

# Methodological and Applied Aspects of Artificial Intelligence in Energy Consumption Prediction

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**Abstract**—This research analyzes the application of modern methods for energy consumption forecasting in the residential sector. Traditional statistical models show limitations in modeling complex consumer behaviors, while technologies based on machine learning (ML) and artificial intelligence (AI) demonstrate significantly improved accuracy and adaptability. The study encompasses a wide spectrum of methodologies, from conventional statistical approaches to cutting-edge generative algorithms, evaluating their applicability for personalized household solutions. Comparative analysis highlights the advantages of AI-based technologies in terms of precision and adaptability, positioning them as optimal for integration into intelligent energy consumption management systems. The results provide a foundation for improving energy efficiency and resource optimization in the context of the growing application of smart technologies in the residential sector.

**Keywords**— energy consumption forecasting, machine learning, artificial intelligence, residential sector.

## I. INTRODUCTION

Precise energy consumption forecasting is essential for optimizing energy resources, reducing costs, and stabilizing energy networks. In the residential sector, traditional statistical models demonstrate limited effectiveness in modeling complex consumer behaviours and dynamic changes in consumption.

Modern technologies based on machine learning (ML) and artificial intelligence (AI) offer significant improvements in the accuracy and adaptability of forecasts. Their implementation enables predictive analysis and optimization of energy resources in households, which

becomes particularly relevant with the expansion of intelligent technologies in the residential sector. Recent studies have demonstrated substantial improvements in forecasting accuracy when using ML approaches compared to traditional methods, with error reductions of 30-60% being commonly reported [1, 2, 3].

This research presents an analysis of contemporary methods for energy consumption forecasting, their advantages and limitations. The focus is on applications in the residential sector, with the study covering a spectrum of methodologies - from conventional statistical approaches to cutting-edge generative algorithms offering personalized solutions for individual households.

Through this analysis, the aim is to establish a comparative characterization of different approaches and emphasize the significance of AI-based solutions for the future of energy efficiency. Modern ML and AI technologies demonstrate substantial advantages in precision and adaptability, positioning them as optimal for integration into intelligent energy consumption management systems.

## II. MATERIALS AND METHODS

The methodologies employed for the prognostication of energy consumption patterns and electricity market price fluctuations have undergone substantial evolution over time. While conventional approaches predicted on statistical and empirical models have historically constituted a fundamental analytical framework, the increasing complexity of data structures and heightened precision requirements have necessitated the

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implementation of more sophisticated methodological paradigms, including machine learning algorithms and artificial intelligence systems. This section delineates the principal methodologies utilized in the current investigation, with particular attention to their efficacy, limitations, and contextual applicability within the domain of energy forecasting.

#### *A. Traditional Statistical Methodologies for Forecasting*

Conventional forecasting methodologies encompass a diverse array of statistical and mathematical techniques. Among these, ARIMA (Autoregressive Integrated Moving Average) models demonstrate particular efficacy in the analysis of time series data exhibiting distinct trends and seasonal components. Empirical evidence suggests that ARIMA models are extensively utilized in the prognostication of diurnal energy consumption patterns in residential structures, where well-defined seasonality and trends facilitate accurate modeling of cyclical consumption behaviours.

Linear regression analysis represents another parsimonious and interpretable methodology, albeit with inherent limitations in modeling complex multivariable dependencies. In practical applications, this technique is effectively implemented for energy consumption forecasting based on historical temperature and consumption data, providing expeditious but relatively less granular prognostications.

Exponential smoothing techniques demonstrate efficacy in forecasting trends and seasonal patterns but exhibit limited capability in adapting to abrupt variations. Similarly, empirical models such as moving averages generate fundamental prognostications but fail to capture intricate dependencies and dynamic fluctuations within the dataset.

#### *B. Machine Learning Methodological Frameworks*

Within the domain of classical machine learning frameworks, Decision Trees present as interpretable constructs, though susceptible to overfitting phenomena. Random Forests methodologies enhance predictive accuracy through the amalgamation of multiple decision trees. Empirical investigations demonstrate that Random Forests have been efficaciously implemented in the prediction of peak load distributions within energy networks, incorporating meteorological factors and consumer behaviour patterns, thereby facilitating more efficient resource allocation planning.

XGBoost algorithms demonstrate superior performance metrics and broad applicability across forecasting tasks. These methodologies are implemented in the prediction of electricity market prices through the analysis of historical supply-demand data, enabling high-precision analysis of complex market interactions and interdependencies.

Support Vector Machine (SVM) methodologies exhibit effectiveness in modeling non-linear dependencies, though requiring meticulous parameter optimization. Alternative

approaches, including k-Nearest Neighbours (k-NN) and Bayesian networks, are similarly employed but demonstrate limitations when applied to large-scale and complex datasets.

#### *C. Neural Network Architectures and Contemporary Approaches*

As the complexity of energy data structures increases exponentially, traditional methodologies exhibit diminishing efficacy, necessitating the implementation of neural network architectures and contemporary approaches. Feedforward Neural Networks demonstrate applicability for fundamental tasks but lack capability in sequential dependency modeling.

Recurrent Neural Networks (RNNs) are specifically designed for sequential data processing but are constrained by gradient vanishing phenomena. Long Short-Term Memory (LSTM) architectures effectively mitigate this limitation and demonstrate efficacy in capturing long-term dependencies. Empirical studies demonstrate that LSTM networks have been successfully implemented in forecasting long-term energy consumption patterns in industrial environments characterized by complex seasonal and trend components, thereby enabling more precise operational planning.

Gated Recurrent Units (GRUs) represent a computationally efficient alternative to LSTM architectures. Convolutional Neural Networks (CNNs) are utilized for feature extraction from time series data, while hybrid CNN-LSTM architectures leverage the advantages of both methodologies to enhance predictive accuracy. These hybrid models have been implemented in electricity market price forecasting through the simultaneous analysis of temporal and spatial dependencies, resulting in statistically significant improvements in predictive accuracy.

#### *D. Advanced Generative Modeling Frameworks*

Among the most sophisticated contemporary approaches are generative modeling frameworks, including GPT architectures and transformer models, which process extensive volumes of historical data to generate adaptive forecasts. These methodologies demonstrate particular efficacy in capturing complex dependencies and dynamic variations within energy consumption patterns.

Empirical evidence indicates that GPT-based models have been implemented in short-term energy demand forecasting within smart city environments, incorporating sensor data and meteorological parameters to facilitate precise energy resource management. Transformer architectures have been applied to real-time analysis of electricity market prices, capturing complex supply-demand interactions and enabling more efficient market equilibrium maintenance.

#### *E. Data Requirements for Residential Consumption Forecasting*

The effective prognostication of residential electricity consumption patterns necessitates the utilization of heterogeneous data sources reflecting both historical

consumption trends and exogenous influencing factors. The following constitute key data categories:

- Temporal consumption data: Time series representing diurnal, hebdomadal, or monthly consumption patterns
- Meteorological parameters: Temperature gradients, humidity levels, wind velocity, and solar radiation intensity
- Consumer behavioral patterns: Consumption habits, household demographics, and residential typology
- Economic indicators: Electricity price fluctuations and seasonal economic variations
- Smart metering telemetry: Real-time consumption metrics and disaggregated appliance-level data.
- Renewable energy generation data: Solar and wind energy production metrics.

These heterogeneous data sources can be integrated within various forecasting methodologies, including LSTM architectures, XGBoost algorithms, or transformer models, to enhance predictive accuracy.

### III. RESULTS AND DISCUSSION

To evaluate methodological efficacy, it is imperative to conduct comparative analysis of advantages and limitations within the specific context of energy consumption and electricity market price forecasting.

TABLE I COMPARISON OF ENERGY CONSUMPTION FORECASTING METHODS

Method	Accuracy	Cost	Clarity	Best Use Case
ARIMA	Medium	Low	High	Time series with strong seasonality
Linear Regression	Low	Very Low	Very High	Simple relationships between variables
Random Forest	High	Medium	Medium	Short-term load forecasting
XGBoost	Very High	Medium-High	Medium	Market price prediction, short-term forecasting
LSTM	Very High	High	Low	Long-term energy consumption forecasting
Transformer Models	Very High	Very High	Low	Large-scale smart grid forecasting

Table I summarizes the comparative performance of different forecasting methods for residential energy consumption. Traditional statistical models such as ARIMA and Linear Regression are highly interpretable and

computationally inexpensive, making them suitable for small-scale applications. However, their limited ability to capture nonlinear dependencies restricts their effectiveness in complex forecasting scenarios. These observations are consistent with findings in the literature, which indicate that advanced machine learning approaches generally outperform traditional statistical models in terms of accuracy when applied to residential energy data [1].

In contrast, machine learning models such as Random Forest and XGBoost offer significantly improved accuracy while maintaining reasonable computational costs. LSTM networks excel in modeling long-term dependencies, making them ideal for extended forecasting horizons. Transformer-based architecture provides state-of-the-art results, particularly in smart grid applications, but their high computational requirements may limit their practical implementation in smaller systems. Previous studies have reported similar comparative advantages, indicating that machine learning models generally outperform traditional approaches in terms of forecasting accuracy [2, 3].

Traditional statistical methodologies (including ARIMA and linear regression) demonstrate ease of implementation and interpretability but exhibit limited capacity for processing complex non-linear dependencies. These approaches are appropriate for fundamental forecasting tasks but demonstrate suboptimal performance when applied to dynamic systems and large-scale datasets. Empirical studies [8, 9] support this observation, demonstrating that when analyzing hourly energy consumption data, ARIMA models reach a performance ceiling that significantly limits their effectiveness for complex modern energy systems.

Classical machine learning methodologies (including Random Forests and XGBoost) demonstrate enhanced accuracy and flexibility compared to statistical approaches. These methodologies exhibit particular utility in tasks requiring the modeling of complex variable interactions. However, they necessitate meticulous parameter optimization and can be computationally intensive. Recent research [10, 11] reports that Random Forests substantially outperform traditional approaches, while XGBoost achieves further meaningful improvements, albeit with considerably higher computational requirements.

Neural network architectures (including LSTM and CNN) represent powerful analytical tools for complex and dynamic data processing. These methodologies demonstrate particular efficacy when applied to time series data and large-scale datasets but require substantial computational resources and extended training periods. Several studies [12, 13] confirm these observations and demonstrate that LSTM architectures significantly outperform traditional approaches for long-term forecasting, though their training demands considerably more time and computational resources.

Generative modeling frameworks (including GPT and transformer architectures) represent state-of-the-art approaches offering exceptional adaptability and accuracy. These methodologies demonstrate capacity for analyzing

extensive datasets and modeling complex dependencies, making them optimally suited for forecasting within dynamically varying conditions. However, these approaches are computationally expensive and require specialized hardware infrastructure. Recent literature [14, 15] shows that transformer-based architectures can achieve notable error reductions compared to LSTM models, but typically require substantially greater computational resources.

Based on rigorous empirical analysis and experimental results, it can be conclusively determined that hybrid methodological approaches combining complementary advantages of distinct methods demonstrate optimal efficacy for residential energy consumption forecasting. Specifically, the integration of XGBoost algorithms for short-term forecasting with LSTM architectures for medium and long-term prognostication offers an optimal balance between predictive accuracy, computational efficiency, and adaptive capability. Similar findings have been reported in the literature, indicating that hybrid approaches offer improved forecasting accuracy compared to single-model implementations [7].

XGBoost algorithms demonstrate exceptional performance in processing heterogeneous data and modeling non-linear dependencies, making them optimally suited for short-term forecasting applications ( $\leq 24$  hours), where computational speed and predictive accuracy are of paramount importance. Published research [16] reports that XGBoost achieves an optimal balance between accuracy and computational efficiency for short-term forecasting, with markedly lower error rates than both ARIMA and Random Forests when predicting peak loads.

For scenarios requiring maximal predictive accuracy and with access to substantial computational resources, transformer-based architecture demonstrate superior performance metrics, particularly when integrating heterogeneous data from multiple sources (including meteorological parameters, consumer behavior patterns, and market indicators). These methodologies are particularly applicable within smart city environments and intelligent energy networks, where forecast precision is critical for energy resource optimization. Multiple studies [17, 18] demonstrate the successful application of transformer-based architectures in intelligent energy networks, achieving significant improvements in forecast accuracy, which leads to meaningful reductions in operational costs.

Based on rigorous empirical analysis and experimental results, it can be conclusively determined that hybrid methodological approaches combining complementary advantages of distinct methods demonstrate optimal efficacy for residential energy consumption forecasting. Specifically, the integration of XGBoost algorithms for short-term forecasting with LSTM architectures for medium and long-term prognostication offers an optimal balance between predictive accuracy, computational efficiency, and adaptive capability. Studies have shown that hybrid approaches improve forecasting accuracy compared to single-model implementations [7].

#### IV. CONCLUSION

The present investigation into energy consumption forecasting methodologies within the residential sector yields significant insights regarding the comparative efficacy of various analytical approaches. Evidence from our analysis demonstrates that while traditional statistical methods provide foundational capabilities, they exhibit substantial limitations when applied to complex and dynamic consumption patterns characteristic of modern residential environments.

Machine learning frameworks, particularly ensemble methods such as Random Forests and XGBoost, demonstrate marked improvements over conventional approaches by capturing non-linear dependencies and multivariable interactions more effectively. Neural network architectures, especially LSTM networks, further enhance forecasting accuracy by modeling temporal dependencies and seasonal variations with greater precision.

Our research establishes hybrid methodological frameworks, specifically the integration of XGBoost algorithms for short-term forecasting with LSTM architectures for extended prediction horizons, provide optimal performance across diverse temporal scales. This hybridization effectively leverages the computational efficiency of XGBoost with the superior long-term dependency modeling of LSTM networks. For applications requiring maximum precision, transformer-based architectures demonstrate exceptional performance, particularly when incorporating heterogeneous data sources, though with correspondingly higher computational requirements.

Future research directions should focus on developing enhanced data integration frameworks, improving model interpretability, optimizing computational efficiency, exploring transfer learning approaches, and investigating edge computing integration. As intelligent energy systems continue to evolve within the residential sector, the implementation of sophisticated forecasting methodologies will become increasingly important for optimizing energy resource utilization and supporting sustainable energy consumption patterns.

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