

AN OPTIMIZE SHIPMENT DEMURRAGE USING MULTIVARIATE ANALYSIS AND ARTIFICIAL NEURAL NETWORK FORECASTING MODEL

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Abstract

In 2019, XYZ companies suffered a payment penalty, demurrage, as a consequence of the delay in shipping their bulk cargo caused by product shortages. Demurrage donates high financial loss to the company; therefore, an optimization model is proposed to prevent it. This study aims to examine the causes of product shortages during shipment, which affect in demurrage then optimize to avoid the financial losses. This research conducted a multivariate statistical analysis to observe factors affected company's inventory. An Artificial Neural Network (ANN) was developed to find an accurate forecasting model for the company's inventory. The result showed that there were two significant factors affected demurrage, initial stock, and forecasting error. The statistical test inspired to developed two strategies in optimizing the demurrage cost, involve reducing forecasting error using the ANN model and increasing the initial stock for safety stock. An ANN model with Conjugate Gradient with Powell/Beale Restarts algorithm, two hidden layers, and 25 neurons was found an accurate model with RMSE value 0.186 for inventory's forecasting. For the initial stock strategy, this paper suggested that the company was expected to continue in maximizing shipments and fulfil more orders on time.

Keywords: Artificial neural network, Demurrage, Forecasting, Inventory, Linear regression, Shipment, Optimization

Introduction

Companies usually have to pay demurrage due to the delay in the shipment process. Demurrage, a financial consequence, is charges levied by the shipping companies on chartering. The financial consequence is referring to the period when the charterer remains in possession of the vessel after the normal period allowed for loading and

unloading cargo (lay-time) (Ndikom *et al.*, 2017). This condition was also faced by XYZ companies in mid-2019. The company had to pay total demurrage nearly US \$ 260,000, as shown in Figure 1, because of delayed shipments due to product shortages. Without a doubt, this condition results in financial losses for the company. This condition has to be

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improved that in the worse situation could lead to customer de-satisfaction and losing any demand (Peng and Lu, 2017).

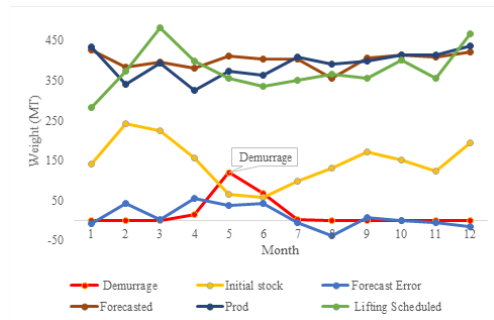


Figure 1. Product inventory condition and shipping data in 2019 for XYZ Company

Many factors could lead to shipment delay, which ends up by paying off the demurrage. Mitigation strategies have been implemented, involve maintaining equipment reliability to eliminate any potential of equipment breakdowns in production (Mad Lazim and Ramayah, 2010) also improving the shipping strategy to reduce breakdown time of loading process (Shaiful *et al.*, 2019). However, these strategies give no significant improvement in the case.

The XYZ company has manufacturing plants, bulk product warehouse, and bulk carrier shipping facilities at the ports. Product shipping or product lifting is scheduled based on stock forecasts. Maximizing the product shipping can certainly increase the company's profit and keep inventory low. In addition, recently company maintaining a low inventory condition to allow any production activities at manufacturing, even the shipping process is interrupted due to any bad weather. A sustain production at the manufacturing plant is very important in the case to reduce a huge cost in the start-up process if it is interrupted. On the other hand, low inventory is possible to interrupt shipping process depending on the supply of the product from the manufacturing plants and the accuracy of stock forecasting. Therefore, unfulfilled product capacity at the shipment and the product shortage during shipment may produce any delay and had to pay shipment demurrages.

This research examines factors that caused product shortages during shipment. As aforementioned, the inventory condition at the manufacture is the main issue to be solved. Therefore, contributing factors to inventory such as stock forecast errors and initial stock are analyzed and forecast using multiple linear regression. This

paper also develops a forecasting model using machine learning which able to handle big data, accurate and faster which is required for the industry. This paper proposed a machine learning model due to its ability to learn data and optimized forecasting result with using an appropriate algorithm (Chapman *et al.*, 2019). An Artificial Neural Network (ANN) as a machine learning technique is proposed for this case which is expected to suggest lower error rates (Bhadouria and Jayant, 2017).

This paper is organized as follows. Research Method, describes the data collection and analysis methods, and the adopted theory. Results and discussion, presents the descriptive statistics of prediction evaluation, forecast error, multiple regression, and discussion. At last, Conclusion, presents the most important findings briefly.

Materials and Method

The first stage of the research is to examine significant factors that contribute to the inventory level. As aforementioned, the inventory level at the manufacturing plant affects the total demurrage cost, therefore, it should be maintained well. In this case, the inventory level factors to be examined are stock forecast errors and initial stock using multiple linear regression. To analyze the effect of demurrage on forecast error and initial stock, we use monthly accumulated demurrage data from the shipping process, initial stock from product inventory, production forecasting being used and monthly production data from the manufacturing plant during 2019, because demurrage has occurred in that year.

Stock forecast errors hold an important role in minimizing demurrage cost. Therefore, an accurate forecasting model with lower error is required to be developed. An Artificial Neural Network (ANN) model is developed to forecast the number of productions to store at the inventory. In this case, algorithms are evaluated to find an accurate model in forecasting and avoid high model error. To develop ANN model, the 2013-2019 monthly production data is applied and expect that fluctuations in production can be well accommodated by the model. An accurate ANN model is required to forecast manufacturing production in case to avoid product shortage and shipment demurrages.

Multiple Regression Analysis to Examine Inventory Factors

The fundamental purpose of regression analysis is to determine the best model in order to

predict the dependent variable or variables (Gusnadi and Topal, 2016). In this case, statistical analysis and hypothesis test is important to find significant factors which are affect the manufacturing inventory and demurrage cost during shipment. It also strengthening the model in formulating further preventive action and mitigation activities to improve demurrage cost level and manufacture efficiency.

If a ship loads and or discharges in less than the prescribed time, the owners pay dispatch money as a reward for time saved. If, on the other hand, the prescribed time is exceeded, then demurrage is payable at an agreed rate to the owner as compensation for the delay of the ship. Demurrage is a penalty charged due to shipment fails to complete on an agreed time. In other case, if buyers face unexpected supply chain disruptions, fast delivery from suppliers allows them to restore normal operations and meet their own customer demands with minimal delays (Peng and Lu, 2017)

Thus, this research involves how demurrage occurs as a consequence of delays in shipment caused by stock out. As the shipments are scheduled according to stock forecast and inventory, this paper examines variables that might contribute to inventory when stock out occurs. As we mentioned earlier that at XYZ co. recently in 2019 there was a decision to reduce the safety stock, our observations focus on the initial stock, error in forecasting and supply of product from the plant to the shipment. Thus, the following hypotheses are assessed in this study:

- H₁: Initial stock affects demurrage.
- H₂: Forecast Error affects demurrage.

To evaluate the statistical relationship of variables, demurrage and initial stock data are collected by direct observation, while forecasting data is obtained from the company's production planning. This paper provides a forecasting model using company's monthly production data from 2013 to 2019 as shown in Figure 2.

A multiple linear regression model is an extension of a simple linear regression model that allows the response variable y to be modeled as a linear function of more than one input variable x_i (Hayter, 2012). The empirical data as shown on Figure 1 are evaluated statistically by performing multiple regression analysis. A linear model established as follow:

$$\text{Demurrage} = \beta_0 + \beta_1 \text{ Forecast Error} + \beta_2 \text{ Initial Stock} \quad (1)$$

The two hypotheses are accepted on the condition that the t statistics associated with β_1 and β_2 are sufficiently large, exceeding the critical limit, where α denotes the significance level and is usually taken as 0.05. Prior to the computation of the t statistics, we perform the ANOVA test to determine the importance of Model (1) globally, where we compute and evaluate the F statistic.

In this stage, this paper will have statistical evidence of the relation between demurrage and forecast error. Furthermore, by the regression equation to achieve demurrage to zero, we can find what is the initial stock can be set up as the consequences that Forecast Error will always exist even how best forecast model is achieved. This action can be considered as one of the mitigations plans in improving the demurrage as there is a situation that more cost-effective to work on mitigating the consequences of forecast errors (Belt, 2017).

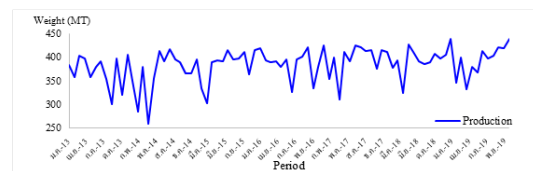


Figure 2. Monthly production of manufacturing plants in 2013-2019

Artificial Neural Network (ANN) for the Forecasting Model

The previous stage will proof any significance relation of forecast error to demurrage. Further, a forecasting model must be developed to improve the error rate in the case to minimize demurrage cost. This paper provides a machine learning model of a forecasting model using Artificial Neural Network (ANN). An ANN has been successfully applied in a broad range of areas for many purposes, involve prediction and knowledge discovery (Doreswamy and Vastrad, 2013).

An ANN model for forecasting is possible developed in a Time-Series or non-Times series form using any type of algorithms. As ANN is a supervised algorithm, therefore the data set must be normalized and divided into data training and testing. The ANN model performance is evaluated to show which algorithm has the lowest error for further applied to the real-world problem.

An ANN model is possible to develop in three different transfer functions, involve log-sigmoid, tan-sigmoid, and linear, which the models are shown in Figure 3 (Demuth and Beale, 2000).

Besides that, (Abhishek *et al.*, 2012) stated that challenges in developing an accurate ANN model for time-series forecasting are focus on these items, as follows:

1. Number of Neurons per Layer: Increasing the number of neurons per layer decreases the MSE, i.e. increases the performance.

2. Number of Samples: Increasing the number of samples decreases the MSE, i.e. increases the performance.

3. Hidden Layers Transfer Function: In all cases, Pure-linear function is kept fixed for the output layer. Because it is a very fast learning rate and sensitivity towards change in the number of samples and neurons per layer, the Tan-Sigmoid function is the best choice for hidden layers over pure-linear function. However, increasing the number of hidden layers of the model above an optimum, for example, increasing it from 5 to 10, it can adversely increase the performance.

4. The number of Hidden Layers: increased the number of hidden layers increasing the chance to accurate as well as free from overfitting. However, when further increased the number of layers, the latter, there is a chance of decline in performance while handling the same information.

5. Overfitting: Sometimes a very low MSE can be mistakenly considered as good accuracy, in fact, it indicates a serious problem called 'overfitting'. The final MSE generated is because of the isolated test data, which is random 20% of the samples. A low MSE may be possible even if the generalization is very poor, in other words MSE of validation data may be much higher.

Root Mean Square Error (RMSE)

To evaluate the performance of the ANN model, RMSE is applied. RMSE is more appropriate when model errors follow a normal distribution, as

found in this research (Chai and Draxler, 2014). RMSE is the standard deviation of a dataset as a root square of the variance of the residuals which is preferable compare to the variance since it is the same unit as the data (Marques de Sa, 2007). Variance is in an absolute or positive value, which is the residuals of the data from the model. To know how close the observed data points are to the model forecasted values, RMSE indicates the absolute fit of the model to the data. Suppose that y_i as observed values, $\hat{y}_j$ as predicted values and n as number of observations, therefore RMSE is formulated as follows:

$$RMSE = \sqrt{\frac{\sum (y_i - \hat{y}_i)^2}{n}} \quad (2)$$

A lower value of RMSE indicate a better fit. Later, when the model is tested and if the RMSE for the testing data is higher than the training data, there is a high chance that the model overfit. In other words, the model performed worse during testing than training.

Results and Discussion

Multiple Regression Analysis for Inventory Factors

We begin to analyze the relationship of initial and forecasting error variable to demurrage through statistic tests with the result of observations are shown in Table 1. In this case, first, we obtain the fitness between the data and the assumed model (1). The coefficient of determination or R^2 equal to 0.667, suggesting the model reasonably fits the data.

The next statistical analysis is the F test to evaluate the significance of the coefficients β_1 and

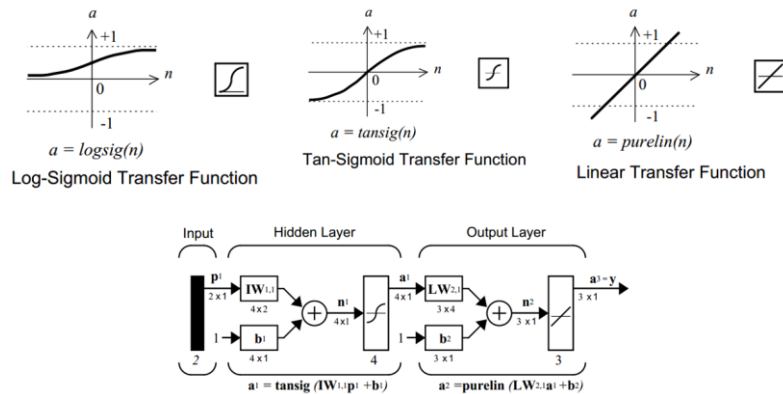


Figure 3. ANN transfer function and structure

β_2 in Equation (1). The null hypothesis for the test is $\beta_1=\beta_2=0$, and the alternative hypothesis is that at least, a coefficient is non zero. In this test, the results are presented in Table 2. The computed F -stat is 9.029 with the p -value of 0.007, suggesting a rejection of the null hypothesis.

The next step in the multiple analysis is the t -test for the two coefficients β_1 and β_2 where the results are presented in Table 3. The results suggest that all two coefficients $\beta_1=0.634$ and $\beta_2=-0.411$ are statistically significant.

As presented in Table 3, we obtain the regression model relating Forecast Error and Initial Stock to Demurrage as the following:

$$\text{Demurrage} = 71.169 + 0.634 \cdot \text{Forecast Error} - 0.411 \cdot \text{Initial Stock} \quad (3)$$

Table 1. The result of R2 for Demurrage cost factors

Model	R	R ²	Adjusted R ²	Std. Error of the Estimate	Durbin-Watson
1	0.817	0.667	0.593	24.09687	2.841

Table 2. The result of the F test for Model (1)

Model	Sum of Squares	df	Mean Square	F-stat	p-value
Regression	10485.256	2	5242.628	9.029	0.007
Residual	5225.932	9	580.659		
Total	15711.188	11			

Table 3. The result of t-test for Model (1)

Model	Unstandardized Coefficients		Std. Coefficients	t-stat	p-value
	B	Std. Error	Beta		
(Constant)	71.169	20.452		3.480	.007
Forecast_Error	.634	.257	.477	2.469	.036
Initial_Stock	-.411	.129	-.617	-3.195	.011

Table 4. Residual Statistics for Forecast Value and Actual Value

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	379.86	416.30	401.44	11.456	12
Residual	-46.138	16.280	.000	15.984	12
Std. Predicted Value	-1.883	1.297	.000	1.000	12
Std. Residual	-2.752	.971	.000	.953	12

Observes regression model at Equation (3), it can be interpreted that shipments might suffer demurrage on the condition of high forecast error and low initial stock, and in reverse, zero demurrage are supported when forecast error is low, and the initial stock is high.

The last part of the regression analysis is to evaluate the assumptions of the regression model by

evaluating the normality and randomness of the residual data, which represents the difference between the model predictions on the demurrage and the contributing factors. The results are presented in Figure 4. These results indicate that the assumption is satisfied, and it concludes our multiple regression analysis.

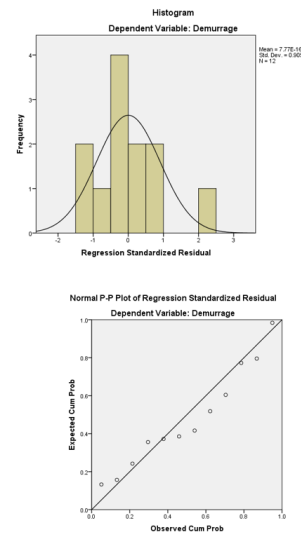


Figure 4. The distribution of residual histogram and probability-probability plot

Developing an Artificial Neural Network for an Accurate Forecasting Model

Our previous analysis found that forecasting error is significant to shipment demurrage. It indicates that a forecasting error should be in a lower condition to avoid any demurrage. Therefore, an accurate forecasting model has to be developed to accommodate a lower error and avoid demurrages. To compare the previous forecast, initially, we identified the previous forecast by collecting the data of 2019 stock of product on a monthly basis, where on the same year demurrage occurred. The data is presented in a Descriptive Residual Statistics, as shown in Table 4. To get the idea of the previous model performance can be seen in its statistics. Regression expressed how far the forecast results to the actual value where is shown in Figure 5.

As observed in Figure 5. and Table 5, the regression for the forecasted value and actual value from the previous model is:

$$\text{Forecasted value} = 273.073 + 0.3277 \cdot \text{Actual value} \quad (4)$$

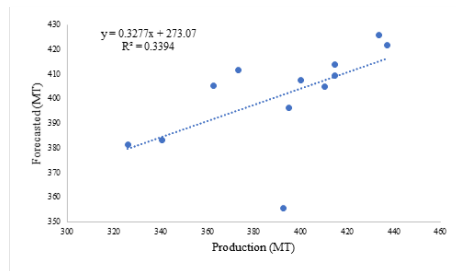


Figure 5. Regression plot forecasted values and the dependent variable are actual production values

Table 5. Model Summary where the independent variable are Forecast Values and the dependent variable are Actual Production Values

Model	R	R ²	Adjusted R ²	Std. Error of the Estimate	Durbin-Watson
1	.583	.339	.273	16.764	1.817

As well as the coefficient of determination or $\beta^2=0.339$ $R=0.583$ and $RMSE=0.2146$ which can be calculated with the normalization factor. It is usually equal to either the difference between the maximum and minimum values or the maximum measured value on the forecast horizon. Normalization factor can be calculated over the entire interval or time horizon or defined short interval of observation (Shcherbakov *et al.*, 2013). In this case, this paper using RMSE model as mentioned at the methods.

Since the errors are squared before averaged, the RMSE gives a relatively high weight to outliers or large errors. Therefore, RMSE is most useful when large errors are particularly unwanted. Model has lower values of RMSE indicate a better fit. By seeing all the above results, we have identified the previous forecast model to be used as reference to compare and find an accurate alternative model with a lower RMSE values. The previous forecast model distribution histogram and P-P plot are shown in Figure 6.

Providing new forecasting model as alternatives, this research develops an ANN model with the steps is shown in Figure 7. We develop a training model with various combinations of algorithms with single and two hidden layers, and using a different number of neurons on each hidden layer. Six months of normalized production data, shown in Figure 8, is used to predict the next month of stock production. These simulations are conducted to find the better model which have lower RMSE value than current model at the value of 0.2147.

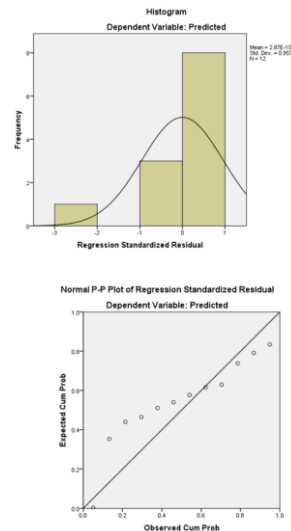


Figure 6. The distribution of residual histogram and probability- probability plot for current forecasting model

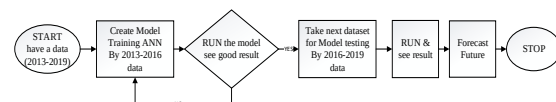


Figure 7. Stages in developing ANN for forecasting model

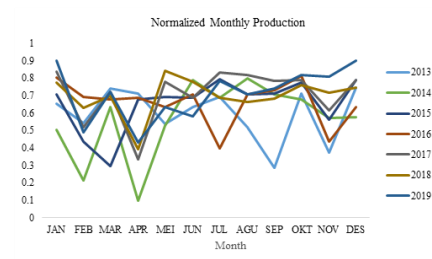


Figure 8. Normalized Data of Monthly Production Period of Year 2013-2019

We have observed that the greater number of either hidden layers or the number of neurons is not guaranteed to achieve an accurate model as expected. Some of algorithms required more time and iterations to reach the best performance, such as on Variable Learning Rate Backpropagation (*traingdx*) algorithm, it takes nearly 30 min for BFGS Quasi-Newton algorithm to reach the best performance with two hidden layers and one hundred neurons on each layer.

As observed on Tables 6-11. We found the RMSE value is less than 0.2147, which belong to the previous forecasting model. A Conjugate

Gradient with Beale-Powell Restarts (*traincgb*) algorithm, two hidden layers with 25 neurons each layer is achieved as the lowest RMSE value at 0.186.

Table 6. RMSE results on different trials of algorithm and number of hidden layers and number of neurons

1 Layer @25 Neurons	Training		Testing	
	R	RMSE	R	RMSE
trainlm	0.99566	0.01975	-0.0306	0.418
trainbfg	0.9828	0.03138	-0.0512	0.47409
trainrp	0.98282	0.03162	-0.2077	0.28245
trainscg	0.98304	0.03142	-0.2456	0.48431
traincgb	0.89669	0.07545	-0.0711	0.35375
traincgf	0.98282	0.03129	-0.273	0.36901
traincgp	0.98331	0.03134	-0.0278	0.41439
trainoss	0.98277	0.03148	-0.1716	0.47515
traingdx	0.98298	0.03162	-0.1684	0.40323

Table 7. RMSE results on different trials of algorithm and number of hidden layers and number of neurons

1 Layer @50 Neurons	Training		Testing	
	R	RMSE	R	RMSE
trainlm	0.99852	0.00969	-0.1756	0.39517
trainbfg	0.98531	0.02901	-0.4446	0.39812
trainrp	0.98286	0.03162	-0.0764	0.32691
trainscg	0.98245	0.0316	-0.0266	0.51176
traincgb	0.95231	0.05173	-0.0237	0.46624
traincgf	0.98266	0.03148	0.0025	0.482
traincgp	0.98312	0.03099	-0.1813	0.28114
trainoss	0.98252	0.03155	0.05965	0.33065
traingdx	0.98278	0.03156	-0.0873	0.37084

Table 8. RMSE results on different trials of algorithm and number of hidden layers and number of neurons

1 Layer @100 Neurons	Training		Testing	
	R	RMSE	R	RMSE
trainlm	0.99948	0.00665	-0.3458	0.45483
trainbfg	0.98422	0.02998	-0.194	0.49696
trainrp	0.98245	0.03161	-0.1688	0.47370
trainscg	0.98373	0.03123	-0.3067	0.37597
traincgb	0.98253	0.03162	-0.1266	0.39350
traincgf	0.98481	0.02969	-0.1644	0.55374
traincgp	0.98359	0.0308	0.13023	0.35228
trainoss	0.98296	0.03118	-0.1284	0.43790
traingdx	0.98242	0.03161	-0.1366	0.37266

Table 9. RMSE results on different trials of algorithm and number of hidden layers and number of neurons

2 Layers @25 Neurons	Training		Testing	
	R	RMSE	R	RMSE
trainlm	0.9865	0.02824	-0.1834	0.35222
trainbfg	0.98277	0.03129	-0.0298	0.27813
trainrp	0.98269	0.03161	-0.0308	0.23396
trainscg	0.98241	0.03161	-0.1133	0.25345
traincgb	0.74301	0.11379	-0.1649	0.18601
traincgf	0.98299	0.03153	-0.0909	0.40352
traincgp	0.98256	0.03155	-0.207	0.28664
trainoss	0.98314	0.03136	-0.2244	0.383
traingdx	0.98283	0.03162	0.01666	0.22545

Table 10. RMSE results on different trials of algorithm and number of hidden layers and number of neurons

2 Layer @50 Neurons	Training		Testing	
	R	RMSE	R	RMSE
trainlm	0.99937	0.01349	-0.1534	0.29523
trainbfg	0.98358	0.03068	-0.2488	0.23378
trainrp	0.9826	0.03162	-0.0021	0.24523
trainscg	0.98308	0.03138	-0.2029	0.3148
traincgb	0.9776	0.03563	-0.1486	0.2633
traincgf	0.98385	0.03072	-0.201	0.2772
traincgp	0.98454	0.03042	-0.112	0.23384
trainoss	0.98356	0.03116	-0.2028	0.33264
traingdx	0.98417	0.03161	-0.1315	0.26865

Table 11. RMSE results on different trials of algorithm and number of hidden layers and number of neurons

2 Layer @100 Neurons	Training		Testing	
	R	RMSE	R	RMSE
trainlm	0.99137	0.02295	0.05246	0.30721
trainbfg	0.98371	0.03129	0.01928	0.30143
trainrp	0.98294	0.03138	-0.2354	0.49757
trainscg	0.98521	0.02942	-0.1483	0.35339
traincgb	0.9851	0.02961	0.09107	0.33503
traincgf	0.98247	0.03158	-0.0511	0.36043
traincgp	0.98338	0.03156	-0.1678	0.33587
trainoss	0.98325	0.03112	0.03133	0.44446
traingdx	0.98339	0.03161	0.24401	0.34854

The following are the results of the ANN model shown in Figure 9 and Figure 10 with those above-mentioned variations to find better model RMSE less than 0.2147 with a different type of algorithm, number of hidden layers, and number of neurons on each layer. While, the normal distribution of the model is shown in Figure 11.

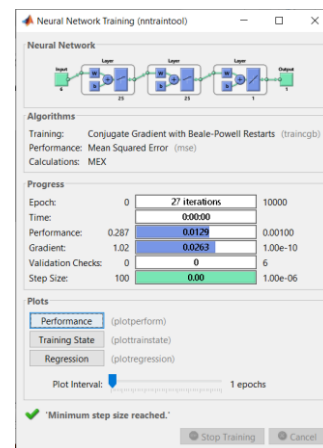


Figure 9. ANN model with Conjugate Gradient with Beale-Powell Restarts (traincgb), 2 hidden layers with 25 neurons each layer

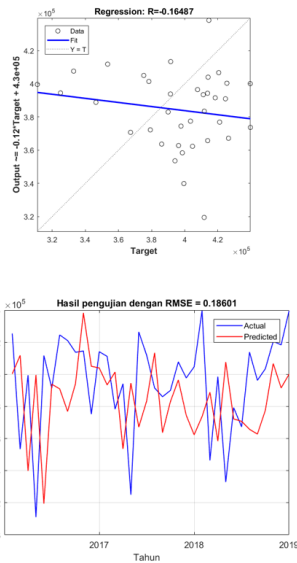


Figure 10. ANN Model found with the lowest RMSE results both on the training and test where the Conjugate Gradient with Powell/Beale Restarts algorithm is used with two hidden layers and 25 neurons each

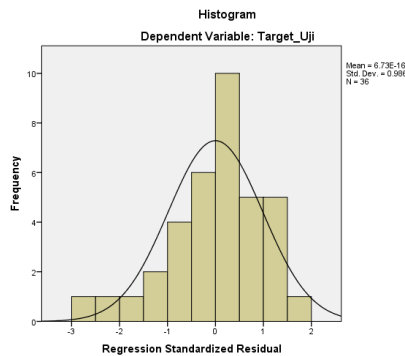


Figure 11. Forecast result of testing model regression standardized residual distribution histogram

Managerial Implication

In this study observes that a financial loss namely demurrage as a consequence of delay in shipment processes because of product shortage. We analyze that at the problem from inventory condition and two contributed factors, stock forecast error and initial stock, where the empirical data and theory fits at $R^2=0.667$. Strong correlations are found Demurrage to Forecast Error and Demurrage to Initial Stock. Both coefficients are statistically significant shown by ANOVA with p -value=0.07, 0.036 and 0.011.

Based on this result, we confidently suggest to optimizing the demurrage through reducing the forecast error. We have identified that the previous stock forecast error where the RMSE value is 0.215, which is quite a good result. However, this paper provides a forecasting model using an Artificial Neural Network model. An ANN model is developed using a Conjugate Gradient with Powell/Beale Restarts algorithm with two hidden layers and 25 neurons produce lower RMSE value at 0.186 for training and testing.

In fact, the forecast errors will be always there, the increment of forecast error, which leads to the need of holding higher safety stocks in order to achieve the target service level (Cannella *et al.*, 2018). To increase the safety stock, we can use the regression Equation (3) as follow:

When the forecast error according to the data is highest (55.659MT), the calculation is:

$$\text{Demurrage} = 71.169 + 0.634 (\text{Forecast Error}) - 0.411 (\text{Initial Stock})$$

$$\begin{aligned} \text{Initial Stock} &= \frac{71.169 + 0.634 (\text{Forecast Error}) - \text{Demurrage}}{0.411} \\ &= \frac{71.169 + 0.634 (55.659) - (0)}{0.411} \\ &= 259.01899 \text{ MT} \end{aligned}$$

and when the forecast error according to the data is lowest (1.284MT), the calculation is as follow:

$$\begin{aligned} \text{Initial Stock} &= \frac{71.169 + 0.634 (1.284) - (0)}{0.411} \\ &= 175.1425 \text{ MT} \end{aligned}$$

Above result it is bringing to the situation that previous safety stock at 150MT (27% of capacity) is the best setup compared to latest reduced Figure at 100MT (18% of capacity). When inventory exactly as safety stock at 150MT, demurrage is achieved at zero and Forecast Error at -15.01. It means forecast slightly underestimated which is normal as forecast fluctuation will be always there. It is shown as below calculation:

$$\begin{aligned} \text{Demurrage} &= 71.169 + 0.634 (\text{Forecast Error}) - 0.411 (\text{Initial Stock}) \\ (0) &= 71.169 + 0.634 (\text{Forecast Error}) - 0.411 (150) \\ 0 &= 71.169 + 0.634 (\text{Forecast Error}) - 61.65 \\ 0 &= 9.519 + 0.634 (\text{Forecast Error}) \\ \text{Forecast Error} &= -\frac{9.519}{0.634} = -15.01 \end{aligned}$$

So, it is very clear that by increasing safety stock to 150MT, it can accommodate more forecast error, the availability of buffer stock minimizes exposure to possible demurrage claims (Branch and Robarts, 2014). However, increasing safety stock at the same time is increasing the potential of storage to become full as well.

Conclusions

We begin this research with interest to understand the relationship between production forecasting and initial stock, and shipping delay due to product shortage leading to demurrage. According to the result, this is mainly affected due to stock forecast error and initial stock in the inventory. An optimization is possible to carry out in two ways. First, decrease forecast errors by providing an ANN model. Second, by increasing the initial stock of products which can also be considered as a new safety stock. This linear regression model fits in this problem, suggesting forecasting error and initial stock to be relevant factors. The ANN model is an alternative solution to suggest forecasting with lower errors; therefore, RMSE can be used to evaluate the model. The company is expected to continue to maximize shipments and fulfil more orders on time.

For future research, a forecasting model is possible to explore using different theories or method of machine learning such as Adaptive Neuro-Fuzzy Inference System (ANFIS) or Auto-Regressive Integrated Moving Average (ARIMA) model.

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