Improving electrical load forecasting by integrating a weighted forecast model with the artificial bee colony algorithm

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ABSTRACT

Nonlinear and seasonal fluctuations present significant challenges in predicting electricity load. To address this, a combination weighted forecast model (CWFM) based on individual prediction models is proposed. The artificial bee colony (ABC) algorithm is used to optimize the weighted coefficients. To evaluate the model's performance, the novel CWFM and three benchmark models are applied to forecast electricity load in Malaysia and Thailand. Performance is assessed using mean absolute percentage error (MAPE) and root mean square error (RMSE). The experimental results indicate that the proposed combined model outperforms the single models, demonstrating improved accuracy and better capturing seasonal variations in electricity load. The ABC algorithm helps in finding the optimal combination of weights, ensuring that the model adapts effectively to different forecasting scenarios.

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1. INTRODUCTION

Accurate electrical load forecasting is vital for the energy sector, facilitating efficient planning and operation of power systems. Reliable load predictions enable operators to manage energy storage and alternative sources more effectively, ensuring a balanced supply. This also enhances the overall reliability of the electrical grid by allowing for proactive identification and resolution of potential issues such as overloads or supply shortages [1]. As systems evolve rapidly and are influenced by increasingly complex factors, achieving accurate forecasts becomes more challenging, particularly due to seasonality and uncertainty. Seasonal data often display similarities between different cycle periods but also exhibit fluctuations and randomness, complicating precise predictions.

Currently, methods for predicting seasonal electricity time series in the literature can be broadly classified into three categories: statistical econometric models, artificial intelligence models, and grey models. The autoregressive integrated moving average (ARIMA) model, a key statistical econometric tool, is extensively utilized for simulating and forecasting seasonal electricity time series. Known for its robust forecasting capabilities, the ARIMA model demonstrates high precision in predicting electricity time series [2], [3]. It aids in understanding the data dynamics within a specific application [2]. While ARIMA effectively models linear patterns in time series, it falls short in capturing nonlinear patterns [3]. Regression models are also commonly employed in time series prediction, particularly for series with clear trends. However, traditional regression models have limitations, such as fewer variable parameters and difficulty adapting to time series prediction [2].

Artificial intelligence prediction models primarily focus on artificial neural networks (ANNs) and support vector machines (SVMs). Recently, ANNs have been widely adopted in electricity forecasting [2]. ANNs have a long history in prediction and have made significant contributions to forecasting, particularly in identifying nonlinear relationships between inputs and outputs, even when there is insufficient information about their relationship [3]. ANNs are favored for forecasting complex nonlinear systems and can realize any complex nonlinear mapping function, as mathematically proven [4]. However, ANNs are prone to falling into local minima and often exhibit overfitting [5].

Support vector regression (SVR) has gained considerable attention in the realm of electricity load forecasting due to its solid theoretical and mathematical underpinnings. SVR performs robust, noise-resistant, and nonlinear regression based on the principle of structural error minimization [6]. It constructs the regression model using the training dataset and then predicts outcomes from the test dataset. SVR's generalization capability surpasses that of neural networks, and the algorithm ensures global optimality [7]. Additionally, various optimization techniques are often employed to enhance SVR learning. Despite its ability to produce highly accurate results, SVR has certain limitations. For instance, selecting numerous parameters through trial and error can be challenging and requires complex calculations to achieve optimal forecasting accuracy [8].

Grey system theory offers a reliable research method for situations with limited data. Grey models have been effectively applied in various fields, including natural gas, electricity, nuclear energy, oil, and overall energy consumption [9]. However, these applications typically involve annual time series with an upward trend and are less frequently used for monthly or quarterly seasonal data characterized by periodicity. To address these limitations, Wang [10] proposed a seasonal grey model (SGM(1,1)) that utilizes accumulation operators generated by seasonal factors to forecast electricity consumption in primary economic sectors. Numerous updated variants of the SGM(1,1) model, such as SFGM(1,1), DTGM(1,1), and SNGBM(1,1), have been developed to enhance the ability of grey models to predict seasonal time series [9]–[11].

Each single prediction model has unique informational characteristics and is suitable for specific conditions. In practice, it is common for one forecasting model to perform well during certain periods, while others excel at different times. Due to the inherent randomness, seasonality, and trends in electricity load, predictions from a single model often fail to fully capture the complexity, leading to lower accuracy. It is difficult to find a forecast model that outperforms all competing models. It was generally concluded that no single predictors can be appropriate for in all aspects of modelling because of their limitations and there was no individual intelligent approach appropriate for all specific problems. To fully leverage the strengths and unique information of each individual forecast model, combination forecasting is an effective approach. This method has become mainstream in forecasting and is increasingly adopted by scholars [2], [3].

Combination forecasting can achieve higher accuracy and more reliable results. The primary reasons are twofold: different methods can capture diverse effective information from power load data, and they can complement each other. It is important to note that while the accuracy of combined forecasting is not always superior to that of individual models, the results are often more reliable [12], [13].

The benefits of forecast combinations depend not only on the quality of the individual forecasts but also on the estimation of the combination weights assigned to each forecast. Numerous studies have explored combination methods, ranging from simple approaches [14]–[16] to more sophisticated techniques [17]–[21]. Despite the complexity of some combination approaches and advanced machine learning algorithms, simple combinations remain competitive. The recent M4 competition demonstrated that simple combinations continue to deliver relatively good forecasting performance [22]. This finding aligns with previous research, which shows that simple combination rules are often preferred by researchers and practitioners and serve as a benchmark for evaluating new weighted forecast combination algorithms [19], [21]–[24].

Although simple combination schemes are straightforward to implement, their success heavily relies on the selection of the weighted forecasts to be combined. The critical aspect of an effective combined method is determining the appropriate weight coefficient. If the weight coefficient is well-chosen, the combined model can yield better prediction results; otherwise, the results may be suboptimal. There are relatively few studies on the methods for determining weight coefficients.

This paper explores the potential of combining forecasts using basic methods of weighted combination forecasting model (WCFM), which effectively harnesses the strengths of each individual model to improve forecasting accuracy. The success of forecast combinations depends significantly on the determination of combination weights. To optimize the model's weights, we employ the ABC algorithm, which maximizes the unique characteristics of each model. The ABC algorithm, inspired by the foraging behavior of honey bees, is an optimization technique that has been successfully applied to various practical problems [24].

2. METHOD

Four prediction models the ARIMA, SVM, SGM and Weighted combination forecasting models are discussed in this section. The following is an explanation of each model:

2.1. Autoregressive integrated moving average model

The ARIMA model, introduced by Box and Jenkins in 1970 [25], is a widely adopted method for forecasting time series data. It operates by using a linear combination of its past values and the lags of forecast errors (random shocks). The formula for an ARIMA (p, d, q) (P, D, Q) s model is

$$\Phi_P(B^s)\phi_p(B)(1-B^s)^D(1-B)^d y_t = \theta_q(B)\Theta_Q(B^s)a_t \tag{1}$$

where y_t is the original value, a_t are error, $\Phi_P(B^s)$ and $\phi_p(B)$ are the seasonal and non-seasonal autoregressive (AR) polynomials, $(1-B^s)^D$ and $(1-B)^d$ are the seasonal and non-seasonal differencing, $\Theta_Q(B^s)$ and $\theta_q(B)$ are the seasonal and non-seasonal moving average (MA) polynomials. The Box-Jenkins methodology, essential for developing ARIMA models, involves five key steps:

a. Stationarity check: Determine if x_t meets the stationary time series condition. If the series is non-stationary, differentiate the original time series x_t to achieve stationarity.
b. Model identification: Use the autocorrelation function (ACF) and partial autocorrelation function (PACF) of the stationary series to select appropriate ARMA models.
c. Parameter estimation: Estimate the model's parameters. Exclude lag orders from the model if any parameters are not significant (significance level less than 5%).
d. Residual diagnostics: Test the model's residuals to check if they are white noise. Ljung and Box [26] proposed the Q statistic for this hypothesis test. If the residual sequence is not white noise, the model needs revision.
e. Model selection: Choose the optimal ARIMA model based on the lowest corrected Akaike information criterion (AICc).

2.2. Support vector machines model

Support vector machines (SVM) introduced by Vapnik [6], are based on statistical learning theory and the principle of structural risk minimization. The fundamental principle of SVM for regression involves transforming the input data into a high-dimensional feature space through nonlinear mapping The regression function for SVM is expressed as (2):

$$f(x) = \sum_{i=1}^{n} w_i\phi_i(x) + b \tag{2}$$

The coefficient $[w_i]_i^n$ are determined by solving the following quadratic programming problem:

$$\begin{gathered}\min_{w,b,\xi,\xi*} \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \\ s.t\begin{cases} y_i - -b \le \varepsilon + \xi_i \\ \langle w_i, \phi_i(x)\rangle - y_i + b \le \varepsilon + \xi_i^* \\ \zeta_i \ge 0, \xi_i^* \ge 0, i = 1,2, \dots, n \end{cases}\end{gathered} \tag{3}$$

By solving this optimization problem, the estimation function is obtained as (4):

$$f(x, \alpha, \alpha^*) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)\langle\phi_i(x)\phi(x)\rangle + b = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)K(x_i, x) + b \tag{4}$$

where $[\phi_i(x)]_i^n$ are the features, and b is the bias term, ξ_i^* are slack variables, and $C > 0$ is a constant that determines penalties. In the equation, $\sum_{i=1}^{n}(\alpha_i - \alpha_i^*) = 0, 0 \le \alpha_i, \alpha_i^* \ge C$), and $K(x_i, x)$ is the kernel function. Among various kernel functions, the radial basis function (RBF) is the most commonly used, defined as (5):

$$K(x_i, x_j) = exp\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right) \tag{5}$$

where σ is width of the RBF.

2.2. Seasonal grey model

Support let's consider the time series $x^{(0)} = \left\{x_1^{(0)}, x_2^{(0)}, \dots, x_k^{(0)}, \dots, x_n^{(0)}\right\}$. The first-order seasonal accumulating generation operator (1-SAGO) is denoted as $x_k^{(1)}S$. Using this operator, a seasonally-affected original series can be defined as (6) [10]:

$$X_s^{(1)} = x^{(0)}S = \{x_1^{(1)}S, x_2^{(1)}S, \dots, x_n^{(1)}S\} \tag{6}$$
with $x_k^{(1)}S = \sum_{i=1}^{k} x_i^{(0)}/f_s(i),\ k = 1,2, \dots, n.$

where $f_s(i)$ is the seasonal factor in the original series occurring at the i^{th} point in time. The $f_s(i)$ could be determined via (7),

$$f_s(i) = \frac{\bar{x}_M^{(0)}(i)}{\bar{x}_{MN}^{(0)}(i)} \tag{7}$$

where M is the number of seasons in a year, and N the time point's i^{th} year. The $\bar{x}_M^{(0)}(i)$ is the average value of the series over the seasonal cycle and the and $\bar{x}_{MN}^{(0)}(i)$ is total average value for all seasons or months. The background value is calculated using (8).

$$z_s^{(1)}(k) = 0.5x_s^{(1)}(k) + 0.5x_s^{(1)}(k-1), \forall k = 2, 3, \dots, n. \tag{8}$$

The following is the SGM(1,1) equation:

$$x_s^{(1)}(k) - x_s^{(1)}(k-1) + a z_s^{(1)}(k) = b \tag{9}$$

The least-square approach is used to estimate the model's parameters in (12). The parameters of the model are computed as follows:

$$\begin{bmatrix} a \\ b \end{bmatrix} = (X^T X)^{-1} X^T Y$$

where

$$Y = \begin{pmatrix} x_s^1(2) - x_s^1(1) \\ x_s^1(3) - x_s^1(2) \\ \vdots \\ x_s^1(n) - x_s^1(n-1) \end{pmatrix} \text{ and } X = \begin{pmatrix} -z_s^{(1)}(2) & 1 \\ -z_s^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z_s^{(1)}(n) & 1 \end{pmatrix} \tag{10}$$

Equation (10) is solved as (11):

$$\hat{x}_s^{(1)}(k) = \left(x_1^{(0)}/f_s(1) - \frac{b}{a}\right) e^{-ak} + \frac{b}{a} \tag{11}$$

Using the inverse 1-SAGO, the predicted value of SGM(1,1) can be determined as (12):

$$\hat{x}^{(0)}(k) = f_s(k)(\hat{x}_s^{(1)}(k) - \hat{x}_s^{(1)}(k-1)), k = 2,3, \dots, n \tag{12}$$

2.4. Weighted combination forecasting model

To enhance forecasting quality, this study selected three individual models - ARIMA, SVM, and SGM(1,1) as base predictors. During the forecasting process, the ARIMA model addresses linear problems, while SVM and SGM(1,1) handle nonlinear series forecasting. Given that electricity load data exhibits seasonality and nonlinearity, but sometimes shows linear features, these three models collectively address both nonlinear and linear forecasting challenges. However, the key to combining forecasting models lies in optimally choosing the combination weights. In this study, the WCFM is used to integrate all forecasted components into an ensemble for the final forecast. The weights in WCFM significantly impact the results and are challenging to determine. Therefore, the weights in WCFM were optimized using the ABC algorithm, which markedly improved accuracy. Experimental results indicate that the proposed combined model outperforms individual models and significantly surpasses the basic WCFM.

Let y_t^c be the true value of the series at time t and y_t^k be the forecast made by the k-th model at time t. The WCFM is given by (13),

$$y_t^c = \sum_{j=1}^{k} w_j y_t^j \tag{13}$$

w_i is the weight coefficient of the k-th model at time t, satisfying:

$$\sum_{j=1}^{k} w_j = 1 \text{ and } 0 \le w_i \le 1\,, j = 1,2,\dots,k. \tag{14}$$

The ABC algorithm is used to find the optimal values for (w) to solve the nonlinear optimization problem. The sum of squared errors (SSE) is employed as the fitness function for the ABC algorithm. The constrained optimization problem to obtain the optimal weights w can be described as follows:

$$\min SSE = \sum_{k=1}^{n} (y_t^c - y_t)^2, \quad \text{subject to } \sum_{j}^{k} w_j = 1 \text{ and } 0 \le w_j \le 1$$

The ABC algorithm is relatively simple, flexible, reliable, and requires fewer tuning parameters [24]. The ABC algorithm is composed of four main elements as explained as follows:
a. Initialization: The algorithm starts by randomly generating an initial population of solutions.
b. Employed Bees: These bees explore the vicinity of their current food source (solution) to discover new, potentially better solutions.
c. Onlooker Bees: These bees assess the quality of the food sources found by the employed bees and select the best ones based on a probability related to their quality.
d. Scout Bees: When a food source is abandoned (*i.e.*, it no longer yields better solutions), scout bees search for new random food sources to explore.

This iterative process continues until a termination criterion is met, such as reaching a maximum number of cycles or achieving a satisfactory solution quality. More details about the entire procedure can be found in [24].

3. EVALUATION METRICS

Evaluation criteria are crucial for assessing the simulation and prediction accuracy of different models. In this study, the root mean square error (RMSE) and the mean absolute percent error (MAPE) are employed as standard metrics to evaluate the performance of the proposed model. The RMSE and MAPE are expressed as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{k=1}^{n}(y_t^c - y_t)^2} \text{ and } MAPE = \frac{1}{n}\sum_{k=1}^{n}\frac{|y_t^c - y_t|}{y_t} \times 100\%$$

The symbols y_t is the actual, y_t^c is predicted values, and n is the number of observations. These metrics provide a comprehensive evaluation of the model's accuracy by measuring the average magnitude of the errors in the predictions. RMSE gives a higher weight to larger errors, making it sensitive to outliers, while MAPE expresses the error as a percentage, providing a normalized measure of prediction accuracy.

4. RESULTS AND DISCUSSION

In this section, we present two real-world case studies to validate the effectiveness and generalizability of the newly proposed method. The study utilizes historical monthly electricity load data from January 2011 to December 2021 for Malaysia and Thailand, as shown in Figure 1. The dataset comprises 144 time points in total. Both countries' data display a wave-like pattern with distinct seasonal variations, making it essential to capture both trend and seasonality for accurate forecasting of complex time series. To ensure high prediction accuracy, the data were divided into training (simulation) and testing (prediction) subsets. The monthly load data from January 2011 to December 2020 were used as the training set, while the final 12 data points from January 2021 to December 2021 served as the test set to evaluate the model's prediction performance.

The ARIMA and SVM models utilize actual data values to estimate parameters and generate forecasts. The SVM model is implemented in R using the e1071 package, while ARIMA is implemented using the forecast package to predict electricity load. For the SVM model, a grid search is conducted to optimize hyperparameters, selecting the penalty coefficient γ from the set (0.01, 0.1, 1, 10, 100, 1000) and the gamma value σ from the range (10^{-3}, 10^{4}), applying the Gaussian kernel.

For the ARIMA model, the forecast package's auto. ARIMA function is used to find the best ARIMA model based on the AICc. By default, this package sets the maximum order for d, P, and Q to 2, D to 1, and p and q to 5. The SARIMA model parameters are estimated using the maximum likelihood estimate (MLE), and the Ljung-Box (LB) test is used to confirm the model's suitability for the data. The AIC is used to choose values for p, P, q, and Q, while the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is applied to choose values for d and D.

Unlike other models, the SGM(1,1) model follows two key steps for parameter estimation: first, the seasonal factor is derived from the original data, and then the parameters are estimated using the modified data with seasonality removed. The forecasting models ARIMA, SVM, and SGM(1,1) are chosen for the combined forecast using WCFM. The MATLAB toolbox is employed to determine the optimal weight coefficients for WCFM, which are calculated using the ABC algorithm.

Table 1 and Figure 2 display the training and testing outcomes and accuracy levels for Malaysia's electricity load. Figure 2 illustrates that the four models can effectively capture seasonal variations and align with the upward trends of the original data. Visually, as shown in Figure 2, the proposed model's training and testing values are closer to the actual data, while other benchmark models exhibit larger deviations, especially during the testing phase. In terms of accuracy, the WCFM performs exceptionally well, with MAPE values of 1.67% for training and 2.67% for testing. According to Table 1, based on MAPE and RMSE during the training and testing phases, the ARIMA model ranks second in accuracy, followed by SVM. Conversely, the SGM(1,1) model shows the poorest performance, with the highest MAPE and RMSE values during both phases, indicating weak forecasting ability. Both Figure 2 and Table 1 indicate that the proposed method provides more precise forecasts than the other models.

Additionally, Table 1 illustrates the accuracy of predicting Thailand's monthly electricity load using MAPE and RMSE metrics. The table confirms that the proposed model delivers the best forecasting performance. The new model has the lowest MAPE and RMSE values during both training and testing stages, while the SGM model has the highest. The ARIMA model ranks second in accuracy, followed by SVM, demonstrating its strong forecasting capability.

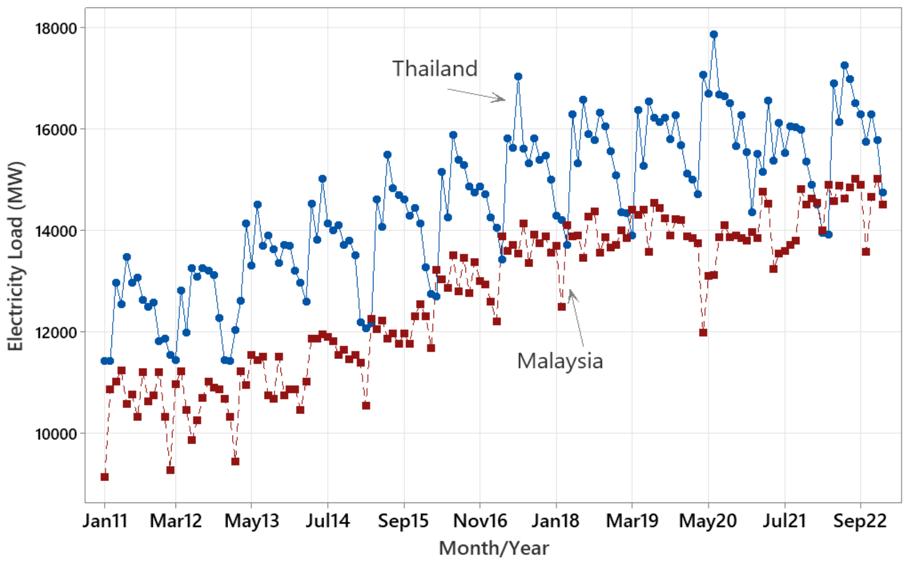

Figure 1. The data restart process

Table 1. Malaysia and Thailand's load forecasting evaluation metrics for various forecasting models

Country	Metric		SGM(1,1)	SVM	ARIMA	WCFM
Malaysia	MAPE	Training	3.20	2.77	2.80	**2.68**
		Testing	4.14	4.38	2.90	**2.82**
	RMSE	Training	533.98	454.56	494.40	**427.05**
		Testing	778.22	703.16	556.28	**482.55**
Thailand	MAPE	Training	2.63%	1.74%	1.77%	**1.67%**
		Testing	5.69%	3.94%	3.21%	**2.67%**
	RMSE	Training	499.81	343.44	338.02	**312.05**
		Testing	933.79	783.76	568.92	**502.98**

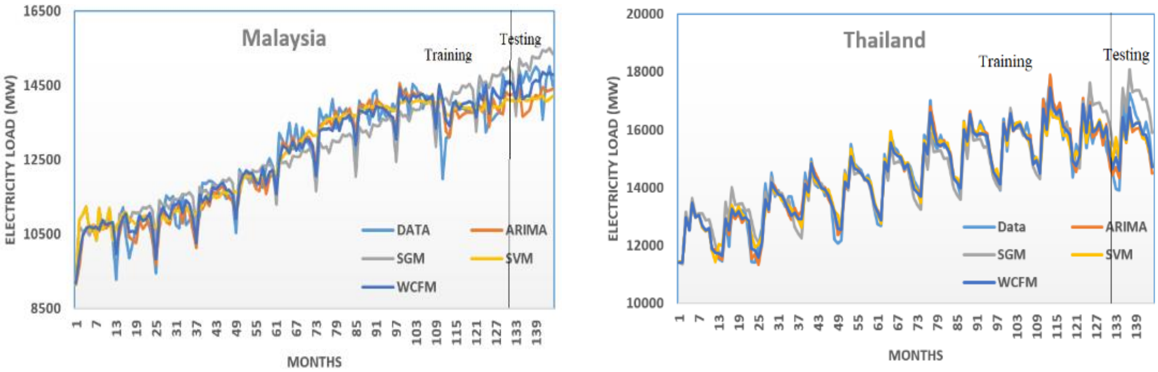

Figure 2. The real value curves and forecasts for Malaysia and Thailand using four different models: ARIMA, SVM, SGM(1,1), and WCFM

Overall, the WCFM model exhibits superior modelling and forecasting accuracy compared to other models. By incorporating the weighted coefficients of each model, the optimized WCFM significantly enhances the forecasting ability of traditional single models, proving its superior adaptability in predicting monthly electricity load. Figure 2 shows the training and testing values of the four models for monthly electricity load, with the WCFM values closely matching the actual data in both stages.

These case studies demonstrate that the WCFM achieves higher precision in training and testing than other models for monthly electricity load forecasting. The ARIMA model ranks second, followed by SVM and SGM, indicating that the proposed model provides relatively low error and reliable prediction capability.

5. CONCLUSION

The global development of electrical load is accelerating, prompting extensive research by scholars into forecasting methods. Widely used models for predicting electrical load data with seasonal and trend characteristics include statistical models, artificial intelligence, and grey models. This study introduces a novel combined WCFM for forecasting monthly electrical load data, utilizing the ABC algorithm to optimize model parameters and enhance forecasting performance.

In our experiments, the innovative WCFM, which integrates three distinct models, effectively addresses both seasonal and linear trend forecasting challenges. Compared to individual models like ARIMA, SVM, and SGM(1,1), the combined model demonstrates significant improvements in accuracy, stability, and trend prediction. Consequently, the WCFM, with its superior accuracy, shows great potential for future applications. Additionally, this combined model can be applied to various fields, including power load forecasting, stock price forecasting, and traffic flow forecasting.

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C	:	**C**onceptualization	I	:	**I**nvestigation	Vi	:	**Vi**sualization
M	:	**M**ethodology	R	:	**R**esources	Su	:	**Su**pervision
So	:	**So**ftware	D	:	**D**ata Curation	P	:	**P**roject administration
Va	:	**Va**lidation	O	:	Writing - **O**riginal Draft	Fu	:	**Fu**nding acquisition
Fo	:	**Fo**rmal analysis	E	:	Writing - Review & **E**diting			

CONFLICT OF INTEREST STATEMENT

The authors declare no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

DATA AVAILABILITY

The datasets that support the findings of this research are openly accessible from official sources: the Energy Policy and Planning Office, Ministry of Energy, Thailand (*https://www.eppo.go.th/index.php/en/*), and the Single Buyer, Malaysia (*https://www.singlebuyer.com.my*).

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