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# Electricity Demand Modelling: A Comparison Using Long Short-Term Memory and Support Vector Regression

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***Abstract*—Electricity is one major ingredient for the economic development of any nation. Industries-small or large, transportation, education, communication, infrastructure development and households cannot operate without relying on electrical power. However, it does not come freely and is yet to be generated through renewable sources. To cater to the demand of this enormous market with reduced wastage and adequate supply is the responsibility of service providers. This task can be made possible by leveraging the consumption data from smart meters installed at every power consumption point, be it at each household or a large scale industry. The energy consumption data obtained from households in a region over a time period may hold patterns of energy use including peak and off peak time periods. This can help forecast the expected consumption for coming periods and hence help the vendors to optimize their supply to ensure that the demand is met without exceeding required supply levels. If prediction of electricity consumption is known to the electricity traders, it will be easy to balance their electricity purchase and sales portfolio. The purpose of this paper is to build a demand model on maximum electricity consumption of households using Long Short-Term Memory (LSTM) and support vector regression (SVR). Comparison between LSTM and SVR is done so as to select the most appropriate model for future prediction. The dataset used is from the London data store, which contains the energy consumption readings for a sample of 5,567 London Households that took part in the UK Power Networks led Low Carbon London project between November 2011 and February 2014.**

**Index Terms—Demand model, Long Short-Term Memory (LSTM), Power consumption, Support Vector Regression (SVR)**

## I. Introduction

Electricity demand prediction is an essential in power system planning and operation [1]. It becomes very important for the service providers to learn the consumption profile of their clients. Once the consumption pattern is known to the electricity suppliers, they can serve the consumers effectively. In the current scenario, the power companies use various statistical regression approaches to estimate their future electricity demand. The underestimation of demand would lead to potential outages that are devastating to life and economy, whereas overestimation would lead to unnecessary idle capacity [2]. There are a number of factors that drive the forecast including market share in manufacturing institutions and electric utilities. The forecast drives the current as well as future activities effectively that may lead to energy conservation which helps in enhancing the profitability of the firms. In making predictions, forecaster check for the feedback effects of policy changes and pricing, participates in designing ways to meet customer demands. Over the years the nature of forecasts has also changed. On annual basis it is not enough to just predict the total energy use. In order to plan the demand side activities to achieve maximum energy conservation, the load shape of end-use components must be known while avoiding undue demand restrictions. The impact of new technology on energy consumption can be assessed by the demand models.

Machine learning has attracted much attention in both academic and empirical fields for tackling real world problems over the last decade [3]. They are powerful tools for design of computer programs and can learn automatically from experience. The machine learning is capable of extracting knowledge and complex patterns from data. It can overcome the difficulties that non-linear problems pose to simpler algorithms that do not gather domain knowledge for each particular problem.

Support Vector Machines (SVM) has been applied to electricity load forecasting effectively by several authors. It can be used for classification and regression tasks. When used in regression, the approach is called Support Vector Regression (SVR) [4]. It is a powerful non-linear technique that keeps higher generalization ability than most neural networks.

Deep learning is also known as deep structured learning or hierarchical learning which is part of a broader family of machine learning methods based on learning data representations, as opposed to task-specific algorithms. Learning can be supervised, semi-supervised or unsupervised. Deep learning allows models composed of multiple layers to learn representations in data. The use of multiple layers allows the learning process to be carried out with multiple layers of abstraction. Long short-term memory (LSTM) units are a building unit for layers of a recurrent neural network (RNN). A RNN composed of LSTM units is often called an LSTM network. This study compares the accuracy in predicting maximum energy consumption in two different approaches: LSTM and SVR.

The rest of the work is structured as follows. In section II a brief introduction of data and the techniques, namely long short-term memory network and support vector regression are described. Model algorithm is described in section III. Results and discussion are given in section IV.

## II. Data and Methodology

The dataset used is a refactorised version of the data from the London data store, which contains the energy consumption readings for a sample of 5,567 London Households that took part in the UK Power Networks led Low Carbon London project between November 2011 and February 2014. The dataset was divided into 112 blocks.

The data from the smart meters is assumed to be associated only to electrical consumption. Out of 112 blocks 10 blocks were randomly taken for analysis. The smart meter data contains consumer id, days, energy median, energy mean, energy min, energy max, energy count and energy sum. In this work, the objective is to find the maximum energy consumption. Consumer id, day and maximum energy consumption for each household is taken from selected blocks. 14 days data were used to predict 15th day. Splitting of train and test data is done with a ratio of 70:30. The splitting is performed randomly. Demand models are built using these data. Predictive modelling tries to find good rules for predicting the values of one or more variables in a data set (outputs) from the values of other variables in the data set (inputs). The two common predictive modelling techniques are regression model and neural network model. The algorithms developed in these modelling techniques arise from methodological research in various disciplines including statistics, pattern recognition and machine learning. These two techniques are applied to analyze the maximum energy consumption. Python is used for SVR and LSTM model building.

### *A. Long Short-Term Memory Networks*

Long Short-Term Memory (LSTM) networks are a particular class of recurrent ANN's where the neurons in the hidden layers are replaced by the memory cells (MC). LSTM was mainly motivated and designed to overcome the vanishing gradients problem of the standard RNN when dealing with long term dependencies.

In the standard RNN, the overall neural network is a chain of repeating modules formed as a series of simple hidden networks, such as a single sigmoid layer. In contrast to the standard RNN which has a series of repeating modules with relatively simple structure, the hidden layers of LSTM have a more complicated structure [5]. Specifically, LSTM introduces the concepts of gate and memory cell in each hidden layer. A memory block mainly consists of four parts: an input gate i, a forget gate f, an output gate o, and self-connected memory cells C. The input gate controls the entry of the activations to the memory cell. The output gate learns what cell activations to filter and output to the successive network. The forget gate helps the network to forget the past input data and reset the memory cells.

### *B. Support Vector Regression*

SVM algorithm implements linear regression by creating linear classifier in higher dimension space. Data points in classification problem belong to a certain class, but to which class data points in regression problem belong is unknown in advance. That is the difference between classification problem and regression problem.By manipulating proper transformation on the set of data points, regression problem can be transformed into classification problem. As a new theory and method, SVR has many research topics worth profound inquiries in training algorithm and practical applications. SVR algorithm can generally guarantee good generalization performance and more reliable results.

## III. Model Algorithm

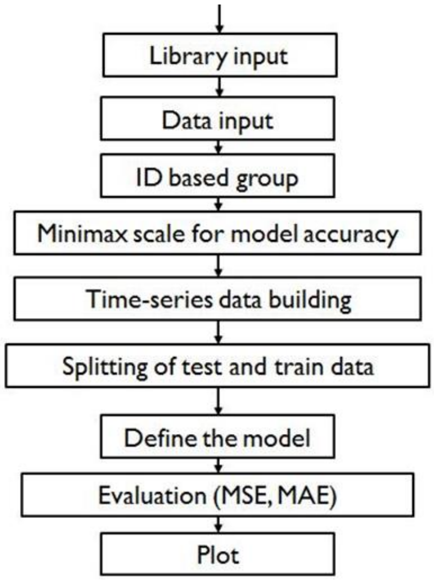


Fig. 1. Algorithm used for deep learning and support vector regression.

The algorithm used for both deep learning and support vector regression are same (shown in figure 1). In library input, three libraries are used namely, Numpy, Pandas and Matplotlib. NumPy is the fundamental package for scientific computing with Python. Pandas is an open source data analysis framework that provides high performance data structures. Matplotlib is a library for creating 2D plots in the style of Matlab, with support of 3D plots as well. Data input consists of the dataset which was discussed in section 2 were given as input one by one. ID based grouping was done for each block which consisting of 50 households (except some blocks which contains only 47 households). Minimax scale is then used to transform features by scaling each feature to a given range. The next task is to build time series data which is to use a certain number of previous observations to predict the future. In this case previous 14 days maximum consumption data are taken to predict 15th day consumption. To evaluate the predictive accuracy, Mean absolute error (MAE) and Mean squared error (MSE) are used. Both MAE and MSE are standard metric used by research community. Final step is to plot a graph which shows the actual and predicted data for a daily basis with maximum consumption on y-axis and days on x-axis.

## IV. Results and Discussion

In the present study, the goal has been to find the best model which predicts maximum energy consumption. For doing analysis 10 blocks were randomly taken from 112 blocks. The selected blocks were block 1, block 6, block 13, block 31,block 47, block 49, block 50, block 67, block 91 and block 101. Each block consists of 50 households. The Fig. 2, shows block-1 representation of LSTM and SVR.

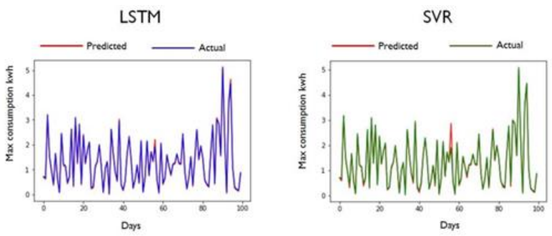


Fig. 2. Block-1 representation of LSTM and SVR

### A. *Performance measures*

To evaluate the predictive accuracy, Mean absolute error (MAE) and Mean squared error (MSE) are used as performance measures. The mean squared error (MSE) of an estimator measures difference between the estimator and what is estimated. The mean absolute error (MAE) is a measure of difference between two continuous variables.

While comparing the mean squared value for LSTM and support vector regression, LSTM has got lower value than SVR. I.e. MSE for LSTM is 0.001194 and for SVR it is 0.005960 and in the case of mean absolute error (MAE) also LSTM has got lower value than SVR. The graph showing block 1 clearly means that LSTM is the perfect model while compared with SVR since the variations are very low compared to SVR. All the blocks taken for the analysis shows a lower value of MSE and MAE for LSTM than that of SVR.

TABLE I
Comparison between LSTM and SVR using performance measures

| Block | No. of households | Model | MSE | MAE |
|---|---|---|---|---|
| 1 | 50 | LSTM | 0.001194 | 0.01829 |
| | | SVR | 0.005960 | 0.05067 |
| 6 | 50 | LSTM | 0.004423 | 0.03825 |
| | | SVR | 0.005768 | 0.05205 |
| 13 | 50 | LSTM | 0.005665 | 0.03052 |
| | | SVR | 0.014556 | 0.05726 |
| 31 | 50 | LSTM | 0.005161 | 0.02840 |
| | | SVR | 0.029317 | 0.07024 |
| 47 | 50 | LSTM | 0.004348 | 0.04280 |
| | | SVR | 0.004437 | 0.05752 |
| 49 | 50 | LSTM | 0.004242 | 0.04088 |
| | | SVR | 0.004708 | 0.05629 |
| 50 | 50 | LSTM | 0.004567 | 0.04025 |
| | | SVR | 0.004619 | 0.04154 |
| 67 | 50 | LSTM | 0.00186 | 0.01150 |
| | | SVR | 0.004147 | 0.05213 |
| 91 | 50 | LSTM | 0.002594 | 0.02655 |
| | | SVR | 0.006425 | 0.06114 |
| 101 | 50 | LSTM | 0.003314 | 0.03913 |
| | | SVR | 0.004129 | 0.05199 |

## V. Conclusion

A wide variety of techniques have been tried for electricity demand prediction during the past years, most of which are based on time series analysis. The goal of the presented work was to investigate the effectiveness in using Long Short-Term Memory and support vector regression for electricity demand prediction. The task of predicting the maximum consumption for a daily basis was considered. LSTM and SVR were used to build prediction model and their performance were evaluated. While comparing the models using performance measures, the results showed that LSTM forecasting method outperformed support vector regression in the challenging electric load forecasting problem. Future work can be done by combining other ways of prediction methods and extending the future predictions to more than 1-step-ahead.

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