**Literature Review**

The use of Machine Learning (ML) techniques in predicting future energy demands is a field that has been widely explored. Through various trials and studies, artificial neural networks (ANN) have been determined as one of the more effective techniques and is now readily used to produce accurate results (Seyedzadeh et al., 2019). After researching, it has become clear that recurrent neural networks (RNN) are particularly efficient when using historic energy usage data as the input (Tun, Y.L et al., 2021). RNN’s loop like structure produces a time delay, which is especially effective when utilizing temperature data (Sun, Y et al., 2020.).

Whilst RNN has been widely used within this field, it also commonly acknowledged that the basic model of RNN has its limitations and drawbacks. Since we are interested in long term energy prediction as well as short term, a naïve RNN has a tendency to forget old information due to the commonly known vanishing gradient problem. To tackle this problem, we instead implement LSTM-RNN model (Berriel, R.F et al., 2017).

The LSTM-RNN model was introduced by Hochreiter and Schmidhuber (1997). In the LSTM model, the summation units of the RNN model are replaced by memory units, providing the LSTM model with the capacity to store and recall information for longer (Heidari, A et al., 2020). The LSTM model has been successfully implemented to forecast energy demands and produced accurate results, some examples of this include (Wang, J.Q et al., 2020) and (Rahman, A et al., 2018).

The literature suggests that the LSTM-RNN model is the most suitable and reliable option for our goals thus we will be implementing it in attempt to predict energy usage. Whilst we are happy with our choice and are confident in producing accurate results, we are aware of some of the potential drawbacks in using this model. Rahman et al (2018) found that the LSTM model assumes knowledge of future weather conditions and does not take into account any potential changes in weather. Hence, should the weather differ significantly from our weather training data, there most probably be a loss in accuracy in our model. Secondly, there have a number of studies that have noted difficulty in hyper-parameter tuning for this model. For example (Kim, T. et al., 2019) noted it took a large amount of trial and error in order to find the optimal parameters. (Ding, Z et al., 2021) noted that it took a combination of trial and error, grid search, random search and Bayesian optimization in order for the optimal parameters to be found.

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