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Performance Analysis of LSTMs and Fbprophet Models for Short Term Load Forecasting

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***Abstract*—With the advent of smart grids, accurate electric load forecasting has become more essential since it may assist power companies in improving load scheduling and reducing surplus energy output. Short term load forecasting (STLF) is gaining popularity owing to its utility in energy usage, demand-side management, energy storage, peak load forecasting and minimize electricity production costs. This study offers four artificial intelligence-based models to enhance 168-hours prediction accuracy. These models are long short term memory (LSTM), bidirectional LSTM (Bi-LSTM), Conv2D LSTM and Fbprophet. The models are trained with hourly energy consumption data of four years. After training and testing, it is depicted that bidirectional LSTM can predict more precisely than other models with an MAPE of 3.59. The MAPE of Conv2D LSTM, LSTM and Fbprophet are found 3.95, 4.91 and 7.75 accordingly. Since bidirectional LSTM utilizes the LSTM regular model twice, they usually have more accuracy than conventional LSTM. The use of bidirectional LSTM may thus make the demand response system more efficient.**

***Index Terms*—Long Short-Term Memory (LSTM), Fbprophet, Bi-LSTM, Conv2D LSTM, MAPE, RMSE, Time series analysis, Recurrent Neural Network (RNN), Neural Network (NN), Short term load forecasting (STLF).**

I. Introduction

The global electricity consumption has risen dramatically in the past few decades due to extensive industrial progress around the world [1]. In recent times, many new technologies such as distributed renewable generation, demand side management, peak load shifting are integrated into the distribution grid. Therefore, accurate forecasting of future demand has played a significant role in terms of surveillance of the power system's stability and smart energy management [2]. Actual demand prediction is indispensable for integrating demand response, utility energy conservation, energy efficiency, load scheduling and overall smooth operation of power grids [3]. According to the energy agencies, even a minor improvement in electricity load forecasting could lower the production costs and boost trade benefits especially when energy usage is at its highest [4].

Load forecasting can be classified into three categories such as short term forecasting (1 hour to 1 week), midterm forecasting (1 week to 1 year) and long term forecasting (from 1 year and above). Previously, statistical methods are mainly used load foretasting but recently different machine learning algorithms are tested to determine the accurate future demand. [5]. In this paper, our aim is to focus on short-term load forecasting (STLF) which is necessary for power system control and scheduling, interchange evaluation, security assessment, robustness and spot price computation all of which demand greater precision than long-term forecasting [6].

Short term load forecasting (STLF) is mainly required to plan power system generation timetable, ensure the safe and reliable operation of power plants, cost-effectiveness, demand side management control and dependability [7]. A short-term (1-2 days) prediction can identify which power sources will be able to access during the next 24 hours, and transmission network resources may be allocated promptly to customers, depending on current transmission needs. Electricity retailers may use an adequate demand and supply prediction to compute energy prices more effectively based on anticipated demand [4]. Short-term load forecasting (STLF) is gaining popularity in smart grids, microgrids, and buildings due to its utility in demand-side management, energy consumption and storage, peak load prediction and risk reduction [8]. In this field, researchers have proposed a variety of approaches. These techniques are divided into two groups: (1) Traditional strategy such as regression, exponential smoothing and Kalman filter (2) Artificial intelligence-based models such as artificial neural networks (ANNs), recurrent neural networks (RNNs), convolutional neural networks (CNNs), fuzzy-based methods, genetic algorithm, support vector regression (SVR), deep learning models [9], [10]. Classical methods rely on statistical computations and presume that the load series is steady. Consequently, these methods are unable to adequately describe the nonlinear relationships between load profile and some variables such as consumption patterns which result in large load forecasting errors. Contrarily, AI-based models are adept at dealing with complicated and nonlinear data, lead to enhanced load forecasting accuracy [9]. Due to their resilience and better performance, deep learning models have been a rising trend for managing time-series data in recent years. Thus they've

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quickly become the paradigm for time series analysis [11]. Using traditional linear models, such as SARIMA, ARIMA, and SARFIMA requires enormous load-data pre-processing and analysis of Auto Correlation and Partial Auto Correlation Functions to determine the appropriate set of mode hyper-parameters for STLF [12]. Despite their simplicity, traditional techniques like regression and multiple regression are still frequently employed, particularly for long-term forecasting, according to a recent study [10]. Unsupervised learning has also been implemented for forecasting and decision making which can generate near ideal result given enough parameters [13]. Though it lacks significant robustness. The Recurrent Neural Network (RNN) is one kind of ANN that performs better with sequential data types [14]. LSTM was developed to overcome the disappearance or explosion of gradients during the backpropagation phase of RNN [15]. In contrast to RNNs, LSTMs include a memory cell that contains input, output and forget gates that allow long term dependency [16]. Bi-LSTM and Conv2D LSTM are special types of LSTM that provide more accurate prediction due to their duet model and convolution operation respectively [17], [18]. Fbprophet is a relatively new model for STLF which has shown impressive results for some particular datasets [19]. The findings indicate that the use of LSTM and Fbprophet resulted in extremely high accuracy for the three currencies, ranging between 93% and 99%, whereas the accuracy of the ARIMA model varies between 82% and 66% [10]. Bi-LSTM and Conv2D LSTM can perform better than other machine learning based models such as multiple linear regression (MLR), k-nearest neighbors regressor (KNN), epsilon-support vector regression (SVR), random forest regressor (RF) [20].

This paper is arranged into four sections. In Section I, the relevant literature review has been provided with an outline of this study. In section II, data description and all the four models, such as Fbprophet, LSTM, Bi-LSTM and Conv2D LSTM are discussed briefly. In section III, the performance of these four models are analyzed and a comparison study is carried out. Finally, the paper is concluded with section IV.

II. Methodology

A. Dataset Description

In this paper, hourly electricity load data of Panama provided by ETESA and CND is used [21]. The time period of the dataset used in this study ranges from January 2015 to April 2019. The dataset has been split into two parts. Around 99.55% data was used for training the models whereas, about 0.45% was used for testing purposes.

It is found that there lies a 72-hours gap between the training and testing data. From the histogram diagram, it is clear that the national electricity demand of Panama ranges from 750 MWh to 1750 MWh, with 1000 MWh repeated maximum times of about 1600.

This panama dataset is very recent, thus there has not been any groundbreaking research done on it yet. The Histogram diagram in fig.1 indicates that the data is almost normally distributed and no data point is missing.

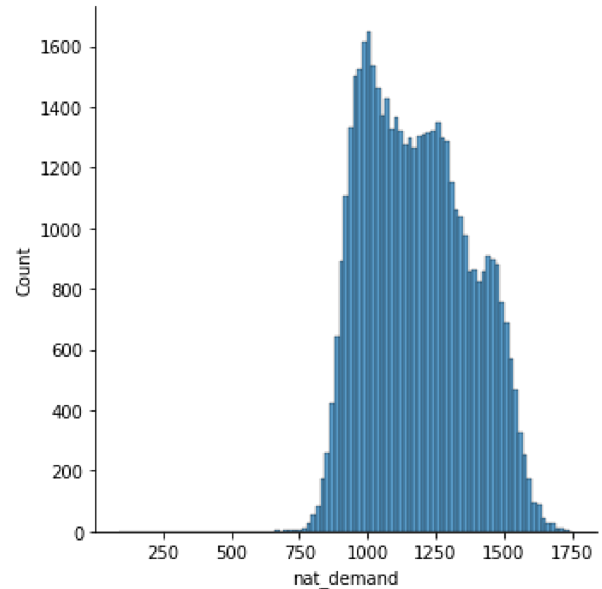


Fig. 1: Histogram of the dataset

Training data has been implemented in our four models and the performance of the models are evaluated using the test data. The workflow is shown in fig. 2.

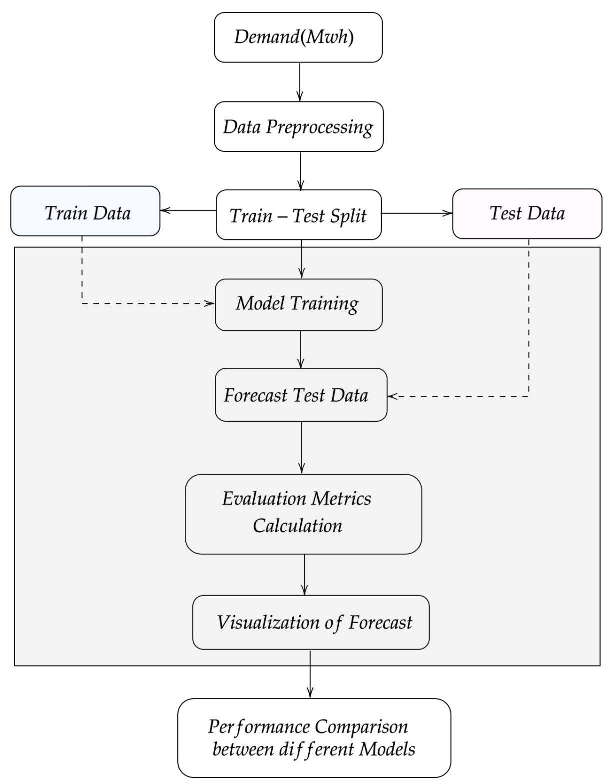


Fig. 2: Flow diagram of system models

B. Description of models

1) Fbprophet: Fbprophet is a time series-based forecasting algorithm that was developed by Facebook. The Prophet prediction model can be broken down into four parts. They are: trend term, seasonal term, holiday effect and the error term. The mathematical representation of the model is as follows: [10]

$$y(t) = q(t) + r(t) + h(t) + \varepsilon_t \tag{1}$$

Here, $q(t)$ is the trend function which is used for modelling the non-periodic changes, $r(t)$ indicates the seasonality or regularity of the time series which models the periodic changes, $h(t)$ represents the holiday effect and finally, ε_t means the error term which illustrates any kind of unusual data that does not fit through the model. By combining this four functions, Fbprophet can predict the time series with a decent amount of accuracy.

2) Long Short Term Memory (LSTM): Traditional Recurrent Neural Network (RNN) models are very popular for analysing sequential data. However, they often struggle while dealing with long term dependencies due to their short term memory [22]. For solving this issue, a new type of RNN known as LSTM was introduced in 1997. Unlike RNN models, LSTMs have an ability to recall important information for an extended amount of time. An LSTM model is a collection of cells and in this cells information is captured and saved. Each individual cell has three gates such as: forget, input and output gate [23].

Forget gate: The sigmoid function present in the forget gate chooses whether the existing information will be kept or removed from the LSTM memory. It generates a number between 0 to 1, where 0 represents totally removing the information and 1 means preserving it.

Input gate: The input gate determines which new information will be stored in the LSTM memory. It has two parts: a sigmoid layer and a tanh layer. The sigmoid layer determines which information has to be modified on the other hand, the tanh function generates a vector of new candidates that can be included on the memory.

The next step is to update the LSTM memory by forgetting the old state and then adding the new possible state.

Output gate: This gate decides which part of the LSTM memory will be the output of the cell. The output is generated based on the cell state, and with filtered and newly included data.

In this paper, four dense layers along with one LSTM cell layer was used for training the entire LSTM model. The summary of this model is shown in fig. 3.

3) Bidirectional LSTM (Bi-LSTM): Bidirectional LSTMs are an extended version of the traditional LSTM models. Unlike regular LSTMs, Bi-LSTMs have two training models. One model is used to train the input sequence in the forward direction and the other model is trained to learn the sequence in the backward direction. As Bidirectional LSTMs use the regular LSTM model twice (forward and reverse), their accuracy is normally higher than the conventional LSTMs [17].

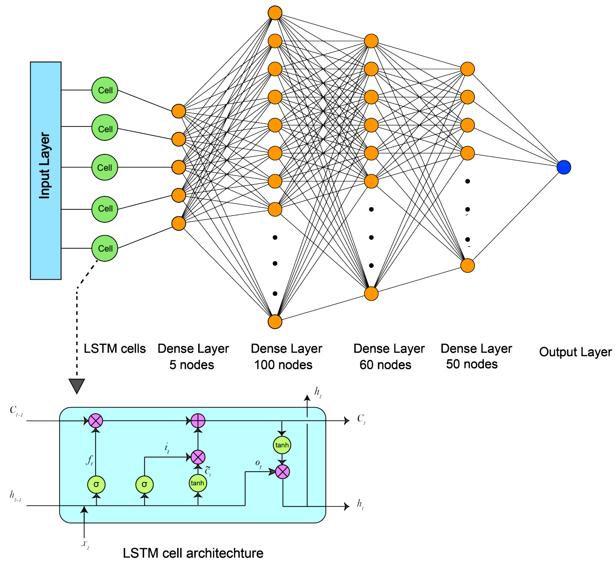


Fig. 3: Summary of LSTM model

In this paper, only one dense layer was used for training the Bi-LSTM model. Fig. 4 illustrates the model summary of Bi-LSTM.

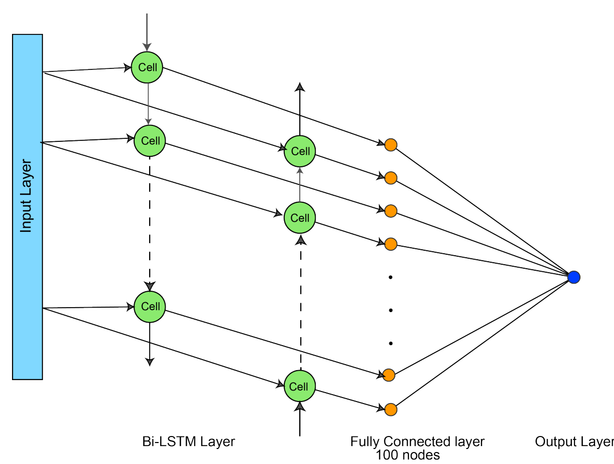


Fig. 4: Summary of Bi-LSTM model

4) Conv2D LSTM: Conv2D LSTM is another special type of LSTM that performs the convolutional operation in the LSTM cell. Traditional LSTMs are modelled in such a way that they can learn long term dependencies easily. However, because of this, a regular LSTM is unable to model spatial information well. The convolutional LSTM overcomes this issue by replacing matrix multiplication with a convolutional operation [18].

Model summary of Conv2D LSTM utilized in this research is represented in fig. 5.

Summary of hyper-parameters for LSTM, Bi-LSTM and Conv2D LSTM are shown in TABLE I.

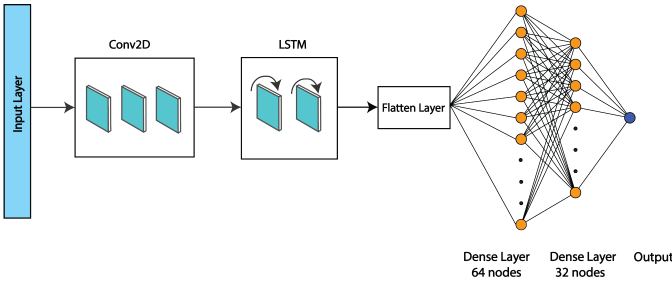


Fig. 5: Conv2D LSTM summary

TABLE I: Hyperparameters of LSTM, Bi-LSTM and Conv2D LSTM

Epoch	200
Batch size	125
Optimizer	ADAM
Loss	Mean squared error
Early stopping	Patience = 30
Random seed	25

III. Results and Discussion

Bi-LSTM, LSTM, Conv2D LSTM and Fbprophet models are applied in our dataset. The actual and predicted results are presented below for all the four models stated above.

Fig. 6 shows that Bi-LSTM can predict considerably more precisely than other models. This occurs owing to the dual model characteristic of the Bi-LSTM, where one model trains the input sequence in forward direction while the other trains backwards. According to the predicting abilities, Conv2D LSTM and LSTM occupy second and third place respectively. It is also evident that Fbprophet has predicted well initially. But in the end, it deviates from the actual values due to the lack of smoothness in test data. Otherwise, it would have been brilliantly done. Prediction performance can be analyzed more effectively by Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE).

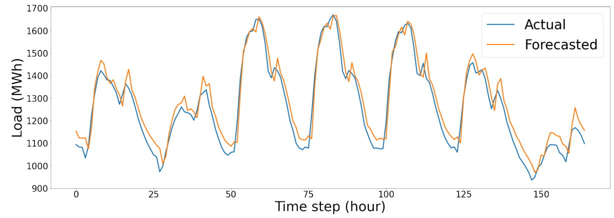
$$\mathrm{MAPE}(\%) = \frac{100}{N} \times \sum_{i=1}^{N} \frac{|x_i - y_i|}{x_i} \tag{2}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(x_i - y_1)^2}{N}} \tag{3}$$

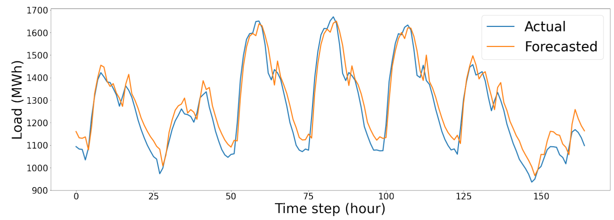
where the actual and forecasted load values are represented by x_i and y_i respectively and N indicates total number of observations.

TABLE II: Error rate comparison of different models

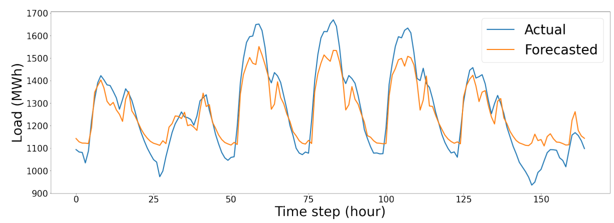
Model Name	**MAPE**	**RMSE**
Bi-LSTM	3.59	49.40
Conv2D LSTM	3.95	54.35
LSTM	4.91	74.14
Fbprophet	7.75	134.17



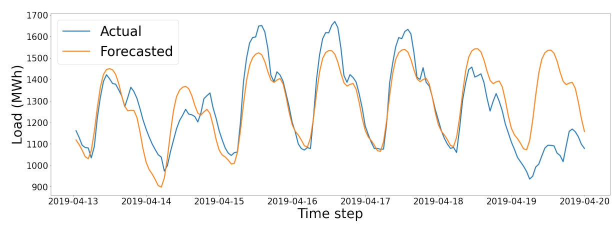
(a) Bi-LSTM



(b) Conv2D LSTM



(c) LSTM



(d) Fbprophet

Fig. 6: Visualizing the performance of different models

We can get a brief idea on performances of all the four models from TABLE II.

The least MAPE is found 3.59 for Bi-LSTM as expected from fig. 6. In this study, our major contributions are: (i) this particular dataset from Panama is implemented in LSTM, Bi-LSTM, Conv2D LSTM and Fbprophet for the first time and found better results than other machine learing models. (ii) The MAPE of 3.59 for Bi-LSTM is the lowest value so far for this particular dataset. The previous least MAPE was found 3.66 by applying the Extreme Gradient Boosting Regressor (XGBoost) model [20]. (iii) In addition, Conv2D LSTM and Fbprophet are relatively new models for STLF that are used in this research.

IV. Conclusion

The current progress in electricity networks requires accurate techniques for predicting demand to maintain their stability and to prevent different energy catastrophes. In this research, three neural network-based models such as LSTM, Bi-LSTM, Conv2D LSTM and a machine learning model Fbprophet are implemented for 168 h load forecasting of Panama. After training and testing, it is observed that neural network-based models are more suitable for this kind of complex, non-stationary, non-uniform dataset. Bi-LSTM performs superior among the three neural network based models for this dataset. Fbprophet might do better if the dataset was smoother. The effectiveness of these models might be improved by using additional historical data. Other models based on neural networks are highly recommended to improve this result. The use of LSTMs with additional hyper-tuned parameters and optimizations may be a useful technique for anticipating power demand and provide superior results. Predictions may be improved by including a variety of input characteristics, such as weather data. AI-based hybrid models may offer a new horizon in order to improve the performance of short term load forecasting (STLF).

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