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Mining and Analyzing Implicit Dataset of Domestic Load Consumption using Neural Network

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Abstract— The recent rise and fall of interest in conserving energy has generated an amazing quantity of load information being used, which boosts the data-driven algorithms for broad application throughout the building trade. This paper presents the recurrent neural network model to make short to medium team predictions using energy consumption data in residential buildings at one-hour resolution. This project reviews the prevailing data-driven approaches under different archetypes including methods for prediction and methods for classification. With advances in sensors and smart technologies, there is a need for short to long term prediction of electricity consumption in residential and commercial buildings to support decision making pertaining to operations, demand response strategies, and installation of distributed generation. Significantly, this project refines a few key tasks for modification of the data-driven approaches in the context of application of neural network to building energy analysis. The conclusions drawn in this project could facilitate future micro-scale changes of energy use for a particular building. For predicting the commercial building's load profiles, the proposed RNN models generally correspond to lower relative error. All these will be useful to establish a better long-term strategy for urban feasibility.
Keywords— Energy-Consumption, Data, Classification, Prediction

1. INTRODUCTION

Energy is fundamental for the economic progress of a nation. Residential electricity consumption (REC) has increased by 50 times since 1971 and now constitutes about a quarter of India's total electricity consumption, up from about 4% in 1971. It is expected to grow further due to rapid electrification, increasing household incomes, and technology development. A better understanding of residential electricity consumption patterns is essential for designing effective and credible energy efficiency programs, optimize planning of capacity addition, and better adaption to the rapidly changing business models and technologies in the Power sector. A realistic future demand, which accounts for potential savings from energy efficiency and conservation measures, can help in optimizing the addition and management of the electricity generation sources. The natural resources are in limited supply. Governments and concerned individuals are working to make use of renewable resources and to lessen the use of natural supplies through conservation. The consumption in residential and commercial sector is going to rise further in the near future, as the population increases. Business and homes represent a significant portion of electricity usage. The motivation for this project arose from this issue. Currently, the residential sector alone contributes 22% of total electricity use and consumption in this sector is rising at rate of 8% annually. Energy efficiency improvements in this sector go a long way in their sustainable development. This project mainly focuses on collecting the residential load consumed on an hourly basis and analyzing that data, it yields an accurate result of how much energy would be required for the next few months.

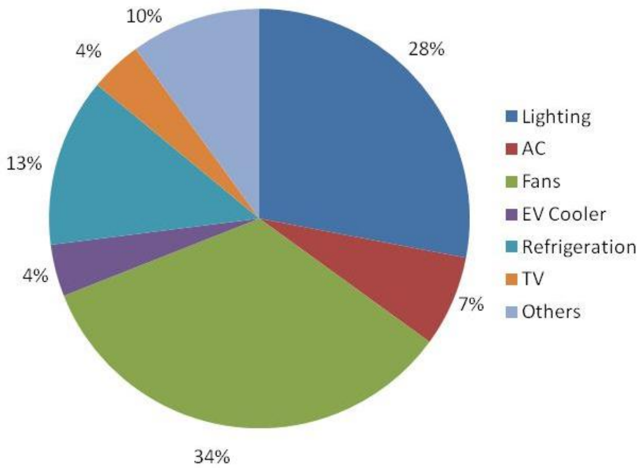

Fig 1.1 Energy consumption in different sectors of Residential building in India

2. METHODOLOGY

2.1.Description of training dataset:

The raw data from the residential sector will be collected on an hourly basis. The total number of unique years in this dataset is 15 years from which count, mean, standard deviation, minimum reading that gradually increases to the maximum will be generated. The format of the dataset would be date (yyyy-mm-dd), time (24 hours) and meter reading.

2.2.Neural Network Architecture:

Artificial neural networks are computing systems, which attempt to simulate the structure and function of biological neurons. Neural networks generally consist of a number of interconnected processing elements or neurons. How the inter neuron connections are arranged and the nature of the connections determine the structure of a network. Neural networks can be classified according to their structures described below into the following two types.

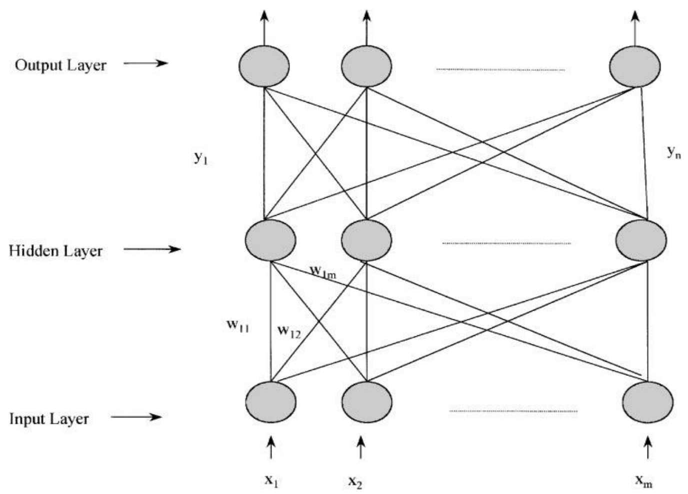

Fig 2.2.1 Architecture of Neural Network

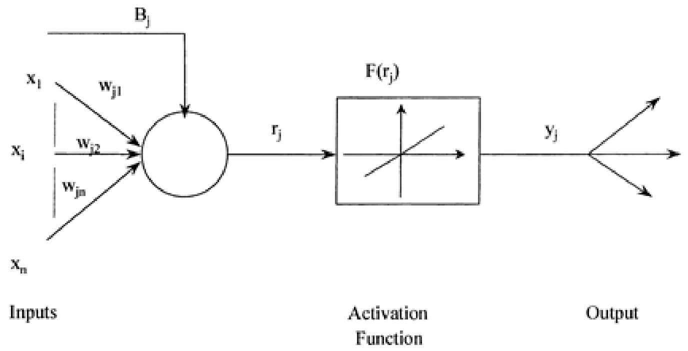

Fig 2.2.2 An Artificial Neuron

2.2.1. Feed forward networks :

In a feed forward network, the neurons are generally grouped into layers. Signals flow always from the input layer through to the output layer via unidirectional connections, the neurons being connected from one layer to the next, but not within the same layer.

2.2.2. Recurrent networks :

In a recurrent network [2], the outputs of some neurons are feedback to the same neurons or to neurons in preceding layers. Therefore, signals can flow in both forward and backward directions. [3] A multi-layer feed forward neural network is shown in Fig. 2.2.1. The network consists of three layers: an input layer, an output layer and an intermediate or hidden layer. The dashed lines in Fig. 1 mean that there are more neurons in each layer than the represented in this figure. Fig. 2.2.2. shows the basic artificial neuron of the hidden layer. [4] The time series estimation or prediction problem using a neural network approach can be separated into three successive steps or subproblems: model building or neural network architecture; the learning or training process; the testing or diagnostic checking. In the present study a multiple network based on backpropagation learning procedure is designed for estimating the building's energy consumption. The selected neural network architecture consists of one hidden layer of 15–22 log-sigmoid neurons followed by an output layer of one linear neuron. Linear neurons are those which have a linear transfer function while the sigmoid neurons use a sigmoid transfer function. Backpropagation networks use the log-sigmoid (logsig), or the tan-sigmoid (tansig), transfer function. Several learning techniques exist for optimization of neural networks. In the present neural network approach learning is achieved using the backpropagation algorithm. Mathematically, backpropagation is gradient descent of the mean square error as a function of the weights. If the mean square error exceeds some small predetermined value, a new ''epoch'' (cycle of presentations of all training inputs) is started after termination of the current one. One of the main parameters of the backpropagation algorithm is the learning rate. The learning rate specifies the size of changes that are made in the weights and biases at each epoch. A learning rate of 0.5 was selected while the number of epochs varied between 3000 and 5000 in all cases.

2.3. Long Short-Term Memory :

A type of RNN architecture that addresses the vanishing/exploding gradient problem and allows learning of long-term dependencies. Recently risen to prominence with state-of-the-art performance in speech recognition, language modeling, translation, and image captioning.
Central Idea: A memory cell (interchangeably block) which can maintain its state over time, consisting of an explicit memory (aka the cell state vector) and gating units which regulate the information flow into and out of the memory.

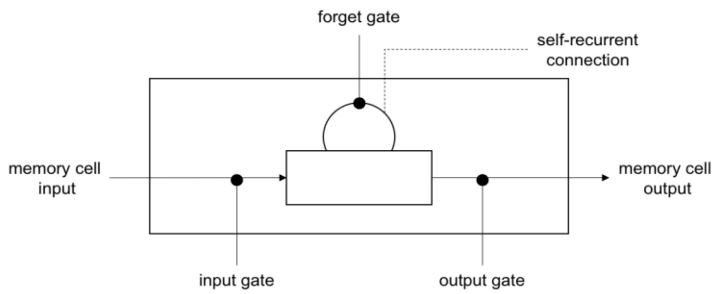

Fig 2.3.1 LSTM Memory Cell

3. RELATED WORKS

With the increasing population and the demand for electricity, consuming energy in an efficient manner is very important. Various research regarding the same has been put with different algorithms used. A well-defined work was given in Elsevier, 2001. In their project, the authors describe algorithms to predict future electricity consumption for a given building in a medium-to-long term time horizon, after being trained on past data specific to that building which is taken as base for this paper. In Elsevier,2015 publication Artificial neural network has emerged as a key method to address the issue of nonlinearity of building energy data and the robust calculation of large and dynamic data with number of days, outdoor temperature and solar radiation as input variables while the output variables are house and heat pump energy consumption.

In ICE Publishing, 2020 a data mining-based methodology is used for setting decision-making rules to identify patterns of energy consumption for a large data set of flats and evaluate the potential effects achievable by retrofitting actions. A supervised classification algorithm to rank flats as 'low', 'medium' or 'high' normalized primary energy demands are developed based on the flats' attributes. The disadvantage of this work is the results may not be accurate and this cannot be implemented in real time.

4. RESULTS AND DISCUSSION

For analyzing the dataset provided, firstly we import various python libraries namely pandas, numpy, seaborn, matplotlib and many others. Initially we display the dataset in a proper format for which code is done to specify the number of columns, general information about the dataset and for identifying the null values present. In the second step the dataset is reformatted in a way to give a clear view in the form of a table. The third step identifies the unique years present in the dataset. A library function "matplotlib" is used to plot the graph that describes the energy consumed each year which is given below.

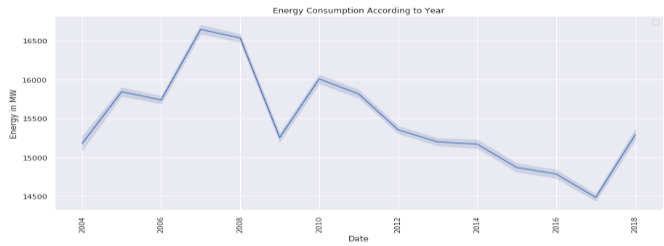

Fig 4.1 Graph showing energy consumption according to year

In the above figure, we can find that the energy consumption in years 2006 to 2008 is maximum. Using "pandas" we can get a more detailed view of the load consumed in the years mentioned

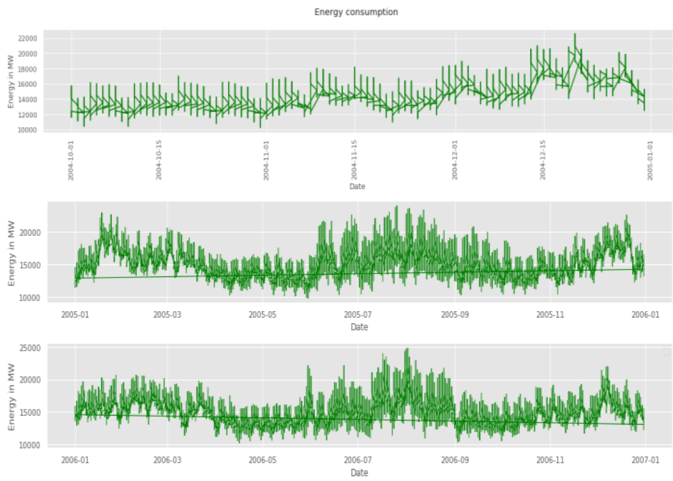

Fig 4.2 Energy graph for three individual years

The load consumed in the years 2004, 2005 and 2006 respectively are shown. From the graph it can be inferred that it attains a peak between the month of November and December which may be due to the usage of heaters as they are winter months. These figures provide only partial information about the energy consumed. The graph given below shows distribution of energy, "seaborn" library function is used for this purpose. It gives a caution path that wholly specifies the energy distribution. For example, here the energy is concentrated from 15000 MW to 17000 MW.

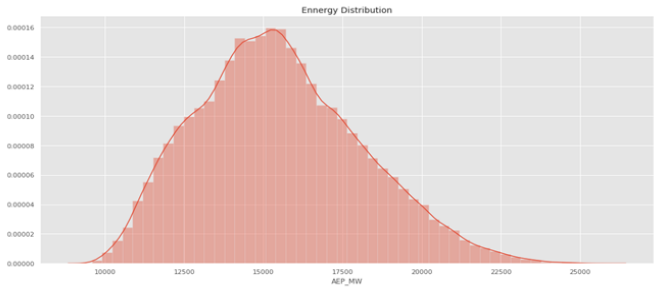

Fig 4.3 Energy Distribution

A graphical representation of energy with respect to time is given below. For this purpose, "line plot" function is used.

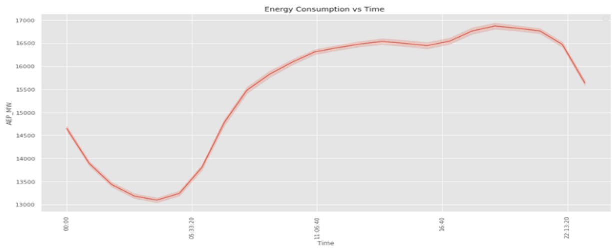

Fig 4.4 Energy consumed versus time graph

It is pretty evident that the energy consumption is reaching a height during the morning and late evening. In the next step, resampling is performed as the number rows in the training set is too high. Resampling is the process done in order to increase the accuracy of the result and for the ease of understanding. It is done in such a way that we have one value for each day. Using "pandas" [1] this is achieved easily. Mathematically it can be explained by the concept of statistics. For instance, if there are 12 readings per day, the mean is calculated and that value becomes the resampled value.

The model takes around 30 to 40 minutes to train the data, after which the test data is provided and finally the future energy consumption is predicted. The final result is as follows

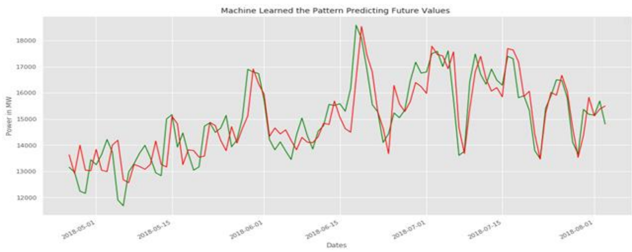

Fig 4.5 Future Predicted graph

Here the green line represents the actual value provided in the input dataset and the red line represents machine learning predicted. The predicted values are accurate as it learns every given value in the dataset.

5. CONCLUSION

Energy efficiency is the wave of the future. An energy efficient home is a personal step towards the direction of renewable energy, environmental protection and sustainable living. Neural network models were trained in the present study to learn the hourly energy consumption values of typical residential buildings. Remarkable success has been achieved in making accurate predictions of future values. Analytically:

1. The building's energy consumption was estimated for several years, using as input to the neural model the dataset containing readings of the energy used on an hourly basis. From this investigation it was found that the neural network approach

is able to estimate with remarkable success the building's energy consumption values for both the warm and the cold period of the year.

2. The proposed RNN model, performs better than a 3-layer multi-layered perceptron model in the case of electric load profiles in residential buildings. The inclusion of artificial NN methods to the estimation of energy consumption, which typically fluctuates and is nonlinear in nature. The NN method is able to address nonlinear data effectively and quickly using various algorithms such as LSTM to minimize the error including back-propagation algorithms. The results from previous studies have shown the NN models perform very well with typical coefficient of determination above 0.9.

3. The results were satisfactory for the given data set and was comparable in terms of statistical analysis with prior literature. Further analysis will be carried with a wider range of data to assess the performance and accuracy of the NN model to predict the outputs. This model trains the data and provides the prediction for two months but this can be further improved for more number of months. A future work may be done expanding the project to help save the energy by giving hints of where the energy is wasted or used more to the residents.

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