Optimising Floating Wind Turbine Layouts with Wake Modelling and Reinforcement Learning

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Background

With 80% of offshore wind resources located at depths greater than 60m, beyond the reach of fixed-bottom turbines, the focus is increasingly on floating offshore wind technologies. This shift towards larger turbines and rotor diameters introduces complex interactions with environmental variables, which traditional simulation methods struggle to model accurately and efficiently.

Our research aims to explore the application of machine learning techniques to predict and optimise the layouts of floating offshore wind farms, considering specific turbine characteristics and geographical constraints. This research will enhance our ability to design optimal layouts for floating wind farms, leading to more sustainable solutions supporting global renewable energy targets and promoting environmental stewardship.

Overall Tool Design

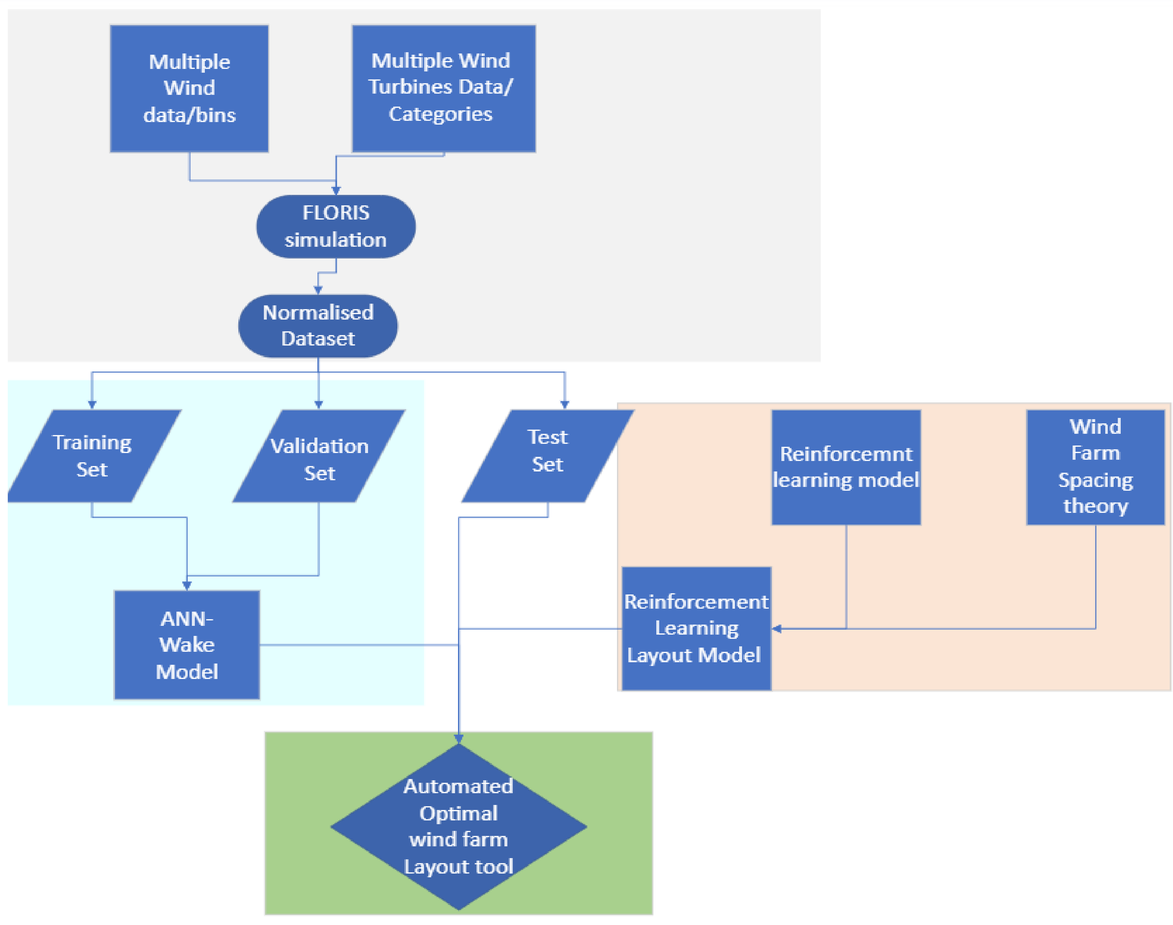

Fig 1. Figure showing the work flow plan for our ML wind farm optimisation toll

Wake Model

Current market FLOW and monopile OFW devices were simulated using a combination of a Gaussian velocity model and the Crespo-Hernandez wake model to account for wake effects and velocity deficits. The simulation was performed using the FLORIS model developed by NREL.

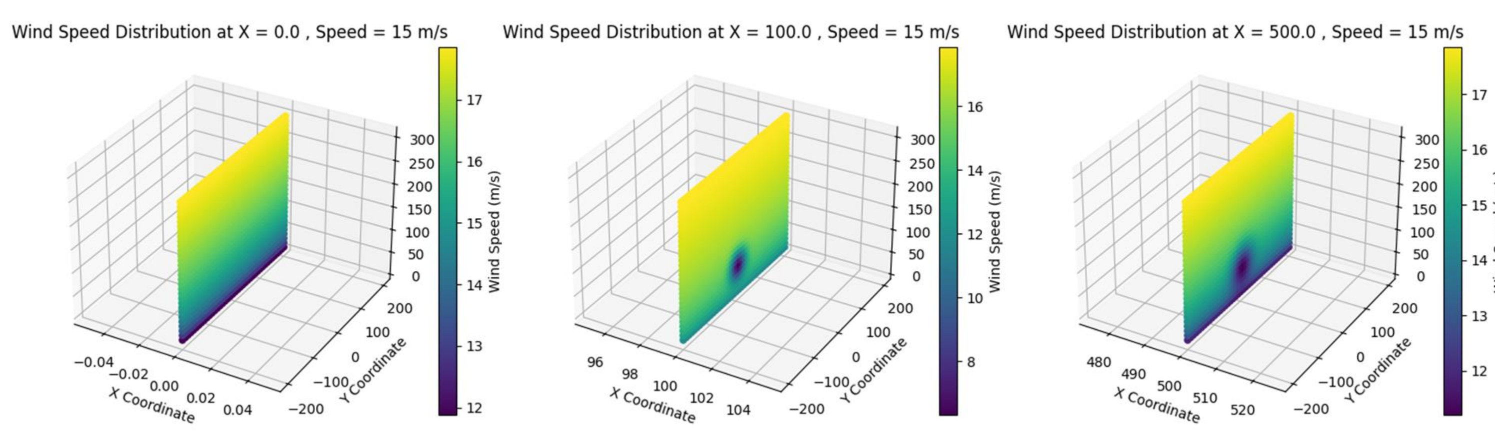

Fig 2. Slices through the FLORIS domain showing the wake expansion of an OWF

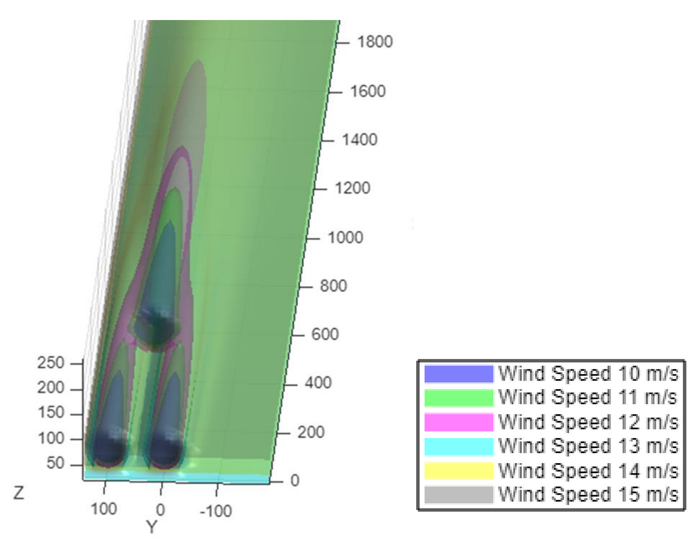

Fig 3. Interaction of 3 turbines in FLORIS

The FLORIS (Flow Redirection and Induction in Steady-state) provides a robust framework for optimising wind farm layout. This combination of velocity and wake model has been shown to accurately predict overall wind power with an error of only 1.33%

Machine Learning Models

1. Paper Based ANN (PANN)

Inspired by previous academic research, we have implemented several features to enhance the accuracy of wake prediction compared to a Fully Connected ANN (FCNN). These features include:

- Inclusion of dropout layers for regularisation
- Use of back-propagation for adjusting the ANN
- Implementation of K-Fold Cross-Validation

These enhancements improve both training and validation loss. The training loss indicates how well the model learns from the training data, while the validation loss shows how well the model generalises to unseen data.

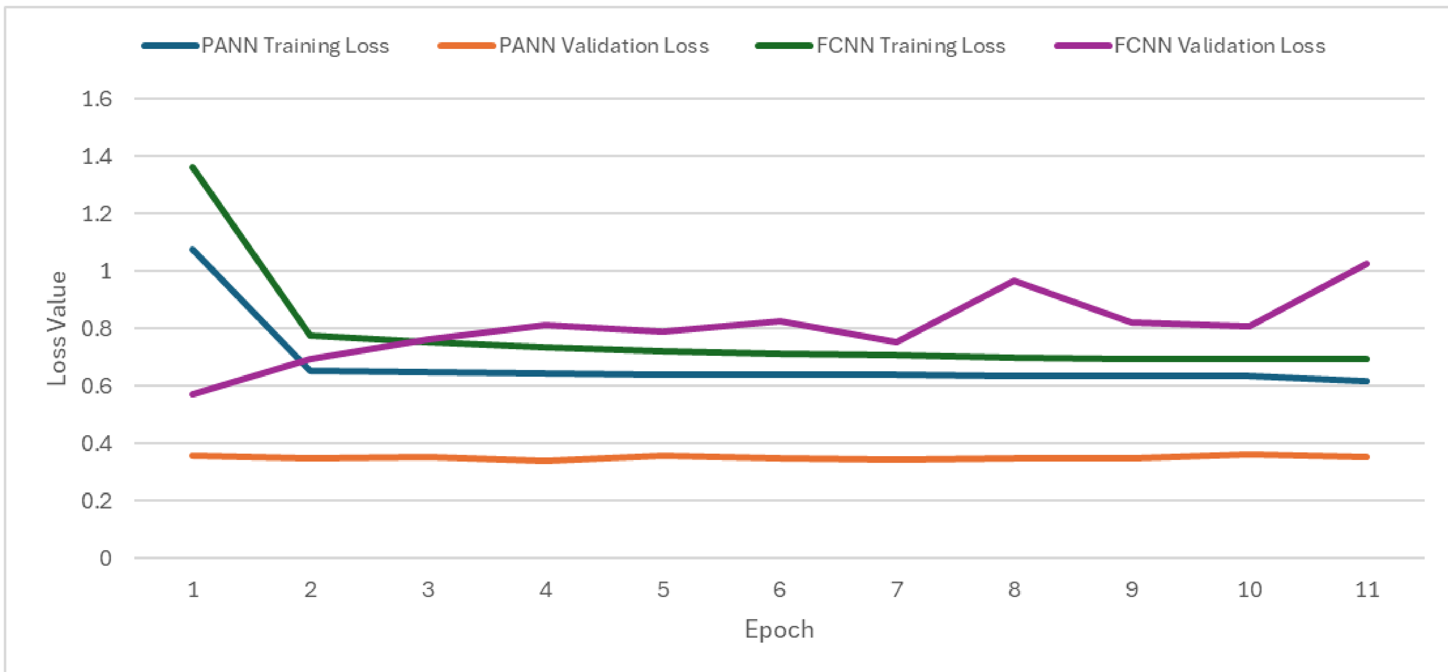

Fig 4. Difference in training and validation loss values through each epoch for the PANN and FCNN

2. Reinforcement Learning Model

The present model inputs are:

- predicted wake expansion from the CNN
- number of turbines
- potential wind farm size

To maximise wind farm efficiency, our reinforcement learning (RL) model iteratively adjusts the arrangement of FLOW devices within a constrained area. The goal is to achieve the optimal Blockage Ratio (BR),as close to zero as possible, and Blockage Distance (BD), as close to one as possible. The relevant equations are presented below.

$$BR_i = \frac{1}{A}\int_{(x,y)\in A} X dxdy$$

$$BD_i = \frac{1}{A}\int_{(x,y)\in A} [L_X + (1 - X)L_x] dxdy$$

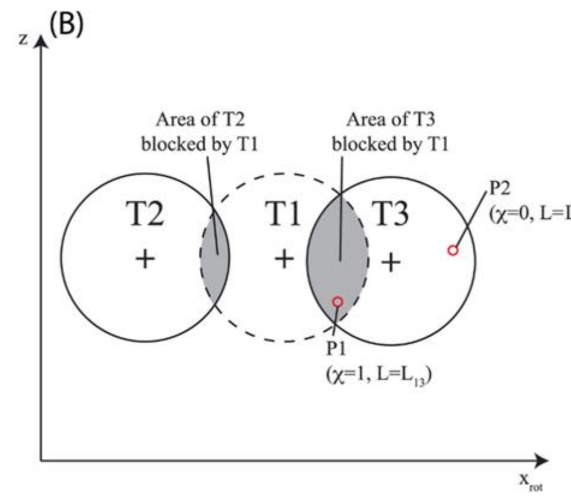

Fig 5. Representation of wind turbines and the related blockage variables

Further Work

As the project progresses, we aim to implement further constraints into the reinforcement learning model. Industry developers have highlighted aspects such as micro siting, cable layout and bird collisions to integrate into the optimisation tool.

In addition, to improve longevity of the tool, we will also start to model predicted future designs of potential FLOW and OWF devices.

Reference

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- Ti, Z., Deng, X.W. and Yang, H. (2020) 'Wake modeling of wind turbines using machine learning', Applied Energy, 257, p. 114025.
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