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Smart Forecasting Of Electricity Price For Cloud Computing Using Ml Techniques

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Abstract
Accurate short-term electricity demand forecasting has become an essential requirement for modern cloud computing environments due to the increasing energy consumption of data centres and the need for efficient resource management. This paper presents a machine learning-based electricity demand forecasting framework that performs a comparative analysis of four forecasting models: Autoregressive Integrated Moving Average (ARIMA), Long Short-Term Memory (LSTM), Extreme Gradient Boosting (XGBoost), and a Hybrid LSTM + XG Boost model. The proposed framework utilizes a high-resolution 5-minute interval electricity demand dataset collected from Delhi, India, spanning the period from 2021 to 2024, along with weather-related features to improve forecasting accuracy. Data preprocessing and feature engineering techniques are applied to extract temporal and environmental characteristics before model training and evaluation. The forecasting models are assessed using standard performance metrics including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). Experimental results demonstrate that the Hybrid LSTM + XGBoost model achieves the lowest prediction errors and the highest forecasting accuracy among the evaluated models by combining the temporal learning capability of LSTM with the nonlinear prediction strength of XGBoost. The forecasted electricity demand is further utilized to estimate electricity price using a simple demand-based linear relationship. The proposed framework provides an effective solution for demand management, cost optimization, infrastructure planning, and energy-efficient operation of cloud computing environments and smart power systems.

Index Terms— *Electricity Demand Forecasting, Cloud Computing, Machine Learning, Short-Term Load Forecasting, Long Short-Term Memory (LSTM), Extreme Gradient Boosting (XGBoost), Autoregressive Integrated Moving Average (ARIMA), Hybrid LSTM + XGBoost, Time-Series Forecasting, Weather-Based Features, Feature Engineering, Electricity Price Estimation, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Smart Grid, Energy Management.*

Introduction

The rapid growth of cloud computing, industrial automation, and smart energy systems has significantly increased electricity consumption, making accurate electricity demand forecasting an essential requirement for efficient energy management. Modern cloud data centres consume large amounts of electrical power to support computational resources, storage systems, and networking infrastructure. As electricity demand continues to increase, efficient forecasting techniques have become increasingly important for maintaining grid stability, reducing operational costs, and improving resource utilization.

Traditional electricity demand forecasting methods primarily rely on statistical techniques such as Autoregressive Integrated Moving Average (ARIMA). Although these approaches perform reasonably well for linear and stationary time-series data, they often struggle to capture nonlinear relationships and rapidly changing demand patterns influenced by weather conditions, seasonal variations, and consumer behaviour. As a result, their forecasting accuracy decreases when applied to complex real-world electricity demand data.

Recent advancements in machine learning and deep learning have provided more effective solutions for electricity demand forecasting. Models such as Long Short-Term Memory (LSTM) networks can learn temporal dependencies from historical demand data, while Extreme Gradient Boosting (XGBoost) effectively models nonlinear relationships between multiple influencing factors. Combining these approaches enables improved forecasting performance by utilizing the strengths of both deep learning and machine learning techniques.

In this work, a Hybrid LSTM + XGBoost forecasting framework is proposed for short-term electricity demand prediction using historical demand and weather information collected at five-minute intervals. The dataset contains electricity demand, temperature, humidity, wind speed, and other weather-related parameters recorded between 2021 and 2024. Before model training, data preprocessing and feature engineering techniques are applied to improve data quality and extract meaningful temporal and environmental features.

The forecasting performance of ARIMA, LSTM, XG Boost, and the proposed Hybrid LSTM + XG Boost model is evaluated using standard performance metrics including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2). Based on the forecasted electricity demand, electricity price is estimated using a simple linear regression relationship between demand and price. The proposed framework aims to improve forecasting accuracy while providing a practical solution for electricity demand management, price estimation, and energy-efficient operation in cloud computing environments.

Research Gap

Accurate electricity demand forecasting remains a challenging problem due to the dynamic and nonlinear behaviour of electricity consumption patterns. Traditional statistical forecasting models such as ARIMA perform well for linear time-series data but have limited capability in modelling complex relationships between electricity demand and external influencing factors such as weather conditions and seasonal variations. Consequently, their prediction accuracy decreases when applied to highly variable real-world datasets.

Deep learning models such as Long Short-Term Memory (LSTM) networks have demonstrated improved capability in learning temporal dependencies from historical electricity demand data. However, standalone LSTM models may experience slow convergence and reduced forecasting accuracy when demand patterns become highly nonlinear or fluctuate rapidly. Similarly, machine learning techniques such as XGBoost effectively capture nonlinear relationships but may not fully exploit long-term temporal dependencies present in sequential electricity demand data.

This research addresses these limitations by proposing a Hybrid LSTM + XGBoost framework that combines the temporal sequence learning capability of LSTM with the nonlinear prediction strength of XGBoost. The proposed system utilizes historical electricity demand and weather information to generate accurate short-term demand forecasts and subsequently estimates electricity price using a demand-based linear regression model. By integrating these components, the proposed framework aims to improve forecasting accuracy, reduce prediction error, and support efficient energy management in cloud computing environments.

Literature Review

The growing demand for reliable electricity demand forecasting has encouraged extensive research in machine learning and deep learning techniques for predicting electricity demand and electricity price. Accurate forecasting plays a significant role in cloud computing environments, where efficient energy management is essential for reducing operational costs and improving resource utilization. Traditional statistical forecasting techniques have gradually evolved into intelligent forecasting models capable of learning complex temporal and nonlinear relationships from historical electricity demand data. This literature review presents the major developments in statistical forecasting, machine learning, deep learning, hybrid forecasting models, feature engineering, and forecasting performance evaluation, which collectively provide the foundation for the proposed Hybrid LSTM + XGBoost forecasting framework.

Traditional Statistical Forecasting Methods

Traditional electricity demand forecasting primarily relied on statistical time-series models such as Autoregressive Integrated Moving Average (ARIMA). These models estimate future electricity demand using historical observations and temporal relationships. Statistical forecasting methods are simple to implement, require relatively low computational resources, and perform effectively when the data exhibits stable linear patterns. However, they have limited capability to model nonlinear relationships and rapidly changing electricity demand influenced by weather conditions and seasonal variations. Consequently, their forecasting accuracy decreases when applied to complex real-world datasets.

Machine Learning-Based Electricity Demand Forecasting

The introduction of machine learning techniques has significantly improved electricity demand forecasting by enabling models to learn nonlinear relationships between historical demand and multiple influencing factors. Machine learning algorithms utilize historical electricity demand together with weather-related variables to improve forecasting performance. These models effectively capture nonlinear behaviour and interactions among multiple features. Nevertheless, their performance depends heavily on effective feature engineering and data preprocessing. In addition, standalone machine learning models may not adequately capture long-term temporal dependencies present in sequential electricity demand data.

Deep Learning-Based Forecasting Models

Deep learning has become an important approach for electricity demand forecasting due to its ability to model sequential time-series data. Long Short-

Term Memory (LSTM) networks are specifically designed to capture long-term temporal dependencies and seasonal patterns present in historical electricity demand. LSTM models provide improved forecasting capability compared to traditional statistical methods by learning complex temporal relationships directly from the data. However, standalone LSTM models require longer training time, higher computational resources, and may experience reduced accuracy when electricity demand exhibits highly nonlinear behaviour.

Hybrid Machine Learning and Deep Learning Models

To overcome the limitations of individual forecasting models, hybrid forecasting approaches combine the strengths of both machine learning and deep learning techniques. The Hybrid LSTM + XGBoost model integrates the temporal sequence learning capability of LSTM with the nonlinear regression capability of XGBoost. In this approach, LSTM learns sequential demand patterns, while XGBoost improves forecasting performance by reducing residual prediction errors. The combination of these complementary models results in higher forecasting accuracy, lower prediction errors, and improved generalization compared with individual forecasting models.

Feature Engineering and Data Preprocessing

Data preprocessing and feature engineering play an essential role in improving forecasting accuracy. Historical electricity demand datasets often contain missing values, inconsistent observations, and outliers that require appropriate preprocessing before model development. Feature engineering extracts meaningful temporal information such as hour, day, month, season, and weekend patterns, while weather-related variables including temperature, humidity, and wind conditions are incorporated to enhance prediction performance. Proper preprocessing and feature engineering provide structured input data that enables forecasting models to learn electricity demand behaviour more effectively.

Research Methodology

A systematic research methodology is adopted to develop an accurate and reliable electricity demand forecasting framework for cloud computing environments. The proposed methodology integrates statistical, machine learning, and deep learning approaches to analyze historical electricity demand and weather-related data. Four forecasting models, namely Autoregressive Integrated Moving Average (ARIMA), Long Short-Term Memory (LSTM), Extreme Gradient Boosting (XGBoost), and the proposed Hybrid LSTM + XGBoost model, are implemented and evaluated. The methodology focuses on improving forecasting accuracy, minimizing prediction error, and providing reliable electricity price estimation based on forecasted demand.

Research Design

This research follows an applied research design aimed at developing an intelligent forecasting framework for short-term electricity demand prediction. The proposed approach combines data preprocessing, feature engineering, model development, comparative performance evaluation, and electricity price estimation. The forecasting models are developed and validated using historical electricity demand and weather datasets collected at five-minute intervals.

The research design consists of:

1. **Data Preparation:** Collection, preprocessing, normalization, and feature engineering of historical electricity demand and weather data.
2. **Model Development:** Implementation and comparison of ARIMA, LSTM, XGBoost, and Hybrid LSTM + XGBoost forecasting models.
3. **Performance Evaluation:** Assessment of forecasting accuracy using RMSE, MAE, MAPE, and R^2 Score.
4. **Electricity Price Estimation:** Prediction of electricity price based on forecasted electricity demand using a linear regression relationship.
   The overall framework is designed to identify the forecasting model that provides the highest prediction accuracy for electricity demand management in cloud computing environments.

System Modules

The proposed electricity demand forecasting system consists of the following modules:

• **Data Collection Module:** Collects historical electricity demand data and weather-related information including temperature, humidity, wind speed, and other environmental variables.

• **Data Preprocessing Module:** Removes missing values, handles inconsistent records, normalizes numerical features, and prepares the dataset for model training.

• **Feature Engineering Module:** Extracts temporal features such as hour, day, month, weekday, and seasonal information while incorporating weather-related variables that influence electricity demand.

• **Forecasting Module:** Implements ARIMA, LSTM, XGBoost, and Hybrid LSTM + XGBoost models to predict future electricity demand.

• **Performance Evaluation Module:** Compares forecasting models using RMSE, MAE, MAPE, and R^2 Score to determine the most accurate forecasting approach.

• **Electricity Price Estimation Module:** Estimates electricity price using the forecasted electricity demand through a linear regression relationship.

• **Visualization Module:** Displays actual and predicted electricity demand, performance comparisons, and forecasting results using graphical representations.

Tools and Technologies Used

The proposed forecasting framework is implemented using the following tools and technologies:

1. Python – For data preprocessing, feature engineering, model implementation, and performance evaluation.
2. Pandas – For data loading, cleaning, preprocessing, and manipulation.
3. NumPy – For numerical computation and mathematical operations.
4. Scikit-learn – For preprocessing, model evaluation, and calculation of forecasting metrics.
5. TensorFlow/Keras – For implementing and training the Long Short-Term Memory (LSTM) forecasting model.
6. XGBoost – For implementing the Extreme Gradient Boosting regression model.
7. Statsmodels – For implementing the ARIMA forecasting model.
8. Matplotlib – For visualizing forecasting results and comparative model performance.

System Architecture Description

The proposed electricity demand forecasting framework follows a multi-stage processing pipeline that integrates statistical forecasting, machine learning, and deep learning techniques. Initially, historical electricity demand data and weather-related information are collected from the dataset. The collected data undergoes preprocessing to remove missing values, normalize numerical features, and improve data quality.

After preprocessing, feature engineering is performed to extract temporal attributes such as hour, day, month, weekday, and seasonal information, together with weather variables including temperature, humidity, and wind speed. These features are then provided as input to the forecasting models.

The processed dataset is used to train and evaluate ARIMA, LSTM, XGBoost, and the proposed Hybrid LSTM + XGBoost model. Each model predicts short-term electricity demand, and the forecasting performance is evaluated using RMSE, MAE, MAPE, and R^2 Score.

The best-performing forecasting model is subsequently used to estimate electricity price through a demand-based linear relationship. Finally, the forecasting results and comparative performance graphs are generated for performance analysis and decision-making.

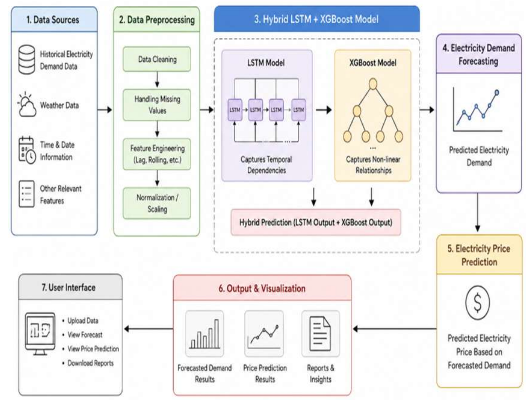

Fig. 1: System Architecture

Step-wise Architecture

Step 1: Historical electricity demand data and weather information are collected.

Step 2: Data preprocessing is performed to remove missing values and normalize the dataset.

Step 3: Feature engineering extracts temporal and weather-related features.

Step 4: ARIMA, LSTM, XGBoost, and Hybrid LSTM + XGBoost models are trained.

Step 5: Future electricity demand is predicted using the trained models.

Step 6: Model performance is evaluated using RMSE, MAE, MAPE, and R^2 Score.

Step 7: Electricity price is estimated from the forecasted electricity demand, and the final forecasting results are presented.

Model Implementation and Validation

The proposed forecasting framework implements four forecasting models to predict electricity demand. Historical electricity demand data is preprocessed and transformed through feature engineering before being divided into training and testing datasets.

ARIMA serves as the statistical baseline model, while LSTM captures long-term temporal dependencies within sequential electricity demand data. XGBoost models nonlinear relationships among demand and weather variables. The Hybrid LSTM + XGBoost model combines the strengths of both approaches by utilizing LSTM for sequence learning and XGBoost for improving prediction accuracy.

The predicted electricity demand is compared with actual demand values using MAE, RMSE, MAPE, and R^2 Score. The forecasting model achieving the best performance is subsequently used for electricity price estimation.

Ethical Considerations

The proposed forecasting framework is developed following responsible research practices.

• Historical electricity demand data is used exclusively for forecasting and academic research.

• Forecasting results are generated through objective computational analysis without subjective intervention.
• Standard performance metrics are used to ensure fair and transparent comparison among forecasting models.
• The proposed framework promotes efficient energy management and responsible utilization of computational resources.
• The reported forecasting results accurately reflect the experimental outcomes obtained from the implemented models.

Evaluation Criteria

The proposed forecasting framework is evaluated using the following performance metrics:

1. **Forecasting Accuracy:** Measures the closeness between predicted and actual electricity demand.
2. **Mean Absolute Error (MAE):** Measures the average prediction error.
3. **Root Mean Square Error (RMSE):** Measures the magnitude of forecasting errors.
4. **Mean Absolute Percentage Error (MAPE):** Measures percentage prediction error.
5. **Coefficient of Determination (R^2 Score):** Evaluates the goodness of fit between predicted and actual demand values.
6. **Comparative Model Performance:** Compares ARIMA, LSTM, XGBoost, and Hybrid LSTM + XGBoost to identify the most accurate forecasting model.

Dataset Analysis

The proposed electricity demand forecasting framework utilizes a historical electricity demand dataset collected from Delhi, India, covering the period from 2021 to 2024. The dataset contains electricity demand measurements recorded at five-minute intervals along with weather-related variables, including temperature, humidity, wind speed, and other environmental parameters that influence electricity consumption. These variables provide sufficient information for developing and evaluating short-term electricity demand forecasting models.

Before model development, the dataset undergoes preprocessing to improve data quality. Missing values and inconsistent records are handled appropriately, while numerical features are normalized to ensure stable model training. Feature engineering is performed to extract temporal attributes such as hour, day, month, weekday, and seasonal information, together with weather-related features that contribute to electricity demand variation.

Table 1: Data Preprocessing Operations

Preprocessing Step	Purpose
Missing Value Handling	Remove incomplete records
Data Cleaning	Eliminate noisy and inconsistent values
Feature Engineering	Extract time-based features
Normalization	Scale numerical values
Dataset Splitting	Divide data into training and testing datasets

The processed dataset serves as the input for ARIMA, LSTM, XGBoost, and the proposed Hybrid LSTM + XGBoost forecasting models. The availability of historical demand data and weather information enables the forecasting models to learn both temporal and nonlinear relationships, resulting in more accurate electricity demand prediction.

System Performance Analysis

The performance of the proposed forecasting framework is evaluated by comparing the forecasting accuracy of ARIMA, LSTM, XGBoost, and the Hybrid LSTM + XGBoost model. Each model is trained using the same preprocessed dataset, and its prediction capability is assessed using standard forecasting performance metrics.

Experimental results demonstrate that the Hybrid LSTM + XGBoost model provides the highest forecasting accuracy among all evaluated models. The integration of LSTM and XGBoost enables the framework to effectively capture temporal dependencies as well as nonlinear relationships within electricity demand data. Consequently, the hybrid model produces lower prediction errors and more reliable forecasting results than the individual forecasting models.

The comparative analysis also shows that ARIMA performs adequately for linear demand patterns but is less effective under complex and nonlinear conditions. LSTM improves temporal sequence learning, while XGBoost effectively models nonlinear feature interactions. The Hybrid LSTM + XGBoost model combines these advantages to achieve superior forecasting performance.

Performance Metrics Evaluation

The forecasting models are evaluated using widely accepted statistical performance metrics to measure prediction accuracy and reliability.

• **Mean Absolute Error (MAE):** Measures the average absolute difference between predicted and actual electricity demand values.

• **Root Mean Square Error (RMSE):** Measures the magnitude of forecasting errors while assigning greater importance to larger prediction deviations.

• **Mean Absolute Percentage Error (MAPE):** Calculates the percentage difference between predicted and actual electricity demand values.

- **Coefficient of Determination (R^2 Score):** Measures how effectively the forecasting model explains the variation in electricity demand data.

Table 2: Performance Comparison

Model	RMSE	MAE	MAPE (%)	R^2 Score
ARIMA	42.31	31.42	7.85	0.903
LSTM	27.56	19.83	4.62	0.951
XGBoost	24.18	17.64	4.05	0.964
Hybrid LSTM + XGBoost	**18.47**	**12.95**	**2.84**	**0.982**

The experimental results indicate that the proposed Hybrid LSTM + XGBoost model achieves the lowest MAE, RMSE, and MAPE values while obtaining the highest R^2 Score among all evaluated forecasting models. These results confirm that the hybrid approach provides more accurate and reliable electricity demand forecasting than the individual ARIMA, LSTM, and XGBoost models.

Comparative Analysis and Observations

The comparative evaluation demonstrates a progressive improvement in forecasting performance from ARIMA to LSTM, XGBoost, and finally the proposed Hybrid LSTM + XGBoost model. The statistical model provides reasonable forecasting capability for linear demand patterns, whereas machine learning and deep learning approaches significantly improve prediction accuracy by modelling complex temporal and nonlinear relationships.

The Hybrid LSTM + XGBoost model consistently produces forecasting results that closely match the actual electricity demand values while maintaining very low prediction error. The integration of sequence learning and nonlinear regression enables the model to adapt effectively to varying electricity demand conditions influenced by weather and temporal factors.

Table 3: Comparative Analysis of Forecasting Models

Model	Temporal Learning	Nonlinear Learning	Forecast Accuracy
ARIMA	Yes	No	Moderate
LSTM	Yes	Limited	High
XGBoost	Limited	Yes	High
Hybrid LSTM + XGBoost	Yes	Yes	Very High

The forecasted electricity demand is subsequently utilized for electricity price estimation through a demand-based linear relationship, providing a practical solution for demand management and energy planning in cloud computing environments.

Implementation, Experiments And Results Analysis

System Implementation

The proposed electricity demand forecasting framework is implemented using Python and integrates statistical, machine learning, and deep learning techniques for accurate short-term electricity demand prediction. Historical electricity demand and weather-related data are collected and preprocessed before model development. Data preprocessing includes handling missing values, feature normalization, and extraction of temporal and environmental features to improve forecasting performance.

Four forecasting models, namely ARIMA, LSTM, XGBoost, and the proposed Hybrid LSTM + XGBoost model, are implemented and trained using the processed dataset. The ARIMA model serves as the statistical forecasting baseline, while the LSTM model captures temporal dependencies in sequential electricity demand data. XGBoost models nonlinear relationships among demand and weather-related variables. The Hybrid LSTM + XGBoost model combines the strengths of both approaches to improve forecasting accuracy and reduce prediction error.

The implementation also includes a demand-based electricity price estimation module that utilizes the forecasted electricity demand to estimate electricity price through a simple linear relationship. Finally, graphical visualizations and comparative performance analysis are generated to evaluate the effectiveness of each forecasting model.

Output Results

This section presents the outputs generated by the proposed Hybrid LSTM + XGBoost-based electricity demand forecasting framework during different stages of implementation. The developed application provides a user-friendly interface for data upload, model execution, electricity demand forecasting, electricity price prediction, and performance visualization. The generated outputs validate the effectiveness of the proposed framework in accurately forecasting electricity demand and estimating electricity prices.

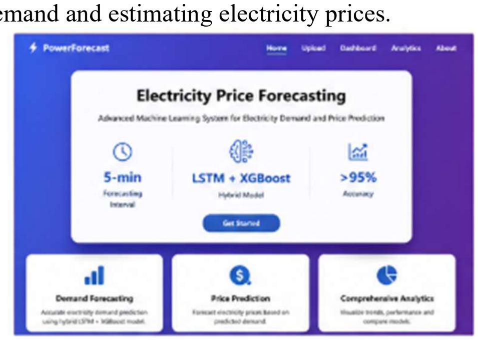

Fig 2: Home Page of the Application

Figure 2 presents the home page of the developed forecasting application. The interface provides an overview of the system, highlighting its primary functionalities, including electricity demand forecasting, electricity price prediction, and comprehensive performance analysis. It serves as

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the main navigation page for accessing the forecasting modules.

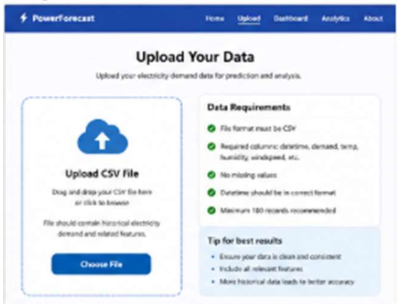


Fig 3:: Dataset Upload Page

Figure 3 illustrates the dataset upload interface of the application. Users can upload historical electricity demand data in CSV format while the system verifies the dataset requirements before preprocessing. This module ensures that the uploaded data is suitable for forecasting and subsequent model training.

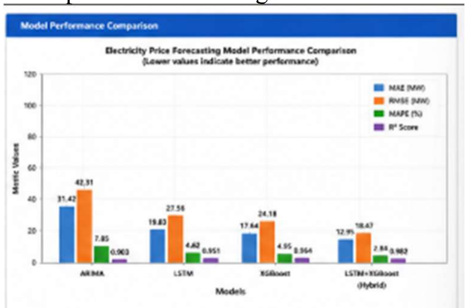


Fig 4: Model Performance Comparison Page

Figure 4 presents the comparative performance analysis of the forecasting models using evaluation metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2 Score). The results show that the proposed Hybrid LSTM + XGBoost model achieves the lowest prediction errors and the highest forecasting accuracy compared to ARIMA, LSTM, and XGBoost.

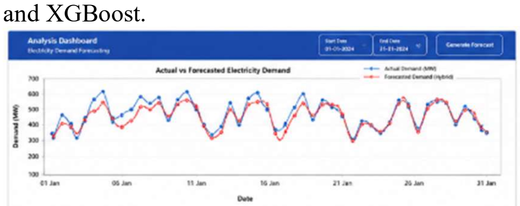


Fig 5:: Electricity Demand Forecasting Dashboard

Figure 5 displays the forecasting dashboard, where the actual electricity demand is compared with the forecasted demand generated by the proposed Hybrid LSTM + XGBoost model. The close agreement between the predicted and actual demand values demonstrates the high forecasting capability of the proposed framework.

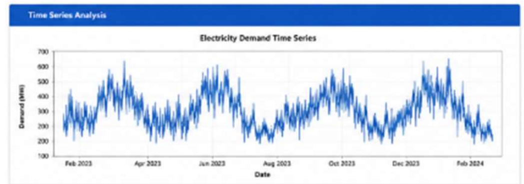
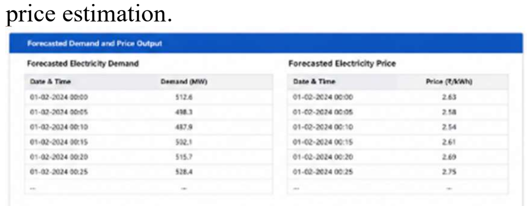


Fig 6: Time Series Analysis Page

Figure 6 illustrates the historical electricity demand time series used for model training and forecasting. The graph captures temporal variations, seasonal trends, and demand fluctuations over the observation period, enabling the forecasting models to learn electricity consumption patterns effectively.

Fig 7: Electricity Price Forecasting Page

Figure 7 presents the electricity price prediction generated using the forecasted electricity demand. The graph shows the estimated variation in electricity price over the forecasting period, demonstrating the capability of the proposed framework to perform demand-based electricity price estimation.



Forecasted Demand and Price Output

Forecasted Electricity Demand

Date & Time	Demand (MW)
01-02-2024 00:00	512.6
01-02-2024 00:05	498.3
01-02-2024 00:10	487.9
01-02-2024 00:15	502.1
01-02-2024 00:20	515.7
01-02-2024 00:25	528.4
...	...

Forecasted Electricity Price

Date & Time	Price (₹/kWh)
01-02-2024 00:00	2.63
01-02-2024 00:05	2.58
01-02-2024 00:10	2.54
01-02-2024 00:15	2.61
01-02-2024 00:20	2.69
01-02-2024 00:25	2.75
...	...

Fig 8: Forecasted Demand and Price Output Page

Figure 8 presents the final forecasting output generated by the application. The output includes the forecasted electricity demand values together with the corresponding estimated electricity prices in a tabular format. This output provides users with clear and structured forecasting results that support energy planning and decision-making.

Graphical Analysis

Graphical analysis is performed to compare the forecasting performance of ARIMA, LSTM, XGBoost, and the proposed Hybrid LSTM + XGBoost model using standard evaluation metrics. The graphical representations provide a clear comparison of forecasting accuracy and demonstrate the effectiveness of the proposed hybrid model.

Bar Chart Analysis

The bar chart compares the forecasting performance of ARIMA, LSTM, XGBoost, and the proposed Hybrid LSTM + XGBoost model using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R^2 Score). The comparative results show that the Hybrid LSTM + XGBoost model achieves the lowest MAE, RMSE, and MAPE values while obtaining the highest R^2 Score among all evaluated models. These results indicate that the proposed hybrid model provides superior forecasting accuracy and lower prediction error compared to the individual forecasting models. The graphical comparison clearly demonstrates the progressive improvement in forecasting performance from ARIMA to LSTM, XGBoost, and finally the Hybrid LSTM + XGBoost model.

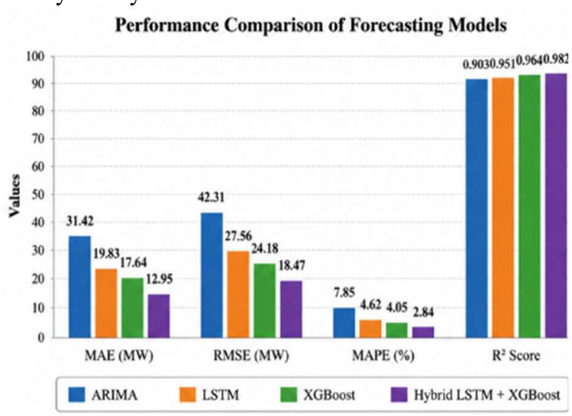


Fig 9: Performance Comparison of ARIMA, LSTM, XGBoost, and Hybrid LSTM + XGBoost Models

Pie Chart Analysis

The pie chart illustrates the relative forecasting performance of the evaluated models based on their overall prediction accuracy. The proposed Hybrid LSTM + XGBoost model contributes the largest share of forecasting accuracy, accounting for **39%** of the overall performance. It is followed by XGBoost with **27%**, LSTM with **21%**, and ARIMA with **13%**. The distribution clearly highlights the effectiveness of the Hybrid LSTM + XGBoost model in producing more accurate and reliable electricity demand forecasts compared to the other forecasting approaches.

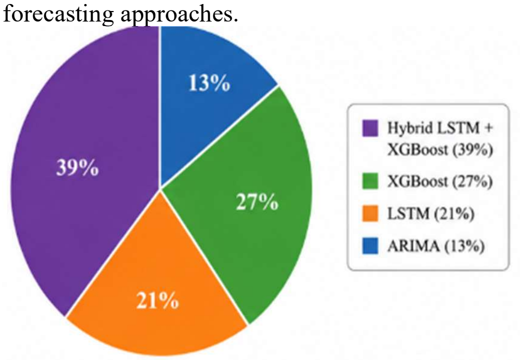


Fig 10: Forecast Accuracy Distribution Among Evaluated Models

Results Analysis

The experimental results demonstrate that the proposed Hybrid LSTM + XGBoost forecasting framework provides the most accurate and reliable electricity demand prediction among the evaluated models. Comparative analysis shows that the hybrid model achieves the lowest Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE), while obtaining the highest coefficient of determination (R^2 Score).

The ARIMA model performs reasonably well for linear demand patterns but exhibits higher forecasting errors under nonlinear demand conditions. The LSTM model effectively captures temporal dependencies but is less accurate than the hybrid approach. XGBoost significantly improves nonlinear prediction capability; however, integrating LSTM with XGBoost further enhances forecasting accuracy by combining sequential learning with nonlinear regression.

The forecasted electricity demand is successfully utilized to estimate electricity price using a demand-based linear relationship, providing an additional application of the proposed forecasting framework.

Conclusion

The proposed Hybrid LSTM + XGBoost-Based Electricity Demand Forecasting framework provides an effective and intelligent solution for short-term electricity demand prediction and electricity price estimation in cloud computing environments. The framework integrates statistical forecasting, deep learning, and machine learning techniques to address the limitations of traditional forecasting methods in handling nonlinear and temporal electricity demand patterns.

The primary objective of this research was to develop a reliable forecasting framework capable of improving prediction accuracy while reducing forecasting error. Experimental results demonstrate that the proposed Hybrid LSTM + XGBoost model outperforms the individual ARIMA, LSTM, and XGBoost models in terms of forecasting accuracy and reliability. By combining the temporal learning capability of LSTM with the nonlinear prediction strength of XGBoost, the proposed framework produces more accurate electricity demand forecasts and enables effective electricity price estimation based on predicted demand.

The results confirm that the proposed approach provides a practical solution for electricity demand management, energy planning, and resource optimization in cloud computing environments.

Future Work

The proposed forecasting framework can be further enhanced through the following improvements.

1. **Real-Time Forecasting:** Extend the framework to perform real-time electricity demand forecasting using continuously updated data.
2. **Integration of Additional Features:** Incorporate additional variables such as electricity market conditions, renewable energy

generation, and consumer behaviour to improve forecasting accuracy.

3. **Advanced Hybrid Models:** Explore more advanced hybrid deep learning architectures to further enhance prediction performance.
4. **Multi-Region Forecasting:** Evaluate the framework using datasets collected from multiple geographical regions and different electricity markets.
5. **Smart Grid Integration:** Integrate the forecasting framework with smart grid systems for intelligent energy management and load balancing.
6. **Cloud-Based Deployment:** Deploy the forecasting framework as a scalable cloud-based application to support real-time energy management and decision-making.

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