Smart Grid Energy Management Using RNN-LSTM: A Deep Learning-Based Approach

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Devinder Kaur
Deakin University

Neeraj Kumar
Thapar Institute of Engineering and Technology (Deemed University), Patiala (Pu...

Mohsen Guizani
Mohamed bin Zayed University of Artificial Intelligence

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Devinder Kaur*, Rahul Kumar *, Neeraj Kumar†, Mohsen Guizani ‡
(e-mail: kaurdevinder07@gmail.com, rahul.cse.ccu@gmail.com, neeraj.kumar@thapar.edu and mguizani@gmail.com)
* School of Computer Science & Engineering, Lovely Professional University, Jalandhar, India
† Computer Science & Engineering Department, Thapar Institute of Engineering & Technology (Deemed to be University), Patiala, India
† University of Idaho, USA

Abstract—**With the rapid increase in the energy demands from different sectors across the globe, there is lot of pressure on the power grid to maintain a balance between the demand and supply. In this context, smart grid (SG) may play a vital role as it provides the bidirectional energy flow between utilities and end users. Contrary to the traditional power grid, it has advanced switching and sensing devices (for example, sensors and actuators) for load balancing and peak shaving. In SG systems, various smart devices and electrical appliances which are placed in the smart buildings regularly generate data related to energy usage, occupancy patterns, or movements of the end users. By applying an efficient data pre-processing and data analytics technique, this data can be analyzed to extract important energy patterns which can be used in demand response management, load forecasting, and peak shaving. But, one of the main challenges in SG systems is to have an integrated approach to pre-process and analyze the data with minimum error rates and higher accuracy. To tackle the aforementioned challenges, an unified scheme based upon the deep learning and recurrent neural networks (RNN) is proposed in this paper. The data collected from smart homes is pre-processed and decomposed using high-order singular value decomposition (HOSVD) and then long short-term memory (LSTM) model is applied on it. As the data collected from SG is time series-based data so LSTM based regression model gives minimum root mean square (RMSE) and mean absolute percentage error (MAPE) values as compared to the other techniques reported in the literature. A case study of 112 smart homes with hourly basis data is considered for evaluation of the proposed scheme in which energy patterns are predicted with least RMSE and MAPE. The results obtained clearly show that the proposed scheme has superior performance in comparison to the other existing schemes.**

Index Terms—**Smart grid, Big data analytics, RNN, LSTM, HOSVD, dimensionality reduction, demand response management, tensors, machine learning.**

I. Introduction

From the last few years, we have witnessed the emergence of one of the most powerful technologies of the modern era called as smart grid (SG). It can be viewed as a modern power grid having advanced information and communication infrastructure which is used for bidirectional flow of energy between end users and utility service providers. It provides a reliable and cost-effective demand response between end users and the service providers which may be located across different geographical locations [1]. Contrary to the traditional power grid, it has advanced switching and sensing devices (sensors and actuators) to generate and transmit this bidirectional flow of energy. In SG environment, there are different levels of information flow for managing the demand response. The first level of information flow is between sensors and smart devices towards the smart meters using short range communication such as Zigbee, 6LowPAN, Bluetooth, and Infrared. The second level is between smart meters to the utilities and data centers, in which various types of medium and long range communications such as WiFi, WiMax, LTE/LTE-A, and cellular networks are used [2]. These different levels of flow of information reduces the gap between demand and response by taking intelligent control decisions. However, it requires intelligent data analytics for maintaining a controlled flow from the utility service providers to the end users.

With an emergence and popularity of various smart devices in SG environment, demand response and energy management have become the most crucial issues which need a special attention. According to the recent statistics provided by U.S. Department of Energy (DOE), the electricity demand has increased by 30% since 1988, while peak demand is expected to rise by 20% in the decades to come. However, the efficiency and capacity of SG systems has only grown by 15% [3]. According to a report by DOE, various projects related to the SG usage have already been started in different areas by the Office of Electricity Delivery and Energy Reliability (OE) [4]. But still, it is a challenging task to manage demand response in SG systems [5].

In SG systems, various smart devices and electrical appliances placed in the smart buildings regularly generate data related to energy usage, occupancy patterns, or movements of the end users. There are various sources from which data is generated such as grid utilities, substations, smart homes, and industries. Phasor Measurement Units (PMU) and Advanced Metering Infrastructure (AMI) are the main data generation sources in SG systems. PMUs are the energy measurement units in SG which measure energy waves and signals. While, AMIs are the integration of smart meters and sensors with advanced two-way communication infrastructure. The data may be generated on hourly basis or even for smaller duration from AMI, which is very large in quantity and is challenging to handle. According to the SG framework given by the National Institute of Standards and Technology (NIST) bulk data generation, data processing and better service provisioning to the end users are the main tasks which need to be performed in SG systems [6].

The bulk amount of data generated in SG systems can be viewed under the domain of big data as it possesses the essential big data characteristics such as volume, velocity and veracity [7]. In order to deal with such a vast amount of data, we need an integrated technique for data pre-processing and analysis. Talking about data pre-processing, firstly data needs to be represented using an efficient and effective model. Tensor model is one of the viable solutions which can be used to represent multi-dimensional big data in an efficient manner. Furthermore, after the representation data needs to pre-processed which involves various steps such as data normalization, removal of duplicate and null values, dimensionality reduction, etc. Dimensionality reduction or data decomposition is one of the major steps involved in data pre-processing which widely affect the data processing. Various authors have proposed different techniques to deal with big data decomposition in the context of tensors and smart grid [8]. But, high order singular value decomposition (HOSVD) is one of the adequate technique that can be utilized to represent the high dimensional data using lower dimensions with minimum reconstruction error [9].

Talking about the big data analytics, deep learning is used in various fields such as speech recognition, audio recognition, bioinformatics, etc. In deep learning, various classes of neural networks are available such as convolutional neural networks (CNN), deep neural networks (DNN), Recurrent neural networks (RNN), etc. to learn the patterns in data and analyze it. In this context, authors in [10] applied CNN model to learn the hidden patterns in energy consumption at the end users in SG systems. Further, authors in [11] surveyed the various methodologies and challenges related to the smart meter data analytics. Similarly, in [12] jindal *et al.* underlined the challenges related to data analytics in SG systems. Authors also proposed a demand response scheme for peak load reduction in SG systems. In the similar manner, authors in [13] proposed a data analytical approach for demand response management in SG using support vector machine(SVM).

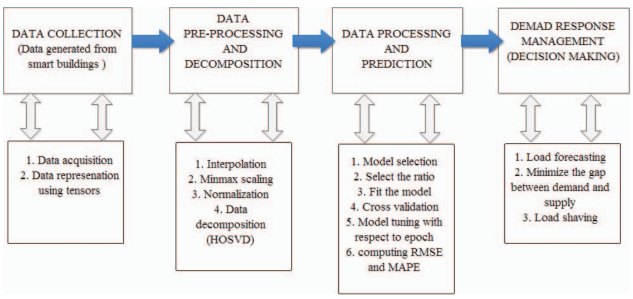


Fig. 1. Flow diagram of the proposed scheme

Although, a significant work is presented by various authors in the field of deep learning and data analytics. But in the field of SG data analytics, there is a lot scope of deep learning which still needs to explored and presented. Talking about various classes of deep learning, RNN is one of the most successful and modern neural class which has the capability to retain the information. But, it suffers from the problem of vanishing gradients due to short memory. Gradients are the values in neural networks which are used to update its weights. When RNN back propagates through time, gradient shrinks shrinks, and if the value of gradient becomes too small then it will not be able to contribute too much in the learning. In order to provide the solution to this problem in RNN, long-short term memory (LSTM) model is used. LSTM is one of the very successful variant of RNN and widely used in the context of time series data [14]. It preserves the long term dependencies in the network with the help its Gating and cell mechanisms. The network in LSTM can store or release memory on the go through the gating mechanism. It attempts to model time or sequence dependent behavior such as language, stock price, and electricity demand and so on. In the context of SG and LSTM, authors in [15] underlined the analysis of large amount of energy data using LSTM. Similarly, in [16] authors proposed an RNN based LSTM model to analyze the time series data of smart grid. Also, they underlined the various issues related to the grid intelligence such as short term forecasting for the energy consumption at the user end. Similarly in [17], authors underlined the importance of using non-linear models for data analytics in SG. Thus, after analyzing the aforementioned proposals, it is inferred that an integrated approach is required to pre-process and analyze the big data in SG systems.

A. Research Contribution of this work

Based upon the above discussion, major contributions of this research work are summarized below.

1) Data representation is done using tensors and data pre-processing is performed which involves removal of null and duplicate values along with the interpolation, data normalization, scaling and dimensionality reduction.
2) Dimensionality reduction is applied using HOSVD. It increases the efficiency of data processing.
3) A RNN-LSTM based deep learning model is proposed to analyze the energy consumption of smart houses using which we predict the future consumptions with least errors and maximum accuracy.

B. Organization

The remaining paper is organized as follows. Section II represents the problem formulation. Section III represents the proposed scheme. The results and discussions are presented in Section IV along with a case study. Finally, Section V concludes the paper.

II. Problem formulation

In this paper, high dimensional big data (D_{ac}) is acquired from SG systems with the help of various smart devices.

D_{ac} is represented using tensor models as T_{ac} shown in equation 2. Tensors are multi-dimensional arrays which are used to represent the various characteristics or dimensions of big data in an efficient manner. A tensor (T) of order n can be represented using following equation:

$$T \in R^{a_1 \times a_2 \times a_3 \ldots \times a_n} \tag{1}$$

$$D_{ac} \rightarrow T_{ac} \tag{2}$$

Where, a_1, a_2, ..., a_n are the orders of tensor which define the various dimensions present in D_{ac}. The different dimensions are pertaining to different attributes in SG big data such as energy consumption, voltage, electrical appliances, smart meter ID, etc. After data representation, data pre-processing is performed in which T_{ac} is cleaned, normalized, and min-max scaling is done on it. As dimensionality reduction is one of the most crucial phase of data pre-processing, so HOSVD is applied on T_{ac} to obtain the reduced core tensor (T_{red}). Core tensor is obtained by n-mode product of n-order tensor (T_{ac}) with orthogonal matrix (U) as shown in the following equation:

$$T_{red} = T_{ac} \times_{x=1}^{n} U_n^T \tag{3}$$

Further, from core tensor an approximated tensor ($\hat{T}_{red}$) is reconstructed to check the reconstruction error using the following equation:

$$\hat{T}_{red} = T_{red} \times_{x=1}^{n} U_n^T \tag{4}$$

The approximation error of the reduced core tensor is calculated with the help of reconstruction error (e) using the following equation:

$$e = |T_{ac} - \hat{T}_{red}| \tag{5}$$

So, one of the objective function of proposed scheme is to minimize the reconstruction error. It is defined using following equation.

$$min(e) \tag{6}$$
$$s.t. \tag{7}$$
$$e = [0, 1] \tag{8}$$
$$T_{ac} > \hat{T}_{red} \tag{9}$$
$$T_{ac}, \hat{T}_{red} > 0 \tag{10}$$

Now, to process the reduced data, core tensor is given as an input to the hidden layer (h_t) of RNN. Hidden layer is activated with the help of activation function. In the context of neural networks, there are various activation functions available such as sigmoid function, tanh function, etc. But in RNN, rectified linear unit (ReLu) is used to fire h_t. ReLu is non-linear in nature and avoids vanishing gradients up to certain extent. It is represented mathematically using the following equation:

$$h_t(rnn) = \theta(u * x_t + w * h_{t-1}) \tag{11}$$

Where θ represents ReLu as an activation function. The mathematical equation for the formula of θ can be represented as follow:

$$f(z) = max(0, z) \tag{12}$$

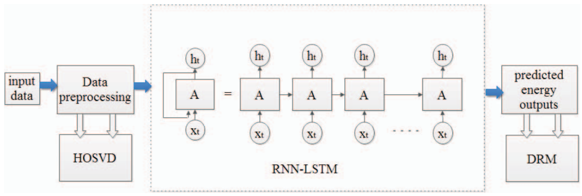


Fig. 2. System model of the proposed scheme

$$s.t. \tag{13}$$
$$\theta = [0, \infty) \tag{14}$$

Recurrent neural networks generally face the problem of vanishing or exploding gradients. So, LSTM model is used to train and test the data. LSTM model is a solution to the vanishing gradient problem in neural networks as it can retain the memory for longer periods. It discards the irrelevant information through its gating mechanism and only important information is passed further. In order to evaluate the model, RMSE score ϵ and MAPE values (ρ) of regression model are considered as objective functions. The mathematical equations for them are represented below.

$$\epsilon = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_{pred}(i) - Y_{act}(i))^2} \tag{15}$$

$$\rho = \frac{1}{n}\sum_{i=1}^{n} \mid \frac{y_{pre(i)} - y_{act(i)}}{y_{act(i)}} \mid \tag{16}$$

Where, $Y_{pred}(i)$ and $Y_{act}(i)$ are the predicted and actual values at i^{th} instance of data. So, the main objective function of the proposed scheme is to minimize the error in prediction values. It is represented by the following equation:

$$min(\epsilon), min(\rho) \tag{17}$$
$$\text{s.t.} \tag{18}$$
$$0 \geq \epsilon \leq 1 \tag{19}$$
$$0 \geq \rho \leq 1 \tag{20}$$
$$\epsilon, \rho = [0, 1] \tag{21}$$

III. Proposed Scheme

The proposed scheme is presented in the following two subsections.

A. RNN-LSTM based data analytics scheme

In this scheme, RNN-LSTM based algorithm is presented to process and analyze the pre-processed SG data. LSTM consists of mainly four components namely a cell, an input gate, an output gate, and a forget gate. The cell is used to remember values over the arbitrary time intervals and the three gates regulate the flow of information into and out of the cell. The

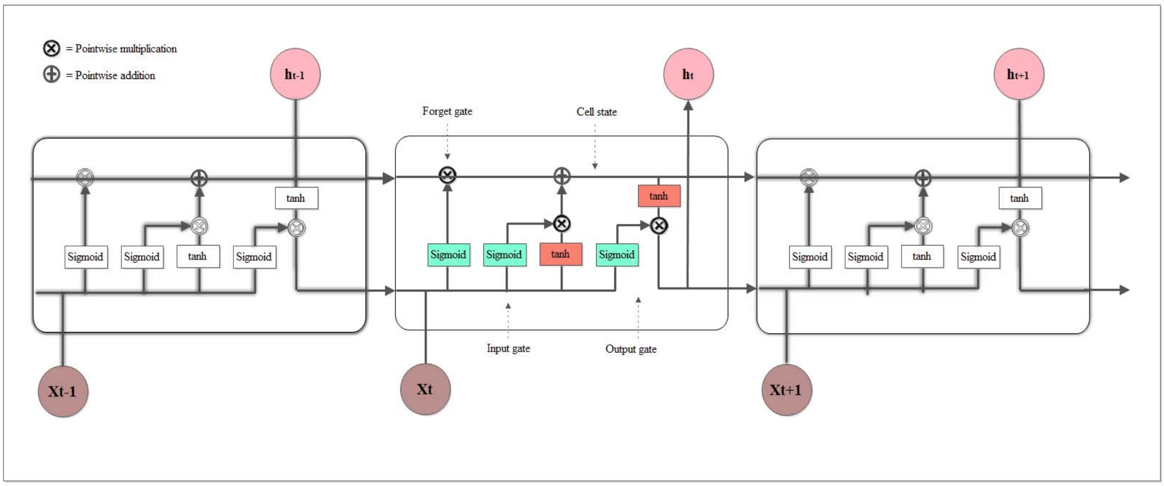


Fig. 3. System architecture of LSTM gates and cell states in proposed scheme

equations for input, forget, and output LSTM gates are given as below, respectively.

$$i_t = \sigma(w_i[h_{t-1}, x_t] + b_i) \tag{22}$$

$$f_t = \sigma(w_f[h_{t-1}, x_t] + b_f) \tag{23}$$

$$o_t = \sigma(w_o[h_{t-1}, x_t] + b_o) \tag{24}$$

$$g_t = \phi(w_o[h_{t-1}, x_t] + b_g) \tag{25}$$

Where ϕ represents the tanh function.

The equation for memory cell state can be given as below:

$$S_t = g_t \otimes i_t + s_{(t-1)} \otimes f_t \tag{26}$$

$$h_t = \phi(s_t \otimes o_t) \tag{27}$$

Where i_t represents the input gate, f_t represents the forget gate, and o_t represents the output gate. σ represents the sigmoid function. W_x represents the weight of respective gate or neuron (x) and h_{t-1} represents the output of previous lstm block at a particular time stamp (t-1). The error which is generated by the loss function is returned via backpropagation through time (BPTT) and used to adjust the weights until it can not go any lower. The number of times it is backpropagated is defined as epoch value. It is used as the optimization function. Total error is calculated as sum of each error at time step (t) as shown in the equation give below.

$$\frac{d\epsilon}{dw} = \sum_{t=1}^{tot} \frac{d\epsilon}{dw} \tag{28}$$

It is also represented using the chain rule as shown in the equation below.

$$\frac{d\epsilon_t}{dw} = \sum_{k=1}^{t} \frac{d\epsilon_t}{dy_t} \frac{dy_t}{dh_t} \frac{dh_t}{dh_k} \frac{dh_k}{dw} \tag{29}$$

Where, ϵ represents the error at a time instance (t).

Algorithm 1 RNN-LSTM based data analytics algorithm

Input: D_{ac} (Acquired high dimensional SG big data)
Output: E_{pre} , E^i_{total}
1: Represent D_{ac} using tensors using equation (1)
2: Perform data cleaning, scaling, and normalization
3: Apply HOSVD on T_{ac} using Eq. (2)
4: Obtain the core tensor
5: Calculate the reconstruction error (e) using Eq.(4)
6: Minimize e w.r.t to constraints using Eq. (5) - (9)
7: Feed T_{red} as input to RNN-LSTM (10)
8: Select train:test
9: Combine previous hidden state (h_{t-1}) and current input
10: Calculate cell state (S_t) using Eq. (26)
11: Calculate the new hidden state (h_t) using Eq. (27)
12: **for** (i=1; i $\leq$ epoch; i++) **do**
13: Iterate the model
14: Perform BPTT
15: Obtain E_{pre}
16: Calculate ϵ using (15)
17: Calculate ρ using (16)
18: Minimize ϵ, ρ w.r.t constraints using Eq. (19) - (21)
19: **end for**
20: Forecast E^i_{total}

The working of the algorithm is described as below. Acquired SG big data (D_{ac}) is fed as an input to the proposed algorithm. It is then represented using tensors and data pre-processing is performed on it (line 1-2). Further, it is decomposed using HOSVD and reduced core tensor is obtained (line 2-6). Then, reduced data is fed to the LSTM model. Training and testing ratio is selected and model starts building (line

7-9). Then, cell state is calculated using sigmoid and tanh as activation functions through gates Using equations (22-26) line(9-10). Then, hidden state (h_t) is obtained to process the data (line 11), and it is passed to next LSTM cell at (t+1). Model is iterated for specific number of times called epochs until threshold is achieved. Predicted values for data are calculated along with the RMSE score and MAPE.

Fig. 3 represents the system architecture for LSTM cell and gates involving the proposed scheme. It shows how previous hidden stats ($h_{(t-1)}$) is passed to current cell at a time (t) and new hidden state (h_t) is calculated. The corresponding gates and activation functions work in accordance with Eq. (22-27).

B. Demand response management and Load forecasting

Demand response is a change in power consumption of consumers in order to match the demand for power with supply. Load forecasting with lesser error plays an important role in SG systems to reduce power generation costs as well as to lower the user's electricity bills. It plays an important role for consumers in the operation of electricity grid by reducing or shifting the power consumption during the peak hours. It has a significant role to balance supply and demand. Our scheme predicts and forecasts the energy needs at the consumer level and during peak levels the consumption can be adjusted depending upon the incentive and price scheme. Considering the total energy consumed to be E^i_{total}, demand and supply can be managed using above proposed scheme by utilizing the predicted energy consumptions. E^i_{total} can be considered for different types of loads present in smart homes. It can be presented using following equation.

$$E^i_{total} = E^i_{SHL} + E^i_{ADL} + E^i_{FDL} \tag{30}$$

Here, SH stands for schedulable load, ADL stands for adjustable loads, and FDL stands for Fixed loads in SG systems.

IV. Results and Discussions

This section presents the simulation results which are obtained by implementing the proposed scheme to the energy related data generated by smart buildings. To verify the performance of proposed scheme, a case study on smart grid data is conducted. The smart meter data related to 112 households is taken [18]. It involves energy consumption in kwh done by each house for 500 days with sampling rate of half an hour. During the analysis, various external factors related to the environment are also considered namely visibility, temperature, wind speed, wind bearing, pressure, cloud cover etc. Data related to weather conditions and energy consumption is merged and then pre-processed and decomposed. Further, using RNN-LSTM based analytics algorithm energy consumptions are predicted for testing and training data sets. The prediction error in the terms of RMSE score and MAPE is given in table I after doing the inverse transformation. MAPE is taken as a measure of accuracy for our model to predict the energy consumption. The model is run for 50 epochs. During the simulation, the batch size is taken as one. Therefore the number of iterations are kept equal to the number of epochs. Although, by increasing the number of iterations the mean square error is supposed to decrease. But, the number of iterations or epochs depend upon various factors such as "early stopping" and the size and nature of data. Four lstm blocks are used for the model building and the default activation function sigmoid is used. The visible layer has only one input and the output layer that makes the single value prediction. The predicted values are computed and stored by performing the inverse transform method to get the actual values.

Fig no. 4(a) shows the pattern of actual values vs predicted values for training data set. The ratio for training and testing is taken to be 70:30. Fig no. 4(b) shows the pattern of actual values vs the predicted values for testing data. Fig no. 4(c) shows a graph which reflects the energy consumption patterns for actual vs training vs testing. As shown in the above graphs and table the values are predicted with minimum RMSE score for our proposed scheme. So using the proposed scheme, the future energy consumptions can be predicted with least errors and depending upon which demand and supply can be managed. Lastly in Fig no. 5, a comparative analysis of proposed scheme is presented with two another schemes. Five different datasets are taken to compute the RMSE score and our RNN-LSTM based analytics scheme shows the minimum error. The RMSE and MAPE value is presented in the table after performing the inverse transformation on original values. So, considering the least RMSE score and MAPE values, energy consumption is predicted and gap between the demand and supply is minimized in SG systems.

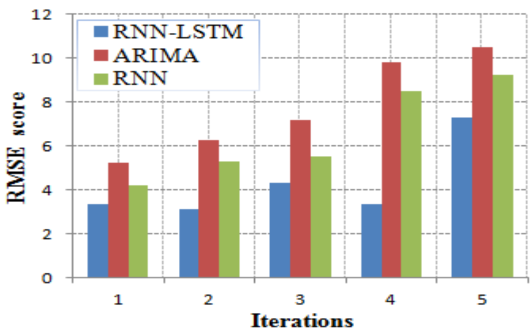
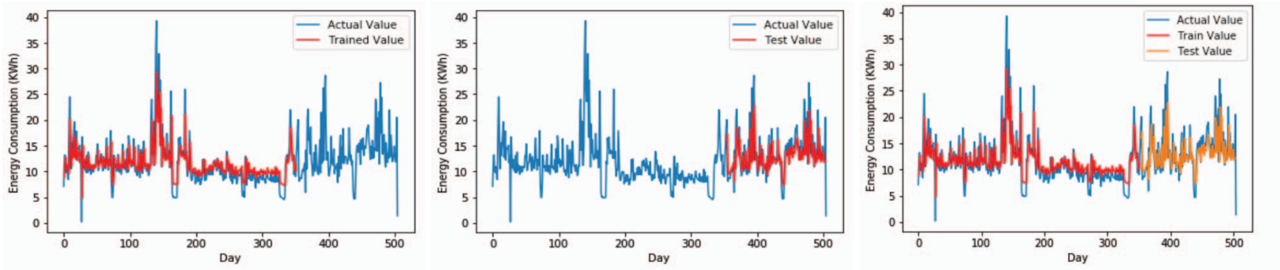


Fig. 5. Comparative analysis of proposed scheme

TABLE I
EVALUATION PARAMETERS FOR PROPOSED SCHEME (AFTER INVERSE TRANSFORMATION)

Technique	RMSE	MAPE
RNN	4.613	17.312 %
ARIMA	4.27	29.18 %
Proposed (RNN-LSTM)	3.35	5.21 %



(a) Actual vs train

(b) Actual vs test

(c) Actual vs train vs test

Fig. 4. Results for the proposed RNN-LSTM based data analytics scheme

V. Conclusion

In this paper, a smart grid energy management scheme is presented using deep learning approach. Big data generated from various smart buildings in SG is acquired, represented using tensors, and pre-processed. Data pre-processing involves various steps such as data interpolation, standard scaling, normalization, and decomposition. In the context of data decomposition HOSVD is used to reduce the dimensions of SG big data. Then, deep learning is used as an integrated approach to predict and analyze the energy consumption patterns in SG systems. An RNN-LSTM based data analytics scheme is proposed in this paper. LSTM as one of the most successful variant of RNN is used to train and test the SG data as it deals with the problem of vanishing gradients effectively with the help of its gating mechanism. To verify the performance of proposed scheme, a case study on SG data is conducted. The smart meter data related to 112 households is taken [18] for 500 days. During the analysis, various external factors related to the environment are also considered namely visibility, temperature, wind speed, wind bearing, pressure, cloud cover etc. Using the proposed scheme energy consumptions patterns are predicted for testing and training data sets with minimum errors. Based upon these prediction demand response management is performed and the gap between energy demand and supply can be minimized. The model is evaluated using two very important evaluations parameters namely RMSE score and MAPE. Results show that the value of RMSE using proposed scheme is least which justifies the efficacy of the proposed scheme.

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