A Predictive Framework for Electricity Consumption

[1]Patrick Ozoh, [2]Shapiee Abd-Rahman and [3]Jane Labadin
[1]Department of Computer Science, Osun State University, Osogbo, Nigeria
[2,3]Department of Computational Science and Mathematics, Faculty of Computer Science and Information Technology, Universiti Malaysia Sarawak, 94300 Kota Samarahan, Sarawak, Malaysia
email: [1]pozoh2@gmail.com, [2]sar@unimas.my, [3]ljane@unimas.my

Abstract - *This study investigates the performance of regression model, Kalman filter adaptation algorithm and artificial neural network to assess their qualities for predictions. It develops predictive algorithms based on price, temperature and humidity as multiple variables affecting time-varying aspect of electricity consumption. In order to meet energy demand through the use of electricity as an energy source for daily activities in buildings such as air conditioning, lighting, computers and cooking stoves., adequate allocation of energy resources and planning should be done, including predicting for electricity consumption. The process involves collecting data from the power grid of Faculty of Computer Science and Information Technology building, Universiti Malaysia Sarawak. The forecasting techniques were tested on the data collected, and the dataset consists of electricity consumption readings, with electricity price, humidity and temperature included in the forecasting model. The performances of regression model, artificial neural network and Kalman algorithm were tested using statistical evaluation parameters, root mean squared error (RMSE) and mean absolute percentage error (MAPE); while the parameter, standard deviation, was used to check the validity of models. This study identified Kalman algorithm as the most effective method of predicting consumption data compared to regression model, and artificial neural network.*

Keywords: Kalman algorithm, regression model, ANN, predictions, price, temperature, humidity, statistical parameters.

1 Introduction

Electricity is a source of energy that cannot be dispensed with in daily life, especially in households. It enables the use of daily appliances (such as computers, medical devices, and telecommunication appliances) that increase people's quality of life. Most appliances used in daily life are powered by electricity and it is generally regarded to be almost impossible to live without them. 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. The issue of obtaining reliable forecasting methods for electricity consumption has been widely discussed by past research works. This is due to the increased demand for electricity and as a result, the development of efficient pricing models. Several techniques have been used in past research for predicting electricity consumption.

Since many countries require primary energy sources for sustainable development, world energy demand has increased tremendously (Taşpınar et al., 2013). International Energy Agency (2013) 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. Anon (2013) 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 analysing energy models would minimize economic losses, since forecasting has become a tool for optimizing energy resources. Also, accurately predicting electricity consumption will allow for an efficient allocation of resources in the energy grid, while improving efficiency in electric appliance use. The research concludes that more energy savings can be achieved if future electricity to be consumed by individual appliances is known.

Tripathi (2014) described artificial neural network technique as the most accurate and widely used method for electricity forecasting models. The analysis of a prediction model built on an artificial neural network based on learning, flexibility and real time response was illustrated by Yedra et al. (2014). Previous methods of using artificial neural network technique to forecast energy models were affected by approximations necessary for estimating data. Ozoh et al. (2014a) identified modified Newton's method as the most reliable technique for predicting electricity consumption. The Kalman filter adaptation algorithm is the same as modified recursive method as used in the research. Both are recursive techniques applied to electricity consumption predictions and both utilize the same algorithm. The Kalman filter adaptation algorithm was chosen because the technique does not approximate data used for estimation, but takes into consideration past errors contained in the data set to make future forecasts. This enabled Kalman algorithm to be more accurate and self-correcting in forecasting electricity consumption.

This research predicts amount of electricity consumed by relating it to influencing factors such as price, temperature and humidity with regression model, artificial neural network and Kalman algorithm used as the modelling instrument. The consumption model is given as:

$$f(price, humidity, temperature) \tag{1}$$

The process involves measuring electricity consumption of appliances in the faculty of computer science and information technology building by connecting the Power Logic PM5350 (Figure 1) to the electricity grid for taking consumption measurements from Sarawak Electricity Supply Corporation (Figure 2).

Figure 1: The Power Logic PM5350

Figure 2: Electricity grid

This study involves testing regression model, artificial neural network, and Kalman algorithm by simulating daily measurements of electric appliances for of 2013. The paper is organized as fellows: Literature review about electricity consumption of appliances is presented in Section 2. Descriptions of 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. Akole et al. (2011) recommended the use of artificial neural network 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 and 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 artificial neural network technique were low compared to multiple regression technique. The artificial neural network is shown by the study to be more accurate and effective than 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 Kandananond (2011). The results in this study were based on error measurements, which showed that artificial neural network is superior to other techniques. Goh (1998) employed 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 the superiority of artificial neural network to other techniques, since it has the lowest mean absolute percentage error value.

Bacher et al. (2013) presented an adaptive linear, forward selecting time-series modelling 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 Chia et al. (1991). 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 Lam et al. (2010). The study analysed 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 analysing 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 Bianco et al. (2009). The variables considered in the research were historical electricity consumption, gross domestic product (GDP), gross domestic product per capita (GDP per capita) and population. Braun et al. (2014) 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 humidity.

A hybrid correction method, which is a combination of linear autoregressive integrated moving average and non-linear artificial neural network techniques was selected for predicting short-term electricity prices (Areekul et al., 2010) . 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 autoregressive integrated moving average technique, artificial neural network and the hybrid approach. The test results from the research showed that the hybrid model gave better predictions than either the autoregressive integrated moving average technique or artificial neural network forecasts, and its forecasting accuracy was better. Azadeh et al. (2011) presented the adaptive network based fuzzy interactive system approach and 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 mean absolute percentage error estimate than that of the autoregressive model. A study by Chogumaira (2011) proposed a combination of artificial neural network 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 (Oldewurtela et al., 2012). The study compared the current control practice with a theoretical benchmark, the performance bound. The research focussed on the control of HVAC, the electric lighting of the building zone, room temperature and the carbon dioxide levels stay 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. Wallace et al. (2012) presented a paper on improving energy efficiency through the application of model predictive control to air conditioning units. The research implemented control strategies on vapour compression cycle in a building model and focussed on applying control measures to air conditioning systems in order to compute predictive estimates.

3 Methodology

This study investigates the performance of regression model, Kalman filter adaptation algorithm and artificial neural network to assess their qualities for predictions. The process involves measuring electricity consumption of appliances in the Faculty of Computer Science and Information Technology (FCSIT) building by connecting the Power Logic PM5350 to individual appliances. It assesses and compares them in order to obtain an appropriate technique for predicting the consumption of electric appliances. In choosing the most appropriate prediction technique, statistical methods were applied to electricity consumption data and the parameters of the models were estimated using these methods. Subsequently, all the models were compared in terms of prediction performance and the most appropriate model was identified and selected.

Data Set Used

The study utilized measured data, collected on a daily basis for 273 days, from January 1 to September 30, 2013. The dataset consisted of electricity consumption readings, with electricity price, humidity and temperature included in the forecasting model. The electricity rate used in this study was charged at a cost of 25 sen for each kWh of electricity consumed , irrespective of time of the day. The daily average temperature and humidity data for the period under study were taken from WeatherSpark, a weather website. The source for electricity prices was taken from the Sarawak Electricity Supply Corporation (SESCO).

Figure 3 shows measurements obtained from the installed power meter for different electric appliances.

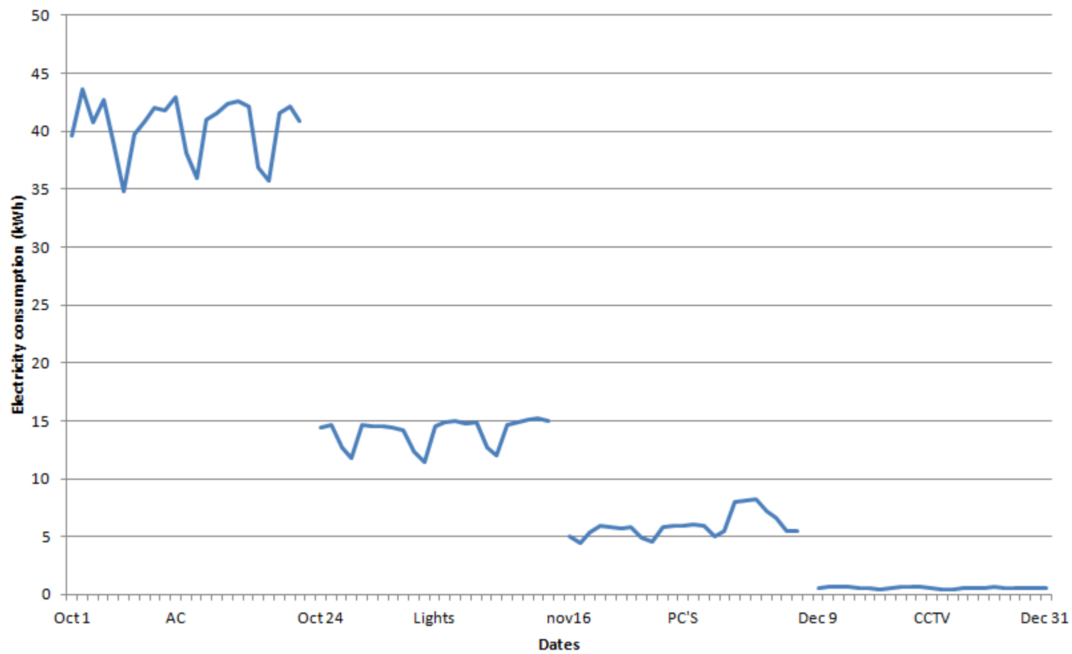

Figure 3: Daily electricity consumption measurements for various appliances during different time periods

The daily consumption for air conditioners was between 34.79 kWh and 43.6 kWh; lighting was between 11.46 kWh and 15.21 kWh; computer was between 4.43 kWh and 8.26 kWh; while that of the CCTV was between 0.46 kWh and 0.68 kWh. The figure shows some deeps or low consumption values over the measurement period. The consumption variations are attributed to holiday periods (students away from campus during holiday time) and excessive usage of electricity (especially for air conditioners and lighting) on resumption of school activities. The weekday's consumption levels are generally higher than those reached during weekends. This tendency is explained by students and staff members using electric appliances more on weekdays. The rate of consumption is high for air conditioners and lighting, while it is low for computers and CCTV. Air This indicates that computers and CCTV can be classified as low power appliances while air conditioners and lightings classified as high power appliances.

The representation for electricity consumption based on price is given in Figure 4. The graph identifies the amount of energy consumed over a period of days, given electricity costs.

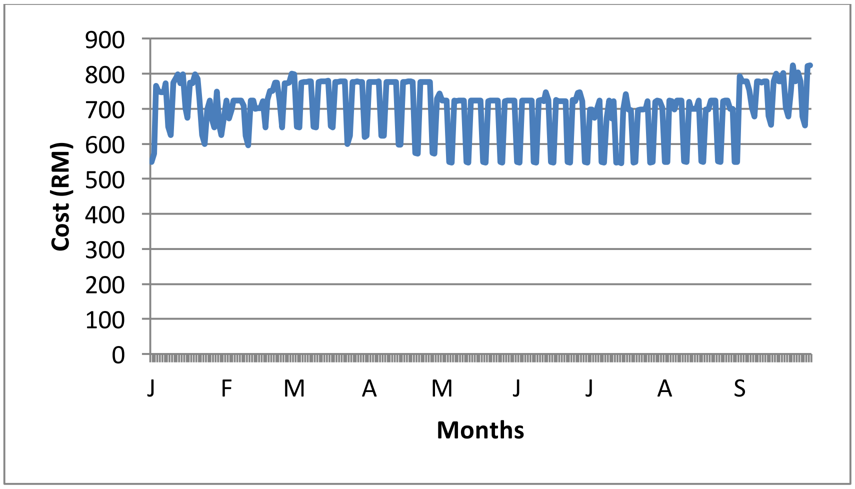

Figure. 4: Daily consumption for 273 days (from Jan1-Sept 30, 2013)

The price for electricity usage is constant, and does not vary, since electricity is charged at a rate of 25 sen per kWh. Figure 4 shows unit price multiplied by amount of electricity used from January 1 to September 30, 2013. Results from simulation of data indicate that consumers do not necessarily react to price rates, as pricing for electricity use does not change irrespective of the appliances' date of use. For example, on 10th of January, cost of electricity consumed was RM774.11; on the 3rd of February, which fell on a weekend, cost of electricity consumed was RM695.31; and on 30th September, cost of electricity consumed was RM824.34. The unit price for electricity consumed for those days remain the same, irrespective of day of use.

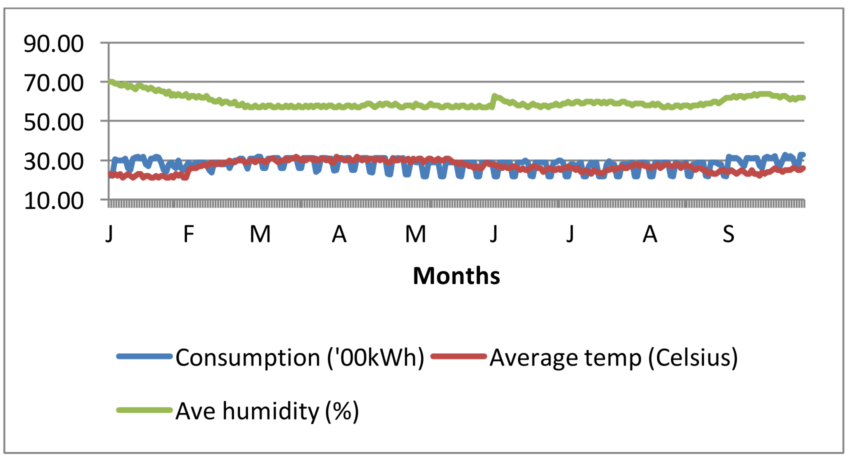

Figure 5: Data exploring consumption with temperature and humidity (from Jan 1 to Sept 30, 2013)

The figure showing the relationship between electricity consumption in the building, humidity and temperature for the same time period is displayed by Figure 5.

The average electricity consumption between the months of January to September, 2013 was compared to the average daily temperature and average daily humidity for the same period in finding a relationship between temperature, humidity and consumption. As temperature increased between January and March, humidity decreased within that same period, and when temperature decreased between March and July, humidity increased within the same period (see Figure 5). This proposes that warm temperature results to a lower than average relative humidity. The average daily temperature reading for January 1 to September, 2013 was between 22 degrees Celsius to 30 degree Celsius, while average daily humidity was between 57 % and 66 %. When temperature was high on 23rd February, 24th February, 30th July, and 31st July with the values 29 degree Celsius, 30 degree Celsius, 27 degree Celsius, and 27 degree Celsius respectively, humidity was low on those dates with values 57%, 58%, 58%, and 58 % respectively. The consumption values on those dates were 2891.17 kWh, 2584.02 kWh, 2885.42 kWh, and 2814.9 kWh. When temperature values were relatively lower on 2nd January, 6th January, 1st September, and 8th September with values 22 degree Celsius, 21 degree Celsius, 24 degree Celsius, and 23 degree Celsius respectively, humidity estimates were higher on those dates. The consumption values on those dates were 2288.93 kWh, 2989.53 kWh, 3174.68 kWh, and 3116.73 kWh respectively. This part of the study shows that there is a direct influence of temperature on consumption in a building, with higher temperature resulting in higher electricity consumption. This indicates that when humidity is low, electricity consumption is high, and when humidity is high, electricity consumption is low. This could be due to higher consumption of air conditioners because of high temperature, since it is the major energy consuming appliance in the building.

The average monthly electricity consumption appliances in the FCSIT building are given in Table I. Also shown is the average monthly temperature and humidity for 2013.

Table I : Average monthly consumption, temperature and humidity values

Months	Consumption (kWh)	Temperature (Celsius)	Humidity (%)
January	2839.11	22	66
February	2872.0479	28	60
March	2929.2161	30	57
April	2899.848	30	58
May	2711.6197	29	58
June	2667.23	26	59
July	2635.1661	26	59
August	2642.3387	26	58
September	3028.8683	24	63

During the months of March, April and May, raging forest fires in Indonesia are thought to be responsible for heating up of the atmosphere in Malaysia and its environs, leading to dry weather. The temperatures for these months are high with average monthly temperature of 30 degree Celsius. The humidity for these months is relatively lower with average monthly humidity of 58%.

3.1 Modeling methodology

The descriptions of models used in this study are briefly discussed in following sections.

3.1.1 Regression models

The regression model is a commonly used method for predicting data because of the high degree of uncertainty involved in the process. The general form of a multiple regression mode, and which was applied to investigating seasonal influences on electricity consumption data in (Kros, 2011), is shown as follows:

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \cdots + \beta_k x_{ki} + \epsilon_i \tag{2}$$

where y_i is the dependent variable, $x_{.i}$ is the independent variable, β_i is the regression coefficient of $x_{.i}$ and ϵ_i is the random error. In order to construct the regression model, the independent variables $(x_{.i})$ are price, temperature and humidity, while the dependent variable (y_i) is electricity consumed. In order to estimate the coefficients of the model, the predicted response is shown in (3).

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_{1i} + \hat{\beta}_2 x_{2i} + \cdots + \hat{\beta}_k x_{ki} \tag{3}$$

3.1.2 Artificial neural network (ANN)

Artificial neural network was described in Damak & Kamoun (2011) as a hidden-layer feedforward network tool and the most widely used technique for time-series modelling and forecasting. Areekul et al. (2010) described artificial neural network model as a network of three layers of simple connected links; it includes input layer, hidden layer, and output layer. The model with t output nodes can be used to forecast multi-step-ahead points directly using all useful past observations as inputs. The t-step-ahead forecasts from the artificial neural network are:

$$\begin{aligned} y_1 &= f_1(x_t, x_{t-1}, \cdots, x_{t-n}) \\ y_2 &= f_2(x_t, x_{t-1}, \cdots, x_{t-n}) \\ &\vdots \\ y_t &= f_t(x_t, x_{t-1}, \cdots, x_{t-n}) \end{aligned} \tag{4}$$

where $f_1, f_2, ..., f_t$ are functions determined by the network. The relationship between the output y_t and the input $f_1, f_2, ..., f_t$ has the following mathematical relationship:

$$y_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j (\beta_{0j} + \sum_{i=1}^{p} \beta_{ij} y_{t-1}) + \in_t \tag{4}$$

where $\alpha_j (j = 0,1,...,q)$ and $\beta_{ij} (i = 0,1,..., p; j = 1,2...,q)$ are model parameters or connection weights, p is the number of input nodes, and q is the number of hidden nodes.

In applying artificial neural network to predict values in this study, available data set was split into a training set (about 70% of the original data set) and a validation set (about 15% of the original data set). The remaining data (about 20 days) were used as test data, to evaluate the generalization ability of the trained network.

3.1.3 Kalman filter adaptation technique

In this study, Kalman filter algorithm was identified as the most reliable technique for predicting electricity consumption compared with regression model and artificial neural network since it is built directly to forecast multi-step successive values for nonlinear systems. In addition, its iterative process produces a single function, which predicts one point at a time and then iterates this function, taking into consideration standard errors of preceding values to predict future values. This technique is self-correcting and combines the attributes of all other methods considered in this study. The Kalman filter adaptation algorithm described by Fox (2002) is represented as:

$$\begin{aligned}
y_{1i} &= \Upsilon_{10} + \Upsilon_{11}x_{1i} + \Upsilon_{12}x_{2i} + \epsilon_{1i} \\
y_{2i} &= \Upsilon_{20} + \Upsilon_{21}x_{1i} + \Upsilon_{22}x_{2i} + \beta_{21}x_{3i} + \epsilon_{2i} \\
y_{3i} &= \Upsilon_{30} + \Upsilon_{32}x_{2i} + \beta_{31}y_{1i} + \beta_{32}y_{2i} + \epsilon_{2i} \\
&\vdots \\
y_{ti} &= \Upsilon_{t0} + \Upsilon_{t,t-1}x_{t-1,i} + \beta_{t1}y_{1i} + \beta_{t2}y_{2i} + \cdots + \beta_{t,t-1}y_{t-1,i} + \epsilon_{t-1,i}
\end{aligned} \tag{6}$$

where $\beta_{t,t-1}$ (t = 1, 2, …) are model parameters of the function developed by the method, y_{ti} are the observed values for electricity consumption data, and $\in_{ti}$ the random errors. In order to construct the model, the independent variable $x_{t-1,i}$ is given as price, temperature and humidity, $y_{t-1,i}$ (i = 0, 1 , 2, …), (t = 1, 2, …) are the recursive estimates for previous data, while the dependent variable y_{ti} is the electricity consumption for period t.

The predicted response is the estimate of (3) given as:

$$\widehat{y_{ıȷ}} = \hat{\gamma}_{i0} + \hat{\gamma}_{i,j-1}x_{i-1,j} + \hat{\beta}_{i1}y_{1j} + \hat{\beta}_{i2}y_{2j} + \cdots + \hat{\beta}_{i,j-1}y_{i-1,j} \tag{7}$$

Equation (7) gives the values between the observed and predicted values.

$$\varepsilon_{ij} = y_{ij} - \widehat{y_{ıȷ}} = (\gamma_{ij} - \hat{\gamma}_{ij})x_{i-1,j} - \left(\beta_{i1} + \hat{\beta}_{i1}\right)y_{i,j} - (\beta_{i2} + \hat{\beta}_{i2})y_{2j} - (\beta_{ij-1} + \hat{\beta}_{i,j-1})y_{i-1,j} \tag{8}$$

The sum square of residuals (*SSE*) is:

$$\text{SSE} = \sum_{i,j}((\gamma_{ij} - \hat{\gamma}_{ij})x_{i-1,j} - \left(\beta_{i1} + \hat{\boldsymbol{\beta}}_{i1}\right)\boldsymbol{y}_{\boldsymbol{i},\boldsymbol{j}} - (\beta_{i2} + \hat{\beta}_{i2})y_{2j} - (\beta_{ij-1} + \hat{\boldsymbol{\beta}}_{\boldsymbol{i},\boldsymbol{j}-\boldsymbol{1}})y_{i-1,j}\,)^2 \tag{1}$$

The coefficients $\hat{\gamma}_{ıȷ}$ and $\hat{\beta}_{i,j-1}$ are obtained by minimizing equation (8).

However, Kalman filter algorithm takes into consideration historical data for its computation, and also the nonlinearity of the models thereby enhancing the output prediction accuracy of estimated parameters.

4 Results and discussion

The statistical software packages of IBM SPSS Statistics 17.0, Excel 2010 and Matlab R2009a were utilized to simulate electricity consumption data by regression model, artificial neural network and Kalman filter adaptation algorithm. The error estimates for the methods are provided in order to compare model performances and their reliability by comparing actual consumption with the simulated energy use of the appliances. This is achieved by computing their respective root mean squared error (RMSE) and mean absolute percentage error (MAPE), as discussed by Zhang et al. (1998) .

The root mean squared error is given as:

$$RMSE = \sqrt{\frac{\sum (e_t)^2}{N}} \tag{10}$$

The mean average percentage error is given as:

$$MAPE = \frac{1}{N}\sum\left|\frac{e_t}{y_t}\right| x100 \tag{11}$$

where e_t is the individual estimated error; y_t is the actual value; and N is the number of error terms. The results from the parameter error estimates from models discussed in this study are summarized in Table II.

Table II: Performance of Multiple regression, ANN and Kalman algorithm

Parameters	Regression model	Artificial Neural Network	Kalman filter
RMSE	5.16	5.5	0.73
MAPE	3.73	4.1	0.39

The root mean square error (RMSE) and mean average percentage error (MAPE) values of Kalman algorithm were low compared to regression model and artificial neural network. Table I show that the RMSE values for Kalman algorithm, regression model, and artificial neural network are 0.73, 5.16, and 5.5 respectively. The MAPE value for Kalman algorithm is 0.39, which is the best result when compared to regression model and artificial neural network, with mean average percentage error values 3.73 and 4.1 respectively. Therefore, Kalman algorithm performs well, when compared to artificial neural network, and regression model.

After simulating consumption data for January 1 to July 31, 2013 using regression model, the prediction model is given by:

$$y = 9.867x_1 - 9.767x_2 - 0.1x_3 + x_4 \tag{12}$$

where y is the predicted value for consumption, x_1 is actual consumption, x_2 is price, x_3 is temperature, and x_4 is humidity. Equation (12) is used to predict electricity consumption as displayed in Figure 6.

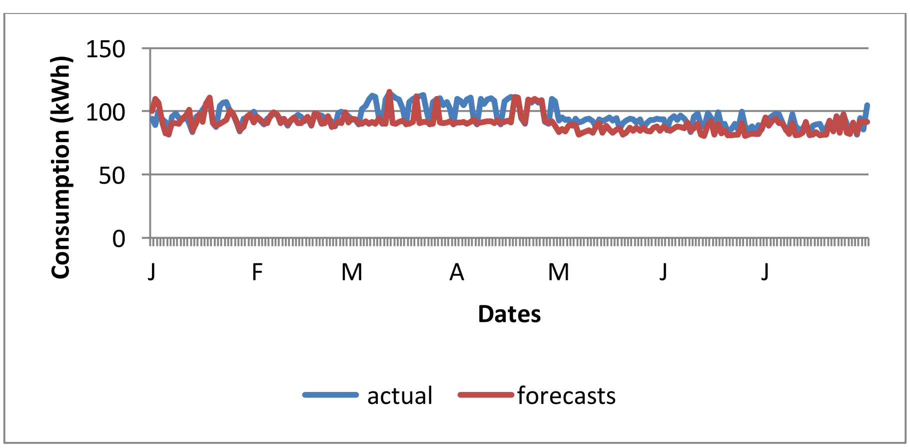

Figure 6. Actual consumption compared with forecasts using regression model (from Jan1-July 31, 2013)

The predicted values for electricity consumption using artificial neural network is given in Figure 7.

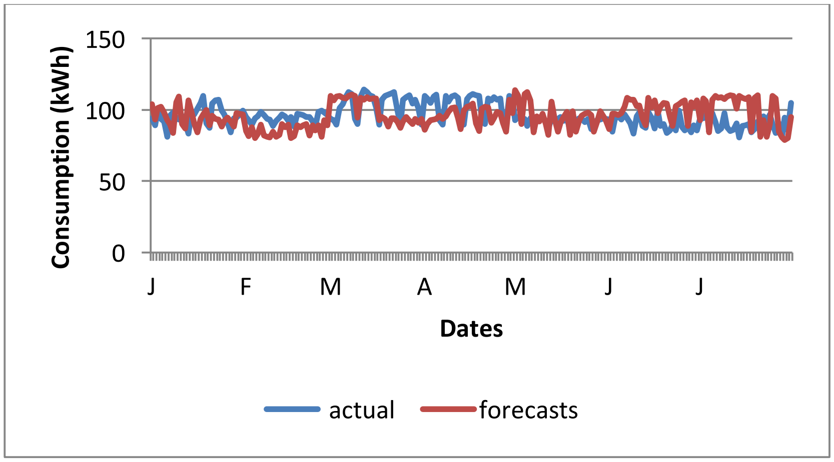

Figure 7. Actual consumption compared with forecasts using ANN (From Jan 1 to July 31, 2013)

Figure 8 shows the results of actual and estimated daily electricity consumption by Kalman adaptive filtering algorithm.

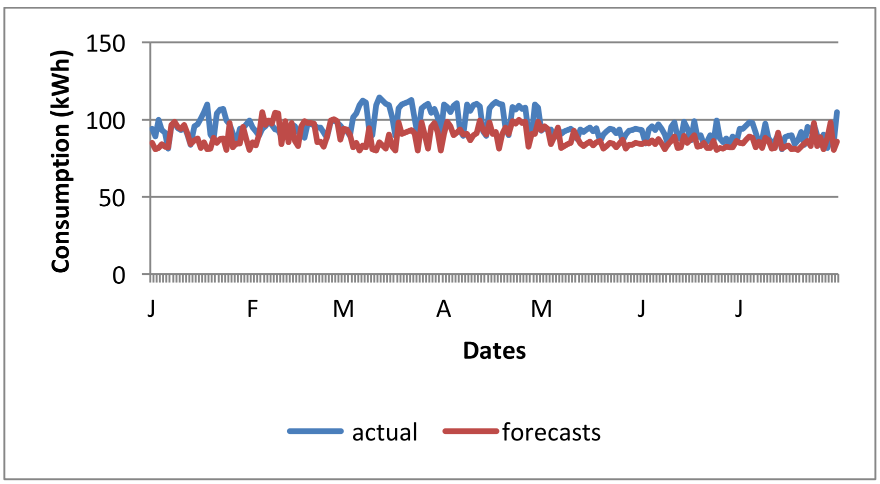

Figure 8. Actual consumption compared with forecasts using Kalman estimates (from Jan 1 to July 31, 2013)

The Kalman method is more consistent than regression model or artificial neural network in predicting electricity consumption as the predicted values neither overestimated nor underestimated data. Furthermore, Figure 8 shows the closeness of predicted values to actual data as compared with Figure 6 and Figure 7. The results from the simulation indicated estimated data are very much similar to the actual one using Kalman algorithm in comparison to regression model and artificial neural network.

In order to show the modelling precision and validity of the forecasting techniques, as given in Erdogdu (2009) and also by Ozoh et al. (2014b), standard deviations of predictions were computed for each of the methods used for predictions. Forecasting methods with low standard deviations for forecasting enhances the accuracy of estimates of parameters. This is because as forecasts are computed, the results obtained become self-correcting, herby increasing the accuracy of the forecasts. Table II shows Kalman algorithm predicted electricity consumption with a low standard deviation of 0.1, thus having a very good forecasting accuracy.

Table II: Descriptive statistics for electricity consumption models

Model	Mean	Std. Dev.
Regression	107.7	8.3
ANN	98.5	11.3
Kalman	98.7	0.1

On the basis of the performed validation test and error analysis presented in this paper, Kalman algorithm can be seen as a valid technique to predict electricity consumption.

5 Conclusions

The main objective of this paper is to provide accurate energy prediction models to increase power system reliability. Modern day energy planning is based on precise values from predicting energy consumption models. This research assessed weather conditions as one of the factors affecting electricity consumption, and in order to build a more general expert system, also considered price as a variable affecting consumption from a holistic view. The performances of regression model, artificial neural network and Kalman algorithm for predicting electricity consumption were tested using the powerlogic pm 5350 readings for 273 days at the Universiti Malaysia Sarawak. From the results discussed in this research, it is observed that predicted values for electricity consumption by Kalman algorithm are very much similar to the actual consumption. The performance evaluation parameters RMSE and MAPE were used for testing the proposed predicting model. The values of these parameters were very low for Kalman method compared to regression model, and artificial neural network. Also the statistical parameter; standard deviation, was used for checking the validity of models and shows the values for Kalman technique to be much better than regression model, and artificial neural network. This study show that Kalman algorithm is the most effective method of predicting consumption data compared to regression model, and artificial neural network. Based on the reviewed literature, the three methods are highly accurate forecasting techniques. However, in this case, Kalman technique was found to be the most reliable technique for modeling the electricity consumption. The technique is very reliable, efficient, and considers multiple parameter constraint violations in its control task and the computation process is very simple to apply, enabling it to possess qualities of a highly effective modeling technique. The technique is also very versatile for predicting non-linear models, which is the form of the data used for this research. Further studies could focus on increasing the number of input parameters for Kalman algorithm so an expert system will be developed for every prediction models considering different effects and situations affecting electricity consumption in buildings. A study detailing cost calculations regarding individual appliances use could be implemented in order to achieve efficiency in electricity consumption.

References

Akole, M., Bongulwar, M. & Tyagi, B. (2011). Predictive model of load and price for restructured power system using neural network. *International Conference on Energy, Automation, and Signal (ICEAS)*, 1–6.

Anon (2013). *World Energy Outlook 2013*. International Energy Agency. Available at: http://www.oecd-ilibrary.org/energy/world-energy-outlook-2013_weo-2013-en.

Areekul, P., Senjyu, T., Toyama, H. & Yona, A. (2010). A Hybrid ARIMA and Neural Network Model for Short-Term Price Forecasting in Deregulated Market. *IEEE Transactions on Power Systems*, 25(1), pp.524–530.

Azadeh, A., Asadzadeh, S.M., Saberi, M., Nadimi, V., Tajvidi, A. & Sheikalishahi, M. (2011). A Neuro-fuzzy-stochastic frontier analysis approach for long-term natural gas consumption forecasting and behavior analysis: The cases of Bahrain, Saudi Arabia, Syria, and UAE. *Applied Energy*, 88, 3850–3859.

Bacher, P., Madsen, H., Nielsen, H.A. & Perers, B. (2013). Short-term heat load forecasting for single family houses. *Energy and Buildings,* 65, 101–112.

Bianco, V., Manca, O. & Nardini, S. (2009). Electricity consumption forecasting in Italy using linear regression models. *Energy*, 34, 1413–1421.

Braun, M.R., Altan, H. & Beck, S.B.M. (2014). Using regression analysis to predict the future energy consumption of a supermarket in the UK. *Applied Energy*, 130, 305–313.

Chia, T.L., Chow, P.C. & Chizeck, H.J. (1991). Recursive parameter identification of constrained systems: an application to electrically stimulated muscle. *IEEE Transactions on Bio-Medical Engineering*, 38, 429–42.

Chogumaira, E. N. (2011). Short-Term Electricity Price Forecasting Using a Combination of Neural Networks and Fuzzy Inference. *Energy and Power Engineering*, 03, 9–16.

Damak, N. & Kamoun, S. (2011). Applications of two identification methods for an electric distribution system. *Journal of Automation & Systems Engineering*, 4(5-4), 176–184.

Erdogdu, E. (2009). Electricity Demand Analysis Using Cointegration and ARIMA Modelling: A case study of Turkey. *Turkey Energy Policy*, 35, 1129–1146.

Fox, J. (2002). Structural Equation Models.

Goh, B. (1998). Forecasting residential construction demand in Singapore: a comparative study of the accuracy of time series, regression and artificial neural network techniques. *Engineering, Construction and Architectural Management*, 5, 261–275.

International Energy Agency, 2013. Key World Energy Statistics. Available at: http://www.iea.org/publications/freepublications/publication/KeyWorld2013.pdf.

Kandananond, K. (2011). Forecasting Electricity Demand in Thailand with an Artificial Neural Network Approach. *Energies*, 4, 1246–1257.

Kros, J. F. (2011). Seasonal Influences on Electricity Demand in the Mid-Atlantic Region. *Advances in Business and Management Forecasting*, 8, 13 – 29.

Lam, J.C., Wan, K.K.W., Liu, D. & Tsang, C.L. (2010). Multiple Regression Models for Energy Use in Air-conditioned Office Buildings in Different Climates. *Energy Conversion and Management*, 51, 2692–2697.

Oldewurtel, F., Parisio, A., Jones, C.N., Gyalistras, D., Gwerder, M., Stauch, V.,Lehmann, B. & Morari, M. (2012). Use of model predictive control and weather forecasts for energy efficient building climate control. *Energy and Buildings*, 45, 15–27.

Ozoh, P., Abd-Rahman, S., Labadin, J. (2014a). A Comparative Analysis of Techniques for Forecasting Electricity Consumption. *International Journal for Computer Applications*, 88, 8–12.

Ozoh, P., Abd-Rahman, S., Labadin, J. (2014b). Modeling Electricity Consumption using Modified Newton's Method. *International Journal for Computer Applications*, 86, 27–31.

Taşpınar, F., Çelebi, N. & Tutkun, N. (2013). Forecasting of daily natural gas consumption on regional basis in Turkey using various computational methods. *Energy and Buildings*, 56, 23–31.

Tripathi, S. (2014). Day ahead hourly load forecast of PJM electricity market and iso new england market by using artificial neural network. *Innovative Smart Grid Technologies Conference*, 1–5.

Wallace, M., McBride, R., Aumi, S., Mhaskar, P., House, J., & Salsbury, T. (2012). Energy efficient model predictive building temperature control. *Chemical Engineering Science*, 69, 45–58.

Yedra, R. M., Díaz, F. R., del Mar Castilla Nieto, M. & Arahal, M. R. (2014). A Neural Network Model for Energy Consumption Prediction of CIESOL Bioclamitic Building. *Advances in Intelligent Systems and Computing*.

Zhang, G., Patuwo, B.E. & Hu, M.Y. (1998). Forecasting with artificial neural networks: The state of the art., *International Journal of Forecasting*, 14, 35–62.