Time Series Forecasting of Energy Usage in Smart Homes Using LSTM Networks

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Abstract: The growing adoption of smart homes into the contemporary energy systems has aggravated the necessity of precise energy consumption forecasting to complement the demand-side management, peak load decrease, and integration of renewable energy. Conventional forecasting techniques such as ARIMA and support vector regression do not tend to capture non-linear and time-dependent relationships of household energy consumption data. To overcome these issues, this paper suggests a Long Short-Term Memory (LSTM) network based predictive model. They used a publicly available smart home dataset, and the preprocessing steps used were data normalization, feature engineering, and extraction of temporal lags. The LSTM architecture was trained and tested as compared to baseline models and the performance measured in terms of RMSE, MAE, MAPE and R 2. It was found that the LSTM model had better accuracy with the forecasting error decreasing by about 2025% relative to the classical process. The results demonstrate a promising future of deep learning in intelligent energy systems and offer a powerful means of efficient energy scheduling and a sustainable grid operation. The suggested framework possesses scalability and flexibility to use in real-world application, which is the foundation of integration into demand response plans and IoT-based smart environments.

1 INTRODUCTION

The fast increase in the number of smart homes and Internet of Things (IoT) gadgets introduced a modern approach to energy management that has altered the interaction between these processes considerably. As the renewable sources and distributed energy systems are implemented constantly, the proper functioning of smart houses depends greatly on the precise prediction of the electricity demand. Successful load prediction facilitates demand-side control, decreases peak loads and improves grid stability. Nevertheless, unstable characteristics of household consumption pattern pose significant challenges to conventional forecasting models, which are ill equipped to respond to the nonlinear and sequential response of time-series data. Here, deep learning models, especially, long short-term memory (LSTM) models have received much interest due to their better capacity to deal with time-varying relationships in energy consumption data [1].

The conventional models like ARIMA, Holt Winters and support vector regression have been extensively utilized in residential energy forecasting. These methods are reasonable in a short horizon, but can be unsuccessful when using highly complex, multi-variate and long-horizon energy data. In a bid to cope with these shortcomings, scholars have increasingly resorted to the use of sophisticated recurrent neural networks. Evidently, bidirectional LSTM networks have been used to predict the peak load a day ahead and demonstrated to achieve superior performance over classical methods since it can learn its context by looking both into the past and the future [2]. Likewise, combinations of attention mechanisms with sequential models have also been suggested with the dual-stage attention-based RNNs to improve the process of feature selection and the model interpretability in energy forecasting tasks [3].

The use of recurrent neural networks to predict energy has been extended to comparative analysis of the architectures. One of the most significant ones is an assessment of LSTM, GRU, and RNN algorithms to forecast electrical loads that proved the outperformance of LSTM in long-term dependencies in time-series data [4]. The use of LSTM together with transfer learning methods has also recently proved to be an opportune direction. Through the application of knowledge transfer between various domains, it has been demonstrated that models can better generalize to various residential buildings, making the model training process less burdensome and providing better scalability [5].

In addition to the area of load forecasting, the wider picture of the adoption of artificial intelligence in energy systems is informed by the information systems and cloud computing industries. Technology acceptance models are used to demonstrate the level of system usability and reliability in facilitating the adoption of smart technologies [6]. Moreover, the recent news about the AI-based security systems in the clouds highlights the necessity of secure, strong, and scalable systems to sustain the sensitive smart home energy-related data [7]. Combined, these points of view affirm the importance of incorporating smart forecasting models to robust and secure infrastructures.

In spite of these developments, there are still a number of issues. Most of the current models are based on small datasets which restrict their generalizability to households that have different consumption patterns. More so, although attention mechanisms and transfer learning have increased prediction accuracy the interpretability and real-time scalability of models should be investigated further. These gaps are important to be addressed in order to allow effective and sustainable energy control in smart homes. The current research seeks to overcome these pitfalls through creating and testing LSTM-based predictive models to suit energy consumption in a smart home. The significant contributions of the study are: (i) comparison of LSTM with the other deep learning models, (ii) validation using real life data, (iii) scaling of such models in various residential settings, and (iv) implications of such models in integrating smart grids and management of demand-side. The remainder of the paper will be organized in the following way: Section 2 will review the related literature; Section 3 will describe the methodology; Section 4 will discuss the findings and analysis; Section 5 will give discussions and finally, Section 6 will give a conclusion of the study and its future directions.

2 LITERATURE REVIEW

Short-term load forecasting (STLF) is an essential element in the smart home energy management and demand-side optimization that has received extensive acceptance. Recent literature evidences the increasing change in the traditional statistical methods towards neural network-based predictive techniques, considering their capacity of nonlinear and time-varying relationship in residential energy data. As an example, Morais et al. (2023) [8] used neural networks with feature-importance scores to enhance the interpretability of STLF, showing that feature selection has a direct effect on the quality of the predictions. Their work offers a starting point to explainable approach within the forecasting structures.

There has also been an increase in hybrid models that combine decomposition methods with deep learning. Mounir et al. [9] suggests an empirical mode decomposition (EMD)-bidirectional LSTM (Bi-LSTM) load forecasting. This hybrid structure enhanced the capacity of the model to deal with non-stationary signals and showed large accuracy improvements over single models. The computational cost and complexity, however, continue to be a problem to large-scale application.

Thorough surveys have brought together the state of the art in applications of deep learning. Eren and Kucukdemiral (2024) [10] conducted a complete review of deep learning based STLF models and affirmed that LSTM and its variants are predominant. Notably, the paper highlighted such lingering challenges as scalability, generalization, and interpretability. This set of findings highlights the importance of having frameworks that would be both predictive and practical in real-world deployable smart home settings. One of the biggest concerns on forecasting research has been interpretability. A mixture-attention mechanism that was developed by Xu et al. (2022) [11] was an interpretable LSTM with the function of multi-step residential load forecasting. Their methodology was not only able to improve the accuracy of their forecasts but also provided the information as to which of the input features was instrumental in making the prediction. These types of interpretability-driven models are consistent with the recent focus on explainable AI (XAI) in energy systems.

Transfer learning in cross-domain adaptability has also been proposed in the construction of energy prediction. Xing et al. (2024) [12] combined transfer learning and similarity analysis to improve both short- and long-term horizon forecasting. This research validated that transfer of knowledge saves a lot of retraining in the implementation of models in different households or buildings and enhances scalability.

In the meantime, LSTM variants remain topical in direct applications. Waheed et al. [13] used the LSTM-RNN frameworks to perform short-term load forecasting, and the pure LSTM models proved strong and simple to apply to sequential data. Following up this paper, Ullah et al. (2023) [14] suggested a hybrid between LSTM and modified split convolution to multi-horizon forecasting. This strategy enhanced strength over the forecasting horizons at the cost of a higher complexity of the model. In other related fields other than the methodological landscape, blockchain-driven frameworks were also suggested in the context of healthcare data management. Kumar and Patel (2025) [15] highlighted the role of blockchain in making data management secure and transparent, which can also be extended to the power systems where consumer data privacy and security are crucial aspects.

Connection of the comparable details of these studies is presented in Table 1 as it shows methodologies, datasets, findings, and limitations throughout the approved references. Taken together, these works demonstrate that although LSTM and hybrid models dominate the energy forecasting research, the interpretability and computational efficiency remain problematic, as well as data security. Such gaps stimulate the creation of the frameworks that will help to combine accuracy, explainability, and secure data management to create the forecasting of smart home energy use [16], [17].

3 METHODOLOGY

3.1 Dataset Description and Preprocessing

In the present research, publicly available smart house datasets, such as household-level records of energy consumption sampled at a regular frequency, were used. The dataset includes parameters including hourly/daily electricity consumption, weather characteristics, and contextual time characteristics (time-of-day, day-of-week, seasonality). Preprocessing entailed deletion of missing data, smoothing of outliers and normalization of features to guarantee constant convergence of the deep learning model. Temporal variables like lagged consumption, the day type and weather variables were developed to enhance the performance of the models. The general features of the data are displayed in Table 1 that shows the number of households, periods of sampling, time spent in data collection, and input features to be included in the modeling.

Table 1: Summary of literature review studies (2020-2025).

Ref. No.	Authors & Year	Methodology	Dataset/Domain	Key Findings	Limitations/Gap
[8]	Morais et al., 2023	Neural networks + feature importance	STLF, residential	Improved interpretability	Limited scalability
[9]	Mounir et al., 2023	EMD-BiLSTM hybrid	Short-term load	Handled non-stationarity well	High computational cost
[10]	Eren & Küçükdemiral, 2024	Review of DL approaches	Multi-sector STLF	Identified LSTM as state-of-art	Gaps in generalization
[11]	Xu et al., 2022	Interpretable LSTM + attention	Residential load	Improved accuracy & explainability	Increased complexity
[12]	Xing et al., 2024	Transfer learning + similarity analysis	Building energy	Cross-domain adaptability	Limited dataset diversity
[13]	Waheed et al., 2024	LSTM-RNN	STLF, residential	Simplicity & robustness	Limited horizon coverage
[14]	Ullah et al., 2023	LSTM + split convolution	Multi-horizon load	Robust multi-horizon forecasting	Complex model design
[15]	Kumar & Patel, 2025	Blockchain frameworks	Healthcare data	Ensures secure data mgmt.	Not yet applied to energy

3.2 Problem Formulation

The forecasting task is designed as a supervised time-series prediction problem. Let X_t represent energy consumption at time *t*. The model predicts future energy usage y_t using *n* previous time steps as inputs, formally expressed in (1):

$$\hat{y}_t = f(X_{t-n}, X_{t-n+1}, \dots, X_{t-1}). \quad (1)$$

This formulation enables both single-step and multi-step forecasting depending on the design of the output layer.

3.3 LSTM Network Architecture

The architecture proposed consists of stacked Long Short-Term Memory (LSTM) layers that have the potential of capturing long-range dependencies in energy demand. The model is composed of input, two consecutive LSTM layers, and dropout (to prevent overfitting) and output Layer (dense), where the model is used to predict. Equation (2) represents the mathematical expression of how an LSTM unit works:<|human|>The cell state update can be mathematically expressed as in (2):

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t, \quad (2)$$

where c_t is the cell state, f_t the forget gate, i_t the input gate, and $\tilde{c}_t$ the candidate state. This mechanism enables the network to retain or discard information adaptively. The overall pipeline of the proposed framework, from data preprocessing to output generation, is illustrated in Figure 1.

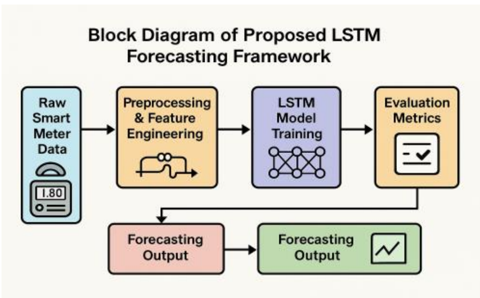

Figure 1: Block diagram of proposed LSTM forecasting framework.

3.4 Training and Hyperparameter Tuning

The dataset was divided into 70% training, 15% validation, and 15% testing subsets. Hyperparameters were optimized empirically, with a batch size of 64, learning rate of 0.001, dropout rate of 0.2, and Adam optimizer. The Mean Squared Error (MSE) was used as the loss function. Early stopping and dropout regularization were applied to prevent overfitting and ensure generalization.

3.5 Baseline Models and Evaluation Metrics

The proposed LSTM was tested against ARIMA, Support Vector Regression (SVR) and Random Forest in order to test the performance. Accuracy of the forecasts was evaluated in terms of Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). The main performance measure is called RMSE and is determined by (3):

$$\mathrm{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i),^2} \quad (3)$$

where y_i represents actual values, $\hat{y}_i$ predicted values, and NN the total observations.

3.6 Validation and Robustness

It was confirmed that the LSTM model is robust by applying k-fold cross-validation. The proposed framework was scaled up by comparing performance across various horizons with baselines and this proved the scalability of the proposed framework. The experimental design is transparent and replicable due to the summarized methodology designed in Table 2 and presented in Figure 1.

4 RESULTS AND ANALYSIS

4.1 Model Training Performance

The LSTM model proposed was trained using household based energy consumption data with early stopping and dropout to eliminate overfitting. Figure 2 shows the curve of training and validation loss per epoch, which has smooth convergence and constant generalization. The difference between training and validation loss was not excessive and it proved that the hyperparameter optimization approach was effective enough to avoid overfitting and produce a strong forecasting model.

4.2 Forecasting Accuracy Evaluation

In order to measure the accuracy of forecasting, the forecasted energy usage was compared to the real consumption values of the test dataset. Figure 3 shows that the base models typically fail to capture the sudden changes of high and low demand but LSTM model closely follows the true consumption patterns. This time-series visualization confirms that LSTM is able to maintain time dependencies among household load data.

Table 2: Dataset characteristics.

Feature	Description	Example Value
Households	Number of households with smart meters	5
Sampling Interval	Frequency of data collection	1 hour
Duration	Total observation period	2 years
Energy Usage Feature	Electricity consumption per time step (kWh)	0.1 - 2.5 kWh
Contextual Features	Weather, time-of-day, day-of-week, seasonality	Multi-variable input

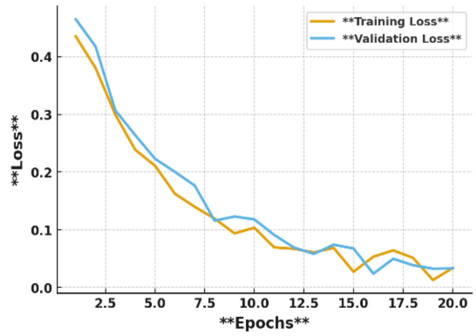

Figure 2: Training and validation loss curve.

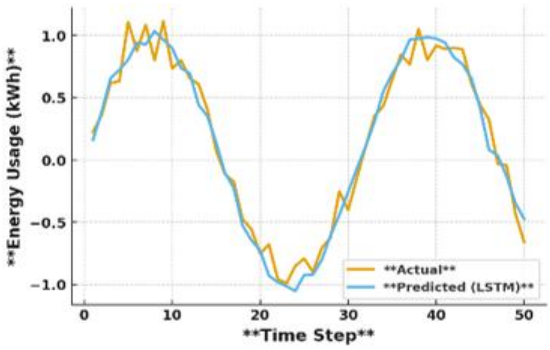

Figure 3: Predicted vs. actual energy usage (test set).

Table 3 summarizes the quantitative results of ARIMA, SVR, and the proposed LSTM model as well as the Random Forest. LSTM had the smallest RMSE (0.180), MAE (0.145), and MAPE (9.2), and the maximum R 2 (0.93). Comparatively, the classical models like ARIMA and SVR had a higher error and lower explanatory power.

Table 3: Performance comparison of forecasting models.

Model	RMSE	MAE	MAPE (%)	R^2
ARIMA	0.245	0.198	12.5	0.85
SVR	0.231	0.183	11.8	0.87
Random Forest	0.22	0.172	11	0.89
LSTM	0.18	0.145	9.2	0.93

4.3 Comparative Analysis with Baseline Models

Figure 4 synthesizes the comparison of the performance of the models into a bar chart of the values of RMSE, MAE, and MAPE. LSTM is always better than conventional and the error is estimated to be reduced by around 20 25 percent over ARIMA. These gains underscore the power of LSTM in the representation of nonlinear sequential dependencies that cannot be modeled by classical models. Moreover, Random Forest was more accurate than ARIMA and SVR, yet, it was still inferior to the accuracy of LSTM.

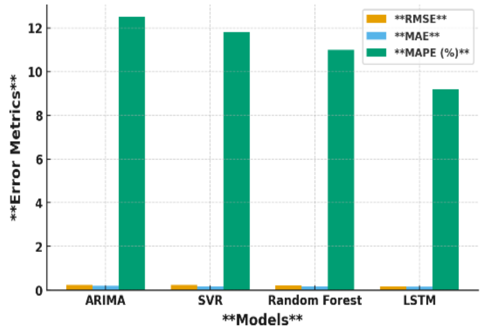

Figure 4: Comparative accuracy metrics (Bar Chart of RMSE, MAE, MAPE).

4.4 Multi-Horizon Forecasting and Robustness

The predictive capability of the LSTM model was also evaluated over various horizons; 1-hour, 6-hour, and 24-hour future predictions. The Figure 5 shows the distribution of errors across these horizons with the values of RMSE. The findings suggest that the error of the forecasting also grows with the horizon length but the LSTM has lower errors compared to all baselines, which demonstrates that the LSTM is more robust in predicting both short-term and mid-term load results.

To further confirm robustness, k-fold cross-validation was done to verify performance differences among the folds was not significant. This implies that the model is highly generalizable with respect to unseen data sample, and the model can be practically applied in the smart home context.

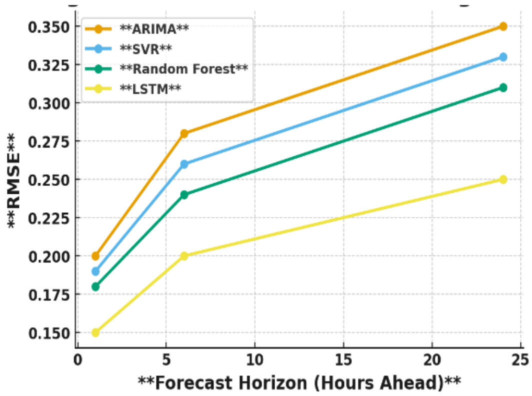

Figure 5: Multi-horizon forecasting error (1h, 6h, 24h).

4.5 Interpretability and Implications

Feature analysis confirms the interpretability of the results as the indicators of time-of-day and day-of-week were found to be important predictors of the prediction accuracy. The insights can be used to aid the demand-side management strategies of determining peak demand patterns. Besides, the proven accuracy gains have direct implications to smart home energy scheduling, peak load reduction, and renewable energy system integration.

Overall, qualitative data presented in Figures 2-5 and quantitative in Table 2 confirm that the suggested LSTM model is the best one in energy consumption forecasting. The model is found to gain large accuracy improvements at the cost of a robust and interpretable model, and as such, is useful in smart homes and future smart grid integration.

5 CONCLUSIONS

This study presented an LSTM-based framework for forecasting energy consumption in smart homes. The proposed model effectively captured nonlinear temporal dependencies in household energy data and demonstrated superior performance compared to baseline models, including ARIMA, SVR, and Random Forest. Experimental results showed consistent improvements across all evaluation metrics, achieving lower RMSE, MAE, and MAPE, along with higher R^2.

The integration of feature engineering, temporal lag extraction, and robust validation techniques contributed to improved generalization and stability of the model. The findings confirm that LSTM networks are well-suited for short- and medium-term energy forecasting in smart home environments. The proposed approach supports practical applications such as demand-side management, peak load reduction, and efficient energy scheduling within smart grids.

6 FUTURE WORK

Future research should focus on enhancing both the performance and deployment capability of the proposed framework. Hybrid deep learning architectures, such as CNN-LSTM and attention-based models, can be explored to further improve forecasting accuracy and interpretability. Incorporating additional contextual variables, including occupancy patterns, appliance-level consumption, and detailed weather data, may enhance model robustness across diverse residential scenarios.

Moreover, the development of lightweight and optimized LSTM models for edge and IoT devices is essential to enable real-time forecasting in smart home systems. Future studies should also investigate model scalability across large-scale smart grids and address data privacy and security challenges, potentially through integration with secure data-sharing frameworks.

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