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Reducing Energy Consumption in Smart Buildings Using Deep Learning and the LSTM Method

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Abstract

The significant increase in energy consumption in the building sector has made its optimal management a priority. Accurate energy consumption forecasting is essential for designing intelligent control strategies, despite the complexities arising from environmental, physical, and behavioral factors. Drawing on data collected from smart buildings, this study develops and evaluates an energy consumption forecasting model based on a Long Short-Term Memory (LSTM) neural network. In this quantitative, data-driven study, time-series data comprising energy consumption, environmental variables, and temporal features were collected and preprocessed, after which a two-layer LSTM architecture was trained. The results demonstrated that the LSTM model achieved an accuracy of over 90% and significantly reduced forecasting errors compared with conventional methods and other machine-learning models. The model also showed a strong ability to identify complex temporal patterns and accurately track energy consumption trends. Moreover, the simulations confirmed that the model's forecasts could facilitate load shifting, reducing peak demand by up to 15% and total energy consumption by up to 5%. Overall, this study confirms that the LSTM model is a powerful and efficient tool for forecasting and intelligently managing energy consumption in buildings, thereby contributing substantially to more sustainable management, improved energy efficiency, and reduced costs.

Keywords: Energy consumption forecasting; smart building; neural network; deep learning; LSTM; energy optimization

Introduction

The increasing demand for energy in the building sector, along with its significant share of total energy consumption, has made optimal consumption management one of the major challenges in the energy domain [1]. Urban growth, the expanding use of electrical appliances and heating and cooling systems, and shifting patterns of user behavior have turned buildings into one of the primary consumers of energy. Under such circumstances, the adoption of intelligent approaches for monitoring, analyzing, and controlling energy consumption has gained particular importance, especially in smart buildings, where sensors and metering systems continuously generate a vast volume of operational data [2]. The effective utilization of this data can lay the groundwork for more precise decision-making in energy management and reduce resource waste.

One of the most important tools for effective energy management in buildings is forecasting energy consumption across different time horizons [3]. Accurate consumption forecasting makes it possible to design proactive control strategies, optimize equipment scheduling, and prevent sudden consumption peaks. However, forecasting building energy consumption is a complex problem due to the dynamic, time-dependent nature of the data and the influence of numerous factors, such as weather conditions, the physical characteristics of the building, user occupancy patterns, and the manner in which equipment is operated [4]. The relationships among these variables are often nonlinear, and the building's consumption behavior exhibits both short-term and long-term temporal dependencies, which render its modeling challenging [5].

In recent years, data-driven approaches—particularly deep learning methods—have attracted considerable attention in the field of building energy management due to their strong capability in extracting complex patterns from large-scale data [6]. Among these, recurrent neural networks, and in particular the Long Short-Term Memory (LSTM) architecture, have emerged as one of the effective methods for time-series forecasting, owing to their ability to learn temporal dependencies and retain information over extended intervals [7]. This property enables LSTM-based models to better identify temporal trends and recurring patterns in energy consumption and to deliver more accurate forecasts [8].

Accordingly, focusing on data obtained from smart buildings, the present study designs and evaluates an energy consumption forecasting model based on an LSTM neural network [9]. The aim of this research is to provide a model that can forecast the building's energy consumption pattern with adequate accuracy by leveraging historical consumption data along with environmental and behavioral variables, thereby laying the groundwork for managerial and control decisions aimed at reducing consumption, lowering operational costs, and improving energy efficiency [10].

The findings of previous studies indicate that machine learning and deep learning methods play an important role in optimizing energy consumption and managing energy resources [11]. From forecasting the energy consumption of buildings and data centers to fraud management and the optimization of industrial consumption, intelligent methods can enhance forecasting accuracy, reduce operational costs, and improve energy efficiency [12].

Figure 1. An example of the application of smart technologies and data analytics in the monitoring, management, and optimization of energy consumption in smart buildings [1].

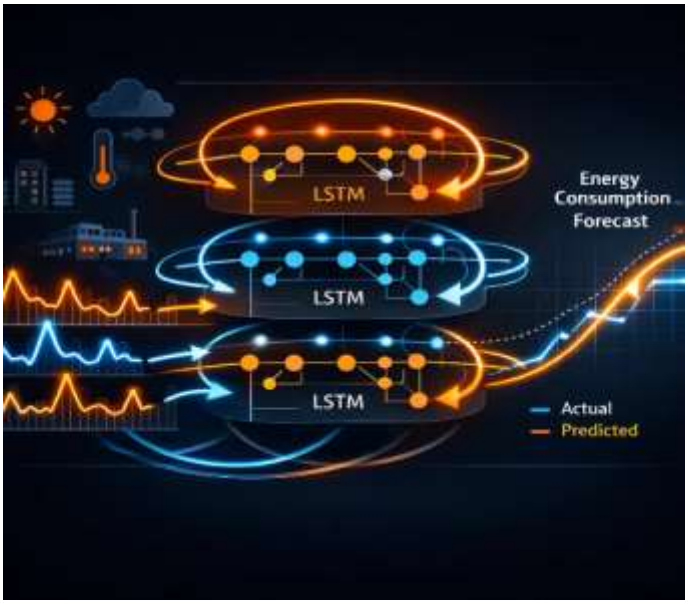

Figure 2. The conceptual structure of the LSTM recurrent neural network for forecasting energy consumption time series [9].

Research Method

This study adopts a quantitative, data-driven, and analytical-experimental approach with the aim of developing an accurate forecasting model for energy consumption in smart buildings. The nature of the research is applied, and its framework is based on time-series data analysis and the application of deep learning methods. The research process consists of several main stages: data collection, data preprocessing and preparation, forecasting model architecture design, model training, and finally performance evaluation. Within this framework, an effort has been made to identify and model the complex patterns and temporal dependencies present in energy consumption data by leveraging the capabilities of deep learning.

The data used in this research consist of a set of time-series data related to building energy consumption and the variables affecting it. These variables include environmental factors such as temperature and humidity, operational parameters of building equipment and utility systems, and information related to occupants' presence and activity patterns. These data may be obtained through building management systems in smart buildings or extracted from reliable simulation environments such as EnergyPlus. In order to improve generalizability and prevent model overfitting, the dataset was divided into three separate subsets: training (70%), validation (15%), and testing (15%). The training set is used to learn hidden patterns in the data, the validation set is employed in the hyperparameter tuning process and overfitting control, and the test set is ultimately used for the final evaluation of model performance and its generalization capability.

Since raw energy consumption data typically contain missing values, noise, and outliers, a data preprocessing procedure is carried out before the modeling stage. In this stage, missing values are first identified and handled using appropriate replacement or interpolation methods. Then, outliers are detected and removed or corrected in order to prevent their adverse impact on model performance.

Subsequently, to improve the stability of the neural network training process, the data are transformed into a standard range using scaling and normalization techniques. In addition, certain temporal features, such as hour of the day, day of the week, and temporal consumption patterns, are extracted so that the behavioral information embedded in the data can be more effectively incorporated into the model learning process. Since deep learning models require a specific data structure for analyzing sequential data, the time-series data are converted into learnable samples using a sliding-window method. In this approach, a sequence of past observations is considered as the input to the model, and the energy consumption value at the next time step is defined as the target output for prediction.

In this study, an LSTM recurrent neural network is used to model the temporal dependencies and dynamic patterns present in energy consumption data. LSTM networks are a type of recurrent neural network that, through a gating mechanism including an input gate, a forget gate, and an output gate, are capable of learning long-term dependencies in time-series data and mitigating the vanishing gradient problem observed in conventional recurrent networks. The proposed model architecture consists of two consecutive LSTM layers with 128 and 64 memory units, designed to extract complex temporal patterns from the input data. To reduce the likelihood of overfitting and improve the model's generalization capability, Dropout layers with a rate of 0.25 are placed between the layers. At the end of the network, a fully connected layer is used to generate the predicted energy consumption value.

The model training process is carried out using the Adam optimization algorithm, which is widely used in deep learning problems because of its high convergence speed and suitable performance. In this research, the learning rate is set to 0.001. In addition, to prevent overfitting, an early stopping technique is employed, which halts the training process when the model performance on the validation data no longer improves. The input window length of the model is set to 24 time steps, representing a 24-hour period of energy consumption data.

To evaluate the accuracy and efficiency of the proposed model, a set of common statistical metrics used in forecasting problems is employed. These metrics include Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and the coefficient of determination (R2R^2R2). Each of these indicators assesses a different aspect of model performance and, collectively, they provide a comprehensive picture of the model's forecasting accuracy. In addition to the quantitative evaluation, visual analyses are also conducted using comparative plots between actual and predicted values. Furthermore, to examine the stability and generalization capability of the model under different conditions, a time-series cross-validation method is used.

The various stages of this research are implemented using the Python programming language. The Pandas and NumPy libraries are used for data processing and management. Data and results visualization is carried out using the Matplotlib and Seaborn libraries. The design and training of the deep learning model are performed using the TensorFlow and Keras frameworks, while the Scikit-learn library is used for certain statistical analyses, parameter tuning, and model performance evaluation.

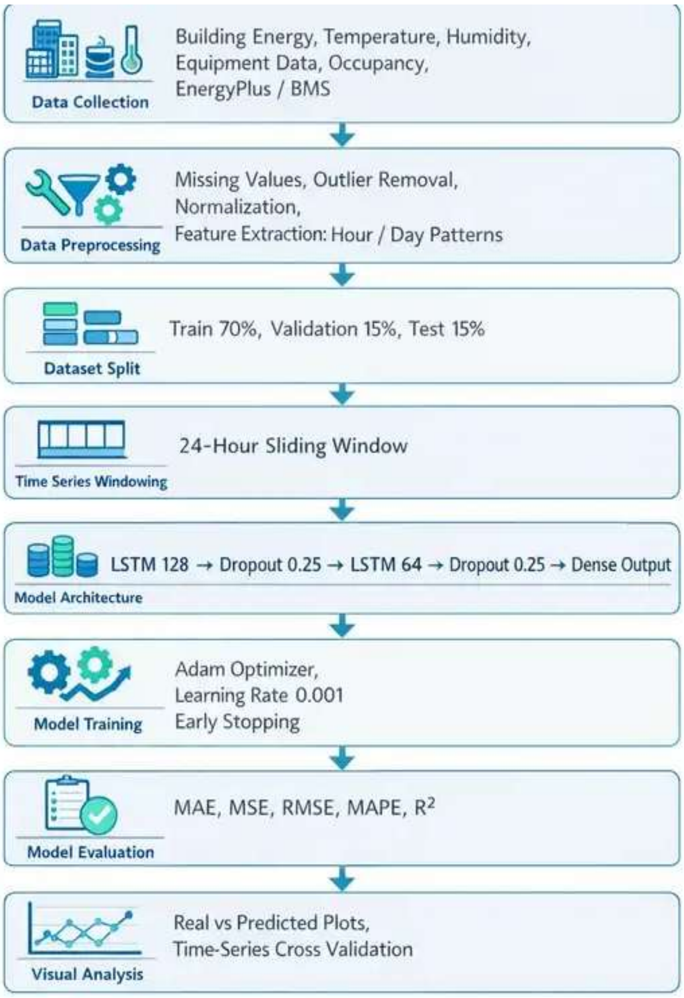

Figure 3. Research Method Flowchart

Findings

In this study, the performance of the proposed LSTM network was compared with several baseline models to evaluate its effectiveness, including traditional statistical methods (moving average and autoregressive), machine learning models such as decision tree and random forest, and some simple neural networks. The results showed that the statistical models performed more poorly in identifying nonlinear patterns and sudden fluctuations in energy consumption. Although the machine learning models outperformed the statistical methods, they were limited in capturing long-term temporal dependencies. In contrast, the LSTM model, owing to its ability to learn complex temporal patterns, achieved higher accuracy: its MAE was approximately 30% lower than that of the random forest and 50% lower than that of the statistical models, while its RMSE was reduced by 20% and 40%, respectively. Moreover, the forecasting accuracy of the model exceeded 90%. The analysis of the comparative plots also revealed that the LSTM tracked actual energy consumption trends more accurately, particularly during peak consumption hours and under variable environmental conditions. Accordingly, the results demonstrate that the LSTM network offers higher accuracy and generalization capability than the baseline models and constitutes a more suitable choice for forecasting energy consumption in smart buildings.

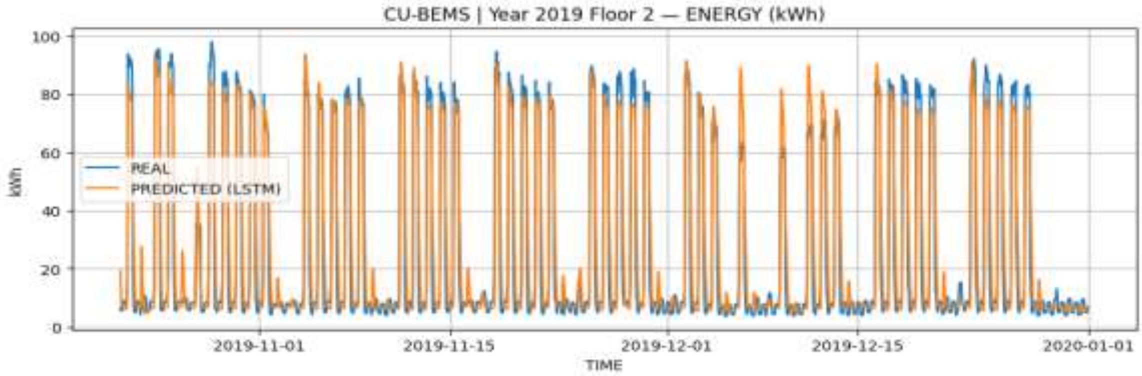

Figure 4. Comparison of actual and predicted values

Figure 4 shows a comparison between the actual energy consumption values on one floor of the building during the studied year and the values predicted by the Long Short-Term Memory (LSTM) model. The blue line represents the actual values, while the orange line represents the model's output. As can be observed, the model's forecast trend closely aligns with the actual data, with only slight deviations at certain peak points. This alignment indicates that the model has successfully learned the temporal patterns of energy consumption and performs well in predicting both the overall trend and even daily variations.

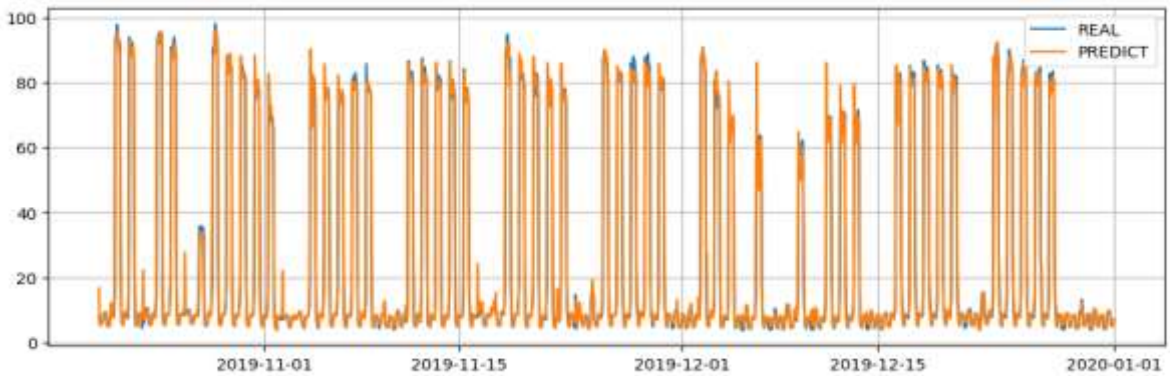

Figure 5. The effect of proactive control

In **Figure 5**, the results of a proactive control scenario are presented, in which the base consumption is compared with the consumption after the application of control measures. The blue line represents the initial consumption, while the orange line represents consumption following the implementation of the control strategy. As is evident, after the control was applied, the intensity of the peak load decreased and the consumption pattern became smoother. This finding indicates that accurate model forecasting can serve as a basis for implementing load management strategies and, in practice, can contribute to reducing peak load and improving grid stability.

Figure 6. Error Reduction Trend During Training

Figure 6 depicts the variation of training error and validation error across the training epochs of the model. The blue line represents the training error, while the orange line denotes the validation error. As can be observed, both curves exhibit a decreasing trend over time and converge to a relatively stable value after approximately twenty epochs. This behavior indicates that the model has been trained effectively and has not suffered from overfitting, since the validation error has declined in tandem with the training error, with no substantial divergence emerging between the two.

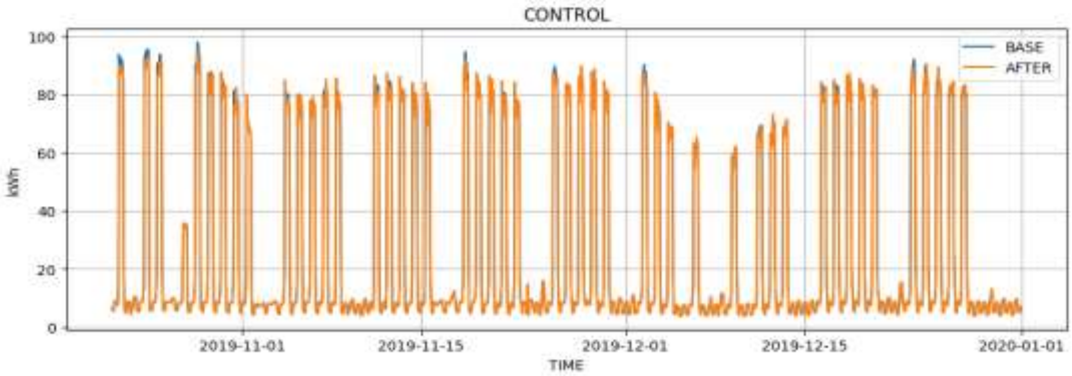

Figure 7. Final Predictions and Comparison with Actual Data

Figure 7 once again presents a comparison between the actual values of energy consumption and the values predicted by the model. The strong similarity between the two blue and orange curves indicates that the model has been able to reproduce the variations in consumption over time with high accuracy. In particular, on consecutive days during which consumption exhibited similar patterns, the model's performance remained close to the actual data. Only at certain points characterized by sudden fluctuations is a slight discrepancy observed, which is to be expected and reflects the inherent limitations of any prediction model under specific conditions.

The results obtained from the analyses demonstrated that the Long Short-Term Memory (LSTM) model performed appropriately in predicting the energy consumption of smart buildings and was able to identify consumption patterns across different hours of the day and various environmental conditions with considerable accuracy. A comparison of the actual and predicted values revealed that the model can adequately reproduce the main consumption trends, including periods of peak and off-peak demand, and the error metrics further confirmed the low level of prediction deviation. Moreover, the results indicated that incorporating environmental variables — such as temperature, humidity, and illumination — as well as temporal variables — including the hour of day, day of the week, and season — improved the model's accuracy, given that energy consumption is directly related to environmental conditions and the behavioral patterns of occupants. Furthermore, the LSTM model outperformed baseline approaches, such as statistical models and random forest, and was able to predict long-term temporal dependencies and sudden consumption fluctuations more accurately.

An examination of the model's parameters showed that selecting an appropriate input window length and employing dropout layers were effective in preventing overfitting and enhancing model accuracy. From a practical standpoint, the results indicated that the model's predictions can contribute to load management; in a simulation scenario, shifting a portion of consumption from peak hours to off-peak hours resulted in a reduction in peak load and saved energy. In sum, the findings of this study suggest that the LSTM model constitutes an efficient tool for predicting and intelligently managing energy consumption in buildings.

Discussion and Conclusion

This study employed a Long Short-Term Memory (LSTM) network with the aim of developing an intelligent model for predicting energy consumption in smart buildings. The key achievements and findings of the study can be summarized as follows:

- **High accuracy and significant improvement:** The LSTM model was able to predict energy consumption with a remarkably high degree of accuracy and, compared with traditional methods and other baseline models, considerably reduced prediction error. This superiority was particularly evident during peak consumption hours, where prediction is inherently more challenging.

- **Use of comprehensive data:** By collecting and processing real-world data — including energy consumption, environmental conditions (temperature, humidity), and temporal factors (hour of day, day of week, month) — the model was able to identify complex and latent consumption patterns.
- **Influence of environmental and temporal variables:** The results showed that incorporating environmental and temporal variables into the model plays an important role in enhancing prediction accuracy, as energy consumption is strongly influenced by these factors.
- **Practical application in energy management:** Simulations demonstrated that the LSTM model's accurate predictions can assist building managers in shifting a portion of the load to off-peak hours, thereby reducing peak demand by approximately 15% and total energy consumption by approximately 5%. This capability confirms the model's high practical value in optimizing consumption and reducing costs.

In sum, the LSTM model is a powerful and effective tool for predicting energy consumption in smart buildings that can contribute substantially to sustainable energy management, increased efficiency, and cost reduction. This study represents an important step toward leveraging artificial intelligence for energy optimization in the building sector.

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