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Prediction of Electric Energy Consumption using Recurrent Neural Networks

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Abstract

The prediction of power consumption is a complex and important task for a smart home, a city, and a country. However, deep learning plays a substantial role in predicting electric energy consumption more efficiently. Recurrent Neural Network (RNN) of deep learning is well capable of handling time-series datasets and predicting the electricity consumption better than the machine learning approaches such as ARMA, SVR. In this work, we use a large electricity consumption dataset of Dominion Virginia Power (DOM) using the proposed RNN approach to identify the hidden patterns of the dataset as well as predict electric power consumption. The results from the proposed approach are compared with the above-mentioned approaches to validate the performance to unveil the hidden patterns and predict the consumption behaviors. The accuracy is varied from 94.02% to 96.86% based on the number of epochs. Also, the error matrices like MSE, RMSE, MAE, and MAPE are demonstrated to validate its robustness for the prediction of electricity consumption. understanding the demand for electric power.

Keywords: *Deep learning, Electric power consumption prediction, Electric power consumption prediction model, Machine learning, Recurrent neural networks*

1. Introduction

Energy consumption is a noticeable factor that is connected to economic growth, as energy demand is going up for most buildings at a high level. 40% of total energy demand is noticed by the domestic and commercial buildings in the United States of America and Europe [1][2]. Therefore, diverse approaches to predict building energy consumption are innovated by researchers [1][3]. Yet, these approaches have limitations in an analytical and predictive process of energy consumption, so it is important to find out the best approach and model to reach the most accurate prediction. This research is based on finding the answers to the following questions:

What are the important factors that affect energy consumption patterns?

What is the difference between the daily electric energy consumption patterns in winter and summer?

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What are the differences in the average usage of electric energy between weekdays and weekends?

What are the limitations of prediction accuracies for different machine learning approaches?

What are the benefits of using deep learning for predicting accuracies of electric energy consumption?

Engineering methods is the comprehensive methods, and it consists of some partial differential equations and thermal dynamics equations as well as density functional theory [4][5][6][7].

Luckily, due to the recent dramatic advances, information technologies are growing with software and its packages which provides effective solutions with a great visualization for these equations. e.g., Bauer and Scartezzini (1998) shown in their work that how energy consumption is related to climatic variables [10]. Dhar et al. (1999) developed a model using the Fourier series which has shown that the cooling and heating loads have a relation with time and temperature of dry-bulb [11].

Aydinalp-Koksal and Ugursal (2005) used conditional demand analysis for the prediction of building energy consumption. Also, statistical methods are used to make the relations among energy consumption and variables that are influencing the empirical models [12]. These are effective for non-linear relations and they can overcome the weaknesses of the engineering methods [13][14].

Nevertheless, these types of research require authenticated historical data and computers with high configurations with large primary memory. Furthermore, it is time-consuming and would make erroneous and insignificant results due to improper selection of the analytical methods.

Machine learning approaches, developed from artificial intelligence, were applied for fixing the limitations of these approaches as different machine learning approaches have been tremendously developed. This can be used as a predictor for avoiding complex processes [15].

Here, support vector machine (SVM) and artificial neural network (ANN) models have become more consistent than existing regression techniques such as linear regression, logistic regression, polynomial regression [16]. Many researchers tend the predict system performance or energy utilization, such as air-conditioning, PV power systems, and different hybrid energy systems [8]. Liu et al. provide a deep review with the analysis of accuracy and comparison of models. The accuracy was determined with different types of variables of historical data, buildings, temporal granularity. Also, support vector machine (SVM) and artificial neural network (ANN) were compared in terms of the complexity and accuracy of these models [9]. Recently, deep learning, a powerful branch of ANN, is using to analyze the time series historical data for prediction which performs with great accuracy. A recurrent neural network is one popular approach to do this type of prediction.

Multi-layer Gated Recurrent Units were used to train several algorithms for predicting electricity price, and then the results from these algorithms were compared with RNNs [17]. One research paper proposed Recurrent Neural Networks (RNN) architecture for predicting short-term and long-term solar consumption and validating the performance [18].

Rahman et al., 2018 focused to compare the accuracy between RNN and multi-layered perceptron model for the prediction of electricity consumption for the building, Public Safety Building, Salt Lake City, Utah [19]. Zia et al., 2020 use Multi-crop Convolutional Neural Network to extract features of Lung Nodule so that they can be detected and classified efficiently [20]. Rahman has used inception V3 of deep learning to detect and classify plant leaf detection efficiently [21]. Another work used support vector machines (SVM) to detect distributed denial of service attacks [22].

The rest of this paper is ordered in the following ways. Dataset, as well as patterns of observations, are provided in Section 2. Methods used to analyze and predict energy consumption describes in Section 3. Section 4 deduces the results and comparison of the experiential analysis, and it concludes with section 5.

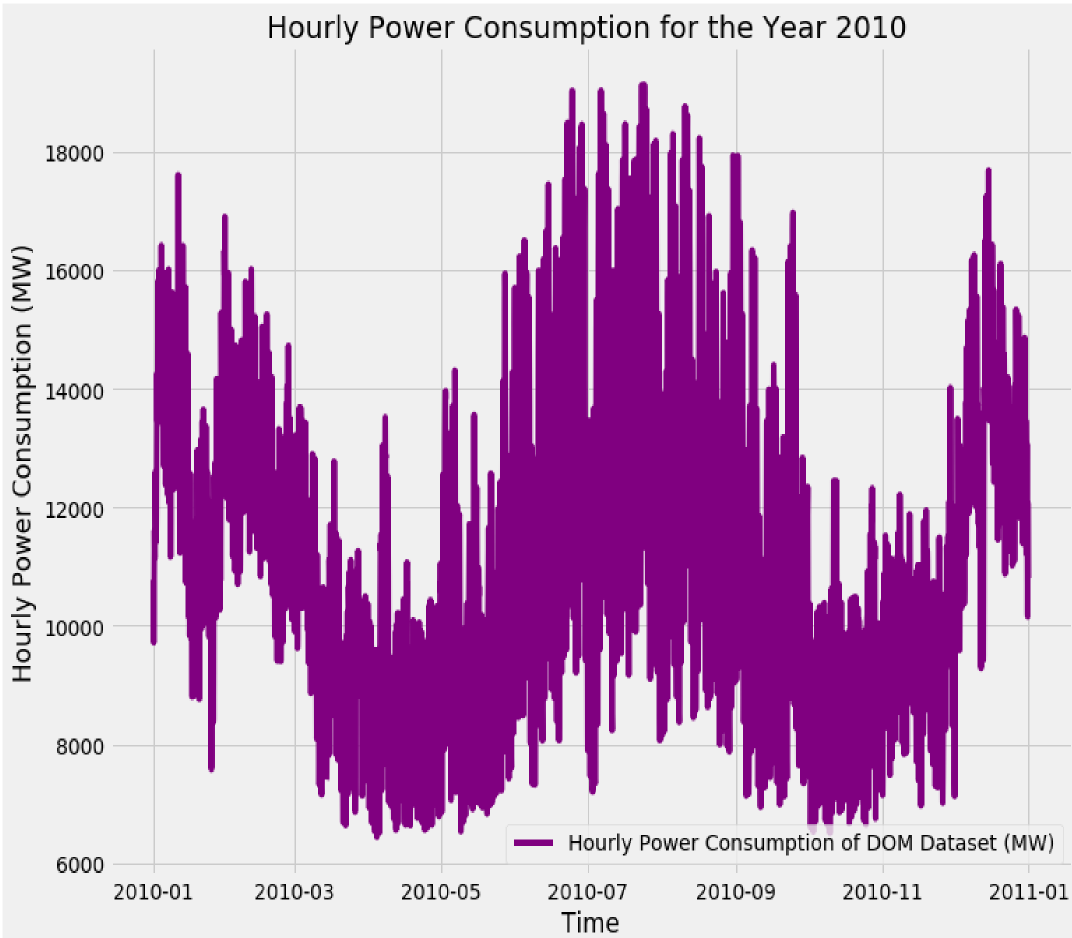


Figure 1. Visualization for hourly electric power consumption of DOM dataset

2. Data

The electricity consumption power of Dominion Virginia Power (DOM) is primarily affected by the various seasons. The DOM hourly time series dataset (116189 observations) is chosen in this work. According to the weekly point of view, lower power consumption is observed at midnight and early morning (1:00-6:00). Moreover, peak hours in the day are after the evening when residents return home as visualized in [Figure 1]. Power consumption in the evening on Saturday is as low as the other midnight and early morning, which tells that inhabitant are supposed to take dinner outside. However, it is high on Sunday in the evening, because they could cook for a couple of days as working days are coming to next day, Monday.

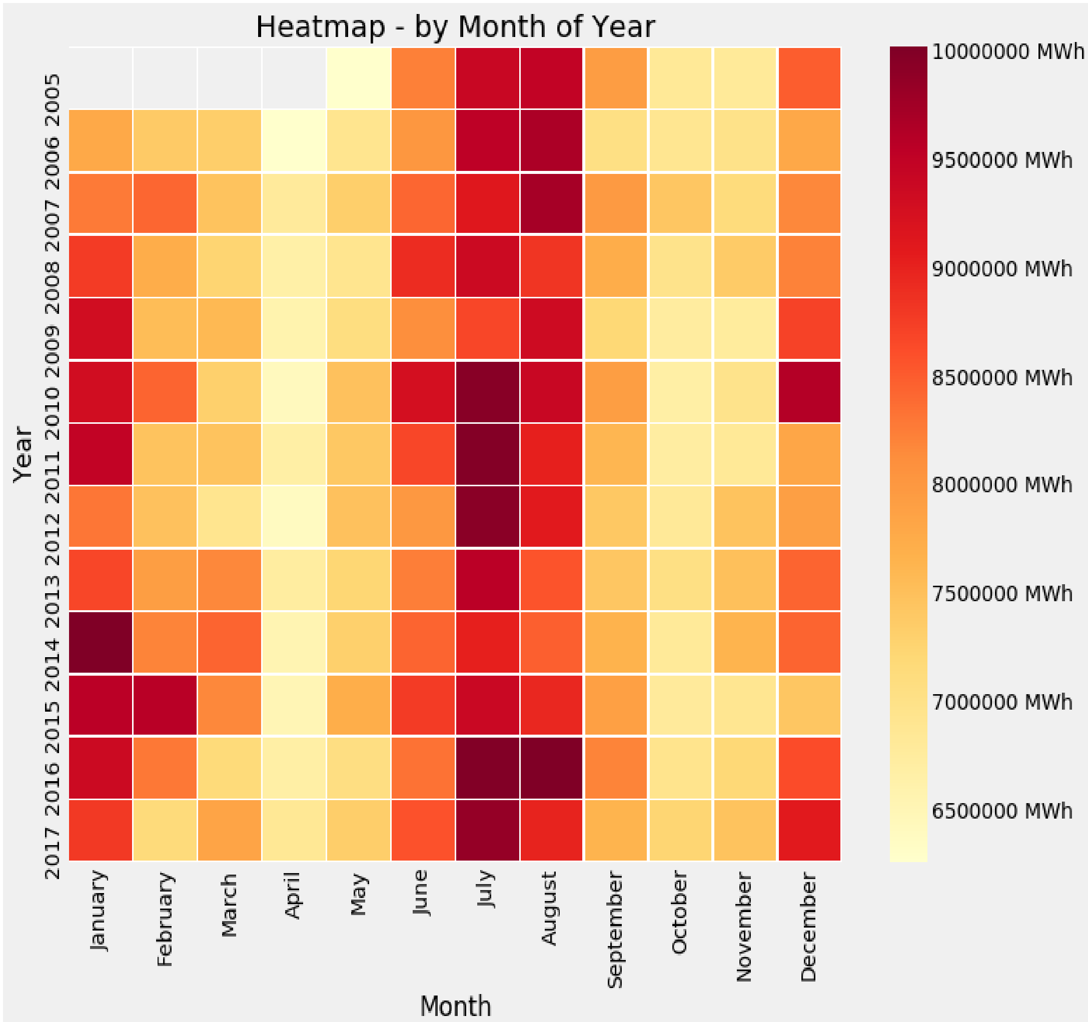
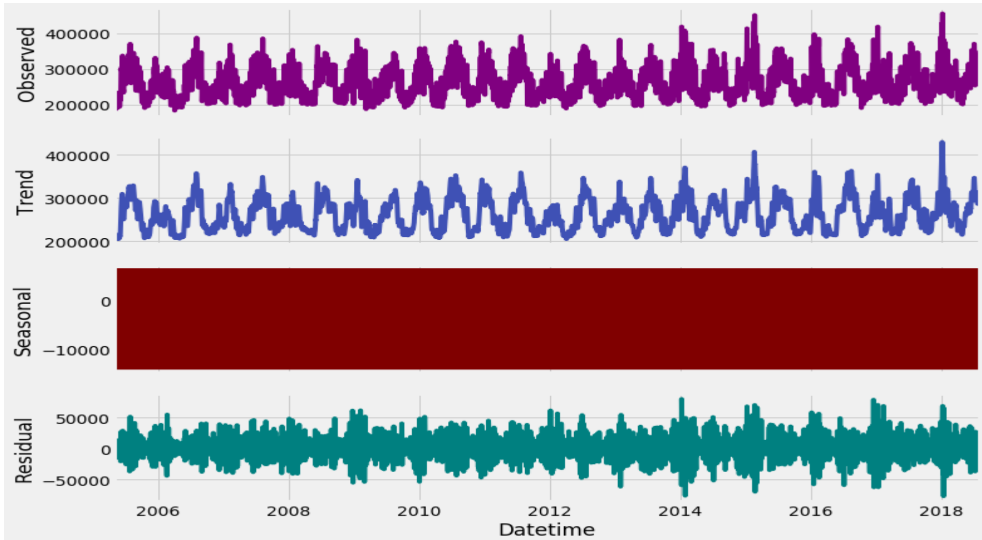
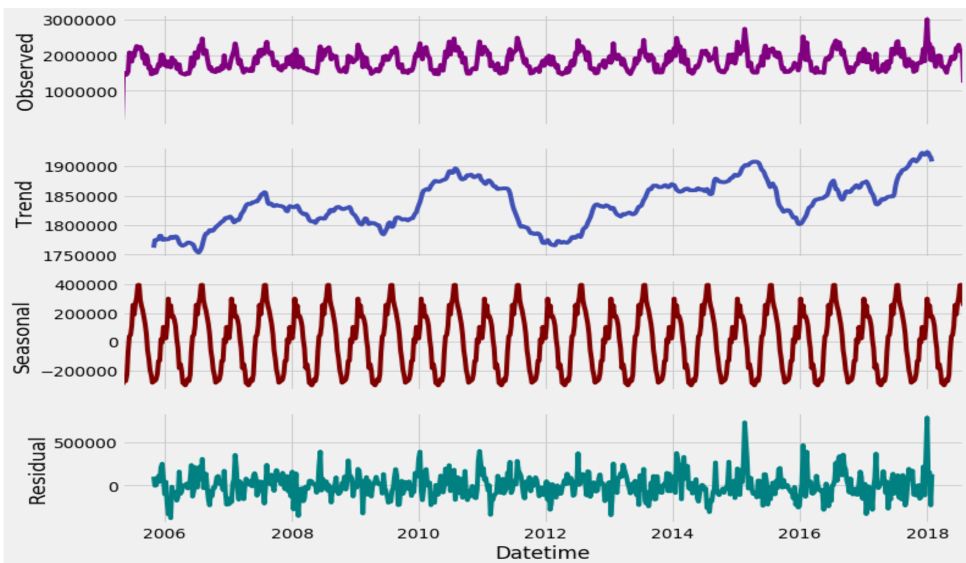


Figure 2. Building electric power consumption is visualized according to the month of the year

This dataset contains observations from May 1, 2005, to August 3, 2018. Each observation keeps hourly records for electric power consumption in a building. In this proposed approach, 80% of observations are used to train and the rest of the observations are used to test the model about how it works. Moreover, there are two peaks on Saturday morning and evening on weekdays. In terms of season, power consumption is highest in Summer (June, July, August) as well as Winter (December, January) and lowest in April and October. These high demands increase the electricity price because hydropower plants are required to produce more electricity, as expressed as a heatmap by [Figure 2].



(a)



(b)

Figure 3. Visualization of components through decomposition: observed, trend, seasonality, and residual-based on (a) daily dataset (b) weekly dataset

Time series decomposition is the task of statistics that decomposes the time series dataset into several components: observed, trend, seasonality, and residual. This is required to understand the dataset better during analysis and prediction. [Figure 3(a)], and [Figure 34(b)] visualize four resulting components after deconstructing our time series dataset for daily data and weekly data respectively. The information about the trend and seasonality from [Figure 3(b)], the series of components looks reasonable. Also, there are huge fluctuations in the residuals with high irregularity in the early and later years of the series for the periods.

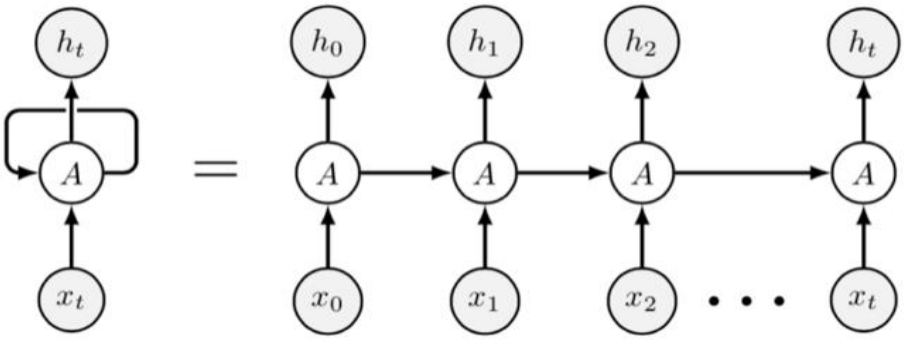


Figure 4. Representation of recurrent neural networks

3. Methods

Recurrent Neural Networks (RNNs) are known as feed-forward neural networks. It uses internal memory to perform the same role for each input data. But the output of the system is produced from the last tier. This produced output is sent back into the recurrent neural network shown in [Figure 4]. To make a decision, it considers the input and output of different tiers. RNN's are very effective for processing time-series data for predicting things. It has the advantage that it trains faster and computational resources are less. Because fewer tensor operations are computed in this approach.

The proposed approach focuses on pre-processing data, cleaning data, normalizing data, building the model, training and testing the model, and evaluating the model to make a good impact to perform better while training and testing this model. [Figure 5] shows the schematic diagram of the proposed RNN model that showing the summary of procedures.

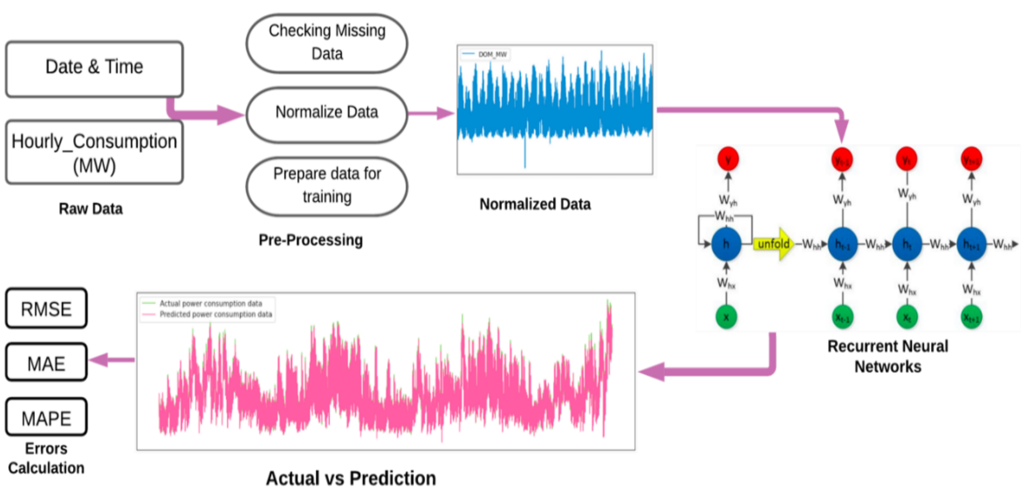


Figure 5. The schematic diagram of the proposed RNN model that showing the summary of procedures

This work has used average data imputation techniques to handle missing data. It uses the average electric consumption value to fill out missing values. Also, it has been vital to rescale the attribute, therefore data normalization was used to distribute the data uniformly to the range of 0 to 1. Through this way, data is prepared for the proposed model in which this data is ready to train the model so that it works well to validate the performance to unveil the hidden patterns and to predict the consumption behaviors.

4. Results and discussion

In this section, we will provide a quantitative analysis of this proposed technique. The most important thing is that the results from RNNs will be established their robustness for predicting consumption patterns by comparing our approach with machine learning and deep learning.

4.1. Evaluation metrics

To evaluate the proposed approach with other approaches, we will use four useful metrics: Mean Square Error (MSE) Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE).

$$MSE = \frac{1}{n}\sum_{1}^{n}(Y_i - \overline{Y_i})^2 \qquad (1)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{1}^{n}(Y_i - \overline{Y_i})^2} \qquad (2)$$

$$MAE = \frac{1}{n}\sum_{1}^{n}|Y_i - \overline{Y_i}| \qquad (3)$$

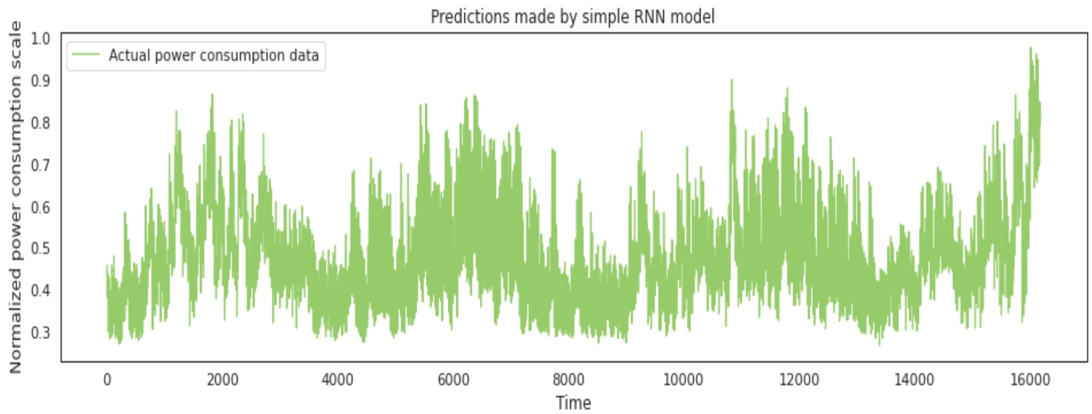
$$MAPE = \frac{1}{n}\sum_{1}^{n}\left|\frac{Y_i - \overline{Y_i}}{Y_i}\right| \qquad (4)$$

4.2. Results and comparison

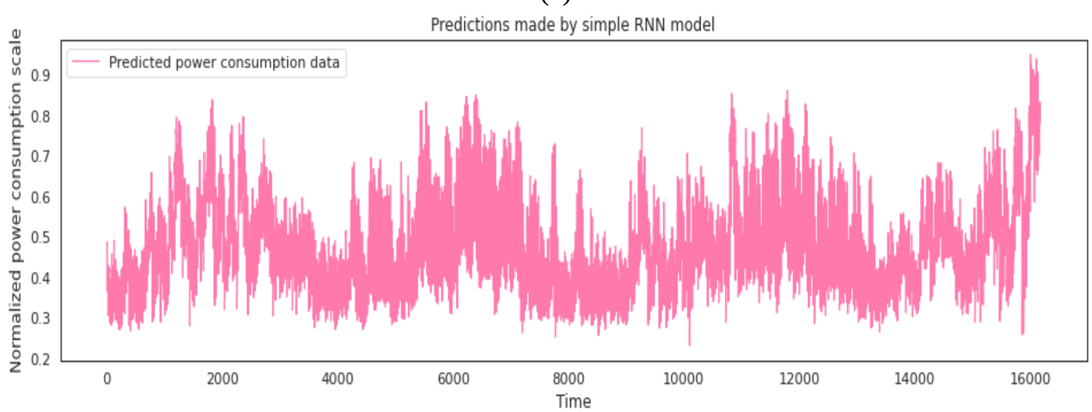
[Figure 6] shows the visualizations of electric energy consumption predicting the result of the proposed approach as well as the actual energy consumption. The result of the actual energy consumption is expressed by [Figure 6(a)], and predicting the result is shown in [Figure 6(b)] at the same time. We show how the predicted result is much overlapped with the actual result in [Figure 6(c)]. It is observed from [Figure 6(c)] that these two results are converged well with each other which verifies the performance of our approach.

The proposed deep learning RNN approach has lower values of errors in terms of MSE, RMSE, MAE, and MAPE compared to traditional machine learning models and deep learning methods in Table 1. According to the DOM hourly dataset, the values of observations gathered from the building are volatile and depend on the seasons as well as the daily activities of the household. The energy consumption is observed by the figures of monthly heat-map as well as seasonal decomposition. [Table 1] compare the results for several existing methods with the proposed method. Our approach has lower errors (MSE: 0.024; RMSE: 0.156; MAE: 0.119; MAPE: 31.06), whereas Kim et al., 2019a and Lee et al., 2019 have errors (MSE: 0.35; RMSE: 0.59; MAE: 0.33; MAPE: --) and (MSE: 0.29; RMSE: 0.54; MAE: 0.39; MAPE: --) in his works respectively, although the values of MAPE are not available in both methods. [Figure 7]. expresses the performance of the proposed approach with the existing approaches in terms of the values of error metrics.

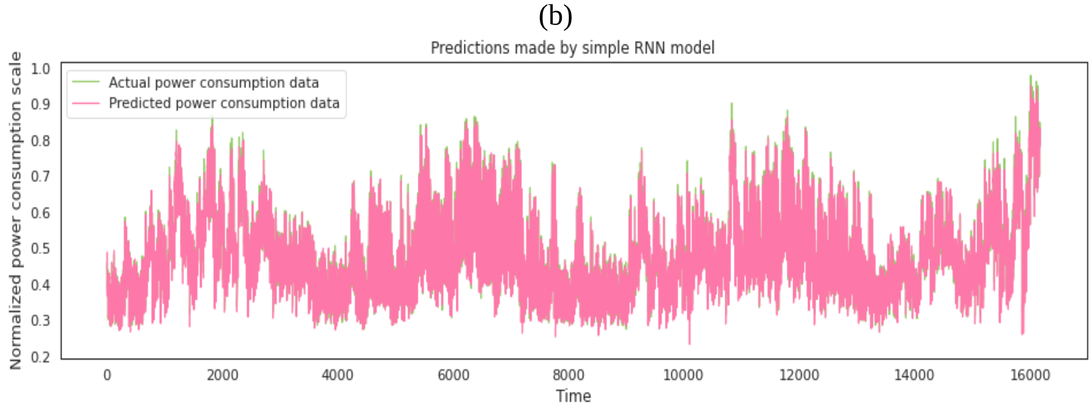
We can conclude from these results that our approach has much more capable of predicting electric energy consumption compared to the existing method such as ARMA, SVM, deep learning, etc. which supports the performance of our approach as more stable and accurate.



(a)



(b)



(c)

Figure 6. Visualizations for the actual and predicted electric energy consumption (a) actual power consumption (b) predicted power consumption (c) combined of actual and predicted power consumption

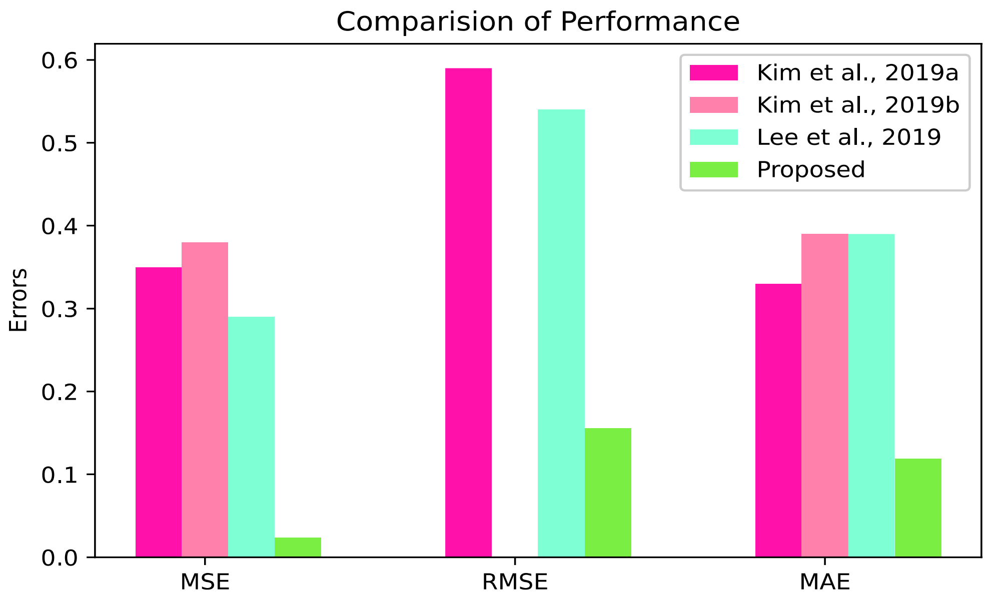


Figure 7. Performance of the proposed approach with existing approaches based on error metrics

Table 1. Compare errors of the proposed approach with existing approaches

	Methods	MSE	RMSE	MAE	MAPE
Traditional Machine Learning models	ARMA(Chujai et al., 2013) [26]	--	0.30	--	--
	SVM(Rajabi et al., 2019) [27]	--	1.25	1.12	--
Deep Learning Methods	Kim et al., 2019a [23]	0.35	0.59	0.33	--
	Kim et al., 2019b [24]	0.38	--	0.39	--
	Lee et al., 2019 [25]	0.29	0.54	0.39	--
	Proposed Method (25 epochs)	0.024	0.156	0.119	31.06

9. Conclusions

This study focused on machine learning as well as deep learning methods for the estimation of electricity consumption through detailed analysis of the DOM hourly electricity consumption dataset for unveiling the hidden patterns through this work. The proposed approach is well capable of handling the time series dataset and predicting the estimation of electricity consumption. The results from the proposed approach are compared with the machine learning as well as deep learning approaches to validate the performance with the prediction accuracy. The accuracy is varied from 94.02% to 96.86% based on the number of epochs. Also, the values of error matrices like MSE, RMSE, MAE, and MAPE are lower than other approaches which indicates its robustness for the prediction accuracy of electricity consumption. We observe limitations that accuracies might be varied slightly for different datasets. In future work, we will focus to solve these issues.

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