Mathematical Statistician and Engineering Applications
ISSN: 2094-0343
2326-9865

A Combined CNN-LSTM Deep Learning Architecture Designed to Predict Power Consumption

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Article Info
Page Number: 2207 - 2226
Publication Issue:
Vol. 72 No. 1 (2023)

Article History
Article Received: *15 November 2022*
Revised: *24 December 2022*
Accepted: *18 January 2023*

Abstract

Currently, the increasing human population and technological developments have raised the power consumption rate in household appliances in real-world. Due to limited power resources, it becomes a challenging task to minimize the power consumption. The excessive power consumption affects the power generation systems and economic growth of the country. Thus, prediction of power consumption has become an important research topic to improve the performance of power generation system. Currently, the power consumption forecasting using machine learning has gained huge attraction from research community, but the traditional approaches suffer from uncertainty, volatility, and user's behavior. Thus, deep learning-based approaches are widely adopted to deal with these issues. In this work, we present an end-to-end model where first, we present a data pre-processing technique to normalize the data and imputing the missing values. In next phase, we present a CNN-LSTM model and incorporated a bidirectional LSTM model to improve the forecasting performance by taking the advantage of forward and backward learning of bidirectional LSTM. The proposed approach is tested on UCI power consumption dataset for individual and household appliances. We compare the obtained performance with existing techniques in terms of RMSE, MSE, MAPE and correlation coefficient. Finally, we explore the comparative analysis to show the robustness of proposed deep learning assisted power consumption forecasting approach.

1. Introduction

During the last two decades, we have noticed a paramount augmentation in population and economic growth worldwide. This economic growth is magnifying the consumption of various resources such as animal resources, forests, natural gas, wind power, solar power, electricity, water resources, and many more [1]. In this work, we consider the electrical power consumption in the current scenario which has surged due to industrial and population growth. In 2017, World power Outlook proclaimed that the global power demand is anticipated by 1.0% compound annual growth rate (CAGR) from 2016-2040 [3]. Several studies have reported that residential buildings are significant contributors in power consumption. A study presented in [4] reported that residential buildings consume 27% of the total global power usage which has a substantial influence on overall power consumption. In United States (US), these residential buildings consume 40% of their national overall power consumption [5]. Moreover, the major cause of power consumption in buildings is wastage of power through various components such as overutilization of appliances such as Heating, Ventilation, Air Conditioning (HVAC) systems, exhaust fans, inappropriate control on the thermal devices, and inappropriate start-up timing of these devices. Thus, proper power consumption is considered as one of the prime tasks to minimize the power consumption which could be obtained by taking the advantage of smart building with desired sensor, measurement devices, and numerous controlling strategies to control the devices [6].

On the other hand, the research community has propounded and proliferate power forecasting approach which is useful to control and optimize the power consumption and production worldwide. These type of forecasting systems are beneficial for environmental and economical systems. Due to increasing demand of power consumption the proper power management systems are essentially required to maintain the sustainable and secure environment. As the electrical power cannot be stored for future use thus it is a crucial stage to produce the power according to the requirement which becomes a real-time problem. Thus, electricity consumption forecasting and prediction is an important technique to deal with the power consumption and wastage issues [7].

These forecasting schemes can be applied at various levels such as building, transformer, household, and community level. As we move towards the finer level of prediction, the prediction task becomes complicated due to randomness and uncertainties due to human behaviour and weather conditions which leads to inaccurate prediction of power consumption at household levels [8]. According to figure 1, the power consumption profile for household can be decomposed into three patterns, as regular patterns, uncertainty, and noise. In current scenario, the appliances in smart buildings are equipped with the small sub-meter and utilizes non-intrusive load monitoring (NILM) to obtain the electricity consumption information without installing sub-meters for each appliance [9]. This helps to obtain the historical power consumption data which can be used to predict the power requirements at finer levels in the buildings. This appliance level power distribution helps to design the efficient solution for power saving plans by presenting better scheduling and allocation according the usage of appliance. Moreover, it helps to obtain the understanding of spatial distribution of power consumption in the buildings or houses.

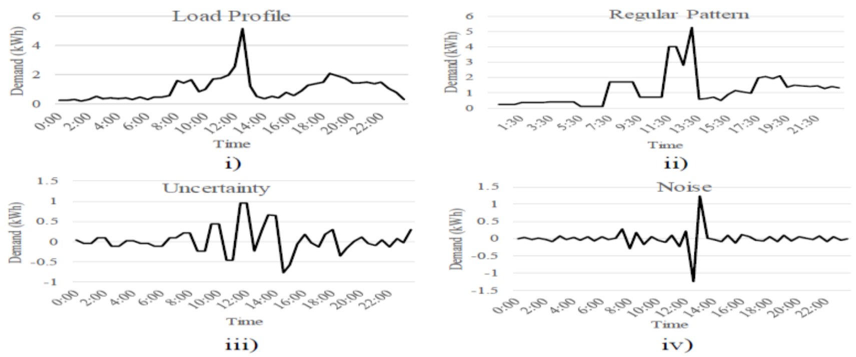

Fig.1. load composition: i) actual load, ii) uniform pattern, iii) irregular and iii) noisy load pattern

The efficient prediction of power consumption is becoming an important topic because it affects the power system operations. A recent study presented in [10] authors discussed that 1% decrease in forecasting or prediction error in power consumption can save £10 million per year for UK power systems. Thus, efficient power consumption planning plays an important role which can be achieved by intelligent forecasting models with the help of machine learning models [11, 12]. Several machine learning algorithms have been developed for power consumption forecasting such as ARIMA [14], time series [15], Neuro-Fuzzy [16], Support Vector Machine [16], Support Vector Regression and linear regression models [16].

The power consumption forecasting/prediction is a time series problem where sensors generate the data which may be contaminated due to uncertainty, redundancy, missing values etc... [13]. Due to these issues, the traditional approaches fail to learn the sequential data patterns that generates inaccurate forecasting. Moreover, the traditional machine learning approaches are not suitable for complex real-world scenario. Thus, current research community has motivated by these issues and adopted deep learning techniques due to their significant nature of pattern learning. The deep learning-based schemes are widely adopted in various domains such as image classification [17], video summarization [17], Natural Language Processing [18], data mining and many more [19]. Thus, the deep learning schemes are adopted by researchers to obtain the improved accuracy in various domains. Similarly, several studies have adopted deep learning method for electricity consumption forecasting including deep reinforcement learning [20], LSTM network & Bi-LSTM Network [21], Recurrent Neural Network (RNN) [8], CNN-LSTM [10] and many more [21]. The performance of these systems suffers from various challenging issues such as computational complexities, learning time, and accuracy. Moreover, hybrid deep learning models are also developed such as hybrid sine-cosine optimization with LSTM [22], hybrid LSTM with stationary wavelet transform (SWT) [23], and CNN and multi-layer bi-directional LSTM networks [12]. These techniques achieve the better performance but increasing the finer levels of prediction in household power consumption leads to inaccurate forecasting which affects the performance of power systems and economical growth of the country. Thus, to overcome these issues, we develop a novel hybrid deep learning approach by using CNN and Bi-LSTM model. The main contributions of this approach are as follows:

- First of all, we study about existing techniques of power consumption forecasting and identified the current challenges in this filed.

- First of all, we present a data pre-processing scheme which deals with the missing values and performs the data normalization.

- To overcome the issues of existing techniques, we develop a new hybrid approach by combining the CNN and LSTM model.

- The performance of LSTM model is further improved by incorporating bi-directional LSTM model.

Rest of the article is organized in following sections as section II describes the brief literature review regarding recent power consumption forecasting schemes, section III presents proposed solution , section IV presents the experimental analysis where we compare the performance of proposed system with existing techniques and finally, section V presents the concluding remarks about this approach.

2. Literature Survey

In this section we briefly describe the existing techniques of power consumption forecasting. As discussed in previous section the deep learning schemes outperforms when compared with traditional machine learning algorithms. Hence, we mainly focus on studying the existing deep learning techniques.

Shi et al. [8] reported that the traditional forecasting schemes use load aggregation, customer classification and spectral analysis to deal with high volatility and uncertainty. However, these techniques are time consuming thus authors developed a new machine learning approach to directly learn the uncertainties using deep learning. This scheme uses pooling based deep recurrent neural network which considers group of customer's load profile as a batch to input to the deep learning network. The complete process is presented in three phases where first of all, the load profile data is loaded, and preprocessed to make it compatible with the network's requirement. In next stage, a load profile pooling scheme is presented and in final stage, deep recurrent neural network is presented to forecast the power consumption.

Khan et al. [10] developed a hybrid deep learning approach by combining CNN with LSTM autoencoder model for power consumption forecasting by considering the data obtained from the smart sensors. According to this approach, first of the CNN model extracts the features from the household power consumption data and later, this data is fed to the LSTM-encoder which helps to generate the encoded sequence. Next phase contains the LSTM-decoder module which decodes the encoded sequence and finally, the decoded data is processed through the final dense layer to obtain the prediction results.

Ullah et al. [11] presented a clustering based approach which helps to divide the load profiles into different levels according to consumption levels. The first phase of this approach performs the training of deep autoencoders which helps to transform the low-level data to high level data. Later, this transformed data is processed through an adaptive self-organizing map (SOM) clustering scheme. Finally, statistical analysis is performed on the clustered data to obtain the prediction of electricity consumption. In their another work Ullah et al [12] presented a short term forecasting with the help of combined CNN and multi-layer bi-directional LSTM networks. This technique is divided into three phases where first of all, data pre-processing is applied to refine and discard the abnormalities of data. In second phase, this pre-processed data is fed into CNN and multi-layer bi-directional LSTM which learns the data pattern efficiently and generates the predicted data. Finally, the predicted and actual data values are compared and performance is measured using error metrics.

Somu et al. [22] presented an power consumption forecasting model by using deep learning and optimization scheme. The deep learning module considers LSTM network and optimization model considers sine-cosine optimization scheme. The optimization process of sine-cosine algorithm is improved by incorporating a Haar Wavelet based mutation operator to improve the divergence. This optimization approach helps to optimize the hyperparameters of LSTM which includes weight decay, learning rate, hidden layers and momentum. Similar to this, Yan et al. [23] also presented hybrid deep learning scheme which considers an ensemble of LSTM with stationary wavelet transform (SWT). The SWT scheme helps to mitigate the volatility issues and improves the dimensionality of data to improve the learning of LSTM which leads to increment in the prediction accuracy.

Syed et al. [24] also presented a hybrid model which is categorized into two stages as data cleaning and building the learning model. The cleaning phase consists of preprocessing technique where the raw data is cleaned for further process. The next step presents the deep learning model where multiple fully connected layers and bi-directional LSTM are combined to learn the data patterns efficiently. Moreover, this architecture extracts the temporal dependency features which improves the training time, computational complexity, and forecasting accuracy.

Aurangzeb et al. [25] reported that similar type of power profiles forecasting is a tedious task. Hence, authors presented a CNN based deep learning architecture in a pyramidal architecture. The similar load profile data is grouped together into clusters by using DBSCAN approach. The pyramidal CNN layers extract the features from the historical clustered data and learns these patterns with the help of deep learning architecture.

Kiprijanovska et al. [26] present HousEEC which is a day-ahead household power consumption model developed using deep learning techniques. This deep learning model extracts the features from multiple source of information such as contextual data and historical load of particular household. Moreover, the domain specific time-series features are also incorporated to improve the feature extraction process. The deep learning model follows a deep residual learning architecture where all extracted features are processed through the residual blocks and concatenated later for further processing.

Alhussein et al. [27] reported that the forecasting for at household level is more challenging when compared to community level due to uncertainty and volatility in the data. Moreover, authors reported that existing techniques fail to obtain the accurate prediction for household load forecasting thus authors developed a hybrid approach by combining CNN and LSTM. The CNN is used for feature extraction and LSTM is used for sequential learning.

3. Proposed Model

In this section, we present the proposed deep learning based solution for household power consumption forecasting to improve the performance of power systems. The first phase of this scheme includes data pre-processing where we normalize the data in a specific range which helps to minimize the data volatility. In next phase, we present the CNN and LSTM models. Finally, we present the proposed hybrid CNN-LSTM model for forecasting. Below given figure shows the complete overall architecture of proposed hybrid model for power consumption forecasting.

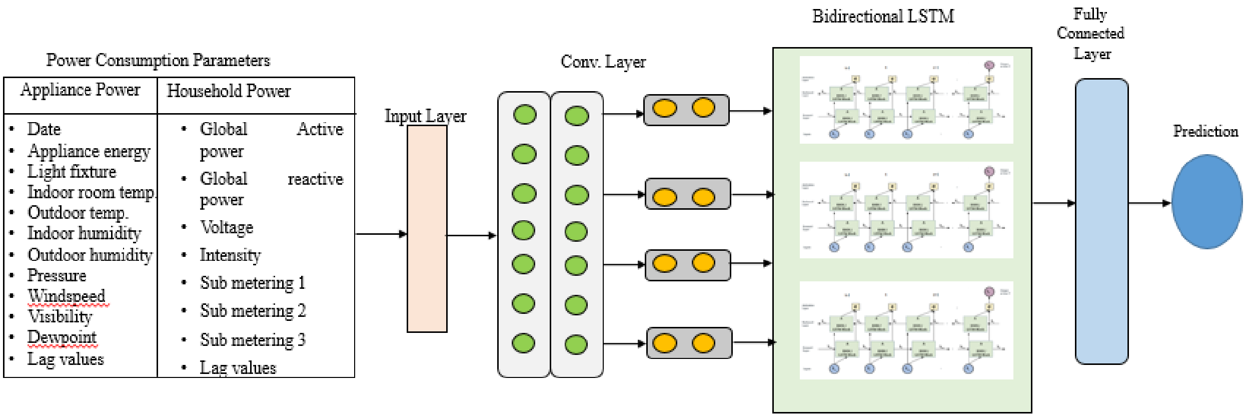

Fig.2. Proposed deep learning architecture for power consumption forecasting

3.1. Data pre-processing phase

The data pre-processing scheme helps to remove the outlier, imputes the missing values and normalize the input data. The appliance power prediction (AEP) dataset contains attributes ranging between 0 to 800 which are normalized in the range of -4 and 6. Similarly, the Individual household electric power consumption (IHEPC) contains the attributes which are ranging between 0 to 250. By applying normalization process, these attributes are normalized between range of -2 to 3. The normalization function is given as:

$$Y = \frac{(A - M\ )}{S}$$
$$Y = \frac{A - A_{min}}{A_{max} - A_{min}} \quad (1)$$

Where A denotes the actual input data, M denotes the mean of this data, S is the standard deviation, A_{max} and A_{min} represent the maximum and minimum values of attributes.

Furthermore, we present a missing value imputation method by using a combined KNN and correlation computation model. The missing value dataset is represented as given in table 1.

	V_1	V_2	V_3	…	V_j	…	V_{m_2}	…	V_p
C_1	y_{11}	y_{12}	NA	…	y_{1j}	…	y_{1m_2}	…	y_{1p}
C_2	y_{21}	y_{22}	y_{23}	…	y_{2j}	…	y_{2m_2}	…	y_{2p}
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
C_i	y_{i1}	y_{i2}	y_{i3}	…	y_{ij}	…	y_{im_2}	…	y_{im_3}
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
C_{m_1}	$y_{m_1 1}$	$y_{m_1 2}$	$y_{m_1 3}$	…	$y_{m_1 j}$	…	$y_{m_1 m_2}$	…	$y_{m_1 p}$

$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
C_q	y_{q1}	y_{q1}	y_{q1}	$\cdots$	y_{q1}	$\cdots$	y_{qm_2}	$\cdots$	y_{qp}

Table 1. Missing value data representation

Based on this missing data representation, we compute the correlation between attributes as follows:

$$r_{m_2j} = \frac{\sum_{i=1}^{q} y_{im_2}y_{ij} - \frac{\left(\sum_{i=1}^{q} y_{im_2}\right)\left(\sum_{i=1}^{q} y_{ij}\right)}{q-1}}{\sqrt{\left[\sum_{i=1}^{q} y_{im_2}^2 - \frac{\left(\sum_{i=1}^{q} y_{im_2}\right)^2}{q-1}\right]\left[\sum_{i=1}^{q} y_{ij}^2 - \frac{\left(\sum_{i=1}^{q} y_{ij}\right)}{q-1}\right]}} \quad (2)$$

Where r_{m_2j} denotes the correlation coefficient between missing data and variable j, C_m is the case which has the missing value, V_{m_2} denotes the variable which has the missing value, y_{im_2} denotes the variable in any case which has the missing data and y_{ij} is the complete data.

For missing value imputation, we apply KNN imputation method for a specified numbers of k. The Euclidean distance between data, and missing data is computed as follows:

$$dist\left(C_{m_1}, C_i\right) = \sqrt{\sum_{j=1}^{p} \left(y_{m_1j} - y_{ij}\right)^2} \quad (3)$$

Here, $dist\left(C_{m_1}, C_i\right)$ denotes the distance between missing value data and complete data, p represents the total number of variables in the dataset and q denotes the total number of cases. The obtained distance values are sorted based on the k values which are closer to the case which has the missing data. By utilizing the aforementioned distance metrics and other parameters, we estimate the missing data attribute values as:

$$\hat{y}_{m_1,m_2} = \frac{\sum_{a}^{k} y_{a,m_2}}{k} \quad (4)$$

$\hat{y}_{m_1,m_2}$ denotes the estimated missing data and y_{a,m_2}represents the data which is the same variable with missing data and closer to the case which is having missing data.

With the help of this process, we generate a pre-processed data which is later used for learning purpose.

3.2. CNN-LSTM Model

This section presents the description about CNN-LSTM model for forecasting approaches. In simple words, CNN-LSTM is a series connection of CNN and LSTM modules which is used to extract the complex features obtained from the various electric consumption sensing devices. These features are further used for power demand forecasting. The first part of the network contains CNN layer which considers several inputs such as voltage, sub-metering and intensity along with household characteristic such as data, time, resident behaviour etc. This information is considered as meta information for CNN layer. The complete CNN module contains several hidden layers and a single output layer which transfers the extracted features to LSTM for further learning process. The hidden layer is comprised of convolution layer which helps to generate the activation map of the data, ReLU (Rectified Linear Unit) layer is used to discard the negative values from activation map and pooling layer which is used to reduce the spatial size resulting in controlling the overfitting.

In this process, the convolution layer performs its operations on the incoming multivariate time series data sequence and passes results to next layers. Let us consider that power consumption vector is expressed as $x_i^0 = \{x_1, x_2, \dots., x_n\}$ where n denotes the time window which is normalized as 60 min unit per window. Thus, the outcome of first convolution layer can be expressed as:

$$y_{ij}^1 = \sigma\left(b_j^1 + \sum_{m=1}^{M} \quad w_m^1, jX_{i+m-1}^0, j\right)$$
$$y_{ij}^l = \sigma\left(b_j^l + \sum_{m=1}^{M} \quad w_m^l, jX_{i+m-1}^0, j\right) \tag{5}$$

The y_{ij}^1 denotes the output of first convolution layer and y_{ij}^l denotes the output of l^{th} convolution layers, b_j^1 denotes the bias for the j^{th} feature map, w represents the kernel weight, m is index value of filter and σ is the activation function. Moreover, the convolution layer consist of a pooling layer which is used to combine the neuron outputs from one layer to another layer. This layer helps to minimize the space size of feature representation resulting in minimizing the number of network parameters and reducing the computational cost. Here, we use the max-pooling operation which considers the maximum value of each from previous layer. The max-pooling operation can be expressed as:

$$p_{ij}^l = y_{i \times T + r, j}^{l-1} \tag{6}$$

Where R is the pooling size, y is the input data and T denotes the stride value.

Further, we consider the LSTM unit which is the second part of this network. This layer stores the important information obtained from the CNN module. Mainly, the LSTM unit consolidates the memory units which helps to update the memory data of previous hidden states. Thus, LSTM has a characteristics to obtain the temporal relationship of long-term multivariate sequence. Further, the output of previous layers are passed to the gated units available in the LSTM network. The LSTM network becomes the prime choice for forecasting problems because of its capacity to handle the gradient vanishing problems when learning using traditional RNN learning approaches.

We can define the LSTM unit as a collection of vector R^d at every time step t. Figure 3 illustrates the basic architecture of LSTM unit.

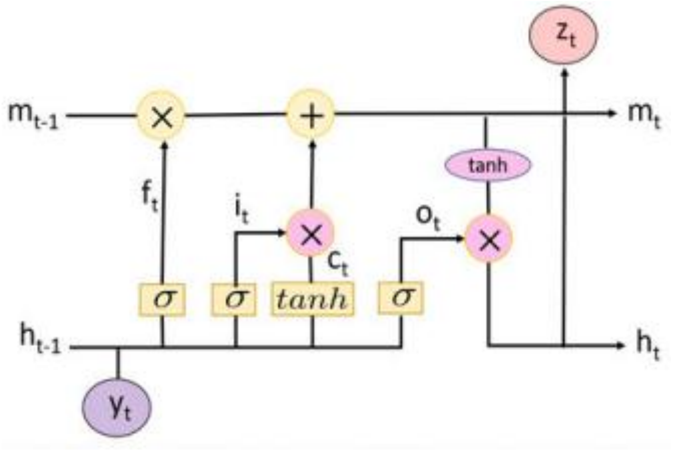

Fig.3. Basic architecture of LSTM Unit

The other components of LSTM are described as:

Memory cell unit (m_t): it stores the intermediate steps of feature learning process. It can be expressed as:

$$m_t = f_t.m_{t-1} + i_t.c_t \quad (7)$$

Here, c_t $=tanh\ tanh\ (W_m.[h_{t-1}, y_t] + b_m)$ where t denotes the current time step, $(t-1)$ denotes preceding time step, $h_{(t-1)}$ is the hidden state at time step $(t-1)$, W_m is the weight matrix for memory cell neurons, y_t is the input data and b_m is the bias for memory cell unit. The LSTM module contains input gate, forget gate, and output gate. These components are denoted as follows:

● Input gate (i_t): it considers the pre-processed power consumption data as input from previous layers of CNN. This can be expressed as:

$$i_t = \sigma(W_i.[h_{t-1}, y_t] + b_i) \quad (8)$$

● Forget gate (i_t): this is the intermediate gate which resets the old memory data. This can be given as:

$$i_t = \sigma(W_i.[h_{t-1}, y_t] + b_i) \quad (9)$$

● Output gate (i_t): this is the final unit of LSTM which generates the final output from learning and prediction steps. This can be given as:

$$o_t = \sigma(W_0.[h_{t-1}.y_t] + b_0) \tag{10}$$

Finally, the hidden cell state (h_t) used by LSTM as hidden units can be expressed as:

$$h_t = o_t * tanh\ tanh\ (m_t) \tag{11}$$

Generally, this modules processes the information from input to output steps in a single direction which suffer from information preserving for accurate forecasting. Thus, to overcome this issue, we have adopted the bi-directional LSTM architecture which processes the data into two directions as forward and backward. In forward direction, the bi-directional LSTM passes the data from past input to future inputs whereas in backward direction it passes the data from future inputs to past inputs. This scheme of bi-directional data processing helps to preserve the learned attributes from past inputs and future inputs while processing through different hidden layers. Further, these outputs are processed through the output layer. Below given figure 4 shows the architecture of bidirectional LSTM

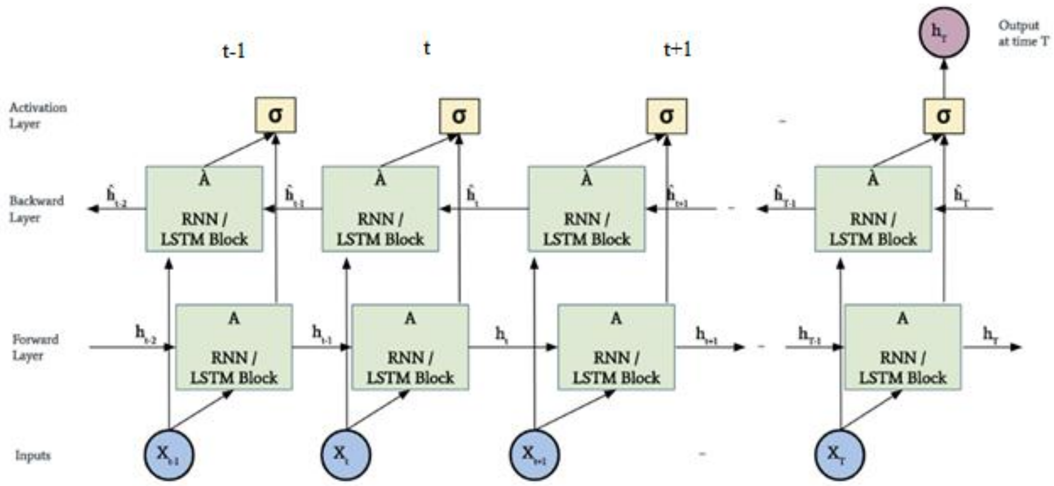

Fig.4. Bi-directional LSTM architecture

The forward process is represented as $\vec{h}$ and backward process is denoted as $h^{\leftarrow}$. The outcome of these forward and backward data processing is computed based on the aforementioned conational equations. The final outcome of this bi-directional LSTM is obtained as $Z_T = [Z_{T-k}, Z_{T-k+1}, \dots, Z_{T-1}]$ where each element of this vector is expressed as:

$$z_t = \sigma(\vec{h}, h^{\leftarrow}) \tag{12}$$

Where σ is the function which helps to integrate the output of forward and backward passes. Similarly, the output of forward pass $\left(\vec{h}\right)$ and backward pass $(h^{\leftarrow})$can be denoted as:

$$\vec{h} = H\left(W_{y\vec{h}}y_t + W_{\vec{h}\vec{h}}\vec{h}_{t+1} + b_{\vec{h}}\right)$$
$$h^{\leftarrow} = H\left(W_{yh^{\leftarrow}}y_t + W_{h^{\leftarrow}h^{\leftarrow}}h^{\leftarrow}{}_{t+1} + b_{h^{\leftarrow}}\right) \quad (13)$$

4. Results and discussion

In this section, we present the experimental analysis using proposed approach and compared the performance with various existing techniques. The proposed scheme is applied on AEP [28] and IHPEPC [29] dataset which are publically available on UCI repository. We have trained this model using NVIDIA RTX 2060 GPU, Intel I core 10th generation processor, 16 GB RAM installed on Linux platform. This implementation includes Keras and Tensorflow libraries for learning along with Adam optimizer.

4.1. Dataset details

In order to measure the performance of this approach we have considered UCI dataset. These datasets are obtained for a five month of period and data collection frequency is fixed at 10 minutes. Below given table 1 shows the different features for appliances.

Table.1. UCI appliance level power consumption dataset parameters and attributes

Attribute number	Attribute Name	Unit	Description
1	Data	mm-dd-yy hh:mm	Date and time for data collection
2	power Used by appliances	Wh	power consumption by household appliances
3	power consumed by light fixtures	Wh	power consumption by household light fixtures
4-12	Room temperature (Indoor)	Celsius	Room temperature data
13-21	Relative Humidity (indoor)	%	Humidity measurement for indoor rooms
22	Room temperature(Outdoor)	Celsius	Outdoor temperature data recordings
23	Relative Humidity	%	Humidity data for outdoor scenario

	(Outdoor)		
24	Pressure	Mm Hg	Atmospheric pressure data
25	Windspeed	m/s	Speed of wind data
26	Visibility	km	Visual capacity data
27	Dewpoint	A°C	Dewpoint temperature data
28-48	Lag values	Wh	Previous values of temperature data.

Similarly, table 2 presents the statistical description of these attributes which includes mean, standard deviation, minimum and maximum values of attributes. The difference between minimum and maximum values shows the high volatility in household power consumption.

Table.2. Statistical description of UCI appliance dataset

Attributes	Std. Dev. (Wh)	Mean (Wh)	Min(Wh)	Max (Wh)
Appliances	102.52	97.69	10	1080
Lights	7.93	3.80	0	70
Indoor temperature features	4.99	19.38	-6.065	29.85
Indoor relative humidity	12.84	42.70	1	99.90
Outdoor temperature	5.31	7.41	-5	26.10
Outdoor humidity	14.90	79.75	24	100
Atmospheric Pressure	7.39	755.52	729.30	772.3
Wind Speed	2.45	4.039	0	14
Visibility	11.79	38.33	1	66
Dewpoint temperature	4.19	3.76	-6.60	15.5
Rv1	14.49	24.98	0.0053	49.99

Similarly, we have considered UCI household dataset obtained from UCI repository. This dataset contains total 2075259 records for 9 attributes. This dataset is collected over a period of 4 years. The dataset collection is frequency is fixed as one minute. The dataset is duration is from December 2006 to November 2010.

Table. 3. Attribute details in UCI household power dataset.

Attribute Number	Attribute	Units	Attribute details
1	Date	Dd/mm/yyyy	Date of recording of power consumption data
2	Time	Hh:mm:ss	Time of recording the power consumption data
3	GAP	kW	Avg. Household global active power in each minute
4	GRP	kW	Avg. Household global reactive power in each minute
5	Voltage	V	Avg. voltage recorded for each minute
6	GCI	Amps.	Avg. intensity recorded for each minute
7	Sub Metering 1	Wh of active power	power sub-metering value of kitchen
8	Sub Metering 2	Wh of active power	power sub-metering value of laundry
9	Sub Metering 3	Wh of active power	power sub-metering value of water-heater
10	Lag Values	kW	Previous global active power value

In above given table, GAP denotes the global active power, GRP symbolizes Global Reactive Power and Global Current Intensity

4.2. Comparative analysis

This section presents the experimental analysis of proposed approach where obtained performance is compared with various existing forecasting techniques. In order to measure the performance, we consider actual and predicted values for both datasets. Below given figure 5 shows the graphical overview of actual predicted values for appliance power use dataset.

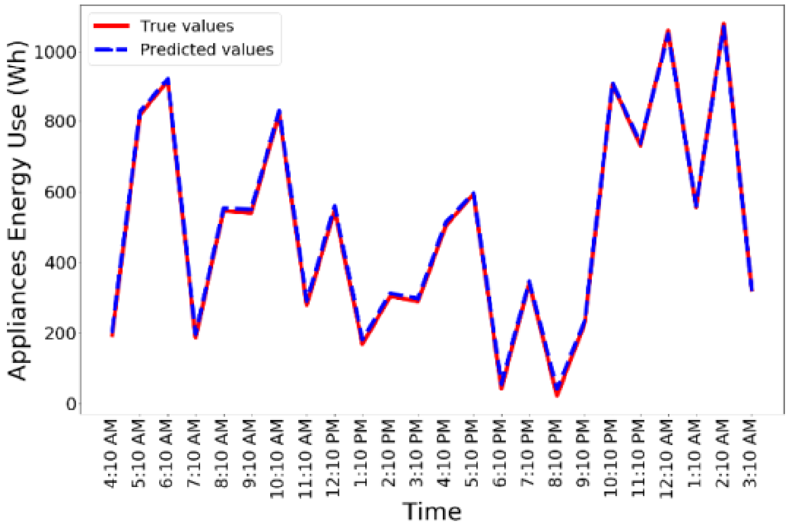

Fig.5. Actual and predicted power consumption illustration for appliance power dataset

Similarly, we measured the actual and predicted power consumption values for household active power consumption as depicted in figure 6.

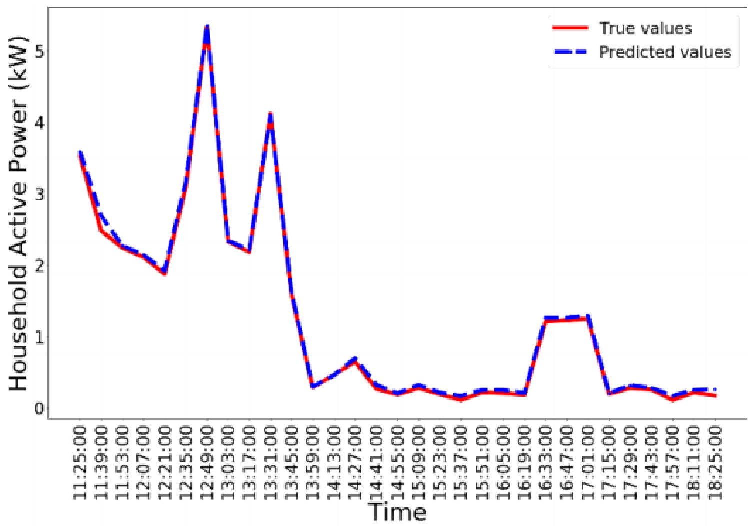

Fig.6. Actual and predicted power consumption illustration for household e power dataset

Figure 5 and 6 depict the prediction performance for two different dataset. The x-axis denotes the time parameter and y denotes the power consumption for appliance and household dataset. From these experiments we analyze that the actual and predicted values are very closer to each other. This shows the less error in predicting the power consumption values.

Further, we measure and compared the performance of proposed approach in terms of Root Mean Square Error (RMSE), MAPE, Mean Absolute Error (MAE), and R2 score/coefficient. These parameters can be computed as follows:

$$RMSE = \frac{1}{n}\sqrt{\frac{1}{n} * \sum_{j=1}^{n} \left(A_j - P_j\right)^2}$$

$$MAE = \frac{\sum_{j=1}^{n} \left|A_j - P_j\right|}{n}$$

$$MAPE = \frac{100}{n} * \sum_{j=1}^{n} \left|\frac{A_j - P_j}{A_j}\right| \quad (14)$$

$$R^2 - Score = 1 - \frac{\sum_{j=1}^{n} \left(A_j - P_j\right)^2}{\sum_{j=1}^{n} \left(A_j - mean(A)\right)^2}$$

Here, A_j represents the actual power consumption data for a given time sequence t, P_j denotes the predicted value of power consumption at time step j and n denotes the total number of time steps in given dataset.

In this experiment, first of all we measure the performance for appliance power consumption dataset and obtained performance is presented in below given table 5.

Table.5. Comparative performance for UCI appliance power consumption dataset

Technique	RMSE (Wh)	MAE(Wh)	MAPE(Wh)	$R^2 - Score$
Linear regression	137.27	85.54	70.30	0.103
Extreme Learning	90.109	53.44	65.87	0.163
Neural nets	86.23	48.93	57.93	0.232
Preprocessing +LSTM	17.55	13.57	7.80	0.997
Preprocessing with 2 Layers of stacked LSTM	15.96	12.83	5.82	0.996
Preprocessing with 3 Layers of stacked LSTM	20.83	17.23	12.28	0.995
AREM	14.38	11.67	5.27	0.997
LSTM Encoder Decoder Model	6.332	4.36	2.55	0.999

CNN-LSTM	19.74	14.97	11.17	0.995
ConvLSTM	7.47	5.55	2.677	0.999
Preprocessing + bi-directional LSTM	12.71	10.13	3.17	0.998
Hybrid Deep learning [24]	5.44	3.45	2.010	0.999
Proposed Model				

Similarly, we measured and compared the performance in terms of RMSE, MAE, MAPE and R^2 coefficient for UCI household power dataset. Below given table 6 shows the comparative analysis for this dataset.

Table.6. Comparative performance for UCI Household power consumption dataset

Technique	RMSE (Wh)	MAE(Wh)	MAPE(Wh)	$R^2 - Score$
Linear regression	70.66	62.97	9.61	0.9952
Extreme Learning	51.48	38.76	7.65	0.9970
Neural nets	51.02	32.88	6.90	0.9970
Preprocessing +LSTM	50.21	36.89	5.099	0.9972
Preprocessing +stacked LSTM (2 Layers)	47.45	32.41	4.673	0.9978
Preprocessing +stacked LSTM (3 Layers)	47.77	27.69	4.44	0.9978
AREM	42.15	28.35	4.08	0.9978
LSTM Encoder Decoder Model	37.76	27.72	4.94	0.9986
0.948CNN-LSTM	37.18	24.27	4.41	0.9480
ConvLSTM	39.14	24.25	6.49	0.9393
Preprocessing + bi-directional LSTM	39.32	25.29	4.67	0.9985
Hybrid Deep learning [24]	29.21	22.24	3.71	0.9986

Proposed Model	16.22	15.24	2.16	0.9995

These experiments reported the improved performance when compared with state-of-art machine learning and deep learning approaches.

5. Conclusion

We have noticed a significant growth in the power consumption in household appliances due to increasing demand of appliances in household applications. Thus, power demand forecasting has become hot research are due to its significant impact on the efficient power generation, scheduling and efficient utilization of power resources. To improve the performance of these power systems, we adopted deep learning-based forecasting model which uses a combination of CNN and bidirectional LSTM. The bidirectional LSTM helps to learn the pattern in forward and backward direction which improves the accuracy of the system. Finally, we present an extensive experimental analysis where proposed approach is tested on UCI repository data. The outcome of this experiment reported that proposed approach logged better performance when compared with existing techniques.

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