Development of Soft Sensor for Mass Flow Rate Estimation in an Ore Reclaimer

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***Abstract*—This paper presents the development and implementation of virtual sensors for estimating the reclaiming rate of a bucketwheel reclaimer in an iron ore processing context. The methodology was structured in two phases. In the first, multiple machine learning algorithms were evaluated for soft sensor modeling based on process variables collected from the field. In the second phase, the linear regression model—selected for its balance between accuracy and implementation simplicity—was integrated into a programmable logic controller (PLC) to enable real-time rate estimation. Data preprocessing techniques, including dead-time compensation and signal alignment, were applied to improve model accuracy. The models were assessed using RMSE, MAE, and correlation coefficient. The results demonstrated that the implemented soft sensor is capable of reliably reproducing belt scale measurements, even under variable operating conditions. These findings reinforce the applicability of data-driven models in enhancing monitoring and control strategies in mining automation systems.**

***Index Terms*—Soft sensors, machine learning, mineral processing, mass flow estimation**

I. Introduction

In the mining industry, the iron ore production chain is extensive and involves multiple processing stages before reaching the final customer in the steel industry. This study focuses on a critical phase of the process, specifically the transition between receiving raw material from different mining fronts (*Run of Mine*—ROM), with varying iron and silica contents, and its beneficiation inside the processing plants. Several factors contribute to the heterogeneity of ROM, including mining operations, transportation, crushing, grinding, storage, and handling [1]. To ensure a stable and consistent feed to the processing plant, homogenization of the material is essential before the ROM is sent to beneficiation.

Typically, this homogenization process is carried out by at least two distinct machines: one responsible for stacking the heterogeneous material received from the mine, known as a stacker, and another tasked with reclaiming the homogenized material from the stockpile, known as a reclaimer. These machines exhibit diverse operational characteristics, ranging from simple translational movements to complex actions such as boom rotation and elevation [1].

For this phase of the process, a bucket-wheel reclaimer is employed. This study specifically focuses on bridge-type bucket-wheel reclaimers. This equipment consists of a bridge structure where rakes and scarifiers are positioned to break up material from the stockpile upon contact. A trolley moves transversely in a direction perpendicular to the pile. The bucket wheel, mounted on the trolley, reclaims the material through rotational movements and deposits it onto a conveyor belt positioned on the Bridge Conveyor. To advance or retreat along the stockpile, the machine is equipped with drive systems that enable longitudinal motion. Figure 1 illustrates this type of reclaimer.

In such industrial applications, sensors are essential for process control, monitoring, and automation. However, field deployment may face challenges due to high installation and maintenance costs, or physical constraints that hinder optimal sensor placement. In these scenarios, soft sensors—virtual models that infer unmeasured process variables from available measurements—offer a promising solution, enhancing process observability and control performance [3, 4, 5]. Soft sensor modeling approaches are commonly classified into three categories:

- Model-driven (interpretable) models: Based on first-

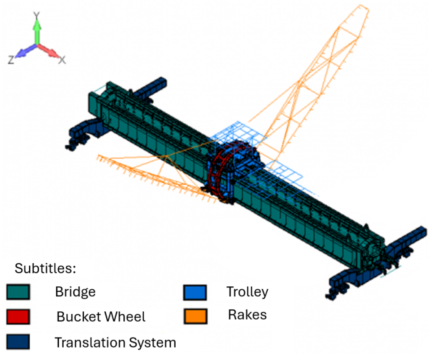


Fig. 1: Model of a Bridge-Type Bucket-Wheel Reclaimer
SOURCE: Adapted from [2]

principles equations that describe the process, these models require deep domain knowledge but offer theoretical rigor.

- Data-driven (non-interpretable) models: These models rely on regression and machine learning techniques trained on operational data, without the need for physical modeling. They are advantageous when first-principles modeling is impractical.
- Gray-box (partially interpretable) models: These combine physical models with data-driven corrections, blending accuracy with interpretability.

In recent studies, Sobreira et al. [6] applied four machine learning techniques to estimate the mass flow rate of iron ore on a conveyor belt using torque, current, and motor speed as inputs. Among the tested models, Random Forest (RF) yielded the second-highest correlation, approximately 94

Guedes [7] developed soft sensors to estimate the iron content from a flotation process, using neural networks and RF algorithms. Out of 1000 trained RF models, several achieved RMSE values below 2, confirming its effectiveness.

Heinzl et al. [8] proposed a soft sensor to infer conveyor belt mass based on motor power, concluding that linear regression provided a viable and interpretable model. Similarly, Väyrynen et al. [9] explored correlations between strain gauges, pressure transducers, and optical sensors with real mass measurements, developing six linear regression models with satisfactory error margins.

This study was conducted at the Timbopeba plant, focusing on the homogenization of beneficiated material. A critical operational challenge in this process is the varying distance between the reclaimer and the integrator scale responsible for measuring ROM mass flow. This distance introduces a variable dead time into the system—ranging from 27 to 148 seconds—making flow stabilization at the operator-defined setpoint more difficult.

To address this, three soft sensors were developed using machine learning algorithms. After performance analysis, the model that used the electrical currents of both the bucket wheel and the bridge conveyor, based on linear regression, was selected for implementation in the plant's programmable logic controller (PLC). Despite not being the top-performing model across all metrics, it offered competitive performance along with simplicity of integration and maintenance.

II. PROBLEM DESCRIPTION

The Timbopeba processing plant includes a homogenization yard composed of two stockpiles, labeled A and B, each with a capacity of approximately 45,000 tons and a total length of around 450 meters. ROM (*Run of Mine*) material from the Fábrica Nova mine is stored in this yard using a stacking machine. Subsequently, a bridge-type bucket-wheel reclaimer (RC) is employed to retrieve the homogenized material and transport it to the beneficiation plant.

At the end of the yard, an integrator scale positioned on Conveyor 1 (TC1) records the mass flow rate of the reclaimed material. As illustrated in Figure 2, the RC moves along the yard during operation, resulting in a variable distance between the machine and the scale. This variation introduces a significant and fluctuating dead time into the system.

Fig. 2: Aerial view of the Timbopeba Homogenization Yard

The RC operates with three degrees of freedom, allowing greater control over material extraction from the stockpiles. However, due to the considerable and variable dead time between the machine and the closest integrator scale, the fixed velocity curve of the trolley does not compensate for fluctuations in feed rate, nor does it prevent peaks exceeding the projected feed rate for the receiving conveyor. Given the high variation in instantaneous feed rate, the currently implemented PI controller regulates the average rate recorded by the scale, calculated using a moving average over a five-minute window.

Figure 3 shows the behavior of the instantaneous and average flow rates, both expressed in tons per hour, over approximately one hour of operation. It highlights large variations in the instantaneous rate and difficulties in maintaining the average flow rate at the operator-defined setpoint.

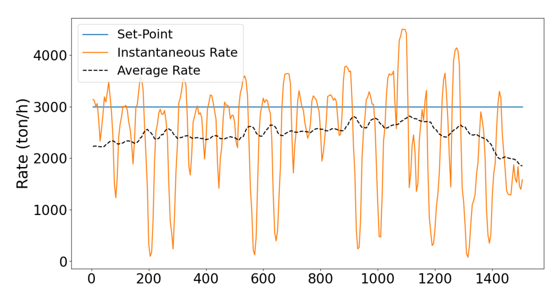


Fig. 3: Comparison between setpoint, instantaneous rate, and average rate of the Timbopeba Reclaimer

The RC is equipped with a reversible bucket wheel mounted on a trolley that traverses the bridge structure. Longitudinal movement along the stockyard is performed via motorized rails. This configuration enables the RC to operate on both stockpiles, increasing its operational flexibility.

To enhance material disaggregation during reclaiming, the RC includes two lateral rakes, each positioned on opposite sides of the yard. These rakes operate at an adjustable inclination angle between 42° and 48°, assisting in material breakdown and promoting a more uniform feed. Figure 4 provides a schematic representation of the RC.

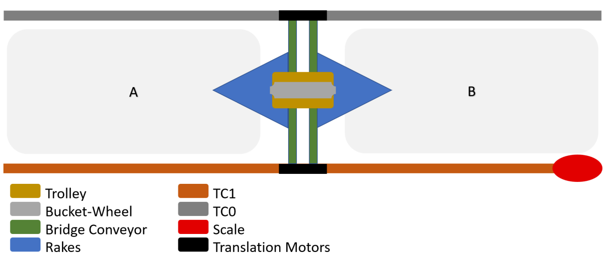
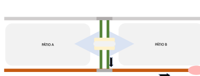


Fig. 4: Illustration of the RC machine in the Timbopeba Homogenization Yard

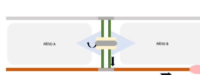
The RC operates automatically following the sequence described below:

1) Start Conveyor TC1 and position the RC at the beginning of the stockpile.
2) Start the Bridge Conveyor.
3) Start the bucket wheel motor.
4) With all systems running, initiate the downward movement of the trolley.
5) Upon reaching the bottom edge, activate the translation motors to move the RC longitudinally over the stockpile.
6) Once movement is complete, as determined by the PI controller based on the integrator scale's average rate, initiate upward trolley movement.
7) Upon reaching the upper edge, activate the translation motors again to advance further along the pile.
8) Repeat steps 5–7 until the entire stockpile is reclaimed.

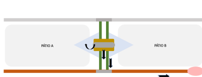
(a) Step 1



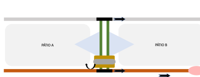
(b) Step 2



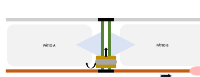
(c) Step 3



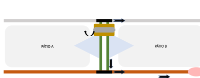
(d) Step 4



(e) Step 5



(f) Step 6



(g) Step 7

Fig. 5: Sequential operation steps of the bucket-wheel reclaimer

III. VELOCITY CONTROL OF THE TROLLEY

The trolley speed is adjusted according to the function presented in Figure 6, where its position varies from 0 to 30 meters, considering transverse movements across the stockpile. The velocity curve is designed to optimize process performance by minimizing time spent at the stockpile edges, where material is scarce, and maximizing time at the center to take advantage of the greater available volume.

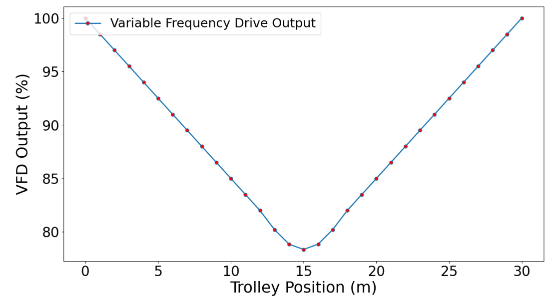


Fig. 6: Trolley speed profile in automatic operation mode

The defined velocity curve, combined with the constant rotational speed of the bucket wheel, produces a sinusoidal variation in the reclaiming rate [10]. This behavior introduces operational challenges, as peak values in the flow rate frequently surpass the nominal capacity of the receiving conveyor, increasing the risk of system overloads.

Longitudinal advancement of the reclaimer is governed by a controller that determines the step length at the end of each trolley pass, based on the average feed rate measured. However, due to the location of the integrator scale—installed at the end of Conveyor TC1—the material must travel through the Bridge Conveyor and the entire length of TC1 before being recorded. Consequently, the time delay between material reclaiming and actual measurement depends on both the machine's longitudinal position and the trolley's transverse position.

This spatial variability introduces a dynamic and non-constant dead time into the system, significantly reducing the effectiveness of the current control strategy in regulating the flow rate at the scale. As a result, peak mass flow values are more likely to occur during operation, compromising system stability.

IV. DEVELOPMENT OF THE SOFT SENSOR

To meet the objective of this study—estimating the mass flow rate reclaimed by the bridge-type bucket-wheel reclaimer—three virtual sensors were developed based on distinct machine learning techniques: *Random Forest*, Neural Networks, and Linear Regression.

The development process was divided into three main stages. First, operational data from the reclaimer were collected, including electrical and positional variables relevant to the reclaiming process. Second, the variable dead time between material extraction and its measurement at the integrator scale was estimated, accounting for the dynamic distance between the machine and the measurement point. Lastly, the dataset was used to train and evaluate the selected machine learning models using algorithms implemented in Python.

Each model aimed to infer the mass flow rate using input variables available from the control system, thereby avoiding the need for additional physical instrumentation. The resulting virtual sensors were later compared in terms of accuracy and implementation feasibility.

A. Data Collection and Analysis

Data collection was carried out from February 1 to February 16, 2024, focusing on the following variables: bucket-wheel current, Bridge Conveyor current, reclaimer position along the stockyard, and trolley position.

To estimate the time required for the mass reclaimed by the RC to reach the TC1 integrator scale, the following field parameters were measured:

- **TC1:** Speed measured at 3.2 m/s using a tachometer.
- **Bridge Conveyor:** Design speed specified as 4.0 m/s.
- **Distance:** 24 m, based on field measurements.

With these inputs, the dead time associated with each data point was calculated using the following expression:

$$DeadTime = \frac{D}{V_{TC1}} + \frac{P_{maq}}{V_{TC1}} + \frac{P_{car}}{V_{ponte}}, \quad (1)$$

where D is the fixed distance between the scale and the yard's zero reference point, V_{TC1} is the velocity of the TC1 Conveyor, V_{ponte} is the velocity of the Bridge Conveyor, P_{maq} denotes the machine position in the yard, and P_{car} corresponds to the trolley position on the bridge.

By applying this formula to each record in the dataset, the estimated dead time ranged from 27 to 148 seconds, depending on the current positions of the machine and the trolley.

Following the data acquisition, a preprocessing phase was performed to exclude non-representative or corrupted records. All entries where current values were equal to or below 5 A were removed to discard intervals when the conveyor or bucket wheel were inactive, as well as periods potentially affected by control system inconsistencies. Additionally, samples marked as *bad* or containing *NaN* values were eliminated, as they typically indicate communication failures or errors in data acquisition between the PLC and the plant's data historian.

V. SOFT SENSOR DEVELOPMENT

To construct the virtual sensors, three model configurations were defined for each of the selected machine learning techniques. The goal was to analyze the individual and combined influence of key attributes on model performance and to identify the most efficient configuration for implementation. The sensor variants were defined as follows:

- Soft Sensor 1 (SS1): Utilizes only the bucket-wheel current as input.
- Soft Sensor 2 (SS2): Utilizes only the Bridge Conveyor current as input.
- Soft Sensor 3 (SS3): Combines both the bucket-wheel and Bridge Conveyor currents as inputs.

Figure 7 presents a schematic representation of the input variables, the model structure, and the desired output.

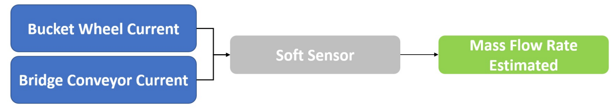


Fig. 7: Developed Virtual Sensor Models

Each model was trained using 80% of the available dataset, while the remaining 20% was set aside for testing purposes. This approach ensured that the test data remained independent from the training set, providing a reliable evaluation of the models' generalization capability.

A. Machine Learning Models

Three machine learning algorithms were evaluated in this study: 1) Random Forest (RF); 2) Neural Network (NN); and 3) Linear Regression (LR).

All models were trained using a dataset split into 70% for training and 30% for testing, employing the *train_test_split* function to ensure proper validation of model generalization. Model performance was assessed using root mean squared error (RMSE), mean absolute error (MAE), and the *Pearson* correlation coefficient between predicted and actual values. In addition, cross-validation was applied to reinforce the robustness of the evaluation and prevent overfitting.

- **Random Forest**: Random Forest is an advanced machine learning technique classified as an ensemble method, designed to improve the performance of decision trees. RF is named for its use of multiple trees to perform regression and/or classification tasks [11]. This method is widely employed in *soft sensors* due to its ability to capture complex relationships within data and reduce the risk of overfitting.
  In this work, the model was implemented using the *RandomForestRegressor* class from the *scikit-learn* library in Python. The configuration included 100 estimators (trees), allowing for robust and stable predictions through aggregation. The choice of 100 trees strikes a balance between predictive performance and computational efficiency: a sufficiently large number of estimators reduces variance and improves generalization, while avoiding excessive training time or unnecessary model complexity.
- **Neural Network**: Artificial neural networks are computational models inspired by biological neural systems. These models are composed of layers of interconnected nodes (neurons), where each connection has an associated weight that is iteratively adjusted during training to minimize prediction errors [11].
  The neural network used in this study was a *Multi-Layer Perceptron* (MLP), implemented via the *MLPRegressor* class from the *scikit-learn* library. The architecture consisted of a single hidden layer with 15 neurons, enabling the model to capture complex nonlinear relationships while avoiding excessive complexity that

could lead to overfitting, given the available dataset size. The maximum number of iterations was set to 1000 to ensure convergence during training, providing a balance between computational efficiency and the ability to reach stable parameter estimates. These hyperparameters were chosen to maintain a model that is expressive enough to approximate the process dynamics while remaining computationally tractable and generalizable.

- **Linear Regression**: Linear regression is a classical statistical method used to model the relationship between a dependent variable and one or more independent variables. The method aims to identify the linear function that best fits the observed data, minimizing the residual errors between predicted and actual values.
  As with the other models, the implementation was performed using the *LinearRegression* class from the *scikit-learn* library in Python.

To mitigate overfitting, specific strategies were adopted for each model. For the neural network, the number of training iterations was limited to prevent the model from excessively adapting to particular patterns in the training data. In the case of the Random Forest model, the number of trees (estimators) was constrained to reduce model complexity and avoid overfitting to the training set. These adjustments aimed to improve generalization performance and ensure more reliable predictions in operational scenarios.

VI. Results and Discussion

A. Linear Regression

Table I presents the results obtained from the three virtual sensors developed using the linear regression model, based on the data collected over 15 days. Among the evaluated models, SS3 achieved the best overall performance, with the lowest error metrics and the highest correlation. SS1, which uses only the bucket-wheel current, yielded results very similar to those of SS3, indicating that the addition of the Bridge Conveyor current had minimal impact on the model's accuracy.

In contrast, SS2—based solely on the Bridge Conveyor current—showed significantly inferior performance, with a correlation of 0.69 and substantially higher error values. These results reinforce the conclusion that the bucket-wheel current is the most informative variable for estimating the mass flow rate measured by the integrator scale.

TABLE I: Test phase results of SS1, SS2, and SS3 sensors: Linear Regression

	SS1	SS2	SS3
RMSE (ton/h)	241.69	362.93	241.63
MAE (ton/h)	185.59	282.27	185.56
Correlation	0.87	0.69	0.87

Figure 8 compares the outputs of the three virtual sensors with the integrator scale measurements. The SS2 model, based solely on the Bridge Conveyor current, exhibits limited ability to reproduce the actual mass flow behavior. In contrast, SS1 and SS3 show a significantly closer approximation to the real signal, effectively capturing the main variations recorded by the scale.

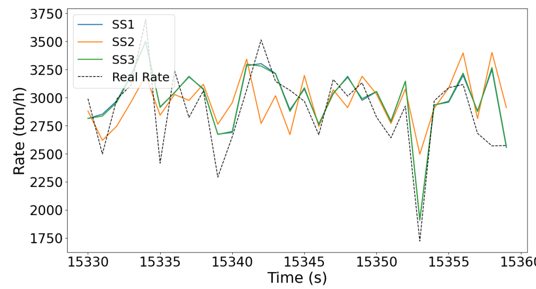


Fig. 8: Linear Regression results compared to the integrator scale data

B. Neural Network

Table II presents the performance metrics for the virtual sensors developed using the neural network model. As in the previous analysis, SS3 achieved the best results, now with a more significant margin compared to SS1. The latter showed inferior performance relative to the linear regression model, particularly in terms of RMSE and MAE. Once again, SS2 yielded the lowest performance, with an RMSE notably higher than the other configurations.

TABLE II: Test phase results of SS1, SS2, and SS3 sensors: Neural Network

	SS1	SS2	SS3
RMSE (ton/h)	281.47	437.32	246.07
MAE (ton/h)	202.78	332.63	173.91
Correlation	0.91	0.79	0.93

Figure 9 compares the results obtained by the three neural network-based models. SS2 once again presented the weakest alignment with the real rate measured by the scale. In contrast, SS3 delivered the most accurate estimations. In this case, the combination of Bridge Conveyor current and bucket-wheel current proved to be more effective than individual variables, yielding the best performance among all tested configurations up to this point.

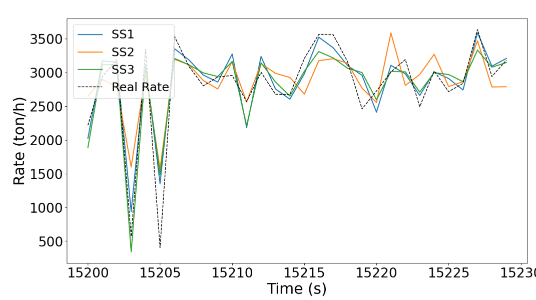


Fig. 9: Neural Network results compared to the integrator scale data

C. Random Forest

Table III presents the performance metrics for the virtual sensors developed using the *Random Forest* model. As observed in previous analyses, SS3 achieved the best overall results, with performance metrics comparable to those obtained through linear regression. SS1 ranked second, with slightly inferior results to SS3. Once again, SS2 exhibited the weakest performance, reinforcing its limited predictive capability across all evaluated models.

TABLE III: Test phase results of SS1, SS2, and SS3 sensors: Random Forest

	SS1	**SS2**	**SS3**
RMSE (ton/h)	287.17	379.99	259.39
MAE (ton/h)	205.57	278.42	185.62
Correlation	0.91	0.84	0.93

Figure 10 shows a comparison between the predictions made by each of the Random Forest-based sensors and the actual values measured by the integrator scale. The SS2 model demonstrates a lower capacity to replicate real behavior, while SS3, supported by the combination of two input variables, once again delivers the most accurate estimation results.

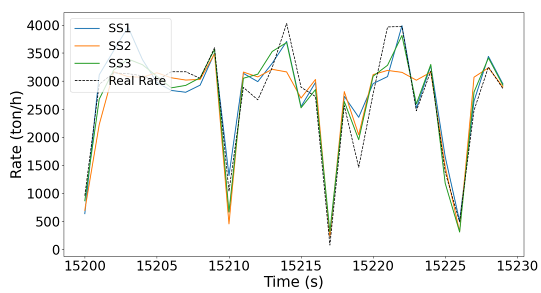


Fig. 10: Random Forest model results compared to the integrator scale data

D. Implementation in PLC

Following the performance analysis of all evaluated models and considering the practical constraints associated with implementation in a programmable logic controller (PLC), the linear regression model based on the currents of the Bridge Conveyor and bucket wheel (SS3) was selected. Although this model did not outperform all others across every metric—namely, RMSE, MAE, and Pearson correlation—it achieved the lowest RMSE among all tested configurations, indicating high predictive accuracy. Its MAE was the third-lowest, and the correlation coefficient, although slightly lower than that of more complex models like neural networks and random forest, remained high and consistent. These results highlight the model's robustness, simplicity, and suitability for real-time implementation in industrial environments.

In addition to its quantitative performance, the decision to adopt the linear regression model was strongly influenced by its implementation simplicity. In industrial environments, especially within PLCs, factors such as ease of coding, low computational complexity, and transparency of the model structure are critical. Furthermore, because the predictive model must be periodically reviewed and recalibrated—due to factors such as equipment wear, variations in material properties, or mechanical interventions—linear regression provides greater flexibility for updates, facilitating both model maintenance and adaptation to evolving process conditions.

The model implemented in the PLC is defined by the following equation:

$$y = (29.51894237 \cdot x_1) + (-0.4375383 \cdot x_2) - 3255.45830328 \tag{2}$$

In this expression, y represents the estimated mass flow rate. The variable x_1 corresponds to the bucket-wheel current (in amperes), and x_2 denotes the current of the Bridge Conveyor (also in amperes).

This soft sensor was deployed in the PLC, and a new data acquisition campaign was conducted between May 18, 2024, and June 12, 2024, to evaluate its real-time performance. The model yielded a mean absolute error (MAE) of 207.61, a root mean squared error (RMSE) of 290.27, and a Pearson correlation coefficient of 0.92 with the actual mass flow rate measured by the integrator scale. These results demonstrate that the virtual sensor was able to reproduce the physical sensor readings with satisfactory accuracy, maintaining an average deviation of approximately 10%.

Figure 11 illustrates the output of the virtual sensor implemented in the PLC alongside the actual mass flow data recorded by the integrator scale. To enable this comparison, the dead time corresponding to each measurement was computed, and the scale data were temporally shifted. This alignment allowed for a proper visual evaluation between the estimated and measured values of mass flow rate.

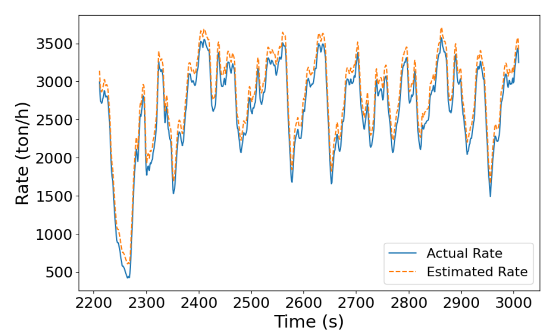


Fig. 11: Verification of Model Effectiveness Applied in PLC

VII. CONCLUSION

Measuring the mass flow rate in the iron ore reclaiming process using bridge-type bucket-wheel reclaimers presents considerable challenges due to the continuous movement of the equipment and the variability in the distance between the reclaimer and the measurement point. Integrator scales installed on conveyor belts, while accurate, entail high implementation costs and require specific physical conditions for installation—factors that often make their application in this context unfeasible.

In this study, a virtual sensor was developed to estimate the mass flow rate reclaimed by the yard reclaimer, thereby eliminating the dead time inherent to the process. Among the models evaluated, linear regression was selected for implementation due to its favorable balance between accuracy, simplicity, and ease of integration with the PLC environment. The implemented model exhibited high correlation with the physical sensor, as well as acceptable MAE and RMSE values, particularly considering that its primary role is to support control actions rather than to provide exact production measurements.

Future work will focus on integrating this virtual sensor into the reclaimer's control logic, effectively closing the control loop. This integration is expected to enable faster system response to process variations and improve control performance by allowing dynamic adjustment of the machine's advancement steps, which are currently determined based on delayed mass flow measurements.

Acknowledgments

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