Load Forecasting using Artificial Neural Network: Case Study at Kolej Komuniti Kuantan

Ahmad Zairi Mohd Zain
Kolej Komuniti Kuantan
zairizain@gmail.com

Abstract

For the electrical power system, load forecasting is important to achieve maximum savings and profit in terms of the megawatt hours available. In pursuit of acquiring ideal and effective methods of predicting electrical energy output or load forecasting, this study applies a load demand dataset collected at Kolej Komuniti Kuantan from 2016 to 2019 over 4 years. The Artificial Neural Network will be used as a method of machine learning to predict load forecasting. In order to demonstrate the efficacy of the proposed machine learning, the mean absolute percentage error (MAPE) and root mean square error (RMSE) is measured, and from the errors found, it can be inferred that the proposed technique provides relatively accurate results and is efficient in forecasting the electrical load forecast. The simulation was conducted in the MATLAB Software environment.

Keywords: load forecasting, artificial neural network (ANN)

1.0 Introduction

Throughout the day, there are different ways of energy use for example, in electricity, solar energy, refined oils, wind energy, LPG, chemical energy in the form of batteries and many other types (A. Singh & Tripathi, 2016). Energy access seems to be a vital component for human quality of life-being, economic stability and the eradicating of poverty. Ensuring that almost everyone has adequate access is a continuing and pressing challenge for worldwide growth (Hannah Ritchie & Max Roser, 2014).

Based on (Rahman et al., 2017), Malaysia has four types of energy users; domestic, commercial, industrial and other. The most basic uses of energy are residential. It involves watching TV, heating and lighting the house, washing clothes, taking a shower, running appliances, cooking and working on a laptop or computer from home. Residential uses energy nearly 40 percent of total global energy uses (Renewable Energy World, 2015). Commercial energy usage, together with institutional energy use, provides companies, public buildings such as libraries, and schools (including universities) with the capacity to serve the public. Commercial sectors such as Kolej Komuniti Kuantan include energy use such as cooling, the lighting of buildings and spaces, electricity utilized by computers, fax machines and workstations, just to name a few.

Electrical load forecasting is a key method for improving electricity generation and utility companies efficiency and revenues (Kuo & Huang, 2018). The primary goal is to continue providing adequate supply to electricity customers and to accomplish the goals, the current and future demand for power must be properly evaluated. Therefore, this load forecasting technique is needed as an approach to gain information about consumer demand and the precise power generation capability.

Demand side load forecasting is now commonly carried out by load aggregators which estimate their customer's accumulated power demand statuses (Glavan, Gradišar, Moscariello, Juričić, & Vrančić, 2019). Many consumers can supervise, forecast and maintain their electricity load statuses, as this would bring some advantages in terms of the financial benefits and significant reduction in consumption. The purpose of this research paper is to show how accurate demand forecasts can be generated from the demand side (electricity consumers) and to reduce differences from the stated profile.

Based on that, the objective of this paper is to show how load forecasts can be provided by using the load demand-side information at Kolej Komuniti Kuantan. This load forecast will be used as a reference in the future energy management.

1.1 Load forecasting

The prime focus of load forecasting is to forecast possible load trends or pattern. The load forecast is sometimes classified by the planned length duration. Even though there is no formal classification in the energy sector, there are four types of load forecasting, and predictions are based on knowledge of several factors influencing the load; very short term load forecasting (VSTLF), short term load forecasting (STLF), medium-term load forecasting (MTLF), and long term load forecasting (LTLF)(Reddy & Jung, 2016). The VSTLF usually anticipates load for a time frame below 24 hours for real-time operation, STLF indicates load for a period greater than 24 hours up to maximum one week for unit commitment and operation, MTLF estimates load for a period of one week up to one year for fuel reserve planning, and unit commitment, meanwhile LTLF forecasts load efficiency within a period longer than one year for generation and power plant planning.

Through a load forecasting analysis history, (Khatoon, Ibraheem, Singh & Priti, 2014) mentioned the impact of different factors, upon on pattern of load demand was defined, studied and applied. It was found, quite early on, that the form of usage influences the overall load shape. Many factors are affecting the power load or load demand, and it's difficult to differentiate exactly the factors of specific influence. According to (Xue & Geng, 2012), the load power potential influences categorized into three types, namely short-term influence factors, middle-term influence factors and long-term influence factors. In certain forecasting periods, the short-term influencing factors often occur, and almost do not have the element of time interval, for example, the unexpected weather transforms. The contributing factors in the mid-term usually last some forecast period and have certain time duration characteristics, such as seasonal climate transform. Long-term influencing factors span a long period, typically several forecast years, and have the characteristic of time interval, e.g. the increase in gross national goods, demography, etc. The significant factors to consider for the forecasting of electricity loads can be described as in Table 1.

In this research, the factors taken into consideration are meteorological (temperature, rainfall, humidity and wind speed), population (numbers of employees, students and longlife learning participants) with random activities (activities, festivals and holidays).

Table 1: Important factors for electric load forecasting (Cavallaro, 2005)

Factors	Key Points
Calendar or Temporal	Hours of the day, days of the week, and timings of year etc.
Meteorological	Weather, solar radiation, climate, humidity, temperature etc.
Economy	GDP, Industrial development etc.
Customer	Number of employees, type of consumption, electric appliances, size of building, etc.
Random	Sports activities, festival etc.

1.2 Artificial neural network

Neural networks form through the interconnection of neurons. Two categories of neural networks exist; Biological Neural Network (BNN) and Artificial Neural Network (ANN) (Nwadiugwu, 2015). The brain neural network is an interconnected platform of biological neural systems which transmits elaborate electrical signal patterns. Dendrites receive input signals in the biological neural network which ignites an output signal depending on the input signals. Figure 1 illustrates a biological neural network developed by an interconnected cell membrane.

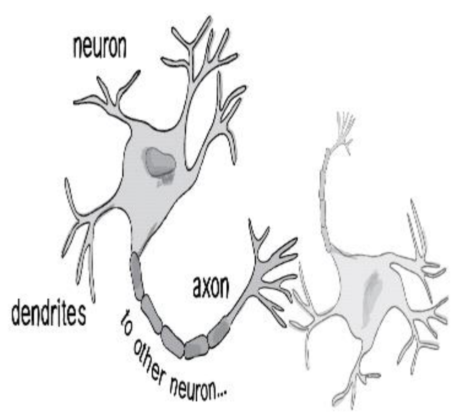

Figure 1: A biological neural network (Nwadiugwu, 2015)

An Artificial Neural Network (ANN) is a computational model which intends to take account of the human brain's parallel nature. It's indeed a primary network of immensely interconnected processing elements (neurons) that act aligned to each other. An ANN can also be used to resolve issues requiring complex intervariable relationships. ANNs are the most common techniques for estimating energy consumption in building (Ahmad et al., 2014).

According to (M. Singh & Maini, 2020) there are different methods for load forecasting, which are regression based models, time series approaches, neural networks, Support Vector Machine (SVM), and hybrid approach. For this research, an artificial neural network is chosen as it can approximate non-linear function present in the electrical system load profile. Another advantage of using ANN is that it can handle many parameters or variables, provide solutions for forecasting problems with the predictive result, and have a feature to continuous learning. Nonetheless, ANN is a black box learning process, cannot perceive input-output relationships and cannot resolve unknowns or uncertainties (Elfaki & Ahmed, 2018). The basic model of an artificial neuron is demonstrated in Figure 2. Here, $x_1, x_2, ...x_p$ are the p inputs to the artificial neuron, and $w_{k1}, w_{k2}, ...w_{kp}$ are connected to the input links.

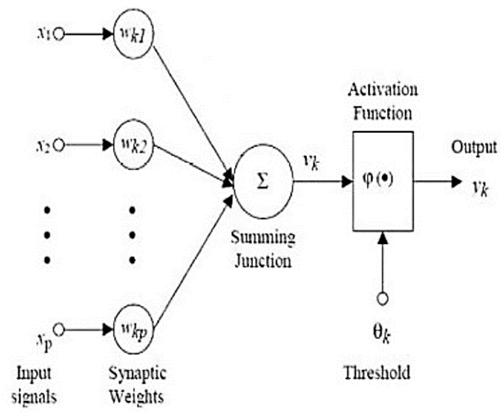

Figure 2: Artificial neural network

Consequently, the amount I obtained by the soma of the artificial neuron is provided by equation below,

$$I = \sum_{i=1}^{n} w_{ki} x_i$$

ANN is prepared to minimize the error among the target and the ANN output, contributing to an optimal response. This is achieved by adjusting the relations between the elements, which requires a weight change $w_{k1}, w_{k2}, ...w_{kp}$. In general, this cycle of adjustment can be interpreted as a' learning' type. The ANN is thus perceived as a form of artificial intelligence (Badran, 1996).

2.0 Methodology

MATLAB neural networks are used in this research; the database is obtained from the Malaysian Meteorological Department (MET) for meteorological data and Kolej Komuniti Kuantan for electric load demand, population and random activities.

2.1 Workflow diagram

Every system of neural networks is special, and it differs. In any case, the network architecture follows these workflow (Werbos, 2004) as shown in Figure 3.

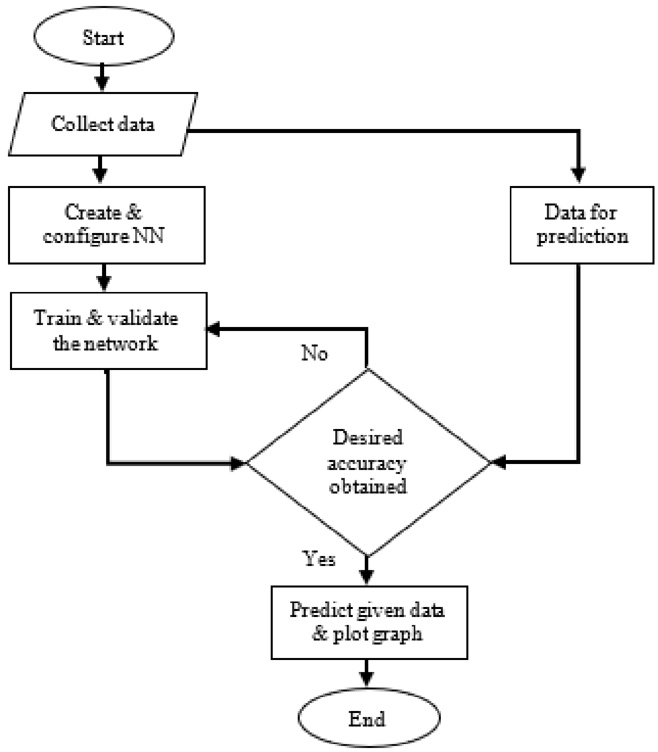

Figure 3: Workflow of neural networks architecture

2.2 Dataset overview

Meteorological dataset features average Temperature (T), Rainfall (R), Humidity (H) and Wind Speed (W) with add on input data population of employees, students and lifelong learning course participants incorporating with activities, festivals and holidays to predict the load demand of electrical energy at Kolej Komuniti Kuantan. Dataset features are presented in Table 2.

Table 2: Summary of dataset features

Feature	Symbol	Type	Unit
Temperature	T	Input	^{0}C
Rainfall	R	Input	mm
Humidity	H	Input	%

Wind Speed	W	Input	m/s
Employees and Students	ES	Input	unit
Lifelong Learning Participants	LL	Input	unit
Load Demand	L	Output	kW

Figure 4 shows the proposed ANN model structure based on perceptron with training for the commercial load. The forecasting is denoted by v_k.

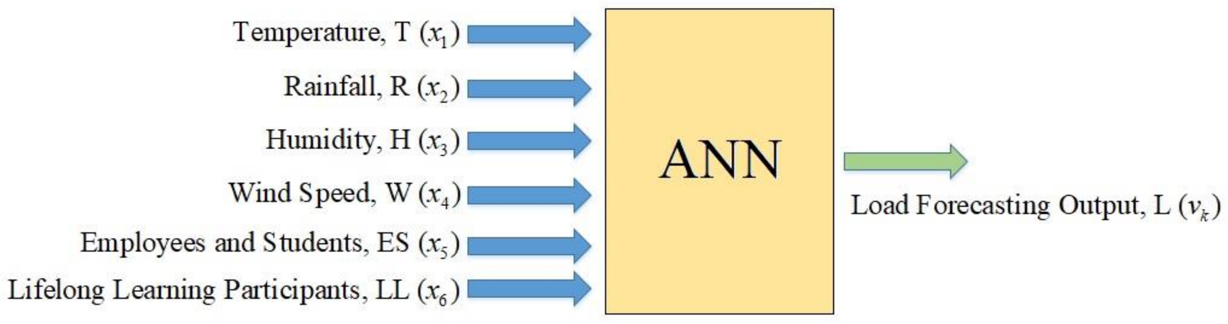

Figure 4: ANN model structure

2.3 Setting of networks

A default network is a two layer feed-forward network with hidden sigmoid neurons and linear output neurons (FITNET) as shown in Figure 5. The total amount of neurons in the hidden layer dictated will, by default, that is 10.

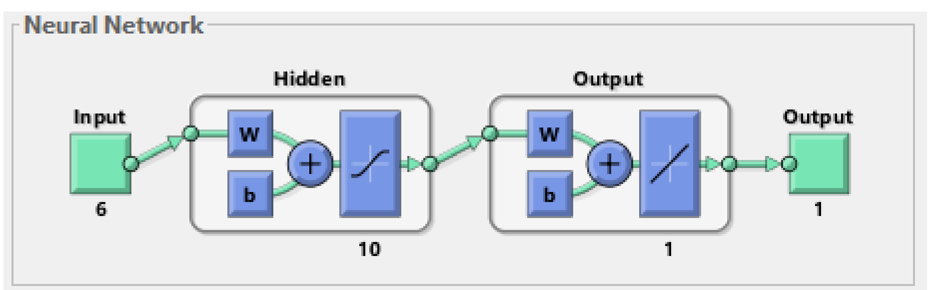

Figure 5: A two-layer feed-forward network configuration

2.4 Training algorithms

It is rather difficult to determine which training algorithm by a given problem will be the fastest and most effective. It varies based on several factors such as the sophistication of the problem, the number of datasets in the training set, the number of weights and biases in the network, the error target and regardless of whether the network will be included for pattern recognition (discriminant analysis) but rather function approximation (regression). Table 3 below assesses the algorithms being studied and the acronyms utilized to describe it (Mathworks, 2015).

Table 3: Type of training algorithm

Acronym	Algorithm	Description
LM	trainlm	Levenberg-Marquardt
BFG	trainbfg	BFGS Quasi-Newton
BR	trainbr	Bayesian Regulation Backpropagation
RP	trainrp	Resilient Backpropagation
SCG	trainscg	Scaled Conjugate Gradient
CGB	traincgb	Conjugate Gradient with Powell/Beale Restarts
CGF	traincgf	Fletcher-Powell Conjugate Gradient
CGP	traincgp	Polak-Ribiére Conjugate Gradient
OSS	trainoss	One Step Secant
GDX	traingdx	Variable Learning Rate Backpropagation

Considering the result obtained by (Dario Baptista, Rodrigues & Morgado-Dias, 2013), the best training algorithms are the trainoss, trainlm and trainscg taking into account the overall standings discussed in their research. Therefore, in this research; the five selected training will be used for testing are trainoss, trainlm and trainscg with two more, in addition, trainbr and trainbfg to find which training algorithm gives a good result.

2.5 Performance analysis

The following indices equation below were calculated to evaluate the forecast accuracy of the entire procedure (Bunnoon, 2011).

$$\text{Mean Square Error (MSE)} = \sum_{i=1}^{M} \frac{\left(Actual_i - Forecast_i\right)^2}{M}$$

$$\text{Mean Absolute Percentage Error (MAPE)} = \frac{1}{M} \sum_{i=1}^{M} \frac{\left|Actual_i - Forecast_i\right|}{Actual_i} \times 100$$

where *Actual* is the real value of monthly load demand at the target year, *Forecast* is the forecasted value in the same year, and *M* is the month.

In the experiment by (Yang & Yang, 2019), the additional implementing considerations were included to assess all of the methods mentioned. The requirements are the root mean square error (RMSE) and mean absolute error (MAE) based on the calculation as follows:

$$\text{Root Mean Square Error (RMSE)} = \sqrt{\sum_{i=1}^{M} \frac{\left(Actual_i - Forecast_i\right)^2}{M}}$$

$$\text{Mean Absolute Error (MAE)} = \frac{1}{M}\sum_{i=1}^{M}\left|Actual_i - Forecast_i\right|$$

It is also claimed that researchers tried to predict load specifically using a mathematical statistics method in much earlier works. The most common practice is the regression analysis, which employs a set of functional linear regression models. Therefore, the obtained results in this research were also compared with those derived from the linear regression model. A default network is a two layer feed-forward network with hidden sigmoid neurons and linear output neurons (fitnet) as shown in Figure 5. The total amount of neurons in the hidden layer dictated will, by default, that is 10.

3.0 Result and discussion

3.1 Overview of load demand in Kolej Komuniti Kuantan

For analysis, four years of load demand dataset are used starting from 2016 till 2019. Electricity consumption or load demand from three commercial building blocks at Kolej Komuniti Kuantan is shown in Figure 6 meanwhile total load demand by years is shown in Figure 7. Based on both graphs, it shows a decreasing trend of load demand throughout the year (up to 10%). This trend is due to several factors, including the savings measures that are used in the Public Sector Conducive System (EKSA) and practised by the Kolej Komuniti Kuantan since 2016.

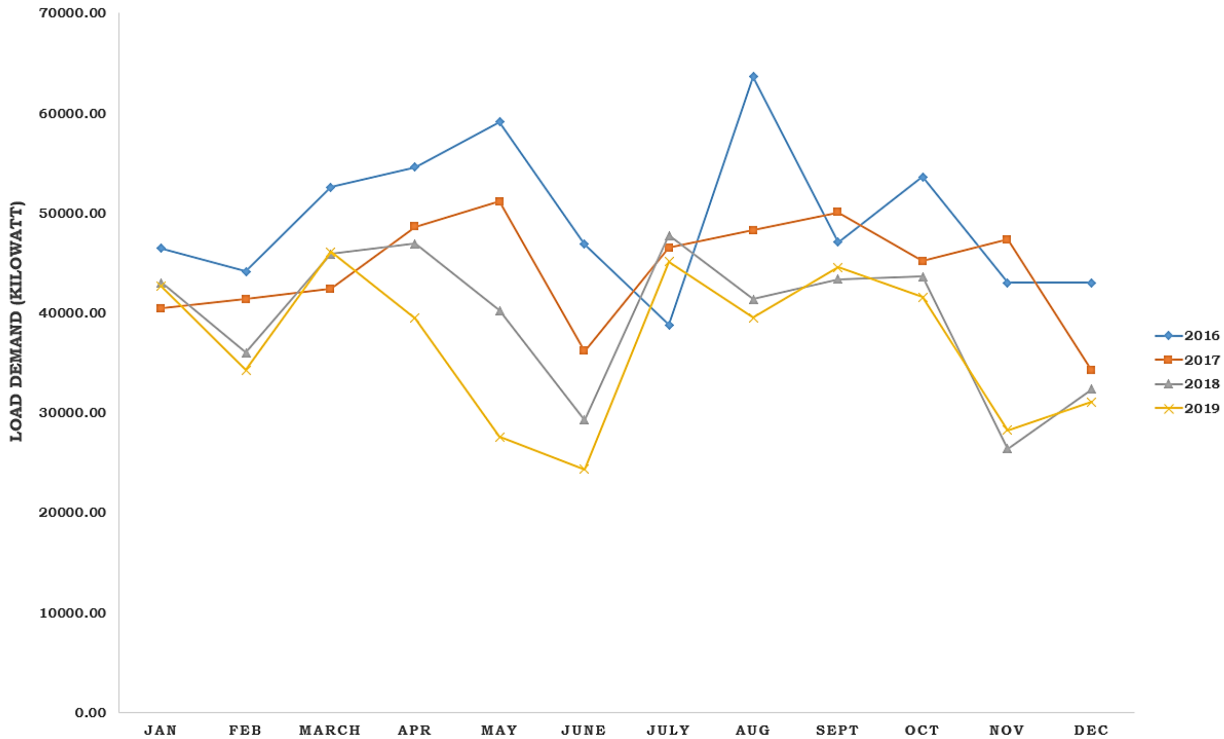

Figure 6: Load demand in Kolej Komuniti Kuantan by months

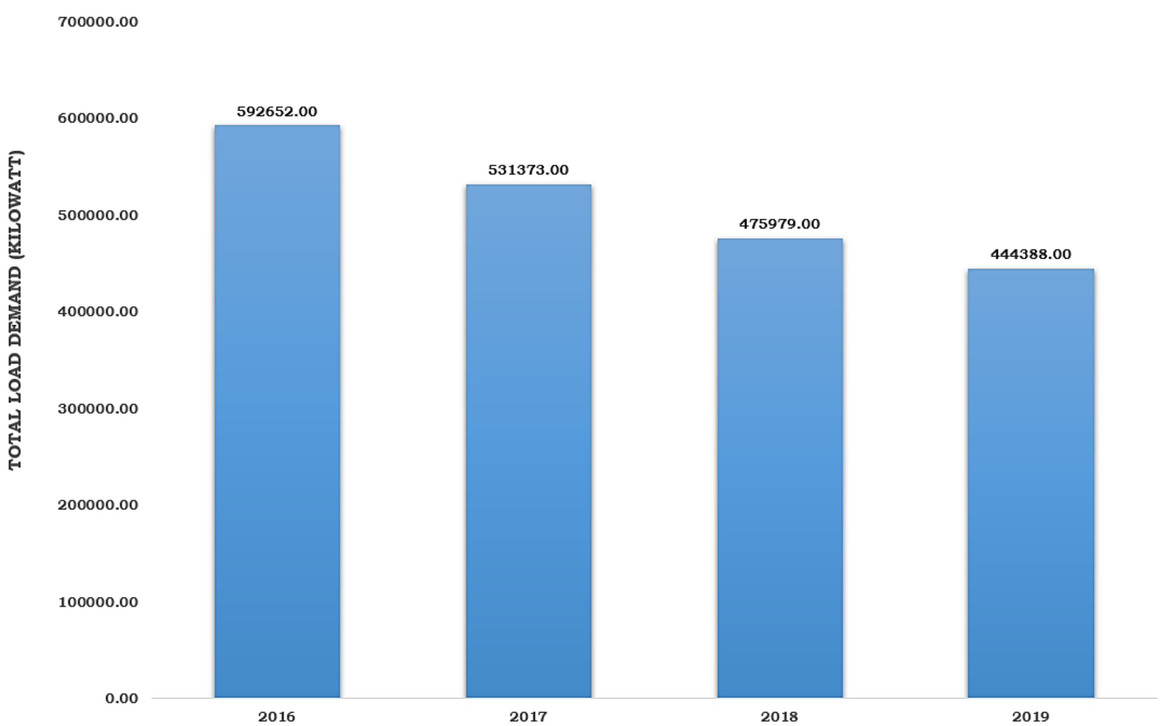

Figure 7: Total load demand in Kolej Komuniti Kuantan by years

3.2 Training algorithm and performance

As mentioned in the previous chapter, MATLAB has developed several training algorithms to speed up the training process, such as traingdm, traingdx, trainrp, or trainlm, etc. In this chapter, performance analysis of five algorithms: (trainoss) One Step Secant algorithm, (trainlm) Levenberg-Marquardt algorithm, (trainscg) Scaled Conjugate Gradient algorithm, (trainbr) Bayesian regularization algorithm and (trainbfg) BFGS Quasi-Newton using the same parameters. The comparison between the training algorithm with performance analysis is shown in Table 4.

Table 4: Comparison between Training Algorithm

Training Algorithm	Regression	MSE $\times 10^6$	RMSE $\times 10^3$	MAE $\times 10^3$	MAPE %
trainoss	0.78	35.90	5.99	5.46	16.28
trainlm	0.78	24.51	4.95	3.60	10.35
trainscg	0.78	28.32	5.32	3.67	12.24
trainbr	0.82	7.63	2.76	2.26	6.57
trainbfg	0.33	124.40	11.15	8.33	27.29

Regression value R is for the prediction or forecast results to be evaluated and compared. R describes the correlation among the result of the load forecast and the actual load or power usage. R=1 implies there is a very close relationship between the results of the forecast and the actual results. The MSE, RMSE, MAE, and MAPE requirements reflect forms of variance between predicted and actual values: the lower the criterion, the higher the forecast accuracy. As in Table 4, the test performance of Bayesian Regularization (trainbr) is better than One Step Secant algorithm (trainoss), Levenberg-Marquardt algorithm (trainlm), Scaled Conjugate Gradient algorithm (trainscg), and BFGS Quasi-Newton (trainbfg).

3.3 Forecast result and error for load demand in 2019

The 2019 forecast and load demand error evaluation were carried out in this section. The setting parameter for this research is shown in Table 5. According to the result above; the training algorithm that will be used is Bayesian Regularization (trainbr) with three years (2016-2018) data as input.

Table 5: Parameter setting for load forecasting in 2019

Parameter	Setting
Dataset	2016 – 2018 (3 years)
Forecast	2019
Variable Used	T, R, H, W, ES, LL and L
Hidden Layer Size	10
Training Algorithm	Bayesian Regularization (trainbr)

The output of load forecasting and actual load demand for 2019 as in Table 6. The predicted result and errors were plotted, as shown in Figure 8 and Figure 9.

Table 6: Comparison between load forecasting and actual in 2019

Months	Actual (kW)	Forecast (kW)	Error (kW)
January	42651	44376	1725
February	34270	33254	-1016
March	46093	41766	-4327
April	39454	40486	1032
May	27590	28188	598.3
June	24328	30024	5696
July	45106	43128	-1978
August	39503	39567	63.62
September	44546	40610	-3936
October	41532	43615	2083
November	28262	25551	-2711
December	31053	29094	-1959
Total	444388	439659	-4729

According to Table 6, the total load demand for 2019 is 444388 kilowatts while the forecasted amount using ANN is 439659 kilowatts with 4729 kilowatt or 6.57% error by MAPE based. There are some significant differences between the values in March, June and September. The sharp increases in March and September were due to the addition of short courses participants (lifelong learning), while the dramatical decline in June was due to the return of computer rentals.

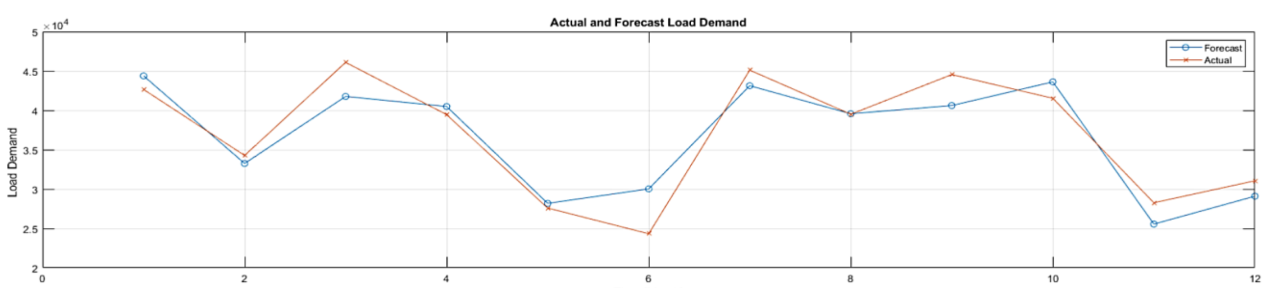

Figure 8: Actual and forecast load demand in 2019

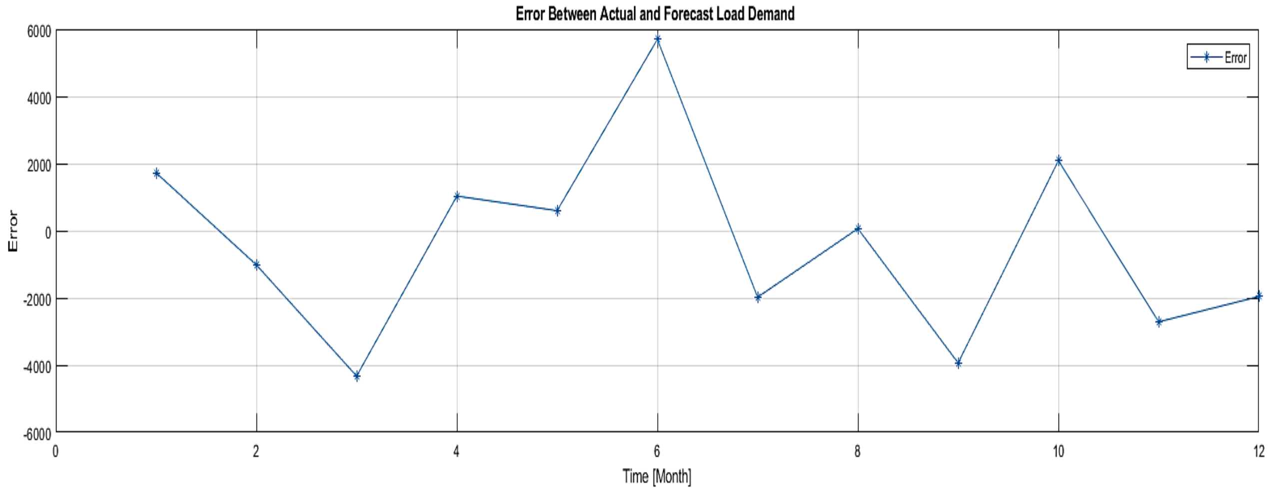

Figure 9: Error between actual and forecast load demand in 2019

3.4 Forecast result for load demand in 2020

Using the same parameter (variable, hidden layer, training algorithm) with the dataset from 2016 till 2019 (4 years as data input), load demand in 2020 can be forecast. The output of load forecasting for 2020 as in Table 7. The predicted result plotted, as shown in Figure 10, with the comparison with actual data of 2018 and 2019.

Table 7 shows that there is an expectation of decreasing electricity consumption by 2020, approximately 16476 kilowatt or 3.71% compared to the previous year. According to Figure 10, the load demand will increase in June. This is due to the effect of datasets of the prior year (2016 to 2018) and the sharp decline in 2019 as a result of the return of rental computers, as mentioned before. Therefore, the new replacement computer rentals beginning from July 2019 will give a significant impact to the load forecast results in 2020.

Starting mid-June 2020, the Kolej Komuniti Kuantan has begun the replacement of 100 units of air conditioners. The old model air conditioner is no longer economically to repair or continually use. The availability of these new units will see continued savings in the future.

Table 7: Load Forecasting in 2020

Months	Forecast 2020 (kW)
January	39945
February	35770
March	44097
April	41310
May	29007
June	27921
July	42970
August	37836
September	39540
October	37551
November	22302
December	29662
Total	**427912**

Figure 10: Forecast Load Demand in 2020

Prime Minister Tan Sri Muhyiddin Yassin made an official speech on 16 March 2020 and formally promulgated the Movement Control Order (MCO) under the 1988 Infectious Disease Prevention and Control Act and the 1967 Police Act. Starting from 18 March 2020, as a result, all teaching and learning activities and lifelong learning are suspended. All community college students have been ordered to return home. Similarly, community college staff need to stay home and follow Work from Home (WFH) order.

The implementation of the MCO to control the COVID-19 pandemic, without doubt, has affected electricity usage at Kolej Komuniti Kuantan. Therefore, drastically reduced load demand is expected to start from March 2020 to August 2020. This practice of 'new norm' will continue and give effect to the power consumption or load demand until the end of 2020.

4. Conclusions

This work used the Artificial Neural Network (ANN) approach to present the results of load forecasting using machine learning or artificial intelligence. The linear regression, MSE, RMSE, MAE and MAPE was calculated and used to show the effectiveness of propose training algorithm. It can be concluded from the result that the proposed methodology delivers reasonably good results and is suitable for predicting electrical load forecasting. The ANN approach has demonstrated to be an excellent electric load forecasting technique with the minimal difference from the actual data. This result can be used for planning and saving of electrical consumption at Kolej Komuniti Kuantan in the future. To get more precise results with higher regression values closer to 1.0 and smaller MAPE, more detailed and accurate data is required. This study also can be extended by incorporating meta-heuristic method such as for example, Particle Swarm Optimization (PSO), Salp Swarm Algorithm (SSA), Grey Wolf Optimization (GWO) and many more to obtain a practical and reliable model. Future work will focus on a deeper understanding of the factor affecting forecasting, for example, electric appliances (air conditioning, computer etc.) and special events including religious and cultural celebration or even pandemic effect such as COVID-19. Sometime these factors will cause random disruptions and enormous spike on the load demand.

References

Ahmad, A. S., Hassan, M. Y., Abdullah, M. P., Rahman, H. A., Hussin, F., Abdullah, H., & Saidur, R. (2014). A review on applications of ANN and SVM for building electrical energy consumption forecasting. *Renewable and Sustainable Energy Reviews*, *33*, 102–109.

Badran, S. M. (1996). Forecasting electrical load using ann combined with multiple regression method.In *12th PSCC Power System Computer Conference* (pp. 453–459).Portugal

Bunnoon, P. (2011). Mid-term load forecasting based on neural network algorithm: a comparison of models. *International Journal of Computer and Electrical Engineering*, *3*(4), 600–605.

Cavallaro, F. (2005). Electric load analysis using an artifical neural network. *International Journal of Energy Research*, *29*(5), 377–392.

Dario Baptista, F., Rodrigues, S., & Morgado-Dias, F. (2013). Performance comparison of ann training algorithms for classification. *2013 IEEE 8th International Symposium on Intelligent Signal Processing, WISP 2013 - Proceedings*, (September), 115–120.

Elfaki, E. A., & Ahmed, A. H. (2018). Prediction of electrical output power of combined cycle power plant using regression ANN Model. *Journal of Power and Energy Engineering*, *06*(12), 17–38.

Glavan, M., Gradišar, D., Moscariello, S., Juričić, Đ., & Vrančić, D. (2019). Demand-side improvement of short-term load forecasting using a proactive load management – a supermarket use case. *Energy and Buildings*, pp*186*,

Hannah Ritchie and Max Roser. (2014). Energy. *OurWorldInData.Org*. Retrieved from https://ourworldindata.org/energy

Kuo, P. H., & Huang, C. J. (2018). A high precision artificial neural networks model for short-Term energy load forecasting. *Energies*, *11*(1), 1–13. https://doi.org/10.3390/en11010213

Mathworks. (2015). Choose a Multilayer Neural Network Training Function. Retrieved June 18, 2020, from MATLAB R2015b website: https://www.mathworks.com/help/deeplearning/ug/choose-a-multilayer-neural-network-training-function.html

Nwadiugwu, M. (2015). *Neural Network, Artificial Intelligence and the Computational Brain*. (August), 1–36. https://doi.org/10.13140/RG.2.1.3942.3204

Rahman, K. A., Leman, A. M., Mubin, M. F., Yusof, M. Z. M., Hariri, A., & Salleh, M. N. M. (2017). Energy Consumption Analysis Based on Energy Efficiency Approach. *Faculty of Mechanical & Manufacturing Engineering, Universiti Tun Hussein Onn Malaysia*, *02003*.

Reddy, S. S., & Jung, C. M. (2016). Short-term load forecasting using artificial neural networks and wavelet transform. *International Journal of Applied Engineering Research*, *11*(19), 9831–9836.

Renewable Energy World. (2015). The Different Uses of Energy in our Daily lives. Retrieved June 15, 2020, from Renewable Energy World website: https://www.renewableenergyworld.com/2015/12/28/the-different-uses-of-energy-in-our-daily-lives/

Singh, A., & Tripathi, V. K. (2016). Load Forecasting Using Multilayer Perceptron Neural Network. *International Journal of Engineering Science*, *6*(5), 5463–5466. https://doi.org/10.4010/2016.1337

Singh, M., & Maini, R. (2020). Various Electricity Load Forecasting Techniques with Pros and Cons. *International Journal of Recent Technology and Engineering*, *8*(6), 220–229. https://doi.org/10.35940/ijrte.f6997.038620

Singla, M. K., Gupta, J., Nijhawan, P., & Oberoi, A. S. (2019). Electrical load forecasting using machine learning. *International Journal of Advanced Trends in Computer Science and Engineering*, *8*(3), 615–619. https://doi.org/10.30534/ijatcse/2019/45832019

Werbos, P. J. (2004). What is a neural network? In *Handbook of Neural Computation*. https://doi.org/10.1887/0750303123/b365c4

Xue, B., & Geng, J. (2012). Dynamic transverse correction method of middle and long term energy forecasting based on statistic of forecasting errors. *10th International Power and Energy Conference, IPEC 2012*, 253–256. https://doi.org/10.1109/ASSCC.2012.6523273

Yang, L., & Yang, H. (2019). Analysis of different neural networks and a new architecture for short-term load forecasting. *Energies*, *12*(8). https://doi.org/10.3390/en12081433

Ahmad, A. S., Hassan, M. Y., Abdullah, M. P., Rahman, H. A., Hussin, F., Abdullah, H., & Saidur, R. (2014). A review on applications of ANN and SVM for building electrical energy consumption forecasting. *Renewable and Sustainable Energy Reviews*, *33*, 102–109. https://doi.org/10.1016/j.rser.2014.01.069

Al., J. M. K. C. D. et. (2020). Commercial energy use - Energy Education. Retrieved June 15, 2020, from https://energyeducation.ca/ website: https://energyeducation.ca/encyclopedia/Commercial_energy_use#cite_note-OED-1

Badran, S. M. (1996). Forecasting Electrical Load using ANN Combined with Multiple Regression Method. *Proc. 12th PSCC Power Syst. Comput. Conf*, *II*(Ii), 453–459.

Bunnoon, P. (2011). Mid-Term Load Forecasting Based on Neural Network

Algorithm: a Comparison of Models. *International Journal of Computer and Electrical Engineering*, *3*(4), 600–605. https://doi.org/10.7763/ijcee.2011.v3.388

Cavallaro, F. (2005). Electric load analysis using an artifical neural network. *International Journal of Energy Research*, *29*(5), 377–392. https://doi.org/10.1002/er.1054

Dario Baptista, F., Rodrigues, S., & Morgado-Dias, F. (2013). Performance comparison of ANN training algorithms for classification. *2013 IEEE 8th International Symposium on Intelligent Signal Processing, WISP 2013 - Proceedings*, (September), 115–120. https://doi.org/10.1109/WISP.2013.6657493

Elfaki, E. A., & Ahmed, A. H. (2018). Prediction of Electrical Output Power of Combined Cycle Power Plant Using Regression ANN Model. *Journal of Power and Energy Engineering*, *06*(12), 17–38. https://doi.org/10.4236/jpee.2018.612002

Glavan, M., Gradišar, D., Moscariello, S., Juričić, Đ., & Vrančić, D. (2019). Demand-side improvement of short-term load forecasting using a proactive load management – a supermarket use case. *Energy and Buildings*, *186*, 186–194. https://doi.org/10.1016/j.enbuild.2019.01.016

Hannah Ritchie and Max Roser. (2014). Energy. *OurWorldInData.Org*. Retrieved from https://ourworldindata.org/energy

Kuo, P. H., & Huang, C. J. (2018). A high precision artificial neural networks model for short-Term energy load forecasting. *Energies*, *11*(1), 1–13. https://doi.org/10.3390/en11010213

Mathworks. (2015). Choose a Multilayer Neural Network Training Function. Retrieved June 18, 2020, from MATLAB R2015b website: https://www.mathworks.com/help/deeplearning/ug/choose-a-multilayer-neural-network-training-function.html

Nwadiugwu, M. (2015). *Neural Network, Artificial Intelligence and the Computational Brain*. (August), 1–36. https://doi.org/10.13140/RG.2.1.3942.3204

Rahman, K. A., Leman, A. M., Mubin, M. F., Yusof, M. Z. M., Hariri, A., & Salleh, M. N. M. (2017). Energy Consumption Analysis Based on Energy Efficiency Approach. *Faculty of Mechanical & Manufacturing Engineering, Universiti Tun Hussein Onn Malaysia*, *02003*.

Reddy, S. S., & Jung, C. M. (2016). Short-term load forecasting using artificial neural networks and wavelet transform. *International Journal of Applied Engineering Research*, *11*(19), 9831–9836.

Renewable Energy World. (2015). The Different Uses of Energy in our Daily lives. Retrieved June 15, 2020, from Renewable Energy World website: https://www.renewableenergyworld.com/2015/12/28/the-different-uses-of-energy-in-our-daily-lives/

Singh, A., & Tripathi, V. K. (2016). Load Forecasting Using Multilayer Perceptron Neural Network. *International Journal of Engineering Science*, *6*(5), 5463–5466. https://doi.org/10.4010/2016.1337

Singh, M., & Maini, R. (2020). Various Electricity Load Forecasting Techniques with Pros and Cons. *International Journal of Recent Technology and Engineering*, *8*(6), 220–229. https://doi.org/10.35940/ijrte.f6997.038620

Singla, M. K., Gupta, J., Nijhawan, P., & Oberoi, A. S. (2019). Electrical load forecasting using machine learning. *International Journal of Advanced Trends in Computer Science and Engineering*, *8*(3), 615–619. https://doi.org/10.30534/ijatcse/2019/45832019

Werbos, P. J. (2004). What is a neural network? In *Handbook of Neural Computation*. https://doi.org/10.1887/0750303123/b365c4

Xue, B., & Geng, J. (2012). Dynamic transverse correction method of middle and long term energy forecasting based on statistic of forecasting errors. *10th International Power and Energy Conference, IPEC 2012*, 253–256. https://doi.org/10.1109/ASSCC.2012.6523273

Yang, L., & Yang, H. (2019). Analysis of different neural networks and a new architecture for short-term load forecasting. *Energies*, *12*(8). https://doi.org/10.3390/en12081433