INTELLIGENT SYSTEMS

FINAL PROJECT REPORT

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Forecasting of energy demand: An application for 6 buildings

Abstract: Given population growth, several countries have been facing the challenge of providing energy resources. One approach that aims to plan and manage such resources is energy demand forecasting. This work addresses the prediction of energy demand required by 6 buildings on campus, using an optimization model based on machine learning algorithms. Data relating to energy demand and production come from [1], in which an IEEE-CIS technical challenge on forecasting energy demand. It is expected that the results of this work can contribute to improving solutions for predicting and optimizing energy availability.

Keywords: forecast; energy; machine learning algorithms; LSTM model.

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1. INTRODUCTION

Since the end of the twentieth century, the demand for energy has increased significantly with the development of industrialization and globalization. About 80% of the energy consumed in the world comes from fossil fuels, such as natural gas, oil and coal. If current energy consumption levels are maintained, it is estimated that global energy consumption is expected to increase by at least 50% by 2030 [1]. It is known that the protection of the environment is fundamental for sustainable living, such as food, water, energy, natural resources, and other relevant environmental factors. However, energy is the most crucial of these elements because it is considered that all activities, whether in a developed or developing country, depend on energy to function. Given that large-scale energy production and consumption have caused damage to the environment, also due to the fact that energy resources, especially commercial ones, are not renewable, industry players have sought to identify effective means for the use of energy and alternative sources of production. A factor that has somehow been driving the use and recurrence (although still slow) of renewable energies at a global level. Since the theme around energy management and demand has been strongly addressed by researchers, this work makes use of machine learning algorithms, in which we analyse the prediction of energy demand, applied in 6 buildings that are located in the Monash Clayton campus in New South Wales, Australia. The motivations of this work are related not only to the fact that energy demand is an important issue but also to the need to know the tools and mechanisms available for the effective management of energy resources. For any nation to develop sustainably, an integrated approach to energy management is needed, as the future world depends on today's decisions.

This work is organized as follows. Section 2 presents a brief bibliographic survey on energy demand management. Section 3 describes the structure of the material containing the processing and execution of the information provided by the database [2], as well as the methods used in the learning algorithm applied in this work. Section 4 shows the results obtained, their validity and performance. Finally, the last section addresses the conclusion of the work and the suggestion of recommendations to be adopted in the next challenges.

2. ENERGY DEMAND MANAGEMENT

Energy demand management involves the efficient use of resources, reliability of supply, effective management of resources, preservation of resources, renewable energy systems, integrated power supply systems, and autonomous power supply systems, among others. Since the creation of easy and reliable interaction between suppliers and consumers is essential to achieve rational electricity consumption, there needs to be demand response capacity for this goal to be achieved. In [3] the authors relied on the definition of the International Energy Agency, which stated in 2003 that demand response behaviours refer to all factors that influence fluctuations in demand and total energy consumption over time. Whereas [4] it is imperative to look for profitable options, profitable options, and sustainable options, since demand management involves the planning, execution and supervision of energy consumption activities aimed at persuading consumers to change their energy consumption patterns. In an environment where new technologies or techniques are developed and introduced to the market, it is necessary to analyze the circumstances under which users decide to adopt these features. The authors emphasize that there are two main factors (costs and legislation) in the energy industry behind the adoption of energy demand management measures. The research states that energy costs represent a large proportion of operating costs in energy-intensive industries, reaching in many cases the rate of 50% as a result of sudden variations and rises in the prices of raw materials for energy production. Which certainly makes the costs represent a significant incentive for industrial energy demand management. Environmental legislation, which punishes companies for polluting, effectively results in penalties for burning (non-renewable) fossil fuels and using derived electricity.

Energy efficiency is promoted by demand-side management for sustainable development. In [6] the authors found that energy demand is closely linked to GDP, population and price. And its management should contribute to the achievement of self-sufficiency and cost-effectiveness with a view to ensuring sustainable economic development. It should also contribute to: the planning of the future requirements, identification of conservation measures; identification and prioritization of energy resources, optimized energy utilization, strategies for energy efficiency improvements; framing policy decisions: and identifying strategies to reduce emissions. [7] states that energy models are developed using macroeconomic variables to predict energy demand. This helps in planning and policymaking for demand-side energy management. In research carried out between the eighties and nineties [8 – 10] it was stated by the authors that energy models are developed for the sustainable progress of any nation. And demand models can be classified in a variety of ways, such as univariate versus multivariate, static versus dynamic, and techniques ranging from time series to hybrid models. [11] looks at how China has used and produced both renewable and traditional energy over the past thirty years. A study of energy management IT tools is carried out to investigate how these tools work to integrate renewable energy into different energy systems [12].

According to the prevailing economic and market circumstances, energy forecasting models are designed specifically for a nation or public utility. And for this reason, in order to assess energy demand, [13] they used a market forecasting approach, where energy substitution and affordability are discussed, namely. Qualitative and quantitative forecasting methods can be combined to increase forecasting accuracy, as demonstrated by [14]. This can mean that when there is a shortage of information or when end-user perception, awareness and approval is required, energy demand is predicted through qualitative approaches such as questionnaires and surveys. Such is the case examined for the city of Bandung in Indonesia, in which [15] they conducted a survey to determine the energy consumption patterns of households.

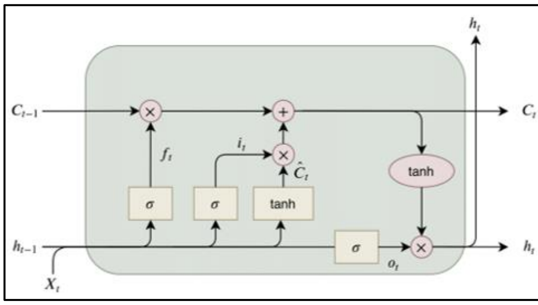
3. METHODS AND FRAMEWORK

3.1. Long short-term memory (LSTM) algorithm

The LSTM method is a deep learning technique and an improved version of the recurrent neural network method. It has the ability to make predictions on sequential data with a good level of learning [16]. On the other hand, [17] claim that the LSTM algorithm is an advanced tool for making accurate predictions on time series-related problems. To deal with the gradient challenge, the method uses special components called memory blocks, which work within the recurring layers. These memory blocks in the algorithm are made up of memory cells connected through three ports: an input port, a forget port, and an output port. Other algorithms can also be employed in energy research to predict various sectors, however the LSTM algorithm has been widely used in studies to make predictions of gas and energy consumption, as mentioned in previous research [18 – 19].

3.2. Tuning Framework

In this work, we use LSTM cells as nodes in recurrent neural networks. Being that within an LSTM cell, there are additional gates, such as the input, forget, and output port, which are used to decide which signals will be sent to the next node. Where W represents the recurring connection between the previous hidden layer and the current hidden layer. U is an array of weights that connects the inputs to the hidden layer. Whereas C is a candidate hidden state calculated based on the current input and the previous hidden state, also representing the internal memory of the drive, which is a combination of the previous memory multiplied by the forgetfulness port and the newly calculated hidden state multiplied by the input port [20 – 21]. The equations that describe the behavior of all the ports in the LSTM cell are explained in Figure 1.



$$
\begin{aligned}
i_t &= \sigma\left(x_t U^i + h_{t-1} W^i\right) \\
f_t &= \sigma\left(x_t U^f + h_{t-1} W^f\right) \\
o_t &= \sigma\left(x_t U^o + h_{t-1} W^o\right) \\
\tilde{C}_t &= \tanh\left(x_t U^g + h_{t-1} W^g\right) \\
C_t &= \sigma\left(f_t * C_{t-1} + i_t * \tilde{C}_t\right) \\
h_t &= \tanh(C_t) * o_t
\end{aligned}
$$

Figure 1. Structure of the LSTM cell and its equations explaining the functions of the gates in each cell. (adapted from [21]).

Neural networks do not solve problems through explicit programming, but rather by learning the solution based on provided examples. There are several ways to teach the neural network how to provide the correct answer, but in this work, we focus on supervised learning. Learning is a process that involves establishing a correspondence between an input and its corresponding output, and in supervised learning, the pair (input, output) is provided to the neural network. During training, the neural network adjusts its weights to generate the correct output based on the input provided. In theory, at the end of training, the neural network should be able to infer the correct answer even for inputs that were not presented during training, this is known as generalization.

3.2.1. Data processing

This study analyses through a model based on the ML algorithm to accurately predict the energy demand required by six buildings located on the Monash Clayton campus in New South Wales, Australia. Initially, the associated data is collected from the energy consumption indices of 15 minutes timestep for 15 months, from August 2019 to November 2020 as shoe in Figure 2. Energy consumption for homes, businesses and public roads were considered. Because machine learning algorithms have different accuracy and performance in their prediction, we considered the Long short-term memory (LSTM) machine learning algorithm for the analysis of each building's energy consumption, given the non-linearity of the data.

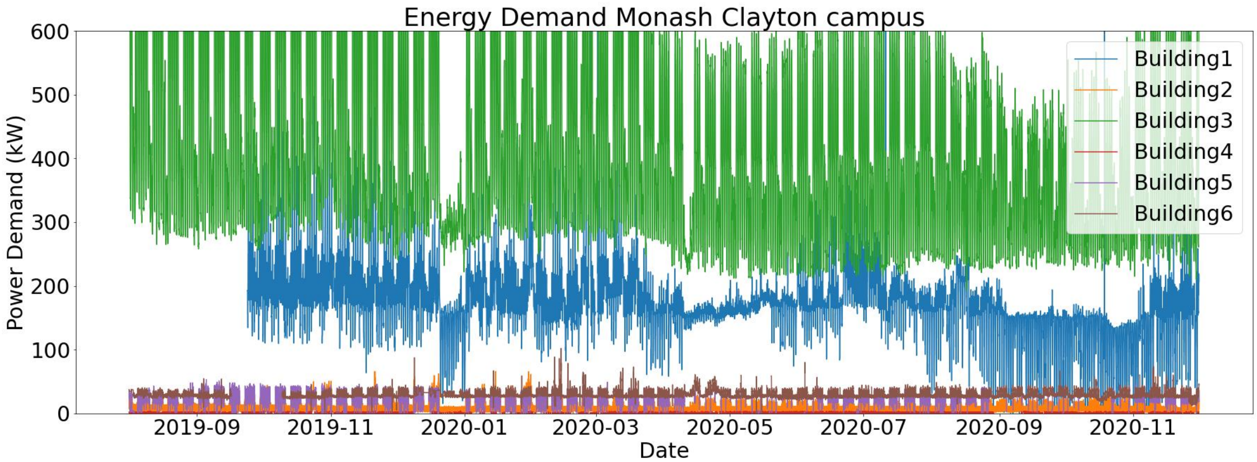


Figure 2. Energy Demand of 6 buildings on the Monash Clayton campus

As shown in Figure 2, there are some missing values that correspond to timestep where the is no data reported due to various factors. To deal with these inconsistencies, it was proposed to normalize the input data, and assign the missing values the normalize mean (zero). Normalizing the dataset was also necessary to improve the performance of the model as the power demand varies in a couple of degrees of magnitude between buildings. Then, with the implementation of a masking layer the model was able to recognize the missing data and mask them in the sequences sets.

We then used the mean absolute error to evaluate the performance of the machine learning algorithm applied to the six buildings. For the implementation of the algorithm, 75% of the data is considered for training, 20 % for validation and 5 % for testing, which correspond to the samples taken in the month of November 2020.

The train, validate, and test datasets are clustered in batches sizes of 24 for a sampling rate of 4 and sequences length of 48. These features are determined as follows; the sampling rate is taken as a 1-hour timestep; the sequence length is assumed to be 48 so to have a sample of 12h in every sequence; and the batch size is set as 24 to ensure the model accuracy. This behaviour is noticeable in Figure 3, where is evident a daily periodicity in the energy demand for most of the buildings.

Then, an LSTM model is implemented with 96 units and a recurrent dropout rate of 25%, to supress overfitting.

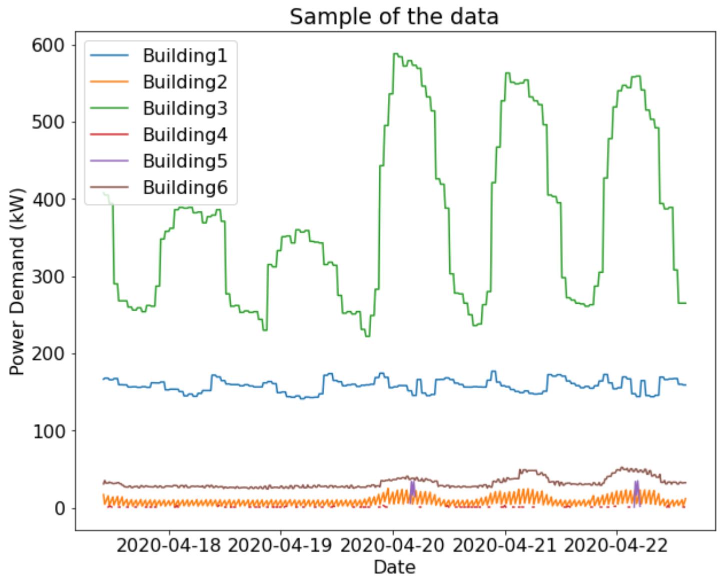


Figure 3. Training and validation Mean Absolute Errors (MAE

4. RESULTS

The validation MAE curve represents the model's performance. Initially, indicating that the model is learning, but then it stabilize reaching a minimum for the 19 epoch as shown in Figure 4. The increasing validation MAE after 20 epochs suggests overfitting. After 19 epochs a MAE of 33.1549 was achived.

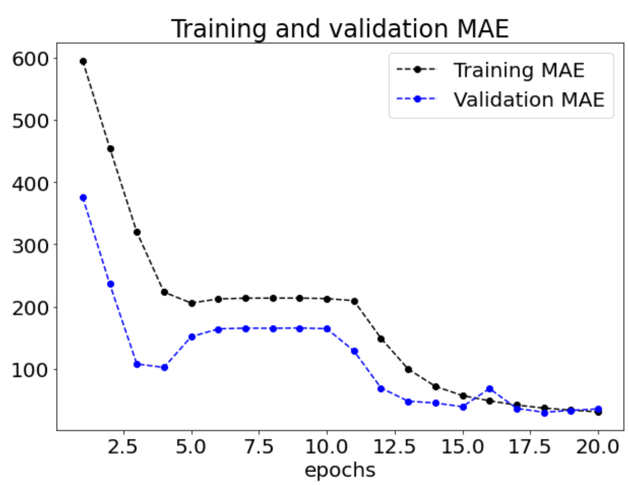


Figure 4. Training and validation Mean Absolute Errors (MAE)

Figure 5 shows the results of the model test, where the precision of the prediction is good as it is in the range of the real data, with a similar mean, but the accuracy is notably low as the model is not able to predict small timestep changes nor daily changes.

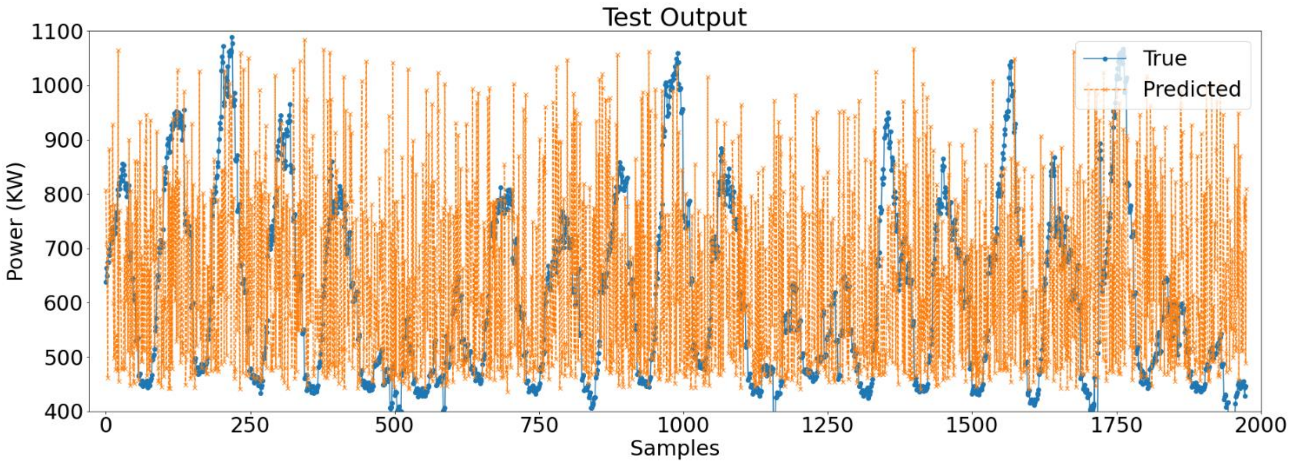


Figure 5. True energy load and predicted power for the month of November 2020

5. CONCLUSION

The model was able to predict the monthly demand with a well behavior of the MAE metric, but the model is not able to predict the daily and hourly behavior of the demand. For that case scenario it may be better to base the model in a prediction of a daily distribution demand instead of a whole month where the accuracy can be notably low. Other suggestion will be to have a bigger dataset with the behavior of monthly demand in several previous years.

Future work should focus on this development to improve the daily forecast of energy demand in order to be able to optimize energy systems, hours of consumption base on the price of electricity or the design of renewable energy systems for microgrid.

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CODE

https://github.com/CamiloAndresPlata/Project.git