Wind Power Forecasting using Hybridised Artificial Neural Network Approaches

1. Background and Introduction

Wind power production is the conversion of kinetic energy in the wind to electricity. It is a rapidly growing renewable energy source which makes up an appreciable part of power grids around the world. While this energy source is extremely promising, it is a highly intermittent form of energy which bring a variety of liabilities to the power system.

Short term power generation forecasting can however negate the negative effects of intermittent power sources by:

- Informing the dispatching of thermal power generation sources
- Informing energy storage needs
- Informing electricity trading in deregulated energy markets.

The accurate forecasting of variable renewable energy sources will play a critical role in facilitating the transition to a future, decarbonised electricity network.

2. Project motivation

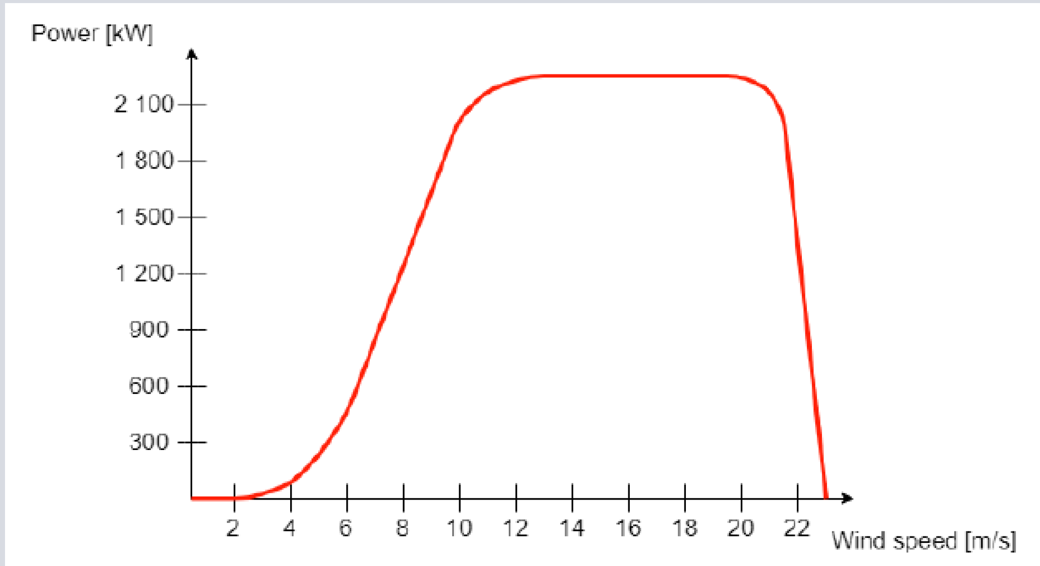
This project is aimed at investigating the factors affecting the performance of artificial neural network (ANN) based wind power forecasting using historical power generation data on a utility-scale wind farm. This project will investigate:

- The development of ANN—based models for a variety of time horizons.
- The effect of hybridising these models with empirical mode decomposition (EMD).
- The effect of different memory mechanisms and ANN topologies in the forecasting error.

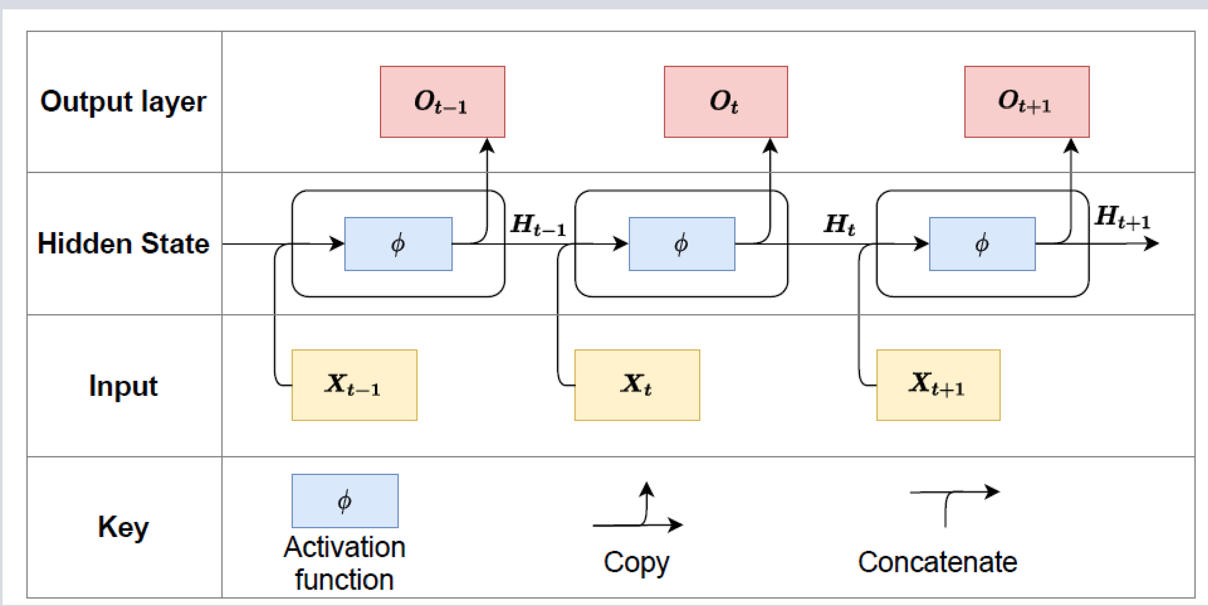
This project aims to lay the groundwork for more accurate wind power forecasting models.

3. Key findings from literature

- The wind power curve governs the behaviour of individual wind turbines and consequentially the behaviour of a wind farm as the turbines are homogenous. A typical Power curve is shown:



- A high penetration of variable renewable energy (VRE) sources in a power system complicates balancing of the power system, energy storage and various aspects regarding electricity trading.
- There is a variety of different techniques to forecast wind power production. Recurrent neural networks (RNNs) are one.
- The main errors found in RNNs are measurement errors, outliers, and missing values. All of these can be truncated or imputed.
- Empirical mode decomposition is a time-series decomposition which decomposes a signal (time series sequence) into its constituent components called intrinsic mode functions (IMFs)
- RNNs performs best when the input datasets are normalised to [-1;1] or [0;1].
- Persistence (memory) is implemented in RNNs as follows:

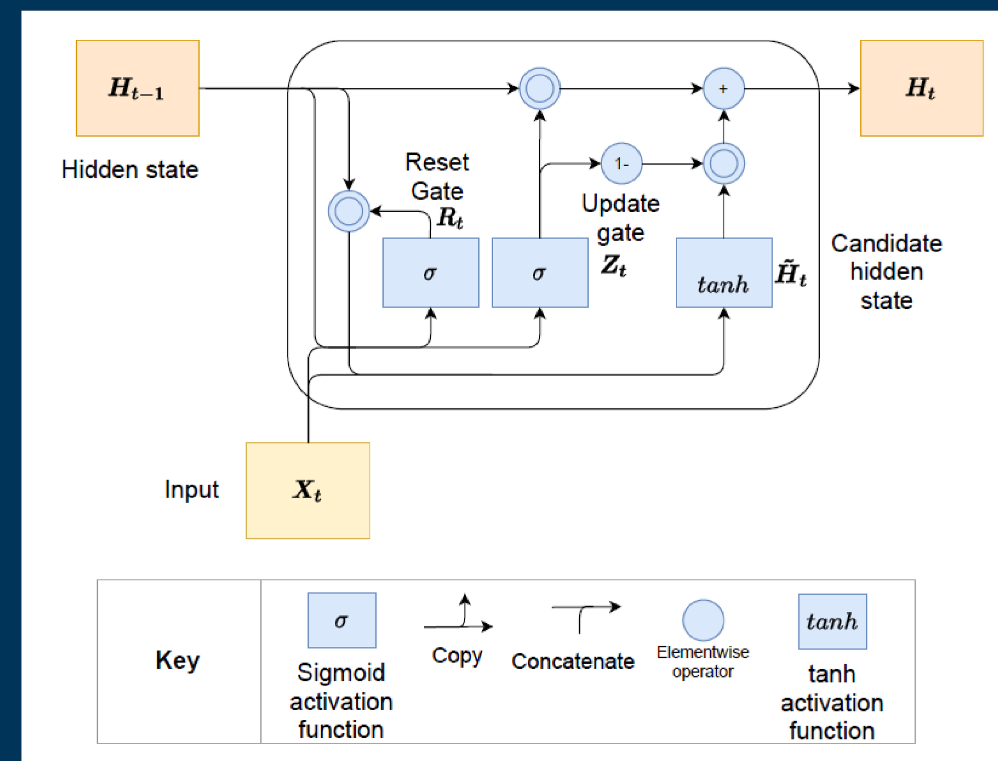


- This structure is governed by the following equations (note that Ht implements the memory mechanism):

$$H_t = \phi(X_t W_{xh} + H_{t-1} W_{hh} + b_h)$$

$$O_t = H_t W_{hq} + b_q$$

- Unfortunately. The normal RNN structure experience the vanishing gradient problem.
- This problem is rectified by using the gated recurrent unit (GRU) or the long short term memory (LSTM) as hidden states in the RNN model.
- The GRU hidden state is given by:



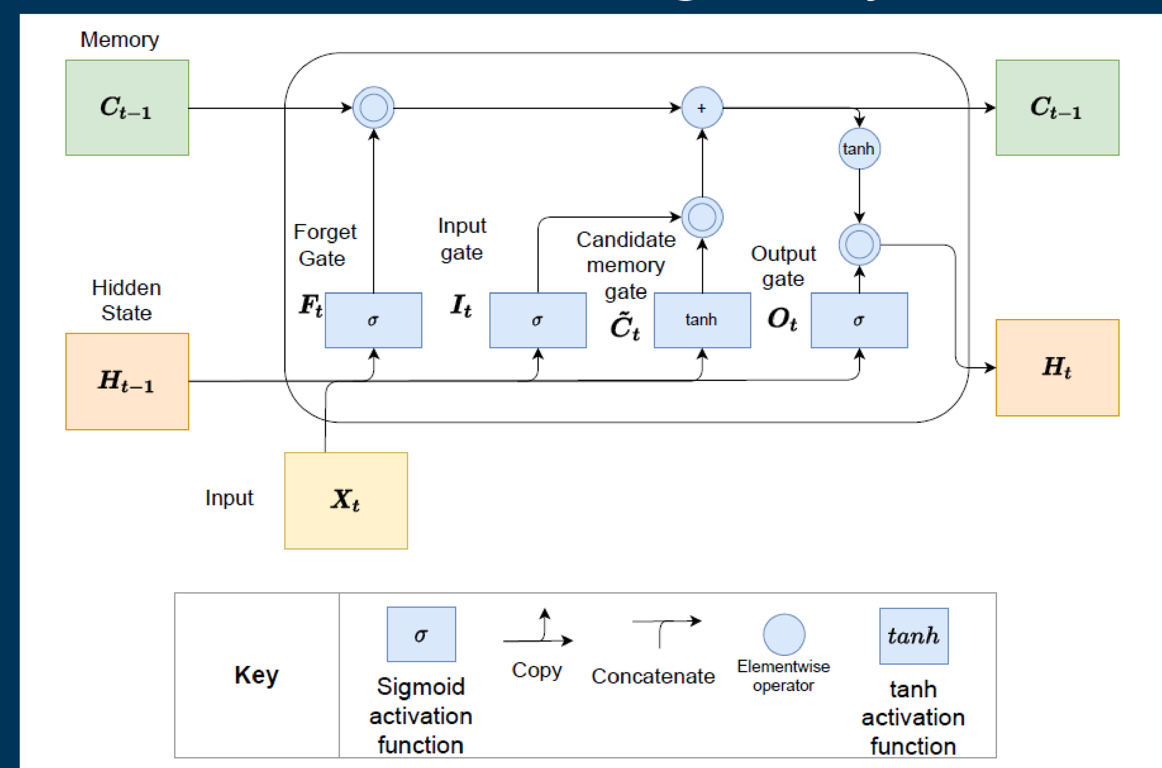
$$R_t = \sigma(X_t W_{xr} + H_{t-1} W_{hr} + b_r)$$

$$Z_t = \sigma(X_t W_{xz} + H_{t-1} W_{hz} + b_z)$$

$$\tilde{H}_t = tanh(X_t W_{xh} + (R_t \odot H_{t-1}) W_{hh} + b_h)$$

$$H_t = Z_t \odot H_{t-1} + (1 - Z_t) \odot \tilde{H}_t$$

- The LSTM hidden state is given by:



$$I_t = \sigma(X_t W_{xi} + H_{t-1} W_{hi} + b_i)$$

$$F_t = \sigma(X_t W_{xf} + H_{t-1} W_{hf} + b_f)$$

$$O_t = \sigma(X_t W_{xo} + H_{t-1} W_{ho} + b_o)$$

$$\tilde{C}_t = \tanh(X_t W_{xc} + H_{t-1} W_{hc} + b_c)$$

$$C_t = F_t \odot C_{t-1} + I_t \odot \tilde{C}_t$$

$$H_t = O_t \odot \tanh(C_t)$$

- There is also a variety of error metrics to be used in time-series forecasting, but we will use mean absolute error (MAE):

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |y_i - x_i|}{n}$$

4. Project Results

5 different model topologies were trained with 6 different forecasting horizons (30 mins, 1 hour, 2 hours, 5 hours, 10 hours, 24 hours). The testing set MAE is plotted for these models:

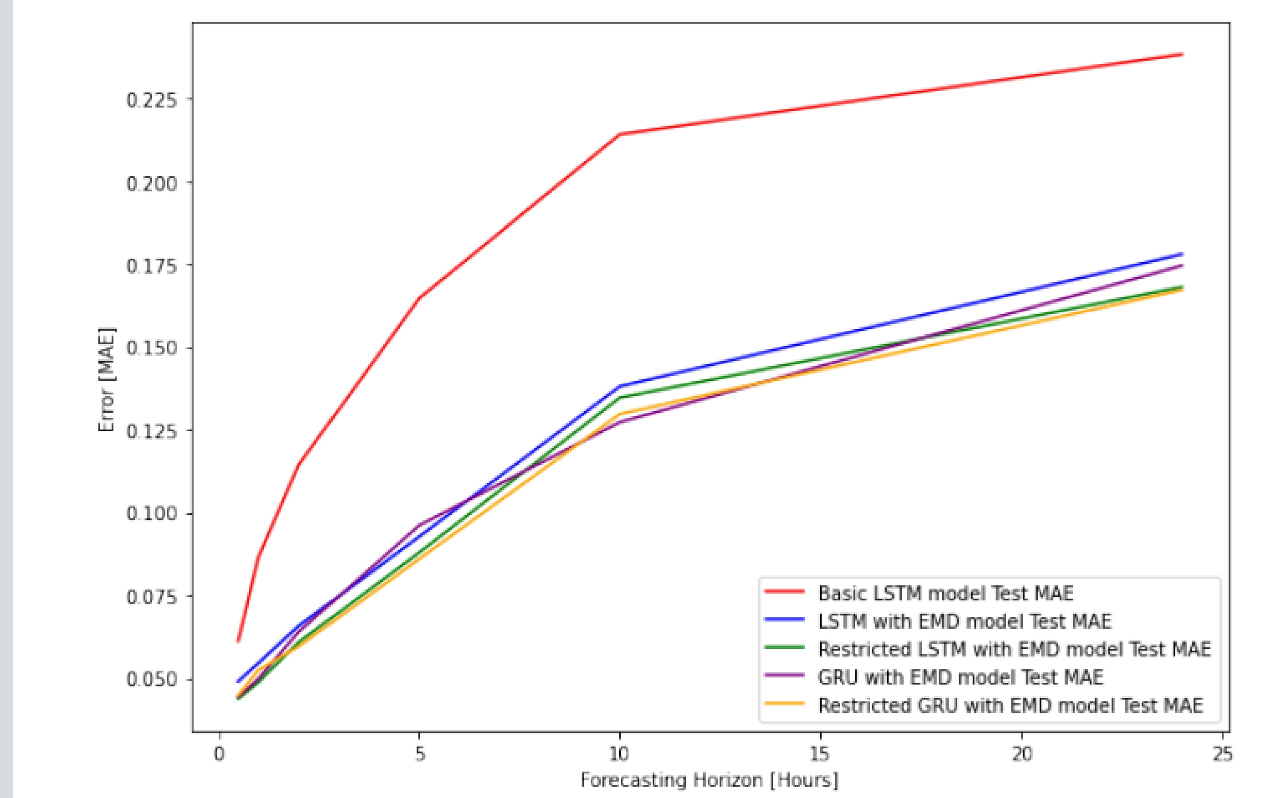


Figure 4.6: Test MAE of all developed ANN-based forecasting models for different time horizons

From the results it is clear that:

- Adding IMFs obtained from EMD to the model inputs improves the performance appreciably.
- Changing the memory mechanism from LSTM to GRU improves the performance marginally.
- Restricting the ANN models to model the wind turbine power curve improves the performance of models slightly.

Some of the predictions run on a trained model is shown: