2019 International Conference on Deep Learning and Machine Learning in Emerging Applications (Deep-ML)

Energy Efficient Smart Buildings: LSTM Neural Networks for Time Series Prediction

İdil Sülo*, Şeref Recep Keskin†, Gülüstan Doğan‡ and Theodore Brown§

* *Department of Computer Engineering, Middle East Technical University*, Ankara, TURKEY,
idil.sulo@metu.edu.tr
† *Department of Computer Engineering, Gazi University*, Ankara, TURKEY,
seref.recep.keskin@gazi.edu.tr
‡ *Department of Computer Science, University of North Carolina Wilmington*, Wilmington, North Carolina, USA
dogang@uncw.edu
§ *Department of Computer Science, Queens College City University of New York*, New York, USA,
tbrown@gc.cuny.edu

***Abstract*—Considering the human resources, time and energy expenditures in the modern technology of today, efficient use of resources provides significant advantages in many ways. As a result of this, the role of intelligent building systems, which are part of the campuses and cities, is becoming much more important day by day. The purpose of these building systems is to ensure that the resources and systems are efficiently used in order to provide comfortable living conditions to the people. For this purpose, in this paper, we investigate the ways to improve the efficiency of the energy used by these buildings. In this study, we use the Long Short Term Memory (LSTM) neural network model to analyze the energy expenditures of the buildings that reside in the campuses of the City University of New York (CUNY). With the help of the neural network model that had been developed, we aim to predict the energy consumption values of these buildings in order to obtain energy efficient smart buildings.**

***Index Terms*—Energy Consumption Prediction, Time Series Data, Long Short-Term Memory, Recurrent Neural Networks, LSTM, Smart Buildings**

I. INTRODUCTION

Energy efficiency can be defined as utilizing the amount of energy consumed with the least waste of resources or effort. Today, buildings cover approximately 40 percent of the world's total energy consumption. Lighting, heating, cooling, ventilation and air conditioning are the most observed energy consumption areas in the buildings. As a result of this situation, the carbon emissions of the buildings are significantly higher than the emissions in any other field such as the transportation sector. Due to this reason, energy efficiency is an important issue for the buildings, and therefore, for the world ecosystem [1].

Generally, intelligent buildings stand out as a process that is carried out in a controlled manner within the building systems, in order to maximize energy efficiency. The important fact about this is that, for any activity which is carried out, all the other parameters are kept at minimum such that the consumption of the energy is fully utilized. To be able to achieve this, the buildings should be designed accordingly where the recent advancements in technology will be used to reduce the energy consumption. It is also required to implement these technologies easily to create buildings that will operate in optimum energy standards.

Smart buildings are such systems through which the energy consumption values of the buildings are automatically controlled by the building's own components and the supplementary types of equipment to improve energy yield [2]. For this reason, the most significant task of the intelligent buildings is to minimize the energy expenditures of the buildings without compromising the ability of user comfort [3].

The main purpose of this study is to make predictions about the energy consumption with the data that is obtained from the City University of New York (CUNY), and to use these estimations in smart building systems to be established. By analyzing the energy usage, it is possible to determine the methods that will reveal the loss in the energy being used that will help people to make future energy plans. This work, by determining the optimal conditions in intelligent buildings and acting in the light of this data, helps us to eliminate the aforementioned loss in energy and also predict the future energy usage. [4].

In this paper, the main topic of investigation is the use of electricity. With this study, it is desired to make predictions about energy use with the data that is obtained from CUNY that has 25 campuses, including the Queens College, the John Jay College and the Brooklyn College. Each campus has many buildings, and these buildings all have different energy expenditures. These values are kept in a database where the data is categorized according to the campus and buildings on the campus. The data includes many attributes such as temperature, wind speed, wind degree, humidity, precipitation, dew point and occupancy. The main backbone of this research is to carry out a study which will help the development of the smart building systems in CUNY, and hopefully in other cities and countries, by combining the recent advancements in the field of artificial intelligence and the issues regarding to the

This work is supported by the Scientific and Technological Research Council of Turkey (TÜBİTAK) under the project named "Energy Efficient Smart Buildings" (project no 1919B011803857).

978-1-7281-2914-3/19/$31.00 ©2019 IEEE
DOI 10.1109/Deep-ML.2019.00012

efficient use of energy.

The rest of this paper is organized as follows. In Section II, we give a brief information on approaches in the literature that are similar to the one that is proposed in this study. In Section III, we introduce the dataset that is used in this study in detail, and in Section IV, we describe the algorithm considered for this study. In Section V, we give a discussion on several different approaches. Finally, in Section VI, we conclude our paper.

II. RELATED WORK

In this section, we review the related work that is associated to our study, and list our contributions.

Benotto and Rossi (2017) [3] have considered the problem of demand forecasting in residential micro-grids. They have applied several artificial intelligence algorithms on the data that they have, and compared the results that are obtained from each of those algorithms. Algorithms that they have applied are ARMA, LSTM, NAR and SVM in successive order when these algorithms are compared by their performance.

Kavaklioglu (2010) [5] has used Support Vector Regression (SVR) methodology to model and estimate the electricity consumption of Turkey. He has used the ε-SVR method among various SVR methods due to the fact that the training pattern set was small. Electricity usage is modeled as a function of socioeconomic parameters. Therefore, in this study, gross national product, import, export and population parameters were used. For the purpose of estimating the electricity usage, different SVR models were created for several input parameters with respect to the data.

Ekonomou (2009) [6] has used artificial neural networks with the aim of estimating Greek long-term energy consumption. In order to estimate Greek long-term energy usage, the multi-layer perceptron model (MLP) was used. The results that are obtained from the artificial neural networks (ANN) were compared to the results that are produced by the support vector machine method (SVM) which is a linear regression method, and also to the real energy usage records. As a result of this comparison, the models that the experiments are conducted on did not outperform each other.

Kaboli, Selvaraj and Rahim (2015) [7] have investigated the effects of the indicators on the electric energy consumption of Iran. The indicators that they have considered can be listed as gross domestic production, population, stock index, export and import. In order to calculate the weighting factors, they have used linear, quadratic, exponential and logarithmic models. On this basis, an artificial cooperative search algorithm is developed to both provide a better-fit solution and improve the accuracy of estimation.

Shi, Xu, and Li (2018) [8] have aimed to directly learn from the uncertainty by applying a new type of machine learning algorithm. Nevertheless, it had been shown that simply adding neural networks reduces the performance of the neural network during prediction due to the problem of over-fitting. Therefore, in this paper, a pooling-based deep recurrent neural network is suggested which batches the load profiles of a group of costumes into a pool of inputs. Basically, the model adresses to the problem of over-fitting by considering variation in the data and volume. This research presents the first ventures to develop a deep learning application for household load forecasting by achieving preliminary success.

In 2017 [9] researchers developed a deep learning approach for energy consumption forecast due to the increase in energy consumption values, and the necessity of modeling energy prediction for the companies working in the power sector. It is also needed to plan how to spend this energy supply, and to estimate their energy consumption in the upcoming years. Considering these issues, deep learning methods are known to be commonly preferred for these kind of problems. Therefore, in this study, deep fully connected, convolutional and long-short term memory neural network models were used over 9 million samples. Based on the results, the system was able to forecast the energy expenditures with an absolute error of 31.83 kWh and a relative error of %17.29.

Mocanu, Nguyen, Gibescu and Kling [10] also addressed the problem of building energy consumption. Moreover, it had been also mentioned that the energy prediction of such building systems is a rather complex issue due to many influencing factors, such as climate, performance of thermal systems, and occupancy patterns. Therefore, in their study, they have proposed the use of deep learning methods, or to be more specific, Conditional Restricted Boltzmann Machines and Factored Conditional Restricted Boltzmann Machines for predicting the energy consumption of the buildings.

In our study, we present the use a deep learning method in order to estimate the energy consumption values of the buildings as well. We also emphasize that prediction of the energy consumption values is crucial as the data that is collected throughout our study depends on multiple variables. For the choice of the deep learning method, we use the Long Short Term Memory (LSTM) recurrent neural network model on the time series data that is collected from the several buildings on the campuses of CUNY. This method is used in order to predict the energy consumption values in kilowatt-per-hour (kWh).

Basically, the neural network model that we had developed forecasts future events based on previously known points. By analyzing the energy expenditures of the campuses in CUNY, energy consumption is estimated with the LSTM model that had been developed. As a result of the predictions of the energy data that is obtained through this study, it is aimed to better interpret the issues regarding to the energy consumption. Moreover, we try to overcome the difficulties that are associated with this problem while providing high audit, control, time and cost savings with the estimations that have been made. The results of this research will be used in the smart university project of CUNY to be created.

III. CUNY ENERGY DATASET

In this section, we describe the dataset that we had used for the experiments with the LSTM recurrent neural network architecture.

A. Dataset Collection

In order to predict the energy consumption values, we have collected a dataset from a platform named CUNY Energy Project that belongs to the City University of New York [11].

Figure 1 that is given below illustrates the energy consumption values, with respect to the change in temperature and humidity through a one week time period.

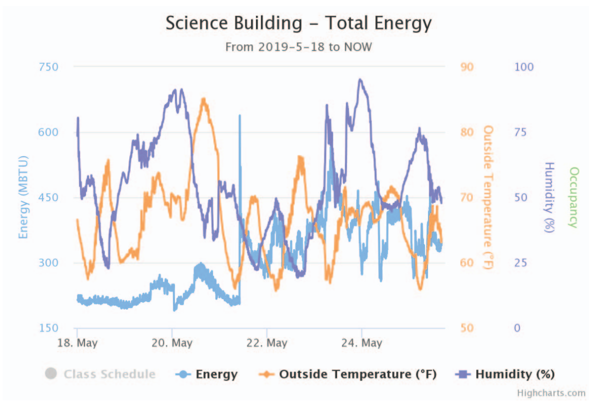

Fig. 1. An example chart that shows the change in energy consumption values, temperature and humidity. [11]

As the data on the platform is updated whenever new measurements are made, through our study we have collected the data on strict time periods. We had chosen the data values that are measured in April, 2019 as a reference in order to conduct the experiments.

B. Properties of the Dataset

TABLE I
SAMPLE VALUES FROM THE CUNY ENERGY DATASET THAT HAD BEEN USED THROUGH OUR EXPERIMENTS.

Energy Consumption Value	Temperature	Dewpoint	Humidity	Wind Speed	Wind Degree
104.5	10.0	-0.9	61.0	15.2	326.0
98.5	10.0	-0.9	61.0	16.075	323.5
100.0	10.0	-0.9	61.0	16.95	321.0
62.0	49.575	49.575	100.0	10.075	170.0
64.0	52.0	52.0	100.0	13.8	170.0
63.0	53.475	51.85	94.5	15.275	170.0

The most important attribute of the collected data is that it depends on a time-related variable. For a time-related variable, the series showing the observation values ordered by time is called "time series". Therefore, the CUNY energy dataset that we had used in this study consists of time series data. Moreover, the collected data is multi-dimensional which means that in addition to the time-dependent energy consumption values, the dataset depends on other variables. These variables can be listed as temperature, dewpoint, humidity, wind speed and wind degree. Several sample values from the CUNY energy dataset that we had used in this study had also been shown in Table I.

IV. METHODOLOGY

In this section, we briefly describe the architecture of the neural network model that had been used for our experiments.

A. LSTM Neural Network Architecture

For the design of the LSTM recurrent neural network, we had used the architecture given in Table II. We had used a neural network with three LSTM units and two Dropout layers. The inner structure of these LSTM units are also shown in Figure 2.

In addition, we have adjusted the input dimension to 6 as the multi-dimensional data that we had used consists of 6 different variables that are mentioned in Section III-B.

TABLE II
THE NEURAL NETWORK ARCHITECTURE USED FOR THE EXPERIMENTS.

Layer	Description
LSTM	neurons: 100, input dimension: 6
Dropout	rate: 0.2
LSTM	neurons: 100
LSTM	neurons: 100
Dropout	rate: 0.2
Dense	neurons: 1, activation: linear

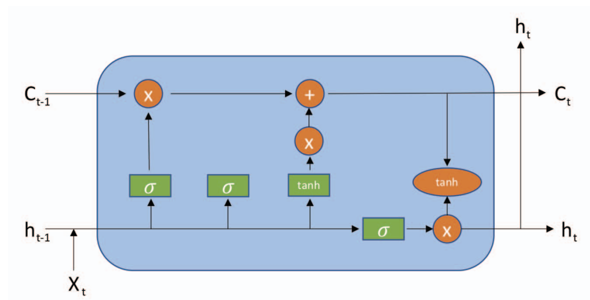

Fig. 2. An illustration that shows the inner structure of an LSTM unit. The orange colored boxes represent the pointwise operations, and the green colored boxes represent the layers. [12]

B. Training and Implementation Details

For training the neural network, we had chosen a specific week from the dataset that corresponds to the values obtained from the Science Building in the campus of CUNY starting from 21.04.2019 00:05:00 up until 28.04.2019 09:10:00. The part of the dataset corresponding to this time period consists of 2127 entries. These values are measured in 5 minute periods.

In order to conduct our experiments, we had split the dataset with a factor of 0.85. The 85% part of the dataset which has 1808 entries had been chosen as the training set, whereas the rest of the dataset which has 319 entries (15%) had been determined as the test set.

While training we had used the normalization factor that is given below:

$$n_i = \frac{e_i}{e_0} - 1,$$

where n corresponds to the the normalized energy values, and e corresponds to the raw list of energy values.

We had also chosen the batch size as 32 and the sequence length which determines how many data points will be considered at the same time as 50. While training the neural network, we had used the Adam optimizer and Mean Squared Error loss.

V. EXPERIMENTS

In this section, we describe the results of the experiments that are conducted through our study.

A. Effect of Attributes of Data

1) Prediction of the Energy Consumption Values as One-Dimensional Data: In our study, we had first started with the prediction of the energy consumption values as a time sequence. Therefore, we have converted the dataset into a one-dimensional form where we had only predicted the values depending on the time values. We had seen that the results obtained from this type of data is not sufficient.

2) Effect of Temperature on Energy Consumption: For the second part of our study, we have examined the effect of temperature values onto the energy consumption prediction with respect to the LSTM neural network model that is described in IV-A. We had observed that when the temperature values are added to the model, the predictions become much more accurate. The results obtained from this experiment can be seen in Figure 3.

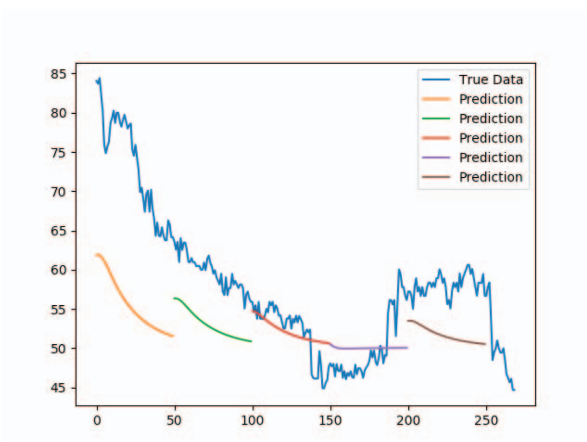

Fig. 3. Prediction of energy consumption with respect to temperature values

3) Effect of Temperature and Humidity on Energy Consumption: Next, we had added the humidity values to the dataset that is considered in Section V-A2. We had seen that the predicted values became much more accurate with the help of the humidity values. The difference on the predicted values that belong to this experiment can be observed in Figure 4.

4) Effect of Temperature, Humidity and Occupancy on Energy Consumption: Lastly, we have also added the occupancy values to our multi-dimensional data. Yet, as the occupancy values are not stable and several occupancy values are missing on the CUNY Energy Project platform [11], we had seen that

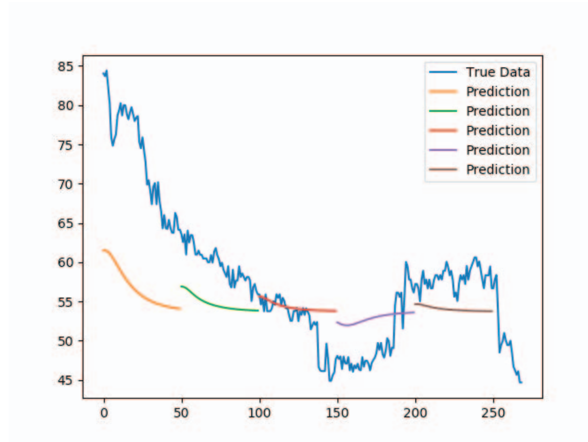

Fig. 4. Prediction of energy consumption with respect to temperature and humidity values

the accuracy of the predictions had became lower compared to the energy consumption predictions that are presented above. The results of this experiments can be seen in Figure 5.

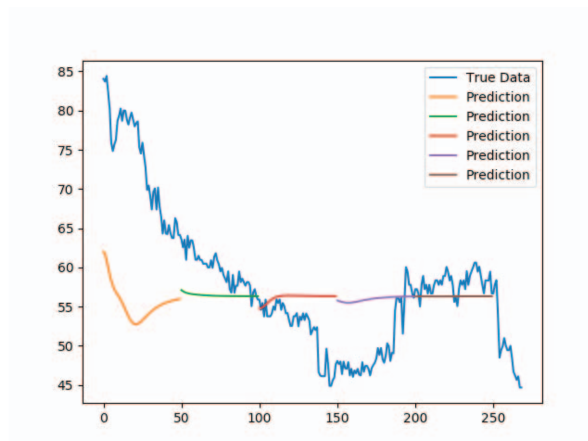

Fig. 5. Prediction of energy consumption with respect to temperature, humidity and occupancy values

B. Comparison of the Obtained Results

In order to compare the results that are presented in Section V-A, we present the loss values that are computed throughout the training of the LSTM neural network model in Table III. As can be seen from Table III, the final loss values increases when the occupancy value is also considered as another dimension.

TABLE III
THE LOSS VALUES COMPUTED THROUGHOUT THE EXPERIMENTS.

Experiment	**Loss Value at Epoch 1**	**Loss at Epoch 2**
Effect of Temperature	0.0637	0.0079
Effect of Temperature and Humidity	0.0595	0.0077
Effect of Temperature, Humidity and Occupancy	0.0965	0.0107

VI. Conclusion

In this study, we have predicted the energy consumption values of the buildings that reside in the campuses of CUNY in order to find the optimal conditions in smart buildings systems which are a part of the campuses and cities. We aimed to predict the future energy usage of the buildings in order to determine the loss of energy. We have developed an LSTM neural network model with respect to the time series data that had been collected several campuses of CUNY, and conducted several experiments to obtain results according to the different attributes of the data.

As a future work, we plan to compare the success of our model with several machine learning models and different deep learning models. We also believe that this work will not be limited to CUNY, and will pave the way for the energy efficient smart building systems in other cities and countries.

Acknowledgement

This work is supported by the Scientific and Technological Research Council of Turkey (TÜBİTAK) under the project named "Energy Efficient Smart Buildings" (project no 1919B011803857). We also would like to thank the City University of New York for granting us access to their CUNY Energy Project platform [11], and giving us the opportunity to use their data which constitutes the backbone of our study.

References

[1] E. D. M. A. G. Dogan, T. Brown and J. Manorge, "Data analytics of building automation systems: A case study," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 2, pp. 123–137, 06 2018.

[2] C. W. Potter, A. Archambault, and K. Westrick, "Building a smarter smart grid through better renewable energy information," in *2009 IEEE/PES Power Systems Conference and Exposition*, March 2009, pp. 1–5.

[3] R. Bonetto and M. Rossi, "Machine learning approaches to energy consumption forecasting in households," *CoRR*, vol. abs/1706.09648, 2017. [Online]. Available: http://arxiv.org/abs/1706.09648

[4] S. A. Kalogirou and M. Bojic, "Artificial neural networks for the prediction of the energy consumption of a passive solar building," *Energy*, vol. 25, no. 5, pp. 479 – 491, 2000. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0360544299000869

[5] K. Kavaklioglu, "Modeling and prediction of turkeyâs electricity consumption using support vector regression," *Applied Energy*, vol. 88, no. 1, pp. 368 – 375, 2011. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0306261910002904

[6] L. Ekonomou, "Greek long-term energy consumption prediction using artificial neural networks," *Energy*, vol. 35, no. 2, pp. 512 – 517, 2010, eCOS 2008. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0360544209004514

[7] S. H. A. Kaboli, J. Selvaraj, and N. Rahim, "Long-term electric energy consumption forecasting via artificial cooperative search algorithm," *Energy*, vol. 115, pp. 857 – 871, 2016. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0360544216312567

[8] H. Shi, M. Xu, and R. Li, "Deep learning for household load forecasting—a novel pooling deep rnn," *IEEE Transactions on Smart Grid*, vol. 9, no. 5, pp. 5271–5280, Sep. 2018.

[9] R. F. Berriel, A. T. Lopes, A. Rodrigues, F. M. Varejão, and T. Oliveira-Santos, "Monthly energy consumption forecast: A deep learning approach," in *2017 International Joint Conference on Neural Networks (IJCNN)*, May 2017, pp. 4283–4290.

[10] E. Mocanu, P. H. Nguyen, M. Gibescu, and W. L. Kling, "Deep learning for estimating building energy consumption," *Sustainable Energy, Grids and Networks*, vol. 6, pp. 91 – 99, 2016. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S2352467716000163

[11] "CUNY Energy Project." [Online]. Available: https://energy.cisdd.org/

[12] "Time series prediction using lstm deep neural networks." [Online]. Available: https://www.altumintelligence.com/articles/a/Time-Series-Prediction-Using-LSTM-Deep-Neural-Networks