Electricity consumption forecasting in smart homes with LSTM networks

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Abstract

The work aims to enhance the efficiency of electricity consumption management in smart homes through a forecasting model based on a Long Short-Term Memory (LSTM) neural network, which significantly improves prediction accuracy by capturing long-term dependencies in time series data. A formalized representation of the system's structure and mathematical relations has been provided to support comprehensive data analysis and parameter tuning. An advanced forecasting algorithm has been designed, incorporating historical electricity usage and external factors such as weather conditions and time of day. A dedicated software solution has been implemented using LSTM-based deep learning architecture, combined with data normalization and encoding of temporal features. Additionally, a data acquisition and processing subsystem has been integrated with smart energy meters to facilitate real-time analytics. The model was validated using both real-world and synthetic datasets, confirming its high forecasting performance. A systematic development approach ensured component modularity, scalability, and robust data protection. The system was developed using Python, TensorFlow, and Keras, with deployment capabilities via modern API tools, ensuring adaptability to dynamic environments and seamless integration with other smart infrastructure. Evaluation results demonstrate that the trained model delivers accurate forecasts with minimal deviation from actual consumption values. Functional testing confirmed the correctness of computations and algorithmic stability. Future research directions include refining hyperparameter optimization methods for the LSTM model, expanding the set of input variables, and integrating the system with automated energy management platforms. These steps will contribute to more efficient energy use, cost reduction, and enhanced reliability of electricity supply under unstable grid conditions.

Keywords

energy forecasting; machine learning; time series analysis; deep learning

1. Introduction

The growing demand for electricity driven by industrialisation and urbanisation has led to a significant increase in global energy consumption. In many countries, including the European Union and Ukraine, the residential sector consumes approximately 40% of the total electricity [1]. This creates the need to implement effective energy management strategies to optimise and reduce losses.

In Ukraine, this problem is particularly relevant in a time of war, when the energy infrastructure is under constant attack, making it difficult to maintain a stable electricity supply. To ensure efficient allocation of resources, accurate forecasts of electricity consumption are needed to enable adaptive load management in the grid and optimise outage schedules.

Long Short-Term Memory (LSTM) neural networks represent one of the most effective approaches for forecasting electricity consumption. This type of recurrent neural network is able to effectively analyse time series, store long-term dependencies, and identify hidden patterns in data [2]. Integrating data from smart meters with external variables such as weather conditions and consumer behaviour can significantly improve the accuracy of forecasts [3].

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The development of smart energy systems is one of the key areas of Ukraine's energy security policy. The use of predictive models based on LSTM can help not only reduce the load on the power system, but also increase the energy efficiency of smart homes. This, in turn, creates opportunities for rational resource allocation and minimisation of the negative consequences of emergency outages.

The study aims to automate the process of forecasting electricity consumption in smart homes using LSTM neural networks, aimed at improving the accuracy of forecasting and efficient energy management in conditions of unstable power supply.

2. Related Works

Forecasting electricity consumption in smart homes is an important task that requires efficient time series analysis methods. In modern research, both traditional statistical methods and approaches based on deep learning, in particular LSTM networks, are widely used.

Studies [4-6] explore the application of classical forecasting methods, such as ARIMA, exponential smoothing, and autoregressive models. It should be noted that although these methods are interpretable and suitable for short-term forecasting, they have limitations when processing complex patterns in time series. This highlights the necessity of employing neural network approaches that more effectively capture nonlinear dependencies in the data.

Studies [7-9] focus on leveraging LSTM networks for electricity consumption prediction. The authors demonstrate the ability of LSTMs to learn long-term dependencies and adapt to changes in energy consumption. Different approaches to tuning LSTM hyperparameters are also considered, including variations in the number of neurons in layers, learning rates, and the use of regularisation mechanisms [10]. This provides a clear rationale for selecting the neural network architecture for the study and determine the parameters of its tuning.

Special attention in the literature is paid to the impact of external factors on electricity consumption forecasting. Publications [11, 12] investigate how seasonal and market factors affect forecasting accuracy. Integration of additional variables into models increases their adaptability to real operating conditions. These approaches have also been employed in studies focused on enhancing energy efficiency and optimizing resource management systems, underscoring the need for a comprehensive strategy in electricity forecasting and demand regulation [13].

Papers [14 - 16] analyse approaches to optimising LSTM networks using various learning and regularisation methods. In particular, the authors investigate the effectiveness of the Adam and RMSprop algorithms for updating the weighting coefficients, and assess the impact of regularisation parameters (Dropout, L1/L2 normalisation) on the generalisation ability of the model. This allows for a well-grounded selection of the neural network architecture and facilitates optimal hyperparameter tuning.

Notably, significant attention has been given to hybrid approaches that integrate LSTM with other models, such as CNN (convolutional neural networks) and GRU (smoothed recurrent units) [17-22]. The authors of these studies show that combined approaches can improve forecasting accuracy by combining the advantages of different neural network architectures. However, this paper prioritizes LSTM networks due to their effectiveness in handling time series data without introducing additional complexity through hybrid models.

Thus, the analysis of recent studies shows that traditional statistical methods, while interpretable and effective for short-term forecasting, have significant limitations when handling complex nonlinear dependencies and long-term trends in electricity consumption. Hybrid approaches that combine LSTM with other neural network architectures demonstrate higher accuracy, but their implementation requires significant computing resources and complicates the setup process. At the same time, LSTM networks strike a balance between forecasting accuracy and computational efficiency, as they are able to learn long-term relationships, adapt to changes in data, and work well with time series. With this in mind, our research will develop an LSTM-based smart home electricity consumption forecasting model, with a focus on optimising hyperparameters and taking into account external factors to improve forecasting accuracy.

3. Materials and Methods

One of the most effective approaches to forecasting electricity consumption is to use models that take into account a wide range of factors, including historical data, weather conditions and time patterns. To achieve high accuracy, it is necessary to apply mathematical methods capable of processing large amounts of data and identifying complex nonlinear relationships between parameters.

Accordingly, the primary forecasting model utilized is the Long Short-Term Memory (LSTM) neural network, a type of recurrent neural network (RNN) that can take into account long-term dependencies in data. Unlike conventional neural networks, an RNN uses the outputs of previous elements to preserve the dependence between elements in a sequence. In classical RNNs, the state is transmitted as follows:

$$h_t = f(W_{xh}x_t + W_{hh}h_{t-1} + b_h), \tag{1}$$

where:

h_t– current hidden state,

x_t – current input,

W_{xh}, W_{hh} – weight matrices,

b_h – bias vector.

However, classical RNNs suffer from the problem of short-term memory, limiting their ability to capture long-range dependencies. LSTM networks address this issue by introducing memory cells and three main gating mechanisms [3].

The forget gate (f_t) determines which information should be discarded, allowing the model to adapt dynamically to new data:

$$f_t = \sigma\big(W_f \cdot [h_{t-1}, x_t] + b_f\big). \tag{2}$$

The input gate (i_t and $\tilde{C}_t$) regulates which new information should be stored in the memory cell, ensuring flexibility in capturing relevant features from the input:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i), \tag{3}$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C). \tag{4}$$

The output gate (o_t) controls the flow of information from the memory cell to the next stage, ensuring consistency between past and new data:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o). \tag{5}$$

The memory state is updated as follows:

$$C_t = f_t \cdot \mathrm{C}_{t-1} + i_t.\tilde{C}_t. \tag{6}$$

These mechanisms ensure that LSTMs can retain important information in time series by adapting to long-term dependencies.

This structure makes an LSTM network ideal for working with time series data, where each element in the sequence depends on previous values. The model can efficiently ‘remember’ important information and use it to predict future electricity consumption.

For the LSTM model to function correctly, careful data preparation is required to ensure consistency and accuracy of forecasts. The main stages of data preparation are resampling and normalisation, categorical feature coding, and data shifting for LSTM.

The first step in data processing is to aggregate values into time periods, such as a day or an hour, depending on the purpose of the analysis. After that, the data undergoes normalisation, which scales it to a limited range, which improves the efficiency and stability of the model.

The data contains information about days of the week and seasons that may affect consumption. Using a categorical variable coding method, such as One-Hot Encoding, allows the model to take these factors into account when making predictions.

One of the key aspects of preparing data for LSTM is to create time windows that allow the model to ‘see’ several previous values before the current one. This enables the model to learn temporal dependencies between past and future observations, which is critical for time series analysis.

To evaluate forecast performance, we use metrics that quantify the model's accuracy, namely the mean absolute error (MAE) and the mean square error (MSE).

Both metrics provide an accurate assessment of the forecast, allowing you to identify how well the model is performing and where potential improvements can be made.

4. Results

The electricity consumption forecasting system is based on a modular architecture that ensures a systematic approach to data processing, model training and optimisation, as well as forecast visualisation. This structure (Fig. 1) enables efficient task distribution, improving project maintainability, testing, and scalability.

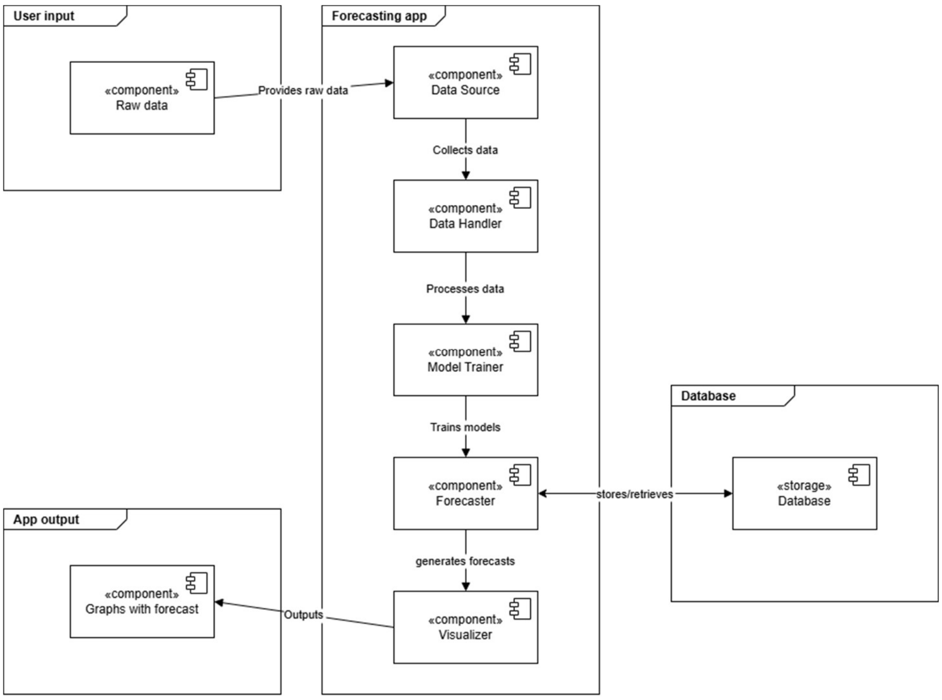

Figure 1: Structure of the electricity consumption forecasting system.

The key stages of the software's operation for developing and training the forecasting model include user interaction with the system at all stages of the process. This involves data uploading and processing, feature analysis, preparation of input parameters for LSTM, model building and training, hyperparameter tuning, as well as evaluation and visualization of results. The final stage is providing the user with the predicted electricity consumption values.

The system utilizes historical consumption data and climate data, which can be collected from relevant databases or meteorological services. Weather data exert a substantial influence on electricity consumption levels, so their integration enhances forecasting accuracy. Initial data processing is performed using Python libraries such as Pandas and NumPy. The processed data is stored in a database for further use in the forecasting module.

Data analysis is conducted using machine learning algorithms such as Random Forest, LSTM (Long Short-Term Memory), or Gradient Boosting. These methods are chosen for their effectiveness in handling time series data, which is crucial for electricity consumption forecasting.

The forecasting results are presented in the form of graphs and charts generated using libraries such as Matplotlib and Seaborn.

The system's modules interact in a coordinated manner to achieve the primary objective of accurate electricity consumption forecasting. The data processing module ensures proper data preparation for the model, which then passes it to the modeling module for training. After training, the visualization module allows users to assess the accuracy and quality of forecasts, which can then be used for real-time decision-making.

The system can be deployed from a workstation or a server machine running Docker for containerization. The benefits of using Docker include isolation, ensuring system stability and reproducibility, ease of deployment and application updates, as well as simplified scalability in case of increased workload. Figure 2 illustrates the organization of the project structure in Python within the PyCharm development environment.

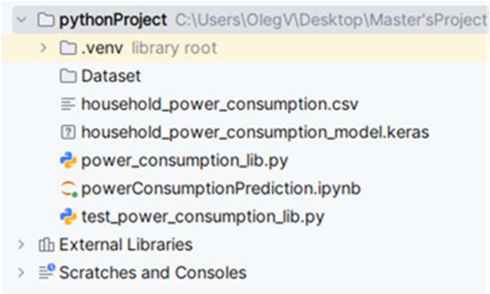

Figure 2: Project structure.

The system's functionality focuses on data processing and the creation of a forecast model based on neural networks.

The LSTM_df_generator function (Fig. 3) creates a dataframe for LSTM models by shifting the initial data by a specified number of rows before (rows_before) and after (rows_after) the current record. During the shift process, new columns with time stamps are created and merged into a single dataframe. After handling missing values and removing unnecessary columns, the function returns the prepared dataset for training.

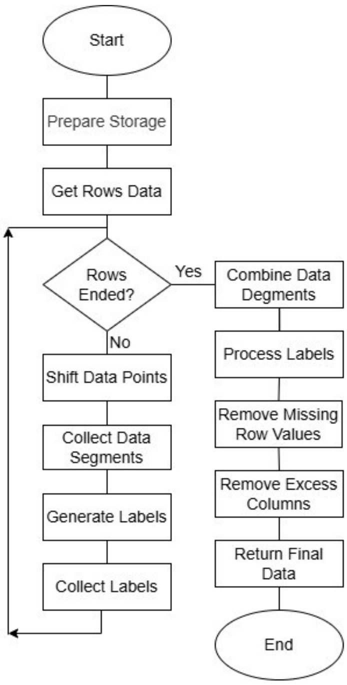

Figure 3: Flowchart of the LSTM_df_generator function.

The create_model function (Fig. 4) implements a deep neural network based on LSTM for time series analysis. The model architecture includes two LSTM layers with a specified number of neurons (units) and Dropout to prevent overfitting (dropout_rate). The model is concluded with a Dense output layer for prediction. Optimization is performed using the Adam algorithm with a specified learning rate (learning_rate), and compilation is done using the mean squared error metric.

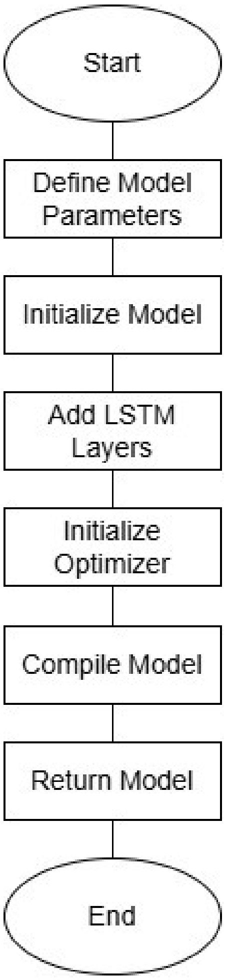

Figure 4: Flowchart of the create_model function.

To evaluate the effectiveness of the electricity consumption forecasting system, experiments were conducted using historical data on electricity consumption in buildings. The dataset, publicly available on GitHub, was selected due to frequent readings taken at one-minute intervals and its broad time coverage. The file size is approximately 150 MB, containing information on total active power, reactive power, voltage, current intensity, and data counts from three subsystems.

At the initial stage, data analysis was performed to examine the key patterns and check for missing values, which helped identify seasonal and time-based consumption patterns.

The forecasting model, based on the LSTM neural network, was trained and tested on the loaded data, with accuracy assessed using mean squared error (MSE). The results showed that the model is capable of providing accurate forecasts, minimizing deviations from actual values.

Additionally, the main functions of the system were tested to ensure the correctness of the core calculations and the stability of the algorithm. The obtained results confirm that the system can effectively forecast electricity consumption, which is valuable for optimizing electricity use in buildings.

Figure 5 presents graphs displaying the results of machine learning. The first graph illustrates the change in Mean Squared Error (MSE), while the second shows the dynamics of losses on training and validation data.

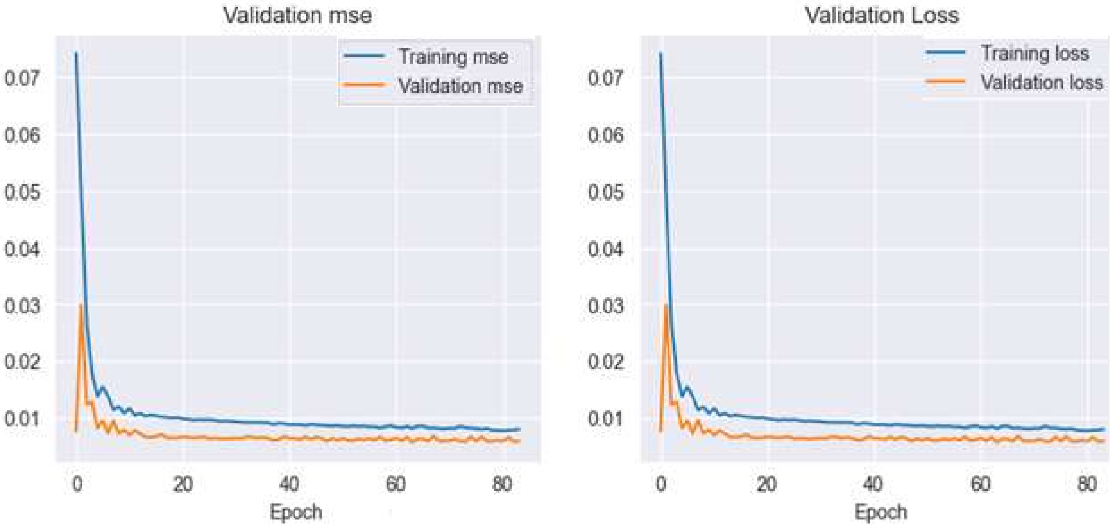

Figure 5: Mean Squared Error (MSE) and Loss graphs.

Figure 6 presents a comparison of the actual and forecasted values, which generally exhibit similar patterns with minor deviations. This chart is crucial for the project as it visually represents the forecasting results.

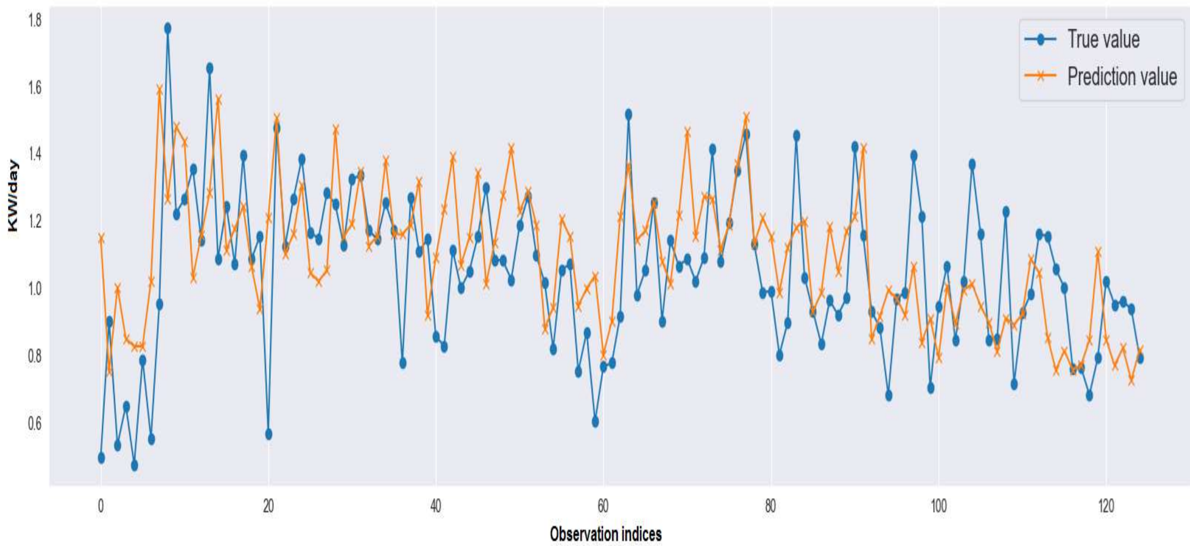

Figure 6: Comparison of actual and forecasted values.

5. Discussions

A comparison of the model's forecasts with the actual values (Table 1) showed that the model accurately captures the main patterns of electricity consumption. However, some discrepancies may be observed during periods of sharp fluctuations in consumption, caused by abnormal weather conditions or other external factors, indicating potential for improvement.

Table 1 also displays the results of the hyperparameter optimization for the forecasting model, such as the number of neurons, learning rate, and optimizer. Out of the 16 variants considered, the best configuration was found with 50 epochs, dropout rate: 0.1, learning rate: 0.01, optimizer: rmsprop, and 100 neurons, which provided the lowest error (Mean Score -0.0745). The search process took approximately 15 minutes, and the table includes only the most representative results. The Mean Score values are presented as negative because, in the Scikit-learn library (in Python) used for this study, some algorithms return errors with a negative sign for convenience in minimization— the closer the value is to zero, the better the model.

Table 1
Comparison of LSTM model hyperparameters and accuracy

Parameters	Mean Score	Std Dev
epochs: 50, dropout rate: 0.3, learning rate: 0.01, optimizer: rmsprop, number of neurons: 200	-0.0765	0.0210
epochs: 50, dropout rate: 0.3, learning rate: 0.01, optimizer: adamax, number of neurons: 50	-0.0753	0.0174
epochs: 50, dropout rate: 0.1, learning rate: 0.01, optimizer: rmsprop, number of neurons: 100	-0.0745	0.0192
epochs: 50, dropout rate: 0.3, learning rate: 0.1, optimizer: sgd, number of neurons: 50	-0.0803	0.0163
epochs: 50, dropout rate: 0.3, learning rate: 0.1, optimizer: rmsprop, number of neurons: 200	-1.0378	0.8965

Table 2 shows the performance evaluation of the selected method compared to other approaches. The data was obtained from real-world electricity consumption forecasting studies, particularly using LSTM and Random Forest for processing time series data [23-27]. The results illustrate the advantages of LSTM, which provides higher forecasting accuracy due to its ability to model long-term dependencies in time series data. This confirms the effectiveness of the developed system for accurate forecasting and energy consumption optimization.

Table 2
Performance evaluation of electricity consumption forecasting methods

Forecasting method	MAE	MSE	Forecast Accuracy (%)
Linear Regression	0.145	0.035	84.7
Random Forest	0.120	0.025	89.2
Bi-directional LSTM	0.078	0.011	96.5
Developed System (LSTM)	0.072	0.009	97.8

The obtained results indicate that the proposed forecasting system can be effectively applied to managing power consumption in buildings. The use of such forecasts helps reduce electricity costs and ensures the rational use of resources.

Although the LSTM method is well-established and frequently utilized in time series forecasting, this study offers a targeted adaptation of the model for the specific needs of intelligent energy consumption prediction in smart homes operating under unstable energy conditions, such as those currently experienced in Ukraine. The forecasting system was designed with a modular architecture that enables flexibility, scalability, and integration into smart energy management platforms. To improve prediction accuracy, the model incorporates both behavioral time features and external climate variables, recognizing their substantial impact on household energy use. While the dataset used for training consists of historical residential energy consumption records, it reflects typical usage patterns that remain relevant for contemporary systems. This allows the model to be trained under stable conditions while being structurally and functionally suited to operate in volatile energy environments. Moreover, the LSTM model was carefully optimized through hyperparameter tuning and empirically evaluated against alternative approaches such as Random Forest and BiLSTM. The resulting system demonstrates high predictive accuracy and robustness, making it applicable to modern smart grid contexts. Thus, the research contributes by aligning proven machine learning methods with present-day challenges, offering practical insights and reinforcing the role of data-driven approaches in energy resilience.

6. Conclusions

Within the scope of the study, a comprehensive effort was made to forecast electricity consumption in smart homes by developing a forecasting model based on LSTM neural networks, which allows for the consideration of long-term dependencies in the data. Additionally, an algorithm for the operation of the forecasting system was proposed, taking into account historical data and external factors. A system for forecasting electricity consumption was developed and implemented, and its effectiveness was evaluated, with the results demonstrating high forecasting accuracy compared to traditional methods. The proposed method can be used for optimizing energy consumption in smart homes, reducing the load on the energy system, and improving energy resource management.

Further research can focus on refining the model by expanding the set of input parameters and integrating it with other automation systems.

Declaration on Generative AI

During the preparation of this work, the authors used ChatGPT for grammar and spelling checks, as well as for improving the clarity of certain passages. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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