Smart home Energy Consumption prediction Using Deep Learning

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***Abstract*—Accurate prediction of energy consumption plays a crucial role in enhancing efficiency within smart homes. By anticipating usage patterns, energy can be optimized to reduce waste and improve sustainability. This ensures smarter management of resources in modern households.This paper applies deep learning models, including LSTM, Bi-directional LSTM, CRNN, and a proposed BiGRAN, to forecast energy usage using second-level time-series data from Kaggle. Key preprocessing steps included missing value imputation, normalization, and sliding window mechanisms.The BiGRAN model, integrating Bi-directional LSTM in both its generator and discriminator, achieved the lowest test loss of 0.00076 after just one epoch, outperforming other models. Despite computational challenges, BiGRAN effectively captured complex temporal patterns, demonstrating its robustness and potential for real-time energy management.**

***Index Terms*—Smart Home, Power, LSTM, Bi-directional LSTM, CRNN, BiRGAN**

I. Introduction

In recent years, the concept of smart homes has emerged as a key innovation in both residential and urban energy management. Smart homes are equipped with connected devices that monitor and control various aspects of home operations, including energy consumption. This technology enables more efficient use of resources by automating processes and providing insights into usage patterns. Given the rising cost of energy and the growing emphasis on sustainability, managing energy consumption has become a critical concern, both for individual households and for society at large.

Energy management in smart homes is not only about reducing costs for homeowners but also about contributing to broader environmental goals, such as reducing carbon footprints and minimizing wasteful energy practices. With the increasing adoption of IoT (Internet of Things) devices that collect and transmit data, smart homes have the potential to optimize energy usage dynamically, responding to real-time needs and conditions. However, achieving meaningful energy savings requires accurate forecasting of household power consumption, a task complicated by the irregular and often unpredictable patterns of usage influenced by factors like weather, time of day, and occupancy.

Predicting energy consumption in smart homes holds significant promise for improving overall energy efficiency. Reliable forecasts enable better energy distribution, peak load management, and more informed decision-making at both consumer and utility levels. Accurate predictions can help guide homeowners in optimizing their usage and costs, while utilities can leverage these insights to improve grid reliability and efficiency. Consequently, effective energy consumption prediction models have become crucial for realizing the full potential of smart homes in the transition to sustainable energy practices.

Accurately predicting energy consumption in smart homes is a complex and challenging task due to several factors that influence household energy usage. One primary challenge is the variability in energy consumption patterns across different homes and even within the same household over time. Individual usage behaviors, lifestyle changes, and the presence of various electrical appliances introduce a high degree of unpredictability. As a result, patterns in energy use can be inconsistent, making it difficult to identify stable, recurring trends.

Another significant challenge is the impact of environmental factors such as temperature, humidity, and seasonal variations. These factors directly affect heating, ventilation, and air conditioning (HVAC) usage, which accounts for a substantial portion of a household's energy consumption. For example, in colder months, energy usage typically increases as heating needs rise, while warmer months may see a spike in cooling-related consumption. Predicting these fluctuations accurately requires a model capable of integrating and interpreting these external influences.

Additionally, conventional statistical methods often struggle to capture the non-linear relationships inherent in energy usage data. Traditional models may fall short when it comes to handling the temporal dependencies and complex interactions between multiple variables, such as past energy consumption patterns, occupancy levels, and environmental conditions. This limitation necessitates the use of more sophisticated approaches that can manage time-series data and account for both short-term and long-term dependencies within the data.

Lastly, smart home data is often collected from various IoT devices, which can lead to issues with data quality, consistency, and privacy. Missing data, irregular sampling, and noise can hinder the accuracy of predictive models. Ensuring data privacy and security also remains a priority, as energy usage patterns can reveal sensitive information about occupants' habits and daily routines.

Together, these challenges highlight the need for advanced predictive techniques, such as deep learning, which can handle the complexity of smart home energy consumption data. By addressing these obstacles, more accurate and reliable energy consumption prediction models can be developed, helping smart homes achieve greater efficiency and sustainability.

Deep learning has emerged as a powerful tool for addressing the complexities of energy consumption prediction in smart homes. Unlike traditional statistical models, deep learning techniques are well-suited for handling the non-linear, high-dimensional relationships typical of energy data. Models such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks excel at analyzing time-series data, making them ideal for capturing temporal dependencies in energy usage patterns. These models can learn from historical data to detect subtle trends and patterns, even amidst irregular usage behaviors and varying environmental influences.

Additionally, deep learning models can incorporate a wide range of variables—from past power consumption to environmental factors like temperature and humidity—allowing them to make more accurate predictions. By leveraging deep learning, smart home energy prediction models can adapt to complex, evolving usage patterns, providing more reliable forecasts that support optimized energy management, cost savings, and sustainable practices.

This research focuses on developing a deep learning-based model to predict energy consumption in smart homes by analyzing historical power usage data alongside key environmental factors, such as temperature, humidity, and seasonality. By leveraging advanced time-series modeling techniques, this study aims to enhance the accuracy of energy forecasts, supporting smarter energy management for households. The proposed model seeks to identify patterns and dependencies in energy usage that can inform both homeowners and utility providers, ultimately contributing to improved efficiency and sustainability in residential energy consumption.

II. Literature Review

Dhowmya et al [1]. Proposed Convolutional Recurrent neural network (CRNN) model for HVAC system and made comparatively analysis shown that CRNN outperforms the CNN, ANN and RNN architectures. They considered Thermal and Operational Characteristics and Energy Consumption and Thermal Comfort characteristics to make predictions. CNN and permutation layers classify image and video characteristics and classifies for optimal energy consumption. RNN uses Bidirectional Gated Recurrent Unit to address gradient problem and uses Batch normalization, Max Pooling and Dropout. Their Experiment results Li-Fi outperforms Wi-Fi, Bluetooth and ZigBee for data transfer. Saidur et al [2] used ensemble learning techniques combining ARIMA, LSTM, Univariate Linear Regression and Multivariate Regression with Mahalanobis distance. They achieved R2 score of 94.55%.

Dabeeruddin et al [3] proposed hybrid stacked bi-directional uni-directional LSTM with fully connected dense layers (HS-BUFC) model which contains Bi-Directional layer connected to LSTM and fully connected and including normalization of data and dropout using Adam Optimizer performs comparatively less Mean Absolute Error (MAE) than existing models with achieved R2 score of 99.867%. Mohammad et al [4] introduces Recurrent Generative Adversial Networks(R-GAN) which replaces Convolutional Layers in GAN with LSTM units apply GELU activation function. They preprocessed with ARIMA, Fourier Transform then Normalize the data and generate samples with Sliding Window. Finally, they achieved an MAPE loss of 6.16% and MAE of 44.13.

S Reddy et al [5]created an ensemble of models (LSTM, Random Forest, DNN) using XGBoost for stacking, which enhanced performance and reduced error by 39%. Pre-processing through differencing removed seasonal trends, making data more predictable. Random search was used for hyperparameter tuning, leading to better accuracy compared to traditional models. Abdelhamid et al [6] used Dipper throated Optimization algorithm. The model is able to achieve RMSE of 0.0047 and R2 of 0.998 by using unidirectional and bidirectional layers.The proposed model compared to base model(SVR,KNN and RANDOM FOREST, MLP sequence to sequence, LSTMs)with MAE of 0.003 and willmott's index (WI) of 0.976. Furtherly broadening the data set include more household types and also addressing seasonal energy patterns.

RF Berriel et al [7] used LSTM models for accurate monthly energy consumption prediction by capturing long and short-term dependencies. Data normalization reduced errors. They also integrated metadata and used stratified k-fold validation to prevent overfitting, which significantly improved accuracy over simpler models like CNN.They achieved MAE 30.93 kWh and MAPE 46.53%. Khan et al [8] proposed an approach by combining 1D convolutional neural networks for feature extraction and bidirectional LSTM in smart homes.By including both temperature and timely parameters the model achieved an accuracy of 90.41 % with 91% as precision.And also Q learning based was used to optimize appliance operation which possess a great utility towards Home Automation. Future scope would be including advancing integration with renewable energy sources. Jiyeon Yu et al [9] studied on deep learning applications on smart home which proves that CNN works well on image related tasks while RNN/LSTM

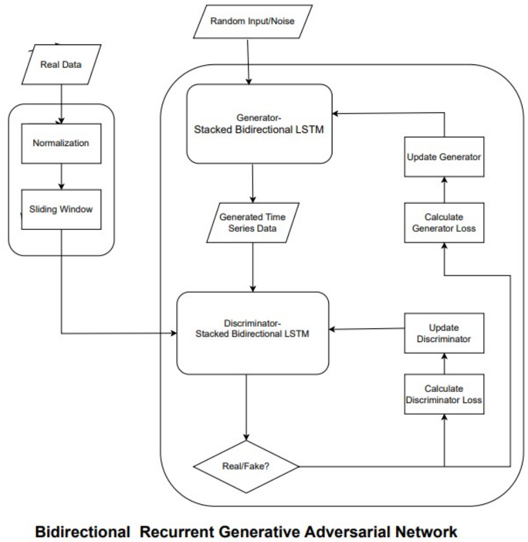

Fig. 1. Bidirectional Recurrent Generative Adversial Network architecture

is better for sequential data like predicting future activities than any other models.They analyzed 43 selected papers and categorized their applications and parameters which are efficient for specific application in smart home.This study compares between multiple loss functions and metrics for every application.Accuracy,precision,recall and F1-score are used and most important metrics in the study reviewed.O Taiwo et al [10] review the use of deep learning models, mainly CNN and RNN/LSTM for smart home applications. The system is capable of monitoring and controlling home appliances as well as measuring and displaying conditions like temperature and humidity. The CNN model was trained on a dataset of human postures to distinguish between home occupants and intruders, showing an accuracy of 99.8%. The paper concludes that the proposed CNN model outperforms other models like SVM, KNN, and complex decision trees in terms of accuracy, precision, recall, and Cohen's kappa.

R.Sunder et al [11] in this research introduces a hybrid deep learning approach for accurate energy load prediction in Smart buildings. This is an approach combining improved CNN,Bi-LSTM,GNN and Transformer model.The dataset of Electric power consumption gives detailed records of electricity usage resulting in RMSE of 5.7532Wh, MAE of 6.7532Wh, MAE of 6.7532Mh and accuracy of 0.9701.A fusion layer enables capture of energy usage patterns and enhances the resource management.S.Vidhya et al [12] presents the optimized hybrid deep learning model combining CNN and Bi-LSTM networks optimized with CPSO for energy consumption prediction. On fine-tuning, the model achieves RMSE of 26.2154W and R2 of 0.9989. This model captures complex patterns in time-series energy data for better energy management. This accuracy supports reduced energy costs and supporting efficient energy use in smart homes.

III. METHODOLOGY

A. Data Collection and Preprocessing

The dataset has been retrieved from Kaggle [13]. It is a second-level time series dataset updated hourly, containing information on appliances' current usage along with environmental parameters such as temperature, pressure, and humidity. Among the 17 output variables, we focused on predicting the House overall variable. This selection was based on its strong correlation with other output labels, implying that accurately predicting House overall could enhance model performance for the remaining variables.

We selected eight environmental input parameters: temperature, humidity, visibility, apparent temperature, pressure, wind speed, wind bearing, and dew point.

Rows with missing values in the output columns were removed. To handle missing data in the input variables, forward-fill and backward-fill techniques were applied. The dataset was then divided into input and output variables and normalized using the MinMaxScaler. Sequential inputs were generated using a sliding window mechanism with a window size of 30. Finally, the data was split into training and testing sets in an 8:2 ratio.

B. Model Selection

We selected four advanced models for our approach: LSTM, Bi-directional LSTM, Bi-Directional Recurrent Generative Adversarial Networks (BiGRAN), and a bespoke CRNN model. These models were selected because they have a track record of successfully handling time-series and sequential data, which is essential for precise energy consumption prediction.

For the LSTM and Bi-directional LSTM models, we utilized three hidden layers. The specific parameters used for these layers, such as the number of units, activation functions, and dropout rates, are detailed in the corresponding table. Bi-directional LSTMs, being an extension of standard LSTMs, process data in both forward and backward directions, enabling them to capture dependencies across the entire sequence more effectively. This bi-directional capability often leads to improved predictive accuracy, particularly in scenarios like energy forecasting where temporal dependencies are significant. Table I shows the layered architecuture of the base models for the proposed model.

TABLE I
ARCHITECTURE BASE MODEL LAYERS AND DESCRIPTIONS

Layer type	Description
Bidirectional	No.of nodes = 128
Dropout	0.2
Bidirectional	No.of nodes = 64
Dropout	0.2
Dense	No.of nodes = 64 , Activation= relu
Dense(Output)	No.of nodes = 1 , Activation = linear

The BiGRAN model represents a hybrid approach where both the generator and discriminator are built using Bi-directional LSTMs. The generator is tasked with predicting future power consumption based on past patterns. Meanwhile, the discriminator acts as a penalty function by evaluating the generator's predictions against the actual data. It identifies discrepancies and penalizes the generator for inaccuracies, indirectly serving as a loss function. By incorporating a discriminator that learns patterns ahead of time, the BiGRAN model creates a robust feedback mechanism, ensuring the generator improves iteratively. Given the demonstrated superiority of Bi-directional LSTMs over standard LSTMs in handling sequential data, they were used in both the generator and discriminator components of the BiGRAN model. Image 1 shows the architecuture model of BiGRAN.

Our customized CRNN model combines Convolutional Neural Networks (CNNs) with Bi-directional LSTMs to leverage the strengths of both architectures. A convolutional layer is employed at the beginning of the model to extract spatial features and transform them into a latent space representation. These transformed features are then passed to the Bi-directional LSTM layers, which process them sequentially. Batch normalization is applied after the convolutional layer to stabilize training, followed by softmax activation and max-pooling to reduce the spatial dimensions while retaining essential features. Image 2 shows the architecuture model of CRNN.

To further enhance the model's performance and avoid overfitting, a dropout layer with a rate of 0.2 is included. This configuration ensures that the CRNN model effectively captures complex patterns in the input data, particularly when dealing with high-dimensional environmental features.

We used mean absolute error (MAE) as the loss function for all models, as it provides a straightforward measure of prediction accuracy, particularly for continuous variables like power consumption. The Adam optimizer was employed due to its efficiency and ability to handle sparse gradients. To prevent overfitting and ensure optimal training, we implemented early stopping with patience levels of 5 and 10 epochs, and a minimum delta value of 0.0001.

The models were trained for 50 epochs, with a batch size of 128, balancing computational efficiency with the need for sufficient updates to the weights. This setup ensures that the models generalize well to unseen data while maintaining computational feasibility.

IV. LIMITATIONS AND CHALLENGES

The models were trained using a 6GB NVIDIA GeForce RTX 3050 graphics card. Training the BiGRAN model proved to be particularly time-intensive due to its complexity and the size of the dataset, with each epoch taking approximately 130.15 minutes to complete.

A significant challenge was the simplicity of the features, which caused the large BiGRAN model to overfit the training data. This overfitting led to poor performance on the validation loss, indicating that the model struggled to generalize effectively.

Finding the optimal parameters for the LSTM and Bi-directional LSTM models also posed difficulties. Networks with too few layers resulted in underfitting, where the model failed to capture the underlying patterns in the data. Conversely, architectures with too many layers produced erratic predictions, deviating significantly from the expected values. After extensive experimentation, we concluded that 2 to 3 layers provided the right balance between complexity and performance, minimizing both underfitting and overfitting issues.

These challenges highlight the need for careful tuning of model architecture and parameters, particularly when dealing with complex models and relatively simple input features.

V. RESULTS

The performance of the proposed models was evaluated using the test loss, where the loss function used was mean absolute error (MAE). The table below presents the test loss achieved by each model.

TABLE II
TEST LOSS COMPARISON ACROSS MODELS

Model Name	Test Loss
LSTM	0.0292
Bi-directional LSTM	0.0158
CRNN	0.0758
BiRGAN (Proposed Model)	0.0076

As shown in Table II, the BiGRAN model significantly outperformed the other models, achieving the lowest test loss of 0.00076. Remarkably, this result was achieved after training BiGRAN for only a single epoch, demonstrating the efficiency and effectiveness of the proposed approach.

The Bi-directional LSTM also performed well, achieving a test loss of 0.0158, while the LSTM model recorded a slightly higher loss of 0.0292. On the other hand, the CRNN model

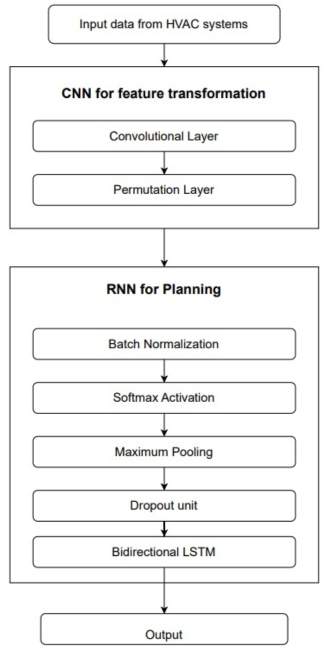

Fig. 2. Convolutional Recurrent Network architecture

had the highest test loss of 0.0758, indicating that it was less effective for the given prediction task.

These results highlight the capability of BiGRAN to capture complex temporal patterns and generalize well, even with minimal training, making it a robust solution for energy consumption prediction in smart home environments.

VI. Conclusion

In this study, we proposed a deep learning-based approach to predict smart home energy consumption, utilizing advanced models such as LSTM, Bi-directional LSTM, CRNN, and BiGRAN. The BiGRAN model, designed as a hybrid of Bi-directional LSTM-based generator and discriminator, demonstrated superior performance, achieving the lowest test loss of 0.00076, even when trained for only one epoch. This highlights the model's efficiency and ability to capture intricate temporal dependencies in energy consumption patterns.

We addressed the challenges associated with model selection and training, such as overfitting and underfitting, by carefully tuning hyperparameters and designing architectures tailored to the characteristics of the dataset. Notably, the BiGRAN model proved to be both effective and computationally intensive, showcasing its robustness in handling time-series data while requiring significant training resources.

The results of this research demonstrate the potential of deep learning models, particularly BiGRAN, in improving the accuracy of energy consumption predictions. These findings can be leveraged to optimize energy usage in smart homes, contributing to enhanced energy efficiency and sustainability. Future work could explore extending this approach to larger datasets, incorporating additional features, or deploying the model in real-time energy management systems.

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