# Predicting Electricity Consumption: A Comparative Analysis of the Accuracy of Various Computational Techniques

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***Abstract*—This research explores the dynamic relation between price, temperature and humidity; and its effect on electricity consumption of electric appliances. It develops prediction models for electricity consumption based on these variables. It is important that reliable methods are employed in modelling and prediction of energy needs otherwise inappropriate models and poor forecasts may occur. In this research, prediction estimates for the daily electricity consumption for a local university in Malaysia was computed using regression model, artificial neural network (ANN) and the kalman filter adaptation algorithm. The estimates of the methods were compared using performance measures based on statistical parameters obtained from identifying the difference between actual and predicted values. This research identified the kalman filter adaptation algorithm as the bests performing method in making predictions for future electricity consumption.**

***Keywords*— dynamic relationship; predictions; kalman algorithm; regression model, ANN; statistical parameters**

## I. INTRODUCTION

Since many countries require primary energy sources for sustainable development, world energy demand has increased tremendously, [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 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.

[4] 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 [5]. Previous methods of using artificial neural network technique to forecast energy models were affected by approximations necessary for estimating data [6]. [7] identified the modified Newton's method as the most reliable technique for predicting electricity consumption. The kalman filter adaptation algorithm is the same as the 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 the 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 and utilized the regression model, artificial neural network and the kalman filter algorithm as modelling instruments. The model relationship with consumption is given as

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

The techniques were tested on data collected from the Universiti Malaysia, Sarawak. The process involved measuring electricity consumption of appliances in the faculty of computer science and information technology building by connecting the powerlogic pm5350 to the electricity grid. This study involves testing the 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.

## II. LITERATURE REVIEW

A number of studies discuss industrial and household energy consumption. [8] 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 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 the superiority of the artificial neural network to other techniques, since it has the lowest mean absolute percentage error value.

[11] 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 [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 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 [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 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, [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 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. [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 mean absolute percentage error estimate than that of the autoregressive model. A study by [18] proposed a combination of the 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, [19] . 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. [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 vapour compression cycle in a building model and focussed on applying control measures to air conditioning systems in order to compute predictive estimates.

## III. METHODOLOGY

This study investigates the performance of the kalman filter adaptation algorithm in relation to the regression model and artificial neural network; 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.

### *A. Data Set Used*

The dataset was obtained from a local university in Malaysia on a daily basis for 273 days, between January 1 and September 30 2013. It consisted of electricity consumption readings, with some factors such as electricity price, humidity and temperature included in the forecasting model. The electricity rate used in this study is charged at a cost of RM16 per watt of electricity consumed, irrespective of time of the day. The daily average temperature and humidity data for the period under study were taken from *weatherspace* [21] , a weather website. The source for electricity prices was taken from the Sarawak electricity Supply Corporation (SESCO).

*Fig.1* shows the daily electricity consumption between January 1 and September 30, 2013 for the different appliances considered in this study. Daily electricity consumption values indicate that air-conditioning consumed the most electricity within this period.

It is possible to show that electricity consumption demonstrates a more regular behaviour when compared with unit electricity price, probably because electricity price been considered as one of the factors affecting load in the deregulated market [8]. The representation for electricity consumption based on price is given in *Fig. 2*. This study indicate that consumers do not necessarily react to price rates, as pricing for electricity use does not change irrespective of the appliances' time of use. The graph only identifies the amount of energy consumed over a period of time, given electricity costs. Temperature does not seem to be linked to humidity, as shown in *Fig. 3(a)* and *Fig. 3(b)*. As temperature increased between January and March, humidity decreased within that same period, and when temperature decreased between July and December, humidity increased within the same period. [15] proposed that warm temperature results to a lower than average relative humidity.

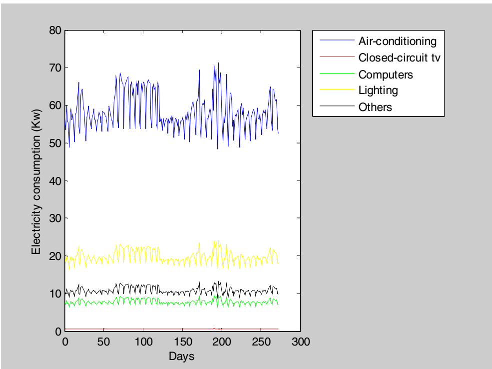


Fig. 1. Daily electricity consumption (Source: Jan1-Sept 30, 2013)

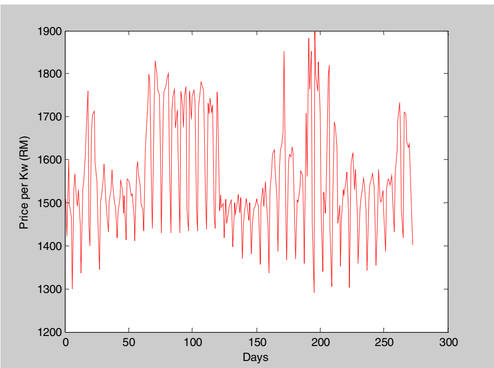


Fig. 2. Daily data exploring price (Source: Jan1-Sept 30, 2013)

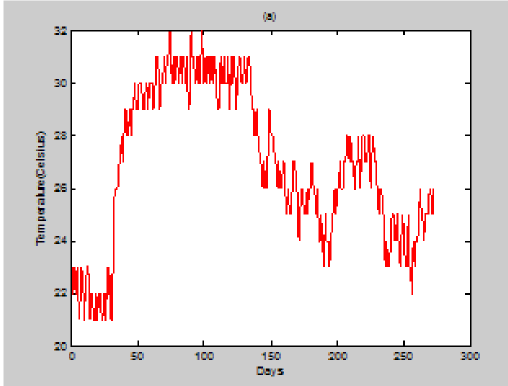


Fig. 3(a). Daily data exploring temperature (Source: Jan1-Sept 30, 2013)

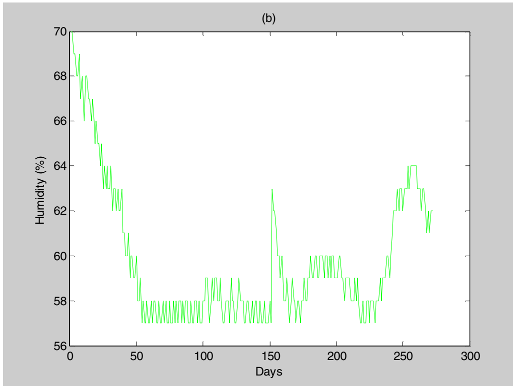


Fig. 3(b). Daily data exploring humidity (Source: Jan 1-Sept 30, 2013)

## *B. Modelling Methodology*

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

*1) Regression model*: 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 [22], is shown as follows:

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

where $y_i$ is the dependent variable, $x_{.i}$ is the independent variable, $\beta_i$ is the regression coefficient of $x_{.i}$ and $\epsilon_i$ 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).

$$\hat{y} = b_0 + b_1 x_{1i} + b_2 x_{2i} + \cdots + b_k x_{ki} \qquad (3)$$

*2) Artificial neural network (ANN)*: Artificial neural network was described in [23] as a hidden-layer feedforward network tool and the most widely used technique for time-series modelling and forecasting. [16] described the 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:

$$y_1 = f_1(x_t, x_{t-1}, ..., x_{t-n})$$
$$y_2 = f_2(x_t, x_{t-1}, ..., x_{t-n})$$
$$\vdots \qquad (4)$$
$$y_t = f_t(x_t, x_{t-1}, ..., x_{t-n})$$

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:

$$y_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j (\beta_{0j} + \sum_{i=1}^{p} \beta_{ij} y_{t-1}) + \in_t \qquad (5)$$

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) Kalman filter adaptation technique*: In this study, the kalman filter algorithm was identified as a more reliable technique for predicting electricity consumption compared with the 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 [24] is represented as:

$$y_{1i} = \Upsilon_{10} + \Upsilon_{11} x_{1i} + \Upsilon_{12} x_{2i} + \in_{1i}$$

$$y_{2i} = \Upsilon 20 + \Upsilon 21 x 1i + \Upsilon 22 x 2i + \beta 21 x 3i + \varepsilon 2i$$

$$y_{3i} = \Upsilon_{30} + \Upsilon_{32} x_{2i} + \beta_{31} y_{1i} + \beta_{32} y_{2i} + \in_{2i}$$

$$\vdots \qquad (6)$$

$$y_{ti} = \Upsilon_{t0} + \Upsilon_{tt-1} x_{t-1,i} + \beta_{t1} y_{1i} + \beta_{t2} y_{2i} + ... + \beta_{t,t-1} y_{t-1},_i + \in_{t-1,i}$$

Where $\Upsilon_{tt}$ and $\beta_{tt}$ (t=0, 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 variables $x_{t-1,i}$ is given as price, temperature and humidity, $y_{t-1,i}$ 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:

$$\widehat{y_{ti}} = b_{t0} + b_{t,t-1} x_{t-1,i} + \propto_{t1} y_{1i} + \propto_{t2} y_{2i} + \cdots + \propto_{t,t-1} y_{t-1,i} \qquad (7)$$

Equation (6) gives the values between the observed and predicted values.

$$\in_{ti} = y_{ti} - \hat{y}_{ti} = b_{to} - b_{t,t-1} x_{t-1,i} - \alpha_{t1} y_{1i} - \alpha_{t2} y_{2i} - ... - \alpha_{t,t-1} y_{t-1,i} \qquad (8)$$

for t = 1,2,…,n

The sum square of residuals (SSE) is:

$$SSE = \sum_i (y_{ti} - b_{to} - b_{t,t-1} x_{t-1,i} - \alpha_{ti} y_{1t} - \alpha_{t2} y_{2i} ... - \alpha_{t,t-1} y_{t-1,i})^2 \qquad (9)$$

The coefficients $b_{to}$, $b_{t,t-1}$ and $\alpha_{t,t-1}$, t = 0, 1, 2…. are obtained by solving (7).

However, the 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.

## IV. 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 the regression model, artificial neural network and the kalman filter adaptation algorithm. The error estimates for the methods is 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 [25] .

The root mean squared error is given as:

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

The mean average percentage error is given as

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

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 I.

TABLE I. PERFORMANCE OF ANN, MULTIPLE REGRESSION AND KALMAN ALGORITHM

| Parameters | By Regression model | By Artificial Neural Network | By 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 the kalman algorithm were low compared to regression model and artificial neural network. Table I show that the RMSE values for the kalman algorithm, regression model, and artificial neural network are 0.73, 5.16, and 5.5 respectively. The MAPE value for the kalman algorithm is 0.39, which is the best result when compared to the regression model and artificial neural network, with mean average percentage error values 3.73 and 4.1 respectively. Therefore, the kalman algorithm performs well, when compared to artificial neural network, and the regression model.

*Fig. 4*, *Fig. 5* and *Fig. 6* show the results of actual and estimated daily electricity consumption by the respective data modelling techniques. In past literature reviewed, the performance of the artificial neural network was good, but was not very effective in this study. For instance, as shown in *Fig. 5*, ANN consistently forecasts in wrong direction, i.e. during days 30-60, it significantly overestimated electricity consumption when real consumption dropped. During days 70-100, when the real consumption jumped up drastically, ANN forecasted the consumption in a decreasing pattern and thus largely underestimated it. The kalman method is more consistent in forecasting electricity consumption as the forecasts neither overestimated nor underestimated data.

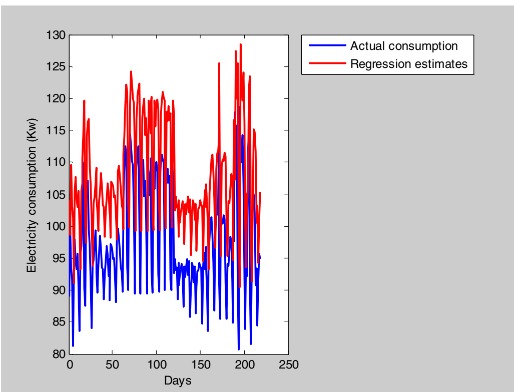


Fig. 4. Actual consumption compared with simulated consumption by regression model (Source: Jan 1- Aug 7, 2013)

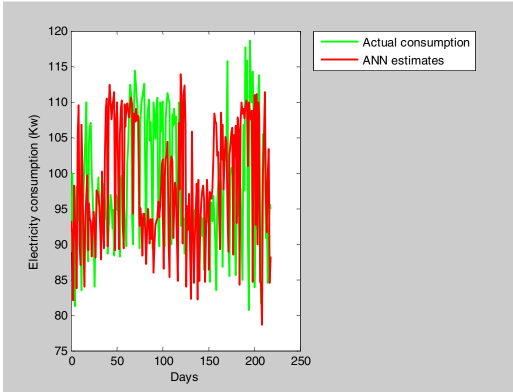


Fig. 5. Actual consumption compared with simulated consumption by ANN (Source: Jan 1-Aug 7, 2013)

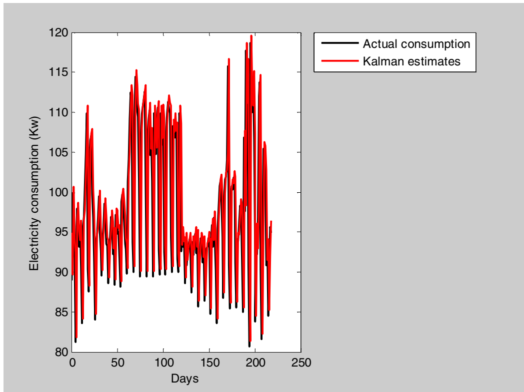


Fig. 6. Actual consumption compared with simulated consumption by kalman algorithm (Source: Jan 1-Aug 7, 2013)

In order to show the modelling precision and validity of the forecasting techniques, as given in [26] and also by [27], standard deviation of predictions was computed for each of the methods used for predictions. Forecasting methods with low standard errors 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 the kalman algorithm predicted electricity consumption with a low standard deviation of 0.1 %, thus with very good forecasting accuracy.

TABLE II. DESCRIPTIVE STATISTICS FOR ELECTRICITY CONSUMPTION MODELS

| Model | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|
| Regression | 107.7 | 8.3% | 90.5 | 128.4 |
| ANN | 98.5 | 11.3% | 78.6 | 113.9 |
| Kalman | 98.7 | 0.1% | 81.3 | 119.6 |

Furthermore, *Fig. 6* shows the closeness of predicted values to actual data as compared to *Fig. 4* and *Fig. 5*. The results from the simulation indicated estimated data are very much similar to the actual one using the kalman algorithm in comparison to the regression model and artificial neural network. On the basis of the performed validation test and error analysis presented in this paper, the kalman algorithm can be seen as a valid technique to predict electricity consumption.

## V. CONCLUSION

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 the regression model, artificial neural network and the kalman algorithm for predicting electricity consumption were tested using the powerlogic pm 5350 readings for 275 days at the Universiti Malaysia Sarawak. From the results discussed in this research, it is observed that predicted values for electricity consumption by the 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 the 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 the regression model, and artificial neural network. This study show that the kalman algorithm is the most effective method of predicting consumption data compared to the regression model, and artificial neural network.

Further studies could focus on increasing the number of input parameters for the 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.

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