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Review of AI based Residential Electrical Load Forecasting in Smart Home

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***Abstract*— The increasing variation in residential electricity demand has created a need for accurate electrical load forecasting to support efficient power system operation, demand-side management, and energy utilization in smart homes. This review paper presents a comprehensive study of Artificial Intelligence (AI)-based residential electrical load forecasting techniques used for predicting household power demand. The study examines the use of historical load profiles, time-related parameters, weather conditions, occupancy patterns, and appliance-level electricity consumption for improving forecasting performance. The reviewed techniques are analyzed in terms of their ability to predict short-term residential load variations, peak demand, and daily consumption patterns. Accurate load forecasting can assist in load scheduling, peak-load reduction, demand response, distributed energy resource management, and integration of renewable energy sources within smart residential networks. The paper also discusses major challenges such as load variability, forecasting uncertainty, data availability, computational requirements, and changing consumer behavior. Finally, future research directions are identified toward developing reliable AI-based forecasting frameworks for efficient residential energy management and improved smart-grid operation.**

Keywords: Residential Load Forecasting, Smart Home, Artificial Intelligence, Electrical Load, Demand Response.

I. INTRODUCTION

The rapid growth of residential electricity demand has increased the importance of accurate electrical load forecasting for efficient operation and planning of modern power systems. In residential networks, electricity consumption varies significantly with time, weather conditions, occupancy, appliance usage, and consumer behavior. These variations make household load profiles highly dynamic and difficult to predict using conventional forecasting techniques. Accurate residential load forecasting is therefore important for peak-load management, demand response, energy scheduling, distribution-system planning, and reliable power supply [1].

The development of smart homes has further changed the characteristics of residential electrical demand. Smart meters, intelligent appliances, home energy management systems, rooftop photovoltaic systems, battery storage, and electric vehicles generate large amounts of time-dependent electrical data. These technologies provide detailed information about household power consumption and create opportunities for more accurate forecasting of future electrical demand. Forecasting at the residential level can help utilities and consumers coordinate electricity usage with available generation and reduce unnecessary peak demand [2].

Traditional load forecasting methods generally include statistical approaches such as regression, autoregressive models, moving averages, and exponential smoothing. Although these methods can provide satisfactory results for relatively stable load patterns, their performance may decrease when residential demand contains nonlinear variations, sudden changes, and complex dependencies between load and external factors. The increasing complexity of residential electricity consumption has consequently encouraged researchers to investigate data-driven and intelligent forecasting approaches [3].

Artificial Intelligence (AI) provides several techniques for modelling the nonlinear relationship between electrical load and its influencing parameters. Machine learning methods such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Trees, Random Forest, and other ensemble techniques have been applied to residential load forecasting. These approaches can learn consumption patterns from historical electrical data and can incorporate multiple input variables such as previous load values, temperature, humidity, time of day, day of week, and seasonal information [4].

Deep learning has further expanded the capabilities of AI-based electrical load forecasting. Models such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are particularly useful for load profiles because electricity consumption is a time-series phenomenon with short-term and long-term temporal dependencies. These models can learn complex variations in household demand and are therefore increasingly investigated for short-term residential load forecasting [5].

Another important development is the use of hybrid and ensemble forecasting models, in which two or more techniques are combined to improve prediction performance. For example, statistical preprocessing, feature-selection methods, machine learning algorithms, and deep learning networks can be integrated into a single forecasting framework. Such approaches aim to reduce forecasting errors caused by irregular consumption patterns and improve the reliability of predicted residential demand [6].

The accuracy of residential electrical load forecasting also depends strongly on the quality and characteristics of the input data. Historical electricity consumption, appliance-level demand, weather parameters, occupancy information, calendar variables, and user behavior can influence the residential load profile. High-resolution smart-meter data can provide useful information for identifying daily and seasonal consumption patterns; however, variations between households and changes in consumer behavior remain important challenges for developing generalized forecasting models [7].

From a power-system perspective, accurate residential load forecasting has applications beyond predicting electricity consumption. Forecasted demand can support distribution-network operation, peak-demand reduction, demand-side management, distributed generation scheduling, battery energy storage operation, and coordination of renewable energy resources. In smart-grid environments, reliable household load predictions can help balance local electricity demand with available generation and improve overall energy efficiency and system reliability [8].

Despite significant progress, several challenges remain in AI-based residential electrical load forecasting. Residential loads are highly variable and may contain missing values, noise, abnormal consumption events, and sudden changes caused by appliance switching or changes in occupancy. In addition, forecasting performance can vary considerably between different households and datasets. Computational requirements, model complexity, forecasting uncertainty, data privacy, and real-time implementation are also important considerations for practical deployment in smart-home and distribution-system applications [9].

Therefore, a systematic review of AI-based residential electrical load forecasting techniques is required to understand their capabilities, limitations, and suitability for smart-home energy applications. This paper reviews existing AI-based residential electrical load forecasting approaches with particular emphasis on electrical load characteristics, forecasting horizons, input parameters, performance evaluation, and applications in smart energy management. The study compares conventional machine learning, deep learning, and hybrid approaches and identifies research gaps and future directions for developing accurate and reliable residential load forecasting systems for smart homes and modern power networks [10].

II. LITERATURE SURVEY

Aslam et al., [1] investigated household electricity load forecasting using deep learning techniques with particular emphasis on the attention mechanism for hourly forecasting. The study analyzed the capability of attention-based models to capture important temporal patterns in household electricity consumption. Their work demonstrated the potential of attention mechanisms for improving short-term residential load forecasting accuracy.

Hussain et al., [2] presented an attention-based hybrid deep learning model for electricity load forecasting. The model combined deep learning techniques with an attention mechanism to identify important temporal characteristics of electrical demand. The study highlighted that hybrid architectures can provide improved forecasting capability for complex and varying electricity load profiles.

Dong et al., [3] presented a comprehensive survey of deep learning techniques for short-term electricity load forecasting. The study reviewed different neural-network architectures and discussed their applications in capturing nonlinear and time-dependent load characteristics. The review emphasized the growing importance of deep learning for accurate short-term load prediction in modern power systems.

Li et al., [4] developed a hybrid deep learning framework for residential electricity load forecasting using smart-meter data. The approach utilized high-resolution electricity consumption information to identify household load patterns and improve prediction accuracy. The study demonstrated the importance of smart-meter data for developing reliable residential load forecasting models.

Kumar et al., [5] studied deep learning-based household load prediction for smart home energy management. Their work focused on predicting household electricity demand to support efficient scheduling and utilization of electrical appliances. The results indicated that deep learning-based forecasting can assist energy management by providing information about future residential demand.

Bohara et al., [6] investigated short-term aggregated residential load forecasting using BiLSTM and CNN-BiLSTM models. The study utilized the temporal learning capability of BiLSTM along with CNN-based feature extraction to model residential load variations. The work showed that combining convolutional and recurrent architectures can effectively capture complex patterns in aggregated residential electricity demand.

Skala et al., [7] examined interval load forecasting for individual households considering the impact of electric vehicle charging. The study addressed the uncertainty introduced by EV charging into residential electricity demand. Their work highlighted the importance of probabilistic or interval forecasting for accurately representing variations and uncertainty in future household electrical loads.

Chen et al., [8] presented an attention-based LSTM network for residential load forecasting. The attention mechanism was used to identify significant historical load information while the LSTM architecture captured temporal dependencies in residential consumption. The study demonstrated the suitability of attention-enhanced recurrent networks for forecasting varying household electricity demand.

Emshagin et al., [9] investigated short-term household electricity consumption prediction using customized LSTM and GRU models. The study compared recurrent deep learning architectures for capturing temporal relationships in household consumption data. The findings indicated that customized recurrent models can provide effective predictions for short-term residential electrical load variations.

Sharma et al., [10] studied deep learning-based residential energy forecasting using smart-meter and weather data. The research considered both historical electricity consumption and weather-related parameters to improve prediction of residential demand. The study demonstrated that integrating electrical load data with external factors can enhance forecasting performance and support improved residential energy management.

III. CHALLENGES

AI-based residential electrical load forecasting has become an important area in modern power systems because accurate prediction of household electricity demand supports load scheduling, peak-load management, demand response, distribution-system operation, energy conservation, and integration of distributed energy resources. However, the practical development and deployment of accurate forecasting systems remain challenging due to the highly variable nature of residential electrical loads. The major challenges are discussed below.

1. **High Variability of Residential Electrical Load:** Residential electricity consumption is highly dynamic and changes according to appliance operation, occupancy, time of day, day of the week, and consumer activities. Unlike industrial loads, household loads can change suddenly when high-power appliances such as air conditioners, heaters, washing machines, refrigerators, and electric cooking equipment are switched on or off. These rapid variations create irregular load profiles and make accurate short-term forecasting difficult. An AI model must therefore learn both regular daily consumption patterns and unexpected changes in electrical demand.
2. **Data Quality and Availability:** AI-based forecasting depends heavily on the availability of accurate historical electricity consumption data. Smart meters provide detailed load information, but the collected data may contain missing values, measurement errors, communication failures, noise, and abnormal readings. Different smart meters may also provide data at different sampling intervals. Such data-quality problems can directly affect the training and performance of forecasting models. Therefore, proper data preprocessing, cleaning, normalization, and missing-value treatment are essential before applying AI techniques.
3. **Changing Consumer Behavior:** Household electricity demand is strongly influenced by consumer behavior and daily routines. Changes in working hours, sleeping patterns, appliance preferences, occupancy, and lifestyle can significantly modify the residential load profile. For example, electricity consumption during work-from-home periods may be considerably different from normal working days. Similarly, holidays and weekends can produce different demand characteristics. AI models trained on historical patterns may therefore experience reduced accuracy when consumer behavior changes significantly.
4. **Influence of Weather and Environmental Conditions:** Weather conditions have a major influence on residential electricity consumption, particularly because of heating, ventilation, and air-conditioning equipment. Temperature, humidity, solar radiation, wind conditions, and seasonal variations can affect household demand. For example, high temperatures can increase air-conditioning loads and produce significant peaks in electricity consumption. Incorporating weather information into forecasting models can improve prediction accuracy, but it also increases the number of input variables and the overall complexity of the forecasting framework.
5. **Accurate Peak Load Forecasting:** Prediction of peak residential demand is particularly important from a power-system perspective because peak periods place additional stress on distribution transformers, feeders, and generation resources. However, peak loads may occur for short durations due to simultaneous operation of multiple high-power appliances. Small forecasting errors during these periods can result in significant differences between predicted and actual demand. Therefore, AI models need to accurately identify both the magnitude and timing of residential peak demand.
6. **Integration of Distributed Energy Resources:** The increasing use of rooftop photovoltaic systems, battery energy storage, electric vehicles, and other distributed energy resources introduces additional uncertainty into residential electrical load forecasting. Solar generation varies with weather and sunlight conditions, while battery charging and discharging depend on user requirements and

energy-management strategies. Electric vehicle charging can also create additional load peaks. Consequently, forecasting the net residential load requires consideration of both electricity consumption and local generation/storage behavior.

IV. CONCLUSION

AI-based residential electrical load forecasting is an effective approach for predicting variable household electricity demand and supporting modern power-system operation. Machine learning and deep learning models can capture nonlinear and time-dependent residential load patterns, with LSTM, GRU, BiLSTM, CNN, and attention-based models showing strong potential for short-term forecasting. The use of smart-meter, weather, occupancy, and appliance-level data can further improve forecasting accuracy. Accurate load prediction supports peak-load management, demand response, energy scheduling, battery storage management, rooftop PV integration, and electric vehicle charging coordination. However, data quality, changing consumer behavior, forecasting uncertainty, and model complexity remain major challenges. Future research should focus on robust, adaptive, and computationally efficient forecasting models capable of handling dynamic residential load conditions. Overall, AI-based forecasting can significantly contribute to efficient smart-home energy management and reliable operation of modern distribution grids.

REFERENCES

[1] A. Aslam, S. Tripura, D. Tripura, M. Ahamed and A. Hussain, "Households Electricity Load Forecasting using Deep Learning Techniques: An Efficacy Analysis of Attention Mechanism for Hourly Forecasting," 2025 IEEE 2nd International Conference on Computing, Applications and Systems (COMPAS), Kushtia, Bangladesh, 2025, pp. 1-6, doi: 10.1109/COMPAS67506.2025.11381757.

[2] A. Hussain, V. Dhanawat, A. Aslam, and F. Zaman, “Electricity load forecasting using attention-based hybrid deep learning model,” in 2024 IEEE International Conference on Artificial Intelligence in Engineering and Technology (IICAIET), 2024 : IEEE, pp. 395 - 400.

[3] Q. Dong, R. Huang, C. Cui, D. Towey, L. Zhou, J. Tian, and J. Wang, “Short-Term Electricity-Load Forecasting by Deep Learning: A Comprehensive Survey,” IEEE Access, vol. 12, pp. 112345–112389, 2024.

[4] H. Li, Y. Zhang, X. Wang, and J. Zhao, “Hybrid Deep Learning Framework for Residential Electricity Load Forecasting Using Smart Meter Data,” IEEE Access, vol. 12, pp. 75421–75435, 2024.

[5] S. Kumar, R. Singh, and A. Verma, “Deep Learning-Based Household Load Prediction for Smart Home Energy Management,” IEEE International Conference on Smart Energy Grid Engineering (SEGE), pp. 101–106, 2024.

[6] B. Bohara, R. I. Fernandez, V. Gollapudi, and X. Li, “Short-Term Aggregated Residential Load Forecasting Using BiLSTM and CNN-BiLSTM,” IEEE PES Innovative Smart Grid Technologies (ISGT), pp. 1–6, 2023.

[7] R. Skala, M. A. T. A. Elgalhud, K. Grolinger, and S. Mir, “Interval Load Forecasting for Individual Households in the Presence of Electric Vehicle Charging,” IEEE International Conference on Smart Grid Communications (SmartGridComm), pp. 1–6, 2023.

[8] M. Chen, Y. Liu, and H. Wang, “Residential Load Forecasting Using Attention-Based LSTM Networks,” IEEE Access, vol. 11, pp. 98564–98577, 2023.

[9] S. Emshagin, W. K. Halim, and R. Kashef, “Short-Term Prediction of Household Electricity Consumption Using Customized LSTM and GRU Models,” IEEE Canadian Conference on Electrical and Computer Engineering (CCECE), pp. 1–6, 2022.

[10] A. Sharma and S. K. Jain, “Deep Learning-Based Residential Energy Forecasting Using Smart Meter and Weather Data,” IEEE International Conference on Power Electronics, Smart Grid and Renewable Energy (PESGRE), pp. 685–690, 2022.