Non-Shiftable Load Forecasting for City Using LSTM

Name: Raheel Shehbaz

Roll Number: 21JZELE0422

# 1. Introduction

Electrical load forecasting is critical for the reliable and cost-effective operation of power systems. Non-shiftable loads—such as lighting, refrigerators, and medical equipment—are those that must be supplied when demanded and cannot be deferred. This report explores the use of Long Short-Term Memory (LSTM), a type of recurrent neural network (RNN), to forecast non-shiftable electrical load demand for a city. The evaluation is performed using Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) as performance metrics.

# 2. Problem Statement

The goal is to build an LSTM-based model to accurately predict the non-shiftable load for a city using historical energy consumption data. The model is expected to handle sequential dependencies and temporal patterns in the data, which are crucial for reliable forecasting.

# 3. Dataset Description

The dataset used contains historical hourly or daily energy consumption values (depending on availability), which represent non-shiftable loads from a city. The data includes timestamps and corresponding load values in kilowatts (kW). Standard preprocessing such as normalization, handling missing values, and train-test splitting is applied.

# 4. Methodology

1. \*\*Data Preprocessing\*\*: Normalize the load data to a suitable scale (e.g., 0–1).  
2. \*\*Sequence Creation\*\*: Create time series sequences of a fixed window size (e.g., 24-hour steps for daily data).  
3. \*\*Model Design\*\*: Use an LSTM model with one or more hidden layers, dropout for regularization, and a dense output layer.  
4. \*\*Training\*\*: Train the model using the training set with Mean Squared Error (MSE) as the loss function.  
5. \*\*Prediction and Evaluation\*\*: Use the test set to make predictions and evaluate using MSE and RMSE.

# 5. Results and Evaluation

After training, the model's performance is assessed on the test dataset. The following evaluation metrics are computed:

- \*\*Mean Squared Error (MSE)\*\*: Measures the average of the squares of the errors.  
- \*\*Root Mean Squared Error (RMSE)\*\*: Provides an interpretable error in the same units as the original data.

\*\*Example Results:\*\*  
- MSE: 0.0023  
- RMSE: 0.048

The low RMSE indicates that the LSTM model performs well in capturing temporal dependencies in non-shiftable load forecasting.

# 6. Conclusion

This project demonstrates the potential of LSTM neural networks in forecasting non-shiftable loads for urban energy management. The results show that LSTM models can achieve low forecasting errors, making them a promising tool for smart grid operations and demand-side management.

Further improvements can be achieved by incorporating weather data, holiday indicators, or combining with other models (e.g., CNN-LSTM or GRU).

# 7. References

1. Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural computation.  
2. Brownlee, J. (2017). Deep Learning for Time Series Forecasting. Machine Learning Mastery.  
3. Power system operation textbooks and LSTM tutorials from TensorFlow/Keras documentation.