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Original Article

Prediction of the Use of Liquid Chemical Materials using Machine Learning Method: A Case Study at XYZ Company

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Abstract - *Control over the availability of liquid chemical materials as raw materials is a crucial factor in the production process at XYZ Company. A shortage of raw materials leads to losses due to additional shipping costs and the inability to meet customer demands. On the other hand, ordering excessive raw materials creates another problem, as the limited warehouse capacity and the presence of dead stock also result in financial losses. Therefore, a more accurate forecasting method is needed compared to the current approach, which relies only on raw material usage in the same month of the previous year and the average of the last three months. To address this issue, two popular forecasting methods are applied: the traditional machine learning method Autoregressive Integrated Moving Average (ARIMA) and the modern deep learning method Long Short-Term Memory (LSTM). This study adopts the Cross-Industry Process for Data Mining (CRISP-DM) framework and utilizes Python software. The aim is to evaluate forecasting accuracy across different time frames by comparing RMSE and MAPE values. The results show that both ARIMA and LSTM perform well, with MAPE values ranging from 9.0% to 18.7%. The ARIMA method, when applied with a monthly time frame, achieved an MAPE of 9.0%, indicating a very high level of accuracy.*

Keywords - *ARIMA, CRISP-DM, Forecasting, LSTM, Python.*

1. Introduction

XYZ is a manufacturing company that produces polyurethane foam, rubber, plastic, and synthetic materials. These products are widely used in the automotive, construction, garment, and industrial parts industries. In the production of these products, a significant amount of liquid chemical raw materials is required, 90% of which are imported from abroad. The daily consumption of these raw materials reaches approximately 25.000 kg in total. Given this high level of usage, ensuring the continuous availability of chemical raw materials is a critical factor in XYZ's production process. Control over the availability of these raw materials is essential because a shortage of chemical supplies can halt production at XYZ Company and result in unmet customer demand. The procurement of these raw materials requires a lead time of approximately one month when shipped by sea before they can be received. In urgent situations, air shipping can be used, which takes around one week but incurs significantly higher costs due to the large daily consumption. For instance, in July 2024, XYZ Company experienced a shortage of 990 kg of chemical material type BXX-2 and 840 kg of type IXX-6, resulting in a total shortage of 1.830 kg. To address this issue, the company was forced to use air freight, which cost USD 27.593, leading to a financial loss in shipping expenses. However, ordering chemical raw materials in excess creates another challenge due to the limited warehouse capacity, which makes it difficult to apply the First In, First Out (FIFO) system. Moreover, if stored for too long, liquid chemical materials risk expiring and becoming unusable. Such expired materials are collected and written off from the warehouse inventory at the end of each year, which is then recorded as a loss for XYZ Company. Losses caused by deadstock materials have increased significantly over the past two years, reaching Rp. 305.266.353 in 2023 and Rp. 689.809.129 in 2024.

In this context, forecasting plays an important role in addressing uncertainty [1]. Accurate forecasting is essential for companies as it can minimize losses caused by excess finished goods in inventory [2] and ensure that customer demand is met, thereby increasing customer satisfaction [3]. Machine Learning is a field of study that enables computers to learn without being explicitly programmed. It can also be defined as the integration of automated computer algorithms with advanced statistical methods to discover hidden patterns within datasets [4]. In general, machine learning methods are divided into two main categories: supervised learning and unsupervised learning. This study focused on supervised learning to conduct time series forecasting. Among the various machine learning techniques, two of the most widely used are ARIMA as a traditional method and LSTM as a modern deep learning based method.

The Autoregressive Integrated Moving Average (ARIMA) method is one of the most widely used techniques for time series prediction. Pandit et al. [5] applied the ARIMA method to forecast milk production in India and achieved good accuracy. Similar to Rizki et al. [6], who conducted a study on predicting rice availability in Indonesia using ARIMA, and also reported reliable results. Furthermore, Noor et al. [7] applied ARIMA to predict reject unit data in manufacturing companies and found that ARIMA is a powerful statistical tool for processing large amounts of data.

Another method for time series prediction is Long Short-Term Memory (LSTM). Manowska et al. [8] applied the LSTM method to forecast crude oil consumption in Poland, evaluated the results using MSE and demonstrated that LSTM is effective for predicting nonstationary and nonlinear time series. Similar to Javaid et al. [9], who conducted a study on forecasting hydrogen production from wind power plants using several methods and found that LSTM achieved the best result. Previous studies, such as those by Sirisha et al. [10] and Wang et al. [11], compared the ARIMA and LSTM methods for forecasting, and the results indicated that LSTM was more accurate than ARIMA. Currently, XYZ Company relies on a manual prediction method by comparing usage from the previous three months with usage in the same month of the previous year, then selecting the higher value between the two.

However, this manual approach often leads to inaccurate results, as discussed earlier, where XYZ Company incurred losses. This method is used because customers are unable to provide annual or monthly demand forecasts, but only weekly demand forecasts. In contrast, XYZ Company requires a one-month lead time to procure materials. Based on these references, this study aims to predict the usage of liquid chemical materials using two methods, ARIMA and LSTM. The prediction results will then be compared to evaluate their performance across different time frames, namely weekly, biweekly, and monthly forecasts.

2. Literature Review

Falatouri et al. [12] conducted Predictive Analytics (PA) to forecast demand in retail Supply Chain Management (SCM) using two methods: SARIMA and LSTM. The dataset consisted of 37 months of retail sales data from Australia. The results showed that both models performed well overall. However, LSTM achieved better performance for products with stable demand. SARIMA produced more accurate forecasts for products with seasonal demand. The evaluation using MAPE and RMSE values to assess the accuracy of the forecasting results.

Sunjaya et al. [13] predicted the number of positive COVID-19 cases in Indonesia from 2020 to 2022 using the ARIMA and LSTM methods. Both methods were applied, and the results were compared to determine which provided greater accuracy. The ARIMA model produced poor prediction results due to unmet assumption criteria. The LSTM model gets better results as reflected in lower RMSE and MAPE values. The study concluded that LSTM outperformed ARIMA in forecasting COVID-19 cases.

Shahi et al. [14] conducted a study on forecasting stock prices using the LSTM and GRU methods. The dataset was obtained from the Nepal Stock Exchange (NEPSE) for the period from 2011 to 2019. The study also incorporated financial news sentiment as an additional variable. The results show that both methods performed well in forecasting stock prices based on MSE values. Moreover, the inclusion of financial news sentiment further improves the forecasting performance.

Angelo et al. [15] conducted a comparative analysis of the ARIMA and Prophet methods to forecast the Bitcoin price. The dataset period is from February 2019 to 2021 and is categorized into daily, weekly, and monthly data. The forecasting results were evaluated using MAE, MAPE, MSE, and RMSE metrics. The findings showed that the Prophet method performed better for daily and weekly data, while the ARIMA method provided accurate results for monthly data.

Rizki et al. [6] predicted rice availability in Indonesia using the CRISP-DM framework and the ARIMA method. The dataset was obtained from the Central Statistics Agency for the period from 2018 to 2020, by comparing several ARIMA parameters and the evaluation metric using the RMSE value. The study demonstrated that the ARIMA method can effectively be used to forecast rice availability in the future.

Song et al. [16] predicted oil production during the oilfield exploration phase using the LSTM model with an additional optimization technique, namely the Particle Swarm Optimization (PSO) algorithm. In addition to LSTM, the study also includes other models for comparison, such as ANN and RNN. Based on MAPE, RMSE, and MAE values, the LSTM method with PSO optimization achieves a strong performance with an MAPE value of 9,88%. The study highlighted that parameter settings are crucial when running the model. Training epochs must be carefully managed to avoid overfitting, and adding hidden layers can improve accuracy. But it also increases computational time.

Dave et al. [17] conducted a study on predicting Indonesian exports using a hybrid ARIMA-LSTM model and compared its performance with ARIMA and LSTM methods. The evaluation was carried out using MAPE and RMSE values. Data was sourced from the Federal Reserve Economic database from 1998 to 2019. The study used the auto_arima method to automatically select the best parameters based on the lowest Akaike Information Criterion (AIC) value. The result identified that Seasonal ARIMA (SARIMA) is the most suitable model, indicating the presence of seasonal patterns in the data. The forecasting results showed that all methods achieved very accurate MAPE interpretations. The hybrid ARIMA-LSTM model performed best and achieved the lowest MAPE value of 7,38%.

Tolesh et al. [18] conducted a study on predicting international migration in Kazakhstan using the ARIMA method. The dataset was obtained from the Bureau of National Statistics from 1991 to 2020. To evaluate prediction accuracy using several metrics such as MAE, RMSE, and MAPE. The results showed that the ARIMA (0,1,0) model achieved a MAPE value of 20,026% which is considered a reasonable category. The findings of this study are expected to support the development of effective immigration policies to minimize negative impacts while maximizing potential benefits.

Kumar et al. [19] predicted natural disasters, especially floods, using data from the Disaster Management Department in Bihar, India, from 1991 to 2022. The study adopted the Long Short-Term Memory (LSTM) method with the addition of the Adam optimizer. The evaluation was conducted using MSE, MAE, and RMSE metrics. The results of the value were 0,20, 0,41, and 0,45. The results are close to zero, indicating that the prediction outcomes are highly realistic.

Torres et al. [20] predicted electricity consumption in Spain using the LSTM method combined with a hyperparameter optimization technique called the Coronavirus Optimization Algorithm (CVOA). The dataset used consists of electricity demand data from 2007 to 2016. For comparison, several other methods were also applied, such as linear regression and decision trees. The performance of each method was evaluated using MAE, MAPE, RMSE, and MSE metrics. The result showed that LSTM outperformed the other methods and achieved the lowest error values with a MAPE of less than 1,5%. That indicates a very high level of accuracy.

Based on previous studies, it can be concluded that various machine learning methods, such as ARIMA, LSTM, SARIMA, GRU, and others, have been widely applied for prediction tasks across diverse fields, including supply chain management, stock markets, cryptocurrency, immigration, and the energy sector. To evaluate the performance of these models, most studies used error metrics such as RMSE and MAPE as the primary benchmarks for comparing the accuracy of different machine learning approaches.

3. Materials and Methods

This study applies the CRISP-DM framework to predict the usage of liquid chemical materials at XYZ Company. CRISP-DM is a widely used framework that serves as a comprehensive guideline for conducting data analysis projects. It explains how to translate business problems into data analysis tasks, supports the selection of appropriate techniques for data transformation and analysis, and emphasizes the evaluation of results and documentation throughout the analytical process. This framework has been broadly adopted by business analysts and practitioners across various industries due to its structured approach to analytical methods and computing technologies [21]. The CRISP-DM process consists of six phases: Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment.

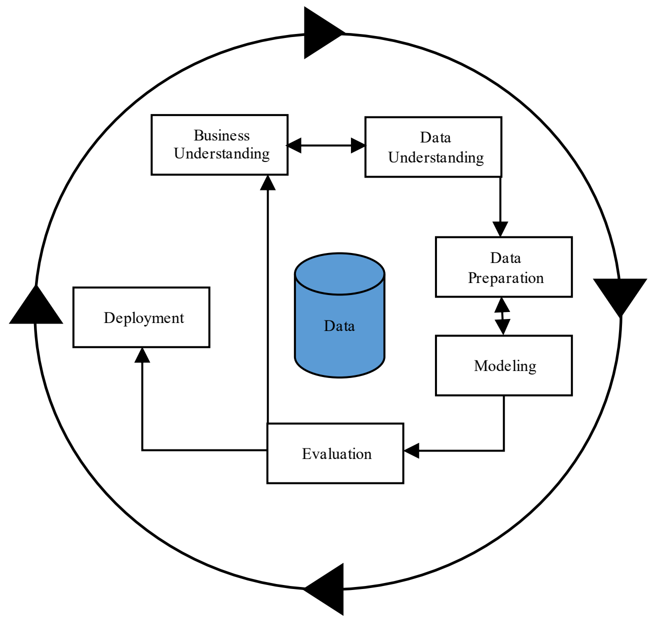

Fig. 1 CRISP-DM process cycle

3.1. Business Understanding

XYZ is a manufacturing company that produces polyurethane foam, rubber, plastic, and synthetic materials. These products are widely applied in the automotive, construction, garment, and industrial parts industries. The production process relies heavily on raw materials made from liquid chemicals, 90% of which are imported from abroad. On average, the company consumes approximately 25.000 kg of these raw materials per day. Given this large volume of usage, ensuring the continuous availability of chemical raw materials is a critical factor in XYZ's production process.

In forecasting imported material purchases, the material control department currently predicts demand by calculating the average usage over the previous three months and comparing it with usage from the same month in the previous year. The higher of the two values is then selected as the forecast. This approach is applied because customers are unable to provide annual or monthly demand forecasts, but only weekly demand forecasts.

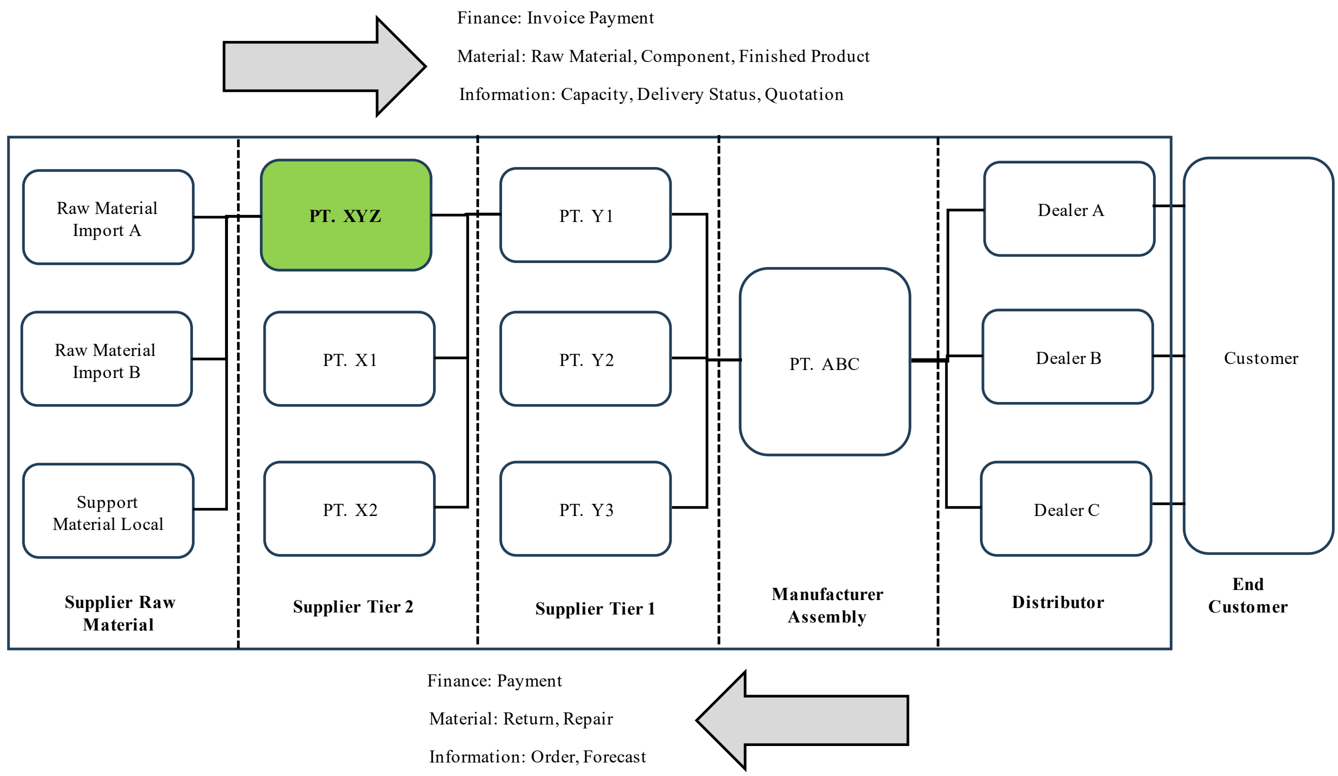

Fig. 2 Supply chain XYZ Company

3.2. Data Understanding

The data used in this study is primary data on the consumption of liquid chemical materials in the production process at XYZ Company, covering the period from January 2022 to July 2024. The dataset consists of 11 attributes, which are as follows:

Table 1. Data attribute

Attribute	Explanation
Production Date	Date of production
No. Formula	Type of product
PXX	PXX usage in kilograms
AXX	AXX usage in kilograms
TXX	TXX usage in kilograms
SXX	SXX usage in kilograms
FXX	FXX usage in kilograms
AdXX	AdXX usage in kilograms
IXX	IXX usage in kilograms
CXX	CXX usage in kilograms
BXX	BXX usage in kilograms

3.3. Data Preparation

This stage consists of several steps. First, data selection is carried out to determine which type of liquid chemical material will be used for prediction. Next, data transformation is performed, where missing values are replaced with 0. This step is necessary because one type of material may consist of various brands, and not all brands are used simultaneously. After that, data integration is conducted on the selected chemical material. The data is then grouped by date, and all formula numbers with the same date are aggregated to obtain the total daily usage of chemical materials. Once daily data is obtained, it is further aggregated into different time frames such as weekly (5 days), biweekly (10 days), and monthly (20 days). In this study, the prediction focuses on the chemical material with the highest consumption, namely PXX.

3.4. Modelling

The modeling stage is carried out to predict the usage of liquid chemical materials using two methods, ARIMA and LSTM. The general structure of the ARIMA model is expressed as follows:

$$\Delta^d y_t = \theta_o + \sum_{i=1}^{p} \varphi_i \Delta^d y_{t-1} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \quad (1)$$

From the equation above, the model can be represented as ARIMA (p, d, q), where ε_t denotes the error term in the ARMA (p, q) process, and y_t represents the ARIMA (p, d, q) process [22]. ARIMA is essentially a linear model. Therefore, its capability is limited when applied to nonlinear time series data. The three key parameters in the ARIMA model are defined as follows:

- p: the Autoregressive (AR) order, representing the number of lagged terms of the dependent variable.
- d: the degree of differencing (I) applied to remove trends or seasonality (if d = 0, no differencing is applied; if d =

1, first-order differencing is applied; and so forth).

- q: the Moving Average (MA) order, representing the number of lagged forecast errors in the prediction equation.

There are four main steps in implementing the ARIMA model. The first step is to analyze the time series pattern through a smoothing process. If the pattern is nonstationary, differencing is applied to achieve stationarity. The second step is to determine the optimal values of parameters p and q using the auto-ARIMA procedure. The third step is to evaluate the model parameters by conducting an Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) test to ensure the appropriateness of the selected model and to identify the correlation at specific lags. Finally, the fourth step is to apply the model with the identified parameters to generate forecasts.

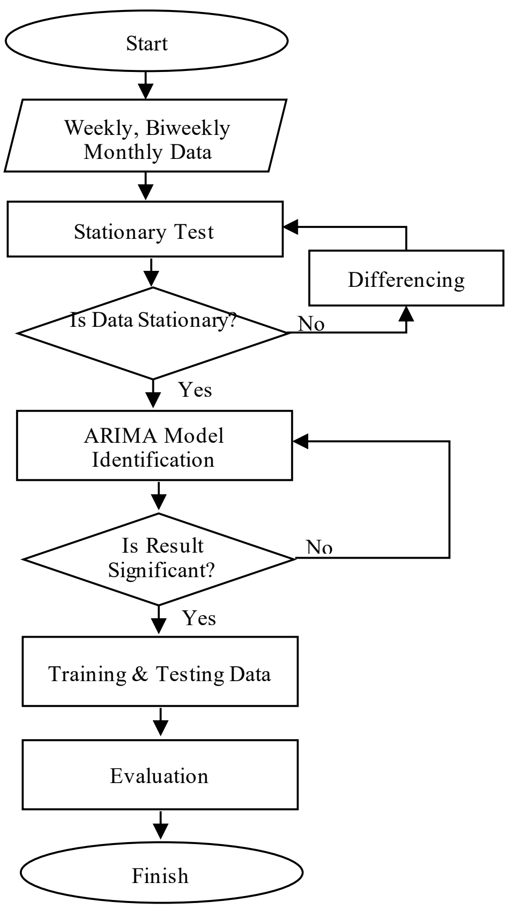

Fig. 3 Flowchart ARIMA

In implementing the ARIMA model using the auto-ARIMA procedure, it is important to consider the presence of seasonality in the data. If seasonal elements are detected, the model selection process must incorporate them. The selection of the best model can be guided by the Akaike Information Criterion (AIC), where a smaller AIC value indicates a better-fitting model [17]. In cases where the seasonal model produces a smaller AIC value than the non-seasonal model, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model is applied. The SARIMA model extends ARIMA by introducing seasonal parameters expressed as (p, d, q)(P, D, Q)$_s$, where (p, d, q) represent the non-seasonal components, (P, D, Q) represent the seasonal components, and s denotes the length of the seasonal cycle.

ARIMA modeling consists of several stages. First, a stationarity test is conducted to determine whether the data is stationary. If the data is nonstationary, differencing is applied until stationarity is achieved. Once the data is stationary, the appropriate ARIMA model is identified based on the selected parameters. After that, the dataset is divided into training data (70%) and testing data (30%). The training data are used to build the model, and the testing data are applied to evaluate the model's forecasting performance.

Long Short-Term Memory (LSTM) is an extension of the Recurrent Neural Network (RNN) designed with higher-dimensional capabilities and nonlinear activation functions at each layer. Unlike traditional RNNs, LSTM can effectively capture nonlinear patterns in time series data and retain information over long periods, thereby overcoming the vanishing gradient problem that is commonly found in RNNs. Due to these advantages, LSTM has been widely successfully applied to various time series forecasting problems [23].

The main advantage of the LSTM structure lies in the presence of three types of gates, such as the input gate, forget gate, and output gate. These gates regulate the flow of information and enabling LSTM to retain relevant information while discarding unnecessary data. In addition, LSTM overcomes the vanishing and exploding gradient problems that are commonly encountered in RNNs. It is also capable of storing information over long periods. The structure of the LSTM cell is illustrated in the Figure, which can be explained mathematically. In the Figure, the symbol (+) represents addition and the symbol (×) represents multiplication. And arrows indicate the direction of information flow.

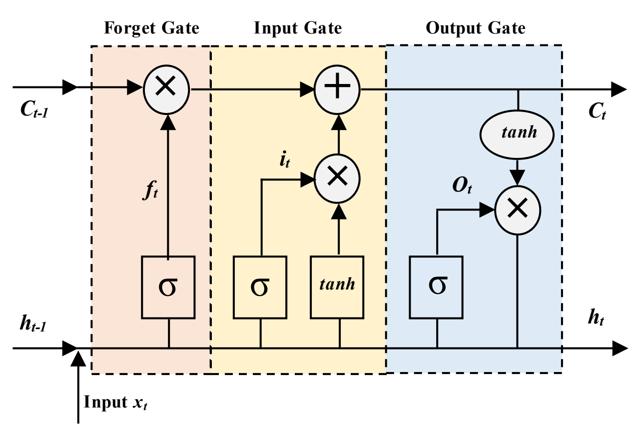

Fig. 4 LSTM cell structure

The first layer is the forget gate, which determines the information that is not needed and is removed from the cell state. Where f_t denotes the forgetting threshold at time t, σ denotes the sigmoid activation function, W_f and U_f denote the weights, x_t denotes the input value, h_{t-1} denotes the output value at time $t-1$, and b_f denotes the bias term. The first layer of the LSTM cell is the forget gate, which is responsible for determining which information is no longer needed and should be removed from the cell state. At this layer, the gate evaluates the current input x_t together with the previous hidden state h_{t-1}. These values are processed through the sigmoid activation function σ using the corresponding weights (W_f, U_f) and bias b_f to generate the forgetting threshold f_t. The value of f_t ranges between 0 and 1, where values close to 0 indicate that the information will be discarded and values close to 1 indicate that the information will be retained. This mechanism ensures that irrelevant information is forgotten and important information will continue to be stored in the cell state.

$$f_t = \sigma\left(W_f \times x_t + U_f \times h_{t-1} + b_f\right) \tag{2}$$

The second layer is the input gate, which determines what information from the current input vector should be stored in the cell state. At this layer, the gate evaluates the current input x_t and the previous hidden state h_{t-1}. After being processed through the sigmoid activation function σ to produce the input threshold, i_t. The values are influenced by the corresponding weights (W_i, U_i) and bias b_i. In parallel, a candidate value for the new cell state is generated through the *tanh* layer using weights (W_c, U_c) and bias b_c. Finally, the cell state at time t is updated by combining the retained past information with the selected new information. This mechanism ensures that only the most relevant information is stored in the memory cell for the current time step.

$$i_t = \sigma(W_i \times x_t + U_i \times h_{t-1} + b_i) \tag{3}$$

$$\boldsymbol{\overline{C_t} = \sigma(W_c \times x_t + U_c \times h_{t-1} + b_c)} \tag{4}$$

$$C_t = f_t \times C_{t-1} + i_t \times \overline{C}_t \tag{5}$$

The third layer is the output gate, which generates the output information from the current cell state. At this stage, the gate evaluates the input x_t and the previous hidden state h_{t-1} through the sigmoid activation function σ to produce the output threshold O_t. These values are influenced by the corresponding weights (W_o, U_o) and bias b_o. The current cell state C_t then passed through the *tanh* activation function to scale its values and combined with O_t to generate the hidden state h_t, which represents the output of the LSTM cell at time t. Through this process, only effective information is released as output and irrelevant information is filtered out.

$$O_t = \sigma(W_o \times x_t + U_o \times h_{t-1} + b_o) \tag{6}$$

$$h_t = O_t \times \tanh(C_t) \tag{7}$$

In implementing the LSTM method, the process begins with data collection, followed by data preprocessing to ensure data quality and readiness for modeling. After that, the dataset is divided into two parts. Data training (70%) and data testing (30%). The training data is used to build and train the LSTM model. The testing dataset is used to evaluate the model's performance. Once the training process is completed, the trained LSTM model is applied to the testing data to generate predictions. Finally, an evaluation process is conducted to assess the accuracy and reliability of the model.

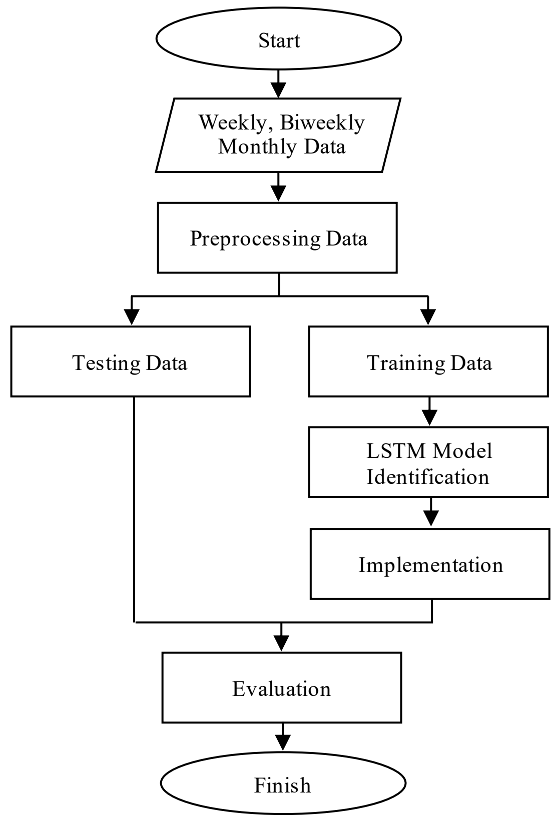

Fig. 5 Flowchart LSTM

3.5. Evaluation

To evaluate the machine learning models, two metrics are used, namely Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) [12]. The evaluation process is carried out by comparing the RMSE and MAPE values obtained from the ARIMA and LSTM models across weekly, biweekly, and monthly time frames. The model with the smallest RMSE and MAPE values is considered to provide the best performance. In particular, the interpretation of MAPE values categorized as value below 20% is classified as good and value below 10% are considered highly accurate.

$$\boldsymbol{RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\hat{y}_t - y_t)^2}} \tag{8}$$

$$\boldsymbol{MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|\hat{y}_t - y_t|}{y_t}} \tag{9}$$

Table 2. MAPE value interpretation

MAPE	Interpretation
<10	Very accurate
10-20	Good
20-50	Fair
>50	Not accurate

3.6. Deployment

After the evaluation stage, the most accurate forecasting method (ARIMA or LSTM) and the most suitable time frame (weekly, biweekly, or monthly) can be identified. The results can be proposed as a recommendation for forecasting liquid chemical material requirements at XYZ Company. Furthermore, the selected method can also be applied to other types of liquid chemical materials, such as IXX and similar materials, to ensure a more reliable and efficient supply planning process across different product categories.

4. Results and Discussion

4.1. Data Preparation

Data preparation in this study begins with data selection, namely, determining the type of liquid chemical material to be used in the prediction process. The selected material is the type with the highest level of usage, which in this case is the liquid chemical material PXX. After that, a data transformation process is carried out to handle missing values. Missing values are converted to 0, because each type of chemical material generally consists of several different brands and not all brands are used simultaneously in the production process. This step ensures that the dataset is complete and ready for further processing without losing important information. After that, data integration is carried out for the PXX type of material, which consists of several variants (P-1 to P-10). The next step is data grouping based on date, where all usage records from different formulas on the same date are aggregated to obtain the total daily consumption of PXX. Once the daily usage data is obtained, the data is further restructured into different time frames. Namely, weekly (5 working days), biweekly (10 working days), and monthly (20 working days). This transformation is carried out to support the prediction process with different time horizons and to compare the accuracy of each model at various aggregation levels.

4.2. ARIMA

In the ARIMA model, the dataset used is the consumption of chemical material PXX from January 2022 to July 2024. The data is aggregated into weekly, biweekly, and monthly total usage. For each time span, a stationarity test is conducted to ensure the data meet the requirements for ARIMA modeling. Data is considered stationary if the p-value < 0,05. If the result of the stationarity test shows a p-value > 0,05, then differencing must be applied to transform the data into a stationary form. The results of the stationarity test for each time span are presented in Table 3 below.

Table 3. Stationary test result

Time Frame	p-value	Differencing	Final p-value
Weekly	0,35	Yes	8,206757969540674e-19
Biweekly	0,41	Yes	9,061716553559969e-18
Monthly	0,46	Yes	0,00015386757329399788

After obtaining stationary data, the dataset was divided into 70% training data and 30% testing data. The next step was to search for the optimal ARIMA parameters using the *pm.auto_arima* function. In this process, both seasonal and non-seasonal ARIMA models were tested. The results indicated that the seasonal ARIMA model produced a lower Akaike Information Criterion (AIC) compared to the non-seasonal model. Therefore, the SARIMA model was selected with the following parameters:

Table 4. Result of ARIMA parameter

Time Frame	Best Parameter
Weekly	ARIMA(0, 0, 1)x(2, 0, 1, 7)
Biweekly	ARIMA(1, 0, 0)x(2, 0, 2, 12)
Monthly	ARIMA(0, 0, 1)x(2, 0, 0, 12)

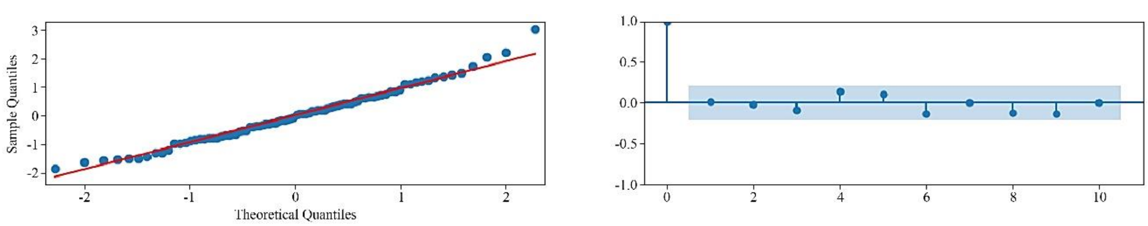

Fig. 6 Diagnostic graphic ARIMA weekly

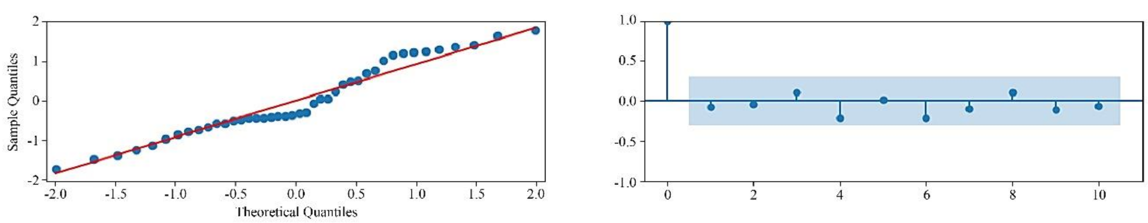

Fig. 7 Diagnostic graphic ARIMA biweekly

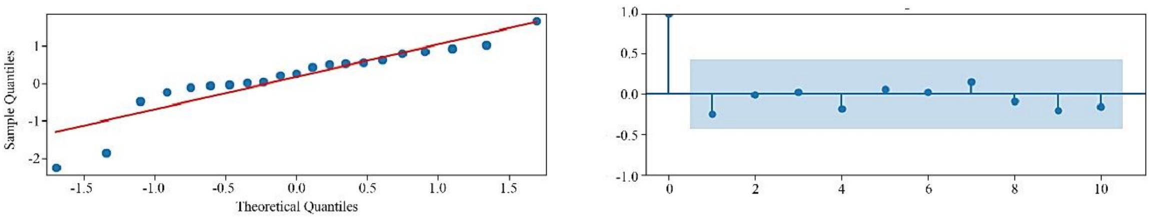

Fig. 8 Diagnostic graphic ARIMA monthly

Modeling was carried out using the selected parameters and the model_fit. The plot_diagnostics function was applied to evaluate the adequacy of the model. Based on the Q-Q plot, the data points were observed to follow the diagonal line, indicating that the ARIMA model nearly satisfies the assumption of a normal distribution. Furthermore, the Autocorrelation Function (ACF) plot showed that most of the points remained within the blue confidence limits, suggesting that the residuals exhibit no significant autocorrelation. From these results, it can be concluded that the ARIMA model performs adequately across all time frames, weekly, biweekly, and monthly. Based on the ARIMA model, the prediction results for each time frame are as follows. For the weekly time frame, the model produced an RMSE of 15.722 and a MAPE of 15,8%, for the biweekly time frame, the RMSE was 30.415 with a MAPE of 15,9%, and for the monthly time frame, the RMSE was 322.101 with a MAPE of 9,0%. These results indicate that the ARIMA model provides better accuracy in the monthly time frame, as reflected by the lower MAPE value, which falls into the "good" prediction category. The comparison between the actual data and the predicted values for each time frame is illustrated in Figures 9-11.

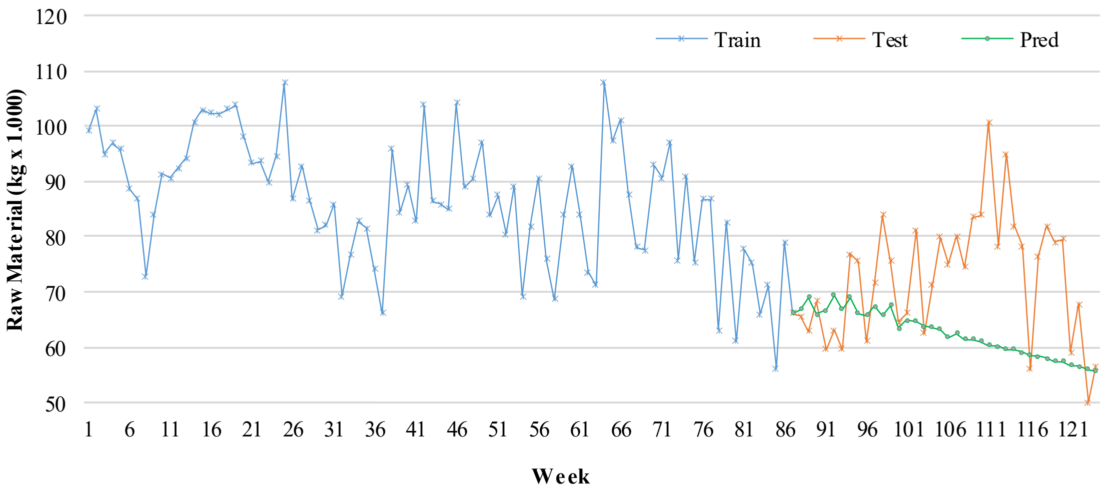

Fig. 9 Model prediction result ARIMA weekly

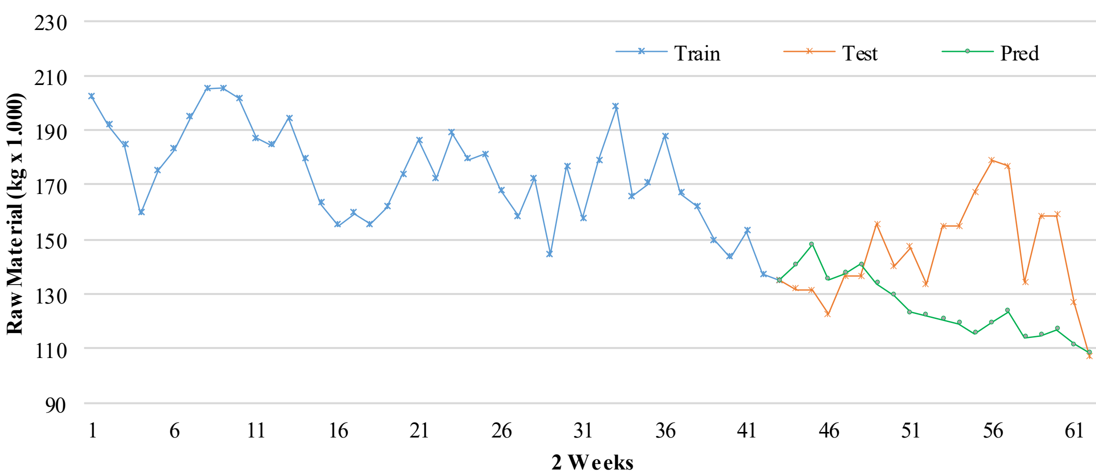

Fig. 10 Model prediction result ARIMA biweekly

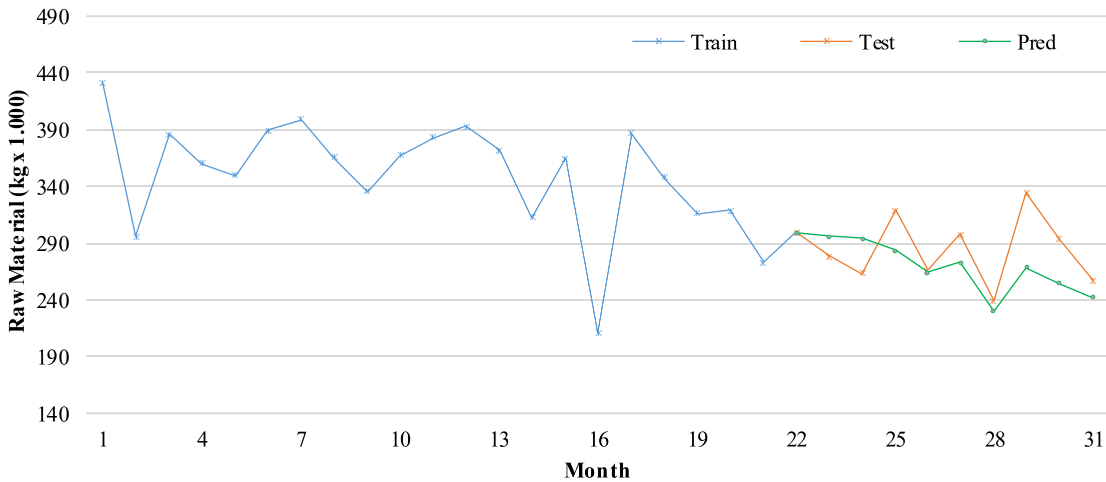

Fig. 11 Model prediction result ARIMA monthly

From the weekly graph, the ARIMA model is quite effective in capturing the actual data pattern, particularly at the beginning of the testing period. However, in the middle and towards the end of the prediction period, the results tend to decline steadily without reflecting the fluctuations observed in the actual data. In the biweekly graph, the model shows a better ability to follow the actual data pattern.

The predicted values closely match the actual data from the beginning to the middle of the testing period. Nevertheless, towards the end, there is a noticeable divergence, with the prediction line showing a downward trend. For the monthly graph, the model performs very well in capturing the actual data pattern. The predicted values closely align with the actual values, with the prediction line almost overlapping the actual data line, indicating high accuracy in this time frame.

After performing the ARIMA modeling process on each time frame, the best ARIMA equations were obtained sequentially for the weekly, biweekly, and monthly models as follows:

$$Y_t = -383.0113 + (-0.7125 * e_{t-1}) + e_t \tag{10}$$

$$\boldsymbol{Y_t = -1598.3571 + (-0.4729 * e_{t-1}) + e_t} \tag{11}$$

$$\boldsymbol{Y_t = -6254.5227 + (-0.8510 * e_{t-1}) + e_t} \tag{12}$$

These equations represent the optimal parameters selected by the auto ARIMA process, considering both seasonal and non-seasonal elements. The chosen models provide the basis for generating predictions across different time frames.

4.3. LSTM

In the LSTM model, the dataset used consists of PXX chemical material consumption records from January 2022 to July 2024. The data is aggregated into weekly, biweekly, and monthly totals with a sliding window of 10, meaning that the model observes the last 10 data points to predict the next value. The dataset is then split into 70% training data and 30% testing data. To optimize performance, the model is enhanced with Batch Normalization and the Adam (Adaptive Moment Estimation) optimizer, which helps stabilize the training process and improve convergence. Prior to full modeling, the val_root_mean_squared_error is examined to evaluate whether the model configuration is optimal.

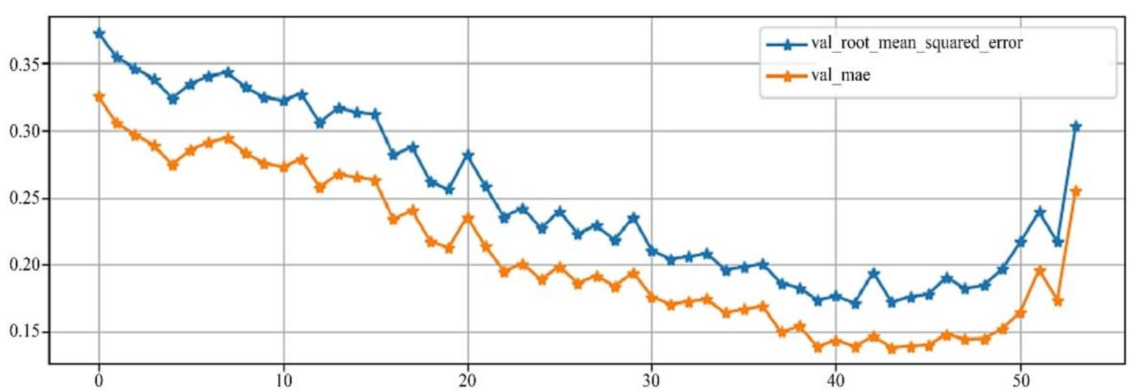

Fig. 12 Model evaluation LSTM weekly

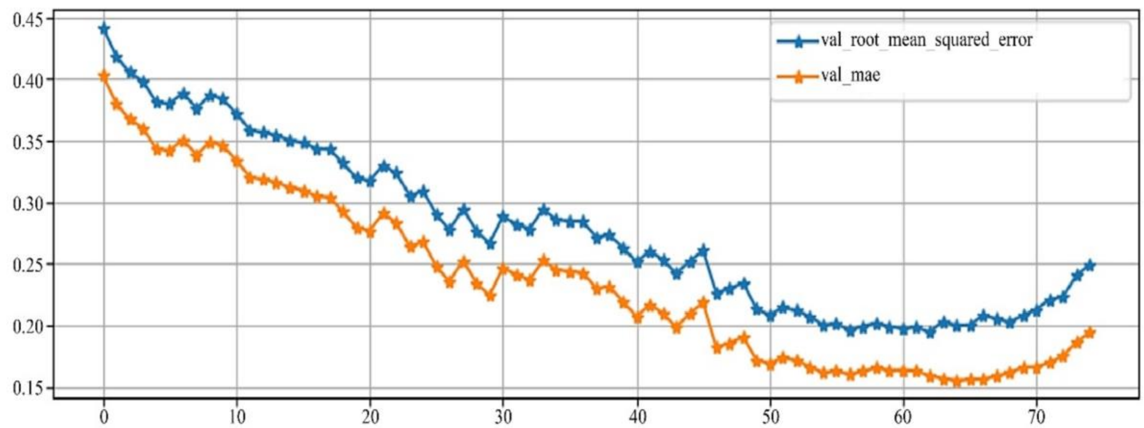

Fig. 13 Model evaluation LSTM biweekly

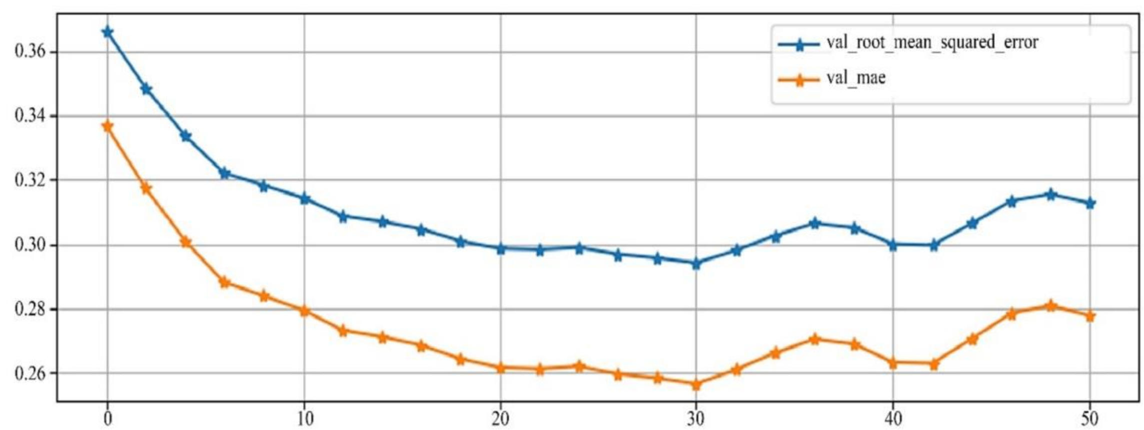

Fig. 14 Model evaluation LSTM monthly

From the model evaluation results, it can be observed that the average error shows a downward trend as the number of epochs increases, which indicates that the model is improving in its predictive capability. The performance of the LSTM model was further assessed using RMSE and MAPE values. For the weekly time frame, the LSTM model achieved an RMSE of 9.921 and a MAPE of 11,3. For the biweekly time frame, the model obtained an RMSE of 19.704 and an MAPE of 11,2. Meanwhile, for the monthly time frame, the results were an RMSE of 64.585 and an MAPE of 18,7.

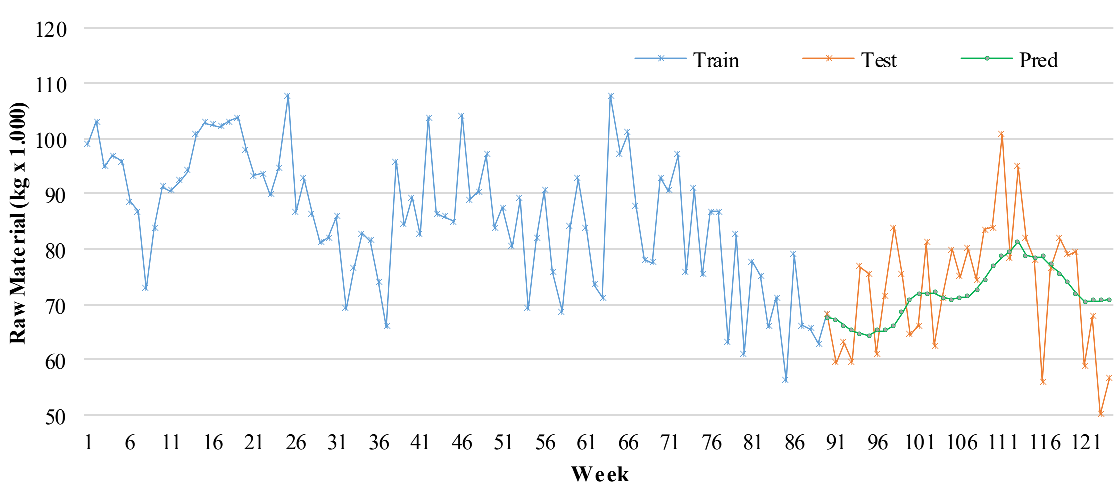

Fig. 15 Model prediction result LSTM weekly

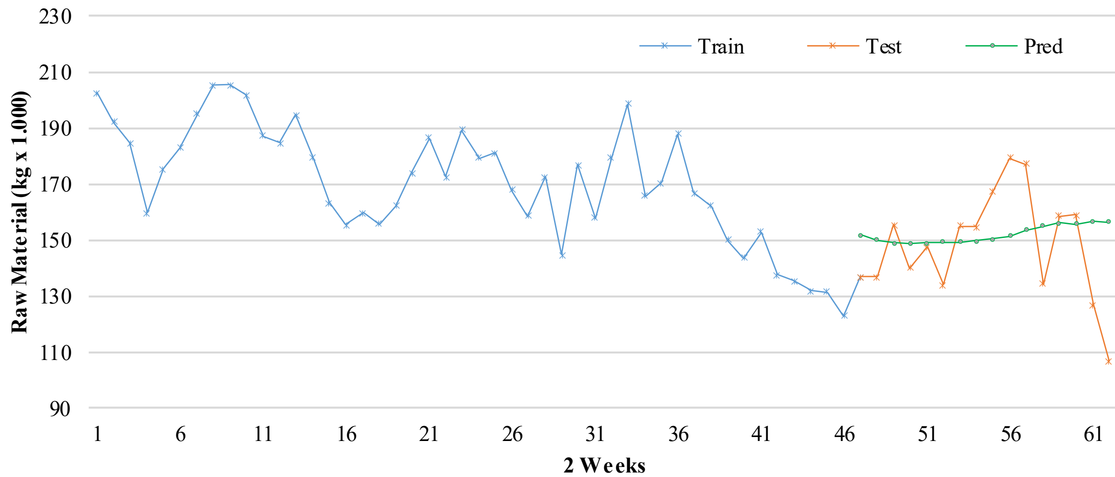

Fig. 16 Model prediction result LSTM biweekly

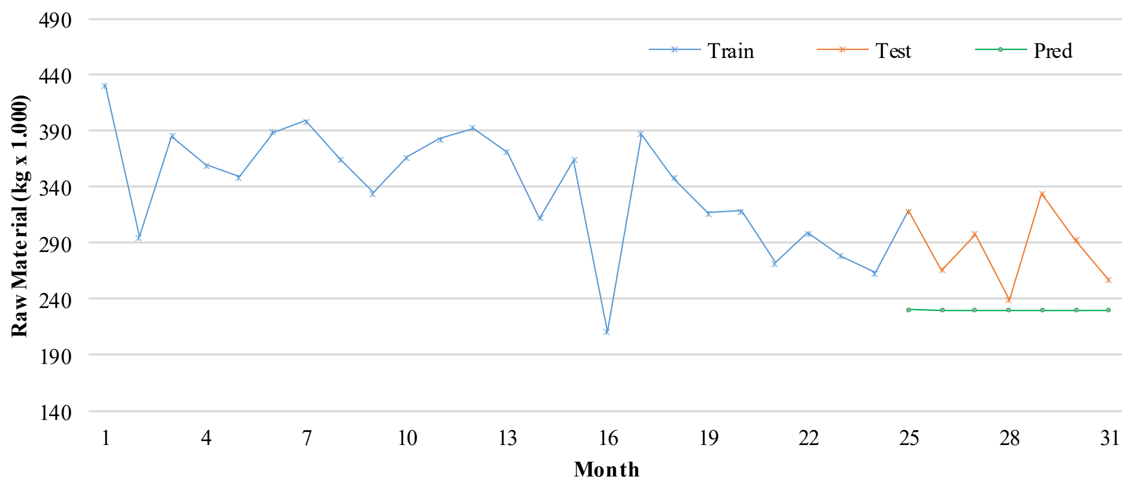

Fig. 17 Model prediction result LSTM monthly

From the weekly graph, the prediction results are quite good at following the actual data trend and are able to capture fluctuations, particularly in the early testing period, where the predicted values are close to the actual values.

However, for the biweekly and monthly time frames, the prediction results tend to show a flatter pattern compared to the actual data, which still exhibits noticeable fluctuations.

4.4. Result Comparison Between ARIMA and LSTM

After predicting the use of chemical materials using the ARIMA and LSTM models, and dividing each model based on weekly, biweekly, and monthly time frames, the comparison results of RMSE and MAPE values are as follows:

Table 5. Results of ARIMA and LSTM

Model	Time Frame	RMSE	MAPE	MAPE Value Interpretation
ARIMA	Weekly	15.722	15,8	Good
ARIMA	Biweekly	30.415	15,9	Good
ARIMA	Monthly	32.101	9,0	Very accurate
LSTM	Weekly	9.921	11,3	Good
LSTM	Biweekly	19.704	11,2	Good
LSTM	Monthly	64.585	18,7	Good

Based on the results obtained, both the ARIMA and LSTM models with different time frames are able to make good predictions, with MAPE values ranging from 9,0% to 18,7%.

The lowest MAPE value is achieved by the ARIMA model in the monthly time frame, with a value of 9,0% which indicates a very accurate prediction. With a relatively small amount of data, the ARIMA model performs better than the LSTM model. On the other hand, the LSTM model tends to become less accurate, as indicated by the increasing MAPE values when the amount of data decreases. However, when more data is available, such as in the weekly time frame. The LSTM model outperforms the ARIMA model, with a MAPE value of 11,2% compared to ARIMA's 15,8%.

4.5. Deployment

The seasonal ARIMA method (0, 0, 1) × (2, 0, 0, 12) with a monthly time frame achieved a MAPE value with a very accurate interpretation compared to the monthly LSTM method. This result aligns with the business needs of XYZ company, which requires a monthly forecasting method for ordering chemical materials. Accurate forecasting will help the company address issues of overstock and shortages of liquid chemical materials.

4.6. Compare Result with Literature Review

The results of this study indicate that the seasonal ARIMA method with a monthly time frame produces the best performance, with a very accurate MAPE value compared to the LSTM method in the same or other time frames. However, when compared with findings from previous studies such as those conducted by Falatouri et al. [12] and Sunjaya et al. [13], which compared SARIMA/ARIMA with LSTM, the evaluation results generally showed that the LSTM method outperformed SARIMA/ARIMA.

In the study conducted by Falatouri et al. [12], the SARIMA method produced better results under conditions of seasonal behavior, while the LSTM method performed better under stable demand. These findings are consistent with the results of the present study, where the ARIMA method applied was Seasonal ARIMA, as the data used contained clear seasonal patterns.

Meanwhile, the study conducted by Sunjaya et al. [13] shows that the LSTM method produced better results with a dataset consisting of 759 data points. When compared to the present study, the weekly time frame has a dataset of 124 data points. The LSTM method shows better performance. However, in the monthly time frame, with a dataset of 31 data points. The seasonal ARIMA method produced more accurate results. This indicates that the amount of data has a significant impact on the accuracy of the LSTM method.

The larger the data, the higher the accuracy. In contrast, the ARIMA method does not require a large amount of data to generate a reliable prediction. In this study, the highest accuracy of the LSTM method was achieved in the weekly time frame with an MAPE value of 11,3%. When compared with studies conducted by Falatouri et al. [12] and Sunjaya et al. [13], the LSTM method in their research obtained MAPE values of 14% and 25,5%. The better MAPE value obtained in this study is attributed to the application of LSTM with BatchNormalization and the Adam (Adaptive Moment Estimation) optimizer, which helped stabilize the training process, as also implemented in the study by Kumar et al. [19].

5. Conclusion

ARIMA, as a traditional machine learning method with seasonal parameters ARIMA (0, 0, 1) × (2, 0, 0, 12). And LSTM, as a modern deep learning based machine learning method optimized with Adam (Adaptive Moment Estimation), can predict the use of liquid chemical materials at PT XYZ with good accuracy.

With a small amount of data in the case study at XYZ Company, the monthly ARIMA method is more suitable, as indicated by its MAPE value, which provides a very accurate interpretation of the results compared to the monthly LSTM method, which only achieves a good interpretation.

The time frame affects the level of accuracy of the ARIMA and LSTM methods. With a weekly time frame, more data is available, enabling the LSTM method to produce better predictions. In contrast, with a monthly time frame, fewer data points are available. Allowing the ARIMA method to perform better. The ARIMA method does not require a large amount of historical data to generate accurate predictions, whereas the LSTM method relies on a larger dataset to achieve better accuracy.

The application of the seasonal ARIMA (0, 0, 1) x (2, 0, 0, 12) method with a monthly time frame aligns with the business needs of XYZ Company, which requires monthly forecasting. Compared to manual forecasting methods, the results are better, as indicated by the MAPE value, which falls into the very accurate category. By utilizing machine learning for forecasting, XYZ Company can effectively address the problems of material shortages and overstock.

Credit Authorship Contribution Statement

Muhammad Furqon: Conceptualization, methodology, software, formal analysis, investigation, resources, data curation, writing – original draft. Tuga Mauritsius: Writing – review & editing, supervision.

Data Availability Statement

Data supporting this study are openly available at https://github.com/mfurqon21/Data/blob/main/Dataset%20Consumption%20Material.xlsx

References

[1] Cyril Koch et al., "A Matheuristic Approach for Solving a Simultaneous Lot Sizing and Scheduling Problem with Client Prioritization in Tire Industry," *Computers & Industrial Engineering*, vol. 165, pp. 1-61, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[2] Keely L. Croxton et al., "The Demand Management Process," *The International Journal of Logistics Management*, vol. 13, no. 2, pp. 51-66, 2002. [CrossRef] [Google Scholar] [Publisher Link]

[3] Emrah Cengiz, "Measuring Customer Satisfaction: Must or Not?," *Journal of Naval Science and Engineering*, vol. 6, no. 2, pp. 76-88, 2010. [Google Scholar] [Publisher Link]

[4] Ricardo P. Masini, Marcelo C. Medeiros, and Eduardo F. Mendes, "Machine Learning Advances for Time Series Forecasting," *Journal of Economic Surveys*, vol. 37, no. 1, pp. 76-111, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[5] Pramit Pandit et al., "ARIMA-Genetic Algorithm Approach for Forecasting Milk Production in India," *Asian Journal of Dairy and Food Research*, vol. 43, no. 4, pp. 784-789, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[6] Faisal Rizki Kurniawan, and Rudi Sutomo, "Forecasting Rice Inventory in Indonesia Using the ARIMA Algorithm Method," *Journal of Multidisciplinary Issues*, vol. 1, no. 2, pp. 1-12, 2021. [CrossRef] [Publisher Link]

[7] Ahamad Zaki Mohamed Noor et al., "Data Prediction of Reject Unit from Manufacturing Company using Auto Regressive Integrated Moving Average (ARIMA) Algorithm," *International Journal of Emerging Trend in Engineering Research*, vol. 8, no. 9, pp. 6164-6169, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[8] Anna Manowska, and Anna Bluszcz, "Forecasting Crude Oil Consumption in Poland Based on LSTM Recurrent Neural Network," *Energies*, vol. 15, no. 13, pp. 1-23, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[9] Ali Javaid et al., "Forecasting Hydrogen Production from Wind Energy in a Suburban Environment Using Machine Learning," *Energies*, vol. 15, no. 23, pp. 1-13, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[10] Uppala Meena Sirisha, Manjula C. Belavagi, and Girija Attigeri, "Profit Prediction Using ARIMA, SARIMA and LSTM Models in Time Series Forecasting: A Comparison," *IEEE Access*, vol. 10, pp. 124715-124727, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[11] Chien-Chih Wang, Chun-Hua Chien, and Amy J. C. Trappey, "On the Application of ARIMA and LSTM to Predict Order Demand Based on Short Lead Time and On-Time Delivery Requirements," *Processes*, vol. 9, no. 7, pp. 1-20, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[12] Taha Falatouri et al., "Predictive Analytics for Demand Forecasting - A Comparison of SARIMA and LSTM in Retail SCM," *Procedia Computer Science*, vol. 200, pp. 993-1003, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[13] Bryan Alfason Sunjaya, Syarifah Diana Permai, and Alexander Agung Santoso Gunawan, "Forecasting of Covid-19 Positive Cases in Indonesia using Long Short-Term Memory (LSTM)," *Procedia Computer Science*, vol. 216, pp. 177-185, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[14] Tej Bahadur Shahi et al., "Stock Price Forecasting with Deep Learning: A Comparative Study," *Mathematics*, vol. 8, no. 9, pp. 1-15, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[15] Michael David Angelo, Ilhas Fadhiilrahman, and Yudy Purnama, "Comparative Analysis of ARIMA and Prophet Algorithms in Bitcoin Price Forecasting," *Procedia Computer Science*, vol. 227, pp. 490-499, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[16] Xuanyi Song et al., "Time-Series well Performance Prediction based on Long Short-Term Memory (LSTM) Neural Network Model," *Journal of Petroleum Science and Engineering*, vol. 186, pp. 1-11, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[17] Emmanuel Dave et al., "Forecasting Indonesia Exports using a Hybrid Model ARIMA-LSTM," *Procedia Computer Science*, vol. 179, pp. 480-487, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[18] Fariza Tolesh, and Svitlana Biloshchytska, "Forecasting International Migration in Kazakhstan using ARIMA Models," *Procedia Computer Science*, vol. 231, pp. 176-183, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[19] Guru Dayal Kumar, Kalandi Charan Pradhan, and Shekhar Tyagi, "Deep Learning Forecasting: An LSTM Neural Architecture based Approach to Rainfall and Flood Impact Predictions in Bihar," *Procedia Computer Science*, vol. 235, pp. 1455-1466, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[20] J.F. Torres, F. Martínez-Álvarez, and A. Troncoso, "A deep LSTM Network for the Spanish Electricity Consumption Forecasting," *Neural Computing and Applications*, vol. 34, no. 13, pp. 10533-10545, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[21] Sanjiv Jaggia et al., "Applying the CRISP-DM Framework for Teaching Business Analytics," *Decision Sciences Journal of Innovative Education*, vol. 18, no. 4, pp. 612-634, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[22] Tingxin Wen et al., "Modeling and Forecasting CO_2 Emissions in China and its Regions using a Novel ARIMA-LSTM Model," *Heliyon*, vol. 9, no. 11, pp. 1-14, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[23] Dongyan Fan et al., "Well Production Forecasting based on ARIMA-LSTM Model Considering Manual Operations," *Energy*, vol. 220, pp. 1-13, 2021. [CrossRef] [Google Scholar] [Publisher Link]