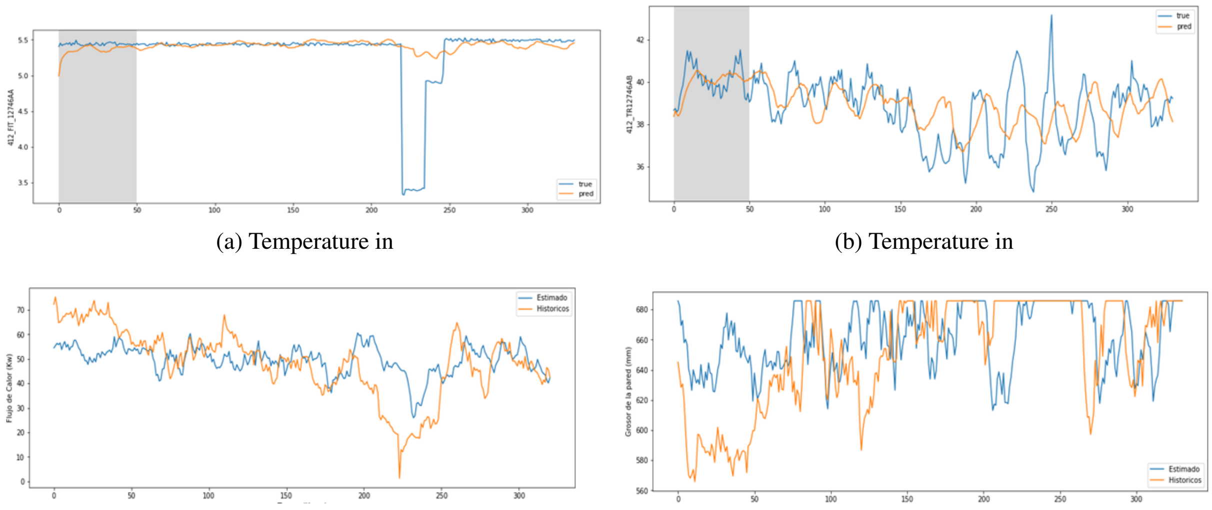


Figure 6: Refrigeration circuits used in the validation

4 Conclusions

- The study allowed us to identify the input variables that best contribute to temperature prediction. 250 random batches were defined, each with a sequence size of 1152 records corresponding to 11



(a) Temperature in (b) Temperature in

(c) Heat flux in (d) Estimated thickness in

Figure 7: Model Results

days of continuous data, according to the change of material pile at the entrance to the furnace.

- In general, the root mean square error (RMSE) values ranged between 3 to 4 degrees Celsius in the predicted thermocouples. This is a good result because of the range of temperatures used in the process, and it is helpful for monitoring.
- A model for estimating the thickness of the middle wall of the FC150 furnace was implemented, which showed consistent results with the expected state of the furnace, and its usefulness was verified using the data collected from one of the furnaces of the CMSA company.
- The thickness predictions present acceptable mean square error values in determining flows and temperatures every hour for up to 11 days.

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