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Doctoral Dissertation

A Study on Hybrid Models for Daily Demand Forecasting in Disrupted Situations: Application to Predict Thailand's Electricity Consumption During COVID-19

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ABSTRACT

The accurate forecasting of electricity demand is crucial for global energy security, cost reduction, and grid stability. Disrupted situations such as the COVID-19 pandemic lead to unpredictable shifts in demand, posing challenges for short-term forecasting. Understanding demand patterns during such crises is essential for managing current circumstances and preparing for future disruptions.

This research aims to develop a precise model for predicting electricity demand, with the primary goal of effectively managing potential future disruptions. The proposed hybrid forecasting model is intended to address scenarios both with and without government intervention during disrupted situations, utilizing Thailand's electricity demand during the COVID-19 pandemic as a case study. The proposed forecasting model integrates various techniques, including stepwise regression, similar day selection-based day type criteria, variational mode decomposition, empirical mode decomposition, fast Fourier transform, neural networks, long short-term memory, and grid search optimization. To enhance the model's flexibility and adaptability, this study introduces new criteria for dataset segmentation and the selection of similar days, facilitating one-day-ahead forecasting with the utilization of rolling datasets.

The study assessed the practicality and effectiveness of the proposed forecasting model through real-world implementation. Comparative analysis against existing models demonstrated the superiority of the proposed model in enhancing flexibility and accuracy, particularly in dynamic and uncertain environments. The model exhibited improved performance with efficient computational processes and independence from input variables dependent on prior forecasts. Furthermore, the study examined the impact of disruptions on the model's accuracy, revealing its robustness and adaptability. Overall, the findings provide valuable insights for decision-making across diverse scenarios.

Keywords: : hybrid approach; daily peak load forecasting; disrupted situation; VMD; EDM; FFT; similar day selection method; stepwise regression; artificial neural network; long short-term memory; COVID-19

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Lalitpat Aswanuwath

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LIST OF ABBREVIATIONS

Abbreviations	Terms
ANN	Artificial Neural Network
EMD	Empirical Mode Decomposition
FFT	Fast Fourier Transform
GS	Grid Search Optimization
IMF	Intrinsic Mode Function
LMA	Lagged Daily Electricity Demand to Moving Average Index
LSTM	Long Short-Term Memory
MA	Moving Average Index
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MLFN	Multi-layer Feedforward Neural Network
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
SD	Similar Day Selection
SVM	Support Vector Machine
VMD	Variational Mode Decomposition
XGBoost	Extreme Gradient Boosting
ARIMA	Autoregressive Integrated Moving Average

CHAPTER 1

Introduction

Accurate and practical forecasting stands as a fundamental aspect of strategic planning across industries. Within the electric utility industry, forecasting demand is essential to predict future electricity needs and ensure sufficient resources are available. [1]. The growing fluctuations in electricity demand have garnered worldwide attention within the industry [2], [3]. Recognizing the potential impact of emergencies on the power industry and effectively managing energy distribution highlights the importance of focusing on this sector [4]. Accurate forecasting serves as a critical tool in assisting the utility industry in making informed decisions regarding load scheduling, allocation of power storage reserves, and optimization of facility layout, thereby fostering overall enhancements within these operational domains [5], [6].

In recent years, there has been a growing global trend among nations to prioritize environmental sustainability, recognizing it as a critical global concern [7]. Accurate forecasting of electricity demand stands as a key in the quest to increase sustainability. By providing precise insights into future energy demand, it enables the development of optimized generation strategies. Moreover, accurate forecasting facilitates efficient resource allocation, improving electricity generation. It also maintains a stable balance between supply and demand, mitigating the risk of electricity network or overloading. Furthermore, accurate forecasting allows both customers and industries to embrace energy-efficient behaviors, leading to improved resource utilization and contributing to improved sustainable energy production. These efforts are essential in promoting long-term sustainability.

The rest of this chapter is organized as follows: statement of problems, research objectives, and chapter organization.

1.1 Statement of Problems

Accurate electricity forecasting is crucial for maintaining a stable and responsive energy infrastructure. However, the disrupted situation has led to unprecedented shifts in consumption behavior, driven by factors such as remote work, varying restrictions, and economic fluctuations, resulting in significant changes in both the magnitude and daily consumption patterns [8]. The dramatic and sudden shifts in electricity demand patterns impact electricity forecasting in short-term. Traditional forecasting models, which rely on historical data and predictable trends, struggle to adapt to the rapid and unpredictable changes in electricity demand caused by natural disasters, remote work arrangements, varying degrees of restrictions, and economic uncertainties. These unforeseen variations make it incredibly challenging for utilities and forecasting systems to accurately predict demand patterns, causing potential mismatches between supply and demand. Furthermore, the lack of historical precedent for such sudden changes further complicates the creation of reliable models, rendering traditional forecasting methods less effective in anticipating and adapting to the dynamic nature of electricity usage during this unprecedented time [9]. Understanding the electricity demand pattern during a pandemic can support the electric utility industry in responding to disruptions, thereby facilitating informed decision-making in rebuilding and fortifying energy systems during unprecedented challenges. Thus, during disrupted situations, an accurate electricity forecasting model is essential for navigating uncertainties, fostering resilience, and facilitating a sustainable and reliable energy landscape.

During the COVID-19 pandemic, the electricity consumption data can illustrate disrupted scenarios, as the pandemic rapidly and adversely influenced various sectors worldwide within a short period [10]–[12]. Notably, the energy sector emerged as one of the hardest hit among these affected industries [12]. Given the substantial impact of disruptive situations on the global energy sector, this research aims to develop a precise model for predicting electricity demand, with the primary goal of effectively managing potential future disruptions. According to the World Bank's records in 2022, Thailand became the 2nd largest economy in Southeast Asia and the 9th largest economy in Asia [13]. The large economic sector relates to the large scale of electricity used. Considering the large economic sector of Thailand and the worldwide impacts of COVID-19 pandemic, this research decides to use Thailand’s electricity supply chain during the pandemic situation as a representative case study to evaluate the forecasting model efficiency.

Based on the literature reviews, two gaps are identified. The first gap exists in creating models for hybrid scenarios that combine aspects of both restricted and unrestricted conditions. Existing models perform well in forecasting demand during either normal conditions or strict restrictions. However, there's a need for frameworks that can adjust to transitional periods, in which restrictions vary or slowly relax. Another gap involves the selection of input variables, particularly the process of choosing similar days for hybrid scenarios. Not considering this procedure could bring in irrelevant or redundant variables, causing overfitting problems that decrease the forecasting model efficiency. It also increases complexity, consuming more computational workloads and time. In addition, several techniques are employed to enhance and strengthen model performance, including data decomposition, hyperparameter optimization, and the use of rolling datasets. Without employing data decomposition, the forecasting model loses seasonal and trend information, making it challenging to manage seasonal patterns. This leads to inaccurate forecasting results, particularly in long-term predictions, as the model fails to recognize fundamental patterns. Similarly, without utilizing hyperparameter optimization, the overfitting and underfitting problem may be the result of incorrect hyperparameter setting, affecting forecasting performance. Manually selecting hyperparameters can also be biased. Furthermore, in dynamic situations such as the ongoing pandemic, adjacent data becomes crucial because it reflects the present state. However, adaptability and the forecasting model's robustness can be impacted by fixed training datasets, resulting in inaccurate forecasting results.

The contribution of this research is filling these two gaps which are constructing a specific model designed for hybrid scenarios, together with the data decomposition, input variable selection, hyperparameter optimization, and a rolling dataset. With these methods all together, it becomes possible to address challenges such as adapting to transitional phases, capturing inherent seasonal patterns, avoiding overfitting, and managing model complexity effectively. Moreover, the most recent data can be utilized by rolling datasets and reducing performance bias in terms of hyperparameters.

To sum up, the research's contribution to knowledge lies in its dedicated effort to address the challenges posed by disruptive events, specifically exemplified by the COVID-19 impact on global energy industry. By developing precise model for predicting electricity demand, the study aims to offer valuable insights and tools for effectively managing and mitigating the potential disruptions that may arise in the future. This contribution enhances the understanding of the complexities involved in energy demand forecasting, fostering resilience and adaptability in the face of unforeseen events. Moreover, the practical applicability of the research extends to empowering policymakers, energy planners, and relevant stakeholders with actionable information, enabling them to make informed decisions and implement strategies that enhance the resilience of energy systems in the face of disruptive circumstances.

1.2 Research Objectives

- To develop a hybrid forecasting model for hybrid scenarios during disrupted situations, using Thailand’s electricity demand during the COVID-19 pandemic as a case study
- To implement the proposed model in a real-world setting to assess its practical applicability
- To conduct a comparative analysis against existing forecasting models
- To analyze how disruptions affect the forecasting model’s accuracy as an external variable
- To provide an understanding of the model’s performance in different scenarios, offering valuable guidance for decision-making in diverse situations

1.3 Chapter Organization

- **Chapter 1** explains the abstract in more detail and introduces the research story, motivation, and importance of the research. It clarifies the research aims and the impact of the research, as well as highlights interesting points and reasons why this research should be conducted. Additionally, it provides the statement of problems, research objectives, and the organization of chapters in this thesis.
- **Chapter 2** presents the literature review, which includes previous works and research related to the research field, encompassing journals, books, and research articles from which information is collected. This section serves to identify gaps, differentiations, and contributions to the research, while also providing background on the methodologies used in this thesis.
- **Chapter 3** explains how the research was conducted including experimental steps and procedure of the proposed model for hybrid scenarios during disrupted situations. It shows methods used in the research composed of theory, mathematical formulas, tools used, and error measurements used in the research.
- **Chapter 4** offers a case study examining the peak electricity consumption in Thailand during the COVID-19 pandemic, structured into several key sections. It begins by detailing the process of data collection and description, outlining the sources and types of data utilized to analyze peak demand patterns during the pandemic period. Subsequently, the chapter discusses the methodology employed for time segmentation and the identification of sensitivity factors. Two distinct cases are then presented: Case 1 explores scenarios where government policies directly interfere with electricity demand patterns, while Case 2 examines situations without government policy interference. Finally, the chapter presents the experimental results derived from the case studies and engages in a comprehensive discussion, offering recommendations for model selection during diverse situations.
- **Chapter 5** serves as the conclusion of the dissertation, summarizing the findings to address the research questions. It highlights the contribution to

current literature and offers recommendations and suggestions for future research.

- **Chapter 6** presents a novel contribution of this research to the knowledge science field, encompassing both practical and theoretical implications. This contribution seeks to enhance the current understanding of electricity demand forecasting during disrupted situations and provide valuable insights that could significantly impact the utility industry.

CHAPTER 2
Literature Reviews
and Research Background

2.1 Literature Review of the Relevant Research

This section explores the impact of recent disrupted situations on the energy sector, with a specific focus on electricity demand forecasting during such scenarios. The recent COVID-19 pandemic has highlighted the necessity of accurate forecasting models that can adapt to rapidly changing circumstances. This literature review delves into the methodologies and techniques used to forecast electricity demand during disrupted situations. The broader impact of recent disruptions on the energy sector is described in **Subsection 2.1.1**, while the specific challenges and methodologies of electricity demand forecasting during such pandemic times are focused on **Subsection 2.1.2**. Through an analysis of existing research, this section aims to identify research gaps and illustrate the strategies and approaches that have been employed to address the unique challenges posed by disrupted situations and identified research gaps.

2.1.1 Impact of Recent Disrupted Situation on the Energy Sector

In this context, due to its global impacts, the recent disruption caused by the COVID-19 pandemic serves as an illustrative example of disrupted events. The COVID-19 pandemic rapidly and negatively influenced various sectors worldwide over a short period [10]–[12]. Among these sectors, the energy industry is significantly impacted [12]. Energy consumption varies across regions, with greater consumption occurring in commercial, industrial, and residential sectors [14]. Residential energy usage tends to increase during periods of restrictions when people stay at home.

Changes in lifestyle and work habits lead to significant fluctuations in electricity demand during different timeframes [15]. Fluctuations in electricity demand can also impact power system control and operation, potentially affecting utility grid equipment like distribution transformers, protection devices, and substations. Failing to effectively manage these fluctuations could pose substantial risks to the stability and functionality of the national power grid [16].

Several researchers have examined the effects of the pandemic on various sectors including the economy, environment, and the power and energy industries. Aktar et al. [17] conducted a comprehensive review to determine how the COVID-19 pandemic has influenced energy demand, CO2 emissions, and economic indicators. Jia et al. [18] explored the effects and responses of the pandemic and oil price fluctuations on energy, economy, and environment. Jiang et al. [19] provided an overview of the COVID-19 impacts on energy demand and consumption, highlighting associated challenges and new opportunities. Ruan et al. [20] focused on the COVID-19 impact on electricity grid and market activities, while Geraldi et al. [21] analyzed electricity demand during lockdown in buildings. Tsao et al. [22] delved into the resilience of renewable energy supply networks in response to the demand, supply, and payment risks arising from COVID-19. Additionally, Klemeš et al. [23] and Pradhan and Ghosh [24] assessed the COVID-19 pandemic from the perspectives of energy, environment, sustainability, and climate change.

Turning focus to the effect of COVID-19 on electricity demand forecasting, Cheshmehzangi [25] investigated the short-term and long-term effects of COVID-19 on household energy usage. Similarly, Abulibdeh et al. [26] examined how the pandemic affected electricity demand and the accuracy of electricity demand forecasting. Following the demonstration of these impacts on electricity demand forecasting, achieving precise forecasting performance becomes a common objective pursued by many researchers.

2.1.2 Electricity Demand Forecasting during Disrupted Situation

Statistical and machine learning techniques are the primary methods commonly used in electricity demand forecasting, both in regular situations and during disrupted situations such as the COVID-19 pandemic. Under regular circumstances, the statistical linear regression model [27], [28] is widely favored for its simplicity and ease of interpretation. Moreover, more advanced prediction methods, including Holt Winter's exponential smoothing model [29], autoregressive integrated moving average model (ARIMA) [30], ARIMA with exogenous variables (ARIMAX) [31], ARIMA model that contains a seasonal component with and without exogenous variables (SARIMAX [32] and SARIMA [33]), and the grey model [34], are also commonly applied.

During the COVID-19 pandemic, there was considerable focus on adjusting to shifts in demand patterns. Advanced methods were also utilized during this period. In order to mitigate the pandemic's impact on forecasting models, Alasali et al. [35] implemented the ARIMAX model with a focus on long-term electricity demand trends. To enhance predictive capabilities, Huang et al. [16] introduced the integration of rolling mechanisms into the grey model to make use of the most recently collected data. However, an advanced model is inadequate to address specific circumstances, inspiring the focus on hybrid models. In a scenario lagging the availability of external variables, the implementation of a hybrid model combining generalized additive models (GAM) and Kalman filtering successfully enhanced the adaptability of the forecasting model [36]. Similarly, in the condition of inadequate data during the pandemic situation, a hybrid model of fractional grey forecasting models with genetic algorithm (GA) optimization was also utilized to handle monthly forecasting with electricity production data [37]. Nevertheless, the limitations of statistical techniques include dealing with the non-linear patterns evident in the recent trends in electricity demand [38]. Therefore, to handle electricity demand problem, machine learning techniques are used. The capabilities include continuous learning, and real-time updates on demand and changes during the disruption, making machine learning algorithms suitable for forecasting under rapidly changing scenarios [39].

Machine learning has gained wide application in electricity demand forecasting due to its several advantages. The application of machine learning models, such as support vector machines (SVM) [40], the artificial neural network (ANN) [41], and long short-term memory (LSTM) networks [42], is commonly used in this field. To manage demand uncertainty during forecasting, combining techniques such as machine learning and statistical methods can address the uncertainty concern. Bayesian regularization, utilizing the Gaussian process [43], can be used to combine the uncertainty with forecasting process, which is valuable for handling complex and limited data availability scenarios. Machine learning models can be used to predict electricity usage during both normal and disrupted situations.

During the early stage of the COVID-19 pandemic, LSTM was used to forecast daily electricity usage [44]. Additionally, during the pandemic, ANN was employed to forecast electricity usage, as it has a non-complex structure enabling it to be used in practical systems [9]. However, training ANN with the common input variables may not yield acceptable results due to the complex and unpredictable nature of consumption patterns caused by unprecedented events such as the COVID-19 pandemic. Chen, Yang, and Zhang [9] promoted the accuracy of ANN forecasts by integrating economic activity-based mobility data. In the absence of sensitivity factors representing the pandemic situation, the implementation of improvement techniques using a hybrid model is necessary to enhance basic machine learning models' accuracy. A hybrid LSTM model is employed, utilizing a simplex optimizer [45] and incorporating grid search and manual search [46], to enhance accuracy using hyperparameter tuning. A hybrid model using the data decomposition technique known as improved complete ensemble empirical mode decomposition with adaptive noise (ICEEMDAN), along with the multi-objective grey wolf optimizer (MOGWO), is utilized to enhance SVM performance [47]. Furthermore, integrating a transfer learning framework with neural networks improves the understanding of the effects of external variables on electricity usage during a pandemic [48]. **Table 1** shows the summarization technique utilized in prior studies during the COVID-19 pandemic, providing a comprehensive overview of the methods and findings.

Table 1 Overview of methods used in prior research during the COVID-19 pandemic.

Paper	Forecasting Model	Data Decomposition	Select Input Variable	Hyper Parameter Optimization	Sensitivity Factor	Rolling Dataset	Study Location	Forecasting Period
[35]	ARIMAX	No	No	No	No	No	Jordan	30 min, Daily, Monthly
[16]	Rolling IMSGM	No	No	No	No	Yes	China	Monthly
[36]	Kalman filtering with GAM	No	No	No	No	No	France	30 min
[37]	Fractional grey model	No	No	GA	No	No	European countries	Monthly
[44]	LSTM	No	No	No	No	No	Turkey	Daily, Monthly
[9]	ANN	No	No	No	Yes	No	European countries, US cities	Daily
[45]	LSTM	No	No	Simplex optimizer	Yes	No	China	Daily
[46]	Bi-LSTM	No	No	Grid search, Manual search	Yes	No	UK	Daily
[47]	SVM	ICEEMDAN	No	MOGWO	Yes	No	US	Daily
[48]	Transfer learning with CNN	No	No	No	No	No	China	Monthly
Proposed Model	**ANN/LSTM**	**VMD-EMD-FFT**	**Stepwise regression, SD**	**Grid search**	**Yes**	**Yes**	**Thailand**	**Daily**

Following the literature, two gaps have been found during the COVID-19 pandemic, see **Table 1**. The first identified gap involves integrating and developing models designed specifically for hybrid scenarios that combine aspects of both lockdown and non-lockdown situations. Despite existing models performing well in predicting usage under normal situations or during lockdowns, the comprehensive framework that can be used during the transitional phases when restrictions fluctuate or gradually loosen is still lacking.

Another gap concerns improvement techniques presented in the literature during the COVID-19 pandemic, aimed at constructing the hybrid model. The first improvement technique is data decomposition. Failure to apply this technique causes the forecasting model to lose seasonal and trend information, leading to increased difficulty in managing seasonal patterns. As a result, inaccurate forecasting results are generated, particularly in long-term forecasting, as the model cannot capture underlying patterns effectively. The second technique involves the selection of input variables. Failure to carry out this process may introduce irrelevant or redundant variables into the model, causing the overfitting problem and the curse of dimensionality. As a result, there is an exponential increase in the computational efforts required for processing, as well as a reduction in forecasting performance. The third technique lies in the hyperparameter optimization technique. Failing to utilize this method can result in the creation of overfitting and underfitting problems due to improper hyperparameter settings, leading to a reduction in the efficiency of the forecasting model. Additionally, manually selecting hyperparameters may increase the risk of bias. The fourth technique is the rolling dataset. In the context of the pandemic, where the situation changes daily, the availability of adjacent data becomes crucial as it reflects the current situation of the pandemic. The dynamic nature of the pandemic necessitates the use of up-to-date information to make informed decisions. Adjacent data, which encompasses the most recent information, is invaluable for understanding and responding to the evolving situation effectively. In contrast, fixed training datasets fail to incorporate the most recent information, which is essential for understanding and responding to the evolving situation effectively, resulting in poor forecasting outcomes. By integrating these four improvement techniques into a hybrid model, the proposed model can mitigate identified limitations and improve the accuracy, adaptability, and robustness of the forecasting model when dealing with the complexity caused by disrupted situations.

2.2 Research Background

This section provides a research background on forecasting models and improvement techniques. **Subsection 2.2.1** describes the history of prediction techniques and explores how forecasting has evolved from simple methods to more advanced ones used today. Along the way, the tools developed to enhance predictions are examined. One of these tools is data decomposition (**Subsection 2.2.2**), which helps break down complex data into smaller parts for better understanding. Another important technique is input variable selection (**Subsection 2.2.3**), which identifies the most crucial factors for accurate predictions. This section offers a better understanding of the research background by reflecting on how forecasting has changed over time and the techniques that have contributed to its improvement.

2.2.1 Forecasting Models

In the areas of electricity demand forecasting, the utilization of time series models, whether employed singularly or in combination, proves to be a reliable method for achieving accuracy. Utilizing trend analysis enables the extrapolation of future electricity demand requirements with precision [49]. A time series refers to a sequential arrangement of values recorded at consistent intervals. Analyzing time series involves two main stages: initially obtaining the structure and underlying patterns within the observed data, followed by fitting a model to facilitate future predictions. A common method in time series analysis involves decomposing the series into three distinct components which are trend, seasonality, and residual [50]. The trend represents the overall direction or movement exhibited by the variable over the observation period, neglecting seasonal fluctuations and irregularities. Seasonality refers to the repeated pattern of fluctuation in the variable under examination, characterized by stable effects in terms of timing, magnitude, and direction. Finally, residuals represent the residual or unexplained portion of the time series data. Despite efforts to capture trends and seasonality, residuals often remain, sometimes with sufficient magnitude to obscure the underlying trend and seasonal patterns [51]. Extensive research literature addresses predictive modeling, revealing two overarching methodological categories: statistical techniques and machine learning algorithms.

Focusing on statistical forecasting techniques, linear regression emerges as one of the most commonly used methods due to its simplicity and ease of implementation. The accuracy of this method depends on how well historical data represent potential future scenarios. Nevertheless, it is feasible to develop a metric to identify unreliable forecasts. This method requires minimal parameters, which can be calculated from historical data using cross-validation techniques [27], [28]. Continuing with multiple regression, it is widely recognized as the most popular method used for forecasting loads affected by various factors such as meteorological effects, electricity prices, and economic growth. Multiple regression analysis in electricity demand forecasting utilizes the technique of least-square estimation. Varadan and Makram [52] applied the least squares approach to determine and quantify different types of loads at power lines and substations. A weather-load model based on regression analysis of historical demand and weather data to predict load demand for Irish electricity was developed by Hyde and Hodnett [53]. Additionally, Broadwater [54] introduced a novel regression-based technique, the nonlinear load research estimator (NLRE). In addition to multiple regression, exponential smoothing is one of the methods used in electricity demand forecasting. In this technique, the load is initially modeled using historical data, followed by the utilization of this model to forecast future load. Winter's method represents one of the existing exponential smoothing techniques capable of directly analyzing seasonal time series. This method relies on stationary, trend, and seasonality, as smoothing constants [55].

In response to evolving environmental conditions, adjustments have been made to traditional forecasting techniques to automatically adapt the parameters of forecasting models. Initially, the auto-regressive (AR) model is utilized to represent the load profile, assuming it is a linear combination of previous loads [56]. To enhance the traditional AR model, Mbamalu and El-Hawary [57] employ least mean square (LMS) algorithms to dynamically update the unknown coefficients in real-time. Moreover, Huang [58] introduces an autoregressive model with an optimal threshold stratification algorithm for hourly load forecasting. To further enhance the adaptability of the AR model, an autoregressive moving average (ARMA) model is developed. This model forecasts the current linear time series value based on previous periods (autoregressive component) and by incorporating previous error values (moving average component). This approach enables the model to capture both short-term dependencies between observations and the impacts of random errors [52], [59], [60]. Lastly, Contreras et al. [61] introduced the auto-regressive integrated moving average (ARIMA) model. This model, widely employed in time series forecasting, integrates autoregression (AR), differencing (I), and moving averages (MA) concepts. With its capacity to capture diverse temporal dynamics and patterns inherent in time series data, ARIMA models are highly versatile and effective for forecasting purposes. They are often preferred over simple ARMA models due to their superior handling of non-stationary time series data through the inclusion of the differencing component (I), which expands their applicability across various time series datasets. Additionally, ARIMA models demonstrate flexibility in capturing both short-term and long-term dependencies within the data, further enhancing their utility for forecasting tasks [55], [62], [63].

However, statistical models have limitations that may not capture complex relationships or causal factors driving the data, especially in situations where variables are interrelated in nonlinear ways [38]. This limitation can result in oversimplified or overly deterministic forecasts that fail to account for nuanced dynamics within the data. Furthermore, statistical forecasting models may require a substantial amount of data to produce reliable forecasts, which can be challenging to obtain in certain contexts. While statistical forecasting models offer valuable insights and are widely used in practice, they are not without limitations and may not always provide accurate predictions in every scenario. To address these limitations, the introduction of machine learning into this field has been proposed.

Machine learning techniques offer continuous learning capabilities, enabling algorithms to offer real-time adjustments as consumption patterns evolve. This adaptability makes them highly suitable for dynamic and fluctuating forecasting scenarios. Furthermore, machine learning techniques facilitate rapid adaptation to new electricity demand patterns by utilizing data representations instead of explicit data features [39]. Through the utilization of algorithms capable of adaptation and learning from data, machine learning systems exhibit a resemblance to the human mind's capacity for reasoning and learning within environments characterized by uncertainty. Within this framework, these systems prioritize adaptability over strict precision, enabling them to make approximate decisions when faced with incomplete or noisy information.

Starting with traditional machine learning methods, fuzzy logic stands as a computational model adept at processing reasoning based on approximate or imprecise data rather than strict binary (true/false) values. This model allows for the representation of subjective concepts, enabling systems to make decisions in scenarios where traditional binary logic may prove insufficient. Notably, fuzzy logic exhibits the capability to identify and approximate any unknown dynamic system, such as electricity demand, with arbitrary precision within a compact set. Extensive research, as exemplified by Liu et al. [56], highlighted the substantial capacity of fuzzy logic systems to discern similarities from extensive datasets. Various techniques have been devised to model loads using fuzzy conditional statements. For instance, Hsu and Ho [64] introduced an expert system employing fuzzy set theory for electricity demand forecasting in the short term, incorporating an updating function. Evaluation of short-term forecasts was conducted within the Taiwan power system. Subsequently, Liang and Hsu [65] devised a fuzzy linear programming model for electric generation scheduling, employing fuzzy set notation to address uncertainties in forecast and input data. Dash et al. [66] further enhanced the hybrid fuzzy-neural approach for load forecasting, yielding accurate predictions across weekdays, public holidays, and adjacent periods. However, one drawback of fuzzy logic is its complexity in designing and tuning fuzzy systems. Creating effective fuzzy logic systems often requires expertise in both the domain being modeled and the intricacies of fuzzy logic itself. Designing appropriate membership functions, defining fuzzy rules, and optimizing system parameters can be challenging and time-consuming tasks. Additionally, fuzzy logic systems may struggle to handle highly nonlinear or dynamic systems effectively. While they excel at modeling and reasoning with imprecise or uncertain information, they may not always accurately capture the complexity of certain real-world phenomena.

Unlike fuzzy logic, which requires expertise for the manual definition of fuzzy sets, rules, and inference mechanisms, genetic algorithms (GA) do not rely on explicit rules. Instead, it evolves solutions based on their fitness in solving the problem, making it more adaptable to a wider range of optimization problems without the need for domain-specific knowledge. GA belongs to the category of evolutionary algorithms, which are inspired by the principles of natural selection and genetics. It operates by iteratively evolving a population of candidate solutions through selection, reproduction, mutation, and crossover processes. Its capability to efficiently search large solution spaces enables it to handle complex optimization and search problems by determining optimal or near-optimal solutions [67]. The application of GA to the load forecasting problem was first introduced by Yang et al. [68]. Subsequent enhancements to the GA algorithm were proposed by Yang and Huang [67], who introduced a fuzzy autoregressive moving average with an external variable (FARMAX) model for electricity demand forecasts. The model is developed as a combinatorial optimization problem and solved using a blend of heuristics and evolutionary programming. Ma et al. [69] employed a genetic algorithm featuring a recently devised mutation-like operator termed the forced mutation. Lee et al. [70] utilized genetic algorithms for electricity demand forecasting in the long term, experimenting with various functional forms and benchmarking outcomes with regression analysis. However, GA has disadvantages in terms of the interpretability of its solutions. GA often produces solutions in the form of parameter sets or configurations, posing challenges for interpretation, particularly in complex scenarios or when the solution space is high-dimensional.

While genetic algorithms are known for their efficacy in optimization and search tasks, neural networks (NN) or artificial neural networks (ANN) offer numerous advantages. These include enhanced interpretability, automatic feature extraction, adaptability to changes in data, and the ability to manage complex relationships, which can help overcome certain limitations associated with genetic algorithms. To mitigate the requirement for a specific functional form in forecasting models, neural networks can be used [71]. Multilayer perceptron networks and self-organizing networks are examples of neural networks. The network comprises multiple hidden layers, each containing numerous neurons. Within these layers, inputs are multiplied by weights and then added to a threshold, resulting in the formation of an inner product number referred to as the net function [72]. One notable advantage of this approach is its ability to perform forecasting without necessitating a load model, as observed in many existing literature methods. However, it is important to acknowledge that the training process typically demands considerable time investment. In this context, the fully connected feed-forward neural networks are employed by Liu et al. [56]. The input and hidden units are connected to the output units using linear functions of the weights to obtain outcome of the network. Throughout the iterative training process, commonly referred to as epochs, the optimization of output weights is achieved through conventional backpropagation to refine hidden unit weights, and the conjugate gradient approach is utilized to optimize linear equations for output weights.

Various studies have demonstrated the efficacy of artificial neural networks (ANN) in load forecasting. ANN is employed for the energy control center, focusing on accurately modeling special situations, for example, holidays, heat waves, and cold snaps that disrupt the normal demand trend [73]. The three-layered feedforward adaptive neural networks are developed to multilayer configurations by Ho et al. [72], while Dillon et al. [74] presented a multilayer feedforward neural networks with a learning algorithm for adaptive training. An ANN based on backpropagation for forecasting, demonstrating its capability over traditional methods, is utilized by Srinivasan and Lee [75]. A set of ANNs is integrated into a supervisory expert system to create expert networks, evaluating their effectiveness in short-term load forecasting using actual load data and backpropagation by Asar and McDonald [76]. Additionally, Dash et al. [66] combined fuzzy logic with neural networks for load forecasting. Chen et al. [77] utilized a supervisory functional ANN technique to forecast electricity demand for substations in Taiwan, correlating load with temperature and customer type. Al-Fuhaid et al. [78] included temperature and humidity impacts in an ANN model for short-term load forecasting in Kuwait. Recurrent neural networks to model short-term load forecasting for the South African utility, utilizing the nonlinear dynamic nature of neural networks to represent load influenced by weather, time, and environmental variables, is proposed by Vermaak and Botha [79]. Furthermore, Sheikh and Unde [80] conducted short-term electricity demand forecasting for their campus in Ahmadnagar using ANN, providing hourly predictions to anticipate future demand.

Temporal dependencies are common in time series data, leading to the development of recurrent neural networks (RNN) to address such dependencies through feedback connections, enabling the recall of prior time step values [81]. RNN is a type of artificial neural network designed to handle sequential or time-series data by incorporating memory mechanisms. Unlike feed-forward neural networks, which process data linearly from input to output, RNN features connections with directed cycles, enabling them to exhibit temporal dynamic behavior [82]. RNN is alternatively referred to as dynamic artificial neural networks due to their interconnected networks, leading to multidirectional signal flow and information exchange [83]. The key feature of RNN is its ability to maintain a memory of previous inputs and use this information to influence the processing of subsequent inputs in the sequence. This memory is achieved through recurrent connections, where the output of a neuron at a particular time step is fed back as input to the same neuron at the next time step. The introduction of RNN to energy prediction has been shown to improve time series forecast accuracy, as demonstrated by Rahman et al. [84]. Furthermore, Ruiz et al. [85] have enhanced RNN forecasting performance by optimizing its weights using GN. Additionally, Egrioglu et al. [86] have presented a novel RNN model based on a multiplicative neuron model, which yielded superior accuracy compared to alternative prediction techniques. Although traditional RNN is effective, it faces challenges in capturing long-term dependencies and encountering issues like vanishing or exploding gradients during training [87]. The standard RNN fails to adequately address long-term dependencies. Therefore, one potential solution to the vanishing gradient problem is the use of RNN with long short-term memory (LSTM).

The LSTM framework includes a memory array with hidden units [88], enhancing its ability to effectively model long-term dependencies. The model optimizes parameter usage by sharing memory among similar gates. It keeps values at gates when activated (set to 1) and clears them when deactivated (set to 0), following gate arbitration. This mechanism allows the network to capitalize on long-range temporal patterns [89]. To address vanishing gradient issues during both the forward and backward stages, steps are taken to mitigate the vanishing gradient, allowing the network to preserve its memory across successive time steps. Qing and Niu [90] employed an LSTM-based network algorithm to forecast electricity consumption and conducted a comparative evaluation with the backpropagation neural networks and multilayer feed-forward neural networks. Their analysis revealed that the LSTM algorithm exhibited superior prediction accuracy compared to the competitive approaches. In efforts to enhance the traditional LSTM approach, Rahman et al. [84] and Mawson and Hughes [91] developed two deep recurrent neural networks by stacking LSTM layers on top of the model using an encoder-decoder framework for load prediction. Recently, Bashir et al. [92] devised a hybrid LSTM model for short-term electricity load forecasting, demonstrating its efficacy in reducing errors with minimal computation time.

In summary, the effectiveness of LSTM-based algorithms in predicting electricity load emphasizes their wider applicability in various fields. Their superior performance, surpassing traditional methods and advanced neural network architectures, underscores the importance of LSTM networks in addressing complex predictive tasks. As research in this field progresses, the integration of improvement techniques such as data decomposition and input variable selection are positioned to further enhance the predictive capabilities of the forecast model. These improvement techniques are crucial as they refine the model's capacity to discern meaningful patterns from data while mitigating the impact of noise, thereby yielding more precise predictions.

2.2.2 Data Decomposition Techniques

When exploring strategies for improvement, data decomposition stands out as a valuable technique for enhancing the accuracy of electricity demand forecasting. This method involves the application of decomposing time series data to separate linear and non-linear elements from the original dataset [93]. Traditional techniques for decomposing data, such as discrete wavelet transform (DWT) and empirical mode decomposition (EMD), are widely utilized across various academic fields. DWT functions by separating original data into low-pass components and high-pass components through dilation, achieved through a series of operations including dilation, scaling, and translation, to effectively cover the wavelet filter. However, DWT's effectiveness is constrained by drawbacks concerning discrimination efficacy, with its performance relying upon expert decisions related to wavelet filter selection and decomposition levels [94].

In response to DWT's constraints, EMD emerged as an alternative, offering the advantage of automatic data decomposition based on inherent data characteristics, thereby eliminating the need for expert intervention [95]. EMD decomposes original data into a set of intrinsic mode functions (IMFs) and a residue. EMD operates through a sifting process, wherein it identifies local extrema (maxima and minima) in the signal and constructs a local mean by interpolating between these extrema. Subsequently, the mean is subtracted from the signal, yielding an IMF. This process is iterated until certain convergence criteria are met, resulting in a series of IMFs that capture the signal's varying frequency components at different scales. After extracting all the IMFs, the residual term is obtained by subtracting the sum of these IMFs from the original signal. This residual term represents any remaining trend or behavior in the signal that is not captured by the IMFs [96]. Despite these advancements, EMD encounters challenges when the number of extrema is abnormal, leading to mode mixing. This problem occurs when a mode cannot be separated into a distinct IMF and instead becomes mixed with another IMF [97]. Researchers have developed various methods to mitigate mode mixing in EMD. One of the effective techniques is ensemble empirical mode decomposition (EEMD), involving introducing white noise to the original data to enhance the separation between frequency components. However, this additional white noise leads to an endpoint effect, causing distortion. Moreover, it amplifies noise levels and complicates the original data, thereby posing a new challenge of creating variability in the number of IMFs during each iteration of the decomposition, further complicating the analysis [98].

Variational mode decomposition (VMD) stands as an advancement over EEMD by effectively addressing issues such as mode mixing, endpoint effect, and variable numbers of IMFs [99]. Through its capabilities, VMD demonstrates both mathematical robustness and flexibility. Jiang et al. [100] employed fast Fourier transform (FFT) to adjust seasonal patterns, enhancing VMD capabilities. During specific periods, these patterns show predictable fluctuations in electricity consumption. Integration of such patterns into forecasting models enhances their capacity to capture underlying trends, thus facilitating more accurate predictions. Nonetheless, the determination of the optimal decomposition level for VMD remains an ongoing research challenge. Determining an appropriate decomposition level for VMD becomes increasingly complex when confronted with intricate non-linear and non-stationary elements within the original dataset. With too low decomposition level, the coexistence of multiple time series data components within a single mode may present. Conversely, an excessively high decomposition level risks the presence of a single time series data component across multiple modes, thereby introducing potential mixing and ambiguity into the decomposition outcomes [101].

Several optimization techniques, including the grasshopper optimization algorithm (GOA) [102], genetic mutation particle swarm optimization (GMPSO) [103], and hybrid grey wolf optimizer (HGWO) [104], have been employed to enhance VMD and determine the most suitable decomposition level. However, these optimization techniques possess inherent drawbacks, encompassing the challenge of achieving global solutions and the intricate implementation of complex optimizers [105]. Dealing with complex problems requires numerous iterations to seek the optimum solution, leading to substantial processing time and resource consumption. To address these challenges, Aswanuwath et al. [106] propose a novel approach that utilizes the appropriate decomposition level acquired from EMD to direct the determination of the suitable decomposition level in VMD. By integrating VMD-based EMD, costs and time requirements for computing the model associated with finding optimized solutions are mitigated, while simultaneously ensuring a more efficient and precise decomposition process.

2.2.3 Input Variable Selection Techniques

Input variables play a crucial role in forecasting model accuracy. Identifying the most valuable inputs is a critical decision in model development, especially when dealing with a large number of available input variables. In such cases, conducting an exhaustive search through all possible variable combinations becomes computationally impractical [107]. Nevertheless, the set of candidate input variables typically encompasses those that may either lack relevance or exhibit redundancy. Irrelevant inputs fail to contribute informative value, instead introducing extraneous noise and unnecessary complexity into the model. Conversely, without providing supplementary predictive advantages, redundant inputs expand the model's dimensionality. Ignoring relevant input variables leads to inaccuracies within the predictive model. Therefore, relevant and non-redundant inputs need to be appropriately selected as they can significantly impact the model's reliability and simplicity, allowing it to generalize effectively to the underlying process. In contrast, a model lacking this selection may yield nonsensical outputs, perform slower, and prove more challenging to interpret [108].

Within the area of machine learning, a variety of techniques are employed for the selection of input variables. These encompass search strategies such as input variable selection (IVS) algorithms [109], exhaustive searches based on predetermined optimality criteria [110], heuristic searches [111], [112], and stepwise selection [113]. Notably, stepwise regression stands out due to its systematic approach and its ability to verify and explain relationships between response and predictor variables. In recent times, the Similar Days Selection (SD) method has been utilized for load forecasting. This method aims to enhance model training by incorporating historical inputs that share the same characteristics as those of the target forecast date [114], [115]. SD achieves this by identifying similar days through an analysis of evaluating the resemblance between the target forecast date and historical days [116]. In cases where external factors including weather conditions are either absent or unavailable on the forecast date, the SD method is still effective by utilizing historical data from days with accessible information to perform accurate predictions. Moreover, the method simplifies data complexity by focusing only on related historical data inputs, thereby resulting in an enhanced forecasting process.

Many methods can be used to enhance the effectiveness of SD. These methods encompass the incorporation of timing information and external factors as input variables, along with the utilization of enhancement techniques such as index-mapping databases [117], a combination of extreme gradient boosting and k-means clustering [118], and reinforcement learning algorithms [119]. Nevertheless, prior studies implementing SD have overlooked the importance of special days and omitted them from the forecasting model. Additionally, numerous studies utilize weather-related variables, including wind speed and precipitation, for identifying similar days. Given that the specific weather conditions are not predetermined, the prediction of these variables becomes necessary. An increased error in the forecasting model due to the use of forecasted data as input variables was presented in Senjyu et al.'s work [120]. The existing work highlighted the research gaps relating to the criteria for input variable selection and the practical application of selecting input variables in disrupted situations.

CHAPTER 3
Methodology of the Proposed Models

3.1 Overall Procedure of the Proposed Models

During periods of disruption, the electricity demand pattern experiences fluctuations and significant alterations, primarily due to various external factors such as governmental policies and regulatory adjustments. These policies can substantially influence people's daily routines, resulting in changes in energy usage trends and access to critical services. Consequently, the forecasting model needs to possess adaptability and flexibility to promptly adjust the sudden shifts in consumption induced by disruptive occurrences and policy modifications. To ensure the model's adaptability in managing these fluctuations, it must be trained using diverse datasets that encompass various time frames. The short-term dataset includes the latest data, allowing the model to accurately reflect the ongoing disruptions. Meanwhile, the medium-term dataset, which includes data spanning an intermediate period, offers insights into transitional patterns between disrupted and normal phases. Furthermore, the long-term input dataset comprises historical data, enabling the model to learn patterns during normal phases.

The proposed framework is primarily designed with a focus on the impact of government intervention policy, see **Figure 1**. As the changes in consumption behavior resulting from government intervention policy present an unusual pattern unprecedented in the past, it is imperative to approach this period distinctively from a disrupted situation lacking government intervention. To ensure the forecasting model can adapt to these changes, a short-term input dataset containing data close to the target forecasting date is used to train LSTM, known for its ability to effectively capture and learn from sequential relationships. However, in cases where the target period remains unaffected by governmental policies, electricity demand reflects a blend of disrupted and normal patterns. To handle these blended patterns, the ANN is trained using input from medium-term and long-term datasets. In order to identify the hidden seasonality and trends present in disrupted situations over the intermediate period, VMD-EMD-FFT is utilized to decompose the data and identify these patterns. Furthermore, an SD with a day type criterion is utilized to identify dates within the normal phase that closely resemble the target forecasting date during the disrupted phase. This method identifies a date within the long-term period that closely matches the target forecasting date, prioritizing similarities in day types. To minimize computational effort required for forecasting, stepwise regression and SD techniques are used to select significant input variables from the medium-term and long-term datasets.

To improve the forecasting model's adaptability to disruptions, the approach incorporates one-day-ahead forecasting. This strategy ensures the model is regularly updated with recent data, enhancing its ability to adjust to changing conditions and improve accuracy during disruptive situations. The short-term input set and processed dataset, after filtering input variables and preprocessing data, are divided into training, validation, and testing sets, incorporating overlapping data points known as a rolling dataset. This method strengthens the model's ability to handle dynamic scenarios effectively. Grid search optimization is employed using the training and validation sets to fine-tune hyperparameters for both ANN and LSTM. Subsequently, the best-performing model identified through hyperparameter optimization is used on the testing set to evaluate its performance and assess the final effectiveness of the forecast model. Detailed explanations of the proposed methodologies are provided in **Section 3.2.**

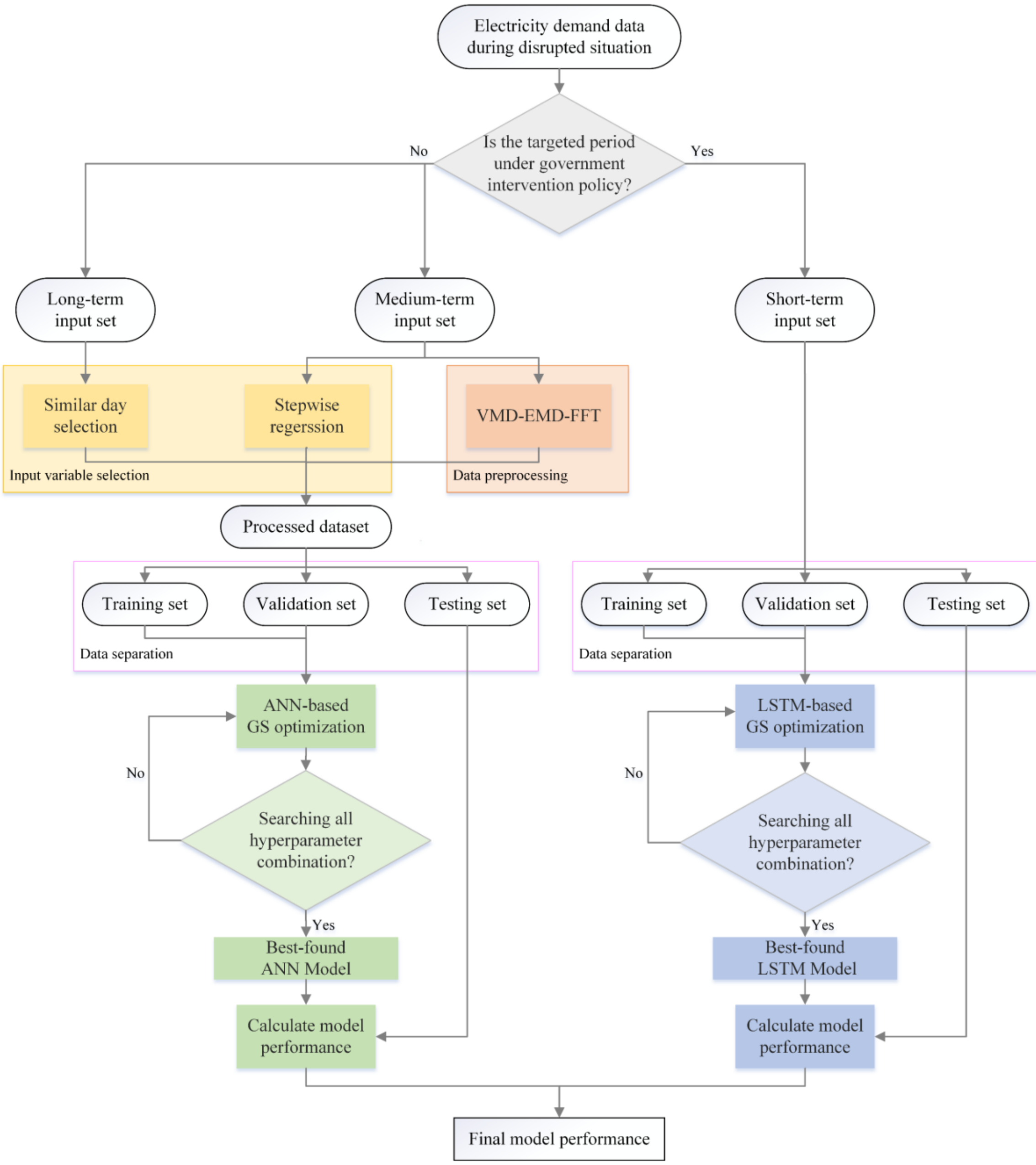

Figure 1 Overall procedure of the proposed models.

3.2 Input Variable Filtering

Input variables need to be properly selected to address practical challenges when using neural networks [121]. The choices made in input selection are imperative for effective forecasting model development. Within the set of candidate variables, there exists the possibility of including irrelevant or redundant elements. Irrelevant inputs introduce extraneous noise and complexity into the model. However, redundant elements inflate the model size and do not improve predictive accuracy. Conversely, overlooking relevant inputs can result in inaccuracies in forecasting outcomes [108]. Filtering input variables provides a better understanding of the generation of underlying data, improves model performance, and decreases processing time [122].

This section outlines two methods of input variable filtering: stepwise regression and SD. Starting from SD, it is utilized to identify similar dates using the day type criterion. Conversely, the stepwise regression method is applied to select importance input variables from candidate variables associated with date and electricity consumption.

3.2.1 Input Variable Definition

For stepwise regression methodology, the input variables are based on categories, including date-related and electricity demand-related variables. These input variables are generated to use as candidates for selection during the stepwise regression process. Date-related inputs contain binary index variables indicating each day of the week (Monday - Sunday) as well as binary index variables indicating special holidays. On the other hand, historical electricity demand-related inputs consist of variables reflecting lagged values ranging from one day $y_{t-1}$to seven days y_{t-7}, lagged daily electricity demand to moving average weekly and monthly index variables ($LMA_t(N)$), and moving average index variables with lagged periods P (MA(P)) spanning from MA(2) to MA(7). $LMA_t(N)$ is utilized for the identification and quantification of repeated patterns occurring at fixed intervals within a time series, while MA(P) is used to describe underlying trends and mitigate the short-term fluctuations effects or noise presented in the dataset. The mathematical equations to compute $LMA_t(N)$ and MA(P) are provided below:

$$LMA_t(N) = \frac{y_t}{\left(\sum_{t=1}^{N} y_t\right)/N} \tag{1}$$

$$MA(P) = \frac{\sum_{p=1}^{P} y_{t-p}}{P} \tag{2}$$

In the given equation, $LMA_t(N)$ denotes lagged daily electricity demand to moving average index, with y_t representing the daily electricity demand at period t. The parameter N indicates the length of the day used for computing LMA_t, while p presents the number of lagged periods, and P denotes the duration in days used to compute MA(P). The values of LMA are calculated both weekly and monthly. To calculate these, L is assigned to 7 days for weekly calculations and 30 days for monthly calculations. For the calculation of MA(2) through MA(7), P is set from 2 days to 7 days.

3.2.2 Stepwise Regression

Regression analysis serves as a technique used to investigate the relationships between variables, often applied to examine the causal impact between them [123]. Widespread among statistical techniques, multiple regression analysis stands out as the commonly utilized technique to investigate the relationship between a single dependent variable and multiple independent variables [124]. Its primary goal is to understand how changes in the independent variables are associated with changes in the dependent variable. A high correlation score signifies a robust linear relationship between the explanatory variables and the response variable, while a poor correlation suggests a weak relationship. Mathematically, it is represented as:

$$y = \beta_0+\beta_1 x_1+\beta_2 x_2+\ldots+\beta_p x_p+\varepsilon, \tag{3}$$

In the given equation, y stands for the response variable of the dependent variable, x_i $(i = 1,2, \ldots, p)$ denotes the independent variables, β_0 denotes the intercept or the value of y when there is no influence from the independent variables, β_i (i = 1,2,…, p) denotes the estimated regression coefficients that represent the relationship between each independent variable and the dependent variable, ε denotes the error term between the observed and predicted values, and P denotes the total number of independent variables.

Stepwise regression is a method commonly employed to enhance the precision and effectiveness of regression models [125]. Its primary goal lies in the selection of significant independent variables from a large pool of potential variables, focusing solely on the variables with an independent influence on the dependent variable [126]. Stepwise regression encompasses three distinct approaches for model selection, including forward, backward, and bidirectional selections [127]. Forward selection systematically adds variables to an empty model until further additions yield no substantial improvements. Conversely, backward selection initially has all candidate input variables in a full model and then gradually eliminates the lowest potential variables to enhance the model, until no further removals significantly improve its performance. Bidirectional elimination combines elements of the previous two selections. It is commonly applied to models with existing correlations among variables.

This study used the bidirectional elimination approach with α-to-enter and α-to-remove criteria, both having value of 0.1. Furthermore, to ensure an adequate amount of input data, a 24-month period preceding the target forecasting date is utilized to ensure a sufficient number of data points for fitting the regression model.

3.2.3 Similar Day Selection for the Disrupted Situation

Similar day selection (SD) is a method used in data analysis and forecasting to identify historical dates that closely resemble a target forecasting date based on certain criteria. This technique involves searching through historical data to find past dates with similar characteristics or patterns to the target forecasting date. In this process, the historical data is identified whether it is similar to the target forecasting date using a selection criterion [119]. However, during the disrupted situation, electricity demand experienced notable fluctuations and shifts in patterns. This situation affects the traditional similar day selection method, which depends on historical data, making the method incapable of identifying similar dates. Consequently, the day type is much more significant than the historical demand pattern. To enhance the effectiveness of the traditional similar day selection method and identification of the similar day across long-term periods, this study utilizes binary index variables representing day types (such as day of the week and special holidays) as the defining criterion for a similar day selection.

The varying electricity demand patterns observed on normal weekdays, weekends, and special holidays present a challenge in forecasting, particularly with special holidays. Electricity demand can be influenced by each special holiday [128]. Due to its extreme demand patterns, it poses a significant challenge, often leading to substantial forecasting errors. Additionally, the use of two distinct calendar systems introduces another complexity in electricity forecasting. Special holidays, in the solar calendar, are fixed dates, and the length of the solar year remains relatively stable. Conversely, the lunar calendar, being based on the phases of the moon, results in variable special holiday dates. To address this issue, this research proposed a procedure for SD, see **Table 2**.

The proposed SD starts from verifying types of the target forecasting date such as a normal day or a special holiday. In the event that the target forecasting date falls on a normal day (referred to as case 1 and case 2), the closest date in the preceding year, having a similar day of the week (Monday - Sunday) as the target forecasting date, will be selected as a similar day. If not, move forward to the next step.

The second step of the process examines special holidays, categorized into two groups: public holidays and bridge holidays. A bridge holiday refers to a weekday designated as a holiday due to two reasons. The first reason is to be a replacement day for a public holiday that happens to be on the weekend. The second reason is to connect between the special holiday and the weekend. If the special holiday in the previous year shares the same day type as the target forecasting date (weekday or weekend), referred to as either case 3 or 4, the same special holiday in the preceding year will be chosen as a similar day. Alternatively, proceed to the third step.

The third step addresses the situations where the target forecasting date is a special holiday. However, it has a dissimilar day type (weekday or weekend) compared to a similar special holiday in the preceding year. In case the target forecasting date is a special holiday occurring on the weekend, a similar day will be selected from a similar special holiday in the previous year if the special holiday in the preceding year falls on a weekday (referred to as case 5). Conversely, in case the target forecasting date is a special holiday occurring on a weekday, a similar day will be selected from the substitute holiday if the special holiday in the preceding year falls on the weekend (referred to as case 6).

Table 2 Procedure for similar day selection during disrupted situations.

<table>
<tr><th rowspan="2">Case</th><th colspan="4">Target Forecasting Date</th><th colspan="2">Type of the Same Special Holiday in the Previous Year</th><th rowspan="2">Similar Day Selection</th></tr>
<tr><th>Normal Day</th><th>Special Holiday</th><th>Weekday</th><th>Weekend</th><th>Weekday</th><th>Weekend</th></tr>
<tr><td>1</td><td>x</td><td></td><td>x</td><td></td><td rowspan="2">N/A</td><td rowspan="2">N/A</td><td rowspan="2">Pick a similar day from the closest date in the previous year that has the same day of the week (Monday–Sunday) as the target forecasting date</td></tr>
<tr><td>2</td><td>x</td><td></td><td></td><td>x</td></tr>
<tr><td>3</td><td></td><td>x</td><td>x</td><td></td><td>x</td><td></td><td rowspan="3">Pick a similar day from the same special holiday in the previous year</td></tr>
<tr><td>4</td><td></td><td>x</td><td></td><td>x</td><td></td><td>x</td></tr>
<tr><td>5</td><td></td><td>x</td><td></td><td>x</td><td>x</td><td></td></tr>
<tr><td>6</td><td></td><td>x</td><td>x</td><td></td><td></td><td>x</td><td>Pick a similar day from the substitute holiday of the special holiday in the previous year</td></tr>
</table>

3.2.4 Example of the Procedure for Similar Day Selection in Disrupted Situation

The dates in the year 2020 are used as the target forecasting dates in this example, while the potential candidate dates include all days from the preceding year, 2019. Two examples are used to demonstrate the proposed SD in disrupted situation, aligned with the cases outlined in **Table 2**.

The initial example demonstrates the process of selecting a similar date when the target forecasting date falls on normal weekdays or weekends (cases 1 and 2 in **Table 2**). In these cases, a similar date is chosen from the nearest date in the preceding year, sharing a similar day of the week (Monday - Sunday) as the target forecasting date, as detailed in **Table 3**. For example, if the target forecasting date is Wednesday, 1st April 2020, the similar date selected from the proposed SD would be Wednesday, 3rd April 2019, as it is the nearest date sharing the same day type (Wednesday).

Table 3 Example of selecting a similar date for Cases 1 and 2: target forecasting date falls on either a normal weekday or weekend.

Target Forecasting Date	Selected Date
1 April 2020 (Wednesday)	3 April 2019 (Wednesday)
2 April 2020 (Thursday)	4 April 2019 (Thursday)
3 April 2020 (Friday)	5 April 2019 (Friday)
4 April 2020 (Saturday)	6 April 2019 (Saturday)

In the second example, the illustration considers the case when the target forecasting date falls on a special holiday. Four scenarios (I–IV) aligning with cases 3 to 6 in **Table 2**, are presented in **Table 4**.

Scenario I, demonstrating cases 3 and 4, arises when the same day type (weekday or weekend) is found on both the target date and a similar special holiday in the preceding year. In this scenario, a similar day is chosen from a similar special holiday in the preceding year. For instance, if the target forecasting date is Mother's Day, occurring on Wednesday, 12th August 2020, a similar day is chosen from the

Mother's Day of the preceding year (Monday, 12^{th} August 2019) as both fall on weekdays. In the same way, in case the target forecasting date is Bridge (Substitute) Asahna Bucha Day, occurring on Tuesday, 7^{th} July 2020, a similar day is chosen from the previous year's Asahna Bucha Day (Tuesday, 16^{th} July 2019), as Bridge Asahna Bucha Day is a special holiday designated because of Asahna Bucha Day falling on Sunday, 5^{th} July 2020.

Scenario II, representing case 5, arises when the day type (weekday or weekend) of the target forecasting date as a special holiday falls on weekend and a similar special holiday in the preceding year falls on weekday. In this scenario, a similar day is chosen from a similar special holiday in the preceding year. For instance, considering the target forecasting date being Asahna Bucha Day, occurring on Sunday, 5^{th} July 2020, a similar day is directly chosen from Asahna Bucha Day in the preceding year (Tuesday, 16^{th} July 2019), as both of them represent special holidays without regular business activities.

Scenario III, describing case 6, arises when the day type (weekday or weekend) of the target forecasting date as a special holiday falls on weekday and a similar special holiday in the preceding year falls on weekend. In this scenario, a similar day is chosen from the substitute holiday of the special holiday in the preceding year. For instance, considering the target forecasting date is King's Birthday, occurring on Tuesday, 28^{th} July 2020, the actual King's Birthday in the preceding year, falling on the weekend (Sunday, 28^{th} July 2019), cannot be chosen as a similar day due to its weekend nature, which does not reflect the characteristics of the special holiday. Consequently, a similar day is chosen from the bridge holiday in the prior year, represented as the Bridge King's Birthday (Monday, 29^{th} July 2019).

Table 4 Example of selecting a similar date for Cases 3-6: target forecasting date is a special holiday.

Target Forecasting Date	Selected Date
I. Target forecasting date and the same special holiday in the previous year have the same day type.	
Mother's Day 12 August 2020 (Wednesday)	Mother's Day 12 August 2019 (Monday)
Substitute Asahna Bucha Day 7 July 2020 (Tuesday)	Asahna Bucha Day 16 July 2019 (Tuesday)
II. Target forecasting date is a weekend, but the same special holiday in the previous year is a weekday.	
Asahna Bucha Day 5 July 2020 (Sunday)	Asahna Bucha Day 16 July 2019 (Tuesday)
III. Target forecasting date is a weekday, but the same special holiday in the previous year is a weekend.	
King's Birthday 28 July 2020 (Tuesday)	Substitute King's Birthday 29 July 2019 (Monday)

3.3 Data Preprocessing

During the early stage, the raw electricity consumption is influenced by noise elements, thereby posing a substantial effect on forecasting accuracy due to inherent volatility and randomness [100]. In disrupted situations, the unprecedented and unpredictable impacts of the pandemic have introduced additional noise into electricity demand data, consequently increasing the presence of uncontrolled noise components. This occurrence complicates the identification of seasonality and trends, thereby posing challenges in identifying underlying patterns within the data and reducing forecast accuracy. To effectively separate the underlying patterns, actual demand changes, noise, and random fluctuations, methods like data decomposition and seasonality identification are used on the medium-term input dataset during the disrupted stage to improve the forecasting model's capacity. The first step involves the use of a data decomposition technique. Specifically, the application of the variational mode decomposition (VMD) technique effectively smooths the time series data by separating non-linear and non-stationary components. However, a limitation of VMD is its lack of an automated capability to adjust the decomposition level. By benefiting from the automatic adjustment capability, empirical mode decomposition (EMD) is employed to adjust VMD's decomposition level, thereby overcoming this drawback. In the second step, after eliminating noise using VMD, the fast Fourier transform (FFT) is utilized to detect and capture the remaining inherent seasonality and trends in the data. Subsequently, the seasonality and trend results are achieved, as illustrated in **Figure 2.**

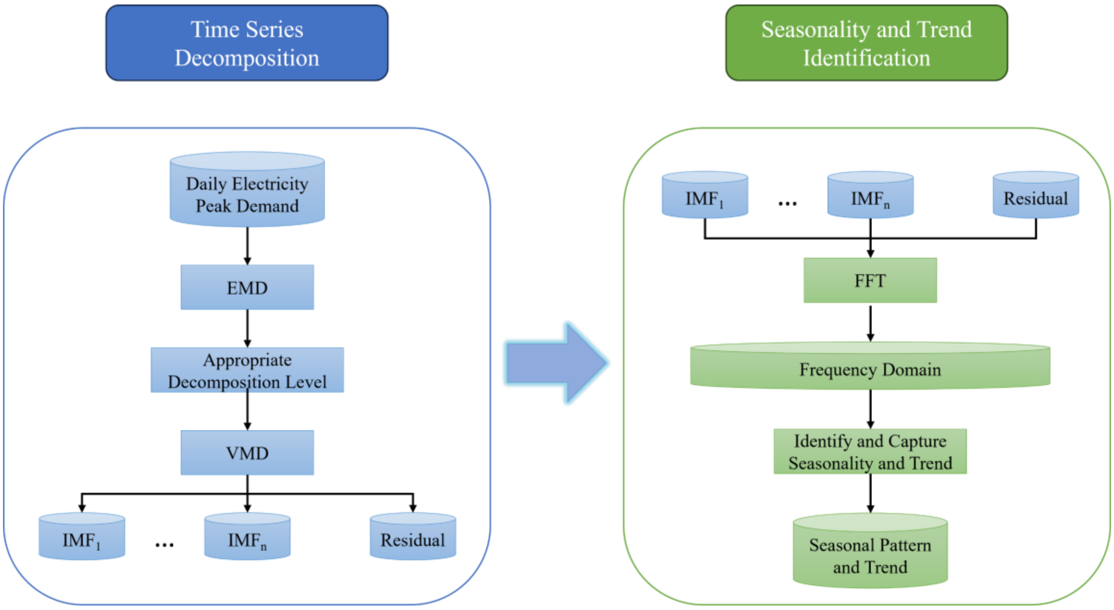

Figure 2 Flowchart of data decomposition and seasonality identification process.

3.3.1 Data Decomposition

Variational Mode Decomposition (VMD) is a signal processing technique that effectively separates non-linear and non-stationary components from the original data, making it useful for analyzing complex time series data. VMD helps the forecasting model to more easily identify underlying patterns and trends by breaking down time series data into a set of intrinsic mode functions (IMFs) and a residual. Each IMF represents a distinct component of the time series characterized by a specific frequency and magnitude, often referred to as a trend in the data. The residual, on the other hand, represents the remaining portion of the signal after extracting the IMFs. By decomposing the time series into IMFs, the model can better understand the various factors influencing the data and improve the accuracy of forecasting models. Recently, VMD has been presented as an alternative to Empirical Mode Decomposition (EMD), particularly for separating components with similar frequencies in cases where EMD struggles [129]. In contrast to the EMD technique, VMD offers a significant advantage by addressing the mode mixing issue more effectively. Through the implementation of the alternating direction method of multipliers, VMD enhances the separation of oscillatory modes, ensuring a clearer distinction between different components in time series data [130].

Determining the suitable decomposition for VMD poses a considerable challenge in the research field. Finding the right balance is crucial, as using too many decomposition levels can result in mode aliasing problems and introduce unnecessary noise into the analysis. Conversely, utilizing too few IMFs may lead to an incomplete representation of the underlying complexity of the original data [131]. Mode aliasing occurs when the decomposition process fails to accurately separate distinct components of the data, resulting in overlapping or misidentified modes. This can introduce distortions into the decomposed data, reducing the effectiveness of subsequent analysis. On the other hand, if there are too few IMFs generated during decomposition, important features or components of the signal may be overlooked or poorly represented. This can lead to a loss of information and accuracy in the analysis or interpretation of the data. To circumvent the trial-and-error process and minimize the time consumed in optimization, automation becomes imperative. Considering EMD's capability of automatically adjusting decomposition levels, it can play a guiding role in determining the suitable decomposition level for VMD [106].

3.3.2 Seasonality and Trend Identification

The fast Fourier transform (FFT) plays a crucial role in time series forecasting by transforming time-domain data into the frequency domain. This conversion enables the identification of specific individual frequencies and prominent frequency components within the data [132]. This transformation allows analysts to identify periodic patterns and dominant frequencies within the data, which are essential for understanding underlying trends and seasonal components. FFT aids in extracting meaningful information for forecasting future trends and patterns. Additionally, it simplifies the identification of hidden seasonality in time series data, enhancing the accuracy of forecasting models by capturing and incorporating these underlying seasonal patterns. This proves its effectiveness in dealing with hidden seasonal patterns exhibited in time series data [106].

During the disrupted situation, electricity demand patterns undergo substantial changes influenced by shifts in societal behaviors, economic activities, and government interventions. To enhance forecasting performance in this situation, it proves advantageous to incorporate insights gleaned from FFT analysis into the forecasting model. Instead of applying the original data, training the model with the transformed data that highlights seasonality and trends enables it to better capture underlying patterns.

The hidden seasonal patterns and trends of electricity consumption during periods of disruption in this study are identified using FFT. The decomposition results are then applied to train the forecasting model, offering supplementary data that reflect the pattern of medium-term demand.

3.4 Data Separation

In the traditional approach, a dataset used in machine learning is typically split into three parts: training, validation, and testing sets [133], [134]. During the training phase, it is common for errors to decrease on both the training and validation sets, demonstrating that the performance of the model is improving. However, cautious consideration must be given to overfitting, where the model becomes overly specialized to the training set, potentially limiting its ability to generalize to new data. An increase in validation set error typically indicates overfitting even as the training set error decreases, highlighting the importance of the validation set in detecting this issue. To enhance performance, training parameters such as weights and biases are fine-tuned through different hyperparameter configurations until achieving the lowest validation set error. This iterative process ensures that the model not only fits the training data well but also prepares it to generalize effectively to unforeseen data represented in the validation set, thereby validating its robustness.

The testing set is used to assess the trained and validated model. Importantly, its error is not included in the training process, ensuring an unbiased assessment of how well the model performs on unforeseen data. The test set error is crucial for comparing the performance of different models, enabling researchers to decide which model performs best on the task at hand [135].

The limited availability of data during disrupted situations significantly impacts the performance of electricity demand forecasting models, as traditional forecasting methods heavily rely on historical data to identify patterns and trends, enabling models to make accurate predictions. In this situation, an overly large proportion of training and validation data can make the model unsuitable for practical applications.

This study addresses this issue by utilizing a training set containing variables derived from daily electricity consumption records spanning the 31-day period prior to the target forecasting date. During disrupted phases, given the dynamic shifts in electricity demand patterns due to emergency measures and government intervention policies, the training set enables the forecasting model to adapt by capturing the patterns of current demand observed in existing data. A separated dataset from the 7 days prior to the target forecasting date is used as a validation dataset to examine the efficacy of the forecasting model. The forecasting performance can be affected by the historical days having a similar day type as the target forecasting date. Therefore, this validation dataset allows the assessment of the model's generalizability. Thus, the accuracy and reliability of the model can be improved.

3.5 Prediction and Optimization

3.5.1 One-Day-Ahead Forecasting with Rolling Dataset

Disrupted situations, such as crises or unforeseen events, introduce unpredictability into electricity consumption patterns, driven by shifts in consumer behavior and supply chain disruptions. These dynamics lead to continuous changes in demand, requiring adaptive responses from the forecasting model. To accommodate these changes, each target forecasting date utilizes a one-day-ahead forecasting technique [47], see **Figure 3**. The forecasted target dates for t, t+1, and t+2 are respectively denoted by blue, green, and yellow boxes. The historical data range used for training for each forecasted date, encompassing data up to the current or most recent dataset available, is demonstrated in each dotted box.

During periods of disruption where data is limited, conventional techniques for splitting datasets may decrease the amount of data available for training. To address this challenge, the utilization of walk-forward testing [134] is employed to maximize the efficient use of data. This technique continuously updates and evaluates models as new data becomes available. It includes dividing the dataset into training, validation, and testing sets that overlap, moving them sequentially along the time series, as shown in **Figure 4**. This technique provides more accurate performance assessment and early detection of model degradation, while effectively adapting to shifting patterns and trends, ensuring adept adaptation.

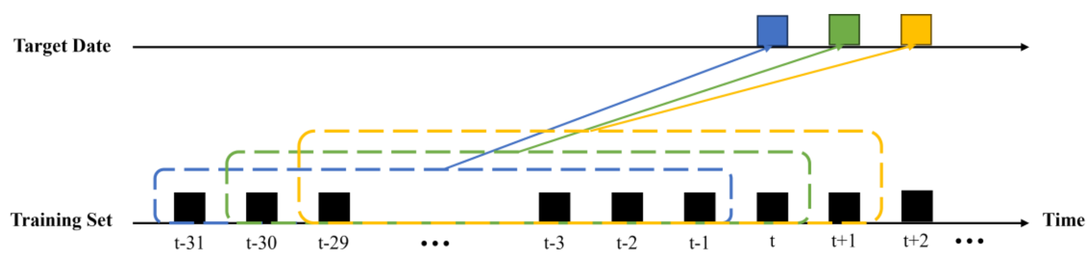

Figure 3 One-day-ahead forecasting technique.

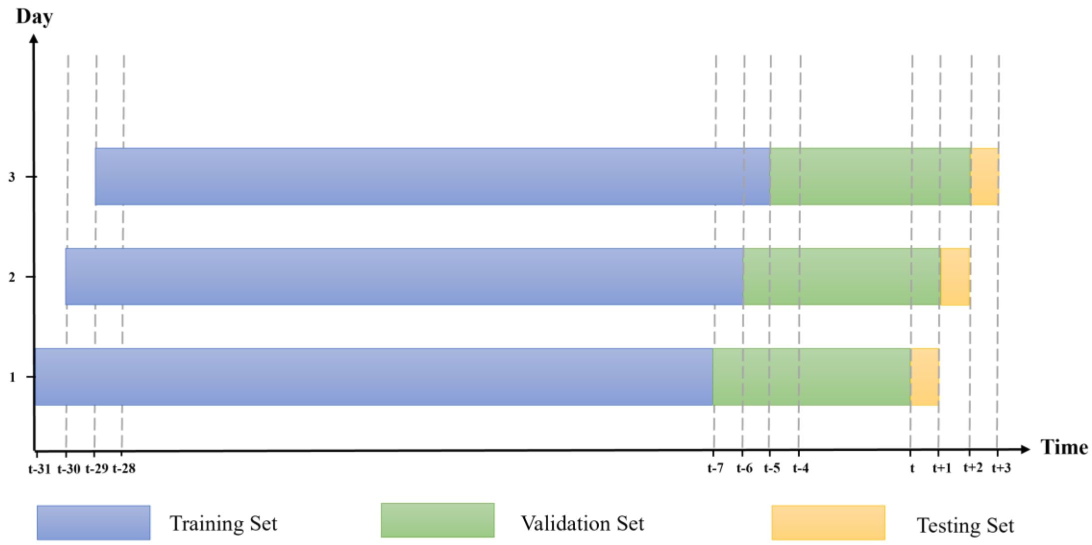

Figure 4 Walk-forward testing technique for the rolling dataset.

3.5.2 Artificial Neural Network

The artificial neural network (ANN) represents a widely recognized computational model that mimics the complex structure and functioning of the human brain [136]. ANN consists of interconnected nodes, known as neurons, which are organized into layers. Through a network of weighted connections, ANN interprets data by learning from input data and subsequently making predictions.

One of the primary strengths of ANN is its capacity to autonomously learn complex patterns and uncover relationships from data without the need for explicit programming. Through a process known as training, ANN adjusts the weights of connections between neurons based on examples provided in a training dataset, gradually improving their performance over time. Moreover, ANN can identify the variables that hold considerable influence on the output, enabling them to prioritize the most relevant information while disregarding less influential data [137].

Multi-layer feedforward neural network (MLFN) is one of the most popular structures in ANN. This network model comprises multiple layers, including an input layer that receives input variables (represented as x_i), one or more hidden layers where weighted inputs (W_{ij}) undergo transformation through non-linear transfer functions (f_j^h) and addition of bias (b), and an output layer that generates the final predictions. Each layer in the MLFN processes and refines information sequentially, with outputs from one layer serving as inputs to the subsequent layer. A mathematical expression of the MLFN with a single hidden layer is presented in **Equation (4)**.

$$\hat{y} = f^{o}\left(\sum_{j=1}^{h} W_j f_j^{h}\left(\sum_{i=1}^{d} W_{ij} x_i\right)\right) + b, \quad (4)$$

In the given equation, $\hat{y}$ denotes the output from the output node, while f^{o} and f_j^{h} represent the transfer functions of the output node and hidden node j respectively. The variable h indicates the number of hidden nodes, and d signifies the number of input nodes. Each x_i represents the input data of input node i, where b denotes the bias assigned to neurons. W_{ij} and W_j denote the adjusted weights sent from input node i to hidden node j, and from hidden node j to the output node respectively.

3.5.3 Long Short-Term Memory

Long short-term memory (LSTM) represents an advancement in the realm of recurrent neural network (RNN), particularly in the domain of time series forecasting. Developed by Hochreiter and Schmidhuber [87], LSTM addresses the drawbacks of RNN in capturing and maintaining long-term dependencies within sequential data. Building upon the RNN architecture, LSTM integrates essential components including input gates, output gates, and forgetting gates within its neuronal structure [138]. The memory cell stands as a core component of the model, functioning as a repository of network state information. The forget gate (f_t) critically decides what information to discard from the cell state. The sigmoid function of the forget gate is represented in a mathematical equation as follows:

$$f_t = \sigma\left(W_f\left[h_{t-1}, x_t\right] + b_f\right), \quad (5)$$

The input gate (i_t) serves the purpose of regulating and controlling the flow of information that enters the memory cell. It determines which new information from the current input and the output of the previous timestep should be stored in the cell state.

This is achieved through a sigmoid activation function. Following this decision process, the cell state (c_t) undergoes an update using a new candidate value vector ($\tilde{c}_t$). This update involves two key steps: first, the old cell state (c_{t-1}) is multiplied by the forget gate output (f_t), which controls the amount of old information retained or discarded. This step effectively filters out irrelevant or outdated information from the previous cell state. Second, the input gate output (i_t) is multiplied by the candidate value ($\tilde{c}_t$) produced by the tanh activation function. This multiplication determines how much of the new candidate values should be added to the cell state. The mathematical expressions for the input gate and the cell state are provided below:

$$i_t = \sigma\,(W_i\,[h_{t-1}, x_t] + b_i), \tag{6}$$

$$\tilde{c}_t = \tanh\,(W_c\,[h_{t-1}, x_t] + b_c), \tag{7}$$

$$c_t = f_t c_{t-1} + i_t \tilde{c}_t, \tag{8}$$

The output gate determines its output by evaluating the cell state. It filters the cell state using a sigmoid layer to extract relevant information. This process involves multiplying the cell state by the output value (o_t). The output gate's function is to regulate how much of the cell state should be exposed to the next layer or used as the final output of the LSTM network. The mathematical expressions for these output processes are outlined below:

$$o_t = \sigma\,(W_o\,[h_{t-1}, x_t] + b_o), \tag{9}$$

$$h_t = o_t \tanh(c_t), \tag{10}$$

In the given equation, x_t represents the input at time t, while h_t signifies the model's output. The weight matrices, W_t, W_f, W_c, W_o are formally defined, along with bias parameters b_t, b_f, b_c, b_o expressed as vectors representing biases.

In disrupted situations where accurate forecasting of electricity demand becomes critical for maintaining the stability and resilience of power systems, LSTM is highly beneficial in this context due to its robustness, adaptability, and ability to capture long-term dependencies. LSTM excels in handling irregular demand patterns that often arise during disruptions, ensuring accurate forecasts despite fluctuating conditions. Moreover, LSTM's adaptability allows it to quickly adjust to abrupt changes in conditions, providing timely and responsive forecasts. Additionally, LSTM's capability to handle missing data enhances reliability in situations where data may be limited. Furthermore, by integrating LSTM into ensemble forecasting frameworks, which combine multiple models for improved accuracy, utilities and policymakers can better anticipate and mitigate the impacts of disruptions on power systems.

3.5.4 Grid Search Optimization

Grid search optimization (GS) technique is applied in machine learning for systematically searching through a predefined set of hyperparameters for a given model. Hyperparameters are parameters that are not learned directly from the data but instead are set prior to the learning process and influence the behavior of the learning algorithm. The combination of hyperparameters that yields the best performance on the validation set is selected as the optimal set.

GS systematically tests all candidate hyperparameter combinations within defined grids to identify the set that yields the best validation performance. This method involves an exhaustive search over the specified hyperparameter space, evaluating each possible combination to determine which configuration offers the highest performance. When an improvement is observed, GS refines its search by conducting finer grid searches within the promising region, ensuring a more precise optimization. By thoroughly exploring different combinations, GS determines the most effective hyperparameter settings for a given task, thereby enhancing the model's performance and robustness [139].

Given its clear and direct approach, this study adopts GS as the preferred hyperparameter optimization technique for fine-tuning the parameters of both ANN and LSTM models.

3.6 Performance Measurement

Mean absolute error (MAE), Mean absolute percentage error (MAPE), and Root mean square error (RMSE) are widely utilized performance metrics in the assessment of predictive models, particularly in the field of machine learning and forecasting. In this study, these three measurements are utilized to estimate and compare the effectiveness of the proposed models.

MAE is a straightforward measure used extensively in evaluating predictive models, calculating the average absolute difference between predicted and observed values. It focuses solely on error magnitude, which is useful in scenarios where all errors, whether overpredictions or underpredictions, are equally important. The mathematical expression is presented as:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right|, \tag{11}$$

MAPE, on the other hand, expresses a percentage measure of the absolute errors between predicted and observed values, making it valuable for assessing prediction accuracy across different scales of data. Unlike MAE, which measures errors in the same units as the original data, MAPE normalizes these errors by the scale of the observed values, allowing for direct comparison across datasets with varying magnitudes. MAPE is expressed mathematically as:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|y_i - \hat{y}_i\right|}{y_i}\times 100, \tag{12}$$

RMSE is a measure that assesses prediction accuracy by calculating the square root of the mean of squared differences between predicted and observed values. Unlike MAE and MAPE, RMSE assigns greater weight to larger errors, making it particularly sensitive to outliers in the dataset. RMSE is expressed mathematically as:

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

In the given equation, y_i denotes the actual value of electricity peak consumption observed during period i, while $\hat{y}_i$ is the forecasted electricity peak consumption in period i. The parameter n denotes the total number of forecasting periods under consideration.

CHAPTER 4
Case Study: Electricity Peak Demand in Thailand during COVID-19 Pandemic

4.1 Data Collection and Explanation

This study examines daily electricity peak consumption during the COVID-19 crisis in Thailand. It serves as a case study to evaluate the effectiveness of the proposed models in managing situations of disruption. Raw input data of daily electricity peak consumption in megawatts (MW), covering January 2018 to December 2020, including a one-year pre-pandemic period, is analyzed to assess the impact. **Figure 5** displays the characteristics of daily electricity peak demand, illustrating fluctuations during the pandemic year (2020) that differ from pre-pandemic patterns (2018 and 2019). For instance, April 2020 experienced a decline in peak consumption compared to the prior pandemic year. Furthermore, typically, the highest demand for electricity consumption is at the end of April, attributed to the resumption of tasks after the Songkran holiday. Nevertheless, the electricity usage at the end of April of the pandemic year did not exhibit a significant increase. These changes stem from various pandemic-related factors such as policies to control COVID-19 cases.

Figure 6 highlights correlations within the peak consumption data. Classical forecasting techniques, which rely on linear correlations, encounter limitations when confronted with complex, nonlinear relationships inherent in disrupted situations. Linear correlation assumes a constant rate of change over time, which may not accurately reflect the dynamic situations influenced by multifaceted factors, such as those encountered during the COVID-19 pandemic. In disrupted situations, where abrupt shifts and irregular patterns are common, linear models struggle to capture the nonlinear relationships present in time series data. Consequently, the adoption of an advanced model becomes essential for effectively capturing these nonlinear relationships.

To understand the COVID-19 pandemic impact, the information related to COVID-19 factors and the level of lockdown are utilized as part of the analysis. The level of lockdown is based on the policy to control the pandemic from the Thailand government and is categorized on a scale announced by this government, ranging from 0 (without lockdown) to 6 (declaration of a state/national emergency). **Table 5** provides an explanation and each lockdown stage timeline in Thailand. Data on six COVID-19 factors, which are daily cases, deaths, recoveries, as well as the number of cumulative cures, vaccinations, and full vaccinations, are sourced from the Thai Ministry of Public Health. These factors and the level of lockdown were recorded on a daily basis from January to December 2020, as illustrated in **Figure 7**. Additionally, **Table 6** provides a statistical summary of daily electricity peak demand alongside the six factors.

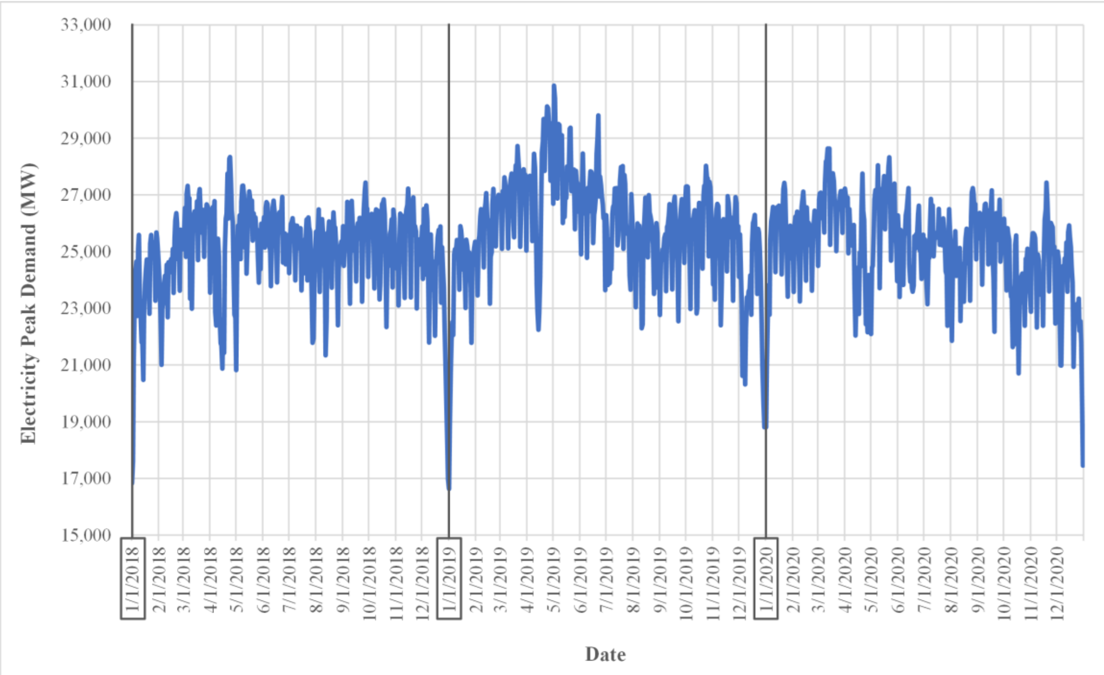

Figure 5 Raw input data of daily electricity peak demand spanning from January 2018 to December 2020.

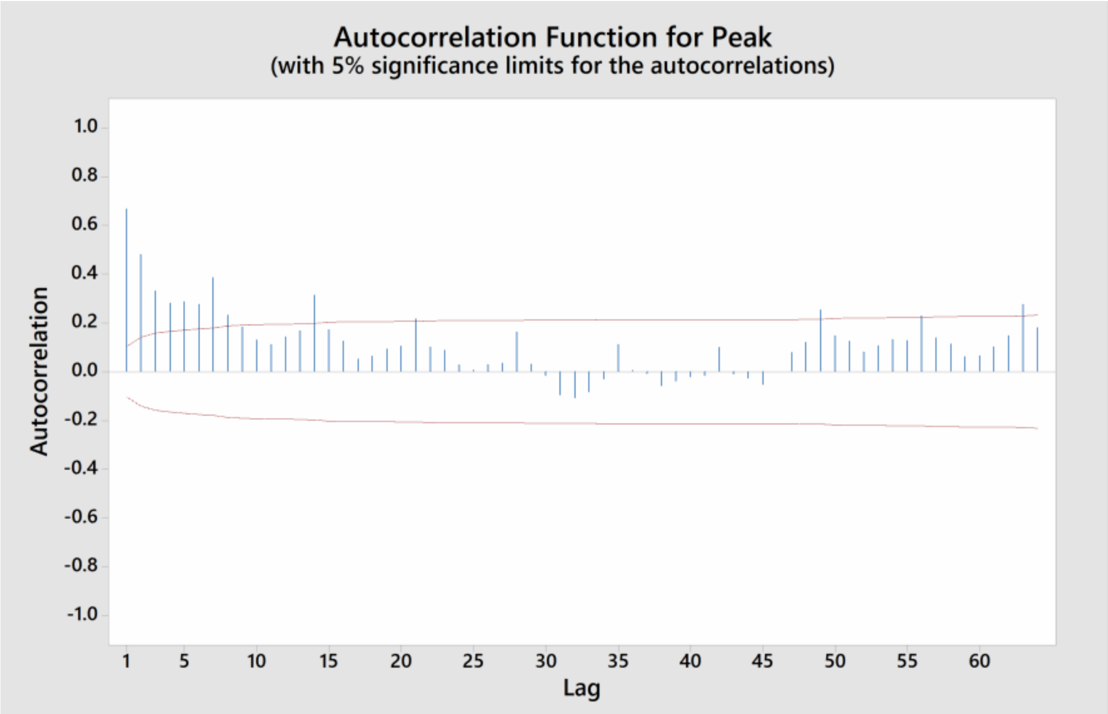

Figure 6 Analysis of autocorrelation in electricity peak demand amid the COVID-19 pandemic.

Table 5 Explanation and comprehensive timeline of COVID-19 lockdown measures.

Date	Lockdown Stage	Event
18 March 2020	5	Declaration of lockdown
3 April 2020	6	Declaration of state/national emergency and announcement of a nationwide curfew
3 May 2020	4	Announcement of the loosened COVID-19 restrictions Phase 1 (re-open market, convenient store, restaurant, and outdoor sport)
17 May 2020	3	Announcement of the loosened COVID-19 restrictions Phase 2 (re-open shopping mall, gym, and reduce curfew period)
1 June 2020	2	Announcement of the loosened COVID-19 restrictions Phase 3 (re-open more public spaces, and reduce curfew period)
15 June 2020	1	Announcement of the loosened COVID-19 restrictions Phase 4 and Repeal of a nationwide curfew (re-open school, hotel, theater, and allow transportation across province)
1 September 2020	0	End of lockdown

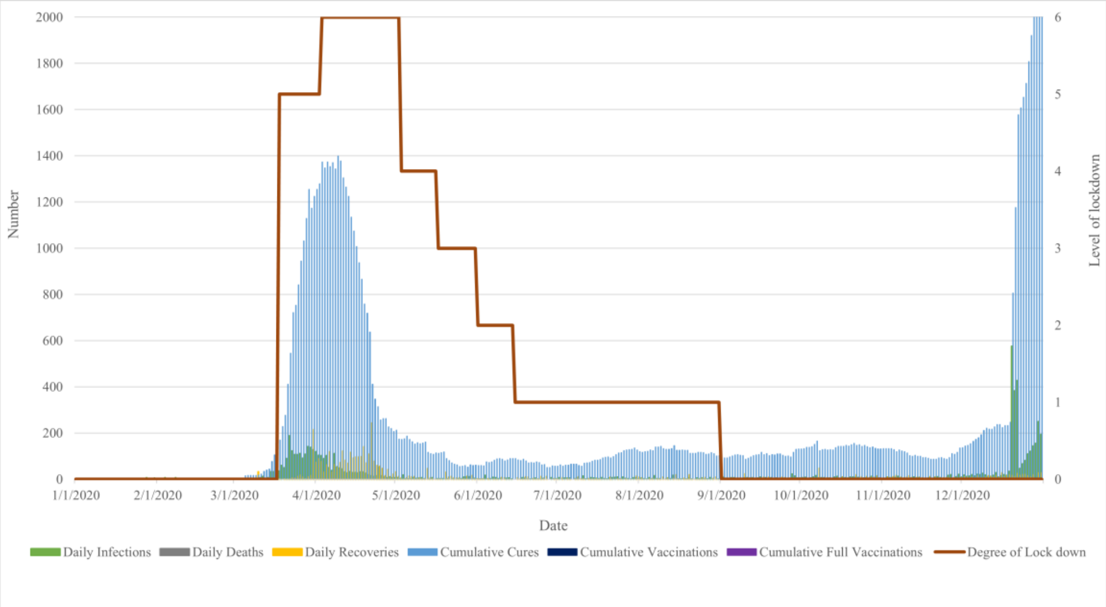

Figure 7 Aggregated dataset comprising six COVID-19 factors and lockdown severity levels.

Table 6 Statistical summary of daily peak electricity demand and COVID-19 Factors.

Dataset	No. of Observation	Max	Min	Average	SD
Electricity Peak Demand	366	28,636.70	17,451.90	25,481.35	1632.73
Daily Infections	366	576	0	5	52.36
Daily Deaths	366	5	0	0	0.62
Daily Recoveries	366	244	0	3	26.93
Current COVID-19 In-Patients	366	2583	0	108	421.00
Cumulative Vaccinations	366	0	0	0	0
Cumulative Full Vaccinations	366	0	0	0	0

4.2 Time Segmentation and Sensitivity Factors Identification

The peak daily electricity demand for the years 2018 – 2020 is categorized, i.e., short-term, medium-term, and long-term set. The short-term dataset comprises the latest data, 1-day prior to the target forecast date. For instance, if the target forecast date is 1st April 2020, the short-term set covers the 1-day period from 31st March 2020 to 1st April 2020, as shown in **Figure 8.**

Meanwhile, the medium-term dataset encompasses data including 1-week and 1-month data preceding the target forecast date. For instance, if the target forecast date is 1st April 2020, the medium-term set covers the 7-day period leading up from 25th March 2020 to 1st April 2020, and the preceding 31-day period from 1st March 2020 to 1st April 2020, as shown in **Figure 9.**

Conversely, the long-term dataset contains 1-year data and the 1-month data of the month before the target forecast date of the previous year. This 1-month buffer before the target forecast date in the prior year is implemented to cover the special holidays of the lunar calendar, which are determined by the phases of the moon. For example, in case the target forecast date is 1st April 2020, the long-term set spans a 365-day period plus a 31-day period, starting from 1st April 2020 and extending back to 1st April 2019, in addition to 1st March 2019, as shown in **Figure 10.**

In situations characterized by disruption, sensitivity factors are crucial for comprehensively understanding the dynamics of pandemics, particularly in relation to daily electricity demand patterns. These factors offer insight into the pandemic's impact on demand patterns, facilitating adaptation to changes in demand trends. In this study, sensitivity factors are determined according to their sensitivity levels. To train the forecasting model, only the sensitivity factors identified by governmental sources as impacting sensitivity levels are chosen. The sensitivity factors used in this study include the level of lockdown as well as six factors of COVID-19-related.

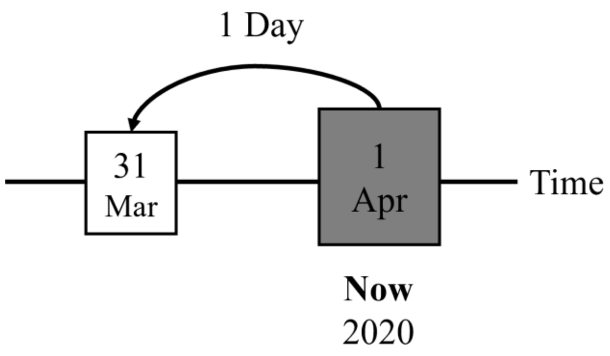

Figure 8 Time segmentation of the short-term set.

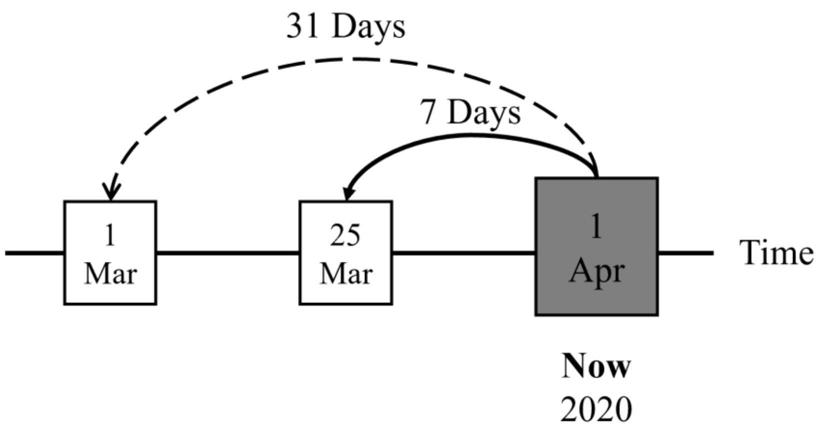

Figure 9 Time segmentation of the medium-term set.

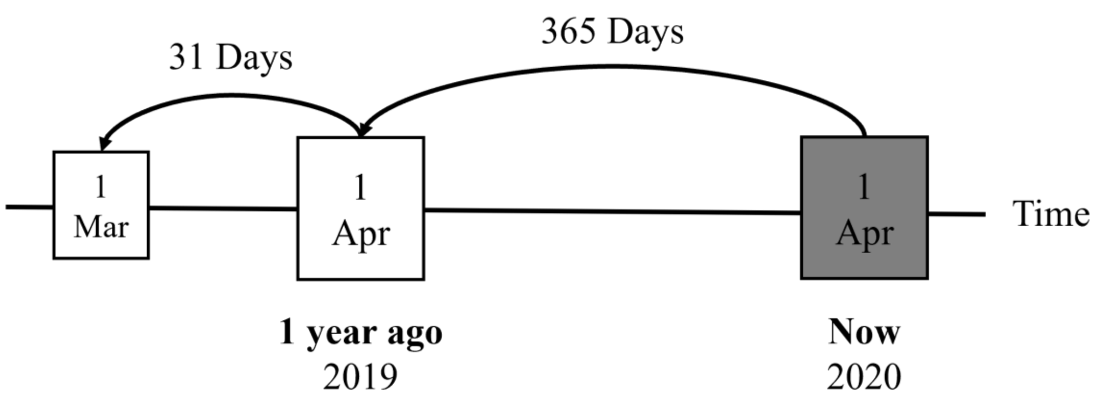

Figure 10 Time segmentation of the long-term set.

4.3 Case 1: Interference with Government Policy

Case 1 occurs when governmental intervention policies impact the targeted period. In this situation, the data separation theory outlined in **Section 3.4** is used to divide the short-term input dataset into three sets: training, validation, and testing sets. Firstly, the training and validation sets are used to develop and enhance the LSTM model, sequentially. The model is developed using the training set to establish its foundational structure. Subsequently, the validation set is employed to fine-tune the model's hyperparameters systematically. This fine-tuning process involves the adjustment of parameters through grid search (GS) methodology, enabling the identification of an optimal hyperparameter set for enhancing the LSTM's predictive accuracy and performance.

In this study, the GS optimization for LSTM is conducted using MATLAB R2022b software. The study considers hidden nodes, training cycles, and learning rates as an array of values. GS involves the adjustment of these hyperparameters. Within the defined range, the GS process trains the LSTM model with every possible combination of hyperparameter values, thereby forming a grid. Initially, the range for grid search optimization is set based on prior experience. If the best configuration of hyperparameters is found at either the minimum or maximum boundary of this range during the optimization process, adjustments are made by narrowing the minimum range or expanding the maximum range. If all the best hyperparameter values fall within their designated boundaries, it indicates that the range was appropriate. The defined range of LSTM hyperparameters used in this study is shown in **Table 7.**

To effectively conduct one-day-ahead forecasting using a rolling dataset, it is essential to ensure that the predictive model adapts to the dynamic nature of the target forecasting date. The input data undergoes updates to capture the latest information relevant to the forecasting task when the target forecasting date transitions to a new value. This process ensures that the model incorporates the most recent data, enhancing its predictive accuracy. Additionally, a new round of GS optimization is conducted to fine-tune the model parameters considering the updated dataset. Consequently, the hyperparameter is optimized on a daily basis. Following a comprehensive exploration of all hyperparameter combinations, the optimal LSTM model is selected based on its ability to generate accurate forecasts. Subsequently, the performance of the optimal model is evaluated using the test set, providing insights into its predictive capabilities.

Table 7 Range of LSTM hyperparameters used in grid search optimization.

Hyperparameter	Definition	GS Range
Hidden node	The number of hidden nodes on a single hidden layer	1, 5, 10
Learning rate	The magnitude of adjustments to weights and biases during training	0.1, 0.01, 0.001
Training cycle	The number of iterations used to update weights and biases	500, 1000, 1500

4.4 Case 2: Noninterference with Government Policy

In situations where the targeted period is not affected by governmental intervention policies, medium-term and long-term input sets are utilized to represent a state where electricity consumption reflects a blend of disrupted and normal patterns. Input variable filtering techniques, such as stepwise regression and SD, are employed to screen the input variables of medium-term and long-term input sets. Data decomposition techniques, such as VMD-EMV and FFT, are utilized to decompose and identify seasonality and trends hidden within the medium-term period. Subsequently, the data separation theory is applied to divide the processed dataset into training, validation, and testing sets, and perform one-day-ahead forecasting with a rolling dataset using ANN-based GS optimization. The details of the following processes are outlined in **Sections 4.4.1- 4.4.3.**

4.4.1 Input Variable Filtering in the Context of COVID-19 Pandemic

The selection of significant input variables for the forecasting model is achieved through the utilization of the stepwise regression methodology, executed by Minitab R2022b software. The dataset utilized for conducting the stepwise regression analysis encompasses a span of 24 months of preceding raw data leading up to the target month. For instance, in case the target forecasting date is 1st January 2020, the data range covers

1st January 2018 to 31st December 2019, capturing trends preceding the forecasted period. As the target month changes, the dataset updates accordingly, and a new stepwise regression analysis is conducted. Each iteration of the regression analysis considers 24 candidate input variables, see **Table 8.** In spite of the stepwise regression process having an iterative nature, the significant input variables change monthly. This methodology is specifically used for the medium-term input dataset to select significant input variables, subsequently using them as the input for the forecasting model.

Table 8 The set of potential input variables utilized in stepwise regression.

Variable Type	Candidate Input Variable
Day of the week index	Monday, Tuesday, …, Sunday (7 binary variables)
Special holiday index	0, 1 (1 binary variable)
Historical electricity peak demand	T − 1, T − 2, …, T − 7 (7 numerical variables)
LMA	Weekly LMA, Monthly LMA (2 numerical variables)
MA(P)	MA(2), MA(3), …, MA(7) (6 numerical variables)

Based on the day type criterion, a date within the long-term input dataset is selected using the SD method to identify a similar day. **Section 3.2.4** describes an illustrative example detailing the steps involved in performing SD under a disrupted situation. The outcome of this method is the selection of the date demonstrating the highest similarity to the target forecasting date. Following this selection, variables corresponding to a similar day, encompassing electricity peak demand, day of the week index, special holiday index, historical electricity peak demand, LMA, and MA(P), are filtered through stepwise regression. These screened variables are then designated for later utilization as long-term input variables.

4.4.2 Data Decomposition and Seasonality and Trend Identification

In reference to **Figure 5**, from 2018–2020, 1096 observations of daily electricity peak consumption exhibit a complex pattern characterized by non-linear and non-stationary components, particularly noticeable during the pandemic. To address this complexity, the medium-term input dataset, using 2020 data, is decomposed using VMD. It breaks down the raw time series into k IMFs, with the decomposition level. For this case study, EMD suggests a decomposition level (k) of five, aligning with the dataset's pattern. The MATLAB software is utilized with default values for other parameters: 500 for the maximum number of optimization iterations, 1000 for the penalty level, and the central frequencies initialized using peak.

In **Figure 11**, the decomposition components are presented, ranging from the highest frequency to the lowest frequency, beginning with IMF1 and extending through IMF5. In contrast, **Figure 12** presents the residual component, indicating the portion of variation in the original signal not explained by the IMFs.

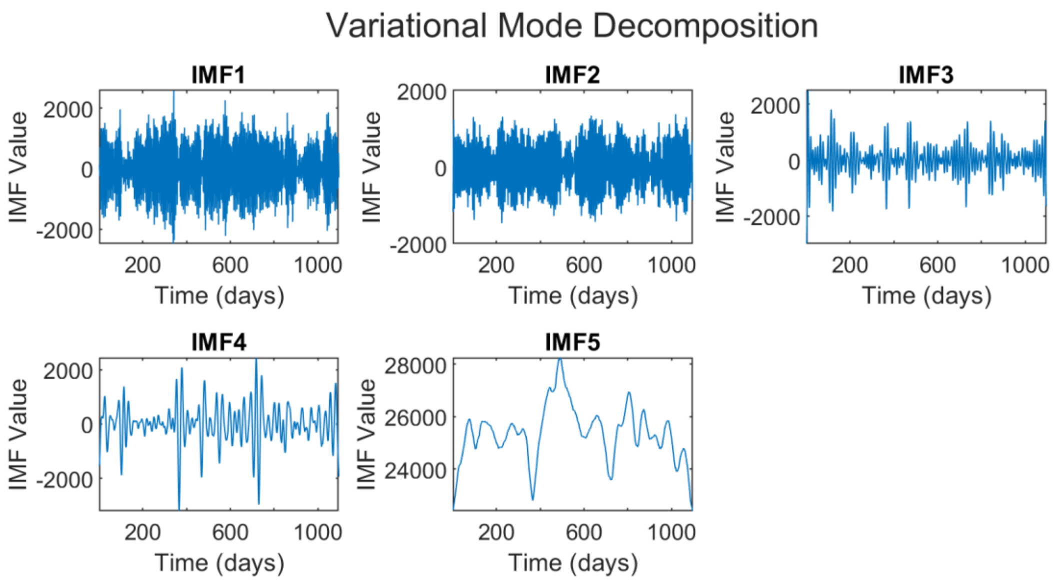

Figure 11 Decomposition results of VMD, breaking down the electricity peak demand from 2018 to 2020 into IMFs (IMF1 to IMF5).

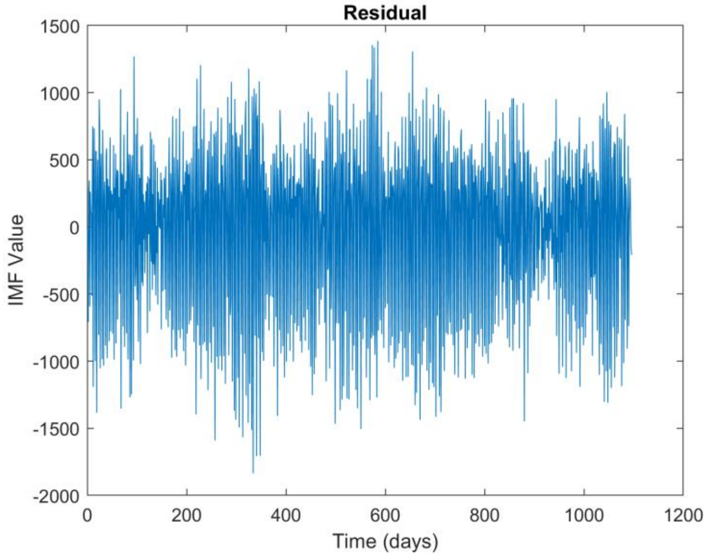

Figure 12 Decomposition results of VMD, breaking down the electricity peak demand from 2018 to 2020 into residual components.

Following the utilization of VMD, across all IMFs and residuals, FFT is employed to identify and capture the concealed seasonality and trend of the pandemic that remain inherent in the medium-term input dataset. Enhanced identification of the seasonality and trend components is achieved through FFT, providing valuable insights into the evolving patterns of the pandemic over time. The analytical results in **Figure 13** offer a comprehensive illustration of the identified temporal patterns, supporting the interpretation and understanding of the underlying dynamics driving the COVID-19 pandemic.

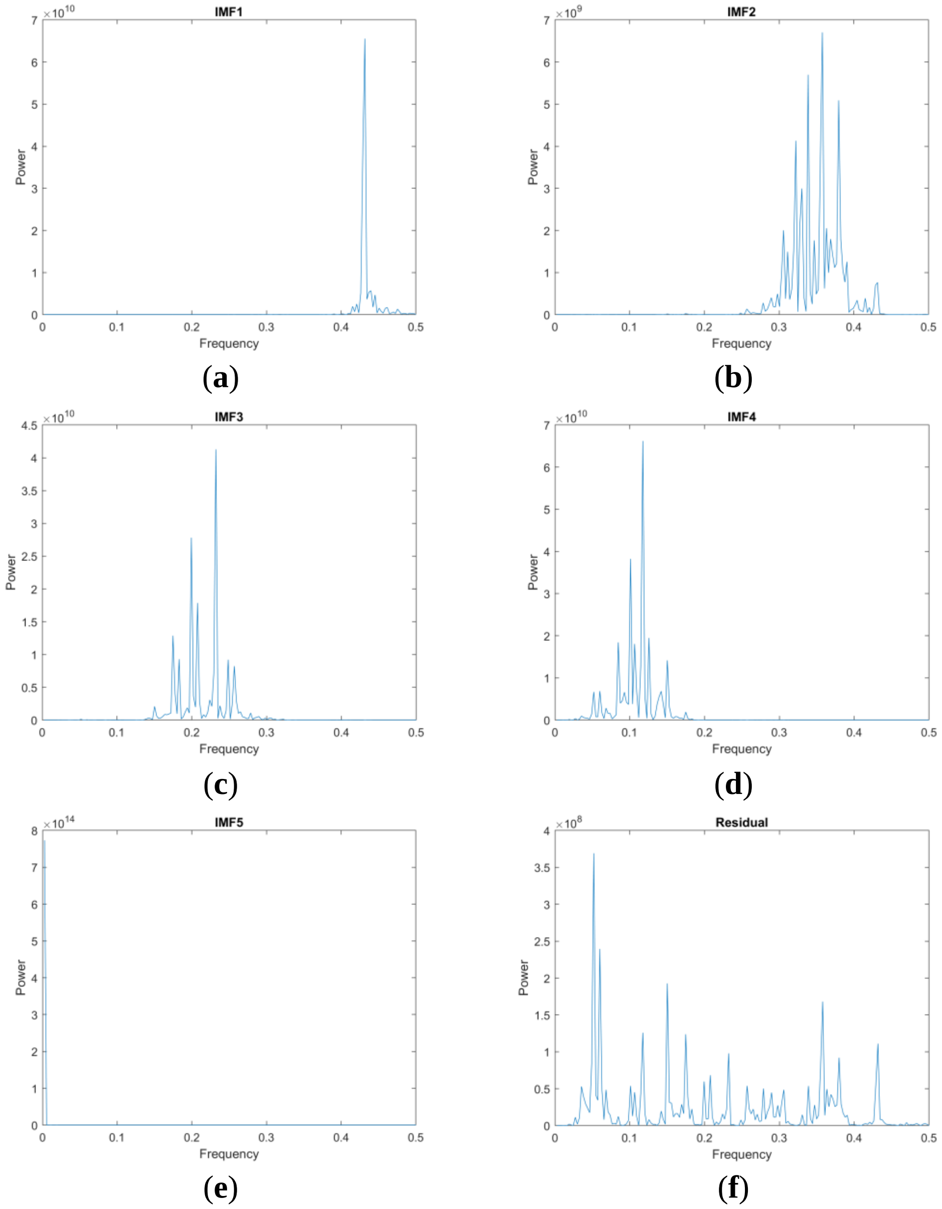

Figure 13 Identification of seasonality and trends using FFT analysis for all IMFs and residuals: (a) IMF1; (b) IMF2; (c) IMF3; (d) IMF4; (e) IMF5; (f) Residual.

4.4.3 Data Separation and ANN-Based GS Optimization

The processed dataset, comprising outputs generated by VMD-EMD-FFT, stepwise regression, and SD, is divided into training, validation, and test sets according to the data separation theory outlined in **Section 3.4.** The ANN is constructed and fine-tuned using training and validation sets, respectively. Particularly, the hyperparameter of ANN is optimized using GS. In this study, the optimization of the ANN through GS is performed using RapidMiner Studio 9.1 software. GS iteratively adjusts hyperparameters (see **Table 9**): the number of hidden nodes, training cycles, and learning rates, each of which is systematically varied within predefined ranges, represented as arrays. In the specified ranges, all possible combinations of hyperparameter values, represented as a grid structure, are used for the GS to fine-tune ANN.

Section 4.3 presents the process of one-day-ahead forecasting using a rolling dataset and GS. This process involves iteratively updating the dataset to accommodate new observations while maintaining a fixed prediction horizon of one day. After conducting an exhaustive search of all hyperparameter combinations through the GS methodology, the ANN model that demonstrates superior predictive performance is selected as the optimal choice. Subsequently, the chosen model is evaluated using the test set to assess its accuracy.

Table 9 Range of ANN hyperparameters used in grid search optimization.

Hyperparameter	Definition	GS Range
Hidden node	The number of hidden nodes on a single hidden layer	1, 5, 10
Learning rate	The magnitude of adjustments to weights and biases during training	0.1, 0.01, 0.001
Training cycle	The number of iterations used to update weights and biases	500, 1000, 1500

4.5 Experimental Results and Discussion of the Case Study

An experiment spanning one year, starting from January 2020 to December 2020, is performed to evaluate the models' efficacy in managing disruptive situations. The proposed model's assumption is validated through comparative analyses against three proposed models, utilizing a dataset covering the entire year. The first proposed model applies an ANN-based GS optimization on preprocessed data derived from stepwise regression, alongside SD utilizing the Euclidean distance criterion, and a decomposition and seasonality-capturing method proposed by Aswanuwath et al. [106]. The second proposed model integrated an ANN-based GS optimization approach, incorporating an important long-term input dataset identified through SD with consideration of day type criterion, along with the selected significant medium-term input dataset based on the result of stepwise regression, and processed data from VMD-EMD-FFT. LSTM-based GS optimization is employed in the third model with a short-term input dataset. A comparative analysis of the testing performance of these three proposed models over the course of one year is presented in **Table 10.**

Based on the findings presented in **Table 10**, the performance of proposed model 1 is less than the performance of models 2 and 3. The difference in performance can be explained by the use of SD based on the Euclidean distance criterion in model 1. Within this framework, the SD primarily focuses on identifying the candidate date in the year prior to the pandemic that has the most similar characteristics, based on demand as one of the factors. Consequently, the model encounters challenges in effectively managing demand during pandemic situations, because the model mainly depends on data from the period prior to the pandemic.

Conversely, proposed model 2 employs SD with the day type criterion, which enables the model's training with diverse datasets containing mid and long-term characteristics. This approach yields satisfactory performance if the target period remains unaffected by government intervention policies (lockdown level = 0). The target period shares similarities in terms of demand with the period prior to the pandemic, as the target period has an increase in business and tourism activities. This provides an explanation for the satisfactory performance. However, the effectiveness of proposed model 2 can be affected by government policy interventions that lead to rapid changes in demand and uncommon demand patterns, as the model relies on mid and long-term data.

On the other hand, the LSTM model demonstrates superior performance in handling rapid changes in demand due to government policies (lockdown level = 1–6). This can be attributed to its proficiency in handling short-term data, enabling rapid adjustment to sudden changes. LSTM is suitable to identify patterns and dependencies from short-term datasets, enabling the model to accurately recognize sudden changes. This capability empowers LSTM to effectively respond to changing situations, rendering it proficient in forecasting remarkable demand fluctuations resulting from government interventions.

These findings offer valuable understanding regarding the performance of each model during different situations. During normal conditions, proposed model 1 is considered appropriate for forecasting electricity demand. However, in situations without government intervention, where external factors disrupt consumption, proposed model 2 proves high accuracy in forecasting electricity demand. Conversely, in scenarios with interventions, proposed model 3 emerges as the preferred option to precisely forecast electricity demand. When applied to the demand data from the pandemic year, the proposed procedure, which combines proposed model 2 and proposed model 3 depending on the period of government intervention, outperforms each individual model. This combination highlights its superior performance and comprehensive approach to forecasting, as evidenced by the results presented in **Table 10.**

Table 10 Monthly results of testing performance over one year (2020).

Month	Proposed Model	Stepwise	SD Criterion	VMD-EMD-FFT	Forecasting Technique	Test			Degree of Lockdown
						MAPE	RMSE	MAE	
January	1	Yes	Euclidean distance	Yes	ANN-based GS	3.04%	971	754	0
	2	Yes	Day type	Yes	ANN-based GS	2.34%	810	595	
	3	No	No	No	LSTM-based GS	3.89%	1303	966	
February	1	Yes	Euclidean distance	Yes	ANN-based GS	3.35%	956	860	0
	2	Yes	Day type	Yes	ANN-based GS	2.64%	925	680	
	3	No	No	No	LSTM-based GS	2.93%	975	751	
March	1	Yes	Euclidean distance	Yes	ANN-based GS	3.24%	1076	866	0, 5
	2	Yes	Day type	Yes	ANN-based GS	3.10%	1130	819	
	3	No	No	No	LSTM-based GS	2.65%	851	714	
April	1	Yes	Euclidean distance	Yes	ANN-based GS	6.95%	2368	1710	6
	2	Yes	Day type	Yes	ANN-based GS	5.57%	2053	1343	
	3	No	No	No	LSTM-based GS	3.46%	1174	830	
May	1	Yes	Euclidean distance	Yes	ANN-based GS	4.85%	1543	1252	6, 4, 3
	2	Yes	Day type	Yes	ANN-based GS	4.31%	1290	1108	
	3	No	No	No	LSTM-based GS	3.23%	1037	841	
June	1	Yes	Euclidean distance	Yes	ANN-based GS	5.95%	1785	1496	2, 1
	2	Yes	Day type	Yes	ANN-based GS	3.27%	1163	812	
	3	No	No	No	LSTM-based GS	2.52%	766	627	
July	1	Yes	Euclidean distance	Yes	ANN-based GS	4.22%	1337	1053	1
	2	Yes	Day type	Yes	ANN-based GS	3.54%	1170	890	

	3	No	No	No	LSTM-based GS	2.80%	833	701	
August	1	Yes	Euclidean distance	Yes	ANN-based GS	4.67%	1486	1166	1
	2	Yes	Day type	Yes	ANN-based GS	4.21%	1298	1056	
	3	No	No	No	LSTM-based GS	2.43%	702	605	
September	1	Yes	Euclidean distance	Yes	ANN-based GS	4.64%	1413	1189	0
	2	Yes	Day type	Yes	ANN-based GS	2.64%	845	676	
	3	No	No	No	LSTM-based GS	2.73%	949	687	
October	1	Yes	Euclidean distance	Yes	ANN-based GS	5.56%	1728	1313	0
	2	Yes	Day type	Yes	ANN-based GS	4.00%	1200	949	
	3	No	No	No	LSTM-based GS	4.48%	1312	1046	
November	1	Yes	Euclidean distance	Yes	ANN-based GS	4.51%	1425	1122	0
	2	Yes	Day type	Yes	ANN-based GS	3.69%	1255	918	
	3	No	No	No	LSTM-based GS	3.95%	1140	977	
December	1	Yes	Euclidean distance	Yes	ANN-based GS	4.62%	1300	1066	0
	2	Yes	Day type	Yes	ANN-based GS	4.46%	1341	1015	
	3	No	No	No	LSTM-based GS	4.73%	1397	1070	
Average 12 Months	Proposed model 1					4.63%	1501	1153	-
	Proposed model 2					3.65%	1244	905	
	Proposed model 3					3.36%	1073	824	
	Proposed procedure					**3.07%**	**999**	**762**	

Throughout the pandemic year, the accuracy of electricity demand forecasting can be impacted by government interventions and the rapidly evolving nature of the pandemic. The pandemic caused significant disruptions to various aspects of society and the economy. Factors such as fluctuating infection rates, shifts in consumer behavior, and economic uncertainty all contributed to the complexity of forecasting electricity demand. Amidst these complexities, the most challenging conditions arose during periods unaffected by government intervention policies (lockdown level = 0). During this phase, electricity demand exhibited a mixed pattern, combining elements from both the year prior to the pandemic and the periods with the intervention policies. Inspired by the lack of government control policy, people remained cautious amid the existence of the pandemic, opting for remote activities. This demand pattern showed a combination of existing behaviors and those shaped by the pandemic, highlighting the multifaceted nature of forecasting electricity demand in such unprecedented situations.

Figure 14 demonstrates the daily errors based on the proposed procedure, with notable peaks observed including the peak in mid-April, mid-November, and December. Particular events and policy adjustments can explain the peaks. During lockdown periods, the largest error occurs at the highest lockdown level. The error decreases when the level continues to be the same and increases when the level shifts, see **Figure 15.** On the other hand, uncommon additional holidays announced in late July can be the cause of an unusual error pattern. Differing from prior trends, in mid-November, a significant error is found following the national emergency declaration extension. During the late year, with the largest number of daily cases, another error can be noticed. Although this period did not have any lockdown, people had reduced interactions because of an increase in daily cases. Consequently, this impacts the demand during the late year. The change in behavior leads to a demand characteristic distinct from the pre-pandemic year, resulting in a substantial forecasting error.

Considering forecasting errors, there are two main types: overestimating and underestimating electricity demand. Overestimating electricity demand in forecasting can lead to inefficiencies and increased operational costs for utilities. When demand is overestimated, excess generation capacity is maintained, resulting in wasted resources and higher electricity prices for consumers. While overestimation can lead to financial inefficiencies and the unnecessary allocation of resources, its consequences are typically less immediate and severe compared to underestimation. Underestimating electricity demand, on the other hand, poses a significant threat to the stability and reliability of the power grid. When demand is underestimated, utilities may not generate sufficient electricity to meet actual consumption needs, leading to power shortages and potential blackouts. This can disrupt economic activities, affect residential comfort, and compromise critical infrastructure services. To mitigate these risks, it is essential to incorporate a forecasting allowance within predictive models. This allowance serves as a buffer to account for unexpected increases in demand, ensuring that utilities are better prepared to handle deviations from the forecasted values. In this case study, a forecasting allowance has been set to at least 10% for the months of February through October, and 20% for the months of January, November, and December.

Table 11 displays the comparative performance of the proposed procedure against previous studies. This analysis includes proposed model 1 [106], LSTM [140], extreme gradient boosting (XGBoost) [141], SVM [142], and ARIMA [143], all conforming to the structural framework outlined in the existing literature. As indicated in the results shown in **Table 11**, the proposed procedure not only exceeds the performance of all proposed models but also surpasses that of all other comparative models across all three evaluated measurements (MAPE, RMSE, and MAE).

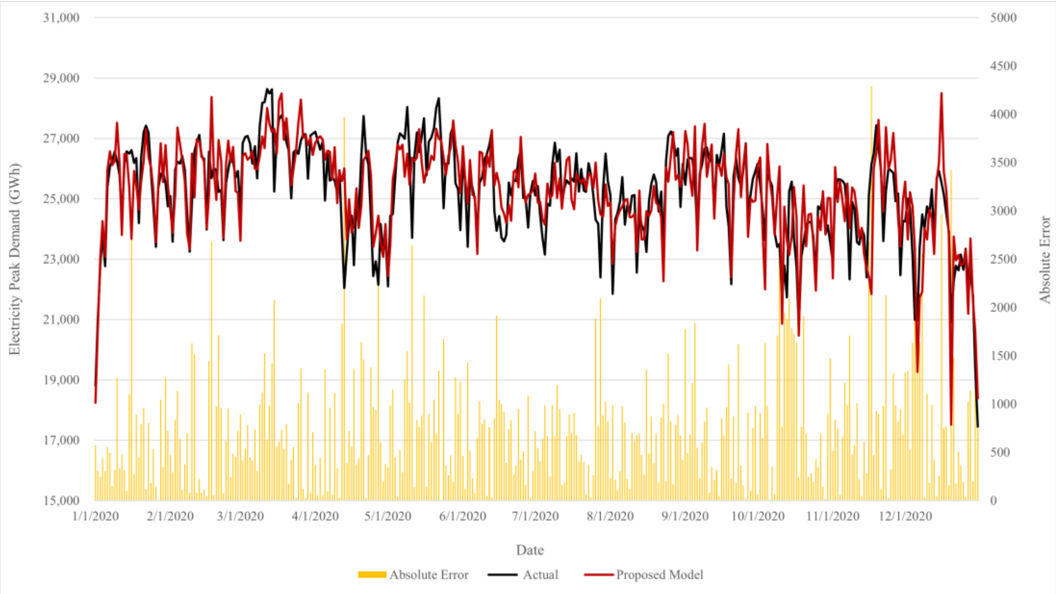

Figure 14 Daily forecasting errors of proposed procedure on test dataset.

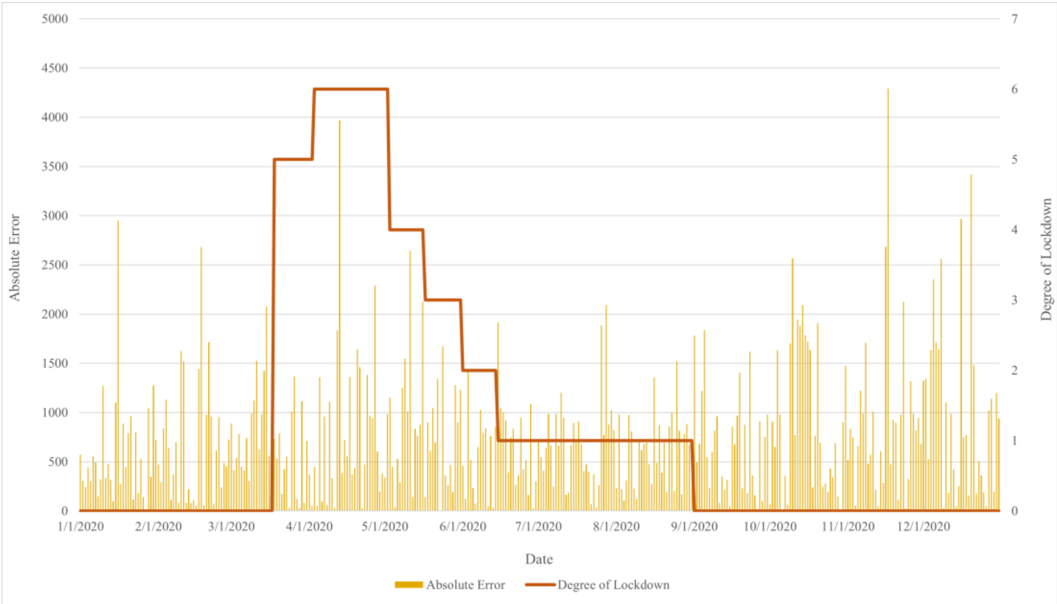

Figure 15 Lockdown level's impact on forecasting error.

Table 11 Comparative performance analysis between proposed procedure and prior studies.

Forecasting Model	**Average 12 Months of Test Performance**		
	MAPE	**RMSE**	**MAE**
Proposed procedure	**3.07%**	**999**	**762**
Proposed model 1 [106]	4.63%	1501	1153
LSTM [140]	5.15%	1632	1266
XGBoost [141]	4.12%	1322	1015
SVM [142]	4.13%	1305	1014
ARIMA [143]	4.37%	1378	1080

The findings reveal that the performance of the proposed procedure on the test dataset substantiates its efficacy in managing disruptions spanning an entire year, both with and without intervention from government policies. This emphasizes the model's adaptability and robustness in diverse scenarios. The proposed procedure, designed to accommodate diverse temporal contexts and specific conditions across various timeframes, enables it to adeptly capture unnoticeable fluctuations in electricity demand throughout the pandemic period. Training the model with short-term, medium-term, and long-term datasets enhances forecasting accuracy by capturing different temporal patterns and trends in electricity demand. Short-term data improves forecasting accuracy by addressing recent changes and daily variations, such as weather conditions and policy changes. Medium-term data helps in understanding weekly and monthly patterns, which are influenced by workweek schedules and monthly climatic changes. Long-term data accounts for seasonal and yearly trends, recognizing annual cycles and significant recurring changes. This comprehensive multi-scale approach improves the model's responsiveness and overall forecasting accuracy. Notably, the model achieves significant improvement while concurrently reducing the number of input variables. This reduction strategy uses significant variables to train the model, particularly those closely aligned with the target forecast date. Moreover, the integration of the GS optimization technique enhances the model's performance by ensuring optimal results without relying on forecasted input variables, thereby upholding reliability and accuracy. In summary, the proposed procedure provides precise and unbiased forecasting outcomes, helping address future disruptions in the electricity sector.

CHAPTER 5

Conclusion and Future Work

The energy sectors of numerous countries have undergone significant transformations due to disrupted situations. The dependable operation of the electricity grid requires high accuracy in terms of electricity demand forecasting. This study aimed to address the challenges posed by disruptive events and mitigate the disruption impact on electricity demand forecasting in the future. The research objective was to develop a hybrid forecasting model designed for hybrid scenarios during disrupted situations (with and without government intervention), with a focus on Thailand's electricity demand as a case study. The main significant of this method is to recognize and apply forecasting models suitable for specific scenarios. Through the integration of data decomposition (VMD-EMD-FFT), input variable selection (stepwise regression and SD-based day type criterion), and hyperparameter optimization (ANN-based GS and LSTM-based GS), the proposed procedure aims to mitigate the identified limitations of the existing forecasting approach. In the context of disrupted situations, this study presents a new criterion for distinguishing between short-term, medium-term, and long-term datasets. Moreover, a new criterion based on similar day selection is introduced to address situations where the demand for a candidate date differs significantly from the target forecasting date. One-day-ahead forecasting is conducted using rolling datasets and pandemic sensitivity factors, improving the adaptability and flexibility of the model in dealing with daily changes.

The implementation of the procedure of the proposed models in a real-world setting allowed for the assessment of its practical applicability and effectiveness. By conducting a comparative analysis against existing forecasting models, the performance and superiority of the approach were evaluated. The findings indicate that the proposed procedure effectively enhanced flexibility and outperformed the comparative models, demonstrating its ability to provide more accurate predictions in dynamic and uncertain environments. Furthermore, it reduces the number of inputs, enhances computational efficiency, and eliminates the necessity for input variables dependent on prior forecasts. Additionally, the findings reveal how disruptions impact the accuracy of the forecasting model as an external variable, thereby clarifying the model's robustness and adaptability. Therefore, the results improve the ability to forecast electricity demand in various scenarios using the proposed models. Proposed model 1 demonstrates effectiveness in normal situations, as shown in **Table 10**, whereas proposed model 2 is preferable in disrupted scenarios without government intervention. However, proposed model 3 is a suitable model to forecast electricity demand under a situation affected by government policies.

Looking to the future, further research could explore enhancements to the proposed hybrid model and overcome its limitations. To improve performance, one potential area is to broaden the scope of model sophistication by investigating advanced machine learning techniques in addition to the current usage of ANN and LSTM. Experimenting with innovative algorithms and methodologies may offer new insights and potentially improve forecasting accuracy and stability. Moreover, expanding the scope of the study to include other regions or sectors affected by disruptions would contribute to a more comprehensive understanding of forecasting challenges and solutions. Considering the rapid growth and transformation of renewable energy on a global scale, it is imperative to incorporate it more comprehensively into forecasting frameworks. However, in this study, the main focus of the proposed forecasting framework is not on renewable energy. Future studies could aim to integrate renewable energy factors into the forecasting framework. This would involve expanding the scope of analysis to encompass a broader range of renewable energy sources and their impact on electricity demand dynamics. By doing so, the forecasting model can better capture the complexities of renewable energy integration and provide more robust forecasting models aligned with evolving energy landscapes, advancing the field of energy forecasting and supporting sustainable energy development.

CHAPTER 6
Thesis Contribution

6.1 Practical Implication

The practical implications of this study are significant for various stakeholders involved in energy forecasting and decision-making processes. By developing a hybrid forecasting model designed for hybrid scenarios during disrupted situations, particularly focusing on Thailand's electricity demand during the COVID-19 pandemic, this research offers valuable tools and insights for policymakers, energy planners, and industry professionals. The ability of the proposed procedure to adapt to transitional phases and capture underlying seasonality patterns enhances its applicability in real-world scenarios where disruptions are prevalent. Moreover, the integration of advanced machine learning techniques and innovative methodologies improves the accuracy, adaptability, and robustness of the forecasting approach, providing decision-makers with more reliable forecasts for strategic planning and resource allocation.

Overall, the practical implications of this study extend beyond academic research, empowering stakeholders with actionable tools and insights to manage uncertain environments and support the resilience of energy systems amidst disruptions.

6.2 Theoretical Implication

The theoretical implications of this research are multifaceted and contribute significantly to advancing the field of energy forecasting and predictive modeling. By developing a hybrid forecasting model specifically designed for hybrid scenarios during disrupted situations, this study enriches our theoretical understanding of how forecasting techniques can be designed to accommodate complex and dynamic environments.

The integration of diverse methodologies, such as data decomposition (VMD-EMD-FFT), input variable selection (stepwise regression and SD-based day type criterion), hyperparameter optimization (ANN-based GS and LSTM-based GS), and a rolling dataset, expands the theoretical framework of forecasting models by demonstrating the efficacy of combining multiple approaches to enhance accuracy, adaptability, and robustness. Additionally, exploring advanced machine learning techniques beyond conventional methods such as ANN and LSTM broadens the theoretical framework of predictive modeling, offering insights into the potential of innovative algorithms to improve forecasting performance.

Furthermore, this study introduces innovative criteria for distinguishing between short-term, medium-term, and long-term input sets in disrupted situations, enhancing the model's adaptability and accuracy. These criteria, along with the novel criterion based on similar day selection, improve the model's ability to forecast electricity demand in dynamic environments. The study also emphasizes the importance of one-day-ahead forecasting using rolling datasets and pandemic sensitivity factors, highlighting the need for real-time data integration and adaptability in forecasting frameworks.

Overall, the theoretical framework developed in this study provides a basis for future research endeavors exploring the intersection of energy forecasting and disruptive events integration, contributing to the theoretical advancement of forecasting research and resilience planning.

6.3 Contribution to Knowledge Science

The contribution to the knowledge science is to advance our understanding of energy forecasting and predictive modeling, particularly in disrupted situations. The development of a hybrid forecasting model and the introduction of innovative criteria designed for such scenarios enrich the theoretical framework of forecasting techniques and contribute to the advancement of knowledge in energy forecasting research. Furthermore, this study offers a precise and adaptable model that addresses the complexities of disrupted situations, empowering policymakers, energy planners, and stakeholders with valuable insights and tools for effective decision-making and resilience enhancement of energy systems. Additionally, the introduction of novel hybrid models improves the existing knowledge base in time series forecasting, facilitating the capture of insights from complex datasets, particularly real-world time series data, thereby contributing to the knowledge discovery process.

Overall, this research makes a significant contribution to knowledge science by offering insights, methodologies, and approaches to address challenges and mitigate the impact of future disruptions in energy forecasting and predictive modeling.

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APPENDIX

To assess the impact of the COVID-19 pandemic on electricity demand, a comparative analysis between the pre-pandemic and pandemic years was conducted. This involved calculating the difference in electricity demand between corresponding dates (e.g., demand on 18/03/2019 minus demand on 18/03/2020). The probability plot of these differences (see **Figure 16**) indicated that the effect of COVID-19 fluctuates and does not follow a normal distribution. Therefore, a nonparametric test was used to evaluate the null hypothesis. The results of the nonparametric test (refer to **Figure 17**) confirmed that the effect was significantly greater than zero, indicating a reduction in electricity consumption during the lockdown year compared to the pre-pandemic year. Specifically, the lockdown led to an average reduction of 957 MW in peak electricity consumption. This suggests that if a similar lockdown were to occur in the future, peak electricity demand could be expected to decrease by an average of 957 MW.

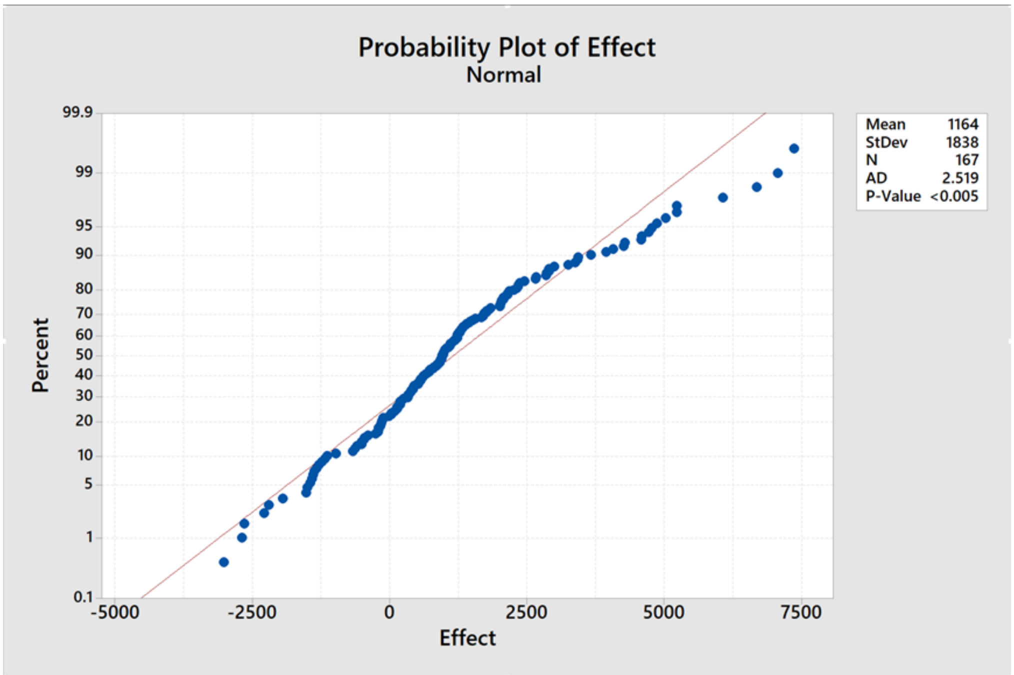

Figure 16 Probability plot of the COVID-19 effect.

Sign Test for Median: Effect

Method

η: median of Effect

Descriptive Statistics

Sample	N	Median
Effect	167	957.7

Test

Null hypothesis	H_0: η = 0
Alternative hypothesis	H_1: η > 0

Sample	Number < 0	Number = 0	Number > 0	P-Value
Effect	37	0	130	0.000

Figure 17 Nonparametric test for measuring the effect of COVID-19 on the electricity demand.

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International Journal

1. Aswanuwath, L., Pannakkong, W., Buddhakulsomsiri, J., Karnjana, J., & Huynh, V. N., An Improved Hybrid Approach for Daily Electricity Peak Demand Forecasting during Disrupted Situations: A Case Study of COVID-19 Impact in Thailand, *Energies*, 17(1), 78, 2023.
2. Aswanuwath, L., Pannakkong, W., Buddhakulsomsiri, J., Karnjana, J., & Huynh, V. N., A Hybrid Model of VMD-EMD-FFT, Similar Days Selection Method, Stepwise Regression, and Artificial Neural Network for Daily Electricity Peak Load Forecasting; *Energies*, 16(4), 1860, 2023.

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1. Aswanuwath, L., Huynh, V. N., Pannakkong, W., Daily Electricity Peak Demand Forecasting using Hybrid Model based on Similar Day Selection Technique. In Proceedings of the 9th International Symposium, IUKM 2022; Ishikawa, Japan, 2022. (Presentation)