# Eletric Power Consumption Forecasting Using Recurrent Neural Networks


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***Abstract*—The research presents a model for estimating electric power usage using time series data that is based on recurrent neural networks (RNNs). Long Short-Term Memory (LSTM) layers are used in the model to identify long-term dependencies in sequential data. To increase forecast accuracy, it takes into account outside variables like temperature, seasonality, and time of day. Better demand management, operational planning, and energy conservation are made possible by this RNN-based forecasting technique, which benefits utility businesses and regulators alike. The model's capacity to produce accurate projections is demonstrated by the results, which promote proactive measures for grid stability and energy efficiency.**



***Index Terms*—Electric Power Usage Forecasting, Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Energy Demand Prediction, Grid Stability and Energy Efficiency**


## I. Introduction

Accurate electric power consumption forecasting is essential for effective energy management and resource allocation as the world's energy demand rises. Accurate demand forecasts are essential for utilities and grid managers to maintain a steady supply of electricity, optimize generating schedules, and avoid expensive shortages or excesses in energy output. Reducing the environmental effect of overproduction and facilitating a more seamless integration of renewable energy sources are two ways that accurate forecasting promotes sustainable energy practices. Because power consumption data is sequential and nonlinear, traditional forecasting techniques have difficulty capturing this feature. For such time series forecasting tasks, recurrent neural networks (RNNs) are ideally suited, especially Long Short-Term Memory (LSTM) networks. To anticipate electric power use, this project suggests an RNN-based method that takes into account past usage data as well as outside variables like the temperature and time of day. The one that

**Objective:**

The objective of this study is to use historical temporal and environmental data to anticipate urban power usage. Reducing operating expenses, improving grid stability, and effectively allocating resources are all made possible by accurate forecasting. Features in the dataset that might affect energy usage include environmental data and time stamp data. By creating a model that reliably forecasts power consumption based on these characteristics, utility firms will be able to improve their energy supply, demand response, and cost management planning, better predict times of high demand, and make data-driven choices about load balancing. There are two varieties of recurrent neural networks (RNNs) in use: simple RNN and long short-term memory (LSTM). Through a comparison of different models' performances, the research seeks to determine which design better reflects the patterns in

This document is a model and instructions for LaTeX. Please observe the conference page limits.

## II. Methodology

### *A. Data Collection and Preprocessing*

Data Loading and understanding:

- The dataset should be loaded into a Data Frame for manipulation and analysis. This step typically includes loading columns that represent temporal data (e.g., timestamp, day, month) as well as environmental features (temperature, humidity, etc.).
- You'll inspect for any missing values, outliers, or inconsistencies that may affect model performance.

Feature Engineering:

- Features like hour, minute, and day_of_week are extracted from the timestamp to capture daily and weekly patterns.
- Time-based features allow the model to learn consumption variations across hours of the day and different days of the week.

Normalization:

- Continuous features (like temperature and humidity) and the target variable (power consumption) are normalized, typically using Min-Max scaling or Standard scaling. This is crucial in neural networks as it speeds up training and often improves performance by ensuring all input values are in a similar range.

### B. Exploratory Data Analysis

Trend Analysis:

- The power consumption patterns are analysed visually, often using line plots to show how consumption varies with time.
- Analysing correlations between environmental variables (like temperature and humidity) and power usage helps identify factors that may significantly impact consumption patterns.

Feature Correlations:

- Pairwise correlation plots or heatmaps are used to highlight relationships between variables. For instance, high correlations between temperature and power usage might indicate that temperature is a key predictor.

### C. Model Selection and Training

*1) Splitting the Data:* Data is divided into training and testing sets to evaluate the model's generalization on unseen data. Often, an 80-20 split is used where 80% of the data is for training, and 20% is for testing.

*2) Reshaping Data for RNNs:* Recurrent Neural Networks (RNNs) and LSTM models require data in a 3-dimensional format [samples, timesteps, features]. Data is reshaped to enable the model to understand sequences in time, where timesteps defines how many historical records (or time steps) the model considers to predict future consumption.

*3) Model Architecture:* Two models are designed:

**LSTM Model**

Long Short-Term Memory (LSTM) networks are designed for sequence prediction problems, especially when learning long-term dependencies is essential. The architecture in the code uses one LSTM layer with 50 units (neurons), followed by a Dense output layer. The LSTM layer captures temporal relationships in the data, and the Dense layer outputs the prediction.

**Simple RNN Model**

Similar to the LSTM model but with a Simple RNN layer instead. While Simple RNNs capture short-term dependencies, they are less effective for long sequences compared to LSTMs. The model also has 50 units in the Simple RNN layer, followed by a Dense layer for output.

*4) Model Compilation:* The models are compiled using the Mean Squared Error (MSE) loss function, which penalizes large errors more heavily, making it suitable for regression tasks. The optimizer used is Adam, which combines the benefits of RMSprop and momentum, resulting in efficient and often faster convergence.

*5) Training the Model::* Both models are trained on the training dataset over multiple epochs (iterations through the entire dataset). The batch size determines how many samples are processed before updating the model weights. validation split=0.2 reserves 20% of the training data for validation, helping monitor for overfitting by observing validation loss alongside training loss. The verbose parameter controls the amount of information printed during training.

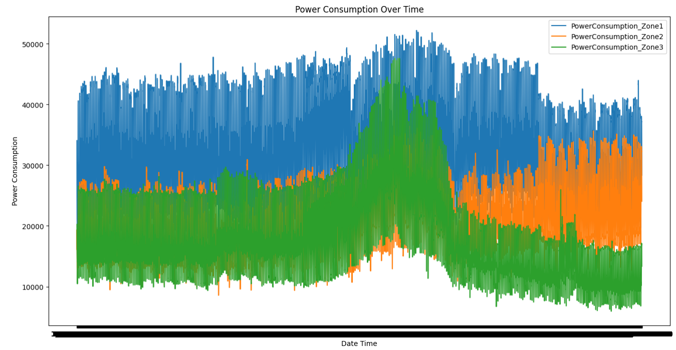


Fig. 1. Power consumption over time for each zone

## III. Results and Discussion

### A. Dataset

The Tetouan Electric Power Consumption dataset provides comprehensive time-series data for analyzing energy usage in Tetouan, a rapidly growing city in northern Morocco with over 550,000 residents. This dataset offers valuable insights into the electricity consumption patterns across three zones within Tetouan, capturing data every 10 minutes for a total of 52,416 observations. The dataset includes various features related to weather conditions (temperature, humidity, and wind speed) and environmental factors (general diffuse flows and diffuse flows), which may influence energy demand in the city. Each entry also records power consumption levels for three distinct distribution zones—Quads, Smir, and Boussafou—that serve as the main power stations supplying low and medium voltage electricity to the region. Collected from the SCADA system managed by Amendis, Tetouan's primary electricity and water distribution operator, this dataset highlights the energy distribution network's role in meeting local demand. Such detailed data provides a foundation for studying the impact of population growth, seasonal changes, and weather variations on energy consumption in a city where energy management is vital.

### B. Model Evaluation

Loss curves for training and validation are plotted for each model to visualize learning progress and diagnose overfitting. If validation loss is much higher than training loss, the model may be overfitting.After training, the models are evaluated on the test set using Mean Squared Error (MSE) and Mean Absolute Error (MAE) as performance metrics. MSE provides insights into the average squared difference between predictions and actual values, while MAE indicates average absolute differences. Lower MSE and MAE values signify better model performance. Power consumption across zones was plotted, showing variations over time. Each zone displayed unique patterns, highlighting potential dependencies on external factors like time and weather. Pair Plots and Correlations: Relationships between features were explored through pair plots, focusing on temperature, humidity, wind speed,

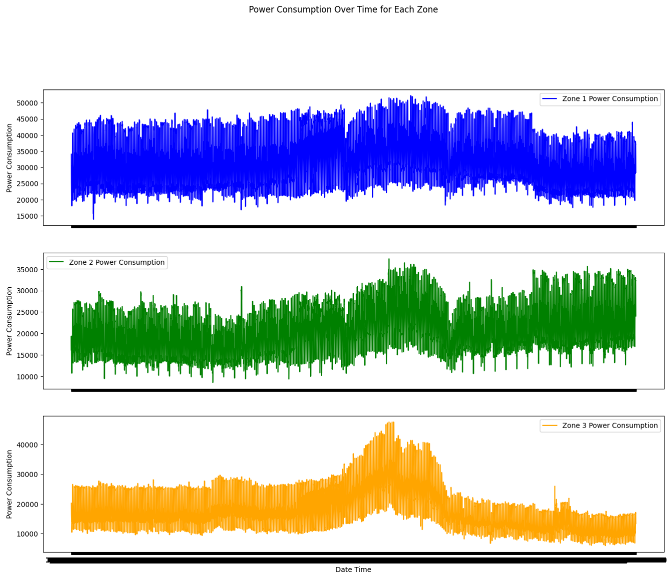


Fig. 2. Power consumption over time for zone1

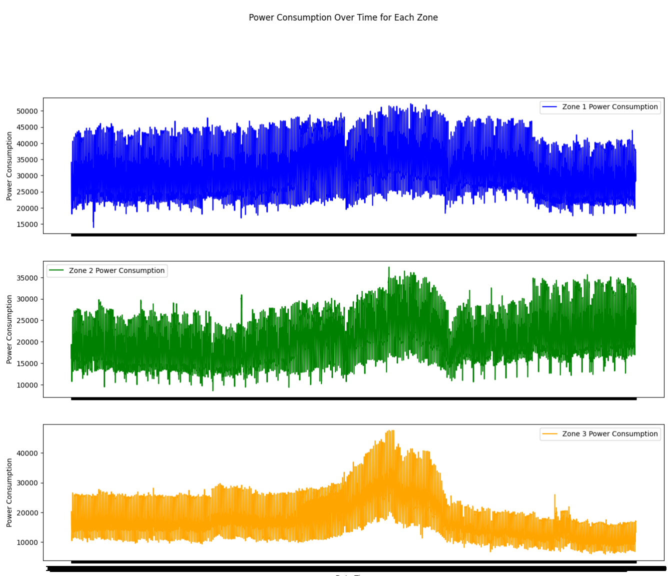


Fig. 3. Power consumption over time for zone2

and power consumption for each zone. The correlation matrix revealed temperature and power consumption have weak correlations, suggesting complex dependencies. Distribution and Summary Statistics: Histograms indicated temperature distribution, and average power consumption across zones was calculated. **Feature Engineering:** Several temporal features were created, including hour, minute, day, month, season, and day-of-week indicators. Additional binary features (e.g., is weekend, is_peak_hour) were added to capture periodic consumption patterns.

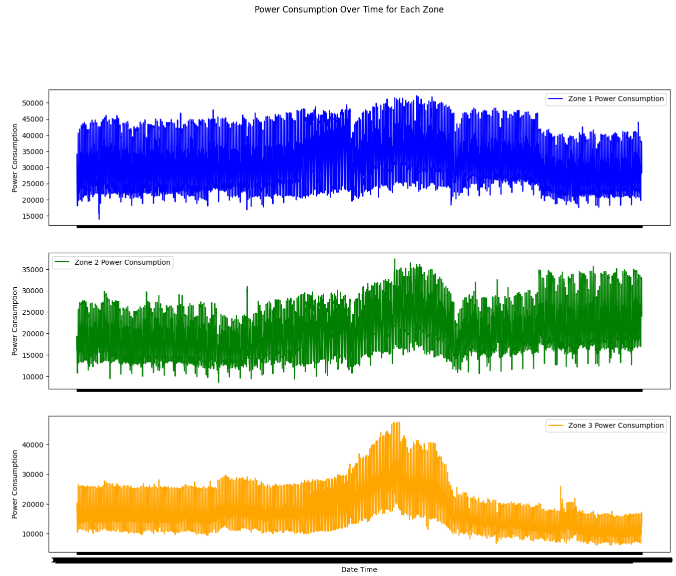


Fig. 4. Power consumption over time for zone3

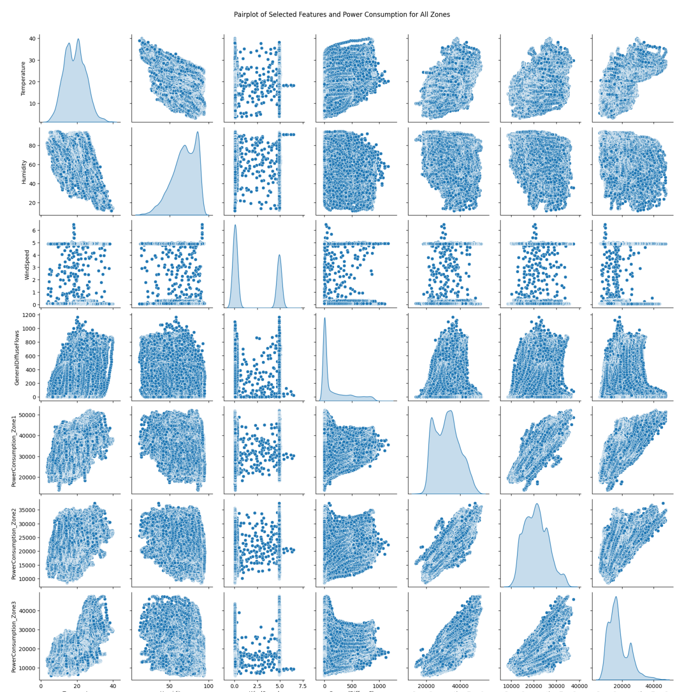


Fig. 5. Selected features and power consumption for all zones

### *C. Modelling with LSTM and RNN:*

- **LSTM Model:** An LSTM model was trained to predict power consumption. Over 50 epochs, the model's loss decreased, reaching a Mean Squared Error (MSE) of 0.2428 on the test set and 0.2470 on the training set. The Mean Absolute Error (MAE) on the test set was 0.3710, suggesting that the LSTM could capture power consumption trends well. **RNN Model:** A Simple RNN model was also trained with similar input data. It per-

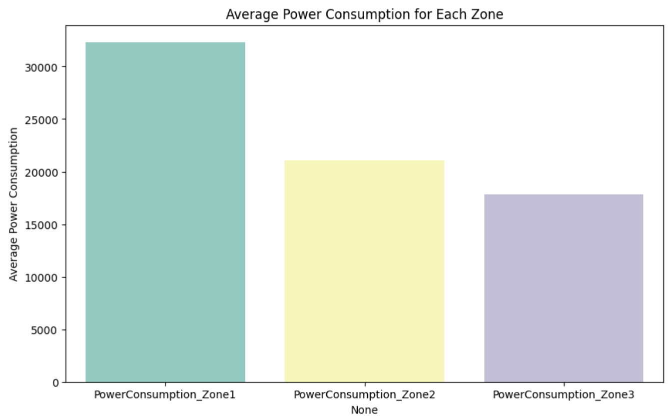


Fig. 6. Average power consumption for each zone

| Layer (type) | Output Shape | Param # |
|---|---|---|
| bidirectional (Bidirectional) | (None, 1, 256) | 157,696 |
| dropout_4 (Dropout) | (None, 1, 256) | 0 |
| bidirectional_1 (Bidirectional) | (None, 1, 256) | 394,240 |
| dropout_5 (Dropout) | (None, 1, 256) | 0 |
| lstm_6 (LSTM) | (None, 64) | 82,176 |
| dropout_6 (Dropout) | (None, 64) | 0 |
| batch_normalization_1 (BatchNormalization) | (None, 64) | 256 |
| dense_4 (Dense) | (None, 64) | 4,160 |
| dropout_7 (Dropout) | (None, 64) | 0 |
| dense_5 (Dense) | (None, 3) | 195 |

**Total params:** 638,723 (2.44 MB)
**Trainable params:** 638,595 (2.44 MB)
**Non-trainable params:** 128 (512.00 B)

Fig. 7. LSTM model summary

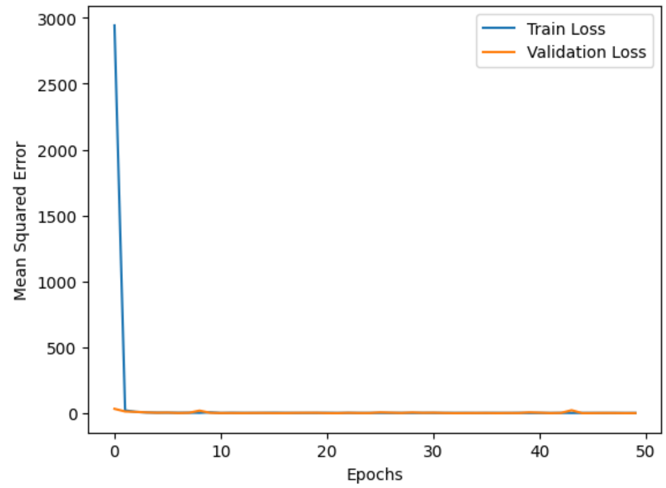


Fig. 8. Simple RNN Loss curve


Fig. 9. LSTM loss curve

formed worse than the LSTM, with an MSE of 1.5360 on the test set and 1.5437 on the training set, and a higher MAE of 0.9569. This difference highlights that LSTM's sequential memory may better capture temporal dependencies in power consumption data.

### D. Discussion and Implications:

LSTM outperformed RNN, demonstrating the utility of sequential memory for time-dependent data. This indicates that temporal structures, like recurring patterns or trends, are significant in power consumption data. Weak correlations between individual environmental factors and power consumption underscore the need for advanced modeling techniques to capture multi-dimensional dependencies. The engineered time features may have played a critical role in enhancing predictive accuracy.

## IV. Conclusion

Recurrent neural networks (RNNs) were employed in the study to forecast urban regions' electric power usage. To find trends in energy use, the models incorporated historical data as well as environmental variables like humidity and temperature. Accurate predicting was demonstrated by both the Long Short-Term Memory (LSTM) and Simple RNN models; however, LSTM outperformed Simple RNN because it could capture longer-term relationships. The results imply that because LSTM models can adjust to seasonal and cyclical energy use, they are appropriate for predicting power consumption. Additional enhancements, including adding environmental factors or investigating different deep learning architectures, may increase the precision of forecasts and energy management strategies.