# Hour-Ahead Load Forecasting for Flexibility Management in Energy Communities

Vishnu Suresh
Faculty of Electrical Engineering
Wroclaw University of Science and Technology
Wroclaw, Poland
vishnu.suresh@pwr.edu.pl

Tomasz Sikorski
Faculty of Electrical Engineering
Wroclaw University of Science and Technology
Wroclaw, Poland
tomasz.sikorski@pwr.edu.pl

Gaetano Zizzo, Senior Member IEEE
Department of Engineering
University of Palermo
Palermo, Italy
gaetano.zizzo@unipa.it

Pierluigi Gallo
Department of Engineering
University of Palermo/CNIT
Palermo, Italy
pierluigi.gallo@unipa.it

***Abstract*—This study investigates the application of different Long Short-Term Memory (LSTM) architectures for hour-ahead load forecasting to support flexibility management in local energy communities. Four architectures are analyzed: Multi-layer LSTM, Unidirectional LSTM, Autoencoder LSTM, and Bidirectional LSTM. The dataset comprises hourly load measurements collected from 2018 to 2021 for a suburb in Poland, with a maximum observed load of 1.68 MW. Forecast performance is evaluated using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Bias Error (MBE). Results show that all models provide closely comparable performance, with RMSE values ranging from 0.031 MW to 0.034 MW, corresponding to approximately 1.89% to 2.06% of the maximum load. The Unidirectional LSTM achieved the best results, exhibiting the lowest RMSE (0.031 MW) and minimal bias. Forecasts remained accurate across different seasons, effectively capturing daily load dynamics and peak periods. The findings emphasize that simpler LSTM architectures can deliver highly competitive and computationally efficient forecasting performance, making them well-suited for real-world flexibility management applications in energy communities.**

***Keywords — Hour ahead forecasting, Load prediction, LSTM architectures, Energy communities, Flexibility management, Deep learning***

## I. Introduction

The integration of renewable energy resources into modern power systems necessitates accurate and reliable forecasting methods to ensure grid stability, effective demand-side management, and optimal exploitation of energy flexibility. In particular, hour-ahead load forecasting is crucial for Distribution System Operators (DSOs) and energy communities to anticipate load variations, manage generation dispatch efficiently, and participate effectively in energy markets [1].

Deep learning techniques, particularly Long Short-Term Memory (LSTM) networks, have emerged as powerful tools for short-term load forecasting tasks [2]. Due to their inherent ability to capture temporal dependencies and handle sequential data, LSTM models have shown superior performance compared to traditional statistical forecasting specific application within real-time operational settings such methods.

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Previous research has extensively validated LSTM architectures for various forecasting horizons; however, their as energy community flexibility management still offers opportunities for exploration and improvement.

In the context of the FlexBIT project, which seeks to exploit energy flexibility at residential, tertiary, and industrial scales, this study aims to implement and validate an hour-ahead deterministic load forecasting method using a Multi-

Layer LSTM model. Accurate forecasts generated by this method will directly support other functionalities such as demand response management, microgrid optimization, and enhanced operational decision-making within the energy community. This contributes significantly towards the overall project objective of creating a robust digital platform for energy and flexibility exchange. The rest of the paper is organized as follows. Section II provides a literature review of relevant recent research on the topic of load forecasting using LSTM based models, Section III briefly describes the models that are used in the study, Section IV presents data and the preprocessing methods used, Section V presents the evaluation metrics and Section VI presents the results which is then followed by conclusions in Section VII.

## II. Literature Review

In this section, recent studies employing LSTM-based models for load forecasting are systematically reviewed. The papers are selected based on their relevance, novelty, and methodological advancements.

In [3] is proposed a novel approach integrating quantile regression with dual attention mechanisms into LSTM networks for hour-ahead short-term load forecasting. This model was validated using data from Panama City and the Islamabad Electric Supply Company (IESCO). The results showed significant performance improvements, achieving reductions in mean absolute percentage error (MAPE) by 2.35% and 5.36% respectively, compared to other baseline models, demonstrating robustness in managing grid stability and economic dispatch efficiency. An optimized LSTM framework explicitly designed for dynamic electricity pricing within smart grid demand response schemes is introduced in [4]. Their model systematically tuned hyperparameters, significantly enhancing forecast accuracy. The day-ahead dynamic electricity pricing was successfully applied, enabling efficient scheduling of price-dependent loads and electric vehicle charging, achieving a Root Mean Square Error (RMSE) of 0.4454 and an $R^2$ value of 0.9677, highlighting the applicability of hyperparameter-tuned LSTM models in smart grids. In [5] was developed a hybrid deep learning model combining Variational Mode Decomposition (VMD), mutual information-based feature selection, and LSTM neural networks to predict building electrical consumption patterns. The performance evaluation, using data from a two-story residential building in Houston, Texas, demonstrated superior forecasting accuracy with an average RMSE of 0.1192 compared to other benchmark models like the generalized regression neural network (GRNN) and adaptive neuro-fuzzy inference system (ANFIS). A clustering fractional-order grey model (C-FGM) combined with LSTM and Transformer models for short-term electrical load forecasting is presented in [6]. Their method utilized fractional-order partial differential equations to describe load data behavior effectively. Simulations on datasets from the Australian Energy Market Operator (AEMO) revealed superior predictive performance, achieving a lower MAPE ranging from 1.97% to 4.67%, significantly outperforming conventional LSTM (average MAPE of 4.34%) and Transformer models (average MAPE of 5.42%).

While the above-mentioned studies highlight innovative techniques combining LSTM with attention mechanisms, hyperparameter tuning, and hybridization with other deep learning architectures, in this work we specifically focus on comparing four classical LSTM architectures for hour-ahead load forecasting. The considered architectures are: (i) Simple LSTM, (ii) Multi-layer LSTM, (iii) Bidirectional LSTM (BiLSTM), and (iv) LSTM Autoencoder. By systematically evaluating and comparing these LSTM variants on a unified dataset, we aim to provide a clear understanding of their relative strengths and weaknesses in practical load forecasting applications.

## III. LSTM ARCHITECTURES FOR LOAD FORECASTING

### A. *Unidirectional LSTM model*

The unidirectional LSTM model is the simplest model available that is quick to train and is efficient. It has been described under several names such as the LSTM Unidirectional model and the LSTM basic model. As shown in Fig. 1 it has an input layer, an output layer, a single dense layer, and an LSTM layer consisting of a number of LSTM cells defined by the user.

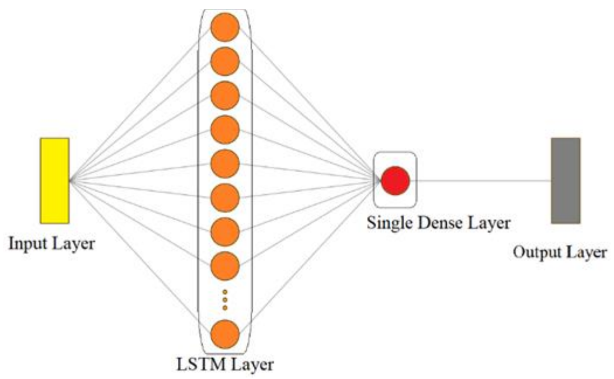


Fig. 1. Unidirectional LSTM model

The input layer is a specialized layer in all LSTM models that requires the input data to be shaped in a 3D formal consisting of samples, number of timesteps and features. The output layer provides the forecast, the single dense layer and the LSTM layer are responsible for ascertaining the long- and short-term dependencies present within the data required to produce a forecast. This model is prevalent in the literature for time series forecasting tasks [7], [8].

### B. *LSTM Autoencoder model*

The LSTM Autoencoder model as shown in Fig. 4 has one input layer, one output layer, two LSTM layers called the encoder and decoder respectively and finally a repeat vector. The encoding layer of the model is responsible for creating a vector from the input data which contains the long- and short-term dependencies present in the data [9]. This vector is of a reduced dimension compared to the input data and can be used in tandem with other machine learning models. This encoded vector is then passed on to the decoder using the repeat vector layer where the input vector is recreated. The effectiveness of the model depends on the accuracy of the recreation of the input data by the decoder [10].

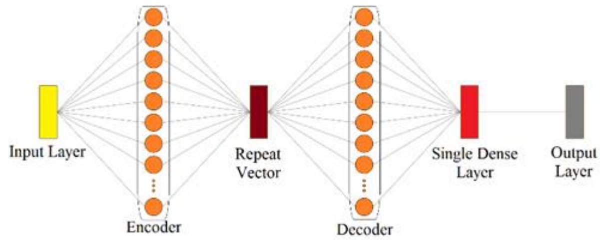


Fig. 2. LSTM Autoencoder model

### C. *BiLSTM model*

The BiLSTM model as shown in Fig. 5 has an input layer, output layer, a single dense layer and a Bi – Directional LSTM layer called the BiLSTM layer. This model is able to capture the temporal relationship in the data by processing sequences in both forward and reverse directions. In essence, when a series of inputs is presented to the model, it comprehensively analyzes the connections between preceding and subsequent elements. This dual-directional approach enables the BiLSTM to integrate insights from both earlier and later points in the sequence. It has been successfully used for the purposes of time series forecasting as shown in [11].

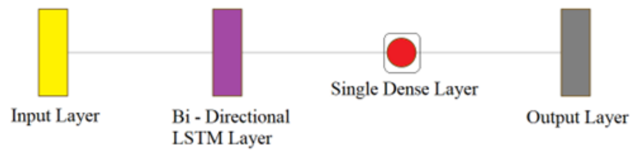


Fig. 3. BiLSTM model

### D. *Multi-Layer LSTM model*

This model, also called the multi-layer LSTM layer model or the deep LSTM model, has a structure similar to the unidirectional model but has an additional LSTM layer. It consists of the input layer, the output layer, the dense layer and 2 LSTM layers. This structure of back-to-back LSTM layers allows for a deeper and more complex representation of sequential data. In this case the output of one LSTM layer becomes the input for the next, enabling the network to learn at various levels of abstraction. The first layer is responsible for capturing basic patterns, while the second layer can interpret more complex structures in the data. This hierarchical learning approach is effective in handling sequences with long-range dependencies. While it is more effective compared to the unidirectional model in extracting temporal relationships, it also has higher training times and consumes more computational power.

## IV. DATA AND PREPROCESSING METHODS

### A. Data description

The load demand data utilized in this study pertains to a local energy community located in a suburb in Poland. The dataset has only hourly load demand values from 01.01.2018 00:00 to 31.12.2021 23:00. The peak load demand value observed in the dataset is 1.68 MW. It is visualized in the figure below.

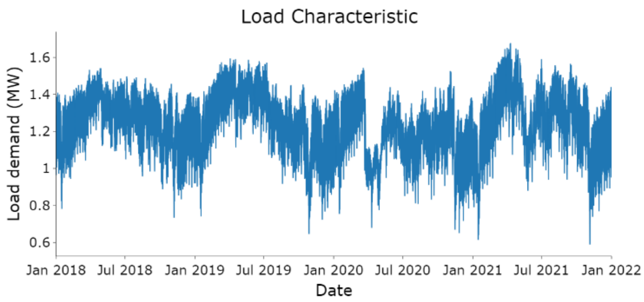


Fig. 4. Load demand dataset

### B. Data preprocessing

This research uses a range of features with differing scales, distributions, and measurement units. To enhance the robustness of the LSTM networks against variations in the input data and to mitigate issues associated with large weight values, normalization of these features is required. For this purpose, a min-max normalization technique, as shown in equation (1). Here, the variable value at every time step is represented by $z_i$, $max(z)$ and $min\ (z)$ are maximum and minimum values of that variable respectively.

$$z_i - \min\ (z) / \max(z) - \min(z) \tag{1}$$

The normalization ensures that each input variable contributes approximately proportionately to the final model. This scaling not only helps in speeding up the training process but also improves the ability of the model to learn from the data more effectively.

**Algorithm 1** Sliding Window Algorithm

1: **Input:** Total time series length **L**, window length **W**

2: **Output:** Array of sliding windows **S**

3: Initialize **t** = 0 for the current position in the time series, and **w_count** = 0 for the count of windows

4: Prepare an empty list **S** to hold the segments

5: while **t** + **W** <= **L** do

- **Ensure:** The end of the time series is not surpassed
- Segment the time series from position t to **t** + **W** and append to **S**
- Update **t** by adding **W** to move to the next segment
- Increment **w_count**

6: **end while**

7: **return S**

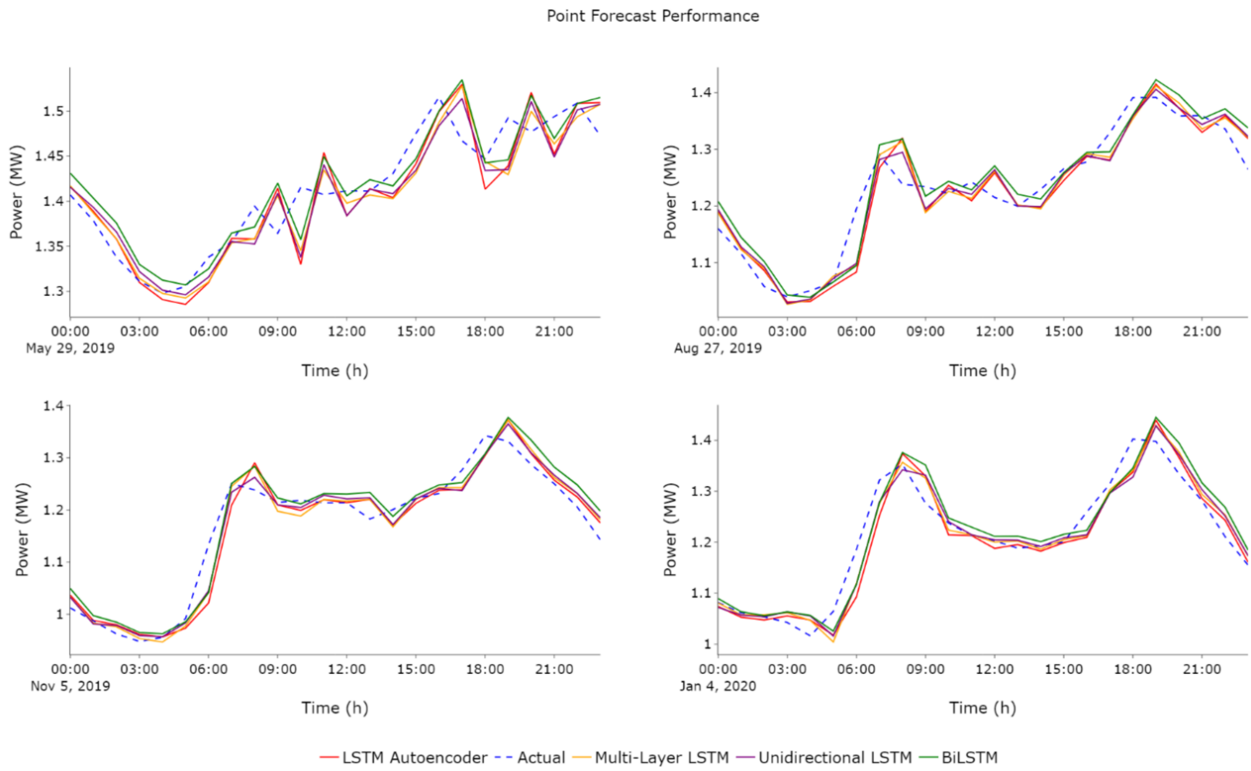


Fig. 5. Forecasting model performances on selected days

The LSTM models need the input data to be in a 3D format consisting of the total number of samples, total number of timesteps and number of features. To achieve this, the sliding window technique as outlined in algorithm 1 is used. This method rearranges the input into a format compatible with the LSTM model. Without employing the sliding window method, the LSTM model would encounter issues due to incompatible input data shape, leading to errors in model processing. This technique ensures that the data is appropriately segmented and sequenced, matching the

LSTM's requirements for effective learning and prediction accuracy.

## V. Evaluation metrics

In this study, the best performing LSTM architecture for hour ahead point load forecasts is identified through the use of the following metrics: The RMSE, the Mean Absolute Error (MAE) and the Mean Bias Error (MBE). The RMSE was chosen because it provides a clear measure of the model's performance in terms of the magnitude of its prediction errors. This metric is particularly sensitive to large errors and is beneficial when they are particularly undesirable, and the square root ensures that the units of RMSE are consistent with the units of the forecast variable [12]. The MAE was chosen because it provides the average error and is a linear score, which means that all individual errors are weighted equally in the average unlike the RMSE. The MBE provides information regarding the average bias in the forecasts [13]. This refers to the general tendency of the forecasting model to under or over predict. The metrics are calculated according to (6) – (9). Where, at every time step $i$ the forecast error $e_i$ is calculated from the true value $y_{i(actual)}$ and the forecast value $y_{i(forecast)}$, based on this error other metrics are calculated where N represents the total number of time steps.

$$MAE = 1/N * \sum_{i=1}^{N} |e_i| \quad (6)$$

$$RMSE = \sqrt{MSE} = \sqrt{1/N * \sum_{i=1}^{N} e_i^2} \quad (7)$$

$$MBE = 1/N * \sum_{i=1}^{N} e_i \quad (8)$$

$$e_i = y_{i(forecast)} - y_{i(actual)} \quad (9)$$

## VI. Results

The forecasting results for all four LSTM architectures, Multi-layer LSTM, Unidirectional LSTM, Autoencoder LSTM, and Bidirectional LSTM presented in Table 1 are generally comparable, with only slight differences in their performance metrics.

TABLE I. Evaluation metrics

| **Architecture** | **Performance of investigated LSTM architectures** | | |
|---|---|---|---|
| | ***RMSE(MW)*** | ***MAE(MW)*** | ***MBE(MW)*** |
| Multi-layer LSTM | 0.032 | 0.025 | 0.001 |
| Unidirectional LSTM | 0.031 | 0.024 | 0.001 |
| Autoencoder LSTM | 0.034 | 0.026 | 0.001 |
| Bidirectional LSTM | 0.034 | 0.027 | 0.012 |

The RMSE and MAE values are relatively close for each model, indicating consistent predictive behavior with low variability in individual forecast errors. For the Multi-layer LSTM, the RMSE is 0.03237 MW, corresponding to approximately 1.93% of the maximum load demand. The Unidirectional LSTM achieves the lowest RMSE at 0.03174 MW, about 1.89% of the maximum load, demonstrating the best overall forecasting accuracy. The Autoencoder LSTM records an RMSE of 0.03437 MW, which is around 2.05% of the maximum load, while the Bidirectional LSTM exhibits an RMSE of 0.03461 MW, equivalent to roughly 2.06% of the maximum load. Regarding bias, all models show low MBE values, indicating minimal systematic over- or under-prediction tendencies. Notably, the Unidirectional LSTM and Multi-layer LSTM present the lowest MBE values, while the Bidirectional LSTM shows a slightly higher positive bias. Overall, the results suggest that all architectures provide reliable hour-ahead forecasts, with the Unidirectional LSTM slightly outperforming others in terms of accuracy and bias.

Fig. 5 presents the point forecast performance of the four LSTM architectures compared to the actual load demand (dashed blue line) across four different days selected from various seasons. The dates analyzed are May 29, 2019 (late spring), August 27, 2019 (summer), November 5, 2019 (autumn), and January 4, 2020 (winter). This selection captures the variability in load behavior associated with different times of the year. On May 29, 2019 (top-left panel), corresponding to late spring, all models accurately track the daytime rise and evening peak, although minor deviations are visible during the midday hours where sharp load increases occur. The forecasts are tightly clustered, showing strong model agreement even during periods of load fluctuation.

On August 27, 2019 (top-right panel), during the peak summer season, higher load variability is observed due to cooling demands. Here, the models maintain good alignment with the actual values, although slight overprediction is visible during the late afternoon and early evening, especially for the Bidirectional LSTM, consistent with its higher positive bias. On November 5, 2019 (bottom-left panel), representing autumn conditions, the load profile shows smoother transitions with less pronounced peaks. The models demonstrate acceptable tracking of the load curve throughout the day, with minimal spread between the predictions and actual observations. All architectures perform similarly well under these milder load variations. Finally, on January 4, 2020 (bottom-right panel), during the winter period, the load profile is characterized by sharp morning and evening peaks likely driven by heating demands. All models successfully capture the morning ramp-up and evening surge, although slight underestimations are visible around the peak periods. The Bidirectional LSTM again shows a tendency to slightly overshoot during high load periods, while the Autoencoder LSTM tends to slightly underpredict. Across all selected days and seasons, the forecasted curves remain consistently close to the actual load, with no significant systematic errors or major divergences observed. This reinforces the finding that all tested LSTM architectures are capable of reliably capturing short-term load dynamics throughout different times of the year.

## VII. Conclusions

This paper presented an evaluation of four LSTM architectures—Multi-layer LSTM, Unidirectional LSTM, Autoencoder LSTM, and Bidirectional LSTM—for hour-ahead load forecasting in a rural energy community context. The forecasting results demonstrate that all architectures provide comparable and reliable predictive performance, with minor variations in accuracy and bias. Notably, the Unidirectional LSTM achieved the lowest RMSE and MAE, highlighting that simpler architectures can often deliver superior results while maintaining low computational complexity. Across different seasons and load profiles, the models consistently tracked the actual demand. The analysis confirms that even basic LSTM configurations are sufficient for effective short-term forecasting required for flexibility management. These insights are valuable for future implementation of AI-based forecasting tools within energy communities where computational efficiency and forecasting reliability are both critical.

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