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Electricity Load Forecasting

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Abstract: *With the increasing load requirements and the sophistication of power stations, knowing in advance about the electrical load not only at short-term periods such as hours or couple of days but also over the longer-term periods such as weeks and months is indispensable for a range of benefits such as important technical and economic impacts. Traditional methods such as ARMA, SARIMA, and ARMAX have been used for decades. In recent years, the artificial intelligence (AI) techniques such as neural networks and deep learning are emerging in the field of time series analysis. Towards this end, the artificial neural networks (ANN) and recurrent neural networks (RNN) are being explored and have shown promises in much better forecasting as compared to traditional methods. Long short term memory (LSTM) networks are a special kind of RNN that have the capabilities to learn the long-term dependencies. In this work, we have picked up an electrical load data with exogenous variables including temperature, humidity, and wind speed. The data is used to train the LSTM network. For a fair comparison, the data is also used in traditional methods to model the load time series. The trained LSTM network and the developed models are then used to forecast over the horizons of 24 hours, 48 hours, 7 days and 30 days. The forecasts generated by the LSTM compared with the results of traditional methods using RMSE and MAPE for all the forecast horizons. The results of a number of experiments show that the LSTM based forecast is better than other methods and have the potential to further improve the accuracies of forecasts.*

Keywords: Forecasts, Long short-term memory, ANN

I. INTRODUCTION

Electricity is currently the most important energy vector in the domestic sector and industry. Unlike fuels, electricity is hard and expensive to store. This creates the need of precise coupling between generation and demand. In addition, the transmission lines of electric power need to be sized for a given maximum power, and overloading them may result in blackout or electrical accidents. For these reasons, energy consumption forecasting is vital. The time scale for forecasting depends on who is interested in such prediction. Grid operators have to predict the electricity demand for the next day, to program the generation accordingly. Grid designers have to predict energy consumption at the scale of years, to ensure that the infrastructure is sufficient. On the other hand, smart grid controllers with almost instant response time may need a prediction on the order of minutes. We have seen that changing the time scale in electricity load forecasting changes the approach, and that depending on the scale different methods should be used to ensure the highest accuracy with the smallest computational cost.

We show here how forecasting accuracy decreases with the increase of time scale due to the impossibility of using of all variables. Several well-established computational models were compared on three different regression based criteria and the results revealed that boosting model was able to outperform their competitors in most of the comparisons[1].

II. BACKGROUND

Technologies are used:

- **Tkinter**: Python offers multiple options for developing GUI .out of all the GUI methods,tkinter is the most commonly used method.It is a standard python interface to the Tk GUI toolkit shipped with Python. Python with tkinter is the fastest and easier way to create the GUI application. Tkinter is the standard GUI library for python. Tkinter provides a powerful object oriented interface to the Tk GUI toolkit. Tk is called Tkinter in Python, or to be precise, Tkinter is the Python interface for Tk. Tkinter is an acronym for "Tk interface". Tk was developed as a GUI extension for the Tcl scripting language by John Ousterhout. The first release was in 1991. Tk proved as extremely successful in the 1990's, because it is easier to learn and to use than other toolkits. Tkinter is Python's de-facto standard GUI (Graphical User Interface) package. It is a thin object-oriented layer on top of Tcl/Tk. Tkinter is not t he only Gui Programming toolkit for Python. Python has a lot of GUI frameworks, but Tkinter is the only framework that's built into the Python standard library.

- **Anaconda** is a free and open-source of the Python and R programming languages scientific computing (data science, machine learning applications, large-scale data processing, analytics, etc.), that aims to simplify management and deployment. The distribution includes data-science packages suitable Windows, Linux, and macOS. It is developed and maintained by Anaconda, Inc., which was by Peter Wang and Travis Oliphant iAnaconda, Inc. product, it is also known Anaconda Distribution or Anaconda Individual Edition, while other products from the company are Anaconda Team Edition and Anaconda Edition, which are both not free. Package versions in Anaconda are managed by the package management system conda. This package manager a separate open-source package as it ended up being useful on its own and for other things than There is also a small, bootstrap version called Miniconda, which includes only conda.

III. Existing System

The current systems are based on Time Series Forecasting with ARIMA Model.

A) Disadvantages

- Less accurate
- There is no seasonality and

IV. PROPOSED SYSTEM

The proposed system uses LSTM Algorithm. Load forecasting is the predicting of electrical power required to meet the short term, medium term or long term demand.

A) Description

- The forecasting helps the utility companies in their operation and management of the supply to their customers.
- Electrical load forecasting is an important process that can increase the efficiency and revenues for the electrical generating and distribution companies.
- It helps them to plan on their capacity order to reliably supply all consumers with the required energy[11].

B) Advantages

- Enables the utility company to plan well since they have an understanding of the future consumption or load demand.
- Minimize the risks for the utility company. Understanding the future long term load helps the company to plan and make economically viable decisions in regard to future generation and transmission investments.
- Helps to determine the required resources such as fuels required to operate the generating plants as well as other resources that are needed to ensure uninterrupted and yet economical generation and distribution of the power to the consumers. This is important for short, medium, and long term planning.
- The load forecasting helps iof the size, location and type of the future generating plant. By determining areas or regions with high or growing demand, the utilities will most likely generate the power near the load. This minimizes the transmission and distribution infrastructures as well as the associated losses.
- Maximum utilization of power generating plants. The forecasting avoids under generation or over generation[1][8].

C) Algorithm Used

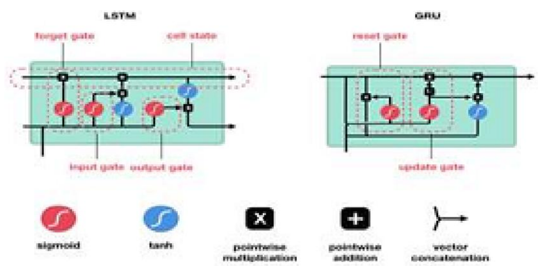
The proposed system uses LSTM Algorithm. Load forecasting is the predicting of electrical power required to meet the short term, medium term or long term demand. The forecasting helps the utility companies in their operation and management of the supply to their customers [8].

V. Functionality Description

Data Collection: In this module we gather and measure the data, information or any variables of interest in a standardized and established manner that enables the to forecasting for the future.

Data analysis in this we inspect, cleanse, transform and model data with the goal of discovering load forecast for future date for decision making.

Data Implementation using LSTM: LSTM stands for long short term memory. We implement the LSTM algorithm in the data we got through data analysis and train, test them to predict the outcome. A futuristic implementation diagram of LSTM is put below[6][8]:



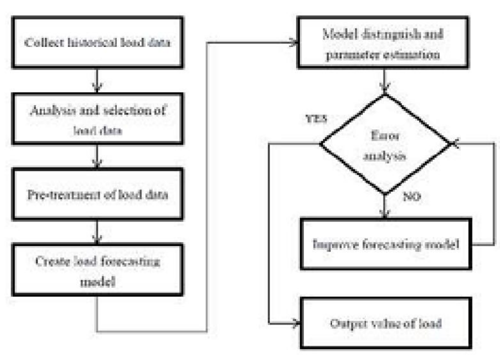


Figure 1: Block Diagram

VI. RESULTS AND DISCUSSIONS

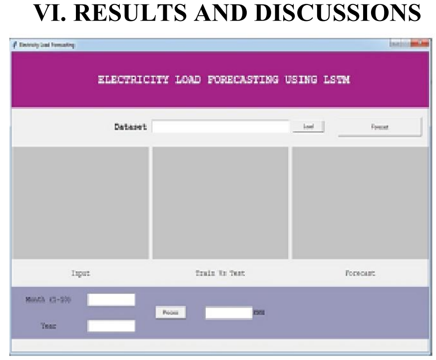


Figure 2: Electricity Load Forecasting Using LSTM

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Figure 3: Load Forecasting Visualization

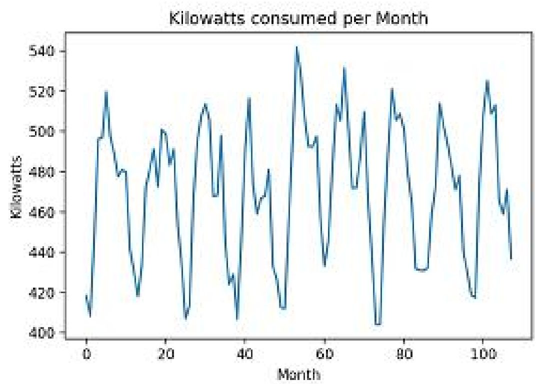

Figure 3: Kilowatts consumption per month

VII. Conclusion

The long-term and short-term learning capabilities of the long short term memory (LSTM) network, a special type of recurrent neural network (RNN), are suitable for the application of time series modelling and forecasting. LSTM is also simple towards handling the provided information easily instead of developing and working over complex equations as in the case of ARMAX. More and more variables can be fed to LSTM in order to improve the accuracy of forecast. Given the appropriate data with appropriate length and features, LSTM can learn all the seasonalities and trends. It has been shown in this work that LSTM outperforms the other traditional methods such as ARMA, SARIMA, and ARMAX and forecasts the load time series with reduced percentage of errors. Further improvements can be brought to LSTM forecast if data over more than one year is available from which LSTM can learn the yearly seasonality and trend as well instead of extracting these features a priori.

References

[1]. A. G. Abdullah, et al. Analysis on anomalous short term load forecasting using two different approaches. International Conference on Science in Information Technology (ICSITech). Bandung, Indonesia, January 2018.

[2]. I. P. Panapakidis, et al. Combining wavelet transform and support vector regression model for day-ahead peak load forecasting in the Greek power system. IEEE International Conference on Environment and Electrical Engineering and IEEE Industrial and Commercial Power Systems Europe (EEEIC / I&CPS Europe). Milan, Italy, July 2017.

[3]. P. Ray, S. Sen, A. K. Barisal. Hybrid Methodology for Short-Term Load Forecasting.IEEE International Conference on Power Electronics, Drives and Energy Systems (PEDES). Mumbai, India, December 2015.

[4]. A. Abdoos, M. Hemmati, A. A. Abdoos. Short term load forecasting using a hybrid intelligent method.Knowledge-Based Systems. March 2015.

[5]. X Chen, L. Wei, J. Xu. House Price Prediction Using LSTM.Computing Research Repository (CoRR).abs/1709.08432, September 2017.

[6]. Malhotra, Pankaj, et al. Long short term memory networks for anomaly detection in time series. Proceedings.Presses universitaires de Louvain, 2015.

[7]. L. Nikolay, J. Yosinski, L. Li, S. Smyl. Time-series Extreme Event Forecasting with Neural Networks at Uber. ICML 2017. Sydney, Australia, 2017.

[8]. F. Karim, S. Majumdar, H. Darabi, S. Chen. LSTM Fully Convolutional Networks for Time Series Classification.Computing Research Repository (CoRR).abs/1709.05206, September 2017.

[9]. W. Bao, J. Yue, Y. Rao. A deep learning framework for financial time series using stacked autoencoders and long-short term memory. PLOS ONE. July 2017.

[10]. J. C. B. Gamboa. Deep Learning for Time-Series Analysis.Computing Research Repository (CoRR).abs/1701.01887, September 2017.

[11]. F. Fahiman, et al. Improving load forecasting based on deep learning and K-shape clustering. International Joint Conference on Neural Networks (IJCNN). Anchorage, AK, USA, July 2017.