A Heuristic Network for electricity demand projection

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***Abstract*—Indonesia's electricity demand in 2025 has been projected by the 2016 Indonesia Energy Outlook (OEI) of 513 TWh based on data obtained during the 2000-2015 period. This study tries to project the total electricity demand during 2016-2025 based on data on nominal GRDP growth, population, electricity sales in the household, commercial and industrial sectors, and electrification ratio. All data obtained in the form of time series data were modeled using MISO-ARX (Multi-Input Single Output Auto Regressive with Exogenous Input). This model is then represented using a Heuristic Network. After the training process, this network is used to predict the growth of total electricity sales in 2016-2025 based on growth data from 2001 - 2015. The prediction results are used to project electricity demand in 2016-2025. The comparison of the projection results using the Heuristic Network with the results of the OEI-2016 project is MAPE = 4.46%. With this relatively small MAPE, the projection results using the Heuristic Network can be considered fairly close to the results of the OEI-2016 projection**

Keywords*—*total electricity demand; MISO-ARX; Heuristic Network; OEI projection

I. INTRODUCTION

Indonesia's electricity consumption in 2015 (203 TWh) was dominated by the household sector (40%), followed by the industrial and commercial sectors (38% and 17%). The other sectors are the smallest (5%). Indonesia's electricity demand in 2025 is projected by OEI at 513 TWh [1], with a target of increasing the electrification ratio by 100%. In the year, nominal GDP growth is expected to increase to 8%. The assumptions used by OEI are an average population growth of 1.2% in 2025 and a nominal GDP growth of 5.02% in 2014.

The electricity demand projection provides significant support for the government in predicting economic conditions, which will later use to formulate economic development strategies. The computational approach can carry out this activity to produce quantitative predictions of the growth of electrical energy demand. Statistical methods are conventional methods that have been proven suitable for predicting and estimating activities. This method assumes that the time series data has stationary properties and meets the linearity requirements when transformed into other forms. Prediction value is obtained by using the principle of inverse transformation of the time series data model that has been made [2]. ARIMA (Auto-Regressive Integrated Moving Average) - Bob Jenkins model is one of the bases of time series data modeling with a parametric approach [3]. Modeling using a non-parametric approach is usually used for times series data that does not meet the requirements for stationary and linearity. The weakness of this approach is the level of complexity. Machine learning method is a modern method that is used to overcome the weaknesses of statistical methods, as well as to improve prediction or forecasting performance [4-7].

Various algorithms have been widely used in the computational approach to representing multiple statistical and machine learning methods. All computational activities are based on logic and reasoning, which have two primary roots: ampliative and non-ampliative. The term "ampliative" is used in the philosophy of logic to mean "extend" or "add to what is already known". Heuristics are classified as ampliative reasoning, while algorithms are non-ampliative reasoning. Heuristics are problem-solving, learning, or discovery approaches that use practical methods that are not guaranteed to be optimal or perfect but are significant enough to achieve goals [8]. The heuristic approach has been widely applied in various fields and research activities, some of which have been published in [9, 10]. The heuristic network is a machine learning method that applies heuristic concepts to increase the weighting of the network. It can predict the distribution of the percentage of GDP (Gross Domestic Product) in [11], whose problem-solving method has been changed using DNN (Deep Neural Network) in [12]. This heuristic network is very different from the heuristic approach used, such as in [9, 10, 13-16]. The Heuristic Network is almost similar to ANN (Artificial Neural Network) but differs in the learning process. In general, ANN uses the back-propagation technique in its learning process, where the weights are adjusted based on the decreasing gradient of the network error per epoch. While in the Heuristic Network, weight adjustment is made by dividing the network error based on the proportion of weights.

This study projects the total demand for electricity for the 2016-2025 period based on nominal GDP data, population, and electricity sales data per sector (household, commercial, industrial) in 2000-2015 [17]. The model of electrical energy demand used is the BPPT-MEDI model (BPPT Model of

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Energy Demand for Indonesia) [1], which assumes the following: 1). electrical energy consumption data obtained from [17]; 2). population growth projection up to 2025 follows the long-term projection of BPS-UNFPA Bappenas; 3). one household is assumed to have four family members; 4). electrification ratio until 2025 following the Electricity Supply Business Plan (RUPTN) of PT. PLN (Persero). The ARX - MISO (Multi-Input Single Output) model is used to model time-series data from total electricity sales. The ARX-MISO model is represented using prediction results compared with the projection results of the OEI-2016.

II. MATERIALS AND METHOD

A. ARX-MISO model

The ARX model is mathematically represented by [3]:

$$y(t) = -a_1 . y(t-1) - \cdots - a_{na} . y(t-n) + b_1 . x(t-1) + \cdots + b_{nb} . x(t - n_k - (n_b - 1)) + e(t) \quad (1)$$

where $x(t-1) \dots x(t - n_k - (n_b - 1))$ is the previous input which depends on the current output, $(n_b - 1)$ is the number of "zeros" in the system, n_k is the number of input samples that occurred before input that affects current output, $y(t-1) \dots y(t-n)$ is the previous output which depends on the current output, and $e(t)$ is white noise. Whereas $y(t)$ is the system output when t. Parameters $a_1 \dots a_{na}, b_1 \dots b_{nb}$ are model parameters to be estimated.

If a function $f(.)$ is considered as a particular approximation model, the ARX model can be restated by:

$$e(t) = y(t) - f\left(y(t-1) \dots y(t-n), x(t-1) \dots x(t - n_k - (n_b - 1)\right) \quad (2)$$

ARX-MISO model refers to Eq. (2) where the input is expressed by $x_1 \dots x_k$ and k is the number of system inputs. If the approximate model, $f(.)$, is trained in such a way that $e\ (t)\ \to\ 0$ then $f(.) \to y(t)$.

B. Heuristic Network

In general, the Heuristic Network used to represent the ARX-MISO model is shown in Figure 1. [11]. The Heuristic Network Architecture, as shown in Figure 1, can be mathematically expressed by:

$$\begin{bmatrix} h_{11} \\ h_{21} \\ h_{31} \\ \cdots \\ h_{n1} \end{bmatrix} = \begin{bmatrix} 0 & w_{12} & w_{13} & \cdots & w_{1n} \\ w_{21} & 0 & w_{23} & \cdots & w_{2n} \\ w_{31} & w_{32} & 0 & \cdots & w_{3n} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ w_{n1} & w_{n2} & w_{n3} & \cdots & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \cdots \\ x_n \end{bmatrix} + \begin{bmatrix} b_{11} \\ b_{21} \\ b_{31} \\ \cdots \\ b_{n1} \end{bmatrix} \quad (3)$$

$$\boldsymbol{h}_{1(n,1)} = \boldsymbol{W}_{(\dim = n)} * \boldsymbol{x} + \boldsymbol{b}_{1(n,1)} \qquad \boldsymbol{H}_1 = \boldsymbol{f}(\boldsymbol{h}_1)$$

Network output is expressed by:

$$\begin{bmatrix} h_{12} \\ h_{22} \\ h_{32} \\ \cdots \\ h_{n2} \end{bmatrix} = \begin{bmatrix} u_{11} \\ u_{21} \\ u_{31} \\ \cdots \\ u_{n1} \end{bmatrix} .* \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ \cdots \\ x_n \end{bmatrix} + \begin{bmatrix} u_{12} \\ u_{22} \\ u_{32} \\ \cdots \\ u_{n2} \end{bmatrix} .* \begin{bmatrix} H_1 \\ H_2 \\ H_3 \\ \cdots \\ H_n \end{bmatrix} + + \begin{bmatrix} b_{12} \\ b_{22} \\ b_{32} \\ \cdots \\ b_{n2} \end{bmatrix} \quad (4)$$

$$\boldsymbol{h}_{2(n,1)} = \boldsymbol{u}_{(n1,1)} .* \boldsymbol{x} + \boldsymbol{u}_{(n2,1)} .* \boldsymbol{H}_{(n,1)} + \boldsymbol{b}_{2(n,1)}$$

$$\tilde{y} = \sum \boldsymbol{h}_{2(n,1)} + + \boldsymbol{b}_3$$

$$\hat{y} = f(\tilde{y})$$

Network errors are expressed by:

$$e = y - (\hat{y}) \quad (5)$$

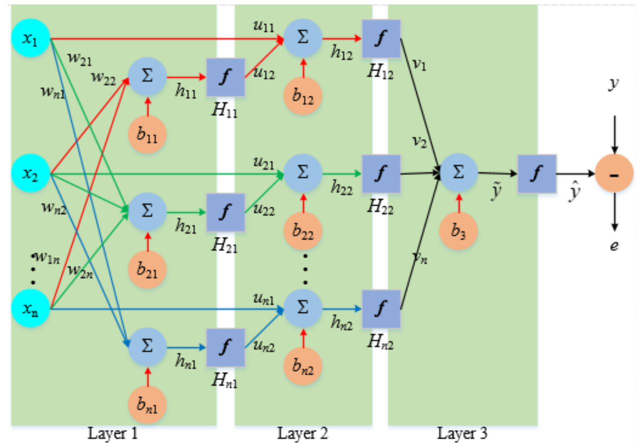


Fig. 1. Heuristic Network

In this study, the error function MSE (Mean Square Error) is used which is stated by:

$$MSE = E = \frac{1}{2} \sum_{k=1}^{K} \left(y^{(k)} - \hat{y}^{(k)}\right)^2 = \frac{1}{K} \sum_{k=1}^{K} \left(e^{(k)}\right)^2 \quad (6)$$

The Heuristic Network is built to optimize all network weights so that $E\ \to\ 0$ is obtained through the training process. Weight adjustment is performed by dividing the network error based on the proportion of weights in the local error. This practical method is the main foundation of the Heuristic Network and a clear differentiator from Artificial Neural Networks (ANN), as shown in Figure 2.

From Figure 1, Figure 2 (b), and Eq.(6), the outer gradient of Layer 3 stated by:

$$\frac{\partial E}{\partial \hat{y}} = \frac{1}{2} \frac{\partial E}{\partial \hat{y}} \sum_{k=1}^{K} \left(y^{(k)} - \hat{y}^{(k)}\right)^2 = e^{(k)} \quad (7)$$

The inner gradient of Layer 3 stated by:

$$\frac{\partial E}{\partial \tilde{y}} = \frac{\partial E}{\partial \hat{y}} . \frac{\partial \hat{y}}{\partial \tilde{y}} = e^{(k)} . \frac{\partial \hat{y}}{\partial \tilde{y}} = e^{(k)} . \frac{\partial f(\tilde{y})}{\partial \tilde{y}} \quad (8)$$

The local error of Layer 3 stated by:

$$d v_i = \frac{\partial E}{\partial v_i} = \frac{\partial E}{\partial \hat{y}} . \frac{\partial \hat{y}}{\partial \tilde{y}} . \frac{v_i}{b_3 + \sum_{i=1}^{n} v_i}$$

$$d b_3 = \frac{\partial E}{\partial \hat{y}} . \frac{\partial \hat{y}}{\partial \tilde{y}} . \frac{b_3}{1 + \sum_{i=1}^{n} H_{i2}} \quad (9)$$

The outer gradient of Layer 2 stated by:

$$d H_{i2} = A . \sum_{i=1}^{n} d v_i . \frac{\sum_{i=1}^{n} v_i}{H_{i2}} \quad (10)$$

The inner gradient of Layer 2 stated by:

$$d h_{i2} = \frac{\partial H_{i2}}{\partial h_{i2}} = \frac{\partial f(h_{i2})}{\partial h_{i2}} \quad (11)$$

The local error of Layer 2 stated by:

$$du_{i1} = dh_{i2} \cdot \frac{x_i}{b_{i2} + x_i + H_{i1}}$$
$$du_{i2} = dh_{i2} \cdot \frac{H_{i1}}{b_{i2} + x_i + H_{i1}} \qquad (12)$$
$$db_{i2} = dh_{i2} \cdot \frac{b_{i2}}{1 + x_i + H_{i1}}$$

The outer gradient of Layer 1 stated by:

$$dH_{i2} = A.du_{i2} \qquad (13)$$

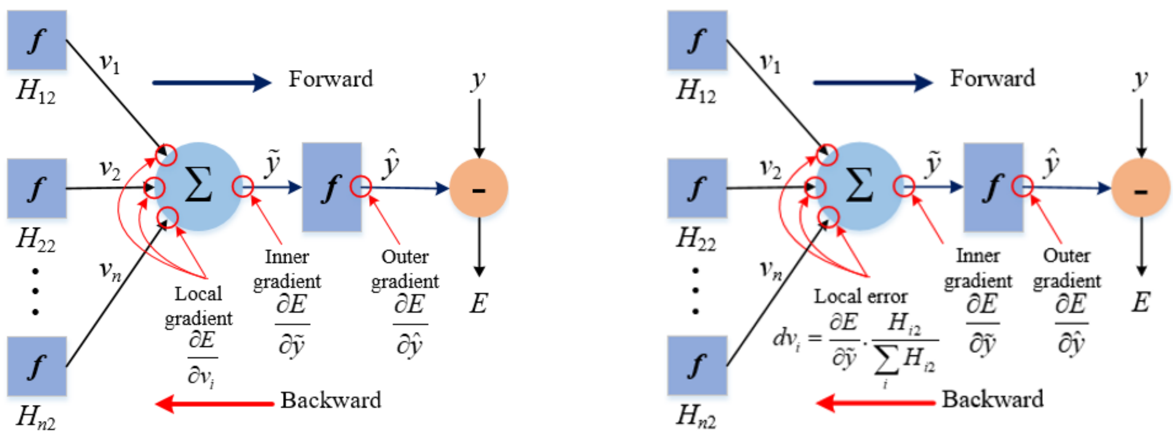
The inner gradient of Layer 1 stated by:

$$dh_{i1} = \frac{\partial H_{i1}}{\partial h_{i1}} = \frac{\partial f(h_{i1})}{\partial h_{i1}} \qquad (14)$$

The local error of Layer 1 stated by:

$$dw_{ij} = du_{i2} \cdot \frac{x_i}{b_{i1} + \sum_{i=1}^{n} w_{ij}}$$
$$db_{i1} = du_{i2} \cdot \frac{b_{i1}}{1 + \sum_{i=1}^{n} w_{ij}} \qquad (15)$$

The constants of b_{i1}, b_{i2}, b_3 are the biases of each layer, while A is the local gradient stabilizer constant with adjustable value in the range $0 < A < 1$.



(a). Learning process of ANN

(b). Learning process of Heuristic Network

Fig. 2. The difference in the learning process between ANN and the Heuristic Network

The network weight adjustment for each process iteration uses the Delta Rule algorithm [18] which is stated by:

$$u_{i1(new)} = u_{i1(old)} + du_{i1}.\alpha$$
$$u_{i2(new)} = u_{i2(old)} + du_{i2}.\alpha \qquad (16)$$
$$b_{ij(new)} = b_{ij} + db_{ij}.\alpha$$
$$w_{ij(new)} = w_{ij} + dw_{ij}.\alpha$$

α is the learning rate with adjustable value in the range $0 < \alpha < 1$. The training process is stopped if it satisfies $E < E_{target}$ where E_{target} is the smallest possible error target. The average of the input values should be close to zero to ensure convergence of the training results. In this case, the best data range is in the range {0 ... 1}. Therefore, both the training input data and the training targets need to be normalized using the following formula:

$$x_n(i) = \frac{x(i) - min(X)}{max(X) - min(X)} \qquad (17)$$

where $x(i) \in X$. The logistic function representing this interval is the tangent-sigmoid function expressed by:

$$f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$$
$$f'(x) = \frac{1}{2} log \left(\frac{1 + f(x)}{1 - f(x)}\right) \qquad (18)$$

C. Datasets

The raw data used in this study were obtained from [17], and specifically for the electrification ratio obtained from [19], as shown in TABLE I. The shaded part is the OEI-2016 projection results. Total electricity demand projections will be carried out in the 2016-2025 period based on historical data from the 2000-2015 period, as shown in TABLE I The dataset used is in the form of growth data, as shown in TABLE II

The training target is the total electricity sales growth. Meanwhile, the training data input is electricity sales growth for each sector (household, commercial and industrial). Nominal GDP and population growth are used as inputs to demonstrate their impact on total electricity sales. The 1st order ARX-MISO was used to model time-series data of the total electricity sales, which is stated by:

$$f(x_1(t-1), x_2(t-1), x_3(t-1), x_4(t-1), \quad x_5(t-1), x_6(t-1), y \qquad (19)$$

$f(.)$ represents the 1st order ARX-MISO model using the Heuristic Network, and $y(t-1)$ is the growth in total electricity sales in the previous year. Moreover, $x_1(t-1) \dots x_6(t-1)$ is the growth of GDP, population, electricity sales in the household, commercial, industrial, and electrification ratios in the previous year, respectively. Meanwhile, $y(t)$ is the growth in total electricity sales for the current year. The Heuristic Network training data is shown in TABLE III.

The trained Heuristic Network is then used to predict the growth in total electricity sales in 2016-2025 using the following model:

$$y(t+1) = f\big(y(t), x_1(t), x_2(t), x_3(t), x_4(t), x_5(t), x_6(t)\big) \quad (20)$$

where $t = 2015 \ldots 2024$.

The performance of the prediction results is calculated using MAPE (Mean Absolute Percentage Error), which is stated by:

$$APE(i) = \frac{|y_{actual}(i) - y_{pred}(i)|}{y_{actual}(i)} \times 100\%$$
$$MAPE = \frac{1}{N}\sum_{i=1}^{N} APE(i) \quad (21)$$

TABLE I. RAW DATA

Year	GDP (trillion rupiahs)	Population (thousand)	Electricity Sales by Sector (GWh)			Electrification Ratio (%)	Total Sales of Electricity (GWh)
			Household	Commercial	Industrial		
2000	1,390	205,843	30,563	10,532	34,013	0.5700	79,165
2001	1,684	208,647	33,340	11,346	35,593	0.5720	84,520
2002	1,863	212,003	33,994	11,792	36,831	0.5730	87,089
2003	2,014	215,276	35,753	13,171	37,497	0.5740	90,441
2004	2,296	217,854	38,588	15,203	40,324	0.5750	100,097
2005	2,774	218,869	41,184	16,968	42,448	0.5830	107,032
2006	3,339	222,192	43,753	18,348	43,615	0.5900	112,610
2007	3,951	225,642	47,325	20,524	45,803	0.6080	121,247
2008	4,951	228,523	50,184	22,845	47,969	0.6230	129,019
2009	5,606	234,757	54,945	24,715	49,204	0.6350	134,582
2010	6,447	237,641	59,825	27,069	50,985	0.6620	147,297
2011	7,423	238,519	65,112	30,093	54,725	0.7050	159,867
2012	8,078	245,425	72,133	30,880	60,176	0.7530	173,991
2013	8,242	248,818	77,211	34,269	64,381	0.8040	187,541
2014	8,971	252,165	84,086	36,128	65,909	0.8400	198,602
2015	9,729	255,462	88,682	36,773	66,079	0.8735	202,846
2016	11,088	259,385	97,498	39,388	66,709	0.9015	223,370
2017	13,402	261,505	102,644	42,507	69,825	0.9275	245,702
2018	15,560	264,196	112,492	43,250	76,975	0.9515	270,141
2019	19,008	269,804	122,796	44,295	84,695	0.9735	295,278
2020	23,248	273,135	130,739	48,572	92,406	0.9535	320,235
2021	26,680	277,907	144,262	49,385	95,238	0.9900	343,891
2022	31,241	283,119	155,548	50,281	95,634	0.9900	372,186
2023	36,616	284,918	165,926	53,246	96,184	0.9900	410,861
2024	41,420	287,243	182,647	54,830	99,335	1.0000	453,612
2025	45,878	294,516	192,955	56,011	109,314	1.0000	500,131

TABLE II. DATASETS

Year	GDP growth (%)	Population growth (%)	Electricity sales growth by sector (%)			Electrification Ratio (%)	Total Electricity Sales Growth (%)
			Household	Commercial	Industrial		
2001	0.2119	0.0136	0.0909	0.0773	0.0465	0.5720	0.0676
2002	0.1063	0.0161	0.0196	0.0393	0.0348	0.5730	0.0304
2003	0.0807	0.0154	0.0517	0.1169	0.0181	0.5740	0.0385
2004	0.1401	0.0120	0.0793	0.1543	0.0754	0.5750	0.1068
2005	0.2084	0.0047	0.0673	0.1161	0.0527	0.5830	0.0693
2006	0.2037	0.0152	0.0624	0.0813	0.0275	0.5900	0.0521
2007	0.1831	0.0155	0.0816	0.1186	0.0502	0.6080	0.0767
2008	0.2532	0.0128	0.0604	0.1131	0.0473	0.6230	0.0641
2009	0.1323	0.0273	0.0949	0.0819	0.0257	0.6350	0.0431
2010	0.1500	0.0123	0.0888	0.0952	0.0362	0.6620	0.0945
2011	0.1514	0.0037	0.0884	0.1117	0.0734	0.7050	0.0853
2012	0.0882	0.0290	0.1078	0.0262	0.0996	0.7530	0.0883
2013	0.0203	0.0138	0.0704	0.1097	0.0699	0.8040	0.0779
2014	0.0885	0.0135	0.0890	0.0542	0.0237	0.8400	0.0590
2015	0.0845	0.0131	0.0547	0.0179	0.0026	0.8735	0.0214

TABLE III. TRAINING DATA

$(t-1)$	$x_1(t-1)$	$x_2(t-1)$	$x_3(t-1)$	$x_4(t-1)$	$x_5(t-1)$	$x_6(t-1)$	$y(t-1)$	(t)	$y(t)$
2001	0.2119	0.0136	0.0909	0.0773	0.0465	0.5720	0.0676	2002	0.0304
2002	0.1063	0.0161	0.0196	0.0393	0.0348	0.5730	0.0304	2003	0.0385
2003	0.0807	0.0154	0.0517	0.1169	0.0181	0.5740	0.0385	2004	0.1068
2004	0.1401	0.0120	0.0793	0.1543	0.0754	0.5750	0.1068	2005	0.0693
2005	0.2084	0.0047	0.0673	0.1161	0.0527	0.5830	0.0693	2006	0.0521
2006	0.2037	0.0152	0.0624	0.0813	0.0275	0.5900	0.0521	2007	0.0767
2007	0.1831	0.0155	0.0816	0.1186	0.0502	0.6080	0.0767	2008	0.0641
2008	0.2532	0.0128	0.0604	0.1131	0.0473	0.6230	0.0641	2009	0.0431
2009	0.1323	0.0273	0.0949	0.0819	0.0257	0.6350	0.0431	2010	0.0945
2010	0.1500	0.0123	0.0888	0.0952	0.0362	0.6620	0.0945	2011	0.0853
2011	0.1514	0.0037	0.0884	0.1117	0.0734	0.7050	0.0853	2012	0.0883
2012	0.0882	0.0290	0.1078	0.0262	0.0996	0.7530	0.0883	2013	0.0779
2013	0.0203	0.0138	0.0704	0.1097	0.0699	0.8040	0.0779	2014	0.0590
2014	0.0885	0.0135	0.0890	0.0542	0.0237	0.8400	0.0590	2015	0.0214

III. RESULT AND DISCUSSIONS

The Heuristic Network training model used is under the amount of input data, and the training target was shown in Figure 3. The Heuristic Network training implementation is carried out using MATLAB (R2013a). The training error target was set at $E_{target} = 10^{-5}$. The performance of the training results was shown in Figure 4.

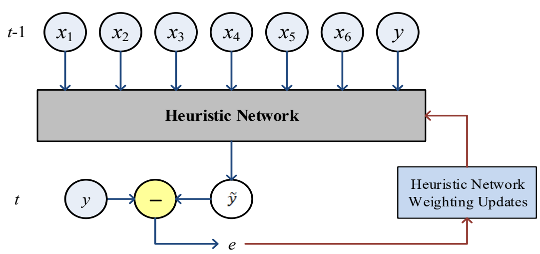


Fig. 3. The Heuristic Network Training Model

The trained Heuristic Network was then used to predict the total electricity sales growth in 2016-2025, as shown in Figure 5. The results of the growth prediction were then converted into total electricity sales in GWh units, as shown in Figure 6. The predicted total electricity sales are considered as a projection of electricity demand in that period, as shown in Figure 7.

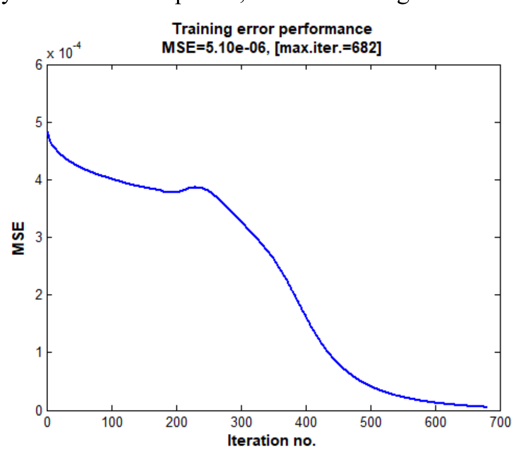


Fig. 4. Training error performance

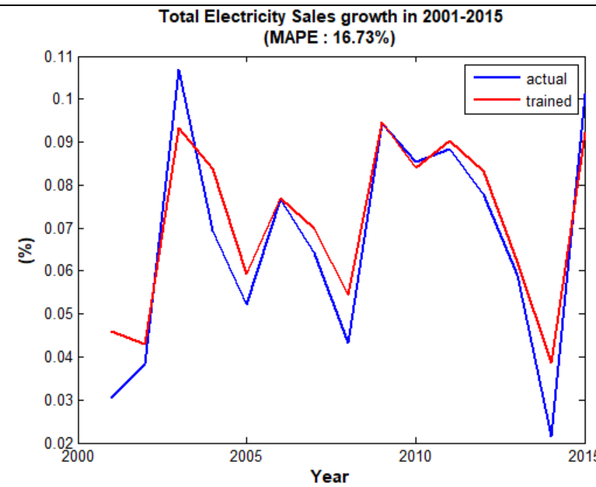


Fig. 5. Total Electricity Sales growth in 2001-2015

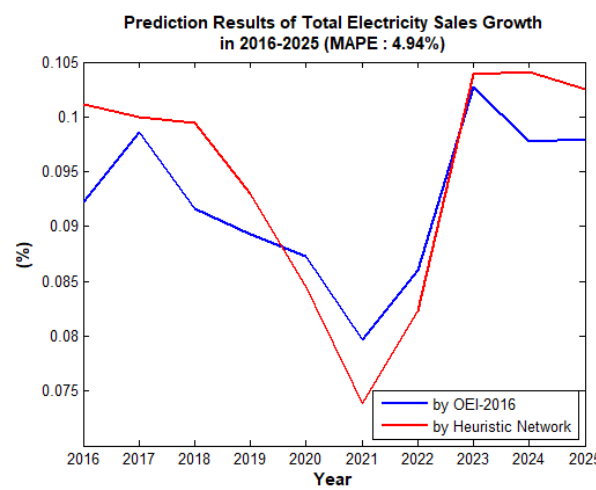


Fig. 6. Prediction Results of Total Electricity Sales Growth in 2016-2025

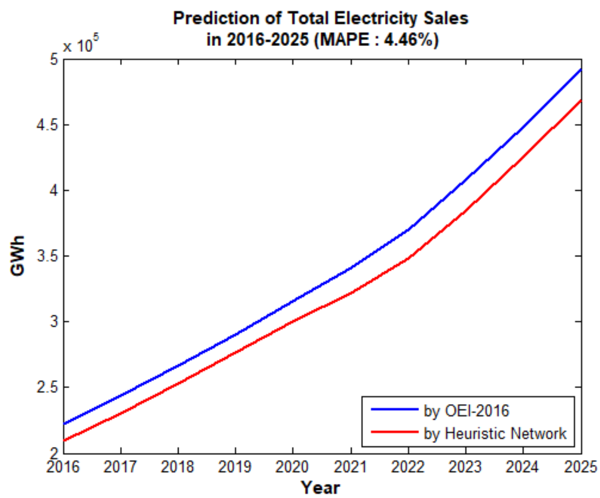


Fig. 7. Prediction of Total Electricity Sales in 2016-2025

Visually, there is a very significant difference between the predicted growth results and the predicted results after conversion. The data used for training is the basis of growth ratios so that the prediction output is in the form of a growth ratio. The results of this prediction are then used as the basis for obtaining a predictive result of total electricity sales by converting them into their actual numbers. The resulting difference in MAPE can be said to be insignificant, with the MAPE of 4.94% for the growth ratio as the basis and MAPE = 4.46% after being converted. With a reasonably small MAPE value, the projection results between the OEI-2016 and the research results can be considered almost the same.

IV. Conclusion

The Heuristic Network is an approach model representing a time-series data model, which in this study is used to represent the first order MISO-ARX time series data model. This model has been used to predict total electricity sales for 2016-2025 based on 2001-2015 growth data. Comparing the predicted results using the Heuristic Network with the OEI-2016 projection results was MAPE = 4.46%. The relatively small MAPE can be used as a basis for argumentation to state that the projection results of total electricity sales using the Heuristic Network are very close to the results of the 2016 OEI projection.

For further studies, the Heuristic Network will be refined to be used as a heuristic-based problem solving that can solve various problems.

Acknowledgment

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