COMPARING NEURAL NETWORK AUTOREGRESSIVE METHOD FOR IMPORT DUTY REVENUE FORECASTING

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INFORMASI ARTIKEL

ABSTRACT:

This study tries to solve the methodological gap in forecasting import duty revenue by suggesting Neural Network as an alternative model. Neural Network is one of the interesting methods in data analytics used to forecast time-series data in the previous years. In one of the initiative strategies, the Directorate General of Customs and Excise (DGCE) compares this method with Holt-Winters exponential smoothing to get more accurate forecasting of import duty revenue. This paper compares Holt-Winters and Neural Network (NN) to get more accurate forecasting for import duty revenue using data from Customs and Excise Information System Automation (CEISA) billing system. As a result, NN gives a better result with a lower Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE). Therefore, neural networks should be used to forecast and monitor the realization of import duty revenue so DGCE can identify the change

ABSTRAK:

Penelitian dalam makalah ini menyajikan *methodological gap* dalam meramalkan penerimaan Bea Masuk dengan menawarkan *Neural Network* sebagai modeling alternatif. *Neural Network* adalah salah satu metode menarik dalam *data analytics* yang digunakan untuk keperluan memprediksi data time-series pada beberapa tahun terakhir. Direktorat Jenderal Bea dan Cukai (DJBC) dalam salah satu inisiatif strategi (IS) membandingkan metode ini dengan *Holt-winter exponential smoothing* untuk mendapatkan peramalan yang lebih akurat pada penerimaan Bea Masuk. Makalah ini membandingkan Holt-Winters dan *Neural Network* (NN) dengan tujuan untuk mendapatkan peramalan yang lebih akurat terhadap penerimaan Bea Masuk menggunakan data *Customs and Excise Information System Automation* (CEISA) Billing. Hasilnya NN memberikan hasil yang lebih baik berdasarkan parameter *Mean Absolute Error* (MAE), *Mean Absolute Percentage Error* (MAPE) dan *Root Mean Square Error* (RMSE) yang lebih rendah. Berdasarkan hasil tersebut, Neural Network dapat dipertimbangkan untuk digunakan dalam melakukan peramalan dan monitoring penerimaan Bea Masuk sehingga DJBC dapat mengidentifikasi perubahan indikator perekonomian makro yang dapat mempengaruhi realisasi penerimaan serta

in economic indicators that can affect import duty revenue earlier and produce the right policy to respond to it.

Keywords: *forecasting, neural network, import duty, revenue, data analytics*, *customs*.

menghasilkan kebijakan yang tepat untuk merespon hal tersebut.

Kata Kunci: *forecasting*, *neural network*, bea masuk, penerimaan, *data analytics*, kepabeanan.

1. INTRODUCTION

Data Analytics became popular in the Ministry of Finance in 2020 after a data analytics competition hosted by the Inspectorate General of the Ministry of Finance. A year after the event, the
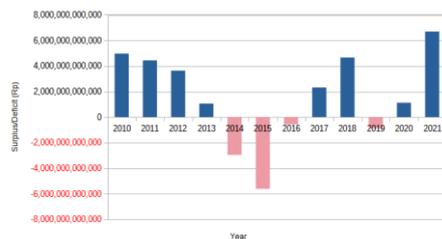

Figure 1 : Proportion of Import Duty Revenue in 2021 (Source : CEISA Billing)

DGCE contributes 20-25% of Indonesia's customs revenue every year (Purwana, 2019). This revenue includes import taxes (value added tax, luxury tax, income tax), import duty and export tax. Conducting on the example of Ukraine, a study from European Research Studies Journal explained that the forecasting of customs revenue is influenced by two main components: monetary and macroeconomics indicators including (GDP, export volumes, import duty rates, and inflation rate (Martyniuk et al., 2021).

Import duty is one kind of state revenue that proportionally reaches 1.94% of total national tax revenue in 2021. DGCE collected 214.96 million rupiahs or 10.73% of total tax revenue. From this number, import duty contributed 18.09% (Figure 1).

Directorate General of Customs and Excise (DGCE), which has a role in collecting state revenue, including import duty, had an Initiative Strategy (IS) in Data Analytics by having a project to forecast import duty revenue.

Figure 2 : Surplus / Deficit of Import Duty Revenue (Source : CEISA Billing)

However, DGCE did not always meet the target of import duty revenue every year (Figure 2). For example, in 2019, DGCE missed the import duty target (38.9 million rupiahs) because it only got 37.45 million rupiahs. As a result, DGCE missed its import duty target four times (Figure 3).
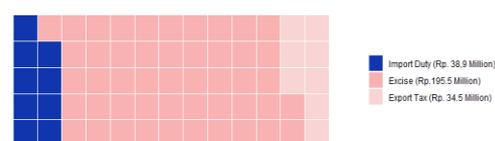

Figure 3 : Import Duty Revenue - Target and Realization (Source : CEISA Billing)

Business experts from the Directorate of Revenue and Strategic Planning (PPS) explained why import duty revenue did not always reach the target. It was mostly because of the change in economic conditions that affect supply and demand in international trade; in this case,

national import value. In addition, there are no real-time forecasting tools to identify whether the target can still be reached or not. Monitoring and evaluation usually happen at the last minute of the current year so that there is no more time to respond with the right policies.

The forecasting of import duty revenue is needed to respond to the change in economic indicators that can affect import duty realization. So in 2021, DGCE conducted a project based on a data analytics initiative strategy using the comparison between *Seasonal Autoregressive Moving Average* (SARIMA) and *Holt-winters Exponential Smoothing* model to find a forecasting model for import duty revenue.

As a result, Holt-Winter's models gave lower MAPE (<10%), so that model was chosen as a forecasting tool for the Initiative Strategic on Data Analytics Project that year. However, the Central Transformation Office (CTO) Ministry of Finance recommended that DGCE consider the machine learning model like Neural Network rather than those two traditional statistics methods. This recommendation based on previous studies in recent global data analytics conferences that use Neural networks as a new trend for forecasting models of the time series data.

Based on that recommendation, the Directorate of Customs and Excise Information and Technology conducts an academic research paper to ensure whether the Neural Network model has better accuracy in predicting the incoming import duty revenue than the existing method or not. The question that needs to be answered in this paper is what is the best model to forecast import duty, Holt-winters or Neural Networks? This paper aims to examine whether neural network analysis has better results to forecast import duty revenue or not compared to holt-winters analysis that was previously used in import duty revenue forecasting based on some statistical parameters. The research gap that was trying to be addressed in this study is the methodological gap.

2. LITERATURE REVIEW

Neural Networks can be defined as a machine learning model inspired by the brain's structure with the capability to add complexity with deep learning in many hidden layers (Figure 4). This model adjusts weights and layers in the process of training with the help of a learning algorithm. According to Zhang and Qi (2005), Neural networks can adaptively learn from experience and predict any complex relationship with high validity. With this capability, Practitioners used neural Networks to forecast time-series data in many pieces of research. Neural Network Autoregressive (NNAR) is the updated version to handle complex connection modeling between inputs and outputs (Karadzic & Pejovic, 2021).
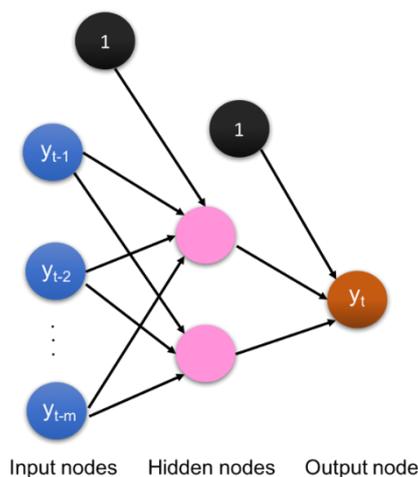
Figure 4 : Neural Network Layers (Zhang & Qi, 2005)

Holt-winters is one variation of the exponential smoothing method in forecasting. This forecasting method focuses on exponentially decreasing priority on longer observation objects. Holt (2004) and Winters (1960) find the seasonality and the trend as components that shape the pattern. Seasonality means the repeating pattern in the short term of the time series data, while the trend is the rise and fall pattern of the time series data in the long term.

No previous studies used Neural networks to forecast import duty revenue in Indonesia. However, many studies have compared Neural Network, ARIMA, and Holt-Winters in recent years to get a more accurate model in time-series data forecasting. An example comes from Nyoni (2019), who used an Artificial Neural Network (ANN) to forecast the imports and exports of Zimbabwe, resulting in a small MAE that indicates his forecast is good. Another

study from the Korean Society of Civil Engineers compared the NNAR and ARIMA to forecast the Water Treatment Plant (WTP). The NNAR models show better prediction in terms of R2 statistics than the ARIMA models to explain the observed values of a time series (Maleki et al., 2018).

At the end of their study, Zhang and Qi conclude that neural networks with detrending and deseasonalization produce better accuracy than seasonal ARIMA. Still, without preprocessing, neural networks have worse forecasting performance than seasonal ARIMA (Zhang & Qi, 2005).

Saba and Elsheikh (2020), in their paper about COVID-19, concluded that *Nonlinear Autoregressive Artificial Neural Networks* (NARANN) have better results than ARIMA to predict the prevalence of COVID-19 outbreak in Egypt. Based on the studies above, I hypothesize that the Neural Networks model has better accuracy in forecasting import duty revenue. Another research in 2020 compared three models: additive HW, multiplicative HW, and SARIMA, to forecast tourism in Turkey and concluded that multiplicative HW gave the best result for accuracy (Sennaroğlu & Zayat, 2020).

Furthermore, da Silva (2022) observed six methods, including HW and NN, to forecast electricity consumption in Brazil, resulting in the Holt-Winters method being the overall best for short-term forecasting.

An interesting result was conducted by a study by Karadzic & Pejovic (2021)

when they compared NNAR, ARIMA, and Holt-Winters to forecast inflation in the European Union and three non-European countries (Montenegro, Serbia, and North Macedonia). The result of this paper was that NNAR gave the best accuracy for Montenegro, Serbia, and North Macedonia. However, ARIMA gave the most accurate forecast for the European Union based on ME, RMSE, MAE, MAPE, MASE, and Theil's U.

The proof from the studies above stated that Neural Networks are considered one of the models used in forecasting time-series data besides ARIMA and Holt-Winters. Since DGCE already compared ARIMA and Holt-Winters, in this study, I put the Neural Network to be an alternative model in the forecasting of import duty revenue.

3. RESEARCH METHOD

I use descriptive statistics to know the condition of the dataset. Using descriptive statistics gives more detailed knowledge about the dataset. Descriptive statistics also produce more understanding that is necessary to perform further analysis. For the next step, I compare two versions of Holt-winters (Additive and Multiplicative) and Neural networks to get a more accurate forecast for import duty. The Holt-Winters (HW) method is the extended version of the Holt method. The holt-winters method has a formula (Kotsialos et al., 2005) :

$$F_{t+m} = (L_t + b_t \sqrt{m}) \, S_{t+m}$$

where L is level, b is the trend and S is seasonality. The Holt-Winters method can be built into two ways: additive and multiplicative. Additive Holt-Winters can be used whenever the seasonal pattern of a data series has a constant amplitude over time. Additive HW captures seasonality and provides smoothed values for the forecast level, trend, and forecast adjustment, adding the seasonality to the trended forecast. The additive HW structure is $Yt = T_t + S_t + t$. The multiplicative HW multiplies the trend forecast by the seasonality (da Silva et al., 2022). The multiplicative HW can be represented by y $Y_t = T_t \times S_t + t$ (Lima et al., 2019) .

The formula of Neural Networks can be described as (Zhang & Qi, 2005) :

$$y_t = \alpha_0 + \sum_{j=1}^{n} \alpha_j \, f\left(\sum_{i=1}^{m} \beta_{ij} y_{t-i} + \beta_{0j} \right) + \varepsilon_t$$

where m is the number of input nodes, n is the number of hidden nodes, α_0 and β_{0j} are weights of arcs leading from the bias terms which have values always equal to 1. f is a sigmoid transfer function such as the logistic: $f(x) = \frac{1}{1+exp(-x)}$. $\{\alpha_j, j = 0,1,\ldots,n\}$ is a vector of weights from the hidden to output nodes and $\{\beta_{ij}, i= 0, 1,$

…, m; j=1,2,...,n} are weights from the input to hidden nodes (Zhang & Qi, 2005).

I divide the dataset to evaluate models by dividing the dataset into two parts: training and testing data with 80:20 ratio. I build the model from the data training (dataset of import duty revenue from January 2010 to October 2019), and measure the accuracy of the model into the data testing (the same time-series data from November 2019 to February 2022). To measure the model's accuracy I used *Mean Absolute Error* (MAE), *Mean Absolute Percentage Error (MAPE) and Root Mean Square Error* (*RMSE*) in order to get a better model from two models with formula:

$$MAE = \frac{1}{k} \sum_{t=1}^{k} |\hat{y}_t - y_t|$$

$$MAPE = \frac{1}{k} \sum_{t=1}^{k} \frac{|\hat{y}_t - y_t|}{y_t}$$

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_t - y_t)^2}{n}}$$

where $\hat{y}$ is the actual value, y is the predicted value, and k is the number of observation points.

For data processing and some visualizations, R studio is used to calculate all of the measurements in this paper. I extracted the time-series data from the *Customs and Excise Information System Automation* (CEISA) billing system (CEISA Billing) from January 2010 to February 2022. I used the CEISA Billing because every transaction in import duty payment has a *State Revenue Transaction Number* (NTPN) to ensure that every rupiah is already put into a state account.

Because of this process, there is no need to check extreme data since the validity in every row of data is already high. Therefore, 146 time-series monthly data is processed to get the conclusion in this paper. Variable import duty that I collect consists of all import duties paid by importers, including general import duty, antidumping, Customs fine, and safeguard.

4. RESULT AND DISCUSSION

To get a general information about dataset of import duty revenue, I put descriptive statistics using r studio, the result shown on the Table 1 below:

Table 1

Descriptive Statistic of the Dataset

Parameter	Value
n	146
Mean	2,717,146 x 10^6

Min	$1,269,899 \times 10^6$
Max	$4,496,480 \times 10^6$
Median	$2,699,398 \times 10^6$
Q1	$2,336,708 \times 10^6$
Q3	$3,083,721 \times 10^6$
SD	582,707,366,589

Table 1 above shows descriptive statistics of the dataset with the mean 2.717×10^{12}. The minimum value of the dataset is 1.269×10^{12} and the maximum value is 4.496×10^{12}. Median value of the dataset is 2.699×10^{12} while Q1 of the dataset is 2.336×10^{12}. The Q3 of the dataset is 3.083×10^{12} with standard deviation 582.71×10^9.
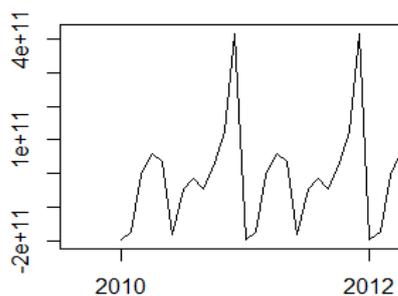
Figure 5 : Seasonality of Import Duty Revenue in two years

Based on Figure 5, the seasonality of import duty revenue repeats every year with two decreasing patterns in the middle

of the year and at the end of the year. As a Muslim country, Ied al Fitri in the middle of the year. At the end of the year, we also have long holidays for Christmas and new year holidays. Importers tend to supply more local needs before the holidays since, during the long holiday of Christmas, the transportation route will be busy with the movement of the people who go back to their hometown and the minimum of working hours during the holidays. This condition affects the increase of import value shortly before the holidays and affects the import duty revenue. Those factors affected the revenue of import duty because the import volume also decreased besides holidays during that period.
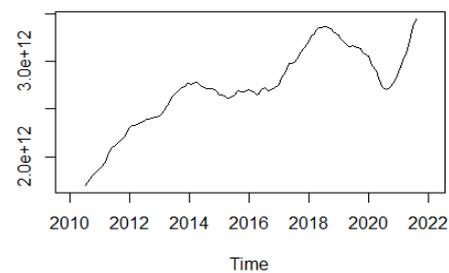

Figure 6 : Trend of Import Duty Revenue between 2010-2022

Purwana (2019) stated that the factors that have significant for import duty revenue are the country's import value, exchange rate, and effective tariff rate. The combination of those macroeconomic indicators affects the yearly import duty revenue of DGCE. Based on the figure above, the trend of import duty revenue fluctuated. It increased from 2010 to 2014, relatively in line with the import value of Indonesia during the same period. However, in 2015, the economic growth of the two main partners of Indonesia's imports, The United States and China,

slowed down, causing a flattened curve during the 2015-2017 period and bouncing in 2018. After that, import duty revenue went down because of the COVID-19 pandemic.
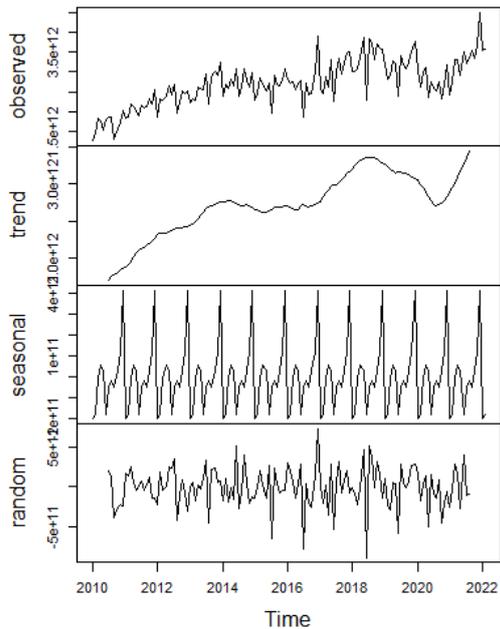

Figure 7 : Decomposition of Additive Time Series.

Decomposition function in R aims to extract trend, seasonal and irregular or random components using moving averages method. This step provides a more clear understanding to know the trends. The result shows in Figure 7. Irregular components or random, also known as noise is residual of time-series data after seasonal and trend were removed from the pattern. Random can be used to detect anomalies or outliers.

Holt-Winters has two different patterns for additive and multiplicative:

Additive

Time-series = Seasonal + Trend + Random

Multiplicative

Time-series = Trend * Seasonal * Random

According to those patterns, the effect of multiplicative Holt-Winters will be bigger than additive Holt-Winters.
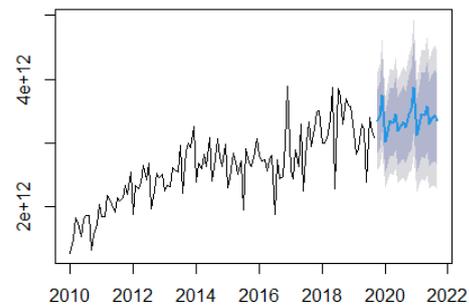

Figure 8 : Forecast from Holt-Winters' Multiplicative Method

Forecasting of the multiplicative Holt-Winters method can be seen on the figure above (Figure 8). The pattern follows the seasonality of the observed data. The gray area shows the confidence interval of the forecasting.
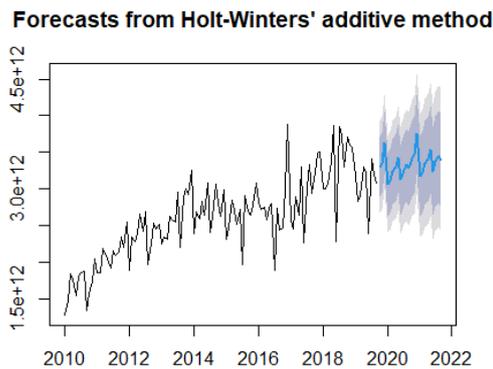
Figure 9 : Forecasting from Holt-Winters'
Additive Method

Figure 9 shows the monthly forecast of import duty based on the Additive Holt-Winters method. The forecasting value shows a repeating pattern that formed from the seasonality and the trend of the observed dataset, but the effect of those factors is different from multiplicative HW.
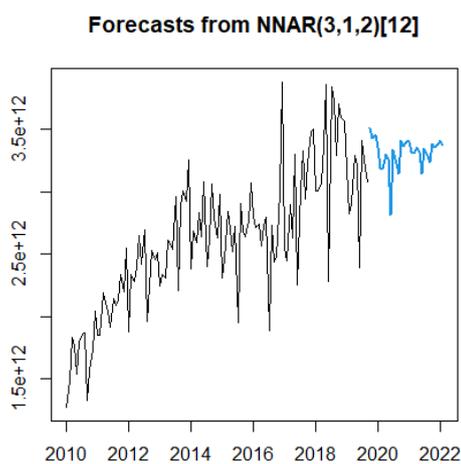
The forecasting of NNAR is described in the picture above. The forecasting value (blue line) is different from the two previous forecast models. The forecasting line is more complex and does not show a repeating pattern. It implies that NNAR can adaptively produce more accurate predictions by calculating all of the historical patterns of import duty revenue.

Table 2

Comparison Accuracy Additive &

	AHW	MHW	NNAR
ME	-3.42E+10	-3.52E+10	2.58E+07
RMSE	2.96E+11	2.99E+11	2.68E+11
MAE	2.24E+11	2.23E+11	2.04E+11
MPE	-2.50	-2.61	-0.98
MAPE	9.08	8.92	7.52
MASE	0.68	0.68	0.62
ACF1	-0.14	-0.07	0.17

Multiplicative Holt-Winters and NNAR

AHW : *Additive Holt-Winters'*

MHW : *Multiplicative Holt-Winters'*

NNAR : *Neural Networks Autoregressive*

Figure 10 : Forecasting from NNAR
Method

The comparison between Holt-winters and NNAR can be seen at the table above. According to the Mean Error, the NNAR model has a smaller result (2.58×10^7) compared to AHW and MHW (-3.42 x 10^{10} and -3.52 x 10^{10}). Furthermore, the Root Mean Square Error (RMSE) of NNAR shows a lower value than both MHW and AHW. The RMSE of NNAR

is 2.68 x 10^{11} while the RMSE of AHW is 2.96 x 10^{11} and MHW is 2.99 x x 10^{11}.

Based on the comparison table, NNAR has lower MAPE (7.59) than Multiplicative Holt-Winters (8.92) and Additive Holt-Winters (9.08), although all models produce very accurate predictions (MAPE <10). Mean Absolute Error (MAE) on NNAR also has lower value (203,803,000,000) than Holt-winters (223,278,749,775) meaning that the NNAR model has better accuracy.

Other parameters such as Mean Absolute Scale Error (MASE) also talk in the same tone, NNAR has smaller results (0.62) comparing both Additive and Multiplicative HW (0.68). Mean Percentage Error (MPE) also shows the same result with other indicators when NNAR has a lower result (-0.98) than Multiplicative HW (-2.61) and Additive HW (-2.50). Based on the result, using time series data of import duty revenue, this paper is in line with the study from Karadzic & Pejovic (2021) using data inflation from Montenegro, Serbia, and North Macedonia.

5. CONCLUSIONS AND RECOMMENDATIONS

Based on the data processed, this research concludes that the Neural Network model has better results in forecasting import duty revenue than the Additive and Multiplicative Holt-winters exponential smoothing model. The conclusion regarding the smaller value of ME, RMSE, MAPE, MASE, and MPE. Those parameters describe the result of the forecasting model have more accurate results compared to testing data. As a recommendation to practitioners, this forecasting technique can be used by the unit that handles revenue targeting of DGCE (Sub Directorate of Revenue, Directorate of Revenue and Strategic Planning), so they can capture the change in macroeconomic indicators that can affect import duty revenue. By knowing the effect of forecasting early, the DGCE can respond with the right policy so that the possibility of reaching the yearly target of revenue will be bigger. For other research in the future, this study recommends conducting a similar model using NNAR for other DGCE revenue like excise or export tax so that DGCE has completed a forecasting model to respond to the change in macroeconomic conditions that can affect the state revenue.

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