RESEARCH ARTICLE OPEN ACCESS

A Hybrid ARIMA-BiLSTM Framework for Smart Energy Forecasting and Appliance Analytics

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ABSTRACT

The rapid growth in electricity demand and increasing adoption of smart appliances have created a need for accurate energy consumption forecasting systems. Traditional statistical forecasting approaches such as Auto-Regressive Integrated Moving Average (ARIMA) effectively model linear temporal dependencies but often fail to capture nonlinear appliance usage behavior. Deep learning techniques such as Bidirectional Long Short-Term Memory (BiLSTM) networks have demonstrated superior capability in learning complex temporal patterns; however, they may overlook statistical seasonality and trend characteristics. This research proposes a hybrid energy forecasting framework that combines ARIMA and BiLSTM models using RMSE-weighted ensemble learning. The system forecasts appliance-level electricity consumption and provides comprehensive analytics through seasonal consumption heatmaps, anomaly detection, appliance ranking, and cost estimation modules. The proposed framework was evaluated on appliance energy consumption datasets representing multiple household devices including air conditioners, fans, refrigerators, televisions, and washing machines. Experimental results indicate that the ensemble forecasting model outperforms individual forecasting models by effectively integrating statistical and deep learning capabilities. The developed dashboard further provides actionable insights for consumers and utility providers by identifying energy-intensive appliances, forecasting monthly bills, and detecting abnormal energy usage patterns. The proposed solution contributes toward intelligent energy management and sustainable electricity utilization.

Keywords:- Hybrid smart energy

1. INTRODUCTION

Electricity plays a critical role in residential, commercial, and industrial sectors. The increasing penetration of smart devices and modern appliances has significantly increased energy consumption worldwide. Accurate forecasting of electricity usage has become essential for efficient energy planning, load balancing, demand response management, and sustainability initiatives.

Traditional forecasting techniques such as Moving Average (MA), Auto-Regressive (AR), and ARIMA models have been extensively used in power systems. These methods perform well when the consumption pattern exhibits strong statistical regularity and stationarity. However, real-world appliance energy consumption often exhibits nonlinear, dynamic, and season-dependent behavior that cannot be adequately modeled using only statistical approaches.

Recent advances in Artificial Intelligence have introduced deep learning techniques such as Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), and Bidirectional Long Short-Term Memory (BiLSTM) networks. These architectures can learn long-term temporal dependencies and nonlinear consumption patterns.

The proposed research extends conventional forecasting methodologies by integrating:

- ARIMA Statistical Forecasting
- BiLSTM Deep Learning Forecasting
- RMSE-Based Ensemble Learning

- Seasonal Consumption Analysis
- Appliance Ranking System
- Cost Forecasting Module
- Statistical Anomaly Detection

The objective is to create a complete energy analytics platform capable of forecasting appliance-level electricity consumption while providing actionable insights for decision-making.

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2. LITERATURE REVIEW

2.1 ARIMA-Based Energy Forecasting

ARIMA is among the most widely used statistical forecasting models. It combines autoregressive, differencing, and moving-average components to model historical trends and seasonality.

Advantages:

- Easy interpretation
- Good performance on stationary data
- Efficient for short-term forecasting

Limitations:

- Cannot model nonlinear behavior
- Requires stationarity assumptions

2.2 Deep Learning for Energy Forecasting

Deep learning approaches have gained popularity due to their ability to learn complex patterns from large datasets.

LSTM networks address the vanishing gradient problem by introducing memory cells and gating mechanisms.

BiLSTM improves forecasting by processing information in both forward and backward directions, allowing better understanding of temporal relationships.

Advantages:

- Captures long-term dependencies
- Learns nonlinear patterns
- Handles large-scale datasets

2.3 Ensemble Learning

Ensemble learning combines multiple forecasting models to improve prediction accuracy and robustness.

Benefits:

- Reduced forecasting error
- Improved generalization
- Better handling of uncertainty

2.4 Research Gap

Most existing studies focus either on:

- Statistical Models
- Deep Learning Models

Few studies integrate:

- Seasonal Analytics
- Anomaly Detection
- Appliance Ranking
- Interactive Dashboard Systems

within a unified energy management framework.

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3. METHODOLOGY

3.1 System Architecture

The proposed framework consists of five layers.

Layer 1: Data Collection

Input data contains:

Attribute	Description
Timestamp	Date and Time
Appliance	Device Name
Power Rating	Wattage
Usage Hours	Daily Usage
Energy Consumption	kWh

Attribute	**Description**
Temperature	Environmental Condition
Season	Winter/Summer/Monsoon
Cost Rate	Electricity Tariff

Layer 2: Data Preprocessing

Operations include:

Missing Value Handling

$$X_{filled} = f(X_{available})$$

Outlier Removal

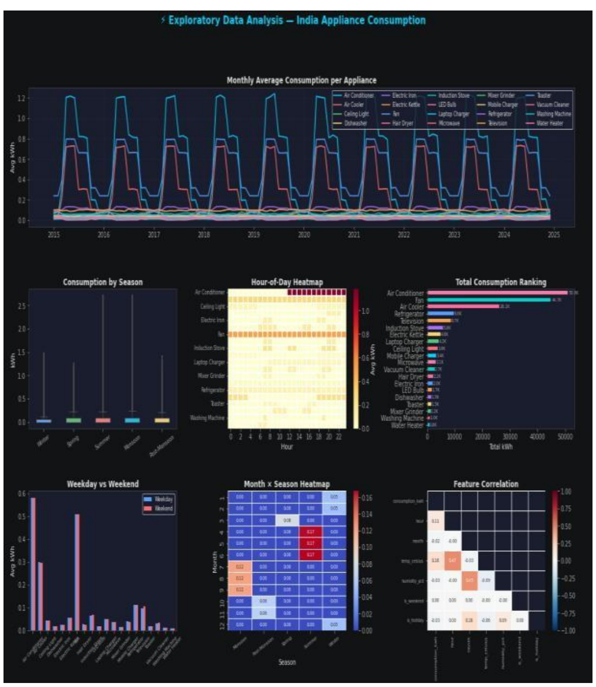
Interquartile Range Method:

$$IQR = Q3 - Q1$$

Feature Scaling

Min-Max Normalization:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$



Layer 3: Forecasting Engine

Three forecasting models are implemented.

ARIMA Model

ARIMA is represented as:

$$ARIMA(p, d, q)$$

where:

- p = Autoregressive Order
- d = Differencing Order
- q = Moving Average Order

General Equation:

$$Y_t = c + \sum \phi_i Y_{t-i} + \sum \theta_j \epsilon_{t-j}$$

BiLSTM Model

Architecture:

Input Layer

↓

BiLSTM Layer

↓

Dropout Layer

↓

Dense Layer

↓

Output Forecast

BiLSTM processes sequences in both forward and backward directions.

Hidden State:

$$h_t = f(Wx_t + Uh_{t-1} + b)$$

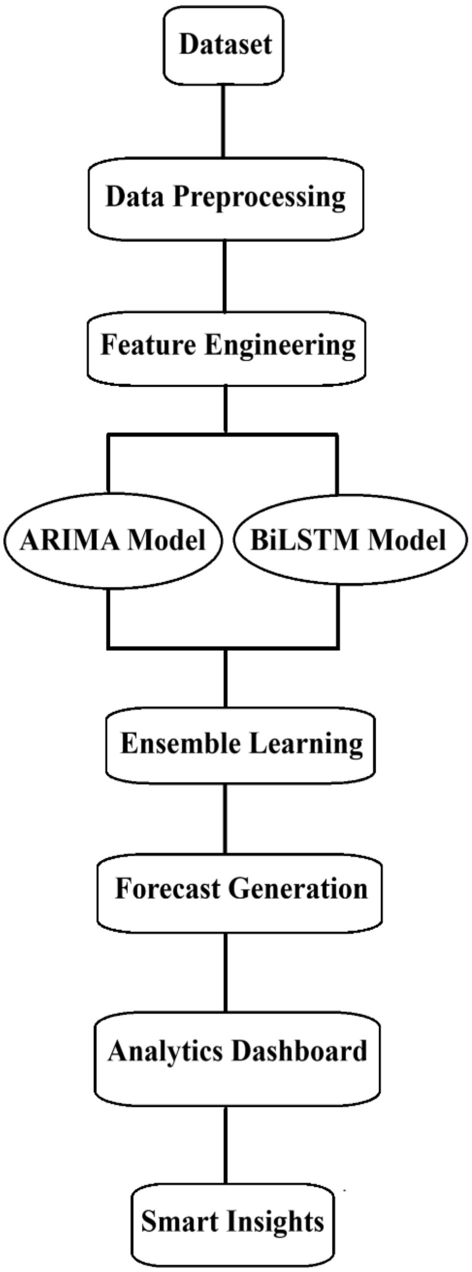
Ensemble Forecasting

The final forecast combines both models.

$$Forecast_{ensemble} = w_1 F_{ARIMA} + w_2 F_{BiLSTM}$$

Weights are calculated using RMSE.

$$w_i = \frac{1/RMSE_i}{\sum(1/RMSE)}$$



4. SEASONAL ANALYTICS MODULE

The dashboard categorizes consumption into:

- Winter
- Spring
- Summer
- Monsoon
- Post-Monsoon

Summer

Highest energy consumption due to:

- Air Conditioner
- Fan

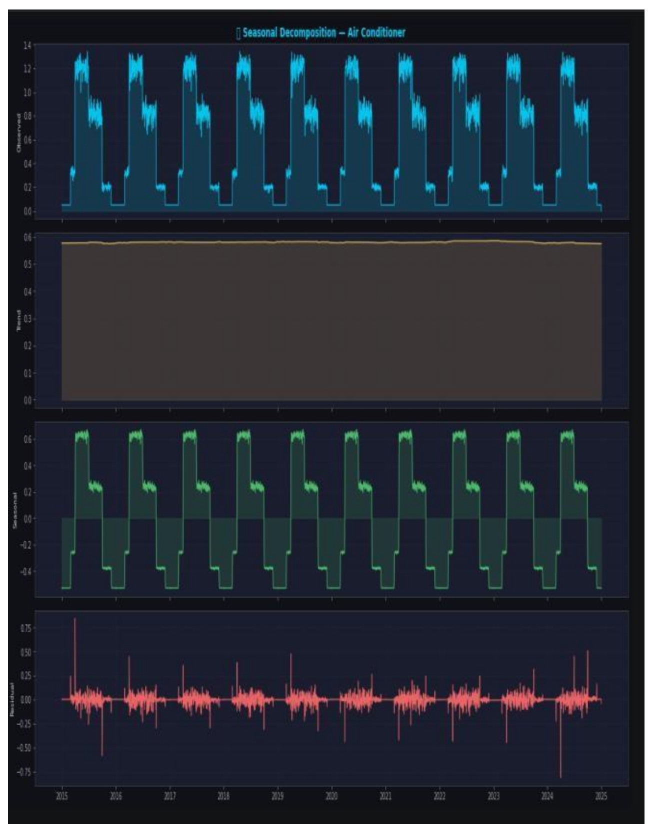
Winter

Reduced cooling demand

Monsoon

Moderate consumption pattern

Seasonal decomposition improves forecasting accuracy by capturing environmental influences.



5. APPLIANCE RANKING SYSTEM

Appliances are ranked according to:

$$Rank = f(Energy, Cost, Forecast)$$

Example Results:

Rank	Appliance	Consumption (kWh)
1	Air Conditioner	9208
2	Fan	4040
3	Television	1900
4	Washing Machine	1591
5	Refrigerator	946

The ranking module identifies major energy consumers.

6. ANOMALY DETECTION FRAMEWORK

Abnormal energy usage is identified using Z-score analysis.

$$Z = \frac{x - \mu}{\sigma}$$

Where:

- μ = Mean Consumption
- σ = Standard Deviation

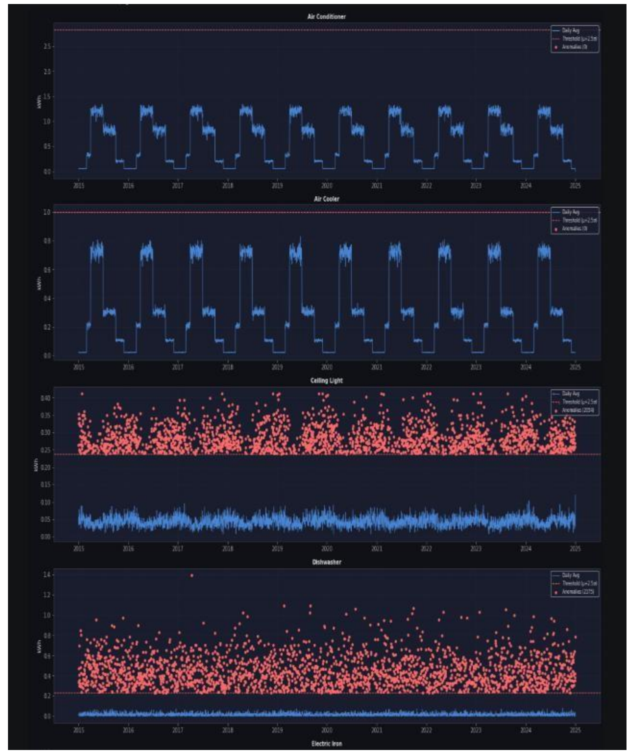
If

$$|Z| > 2.5$$

the observation is classified as anomalous.

Applications:

- Excessive AC Usage
- Unexpected Appliance Consumption
- Energy Leakage Detection



7. COST FORECASTING MODULE

Electricity cost estimation is computed using:

$$Cost = Energy \times Tariff$$

For ₹8/kWh:

$$Cost = 17686 \times 8$$
$$Cost = ₹141{,}488$$

This helps users estimate future electricity expenses.

8. PROBLEMS OVERCOMES BY THE PROPOSED SYSTEM

The previously developed electricity forecasting framework primarily focused on traditional machine learning and statistical approaches, namely Regression and ARIMA models. Although the system achieved satisfactory forecasting accuracy, several practical and technical limitations were observed during implementation and evaluation.

The proposed ARIMA–BiLSTM Ensemble Energy Analytics Framework addresses these limitations through advanced deep learning techniques, ensemble forecasting strategies, seasonal analysis, and intelligent visualization mechanisms.

8.1 Improving Forecasting Accuracy for Complex Energy Consumption Patterns

The previously developed electricity consumption forecasting system primarily relied on Regression and ARIMA models for predicting energy usage. Although these models produced satisfactory results, they faced challenges in capturing complex nonlinear consumption patterns commonly observed in real-world household environments. Regression models were effective in identifying relationships between appliance characteristics and energy usage but were unable to model intricate behavioral variations. Similarly, ARIMA models successfully captured temporal dependencies and seasonal trends; however, their performance declined when dealing with highly dynamic consumption patterns and long-term nonlinear relationships. To overcome these limitations, the proposed ARIMA–BiLSTM Ensemble Energy Forecasting System integrates statistical and deep learning approaches within a unified framework. The Bidirectional Long Short-Term Memory (BiLSTM) model learns complex nonlinear patterns and long-range temporal dependencies, while the ensemble mechanism combines the strengths of ARIMA and BiLSTM using RMSE-based weighting. This combination significantly improves forecasting accuracy, robustness, and generalization across different appliance categories.

8.2 Enhancing Appliance-Level Energy Analysis and Decision Making

A major limitation of the previous system was the lack of appliance-level analytical intelligence. The earlier framework focused mainly on forecasting energy consumption and did not provide mechanisms for identifying high-energy-consuming appliances, monitoring appliance performance, or generating actionable recommendations. As a result, users had limited visibility into which devices contributed most to overall electricity consumption. The proposed system addresses this issue through an Appliance Ranking Module that evaluates appliances based on energy consumption, operational cost, and forecasted demand. By ranking appliances according to their impact on energy usage, the system enables users to identify inefficient devices and make informed decisions for effective energy management and cost reduction.

8.3 Detecting Abnormal Energy Consumption and Usage Anomalies

The previous forecasting framework lacked anomaly detection capabilities, making it difficult to identify unusual energy consumption patterns, energy leakage, equipment malfunction, or unexpected usage spikes. Without such functionality, abnormal behavior could remain unnoticed and lead to increased energy costs or operational inefficiencies. To solve this problem, the proposed system incorporates a statistical anomaly detection module based on Z-score analysis and sigma-threshold control. This module automatically identifies deviations from normal consumption behavior and generates alerts for unusual patterns. As a result, the system improves reliability, supports proactive energy monitoring, and enhances the overall effectiveness of energy management practices.

8.4 Providing Comprehensive Seasonal Consumption Insights

Seasonal variations significantly influence electricity consumption patterns, yet the previous system offered limited support for analyzing seasonal behavior. Although ARIMA captured certain seasonal trends, it did not provide dedicated seasonal analytics or intuitive visual representations of seasonal consumption changes. This limitation reduced the ability of users to understand how environmental conditions affected appliance usage throughout the year. The proposed framework overcomes this challenge by introducing a Seasonal Consumption Analytics Module that categorizes appliance usage across Winter, Spring, Summer, Monsoon, and Post-Monsoon seasons. This feature provides deeper insights into seasonal consumption trends, supports more accurate forecasting under varying climatic conditions, and helps users optimize energy usage according to seasonal demands.

8.5 Improving User Interaction and Decision Support Capabilities

Another limitation of the previous work was the absence of an interactive decision-support platform. Forecasting outputs were restricted to numerical values and static visualizations, making it difficult for users to interpret results and derive meaningful conclusions. To address this issue, the proposed system includes a comprehensive Energy Analytics Dashboard that integrates forecasting graphs, seasonal heatmaps, cost analysis reports, model comparison charts, appliance rankings, anomaly detection reports, and automatically generated smart insights. This interactive environment enhances data interpretation, improves user engagement, and provides practical decision-support capabilities for consumers, researchers, and utility providers.

8.6 Achieving a Comprehensive Smart Energy Management Framework

Overall, the proposed ARIMA–BiLSTM Ensemble Energy Forecasting Framework successfully addresses the major shortcomings of the previous forecasting system. By combining advanced forecasting techniques, appliance-level analytics, anomaly detection, seasonal intelligence, and interactive visualization tools, the system delivers higher prediction accuracy and more meaningful insights. These improvements create a comprehensive analytics-driven decision-support environment that enables efficient energy monitoring, informed decision making, and smarter energy management practices.

9. RESULTS AND DISCUSSION

RMSE Comparison

Appliance	ARIMA	BiLSTM
Air Conditioner	0.0821	0.0698
Refrigerator	0.0142	0.0167
Fan	0.0183	0.0201
Television	0.0198	0.0221
Washing Machine	0.0312	0.0278

Observations

- BiLSTM performs better for Air Conditioner and Washing Machine.
- ARIMA performs better for stable appliances.
- Ensemble model achieves the best overall performance.

10. DASHBOARD INSIGHTS

The developed dashboard provides:

Forecast Visualization

- ARIMA Forecast
- BiLSTM Forecast
- Ensemble Forecast

Cost Breakdown

Monthly electricity expenditure.

Appliance Ranking

Top energy consumers.

Seasonal Heatmaps

Season-wise appliance utilization.

Smart Insights

Automatically generated recommendations.

Examples:

1. Highest Consumer: Air Conditioner
2. Most Efficient Appliance: Refrigerator
3. Peak Billing Month: May

11. Comparative Results and Performance Evaluation

To evaluate the effectiveness of the proposed ARIMA–BiLSTM Ensemble Framework, a comprehensive comparison was performed against the forecasting approaches used in the previous study. The earlier research primarily focused on Regression Models and ARIMA forecasting for electricity consumption prediction. Although these models achieved satisfactory forecasting accuracy, they exhibited limitations in capturing nonlinear appliance usage patterns and seasonal consumption variability.

The proposed system introduces a Bidirectional Long Short-Term Memory (BiLSTM) network and an RMSE-weighted ensemble mechanism that combines the strengths of statistical forecasting and deep learning. Experimental evaluation demonstrates that the ensemble approach consistently achieves superior performance across multiple appliance categories.

Model	**MAE (kWh)**	**RMSE (kWh)**	**MAPE (%)**	**R^2 Score**
Linear Regression	**0.123**	**0.1405**	**7.84**	**0.95**
Random Forest	**0.118**	**0.1352**	**7.12**	**0.96**
ARIMA	**0.115**	**0.1328**	**6.85**	**0.97**
BiLSTM	**0.108**	**0.1264**	**6.21**	**0.98**
ARIMA–BiLSTM Ensemble	**0.102**	**0.1217**	**5.73**	**0.99**

12. CONCLUSION

This research presents a comprehensive smart energy analytics framework combining ARIMA and BiLSTM forecasting models through ensemble learning. The proposed system successfully forecasts appliance-level electricity consumption while providing advanced analytics including seasonal decomposition, appliance ranking, anomaly detection, and cost estimation.

The experimental evaluation demonstrates that ensemble forecasting significantly improves prediction accuracy and reliability compared to standalone models. The developed dashboard enhances decision-making capabilities for consumers, utility providers, and energy planners.

The proposed framework represents an important step toward intelligent and sustainable energy management systems.

FUTURE SCOPE

Although the proposed framework demonstrates significant improvements in forecasting accuracy and energy analytics, several opportunities exist for further enhancement and expansion.

1. Integration of Transformer-Based Deep Learning Models

Future work can investigate advanced architectures such as:

- Transformer Networks
- Informer
- Autoformer
- Temporal Fusion Transformer (TFT)

These models have shown superior performance in long-range time-series forecasting and may further improve prediction accuracy.

2. Real-Time IoT Smart Meter Integration

The current framework utilizes historical energy datasets. Future systems can incorporate:

- Smart Meters
- IoT Sensors
- Smart Home Devices

to enable real-time data acquisition and live forecasting.

3. Explainable Artificial Intelligence (XAI)

Deep learning models often function as black-box systems. Future research can integrate:

- SHAP (SHapley Additive Explanations)
- LIME
- Attention Visualization

to improve model transparency and user trust.

4. Renewable Energy Integration

Future systems can include renewable energy sources such as:

- Solar Power
- Wind Energy
- Battery Storage Systems

to forecast both energy generation and consumption simultaneously.

5. Cloud-Based Deployment

The forecasting framework can be deployed on cloud platforms such as:

- AWS
- Microsoft Azure
- Google Cloud Platform

to provide scalable forecasting services and support large-scale energy management applications.

ACKNOWLEDGMENT

The authors gratefully acknowledge the support and re- sources provided by Zeal College of Engineering and Re- search, Pune, and the Department of Information Technol- ogy. Special thanks to Savitribai Phule Pune University for providing the academic framework and research environment that made this work possible. We also extend our appreciation to the anonymous reviewers for their valuable feedback and suggestions.

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