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Project Report for

PRICE FORECASTING

For Exploratory Project (EE-272)

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Preface

This project has been made by the efforts of Harsh Goyal, Muskan Chourase, and Ashish Kumar Yadav as a part of the Exploratory Project for Even Semester 2021-2022 under the guidance of Professor S. P. Singh. The project is based on Price Forecasting of Electricity, to predict the spot and forward prices in wholesale. While preparing the report and model, care has been taken to avoid any mistakes, but still, if some discrepancy occurs it should be ignored.

Acknowledgment

We would like to extend our gratitude to Professor S. P. Singh for allowing us the opportunity to work on this project “Price Forecasting”, and for his valuable input, able guidance, encouragement, wholehearted cooperation, and constructive criticism throughout our project. While working on this project, we came to know a lot of new things about the topic. We would also like to thank our friends and family for encouraging and helping us throughout the project's entirety. Last but not least we express our thanks to our team for their cooperation and support.

Abstract

Electricity demand forecasting is a central and integral process for planning periodical operations and facility expansion in the electricity sector. Demand pattern is almost very complex due to the deregulation of energy markets. Therefore, finding an appropriate forecasting model for a specific electricity network is not an easy task. Although many forecasting methods were developed, none can be generalized for all demand patterns. This review article aims to explain the complexity of available solutions, their strengths and weaknesses, and the opportunities and threats that the forecasting tools offer or that may be encountered.

1. INTRODUCTION

Since the advancement of the electricity markets, power cost estimating has turned into a fundamental assignment for every one of the players in the power markets in light of multiple factors. Energy supply organizations, particularly dam-type hydroelectric, gaseous petrol, and fuel oil power plants could streamline their obtainment methodologies as per the power cost gauges. Besides, costs of the energy subordinates are moreover based on electricity price forecasts. Electric Load Forecasting is an imperative cycle in the preparation of the power industry and the activity of electric power frameworks. Exact figures lead to significant investment funds in working and upkeep costs, expanded unwavering quality of force supply and conveyance framework, and right choices for the future turn of events.

This paper presents a pragmatic forecasting methodology for analyzing the electric load pattern and predicting the future load demand for short, medium, and/or long terms using LSTM (Long Short Term Memory). In particular, Recurrent Neural Networks are capable of faithfully preserving the key time-dependent patterns for natural language processing type problems.

2. DATASET:-

We are using load data and price data of the Independent Electricity System Operator (IESO) works at the heart of Ontario's power system data which can be found at https://www.ieso.ca/power-data. Both Load data and Price data are available at a time step of 1 hour.

3. METHODS:-

In this section, we describe the Neural Network architectures we used for electricity price estimation.

3.1 Recurrent Neural Networks (RNN)

RNNs are networks with loops in them, allowing information to persist. They are used to model time-dependent data. The information is fed to the network one by one and the nodes in the network store their state at the one-time step and use it to inform the next time step. Unlike MLP, RNNs use temporal information of the input data, which makes them more appropriate for time series data. An RNN realizes this ability by recurrent connections between the neurons. s. A general equation for RNN hidden state h_t given an input sequence $x = (x_1, x_2, \ldots, x_T)$ is the following:

$$h_t = \begin{cases} 0 & ;\text{if } (t = 0) \\ \varphi(h_{t-1}, x_t) & ;\text{otherwise} \end{cases}$$

where φ is a non-linear function. The update of the recurrent hidden state is realized as:

$$h_t = g(Wx_t + Uh_{t-1})$$

where g is a hyperbolic tangent function.

In general, this generic setting of RNN without memory cells suffers from vanishing gradient problems. In this study, we investigated the performance of one RNNs with memory cells for electricity price forecasting, namely, LSTMs .

3.1.1. Long Short-Term Memory (LSTM) Networks

LSTM is a special type of RNN that is able to deal with remembering information for a much longer time. In LSTM, each node is used as a memory cell that can store other information in contrast to simple neural networks, where each node is a single activation function. Specifically, LSTMs have their own cell state. Normal

RNNs take in their previous hidden state and the current input and output a new hidden state. An LSTM does the same, except it also takes in its old cell state and outputs its new cell state c^j_t. This property helps LSTMs address the vanishing gradients problem from the previous time steps.

We visualize the LSTM structure in Figure (a) to define the guiding equations of LSTM. LSTM has three gates: input gate it, forget gate ft, and output gate o_t, as visualized in Figure (a). The sigmoid function is applied to the inputs s_t and the previously hidden state h_{t-1}. The goal of the LSTM is to generate the current hidden state at time t. The hidden state h_j^t of LSTM unit is defined as:

$$h_j^t = o_j^t \tanh(c_j^t)$$

where o_j^t modulates the memory influence on the hidden state. The output gate is computed as:

$$o_j^t = \sigma(W_o x_t + U_o h_t - 1 + V_o ct)^j$$

where σ is the logistic sigmoid function and V_o is a diagonal matrix. The memory cell c_j^t is updated partially following the equation

$$c_j^t = f_j^t\, c_j^{t-1} + i^j_t c^{\sim j}_t$$

where the memory content is defined by a hyperbolic tangent function:

$$c^{\sim j}_t = \tanh(W_c x_t + U c h_{t-1})^j$$

Forget gate f_j^t controls the amount of old memory loss. Instead, input gate i^j_t controls new memory content that is added to the memory cell. Gates are computed by:

$$f^{j}_{t} = \sigma(W_f x_t + U_f h_{t-1} + V_f\, c_{t-1})^{j}$$

$$i_j^{t} = \sigma(W_i x_t + U_i h_{t-1} + V_i c_{t-1})^{j}$$

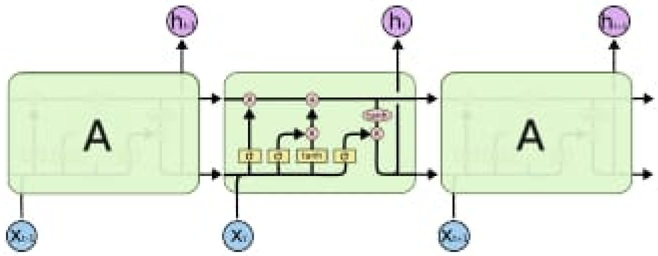

Fig. 4: A LSTM cell

Figure (a). Illustration of: (a) LSTM (a) i, f, and o are the input, forget and output gates, respectively. c and c˜ denote the memory cell and the new memory cell content.

LSTM unit is robust compared to traditional RNN, thanks to the control over the existing memory via the introduced gates. LSTM is can pass information that is captured in early stages and easily keeps the memory of this information for the long term, which enables the opportunity to generate potential long-distance dependencies as underlined by.

Conclusion:-

LSTM model is implemented to predict the load and hence price. While the performances vary every day because all the models are trained everyday incorporating the last day's data in training set, LSTM is among the best performing model. The LSTM network make a significant improvement in forecasting results in comparison with other benchmarking networks. The accurate forecasting task has financial and technical benefits in modern that are going to participate in day-ahead and real-time energy markets or implement energy management programs such as demand respons. Because with a precise estimation of the power system situation , the distribution system operator can make better decisions with lower risk and error.

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