Artificial Neural Network Modeling Studies to Predict the Amount of Carried Weight by Rail Transportation System

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ABSTRACT

Keretapi Tanah Melayu Berhad (KTMB) is the main rail operator in Peninsular Malaysia. KTMB provides cargo services which are safe, efficient and trustworthy. KTMB also has services that are connected to the port and inland port in Peninsular Malaysia. However, they suffered three major derailments in 2017. On November 23, a cargo train had an accident when 12 cargo trains traveling southward slipped between National Bank Station and Kuala Lumpur Station due to heavy weight and oversized loads carried by the cargo train. This study is conducted to predict the amount of carried weight of cargo by KTMB using Artificial Neural Network model. Datasets used in this study was taken from Department of Statistics Malaysia Official Portal from year 2001 to 2016. There are three algorithms chosen in this study which are Conjugate Gradient Descent (CGD), Quasi-Newton (QN) and Lavenberg-Marquardt (LM) algorithm. The best algorithm is selected to predict the amount of carried weight by comparing the value of error measures of the three algorithms which are Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). Therefore, CGD is the best algorithm that produces smallest error of RMSE and MAPE. By using CGD algorithm, the results show the forecast value of carried weight for five years ahead which is from year 2017 until 2021 is decrease.

Keywords: *Artificial Neural Network (ANN), Conjugate Gradient Descent (CGD), Quasi-Newton (QN), Lavenberg-Marquardt (LM), algorithm*

INTRODUCTION

Carried weight is the amount of goods that are carried on a ship, plane, or truck. The amount of carried weight is very important in logistic transportation system to make sure all the goods arrive to the destination safely at the right time. In Peninsular Malaysia, KTMB is the main rail operator. KTMB provides many types of services such as that Electric Train Service (ETS), Intercity, Commuter, and Cargo. KTMB also provide cargo services which are safe, efficient and trustworthy. KTMB also has services that are connected to the port and inland port in Peninsular Malaysia. There are three types of train services of KTMB Freight Service which are Train Contena Service, Train Cargo Conventional Service and Train *Landbridge* Service

KTMB has suffered three major derailments in 2017. On August 21, a cargo train wrecked at Jalan Kucing and caused delays for a few days. On September 23, a snapped electrical cable between Rawang and Kuang stations had to close their track for two days. On November 23, once again cargo train had an accident when 12 cargo trains traveling southward slipped between National Bank Station and Kuala Lumpur Station due to heavy weight and oversized loads carried by the cargo train (Alias, 2017). Consequently, KTM commuter and ETS services were disrupted for several routes around the Klang Valley. One of the major causes of this tragedy was because of the overload of the wagons of the cargo train.

The prediction of the amount of carried weight is important because it can help KTMB improves operation efficiently. KTMB can manage its cargo items well so that it can overcome the accident that will cause delays of other services such as Keretapi Tanah Melayu commuter and ETS services. KTMB has to organise effective management and schedules well to overcome the accident problem and improve the terminal operation to fulfil customer needs at the right time and in the right condition. An effective planning can also help KTMB against any loses. If there is no action towards this problem, there will be dissatisfaction from the customers that can affect KTMB's reputations.

The objective of this study is to predict the amount of carried weight on KTMB Freight Service for five years from 2017 to 2021 by using the best algorithm in Artificial Neural Network (ANN). The data regarding on freight traffic by types of cargo are taken from Department of Statistics Malaysia Official Portal which is from year 2001 to 2016. In this study, the softwares that have been chosen are Alyuda NeuroIntellegence and Microsoft Excel 2010. This study only focuses on Conjugate Gradient Descent (CGD), Quasi-Newton (QN) and Lavenberg-Marquardt (LM*)* and it chooses the best algorithm based on smallest error measures which are RMSE and MAPE.

This research significantly gives benefits to KTMB as it can help to improve their services efficiently and to know about their amount of carried weight for five years. Therefore, they can plan their management effectively such as the weight of goods and train schedule. The goods also will arrive safely and will not disrupt other KTMB services. KTMB can also decrease its cost and increase its profits through effective planning.

RELATED WORKS

Carried Weight

Rahman et al. (2014) studied about ANN to predict carried weight. There are three classes of ANN which are incremental back propagation algorithm, genetic algorithm and Levenberg-Marquardt algorithm. This study was applied in an automobile industry, Iran Khodro Company (IKCO). An organization can appropriately provide the machinery resources, labour, transport system and for appropriate organization if it is wise about the amount of the demand. The demand rates can be surveyed by utilizing different strategies, the most significant is load-count analysis, weight volume analysis, and material balance analysis (Smith, 2012). ANN was used to test the weekly data of carried weight given by IKCO transportation system based on the observation of the number of trucks, van lorry and fuel consumption.

Petraska et al. (2017) analyzed the problem of optimization of transportation processes of heavyweight and overload. The authors formulated the universal multi-criteria assessment system of route and guarantee rational choice of heavyweight loads routes of rail transportation. This study revealed a set issue related to heavyweight and oversized loads transportation. Rail mode transport is not flexible routing compared to road transport due to a new segment of the track or the improvement of the current which is very expensive and complex than to enhance the same length of the car road section. The problem of heavyweight and oversized loads by rail often increases, cargo size is not the problem but the main issue is loads weight. Evaluation about suitability of rail transport mode for transportation about heavyweight and oversized loads will be practically often associated with the limit value of the load size. The different areas of their density is very different which was recognised by analysing rail network (Jarasuniene, 2009).

Artificial Neural Network

Tosun and Calik (2016) studied failure load prediction of single lap adhesive joints using ANN. The goal of this study is to predict the failure load in single lap adhesive joints using ANN. The experimental data acquired from the literature covers the single lap adhesive joints with different geometric models under the tensile loading. ANN model was developed to estimate the relationship between failure loads by utilizing geometric measurements of bond range as input data. A three-layer feed forward artificial neural network system that used LM algorithm model was utilized as a part of request to prepare the train network. It was observed that ANN model can estimate the failure load of single lap adhesive joints with minimum mistake. The outcomes demonstrated that the ANN is an efficient option strategy in prediction and supported by Amani and Moeini (2012) who proposed an ANN is the best model compared to Adaptive Neuro-Fuzzy Inference System (ANFIS). This research used ANN and ANFIS to predict the shear strength of reinforced concrete beam. This study compared the models with American Concrete Institute and Iranian Concrete Institute empirical codes. The main objective of this study is to design and develop ANN and ANFIS models for predicting RC beam shear strength. As a result, the prediction of ANN is better than ANFIS model.

Based on the previous research, many methods and techniques that have been used for forecasting and it can be concluded that ANN technique is the best model to predict the amount of carried weight.

RESEARCH METHODOLOGY

The method that will be used in this study is ANN technique. In this study, the software that has been chosen is Alyuda NeuroIntellegence. In this software, there are seven algorithm which are Quick Propagation, Conjugate Gradient Descent, Quasi-Newton, Limited Memory Quasi-Newton, Levenberg-Marquardt algorithm, Online Back Propagation algorithm and Batch Back Propagation algorithm. This study only focuses on, Quasi-Newton (QN), Conjugate Gradient Descent (CGD) and Levenberg-Marquardt (LM) algorithms and chooses the best algorithm based on the smallest error measures. There are six steps to develop ANN using this software.

Step 1: Data Analysis

Data is analyzed using Alyuda NeuroIntelligence software. This stage will analyze the input data to define the column parameters and identify irregular data in “Analysis Report”.

Step 2: Data Preprocessing

At data preprocessing stage, the data will be normalized by adding 0.1 in every variable to make sure the data is accurate and fulfill the neural network requirement. The data will scale in range between [-1, 1] or [0, 1] by the input neuron. The modified data in this stage will enter to the neural network.

Step 3: Designing Network

After data preprocessing, the best model of the neural network will be designed at this stage. The number of layers and hidden neurons will be chosen in this stage. The network architecture will be generated to develop the model and to determine the best model based on a few criteria such as Akaike’s Criterion (AIC), fitness criterion, least error and R-Squared value.

Step 4: Training Network

At this stage, the number of training algorithm, parameter and the number of iteration chosen. The training process will provide a visual representation.

Step 5: Testing Network

The input data will be tested and generated the output data. From the output data, the error measure can be calculated which are RMSE and MAPE. The results shows the value of the correlation coefficient between the original data and modelled data. Error measure is a criteria is used to differentiate between a poor forecast model and a good forecast model. The usual measurement being error measure that has the smallest value. There are two error measures that are considered and the most popular among researchers which are RMSE and MAPE.

The first error measure is Root Mean Squared Error (RMSE). This is also the most favourite error measure among researcher even though it is unit free (Lazim, 2011). RMSE also gives equal weights to all errors. It is given as,

$$\text{RMSE}=\sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(y_t-\hat{y}_t\right)}, \qquad (1.1)$$

Where;
$e_t = y_t - \hat{y}_t$
y_t = The actual observed value in time t
$\hat{y}_t$ = The fitted value in t

The second error measure is Mean Absolute Percentage Error (MAPE). This is most widely used unit free measure (Armstrong and Collopy, 1992). MAPE is written as,

$$\text{MAPE} = \sum_{t=1}^{n}\frac{\left|\left(e_t / y_t\right)*100\right|}{n}, \qquad (1.2)$$

Where,
$e_t = y_t - \hat{y}_t$
y_t = The actual observed value in time t
n = Denotes effective data point,
$\left|\left(e_t / y_t\right)*100\right|$ = The Absolute Percentage Error calculated on the fitted values.

Step 6: Querying Network

After testing the network is done, choose the “Query” from the menu bar. The forecast value of the carried weight for five years are generated.

RESULT AND DISCUSSION

Data Preprocessing

Table 1 shows the parameter output from data preprocesses of the carried weight of cargo. From the result, the scaling range of input neurons in neural network is between -1 to 1 is approved.

Table 1: Data Preprocessing Output for Carried Weight of Cargo

Column Details	
Scaling range	[-1…1]
Min	3803
Max	8005
Mean	5464.6875
Std. deviation	1145.9293

Designing Network

Table 2 shows the generated results from the network architecture. From the result, it was found that the best architecture of neural network is [2-6-1] model. This model has the largest fitness value compared to other model, which is 0.02143. The value of AIC is low and also has the least value of test error. In addition, the correlation value is 0.6872 which indicates a good relationship.

Table 2: Architecture Network of ANN

ID	Architecture	Fitness	Test Error	AIC	Correlation
1	[2-1-1]	0.01186	84.34	59.40	0.2859
2	[2-7-1]	0.01146	87.29	106.54	-0.3922
3	[2-4-1]	0.00445	224.83	84.16	0.6731
4	[2-5-1]	0.01654	60.46	86.19	0.6747
5	[2-6-1]	0.02143	46.66	94.83	0.6872

Training Network

In this study, the network was trained by three algorithms which are CGD, QN and LM. The result in table 3 shows that CGD has the smallest network error and absolute error for training while LM has the smallest error of network error for validation part compared to others. This result also shows the correlation and R-squared values which is the highest correlation between these three algorithms remove is belong to CGD.

Table 3: Testing Network Output of ANN

	CGD		QN		LM	
	Training	Validation	Training	Validation	Training	Validation
Network Error	207.3022	2126.1322	207.3559	2127.3360	941.8026	1124.0743
Absolute Error	0.005221	0	0.005217	0	0.067597	0
No. of Iteration	501		501		55	
Correlation	0.4834		0.4255		-0.2285	
R-squared	-1.3509		-1.5552		-15062.7325	

Testing Network

Table 4 shows the error measures of CGD, QN and LM algorithms. It was found that CGD algorithm has the lowest error compared to other algorithms. Therefore, the best algorithm is CGD algorithm.

Table 4: The Comparison of Error Measures between the Algorithms

	Conjugate Gradient Descent (CGD)	Quasi-Newton (QN)	Lavenberg-Marquardt (LM)
RMSE	23.7809	25.5991	30.0360
MAPE	9.3386	10.8449	17.1848

The best algorithm of ANN is CGD to predict the amount of cargo carried weight by rail transportation system. Table 5 shows the results of prediction of carried weight for five years remove which from 2017 to 2021. The forecast value for the five years ahead from year 2017 to 2021 is decreasing.

Table 5: The Forecast Value from Year 2017 to 2021

Year	Forecast Value
2017	5972.39572
2018	5917.377089
2019	5894.378683
2020	5873.076015
2021	5859.948331

CONCLUSION AND RECOMMENDATION

In this study, the objective is to predict the amount of carried weight of rail transportation system using ANN modelling. The data of carried weight of cargo by KTMB was taken from year 2001 until 2016 using ANN method to obtain the accurate result. To obtain the best result of forecast, there are three algorithms that have been analysed which are CGD, QN and LM algorithms. The best algorithm to predict the amount of carried weight by rail transportation system is CGD algorithm because CGD algorithm gives the smallest error compared to another two methods. The result of forecast value of carried weight of rail transportation system is decreasing from year 2017 to 2021. Future study, researcher can compared ANN with another method that will gives better performance in prediction. ANN also can use to predict another elements such as sales for the company and any agricultural plants.

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