Journal of Advanced Research in Applied Sciences and Engineering Technology 30, Issue 3 (2023) 79-90

Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage:
https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index
ISSN: 2462-1943

Educational Level Impact on Energy Consumption in Malaysia Office Building using Neural Network Method

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ARTICLE INFO

Article history:
Received 3 December 2022
Received in revised form 10 April 2023
Accepted 17 April 2023
Available online 7 May 2023

Keywords:
Energy consumption; artificial neural network; educational impact

ABSTRACT

The level of education has had a considerable impact on energy usage. Office activity requires energy, and this one area is especially subject to changes in demand patterns. The understanding on this trend is applicable to office buildings which has found many benefits like cost saving and better productivity among workers who have access to higher education level. Neural networks are appealing in the field of prediction. The use of artificial neural network technology provides a benefit in reducing the energy consumption in office buildings. The neural network uses neural networks to predict based on capacity. The researchers used a neural network model to predict energy consumption based on data from more than 1,006 samples taken from 13 office building location in 150day periods. The educational level has significantly influence on the energy consumption of an office building. The result indicates that the Degree and above categories contribute higher usage of energy. This study sought to address the contradiction between previous research on educational level impact on energy consumption by examining the levels of educational attainment over time and calculating the impact on building energy consumption.

1. Introduction

Energy is necessary for all economic activity, and during the past century, industrialization and economic growth processes have been marked by breakthroughs in energy-intensive technologies as well as increased energy consumption [1]. Understanding the relationship between energy use and economic growth is essential. The connection between energy use and economic growth has significant consequences for governments and policymakers who are concerned with both economic growth and the environment and resource scarcity [2].

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https://doi.org/10.37934/araset.30.3.7990

Malaysia has experienced rapid economic growth and industrialization over the past few decades, which has led to a significant increase in energy consumption. The building sector is a major contributor to this trend, and improving energy efficiency in buildings has become a key priority for policy makers in Malaysia.

With 79.4% of all emissions in Malaysia coming from the energy sector in 2016, this sector remained the country's main source of greenhouse gas emissions. Next, we have the garbage and IPPU sectors, which combined accounted for about 8.6% of the total emissions. Agriculture has the lowest industry-wide emissions contribution, at 3.4%, whereas LULUCF is a net sink. CO_2 emissions accounted for 80% of all gaseous emissions of GHGs in 2016 [3].

In 2017, the economy's primary energy supply increased at a slower rate of 1.8 percent compared to 4.15 percent in 2016, which may be primarily ascribed to a 46.5 percent decrease in the supply of petroleum products. The two main fuels used to produce electricity in the power sector in Malaysia are coal and natural gas, while some thermal plants still use a minor amount of diesel and fuel oil. These basic energy sources serve as the fuel for producing electricity, which is regarded as a secondary energy source, in this context. The end user will then utilise this secondary energy source. Seven end user categories, including residential, commercial, industrial, transportation, agriculture, fishing, and non-energy uses [4]. Malaysia suffers solar radiation fluctuation, which is one of the numerous difficulties encountered while measuring energy consumption in a building due to its proximity to the equator. This is a result of the irregular and unpredictable solar radiation Malaysia receives. Establishing an accurate prediction model is crucial for overcoming this challenge [5].

This study addresses this gap by investigating the relationship between educational level and energy consumption in office buildings in Malaysia, using a neural network method. In this research, the users will be classified into four (4) categories based on their education levels. Then, an artificial neural network (ANN) model is designed to predict the level of energy consumption in the office building using specific groups occupation as input parameters. After that, each predicted model output value is compared with its real output value through cross validation method and statistical algorithms to measure accuracy of both models.

Artificial neural networks (ANNs) are a form of machine learning method that employ artificial neurons to identify patterns and make choices [6]. The most popular method for solving statistical engineering problems is the use of numerical models. However, it has been demonstrated that ANNs are a very good alternative to this conventional strategy and even produce better results, particularly when the problem is random and contains non-linear patterns, thanks to the advancement of machine learning [7,8]. Moreover, Artificial neural networks (ANNs) are capable of handling the nonlinear variation of integrated energy system components as well as the intermittent nature of solar and wind energy sources. They also do not require the availability of weather data when sizing integrated energy systems at remote locations [9]. Due to the lack of rigid guiding principles that distinguish ANNs from standard statistical models, the former is better suited for issues with a random distribution of variables [8]. The interpretability of artificial neural networks, which is crucial in many domains such as medical and engineering due to model robustness, serves as additional justification [10-12].

2. Literature Review

The United Nations Development Programme (UNDP) dedicates a global, regional, or even country report to human development inequalities every year due to serious concern for the world. According to the UNDP (2019), lack of basic necessities and advanced capacities have an impact on inequalities in human development (the actions of humans in society). Improvements in income play a role in human development by making it easier to afford healthcare and education [13].

2.1 Educational Level and Energy Consumption

Multiple research findings have confirmed that consumers' concerns about exhibiting pro-environmental behaviours increase with their level of knowledge on environmental issues [14,15]. An online survey was employed in the study by Paço and Lavrador [16] to examine whether the respondents' levels of environmental knowledge had any discernible effects on their attitudes and behaviours toward energy conservation. The research indicates that the higher levels of environmental literacy do not always translate into more virtuous attitudes and actions. Another study conducted by Wang and Wu [17] revealed that over the entire Guangdong province, the degree of education has had a considerable impact on energy usage. This effect was more pronounced in cities with lower levels of education. However, in areas with higher levels of education, other, more important criteria, such income level, eclipsed this impact [17]. Figure 1 shows Wang and Wu [17] mechanism paths of education level inequality on energy consumption. The mechanism provides an overview of the factors, indicators, and paths that define the mechanism.

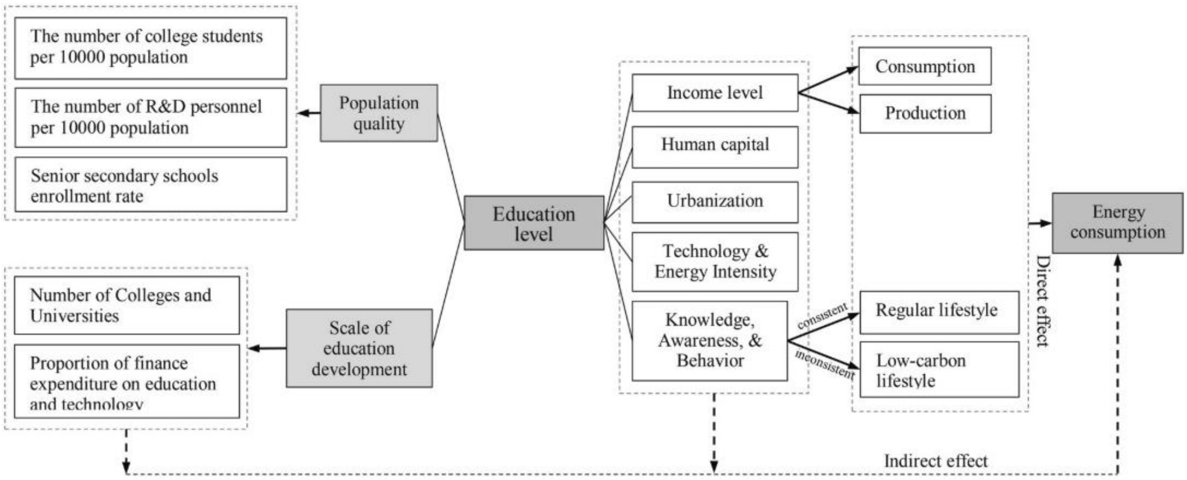

Fig. 1. Mechanism paths of education level inequality on energy consumption [18]

A summary of relevant studies on the effect of education on energy use is provided in Table 1. There are details regarding sample size, technical parameter use, educational data use, and country of origin.

Table 1
Educational level impact on energy research and related attributes

Source	Data Type*	Sample	Technical Parameter Use	Education Data Use	Country
Paço and Lavrador [16]	SV	800 people @11.25%	-	General Environmental Knowledge	Portugal
Wang and Wu [17]	A	2002 to 2017 data	Statistical Yearbook & Urban Statistical Yearbook	Education level of the population	Guangdong Province, China
Rej and Nag [19]	A	1990 to 2016 data	JJ cointegration technique and through VECM	Education Level to energy consumption	India

*Data Type: A= Actual, S = Simulation, SV=Survey

Based on Rej and Nag [19] research using the causality test for India population. The empirical analysis from the research indicates the existence of long run unidirectional causality from educational index to per capita energy consumption. The research findings suggested that the energy policy of India needs to consider the positive feedback effect of improved education to energy consumption [19].

The study indicates that few results that contradict between research. In Paço and Lavrador [16] research, higher levels of environmental literacy do not always translate into more virtuous attitudes and actions. The study's main finding is that even if students are in higher education and have some awareness of environmental issues, these variables do not necessarily result in more optimistic attitudes. Despite being significant at a 0.001 level of confidence ($p = 0.008$), the research's findings support a very poor level of connection between environmental knowledge (EK) and behaviour (0.094) [16].

According to studies by Wang and Wu [17] the level of education significantly influenced energy use. According to the research, increasing the amount of money spent on technology and education by 1% results in a 0.421791% drop in per-person energy usage. In contrast, a 1% increase in colleges and universities was demonstrated to result in a 0.2654% rise in per capita energy usage. However, other important criteria, such as income level, eclipsed this effect. Energy consumption is highly influenced by income level. According to the research, an increase in income of 1% was found to result in an increase in per-person energy usage of 0.39056% [17].

According to study by Rej and Nag [19], education has a big impact on how much energy is used. The research variance decomposition technique shows that, over the long term of five years and beyond, Educational Index is found to explain the majority (67%) of variation in energy consumption per capita, while Educational Index is found to explain the majority (58%) of the variance in the same time frame [19].

Based on the findings, it is evident that the research employed an innovative methodology to ascertain how education affects energy usage. The various regions showed the general research findings. Due to these variations and the size of the nation's population, it may be difficult to identify links between linked demographic features and energy consumption outcomes. The results of each study did not concur with one another as a result.

2.2 Space Standard Occupancy Load

In Malaysia, Uniform Building by-law 1984 (UBBL 1984) used as standard to regulate the requirement for all buildings. The space standards for calculating occupancy loads are determined using this standard. The maximum office occupancy load permitted shall be determined by dividing the net floor area or space assigned to the use by the square metre per occupant. Based on the UBBL 1984, the office area occupancy load is referred to the area having fixed seats shall be determined by the number of fixed seats installed [20].

2.3 Research Framework

The research's analysis of space occupancy load is dependent on actual data, artificial neural networks are used to ascertain how different educational levels affect energy usage. For segregated educational level occupancy value and off range occupancy value, the artificial neural network is capable of making predictions based on actual data.

Therefore, the research will use a neural network approach. This approach enables data analysis and the development of statistical models. Since various demographic categories were used in each nation and no comparable data from another nation was available, overall results varied. The neural network research model will examine whether the research's conclusions are the same as those of the research that was previously described.

3. Methodology

This study looked at how educational level factor affected how much energy was used by office building. It is challenging to analyse large amounts of data using only conventional statistical methods such as regression analysis and correlation. In this research, large volumes of data are modelled and analysed using artificial neural networks. To provide a precise prediction of the energy consumption model, a neural network with back propagation is used.

3.1 Data Collection

A systematic data gathering strategy that gathers primary data of 150 days data collection sampling which involved 484 personnel. The source sample data were gathered from 13 similar size, comparable purposes office area, similar weather properties and similar design properties sample location. Each personnel educational level is tabulated. The educational levels are separated into 4 educational levels which are High School and below, Certificate, Diploma and Degree and above. The educational level of each person attendant in each floor are used to calculate the daily total occupancy. Magnetic door sensor station at each access door is used to record the attendant. Meanwhile, data loggers are used to measure the energy consumption in each dedicated area electrical riser. The data logger will measure and stored the daily cumulative energy consumption in an hour interval.

3.2 Data Pre-processing

Raw data logger and Magnetic Door Station Main data source collected is pre-process using Microsoft Excel Data Vlookup which filtered and selected the needed data. Each daily sample location data will be combined cleaning, normalizing, and transforming it into a suitable format for AI model training.

3.3 Data Analysis

Before an ANN is used for forecasting it has to be trained. The most common procedure is to use the 70–80% of the data to train the network and the remaining 20–30% to test its performance [6]. For this research, 70% data is used to train the network, 15% used to validate the samples whereas 15% is used for testing. The Artificial Neural Network fitting MatLab analysis provides the foundation for data testing and validation. Neural network fitting is set to use 70% of the training data, or 704, 15% of the validation samples, or 151, and 15% of the testing samples, or 151. The neural network diagram is displayed in Figure 2. The training's outcomes are based on the Lavenberg-Marquordt algorithm.

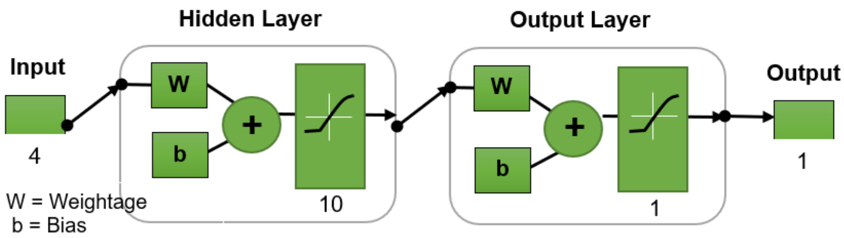

Fig. 2. Neural network diagram

4. Result of the Empirical Research

The result of samples descriptive statistics shows that 1,006 samples has been analysed. The respective descriptive range, minimum, maximum and mean value are given in Table 2.

Table 2
Descriptive statistics

	N	Range	Minimum	Maximum	Mean
High_School_and_below	1006	59.00	1.00	60.00	27.7515
Certificate	1006	16.00	.00	16.00	7.1292
Diploma	1006	22.00	.00	22.00	8.6928
Degree_and_above	1006	15.00	.00	15.00	7.3867
Energy_Consumption	1006	159.66	.04	159.70	51.9904

Based on Uniform Building by-law 1984 (UBBL 1984) which discussed before, the space standards for calculating occupancy loads is tabulated in Table 3. Table 3 summarized the maximum Space Occupancy Load in the sample location.

Table 3
Space occupancy load

Educational Level Categories	Sample Net Floor Area for occupancy (m^2)	Working Area Size (m^2)	Maximum Space Occupancy Loads
High_School_and_below	602	2.0	301
Certificate	602	5.0	120
Diploma	602	8.0	75
Degree_and_above	602	16.0	37

Comparatively, the similar data are analysed using Matlab Neural Network. Using Lavenberg-Marquordt algorithm. The data are trained and automatically stops when generalization stops improving, as indicated by an increase in the mean square error of the validation samples. The Mean Squared Error and Regression R Values are given in Figure 3.

	Samples	**MSE**	**R**
Training:	704	529.31111e-0	8.21367e-1
Validation:	151	607.96666e-0	8.13053e-1
Testing:	151	485.28528e-0	8.00035e-1

Fig. 3. Lavenberg-Marquordt algorithm result

Figure 4 illustrates the use of Matlab Plot Graph to display data pertaining to educational level, and energy consumption. The results show a consistent uniformity in the overall educational level, as compared to the energy consumption. Further analysis was conducted to examine the relationship between the specific educational level, and energy consumption, as shown in Figure 5. The findings suggest that there is an inconsistency in the uniformity of the data, although it is not yet possible to conclusively identify the factors responsible for this variation.

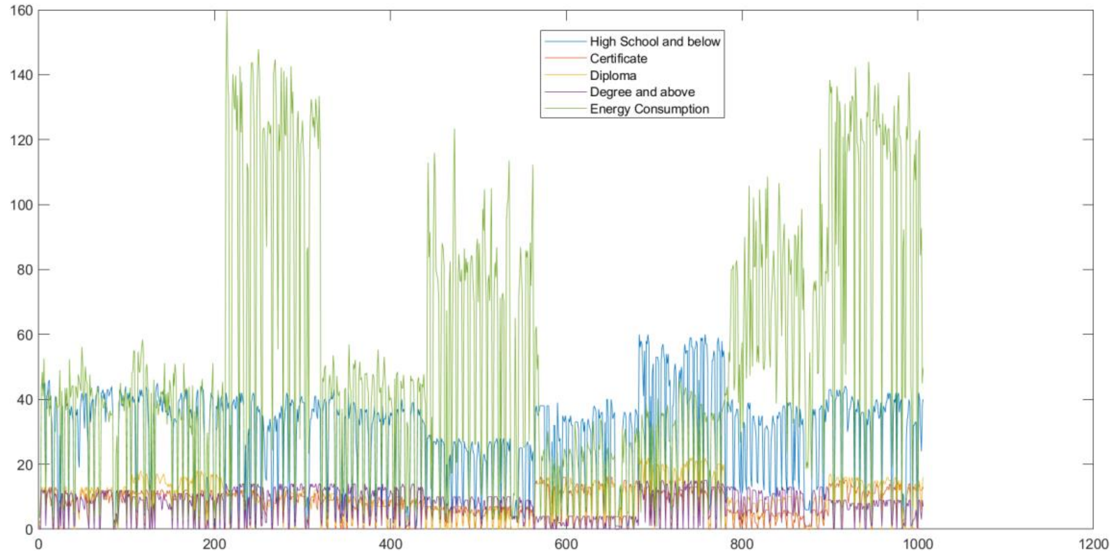

Fig. 4. Matlab plot graph on overall educational level and energy consumption

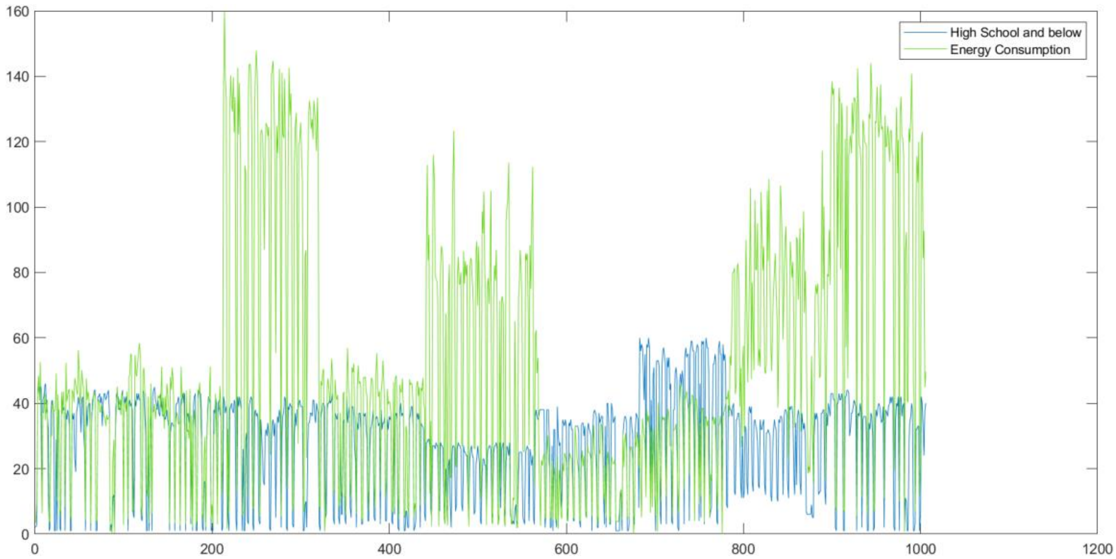

Fig. 5. Matlab plot graph on specific educational level vs energy consumption

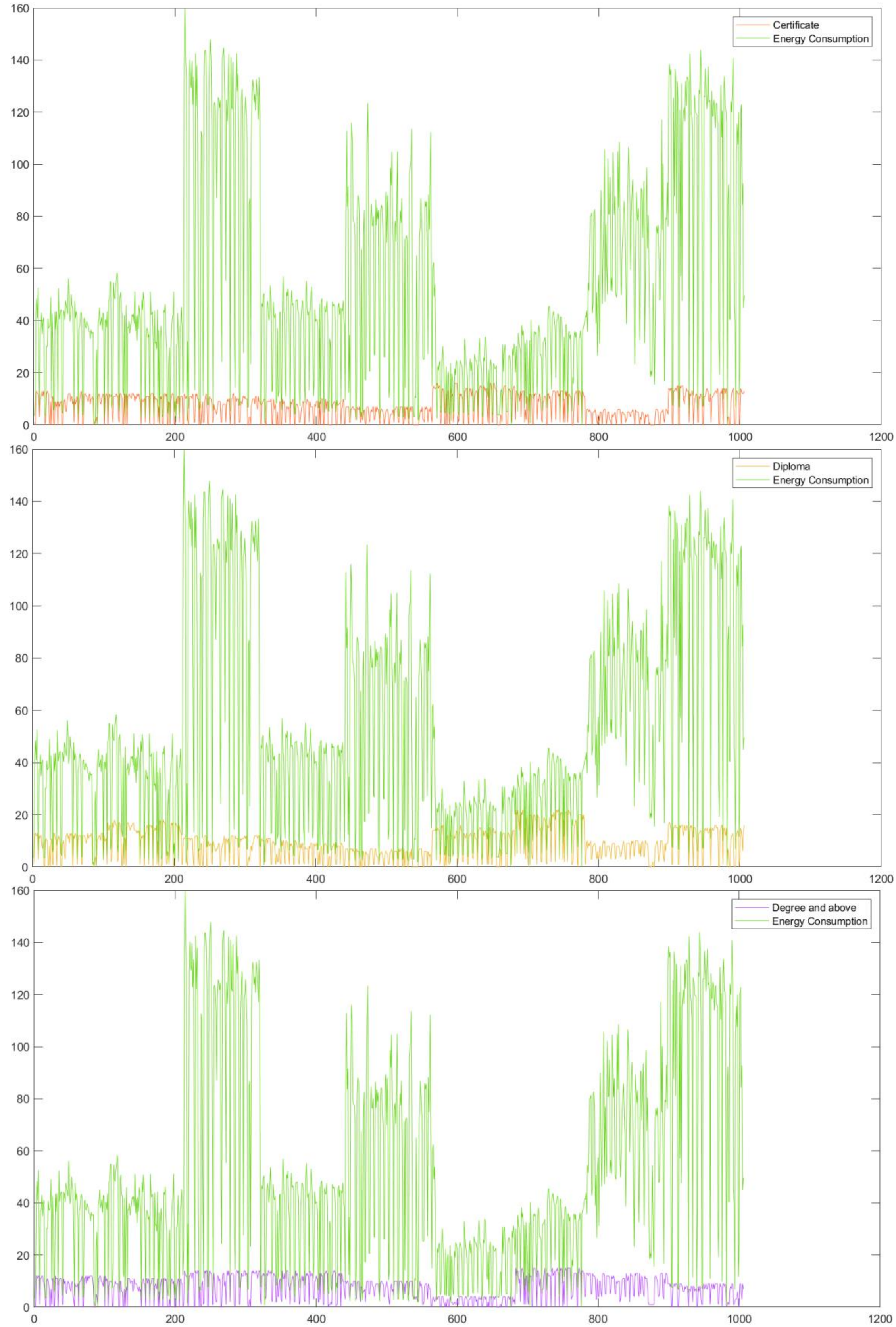

Fig. 5. Matlab plot graph on specific educational level vs energy consumption (cont'd)

The use of Matlab Bar Plotting demonstrated the impact of education on energy consumption. However, the presence of noise in the data prevented a reliable evaluation of the impact value. Therefore, a comparison between the collected data and a model will be necessary to gain a more comprehensive understanding of the influence of educational factors on energy consumption. Matlab's Artificial Neural Network was employed to create a model based on sample data. The use of this technique can aid in understanding and forecasting the values of data pertaining to distinct educational levels. Figure 6 shows the Matlab Neural Network Fitting on regression plotting.

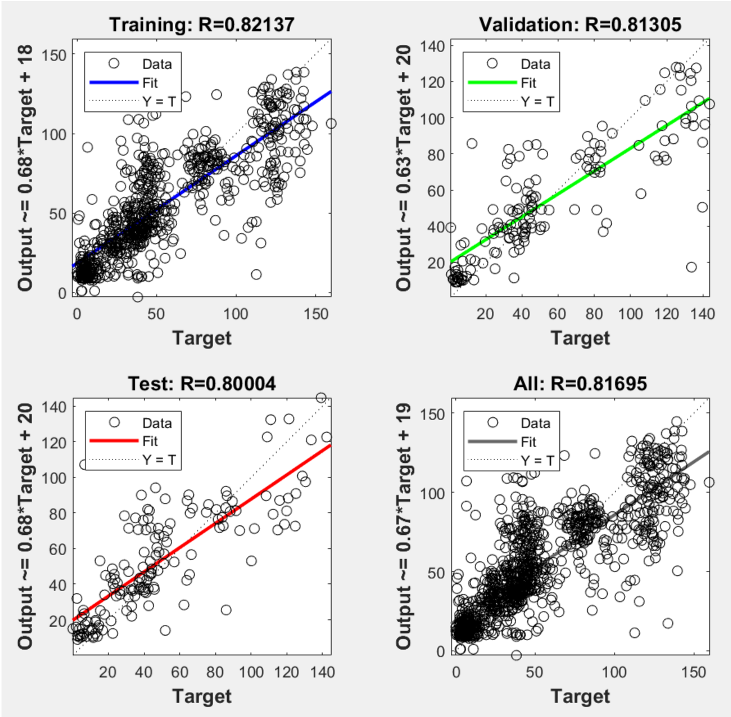

Fig. 6. Matlab Neural Network Fitting on regression plotting

Through the utilization of Artificial Neural Networks (ANNs), a comparative analysis between the Model Plotting Result and Actual Model Plotting Result was conducted. The resulting data was subsequently analyzed to identify commonalities between the models. The model developed in this study combines both high-performance actual data models and computer simulation models to predict energy consumption in office buildings. Figure 7 displays the results of this analysis.

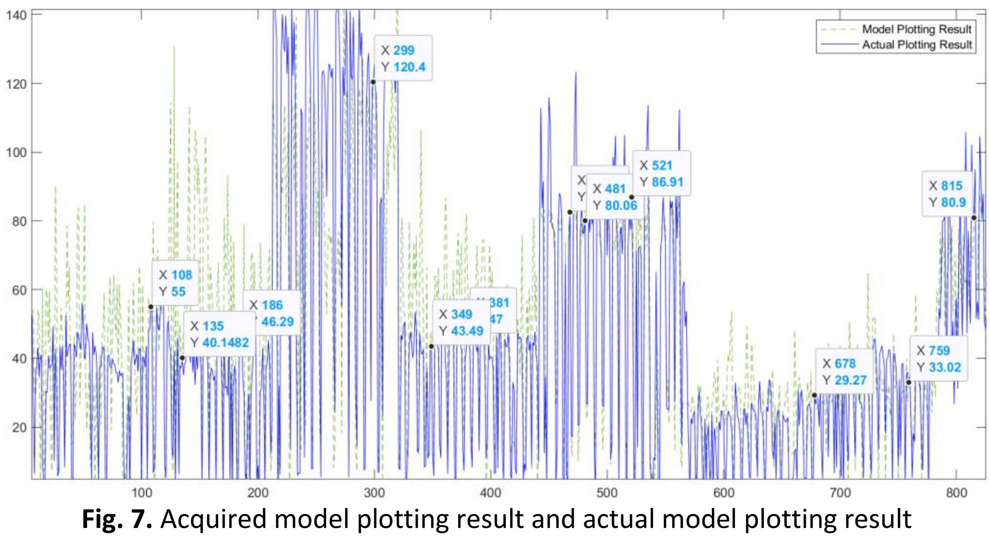

Fig. 7. Acquired model plotting result and actual model plotting result

Based on Figure 7, the 15 matching point which identify commonalities between the models is tabulated. These values are compared to actual data to retrieved each educational level variables values on each 15-matching point. The energy consumption value during maximum Space Occupancy Load as tabulated in Table 3 and 15 matching points educational level is determined using Acquired Model from Artificial Neural Networks (ANNs). Energy consumption value acquired is tabulated in Table 4.

Table 4
Individual educational level, 15 matching point model and maximum space occupancy load energy consumption values

No.	Sample Sequence	Educational Level Variable Value				Model Energy Consumption Value (kWh)
		High School and below	Certificate	Diploma	Degree and above	
Individual Educational Level						
High School and Below		1	0	0	0	12.1971
Certificate		0	1	0	0	14.3491
Diploma		0	0	1	0	7.6119
Degree and above		0	0	0	1	15.0131
15 Matching Point						
1	108	39	11	14	10	56.1710
2	135	45	12	17	11	40.1482
3	186	43	12	17	10	48.3010
4	299	41	11	11	14	119.6949
5	349	35	9	7	11	47.7801
6	381	35	9	9	10	44.5344
7	468	23	6	6	6	80.0023
8	481	26	7	6	8	83.2677
9	521	28	7	7	10	85.9201
10	678	32	13	12	3	28.7386
11	759	57	11	21	15	33.5037
12	815	32	2	8	12	84.8629
13	884	34	5	8	10	78.1484
14	920	30	10	12	6	117.2022
15	953	40	14	14	9	122.1808
Maximum Space Occupancy Load						
High School and Below Maximum Space Occupancy Load		301	0	0	0	-69.1313
Certificate Maximum Space Occupancy Load		0	120	0	0	14.8404
Diploma Maximum Space Occupancy Load		0	0	75	0	103.2058
Degree and Above Maximum Space Occupancy Load		0	0	0	37	-77.4231

The analysis of individual energy consumption data reveals that individuals categorized as having a Degree or above education utilized the greatest amount of energy, consuming 15.0131 kWh, as compared to other educational categories. In contrast, individuals categorized as having a Diploma education consumed 50.7% less energy when compared to those with a Degree or higher education.

Utilizing the 15 matching point result value, a comparative analysis can be conducted. Specifically, when comparing the sample sequences 349 and 381, which share similar values for high school and below as well as certificate education, it is evident that individuals categorized as having a Degree or higher education consume a greater amount of energy.

Interestingly, this result is observed despite the Diploma category having one less occupant. Additional support for this argument is found when comparing sample sequences 678 and 815. Despite higher occupancies within the Certificate and Diploma categories, the increase in the Degree and above category substantially elevates energy consumption levels.

When utilizing Maximum Space Occupancy Load as a limiting factor, it is evident that only individuals categorized as having a Diploma education display a reasonable energy consumption value of 103.2058 kWh. This determination was made following a comparative analysis with sample sequences 299, 920, and 953, which have relatively similar occupancies.

5. Conclusions

Therefore, the research will use a neural network approach. This approach enables data analysis and the development of statistical models. Since various demographic categories were used in each nation and no comparable data from another nation was available, overall results varied. The neural network research model will examine whether the research's conclusions are the same as those of the research that was previously described.

The research used neural network approach to compare actual data and predicted data model. The result suggests that individuals categorized as having a Degree or higher education consume a greater amount of energy in comparison to other educational categories. Nonetheless, it is important to acknowledge that other factors may contribute to the observed higher energy consumption among this category. For instance, increased usage of appliances for work purposes, such as laptops and printers, might play a role in elevating energy consumption levels. In additional, the use of “nice to have" appliances, such as air-conditioning units, personal freezers, and air purifiers, was also observed throughout this research. While, different between other categories cannot be determine clearly.

It is important to acknowledge that there may be various other variables or factors that contribute to the outcomes observed in this research. Factors such as age, job position (technical or non-technical), size of occupancy or workspace, and other pertinent factors may have an impact on energy consumption patterns which need to be studied on future research.

Acknowledgement
This research was not funded by a grant.

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