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Estimation of Energy Demand in Indonesia using Artificial Neural Network

Satrio Mukti Wibowo[1]*, Dedi Budiman Hakim[2], Baba Barus[3], Akhmad Fauzi[2]

[1]Ministry of Energy and Mineral Resources, Jakarta, 10110, Indonesia, [2]Faculty of Economy and Management, Bogor Agricultural University, Bogor 16680, Indonesia, [3]Department of Soil and Land Resources, Faculty of Agriculture, Bogor Agricultural University, Bogor 16680, Indonesia. *Email: satrio_mw@outlook.com

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ABSTRACT

Although Indonesia has many variations in energy types, Indonesia is currently a Net Oil Importer Country. Therefore, accurate energy demand estimation is very important for energy policy making in Indonesia. This study proposes a neural network model to efficiently, precisely and validly estimate energy demand for Indonesia. This model has four independent variables, such as gross domestic product (GDP), population, imports, and exports. Data obtained from Central Bureau of Statistics of Indonesia and The Ministry of Energy and Mineral Resources. Energy estimation is using a pessimistic, realistic and optimistic scenario that estimates of energy demand in the next 10 years using artificial neural networks shows that energy demand in Indonesia continues to increase every year, both in pessimistic, realistic and optimistic scenarios.

Keywords: Energy Demand, Energy Policy, Artificial Neural Networks
JEL Classifications: Q41, Q47

1. INTRODUCTION

Indonesia is the largest archipelago country in the world that is passed by the equator and is surrounded by the Pacific ring of fire, this unique characteristic causes Indonesia to have many types of energy sources, both fossil energy such as oil, gas and coal as well as new and renewable energies such as sun, water, ocean, geothermal, wind and biofuels.

Indonesia as a developed country with such a great potential for energy growth in the developing world, but an equally great uncertainty over the magnitude and timing of this growth, efforts aimed at reducing this uncertainty should prove valuable (Dahl, 1994).

It is well known that energy demand is derived, since energy is required not for its own sake but for the energy services it produces such as heating, lighting, and motive power (Hunt, 2014), so energy is a necessity. Given its importance for household welfare, public investments and environmental considerations (Gundimeda, 2006).

The self-evident importance of energy in contemporary developed societies and economies constitutes a first reason for deep academic analysis in the field. There are also other issues and facts, most of them quite recent, which reinforce research needs and interests such as sharp price fluctuations and increasing environmental and distributional concerns, among other issues, have led to a renewed academic interest in energy demand (Labandeira, 2006).

According to Extractive Industries Transparency Initiatives (EITI) report in 2016, the country is a resource-rich country both in hydrocarbons and mining. However, oil production has substantially declined in the last two decades from its peak of 1,624 thousand barrels a day in 1995 down to 804 thousand barrels of oil per day in 2017, according to regulator Ministry of Energy and

Table 1: GDP and energy indicator

	Unit	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
GDP at 2010 constant price	Trillion rupiahs	6.864	7.288	7.727	8.156	8.565	8.983	9.435	9.913	10.425	10.949
GDP nominal	Trillion rupiahs	6.864	7.832	8.616	9.546	10.570	11.526	12.407	13.590	14.838	15.834
GDP nominal per capita	Thousand rupiahs	27.029	33.461	33.582	32.464	41.916	45.120	47.957	51.891	55.990	59.065
Population	Thousand	238.519	241.991	245.425	248.818	252.165	255.462	258.705	261.891	265.015	268.075
Number of households	Thousand	61.384	62.246	63.097	63.938	64.767	65.582	66.385	67.173	67.945	68.701
Primary energy supply	Thousand BOE	1.075.175	1.204.636	1.242.479	1.221.019	1.241.900	1.305.185	1.247.193	1.334.739	1.466.057	1.559.295
Primary energy supply per capita	BOE/capita	4,51	4,98	5,06	4,91	4,92	5,11	4,93	5,10	5,53	5.82
Final energy consumption	Thousand BOE	669.597	753.142	816.875	747.855	761.386	758.097	736.695	780.600	868.581	945.867
Final energy consumption per capita	BOE/capita	2.81	3.11	3.33	3.01	3.02	2.97	2.85	2.98	3.28	3.53

Mineral Resources. Due to this decline in production and a rapid increase in domestic consumption, Indonesia is now a net importer of oil. Bank of Indonesia reports that as of December 2018, oil and gas exports value amounted to USD 1.3 billion while imports amounted to USD 3 billion.

Oil constitutes 35.03% of total energy consumption in 2019, it is decreasing compared to 47.35% in 2009. As well as Gas constitutes 35.03% of total energy consumption in 2019, compared to 18.51% in 2009. This percent decrease is due to growth in Coal and Renewable Energy usage over the same period. Coal is Indonesia's largest energy source, accounting for 37.28% of energy demands in 2019. Renewable energy sources is also increasing in total energy consumption from 4.35% in 2009 to 9.18% in 2019, with the largest portion from Biofuel accounting for 2.95% of energy demands in 2019, Hydropower accounting for 2.52% of energy demands in 2019 and Geothermal accounting for 1.68% of energy demands in 2019.

As seen in Table 1 that GDP, total population, final energy consumption and primary energy supply have increased from year to year. This shows that energy demand is likely to increase from year to year. Hence it requires energy resources to meet the demand.

From the previous paragraph explain that Indonesia has many types of energy resources, both fossil energy such as oil, gas and coal as well as new and renewable energies, so if the energy management is done properly and correctly, this advantages can provide benefits for the state and nation of Indonesia, because energy is one of the most important factor for improving the quality of life, as well as economic and social progress (Yusgiantoro, 2000). Therefore an increase in energy demand reflects an increase in the economy (Kraft and Kraft,1978).

As a developing country, we need a robust planning and/or approaches to utilize energy sources for the future. The projections may help planners to plan their future energy need. (zhang, 2009).

Furthermore for mid-long term energy forecasting, one of the most important values of it is to get the quantitative relationship (equation) between the energy demand and other economy indexes, this will be very important for policy adjusting (Meng, 2011).

There are several factors to determine the energy policies, which are considered to be important for forecasting the future projections in a country. These factors are population growth, economic performance, technological developments, import, export and consumer tastes (Sozen,2005)

Therefore, the identification and analysis of energy problems and the creation of energy policy options are necessary. Energy demand forecasting is a key policy tool used by decision makers around the world. Overestimating energy demand can lead to resource redundancy, whereas underestimating energy demand can lead to a serious energy crisis. The development of sufficient, safe and reliable energy sources is a top priority for energy policy in Indonesia. To overcome dependence on `importing fossil fuels and take the necessary precautions, Indonesia's future energy demand must be realistically known.

So, an important factor for Indonesia's energy policy is an accurate assessment of future energy needs. The purpose of this research is to present a realistic and accurate model in estimating energy demand in Indonesia by using soft computing techniques or it can be called artificial intelligence. The artificial intelligence method is the best method today to make estimates and predict the future. ahead because it provides several advantages, such as nonlinear mapping capabilities, more accurate forecasting capabilities, and the ability to handle noise data.

Artificial Intelligent methods that are often used and are among the best in energy forecasting are Artificial Neural Networks.

Research on forecasting energy demand and the factors that influence it using artificial neural networks has never been carried out in Indonesia. Therefore, this research focuses on forecasting energy demand in Indonesia, based on demographic and socio-economic indicators. The model is created using GDP (gross domestic product), population, imports, and exports in Indonesia as input. Three different scenarios are used to estimate the value of future energy demand.

In this model use the term ceteris paribus to signify that all the relevant variables, except those being studied at that moment, are held constant (Mankiw, 2008) and assuming that demand functions for specific types of energy are proportional to total spending on energy (Nicholson, 2000).

2. LITERATURE REVIEW

Since the early 1970s, several methods have been used to estimate energy demand. These methods are classified into two categories according to the data used. The first category is the time-series forecasting method, which uses only historical energy demand data to establish a predictive model, such as Estimation The Demand of Electricity, Structural and Time Series Approaches (Berndt, 1991). The most widely used method under this category is the autoregressive integrated moving average model (ARIMA), an example is a journal that is forecasting Turkey's primary energy demand which estimates energy demand needs in 2005 – 2020 (Ediger and Akar 2007) and other examples is journal with the title is Forecasting electricity price and demand using a hybrid approach based on Wavelet transform (Voronin and Partenen 2014), ARIMA and neural network which estimates forecast electricity demand using ARIMA and Neural Network. Another category is multi-factor-influenced forecasting methods, which estimate energy demand (dependent variable) with several explanatory variables. The most widely used methods under this category are the multiple linear regression model (MLR), the partial-quadratic regression model, and the logarithmic-linear regression model whose journal examples are the journal with the title Forecasting electricity demand in New Zealand using economic and demographic variables that estimate the demand of electrical energy in New Zealand (Mohamed and Bodger, 2005), another example is journal with the title Projection of Future Transpot energy demand of Thailand which predicts energy needs for transportation in Thailand in the future (Limanond et al., 2011).

All the methods mentioned above must first assume the model type. However, in the real world, assuming that the system in a single type is usually difficult and the model is less precise. So, Artificial Intelligent (AI) is becoming popular in formulating forecasting models because AI forecasting methods do not need to assume the type of model. The AI method also provides several advantages, such as nonlinear mapping capabilities, better forecasting capability, and the ability to handle noise data.

The Artificial Intelligent method that is widely used and the best in energy forecasting is the Artificial Neural Network, an example of which is the journal with the title Transport energy demand modeling of South Korea using an artificial neural network that predicts the energy needs of transport in South Korea using the Artificial Neural Network model (Zong, 2011). Another example is journal the title Energy demand estimation of South Korea using Artificial Neural Network which predicts energy demand in South Korea using Artificial Neural Network model (Geem et al., 2009) and the next example is journal with the title Estimates of energy demand in Turkey using Artificial Neural Network with the teaching-learning-based optimization algorithm that predicts energy demand in Turkey (Uzlu et al., 2014). The three studies above produce good, valid and accurate forecasts.

3. METHODOLOGY

3.1. Types and Sources of Data

This study uses secondary data obtained from the Central Statistics Agency (BPS) and the Ministry of Energy and Mineral Resources. The data used are Indonesian Energy Demand Data, Indonesian Economic Data (GDP, Exports, Imports), Indonesian Demographic Data (Total Population) in the last 30 years (from 1990 to 2019).

In macroeconomics, emphasis was on the idea that economic activity could be explained by a set of relationship between economic variables (Spencer, 1993), as well as energy demand forecasting which can be calculated with several variables that influence it.

3.2. Energy Demand Prediction Method

In this study to predict the total energy demand in Indonesia, the model used is the Artificial Neural Network Model. Energy demand is predicted for the next 10 years. That is until 2029. Prediction of energy demand in this study is carried out based on the value of forecasting five categories (GDP, population, import, export, and energy demand) of data were collected from ministry of energy mineral resources and Central Bureau of Statistics of Indonesia. Four independent variables (GDP, population, import and export amounts) and dependent variable (Energy Demand) are identical or similar to precedent researches from (Ceylan and Ozturk, 2004; Toksari, 2007; Zong et al., 2009). Before predicting Energy Demand, it is necessary to predict the independent variables in advance.

The forecasting method that will be used to predict the independent variable (x variable) in this study is the ARIMA (Autoregresive Integrated Moving Average) method. The Autoregressive Integrated Moving Average (ARIMA) model is a time series forecasting technique that uses one time series (univariate) variable. The ARIMA model ignores the independent variables because this model uses the present and past values of the observed variables to produce a short-term forecast of the variables themselves. In general, ARIMA, which is also often called the Box-Jenkins method, is written with the ARIMA notation (p, d, q) where p represents the order of the autoregressive process (AR), d represents the differencing and q represents the order of the moving average (MA) process (Juanda, 2012). The form of the ARIMA Model is as follows:

$$\left(1-\varnothing_1 B+\ldots+\varnothing_p B^p\right)(1-B)^d X_t=\mu^{'}+(1-\theta_1 B-\ldots-\theta_q B^q)e_t$$

Description:

$$B^P X_t = X_{t-p}$$

$$B^q e_t = X_{t-q}$$

$$\varnothing_p = coefisien\ AR$$

$$\theta_q = coefisien\ MA$$

But if the independent variable cannot be predicted using ARIMA then an alternative method is used which is one of the Smoothing method.

Forecasting on energy demand is not only predicted in one scenario where the scenario that is usually used is the result of forecasting from a certain forecasting method used and the results of this forecast can be called realistic value forecasting. Forecasting on Energy Demand will also be forecast with pessimistic (Forecasting Lower) and optimistic scenarios (Forecasting Upper). Forecasting in both scenarios is obtained from the lower and upper limits of the forecast confidence interval.

$$Forecasting\ Lower = F - Z_{\alpha:2}\frac{s}{\sqrt{n}}$$

$$Forecasting\ Upper = F + Z_{\alpha:2}\frac{s}{\sqrt{n}}$$

Description:

F is the result of forecasting d (Middle value)

$Z_{a:2}$ is the Z value table with $\alpha = 0.05$ or the Z table value with a confidence level of 95% in other words value $Z_{0.05:2}$=1.96.

S is the Standard deviation with

$$S=\sqrt{\frac{\sum_{i=1}^{n}(Fi-\bar{F})^2}{n-1}}$$

For export and import independent variables, after going through the steps of the Box Jenkins method in forming the ARIMA model order, ARIMA (0,1,0) is obtained. AR index is equal to 0 so that export and import data cannot be formed in an Autoregresive model. The MA index is equal to 0 so that export and import data cannot be formed in the Moving Average model. This is because Autocorrelation function (ACF) and Partial autocorrelation function (PACF) have no lag which has a significant correlation value. In other words, in the context of ARIMA modeling, export and import data are not influenced by export data in the previous period so that export and import data cannot be modeled using ARIMA. Therefore, the next forecasting method when export and import data cannot be modeled with ARIMA, one of the smoothing methods is used, namely, the Double Exponential Smoothing method or it can be called the Two-Parameter Holt method. So, of the four independent variables, only two variables can be predicted by Arima, that is the total population and GDP.

The forecasting method used to predict the dependent variable (y variable) in this study is the ANN (Artificial Neural Network) method. After the variables of Export, Import, GDP and Total Population have been predicted for the next 10 years respectively so that this data can be used as predictor data to predict Energy Demand. The Energy Demand data used is Indonesian Energy Demand data with an annual period from 1990 to 2019.

3.3. Artificial Neural Network Model

The model used in this study to predict the total energy demand in Indonesia is the Artificial Neural Network Model. The ANN method is a form of artificial intelligence and represents an imitation of the neural network in the human brain that has the ability to learn from existing data to solve complex problems (Graupe, 2007). These artificial nerves are connected in a model similar to the brain nerve network (Rahma, 2019). The ANN model is inspired by the ability of the human brain, which has extraordinary capacities and capabilities in analyzing incomplete, unclear or obscure information, and can make decisions or judgments about it.

An ANN model generally consists of three layers, that is the input layer, hidden layer and output layer (Kukreja et al., 2016). This multi-layer model is called the Multi Layer Perceptron (MLP).

The ANN model used in this study is the Multi Layer Perceptron (MLP) and the training process used is supervised training. The

Figure 1: ANN multilayer structure

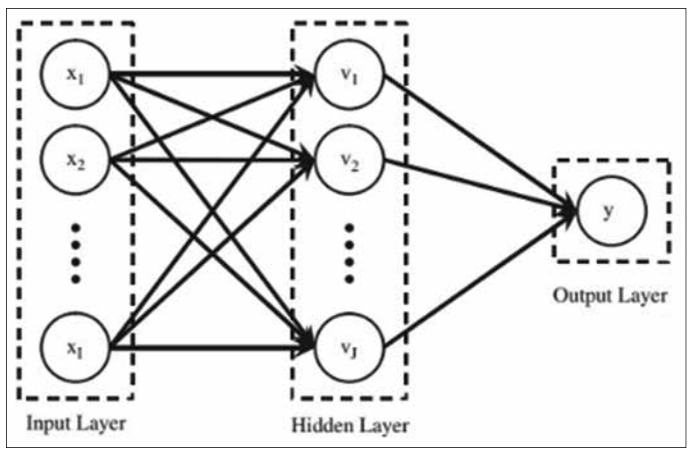


Figure 2: Indonesian Ekspor chart

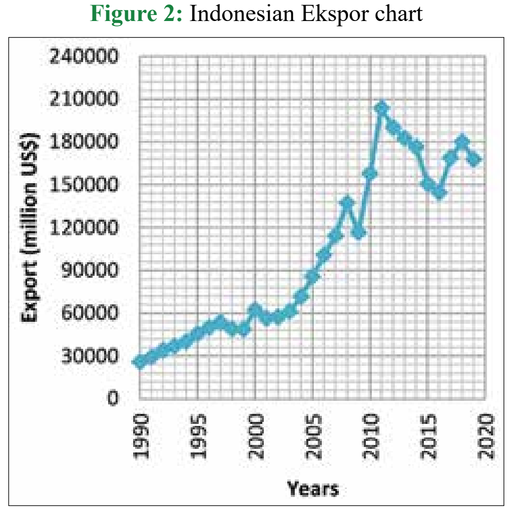


Table 2: Energy demand data and indicator data in indonesia

Years	Energy demand (BOE)	Export (US$Juta)	Import (US$Juta)	GDP (Milyar Rupiah)	Population (people)
1990	449715275.9	25675.3	52116.5	195597.2	177325690
1991	467805082.4	29142.4	60083.8	227450.2	179803796
1992	494501979	33967	63296.1	259884.5	182316534
1993	519695447.1	36823	28327.8	329775.8	184864386
1994	540963417	40053.3	31988.6	382219.7	187447845
1995	569027429.9	45418.2	40654.1	454514.1	190067407
1996	590514719.7	49814.7	42928.6	532568	192723577
1997	619660984.9	53443.6	41679.8	627695.4	195416867
1998	617939195.3	48847.6	27336.9	955753.5	198147795
1999	666405829.8	48665.5	24003.3	1099731.6	200916888
2000	737531976.9	62124	33514.8	1389769.9	205132500
2001	753800971.2	56323.1	30962.1	1646322	208250500
2002	751391363	57105.8	31288.9	1821833.4	211415900
2003	791430148.8	61034.5	32550.7	2013674.6	214629400
2004	812885587.6	71584.6	46524.5	2295826.2	217891800
2005	810247867.6	85659.9	57700.9	2774281.1	221203700
2006	815162676.3	100798.6	61065.5	3339216.8	224566000
2007	887860066.4	114101	74473.4	3950893.2	227979400
2008	712157822.4	137020.4	129197.3	4948688.4	231444700
2009	713527207.3	116510	96829.2	5606203.4	234962700
2010	777361666.8	157779	135663.3	6864133.1	238518787
2011	859644632.1	203496.6	177435.7	7831726	241990736
2012	917698803	190031.8	191691	8615704.5	245425244
2013	844527323.3	182551.9	186628.7	9546134	248818090
2014	855552434.7	176292.7	178178.8	10569705.3	252164786
2015	844266162.1	150393.3	142694.5	11526332.8	255461700
2016	817783885.4	144489.7	135652.8	12401728.5	258705000
2017	846232028.3	168828.2	156985.5	13589825.7	261890900
2018	936345658.9	180012.7	188711.2	14838311.5	265015300
2019	1007259754	167683	170727.4	15833943.4	268074600

MLP model is used because it is considered more capable of solving more complex problems than the single layer perceptron model. For the training process, the feedforward ANN method is used with the backpropagation learning algorithm, which is the standard algorithm for supervised training.

The ANN model used in this study is the Multi Layer Perceptron (MLP) and the training process used is supervised training. The MLP model is used because it is considered more capable of solving more complex problems than the single layer perceptron model. For the training process, the feedforward ANN method is used with the backpropagation learning algorithm, which is the standard algorithm for supervised training. Back propagation is widely used by the MLP model to change the weights of the inter-node relationships that exist in the hiddenlayer.

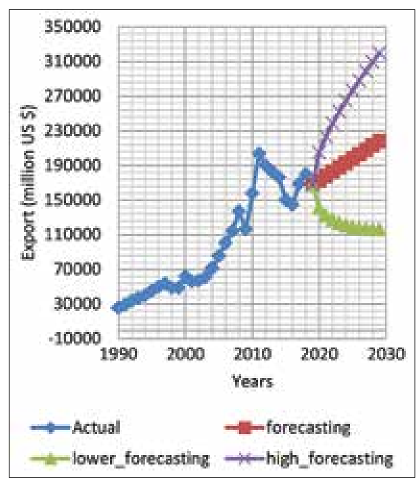
The structure of the ANN feed-forward network in the MLP method used is shown in Figure 1. The figure shows the ANN model with many layers (multilayers), that is the input layer, hidden layer and output layer, which are characterized by their structure that represents the connection patterns between nodes.

4. RESULTS AND DISCUSSION

4.1. Forecasting of Independent Variable

To create an estimation model for energy demand in Indonesia, there are five categories (GDP, population, imports, exports, and energy demand) data were collected from the Central Statistics

Figure 3: Indonesian export forecasting



Agency BPPT (BBPT, 2018) and the Ministry of Energy and Mineral Resources (Kementerian Energi dan Sumber Daya Mineral, 2018) as shown in Table 2.

The export data used is Indonesian export data with an annual period from 1990 to 2019 can be seen in Figure 2.

In Figure 2 it can be seen that Indonesia's exports have an upward trend in 2008, due to the world economic crisis in 2008, in 2009 exports experienced a quite drastic decline in exports but after that it increased drastically until 2011. After 2011, the value of exports experienced a decrease and an increase that was not too extreme until 2019. Overall, the trend seems to be increasing, so there is a possibility that when it is predicted in the next 10 years it will also tend to increase as happened in the export trend in the last 30 years. To ensure this, the Export data will be predicted using the ARIMA method.

After going through the steps of the Box Jenkins method in the formation of the ARIMA model order, the ARIMA (0,1,0) is obtained. AR index is equal to 0 so that the export data cannot be formed in an Autoregresive model. The MA index is equal to 0 so that the export data cannot be formed in the Moving Average model. This is because ACF and PACF have no lag which has a significant correlation value. In other words, in the context of ARIMA modeling, export data is not influenced by export data in the previous period so that export data cannot be modeled using ARIMA.

The next alternative forecasting method when the export data cannot be modeled with ARIMA, the smoothing method is used, that is, the Double Exponential Smoothing method or it can be called the Two Parameter Holt method. The results of forecasting exports using the Double Exponential Smoothing (Holt) method can be seen in Figure 3.

Forecasting results (middle value) in Figure 3 show that the value of exports in the next 10 years tends to increase.

Perhaps this is due to the increasing trend of data in the last 30 years. On the other hand, the results of export forecasting in the pessimistic scenario show results that continue to decline drastically. Meanwhile, in the optimistic scenario, the forecast results increase drastically.

Import data used is Indonesian import data with an annual period from 1990 to 2019. The graph can be seen in Figure 4.

In Figure 4 it can be seen that Indonesia's imports have an upward trend starting in 2003. Whereas in previous years the value tended not to change. There is a possibility that when it is predicted that in the next 10 years it will also tend to increase as happened in the import trend after 2003 to 2019. To ensure this, Import data will be predicted using the ARIMA method.

After going through the steps of the Box Jenkins method in the formation of the ARIMA model order, ARIMA (0,1,0) is obtained. AR index is equal to 0 so Import data cannot be formed in Autoregresive model. MA index is equal to 0 so Import data cannot be formed in the Moving Average model. This is because ACF and PACF have no lag which has a significant correlation value.

In other words, in the context of ARIMA modeling, Import data is not influenced by Import data in the previous period so that Import data cannot be modeled using ARIMA. The next alternative forecasting method when the imported data cannot be modeled with ARIMA, the smoothing method is used, that is, the Double Exponential Smoothing method or the Two Parameter Holt method.

The results of forecasting imports using the Double Exponential Smoothing (Holt) method can be seen in Figure 5.

Figure 4: Chart of Indonesian imports

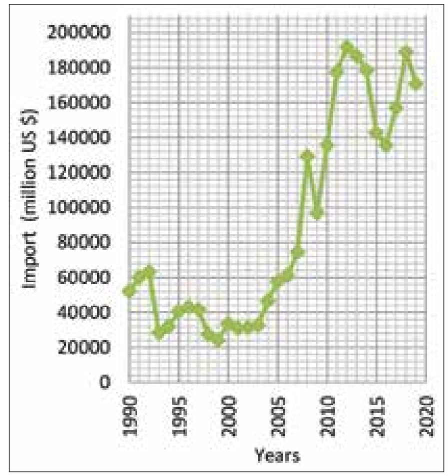


Figure 5: Indonesian imports forecasting

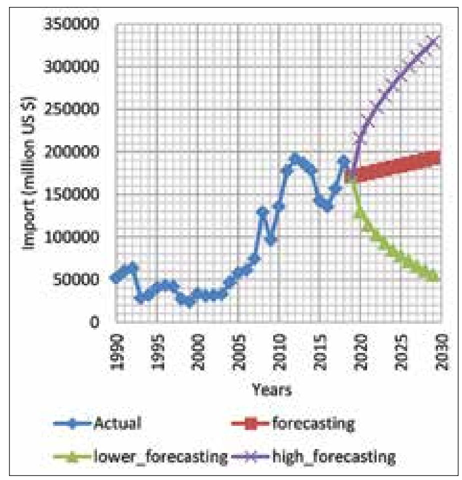


Figure 6: Graph of Indonesia's GDP

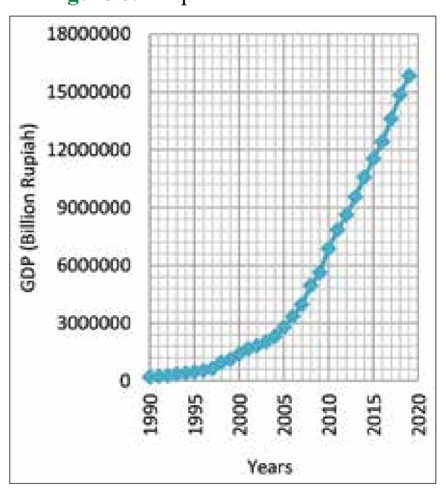


Figure 5 shows that the value of imports in the next 10 years will tend to increase. Perhaps this is due to the increasing trend of data in the last few years. On the other hand, the results of the import forecast in the pessimistic scenario show results that continue to decline drastically. Meanwhile, in the optimistic scenario, the forecast results increase drastically.

The GDP data used is Indonesia's GDP data with an annual period from 1990 to 2019. The time series data plot can be seen in Figure 6.

In Figure 6, it can be seen that Indonesia's GDP have had an upward trend in the last 30 years. From 1990 to 2019, Indonesia's GDP has almost never decreased. There is a possibility that when it is predicted that the next 10 years will tend to increase as well, as happened in the GDP trend in the last 30 years. To ensure this, GDP data will be predicted using the ARIMA method.

After going through the steps of the Box Jenkins method in forming the order of the ARIMA model, ARIMA (1,2,0) is obtained. AR index is equal to 1 so that GDP data can be formed in the Autoregresive model at lag 1.

The results of parameter estimation in the ARIMA model (1,2,0) show that the AR (1) parameter is –0.4575 and the $P < 0.05$ or in other words the AR coefficient (1) is significant. If these parameters are substituted into the ARIMA model it will be as below.

ARIMA general model (Juanda, 2012):

$$\left(1-\varnothing_1 B+\ldots+\varnothing_p B^p\right)\left(1-B\right)^d Y_t = \mu' + (1-\theta_1 B-\ldots-\theta_q B^q)e_t$$

$$\left(1-\varnothing_1 B\right)\left(1-B\right)^2 Y_t = \mu' + e_t$$

$$\left(1-\varnothing_1 B\right)(1-2B+B^2)Y_t = \mu' + e_t$$

$$(1-2B+B^2-\varnothing_1 B+2\varnothing_1 B^2-\varnothing_1 B^3)Y_t = \mu' + e_t$$

$$Y_t - 2Y_{t-1} + Y_{t-2} - \varnothing_1 Y_{t-1} + 2\varnothing_1 Y_{t-2} - \varnothing_1 Y_{t-3} = \mu' + e_t$$

$$Y_t = \mu' + 2Y_{t-1} - Y_{t-2} + \varnothing_1 Y_{t-1} - 2\varnothing_1 Y_{t-2} + \varnothing_1 Y_{t-3} + e_t$$

So that the forecasting model:

$$Y_t = \mu' + 2Y_{t-1} - Y_{t-2} - 0.4575(Y_{t-1} - 2Y_{t-2} + Y_{t-3}) + e_t$$

From this model, an RMSE of 171953 is obtained. This means that the average difference between the forecast results (fitted) and the actual data is 171953.

The forecast results can be seen in Figure 7.

Figure 7: Forecasting Indonesia's GDP

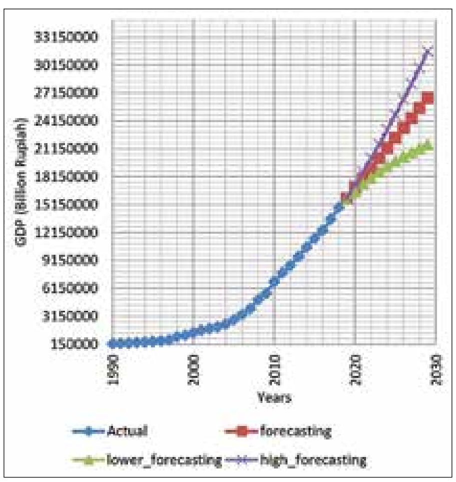


Figure 7 shows that the value of GDP in the next 10 years will tend to increase. Perhaps this is due to the trend of data in the last 30 years which tends to increase. On the other hand, the GDP forecasting result in the pessimistic scenario has an upward trend, while the GDP forecasting result in the optimistic scenario has a extreme upward trend.

The population data used is the total population data of Indonesia with an annual period from 1990 to 2019. The time series data plot can be seen in Figure 8.

In Figure 8 it can be seen that the population of Indonesia has had an upward trend in the last 30 years where the number has continued to increase linearly. It is very likely that when it is predicted that the next 10 years will tend to increase as well as what happened in the trend of the Population Number in the last 30 years. To ensure this, the Total Population data will be predicted using the ARIMA method.

Figure 8: Graph of population

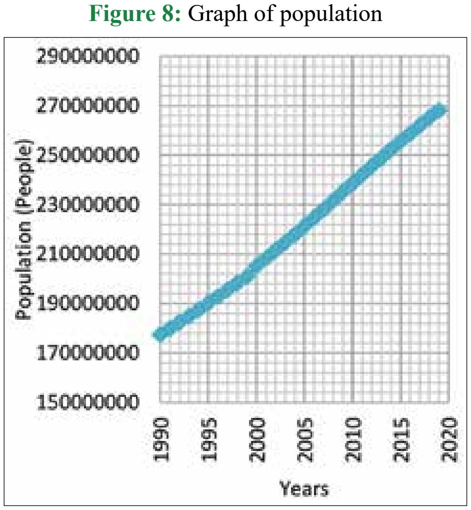
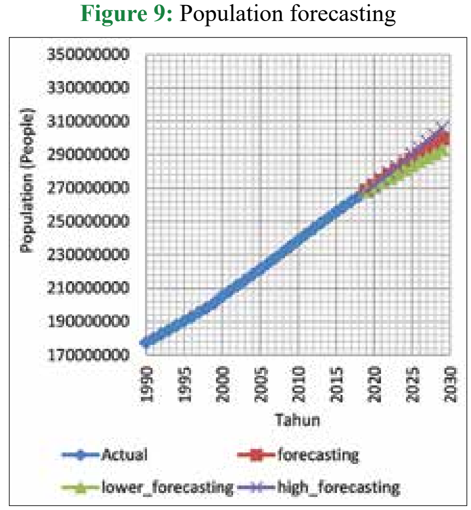


Figure 9: Population forecasting



After going through the steps of the Box Jenkins method in forming the order of the ARIMA model, ARIMA (0,2,1) is obtained. AR index is equal to 0 so that the Total Population data cannot be formed in the Autoregressive model. Integrated index is equal to 2, meaning that the data is stationary after two differencing is done. The MA index is equal to 1 so that the Total Population data can be formed in the Moving Average model at lag 1.

The results of parameter estimation in the ARIMA model (0,2,1) show that the MA (1) parameter is –0.5305 and the P < 0.05, or in other words the MA coefficient (1) is significant. If these parameters are substituted into the ARIMA model it will be as below.

ARIMA general model:

$$\left(1-\varnothing_1 B+\ldots+\varnothing_p B^p\right)(1-B)^d Y_t=\mu^{'}+(1-\theta_1 B-\ldots-\theta_q B^q)e_t$$

$$(1-B)^2 Y_t=\mu^{'}+(1-\theta_1 B)e_t$$

$$(1-2B+B^2)Y_t=\mu^{'}+e_t-\theta_1 e_{t-1}$$

$$Y_t-2Y_{t-1}+Y_{t-2}=\mu^{'}+e_t-\theta_1 e_{t-1}$$

$$Y_t=\mu^{'}+2Y_{t-1}-Y_{t-2}-\theta_1 e_{t-1}+e_t$$

So that the forecasting model:

$$Y_t=\mu^{'}+2Y_{t-1}-Y_{t-2}+0.5305_1 e_{t-1}+e_t$$

From this model, an RMSE of 291827 is obtained. This means that the average difference between the forecast results (fitted) and the actual data is 291827.The results of population forecasting can be seen in Figure 9.

Visually, forecasting the total population of Indonesia until 2029 from the three scenarios has quite a small difference between the three. The three scenarios have the same tendency to increase for the next 10 years. This is probably due to the data on the total population of the last 30 years which has continued to increase in value.

4.2. Forecasting Y variable with ANN

The variables of Export, Import, GDP and Total Population have been predicted for the next 10 years respectively so that this data can be used as predictor data to predict Energy Demand. The Energy Demand data used is Indonesian Energy Demand data with an annual period from 1990 to 2019. The time series data plot can be seen in Figure 10.

Table 3: MSE and RMSE model of ANN

Hiden layer nodes	RMSE	MSE	R-square
1	0.100393	0.316848	0.895808
2	0.027036	0.164428	0.972082
3	0.025207	0.158766	0.973816
4	0.024206	0.155582	0.974924
5	0.020286	0.142429	0.978995
6	0.017236	0.131287	0.982127
7	0.011429	0.106908	0.98815
8	0.005386	0.07339	0.994413
9	0.019544	0.139801	0.979744
10	0.005932	0.077016	0.993845

Figure 10: Energy demand graph

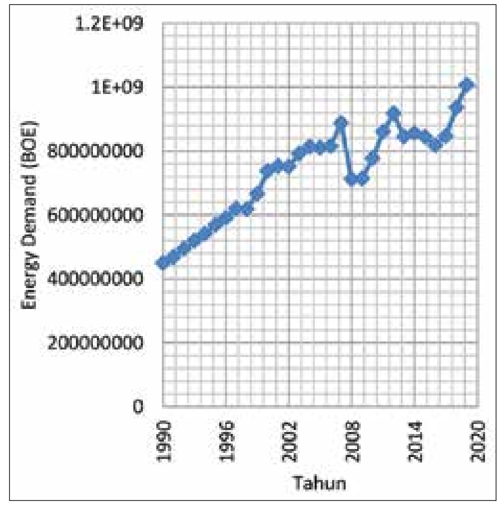


Figure 11: ANN model (hiden nodes = 8)

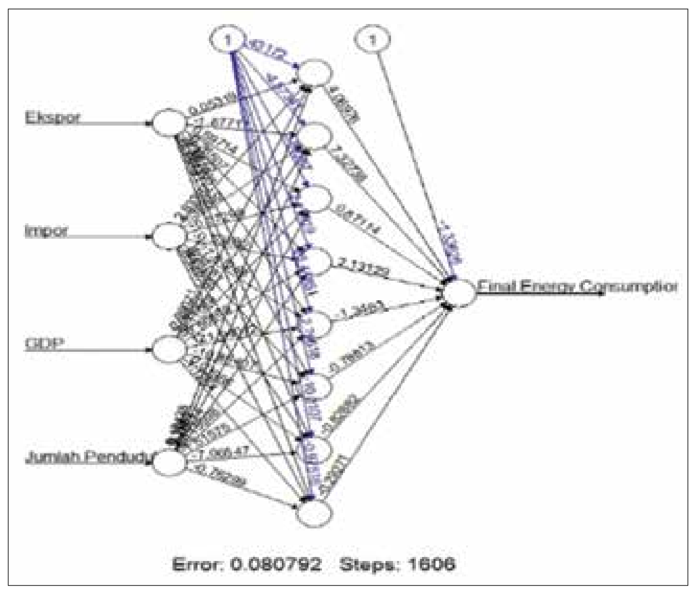
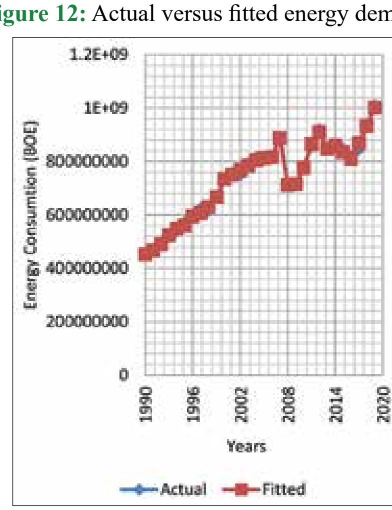


Figure 12: Actual versus fitted energy demand



In Figure 10, it can be seen that Indonesia's Energy Demand has an upward trend from 1990 to 2007. It experienced a decline in 2008 due to the global crisis in 2008. Then it increased slowly until 2012 and decreased again in 2012. Starting from 2016, energy demand continues to increase until 2019. The fluctuating condition of Indonesia's energy demand from year to year makes forecasting for the next 10 years difficult. To facilitate this, the Energy Demand data will be predicted using the ANN method.

Before forecasting using the ANN method, what must be sought first is the ANN model. The ANN model is somewhat different from statistical models such as ARIMA, regression, and others. The ANN model is issued in the form of a visualization which includes an input layer, a hidden layer and an output layer. The number of neurons or nodes in the input layer is as much as the X variable, which is 4 neurons. The number of nodes in the output layer is as much as the Y variable, namely 1. The number of nodes in the hidden layer is not certain because of their hidden nature so that in this study several possible numbers of nodes in the hidden layer will be tried. In this research, we will try to hide layers with nodes 1 to 10 and will be selected based on the smallest MSE and RMSE values. The results can be seen in the table below.

From Table 3 it can be seen that the ANN model with the smallest MSE (0.005386) and its RMSE (0.07339) is the ANN model with Hiden Nodes 8. Besides, the number of nodes 8 in the hidden layer has a very high R-SQUARE, which is equal to 0.994413 or 99.44%. In other words, the ANN model is able to explain the diversity of energy demand by 99.4%. Then the ANN model that will be used for forecasting Energy Demand is a model with a hidden layer with 8 nodes. The ANN model with a hid nodes 8 can be seen in Figure 11.

Figure 13: Forecasting energy demand

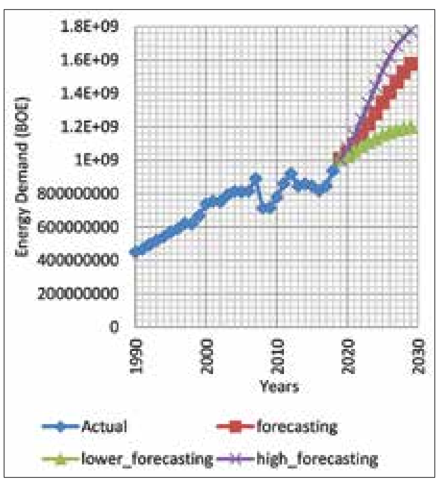


Table 4: Forecasting energy demand

Years	Forecasting	Forecasting lower	Forecasting upper
2020	1043715597	1023094950	1071564596
2021	1095807650	1054660622	1149895189
2022	1154475372	1083109941	1242551230
2023	1216115044	1108632531	1341035323
2024	1280427215	1131243431	1441599496
2025	1345079247	1150808442	1536132323
2026	1408547958	1167409932	1618818707
2027	1469040441	1181051857	1685906214
2028	1525249852	1191827494	1736902214
2029	1576189581	1199808933	1773497696

In Figure 11, it can be seen that the ANN algorithm will stop or converge at the 1606th epoch. In other words, the estimated weighting values obtained will converge at the 1606th epoch.

After obtaining the best ANN model, that is the ANN model with Hiden Nodes 8, the next step is to compare the actual value with the predicted value (fitted) with the aim of seeing whether the prediction results. The comparison can be seen in the time series graph in Figure 12.

In Figure 12 it can be seen that the actual value and the fitted value are very close together and almost the same when seen visually. In other words, the ANN model obtained is quite good because it can predict the value of Energy Demand which will not be far from the actual Energy Demand.

Furthermore, the forecasting of energy demand in the next 10 years can be seen in Figure 13 and Table 4.

In Table 3, it can be seen that the results of forecasting Indonesia's energy demand in the next 10 years tend to increase where Energy Demand in 2029 reaches 1576189581. On the other hand, the results of forecasting Energy Demand in the pessimistic scenario also have an upward trend but the increase is lower than the forecasting of the mean value Energy Demand in 2029 is 1199808933. While the results of forecasting Energy Demand in the optimistic scenario have a extreme upward trend, where the energy demand value in 2029 is 1773497696.The results of the forecasting can also be seen visually in Figure 13.

Where visually, the forecasting of Total Demand until 2029 from the realistic scenario and the optimistic scenario has quite a small difference. Meanwhile, the forecast results from the pessimistic scenario differ significantly from the other two scenarios. Even though in the end, the three scenarios have the same tendency to increase over the next 10 years.

The next step is to identify the significant differences between the three forecasting scenarios of energy demand using the Analysis of Variance (ANOVA). Anova is a statistical test procedure similar to the t test. But ANOVA can be used to test for differences in more than two groups. The way Anova works is to compare the variance (variance) of three or more sample groups. Anova produces a test called the F test which will answer the research hypothesis to be tested.

The hypothesis is as follows:

- H0: $\mu_1=\mu_2=...=\mu$ (there is no significant different between groups of forecasting scenario)
- H1: There are at least a pair of groups (μ_i,μ_i') that are not the same (there are significant differences between groups of forecasting scenarios)

The criterion for rejection of H0 is reject H0 if F-Count > F-table or P-value < alpha (0.05).

The ANOVA P = 0.00165 and smaller than alpha 0.05, so it can be said that there is a significant difference between the three forecasting scenarios with a 95% confidence level.

5. CONCLUSION AND RECOMMENDATION

This study proposes the use of the ANN model to estimate effectively and efficiently energy demand for Indonesia. This model has four independent variables: GDP, population, imports, and total exports. In this study, using three forecasting scenarios that is optimistic forecasting, realistic forecasting and pessimistic forecasting.

The artificial neural network can be used as a solution and estimation technique to forecasting energy demand in Indonesia. The model developed is flexible in nature to provide many near optimal solutions to estimate the future trends of energy demand. This advantage comes from artificial neural network approach itself because the ANN model starts the solution of the problem from a large population base. The model is actually a multi-parameter solution, which has many feasible solution points. Hence, the ANN model can be used for estimating the energy demand in the future by optimizing the parameter values using the past data. The results also indicate that there is a strong relation between the import and export figures of energy demand estimation as well as the GNP and the population.

With three forecasting scenarios, energy demand is predicted for the years 2020–2029. In general, we can see the differences between the three scenarios through visualization in the form of time series charts and through the table of forecasting results of the three scenarios, besides that according to the ANOVA test results there are significant differences. Between the three scenarios mentioned above, the realistic scenario and the optimistic scenario have quite a small difference, while the forecast results from the pessimistic scenario have quite a big difference from the other two scenarios.

Even though in the end, the three scenarios have the same tendency to increase over the next 10 years. This is because the population continues to increase, the value of GDP which has increased from year to year is supported by the value of exports and imports which continues to increase causing the increasement of energy demand in Indonesia.

Because energy demand has increased for both pessimistic, realistic and optimistic scenarios. Therefore, preparations are needed to increase energy production in Indonesia, both from fossil and non-fossil sources, but because fossil energy in the future will run out and emit emissions that cause environmental pollution, it is better for energy production to focus on renewable energy that is more environmental friendly.

The Indonesian government can collaborate with universities and stakeholders in Indonesia in research and regulatory concepts for incentives for the use of renewable energy aimed at increasing renewable energy production in Indonesia.

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