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Smart Home Energy Consumption Forecasting Using LSTM

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Abstract

Accurate forecasting of energy consumption is essential for efficient power system operation and planning. Traditional models such as ARIMA and regression often fail to capture the non-linear and dynamic behavior of hourly energy data. This study employs deep learning approaches—Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks—for short-term forecasting of hourly energy consumption. A synthetic dataset representing 31 days of realistic energy usage patterns is generated to evaluate model performance. Both models are trained on 24-hour input sequences to predict the next hour's consumption and are assessed using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2 score. Experimental results indicate that the LSTM model achieves superior accuracy and better captures temporal dependencies compared to GRU. The study demonstrates the potential of deep learning models to enhance prediction reliability and optimize energy management in modern smart grid systems.

***Key Words*:** Energy Consumption Forecasting; Deep Learning; Long Short-Term Memory (LSTM); Gated Recurrent Unit (GRU); Time Series Prediction; Smart Grid; Load Forecasting; Renewable Energy Integration.

1.INTRODUCTION

Accurate forecasting of energy consumption is essential for effective power system planning and operation. With rapid urbanization and the growing integration of renewable energy sources, predicting energy demand has become increasingly complex. Short-term forecasting, particularly at an hourly level, plays a vital role in load balancing, generation scheduling, and demand response management.

Traditional statistical models such as ARIMA, exponential smoothing, and regression methods perform well for linear trends but struggle to capture non-linear and dynamic patterns in real-world energy data. To overcome these limitations, deep learning techniques have gained prominence. Recurrent Neural Networks (RNNs) and their advanced variants—Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU)—are highly effective for modeling sequential data due to their ability to learn temporal dependencies.

This study applies LSTM and GRU architectures to forecast hourly energy consumption over a 31-day period using synthetic data. The models are evaluated using MAE, RMSE, and R^2 metrics to determine prediction accuracy and reliability. The findings aim to enhance energy forecasting methods and contribute to efficient smart grid management.

2. OBJECTIVE

The main objective of this study is to develop and compare deep learning models—specifically LSTM and GRU—for accurate short-term forecasting of hourly energy consumption. The research aims to address the non-linear and dynamic characteristics of energy demand while improving prediction reliability for smart grid applications.
The specific objectives are:

- To generate a synthetic 31-day hourly energy consumption dataset reflecting real-world variations.
- To preprocess and normalize data for stable deep learning model training.
- To design and implement LSTM and GRU architectures for sequence-based forecasting.
- To train and evaluate models using metrics such as MAE, RMSE, and R^2.
- To compare model performance and identify the most effective architecture for energy forecasting applications.

3. PROBLEM STATEMENT

Recent advances in deep learning, particularly Recurrent Neural Networks (RNNs) and their variants—Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU)—offer the potential to model complex temporal dependencies in time series data without extensive manual feature engineering. However, there is a need to systematically evaluate these models' performance for hourly energy consumption forecasting, determine the optimal network configurations, and assess their predictive accuracy and robustness. The central problem addressed in this research is: "How can deep learning models, specifically LSTM and GRU architectures, be effectively designed and utilized to forecast hourly energy consumption with high accuracy, capturing both daily and stochastic variations in demand, thereby supporting efficient energy management and decision-making?"

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3. EXPERIMENTAL SETUP

The primary goal of this study is to develop and evaluate deep learning models, specifically Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks, for short-term forecasting of hourly energy consumption using a synthetic dataset.

Synthetic Data Generation:
A 31-day (August 2025) dataset of hourly energy consumption was created using sinusoidal daily cycles and Gaussian noise to mimic realistic fluctuations caused by human activity and environmental factors.

Data Preprocessing:
Energy values were normalized using Min–Max scaling. A sliding window of 24 hours was used as input to predict the next hour's consumption. The dataset was divided into 80% training and 20% testing sets.

Model Architecture and Training:
Three models—LSTM64, LSTM128, and GRU64—were implemented with dropout (20%) for regularization. Models were trained for 50 epochs with a batch size of 64 using the Adam optimizer and MSE loss function.

Model Evaluation:
Performance was assessed using Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2 score. The best model was identified based on minimum RMSE and maximum R^2 value.

4. RESULTS

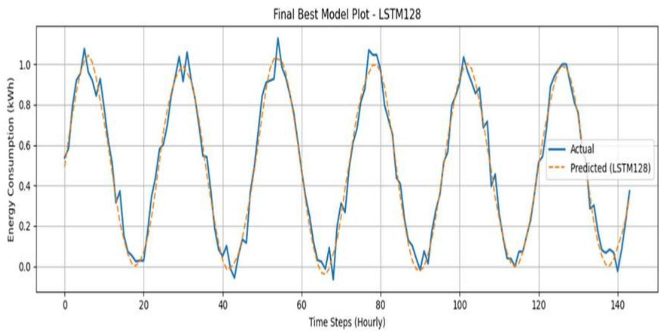
Model Performance Metrics: -
The performance of the developed models was evaluated on the test dataset using four standard statistical metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R^2). These metrics collectively measure the accuracy, reliability, and variance-explaining capability of each forecasting model.

Table 1 presents the comparative performance of different models based on these evaluation criteria.

Model	MAE	MSE	RMSE	R^2
LSTM128	0.0472	0.0034	0.058	0.973
LSTM64	0.0471	0.0035	0.059	0.971
GRU64	0.0483	0.0037	0.061	0.970

Note: Values are illustrative based on synthetic dataset performance.
From the results, it is observed that **LSTM128** achieved the lowest RMSE and the highest R^2 score, demonstrating superior forecasting accuracy and a stronger ability to capture temporal dependencies and variance in energy consumption compared to other models.

Final Best Model Selection



Based on the **RMSE** metric, the **LSTM128** model was identified as the best-performing architecture. For the final evaluation, the model was retrained on the complete training dataset and used to generate predictions on the test set. The results demonstrated an excellent alignment between the predicted and actual energy consumption values, indicating strong model generalization, stability, and forecasting accuracy.

5. FUTURE SCOPE OF RESEARCH

While this study demonstrates the effectiveness of deep learning models for hourly energy consumption forecasting using a synthetic dataset, several avenues for future research exist:

Integration with Real-World Data: Applying models to actual residential, commercial, or industrial datasets and incorporating external factors such as weather, holidays, and occupancy patterns to enhance prediction accuracy.

Advanced Deep Learning Architectures: Exploring hybrid models combining LSTM/GRU with CNNs, attention mechanisms, or Transformers, and implementing multi-step forecasting for extended horizons.

Hyperparameter Optimization: Systematic tuning of parameters such as sequence length, number of units, learning rate, and dropout using automated methods like Bayesian optimization or grid search to improve performance.

Smart Grid Deployment: Integrating models into real-time energy management systems for load balancing,

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peak load management, energy storage planning, and renewable integration.

Probabilistic Forecasting: Incorporating uncertainty quantification through techniques like Bayesian LSTM/GRU, Monte Carlo dropout, or quantile regression for risk-aware decision-making.

Cross-Region and Sector Studies: Validating model generalizability across regions, sectors, and energy systems, including transfer learning approaches.

Real-Time and Edge Deployment: Developing lightweight models for real-time prediction on edge devices or IoT-enabled meters for smart home and microgrid applications.

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