A Comparative Analysis of BiLSTM-GRU and RNN Models for Smart Home Energy Consumption Forecasting

Abstract Energy conservation in smart homes is crucial for optimizing electricity usage, reducing costs, and contributing to sustainability efforts. This study evaluates the performance of two deep learning models, the Bidirectional Long Short-Term Memory with Gated Recurrent Units (BiLSTM-GRU) and the traditional Recurrent Neural Network (RNN), in forecasting smart home energy consumption. The research employs comprehensive data preprocessing, model implementation, training, and evaluation to determine the superior model. Experimental results demonstrate that the BiLSTM-GRU model consistently outperforms the RNN model across multiple forecasting windows, offering higher accuracy and robustness. The study provides insights into model selection for energy management applications and discusses the trade-offs between model complexity, interpretability, and computational efficiency.

Keywords: Smart homes, Machine learning, Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), Recurrent Neural Networks (RNN).

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1. Introduction

Energy consumption forecasting is a critical component of smart home management, enabling homeowners and energy providers to optimize electricity usage and reduce wastage. Traditional statistical models have shown limitations in capturing complex temporal dependencies in energy data, leading to the increasing adoption of deep learning techniques. This study investigates the comparative performance of BiLSTM-GRU and RNN models in predicting energy consumption patterns within smart homes.

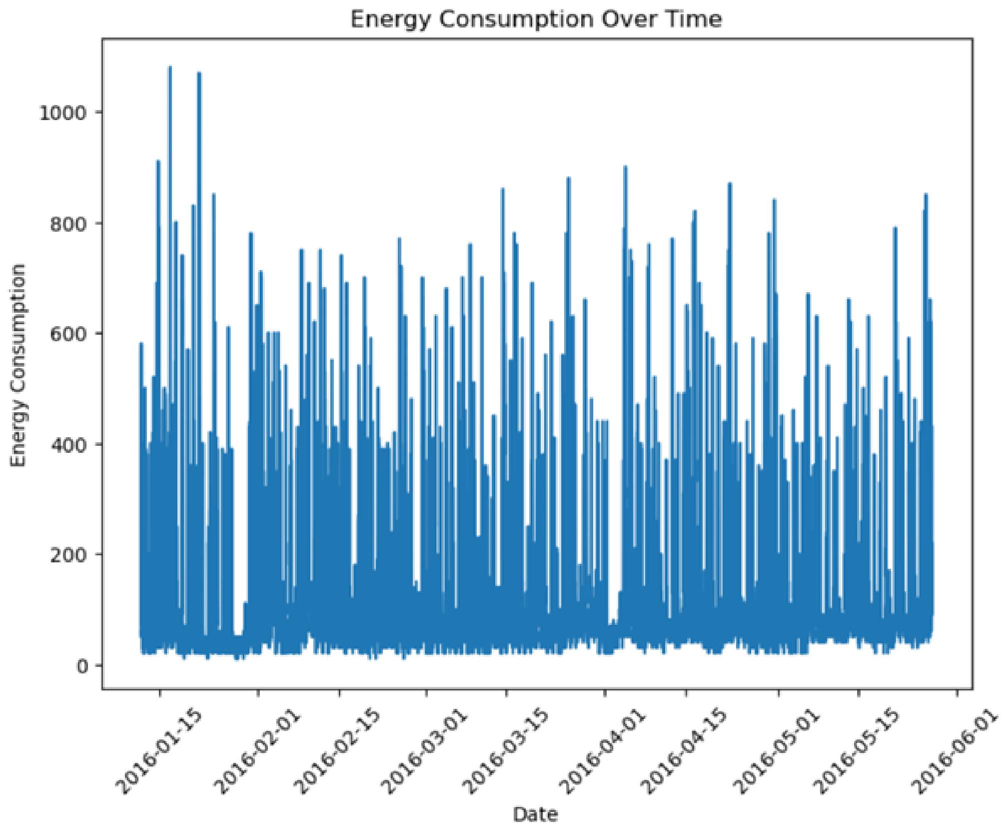

Figure 1: Energy Consumption over time

2. Related Works

Recent research on smart home energy forecasting has compared traditional statistical models, such as linear regression, dynamic regression, and ARIMA, with advanced machine learning (ML) methods. While statistical approaches provide interpretable results, they often fail to capture complex nonlinear patterns and long-term dependencies.

Sachin et al. (2020) demonstrated that RNN and LSTM models outperform ARIMA, particularly in long-term predictions. Similarly, Zhou et al. (2019) reported significant error reduction using LSTM compared to ARIMA and BP neural networks, even with short-term datasets. Fanti et al. (2021) improved ARIMA predictions by integrating Gradient Boost Regression Trees, while Sameh et al. (2022) found Drop-GRU to yield superior accuracy over both GRU and LSTM.

Bourhnane et al. (2020) applied ANN with genetic algorithms for prediction and scheduling, achieving higher accuracy than statistical models, though tested on limited datasets. Other works, such as Gopikrishna and Jiju (2021) and Khaoula et al. (2023), explored single-model approaches or compared multiple ML models (ANN, SVM, RF, decision trees) using real-world data. Alduailij et al. (2020) reviewed forecasting methods by timeframe but did not conduct experimental validation.

These studies highlight the potential of deep learning—particularly hybrid and gated architectures—in improving accuracy and adaptability. However, gaps remain in testing across larger, diverse datasets and in directly comparing advanced architectures under equal conditions. To address these, our study evaluates a BiLSTM-GRU hybrid against a traditional RNN baseline, aiming to capture temporal dependencies more effectively while assessing computational trade-offs

3. Methodology

The study follows a structured approach, including:

3.1 Data Collection and Preprocessing

- **Dataset Description:** The study uses a publicly available dataset from [source]. The dataset includes energy consumption readings, weather conditions, and occupancy trends.
- **Feature Engineering:** Time-series transformation, normalization, missing value handling, and outlier removal.
- **Train-Test Split:** The dataset is divided into 80% training and 20% testing.

Table 3: Variables, description and data types of our dataset

Variable Name	Role	Type	Description	Units	Missing Values
Date	Feature	Date	time year-month-day hour:minute:second		no
Appliances	Target	Integer	energy use in Wh	Wh	no
Lights	Feature	Integer	energy use of light fixtures in the house in Wh	Wh	no
T1	Feature	Continuous	Temperature in kitchen area, in Celsius	C	no
RH_1	Feature	Continuous	Humidity in kitchen area, in %	%	no
T2	Feature	Continuous	Temperature in living room area, in Celsius	C	no

RH_2	Feature	Continuous	Humidity in living room area, in %	%	no
T3	Feature	Continuous	Temperature in laundry room area	C	no
RH_3	Feature	Continuous	Humidity in laundry room area, in %	%	no
T4	Feature	Continuous	Temperature in office room, in Celsius	C	no
RH_4	Feature	Continuous	Humidity in office room, in %	%	no
T5	Feature	Continuous	Temperature in bathroom, in Celsius	C	no
RH_5	Feature	Continuous	Humidity in bathroom, in %	%	no
T6	Feature	Continuous	Temperature outside the building (north side), in Celsius	C	no
RH_6	Feature	Continuous	Humidity outside the building (north side), in %	%	no
T7	Feature	Continuous	Temperature in ironing room , in Celsius	C	no
RH_7	Feature	Continuous	Humidity in ironing room, in %	%	no
T8	Feature	Continuous	Temperature in teenager room 2, in Celsius	C	no
RH_8	Feature	Continuous	Humidity in teenager room 2, in %	%	no
T9	Feature	Continuous	Temperature in parents room, in Celsius	C	no
RH_9	Feature	Continuous	Humidity in parents room, in %	%	no
T_out	Feature	Continuous	Temperature outside (from Chievres weather station), in Celsius	C	no
Press_mm_hg	Feature	Continuous	Pressure (from Chievres weather station), in mm Hg	mm Hg	no

RH_out	Feature	Continuous	RH_out, Humidity outside (from Chievres weather station), in %	%	no
Windspeed	Feature	Continuous	Wind speed (from Chievres weather station), in m/s	m/s	no
Visibility	Feature	Continuous	Visibility (from Chievres weather station), in km	km	no
Tdewpoint	Feature	Continuous	Tdewpoint (from Chievres weather station), Â°C	C	no
rv1	Feature	Continuous	Random variable 1, nondimensional		no
rv2	Feature	Continuous	Random variable 2, nondimensional		no

3.2 Model Implementation

- **RNN Model:** Basic recurrent architecture with tanh activation and fully connected layers.
- **BiLSTM-GRU Model:** Incorporates bidirectional processing, dropout regularization, and GRU units for improved memory retention.

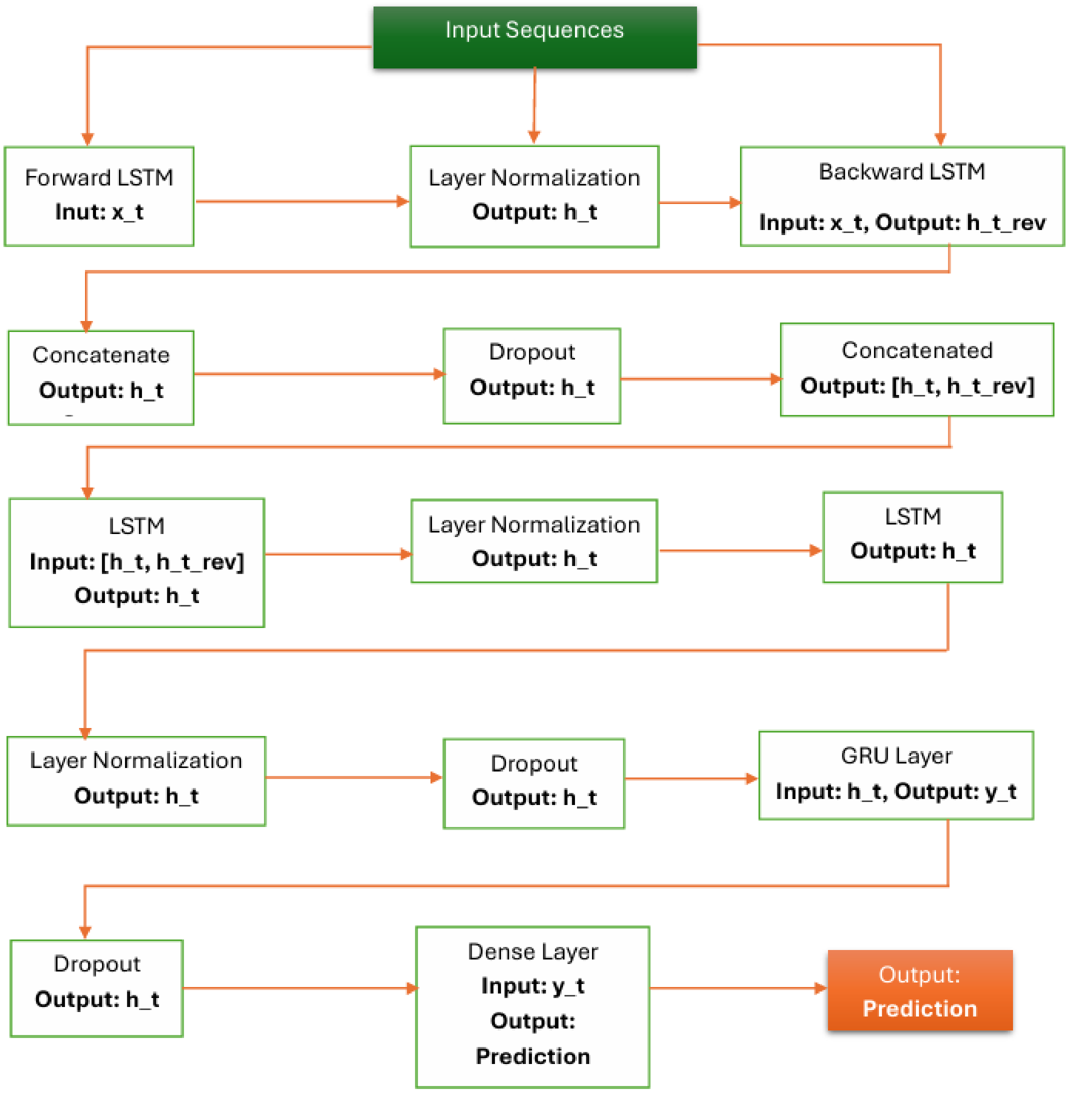

Figure 3: Architectural Diagram of BiLSTM-GRU

3.3 Training and Evaluation Metrics

- **Hyperparameter Tuning:** Grid search for optimal learning rates, batch sizes, and dropout rates.
- **Performance Metrics:** Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-Squared (R^2) scores.

Table 3: Hyperparameters used for BiLSTM-GRU implementations.

Hyperparameters	Description	Value
Number of Layers	Number of recurrent layers in the model	3-4
Number of Units	Number of neurons in each recurrent layer	LSTM: 512, 256, 128, 64; GRU: 32
Activation Function	Activation function used in recurrent layers	LSTM: sigmoid, tanh; GRU: swish
Dropout rate	Fraction of the input units to drop during training	0.1
Batch Size	Number of samples per gradient update	32, 64, 128, 256
Learning Rate	Step size for updating model weights	0.0001(Adam)
Sequence Length	Length of input sequences (time steps)	1
Epochs	The quantity of thorough runs over the training dataset	50, 100, 150
Early Stopping Patience	The number of epochs in which there is no development before training is discontinued	10

4. Results and Discussion

The models were tested on a dataset comprising time-stamped energy consumption data, weather patterns, and occupancy trends. The BiLSTM-GRU model demonstrated superior accuracy across different forecasting windows (1 week, 4 weeks, and 12 weeks) compared to the traditional RNN model.

4.1 Model Performance Comparison

- **Higher Accuracy:** The BiLSTM-GRU model consistently achieved lower MAE, MSE, and RMSE values than RNN, indicating improved predictive performance.
- **Better Generalization:** The BiLSTM-GRU model showed enhanced ability to capture long-term dependencies and non-linear patterns in energy consumption.
- **Computational Trade-offs:** While RNN models trained faster and required fewer computational resources, they exhibited lower accuracy and struggled with long-term dependencies.

Here is a tabular comparison of the evaluation metrics for our BiLSTM-GRU model:

Table 4.1: Results after experiment for BiLSTM-GRU

Window	MAE	MSE	RMSE	R2 Score	Best Parameters			
					Batch	Epochs	1st layer activation	Learning rate
1 week	0.0238	0.0024,	0.0496,	0.3303	64	150	Sigmoid	0.0001
4 weeks	0.0223,	0.0021	0.0464	0.2933	32	150	Sigmoid	0.0001
12 weeks	0.0216	0.0021	0.0467	0.2955	32	150	Sigmoid	0.0001

Table 4.2: Results after experiment for RNN

Window	MAE	MSE	RMSE	R2 Score	Best Parameters			
					Batch	Epochs	1st layer activation	Learning rate
1 week	0.0243	0.0026	0.0518	0.2685	32	150	Sigmoid	0.0001
4 weeks	0.0224	0.0022	0.0471	0.2711	32	150	Sigmoid	0.0001
12 weeks	0.0314	0.0035	0.0595	-0.1456	64	100	Sigmoid	0.0001

The tables 3.1 and 3.2 above highlights that our proposed BiLSTM-GRU model outperforms the RNN model across all performance metrics (MAE, MSE, RMSE, and R^2 Score) and window sizes (1 week, 4 weeks, and 12 weeks). This suggests that for this dataset and prediction task of smart home energy consumption prediction, the BiLSTM-GRU model is more effective and provides more accurate predictions compared to the traditional RNN model. data.

4.2 Interpretation of Results

- MAE, MSE, and RMSE: Lower values of MAE, MSE, and RMSE indicate better model performance, as they suggest smaller prediction errors.
- R2 Score: A higher R2 score closer to 1 indicates that a larger proportion of the variance in energy consumption is explained by the model, implying better predictive power.

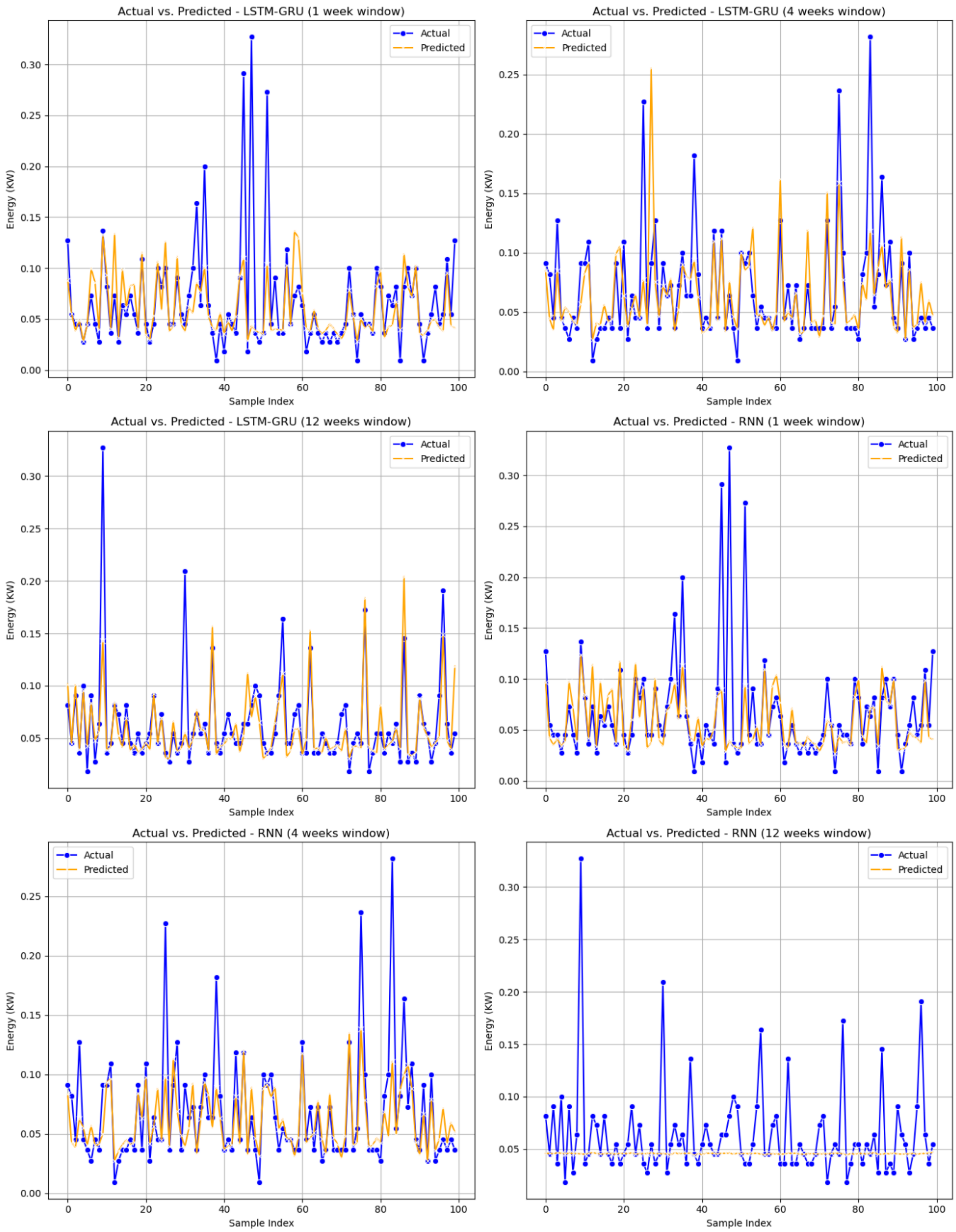

Figure 4: Comparison of Actual vs Predicted Energy Consumption for both models

5. Conclusion and Future Work

This study highlights the advantages of BiLSTM-GRU over RNN for energy consumption forecasting in smart homes. The results suggest that BiLSTM-GRU models are more effective in capturing temporal dependencies, making them ideal for real-world energy management applications.

5.1 Key Findings

- The BiLSTM-GRU model outperforms the RNN model in accuracy and generalization.
- RNN models are computationally less expensive but less effective for long-term forecasting.

5.2 Future Work

- Integration of reinforcement learning techniques for adaptive energy consumption forecasting.
- Real-time deployment and testing on IoT-based smart home systems.
- Further research into hybrid architecture combining LSTM-GRU with transformer models.

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