Advancing wind farm performance with aerodynamics and AI

Over the last three years, artificial intelligence or AI, has boomed, with the release of language models such as OpenAI's ChatGPT. Its ability to sustain coherent conversations about any topic has captured the imagination of people across the globe. This increased awareness of the capabilities of AI, has created the largest demand to adopt a technology since the creation of the internet. For all businesses, the ability to derive previously unknown connections or trends from existing data provides near-limitless potential. This opportunity is no different for the wind sector.

As a sector producing vast amounts of data from the early design and planning stages to live operations, the challenge is finding the best use cases for AI that ultimately provide the most long-term impact.

This requirement to define the problem statement is step zero for any successful AI project. With a diverse range of operations in any sector, no one-size-fits-all model can solve all parts of the supply chain. This article will focus on how AI can revolutionise the aerodynamic understanding of wind farms and improve their design and control.

When developing any new project, the objective remains the same. Maximise efficiency and reduce costs. The unique nature of any new wind farm means 'optimal' can look very different depending on the budget and location, alongside a variety of other factors.

By developing more sophisticated modelling techniques, we can simulate with a greater accuracy to reality.

However, the traditional numerical model used in computational fluid dynamics (CFD) still approximates reality. Over 25 years, any errors in the modelling will compound until tangible losses are felt by both owners and investors.

Modelling error has become a reality for many site developers in the last few years, including industry leaders such as Ørsted. In 2019, the company announced that it would scale back production targets by up to 8.5%. The underestimation focused on two key areas: wake and blockage effects. These relate to the wind speed behind the turbine and the slowing effect as the wind approaches the front of the turbine.

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These are also of concern during the planning stages for new and expanding sites. With larger turbines and an increased number of turbines in a cluster, the downstream effects on neighbouring sites can have a huge impact on energy yields. RWE recently estimated the impact of wake effects to be observable over 200 km from the cluster and the reduction in energy yields as much as 10%.

In areas such as Germany, the proximity of offshore sites could negatively impact yields and limit future expansion. It is therefore imperative that developers are aware of these, to minimise delays caused by disputes with neighbouring sites.

Both these problems can be mitigated in some part through advancing modelling techniques. Whilst the advancement of numerical methods could provide a solution, the problem of extensive computational time will not be solved without innovation in areas such as quantum computing.

In practice, monitoring these wake effects is very difficult, given the limited sensing options that can accurately cover such large distances. Without proper real-time insight, the ability to mitigate these problems becomes even more difficult. At Aventuri, we believe the solution lies within advanced data analytics, machine learning and AI.

Aventuri develops AI solutions for real-time aerodynamic performance analysis, enabling operators to improve the design and control of wind farms. By combining simulation and operational data, we provide a complete insight into the flow across a wind farm by only utilising existing data and sensors. Our goal is to minimise additional CAPEX whilst retaining flow prediction accuracy and building a platform that can be scaled to wind farms globally.

Some examples of use cases include optimising the layout of a new wind farm based on the atmospheric conditions and proposed turbines or building control strategies to manage wake effects through wake steering. In our most recent case study, we showcased how our models could be used to predict the flow field using only four localised LiDAR wind speed measurements.

For this example, we trained our model using data collected from NREL's FLORIS simulation tool. The data set generated provides the model exposure to different conditions by varying parameters such as wind speed, direction and yaw angles for each turbine. By estimating the expected signal noise of each measurement, this data was also augmented to build robustness into the model to handle the uncertainty observed in reality.

In our validation tests, we found the average accuracy of our model to be 99.6% when compared to the reference FLORIS data. With similar modelling performance, the primary advantage of using machine learning over a numerical method is the speed to generate new results. For even a small numerical domain, the model generated results 10x faster which would only increase as the domain size and modelling complexity increases.

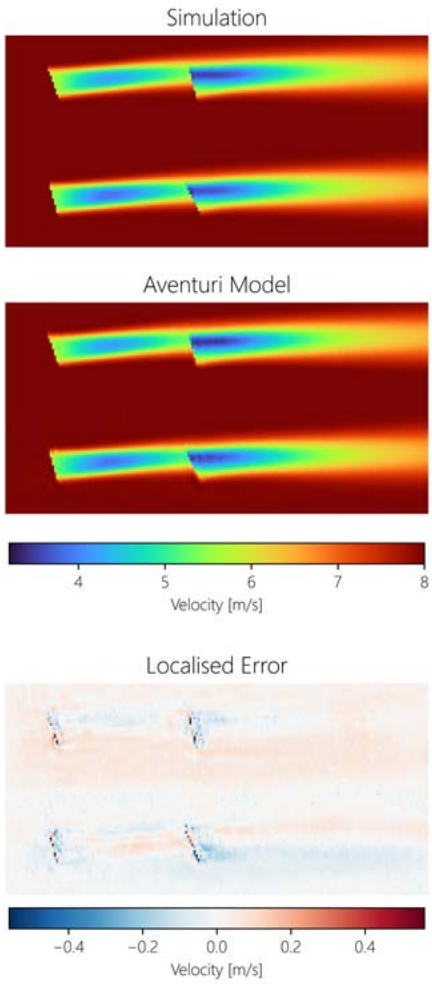
To contextualise and quantify what this could bring to a wind farm, we estimated the benefits of wake steering to energy production. From a baseline of no steering, with all turbines facing the wind, to the most optimal yaw configuration, the increase was as high as 10%. With prediction speeds below a tenth of a second, this case study shows Aventuri can solve the requirements for effective wake management and dynamic control strategies to maximise the potential yields.

Our next case study will be into optimising the layout of an offshore wind farm using the same machine learning models showcased here. By utilising the speed and precision of machine learning, our goal is to simulate the expected yields across the operating window for different layout configurations.

Allowing developers to evaluate their plans faster and optimise for both energy production and development costs. Through the combination of the work detailed in this article and our plans for further refinement, we aim to bring a single solution that can solve fundamental challenges from initial conception throughout the life of the wind farm.

Currently, we have work planned for later this year to validate our methodology and show our techniques are reliable in a practical setting. However, we are still actively seeking partnerships to validate our findings using real-world data to show that our models can work in practice and come on board as early adopters to evaluate the benefits they can bring to them.

The benefits of AI and machine learning for the industry are limitless and so far, the current developments are only scratching the surface. Whilst the focus here has been on aerodynamics, many other data-rich aspects of the wind sector are prime for AI and machine learning.



Comparison of modelling performance between NREL's FLORIS simulation, upper, Aventuri's machine learning model, middle and error between the two models lower

The challenge to overcome is ensuring that data is open and available for different parties across the industry to enable innovation. With previous modelling techniques generating erroneous predictions, the 'black box' approach of AI has been a point of scepticism for critics. The way to mitigate these concerns is to ensure transparency in the data utilised in development and robust testing of outputs to understand the inner workings.

For modelling aerodynamics using AI, Aventuri aims to be a leader in real-time performance analysis. Our goal is to work with the industry to develop more efficient wind farms that provide a greener future for society.

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