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Daily Container Volume Throughput Forecasting at Container Terminal Using Long-Short Term Memory (LSTM) Recurrent Neural Network

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Abstract

Container throughput is an important indicator for measuring the efficiency of a kontainer terminal. Kontainers that enter and exit are those transported to and from the terminal, respectively. Kontainers are stacked in the kontainer yard before they leave the terminal. Handling these kontainers accounts for a major workload at the terminal. Therefore, accurate short-term forecasting of daily kontainer gate-in and Gate-Out at a kontainer terminal is crucial for operational planning. While most forecasts are made at the strategic level of overall kontainer throughput, this study focuses on the daily kontainer gate-in and Gate-Out quantities with a case study at the TPKNM Makassar Kontainer Terminal. The study results show that the Epoch for each training set and performance metrics for each feature are 10, 50, and 100. Based on this, the difference in prediction performance with different epoch sizes is quite significant. The larger the Epoch, the smaller the MSE level.

Keywords: Kontainer Forecasting; Peramalan Container Troughput; LSTM, Recurrent Neural network

Abstrak

Throughput peti kemas merupakan indikator penting untuk mengukur efisiensi terminal peti kemas. Peti kemas yang masuk dan keluar adalah peti kemas yang diangkut ke dan dari terminal. Peti kemas ditumpuk di lapangan penumpukan peti kemas sebelum meninggalkan terminal. Penanganan kontainer ini menyumbang beban kerja yang besar di terminal. Oleh karena itu, prakiraan jangka pendek yang akurat untuk pintu masuk dan keluar peti kemas harian di terminal peti kemas sangat penting untuk perencanaan operasional. Sementara sebagian besar peramalan dibuat pada tingkat strategis dari keseluruhan throughput peti kemas, studi ini berfokus pada jumlah gate-in dan gate-out peti kemas harian dengan studi kasus di Terminal Peti Kemas TPKNM Makassar. Hasil penelitian menunjukkan bahwa Epoch untuk setiap training set dan performance metrics untuk setiap fitur adalah 10, 50, dan 100. Berdasarkan hal ini, perbedaan performa prediksi dengan ukuran epoch yang berbeda cukup signifikan. Semakin besar Epoch, semakin kecil tingkat MSE

Kata-kata kunci: *Keamanan siber, Era digital, Ancaman dan Serangan*

1. Introduction

PT Pelabuhan Indonesia IV serves as a key entry point for both domestic and international vessels and goods. Situated in the Makassar Strait, this port is the largest in Eastern Indonesia and plays a crucial role in the nation's economic development. It facilitates the movement of goods and people between land and sea. A vital component of port operations is the container terminal, a designated area for the unloading and loading of containers filled with various goods. The New Makassar Container Terminal (TPKNM) is an essential part of PT Pelabuhan Indonesia IV (Persero). TPKNM has significantly contributed to the growth of primary commodities from South Sulawesi, accounting for 46.92 percent of this growth, particularly through its domestic and international shipping services. [1].

The New Makassar Container Terminal (TPKNM) is currently undergoing several positive developments. The terminal, managed by PT Pelabuhan Indonesia IV, is witnessing an increase in container throughput, as evidenced by the growth in container loading and unloading activities from 2019 to 2022.

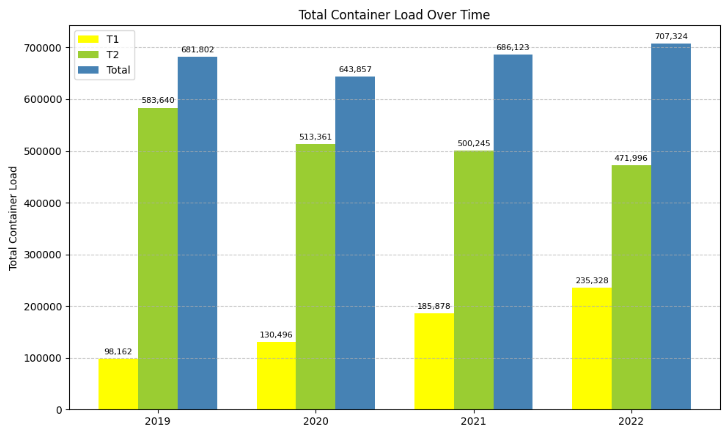

Figure 1. TPKNM Container Traffic Growth

The growth of the container industry has a major impact on the performance of the port business. In TPKNM, loading and unloading activities are very important because they directly affect the efficiency and performance of the port. This activity is greatly influenced by the volume of cargo traffic entering the port. [2]. The higher the volume of transport, the greater the container handling capacity [2]. Following initial interviews with the planning and control division, we gathered information regarding container loading and unloading activities from January to June 2023. The data encompasses four types of commodity clusters: General (GE), Hazardous (HZ), Material (MT), and Refrigerated (RF), with each category available in both 20-foot and 40-foot containers. Notably, the 20-foot GE commodity consistently demonstrated the highest activity each month, as evidenced by a total of 1,715 containers in January. Additionally, the highest handling time recorded was for the 20-foot containers within the GE category, reaching a total of 623.23 minutes. This data is further illustrated in the service time **Table 1**.

Tabel 1. TPKNM Service Time

Comodity	**Container Size**	***Gate In***		***Gate Out***		**Waiting Time (Min)**
		Qty	**Avg. (Min)**	**Qty**	**Avg. (Min)**	
GE	20	1715	400.8	1833	629.73	623.23
	40	879	438.24	502	532.61	526.11
HZ	20	4401	480.40	6509	635.27	628.77
	40	1041	485.66	1298	622.21	615.71
MT	20	2017	434.63	1684	555.32	548.82
	40	748	561.31	1377	472.61	466.11
RF	20	2597	571.54	773	397.97	391.47
	40	1314	467.69	624	340.96	334.46
Total						4134.68

In January, the service waiting time for all commodities reached 4,134.68 minutes. This elevated waiting time can be addressed through various strategies, such as adding port gates and closely monitoring container arrivals and departures. While adding port gates entails significant costs and complex planning, analyzing and forecasting container throughput patterns is a more suitable solution. Container throughput is a crucial metric for assessing the efficiency of container terminals [3], [4], [5], [6]. Incoming and outgoing containers are transported to and from the terminal, respectively. Containers are stacked in the container yard before they leave the terminal. Handling these containers contributes to the main workload at the terminal. [7]. Accurate short-term forecasting of daily incoming and outgoing containers at container terminals is essential for effective operational planning. [3], [8]. While most forecasting is done at the strategic level of overall container throughput, this study focuses on the number of containers entering and leaving each day with a case study at the TPKNM Makassar Port Container Terminal.

Gate-in and Gate-Out container data represent a specific type of time-series data. Time series forecasting involves analyzing historical data from a variable, which serves as a foundation for a model that captures the relationships within the data patterns. This model is then utilized to predict future values of the time series data [9]. Long Short-Term Memory (LSTM) is a technique derived from Recurrent Neural Networks (RNN) that effectively extracts information from long-term, sequential, or time-series data [10]. This study aims to forecast the volume of containers entering and exiting TPKNM by employing the LSTM neural network, carefully considering the epoch dynamics to minimize error during the forecasting process.

2. Method

2.1. CRISP-DM Approach

This study uses the Cross-Industry Standard Process for Data Mining (CRISP-DM) methodology, which is a methodology for developing data mining solutions. This methodology explains six main steps in implementing a data mining model [11], [12].

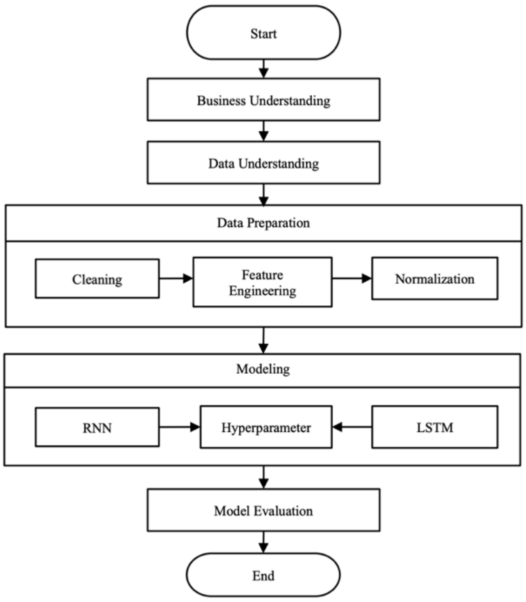

Figure 2. CRISP-DM Process

The stages in CRISP-DM include: 1) Business Understanding, which involves a deep understanding of customer needs. Activities include determining business objectives, assessing available resources, setting data collection objectives, and creating a project plan. 2) Data Understanding is the data understanding stage that includes identifying, collecting, and analyzing relevant data to achieve project objectives. Activities include initial data collection, explanation, exploration, and quality verification. 3) Data Preparation, often called "data mining," is preparing the final data for modeling. Activities include improving the data quality to suit the modeling process that will be carried out later. 4) Modeling involves creating and evaluating various models using different techniques. This stage has four main tasks: choosing a modeling technique, designing tests, building models, and evaluating models. 5) Model Evaluation is the phase to assess the model that best suits business needs and determine the next steps. The three main activities in this phase are evaluating results, reviewing the process, and determining the next st

The Data Mining Model used in this study is a Long-Short-Term Memory Recurrent Neural Network (RNN). RNNs are machine learning methods that can be used to predict time series data and have quite good accuracy **[13], [4]** . Long-short-term memory (LSTM) is a method developed from RNN that can extract information from long-term, time series, or sequential data **[10]**.

2.2. LSTM *Neural network*

Long Short-Term Memory (LSTM) is a specialized artificial neural network that addresses the vanishing gradient problem commonly encountered in traditional Recurrent Neural Networks (RNNs) **[13]**. LSTM networks excel in retaining information over extended periods while effectively filtering out irrelevant data, making them particularly effective for processing time-series data, including text, audio, and other signals [14]. Gate-in and Gate-Out container data represent a specific form of time-series data. Time series forecasting involves the analysis of historical data from a variable to develop a model that reveals the relationships within the data patterns. This model is then utilized to predict future values of the time series data [9] [3], [8], [10]. The initial step in addressing time series data challenges is gathering and selecting the appropriate variables and then choosing the most suitable model to achieve optimal accuracy [15]. One commonly used method for time series analysis is the Autoregressive Integrated Moving Average (ARIMA).

The ARIMA model has notable limitations, primarily its assumption of linearity and the existence of non-linear elements in the residuals it generates. While ARIMA excels in short-term forecasting, its accuracy diminishes when applied to long-term predictions **[16]**. In contrast, the LSTM model can process linear and non-linear data, though it requires a significant amount of time and tuning of various parameters to reach optimal performance. Furthermore, LSTM proves advantageous for long-term forecasting due to its memory cells, which can retain information over extended periods **[14]**. By employing LSTM, the limitations of ARIMA can be addressed, allowing for the identification of non-linear data patterns and enhancing long-term forecasting accuracy. This study focuses on predicting the volume of containers entering and leaving TPKNM using the LSTM neural network [17]. The following outlines the steps involved in LSTM implementation **[10], [13]**.

1) 1) Determine the Forgate Gate to be removed from the main memory cell. This stage is carried out on the sigmoid activation layer. This layer functions to determine which layer will be used and which layer will be forgotten. The forget gate produces the numbers 0 and 1 for the memory state of cell C_{t-1}. The number 1 represents to retain memory and 0 to forget the stored memory.

$$f_t = \sigma((W_f . x_t)(U_f . h_{t-1}) + b_f)$$

2) 2) Determine the Input Gate that will be the input for the initial state cell. At this stage, there are two layers: the sigmoid layer and the tanh layer. The sigmoid or input layer affects which value or layer will be updated. Meanwhile, the tanh layer forms a vector of new feasible candidate values $C^{\rightarrow} t$, which will be enumerated into the state cell. Then, the old state cell, C_{t-1} is updated to become a new state cell, Ct.

$$i_t = \sigma((W_i . x_t)(U_f . h_{i-1}) + b_i)$$
$$\vec{C}_t = \tanh h \ ((W_{\vec{C}_t} . x_t)(U_{\vec{C}_t} . h_{t-1}) + b_{\vec{C}_t})$$

3) Update new information, then implement the decisions made in the previous stage.

$$C_t = f_t * C_{t-1} + i_t * \vec{C}_t$$

4) The sigmoid layer will be executed to identify which portion of the cell state will be outputted. Subsequently, the cell state will be processed through the tanh function to constrain its values between -1 and 1. This result will then be multiplied by the output of the sigmoid layer, ensuring that only the designated portion is included in the output.

$$o_t = \sigma((W_o . x_t)(U_o . h_{t-1}) + b_o)$$
$$h_t = o_t * tanh(C_t)$$

5) Determine the sigmoid activation function.

3. Results and Discussion

3.1 Model LSTM Input Feature

In predicting the number of incoming and outgoing containers, several input features are needed, such as the length of service waiting time, type and size of container, and the number of containers entering and leaving the port. The LSTM model can accommodate datasets that have one feature variable and one target variable or are called univariate LSTM. Meanwhile, the LSTM model that has more than one feature variable and one target variable is called Multivariate LSTM **[18]**. This study uses one feature variable and one target variable to predict the number of containers entering and leaving the port gate. The feature variable is the variable date of the container entering and leaving and the target variable is the number of incoming containers, both 20-foot and 40-foot containers. To facilitate the calculation of the number of containers, each container entering or leaving the port will be converted into teuz units.

The input data for the LSTM model consists of daily records of containers entering and leaving the port from 2019 to 2023. The initial dataset used in this study contains outliers—data points that deviate significantly from the average. The training process of the LSTM model is susceptible to the distribution and range of these data points, making it challenging to extract features during training effectively **[14]**. As a result, the first step taken is data preprocessing, which includes the removal of outliers. This study employs the interquartile range (IQR) method to identify outliers **[12], [18]**. Specifically, a value is considered an outlier and removed from the dataset if it exceeds the third quartile plus 1.5 IQR or is below the first quartile minus 1.5 IQR. Below is the initial dataset of containers entering and leaving the port, measured in TEUs.

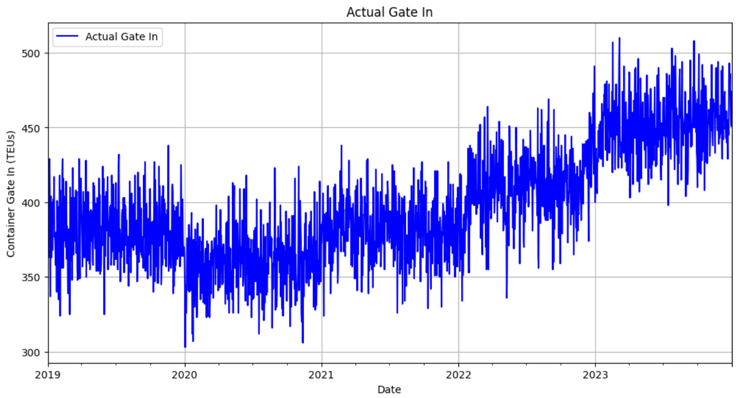

Figure 3. Container Gate-In Dataset after *Preprocessing*

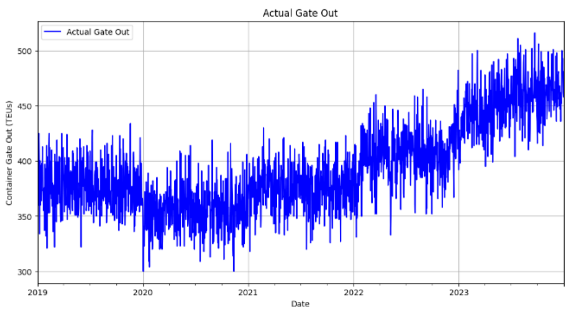

Figure 4. Container Gate-Out Dataset after *Preprocessing*

The volume of containers moving in and out of the port generally follows a similar pattern. However, the actual numbers for containers entering and leaving the port show slight variations. Initial calculations indicate that, on average, the difference between the number of containers entering and leaving is about 1.2%, with a tendency for more containers to enter the port. The volume of containers entering and leaving the port has increased yearly. A downward trend was observed in 2020, primarily due to the impact of the COVID-19 pandemic. However, between 2022 and 2023, port activities have been on the rise as we transitioned into a new normal following the end of the pandemic.

3.2 Architectur Model

This study utilizes a Univariate LSTM Neural Network model, which consists of two LSTM layers, a single dropout layer, and two dense layers to predict the volume of incoming and outgoing containers at the port. The four input features are formatted into a training set. The data is then processed through two LSTM layers, with 50 and 100 units, respectively, in each layer. The 'relu' activation function is applied in both LSTM layers, and a dropout layer is incorporated to prevent overfitting and enhance the training process of the artificial neural network. The two dense layers transform the output vector from the LSTM layer into a single dimension corresponding to the predicted volume of incoming containers. Specific parameters for each layer are provided in the accompanying table.

Table 2. LSTM Model Parameter Spesification

Layer	**Parameter**
LSTM 2	Unit = 100 Fungsi Aktifasi = Relu input_shape=(n_input, n_features)
***Dense* 2**	Unit = 1 Fungsi Aktifasi = Relu
Dropout	*Dropout* rate = 0.2
Model Compailer	Optimizer= adam Learning rate = 0.001 *Loss* = Mean Square Error

3.3 Container Troughput Prediction *Time series* Result

The LSTM model used in this study was implemented using Google Colab Pro on a MacBook Pro with an M1 processor. The setup did not utilize a GPU and ran on the Sequoia 15.1.1 operating system. Google Colab offers various automated library services, including the

Keras deep learning library and TensorFlow, essential for neural network computing. These libraries provide various standard Python features without needing separate installation. The input dataset for training the model consists of 5,472 datasets of container data entering and leaving the TPKNM Makassar Port from January 2019 to December 2023. To predict the volume of containers entering and leaving the port, the dataset has been filtered to focus specifically on Gate-In and Gate-Out container records.

The dataset is divided into an 80% training set and a 20% test set for each input model, maintaining a non-randomized time sequence. The performance of the proposed model is evaluated using the standard mean square error (MSE) metric. The number of epochs for each training set and the performance metrics for each feature are set at 10, 50, and 100. Based on these settings, the differences in prediction performance across various epoch sizes are significant; specifically, a larger number of epochs results in a lower MSE. [8], [18].

Table 3. Epoch dan MSE Value Comparison for Gate-In dan Gate-Out Activity

Neuron	**Epoch**	**MSE Gate-In**	**MSE *Gate-Out***
100	10	16.523	22.014
100	50	0.0089	0.176
100	100	0.00294	0.0554

An epoch refers to one complete cycle through the entire dataset during the model training process [19]. Each epoch allows the model to update its weights based on the training data [20]. One standard metric used to evaluate model performance is the Mean Squared Error (MSE), which measures the average squared difference between the model's predicted and actual values. A lower MSE indicates better performance. At the beginning of training, the MSE is typically high because the model has not yet learned the patterns within the data. As the number of epochs increases, the model learns from the data, causing the MSE to decrease, which signifies improved prediction accuracy. However, if the number of epochs is excessive, the model may overfit the training data. It learns too many details specific to the training set and cannot generalize to new data. As a result, the MSE on the validation or testing data may increase after a certain point. The graph depicting the relationship between the number of epochs and MSE usually shows a sharp decrease in MSE at the beginning of training, followed by a gradual decline, which eventually stabilizes or even increases if overfitting occurs [20].

The following are the results of training, validation, and testing data after the initial dataset is split into several windows (window dataframes). Window Dataframe is a way to restructure time series data so that it can be used in machine learning models, especially those designed for sequence prediction such as LSTM. Windowing helps frame time series data in a way that is suitable for sequence-based machine learning models.

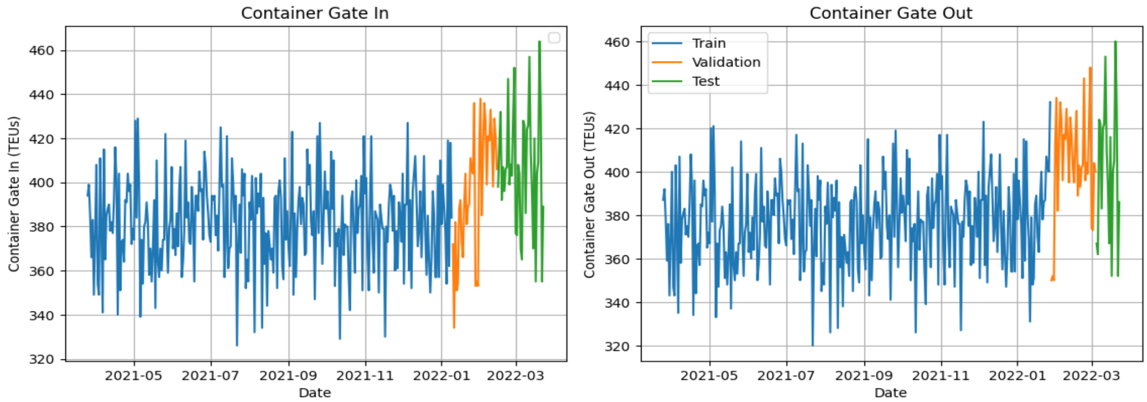

Figure 5. Initial Dataset for Train, Validation, dan Test Process

Figure 5 illustrates the performance of the LSTM model with dropout regularization. The model can track fluctuations and changes in the training data, although some segments show lower accuracy in the testing data. This indicates that the LSTM architecture can effectively predict data with temporal dependencies, even with no specific sequential pattern, as with the gate-in and gate-out container volume data from the Makassar TPKNM Port. Additionally, these results suggest that the model does not experience overfitting, whether with the training or testing data. Using dynamic parameters enables the model to generalize well, allowing it to identify patterns in the training data without becoming overly complex. Consequently, the model can effectively apply the patterns it learned from the training data to new data.

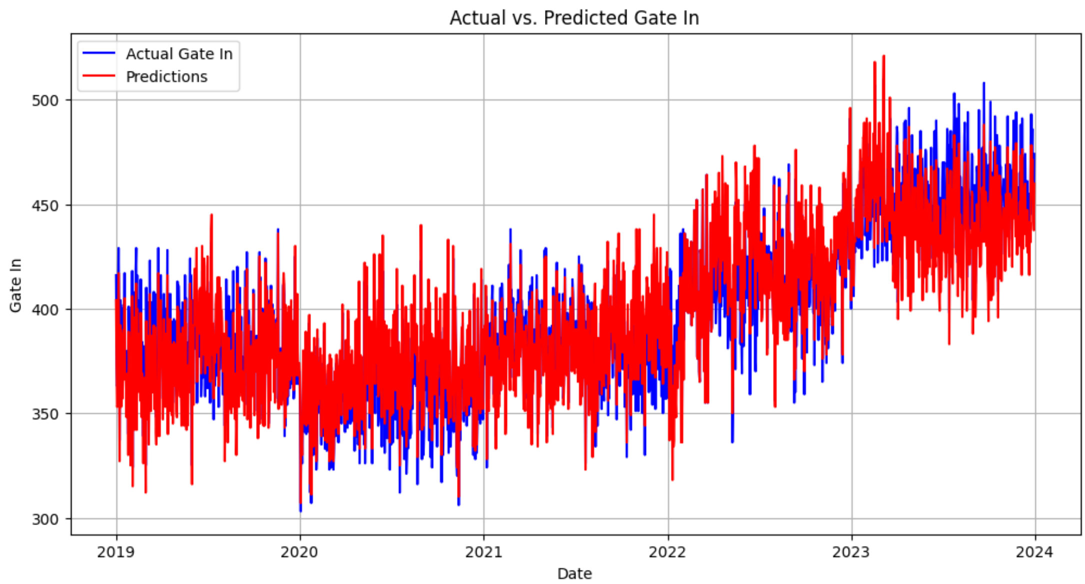

Figure 6. Actual vs Predicted Result Gate In

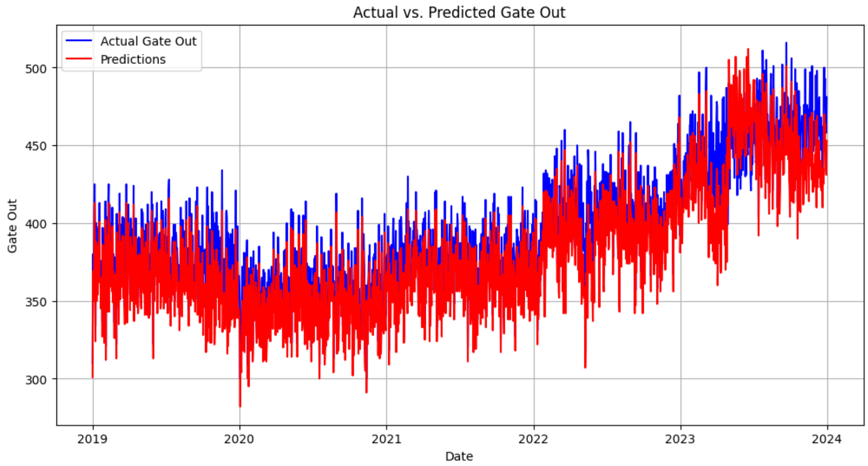

Figure 7. Actual vs Predicted Result Gate Out

According to the prediction results illustrated in the graph above, there is a noticeable downward trend in the number of containers entering and leaving the port. This information can serve as a valuable reference for port managers when setting targets, determining container yard capacity, regulating incoming and outgoing containers, and enhancing service policies. Additionally, it can guide the development of work plans and informed decision-making, such as planning for container yard requirements, managing financial risks, and considering the potential for adding gate facilities. These measures aim to improve the performance of port operators, which ultimately contributes to the smooth operation of the regional economy.

4. Conclusion

Gate-in and Gate-out container data represent a specific type of time-series data. The Long Short-Term Memory (LSTM) model is suitable for datasets with one feature variable and one target variable, explicitly focusing on container entry and exit dates and the volume of containers entering and leaving the port. The input dataset used to train the model consists of container data from the TPKNM Makassar Port, covering the period from January 2019 to December 2023, totaling 5,472 entries. The model training involved different epochs for each dataset, specifically 10, 50, and 100. The differences in prediction performance across these epoch sizes were quite notable. Generally, as the epoch count increases, the Mean Squared Error (MSE) tends to decrease.

5. *Acknowledgement*

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