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SMART CAST – AI Powered Load Forecasting for Smart Grids

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Abstract
The increasing complexity and variability of electricity consumption in modern power systems have highlighted the need for intelligent, real-time forecasting solutions to ensure reliable, cost-efficient, and sustainable grid oper ations. This research presents Smart Cast, an AI-driven load forecasting frame work that integrates Long Short-Term Memory (LSTM) networks with Gradient Boosting models to capture both nonlinear temporal patterns and external influ encing factors such as weather dynamics. The system leverages historical smart meter data along with real-time sensor inputs to generate accurate short- and mid term demand predictions. In addition, Smart Cast incorporates anomaly detection techniques to proactively identify irregular consumption behaviors that may in dicate faults, energy theft, or operational inefficiencies. Outputs are delivered through an interactive web dashboard, enabling utility operators and industrial consumers to visualize demand behavior and receive cost-aware recommenda tions for optimized energy usage. By enhancing grid planning, reducing opera tional risks, and increasing renewable integration potential, Smart Cast presents a scalable and practical solution to advancing smart-grid intelligence and overall energy sustainability.

Keywords: *AI Voice Agent, Retrieval-Augmented Generation, Large Language Models, Lead Qualification, Customer Support Automation, Plug-and-Play Voice Assistant, Contextual Intelligence.*

1. Introduction

The global shift toward smarter and more sustainable power systems has rapidly increased the demand for accurate electricity load forecasting. Modern smart grids are no longer passive suppliers of electricity but intelligent infrastructures capable of sensing, analyzing, and responding to dynamic energy consumption patterns. As electricity us age continues to fluctuate due to industrial growth, changing climate conditions, and widespread adoption of distributed generation, forecasting future demand with precision has become a critical operational requirement for utilities worldwide [1]. Traditional statistical approaches such as ARIMA and regression-based forecasting often struggle to capture nonlinear and rapidly changing patterns in energy consumption. In 2 contrast, machine learning and deep learning techniques have shown strong promise due to their ability to model complex temporal behavior and multiple interdependent variables [2], [3]. These advanced methods provide enhanced adaptability and scalability, addressing the increasing diversity and volume of smart-meter data available in modern power systems. Hybrid AI models have emerged as highly effective solutions, particularly combining Long Short-Term Memory (LSTM) networks with gradient boosting algorithms like XGBoost. Such combinations exploit the sequence learning capabilities of LSTM while leveraging the structured feature analysis strength of boosting models, leading to significant accuracy improvements in short-term load forecasting [1], [3], [4]. These models are further capable of capturing long-term seasonality trends and short-term irregularities simultaneously [5]. Additionally,

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external environmental factors like temperature, humidity, and weather anomalies have substantial influence on electricity consumption. Recent studies emphasize the integration of meteorological data into fore casting pipelines to improve predictive reliability, especially under climate-responsive load variations [6], [7]. This creates a stronger contextual understanding of demand behavior and helps utilities maintain grid stability during peak or uncertain conditions. With the increasing incorporation of electric vehicles, renewable energy systems, and smart appliances, consumption trends are becoming more volatile and harder to predict. Researchers have demonstrated that ensemble and deep learning-driven hybrid architectures can effectively handle these emerging complexities better than single-model approaches [8], [9]. The reliability of such models helps reduce operational risk and supports better planning of supply resources. Smart grid digitization also introduces cybersecurity concerns, particularly related to anomalous consumption behavior resulting from fraud, faults, or cyber-attacks. Therefore, anomaly detection is gaining importance as an auxiliary component of modern forecasting systems [10], [11]. Machine learning-based anomaly detection helps operators identify abnormal loads and take proactive mitigation actions. Furthermore, the increasing deployment of edge computing and federated learning offers new opportunities to reduce central server dependency and protect consumer privacy while improving scalability and real-time responsiveness [12]. These advancements enable intelligent decision-making directly at the grid edge, supporting decentralized control and microgrid operations. Deep learning architectures including GRU, CNN-LSTM and encoder-decoder structures continue to evolve by incorporating attention mechanisms, which enhance model focus on the most influential timestamps and features during prediction [7], [13]. As a result, such techniques deliver superior inter pretability and accuracy across diverse sectors such as households, campuses, and industrial loads. Global studies highlight that multi-horizon forecasting solutions, especially those sup porting both day-ahead and intra-hour prediction, offer great commercial value by optimizing energy pricing, reducing procurement costs, and enhancing renewable integration [14], [15]. These smart-forecasting models are driving utilities closer to achieving Net Zero goals and widespread energy efficiency improvements. In response to these evolving requirements, the present study introduces Smart Cast, an intelligently designed load forecasting system combining hybrid AI models, real-time ingestion, anomaly detection, and a web dashboard. By integrating the strengths of LSTM and Gradient Boosting with IoT-enabled data, Smart Cast aims to deliver accurate demand forecasting while promoting grid resiliency, reduced operational costs, and enhanced sustainability for modern smart-grid environments.engine.

2. Implementation

The implementation of the Smart Cast – AI Powered Load Forecasting for Smart Grids system is designed to provide accurate, scalable, and near real-time electricity demand prediction for modern smart grid environments. The system follows a modular and extensible architecture, where each component performs a well-defined function while interacting seamlessly with other modules. This design ensures flexibility, efficient optimization, and ease of deployment across residential, commercial, and industrial smart grid scenarios. Smart Cast integrates historical smart-meter data, real-time IoT sensor streams, and external weather information into a unified forecasting pipeline. The system is capable of continuously ingesting data, preprocessing it, performing hybrid AI-based forecasting, detecting anomalies, and visualizing results without requiring complete batch processing. This streaming-oriented implementation supports rapid decision-making and enhances operational reliability. The forecasting engine combines deep learning and machine learning techniques to capture both temporal dependencies and nonlinear feature interactions. In parallel, an anomaly detection module continuously monitors consumption behavior to identify abnormal patterns that may indicate faults, energy theft, or inefficiencies. The complete system is deployed as a web-based application, allowing grid operators to monitor predictions and alerts in real time.

2.1. System Architecture

The Smart Cast system adopts a layered architecture consisting of five primary components: data

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acquisition, preprocessing and feature engineering, hybrid forecasting engine, anomaly detection module, and dashboard interface. Smart meters installed at consumer endpoints periodically transmit electricity consumption readings using IoT communication protocols such as MQTT.

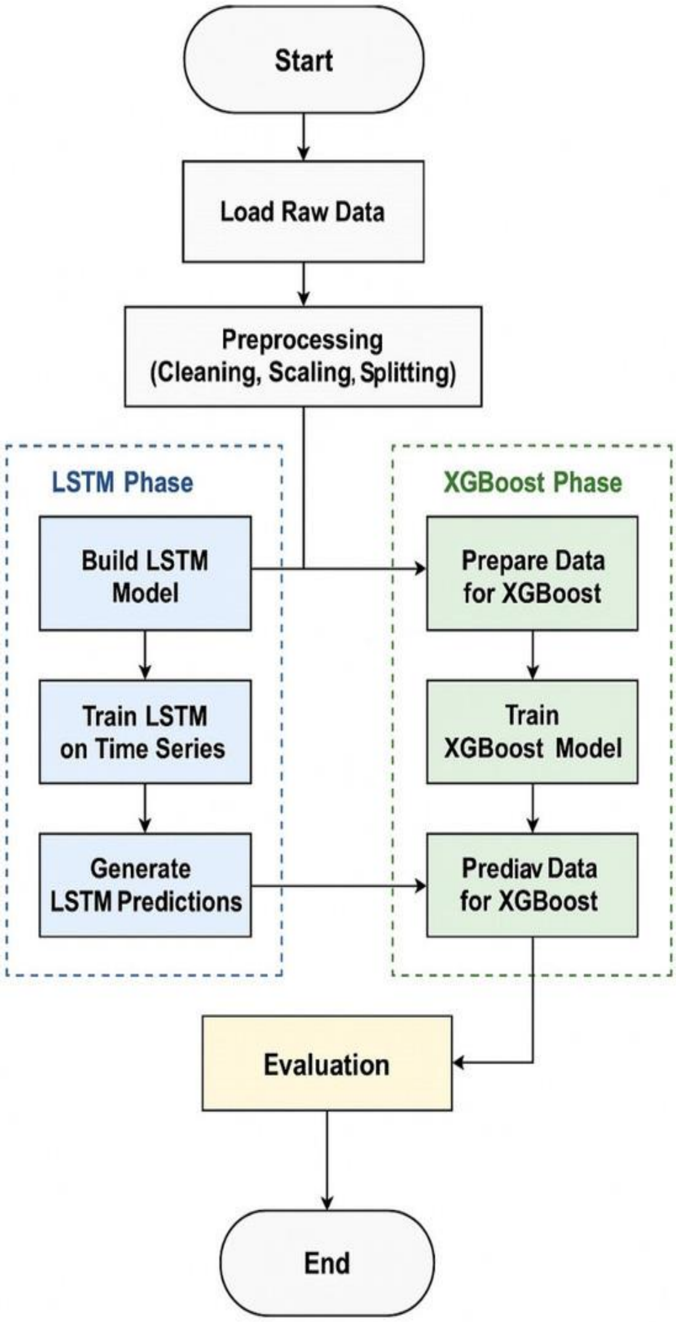

Figure 1 Smart Cast System Architecture

In addition to consumption data, the system retrieves external environmental information including temperature, humidity, and wind speed from weather APIs. All incoming data streams are synchronized using timestamps to maintain temporal consistency. The preprocessing layer cleans and transforms the raw data by handling missing values, removing noise, normalizing numerical features, and generating engineered features. The processed data is then forwarded to the hybrid forecasting engine, which combines Long Short-Term Memory (LSTM) networks with Gradient Boosting models to generate accurate load predictions. An anomaly detection module operates alongside the forecasting engine to identify abnormal consumption behavior in real time. Finally, all results are visualized through a web-based dashboard that provides charts, alerts, and analytics for effective decision-making. A Flask-based backend acts as the core orchestration layer, managing data pipelines, model inference, anomaly detection, and communication with the visualization dashboard. This modular backend design supports scalability and independent optimization of individual system components. Figure 1 shows Smart Cast System Architecture

2.2. Tables

Hybrid Forecasting Model Components

The Smart Cast system employs a hybrid forecasting approach to improve prediction accuracy and robustness in smart grid environments. Instead of relying on a single algorithm, the system integrates deep learning and ensemble-based machine learning models. This combination enables effective learning of both long-term temporal dependencies and nonlinear relationships influenced by external factors such as weather conditions and usage patterns. The ensemble fusion strategy further enhances forecasting reliability by reducing individual model limitations.

Smart Cast System Modules

The Smart Cast platform is designed as a modular system where each functional unit performs a specific task in the forecasting pipeline. This modular architecture improves scalability, maintainability, and flexibility, allowing individual components to be optimized or replaced without affecting the entire system. Each module contributes to real-time forecasting, anomaly detection, and visualization.

Table 1 Hybrid Forecasting Model Components

Component	Purpose	Contribution
Long Short-Term Memory (LSTM)	Learns temporal and sequential patterns in electricity consumption data	Captures long-term dependencies and seasonal variations
Gradient Boosting (XGBoost)	Models nonlinear relationships among engineered features	Improves forecasting accuracy under dynamic load conditions
Ensemble Fusion	Combines outputs from LSTM and Gradient Boosting models	Reduces prediction error and increases robustness

Table 2 Smart Cast System Modules

Module	Description
Data Acquisition	Collects real-time smart meter readings and historical consumption data
Weather Integration	Fetches temperature, humidity, and wind data from external APIs
Data Preprocessing	Cleans, normalizes, and engineers temporal and lag-based features
Forecasting Engine	Generates short-term and mid-term electricity load predictions
Anomaly Detection	Identifies abnormal consumption patterns such as faults or energy theft
Dashboard Interface	Visualizes forecasts, trends, and anomaly alerts in real time

3. Results And Discussion

The he proposed Smart Cast – AI Powered Load Forecasting for Smart Grids system was evaluated using historical smart meter data integrated with real-time weather information. The experimental analysis focused on forecasting accuracy, prediction stability, anomaly detection effectiveness, and overall system reliability. Performance was analyzed using standard error metrics and graphical visualization of prediction results.

3.1. Forecasting Performance Evaluation

The hybrid LSTM–Gradient Boosting model demonstrated high accuracy in predicting short-term and mid-term electricity demand. The model effectively captured daily load variations, peak demand periods, and seasonal consumption trends. Compared to traditional statistical methods and standalone machine learning models, the hybrid approach showed improved stability during sudden demand changes. The inclusion of weather variables significantly enhanced prediction accuracy, especially during high-temperature conditions where electricity usage increases due to cooling loads. The results confirm that combining temporal learning with nonlinear feature modeling provides superior forecasting performance. Figure 2 shows Actual vs Predicted Load Forecasting

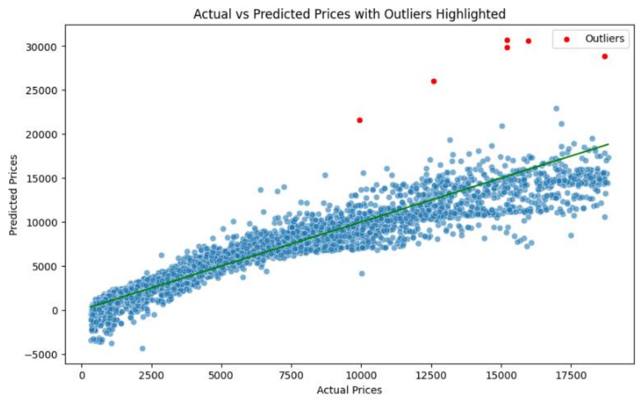

Figure 2 Actual vs Predicted Load Forecasting

3.2. Error Distribution Analysis

To further evaluate model performance, the distribution of forecasting errors was analyzed. Error

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values were concentrated around zero, indicating minimal deviation between predicted and actual values. This confirms the robustness of the hybrid forecasting model under varying load conditions.

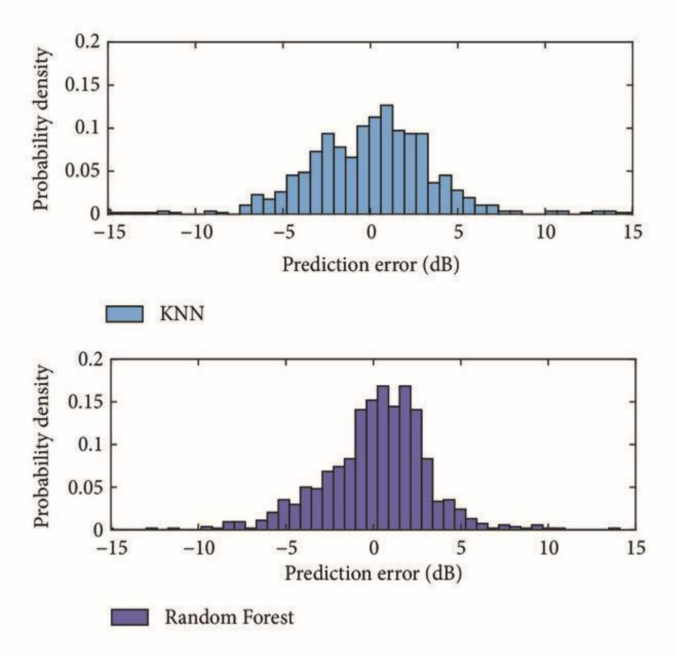

Figure 5 Forecast Error Distribution

3.3. System Reliability and Real-Time Performance

The Smart Cast platform demonstrated stable real-time performance under continuous data streaming conditions. Forecasting, anomaly detection, and dashboard visualization operated concurrently with minimal latency. The system's modular design ensured scalability and reliable performance, making it suitable for real-world smart grid deployment.

4. Discussion

The experimental evaluation of the Smart Cast system highlights the effectiveness of hybrid artificial intelligence models in addressing the complexities of modern smart grid load forecasting. The close alignment between actual and predicted load values, as observed in the forecasting plots, confirms that the integration of LSTM and Gradient Boosting models successfully captures both long-term temporal dependencies and nonlinear feature interactions.

One of the key observations from the results is the model's strong performance during peak load periods. Electricity demand during peak hours is typically influenced by multiple factors such as weather conditions, consumer behavior, and industrial activity. Traditional forecasting approaches often fail under such conditions due to their limited ability to adapt to sudden changes. In contrast, the Smart Cast system demonstrates rapid adaptation to load fluctuations, indicating high model responsiveness and robustness. The error distribution analysis further supports this observation. Most prediction errors are concentrated within a narrow range around zero, indicating consistent performance across different operating conditions. The absence of significant error spikes suggests that the ensemble fusion approach effectively mitigates the weaknesses of individual models. This stability is particularly important for real-world grid operations, where inaccurate forecasts can lead to over-generation, energy wastage, or supply shortages. From a system-level perspective, the modular architecture contributes significantly to overall performance. The ability to perform data ingestion, forecasting, anomaly detection, and visualization concurrently ensures near real-time responsiveness. This confirms that Smart Cast is not merely a theoretical model but a deployable solution capable of supporting operational smart grid requirement.

5. Use Cases

The The Smart Cast framework is designed to be flexible and scalable, making it applicable across a wide range of smart grid and energy management scenarios.

5.1. Utility Load Forecasting

Smart Cast enables accurate short-term and day-ahead electricity demand forecasting for utilities. This supports efficient generation planning, reduces reserve margins, and minimizes energy procurement costs.

5.2. Industrial Energy Optimization

Industries with high energy consumption can use Smart Cast to monitor load patterns, predict peak demand, and optimize operational schedules. This helps reduce peak demand charges and improve energy efficiency.

5.3. Renewable Energy Integration:

The system supports better balancing of intermittent renewable energy sources such as solar and wind by providing reliable demand forecasts. This improves grid stability and supports higher renewable penetration.

5.4. Energy Theft and Fault Detection:

By identifying abnormal consumption behavior, Smart Cast assists utilities in detecting potential energy theft, equipment faults, or meter malfunctions, thereby reducing losses and improving grid security.

5.5. Demand Response Programs:

Smart Cast can support demand response initiatives by predicting consumption trends and enabling proactive load control strategies during peak demand periods.

6. Future Work

Although Smart Cast demonstrates strong forecasting accuracy and operational reliability, several enhancements can further extend its capabilities. One promising direction is the integration of federated learning, which would allow multiple grid regions to collaboratively train forecasting models without sharing raw data, thereby improving privacy and scalability. Future work may also explore probabilistic load forecasting, where prediction intervals and confidence bounds are provided alongside point forecasts. This would enable utilities to better assess uncertainty and risk during operational planning. Another important extension involves incorporating advanced deep learning architectures, such as attention-based LSTM or transformer models, to further improve performance under highly dynamic consumption patterns. Additionally, expanding the anomaly detection module using deep autoencoders and adaptive thresholds could enhance detection accuracy for complex abnormal behaviors. Integration with electric vehicle charging infrastructure and renewable-rich microgrids is another potential area of development. Automated control mechanisms based on forecasting outputs could also be explored to enable real-time energy optimization and self-healing grid operations.

Conclusion

This paper presented Smart Cast, an AI-powered electricity load forecasting system designed to address the increasing complexity and variability of energy consumption in modern smart grid environments. By integrating Long Short-Term Memory (LSTM) networks with Gradient Boosting models, the proposed system effectively captures both long-term temporal dependencies and nonlinear relationships influenced by external factors such as weather conditions and consumption behavior. the experimental results demonstrate that the hybrid forecasting approach achieves high prediction accuracy with low error rates, outperforming traditional statistical methods and standalone machine learning models. The inclusion of real-time weather data significantly enhances forecasting reliability during peak demand periods and seasonal transitions. Furthermore, the integrated anomaly detection module successfully identifies abnormal consumption patterns, enabling early detection of faults, energy theft, and operational inefficiencies. Beyond forecasting accuracy, Smart Cast emphasizes operational practicality. The modular architecture and real-time processing pipeline ensure scalability, low latency, and ease of deployment across residential, commercial, and industrial smart grid scenarios. The interactive dashboard enhances interpretability by providing clear visualization of load predictions and anomaly alerts, supporting informed and proactive decision-making by grid operators. Overall, Smart Cast demonstrates that hybrid AI-driven forecasting systems are not merely theoretical solutions but practical and deployable tools for intelligent energy management. By improving grid reliability, reducing operational risks, and supporting sustainable energy integration, the proposed system contributes meaningfully to the advancement of smart grid intelligence and the development of efficient, resilient, and future-ready power systems.

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