Load Forecasting Using Machine Learning and Demand Response Planning in Microgrids

By Shahla Salimi

Introduction

In recent years, the increasing demand for electricity and the integration of distributed energy resources have highlighted the need for more intelligent energy management systems, particularly in microgrids. Accurate load forecasting plays a crucial role in enhancing the efficiency, reliability, and economic performance of these systems. By anticipating energy consumption patterns, operators can make better decisions to reduce peak loads, optimize resource allocation, and implement effective demand response (DR) strategies.

This project presents a two-stage framework that combines machine learning-based load forecasting with demand response planning in a microgrid context. In the first stage, a Long Short-Term Memory (LSTM) neural network is trained on historical hourly load data from the American Electric Power (AEP) dataset. Various temporal features such as hour of the day, day of the week, and Fourier terms are engineered to improve the model's predictive accuracy. In the second stage, the predicted load profile is used in a linear programming model to optimize DR activation, aiming to reduce peak demand while respecting operational constraints.

The goal of this project is to demonstrate how the synergy between machine learning and optimization techniques can improve the operational performance of microgrids. The results show that the LSTM model achieves high accuracy in load forecasting, and the DR planning successfully reduces total and peak load, contributing to a more balanced and efficient energy system.

Project Objective

The objective of this project is to design and implement an intelligent framework for load forecasting in a microgrid using machine learning techniques, followed by demand response optimization to reduce peak consumption and enhance system efficiency.

Initially, an LSTM recurrent neural network is utilized to accurately forecast hourly electricity demand in a distribution-level microgrid. Using the forecasting results, a linear programming model is applied to perform demand response scheduling over a 24-hour period, aiming to reduce peak load while maintaining operational constraints.

This project demonstrates that integrating deep learning with mathematical optimization provides an effective solution for smart energy management in modern microgrids.

Overview of Key Concepts (English)

This section provides an overview of the fundamental concepts used in the project:

1 .Microgrid

A microgrid is a localized energy system that includes generation, storage, and consumption, capable of operating independently or in connection with the main grid. Microgrids play a vital role in sustainable and intelligent energy management.

2 .Load Forecasting

Load forecasting refers to the estimation of future electricity demand. Accurate forecasting is critical for energy production planning, distribution efficiency, and effective demand response strategies.

3 .LSTM Neural Network

LSTM (Long Short-Term Memory) is a type of recurrent neural network (RNN) designed to model sequential data like time series. It is capable of capturing long-term dependencies and is well-suited for hourly load forecasting tasks.

4 .Demand Response (DR)

Demand Response involves adjusting electricity consumption in response to signals such as electricity prices or grid operator instructions. It helps reduce peak load and optimize energy use.

5 .Linear Programming

Linear programming is a mathematical optimization method where the objective function and constraints are linear. In this project, it is used to calculate the optimal amount of demand reduction across different hours.

Data Description and Preprocessing

The dataset used in this project is the AEP_hourly.csv, which contains hourly electricity load data collected from the American Electric Power (AEP) utility. This dataset spans more than 10 years, offering a rich and diverse temporal structure that is well-suited for time series modeling using machine learning techniques. The data is publicly available from the UCI Machine Learning Repository, ensuring both credibility and accessibility.

1 .Handling Missing and Outlier Values

The first step involved identifying and processing missing and anomalous data points. Missing values were either removed or imputed using local averaging techniques. Outliers were detected based on statistical measures (such as standard deviation from the mean), and depending on their impact, were either excluded or adjusted. This step ensures data quality and prevents biased learning during model training.

2 .Temporal Feature Engineering

To enhance model performance, additional temporal features were extracted from the original timestamp column. These included:

- Hour of the day,
- Day of the week,
- Month,
- Fourier terms to capture seasonality,
- Rolling averages (6-hour, 12-hour, and 24-hour moving averages).

These features help the model learn both short-term patterns and long-term seasonal trends in the load behavior.

3 .Data Normalization

The load values were normalized using Min-Max Scaling to map them to the range 0,1 . Normalization ensures numerical stability during training and speeds up convergence by preventing features with large scales from dominating the learning process.

4 .Sequence Structuring for LSTM

Since LSTM networks operate on sequences, the data was restructured using a sliding window approach. For each prediction, a fixed-length sequence (e.g., the previous 24 hours) was used as input to predict the next hour's load. This structure captures the temporal dependencies essential for accurate forecasting.

5 .Train-Test Split

The dataset was split chronologically into 80% training data (96,465 records) and 20% testing data (24,117 records), maintaining the time order to avoid data leakage. This separation ensures that the model is evaluated on unseen future data, mimicking a realistic forecasting scenario.

Model Design and Training (LSTM)

In this project, we employed a Long Short-Term Memory (LSTM) neural network to forecast electricity load due to its proven effectiveness in capturing temporal dependencies and long-range patterns in time series data.

1 .Why LSTM?

LSTM is a specialized type of recurrent neural network (RNN) designed to overcome the limitations of traditional RNNs, such as the vanishing gradient problem. It maintains a memory cell that enables it to learn long-term dependencies, which is particularly important in electric load forecasting where daily, weekly, and seasonal patterns exist.

2 .Model Architecture

The implemented LSTM model consists of the following layers:

- Input Layer: Receives sequences of past load values and temporal features.
- LSTM Layer: A single LSTM layer with 64 units, which captures sequential patterns.
- Dropout Layer: A dropout rate of 0.2 to prevent overfitting.
- Dense Layer: A fully connected output layer with one neuron to predict the next hour's load.

The model was compiled with:

- Loss function: Mean Squared Error (MSE)
- Optimizer: Adam
- Metrics: Mean Absolute Error (MAE)

3 .Training Process

- Epochs: 50
- Batch Size: 32
- Validation Split: 10% of the training data was used for validation.

- Early Stopping was considered based on validation loss to prevent overfitting (though not triggered within 50 epochs).

During training, the model's performance improved rapidly in the first few epochs, and validation loss reached its minimum around epoch 8, indicating high predictive stability.

4 .Model Saving

After training, the best-performing model was saved in HDF5 format (.h5), allowing it to be reloaded for prediction without retraining. This model was later used for generating predictions and further optimization in demand response planning.

Model Evaluation and Results

After training the LSTM model, its performance was evaluated on the test dataset using common time series forecasting metrics. This evaluation aimed to assess the model's accuracy and stability in predicting real-world electricity load values.

1 .Evaluation Metrics

The model was assessed using the following metrics:

- MAE (Mean Absolute Error): 154.87 MW
- RMSE (Root Mean Squared Error): 202.16 MW
- MAPE (Mean Absolute Percentage Error): 1.06%
- R^2 (R-squared): 0.9932

These values indicate excellent prediction accuracy. An R^2 score of 0.9932 means the model explains over 99% of the variance in the actual load data.

2 .Visual Analysis

- "Actual vs Predicted Load" Plot:

Demonstrates how closely the model's predictions follow the real load patterns, including seasonal and daily trends, with very small deviations.

- "Prediction Error Distribution" Plot:

Shows that prediction errors are centered around zero and resemble a normal distribution. This implies the model is statistically stable and free from systematic bias.

3 .Conclusion

The trained LSTM model shows outstanding performance in forecasting load. Its high accuracy—both numerically and visually—makes it a reliable foundation for the next phase of the project, namely demand response optimization.

Demand Response Optimization

In the second stage of this project, a Linear Programming model was employed to implement a Demand Response (DR) strategy within a microgrid. The objective was to reduce peak demand and distribute the energy load more evenly across the day with minimal disruption to end users.

1 .Load Profile Setup

A 24-hour load profile was created to represent a typical weekday demand within the microgrid. This profile served as the input for the optimization process.

2 .Optimization Model

The optimization was formulated as a linear programming problem with the following elements:

- Objective Function: Minimize total adjusted load
- Constraints:
  - Maximum DR activation percentage per hour
  - Limits on the number of hours DR can be active
  - Maintaining base-level service requirements

3 .Optimization Results

- Total initial load: 1103.00 kW
- Total load after DR: 1054.47 kW
- Load reduction achieved: 48.53 kW

The highest DR activation occurred during hours 8 to 10 AM, which aligns with peak demand periods. No significant load adjustments were applied during nighttime or off-peak hours.

4 .DR Visualization Analysis

The load comparison plot before and after DR clearly shows the effectiveness of peak shaving. This adjustment contributes to better system stability and reduces strain on power generation infrastructure.

5 .Conclusion

This demand response optimization demonstrated that energy consumption during peak hours can be significantly reduced using relatively simple but effective algorithms. Combined with the accurate load forecasting model, this strategy provides a robust solution for intelligent energy management in microgrids.

Final Conclusion

This project was developed with the aim of forecasting power demand in a distribution network and optimizing demand response (DR) within a microgrid. In the first phase, an LSTM deep learning model was implemented to forecast hourly electricity demand. The results demonstrated high accuracy, with a Mean Absolute Error (MAE) of 154.87 MW and a coefficient of determination (R^2) of 0.9932.

In the second phase, a simple yet effective linear programming algorithm was applied for demand response planning. The algorithm successfully reduced peak loads during high-demand hours and contributed to improved grid stability. The total daily load reduction achieved (approximately 48.5 kW) confirms the practical impact of this approach.

The integration of load forecasting and DR optimization highlights the potential of intelligent energy systems powered by data-driven machine learning and optimization methods. This framework can serve as a foundation for future developments in automated energy control, smart grids, and sustainable power systems.