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Sustainability-Driven Hourly Energy Demand Forecasting in Bangladesh Using Bi-LSTMs

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Abstract

This research presents a comprehensive study on developing and evaluating a deep learning-based forecasting model for hourly energy demand prediction in Bangladesh. Leveraging a novel dataset obtained from the Power Grid Company of Bangladesh (PGCB), the proposed model utilizes bi-directional long short-term memory networks (Bi-LSTMs), implemented through TensorFlow and Keras libraries. The study meticulously preprocesses the data, handling missing values and ensuring compatibility with the selected models. The models are trained and evaluated using Mean Absolute Error (MAE) and Mean Squared Error (MSE) metrics, revealing promising results of 376.72 of MAE. The experimental findings demonstrate the effectiveness of the developed forecasting model, showcasing its capability to predict energy demand accurately. The insights derived from this study pave the way for enhanced energy management strategies, fostering sustainable and efficient energy utilization practices.

Keywords: Energy demand prediction; Deep learning; Short term demand forecasting; Bi-LSTM

1. Introduction

In an era characterized by rapid urbanization, industrialization, and rising populations, there has been an unparalleled surge in the need for energy [37]. In recent years, Bangladesh, a nation located in South Asia with a high population density, has seen noteworthy advancements in its economic development [10]. The expansion has been accompanied by a notable increase in energy consumption, mostly derived from finite fossil fuel resources. The substantial dependence on traditional energy sources presents notable environmental obstacles and jeopardizes the nation's energy security in the long run [36]. In the present scenario, the significance of sustainability in energy man-

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agement assumes utmost importance, with a primary emphasis on mitigating the carbon footprint and advocating for the widespread use of environmentally friendly energy sources [63, 49].

Predicting energy demand is crucial in facilitating the shift towards sustainable energy practices. Forecasting hourly energy demand patterns poses significant difficulties owing to the intrinsic unpredictability and intricate nature of the elements influencing energy use. Several machine learning (ML) and deep learning (DL) models have been developed as effective tools in diverse application domains including anomaly detection [75, 76, 45], signal analysis [25, 27, 26, 24, 23, 61, 70, 72, 28, 21, 67, 78, 13], neurodevelopmental disorder assessment and classification focusing on autism [69, 7, 6, 15, 32, 3, 47, 73, 74], neurological disorder detection and management [5, 41, 8, 16, 66, 35, 39], supporting the detection and management of the COVID-19 pandemic [40, 65, 14, 44, 46, 58, 54, 11], elderly monitoring and care [53], cyber security and trust management [29, 31, 2, 38, 22, 77], ultrasound image [68], various disease detection and management [79, 51, 20, 48, 18, 43, 52, 62], smart healthcare service delivery [30, 42, 17], text and social media mining [1, 59, 33], understanding student engagement [60, 4], etc. A subset of these have also been utilised in time-series forecasting, presenting the opportunity to enhance the precision of energy demand estimates. In recent years, several studies have been conducted by esteemed scholars worldwide, focusing on energy demand forecasting via the use of ML and DL techniques.

The effectiveness of several algorithms based on deep learning, such as RNN, LSTM, and GRU, in forecasting the demand for energy for a smart city project was studied by Amalou et al. [9]. The analysis was conducted utilizing datasets spanning from 2010 to 2014. RMSE, MAE, and R2 metrics assess the models' performance. The findings indicate that the Gated Recurrent Unit (GRU) has superior performance compared to both the basic Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) models. The GRU exhibits the smallest Root Mean Square Error (RMSE) and the greatest R2 score among the three models. The research conducted by Taleb et al. introduced a hybrid machine-learning framework incorporating CNN into an automated weight adjustment mechanism, using historical mistakes [71]. The versatile nature of this model enables its use in the forecast of energy consumption demand across diverse temporal intervals and geographical locations. For the forecast of energy demand for Mayotte Island, the usefulness of the suggested model found an MAE of 372.08. Rosato et al. introduced a new deep-learning methodology that combines CNN and LSTM algorithms [64]. Their strategy yielded the smallest RMSE, respectively, of 2.252 for the standard 1-day prediction.

Moreover, several research studies have been undertaken to predict the energy demand of countries like Bangladesh. Piyal et al. investigated the use of contemporary energy management technologies, in particular machine learning-based load forecasting methods, to solve the energy-related issues of Bangladesh [57]. Artificial neural networks (ANNs), more precisely LSTM, were chosen due to the unpredictability of electric load demand. The study compared the effectiveness of many machine learning algorithms for load demand forecasting, such as LSTM, Seasonal Auto-Regressive Integrated Moving Average with eXogenous components (SARIMAX), and Fbprophet. The results show that LSTM approaches work better than SARIMAX and Fbprophet, with the lowest Mean Absolute Percentage Error (MAPE) and RMSE values. A regression decision tree machine learning system was used to anticipate hourly regional electricity consumption in [19]. The algorithm was developed utilizing the data from Bangladesh Power Grid Company (PGCB) of three locations across six days in March 2018. It is built for load prediction to maintain equilibrium between demand and supply and prepare for emergencies. The research compares the model outcomes with and without pruning. MATLAB simulation has been executed to evaluate the accuracy of the model. Haque et al. explored the worldwide supremacy of machine learning in energy consumption and demand forecasting and its implications in Bangladesh [34]. This study classified energy use by accessibility for builders and end-users, leading to short-, medium-, and long-term consumption prediction. It examined medium-term energy consumption using conventional machine learning models on a residential apartment dataset for a year. In this work, an energy management plan for Bangladesh was also addressed, bringing significant insights into energy optimization.

Though some research on energy demand forecasting in Bangladesh has been done, the energy demand prediction based on Bangladesh's hourly real-time electricity generation data is still missing. Besides, research on the potential advantages of precise demand forecasting combined with sustainable energy management to improve the stability of the energy system is yet to be done. Hence, the primary contribution of this study lies in introducing an innovative deep learning framework founded on Bidirectional Long Short-Term Memory (Bi-LSTM) networks, applied to real-time energy demand data sourced from the Power Grid Company of Bangladesh. This research not only introduces this novel architecture but also presents the preliminary findings of the experiment, providing an initial insight into its effectiveness and potential applications.

The subsequent sections of this paper are structured as follows: Section 2 elucidates the methodologies applied in this research endeavor, detailing the techniques and approaches harnessed. Following this, Section 3 meticulously elucidates the experimental outcomes and comprehensively discusses these results. Section 4 encapsulates the study, drawing together the findings and implications into a coherent conclusion.

2. Methodology

This section discusses the methodology employed in this study. The methodology includes data collection and processing, deep learning-based forecasting model development, evaluation metrics, and experimental setup. The following sections describe each of the steps briefly.

2.1. Data Collection and processing

The research utilized real-time data from the Power Grid Company of Bangladesh (PGCB), the government's designated entity responsible for nationwide power transmission [56]. PGCB publishes daily energy demand data on their website, detailing each hourly demand in Microsoft Excel format [55]. The researchers downloaded data spanning two years, from June 2, 2021, to June 30, 2023, stored in individual files for each day. Subsequently, this data was consolidated into a single file, resulting in 18,144 data points representing hourly energy demands across Bangladesh. The dataset also included specific data regarding energy generation from various sources. However, disregarding individual sources, this study focused solely on the total energy demand measured in MegaWatts (MW).

Following data collection, preprocessing was necessary. Firstly, the data was checked for missing values, which were absent. Next, the collected data was transformed into timestamp format because the date and time were originally stored in separate columns. The 24:00-hour notation was converted to the 00:00-hour format, and dates were adjusted accordingly. Subsequently, the data underwent normalization using the MinMaxScaler method. This process ensured uniformity and prepared the dataset for detailed analysis. Algorithm 1 shows the steps involved in data processing.

Algorithm 1: Data Preprocessing and Normalization

Input: Dataset in CSV format ('datasetv2C.csv')
Output: Normalized data for 'Total(Mw)'

```
df = pd.read_csv('datasetv2C.csv');
df['Timestamp'] = pd.to_datetime(df['Date'] + ' ' + df['TIME'], format='%m/%d/%Y
  %H:%M', errors='coerce');
df['Timestamp'] = df['Timestamp'].fillna(df['Timestamp'] + pd.DateOffset(days=1));
df.drop(['Date', 'TIME'], axis=1, inplace=True);
df.set_index('Timestamp', inplace=True);
target_col = 'Total(Mw)';
data = df[target_col].values.reshape(-1, 1);
scaler = MinMaxScaler();
data_scaled = scaler.fit_transform(data);
```

Algorithm 1 conducts essential preprocessing steps on the dataset provided in CSV format. Initially, the dataset is loaded into a pandas DataFrame, and the 'Date' and 'TIME' columns are merged to create a unified 'Timestamp' column, effectively combining date and time information. An important consideration is made for instances where the time is represented as "24:00"; this is adjusted to "00:00", and the corresponding date is incremented by one day to maintain accurate temporal data. Subsequently, unnecessary columns ('Date' and 'TIME') are removed for simplicity. The 'Timestamp' column is the DataFrame's index, enabling efficient time-based analysis. The target variable, 'Total(Mw)' is isolated, and the data is reshaped into a one-dimensional array. To ensure consistency in the dataset, Min-Max scaling is applied, transforming the 'Total(Mw)' values into a normalized range between 0 and 1.

These preprocessing steps collectively refine the dataset, making it suitable for various machine learning applications by resolving temporal discrepancies, focusing on relevant variables, and standardizing the data for further analysis and modeling purposes.

2.2. Forecasting Model Development

Various research studies have consistently demonstrated the superior predictive capabilities of deep learning-based forecasting models compared to traditional statistical and classic machine learning approaches [50, 12]. In light of this evidence, this study primarily delved into developing a deep learning-based forecasting model and presented the preliminary findings. Deep learning techniques, such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory networks (LSTM), and Gated Recurrent Units (GRU), have been explored extensively. This research employed a Bidirectional LSTM (Bi-LSTM) approach, augmented with a dense and dropout layer. The model architecture was kept relatively straightforward, utilizing the rectified linear unit (ReLU) as the activation function within the Bi-LSTM layer and Adam optimizer during model compilation. Mean squared error was chosen as the appropriate loss function to gauge the model's performance. Early stopping with a patience parameter of 3 was also implemented to mitigate the risk of overfitting. These architectural choices represent a strategic blend of advanced deep learning techniques, ensuring a balance between complexity and model performance in the context of forecasting tasks. Bi-LSTMs can model both long-term and short-term temporal dependencies in time series data. This is crucial for energy demand forecasting, where daily and seasonal patterns are important. Bi-LSTMs can learn bidirectional relationships, capturing past and future context. Energy demand depends on historical trends as well as future events. Compared to uni-directional LSTMs, Bi-LSTMs reduce bias and improve accuracy by processing sequence information in both directions. Figure 1 shows the architecture of the proposed model.

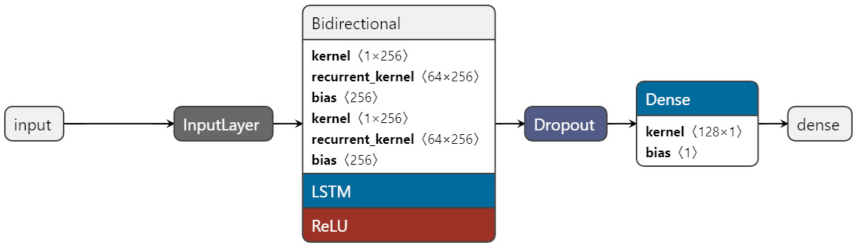

Fig. 1. Architecture of the proposed forecasting model

The core of the model centers around the BiLSTM model. It constructs a Sequential model, starting with a Bidirectional LSTM layer equipped with 64 units and a rectified linear unit (ReLU) activation function. Bidirectional LSTM allows the model to capture dependencies in both forward and backward directions, making it adept at modeling time series data. To prevent overfitting, a Dropout layer is introduced with a dropout rate 0.2. Dropout randomly deactivates some input units during training, promoting model generalization. A Dense layer with a single unit forms the model's output layer.

The model is compiled using the Adam optimizer with a learning rate of 0.001, and the mean squared error is designated as the loss function. This configuration optimally suits time series forecasting tasks, aiming to minimize the discrepancy between predicted and actual values. To safeguard against overfitting, the model design employs early stopping. With a patience setting of 3, training halts if the validation loss fails to improve for three consecutive epochs. This mechanism promotes a well-generalized model that doesn't overly adapt to the training data's noise.

Finally, once the model has been successfully trained, it is saved in a file named ”pgcb-lstmV1.h5” This saved model file can later be utilized for making predictions on new data without requiring the time-consuming retraining of the model.

2.3. Evaluation metrics

To assess the accuracy and reliability of the forecasting model, two fundamental metrics were employed: Mean Absolute Error (MAE) and Mean Squared Error (MSE). These metrics quantify the disparities between the model's predictions ($\hat{y}_i$) and the actual observations (y_i), where i represents the individual data points.

2.3.1. Mean Absolute Error (MAE)

Mean Absolute Error (MAE) calculates the average absolute differences between the predicted and actual values, providing a straightforward measure of the model's accuracy. It is defined as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

where n represents the total number of data points.

2.3.2. Mean Squared Error (MSE)

Mean Squared Error (MSE) emphasizes larger discrepancies by squaring the differences between predictions and actual values. It is calculated as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

where n signifies the total number of data points.

These metrics provide essential insights into the model's performance, enabling a quantitative assessment of its forecasting accuracy.

2.4. Experimental Setup

The experimental setup for this study was intricately designed, drawing upon an array of potent tools and libraries within the Python programming language. These experiments were meticulously conducted within the Google Colab environment, a cloud-based Python notebook platform renowned for its accessibility and high-performance computing capabilities. Operating on a Windows-based host machine, the experiments were seamlessly facilitated through the Microsoft Edge browser, ensuring a streamlined and efficient workflow.

Regarding the Colab configuration, the environment was tailored with a CPU processor and a substantial 12.7 GB of RAM. This configuration was carefully chosen to guarantee the computational resources required for the intricate modeling and analysis inherent to this study.

3. Results and Discussion

Once the model has been trained, the experimental results are collected and analyzed. The proposed model yielded a Mean Absolute Error (MAE) of 376.72 and Mean Squared Error (MSE) of 340494.74. By squaring the errors, MSE emphasizes larger deviations between predictions and reality, assigning them more significant weight in the calculation. In our experiment, where MSE equals 340494.74, it signifies that, on average, the squared differences between the model's predictions and the true values amount to 340494.74. On the other hand, Mean Absolute Error (MAE) offers a different perspective by measuring the average of the absolute differences between the actual and predicted values. Unlike MSE, MAE does not square the errors, treating all deviations equally, regardless of their size. In our experiment, MAE equals 376.72, implying that, on average, the absolute differences between the model's predictions and the real values amount to 376.72. Table 1 shows energy demand data's actual and forecasted values with error percentages.

Table 1 meticulously dissects the accuracy of a forecasting model by comparing actual electricity demand with forecasted values over a specific time frame, ranging from 7/1/2023 0:00 to 7/1/2023 23:00. Each row in the table chronicles a distinct hourly interval, offering a granular examination of the model's predictive capabilities.

Table 1. Comparison of Actual and Forecasted Demand for 24 hours

Timestamp	Actual Demand	Forecasted Demand	Absolute Error	Error Percentage (%)
7/1/2023 0:00	10618	10225	393	3.70
7/1/2023 1:00	9544	10155	611	6.40
7/1/2023 2:00	9128	9989	861	9.43
7/1/2023 3:00	8925	9744	819	9.18
7/1/2023 4:00	8675	9471	796	9.18
7/1/2023 5:00	8613	9179	566	6.57
7/1/2023 6:00	8256	8884	628	7.61
7/1/2023 7:00	8178	8643	465	5.69
7/1/2023 8:00	8071	8468	397	4.92
7/1/2023 9:00	8086	8339	253	3.13
7/1/2023 10:00	8019	8264	245	3.06
7/1/2023 11:00	8180	8296	116	1.42
7/1/2023 12:00	8701	8383	318	3.65
7/1/2023 13:00	9026	8453	573	6.35
7/1/2023 14:00	9026	8357	669	7.41
7/1/2023 15:00	8647	8162	485	5.61
7/1/2023 16:00	8141	7984	157	1.93
7/1/2023 17:00	7954	7941	13	0.16
7/1/2023 18:00	8297	8092	205	2.47
7/1/2023 19:00	9308	8442	866	9.30
7/1/2023 20:00	10582	8871	1711	16.17
7/1/2023 21:00	11031	9273	1758	15.94
7/1/2023 22:00	11198	9673	1525	13.62
7/1/2023 23:00	11058	9964	1094	9.89

In the context of this analysis, the “Timestamp” column acts as a temporal anchor, delineating the date and hour at which the demand data was recorded. This chronological arrangement enables a precise evaluation of the model’s performance across different times of the day. The “Actual Demand” column reflects the genuine electricity consumption during these hours, serving as a benchmark of real-world data acquired directly from the system. Concurrently, the “Forecasted Demand” column presents the corresponding predictions generated by the forecasting model. These values represent the anticipated electricity consumption for each hour, calculated through the applied algorithm. The disparity between actual and forecasted demand is quantified in two distinct measures. The “Absolute Error” column quantifies the raw numerical difference between the actual and forecasted values. A lower absolute error signifies a closer alignment between the model’s predictions and the observed data, highlighting the model’s precision in capturing the intricacies of electricity demand fluctuations.

Complementing the absolute error, the “Error Percentage (%)” column provides a relative assessment of the forecasting accuracy. This metric expresses the error as a percentage of the actual demand, offering a normalized view of the prediction discrepancies. A smaller error percentage indicates a more proportionate error concerning the actual demand, underscoring the model’s effectiveness in foreseeing electricity consumption patterns. From the experiment, it is found that the average error percentage is 6.78, which is quite acceptable in the assessed scenario.

The comparative analysis between actual and predicted data is visually elucidated through graphical representations. Figure 2 illustrates the model’s predictive performance on the training dataset. Each data point within the training set undergoes prediction after the model’s rigorous training and testing phases, thereby demonstrating the model’s capacity to generalize. Conversely, Figure 3(a) presents the model’s forecasts for energy demand over the subsequent 24 hours, derived from the initial dataset. Subsequently, Figure 3(b) directly compares the forecasted and actual demands within the predicted timeframe. These visualizations are pivotal in comprehending the model’s efficacy in training and real-world predictive scenarios.

Hourly energy demand prediction acts as a cornerstone for sustainable energy practices. It aligns energy production with actual needs, reduces waste, encourages renewable energy integration, enhances grid stability, fosters innovation, reduces environmental impact, and ensures cost efficiency. These collective efforts contribute significantly to the global

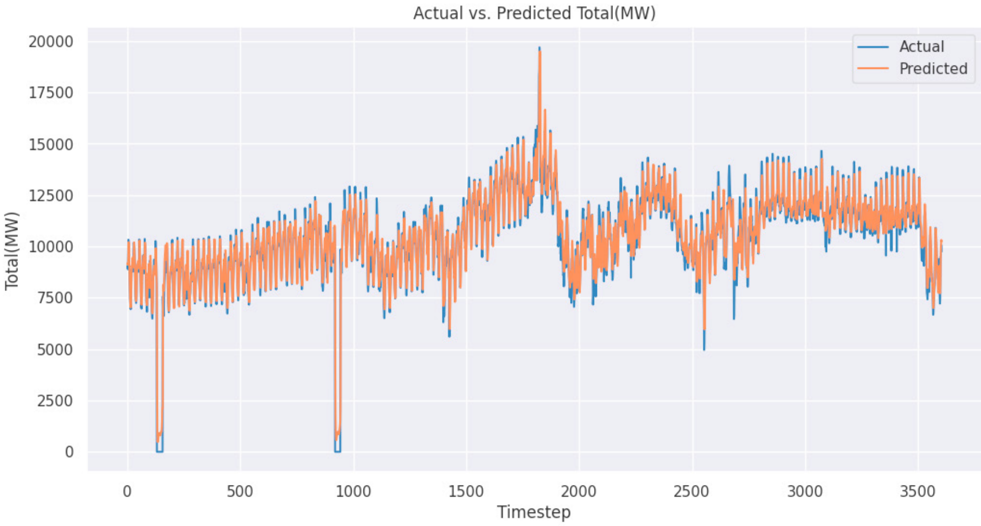

Fig. 2. Actual vs. predicted plot for all the training data points

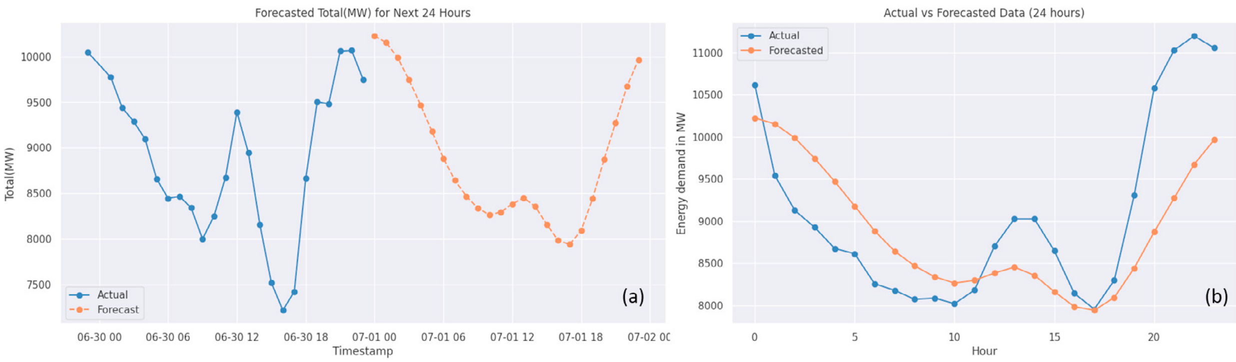

Fig. 3. (a) Forecasted energy demand for next 24 hours, (b) Actual vs. predicted energy demand plot for the forecasted 24 hours

pursuit of sustainable energy solutions and a greener future. From the experimental results, it is clear that the proposed model's performance is acceptable and can impact sustainability.

4. Conclusion

This study has delved into energy demand forecasting using advanced deep learning techniques. Leveraging a unique dataset from the Power Grid Company of Bangladesh (PGCB), our proposed model, employing bi-directional long short-term memory networks (Bi-LSTMs), has exhibited promising results. Our model demonstrated a remarkable accuracy in predicting energy demand patterns through meticulous data preprocessing and rigorous evaluation using Mean Absolute Error (MAE) and Mean Squared Error (MSE) metrics. The outcomes of our research underline the potential of deep learning methodologies in enhancing the precision of energy demand predictions. By harnessing the power of recurrent neural networks, we have substantially advanced forecasting accuracy, laying the foundation for more effective energy management strategies.

Moreover, the findings of this study have far-reaching implications for the energy sector. Accurate energy demand predictions are pivotal for optimizing production, reducing wastage, and promoting sustainable energy practices. The insights garnered from this research can inform policy-making, aid in grid stability, and facilitate the integration of renewable energy sources. Further refinements and extensions to our model are anticipated as we move forward.

Incorporating real-time data streams and exploring hybrid models integrating traditional statistical methods with deep learning architectures are avenues for future research. Such endeavors will bolster the accuracy of energy demand forecasts and contribute significantly to the ongoing global efforts toward a sustainable and energy-efficient future.

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