

Prediction of Electricity Consumtion based on Complex **Computational Method**

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ABSTRACT

The tasks of finding and selecting an accurate computational method that exists to undertake individual characteristics with various computational methods were considered difficult and would take a long completing time. The main objective of this research is to conduct a thorough study involving techniques of various computational methods that normally used in modeling and forecasting real-world problems. This paper presents the comparison results of the computational modeling methods that tested on electricity consumption data of Sarawak Energy Malaysia. The three computational methods compared in this study were Box-Jenkins technique, regression method, and artificial neural network. The models were tested on data collected from Sarawak Energy in Malaysia with regard to electricity consumption by using MATLAB software. The verification of the three methods was done using the computational statistics measurement namely the root means square error and the mean absolute percentage error. The results show that the artificial neural network was the most outperformed technique in generating the accurate prediction.

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1. Introduction

Investigations with modeling of actual challenges have useful characteristics in decisionmaking for various applications such as in the manufacturing systems, construction, military applications, health applications, logistic and transportation distribution. Machine learning that was known as a complex computational technique has become a big business in the last few years since the emergence of Industrial 4.0 era. However, this new demand analysis tool has largely outpaced the implementation of good methods due to its complicated. To apply the methods comprises complex parts of mathematical principles and tricks, which hinder the inexpert data scientist to conduct the study. The contributions of this research paper are as follows. Firstly, it provides a study of the review of the common machine learning techniques in mathematical description. The selected machine learning are Box-Jenkins, regression and artificial neural network. Secondly, this paper presents the simple evaluation method to be compared among the three methods when tested on a prediction problem. The problem was taken from the real cases of electricity consumption from the Sarawak Energy in Malaysia. Based on the the evaluation, a decision has been made to select the reliable modeling technique on the tested dataset. To the best of our knowledges, the existing





literatures have not yet employed the three selected machine learning modeling to be compared on the problem of electivity consumption prediction.

2. Literature Review

To apply appropriate machine learning tools to modeling problems, it is expedient to analyze various techniques to identify the method that will produce accurate estimates [1]. Researchers in [2] explore establishing quantitative methods exploring challenges, consequently enhancing competence. Also, researchers in [3] highlight the important objectives with quantitative methods when describing effectiveness. The paper specifically focused at length on different researches relating to using quantitative methods. It reviews special computational methods, together with their algorithms. The paper states that typical computational methods are less accurate than deep learning methods. Although deep learning methods. This research evolves representations employing fusion using different tine series methods [4]. The technique was used to analyze consumer behavior for developed models. Decision-making needs to be inferred from models to improve efficiency [5]. While in [6] states that in overall, the developments of computational method will inherent enabling reasoning. The paper reviews various computational techniques that covered several areas and machine-learning models were utilized to classify various problems. Techniques without machine learning have also been utilized for comparison.

In this paper, the interest was coined on the complex computational model on energy consumtion. The International Energy Agency proposed that world total energy consumption presents increasing consumption for electricity from the past to the present. The paper presents that proper planning is needed for obtaining crucial energy policy for decision-makers to reduce losses [7]. A good problem is using quantitative techniques in treating medical challenges. Several perceptions can be used for categorization [8]. The COVID-19 disease impacts this world, causing the deaths of many [9]. A reliable prediction of stock markets is desirable because of its constant changes. Establishing quantitative techniques has improved calculation skills and productivity [10]. The work utilizes computational methods for forecasting requisite product prices with different organizations. Due to challenges encountered in research on electricity consumption behavior, [11] examine the electricity consumption characteristics in residential buildings. This paper utilizes cluster analysis and classification techniques. This research is differentiated from previous models using simulation analysis.

3. Research Method

A study of the computational modeling methods was undertaken to identify an accurate method for modeling and forecasting data. The collection of data was taken from Sarawak Energy in Malaysia. The platform for the implementation of the results was done with the MATLAB software.

3.1 Dataset

This research utilizes actual electricity consumption data collected from Sarawak Energy Berhad, where doctoral research was undertaken by the first author. The data was taken from a building at the Universiti Malaysia, Sarawak (UNIMAS). These consist of data collected from a Power Logic PM5350 (PM5350) power meter installed in the Faculty of Computer Science and Information Technology (FCSIT) building by Sarawak Energy Berhad (SEB). The actual electricity consumption readings for individual electricity appliances were collected between 2009 and 2012 and applied to the models. The data-set was split into two; 70% of the data for training, and 30% for the testing.

This research describes estimating models based on electricity consumption, including the theories behind the techniques. For comparisons, statistical tests performance measures were used to test the accuracy of the derived models. A power meter was installed in the FCSIT building to take aggregate consumption readings for SEB. Data consists of the power bills provided by the Asset Management Division, UNIMAS and also collected from the power meter installed by the SEB.

The target variable for the data-set is total monthly electricity consumption data for the FCSIT building for the four years (2009-2012). A set of four variables are used as the independent variables, including the floor level, room temperature, occupancy rate of the rooms, and electric consumption for individual appliances.

3.2 Box-Jenkins Technique

The Box-Jenkins technique used in this study applies auto regressive integrated-moving average (ARIMA) process as a modeling method. The purpose of utilizing representation is for reporting the characteristics of the model. The sustainability of time series modeling was discussed by [12] and highlighted that the technique was able to estimate models for meeting various needs. For an example, researchers in [13] presents a database showing the challenges in COVID-19 and also shows day by day effects of the disease based on the forecasting model developed with Box-Jenkins. Moreover, the objective of research in [14] is to forecast the number of Schizophrenia Disorder by using Box-Jenkins.

A probability function of models useful to predict the probability of future behavior. The models are stochastic time series, where a sequence of numbers is produced in the stochastic process. The *backward shift operator* is applied to the computation of the Box-Jenkins technique as the equation (1).

$$\nabla z_t = z_t - z_{t-1} = (1-B) z_t \tag{1}$$

The stochastic models are based on the idea that an observable time series z_t , which is transformed to the process a_t , with $\psi_1, \psi_2, ...$ as weights as in the equation (2)

$$z_t = \mu + a_t + \psi_1 a_{t-1} + \psi_2 a_{t-2} + \dots = \mu + \psi(B) a_t$$
⁽²⁾

In general,

$$\psi(B) = 1 + \psi_1 B + \psi_2 B^2 + \dots$$

when $t - 1, t - 2,\dots$ be z_{t-1}, z_{t-2},\dots

Also, let $z_t = z_t - \mu$ be the series of deviations from μ , The autoregressive model given by equation (2) may be written economically as $\phi(B)\tilde{z}_t = a_t$ and the model consists of $\mu, \phi_1, \phi_2, ..., \phi_p, \sigma_a^2$ substitude as equation (3).

$$\tilde{z}_{t-1} = \phi_1 \tilde{z}_{t-2} + \phi_2 \tilde{z}_{t-3} + \dots + \phi_p \tilde{z}_{t-p-1} + a_{t-1}$$
(3)

Hence, the following equation (4)

$$\tilde{z}_{t} = \phi^{m+1} \tilde{z}_{t-m-1} + a_{t} + \phi a_{t-1} + \phi^{2} a_{t-2} + \dots + \phi^{m} a_{t-m}$$
(4)

can be generally defined as equation (5)

$$\tilde{z}_{t} = \phi^{-1}(B)a_{t} = \psi(B)a_{t}$$

$$(5)$$

$$(5)$$

with $\psi(B) = \phi^{-1}(B) = \sum_{j=0}^{\infty} \psi_j B^j$

To becomes

$$\varphi(B)z_{t} = \phi(B)\nabla^{d}z_{t} = \theta_{o} + \theta(B)a_{t}$$
(6)
where $\theta(B) = 1 - \theta_{1}B - \theta_{2}B^{2} - \dots - \theta_{q}B^{q}$.

Based on the mathematical notations, the algorithm of Box-Jenkins can be summarized as: Step 1: Set up stationarity of the time series

Step 2: Pick out the model for data

Step 3: Describe and model

Step 4: Estimate model variables

Step 5: Perform model evaluation

3.3 Regression Technique

Regression technique called as simple regression, to describe the relationship between independent variables to the dependent variable. A utilization of regression analysis proposed by [15] is to resolve the prediction model of atmospheric applications. Researchers in [16] developed multiple regression-based models for gas data. This begins with a hypothesis about how several variables might be related to another variable and the relationship. The following describe regression model. Given a straight line, and let

$$\varepsilon^2 = \Sigma (y_i - y_p)^2 \tag{7}$$

where y_p = predicted values, and y_i = actual values. Also, let

$$y_p = m x_i + b \tag{8}$$

Then, combine equation (7) and equation (8) where

equation (9) is at a minimum

$$\frac{ds^z}{dm} = 0 \quad \frac{ds^z}{db} = 0 \tag{9}$$

Solving for equation (9), gives

$$\frac{ds^z}{dm} = 2m\Sigma x_i^2 + 2b\Sigma x_i - 2\Sigma(x_i y_i) = 0$$
(10)

Solving for equation (10), gives

$$\frac{ds^z}{db} = 2m\Sigma x_i + 2\Sigma b - 2\Sigma y_i = 0$$
(11)

To simplify the notations in equation (10),

$$Sxy = mSxx + bSx \tag{12}$$

$$Sy = mSx + nb \tag{13}$$

The optimized values for *m* and *b* are respectively given as:

$$m = \frac{n \sum x_{i} y_{i} - \sum x_{i} y_{i}}{n \sum x_{i}^{2} - (\sum x_{i})^{2}} \quad b = \frac{\sum y_{i}}{n} - \frac{m \sum x_{i}}{n}$$

Therefore, the algorithm for regression based on the mathematical derivation can be summarized as:

Step 1: Start the input of variables

From equation (11),

Step 2: Forecast the dependent factor by the input of an independent factor

Step 3: Compute the error for forecasting in the data

Step 4: Compote the variables concerning a₀ and a₁

Step 5: Compute and add the dependent variables

3.4 Artificial Neural Network

Reseachers in [17],[18] reports Artificial Neural Network (ANN) computational methods. The ANN process is classified into training, validation, and evaluation. The definitions of these terminologies were discussed by [19], and are described with three important elements as follow: *Training set* as the database for modifying weights.

Validation set that consists of using errors to adjust the database.

Evaluation that is using real data for analysis.

Researchers in [20] presented an adaptive forward selecting modeling technique for the ANN model to predict load for space heating in buildings. Aside from providing the important tools, the researchers demonstrates the used of the tools for images classification based on feedforward ANN[21]. The model of feedforward ANN is illustrated in Figure 2 denoted in equation (14) and equation (15).

$$u_k = \sum_{j=1}^m w_j x_j \tag{14}$$

and

$$v_k = \varphi(u_k + b_k) \tag{15}$$

where $x_1, x_2, ..., x_m$ are the input signals; $w_1, w_2, ..., w_m$ are weights; u_k is output; b_k are errors. $\varphi(\cdot)$ are variables and y_k is signal for ANN. Also as denoted in equation (16),

$$v_{i} = u_{i} + b_{i} \tag{16}$$

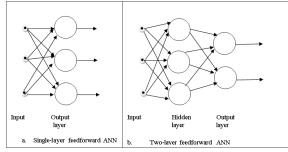


Figure 2. Feedforward ANNs topology

The algorithm for the neural network can be summarized as:

- Step 1: Acquire fundamental knowledge of the problem
- Step 2: Get various techniques
- Step 3: Disintegrate the problem into varicose steps
- Step 4: Begin with a basic illustration
- Step 5: Verify model computations
- Step 6: Make a note of the study

3.5 Comparison of Models

In this study, comparing the performance of the models involves identifying an accurate technique by comparing their Root Means Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) for their respective estimates. The error values for the models are given to have an insight into the performance of the models. The errors are calculated based on an average of weighted values. To select an accurate model, the following process is taken into consideration: Step 1: Select a model based on an observed pattern.

Step 2: Produce a fitted value of data.

Step3: Compute the error.

Step 4: Produce a decision for the model based on the error.

Then, the one-sided moving average for the forecasting to be used by the selected machine learning is defined as:

$$F_{t+1} = \frac{X_t + X_{t-1} + \dots + X_{t-n+1}}{n}$$

= $\frac{1}{n} (\sum_{i=t-n+1}^{t} X_i)$ (17)

where t is the current value and t + 1 is the next value. Then,

$$F_{t+1} = \frac{1}{n} \left(\sum_{i=t-n}^{t-1} X_i \right) + \frac{1}{n} \left(X_t - X_{t-n} \right)$$

= $F_t + \frac{X_t}{n} - \frac{X_{t-n}}{n}$ (18)

$$F_{t+1} = \frac{X_t}{n} - \frac{F_t}{n} + F_t$$
(19)

$$F_{t+1} = \frac{1}{n}X_t + \left(1 - \frac{1}{n}\right)F_t$$
(20)

$$F_{t+1} = \propto X_t + (1 - \alpha)F_t \tag{21}$$

where t is the current value, F_{t+1} and F_t are estimates, and X_t is the present value. \propto is defined as the smoothing constant. It is between zero and unity. In evaluating the accuracy of a model can be denoted as equation (22).

$$e_t = X_t - F_t \tag{22}$$

4. Results and Discussion

Based on the 23 data of the testing dataset, the actual data and the estimates results obtained for the Box-Jenkins, Regression and ANN models are given in Table 1.

Table 1. Actual data and estimates for three machine learning methods

Box-Jenkins		Regression		ANN	
Actual data	Estimates	Actual data	Estimates	Actual data	Estimates
39.59	46.11	39.59	43.56	39.59	44.18
43.60	48.43	43.60	46.77	43.60	47.91
40.74	44.67	40.74	43.14	40.74	43.94
42.75	48.95	42.75	46.32	42.75	47.01
39.18	46.21	39.18	43.34	39.18	44.22
34.79	40.66	34.79	37.21	34.79	38.54
39.68	45.79	39.68	43.11	39.68	44.32
40.84	44.41	40.84	42.32	40.84	42.99
42.03	45.76	42.03	43.01	42.03	43.87
41.78	46.46	41.78	43.32	41.78	44.58
42.94	46.42	42.94	43.11	42.94	44.36

38.12	43.68	38.12	39.92	38.12	40.93
35.91	40.43	35.91	37.88	35.91	38.03
40.95	45.74	40.95	42.43	40.95	43.46
41.56	47.32	41.56	44.47	41.56	45.84
42.34	45.46	42.34	43.13	42.34	43.79
42.64	46.34	42.64	43.73	42.64	44.74
42.15	46.85	42.15	43.58	42.15	44.36
36.90	40.85	36.90	37.41	36.90	38.58
35.76	39.47	35.76	36.74	35.76	37.74
41.58	45.27	41.58	42.82	41.58	43.43
42.15	46.11	42.15	43.15	42.15	44.85
40.92	44.32	40.92	41.89		

The results of the comparisons are shown in Table 2.

Table 2. Evaluation of Box-Jenkins, ANN, and regression.

	Box-Jenkins	ANN	Regression
RMSE	0.873	0.596	0.704
MAPE (%)	1.957	0.921	1.199

The output for the RMSE and MAPE of Box-Jenkins, ANN, and regression indicate that ANN is the most accurate for estimating data. The RMSE and MAPE values of the neural network are smaller evaluated with Box-Jenkins and regression. Table 2 indicates that RMSE for Box-Jenkins, ANN, and regression are 0.873, 0.596, and 0.704 respectively. The MAPE for the neural network is 0.921%, which is the smallest compared with Box-Jenkins, and regression with MAPE values of 1.957%, and 1.199% respectively.

The inherent features of applying techniques are summarized in Table 3. The techniques discussed in this section were examined to determine their strengths and weaknesses. In summary, challenges in applying these techniques are discussed and analyzed.

Method	Positive Attributes	Negative Attributes
Box-Jenkins	 Adapts multiple variables Solution based on multi-variables Simple input data Possible to adjust the model to more variables Discusses trends 	 Does not differentiate between components of variables There is no explicit description of the components of variables Need to identify a more appropriate technique for modeling Does not specify requirements for individual variables No information on the specific effect of individual variables on the dependent variable

Table 3. Characteristics of methods

Regression Analysis	 Incorporates multiple variables Information on the effect of individual variables on the dependent variable General mathematical model to estimate variables Handles larger data than the Box- Jenkins technique Model shows when entering into the model or not 	 Small and large transitions in time are under-represented in the model There is no explicit description of components of individual variables Does not differentiate between components of variables
Artificial Neural Networks	 Discusses the use of multiple variables Introduces artificial intelligence for model Discusses modeling by validating and testing data. Determines the model's behavior. Handles large data 	 Does not specify model requirements for individual variables No information on the effect of individual variables on the dependent variable.

5. Conclusion

A critical study of computational techniques was carried out to be reported in this paper. Each technique has its limitations and challenges. Modeling data requires a high degree of accuracy such that any deviation from expectation may result in obtaining accurate estimates. The techniques used in the various studies were existing machine learning techniques applied to heterogeneous problems. According to reviewed papers, the following challenges were identified for Box-Jenkins, regression analysis, ANN:

- The need to identify a more accurate and generic technique for predicting data.
- Models to handle big data.
- Lack of insight into the estimation of components for variables.
- To apply a technique for modeling.
- The study of the extent to which various components affect variables.

In this study, ANN have been identified as the most reliable technique for case of the tested data on Sarawak Energy Consumtion. Machine learning tools can model non-linear problems due to real-life challenges, some of which are complex. These tools can deduce unrevealed interconnection between variables, thereby producing indeterminate models for concealed information. Different from the techniques that have been reviewed in this study, the ANN has no limitations with the development of models.

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Conflict of Interest

The authors declare no conflict of interest in the subject matter or materials discussed in this manuscript.

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