

CHAPTER V

CONCLUSION

5.1 Conclusion

This study proposes a method for developing a one-day advance electricity load forecasting model using data from Suranaree University of Technology. It employs deep learning techniques, including Day-Aware Data Arrangement (DGA), to compare deep learning models such as LSTM, GRU, Bi-LSTM, and Bi-GRU. The results indicate that LSTM and Bi-LSTM tend to provide the most accurate forecasts, with GRU showing the fastest simulation time in initial testing. Subsequently, selected models—Deep Learning, DNN, LSTM, Bi-LSTM, CNN-LSTM, and Attention-LSTM—were further selected for comparison with baseline models to improve accuracy and reliability. This was achieved through Mutual Information (MI) and Shapley Additive Explanation (SHAP) analysis, optimized through data collection and feature engineering tailored to the context of the university's integrated solar power generation capacity. Using three accuracy indices—Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Squared Error (RMSE)—the model from the NN group, the Bi-LSTM model using the SHAP 3 feature selection method for the top 3 most important features, provided the best overall forecasting performance from all test datasets. The Bi-LSTM model was also the most accurate, yielding the lowest metric values for daily forecasts compared to all other models. Feature selection that aligns with the model's learning mechanism has a greater impact on performance than considering statistical relationships alone. However, experimental results also indicate that using only the top three features does not always yield the best results. In highly complex datasets, such as those with holidays, seasons, and weather influences, using multiple features allows the model to learn the data context more comprehensively. Another dataset used for simulation, the ISO New England dataset, showed that the Attention-LSTM model performed best in forecasting electricity load across all test datasets. With the

lowest RMSE and MAE/MAPE values, CNN-LSTM is the most suitable model for this type of dataset, exhibiting the best overall forecasting performance. The CNN-LSTM model also shows the highest accuracy in daily pre-load forecasting. Time-sequence models, particularly Bi-LSTM and CNN-LSTM, significantly outperform time-structure insensitive models, reflecting the fact that the ability to learn past and future relationships in time-sequence data is a crucial factor in electricity load forecasting accuracy.

Analysis of the features that have the greatest impact and influence on electricity load forecasting using both MI statistical analysis and SHAP principles revealed that the lag load feature, or the value of electricity load over the past 1 day, is the feature most correlated with the forecasting target and has the greatest impact on the model's decision-making. This characteristic was consistent across both datasets. MI, as a statistical measure, can capture nonlinear relationships and is easy to use, but it's unclear how the feature is actually utilized by the model. It's suitable for initial feature screening and as a statistical indicator of how much a feature shares information with the target variable, independent of any model. In contrast, SHAP analysis can show the relationship between data and the model, allowing for the selection of necessary features and reducing forecasting errors. It's suitable for datasets that show relatively consistent electricity load behavior, clear time-repeating patterns, and are driven by only a few key features, leading to more accurate forecasts. It's ideal for in-depth feature selection. However, the priority of features obtained from MI and SHAP differs due to their different objectives.

The performance of electricity load forecasting does not depend solely on the model or feature selection method but also on the consistency between the data structure, model, and shared feature set. The findings can be applied to the design of electricity load forecasting systems in the context of smart energy systems and provide guidance for selecting appropriate models and features for future time-scheduling forecasting tasks.

5.2 Suggestions

Based on the findings of this study, several recommendations can be proposed to enhance the applicability and robustness of short-term electricity load forecasting models in future research. First, the incorporation of additional explanatory variables, such as electricity price signals, socioeconomic factors, and distributed energy resource penetration, may further improve forecasting accuracy and model generalization under more diverse operating conditions.

Second, although this study demonstrates the effectiveness of advanced recurrent neural network architectures combined with feature selection and interpretability techniques, future work could explore hybrid and ensemble learning strategies to leverage the complementary strengths of different model structures. The integration of probabilistic forecasting approaches is also recommended to provide uncertainty information that can support more informed decision-making in power system operation and planning.

Third, the use of advanced model interpretability techniques could be further extended to investigate dynamic feature importance across different time periods and operating scenarios. This would provide deeper insights into how electricity consumption patterns evolve over time and under varying conditions, particularly during extreme events or atypical load behaviors.

Finally, future studies may consider applying the proposed forecasting framework to larger-scale power systems or multi-region datasets with different load characteristics to further validate its robustness and generalizability. Such extensions would contribute to the development of reliable, interpretable, and practical electricity load forecasting systems for real-world applications.