

CHAPTER II

LITERATURE REVIEW

2.1 Introduction

Load forecasting is the heart of power system management in the digital age, especially in the context of smart grids that require short-term and long-term forecasting accuracy to increase efficiency in planning energy production and distribution with stability and efficiency. Due to the complexity of time series data that is nonlinear and has various environmental factors that affect electricity loads, such as weather, consumer behavior, working days or holidays, etc., it is necessary to develop analysis techniques that can handle such data appropriately. In recent years, deep learning techniques have been increasingly popular for load forecasting, especially sequence models. However, the accuracy of forecasting models does not only depend on the model structure but also on appropriate feature selection and feature engineering that allow the model to learn data more deeply. In addition, model explainability is another important issue, especially in systems that require transparency and reliability to meet the requirements of accuracy, explainability, and appropriate feature selection. This research is interested in the approach that focuses on developing an explainable time series model by combining contextual feature selection and temporal cross-validation to obtain reliable results in the context of real load forecasting. The following topics will explore the knowledge related to various research areas, including data preparation and feature selection techniques, the development of deep learning time series models, model description techniques, and comprehensive model evaluation approaches in load forecasting.

2.2 Literature Overview

To provide an overview of past approaches to load forecasting using deep learning techniques, this research has compiled and compared related research, divided into 2 groups: the research group using deep learning models for load forecasting and evaluating model performance and the research group focusing on feature selection and creation and model explainability methods. Table 2.1 summarizes the main components of each research, including feature engineering, selecting the best model from forecasts compared to other models or categories, metrics used for evaluation, techniques used for feature selection, and model explainability.

From the analysis of the research in Table 2.1, many works using various deep learning models in the context of load forecasting can teach temporal relationship and non-linear behavior better, along with the selection and design of specific features in contextual feature engineering. However, there is still a lack of non-linear feature selection, evaluation by time-based data partitioning, and the clear description of the model results. Therefore, our research aims to develop an approach that combines the selection of non-linear features using MI, time-based cross-validation for time series data, and model description using SHAP for deep analysis under the framework of LSTM, GRU, Bi-LSTM, and Bi-GRU models to create an accurate and easy-to-understand load forecasting framework.

Table 2.1 Overview of Feature Techniques, Model Selection, Evaluation Techniques, and Feature Selection in Electrical Load Forecasting

Ref	Feature Engineering	Best Model	RMSE	MAE	MAPE	Feature Selection	Model Explainability
Panapon gpakorn & Banjerdpongchai, 2019	✓	LSTM	✓	✓	-	MI	-
Vanitha & Swaroop an, 2023	✓	Bi-LSTM	✓			Correlation	-
Mpaweni mana et al., 2020	STDAN	LSTM	-	✓	✓	Active Power	-
Prakash et al., 2023	✓	LSTM, Bi-LSTM	✓	✓	✓	-	-
Habbak et al., 2023	✓	NN	✓	-	✓	-	-
Atef & Eltawil, 2020	✓	Bi-LSTM	✓	✓	✓	-	-
Pavlatos et al., 2023	✓	Bi-LSTM	✓	-	✓	-	-

Table 2.1 Overview of Feature Techniques, Model Selection, Evaluation Techniques, and Feature Selection in Electrical Load Forecasting (Continued)

Ref	Feature Engineering	Best Model	RMSE	MAE	MAPE	Feature Selection	Model Explainability
Sias et al., 2024	✓	Multi Bi-GRU	-	✓	✓	-	-
Abumohsen et al., 2023	✓	GRU	✓	✓	✓	-	-
Cordeiro-Costas et al., 2023	✓	LSTM	Normalized	✓	-	-	-

Table 2.2 Comprehensive Overview of Modeling, Feature Engineering, Evaluation, Feature Selection, and Explainability in Load Forecasting Research

Ref	Feature Engineering	Model	RMSE	MAE	MAPE	Feature Selection	Model Explainability
Lee et al., 2023	✓	XG Boost	-	-	✓	-	SHAP value based
Neubauer et al., 2025	✓	ED, XG Boost	Normalized	✓	-	-	SHAP, Attention
van Zyl et al., 2023	✓	CNN	✓	-	✓	MI	SHAP, Grad-CAM
Jang et al., 2023	✓	RAID	-	-	✓	-	SHAP
Koprinska et al., 2015	✓	LR, BPNN	✓	-	-	MI, Relief	-
Pirbazi et al., 2019	✓	GBRT	-	✓	-	MI, RFE, Elastic Net, F-regression	-
Liu et al., 2024	✓	KAN, Transformer, Informer	✓	-	-	Correlation Feature Self-Assignment Module	KAN

Table 2.2 Comprehensive Overview of Modeling, Feature Engineering, Evaluation,
Feature Selection, and Explainability in Load Forecasting Research
(Continued)

Ref	Feature Engineering	Model	RMSE	MAE	MAPE	Feature Selection	Model Explainability
Maarif et al., 2023	✓	SL-LSTM, DL-LSTM, Bi-LSTM	✓	-	-	SHAP	SHAP
Wang et al., 2025	✓	SMLR, XG Boost, LASSO-XG Boost	✓	✓	✓	SHAP	SHAP
Van Zyl et al., 2024	✓	1D-CNN	✓	✓	✓	SHAP, XG Boost, Feature Importance, Variance Threshold, NSGA-II	SHAP, Grad-CAM
Wu et al., 2020	✓	Attention-LSTM	✓	✓	-	Attention weights	Attention weights
Ullah et al., 2024	✓	CNN-LSTM	✓	✓	✓	Correlation	-
Fan and Hyndman, 2012	✓	Semi-parametric additive	✓	✓	-	-	-
Shi et al., 2018	✓	Deep RNN	✓	✓	-	-	-

From Table 2.1, additional research related to the introduction of feature selection techniques and model description capability in load forecasting is summarized in Table 2.2, which summarizes the main components of each research study, including feature engineering, all models used in forecasting, evaluation metrics, feature selection techniques, and model description capability. The trend of developing load forecasting models focuses on interpretability and accurate feature selection to increase both efficiency and transparency. Many research studies focus on using SHAP and other XAI techniques to analyze feature importance. However, there are still gaps in using filter-based methods such as MI and temporal cross-validation, including using SHAP for feature selection, which our research will supplement to obtain a system that is both accurate, interpretable, and reliable in the long run.

2.3 Overview of Feature Techniques, Model Selection, Evaluation

Techniques, and Feature Selection in Electrical Load Forecasting

To delve deeper into the trends, technologies, and limitations of the related research in Table 2.1, this section describes in-depth details of each selected research, focusing on feature selection methods, techniques used for load forecasting, proposed models, evaluation metrics, and limitations of each work, and proposes ways in which we can improve upon those limitations within the framework of load forecasting with deep learning.

(Panapongpakorn & Banjerdpongchai, 2019) This research presents a non-linear feature selection (Mutual Information—MI) method, where the information relationship between two variables captures the non-linear relationship to select the important input variables for the model. This research aims to apply autoregressive integrated moving average (ARIMA) and seasonal autoregressive integrated moving average (SARIMA), artificial neural network (ANN), and long-short term memory (LSTM)-based recurrent neural network (RNN) to improve the performance of short-term electrical load forecasting (STLF) in energy management systems (EMS). Time series features were structured, and the performance was measured with Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). The models from neural networks have

better performance than the models from time series analysis, with the best performing model being LSTM. However, the performance does not cover the division of train/validation sets by time, and there is no time-aware dataset division (temporal cross-validation), so the model still cannot learn well in all time periods. The technique used to describe the model, which features affect the model output, has not been mentioned, and there is still a lack of in-depth analysis of the specific model directly.

(Vanitha & Swaroopan, 2023) This paper proposes a method to compare Stacked GRU-RNN and Bidirectional LSTM (Bi-LSTM) artificial neural network models in forecasting electricity load and renewable energy production in Smart Grid systems using real energy consumption data along with the analysis of the relationship of the input data to select the most influential features from the use of correlation analysis. The feature selection is linear relationship statistics. The linear relationship between 2 variables has a point that it does not support non-linear relationships from some features, so it does not cover all the impacts of the features on the model output. The results show that the Bi-LSTM model provides high accuracy in energy and load forecasting.

(Mpawenimana et al., 2020) This paper compares the short-term and medium-term energy load forecasting capabilities of LSTM and ARIMA models in the context of a smart home with an energy harvesting system. A new data preparation technique called STDAN (Same Time a Day Ago or Next) is proposed for handling missing values, which performs better than the average or previous value filling method. The paper states that the prediction uses only active power data from the dataset, which can be considered a feature selection, focusing on a single feature believed to be related to the energy load, which is a manual selection. The experiments show that LSTM significantly outperforms ARIMA in all cases. More sophisticated feature engineering can also be developed to help the model learn better. There is no mention of efficient feature selection and no explanation of which features influence the results.

(Prakash et al., 2023) This paper presents a forecast of the daily COVID-19 cases in India over the next 6 months using time series analysis techniques such as machine learning and deep learning, as well as a hybrid model. To compare the performance of different models in predicting the number of infected people using historical data

and evaluating the performance through statistical indicators. The experimental results show that basic models such as Prophet, Vanilla LSTM, and Bi-LSTM give more accurate results than complex or hybrid models. This research is not directly in the context of energy or electrical load, and there is no feature selection or model description.

(Habbak et al., 2023) This article is a systematic review covering load forecasting techniques in smart grids. The analysis results show that techniques using Machine Learning (ML) and Neural Networks (NN) provide the highest forecasting accuracy, with significantly lower Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) values than other methods. No new methods or in-depth comparisons were found, efficient feature selection, and lack of approaches to explain causal models.

(Atef & Eltawil, 2020) This article presents a comparative study between unidirectional (uni-LSTM) and bidirectional (bi-LSTM) LSTM models in 1, 2, and 3-layer nesting, using an automatic parameter tuning tool to find the best model. The experimental results show that Bi-LSTM significantly outperforms Uni-LSTM and Support Vector Regression (SVR) in terms of forecasting accuracy. When considering error values such as RMSE, MAPE, and MAE, deep nested models do not significantly outperform single-layer models, and they take longer to compute. There is no mention of efficient feature selection, and there is no explanation of how each feature affects the other.

(Pavlatos et al., 2023) This paper proposes a Bi-LSTM based neural network-based electrical load forecasting framework that can simultaneously process historical and future data to improve the forecast accuracy of temporal data. Experiments on multiple datasets show that Bi-LSTM significantly outperforms RNN, LSTM, and GRU. MAE and RMSE are used for performance evaluation. It is found that additional performance evaluation techniques can be added to cover more comprehensive models. There is still no efficient feature selection, and there is a lack of approaches to explain the causal model.

(Sias et al., 2024) This research presents a multivariate bidirectional GRU model combined with periodic features for forecasting energy loads and renewable energy sources (e.g., solar cells). The model uses multivariate data, such as system energy

data and weather data (for power generation), and tests are conducted on daily, hourly, and minute data levels. The experimental results show that the proposed model has the highest accuracy. And it takes less processing time than the basic Bi-GRU and Bi-LSTM models. From this research, it is not clear which features affect the model performance, and it lacks the step of explaining the relationship of the features to the results.

(Abumohsen et al., 2023) This paper uses deep learning techniques to forecast electrical power loads: Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Recurrent Neural Networks (RNN). By testing all three models, it was found that the GRU model gave the best results in terms of accuracy and the lowest error. There are still limitations found in this research: the lack of feature selection steps and model result explanations, and the analysis only analyzes the results, not the components of the model. It is possible to analyze the behavior of the GRU in more detail.

(Cordeiro-Costas et al., 2023) This paper focuses on evaluating and comparing the accuracy of various artificial intelligence (AI) techniques in forecasting electrical loads in buildings. To compare with the forecasting of loads in single-family homes in the United States, using a 10-fold cross-validation technique to assess the bias and variance of each model. The experimental results found that LSTM is the model with the lowest error distribution in the validation and test datasets. Using cross-validation General models may not be suitable for time series data and lack in-depth analysis of feature selection.

From the research studies in the past few years, there is a clear trend in applying deep learning techniques together with the selection and design of specific features, or so-called contextual feature engineering, to address the complexity of electrical load data in real contexts. Traditional models such as ARIMA or linear regression often cannot effectively handle behaviors that change with context, such as days of the week, weather conditions, or holidays. While deep models such as LSTM and GRU can learn temporal relationships and non-linear behaviors better. However, these models are most effective only when they receive input data with appropriately designed features, such as adding calendar effects, temperature, humidity, sunlight, and various time indicators such as rush hours or public holidays, which allow the

model to learn complex patterns of electrical loads more accurately. Therefore, research in this direction is continuously increasing, focusing on both developing model architectures and enhancing the potential of input data.

2.4 Comprehensive Overview of Modeling, Feature Engineering, Evaluation, Feature Selection, and Explainability in Load Forecasting Research

To address the challenge of developing a load forecasting model that is not only accurate but also transparent and interpretable, several recent studies have focused on appropriate feature selection, comprehensive evaluation, and the use of Explainable AI (XAI) techniques to enhance the reliability of the model. This chapter presents an in-depth analysis of those studies, examining the key elements of the model, feature selection, evaluation, and model explanation, and points out the limitations and solutions that will be further developed in our work. From Table 2.2, it can be explained as follows:

(Lee et al., 2023) Using Explainable AI for Transparency in Load Forecasting, we propose a new metric that makes the feature importance analysis more reliable, supporting applications in real systems that require transparency, such as energy systems. Since the work has not been tested with multiple datasets or models, which may limit the generality of the metric.

(Neubauer et al., 2025) This paper presents a multi-step heating load forecasting model that emphasizes the ability to explain AI using SHAP values and temporal attention mechanisms to enhance the understanding of the process of data-driven forecasting models. Comparison with other explainable techniques such as MI is not discussed.

(van Zyl et al., 2023) This article analyzes and compares the capabilities of two types of Explainable Artificial Intelligence (XAI) techniques: Grad-CAM (Gradient-weighted Class Activation Mapping) and SHAP (Shapley Additive Explanations) in performing feature selection for energy demand forecasting models from large time series using a multi-headed CNN as the model base. CNN models may not be suitable

for time series load data with clear temporal dependency and lack of comparison with other models for comprehensive results.

(Jang et al., 2023) This article presents a Robust and Interpretable DPLF (RAID) model for Daily Peak Load Forecasting (DPLF) that is both accurate and interpretable using multiple Deep Neural Networks (DNNs) with SHAP values analysis to explain the importance of features. However, there is no evaluation of temporal generalization or cross-time validation.

(Koprinska et al., 2015) This paper presents a two-step feature selection method for 5-minute electricity load forecasting. Initially, features are selected based on daily and weekly electricity usage patterns, such as load from the previous hour, and feature selection techniques such as Relief and Mutual Information are used to assess the importance of features and select the most suitable feature set. The results show that using this feature selection method can reduce the number of features without compromising the forecast accuracy. However, the work has not included the interpretability perspective from XAI or analyzed the impact of deep features.

(Pirbazari et al., 2019) studied the effectiveness of feature selection methods in short-term household energy forecasting, especially in the context of smart meter data. It shows that feature selection techniques can effectively screen out suitable variables specific to each household, speed up model training, reduce model complexity, and produce forecasting results that are close to or better than those without feature selection. This research lacks the mention of deep model description techniques.

(Liu et al., 2024) This paper proposes a new model called Correlation Feature Self- Assigned to flexibly combine features based on the degree of data correlation, the Interpretable Kolmogorov-Arnold Network (KAN) is the ultimate predictor for forecasting various types of energy loads in IES. There is no comparison with other XAI techniques such as SHAP or MI, which are suitable for non-linear data.

(Maarif et al., 2023) This research successfully developed an energy forecasting model using LSTM combined with XAI, which is not only efficient in forecasting but also clearly explains the model results, allowing users to understand and trust the results obtained from the model. The Bi-LSTM and double-layer LSTM models perform

slightly better than single-layer LSTM, with lower RMSE. This research uses SHAP to select important features and train a new model, which significantly improves forecasting performance. However, there is no mention of feature selection before model training. Immediately introducing all features into the model may cause overfitting or noise from unimportant features. The work does not mention the use of techniques such as k-fold cross-validation or other data partitioning to prevent overfitting. A single train/test partition may result in model bias or incorrect performance evaluation in real-world use cases.

(Wang et al., 2025) This research demonstrates the effectiveness of using the SHAP technique to analyze the importance of features in a short-term load forecasting model by identifying the features that have the most impact on the model results, which helps to improve the model accuracy and reduce the complexity of the model by removing unnecessary features. Using the SHAP technique also increases the transparency of the model operation, allowing users to understand and verify the model operation effectively, which is very useful for applying the model in real situations that require reliability and transparency. The research found that the model description from SHAP has not been linked to a systematic feature selection strategy.

(Van Zyl et al., 2024) This article presents the ability of SHAP to reduce the number of features without significantly degrading the model performance. In some cases, it helps to make the model more stable and improve the interpretation of the results. However, it is not suitable as a method for selecting “initial” features but is suitable for fine-tuning after obtaining the initial feature set. Although SHAP is not a direct feature selection technique, the researchers use SHAP scores to rank the features and then build a new model by comparing it with other feature selection methods. Therefore, SHAP is used strategically to “select features by importance.” Although this work uses a variety of feature selection methods, it still lacks a filter method that supports non-linear relationships. Independent of the model, such as MI, the addition of MI enhances the “pure data” view that is independent of the structure or bias of any model. In addition, a single model (1D-CNN) is used as the basis for analysis. The results of SHAP depend on the model used. If other models are used for comparison, such as LSTM or Bi-LSTM, the ranking of features may be different. Using only one model may

limit the reliability of the conclusion of "which features are important" after model training. And cross-validation is used to evaluate the accuracy of the model for each selected feature set.

(Wu et al., 2020) This paper proposes a combined deep learning framework based on an attention-based LSTM model to improve short-term forecasting performance by selectively focusing on important temporal features. The attention mechanism enhances the model's ability to capture key dependencies in time-series data and improves prediction accuracy. However, the study does not perform explicit feature selection, and the explainability of the model is limited to attention weights without providing a comprehensive feature-level interpretation such as SHAP.

(Ullah et al., 2024) This paper presents a comprehensive review and simulation study of short-term load forecasting using CNN–LSTM hybrid models, highlighting their ability to extract spatial features via CNN and temporal dependencies via LSTM. The results demonstrate improved forecasting accuracy compared to single models. However, the study mainly focuses on performance evaluation and lacks feature selection analysis and model explainability techniques to interpret how input features influence the forecasting outcomes.

(Fan & Hyndman, 2012) This paper proposes a semi-parametric additive model for short-term electrical load forecasting by decomposing load patterns into trend, seasonal, and smoothing components using statistical feature engineering techniques. The model provides good interpretability and stable forecasting performance; however, it is limited in capturing complex nonlinear relationships and does not incorporate feature selection or advanced model explainability methods.

(Shi et al., 2018) This paper proposes a deep learning-based load forecasting framework using a novel pooling deep recurrent neural network to capture complex temporal dependencies in household electricity consumption. The proposed model significantly improves forecasting accuracy compared to traditional methods; however, it treats the model as a black box and does not provide explicit feature importance analysis, feature selection, or explainability to support model interpretability and reliability.

While deep learning models have become increasingly popular due to their ability to produce highly accurate results, a major problem is the interpretability of the models, which often have a black box appearance. That is, even if the results are accurate, they cannot clearly explain which factors the model uses to make decisions. In the context of energy management in institutions or organizations, accurate forecasting alone may not be enough if decision-makers cannot understand or trust the decision-making process of the model. Therefore, modern research has begun to focus on interpreting model results using techniques such as Shapley Additive Explanations (SHAP), which can indicate how much each feature influences the model's results. This technique allows for a transparent analysis of which factors drive the forecast results, such as temperature, time of day, or day of the week, and can be used to further develop energy policies or improve models in the future. Combining the ability to explain results with forecast accuracy is an important direction in the development of AI models for sustainable energy management.

2.5 Research Gaps in Load Forecasting Framework

From the review of past research, it was found that there is a tendency to use various deep learning models, such as LSTM, Bi-LSTM, and CNN, in the context of energy load forecasting, both short-term and long-term, which allows the model to learn the temporal characteristics of the data efficiently. However, many researchers still lack feature selection in a way that supports non-linear relationships, including model evaluation in a way that is appropriate for temporal data, such as time-aware data partitioning or temporal cross-validation. In addition, although many researchers have started to use Explainable AI (XAI) techniques such as SHAP and Grad-CAM to analyze the importance of features and increase the transparency of the model results, there are still significant gaps in the application together with filter-based feature selection methods such as Mutual Information (MI), which can help filter important features directly from the data, independent of the model, and reduce bias from the model structure itself. In evaluating the forecast results, most researchers use various indicators to measure the performance of the model in many dimensions, including the accuracy of the prediction value, the average absolute error, and the relative error

to the actual value. Using these indicators together allows for a more comprehensive analysis of the quality of the model, especially when applied in real situations that require both accuracy and reliability.

Based on the above findings, this research aims to develop a comprehensive load forecasting approach encompassing three main dimensions: feature selection using mutual information to support nonlinear relationships; modeling results through Moving Average, DNN, LSTM, Bi-LSTM, CNN-LSTM, and Attention-LSTM models for multi-dimensional model coverage; detailed model description within the NN group using SHAP; evaluation using Temporal Cross-validation suitable for timeline data; feature development and enhancement using Feature Engineering to suit data characteristics; and the use of multi-dimensional metrics including RMSE, MAE, and MAPE. This will result in a developed forecasting system that is accurate, transparent, and interpretable, suitable for use in smart energy systems requiring long-term reliability.