A Markov chain grey model: A forecasting of the Philippines electric energy demand

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A Markov Chain Grey Model: A Forecasting Of The Philippines Electric Energy Demand

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Abstract. The aim of this paper is to develop a prediction model of energy demand of the Philippines. A Markov Chain Grey Model (MCGM) is proposed to forecast the monthly energy demand of the Philippines. Data were gathered and obtained from the Department of Energy that covers a total of 17 years starting from year 2000 to 2016. The proposed Markov Chain Grey Model (MCGM) is compared to Grey Model (GM) using forecasting accuracy such as Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Squared Error (MSE), and Normalized Mean Square Error (NMSE). The comparison reveals that MCGM is the best model among the two models to forecast the monthly energy demand of the Philippines in the year 2017 to 2022.

Keywords: Grey Model, Markov Chain Grey Model, Energy, Demand

INTRODUCTION

The Philippines is an emerging economy and its economy has greatly shifted from agriculture to industry. In terms of energy use, conventional fossil fuels (oil and gas) are the main source for its primary energy demands. According to the 2011 primary energy consumption of the Philippines, 31% of the consumption was met by oil, 20% by coal, 22% by geothermal, 12% by biomass, 6% by hydro and 1% by other renewable energy like wind, solar and biofuel (Philippines Energy Situation, 2017). As the 12th-largest nation in the world, the Philippines has a population of more than 100 million people spread over 7,000 islands, presenting several electricity infrastructure challenges. By the year 2015, the country faced growing concerns over resource adequacy in its power sector, as the nation is challenged to add supply quickly enough to keep up with growing demand (Supply shortages lead to rolling power outages in the Philippines,2015). Electric energy demand forecasting is a fundamental tool that can be used to prevent such scenarios.

Various technical and statistical methods for energy demand forecasting have been proposed in the last few decades with varying results. GM is suitable for forecasting the competitive environment where decision makers can refer only to a limited historical data. But the forecasting precision for data sequences with large random fluctuation is low. The Markov-chain forecasting model can be used to forecast a system with randomly varying time series. It is a dynamic system which forecasts the development of the system according to transition probabilities between states which reflect the influence of all random factors. So the Markov-chain forecasting model is applicable to problems with random variation, which could improve the GM forecasting model (Min Huang et al., 2007).

This work is focused on monthly prediction, which is useful for the maintenance planning of grids and as market research for electricity producers and resellers. The energy demand of industry sector of the Philippines has been forecasted using the MCGM for the time span 2017 to 2022

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Objective of the Study

This research aims to compare the two models that is established by the Grey Model and Markov Chain Grey Model and choose the best suitable model for predicting the monthly energy demand of the Philippines. Also, to forecast the monthly energy demand of the Philippines from 2017 to 2022.

Research Paradigm

The researchers make use of the monthly data of electric energy demand in terms of megawatts of the Philippines. The researchers input the monthly data of electric demand of the Philippines.

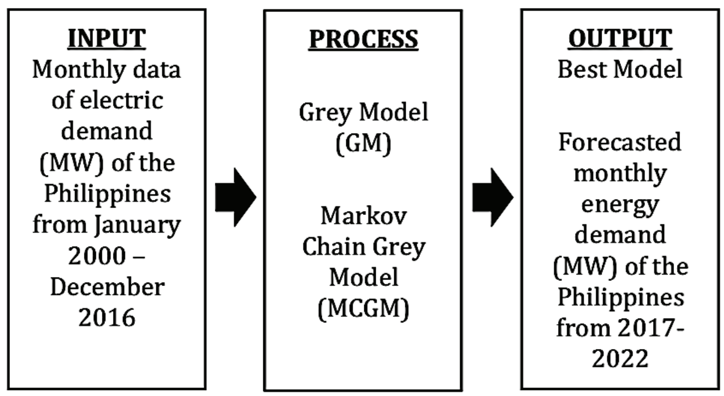

FIGURE 1. Research Paradigm

In this study, the researchers formulated two models namely Grey Model (GM) and Markov Chain Grey Model (MCGM) to produce the predicted and forecasted monthly energy electric demand of the Philippines.

Statement of the Problem

Specifically, this research aims to answer the following questions which lead to formulating the mathematical model for energy demand of the monthly system peak demand of the Philippines:

1. What is the trend of the graph of the electric demand of the Philippines from year 2000 to 2016?
2. What is the statistical model that can be formulated using the models;
   a. Grey Model;
   b. b. Markov Chain Grey Model?
3. What model between MCGM and GM is the best suitable to forecast the electric demand of the Philippines.
4. Is there a significant difference between the actual and predicted values obtained using the best formulated model for monthly system peak demand of the Philippines?
5. What is the forecasted values from the year 2017 to 2022 produced by the best model?

Scope and Limitation

A total of 204 observations were considered in this study. These observations are the monthly electric demand of the Philippines from year 2000 to 2016 which are gathered and obtained from https://www.doe.gov.ph. The researchers of this study will only forecast the monthly electric demand for the year 2017 up to 2022.

Review on Related Literature

In a study conducted by A. Kazemi et.al, three forecasting models namely Grey Model (GM), Markov Chain Grey Model (MCGM) and Regression were presented and compared to be used for developing a prediction model of energy demand of Iran's industry sector. The results of their study showed that the accuracy of MCGM in forecast energy demand of industry sector from year 2009 to 2020 is higher than those of GM and regression forecasting model (Kazemi et al., 2011).

Another study conducted Q. Yan et.al, from the retail electricity market of Guangdong province in China a market share forecasting model was established based on Markov chain, and a system dynamics model was constructed to forecast the electricity consumption based on the analysis of five factors which are economic development, policy factors, environmental factors, power energy substitution, and power grid development (Yan et al., 2018).

A study entitled AGM(1,1)Markov chain combined model with an application to predict the number of Chinese international airlines provides a proposed new dynamic analysis model which combines the first-order one-variable grey differential equation model (abbreviated as GM(1,1) model) from grey system theory and Markov chain model from stochastic process theory. The combined GM(1,1)Markov chain (MC) model was abbreviated as MCGM(1,1) model. This combined model takes advantage of the high predictable power of GM(1,1) model and at the same time take advantage of the prediction power of Markov chain modelling on the discretized states based on the GM(1,1) modelling residual sequence. For prediction accuracy improvements, Taylor approximation was applied to MCGM(1,1) model. The researchers on this study call the improved version as T-MCGM(1,1) model. As an example, they use the statistical data of the number of Chinese international airlines from 1985 to 2003 for a validation of the effectiveness of the T-MCGM(1,1) model (Li et al., 2018).

Lei-Chuan Lin and Shan-Yau Wu's study utilizes the black swan theorem to discuss how to face the lack of historical data and outliers. They may cause huge influences which make it impossible for people to predict the economy from their knowledge or experiences. Meanwhile, they cause the general dilemma of which prediction tool to be used which is also considered in this study. For the reason above, this study uses 2009 Q1 to 2010 Q4 quarterly revenue trends of Taiwan's semiconductor packaging and testing industry under the global financial turmoil as basis and the grey prediction method to deal with nonlinear problems and small data. Under the lack of information and economic drastic changes, this study applies Markov model to predict the industry revenues of GM(1,1) and DGM(1,1) results. The results show that the accuracy of 2010 Q1Q3 is 88.37%, 90.27%, sand 91.13%, respectively. Besides, they are better than the results of GM(1,1) and DGM(1,1) which are 86.51%, 77.35%, 75.46% and 73.77%, 74.25%, 59.72%. The results show that the prediction ability of the grey prediction with Markov model is better than traditional GM(1,1) and DGM(1,1) is facing the changes of financial crisis. The results on this study also prove that the grey-Markov chain prediction can be the perfect criterion for decision maker's judgement even when the environment has undergone drastic changes which bring the impact of unpredictable conditions (Lin et al., 2013).

METHODOLOGY

Statistical Tool

MATLAB

IThe researchers used the software MATLAB to program and forecast, which played the advantages of big data and high prediction accuracy for MCGM, at the same time, utilized Grey Model for forecasting electric demand.

Statistical Treatment

Grey Model

Grey prediction (GP) has three basic operations: accumulated generating operator (AGO), inverse accumulating operator (IAGO) and grey model (GM). The steps of GP are shown below (Kazemi et al., 2011).

Step 1: Original time sequence with n samples (time point) is expressed as

$$x^{(0)} = \{x^{(0)}(1), x^{(0)}(2), ..., x^{(0)}(n)\} \tag{1}$$

AGO operator is used to convert chaotic series x(0) into monotonically increasing series.

$$x^{(1)} = \{x^{(1)}(1), x^{(1)}(2), ..., x^{(1)}(n)\} \tag{2}$$

where

$$x^{(1)}(j) = \sum_{i=1}^{j} x^{(0)}(i) \tag{3}$$

It is obvious that the original data $x^{(0)}(i)$ can be easily recovered from $x^{(1)}(i)$ as

$$x^{(0)}(i) = x^{(1)}(i) - x^{(1)}(i-1) \tag{4}$$

where $x^{(0)}(1) = x^{(1)}(1)$, $x^{(1)}(i) \in x^{(1)}$. This operation is called IAGO.

Step 2: Form the GM model by establishing a first order grey differential equation

$$x^{(0)}(i) + az^{(1)}(i) = b \tag{5}$$

where $z^{(1)}(i) = \frac{1}{2}(x^{(1)}(i) + x^{(1)}(i+1))$ In Eq. (3), $i(i = 2, ..., n)$ is a time point. a is called the development coefficient and b is called driving coefficients. Using least mean square estimation technique coefficients, can be estimated as, $[a, b]^T$

$$\begin{bmatrix} a \\ b \end{bmatrix} = (A'A)^{-1}A'X_n \tag{6}$$

$$A = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \tag{7}$$

$$X_n = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix} \tag{8}$$

Step 3: According to the estimated coefficients a and b, GP equation can be obtained by solving differential equation in Eq. (3). Consider this predicted equation by IAGO,

$$\hat{x}^{(0)}(i+1) = \hat{x}^{(1)}(i+1) - \hat{x}^{(1)}(i) = (x^{(0)}(1) - \frac{a}{b})(1 - e^{a})e^{-a} \tag{9}$$

Markov Chain Grey Model

In order to make a new model which is the Markov Chain Grey Model (MCGM), the original data are first modelled by the GM, and then the residual errors between the predicted values and the actual values for all previous time steps are obtained. The idea of the MCGM is to establish the transition behavior of those residual errors by Markov transition matrices, and then the possible correction for the predicted value can be made from those Markov matrices. The detailed procedure is shown as follows (Gou-Dong et al., 2007).

The Division of States

For original data series, use GM forecasting model to obtain the predicted value $\hat{x}^{(0)}(i)$. Then, the residual error $e(i) = x^{(0)}(i) - \hat{x}(i)$ can also be obtained. Assume that there exists some regular information in the residual error series of GM. We can establish Markov state transition matrices; r states are defined for each time step. Thus the dimension of the transition matrix is $r \times r$. The residual errors are partitioned into r equal portions called states. Each state is an interval whose width is equal to a fixed portion of the range between the maximum and the minimum of the whole residual error. Then, the actual error can be classified into those states. Let $S_i j$ be the jth state of the ith time step $S_i j \in \{L_i j, U_i j\}$ where $L_i j$ and $U_i j$ are the lower boundary and upper boundary of the j^{th} state for the i^{th} time step of the residual error series. $e(i)$ is residual error of GM.

$$L_{ij} = min\ e(i) + \frac{j-i}{r}(max\ e(i) - min\ e(i)) \tag{10}$$

$$U_{ij} = min\ e(i) + \frac{j}{r}(max\ e(i) - min\ e(i)) \tag{11}$$

Establishment of transition probability matrix of state If the transition probability of state is $P_{ij}^{(m)} = \frac{M_i j^{(m)}}{M_i}$, $j = 1, 2, ..., r$ where $P_{ij}^{(m)}$ is the probability of transition from state i to j by m steps. $M_{ij}^{(m)}$ is the transition times from state i to j by m steps and Mi is the number of data belonging to the ith state. Because the transition for the last m entries of the series is indefinable, Mi should be counted by the first as $n \times m$ entries; n is the quantity of entries of the original series. Then, the transition probability matrix of state can be written as

$$R^m = \begin{bmatrix} P_{11}^{(m)} & P_{12}^{(m)} & \cdots & P_{1r}^{(m)} \\ P_{21}^{(m)} & P_{22}^{(m)} & \cdots & P_{2r}^{(m)} \\ \vdots & \vdots & \ddots & \vdots \\ P_{r1}^{(m)} & P_{r2}^{(m)} & \cdots & P_{rr}^{(m)} \end{bmatrix} \tag{12}$$

Obtaining the predicted values.

The residual error series $e(i)$ is divided into r states, then there is r transition probability row vectors. The possibilities of a certain error state for the next step are obtained by the probabilities in r row vectors, denoted as $\{a_i(T), i = 1, 2, ..., r\}$at time step T. Define the centres of r states as $v_i(i = 1, 2, ..., r)$. Then, the predicted value for the next step is

$$\bar{x}^{(0)}(T + 1) = \bar{x}(T + 1) + \sum a_i(T)v_i \tag{13}$$

where $[a_1(T), a_2(T), ..., a_r(T)] = a^(T - 1)R^m$ and

$$\begin{aligned} a^{(T+1)} &= a^{(T)}R^{(m)} \\ a^{(T+2)} &= a^{(T+1)}R^{(m)} \\ \vdots &= \vdots \\ a^{(T+k)} &= a^{(T+k-1)}R^{(m)} \end{aligned} \tag{14}$$

where $m = 1$

Forecasting Accuracy including Paired t-test

Mean Absolute Percentage Error (MAPE)

This mechanism is used to estimate a pattern in the future, it measures the accuracy in the future value, and it is expressed as a ratio of difference in the estimated value with the actual value divide over every observation.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|a_t - f_t|}{a_t} \times 100 \tag{15}$$

where a_t be the actual value and f_t be the future value.

The actual value is summed up for every estimated point and divide by the number of points (MAPE).

Mean Absolute Error (MAE)

The mean absolute error is another useful measure widely used in model evaluations

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |\ e_i\ | \tag{16}$$

where e_i is the difference between the predicted and actual observation (T. Chai et al., 2014).

Root Mean Square Error (RMSE)

The root mean square error has been used as a standard statistical metric to measure model performance in meteorology, air quality, and climate research studies.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(e_i)^2} \tag{17}$$

where e_i is the difference between the predicted and actual observation (T. Chai et al., 2014).

Mean Squared Error (MSE)

In statistics, the concept of mean squared error is an important criterion that is utilized in order to measure the performance of an estimator. The mean squared error, abbreviated as MSE, is quite important for relaying the concepts of precision, bias and accuracy during the statistical estimation.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(\hat{X}_i - X_i)^2 \tag{18}$$

where $\hat{X}_i$ be the vector denoting values of n number of predictions and X_i be a vector representing n number of true values (Mean Square Error).

Normalized Mean Square Error (NMSE)

Normalized Mean Square Error can be expressed as

$$NMSE = \frac{\bar{d}^2}{\bar{C}_0(\bar{C}_0 - \bar{d})} = \frac{\sigma_d^2 + \bar{d}^2}{\bar{C}_0(\bar{C}_0 - \bar{d})} \tag{19}$$

where $\bar{d}$ and σ_d^2 indicate the mean and the standard deviation of

$$d_i = C_{oi} - C_{pi} \tag{20}$$

where C_0 and C_p are respectively, observed and predicted concentrations, while the overbar indicates the mean over the sampling points and i indicates the i^{th} sampling point (Poli et al., 1993).

Paired t-test

Paired sample t-test is a statistical technique that is used to compare two population means in the case of two samples that are correlated. Paired sample t-test is used in before-after studies, or when the samples are the matched pairs. There are some assumptions to be satisfied before performing a paired t-test which includes the following:

1. Samples must be a matched pair.
2. Normal distribution are assumed
3. The variance of two samples is equal.
4. Cases must be independent of each other.

To calculate the parameter, the formula to be used is written as:

$$t = \frac{\bar{y}}{\sqrt{\frac{s^2}{n}}} \tag{21}$$

where $\hat{y}$ is the mean difference between two samples, s^2 is the sample variance, n is the sample size and t is a paired sample t-test with $n - 1$ degrees of freedom (Paired Sample T-test).

Results and discussion

Trend of the graph of the electric energy demand of the Philippines

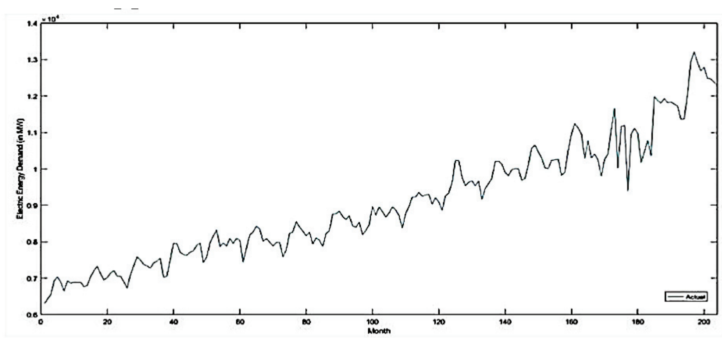

FIGURE 2. The actual values of Electric Energy demand of the Philippines (2000-2016)

Based on the historical data of the energy demand of industry sector in the Philippines from 2000 to 2016, a trend curve equation is increasing with 13209 megawatts as the highest recorded electric energy demand (May 2016) while 6293 megawatts is the lowest recorded electric energy demand (January 2000) as shown in Figure 1. The highest and lowest recorded electric energy is due to the changes of weather in the Philippines.

Statistical Models Grey Model

The original data sequence of monthly electric demand of the Philippines from the year 2000 to 2016 is listed in tables 1 to 17, and then the researchers applied Grey-Markov forecasting model to forecast the electric energy with a time span of 2017-2022. According to the methodology proposed in section 3, the forecasting steps are:

Building GM(1,1) forecasting Model Based on the data of electric energy demand of the Philippines from 2000 to 2016, the value a = 0.002932787, b = 6604.315361 can be obtained by using the MatLab.

TABLE 1. GM Predicted Results for the Year 2000

Month	Actual Value	Predicted Value	Relative Error e(i)	State
January	6293	6293	0	4
February	6425	6651.972722	-3.532649371	3
March	6548	6671.510179	-1.886227528	3
April	6928	6691.105018	3.41938484	4
May	7034	6710.75741	4.595430624	4
June	6890	6730.467522	-1.522567684	5
July	6649	6750.235525	-1.522567684	3
August	6925	6770.061589	2.237377781	4
September	6862	6789.945883	1.050045424	4
October	6890	6809.888579	1.162720184	4
November	6885	6829.889849	0.80043792	4
December	6885	6849.949865	0.509079671	4

Same process was repeated until we get the forecasted value for the year 2016 using GM forecasting model as shown on Table 2.

TABLE 2. GM Predicted Results for the year 2016

Month	Actual Value	Predicted Value	Relative Error e(i)	State
January	11365	11647	-2.484088869	3
February	11370	11681	-2.739893946	3
March	12040	11715 83566	2.692394858	4
April	12946	11750 24615	9.236473449	5
May	13209	11784 7577	10.78236277	5
June	12925	11819 37062	8.554192488	5
July	12694	11854 0852	6.616628322	5
August	12786	11888 90174	7.016254179	5
September	12491	11923 82054	4.540704988	4
October	12473	11958 8419	4.122168693	4
November	12380	11993 96612	3.118205826	4
December	12286	12029 1935	2.09023684	4

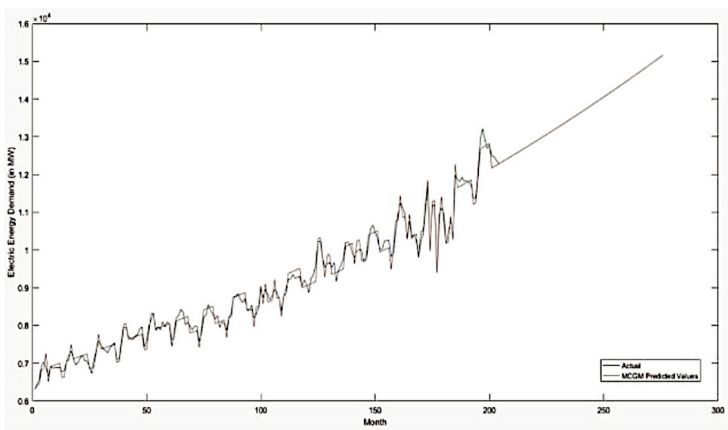

FIGURE 3. The actual and predicted values by Grey Model (GM)

Based on the historical data of the energy demand of industry sector in the Philippines from 2000 to 2016, a trend curve equation is built by GM forecasting model. GM forecasting model was established by

$$x(i) = (6293 - (\frac{6598.33638033476}{-0.00293278726059713})(1 - e^{-0.00293278726059713(i)})(e^{-0.00293278726059713(i)}) \tag{22}$$

As a result, the actual and predicted generated data series and original data are plotted in figure 3.

Jan'17	12064.52	Jan'18	12496.68
Feb'17	12099.96	Feb'18	12533.38
Mar'17	12135.5	Mar'18	12570.19
Apr'17	12171.14	Apr'18	12607.11
May'17	12206.89	May'18	12644.14
Jun'17	12242.74	Jun'18	12681.28
Jul'17	12278.7	Jul'18	12718.52
Aug'17	12314.76	Aug'18	12755.88
Sep'17	12350.93	Sep'18	12793.34
Oct'17	12387.21	Oct'18	12830.92
Nov'17	12423.59	Nov'18	12868.6
Dec'17	12460.08	Dec'18	12906.4
Jan'19	12944.31	Jan'21	13888.25
Feb'19	12982.33	Feb'21	13929.04
Mar'19	13020.46	Mar'21	13969.95
Apr'19	13058.7	Apr'21	14010.98
May'19	13097.05	May'21	14052.13
Jun'19	13135.52	Jun'21	14093.41
Jul'19	13174.1	Jul'21	14134.8
Aug'19	13212.8	Aug'21	14176.31
Sep'19	13251.6	Sep'21	14217.95
Oct'19	13290.52	Oct'21	14259.71
Nov'19	13329.56	Nov'21	14301.59
Dec'19	13368.71	Dec'21	14343.6
Jan'20	13407.97	Jan'22	14385.73
Feb'20	13447.35	Feb'22	14427.98
Mar'20	13486.85	Mar'22	14470.36
Apr'20	13526.46	Apr'22	14512.86
May'20	13566.19	May'22	14555.48
Jun'20	13606.04	Jun'22	14598.23
Jul'20	13646	Jul'22	14641.11
Aug'20	13686.08	Aug'22	14684.11
Sep'20	13726.28	Sep'22	14727.24
Oct'20	13766.59	Oct'22	14770.49
Nov'20	13807.02	Nov'22	14813.88
Dec'20	13847.58	Dec'22	14857.39

FIGURE 4. Forecasted value (2017-2022) using GM model

As shown in figure 4 the forecasted energy demand given by the GM model is increasing from 12064.52 MW (January 2017) to 14857.39 MW (December 2022)

Markov Chain Grey Model

Dividing states by Markov forecasting model According to relative error (see tables 1 and 2) from 2000 to 2016, five states are divided as follows, and the circumstances that relative error lies in the state are listed in these tables.

$$\begin{aligned}
\otimes_1 &= [-18.17116818, -12.3846199],\\
\otimes_2 &= [-12.3846199, -6.589755803],\\
\otimes_3 &= [-6.589755803, -0.799049614],\\
\otimes_4 &= [-0.799049614, 4.991656576],\\
\otimes_5 &= [4.991656576, 10.78236277]
\end{aligned} \tag{23}$$

Calculating transition probability matrix Transition probability matrix can be calculated according to the method introduce in this paper.

$$\text{P(1)=}\begin{bmatrix}0&0&0&0&0\\0&0&6&1&0\\0&6&42&21&1\\0&0&21&69&8\\0&1&1&8&7\end{bmatrix}, \text{P(2)=}\begin{bmatrix}0&0&0&0&0\\0&1&5&4&0\\0&7&35&61&8\\1&2&34&57&6\\0&0&1&13&73\end{bmatrix}, \text{P(3)=}\begin{bmatrix}0&0&1&0&0\\1&1&5&7&1\\0&7&30&23&13\\0&2&40&57&1\\0&0&2&14&2\end{bmatrix}$$

$$\text{P(4)=}\begin{bmatrix}0&1&0&0&0\\0&1&2&5&3\\0&7&25&34&8\\0&2&45&47&4\\1&0&0&12&1\end{bmatrix}, \text{P(5)=}\begin{bmatrix}0&0&0&0&0\\0&1&0&9&0\\0&5&18&43&7\\1&4&50&34&9\\0&0&0&12&0\end{bmatrix}$$

Due to five divided states, latest five months data near to prediction time are selected to make state prediction table (table 4), the transition step are defined as 1,2,3,4,5.

TABLE 3. GM Predicted Results for the year 2016

	Initial State	Transition	State 1	State 2	State 3	State 4	State 5
Nov 2022	4	1	0	0	21	139	8
Oct 2022	4	2	1	2	34	127	6
Sept 2022	4	3	0	2	40	127	1
Aug 2022	4	4	0	2	45	117	4
July 2022	4	5	1	4	50	103	9
Sum			2	10	190	597	28

Calculating forecasting values The sum of all transition probability from any state to state 5 is maximal (242), and then the relative error of January 2017 is in the state 4: ?4 = [?0.799049614, 4.991656576], the forecast value of GM(1,1) is calculated by eq.(3), the forecast value of January 2017 obtained by GM(1,1) is 12064.5244, so the forecast value obtained by Grey-Markov is 12317.4334 , that is $12064.5244(1 + \frac{-0.799049614+4200.991656576}{200}) = 12317.4334$.

Same process from the steps above was done to predict electric energy demand of the Philippines from February 2017 until we have predicted the electric energy demand of December 2022.See Table 4.

TABLE 4. State Prediction of December 2022

	Initial State	Transition	State 1	State 2	State 3	State 4	State 5
Dec 2016	4	1	0	0	21	69	8
Nov 2016	4	2	1	2	34	57	6
Oct 2016	4	3	0	2	40	57	1
Sept 2016	4	4	0	2	45	47	4
Aug 2016	5	5	0	0	3	12	0
Sum			1	6	143	242	19

By the state of each entry, the transition probability matrices of state Pi, i = 3 can be evaluated. According to the four states, we can calculate their centre values. The model fitted and predicted values by MCGM forecasting model, and the experimental original data are plotted in figure 3 by the equation $x(i) = (GM\ predicted\ value)(1+(\frac{L_i+U_i}{200})$ where L_i are the lower boundaries of each states, $i = 1, 2, ..., 4$ and U_i are the upper boundaries of each states, $i = 1, 2, ..., 4$.

Error Analysis

To examine the accuracy of the different forecasting models, the researchers compare the forecasting results of the value using data from 2000 to 2016.

TABLE 5. Comparison of forecast results with two models

Models	MAPE	MAE	RMSE	MSE	NMSE
GM	0.0342	3.0980530	393.52246	16.233479	0.0018876
MCGM	0.0165925	1.4591596	159.9206	3.0341765	0.0003125

Since the Markov Chain Grey Model (MCGM) has the least error based on table 5, it is considered the best statistical model in forecasting the energy demand of the Philippines.

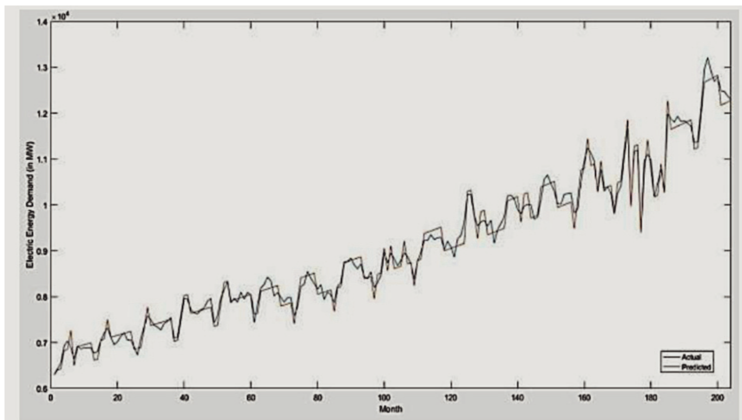

FIGURE 5. The actual and predicted values from 2000-2016

TABLE 6. Paired T-Test

Model	P-value	Remark
Actual vs Predicted	0.391	Not Significant

The paired T-test shows that the null hypothesis is rejected which indicates that the mean difference between the paired observations does not differ from each other or the actual and predicted values are close enough to conclude that the model is nearly fitted

Forecasted Values

Using the formulated mathematical model with the equation $x(i) = (GM\ predicted\ value)(1 + (\frac{L_i+U_i}{200}))$ where L_i are the lower boundaries of each states, $i = 1, 2, ..., 5$ and U_i are the upper boundaries of each states, $i = 1, 2, ..., 5$, the researchers are able to predict the values of the electric demand of the Philippines starting from year 2017 to 2022 as shown in figure 6.

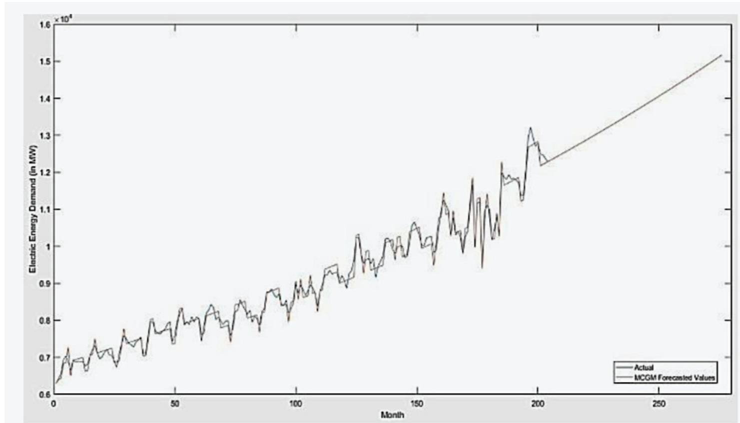

FIGURE 6. Actual and Predicted Values for Electric Demand by Markov Chain Grey Model (MCGM)

Jan'17	12317.43	Jan'20	13689.05
Feb'17	12353.61	Feb'20	13729.25
Mar'17	12389.89	Mar'20	13769.58
Apr'17	12426.28	Apr'20	13810.02
May'17	12462.78	May'20	13850.58
Jun'17	12499.39	Jun'20	13891.26
Jul'17	12536.1	Jul'20	13932.06
Aug'17	12572.92	Aug'20	13972.98
Sep'17	12609.85	Sep'20	14014.02
Oct'17	12646.88	Oct'20	14055.18
Nov'17	12684.03	Nov'20	14096.46
Dec'17	12721.28	Dec'20	14137.86
Jan'18	12758.64	Jan'21	14179.39
Feb'18	12796.12	Feb'21	14221.03
Mar'18	12833.7	Mar'21	14262.8
Apr'18	12871.4	Apr'21	14304.69
May'18	12909.2	May'21	14346.71
Jun'18	12947.12	Jun'21	14388.85
Jul'18	12985.14	Jul'21	14431.11
Aug'18	13023.28	Aug'21	14473.49
Sep'18	13061.53	Sep'21	14516
Oct'18	13099.89	Oct'21	14558.64
Nov'18	13138.37	Nov'21	14601.4
Dec'18	13176.96	Dec'21	14644.28
Jan'19	13215.66	Jan'22	14687.3
Feb'19	13254.48	Feb'22	14730.43
Mar'19	13293.41	Mar'22	14773.7
Apr'19	13332.45	Apr'22	14817.09
May'19	13371.61	May'22	14860.61
Jun'19	13410.88	Jun'22	14904.26
Jul'19	13450.27	Jul'22	14948.03
Aug'19	13489.78	Aug'22	14991.93
Sep'19	13529.4	Sep'22	15035.97
Oct'19	13569.13	Oct'22	15080.13
Nov'19	13608.99	Nov'22	15124.42
Dec'19	13648.96	Dec'22	15168.84

FIGURE 7. Forecasted value (2017-2022) using MCGM model

As shown in figure 7 the forecasted energy demand given by the MCGM model is increasing from 12317.43 MW (January 2017) to 15168.84 MW (December 2022)

CONCLUSIONS

The major purpose of this paper was to develop the prediction model of energy demand of industry sector in the Philippines. Through using the statistics data of the energy demand of industry sector from 2000 to 2016, two forecasting models were presented and compared. The results showed that the accuracy of MCGM in forecast energy demand of industry sector is higher than GM forecasting model. Also energy demand of industry sector of the Philippines from 2017 to 2022 was forecasted. The MCGM forecasting model could be applied to forecast other time series problems with large random fluctuation. This study has an impact to production and distribution of electric companies because it provides them with a prediction of the market demand of electric energy. It helps them to predict future electric energy demand.

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