Istraživanja i projektovanja za privredu
ISSN 1451-4117
DOI:10.5937/jaes0-53547
www.engineeringscience.rs

iipp publishing

Journal of Applied Engineering Science
Vol. 23, No. 1, 2025
Original Scientific Paper
Paper number: 23(2025)1, 1254, 82-89

REAL-TIME IOT MONITORING AND BRIX VALUE PREDICTION IN FOOD PROCESSING USING WEIGHT RATIO AND LINEAR REGRESSION

Erwin Erwin*[1,2], Dhimas Satria[2], Slamet Wiyono[1,2], Faiza Yuniati[3]

[1] Sultan Ageng Tirtayasa University, Renewable Energy Design Laboratory, Cilegon, Indonesia
[2] Sultan Ageng Tirtayasa University, Department of Mechanical Engineering, Cilegon, Indonesia
[3] Health Polytechnic of Palembang, Department of Epidemiology Surveillance, Palembang, Indonesia
** erwin@untirta.ac.id*

This study investigates the application of real-time Internet of Things (IoT) monitoring and predictive algorithms for optimizing liquid palm sugar production. By focusing on the prediction of Brix values, which indicate sugar concentration, the research aims to enhance process efficiency and product quality. Traditional manual methods of measuring Brix levels are often time-consuming and prone to inaccuracies. To address this, the study integrates IoT-based sensors that collect data on temperature, pressure, and weight during the evaporation process, using a linear regression model to predict Brix values in real time. Experimental results show that weight ratio-based predictions align well with manual refractometer readings, particularly in the early stages of production. However, deviations at higher Brix levels were noted, prompting the introduction of polynomial regression for improved accuracy. These findings suggest that IoT systems combined with predictive models offer a significant advancement in sugar production monitoring, reducing manual interventions and enhancing process control. The research contributes to the growing body of work on IoT applications in food production, particularly for liquid palm sugar processing, and provides a novel approach to addressing current challenges in Brix measurement.

Keywords: IoT monitoring, brix, liquid palm sugar, weight ratio, linear regression

1 INTRODUCTION

The application of real-time Internet of Things (IoT) technologies in food production has gained significant attention due to its potential to enhance process monitoring and control also [1], for maintaining quality and safety standards in food production [2]. In particular, IoT has been instrumental in continuous monitoring of various production processes, enabling producers to maintain product quality and optimize operational efficiency. In the context of sugar production, accurate monitoring of Brix value, which indicates the sugar concentration, is crucial for determining the quality of the final product. Brix measurements, typically conducted using refractometers or hydrometers, offer real-time insight into the sugar content, yet they may be limited by manual data collection and delays in processing [3].

Recent developments have also highlighted the use of low-cost sensors for real-time monitoring, which can measure Brix levels and other parameters like temperature and pressure during production. These advancements align with the increasing demand for data-driven solutions that allow for precise monitoring in industries such as the palm sugar sector [4]. Furthermore, the nutritional and economic significance of palm sugar, which offers advantages over refined sugars, has been well-documented, reinforcing the need for innovative monitoring approaches [5].

Despite advances in sensor technology and Brix measurement techniques, traditional methods still face challenges, such as residue buildup during production and inconsistencies in sugar content monitoring. These limitations, particularly evident in liquid palm sugar processing, affect the accuracy of Brix measurements and, consequently, the quality control of the final product [6]. Moreover, conventional monitoring processes often involve manual interventions, which can introduce delays and inefficiencies in identifying the optimal time to end the production cycle.

To address these issues, the integration of IoT monitoring systems with predictive algorithms offers a promising solution. Real-time monitoring allows continuous data collection on temperature, pressure, and weight changes during the production process, which can be leveraged to predict Brix values. By using weight ratios and linear regression models, it becomes possible to predict Brix levels with greater accuracy, reducing reliance on manual refractometer readings and improving process efficiency. Real-time monitoring technologies can significantly reduce food loss and waste by continuously tracking product conditions [7]. points out that IoT-based food monitoring systems can track food conditions in real-time, ensuring compliance with quality standards and minimizing environmental impacts associated with food waste [8].

Numerous studies have explored the use of IoT technologies for real-time monitoring in agricultural and food production settings. For example, [9] Gomes et al. applied hyperspectral imaging and deep learning techniques to predict sugar and pH levels in wine grape berries, demonstrating the feasibility of using machine learning models for precise sugar content prediction. Such approaches could be adapted to palm sugar processing to predict Brix values using weight ratio and temperature data, optimizing production cycles and improving quality control.

In the context of palm sugar, the use of advanced IoT systems can significantly enhance process monitoring. Studies by [10] Wiyono et al. have shown that vacuum evaporation and controlled pressure conditions are critical factors influencing the quality and Brix levels of liquid palm sugar. By implementing IoT-based monitoring systems to regulate these parameters, producers can achieve higher precision in maintaining product quality. This also supports efforts to reduce the processing time, particularly by optimizing temperature and vacuum pressure settings to ensure a consistent evaporation rate.

Furthermore, machine learning models such as linear regression have been successfully applied to predict outcomes in various agricultural contexts, providing a foundation for their use in predicting Brix values during liquid palm sugar processing [11]. By integrating these models with IoT data, producers can continuously predict and adjust the production process, ensuring that the final product meets the desired Brix value.

While previous research has demonstrated the effectiveness of IoT-based monitoring systems in various agricultural and food production processes, few studies have specifically applied these technologies to liquid palm sugar processing. Existing studies primarily focus on the measurement of Brix values in raw sugar solutions or the influence of processing conditions on sugar content, but there is limited exploration of real-time prediction models for Brix values using weight ratios during the production cycle [4]. Furthermore, although machine learning techniques have shown promise in predicting sugar content in other contexts, their application in palm sugar production remains underexplored.

Additionally, research on palm sugar processing has largely focused on traditional methods, such as vacuum evaporation, without fully integrating real-time monitoring and predictive models into the production process [10]. This highlights a gap in the literature regarding the development of more advanced, data-driven approaches to optimize Brix measurement and production efficiency in palm sugar processing. Research indicates that the sugar-acid ratio, which can be derived from Brix measurements, plays a vital role in determining the flavor profile of sugar products [12].

The objective of this study is to evaluate the effectiveness of real-time IoT monitoring systems and predictive models in optimizing the production of liquid palm sugar. Specifically, the research investigates the use of weight ratios and linear regression techniques to predict Brix values during the production process, thereby reducing reliance on manual refractometer readings and improving process efficiency. In palm sugar production, understanding the Brix value helps in assessing the quality of the sap (nira) collected from palm trees, which is the primary raw material for sugar production [13]. This research is novel in its application of IoT technologies and predictive algorithms to palm sugar processing, offering a data-driven approach to enhance product quality and operational efficiency. linear regression has been effectively utilized to correlate Brix values with other measurable parameters in sugarcane and palm sugar processing [11, 14]. By employing linear regression models that incorporate weight ratios of various components, producers can enhance the accuracy of Brix predictions, leading to better quality control and product consistency [15].

The scope of the study includes experimental research conducted in Banten Province, Indonesia, focusing on monitoring key production parameters such as temperature, pressure, and weight changes. The research aims to predict Brix values throughout the production cycle, with the ultimate goal of determining the optimal endpoint for the process when the final Brix value is achieved. The integration of real-time IoT monitoring with predictive algorithms represents a novel approach in palm sugar production, addressing the current gaps in process optimization and quality control.

The scope of this study includes experimental research conducted in Banten Province, Indonesia, focusing on monitoring key production parameters such as temperature, pressure, and weight changes in palm sugar production. The specific objective of this research is to predict Brix values throughout the production cycle and determine the optimal endpoint when the desired final Brix value is achieved. By explicitly integrating real-time IoT monitoring with predictive algorithms, this study aims to optimize the production process and improve quality control, addressing existing gaps in process efficiency and consistency.

2 METHODOLOGY

The primary materials utilized in this study include raw liquid Arenga pinnata sap, sourced from local suppliers in Indonesia. The production process also involves the use of a vacuum evaporator, designed to operate at specific pressures and temperatures to minimize nutrient loss due to the Maillard reaction, as indicated by Wiyono et al. (10). The experimental setup further incorporates IoT-based sensors, such as a load cell to measure the weight of the evaporated liquid, and temperature sensors for real-time monitoring of thermal conditions. The ESP32 microcontroller serves as the central processing unit, responsible for data acquisition and transmission to an external spreadsheet, facilitating accurate data collection and process control.

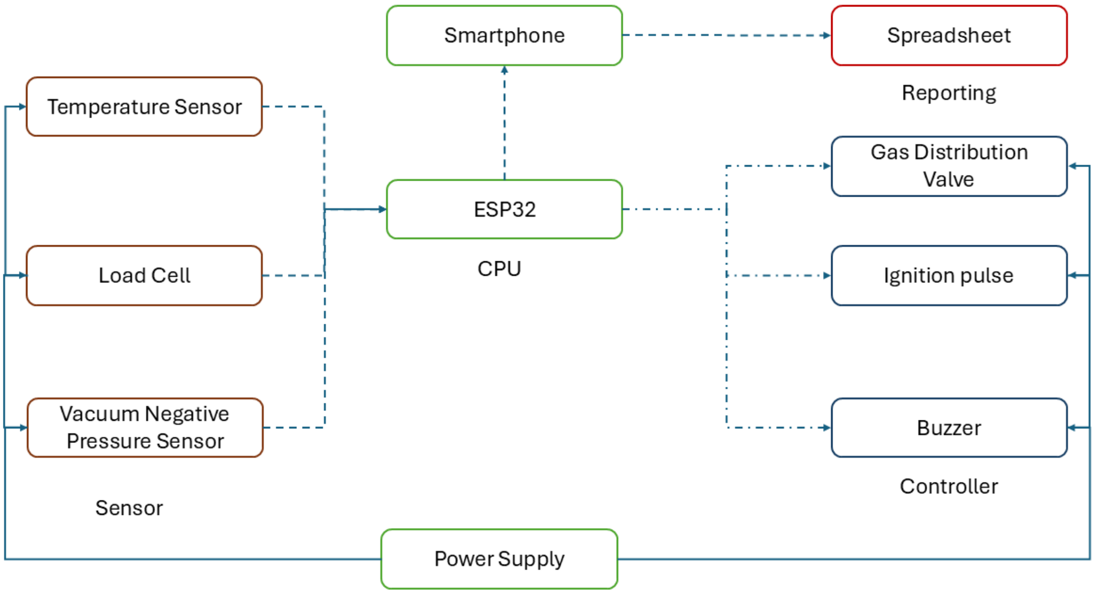

Fig. 1. Diagram Block of IoT System

Prior to experimentation, the liquid Arenga pinnata sap was pre-filtered to remove solid particles, ensuring uniform consistency for all trials. Each batch of sap was then weighed to ensure a starting mass of 10 kg, as recommended by standard industry practices [4]. The samples were subjected to various temperature and vacuum pressure conditions, as described in the subsequent experimental setup, to determine the optimal evaporation rate. The venturi effect was employed to maintain a consistent vacuum throughout the process. The sap was heated in the vacuum evaporator until the mass was reduced to 20% of the original sample, following the approach of [6].

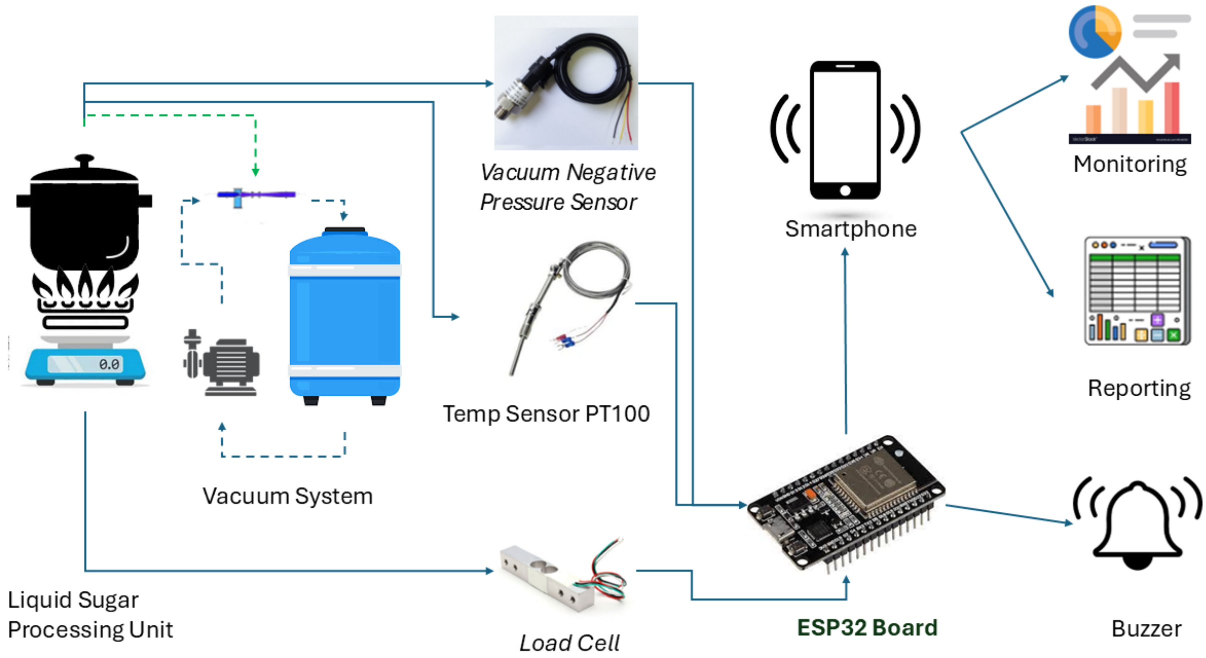

Fig. 2. Set up experiment

2.1 Experimental Setup

The experimental setup, depicted in Figure 2, consists of a vacuum evaporator, an ESP32 microcontroller, and sensors for temperature and mass measurements. The vacuum evaporator was calibrated to three temperature settings: 60°C, 70°C, and 80°C, with corresponding vacuum pressures of 0.4 bar (-0.6 gauge), 0.3 bar (-0.7 gauge), and 0.2 bar (-0.8 gauge) [16]. The data acquisition system was activated when the sap reached its boiling point, ensuring uniformity across all trials. Data were continuously collected until the sample mass was reduced by 80%. Each temperature and pressure variant were tested to determine the impact on evaporation rate and product quality, in alignment with studies on vacuum evaporation techniques [10].

The primary parameters measured during the experiments were the temperature, vacuum pressure, and mass of the liquid Arenga pinnata sap, with Brix values serving as an indicator of sugar concentration. The temperature sensors, integrated with the ESP32 microcontroller, measured the internal temperature of the sap during evaporation, while a load cell captured real-time changes in mass. Additionally, Brix values were periodically measured using a refractometer for validation purposes [17]. These parameters were chosen to provide insight into the correlation between temperature, pressure, and sugar concentration in the sap, following similar methodologies outlined by Nawi et al. [11].

2.2 Statistical Analysis

During processing liquid sugar, two methods for obtaining Brix values, first by using Direct measurement using a refractometer, and two predicting Brix values based on the water reduction ratio (weight ratio) during the production process. To predict the Brix value, the following basic formula is used:

$$B_{pred} = \frac{B_{initial}}{1-R_{water\_reduction}} \tag{1}$$

Where,

Bpred	: The predicted Brix value.
Binitial	: The initial Brix value.
Rwater_reduction	: The water reduction ratio during production.

Arenga sap consists of soluble solids (sugars and non-sugars) and water. As water content decreases due to evaporation, the concentration of soluble solids increases. Among the soluble solids, the sugar concentration ranges from 13% to 14.5%, while non-sugar components such as protein, minerals, and fats are present in small amounts. The protein content in Arenga sap is relatively low, approximately 0.41%, but when calculated based on total dry matter, it can reach 0.78%. The ash content, which reflects the mineral content, ranges from 0.04% to 0.28%. The fat content is extremely low, approximately 0.02%, and in some samples, it is undetectable. Thus, for initial predictions, Equation 1 can be applied.

However, discrepancies arise between the Brix values measured using a refractometer (9) and those predicted based on the weight ratio. To address these differences, linear regression was applied to modify the prediction results for improved accuracy. Subsequently, polynomial regression adjustments were introduced, resulting in a refined prediction model.

The equation serves as a more accurate predictive model to determine Brix values during the liquid palm sugar production process. The application is as follows:

a. Monitoring Production Parameters

   Researchers monitor key parameters such as temperature, pressure, and weight throughout the palm sugar production process. Weight changes reflect water reduction, which serves as the basis for calculating Brix values using the weight ratio.

b. Calculating Brix Values

   The initial Brix value () is determined at the start of the production process. As water content decreases, Brix values are predicted using the basic formula:

c. Prediction Correction

   Using Regression Models Due to the discrepancies between refractometer measurements and initial predictions, polynomial regression is applied to refine the predictions. The polynomial regression model:

   – The Brix by weight ratio is calculated based on water reduction data.
   – This regression model improves the predicted values, aligning them more closely with the actual refractometer measurements.

d. Optimizing the Production

   Endpoint With more accurate Brix predictions, researchers can determine the optimal production endpoint when the desired final Brix value is achieved. This enhances efficiency and improves product quality in the production of liquid palm sugar.

The accuracy of these models was assessed using the coefficient of determination (R^2) to quantify the strength of the relationship between the variables. Additionally, ANOVA tests were conducted to compare the effects of different temperature and vacuum pressure combinations on the evaporation rate and sugar concentration. Statistical significance was determined at a 95% confidence interval, ensuring the robustness of the results, consistent with the methodologies used in previous sensor technology studies [3].

3 RESULTS

Figure 3 illustrates the rate of evaporation during the production process of liquid sugar, where the highest evaporation rate occurs between the 6th and 16th hour with minor variations, averaging around 1 kg per hour. This is significantly lower than the evaporation rates achieved in other studies, where the peak evaporation reached up to 3 kg per hour using the same experimental setup [16].

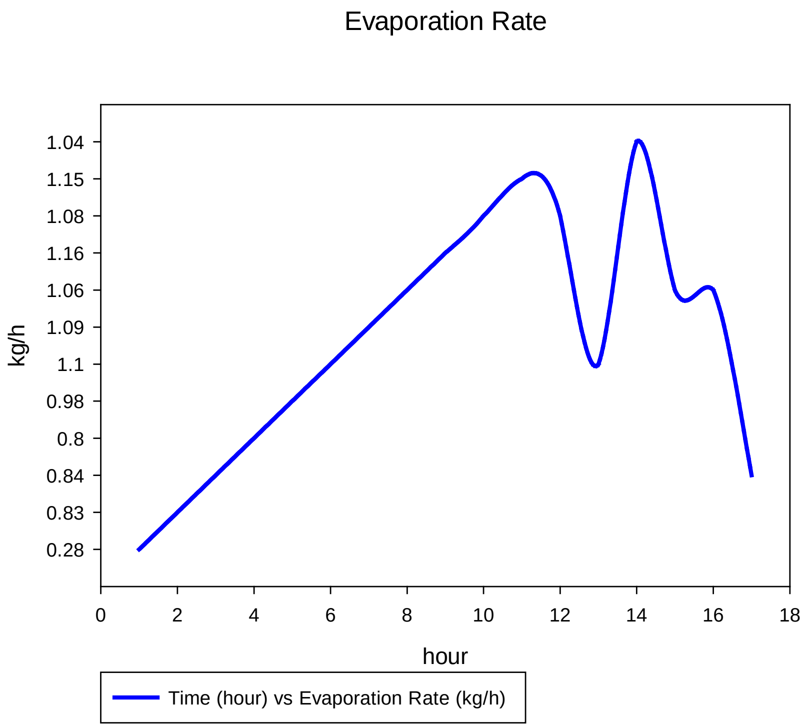

Fig. 3. Evaporation Rate

The experimental results demonstrated that the predicted Brix values obtained using weight ratio calculations closely aligned with the manual refractometer readings up to a Brix level of 20. This significant correlation indicates that the weight ratio method can be used effectively in the initial stages of the palm sugar production process. However, as the Brix values increased beyond 20, discrepancies were observed between the two methods. The manual refractometer readings reached a final Brix value of 66, while the predicted Brix values based on weight ratio calculations only reached 44 (Figure 4).

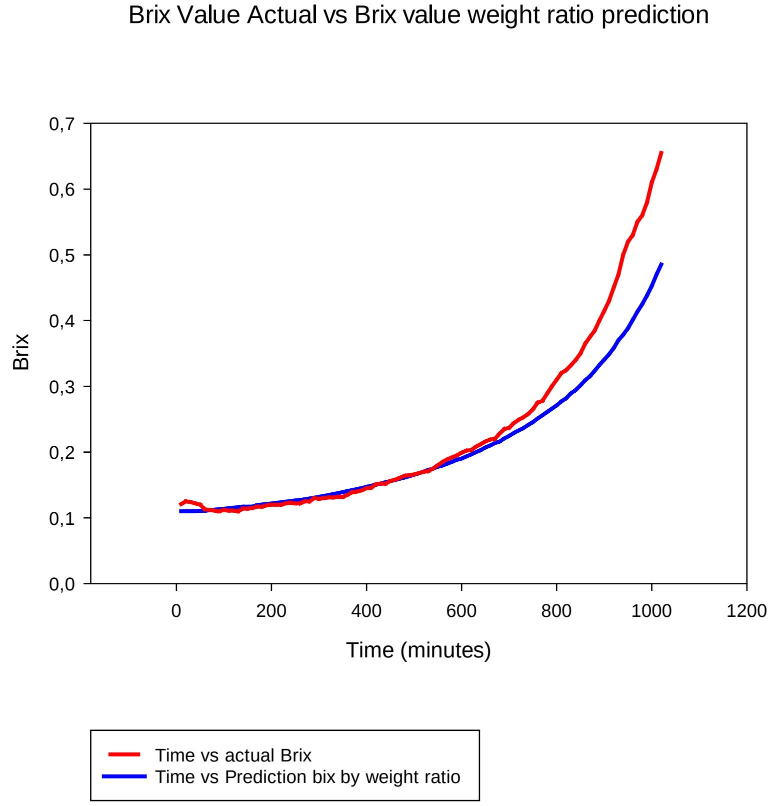

Fig. 4. Actual Brix Vs Weight Ratio Prediction Brix

Brix measurements obtained using a refractometer and the calculated Brix values based on the weight ratio. The following is the prediction of Brix values based on water content reduction during the liquid palm sugar production process. The Brix values are predicted using a formula that links the water reduction ratio with the final Brix value, equation a.

Due to the difference in Brix values at the end of the graph between the Brix measurements using the refractometer and the predicted Brix values based on the weight ratio (fig 4), a linear regression was added to the calculation of the predicted Brix values from the weight ratio.

To enhance the accuracy of the predictions, polynomial regression adjustments were applied, yielding a refined prediction model:

$$Brix_{predicted} = 1.421592\ x\ \left(Brix_{by\ weigth\ ratio}\right) - 0.0626181 \tag{2}$$

Brix Value Cctual VS Brix Value Weight Ratio and Linear Regression

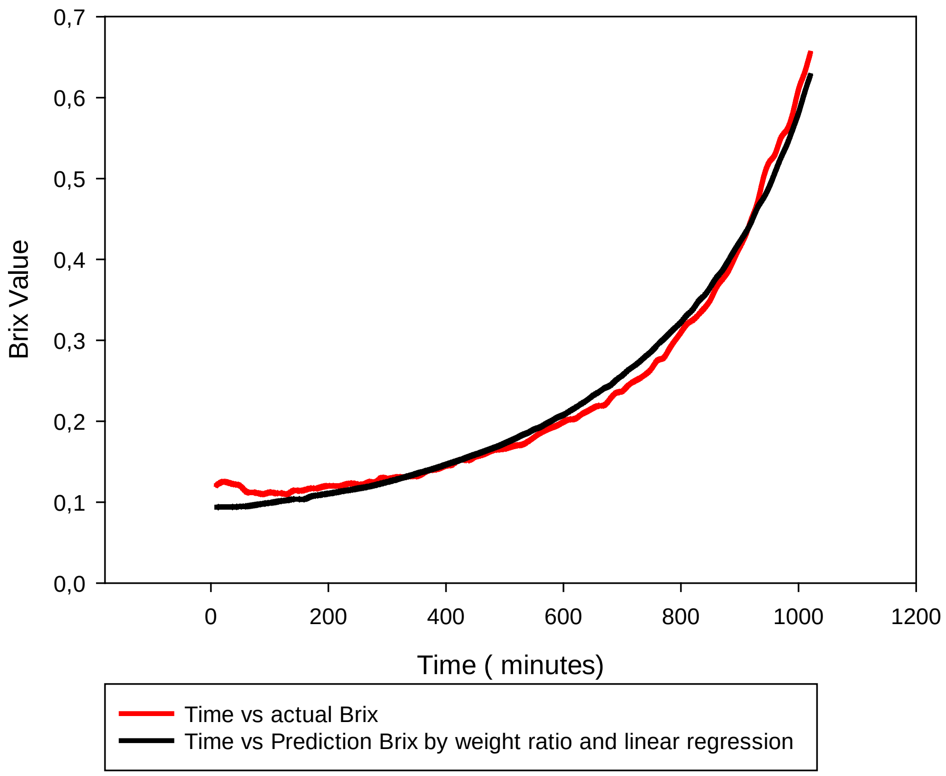

Fig. 5. Actual Brix Vs Weight Ratio and linear regression Prediction Brix

Figure 5 shows the graph of the actual Brix values measured using the refractometer, the predicted values from linear regression, and the predicted Brix values based on the weight ratio.

To evaluate whether the predicted Brix values by IoT system have improved, the levels of accuracy and precision of these Brix values were used as assessment criteria.

$$Accuracy = 100 - \left(\frac{\sum[B_{pred} - B_{act}]}{\sum B_{Act}} x100\right)\% \tag{3}$$

Where:

- Bpred is the predicted Brix value. By IoT system.
- Bactual is the actual Brix value measured by the refractometer

$$Precission\ (RMSE) = \sqrt{\frac{1}{n}}\ \sum\left(B_{pred} - B_{act}\right)^2 \tag{4}$$

Where:

- n is the number of measurements.

Accuracy is often expressed as an error metric, like Mean Absolute Percentage Error (MAPE). The lower the error, the more accurate the prediction. An accuracy value close to 100% is ideal, meaning the predicted values are very close to the actual values. A lower percentage indicates less accurate predictions.

Precision is often measured using standard deviation or Root Mean Square Error (RMSE). A smaller RMSE indicates higher precision, meaning the predictions are consistently close to each other. The closer the RMSE is to zero, the better the precision. This implies less variation or spread in the predicted values compared to the actual values.

Table 1. Accuracy and Precision from 2 prediction model

	Weight Ratio Prediction Brix	Weight Ratio and linear regression Prediction Brix
Accuracy	99,8885 %	99,9708 %
Precision	246,2127	8,5573

From the calculation of accuracy and precision, the weight ratio prediction model combined with linear regression provides better results compared to the weight ratio prediction model. By using a weight ratio prediction model combined with linear regression, the performance of the IoT system in predicting Brix values is enhanced.

3.1 Comparative Analysis with Literature Data

The results align with prior studies that emphasize the challenges of accurately predicting Brix levels in sugar-based solutions. Similar findings were reported by Jaywant et al [6], where low-cost sensors showed reliable correlations at lower Brix values but encountered limitations at higher concentrations due to sensor residue buildup. Ahmed et al. (2022) also noted the importance of manual calibration in digital Brix measurement tools, particularly when measuring raw sugar solutions at higher concentrations. In the context of palm sugar, Kurniawan et al. [17] discussed how variations in processing methods can lead to differences in Brix values, corroborating the observed deviations in this study. These findings reinforce the need for real-time adjustments and advanced algorithms, such as polynomial regression, to improve predictive accuracy at higher Brix levels.

3.2 Scientific and Practical Implications

The findings of this study have important implications for both scientific research and practical applications in the palm sugar industry. The successful use of weight ratios and predictive algorithms offers a promising alternative to manual refractometer readings, particularly in the early stages of sugar production, where the correlation between the two methods is strong. This can lead to increased process efficiency by reducing manual intervention and allowing for continuous monitoring of sugar concentration. Furthermore, the application of polynomial regression to adjust for deviations at higher Brix values provides a more robust framework for predicting sugar concentration throughout the production process. This contributes to the broader goal of integrating IoT technologies into palm sugar processing, as advocated by Wiyono et al. [10], and aligns with the industry's shift toward data-driven, automated production systems.

4 CONCLUSIONS

This study demonstrates the effectiveness of integrating real-time IoT monitoring and predictive algorithms to optimize liquid palm sugar production. By utilizing weight ratios and linear regression, accurate Brix value predictions were achieved, particularly during early stages of production. Polynomial regression further improved accuracy at higher Brix levels. This approach reduces reliance on manual refractometer readings, enhancing process efficiency and product quality control. The findings highlight the potential of data-driven methods to improve monitoring in palm sugar processing, contributing to the broader adoption of IoT technologies in food production industries. Future work may focus on refining predictive models for higher precision.

5 ACKNOWLEDGMENT

This research was funded by the Indonesian Directorate General of Higher Education (DIKTI) under the 2024 Regular Fundamental Research Grant scheme, with contract number B/761/UN43.9/PT.00.03/2024.

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Paper submitted: 18.09.2024.

Paper accepted: 24.01.2025.