Uncertainty Quantification in Measuring Ore Mass Flow Rate with Data-Driven Soft Sensors

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Abstract*—In the context of Industry 4.0, there is a growing need for reliable information. Understanding uncertainties in models and data can improve decision-making, safety, and efficiency in the mining sector, especially where machine learning-based soft sensors are utilized. This is particularly relevant in ore transport, where machine learning-based soft sensors estimate the mass flow rate of transported ore. However, these applications often utilize traditional machine-learning techniques to make single-output predictions, limiting their utility. Therefore, this study seeks to advance the performance of such sensors by quantifying the prediction's uncertainties. As a result, the electrical current from a conveyor belt was used to develop a model utilizing feature selection, engineering, and the Light Gradient Boosting Machine (LightGBM) algorithm, producing interval predictions. Four methods of uncertainty quantification were evaluated: T-Student, Bootstrap, Split Conformal Prediction (SCP), and Full Conformal Prediction (FCP). The results show that LightGBM, together with feature engineering and selection, decreased the soft sensor error compared to the previous study. The Bootstrap and FCP methods provided effective prediction intervals, achieving the intended coverage with minimal interval widths, suggesting their superior ability to balance accuracy and adaptability.

***Index Terms*—Data-driven Soft Sensors, Mass Flow Rate, Uncertainty Quantification, Conformal Prediction, Mineral Industry.**

I. Introduction

With the advent of Industry 4.0, there has been an increasing demand for high-confidence information across various sectors, and the mining industry is no exception. Machine learning (ML) provides a promising approach to increase efficiency, improving decision-making and cost-effectiveness by streamlining various stages of the ore production chain, from extraction and processing to logistics and transportation, as already evidenced by Bertolini et al. [1]. ML has been employed to enhance instrument capabilities, from classification and regression tasks to auto-calibration and auto-diagnostics. Several studies have significantly contributed to this scenario, particularly in applying ML to mining processes. Leveraging these contributions, ML offers effective solutions for developing soft sensors. One promising area is ore transport, where ML can be leveraged to create data-driven approaches for evaluating the mass flow rate of the ore when conveyor belts transport it.

Conveyor belts are widely used to transport bulk material in the mining industry due to their cost-effectiveness. They are responsible for transporting the ore from one beneficiation process to another [2]. Therefore, evaluating mass flow is essential for operational control, preventing conveyor belt overload [3].

Traditionally, the mass flow rate is measured through belt scales, which are widely used to weigh materials on conveyor belts. They are costly and often limited in the quantity of equipment installed in a mining plant. This shortage can negatively impact automatic control strategies because often there is a dead time between the actuator and the mass flow rate sensor due to their distance apart. When this dead time is large, the effectiveness of feedback controllers, such as the Proportional Integral Derivative (PID), is reduced [4], [5]. These limitations emphasize the need for soft sensors to enhance efficiency and lower costs while reducing capital expenditure.

To address this concern, many researchers have developed soft sensors to evaluate mass flow rate without relying directly on belt scales [3], [4], [6]. However, these approaches rely on lightweight ML algorithms, as industrial automation algorithms need to be embedded in Programmable Logic Controllers, which often cannot meet the demands of more complex strategies [7]. Hence, traditional ML often has difficulty effectively modeling complex processes inherent in industrial settings. Furthermore, none of the applications take into account the uncertainties inherent in their predictions. In many estimation or prediction tasks, machine learning (ML) models provide a single output value, often overlooking the associated error distribution. This oversight can result in reduced reliability and limit the models' applicability in dynamic environments.

Uncertainty quantification (UQ) provides a way to assess and communicate these uncertainties, which are not naturally considered by most ML models. Following the perspective of Zaffran et al. [8], we argue that incorporating UQ can lead to a safer and more robust decision-making process by making uncertainty explicitly part of the model's output. According to Nemani et al., [9], UQ serves as a crucial safety layer, enabling more informed decision-making by facilitating effective risk assessment and management. Furthermore, quantifying uncertainty in soft sensors is crucial for detecting performance deterioration caused by uncertainty in process conditions and for enhancing their robustness [10]. This process ensures that the sensors remain reliable and effective, even in dynamic and uncertain environments, by enabling adaptive strategies to mitigate variability and improve predictive accuracy.

In response to the need for enhanced predictive models and to quantify their output uncertainty, this study aims to extend the contributions of Pereira et al. [4], who developed a mass flow rate soft sensor on a conveyor belt. We compared the Light Gradient Boosting Machine (LightGBM) [11] with traditional machine learning algorithms previously used by Pereira et al. [4]. We also explored an alternative approach to feature selection and engineering to improve the model's predictions. LightGBM utilizes a gradient-boosting framework and incorporates decision tree algorithms optimized for speed and resource efficiency [11]. Hence, implementing the LightGBM algorithm along with feature selection and engineering could significantly enhance the accuracy of the soft sensor compared to the developed by Pereira et al. [4].

Moreover, we quantified and compared the uncertainties in predictions generated by the LightGBM algorithm using various approaches. Specifically, we evaluated four methods for generating prediction intervals for uncertainty quantification: T-Student intervals, Bootstrap Prediction Intervals, Split Conformal Prediction (SCP), and Full Conformal Prediction (FCP). Additionally, we assessed each method with random selection and sliding window backtesting to enhance the robustness of the intervals and provide more reliable and adaptive predictions in complex industrial operations. Our findings indicated that the Bootstrap and FCP methods produced effective prediction intervals, achieving the desired coverage with minimal interval widths. This suggests that these methods are superior in balancing accuracy and adaptability.

This article is structured as follows: Section 2 (Background) introduces key concepts on T-Student, bootstrapped prediction intervals, and Conformal Prediction (CP). Section 3 (Related Works) reviews relevant research. Section 4 (Experimental Setup) describes the data and experimental configuration. Section 5 (Methodology) details the machine learning models and uncertainty quantification methods. Section 6 (Results and Analysis) examines model performance and prediction intervals. Finally, Section 7 (Conclusion) summarizes key findings and suggests future research directions.

II. Background

A. T-Student and Bootstrapped Prediction Intervals

According to Hyndman and Athanasopoulos [12], a prediction interval (PI) provides an interval within which we expect the future value y_t to lie with a specified probability and, generally, can be written as: $\hat{y}_{t+h|t} \pm c\hat{\sigma}_h$; where a prediction, $\hat{y}_{t+h|t}$, is associated with $\hat{\sigma}_h$, which is an estimate of the standard deviation of the h-step forecast distribution. The multiplier c depends on the desired coverage probability. Hyndman and Athanasopoulos [12], add that, on occasions where a normal distribution for forecast errors, e_t, is an unreasonable assumption, bootstrapped prediction intervals can be computed by calculating the $\alpha/2$ and $1-\alpha/2$ percentiles at each forecasting horizon, by knowing that: $y_t = \hat{y}_{t|t-1} + e_t$. We can simulate the next observation of a time series using: $y_{t+1} = \hat{y}_{t+1|t} + e_{t+1}$; where $\hat{y}_{t+1|t}$ is the one-step forecast and e_{t+1} is the unknown future error. Assuming future errors will be similar to past errors, we can replace e_{t+1} by sampling from the collection of errors we have seen in the past (i.e., the residuals).

B. Conformal Prediction (CP)

Conformal Prediction, introduced by Vovk et al. [13]–[15], creates prediction intervals that inherently take uncertainty into account instead of delivering a single result. This approach has gained traction for uncertainty quantification in machine learning models [16]. According to Angelopoulos and Bates [17], CP is versatile and applicable regardless of whether the underlying problem involves discrete or continuous outputs and whether it is a classification or regression task.

Formally, suppose $(X_i, Y_i)_{i=1,\dots,n}$ and $(X_{\text{test}}, Y_{\text{test}})$ are i.i.d. with a regression model that outputs predictions $\hat{y}_{\text{test}+h|\text{test}}$ and we reserve number n_cal of fresh i.i.d. pairs of data unseen during training, $(X_i, Y_i)_{i=1,\dots,n\_cal}$, for use as calibration data. Using the regressor model and the calibration data, we seek to construct a prediction set of possible labels $C(X_{\text{test}}, h)$ that satisfy the validity property:

$$1-\alpha \leq \mathbb{P}(\mathbf{y}_{\text{test}+h} \in C(\mathbf{x}_{\text{test}}, h)) \leq 1-\alpha+\frac{1}{n\_cal+1}. \quad (1)$$

Where: $(\mathbf{x}_{\text{test}}, \mathbf{y}_{\text{test}+h})$ is a recent test point from the same distribution for each horizon h, and $\alpha \in [0,1]$ is the error rate chosen by the user, while n_cal represents the number of data points used to calculate the non-conformity scores. Thus, the probability that the forecast set contains the correct value for each step horizon is almost exactly $1-\alpha$; this is the principle of the *marginal coverage* property, by Vovk et al. [13]–[15].

Still according to Angelopoulos and Bates [17], the steps for performing conformal prediction are: 1 - Identification of a heuristic notion of uncertainty using the pre-trained model on time series; 2 - Definition of the score function to cumulate the calibrations scores: here is use the absolute error: $s_t = |y_t - \hat{y}_{test} + h[t]|$; many other score functions can be used depending on the specific characteristics and requirements of the problem; 3 - Compute $\hat{q}$ as the $\left\lfloor \frac{(n\_cal+1)(1-\alpha)}{n\_cal} \right\rfloor$-th quantile of the calibration scores. 4 - Using the quantile to form forecast sets for new examples in multiple horizons: $C(\mathbf{x}_{\text{test}}, h) = \left[\hat{y}_{\text{test}+h|\text{test}} \pm \hat{q}\right]$.

The above condition is just a special case of CP, called Split Conformal Prediction (SCP), presented by Papadopoulos et al.

and Lei et al. respectively, [18], [19], which uses a calibration set to reduce the computational cost during the process of generating prediction intervals. The original CP proposal by Vovk et al. [13]–[15], called Full Conformal Prediction (FCP), uses the entire training set to accumulate prediction residuals, which is more computationally expensive.

III. Related Works

Soft sensing refers to approaches and algorithms that may estimate processes' variables based on available measurements and knowledge [20]. It can be defined through the use of mathematical or statistical models, along with sensors, analytical devices, instruments, and actuators that generate new real-time or near-real-time information, which can predict certain aspects of a process [20], [21]. Soft sensing approaches can be classified into three categories: model-driven, grey-box methods, and data-driven. Model-driven approaches rely on mathematical models representing the underlying process, while data-driven methods utilize historical data to develop the soft sensor. Gray-box approaches combine elements of both, leveraging theoretical models alongside empirical data for enhanced accuracy.

Several studies have implemented model-driven/gray box soft sensors to measure the mass flow rate of bulk materials transported by conveyor belts. For instance, Moraes et al. [5] used a model-driven approach to predict a delayed mass flow rate measurement employing a Smith predictor. On a gray-box approach, Hulthén [22] presented a mathematical model that utilizes the power draw of a conveyor belt and its geometric properties to estimate the mass flow rate. This model has also been employed by Itävuo et al. [23] to measure the mass flow of multiple conveyor belts within a crushing circuit, thereby validating mass balance.

Heinzl et al. [24], [25] employed the power draw of a conveyor belt as input for a linear regression model to estimate the mass flow rate. It was tested in a virtual environment to validate the model's accuracy and compared with measurements obtained from a belt scale. Similarly, Väyrynen et al. [6] also developed a soft sensor that uses a power transducer and the belt's geometry to estimate the mass flow rate.

Effective model-driven/grey box approaches require previous process knowledge or solid domain application understanding. This may limit certain contexts, making it beneficial to develop data-driven approaches to address this issue [26]. Sobreira et al. [3] proposed a data-driven soft sensor to estimate the mass flow of ore on a conveyor belt without a belt scale. Virtual sensors were created using a conveyor belt's current, torque, and motor speed data, supplemented by iron ore flow measurements from a belt scale installed on a different conveyor. The authors assessed three distinct machine learning models: REPTree, Random Forest, and M5P. Pereira et al. [4] also focused on developing a data-driven soft sensor integrated into a control system for an industrial mineral processing circuit. The study evaluated various machine-learning techniques, such as decision trees, multilayer perceptrons, and linear regression.

While these studies demonstrate machine learning techniques to estimate mass flow rate using soft sensors, they do not address uncertainty quantification. Hence, this study aims to build upon the dataset developed by Pereira et al. [4], extending its contributions by applying the LightGBM algorithm in conjunction with an alternative approach to feature engineering and selection. Furthermore, the study seeks to quantify the uncertainties associated with the predictions generated by the machine learning model, enhancing both its predictive accuracy and reliability. Table I summarizes the related works, focusing on soft sensor development.

TABLE I: Related works on estimating the mass flow rate of bulk materials transported by conveyor belts.

Work	**Model-driven**	**Gray-box**	**Data-driven**	**UQ**
Moraes et al. [5]	●	○	○	○
Hulthén [22]	○	●	○	○
Itävuo et al. [23]	○	●	○	○
Väyrynen et al. [6]	○	●	○	○
Heinzl et al. [24], [25]	○	●	○	○
Sobreira et al. [3]	○	○	●	○
Pereira et al. [4]	○	○	●	○
Our work	○	○	●	●

IV. Experimental Setup

Fig. 1 illustrates the domain of this work, a processing circuit used by a copper plant in Vale S.A., a mining company in Brazil. The circuit outlines the configuration for crushing and transporting material from the mine to the processing plant. In this setup, the initially extracted material is sent to a crusher, which reduces its size. The crushed material is then stored in a silo, from which a variable-speed feeder extracts it. The extraction rate is controlled by the speed of the feeder. The material is subsequently transported via three conveyor belts to a yard, where an ore pile is formed. From this pile, the ore undergoes further treatment. Since the belt scale is installed at CB-02, which is significantly distanced from the CB-01 conveyor belt, automatic control strategies are jeopardized due to the dead time between measuring the mass flow rate and the actuator (feeder). Therefore, a soft sensor is needed to estimate the mass flow rate, helping to minimize this delay.

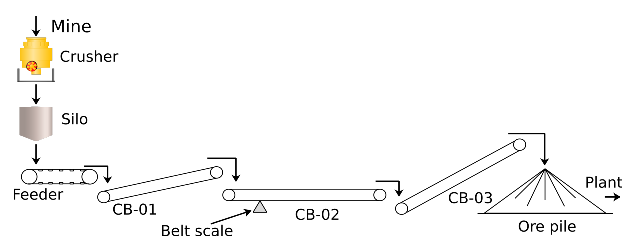

Fig. 1: Crushing and transportation diagram [4].

We used the same dataset presented by Pereira et al. [4] originated from the crushing and transportation circuit. The dataset is from a day of operation and comprises the current (A) of the conveyor belt CB-01 and the mass flow rate (t/h) from the belt scale installed on CB-02. Both measurements were gathered with a time interval of 1 s and were synchronized due to the temporal displacement between the sensors' measurements.

V. Methodology

A. Machine learning models

We compared the previously tested by Pereira et al. [4] machine-learning techniques, decision trees (DT), multilayer perception (MLP), and linear regression (LR) with LightGBM. We employed a repeated random hold-out technique for training and testing to evaluate each model. In each iteration, 80% of the dataset was randomly selected for training, while the remaining 20% was used for testing. This process was repeated 20 times, with different training and testing splits in each iteration. We used the Mean Absolute Error (MAE) metric to measure model performance and quantify disparities.

Firstly, we used for the model input the average and standard deviation over ten conveyor belt motor electrical current samples, as made by Pereira et al. [4]. We processed the electrical current data to analyze the models' response to different inputs by generating new input features such as means, lags, differences, and standard deviations. To prevent redundancy and overload, we used a correlation-based method to eliminate features with correlations above 0.9, retaining those most correlated with the target variable.

Feature selection was further refined using the model's variable importance. After training, importance scores were normalized to sum to 100%, and variables were ranked in descending order. Using the Pareto principle (80/20), we selected the top contributors to model performance. The final input features were *lag_60s*, *lag_30s*, *diff_1s*, *mean_10s*, and *diff_10s*.

B. Uncertainty quantification

To further enhance the predictions' reliability, we constructed a sequence of prediction intervals with a confidence level of $1 - \alpha$. For the results presented here, we consider the value of α equal to 0.05. The data was partitioned into training and testing sets according to a fixed proportion: the initial 90% was allocated to training, and 10% was reserved for testing purposes. Only for the SCP method, we use 80%-10%-10% (train, calibration, and test, respectively). Additionally, we implemented a Sliding Window-based methodology, to train the model with different window sizes (100, 150, 190, 250, 360, and 720 samples). This approach enables continuous evaluation of the model with new data over time, simulating a scenario where the model is consistently updated and tested with fresh information while maintaining the proportions of the training, calibration, and test sets.

The Regression Coverage Score (RCS) and Regression Mean Width Score (RMWS) were used to evaluate the uncertainty of predictions. RCS quantifies the proportion of true outcomes that fall within the prediction intervals generated by the model, indicating how effectively these intervals capture the actual values. Meanwhile, the RMWS, calculates the mean width of these prediction intervals, providing insight into the model's uncertainty in its predictions. A smaller range suggests greater confidence, as long as the coverage remains adequate for the projected confidence level as explained by Khosravi et al. [27].

The Regression Coverage Score (RCS) is defined as $RCS = \frac{1}{n}\sum_{i=1}^{n} 1\left(\hat{y}_i^{\text{low}} \leq y_i \leq \hat{y}_i^{\text{up}}\right)$, and the Regression Mean Width Score (RMWS) is given by $RMWS = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_i^{\text{up}} - \hat{y}_i^{\text{low}}\right)$. Where n is the number of samples; y_i is the true value for the i-th sample; $\hat{y}_i^{\text{low}}$ and $\hat{y}_i^{\text{up}}$ are the lower and upper bounds of the prediction intervals, respectively, for the i-th sample. The code and dataset developed for this study are publicly available on GitHub. The repository includes two implementations: one using a Sliding Window approach and another with a Random selection of data.

VI. Results and Analysis

A. Machine learning models

When using the current mean and standard deviation of ten samples (inputs from Pereira et al.), the LightGBM model demonstrated remarkable improvements over other ML models for MAE, scoring on average 43.09 t/h against 52.05, 51.35, 52.09 (t/h) from DT, MLP, and LR, respectively.

Using the features proposed in this study, all models demonstrated superior performance compared to the Pereira et al. inputs. The LightGBM model after applying feature engineering and selection techniques, achieved a 19.75% reduction in error. These results highlight the effectiveness of the feature engineering and selection method in enhancing sensor accuracy.

Moreover, the LightGBM model demonstrates notable improvements over the previous machine learning models regarding the MAE. It obtained around 17% improvement over the others when the same inputs are considered. These results show the effectiveness of LightGBM in delivering more accurate predictions across various techniques. Table II shows the average MAE obtained in each model.

TABLE II: Average MAE Comparison Across Algorithms and Feature inputs.

Suggested inputs	**Average MAE (t/h)**			
	LightGBM	**DT**	**MLP**	**LR**
Pereita et al.	43.09	52.05	51.35	52.09
This study	**34.58**	41.11	41.01	41.75

B. The Predictions Intervals

When using the sliding window (SW) approach to estimate prediction intervals, evaluation metrics are calculated at each step of the SW. In Fig. 2, is possible to see the values of the MAE metric for different window sizes. The smaller the window size, the greater the variability of the errors associated with the prediction. This is because, at some points, the models cannot fit well with the true data, and the space of one window or another may occupy a partition of greater error between the predicted values and the actual values.

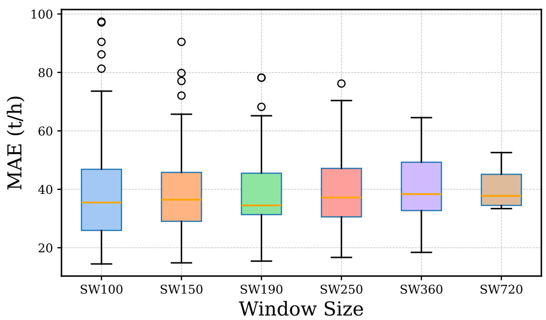

Fig. 2: LightGBM with SW in differents sizes.

Moving on to the metrics associated with the quality of the intervals, we can take the SW190 size window as an example. The results can be effectively summarized and presented in the box plots shown in Fig. 3. For most steps of the SW190 application, coverage remained within the range of 90% to 100%. However, we also observed some steps where coverage fell significantly below the projected level. These deviations are likely associated with instances where prediction errors are higher, as greater prediction errors reduce the probability of achieving effective coverage. Furthermore, another important aspect observed during the experiments is that as the window size decreases, there is a greater tendency for steps to appear where the coverage is lower than expected. Regarding Average Width, the Bootstrap PI and FCP methods demonstrated greater stability, with smaller intervals around 164 t/h. The SCP method exhibited slightly more variability in interval width, ranging from 170 to 200 t/h. The T-Stundent's method showed stability but with larger intervals of around 184 t/h.

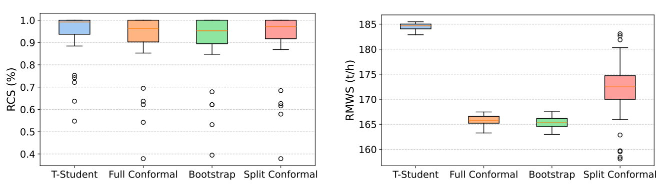

Fig. 3: (Left) Regression Coverage Score and (Right) Regression Mean Width Score with SW Size 190.

The most favorable results in terms of coverage were achieved without the SW and through random data selection. Fig. 4, illustrates the distribution of results using box-plot representations for coverage and the mean width score in this case. The Mean Width values for the random selection were similar to those found using SW190, except for the SCP method, which, with randomness, can stabilize its results more efficiently, ranging from around 165 to 170 t/h. However, the approach without the SW generates prediction intervals with a static width, meaning the interval size remains constant over time. This characteristic may limit the approach's applicability in complex and dynamic industrial scenarios, where adaptability to changing conditions is often required.

In addition, we applied the Shapiro-Wilk test to verify the normality of the metric results. Since not all results presented a normal distribution, we used the Kruskal-Wallis test to determine the existence of significant differences between the groups. We followed with the Dunn test to identify which specific groups presented substantial differences, using the Bonferroni adjustment to avoid false positives. For the implementation with SW190, the results in terms of Coverage can be considered the same for all methods. In terms of Width, a similarity was identified between the Full Conformal and Bootstrap methods, which presented similar width intervals and were smaller than the other methods. Considering the analysis with random data selection, about Coverage, it was identified that the only methods that did not present a considerable difference were Full and Split Conformal. To Average Width, besides Full and Split, it was impossible to identify a significant difference between Bootstrap and Full Conformal.

All methods achieved coverage close to the target level of 95%. The main difference between them was the average width of the intervals required to achieve this level of coverage. In this sense, the most efficient method is the one that achieves the projected coverage level with the smallest average interval width, as indicated in the study of Khosravi et al. [27]. Therefore, Bootstrap stands out, followed by Full Conformal, which offers narrower intervals than Split Conformal. The T-Student managed to provide slightly higher coverage than the target level; however, this came at the cost of significantly wider coverage intervals compared to other methods. The final result of this model is presented in Fig. 5, where the Mass Flow Rate (t/h) predicted by LightGBM with Bootstrap Predictive Intervals is illustrated.

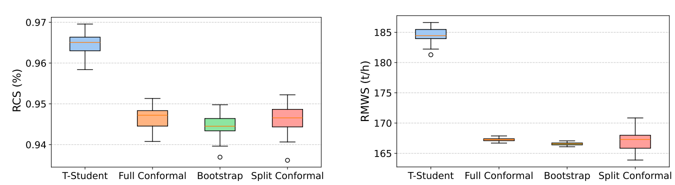

Fig. 4: (Left) Regression Coverage Score and (Right) Regression Mean Width Score with Random Selection.

VII. Conclusion

In this paper, we improved the performance of a mass flow rate soft sensor through LightGBM and feature engineering and selection techniques and explored the application of uncertainty quantification in the predictive system. Four methods for constructing prediction intervals are examined: T-Student, Bootstrap, SCP, and FCP. The Bootstrap and FCP methods provided effective prediction intervals, balancing accuracy, and adaptability. These results indicate that applying techniques to a crushing and transportation mining circuit could enhance information robustness and increase decision-making efficiency.Furthermore, the predicted ranges allow the projection of different scenarios, with a confidence level of $1-\alpha$, with probabilistic guarantees adapted to the needs of the requesting area. This way, the interval estimate can generate

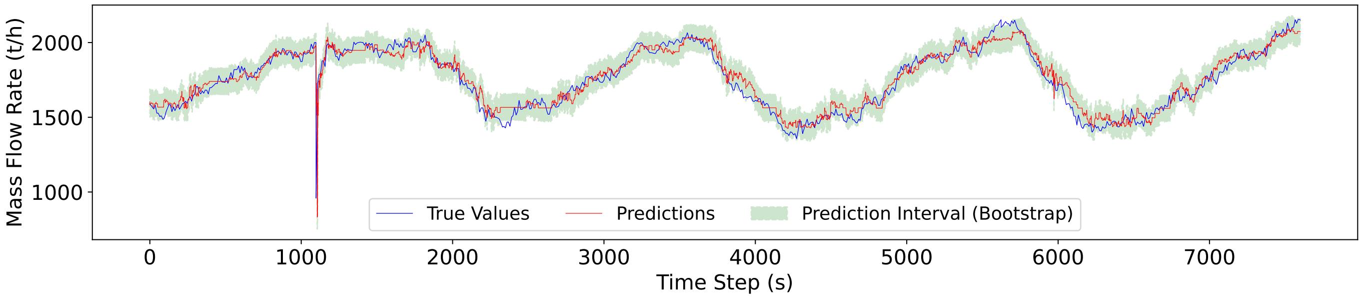

Fig. 5: Mass Flow Rate (t/h) by LightGBM with Bootstrap Predictive Intervals.

analyses for different scenarios with pessimistic, realistic, and optimistic perspectives.

As future research directions, we plan to evaluate other methods of UQ available in the literature, including those based on CP and other approaches, to compare the results with those obtained in this study. We also intend to embed the techniques suggested in this study into the industry's programmable logic controller (PLC). The suggested algorithms have low computational complexity, ensuring they can be embedded into PLCs on Structured Text program language. These would facilitate process monitoring and automation by using the predictions to feed automatic control structures.

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