Container Throughput and Direction Forecasting for the Port of Vancouver

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Abstract. Classical statistical methods are a common method of forecasting monthly container throughput. The Port Authority of Vancouver, however, is looking to optimize supply chain efficiency through accurate daily forecasts per terminal. Further, the Port is looking to know the direction of said cargo and the amount of cargo that is rail-bound versus truck-bound. Accurate daily forecasts in combination with rail-bound percentages are needed to ensure rail companies have enough lead time to assemble the required rail cars from across the country. The direction of cargo informs the rail companies of the duration of which their railcars will be used. Demurrage of excess rail cars is expensive, and demurrage of cargo leads to a supply chain delay. Optimizing throughput forecasts optimizes supply chain efficiency, leading to a faster delivery of goods nationwide.

1 Introduction

The Port of Vancouver is Canada's largest and most critical port, leading in the facilitation of the country's goods exchange with the world, transiting over $200 billion in merchandise yearly. That underpins activities worth $305 billion of goods traded annually, contributing to $11.9 billion in national GDP and supporting over 115,000 jobs. This trade is governed by the Vancouver Fraser Port Authority, and it is colossal in geographical scope. Such geographical coverage entails a series of land, water, and coastlines that are very integral to the economic make-up of the country, ensuring reach for goods without any kind of hindrance. The Port wants to optimize the efficiency of its cargo flow by extending its forecasting window of incoming container volume.

Presently, the Port receives information on expected incoming cargo from the Canada Border Services Agency (CBSA) approximately two weeks before arrival. Unfortunately, two weeks does not give rail companies enough time to optimally assemble their rail cars. The rail companies marshall their cars from across the continent with a potential four-week lead time to their arrival in Western Canada. Three critical fields of information were identified by the Port: Daily twenty-foot equivalent unit (TEU) count, percentage of daily cargo that is rail-bound, and destination of the containers. TEU is the measure of the volume of cargo that comes off a given vessel. The percentage of that cargo that is rail-bound determines the number of railcars required to carry it. The destination further informs the rail company of the duration their railcars will be used. For example, shipping to Maine has an 8-day travelling time from Vancouver thereby resulting in 16 days of usage in round-trip time back to Vancouver. On the other hand, cargo bound for Seattle has an approximately 2-day round trip. This paper aims to give a daily estimate of TEUs at the busiest terminal of the Port of Vancouver: Deltaport.

Previous literature on forecasting methods looks at trends over months and years, establishing and identifying the need for infrastructure investments to support the growth of the respective port. Classical statistical methods are suitable for long-term forecasts, but a different approach is needed for short-term forecasts. We approach this problem with machine learning algorithms. Long short-term memory models (LSTM) have been shown to effectively forecast daily container volume based on historical data. Recurrent neural networks (RNNs) have shown decreased efficiency when coupled with long-term forecasting. The LSTM model is a variation of the RNN, specialized to solve the vanishing gradient problem. The vanishing gradient problem occurs when the entering sequence length in an RNN is too long, and the training of the model encounters errors. LSTM is a version of an RNN that is built to overcome this issue. (Bengio, Courville, and Vincent 2013).

The Port of Vancouver provided us with approximately eight full years of historical TEU volumes (2016-2024 inclusive). Included with the data were columns that indicated the destination for each TEU, whether the TEU was rail-bound or truck-bound, and the date the TEU was received.

In this research, we focus on enhancing the predictive models used at the Port of Vancouver, shifting from traditional methodologies like seasonal auto-regressive integrated moving average (SARIMA) and multilayer perception (MLP) to the more advanced LSTM networks. While the older models served well in certain instances, they struggled to fully grasp the complex and dynamic patterns of container traffic in a port environment. LSTM networks have proven to be more accurate and efficient at understanding these complexities due to their ability to process data over longer sequences without losing crucial information.

Our approach utilizes LSTM's capacity to analyze vast amounts of historical data, thus providing more reliable forecasts of daily container arrivals. This capability allows for improved operational planning and handling of the port's cargo movements. As the Port of Vancouver grapples with the challenges of managing its extensive trade activities, the adoption of LSTM networks signifies an important progression towards a more efficient and responsive system.

This transition showcases the Port of Vancouver's commitment to technological advancement and reflects a broader movement within the maritime industry toward embracing sophisticated data analysis tools. The findings from our LSTM-based models promise a significant impact on the port's daily operations, offering the potential for smoother coordination, and ultimately a more time-saving flow of goods through this crucial gateway to international trade.

This document is structured as follows: Section 2 gives background details on the pitfalls of traditional forecasting models and the merits of using LSTM in the prediction of container throughput at the Port of Vancouver. Section 3 explains the method of modelling using machine learning and LSTM to overcome the challenges in forecasting the daily volumes of containers. Section 4 elaborates on the data analysis, with much elaboration on the time series data and how well they predict the predictive power. In Section 5, the results of the application with the LSTM model are presented and they showed the successful performance of forecasting. The results will be discussed in more detail in section 6, in line with the meaning and implication of the study. In Section 7, we focus on future work and possible areas that may lead to further research that have been identified appropriately for an opportunity to enhance forecasting models. Section 8, the impact of accurate forecasting on supply chain efficiency and the bigger impact on the Port of Vancouver. Finally, Section 9 concludes the shift towards more advanced machine learning techniques that help in improving forecasting, but most importantly, the role of technology in the modernization of port operations.

2 Literature Review

Most forecasting literature for ports analyzes trends over months and years. Six classic statistical methods were compared for three ports in Taiwan and found SARIMA to be the most accurate model (Huang, Chu, and Tsai 2020). Another study on the same three Taiwanese ports using the same six methods found the classical decomposition model to be the most accurate for forecasting container throughput with seasonal variations (Peng and Chu 2009). Five of the six same methods (including SARIMA) were compared for three ports in China and concluded that hybrid grey forecasting was the most accurate method (Huang, Chu, and Hsu 2022). All recommended a form of classical decomposition model for ease of use and simplicity. Neural networks in conjunction with grey modeling were used for forecasting at Ningbo-Zhoushan port (B. Liu, X. Wang, and Liang 2023).

Container throughput at the Tanjung Priok Port in Indonesia was studied using SARIMA, additive and multiplicative seasonal Holt-Winters, and the vector error correction model (Pang and

Gebka 2017a). They found SARIMA to be the worst-performing in-sample model. (Munim et al. 2023) studied the newer prophet model and found that it performs well based on in-sample data, but poorly in out-of-sample performance. They further concluded that models optimized for mean absolute percentage error (MAPE) performed best. Their research concurs with (Pang and Gebka 2017b) and (**peng**) that more complex methods do not necessarily yield better results. There is no consensus in the literature on the ideal model for forecasting, and more data is needed.

There have also been multiple studies on using neural networks as forecasting methods. The LSTM neural network model was compared to a classic statistical method and found, on average, that neural networks produce a more accurate model, with LSTM being much more accurate than SARIMA (Yinping Gao and Fan 2019). Further research on this issue has found that the model can be further improved with the application of external economic indicators, time series decomposition, and multivariate LSTM models for forecasting volumes at major ports(Eunju Lee and Bae 2021). It is not only more accurate than conventional statistical methods; this method is also applicable without being limited by a situation like unexpected global phenomena, in this case, economic fluctuation.

LSTM models are used to make predictions at the ports in China on a daily basis (Gao, Chang, Chen, et al. 2018). The LSTM model forecasted data compared with actual out-of-sample data, whereby an error was recorded at 12.39%. Another research in the Journal of Data Information Management compared statistical and machine learning-based models to predict volume of air cargo using two techniques: multiple linear regression and ARIMA, three machine learning models, which include a neural network (NN), support vector regression (SVR), gradient boosting regression tree (GBR). 365 observations were used to conduct this experiment. Finally, it was concluded that the ARIMA method is the model which gives the most precise forecast for the short term, while the SVR model is the one that gives the most accurate forecast for a long term(J. Liu et al. 2020).

Long Short Term Memory (LSTM) networks were observed to be effective in the maritime logistics industry by (Cui et al. 2022) and (Jiang, Xie, and S. Wang 2021), who have highlighted the capability of the networks in handling critical patterns of cargo movement and port activities. There can be more accuracy in the prediction of cargo volume. Using LSTM in container throughput and vessel arrival forecasting is revolutionary in the sense that there can be a more accurate prediction of cargo volume. This level of accuracy in prediction makes proper allocation of resources an easy task and, at the same time, increases the efficiency of cargo processing, decreases traffic, and greatly streamlines the operational procedures at the port. The LSTM model presents such flexibility and capacity for constant learning, allowing them to improve the forecast over time with the new data, hence guaranteeing that changes in trends and the pattern of data do not reduce accuracy. It ensures improvement in operational planning with the use of an LSTM-based forecasting approach. Assuring the Port of Vancouver readiness in handling changed cargo quantity and making the operation smoother and more effective. It also makes the port management strategy more proactive since changes can be made in real-time with all the required information availed and problems tackled before their occurrence.

The authors (Zhang, Y. Liu, and Yu 2019) and (Tang and Farzan 2021) emphasize the significance of anticipative thinking in keeping a competitive edge in a very dynamic world of global trade, where timeliness and adaptability are key. This way, the Port remains flexible for infrastructure investment and resource allocation decisions based on data requiring predictive insights from LSTM projections. Integration of LSTM models in the Vancouver forecasting framework would, therefore, make a very key step towards the advancement of machine learning integration. As argued by these authors, this shift only from traditional statistical models to sophisticated machine learning techniques represents using historical data to increase forecast accuracy. This will, therefore, ensure that the Port of Vancouver is on top of the international maritime sector in maintaining the ability to maximize operational readiness and adaptability to changing circumstances through the use of LSTM network implementations.

The crux of the project centers on the application of LSTM networks; this is a type of RNN network excelling in modeling and forecasting time-series data. In fact, the architecture of LSTMs is unique and very useful for predicting sequences with long interval dependencies. Therefore, while dealing with time series forecasting, an architecture like LSTM would be very suitable. In the scope of port operations, these predictive capabilities yield precise predictions of container arrivals, optimizing the logistic process in this way, and increasing the general efficiency (Jiang, Xie, and S. Wang 2021). This evolution of forecasting methodologies points out benefits that can be obtained by moving from traditional statistical models toward new state-of-the-art machine-learning techniques. By ditching the prior literature-based insights and deploying the LSTM network, the present model well leverages the historical information to bring substantial improvement in forecast accuracy.

3 Model

The goal of machine learning is to develop algorithms that improve through practice, which enhances their ability to classify and make predictions. This process involves creating a classifier function from the provided training data, which is then applied to new datasets in order to evaluate its performance and accuracy (Staudemeyer and Morris 2019).

3.1 Recurrent Neural Networks

Various architectures have been developed for machine learning; amongst them, RNNs stand out, particularly for their ability to process sequential data. Unlike feedforward neural networks (FFNN), where information moves from input to output, RNNs incorporate a looped network structure. This feature enables the network to retain memory from previous inputs by incorporating the output of the hidden layer at each time step back into the hidden layer as part of the input for the following time step.

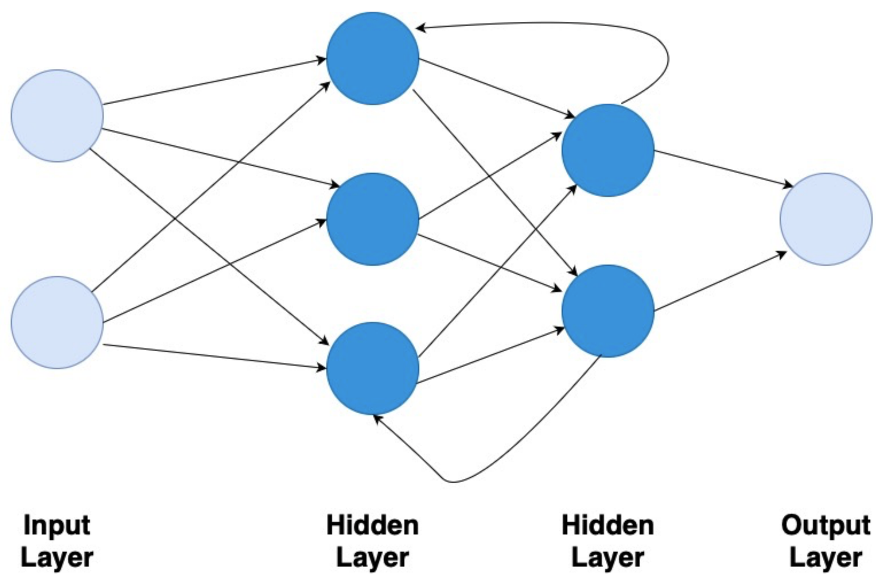

Figure 1: Structure of an RNN, where a hidden layer loops back to the previous hidden layer

This allows RNNs to utilize information from past events to current sequences, building a temporal knowledge base that works well for time-series events analysis. This capability is advantageous for the task of forecasting container throughput at the Port of Vancouver, where analysis of historical data allows for accurate future predictions.

3.2 Training RNNs

A common method to train RNNs is Backpropagation Through Time (BPTT). This training method is an extension of the traditional backpropagation training algorithm, where the key component involves adapting the temporal sequence processing of RNNs. This method involves unrolling the RNN through time, transforming it into a FFNN, where each layer represents the network at a different time. Figure 2 depicts the unrolling of a single node through time.

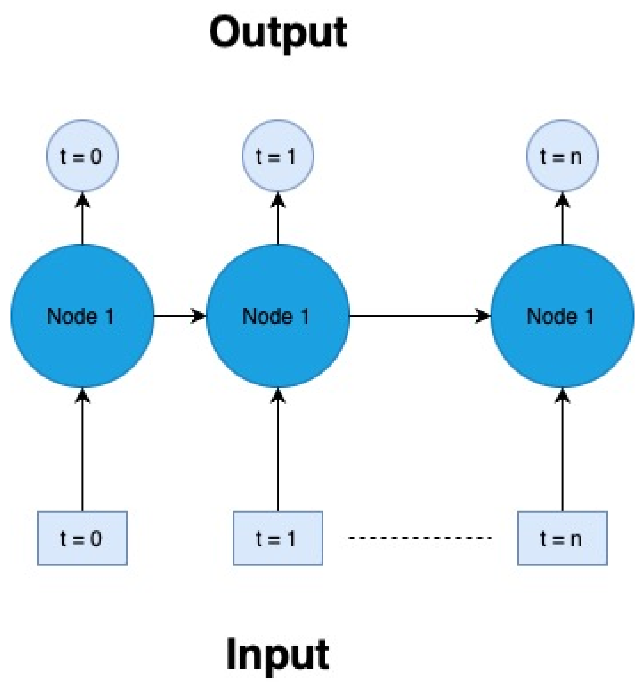

Figure 2: Unrolled RNN of a single node

This allows the RNN to update its corresponding weights based on the errors derived from the entire sequence. During this process, we calculate gradients, which are essentially signals that tell us how to adjust the weights to reduce errors in predictions. (Staudemeyer and Morris 2019).

However, an issue arises when training RNNs with BPTT, mainly the vanishing gradient problem, where gradients tend to diminish or decay as they are propagated back through time. Another issue is the exploding gradient problem. Similar to the vanishing gradient, but in this case the gradients tend to exhibit exponential growth rather than decay. In the case of the vanishing gradient, long-term error signals are lost as they are overwhelmed by the un-decayed short-term signals. In the case of the exploding gradient, the short-term signals are overwhelmed by the long-term signals (Martens and Sutskever 2011).

3.3 LSTM Architecture

LSTM networks propose a solution to these challenges. LSTMs retain the RNNs framework and integrate a specialized architecture that is designed to address the vanishing gradient and exploding gradient problems.

LSTMs have several key components that regulate the flow of information. This allows the network to include long-term dependencies while discarding irrelevant data. The components of LSTM networks are:

- **Cell State:** The cell state acts as the network's long-term memory. It ensures the gradient can move across many time steps, this reduces the probability of vanishing or exploding gradients occurring.

- **Forget Gate:** The cell state acts as the network's long-term memory. It ensures the gradient can move across many time steps, this reduces the probability of vanishing or exploding gradients occurring.

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

  where f_t is the forget gate's activation vector at time t, σ denotes the sigmoid function, W_f represents the weight matrix for the forget gate, h_{t-1} is the previous hidden state, x_t is the input at time t, and b_f is the forget gate's bias term.

- **Input Gate:** This gate controls the flow of new information being stored in the cell state. Here the network's memory is updated with new data. There are two parts: a sigmoid layer that decides which values to update and a tanh layer that creates a vector of new possible values, calculated as follows:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

  where i_t is the input gate's activation vector, and $\tilde{C}_t$ represents the new possible values for the state.

- **Output Gate:** This gate determines the next hidden state, containing information based on the previous input and the current cell state, which is used for predictions. The hidden state is updated as follows:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t * \tanh(C_t)$$

  where o_t is the output gate's activation vector, and h_t is the hidden state at time t.v

With the integration of these components, LSTMs effectively mitigate the challenges presented by traditional RNNS, such as the vanishing and exploding gradient problem (Gao, Chang, Fang, et al. 2019). This allows LSTMS to be well suited for many applications, particularly the challenge at hand: predicting container throughput at the Port of Vancouver.

4 Data Analysis

4.1 Data Preprocessing

The data used was provided by the Port of Vancouver, where each row represents a unique container with its unique associated date. The data aggregation process is essential for analysis to group the data into specific dates for time-series forecasting. The total volume of containers (measured in TEU) is summarized per day.

Next, we identified any abnormal data points that might skew the model's output. This involves detecting outliers, which can be caused by various factors, such as weather delays, special events, or anomalies in operations. Outliers are detected using the Interquartile Range method and defined to be less than (Q1 - 1.5 * IQR) or more than (Q3 + 1.5 * IQR). To ensure that the modified values reflect a realistic estimation of container volume for that day, we treated the outliers as missing values and filled them with the mean of the data before and after the outlier modification (Yinping Gao and Fan 2019).

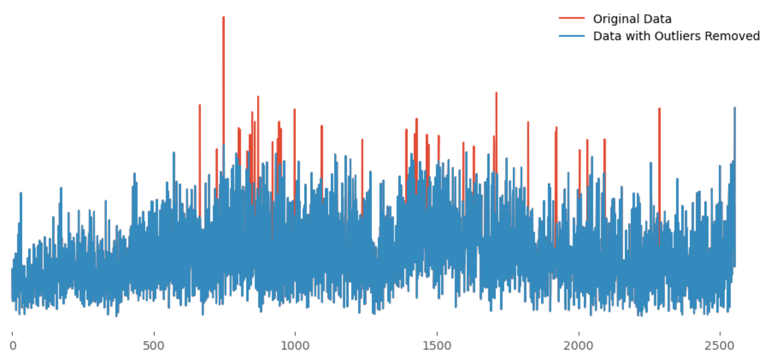

Figure 3: Preprocessed Dataset from 2016 to 2024

To analyse time series data, the method of time-series decomposition is used to break down the data into several components, such as trend, seasonal, and residual. By separating the time series, it allows us to understand the structure of the days, as well as the long-term trends or recurring seasonal patterns.

- **Trend:** Represents the long-term trend of the data, whether or not it is growing or declining over time.
- **Seasonal:** Regular and Repeated patterns according to the time period of the data, such as daily, weekly, or biweekly patterns.
- **Residual:** The remaining components after trend and seasonal information are removed.

Residuals have no correlation and are comprised of irregular events to analyze unusual events or anomalies.

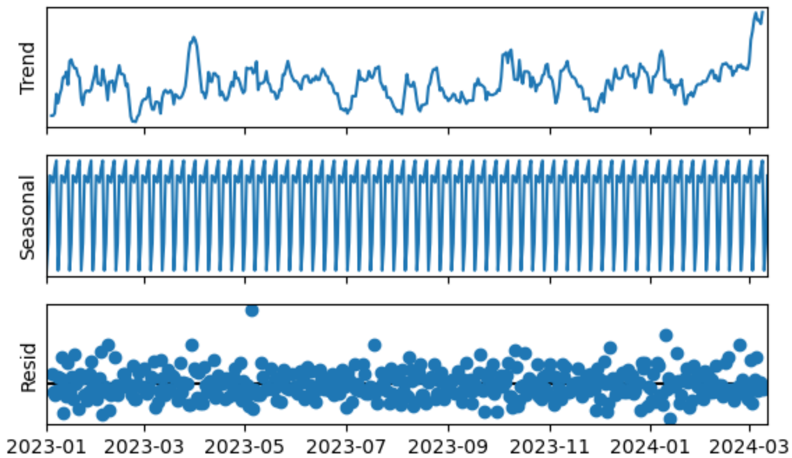

Figure 4: Container Volume Components Visualization

Afterward, we scale and normalize the input data within the range of [0,1]. This prevents large values from specific values to dominate the learning process. Finally, we generate sequences that the LSTM model can process. We look back at the last m-days and train the data to predict the n-days. For this section, we will look at the sequence where we look at the last 20 days to predict the next 20 days.

As the daily Port volume fluctuates on a daily basis, we incorporate the rolling forecast method where the model is updated continuously as new data becomes available to predict n-days out with the previous m-days. After making a prediction, the data input values are shifted forward to include the data point for the most recent day and excluding the oldest day until we reach the end of our dataset. By keeping the 20th-day forecast for each sequence, we compile a series of predictions to evaluate the model's forecasting performance over an extended period of time based on the most current data.

4.2 Model Configuration

The model and experiments were run on MacOS using Python 3.10 and the Keras framework running on top of TensorFlow. Datasets used for experiments include the raw dataset of containers from the Port of Vancouver from 2017-2023 to evaluate and train the model.

Parameters	Model
Recurrent Layer	3 LSTM Layer
Hidden Units	128 for each Layer
Activation Function	relu
Dropout	0.2
Hidden Units	Number of Forecast Days
Loss function	Mean Square Error
Optimizer	Adam
Early Stopping	Validation Loss (15)

Table 1: Model Configuration

4.3 LSTM Prediction

Following the decomposition of our time series data into trend, seasonality, and residue components, we develop a unique Long Short-Term Memory model for each component to accurately capture the patterns and characteristics of each.

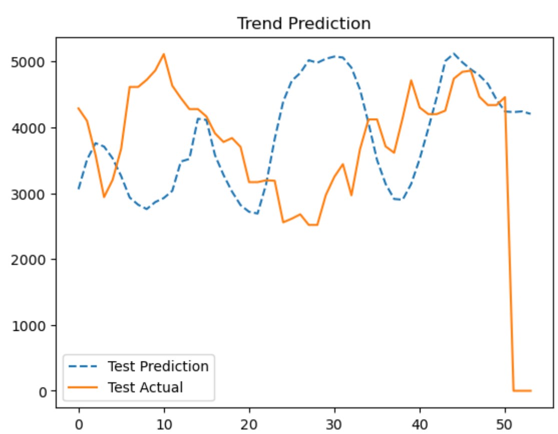

Figure 5: Trend Prediction

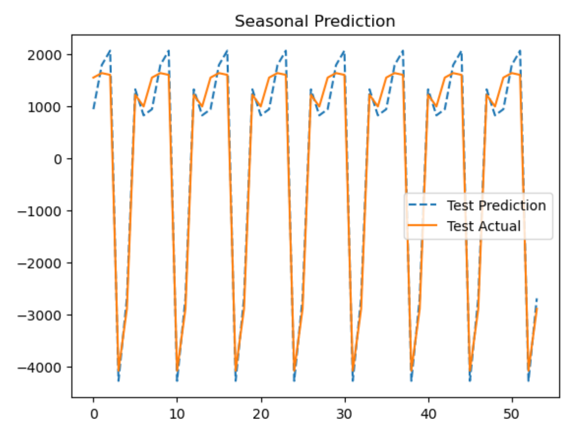

Figure 6: Seasonality Prediction

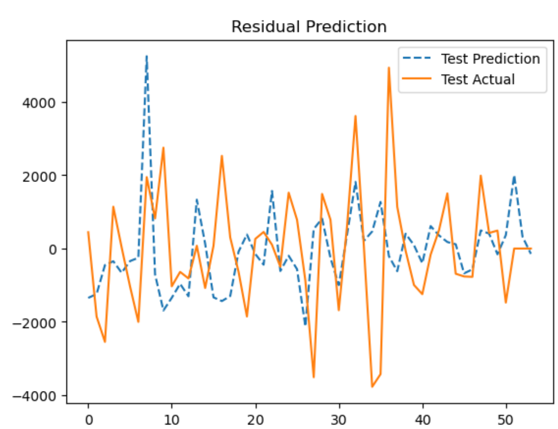

Figure 7: Residual Prediction

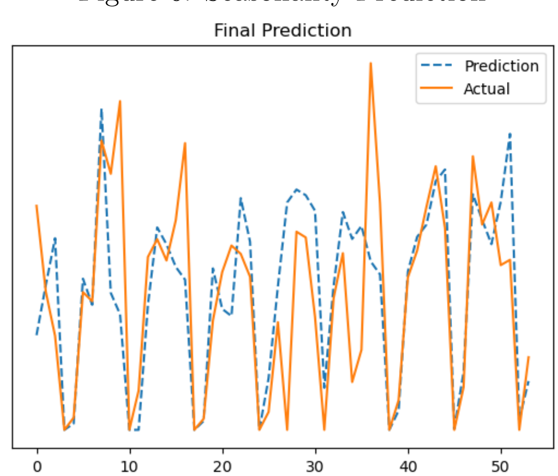

Figure 8: Final Prediction

$$\text{Final Prediction} = \text{Trend Prediction} + \text{Seasonality Prediction} + \text{Residue Prediction} \tag{1}$$

The final predicted volume can be obtained by combining the derived trends, seasonality, and residuals back together to construct the forecast. Below is an example using a training set of the first 3 quarters of 2023, with the prediction for the last quarter of 2023.

5 Results

An in-sample data set of 2021-2023 was chosen to train the RNN. Data from 2024 was excluded and used for the out-of-sample comparison. Our LSTM model was used to generate a single forecast prediction for the first 35 days of 2024. Predicted TEU vs actual TEU numbers appear in Figure 9 below:

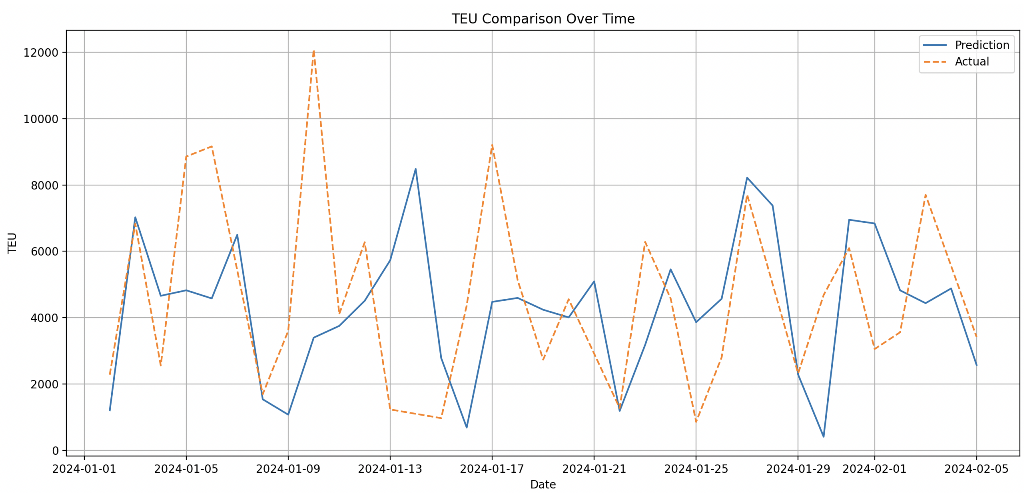

Figure 9: Predicted vs. Actual (Single Forecast)

Error predictions were then run on the actual versus predicted results. The following calculations were used. Mean absolute error (MAE)(1): calculates the average of the absolute value of errors between predicted and actual values. Mean absolute percentage error (MAPE)(2): measures the average percentage error between predicted and actual values. Root mean squared error (RMSE)(3): calculates the square root of the average of squared differences between predicted and actual values. Mean bias error (MBE)(4): measures the average bias (under or overestimation) in the predictions. Mean squared logarithmic error (MSLE)(5): calculates the average of squared differences between the log-transformed predicted values and the actual values. The equations are listed in the enumerated list below. In the equations, n is the number of samples being compared, y_i is the predicted value, and $\hat{y}_i$ is the actual value.

1. $\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$
2. $\text{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n} \left|\frac{y_i - \hat{y}_i}{y_i}\right|$
3. $\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$
4. $\text{MBE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)$
5. $\text{MSLE} = \frac{1}{n}\sum_{i=1}^{n}(\log(1 + y_i) - \log(1 + \hat{y}_i))^2$

The calculated error metrics appear in Table 2 below:

Metric	Value
MAE	2214.20
MAPE	106.53
RMSE	2939.26
MBE	-736.65
MSLE	0.78

Table 2: Error Metrics

Additionally, we calculated the percentage error (PE) of each data point and listed the results in descending order in Table 3:

Table 3: Predicted vs. Actual TU Counts with PE for 2024

Trans Date	Predicted	Actual	PE (%)
01-30	411.50	4682.00	1037.79
01-16	689.15	4367.75	533.78
01-10	3397.94	12082.50	255.58
01-09	1077.30	3601.75	234.33
01-17	4476.31	9204.25	105.62
01-06	4580.05	9160.50	100.01
01-23	3181.16	6283.50	97.52
01-02	1205.74	2282.50	89.30
01-05	4825.01	8855.25	83.53
01-13	5730.31	1233.75	78.47
01-25	3863.71	860.00	77.74
02-03	4436.84	7702.25	73.60
01-15	2784.27	972.25	65.08
02-01	6839.11	3054.75	55.33
01-04	4658.99	2560.25	45.05

Trans Date	Predicted	Actual	PE (%)
01-12	4508.80	6273.50	39.14
01-26	4569.78	2804.50	38.63
01-19	4238.98	2736.25	35.45
02-05	2574.64	3420.75	32.86
02-02	4823.36	3560.00	26.19
01-24	5456.55	4579.75	16.07
01-20	4007.99	4555.50	13.66
01-31	6950.02	6096.00	12.29
01-18	4595.02	5127.25	11.58
01-08	1540.07	1694.00	10.00
01-11	3751.60	4105.00	9.42
01-22	1188.28	1277.25	7.49
01-27	8218.76	7707.25	6.22
01-03	7025.94	6831.75	2.76
01-29	2284.81	2319.50	1.52

The total average prediction error rate is 106.53%. Excluding the top 4 outliers this percentage drops to 43.63%. Given the error metric calculations and assessment of Figure 9, we can conclude that the plot captures dips exceedingly well, but struggles with peaks. Three of the four outliers in PE occur at a peak.

Given the error metrics and the plot of data, there are a few inferences we draw:

- The model tends to underpredict actual values - indicated by the negative MBE value. This correlates with our poor performance of predicting peaks.
- The high MAPE values indicate that for many predictions, the model is incorrectly predicting by a large margin.
- The high RMSE score compared to the MAE indicates that there are a few large errors in the prediction. These large errors can be seen as the top 4 PE calculations.

Further analysis was done to assess the model's issues with predicting peaks.

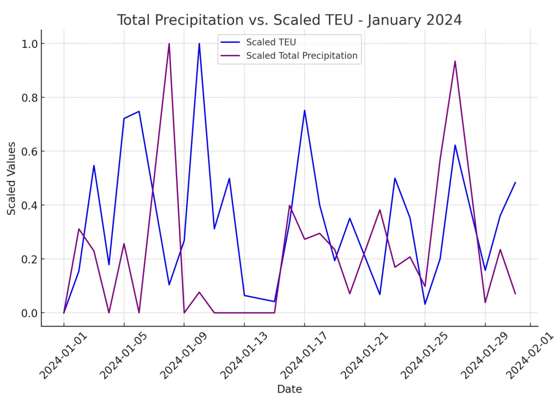

Figure 10: TU vs. Rain

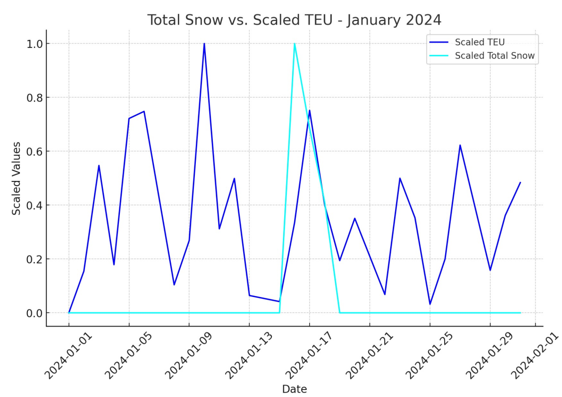

Figure 11: TU vs. Snow

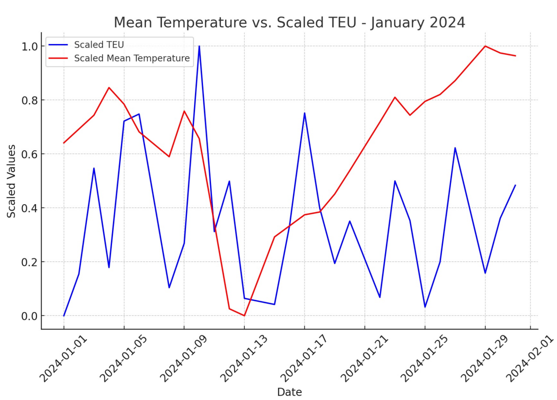

Figure 12: TU vs. Temp

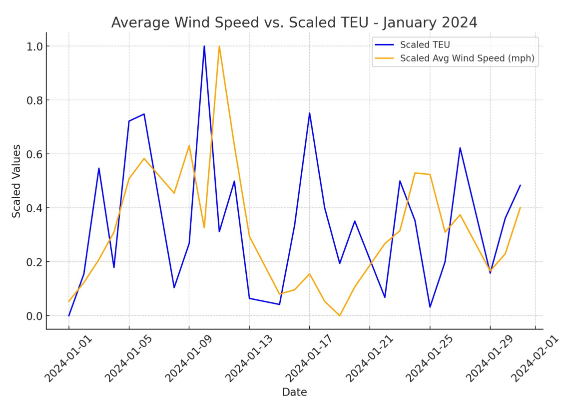

Figure 13: TU vs. Wind

Climate data was taken from climatedata.ca, whose data is provided by the Meteorological Service of Canada and Environment and Climate Change Canada(*Climate Data - Environment and Climate Change Canada* Accessed: 2024). The weather monitoring terminal used for data is located 5.1km away from the Deltaport terminal. Precipitation, average wind speed, snow, and mean temperature were plotted against the actual TEU count for January. All of the data was scaled and is seen in Figures 10-13. To add clarity to the scaled weather components, Table 4 includes the maximum and minimum of the respective elements:

Metric	**Maximum**	**Minimum**
Total Precipitation (mm)	36.6	0.0
Total Snow (cm)	14.6	0.0
Mean Temperature (°C)	12.5	-7.0
Average Wind Speed (mph)	21.4	2.7

Table 4: Max and Min Weather Metrics for January 2024

No obvious correlation can be drawn from these events. It is seen that the large occurrence of snow could be the cause of a 1-day delay in the spike occurring on January 17^{th}. There is, however, a possibility that the inclusion of these variables into the model could increase accuracy, and is worthy of further work.

One of the simplest observable trends is the total TEU count versus the number of ships that unloaded cargo on a given day. A scatter plot is seen in Figure 14 with a line of best fit showing the trend.

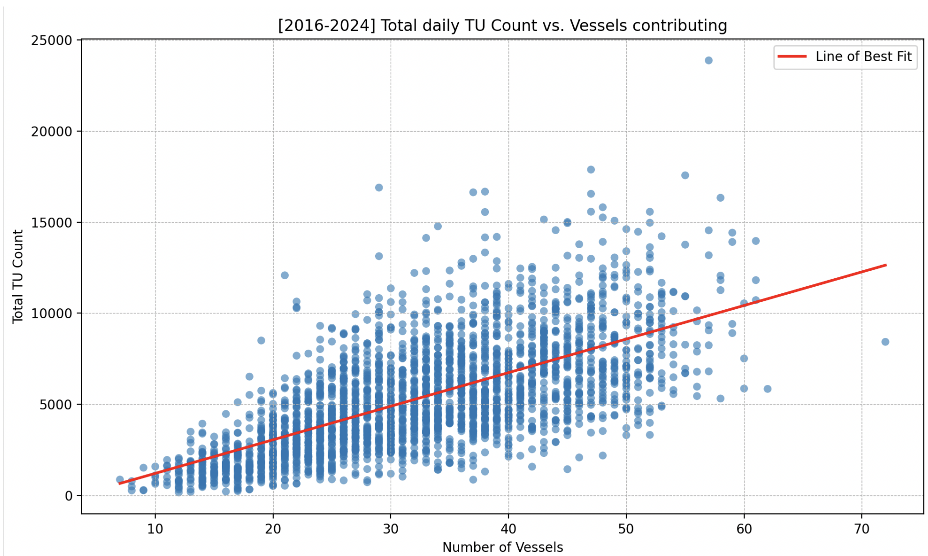

Figure 14: Number of vessels present vs. total received TU's

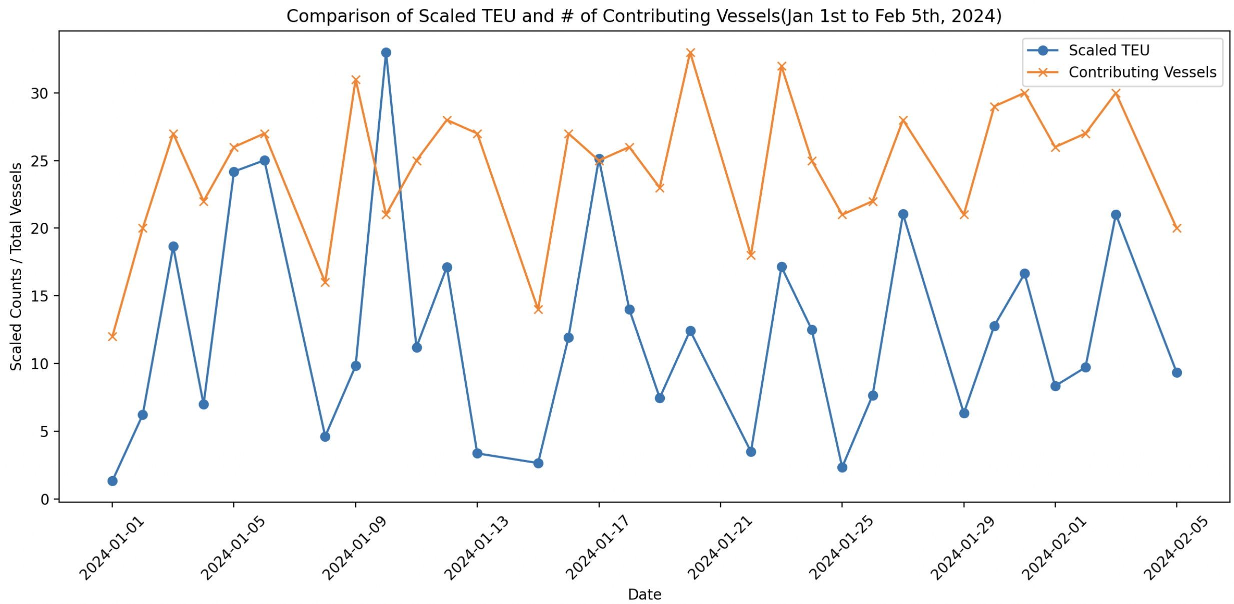

Figure 15: Out-of-sample scaled actual TEU data versus contributing vessels

It follows that there is an obvious linear trend between the number of vessels contributing and the total TU count on a given day. Figure 15 identifies the number of vessels contributing versus the total TU count for the out-of-sample dates. A strong correlation exists between the spikes and dips of the TEU count versus the vessels contributing. There are 662 unique vessels recorded visiting Deltaport over the data set. Further, 213 different vessels delivered containers to Deltaport in 2023. In analyzing these ships, the top 25 out of 213 ships are responsible for 50.272% of the total TEU count for Deltaport in 2023. Even more, the top 10 ships are responsible for 24.975% of the total TEU count, with the top 5 being responsible for approximately 14.209% of the total TEU counts for 2023. These insights can greatly contribute to the height of the spikes that the model experiences, and can curtail the predicted spikes to more accurately reflect the actual outcome. Figure 16 shows the total percent contribution of each vessel in 2023 (excluding vessels with less than 0.1% contribution). For model incorporation, the Port would need to be aware of which ships are arriving and when ahead of time. This information is publicly available and knowledge of a vessel's arrival is scheduled for 30 days out (Global Terminals 2024).

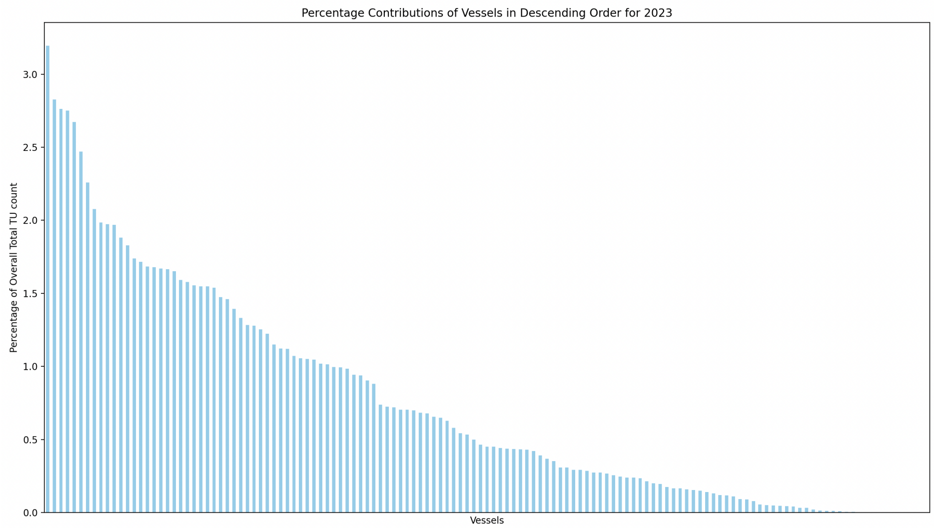

Figure 16: Total TEU contribution per vessel that contributed in 2023

Knowledge of rail-bound cargo is crucial as this number combined with the daily TEU count forms the number of rail cars required to transport the cargo. Average daily rail percentages for 2023 can be seen in Figure 17. Daily percentages of average rail counts have similar spikes and dips compared to TEU counts. Further investigation shows some vessels, however, are responsible for more rail-bound cargo than others. Out of the 219 vessels delivering to the Port from 2023 - 2024, 90 vessels have a recorded history of only bringing in goods for rail, and 11 vessels only bringing in goods for exclusively trucks. Figure 18 shows the average rail percentages for all vessels that delivered TEUs in 2023 (excluding vessels with less than 0.1% contribution). Figures 19 and 20 show the weekly rail percentages for the largest TEU-contributing vessel in 2023.

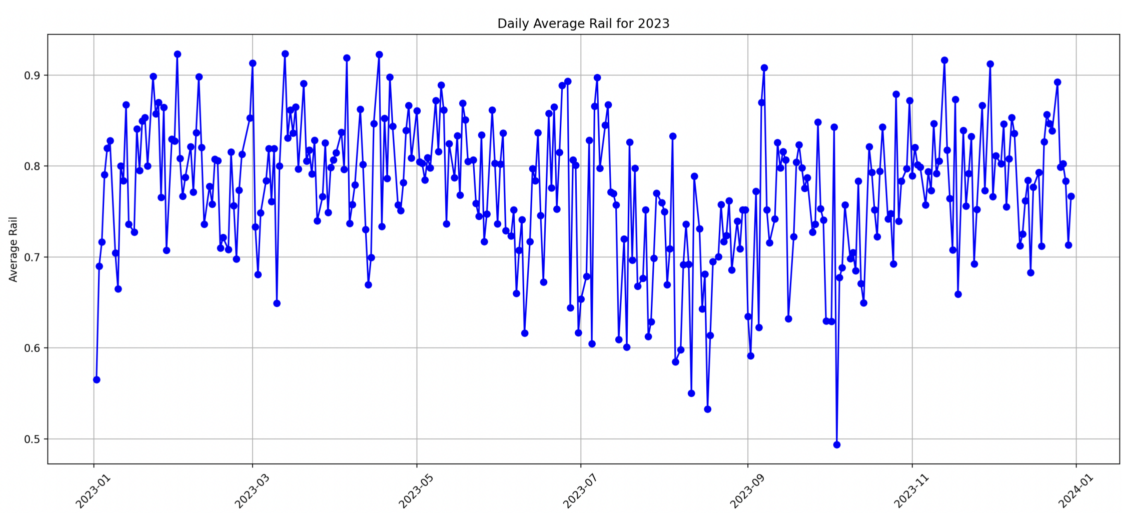

Figure 17: Average daily rail percent

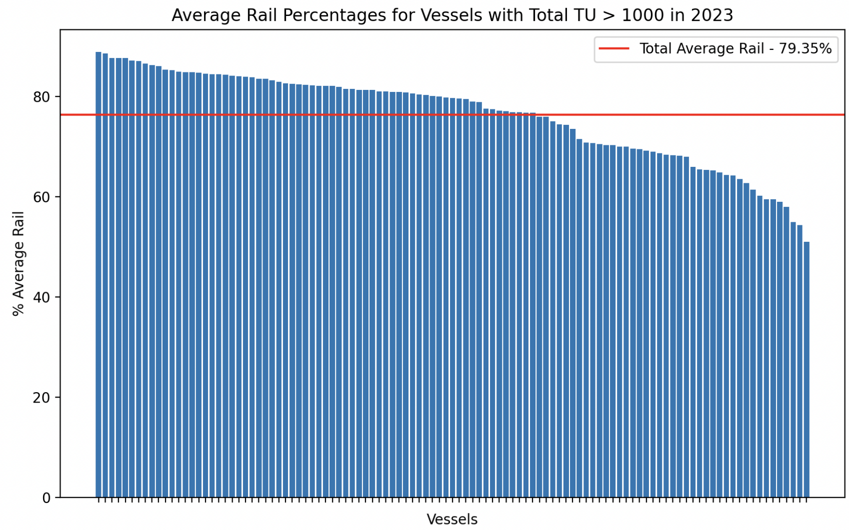

Figure 18: Plot of average TEU rail cargo across vessels contributing more than 0.1%

The total average rail percentage for this vessel in 2023 was 84.13%. However, looking at the graph we can see plenty of data points that are 100% rail and it's clear that further analysis is needed to identify a trend in the cargo. Further, knowledge of a vessel is a good insight into the percentage of cargo that is rail-bound. Analysis was done to identify a stronger trend in the prediction of incoming rail cargo.

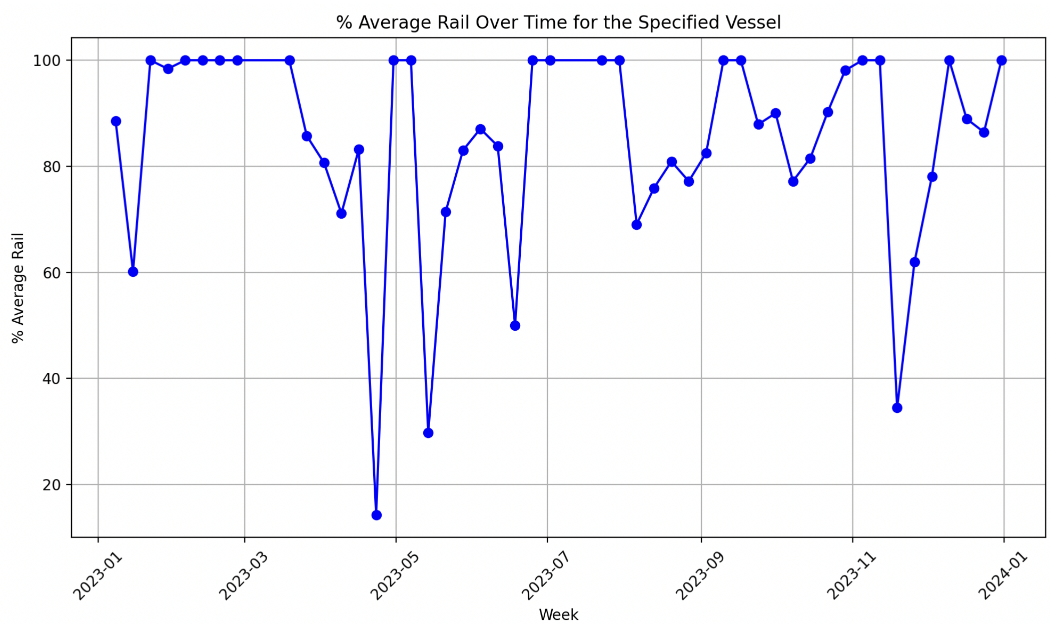

Figure 19: Average weekly percent rail-bound cargo by largest contributing vessel

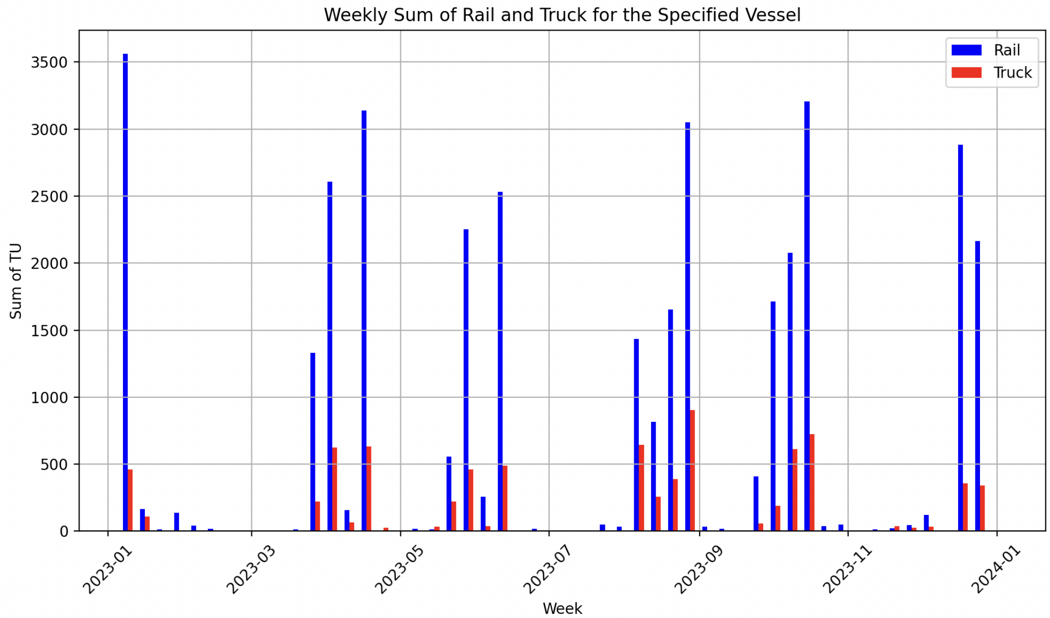

Figure 20: Rail cargo versus truck cargo of largest contributing ship in 2023

The weekly average TEU count for 2023 was calculated and found to be 26892.63 TEUs. The average rail percentages for the year 2022 were then used as a predictor for 2023. The calculation found an average weekly error of 1151.61 TEUs, or a 4.28% weekly average error across 2023. A maximum weekly error of 2621.18 TEUs was found, while the minimum was 56.59 TEUs. This idea was expanded on, and monthly averages from 2022 were then used to predict weekly rail percentages in 2023. This calculation dropped the average weekly error in TEU prediction to 755.00, down from 1151.61, resulting in a decrease in average error for rail prediction from 4.28% to 2.81%. Further, the maximum weekly error was reduced from 2621.18 TEUs to 2609.10 TEUs, and the minimum was reduced from 56.59 TEUs to 6.82 TEUs. The week on which the maximum error occurs for both sets of predictions is the weekend beginning on Christmas Day in 2023. This outlier could easily be accounted for. It follows that there is an identifiable trend in the rail percentages, and even using previous yearly averages gives a close approximation. Figures 21, 22, and 23 show the weekly average rail percentages for 2022, 2023, and 2024 respectively.

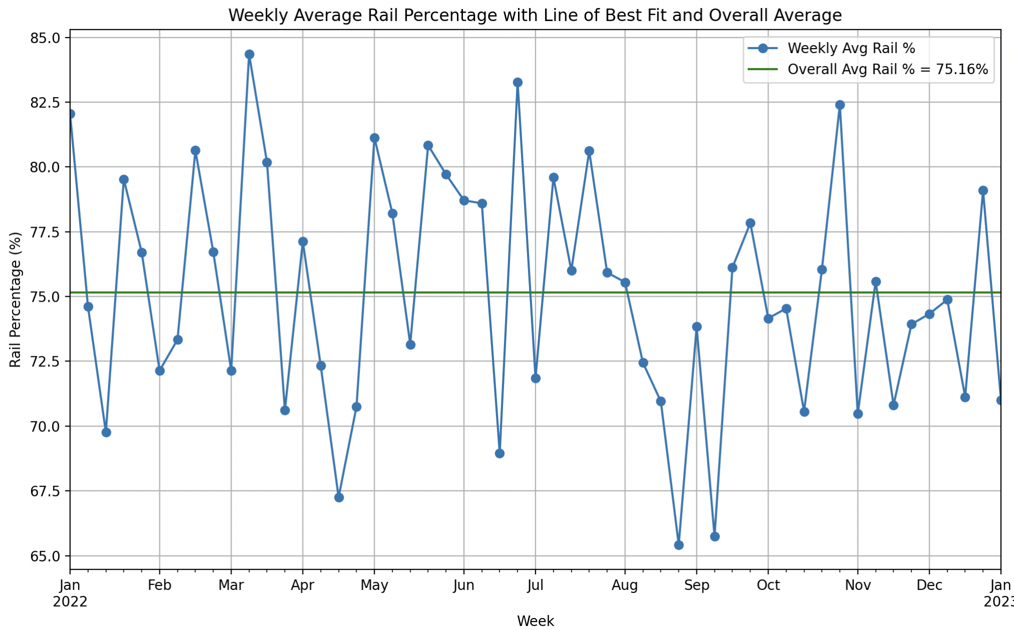

Figure 21: Weekly average rail for 2022

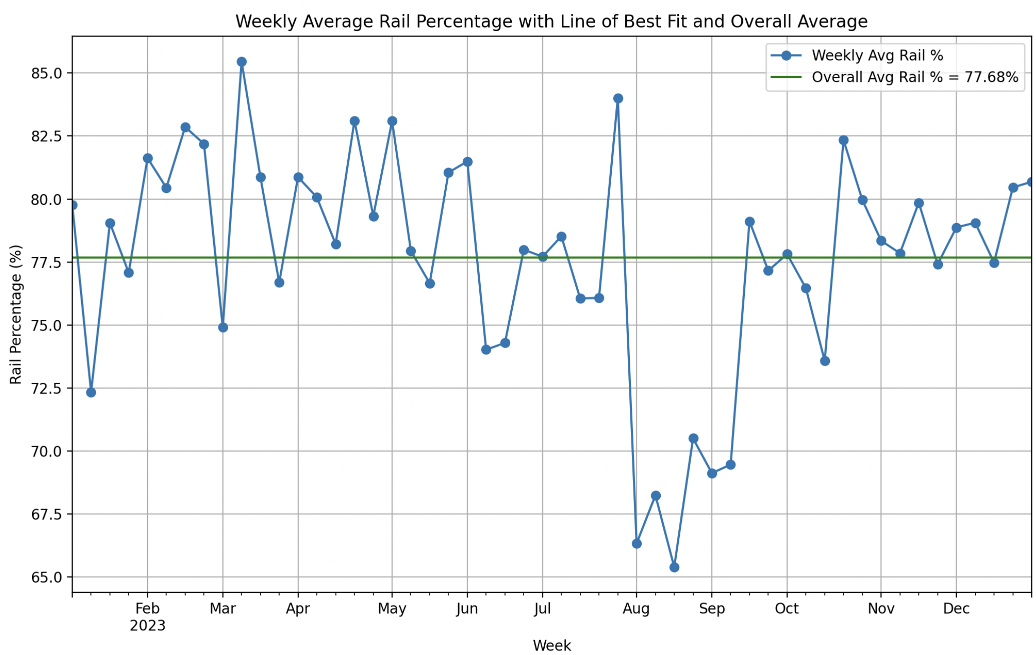

Figure 22: Weekly average rail for 2023

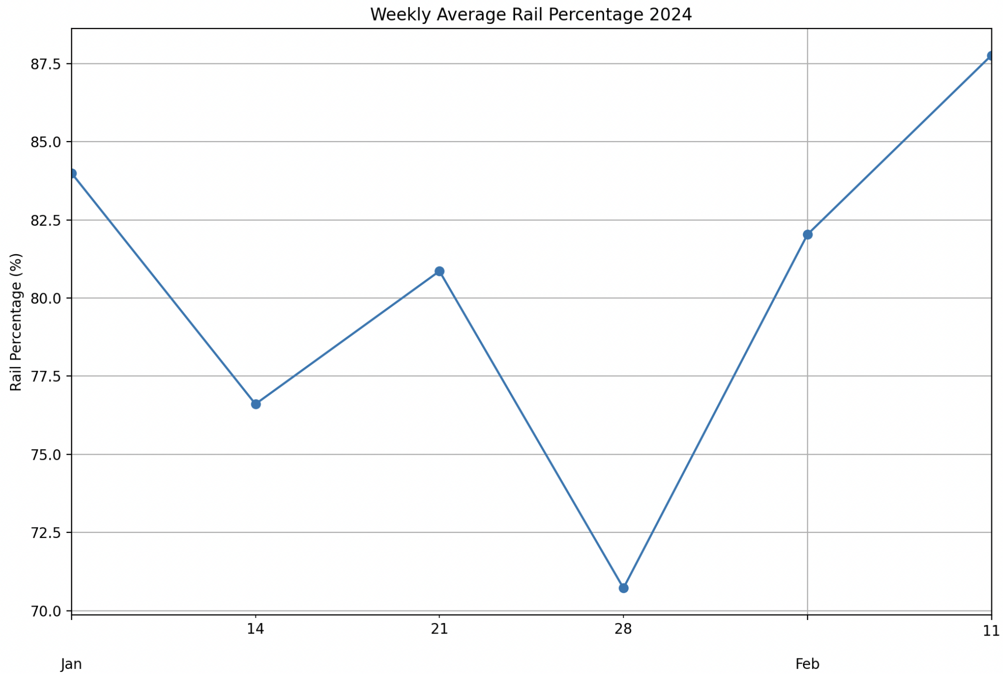

Figure 23: Weekly average rail for out-of-sample dates in 2024

The destination of the incoming cargo is also desired knowledge for the Port. Cargo destinations were geolocated through an Opencage license. Only the top 200 destinations were considered, making up a total of 94.73% of all destinations across 2023. The following results were also calculated:

- 28.11% of all destination cargo in 2023 had a destination less than 500km away from Vancouver, BC.
- 71.72% of all destination cargo is greater than 500km away, with 59% being greater than 2500 and 16% being greater than 5000km away.

There is a 4% confidence interval on the previous calculations, given not every destination was considered in the calculations. The cargo arriving at Deltaport can have destinations as far as Faridabad, India (11,161 km) or Kagoshima, Japan (8465 km). Figure 24 shows a map of rail-bound cargo's destination in North America. The significance of the plot points were determined by the number of TEU's that were sent there in 2023. Further analysis is required to properly identify a trend in the direction of rail-bound cargo.

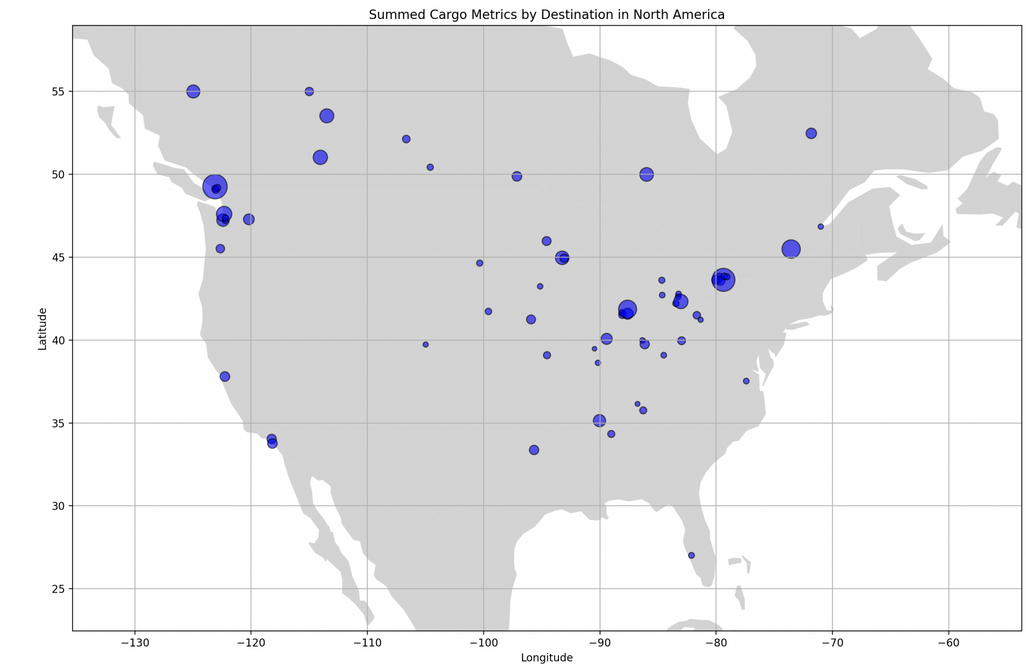

Figure 24: Bubble map of 2023 rail-bound TEU destinations

Additionally, The top five busiest and top 5 slowest days and weeks were averaged. The monthly averages were also taken. Calculations were done across the entire scope of the dataset and can be seen in Tables 5-10 below:

Day	**Average TEU**
05-26	8412.29
07-30	7948.54
07-18	7940.88
07-06	7873.53
07-22	7810.93
03-30	7765.59
10-28	7680.06
07-23	7676.04
01-10	7614.71
09-20	7463.71

Table 5: Top 10 Average Volume Days

Day	**Average TEU**
01-01	3724.00
12-10	3712.71
03-21	3685.54
01-30	3556.14
01-13	3552.69
02-19	3369.79
02-29	3331.75
02-08	2803.08
12-26	2731.11
01-02	1880.00

Table 6: Bottom 10 Average Volume Days

Week	Average TEU
29	6148.59
21	6104.27
30	6027.35
38	5923.84
44	5920.04

Table 7: Top 5 Average Volume Weeks

Week	Average TEU
8	4181.88
6	4586.88
1	4796.05
5	4806.87
7	4809.76

Table 8: Bottom 5 Average Volume Weeks

Month	Average TEU
7	5883.92
9	5844.24
10	5687.26
11	5673.11
8	5651.68
6	5651.59

Table 9: Average Monthly TEU Volume in Descending Order (Part 1)

Month	Average TEU
3	5514.39
5	5279.73
12	5198.10
4	5109.43
1	5016.27
2	4588.61

Table 10: Average Monthly TEU Volume in Descending Order (Part 2)

6 Discussion

The model involved in generating predictions was able to capture the general direction for the first 35 days of 2024, based on training from data from 2021 to 2023. Changes shown in the trends and residuals were taken into account and affected the performance of the model.

However, the model faced challenges and was unable to accurately predict sudden spikes in volume, as evidenced by substantial errors in certain dates. This could be due to various factors including external influences not captured in the data given from the Port. A reason behind this could be the model's current configuration to train to minimize validation loss during the training process. This inherently limits its sensitivity to accurately detect and forecast sudden sharp changes in container volume. This causes the prediction to "smooth over" the peaks in the data rather than predict it. This is especially apparent when you input and forecast a large number of days at once.

Due to the dynamic nature of container volume due to port policies, operational changes, or other external factors, the seasonality of the Port may change over time. The current model trained on data from 2021 to 2023, does not accurately capture the trends and seasonal patterns in earlier years, such as 2017 to 2021. Therefore, new seasonality values must be considered for a longer forecasting period, as the likelihood of encountering different seasonality patterns increases.

7 Further work

Foremost, we need to address that in our implementation of the model we were given Canada Border Service Agency (CBSA) data and not the actual master dataset. This dataset contains vessel information approximately two weeks before arrival. The peaks and dips reflected in the TEU count from this dataset do not necessarily model the same throughput that the Port experiences. This affects our analysis and model performance. As of April 19^{th}, 2024, we have received access to the master vessel schedule but have not had enough time to run further analysis.

To properly analyze the flow of daily cargo through the terminal, a few steps need to be taken:

1. Geolocate all destinations in the dataset and remove any locations that are listed outside of North America. In conversation with the Port, these destinations are faulty data.
2. Given a vessel, sum the TEU counts from the CBSA data within a predetermined window.
3. Create an average of TEU count delivered per day for each vessel, determined by the vessel's summed total and divided by its length of stay.
4. Sum all these averages across all berths for each day and create a daily input flow of cargo.

Additionally, real-world tests would be required to validate the model's actual accuracy. It is possible that our estimation of daily flow does not reflect the actual flow of cargo through the Port. In discussion with them, they currently do not have an actual count for the daily flow of cargo through the terminal. Incorporating the correct dataset would allow for better analysis of our model's faults. Currently, we're analyzing the government's ability to process the data, and not the actual flow through the Port. Another area of future work is the implementation of additional input columns for the LSTM model to handle. Currently, the model only handles dates and the corresponding total TU count of containers that were received on that day. The model can be adjusted to include vessel IDs, as a certain number of ships are responsible for the total number of cargo. It is also important to note that vessel congestion at the Port of Vancouver has a significant impact on our model's predictive capabilities. If not properly accounted for, this can lead to inaccuracies in cargo throughput. A possible solution to this is to adjust the model for berth schedules, where it considers when a ship arrives at the Port and adjusts the daily TEU count respectively.

Additionally, to further increase the accuracy of predictions it should be noted that weather could also be considered. Our current weather calculations are currently being compared against CBSA processing and this data could be useful when compared to actual Port cargo flow. Fluctuations in weather affect cargo movement, potentially delaying ship departures and arrivals. A model that incorporates weather variability may lead to better predictions of daily incoming cargo. Another variability to be considered is stock market volatility, as this may reflect broader economic conditions that can directly influence cargo volume.

8 Impact

An accurate forecast has the potential for a dramatic increase in supply chain efficiency. The more optimized a forecast is, the better the rail companies can manage the flow of their railcars, and the smoother cargo will flow through North America. An increase in the forecasting window allows for better planning, and a better handling of any delays due to weather, rail issues, or extreme events. With the introduction of LSTMs, the Port can achieve these goals. It's not just about saving time; it's about making the Port flexible and ready to meet the changing needs of international shipping.

Increasing forecasting accuracy also shows the Port's dedication to the environment, and strengthens its economic capabilities. Better forecasts are also better for the planet, reducing the time ships spend idling and cutting emissions. This careful approach to managing the Port's operations helps meet environmental goals and shows how maritime operations can be greener. On the economic side, these improvements can lower shipping costs, benefiting everyone in the supply chain and supporting growth by handling more cargo.

Using LSTM for forecasting at the Port of Vancouver is a sign of what is to come for ports globally. Modern technology can not only improve operations but also support wider goals like sustainability and economic strength. As ports around the world look to the future, Vancouver's approach offers a glimpse of how blending technology with smart planning can lead to a more efficient, sustainable, and economically strong maritime sector.

9 Conclusion

This paper makes predictions of a daily TEU count for incoming cargo at Deltaport for the Port Authority of Vancouver. The historical dataset of TEU counts from the CBSA is preprocessed and outliers are detected and removed using the Interquartile Range method, and then replaced with the mean of the data before and after the outliers are modified. This preprocessed data is then used to train the LSTM model which is designed to predict future incoming TEU volume. Our predictions are then analyzed for accuracy using various error prediction calculations. The current version of the model has reasonable accuracy in daily volume predictions. A simple analysis of rail percentages reveals an accurate prediction of future rail percentages. There is space for an LSTM model to be applied to rail percentages as well. Further analysis is needed to assess cargo destinations. With improvements, our model can make a profound impact on operational efficiency. With an accurate prediction of daily TEU volume and rail-bound cargo predictions, the Port can enhance its cargo handling processes, readily having the correct number of rail cars required to move the cargo abroad.

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