**CHAPTER FIVE**

**SUMMARY AND CONCLUSION**

**5.1 Summary**

This research explored the application of machine learning algorithms for short-term energy load forecasting in urban Nigerian environments prone to supply instability. Using historical energy consumption records from the UCI Machine Learning Repository, the study modeled load behavior using both the Prophet and LSTM frameworks. Prophet was deployed with seasonality components and holiday regressors, offering a decompositional approach with rapid training. LSTM, on the other hand, implemented sequential deep learning logic with a 24-hour input window to predict stability index values. Implementation was carried out in Google Colab using Python, TensorFlow, Keras, and other scientific computing libraries. Both models were trained on 80% of the dataset and tested on the remaining 20%. Performance was evaluated using MAE, RMSE, and MAPE across blackout and stable sequences. Results indicated that while Prophet captured seasonal patterns and holiday-induced variations, it lagged during sudden spikes in demand. LSTM showed improved adaptation to baseline patterns but had difficulty accurately forecasting abrupt transitions, with a notable smoothing effect during high-volatility segments. The final LSTM performance metrics (MAE = 0.005 kWh, RMSE = 0.005 kWh, MAPE = 34.73%) reinforce the model’s moderate reliability in stable conditions but suggest limitations in volatile periods.

**5.2 Recommendations for Future Research**

Future research can build upon the limitations identified in this study by enhancing the architectural depth and adaptive responsiveness of the models employed. One promising direction would be the integration of attention mechanisms or transformer-based layers into the existing LSTM framework. These advanced components could enable the model to focus dynamically on critical periods within the input sequence, thereby improving its ability to respond to sharp load transitions often triggered by blackout recovery or abrupt consumption shifts. Another strategic improvement lies in the development of hybrid models that combine Prophet’s effective seasonal decomposition with LSTM’s temporal pattern recognition. Such an ensemble framework could leverage the strengths of both approaches, yielding forecasts that are not only interpretable but also capable of capturing nonlinear behaviors under fluctuating supply conditions. In addition, incorporating real blackout event markers into the dataset—such as timestamps from NEPA outage logs or Smart Meter drop intervals—could serve as powerful exogenous features that guide the models toward better identification and prediction of discontinuities. By explicitly recognizing these moments in the input data, forecasting tools may become more robust in anticipating demand rebounds. Finally, expanding the dataset to include broader categories of energy consumption, particularly from industrial and commercial sources, would improve the generalizability of future models. While the current study focuses on residential usage, capturing load dynamics across sectors will offer richer insights and support more comprehensive grid planning strategies tailored to Nigeria’s diverse energy landscape.

**5.3 Conclusion**

This study has successfully demonstrated the use of Prophet and LSTM models for forecasting energy stability index values in Nigeria's erratic grid environment. While both models achieved acceptable error rates under stable conditions, their limitations under blackout recovery sequences suggest the need for more robust architectures and deeper temporal modeling techniques. Nonetheless, the models offer promising foundations for decision-support systems in low-resource energy planning, with potential for enhancement through hybridization and data enrichment strategies.

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