Imperial College London

Department of Earth Science and Engineering

MSc in Applied Computational Science and Engineering

Independent Research Project

Project Plan

Wind farm wake modelling using artificial neural networks

by

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GitHub repository: https://github.com/acse-2019/irp-acse-sa1619

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1. Introduction

Wind power has maintained a significant share of the total worldwide energy production of the 21st century (4.8% by the end of 2018 [1]) and is expected to grow by 18% within the next 3 decades [2]. Wind energy production has increased over the past few years due to extensive efforts towards the modelling of turbine wakes and wind farm configurations that include a variety of analytical, experimental as well as high-fidelity numerical approaches.

Analytical wake modelling has been present from the earliest stages of modern wind turbines and is still playing an important role in producing low-cost wake predictions of the wake deficit profile. Some of the most commonly used models such as Larsen [3], Jensen [4] and Gaussian [5] are usually incorporated in packages available in the industry (FLORIS, WasP, WindPro etc) and depending on the application, they can significantly reduce the complexity of parametric studies or turbine array set-ups. However, since they usually involve simplified physics and are mainly focusing on averaged velocity profiles and not transient turbulent wakes, they do not constitute a method that produces results of high-accuracy [6], [7]. Furthermore, the analytical models rely on empirical constants which require fine-tuning through computationally-expensive CFD simulations. Although these models are not able to capture a detailed representation of the velocity deficit, the trade-off between accuracy and low-computational time is very often made in support to high-fidelity CFD studies in optimisation problems.

During the last two decades, the exponential advancements in CPU as well as GPU architectures have led to a significant progress towards wake modelling using computational methods [8], [9]. Coupled numerical models such as large-eddy simulation (LES) and Raynolds-averaged Navier-Stokes (RANS) are now capable of describing steady as well as transient wake flows very accurately and provide a realistic illustration of wind-turbine interaction physics [10], [11]. Nevertheless, accurately representing the wind flow profile, especially through the turbine blades which are moving at very high rotational speeds, requires very fine mesh settings in order to capture the boundary layer properties. Even then, some of the most widely used models for turbulence like k-ε, tend to overestimate the turbulence viscocity [12] leading to discrepancies between the numerical results and experimental measurements [13]. Thus, CFD is rarely used as a standalone method, even less when dealing with array optimisation problems (e.g. using Adjoint methods) which require multiple high-computational-cost runs.

Through the recent increase of computational power, the application of artificial/deep neural networks (ANN, DNN) as well as convolutional neural networks (CNN), has been successfully tested across a wide variety of scientific fields, including fluid mechanics [14], [15], [16]. On wind turbines, there have been some recent efforts towards modelling of source terms with an ANN [17] and correlating Reynolds stress anisotropy with strain [18]. An ANN was constructed in order to assess the performance of wind turbines using the power vs torque curves [19], [20]. Very recently, a simple ANN architecture was trained on a large high-fidelity dataset and correlated two inputs (inlet wind speed and turbulence intensity) to produce 3D wake profiles of wind turbines in a single row [21]. So far, in the limited available research, neural networks appear to be very efficient in the challenging task of building relationships between inflow conditions, rotor specifications and fluid properties. Traditional methods face difficulties in producing fast results that at the same time are accurate enough to support parametric studies. A well constructed and well trained neural network could be deployed and provide reliable results within minutes in order to predict flow properties of a wind farm that would otherwise require orders of magnitude higher computational times. At the moment, the use of powerful machine learning and regression tools shows promising results and could pave the way to even more sophisticated optimisation approaches in the future.

2. Project Plan

2.1 Problem description

The two main methods adopted in wind and tidal turbine studies are analytical and numerical models. While analytical models produce results very fast they have many limitations regarding their accuracy, as well as their ability to describe transient flows. Thus, they are rarely used as standalone approaches. On the other hand, although numerical models can produce realistic results they tend to be very computationally demanding, which makes parametric studies and array optimisations a very difficult problem to be solved within a specific time frame.

The current study aims to construct a novel artificial neural network, initially trained on analytical models, which will be capable of reproducing the same results for the wake of a single turbine at lower computational cost, and with a high accuracy. Therefore, the aim is initially at composing an efficient neural network architecture, the novelty of which will be in describing the correlations between multiple parameters, such as the turbulence intensity, inlet wind speed, the yaw of the turbine etc. Minimising training times is also an important factor affected by the network's architecture, which contributes in assessing its performance. The network could later be re-trained further using transfer-learning on a smaller high-fidelity CFD dataset which could significantly improve its capabilities for real-world applications. The computational cost gains would thus be increased even further, since a CFD simulation would take hours whereas using the retrained ANN/DNN producing results could be a matter of a few seconds. The finalised network will be deployed to produce the wakes of wind turbines that could later be superimposed to produce the velocity deficit of a 2D wind farm using a neural network, for the first time in the available literature, which could later be used instead of or in cooperation with traditional optimisation adjoint methods.

2.2 Progress to date

A vanilla version ANN has been built which constitutes of 200 x 200 parallel and independent smaller networks of 10 neurons each, as can be seen in Figure 1. So far, up to 3 inputs have been tested, namely the turbulence intensity, the inlet velocity at the hub and the wind direction. Each individual sub-network is trained based on a dataset produced by FLORIS, using the Gaussian wake model on a 15MW wind turbine. For the vanilla version, the sub-networks are trained to produce a single output, which corresponds to the mean velocity at a specific point on the 200 x 200 grid (Fig. 1), thus producing the wake deficit contour. Several additional architectures are currently being tested in order to optimise the ANN's accuracy and minimise the training time. The alternative architecture (version B) requires 50 neurons in each individual sub-network which are trained on either a single row or column of the wake deficit produced by the analytical model.

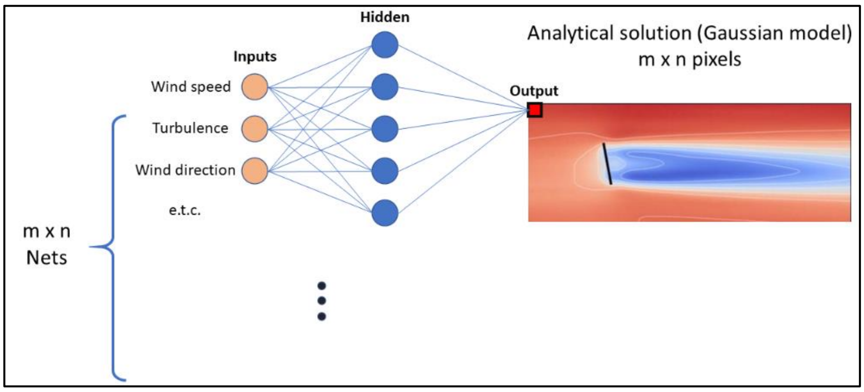

Figure 1. Vanilla ANN architecture producing the 200 x 200 individual pixels of the wake deficit from the given inputs (e.g. wind speed, turbulence intensity, wind direction).

An indicative training-validation plot is shown in Figure 2, which is representative of the general behaviour of each sub-network during training. It is important to note that the vanilla version takes about 5 hours to train, since it consists of 40000 sub-networks whereas the version B (200 sub-networks) takes about 5 minutes.

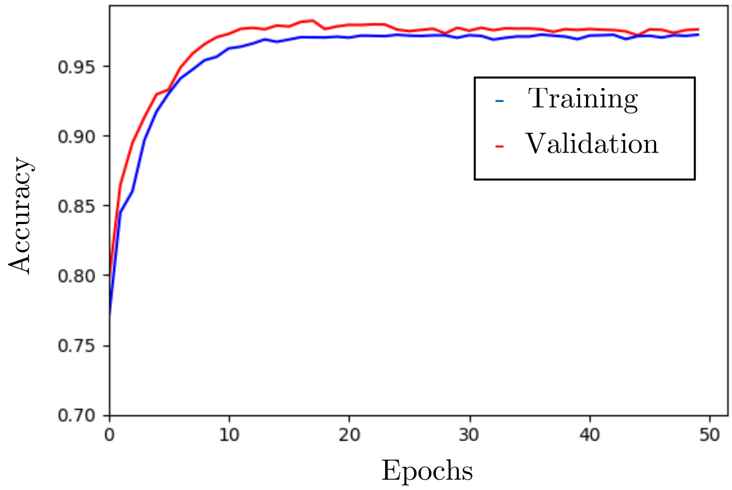

Figure 2. Indicative training and validation curves for a single sub-network of 10 neurons which appears to converge after about 25 epochs.

The results of the architectures mentioned above are shown in Figure 3 (Vanilla) and Figure 4 (Version B), where the analytical and neural wake deficits are plotted (Figs. 2a, 2b and Figs. 4a-d respectively). The absolute error (%) (normalised with the free stream velocity) between the analytical and the neural results varies from ~2 to ~5 % (Fig. 3c and Figs. 4e, 4f). Note that the 2D space is transformed from 500 x 1270 to 200 x 200 in the analytical model in order to maintain a square computational grid, thus the 200 x 200 box is plotted stretched with the suitable aspect ratio. Although there is an increase of 3% in the error from vanilla to version B the significant decrease in training time could constitute a valid compromise for the selected ANN. It is also worth noting that version B produces a single wake deficit slice 50% faster than the Gaussian model (1 s vs 1.5 s) which for the production of a large 3D dataset would be a considerable gain in computational speed.

However, the final version of the neural network has not been completed yet, as it appears that changes in the architecture can have a considerable effect on its performance, which is evident form the results of Figure 4. Further changes could include additional layers or inverse convolutions in order to introduce dependencies between the parallel sub-networks, depending on their neighbours stencil.

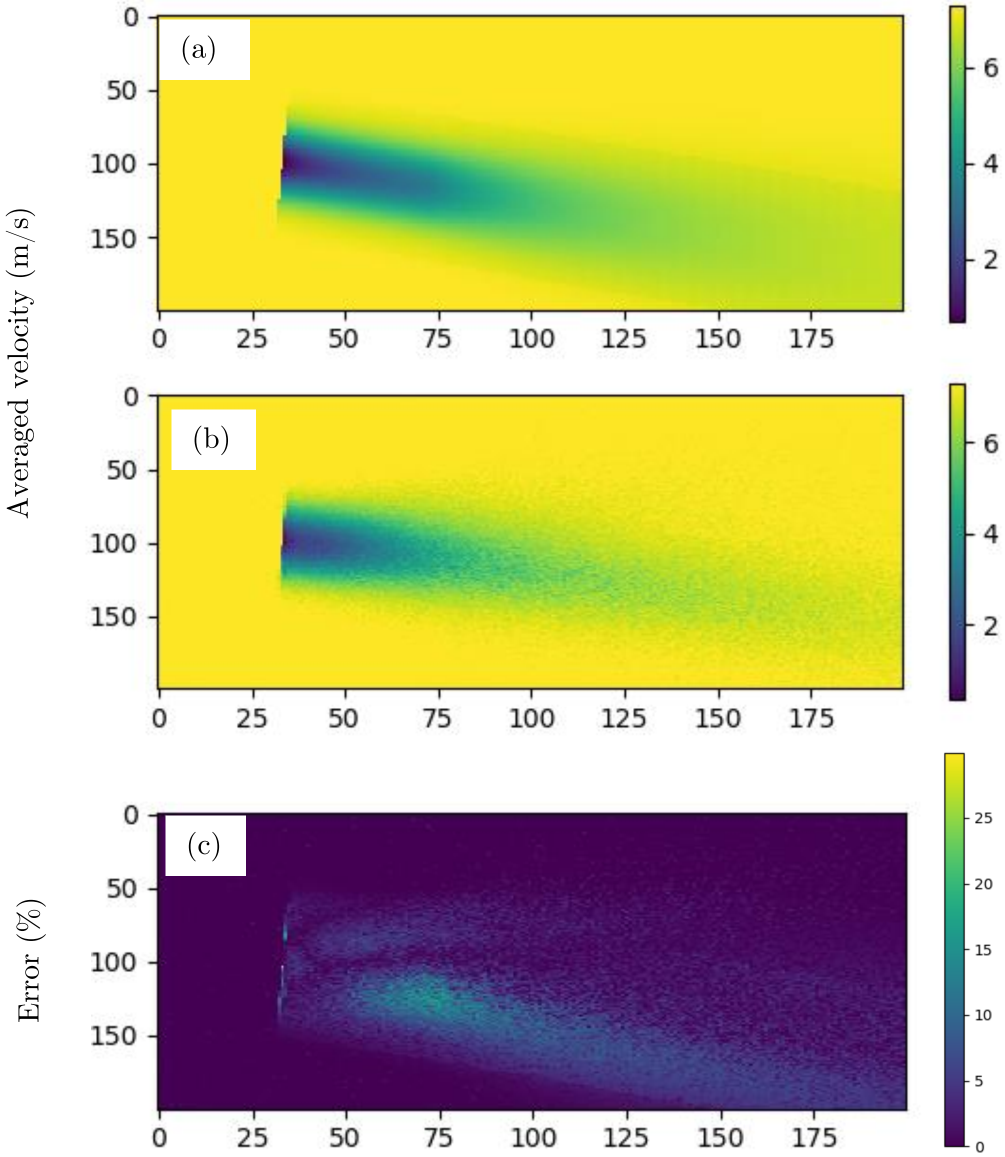

Figure 3. Analytical (a), neural (b) wakes and absolute error (%) (c) for 7m/s, 0.2, 30º inlet conditions (speed, turbulence intensity and wind direction, respectively).

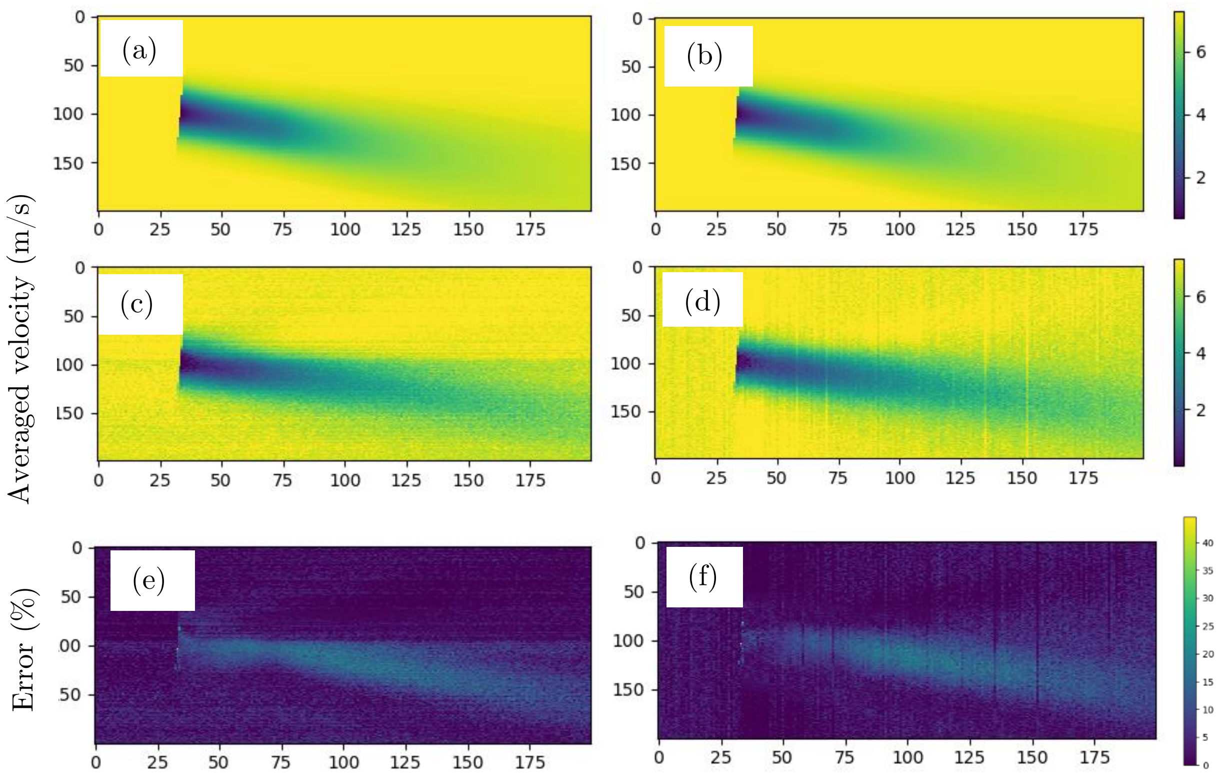

Figure 4. Neural-net trained to output a single row (left) and column (right). Analytical (a), neural (b) wake deficit plots and absolute error (%) (c).

2.3 Schedule

An indicative schedule is presented below which could be subject to changes in the future, depending on whether the focus will remain on improving the first neural network or also creating a second one for array optimisations.

Milestones:

- Research existing literature.
- Experiment with Floris library.
- Construct a vanilla version of the ANN.
- Experiment with different analytical models and architectures.
- ➢ Add more inputs (e.g. rotor characteristics, height of computational plane).
- Finalise network and apply superposition for farm modelling.
- Construct 2^{nd} Neural network for array optimisation.
- Assess accuracy compared to traditional methods.

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