

CHAPTER I

INTRODUCTION

1.1 General Introduction

From the Smart Grid Driving Plan, according to the framework of the Master Plan for the Development of Thailand's Smart Grid System 2015-2036, it will promote the development of various infrastructures and the management of resources in the power distribution system that are necessary to support the transition to a new generation of power grids efficiently and environmentally friendly. This will help support Thailand to move towards clean energy and reduce carbon dioxide emissions, as well as to support the energy transition, which requires the development of a flexible power system to support the increase in renewable energy in line with the national energy plan targets. This will be an option for maintaining the country's electricity balance and managing peak electricity demand efficiently, divided into 5 main pillars, one of which is the Load Response and Energy Management System (DR & EMS). In the past few years, the demand for energy has grown rapidly. The increasing use of renewable energy and the development of digital technology have changed the operation and planning of the power system. These changes have caused both utilities and energy consumers to adopt smarter and more demand-responsive solutions to manage energy more efficiently and sustainably.

Electricity usage forecasting, which is the ability to predict future energy use, plays an important role in achieving this goal. Especially in universities or commercial buildings where electricity usage fluctuates with academic calendars, holidays, seasons, and weather conditions. Accurate short-term forecasting is essential to effectively manage the demand side, schedule, and integrate with renewable energy sources. One case is Suranaree University of Technology (SUT), located in Nakhon Ratchasima, Thailand. The university has a photovoltaic (PV) solar system and is monitored by smart meters that report electricity usage every 15 minutes. However,

the presence of solar power makes it difficult to directly observe the actual electricity demand (net load) because the measured grid load is compensated for by solar power generation. This study reconstructs the pure load by combining the grid load and solar power generation to represent the university's actual energy demand, which serves as the target for one-day load forecasting.

This research utilizes deep learning models in the field of neural networks combined with advanced methods such as K-fold validation, Mutual Information (MI), and Shapley Additive Explanation (SHAP) interpretation to improve forecasting accuracy and clarity. The goal is not only to accurately forecast electricity consumption but also to enhance the intelligence and responsiveness of the university-level energy system in line with the direction of Thailand's national smart grid system.

1.2 Problem Statement

In an era where energy demand is highly volatile and renewable energy systems are continuously integrated into the power grid, accurate electricity load forecasting is crucial for efficient energy management, especially in educational institutions like Suranaree University of Technology (SUT), which has inconsistent energy usage patterns that vary depending on weekdays, public holidays, semesters, and weather conditions such as temperature and humidity that affect air conditioning usage. The solar PV system installed within the university further complicates energy measurement because the energy meter only reports the net load after deducting the energy generated by the solar cells. This results in missing data on actual energy usage, which makes forecasting using traditional methods such as linear regression or ARIMA inaccurate and unable to handle contextual complexity.

The problem statement is as follows,

- 1) Accurate electricity load forecasting is essential for efficient energy management, especially in systems integrated with solar PV. However, existing models often rely on incomplete load data derived from subtracting PV generation from metered values, resulting in inaccurate representations of actual energy consumption. Additionally, traditional forecasting methods struggle to capture the complex, context-

dependent nature of energy usage patterns influenced by time, weather, and behavioral variations.

2) Improving the accuracy of electricity load forecasting requires efficient feature engineering. Because energy consumption behavior data is complex and changes with contexts such as time, weather, weekdays, or holidays, which have non-linear relationships with electricity load. However, traditional methods using linear techniques such as correlation analysis or feature selection based on statistical values often cannot capture these deep or hidden relationships. As a result, the resulting models have low performance and cannot accurately reflect energy consumption behavior in real situations or do not cover important contexts.

3) The transparency of deep learning models is also a limitation in practical applications. Although deep learning models can provide accurate predictions, they have limitations in interpreting and explaining the results. They cannot explain models with the characteristics of a black box, resulting in a lack of transparency and an inability to effectively support decision-making.

1.3 Research Objectives

To address such challenges, this study aims to develop a novel short-term electricity load forecasting model using deep learning techniques in the RNN family and enhance its accuracy with contextual feature engineering and interpretability tools to enable more accurate, transparent, and efficient energy decision-making for short-term (one-day-ahead) electricity load forecasting.

The main objectives of this thesis are as follows,

1) To develop a one-day electricity load forecasting model using deep learning techniques. We will compare deep learning models with basic models, including Moving Average, DNN, LSTM, Bi-LSTM, CNN-LSTM, and Attention-LSTM. Specifically, we will examine the model with the highest accuracy based on real-world load data reconstructed from electricity meters and solar panels.

2) To improve accuracy and reliability through the design of appropriate and high-quality features. Mutual Information (MI) is a promising approach for capturing

complex nonlinear energy consumption patterns. and systematic evaluation using performance indicators including RMSE, MAE, and MAPE.

3) To improve the transparency and interpretability of the model, SHAP analysis is used to identify influential features and analyze their importance to gain a deeper understanding of the model's performance.

1.4 Scope and limitations

1.4.1 Scope

This study focuses on electrical load forecasting using deep learning techniques. In addition, it studies the use of feature engineering techniques to improve the input data for the learning model, including the selection of necessary features and the description of variables through the model. In summary, the scopes are considered as follows:

1) This study focuses on the development of a one-day-ahead electricity load forecasting model for Suranaree University of Technology (SUT) using deep learning techniques including moving average, DNN, LSTM, Bi-LSTM, CNN-LSTM, and Attention-LSTM.

2) The target variable used in the forecasting model is the pure load, reconstructed by combining grid-based electricity consumption with solar PV generation data to represent the university's actual energy demand.

3) The input features are designed to reflect real-world contexts, including temporal data (e.g., yearly hours, quarter-hour intervals), calendar effects (e.g., weekdays, holidays, long weekends), environmental factors (e.g., ambient temperature, relative humidity), and lag-based load patterns (e.g., previous day's load).

4) Model training utilizes K-Fold cross-validation, and performance is evaluated using standard forecasting metrics: RMSE (Root Mean Square Error), MAE (Mean Absolute Error), and MAPE (Mean Absolute Percentage Error).

5) The study incorporates SHAP (Shapley Additive Explanations) to interpret model outputs, allowing for an understanding of feature importance and offering insights for practical improvements in energy management strategies.

1.4.2 Limitations

The limitations of this study are to consider three case studies as follows:

1) While the pure load is reconstructed by combining grid and PV data, minor discrepancies may exist due to unaccounted factors such as system losses or unmonitored sub-loads.

2) SHAP analysis for RNN-based models provides approximate feature importance and may not fully capture all intricate dependencies within deep neural networks.

1.5 Conception

The main idea of this research comes from the need for accurate and interpretable electricity load forecasting, which is essential for planning and managing energy systems in an era of rapid and uncertain energy usage patterns, especially in the context of complex power systems that require transparent, data-backed decision-making.

This research proposes a forecasting structure for electricity consumption using time-sequence deep learning models, including LSTM, GRU, Bi-LSTM, and Bi-GRU. Moving Average, DNN, CNN-LSTM, and Attention-LSTM are compared to obtain comprehensive results. Electricity consumption data is organized using Day-Aware Data Arrangement to clearly distinguish electricity usage patterns. Feature engineering is performed to identify influential variables, and model robustness is evaluated using twelve carefully designed test sets representing different times and operating conditions. To increase the reliability and understanding of the model, the system applies SHAP (Shapley Additive Explanations) to explain the model results and uses Mutual Information (MI) to select non-linear features, as well as Time Series Cross-Validation (TSCV) to evaluate the results comprehensively according to the context of time-sequence data, covering accuracy indicators of RMSE, MAE, and MAPE to evaluate the model's capabilities in multiple dimensions.

The integration of these components aims to create an electricity load forecasting system that is not only highly accurate but also whose results can still be interpreted well, are reliable, and can be confidently applied in real situations.

1.6 Research Benefits

This research presents a practical and interpretable deep learning-based framework for one-day-ahead electricity load forecasting, using real-world data from a university campus with integrated solar PV systems. By reconstructing the pure load and incorporating contextual features such as weather, time, and holidays, the model better reflects actual electricity demand and addresses forecasting challenges in renewable-integrated environments.

At the institutional level, the model supports more accurate energy planning, demand-side management, and cost optimization. At a broader level, it serves as a scalable solution for similar commercial or academic settings, promoting efficient energy use and integration of renewable energy. At the national level, the study aligns with the goals of energy transition and smart grid development by enabling more flexible, data-driven, and responsive electricity systems that can support peak demand management and sustainability targets.

By combining forecasting accuracy with explainability through SHAP, the research contributes not only to academic advancement but also to the foundation of smarter and more sustainable energy infrastructure.

1.7 Structure of thesis

This thesis is organized into five chapters, outlined as follows:

Chapter I: This chapter presents the background and significance of the thesis, including the challenges arising from complex variations in electrical load patterns. It discusses the problem, research objectives, scope and limitations, the proposed methodology concept, and the overall structure of the thesis.

Chapter II: This chapter covers theoretical principles and research on electrical load forecasting models, including a review of relevant optimization methods, feature analysis, and gap analysis in existing research.

Chapter III: This chapter presents one-day forecasting of electricity consumption using supervised deep learning techniques combined with daily data sorting to select models most likely to be further developed for maximum accuracy and to find the most efficient data management methods for achieving optimal results.

Chapter IV: This chapter discusses an advanced data-driven load forecasting framework for high-volume solar power systems: a case study of the SUT campus and data from ISO New England, demonstrating data preparation, model selection, simulation, and feature analysis using various tools for forecasting accuracy and reliability.

Chapter V: The final chapter summarizes the key research findings and evaluates the effectiveness of the proposed methodology, including a comparison of the results of the models and feature analysis tools from simulation and analysis results.