

# Deep Learning Based Load Prediction Framework for household Smart Energy Management

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**Abstract:** Energy consumption forecasting plays a pivotal role in optimizing energy generation, distribution, and consumption, especially in the context of growing global demand and the integration of renewable energy sources. Accurate forecasting enables efficient load balancing, cost reduction, and improved decision making for utility providers and policymakers. The paper presents a Deep Learning Based Load Prediction Framework designed to enhance smart energy management in residential settings. Utilizing a combination of convolutional neural networks (CNN) for feature extraction and gated recurrent units (GRU) for time series forecasting, the framework accurately predicts household electricity consumption by integrating both historical usage patterns and external contextual factors such as weather conditions and holidays. The proposed model processes high resolution data from smart meters, aggregated on a daily basis, and applies advanced data preprocessing techniques including normalization and feature engineering to improve prediction accuracy. Evaluation metrics such as MSE, RMSE, MAE, and MAPE demonstrate that the framework outperforms traditional models, offering a reliable solution for optimizing energy usage and supporting intelligent decision making in smart home environments.

**Keywords:** Deep learning, Energy Management, CNN, Machine Learning

## 1. INTRODUCTION

In the modern era, the demand for energy is increasing at an unprecedented rate due to rapid urbanization, population growth, industrial expansion, and the proliferation of smart technologies. Efficient energy management has become a pressing global challenge, particularly as the world moves towards sustainability and clean energy transitions. One of the most critical components of energy management is *energy consumption forecasting*, which involves predicting the amount of energy required over a specific time period based on various influencing factors [1]. Accurate forecasts enable energy providers to optimize generation, reduce operational costs, manage load balancing, prevent blackouts, and make informed decisions about energy procurement and infrastructure development.

Traditional energy forecasting methods primarily relied on statistical and mathematical models such as Autoregressive Integrated Moving Average (ARIMA), exponential smoothing, and linear regression. While these models were suitable for capturing linear and stationary patterns in historical data, they struggled to adapt to complex, nonlinear, and highly dynamic real world energy consumption patterns [2]. With the advent of digital transformation and the availability of massive volumes of smart meter and sensor data, there has been a paradigm shift towards data driven approaches—most notably, machine learning (ML) and deep learning (DL) techniques.

Machine learning techniques have demonstrated significant success in modeling nonlinear relationships and discovering hidden patterns from historical data. Algorithms such as [3 5] Support Vector Machines (SVM), Decision Trees (DT), k Nearest Neighbors (k NN), and Random Forests (RF) are frequently employed in short- and medium-term energy demand prediction due to their interpretability and relatively low computational cost. These models perform well when sufficient training data and relevant features—such as temperature, day of the week, holiday information, and historical load—are available.

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On the other hand, deep learning techniques [6 8], particularly Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and Convolutional Neural Networks (CNN), have opened new possibilities for highly accurate forecasting. DL models are particularly suited to time series prediction tasks, as they are capable of learning temporal dependencies and hierarchical representations without the need for extensive feature engineering. These models excel in scenarios involving large, complex datasets and can be adapted to different forecasting horizons (hourly, daily, weekly, and seasonal).

In recent years, there has been an increasing trend towards hybrid and ensemble models, which combine the strengths of multiple ML/DL algorithms to improve accuracy and robustness. Additionally, innovations in attention mechanisms, transformers, and transfer learning have begun to reshape the field by enabling models to better focus on relevant inputs and generalize across diverse domains. These advancements are particularly relevant in handling the stochastic and volatile nature of energy consumption influenced by weather conditions, human behavior, and economic activities. Despite the progress, several challenges still hinder the full potential of ML and DL in energy forecasting. Issues such as data quality, data sparsity in certain regions, lack of real time adaptability, high computational cost of DL models, and limited model interpretability are critical concerns [9 10]. Moreover, there is a lack of standardization in benchmarking datasets and evaluation metrics, making it difficult to compare model performance across studies.

## 2. RELATED WORK

Figure 1 summarizes the evolution of electricity consumption forecasting approaches over time. Early research predominantly focused on improving forecast accuracy using statistical models such as Autoregressive Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA). These models were effective for small, stationary datasets with clear time series patterns. For instance, in [3] and [14], the ARMA model was employed to analyze Japan's household electricity consumption data, demonstrating good performance for short term forecasting in stationary environments. However, ARIMA was introduced as a more robust alternative for handling non stationary data, especially where seasonal or trend components were present. While ARMA models are simpler and computationally efficient, ARIMA models are better suited for capturing complex variations in consumption data over time (Figure 1).

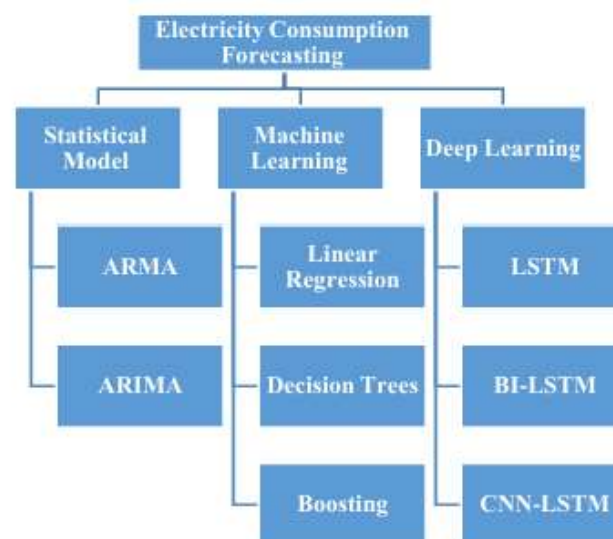


Figure 1: Types of electricity consumption forecasting methods

The emergence of smart meters has dramatically increased the volume and variety of electricity consumption data, introducing irregularities and nonlinear patterns that traditional statistical models struggle to capture. This shift has encouraged the development of machine learning (ML) and deep learning (DL) techniques to improve forecasting performance. Studies such as [11], [12], and [13] introduced advanced ML models including Random Forest (RF), Genetic Algorithms (GA) for feature

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selection, and XGBoost for high performance ensemble learning. These models were applied to household level electricity datasets to enhance classification and prediction accuracy. Furthermore, hybrid models have gained popularity, integrating multiple ML algorithms and optimization techniques to better model complex dependencies in the data.

Recent advancements have emphasized deep learning approaches, particularly Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, for their ability to model sequential data and long-term dependencies. For example, [13] and [14] demonstrated the superior forecasting performance of LSTM models in predicting individual household power consumption. Other researchers explored hybrid DL models, combining Convolutional Neural Networks (CNNs) for feature extraction with LSTMs for temporal forecasting, as in [15] and [17]. Bidirectional LSTM (BiLSTM) networks have also been incorporated to enhance model accuracy by learning from both past and future contexts. These architectures have been tested with large scale smart meter data, providing more accurate predictions compared to traditional models.

Additionally, research in [16] investigated the use of multiple smart meters to record and predict household electricity consumption. The proposed hybrid CNN–BiLSTM framework captured both spatial and temporal aspects of consumption behavior. Despite these advancements, several limitations remain in existing approaches. Many models rely solely on numerical features, neglecting contextual factors such as weather, appliance usage, occupancy patterns, and user behavior, which can significantly influence energy demand. Moreover, while LSTM models are widely used and effective, they can be computationally intensive and memory hungry due to their complex internal structure.

To address these challenges, recent studies suggest the integration of additional contextual features into forecasting models and the use of more efficient architectures. For instance, models combining CNNs for feature extraction with stacked Gated Recurrent Units (GRUs) have shown promise in improving both forecasting accuracy and computational efficiency. Despite the progress, enhancing model generalization, interpretability, and scalability across different regions and household types remains a significant research focus. Therefore, this review highlights the importance of continued exploration of hybrid deep learning models and feature rich datasets to meet the growing demands of intelligent energy management systems.

### 3. PROBLEM STATEMENT AND MOTIVATION

Accurate electricity consumption forecasting is a fundamental requirement for effective energy management, especially in the face of rising demand volatility influenced by factors such as climate variability, economic fluctuations, and changes in consumer behavior. Traditional forecasting methods, including statistical and rule-based models, often fail to effectively capture the inherent nonlinear and dynamic nature of electricity consumption data. These models are particularly limited when dealing with large scale, high dimensional, and time dependent datasets. The proliferation of smart meters and the rapid digitization of power systems have led to the availability of massive and granular consumption datasets. This presents a compelling opportunity to explore advanced deep learning techniques to improve the precision and reliability of short-term electricity demand forecasting.

This research is motivated by the need to overcome the limitations of conventional models and develop a hybrid deep learning based framework that integrates historical consumption trends with external variables such as temperature, holidays, and economic indicators. The goal is to enhance predictive accuracy while maintaining computational efficiency. To this end, we examine three key research questions:

1. How do deep learning models influence the accuracy of electricity consumption forecasts?
2. Which external factors significantly affect short term electricity demand?
3. How can these external features be effectively incorporated into deep learning architectures to improve model performance?

Recent studies have demonstrated the growing success of nonlinear and intelligent approaches, including fuzzy logic systems, expert systems, and deep neural networks, in energy forecasting tasks. In particular, the use of Recurrent Neural Networks (RNNs) has been central due to their inherent capability to process sequential and time series data. RNNs are designed to learn from temporal patterns

by retaining memory of previous inputs, making them suitable for predicting future electricity demand based on historical data. However, standard RNNs face challenges such as vanishing or exploding gradients, which limit their ability to capture long term dependencies effectively. To address these shortcomings, the Long Short-Term Memory (LSTM) architecture was introduced. LSTM extends RNN capabilities by incorporating memory cells regulated by input, output, and forget gates, enabling the model to retain critical information over extended sequences. While LSTM significantly improves forecasting performance, it comes with increased computational complexity and memory usage, particularly due to its multi gate structure, which may be inefficient for smaller datasets or real time applications.

In response to these concerns, Gated Recurrent Units (GRUs) were proposed as a simplified alternative to LSTM. GRUs utilize only two gates—reset and update—and a single hidden state, striking a balance between model complexity and forecasting power. GRUs have demonstrated comparable or even superior performance to LSTM in many time series applications, particularly where training speed and lower memory consumption are priorities. Another critical aspect of building robust deep learning models for electricity forecasting lies in the feature extraction process. Deep learning models are highly sensitive to the quality and structure of input features. Therefore, extracting the most relevant features while reducing dimensionality is essential to improving model accuracy and generalization. In this context, Convolutional Neural Networks (CNNs) have emerged as powerful tools for feature extraction, especially in high dimensional and unstructured data environments.

CNNs operate through a series of layers—including convolutional, pooling, and activation functions—to automatically learn hierarchical feature representations. This process enables the model to identify significant patterns and relationships within the input data without manual intervention. When integrated with RNN based architectures (such as GRU or LSTM), CNNs enhance the model's ability to learn both spatial and temporal patterns, making the hybrid approach particularly effective for electricity consumption forecasting.

In conclusion, while deep learning offers significant advantages over traditional forecasting techniques, challenges such as model interpretability, data preparation, and computational efficiency remain. This research addresses these challenges by proposing a hybrid model that leverages CNNs for feature extraction and GRUs for temporal forecasting. The proposed approach aims to enhance the accuracy, adaptability, and efficiency of short-term electricity consumption prediction, ultimately contributing to the development of smarter and more sustainable energy systems.

#### 4. PROPOSED MODEL ARCHITECTURE

The proposed model is structured into two primary stages: data preparation and model development. The first stage involves the preprocessing and transformation of the input data, which is derived from an individual household electricity consumption dataset. This step includes cleaning, normalization, and integration of contextual information such as weather conditions and holiday indicators—factors known to influence energy usage patterns. These external variables are incorporated to enhance the robustness of the forecasting model and capture a more comprehensive picture of consumption behavior.

The second stage focuses on the construction of the deep learning model, which integrates two key neural network architectures: Convolutional Neural Networks (CNN) and Gated Recurrent Units (GRU). The CNN component acts as a feature extraction layer, effectively identifying and capturing significant features from the pre-processed data. This architecture is well suited for learning complex spatial dependencies and is instrumental in reducing dimensionality while preserving relevant information, as supported by findings in [15] and [21]. The extracted feature set is then passed to the GRU layer, which is responsible for temporal sequence learning and electricity consumption forecasting.

The GRU, a variant of the Recurrent Neural Network (RNN), is chosen for its efficiency in handling time series data and its capability to model both short- and long-term dependencies with reduced computational complexity compared to traditional LSTM networks. Given the challenges in integrating contextual and consumption-based features highlighted in [15] and [22] the proposed hybrid model

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addresses this by learning temporal trends alongside external influencers such as holidays and meteorological conditions. To evaluate the effectiveness of the model, several standard performance metrics are employed: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). These metrics provide a comprehensive evaluation of the forecasting accuracy, quantifying both absolute and relative errors in prediction. The overall objective of the proposed architecture is to deliver a more accurate, context aware short term electricity consumption forecasting model by leveraging the complementary strengths of CNN and GRU.

### Stage 1: Data Preparation

The study utilizes the Individual Household Electric Power Consumption (IHEPC) dataset [23], a benchmark time series dataset collected over 47 months (Dec 2006–Nov 2010) from a household in Sceaux, France. It contains 2,075,259 one-minute interval readings and includes nine core electricity consumption attributes. To enrich the forecasting model, external variables like weather data and holidays (attributes 10–16) were incorporated from trusted external sources [25][26] (Figure 2). For this study, the dataset was aggregated to daily and weekly levels, allowing for temporal flexibility and computational efficiency in modeling. The raw data underwent several key preprocessing steps:

- Aggregation: Converted minute level readings into daily averages for core features (e.g., global active power, voltage, submeters).
- Integration: Daily electricity data was merged with corresponding weather conditions and holiday types using date and location alignment.
- Normalization: Applied Min Max scaling (Equation 1) to normalize the data in the  $[0,1]$  range for neural network compatibility.
- Missing Data Handling: Filled missing values with the mean of the respective feature.
- Feature Engineering: Ensured temporal consistency and constructed final feature vectors including both time series and contextual data, enabling the model to better understand day specific consumption behavior.

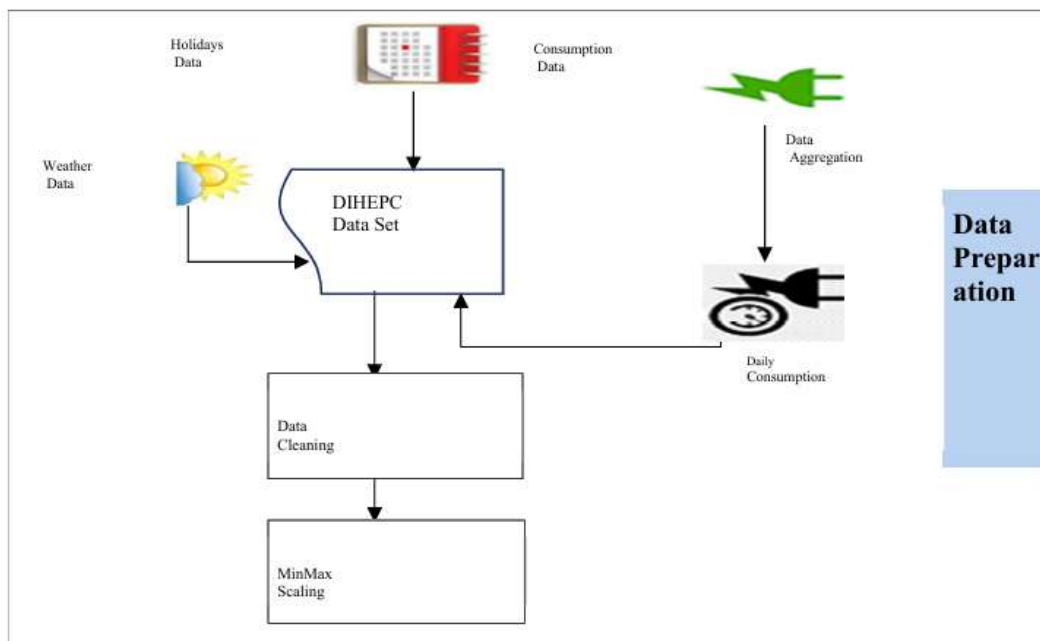


Figure 2: Process of data pre-processing for electricity forecasting

The forecasting problem is then formulated as a multivariate time series problem where each day's input includes electricity data and contextual parameters like weather and holidays

## Stage 2: Model Building

In the feature extraction phase, Convolutional Neural Networks (CNNs) are employed due to their ability to automatically learn deep, noise resistant features from input sequences [19][27]. The CNN architecture comprises two convolutional layers followed by max pooling and flattening layers, which transform raw data into meaningful representations for downstream forecasting tasks. This process eliminates the need for manual feature engineering. For sequence modeling and prediction, Gated Recurrent Units (GRUs) are chosen for their efficiency and ability to model long term dependencies. Multiple GRU layers are stacked to deepen the network, enhancing learning capacity. Dropout layers are included for regularization, mitigating overfitting during training. Key stages of forecasting include:

- **Model Selection:** A hybrid CNN GRU architecture is proposed, integrating both time series electricity data and external contextual variables (weather, holidays).
- **Model Training:** The model is trained on 80% of the data, with the remaining 20% reserved for testing. The final dataset consists of 1433 daily samples and 15 features.
- **Forecasting:** Once trained, the model predicts future consumption using past electricity usage and external conditions.
- **Model Evaluation:** Performance is assessed using standard error metrics:

Results show that the proposed CNN GRU model surpasses existing methods (LSTM, BI LSTM, Linear Regression), demonstrating improved forecasting accuracy and robustness.

## STEP 3: Energy Forecasting

In the energy forecasting stage, a stacked Gated Recurrent Unit (GRU) neural network is utilized to predict household electricity consumption (Figure 3). GRUs are chosen for their ability to handle time series data efficiently, especially when combined in multiple layers, which enhances the model's learning capacity and accuracy.

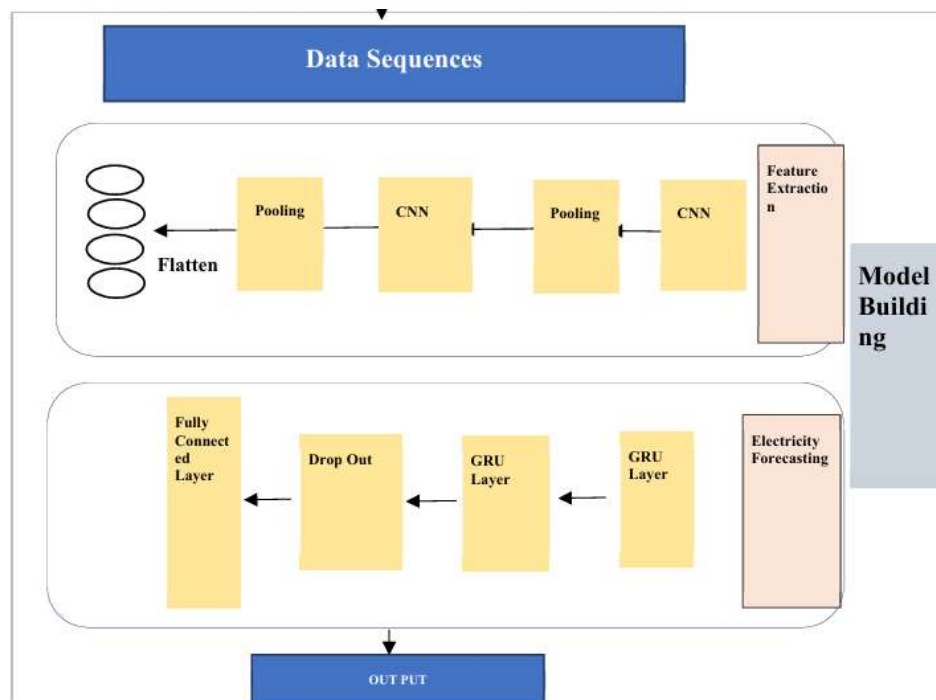


Figure 3: Model building steps for electricity forecasting

To prevent overfitting during training, dropout layers are incorporated to randomly deactivate neurons and their connections, thus improving generalization. The proposed CNN stacked GRU model integrates both time series electricity consumption data and external features such as weather conditions and holiday indicators, offering a dynamic and context aware forecasting framework. The model is trained using 80% of the data and tested on the remaining 20%, with a dataset comprising 1,433 daily

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samples across 15 features. After training, the model performs forecasting based on past consumption, weather, and calendar data. Model accuracy is evaluated using standard error metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE), showing superior performance compared to traditional models such as LSTM, Bi LSTM, and Linear Regression.

## 5. DATA SET

The dataset used in this study is the Individual Household Electric Power Consumption (IHEPC) dataset, a widely recognized benchmark for electricity consumption forecasting. It contains over 2 million observations collected from a single household in Sceaux, France, spanning December 2006 to November 2010. The data is recorded at one-minute intervals and includes key electrical features such as global active and reactive power, voltage, current intensity, and energy sub metering across different household zones (kitchen, laundry room, water heater/AC). To enhance the forecasting capability, the dataset is enriched with external variables including daily weather data—such as average, minimum, and maximum temperatures, wind speed and direction, and precipitation as well as holiday information. For model input, the raw data was aggregated to daily and weekly levels and pre-processed using techniques such as normalization and missing value imputation to prepare it for deep learning-based time series analysis (Table 1).

Table 1: Dataset Attributes Description

ID	Attribute Name	Description
1	Date	Date in the format dd/mm/yyyy.
2	Time	Time in the format hh:mm:ss.
3	Global Active Power	Minute averaged global active power (in kilowatts).
4	Global Reactive Power	Minute averaged global reactive power (in kilowatts).
5	Voltage	Minute averaged voltage (in volts).
6	Global Intensity	Minute averaged household current intensity (in amperes).
7	Sub_metering_1	Energy consumption of kitchen appliances (in watt hours).
8	Sub_metering_2	Energy consumption of laundry room appliances (in watt hours).
9	Sub_metering_3	Energy consumption of water heater and air conditioner (in watt hours).
10	Tavg	Average daily temperature (in °C).
11	Tmin	Minimum temperature recorded for the day (in °C).
12	Tmax	Maximum temperature recorded for the day (in °C).
13	Wdir	Wind direction for the day.
14	Wspd	Wind speed for the day.
15	Prcp	Precipitation level for the day.
16	isHoliday	Numeric indicator for type of day: working day, weekend, or public holiday.

## 6. CONCLUSION

This paper introduces a conceptual framework for deep learning-based load prediction aimed at optimizing smart energy management in households. The proposed architecture integrates Convolutional Neural Networks (CNN) for feature extraction with Gated Recurrent Units (GRU) for sequential forecasting, offering a comprehensive approach to handle both time series consumption data and contextual features such as weather conditions and holidays. By outlining a structured data preparation process and detailing the model design, this framework sets the foundation for developing a more accurate and intelligent energy forecasting system tailored to individual household consumption patterns. Although experimental results are not presented in this study, the framework has been designed with flexibility, scalability, and performance in mind. It addresses key challenges in energy forecasting,

such as capturing nonlinear dependencies, incorporating external factors, and preventing overfitting through dropout and model stacking. Future work will focus on implementing and validating this framework on real world datasets, evaluating its forecasting accuracy using standard metrics, and exploring its potential applications in real time smart home energy systems and demand response programs.

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