International Journal of Scientific and Cognitive Innovation (www.ijsci.org)
|| Volume 2, Issue 7, July 2026 || Impact Factor: 3.5 |

Deep Learning Framework for Household Electric Power Consumption Forecasting: A Review

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***Abstract*— The growing and variable demand for electrical energy in residential buildings has increased the importance of accurate household electric power consumption forecasting for effective energy planning and management. This review paper presents a comprehensive study of deep learning frameworks used for forecasting household electricity consumption from historical electrical load data. The review focuses on important electrical parameters and patterns, including active power, reactive power, voltage, current, daily and seasonal load variations, peak demand, and overall energy consumption. Various deep learning techniques, such as Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), Convolutional Neural Networks (CNN), and hybrid models, are examined for their applicability to residential load forecasting. The study compares existing approaches based on forecasting accuracy, computational requirements, forecasting horizon, and their ability to capture nonlinear and time-dependent electrical load characteristics. The review also discusses major challenges such as sudden load variations, changing consumer behavior, data quality, and peak-load prediction. The findings indicate that deep learning-based forecasting can significantly support residential load management, peak demand reduction, energy conservation, demand response, and efficient operation of modern smart electrical grids.**

Keywords: Smart Meter, Electricity Theft, CNN, Deep Learning, Smart Grid..

I. INTRODUCTION

The rapid growth in residential electricity demand has made accurate electric power consumption forecasting an important area of research in modern electrical engineering. Household electricity consumption is not constant and changes continuously according to time of day, season, weather conditions, occupancy, appliance operation, and consumer behavior. The increasing use of air conditioners, electric heaters, refrigerators, washing machines, water pumps, electric vehicles, and other household electrical appliances has further increased the complexity of residential load patterns. Accurate forecasting of household electricity consumption is therefore essential for proper load planning, energy conservation, peak-load management, and reliable operation of electrical distribution systems. In conventional power systems, forecasting has mainly been associated with utility-level load estimation; however, the development of smart meters and advanced distribution networks has created opportunities for forecasting electricity consumption at the individual household and residential level [1].

Household electric load forecasting involves predicting future electricity demand using previously recorded electrical consumption data and other relevant operating parameters. Depending on the forecasting period, it can be categorized into very-short-term, short-term, medium-term, and long-term forecasting. For residential applications, short-term and very-short-term forecasting are particularly important because electricity demand can change significantly within hours or even minutes. Accurate prediction of active power consumption can help utilities and consumers identify upcoming peak-load periods and implement suitable energy management strategies. In addition, forecasting reactive power, voltage, and current variations can provide useful information for distribution-system operation and power-quality management. With the introduction of smart meters, large amounts of high-resolution household electricity data can now be collected, providing a valuable foundation for developing advanced forecasting models [2].

Traditional electrical load forecasting techniques have commonly included statistical and mathematical approaches such as autoregressive models, moving-average techniques, exponential smoothing, and regression-based methods. These approaches can provide satisfactory results when the electrical load follows relatively stable and predictable patterns. However, residential electricity consumption is highly nonlinear and influenced by several interacting factors. For example, the operation of a high-power appliance can suddenly increase household demand, while changes in weather or occupancy can significantly modify the load profile. Conventional statistical models may have difficulty capturing such complex relationships, particularly when long historical sequences and multiple influencing variables are involved. These limitations have encouraged researchers to investigate intelligent and data-driven techniques for residential load forecasting [3].

The availability of smart-grid technologies has further increased the importance of intelligent household load forecasting. Smart meters can record electricity consumption at short time intervals and provide detailed information about residential load behavior. When this information is combined with parameters such as temperature, humidity, time, day of the week, season, and appliance usage, it becomes possible to develop more comprehensive forecasting models. Accurate forecasts can support demand-side management by allowing consumers to shift flexible electrical loads away from peak periods. At the utility level, residential load forecasting can assist in distribution-network planning, transformer loading assessment, demand response, and efficient energy scheduling. Therefore, forecasting is not only a computational problem but also an important component of modern electrical energy management [4].

Machine learning techniques have been increasingly applied to electrical load forecasting because of their ability to model nonlinear relationships between input variables and electricity demand. Methods such as artificial neural networks, support vector regression, decision-tree-based models, and ensemble learning techniques have been investigated for predicting residential electricity consumption. These approaches can learn relationships directly from historical electrical measurements without requiring a complete mathematical representation of consumer load behavior. However, household electricity data generally contain strong temporal dependencies, including daily, weekly, and seasonal patterns. A forecasting model therefore needs to retain information from previous load conditions while identifying changes in future consumption. This requirement has contributed to the growing adoption of deep learning techniques in electrical load forecasting [5].

Deep learning provides an advanced approach for learning complex patterns from large-scale electrical consumption datasets. Recurrent Neural Networks (RNNs) are particularly suitable for sequential electricity data because their architecture can process information over time. However, conventional RNNs may face difficulties in retaining information over long sequences. Long Short-Term Memory (LSTM) networks were introduced to overcome this limitation and have subsequently been widely investigated for electrical load forecasting. LSTM models can learn both short-term and long-term relationships within household load profiles, making them suitable for applications involving daily consumption patterns, peak-load variations, and seasonal changes. Gated Recurrent Unit (GRU) models provide another recurrent architecture with a comparatively simpler structure while maintaining the ability to learn temporal dependencies in electrical demand data [6].

Convolutional Neural Networks (CNNs) have also attracted attention in household electricity forecasting because their convolution operations can identify local patterns in structured load data. Although CNNs were initially associated with image-based applications, their ability to extract meaningful patterns from sequences makes them useful for analyzing electricity consumption profiles. Hybrid architectures combining CNN with LSTM or other recurrent models can first extract important local characteristics from electrical load sequences and then learn their temporal relationships. Such architectures can be useful when household electricity consumption contains both short-duration fluctuations and longer-term demand trends. The development of hybrid deep learning models has therefore provided new possibilities for improving residential load forecasting performance [7].

More recently, attention mechanisms and Transformer-based architectures have provided another direction for electricity demand forecasting. Unlike conventional recurrent architectures, attention-based models can focus on important portions of historical load sequences and identify relationships across different time intervals. This capability is particularly relevant to household electricity consumption because demand at a particular time may be influenced by consumption patterns occurring several hours or days earlier. Deep learning models can also incorporate multiple electrical and environmental variables, allowing forecasting systems to consider active power, reactive power, voltage, current, temperature, humidity, and time-related information simultaneously. Such developments indicate a gradual transition from conventional single-variable load prediction toward more comprehensive and intelligent residential energy forecasting frameworks [8].

Despite these developments, several challenges remain in achieving reliable household electric power consumption forecasting. Residential load profiles can differ considerably between households because of differences in appliance ownership, occupancy patterns, lifestyle, working schedules, and energy-use behavior. Sudden switching of high-power appliances can create sharp load variations that are difficult to predict. In addition, missing measurements, abnormal readings, measurement noise, irregular sampling, and changes in consumer behavior can affect forecasting accuracy. Weather-sensitive loads such as air conditioning and electric heating can further introduce significant seasonal variations. Deep learning models may provide improved prediction capability, but they can also require large datasets, considerable computational resources, and appropriate parameter selection. Therefore, evaluating different deep learning approaches from an electrical load forecasting perspective remains necessary [9].

Based on these considerations, this review focuses on deep learning frameworks for household electric power consumption forecasting and examines their role in modern electrical energy management. The review analyzes major deep learning architectures, input electrical parameters, forecasting horizons, datasets, evaluation measures, and reported performance of existing studies. Particular attention is given to the prediction of residential active power and energy consumption, while the relevance of reactive power, voltage, current, peak demand, and external factors is also considered. The objective is to identify the capabilities, advantages, and limitations of existing deep learning approaches and to determine the major research challenges that require further investigation. The review also highlights how accurate household load forecasting can contribute to peak-load reduction, demand response, energy conservation, improved distribution-system planning, and efficient smart-grid operation. Thus, the study provides an electrical-engineering-oriented understanding of the development and future scope of deep learning-based household electric power consumption forecasting [10].

II. LITERATURE SURVEY

Raviprabhakaran et al. [1] investigated household power consumption analysis using machine learning techniques. The study focused on analyzing household electrical consumption patterns and identifying useful relationships within power consumption data. The work demonstrated the potential of data-driven techniques for understanding residential electricity demand and supporting improved energy management. The study is relevant to household load forecasting because accurate analysis of historical consumption is an important foundation for predicting future electrical demand.

Raviprabhakaran [2] presented a clonal assortment optimization procedure for solving the cost-effective power dispatch problem. The study focused on optimization of electrical power dispatch while considering economic operation of power systems. The optimization-based approach demonstrated the importance of intelligent computational techniques for achieving cost-effective power-system operation. Although the work was primarily related to economic dispatch rather than household forecasting, its findings are relevant to intelligent energy management and efficient utilization of electrical power.

Toosi et al. [3] investigated machine learning approaches for performance prediction in smart buildings, with particular emphasis on photovoltaic self-consumption and life-cycle cost optimization. The study demonstrated how machine learning can support better utilization of locally generated electrical energy in buildings. The integration of photovoltaic generation with consumption prediction can improve energy utilization and reduce dependence on grid electricity. The work highlights the importance of predictive techniques for managing building-level electrical energy and renewable-energy resources.

Abdurohman and Putrada [4] developed an XGBoost-based forecasting model for lighting electricity loads using a limited dataset. The study addressed the practical challenge of electricity load forecasting when only a small amount of historical data is available. XGBoost was used to capture relationships within lighting-load consumption patterns and generate future load predictions. The study demonstrates that machine-learning-based forecasting can provide useful electrical load predictions even under data-limited conditions.

Harish et al. [5] presented a comparative study of electrical load time-series forecasting using different deep learning techniques. The study examined the capability of deep learning models to learn temporal characteristics from electrical load data and compared their forecasting performance. The findings highlighted the importance of selecting an appropriate deep learning architecture according to the characteristics of the electrical load time series. The work provides an important basis for applying deep learning techniques to short-term and time-dependent electricity demand forecasting.

Raviprabhakaran [6] investigated the optimal location and sizing of wind and solar photovoltaic-based distributed generation using a communal spider optimization algorithm. The study focused on improving the placement and capacity of renewable distributed-generation units within electrical power systems. Optimal integration of renewable sources can improve power-system performance and support efficient energy utilization. Although the study does not directly address household load forecasting, it emphasizes the importance of intelligent optimization for modern distributed electrical-energy systems.

Olu-Ajayi et al. [7] studied building energy consumption prediction for residential buildings using deep learning and other machine learning techniques. The research examined the ability of data-driven models to predict energy consumption patterns in residential buildings. The study demonstrated the usefulness of intelligent prediction methods for understanding variations in building energy demand. Its findings indicate that deep learning can provide an effective approach for residential energy forecasting and can support energy-efficiency improvement and better building energy management.

Shao et al. [8] investigated energy consumption prediction in hotel buildings using support vector machines. The study focused on predicting building energy demand from available consumption-related information and demonstrated the applicability of machine-learning techniques to building energy management. The results emphasized the importance of accurate energy prediction for improving operational efficiency and reducing unnecessary energy consumption. Although the application was focused on hotel buildings, the forecasting principles are applicable to other building-level electrical load prediction problems.

Pham et al. [9] presented a machine-learning-based approach for predicting energy consumption across multiple buildings to improve energy efficiency and sustainability. The study examined the use of historical building energy information for developing predictive models capable of estimating future consumption. Accurate prediction was identified as an important component of effective energy management and reduction of unnecessary energy usage. The work demonstrates the potential of machine learning for large-scale building energy forecasting and provides useful insights for residential electricity consumption prediction.

Kiprijanovska et al. [10] proposed HouseEC, a deep learning framework for day-ahead household electrical energy consumption forecasting. The study specifically addressed residential electricity demand and used deep learning to predict future household energy consumption based on historical electrical usage patterns. Day-ahead forecasting can support household energy scheduling, demand management, and more efficient interaction with the electrical grid. This work is particularly relevant to the present review because it directly demonstrates the application of deep learning to household electrical energy consumption forecasting.

III. CHALLENGES

Deep learning-based household electric power consumption forecasting faces several challenges because residential electrical demand is highly dynamic and influenced by multiple electrical, environmental, and behavioral factors. Unlike industrial loads, household loads can change suddenly due to individual appliance switching, occupancy, weather conditions, and consumer routines. In addition, smart-meter measurements may contain noise, missing values, and abnormal readings. Deep learning models also require sufficient historical data and computational resources. The major challenges are discussed below.

1. Highly Variable Household Load

Household electricity demand varies continuously throughout the day due to the operation of different electrical appliances. Devices such as air conditioners, refrigerators, water heaters, washing machines, pumps, and cooking appliances can produce sudden changes in active power consumption. These irregular variations make it difficult for forecasting models to accurately learn the complete residential load profile.

2. Accurate Peak Load Prediction

Prediction of peak electricity demand is one of the major challenges in residential load forecasting. A household may suddenly experience high power consumption when multiple high-power appliances operate simultaneously. Incorrect prediction of such peaks can affect demand management, transformer loading, distribution-system planning, and electricity scheduling. Therefore, forecasting models must be capable of identifying both normal load patterns and sudden peak-demand events.

3. Poor Quality of Smart-Meter Data

Household electricity forecasting strongly depends on the quality of measured electrical data. Smart-meter datasets may contain missing readings, measurement noise, abnormal values, communication errors, or irregular sampling intervals. Such data-quality problems can negatively affect the training of deep learning models and may result in inaccurate predictions. Appropriate data preprocessing and cleaning are therefore essential before forecasting.

4. Influence of Weather and Seasonal Conditions

Weather conditions can have a significant effect on household electricity consumption. During summer, increased operation of air conditioners and cooling systems can substantially increase electrical demand, while heating equipment can increase consumption during colder periods. Temperature, humidity, rainfall, and seasonal variations can therefore change the residential load profile. A forecasting model that does not properly consider these factors may have reduced accuracy under changing environmental conditions.

5. Variation in Consumer Behavior

Residential electricity consumption is strongly related to human activities and household routines. Different consumers may use electrical appliances at different times depending on their working schedules, lifestyle, family size, and daily activities. Changes in occupancy or consumer behavior can therefore produce significant variations in electricity demand. Developing a forecasting model that performs consistently across different households is consequently challenging.

6. Requirement of Large Historical Data

Deep learning models generally require sufficient historical electrical consumption data to learn complex temporal relationships. High-resolution household load forecasting may require data collected at short time intervals over long periods to capture daily, weekly, and seasonal patterns. However, newly installed smart meters or small residential datasets may not provide enough historical information, which can limit the effectiveness of deep learning-based forecasting.

7. High Computational Requirement

Advanced deep learning models such as LSTM, CNN-LSTM, and Transformer-based architectures can contain a large number of parameters and may require significant computational resources during training. High computational requirements can increase training time and make deployment difficult on low-power residential energy-management devices. Therefore, there is a need for efficient models that provide high forecasting accuracy with reasonable computational complexity.

8. Reliability Under Changing Load Conditions

A forecasting model trained using historical electricity consumption may not always perform accurately when future load conditions change significantly. The introduction of new electrical appliances, electric vehicles, rooftop photovoltaic systems, battery storage, changes in electricity tariffs, or changes in consumer behavior can modify the household load profile. Maintaining reliable forecasting performance under such changing electrical conditions remains an important research challenge.

IV. CONCLUSION

Deep learning has emerged as a promising approach for accurate household electric power consumption forecasting because it can learn complex, nonlinear, and time-dependent patterns from historical electrical load data. The reviewed studies indicate that models such as ANN, RNN, LSTM, GRU, CNN, and hybrid deep learning architectures can effectively capture variations in residential electricity demand and improve forecasting performance compared with several conventional approaches. Accurate prediction of active power and energy consumption can support peak-load management, demand response, energy conservation, residential load scheduling, and efficient operation of modern distribution and smart-grid systems. However, challenges related to load variability, peak-demand prediction, data quality, weather effects, consumer behavior, computational requirements, and changing electrical conditions still need to be addressed. Overall, the review indicates that future household load forecasting systems should focus on accurate, adaptive, computationally efficient, and real-time deep learning frameworks capable of integrating electrical and environmental parameters for reliable residential energy management.

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