

DESIGN AND IMPLEMENTATION OF AN EDUCATIONAL ELECTRICITY LOAD FORECASTING SYSTEM: A MODULAR AND ADAPTIVE APPROACH

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INTRODUCTION

Accurate electricity load forecasting is essential for reliable energy management and grid optimization. Traditional methods like ARIMA often fail to capture nonlinear relationships or adapt to complex external factors such as weather and holidays.

This project applies deep learning techniques—specifically Multilayer Perceptron (MLP) and Long Short-Term Memory (LSTM) models—to improve short-term load forecasting accuracy. The system is designed with modularity and reproducibility in mind, providing a professional yet educational framework for energy prediction.

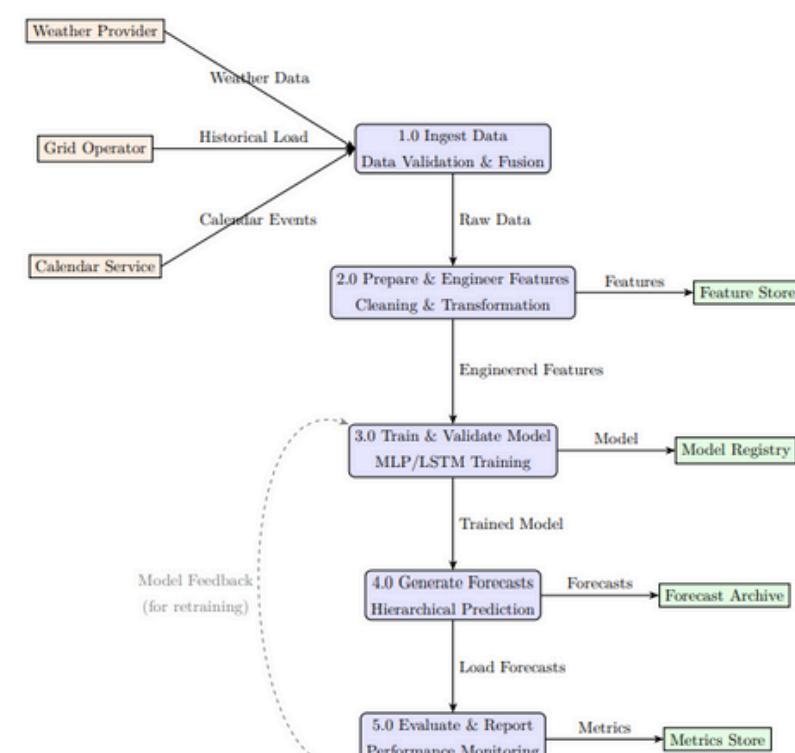
GOAL

To design and implement a modular and adaptive forecasting system that integrates MLP and LSTM models for electricity demand prediction, ensuring accuracy, transparency, and reproducibility.

RESULTS

The project is still under active development. Model implementation and system integration are ongoing, and testing phases have not yet been completed. Preliminary experiments will be conducted once the data preprocessing and feature engineering modules are finalized.

Final performance evaluation and comparative analysis between MLP and LSTM models will be presented in the completed version of the project.



METHODS

The proposed system follows a Clean ML Architecture structured into five layers:

- Data Layer: Collects and preprocesses load, weather, and calendar data. Handles missing values and detects anomalies.
- Feature Layer: Generates engineered variables such as lagged load, hour-of-day, and Heating/Cooling Degree Days (HDD/CDD).
- Model Layer: Implements MLP and LSTM models with dropout, batch normalization, and adaptive learning rate optimization.
- Validation Layer: Applies rolling-origin cross-validation using RMSE and MAPE metrics to mimic real-world forecasting scenarios.
- Application Layer: Coordinates the end-to-end workflow, manages model retraining, and enables visualization of forecasts.

This modular structure enhances flexibility, transparency, and facilitates the educational exploration of forecasting techniques.

FUTURE DIRECTIONS

Future work will focus on completing the development of the forecasting models and evaluating their performance. Specific next steps and system extensions will be defined once the current implementation and testing phases are finished. These directions will guide the refinement of the modular architecture and the preparation of final results for presentation.

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