# Literature Review

Short-term electrical load forecasting allows for electrical companies to make decisions to ensure resources are being employed appropriately to keep up with demand. This helps reduce both shortages in supply and resource wastage. In their paper, Hosein and Hosein explore how Deep Neural Networks perform in forecasting electricity demand when compared to traditional machine learning algorithms.

Baseline algorithms used for forecasting include Weighted Moving Average (WMA), Multiple Linear Regression (MLR), Multiple Quadratic Regression (MQR), Regression Tree (RT) and Support Vector Regression (SVR) and Multilayer Perceptrons (MLP). Deep Neural Network techniques used included using a Deep Neural Network without pretraining (DNN-W), one with pretraining (DNN-SA), Recurrent Neural Networks (RNN), and RNNs and Long Short-Term Memory (RNN-LSTM).

Daily data collected from smart meters for one year from residential customers were analyzed. The data was split into two datasets based on weekday and weekend. A limitation thus emerged where weekend data was less than weekday data. The MAPE in predicting weekend data was thus higher than in predicting weekday data across models.

Traditional models were outperformed by Neural Network models. MLR had the highest MAPE while RT had the lowest. MQR, although not the best performing model, performed almost two times better than MLR, proving that the problem is not linear. Although WMA performed second best, it took almost 7 times as much time as the top-performing model.

The Neural Network models were run for 200 and 400 epochs. The feed-forward MLP can be considered a baseline for neural networks. Although it did not perform the worst, it was consistently among the lowest performers amongst epochs. The DNN-SA models consistently performed amongst the best between epochs. DNN-SA performs considerably well on time when compared to models such as RNN and RNN-LSTM, where RNN more than double the time taken and DNN-SA takes exponentially more time still.

DNN-SA performs well in terms of MAPE, MSE and time and should be used for prediction in this case. These results are in line with other papers done on the topic. One study found that using a pre-trained DNN as compared to traditional machine learning models could reduce MAPE up to more than 15% (Ryu, Noh and Kim). Limitations introduced by dividing the dataset based on weekday or weekend can be avoided if different time frames are used. Energy consumption based on month or season can be predicted. Thus, companies can make decisions on how much resources to procure during certain months/seasons. Other methods can be considered for pretraining to determine which is least expensive.

Using a Deep Neural Network preprocessed using stacked encoders is an appropriate model for short-term load forecasting, producing MAPE of less than 3% and MPE of less than 2%.

# References

Hosein, Stefan and Patrick Hosein. "Load Forecasting using Deep Neural Networks." *2017 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT)*. Washington DC, 2017. 1-5.

Ryu, Seunghyoung, Jaekoo Noh and Hongseok Kim. "Deep Neural Network Based Demand Side Short Term Load Forecasting." *Energies* 2017: 10,3.