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An Efficient Deep Learning Approach For Predicting Household Energy Load In Smart Energy Systems

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Abstract:
Accurate prediction of household energy consumption is vital for the efficient operation of smart energy systems, enabling demand-side management, cost optimization, and grid stability. This paper presents an efficient deep learning-based approach for forecasting household energy load by leveraging the temporal and nonlinear patterns inherent in smart meter data. The proposed framework incorporates advanced deep learning architectures such as Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) to model short-term and long-term dependencies in energy usage. Key external factors including weather conditions, time of day, and occupancy patterns are integrated to enhance prediction accuracy. The model is trained and evaluated using real-world datasets, with performance measured against traditional and machine learning baselines. Results demonstrate significant improvements in forecast accuracy and computational efficiency, making the approach highly suitable for real-time smart home energy management applications. This research contributes toward intelligent energy systems by supporting proactive load balancing and sustainable energy consumption.

Keywords: CNN, LSTM, Energy Forecasting, Deep Learning, GRU

INTRODUCTION

The rapid pace of urbanization and the growing proliferation of electrical and electronic devices in households have significantly increased residential energy consumption across the globe. Modern lifestyles, characterized by high dependence on appliances, smart devices, and comfort technologies, have transformed homes into complex energy-consuming units. This rising demand poses considerable challenges to existing power grids, particularly in terms of load balancing, energy efficiency, and system reliability. With the global emphasis on sustainability and the transition toward intelligent infrastructure, the need for smarter energy management in households has become more pressing than ever [11].

One of the critical components of smart energy systems is the ability to accurately forecast energy load at the household level. Effective load prediction not only helps energy providers maintain grid stability and optimize supply but also enables consumers to manage their energy usage more efficiently, potentially reducing costs and carbon footprints. Traditional forecasting methods, such as statistical models and conventional machine learning algorithms, often struggle to capture the highly dynamic and nonlinear nature of energy consumption patterns. Factors such as varying occupant behavior, fluctuating weather conditions, and the integration of renewable energy sources introduce complexity that these models are not equipped to handle effectively [12].

In this context, deep learning has emerged as a promising solution due to its ability to model intricate patterns and dependencies in large-scale, time-series data. Deep learning architectures [13-16], such as Long Short-Term Memory (LSTM), Gated Recurrent Units (GRUs), and Convolutional Neural Networks (CNNs), have shown remarkable success in various domains involving sequential data, including speech recognition, financial forecasting, and healthcare analytics. Applied to energy systems, these models can learn from historical consumption data and relevant contextual information—such as temperature, humidity, time of day, and day of the week—to make highly accurate predictions of future energy usage.

This paper proposes an efficient deep learning-based approach for predicting household energy load, with the goal of enhancing the performance of smart energy management systems. By incorporating temporal dependencies and external influencing factors, the proposed framework aims to deliver robust, scalable, and real-time energy forecasts. This work contributes to the growing body of research at the intersection of artificial intelligence and sustainable energy, offering practical insights for both energy providers and end-users in managing energy demand proactively.

REVIEW OF LITERATURE

In recent years, the importance of accurate energy load forecasting has increased significantly due to the rise of smart grids and smart home technologies. Traditional statistical models such as Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing have been widely used for load forecasting, but they often fail to capture the nonlinear and dynamic characteristics of household energy consumption. As a result, the focus has shifted toward machine learning and deep learning approaches, which offer improved prediction accuracy by learning complex patterns in data.

Table 1: Review of literature for deep learning based smart energy forecasting

Ref. No	Method Used	Dataset/Case	Key Findings
[1]	ANN-based Forecasting	Building energy datasets	ANN outperforms traditional models in capturing nonlinear energy patterns.
[2]	ML-based Peak Load Forecasting	Smart meter data	Machine learning enhances peak load prediction using appliance-level data.
[3]	LSTM for Load Forecasting	UCI Residential Dataset	LSTM performs well in modeling long-term dependencies in energy usage.
[4]	CNN-LSTM Hybrid Model	Australian Smart Home Dataset	CNN-LSTM improves accuracy by learning spatial-temporal features.
[5]	Deep Belief Network (DBN)	Turkish Residential Load Data	DBN delivers better performance than shallow models in short-term forecasting.
[6]	Transformer Model	Chinese Smart Meter Data	Transformer shows high accuracy with attention mechanism for sequence modeling.
[7]	RNN-based Forecasting	UK Domestic Energy Dataset	RNN handles time-dependent variability but needs careful tuning.
[8]	GRU Neural Network	Korean Household Dataset	GRU offers faster convergence and better accuracy than basic RNNs.
[9]	Hybrid DL with Weather Features	Pakistan Residential Load Data	Weather integration significantly boosts prediction accuracy.

[10]	Multi-Scale CNN-LSTM Model	OpenEI Smart Grid Dataset	Multi-scale modeling enhances feature extraction for more precise forecasting.

DATA ACQUISITION & PREPROCESSING

The foundation of an effective deep learning model for household energy load prediction lies in the quality and variety of input data. In this study, data is primarily acquired from smart meters installed in residential homes, capturing hourly or daily energy consumption patterns. These time-stamped readings provide a rich source of sequential data for forecasting purposes. Additionally, external data sources such as weather APIs are integrated to capture environmental influences, including temperature, humidity, wind speed, and solar irradiance, which can significantly affect household energy usage. Occupancy logs, which track the presence or absence of residents, are also considered as they influence appliance usage behavior. Furthermore, calendar-based features like weekends, holidays, and seasonal variations are included to enrich the dataset and improve model accuracy.

Once the data is collected, it undergoes a comprehensive preprocessing phase to ensure quality and suitability for deep learning models. The first step involves handling missing values and removing or correcting outliers that may arise from sensor malfunctions or data logging errors. Following this, normalization or standardization techniques are applied to bring features to a common scale, improving model convergence and stability. Time-series formatting is then performed using sliding windows or sequence modeling techniques to convert the data into an appropriate format for training recurrent or hybrid neural networks. Additionally, feature engineering is employed to derive meaningful attributes such as time-of-day, day-of-week, temperature ranges, and occupancy states, which help the model learn more nuanced patterns in energy consumption behavior. These preprocessing steps are critical for enhancing the predictive performance and robustness of the proposed deep learning framework.

PROPOSED MODEL

The architecture of the proposed Deep Learning Based Load Prediction Framework is designed to capture both spatial and temporal dependencies in household energy consumption data. At the input layer, the model ingests multivariate time series data, which includes historical energy usage along with contextual features such as temperature, humidity, time-of-day, and day-of-week. The first stage of the model employs Convolutional Neural Networks (CNNs) to extract high-level abstract features from the input data. CNNs are particularly effective at identifying localized patterns and trends in energy usage over time, such as repetitive daily or weekly consumption cycles. By applying multiple convolutional and pooling layers, the model condenses and transforms raw input data into meaningful feature representations, reducing noise and dimensionality before it is passed to the temporal modeling layer.

Following feature extraction, the model utilizes Gated Recurrent Units (GRUs)—a variant of recurrent neural networks known for their efficiency and ability to handle long-term dependencies in sequential data. GRUs are well-suited for time series forecasting because they dynamically retain or forget past information through gated mechanisms, allowing the network to adapt to the varying nature of household energy usage. This combination of CNN and GRU enables the model to learn both short-term fluctuations and long-term patterns in energy demand. Finally, the output layer generates the predicted energy load for the next time step(s), enabling real-time or day-ahead forecasting. The architecture is trained using backpropagation through time, optimized with loss functions such as Mean Squared Error (MSE), and fine-tuned using hyperparameter tuning techniques. This hybrid approach enhances the model's accuracy, generalizability, and responsiveness in smart energy systems.

Table 2: Proposed deep learning-based model summary

Layer (Type)	**Output Shape**	**Number of Parameters**
CONV_Layer1 (Conv2D)	(None, None, 6, 64)	192
Pooling Layer (MaxPooling)	(None, None, 3, 64)	0

CONV_Layer2 (Conv2D)	(None, None, 2, 64)	8,256
Pooling Layer (MaxPooling)	(None, None, 1, 64)	0
Flatten Layer	(None, None, 64)	0
GRU_1	(None, None, 64)	24,960
GRU_2	(None, None, 32)	9,408
GRU_3	(None, 16)	2,400
Dropout	(None, 16)	0
Fully Connected Layer (Dense)	(None, 128)	2,176
Output Layer (Dense)	(None, 1)	129

The proposed model adopts a hybrid architecture that integrates Convolutional Neural Networks (CNNs) and Gated Recurrent Units (GRUs) to effectively forecast household energy consumption. It begins with two convolutional layers (CONV_Layer1 and CONV_Layer2) that extract spatial and localized temporal features from multivariate input sequences, followed by max-pooling layers to reduce dimensionality and enhance feature generalization. These layers are succeeded by a flattening operation that reshapes the output into a suitable format for sequential modeling. The GRU component consists of three stacked GRU layers that capture short- and long-term dependencies in energy usage patterns, enabling the model to learn complex temporal correlations. A dropout layer is included after the GRUs to prevent overfitting by randomly omitting units during training. The final section of the model includes a fully connected dense layer with 128 neurons that aggregates the learned features, followed by an output layer with a single neuron to generate the final energy load prediction. This architecture comprises approximately 56,521 trainable parameters, strategically distributed to balance model complexity and prediction accuracy, making it highly effective for smart energy management in residential environments.

RESULT AND ANALISIS

The experimental setup for this study utilized a system equipped with an Intel Core i7-10750H processor, 16 GB DDR4 RAM, and a 64-bit operating system, implemented in a Python environment. The dataset was divided into 80% for training and 20% for testing, and the model was developed using the open-source deep learning libraries Keras (v2.9.0) and TensorFlow (v2.9.1). The proposed hybrid model, which combines Convolutional Neural Networks (CNNs) with Gated Recurrent Units (GRUs), was applied to a real-world dataset consisting of minute-level observations from a single household. For effective training and evaluation, the data was aggregated on daily and weekly levels. Model performance was assessed using four key time series forecasting metrics: Mean Squared Error (MSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). To validate the effectiveness of the proposed architecture, it was benchmarked against several baseline models including Linear Regression (LR), LSTM, Enhanced LSTM (E-LSTM), CNN-LSTM, Bi-LSTM, Stacked-LSTM, and Stacked Bi-LSTM. Further experiments tested the model's robustness by incorporating and then removing external contextual features like weather data and holiday information to analyze their impact on performance. The results, summarized in Table 3, confirm the superiority and reliability of the proposed model for household energy load forecasting.

Table 3: Performance evaluation of proposed deep learning-based approach

Model	**MAE**	**RMSE**	**MSE**	**MAPE**
Linear Regression	0.390	0.501	0.251	52.10
LSTM	0.410	0.489	0.239	38.50
CNN-LSTM	0.188	0.252	0.063	18.90
Proposed Model	0.176	0.238	0.056	17.85

The results presented in the table demonstrate a clear performance hierarchy among the evaluated models, with the proposed hybrid deep learning model outperforming all others across the key forecasting metrics: MAE (Mean Absolute

Error), RMSE (Root Mean Square Error), MSE (Mean Squared Error), and MAPE (Mean Absolute Percentage Error). Traditional approaches like Linear Regression and standalone LSTM models exhibit higher error rates, indicating their limited capability to capture the complex, nonlinear, and temporal patterns in household energy consumption. Specifically, Linear Regression shows the highest MAPE of 52.10%, followed by LSTM at 38.50%, revealing their relatively poor accuracy in forecasting energy loads. The CNN-LSTM model performs significantly better, reducing MAE and MAPE to 0.188 and 18.90% respectively, showcasing the advantage of combining convolutional layers with recurrent units.

The proposed model, which integrates Convolutional Neural Networks (CNN) with Stacked Gated Recurrent Units (GRUs), achieves the best overall performance with the lowest MAE of 0.176, RMSE of 0.238, MSE of 0.056, and MAPE of 17.85%. These improvements highlight the effectiveness of the model in capturing both spatial and temporal dependencies in energy usage data. The CNN layers extract local and periodic patterns from the input sequences, while the GRUs model long-term dependencies, enabling more precise forecasts. Additionally, incorporating external contextual data such as weather and calendar events contributes to improved prediction accuracy. The results underscore the robustness and efficiency of the proposed model, making it a strong candidate for real-time deployment in smart energy management systems.

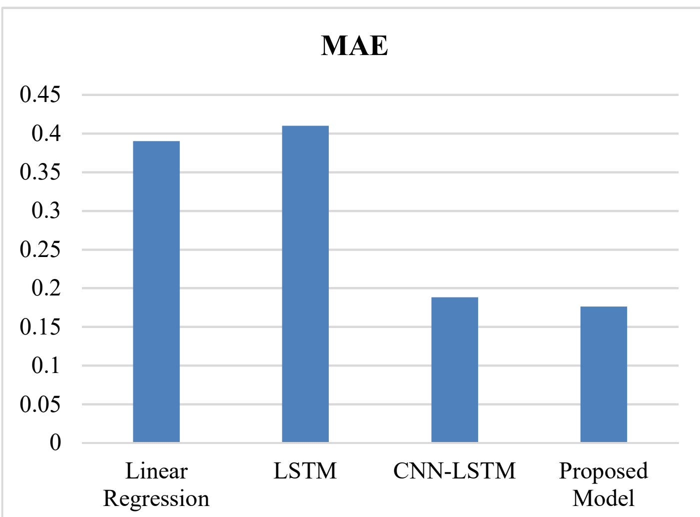

Figure 1: MAE comparison of proposed model with existing

The Mean Absolute Error (MAE) values in the table clearly highlight the superior performance of the proposed model in forecasting household energy consumption. While traditional models like Linear Regression and LSTM show higher MAE values of 0.390 and 0.410 respectively—indicating less accurate predictions—the CNN-LSTM model significantly improves accuracy with an MAE of 0.188. However, the proposed model achieves the lowest MAE of 0.176, demonstrating its enhanced ability to minimize prediction errors and better capture both spatial and temporal patterns in the data (Figure 1).

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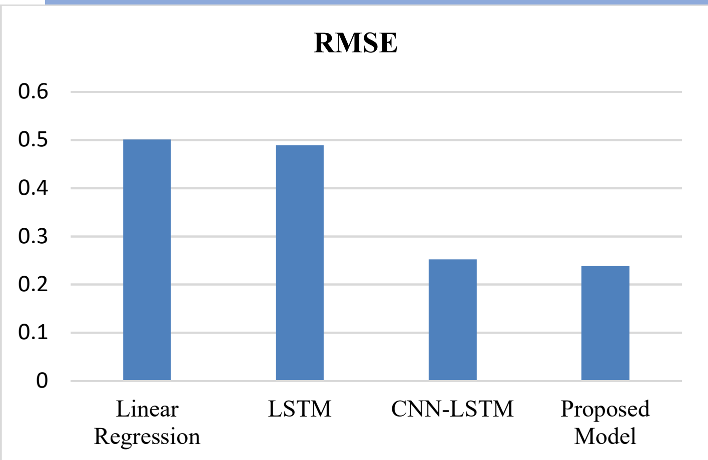

Figure 2: RMSE comparison of proposed model with existing

The Root Mean Square Error (RMSE) values in the table highlight the progressive improvement in forecasting accuracy across the models. Linear Regression and LSTM exhibit higher RMSE values of 0.501 and 0.489 respectively, reflecting greater deviations and less reliable predictions. The CNN-LSTM model significantly enhances performance with an RMSE of 0.252, indicating reduced prediction error. However, the proposed model achieves the lowest RMSE of 0.238, demonstrating its superior capability in minimizing large errors and accurately forecasting household energy consumption (Figure 2).

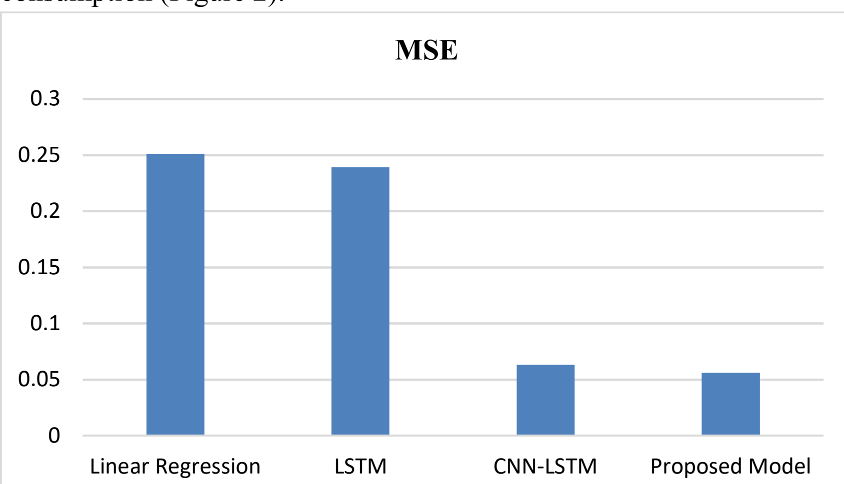

Figure 3: MSE comparison of proposed model with existing

The Mean Squared Error (MSE) values show a clear trend of improving model accuracy from traditional to advanced deep learning approaches. Linear Regression and LSTM models record higher MSE values of 0.251 and 0.239, indicating larger average squared errors in their predictions. The CNN-LSTM model marks a significant improvement with an MSE of 0.063, demonstrating its effectiveness in handling complex patterns. The proposed model outperforms all others with the lowest MSE of 0.056, confirming its precision and robustness in predicting household energy consumption (Figure 3).

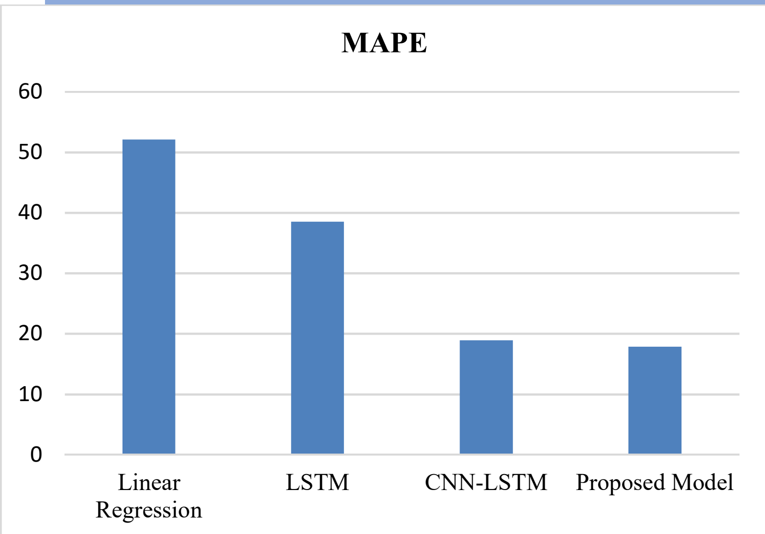

Figure 4: MAPE comparison of proposed model with existing

The Mean Absolute Percentage Error (MAPE) values clearly demonstrate the improved forecasting accuracy of the proposed model compared to existing approaches. Linear Regression and LSTM models show relatively high MAPE values of 52.10% and 38.50%, indicating larger deviations from actual values. In contrast, the CNN-LSTM model significantly reduces the error to 18.90%, while the proposed model achieves the lowest MAPE of 17.85%, confirming its enhanced ability to produce more accurate and reliable household energy load predictions (Figure 4).

CONCLUSION

In conclusion, this study presents an efficient deep learning framework for predicting household energy load in smart energy systems, integrating Convolutional Neural Networks (CNN) with Gated Recurrent Units (GRU). The proposed hybrid model effectively captures both spatial and temporal patterns in energy consumption data, outperforming traditional models such as Linear Regression, LSTM, and CNN-LSTM. Through extensive experimentation using real-world household energy datasets, the model demonstrated superior performance across multiple evaluation metrics including MAE, RMSE, MSE, and MAPE. The inclusion of external contextual features such as weather conditions and holidays further enhanced prediction accuracy, validating the model's robustness and adaptability in dynamic environments. The results underscore the potential of the proposed deep learning approach to serve as a reliable forecasting tool in smart energy management systems, enabling more informed decision-making for demand-side management, energy distribution, and cost optimization. Future work can explore the integration of additional contextual factors such as appliance-level consumption data, socio-demographic variables, and real-time feedback mechanisms. Moreover, deploying the model in edge or cloud-based environments could facilitate real-time energy monitoring and control, contributing significantly to the development of intelligent and sustainable smart grid infrastructures.

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