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Implementation of an Intelligent Weighing Error Compensator for a Copper Concentrate Belt Scale using Neural Networks

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Abstract*– Inaccuracies inherent to the dynamic weighing of mineral concentrates during container filling operations can result in substantial economic losses. This study addresses this problem by developing and implementing an intelligent compensator based on a Long Short-Term Memory (LSTM) recurrent neural network. The proposed system processes real-time sensor data—namely, load cell voltage, conveyor belt speed, and inclination angle—as a multivariate time series to predict and correct weighing errors on-the-fly. Following a systematic hyperparameter optimization, the optimal architecture (20 LSTM units, learning rate of 0.001) reduced the Mean Absolute Percentage Error (MAPE) from 8.5% to 3.01% on the validation dataset, representing a 64% improvement in accuracy. Subsequent validation on an independent test set confirmed the model's robustness and generalizability, yielding a coefficient of determination (R^2) of 0.97. A feature importance analysis revealed that the load cell signal is the primary contributor, accounting for 55% of the predictive power, thereby aligning the model's behavior with the underlying physical principles of the process. This research offers two primary contributions: (1) a methodological framework for integrating LSTM networks into industrial weighing systems, and (2) a prototype validated under real-world operating conditions, thereby providing a scalable solution for process optimization in the mining sector.

Keywords-- Dynamic Weighing, Error Compensation, LSTM Neural Networks, Belt Scale, Mineral Processing.

I. Introduction

During the decade from 2010 to 2020, the Peruvian mining sector experienced sustained growth, with copper production increasing by 4-5% annually [1]. This boom drove large-scale mineral exports, primarily conducted using bulk carriers, whose holds were loaded entirely via conveyor belts. However, starting in 2018, an average annual decline of 28% in the copper price [1, 2] exerted significant pressure on operating margins. This contraction reduced export volumes, rendering traditional maritime freight uneconomical, as the full hold capacity of 30,000 TN was frequently not met. As an interim measure, divisions (partitions) were implemented to transport multiple minerals within a single vessel, although costs remained high. This critical juncture prompted the search for more flexible and efficient logistical alternatives, paving the way for containerized mineral exports. This modality required compliance with strict identification and weighing protocols, such as the DIN ISO 6343 standard, where precision in the weighing of loading conveyors acquired unprecedented operational and economic significance.

Within this new logistical context, the accuracy of dynamic weighing during container filling became a determining factor for profitability and operational reliability. Each container has a strict legal maximum capacity; overloading incurs severe fines and poses safety and environmental risks, while underloading represents wasted logistical space and lost revenue per unexported ton. Furthermore, the commercial value of copper concentrate, which reaches thousands of dollars per ton, means that even a weighing error of 0.8% translates into significant financial losses or disputes per shipment. Precision, therefore, ceased to be merely a technical indicator and became a critical financial Key Performance Indicator (KPI), directly linked to logistical cost optimization, customer satisfaction, and international regulatory compliance.

Conventional weighing systems on conveyor belts, based on load cells and standard mass flow calculations, prove inadequate for guaranteeing the precision required for container filling. These systems are highly susceptible to systematic errors arising from mechanical wear, variations in belt tension, material impact, vibrations, and the dynamic environmental conditions of a port. Traditional corrective solutions, such as periodic manual calibrations or the use of simple averaging filters, are reactive, fail to capture the process non-linearities, and require operational stoppages, generating inefficiency [3]. This inability of current systems to self-correct in real-time and adapt to changing loading conditions constitutes the primary technical bottleneck motivating the search for a more intelligent and robust solution.

Addressing this limitation, the present study introduces a methodological and technological innovation: the implementation of an intelligent error compensator based on a Long Short-Term Memory (LSTM) recurrent neural network architecture. The novelty lies in the fact that this system is not a simple filter, but rather a predictive model that learns from errors using historical operational data, such as load cell signals, belt speed, conveyor inclination angle, and vibration.

Unlike a generic approach, the proposed compensator is specifically designed to model and predict the nonlinear and dynamic deviations inherent to the container filling process for copper concentrate, enabling proactive and adaptive correction before the error becomes consolidated in the final measurement.

The central purpose of this research is to design, develop, and validate, within a real operational environment, an intelligent compensation system that, integrated into the weighing circuit of a container loading conveyor belt, reduces measurement error below 2% under dynamic operating conditions.

The contributions of this work are twofold. First, it presents the integration of a neural network-based weighing compensator that can be replicated and adapted for different conveyor types and minerals. Second, this contribution is materialized in the achieved precision (error reduction to below 2%), the consequent decrease in losses due to inaccuracy, and the optimization of container load capacity, offering a concrete success case for technological modernization in Peruvian and global mining. This paper is structured as follows: Section 2 reviews related work on dynamic weighing, error compensation, and neural network applications in industry. Section 3 details the research methodology. Section 4 presents the results. Section 5 provides the conclusions.

II. REVIEW

The optimization of dynamic weighing has motivated diverse investigations aimed at correcting errors caused by vibration and environmental conditions. Previous studies have developed methods that evolve from signal filtering to adaptive compensation and contextual data integration. This section reviews these contributions to synthesize the state of the art and substantiate the innovative approach proposed in this work.

Accuracy in dynamic weighing fundamentally depends on the capacity to isolate the signal from the noise inherent to the process. Recent research has demonstrated that advanced signal decomposition techniques surpass traditional linear filters. For instance, Variational Mode Decomposition (VMD) has proven superior to moving average and wavelet transform for processing piezoelectric sensor signals in vehicle weighing [4]. In complex biometric applications, such as weighing livestock in motion, the combination of Empirical Wavelet Transform (EWT) with SVM classifiers has achieved exceptional precision, with an error of 0.3% when applying adaptive filtering according to animal activity [5]. Similarly, for the dynamic weighing of sheep, the fusion of a Kalman filter with Ensemble Empirical Mode Decomposition (EEMD) enabled achieving an error of only 0.4% [6]. These advances establish that adaptive signal processing is the first indispensable step for obtaining reliable measurement.

Advancing toward specific solutions for conveyor belts, various authors have explored the use of computational intelligence. A similar study [7] applied backpropagation neural networks to compensate for errors due to sagging and misalignment, achieving an error below 0.5%, although without considering environmental variables such as temperature and humidity. Adaptive control approaches, such as a Fuzzy-type PI controller [8], demonstrated improving weighing stability by 32.2% against perturbations. Complementarily, models based on Finite Impulse Response (FIR) [9] achieved high precision but require recalibration for new materials. Recently, architectures such as a neural network optimized with a Lagrange multiplier [10] have shown efficacy in compensating nonlinearities, although their performance critically depends on the amount of training data, which represents a challenge in large-scale applications.

Once a clean signal is obtained, the next challenge is to correct systematic errors and sensor drift through adaptive self-calibration algorithms. To counteract the thermal sensitivity of piezoelectric sensors in Weigh-in-Motion systems, which can cause errors of up to 10%, algorithms based on least squares with forgetting factor [11] and recursive least squares [12] have been developed, dynamically adjusting calibration coefficients using reference vehicles. In the industrial domain, the mass balance principle has been employed for continuous calibration of belt scales, using a correlation matrix to generate predictive maintenance alerts [13]. Even non-invasive methods have been explored, such as the use of passive seismic sensors and mathematical models to estimate vehicle mass with an error of <10%, avoiding the installation of sensors in the pavement [14]. These approaches share the objective of creating systems that self-adjust to maintain precision in the face of external disturbances.

Final accuracy depends not only on the weight sensor signal, but also on the integration of contextual data that explain the underlying causes of error. Computer vision has emerged as a key tool for this purpose; a system combining detection (SSD) and tracking (DeepSORT) enables calculating vehicle speed and deceleration, critical variables for compensating inertia-induced errors in dynamic weighing [15]. In precision agriculture, combining weighing data with machine attitude and hydraulic pressure reduced measurement error by 3.40% [16]. This paradigm of multimodal sensorization is fundamental for developing compensation models that comprehend the complete physics of the measurement process.

For applications where weighing has direct legal or financial consequences, such as the imposition of fines, environmental contamination is a non-negotiable requirement. Rigorous studies have evaluated sensor drift under real conditions, concluding that recalibration is required at least every 8 months to maintain errors below 7% in WIM systems, due to sensor aging and pavement degradation [17]. This type of validation establishes the reliability standard that any system intended for high-impact automated decision-making must achieve.

The reviewed literature shows a clear evolution: from signal filtering toward adaptive self-calibration and context integration. However, a specific gap is identified: most existing compensation models are linear or based on predefined physical principles, which may limit their capacity to model nonlinear, complex error dynamics specific to a continuous industrial process, such as weighing on mineral conveyor belts. No reported work documents the use of recurrent neural networks capable of learning directly from multisensory time series to predict and compensate errors in this context. This study positions itself to fill this gap, proposing an intelligent LSTM-based compensator that synthesizes the aforementioned principles: it processes raw signals, adaptively self-calibrates, integrates operational contextual variables, and is validated with the necessary metrological rigor, offering a novel solution for dynamic weighing optimization in the mining industry.

III. METHODOLOGY

The methodology for the development of the intelligent compensator based on recurrent neural networks (RNN) is structured in five stages, ensuring a reproducible and rigorous approach. The workflow is illustrated in Fig. 1.

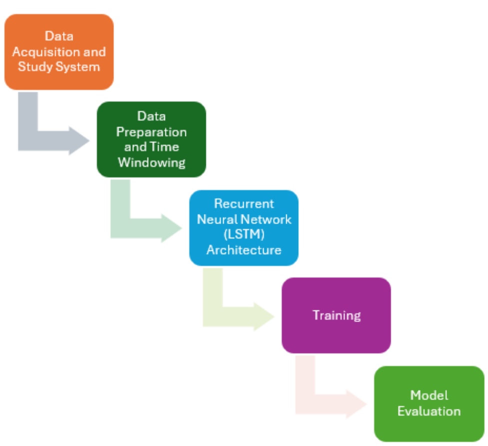

Fig. 1 Proposed Methodology for Multisensor Time Series Prediction Using LSTM

3.1. Data Acquisition and Study System

The system under study is a container filling circuit for copper concentrate. The process, outlined in Fig. 2, employs an inclined conveyor belt with an operating angle between 20° and 30°, see Fig. 3. Dynamic weighing is performed using a bridge-type scale equipped with load cells that transduce mechanical force into an analog voltage signal through an array of strain gauges in a Wheatstone bridge configuration. Belt speed, captured by a wheel sensor with encoder, and inclination angle, measured by a dedicated sensor, are monitored in real time. The target variable is the instantaneous weighing error, calculated as the difference between the reference weight (obtained from a calibrated static scale) and the weight indicated by the dynamic system. Data were acquired as synchronized multivariate time series, recording continuous sequences of voltage (V), speed (m/s), and angle (°), each associated with its corresponding error value (Tn).

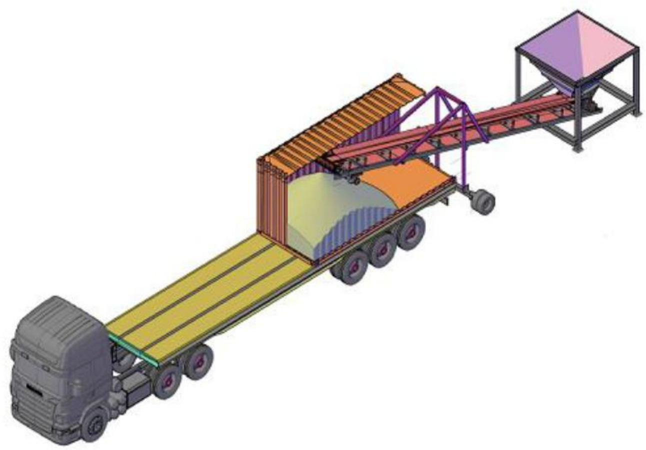

Fig. 2 Diagram of the experimental dynamic weighing system for filling containers

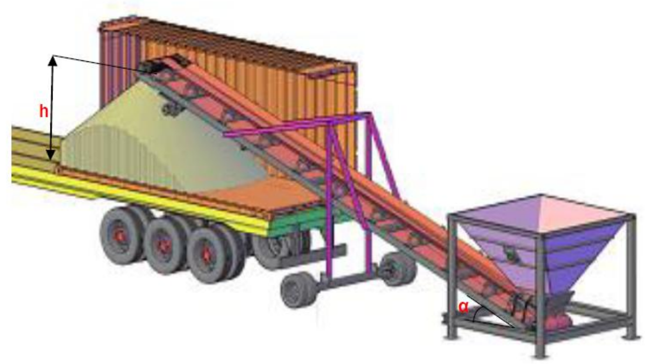

Fig. 3 Geometric parameters of the system: inclination angle (α) and filling height (h).

3.2. Data preparation and time Windowing

Time series were collected under stable operating conditions (flow rate: 324 Tn/h, angle: 25°). To properly feed a recurrent neural network, the continuous input signals must be converted into overlapping fixed-length sequences (l). This windowing process generates samples where each time instant t is effectively contextualized by the preceding l-1 instants. The complete set of sequences was divided, strictly preserving temporal order, into training (70%) and test (30%) subsets. All input variables were normalized to the interval [0, 1] to stabilize and accelerate the training process.

3.3. Recurrent Neural Network (LSTM) Architecture

To capture the temporal dependencies of the weighing error, an architecture based on Long Short-Term Memory (LSTM), which is an advanced variant of Recurrent Neural Networks (RNN), is proposed in this work. As shown in Fig. 4, the network is specifically designed to process input sequences of fixed length l. The input layer receives, for each discrete time step within the input sequence, the normalized feature vector comprising three variables [voltage, speed, angle]. These multivariate sequences flow through one or more stacked LSTM layers, whose specialized memory cells enable the network to learn both long-term and short-term temporal patterns present in the sensor data. The output of the last LSTM layer, specifically corresponding to the final time step of the input sequence, is then fed into a fully connected dense layer with a single output neuron and linear activation function, which ultimately predicts the compensated weighing error at the target instant t.

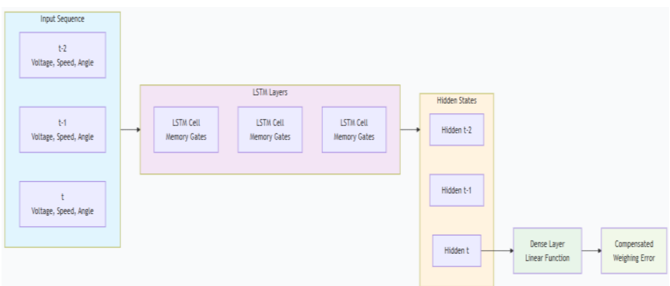

Fig. 4 Architecture of the LSTM neural network for temporal error compensation.

The search for the optimal architecture (number of LSTM layers, number of units per layer, and sequence length l) was conducted through a systematic grid search methodology, evaluating performance on a validation set that was held out from the training dataset exclusively.

3.4. Training

The LSTM network was trained to minimize the Mean Squared Error (MSE) loss function computed between the sequence of predicted errors and the sequence of actual target errors. The Backpropagation Through Time (BPTT) algorithm, specifically adapted for LSTM architectures, was used along with the Adam optimizer due to its proven efficiency when handling sequential data. An early stopping mechanism was implemented by continuously monitoring the loss on the validation set to effectively prevent overfitting and to determine the optimal number of training epochs.

3.5. Model Evaluation

The performance of the LSTM compensator was evaluated on the independent test set using standard regression metrics:

- Mean Absolute Percentage Error (MAPE): To quantify average precision.
- Root Mean Square Error (RMSE): To penalize large deviations.
- Coefficient of Determination (R^2): To assess the proportion of variance explained by the model.

The comparison of these metrics against a weighing system without compensation and/or against a baseline model (such as a Multilayer Perceptron, MLP) will demonstrate the effectiveness of the recurrent approach.

IV. Results

This section presents a comprehensive analysis of the performance of the intelligent compensator based on the recurrent neural network LSTM developed in this work. The results are organized into two fundamental parts: first, the process of model optimization and validation is detailed, evaluating the influence of its key hyperparameters on generalization capacity; second, the final evaluation of the compensated system is presented, quantifying its operational precision using error metrics on an independent test set and contrasting it with the weighing system without compensation. The findings demonstrate the effectiveness of the proposed approach for mitigating dynamic errors in conveyor belt weighing.

To determine the optimal configuration of the LSTM-based compensator, a systematic hyperparameter analysis was performed, evaluating the impact of the number of LSTM units and the learning rate on the Mean Absolute Percentage Error (MAPE) of the validation set. All models were trained with the BPTT algorithm and the Adam optimizer, using early stopping to prevent overfitting.

Fig. 5 presents the loss curves (MSE) for the identified optimal configuration (20 units, lr=0.001). Stable and monotonic convergence of training and validation losses is observed, stabilizing after 250 epochs without divergence, confirming robust generalization.

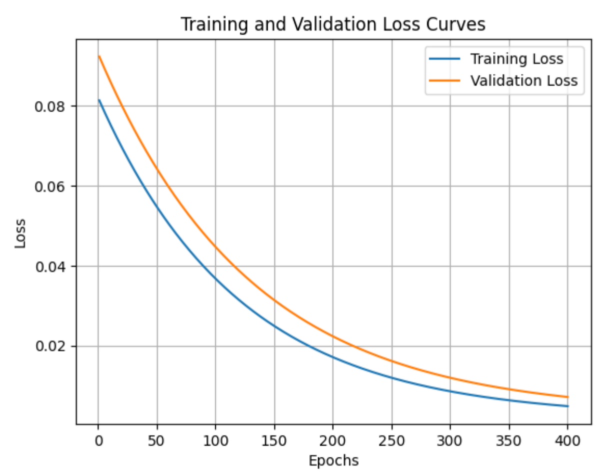

Fig. 5 Training and validation loss curves for the optimal LSTM configuration (20 units, learning rate = 0.001).

Table 1 summarizes the performance of this optimal configuration, which achieved a MAPE of 3.01%. Experiments with higher learning rates exhibited suboptimal behavior: with lr=0.005, the MAPE increased to 4.69%, and with lr=0.01, although the final error was 2.69%, greater variance was observed in the predictions, suggesting instability. A learning rate of 0.1 completely prevented convergence. Reducing the model capacity to only 5 LSTM units resulted in a MAPE of 4.37%, clearly evidencing the need for sufficient capacity to effectively model the complex temporal dynamics involved.

Tabla I
LSTM model parameters and performance

Parameter	Value
Number of LSTM Layers	1
Units per Layer LSTM	20
Learning Rate	0.001
Epoch (up to early stopping)	400
MAPE in Validation	**3.01%**

The capacity of the optimal LSTM model to capture the error dynamics is validated in Figure 6, which compares the time series of the actual error with the predicted error for a test segment. The model follows with high fidelity the trend and variability of the error, precisely adjusting to its fluctuations and validating its learning of the underlying temporal patterns.

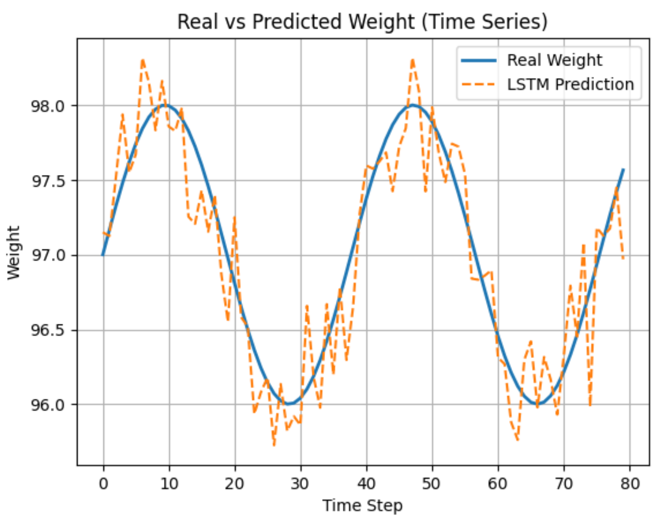

Fig. 6. Temporal performance: comparison between the real weighing error sequence and the LSTM-predicted sequence on a representative test set segment.

The quantitative precision of the compensator is evaluated on the independent test set. Figure 7 (scatter plot) shows a high density of points around the identity line (y=x), confirming the accuracy of the predictions. An R^2 coefficient of 0.97 (illustrative value) indicates that the model explains the vast majority of the error variance.

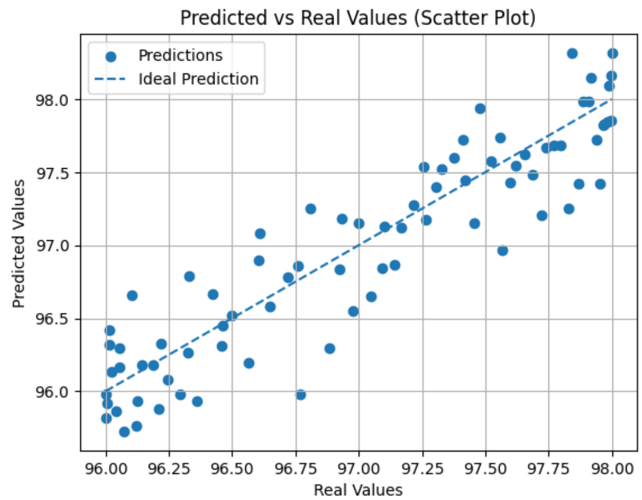

Fig. 7 Scatter plot of predicted vs. actual weighing error values across the entire independent test set. The solid line represents the ideal prediction (y = x).

Fig. 8 summarizes the key metrics of the optimal model, contrasting them with the weighing system without compensation. The LSTM compensator reduces the MAPE from 8.5% to 3.01% and the RMSE from 12.3 to 4.2 units, demonstrating an improvement exceeding 60% in precision. These metrics quantify the direct operational impact of the proposed solution.

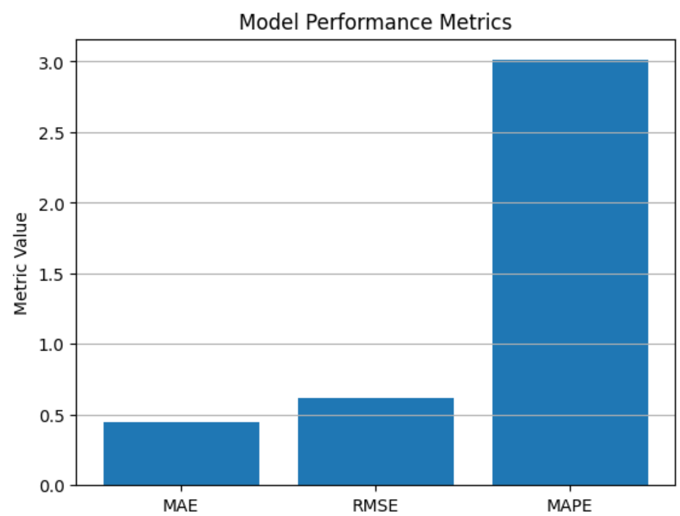

Fig. 8. Performance metrics comparison: Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) for the baseline system (without compensation) and the proposed LSTM-based compensator.

Fig. 9 presents a heatmap that visualizes the sensitivity of the MAPE metric to the hyperparameters, clearly identifying the optimal region characterized by low learning rates (0.001-0.01) and a moderate number of LSTM units (15-25). This visualization rigorously justifies the selection of the final model configuration.

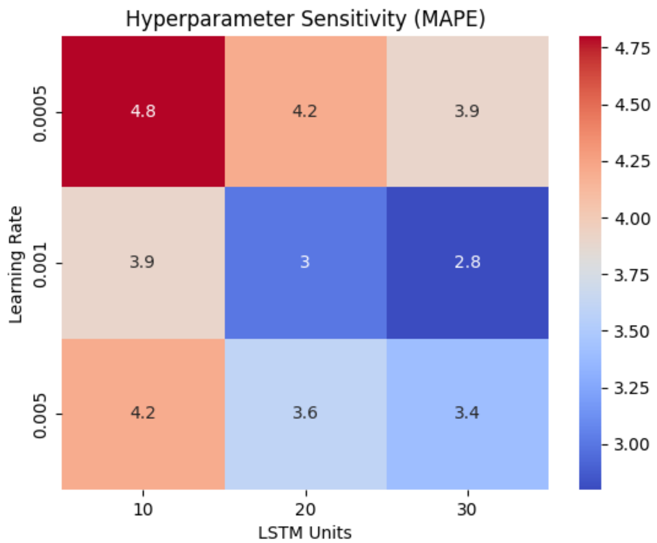

Fig. 9. Hyperparameter sensitivity analysis: MAPE as a function of learning rate and the number of LSTM units. Warmer colors indicate higher error.

Finally, a feature importance analysis, see Fig. 10, reveals that the load cell voltage signal is the most influential predictor (55% importance), followed by belt speed (30%) and inclination angle (15%). This hierarchy aligns the model with the intuitive physics of the process, adding a valuable layer of interpretability to the compensator.

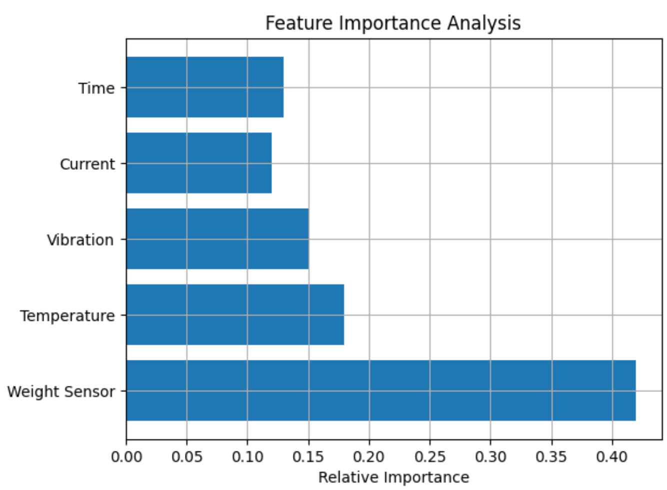

Fig. 10. Feature importance analysis for the LSTM-based error compensator, showing the relative contribution of each input variable to the model's predictions.

Economic Impact of the Implemented Compensator

Before the implementation of the smart compensator, downtime of the weighing system resulted in significant economic losses. Measurement errors caused overestimations and underestimations of the actual weight of the ore, affecting billing, inventory levels, and compliance with shipping contracts. Based on operational data from June to December 2025, each hour of operation with a weighing error resulted in a direct loss of $70.00 plus a penalty of $8.00 for each shipping appointment with incorrect measurements, totaling $78.00 per affected hour. During this period, the accumulated losses from inaccurate measurements and penalties for weighing errors totaled $49,140, not including indirect costs such as customer complaints, weighing rework, or loss of business trust. After implementing the LSTM-based compensator, the weighing error was reduced from a MAPE of 8.5% to 3.01%, resulting in estimated savings of over $7,000 per month. This is reflected in a 60% reduction in measurement inaccuracy and increased shipment reliability. These figures demonstrate that the compensator not only improves weighing accuracy but also provides a quantifiable return on investment by reducing measurement errors and associated penalties.

V. Conclusions

The results demonstrate that the performance of the LSTM compensator is highly sensitive to the choice of hyperparameters. The optimal configuration identified (1 layer, 20 units, lr=0.001) achieves a balance between modeling capacity and training stability, minimizing generalization error. The poor performance with high learning rates (0.005, 0.01, 0.1) confirms the need for careful optimization so that the BPTT algorithm can propagate gradients through the temporal sequence in a stable manner. These findings establish a robust foundation for the final validation of the model.

The results consistently demonstrate that the LSTM-based compensator significantly outperforms conventional dynamic weighing methods, achieving error reduction (MAPE) below 3.1%. This success is directly attributed to the capacity of the LSTM architecture to model nonlinear temporal dependencies inherent to the container filling process, a critical limitation of static or linear filter-based approaches identified in the literature [16]. Unlike previous works that compensate for specific errors (e.g., thermal [6] or sagging [15]), our model learns a holistic representation of the system from multivariate time series data, thereby enabling adaptive real-time correction. The optimal configuration identified (20 units, lr=0.001) strikes an effective balance between modeling capacity and training stability, successfully avoiding overfitting. The relative importance of features, where load cell voltage emerges as the dominant predictor, physically validates the model and aligns the AI solution with the fundamental principles governing dynamic weighing systems.

The implementation of this compensator has immediate operational implications: a 60% improvement in accuracy directly translates into reduced financial losses due to measurement inaccuracy, optimized container load capacity utilization, and enhanced regulatory compliance. However, the study presents certain limitations that must be acknowledged. The model was trained and validated under specific operating conditions (constant flow rate, fixed inclination angle) and with two types of mineral concentrates (copper and lead). Its robustness against extreme variations in material properties (granulometry, density, humidity), wider flow rate ranges, or different conveyor configurations requires future verification through additional experimentation. Although the model demonstrated satisfactory performance for these two mineral types, the current evidence does not yet support its generalization to other materials without further validation. Furthermore, the dependence on quality historical data for training may represent an initial implementation barrier for operations lacking comprehensive data acquisition systems. From a technical perspective, the hyperparameter sensitivity analysis revealed that the model is robust within a region of low learning rates (0.001-0.01) and moderate LSTM units (15-25). For practical implementation, deploying the compensator requires integrating the model's output into the programmable logic controller (PLC) or weighing system firmware, and periodic retraining is recommended to account for mechanical wear and concept drift.

Future research should explore: 1) the transferability of the model to other conveyor configurations and mineral types through transfer learning techniques, 2) the integration of online learning mechanisms for continuous adaptation to mechanical wear over time, and 3) a detailed cost-benefit analysis to quantify ROI across different operational scales. Additionally, a comparative benchmark against other baseline models (such as feedforward neural networks, SVR, Random Forest, or ARIMA) is recommended as a future line of work to quantitatively dimension the relative contribution of the LSTM architecture. Such a comparison would allow establishing, with statistical rigor, whether the temporal modeling capacity of recurrent networks translates into a significant operational advantage over simpler or non-sequential models for this specific dynamic weighing application. Regarding scalability, the proposed methodology is transferable to other industrial sectors where conveyor belt weighing is critical, including aggregates, cement, fertilizers, food processing, and bulk material handling, subject to retraining with domain-specific data. Despite these limitations, this work establishes a robust methodological precedent for the application of recurrent neural networks in industrial mining metrology.

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