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Research paper

A Hybrid Modeling of Long-Term Electricity Consumption Forecasting Based on ARIMA and ANN: The Case of Thailand with Projection

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Abstract

Modeling and forecasting of electricity consumption can provide reliable guidance for power operation and planning in developing countries such as Thailand. In this study, formulates the effects of two different historical data type is modeled by auto regressive integrated moving averaged (ARIMA) and artificial neural network (ANN) based on population and gross domestic product per capita (GDP). The derived model is validated by various statistical approaches such as the determination coefficient. Additionally, the performances of the derived model are assessed using mean absolute percentage error (MAPE), root mean square error (RMSE) and mean absolute error (MAE). Three scenarios are used for forecasting Thailand's electricity consumption in 2011 – 2015. The simulation results are validated by actual data sets observed from 1993 to 2010. Empirical results showed that the proposed method has higher accuracy compared to single ARIMA and artificial intelligence based models.

Keywords: *ARIMA; Hybrid Forecasting Model; Neural Network; Thailand Electricity Consumption*

1. Introduction

Electrical energy is vital important foe development of every country from the economic and environmental perspective with the last decades presenting a sequence of crisis in the sector, the government, state, enterprise and electrical.
Electrical companies are looking for accurate models with the ability to reflect the best predictions of electricity consumption in an unstable economy scenario.
The investment on infrastructure and operation trends to produce better results when they are based on linearity scenarios.
To cope with the uncertainties on demand and mitigate the risks of economic and financial loses; the decision making is based on long term demand forecasts [1].
As electrical is a crucial input to industrial part of the country, electrical demand increase along with the industrial function increase. Rapid changes in industry and economy strongly affect electricity consumption. Therefore, electricity consumption is an important economical index that represents economic development of a city or the country [2]. As over the past decade global energy consumption has increased rapidly because of population and economic growth [3], [4].
According to wide growth of electricity consumption in the last decade, electrical demand management is very important for achieving economic success, environment preservative and suitable planning for existing resources that result in self-sufficiency and economic development. Therefore, various techniques have been used for electrical demand management to forecast future electrical demands accurately [4].
According to the time horizon, the electricity consumption forecasting is classified as short-term, medium-term and long-term forecasting.
Short-term forecasting (Several days ahead in hourly steps) has attracted substantial due to its importance for power system control, economic dispatch and order of unit commitment in electricity markets.
Medium-term forecasting (Several months ahead in weekly steps) is especially interesting for companies operating in a deregulated environment, as it provides them with valuable information about the market need of electricity, scheduling the maintenance of the units and electrical imports/exports.
Long-term forecasting (Years ahead in annual steps) has been always playing a vital role in power system management and planning. The long-term forecast directly impacts on effectiveness of electrical trading, system reliability, operation and maintenance costs and generator scheduling. Moreover, accurate long-term forecasting can provide reliable guidance for power consumption planning, which is important for the sustainable development of all countries.
For long-term planning, all approaches for forecasting require historical data as statistical models for electricity consumption forecasting while dependent and independent variables face too much fluctuation, Table 1 outlines the summary of all approaches.
One of the most important and widely used time series models is the auto regressive integrated moving average (ARIMA) model, Box-Jenkins methodology and Grey model (GM) in the modelling process [5].
Although ARIMA models are quite flexible as they can represent several different types of times series, their major limitation is the pre-assumed linear form of the model.

Artificial neural network (ANN) is the most important and widely used techniques among the artificial intelligence based approaches, applied in the field of energy management [6] - [9]. Despite the performance of ANN methods for electricity consumption forecasting based on the input historical data [10], [11]. Summary of studies on long-term electricity consumption forecasting for various countries showed in Table 1.

Table 1: Summary of Studies on Long-Term Electricity Consumption Forecasting for Various Methods Countries.

Methods	Country	Period	Input Variables	MAPE (%)
Single Methods				
ANFIS	G7 [13]	2008-2015	GDP, POP	1.49
SVM	Taiwan [14]	1981-2000	Previously observed values	1.29
KBES	Egypt [15]	1981-2007	Years, Temperature	1.33
GP	Turkey [16]	1994-2010	Previous demand, Climate	1.16
Data mining	Turkey [14]	1980-2025	Previously observed values	3.25
GEP	Thailand [17]	1986-2009	GDP, POP, EXP, Stock index	0.37
PSO	Iran [18]	1982-2030	GDP, POP, IMP, EXP	1.16
ACS	Iran [19]	1992-2030	GDP, POP, IMP, EXP,Stock index	0.75
ABC	Turkey [20]	1979-2025	GDP, POP, IMP, EXP	2.26
Combined Methods				
PSO-GA	Iran [21]	1980-2006	GDP, POP, Number of customers	0.98
Fuzzy-data mining	Iran [19]	1995-2005	Previous observed values	2.00
ANN-PSO	Iran, USA [16]	1967-2030	GDP, POP, IMP, EXP	1.51
ANN-GA	Iran [22]	1981-2008	Price number of customers, value added	3.68
Simulated-ANN	Iran [18]	1994-2005	Previously observed values	1.80
GRNN-FOA	China [23]	1978-2012	Previously observed values	1.15
Simulation-ANFIS	Iran [24]	1994-2005	Previously observed values	1.55
SVR-DE	China [15]	1987-2008	Previously observed values	1.10
LS-SVM-FOA	China [25]	1998-2011	Previously observed values	1.03
Optimized GM	Turkey [26]	1945-2025	Previously observed values	3.28
ARIMA-PSO	China [27]	2006-2010	Previously observed values	2.19
Fuzzy-GA	China [28]	1990-2010	Previously observed values	7.45
GP-SA	Thailand [29]	1986-2009	GDP, POP, EXP, Stock index	0.50
MLP-ANN	Greece [30]	2010-2015	Previously observed values	2.19
ANN-Fuzzy	India [31]	2006-2010	Previously observed values	1.76
GD-ANN	Iran [32]	2010-2030	GDP, POP, IMP, EXP	5.41
PSO-ANN	Iran [32]	2010-2030	GDP, POP, IMP, EXP	5.02
IPSO-ANN	Iran [32]	2010-2030	GDP, POP, IMP, EXP	1.94

2. Arima-Hybrid Forecasting Model

Both ARIMA and ANN models have good performance in linear and non-linear structures but none of them is comprehensive to be able to forecast various time series structures. The studies showed that using dissimilar models improve time series forecasting where data set or pattern is varying and unstable [12]. The ARIMA and soft computing techniques improves precision of energy demand forecasting [4].

In other proposed methodology, time series (y_t) is considered as a function of linear and nonlinear component. Zhang [5] proposed a hybrid model that consists of two steps: step (1) is applying linear model and step (2) is applying nonlinear model using linear model's residuals. The proposed forecasting system is shown in Figure 1.

$$y_t = f\left(L_t, N_t\right) \tag{1}$$

Where, L_t denoted the linear part and N_t denotes the nonlinear part, one of the most efficient models in improving forecast accuracy, can establish the additive relationship between linear and nonlinear parts. Consequently can write

$$y_t = L_t + N_t \tag{2}$$

3. Problem description and methodology

In this section, ARIMA-ANN hybrid patterns are employed according to the methods. In the first step, after forecasting electricity consumption with ARIMA, its errors which are differences between actual and forecasted consumptions are calculated and forecasted using population and GDP.

The design hybrid forecasting of ARIMA and ANN models for electricity consumption is show in Figure 2. Therefore, the proposed ensemble based ARIMA-ANN hybrid models were used in forecasting. The independent variables, including the following: population and gross domestic product per capita (GPP) used as inputs to the models in electricity consumption forecasting. It seems that these two factors have the most impact on electricity consumption, population and GPP data from 1993 to 2015, were used for modelling electricity consumption. The data were collected from statistics of Thailand are show in Table 2. The data set trends similarity of historical data show in Figure 3. The data were divided into train and test sets, where data for 1993-2010 is used for training of the models and that for 2011-2015 is utilized for testing of the models show in Figure 4.

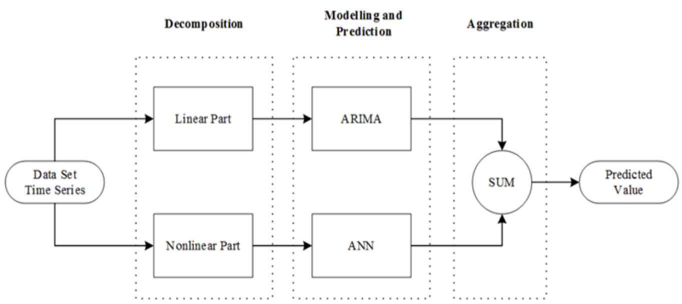

Fig. 1: A hybrid forecasting system

Table 2: Electricity Consumption, Population and GPP Data from 1993 to 2015

Year	Electricity Consumption (Million Kilowatt hour)	Population (Million)	GDP per Capita (Million Baht)
1993	64,822.35	58.44	74,281.18
1994	74,165.28	59.24	79,138.03
1995	82,152.89	59.28	85,506.51
1996	84,886.99	59.90	89,404.59
1997	82,672.77	60.50	86,080.51
1998	83,566.15	61.20	78,599.93
1999	89,861.03	61.80	81,395.76
2000	93,296.41	61.88	84,912.57
2001	100,684.30	62.31	87,231.01
2002	107,171.40	62.80	91,872.26
2003	114,541.11	63.08	98,040.14
2004	117,853.49	61.97	106,072.70
2005	124,483.46	62.42	109,718.12
2006	130,364.02	62.83	114,417.28
2007	132,882.14	63.04	120,234.11
2008	133,829.35	63.39	121,633.63
2009	147,720.59	63.53	120,469.56
2010	147,227.81	63.88	128,803.27
2011	158,153.16	64.08	129,471.74
2012	159,265.90	64.46	138,015.33
2013	127,375.84	64.79	141,022.70
2014	163,552.79	65.12	141,455.27
2015	164,345.35	65.72	144,116.01

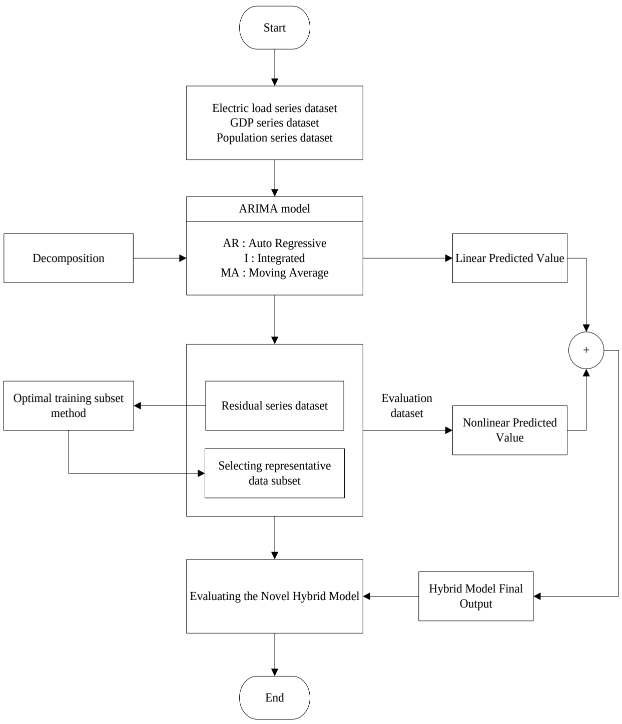

Fig. 2: The Design Hybrid Forecasting of ARIMA and ANN Models for Electricity Consumption

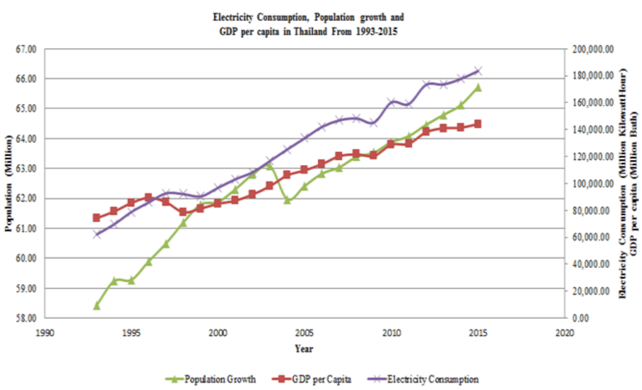

Fig. 3: Data Set Trends Similarity of Historical Data

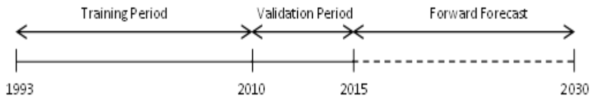

Fig. 4: Process timeline

4. Results and discussion

To evaluate the prediction performance of the proposed hybrid model we carry out prediction experiment using a single model ARIMA, ANN. Using the Root Mean Square Error (RMSE), the Mean Absolute Error (MAE) and the Mean Average Percentage Error (MAPE) are formally given in (3) - (5).

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(y_t - \hat{y}_t)^2} \tag{3}$$

$$\text{MAE} = \frac{1}{N}\sum_{t=1}^{N}|y_t - \hat{y}_t| \tag{4}$$

$$\text{MAPE} = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{y_t - \hat{y}_t}{y_t}\right| \tag{5}$$

Where N is the size of the test set, and $\hat{y}_t$ is the predicted value of y_t.

The forecast evaluation results are reported in Table 3. It shows that the ARIMA-ANN model outperforms all techniques in term of prediction accuracy. The proposed ARIMA-ANN model prediction error is the smallest for all evaluation criteria show in Figure 5. The superior performance of all the ARIMA, ANN and ARIMA-ANN models can be seen in Figure 6, cumulative error tend to remain close to zero, while the ARIMA model's cumulative error deviate from zero more dramatically. The additional beneficial impact of including exogenous variables in the model can also be seen by the ARIMA-ANN model's cumulative error remaining close to zero.

Table 3: The Prediction Errors for The ARIMA, ANN and ARIMA-ANN

Models	RMSE	MAE	MAPE (%)
ARIMA	0.7699	0.5580	13.95
ANN	0.0645	0.0258	10.90
ARIMA-ANN	**0.0358**	**0.0132**	**6.47**

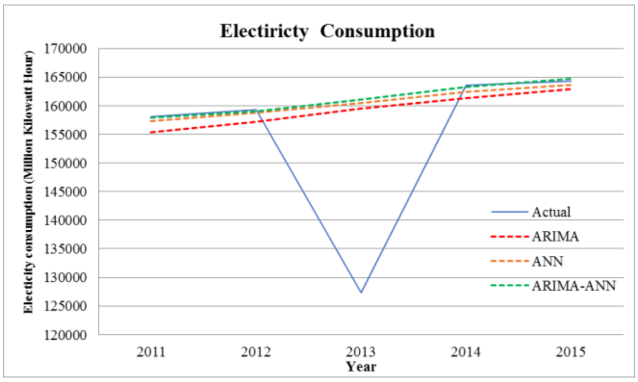

Fig. 5: Forecast Evaluation Results Comparison

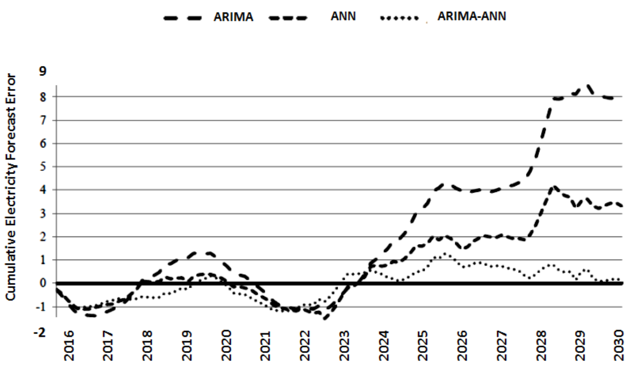

Fig. 6: Cumulative Error Results

5. Conclusion

In this study, a hybrid ARIMA-ANN models for long-term electricity consumption forecasting using two different historical data types are developed. The solution framework is implemented for Thailand, as developing and developed economies. Based on the lowest MAPE, the results demonstrate that ARIMA-ANN is the most accurate models, it achieves the MAPE. Moreover, in this study, the effects of implementing dataset on accuracy of Thailand forecasting are examined. Therefore, the proposed model leads to improved performance. It can be an effective way in the forecasting task, especially when higher forecasting accuracy is needed. This procedure supports the validity of the suggested forecasting method.

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