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Research Paper

Neural network based projection of electricity demand in Indonesia using repetitive training method

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Abstract

Indonesia Energy Outlook (IEO) 2016 published by BPPT projected the electricity demand in 2025 significantly will increase more than twice to 513 TWh from 203 TWh in 2015. This projection is based on the target of 100% electrification ratio in 2025. Assuming an average population growth of 1.2% in 2025 and a nominal GDP growth of 5.02% in 2014 which are expected to increase to 8% in 2025.This study projected the total electricity demand for the period 2016-2025 based on GDP, population, and electricity sales per sector (household, commercial, and industry) from the period of 2000-2015. Time series data modeling using Auto Regressive (AR) model and Autoregressive model with exogenous input (ARX) implemented using Artificial Neural Network Back-Propagation (ANN-BP). The repetitive training method is used to achieve the specified target error.

Keywords: *total electricity demand, electricity sales, AR/ARX models, repetitive NNBP*

1. Introduction

Indonesia's electricity consumption in 2015 is 203 TWh. Household electricity consumption is still dominant (40%), followed by industrial sector (38%), commercial sector (17%), and other sectors (5%). In alignment with population growth rate of 0.74% per year, energy demand in household sector increases slightly. The decrease of firewood and kerosene utilization in the household sector, during the period of 2014 - 2050, causes share of energy demand in household sector to also decrease from 11.5% in 2014 to 4.5% and 4.3% for base scenario and high scenario respectively. The energy demand of industrial sector, which is considered as the national economy driver, is expected to increase and dominate the total final energy demand followed by transportation sector which supports the economic activity. Energy demand in the commercial sector is influenced by the fast development of commercial buildings such as hotels, offices, hospitals and property and causes energy demand in this sector rise rapidly. The share of energy demand in this sector is 2.2% of total final energy demand in 2014 and then rises to 4.6% in 2050 for both scenarios.

Although the role of the commercial sector is still very small, the growth rate of its energy demand is the highest. The commercial sector such as offices, hotels, and other services is more easily developed in Indonesia as a developing country than other sectors. The growth rate of energy demand in the commercial sector is 5.5% per year for base scenario and 6.2% per year for the high scenario.

Activities in the other sector including agriculture, construction and mining involve heavy equipment which consumes oil fuel consist of gasoline, kerosene, diesel oil, fuel oil, and biodiesel. The share of energy demand in this sector is 1.6% in 2014 and will increase to 2.3% for base scenario and 2.4% for a high scenario in 2050.

With an increase in 100% electrification ratio target by 2025, electricity demand projected by IEO 2016 [1] will increase significantly by more than twice to 513 TWh by 2025. This projection is based on the assumption of an average population growth of 1.2% in 2025 and nominal GDP growth of 5.02% in 2014 which is expected to increase to 8% by 2025.

Projection of electricity demands are needed to forecast the availability of power plant, fuel consumption for the power plant, additional power plant, and estimated energy reserves.

In some forecasting cases, statistical methods have worked out well. Many statistical forecasting methods are based on the assumption that the time series can be given on a stationary basis. Once the prediction is made on the stationary time series, it can be converted back to the original series. However, researchers have tried to improve forecasting results by applying various machine learning methods and their combinations (Fuzzy Logic, Genetic Algorithm, Neural Network, etc.) [2-9]. In some specific forecasting cases, machine learning methods have proven to be a better method than statistical methods. The hybrid method, whether between statistics and machine learning or between machine learning methods, is usually also used to improve the performance of forecasting results or to compare performance among several methods [3, 6, 10-14].

Time series data can be considered as a system, either continuous or discrete. There are several model structures that can be used to represent a particular system. Some commonly used models are MISO/MIMO - AR/ARX (Multi Input Single Output / Multi-Output - Autoregressive / with external input), ARMAX (Auto-regressive Moving Average with external input) [15], ARIMA [16][17] and α-Sutte Indicator [18][19].

The term of projection in this study is used to describe the result of forecasting a number of values of the next state data in short, medium, or long-term periods, based on the dataset in the current and/or previous state. This study projected the total electricity demand for the period of 2016-2025 based on nominal GDP, population, and electricity sales data per sector (household, commercial, industrial) from the period of 2000-2015 [20-24]. The AR model is used to model time series data of electricity sales growth per sector, nominal GDP growth and population growth. The Multi-Input Single Output (MISO)-ARX model is used to model time series data of total electricity sales. Both models are implemented by using Artificial Neural Network Back-Propagation (ANN-BP). The repetitive training method is used to achieve the specified target error.

2. Time series data modeling using ANN

In this study using two-time series data models, the AR and ARX models. The AR model is used to model time series data where current data is modeled based on previous data. The ARX model is an AR model with an external input. The AR model expressed by:

$$y(t)+a_1 y(t-1)+...+a_n y(t-1)=e(t) \tag{1}$$

In Eq. (1), $y(t)$ is the output at time *t*, $a_1 \ldots a_n$ are the parameters to be estimated, n is the order number of the system, $y(t-1)...y(t-n)$ are the previous outputs, and $e(t)$ is a white noise.

The ARX model expressed by:

$$\begin{aligned} y(t)+a_1 y(t-1)+...+a_n y(t-1)= \\ b_1 x(t-1)+...+b_m x(t-m)+e(t) \end{aligned} \tag{2}$$

In Eq. (2), $x(t-1)+...+x(t-m)$ are the previous inputs and *m* is the number of input.

The AR model can be approximated by using Feed Forward Neural Network (FFNN) and expressed by:

$$e(t)=y(t)-N_{AR}\left(y(t-1),...,y(t-n)\right) \tag{3}$$

The ARX model can be approximated by using FFNN and expressed by:

$$e(t)=y(t)-N_{ARX}\begin{pmatrix} y(t-1),...,y(t-n), \\ x(t-1),...,x(t-m) \end{pmatrix} \tag{4}$$

By training $N_{AR/ARX}(\bullet)$ using a certain method such that $e(t)\rightarrow 0$ then obtained $N_{AR/ARX}(\bullet)\rightarrow y(t)$.

In its implementation, $e(t)$ is set as small as possible. The FFNN architecture used [25] is shown in Figure 1.

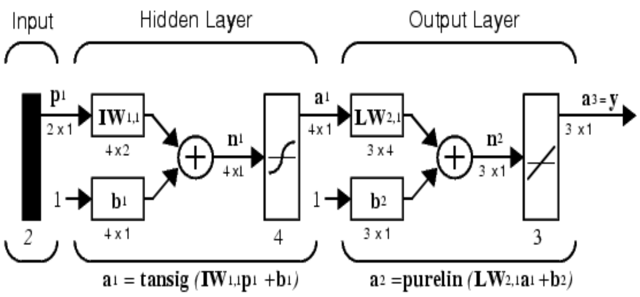
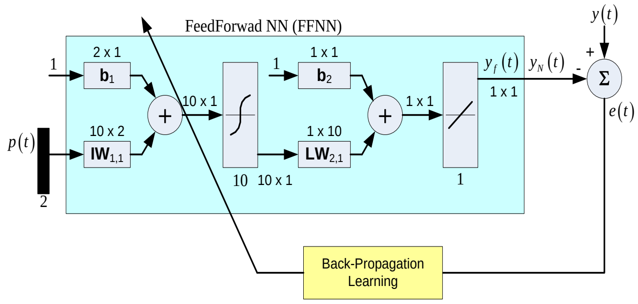


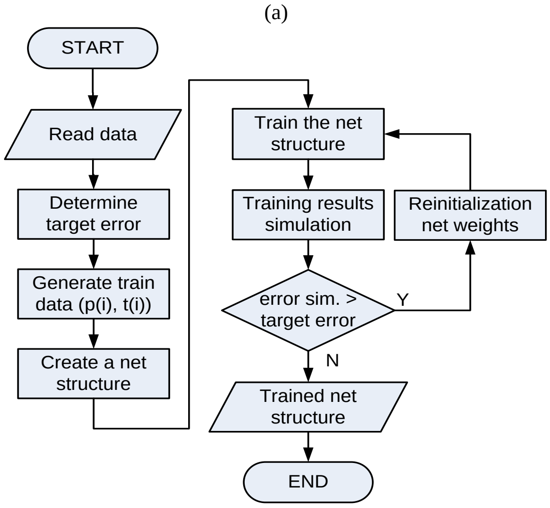
Fig. 1: FFNN Architecture

Backpropagation is related to the way in which gradient errors are calculated for nonlinear multilayer networks. There are a number of variations on the basic algorithm for calculating the gradient error, such as conjugate gradients and Newton methods. A well trained back propagation network will tend to give proportional answers when given new feedback that is not in the training dataset. Typically, the new input will produce the same output with the correct output for the input vector used in the training similar to the newly presented input [26].

In this study using ANN-BP as shown in Figure 2 (a). Under certain conditions for various reasons, ANN-BP cannot reach the specified target error. To overcome this, another method is required or modifies existing training methods in such a way as to enable the network to reach the specified target error. By utilizing the concept of back propagation, the repetitive training method is built to initialize each layer's weights of ANN-BP. The repetitive training method as shown in Figure 2 (b).



(a)



(b)

Fig. 2: (a).ANN-BP, (b).Repetitive Training method

The created net structure uses 10 hidden neurons. ANN-BP performance function based on repetitive training method using MSE (Mean Squared Error) which expressed by:

$$MSE=\frac{1}{N}\sum_{i=1}^{N}\left(y(t_i)-y_{NN}(t_i)\right)^2 \tag{5}$$

In Eq. (5), *N* is the number of training data, $y(t_i)$ is the *i*th training target, $y_{NN}(t_i)$ is the *i*th output of ANN-BP.

The performance of projection results is measured by using Mean Absolute Percentage Error (MAPE) which is declared as:

$$\begin{aligned} APE(i) &= \frac{\left|Projection_{\text{IEO}}(i)-Projection_{\text{AR}}(i)\right|}{Projection_{\text{IEO}}(i)}\times 100\% \\ MAPE &= \frac{1}{N}\sum_{i=1}^{N} APE(i) \end{aligned} \tag{6}$$

In Eq. (6), $Projection_{\text{IEO}}$ is the result of projection by IEO 2016, and $Projection_{\text{AR}}$ is the result of projection by AR model.

In this study, the growth is calculated by the following formula:

$$x_{growth}(i)=\frac{x(i)-x(i-1)}{x(i-1)} \tag{7}$$

The implementation of the ANN-BP based on repetitive training method is conducted using MATLAB programming tools.

3. Implementation of methods

The projection of total electricity demand is carried out for the period 2016-2025 based on historical data from the period 2000-

2015 as shown in Table 1 and Table 2 as the result of data processing obtained from [20-24]. Table 3 is an example of source data to calculate growth as shown in Table 1 and 2.

Total electricity sales growth is used as the training target. The electricity sales growth for each sector (*household, commercial, and industry*) is used as the training data input. The growth of electricity sales from *others* sector is not used because it has a very small share to total electricity sales. The nominal GDP and *population growth* are also used as inputs to show their impact on total electricity sales.

Table 1: Nominal GDP and Population Growth

Year	Nominal GDP Growth (%)	Population Growth (%)
2001	0.2119	0.0136
2002	0.1063	0.0161
2003	0.0807	0.0154
2004	0.1401	0.0120
2005	0.2084	0.0047
2006	0.2037	0.0152
2007	0.1831	0.0155
2008	0.2532	0.0128
2009	0.1323	0.0273
2010	0.1500	0.0123
2011	0.1514	0.0037
2012	0.0882	0.0290
2013	0.0203	0.0138
2014	0.0885	0.0135
2015	0.0845	0.0131

Table 2: Electricity sales by sector, electrification, and total electricity sales growth

Year	Electricity sales growth by sector (%)			Electrification Ratio (%)	Total Electricity sales growth (%)
	House hold	Com mercial	Indus-try		
2001	0.0909	0.0773	0.0465	0.5720	0.0676
2002	0.0196	0.0393	0.0348	0.5730	0.0304
2003	0.0517	0.1169	0.0181	0.5740	0.0385
2004	0.0793	0.1543	0.0754	0.5750	0.1068
2005	0.0673	0.1161	0.0527	0.5830	0.0693
2006	0.0624	0.0813	0.0275	0.5900	0.0521
2007	0.0816	0.1186	0.0502	0.6080	0.0767
2008	0.0604	0.1131	0.0473	0.6230	0.0641
2009	0.0949	0.0819	0.0257	0.6350	0.0431
2010	0.0888	0.0952	0.0362	0.6620	0.0945
2011	0.0884	0.1117	0.0734	0.7050	0.0853
2012	0.1078	0.0262	0.0996	0.7530	0.0883
2013	0.0704	0.1097	0.0699	0.8040	0.0779
2014	0.0890	0.0542	0.0237	0.8400	0.0590
2015	0.0547	0.0179	0.0026	0.8735	0.0214

Table 3: Examples of GDP, Population, and Electricity Sales by sector, and Total Electricity Sales

Year	GDP (trillion rupiahs)	Pop. (thou-sand)	Electricity sales by sector (GWh)			Total Electricity sales (GWh)
			House hold	Com-mercial	Indus-try	
2000	1,390	205,843	30,563	10,532	34,013	79,165
2001	1,684	208,647	33,340	11,346	35,593	84,520
2002	1,863	212,003	33,994	11,792	36,831	87,089

The AR model using FFNN is used to model the time series data for each variable used as input data to predict these variables in period 2016-2025. The model uses fifth order and declared as:

$$N_{AR}\left(y(t-1),...,y(t-5)\right) \rightarrow y(t)$$

This model also used to model total electricity sales as comparative data. After the training, the net structure then used to predict the data in the next year which is declared as:

$$y(t+1) = N_{AR}\left(y(t),...,y(t-4)\right)$$

Firstly, the training data sets are as follows:

Data in period 2001-2010 $\rightarrow y(t-5)$

Data in period 2002-2011 $\rightarrow y(t-4)$

Data in period 2003-2012 $\rightarrow y(t-3)$

Data in period 2004-2013 $\rightarrow y(t-2)$

Data in period 2005-2014 $\rightarrow y(t-1)$

As the training target is:

Data in period 2006-2015 $\rightarrow y(t)$

The target error used in training process is $e(t) = 10^{-6}$ with the training results as shown in Figure 3. After predicting data in 2016, this prediction data is used as training data to model time series data from 2001 to 2016. This process repeated continuously until obtained the predicted data in the year 2025. In the same way, it is also done for the data variable growth of population, electricity sales per sector and total electricity sales.

The MISO-ARX model using FFNN is used to model the time series data of *total electricity sales*. The model uses third order and declared as:

$$N_{ARX}\begin{pmatrix} y(t-1),...,y(t-3), \\ x_1(t-1)...,x_1(t-3), \\ x_2(t-1)...,x_2(t-3), \\ x_3(t-1)...,x_3(t-3), \\ x_4(t-1)...,x_4(t-3), \\ x_5(t-1)...,x_5(t-3), \\ x_6(t-1)...,x_6(t-3) \end{pmatrix} \rightarrow y(t)$$

Where x_1 is nominal GDP growth, x_2 is population growth, x_3 is electricity sales growth from the household sector, x_4 is electricity sales growth from the commercial sector, x_5 is electricity sales growth from the industrial sector, and x_6 is electrification ratio obtained from National Electricity Business Plan for the period of 2015-2034 [27].

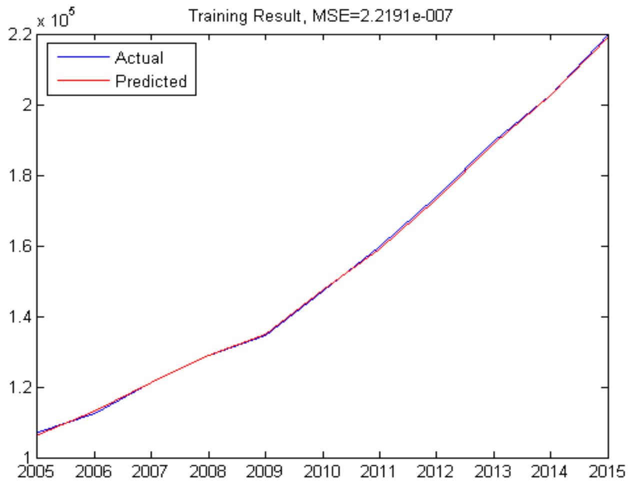


Fig. 3: Training result of ANN-based AR model of nominal GDP growth

After the training, the net structure then used to predict the data in the next coming year which is declared as:

$$y(t+1) = N_{ARX}\begin{pmatrix} y(t),...,y(t-2),x_1(t)...,x_1(t-2), \\ x_2(t)...,x_2(t-2),x_3(t)...,x_3(t-2), \\ x_4(t)...,x_4(t-2),x_5(t)...,x_5(t-2), \\ x_6(t)...,x_6(t-2) \end{pmatrix}$$

In the same way as in AR model, then obtained the training results as shown in Figure 4.

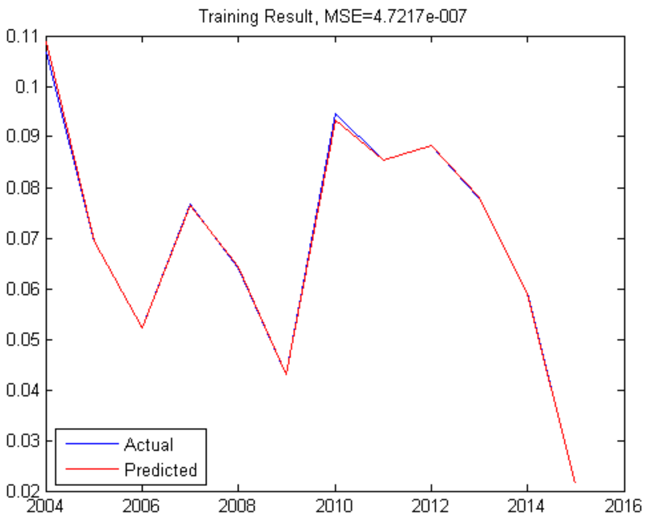
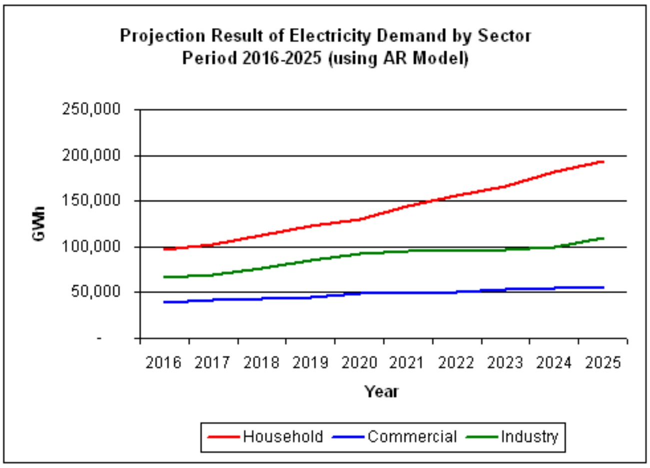


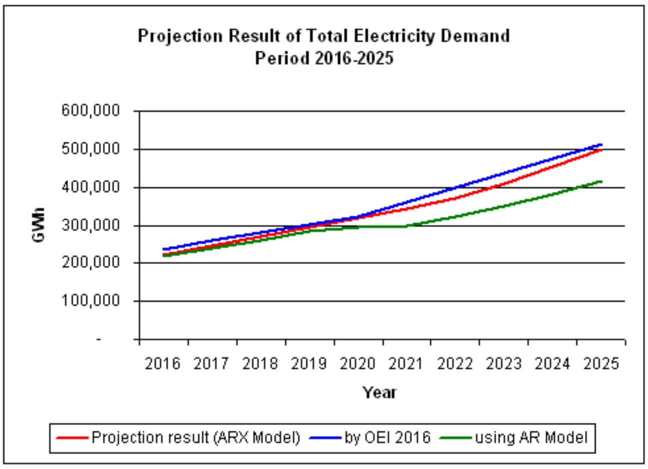
Fig. 4: Training result of ANN-based ARX model

4. Results and discussions

Projection result of electricity demand by sector by AR model shown in Figure 5 (a) and projection result of total electricity demand by MISO-ARX model shown in Figure 5 (b). Data that used for comparison is the projection of total electricity demand for the period of 2016-2025 by IEO 2016 and by AR model.
The performance of projection results is measured by using Eq. (6) with the results as shown in Table 4.
Table 4 shows that the MISO-ARX model projection has a better performance with MAPE of 4.2% than AR model with MAPE of 13.27%.



(a)



(b)

Fig. 5: (a).Projection of electricity sales by sector, (b).Projection of total electricity sales

Table 4: Performance measurement results

Year	Projection by IEO 2016	Projection by MISO-ARX	APE	Projection by AR model	APE
2016	237,400	223,370	**5.91%**	219,128	**7.70%**
2017	258.800	245,702	**5.06%**	238,796	**7.73%**
2018	280,200	270,141	**3.59%**	260,215	**7.13%**
2019	301,600	295,278	**2.10%**	283,244	**6.09%**
2020	323,000	320,235	**0.86%**	295,288	**8.58%**
2021	361,000	343,891	**4.74%**	298,326	**17.36%**
2022	399,000	372,186	**6.72%**	320,831	**19.59%**
2023	437,000	410,861	**5.98%**	350,190	**19.87%**
2024	475,000	453,612	**4.50%**	381,589	**19.67%**
2025	513,000	500,131	**2.51%**	415,389	**19.03%**
MAPE			**4.20%**		**13.27%**

5. Conclusions

Repetitive training methods have been implemented in ANN-BP to project electricity demand in the period 2016-2025 based on historical data in the 2001-2015 period. The proposed method has successfully anticipated the inability of ANN-BP in terms of achieving target errors established under various conditions of training data used. Variations of conditions are encountered when each predicted result of trained ANN-BP is used as a training dataset to predict in the next period. The result of the study also shows that the projection result using the ANN-based MISO-ARX model is better than the result of projection using ANN-based AR model. Future work is to improve the performance of repetitive training methods with test data that have more complex patterns.

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