**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 tends 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 (Wang, J.Q et al., 2020) (Rahman, A et al., 2018).

There has also been some literature that has made us aware of some of the potential drawbacks in using this model. It has been recognised that the LSTM model assumes knowledge of future weather conditions and does not consider any potential changes in weather (Rahman, A et al., 2018). 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. These difficulties includea large amount of trial and error in order to find the optimal parameters (Kim, T et al., 2019). It has also been noted that it took a combination of trial and error, grid search, random search and Bayesian optimization for the optimal parameters to be found (Ding, Z et al., 2021).

Keen to explore different avenues of approach for this problem, we decided to investigate further possible models we could use. After some research we decided that using a K nearest-neighbours (KNN) would be a suitable technique. KNN is used often in the field of prediction, but as of yet has not had much in energy prediction (Olu-Ajayi, R et al ., 2022). However, there are several studies that demonstrate that KNN can be used effectively in this field whilst producing accurate results (Wahid, F et al., 2016) (Troncoso Lora, A et al., 2003). There has also been a variety of different studies where KNN has been used on its own and in a hybrid model and produced accurate results (Deb, C et al., 2017).

A common drawback when trying to implement a KNN model is it can sometimes be difficult to select the optimal value for k (Deb, C et al., 2017). When determining our optimum value for k, we will , loop through a range of values for k and select k based on the lowest RMSE score, which has been proven to be effective (Long, H et al., 2014). . It is also unsuitable for larger datasets due to the run time and memory requirements it innately has.

Thirdly, we have decided to implement a decision tree model. There have been a sufficient number of successful studies that have given us enough confidence in this model. However, from our readings we have understood for the ease of use and the fact that decision trees are typically computationally inexpensive comparatively to other models, we may be giving up a small amount of performance (Amasyali, K et al., 2018). Based on our research we are under the impression that to produce accurate results with LSTM-RNN and KNN, it may be difficult and time consuming. Thus, we are happy to potentially lose a small amount of accuracy, as this will allow us to explore different techniques and produce further results to analyse and discuss. Nevertheless, there are still examples of decision tree models that have produced accurate results (Yu, Z et al., 2010) with decision tree models for energy demand prediction in buildings and their model providing 92% accuracy. In addition to this, it has been found that out of a neural network model, regression analysis and decision trees, it was in fact the simpler decision tree model that produced the best results (Tso, G.K et al., 2007). It is worth noting that this study was carried out in 2007 and hence there have been developments in machine learning techniques since then.

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