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Article

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Electricity Consumption Forecasting in Thailand using Hybrid Model SARIMA and Gaussian Process with Combine Kernel Function Technique

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ABSTRACT

Electricity consumption forecasting plays a significant role in planning electric systems. However, this can only be achieved if the demand is accurate estimation. This research, different forecasting methods hybrid SARIMA-ANN and hybrid model by SARIMA-Gaussian Processes (GP) with combine Kernel Function technique were utilized to formulate forecasting models of the electricity consumption. The objective was to compare the performance of two approaches and the empirical data used in this study was the historical data regarding the electricity consumption (gross domestic product: Forecast values calculated by SARIMA model and electricity consumption) in Thailand from 2005 to 2015. New Kernel Function design techniques for forecasting under GP are presented in sum and product formats. The results showed that the hybrid model by SARIMA - GP with combine Kernel Function technique outperformed the SARIMA-ANN model have the Mean absolute percentage error is 4.7072e-09, 4.8623 respectively.

Keywords: Forecasting, Electricity Consumption, Model, Gaussian Process
JEL Classifications: C13, C32, E27, P28

1. INTRODUCTION

Electricity is a source of energy being essential factor to drive economy and development of a country. It also plays a vital role as being an economy indicator. Electricity consumption is able to reflect national economic development as it is a vital foundation for continual economy development of a country. Thus, security in electricity system is a major subject for everybody to take into account as insufficient electricity supply for some period of time or interruptible power and power outage are considered huge expenditure for economy and result in decision making of private investors. Electricity holds special characteristics as it can be generated but cannot be kept in stock like other products. It has to be transmitted to customers or electricity users immediately through transmission and distribution system and demand of using electricity in each period of time is not equal, then sufficient supply is have to be done at all time to serve the need of use. Increasing production capacity to generate electricity cannot be done in a short time since it requires 5-7 years to construct electric power system, transmission power lines, distribution power lines, and electric power plant. So, investment needs estimation for electricity end-use demand. As demand for electricity in the future increases according to the growth of population and economy, it is extremely substantial to carry out long-term planning for developing electricity generation in the country by providing sufficient electricity supply to facilitate the country development as well as the concern of environmental effect. However, uncertainty of situations, predictable and unpredictable, such as political conflicts that result in economic expansion of the country, change of atmosphere affecting electric power using, are the factors that change future electricity demand.

Consequently, it is necessary to forecast electricity consumption to assess how the consumption in the future will be and how much electricity demand will be increased. Then, accurate estimation of electricity consumption in an organization is important to plan and carry out electricity generation to meet with demand of domestic consumption and economy growth. The forecast with a slight decline of error plays a crucial role in security in electric power (Hamzaçebi, 2016) because if the forecast is lower than the actual results, the supply of electricity will not be sufficient for domestic consumption. Interruptible power and power outage can affect manufacturing business and service business which result in economic system as a whole. In contrast, if the forecast is higher than the actual results, there will be oversupply of electricity generation or the construction of electric power plants and distribution system. People will have to bear the cost of soaring electricity prices. Knowing electricity consumption contributes to expect the size and numbers of electric power plants in each type to be constructed in accordance with electricity demand and consumption in the future. With regards to accurate electricity consumption forecasting, there are numerous factors concerning the consumption such as fluctuation in the world economy and energy prices, political issues, global warming effects and environmental impacts that have effect and influence on consuming and supplying national energy. The forecast of change in the future of the mentioned factors is difficult to do and perhaps different immensely from the fact. Therefore, the old planning energy consumption referring to economy growth has a high level of error while providing a reliable model for forecasting electricity consumption requires forecast methods, hypotheses and considerable related data.

This research was focus to forecast long term electricity consumption in Thailand with hybrid SARIMA and Gaussian processes (GP) with the key element called Hybrid Kernel Function for the accuracy of forecasted data which will be most beneficial for making a plan and developing strategy in generating electricity and seeking energy sources, as well as planning financial strategy for investment in different projects for seeking fuel for electricity generation and increasing production capacity in the future. The most important thing for the accurate forecasted data is to be applied for planning and setting policies in using alternative energy to reduce effect on energy crisis that may occur in the future and plays a part in making decision by those who get involved with strategies development to reduce risk and increase economic benefits.

2. RELEVANT LITERATURE

Electricity consumption forecasting (Kandananond, 2011; Sigauke and Chikobvu, 2012; Ardakani and Ardehali, 2014; Kialashaki and Reisel, 2014; Jiang et al., 2014; Demir and Ozsoy, 2014; Ismail et al., 2015; Kaytez et al., 2015; Gaillard and Goude, 2015; Panklib et al., 2015; Ambera et al., 2015; Zhao et al., 2016; Hamzaçebi, 2016) plays a significant role in planning electric systems and operation. A hybrid forecasting model (Hybrid model) was developed in 2003 by Zhang (Khashei and Bijari, 2011; Babu and Reddy, 2014; Barak and Sadegh, 2016) and has been widely used for time series data forecasting. Since data for forecasting electricity consumption are comprised of both linear and non-linear structures, forecasting with only one model may not describe the variation of data accurately. Though the forecasting model has been improved its model efficiency more or less through a certain method, it is quite difficult to improve accuracy in forecasting some points to make forecast results of power load be accurate in all cases (Chen et al., 2016).

Hybrid models for forecasting electricity consumption are used in some researches, namely, Wang et al. (2011) used hybrid AR-GARCH model for short-term load forecasting in electric power market in Norway; Kavousi-Fard and Kavousi-Fard (2013) used hybrid autoregressive integrated moving average (ARIMA) model, support vector regression (SVR) and cuckoo search algorithm for optima power load forecasting in Iran; Kavousi-Fard et al. (2014) used hybrid SVR and modified firefly algorithm for electricity consumption forecasting in Iran; Fard and Akbari-Zadeh (2014) and Shafaei et al. (2016) used hybrid Wavelet-SARIMA-Ann for short term electricity consumption forecasting; Jeong et al. (2014) predicted electricity consumption in educational institutes in Seoul, South Korea by using SARIMA and ANN models; Babu and Reddy (2014) used hybrid ARIMA-ANN for forecasting electricity expenses of New South Wales (NSW) state, Australia; Abreu et al. (2015) used hybrid ARIMA-ANN for forecasting power load in Brazil; Dong et al. (2016) applied hybrid models for forecasting short-term load in NSW state, Australia with hybrid Data Decomposition Hybrid; Chen et al. (2016) predicted power load with hybrid Least squares support vector machine and Fuzzy time series and Global harmony search algorithm in Guangdong province, China; Peng et al. (2016) predicted power load in NSW state, Australia and New York, United States of America with hybrid SVR and DEMD and Quantum PSO which was called DEMD-QPSO-SVR-AR model; Toksari (2016) used hybrid Ant colony optimization model for forecasting electricity consumption in Turkey, and Iterated local search Li et al. (2017) used hybrid GRNN and SVR models for forecasting electricity demand in NSW and Victorian State in Australia.

GP for machine learning (Wu et al., 2012; Salcedo-Sanz et al., 2014; Sun et al., 2014; Hachino et al., 2015; Lei et al., 2015; Senanayake et al., 2016; Ludkovski et al., 2016) are currently recognized as an effective tool for solving problems of regression, classification and decision in machine learning. It worked effectively even with less training data, had better convergence rate than SARIMA, ANN, and supported Regression Vector machine (Williams and Rasmussen, 2006). GP was advantageous over other machine learning techniques because of its full capabilities in forecasted probability distribution, as well as prediction of uncertainty of forecasting. These features made GP an ideal tool for forecasting purposes (Claveria et al., 2016).

3. HISTORICAL DATA

Thailand is a developing country having the growth in energy demand especially electricity. The increasing trend can be attributed to the growing sectors of industry, business, and household, city expansion; from city to urban and rural areas, increase in household income, improving of the production structure that emphasis is placed on services, population that are growing continuously, the advancement of knowledge and technology including the rapid expansion of economy and industries. Thus, the energy consumption and power demand also increase accordingly as shown in Figure 1.

Forecasting long term electricity consumption in Thailand with hybrid SARIMA and new Kernel function in GP models includes monthly electricity consumption data, gross domestic product (GDP) during January 2005 to December 2013. Data were from 108 months as training data and electricity consumption data of the next 24 months during January 2014 to December 2015 as data set for testing ability of algorithms that required only time variables (GDP was not required). This data set was called a test dataset. The historical data set regarding these factors was collected annually from 2005 to 2015.

4. METHODOLOGY AND DATA ANALYSIS

4.1 SARIMA Model

SARIMA model stands for Seasonal ARIMA model. Time series data forecasting using SARIMA model, the Box-Jenkins techniques, was developed by George E. P. Box and Gwilym M. Jenkins in 1970 (Camara et al., 2016). SARIMA is a forecasting method bringing time series data to find an appropriate time series model. The obtained model can be used to forecast future time series data. SARIMA model can be used with all types of non-stationary data. The time series data used for analysis have to be stationary.

SARIMA (p,d,q) (P,D,Q)s, the Box-Jenkins method, used in this study is based on the following equation:

$$\left(1-\phi_1 B^2-\ldots-\phi_p B^p\right)\left(1-\Phi_1 B^S-\Phi_2 B^{2S}-\ldots-\Phi_p B^{PS}\right)$$
$$(1-B)^d\left(1-B^S\right)^D Y_t = (1-\theta_1 B-\theta_2 B^2-\ldots-\theta_q B^q)$$
$$(1-\Theta_1 B^S-\Theta_2 B^{2S}-\ldots-\Theta_Q B^{QS})\varepsilon_t \quad (1)$$

4.2. Inspection of Stationary Process of Time Series

From Figure 2, based on characteristic movement of time series; monthly consumption of electricity from January 2005 to December 2015, it was found that the time series had higher potential, monthly consumption of electricity in Thailand was expected to increase and seasons were involved. Duration of seasons varied to times. Heteroskedasticity was found.

Inspection results of the stationary process of monthly consumption of electricity in Thailand with Graph autocorrelation function graph (ACF) as shown in Figure 3 and Graph partial ACF (PACF) in Figure 4 revealed that the time series were not stationary. The data were then transferred with natural logarithms (replaced with In Y) to find the 1st nonseasonal (d=1) differencing and the 1st seasonal (D=1) differencing in order to allow the time series to have a constant average in the same level and could be

Figure 1: Electricity consumption in Thailand and Peak demand

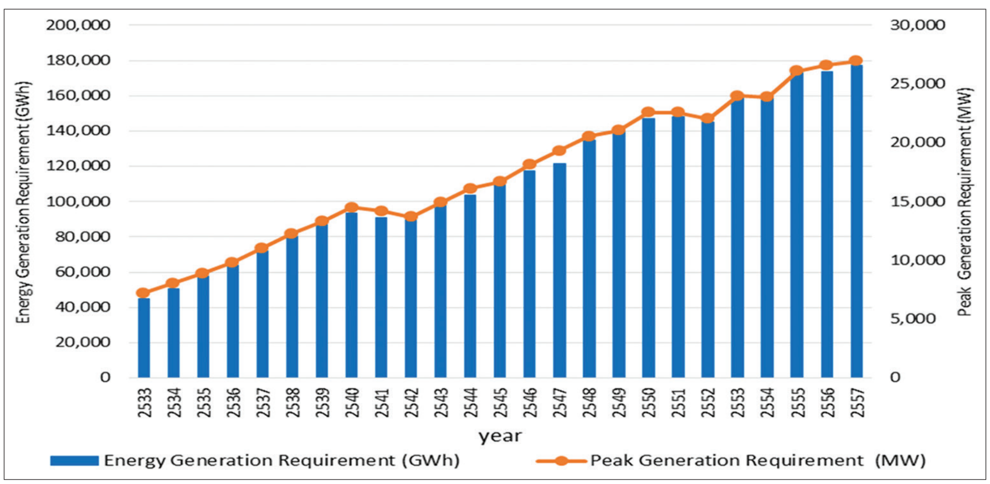


Figure 2: The monthly electricity consumption in Thailand

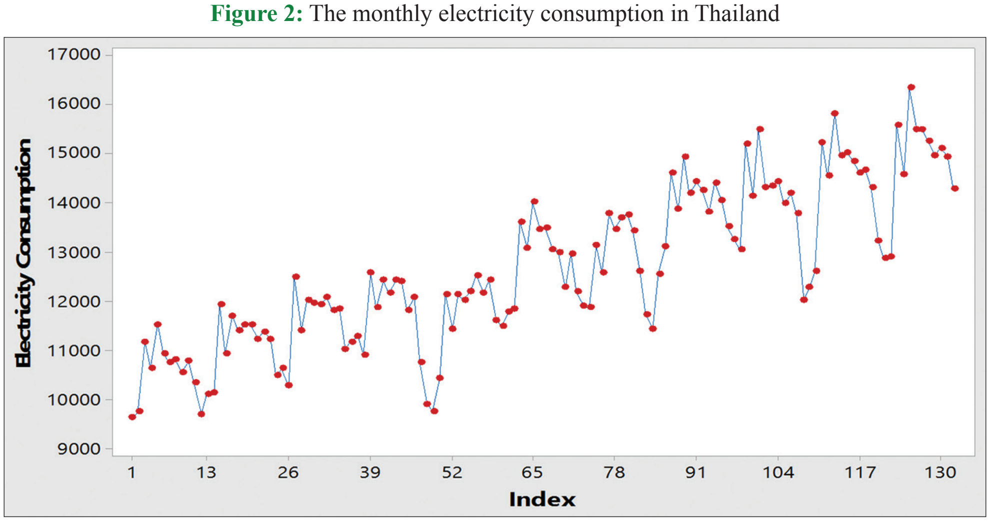


Figure 3: Graph ACF of the time series of monthly consumption of electricity in Thailand

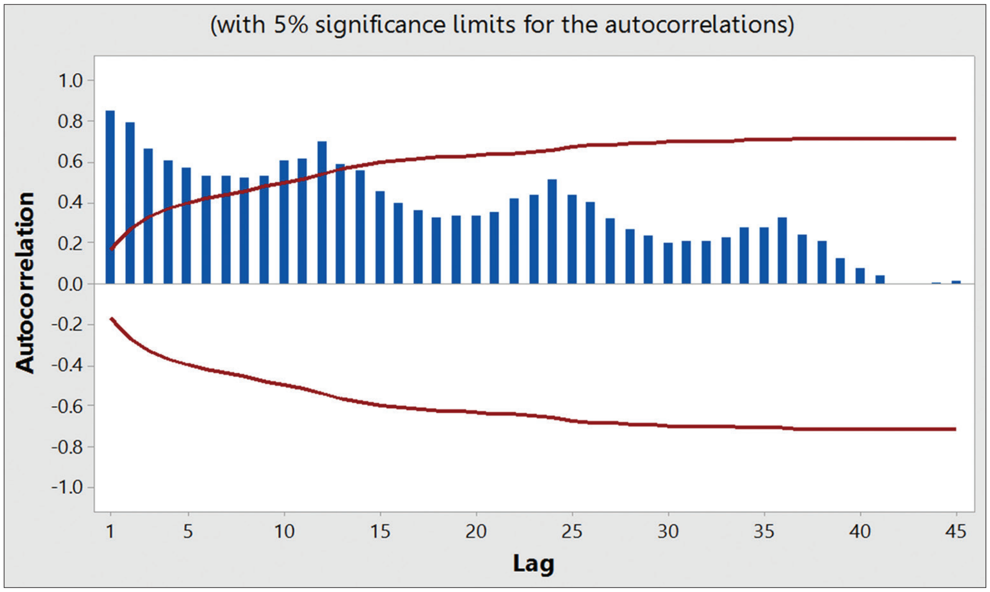
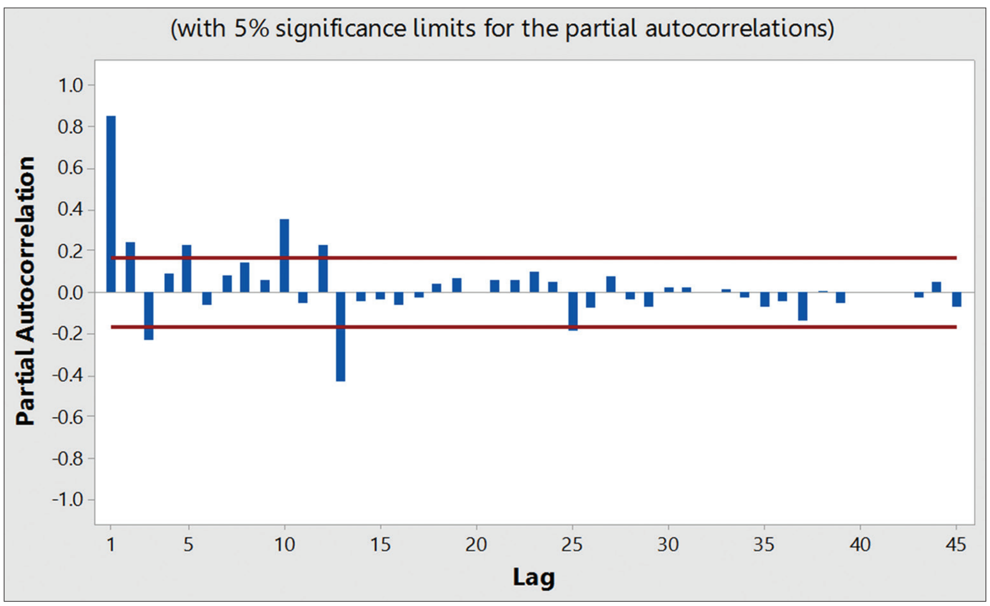


Figure 4: Graph partial autocorrelation function graph of the time series of monthly consumption of electricity in Thailand



written an ACF as shown in Figure 5, and partial PACF as shown in Figure 6.Based on Graph ACF and PACF after differencing and seasonal differencing, there were totally potential 15 models as shown in Table 1.

4.3. Estimation of Parameters in the Models

Based on Graph ACF and PACF after differencing and seasonal differencing, there were totally potential 15 models. Estimation of the parameters of all 15 models revealed that only 2 models were appropriate to be used for forecasting, namely SARIMA(1,1,1) $(0,1,1)_{12}$ and SARIMA (1, 1,1)$(1,1,0)_{12}$ The details were shown in Table 2.

The results of parameter estimation with least squares method indicated that SARIMA forecasting model (1,1,1) $(0,1,1)_{12}$ had parameter estimation value $\varnothing_1 = 0.6233$ (P = 0.000), parameter $\theta_1 = 0.9208$ (P = 0.000), parameter $\Theta_1 = 0.8055$ (P = 0.000). SARIMA forecasting model (1,1,1) $(1,1,1)_{12}$ had parameter estimation value $\varnothing_1 = 0.6861$ (P = 0.000), parameter $\Phi_1 = -0.5081$ (P = 0.000), parameter $\Theta_1 = 0.9736$ (P = 0.000).

The forecast efficiency of the models from Table 3. Revealed that the parameter estimation values of the 2 models were not equal to 0. It interpreted that the parameter values from the 2 models were appropriate. Compared to BIC and MAPE values of the 2 models, SARIMA model (1,1,1) $(0,1,1)_{12}$ had BIC value equal to 11.694 and MAPE was 1.986 which less than the SARIMA model (1,1,1) $(1,1,0)_{12}$ that had BIC value equal to 11.753 and MAPE value was 2.062. As a result, the SARIMA model (1,1,1) $(0,1,1)_{12}$ indicated a better fit for forecasting.

Inspection of the appropriateness of the model with Graph ACF as shown in Figure 7 and Graph PACF as shown in Figure 8 indicated that autocorrelation and partial autocorrelation of

Figure 5: Graph autocorrelation function graph of the time series of monthly consumption of electricity in Thailand when data were transferred with differencing and the 1st seasonal differencing

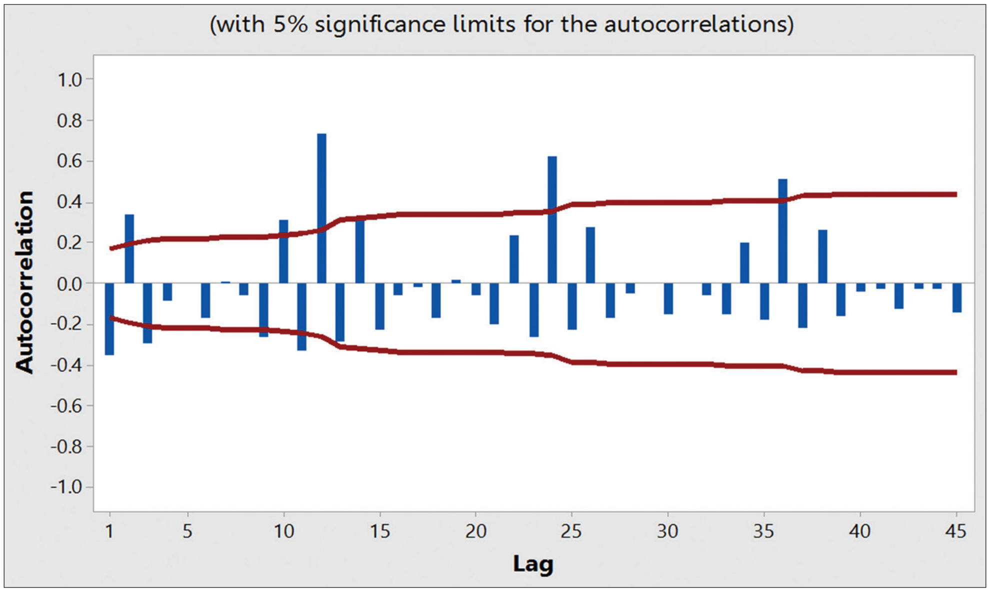
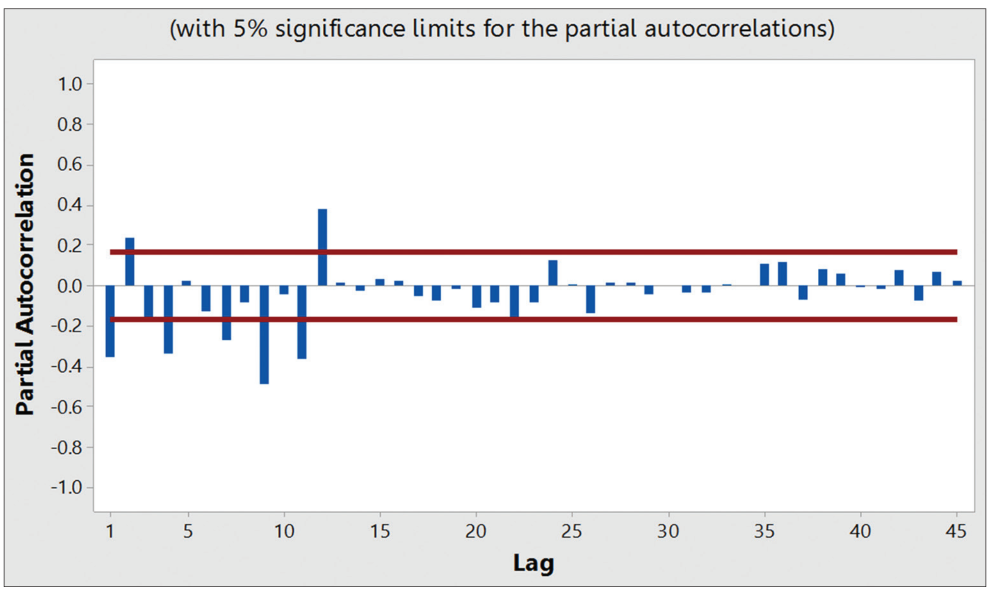


Figure 6: Graph partial autocorrelation function graph of the time series of monthly consumption of electricity in Thailand when data were transferred with differencing and the 1st seasonal differencing



the errors of SARIMA model (1,1,1) $(0,1,1)_{12}$ were in the 95% confidence interval. That meant the SARIMA model (1,1,1) $(0,1,1)_{12}$ was appropriate. The inspection the appropriateness with statistical Q-test as shown in Table 4 indicated that statistics $Q_{12} = 16.1$ (P = 0.051), statistics $Q_{24} = 22.4$ (P = 0.319), statistics Q_{36} = 31.9 (P = 0.470), statistics Q_{48} = 42.2 (P = 0.5.49). It concluded that the SARIMA model (1,1,1) $(0,1,1)_{12}$ was appropriate to be used for forecasting since having P > 0.05 at all periods of time (Lag).

Comparison results between the actual and forecast values of electricity consumption from January 2005 to December 2015 obtained from SARIMA model (1,1,1) $(0,1,1)_{12}$ from Figure 9 indicated that the actual and forecast values were close to each other. Forecasting error measured by MAPE = 1.986, MAE = 234.486 and coefficient of determination (R^2) = 94.1%. The forecast value of monthly consumption of electricity in the next 10 years was shown in Figure 10.

Table 1: Identification of appropriate models

No.	Model	No.	Model
1	SARIMA (0,1,0)(0,1,1) 12	9	SARIMA (1,1,0)(0,1,1) 12
2	SARIMA (0,1,0)(1,1,0) 12	10	SARIMA (1,1,0)(1,1,0) 12
3	SARIMA (0,1,0)(1,1,1) 12	11	SARIMA (1,1,0)(1,1,1) 12
4	SARIMA (0,1,1)(0,1,0) 12	12	SARIMA (1,1,1)(0,1,0) 12
5	SARIMA (0,1,1)(0,1,1) 12	13	SARIMA (1,1,1)(0,1,1) 12
6	SARIMA (0,1,1)(1,1,0) 12	14	SARIMA (1,1,1)(1,1,0) 12
7	SARIMA (0,1,1)(1,1,1) 12	15	SARIMA (1,1,1)(1,1,1) 12
8	SARIMA (1,1,0)(0,1,0) 12		

Figure 7: Inspection results of the appropriateness of SARIMA model (1, 1, 1) (0, 1, 1)12 with Graph autocorrelation function graph

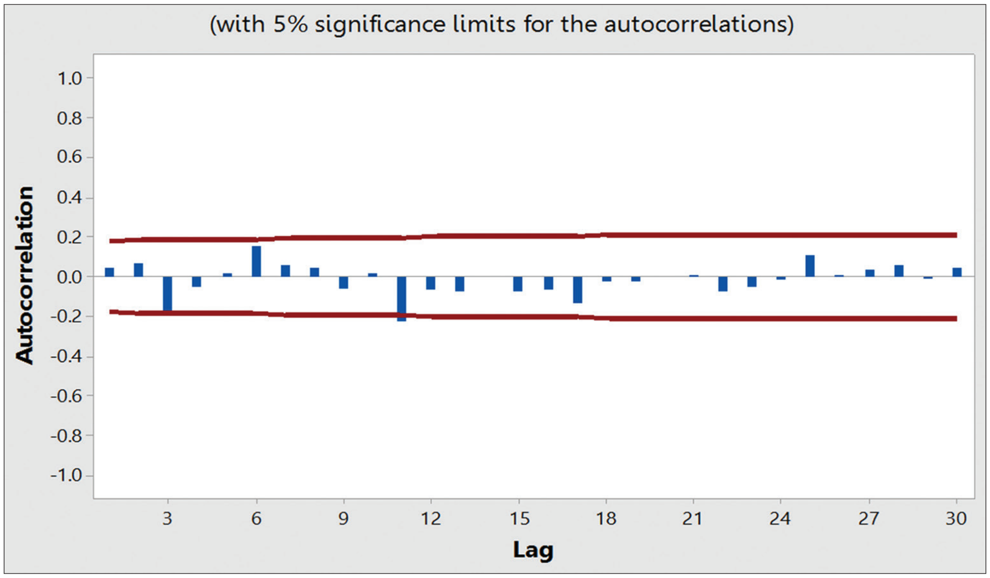


Figure 8: Inspection result of the appropriateness of SARIMA model (1, 1, 1) (0, 1, 1)12 with Graph PACF

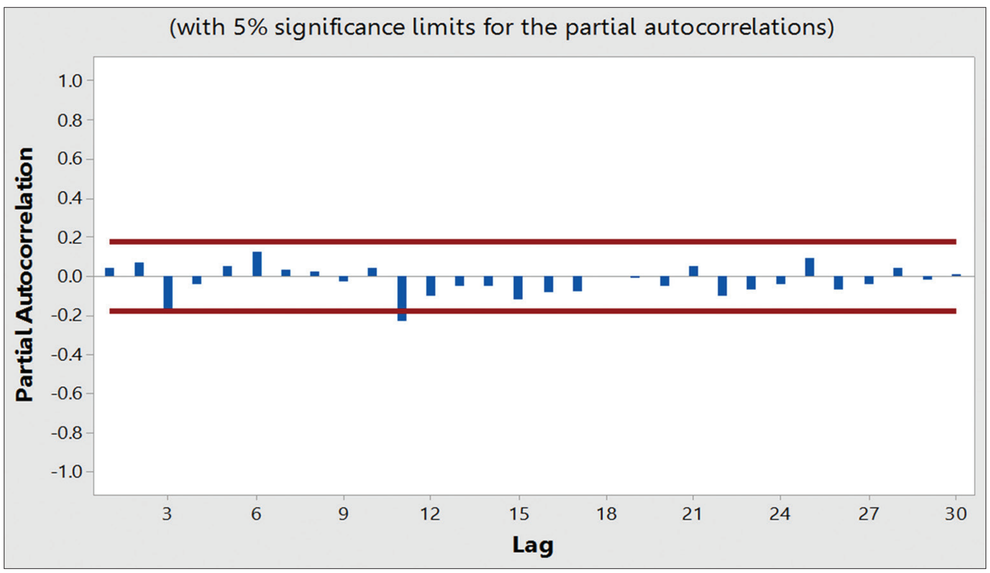


Table 2: Parameter estimation values of SARIMA model (1, 0, 0) (0, 1, 1)$_{12}$

Model	Estimation value	SE	t	P
SARIMA (1, 1, 1)(0, 1, 1)$_{12}$				
AR 1 $Ø_1$	0.6233	0.1049	5.94	0.000
MA 1 $θ_1$	0.9208	0.0648	14.21	0.000
SMA 12 $Θ_1$	0.8055	0.0943	8.54	0.000
SARIMA (1, 1, 1)(1, 1, 0)$_{12}$				
AR 1 $Ø_1$	0.6861	0.0723	9.49	0.000
SAR 12$Φ_1$	−0.5081	0.0824	−6.17	0.000
MA 1 $Θ_1$	0.9736	0.0299	32.59	0.000

4.4. GP Methods

GP is a stochastic process, a collection of random variables indexed by time or space (Barkan, et al., 2016; Ghoshal and Roberts, 2016). Multivariable Gaussian distribution is defined by probability density function (PDF) according to the equation (2).

$$\mathcal{N}(\mu,\Sigma)=\frac{1}{(2\pi)^{\frac{d}{2}}\sqrt{|\Sigma|}}exp\left(-\frac{1}{2}(x-\mu)\Sigma^{-1}(x-\mu)^{T}\right) \tag{2}$$

Where x~$\mathcal{N}$ (μ,) has a random vector as $x\epsilon R^d$ with the mean (Mean: μ=E[x]ϵR^d) and covariance (Covariance: $\Sigma=\mathbb{E}[(x–\mu)(x–\mu)^{T}]\epsilon R^{d\times d}$) whereas d refers to Number of dimensions (Simionovici, 2016).

From Figure 11, on the left is GP distribution over two variables following the equation (2) between variable X_1 and X_2 when $x_1 \epsilon X_1$ and $x_2 \epsilon X_2$ have average as $\mu=\begin{bmatrix}\mu_1\\ \mu_2\end{bmatrix}$ and the covariance is equal to $\Sigma=\begin{bmatrix}\Sigma_{11} & \Sigma_{12}\\ \Sigma_{21} & \Sigma_{22}\end{bmatrix}$. The right figure indicates the conditional probability of $P(X_1 X_2=x_2$ having average according to the equation (3) and covariance according to the equation (4) respectively.

Figure 9: Forecast value of electricity consumption in comparison to the actual consumption with SARIMA model

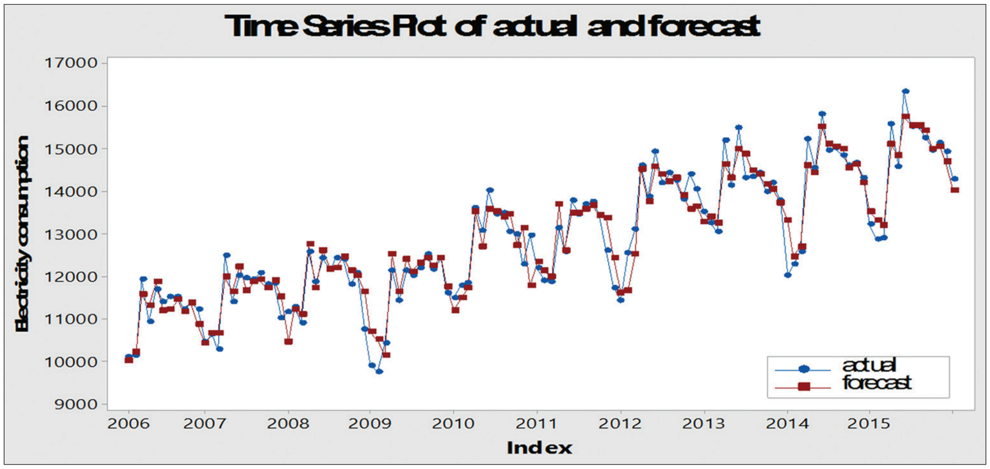


Figure 10: Forecast value of monthly consumption of electricity in Thailand in the next 10 years with SARIMA model (1, 1, 1) (0, 1, 1)12

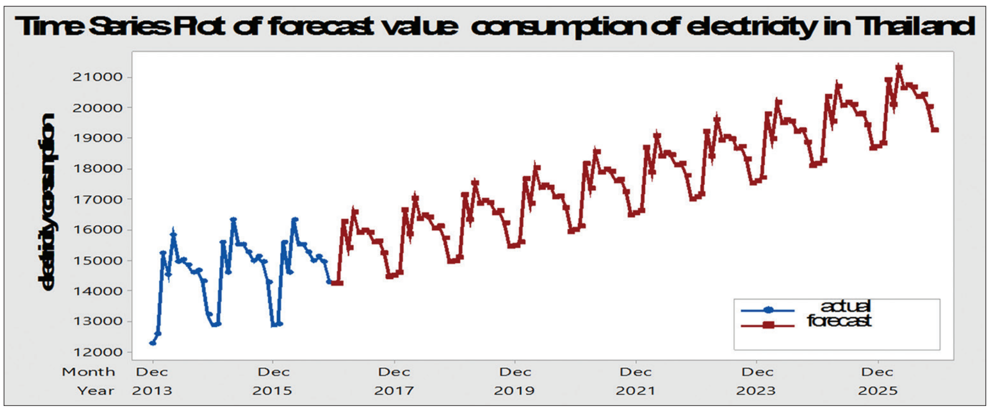


Table 3: Forecast efficiency of the models

Model	RMSE	MAPE	MAE	Normalized BIC
SARIMA $(1,1,1)(0,1,1)_{12}$	323.127	1.986	234.486	11.694
SARIMA $(1,1,1)(1,1,0)_{12}$	332.842	2.062	243.511	11.753

Table 4: Inspection results of the appropriateness of SARIMA model (1, 1, 1) (0, 1, 1)$_{12}$ with statistical Q-test

Lag	12	24	36	48
Chi-square	16.1	22.4	31.9	42.2
DF	8	20	32	44
P	0.051	0.319	0.470	0.549

$$\mu_{1|2} = \mu_1 + \Sigma_{12}\Sigma_{22}^{-1}\left(x_2 - \mu_2\right) \tag{3}$$

$$\Sigma_{1|2} = \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21} \tag{4}$$

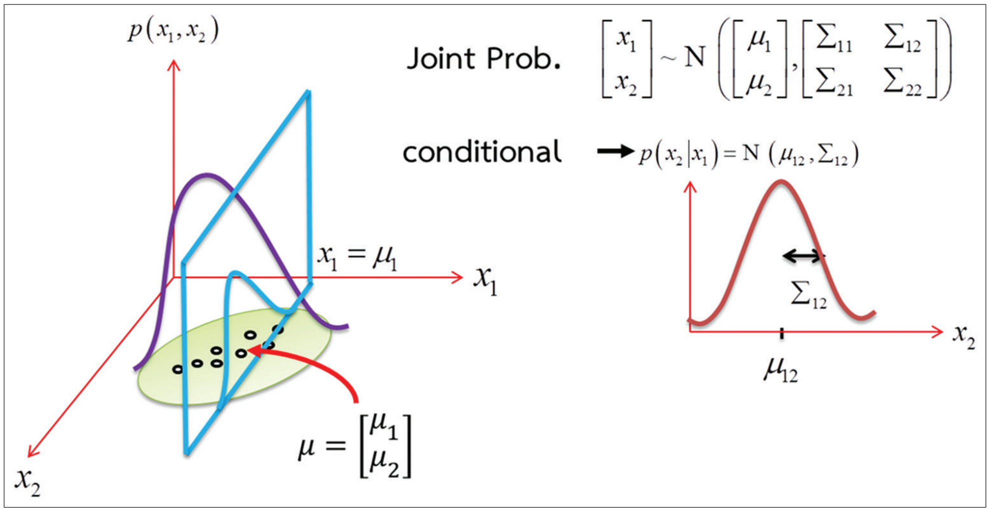
Steps in creating GP Model with combine Kernel Function:

1. Determine the data for electricity consumption forecasting. The data used in this work is the monthly electricity consumption is from January 2005 to December 2015, with a total of 132 months, divided into 3 periods. The Training Period, which is the period from January 2005 to December 2013, is the first 108 months, the Validation Period is the next 24-month consumption data that matches the January 2014 period. The forecasting period is a 120-month forecast of electricity consumption from January 2016 to December 2025.
2. Consider the format of a GP. The objective of this paper is forecasting long-term f(x_j), where 133≤ j ≥ 253, which is between January 2016 and December 2025, is 120 months ahead. Using the first 108 months of training data and will be used to calculate the mean and kernel functions of the GP for forecasting electricity consumption.
3. Consider training data system with (N) length by defining set values of set X and set function *f* matching to X as

$$X \in \mathbb{R}^{N*D} = \left\{x' = \left(x_{i,1}, x_{i,2}, x_{i,3} \ldots x_{i,d}\right)\right\}_{i-1}^{N} f \in \mathbb{R}^{N*1} =$$
$$f\left(x_1\right), f\left(x_2\right) \ldots f\left(x_N\right)' D = \{X, f\} \tag{5}$$

Where *D* is called Training data set $\mathcal{GG}$ Prior when Training data with (*N*) length This research uses the GP to predict the electricity consumption. Data between 2005 and 2013 is a training data set, 1. Electricity consumption 2. Time (month) 3. GDP and 4. Electricity consumption forecast by SARIMA. Data between 2014 and 2559 is a test of the ability of the algorithm, using only time variables (no GDP and SARIMA predictions).

Figure 11. : Calculating conditional probability of $P(X1 \mid X_2=\chi_2)$



4. Determine Kernel function for forecasting. This research used New Kernel Function with kernel combination techniques created from Squared Exponential Kernel, Periodic Kernel, Rational Quadratic Kernel and Linear Kernel by applying the Sum and Product structures. The appropriate kernel function was $k_{SE*RQ*LIN}+k_{PER*LIN}+k_{LIN}$ with a form of kernel function according to the equation being

$$k(x,x') = \left(\sigma^2 \exp\left(-\frac{(x-x')^2}{2\ell^2}\right) \left(\frac{(1+\frac{(x-x')^2}{p}}{2\alpha\ell^2} \right)^{-\alpha} (x-\ell)(x'-\ell) \right) +$$

$$\left(\sigma^2 \exp\left(\frac{2\sin^2(\pi(x-x')/p}{\ell^2} \right) \text{üüü} (x-\ell)(x'-\ell) \right) + (\sigma \quad -\ell \quad ' -\ell) \tag{6}$$

5. Calculate values of Hyper-Parameters θ, where $\theta=[\theta_1,\theta_2,\theta_3,\ldots,\theta_N]T$ being key elements in kernel functions. Finding values of hyper-parameters uses knowledge from training data and logarithm equation of marginal data.

$$\log p\left(y \middle| X;\theta,\sigma_\varepsilon^2\right) = -\frac{N}{2}\log 2\pi - \frac{1}{2}\log \left|K(X,X)+\sigma_\varepsilon^2 I_N\right| - \frac{1}{2}y^T\left(K(X,X)+\sigma_\varepsilon^2 I_N\right)^{-1} y \tag{7}$$

6. Model Selection: Since the feature of time function f(x) is controlled by covariance or kernel functions k(x,x') as well as hyperparameters θ. Therefore, the model selection for GP uses kernel functions and hyperparameter learning θ from marginal likelihood and probability density of data y, where $p(y|\theta,X)=\int p(y|f,X,\theta)p(f|\theta,X)d$ (8)

Under GP. Function $p(f|X,\theta)\sim N(0,K)$ is equal to

$$\log p(f|X,\theta) = -\frac{1}{2}f^T K^{-1} - \frac{1}{2}\log|K| - \frac{N}{2}log 2\pi \tag{9}$$

Calculating logarithm of log marginal likelihood whereas probability data of p(y|f) has Gaussian distribution $N(y;f,\sigma^2)$ which the format of function being:

$$\log p(y|\theta,X) = -\frac{1}{2}y^T\left(K(X,X)+\sigma_e^2 I_N\right)^{-1}$$

$$y - \frac{1}{2}\log\left|K(X,X)+\sigma_e^2 I_N\right| - \frac{N}{2}log 2\pi \tag{10}$$

K(X,X) means covariance matrix with the size of N×N and the set of data $y=[y_1,y_2,y_3,\ldots,y_n]^T$. The method used to calculate hyperparameter values θ of kernel function k(x,x') is a numerical method to find hyperparameter values which can be obtained by maximizing the marginal likelihood (Maximization Log Likelihood) in log p(y|θ,X).

7. Forecast $f(x_j^*)$ data whereas,

$f^* = \left[f(x_1^*), f(x_2^*), K, f(x_M^*)\right]'$ Joint Gaussian pdf of latent variables f and f*.

$$f^* = \left[f(x_1^*), f(x_2^*), K, f(x_M^*)\right]' \tag{11}$$

Where $\in i^{(N\times N)}=k(X,X|\theta)$, $K_{(f,f^*}\in i^{(N\times N)}=k(X,X|\theta$ and $K_{f^*,f^*}\in i^{N\times N}=k(X^*,X^*|\theta)$ and Marginal Gaussian Probability is defined as:

Forecasting by SARIMA and GP with combine Kernel Function model is the forecasting of monthly consumption of electricity in Thailand from January 2016 to December 2025, totally 120 months. The interested variables were forecast value from SARIMA model monthly timeline, and the GDP. The data for forecasting electricity consumption was the monthly consumption of electricity during January 2005 to December 2015, totally

132 months. Timelines were divided into 3 periods; Training period that falls on January 2005 to December 2013, the first 108 months, Validation period was data of electricity consumption for the next 24 months that falls on January 2014 to December 2015, and Forecasting period was the forecast of electricity consumption for 120 months starting from January 2016 to December 2025. GP was used in this research for forecasting electricity consumption based on the data during 2005–2013 which were training data set comprised of (1) Electricity consumption, (2) Time (month, year), (3) GDP, and (4) Electricity consumption from forecasting with SARIMA model. The data between 2014 and 2016 which were testing data to evaluate the ability of algorithm. The variable used was only time (No GDP and forecasting value from SARIMA model). The format of function being: $k_{SE*RQ*LIN}+ k_{Per*LIN}+k_{LIN}$.

Forecasting results of monthly consumption of electricity in Thailand for the next 10 years by SARIMA and GP with Hybrid Kernel Function were shown in Figure 12. The mean square error and the mean absolute deviation were equal to 5.5083E-09 and 5.6903E-05 and the mean absolute percentage error was equal to 4.7072E-09 as shown in Table 5.

4.5. Artificial Neural Network

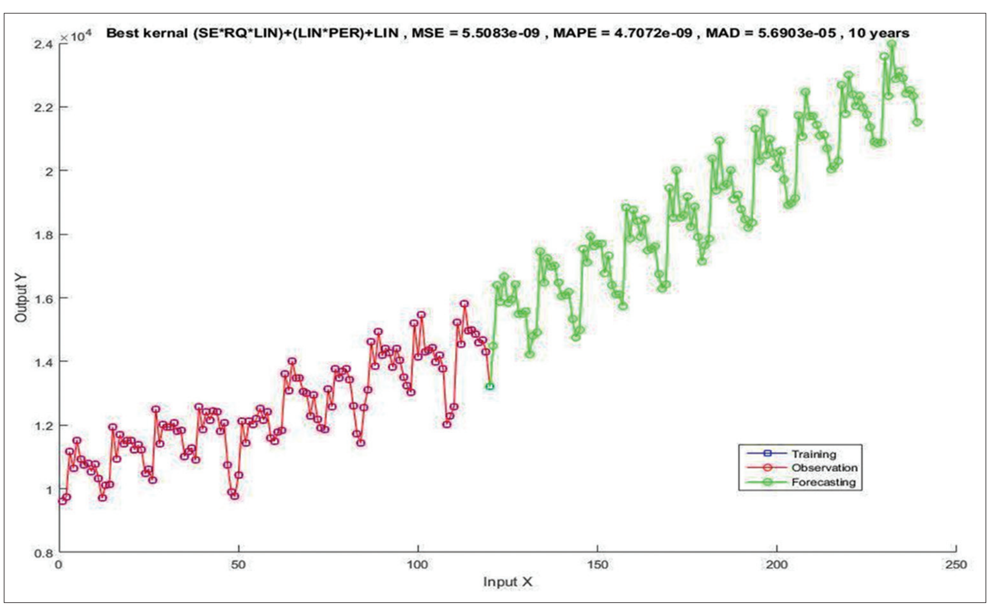
In this paper, the researcher uses a back propagation neural network (BPN), a multi-layered framework. To assist in learning the complex relationship well and using supervised learning, the learning process or the division of the experimental sessions is divided in the same way as the GP. The first is the learning phase. The second is the test phase and the third is the forecasting period. The network learns the data by adjusting the weight to reduce the difference between the value of the output variable of the network and the value of the actual output data to the minimum. And adjust the weight will adjust little by little. By repeating process with data set individually. Until the weight in the convergence network to find the value of the output variable, which is The value of the forecast The network model is modeled as Figure 13. There are 10 hidden layers and 3 hidden units. The learning rate is the learning rate. It is 0.01. Momentum 1.0E-3 Learn (Iterations) is 1000 rounds.

Forecasting by SARIMA and Neural Networks is the forecasting of monthly consumption of electricity in Thailand from January 2016 to December 2025, totally 120 months. The interested variables were forecast value from SARIMA model, monthly timeline, and the GDP. The data for forecasting electricity consumption was the monthly consumption of electricity during January 2005 to December 2015, totally 132 months. Timelines were divided into 3 periods; Training period that falls on January 2005 to December 2013, the first 108 months, Validation period was data of electricity consumption for the next 24 months that falls on January 2014 to December 2015, and Forecasting period was the forecast of electricity consumption for 120 months starting from January 2016 to December 2025. Neural Networks was used in this research for forecasting electricity consumption based on the data during 2005 – 2013 which were training data set comprised of 1. Electricity consumption, 2. Time (month, year), 3. GDP, and 4.Electricity consumption from forecasting with SARIMA model and the data between 2014-2016 which were testing data to evaluate the ability of algorithm. The variable used was only time (No GDP and forecasting value from SARIMA model. Forecasting results of monthly consumption of electricity in Thailand for the next 10 years by SARIMA and Neural Networks were shown in Figure 14. The mean square error and the mean absolute deviation were equal to 5.5083E-09 and 5.6903E-05 and the mean absolute percentage error was equal to4.7072E-09 as shown in Table 6.

Table 5: Forecast error of SARIMA and GP with Combine Kernel Function

Model	MSE	MAPE	MAD
SARIMA and GP with combine Kernel Function	5.5083E-09	4.7072E-09	5.6903E-05

Figure 12: Forecast results of monthly consumption of electricity in Thailand in the next 10 years by SARIMA and Gaussian Processes with Combine Kernel Function



Forecasting by SARIMA and GP with Combine Kernel Function found that the forecast of long-term electricity consumption of the country indicating an increase of electricity consumption nearly two times higher than at present. The forecast value of electricity consumption by the end of 2025 is approximately 269,328 gigawatt-hours rising from the year 2016 averagely 9,290 gigawatt-hours per year or 4.23 percent per year.

5. RESULTS

The errors from the above three methods are compared in Table 7. The results showed that the error minimization capability of SARIMA and GP with combine Kernel Function model (4.7072E-09) outperformed the other approaches (4.8623).

Table 8 revealed that the forecasting value obtained from SARIMA and GP with combine Kernel Function model was close to the actual value. The mean of the differencing was 0.65%. The mean difference of SARIMA and Neural Networks is equal to 11.90%.

However, the performance of ANN model was compared with SARIMA- Neural Networks and SARIMA - GP with combine Kernel Function models by utilizing two dependent samples tests. Therefore, the Wilcoxson signed-rank test and paired t-test were performed to assess the significant difference of the errors.

The results of the Wilcoxson signed-rank test and the paired t-test in Table 9 showed that there was significant difference between the errors of SARIMA -ANN and SARIMA- GP with combine kernel functions since their P-values (0.008 and 0.000 respectively) were less than 0.05.

5. DISCUSSION

Electricity consumption data is characterized by time-series data that is in accordance with seasonal and cycle trends. A model for predicting the time series of influential seasonal influences that is considered suitable for usage in forecasting is the SARIMA model, which is a model that describes the movement of data that relies on the characteristics, explaining correlation and stationary characteristics in linear form, which is very accurate in both short and medium term forecasting. However, there are limits to the SARIMA model. It is only suitable for linear time series with at least 50 observations, so it is appropriate for the SARIMA model to be used for forecasting. However, the data on the consumption of electricity does not have the relationship of the data as a linear function in the term of the meter. Forecasting with SARIMA alone can be very misleading. The use of hybrid models brings the advantages of each model together, resulting in better predictive efficiency than the use of one-way forecasting methods. In addition, the hybrid model uses the principle of one-way forecasting. In order to adjust the parameters of another method, the data parameters are optimized. This research uses the SARIMA model in combination with the GP because the SARIMA model is considered to be a robust statistical model for short- and medium-range linear prediction with high accuracy when combined with a robust GP in the amount of data. Even with minimal training, it has the full capabilities to distribute probability forecasts, including estimates of forecast uncertainty. It can be predicted only by the time series in the nonlinear part of the parameter. But the core of the GP is the kernel function. The predictive accuracy of the GP algorithm depends on the selection of the appropriate kernel function. The key issue is to choose which kernel functions to use to better predict the predictions and to have higher predictive accuracy. The researchers have redesigned the kernel function to be able to use this kernel function with every problem or situation under all time series data types, resulting as the combination of the two. The SARIMA prediction is one of the input variables of a GP that uses the new kernel function. Therefore, the forecast has less error. This is because of the predictive value of the SARIMA model. This is a linear prediction. This predictive value is used as an input variable in the learning process of the GP. With new kernel function comprehensive with all time series data types, it is a robust model of data structure, which has linear components. And nonlinear Accurate predictability in the long term and can be used with a wide variety of situations and phenomena, even in small amounts. It can also be applied to any problem without modifying the kernel function. This model is suitable for forecasting with every situation.

Figure 13: Hybrid model SARIMA - Neural Networks

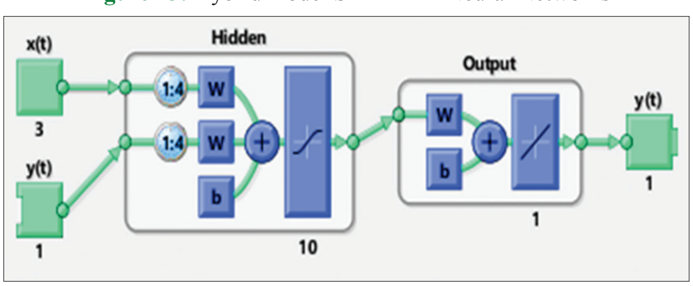


Table 6: Forecast error of SARIMA and Neural Networks

Model	MSE	MAPE	MAD
SARIMA and Neural Networks	6.2107E-07	4.8623	4.6702E-03

Table 7: The comparison of errors from the two methods

Model	MAPE
SARIMA and GP with combine Kernel Function	4.7072E-09
SARIMA and Neural Networks	4.8623

6. CONCLUSIONS

Electricity consumption Forecasting in Thailand With hybrid model SARIMA -ANN and SARIMA- GP with combine kernel functions found that SARIMA- GP with combined kernel functions had a lower MAPE than the SARIMA-ANN model. The SARIMA- GP with combined kernel functions Predictive accuracy and less error than the SARIMA-ANN model. In conclusion, electricity consumption forecasting with hybrid model SARIMA - GP with combined kernel function is appropriate. The results obtained from the forecasting can be used to make a plan and determine the size and numbers of power plants in each type to be constructed to meet with electricity consumption happening in the future as well as fuel consumption. Each type of power plants consumes different fuels such as natural gas, hydropower, biomass, solar and

Figure 14: Forecast results of monthly consumption of electricity in Thailand in the next 10 years by SARIMA and Neural Networks

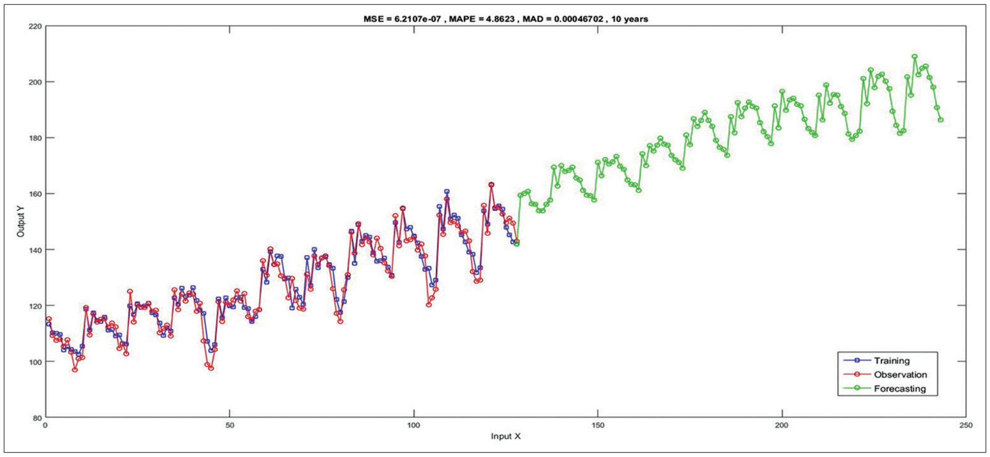


Table 8: Monthly consumption of electricity from January 2017 to September 2017 in comparison to forecasting value from SARIMA and GP with Combine Kernel Function model and SARIMA and Neural Networks model

Month	Actual	SARIMA and GP with combine Kernel			SARIMA and Neural Networks		
		Forecasting value	Error	Difference %	Forecasting value	Error	Difference%
January	14,070.6	14,340	−269.40	−1.91	16,266	−2,195.40	−15.6027
February	13,618.0	14,812	−1,194.00	−8.76	16,575	−2,957.00	−21.7139
March	16,539.2	13,916	2,623.20	15.86	17,941	−1,401.80	−8.47562
April	15,326.1	16,454	−1,127.90	−7.35	17,056	−1,729.90	−11.2873
May	16,511.0	15,466	1,045.00	6.32	17,873	−1,362.00	−8.24905
June	15,921.6	16,256	−334.40	−2.10	17,658	−1,736.40	−10.9059
July	15,672.8	15,982	−309.20	−1.97	17,704	−2,031.20	−12.96
August	16,403.5	15,016	1,387.50	8.45	17,844	−1,440.50	−8.78166
September	16,048.0	16,476	−428.00	−2.667	17,509	−1,461.00	−9.10394

Table 9: Wilcoxson signed-rank test and Paired t-test for each pair of forecasting SARIMA -ANN and SARIMA- GP with combine kernel functions methods

Samples tests	P
Wilcoxson signed-rank test	0.008
Paired t-test	0.000

wind. Each fuel has different capacity in generating electricity. Knowing electricity consumption in each year in long term will lead to investment and preparation in seeking appropriate fuels for generating electricity accordingly. It also helps determine sizes and numbers of power plants in each type to be constructed to serve the need of electricity consumption in the future.

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