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**COMP 3610 – BIG DATA ANALYTICS**

**Literature Review: Load Forecasting using Deep Neural Networks**

The necessity to determine a reliable forecast of energy and specifically electricity has been explored recently, as it has been dubbed as a critical means for the deciding the verdicts that would influence operating costs, profits and overall efficiency of the production of electricity (Hosein and Hosein 2017; Mirasgedis et al 2006) The study by Hosein (2017) explored how using Deep Neural Networks (DNN) are superior to traditional methods, while exploring short term load forecasting for electricity using data collected over a year for a tropical country. Deep neural network is an artificial neural network with varying layers among the input and output layers. This achieves complex functions by using simple nonlinear modules to transform the level given to a higher level (Engineering Science Reference 2019). The 2017 study compared deep architectures which included Stacked Autoencoders, Convolutional Neural Networks, Recurrent Neural Networks and Long-Short-Term memory with traditional methods of moving averages, regression trees and support vector regressions.

The year’s data utilized included hourly samples; divided into 65%, 15% and 20% and variable such as day of the week, hour of day, holiday, temperature and humidity. The traditional algorithms used included Weighted Moving Average (WMA), Multiple Linear Regression (MLR), quadratic (MQR), Regression Tree (RT), Support Vector Regression (SVR) and Multilayer Perception (MLP). The DNN used was the Deep Neural Network without pretraining (DNN-W), DNN with pretraining used in Stacked Autoencoders, Recurrent Neural Networks (RNN) and Long Short Term Memory (RRN-LSTM). The study determined that the traditional method MLR had the poorest performance, and the RT had the best among the traditional method, where it was seen that having a node in the RT that determined the time of the day improved the accuracy. Notably, the run time for these were short. DNN has a longer running time, and the research was limited to 200 – 400 epocs. However, a lower error (MAPE) was seen with the higher epocs. Multilayer perception did not perform the worst but was in the lower half when accuracy was considered. DDN-W performed the best in the 200 epocs, however DNN-SA had a lower error, and was the best when the epoc was increased to 400. All data showed that DNN outperformed traditional methods, however had the disadvantage of requiring more time. Therefore, when choosing a model, time available and the level of accuracy required can be used to determine the appropriate model. DNNs determined more accurate predictions when given more data (ie weekdays vs weekends).

Electricity providers are interested in the change of electrical loads this can be determined using the Mean Percentage Error (MPE). The MPE would tell that a model with a positive value” under-predicts” the load while a negative value “over-predicts” the actual value and they can then adjust their operations accordingly. It was found that the traditional methods over predict and DNNs under predicts the actual loads. Using the results from STLF (MAPE and MPE), a company can now accurately predict upcoming load. This would mean that a power generating company, can now produce energy at a much more precise amount to prevent wastage of excess energy. In conclusion this literature review showed that deep learning has been successful in other applications but has not been demonstrated in the power sector. The results indicated that the DNN has a greater accuracy than traditional methods however DNNs suffer long computational times but are still preferable. Electrical companies can use the information gathered to make precise decisions on pricing and projected load, among others.

References:

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