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Enhanced Electricity Load Forecasting Based on an Improved Group Method of Data Handling with Fourier Residual Modification Approach

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Abstract Electricity load forecasting is crucial to modern energy management, planning and distribution in a highly developed country. Therefore, accurate electricity load prediction plays a vital role in maintaining optimal energy production and minimizing operational costs. This paper discussed an enhanced electricity load forecasting method based on a conventional statistical time series model with a combination method based on the Empirical Mode Decomposition (EMD) and Group Method of Data Handling (GMDH) model, namely EMD-GMDH. This study also presents a comparison between the proposed model of EMD-GMDH and a reconstruction of the Intrinsic Mode Function (IMFs) of decomposition integrated with Fourier residual modification, referred to as FM-EMD-GMDH. The Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) criteria were employed to measure the accuracy of each proposed model. From the empirical simulation, results reveal that the FM-EMD-GMDH model gained the best performance and better accuracy compared to other predictive models. Hence, it is concluded that the combination and reconstruction in the proposed model contribute to higher forecasting accuracy and performance.

Keywords Empirical Mode Decomposition; Group Method of Data Handling; Fourier Residual Modification; Forecasting; Time Series.

Mathematics Subject Classification 37M10, 62M10, 68T05.

1 Introduction

Electricity forecasting is a critical component of modern energy management, encompassing the prediction of future electricity demand to ensure power supply and distribution stability and efficiency. It involves predicting the amount of electrical power that consumers will demand over a specific period. This involves estimating future electricity demand based on various factors such as historical consumption patterns, weather conditions, economic activities, population growth and technological changes. Notably, accurate prediction contributes to preventing blackouts, managing proper peak loads, and facilitating coordination with the demand for economic growth. Additionally, accurate electricity load estimation is essential for balancing and optimizing the operation of power plants and minimizing costs associated with energy production. Hence, accurate load forecast supports the efficient allocation of resources, helping to avoid both energy shortages and excessed that could lead to waste or higher rest.

To date, various methods have been developed and introduced to measure electricity load forecasting, including time series analysis and also regression methods. Time series statistical approaches have been broadly utilized in numerous fields such as wind forecasting [1], water demand forecasting [2], gold price forecasting [3] and other numerous fields as well. Over the past decade, most research has been conducted using a linear technique such as the Box-Jenkin approach [4], exponential smoothing [5], and regression methods [6]. The aforementioned statistical approaches offer simplicity and straightforward implementation. Their mathematical foundations are well-established, making the results and findings easy to interpret. However, the primary limitation of these approaches is their inability to capture and forecast the nonlinear patterns in the dataset accurately. This is especially true in the electricity load time series dataset due to the influence of factors such as weather conditions, economic growth, and social conditions.

To address these limitations, an increasing number of researchers have employed Artificial Intelligence (AI) methodologies in forecasting to overcome the downsides and constraints of traditional statistical forecasting methods. A wide range of AI-driven models are capable of identifying complex patterns and trends of datasets. It has been applied in order to improve the performance and accuracy in time series forecasting issues such as Artificial Neural Networks (ANN) [7], Support Vector Machine [8] and recently, Group Method of Data Handling (GMDH) [9]. Promising results have revealed that the GMDH offer better forecasting performance and accuracy [10]. Moreover, current researchers have demonstrated an increased interest in a combination technique in prediction that contributes towards more reliability and enhances the prediction precisely by integrating with a data pre-processing technique such as Empirical Mode Decomposition (EMD). For instance, such combination models are like ARIMA-ANN [11], EMD-SVM [12], SVR-ANN [13], ARIMA-GMDH model [14], and EMD-ARIMA [15]. Hence, this study proposes an enhanced electricity load forecasting model together with a comprehensive analysis of a statistical time series Autoregressive Integrated Moving Average (ARIMA) model, combining the method EMD-GMDH model with the modified EMD-GMDH model by introducing a Fourier residual modification approach, aiming to decrease the residual and improve prediction accuracy. This paper is set as follows. Section 2 introduces the concepts and procedures of the methodologies. Next, Section 3 discussed the framework of modified combined models, followed by the findings and empirical results. Finally, the last section includes recommendations and conclusions.

2 Methodologies

This section outlines the technique, methodologies and mathematical models including the equations related in this study.

2.1 Autoregressive Integrated Moving Average (ARIMA) Model

In time series analysis, the Box-Jenkins method, named after statisticians George Box and Gwilym Jenkins, employs ARIMA models to identify the best fit for time series forecasting [16]. The ARIMA model consists of three crucial steps: model identification, parameter estimation and diagnostic testing. In the first step, the Autocorrelation (ACF) and Partial Autocorrelation (PACF) are utilized to determine the stationary and seasonal or nonseasonal in order to identify the ARIMA model. Then, in the second step, the parameters of the model are predicted after the tentative model is determined. Finally, the third step is to examine the adequacy of the fitted model using the Ljung-Box test. Hence, the ARIMA model is built up by three terms, which are p, d, and q. The order of Autoregressive is denoted by p, the order of Moving Average (MA) is denoted by q, and the number of differencing is denoted by d. The ARIMA model (p, d, q) model can be expressed as follows:

$$\left(1-\sum_{i=1}^{p}\phi_i B^i\right)(1-B)^d y_t=\left(1-\sum_{i=1}^{q}\theta_i B^i\right)\varepsilon_t, \tag{1}$$

where B is the backshift operator and ε_t is the error.

2.2 Group Method of Data Handling

GMDH stands for Group Method of Data Handling and was introduced by Ivakhnenko [17] with the ultimate objective to solve higher-order regression polynomials. GMDH represent a pioneering approach in the field of machine learning and AI methods. It is a heuristic method and is particularly notable for its self-organize and optimize model structures, making it highly suitable for complex, nonlinear and multi-dimensional data [18]. In addition, it generates models by combining various polynomial functions of the input variables, effectively discovering and representing the underlying patterns within the data. In addition, a GMDH able to identify a complex system without following the input-output relationships path. The relationship is typically by a complex series known as Kolmogorov-Gabor polynomials [17], such as:

$$y=a_0+\sum_{i=1}^{K}a_i x_i+\sum_{i=1}^{K}\sum_{j=1}^{K}a_{ij}x_i x_j+\sum_{i=1}^{K}\sum_{j=1}^{K}\sum_{l=1}^{K}a_{ijk}x_i x_j x_l+\dots \tag{2}$$

where x denotes the input of the system, K represents the number of inputs, and a is the coefficients of the weights of the terms. In the GMDH, the Kolmogorov-Gabor polynomials are predicted using the second-order polynomial in the form of

$$\hat{y}=a_0+a_1x_i+a_2x_j+a_3x_ix_j+a_4x_i^2+a_5x_j^2, \tag{3}$$

where $\hat{y}$ is the forecasted output. In this research, the algorithm framework for the GMDH model is as follows:

- **Step 1:** Selection of the input variables, $x=\{x_1, x_2, \dots, x_M\}$ where M is the summation number of inputs. The data are classified into the training dataset, which is used to develop a GMDH model, while the testing dataset is used to evaluate the predicted GMDH model.

- **Step 2:** The number of groupings for each layer is designed using $L = \frac{K(K-1)}{2}$. The traditional GMDH model is built up by using polynomial methods, where regression is used to obtain the coefficient values as in Eq 3.
- **Step 3:** The partial description coefficient is predicted, and the Least Squares Method is used to find the partial description coefficient vectors.
- **Step 4:** The stopping criteria are confirmed by evaluating whether the current layer outperforms the previous layer. The GMDH model is ultimately obtained.

2.3 Empirical Mode Decomposition

EMD is a completely data-driven and adaptive technique used for analyzing nonlinear and non-stationary time series data. The fundamental principle of EMD is to decompose a given time series into a finite set of Intrinsic Mode Functions (IMFs) and a residual, representing various underlying oscillatory modes present in the data [19]. Based on [20], every IMF must fulfil the following two conditions, which are (i) each IMFs extreme points and zero crossing must differ by not more than 1. (ii) at every point, the envelope created by the local maxima and minima has a mean value of zero. The EMDs algorithm can be explained as follows:

1. Each local maxima and minima in data series $y(t)$ for $t = 1, 2, \ldots$ are identified.
2. Spline interpolation is used to link each local extrema in order to obtain the upper and lower envelopes, $y_U(t)$ and $y_L(t)$, respectively.
3. The average upper and lower are estimated using the following formula:
$$m_{(t)} = \frac{[y_L(t) - y_U(t)]}{2} \tag{4}$$
4. Compute the difference between $y(t)$ and $m(t)$ where $z(t) = y(t) - m(t)$ to obtain details.
5. Verify that $z(t)$ satisfies the condition of IMF. When $z(t)$ meets the condition, IMF is produced, and $y(t)$ is then substituted with the residue. Nevertheless, if $z(t)$ fails to meet the conditions, $y(t)$ will be replaced with $z(t)$.
6. Step 1 through Step 5 should be repeated until the last residue, $r_n(t)$ turns into a monotone function, and there is no more IMF to be extracted.

As the final step, the original time series $y(t)$ can be represented as the sum of all the IMF components plus one residual component by applying the aforementioned algorithm as below.

$$y(t) = \sum_{t=1}^{n} z_i(t) + r_n(t). \tag{5}$$

2.4 Fourier Residual Modification

The excellent performance of the Fourier residual modification resulted in a low number of Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Square Error (MSE), which contributes to the improvement of Grey Model GM $(1,1)$ forecasting accuracy [21]. Consequently, in order to compare the forecasting accuracy of the GMDH and ARIMA models, this potential methodology approach should be investigated. A Fourier residual modification was explained in the steps as follows.

- **Step 1:** Create a forecasting model.
- **Step 2:** From the forecast series, $\hat{y}^{(0)}$, a residual series $\varepsilon^{(0)}$ is defined as:

$$\varepsilon^{(0)} = \left\{\varepsilon_2^{(0)}, \varepsilon_3^{(0)}, \ldots, \varepsilon_k^{(0)}, \ldots, \varepsilon_n^{(0)}\right\}, \tag{6}$$

where

$$\varepsilon_k^{(0)} = y_k^{(0)} - \hat{y}_k^{(0)}. \tag{7}$$

- **Step 3:** Expressed in the Fourier Series, $\varepsilon_k^{(0)}$ is defined as

$$\varepsilon_k^{(0)} = \frac{1}{2}a_0 + \sum_{i=1}^{D}\left[a_i \cos\left(\frac{2\pi i}{n-1}k\right) + b_i \sin\left(\frac{2\pi i}{n-1}k\right)\right], \tag{8}$$

where $D = \dfrac{n-1}{2} - 1$. The residual series can be expressed as

$$\varepsilon^{(0)} = P \cdot C,$$

where

$$P = \left(\left[\frac{1}{2}\right]_{(n-1)\times 1} \quad P_1 \ldots P_k \ldots P_D\right).$$

The matrix P_k is given as:

$$P_k = \begin{pmatrix} \cos\left(\dfrac{2\pi \times 2k}{n-1}\right) & \sin\left(\dfrac{2\pi \times 2k}{n-1}\right) \\ \cos\left(\dfrac{2\pi \times 3k}{n-1}\right) & \sin\left(\dfrac{2\pi \times 3k}{n-1}\right) \\ \vdots & \vdots \\ \cos\left(\dfrac{2\pi \times nk}{n-1}\right) & \sin\left(\dfrac{2\pi \times nk}{n-1}\right) \end{pmatrix}, \tag{9}$$

$$C = \left[a_0, a_1, b_1, a_2, b_2, \ldots, a_D, b_D\right]^T.$$

The parameters $a_0, a_1, b_1, b_2, \ldots, a_D, b_D$ can be obtained using the Ordinary Least Squares (OLS) method, yielding the equation:

$$C = (P^T P)^{-1} P^T \left[\varepsilon^{(0)}\right]^T. \tag{10}$$

The predicted residuals $\hat{\varepsilon}_k^{(0)}$ can be obtained by applying the following expression:

$$\hat{\varepsilon}_k^{(0)} = \frac{1}{2}a_0 + \sum_{i=1}^{D}\left[a_i \cos\left(\frac{2ik\pi}{n-1}\right) + b_i \sin\left(\frac{2ik\pi}{n-1}\right)\right]. \tag{11}$$

- **Step 4: Complete the Residual Modification**

  Finally, the predicted series $\hat{x}^{(0)}$ attained from the forecasting model and the predicted series $\tilde{x}^{(0)}$ of the revised model are determined by

$$\tilde{x}^{(0)} = \left\{\tilde{x}_1^{(0)}, \tilde{x}_2^{(0)}, \ldots, \tilde{x}_k^{(0)}, \ldots, \tilde{x}_n^{(0)}\right\}, \tag{12}$$

  where

$$\begin{cases} \tilde{x}_1^{(0)} = \hat{x}_1^{(0)}, \\ \tilde{x}_k^{(0)} = \hat{x}_k^{(0)} + \hat{\varepsilon}_k^{(0)}. \end{cases}$$

3 The Architecture of the Proposed Model

In this study, the architecture of the Fourier-modified EMD-GMDH model is proposed. The methodologies framework model can be categorized into four stages: the decomposition stage, reconstruction stage, individual forecasting stage, and ensemble forecasting stage. Firstly, the EMD technique is employed in the original dataset in order to decompose into a number of IMFs and a residual. At the same time, ACF is utilized to divide the IMFs into two components, namely stochastic and deterministic. The IMF will be categorized as stochastic once the ACF is less than a threshold value of $|0.95|$ and deterministic otherwise. Moving to the reconstruction stage, each stochastic IMF is modelled independently; a distinct model is selected for each stochastic IMF, and all of the models forecasts are used for the final forecasting ensemble. Meanwhile, each and every deterministic IMF would be overseen as a single component. The GMDH model will be estimated for each stochastic IMF and the deterministic component. In the individual forecasting phase, all the components will be added together, and the Fourier residual modification is calculated. Lastly, the final proposed model forecast output is denoted by the FM-EMD-GMDH model. The entire framework of the proposed model is depicted in Figure 1.

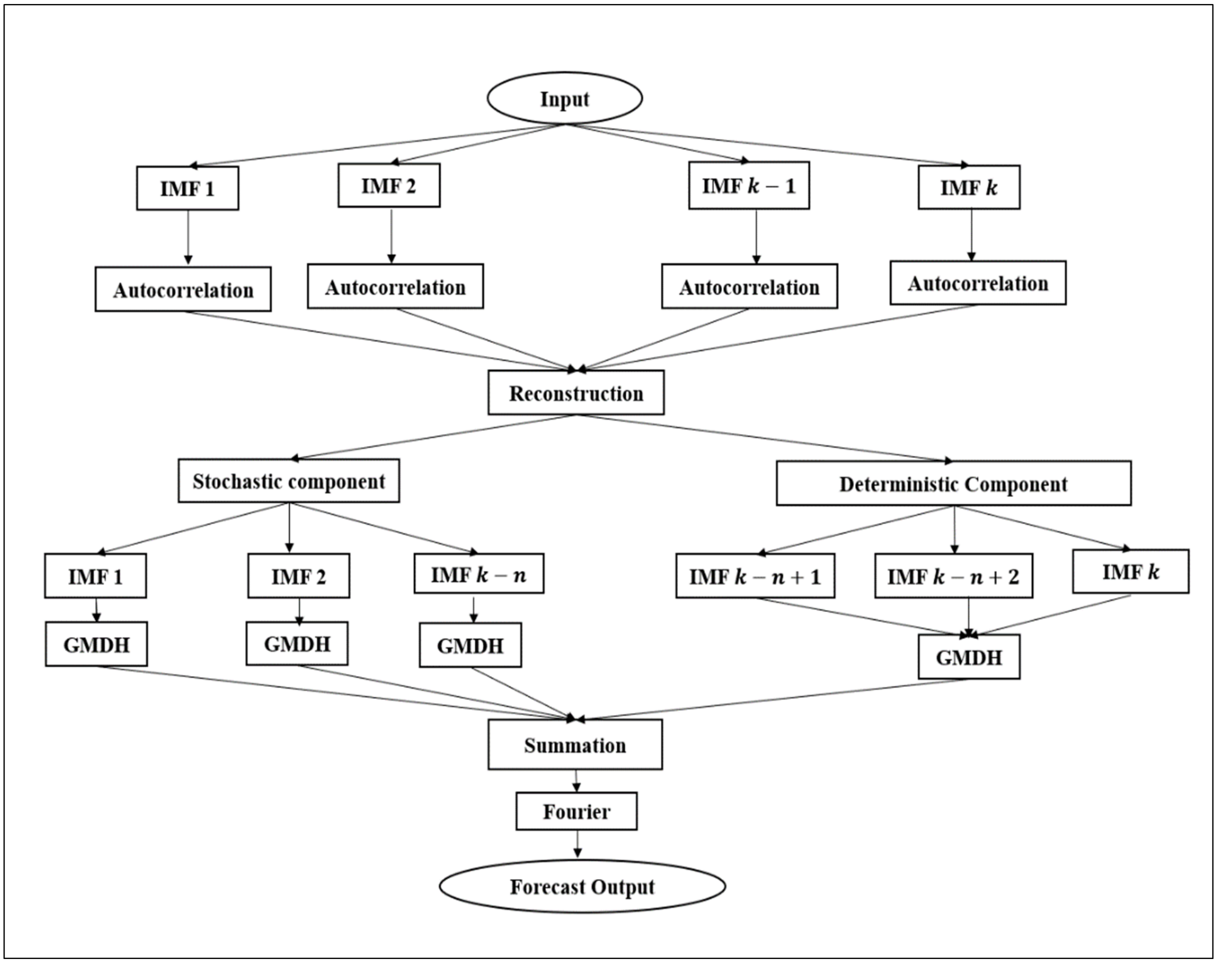

Figure 1: The framework of proposed model

3.1 Forecast Assessment Criteria

Forecast assessment criteria are essential benchmarks applied to evaluate the accuracy and reliability of the predictive models. The best model can be identified by evaluating and finding the smallest possible error values in the training and testing data series. The performance assessment of each model can be measured based on Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE). The formula for the measurement is provided in Eqs 13, 14 and 15, respectively.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{13}$$

$$\text{MAPE} = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{14}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{15}$$

4 Result and Discussion

4.1 Dataset

This study uses monthly electricity consumption dataset (in GWh) for four countries located in Southeast Asia namely Malaysia, Thailand, Singapore and Myanmar. All the dataset were obtained from various sources such as Single Buyer Department, CEIC Data platform and also from the official ministry website of the country.

4.1.1 Malaysia

A plot of Malaysias electricity consumption from January 2011 to December 2022 is depicted in Figure 2. Malaysia, a rapid developing nation in Southeast Asia, has seen significant growth in both its economy and population over the past few decades. This progress has been accompanied by a substantial increase in electricity consumption, driven by industrial expansion, urbanization, and rising living standards. As Malaysia continues to modernize, understanding the dynamics of electricity consumption becomes crucial for ensuring sustainable development.

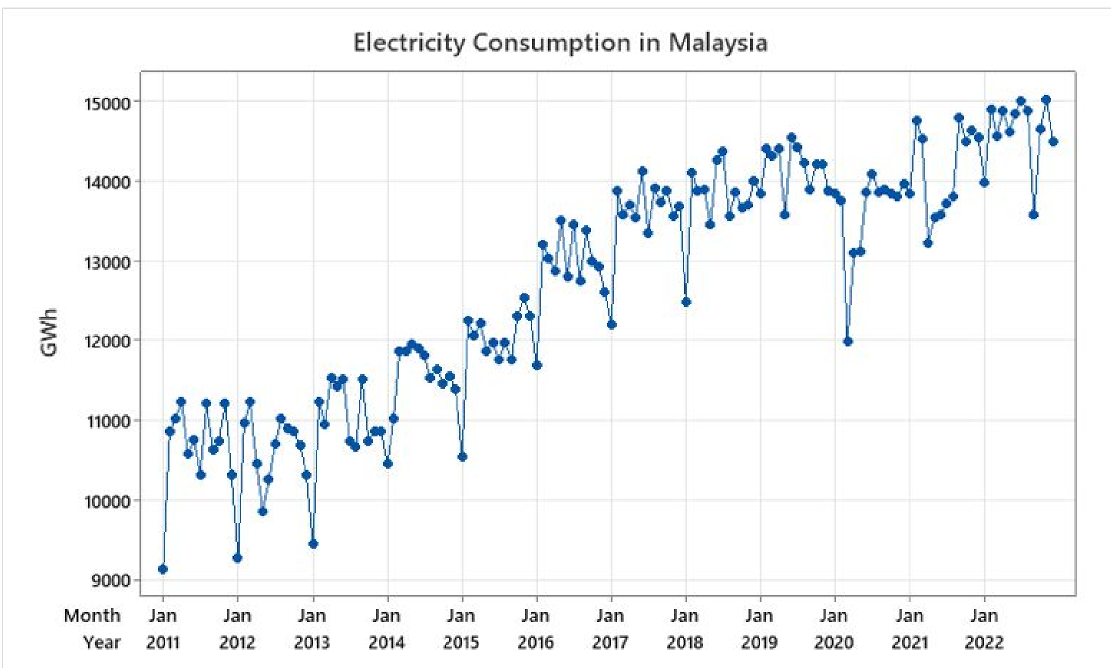

Figure 2: Electricity Consumption in Malaysia from 2011 to 2022

4.1.2 Thailand

A plot of Thailands electricity consumption from 2002 to 2021 is presented in Figure 3. Thailand, a major country in Southeast Asia, has seen a lot of growth in recent years, with more factories, businesses, and people moving into cities. This growth has led to a big increase in electricity use, as more energy is needed to power homes, industries, and everyday life. As the country progresses, its electricity consumption has surged, reflecting the increased demand from both the industrial sector and a growing population. Thailand's energy landscape is shaped by a mix of traditional and renewable sources, with ongoing efforts to balance energy security, affordability, and environmental sustainability.

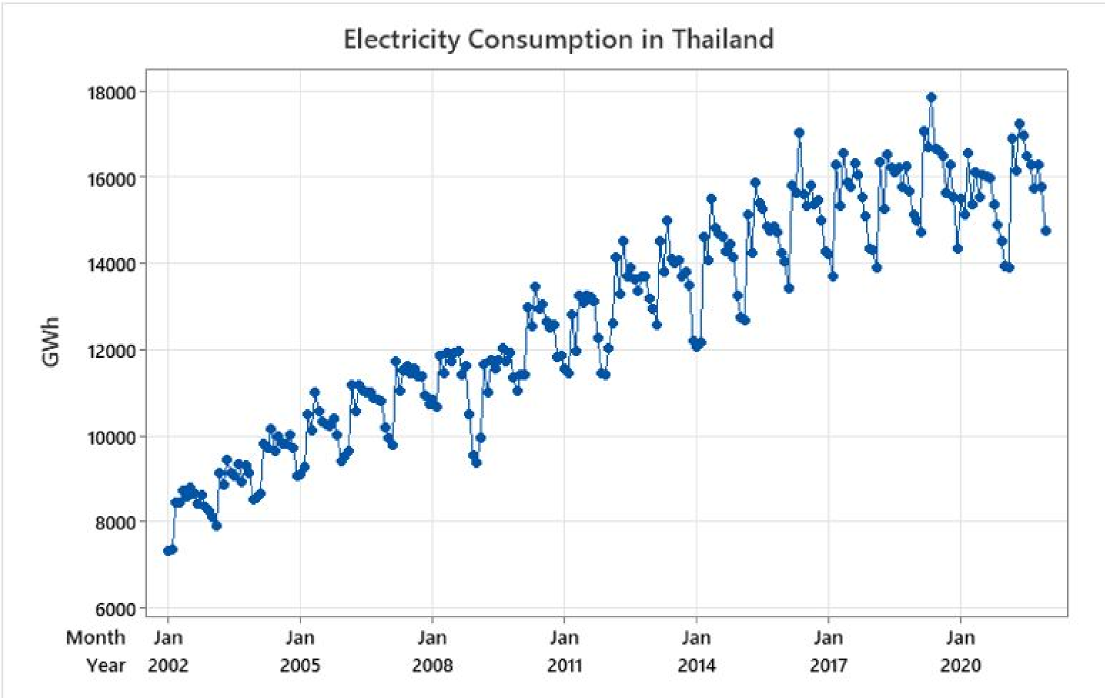

Figure 3: Electricity Consumption in Thailand from 2002 to 2021

4.1.3 Singapore

A plot of Singapores electricity consumption from 1996 to 2021 is shown in Figure 4. Singapore, known for its rapid development and high standard of living, has seen a steady rise in electricity consumption over the years. As a densely populated city-state with a thriving economy, the demand for energy has grown alongside its industrial, commercial, and residential needs. However, Singapore faces unique challenges due to its limited land and natural resources, which make energy efficiency and sustainability crucial.

4.1.4 Sri Lanka

A plot of Sri Lankas electricity consumption from 1995 to 2019 is presented in Figure 5. Sri Lanka, an island nation known for its lush landscapes and vibrant culture, is experiencing a growing demand for electricity as it continues to develop its economy and improve living standards. With increasing urbanization and industrial activity, the countrys electricity consumption has risen significantly. Sri Lanka relies on a mix of energy sources, including hydro, coal, and renewables, to meet its needs. However, it faces challenges such as managing energy production and distribution while striving for sustainability and reducing dependency on imported fuels.

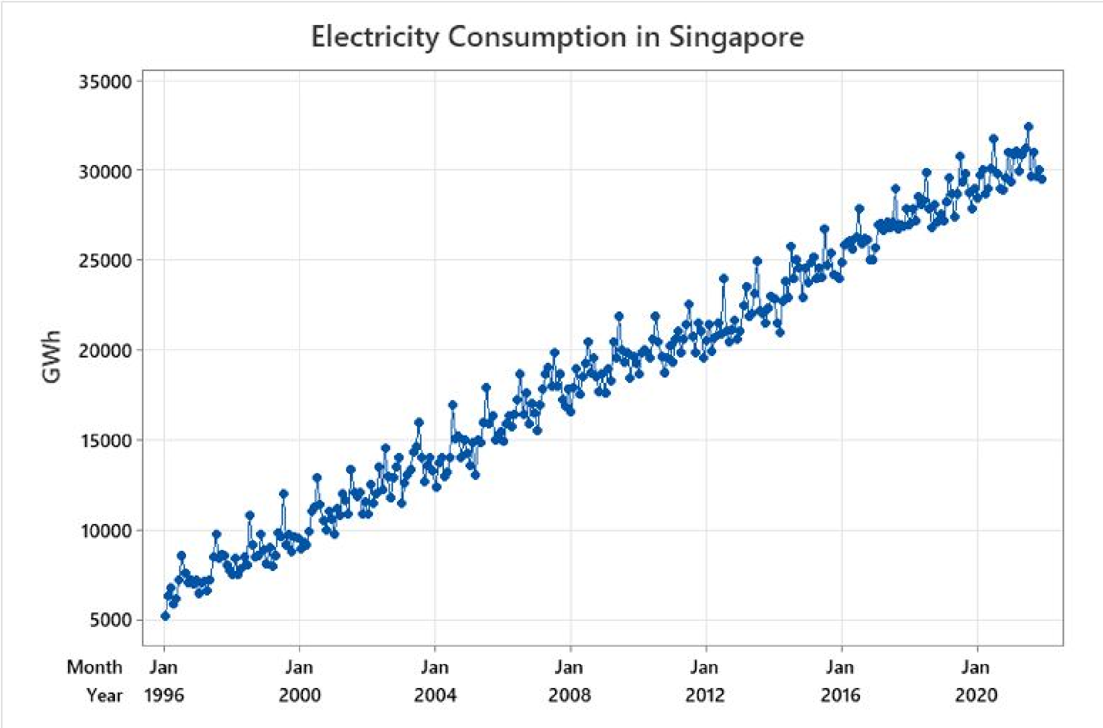

Figure 4: Electricity Consumption in Singapore from 1996 to 2021

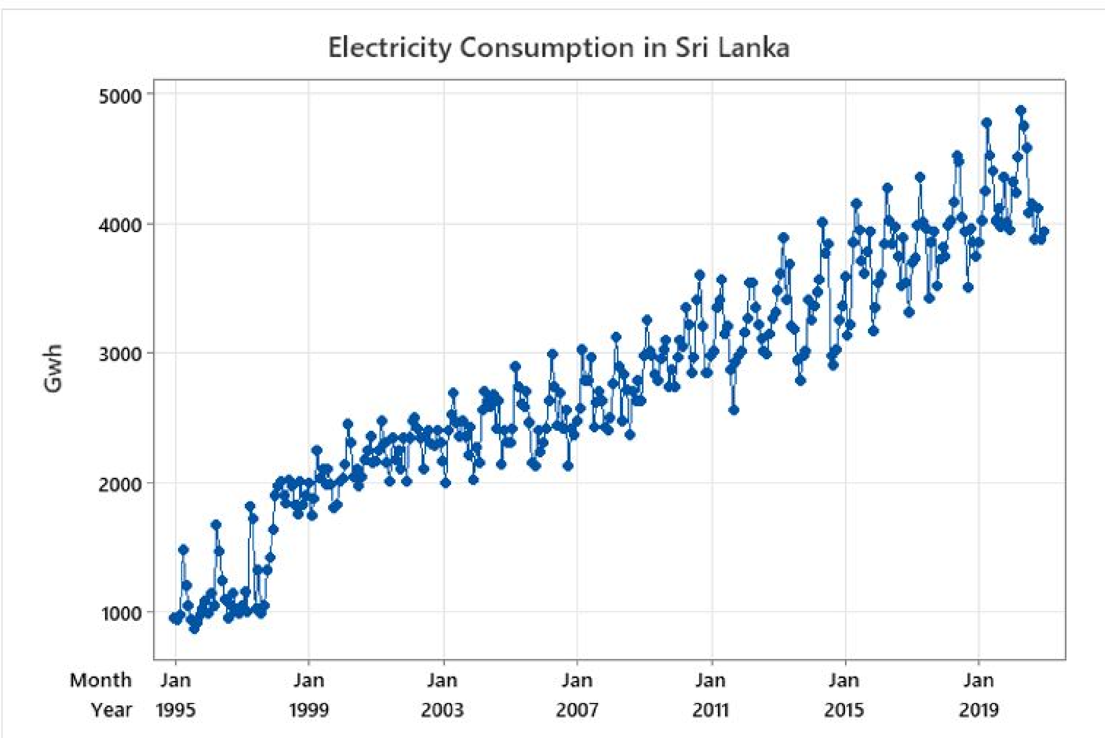

Figure 5: Electricity Consumption in Sri Lanka from 1995 to 2019

5 Empirical Result

In this study, five models were developed, which are ARIMA, GMDH, EMD-GMDH, Modified EMD-GMDH or, in short, M-EMD-GMDH and the proposed model Fourier Modified EMD-GMDH denoted by FM-EMD-GMDH to create a one-step-ahead prediction for the load demand forecasting. This work utilized the real historical monthly data from January 1998 to December 2021 from four Southeast Asia countries: Malaysia, Singapore, Thailand, and Sri Lanka. The time series dataset is separated into two parts, of which 90% is for the training set while the remaining 10% is for the testing set. The simulation work in this study is executed using R software and MATLAB 2014a software. The comparisons of the forecast evaluation statistics for five models in terms of RMSE, MAE and MAPE for both training set and testing set are described in Tables 1, 2, 3 and 4 for Malaysia, Thailand, Singapore and Sri Lanka, respectively.

Table 1: Forecast evaluation statistics values of the dataset in Malaysia

Model	**Training**			**Testing**		
	RMSE	**MAE**	**MAPE**	**RMSE**	**MAE**	**MAPE**
ARIMA	523.79	389.52	3.21	467.79	349.01	2.43
GMDH	461.66	344.27	2.76	550.77	478.00	3.28
EMD-GMDH	297.78	245.77	2.06	386.65	314.04	2.17
M-EMD-GMDH	335.10	296.11	2.69	404.37	316.90	2.58
FM-EMD-GMDH	192.49	158.87	1.45	248.73	226.9	1.86

Table 2: Forecast evaluation statistics values of the dataset in Thailand

Model	**Training**			**Testing**		
	RMSE	**MAE**	**MAPE**	**RMSE**	**MAE**	**MAPE**
ARIMA	594.75	444.17	3.49	958.48	761.58	4.93
GMDH	372.46	281.90	2.21	673.34	492.58	3.20
EMD-GMDH	332.51	247.98	2.03	516.67	405.77	2.54
M-EMD-GMDH	315.20	229.44	1.88	477.52	359.65	2.36
FM-EMD-GMDH	216.36	160.81	1.35	342.71	253.44	1.68

Table 3: Forecast evaluation statistics values of the dataset in Singapore

Model	Training			Testing		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE
ARIMA	967.78	748.53	4.70	1000.16	880.84	2.89
GMDH	971.15	786.20	4.59	1083.29	984.08	3.23
EMD-GMDH	556.87	439.20	2.95	488.63	391.45	1.27
M-EMD-GMDH	556.70	439.45	2.95	485.61	394.51	1.28
FM-EMD-GMDH	430.67	333.49	2.27	263.16	208.13	0.67

Table 4: Forecast evaluation statistics values of the dataset in Sri Lanka

Model	Training			Testing		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE
ARIMA	207.87	161.69	0.06	244.32	202.25	0.04
GMDH	208.26	165.16	0.06	250.45	211.19	0.05
EMD-GMDH	117.63	98.83	0.04	100.47	84.17	0.02
M-EMD-GMDH	117.81	99.07	0.04	101.45	85.58	0.02
FM-EMD-GMDH	79.05	64.20	0.02	104.72	81.16	0.01

The results of the forecasting of the electricity consumption for the four countries that were studied in this work are tabulated accordingly to the forecasting models are presented in Tables 1-4. It has been observed that the proposed model, FM-EMD-GMDH model, for every country, is benchmarked with other single models, such as ARIMA and GMDH, compared with a hybrid model, which is a hybrid EMD-GMDH model and M-EMD-GMDH where reconstruction of the IMFs to be separated into stochastic or deterministic. The statistic performance criteria are evaluated for all models in the study. Table 1 presents the computation results of training and testing for the forecasting electricity consumption in Malaysia. Clearly, the FM-EMD-GMDH model produced the lowest MAPE value for both training and testing which was 1.45% and 1.86% respectively. On the other hand, ARIMA model obtained the highest MAPE value of 3.21%, showing that this model is less least effective in forecasting the electricity consumption for dataset in Malaysia.

Table 2 presents the forecast evaluation statistics values of the dataset in Thailand. Model FM-EMD-GMDH obtained the smallest MAPE value for both training and testing set with 1.35% and 1.68% respectively. However, ARIMA model produced the highest value of MAPE compare to the other predictive models. The proposed model FM-EMD-GMDH constantly shows the best model in forecasting electricity consumption based on the two datasets evaluated. Moving to Table 3, it presents forecasting results from Singapore whereby the FM-EMD-GMDH model produced the lowest RMSE, MAE and MAPE at 216.36, 160.81 and 13.35% respectively. However, there was a large difference in the MAPE of the ARIMA model compared to the other three models. ARIMA model produced the highest MAPE for both training and testing set. This shows that ARIMA model is less accurate in forecasting electricity consumption in this study.

Table 4 presents the forecast evaluation statistics of the dataset in Sri Lanka. Based on the table, the proposed model FM-EMD-GMDH consistently produced the smallest value of MAPE for both training and testing at 2% and 1% respectively. However, GMDH model produced a slightly highest value of RMSE and MAE compared to ARIMA model for both set. Both ARIMA and GMDH model obtained the same value of MAPE at 6%. Overall, in every country, the proposed FM-EMD-GMDH model exhibited a promising result with the lowest value of RMSE, MAE and MAPE compared to the other models. This indicate that FM-EMD-GMDH model was the most accurate, reliable and preferred model in forecasting electricity consumption.

6 Conclusions

Overall, this paper aims to discuss and improve the accuracy of electricity load forecasting by introducing the Fourier residual modification approach. The proposed model, namely MF-EMD-GMDH, begins with decomposition from the original data into several numbers of IMFs and a residual, which then undergo a reconstruction phase, either stochastic or deterministic. At the same time, a GMDH model is employed in each part, and finally, in the ensemble phase, a Fourier residual modification is introduced. To measure the performance of the proposed approach, real-world load time series data were considered in order to compare the performance with other single and hybrid models such as ARIMA, GMDH, EMD-GMDH and M-EMD-GMDH model. The experimental results reveal that the proposed model is considered the best due to the smallest result in RMSE, MAE, and MAPE, and it achieved a high rank compared to other models. Hence, this work contributes by providing an effective potential approach for better prediction accuracy and is also expected to help predict electricity load demand in power system management.

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