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Short term residential load forecasting using long short-term memory recurrent neural network

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ABSTRACT

Load forecasting plays an essential role in power system planning. The efficiency and reliability of the whole power system can be increased with proper planning and organization. Residential load forecasting is indispensable due to its increasing role in the smart grid environment. Nowadays, smart meters can be deployed at the residential level for collecting historical data consumption of residents. Although the employment of smart meters ensures large data availability, the inconsistency of load data makes it challenging and taxing to forecast accurately. Therefore, the traditional forecasting techniques may not suffice the purpose. However, a deep learning forecasting network-based long short-term memory (LSTM) is proposed in this paper. The powerful nonlinear mapping capabilities of RNN in time series make it effective along with the higher learning capabilities of long sequences of LSTM. The proposed method is tested and validated through available real-world data sets. A comparison of LSTM is then made with two traditionally available techniques, exponential smoothing and auto-regressive integrated moving average model (ARIMA). Real data from 12 houses over three months is used to evaluate and validate the performance of load forecasts performed using the three mentioned techniques. LSTM model has achieved the best results due to its higher capability of memorizing large data in time series-based predictions.

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1. INTRODUCTION

Due to the increased penetration of renewables and rapid power system growth, the complexity of the system has been significantly expanding [1], [2]. The variable and erratic nature of residential load consumption data make it challenging for the forecasts. Forecasting is the process of making predictions of the future, based on past and present data and most commonly by analyzing trends. Load forecasting refers to the prediction of power demand behavior for maintaining a balance between supply and demand. Load forecasting plays an essential role in the upfront planning and organization of the power system [3], [4].

Power system planning and reliability require accurate load forecasts for upfront planning of generation facilities, managing transmission line structures, properly controlling distribution systems, encouraging demand response (DR) programs, and participating in day-ahead electricity markets. The nature of load consumption data is primarily time series based, and forecasting is used to predict time series-based information. These time series-based data have some output value corresponding to continuous and consecutive time sequences. Based on the nature of forecasting, techniques used for forecasting load demand can be broadly divided into two types, i) extrapolation and ii) correlation. Extrapolation refers to time series methods based on historical and present demand; future load demand is predicted. Forecasting based on correlation can be further divided into two types, econometric and determination to identify underlying factors that might affect load demand. In econometric forecasting, economic factors affecting the load profile such as pricing. are used for forecasting, whereas underlying factors that might contribute to the load demand includes temperature, weather, holidays, and events. are utilized for accurate load prediction. Based on the time duration of load forecasting, it can be classified into three types, short-term forecasts [5], [6], intermediate or medium-term forecasts [7].

Short-term forecasts primarily span over a few hours to several weeks, whereas medium and long-term forecasts refer to the prediction of load demand over several months and years, respectively [8]. Long-term forecasts are needed for the maintenance and scheduling of the power system, whereas medium-term forecasts enable fuel scheduling and hydro reservoir management. For the day-to-day and weekly operations of the power system, short-term load forecasts play an essential role. Short-term load forecasting is a time series-based prediction problem, and its vital role cannot be ignored in a smart grid environment [9]. Accurate and time-efficient load forecasting algorithms and techniques are a need of the hour. These techniques are primarily based on various machine learning algorithms in the smart grids ecosystem. Data monitoring of historically available data for a particular location considering the transient effects of weather over this load demand is an essential requirement from the perspective of different small power producers and end-users in commercial or industrial buildings.

Several forecasting methods have been proposed over the past few years. The forecasting can divide into two models physical model and statistical model. The physical model needs measured data with good quality, and the statistical model needs historical data. The artificial neural network (ANN) model and auto-regressive integrated moving average (ARIMA) model belong to statistical modeling [10]. Box-Jenkins's approach [11] is an effective tool to identify parameters in time series while Kalman filter [12] technique, also a parametric model, both model based on historical data. The widely used single models include fuzzy logic, ANN [13], support vector machine (SVM) [14], [15], wavelet transform (WT), genetic algorithm, and expert system. The hybrid system is to integrate one or more algorithms to get more forecasting accuracy [16]. Therefore, with the arrival of the Covid-19 pandemic [17], people are forced to stay at their own residential houses more, which increases the electric load demand. Motivated by this, we attempt to predict the electric load demand. In this paper, three techniques have been chosen to forecast the electric load demand of residential houses. These techniques comprise of ANN model, ARIMA [18], [19], and exponential smoothing. In ANN, a sub-type recurrent neural network (RNN) [20] is used with some parameters and optimizer, whereas the other two techniques are used for comparison. For a fair comparison among these algorithms, data is acquired from 12 houses over a period of 3 consecutive months of a particular year. The real-world data is collected both from the real world and available online resources [21]. For ANN and ARIMA, the collected data set is divided into training and testing data set.

This paper is organized as follows. Section 2 presents a comprehensive analysis of used algorithms, and the details of the proposed model of long short-term memory (LSTM) are discussed. Section 3 describes the characteristics and nature of the data set utilized and discusses a comparison performed over the data set based on the results of three algorithms. Section 4 provides the model performance evaluation, and finally, section 5 concludes the paper.

2. RESEARCH METHOD

This section provides the dataset description and the research methodology used in this study. The first section focuses on the data collection, while the remaining section focuses on exponential smoothing. Auto-regressive integrated moving average, and the proposed LSTM model, respectively.

2.1. Data collection and description

Data is collected from two sources; source 1 data set consists of load consumption of 2 volunteer's houses in one month, from March 2018 to April 2018, with a granularity of data being one hour, giving a total number of hours calculated as 745. For LSTM and ARIMA, data is divided into two parts; i) for training, 65% of data is used and ii) for testing, 35% of data is used. Source 2 data set consists of load consumption of 10 houses for the period of 3 consecutive months. This data is collected from available online resources [22]. The granularity of the acquired data was 5 minutes, but for comparison purposes, the time interval used is one hour, giving the total number of hours as 2,184. For ARIMA and LSTM models [23],

[13], data is divided into two parts as previously done for volunteer houses *i.e.*, 65% of data is used for training, and 35% of the dataset is utilized for testing 5. Therefore, this paper uses three machine learning techniques for time series-based predictions and comparisons. These three methods are discussed in the following subsections.

2.2. Exponential smoothing

The exponential smoothing scheme uses exponentially decreasing weights to smooth past observations; it is a popular way to produce smoothed time series [24]. When the observation gets older, the weights decrease exponentially. 1/N is the weight assigned to the observations in moving averages. When applying exponential smoothing, it is necessary to determine (or estimate) at least one smoothing parameter and determine which weights should be assigned to each observation [25]. The smoothing parameter is alpha. Forecasting the next point as (1):

$$s_{t+1}=(\alpha * y_t)+(1-\alpha) * s_t \tag{1}$$

where, s_{t+1} is predicted value at time $t+1$, α is a parameter that decide the weightage of predicted and actual output, and y_t is actual output at time (1) can be written as (2):

$$s_{t+1}=s_t+\alpha * s_t \tag{2}$$

where, s_t is the forecast error (actual-forecast) for time period t. Specifically, the new forecast is the old one plus an adjustment for the error that occurred in the last forecast [26]. Forgiven data set, forecasting α=0.5 is used. Exponential smoothing does not require any training. It is good only for comparison purposes.

2.3. Auto-regressive integrated moving average (ARIMA)

It combines auto-regressive (AR) and moving average (MA) models. The I stand for "integrated" represents the fact that the data have been substituted with a number, which is the difference between their values and the foregoing values [27]. ARIMA (p, d, q) [28] can be used to represent non-seasonal ARIMA. *P* is order (number of time lags) of the auto-regressive model, *d* is degree of difference (the number of times the data subtracted from past value), *q* is order of the moving-average model.

If d = 0: $y_t = y_t$
If d = 1: $y_t = y_t - y_{t1}$
If d = 2: $y_t = y_t - (y_{t1})\ y_{t1} - y_{t2}$

Where, y_t is actual output at any time (t). And d is the degree, which represents the influence of past time at level d [26]. Forgiven data set forecasting *p*=3, *d*=2 and *q*=0 is used. Figure 1 shows the flow that is used to run the ARIMA algorithm.

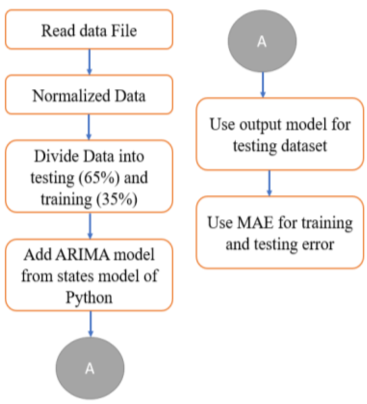


Figure 1. Flow chart for ARIMA algorithm

2.4. Deep learning neural networks (DLNN)

It is a nonlinear model where any prior knowledge of the relationship between input and output is needed [29]. Therefore, DLNN gives good results for pattern recognition [30], [31], sequence prediction [32],

[33] and forecasting problems [34]. The main parameters of DLNN are the number of input vectors, the number of layers, the number of neurons in each layer. In this paper, for forecasting load demand of multiple residential buildings, RNN is used among all the techniques due to its feasibility and nature of the load forecast. Additionally, the human mind does not begin from scratch every second. It makes use of previous knowledge to come up with answers and analyze problems. This is a major shortcoming of traditional neural networks [35]. Consider an example where you want to categorize the events that occur in a movie. It is unclear how a conventional neural network could use earlier occurrences in the film to inform subsequent events [36]. This issue is addressed by recurrent neural networks. They are networks that contain loops, which enable information to endure [37], [38].

Figure 2 shows a chunk of the neural network is depicted with an input x_t and an output h_t. A loop enables data to be transmitted from one network stage to the LSTM. The LSTM algorithm is a type of RNN that is capable of learning long-term dependencies. All recurrent neural networks have the form of a chain of neural network modules. In standard RNNs, this repeating module will have a simple structure [39]. Figure 3(a) can be described as; f_t, c_t, o_t, and it is activation functions for hidden, context, output, and input layers, respectively. All these are sigmoid functions, where t represents time instance, h_t is output at time t, x_t is input at time t, Bias values (b_o (output bias), b_i is the input bias, and b_f Hidden layer bias, Crosses(X) represents multiplication operation, and T represents the activation function.

2.5. Proposed model of LSTM

LSTM is used to forecast the given data set and root mean square propagation (RMSprop) optimizer to propagate the error. In which learning rate=0.1, decay=0.9, momentum=0.0, epsilon=1 e^{-10}. The learning rate is step size, whereas decay is discounting factor for the history/coming gradient. Momentum is a floating-point value, which helps to avoid getting stuck in the local minimum. Epsilon is a small value to avoid zero denominators. Four active hidden nodes and three active context nodes with one layer is used. A deep learning tool TensorFlow [31] is used to add the LSTM model. The tensor flow determines activation functions and bias values. Figure 3(b) shows the flow of LSTM. Mean absolute error (MAE) is computed for accuracy measure using (3) [40].

$$MAE = \frac{1}{n} \sum_n |X_P - X| \quad (3)$$

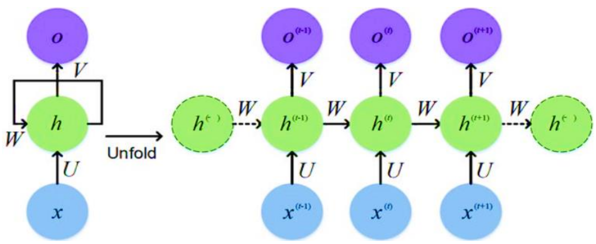
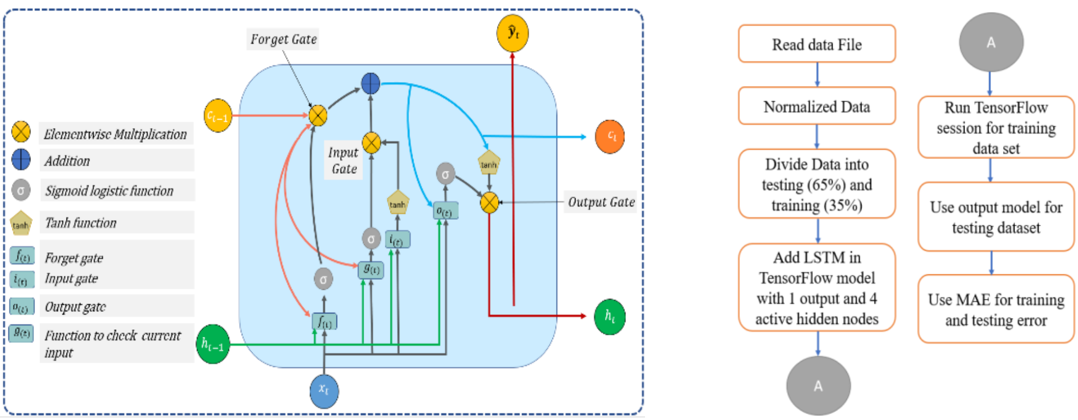


Figure 2. Recurrent neural network architecture [34]



(a) (b)

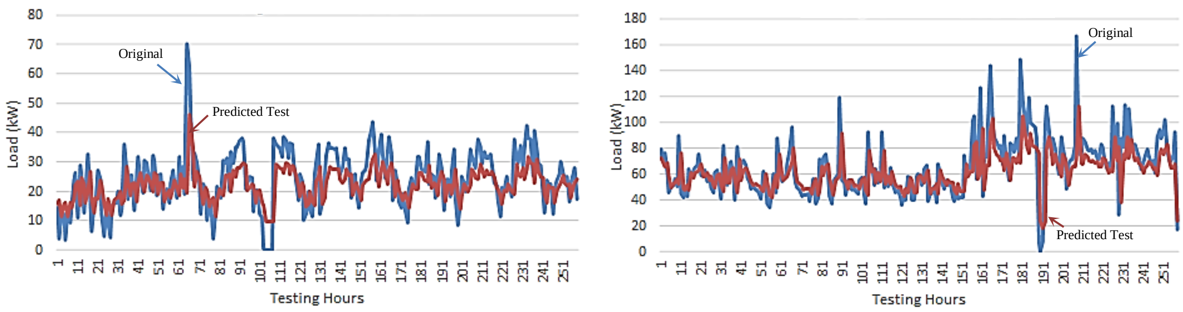
Figure 3. Illustrations of (a) LSTM model architecture and (b) algorithm flow chart for LSTM

3. EXPERIMENTAL RESULTS AND DISCUSSION

The experimental results used in this study are discussed in detail in this section for both real-world and benchmark datasets. The first section is providing the LSTM model testing results with source 1 houses. While section 2 provides the source 1 houses results using ARIMA model and the last section shows the results using the exponential smoothing technique.

3.1. Source 1 houses results using LSTM

From Figure 4 (a), it can be seen that predicted load behavior is similar to the tested load demand, but the foretasted values differ appreciably from the original load values. It can be concluded that due to a large variety of load patterns with respect to increasing time intervals, it becomes difficult for the model to predict the actual or approximately actual load demand for the tested time period. Figure 4(b) signifies that where the load nature of the profile is relatively consistent, the results obtained are quite proximate to the original data. Further, Figure 5 also shows that even though the nature of the aggregated residential load is erratic, forecasting through LSTM gives quite reasonable approximates to the original values.



(a) (b)

Figure 4. Illustrations of (a) LSTM results for house 1 and (b) LSTM results for house 2

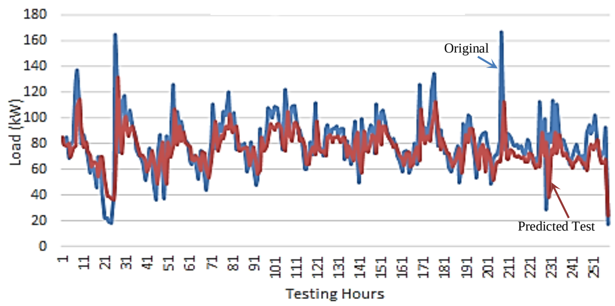


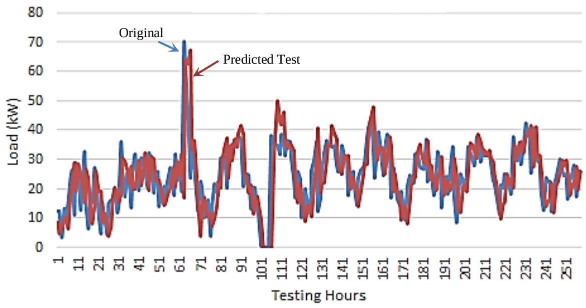
Figure 5. LSTM results for aggregated load of house 1 and house 2

3.2. Source 1 houses results using ARIMA

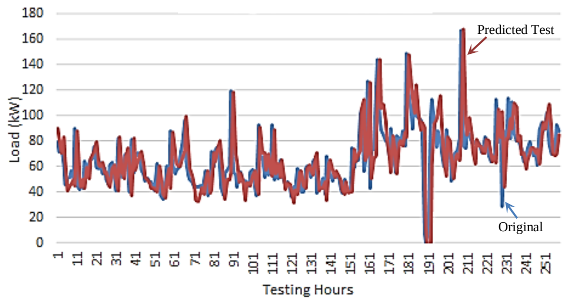
As presented in Figures 6(a) and 6(b) and Figure 7, it can be verified that accepting the values, ARIMA [36], perform like LSTM. The trend of load pattern is maintained in the tested results, but the tested values differ significantly from the original data. These results obtained from ARIMA manifest that LSTM models outperform them for individual and aggregated residential load demand.

3.3. Exponential smoothing results source 1

Figures 8(a) and 8(b) and Figure 9 show the testing results based on the exponential smoothing technique. These results show that the load profile is maintained during the testing compared to the original values. Exponential smoothing performs better than ARIMA, but results confirm that LSTM performance is better than both algorithms. Further, to validate the results, analysis is performed for ten more individual houses over three months. As mentioned earlier, data is collected through available online resources, and evaluation is done for the time granularity of one hour. The details of training and testing data sets are similar to the source 1 data *i.e.*, 65% of data is used for training purposes, and the rest of the data is used for validation and testing the results.



(a)



(b)

Figure 6. Illustrations of (a) ARIMA results of house 1 and (b) ARIMA results of house 2

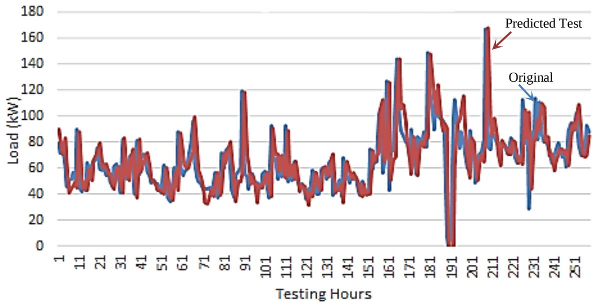
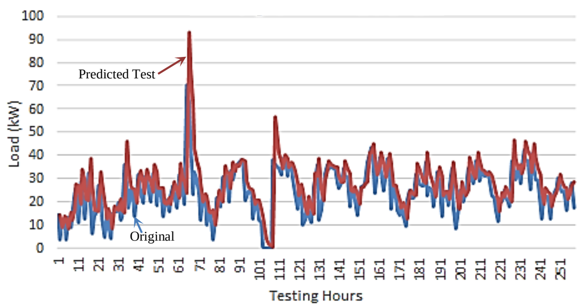
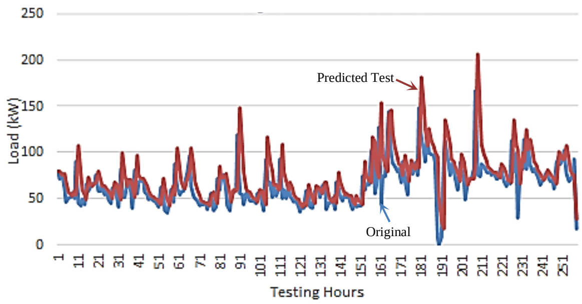


Figure 7. ARIMA results for aggregated load of house 1 and house 2



(a)



(b)

Figure 8. Illustrations of (a) exponential smoothing results for house 1 and (b) exponential smoothing results for house 2

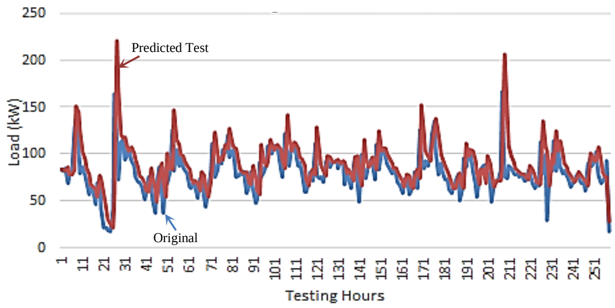


Figure 9. Exponential smoothing results for aggregated load of house 1 and house 2

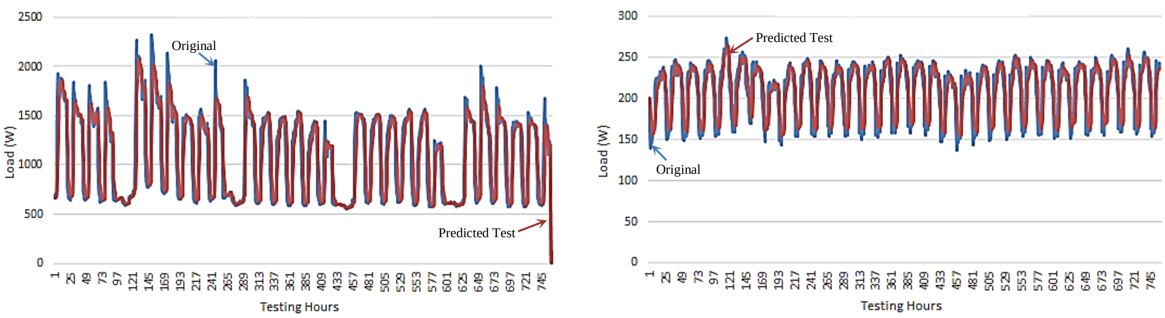
4. PROPOSED MODEL EVALUATION

Table 1 shows a comparison among techniques used based on MAE values for source 1. It justifies the use of LSTM as a novel and effective method for accurate and precise load forecasts. LSTM proves to be the best among the available algorithms for time series-based predictions for individual and aggregated residential load demands. MAE rationalizes the fact that the on average lowest possible error is obtained from its results and analysis. ARIMA and exponential smoothing provide quite acceptable results based on MAE, but precise and exact load forecasts are quite necessary for the smart grid environment. To encourage the users or consumers to participate in DR based programs, actual or near actual load demand must be known so that control action can be correspondingly initiated for maintaining a balance between supply and demand. Further, to engage customers in day-ahead electricity markets, the utility and customer must know accurate load information. Consequently, the application of LSTM models for time series-based load forecasts can prove to be a viable solution to all the mentioned problems.

Table 1. Compression among proposed algorithms using MAE for source 1 (volunteer houses)

House#	LSTM (MAE)	ARIMA (MAE)	Smoothing (MAE)
House 1	4.8679	10.8033	13.0061
House 2	6.8028	15.2129	16.2681
Aggregated	2.4473	14.6014	16.7663

Additionally, the proposed three models have been further validated using an online benchmark dataset for 10 different houses. Some of the LSTM forecasting results for source two are shown in Figures 10(a) and 10(b). LSTM gives quite accurate and exact results when compared with the original values. It can be observed that where the nature of the load profile is volatile, the tested results deviate from the actual values quite significantly. Although the load pattern or load curve is precisely replicated in all scenarios as shown in the results of LSTM, whether the load demand curve is erratic or consistent, the predicted values differ notably where the load demand becomes inconsistent. Figures 10(a) and 10(b) presented an example of the forecasting results obtained using LSTM for two random cases for house one and house 5 in the second dataset

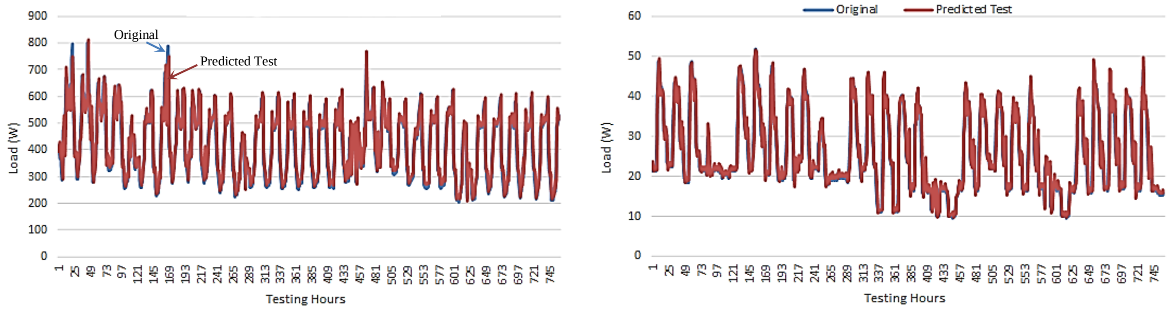


(a) (b)

Figure 10. An example of (a) LSTM results for house 1 and (b) LSTM results for house 5

Figures 11(a) and 11(b) shows that exponential smoothing does not perform very acceptably. The results are not accurate and exact; rather, only a similar trend as original data is observed. Thus, it serves inferior to the other two models, LSTM and ARIMA. The consideration here to make is that LSTM performs better on average for all the houses and proves to be the prime choice for time series-based load forecasts.

Table 2 shows compassion between the three technologies used, exponential smoothing, ARIMA, and LSTM, based on MAE calculated for all ten houses. It signifies the fact that due to, on average lowest values of MAE for LSTM, it substantiates as the viable algorithm for accurate and precise load demand predictions. Further, ARIMA performs better than exponential smoothing due to the autoregressive and integrated nature of the used algorithm. Exponential smoothing can only be used for load forecast at immediate next time interval based on the historical load demand values, but it cannot predict weekly or monthly load demands based on the past load data values and trends. As presented in the comparative analysis in Table 2, the LSTM method has outperformed the other two methods in all the houses load predictions in term of MAE.



(a) (b)

Figure 11. An example of (a) exponential smoothing results for house 3 and (b) exponential smoothing results for house 6

Table 2. Compression between proposed algorithms using MAE for source 2 (benchmark dataset)

House#	LSTM (MAE)	ARIMA (MAE)	Smoothing (MAE)
House 1	36.133	40.330	54.994
House 2	65.232	95.687	108.363
House 3	74.937	98.490	142.259
House 4	2.049	2.434	3.224
House 5	9.1396	10.877	16.031
House 6	11.365	13.708	14.117
House 7	11.812	13.705	14.142
House 8	112.242	137.198	124.569
House 9	25.603	32.433	36.896
House 10	35.812	48.524	50.648

For short-term residential load forecasting, we were unable to obtain any study contribution that were evaluated on the same experimental scenario. However, we have compared the results with the two recently proposed approaches for short-term residential load forecasting [4], [6], [8] shown in Table 3. This study presents comparisons for only available metrics, but essentially demonstrates to the reader the promising results of the proposed model.

Table 3. A comparison of the approach proposed with relevant literature contribution

House#	LSTM (MAPE)	ARIMA (MAPE)	Smoothing (MAPE)
Proposed model	22.13	28.63	42.97
Kong *et al.* [4]	44.39 %	N/A	N/A
Kong *et al.* [6]	21.99%	N/A	N/A
Nair *et al.* [8]	N/A	54.61%	N/A

5. CONCLUSION

This paper proposes a novel model based-LSTM technique for accurate and precise short-term load forecasts. The suggested model is validated and compared with the other two models, exponential smoothing and ARIMA, based on MAE performance evaluation metrics. LSTM models, due to their higher capability of memorizing large data establish their utilization in time series-based predictions. Results from both source 1 and source 2 confirm that LSTM outperforms all other models keeping in view the erratic and volatile nature of residential load demand. It can be inferred that accurate load forecasts are required to encourage customers to participate in DR programs.

Moreover, for engaging customers in day-ahead electricity markets, load forecasting proves to be very pertinent to the problems arising in the smart grid environment. LSTM model and the data from smart progressed meters ensure the power system's valid and effective planning and operation. Further, the technique can be extended for application in home area networks (HAN), enabling smart energy management of individual devices within a home.

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