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Adaptive Neuro-Fuzzy Inference System-Based Prediction Model for Malaysia's Overall Energy Consumption

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***Abstract*:** Malaysia is one of the developing countries in Southeast Asia that showed a rising in energy consumption every year. In this paper, three predictive models on total energy consumption are constructed using the Adaptive Neuro-Fuzzy Inference System (ANFIS). Three major steps are proposed to determine the predictive models using ANFIS, which are data extraction, construction of ANFIS and comparison of predictive and actual predictive models. In data extraction, yearly energy consumption, growth of populations and GDP are determined. Next, the construction of ANFIS involved the normalization of data and MATLAB as a simulation to stimulate the predictive model. A comparison between predictive and actual predictive models is included to justify the correctness of the model. To construct the most appropriate prediction model, three models based on two input-partitioning methods—grid partitioning with two layers of the Gaussian membership function and subtractive clustering with radii of 0.6 and 0.7—have been chosen and compared. Three statistical methods, including the correlation coefficient, mean absolute error (MAE), and root means square error (RSME), were used to assess the ANFIS model's performance. The findings indicated that the RMSE values are 0.0601, 0.1591 and 0.0860, respectively, whereas the MAE values are 0.0560, 0.1480 and 0.4386. Additionally, Model 1, which represents the subtractive clustering of 0.6 radii, has a correlation coefficient that is close to 1, making it the most appropriate model for this study's prediction of energy consumption through the year 2029. The ability to estimate future energy use is crucial for ensuring that there is always enough energy available to meet demand and promote sustainability.

***Keywords*:** Energy consumption, Adaptive Neuro-Fuzzy Inference System, population, Gross Domestic Product, predictive modelling.

1. Introduction

Malaysia is one of the developing countries in Southeast Asia which looks toward approaching the Fourth Industrial Revolution (IR4.0) to enhance the growth of productivity for the manufacturing sector as well as speed up the process of socioeconomic life. IR4.0 is a concept of connecting technology with people through digitalization [1]. The implementation of IR4.0 can be able to increase the growth of the Gross Domestic Product (GDP) of the country and hence, increase energy consumption. The GDP in Malaysia has linearly increased from MYR 1.17x1011 in 1994 to MYR 3.44x1011 in 2017 [2]. Another parameter that affects the rising in energy consumption is the growth of the population. The growth of the population in Malaysia has shown a steady increase between 1percent to 3percent from 17,517,054 in 1990 to 33,573,221 in 2021 [3]. The growth of populations has created a negative impact on energy consumption as more energy usage is required to support the demands and lifestyles of the people in urban areas. According to the Energy Commission [4], Malaysia's energy usage is expected to grow by up to 1.8percent per annum for the years 2020 to 2030.

Forecasting future energy consumption in various sectors can predict the energy supply needed to be supplied by the energy provider. Before forecasting future energy consumption, however, a predictive model needs to be built to ensure the acceptability of the modelling. Several researchers have performed predictive models to determine future energy consumption in different types of sectors. Kant and Sangwan [5] developed an appropriate predictive model in machining by using Artificial Neutral Network (ANN) for sustainable performance characteristics. The results showed that the mean relative error is good accuracy in predicting energy in machining which is 1.50percent. However, the study is only limited to machining. Ferlito et al. [6] then extended the development of the predictive model on building energy consumption. Based on the results, the percentage error of the root means square is in the range of 15.7percent and 17.97percent. In a mid-size autonomous electric vehicle cab in New York City, Zhang et al. [7] used the predictive model to assess energy consumption and greenhouse gas emissions for two driving scenarios with and without a driver. According to the research, the average energy consumption for the two scenarios falls between 325 and 361 Wh/km for the electric taxi with a driver and 340 and 397 Wh/km for the electric taxi without a driver. A recent study on predicting energy consumption in residential buildings has been conducted by Olu-Ajayi et al. [8] using deep learning, ensemble, and other machine learning models.

Chua and Oh [9] revealed that the energy consumption in Malaysia has increased from 1,243.7 petajoules (PJ) in 2000 to 2,217.9 PJ in 2010. The drastic increase in energy consumption within the 10 years is due to the change of governments' policy from an agricultural-based economy to a technological one [10]. Due to the drastic changes in energy consumption, predictive modelling is required to be performed in Malaysia to predict how much energy is required by the energy provider. The study on a predictive model for predicting energy in Malaysia's smart commercial building has been done by Mazlan et al. [11] using the Internet of Things and machine learning. The results showed that by using the k-nearest neighbour method in two smart commercial buildings, a value of 5 is the best as compared with 3 and 4. However, it is difficult to investigate the method either it is the best since no comparison had been made. Hence, Shapi et al. [12] developed two predictive methods, namely Support Vector Machine (SVM) and ANN to determine which method is the best for predicting energy consumption. Based on the study done by Shapi et al. [12], the SVM method showed the most promising result as compared with the k-nearest neighbour and ANN since it does not depend on the performance of the hardware it is running on. The latest study on forecasting energy consumption of Malaysia's resident sector until the year 2032 has been performed by Ishak et al. [13] through three different methods, namely simple exponential smoothing, Holt's exponential smoothing and Brown exponential smoothing. The results presented that Holt's exponential smoothing is the most appropriate modelling to predict energy consumption. However, the previous study does not include predictive modelling of energy consumption in various sectors in Malaysia. Hence, this paper aims to develop predictive modelling of energy consumption in various sectors in Malaysia by using the Adaptive Neuro-Fuzzy Inference System (ANFIS). ANFIS is a universal predictive approach that is initiated by Jang [14] which is based on ANN through the integration of Fuzzy Logic and Network-based to transform inputs into the desired output. The development of predictive modelling is important before future predictions can be made to minimize the error in future analysis. The future prediction of energy consumption is necessary for the energy providers to predict and analyse future energy generations.

2. Methodology

This paper considerably developed a methodology for predicting energy consumption in various sectors in Malaysia through the use of ANFIS as a tool. The method consists of three main steps which are data extraction, construction of ANFIS and calculation of errors between actual and prediction values for ANFIS performance evaluation. The summarized methodology is shown in Figure 1. In this case study, three main sectors in Malaysia are evaluated which represent the most energy usage, namely the commercial, industrial, and residential sectors. As stated by Chong et al. [15], the industrial sector constitutes the most energy consumption in Malaysia which is 48.8percent, followed by the commercial (29.8percent) and residential (20.7percent). The percentage of energy usage in various sectors is assumed to be the same throughout every year to ease the demonstration of the methodology. This is because energy consumption is influenced by four (4) main categories which are weather and location, the physical characteristic of the building, appliance and electronics stock and occupancy and occupant's behaviour towards energy consumption [16]. Since Malaysia has experienced high humidity and a hot climate throughout the year with an average temperature of between 22 degree Celsius to 32 degree Celsius [10], the weather and location, the physical characteristic of the building and the usage of the appliance and electronics shock have created energy consistency of the demands. The occupancy and occupant's behaviour towards energy consumption, on the other hand, are dependent on the behaviours and based on the study done by [17], most organizations have little emphasis on energy efficiency. Hence, in this paper, the predictive modelling of energy consumption in Malaysia is closely related and analysed through the growth of populations and GDP.

In the first step, yearly energy consumption in different sectors, growth of populations and GDP are required to be obtained as a dataset to initiate the analysis. The growth of population and GDP data with their rates are collected from the year 1994 until 2019 and it is presented in Table 1. Total energy consumption in Malaysia from 1994 until 2021 is proposed as shown in Table 2. Based on the two tables shown, the energy consumption, and rate of population growth are gradually increasing but as for the GDP, the rate is inconsistent. Hence, all of the datasets need to be normalized by using Equation Eq. (1) to normalize the values in the range of 0-1 scaler. The normalized training datasets on yearly total energy consumption, growth of populations and GDP from the year 1994 until 2010 are shown in Table 3.

$$X_N = (X - X_{\min})/(X_{\max} - X_{\min}) \tag{1}$$

Where;
X_N =Normalized data on population growth, GDP and energy consumption.
$X_{\min}$ =Minimum data on population growth, GDP and energy consumption.
X =Actual data on population growth, GDP and energy consumption.
$X_{\max}$ =Maximum data on population growth, GDP and energy consumption.

Next, the second step involved in the methodology is the construction of ANFIS. The use of ANFIS as an integration of the Neural Network and Fuzzy Inference system has been applied to predict various kinds of network approaches such as energy, carbon, water and property. In this paper, a predictive model of total energy consumption in Malaysia is constructed concerning the rising population and GDP, hence these two variables were selected as the data input. The ANFIS model development and evaluation are carried out by using the MATLAB computing platform.

The normalized data from step one were separated into training and testing data to develop the ANFIS models. Datasets from the year 1994 to 2010 were sorted as training data. Two input-partitioning methods were incorporated

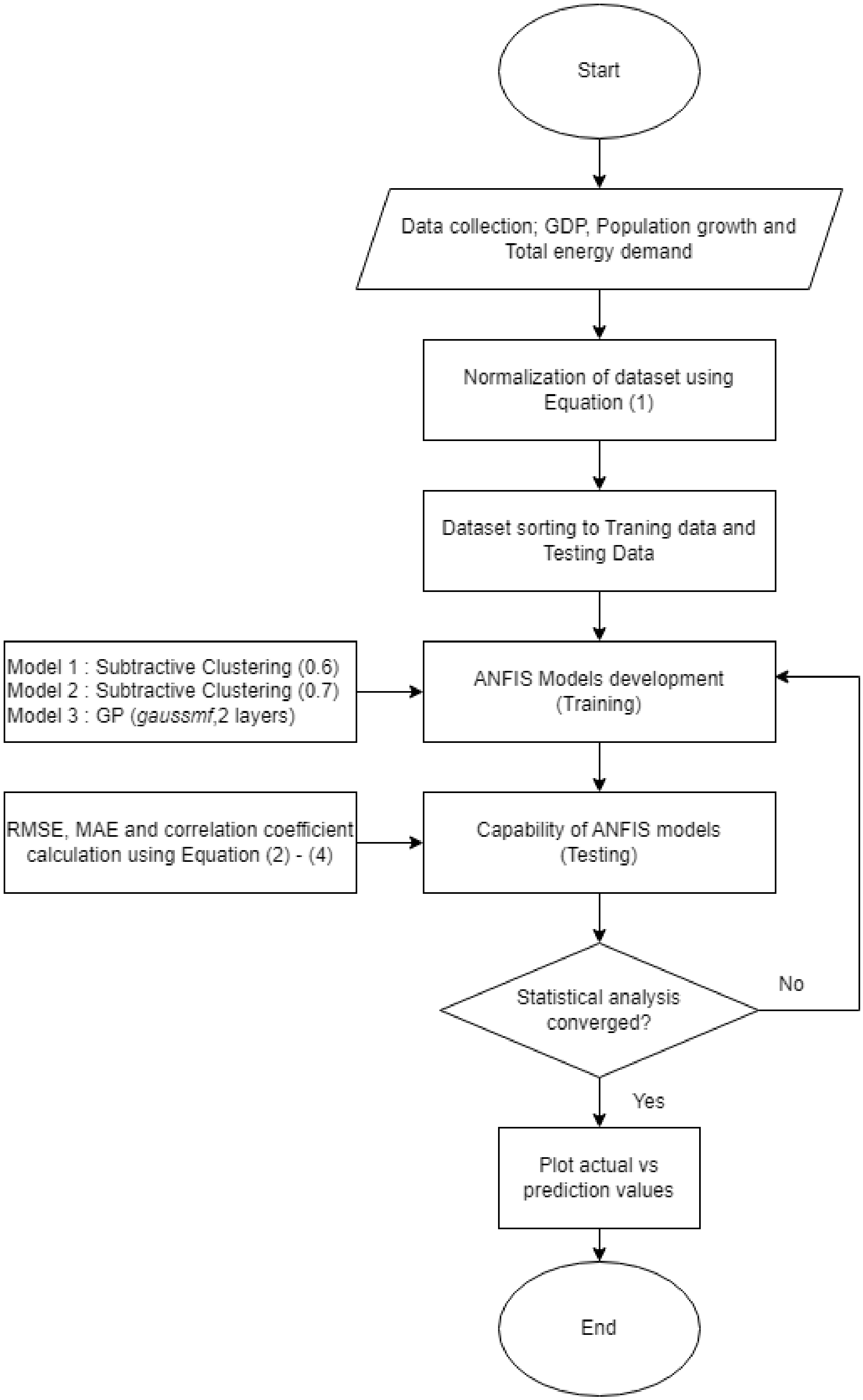

Figure 1. Summary of the overall methodology

Table 1. Yearly growth of population and GDP in Malaysia from 1994 until 2021 with rates [2, 3, 18]

Year	Population growth	Population growth rate	GDP	GDP growth rate
1995	20136888	2.80	128613226382	9.8
1996	20689051	2.74	141478022477	10.0
1997	21249178	2.71	151838092825	7.3
1998	21810542	2.64	140663697153	-7.4
1999	22368655	2.56	149297089131	6.1
2000	22945150	2.58	162523121449	8.9
2001	23542517	2.60	163364463537	0.5
2002	24142445	2.55	172171422651	5.4
2003	24739411	2.47	182137564217	5.8
2004	25333247	2.40	194492752476	6.8
2005	25923536	2.33	204863376673	5.3
2006	26509413	2.26	216304682965	5.6
2007	27092604	2.20	229929251902	6.3
2008	27664296	2.11	241038904256	4.8
2009	28217204	2.00	237390711217	-1.5
2010	28717731	1.77	255016609233	7.4
2011	29184133	1.62	283214119400	5.3
2012	29660212	1.63	283214119400	5.5
2013	30134807	1.60	296507404303	4.7
2014	30606459	1.57	314317779640	6.0
2015	31068833	1.51	330321318804	5.1
2016	31526418	1.47	344272143057	4.2
2017	31975806	1.43	364573903325	5.9
2018	32399271	1.32	358790000000	-1.5
2019	32804020	1.25	365180000000	1.7

in this paper which are subtractive clustering and grid partitioning (GP). In the subtractive clustering, 0.6 and 0.7 of the cluster radii were set while for the GP method, 2 layers of Gaussian membership function (MF) were chosen to develop the ANFIS models. These three models then underwent 500 iterations of the backward and forward pass in the training session to allow the models to learn and mapped the input-output dataset for prediction.

The next step is to investigate the capability of the trained ANFIS models in predicting the output by using the data from the year 2011 until 2019. Then, the comparison between the predicted and actual values is carried out via statistical analysis to determine the accuracy of the models. The details of the comparison study can be found in the next step.

Finally, the last step is through the calculation of errors between actual and prediction values as well as the correlation coefficient to determine the ANFIS model performances. The comparison is made between actual and prediction values by calculating the root-mean-square error (RMSE) and mean absolute error (MAE) between those values to ensure the formation of the predictive model is accurate and acceptable. While the correlation coefficient is to investigate the relationship between actual and predicted values. RMSE is defined as the standard deviation of the prediction errors to inform the best-concentrated data around the best-fit line of the real case study for verifying results. Equations (2) – (4) were used to calculate the RMSE, MAE and correlation coefficient between the actual and prediction values of energy consumption in the selected sectors.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(x_i - (x_i)')^2}{N}} \tag{2}$$

$$MAE = \frac{1}{N\sum_{i-1}^{N}(x_i - (x_i)')}$$

$$\text{Correlation coefficient} = 1 - \frac{\sum_{i=1}^{N}(x_i - (x_i)')^2}{\sum_{i=1}^{N}(x_i - (\overline{(x_i)'})^2} \tag{3}$$

Where;

$i =$ Variable i

$N =$ Number of non-missing data points

$x_i =$ Actual observations energy series

$x_i =$ Estimated energy series

$x_i =$ Mean of the Actual observations' energy series

3. Discussions

The methodology has been conducted to determine whether the predictive model is accurate and acceptable. Table 4 showed the results of the RMSE, MAE and correlation coefficient for the 0.6 radii subtractive clustering, 0.7 radii subtractive clustering and GP 2MF layers. Figure 2 depicts the total energy consumption based on actual and predicted values. Based on the results shown, the RMSE between actual and

Table 2. Yearly total energy consumption (MW) in Malaysia from 1994 until 2021 [19–22]

Year	Total Energy Consumption
1994	34099
1995	39251
1996	43915
1997	50986
1998	53231
1999	55999
2000	61197
2001	65047
2002	68873
2003	73420
2004	77258
2005	80747
2006	84724
2007	89504
2008	92889
2009	96378
2010	104589
2011	107403
2012	116428
2013	123162
2014	128418
2015	132559
2016	144142
2017	146608
2018	152958
2019	158715
2020	113900
2021	116389

prediction values of Models 1, 2 and 3 are 0.0601, 0.1591 and 0.0860, while the MAE have resulted with 0.0560, 0.1480 and 0.4386, respectively. As for the relationship between actual and predicted values through the correlation coefficient, Model 1 exhibits a strong correlation as the statistical value calculated is near 1. Hence, the most suitable predictive model that can be selected in this study to predict future energy consumption is 0.6 radii clustering or Model 1. This is due to the reason that the model has the lowest RMSE and MAE which are near-zero values which reflects the accuracy of the model compared to others. It is notable that when the 0.6 subtractive clustering predictive model as an ANFIS method is used as a forecasting approach technique, the RMSE between the actual and predictive values is the lowest. In addition, the prediction of total energy consumption from 2011 to 2019 of this model has a good correlation and accuracy with the actual values.

Based on the Energy Commission [4], Malaysia's energy usage is expected to grow by up to 1.8% per annum for the years 2020 to 2030. To verify the accuracy of the predictive model, the prediction values of the total energy consumption had been extended from 2020 until 2029. Total energy consumption from 2020 until 2021 is taken from [22], stating that Malaysia's energy usage in 2020 and 2021 is 113,900 MW and 116,389 MW. Malaysia's energy usage

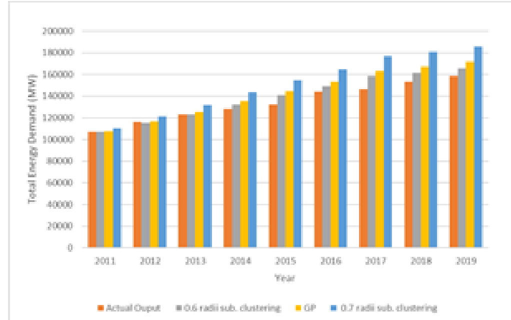

Figure 2. Actual and prediction values of the total energy consumption from 2011 up to 2019.

starting from 2022 until 2029 is considering that the energy usage will be increasing by 1.8%, yearly as stated by Energy Commission [4]. For the prediction of total energy consumption using ANFIS, prediction of population growth and GDP are needed for the analysis from 2021 to 2029, as shown in Table 5. Figure 3 shows the comparison between prediction values of the total energy consumption from 2020 until 2029. Based on the results, from 2020 to 2021, the model was unable to predict accurately due to the pandemic Covid-19 that caused the demand for energy to decrease [22]. Nevertheless, the ANFIS model can forecast energy consumption and can be used as a promising predictive tool for various applications.

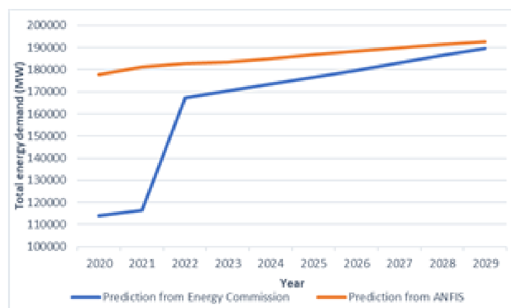

Figure 3. Comparison between the prediction of total energy consumption from the Energy Commission [4] and modelling developed from ANFIS

4. Conclusion

This paper has developed and analysed the predictive models based on the ANFIS method to future predict the total energy consumption in Malaysia using MATLAB. The energy consumption data collected from the year 1994 until 2019 have been normalized and sorted for training and testing processes. From the statistical analysis, this study found that Model 1 is the most suitable model to predict future energy consumption as the RMSE and MAE calculated were the lowest among the others as well as demonstrating the strong correlation coefficient between actual and predicted values. This shows that the model is capable of predicting the total energy consumption in Malaysia. Hence, the ANFIS methods could be used as a tool to forecast the amount of energy supply needed to ensure energy generation and sustainability in the future.

Table 3. Normalized training datasets on yearly total energy consumption, growth of populations and GDP from the year 1994 until 2010

Year	Normalized Population growth	Normalized GDP	Normalized Total Energy Consumption
1994	0.00	0.00	0.00
1995	0.05	0.05	0.05
1997	0.14	0.15	0.15
1998	0.19	0.10	0.17
2000	0.28	0.20	0.25
2001	0.33	0.20	0.28
2003	0.43	0.29	0.36
2004	0.48	0.34	0.39
2006	0.58	0.44	0.46
2007	0.63	0.50	0.50
2009	0.72	0.53	0.57
2010	0.76	0.61	0.64

Table 4. Statistical analysis of trained ANFIS models

Model	Input Partitioning method	RSME	MAE	Correlation coefficient
1	Subtractive Clustering 0.6 radii	0.0601	0.0560	0.7862
2	Subtractive Clustering 0.7 radii	0.1591	0.1480	-0.4965
3	GP 2MF Layers	0.0860	0.4386	0.5631

Table 5. Statistical analysis of future ANFIS models

Year	GDP (billion USD)	GDP growth rate	Population growth	Population growth rate
2021	373.034	-	32,776,194	-
2022	434.059	16.36	33,181,072	1.24
2023	467.459	7.69	33,579,265	1.20
2024	503.110	7.63	33,969,290	1.16
2025	539.616	7.26	34,349,936	1.12
2026	577.156	6.96	34,720,347	1.08
2027	615.011	6.56	35,080,112	1.04
2028	640.226	4.10	35,429,087	0.99
2029	665.836	4.00	35,767,388	0.95

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