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DUONG NGOC HUNG

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SUMMARY OF THESIS

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Scientific instructor 1: Assoc. Dr. PHAN THI THANH BINH

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[1] **Duong, N.-H.**, Nguyen, M.-T., Nguyen, T.-H. and Tran, T.-P. 2023. "Application of Seasonal Trend Decomposition using Loess and Long Short-Term Memory in Peak Load Forecasting Model in Tien Giang". Engineering, Technology & Applied Science Research. 13, 5 (Oct. 2023), 11628–11634. DOI:https://doi.org/10.48084/etasr.6181.

Domestic magazines:

[2] **Dương Ngọc Hùng**, Nguyễn Tùng Linh, Nguyễn Thanh Hoan, Nguyễn Minh Tâm. "Mô hình kết hợp HHO-GCN-LSTM ứng dụng trong dự báo đồ thị phụ tải cho lưới điện nhỏ," *Tạp chí Khoa học và Công nghệ Đại học Công Nghiệp Hà Nội*, vol. 58, no. 4, pp. 8-15, 2022, [Online]. Available: https://jst-haui.vn/media/30/uffile-upload-no-title30857.pdf.

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GENERAL

1. Reason for choosing the topic

Electricity is a highly flexible and widespread energy source, playing an indispensable role in daily life as well as in industry. In addition, electrical energy better and more efficiently meets societal demands, while being more environmentally friendly compared to other traditional energy sources such as oil, coal, and natural gas [1]. The importance of electricity has increased significantly in recent years, and electricity forecasting has become a necessary problem in research [2]. However, electricity is a unique product with many characteristics that differentiate it from other types of products. Electrical energy cannot be stored in large capacities; it must be produced instantaneously when there is a demand for use. Additionally, the demand for electricity will rise sharply across the country due to population growth along with the development of industrial zones that use large-power equipment. These factors lead to challenges in managing the power system [3]. Therefore, load forecasting is necessary for the electricity industry to plan electricity production.

Load forecasting is a crucial process in planning and operating power systems, closely linked to economic development, national security, and the daily activities of society [4]. Therefore, the error of the forecasting model is important for creating operation plans, power generation capacities, and power system management. The accuracy of the model helps save operational costs, maintenance, and make the right decisions for the development of production, transmission, and distribution facilities in the coming period. However, the accuracy of the load forecasting model is influenced by many factors such as economic development, national policies, climate change, and human activities [5]. In summary, electricity plays a crucial role in society. Global energy consumption continues to increase due to population growth, economic development, and weather factors, particularly in developing countries. The change in consumption patterns makes it difficult for the power system to balance supply and demand in real-time. This thesis proposes forecasting models based on deep learning to solve the "**Forecasting electrical system load**" problem in order to forecast the peak power Pmax for the next day and the electricity load profile for the next 24 hours. The input data for the model is used from historical data of the Tien Giang power grid area.

2. Subject and scope of research

- Forecast Pmax and load for the next 24 hours. Analyze factors affecting load demand.
- Collect historical load data, temperature, and seasonal factors for the applied area.
- Explore deep learning-based models in STLF. Common models include LSTM, CNN-LSTM, WaveNet, and combined models such as GCN-GRU, FF-DNN combined with R-DNN, SEQ2SEQ-LSTM, and preprocessing models using Wavelet combined with optimization algorithms and GCN-LSTM networks.
- Apply the proposed model to forecast for a specific power grid area (Tien Giang power grid).
- Results are only compared with other models using the same dataset. The study does not consider ultra-short-term, medium-term, or long-term forecasting, and it is only applied to weekdays, excluding holidays and festivals.
- Since the forecast covers the next 24 hours and Pmax for the following day, real-time forecasting time is not prioritized in this model. The forecasting model results only focus on the mean absolute percentage error according to Decision No. 07/QD-DTL in 2013. The root meaning square error is not considered in the study.
- The temperature for the forecast day is taken from data provided by the meteorological station.
- The proposed models, GCN-GRU and Wavelet-HHO-GCN-GRU, require significant computational resources. The study does not analyze costs related to technology or processing time when applied to real-world models, especially for short-term forecasts or large data volumes. Evaluation requires real-world experimental statistics.

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3. Research goals and tasks

- Build a deep learning-based model to forecast the peak load for the next day and the load curve for the next 24 hours. Evaluate the performance of the proposed deep learning forecasting model (compared to traditional forecasting methods). Apply the proposed model to forecast the peak load Pmax and load curve for a specific power grid area.
- Collect historical data, evaluate, and analyze the factors impacting on the results of the load forecasting problem.
- Select and build common deep learning architectures: LSTM, CNN-LSTM, and WaveNet. Propose combined models like GCN-GRU and Wavelet-HHO-GCN-LSTM to forecast peak load and corresponding load curves.
- Integrate input factors to design the forecasting model. Train and test the model.

4. Research Methods

Research PyCharm software, Python language, and TensorFlow library to implement the training and forecasting program. Collect historical data. Use common peak load forecasting models (LSTM, CNN-LSTM, WaveNet network) and GCN-GRU: Train the model, run experiments, evaluate, and compare. Use common load curve forecasting models and the combined Wavelet-HHO-GCN-LSTM model. Process input data using Wavelet transform, train, run experiments, evaluate, and compare.

5. New point of the thesis

- The analysis and evaluation of data in the STLF problem have been carried out using a new assessment approach, which takes into account spatial and temporal dependencies. Through this, the dissertation proposes new forecasting methods to improve the error in the forecasting problem. A novel deep learning model has been developed to forecast peak load: GCN-GRU (T-GCN), and the proposed model yields high accuracy results.
- Three deep learning models have been built to forecast the load curve: the model architecture combining FF-DNN and R-DNN, Seq2Seq-LSTM, and the Wavelet transformation combined with the optimization algorithm HHO-GCN-LSTM. The results of the proposed model show small errors, and the Mean Absolute Percentage Error (MAPE) index is within the acceptable range specified by the electricity regulatory authority.

6. Practical value of the thesis

- The dissertation has made a positive and effective contribution by proposing new methods to solve the electricity load forecasting problem based on deep learning networks through novel combination methods: GCN-GRU (T-GCN); FF-DNN and R-DNN model architectures; SEQ2SEQ-LSTM based on the encoding-decoding mechanism; Wavelet data preprocessing combined with HHO algorithm and GCN-LSTM network. The results of peak load forecasting are crucial and necessary for energy management planning and efficient electricity source regulation.
- The results of the daily load curve forecasting are accurate, supporting the planning of safe and reliable operation and utilization of the electricity system in the area. The results of the peak load forecasting for the next day and the 24-hour load curve have significant meaning for the power grid, especially with the involvement of Battery Energy Storage Systems (BESS) and Electric Vehicles (EV). The proposed model for forecasting peak load for the next day and the 24-hour load curve can be applied in practice, meeting all the requirements and regulations of the electricity regulatory authority regarding the load forecasting process.

7. Layout of the thesis

Chapter 1: Overview

Chapter 2: Theoretical basis

Chapter 3: Peak load forecasting

Chapter 4: Forecasting load graph

CHAPTER 1. OVERVIEW

1.1. Introduce

In recent years, the development of science, particularly computer science, has significantly contributed to positive changes, with information technology applications in forecasting being widely implemented across various fields [6]. Currently, electricity load forecasting is one of the areas that the government is particularly concerned with, providing guidance and issuing specific regulations through Circular No. 19/2017/TT-BCT, which outlines the content, methods, and procedures for studying electricity load by the Ministry of Industry and Trade in 2017, and Decision No. 07/QĐ-ĐTĐL on the forecasting process for the national electricity system demand by the Electricity Regulatory Authority of Vietnam – Ministry of Industry and Trade in 2013. The electricity load forecasting problem has attracted researchers and is closely monitored by energy management authorities and power system operators. Load forecasting provides essential information for future investment planning, and it also impacts system operation and production plans. If the forecasted results significantly exceed actual demand, it may lead to the mobilization of funds for investment in power generation sources. However, in practice, capacity is often not fully utilized, leading to waste. Conversely, if the forecast is lower than the actual demand, it may reduce the safety of electricity supply, causing widespread power outages and serious economic, social, and national security damages [7].

In summary, electricity load forecasting in general, and Short-Term Load Forecasting (STLF) in particular, plays a crucial role in ensuring the efficient and reliable operation of power systems. Currently, both domestically and internationally, numerous forecasting methods have been proposed, each with its own advantages and limitations.

1.2. Research situation in the country

Recently, there have been many studies on electricity load forecasting in Vietnam. Study [8] examines the quality of historical data before inputting it into the STLF forecasting model for the Ho Chi Minh City power grid. Study [9] proposes SOM & K-Means clustering to improve results and reduce computation time. Study [7] applies data grouping techniques combined with statistical probability, enhancing accuracy and flexibility. Study [10] uses artificial neural networks in MATLAB to forecast peak power demand, achieving an error of 0.19%. The research group in [6] proposes a supervised learning algorithm and adjusts the forecast values to reduce negative deviations and improve accuracy.

1.3. Research situation abroad

Classic methods such as ARMAX, ARIMA, and SARIMA are widely used for STLF forecasting [11]. The ARIMA model [12] forecasts hourly load with a MAPE of 4.46%. The ARIMA-SVR model [13] consists of two steps: ARIMA handles the linear function, while SVR adjusts the deviations, achieving an error of 4.757%. Recent studies have utilized neural networks and deep learning to improve accuracy compared to statistical methods. The CS-SSA-SVM model [5] combines SSA, SVM, and CS to filter signals and optimize forecasts. The Wavelet-FNN model [14] is optimized using the hawk optimization algorithm, achieving a MAPE of 1.2262%. The MWCNN model [15] exploits the cyclical characteristics of load data. Methods combining PSO [16], GOA [17], EMD [18], and GTA-PSO [19] have also been applied in STLF.

The Prophet-LSTM model [20] forecasts peak load with an MAE of 8.569 and RMSE of 11.68. The CNN-LSTM model [21] forecasts monthly peak load over 3 years, achieving high accuracy. The PRISMA-P method [22] helps with synthesis analysis and selection of the optimal forecasting strategy. AI, ML, and DL methods [23] improve accuracy with optimal MAPE errors. The CNN-LSTM hybrid model [24] combines CNN for pattern recognition and LSTM for learning sequential features. The multi-dimensional feature extraction method [25] helps reduce RMSE errors from 5%

This dissertation develops a novel hybrid forecasting model, Wavelet-HHO-GCN-LSTM, representing a new and effective approach. The model is designed to leverage the advantages of noise filtering and data analysis using Wavelet, combined with the optimization capability of HHO and the power of deep learning networks such as GCN-LSTM in modeling complex data. In the experimental results section, this chapter provides a detailed comparison between the proposed model and forecasting models such as FF-DNN, R-DNN, and Seq2Seq-LSTM for electricity load prediction. The results demonstrate that the Wavelet-HHO-GCN-LSTM model outperforms others in terms of accuracy, achieving significantly lower MAPE values compared to models like LSTM, CNN-LSTM, and WaveNet, while proving its ability to forecast electricity load with high precision and reliability.

In addition to achieving lower error rates compared to traditional models, the Wavelet-HHO-GCN-LSTM model offers several outstanding advantages in load profile forecasting. First, the Wavelet filter decomposes data into different frequency components, eliminating noise and extracting useful features before feeding them into the deep learning model, significantly improving input quality. Next, the HHO optimization algorithm is employed to fine-tune the model parameters, optimizing the training process, minimizing errors, and enhancing convergence performance.

Additionally, the integration of GCN and LSTM in the model effectively captures both spatial and temporal relationships in load data. GCN can learn the structural patterns of data in graph form, making it well-suited for modeling the complex interconnections between substations and electricity consumption areas. Meanwhile, LSTM retains sequential information over time, which is particularly useful for load forecasting with data that exhibit seasonal and hourly variations.

Experimental results demonstrate that the proposed model not only outperforms common deep learning models such as LSTM, CNN-LSTM, and WaveNet in terms of accuracy but also exhibits better generalization compared to previous hybrid models like FF-DNN, R-DNN, and Seq2Seq-LSTM. This confirms the effectiveness of the new approach in electricity load forecasting, especially in the context of increasingly complex and volatile power systems driven by the growth of renewable energy and environmental factors.

The study has focused on the power grid in Tien Giang, but the scalability of the model to other regions with different socio-economic and climatic conditions may not have been thoroughly considered. The model needs to be validated for its applicability and flexibility to ensure its adaptability to areas with varying grid structures. Evaluations for other data sources and regions have not been conducted. However, the implementation of forecasting methods can be considered, along with real-world testing and adjustments.

2. Recommendation

The dissertation has analyzed and proposed methods for peak power and load forecasting. However, there are still some limitations, as not all influencing factors have been considered. The researcher will continue studying extended problems, such as:

- Forecasting peak power and load profiles for special days of the year, including holidays, the Lunar New Year, or periods with significant fluctuations in electricity demand, to improve model accuracy in unusual situations.
- Integrating electricity prices as an input factor in the forecasting model to reflect the impact of pricing policies on consumption behavior, especially when seasonal or time-based price adjustments occur.
- Considering economic and environmental factors that influence electricity consumption behavior, such as GDP, humidity, and rainfall, to assess the indirect effects of these factors on electricity demand in industrial, commercial, and residential sectors.

CONCLUSION – RECOMMENDATION

1. Conclusion

The dissertation "**Forecasting electrical system load**" proposes a model to address two problems: forecasting peak power and load profiles.

Problem 1: The study developed a hybrid model combining Graph Convolutional Networks (GCN) with Gated Recurrent Units (GRU) for peak power forecasting. In Chapter 3 of the research, key content includes forecasting the peak power Pmax using the GCN-GRU algorithm. The task of forecasting peak power Pmax plays a crucial role in the study, based on the analysis of past Pmax data and influencing factors. The proposed model, called GCN-GRU, was applied to the Tien Giang power grid region dataset. The inputs for the forecasting model include Pmax/hour, temperature/hour, and seasonal influencing factors. The results of the algorithm showed a very low mean absolute percentage error MAPE of 0.0006%, as shown in Table 3.2.

The forecast results of the model were also compared with commonly used deep learning forecasting models such as LSTM, CNN-LSTM, and WaveNet. These conventional deep learning models were tested on the same dataset as the GCN-GRU model (Tien Giang power grid region). According to the results in Table 3.2, the proposed GCN-GRU model exhibited the smallest error, demonstrating an improvement in performance. This improvement stems from the new approach to understanding spatial and temporal relationships in the forecasting problem. The model's error meets the evaluation criteria for the forecasting task. The results of this study were published in [69].

In addition to improving forecasting accuracy, the GCN-GRU model offers several key advantages over traditional methods. First, the integration of Graph Convolutional Networks (GCN) enables the model to capture spatial relationships between data points in the power grid—an aspect that sequential deep learning models like LSTM and CNN-LSTM have yet to optimize fully. Second, the Gated Recurrent Unit (GRU) effectively retains information over time, mitigating the vanishing gradient problem when handling long-term sequential data.

Furthermore, experimental results on the Tien Giang power grid dataset demonstrate the model's strong generalization capability, even when applied to different weather conditions and load patterns. This highlights the potential of applying GCN-GRU to power grids in other regions with distinct operational characteristics, supporting system operators in planning, resource optimization, and minimizing risks associated with forecasting errors.

With these advantages, the study not only proposes a highly accurate model but also contributes to expanding a new approach to electricity load forecasting. This is particularly significant in the context of increasingly complex power systems, driven by the growing integration of renewable energy sources and the spatial and temporal variability of load demand.

Problem 2: Developing a hybrid network model combining the Wavelet filter, HHO optimization algorithm, and graph convolution with long/short-term memory (Wavelet-HHO-GCN-LSTM) for load profile forecasting. The experimental model is applied to Tiền Giang's dataset. The input features for the forecasting model include hourly electricity consumption, hourly temperature, and seasonal factors. The proposed model achieves a low error rate, with the Mean Absolute Percentage Error (MAPE) recorded at 0.54, compared to other models presented in the study. To obtain optimal forecasting results, the research evaluates three deep learning-based models: LSTM, CNN-LSTM, and WaveNet. Their respective MAPE values are 4.6159, 3.7519, and 0.8749, all meeting the acceptable error threshold. Based on these promising results, the study further applies three hybrid models to the load profile forecasting problem, improving upon previously implemented deep learning models. These include Model 1 (FF-DNN, R-DNN) and Model 2 (Seq2Seq-LSTM), which were re-evaluated using Tiền Giang's dataset. The error results are presented in Table 4.4.

to 12%. The ANFIS model [26] forecasts building energy with low errors. The LSTM-GRU-RNN model [27] forecasts load from SCADA data, helping optimize energy planning and balance supply and demand.

The dissertation proposes two main algorithms: GCN-GRU for forecasting peak power for the next day and Wavelet-HHO-GCN-LSTM for forecasting the 24-hour load profile. Other models were tested for comparison.

1.4. General introduction to the power system of Tien Giang province

According to the report on the results of the implementation of the 2021 and 2022 plans of the Tien Giang Power Company [28], the characteristics of the Tien Giang power grid include: Tien Giang is a province located in the Mekong Delta (Southwest region), along the northern bank of the Tien River, a branch of the Mekong River, approximately 120 km long. Tien Giang has 11 administrative districts (8 districts, 1 city, 2 towns), and 173 administrative units at the commune level, with My Tho city being the type I urban area under Tien Giang province. The climate of Tien Giang is divided into two distinct seasons: the dry season from December to April and the rainy season from May to November. The average annual temperature is around 27°C, with annual rainfall reaching approximately 1,467 mm. The economic development in Tien Giang is uneven, mainly concentrated in the Tan Huong industrial zone and the Long Giang industrial zone, leading to significant differences in power demand in these areas. The power demand is mainly concentrated in the developed industrial zones. In less developed areas, the peak demand is mostly residential, which poses a great challenge for the economic operation of the power system. The components of the load are shown in Figure 1.1.

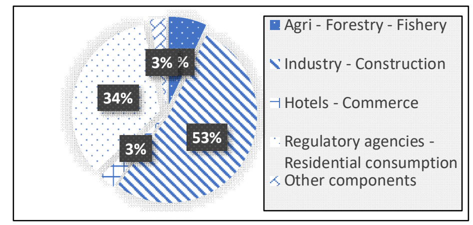


Figure 1.1: The composition of the electricity load in Tien Giang

The power grid in the Tien Giang region is part of the national grid, so the load forecasting for the Tien Giang area follows the regulations of the Electricity Regulatory Authority (Decision No. 07/QĐ-ĐTĐL). The previous methods of load forecasting as per the regulations included: extrapolation methods, regression methods, elasticity coefficient methods, artificial neural network methods, correlation-trend methods, expert methods, and other methods. Currently, the Dispatch Center at Tien Giang Power Company is implementing load forecasting using software such as SPC and NSMO. The current error in forecasting for the Tien Giang grid ranges from 5% to 10%. However, in practice, these methods still face challenges when applied to Short-Term Load Forecasting (STLF) in the Tien Giang power grid, resulting in lower-than-actual forecast values and larger model errors. This creates difficulties in making appropriate decisions.

1.5. Conclusion of chapter 1

In this chapter, the research has introduced an overview of the electricity load forecasting problem, with STLF playing a crucial role in ensuring the efficient and reliable operation of the power system. The study has compiled the current research situation both domestically and internationally, as well as the methods proposed, thus capturing important information and results in the electricity load forecasting problem. This research has been updated as the basis for further studies in the following chapters. Moreover, this chapter reflects the current status of load forecasting efforts in the Tien Giang power grid area, where the model error is still high, leading to operational difficulties in the power system. To address the issue of high model errors, which range from e_{MAPE} 5% to 10% in the Tien Giang area, the research will continue to tackle this problem in the dissertation.

CHAPTER 2. THEORETICAL BASIS

2.1. Analysis of electricity load forecasting diagram

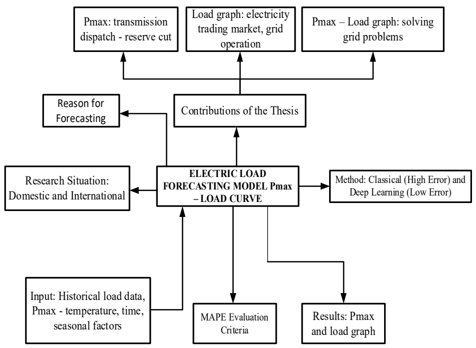


Figure 2.1: Analysis diagram of "**Electricity load forecasting**"

Based on domestic and foreign research works of STLF, the purpose of load forecasting is to estimate the load in the next hour, the next day [29], except for loads with their own power supply. Figure 2.1 analyzes the load forecast diagram, the basis for making annual investment plans for developing the distribution grid, distribution power system operation plans, electricity market operation plans and plans, in addition to forecasting the electricity output of a power system or a specific area in the near future, usually within a period of one hour to one week.

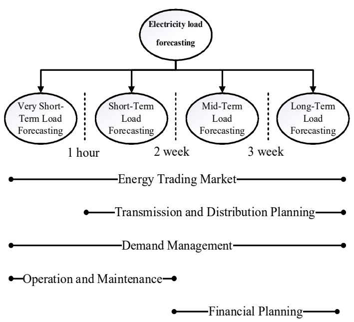


Figure 2.2: Types of electricity load forecasting

The classification of load forecasting into different types plays an important role. Each type of forecasting has its own characteristics and is suitable for different models. Therefore, this division helps to research, build models and perform forecasting effectively [30]. Below are the types of forecasting: Long-Term Load Forecasting (LTLF), Medium-Term Load Forecasting (MTLF), Short-Term Load Forecasting (STLF), Very Short-Term Load Forecasting (VSTLF)

Error assessment index in electricity load forecasting problem: The forecasting index is constructed with an average absolute percentage error. e_{MAPE} and mean square root e_{RMSE} represented by [31]

$$e_{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[x(i)-y(i)\right]^2} \qquad (2.1)$$

$$e_{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x(i)-y(i)}{x(i)}\right| \times 100\% \qquad (2.2)$$

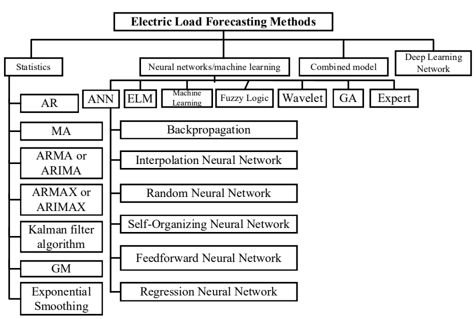


Figure 2.3: Methods of electricity load forecasting [33]

In the study [32], the e_{MAPE} index statistics are as follows:

Table 2.1: Evaluation criteria for reference mean absolute percentage error

MAPE	Dự báo
MAPE ≤ 10%	Kết quả cao
10%<MAPE ≤ 20%	Kết quả tốt
20%<MAPE ≤ 50%	Kết quả phù hợp
MAPE>50%	Kết quả thấp

graphs, instead of grid data. In electrical load forecasting, the GCN network exploits spatial relationships between features, enhancing the accuracy of the forecasting model. Third, the LSTM network efficiently processes time-series data, retains long-term information, and is suitable for the fluctuating nature of electrical load. It can handle nonlinear and unstable time relationships. Moreover, the HHO algorithm optimizes the parameters of the GCN-LSTM network, improving the convergence ability and forecasting accuracy of the model. With these outstanding features, this study has built the second group of forecasting methods (combined models): FF-DNN and R-DNN; SEQ2SEQ-LSTM; Wavelet-HHO-GCN-LSTM filter, to compare the results of the proposed model on the same dataset (Tien Giang power grid area). For the FF-DNN and R-DNN models and SEQ2SEQ-LSTM, the MAPE% errors are 0.5376 and 0.5450, respectively, both of which have errors less than 1%, meeting the required error threshold. The Wavelet-HHO-GCN-LSTM filter model has a MAPE% error of 0.5473 for the load group from day 2 to day 6. Additionally, the results of this model are also compared with the HHO-GCN-LSTM model (without using the Wavelet filter). The MAPE% error for the HHO-GCN-LSTM model is 0.5828. This demonstrates that the collected historical data for electricity generation is unstable and inaccurate. The Wavelet preprocessing significantly improves the model's error. In general, all three proposed combined models have a MAPE% error of less than 1%, meeting the error requirements set by the electricity regulation department.

Based on Table 4.4, the error for the LSTM and CNN models is less than 5%, while the other models, including WaveNet, FF-DNN and R-DNN, SEQ2SEQ-LSTM, HHO-GCN-LSTM, and Wavelet-HHO-GCN-LSTM filters, all have errors of less than 1%, meeting the MAPE error requirements for forecasting. To address cases where the forecasted and actual values (peaks or valleys) diverge significantly, the electricity forecasting system (HTĐ) must handle the situation as follows:

- For the forecasting program: the actual value will be updated in the model's input to compare with the forecasted value, calculate the error, and the model may be rerun to improve the forecast.
- For electricity grid operation: in the case of peak power (Pmax), Pmax is used in the electricity market for trading and supply (weekly or monthly). Generally, when there is an error between the forecasted and actual values, the forecast result is adjusted by adding a 5% buffer to prepare for grid operation. The principle is that the forecasted value used in the system should be greater than the actual value (but not too much). In the case of load curves, electricity load forecasting serves the purpose of grid structure, operational methods, and load response. The electricity grid always has reserves, but in cases of significant discrepancies, temporary power sources must be changed.

Based on the result graph in Figure 4.14, the forecasting results from 03/10/2022 to 07/10/2022 show that the Wavelet-HHO-GCN-LSTM model provides very good forecasting results when applied to real data.

4.4. Overall forecast results

Table 4.4: Overall forecasting results

Model	MAPE (%)
LSTM	4,6159
CNN-LSTM	3,7519
WaveNet	0,8749
FF-DNN và R-DNN	0,5376
Seq2Seq -LSTM	0,5450
HHO-GCN-LSTM	0,5828
Bộ lọc Wavelet -HHO-GCN-LSTM (T2-T6)	0,5473

According to the results shown in Table 4.4, the load curve forecasting results with various forecasting methods were tested with the same dataset from the Tien Giang power grid area. Based on the graphs in Figures 5.3, 5.4, 5.5, 5.8, 5.13, and 5.14, the methods show that the forecasted values closely align with the actual values. The mean absolute percentage error (MAPE%) is less than 5%. For the deep learning-based forecasting methods commonly used, including LSTM, CNN-LSTM, and WaveNet networks, the LSTM-based forecasting model yields a MAPE% of 4.6159, the CNN-LSTM model achieves a MAPE% of 3.75, and the WaveNet model (WaveNet = Wavelet + CNN) has a MAPE% of 0.8749, which is less than 1%. This indicates that the data collected and applied for testing the forecasting model has high noise during the data collection process. In the WaveNet model, thanks to the Wavelet data preprocessing before the data is input into the forecasting model, the reliability of the data source is improved. This also forms the basis for the proposed Wavelet-HHO-GCN-LSTM model.

4.5. Conclusion of chapter 4

In Chapter 4, building on both domestic and international research, this study has developed an overview diagram of the load curve forecasting model (Figure 4.2) by analyzing the factors influencing the results of the load curve forecasting problem. The study has identified the input variables for the load curve forecasting problem: past electricity generation (MWh), weather factor temperature, and time characteristics. The dissertation develops two groups of methods for forecasting electricity load curves. The first group consists of commonly used forecasting models, including LSTM, CNN-LSTM, and the WaveNet network. Specifically, the LSTM forecasting model yields a MAPE% error of 4.6159, CNN-LSTM produces a MAPE% of 3.7519, and the WaveNet network (WaveNet = Wavelet + CNN) achieves a MAPE% of 0.8749, all of which are less than 5%. Based on the graphs in Figures 4.3, 4.4, and 4.5, the load curve forecasts using the LSTM and CNN-LSTM models show good alignment with the forecast values. However, there are still high errors at peak points. The WaveNet model outperforms the others in error due to the data transformation process that enhances data quality and reduces model errors.

Based on the error results from the first group of methods, this study has developed the second group, which combines the advantages of the models from the first group. First, the Wavelet filter helps to analyze and separate the frequency components in load data, reducing noise and extracting features effectively to improve forecasting accuracy by processing signals at different levels of resolution. Wavelet is suitable for non-stationary and unstable data often encountered in load forecasting problems. Second, the CNN is generalized into GCN to handle unstructured data on

2.2. Long Short-Term Memory Network LSTM

From the shortcomings of the classical RNN network (long-step memory processing), LSTM is an improved network of RNN. LSTM is long-short-term memory/short-long/short-term memory is one of the artificial neural networks used in the field of deep learning, unlike feedforward neural networks. LSTM includes feedback connections. LSTM not only processes single data points, but also processes the entire data through the control gate.

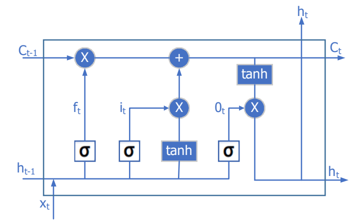


Figure 2.4: Internal structure of LSTM [34]

$$i_t = \sigma\left(W_i \times \left[h_{t-1,x_t}\right] + b_i\right) \quad (2.3)$$

$$f_t = \sigma\left(W_f \times \left[h_{t-1,x_t}\right] + b_f\right) \quad (2.4)$$

$$C_t = f_t \times C_{t-1} + i_t \times \left(\tanh\left(W_c \times \left[h_{t-1,x_t}\right] + b_c\right)\right) \quad (2.5)$$

$$O_t = \sigma\left(W_o \times \left[h_{t-1,x_t}\right] + b_o\right) \quad (2.6)$$

$$h_t = O_t \times \tanh\left(C_t\right) \quad (2.7)$$

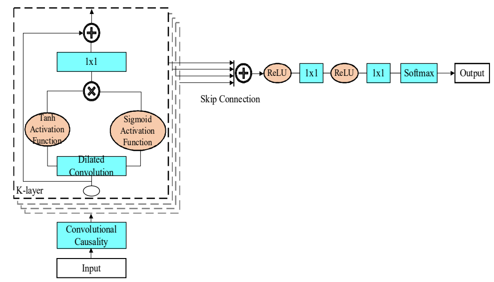


Figure 2.5: WaveNet Architecture [35]

2.3. WaveNet Network (WaveNet Network = Wavelet transform + CNN)

WaveNet network architecture is designed to generate raw audio waveforms [36], [37]. The WaveNet model can be extended beyond audio to be applied to any type of time series forecasting problem, capturing long-range dependencies without requiring too many parameters.

2.4. Gated Recurrent Unit GRU

In studies [38], [39], Long Short-Term Memory (LSTM) networks can address the issues of gradient explosion and vanishing gradients in RNNs, and LSTM has been widely used in the field of data processing in recent years.

GRU is a variant of LSTM with fewer internal units; it combines the input gate and the forget gate into a single update gate. It simplifies the training process and is computationally more efficient compared to LSTM. The substructure of the GRU is shown in Figure **2.6**, which has only two gates: specifically, the update gate and the reset gate. Its mathematical description is provided in equation (2.19).

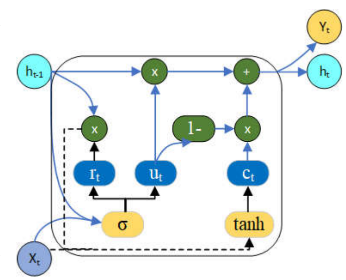


Figure 2.6: GRU Architecture [38]

$$\begin{cases} r_t = \sigma\left(W_r.\left[h_{t-1}, x_t\right]\right) \\ z_t = \sigma\left(W_z.\left[h_{t-1}, x_t\right]\right) \\ \tilde{h}_t = \phi\left(W_{\tilde{h}}.\left[r_t \times h_{t-1}, x_t\right]\right) \\ h_t = \left(I - z_t\right) \times h_{t-1} + z_t \times \tilde{h}_t \\ y_t = \sigma\left(W_0.h_t\right) \end{cases} \quad (2.8)$$

2.5. Wavelet transform

In studies [40], [41], [42], the Wavelet transform method is widely used in research, with the goal of the Wavelet filter: relying on the ability to analyze and transform data from the time domain to the frequency domain and vice versa. The transformation using Wavelet filters helps analyze data at different frequencies, applying filter coefficients to various frequency components, reducing noise while preserving important information. The mathematical model of the Wavelet is as follows:

A class of square-integrable functions can be represented by the Wavelet transform.

One of the important applications of the Wavelet transform is noise filtering, especially in image and signal processing. Wavelets have the ability to separate useful information from noise because they allow distinguishing between components at different levels of detail. In the noise filtering process, the wavelet coefficients that reflect noise are usually smaller and can be reduced or eliminated, while keeping the coefficients that represent important information.

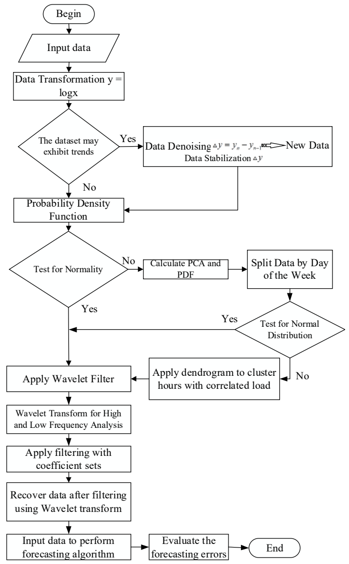


Figure 2.7: Wavelet Filter Algorithm Flowchart

$$f(x) \in L^2(R) \Rightarrow \int_{-\infty}^{\infty} |f(x)|^2 dx < \infty \quad (2.9)$$

$$\psi_{s,\tau}(x) = \frac{1}{\sqrt{|s|}} \psi\left(\frac{x-\tau}{s}\right) \quad \text{với} \quad s,\tau \in R, \quad s \neq 0 \quad (2.10)$$

Model applying Wavelet transform for data filtering in load forecasting

Step 1: Raw input data

Step 2: Perform data transformation using logarithmic function $y = \log(x)$

Step 3: Plot a graph to check if the data has a trend

Step 4: Calculate the Probability Density Function (PDF) for $\triangle y$

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad (2.11)$$

$$\Sigma = \frac{1}{n-1} X^T X \quad (2.12)$$

Z-Transformation : $Z = XW$ (2.13)

- Covariance Matrix: $\Sigma = \frac{1}{n-1} X^T X$ (2.14)

- Eigenvalue Equation: $\Sigma \upsilon = \lambda \upsilon$ (2.15)

- Data Transformation: $Z = XW$ (2.16)

Step 5: Calculate Dendrogram for Saturday and Sunday groups to cluster into hourly groups.

Dendrogram Formula

$$d(x_i, x_j) = \sqrt{\sum_{k=1}^{n} (x_{ik} - x_{jk})^2} \quad (2.17)$$

Distance between clusters:

Single linkage:

$$d(A,B) = \min\{d(x_i, x_j) \mid x_i \in A, x_j \in B\} \quad (2.18)$$

Complete linkage:

$$d(A,B) = \max\{d(x_i, x_j) \mid x_i \in A, x_j \in B\} \quad (2.19)$$

provides significantly lower values compared to the methods compared.

Adam-WaveNet	1062,31	4,49
RMSprop-WaveNet	95,93	0,51
HHO-WaveNet	56,13	0,30

According to the results shown in Table 4.3, the forecasting model using Adam-WaveNet has the highest error with an MAPE of 4.49. The Adagrad-WaveNet and SGD-WaveNet models yield better error results with MAPE values of 1.69% and 0.58%, respectively. In the RMSprop-WaveNet model, the MAPE decreased to 0.51. The proposed HHO algorithm optimized for the WaveNet network significantly improved results with a MAPE of 0.3%.

In summary, HHO is designed to operate efficiently in large parameter spaces due to its strong exploration and exploitation capabilities, enabling optimal search over large and complex parameter domains. The flexible transition between exploration and exploitation in HHO helps balance global search of the entire parameter space and local optimization, allowing HHO to avoid falling into local optima and improving computational quality. Additionally, the HHO algorithm significantly reduces computation time compared to classical methods, thanks to its simple and efficient optimization mechanism that quickly converges to the optimal region. These factors make HHO well-suited for problems with large and complex parameter spaces.

Forecasting results of the proposed model for load curve prediction.

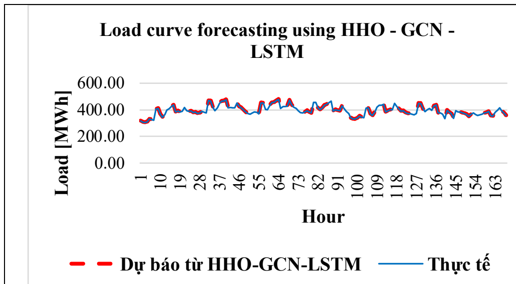


Figure 4.13: Load curve forecasting results using the HHO-GCN-LSTM network from 03/10/2022 to 09/10/2022

Based on Figure 4.13, it can be seen that the HHO-GCN-LSTM method provides better forecasting results compared to the WaveNet network when applied to real data. The MAPE error is 0.5828, with some peak points on March 9, 2023, and March 10, 2023 showing higher discrepancies.

Load curve forecasting using Wavelet-HHO-GCN-LSTM

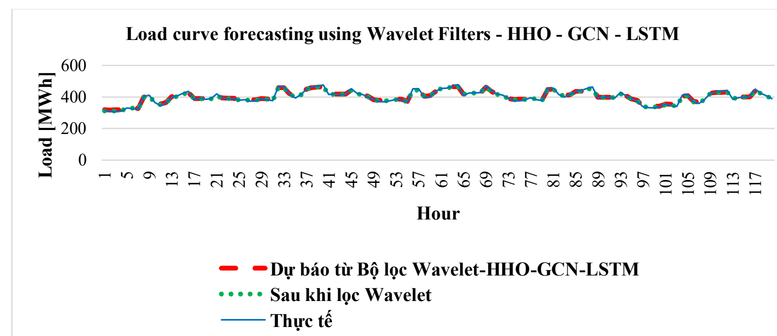


Figure 4.14: Forecasting results of the load curve using the Wavelet-HHO-GCN-LSTM filter from 03/10/2022 to 07/10/2022.

4.3.3. Load curve forecasting using Wavelet-HHO-GCN-LSTM filter model

In the STLF problem, this dissertation proposes the HHO-GCN-LSTM model, which considers the reliability of the input data through the Wavelet data preprocessing filter [79], [80]. The data consists of the electricity output from January 1, 2020, to December 4, 2023, of the Tien Giang power grid area, aimed at minimizing noise and erroneous data during the data collection process. The processed data is then used as input for the proposed model.

Figure 4.12 illustrates the integrated model of the Wavelet data preprocessing filter combined with the HHO-GCN-LSTM algorithm. In GCN-LSTM, the weights during the training process are optimized by the HHO optimization algorithm. The data, after being filtered by the Wavelet filter, is split into two datasets: 80% of the data is used for model training, and the remaining 20% is used for forecasting.

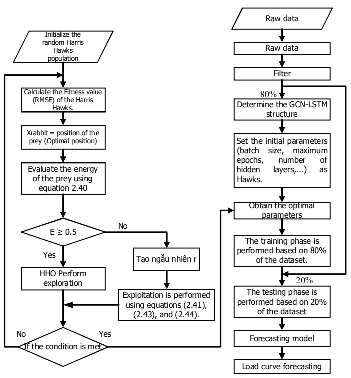


Figure 4.12: Proposed algorithm integrating Wavelet Filter – HHO – GCN – LSTM

Study [73] indicates that HHO is commonly used to optimize complex problems such as power distribution networks, multi-objective problems, and optimization in machine learning. In the HHO algorithm, X_{rabbit} is not calculated directly by a specific formula, but rather it represents the current best position in the population, corresponding to the individual with the smallest (or best, depending on the optimization problem) fitness value.

Table 4.2: Training parameters of the HHO-GCN-LSTM network

Parameters in the training model	Value
Learning rate (Training frequency)	0,03
Dim (The number of input features fed into each training iteration)	24
Lb (The lowest value of the data.)	0
Ub (The highest value of the data)	5000
Popsize (The element size for the optimization algorithm used for training the network)	50
Maxiter (The number of iterations (epochs) for the optimization algorithm used in training the network)	100
Epochs (Number of training iterations)	25
Bach_size (The size of the data frame is obtained from a single training iteration)	10

Like peak load forecasting, the forecast results from the trained model, in decimal form within the [0, 1] range, are subjected to reverse transformation using the original normalization function (which involves logarithmic and exponential functions) and are added to the initial base value – used in the process of converting data to normal distribution groups. After the reverse transformation back to the actual value domain, the resulting forecast will be evaluated for error against the actual values.

Comparing the HHO algorithm with other optimization algorithms

The research results presented in Table 4.3 show the performance of the discussed models. The HHO-WaveNet model performs better than the SGD-WaveNet, Adagrad-WaveNet, RMSprop-WaveNet, and Adam-WaveNet models. The mean absolute percentage error (MAPE) clearly demonstrates the superiority of the proposed method. Among them, the proposed model

Table 4.3: Forecasting results of the optimization algorithms combined with the WaveNet network

Model	RMSE	MAPE (%)
SGD- WaveNet	101,48	0,58
Adagrad-WaveNet	323,74	1,69

Hierarchical Clustering Algorithm:

Step 1: Calculate the distance between all pairs of points in the dataset.

Step 2: Find the pair of clusters with the smallest distance and merge them into a new cluster.

Step 3: Recalculate the distance between the new cluster and all remaining clusters.

Step 4: Repeat steps 2 and 3 until all points are merged into a single cluster.

Step 5: Perform Wavelet filtering with data groups for Saturday, Sunday hourly groups, and the remaining days as one group, applying filtering with wavelet coefficients to the transformed data in the frequency domains, followed by inverse transform: recovering data from frequency domain back to time domain.

Bước 6: Use the filtered data for forecasting.

2.6. HHO algorithm

In the studies [43], [44], the modeling of the exploration and exploitation stages of HHO is proposed, inspired by the hunting exploration, surprise attack, and different attacking strategies of Harris's hawk. HHO is a gradient-free optimization technique, based on population. Therefore, it can be applied to any optimization problem.

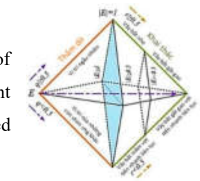


Figure 2.8: Stages of HHO

- Exploration stage

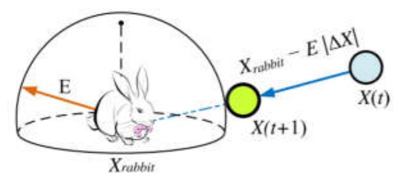
$$X(t+1)=\begin{cases} X_{rand}(t)-r_1\left|X_{rand}(t)-2r_2X(t)\right| & q\ge 0.5 \\ \left(X_{rabbit}(t)-X_m(t)\right)-r_3\left(LB+r_4(UB-LB)\right) & q<0.5 \end{cases} \tag{2.20}$$

$$X_m(t)=\frac{1}{N}\sum_{i=1}^{N}X_i(t) \tag{2.21}$$

- Transition from exploration to exploitation

$$E=2E_0\left(1-\frac{t}{T}\right) \tag{2.22}$$

- Exploitation stage



- Light trapping

$$X(t+1)=\Delta X(t)-E\left|JX_{rabbit}(t)-X(t)\right| \tag{2.23}$$

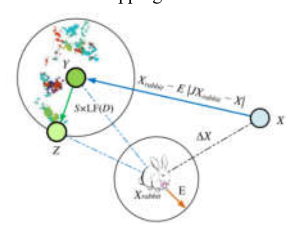
$$\Delta X(t)=X_{rabbit}(t)-X(t) \tag{2.24}$$

- Intense trapping

$$X(t+1)=X_{rabbit}(t)-E\left|\Delta X(t)\right| \tag{2.25}$$

Figure 2.9: Example of the overall vector in the case of intense trapping [43]

- Soft trapping with continuous fast progress.



$$Y=X_{rabbit}(t)-E\left|JX_{rabbit}(t)-X(t)\right| \tag{2.26}$$

$$Z=Y+S\times LF(D) \tag{2.27}$$

$$LF(x)=0.01\times\frac{u\times\sigma}{|v|^{\frac{1}{\beta}}},\sigma=\left(\frac{r(1+\beta)\times\sin\left(\frac{\pi\beta}{2}\right)}{r\left(\frac{1+\beta}{2}\right)\times\beta\times 2^{\left(\frac{\beta-1}{2}\right)}}\right)^{\frac{1}{\beta}} \tag{2.28}$$

Figure 2.10: Example of overall vectors in the case of soft trapping with continuous fast progress [43]

$$X(t+1)=\begin{cases} Y & if \quad F(Y)<F(X(t)) \\ Z & if \quad F(X)<F(X(t)) \end{cases} \quad (2.29)$$

- Intense trapping with continuous fast progress

$$X(t+1)=\begin{cases} Y & if \quad F(Y)<F(X(t)) \\ Z & if \quad F(X)<F(X(t)) \end{cases} \quad (2.30)$$

$$Y = X_{rabbit}(t) - E\left|JX_{rabbit}(t) - X_m(t)\right| \quad (2.31)$$

$$Z = Y + S \times LF(D) \quad (2.32)$$

2.7. GCN model theory

Studies [45], [46], [47], Graph Convolutional Network (GCN): Able to extract spatial and temporal features from the collected data source.

Definition of spatial data representation: The spatial dependency of the data is the relationship between the load values at nodes at the same time point, which is a key factor in solving the load forecasting problem.

For peak load forecasting:

$$G=(V,E)=X_t=G_t=\begin{bmatrix} P_{\max 1} & T_1^0 \\ P_{\max 2} & T_2^0 \\ P_{\max 3} & T_3^0 \end{bmatrix} \quad (2.33)$$

For load curve forecasting:

$$G=(V,E)=X_t=G_t=\begin{bmatrix} A_1 & T_1^0 \\ \vdots & \vdots \\ A_{24} & T_{24}^0 \end{bmatrix} \quad (2.34)$$

$$\left[X_{t+1},\dots,X_{t+T}\right]=f\left(G,\left(X_{t-n},\dots,X_{t-1},X_t\right)\right) \quad (2.35)$$

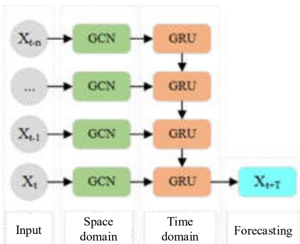
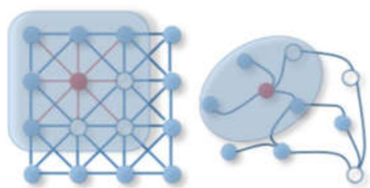


Figure 2.11: GCN and GRU hybrid network



(a) (b)

Figure 2.12: Sample model for GCN

2.8. Conclusion of chapter 2

Chapter 2 of the study focused on analyzing the factors affecting electricity consumption behavior based on historical data obtained from the electricity grid in Tien Giang, with the aim of selecting input variables for the proposed forecasting model. Additionally, the study outlined the reasons, roles, and importance of forecasting, classified forecasting, and summarized various load forecasting methods, including classical methods and deep learning network models with combinations. Moreover, the chapter provided a detailed presentation of the deep learning networks used in the research. Specifically, it developed a flowchart for the Wavelet filtering algorithm to process input data and enhance data quality before feeding it into the forecasting model. In addition, the HHO algorithm was proposed to optimize the deep learning GCN-LSTM network weights during the training process to create a load forecasting model. Finally, the research successfully developed a general load forecasting model based on deep learning networks, serving as a foundation for Chapters 3 and 4.

The thesis proposed a second model for forecasting the load curve to improve the accuracy of the electricity load curve prediction compared to the first model. This model is developed from a sequence-to-sequence forecasting approach by combining multiple LSTMs with irregular inputs, and this model supports variable-length input and output, aiming to improve the accuracy of the results compared to the first model. Essentially, the Seq2Seq-LSTM is an LSTM network applied for encoding and decoding. The input of the encoder is a sequence of variable length, and then the input data sequence is transformed into an encoded state by the LSTM network. The decoder is essentially another LSTM network, which converts the encoded state from a fixed format into a variable-length sequence. This is known as the encoding-decoding model, as illustrated in Figure 4.9.

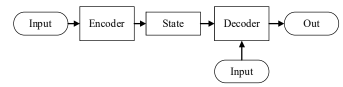


Figure 4.9: Diagram of encoder – decoder

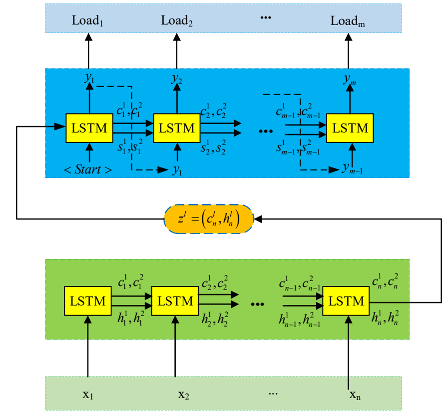


Figure 4.10: Seq2Seq-LSTM Model

Figure 4.10 illustrates the proposed LSTM model combined with Seq2Seq for predicting the load curve. The input data sequence $x=(x_1,x_2,\dots,x_n)$ is encoded using a multi-layer LSTM network, and the hidden state $h=(h_1,h_2,\dots,h_n)$ output from the first LSTM layer is used as the input to the second LSTM network.

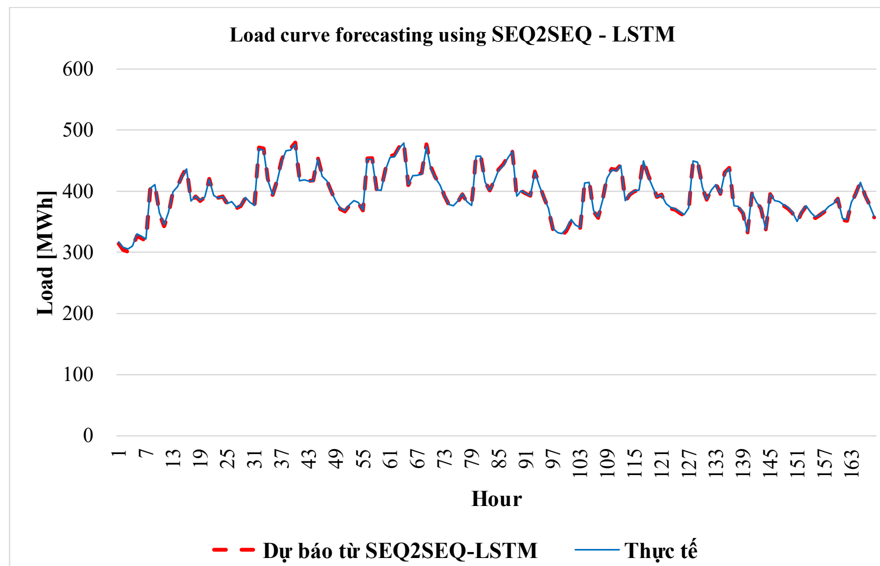


Figure 4.11: Load curve forecasting results using the Seq2Seq-LSTM network from 03/10/2022 to 09/10/2022

4.3.1. Load curve forecasting using FF-DNN and R-DNN

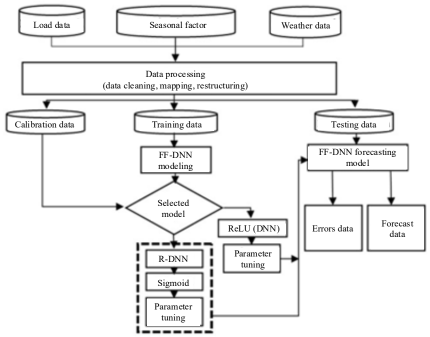


Figure 4.7: FF-DNN and R-DNN model architectures

The thesis proposes the first model in the load profile forecasting problem, combining deep learning techniques such as FF-DNN and R-DNN. The algorithm diagram is shown in Figure 4.7. This method provides faster and more accurate forecasting results. The study suggests that the algorithm strategy for short-term forecasting is based on deep learning techniques, where the output of each previous module is used as input for the next modules.

Table 4.1: Simulation parameters

Parameters in the training model	Value
Total sampling time	34416
Training data	27533
Test data	6883
Training algorithm	trainlm
Days of the week	[1 ~ 7]
Hours of the day	[0 ~ 23]
Learning rate (Training frequency)	0.05
Dim (The number of input sample dimensions fed into each training iteration)	3
Lb (The minimum value of the data.)	0
Ub (The maximum value of the data.)	5000
Popsize (The element size for the optimization algorithm used for training the network)	50
Maxiter (The number of iterations (epochs) for the optimization algorithm used for training the network)	100
Epochs (Number of training iterations)	25
Bach_size (The size of the data frame taken in one training iteration)	10

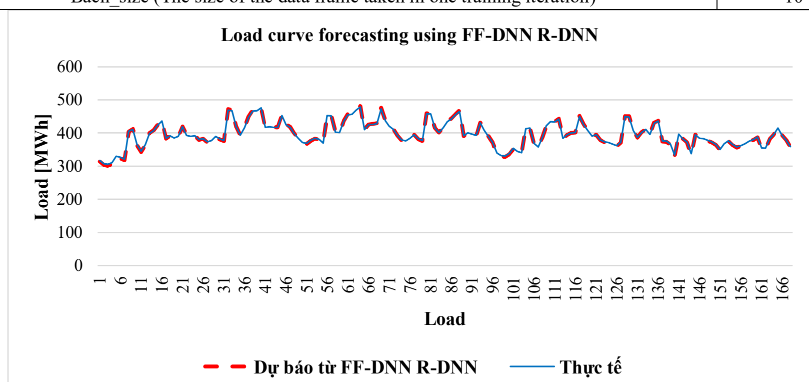


Figure 4.8: Load curve forecasting results using the FFDNN-RDNN network from 03/10/2022 to 09/10/2022

4.3.2. Load curve forecasting using Seq2Seq-LSTM model

CHAPTER 3. PEAK LOAD FORECASTING

3.1. Introduction to research problem

Peak load is the maximum value of the daily electricity demand curve [64]. Peak load forecasting plays a crucial role in mobilizing, coordinating, and planning power system operations to ensure grid stability and comply with environmental policies. However, accurate forecasting remains challenging due to the nonlinear and fluctuating nature of the data. Traditional time series and regression models struggle to capture the nonlinear relationships between inputs and outputs. Time series data are large, nonlinear, and noisy, requiring more advanced algorithms. The current trend is to combine statistical models with machine learning and deep learning to enhance forecasting performance [65].

The RNN-LSTM model [40] forecasts peak load with a MAPE of 8.6%, which is lower than the 10% standard. Daily peak load forecasting is a crucial factor in smart grids, helping optimize load balancing [64]. The multi-resolution model [66] combines high- and low-resolution information to predict the timing and magnitude of peak loads, reducing energy costs by implementing peak-hour saving measures. The sequence-to-sequence Bi-LSTM model [67] forecasts peak load for the next 24 hours and can be applied to both holidays and regular days. However, holiday data is often limited, making accurate forecasting more challenging. Studies [41] [68] developed a generalized model for forecasting peak power demand (Pmax) based on historical data and spatial-temporal factors. This research provides a generalized framework for Pmax peak power forecasting (Figure 3.1).

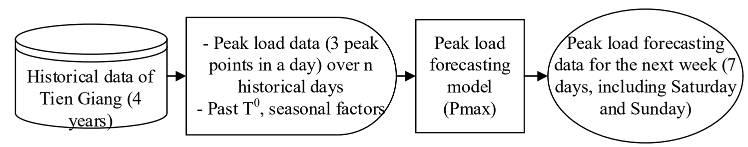


Figure 3.1: Process for preparing data for peak load forecasting

The input variables are determined by the factors affecting electricity consumption behavior from Figure 3.1. The dissertation proposes a peak power forecasting algorithm for the next day, using the combined GCN-GRU model. The mean absolute percentage error (MAPE) is used as the performance evaluation metric for the proposed model.

Figure 3.2 illustrates the overview diagram of the Pmax forecasting model based on deep learning, with input data including peak load, temperature at the time of Pmax, and time factors. This data is then normalized to reduce scale differences between input variables, ensuring consistency, quality, and effectiveness in the model training process. Next, the data is divided into two parts: 80% is used for training and model selection in the GCN-GRU, and the remaining 20% is used for forecasting.

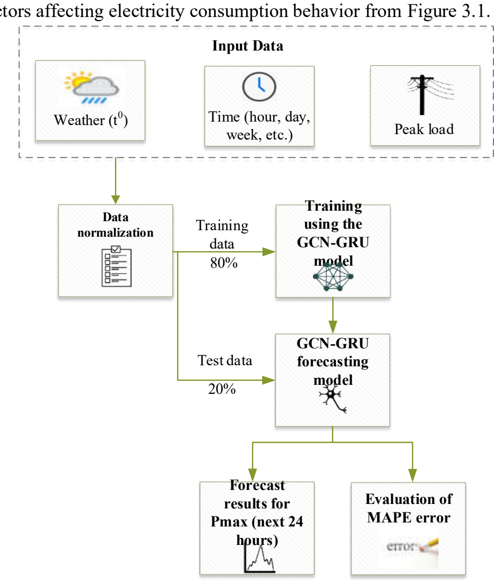


Figure 3.2: Overview diagram of the Pmax forecasting model

3.2. Analysis and evaluation of historical peak power data of Tien Giang province grid area

Based on the analysis of peak load data over a week, as shown in Figure 3.3, the red box marks one day's sample. A day's data, presented on the graph, shows that the peak load is divided into three highest points, and the other days of the week also have similar patterns with three peaks. For the last day of the week (Sunday), the peaks are less distinct (indicating a significant decrease in electricity usage). Therefore, the study analyzes the actual characteristics of peak loads in the Tien Giang power grid area; it divides the daily peak load into three time slots: from 0:00 to 11:00, from 11:00 to 17:00, and from 17:00 to 23:59. The study selects peak load points (the highest load at each time slot) and matches them with temperature data at those peak load points. The results of the relationship between peak loads over the three time slots and temperature are shown in Figure 3.3.

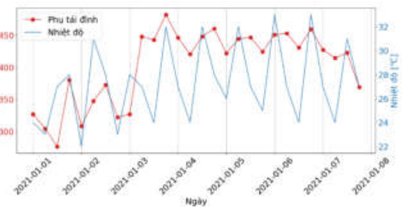


Figure 3.3: Peak load and temperature by hourly intervals over a week in Tien Giang

3.3. Proposed model for forecasting peak power Pmax – applying data from Tien Giang province

3.3.1. GCN-GRU 1-Cell Architecture

Figure 3.4 illustrates the GCN model on the left and the specific structure of a GRU cell on the right. The formula (2.21) of GCN-GRU extracts the spatial and temporal features of the data source, which helps to solve the peak load forecasting problem.

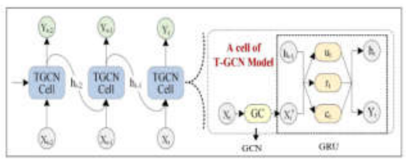


Figure 3.4: Detailed architecture of a GCN-GRU unit [41]

3.3.2. Spatial dependent data analysis

$$X_t = G = (V, E) \quad (3.1$$

$$G_t = \begin{bmatrix} P_{\max 1}\, T_1^0 \\ P_{\max 2}\, T_2^0 \\ P_{\max 3}\, T_3^0 \end{bmatrix} \quad (3.2)$$

$$E = \left(P_{\max} - T^0\right) \quad (3.3)$$

$$V = \{E_1, E_2, E_3\} \quad (3.4)$$

3.3.3. Time-dependent data analysis

$$X^{NxP} = \{X_t\}_{Dngay} = \{G(V,E)\}_{Dngay} \quad (3.5)$$

3.3.4. Peak power space-time relationship

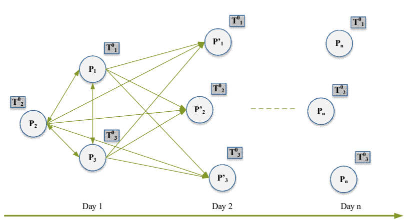


Figure 3.5: The relationship of spatial and temporal dependencies

The study [41] shows that the data in the peak demand prediction problem exhibits dependency as shown in Figure 3.5.

4.2. Common load curve forecasting model

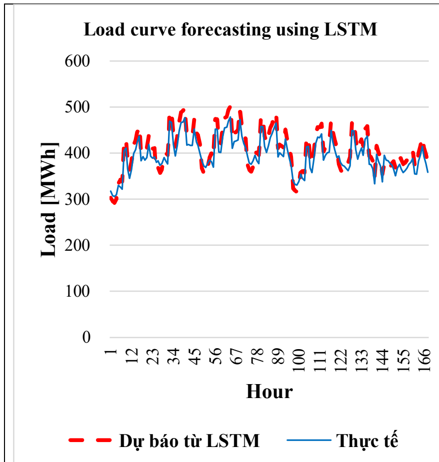


Figure 4.3: Forecasting results of the load curve using LSTM network from 03 to 09/10/2022

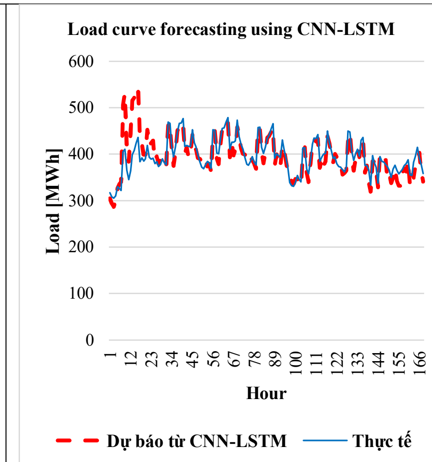


Figure 4.4: Forecasting results of the load curve using CNN - LSTM network from 03 to 09/10/2022

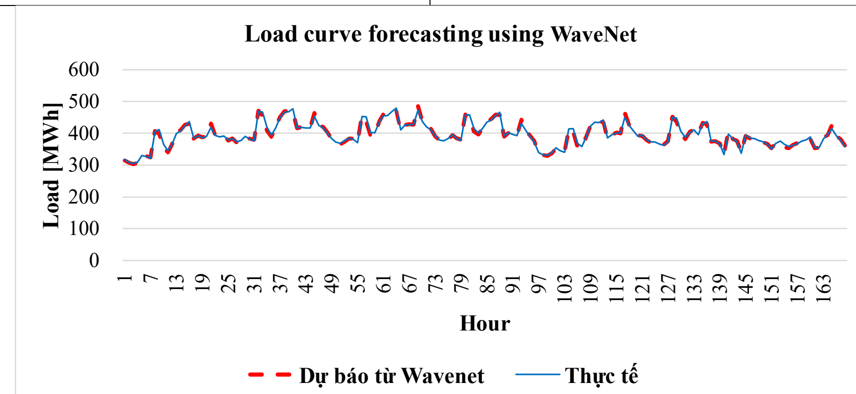


Figure 4.5: Forecasting results of the load curve using WaveNet network from 03 to 09/10/2022

4.3. Proposed model for load curve forecasting

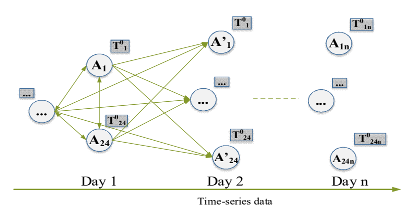


Figure 4.6: Representing the spatial and temporal dependencies in the dataset of the electricity load forecasting problem

CHAPTER 4. FORECASTING LOAD GRAPH

4.1. Introduction to research problem

Electrical load: Electrical devices connected to the power grid consume electrical energy and convert it into other forms of energy (light, mechanical energy, or thermal energy). These devices consume electrical energy in the form of current overtime. The unit of measurement for electrical load is [MWh]. The load diagram represents the electricity consumption characteristics over time of the system, its components, groups, and subgroups of electrical loads.

In [71], the power industry faces many challenges in power flow analysis, planning, and control of the power system. STLF has many studies aimed at improving forecasting accuracy. In [43], [51], [72], Wavelet is used for data preprocessing. The studies [60], [73] apply HHO to optimize the neural network weights. In [41], T-GCN is applied in forecasting. The Graph Convolutional Network (GCN) [74] combines GCN and GRU to learn spatial and temporal dependencies. CNN handles spatial features, while GCN is extended for graph data. RNN is commonly used for time series but has limitations, which are improved by LSTM and GRU [75], [76]. The study [70] demonstrates that LSTM and GRU are variants of RNN.

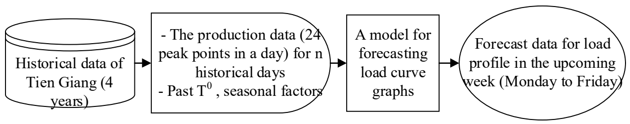


Figure 4.1: Method of using data for load profile forecasting

Therefore, in this dissertation, a combined model is proposed to solve the load forecasting problem, based on equation (2.35) as the foundation, with the aim of enhancing the input data by using a Wavelet filter and the HHO optimization algorithm for the GCN-LSTM network.

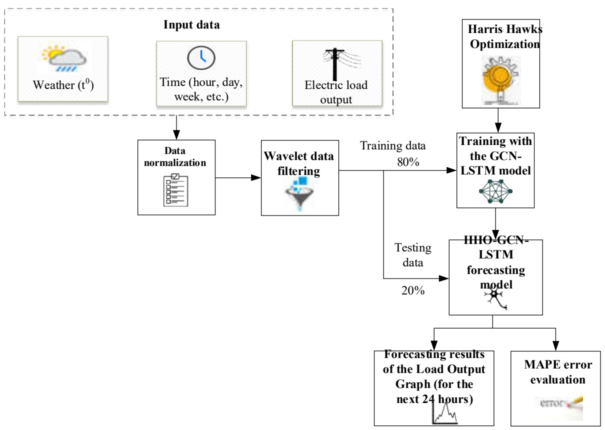


Figure 4.2: Overview diagram of the load forecasting model

Figure 4.2 presents an overview diagram of the STLF model. The raw input data, after going through the normalization process (to reduce the size and ensure consistency of the data source), is passed through a Wavelet filter to enhance the quality of the input data due to errors in the measurement process, as well as the unevenness of the load values at different time points. The dataset is split into two components: the first component (80%, corresponding to 27,533 samples, or 1,147 days) is used to train the model, while the second component (20%, corresponding to 6,883 samples, or 287 days) is used to test the model. During the training of the deep learning neural network GCN-LSTM, the loss function is aimed at reducing the error as quickly as possible. The HHO optimization algorithm is used to optimize the weights of the neural network during the training process. At the end of this process, the forecasting model is selected, and the mean absolute percentage error (MAPE) is used as the evaluation metric for the model.

3.3.5. Proposed model

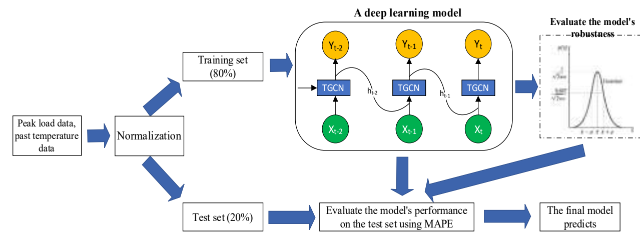


Figure 3.6: Proposed algorithm model for peak load forecasting GCN-GRU

The proposed Pmax forecasting model, GCN-GRU (T-GCN), uses the following input variables: 3 Pmax values within a day corresponding to the Tmax temperature at the Pmax peak points during the day. The training and testing process for the proposed model is carried out using the Tiền Giang grid dataset, with Pmax and temperature data collected from 1434 samples, corresponding to 34,416 samples in total. Through the analysis of the peak points within a day, which are 3 peaks, the corresponding number of Pmax peaks in the dataset is 4302 samples.

The input data is normalized to the range [0,1]. Then, the dataset is split into two components: 80% of the data is used for the training set (3442 samples, corresponding to 1147 days), and the remaining 20% is used as the test set for forecast predictions (860 samples, corresponding to 287 days). The training dataset is fed into the T-GCN deep learning network for training. The output from the T-GCN network layers, including the final layer, is combined using a Gaussian function to generate noise. The results, combined with the Gaussian function, are compared with the model after training from the T-GCN network. The MAPE index is evaluated for the model, aiming to assess the effectiveness of the forecast model under the influence of Gaussian noise.

Table 3.1: Training parameters of GCN-GRU

Parameters in the training model	Value
Learning rate (Training frequency)	0.05
Dim (The number of input features fed into each training iteration)	3
Lb (The lowest value of the data.)	0
Ub (The highest value of the data)	5000
Popsize (The element size for the optimization algorithm used for training the network)	50
Maxiter (The number of iterations (epochs) for the optimization algorithm used in training the network)	100
Epochs (Number of training iterations)	25
Bach_size (The size of the data frame is obtained from a single training iteration)	10

Forecast results from the training model, represented as decimal numbers in the range [0, 1], are subject to inverse transformation using the initial normalization function (which includes logarithmic and exponential functions) and then added to the original baseline value used in the process of transforming data into normally distributed groups. After transforming the values back to the actual value range, the results are evaluated for errors with the actual values to select the forecasting model with the best error performance for peak load forecasting.

3.4. Overall peak power Pmax forecast results

Table 3.2: Results of forecasting using different methods

Model	MAPE (%)
LSTM	4.7093
CNN-LSTM	4.0972
WaveNet	1.1109
GCN-GRU	0.0006

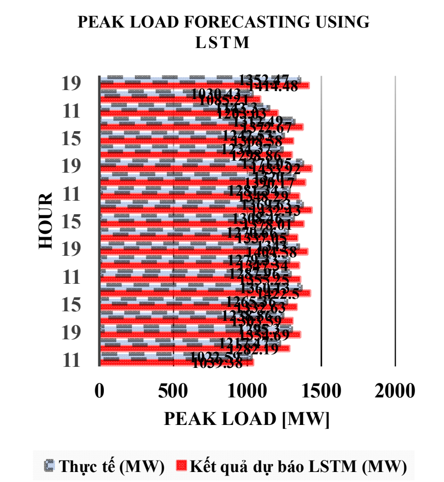


Figure 3.7: The forecasted peak load results using LSTM from March 20, 2023, to March 26, 2023

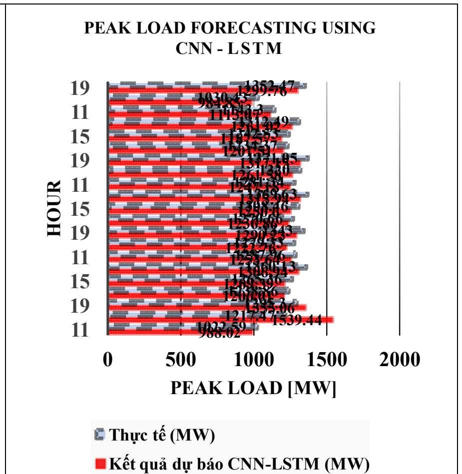


Figure 3.8: The forecasted peak load results using CNN-LSTM from March 20, 2023, to March 26, 2023

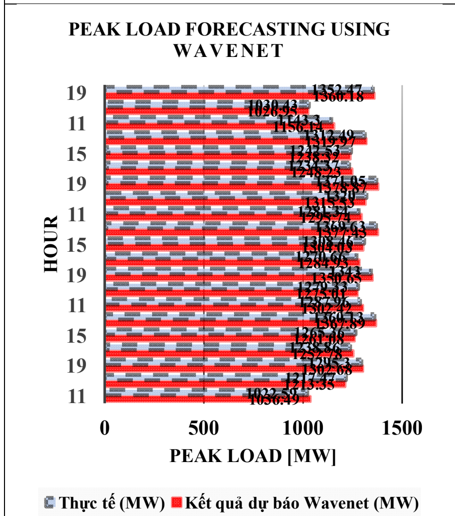


Figure 3.9: The forecasted peak load results using the WaveNet network March 20 - 26, 2023

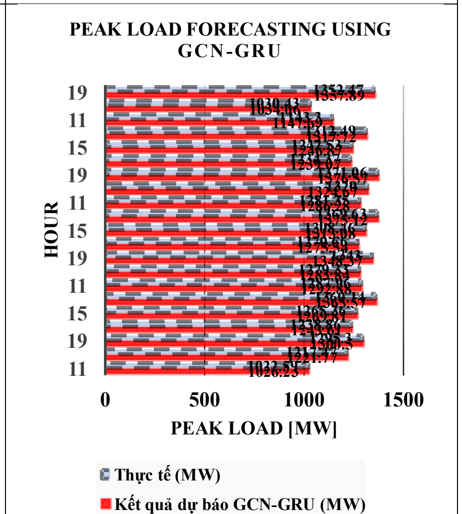


Figure 3.10: The forecasted peak load results using the GCN-GRU model from March 20 - 26, 2023

According to Table 3.2, the results of the mean absolute percentage error (MAPE%) for different peak load forecasting methods are presented. In most of the forecasting methods, the forecasted and actual values are closely aligned. However, there are differences in the MAPE error at the peak points. The LSTM model has a MAPE of 4.7093%, with higher errors at peak hours (11, 15, and 19). The LSTM network is effective in peak load forecasting but

still has some limitations. It requires a large amount of data and high-quality historical data to achieve good results, and the training time for LSTM is usually long due to its complex structure and numerous parameters that need to be optimized. Furthermore, LSTM does not adapt well to noisy data, which can reduce the accuracy of the model. The combined CNN-LSTM model has a MAPE of 4.0972%, showing an improvement over the LSTM model. However, the error is still high at peak points, with a significant discrepancy between the forecasted and actual values at the 19:00 peak point, where there is a large load change (household and industrial loads). The CNN-LSTM network is limited in its ability to generalize data when there are abnormal fluctuations. The WaveNet model shows a significant improvement in error compared to both the LSTM and CNN-LSTM models, with a MAPE of 1.1109%. The forecasted and actual values closely align, with very low errors at peak points compared to the LSTM and CNN-LSTM models. WaveNet effectively handles non-linear relationships with complex features in past peak load data. Moreover, WaveNet uses dilated convolution layers, allowing the network to learn long-term relationships in time-series data. This is particularly useful for peak load forecasting, as load trends often have long cycles such as daily, weekly, or seasonal patterns. The WaveNet model is a combination of a Wavelet filter and CNN, where the data is pre-processed by removing noise using the Wavelet filter before being fed into the CNN for forecasting. The proposed model in the thesis for peak load forecasting is the GCN-GRU model, which combines graph convolutional networks with gated recurrent units. This model takes a new approach to analyzing and evaluating spatial and temporal dependencies in peak load forecasting. As a result, the proposed GCN-GRU forecasting model achieves a MAPE of 0.0006%, with no errors at peak points in the given time frames. The GCN-GRU model effectively leverages spatial dependencies from historical data, and the GRU efficiently handles time-series data, ensuring connectivity and accurate forecast results. The results demonstrate that the proposed GCN-GRU peak load forecasting model meets the regulations set by the power regulatory authority.

3.5. Conclusion of chapter 3

In Chapter 3, the study focuses on forecasting peak load, and the proposed model is tested using data from the Tien Giang power grid. Through the analysis of factors positively influencing peak load, the study selects the following input variables: past peak load, temperature, and seasonal factors (presented in Appendix 1 and Appendix 3). The dataset used in the study was collected from the Tien Giang power grid from January 1, 2020, to December 4, 2023. By analyzing and evaluating historical peak load data, it was found that the peak points in a day are 3 peak points. The first step of the study implemented peak load forecasting models using popular deep learning models such as LSTM, CNN-LSTM, and WaveNet. Among these models, LSTM and CNN-LSTM provided forecasts that closely matched the actual values. However, the error in these two methods was still high at peak points during the day due to the influence of temperature changes, residential load, and industrial production at different times of the day.

For the WaveNet model, the error at peak points is small, and the model's performance improves significantly. Building on the results of the three common forecasting models, the study developed the GCN-GRU peak load forecasting model, leveraging the ability of GCN to handle spatial and temporal data. The GCN network can learn the relationships between data nodes, while the GRU processes time series data, historical load data, and the time when the peak load occurs, capturing the trend and cyclic nature of the data. In the hybrid GCN-GRU model, LSTM is replaced by GRU to handle long-term memory time series, like the WaveNet model. The difference lies in the combination of GCN instead of WaveNet, enhancing the reliability of the past data collected. This improved the MAPE error to 0.0006%, and the performance of the proposed model significantly improved the MAPE index, meeting the criteria for the mean absolute percentage error.