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# Demand Response for Energy Management Using Machine Learning and LSTM Neural Network

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**Abstract -** *Prediction of power demand plays a necessary role within the electrical trade, because it provides the premise for creating selections in installation designing and operation. In a dynamic atmosphere standard prediction technique aren't enough, and a lot of refined ways area unit required. This paper proposes an hour-ahead demand response prediction for energy management systems. Advanced Reinforcement learning and Artificial Neural Network for modelling and understanding very complex systems will allow companies to represent the complexity of electricity demand in a way previously unachievable. With the help of hour-ahead demand response algorithm for energy management systems, a steady price prediction model based on LSTM neural network is presented. More specifically, the objective is to achieve more accurate forecasts for the electricity demand. A proper scheme of energy management can be achieved for multiple units minimize user energy bills and help the user to significantly reduce its electricity cost compared with a benchmark without demand response.*

***Key Words***: Machine learning, LSTM neural network, demand response, energy management

## 1. INTRODUCTION

Changes in electric variables such as electricity price, energy consumption and its operations requires energy management systems to take accurate real time actions correctly and instantly[1].Demand response become significant role in terms of promoting efficiency and reliability of energy systems with the help of modern advances in information and communication systems (ICT's) and smart metering infrastructure, as it affords the capacity to balance electricity supply and demand incongruity by regulating loads[2]. A well-designed DR scheme in an EMS can have significant positive effects on society, like improving human comfort levels, facilitating the accommodation of renewable resources, reducing worldwide energy expenditure, and reducing reliance on fuel resources related to high carbon emissions [3],[4]. Several energy management system (EMS) structures under an hourly pricing DR were developed to determine the optimal appliance scheduling based on a mixed-integer linear programming (MILP) approach, with the aim of reducing user costs and enhancing energy efficiency [5]-[7].

## 2. RELATED WORKS

For past few years, with the rapid evolution of artificial intelligence (AI), much attention has been devoted to the use of AI for optimal decision-making. Through the studies developed, considers reinforcement learning (RL) for optimal decision making [8]. Some research has also been done on adopting RL for solving decision-making problems in energy management. For example, in [9], [10], the authors applied RL-based algorithms to energy trading games among different strategic players with incomplete information, enabling each player used the learning scheme to choose a strategy to trade energy in an independent market, so as to maximize the average revenue.

Recently, the authors of [11], [12] presented a price-based DR scheme linking the service provider to its customers via RL methodology, where the scheme was modelled as a Markov decision process (MDP), then Q-learning was used to make optimal decisions. However, despite these efforts, there still exist two significant limitations. The studies in [13], [14] proposes batch RL algorithm schedule loads under day ahead pricing schemes. In [15]-[17], RL algorithms used to obtain an energy consumption plan for electronic vehicles (EV). First, most studies focused on only one kind of appliance such as thermostatically control load or EV that did not consider how the proposed learning algorithms would enable decision-making when dealing with multiple types of appliances. Second, all studies considered day-ahead energy management, but the hour-ahead DR exhibits greater potential for balancing power systems due to the dynamic constraints associated with energy generation and the uncertainty in prediction [18].

Going through the above-mentioned issues, this paper proposes an hour ahead demand response algorithm for multiple units of load in a grid. To solve issues regarding uncertainty in future price, a stable price forecasting model is presented using Long Short-Term Memory (LSTM)Neural Network. Over a past few years, price forecasting methods become an important topic in electrical engineering and several implementation methods attempted. And by using LSTM the power consumption can be monitored and advanced measures can be taken by the service providers based on the predicted output. The LSTM approach is comparatively easy to implement and have good performance than other techniques such as ARIMA model [19].

## 3. SYSTEM DESIGN

First of all we must understand about an energy management system and its architecture. Here a block diagram shows a structure of energy management systems across a grid. This area contains several energy consumption units under service provider.

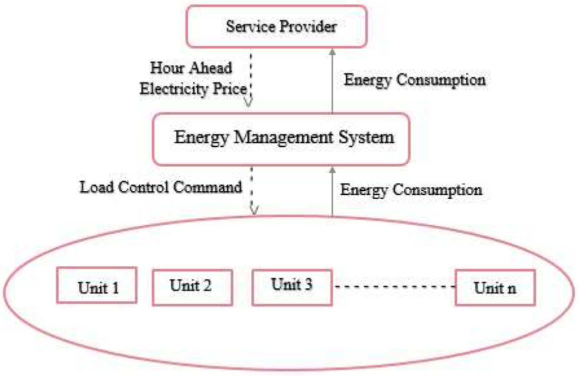


**Fig -1**: Energy Management System Architecture

### 3.1 Vector Conversion

Vectors are a foundational element of linear algebra. Vectors are used throughout the field of machine learning in the description of algorithms and processes such as the target variable (y) when training an algorithm. A vector is a tuple of one or more values called scalars. Vectors are built from components, which are ordinary numbers. The LSTM input layer is specified by the "*input shape*" argument on the first hidden layer of the network. The three dimensions of this input are:

a) **Samples**. One sequence is one sample. A batch is comprised of one or more samples.

b) **Time Steps**. One time step is one point of observation in the sample.

c) **Features**. One feature is one observation at a time step.

This means that the input layer expects a 3D array of data when fitting the model and when making predictions, even if specific dimensions of the array contain a single value, e.g. one sample or one feature. When defining the input layer of your LSTM network, the network assumes you have 1 or more samples and requires that you specify the number of time steps and the number of features. You can do this by specifying a tuple to the "*input shape*" argument..

### 3.2 Understanding LSTM Neural Network Vector Conversion

Recurrent neural networks re unrolled programmatically during training and prediction. An LSTM network is a recurrent neural network that has LSTM cell blocks in place of our standard neural network layers. These cells have various components called the input gate, the forget gate and the output gate.

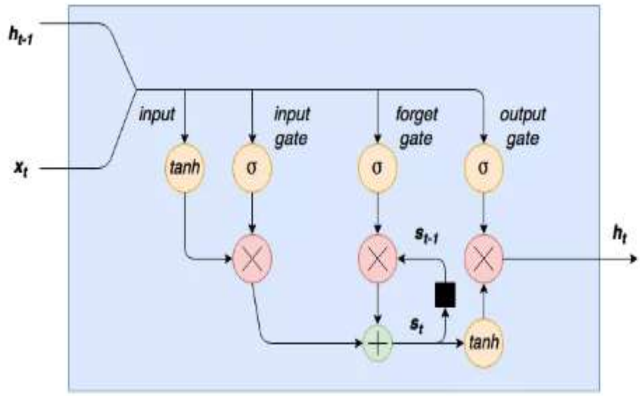


**Fig -2:** LSTM cell diagram

Notice first, on the left hand side, we have our new word/sequence value *xt* being concatenated to the previous output from the cell *ht−1*. The first step for this combined input is for it to be squashed via a *tanh* layer. The second step is that this input is passed through an *input gate*. An input gate is a layer of sigmoid activated nodes whose output is multiplied by the squashed input. These input gate sigmoids can act to "kill off" any elements of the input vector that aren't required. A sigmoid function outputs values between 0 and 1, so the weights connecting the input to these nodes can be trained to output values close to zero to "switch off" certain input values (or, conversely, outputs close to 1 to "pass through" other values).

The next step in the flow of data through this cell is the internal state or forget gate loop. LSTM cells have an internal state variable *st*. This variable, lagged onetime step i.e. *st−1* is *added* to the input data to create an effective layer of recurrence. This *addition* operation, instead of a multiplication operation, helps to reduce the risk of vanishing gradients. However, this recurrence loop is controlled by a forget gate – this works the same as the input gate, but instead helps the network learn which state variables should be "remembered" or "forgotten". Finally, we have an output layer *tanh* squashing function, the output of which is controlled by an *output gate.* This gate determines which values are actually allowed as an output from the cell *ht*. The mathematics of the LSTM cell looks like this: Input First, the input is squashed between -1 and 1 using a *tanh* activation function.

### 3.3 System Structure

The structure shows the load or energy consumption is monitored by the service provider. The service provider gives the hour ahead electricity price to the energy management system and the system can give the load control command across the units. In designing, the model is started with a dataset that used as input and by training and testing this dataset, and an output is plotted as graph. Using this graph, the predicted values can be analysed. The following figure shows the bock diagram of the system.

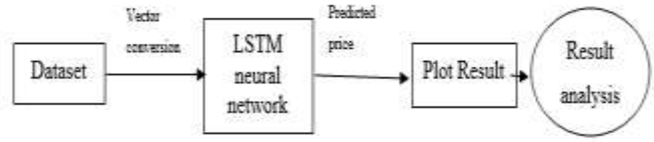


**Fig -3**: System Structure

### 3.4 Predicted Result

By performing the complete machine learning purpose through LSTM neural network, the output is the forecasted price on the hour ahead manner. After training the data , we test the prediction result in order to make sure about the efficiency of the system. For which the data has been splitted as 90% for training and 10% for testing. The result can be plotted on a graph such that electricity load in y axis and hours in x axis. This can be figured out as shown below.

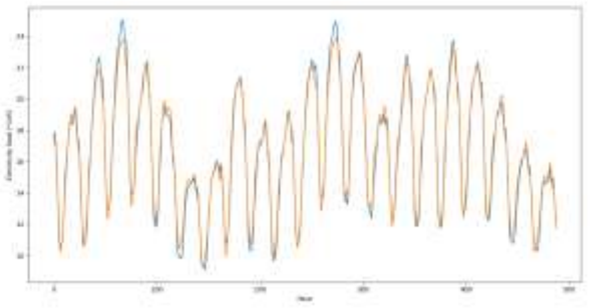

**Fig -4**: Plotted Graph

## 4. PERFORMANCE EVALUATION

Performance of the price forecasting model is evaluated on the basis of some data collected during the previous years. Figure 6 shows a comparison of forecasted prices for last 7 days of January 2020, where the blue line represents the actual price and red line denotes the forecasted price. From the figure we can see that the trends in actual price is quite same as forecasted price. Compared to the price forecasting results in [20], [21], indicating that the LSTM model in this paper make accurate and reasonable price forecasting method.

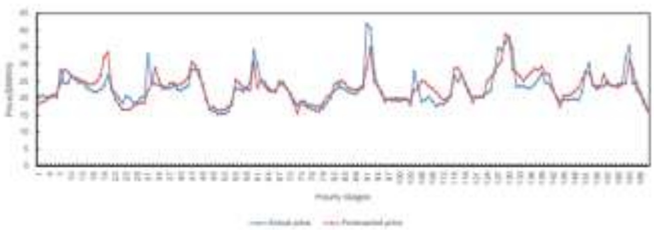

**Fig -5**: Result analysis

## 5. CONCLUSION

In this paper we proposed a price-based demand response for energy consumption in a day ahead energy system using LSTM neural network. The performance evaluation done and shows that actual and forecasted prices are tends to be same.

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