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IFAC PapersOnLine 59-32 (2025) 84–89

Enhancing Operational Safety with Conformal Prediction in Soft Sensors

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Abstract: This study proposes a method to quantify uncertainty in soft sensors' measurements for estimating ore mass flow rate on conveyor belts in mining. A linear regression model previously implemented in a PLC is extended with Conformal Prediction (CP) and a sliding window to generate adaptive prediction intervals. Residuals are updated incrementally for efficiency and adaptability. One-way ANOVA and Tukey's HSD showed that window size significantly affects interval coverage and width. Larger windows (W100) yielded wider intervals (286.62 t/h) and higher coverage (95.3%), while smaller windows (W40) were narrower (243.97 t/h) with lower coverage (84.9%) but greater responsiveness. Processing time stayed under 0.1 seconds across all configurations, confirming suitability for real-time PLC use. The approach balances robustness and responsiveness, offering a lightweight, interpretable solution for uncertainty-aware control in industrial environments.

Keywords: Soft Sensors, Machine Learning, Uncertainty Quantification, Conformal Prediction, Decision Making, Operational Safety.

1. INTRODUCTION

Soft sensors are pivotal to Industry 4.0, enhancing the control and optimization of industrial processes through real-time estimation of critical variables (Li et al., 2020). Soft sensors are useful when physical sensors are not appropriate for measurement. Utilizing machine learning (ML) models to create these soft sensors is crucial for the digital transformation of manufacturing processes. Soft sensors made by ML are also known as data-driven soft sensors, and they aid in predictive maintenance, anomaly detection, and intelligent decision-making across various sectors. Their importance is magnified in high-risk sectors like mining, where operational hazards cannot be fully eliminated. In such environments, ML emerged as a key tool for mitigating accidents and improving safety (Matloob et al., 2021). However, the reliability of ML-driven decisions depends on robust uncertainty quantification (UQ), which evaluates the confidence of model predictions and is indispensable in high-stakes, uncertain scenarios (Wang et al., 2025).

Recent advances in predictive maintenance have shown the potential of data-driven models not only to detect equipment failures but also to optimize decision-making by anticipating them with higher accuracy and lower cost (Züfle et al., 2021). According to Stachowiak et al. (2021), belt conveyors—commonly used in mining for the continuous transport of bulk materials—are susceptible to failures that can halt production, lead to financial losses, and pose safety risks to personnel (Matos et al., 2024).

Automated monitoring systems are thus essential, particularly those enabling accurate mass flow measurements for process control (Heinzl et al., 2021). Recent advancements in mining logistics have focused on intelligent monitoring and failure detection. For instance, Wang et al. (2024) and Zohra et al. (2022) developed sensor-based strategies using intelligent algorithms to ensure conveyor belt integrity. Considering the noisy and dynamic nature of real-world industrial processes, robust predictive models such as those proposed by Yang et al. (2024) are critical.

Parallel efforts have explored soft sensors as cost-effective alternatives to traditional instrumentation. Data-driven approaches, such as the ML-based soft sensor by Bovo et al. (2022) for polyvinyl chloride (PVC) tubes extrusion flow rate estimation, demonstrate their utility in scenarios where direct measurement is impractical. In mining, Sobreira et al. (2023) and Pereira et al. (2024) proposed virtual sensors for ore mass flow estimation on conveyor belts, integrating them into programmable logic controllers (PLCs) with promising accuracy and simplicity. Similarly, Heinzl et al. (2021, 2022) validated indirect mass flow estimation via motor power consumption, underscoring the robustness of data-driven methods. Despite these advances, the studies cited so far maintain a critical gap:

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Peer review under responsibility of International Federation of Automatic Control.
10.1016/j.ifacol.2025.12.401

the lack of quantification of uncertainty in soft sensor outputs, which can limit the reliability of safety-critical decision-making Diniz et al. (2024). This work builds upon the contributions of Pereira et al. (2024) by extending their soft sensor model for ore mass flow estimation with a formal uncertainty quantification (UQ) mechanism. Specifically, we incorporate adaptive prediction intervals using a combination of Conformal Prediction (CP) and Sliding Windows (SW). This integration enhances the interpretability and reliability of the soft sensor's outputs, contributing to safer and more informed decision-making in real-time industrial operations—a domain where UQ techniques remain underutilized, particularly in mining logistics. However, applying UQ in such constrained environments, especially those relying on programmable logic controllers (PLCs), poses several challenges. Industrial processes are often dynamic and potentially non-stationary, which limits the effectiveness of standard UQ methods due to their inability to adapt to changing conditions quickly. This raises fundamental questions about balancing statistical reliability with operational adaptability. Accordingly, this study investigates two core research questions: (i) How does the size of the sliding window in Conformal Prediction influence the trade-off between statistical validity (empirical coverage) and the width of uncertainty estimates in a real-time soft sensor for ore mass flow? (ii) Is it feasible to implement this adaptive UQ method (SW-CP) within the computational constraints typical of PLC-based industrial environments?

2. BACKGROUND

2.1 Soft Sensors

Traditionally based on ML techniques, soft sensors are inferential models used to estimate difficult-to-measure variables from accessible variables, allowing real-time control and monitoring at low cost (Curreri et al., 2021). Soft sensors can be classified into three categories: model-driven (white-box modeling), data-driven (black-box modeling), and hybrid models (gray-box modeling). Model-driven models are based on physical laws and known equations of the process. Data-driven models use only historical data, without incorporating prior physical knowledge. Finally, gray-box models combine elements of both approaches, integrating data with part of the available physical knowledge to improve the accuracy and interpretability of the model (Markovsky et al., 2023). The choice between model-driven, data-driven, or hybrid approaches depends on the specific application context, data availability, and the level of process understanding. In this work, the focus is placed on data-driven soft sensors due to their adaptability to dynamic environments and suitability for integration with uncertainty quantification and incremental learning techniques, which are key to enhancing robustness and real-time decision-making in critical process operations.

2.2 Uncertainty Quantification (UQ)

According to Soize (2017), uncertainties in computational modeling are typically categorized into two types: aleatory and epistemic. Aleatory uncertainties are inherent to physical phenomena and stem from natural randomness. These variations are unpredictable and irreducible, even with additional data. In contrast, epistemic uncertainties arise from limited knowledge about the system or model. Hüllermeier and Waegeman (2021) emphasize the fundamental role of uncertainty in machine learning methodologies. While traditionally linked to probabilistic modeling and inference, the concept of uncertainty is becoming increasingly critical in real-world applications that demand high levels of reliability, such as safety-critical systems and decision-making processes. In the same vein, Abdar et al. (2022) argue that enhancing trust in AI systems requires not only acknowledging the presence of uncertainty but also effectively identifying and quantifying the different types of uncertainties inherent in their predictions. Prediction intervals are a widely used tool to quantify prediction uncertainty in regression problems (Lai et al., 2022).

In predictive settings, the goal is often to estimate the range in which a future observation is likely to fall. A $(1-\alpha)\%$ *prediction interval* defines a range $(X_{\text{Lower}}, X_{\text{Upper}})$ such that $P(X_{\text{Lower}} < \bar{X} < X_{\text{Upper}}) = 1-\alpha$, ensuring that the next value lies within this interval with high confidence (Ross, 2009). One way to construct prediction intervals applied to online monitoring and control systems is conformal prediction (CP), which will be presented in the next session.

2.3 Conformal Prediction (CP)

The work of Dewolf et al. (2023) highlights Conformal Prediction (CP), originally introduced by (Vovk et al., 2005), as a promising and general framework for constructing prediction sets that inherently account for uncertainty. CP has proven effective in calibrating models that initially yield unreliable results, offering a systematic way to improve the validity of prediction intervals. As a result, CP has gained increasing attention as a robust method for uncertainty quantification in predictive models (Farinhas et al., 2023). Following the guidelines presented by Angelopoulos and Bates (2021), the Conformal Prediction (CP) procedure can be summarized into four main steps, given a general input-output pair (x, y):

(1) A pre-trained model is used to define a heuristic notion of uncertainty.
(2) A nonconformity score function $s(x, y) \in \mathbb{R}$ is selected, where higher values represent worse agreement between x and y.
(3) Using the calibration set $(X_1, Y_1), \ldots, (X_n, Y_n)$, the quantile $\hat{q}$ is computed as the $\left\lceil \frac{(n+1)(1-\alpha)}{n} \right\rceil$-th empirical quantile of the scores:
$$s_1 = s(X_1, Y_1), \ldots, s_n = s(X_n, Y_n). \tag{1}$$
(4) For a new input X_{test}, the prediction set is defined as:
$$C(X_{\text{test}}) = \{y : s(X_{\text{test}}, y) \leq \hat{q}\}. \tag{2}$$

One of the most important theoretical properties of CP is its ability to offer statistical guarantees on the prediction sets, even without assumptions about the underlying distribution. As demonstrated in Angelopoulos and Bates (2021), for any score function and unknown data distribution, the resulting prediction sets satisfy the marginal coverage property:

$$1-\alpha \leq \mathbb{P}(Y_{\text{test}} \in C(X_{\text{test}})) \leq 1-\alpha+\frac{1}{n+1}, \quad (3)$$

where $(X_{\text{test}}, Y_{\text{test}})$ is a new, unseen test sample, and $\alpha \in [0,1]$ is a user-defined miscoverage rate. This means that the prediction set will contain the true value with a probability close to $1-\alpha$, on average over the randomness in the calibration and test points. Still according to Angelopoulos and Bates (2021), the Divided Conformal Prediction proposed by (Lei et al., 2018), is one of the simplest practical ways of applying CP, it uses a small portion of data as a calibration set and presents a formal guarantee of coverage given by:

$$\mathbb{P}(Y_{\text{test}} \in C(X_{\text{test}})) \geq 1-\alpha. \quad (4)$$

3. MATERIALS AND METHODS

3.1 Proposed Algorithm: Sliding Conformal Prediction

The algorithm used in this study can be interpreted as a variation of Split Conformal Prediction (SCP), where instead of a fixed calibration set, a sliding window of residuals is maintained and updated at each new observation. This allows the prediction intervals to adapt to recent data dynamically. Let $\hat{y}_t$ be the soft sensor prediction and y_t the true value at time t. Define the residual as: $e_t = |\hat{y}_t - y_t|$, like in step 02. The mean difference here is that a sliding window R_t stores the most recent n residuals: $R_t = \{e_{t-n+1}, e_{t-n+2}, \ldots, e_t\}$. Based on step 3, the empirical quantile q_t at level $1-\alpha$ is computed from the sorted residuals in the sliding window R_t using: $q_t = \text{Quantile}\left\lceil \frac{(n+1)(1-\alpha)}{n} \right\rceil (R_t)$. The prediction interval at time t is defined as: $\mathcal{C}_t = [\hat{y}_t - q_t, \hat{y}_t + q_t]$. A coverage indicator $c_t \in \{0,1\}$ is also recorded:

$$c_t = \begin{cases} 1, & \text{if } y_t \in \mathcal{C}_t \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

This procedure is repeated for each new observation, allowing the calculation of evaluation metrics such as empirical coverage and mean width. The use of a sliding window ensures that the model remains responsive to recent variations in the data. As demonstrated in studies such as that by Diniz et al. (2024), which compares different uncertainty quantification methods, SCP can provide coverage guarantees close to those of known more computationally expensive methods, such as the bootstrap resampling method or Full Conformal Prediction, and with mean interval widths smaller than a Student's t-distribution method. Therefore, SCP, due to its versatility and efficiency, can be a valuable tool for increasing reliability in industrial control systems.

3.2 Evaluation Metrics

When assessing prediction intervals, the objective is to achieve the narrowest possible width while still meeting the desired confidence level. As highlighted by Khosravi et al. (2010), a narrower interval reflects higher confidence, provided that it maintains the required coverage. In this context, two metrics were employed to evaluate prediction uncertainty: the Regression Coverage Score (RCS) and the Regression Mean Width Score (RMWS). The RCS measures the proportion of true values that fall within the predicted intervals, indicating how reliably the model captures actual outcomes. Meanwhile, the RMWS reflects the average width of these intervals, offering a sense of the model's uncertainty. These metrics were computed using MAPIE (Model Agnostic Prediction Interval Estimator), an open-source Python library introduced by Taquet et al. (2022) to support uncertainty quantification and risk control in machine learning models. In addition, computational time was also considered as a key evaluation metric. The experiments in this study were conducted using the Python programming language within the Visual Studio Code (VS Code) development environment. The hardware platform was a Dell G15 laptop equipped with a 13th Generation Intel® Core™ i5-13450HX processor (2.40 GHz, x64 architecture) and 16 GB of installed RAM (15.7 GB usable), running a 64-bit Windows operating system. To assess the feasibility of deploying the proposed Sliding Conformal Prediction method in real-time industrial environments, we measured the execution time required to generate prediction intervals for each sliding window configuration ($w = 10, 20, \ldots, 100$), for this Python's `time.perf_counter()` function was employed. This analysis provides insights into the scalability and operational viability of the method, particularly for implementation in PLCs, where computational resources and response times are critical constraints.

4. EXPERIMENTAL SETUP

Figure 1 presents the operational environment addressed in this study: a material handling circuit employed in a copper processing facility operated by Vale S.A., a major Brazilian mining company. This circuit encompasses the stages involved in crushing and conveying ore from the extraction site to the processing unit. Initially, raw material is directed to a crusher that reduces its particle size. The crushed ore is stored in a silo, from which a feeder with variable speed control extracts it. The feed rate is regulated by adjusting the feeder's speed.

The material is then transported along a series of three conveyor belts until it reaches a stockyard. From this point, the ore proceeds to the next beneficiation stages. Notably, the belt scale is positioned at CB-02, which is located well downstream of conveyor CB-01, introducing a significant delay between actuation (feeder adjustment) and measurement (mass flow rate), complicating automatic control implementations. To mitigate this issue, a soft sensor is proposed to estimate mass flow rate in real time, thus reducing the impact of dead time on control strategies.

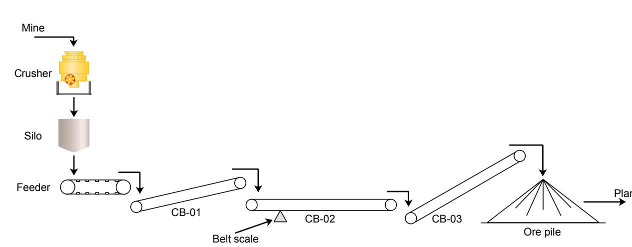

Fig. 1. Material crushing and conveying system adapted from (Pereira et al., 2024).

The dataset employed in this study is the same as that used by Pereira et al. (2024), collected from the crushing and transport process described. It consists of time-series data from a single day of plant operation, including electrical current (A) measurements from the CB-01 conveyor motor and mass flow rate (t/h) data from the belt scale located at CB-02. Both signals were recorded at 1-second intervals and aligned temporally to account for the time delay between the sensor readings. In the previous study by Pereira et al. (2024), several machine learning models (such as Decision Trees, Multilayer Perceptrons, and Linear Regression) were evaluated for the construction of the soft sensor. Linear Regression was the final choice for field deployment. This choice was motivated by its ease of implementation, lower computational cost, and satisfactory accuracy compared to more complex models. Therefore, this study focuses exclusively on Linear Regression for emulating soft sensor uncertainty quantification. The estimated mass flow rate $\dot{m}_{ss}$ is calculated as $\dot{m}_{ss} = 116.63 \cdot avg_{cur} + 39.25 \cdot std_{cur} - 905.17$, where avg_{cur} and std_{cur} denote the mean and standard deviation of the last 10 current readings, respectively. The code and dataset for this implementation are available at the following GitHub repository.

5. RESULTS AND ANALYSIS

This study builds upon the linear regression model developed in the previous work, which is already deployed in industrial applications. Rather than proposing a new predictive model, our contribution lies in the integration of prediction intervals to enable uncertainty quantification for the existing solution. To this end, we implemented a Conformal Prediction (CP) framework enhanced with a sliding window mechanism, which allows residuals to be continuously updated, thereby improving both computational efficiency and adaptability to data with high variability. The method can be viewed as a variation of Split Conformal Prediction (SCP), where a small portion of the dataset serves as a dynamic calibration set. The residual window size is a key factor in balancing adaptability and reliability. To assess its influence, we ran 15 iterations per window configuration, each using 1000 data points containing both soft sensor predictions and actual mass flow rates.

Figure 2 displays box plots for coverage (left) and mean width (right) across different window sizes. As shown in Figure 3, a sliding window of size 40 produced an average interval width of 243.97 t/h, achieving 84.9% coverage, below the targeted 95%. In contrast, increasing the window size to 100 (Figure 5) improved coverage to 95.3%, but widened the intervals to an average of 286.62 t/h. Figures 4 and 6 reveal that larger windows result in slower updates to the quantile value, yielding more stable but less responsive intervals. To formally assess whether these differences were statistically significant, we conducted a one-way ANOVA comparing the 10 sliding window groups (SW10 to SW100) for both metrics. The results confirmed that window size significantly influences both coverage and mean width ($p < 0.001$ in both cases). Tukey's Honestly Significant Difference (HSD) post hoc test further revealed that differences were especially pronounced between extreme configurations (e.g., SW10 vs. SW100), reinforcing the systematic effect of window size. Specifically: (i) **Coverage** increases with window size, approaching the desired confidence level and offering more reliable uncertainty bounds. (ii) **Mean Width** also grows with the window size, indicating more conservative intervals with less fluctuation across iterations. These findings highlight a clear trade-off: larger windows improve coverage stability and robustness but yield wider prediction intervals, which may reduce their practical utility. Smaller windows, on the other hand, provide narrower, more adaptive intervals, albeit with greater variability and reduced alignment with the intended confidence level. Figure 7 shows the total computational time for different sliding window sizes (W10 to W100), averaged over 15 iterations. Processing time increased monotonically with window size: W10 and W20 remained below 0.05 seconds, while W100 approached 0.10 seconds. Despite this increase, all configurations stayed within the real-time constraints typical of PLC-based industrial systems. Statistical analysis using one-way ANOVA and Tukey HSD tests confirmed significant differences among configurations ($p < 0.05$). Smaller windows (e.g., SW10 and SW20) consistently achieved lower computational costs, highlighting their suitability

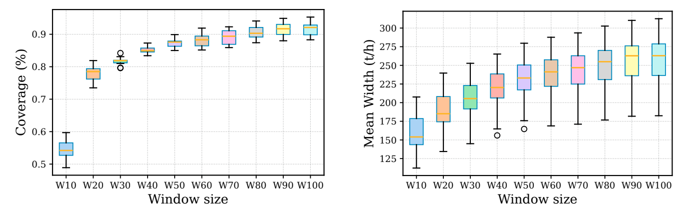

Fig. 2. Box plots for (left) coverage probability and (right) mean interval width across different residual window sizes.

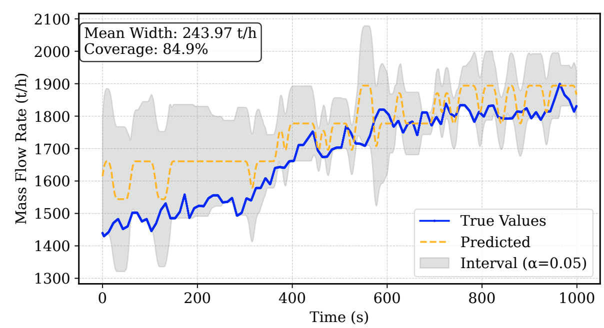

Fig. 3. Prediction intervals simulated in the PLC using a sliding window of size 40.

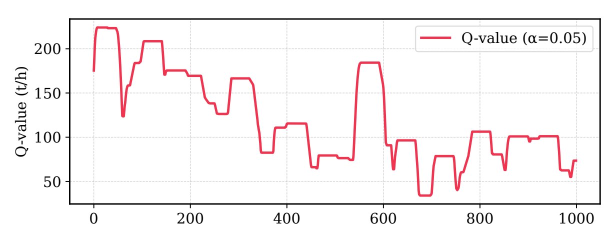

Fig. 4. Q-value evolution for a sliding window of size 40 residuals.

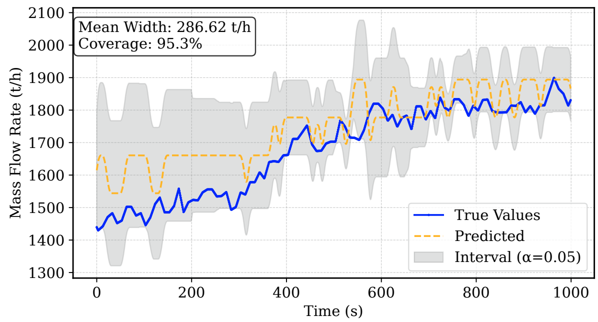

Fig. 5. Prediction intervals simulated in the PLC using a sliding window of size 100.

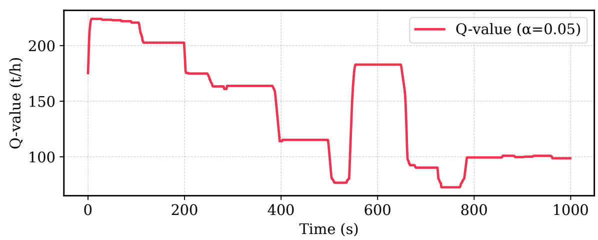

Fig. 6. Q-value evolution for a sliding window of size 100 residuals.

for deployment in resource-constrained environments. To quantify these effects, Table 1 presents pairwise comparisons of mean processing times. Larger windows systematically incurred higher computational overheads, with SW100 requiring approximately 33.16% more time than SW10. Incremental changes between adjacent windows typically led to increases around 3%. These results reinforce the trade-off between robustness and computational efficiency, while demonstrating the feasibility of real-time deployment across all tested window sizes.

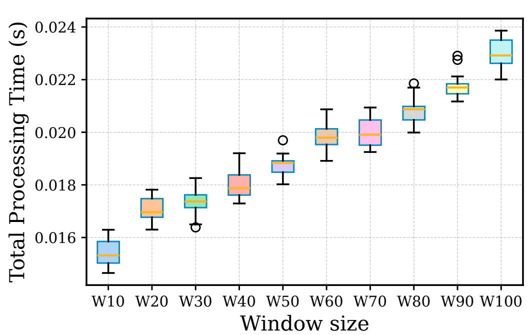

Fig. 7. Total processing time (s) across different residual window sizes.

Table 1. Pairwise comparison of mean processing times between window sizes (%).

	SW10	SW20	SW30	SW40	SW50	SW60	SW70	SW80	SW90
SW20	9.69								
SW30	11.81	2.35							
SW40	14.29	5.09	2.81						
SW50	18.66	9.93	7.76	5.09					
SW60	22.62	14.31	12.25	9.71	4.87				
SW70	23.06	14.80	12.75	10.23	5.41	0.57			
SW80	26.62	18.75	16.79	14.39	9.80	5.18	4.64		
SW90	29.41	21.84	19.96	17.64	13.23	8.78	8.26	3.80	
SW100	33.16	25.99	24.21	22.02	17.84	13.63	13.14	8.91	5.31

6. CONCLUSION

This work introduced an implementation of Conformal Prediction (CP) combined with a sliding window strategy to enable uncertainty quantification in a soft sensor designed to estimate ore mass flow on conveyor belts. Leveraging the linear regression model already embedded in the industrial control system (Pereira et al., 2024), the proposed approach focused on generating adaptive prediction intervals that enhance both interpretability and operational safety.

Experimental results demonstrated that larger residual windows yield prediction intervals with higher coverage, more closely aligning with the desired confidence level. For instance, a window size of 100 achieved 95.3% coverage with an average width of 286.62 t/h, while a smaller window of size 40 produced narrower intervals (243.97 t/h) but with lower coverage (84.9%). These findings emphasize the trade-off between adaptability and reliability: smaller windows are more responsive to new data, while larger windows offer greater statistical robustness at the cost of increased interval width. In addition to statistical performance, computational efficiency was carefully evaluated. Despite the monotonous increase in processing time with increasing window size, all configurations maintained execution times below 0.1 seconds. This result may indicate that the method is compatible with the real-time processing requirements typical of PLC-based industrial environments. This reinforces the method's suitability for applications requiring fast and reliable predictions with limited computational resources. It is important to emphasize that this implementation is not limited to the mining sector. The proposed approach can be extended to a wide range of industrial applications, including, for example, pulp and paper, oil and gas, and manufacturing, wherever there is a need to employ virtual sensors for monitoring critical process variables. Based on these findings, several avenues can be explored in future research. A natural next step is to validate the approach in a real industrial setting, assessing its robustness under operational variability, sensor noise, and communication delays. Moreover, dynamically adjusting the residual window size according to process conditions or model confidence levels could further optimize the balance between responsiveness, coverage, and computational cost. Finally, extending the framework to multivariate settings or incorporating additional sources of uncertainty could broaden its applicability across different stages of mineral processing.

ACKNOWLEDGEMENTS

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001, the Conselho Nacional de Desenvolvimento Científico e Tecnológico - Brasil (CNPq), the Fundação Gorceix, the Instituto Tecnológico Vale (ITV) the Escola de Minas, and the Universidade Federal de Ouro Preto (UFOP).

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