Forecasting Electricity Consumption Under the Responsibility of the Provincial Electricity Authority (PEA): A Sectoral Approach

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Abstract

The Forecasting electricity consumption under the responsibility of the Provincial Electricity Authority (PEA) for seven years from 2017 to 2023 is examined by exploring all five sectors, namely residential, commercial, industrial, agricultural, and non-profit, and comparing the effectiveness of each forecast model. The four models under study are the Holt-Winters' two parameters linear exponential smoothing non-seasonal (Holt-Winters' non-seasonal), Autoregressive Integrated Moving Average (ARIMA), Artificial Neural Network (ANN), and Support Vector Machine-Regression (SVM-R). The Mean Absolute Percentage Error (MAPE) was used to determine the most suitable and effective model. MAPE was the first to be considered, and the comparative results of the lowest MAPE values indicate that the Holt-Winters' non-seasonal model was the most suitable for forecasting electricity demand in the residential, industrial, and non-profit sectors, with ARIMA(3,1,0) and ANN being most appropriate for the commercial and agricultural sectors. Total electricity demand from 2017 to 2023 for five sectors is projected to continuously increase. The annual electricity capacity of the PEA shows a continuous decrease when compared to total electricity demand from 2017 to 2023. The distributed volume was 369.86, 335.35, 292.18, 270.93, 246.03, 223.60, and 207.42 million kWh respectively, due to the continuous decrease in electricity sales significantly impacting on the management of electricity production and distribution. Consequently, in the future, there may be a shortfall in electricity production and distribution under the responsibility of the PEA.

KEYWORDS: sectoral, forecasting electricity consumption,

Provincial Electricity Authority (PEA)

Introduction

The Electrical energy is fundamental to the daily lives of the global population and the economy. For Thailand, the energy supply procurement and distribution of electrical power require a great deal of investment. The International Energy Agency (IEA) estimates that from 2011 to 2030, investment in the electrical energy sector for production and distribution in China, India, and the ASEAN countries will increase by up to 32% (IEA, 2014). As a developing country, it is undeniable that for Thailand, energy plays a critical role in driving economic growth and improving competitiveness. It is also important for illumination and cooking. The provision of energy is a critical part of the infrastructure and economic activities of Thailand since electrical energy can help to foster growth as well as social and economic development. However, electrical energy cannot be quarantined and demand varies at different times. Therefore, the relevant authorities have a key role to play in efficient electrical energy management and the provision of sufficient supplies to meet consumption demand. Such authorities include the Electricity Generating Authority of Thailand (EGAT)[1], the Metropolitan Electricity Authority (MEA)[2], and the Provincial Electricity Authority (PEA)[3]. However, in most parts of the country, the PEA is responsible for providing services to 74 of the 77 provinces. The country's average usage has recently shown an increase in similar annual proportions. In 2016, the total annual usage was 182,847 GWh or 182,847 million KWh; an increase of 4.6% from the previous year (Power Economic Division, PEA, 2017). In addition, electricity demand in Thailand has also been forecast for uncategorised user groups from 2008 to 2021, measured by Megawatts (MW). The results indicate that the demand for electricity is expected to increase from 28,748.40 MW in 2008 to 58,749.60 MW in 2021, representing a rise of 30,001.21 MW. However, the production and distribution capacity is projected to be 58,199.60 MW in 2019; exceeding consumption demand (Phupha et al, 2010).

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[1] Electricity Generating Authority of Thailand (EGAT) is an enterprise under the Ministry of Energy, carrying on the business of electricity production, provision, and supply to the MEA and PEA (OIC, 2016).

[2] Metropolitan Electricity Authority (MEA) is a state enterprise under the Ministry of Interior, with a duty to produce and distribute electricity to people living in Bangkok, Nonthaburi, and Samut Prakan Provinces (OIC, 2016).

[3] Provincial Electricity Authority (PEA) is a state enterprise under the Ministry of the Interior with a duty to produce and distribute electricity to 74 of the 77 provinces in Thailand. The exceptions are Bangkok, Nonthaburi, and Samut Prakarn which come under the responsibility of the MEA (OIC, 2016).

In accordance with the foregoing, it is clear that electricity energy consumption in Thailand is continuously increasing. Meanwhile, the investment process and service expansion of the PEA is expected to take at least two to four years per an electricity production and distribution station from the start of the construction process. Since current electricity demand is increasing, Thailand needs to take the necessary steps to ensure an adequate supply of electrical power (Project Planning Division, PEA, 2017).

If the current situation is allowed to continue, it could the result in an electricity energy crisis. Therefore, it is necessary to undertake a thorough study of development of electrical power or expansion of its availability to meet all economic activity requirements in the areas for which PEA is responsible. These include 74 provinces, excluding Bangkok, Nonthaburi, and Samut Prakan since these are under an obligation to purchase electricity from the Electricity Generating Authority of Thailand (EGAT) which produces some of its own electrical power to cover the area concerned. The number of electricity users currently stands at 18,893,916, accounting for 99% of the total area of the country. Thus, EGAT plays an essential role in Thailand's energy security (Public Relations Department, PEA, 2016) and as a consequence, the service extension in remote rural areas has not been fully completed. Ultimately, this may lead to an electricity power shortage in the country if Thailand is unable to import sufficient electricity.

Objectives

Due to the previously mentioned restrictions, the objectives of this research are:

1. To study and forecast the level of electricity consumption for the seven years from 2017 to 2023.

2. To compared four forecasting methods to find the most effective forecasting method in each sector.

In this paper consists of five parts: 1. Literature review; 2. Research framework; 3. Data and methodology; 4. Results and discussion; and 5. Conclusion and suggestions.

Literature Review

The following is a brief review of the previous research on forecasting electrical energy based on time series data, divided into two parts: an overall literature review and a literature review in the context of Thailand.

Overall Literature Review

Shakibai & Koochekzadeh (2009) investigated modelling and the prediction of agricultural energy consumption in Iran based on time series data by using ANN and ARIMA models for forecasting. The performance of the two models was compared on the basis of MAD, RMSE, and MAPE, respectively. The results showed that the ANN model had better predictive power than ARIMA model for energy consumption in the agricultural. Erol, et al. (2012) forecasted electrical power consumption of residential and commercial sectors in Turkey based on time series data using the Holt-Winters, SARIMA, and ANN models, then considered those providing the lowest MAE and RMSE values to compute suitable models for each sector. Their findings indicate that the most efficient model for forecasting electrical power consumption in the residential and commercial sectors was the Holt-Winters'; whereas Katara, et al. (2014) conducted a time series analysis of electricity demand in Tamale, Ghana by using the ARIMA model to forecast the demand for electrical power by exploring three sectors: domestic, industrial, and commercial to determine the performance of different models, namely RMSE, MAPE, and MAE. The results indicate that the domestic and commercial sectors are likely to experience greater demand for electrical power than the industrial sector. These findings are consistent with the work carried out by S. A. Sankodie (2017) forecasting electricity consumption in Ghana using time series data and ARIMA model. Evidence from the ARIMA model forecast shows that Ghana's electricity consumption will grow from 8.52 billion kWh in 2012 to 9.56 billion kWh in 2030 in the predicted scenario. Unakitan & Turkekul (2014) on the demand of the agricultural sector for diesel consumption in Turkey using annual time series data for diesel consumption in the Turkish agricultural sector from 1970 to 2006 in the forecasting based on the ARIMA model. According to the model's results, diesel consumption is predicted to be over four million tonnes in 2020. Sabir (2018) predicted household energy demand by using the Holt-Winters' non-seasonal, ARIMA, ETS, and naive methods and considered those that provided the lowest MAE, MAPE, Max AE, and Sigma to compare the most suitable forecasting models. Shao & Tsai (2017) the prediction of industrial and commercial electricity sales in Taiwan using ARIMA, ANN, and integrated ARIMA-ANN techniques and time series data. The performance of the three models was compared using MAPE. The results indicated that the most efficient was the integrated ARIMA-ANN model. Nichiforov, et al. (2017) studied energy consumption forecasting using ARIMA and nonlinear autoregressive neural network (NAR) models and time series data for analysis. The performance of the models was compared by considering MSE, RMSE, MAE, and MAPE. The results showed that ARIMA had better predictive power than the NAR model. Rahman & Ahmar (2017) investigated the forecasting of primary energy consumption in the United States using two predictive models, namely ARIMA and Holt-Winters' models with time series data for analysis. The performance of ARIMA and the Holter-Winters' model was compared on the basis of MAE, RSS, MSE, and RMSE. The Holt-Winters' model was found to have higher predictive accuracy than the ARIMA. Usha & Balamurugan (2016) studied seasonal-based electricity demand forecasting in the Tamil Nadu area of India over three seasons; summer, winter, and monsoon using seasonal monthly time series data for the electricity power consumption and four forecasting techniques. These consisted of the ANN multilayer perceptron, SVM, linear regression, and Gaussian process to measure the efficiency of the model using MAE, MAPE, and Direct Accuracy. The SVM model was found to be a suitable and effective model for forecasting the electricity power consumption. The study by As'ad (2012) on finding the best ARIMA model to forecast daily peak electricity demand for the first seven days of June 2011 in New South Wales, Australia used half-hourly time series demand data and four appropriate ARIMA models based on the previous three, six, nine, and twelve months of data. The RMSE and MAPE methods were applied to measure the forecast accuracy and the results showed that the ARIMA model based on the previous three months of data was the best model in terms of forecasting two to seven days ahead, and the ARIMA model based on the previous six months' data was the best model at forecasting one day ahead. Salahat & Awad (2017) investigated short term electricity forecasting consumption in Palestine, based on time series data using the ANN model and measuring its efficiency based on the MSE value. For Ogcu, et al. (2012) studied electricity demand in Turkey using monthly time series data analysis. ANN and SVM-R methods were used and the forecast accuracy was compared on the basis of MAPE. The results showed that the SVM-R method had more predictive accuracy than the ANN method.

Literature Review in the Context of Thailand

Bunchongsilp (2007) forecasted large industry electrical energy usage for six provinces in Thailand, consisting of Phatthalung, Satun, Songkhla, Pattani, Yala, and Narathiwat, using time series data and seven forecasting methods, namely trend analysis, time series decomposition, moving average length 3, moving average length 4, single exponential smoothing, double exponential smoothing, and Holt-Winters' exponential smoothing. Model accuracy performance was measured by considering the value of MAPE. Newinpun, et al. (2012) investigated the forecasting of peak electricity demand in the central region of Thailand using time series data and four forecasting methods: Holt-Winters' exponential smoothing, dummy variable regression, Box-Jenkins, and fuzzy dummy variable regression. Suitable forecasting methods were chosen by considering the value of MAPE. The results showed that Holt-Winters' exponential smoothing was the most accurate method. Chujai, et al. (2013) studied the forecasting of electrical power demand in the residential sector of Nakhon Ratchasima Province in Thailand, based on time series data using the ARIMA and ARMA models. When considering the value of RMSE to compare the two models, the ARIMA model was found to be the most suitable for providing monthly and quarterly forecasts. Whereas, ARMA model was the most accurate model for providing daily and weekly forecasts. Kaewhawong (2015) investigated the forecasting electricity consumption of Thailand based on time series data and two forecasting methods, namely SARIMA and regression models with ARMA Errors. Accuracy of the model was considered using the MAPE value. The results indicated that the regression model with ARMA Errors was accurate. Sujjaviriyasup (2017) studied the aggregate forecasting of peak electricity in Thailand, based on the peak electricity consumption time series data, using a hybrid SVM and genetic algorithm including ARIMA. Considering the value of MAE, RMSE, MAPE, MdAPE, RMSPE, and R^2 to compare the three models, the hybrid SVM and GM model was found to be the most accurate for forecasting. Sutthison (2019) forecast electricity consumption in three education institutions: Rajabhat Nakorn Ratchasima, Rajabhat Ubon Ratchathani, and Rajabhat Loei, using time series data and a hybrid model (the Box-Jenkins and SVM-R). The most suitable model was considered by using the MAPE value. Singchai & Keeratiwintakorn (2014) forecast the electricity demand in Thailand by considering three sectors: residential, commercial, and industrial. Time series data and two forecasting methods were used, namely ANN and SVM-R with the radial basis function. To identify a suitable model for each sector, MSE and R^2 were considered. Kornkrua & Boonlha (2016) studied electricity forecasting in Phitsanulok, Thailand using time series data and two forecasting methods: Holt-Winters' multiplicative and Box-Jenkins. The suitable models were considered using the MSE value. The results indicated that the best forecasting model was obtained by the Box-Jenkins method.

For research involving independent variables (Kandananond, 2011), electricity demand forecasting in Thailand has used time series data and three forecasting methods: ARIMA, ANN, and MLR. A suitable and effective model was considered using the MAPE value. The results indicated that ANN was the most accurate model for forecasting. These findings are consistent with the work carried out by K. Panklib, et al. (2015) who forecast electricity consumption in Thailand using time series data and ANN and MLR methods. Model performance was measured by considering MAPE and RMSE. The results indicated that ANN was the best model.

According to the literature review, the most previous studies predict electricity consumption including demand for individual sectors. Moreover, prior studies mainly predict the aggregate for electricity or produce forecasts for up to three groups. Thus, the results might not fully represent the activities of all economic sectors.

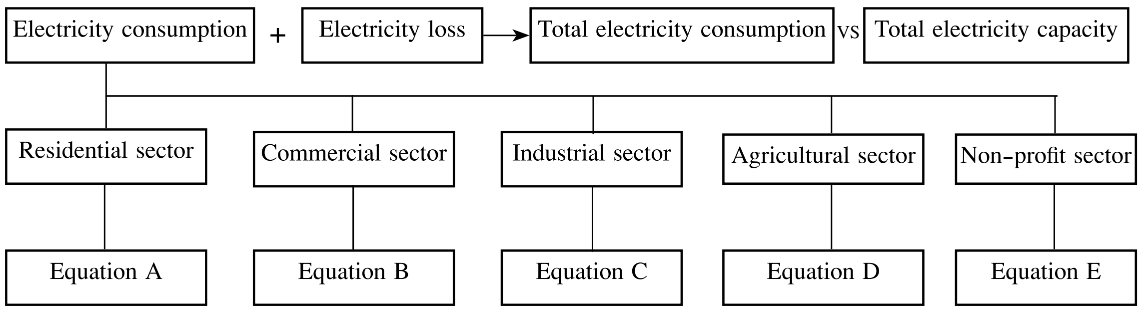
Therefore, to reduce the knowledge gap by forecasting electricity consumption in a different way from other studies, this study aims to predict the demand for electricity in five sectors: residential, commercial, industrial, agricultural, and non-profit using popular and efficient forecasting models including Holt-Winters' two parameters linear exponential smoothing, Autoregressive Integrated Moving Average (ARIMA), Artificial Neural Network (ANN), and Support Vector Machine-Regression (SVM-R). The procedure applied in this research is explained in the following section.

Research Framework

This research focuses on the forecasting of electricity consumption for the PEA. The forecasting is based on the sectoral approach, using information relating to the electricity consumption of five sectors: residential, commercial, industrial, agricultural, and non-profit. And comparisons are subsequently made between the total forecasting electricity consumption and total electricity capacity of the PEA.

In this research, the country's long term electricity energy consumption for each user segment. And the research framework for forecasting the electricity consumption of the PEA is shown in Figure 1.

Figure 1. Research framework



Source: Author (Saran Kumjinda)

Figure 1 demonstrates the difference between this research and other previous studies. The strength of this research is that it forecasts electricity consumption under the responsibility of the PEA and covers all five sectors of the country. This research provides a more detailed explanation of the results for electricity consumption than previous studies where only a few sectors or aggregate of electricity usage in Thailand was considered. In addition, this research covers most areas of Thailand. Moreover, this research can be used by the PEA for planning of electricity production and distribution as well as for capacity expansion to support electricity consumption in the future.

Data and Methodology

This research involves the collection of historical time series data on electricity consumption from the Power Economic Division, PEA, Main Office. Time series data was collected using kilowatt hour (KWh) as the variable. Five sectors were monitored: residential, commercial, industrial, agricultural, and non-profit sectors. In each sector, time series data between 1992 and 2016 was investigated under 25 observations, including estimating electricity capacity data of the PEA. Electricity loss was calculated using the technical loss method.

From the data and reviewing research, in this research utilised four forecasting methods in order to forecast the electricity consumption for all five sectors under the responsibility of the PEA. These methods include Holt-Winters' two parameters linear exponential smoothing non-seasonal, Autoregressive Integrated Moving Average (ARIMA), artificial neural network (ANN), and Support Vector Machine-Regression (SVM-R). For the performance of four forecasting methods was compared and evaluated using criteria: Mean Absolute Percent Error (MAPE). For the details can be shown as follows:

Holt-Winters' Two Parameters Linear Exponential Smoothing Non-Seasonal

This forecasting method is used to fix moving average problem since exponential smoothing emphasises the importance of current data. Older data will be marked as less important, according to its relevant time frame. The data will be altered and adjusted according to the trend, smoothing it for a more accurate result. Another parameter is being added to α alone, to create α and δ. The value of α is being set as a constant because it analyses the relevant timeframe of data according to how much it affects the result; for instance, past data might not have a significant impact on the current result. An α value range of between 0 and 1 or ($0 \leq \alpha \leq 1$), and the closer the value is to 1, the more significant the data. Value δ is the parameter or constant value used for "smoothing" the real trend value with the trend estimator for which the value also ranges between 0 and 1 or ($0 \leq \alpha \leq 1$).This helps to reduce the number of random factors or variables for which the method (Suttichaimethee, 2010) is:

$$F_{t+m} = F_t + T_t\,(m) \qquad (1)$$

When: F_{t+1} is a forecast in the next period; F_t is a forecast in the current period; is the slope of time series data; m is time to forecast ahead. Where: F_t is $\alpha Y_t + (1 - \alpha)(F_{t-1} + T_{t-1})$; T_t is $(F_t - F_{t-1}) + (1 - \delta)T_{t-1}$.

Autoregressive Integrated Moving Average (ARIMA)

Suttichaimethee (2010) described ARIMA method is used to analyse time series data in a stochastic process. In other words, this method of forecasting helps to explain the correlation and stationarity of the time series data. ARIMA method process consists of the implementation of five steps. Each step is discussed in greater detail as follows:

Stationary Test

Stationary test is a process in the creation of a pre-ARIMA model. The time series data must be validated before it can be processed to determine whether or not it has unit root properties. This can be performed in various ways. This study uses the augmented Dickey-Fuller (ADF) test to determine the unit root properties of time series data. If non-stationary time series data is found following the test, the original time series data must be converted into stationary time series data by eliminating trend, seasonality, and changes to provide a constant variance. For the stationary time series data can be obtained by using differencing.

Identification Procedure

Identification procedure involves setting ARIMA(p,d,q) to make it suitable for stationary time series data. The procedure starts by determining the autoregressive AR(p) and moving average MA(q) models by considering the ACF and PACF graph. The integrated I(d) as stationary time series data has already been differenced. The joint consideration of AR(p), MA(q), and I(d) results in the ARIMA(p,d,q) model.

Parameter Estimation

Parameter estimation is the process following consideration of ARIMA (p,d,q) for forecasting model, and appropriate for time series data. The parameter is estimated using the ordinary least square (OLS) method.

Diagnostic Checking

Diagnostic checking of ARIMA(p,d,q) takes place following the identification procedure and parameter estimation. Verification must take place to determine the suitability and reliability of estimation and forecasting by considering autocorrelation. In this research, considers the Box-Pierce (*Q*-statistic).

Forecasting

Forecasting is the final procedure when a suitable model is obtained, as well as preparing forecasting equation and parameter estimator. The forecast value is then calculated from the determined model to forecast future electricity consumption.

Artificial Neural Networks (ANNs)

In this research, supervised learning with a backpropagation algorithm learning process is applied. In general, the backpropagation algorithm of the artificial neural network (ANN) model involves data movement processing in the form of a feedforward neural network (FNN) and multilayer perceptron (MLP) architecture containing three concatenation layers including input, hidden, and output. The ANN model with a backpropagation algorithm learning process distinguishes two passes are forward pass and backward pass, presented as follows (Haykin, 2009):

Forward Computation

Let a training example in epoch be denoted by $(x(n),d(n))$, with the input vector $x(n)$ applied to the input layer of the computation nodes and the desired response vector. The input vector $x(n)$ is presented to the output layer of sensory nodes. The induced local fields and function signals of the network are computed by proceeding forward through the network, layer by layer. The induced local $v_j^{(l)}(n)$ field for neuron j inlayer l is:

$$v_j^{(l)}(n) = \sum_i w_{ji}^{(l)}(n) v_i^{(l-1)}(n) \tag{2}$$

Where: $y_i^{(l-1)}$ is the output (function) signal of neuron l in the previous layer $(l - 1)$ at iteration n, $w_{ji}^{(l)}(n)$ and is the synaptic weight of neuron j in layer l that is fed from neuron i in layer in layer $(l – 1)$. For $i = 0$, we have $y_0^{(l-1)}(n) = +1$, and $w_{j0}^{(l)}(n) = b_j^{(l)}(n)$ is the bias applied to neuron j in layer l.

The output of neuron j in the hidden layer is calculated by using the transfer function where sigmoid nonlinearity is the activation function commonly used in MLP. This consists of two forms: logistic function and hyperbolic tangent function. The logistic function is the most widely used, sigmoid nonlinearity, in its general form, is defined by:

$$\varphi_j\left(v_j^{(l)}(n)\right) = \frac{1}{1+exp^{\left(-\alpha v_j^{(l)}(n)\right)}}, \alpha > 0 \tag{3}$$

Where: $v_j^{(l)}(n)$ is the induced local field of the neuron j and α is an adjustable positive parameter. According to this nonlinearity, the amplitude of output lies inside the range $(0 \leq y_i^{(l)} \leq 1)$.

Backward Computation

Starting with the calculation of the specific slope (δ) from the current layer to the previous layer (i.e. local gradients) of the network, defined by the following equation:

$$\delta_j^{(l)}(n) = \begin{cases} e_j^{(L)}(n)\varphi_j'\left(v_j^{(L)}(n)\right) \\ \varphi_j'\left(v_j^{(l)}(n)\right)\sum_k \delta_k^{(l+1)}(n)w_{kj}^{(l+1)}(n) \end{cases} \tag{4}$$

Where: $\delta_k^{(l+1)}$ is the specific slope of node *k* at layer *(l+1)*, $w_{kj}^{(l+1)}$ is the weight linking node *k* at layer *(l+1)* with the node *j* at layer *1*, and the prime in $\varphi_j'(\bullet)$ denotes differentiation with respect to the argument.

The synaptic weights of the network in layer *l* are adjusted according to the generalised delta rule. After the specific slope is determined, the weight is computed as follows:

$$w_{ji}^{(l)}(n+1) = w_{ji}^{(l)}(n) + \alpha\left(\Delta w_{ji}^{(l)}(n-1)\right) + \eta\delta_j^{(l)}(n)y_i^{(l-1} \tag{5}$$

Where: η is learning rate parameter, α is momentum constant and *n* is the number of training cycles.

For the last step, the forward and backward computations are iterated under Equations 2 and 5 by presenting new epochs of training examples to the network until the chosen stopping criteria has been met. Further calculation is then perform followed by forecasting.

Support Vector Machine-Regression (SVM-R)

Support vector machine-regression (SVM-R) was applied to the support vector machine (SVM) proposed by Vapnik (1995) for regression analysis between an input vector in dimension $n(x \in R^n)$ and the output variable ($y \in R$) which can be used to forecast time series data by categorising the classes. The SVM-R equation can be shown as follows: (Haykin, 2009):

$$d = w^t x + b \tag{6}$$

Where: the parameter vector and the bias *b* are the slope and offset of the regression line, setting the value of *w* and *b* to determine the lowest value or risk function *(R)*:

$$R = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{N}|y_i - d_i|_\varepsilon \tag{7}$$

Where: the summation accounts for the ε-insensitive training error and *C* is a constant that determines the tradeoff between the training error and the penalising term, and $\|w\|^2$. y_i is the estimator output produced in response to example x_i.

The SVM-R method is used to predict output using the input vector. The process creates an epsilon tube for loss function which is available in many forms. This study uses the ε-insensitive loss function. The ε-insensitive loss conditions are shown in the following equation:

$$L_\varepsilon(d,y) = \begin{cases} |d-y| - \varepsilon \text{ for} |d-y| \geq \\ 0 \quad otherwise \end{cases} \tag{8}$$

Where: ε is a prescribed parameter. The loss function $L_\varepsilon(d,y)$ is called the ε-insensitive loss function.

The SVM-R equation is created in order to predict output from the input vector as shown in the following equation:

$$d = w^T x + b = \sum_{i=1}^{N} (\alpha_i - \alpha_i^{'}) x_i^T x + b \tag{9}$$

This is a regression equation. Nevertheless, in a nonlinear regression equation, the input vector cannot be sent to a high dimensional feature space. Thus the kernel function can be applied to the solution. In this research, dot kernel function is applied in forecasting electricity consumption as shown following equation (Adhikari et al., 2013).

$$K(x_i, y_i) = (x_i . y_i) \tag{10}$$

Where: $K(x_i, y_i)$ is the inner product of x_i and y_i.

Therefore, the above equation can be written in the form of nonlinear regression as in the following equation (Haykin, 2009):

$$d = \sum_{i=1}^{N} (\alpha_i - \alpha_i^{'}) . K(x_i, y_i) + b \tag{11}$$

After nonlinear regression equation is obtained, it is used to forecast further.

Modelling Performance Evaluation

The criteria used to determine the effectiveness of the four forecasting methods are designed to establish the most appropriate or closest model to the actual situation. The criteria values for determining the efficiency of the model is the Mean Absolute Percent Error (MAPE) (Klimberg et al., 2010).

$$\text{MAPE} = \frac{\sum \frac{|Y_t - F_t|}{Y_t}}{n} \tag{12}$$

Where: t is time period; n is the number of periods forecast; Y_t is actual value in time period t; F_t is forecast value in time period t.

Results and Discussion

In this section presents the results and discusses for the forecasting electricity consumption under the responsibility of the PEA in all five sectors, divided into four sections: analysis of primary historical time series data, the suitable model detail, forecasting the results using the most suitable model, and the results of forecasting electricity consumption.

Analysis of Primary Historical Time Series Data for Five Sectors

The analysis results for the historical electricity consumption time series data between 1992 and 2016 in five sectors using freehand[4] reveals that the movement of time series data incorporates the trend component without seasonal influences and no errors. Therefore, it is possible to use time series data for the five sectors as the default method for further forecasting.

The Suitable Model Detail

This section presents the most reliable and effective models for forecasting electricity consumption of each of the five sectors based on MAPE; the details of which is shown in Table 1. From Table 1, it can be concluded that the most reliable models for forecasting electricity consumption in the five sectors are those shown in Table 2.

[4] Freehand method is also call the graphic method in the sense that the trend line is determined by inspecting the graph of the series. According to this method, the trend values are determined drawing freehand straight line through the time series data that is judged by the analyst to represent adequately the long term movement in the series (U. K. Srivastava, et al. 1989).

Table 1. Model performance evaluation of four forecasting methods for five sectors

Sectors	MAPE			
	Holt Winters	ARIMA	ANN	SVM-R
Residential	**2.29**	2.43	5.39	5.94
Commercial	3.23	**2.87**	7.77	7.36
Industrial	**4.04**	16.16	10.05	68.08
Agricultural	12.39	13.25	**11.22**	14.39
Non-profit	**3.84**	3.98	12.58	8.43

Note: Bold font is the most reliable and effective forecasting methods.

Source: Author's calculation

Table 2 The most reliable and effective forecasting methods for five sectors

Sectors	Suitable Forecasting Methods			
	Holt-winters	ARIMA	ANN	SVM-R
Residential	/			
Commercial		/		
Industrial	/			
Agricultural			/	
Non-Profit	/			

Note: Check is the most reliable and effective forecasting methods.

Source: Author's calculation

The results in Tables 1 and 2 indicate that the most reliable and effective models for forecasting electricity consumption in each of the residential, industrial, and non-profit sectors is the Holt-Winters' model. Whereas, the most suitable model for the commercial and agricultural sectors are the ARIMA and ANN. Details of the forecasting procedure applied to these five sectors are as follows:

Residential, Industrial, and Non-profit Sectors (Holt Winters' Method) Parameter Estimation and Diagnostic Checking

Parameter estimation and diagnostic checking of the Holt-Winters' non-seasonal model for the residential, industrial, and non-profit sectors can be as shown in Table 3. Diagnostic checking of the model based on the Ljung-Box (*Q*-statistic)[5].

Table 3 Parameter estimation and diagnostic checking of the Holt-Winters' non-seasonal method

Sectors	Parameters	Estimate	SE	t	P-Value
Residential	Level *(α)*	0.273	0.149	1.829	0.080
	Trend *(δ)*	1.000	0.711	1.406	0.173
***Q*-statistic**	**0.474**				
Industrial	Level *(α)*	0.089	0.120	0.740	0.467
	Trend *(δ)*	4.35E-7	0.057	7.577E-6	1.000
***Q*-statistic**	**0.313**				
Non-profit	Level *(α)*	0.999	0.229	4.367	0.000
	Trend *(δ)*	2.187E-6	0.192	1.137E-5	1.000
***Q*-statistic**	**0.436**				

Source: Author's calculation

Forecasting Equation

From parameter estimation and diagnostic checking can be developed as shown in the following equations:

Residential
$$\big(0.273y_t + (1 - 0.273)\big) + \big(1.000(F_t - F_{t-1})\big) + \big((1 - 0.1000)T_{t-1}\big) \tag{13}$$

Industrial
$$\big(0.089y_t + (1 - 0.089)\big) + \big(4.354E\ (F_t - F_{t-1})\big) + \big((1 - 1.354E)T_{t-1}\big) \tag{14}$$

Non-profit
$$\big(0.999y_t + (1 - 0.999)\big) + \big(2.187E\ (F_t - F_{t-1})\big) + \big((1 - 2.187E)T_{t-1}\big) \tag{15}$$

[5] Ljung-Box (Q-statistic) is a diagnostic tool used to test the lack of fit of a time series model. It is a type of statistical test of whether any of a group of autocorrelations of a time series is different from zero. Instead of testing randomness at each distinct lag, it tests the "overall" randomness based on a number of lags (wikiljungbox, 2010). Therefore, it can be concluded that the model is reliable and can be applied effectively to forecasting.

Commercial Sector (ARIMA(3,1,0) Method)

Stationary Test

In this research used Augmented Dickey-Fuller (ADF) stationarity test is shown in Table 4. These results can be applied to develop a further forecasting model.

Table 4 Stationarity test using Augmented Dickey-Fuller (ADF)

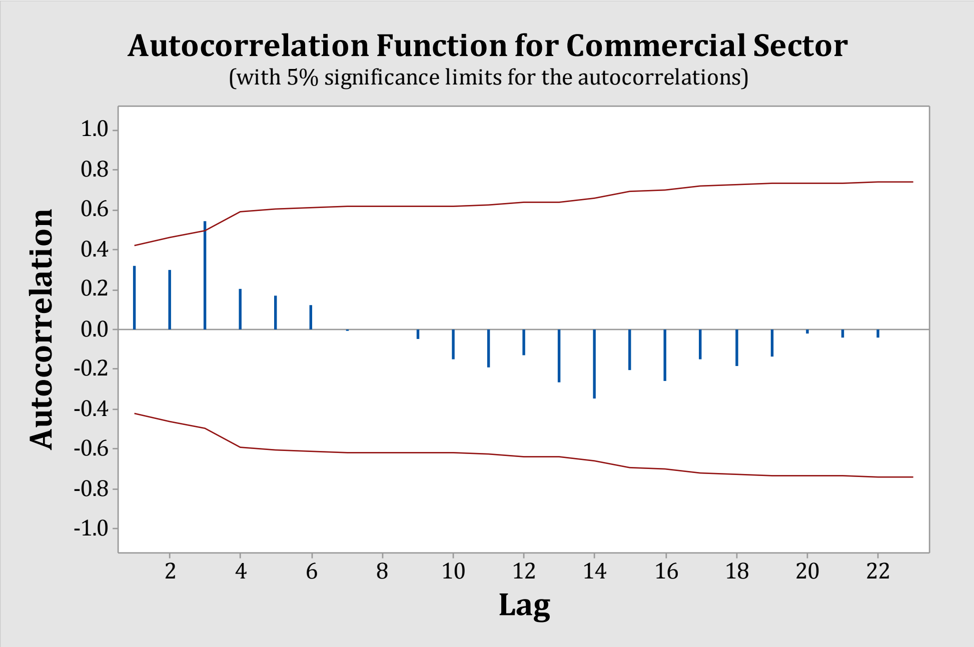
Sector	P-Value	Mackinnon Critical Value			Level	Results
		1%	5%	10%		
Commercial	0.991	-4.441	-3.633	-3.255	I(0) or Y_t	Non-stationary
	0.032	-4.441	-3.633	-3.255	I(1) or ΔY_t	Stationary

Source: Author’s calculation

Identification Procedure

The ARIMA(p,d,q) is considered with the use of autocorrelation graph for a new set of time series data after differencing at first level ΔY_t. The results indicate that AR(P) is (Lag 3) and MA(q) is 0. The ARMA(p,q) model can be determined as ARIMA(3,0) as Figure 1. When the results of the differencing at first level ΔY_t and ARIMA (3,0) are considered together, they can be modelled as ARIMA(3,1,0) model as shown in Table 5.

Figure 1 Autocorrelation (ACF) graph of a new set of time series data



Source: Author's calculation

Table 5 ARIMA(3,1,0) method

Integrated I(d)	ARMA(p,q)	ARIMA(p,d,q)
I(1)	ARMA(3,0)	ARIMA(3,1,0)

Source: Author's calculation

Parameter Estimation and Diagnostic Checking

Table 6 shows that the parameter estimation and diagnostic checking procedure of the ARIMA(3,1,0) for the commercial sector. The diagnostic checking of ARIMA (3,1,0) model is based on the Ljung-Box (Q-statistic).

Table 6 Parameter estimation and diagnostic checking of the ARIMA(3,1,0) method

Parameters	Estimate	SE	t	P-Value
Constant *(α)*	556.493	190.638	2.919	0.008
AR(Lag 1)	0.123	0.199	0.615	0.545
AR(Lag 2)	0.117	0.202	0.578	0.570
AR(Lag 3)	0.469	0.204	2.293	0.033
***Q*-statistic**	**0.767**			

Source: Author's calculation

Forecasting Equation

From the process of the ARIMA(3,1,0) model for forecasting electricity consumption of the commercial sector can be performed as in the following equation:

$$\text{Commercial} = 556.493+0.123y_{t-1}+0.117y_{t-2}+0.469y_{t-1}+ \varepsilon_t \quad (16)$$

Agricultural Sector (ANN Method)

Parameter Estimation and Accuracy Value

Table 7 shows the parameter estimation and accuracy value of the ANN model, which is reliable and effective for forecasting electricity in agricultural sector.

Table 7 Parameter estimation and accuracy value of the ANN model

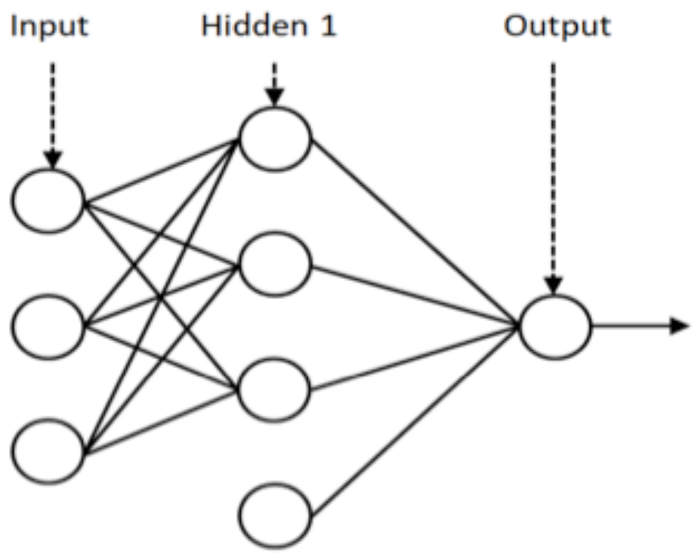
Parameters	Estimate
Learning rate *(η)*	0.300
Momentum rate *(α)*	0.200
Error epsilon	1.0E-5
Training cycles *(n)*	500
Transfer function	Sigmoid function
Accuracy value	**0.800**

Source: Author's calculation

ANN Model Architecture

From Table 7, a reliable model for creating ANN model architecture is 3:4:1 as shown in Figure 2.

Figure 2 ANN architecture for forecasting of agricultural sector



Forecasting Equation

The forecasting electricity consumption equation of agricultural sector as equation follows.

$$\text{Agricultural} = w_{ji}^{(l)}(n + 1) = w_{ji}^{(l)}(500) + 0.200\left(\Delta w_{ji}^{(l)}(500 - 1)\right) + 0.300\delta_j^{(l)}(500)y_i^{(l-1)}(500) \tag{17}$$

Results

Based on the appropriate and effective forecasting models in each sector, when such models are applied to all five sectors for the next seven years, the results indicate an increased consumption for electricity from 2017 to 2023. When individual sectors are classified, the results of forecasting electricity consumption for five sectors are as shown in Table 8 and Figure 6(a), (b), (c), (d), and (e).

Table 8 The results of forecasting electricity consumption for five sectors

Forecast period	Sectors				
	Residential	**Commercial**	**Industrial**	**Agricultural**	**Non-profit**
2017	32,272.04	17,458.56	77,925.90	378.22	4,855.75
2018	33,924.03	18,227.20	80,480.16	379.47	4,986.81
2019	35,576.02	19,002.72	83,034.43	380.42	5,117.87
2020	37,228.01	19,626.57	85,588.70	381.16	5,248.93
2021	38,879.99	20,316.32	88,142.97	381.73	5,379.99
2022	40,531.98	20,999.69	90,697.24	382.19	5,511.05
2023	42,183.97	21,618.87	93,251.51	382.57	5,642.11
Total	**260,596.05**	**137,249.91**	**599,120.91**	**2,665.77**	**36,742.50**

Source: Author's calculation from equation 13, 14, 15, 16, and 17

Figure 6 Forecasting electricity consumption graph for five sectors

Figure 6(a) residential sector (Holt-Winters)

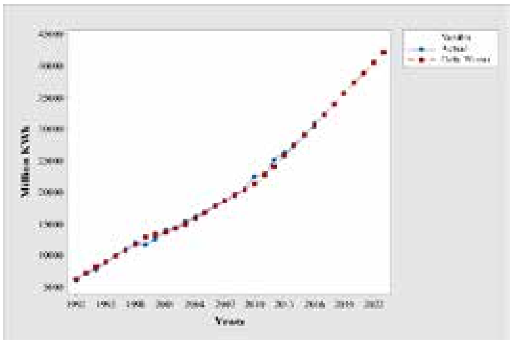


Figure 6(b) commercial sector ARIMA(3,1,0)

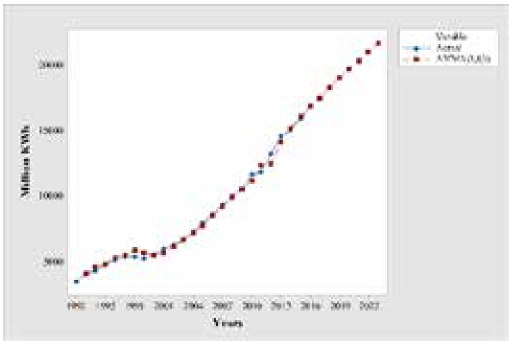


Figure 6(c) Industrial sector (Holt-Winters)

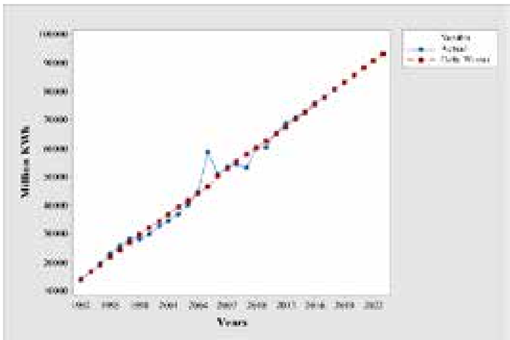


Figure 6(d) Agricultural sector (ANN)

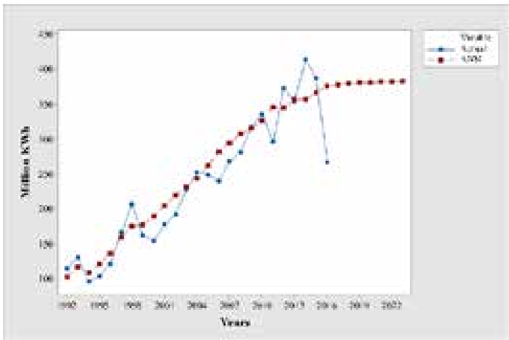
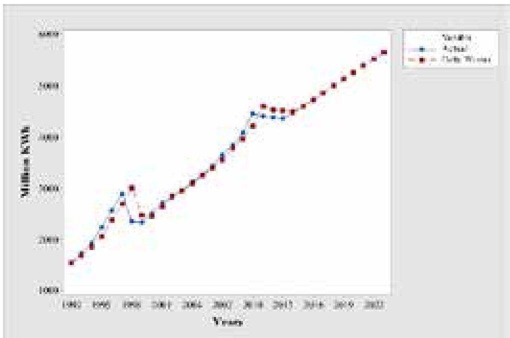


Figure 6(e) Non-profit sector (Holt-Winters)



Source: Author's calculation

After forecasting electricity consumption for five sectors, the results of electricity consumption from Table 8 and electricity loss[6] between 2017 and 2023 are summarised to obtain total forecasting electricity consumption. In other words, total electricity consumption covers loss incurred during distribution to users as shown in the following equation:

$$Y=(R+C+I+A+N)+Loss \tag{18}$$

Where: Y is total electricity consumption,

R is residential electricity consumption,

C is commercial electricity consumption,

I is industrial electricity consumption,

A is agricultural electricity consumption,

N is non-profit electricity consumption,

$Loss$ is electricity loss.

The above equation shows that the total forecasting electricity consumption also covers electricity loss during the period from 2017 to 2023 and forecasting electricity consumption of five sectors are likely to increase continuously as presented in Table 9.

[6] Electricity loss or loss refers to units lost in electrical or electrical distribution systems. There are two calculation methods for electricity loss: technical loss and non-technical loss (Power Economics Division, PEA, 2017). This research uses the technical loss calculation.

Table 9 Summary of the projected total electricity consumption

Unit: Million Kilowatt Hour (kWh)

Years	Sectors					Loss (%)	Total consumption
	Residential	Commercial	Industrial	Agricultural	Non-profit		
2017	32,272.04	17,458.56	77,925.90	378.22	4,855.75	5.14	139,718.77
2018	33,924.03	18,227.20	80,480.16	379.47	4,986.81	4.81	144,634.78
2019	35,576.02	19,002.72	83,034.43	380.42	5,117.87	4.42	149,433.45
2020	37,228.01	19,626.57	85,588.70	381.16	5,248.93	4.19	154,273.20
2021	38,879.99	20,316.32	88,142.97	381.73	5,379.99	3.93	159,116.61
2022	40,531.98	20,999.69	90,697.24	382.19	5,511.05	3.69	163,957.54
2023	42,183.97	21,618.87	93,251.51	382.57	5,642.11	3.50	168,792.22
Total	**260,596.05**	**137,249.91**	**599,120.91**	**2,665.77**	**36,742.50**	**29.68**	**1,079,926.57**

Source: Author’s calculation

According to Table 9, when total electricity consumption is compared with total electricity capacity of the PEA between 2017 and 2023 as shown in Table 10, the results can be used to plot the decreasing electricity capacity of the PEA as shown by the graph in Figure 7.

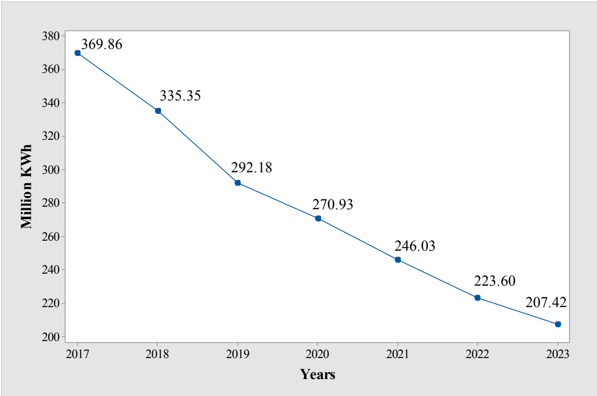
Table 10 Comparison of the projected total electricity consumption and total electricity capacity of the PEA

Unit: Million Kilowatt Hour (kWh)

Years	Total electricity consumption	Total electricity capacity	Excess electricity capacity
2017	139,718.77	140,088.63	369.86
2018	144,634.78	144,970.13	335.35
2019	149,433.45	149,725.63	292.18
2020	154,273.20	154,544.13	270.93
2021	159,116.61	159,362.64	246.03
2022	163,957.54	164,181.14	223.60
2023	168,792.22	168,999.64	207.42
Total	**1,079,926.57**	**1,081,871.94**	**1,945.37**

Source: Author’s calculation

Figure 7 Annual comparison of the projected total electricity consumption and total electricity capacity of the PEA (exess electricity capcity)



Source: Author’s calculation

Electricity consumption is forecast to increase continuously until it approaches the capacity of the PEA, whereas the excess electricity capacity between 2017 and 2023 is equal to 369.86, 335.35, 292.18, 270.93, 246.03, 223.60, and 207.42 million kWh, respectively. Consequently, the total excess electricity capacity is expected to be 1,945.37 million kWh, indicating that although there is currently enough for electrical power to satisfy consumption, the trend indicates that the future consumption is likely to be close to capacity.

However, this situation may affect electricity capacity as consumption catches up and the volume decreases steadily. This may have a direct impact on the energy security of the PEA area and most areas of Thailand in the future. Therefore, forecasting it is necessary in order to provide guidelines for the production of sufficient and timely electrical energy capacity policy to meet the increased electricity power consumption in accordance with current and future economic and social changes.

Conclusion and Suggestion

In forecasting electricity consumption under the responsibility of the PEA in five sectors, MAPE models were found to be the most suitable for the residential, industrial, and non-profit sectors, and therefore, the Holt-Winters' non-seasonal model was applied, while for the commercial and agricultural sectors, ARIMA(3,1,0) and ANN models were considered to be most suitable. The results of forecasting electricity consumption for the next seven years in all five sectors show an increasing continuous trend from 2017 to 2023. When considering the forecasting electricity consumption results of each sector from 2017 to 2023, the residential sector was found to have a higher demand at 260,596.05 million KWh. Meanwhile, demand for electricity in the commercial, industrial, agricultural, and non-profit sectors is forecast to be 137,249.91, 599,120.91, 2,665.77, and 36,742.50 million KWh, respectively, indicating that the total annual electricity consumption of the five sectors from 2017 to 2023 is projected to increase. In the classification of individual sectors, demand for electricity in the five sectors is 139,718.77, 144,634.78, 149,433.45, 154,273.20, 159,116.61, 163,957.54, and 168,792.22 million KWh respectively.

When the total electricity consumption is compared with the total electricity capacity of the PEA, which the results indicate consumption may exceed capacity in 2017, 2018, 2019, 2020, 2021, 2022, and 2023 by 369.86, 335.35, 292.18, 270.93, 246.03, 223.60, and 207.42 million KWh respectively, creating a total electricity capacity shortfall of 1,945.37 million KWh. The results imply that this may affect future electricity security in the area under the responsibility of the PEA.

Since the time series data for all sectors in this study contains a low number of observations, this affects the efficiency of some models such as ANN and SVM-R where forecasting efficiency is based on the amount of time series data used to create the model structure. If more time series data is available, it can make the forecasting model more accurate. In order to increase the forecasting efficiency of the ANN and SVM models, additional information should be added to the model for further learning. This will affect the efficiency of the forecasting electricity consumption model.

For future study, the researcher's aim to examine the PEA's investment plan and analyse the cost of electricity production and distribution of the PEA. This would help to describe the electricity usage amount, the capacity to produce and distribute electrical energy, and the ability to meet the consumption for electricity, due to changes in society and the economy.

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