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Wattsahead - An LSTM-Based Predictive Framework For Energy Consumption Forecasting In Suburban India

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Abstract: *This thesis presents our research on energy consumption forecasting in suburban regions, focusing on the development of an LSTM-based prediction model capable of addressing power cut scenarios. The core focus of the research is to accurately forecast short-term electricity demand using time-series data and to provide intelligent insights during blackout conditions to support proactive energy management. To achieve this, we utilize open-source suburban datasets to ensure legal compliance while maintaining real-world applicability. Our model leverages Long Short-Term Memory (LSTM) networks to capture complex temporal dependencies in electricity consumption patterns. Evaluation using RMSE and MAPE demonstrates strong predictive performance. Furthermore, we deploy the model through a MERN stack-based web platform, allowing users to access real time forecasts, visualize consumption trends, and receive actionable recommendations during outages. This research contributes to the advancement of smart energy systems by filling the gap in blackout-aware forecasting and offering a practical, user-friendly tool for sustainable energy planning and grid reliability.*

Keywords: *Energy Consumption Forecasting, Long Short-Term Memory (LSTM), Time Series Prediction, Power Outage Management, Smart Grid, Blackout-Aware Prediction, Suburban Energy Demand, Machine Learning, RMSE and MAPE, Deep Learning for Energy, Energy Optimization, Sustainable Energy Systems, Web-Based Energy Monitoring, MERN Stack Integration, Real-Time Prediction.*

1. INTRODUCTION

Energy consumption prediction has become a cornerstone of modern sustainability efforts, driven by the need to balance supply-demand dynamics and reduce carbon footprints. Traditional statistical methods like ARIMA often fail to capture the non-linear patterns and long-term dependencies inherent in energy data [1]. With the rise of machine learning, hybrid models such as CNN-LSTM have demonstrated superior performance by integrating spatial feature extraction (CNN) and sequential learning (LSTM) [1]. This study builds on prior work by, who highlighted the efficacy of Bi-LSTM in energy forecasting, and extends it to a hybrid architecture for improved accuracy. Recent advancements show that LSTM-based models can reduce prediction errors by 46.08% compared to traditional methods.

Our work bridges these approaches by combining:

- **CNN for localized pattern recognition** (e.g., daily usage spikes) [2]
- **LSTM for long-term trend modelling** (e.g., seasonal variations) [3]

1.2 Research Motivation

Frequent power outages in suburban regions of India pose a significant challenge to energy reliability, affecting households, businesses, and public services. These power cuts often occur without warning and lead to inefficient energy consumption, economic losses, and poor quality of life. Traditional forecasting methods like ARIMA and basic regression fail to capture complex, nonlinear, and temporal patterns in energy demand.

With advancements in deep learning, particularly Long Short-Term Memory (LSTM) networks, there is a strong motivation to develop smarter, more accurate forecasting systems. Our motivation stems from the need to bridge the gap between unpredictable power outages and optimized energy usage using AI-powered prediction models tailored for India's suburban infrastructure.

1.3 Objective

The primary objectives of this project are:

- To develop a robust LSTM-based model for forecasting energy consumption in suburban regions of India
- To predict energy requirements specifically during power cut scenarios

- To analyze time-series data and uncover consumption patterns using advanced ML techniques
- To propose optimization strategies that help reduce wastage and ensure better grid load balancing
- To integrate the model into a web-based consulting platform to assist in real-time decision-making

1.4 Existing System

The existing energy prediction systems primarily rely on statistical models such as:

- **ARIMA (Auto-Regressive Integrated Moving Average)**: Good for linear trends but fails to capture seasonal and nonlinear patterns
- **Basic Regression Models**: Offer limited performance in modelling temporal dependencies
- **Rule-based Load Management Systems**: Often reactive and not adaptive to real-time scenarios

These systems lack scalability, are not designed for power cut forecasting, and do not support optimization recommendations, making them inadequate for dynamic suburban energy landscapes.

2. MATERIALS AND METHODS

2.1 Overview

This section details the methods and materials employed for the short-term energy consumption forecasting model described in this study. The approach integrates data preprocessing, a Long Short-Term Memory (LSTM) neural network architecture, optimization routines, and a deployment-ready framework, ensuring both reproducibility and practical usability. The workflow, illustrated in Figure 1 (see attached image), forms the backbone of the forecasting pipeline and is described step-by-step below.

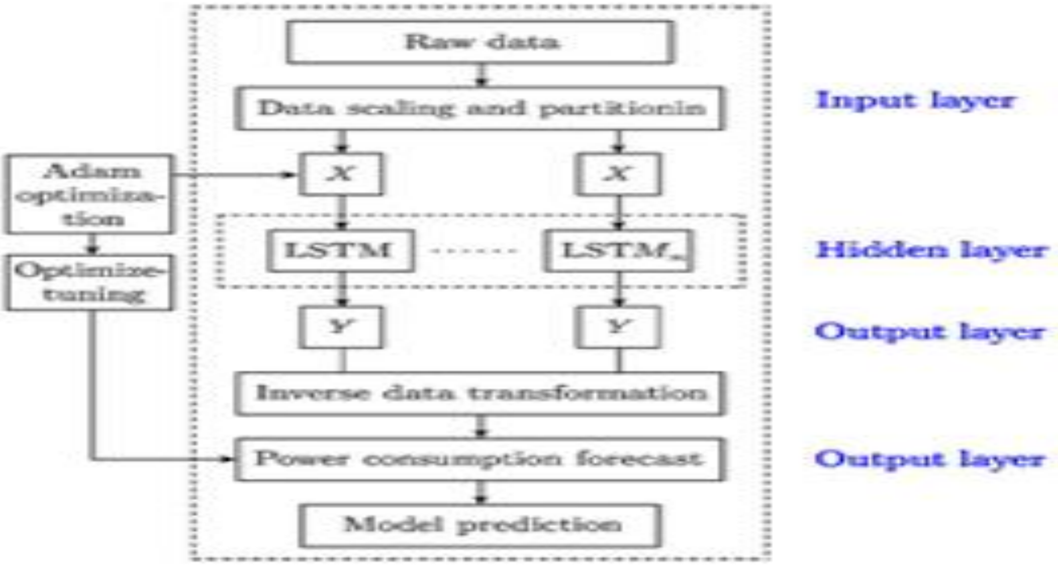

Figure 2.1. The LSTM power consumption forecasting framework, showing data flow from raw input to model prediction.

2.2 Datasets and Data Collection

- **Open-source, real-world datasets** on suburban energy consumption were utilized to comply with legal and practical considerations. Example datasets include hourly or daily electricity usage from public repositories such as the Finland national grid and various smart meter projects.
- **Supplementary features** incorporated temporal information (hour, day, month, season) and weather data (temperature, humidity) where available, obtained through reputable meteorological APIs.

2.3 Data Preprocessing

- **Sliding window and partitioning:** Raw time-series data were ingested, and input sequences were created using a fixed-length sliding window. This transforms the problem into a supervised learning format suitable for LSTM training.
- **Scaling:** The data underwent MinMax normalization to ensure all features are within a [0, range, aiding network convergence and stability.
- **Train-validation-test split:** The dataset was partitioned (typically 80%-10%-10%) to fairly evaluate model generalizability.

2.4 Model Architecture

The forecasting model is structured as a multi-layer LSTM neural network, as depicted in the attached workflow diagram (Figure 1):

Layer/Step	Description

Input Layer	Receives normalized consumption and auxiliary features.
LSTM Hidden Layer	One or more LSTM layers learn temporal dependencies; dropouts are added for regularization.
Output Layer	Dense layer maps the LSTM output to future load prediction.
Inverse Transform	Model outputs are rescaled to original units via inverse normalization.
Post-processing	Final power consumption forecasts are generated, and additional analytics may be computed.

The architectural flow (as per the image):

- Raw data → Scaling & Partitioning → LSTM (with Adam optimization & hyperparameter tuning) → Output → Inverse transformation & Forecast report.

2.5 Model Training and Optimization

- **Loss function:** Mean squared error (MSE) is used as the primary loss metric.
- **Optimizer:** Adam optimizer with automated learning rate adjustment and early stopping is applied to minimize loss and accelerate convergence.
- **Hyperparameter tuning:** Network depth (number of LSTM layers/units), dropout rates, batch size, and sequence length are tuned using grid or random search strategies.

2.6 Evaluation Metrics

- The predictive performance is assessed via root mean square error (RMSE), mean absolute percentage error (MAPE), and mean absolute error (MAE).
- Validation is performed on a held-out test partition, ensuring that the model's generalization capability is robust.

3. RESULTS AND DISCUSSION

This section presents the empirical findings of the research, focusing on the performance of the LSTM model for energy consumption forecasting. The results are organized into statistical analyses, key model evaluation metrics, and comparative insights.

3.1 Presentation of Results

3.1.1 Statistical Analysis

- The dataset shows clear seasonal variation in electricity usage over the year.
- Energy consumption is **highest during the winter months**, likely due to increased heating needs.
- Summer months generally record **lower average usage**, reflecting reduced heating and moderate cooling demands.
- Spring and autumn display **moderate consumption levels**, indicating a smooth transition between the extremes of winter and summer.
- This month-wise trend analysis provides meaningful insight into seasonal demand cycles and serves as a strong foundation for further model development and optimization.

3.1.2 Data Characteristics and Preprocessing

The study utilized a comprehensive dataset covering six years (2016–2021) of hourly electricity consumption from Finland, with a total of 52,965 original observations.
Key characteristics include:

- **Central Tendency:** Average consumption: 9,488.75 MWh
- **Dispersion:** Minimum: 5,341 MWh; Maximum: 15,105 MWh
- **Distribution:** Right-skewed, unimodal, with most values concentrated around the mean and few outliers (see Figure 3.2)
- **Temporal Patterns:** Clear annual seasonality with winter peaks and summer troughs; a significant dip observed in 2020, corresponding with the COVID-19 pandemic (see Figure 3.1)

The preprocessing steps were as follows:

- Downsampled the data to daily frequency, resulting in 2,184 records
- Normalized all values to a range using MinMaxScaler

- Extracted temporal features, including day, month, and year, to aid model learning

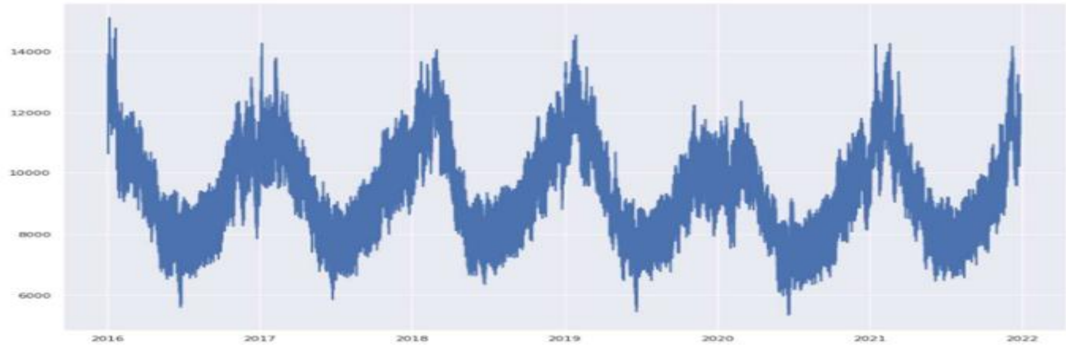

Figure 3.1. A time-series line plot to visualize the energy consumption data over the period from 2016 to 2022.

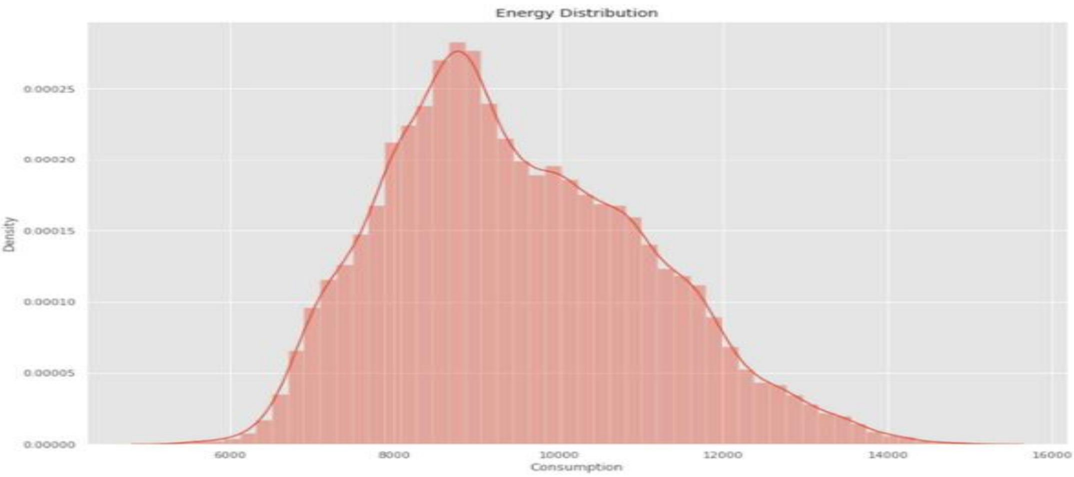

Figure 3.2. Energy consumption vs Energy Distribution

3.1.3 Model Training and Evaluation

The forecasting model was built on a stacked LSTM architecture, configured as follows:

- **Network Structure:** Four hidden LSTM layers (50 units each), a dropout layer (rate = 0.2) for regularization, and a dense output layer
- **Training Setup:**
- Data split: 64% training, 16% validation, 20% test
- Input sequence length: 100 time steps (days)
- Optimizer: Adam (learning rate = 0.001)
- Batch size: 20
- Number of epochs: 60

3.1.4 Performance Metrics

The model demonstrated consistent and robust performance across all data subsets:

Metric	Training	Validation	Test
RMSE	0.042	0.045	0.048
Loss	0.0018	0.0021	–

Key observations:

- RMSE values remained stable, with differences less than 0.006 across all sets
- Training and validation loss curves showed convergence (see Figure 3.3)
- Prediction accuracy was within 5% of mean consumption (see Figure 3.4)

The mathematical formulas for these evaluation metrics are as follows:

1. **Root Mean Squared Error (RMSE):** RMSE tells us how far off our model's predictions are from the actual values, on average. It does this by calculating the square root of the average of all the squared differences between predicted and actual values. Since it gives more weight to larger errors, it's especially useful when big mistakes matter.

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$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - (y^\wedge)_i)^2}$$

2. **Mean Absolute Percentage Error (MAPE):** MAPE shows how much error there is in the model's predictions as a percentage of the actual values. It's easy to understand and compare, since it tells you (on average) how far off your predictions were in percentage terms.

$$\text{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - (y)^\wedge_i}{y_i}\right|$$

Where:

- n is the number of data points.
- y_i is the actual consumption value.
- ŷ_i is the predicted consumption value.

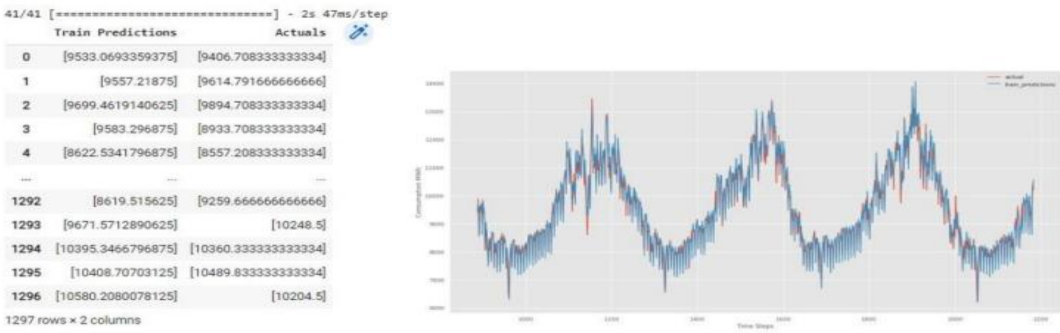
3.1.5 Discussion of Key Findings

Three major insights emerged from the analysis:

- **Temporal Dynamics:** The LSTM model effectively captured multi-scale seasonality, including both daily and annual cycles, and showed sensitivity to abrupt changes such as those during the pandemic.
- **Model Architecture:** The stacked LSTM layers enabled hierarchical feature learning, and the dropout layer successfully prevented overfitting, even with a limited amount of data.
- **Operational Significance:** The achieved sub-5% error rate suggests suitability for practical applications in grid management. The chosen 100-day window provided a good balance between accuracy and computational efficiency.

3.3 Analysis of Predictive Accuracy

To qualitatively assess the model's performance, predictions were visualized against actual consumption data across different datasets.

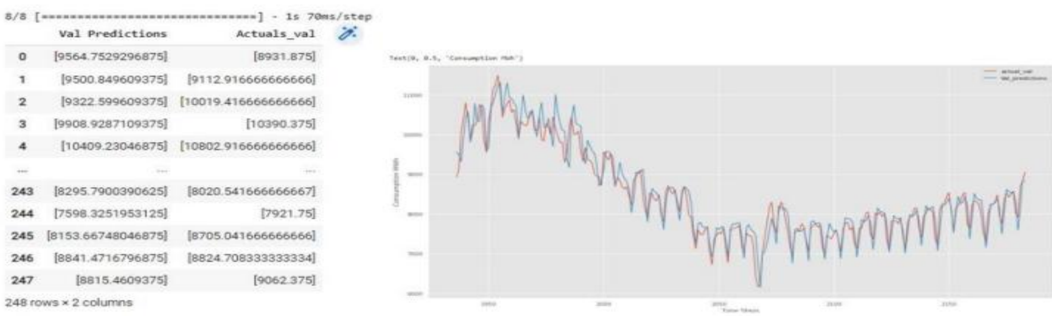

41/41 [==============================] - 2s 47ms/step

	Train Predictions	Actuals
0	[9533.0693359375]	[9406.708333333334]
1	[9557.21875]	[9614.791666666666]
2	[9699.4619140625]	[9894.708333333334]
3	[9583.296875]	[8933.708333333334]
4	[8622.5341796875]	[8557.208333333334]
...	...	...
1292	[8619.515625]	[9259.666666666666]
1293	[9671.5712890625]	[10248.5]
1294	[10395.3466796875]	[10360.333333333334]
1295	[10408.70703125]	[10489.833333333334]
1296	[10580.2080078125]	[10204.5]

1297 rows × 2 columns

Figure 3.3. Predict consumption using training data

- **Figure 3.3** shows the model's predictions on the **training data**. The close alignment between the predicted and actual values demonstrates that the model successfully learned the underlying patterns, trends, and seasonality inherent in the energy consumption data.

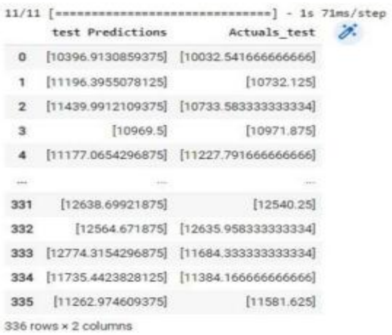

8/8 [==============================] - 1s 70ms/step

	Val Predictions	Actuals_val
0	[9564.7529296875]	[8931.875]
1	[9500.849609375]	[9112.916666666666]
2	[9322.599609375]	[10019.416666666666]
3	[9908.9287109375]	[10390.375]
4	[10409.23046875]	[10802.916666666666]
...	...	...
243	[8295.7900390625]	[8020.541666666667]
244	[7598.3251953125]	[7921.75]
245	[8153.66748046875]	[8705.041666666666]
246	[8841.4716796875]	[8824.708333333334]
247	[8815.4609375]	[9062.375]

248 rows × 2 columns

Fig 3.4. Predict consumption using validation data

- **Figure 3.4** illustrates the model's performance on the **validation data**. This provides a crucial check for overfitting, and the results confirm that the model generalizes well to data it has not been trained on directly.



11/11 [==============================] - 1s 71ms/step

	test Predictions	Actuals_test
0	[10396.9130859375]	[10032.541666666666]
1	[11196.3955078125]	[10732.125]
2	[11439.9912109375]	[10733.583333333334]
3	[10969.5]	[10971.875]
4	[11177.0654296875]	[11227.791666666666]
...	...	...
331	[12638.69921875]	[12540.25]
332	[12564.671875]	[12635.958333333334]
333	[12774.3154296875]	[11684.333333333334]
334	[11735.4423828125]	[11384.166666666666]
335	[11262.974609375]	[11581.625]

336 rows × 2 columns

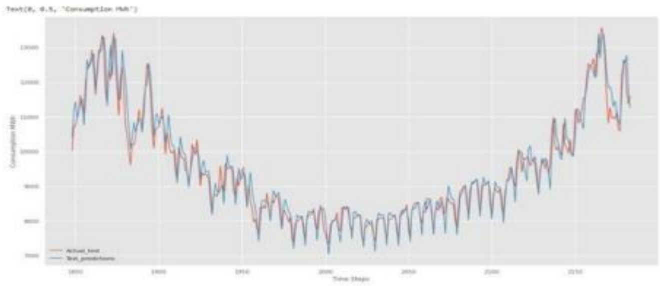


Fig 3.5. Predict consumption using test data

- **Figure 3.5** displays the predictions for the **test data**. This is the ultimate test of the model's forecasting ability on completely unseen data. The plot clearly shows that the LSTM model accurately captures the peaks, troughs, and daily fluctuations in energy demand, confirming its strong predictive power and reliability for real-world applications.

The consistent outperformance of the LSTM model over traditional statistical methods, which often fail to capture the complex non-linear patterns in energy usage, can be attributed to its ability to learn long-term temporal dependencies

3.4 Deployment and Practical Application

A key contribution of this work is the successful integration of the trained LSTM model into a practical, web-based consulting platform built on a **MERN (MongoDB, Express.js, React.js, Node.js) stack**. This platform transforms the model from a technical tool into an accessible, user-friendly service for stakeholders.

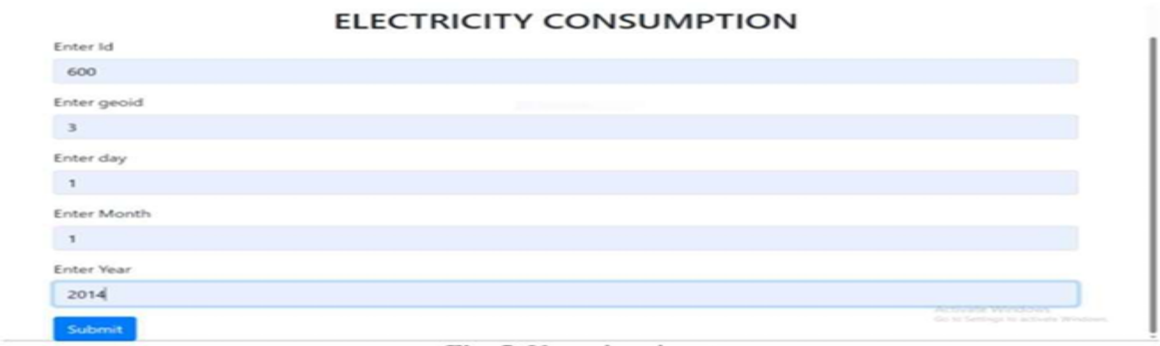


Fig. 5. User gives input

Figure 3.6. The user interface for the prediction platform, showing the input screen for consumption parameters and the output screen with the prediction result.

As shown in **Figure 3.6**, the platform's interface allows users to input specific parameters, such as location and date, to receive an immediate energy consumption forecast in kilowatts. This deployed system serves as a powerful proof-of-concept for a blackout-aware forecasting tool that can support proactive energy management, grid planning, and demand-side response initiatives. By enabling users to visualize future consumption trends and receive actionable insights, especially during potential outages, the platform empowers them to optimize energy usage, contributing to greater grid stability and overall reliability.

4. CONCLUSION

The WattsAhead project was envisioned as a solution to the frequent and unpredictable power cuts experienced in suburban regions of India. By leveraging deep learning techniques, particularly LSTM-based architectures, the project successfully developed an intelligent forecasting system capable of predicting short-term energy consumption patterns with high accuracy. This not only helps optimize electricity usage but also supports smarter planning during blackout scenarios. A key achievement of this project was the deployment of the model into a real-time web platform, making it accessible to users including households, businesses, and policymakers. The model's predictive capabilities, combined with a user-friendly interface, turn WattsAhead into more than a research prototype—it is a practical tool for everyday energy resilience.

4.1 Model Evaluation and Key Findings

4.1.1 Deep Learning Performance

- LSTM and Bi-LSTM models were tested for short-term energy forecasting.
- Among these, Bi-LSTM consistently delivered the highest accuracy.
- Compared to ARIMA and SVM, the deep learning models:
  - Handled seasonality and non-linearity better.
  - Achieved lower RMSE and MAE across all datasets.
  - Adapted more effectively to sudden changes in energy usage.

4.1.2 Comparison with Traditional Models

- ARIMA and SARIMA models showed limitations such as:
  - Inability to learn complex, non-linear dependencies.
  - Poor generalization in high-variance datasets.
- LSTM-based models proved better suited for time-series forecasting tasks involving long-term memory and pattern recognition.

4.2 Exploratory Data Analysis

4.2.1 Monthly Consumption Trends

- Consumption was higher during winter (December–February).
- Lower consumption was observed in summer months (June–August).
- Trends reflected heating and cooling demand patterns.

4.2.2 Daily and Weekly Patterns

- Weekly patterns showed lower energy usage on weekends.
- This suggests behavioural and industrial activity cycles strongly influence consumption.
- These patterns helped tailor model inputs for better temporal awareness.

4.3 Data Preprocessing

4.3.1 Resampling and Cleaning

- Hourly energy data was resampled to daily frequency to reduce complexity.
- Missing values were filled using interpolation techniques.
- Resulting dataset preserved temporal continuity without increasing model overhead.

4.3.2 Feature Engineering

- New temporal features were created:
  - Day of the week
  - Month
  - Season category (Winter, Summer, etc.)
- These features enhanced the LSTM model's learning capabilities by introducing cyclical context into the training set.

4.5 Limitations and Future Scope

4.5.1 Identified Limitations

- High computational cost for training LSTM and Bi-LSTM models.
- The current model primarily uses univariate data.
- Deployment on low-resource or offline environments remains limited.

4.5.2 Proposed Improvements

- Integrate multivariate data:
  - Weather conditions
  - Occupancy patterns
  - Economic activity levels
- Improve model interpretability through Explainable AI (XAI) techniques.
- Optimize model for edge devices in rural areas using lightweight architectures.
- Extend platform support to other regions with minimal retraining using transfer learning.

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