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A Procedure for the Analysis of Multivariate Factors Affecting Electricity Consumption

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ABSTRACT
This research explores the dynamic relationship between temperature and level of building occupancy; and their effect on electricity consumption of electric appliances. It develops a model for electricity consumption based on these variables. It is important that reliable electricity consumption models are employed in finding solution to energy needs, otherwise inappropriate models may result in poor estimates for decision making. In this research, models for the daily electricity consumption for a local university in Malaysia was developed based on extraneous factors, such as temperature and level of building occupancy . As a result of developing such models, social and economic welfare will be improved.

Keywords
Dynamic relationship, modeling, reliability, energy needs, decision making.

1. INTRODUCTION
This study explores the relationship between temperature and level of building occupancy at different periods of the year, and their effect on the electricity consumption of electric appliances in buildings. Since many countries require primary energy sources for sustainable development, world energy demand has increased tremendously. This has resulted in higher energy costs for consumers. There is a need to know the daily usage pattern of electricity with regards to some extraneous factors, like temperature and occupancy level in buildings.

[1], [2] discussed total world consumption, taking into consideration different energy sources, which shows an increasing demand for electricity from 1971 to the present, as a result of economic, social and technological development. The paper proposed that proper planning is required for achieving proper energy management policy for decision makers, to minimize economic losses, by selecting appropriate forecasting models. [3] in its presentation identified selecting appropriate prediction models for planning and management in the energy market as a means of achieving efficient electricity consumption in electrical appliance use. The study indicated that introduction of new tools in analyzing energy models would minimize economic losses, since forecasting has become a tool for optimizing energy resources and accurately predicting electricity consumption, improving efficiency in electric appliance use. The research concludes that more energy savings can be achieved if future electricity to be consumed by appliances is known.

[4] described artificial neural network technique as the most accurate and widely used method for forecasting electricity models. The analysis of a prediction model built on an artificial neural network based on learning, flexibility and real time response was illustrated by [5]. Previous methods of using ANN technique to forecast energy models were affected by approximations necessary for estimating data [6]. [7] identified the modified Newton's method (MNM) as the most reliable technique for predicting electricity consumption. The MNM is a recursive technique used to predict electricity consumption.

This research models the amount of electricity consumed by relating it to influencing factors such as temperature and level of building occupancy. The model showing this relationship is given as:

$$f(occupancy, temperature, k) \qquad (1)$$

where, *occupancy* is number of people in the building when electricity is being consumed, *temperature* is average temperature for the day and k is constant coefficient.

This paper is organized as fellows: Literature review about the analogy of electricity consumption of appliances is presented in Section 2. Description of the datasets used in this study and the proposed techniques are given in Section 3. Section 4 contains model results for techniques used in this study. The last section presents the conclusion of the paper.

2. LITERATURE REVIEW
A number of studies discuss industrial and household energy consumption. [8] recommended the use of artificial neural network (ANN) to predict half hourly ahead load and price. The research utilized historical weather, load consumption, price and calendar data for testing the performances of multiple regression (MR) and the artificial neural network respectively. The performance evaluation parameters of the prediction models for these techniques were computed using mean absolute percentage error, mean square error, root mean square error and percentage error. The result of the research indicated that values of parameters for the artificial neural network technique were low compared to the multiple regression technique. The artificial neural network is shown by the study to be more accurate and effective than the multiple regression for load and price forecasting. A research utilizing autoregressive integrated moving average, artificial neural network and multiple linear regression to formulate prediction models of electricity demand in Thailand was presented by [9]. The results in this study were based on error measurements, which showed that the artificial neural network is superior to other techniques. [10] employed the univariate Box-Jenkins approach, multiple log-linear regression and artificial neural network techniques to compare forecasting accuracy of residential consumption demand. The forecasting accuracy of the methods was achieved using percentage errors for the three techniques. The study indicated

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the superiority of the artificial neural network to other techniques, since it has the lowest mean absolute percentage error (MAPE) value.

[11] presented an adaptive linear, forward selecting time-series modeling technique to forecast load for space heating in buildings. It utilized ambient temperature, global radiation and wind speed as inputs to its model. The presented heat load forecasts in the study were used as input for the optimization of heat supply to buildings in smart grid applications. The recursive identification method for predicting parameters in electrically stimulated muscles was introduced by [12]. The study improved output prediction at future times; hence, its application to predictive adaptive controllers. The adoption of multiple regression technique to develop simple energy estimation models for office buildings in five cities of China was presented by [13]. The study analyzed weather conditions as they relate to energy use. The coefficient of determination R^2 was used to explain variations in energy use. The research estimated the likely energy savings to be obtained from analyzing data for different building schemes. The use of regression models using economic and demographic variables to develop a long-term consumption forecasting model was proposed by [14]. The variables considered in the research were historical electricity consumption, gross domestic product (GDP), gross domestic product per capita (GDP per capita) and population. [15] described the energy consumption of a supermarket in Northern England by means of a multiple regression analysis based on its gas and electricity data. As part of the study, the research utilized prevalent weather conditions such as temperature and level of building occupancy.

A hybrid correction method, which is a combination of linear auto regressive integrated moving average (ARIMA) and non-linear artificial neural network techniques (ANN) was selected for predicting short-term electricity prices, [16]. The technique involved generating new price data by correcting historical data with the help of price correction rates. The study verified the predictive ability of the selected method by performing simulations of price forecasting by ARIMA, ANN and the hybrid approach. The test results from the research showed that the hybrid model gave better predictions than either ARIMA or ANN forecasts, and its forecasting accuracy was better. [17] presented the adaptive network based fuzzy interactive system approach and the autoregressive model for forecasting long-term natural gas demand, with gross domestic product and population used as input variables. The performance of the forecasting techniques was compared using their mean absolute percentage errors. In the study, the adaptive network based fuzzy interactive system model produced more accurate results for long-term prediction of natural gas consumption, since it had a smaller MAPE estimate than the autoregressive model. A study by [18] proposed a combination of ANN and fuzzy inference technique for forecasting short-term electricity prices using past prices and demand data. The results obtained from this study showed considerable improvement in performance, achieving a mean absolute percentage error of less than 2% for hours with steady prices and 8% for those with price spikes.

The energy savings potential in integrated room automation was estimated in a large-scale simulation study by varying the building type, heating ventilation and air conditioning (HVAC) system, and weather conditions, [19]. The study compared the current control practice with a theoretical benchmark, the performance bound. The research focused on the control of HVAC, the electric lighting of the building zone, room temperature and the carbon-dioxide levels staying within the comfort zone. The Stochastic Model Predictive Control (SMPC) was utilized in the paper as a development and analysis strategy for building climate control, taking into account uncertainty due to weather conditions. The result produced a significant energy saving potential for SMPC. [20] presented a paper on improving energy efficiency through the application of model predictive control to air conditioning units. The research implemented control strategies on vapor compression cycle in a building model and focused on applying control measures to air conditioning systems in order to compute predictive estimates.

The issue of obtaining reliable models for electricity consumption has been widely discussed in this section. Due to increased demand for electricity, the development of efficient models to model electricity usage is highly essential. Electricity is a source of energy that cannot be dispensed with in real life. It enables the use of daily appliances such as computers, medical devices, telecommunication appliances that increase people’s quality of life. As a result, electricity is seen as a necessity for social and economic welfare. It is essential to maintain economic activity in modern industrialized nations and social development.

3. METHODOLOGY

In this section, the characteristics of the data collected from the Faculty of Computer Science and Information Technology (FCSIT) building, Universiti Malaysia Sarawak (UNIMAS) is analyzed. The datasets used to implement the models are described using basic statistical attributes. This consists of data collected from power meter installed in the FCSIT building by Sarawak Energy Berhad (SEB). The dataset for this study consists of electricity consumption readings, including such factors as level of building occupancy and temperature, which are included in the consumption model. The daily average temperature data for the period under study was taken from *weatherspace* [21, a weather website. The weather site consists of a global database of daily weather readings. The process of modeling electricity consumption in a building is given by Figure 1.

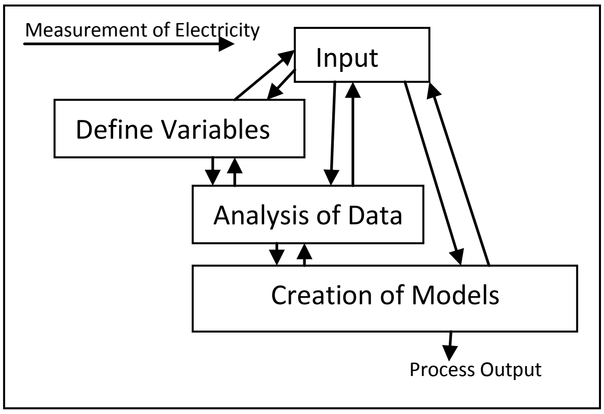

Fig 1: Developing electricity consumption models

4. RESULTS AND DISCUSSION

In describing the electricity consumption usage pattern for the FCSIT building, the consumption data for the whole FCSIT building for 2009-2012 was analyzed. This is done by modeling monthly electricity consumption for the building for the four-year period. The data is graphed and is shown in Figure 2.

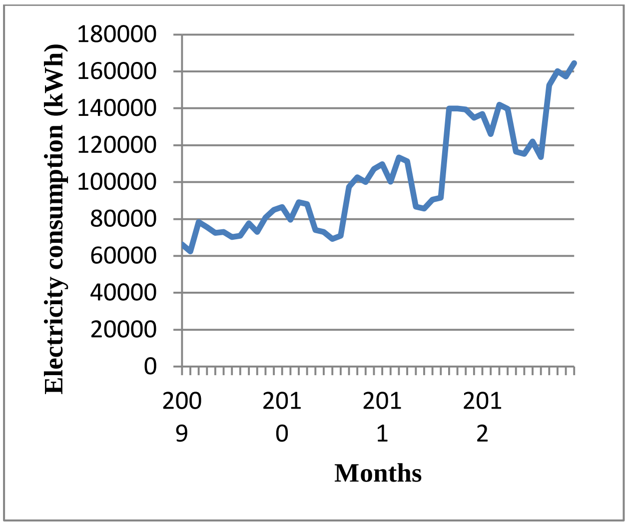

Figure 2: Electricity Consumption for FCSIT Building (from January 2009 to December 2012)

The decrease or rise in the graph signifies either a reduction in consumption, when students are not in session or increase in consumption due to exam period when the biggest hall in UNIMAS, DeTAR, is being used for examinations. High electricity consumption in the faculty building can be attributed to high occupancy in the building such as when the university was in full academic session. Overall, there was an increasing trend in monthly consumption from 2009 to 2012, except for the months of May to August. These decreases were due to students being on inter-session vacation during these months; hence there was a decrease in the amount of electricity consumed. The peak month for all the years was in December. This was due to high occupancy level at that time of the year and energy resources were stretched. Occasionally, electricity consumption dropped as a result of the air conditioning system not functioning. For instance, in December 2011 when the university was in full academic session, total power consumption in FCSIT building dropped to 134,819 kWh from 139,450 kWh in November 2011. This was due to air conditioning system malfunction in the building. Demand for electricity has had an upward trend, as indicated when electricity consumption steadily increased from 2009 to 2012. This makes it imperative for more efficient use of electricity and for the development of models that will assist in its efficient use.

The monthly electricity consumption for the FCSIT building over the years 2009-2012 is given in Table 1. The data displayed by the table captures monthly electricity consumption readings from 2009-2012. The percentage increase for 2009-2010 is 26.7%, 2010-2011 is 26.45%, and 2011-2012 is 24.47%. The table shows that the highest amount of electricity consumed in 2009 was in December with 85,032 kWh consumed. This is relatively low compared with the highest amount consumed in 2010, which was 107,067 kWh in December; 134,819 kWh was consumed in December 2011; and 164,437 kWh was consumed in December 2012.

Table 1. Monthly Consumption for 2009-2012

Months	Consumption (kWh)			
	2009	2010	2011	2012
Jan	66,170	86,549	109,785	136,926
Feb	62,448	79,586	100,190	125,988
Mar	78,358	89,143	113,370	141,922
Apr	75,521	88,118	111,365	139,734
May	72,500	74,020	86,763	116,480
Jun	72,992	73,020	85,701	153,588
Jul	70,223	69,150	90,491	122,002
Aug	70,794	70,906	91,566	113,625
Sept	77,668	97,455	139,939	152,564
Oct	72,951	102,651	139,861	160,211
Nov	80,687	100,104	139,450	157,167
Dec	85,032	107,067	134,819	164,436

Results from Table 1 shows that the electricity consumed has been following an increasing trend over the years. Increasing consumption from 2009 to 2012 can be attributed to the growth in student and staff population, buildings and facilities. The table show there was a wide gap in electricity consumption in the building between 2009 and other years because the population of students and staff has increased progressively over the years, therefore, so also has demand for electricity for appliances usage.

The dataset of analyzing the characteristics of electricity usage in the building consists of electricity consumption readings, with some factors such as atmospheric temperature and building occupancy. The temperature values, obtained for periods electricity was consumed by appliances, were measured. The daily average temperature data for the period under study were taken from. weatherspace [21]. Building occupancy data consisted of occupant's active and inactive periods of electricity usage in the building during all periods of the year. The active periods were times the university was in session, whereas the inactive periods were times the university was on semester break. The model consists of electricity consumption (kWh), occupancy status in the building (active or inactive) and temperature (°C). This approach attempts to characterize the properties of the measured data in simple parametric relationships over time. These factors are highly time-varying and therefore the consumption pattern of electric appliances and, consequently, parameters of the statistical model describing consumption pattern are constantly changing with time. The relationship between electricity consumption, atmospheric temperature, and building occupancy is investigated by analyzing daily data set for January 1 to September 30, 2013. The correlation matrix and p-value table showing the relationship between electricity consumption, temperature, and building occupancy are given in Table 2 and Table 3 respectively.

Table 2. Correlation Matrix between Consumption, Temperature and Occupancy

Correlation (r)	Consp	Temp	Occup
Consp	1		
Temp	0.663791	1	
Occup	0.847802	0.471397	1

Table 3. *p*-values for Correlation Coefficients between Consumption, Temperature and Occupancy

p-value	Consp	Temp	occup
Consp			
Temp	0.0024		
Occup	0.0018	0.0037	

There is a positive correlation between consumption in the building and temperature (r = 0.663791) in Table **2**. This could be due to higher energy consumption by air-conditioners as temperature increases. Consumption of electric appliances in the building and building occupancy are highly correlated (r = 0.847802). This indicate that electricity consumption depend on occupancy. When the University is on vacation, electricity consumption decreased within the same period. When the University is in session, consumption increased within the same period. This proposes that the availability of students has an effect on electricity consumed in the building. Also, at $\propto$ = 0.01, the *p*-value for the correlation coefficient between consumption and temperature (p = 0.0024) shows there is a linear relationship between consumption and temperature. Similarly, at $\propto$ = 0.01, the *p*-values show there are significant relationships between consumption and occupancy, and between temperature and occupancy.

5. CONCLUSION

The main objective of this paper is to develop accurate energy consumption models to increase power system reliability. Modern day energy planning is based on obtaining precise estimates from energy consumption models. In order to build a general expert system, this research assessed temperature and building occupancy as factors affecting electricity consumption.

To meet energy demand through the use of electricity as an energy source for daily activities in buildings such as air conditioning, lighting, etc., adequate allocation of energy resources and planning can be done by developing models for electricity consumption. This is beneficial to the electricity network as electricity would be allocated to consumers more efficiently. It is intended that a database of electricity consumption and usage patterns will support a large-scale simulation to explore the modeling of electricity consumption, thereby improving energy usage efficiency.

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