Contents list avaliable at Directory of Open Access Journals (DOAJ)

JUTIN : Jurnal Teknik Industri Terintegrasi

Volume 6 Issue 4 2023, Page 1065-1078

ISSN: 2620-8962 (Online)

Journal Homepage: https://journal.universitaspahlawan.ac.id/index.php/jutin/index

Forecasting Modelling For Oil Country Tubular Goods (OCTG)

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DOI: 10.31004/jutin.v6i4.19164

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Article Info

Kata kunci:
Kata kunci 1; Rantai pasokan
Kata kunci 2; peramalan
Kata kunci 3; OCTG
Kata kunci 4; LSTM
Kata kunci 5; ARIMA

Abstrak

Dalam teori, parameter dan distribusi permintaan diketahui, tetapi dalam praktiknya, berbagai ketidakpastian membuatnya sulit untuk menentukan faktor-faktor ini, terutama karena permintaan yang sporadis dan tidak terduga. Permintaan untuk produk oil country tubular goods (OCTG) bersifat fluktuatif dan tidak teratur, dan persediaan keselamatan adalah strategi umum untuk mengelola ketidakpastian pasokan dan permintaan. Ada beberapa metode yang tersedia untuk meramalkan permintaan yang tidak teratur, seperti model statistik, deret waktu, Croston, dan metode deep learning. Penelitian ini menggunakan metode long short-term memory (LSTM) untuk meramalkan permintaan OCTG dan membandingkannya dengan metode autoregressive integrated moving average (ARIMA), dengan menggunakan data penjualan dari periode tertentu. Untuk menilai akurasi ramalan, tingkat kesalahan dihitung, termasuk mean square error (MSE), root mean square error (RMSE), dan mean absolute error (MAE). Meskipun baik metode LSTM maupun ARIMA tidak memberikan hasil yang memuaskan dengan menggunakan data penjualan harian, data penjualan bulanan menghasilkan hasil yang lebih baik. Dengan menggunakan data 6 bulan, baik LSTM maupun ARIMA menghasilkan hasil yang relatif baik, dengan LSTM menunjukkan kesalahan yang lebih kecil daripada ARIMA. Mengingat waktu pembelian pipa hijau dari pemasok sekitar 5 bulan, data kumulatif terbatas pada 6 bulan. Berdasarkan hasil penelitian, metode LSTM dapat digunakan untuk meramalkan permintaan produk OCTG dan menentukan tingkat persediaan keselamatan yang diperlukan.

Keywords:
Keyword 1; Supply chain
Keyword 2; forecasting
Keyword 3; OCTG
Keyword 4; LSTM
Keyword 5; ARIMA

Abstract

In theory, the parameters and distribution of demand are known, but in practice, various uncertainties make it difficult to determine these factors, particularly due to sporadic and unpredictable demand. Demand for oil country tubular goods (OCTG) products is volatile and intermittent, and safety stock is a common strategy for managing supply and demand uncertainty. There are several methods available for forecasting intermittent demand, such as statistical models, time series, Croston, and deep learning methods. This study uses the long short-term memory (LSTM) method to forecast OCTG demand and compares it with the autoregressive integrated moving average (ARIMA) method, using sales data from a certain period. To assess the accuracy of the forecast, error rates are calculated, including mean square error (MSE), root mean square error (RMSE), and mean absolute error (MAE). While neither LSTM nor ARIMA methods provide satisfactory results using daily sales data, monthly sales data produces better results. Using 6-month data, both LSTMs and ARIMAs produce relatively good results, with

Received 13 September 2023; Received in revised form 14 September 2023 year; Accepted 10 October 2023
Available online 20 Occtober 2023 /

LSTMs showing smaller errors than ARIMAs. Given that the time to purchase green pipe from suppliers is about 5 months, the cumulative data is limited to 6 months. Based on the study's results, the LSTM method can be used to forecast OCTG product demand and determine the required level of safety stock.

1. INTRODUCTION

Risk management in supply chain systems and logistics is an important topic in both academia and industry (Choi et al., 2016). Price competition is not enough to attract the attention of consumers, but quality, speed of delivery, and customer service are very important. Among the elements of customer service, it has been recognized that the speed of delivery and the consistency of delivery time are the two most important ones (Ballou, 1998).

In the oil and gas industry, drilling is the only way to extract oil and gas from deep within the earth (Liu, 2021). As a result of the development of drilling technologies, drilling activities need huge amounts of oil country tubular goods (OCTG) in order to achieve the operating objectives, which is one of the main activities in the oil and gas industry (Gelfgat et al., 2005). Based on the standard specification of the American Petroleum Institute (API) 5CT, there are 2,198 types of OCTG products with a combination of outside diameter (OD), weight (lb/ft), and grade. OCTG (tube or pipe) raw material is called a green pipe. Each green pipe is manufactured by Mill from a piece of solid cylindrical pipe called a billet. The production process includes heating the billet to a high temperature, making holes in the billet so that it forms a round cavity, and adjusting the outer diameter and inner diameter of the pipe. The final product is called "finished pipe," where the pipe characteristics are in accordance with the provisions stipulated in the API 5CT specification (Liu, 2021).

PT. Citra Tubindo Tbk. is processing green pipes to be finished pipes. The capacity of the heat treatment process at PTCT is from 2-3/8 inches to 13-5/8 inches OD. Thus, the combinations of products that can be processed by PTCT based on the outside diameter (OD), weight (lb/ft), and grade are 1,904 types of products. The green pipe is exported, with the main suppliers being Germany, Brazil, and China. Capacity and lead times are different among all suppliers.

It is well known in the oil and gas (O&G) industry that the event design of conventional and unconventional fields is difficult and can lead to illogical production forecasts and project overruns. With the provision chain accounting for approximately 65% of the cost of a well, the optimal style of an integrated supply chain network (SCN) has become one of the most important challenges facing modern O&G companies in the aftermath of the shale revolution (Montagna & Cafaro, 2019). This phenomenon has a direct impact on the uncertain demand for OCTG products. Product demand from customers is uncertain, in terms of product type (outside diameter, weight, and grade), number of products purchased, price, and time of purchase. Strategies such as safety stock and safety lead time are two things that are commonly used in inventory management to deal with demand uncertainty (Van Kampen et al., 2010).

Safety stock, also known as buffer stock, is additional inventory held to manage supply and demand uncertainties to prevent stockouts. It is designed to meet unexpected demand, and safety stock in the form of raw materials is used to protect against raw material supply problems that can cause production to stop (Barros et al., 2021)

The determination of safety stock in the OCTG industry is not enough. Due to a large number of product types (1904 types), the price of the material (green pipe) is expensive, the material storage area requires a large space (the average length of the pipe is 12 meters), and also the limited storage time (1 year) is not possible to provide safety stock for all types of products. Therefore, a strategy is needed to determine the type of product (Outside Diameter, Weight, and Grade) and the minimum amount that will be used as safety stock. The results of selecting the type of product and the minimum amount of safety stock proposed as strategic stock.

This research was conducted to optimize the safety stock level for OCTG products based on the 46th edition of the API (American Petroleum Institute) specification. The data used as a source of research is pipe purchase data for the domestic market at PT. Citra Tubindo Tbk., Batam-Indonesia, starting from 2010.

1. Oil Country Tubular Goods (OCTG)

Since the last decade, drilling companies have started experimenting with a type of pipe called Casing to drill wells (N. Velmurugan, 2015). The use of casing provides better drilling efficiency than the previous method, and the development of this method continues to be developed until now. Based on its function, the pipes used in the oil and gas drilling process are divided into two major parts, namely Casing, and Tubing. The casing is a pipe that becomes a permanent part of a drilling well and the Tubing is a part that can be moved or replaced. The casing is a pipe with an outer diameter (OD) size ranging from 4-1/2 inches to OD 20 inches. From each OD, it is subdivided based on the Weight which indicates the thickness of the pipe (Wall Thickness). In the specification API 5CT Weight is generally indicated by lb/ft. Tubing is a pipe with an outside diameter (OD) ranging from 1,050 inches to OD 4-1/2 inches. The grade in the API 5CT specification is a value that shows the characteristics of the pipe material which is regulated based on the value of the chemical composition, Tensile test value, and material hardness testing with Charpy V-notch.

2. Steel Pipe Manufacturing Process

Seamless pipe with outside diameter (OD) from 21 mm to 178 meters is usually produced by a continuous mandrel rolling process (Figure 1), and OD between 140 mm to 406 mm is usually produced by the plug process (Figure 2). Seamless pipes with OD between 250 mm to 660 mm also can be produced with the mandrel process.

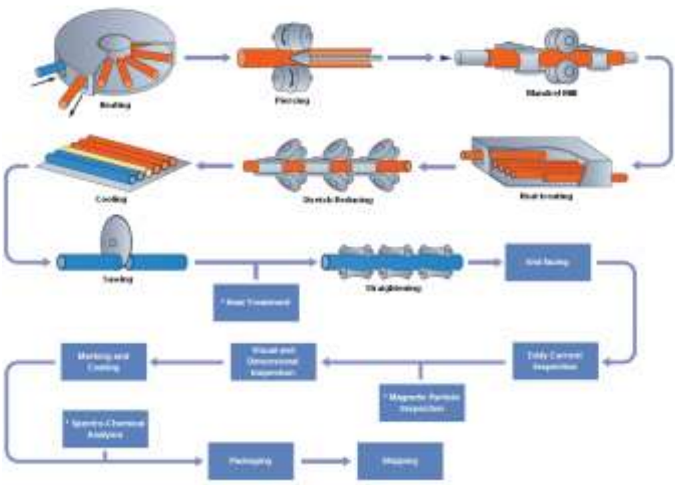

Figure 1. Mandrel Process
(https://www.wermac.org/pipes/pipemaking.html)

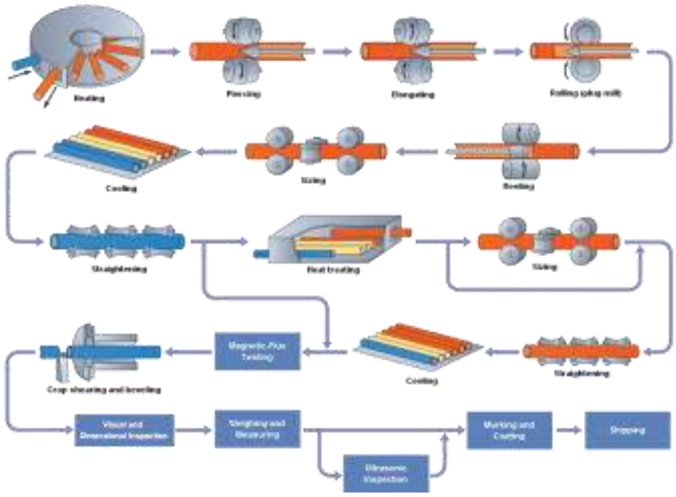

Figure 2. Plug Process
(https://www.wermac.org/pipes/pipemaking.html)

3. Demand Uncertainty

Various uncertainties and risks exist in the procurement process, such as lead time uncertainties, demand uncertainties, price uncertainties, yield uncertainties, supplier delays, supplier restrictions, and order overlaps (Barros et al., 2021). For OCTG manufacturing, lead time uncertainty, yield uncertainty, supplier delay, supplier constraints, and order cross-over can be ignored as the lead time from each green pipe supplier is known, and the ex-mill delivery, detail of product, and quality agreement are discussed and agreed before placing an order to the supplier.

The fluctuation of green pipe price depends on the iron ore price. But the uncertainty of price will not be a blocking point for the Company to order green pipe from supplier, because the final price to the Customer will be adjusted based on the green pipe price.

The green pipe price is subject to fluctuations depending on the price of iron ore. However, this price uncertainty does not hinder the company from ordering green pipe from suppliers because the final price to the customer will be adjusted based on the green pipe price. On the other hand, demand uncertainty is a crucial factor that affects the decision to establish a safety stock level. This uncertainty encompasses factors such as errors in demand forecasting, changes in customer orders, and uncertainty about the product specifications ordered by customers (Angkiriwang et al., 2014). Accurately estimating demand forecasting is a complex task (Lambert, 1998), and inaccurate demand forecasting can result in inventory shortages or surpluses, low service levels, rush orders, inefficient resource utilization, and the propagation of the bullwhip effect along the supply chain (Chopra & Meindl, 2007). There are various strategies available to deal with demand uncertainty, including part commonality, risk pooling, safety stock, safety lead times, flexible supply contracts, subcontracting or outsourcing, and deferral (Angkiriwang et al., 2014).

4. Safety Stock

Safety stock, also called buffer stock, consists of extra inventory to cope with both demand and supply uncertainties to prevent stockouts (Yamazaki et al., 2016). Strategies like safety stock and safety leadtime are typically used in inventory management to address demand and supply uncertainties (Van Kampen et al., 2010). In line with (Van Kampen et al., 2010), safety stock is considered to be an appropriate strategy for the prevention of stock-outs and the management of supply and demand variability (Gonçalves et al., 2020). In fact, despite the challenges inherent in their management, safety stocks are one of the most robust supply and demand uncertainty mitigation strategies (Koh et al., 2002). On the other hand, the traditional models used to determine the appropriate level of safety stock may result in higher levels of safety stock than necessary at the levels of the sub-assembly and finished good, and thus lead to higher inventory carrying costs than desired (Ruiz-Torres, 2010).

5. Intermittent Demand Forecasting

Inventory management for any item begins with the estimation of the mean and variance of the lead-time demand, and then the fitting of a demand distribution to these two parameters. This information is typically used for the calculation of optimal safety stock levels in order to meet a specific availability target or to minimize total system cost. A time series forecasting technique is usually used in the forecasting process. Time series forecasting methods are widely used in practice. This is because they are simple and easy to implement. Time series forecasting methods are primarily based on historical data.

2. METHODS

a. ARIMA

Box and Jenkins proposed an autoregressive integrated moving average model (ARIMA) as a method for forecasting time series. This method mainly analyzes the past and present data, examines their autocorrelation and partial autocorrelation functions and other characteristics to identify, estimate and diagnose the three-step model building process, fit the best model, and carry out data analysis forecasting (Wang, 2021).

ARIMA is a generalized autoregressive moving average (ARMA) model that combines autoregressive (AR) and moving average (MA) processes to create a composite model of time series. As the acronym suggests, ARIMA(p,d,q) captures the key elements of the model:

AR: Autoregressive. A regression model that uses dependencies between observations and a series of staggered observations (p).

I: Integrated. Make the time series stationary by measuring the difference in observations at different times (d).

MA: moving average. A method that accounts for the dependence between observations and residual error terms when using a model for lagged observations (q).

A linear process representing a simple form of an autoregressive model of order p (AR(p)) can be written as:

$$x_t = \mathrm{c} + \sum_{i=1}^{p} \emptyset_i x_{t-1} + \epsilon_t \qquad (1)$$

where:

x_t : the stationary variable

C : constant

$\emptyset_i$: autocorrelation coefficients at lags 1, 2, , p

ϵ_t : the residuals, are the Gaussian white noise series with mean zero and variance σ_ϵ^2

An MA model of order q, i.e., MA(q), can be written as:

$$x_t = \mu + \sum_{i=0}^{q} \theta_i \epsilon_{t-1} \qquad (2)$$

where:

μ : is the expectation of x_t

θ_i : weights applied to the current and prior values of a stochastic term in the time series

These two models are combined to form ARIMA model of order (p, q):

$$x_t = \mathrm{c} + \sum_{i=1}^{p} \emptyset_i x_{t-1} + \epsilon_t + \sum_{i=0}^{q} \theta_i \epsilon_{t-i} \qquad (3)$$

where:

x_t : the stationary variable

c : constant

$\emptyset_i$: autocorrelation coefficients at lags 1, 2, , p

ϵ_t : the residuals, are the Gaussian white noise series with mean zero and variance σ_ϵ^2

Where $\emptyset_i \neq 0, \theta_i \neq 0$, and $\sigma_\epsilon^2 > 0$.

b. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) is a type of Recurrent Neural Network (RNN) developed by Hochreiter and Schmidhuber. LSTM is a unique sort of RNNs with additional capabilities to memorize the sequence of information. The memorization of the earlier trend of the data is possible through a few gates together with a reminiscence line included in a standard LSTM (Siami, 2018).

The main difference between an RNN and LSTM is that LSTM can store long-range time dependency information and can suitably map between input and output data (Abbasimehr, 2020).

The LSTM algorithms continue to improve after training, so the inner neurons become an intact working structure and eventually discover the most appropriate weight ratio on the output parameters. Therefore, its predictions are better than general recursive neural network models when LSTM processes data related to time-series predictions in terms of errors and outcomes.

The LSTM algorithm consists of three types of gates, each serving a distinct purpose: Forget gates, Input gates, and Output gates.

The Forget gate is responsible for discarding irrelevant information from the cell. It achieves this by calculating the value of the forget gate using equation (4).

$$f_t = \sigma\left(W_f\, x_t + U_f\, h_{t-1} + b_f\right), \quad 4)$$

where f_t is the value of the forget gate, W_f is the weight for the input value at time t, x_t is the input value at time t, U_f is the weight for the output value from time t-1, h_{t-1} is the output value from time to t-1 and b_f is the forget gate bias and σ is the sigmoid function.

Furthermore, the memory cell state is calculated using equation (5).

$$C_t = i_t \odot C_t + f_t \odot C_{t-1}, \quad (5)$$

where C_t is the memory cell state value, i_t is the input gate value, C_t is the memory cell state candidate value, f_t is the forget gate value and C_{t-1} is the memory cell state value in the previous cell, and and $\odot$ is the Hadamard Product of the matrices (the product of the elements in the same position of the two matrices).

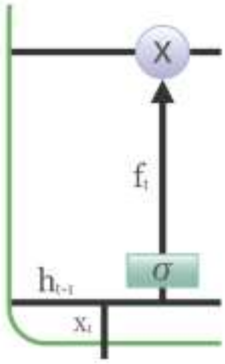

Figure 3. Forget Gate (geeksforgeeks.org)

If the output is 0, then the information is considered no longer useful and can be deleted. Vice versa, if the output is 1 then the information is stored for future use.

The addition of useful information to the cell state is performed by the input gate.

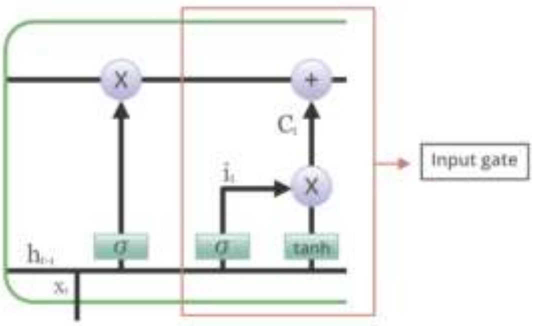

Figure 4. Input Gate (geeksforgeeks.org)

The calculation of the input and candidate gate values from the state of the cell is carried out using equations 6 and 7.

$$i_t = \sigma(W_i\, x_t + U_i\, h_{t-1} + b_i) \quad (6)$$

((**Error! No text of specified style in document.**.5) where i_t is the input gate value, W_i is the weight of the input value at time t, x_t is the input value at time t, U_i is the weight of the input value from time t-1, h_{t-1} is the input value from time t -1, b_i is the bias of the input gate and σ is the sigmoid function.

$$C_t = tanh(W_c\, x_t + U_i\, h_{c-1} + b_c) \tag{7}$$

where C_t is the candidate cell state value, W_c is the weight for the input value in cell to c, x_t is the input value at time t, U_i is the weight for the output value from cell to c-1, h_{c-1} is the output value from cell to c-1 and b_c is the bias in cell to c and tanh is the hyperbolic tangent function.

The task of extracting useful information from the current cell state to be presented as an output value is performed by the output gate.

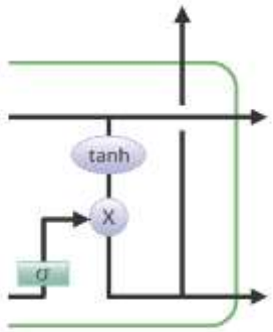

Figure 5. Output Gate (geeksforgeeks.org)

After the new memory cell state is generated, the value of the output gate can be calculated using equation (8).

$$o_t = \sigma(W_o\, x_t + U_o\, h_{t-1} + b_o) \tag{8}$$

where $o_t$is the value of the output gate, W_o is the weight for the input value at time t, x_t is the input value at time t, U_o is the weight for the output value from time t-1 , h_{t-1} is the output value from time to t-1 and b_o is the bias at the gate output and σ is the sigmoid function.

The final output value is calculated using equation (9).

$$h_t = o_t \odot tanh(C_t) \tag{9}$$

where h_t is the final output, o_t is the gate output value, C_t is the new memory cell state value and tanh is the hyperbolic tangent function.

c. Performance Evaluation

To validate model performance, the collected historical time series data is divided into training data and test data. Training data is used to build the model and to estimate the parameters of the individual models embedded in the procedure. Test data is used to measure the overall forecasting performance. Three different error measures are used to evaluate the forecasting accuracy of the approaches, including root mean square error (RMSE), mean absolute error (MAE), and mean scaled error (MSE) (Hyndman, 2006).

Root-mean-square error (RMSE) is a commonly used measure of model prediction accuracy. It is a measure of the differences, or residuals, between the actual values and the predicted values. The metric does not compare across data sets, but rather compares the prediction errors of different models for a given set of data.

The RMSE for series y at time period t is given by:

$$RMSE = \left(\frac{1}{t}\sum_{t=1}^{T}(x_t - y_t)^2\right)^{\frac{1}{2}} \tag{10}$$

MAE will calculate the absolute average value of the errors obtained based on the results of forecasting the test data.

The MAE for series y at time period t is calculated as:

$$MAE = \frac{1}{T}\sum_{t=1}^{T}|x_t - y_t| \tag{11}$$

MSE is suitable for evaluating the accuracy of intermittent demand series, since it is never undefined or infinite, even when sporadic cases are encountered, and its formulation for series y at time period t is:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{12}$$

d. Research Framework

The primary objective of this study is to determine the optimal safety stock level for OCTG products by forecasting their demand. To accomplish this goal, we employ the advanced deep learning technique known as LSTM and compare its performance against that of the well-established ARIMA method. The study's research framework is depicted in Figure 6.

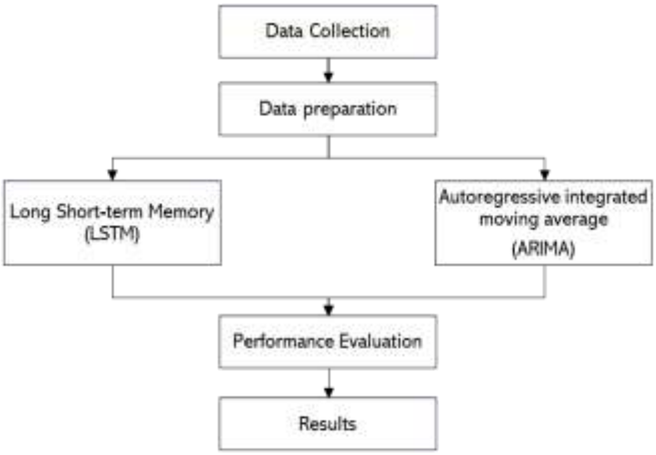

Figure 6. Research Framework

e. Data Preparation

Sales data covering the period from January 2010 to August 2022 was extracted, with the product range limited to sizes that can be produced by the Company, specifically from 2 3/8 inch up to 13 3/8 inch. The extracted dataset comprised more than 17,000 sales records, including all products and services supplied by the Company. However, to prepare the data for forecasting, certain pre-processing steps were necessary. First, all sales data for supporting materials not indicated as pipe (casing and tubing), such as running dope, protectors, and seal rings, were removed. Second, sales data for services like fumigation, sand blasting, and perforation, as well as sales data for non-pipe accessories like x-overs, lifting/handling plugs, and end caps, were also removed. Third, sales data for non-API 5CT specification products, including Line Pipe, Drill Pipe, and CRA, were removed. Finally, sales data for non-API 5CT grades, such as material 4140 80/110/125ksi and proprietary grades, were removed from the dataset.

After data cleaning, the sales data for casing and tubing that meet the predetermined criteria were obtained. Similar data processing should be applied to each pipe size. However, for the purpose of this study, only one product with the highest demand will be used for analysis.

From the dataset, it was found that the most commonly purchased pipe size by consumers is the 9-5/8 inch pipe, as depicted in Figure 7.

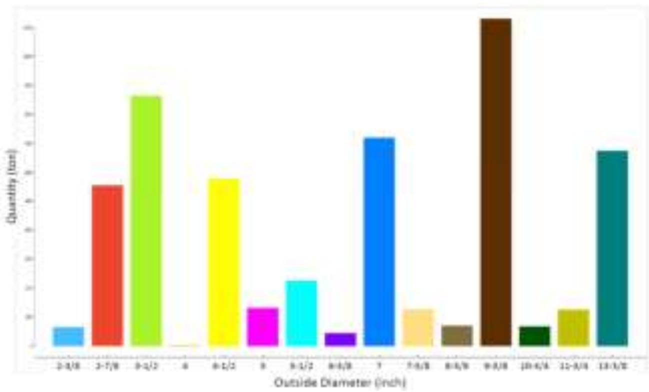
Figure 7. Total Sales Quantity for Each Pipe Size

To complement the analysis of the best-selling pipe sizes, it is important to identify the most commonly purchased grade for each of these sizes.

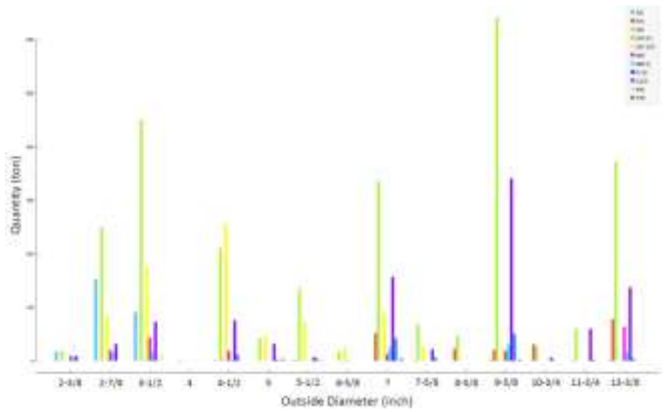

Figure 8. Purchased Pipe Grade for Each Size

Based on the dataset, Figure 8 demonstrates that the L80 grade is the most frequently purchased grade for the 9-5/8 inch size. Moreover, Figure 9 shows that L80 is also the most commonly purchased grade among all pipe sizes.

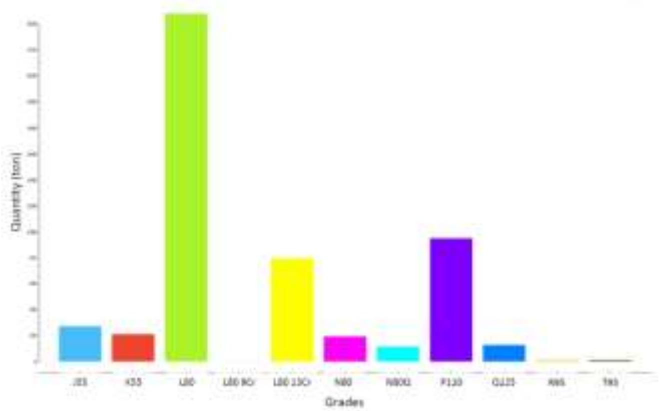

Figure 9. Purchased Pipe Grade for All Pipe Sizes

To further understand the 9-5/8 inch pipe, it is important to also determine its most frequently purchased weight.

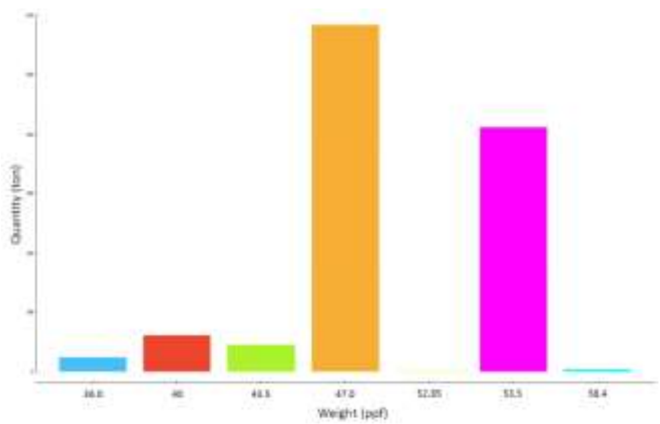

Figure 10. Purchased Pipe Weight for Pipe Size 9-5/8 inch

Figure 10 displays that the weight of 47.0 ppf is the most frequently purchased weight for the 9-5/8 inch pipe size. After this data processing, we selected one product as an example for demand forecasting using the LSTM method, which is the 9 5/8 inch 47.0 ppf L80 pipe. The sales data for this product from January 2010 to August 2022 is illustrated in Figure 11. The demand pattern for this product is intermittent, meaning that it is not consistent over time.

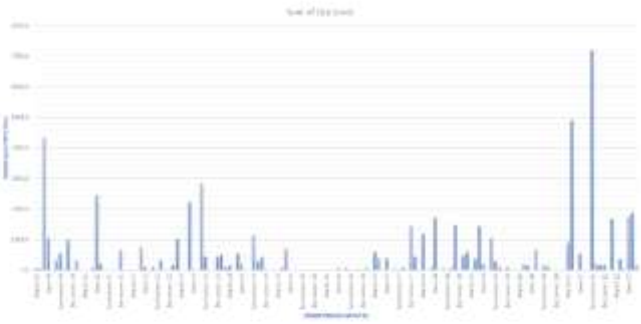

Figure 11. Purchased Pipe Grade for All Pipe Sizes

3. RESULT AND DISCUSSION

a. LSTM Results

Initially, we attempted to use daily sales data of OCTG products to forecast future sales using the LSTM method. However, the results were suboptimal, as evidenced by uncorrelated graphs between the predicted and actual data and high error levels. As an alternative approach, we resorted to simulating the data using monthly sales data. The dataset was divided into two parts, namely training data (train) and testing data (test), comprising 144 and 12 data points, respectively, representing a 12-month period from January 2010 to August 2022. LSTM was applied to the training data to generate the forecasting model, which was optimized using the Adam optimizer parameter over 100 epochs. The LSTM model produced more promising results than the previous attempt, as illustrated in Figure 12, which depicts monthly sales forecasts.

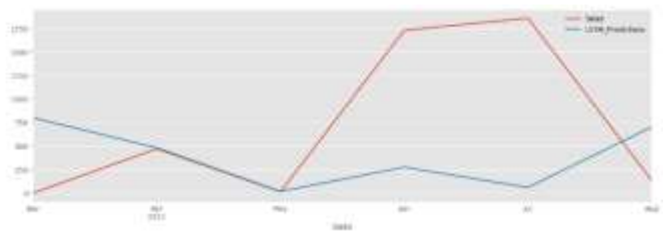

Figure 12. Comparison of LSTM vs Sales

To provide a comparison with the LSTM model, we also applied the ARIMA model for forecasting. The same amount of training and testing data was used as with the LSTM model. The results are displayed in Figure 13.

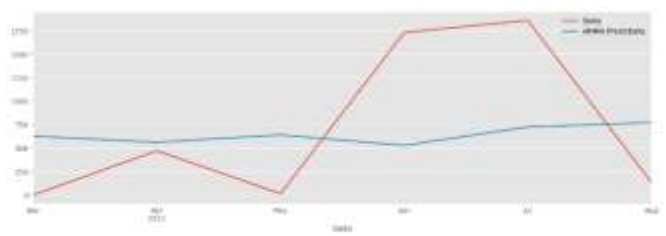

Figure 13. Comparison of ARIMA vs Sales

From the results of LSTM and ARIMA forecasting which were carried out using Python, a comparison of the results of the two can be seen in Figure 14.

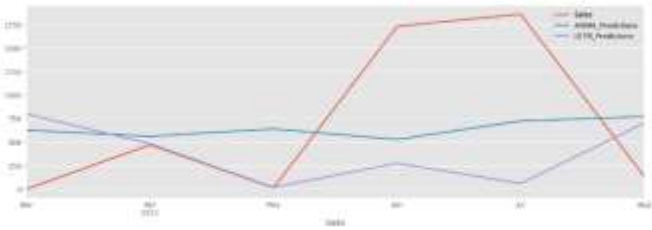

Figure 14. Comparison of LSTM vs ARIMA vs Sales

The graph shown in Figure 14 indicates that there is no significant difference between the forecasting results of the LSTM and ARIMA methods. However, it's important to note that the error rates for both methods differ, and these can be seen in Table 1.

Table 1. Comparison of LSTM and ARIMA Error Values

Models	RMSE Errors	MSE Errors	MAE Errors
ARIMA	810.08	6.562419e+05	719.97
LSTM	1026.50	1.053705e+06	772.94

Several experiments were conducted using monthly purchasing data, and it was observed that for intermittent requests, neither the ARIMA nor the LSTM methods produced satisfactory graphical results or error rates. Specifically, the forecasting results did not match the same pattern as the actual data, indicating limitations of both models in predicting this type of demand.

b. Data Processing for Every 6 Months

Since the ARIMA and LSTM methods did not yield satisfactory results for intermittent demand data, we attempted to forecast based on data aggregated every 6 months. This approach was motivated by considerations.

The daily and monthly data contain a large number of zeros, which can affect the modeling results of the ARIMA and LSTM methods, resulting in suboptimal graphical and error rate outcomes.

The quality standards stipulate that OCTG pipes should not be stored in yards for more than 12 months, after which the pipes require additional maintenance, such as inspection and re-coating, which increases storage costs. Thus, we set the target storage length for safety stock at 12 months, and a forecasting period of 6 months still falls within this requirement.

It takes 19 weeks (i.e., 4 months and 3 weeks) to purchase a pipe from the nearest Rolling Mill, which includes 12 weeks for the rolling process and 7 weeks for transportation to Batam. By forecasting the pipe demand data in 6-month intervals, the company can order pipes from the rolling mill in a timely manner.

We continued the analysis using the same product, namely an OCTG pipe with a size of 9 5/8 inches, weight of 47 ppf, and grade of L80. Figure 15 displays the data aggregated every 6 months.

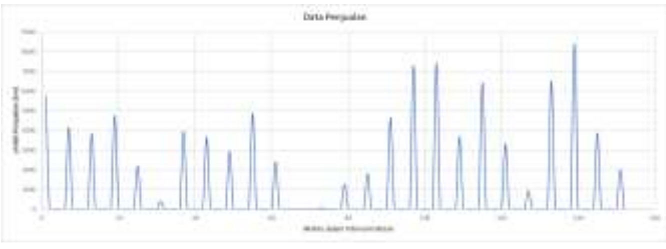

Figure 15. Graph of Purchased Pipes Size 9-5/8 inch, weight 47 ppf and grade L80 every 6 months

Figure 16 depicts the trend in the cumulative sales data of the OCTG product, obtained every 6 months between January 2010 and August 2022, using Python.

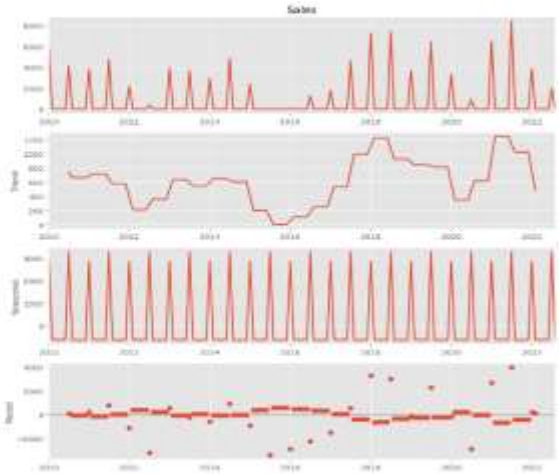

Figure 16. Graph of Sales Trends in the Period of January 2010 to August 2012 every 6 months

c. LSTM Results Using 6 Monthly Data

Forecasting was performed using the LSTM method, with sales data for every 6-month interval as input. The model was trained using the Adam optimizer with 100 epochs. Figure 17 displays the results obtained from the LSTM model.

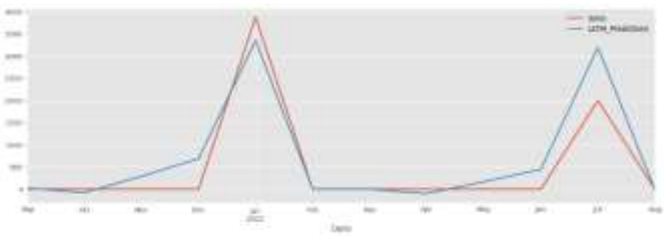

Figure 17. Comparison of LSTM Forecasting Results vs Sales Data Every 6 Months

d. ARIMA Results Using 6 Monthly Data

The ARIMA model was used for comparison with the LSTM model. The same amount of train and test data as used in the LSTM model was used in the ARIMA model. The results obtained from the ARIMA model are presented in Figure 18.

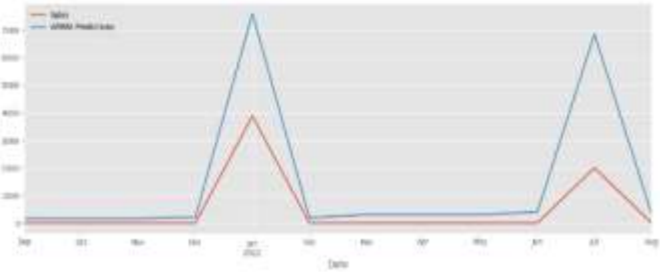

Figure 18. Comparison of ARIMA Forecasting Results vs Sales Data Every 6 Months

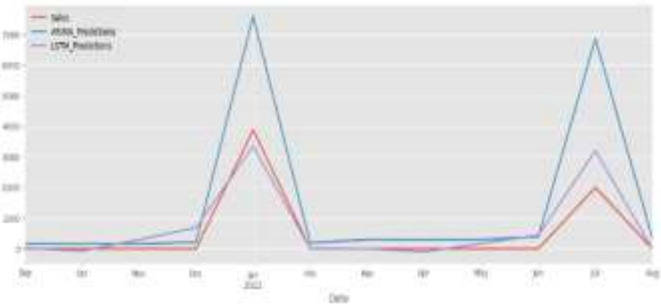

Figure 19 and Table 2 present a comparison between the results of LSTM and ARIMA forecasting, which were implemented using Python.

Figure 19. Comparison of LSTM Forecasting Results and ARIMA Data Every 6 Months

Table 2. Comparison of LSTM Error Values and ARIMA Data Every 6 Months

Models	RMSE Errors	MSE Errors	MAE Errors
ARIMA	1777.63	3.159985e+06	920.96
LSTM	457.90	2.096812e+05	295.55

Figure 20 highlights a noticeable discrepancy between the forecasting results generated by the LSTM and ARIMA methods. The error rates for both methods are presented in Table 3. A similar experiment was conducted on the second highest sales data for pipes, which were those with OD 9 5/8 inches, 53.50 ppf, and Grade N/L/R/P. Figure 17 and Table 3 demonstrate that the LSTM method outperformed the ARIMA method in generating accurate predictions.

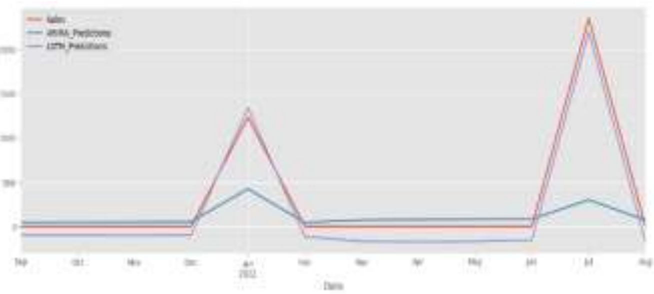

Figure 20. Comparison of Forecasting Results of LSTM and ARIMA Data Every 6 Months for OD 9 5/8 inches 53.50 ppf and Grade N/L/R/P

Table 3. Comparison of LSTM and ARIMA Error Values Data Every 6 Months for OD 9 5/8 inches 53.50 ppf and Grade N/L/R/P

Models	RMSE Errors	MSE Errors	MAE Errors
ARIMA	639.31	408728.50	290.05
LSTM	138.29	19125.32	134.63

4. CONCLUSION

The present study aims to predict sales of OCTG products at PT. Citra Tubindo by utilizing the LSTM method and comparing it with the ARIMA method. This choice of methodology is attributed to the intermittent nature of the sales data which lacks a seasonal pattern. Previous studies have demonstrated that simple time series forecasting methods are inadequate in generating accurate predictions.

The data processing and analysis carried out in this study have led to several conclusions. It has been observed that the demand for OCTG products is intermittent. Consistent with the findings of previous studies, it has been found that simple time series forecasting methods are not effective in generating accurate predictions for intermittent demand data. Furthermore, both the LSTM and ARIMA methods employed on the daily sales data of OCTG products have failed to produce satisfactory results in terms of graphical representation and error rates.

Analysis of monthly sales data for OCTG products using the LSTM and ARIMA methods has yielded better results than that of daily data. However, the predictions are not entirely satisfactory either in terms of graphical representation or error rates. In contrast, the use of 6-monthly (semester) sales data with the LSTM and ARIMA methods has produced superior outcomes compared to monthly data, both in terms of graphical representation and error rates. The LSTM method applied to the 6-monthly sales data can be utilized to predict the sales data for the next 6 months, which would enable the determination of the optimal level of safety stock for OCTG products. Future Research

The study results suggest several avenues for further research. Firstly, the methodology adopted in this study can be compared with alternative methods such as Croston, Teunter Syntetos & Babai (TSB), and simulations to explore their efficacy in forecasting intermittent data. Secondly, the research can be expanded to include other OCTG products with the highest sales levels. The forecasting results for the next period can be calculated, and the optimal level of safety stock for each product with a cost limit can be determined. Such an investigation would provide valuable insights into the demand patterns of other OCTG products, which would assist in optimizing inventory management and planning.

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5. ACKNOWLEDGMENTS (Optional)

The authors would like to express gratitude to the Bina Nusantara Graduate Program of Bina Nusantara University which offered assistance and assets for this research.

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