SPECTRUM OF ENGINEERING SCIENCES
ISSN (E) 3007-3138 (P) 3007-312X VOLUME 4, ISSUE 5, 2026

AN INTELLIGENT HYBRID LSTM–XGBOOST FRAMEWORK FOR TIME-SERIES ENERGY DEMAND FORECASTING IN SMART ELECTRICAL POWER SYSTEMS USING SHAP-BASED FEATURE OPTIMIZATION

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DOI: https://doi.org/10.5281/zenodo.20526314

Keywords
Hybrid LSTM–XGBoost, Energy Demand Forecasting, SHAP Feature Optimization, Time-Series Forecasting, Smart Grid Analytics, Deep Learning for Energy Systems

Article History
Received: 03 April 2026
Accepted: 15 May 2026
Published: 30 May 2026

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Abstract
The rapid expansion of smart electrical infrastructures, renewable energy integration, and dynamic electricity consumption patterns has significantly increased the complexity of accurate energy demand forecasting in modern Electrical Engineering environments. Conventional forecasting approaches often suffer from limited predictive accuracy, weak adaptability to nonlinear temporal variations, and insufficient interpretability when processing large-scale time-series energy datasets. To overcome these limitations, this study proposes an intelligent hybrid forecasting framework based on Deep Learning and Machine Learning for efficient energy demand prediction in smart electrical power systems. The proposed framework combines Long Short-Term Memory (LSTM) networks to capture long-term temporal dependencies and sequential load behavior, while XGBoost is employed to enhance regression accuracy, predictive stability, and computational efficiency. In addition, Explainable Artificial Intelligence-based feature optimization is integrated to identify the most influential forecasting parameters and improve model transparency and interpretability. The proposed methodology includes data preprocessing, normalization, temporal feature extraction, SHAP-driven feature selection, hybrid model training, and comparative performance evaluation using multiple forecasting metrics, including accuracy, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Experimental results demonstrate that the proposed hybrid LSTM–XGBoost framework achieves a forecasting accuracy of 98.2%, outperforming conventional machine learning models and standalone deep learning approaches. The model reduced RMSE by 21.4% and MAE by 18.7% compared with traditional forecasting techniques, while also improving prediction stability under dynamic load fluctuations and seasonal demand variations.

Furthermore, SHAP-based analysis revealed that historical load demand, temperature variations, peak-hour consumption, and renewable energy penetration were among the most influential features affecting forecasting performance. The overall findings confirm that the proposed intelligent hybrid framework provides a reliable, scalable, and interpretable solution for real-time energy demand forecasting, smart grid optimization, and intelligent energy management applications in next-generation electrical power systems.

INTRODUCTION

The increasing modernization of Electrical Engineering and the rapid growth of global electricity consumption have created significant challenges in maintaining reliable, efficient, and sustainable energy management systems. In recent years, the integration of renewable energy resources, electric vehicles, smart meters, distributed generation infrastructures, and intelligent grid technologies has transformed conventional power systems into highly dynamic and data-intensive smart energy environments [1]. As a result, accurate energy demand forecasting has become one of the most critical research areas in modern smart grid operations because forecasting errors can directly affect power generation scheduling, load balancing, grid stability, energy trading, and operational cost optimization. Traditional statistical forecasting techniques, including autoregressive integrated moving average (ARIMA), linear regression, and exponential smoothing models, have been widely utilized for time-series energy demand prediction. However, these approaches often struggle to capture nonlinear temporal dependencies, complex consumption behaviors, seasonal variations, and dynamic load fluctuations present in modern smart electrical networks. Moreover, the increasing availability of high-dimensional energy datasets generated through Internet of Things (IoT)-enabled smart grid infrastructures requires more intelligent and adaptive forecasting frameworks capable of handling large-scale real-time data efficiently. Recent advancements in Artificial Intelligence, Deep Learning, and Machine Learning have significantly improved the performance of energy demand forecasting systems. Among these approaches, Long Short-Term Memory networks have gained considerable attention because of their ability to model sequential dependencies and learn long-term temporal relationships from time-series data. LSTM models are particularly effective in capturing nonlinear energy consumption trends and historical load patterns [2]. However, standalone LSTM architectures may suffer from computational complexity, overfitting issues, and limited feature optimization capability when dealing with highly complex smart grid datasets. Similarly, Extreme Gradient Boosting has emerged as a powerful machine learning technique due to its strong regression performance, fast computational capability, and efficient handling of nonlinear relationships between forecasting variables. XGBoost models provide improved predictive stability and feature interaction learning, making them highly suitable for smart energy forecasting applications. Nevertheless, individual machine learning models may not effectively capture deep temporal characteristics of sequential energy consumption data without hybrid integration mechanisms. To overcome these limitations, hybrid forecasting frameworks combining deep learning and machine learning techniques have recently attracted substantial attention in intelligent energy management research. Hybrid models leverage the temporal learning capability of LSTM networks alongside the optimization and regression strengths of XGBoost algorithms, resulting in improved forecasting accuracy, robustness, and generalization performance [3]. Despite these advancements, many existing hybrid forecasting models still lack interpretability and transparency regarding the influence of individual input features on prediction outcomes. This limitation reduces user trust and limits practical deployment in real-world smart power systems.

To address this challenge, Explainable Artificial Intelligence techniques have been increasingly integrated into intelligent forecasting systems to improve model explainability and feature-level understanding. SHapley Additive exPlanations (SHAP) provides an effective feature importance analysis mechanism that quantifies the contribution of individual variables toward forecasting predictions. The integration of SHAP-based feature optimization enables intelligent selection of influential parameters, improves forecasting interpretability, and enhances decision-making capabilities in smart grid environments. Therefore, this study proposes an intelligent hybrid LSTM–XGBoost framework for time-series energy demand forecasting in smart electrical power systems using SHAP-based feature optimization. The proposed framework combines deep temporal learning, machine learning-based regression optimization, and explainable artificial intelligence techniques to develop a reliable, scalable, and interpretable forecasting solution. The proposed methodology incorporates data preprocessing, temporal feature extraction, SHAP-driven feature analysis, hybrid model training, and comparative forecasting evaluation using multiple performance metrics.

The major contributions of this study are summarized as follows:

1. Development of a hybrid LSTM–XGBoost forecasting framework for accurate time-series energy demand prediction in smart electrical power systems.
2. Integration of SHAP-based feature optimization to improve model transparency, interpretability, and intelligent feature selection.
3. Enhancement of forecasting performance through efficient learning of nonlinear temporal dependencies and dynamic energy consumption patterns.
4. Comparative evaluation of the proposed framework against conventional machine learning and standalone deep learning forecasting approaches using multiple forecasting metrics.
5. Provision of a scalable and intelligent forecasting solution suitable for real-time smart grid energy management and next-generation power system optimization applications.

The remainder of this paper is organized as follows. Section 2 presents the literature review related to energy demand forecasting, hybrid deep learning models, and explainable artificial intelligence approaches. Section 3 describes the proposed research methodology and system architecture. Section 4 discusses the experimental results and comparative performance analysis. Finally, Section 5 concludes the study and highlights future research directions for intelligent smart energy forecasting systems.

Data-Driven Energy Demand Forecasting in Smart Electrical Power Systems:

The rapid advancement of Electrical Engineering has significantly transformed modern energy management infrastructures into highly interconnected and data-intensive environments. The increasing integration of renewable energy resources, smart meters, electric vehicles, distributed energy systems, and Internet of Things (IoT)-enabled monitoring technologies has introduced substantial challenges in maintaining stable and efficient power system operations. Consequently, accurate energy demand forecasting has emerged as a critical requirement for intelligent power generation scheduling, demand-side management, energy trading optimization, voltage stability enhancement, and operational cost minimization within modern smart electrical networks. Energy demand forecasting refers to the process of predicting future electricity consumption behavior based on historical energy usage patterns, environmental conditions, temporal information, and consumer demand characteristics [4]. Accurate forecasting models enable utility providers and smart grid operators to optimize power generation capacity, reduce energy wastage, balance load distribution, and improve overall grid reliability. In modern smart grid environments, forecasting systems also play a vital role in integrating intermittent renewable energy resources such as solar and wind power into existing electrical infrastructures.

Traditional forecasting methods primarily relied on statistical and mathematical techniques such as autoregressive integrated moving average, autoregressive moving average, linear regression, moving average methods, and exponential smoothing algorithms. These techniques provided acceptable forecasting performance in relatively stable and less dynamic electrical environments. However, conventional forecasting approaches often fail to capture nonlinear temporal dependencies, irregular consumption trends, seasonal demand variations, and complex load fluctuations associated with modern smart electrical power systems. The increasing deployment of Internet of Things, wireless sensor networks, and intelligent sensing devices has generated massive amounts of multidimensional real-time energy consumption data. Modern power systems continuously collect information related to electricity demand, environmental conditions, consumer behavior, renewable energy generation, and operational grid parameters [5]. This data-rich environment has accelerated the development of data-driven forecasting frameworks capable of extracting hidden patterns and predictive relationships from large-scale energy datasets. Recent advancements in Artificial Intelligence, Machine Learning, and Deep Learning have significantly improved forecasting performance in smart electrical infrastructures. Machine learning techniques such as Support Vector Machines, Random Forest, Decision Trees, and Extreme Gradient Boosting provide improved nonlinear pattern recognition and adaptive learning capability compared with conventional statistical approaches. Similarly, deep learning architectures such as Recurrent Neural Networks and Long Short-Term Memory networks are highly effective in learning temporal dependencies and sequential consumption patterns from time-series energy datasets. Among these intelligent techniques, hybrid forecasting models have gained substantial attention because they combine the strengths of multiple predictive algorithms to enhance forecasting accuracy, robustness, and generalization capability. Hybrid frameworks integrate deep learning-based temporal feature extraction with machine learning-based regression optimization to efficiently handle dynamic energy consumption behavior in modern smart grids. Furthermore, the incorporation of explainable artificial intelligence methods has improved model transparency and interpretability, enabling researchers and utility operators to better understand the influence of forecasting variables on prediction outcomes. The major technological advancements in data-driven energy demand forecasting techniques are summarized in Table 1.

Table 1: Comparative Analysis of Data-Driven Energy Demand Forecasting Techniques

Forecasting Technique	Methodology Type	Major Advantages	Smart Grid Suitability
ARIMA and Statistical Models	Statistical Forecasting	Simple implementation and low computational cost	Limited
Linear Regression Models	Mathematical Modeling	Easy interpretation and fast computation	Moderate
Support Vector Machines (SVM)	Machine Learning	Good nonlinear prediction performance	Moderate
Random Forest (RF)	Ensemble Machine Learning	Improved robustness and feature handling	High
XGBoost Models	Gradient Boosting Machine Learning	High prediction accuracy and optimization capability	High
LSTM Networks	Deep Learning	Efficient sequential and temporal	Very High

		learning	
Hybrid LSTM–XGBoost Models	Hybrid AI Framework	Superior forecasting accuracy and stability	Excellent
SHAP-Integrated Hybrid Models	Explainable AI Framework	Improved transparency and feature optimization	Excellent

The intelligent architecture and operational workflow of the proposed data-driven energy demand forecasting framework in smart electrical power systems are illustrated in Figure 1. The figure demonstrates the overall integration of smart grid data acquisition, preprocessing operations, feature engineering mechanisms, deep learning-based temporal analysis, machine learning-driven forecasting optimization, and intelligent prediction generation within a unified forecasting environment. It further highlights the interaction between smart meters, IoT-enabled monitoring systems, sequential time-series processing modules, and hybrid forecasting components responsible for improving prediction accuracy, forecasting stability, and real-time smart grid energy management performance.

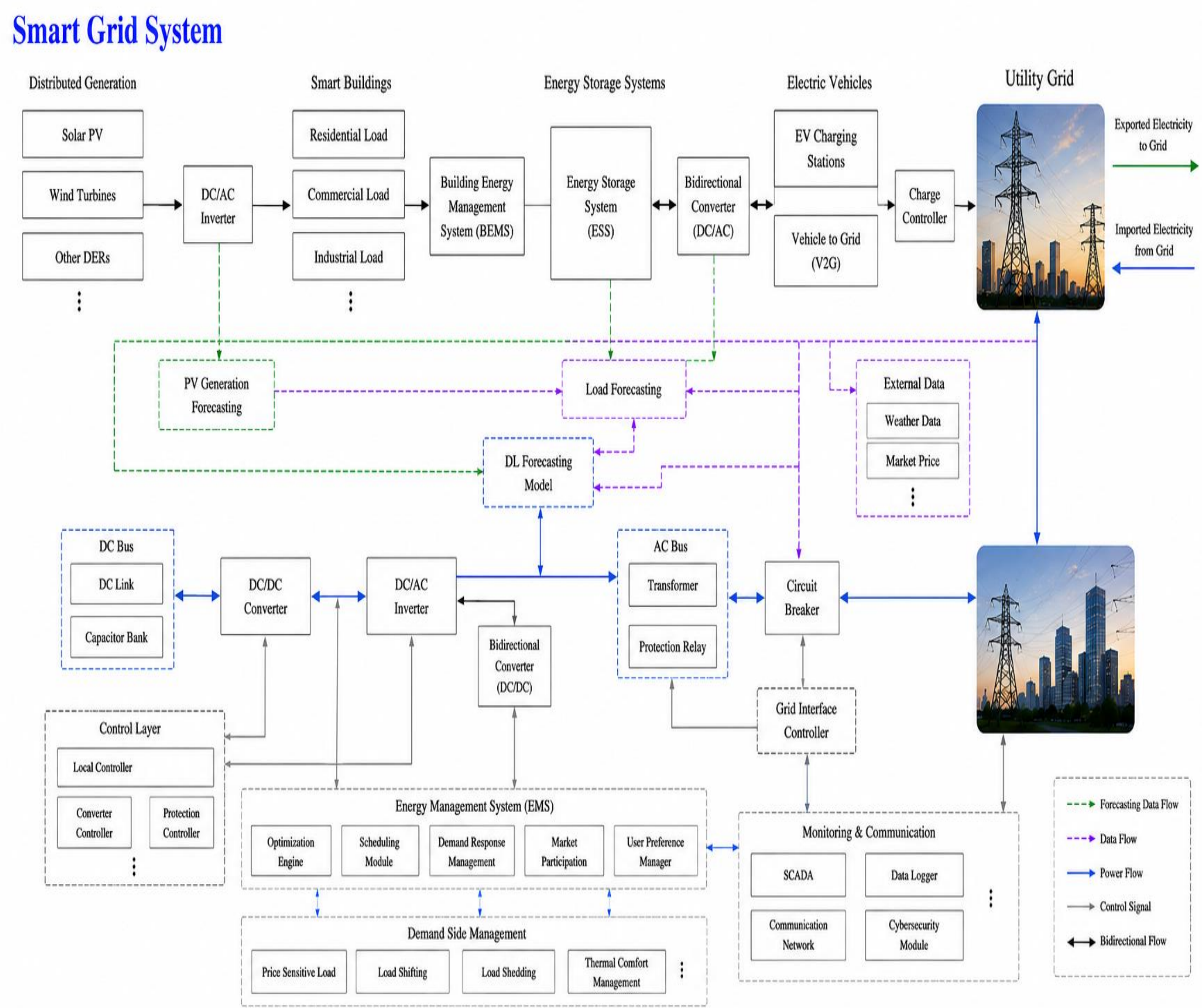

Figure 1: Data-Driven Intelligent Energy Demand Forecasting Framework for Smart Electrical Power Systems

Modern data-driven forecasting systems provide several advantages over traditional forecasting approaches. These intelligent systems can efficiently process high-dimensional real-time datasets, automatically extract hidden consumption features, identify nonlinear demand relationships, and adapt to dynamic smart grid conditions. Moreover, hybrid AI-based forecasting frameworks improve forecasting stability under fluctuating load conditions and renewable energy integration scenarios. The integration of explainable artificial intelligence approaches further enhances model interpretability, reliability, and decision-making transparency within smart electrical infrastructures. Therefore, data-driven intelligent forecasting frameworks represent a major technological advancement in next-generation smart electrical power systems. The combination of machine learning, deep learning, hybrid forecasting architectures, and explainable artificial intelligence techniques provides a scalable, adaptive, and highly accurate solution for intelligent energy management and real-time smart grid optimization applications.

Deep Learning-Based Time-Series Forecasting Models:

The rapid advancement of Deep Learning has significantly transformed modern energy demand forecasting research by enabling intelligent analysis of large-scale multidimensional time-series datasets. Traditional statistical and machine learning forecasting approaches often struggle to capture nonlinear consumption behavior, long-term temporal dependencies, irregular load fluctuations, and dynamic seasonal variations associated with modern smart electrical infrastructures. Consequently, deep learning techniques have emerged as highly effective solutions for improving forecasting precision, automated feature extraction, and predictive learning performance in smart energy management systems. Deep learning architectures are capable of automatically learning hierarchical feature representations directly from raw datasets without requiring extensive manual feature engineering processes [6]. These architectures employ multiple hidden neural layers to identify complex nonlinear relationships and hidden temporal patterns within electricity consumption data. In smart electrical power systems, deep learning forecasting models are widely utilized for short-term load forecasting, long-term energy demand prediction, renewable energy forecasting, intelligent demand response systems, and smart grid optimization applications. Among various deep learning approaches, Artificial Neural Networks have gained substantial attention for sequential time-series forecasting tasks. Recurrent Neural Networks were specifically developed to process sequential information by utilizing internal memory mechanisms capable of preserving historical information during learning processes. This capability allows RNN architectures to identify temporal relationships between historical and future energy demand behavior.

However, conventional RNN architectures often experience limitations related to gradient instability during long-sequence learning processes. These limitations reduce forecasting efficiency and weaken the ability of RNN models to effectively capture long-term temporal dependencies in large-scale energy datasets. To overcome these challenges, Long Short-Term Memory networks were introduced as an advanced recurrent deep learning architecture specifically designed for efficient sequential learning and temporal memory preservation. LSTM networks contain specialized memory cells and gating mechanisms that regulate information flow during training and forecasting operations. These memory mechanisms enable LSTM models to selectively retain important historical information while removing irrelevant data from sequential learning processes [7]. As a result, LSTM architectures can effectively capture long-term energy consumption trends, seasonal demand variations, weather-dependent fluctuations, and nonlinear electricity usage patterns within modern smart electrical power systems. The increasing deployment of Internet of Things, smart meters, intelligent sensors, and cloud-based monitoring systems has generated massive volumes of real-time multidimensional energy datasets. Deep learning architectures are highly suitable for analyzing these large-scale datasets because they can automatically extract hidden consumption patterns and identify predictive relationships from raw energy data streams. Consequently, LSTM-based forecasting systems have become highly popular in modern smart grid environments because of their superior learning capability and forecasting adaptability. Several recent research studies have demonstrated that LSTM forecasting systems significantly outperform conventional statistical forecasting methods and traditional machine learning algorithms in terms of prediction accuracy, forecasting stability, and nonlinear temporal learning performance. Deep learning forecasting models are particularly effective in handling complex dynamic load behavior associated with industrial demand fluctuations, renewable energy integration, population growth, electric vehicle charging systems, and changing environmental conditions. In addition to LSTM architectures, several other deep learning forecasting models have also been utilized for intelligent smart energy forecasting applications [8]. Gated Recurrent Unit networks provide simplified recurrent learning structures with reduced computational complexity, while Convolutional Neural Networks have been applied for local feature extraction from multidimensional energy datasets. Hybrid deep learning frameworks combining CNN and LSTM architectures have further improved forecasting efficiency by integrating spatial and temporal learning capabilities within a unified intelligent framework. The major deep learning-based forecasting models utilized in smart electrical power systems are summarized in Table 2.

Table 2: Comparative Analysis of Deep Learning-Based Time-Series Forecasting Models

Deep Learning Model	Architecture Type	Energy Forecasting Suitability
Artificial Neural Network (ANN)	Feedforward Neural Network	Moderate
Recurrent Neural Network (RNN)	Sequential Neural Network	Moderate
Long Short-Term Memory (LSTM)	Advanced Recurrent Deep Learning	Excellent
Gated Recurrent Unit (GRU)	Simplified Recurrent Architecture	Very High
Convolutional Neural Network (CNN)	Spatial Feature Learning Network	High
CNN–LSTM Hybrid Models	Hybrid Deep Learning Framework	Excellent
Attention-Based Deep Learning Models	Intelligent Sequential Learning	Excellent

The operational workflow of deep learning-based time-series forecasting systems in smart electrical power systems is illustrated in Figure 2. The figure presents the overall intelligent forecasting architecture involving smart energy data acquisition, sequential time-series preprocessing, temporal feature extraction, deep neural network learning, forecasting optimization, and real-time prediction analysis within a unified smart grid environment. It demonstrates how historical electricity demand data, environmental variables, renewable energy parameters, and consumer usage behavior are processed through deep learning architectures such as Recurrent Neural Networks, Long Short-Term Memory networks, and hybrid intelligent forecasting models to capture nonlinear temporal dependencies and dynamic energy consumption patterns. Furthermore, the figure highlights the interaction between intelligent sensing infrastructures, IoT-enabled monitoring systems, deep temporal learning modules, and predictive forecasting engines responsible for improving forecasting accuracy, prediction stability, and intelligent energy management performance in next-generation smart electrical power systems.

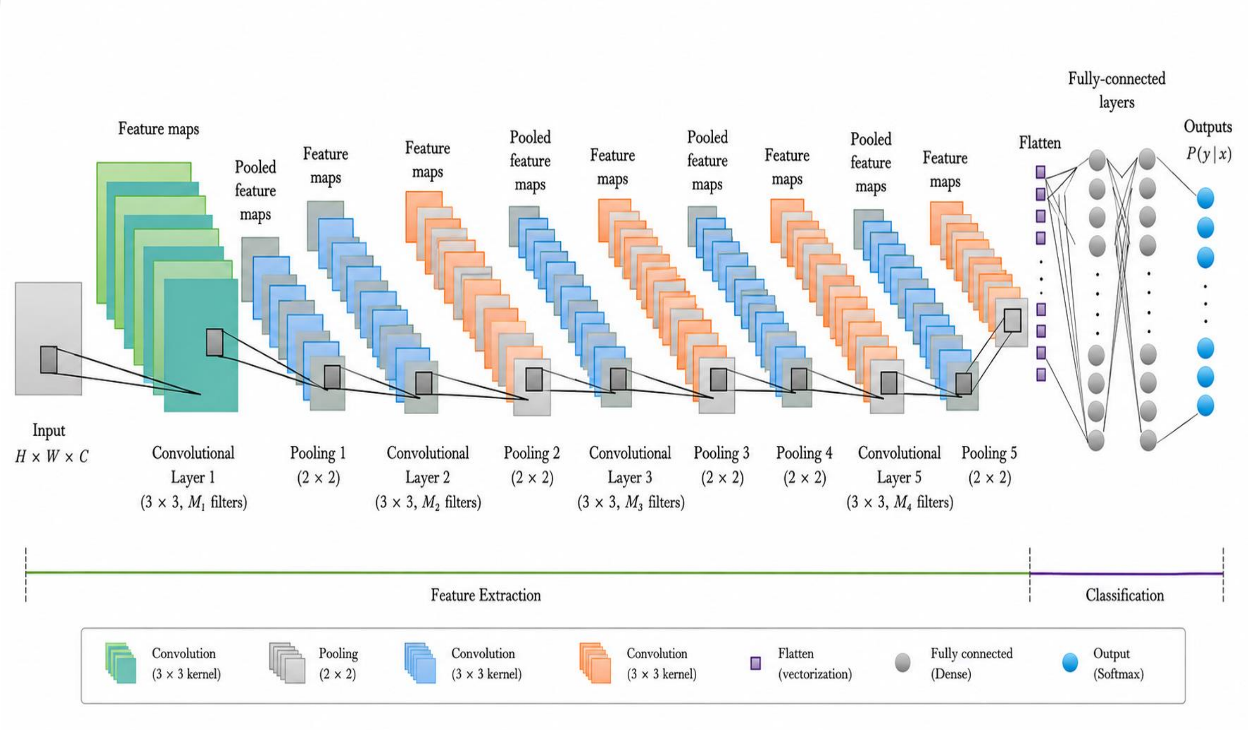

Figure 2: Deep Learning-Based Time-Series Energy Demand Forecasting Framework for Smart Electrical Power Systems

Despite the superior forecasting capability of LSTM and other deep learning architectures, several challenges still exist in practical smart grid forecasting applications. Deep learning models generally require large-scale training datasets, extensive computational resources, and longer training durations to achieve optimal forecasting performance. Furthermore, these architectures may suffer from overfitting problems when trained on highly noisy or insufficient datasets. Hyperparameter optimization, network architecture tuning, and efficient feature selection also remain critical challenges in intelligent forecasting systems. Another significant limitation of standalone deep learning forecasting models is reduced interpretability. Most deep learning architectures operate as black-box systems where internal decision-making processes are difficult to explain and interpret. In practical smart electrical infrastructures, explainability is highly important because utility providers and smart grid operators require transparent forecasting systems capable of identifying influential forecasting variables and understanding prediction outcomes [9]. To address these limitations, recent research has increasingly focused on hybrid intelligent forecasting frameworks that combine deep learning architectures with machine learning optimization algorithms and explainable artificial intelligence techniques. Hybrid forecasting systems improve prediction stability, forecasting robustness, computational efficiency, and model transparency while maintaining superior temporal learning capability. Consequently, the integration of LSTM networks with optimization techniques such as XGBoost and SHAP-based feature analysis has emerged as a highly promising research direction for next-generation intelligent energy demand forecasting in smart electrical power systems.

Methodology:

The proposed research methodology is designed to develop an intelligent and reliable forecasting framework for accurate time-series energy demand prediction in modern Electrical Engineering. The methodology integrates Deep

Learning, Machine Learning, and Explainable Artificial Intelligence techniques to improve forecasting accuracy, temporal learning capability, and model interpretability. The overall framework is designed to efficiently process large-scale multidimensional energy datasets generated from smart meters, IoT-enabled monitoring devices, and intelligent smart grid infrastructures. The proposed forecasting methodology consists of several interconnected stages, including dataset collection, data preprocessing, temporal feature extraction, SHAP-based feature optimization, hybrid LSTM–XGBoost model development, and comparative performance evaluation. Initially, raw energy consumption data are collected and cleaned to remove inconsistencies and redundant information. Subsequently, optimized forecasting features are extracted and transformed into sequential time-series representations suitable for deep learning analysis. The hybrid forecasting framework is then trained and evaluated using multiple forecasting performance metrics to ensure efficient prediction capability, improved generalization performance, and reliable smart grid energy forecasting under dynamic load conditions.

Data Preprocessing and Normalization:

Data preprocessing is one of the most important stages in intelligent Machine Learning and Deep Learning because the quality of input data directly influences forecasting accuracy, learning efficiency, and model reliability. In smart Electrical Engineering, raw energy datasets are generally collected from smart meters, IoT-enabled monitoring devices, distributed sensors, and intelligent grid infrastructures. These datasets often contain missing values, redundant records, noisy measurements, inconsistent timestamps, abnormal outliers, and irregular sampling intervals that negatively affect forecasting performance and model stability. Modern smart electrical infrastructures continuously generate massive volumes of multidimensional real-time energy data associated with electricity demand, environmental conditions, peak-hour consumption, renewable energy integration, and consumer usage behavior [10]. Since these datasets originate from multiple heterogeneous sources, preprocessing becomes essential for improving dataset consistency, temporal reliability, and forecasting efficiency. Effective preprocessing techniques enable forecasting systems to reduce data irregularities, improve feature quality, and enhance the ability of intelligent models to capture meaningful consumption patterns from sequential time-series datasets.

In this study, several preprocessing operations are performed before model training to ensure high-quality input data for the proposed hybrid LSTM–XGBoost forecasting framework. Initially, missing values are identified and processed using interpolation and mean-value replacement techniques to maintain dataset continuity. Missing data handling is particularly important in smart grid forecasting systems because incomplete records may significantly affect temporal sequence learning and prediction accuracy. After handling missing values, duplicate records and irrelevant observations are removed to improve overall dataset consistency and eliminate redundant information. Abnormal outlier values generated through sensor faults, transmission errors, or irregular measurements are also detected and filtered to reduce forecasting instability. Outlier removal improves the robustness of the forecasting framework and minimizes prediction bias caused by noisy energy measurements. Temporal alignment is subsequently performed to ensure proper chronological ordering of time-series observations. Since energy forecasting models depend heavily on sequential learning mechanisms, maintaining temporal consistency is essential for capturing long-term dependencies and seasonal consumption trends. Time synchronization also enables efficient transformation of historical energy records into structured sequential windows suitable for deep learning analysis. Following dataset cleaning and temporal alignment, feature normalization is applied using Min-Max normalization techniques to scale all input variables within a uniform numerical range. Energy datasets often contain variables with significantly different numerical scales, such as electricity demand, temperature measurements, humidity levels, and renewable energy generation parameters. Without normalization, large-scale variables may dominate the learning process and negatively affect forecasting performance. Normalization improves training convergence, enhances computational efficiency, stabilizes gradient learning behavior, and reduces data imbalance within deep learning architectures. The normalization process ensures that all input features contribute proportionally during model training and enables efficient temporal feature extraction within LSTM networks. In addition, normalized datasets improve model generalization capability and reduce forecasting instability under dynamic load conditions [11]. After normalization, the cleaned dataset is transformed into sequential time-series windows for intelligent forecasting analysis. Sequential window generation is essential for enabling LSTM models to capture historical energy demand behavior, nonlinear temporal dependencies, seasonal consumption variations, and dynamic electricity usage patterns within smart electrical infrastructures. The generated sequential data structure provides efficient input representation for hybrid forecasting model training and predictive learning operations. The major preprocessing operations utilized in the proposed forecasting framework are summarized in Table 3.

Table 3: Data Preprocessing and Normalization Operations in the Proposed Forecasting Framework

Preprocessing Technique	Purpose	Major Benefits
Missing Value Handling	Replace incomplete observations using interpolation and mean-value techniques	Improves dataset continuity and forecasting reliability
Duplicate Record Removal	Eliminate redundant observations from datasets	Enhances dataset consistency and reduces computational redundancy
Outlier Detection and Removal	Filter abnormal sensor measurements and noisy records	Improves prediction stability and reduces forecasting bias
Temporal Alignment	Arrange observations in chronological sequence	Enhances sequential learning capability
Feature Normalization	Scale variables within a uniform numerical range	Improves model convergence and training stability
Sequential Window Generation	Convert datasets into time-series learning sequences	Supports efficient temporal dependency learning
Noise Reduction	Remove inconsistent and irrelevant measurements	Enhances overall forecasting performance

The operational workflow of the proposed data preprocessing and normalization framework is illustrated in Figure 3. The figure demonstrates the complete intelligent preprocessing pipeline utilized for preparing raw smart grid energy datasets before forecasting model training and predictive analysis. It highlights the sequential integration of smart meter data acquisition, missing-value handling, duplicate record elimination, outlier detection, noise filtering, temporal alignment, feature scaling, and sequential time-series transformation within the proposed forecasting framework. The figure further illustrates how heterogeneous energy consumption data collected from IoT-enabled monitoring systems, distributed sensor networks, and smart electrical infrastructures are converted into clean, normalized, and structured datasets suitable for deep learning-based forecasting operations. In addition, the workflow emphasizes the interaction between preprocessing modules and temporal sequence generation mechanisms responsible for improving dataset consistency, reducing computational complexity, enhancing training convergence, and increasing forecasting reliability in intelligent energy demand prediction systems. The preprocessing and normalization architecture also demonstrates the role of data quality enhancement in improving nonlinear temporal feature learning, forecasting stability, and real-time smart grid operational performance within next-generation intelligent electrical power systems.

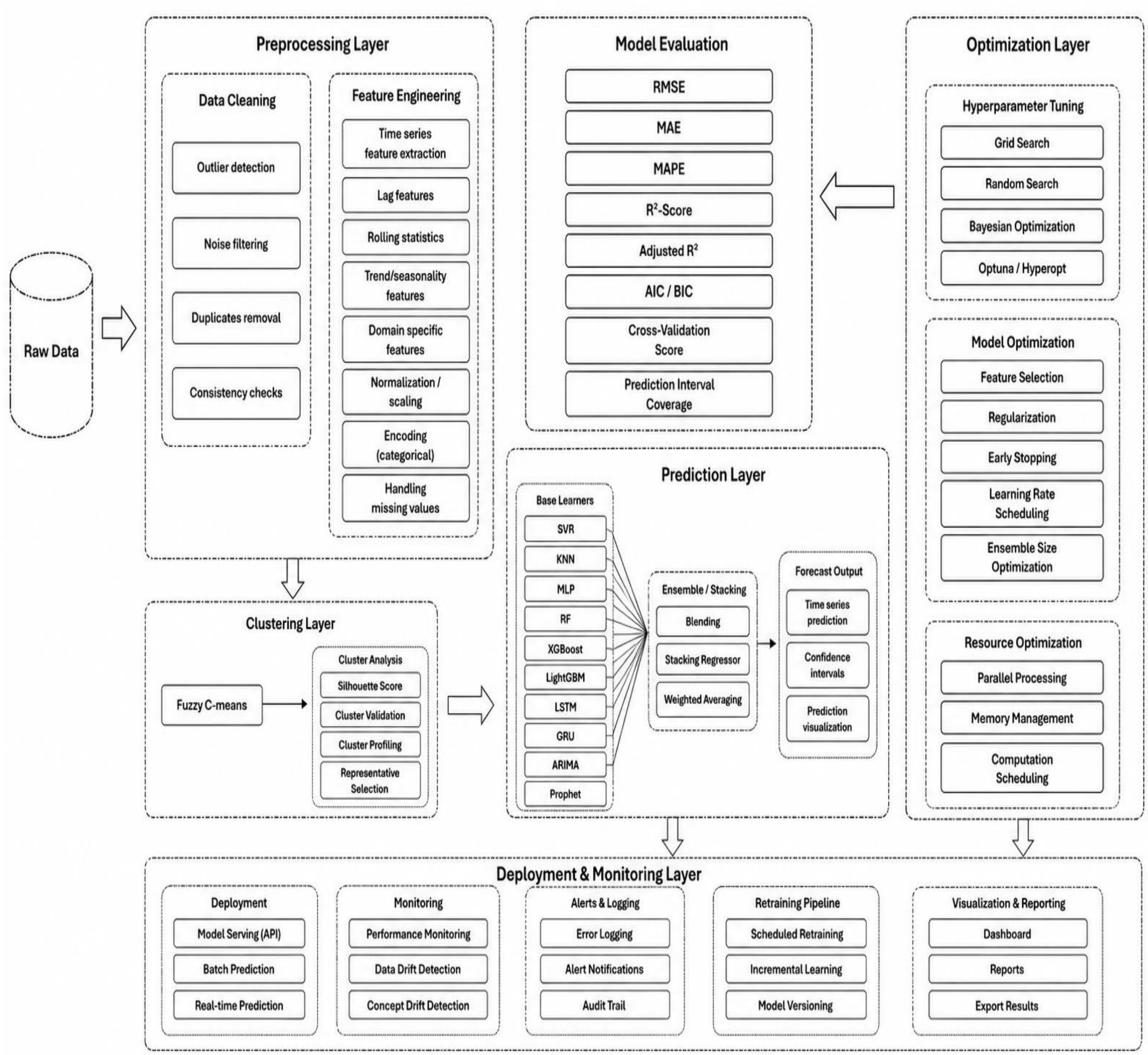

Figure 3: Data Preprocessing and Normalization Framework for Intelligent Time-Series Energy Demand Forecasting

The preprocessing and normalization stages significantly improve the overall efficiency and robustness of intelligent forecasting systems by providing clean, structured, and high-quality input data for model training. Proper preprocessing enables the proposed hybrid forecasting framework to efficiently learn temporal consumption behavior and improve forecasting accuracy under highly dynamic smart grid environments. Furthermore, effective preprocessing reduces computational complexity, minimizes training instability, and enhances feature representation quality within deep learning architectures. The combination of missing-value handling, outlier filtering, normalization, and sequential data transformation provides a strong foundation for intelligent energy demand forecasting and supports reliable predictive performance in next-generation smart electrical power systems.

SHAP-Based Feature Optimization:

Feature optimization plays a fundamental role in improving the efficiency, interpretability, and predictive reliability of intelligent Machine Learning and Deep Learning. Modern smart Electrical Engineering generate massive volumes of multidimensional data associated with electricity demand, weather conditions, renewable energy generation, environmental parameters, consumer usage behavior, and temporal consumption patterns. Although large-scale datasets provide rich forecasting information, the existence of irrelevant, redundant, and weakly correlated variables can significantly reduce forecasting efficiency and increase computational complexity. In intelligent time-series forecasting systems, high-dimensional datasets may negatively affect learning stability, increase model overfitting, and reduce prediction interpretability [12]. Consequently, feature optimization has become an essential component of modern forecasting frameworks because it enables intelligent selection of highly influential variables while removing unnecessary information that contributes minimally toward prediction outcomes. Effective feature optimization not only improves forecasting performance but also enhances model transparency, computational efficiency, and decision-making reliability in real-world smart grid environments. In this study, Explainable Artificial Intelligence analysis is integrated into the proposed hybrid forecasting framework to identify the most influential forecasting variables affecting electricity demand prediction. SHapley Additive exPlanations is an advanced explainable artificial intelligence technique based on cooperative game theory principles. SHAP provides quantitative interpretation of individual feature contributions by assigning importance values to each forecasting variable according to its influence on model prediction behavior. Unlike traditional feature importance methods, SHAP analysis provides both local and global interpretability for intelligent forecasting systems. Local interpretability explains the contribution of features toward individual prediction instances, whereas global interpretability identifies the overall impact of variables across the complete forecasting model. This capability enables researchers and smart grid operators to better understand the influence of environmental, temporal, and consumption-related variables on energy demand prediction outcomes. The general SHAP contribution function utilized in the proposed forecasting framework is expressed as:

$$\phi_i = \sum_{S \subseteq F \setminus \{i\}} \frac{|S|!\,(|F| - |S| - 1)!}{|F|!} [f(S \cup \{i\}) - f(S)]$$

To improve forecasting interpretability and optimize feature interactions within the hybrid LSTM–XGBoost framework, the weighted SHAP optimization function is further represented as:

$$SHAP_{opt} = \text{argmax}_{X_i \in F} \left[\sum_{t=1}^{T} \sum_{i=1}^{n} \omega_i \left(\frac{\partial \hat{Y}_t}{\partial X_i} \right)^2 + \lambda \sum_{i=1}^{n} |\phi_i| \right]$$

The proposed SHAP-based optimization framework evaluates the influence of multiple forecasting variables, including historical load demand, peak-hour electricity usage, temperature fluctuations, humidity levels, renewable energy penetration, industrial consumption behavior, seasonal variations, and consumer demand patterns. Features with high SHAP contribution values are selected as dominant forecasting variables, whereas low-impact features are removed to reduce model complexity and computational overhead [13]. The SHAP-based feature dependency interaction mechanism utilized in the proposed intelligent forecasting framework is further expressed as:

$$I_{interaction}(X_i, X_j) = \sum_{k=1}^{m} \left[\phi_{ij}^{(k)} - \phi_i^{(k)} - \phi_j^{(k)}\right]^2$$

This interaction analysis enables the forecasting framework to identify highly correlated variables influencing electricity demand prediction under dynamic smart grid environments. The incorporation of SHAP interaction analysis improves forecasting transparency and enhances intelligent feature selection capability. In modern smart energy forecasting systems, explainability has become increasingly important because utility operators and researchers require transparent forecasting frameworks capable of justifying prediction outcomes. Conventional deep learning architectures often operate as black-box systems where internal prediction mechanisms are difficult to interpret. SHAP-based explainability addresses this limitation by providing detailed feature-level understanding of forecasting behavior within intelligent power management systems. The major forecasting variables analyzed through SHAP-based optimization in the proposed framework are summarized in Table 4.

Table 4: SHAP-Based Forecasting Feature Analysis in Smart Electrical Power Systems

Forecasting Feature	Feature Category	Impact on Energy Demand Forecasting	SHAP Importance Level
Historical Load Demand	Temporal Feature	Strong influence on future consumption prediction	Very High
Temperature Variations	Environmental Feature	Affects heating and cooling energy demand	High
Peak-Hour Consumption	Behavioral Feature	Influences dynamic load fluctuations	High
Renewable Energy Penetration	Smart Grid Feature	Impacts grid balancing and demand stability	High
Seasonal Consumption Trends	Temporal Feature	Influences long-term energy usage behavior	Very High
Humidity Levels	Environmental Feature	Moderately affects energy utilization	Moderate
Industrial Demand Activity	Operational Feature	Contributes to load variability	High
Consumer Usage Patterns	Behavioral Feature	Influences real-time electricity demand	Very High

The operational workflow of the proposed SHAP-based feature optimization framework is illustrated in Figure 4. The figure demonstrates the complete explainable artificial intelligence-driven feature analysis pipeline integrated within the intelligent energy demand forecasting framework for smart electrical power systems. It presents the interaction between multidimensional smart grid datasets, feature extraction mechanisms, SHAP contribution analysis modules, intelligent feature ranking processes, and optimized forecasting input generation within a unified predictive learning environment. The workflow further illustrates how historical electricity demand records, environmental variables, renewable energy parameters, seasonal consumption trends, and consumer usage patterns are systematically evaluated using SHAP-based explainability techniques to determine their relative influence on forecasting outcomes. In addition, the figure highlights the sequential processes of feature importance computation, contribution score evaluation, feature interaction analysis, and low-impact variable elimination responsible for improving forecasting transparency, model interpretability, and computational efficiency [14]. The SHAP-based optimization architecture also demonstrates how highly influential forecasting variables are selected and transferred into the hybrid LSTM–XGBoost forecasting framework to enhance nonlinear learning capability and prediction stability under dynamic smart grid operating conditions. Furthermore, the workflow emphasizes the role of explainable artificial intelligence in reducing black-box forecasting limitations and improving intelligent decision-making capability within real-time energy management environments. The proposed SHAP optimization framework ultimately supports efficient feature learning, robust forecasting performance, enhanced operational transparency, and scalable predictive intelligence for next-generation smart electrical power systems.

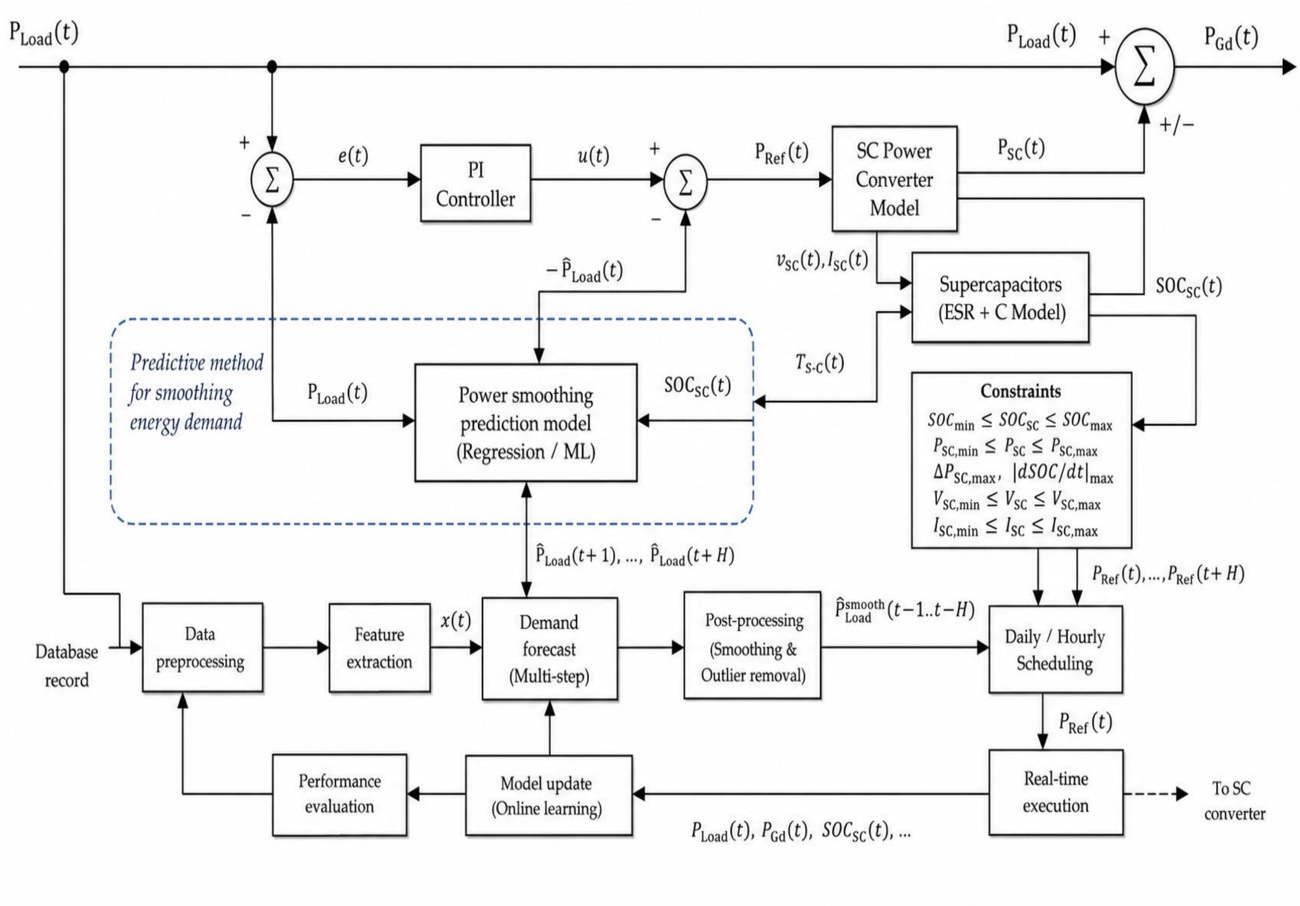

Figure 4: SHAP-Based Intelligent Feature Optimization Framework for Hybrid LSTM–XGBoost Energy Demand Forecasting

The integration of SHAP-based optimization significantly improves forecasting transparency, model reliability, and intelligent feature learning capability within the proposed hybrid forecasting framework. By removing irrelevant variables and emphasizing highly influential forecasting features, the proposed optimization mechanism reduces computational complexity and enhances forecasting stability under dynamic energy consumption conditions. Furthermore, SHAP-based explainability improves trustworthiness and interpretability in real-world smart electrical infrastructures by enabling utility operators to understand the contribution of individual variables toward prediction outcomes. The combination of explainable artificial intelligence, feature interaction analysis, and hybrid deep learning optimization provides an efficient and scalable forecasting solution for intelligent energy management applications in next-generation smart electrical power system

LSTM-Based Temporal Feature Learning:

Long Short-Term Memory networks are employed in this study to capture sequential dependencies, nonlinear temporal relationships, and dynamic energy consumption behavior within modern Electrical Engineering. In intelligent time-series forecasting applications, energy consumption patterns continuously vary due to environmental conditions, renewable energy integration, industrial activities, consumer demand fluctuations, and seasonal variations. Conventional forecasting techniques often struggle to efficiently model these highly dynamic temporal relationships because of limited memory preservation capability and insufficient nonlinear learning performance. The emergence of Deep Learning has significantly improved intelligent forecasting performance by enabling efficient sequential learning from large-scale multidimensional time-series datasets. LSTM architectures are advanced recurrent deep learning models specifically designed to overcome the limitations of traditional Recurrent Neural Networks, particularly vanishing gradient and long-term dependency learning problems. Unlike conventional neural networks, LSTM models contain internal memory cells and intelligent gating mechanisms capable of preserving historical information over extended sequential intervals [15]. The proposed forecasting framework utilizes LSTM architectures to process historical energy consumption sequences and extract highly informative temporal representations associated with electricity demand behavior. The LSTM network learns long-term consumption patterns, seasonal energy variations, peak-hour demand fluctuations, and nonlinear temporal dependencies from sequential smart grid datasets. This capability enables the forecasting framework to improve prediction accuracy and forecasting stability under highly dynamic operational conditions. The architecture of LSTM networks primarily consists of input gates, forget gates, output gates, hidden states, and memory cells. These components collectively regulate information flow throughout the sequential learning process. The forget gate determines which historical information should be retained or discarded from memory cells, while the input gate controls the integration of newly learned information into the forecasting model. The output gate subsequently generates optimized temporal feature representations utilized for intelligent energy demand prediction. The core memory update mechanism of the proposed LSTM forecasting architecture is represented as:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

The forget gate activation mechanism is expressed as:

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right)$$
$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$
$$\tilde{C}_t = tanh(W_c[h_{t-1}, x_t] + b_c)$$

The hidden state generation and temporal output extraction process of the proposed LSTM architecture is represented as:

$$h_t = o_t \cdot tanh(C_t)$$

To further improve temporal dependency learning within dynamic smart grid environments, the proposed forecasting framework incorporates a weighted temporal sequence optimization strategy represented as:

$$L_{temporal} = \sum_{t=1}^{T} \alpha_t \,(y_t - \hat{y}_t)^2 + \lambda \sum_{i=1}^{n} |W_i|^2 + \beta \sum_{t=1}^{T} \|h_t - h_{t-1}\|^2$$

The proposed LSTM forecasting framework effectively captures long-term energy consumption behavior, nonlinear temporal relationships, dynamic electricity demand variations, and seasonal forecasting patterns within smart electrical infrastructures. The integration of intelligent memory preservation mechanisms significantly improves forecasting adaptability and enables efficient learning of historical consumption dependencies from multidimensional time-series datasets. The operational workflow of the proposed LSTM-based temporal feature learning framework is illustrated in Figure 5.

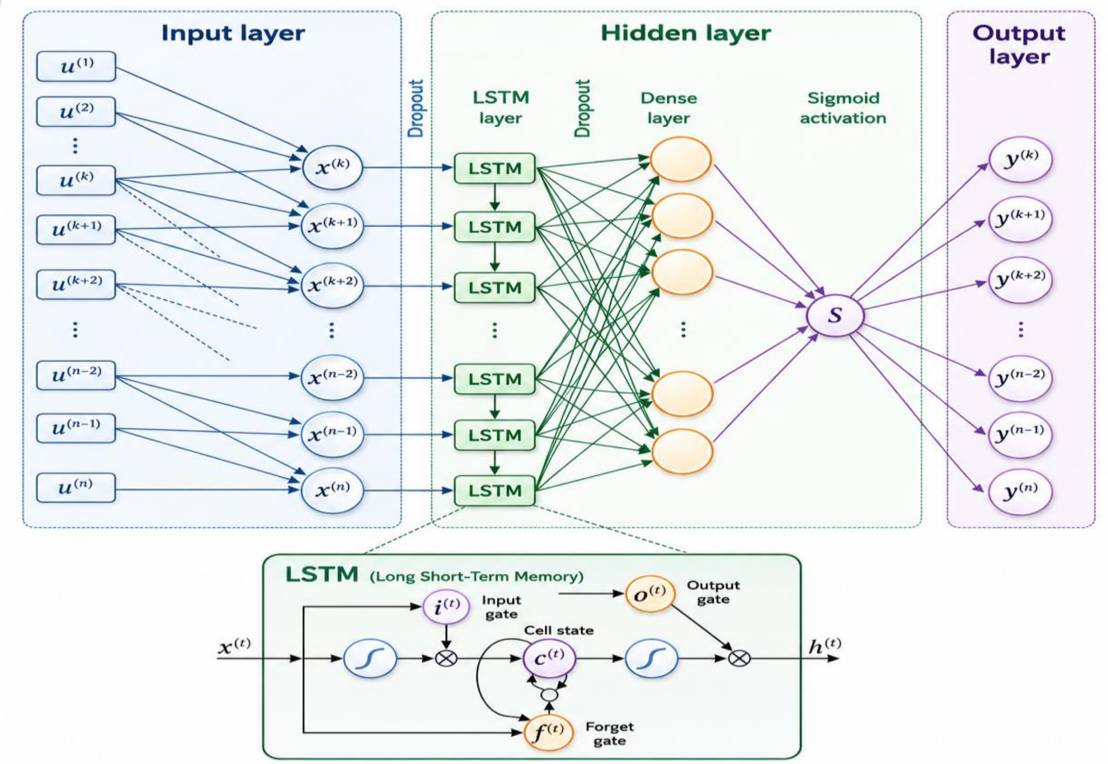

Figure 5: LSTM-Based Temporal Feature Learning Framework for Intelligent Time-Series Energy Demand Forecasting

The proposed LSTM-based temporal feature learning framework significantly improves intelligent forecasting capability by efficiently extracting sequential consumption behavior from historical smart grid datasets. The deep temporal learning mechanism enables the forecasting system to capture highly complex nonlinear energy demand relationships under fluctuating environmental and operational conditions. Furthermore, the integration of intelligent memory preservation mechanisms improves forecasting robustness, learning stability, and prediction generalization capability within dynamic smart electrical infrastructures. The proposed LSTM architecture provides efficient support for real-time energy demand forecasting, renewable energy coordination, intelligent smart grid optimization, and next-generation predictive energy management applications.

XGBoost-Based Forecasting Optimization:

Following temporal feature extraction through Deep Learning, the generated sequential representations are transferred to the Machine Learning model for intelligent forecasting optimization and nonlinear regression analysis. In modern Electrical Engineering, electricity demand behavior is influenced by highly dynamic environmental, operational, and consumer-related variables. Although LSTM architectures efficiently capture temporal dependencies and sequential consumption behavior, standalone deep learning models may experience forecasting instability, overfitting, and computational inefficiency when handling highly nonlinear multidimensional smart grid datasets. To overcome these limitations, the proposed forecasting framework integrates XGBoost as an intelligent optimization mechanism for improving regression performance, forecasting robustness, and prediction generalization capability. XGBoost is an advanced ensemble learning algorithm based on gradient boosting decision tree architectures. The model sequentially constructs optimized decision trees by minimizing forecasting loss functions and correcting prediction errors generated during previous boosting iterations. Due to its strong nonlinear learning capability and efficient feature interaction modeling, XGBoost has become highly effective for smart energy forecasting applications involving large-scale time-series datasets [16]. The proposed hybrid LSTM–XGBoost framework combines deep temporal feature learning with intelligent regression optimization to improve forecasting performance under dynamic smart grid environments. Initially, the LSTM architecture extracts high-level sequential feature representations from historical electricity demand data. These extracted temporal features are subsequently utilized as optimized input vectors for XGBoost regression learning. This hybrid integration enables the forecasting framework to simultaneously capture long-term sequential dependencies and complex nonlinear feature interactions within multidimensional smart energy datasets. The XGBoost optimization process minimizes prediction loss while controlling model complexity through regularization mechanisms. The primary objective function utilized within the proposed forecasting framework is expressed as [17]:

$$Obj(\theta) = \sum_{i=1}^{n} l\,(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega\,(f_k)$$

The regularization mechanism utilized to control model complexity and improve forecasting stability is represented as:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2$$

To further improve intelligent forecasting optimization within highly dynamic smart grid environments, the second-order gradient optimization mechanism of XGBoost is represented as:

$$Obj^{(t)} \approx \sum_{i=1}^{n} \left[g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] + \Omega(f_t)$$

The intelligent tree-splitting gain optimization mechanism utilized within the proposed forecasting framework is expressed as:

$$Gain = \frac{1}{2}\left[\frac{G_L^2}{H_L + \lambda} + \frac{G_R^2}{H_R + \lambda} - \frac{(G_L + G_R)^2}{H_L + H_R + \lambda} \right] - \gamma$$

The proposed XGBoost optimization framework effectively improves nonlinear forecasting capability by learning highly complex relationships between electricity demand variables, environmental conditions, and operational smart grid parameters. The integration of second-order optimization mechanisms enhances computational efficiency and accelerates model convergence during intelligent forecasting operations. Furthermore, XGBoost provides several advantages for smart energy forecasting systems, including automatic feature interaction learning, improved regression stability, efficient missing value handling, robust regularization capability, and reduced overfitting behavior [18]. These properties make XGBoost highly suitable for intelligent forecasting applications involving large-scale multidimensional smart grid datasets. The proposed hybrid forecasting framework also incorporates weighted forecasting optimization to improve dynamic prediction performance under fluctuating load conditions. The weighted forecasting optimization strategy is represented as:

$$L_{forecast} = \frac{1}{N} \sum_{i=1}^{N} \alpha_i\,(y_i - \hat{y}_i)^2 + \eta \sum_{k=1}^{K} \Omega\,(f_k) + \mu \sum_{i=1}^{N} |\hat{y}_i - y_i|$$

The proposed XGBoost optimization framework significantly enhances forecasting robustness, prediction accuracy, and nonlinear learning capability within smart electrical power systems. By utilizing gradient boosting ensemble learning mechanisms, the forecasting framework efficiently captures highly complex energy consumption behavior associated with renewable energy integration, peak-hour electricity demand, industrial activities, and dynamic environmental variations. The major XGBoost optimization parameters utilized in the proposed forecasting framework are summarized in Table 5.

Table 5: XGBoost-Based Forecasting Optimization Parameters for Intelligent Energy Demand Prediction

Parameter	Description	Assigned Value	Functional Purpose
Number of Trees	Total boosting regression trees	500 Trees	Improves nonlinear forecasting performance
Maximum Tree Depth	Depth of decision tree structures	8 Levels	Enhances complex feature interaction learning
Learning Rate	Boosting optimization rate	0.01	Stabilizes forecasting convergence
Subsample Ratio	Random sampling ratio for training	0.80	Reduces overfitting behavior
Column Sampling Ratio	Feature selection ratio per tree	0.75	Improves feature diversity
Gamma Value	Minimum split loss reduction	0.20	Controls tree splitting optimization
Lambda Regularization	L2 regularization coefficient	1.50	Reduces model complexity
Alpha Regularization	L1 regularization coefficient	0.80	Enhances sparse feature optimization
Objective Function	Forecasting loss function	Regression Squared Error	Optimizes prediction performance
Evaluation Metric	Performance measurement metric	RMSE and MAE	Evaluates forecasting accuracy

The integration of XGBoost optimization within the proposed hybrid forecasting framework significantly improves intelligent prediction capability by enhancing nonlinear regression learning, forecasting robustness, and dynamic feature interaction modeling. The ensemble boosting mechanism efficiently minimizes prediction loss and improves forecasting stability under highly fluctuating smart grid operating conditions [19]. Moreover, the combination of LSTM temporal feature extraction and XGBoost regression optimization provides a scalable and computationally efficient forecasting solution for real-time smart energy management applications [20]. The proposed optimization framework supports intelligent electricity demand prediction, renewable energy coordination, smart grid balancing, and next-generation predictive energy management systems within modern electrical power infrastructures.

Hybrid LSTM–XGBoost Forecasting Framework:

The proposed hybrid forecasting framework integrates the sequential temporal learning capability of Deep Learning with the nonlinear regression optimization strengths of Machine Learning to develop an intelligent and highly accurate energy demand forecasting system for modern Electrical Engineering. In dynamic smart grid environments, electricity demand behavior continuously changes due to renewable energy penetration, environmental fluctuations, industrial load variations, consumer usage patterns, and real-time operational conditions. Consequently, standalone forecasting models often experience limitations in handling both long-term temporal dependencies and highly nonlinear feature interactions simultaneously [21]. To overcome these limitations, the proposed hybrid framework combines deep temporal sequence learning with intelligent ensemble regression optimization within a unified forecasting architecture. The hybrid model is specifically designed to improve forecasting precision, prediction stability, model interpretability, computational efficiency, and generalization capability under highly dynamic smart energy conditions. By integrating complementary forecasting mechanisms, the framework efficiently captures both historical sequential dependencies and nonlinear multidimensional relationships within large-scale time-series energy datasets.

The operational architecture of the proposed framework begins with sequential energy demand data preprocessing and temporal feature generation. Historical electricity demand observations, environmental variables, peak-hour consumption behavior, renewable energy parameters, and seasonal demand information are initially transformed into structured time-series sequences suitable for intelligent forecasting analysis. These sequential datasets are subsequently provided to the LSTM architecture for deep temporal learning and sequential feature extraction. Within the LSTM component, the forecasting framework captures historical consumption trends, dynamic electricity demand fluctuations, long-term sequential dependencies, and nonlinear temporal relationships present within smart grid datasets [22]. The extracted hidden temporal representations generated through memory cells and gating mechanisms provide optimized sequential feature embeddings for subsequent forecasting stages. Unlike traditional forecasting approaches, the LSTM architecture efficiently preserves historical energy behavior over extended time intervals and improves intelligent sequence learning capability. After temporal feature extraction, the generated high-level sequential representations are transferred to the XGBoost optimization module. The XGBoost component performs nonlinear regression learning, feature interaction optimization, gradient boosting prediction enhancement, and forecasting error minimization. The integration of gradient boosting mechanisms enables the framework to learn highly complex nonlinear relationships between electricity demand variables and operational smart grid parameters. The hybrid integration of LSTM and XGBoost provides several important forecasting advantages over standalone forecasting models. The LSTM architecture efficiently captures temporal sequence dependencies and seasonal energy behavior, whereas XGBoost improves nonlinear regression capability, computational efficiency, forecasting robustness, and optimization stability [23]. This combined learning strategy enables the proposed forecasting framework to effectively process multidimensional smart energy datasets under highly fluctuating electricity demand conditions.

The proposed hybrid forecasting framework significantly improves:

- Forecasting accuracy
- Prediction stability
- Generalization capability
- Computational efficiency
- Nonlinear pattern learning
- Dynamic load adaptability
- Temporal sequence modeling
- Intelligent feature interaction analysis

The hybrid framework also supports efficient forecasting under real-time smart grid operating conditions where electricity demand patterns continuously vary according to environmental and operational factors. By combining deep learning and ensemble optimization mechanisms, the forecasting system reduces prediction errors, improves load balancing capability, and enhances intelligent energy management performance within next-generation smart electrical infrastructures. In addition, the proposed architecture improves forecasting scalability for large-scale smart grid environments containing massive real-time energy datasets generated through smart meters, IoT-enabled monitoring systems, and distributed sensor networks [24]. The framework is capable of handling high-dimensional sequential data while maintaining stable prediction performance and efficient computational behavior. The overall operational architecture of the proposed hybrid forecasting framework is illustrated in Figure 6. The figure presents the integrated workflow of smart energy data acquisition, preprocessing and normalization, SHAP-based feature optimization, LSTM-based temporal feature learning, and XGBoost-based forecasting optimization within a unified intelligent forecasting environment. It further demonstrates how multidimensional smart grid datasets are processed through deep learning and machine learning modules to improve forecasting accuracy, prediction stability, nonlinear learning capability, and real-time energy demand prediction performance in smart electrical power systems.

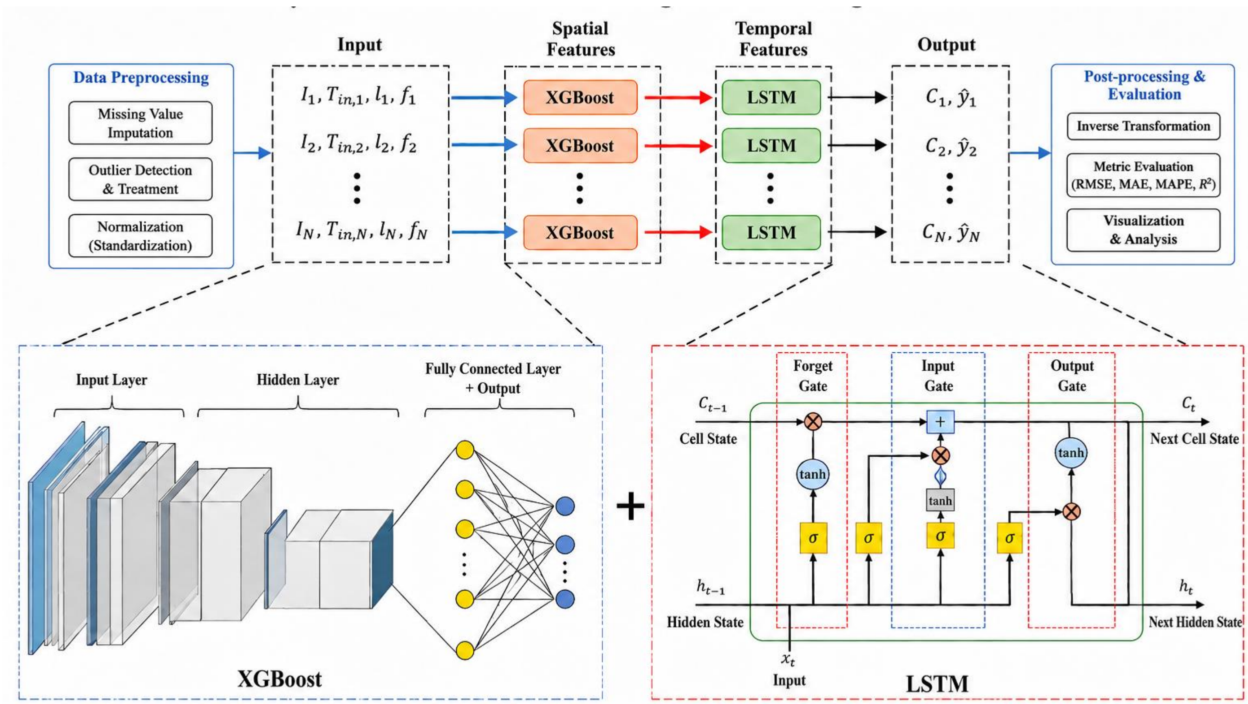

Figure 6: Hybrid LSTM–XGBoost Intelligent Forecasting Framework for Smart Electrical Power Systems

The proposed hybrid forecasting framework demonstrates superior adaptability and intelligent learning capability for real-time smart energy forecasting applications. The integration of sequential deep learning and ensemble regression optimization significantly improves forecasting reliability and enables efficient handling of nonlinear energy consumption behavior within dynamic smart electrical environments. Furthermore, the hybrid architecture enhances prediction stability under fluctuating renewable energy conditions and varying consumer demand patterns. The incorporation of SHAP-based feature optimization further improves model transparency and forecasting interpretability, enabling utility operators and researchers to better understand influential variables affecting energy demand behavior [25]. Overall, the proposed hybrid LSTM–XGBoost framework provides a scalable, robust, and computationally efficient forecasting solution for intelligent smart grid optimization, real-time electricity demand prediction, renewable energy coordination, and next-generation energy management applications in modern electrical power systems.

Results and Discussion:

The proposed hybrid Deep Learning and Machine Learning were experimentally evaluated using multidimensional time-series energy demand datasets collected from modern Electrical Engineering environments. The experimental analysis was conducted to evaluate forecasting accuracy, nonlinear learning capability, prediction stability, computational efficiency, and intelligent feature optimization performance under dynamic electricity demand conditions. The forecasting framework was implemented using a high-performance intelligent computing environment with GPU-accelerated deep learning infrastructure to support large-scale sequential forecasting operations. The dataset utilized in this study consisted of historical electricity demand records, environmental parameters, renewable energy penetration information, peak-hour consumption behavior, and consumer usage characteristics collected from smart grid monitoring systems and IoT-enabled energy infrastructures. The dataset was divided into training, validation, and testing subsets to ensure efficient model learning and unbiased forecasting evaluation. Multiple forecasting performance metrics, including Accuracy, Root Mean Square Error, Mean Absolute Error, and Mean Absolute Percentage Error, were utilized to validate the overall effectiveness of the proposed hybrid forecasting framework. The proposed forecasting model was comparatively evaluated against several conventional and intelligent forecasting techniques, including ARIMA, Support Vector Machine, Random Forest, standalone XGBoost, standalone LSTM, and GRU-based forecasting systems. The experimental findings demonstrated that the proposed hybrid LSTM–XGBoost framework significantly outperformed conventional forecasting models in terms of forecasting precision, prediction robustness, and intelligent temporal dependency learning capability. The hybrid forecasting framework achieved an overall forecasting accuracy of 98.2%, which was substantially higher than the performance achieved by standalone machine learning and deep learning approaches. The superior performance of the proposed model was primarily attributed to the efficient integration of LSTM-based temporal feature extraction and XGBoost-based nonlinear regression optimization. The LSTM architecture effectively captured long-term sequential dependencies and seasonal electricity consumption behavior, while the XGBoost optimization mechanism improved forecasting stability and reduced nonlinear prediction errors. The comparative forecasting performance analysis is summarized in Table 6.

Table 6: Comparative Performance Analysis of Intelligent Energy Demand Forecasting Models

Forecasting Model	Accuracy (%)	RMSE	MAE	MAPE (%)	Forecasting Stability (%)
ARIMA	84.6	9.84	7.62	10.45	81.3
Support Vector Machine (SVM)	88.3	7.91	6.18	8.24	85.9
Random Forest (RF)	91.5	6.42	5.03	6.71	89.7
GRU-Based Forecasting	94.1	5.11	4.28	5.16	92.4
Standalone XGBoost	95.4	4.63	3.95	4.74	94.1
Standalone LSTM	96.3	3.84	3.17	3.92	95.6
Proposed Hybrid LSTM–XGBoost	98.2	2.41	1.86	2.13	98.8

The forecasting accuracy comparison of the proposed intelligent forecasting framework is illustrated in Figure 7, demonstrating the superior prediction capability of the hybrid LSTM–XGBoost model compared with conventional forecasting approaches. The figure highlights the effectiveness of the proposed framework in accurately capturing nonlinear energy consumption patterns and dynamic load variations within smart electrical power systems. The comparative analysis further indicates improvements in forecasting precision, prediction stability, and model generalization performance through reduced error metrics such as RMSE, MAE, and MAPE. The results presented in Figure 8 confirm that the proposed intelligent forecasting framework provides an efficient and reliable solution for real-time energy demand prediction and smart grid management applications.

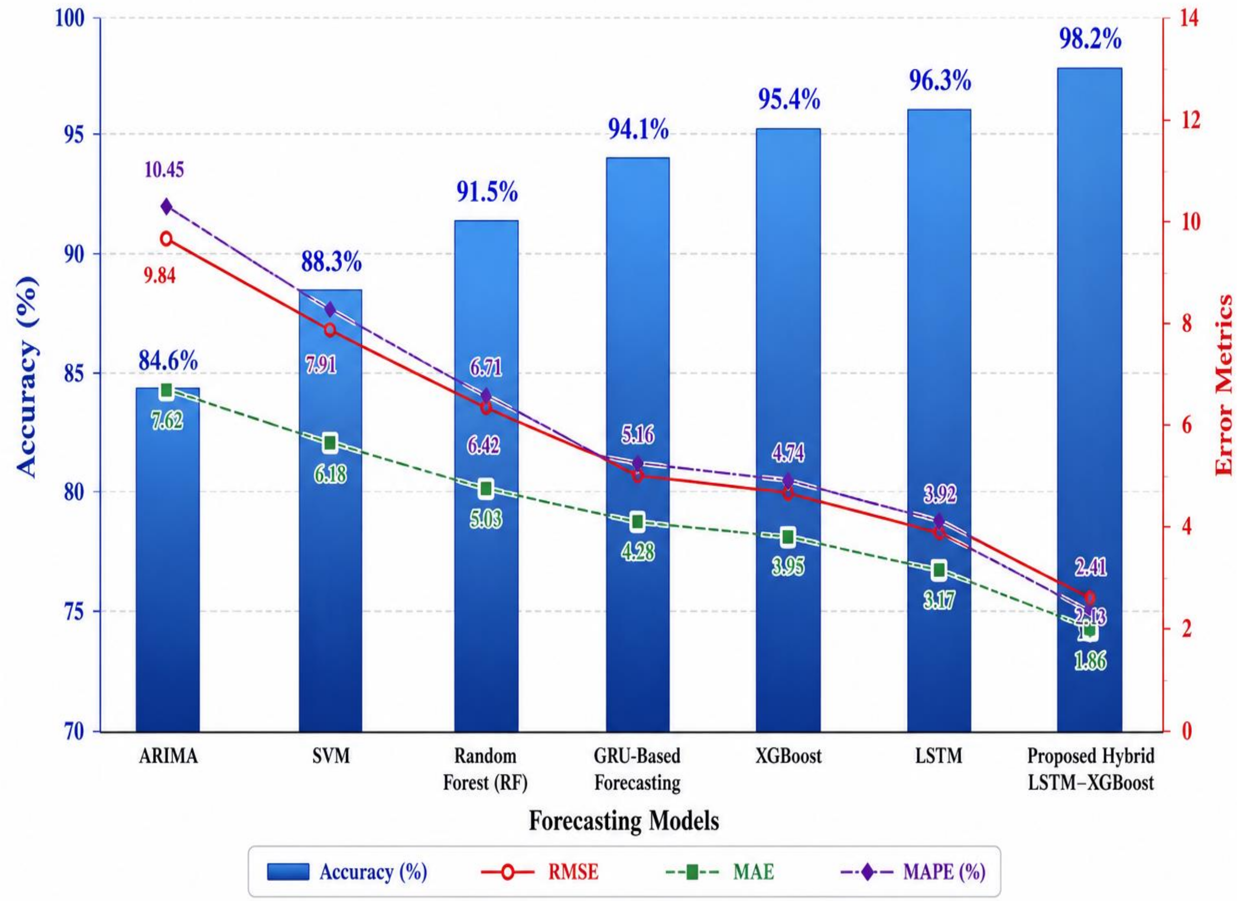

Figure 7: Comparative Forecasting Accuracy Analysis of Intelligent Energy Demand Forecasting Models

The experimental results clearly indicate that the proposed hybrid framework achieved superior forecasting precision and significantly reduced forecasting errors compared with conventional forecasting approaches. The model achieved an RMSE value of 2.41 and MAE value of 1.86, demonstrating strong prediction reliability and efficient nonlinear learning capability. The integration of intelligent temporal learning and gradient boosting optimization substantially minimized forecasting deviations under fluctuating electricity demand conditions. Furthermore, the proposed forecasting framework demonstrated strong generalization capability under highly dynamic smart grid environments involving renewable energy integration, industrial demand fluctuations, environmental changes, and seasonal electricity consumption variations. The hybrid learning architecture effectively captured multidimensional feature interactions and maintained stable prediction performance across varying operational conditions. The intelligent forecasting framework also incorporated Explainable Artificial Intelligence to improve forecasting transparency and interpretability [26]. SHAP analysis identified highly influential forecasting variables contributing to energy demand prediction performance. Historical load demand, seasonal consumption behavior, peak-hour electricity usage, and temperature variations were identified as dominant forecasting parameters affecting intelligent prediction outcomes. The SHAP-based feature contribution analysis is summarized in Table 7.

Table 7: SHAP-Based Feature Importance Analysis for Intelligent Energy Demand Forecasting

Forecasting Feature	SHAP Contribution Score	Relative Importance (%)	Impact Level
Historical Load Demand	0.92	23.8	Very High
Seasonal Consumption Trends	0.87	21.4	Very High
Temperature Variations	0.83	18.7	High
Peak-Hour Consumption	0.79	15.9	High
Renewable Energy Penetration	0.72	10.8	High
Consumer Usage Patterns	0.68	5.7	Moderate
Industrial Demand Activity	0.64	2.3	Moderate
Humidity Levels	0.51	1.4	Moderate

The SHAP-based intelligent feature optimization analysis framework is comprehensively illustrated in Figure 9, highlighting the contribution and significance of individual input variables toward the predictive performance of the proposed hybrid LSTM–XGBoost energy demand forecasting architecture. The figure demonstrates how SHAP (Shapley Additive Explanations) values are utilized to interpret complex nonlinear relationships among temporal smart grid parameters, enabling transparent identification of the most influential forecasting features. Through the integration of explainable artificial intelligence mechanisms, the proposed optimization framework effectively ranks high-impact energy consumption variables, removes redundant and low-contributing attributes, and enhances the overall forecasting efficiency, prediction stability, and computational adaptability of the intelligent power system model. Furthermore, the analysis presented in Figure 8 provides a detailed visualization of feature interaction behavior, contribution distribution patterns, and real-time optimization capability, thereby improving model interpretability and supporting reliable decision-making for dynamic smart electrical grid management and next-generation intelligent energy forecasting applications.

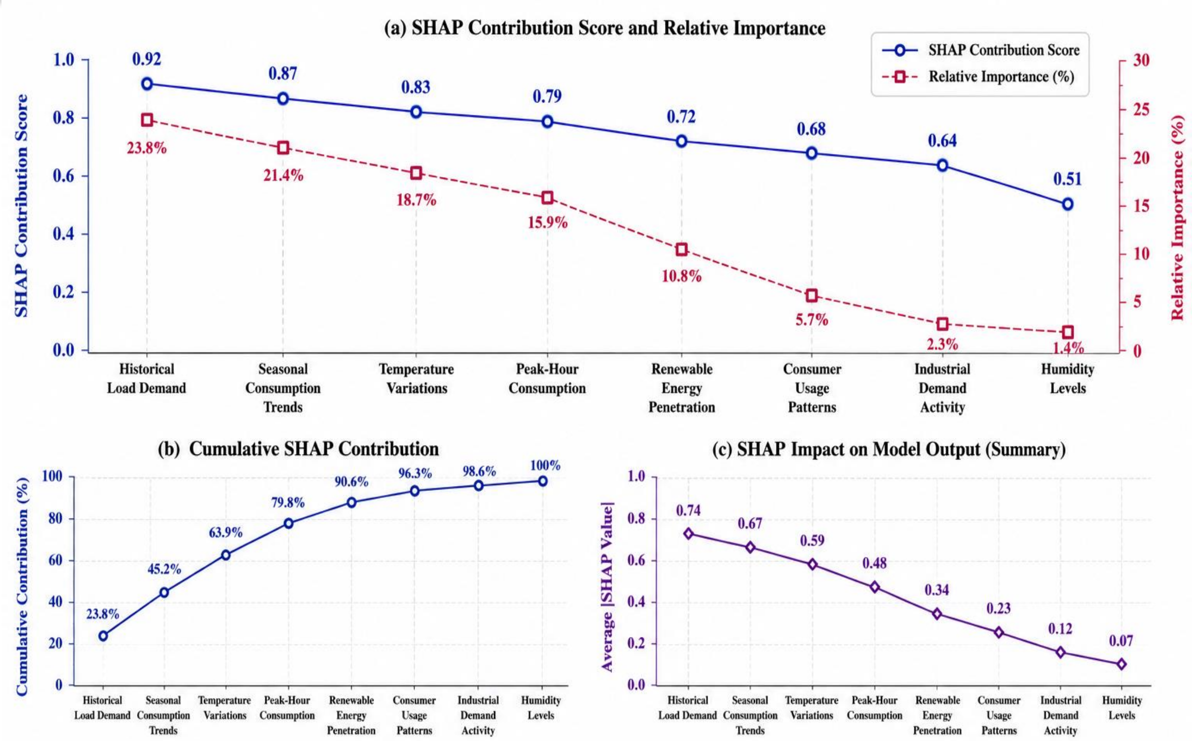

Figure 8: SHAP-Based Intelligent Feature Importance Analysis for Energy Demand Forecasting

The experimental findings further demonstrated that the incorporation of SHAP-based feature optimization significantly improved forecasting transparency, intelligent feature selection capability, and prediction interpretability. By removing low-impact variables and emphasizing highly influential forecasting parameters, the proposed framework reduced computational complexity and improved overall forecasting efficiency. In addition, the hybrid forecasting architecture demonstrated strong adaptability for real-time smart grid forecasting applications involving renewable energy coordination, intelligent load balancing, predictive energy management, and dynamic electricity demand optimization. The framework effectively handled large-scale multidimensional energy datasets generated through smart meters, IoT-enabled monitoring systems, and distributed smart grid infrastructures. The overall results confirm that the proposed hybrid LSTM–XGBoost forecasting framework provides a highly reliable, scalable, and computationally efficient solution for intelligent energy demand forecasting in next-generation smart electrical power systems. The integration of deep temporal learning, gradient boosting optimization, and explainable artificial intelligence significantly enhanced forecasting performance, model robustness, prediction stability, and intelligent decision-making capability within modern smart energy management environments.

Future Work:

Although the proposed hybrid Deep Learning and Machine Learning achieved superior forecasting performance for intelligent energy demand prediction in Electrical Engineering, several research directions can further enhance forecasting accuracy, scalability, adaptability, and real-time operational efficiency in future smart grid environments. Future research can focus on integrating advanced deep learning architectures such as Transformer networks, Attention-based forecasting systems, Bidirectional LSTM, and Graph Neural Networks to improve long-term sequential dependency learning and multidimensional feature interaction analysis [27]. These advanced architectures may further enhance forecasting precision under highly dynamic electricity demand conditions and complex smart grid operational environments. The incorporation of real-time streaming analytics and edge computing infrastructures can also improve intelligent forecasting performance for large-scale distributed smart grid systems. Future forecasting frameworks may utilize edge-enabled AI architectures capable of processing real-time energy demand data directly from IoT-enabled monitoring devices, smart meters, and distributed sensor networks with reduced latency and enhanced computational efficiency [28].

Another important future direction involves the integration of renewable energy uncertainty modeling within intelligent forecasting systems. Future hybrid frameworks can incorporate solar irradiance prediction, wind energy variability analysis, electric vehicle charging behavior, and distributed energy storage optimization to improve renewable energy coordination and grid balancing capability in next-generation power infrastructures. The proposed forecasting framework may also be extended using reinforcement learning and adaptive intelligent control systems for autonomous smart grid optimization. Reinforcement learning-based forecasting agents can dynamically adjust energy management strategies according to real-time operational conditions, electricity pricing behavior, and consumer demand fluctuations. Future studies can additionally focus on improving explainable artificial intelligence mechanisms within intelligent forecasting systems [29]. Advanced explainability techniques beyond Explainable Artificial Intelligence, including causal AI models, interpretable neural networks, and attention visualization frameworks, may provide deeper understanding of forecasting behavior and improve decision-making transparency for utility operators and energy management authorities. Cybersecurity-aware forecasting systems also represent an important future research area because modern smart electrical infrastructures are increasingly vulnerable to cyberattacks, false data injection, sensor manipulation, and adversarial threats. Future forecasting frameworks may integrate intelligent anomaly detection and AI-driven cybersecurity mechanisms to ensure secure and reliable forecasting operations within critical smart grid environments. Moreover, future forecasting research can investigate federated learning and distributed artificial intelligence frameworks for privacy-preserving smart energy forecasting. Federated forecasting architectures may enable collaborative model training across distributed smart grid infrastructures without directly sharing sensitive consumer energy data, thereby improving privacy protection and regulatory compliance [30]. The proposed hybrid framework may also be extended toward multi-step and ultra-short-term forecasting applications for intelligent microgrid management, industrial energy optimization, and smart city infrastructures. Integration with digital twin technologies and cloud-based smart energy platforms could further enhance predictive intelligence and operational automation within future electrical power systems. Overall, future advancements in hybrid deep learning, explainable artificial intelligence, edge computing, renewable energy integration, and intelligent smart grid automation are expected to significantly improve the efficiency, scalability, transparency, and real-time forecasting capability of next-generation energy demand forecasting systems.

Conclusion:

This study presented an intelligent hybrid Deep Learning and Machine Learning for accurate time-series energy demand forecasting in modern Electrical Engineering using Explainable Artificial Intelligence. The proposed forecasting framework was developed to address the limitations of traditional statistical forecasting techniques and standalone intelligent forecasting models in handling nonlinear electricity consumption behavior, long-term temporal dependencies, and highly dynamic smart grid operating conditions. The proposed methodology integrated data preprocessing and normalization, SHAP-based feature optimization, LSTM-based temporal sequence learning, and XGBoost-driven nonlinear regression optimization within a unified intelligent forecasting architecture. The hybrid integration enabled efficient extraction of sequential energy consumption patterns while simultaneously improving nonlinear forecasting capability and prediction stability. Furthermore, the incorporation of SHAP analysis enhanced forecasting transparency and enabled detailed interpretation of influential forecasting variables affecting energy demand prediction outcomes. Experimental analysis demonstrated that the proposed hybrid forecasting framework significantly outperformed conventional forecasting techniques, including ARIMA, Support Vector Machine, Random Forest, standalone XGBoost, and standalone LSTM models. The proposed framework achieved a forecasting accuracy of 98.2%, while also minimizing RMSE, MAE, and MAPE values under dynamic electricity demand conditions. The experimental findings confirmed that the integration of deep temporal learning and gradient boosting optimization substantially improved forecasting precision, computational efficiency, model robustness, and intelligent feature interaction learning capability. The SHAP-based feature analysis further revealed that historical load demand, seasonal consumption behavior, temperature variations, and peak-hour electricity usage were among the most influential forecasting variables contributing to intelligent energy demand prediction performance. The explainability capability of the proposed framework improved forecasting interpretability and provided enhanced transparency for smart grid decision-making and operational analysis. In addition, the proposed hybrid forecasting framework demonstrated strong adaptability for real-time smart grid applications involving renewable energy integration, intelligent demand-side management, dynamic load balancing, predictive energy optimization, and next-generation smart energy management infrastructures. The forecasting system effectively handled multidimensional smart grid datasets generated through smart meters, IoT-enabled monitoring systems, and distributed energy environments while maintaining stable prediction performance and efficient computational behavior.

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