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# Energy Consumption Forecasting and Optimization in Smart HVAC Systems Using Deep Learning

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**Abstract:** *This research details a method for predicting power usage that makes use of deep learning (DL) techniques, namely Bidirectional LSTM (BiLSTM) and Long Short-Term Memory (LSTM) models. For both the training and evaluation of the models, a real-world dataset was utilized, which included the hourly electricity usage of a Phoenix, USA, hospital building. Effective learning of temporal patterns was made possible by preprocessing, normalizing, and segmenting the data into sequences. Both LSTM and BiLSTM networks were developed and trained to perform 24-hour (short-term), 7-day (medium-term), and monthly (long-term) electricity consumption forecasting. A recursive multi-step prediction strategy was employed for extended forecasting horizons. They employed such measures of industry standards as MSE and Root RMSE to analyze prediction's accuracy. Based on the findings, BiLSTM is superior to LSTM in the area of capturing complex consumption patterns, indicating that the former can be deployed to enhance energy control and optimization of smart HVAC systems and their energy management and planning*

**Keywords**: Electricity Forecasting, LSTM, BiLSTM, Deep Learning, Time Series Prediction, Energy Consumption, Smart HVAC Systems, RMSE, MSE, Multi-step Forecasting

## I. INTRODUCTION

When the buildings are in operation, a lot of energy is wasted because of technical problems and human error. Any plan to reduce energy consumption and carbon emissions that focuses on reducing energy use in buildings is a big deal [1][2]. Now, smart building facilities work in tandem with BEMS to track energy consumption, identify unusual patterns, and notify building managers to implement appropriate cost-cutting measures [3][4][5]. Consequently, this study proposes a model for energy consumption forecasting that is based on deep neural networks (DNN). A Building Energy Management System (BEMS), a complex of software and hardware technologies, can be used to track, control, and optimize the energy consumption of organizations buildings. The BEMS are capable of monitoring and controlling a broad range of building systems like lighting, HVAC, and other energy consuming systems. Using information gathered from various sensors and meters, Better Energy Management Systems (BEMS) evaluate and improve a structure's energy usage [6][7][8]. Decisions about the improvement of energy efficiency can be data-driven using the real-time data provided by BEMS, which building owners and facility managers can use. Building energy efficiency strategies is crucial to ensuring a sustainable future. In addition, data-driven approaches to energy consumption prediction have been developed because of the BAS's extensive database of building operational data [9][10][11]. Smart meters and sensors are becoming ubiquitous in today's structures as a result of the proliferation of these devices [12][13]. These devices' data analysis alerts the building manager if consumption patterns deviate from typical profiles. This enables the implementation of crucial energy-saving measures. Even more crucially, safety-critical building services, like gas consumption, may be better protected against disastrous events if abnormal behavior, like gas leaks, is detected and reported early enough [14][15]. Also, the rapid generation of data by sensors makes it hard to spot anomalous consumption patterns. Using unsupervised learning on unlabeled data, this work aims to propose a way to capture consumption trends in the past [16][17]. The framework constructs a model of typical consumer behavior based on the assumption that previous data are mostly normal. It then uses this model to discover new patterns [18].

The demand for more precise monitoring systems that can identify pattern's consumption automatically and deliver correct information about relevant factors prompted this endeavor. No one has the time to monitor energy usage and look for unusual patterns, including energy service providers and management [19]. On the contrary, these capabilities should equip BEMS to promptly identify and report such occurrences. Using energy data collected from multiple commercial buildings via various web sources, the idea was put into action, and the benefits of this strategy were demonstrated. Methods suggested for use in narrow contexts have dominated the majority of recent studies in this area. Most of the current methods for symbolic sequences are either oriented toward biological sequences or system call intrusion detection, two fields where abnormalities in data are commonly seen. Even less is known about univariate time series data, particularly in area of building energy [20][21].

**Application of Deep Learning in Building Energy Consumption Forecast**

Three distinct approaches are utlized to forecast an organization's energy use. Here one can find methods like the numerical technique, the engineering method, and hybrid method [22]. It is clear from perusing the published works that previous studies have made use of both statistical and machine learning methods. As an example, a machine learning method was suggested in [23] by the authors to forecast commercial buildings' fuel, electricity, and natural gas consumption using accessible building attributes and natural data from CBECS. In addition, the authors of [24] compare various HVAC and energy consumption prediction models, finding that Support Vector Machine (SVM) provides the most accurate results. Just like in [25], an ARIMA was used to predict power consumption. As an example, in [26], the authors examine the relative merits of neural networks, decision trees, and linear regression models in the context of power consumption modeling for buildings in Hong Kong. Although linear models were able to attain a satisfactory level of prediction accuracy, the scientists discovered that machine learning methods yielded superior results. The writers of [27], furthermore use automated neural networks and bagged aggregating trees to predict loads, with data received from weather agencies. Compared to other models, Neural Network performs better in both cases. Important data must be present for statistical, engineering, and hybrid models to function properly. There has been very little research on medium- and long-term prediction at either the sub- or hourly periods; the latter is inherently more difficult to do. Predictions for the medium to long term often have a relative inaccuracy of more than 40% to 50% [28].

Deep neural networks allow for the aforementioned machine learning, with the ability to model more complex functions through the use of numerous levels of abstraction. In the field of energy forecasts, these methods have lately found usage; for instance, in [29], the authors employed a deep learning strategy to estimate cooling loads; deep learning outperformed BPNN and SVM in terms of fitness and accuracy. In addition, the authors of [30] introduce a DL method for predicting the load on building profiles. In particular, when using DNN in an unsupervised fashion, better performance was attained. Using a reinforcement algorithm that can target the building qualities in conjunction with DBN greatly improved the prediction accuracy in [31]. There is a temporary pattern to the electricity consumption. The consumption pattern might be influenced by long-term dependence. Energy prediction has made use of RNNs, a class of algorithms that appropriately accommodates relationships between successive time steps.

The use of RNNs is known to improve the accuracy of time series forecasts, as shown in [32]. In, researchers employ a genetic algorithm to determine the optimal ENN weight. Compared to previous research, this one yielded better result. Also, the authors of [33] demonstrate that their new RNN model—based on a multiplicative neuron model performed better than the competitors when comparing many prediction approaches. Even if RNN modelling of time series problems produces great performance improvement, the problem of vanishing gradient is still there. Recurrent neural networks aren't up to snuff when it comes to dependencies that span years. A Recurrent Neural Network (RNN) equipped with Long Short-Term Memory (LSTM) could be an answer to the disappearing gradient issue. Compared to alternative techniques such as Back Propagation Neural Networks and Multi-layer Feed-forward Neural Networks, the LSTM-based network technique used by the authors of improved the accuracy of electricity usage prediction. By utilizing encoder-decoder architecture, the authors of [34] constructed two deep recurrent neural networks, one for commercial buildings and one for residential ones, to predict the power demand of these structures. The multi-layered perceptron is outperformed by both ANNs. Likewise, DNNs and RNNs were proposed by the authors of for the purpose of short-term power usage forecasting. Impressively, the recurrent model attained a 96.82% accuracy rate. The interior humidity estimate did, however, have a sizable margin of error.

**Background of Prediction Techniques**

A concise overview of the computational methods used in energy consumption forecasting as described in literature is provided in this section.

**A. Artificial Neural Network (ANN)**

ANN referred to as "neural networks" these days are actually simulations of how the brain's actual neurons work. It is feasible to simulate the input-output relationship by sending signals to the output node after activating all of the neurones at the input node. In a traditional artificial neural network (ANN), the input, hidden, and output layers are the main components. Every one of these levels is composed of a number of neurons that activate. To characterize ANN, one uses the connection mode; to explain the learning technique, one uses the activation function. Data mining, robotic control, energy prediction, picture processing, speech recognition, and countless more fields have used ANN. There isn't a solid method for choosing the right hidden layer level for an ANN. When training a network, it is usual practice to try out various values for the amount of hidden layers. During training, the network's load is tuned to minimize the chance of making mistakes. When the gradient performance hits a specific level or the value needed for the lowered error is achieved, training terminates. While ANN is computationally powerful, it has a few drawbacks, such as the risk of model overfitting, random weight optimization, and reaching a local optimal solution.

**B. Deep Belief Network (DBN)**

Since its introduction by Hinton, a DBN has found numerous useful applications in AI, including image recognition, categorization, filtering, and many more. In a nutshell, a DBN is a network that combines RBM with a logistic regression layer to create an unsupervised network. Both logistic regression and RBM training can extract features, but the latter can also produce predictions. One way to look at a DBN is as a stack of many RBMs, with each sub-network's hidden layers serving as the visible layer for the one below it [35].

**C. Deep Recurrent Neural Network (LSTM and GRU)**

There are a number of ways to extend an RNN into a DRNN. One can build a DRNN by adding depth to the hidden-output, transition, and hidden-hidden functions using the RNN architecture. Their focus was on popular deep recurrent neural network variants, such as LSTM and GRU, which are often used for power forecasting. The LSTM framework is great at modeling long-term dependencies because of its memory array, which contains hidden units. In an effort to reduce the parameters, memories of comparable gates share cells. When the value at the gates is 1, the model preserves them; when it's 0, the model deletes them, according to the gates' arbitration. Because of this, the network can take advantage of trends in time that span a vast distance. The network is able to preserve its memory over time steps by mitigating the vanishing gradient, which helps with the forward and backward stages. The authors first proposed the idea of RNN with gated apartments. Not long ago [36], introduced a common form of RNNs with gated units: the gated recurrent unit. Find out that GRU and LSTM are similar by reading about it in when compared to other RNNs, such as vanilla, GRU's training speed is faster due to the fact that it uses fewer parameters.

**D. Multilayer Perceptrons Neural Network (MLP)**

The MLP neural network Universal approximations are a special kind of feed forward network that neural networks use. The most popular neural network framework includes MLP because of its simplicity [37]. The architecture relies on a hierarchical structure, where each layer receives input from the layer below it that is directly linked and delivers its own output to the layer above it. There are several fully-linked units in neighboring levels, but none inside the same layer. Sometimes called a multi-layer perceptron, a two-layer neural network.

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**E. Convolutional Neural Network (CNN)**

To process images, LeCun first suggested using a convolutional neural network. CNNs have found useful applications in several domains of computer science, including sequential data, NLP, speech recognition, and picture categorization. CNNs primarily aim at learning abstract information through the stacking and alternating of pooling and convolution layers. A convolutional neural network (CNN) uses a series of local filters in its convolution layers to modify local features. It is a transformation achieved across multiple rules such as average, max and executed in stages with a predetermined length of the raw input material and pooling layers that occur afterwards [25].

## II. PROPOSED METHODOLOGY

The methodology, used in the current study, includes four primary components, namely, the preparation of a dataset used, model construction, forecasting, and the evaluation of performance. The data set is composed of hourly data on electricity consumption of a full years period (8,760 data points) of a hospital facility in Phoenix, USA. Before the model was run, data was cleaned and preprocessed, and then broken down into fixed-length sequences, which could be inputted into a time series prediction model. This was done by building two DL models, LSTM and BiLSTM. LSTM networks are advantageous when it comes to capturing the temporal dependencies in the network because gated memory units capture the temporal dependency, whereas their BiLSTM counterparts have the advantage of processing the input sequences in both backward and forward directions, therefore, improving the predictive accuracy. A recursive forecasting plan was adopted, It uses the results of one time step to inform the predictions of subsequent steps. 24-hour (short-term), 7-day (medium-term), and monthly (long-term) forecasting cases were also taken care of using this technique. Root Mean Squared error (RMSE) and Mean Squared Error (MSE) served as main metrics to check the model performance. These measures allowed to conduct a comparative analysis of how accurately the LSTM and BiLSTM models forecast, which evidences their efficiency to predict the patterns of electricity consumption architecture, as shown in Figure 1 are given below:

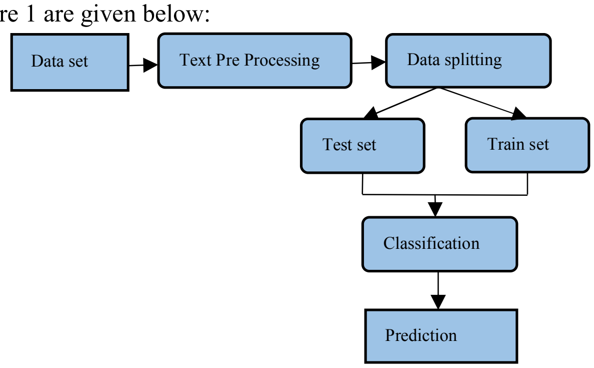


Fig. 1.System Architecture of consumption of electricity

**A. Model Training and Forecasting: LSTM and BiLSTM**

**Dataset Preparation**

The data that is being used to predict the consumption of electricity covers a period of 1 year (8760 hours). The data contains hourly readings of power consumption, which follow the common daily trends, i.e. more consumption during weekdays and less consumption during weekends. T Deep learning methods like LSTM and BiLSTM need to be preprocessed through restricting the values of the data to the range [0, 1]. Some of the data are used in testing the model, and the rest are used in training model. In order to evaluate the performance of the model further during training and to prevent overfitting, the training dataset has been divided into validation set and training set.

**Training and Testing Data Splitting**

- **Training Data (90%)**: Trained to learn patterns in the data.
- **Test Data (10%)**: Applied to measure post training model performance.
- **Validation Set**: The model is validated using some of the training data to avoid overfitting.

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### LSTM Model Training

The LSTM model is composed of an input layer that takes a sequence of numbers (say, 50) and then a single LSTM layer. Second, in order to get a scalar output, the output is passed via a regression layer and a fully connected layer. By utilizing the training dataset, which comprises 90% of the total data, the LSTM model acquires knowledge of the time-series data's temporal dependencies. Overfitting can be prevented during training by using a validation set. Through trial and error, the model's hyper parameters including learning rate, layer count, and batch size are fine-tuned. When performance improvement stalls or the model converges, training terminates. The Adam optimizer is typically used to minimize the loss function, which is usually MSE or Root Mean Squared Error (RMSE).

### BiLSTM Model Training

Two LSTMs, one for future-to-past processing and the other for past-to-future processing, make up BiLSTM, which is an extension of the LSTM architecture. The bidirectional nature of the model allows it to understand the present and future interdependencies inside the time-series data. Training the BiLSTM model is very similar to training the LSTM model; both models use the same dataset. However, due to its bidirectional nature, BiLSTM tends to capture a more comprehensive set of patterns, especially in datasets where future values influence past values. As with LSTM, training involves using a validation set and optimizing hyperparameters to prevent overfitting. The BiLSTM model predicts future power consumption values using both past and future information, potentially offering more accurate predictions than LSTM, especially for complex time-series data.

### Forecasting with LSTM and BiLSTM

Once the LSTM model is trained, forecasting is performed step-by-step. The model predicts the next time step using the last available observation. This prediction is then fed back into the model for subsequent predictions. The final output is the forecasted future electricity consumption over the desired forecast horizon (e.g., 24 hours, 7 days). Similarly, BiLSTM forecasts future values step-by-step but benefits from processing data in both directions. By considering both past and future context, BiLSTM often provides more accurate forecasts, especially when the future values have a important impact on predicted consumption.

## III. RESULTS AND DISCUSSION

In this MATLAB simulation, a deep learning-based approach was implemented to forecast electricity consumption using LSTM and Bidirectional LSTM (BiLSTM) neural networks. The model was trained on a real-world dataset comprising 8760 hourly electricity usage readings from a hospital building over a one-year period. The data was normalized, and time-series sequences were prepared for training and testing both LSTM

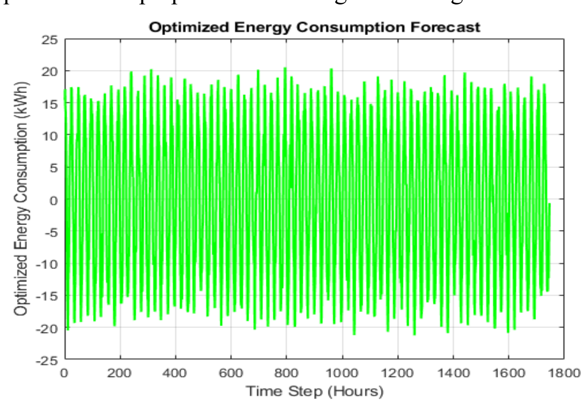


Fig. 2. System Architecture

Figure 2 shows the general layout of the electricity consumption forecasting system. It includes stages such as data collection, preprocessing (including normalization and sequence formatting), model training using LSTM and BiLSTM neural networks, and performance evaluation. The architecture emphasizes the flow from raw hourly consumption data to the generation of forecasted outputs. It highlights the use of MATLAB for model development and testing.

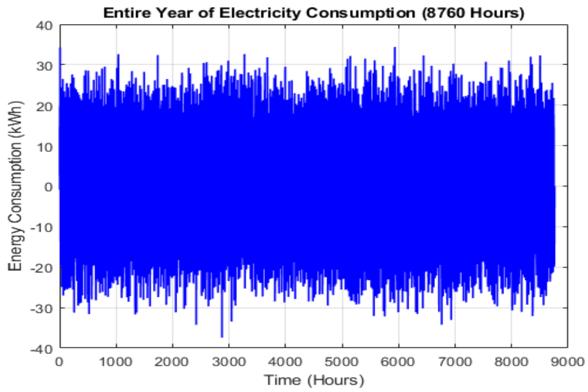


Fig. 3. Yearly Energy Consumption

Figure 3 presents the total electricity consumption pattern across the entire year, covering all 8760 hourly data points. It helps visualize overall trends, seasonal variations, and potential anomalies in energy usage. Peaks and troughs indicate times of high and low electricity demand, providing an essential overview of the hospital's annual energy behavior.

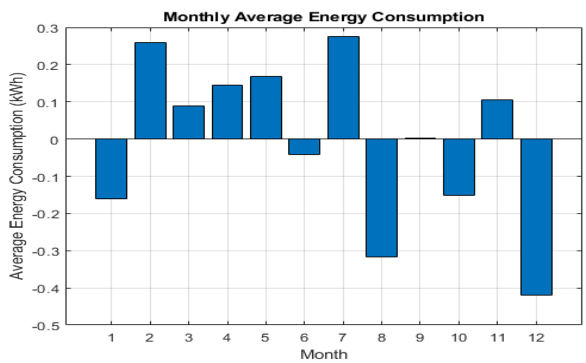


Fig. 4. Monthly Average Energy Consumption

Figure 4 breaks down the energy usage into monthly averages, allowing for a clearer understanding of how consumption varies across different months. It helps identify specific months with higher energy needs possibly due to seasonal temperature changes or operational demands and supports monthly-level forecasting accuracy assessments.

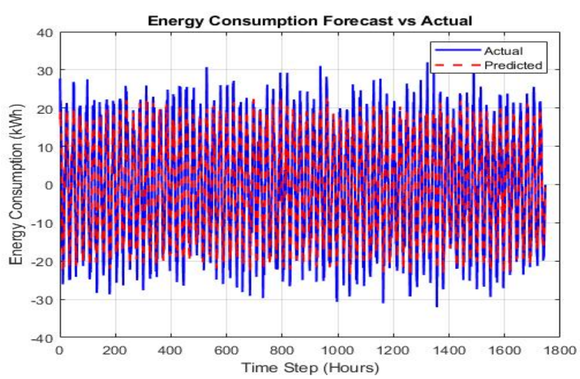


Fig. 5. Energy Consumption Forecast Vs. Actual

Figure 5 shows the difference between the actual and expected energy usage data using the LSTM-based forecasting model. The visualization can be utilized to measure how model can intimately follow the actual consumption patterns. Close correspondence of the real and the forecast curve indicates a good forecasting behavior whereas apparent

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difference implies areas where more adjustment in the model is required.

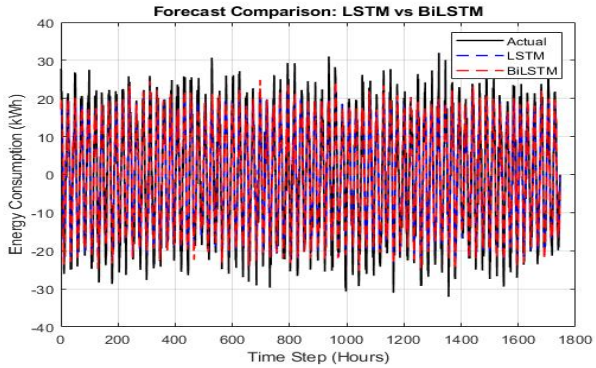


Fig. 6. Forecast Comparison LSTM Vs.BiLSTM

Figure 6 the results of the forecasting of both the LSTM and BiLSTM are compared. It demonstrates the way the two models follow actual energy consumption information and highlights the variances in the prediction accuracy. BiLSTM is usually more effective because it allows the time series to take into account both the past and present context to make smoother and more accurate predictions. This comparison justifies the benefit of the bidirectional processing in serial modeling activities.

## IV. CONCLUSION

According to the historical time-series information, this paper is a comparative analysis of the effectiveness of LSTM and BiLSTM models to predict the use of electricity. The power use data per hour were trained and tested on an annual dataset of power use. The LSTM model was best suited in the short-term forecasting because When it came to capturing the data's dependence on time, it worked. Conversely, the BiLSTM model was superior in all other aspects since its bidirectional nature enabled it to display trends in the past as well as future hence it made the best decisions as far as correct predictions are concerned, particularly when considering the long run. Better accuracy of forecasting was largely due to modifications on model parameters such as the learning rate and the number of layers. In the case that past and future are both equally important, the BiLSTM was superior to the LSTM, which suits sequential forecasting applications. With time-series data with complex dependencies, the findings suggest that BiLSTM makes the most suitable choice when it comes to complex forecasting jobs. LSTM may also be an option in situations where the cost of computing is important, or when the forecasting problem is relatively simple. Future studies could explore hybrid models that incorporate an LSTM and BiLSTM or add additional components such as weather data or individual events as an additional measure to increase the accuracy and resilience of the forecasting models.

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