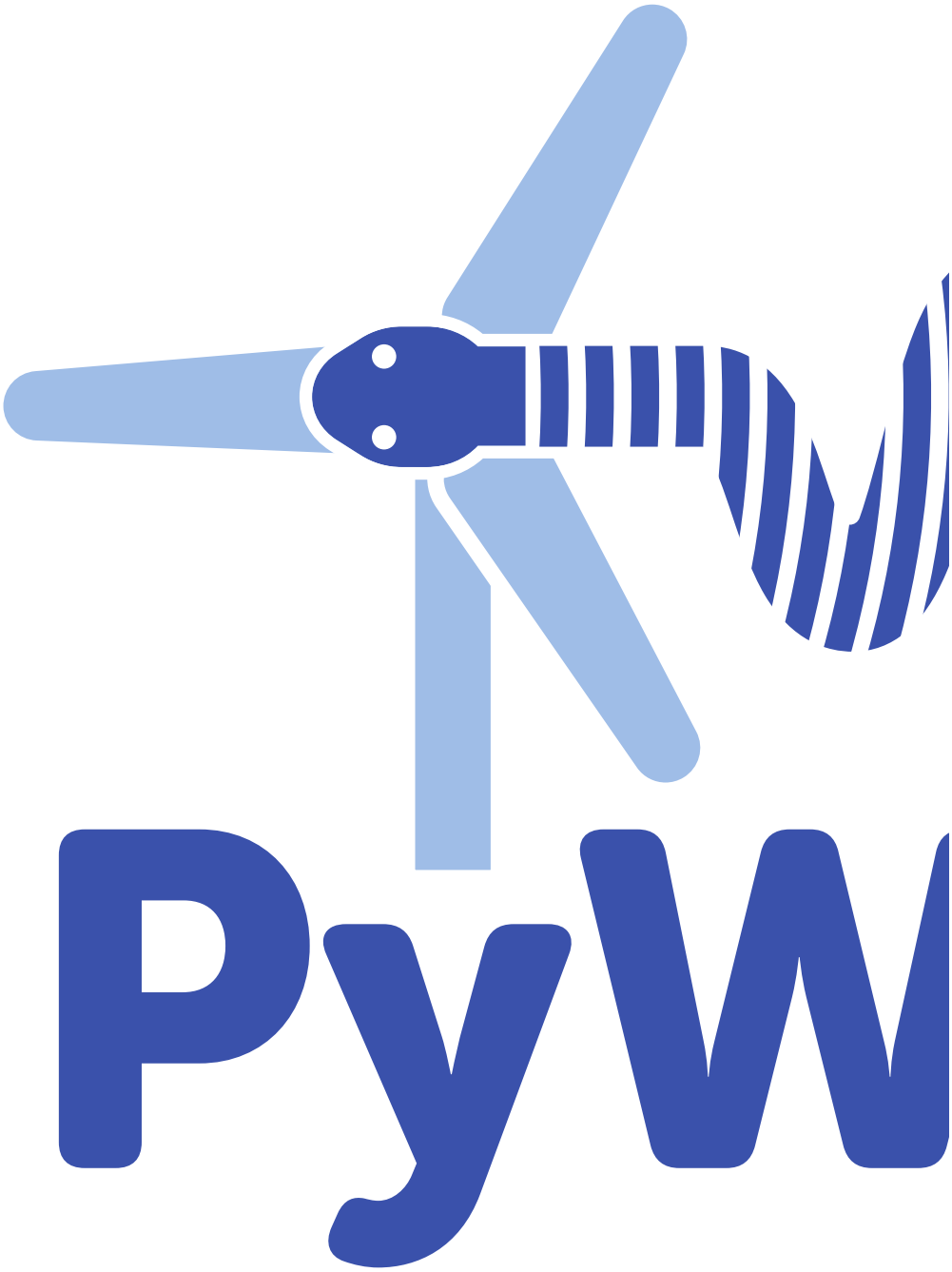
Welcome to PyWake



PyWake is an open-sourced and Python-based wind farm simulation tool developed at DTU capable of computing flow fields, power production of indivic different engineering models as well as CDF RANS (PyWakeEllipSys). It is highly efficient in calculating how the wake propagates within a wind farm and c

What Can PyWake Do?

The main objective of PyWake is to calculate the wake interaction in a wind farm in a computationally inexpensive way for a range of steady state conditi configuration. Some of the main capabilities of PyWake that have been in constant development in the last few years include:

- The possibility to use different engineering wake models for the simulation, such as the NOJ and Bastankhah wake deficit models.
- The option of choosing between different sites and their wind resource, with the additional option of user-defined sites.
- The ability to have user-defined wind turbines or import turbine files from WAsP.
- The capability of working with chunkification and parallelization.
- The advantage of visualizing flow maps for the wind farm layout in study.

For installation instructions, please see the Installation Guide.

Source code repository and issue tracker:

https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake

License:

MIT

Getting Started

PyWake is equipped with many capabilities that can range from basic to complex. For new users, the Overview section contains a basic description of PyW
PyWake.

Explanations of PyWake's core objects can be found in the following tutorials:

- Site: this tutorial walks through the set up of pre-defined sites in PyWake as well as the possibility for user-defined sites.
- Wind Turbine: this example demonstrates how to set up a wind turbine object and also to create user-defined turbines with specific power and CT
- Engineering Wind Farm Models: here there is a detailed explanation of all the engineering wind farm models used in PyWake, which have been ada
  turbulence models, etc., can be found under the main components section.

The Wind farm simulation example shows how to execute PyWake and extract relevant information about the wind farm studied. In addition, PyWake's c
TOPFARM is available in the Optimization tutorial.

Lastly, the remaining notebooks illustrate some relevant examples and exercises to see the different properties that PyWake has to offer.

How to Cite

Version 2.5.0

Mads M. Pedersen, Alexander Meyer Forsting, Paul van der Laan, Riccardo Riva, Leonardo A. Alcayaga Romàn, Javier Criado Risco, Mikkel Friis-Møller, Julian Quick, open-source wind farm simulation tool. DTU Wind, Technical University of Denmark.

```
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    pywake2.5.0_2023,
    title={PyWake 2.5.0: An open-source wind farm simulation tool},
    author={Mads M. Pedersen, Alexander Meyer Forsting, Paul van der Laan, Riccardo Riva, Leonardo A. Alcayaga Romàn, Javier Criado Risco, Mikkel F
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```

Contents

Main Components

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- Predefined Engineering wind farm model classes
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Installation Guide

Pre-Installation

Before you can install the software, you must first have a working Python distribution with a package manager. For all platforms we recommend that you download and install Anaconda - a professional grade, full-blown scientific Python distribution.

To set up Anaconda, you should:

- Download and install Anaconda (Python 3.x version, 64 bit installer is recommended) from https://www.continuum.io/downloads
- Update the root Anaconda environment (type in a terminal):

  ```
  >> conda update --all
  ```

- Activate the Anaconda root environment in a terminal as follows:

  ```
  >> activate
  ```

It is recommended to create a new environment to install PyWake if you have other Python programs. This ensures that the dependencies for the different packages do not conflict with one another. In the command prompt, create and active an environment with:

```
conda create --name pywake python=3.8
activate pywake
```

Simple Installation

PyWake's base code is open-sourced and freely available on GitLab (MIT license).

- Install from PyPi.org (official releases):

  ```
  pip install py_wake
  ```

- Install from GitLab (includes any recent updates):

  ```
  pip install git+https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake.git
  ```

Developer Installation

We highly recommend developers to install PyWake into the environment created previously. The commands to clone and install PyWake with developer options including dependencies required to run the tests into the current active environment in an Anaconda Prompt are as follows:

```
git clone https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake.git
cd PyWake
pip install -e .[test]
```

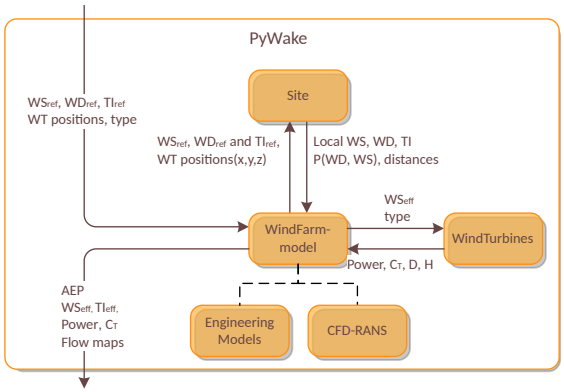
Open in Colab Edit on Gitlab

Overview

PyWake is an open-source wind farm simulation tool used for studying the interaction between turbines within a wind farm and its influence on the farm's flow field and power production. Based in Python, PyWake is capable of accurately computing the physics behind wind farms as well as obtaining their AEP. It provides a unified interface to wind farm models of different fidelities, e.g., different engineering models and CFD-RANS (commercial plugin). Given its heavy vectorization and use of numerical libraries, PyWake is a very fast tool that can handle many variables at once.

The PyWake Philosophy

"Empowering users" underlines the formulation of PyWake. Its highly modular architecture (shown in the figure below) allows users to combine different AEP modelling blocks in all sorts of fashions - giving the flexibility to shape PyWake around the particularities of real-world problems more accurately. Yet with power also comes responsibility - the user needs to make an informed decision when combining the multitude of building blocks PyWake supplies. Essentially, everyone can build their *own* AEP model chain leveraging PyWake's flexibility, so there is not *one* PyWake solution either; users should thus ensure to report the particular PyWake building blocks they used to transparently communicate their results and methodology.

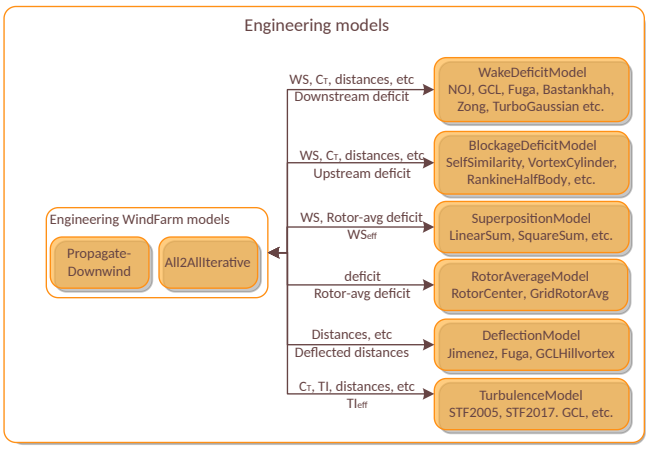


The main object in PyWake's architecture is the `WindFarmModel`, which is initialized with a `Site` and a `WindTurbines` object. It returns a `SimulationResult` object containing the calculated effective wind speed, power production, and thrust coefficient of individual turbines. In addition, it relies on methods to calculate the AEP and generate flow maps of entire wind farms.

- **Site**: for given turbine positions (x, y), reference wind speed (WSref) and wind direction (WDref), the Site object provides the local wind condition in terms of wind speed (WS), wind direction (WD), turbulence intensity (TI), and the probability of each combination of wind direction and wind speed. Furthermore, the Site object is responsible for calculating the down-wind, cross-wind, and vertical distance between wind turbines (which in non-flat terrain is different from the straight-line distances).
- **WindTurbines**: for a given wind turbine type and effective wind speed (WSeff), the WindTurbines object provides the power curve, thrust coefficient (CT) curve, as well as the wind turbine's hub height (h) and diameter (D).

The **Tutorials** section provides examples on how to define both the WindTurbines and Site objects in PyWake.

Engineering models



The engineering wind farm models (`EngineeringWindFarmModel`) in PyWake are composed of one or two wind farm models in combination with a wake deficit model, a superposition model, and optionally a blockage deficit and a turbulence model. The two main objects correspond to the `PropagateDownwind` and `All2AllIterative` objects. These two define the procedure that determines how wake and blockage deficits propagate in the wind farm. `PropagateDownwind` does not consider blockage effects whereas `All2AllIterative` does. The Engineering Wind Farm Models notebook depicts a much more detailed definition of these two.

Whereas a wake deficit model always needs to be selected, all other components are optional. Here is a quick overview of the different building blocks forming part of the engineering model setup:

- **Wake Deficit Model**: calculates the wake deficit from one turbine to downstream wind turbines or sites in the wind farm. A set of predefined wake models are available in PyWake, please refer to the Wake Deficit Models notebook for more details.
  - `rotorAvgModel`: Option to select the way the wind speed is averaged on the turbine rotor.
  - `groundModel`: Option for modelling the ground effect.
  - `use_effective_ws`: Option for using the local wind speed at the rotor to compute the deficit.
  - `use_effective_ti`: Option for using the local turbulence intensity at the rotor to compute TI dependant quantities.
- **Blockage Deficit Model**: calculates the blockage deficit (speed-ups) from one wind turbine to upstream/downstream turbines or sites in the wind farm. Please refer to the Blockage Deficit Models notebook for more details.
- **Superposition Model**: defines how deficits from multiple sources add up. Please refer to the Superposition Models notebook for more details.
- **Rotor Average Model**: defines how the wind speeds are reaching the swept area of a turbine rotor and estimates the rotor-average wind speed. Please refer to the Rotor Average Models notebook for more details.
- **Deflection Model**: defines the wake deflection due to yaw misalignment, sheared inflow, etc. It does this by modifying the down- and cross- wind distances. Please refer to the Deflection Models notebook for more details.
- **Turbulence Model**: calculates the added turbulence in the wake from one wind turbine to downstream wind turbines or sites in the wind farm. Please refer to the Turbulence Models notebook for more details.
- **Ground Models**: are used to model the effects that the ground has on the inflow and wake. Please refer to the Ground Models notebook for more details.

This list should only serve as a rough overview of the different components constituting the `EngineeringWindFarmModel` and the available options - a more detailed description of each type of models can be found in the **Tutorials** section.

> **Disclaimer**
>
> The specific implementation of the different models might differ from the respective published method, either due to practical reasons, to make it more versatile or to incorporate our own improvements.

Available models in PyWake

Wake Deficit Model	Blockage Deficit Model	Superposition Model	Turbulence Model	Rotor Average Model	Deflection Models
NOJ	Fuga	Linear Sum	Steen Frandsen 2005	Rotor Center	Jimenez
Bastankhah Gaussian	Self Similarity Deficit	Squared Sum	Steen Frandsen 2017	Grid Rotor Average	Fuga
Zong Gaussian	Vortex Cylinder	Max Sum	GCL	Eq Grid Rotor Average	GCL Hill
Niayifar Gaussian	Vortex Dipole	Sqr Max Sum	Crespo Hernandez	GQ Grid Rotor Average	
Turbo Gaussian	Rankine Half Body	Weighted Sum		Polar Grid Rotor Average	
Turbo NOJ	Hybrid Induction			CGI Rotor Average	

Wake Deficit Model	Blockage Deficit Model	Superposition Model	Turbulence Model	Rotor Average Model	Deflection Models
Fuga	Rathmann				
Super Gaussian					
Carbajo Fuertes Gaussian					
GCL					

EllipSys3D (RANS-CDF)

The EllipSys wind farm model is based on a Reynolds-Averaged Navier-Stokes method as implemented in the general purpose flow solver EllipSys3D, initially developed by Jess A. Michelsen at DTU Fluid Mechanics[1,2] and Niels N. Sørensen in connection with his PhD study[3].

EllipSys3D is a closed-source licensed software and it is based on Fortran and MPI. The EllipSys wind farm model uses PyEllipSys, which is a direct memory Python interface to the Fortran version of EllipSys3D. This means that it is possible to import EllipSys3D as a Python object and change flow variables during a simulation.

The wind turbines are represented by actuator discs (AD) and the inflow is an idealized atmospheric boundary layer including effects of Coriolis and atmospheric stability. The main setup uses flat terrain, with a homogeneous roughness length, but the EllipSys wind farm model can also be run with complex terrain. More information can be found here: https://topfarm.pages.windenergy.dtu.dk/cuttingedge/pywake/pywake_ellipsys/.

Installation

The EllipSys wind farm model only runs in a linux environment and it requires the commercial cutting-edge plugin `py_wake_ellipsys`. Contact us if you are interested to get access to it.

References

1. Jess A. Michelsen, *Basis3D - a Platform for Development of Multiblock PDE Solvers*, AFM 92-05, Department of Fluid Mechanics, Technical University of Denmark, December 1994.
2. Jess A. Michelsen, Block structured Multigrid solution of 2D and 3D Elliptic PDEs, AFM 94-06, Department of Fluid Mechanics, Technical University of Denmark, May 1994.
3. Niels N. Sørensen, *General Purpose Flow Solver Applied to Flow Over Hills*, Risø-R-827, Risø National Laboratory, Roskilde, Denmark, 1995.

General modelling considerations

By Alexander Meyer Forsting (alrf@dtu.dk)

The never ending stream of publications concerning wind farm flows nicely demonstrates the difficulty we are still facing in accurately modelling the aerodynamic phenomena within the field of wind energy. There is currently not a single accepted method that could possibly capture the extensive range of flow scales we are dealing with - from aerofoil boundary layers to farm-to-farm interactions - especially not one that is sufficiently cheap to allow AEP predictions. Engineering wind farm models present a reasonable balance between accuracy and costs for wind farm AEP simulations, yet they rely on multiple sub-models that need to be selected wisely according to the problem at hand. A certain model and parameter combination might work for one particular case but not another - as demonstrated in an endless number of published model comparisons/validations. PyWake's engineering wind farm models are therefore also completely modular, allowing to combine different single wake models with different superposition, blockage, turbulence and deflection models to simulate wind farm flows. Each respective model is also configurable and its parameters tunable.

The sheer amount of possible sub-model combinations and settings can be overwhelming, so here we would like to give a very general guidance on how to combine them and what choices to consider.

1) Selection of the superposition model

Here you mainly have to decide between `SquaredSum` or `LinearSum`. The former does not really have a clear physical foundation, but was found to give some promising results in deep-arrays, as it isolates the most severe deficits, much like `MaxSum`. Beware, though, that its successful application largely depends on how the deficits are calculated inside the farm. Depending on the control volume one considers, one could either use the wind farm free-stream wind speed (even for turbines inside the array) or the incoming wind speed at each turbine (if isolating individual turbines). When studying a single turbine, the deficits from upstream turbines (and blockage from upstream/downstream) is included. Whilst physically it is hard to argue for using the free-stream velocity inside the array, one could choose to do so, as many have done before; however, it is then imperative to avoid using `LinearSum`. Since PyWake uses the *effective wind speed* at each turbine to calculate the thrust, power and deficit, if the free-stream velocity is chosen as *effective wind speed* the deficits will be extremely large - even inside the array - and the flow speed can turn negative when summing them linearly. A more consistent approach (in line with using single wake models) is to use the turbine's incoming wind speed as *effective wind speed* by

setting `use_effective_ws=True`. Then, the deficits are to be combined with the `LinearSum` model. Note that the `SquaredSum` actually leads to double counting (see Park2 model description for details).

There is also the `WeightedSum` approach by Zong et al but it is only available for Gaussian wake deficit models so far, and tends towards the `LinearSum` results. It is an iterative method with high memory requirements and only differs from the `LinearSum` when combining extremely deep deficits. It should individually be judged whether its benefits outweigh the additional costs. A more lightweight alternative constitutes Bastankhah et al's `CumulativeWakeSum`, which was derived for the Gaussian wake models. Despite its theoretical foundation it ultimately still relies on empiricism and its accuracy is fully dependant on the optimal configuration of the underlying wake deficit model (same applies to the Zong superposition model performance).

2) Selection of the wake deficit model and its configuration

Here the general recommendation is to use a Gaussian type model. They can conserve deficit momentum (in isolation) and avoid singular behavior (step changes). In addition, they are faster than the top-hat model. The available Gaussian model versions differ in their formulation of the streamwise wake expansion, which is governed by the initial wake diameter (at the wake origin) and its rate of expansion with downstream distance. The expansion can be constant (pre-set by user) or based on the *effective turbulence intensity (TI)*. Increasing TI leads to greater mixing and thus quicker expansion/deficit attenuation (users can change the coefficients if desired).

When using a **turbulence model**, the wake added turbulence in a farm is combined (the superposition of TI is another area of great uncertainty, but can also be modified by the user) and leads to spatially varying TI. As with the deficit, the user can choose to use the local TI at the rotor (`use_effective_ti=True`) or the free-stream TI. Whilst physically one might argue for using the local TI, this approach leads to excessive wake expansion deep inside the array when summing all contributions. Thus, the wake added turbulence is overestimated, making the free-stream TI a better reference for the wake expansion set up given the simplistic representation of turbulence by a single figure and its connection to wake expansion. The free-stream TI describes the atmospheric turbulence and thus also the larger scales contributing to wake-meandering and wake breakdown. On the other hand, the wake-added turbulence is small scale and dissipates quicker; therefore, it contributes differently to wake mixing and its superposition is not straight forward. For this reason, the Fuga and Dynamic Wake Meandering (DWM) models simulate only the free-stream TI governs wake expansion, as it is also the case in the more recent TurbOPark. One should also keep in mind that the Gaussian wake shape is a time-averaged solution, that incorporates meandering, shear-layer breakdown and mixing without differentiating between them.

Classically, Gaussian models are far-wake models, so the near-wake is rather crude. Shapiro et al introduced a smooth growth in the deficit, which also forms part of the Zong deficit model (not to be confused with the superposition model). The latter also sets the initial wake diameter by the near-wake length to capture the effect of TI and tip speed ratio on near-wake breakdown and subsequent far-wake onset. Other near-wake updates exist, yet their value is limited in AEP computations as turbines are usually placed outside this region in wind farms.

3) Simulation of the ground effect

In PyWake it is also possible to introduce a mirror plane to represent the **ground effect**, i.e turbines mirrored in the ground plane. This is a method commonly employed in vortex models, as it enforces zero wall normal velocity. However, while highly recommended for blockage modelling, it is less obvious whether to use a mirror plane for wakes. Wake models are generally tuned to measurement or simulation data that intrinsically contain the ground effect - so additional modelling could lead to double counting. This is also the reason why the `groundModel` can be set separately for blockage and wake models.

4) Implementation of a wind turbine model

PyWake uses power and CT curves, which can also be multi-dimensional (more suited to wind farm simulations), which need to be a function of the *free-stream* (reference) wind speed. In PyWake, a turbine's blockage and wake effects on itself, as well as its own mirror contributions (performance curves already include the ground effect), are zero. Thus, the wind speed at the rotor can be used to interpolate power and CT from the reference curves. The velocity at the rotor can be computed in different ways using the `rotorAvgModel` object. The default is extracting the velocity at the rotor-centre, however one can also opt for more rotor-equivalent wind speed quantities. Yet, one should consider that a turbine's performance curves are usually generated by using the rotor-centre velocity. The wind speed used for interpolation and deficit computation are always identical. As the power and CT curves are non-linear, users are advised to use higher-order splines in their interpolation (for instance `pchip`). A final issue relates to the often singular behaviour of power/thrust curves around cut-in and cut-out. Firstly, sudden jumps in production can occur around those wind-speeds as turbines are close to switch on/off, so even small changes in wind speed/direction can lead to strong relative changes. Secondly, in combination with blockage there is no definite solution, as some turbines might be on or off - either would be correct. This is mostly related to the downstream speed-up that blockage can cause in addition to upstream deficit. In the `All2AllIterative` model, on/off oscillations are avoided by tracking unstable turbines and switching them all off.

We hope the above recommendations will help you getting started with PyWake and enjoy exploring its flexibility in your own work. We are happy to receive any comments, suggestions and ideas for collaboration.

The PyWake Team

Updates log

PyWake 2.5 (February 15, 2023)

New Features and API changes

- PyWake conda package available. Install by `conda install -c https://conda.windenergy.dtu.dk/channel/open py_wake`
- Before `RotorAvgModel` was an input to the WindFarmModel. This is ambigious as the rotor average models may be applied to both wake deficit, blockage deficit and turbulence. Instead the `RotorAvgModel` is now an input option to `WakeDeficitModel`, `BlockageDeficitModel` and `TurbulenceModel`
- Before the an area overlapping rotor average model was integrated into the `NOJDeficit` Model. These models have now been separated. The default behaviour is unchanged as the default rotor average model of `NOJDeficit` is set to `AreaOverlapAvgModel`
- The `IEA37SimpleBastankhahGaussian` wind farm model is deprecated. Please use the `IEA37CaseStudy1` model from py_wake.literature.iea37_case_study1 instead
- Notebook with verification of the TurbOPark model from Ørsted
- New netcdf-based Fuga look-up table format. The function `dat2netcdf` py_wake.utils.fuga_utils can be used to convert files from the old deprecated format to the new format.
- Wind turbine positions may now depend on wind direction and wind speed (e.g. floating wind turbines or multirotors)
- Before `All2AllIterative` took an input `initialize_with_PropagateDownwind` which defaulted to True to decide whether the effective wind speed in `All2AllIterative` should start with the free stream value or the effective wind speed computed by `PropagateDownwind` (i.e. without blockage). This input has been replaced with the optional input argument `WS_eff`. If `WS_eff=None` (default) then the initial effective wind speed is obtained from `PropagateDownwind`. Alternatively, the initial effective wind speed can be set to the free wind by `WS_eff=0` or directly to a custom value by `WS_eff=effective wind speed`. Note, however, that bypassing some iterations by setting the "correct" effective wind speed may result in wrong gradients
- `All2AllIterative` will now return after first iteration if `convergence_tolerance` is set to `None`. This only makes sense if CT and the deficit are independent of the effective wind speed, like the IEA37CaseStudy1 setup.
- The default behaviour of `StraightDistance` is now to use the reference wind direction

- New method to avoid deficit and turbulence from wind turbines on themselves. This allows flow maps without discontinuties at the wind turbines
- New `InputModifierModel` type that capable of modifying inputs before or during the simulations. This enables simulation of multirotor and floating wind turbines

New models and functions

- DeficitModels
  - FugaMultiLUTDeficit, which allows different wind turbine types
  - XRDeficitModel for deficit models based on xarray.dataarray look-up table (with linear interpolation)
- RotorAvgModels
  - GaussianOverlap. The model is based on a lookup table with numerically integrated overlap factors based on normalized input of downstream rotor diamter and crosswind distance.
- TurbulenceModels
  - XRTurbulenceModel for turbulence models based on xarray.dataarray look-up table (with linear interpolation)
- Predefined WindFarmModels
  - TurbOPark. A setup very similar to the original Ørsted implementation
- InputModifierModels
  - MultiRotor. Model to change the position of the rotors on a multirotor wind turbine depending on the wind direction
- ISONoiseModel. Simple noise propagation model, see https://topfarm.pages.windenergy.dtu.dk/PyWake/notebooks/Noise.html
- InputModifierModel. New model type that allows to modify inputs before or during the simulations. This allows multirotor
- Functions
  - New `circular` method in py_wake.utils.layouts to generate circular layouts

Bug fixes

- Fix a bug in `WindFarmModel.aep` that ignored the `n_cpu`, `wd_chunks` and `ws_chunks` arguments and always computed on only one CPU.
- Fix `NOJLocalDeficit`. Before a layout term was precalculated, but in the local version this term depends on the effective TI which was unknow at this stage
- Fix error `ModuleNotFoundError: No module named 'xarray.plot.plot'` occurring with newer version of xarray
- Fix parallel executino with FugaDeficit
- and many more

PyWake 2.4 (July 6, 2022)

New features and API changes

- Before, the `Mirror` ground model used linear superposition of the above- and below-ground wind turbines while `MirrorSquaredSum` used squared sum. In this version the `MirrorSquaredSum` has been removed and `Mirror` is now using the superposition model of the wind farm model to calculate the sum. I.e. `Mirror` behaves as before if the superposition model is `LinearSum` and as the previuos `MirrorSquaredSum` if the superposition model is `SquaredSum`.
- Easy chunkification and parallelization via the arguments `n_cpu`, `wd_chunks` and `ws_chunks`, see https://topfarm.pages.windenergy.dtu.dk/PyWake/notebooks/RunWindFarmSimulation.html#Chunkification-and-parallelization and https://topfarm.pages.windenergy.dtu.dk/PyWake/notebooks/Optimization.html#Chunkify-and-Parallelization.
- Change dAEPdxy to automatically compute gradients of aep wrt. the concatenated list of x,y which is faster than computing first wrt. x then y.
- `py_wake.utils.layouts` contains functions to create rectangular and square wind turbine layouts.
- New approach to switch numpy backend (used when switching to `autograd.numpy`, `Numpy32` (see below, etc.). The new approach requires all modules to import np from py_wake, i.e. `from py_wake import np`.
- Easy way to switch between double presicion (standard numpy) and single precision (`Numpy32`), see https://topfarm.pages.windenergy.dtu.dk/PyWake/notebooks/gradients_parallellization.html#Precision.
- New function `floris_yaml_to_pywake_turbine` (see https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake/-/blob/master/py_wake/utils/floris_wrapper.py). This function creates a PyWake WindTurbine object from a Floris wind turbine yaml file and allows more direct comparison.
- Previuosly, `LocalWind` (returned by `site.localWind`) was an xarray `Dataset` subclass. Due to issues with autograd and cupy, this has been changed such that `LocalWind` is now a `dict` subclass with numpy arrays, `{'WS_ilk': np.array([...])}`. Xarray DataArrays are created by `LocalWind` when requesting attributes without `_ilk`, e.g. `localWind.WS`.
- Long list of bug and issue fixes.

New models

- RotorAvgModels
  - New WSPowerRotorAvg, which computes the rotor average deficit by, $deficit = WS - \sqrt[\alpha]{\frac{1}{N}\sum_i (WS - deficit_i)^\alpha}$. Note that `WS` is the rotor center wind speed and thus shear and terrain-dependent inflow variation are not taken into account when computing the rotor average deficit.
- Power/Ct functions
  - New `DensityCompensation` which scales the wind speed wrt. air density. In most cases this model is more realistic than the existing alternative model, `DensityScale`, which scales the

power and ct wrt. air density.

PyWake 2.3 (March 18, 2022)

New features and API changes

- `GroundModel` is now an input to `DeficitModel` instead of `WindFarmModel`. This means that a ground model can be applied to the blockage or wake, only.
- PyWake can now compute gradients via finite differnece, complex step and automatic differentiation, see https://topfarm.pages.windenergy.dtu.dk/PyWake/notebooks/gradients_parallelization.html#Gradients. Most models supports all three methods, while a few do not work yet.
- Flow maps can be computed in both the vertical downwind and crosswind plane.

New models

- WakeDeficitModels
  - CarbajofuertesGaussianDeficit
  - TurboNOJDeficit
  - TurboGaussianDeficit
- BlockageDeficitModels
  - RathmannScaled
- DeflectionModels
  - GCLHillDeflection
  - JimenezWakeDeflection (extended with vertical deflection due to rotor tilt)
- WeightModels (to be used with the STF2005 and STF2017 TurbulenceModels)
  - FrandsenWeight (the previous implementation)
  - IECWeight (weight as specified in the IEC standard)
- SiteModels
  - GlobalWindAtlasSite (site with data from online global wind atlas)
  - DistanceModels
    - JITStreamlineDistance (compute distances between wind turbines along streamlines)
  - ShearModels
    - LogShear

PyWake 2.2 (March 26, 2021)

New features and API changes

- All DeficitModels should inherit either `WakeDeficitModel` or `BlockageDeficitModel`.
- All Sites are now subclasses of XRSite.

- WeightedSum SuperpositionModel reimplemented to be more efficient.
- TurbulenceModels now take a RotorAvgModel as optional input. This allows PyWake to use different RotorAvgModels for wake and turbulence.
- Validation feature updated, see here.
- The Power/Ct curve functionality of `WindTurbines` has been updated to support multidimensional Power and Ct curves, e.g. curves depending on turbulence intensity, air density, yaw misalignment, operational mode etc. This means that instantiating `WindTurbines` and `OneTypeWindTurbines` with the old set of arguments, i.e. `name, diameter, hub_height, ct_func, power_func, power_unit`, is deprecated. Use the the new `WindTurbine` and `Windturbines` classes with the arguments `name, diameter, hub_height, powerCtFunction` instead, see here. Backward compatibility is ensured (with runtime warning) for most use cases. The `powerCtFunction` can be one of the classes from py_wake.wind_turbines.power_ct_functions, i.e.
  - `PowerCtFunction`
  - `PowerCtTabular`
  - `PowerCtFunctionList`
  - `PowerCtNDTabular`
  - `PowerCtXr`
  - `CubePowerSimpleCt`
- Support for time series of wd and ws, see here. Possible use cases:
  - Time-dependent inflow, e.g. measurements of wd, ws, ti, shear, density, etc.
  - Time-dependent operation, e.g. periods of failure or maintaince of a wind turbine
- Added support for load surrogates to predict wind turbine loads.

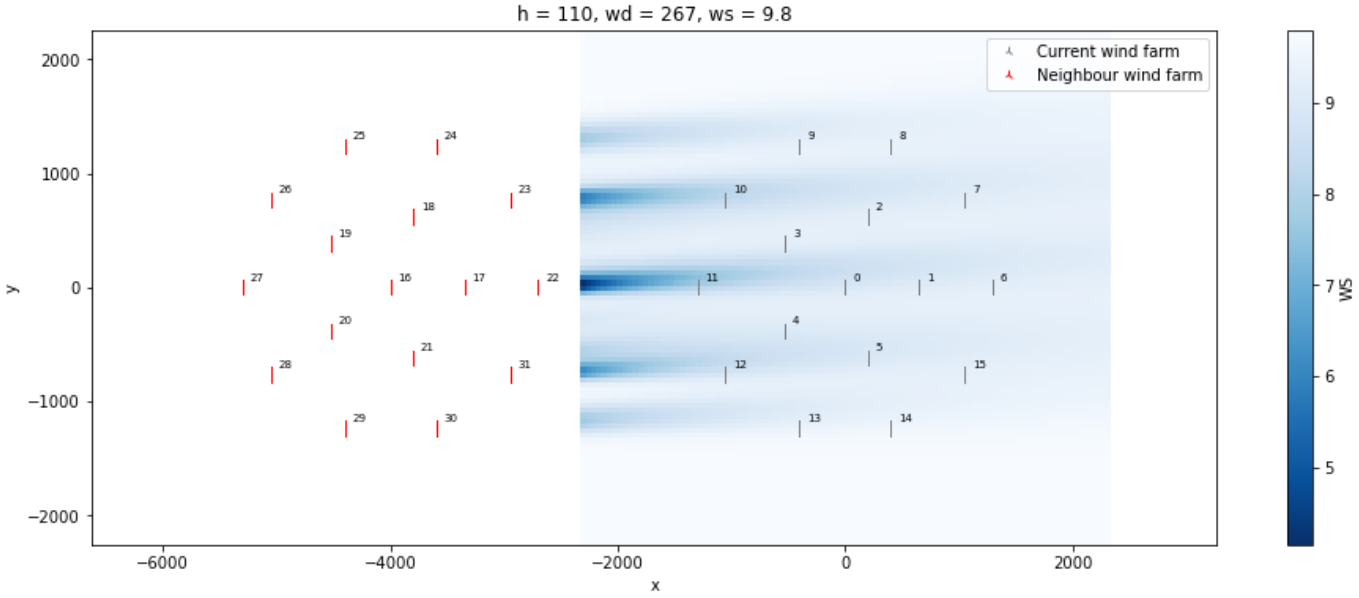
New models

- BlockageDeficitModels (see here)
  - SelfSimilarityDeficit2020
  - HybridInduction
  - RankineHalfBody
  - VortexCylinder
  - VortexDipole
  - Rathmann
- DeflectionModels
  - FugaDeflection (requires Fuga look-up tables, `UL`, `UT`, `VL`, `VT`)
- GroundModels
  - Mirror
  - MirrorSquaredSum

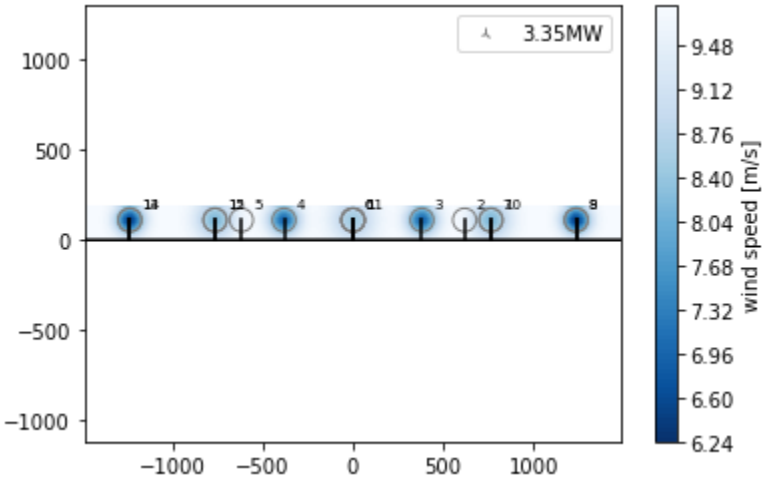
PyWake 2.1 (September 14, 2020)

New features and API changes

- New xarray data structure
  - LocalWind, SimulationResult and FlowMap are now `xarray.Dataset`-objects with some additional methods and attributes.
  - `simulationResult.aep()` now returns a `xarray.DataArray` with aep for all wind turbines, wind directions and wind speeds. To get the total AEP as before, use `simulationResult.aep().sum()`.
  - New general XRSite where the site is defined as an xarray with the following structure:
    - Required data variables:
      - P(probability) or f(sector frequency), A(Weibull scale), k(Weibull shape)
    - Optional data variables:
      - WS(defaults to reference wind speed, ws), TI(turbulence intensity), SpeedUp, Turning
    - All data variables may be constant or dependent on any of:
      - ws (reference wind speed)
      - wd (reference wind direction)
      - position in terms of
        - gridded 2D position, (x,y)
        - gridded 3D position, (x,y,z)
        - wt position, (i)
- Include effects of neighbouring wind farms in site (wind resource) to speed up optimization of a wind farm with neighbouring farms.



- Vertical flow map via the YZGrid.



New models

- New `RotorAverageModel`, see here. The default model, `RotorCenter`, behaves as before as it estimates the rotor-average wind speed from the wind speed at the rotor center. Other models, however, provide a more accurate estimate based on multiple points on the cost of computation. The `CGIRotorAvg(4)` and `CGIRotorAvg(7)` with 4 and 7 points, respectively, provide good compromises between accuracy and computational cost.
- Deficit model:
  - GCLDeficit: The Gunner Larsen semi-analytical wake model.
- Superposition model:
  - WeightedSum A weighted sum approach taking wake convection velocity into account. The model is so far only applicable to the gaussian models. The model is based on “A momentum-conserving wake superposition method for wind farm power prediction” by Haohua Zong and Fernando Porté-Agel, J. Fluid Mech. (2020), vol. 889, A8; doi:10.1017/jfm.2020.77.

PyWake 2.0 (April 15, 2020)

- New structure
  - Purpose:
    - Easier combination of different models for flow propagation, wake and blockage deficit, superposition, wake deflection and turbulence.
    - More consistent interface to and support for engineering models and PyWake-Rans.
  - Changes
    - `WakeModel` class refactored mainly into the `WindFarmModel`s `EngineeringWindFarmModel` and `PropagateDownwind`.
    - `WindFarmModel`s, e.g. `NOJ`, `Fuga`, `BastankhahGaussian` returns a `SimulationResult` containing the results as well as an AEP and a flow_map method. See the QuickStart tutorial,
    - and many more.
  - Backward compatibility
    - AEP Calculator works as before, but is now deprecated.

    - Lower level interfaces and implementations has changed.
- New documentation matching the new structure.
- Optional blockage deficit models and implementation of the SelfSimilarity model.
- Optional wake deflection models and implementation of a model by Jimenez.

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Publications

If you want to cite PyWake, please use this citation:

Version 2.5.0

```
Mads M. Pedersen, Alexander Meyer Forsting, Paul van der Laan, Riccardo Riva, Leonardo A. Alcayaga Romàn, Javier Criado Risco, Mikkel Friis-Møller,
PyWake 2.5.0: An open-source wind farm simulation tool. DTU Wind, Technical University of Denmark.
```

```
@article{
    pywake2.5.0_2023,
    title={PyWake 2.5.0: An open-source wind farm simulation tool},
    author={Mads M. Pedersen, Alexander Meyer Forsting, Paul van der Laan, Riccardo Riva, Leonardo A. Alcayaga Romàn, Javier Criado Risco, Mikkel F
    url="https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake",
    publisher={DTU Wind, Technical University of Denmark},
    year={2023},
    month={2}
}
```

Scientific articles

- Fischereit, J., Schaldemose Hansen, K., Larsén, X. G., van der Laan, M. P., Réthoré, P.-E., and Murcia Leon, J. P.: Comparing and validating intra-farm and https://doi.org/10.5194/wes-7-1069-2022, 2022.
- Nyborg, C. M., Fischer, A., Réthoré, P.-E., and Feng, J.: Optimization of wind farm operation with a noise constraint, Wind Energ. Sci. Discuss. [preprint]
- Meyer Forsting A., Rathmann O. S., van der Laan M. P., Troldborg N., Gribben B., Hawkes G., Branlard E. (2021). Verification of induction zone models f 6596/1934/1/012023
- Riva, R., Liew, J., Friis-Møller, M., Dimitrov, N., Barlas, E., Réthoré, P-E., Beržonskis, A. (2020). Wind farm layout optimization with load constraints usin (Online) https://doi.org/10.1088/1742-6596/1618/4/042035
- Krabben, I. G. W., van der Laan, M. P., Koivisto, M. J., Larsen, T. J., Pedersen, M. M., & Hansen, K. S. (2019). Why curved wind turbine rows are better th Series (Online) https://doi.org/10.1088/1742-6596/1256/1/012028
- Vitulli, J. A., Larsen, G. C., Pedersen, M. M., Ott, S., & Friis-Møller, M. (2019). Optimal open loop wind farm control. In Proceedings of the Wake Confer 6596/1256/1/012027
- M.P. van der Laan et al. (2019) Brief communication: Wind speed independent actuator disk control for faster AEP calculations of wind farms using CF

Master thesis

- Patrick Arthur Redmond Duffy (2019). Effect of wind speed gradients on AEP in a wind farm cluster https://repository.tudelft.nl/islandora/object/uuid:

Presentations

- Arconada, J. O. (Author), Réthoré, P-E. (Author), Hasager, C. B. (Author), Bech, J. I. (Author), Friis-Møller, M. (Author), Pedersen, M. M. (Author), ... Skrzy
- Mads Mølgaard Pedersen, & Gunner Chr. Larsen. (2019, August). 2.5a_Pedersen: The influence of wind farm control on optimal wind farm layout. Zen

Other

- van der Laan, P., Andersen, S. J., & Réthoré, P-E. (2019). Brief communication: Wind speed independent actuator disk control for faster AEP calculatior

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Quickstart

In this tutorial, the basic capabilities of PyWake are shown. Essentially, how to calculate a wind farm's AEP using the wind farm simulation tool and how to flow maps is also shown.

Install PyWake if needed

[1]:
```
# Install PyWake if needed
try:
    import py_wake
except ModuleNotFoundError:
    !pip install git+https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake.git
```

Import and set up of wind turbines, site, and flow model

There are many sites and wind turbines available in PyWake, some of them include:

- Hornsrev1 offshore wind farm
- Lillgrund offshore wind farm
- IEA Task 37 Site land-based wind farm
- Vestas V80 turbine
- IEA 3.4 MW turbine
- DTU 10MW reference turbine

For detailed information on the sites and wind turbine object features, please see the Site and Wind turbine examples.

[2]:
```
from py_wake.examples.data.hornsrev1 import Hornsrev1Site, V80, wt_x, wt_y, wt16_x, wt16_y
from py_wake import NOJ

#here we import the turbine, site and wake deficit model to use.
windTurbines = V80()
site = Hornsrev1Site()
noj = NOJ(site,windTurbines)
```

```
/builds/TOPFARM/PyWake/py_wake/deficit_models/noj.py:88: UserWarning: The NOJ model is not representative of the setup used in the literature.
  DeprecatedModel.__init__(self, 'py_wake.literature.noj.Jensen_1983')
```

Now we run the model using the initial positions of the wind farm

For more information about the `SimulationResult` object and the paratemers included, please see the wind farm simulation example.

[3]:
```
simulationResult = noj(wt16_x,wt16_y)
```

To calculate the AEP, we use the **simulationResult.aep()** command. This will show an xarray with the characteristics of the site, including the number of tu addition, it will show the AEP of each turbine for each flow case.

[4]:
```
simulationResult.aep()
```

[4]:
xarray.DataArray 'AEP [GWh]' (**wt**: 16, **wd**: 360, **ws**: 23)

Coordinates:

Indexes: (3)

Attributes:

To obtain the total AEP, we use the **.sum()** command.

[5]:
```
print ("Total AEP: %f GWh"%simulationResult.aep().sum())
```

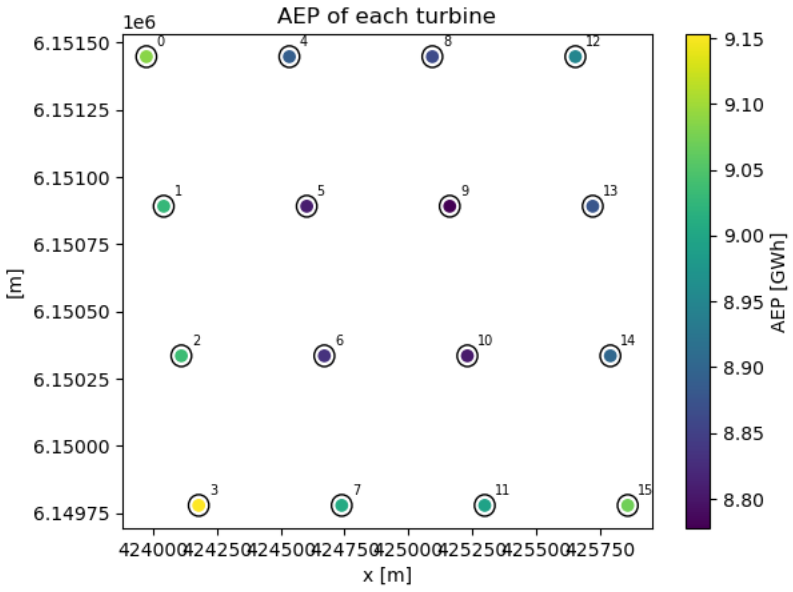
```
Total AEP: 143.074909 GWh
```

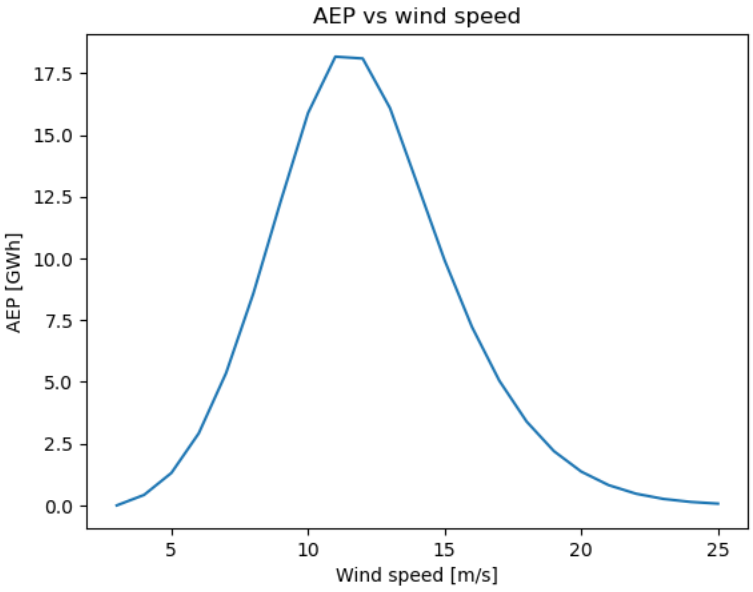
Plot AEP as function of wind turbines, wind direction and wind speed

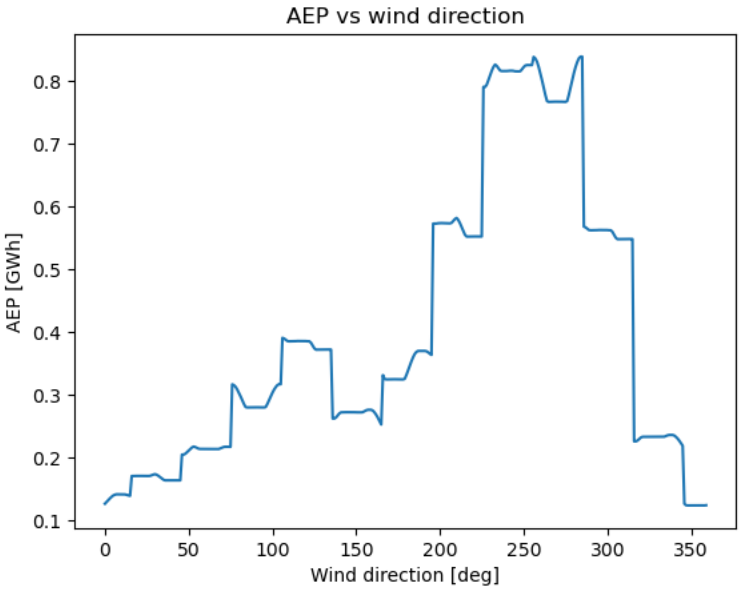
There is also the possibility of plotting the individual AEP for each turbine for the flow cases studied. In addition, the AEP can be plotted against either the

[6]:
```
import matplotlib.pyplot as plt
%matplotlib inline

plt.figure()
aep = simulationResult.aep()
windTurbines.plot(wt16_x,wt16_y)
c =plt.scatter(wt16_x, wt16_y, c=aep.sum(['wd','ws']))
plt.colorbar(c, label='AEP [GWh]')
plt.title('AEP of each turbine')
plt.xlabel('x [m]')
plt.ylabel('[m]')

plt.figure()
aep.sum(['wt','wd']).plot()
plt.xlabel("Wind speed [m/s]")
plt.ylabel("AEP [GWh]")
plt.title('AEP vs wind speed')

plt.figure()
aep.sum(['wt','ws']).plot()
plt.xlabel("Wind direction [deg]")
plt.ylabel("AEP [GWh]")
plt.title('AEP vs wind direction')
```

[6]: Text(0.5, 1.0, 'AEP vs wind direction')







Plot flow maps

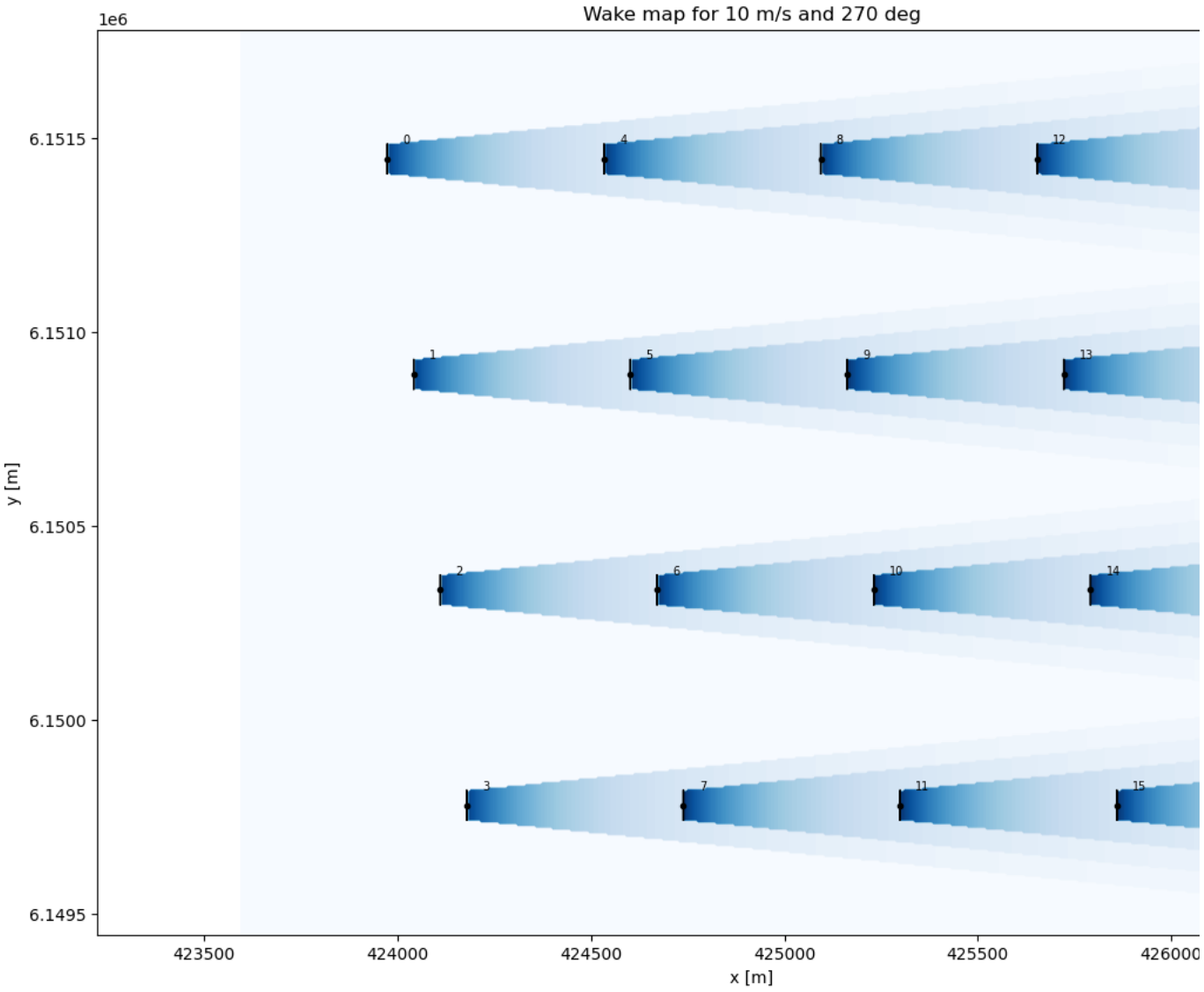
It is also possible to plot the wind farm wake map. This shows the wake behavior for each turbine given the flow cases studied.

You can change the values of the wind speed and wind direction to visualize the wake maps for different flow cases.

[7]:
```
wind_speed = 10
wind_direction = 270

plt.figure()
flow_map = simulationResult.flow_map(ws=wind_speed, wd=wind_direction)
plt.figure(figsize=(18,10))
flow_map.plot_wake_map()
plt.xlabel('x [m]')
plt.ylabel('y [m]')
plt.title('Wake map for' + f' {wind_speed} m/s and {wind_direction} deg')
```

[7]:
```
Text(0.5, 1.0, 'Wake map for 10 m/s and 270 deg')
```

```
<Figure size 640x480 with 0 Axes>
```



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Site Object

For a given position, reference wind speed (WSref) and wind direction (WDref), `Site` provides the local wind condition in terms of wind speed (WS), wind direction (WD), turbulence intensity (TI) and the probability of each combination of wind direction and wind speed. Furthermore, `Site` is responsible for calculating the down-wind, cross-wind and vertical distance between wind turbines (which in non-flat terrain is different from the straight-line distances).

Intall PyWake if needed

[1]:
```
# Install PyWake if needed
try:
    import py_wake
except ModuleNotFoundError:
    !pip install git+https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake.git
```

Predefined example sites

PyWake contains a few predefined sites of different complexities:

- **IEA37Site**: `UniformSite` (fix wind speed (9.8m/s), predefined wind sector probability).
- **Hornsrev1**: `UniformWeibullSite` (Weibull distributed wind speed, predefined wind sector propability, uniform wind a over flat wind area).
- **ParqueFicticioSite**: `WaspGridSite` (position-dependent Weibull distributed wind speed and sector probability. Terrain following distances over non-flat terrain). Loaded from a set of *.grd files exported from WAsP.

First we import all sites and Python elements for later use

[2]:
```
import numpy as np
import matplotlib.pyplot as plt
```

[3]:
```
from py_wake.examples.data.hornsrev1 import Hornsrev1Site
from py_wake.examples.data.iea37 import IEA37Site
from py_wake.examples.data.ParqueFicticio import ParqueFicticioSite

sites = {"IEA37": IEA37Site(n_wt=16),
         "Hornsrev1": Hornsrev1Site(),
         "ParqueFicticio": ParqueFicticioSite()}
```

PyWake also allows for user-defined sites

You can define your own site using one of the `Site` classes:

- UniformWeibullSite: Site with uniform sector-dependent Weibull distributed wind speed.
- WaspGridSite: Site with gridded non-uniform inflow based on *.grd files exported from WAsP.
- XRSite: The flexible general base class behind all Sites.

For more information on these classes, please see the API reference on the Site object.

UniformWeibullSite

[4]:
```
from py_wake.site import UniformWeibullSite

#specifying the necessary parameters for the UniformWeibullSite object
site = UniformWeibullSite(p_wd = [.20,.25,.35,.25],                          # sector frequencies
                          a = [9.176929,  9.782334,  9.531809,  9.909545],   # Weibull scale parameter
                          k = [2.392578, 2.447266, 2.412109, 2.591797],      # Weibull shape parameter
                          ti = 0.1                                           # turbulence intensity, optional
                         )
```

WaspGridSite

[5]:
```
from py_wake.site import WaspGridSite
from py_wake.examples.data.ParqueFicticio import ParqueFicticio_path
```

```
site = WaspGridSite.from_wasp_grd(ParqueFicticio_path)
```

XRSite

The `XRSite` is the most general and flexible `Site`. For the input dataset there are some required and optional data variables, such as:

- Required data variables:
  - `P`: probability of flow case(s)

  or

  - `Weibull_A`: Weibull scale parameter(s)
  - `Weibull_k`: Weibull shape parameter(s)
  - `Sector_frequency`: Probability of each wind direction sector
- Optional data variables:
  - `WS`: Wind speed, if not present, the reference wind speed `ws` is used
  - `Speedup`: Factor multiplied to the wind speed
  - `Turning`: Wind direction turning
  - `TI`: Turbulence intensity
  - xxx: Custom variables needed by the wind turbines to compute power, ct or loads
- Each data variable may be constant or depend on a combination of the following inputs (Note, the input variables must be ordered according to the list, i.e. `P(wd,ws)` is ok, while `P(ws,wd)` is not):
  - `i`: Wind turbine position (one position per wind turbine)
  - `x`, `y`: Gridded 2d position
  - `x`, `y`, `h`: Gridded 3d position
  - `time`: Time
  - `wd`: Refernce wind direction
  - `ws`: Reference wind speed

[6]:
```
from py_wake.site import XRSite
from py_wake.site.shear import PowerShear
import xarray as xr
import numpy as np
from py_wake.utils import weibull
from numpy import newaxis as na

f = [0.036, 0.039, 0.052, 0.07, 0.084, 0.064, 0.086, 0.118, 0.152, 0.147, 0.1, 0.052]
A = [9.177, 9.782, 9.532, 9.91, 10.043, 9.594, 9.584, 10.515, 11.399, 11.687, 11.637, 10.088]
k = [2.393, 2.447, 2.412, 2.592, 2.756, 2.596, 2.584, 2.549, 2.471, 2.607, 2.627, 2.326]
wd = np.linspace(0, 360, len(f), endpoint=False)
ti = .1

# Site with constant wind speed, sector frequency, constant turbulence intensity and power shear
uniform_site = XRSite(
    ds=xr.Dataset(data_vars={'WS': 10, 'P': ('wd', f), 'TI': ti},
                  coords={'wd': wd}),
    shear=PowerShear(h_ref=100, alpha=.2))

# Site with wind direction dependent weibull distributed wind speed
uniform_weibull_site = XRSite(
    ds=xr.Dataset(data_vars={'Sector_frequency': ('wd', f), 'Weibull_A': ('wd', A), 'Weibull_k': ('wd', k), 'TI': ti},
                  coords={'wd': wd}))

# Site with a speedup and a turning value per WT
x_i, y_i = np.arange(5) * 100, np.zeros(5)  # WT positions

complex_fixed_pos_site = XRSite(
    ds=xr.Dataset(
        data_vars={'Speedup': ('i', np.arange(.8, 1.3, .1)),
                   'Turning': ('i', np.arange(-2, 3)),
                   'P': ('wd', f)},
        coords={'i': np.arange(5), 'wd': wd}),
    initial_position=np.array([x_i, y_i]).T)

# Site with gridded speedup information
complex_grid_site = XRSite(
    ds=xr.Dataset(
        data_vars={'Speedup': (['x', 'y'], np.arange(.8, 1.4, .1).reshape((3, 2))),
                   'P': ('wd', f)},
```

```
        coords={'x': [0, 500, 1000], 'y': [0, 500], 'wd': wd}))

# Site with ws dependent speedup and wd- and ws distributed probability
P_ws = weibull.cdf(np.array([3, 5, 7, 9, 11, 13]), 10, 2) - weibull.cdf(np.array([0, 3, 5, 7, 9, 11]), 10, 2)
P_wd_ws = P_ws[na, :] * np.array(f)[:, na]

complex_ws_site = XRSite(
    ds=xr.Dataset(
        data_vars={'Speedup': (['ws'], np.arange(.8, 1.4, .1)),
                   'P': (('wd', 'ws'), P_wd_ws), 'TI': ti},
        coords={'ws': [1.5, 4, 6, 8, 10, 12], 'wd': wd}))
```

Wake effects from neighbouring wind farms

In some cases, calculation of wake interaction between the wind farm to optimize and neighbouring wind farms considerably slow down an optimization work flow. To avoid this, a site, which includes wake effects from neighbouring wind farms, can be pre-generated and used for the optimization.

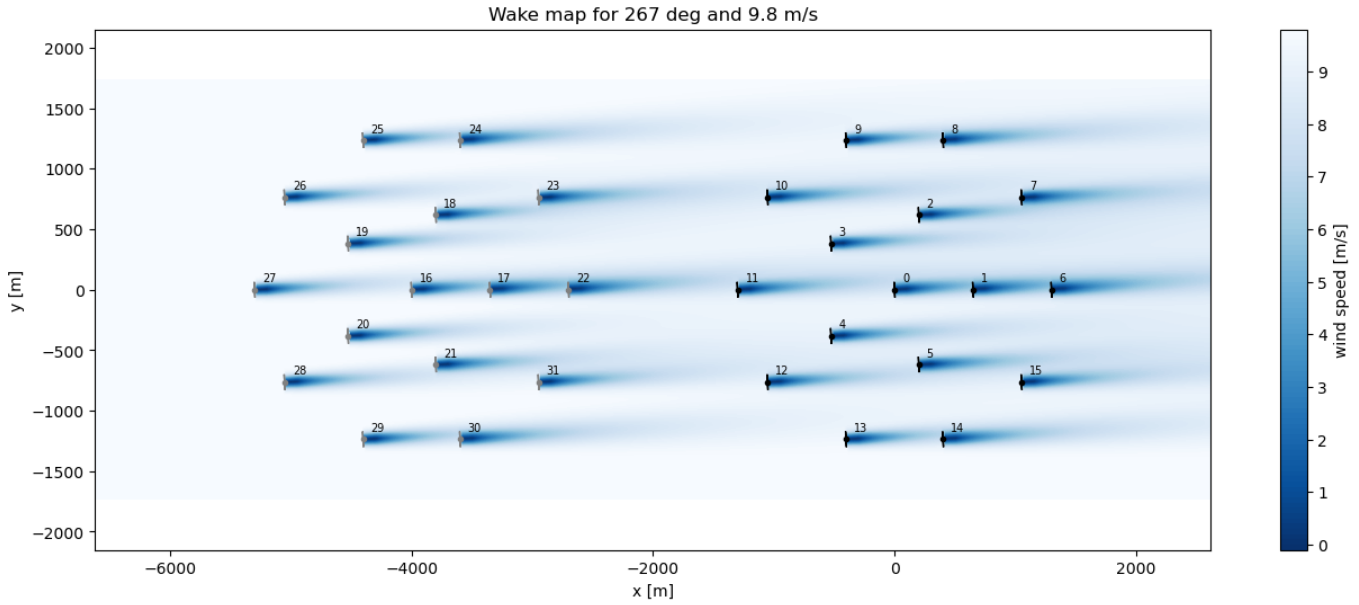
The speed up of this solution depends on the number of turbines in both the current and neighbouring wind farms, as well as the type of sites. If the original site is a uniform site, then a pre-generated site with wake effects from neighbouring wind farms may slow down the workflow as it adds interpolation of inflow characteristics in space.

Note also, that a pre-generated site with wake effects from neighbouring wind farms is only eqivalent to the full simulation if the applied deficit model uses the effective wind speed (some models have an option to switch between effective and free-stream local wind speed).

[7]:
```
# import and setup site and windTurbines
from py_wake.examples.data.iea37 import IEA37Site, IEA37_WindTurbines
from py_wake.deficit_models.gaussian import BastankhahGaussianDeficit
from py_wake.wind_turbines import WindTurbine, WindTurbines
from py_wake.wind_farm_models import PropagateDownwind
from py_wake.superposition_models import LinearSum

site = IEA37Site(16)

# setup current, neighbour and all positions
wt_x, wt_y = site.initial_position.T
neighbour_x, neighbour_y = wt_x-4000, wt_y
all_x, all_y = np.r_[wt_x,neighbour_x], np.r_[wt_y,neighbour_y]

windTurbines = WindTurbines.from_WindTurbine_lst([IEA37_WindTurbines(),IEA37_WindTurbines()])
windTurbines._names = ["Current wind farm","Neighbour wind farm"]
types = [0]*len(wt_x) + [1]*len(neighbour_x)

wf_model = PropagateDownwind(site, windTurbines,
                             wake_deficitModel=BastankhahGaussianDeficit(use_effective_ws=True),
                             superpositionModel=LinearSum())

# Consider wd=270 +/- 30 deg only
wd_lst = np.arange(240,301)
```

[8]:
```
#plotting the wake maps for the desired flow case
wsp = 9.8
wdir = 267

plt.figure(figsize=(16, 6))
wf_model(all_x, all_y, type=types, wd=wdir, ws=wsp, h=110).flow_map().plot_wake_map()
plt.xlabel('x [m]')
plt.ylabel('y [m]')
plt.title('Wake map for'+ f' {wdir} deg and {wsp} m/s')
```

[8]:
```
Text(0.5, 1.0, 'Wake map for 267 deg and 9.8 m/s')
```



Now, we run the simulation of all wind turbines and calculate AEP of current wind farm

[9]:
```
print("Total AEP: %f GWh"%wf_model(all_x, all_y, type=types, ws=[wsp], wd=wd_lst).aep().isel(wt=np.arange(len(wt_x))).sum())
```

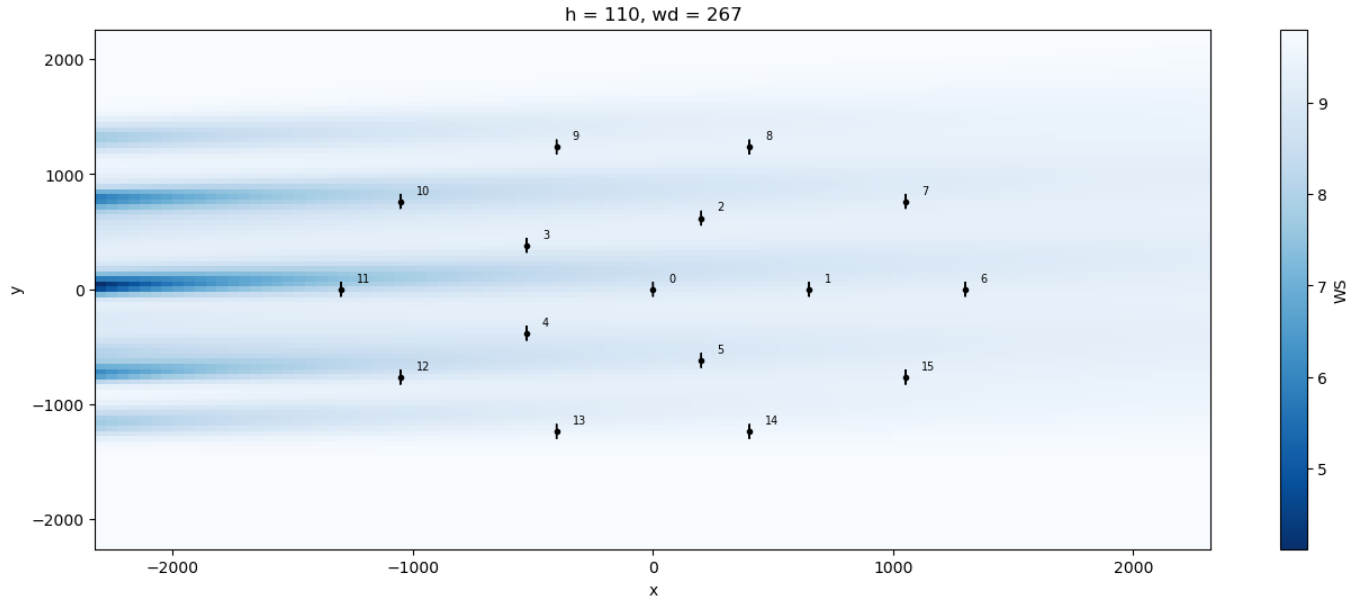
```
Total AEP: 85.187662 GWh
```

We can also calculate the AEP of the current wind farm by enclosing it in a flow box and setting up a new wind farm model

[10]:
```
#making a flow box covering the area of interest (i.e the current wind farm + 100m)

ext = 1000
flow_box = wf_model(neighbour_x, neighbour_y, wd=wd_lst).flow_box(
    x=np.linspace(min(wt_x) - ext, max(wt_x) + ext, 101),
    y=np.linspace(min(wt_y) - ext, max(wt_y) + ext, 101),
    h=110)

#creating new site based on the flow box

from py_wake.site.xrsite import XRSite
wake_site = XRSite.from_flow_box(flow_box)
```

Now, we plot the “free-stream” inflow wind speed of the current wind farm.

[11]:
```
plt.figure(figsize=(16, 6))
wake_site.ds.WS.sel(wd=267).plot(y='y', cmap = 'Blues_r')
windTurbines.plot(all_x, all_y, types, wd=270)
```



Then, we setup a new wind farm model with the new pre-generated site and calculate the AEP.

[12]:
```
wf_model_wake_site = PropagateDownwind(wake_site, windTurbines,
                                       wake_deficitModel=BastankhahGaussianDeficit(use_effective_ws=True),
                                       superpositionModel=LinearSum())
```

[13]:
```
print("Total AEP: %f GWh"%wf_model_wake_site(wt_x, wt_y, ws=[wsp], wd=wd_lst).aep().sum())
```

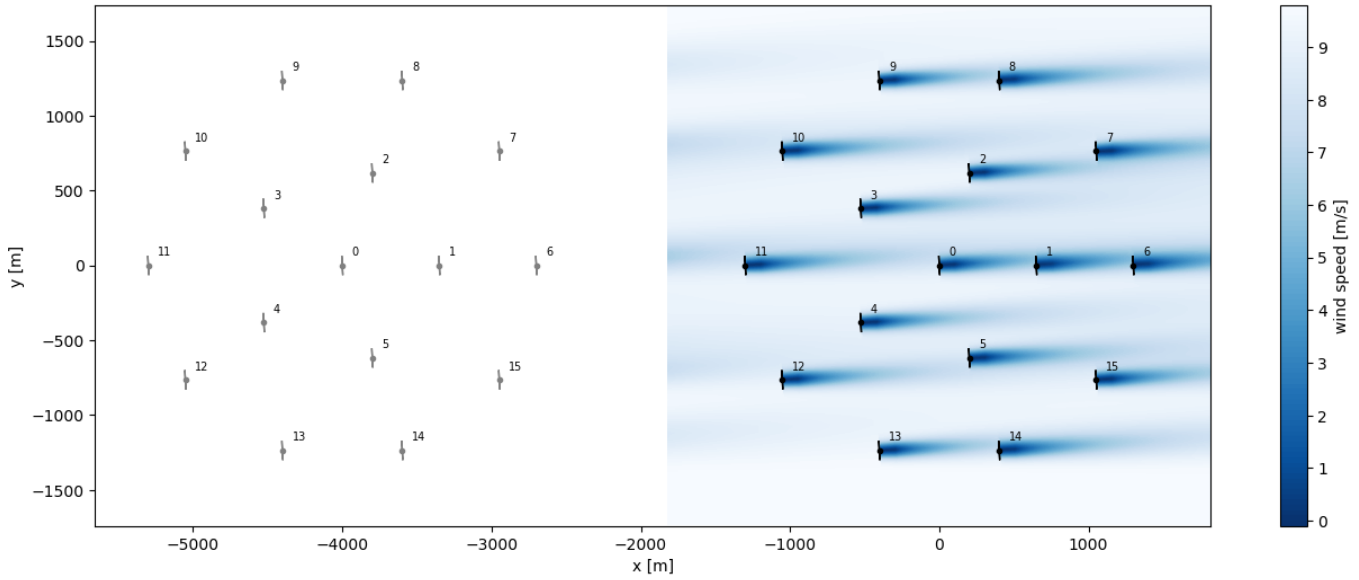
```
Total AEP: 85.187032 GWh
```

Note that the AEP is not exactly equal due to interpolation errors. The discrepancy can be lowered by increasing the resolution of the flow box.

Lastly, we plot the flow map of the current wind farm with the selected flow box.

[14]:
```
plt.figure(figsize=(16, 6))
wf_model_wake_site(wt_x, wt_y, wd=wdir, ws=wsp, h=110).flow_map().plot_wake_map()
windTurbines.plot(neighbour_x, neighbour_y, type=1, wd=wdir)
plt.xlabel('x [m]')
plt.ylabel('y [m]')
```

[14]:
```
Text(0, 0.5, 'y [m]')
```



Local wind

The method `local_wind` is used to calculate the local wind in a wind farm given certain turbine positions or coordinates. The class returns a `LocalWind`-dictionary.

[15]:
```
localWinds = {name: site.local_wind(x=site.initial_position[:,0],          # x position
                                    y = site.initial_position[:,1],        # y position
                                    h=site.initial_position[:,0]*0+70,     # height
                              ws=None,                                       # defaults to 3,4,..,25
                              wd=None,                                       # defaults to 0,1,...,360
                              ) for name, site in sites.items()}
```

`LocalWind.coords` contains the current coordinates, e.g.:

- i: Point number. Points can be wind turbine position or just points in a flow map
- wd: Ambient reference wind direction
- ws: Ambient reference wind speed
- x,y,h: position and height of points

while the dictionary itself contains some data variables:

- WD: Local wind direction
- WS: Local wind speed
- TI: Local turbulence intensity
- P: Probability of flow case (wind direction and wind speed)

The `IEA37` site has 16 wind turbines on a uniform site with a fixed wind speed of 9.8 m/s and the data variables therefore only depend on wind direction.

[16]:
```
print (localWinds['IEA37'].coords.keys())
localWinds['IEA37'].P
```

```
dict_keys(['wd', 'ws', 'i', 'x', 'y', 'h'])
```

[16]:

xarray.DataArray (**wd**: 360)

Coordinates:

Indexes: (1)

Attributes:

The `Hornsrev1` site has 80 wind turbines on a uniform site and the data variables therefore depend on wind direction and wind speed.

[17]:
```
localWinds['Hornsrev1'].P
```

[17]:

xarray.DataArray (**wd**: 360, **ws**: 23)

Coordinates:

Indexes: (2)

Attributes:

Finally, the `ParqueFicticio` site has 8 turbines in a complex terrain and the data variables therefore depend on wind direction, wind speed, and position.

[18]:
```
localWinds['ParqueFicticio'].P
```

[18]:

xarray.DataArray (**i**: 8, **wd**: 360, **ws**: 23)

Coordinates:

Indexes: (3)

Attributes:

Wind speeds at the wind turbines for reference wind speed of 3m/s (k=0):

- `IEA37`: Constant wind speed of **9.8m/s**
- `Hornsrev1`: Constant wind speed over the site, **3 m/s**
- `ParqueFicticio`: Winds speed depends on both wind direction and position

[19]:
```
for name, lw in localWinds.items():
    print (name)
    print (lw.WS.values, 'm/s')
    print ("="*100)
```

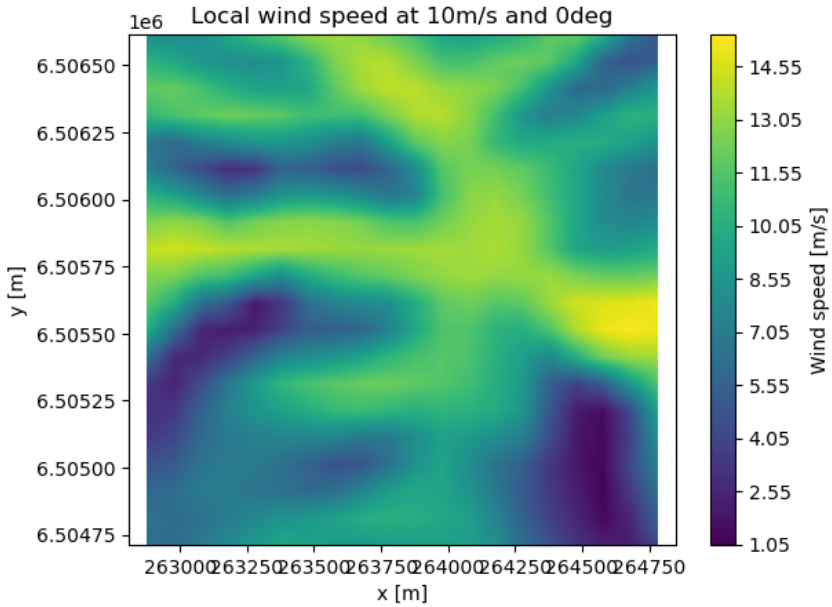
```
IEA37
9.8 m/s
====================================================================================================
Hornsrev1
[ 3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25] m/s
====================================================================================================
ParqueFicticio
[[[ 3.78471012  5.04628015  6.30785019 ... 29.01611089 30.27768093
   31.53925096]
```

```
 [ 3.80282588  5.07043451  6.33804314 ... 29.15499845 30.42260708
  31.69021571]
 [ 3.82094165  5.09458887  6.36823609 ... 29.29388601 30.56753323
  31.84118045]
 ...
 [ 3.73730114  4.98306819  6.22883524 ... 28.6526421  29.89840915
  31.1441762 ]
 [ 3.75310413  5.00413885  6.25517356 ... 28.77379836 30.02483307
  31.27586779]
 [ 3.76890713  5.0252095   6.28151188 ... 28.89495463 30.151257
  31.40755938]]

[[ 3.95569235  5.27425647  6.59282059 ... 30.3269747  31.64553882
  32.96410294]
 [ 3.97160588  5.29547451  6.61934314 ... 30.44897845 31.77284708
  33.0967157 ]
 [ 3.98751942  5.31669256  6.64586569 ... 30.5709822  31.90015533
  33.22932847]
 ...
 [ 3.9194794   5.22597253  6.53246567 ... 30.04934207 31.35583521
  32.66232834]
 [ 3.93155038  5.24206718  6.55258397 ... 30.14188628 31.45240308
  32.76291987]
 [ 3.94362137  5.25816182  6.57270228 ... 30.23443049 31.54897095
  32.8635114 ]]

[[ 3.54177811  4.72237081  5.90296351 ... 27.15363216 28.33422487
  29.51481757]
 [ 3.56318035  4.75090714  5.93863392 ... 27.31771603 28.50544282
  29.6931696 ]
 [ 3.5845826   4.77944346  5.97430433 ... 27.4817999  28.67666076
  29.87152163]
 ...
 [ 3.53682328  4.71576437  5.89470547 ... 27.11564514 28.29458624
  29.47352733]
 [ 3.53847489  4.71796652  5.89745815 ... 27.12830748 28.30779911
  29.48729074]
 [ 3.5401265   4.72016867  5.90021083 ... 27.14096982 28.32101199
  29.50105416]]

...

[[ 3.38782152  4.51709536  5.6463692  ... 25.97329831 27.10257215
  28.23184598]
 [ 3.39601996  4.52802661  5.66003327 ... 26.03615302 27.16815968
  28.30016633]
 [ 3.4042184   4.53895787  5.67369734 ... 26.09900774 27.23374721
  28.36848668]
 ...
 [ 3.41634561  4.55512748  5.69390936 ... 26.19198304 27.33076491
  28.46954678]
 [ 3.40683758  4.54245011  5.67806264 ... 26.11908813 27.25470065
  28.39031318]
 [ 3.39732955  4.52977273  5.66221592 ... 26.04619322 27.1786364
  28.31107958]]

[[ 2.90165596  3.86887461  4.83609327 ... 22.24602903 23.21324768
  24.18046634]
 [ 2.90889396  3.87852528  4.8481566  ... 22.30152035 23.27115167
  24.24078299]
 [ 2.91613196  3.88817594  4.86021993 ... 22.35701167 23.32905566
  24.30109964]
 ...
 [ 2.93079949  3.90773265  4.88466582 ... 22.46946275 23.44639592
  24.42332908]
 [ 2.92108498  3.89477997  4.86847497 ... 22.39498485 23.36867984
  24.34237483]
 [ 2.91137047  3.88182729  4.85228412 ... 22.32050694 23.29096376
  24.26142059]]

[[ 2.93723526  3.91631367  4.89539209 ... 22.51880362 23.49788204
  24.47696046]
 [ 2.94254094  3.92338792  4.9042349  ... 22.55948056 23.54032754
  24.52117452]
 [ 2.94784663  3.93046217  4.91307772 ... 22.6001575  23.58277304
  24.56538859]
 ...
 [ 2.97948279  3.97264372  4.96580465 ... 22.84270139 23.83586232
  24.82902325]
 [ 2.96540028  3.95386704  4.9423338  ... 22.73473547 23.72320223
  24.71166898]
 [ 2.95131777  3.93509036  4.91886294 ... 22.62676954 23.61054213
  24.59431472]]] m/s
```

The ParqueFicticio site models variations within the site, so the local wind speed varies over the area.

[20]:
```
s = sites["ParqueFicticio"]
x = np.linspace(262878,264778,300)
y = np.linspace(6504714,6506614,300)
X,Y = np.meshgrid(x,y)
lw = s.local_wind(X.flatten(),Y.flatten(),30, ws=[10],wd=[0])
Z = lw.WS_ilk.reshape(X.shape)
c = plt.contourf(X,Y,Z, levels=100)
plt.colorbar(c,label='Wind speed [m/s]')
plt.title("Local wind speed at 10m/s and 0deg")
plt.xlabel('x [m]')
plt.ylabel('y [m]')
plt.axis('equal')
```

[20]: (262878.0, 264778.0, 6504714.0, 6506614.0)



Distance

We can also calculate the distance between points of a specific site for either flat or complex terrain.

For the `IEA37Site` and the `Hornsrev1` sites the distances between points are straight line distances, as these sites are characterized by flat terrain.

For the `ParqueFicticioSite`, on the other hand, the down-wind distance is larger as it follows the non-flat terrain.

[21]:
```
wd = [0, 30,90] # wind direction at source

for name, site in sites.items():
    print ("------- %s -------"%name)
    wt_x, wt_y = site.initial_position[0]
    site.distance.setup(src_x_ilk=[wt_x, wt_x], src_y_ilk=[wt_y, wt_y-1000], src_h_ilk=[70,90], src_z_ilk=[0,0]) # wt2 1000m to the south
    dw_ijlk, cw_ijlk, dh_ijlk = site.distance(wd_l=wd, src_idx=[0], dst_idx=[[1,1,1]])


    print ('Wind direction: \t\t%d deg\t\t%d deg\t\t%d deg'%tuple(wd))
    print ('Down wind distance [m]: \t%.1f\t\t%.1f\t\t%.1f'%tuple(dw_ijlk[0,0,:,0]))
    print ('Cross wind distance [m]: \t%.1f\t\t%.1f\t\t%.1f'%tuple(cw_ijlk[0,0,:,0]))
    print ('Height difference [m]: \t\t%.1f\t\t%.1f\t\t%.1f'%tuple(dh_ijlk[0,0,:,0]))
    print()
```

```
------- IEA37 -------
Wind direction:                 0 deg           30 deg          90 deg
Down wind distance [m]:         1000.0          866.0           0.0
Cross wind distance [m]:        0.0             500.0           1000.0
Height difference [m]:          20.0            20.0            20.0

------- Hornsrev1 -------
Wind direction:                 0 deg           30 deg          90 deg
Down wind distance [m]:         1000.0          866.0           0.0
Cross wind distance [m]:        0.0             500.0           1000.0
Height difference [m]:          20.0            20.0            20.0

------- ParqueFicticio -------
Wind direction:                 0 deg           30 deg          90 deg
Down wind distance [m]:         1023.6          886.5           -0.0
Cross wind distance [m]:        0.0             500.0           1000.0
Height difference [m]:          20.0            20.0            20.0
```

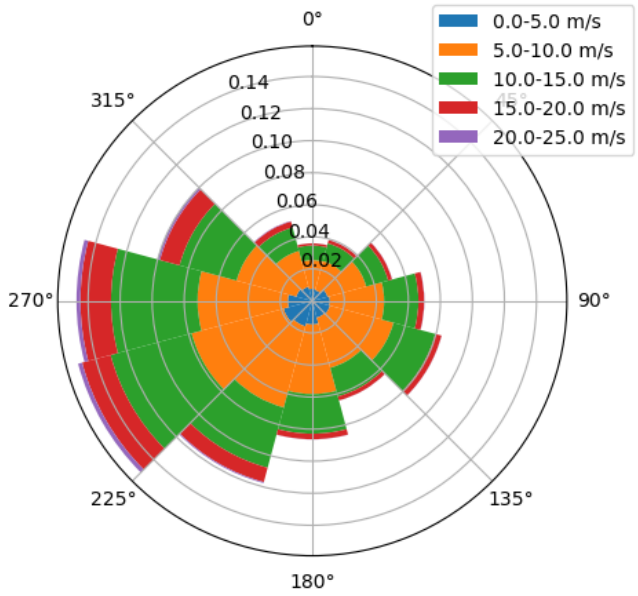
Wind resource distribution plots

The `Site` object has a few plot function to visualize its properties, mainly the wind resource given by the wind rose and the probability functions.

[22]:
```
import matplotlib.pyplot as plt
site = sites['Hornsrev1']
```

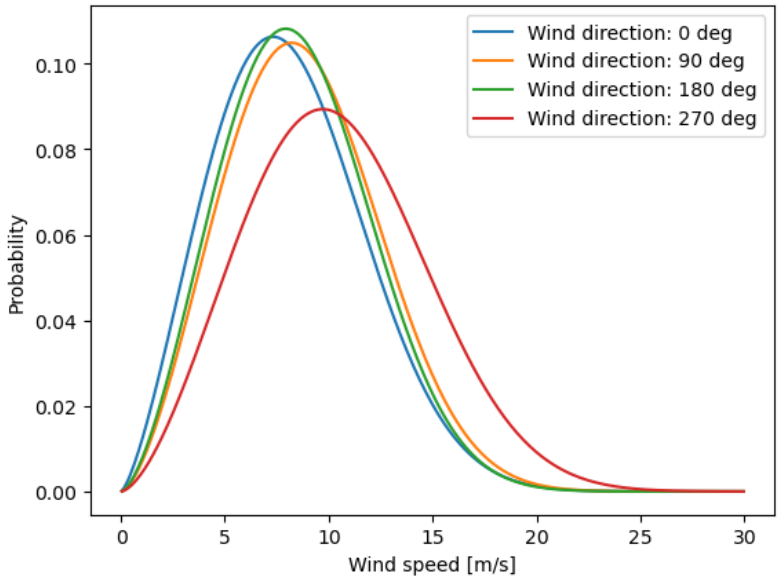
Plotting wind rose.

[23]:
```
_ = site.plot_wd_distribution(n_wd=12, ws_bins=[0,5,10,15,20,25])
```



Plotting probability density function for the four sectors studied.

[24]:
```
_ = site.plot_ws_distribution(wd=[0,90,180,270])
```

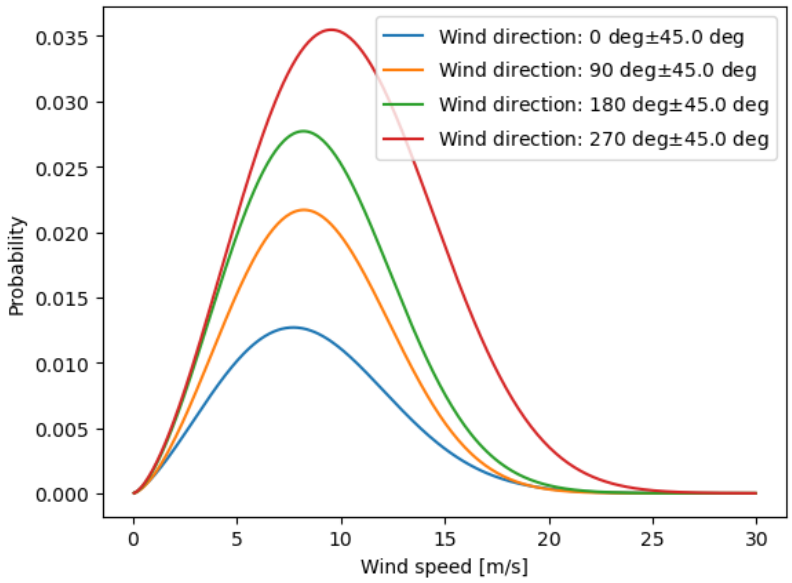


Plotting probablity density function for the four sector studied $\pm$ 45 degrees.

If **include_wd_distribution=true**, the wind speed probability distributions are multiplied by the wind direction probability.

The sector size is set to 360 / len(wd). This only makes sense if the wd array is evenly distributed

[25]:
```
_ = site.plot_ws_distribution(wd=[0,90,180,270], include_wd_distribution=True)
```



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Wind Turbine Object

For a given wind turbine type and effective wind speed (WSeff), the `WindTurbine` object provides the power and thrust coefficient (CT), as well as the win

Install PyWake if needed

[1]:
```
# Install PyWake if needed
try:
    import py_wake
except ModuleNotFoundError:
    !pip install git+https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake.git
```

Setting up Windturbine objects

Predefined WindTurbines example

PyWake contains a few predefined turbines, e.g. the V80 from Hornsrev1, the 3.35MW from IEA task 37 and the DTU10MW reference turbine.

First we import basic Python elements

[2]:
```
import os
import numpy as np
import matplotlib.pyplot as plt
```

Now we import the wind turbines available in PyWake

[3]:
```
from py_wake.wind_turbines import WindTurbine, WindTurbines
from py_wake.examples.data.hornsrev1 import V80
from py_wake.examples.data.iea37 import IEA37_WindTurbines, IEA37Site
from py_wake.examples.data.dtu10mw import DTU10MW

v80 = V80()
iea37 = IEA37_WindTurbines()
dtu10mw = DTU10MW()
```

You can also import wind turbine files from WAsP .wtg files

[4]:
```
from py_wake.examples.data import wtg_path

wtg_file = os.path.join(wtg_path, 'NEG-Micon-2750.wtg')
neg2750 = WindTurbine.from_WAsP_wtg(wtg_file)
```

In addition, user-defined WindTurbine objects is also supported by PyWake

Here it is necessary to specify the thrust coefficient (CT) and power curve of the wind turbine you want to create. The hub height and diameter are also p

[5]:
```
from py_wake.wind_turbines.power_ct_functions import PowerCtTabular

u = [0,3,12,25,30]
ct = [0,8/9,8/9,.3, 0]
power = [0,0,2000,2000,0]

my_wt = WindTurbine(name='MyWT',
                    diameter=123,
                    hub_height=321,
                    powerCtFunction=PowerCtTabular(u,power,'kW',ct))
```

PyWake has a `GenericWindTurbine` class which make a wind turbine where the power is computed by an analytical model based on diameter and nominal

The model takes a lot of optional inputs which default to empirical values, e.g.

- **air_density**= 1.225 kg/m^3
- **max_cp**= .49
- **constant_ct**= .8
- **gear_loss_const**= .01
- **gear_loss_var**= .014
- **generator_loss**= 0.03

- converter_loss= .03

[6]:
```
from py_wake.wind_turbines.generic_wind_turbines import GenericWindTurbine

#for a diameter of 178.3m and hub height of 119m
gen_wt = GenericWindTurbine('G10MW', 178.3, 119, power_norm=10000, turbulence_intensity=.1)
```

Multi-type Wind Turbines

You can collect a list of different turbine types into a single WindTurbines object

[7]:
```
wts = WindTurbines.from_WindTurbine_lst([v80,iea37,dtu10mw,my_wt,gen_wt,neg2750])
```

[8]:
```
types = wts.types()
print ("Name:\t\t%s" % "\t".join(wts.name(types)))
print('Diameter[m]\t%s' % "\t".join(map(str,wts.diameter(type=types))))
print('Hubheigt[m]\t%s' % "\t".join(map(str,wts.hub_height(type=types))))
```

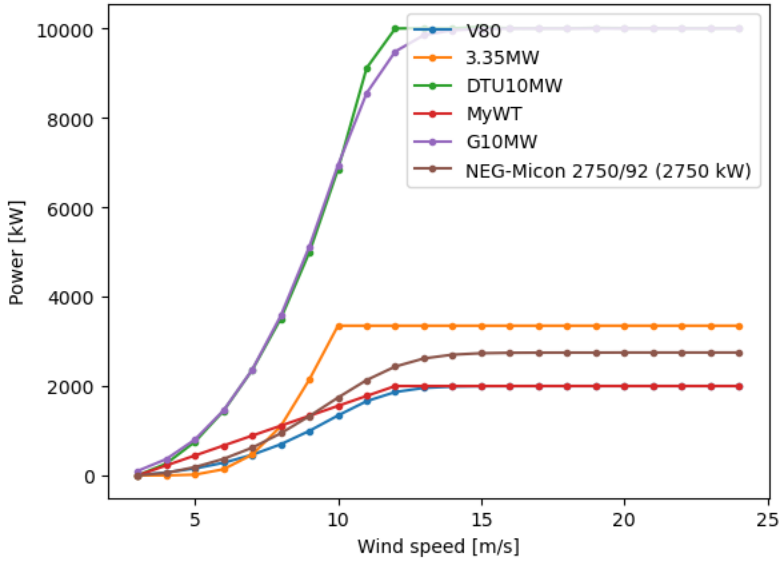
```
Name:           V80     3.35MW  DTU10MW MyWT    G10MW   NEG-Micon 2750/92 (2750 kW)
Diameter[m]     80.0    130.0   178.3   123.0   178.3   92.0
Hubheigt[m]     70.0    110.0   119.0   321.0   119.0   70.0
```

Power curves and CT curves

We plot first the power curve of the all turbines previously defined

[9]:
```
ws = np.arange(3,25)
plt.xlabel('Wind speed [m/s]')
plt.ylabel('Power [kW]')

for t in types:
    plt.plot(ws, wts.power(ws, type=t)*1e-3,'.-', label=wts.name(t))
plt.legend(loc=1)
```

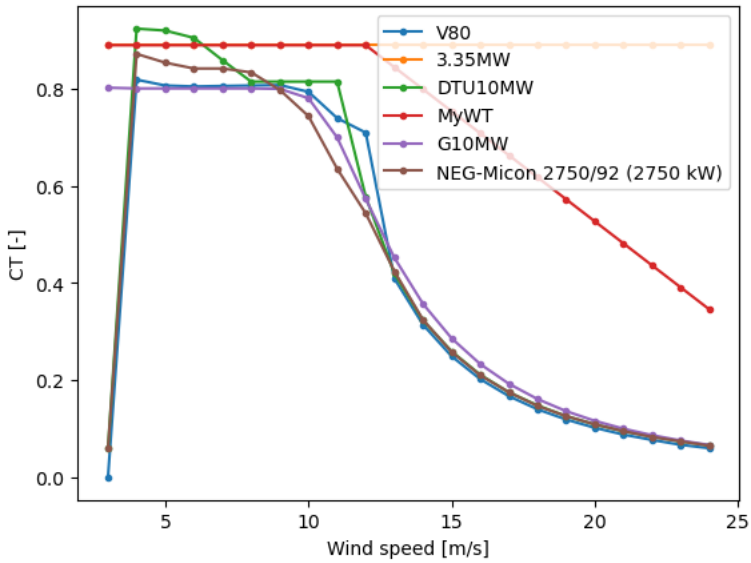
[9]: <matplotlib.legend.Legend at 0x7f1d1109d780>



Now, we do the same for the CT curve of all turbines

[10]:
```
plt.xlabel('Wind speed [m/s]')
plt.ylabel('CT [-]')

for t in types:
    plt.plot(ws, wts.ct(ws, type=t),'.-', label=wts.name(t))
plt.legend(loc=1)
```

[10]: <matplotlib.legend.Legend at 0x7f1d0deb31c0>

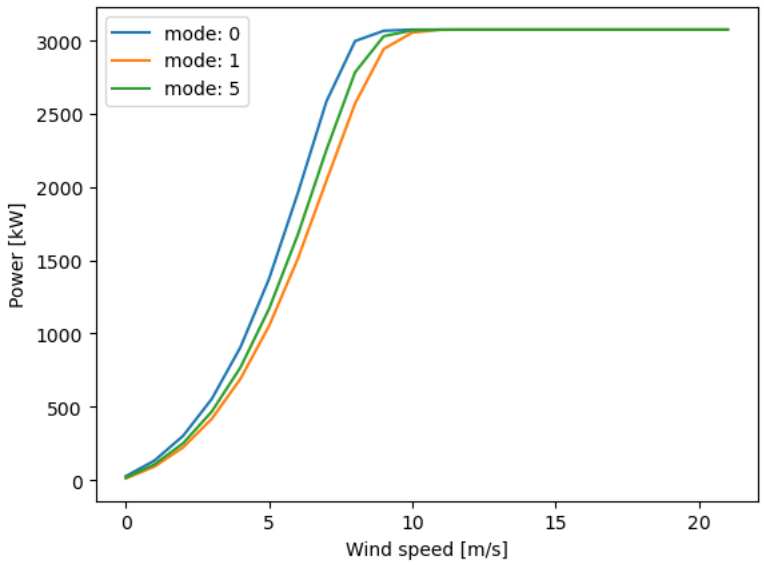


You can also plot Multidimensional Power/CT curves

Some WAsP wtg files define multiple wind turbine modes. E.g. the `Vestas V112-3.0 MW.wtg` which has 12 modes representing different levels of air densit

[11]:
```
wtg_file = os.path.join(wtg_path, 'Vestas V112-3.0 MW.wtg')
v112 = WindTurbine.from_WAsP_wtg(wtg_file)
required_inputs, optional_inputs = v112.function_inputs
upct = {}

#selecting the modes to plot
for m in [0,1,5]:
    plt.plot(v112.power(ws, mode=m)/1000, label=f'mode: {m}')

p0,ct0 = v112.power_ct(ws, mode=0)
p1,ct1 = v112.power_ct(ws, mode=1)

plt.ylabel('Power [kW]')
plt.xlabel('Wind speed [m/s]')
plt.legend()
```

[11]:
```
<matplotlib.legend.Legend at 0x7f1d2eddd7e0>
```



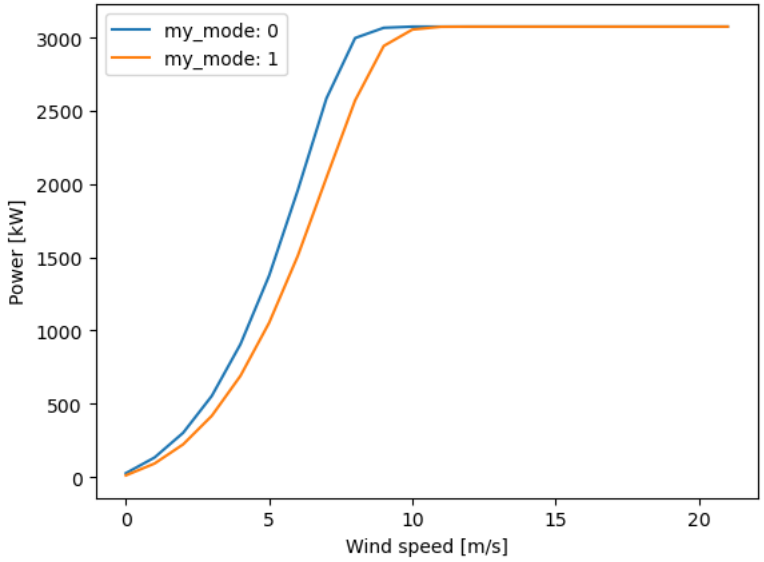
Discrete dimensions (e.g. operational mode)

WindTurbines can be defined using a `PowerCtFunctionList`. In fact this is the approach used by multi-mode WAsP wind turbines and also when creating n

[12]:
```
from py_wake.wind_turbines.power_ct_functions import PowerCtFunctionList

mode0_power_ct=PowerCtTabular(ws, p0, 'w', ct0)
mode1_power_ct=PowerCtTabular(ws, p1, 'w', ct1)

multimode_power_ct = PowerCtFunctionList(key='my_mode',
                                         powerCtFunction_lst=[mode0_power_ct, mode1_power_ct],
```

```
                                        default_value=None)

#specifying a diameter of 112m and hub height of 84m
wt = WindTurbine('MultimodeWT', 112, 84, powerCtFunction=multimode_power_ct)

for m in [0,1]:
    plt.plot(wt.power(ws, my_mode=m)/1000, label=f'my_mode: {m}')
plt.ylabel('Power [kW]')
plt.xlabel('Wind speed [m/s]')
plt.legend()
```

[12]: <matplotlib.legend.Legend at 0x7f1d2ee83ee0>

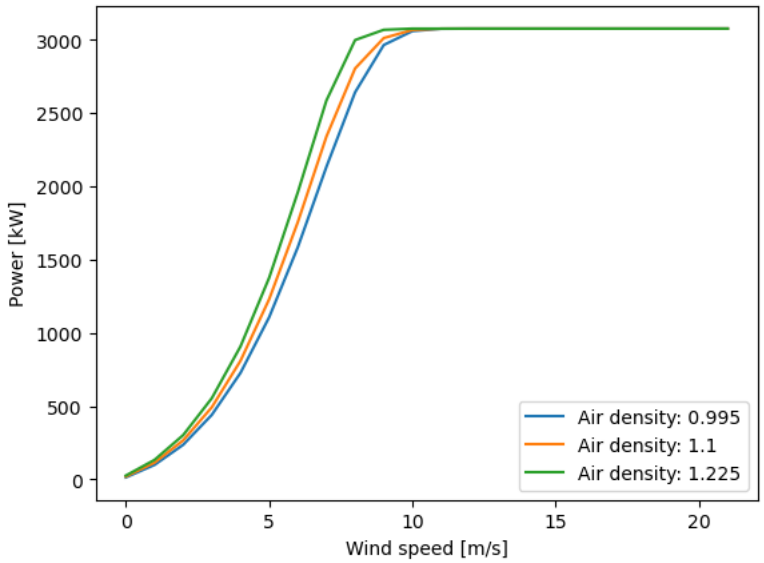


It is also possible to setup a wind turbine using a multidimensional power and CT tabular array.

In this case, the power and CT values will be calculated using multidimensional linear interpolation.

[13]:
```
from py_wake.wind_turbines.power_ct_functions import PowerCtNDTabular

# setup multidimensional power and ct tabulars
# p0,ct0 ~ rho=0.95
# p1,ct1 ~ rho=1.225

power_array = np.array([p1,p0]).T
ct_array = np.array([ct1,ct0]).T
density = [0.95,1.225]

powerCtFunction = PowerCtNDTabular(input_keys=['ws','rho'],
                 value_lst=[ws,density],
                 power_arr=power_array, power_unit='w',
                 ct_arr=ct_array)

#specifying a diameter of 112m and hub height of 84m
wt = WindTurbine('AirDensityDependentWT', 112, 84, powerCtFunction=powerCtFunction)

#looping through different values for air density
for r in [0.995, 1.1, 1.225]:
    plt.plot(wt.power(ws, rho=r)/1000, label=f'Air density: {r}')
plt.ylabel('Power [kW]')
plt.xlabel('Wind speed [m/s]')
plt.legend()
```

[13]: <matplotlib.legend.Legend at 0x7f1d2ee83220>

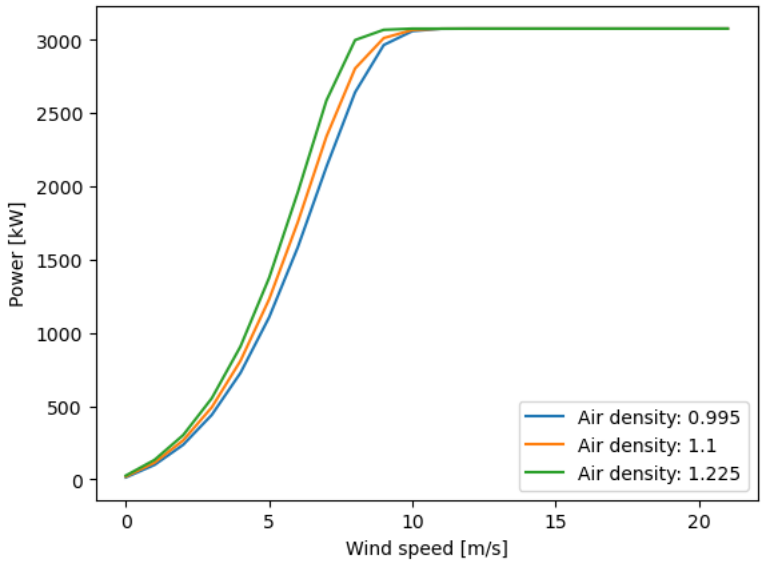


Alternatively, the data can be passed as an xarray dataset.

The dataset must have the data variables, `power` and `ct`, and the coordinate, `ws`.

[14]:
```
import xarray as xr
from py_wake.wind_turbines.power_ct_functions import PowerCtXr

ds = xr.Dataset(
        data_vars={'power': (['ws', 'rho'], np.array([p1,p0]).T),
                   'ct': (['ws', 'boost'], np.array([ct1, ct0]).T)},
        coords={'rho': [0.95,1.225], 'ws': ws})

curve = PowerCtXr(ds, 'w')

#specifying a diameter of 112m and hub height of 84m
wt = WindTurbine('AirDensityDependentWT', 112, 84, powerCtFunction=powerCtFunction)

#looping through different values of air density
for r in [0.995, 1.1, 1.225]:
    plt.plot(wt.power(ws, rho=r)/1000, label=f'Air density: {r}')
plt.ylabel('Power [kW]')
plt.xlabel('Wind speed [m/s]')
plt.legend()
```

[14]:
```
<matplotlib.legend.Legend at 0x7f1d2ecec550>
```

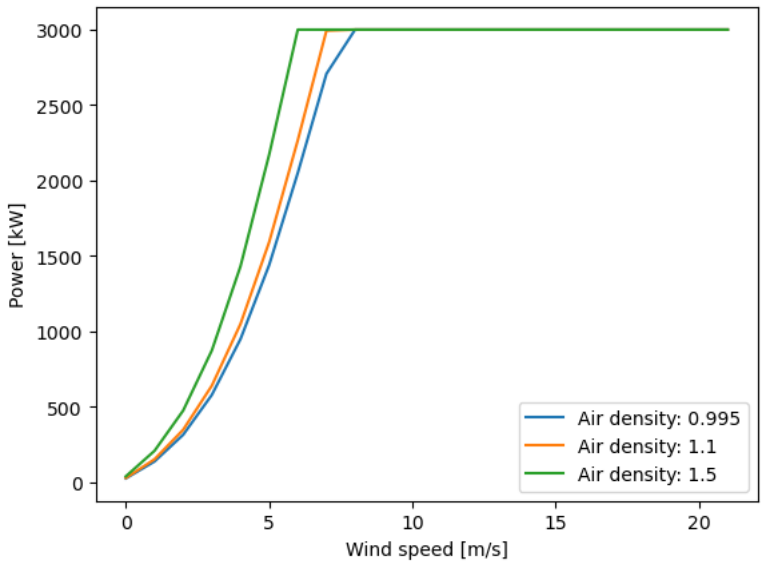


Finally, the Power and CT values can be calculated using a function which may take multiple input variables.

[15]:
```
from py_wake.wind_turbines.power_ct_functions import PowerCtFunction

def density_scaled_power_ct(u, run_only, rho=1.225):
    # function to calculate power and ct
    if run_only==0: # power
        rated_power = 3e6
```

```
        density_scale=rho/.95
        return np.minimum(np.interp(u,ws, p0) * density_scale, rated_power) # density scaled power, limited by rated power
    elif run_only==1: #ct
        return 0*u # dummy ct, not used in this example

powerCtFunction = PowerCtFunction(
    input_keys=['ws','rho'],
    power_ct_func=density_scaled_power_ct,
    power_unit='w',
    optional_inputs=['rho'], # allowed to be optional as a default value is speficifyed in density_scaled_power_ct
)

#specifying a diameter of 112m and hub height of 84m
wt = WindTurbine('AirDensityDependentWT', 112, 84, powerCtFunction=powerCtFunction)

#looping through different values for air density
for r in [0.995, 1.1, 1.5]:
    plt.plot(wt.power(ws, rho=r)/1000, label=f'Air density: {r}')
plt.ylabel('Power [kW]')
plt.xlabel('Wind speed [m/s]')
plt.legend()
```

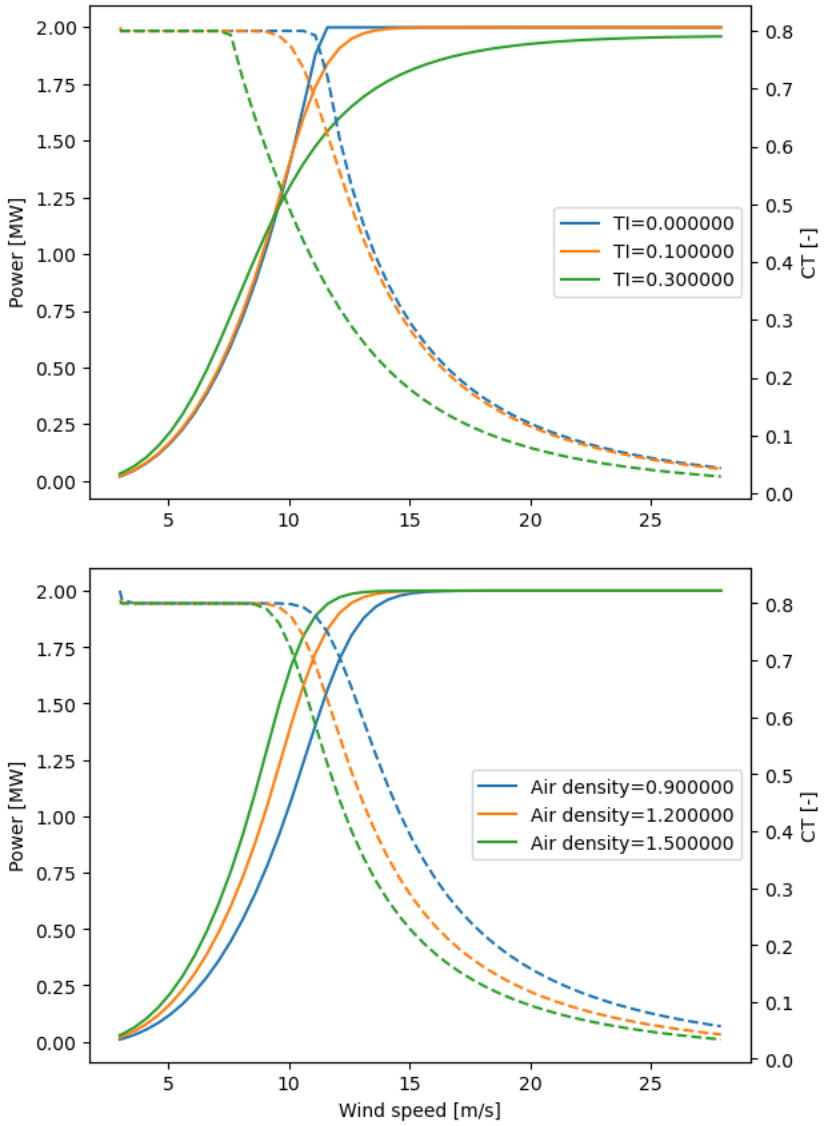
[15]: <matplotlib.legend.Legend at 0x7f1d2edfdc30>



You can also use the `GenericTIRhoWindTurbine` class, which extends the `GenericWindTurbine` with multidimensional power/CT curves that depend on turb
(`Air_density`).

[16]:
```
from py_wake.wind_turbines.generic_wind_turbines import GenericTIRhoWindTurbine

#specifying a diameter of 80m and hub height of 70m for different turbulence intensities
wt = GenericTIRhoWindTurbine('2MW', 80, 70, power_norm=2000,
                             TI_eff_lst=np.linspace(0, .5, 6), default_TI_eff=.1,
                             Air_density_lst=np.linspace(.9, 1.5, 5), default_Air_density=1.225)

u = np.arange(3, 28, .1)
ax1 = plt.gca()
ax2 = plt.twinx()

#looping through different values of turbulence intensity
for ti in [0, .1, .3]:
    p, ct = wt.power_ct(u, TI_eff=ti)
    ax1.plot(u, p / 1e6, label='TI=%f' % ti)
    ax2.plot(u, ct, '--')
ax1.legend(loc='center right')
ax1.set_ylabel('Power [MW]')
ax2.set_ylabel('CT [-]')

plt.figure()
u = np.arange(3, 28, .1)
ax1 = plt.gca()
ax2 = plt.twinx()

#looping through different values of air density
for rho in [.9,1.2,1.5]:
    p, ct = wt.power_ct(u, Air_density=rho)
    ax1.plot(u, p / 1e6, label='Air density=%f' % rho)
    ax2.plot(u, ct, '--')
ax1.legend(loc='center right')
ax1.set_ylabel('Power [MW]')
ax2.set_ylabel('CT [-]')
ax1.set_xlabel('Wind speed [m/s]')
```

[16]: Text(0.5, 0, 'Wind speed [m/s]')



Power/CT input arguments

The input arguments for the Power and CT curves can be obtained from:

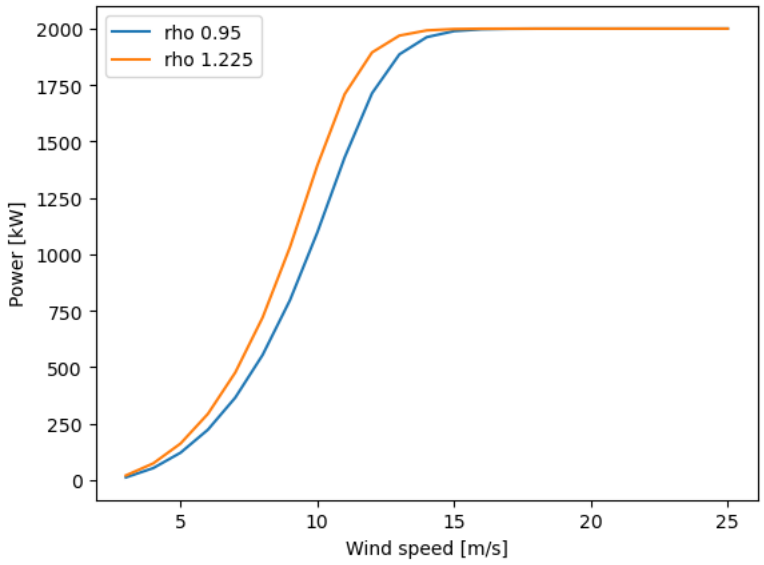
- Arguments passed when calling the `WindFarmModel`
- Data present in the `Site` - object
- Values computed in the simulation, i.e. `WS_eff` and `TI_eff`. Note that `WS_eff` is passed as `ws`

1) Arguments passed to `WindFarmModel` call

[17]:
```
from py_wake.examples.data.hornsrev1 import Hornsrev1Site
from py_wake.deficit_models.noj import NOJ

wfm = NOJ(site=Hornsrev1Site(), windTurbines=wt)

for rho in [0.95,1.225]:
    sim_res = wfm([0], [0], wd=0, Air_density=rho) # rho passed to WindFarmModel call
    power = sim_res.Power.squeeze() / 1000
    plt.plot(power.ws, power, label=f'rho {rho}')
plt.xlabel('Wind speed [m/s]')
plt.ylabel('Power [kW]')
plt.legend()
```

```
/builds/TOPFARM/PyWake/py_wake/deficit_models/noj.py:88: UserWarning: The NOJ model is not representative of the setup used in the literature.
  DeprecatedModel.__init__(self, 'py_wake.literature.noj.Jensen_1983')
```

[17]: <matplotlib.legend.Legend at 0x7f1d0dc436a0>

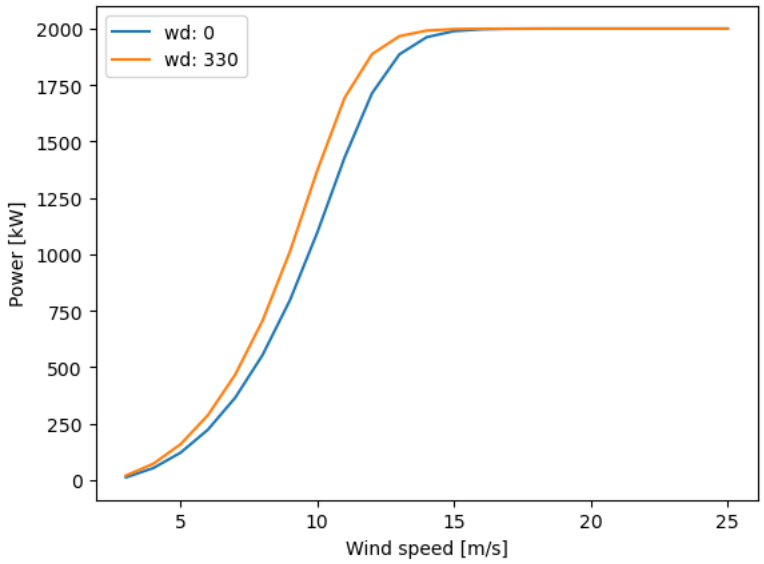


2) Data present in `Site`

[18]:
```
from py_wake.examples.data.hornsrev1 import Hornsrev1Site
from py_wake.deficit_models.noj import NOJ

site = Hornsrev1Site()
site.ds['Air_density'] = ('wd',np.linspace(.95,1.225,13)) # wd-dependent rho added to site

wfm = NOJ(site=site, windTurbines=wt)

for wd in [0,330]:
    sim_res = wfm([0], [0], wd=wd)
    power = sim_res.Power.squeeze() / 1000
    plt.plot(power.ws, power, label=f'wd: {wd}')
plt.xlabel('Wind speed [m/s]')
plt.ylabel('Power [kW]')
plt.legend()
```

```
/builds/TOPFARM/PyWake/py_wake/deficit_models/noj.py:88: UserWarning: The NOJ model is not representative of the setup used in the literature.
  DeprecatedModel.__init__(self, 'py_wake.literature.noj.Jensen_1983')
```

[18]:
```
<matplotlib.legend.Legend at 0x7f1d0db21bd0>
```



Interpolation method

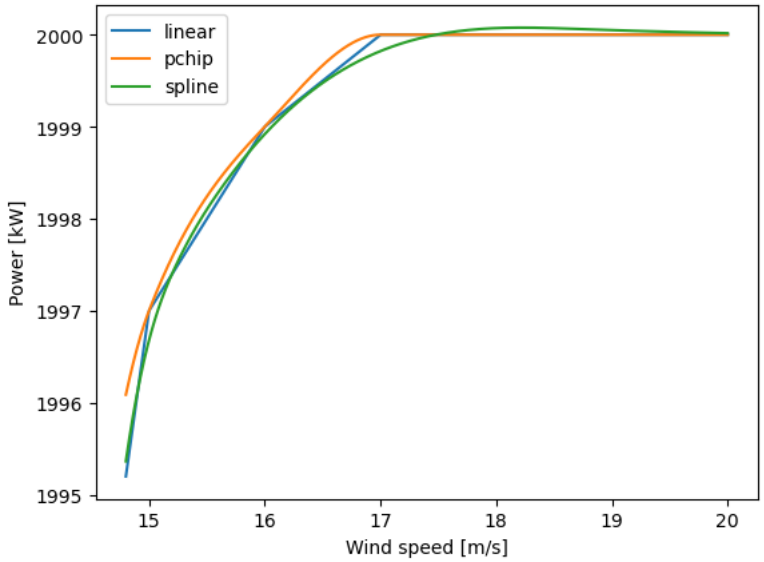
`PowerCtTabular` which is used by most predefined wind turbines takes a `method` argument which can be:

- `linear`: Linear interpolation (default)
- `pchip`: Piecewise Cubic Hermite Interpolating Polynomial. Smooth interpolation with continous first order derivatives and not overshoots
- `spline`: Smooth interpolation with continous first and second order derivatives. Closer to original piecewise linear curve, but may have overshoots

When using the N-dimensional `PowerCtNDTabular`, only linear interpolation is supported.

[19]:
```
wt_lst = [(m, V80(method=m)) for m in ['linear','pchip','spline']]

_ws = np.linspace(14.8,20,1000)

for n, _wt in wt_lst:
    plt.plot(_ws, _wt.power(_ws)/1e3, label=n)
plt.ylabel('Power [kW]')
plt.xlabel('Wind speed [m/s]')
plt.legend()
```

[19]:
```
<matplotlib.legend.Legend at 0x7f1d0dc68460>
```

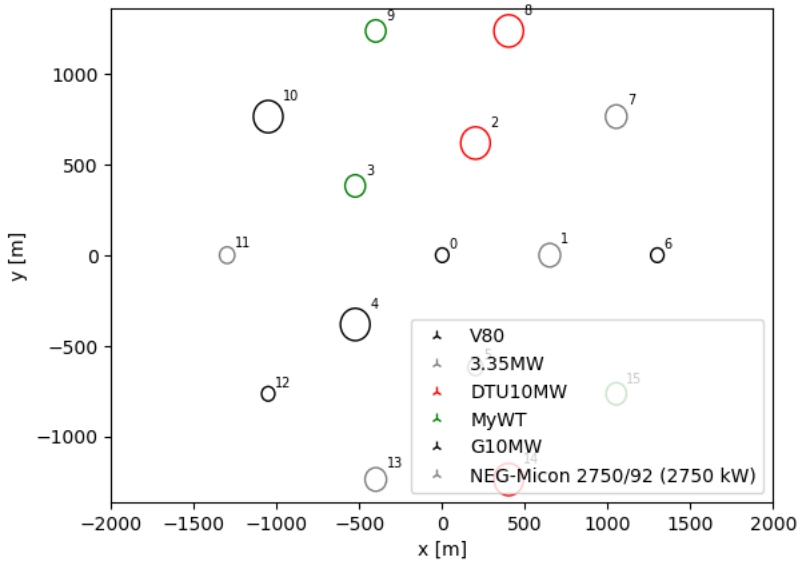


Plotting the wind turbines

Top-view plot

[20]:
```
s = IEA37Site(16)
x,y = s.initial_position.T

plt.figure()
wts.plot_xy(x,y,types=np.arange(len(x))%len(types))
plt.xlim(-2000,2000)
plt.xlabel('x [m]')
plt.ylabel('y [m]')
plt.legend()
```

[20]:
```
<matplotlib.legend.Legend at 0x7f1d0db23610>
```

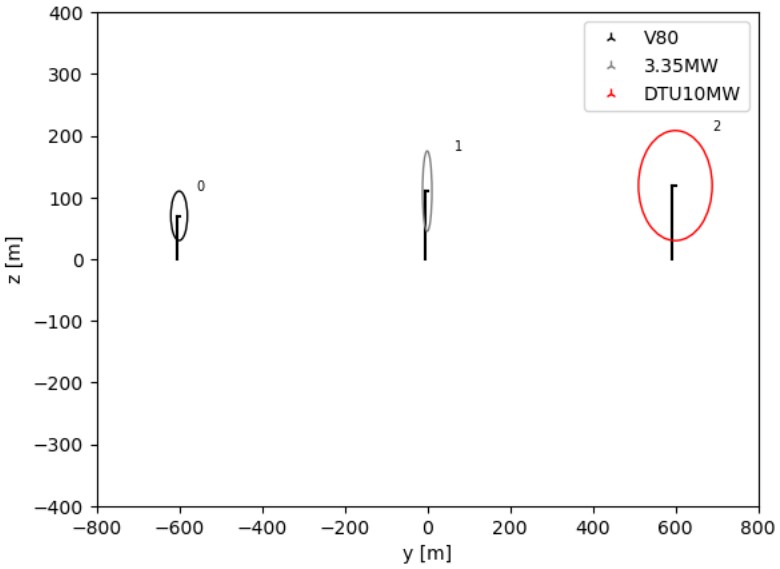


Side-view plot

[21]:
```
#here you can also specify yaw angles for the turbines
plt.figure()
wts.plot_yz(np.array([-600,0,600]), wd=0, types=[0,1,2], yaw=[-30, 10, 90])
plt.ylim(-400,400)
```

```
plt.xlim(-800,800)
plt.xlabel('y [m]')
plt.ylabel('z [m]')
plt.legend()
```

[21]: <matplotlib.legend.Legend at 0x7f1d0c16abc0>



Open in Colab Edit on Gitlab

Engineering Wind Farm Models Object

PyWake contains three general engineering wind farm models, namely PropagateDownwind, All2AllIterative and PropagateUpDownIterative.

The table below compares their properties:

/	`All2AllIterative`	`PropagateDownwind`	`PropagateUpDownIteartive`
Includes wakes	Yes	Yes	Yes
Includes blockage	Yes	No	Yes
Memory requirement	High	Low	Low
Simulation speed	Slow	Fast	Medium

In addition different [pre-defined models}(#Predefined-Wind-Farm-Models) exits. The predefined models covers often-used model combinations and mod
superposition models, turbulence models, etc. However, these are easily customizable to study the impact of different models on the results.

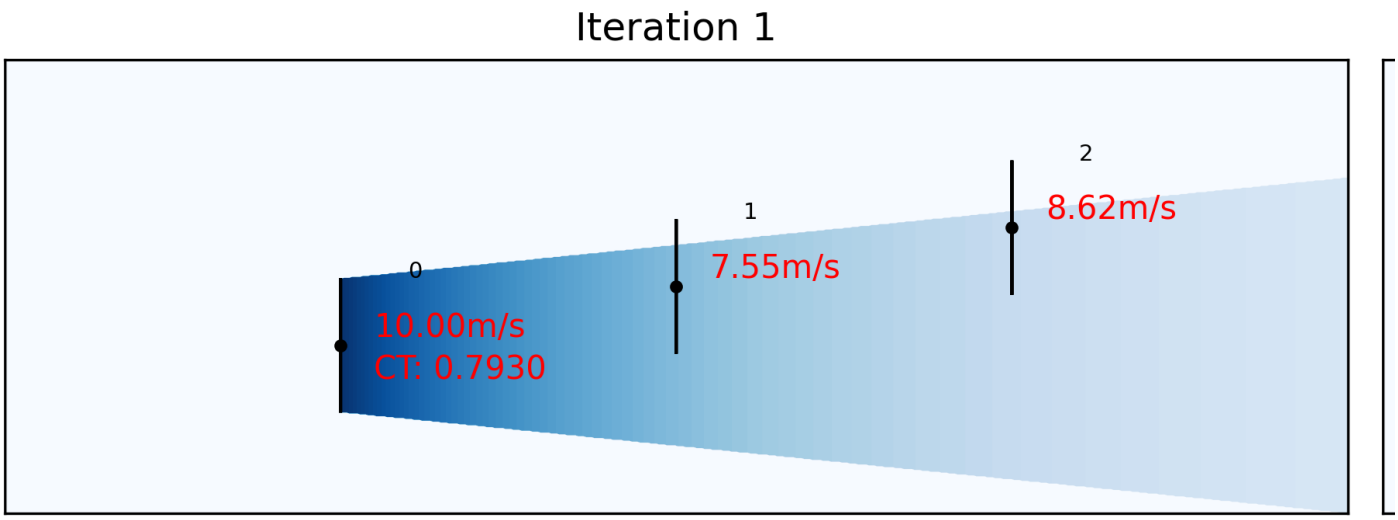
PropagateDownwind

The `PropagateDownwind` wind farm model is very fast as it only performs a minimum of deficit calculations. It iterates over all turbines in downstream orde
from upstream sources. Based on this effective wind speed, it calculates the deficit caused by the current turbine on all downstream destinations. Note, tl

```
for wt in wind turbines in downstream order:
    ws_eff[wt] = ws[wt] - superposition(deficit[from_upstream_src,to_wt])
    ct = windTurbines.ct(ws_eff[wt])
    deficit[from_wt,to_downstream_dst] = wakeDeficitModel(ct, distances[from_wt,to_downstream_dst], ...)
```

The proceedure is illustrated in the animation below:

- **Iteration 1:** WT0 sees the free wind (10m/s). Its deficit on WT1 and WT2 is calculated.
- **Iteration 2:** WT1 sees the free wind minus the deficit from WT0. Its deficit on WT2 is calculated and the effective wind speed at WT2 is updated.



In PyWake, the class is represented as follows:

[1]:
```
# Install PyWake if needed
try:
    import py_wake
except ModuleNotFoundError:
    !pip install git+https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake.git
```

[2]:
```
from py_wake.wind_farm_models import PropagateDownwind
help(PropagateDownwind.__init__)
```

```
Help on function __init__ in module py_wake.wind_farm_models.engineering_models:

__init__(self, site, windTurbines, wake_deficitModel, superpositionModel=<py_wake.superposition_models.LinearSum object at 0x7ff227863130>, def
    Initialize flow model

    Parameters
    ----------
    site : Site
        Site object
    windTurbines : WindTurbines
        WindTurbines object representing the wake generating wind turbines
    wake_deficitModel : DeficitModel
        Model describing the wake(downstream) deficit
    rotorAvgModel : RotorAvgModel, optional
        Model defining one or more points at the down stream rotors to
        calculate the rotor average wind speeds from.

        if None, default, the wind speed at the rotor center is used
    superpositionModel : SuperpositionModel
        Model defining how deficits sum up
    deflectionModel : DeflectionModel
        Model describing the deflection of the wake due to yaw misalignment, sheared inflow, etc.
    turbulenceModel : TurbulenceModel
        Model describing the amount of added turbulence in the wake
```

`site` and `windTurbines` and `wake_deficitModel` are required inputs. By default, the class uses the `LinearSum` superposition model to add the wakes fror

All2AllIterative

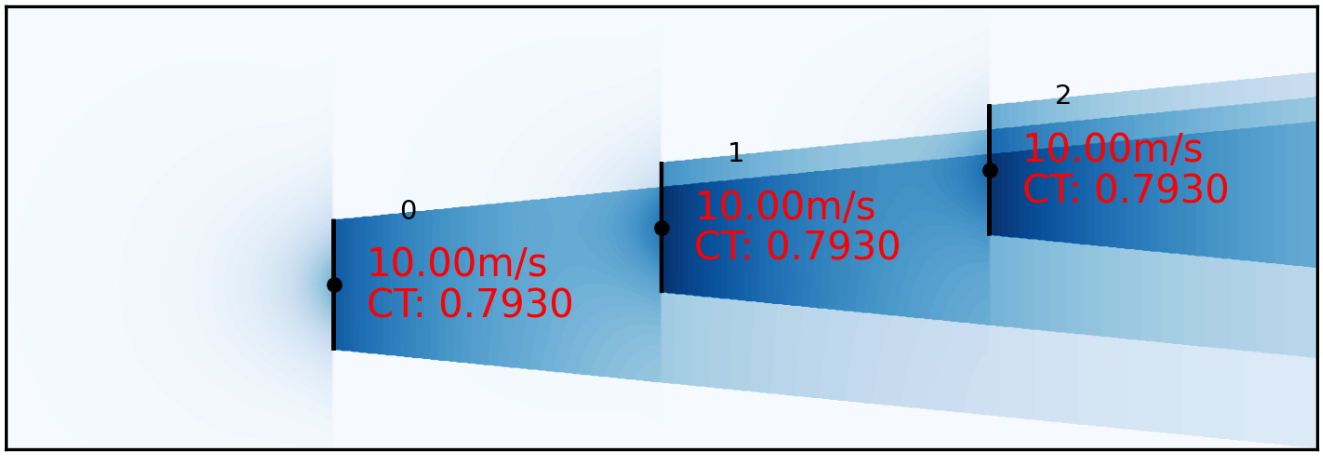
The `All2AllIterative` wind farm model is slower but is capable of handling blockage effects. It iterates until the effective wind speed converges or it reac all wind turbine sources and calculates the deficit caused by the all wind turbines turbine on all wind turbines.

```
while ws_eff not converged:
    ws_eff[all] = ws[all] - superposition(deficit[from_all,to_all])
    ct[all] = windTurbines.ct(ws_eff[all])
    deficit[from_all,to_all] = wakeDeficitModel(ct[all], distances[from_all,to_all], ...)
```

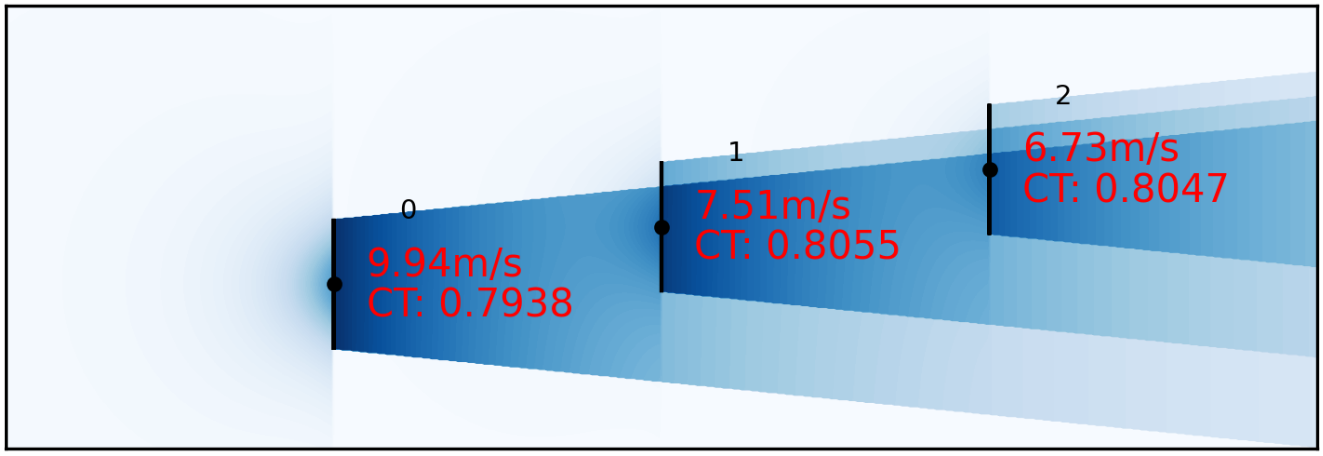
The proceedure is illustrated in the animation below:

- **Iteration 1:** All three WT see the free wind (10m/s) and their CT values and resulting deficits are therefore equal.
- **Iteration 2:** The local effective wind speeds are updated taking into account the wake and blockage effects of the other WT. Based on these wind spee
- **Iteration 3:** Repeat until the flow field has converged.

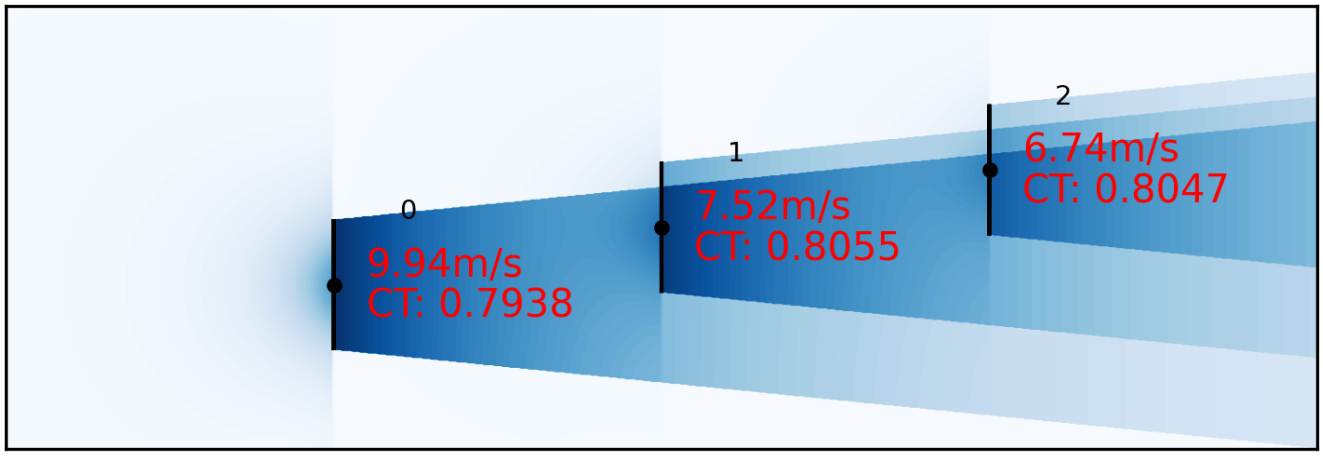
Iteration 1



Iteration 2



Iteration 3



In PyWake, the class is represented as follows:

[3]:
```
from py_wake.wind_farm_models import All2AllIterative
help(All2AllIterative.__init__)
```

```
Help on function __init__ in module py_wake.wind_farm_models.engineering_models:

__init__(self, site, windTurbines, wake_deficitModel, superpositionModel=<py_wake.superposition_models.LinearSum object at 0x7ff2278dbaf0>, blo
    Initialize flow model

    Parameters
    ----------
    site : Site
        Site object
    windTurbines : WindTurbines
        WindTurbines object representing the wake generating wind turbines
    wake_deficitModel : DeficitModel
        Model describing the wake(downstream) deficit
    rotorAvgModel : RotorAvgModel, optional
        Model defining one or more points at the down stream rotors to
        calculate the rotor average wind speeds from.

        if None, default, the wind speed at the rotor center is used
    superpositionModel : SuperpositionModel
        Model defining how deficits sum up
    blockage_deficitModel : DeficitModel
        Model describing the blockage(upstream) deficit
    deflectionModel : DeflectionModel
        Model describing the deflection of the wake due to yaw misalignment, sheared inflow, etc.
    turbulenceModel : TurbulenceModel
        Model describing the amount of added turbulence in the wake
    convergence_tolerance : float or None
        if float: maximum accepted change in WS_eff_ilk [m/s]
        if None: return after first iteration. This only makes sense for benchmark studies where CT,
        wakes and blockage are independent of effective wind speed WS_eff_ilk
```

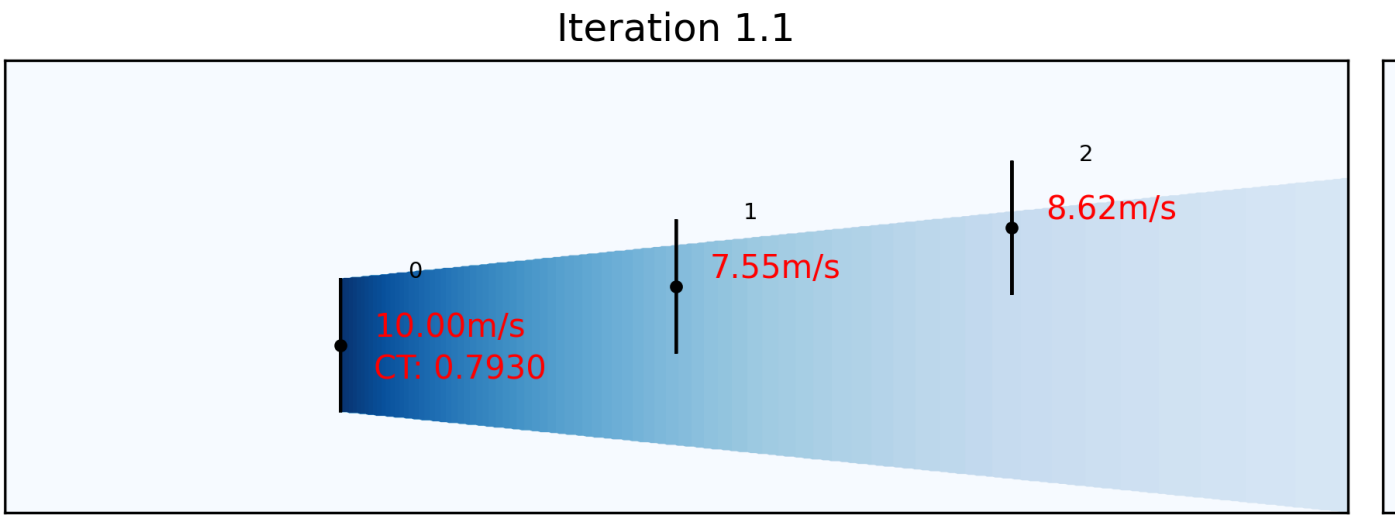
In addition to the parameters specified in the `PropagateDownwind` class, here we determine a convergence tolerance in terms of the maximum accepted ch engineering wind farm model used.

As default, the `All2AllIterative` simulation runs a `PropagateDownwind` simulation during initialization and uses the resulting effective wind speed as start

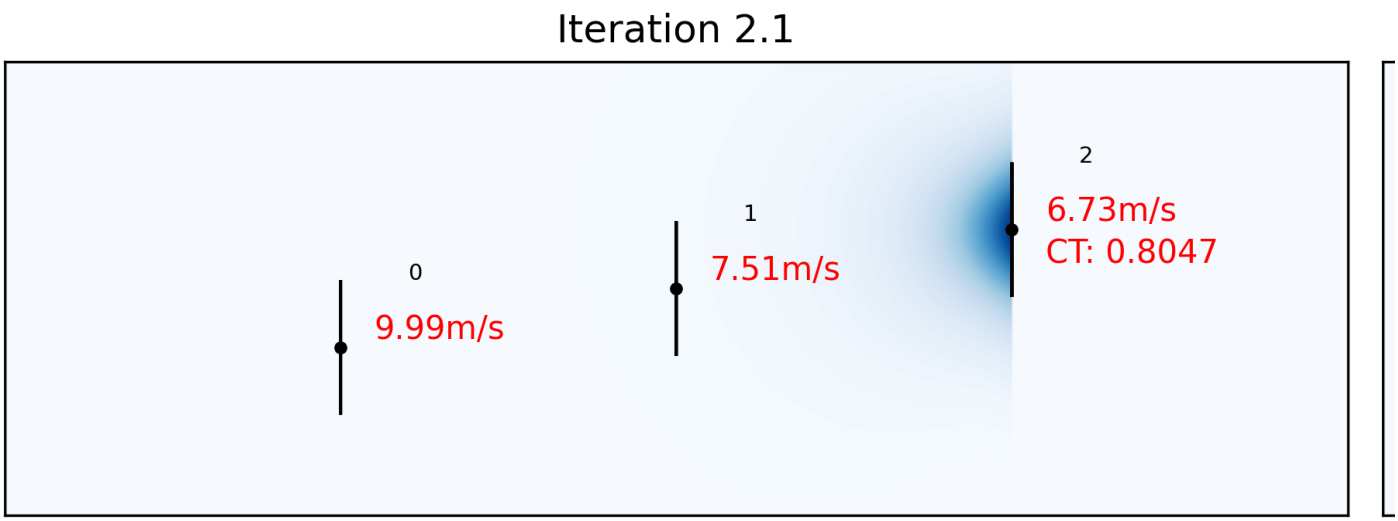
PropagateUpDownIterative

The `PropagateUpDownIterative` wind farm model combines the approaches of `PropagateDownwind` and `All2AllIterative`

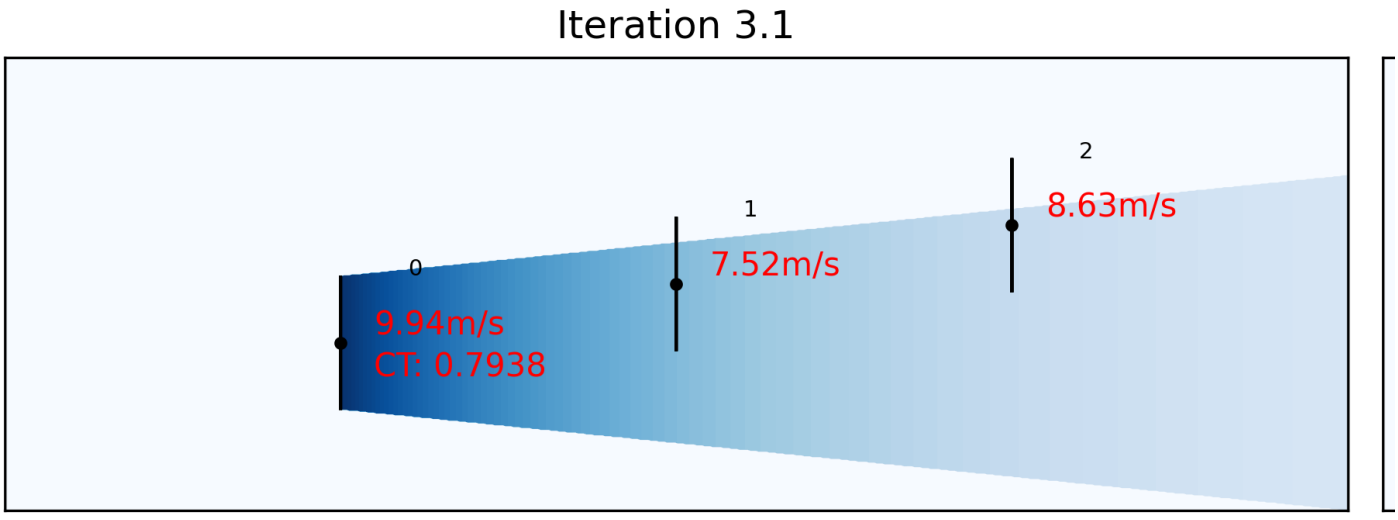
- **Iteration 1 (Propagate wake down):**
  - **Iteration 1.1:** WT0 sees the free wind (10m/s). Its wake deficit on WT1 and WT2 is calculated.
  - **Iteration 1.2:** WT1 sees the free wind minus the wake deficit from WT0. Its wake deficit on WT2 is calculated and the effective wind speed at WT



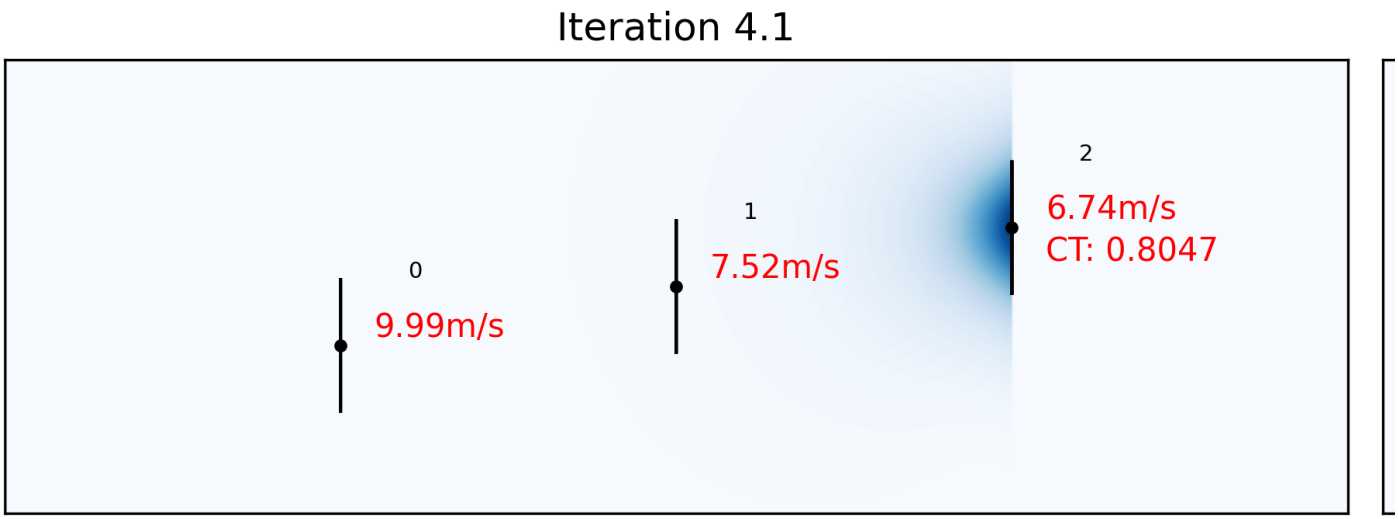
- **Iteration 2 (Propagate blockage up)**
  - **Iteration 2.1:** All wind turbines see the free wind speed minus the wake deficit obtained in iteration 1. WT2 sees 6.73m/s and its blockage deficit c
  - **Iteration 2.2:** WT1 sees the free wind speed minus the wake deficit obtained in iteration 1 and the blockage deficit from WT2. Its blockage deficit



- **Iteration 3 (Propagate wake down):**
  - **Iteration 3.1:** All wind turbines see the free wind minus the blockage obtained in iteration 2. WT0 seees 9.94 m/s and its wake deficit on WT1 and
  - **Iteration 3.2:** WT1 sees the free wind minus the blockage deficit obtained in iteration 2 and the wake deficit from WT0. Its wake deficit on WT2 is



- **Iteration 4 (Propagate blockage up)**
  - **Iteration 4.1:** All wind turbines see the free wind speed minus the wake deficit obtained in iteration 3. WT2 sees 6.74m/s and its blockage deficit c
  - **Iteration 4.2:** WT1 sees the free wind speed minus the wake deficit obtained in iteration 3 and the blockage deficit from WT2. Its blockage deficit



The constructor of `PropagateUpDownIterative` is very similar to the constructor of `All2AllIterative`:

[4]:
```
from py_wake.wind_farm_models import PropagateUpDownIterative
help(PropagateUpDownIterative.__init__)
```

```
Help on function __init__ in module py_wake.wind_farm_models.engineering_models:

__init__(self, site, windTurbines, wake_deficitModel, superpositionModel=<py_wake.superposition_models.LinearSum object at 0x7ff2278630d0>, blc
    Initialize flow model

    Parameters
    ----------
    site : Site
        Site object
    windTurbines : WindTurbines
        WindTurbines object representing the wake generating wind turbines
    wake_deficitModel : DeficitModel
        Model describing the wake(downstream) deficit
    rotorAvgModel : RotorAvgModel, optional
        Model defining one or more points at the down stream rotors to
        calculate the rotor average wind speeds from.

        if None, default, the wind speed at the rotor center is used
    superpositionModel : SuperpositionModel
        Model defining how deficits sum up
    deflectionModel : DeflectionModel
        Model describing the deflection of the wake due to yaw misalignment, sheared inflow, etc.
    turbulenceModel : TurbulenceModel
        Model describing the amount of added turbulence in the wake
```

Predefined Wind Farm Models

The pre-defines wind farm models are adapted from the literature, where their corresponding default superposition model, turbulence model and calibrat

The engineering wind farm models comprise:

Reference	Name	WindFarm Model	Wake Deficit Model	Blockage
1	Jensen_1983	PropagateDownwind	NOJDeficit	•
2	Ott_Nielsen_2014	PropagateDownwind	FugaDeficit	•
3	Ott_Nielsen_2014_Blockage	All2AllIterative	FugaDeficit	FugaDefi
4	Bastankhah_PorteAgel_2014	PropagateDownwind	BastankhahGa ussianDeficit	•

Reference	Name	WindFarm Model	Wake Deficit Model	Blockage
5	IEA37CaseStudy1	PropagateDownwind	IEA37SimpleBastankhahGaussianDefic it	•
6	Niayifar_PorteAgel_2016	PropagateDownwind	Niayifar GaussianDeficit	•
7	Zong_PorteAgel_2020	PropagateDownwind	` ZongGaussianDeficit <WakeDeficitModels.ipynb#ZongGaussianDeficit>`__	•
8	Nygaard_2022	PropagateDownwind	Tu rboGaussianDeficit	•
9	Blondel_Cathelain_2020	PropagateDownwind	BlondelSuperG aussianDeficit2020	•

- Default rotor-average model: `RotorCenter`
- Default turbulence model: `None`

All models require a `Site` and a `WindTurbine` object to run, and each of them may require additional inputs such as calibration parameters. The paramete

In the case of Fuga, a file with look up tables is needed; the file is created by specifying the turbine's rotor diameter, hub height and roughness length of tl

For information on the calculation of the velocity deficit for each model, please refer to the Wake Deficit Models notebook.

Below are some examples of different wind farm models under the `PropagateDownwind` base class. The full set of pre-defined wind farm models can be fou

1) Bastankhah Gaussian

```
class Bastankhah_PorteAgel_2014(PropagateDownwind):
def __init__(self, site, windTurbines, k=0.0324555, ceps=.2, ct2a=ct2a_madsen, use_effective_ws=False,
                rotorAvgModel=None, superpositionModel=SquaredSum(),
                deflectionModel=None, turbulenceModel=None, groundModel=None):
```

2) Niayifar Gaussian

```
class Niayifar_PorteAgel_2016(PropagateDownwind):
def __init__(self, site, windTurbines, a=[0.38, 4e-3], ceps=.2, superpositionModel=LinearSum(),
                deflectionModel=None, turbulenceModel=CrespoHernandez(), rotorAvgModel=None, groundModel=None,
                use_effective_ws=True, use_effective_ti=True):
```

3) Zong Gaussian

```
class Zong_PorteAgel_2020(PropagateDownwind):
def __init__(self, site, windTurbines, a=[0.38, 4e-3], deltawD=1. / np.sqrt(2), lam=7.5, B=3,
                rotorAvgModel=None, superpositionModel=WeightedSum(), deflectionModel=None,
                turbulenceModel=CrespoHernandez(), groundModel=None, use_effective_ws=True, use_effective_ti=True):
```

3) TurbOPark

```
class Nygaard_2022(PropagateDownwind):
def __init__(self, site, windTurbines):

        wake_deficitModel = TurboGaussianDeficit(
            ct2a=ct2a_mom1d,
            groundModel=Mirror(),
            rotorAvgModel=GaussianOverlapAvgModel())
```

4) Fuga

```
class Ott_Nielsen_2014(PropagateDownwind):
    def __init__(self, LUT_path, site, windTurbines,
                rotorAvgModel=None, deflectionModel=None, turbulenceModel=None, remove_wriggles=False):
```

In addition, Fuga's wind farm model comes with the possibility of modeling blockage. For this, the `All2AllIterative` base class is used.

```
class Ott_Nielsen_2014_Blockage(All2AllIterative):
    def __init__(self, LUT_path, site, windTurbines, rotorAvgModel=None,
                 deflectionModel=None, turbulenceModel=None, convergence_tolerance=1e-6, remove_wriggles=False):
```

Open in Colab Edit on Gitlab

Wake Deficit Models

The wake deficit models compute the wake deficit caused by a single wind turbine. In PyWake, there are several wake deficit models, which include:

- NOJDeficit
- TurboNOJDeficit
- FugaDeficit
- BastankhahGaussianDeficit
- IEA37SimpleBastankhahGaussianDeficit
- NiayifarGaussianDeficit
- ZongGaussianDeficit
- CarbajofuertesGaussianDeficit
- TurboGaussianDeficit
- GCLDeficit
- SuperGaussianDeficit

Note: The implementation of the deficit models is highly vectorized and therefore suffixes are used to indicate the dimension of variables. The suffixes us

- i: source wind turbines
- j: destination wind turbines
- k: wind speeds
- l: wind directions

This means that `deficit_ijlk[0,1,2,3]` **holds the deficit caused by the first turbine on the second turbine for the third wind direction and fourth wind s**

Install PyWake if needed

[1]:
```
# Install PyWake if needed
try:
    import py_wake
except ModuleNotFoundError:
    !pip install git+https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake.git
```

[2]:
```
#here we import all wake deficit models available in PyWake
import numpy as np
import matplotlib.pyplot as plt
import os
import py_wake

from py_wake.examples.data.hornsrev1 import V80, Hornsrev1Site

site = Hornsrev1Site()
windTurbines = V80()

from py_wake import NOJ
from py_wake import Fuga
from py_wake import FugaBlockage
from py_wake import BastankhahGaussian

# Path to Fuga look-up tables
lut_path = os.path.dirname(py_wake.__file__)+'/tests/test_files/fuga/2MW/Z0=0.03000000Zi=00401Zeta0=0.00E+00.nc'

models = {'NOJ': NOJ(site,windTurbines),
          'Fuga': Fuga(lut_path,site,windTurbines),
          'FugaBlockage': FugaBlockage(lut_path,site,windTurbines),
          'BGaus': BastankhahGaussian(site,windTurbines)
         }
```

```
/builds/TOPFARM/PyWake/py_wake/deficit_models/noj.py:88: UserWarning: The NOJ model is not representative of the setup used in the literature.
  DeprecatedModel.__init__(self, 'py_wake.literature.noj.Jensen_1983')
/builds/TOPFARM/PyWake/py_wake/deficit_models/fuga.py:209: UserWarning: The Fuga model is not representative of the setup used in the literatur
  DeprecatedModel.__init__(self, 'py_wake.literature.fuga.Ott_2014')
/builds/TOPFARM/PyWake/py_wake/deficit_models/fuga.py:238: UserWarning: The FugaBlockage model is not representative of the setup used in the l
  DeprecatedModel.__init__(self, 'py_wake.literature.fuga.Ott_2014_Blockage')
/builds/TOPFARM/PyWake/py_wake/deficit_models/gaussian.py:124: UserWarning: The BastankhahGaussian model is not representative of the setup use
  DeprecatedModel.__init__(self, 'py_wake.literature.gaussian_models.Bastankhah_PorteAgel_2014')
```

In addition, these models can easily be combined with other models to better describe the wake behind the turbine, e.g. NOJ with linear sum superpositio

[3]:
```
from py_wake.superposition_models import LinearSum
```

```
models['NOJLinear'] = NOJ(site,windTurbines,superpositionModel=LinearSum())
```

Or models can be combined in custom ways, e.g. `NOJDeficit` for the wake, `LinearSum` superposition and `SelfSimilarityDeficit` for the blockage:

[4]:
```
from py_wake.wind_farm_models import All2AllIterative
from py_wake.deficit_models import NOJDeficit, SelfSimilarityDeficit

models['NOJ_ss'] = All2AllIterative(site,windTurbines,
                                    wake_deficitModel=NOJDeficit(),
                                    superpositionModel=LinearSum(),
                                    blockage_deficitModel=SelfSimilarityDeficit())
```

Definition and configuration

First, we create some functions to visualize wake maps for different conditions and wake models.

[5]:
```
from matplotlib import cm
from matplotlib.colors import ListedColormap, LinearSegmentedColormap
from py_wake.deficit_models.deficit_model import WakeDeficitModel, BlockageDeficitModel
from py_wake.deficit_models.no_wake import NoWakeDeficit
from py_wake.site._site import UniformSite
from py_wake.flow_map import XYGrid
from py_wake.turbulence_models import CrespoHernandez
from py_wake.utils.plotting import setup_plot

#turbine diameter
D = 80

def get_flow_map(model=None, grid=XYGrid(x=np.linspace(-200, 500, 200), y=np.linspace(-200, 200, 200), h=70),
                 turbulenceModel=CrespoHernandez()):
    blockage_deficitModel = [None, model][isinstance(model, BlockageDeficitModel)]
    wake_deficitModel = [NoWakeDeficit(), model][isinstance(model, WakeDeficitModel)]
    wfm = All2AllIterative(UniformSite(), V80(), wake_deficitModel=wake_deficitModel, blockage_deficitModel=blockage_deficitModel,
                           turbulenceModel=turbulenceModel)
    return wfm(x=[0], y=[0], wd=270, ws=10, yaw=0).flow_map(grid)

def plot_deficit_map(model, cmap='Blues', levels=np.linspace(0, 10, 55)):
    fm = get_flow_map(model)
    fm.plot(fm.ws - fm.WS_eff, clabel='Deficit [m/s]', levels=levels, cmap=cmap, normalize_with=D)
    setup_plot(grid=False, ylabel="Crosswind distance [y/D]", xlabel= "Downwind distance [x/D]",
               xlim=[fm.x.min()/D, fm.x.max()/D], ylim=[fm.y.min()/D, fm.y.max()/D], axis='auto')

def plot_wake_deficit_map(model):
    cmap = np.r_[[[1,1,1,1],[1,1,1,1]],cm.Blues(np.linspace(-0,1,128))] # ensure zero deficit is white
    plot_deficit_map(model,cmap=ListedColormap(cmap))
```

Below are the two models in PyWake that follow a top-hat shape, and are only valid in the far wake.

NOJDeficit

The NOJDeficit model is implemented according to Niels Otto Jensen, “A note on wind generator interaction.” (1983), i.e. a top-hat wake.

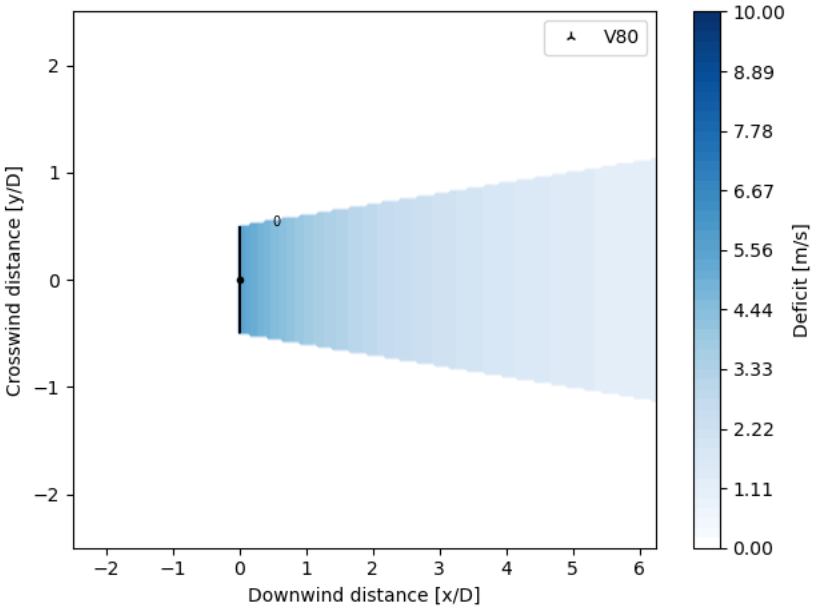
According to Jensen, the velocity in the wake V is defined as:

$$V = U\left(1 - 2a\left(\frac{r_o}{r_o + \alpha x}\right)^2\right)$$

where U is the free stream velocity, r_o the wake radius, x the downstream distance and α the entraintment constant (with a value of 0.1).

Only valid in the far wake.

[6]:
```
from py_wake.deficit_models import NOJDeficit
plot_wake_deficit_map(NOJDeficit())
```



TurboNOJDeficit

Implemented according to Nygaard 2020 J. Phys.: Conf. Ser. 1618 062072 https://doi.org/10.1088/1742-6596/1618/6/062072 [1].

Modified definition of the wake expansion given by Nygaard [1], which assumes the wake expansion rate to be proportional to the local turbulence intens added turbulence. Using the added wake turbulence model by Frandsen and integrating, an analytical expression for the wake radius can be obtained.

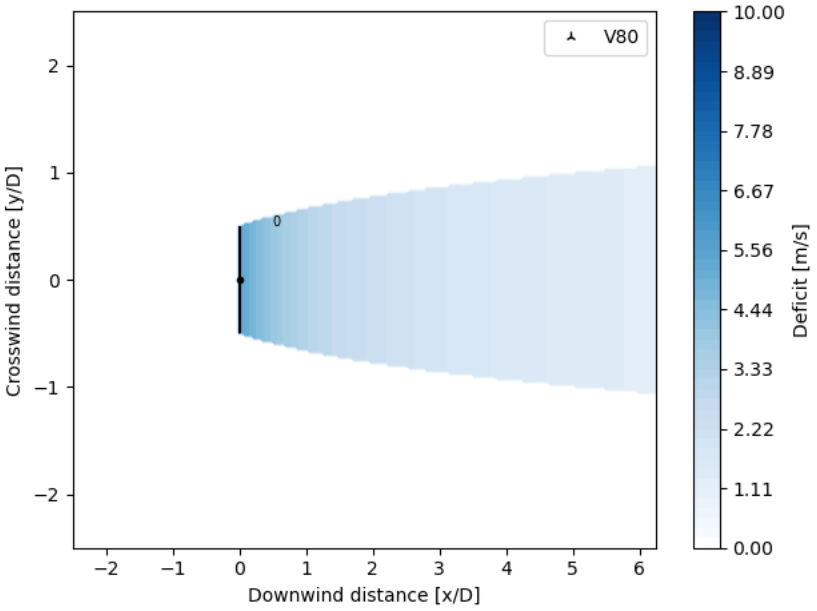
The definition in [1] of ambient turbulence is the free-stream TI and for this the model constant A has been tuned, however a fully consistent formulation upstream turbines.

The velocity deficit is calculated as in the `NOJDeficit` model, with a modification of the wake radius term r_o, given by:

$$D_w(x) = 0.5 + \frac{AI_0D}{\beta} \times \left(\sqrt{(\alpha + \beta x/D)^2 + 1} - \sqrt{1 + \alpha^2} - \ln \left[\frac{\left(\sqrt{(\alpha}\right.}{\left(\sqrt{1}\right.} \right.$$

where A is the wake expansion parameter, set to a constant value of 0.6, I_0 is the free stream TI, D is the rotor diameter, x the downstream distance an

[7]:
```
from py_wake.deficit_models import TurboNOJDeficit
plot_wake_deficit_map(TurboNOJDeficit())
```



The rest of the models follow a Gaussian shape, with the advantage of having models for calculation of the near wake (Fuga, Zong Gaussian, Super Gaus

BastankhahGaussianDeficit

The Bastankhah Gaussian Deficit model is implemented according to Bastankhah M and Porté-Agel F. “A new analytical model for wind-turbine wakes” J.

By applying mass and momentum conservation and assuming a self-similar Gaussian profile for the wake, a general expression for the velocity deficit is de

$$\frac{\Delta U}{U_\infty} = C(x)e^{-\frac{x^2}{2\sigma^2}}$$

The maximum velocity deficit at the center of the wake $C(x)$ is defined by:

$$C(x) = 1 - \sqrt{1 - \frac{C_\mathrm{T}}{8(\sigma/d_0)^2}}$$

and the wake width (σ) is defined as:

$$\frac{\sigma}{d_0} = k^* x/d_0 + \varepsilon$$

where k represents the wake expansion parameter and ε = 0.2 β, with β being a parameter function of the turbine's C_T.

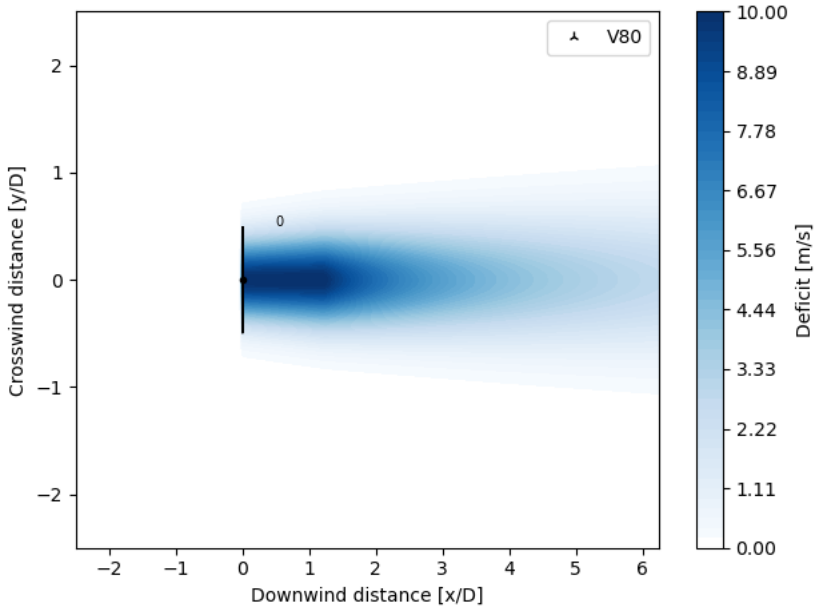
Thus, the normalized velocity deficit can be calculated as:

$$\frac{\Delta U}{U_\infty} = \left(1 - \sqrt{1 - \frac{C_\mathrm{T}}{8(k^* x/d_0 + \varepsilon)^2}}\right) \times \exp\left(-\frac{1}{2(k^* x/d_0 + \varepsilon)^2}\left\{\left(\frac{z - z_\mathrm{h}}{d_0}\right)^2 +\right.\right.$$

where C_T is the turbine's thrust coefficient, x the downstream distance, z_H the turbine's hub height, and y and z the spanwise and vertical coordinates,

The model is valid in the far wake only.

[8]:
```
from py_wake.deficit_models import BastankhahGaussianDeficit
plot_wake_deficit_map(BastankhahGaussianDeficit())
```



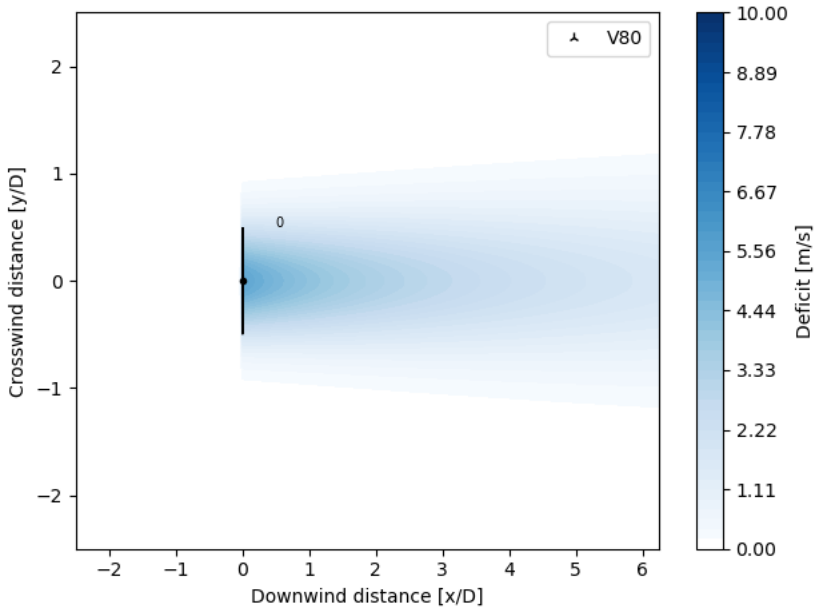
IEA37SimpleBastankhahGaussianDeficit

The IEA37 Simple Bastankhah Gaussian Deficit model is implemented according to the IEA task 37 documentation and is equivalent to `BastankhahGaussia`

$$beta = 1/\sqrt{8} \sim ct = 0.9637188$$

The model is valid in the far wake only.

[9]:
```
from py_wake.deficit_models import IEA37SimpleBastankhahGaussianDeficit
plot_wake_deficit_map(IEA37SimpleBastankhahGaussianDeficit())
```



NiayifarGaussianDeficit

Implemented according to Amin Niayifar and Fernando Porté-Agel, "Analytical Modeling of Wind Farms: A New Approach for Power Prediction", Energies

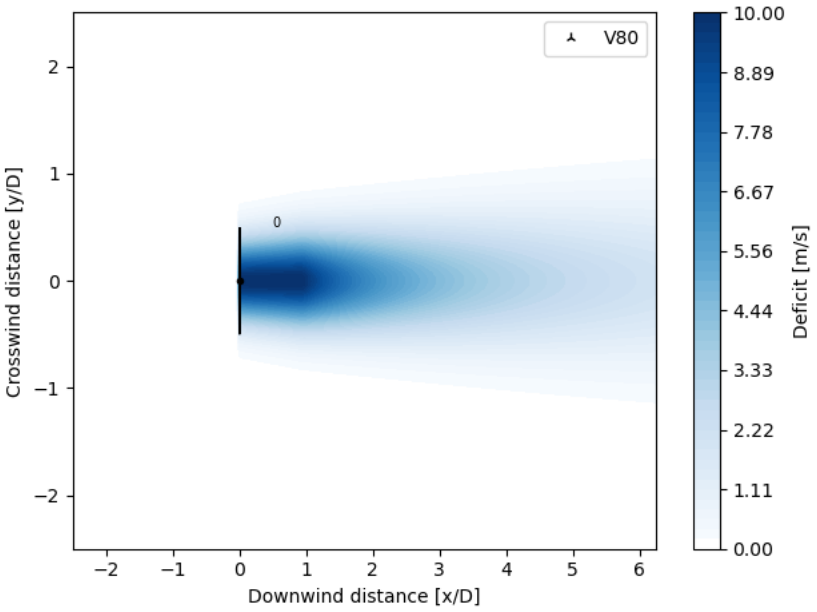
The calculation of the velocity deficit is made as in `BastankhahGaussianDeficit`, with the modification of the wake expansion parameter k^*.

This wake deficit model accounts for the local turbulence intensity when evaluating the wake expansion. The expansion rate k^* varies linearly with local t

$$k^* = a1I + a2$$

The default constants are set according to publications by Porte-Agel's group, which are based on LES simulations, where $a1 = 0.3837$ and $a2 = 0.0$ selection.

[10]:
```
from py_wake.deficit_models import NiayifarGaussianDeficit
plot_wake_deficit_map(NiayifarGaussianDeficit(a=[0.38, 4e-3]))
```



ZongGaussianDeficit

Implemented according to Haohua Zong and Fernando Porté-Agel, “A momentum-conserving wake superposition method for wind farm power prediction

Based on the `NiayifarGaussianDeficit` model, the wake expansion is also function of the local turbulence intensity and the wake width expression now f
σ) expression, which uses the near-wake length estimation by Vermeulen (1980).

The near-wake length expression is defined as:

$$x_n = \frac{\sqrt{0.214 + 0.144m}(1 - \sqrt{0.134 + 0.124m}}{(1 - \sqrt{0.214 + 0.144m})\sqrt{0.134 + 0.124m}}$$

With the new expression for the wake width represented by:

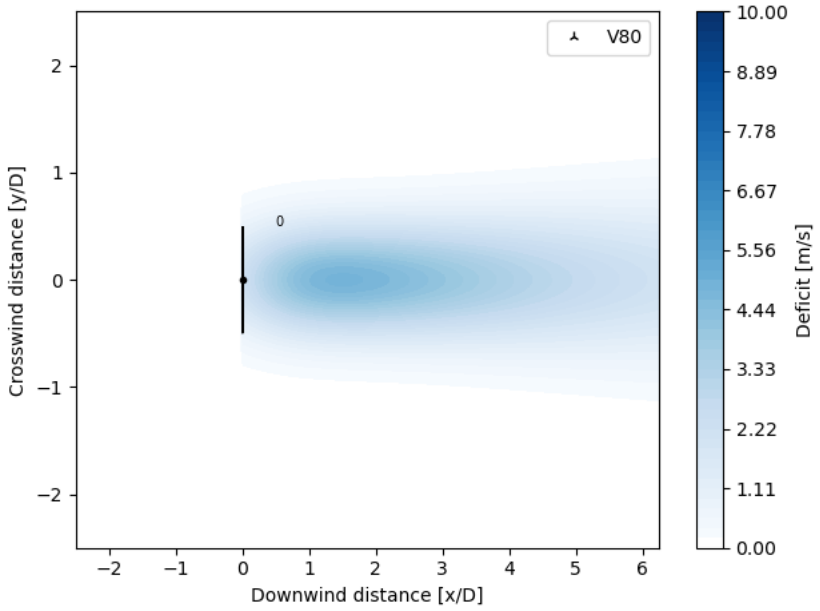
$$\sigma = \epsilon + k_w \ln\left[1 + \exp\left(\frac{x - x_n}{D}\right)\right] * i$$

where $\epsilon = (1/\sqrt{8})C_T$ and k_w is the wake expansion rate.

The thrust coefficient used in the deficit calculation is now written as an error function of the streamwise coordinate due to the effect of the near-wake p

$$C_{it}(x) = C_T(1 + \mathrm{erf}(x/D))/2$$

[11]:
```
from py_wake.deficit_models import ZongGaussianDeficit
plot_wake_deficit_map(ZongGaussianDeficit(a=[0.38, 4e-3]))
```

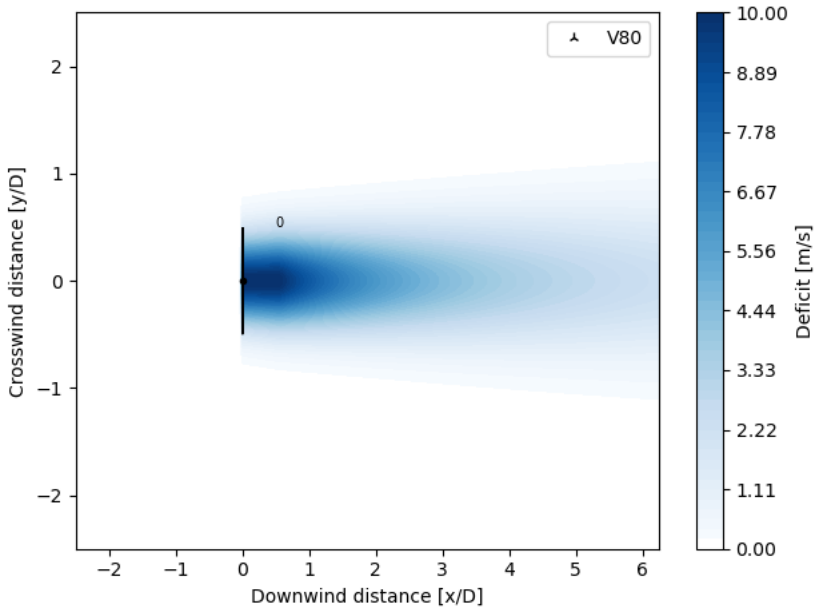


CarbajoFuertesGaussianDeficit

Modified version from the `ZongGaussianDeficit` model with Gaussian constants, as seen in: Fernando Carbajo Fuertes, Corey D. Markfor and Fernando P Model Validation", Remote Sens. 2018, 10, 668; doi:10.3390/rs10050668.

Carbajo Fuertes et al. derived Gaussian wake model parameters from nacelle liadar measurements from a 2.5MW turbine and found a variation of epsilon fixed for Carbajo Fuertes at $xth = 1.91(x/D)$. We took the relationships found by them and incorporated them into the Zong formulation. This wake factor equation.

[12]:
```
from py_wake.deficit_models import CarbajofuertesGaussianDeficit
plot_wake_deficit_map(CarbajofuertesGaussianDeficit())
```



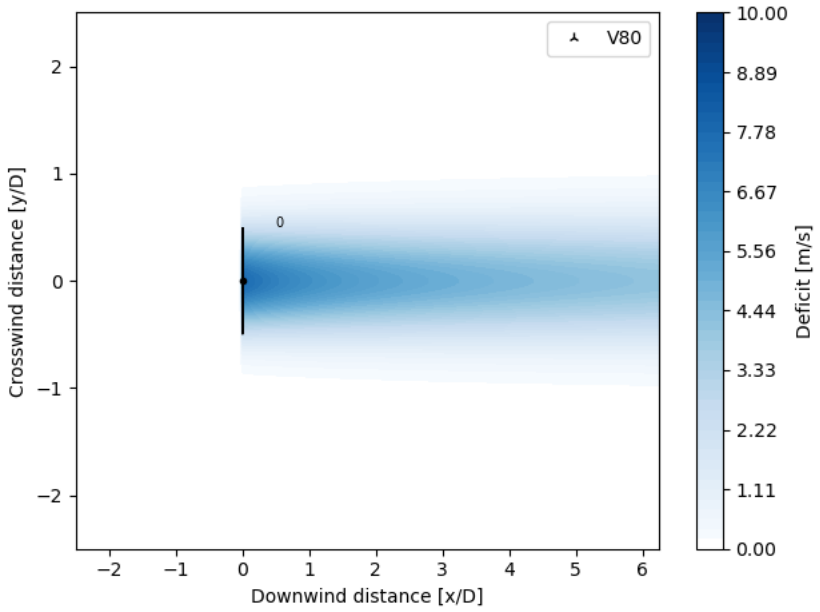
TurboGaussianDeficit

Implemented similar to Ørsted's TurbOPark model (https://github.com/OrstedRD/TurbOPark).

The calculation of the deficit is similar to that in `TurboNOJDeficit` with the distinction of assuming a Gaussian shape for the expansion of the wake using t `BastahnkhahGaussianDeficit`, 0.2 β.

$$\frac{\sigma_{w,i}\left(\hat{x}_i\right)}{D_i} = \epsilon_i + \frac{AI_0}{\beta}$$
$$\times \left(\sqrt{\left(\alpha + \beta\hat{x}_i/D_i\right)^2 + 1} - \sqrt{1+\alpha^2} - \ln\left[\frac{\left(\sqrt{(}\right.}{\left(\sqrt{1}\right.} \right.$$

[13]:
```
from py_wake.deficit_models import TurboGaussianDeficit
plot_wake_deficit_map(TurboGaussianDeficit())
```



SuperGaussianDeficit

Implemented according to Blondel and Cathelain (2020), "An alternative form of the super-Gaussian wind turbine wake model" Wind Energ. Sci., 5, 1225-

New calibrated parameters taken from Blondel (2023), "Brief communication: A momentum-conserving superposition method applied to the super-Gauss 141-2023 [2].

The Super Gaussian deficit model is derived from the general equation for velocity deficit seen in `BastankhahGaussianDeficit` with the addition of the sup from top-hat to gaussian, with high values of n representing the near wake and low values (approaching $n = 2$) representing a purely Gaussian profile.

The velocity deficit is calculated as follows:

$$\frac{U_\infty - U_\mathrm{w}}{U_\infty} = C(x) e^{-\bar{r}^n/(2\sigma^2)}$$

where the maximum velocity deficit $C(x)$ is defined as:

$$C(x) = 2^{2/n-1} - \sqrt{2^{4/n-2} - \frac{nC_T}{16\Gamma(2/n)\sigma^2}}$$

The characteristic wake width (σ) is also a function of the TI as in the Bastankhah Gaussian model.

$$\sigma = (a_s T_i + b_s)x + c_s\sqrt{\beta}$$

Lastly, the analytical super gaussian parameter n is based on curve fitting and represented by:

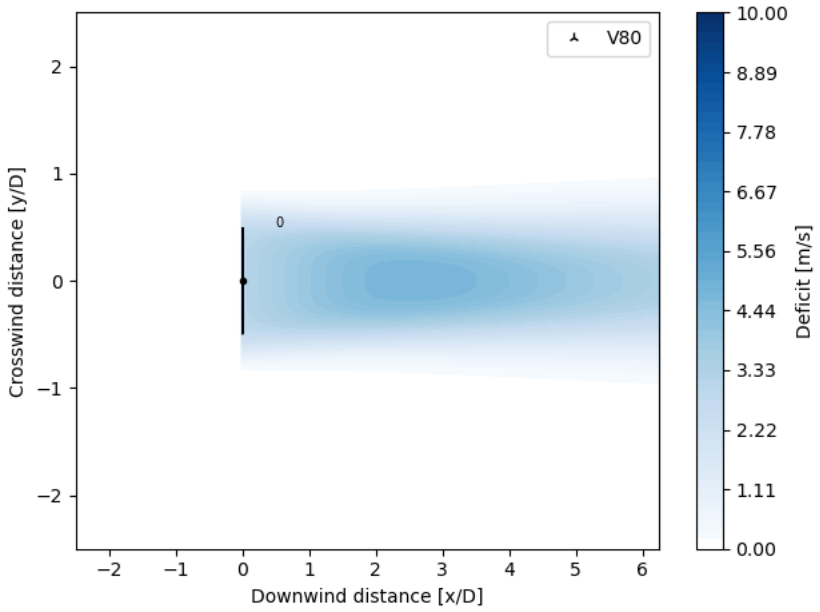
$$n = a_f e^{b_f x} + c_f$$

The parameters used for the model ($a_s, b_s, c_s, a_f, b_f, c_f$) are calibrated with two measurement campaings: particle velocimetry measurements and lida as seen in [1].

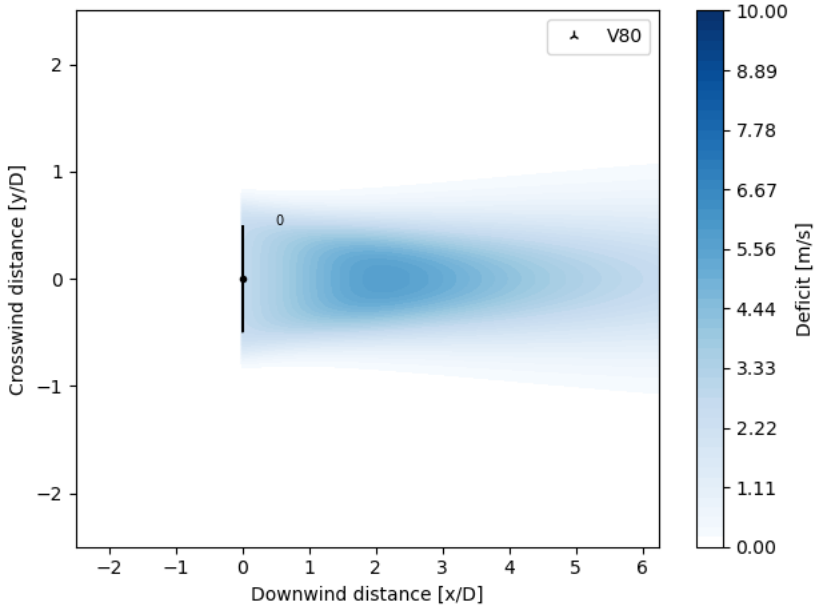
There are two classes defined:

- `BlondelSuperGaussianDeficit2020`: which uses the calibrated parameters in Table 2 and 3 in [1].
- `BlondelSuperGaussianDeficit2023`: which uses the latest calibrated parameters found in Table 1 in [2].

[14]:
```
from py_wake.deficit_models.gaussian import BlondelSuperGaussianDeficit2020
plot_wake_deficit_map(BlondelSuperGaussianDeficit2020())
```



[15]:
```
from py_wake.deficit_models.gaussian import BlondelSuperGaussianDeficit2023
plot_wake_deficit_map(BlondelSuperGaussianDeficit2023())
```



FugaDeficit

The FugaDeficit model calculates the wake deficit based on a set of look-up tables computed by a linearized RANS solver. The look-up tables are created

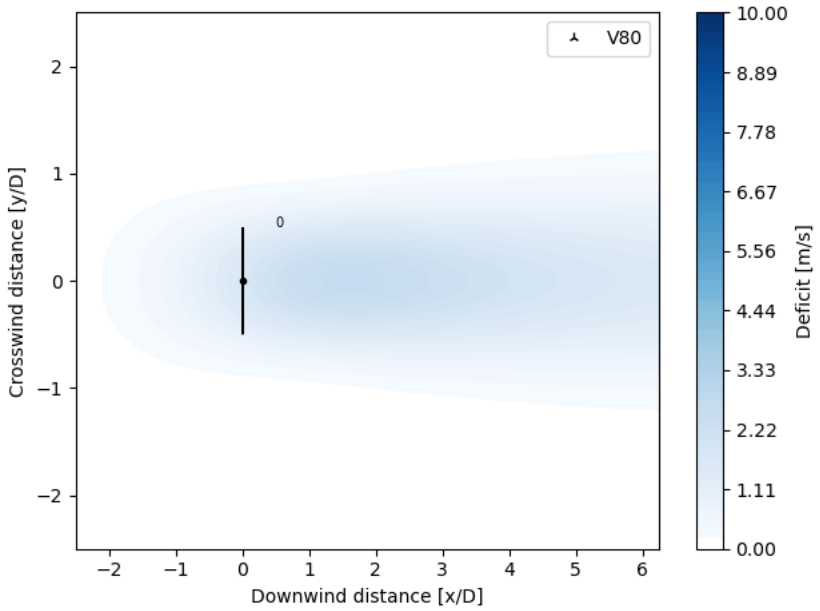
The most important parameters to create the look-up tables are:

- Wind turbine diameter
- Wind tubine hub height
- Terrain roughness length
- Lower and upper height of output domain (if, for example, the wake is to be studied around the rotor only or for a whole wind farm)

The FugaDeficit model can model the near wake, far wake and blockage deficit.

[16]:
```
import py_wake
from py_wake.deficit_models import FugaDeficit
```

```
# Path to Fuga look-up tables
lut_path = os.path.dirname(py_wake.__file__)+'/tests/test_files/fuga/2MW/Z0=0.03000000Zi=00401Zeta0=0.00E+00.nc'

plot_wake_deficit_map(FugaDeficit(lut_path))
```

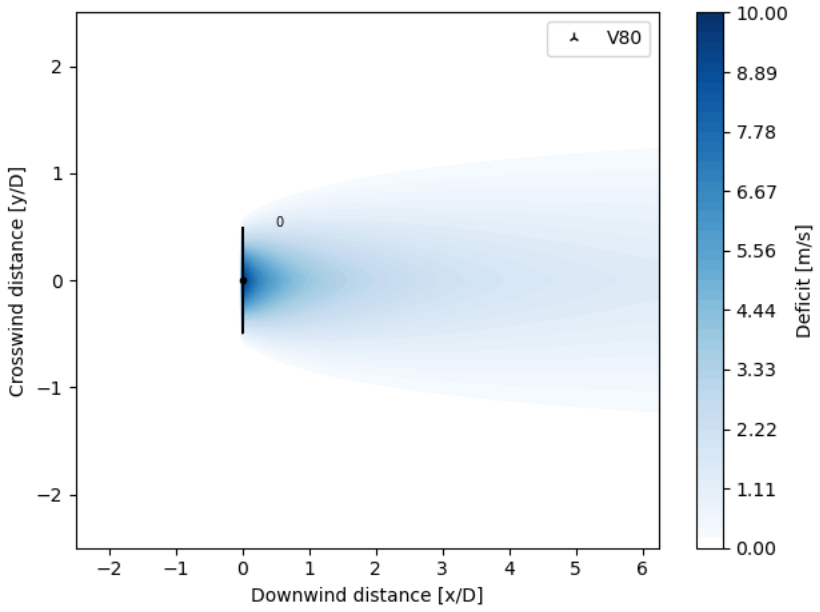


GCLDeficit

Implemented according to Larsen, G. C. (2009), “A simple stationary semi-analytical wake model”, Risø National Laboratory for Sustainable Energy, Techni

It is based on an analytical solution of the thin shear layer approximation of the NS equations. The wake flow fields are assumed rotationally symmetric, a
accounted for by imposing suitable empirical downstream boundary conditions on the wake expansion that depend on the rotor thrust and the ambient t

[17]:
```
from py_wake.deficit_models import GCLDeficit
plot_wake_deficit_map(GCLDeficit())
```



Comparing wake deficit models

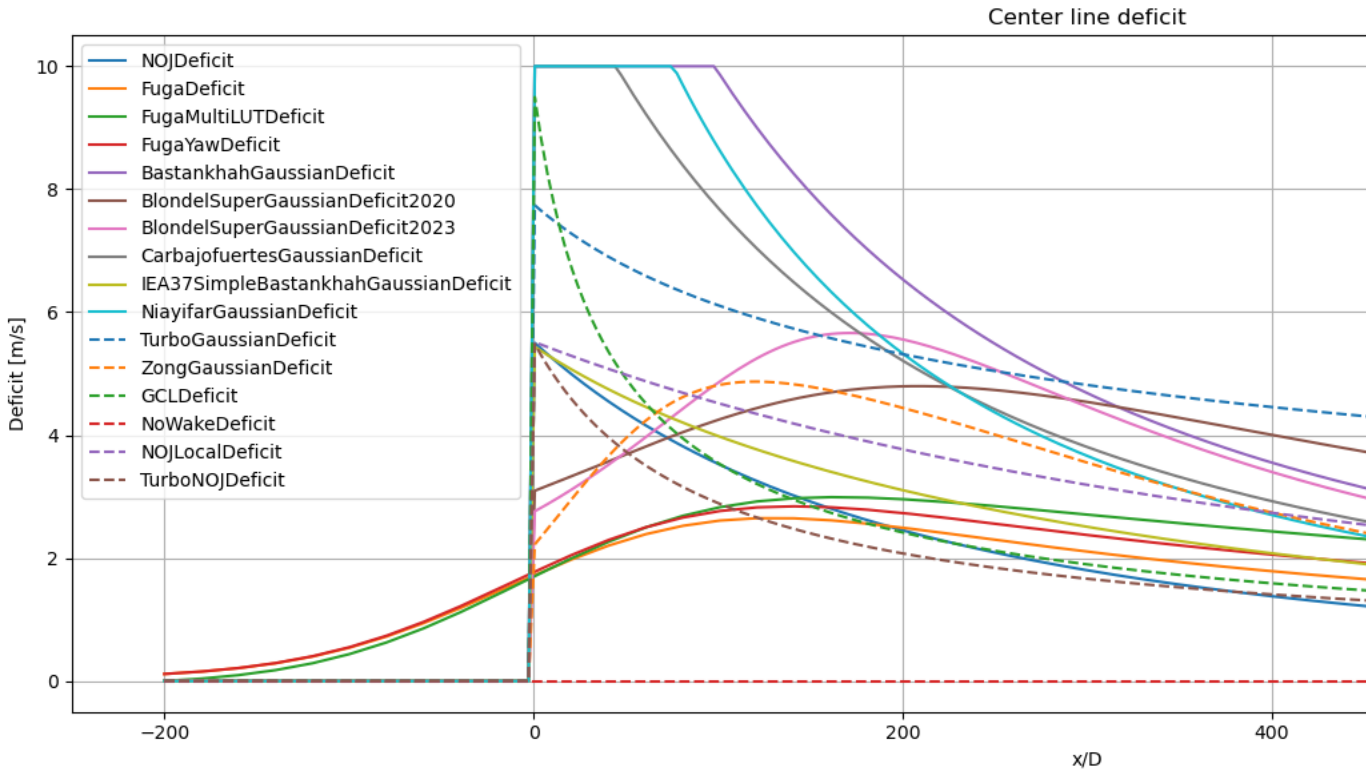
[18]:
```
#printing all available wake deficit models in PyWake
from py_wake.utils.model_utils import get_models
from py_wake.deficit_models.deficit_model import WakeDeficitModel

deficitModels = get_models(WakeDeficitModel)
for deficitModel in deficitModels:
    print (deficitModel.__name__)
```

```
NOJDeficit
FugaDeficit
```

```
FugaMultiLUTDeficit
FugaYawDeficit
BastankhahGaussianDeficit
BlondelSuperGaussianDeficit2020
BlondelSuperGaussianDeficit2023
CarbajofuertesGaussianDeficit
IEA37SimpleBastankhahGaussianDeficit
NiayifarGaussianDeficit
TurboGaussianDeficit
ZongGaussianDeficit
GCLDeficit
NoWakeDeficit
NOJLocalDeficit
TurboNOJDeficit
```

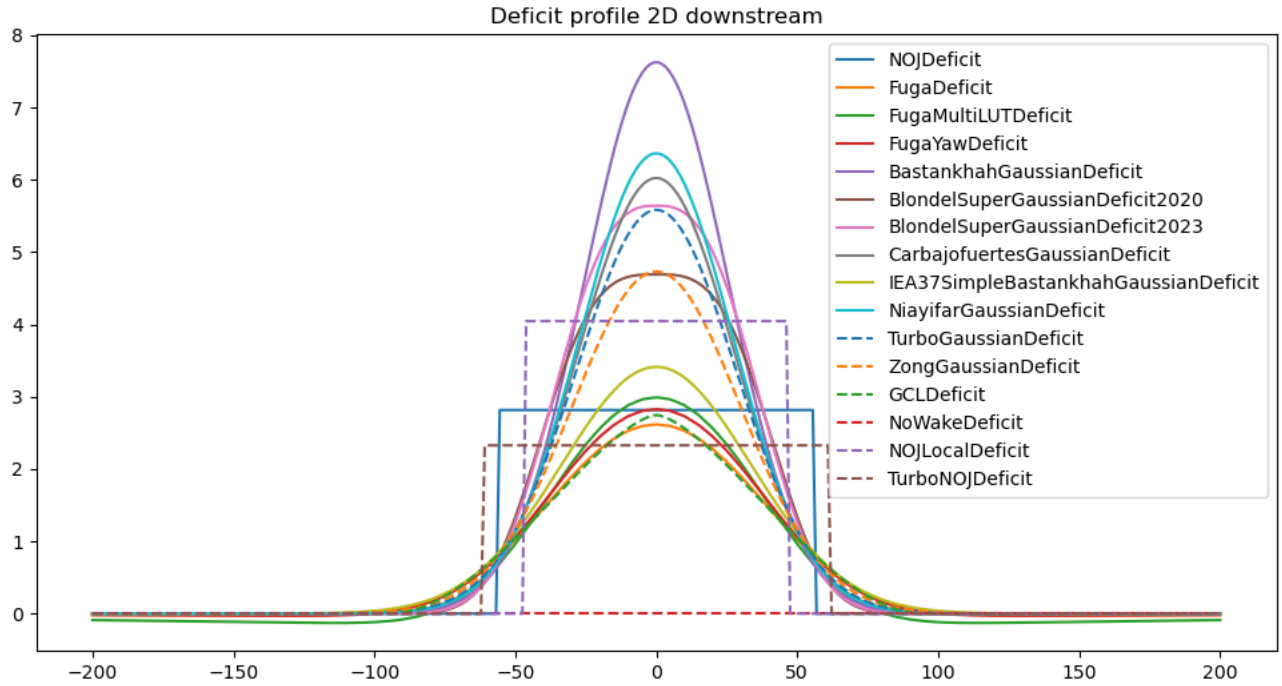
1) Deficit along center line

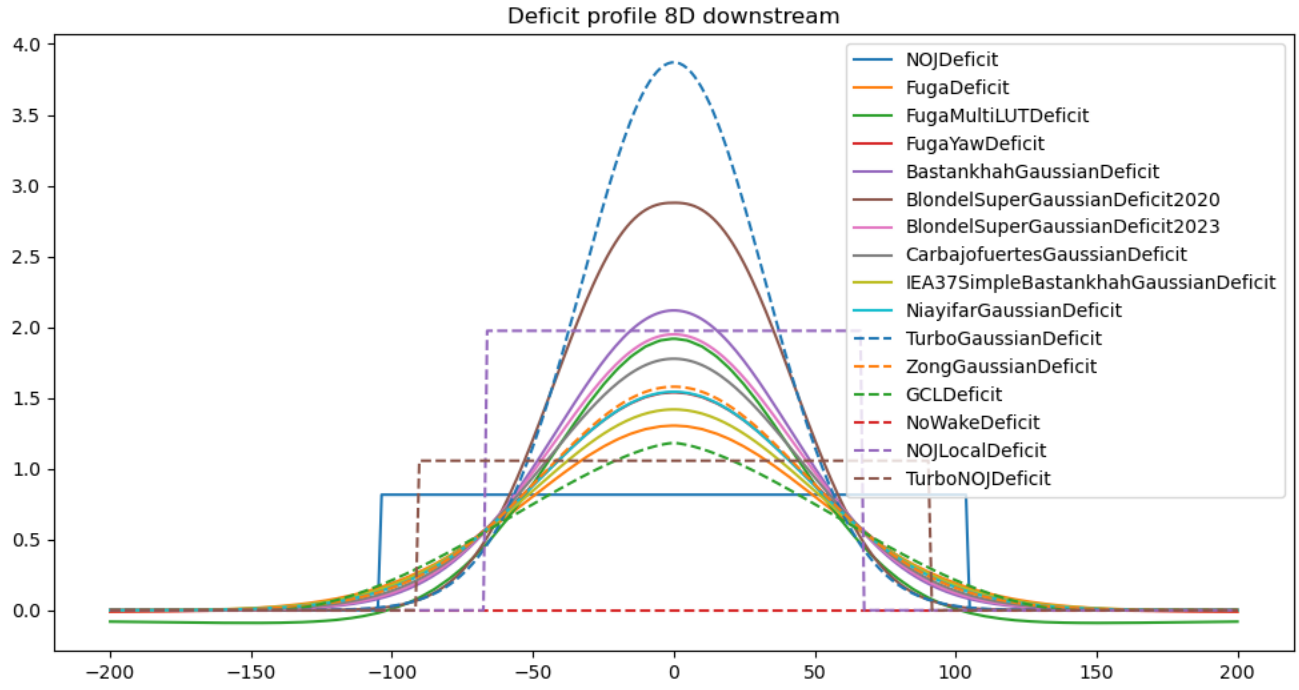
[19]:
```
plt.figure(figsize=((16,6)))
for i, deficitModel in enumerate(deficitModels):
    fm = get_flow_map(deficitModel(), XYGrid(x=np.linspace(-200,800,300), y=0))
    plt.plot(fm.x, 10-fm.WS_eff.squeeze(), ('-','--')[i//10], label=deficitModel.__name__)
setup_plot(title="Center line deficit", xlabel='x/D', ylabel='Deficit [m/s]')
```

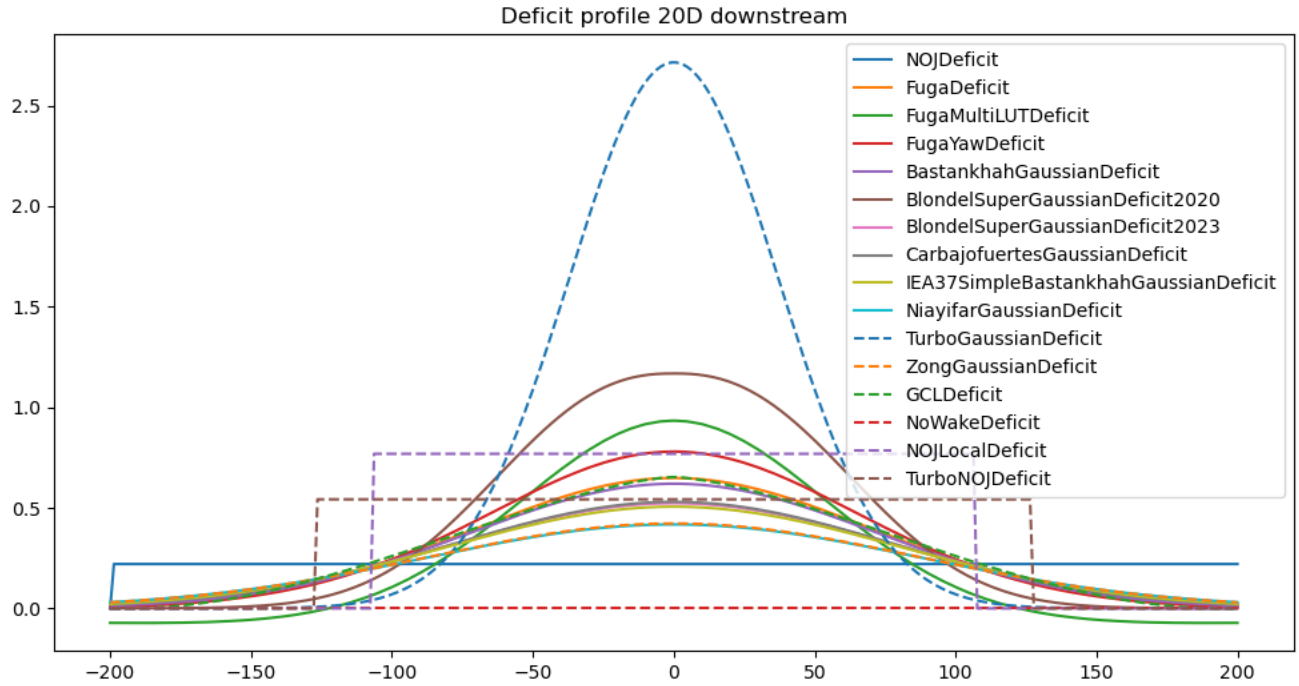


2) Deficit profile downstream

[20]:
```
for d in 2,8,20:
    plt.figure(figsize=((12,6)))
    for i, deficitModel in enumerate(deficitModels):
        fm = get_flow_map(deficitModel(), XYGrid(x=d*D, y=np.linspace(-200,200,300)))
        plt.plot(fm.y, 10-fm.WS_eff.squeeze(), ('-','--')[i//10], label=deficitModel.__name__)
    plt.title(f'Deficit profile {d}D downstream')
    plt.legend()
```





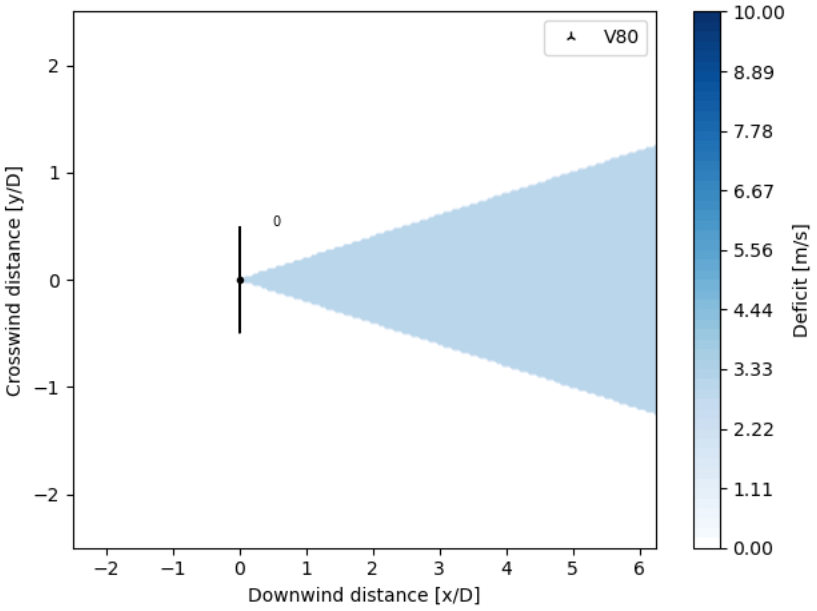


Implement your own deficit models

Deficit models must subclass `DeficitModel` and thus must implement the `calc_deficit` method and a class variable, `args4deficit` specifying the argume

```
class DeficitModel(ABC):
    args4deficit = ['WS_ilk', 'dw_ijlk']

    @abstractmethod
    def calc_deficit(self):
        """Calculate wake deficit caused by the x'th most upstream wind turbines
        for all wind directions(l) and wind speeds(k) on a set of points(j)

        This method must be overridden by subclass

        Arguments required by this method must be added to the class list
        args4deficit

        See class documentation for examples and available arguments

        Returns
        -------
        deficit_ijlk : array_like
        """
```

[21]:
```
from py_wake.deficit_models.deficit_model import WakeDeficitModel
from numpy import newaxis as na
class MyDeficitModel(WakeDeficitModel):

    def calc_deficit(self, WS_ilk, dw_ijlk, cw_ijlk,**_):
        # 30% deficit in downstream triangle
        ws_10pct_ijlk = 0.3*WS_ilk[:,na]
        triangle_ijlk = (self.wake_radius(dw_ijlk=dw_ijlk)>cw_ijlk)
        return ws_10pct_ijlk *triangle_ijlk

    def wake_radius(self, dw_ijlk, **_):
        return (.2*dw_ijlk)

plot_wake_deficit_map(MyDeficitModel())
```



Superposition Models

The superposition models calculate the effective wind speed given the local wind speed and deficits (typically from multiple sources) or the effective turbulences from multiple sources. In PyWake, the effective wind speed is representative of the wind speed perceived by the ith turbine's rotor on the wind farm (u_{i0}), as it is usually mentioned in the literature.

There are four different wake superposition models in PyWake:

- LinearSum: Deficits sum up linearly.
- SquaredSum: Deficits sum as root-sum-square.
- MaxSum: Only the largest deficit is considered.
- WeightedSum: A weighted sum of the invidiual wake velocity deficits is performed to obtain the total deficit. The ratio between the mean convection velocity and the convection velocity of the combined wake is used to determine the weights. This superposition model is capable of conserving momentum in the streamwise direction.

And one turbulence superposition model in PyWake:

- SqrMaxSum: The root-sum-square of the local turbulence intensity and the maximum value of the added turbulence caused by the source turbine is considered.

Install PyWake if needed

[1]:
```
# Install PyWake if needed
try:
    import py_wake
except ModuleNotFoundError:
    !pip install git+https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake.git
```

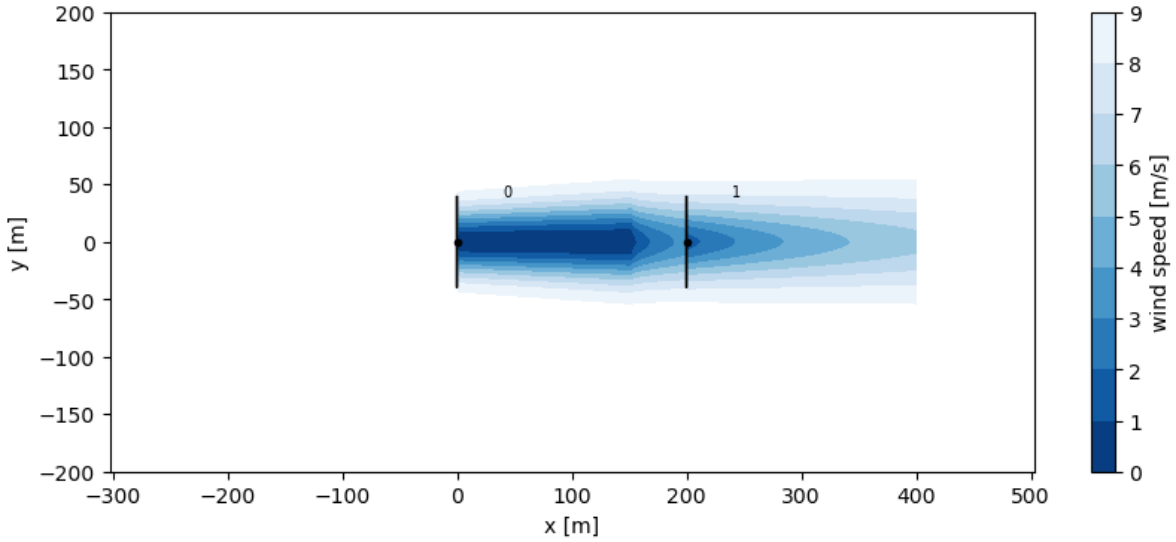
[2]:
```
import numpy as np
import matplotlib.pyplot as plt

from py_wake.literature.gaussian_models import Bastankhah_PorteAgel_2014
from py_wake.literature.gaussian_models import Zong_PorteAgel_2020
from py_wake.turbulence_models import CrespoHernandez
from py_wake.examples.data.hornsrev1 import V80, Hornsrev1Site

site = Hornsrev1Site()
windTurbines = V80()
```

LinearSum

In general, LinearSum should be used in combination with `use_effective_ws=True` which makes downstream wind turbines feel the effective wind speed (including wake effects from upstream turbines) instead of the ambient free-stream wind speed. Otherwise negative wind speeds may occur.

[3]:
```
from py_wake.superposition_models import LinearSum

linear_sum = Bastankhah_PorteAgel_2014(site, windTurbines, k=0.0324555, superpositionModel=LinearSum(), use_effective_ws=True)
plt.figure(figsize=(10,4))
linear_sum([0,200],[0,0],wd=270,ws=10).flow_map().plot_wake_map(levels=np.arange(0,10))
plt.xlabel('x [m]')
plt.ylabel('y [m]')
```

[3]:
```
Text(0, 0.5, 'y [m]')
```

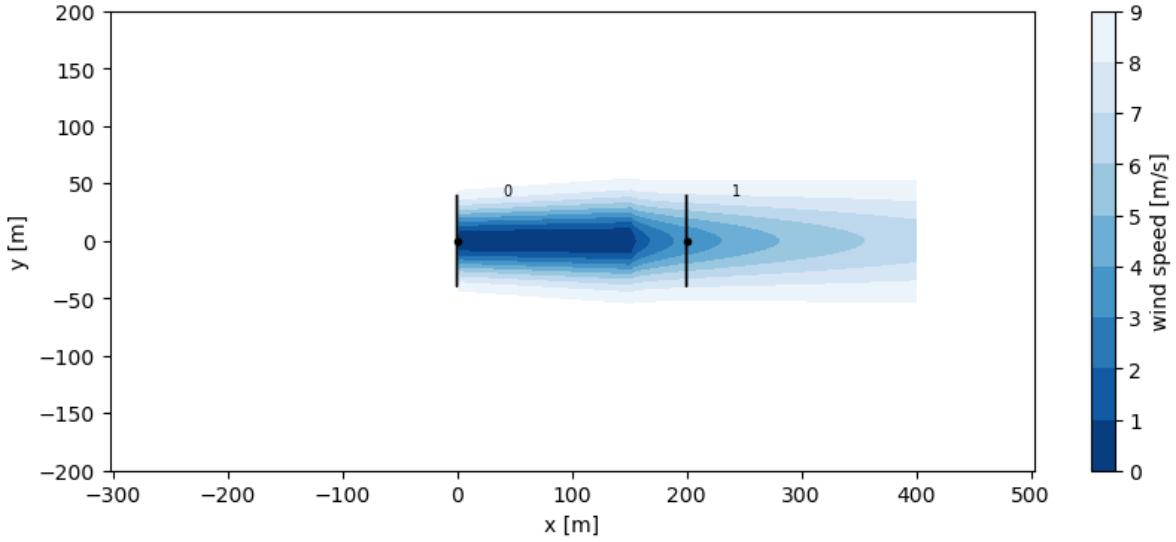


SquaredSum

The SquaredSum model is often used in combination with wake deficit models where the downstream wakes are scaled with the ambient free-stream velocity to avoid negative wind speeds. It is, however, a method to compensate for an inconsistent formulation, see section 2.2 in https://backend.orbit.dtu.dk/ws/portalfiles/portal/151671395/Park2_Documentation_and_Validation.pdf

[4]:
```
from py_wake.superposition_models import SquaredSum

squared_sum = Bastankhah_PorteAgel_2014(site, windTurbines, k=0.0324555, superpositionModel=SquaredSum())
plt.figure(figsize=(10,4))
squared_sum([0,200],[0,0],wd=270,ws=10).flow_map().plot_wake_map(levels=np.arange(0,10))
plt.xlabel('x [m]')
plt.ylabel('y [m]')
```

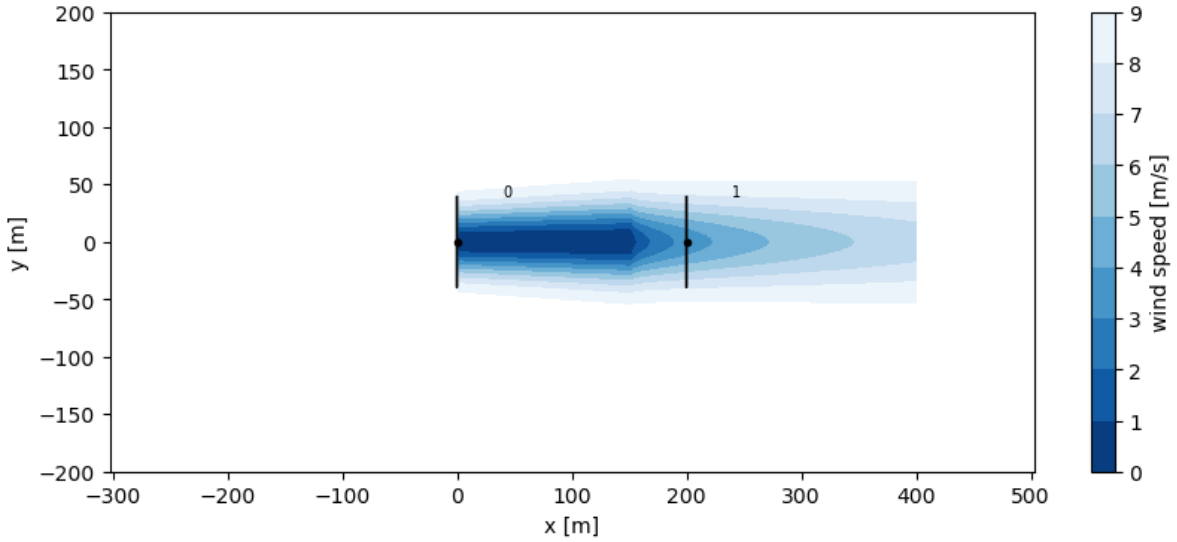
[4]: Text(0, 0.5, 'y [m]')



MaxSum

[5]:
```
from py_wake.superposition_models import MaxSum

max_sum = Bastankhah_PorteAgel_2014(site, windTurbines, k=0.0324555, superpositionModel=MaxSum())
plt.figure(figsize=(10,4))
max_sum([0,200],[0,0],wd=270,ws=10).flow_map().plot_wake_map(levels=np.arange(0,10))
plt.xlabel('x [m]')
plt.ylabel('y [m]')
```

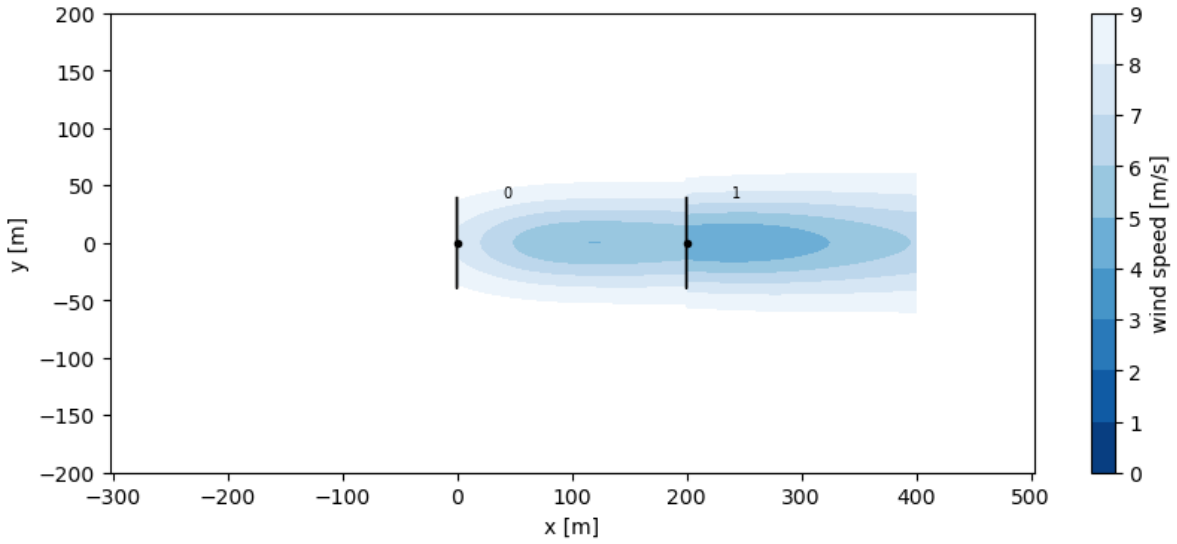
[5]: Text(0, 0.5, 'y [m]')



WeightedSum

[6]:
```
from py_wake.superposition_models import WeightedSum

weighted_sum = Zong_PorteAgel_2020(site, windTurbines, use_effective_ws=True, superpositionModel=WeightedSum())

plt.figure(figsize=(10,4))
weighted_sum([0,200],[0,0],wd=270,ws=10).flow_map().plot_wake_map(levels=np.arange(0,10))
plt.xlabel('x [m]')
plt.ylabel('y [m]')
```

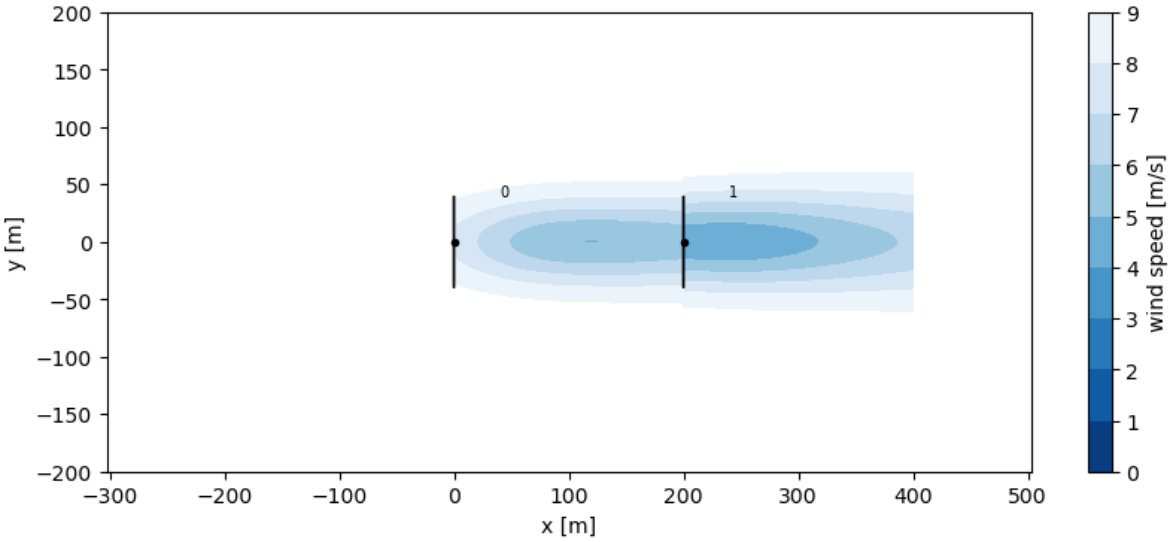
[6]: Text(0, 0.5, 'y [m]')



SqrMaxSum

[7]:
```
from py_wake.superposition_models import SqrMaxSum

sqr_max_sum = Zong_PorteAgel_2020(site, windTurbines, use_effective_ws=True, superpositionModel=WeightedSum(),
                                  turbulenceModel=CrespoHernandez(addedTurbulenceSuperpositionModel=SqrMaxSum()))
plt.figure(figsize=(10,4))
sqr_max_sum([0,200],[0,0],wd=270,ws=10).flow_map().plot_wake_map(levels=np.arange(0,10))
plt.xlabel('x [m]')
plt.ylabel('y [m]')
```

[7]: Text(0, 0.5, 'y [m]')



Blockage Deficit Models

The blockage deficit models compute the blockage effects caused by a single wind turbine.

Their structure are quite similar to the Wake Deficit Models. They model upstream blockage effects (wind speed reduction) and in addition, some models also models downstream speed-up effects. There are several blockage models available, which include:

- SelfSimilarityDeficit
- SelfSimilarityDeficit2020
- FugaDeficit
- VortexCylinder
- VortexDipole
- RankineHalfBody
- HybridInduction
- Rathmann

Install PyWake if needed

[1]:
```
# Install PyWake if needed
try:
    import py_wake
except ModuleNotFoundError:
    !pip install git+https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake.git
```

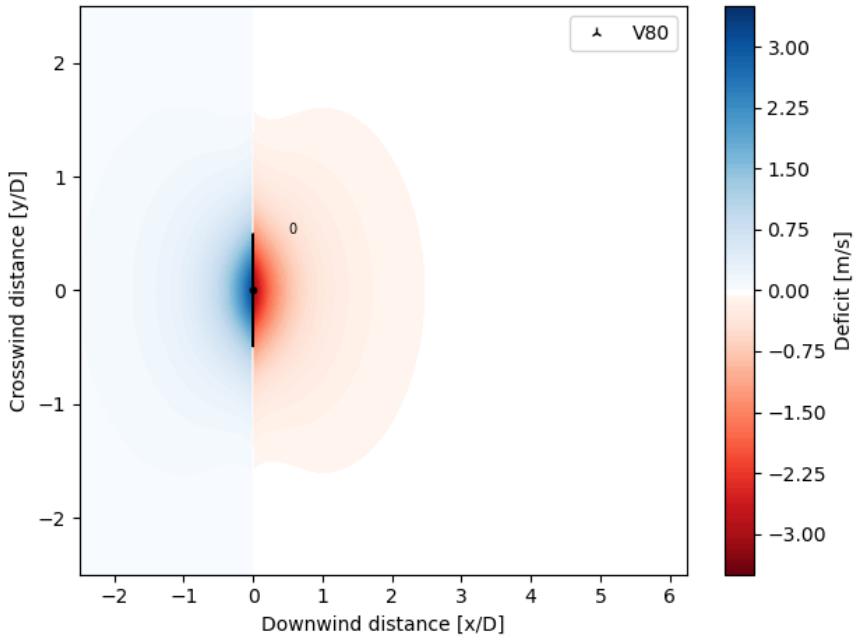
[2]:
```
import numpy as np
import matplotlib.pyplot as plt
from matplotlib import cm
from matplotlib.colors import ListedColormap, LinearSegmentedColormap

# import and setup site and windTurbines
import py_wake
from py_wake.examples.data.hornsrev1 import V80, Hornsrev1Site

site = Hornsrev1Site()
windTurbines = V80()
wt_x, wt_y = site.initial_position.T
```

[3]:
```
from py_wake.deficit_models.deficit_model import WakeDeficitModel, BlockageDeficitModel
from py_wake.deficit_models.no_wake import NoWakeDeficit
from py_wake.site._site import UniformSite
from py_wake.flow_map import XYGrid
from py_wake.turbulence_models import CrespoHernandez
from py_wake.utils.plotting import setup_plot
from py_wake.wind_farm_models import All2AllIterative

#turbine diameter
D = 80

def get_flow_map(model=None, grid=XYGrid(x=np.linspace(-200, 500, 200), y=np.linspace(-200, 200, 200), h=70),
                 turbulenceModel=CrespoHernandez()):
    blockage_deficitModel = [None, model][isinstance(model, BlockageDeficitModel)]
    wake_deficitModel = [NoWakeDeficit(), model][isinstance(model, WakeDeficitModel)]
    wfm = All2AllIterative(UniformSite(), V80(), wake_deficitModel=wake_deficitModel, blockage_deficitModel=blockage_deficitModel,
                           turbulenceModel=turbulenceModel)
    return wfm(x=[0], y=[0], wd=270, ws=10, yaw=0).flow_map(grid)

def plot_deficit_map(model, cmap='Blues', levels=np.linspace(0, 10, 55)):
    fm = get_flow_map(model)
    fm.plot(fm.ws - fm.WS_eff, clabel='Deficit [m/s]', levels=levels, cmap=cmap, normalize_with=D)
    setup_plot(grid=False, ylabel="Crosswind distance [y/D]", xlabel= "Downwind distance [x/D]",
               xlim=[fm.x.min()/D, fm.x.max()/D], ylim=[fm.y.min()/D, fm.y.max()/D], axis='auto')

def plot_blockage_deficit_map(model):
    from matplotlib import cm
    from matplotlib.colors import ListedColormap, LinearSegmentedColormap
    cmap = np.r_[cm.Reds_r(np.linspace(-0,1,127)),[[1,1,1,1]],[1,1,1,1]],cm.Blues(np.linspace(-0,1,128))] # ensure zero deficit is white
    plot_deficit_map(model,cmap=ListedColormap(cmap), levels=np.linspace(-3.5,3.5,113))
```

SelfSimilarityDeficit

Simple induction model, described in N. Troldborg, A.R. Meyer Fortsing, Wind Energy, 2016

[4]:
```
from py_wake.deficit_models import SelfSimilarityDeficit
plot_blockage_deficit_map(SelfSimilarityDeficit())
```

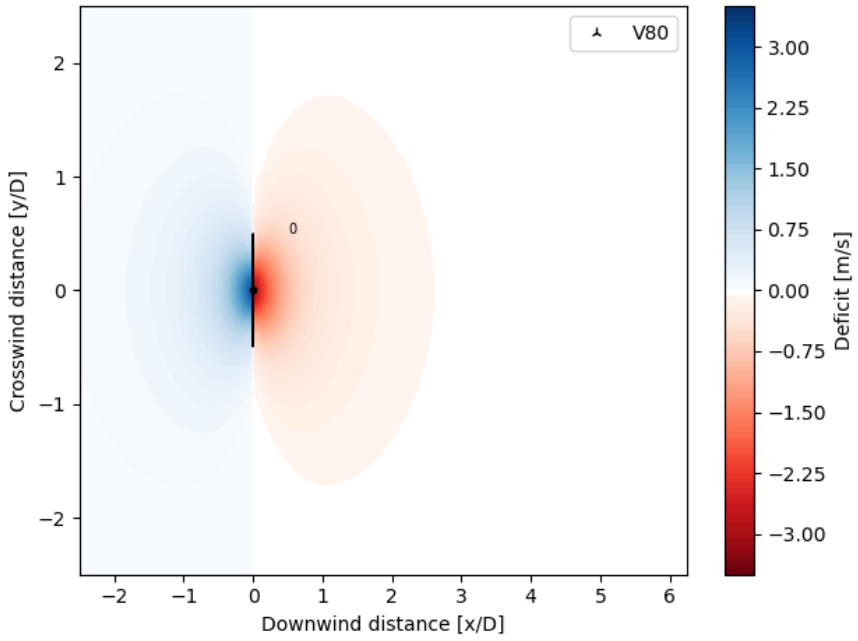


SelfSimilarityDeficit2020

This is an updated version of N. Troldborg, A.R. Meyer Fortsing, Wind Energy, 2016. The new features are found in the radial and axial functions:

1. Radially Eq. (13) is replaced by a linear fit, which ensures the induction half width, `r12`, to continue to diminish approaching the rotor. This avoids unphysically large lateral induction tails, which could negatively influence wind farm simulations.
2. The value of gamma in Eq. (8) is revisited. Now gamma is a function of CT and axial coordinate to force the axial induction to match the simulated results more closely. The fit is valid over a larger range of thrust coefficients and the results of the constantly loaded rotor are excluded in the fit.

[5]:
```
from py_wake.deficit_models import SelfSimilarityDeficit2020
plot_blockage_deficit_map(SelfSimilarityDeficit2020())
```



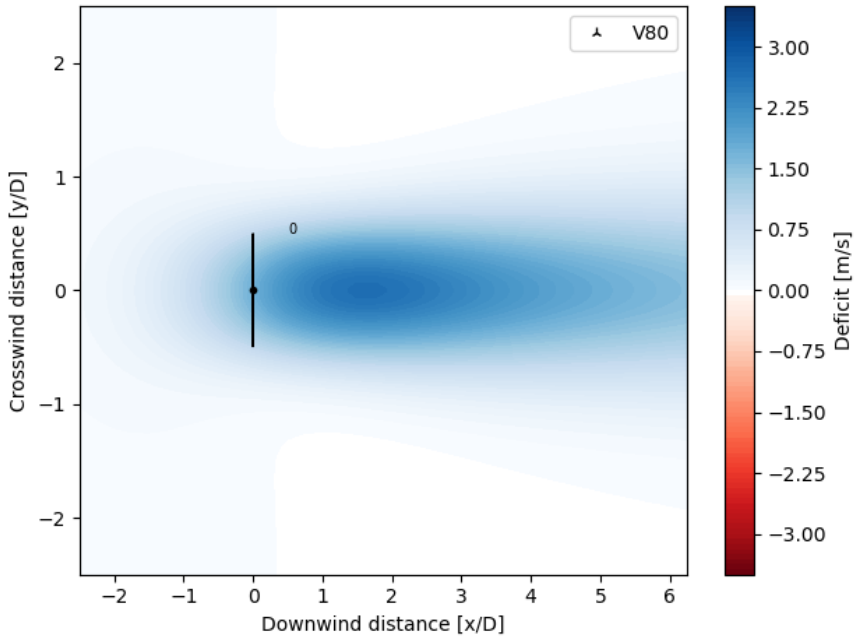
FugaDeficit

The FugaDeficit model calculates the wake deficit based on a set op look-up tables computed by a linearized RANS solver. The look-up tables be created in advance using the Fuga GUI.

The FugaDeficit models the near wake, far wake and blockage deficit effects.

Note, the present look-up table generator introduces some unphysical wriggles in the blockage deficit/speed-up.

[6]:
```
from py_wake.deficit_models import FugaDeficit
plot_blockage_deficit_map(FugaDeficit())
```



VortexCylinder

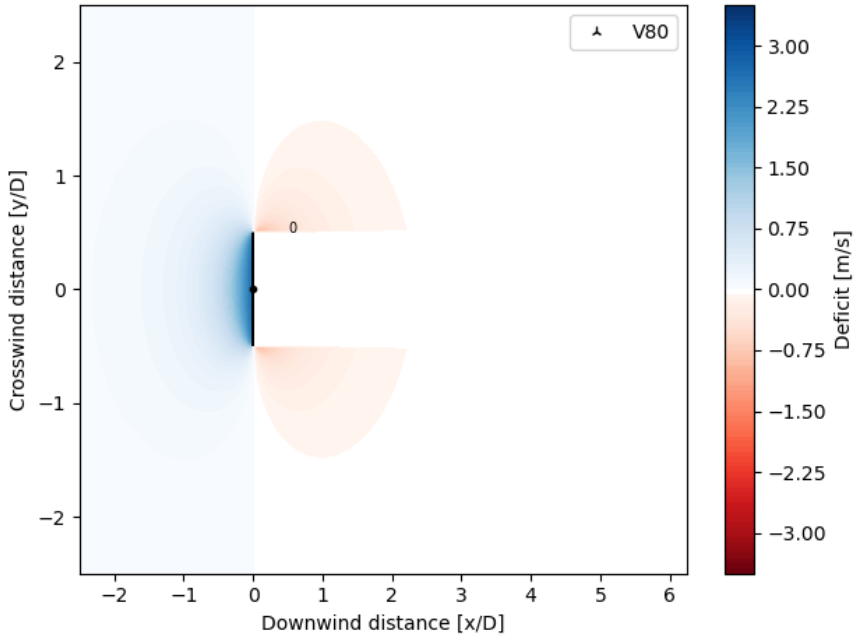
Induced velocity from a semi-infinite cylinder of tangential vorticity, extending along the x axis.

This model is an adapted version of the one published by Emmanuel Branlard at
https://github.com/ebranlard/wiz/blob/master/wiz/VortexCylinder.py

References:

- E. Branlard, M. Gaunaa, Cylindrical vortex wake model: right cylinder, Wind Energy, 2014, https://onlinelibrary.wiley.com/doi/full/10.1002/we.1800
- E. Branlard, Wind Turbine Aerodynamics and Vorticity Based Method, Springer, 2017
- E. Branlard, A. Meyer Forsting, Using a cylindrical vortex model to assess the induction zone in front of aligned and yawed rotors, in Proceedings of EWEA Offshore Conference, 2015, https://orbit.dtu.dk/en/publications/using-a-cylindrical-vortex-model-to-assess-the-induction-zone-inf

[7]:
```
from py_wake.deficit_models import VortexCylinder
plot_blockage_deficit_map(VortexCylinder())
```

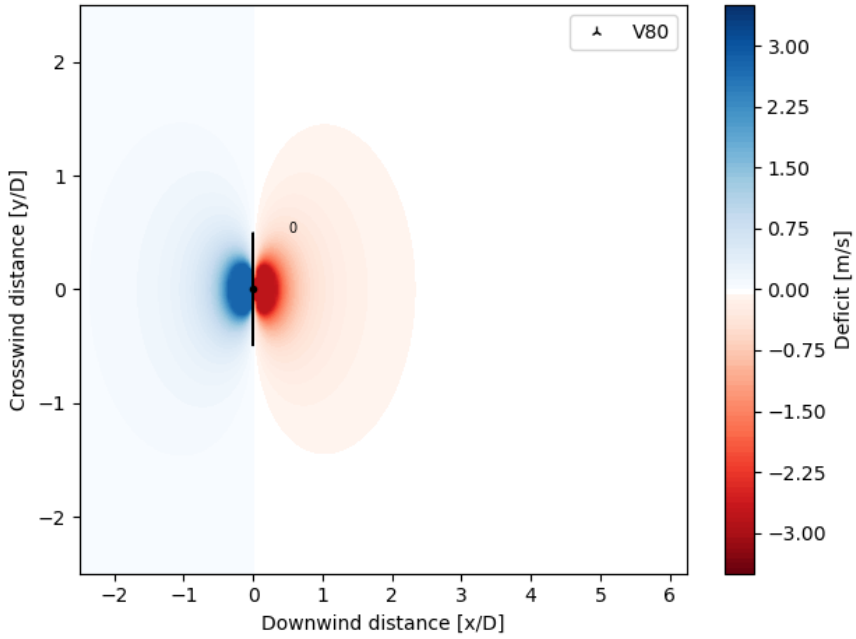


VortexDipole

The vorticity originating from a wind turbine can be represented by a vortex dipole line (see Appendix B in [2]). The induction estimated by such a representation is very similar to the results given by the more complex vortex cylinder model in the far-field r/R > 6 [1,2]. The implementation follows the relationships given in [1,2]. This model is an adapted version of the one published by Emmanuel Branlard: https://github.com/ebranlard/wiz/blob/master/wiz/VortexDoublet.py

References: - [1] Emmanuel Branlard et al 2020 J. Phys.: Conf. Ser. 1618 062036 - [2] Branlard, E, Meyer Forsting, AR. Wind Energy. 2020; 23: 2068– 2086. https://doi.org/10.1002/we.2546

[8]:
```
from py_wake.deficit_models import VortexDipole
plot_blockage_deficit_map(VortexDipole())
```



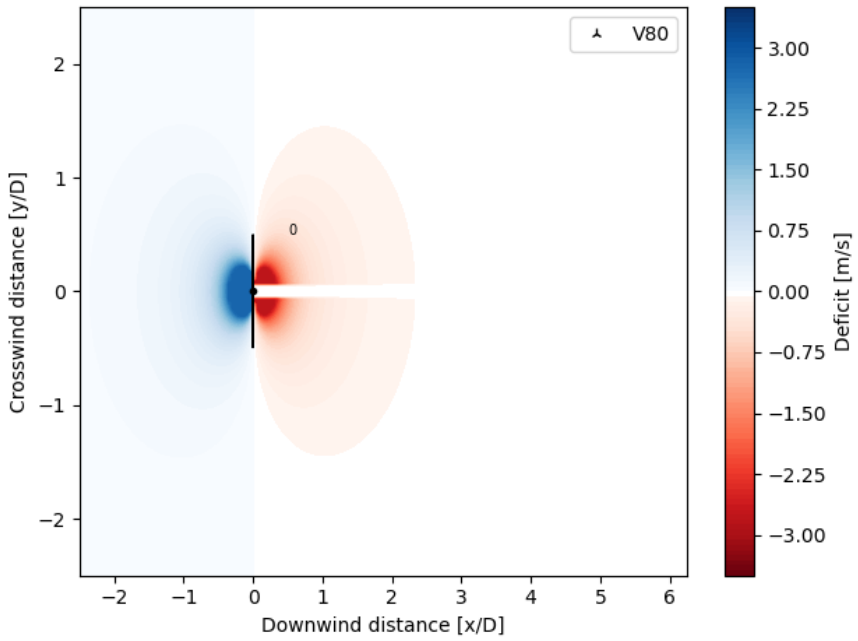
RankineHalfBody

A simple induction model using a Rankine Half Body to represent the induction introduced by a wind turbine. The source strength is determined enforcing 1D momentum balance at the rotor disc.

References:

- B Gribben, G Hawkes - A potential flow model for wind turbine induction and wind farm blockage - Technical Paper, Frazer-Nash Consultancy, 2019

[9]:
```
from py_wake.deficit_models import RankineHalfBody
plot_blockage_deficit_map(RankineHalfBody())
```

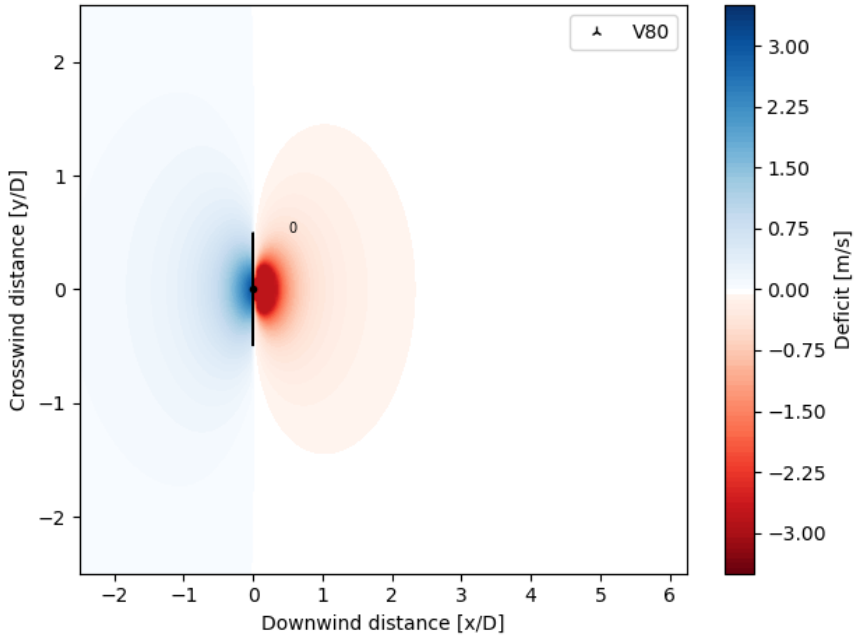


HybridInduction

The idea behind this model originates from [2,3], which advocates to combine near-rotor and farfield approximations of a rotor's induced velocities. Whereas in [1,2] the motivation is to reduce the computational effort, here the already very fast self-similar model [1] is combined with the vortex dipole approximation in the far-field, as the self-similar one is optimized for the near-field (r/R > 6, x/R < 1) and misses the acceleration around the wake for x/R > 0. The combination of both allows capturing the redistribution of energy by blockage. Location at which to switch from near-rotor to far-field can be altered though by setting switch_radius.

References: 1. N. Troldborg, A.R. Meyer Fortsing, Wind Energy, 2016 2. Emmanuel Branlard et al 2020 J. Phys.: Conf. Ser. 1618 062036 3. Branlard, E, Meyer Forsting, AR. Wind Energy. 2020; 23: 2068– 2086. https://doi.org/10.1002/we.2546

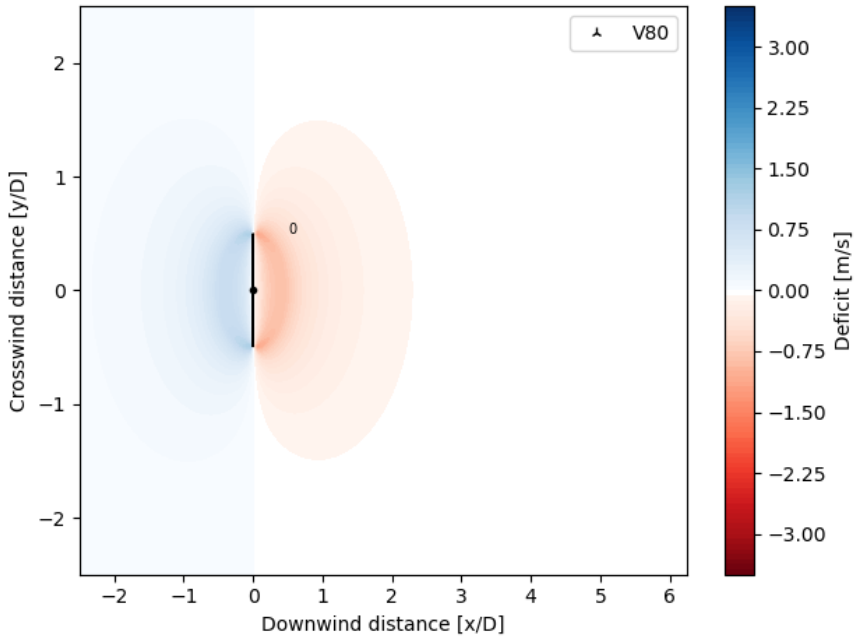
[10]:
```
from py_wake.deficit_models import HybridInduction
plot_blockage_deficit_map(HybridInduction())
```



Rathmann

Ole Sten Rathmann (DTU) developed in 2020 an approximation to the vortex cylinder solution (E. Branlard and M. Gaunaa, 2014). In speed it is comparable to the vortex dipole method, whilst giving a flow-field nearly identical to the vortex cylinder model for x/R < -1. Its centreline deficit is identical to the vortex cylinder model, whilst using a radial shape function that depends on the opening of the vortex cylinder seen from a point upstream. To simulate the speed-up downstream the deficit is mirrored in the rotor plane with a sign change.

[11]:
```
from py_wake.deficit_models import Rathmann
plot_blockage_deficit_map(Rathmann())
```



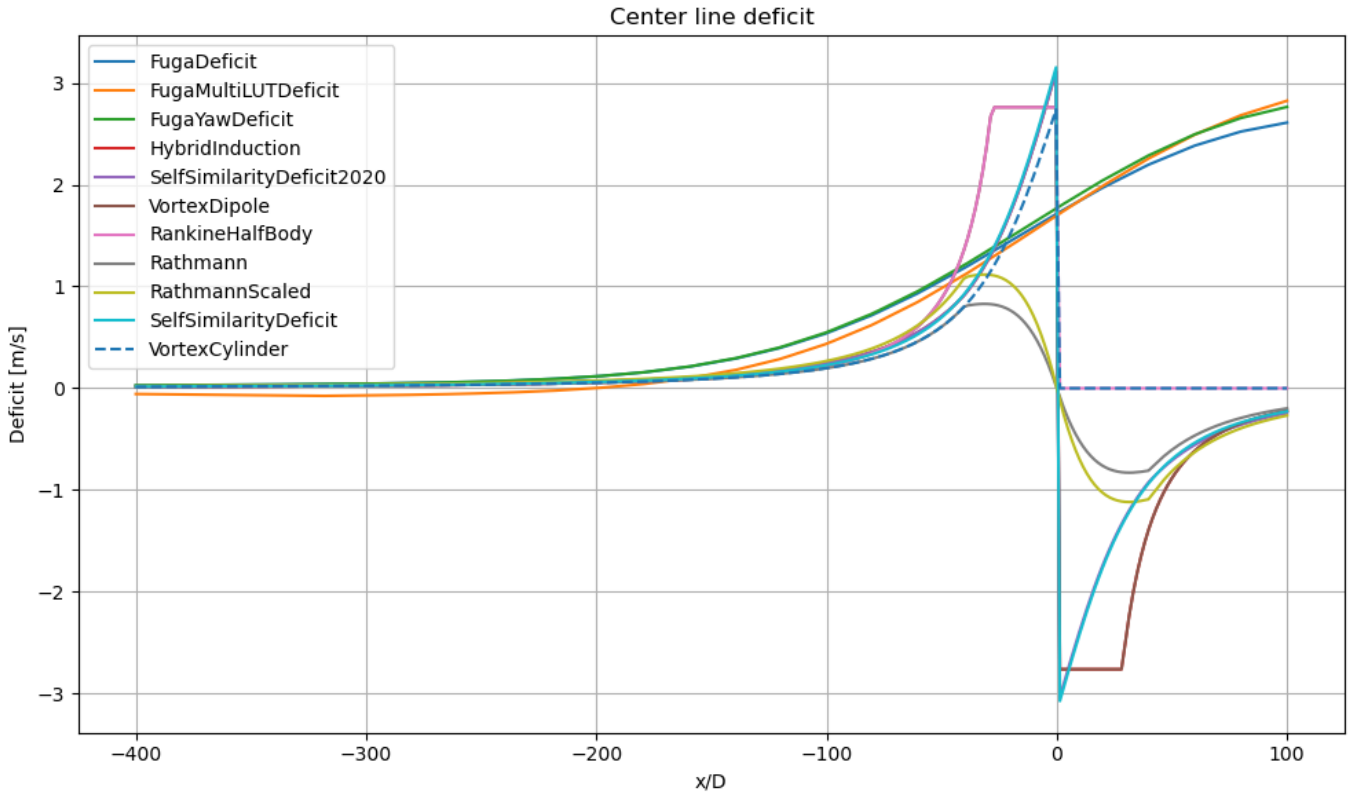
Comparing different blockage deficit models

[12]:
```
from py_wake.utils.model_utils import get_models
from py_wake.deficit_models.deficit_model import BlockageDeficitModel

blockage_deficitModels = get_models(BlockageDeficitModel, exclude_None=True)
for deficitModel in blockage_deficitModels:
    print (deficitModel.__name__)
```

```
FugaDeficit
FugaMultiLUTDeficit
FugaYawDeficit
HybridInduction
SelfSimilarityDeficit2020
VortexDipole
RankineHalfBody
Rathmann
RathmannScaled
SelfSimilarityDeficit
VortexCylinder
```

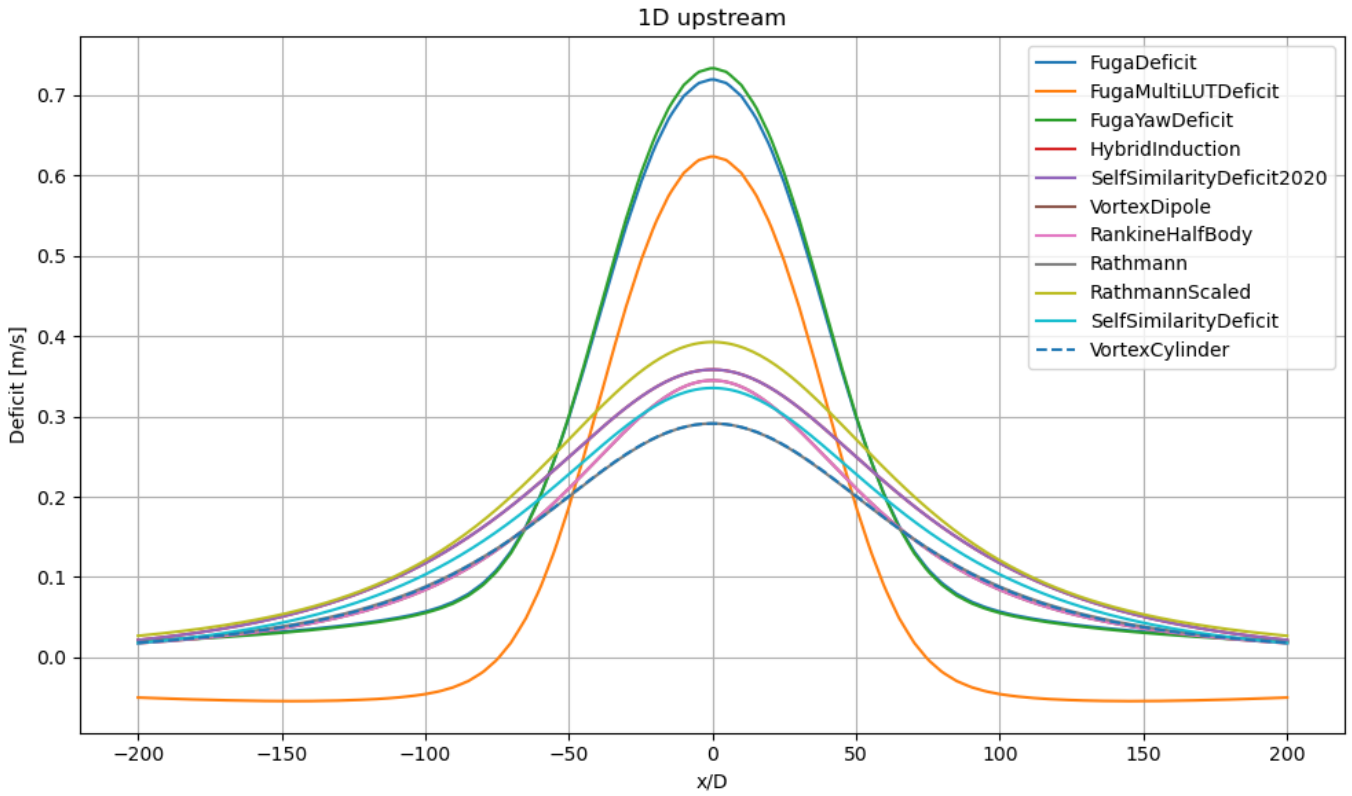
1) Deficit along center line

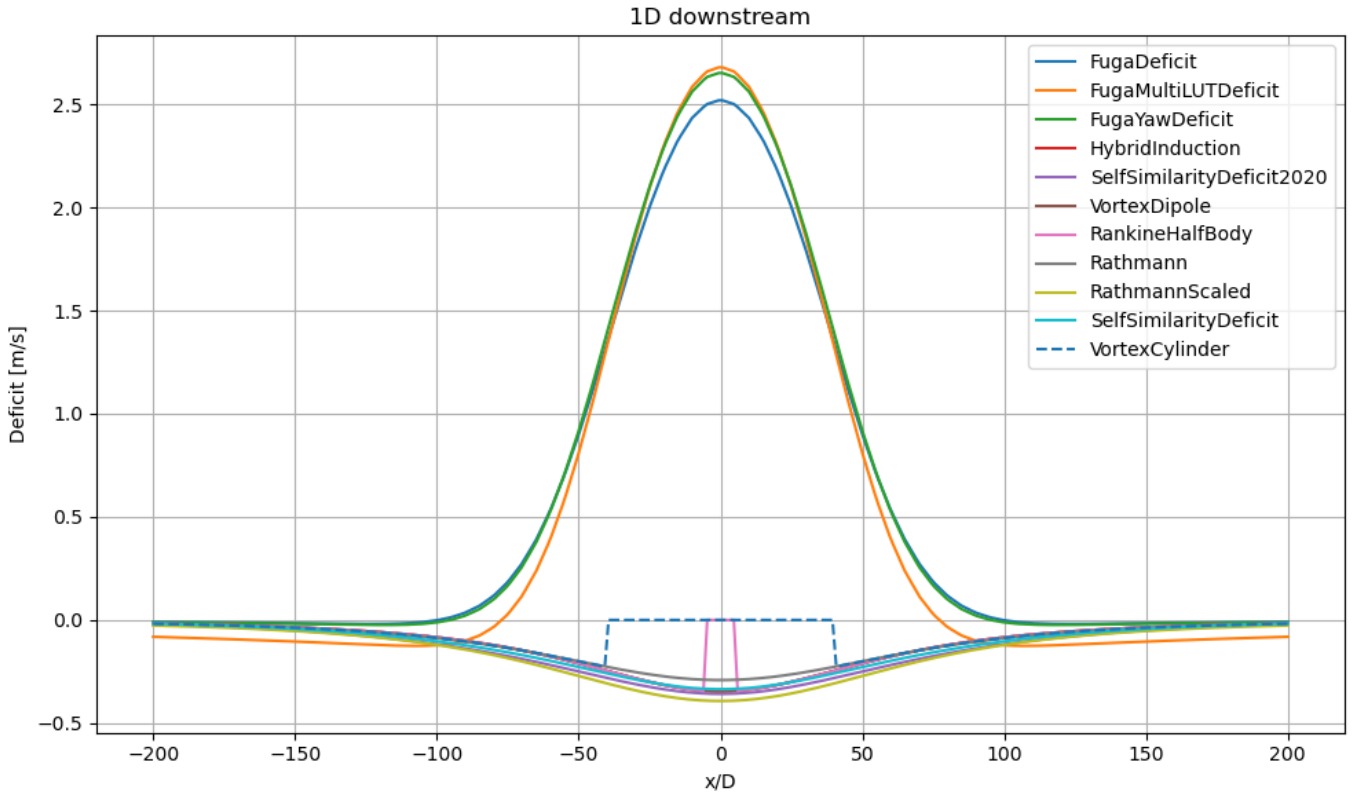
[13]:
```
plt.figure(figsize=((10,6)))
for i, deficitModel in enumerate(blockage_deficitModels):
    fm = get_flow_map(deficitModel(), XYGrid(x=np.linspace(-400,100,300), y=0))
    plt.plot(fm.x, 10-fm.WS_eff.squeeze(), ('-','--')[i//10], label=deficitModel.__name__)
setup_plot(title="Center line deficit", xlabel='x/D', ylabel='Deficit [m/s]')
```



2) Deficit profile 1 up- and downstream

[14]:
```
for d in [-1,1]:
    plt.figure(figsize=((10,6)))
    for i, deficitModel in enumerate(blockage_deficitModels):
        fm = get_flow_map(deficitModel(), XYGrid(x=d*D, y=np.linspace(-200,200,300)))
        plt.plot(fm.y, 10-fm.WS_eff.squeeze(), ('-','--')[i//10], label=deficitModel.__name__)
    setup_plot(title="%sD %sstream"%(abs(d),('down','up')[d<0]), xlabel='x/D', ylabel='Deficit [m/s]')
```





[ ]:

Open in Colab Edit on Gitlab

Rotor Average Models

The rotor average model in PyWake defines one or more points at the turbine rotor to calculate a (weighted) rotor-average deficit. It includes:

- RotorCenter: One point at the center of the rotor
- GridRotorAvg: Custom grid in Cartesian coordinates'
- EqGridRotorAvg: Equidistant N x N Cartesian grid covering the rotor
- GQGridRotorAvg: M x N cartesian grid using Gaussian quadrature coordinates and weights
- PolarGridRotorAvg: Custom grid in polar coordinates
- CGIRotorAVG: Circular Gauss Integration

Install PyWake if needed

[1]:
```
# Install PyWake if needed
try:
    import py_wake
except ModuleNotFoundError:
    !pip install git+https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake.git
```

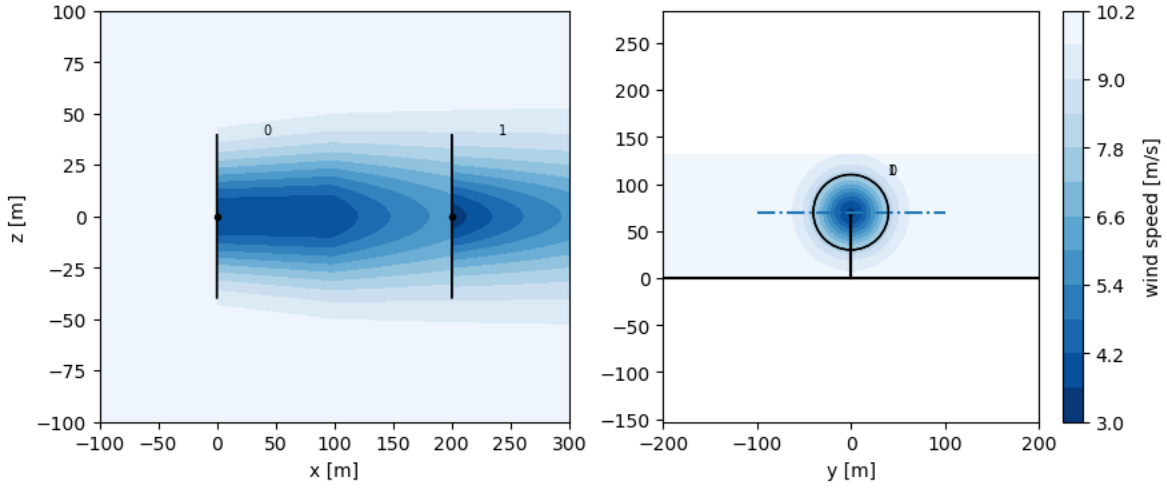
[2]:
```
import numpy as np
import matplotlib.pyplot as plt

# import and setup site and windTurbines
import py_wake
from py_wake.examples.data.hornsrev1 import V80, Hornsrev1Site

site = Hornsrev1Site()
windTurbines = V80()
wt_x, wt_y = site.initial_position.T
```

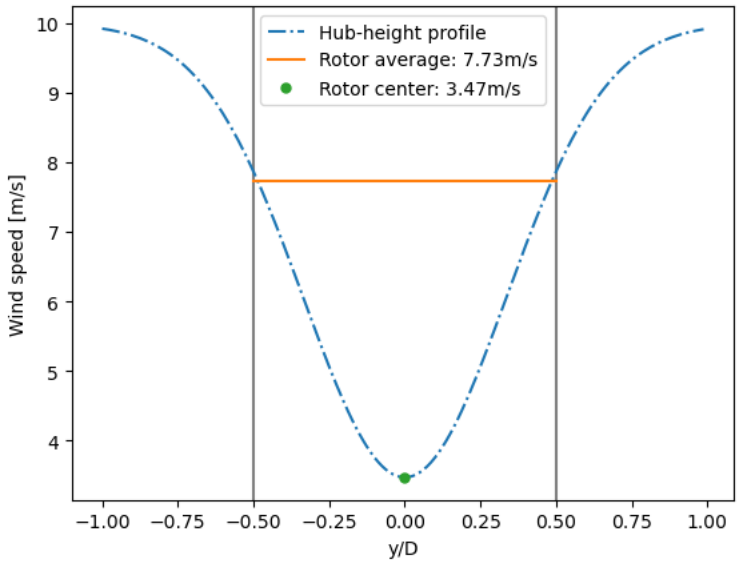
In the plots below, it is clearly seen that the wind speed varies over the rotor, and that the the rotor-average wind speed is not well-defined by the wind s

[3]:
```
from py_wake.superposition_models import SquaredSum
from py_wake.flow_map import HorizontalGrid, YZGrid
from py_wake import BastankhahGaussian

D = 80
R = D/2
wfm = BastankhahGaussian(site, windTurbines, superpositionModel=SquaredSum())
sim_res = wfm([0,200],[0,0],wd=270,ws=10)

fig,(ax1,ax2) = plt.subplots(1,2, figsize=(10,4))
ax1.set_xlabel("x [m]"), ax1.set_ylabel("y [m]")
sim_res.flow_map(HorizontalGrid(extend=.1)).plot_wake_map(10, ax=ax1, plot_colorbar=False)
sim_res.flow_map(YZGrid(x=199.99)).plot_wake_map(10, ax=ax2)
ax2.plot([-100,100],[70,70],'-.')
ax2.set_xlabel("y [m]"), ax1.set_ylabel("z [m]")

plt.figure()
flow_map = sim_res.flow_map(HorizontalGrid(x=[199.99], y=np.arange(-80, 80)))

for x in [-.5,.5]:
    plt.gca().axvline(x,color='grey')
plt.plot(flow_map.Y[:, 0]/D, flow_map.WS_eff_xylk[:, 0, 0, 0], '-.', label='Hub-height profile')
plt.plot([-.5,.5],[7.73,7.73],label='Rotor average: 7.73m/s')
rc_ws = flow_map.WS_eff_xylk[80, 0, 0, 0]
plt.plot(flow_map.Y[80, 0]/D, rc_ws,'.', ms=10, label='Rotor center: %.2fm/s'%rc_ws)
plt.legend()
plt.xlabel("y/D")
plt.ylabel('Wind speed [m/s]')
```

```
/builds/TOPFARM/PyWake/py_wake/deficit_models/gaussian.py:124: UserWarning: The BastankhahGaussian model is not representative of the setup use
  DeprecatedModel.__init__(self, 'py_wake.literature.gaussian_models.Bastankhah_PorteAgel_2014')
```

[3]: `Text(0, 0.5, 'Wind speed [m/s]')`





First we create a simple function to model all of the rotor-average models available in PyWake.

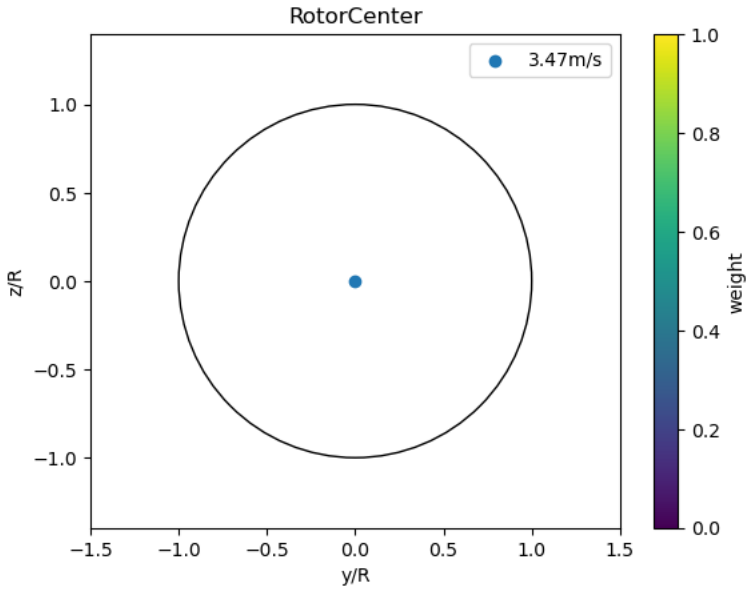
[4]:
```
from py_wake.rotor_avg_models import RotorCenter, GridRotorAvg, EqGridRotorAvg, GQGridRotorAvg, CGIRotorAvg, PolarGridRotorAvg, PolarRotorAvg,
from py_wake.flow_map import HorizontalGrid

R=D/2

def plot_rotor_avg_model(rotorAvgModel, name):
    plt.figure()
    m = rotorAvgModel
    wfm = BastankhahGaussian(site,windTurbines,rotorAvgModel=m)
    ws_eff = wfm([0, 200], [0, 0], wd=270, ws=10).WS_eff_ilk[1,0,0]
    plt.title(name)
    c = plt.scatter(m.nodes_x, m.nodes_y,c=m.nodes_weight,label="%.2fm/s"%(ws_eff))
    plt.colorbar(c,label='weight')
    plt.gca().add_artist(plt.Circle((0,0),1,fill=False))
    plt.axis('equal')
    plt.xlabel("y/R"); plt.ylabel('z/R')
    plt.xlim([-1.5,1.5])
    plt.ylim([-1.5,1.5])
    plt.legend()
```

RotorCenter

Setting `rotorAvgModel=None` determines the rotor average wind speed from the rotor center point. Alternatively, you can use the `RotorCenter` model whic

[5]:
```
plot_rotor_avg_model(RotorCenter(), 'RotorCenter')
```

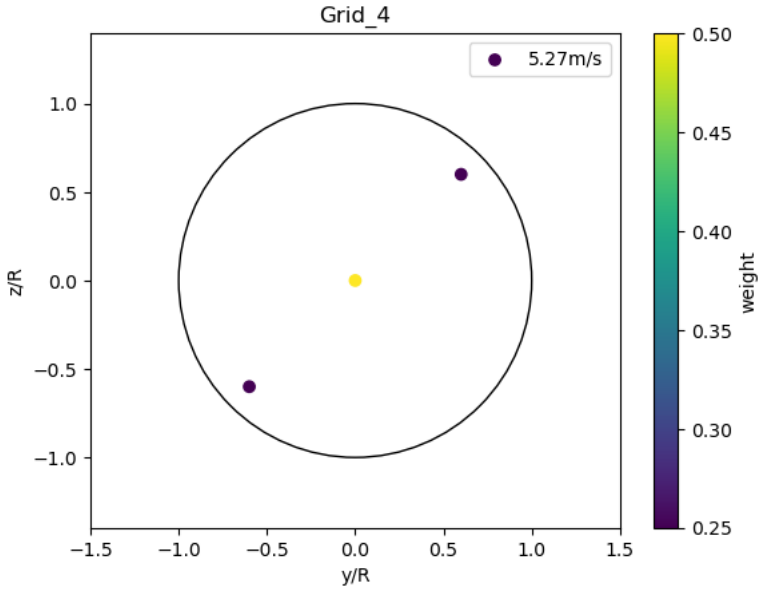
```
/builds/TOPFARM/PyWake/py_wake/deficit_models/gaussian.py:124: UserWarning: The BastankhahGaussian model is not representative of the setup use
  DeprecatedModel.__init__(self, 'py_wake.literature.gaussian_models.Bastankhah_PorteAgel_2014')
```



GridRotorAvg

The `GridRotorAvg` defines a set of points in cartesian coordinates.

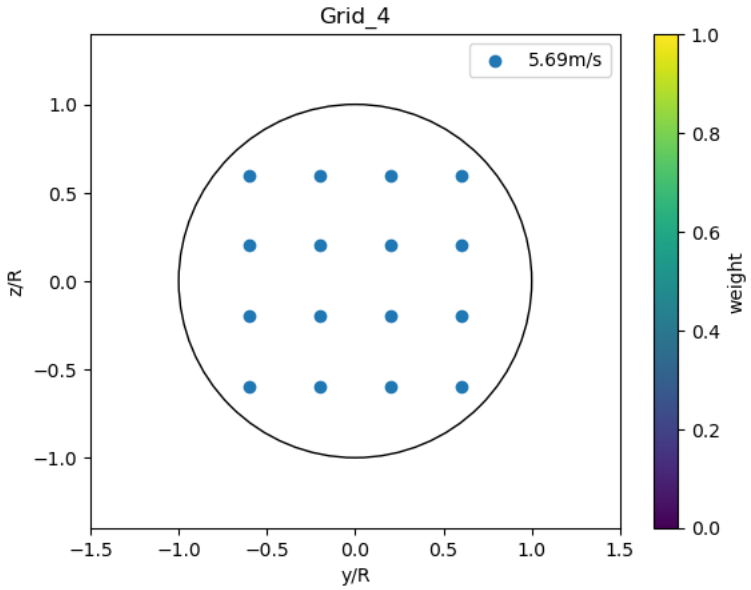
[6]:
```
x = y = np.array([-.6, 0,.6])
plot_rotor_avg_model(GridRotorAvg(x,y,nodes_weight = [0.25,.5,.25]), 'Grid_4')
```



EqGridRotorAvg

The `EqGridRotorAvg` defines a NxN equidistant cartesian grid of points and discards points outside the rotor.

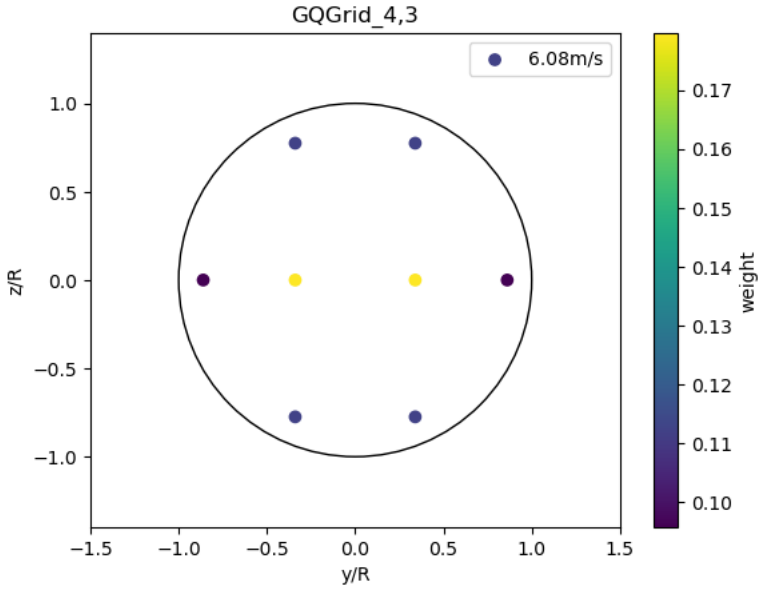
[7]:
```
plot_rotor_avg_model(EqGridRotorAvg(4), 'Grid_4')
```



GQGridRotorAvg

The `GQGridRotorAvg` defines a grid of M x N cartesian grid points using Gaussian quadrature coordinates and weights.

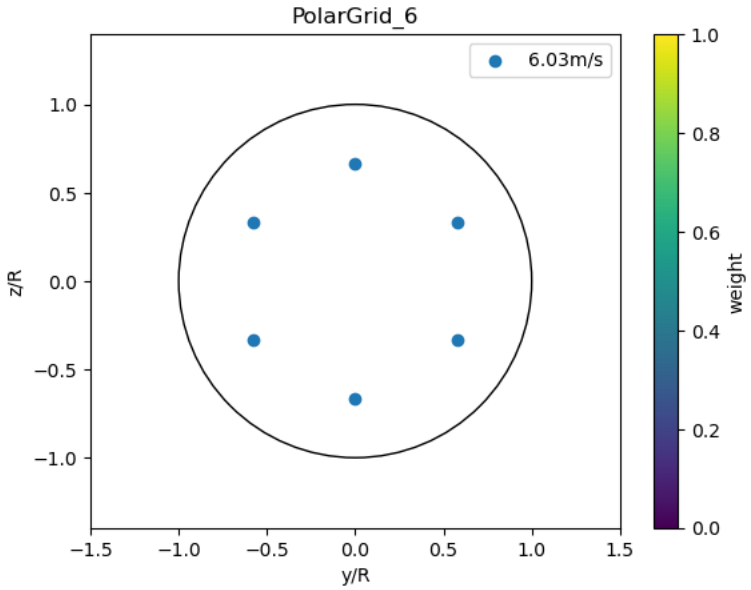
[8]:
```
plot_rotor_avg_model(GQGridRotorAvg(4,3), 'GQGrid_4,3')
```



PolarGridRotorAvg

The `PolarGridRotorAvg` defines a grid in polar coordinates.

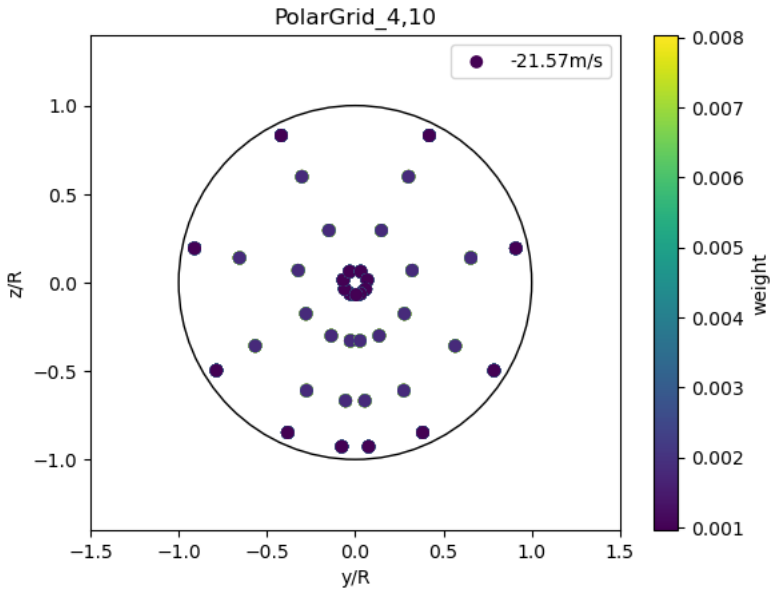
[9]:
```
theta = np.linspace(-np.pi,np.pi,6, endpoint=False)
r = 2/3
plot_rotor_avg_model(PolarGridRotorAvg(r=r, theta=theta, r_weight=None, theta_weight=None), 'PolarGrid_6')
```



The polar grid can be combined with Gaussian Quadrature.

This is similar to the implementation in FusedWake: https://gitlab.windenergy.dtu.dk/TOPFARM/FUSED-Wake/-/blob/master/fusedwake/gcl/fortran/GC

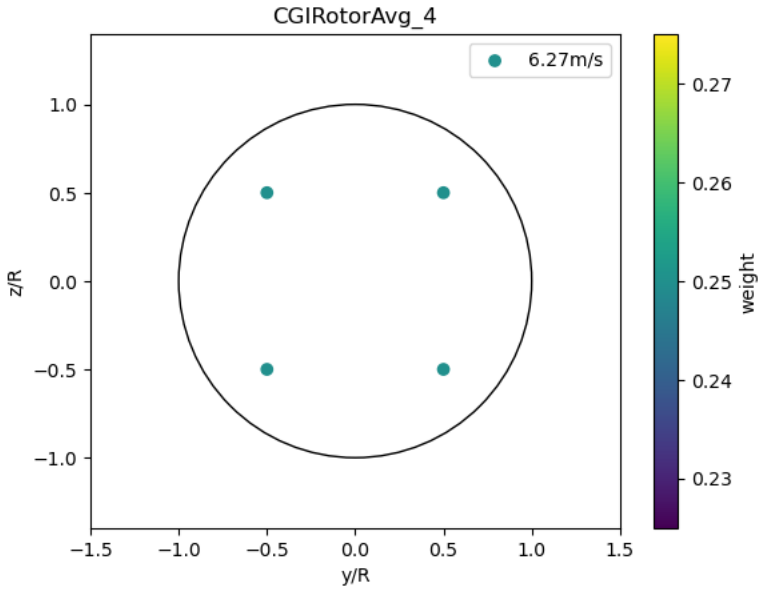
[10]:
```
plot_rotor_avg_model(PolarGridRotorAvg(*polar_gauss_quadrature(4,10)), 'PolarGrid_4,10')
```

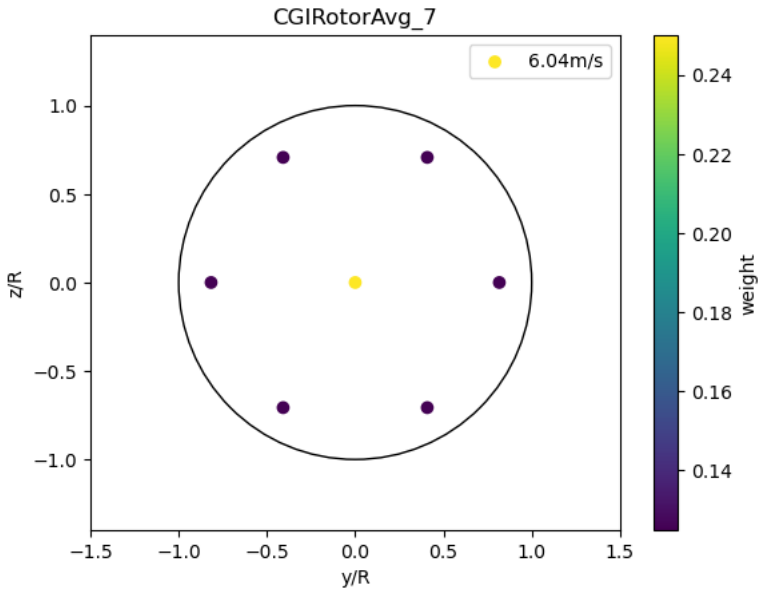


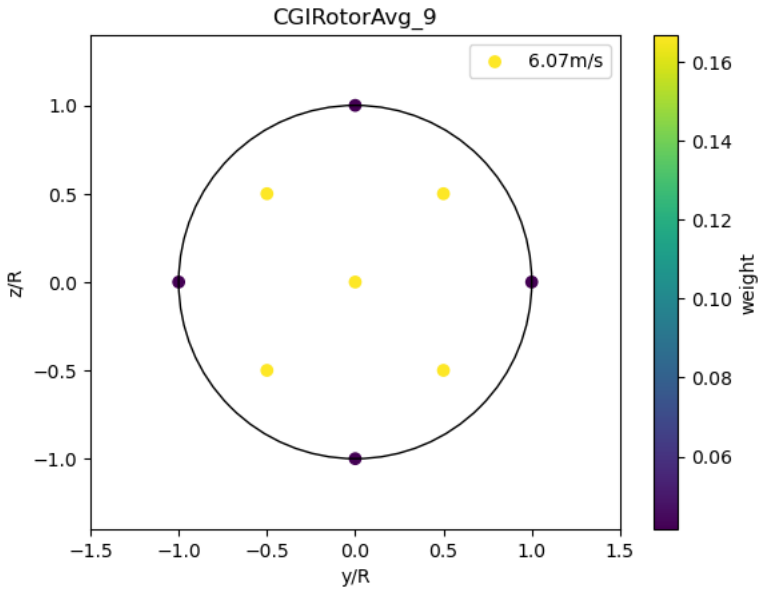
CGIRotorAvg

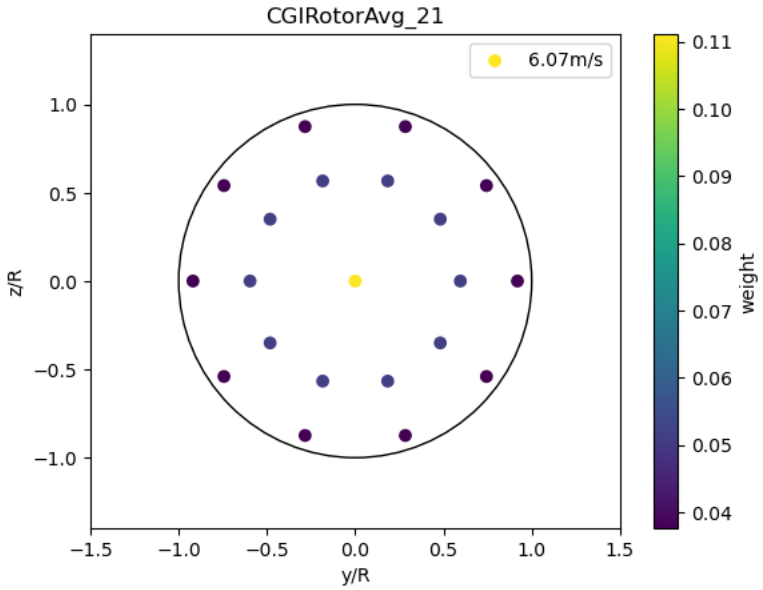
Circular Gauss integration with 4,7,9 or 21 points as defined in Abramowitz M and Stegun A. Handbook of Mathematical Functions. Dover: New York, 19

[11]:
```
for n in [4,7,9,21]:
    plot_rotor_avg_model(CGIRotorAvg(n), 'CGIRotorAvg_%d'%n)
```





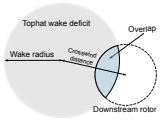




AreaOverlapModel

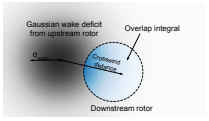
The AreaOverlapModel calculates the fraction of the downstream rotor that is covered by the wake from an upstream wind turbine. This model makes se

The calculation formula can be found in Eq. (A1) of Feng, J., & Shen, W. Z. (2015). Solving the wind farm layout optimization problem using random searc



GaussianOverlapAvgModel

The GaussianOverlapModel computes the integral of the gaussian wake deficit over the downstream rotor. To speed up the computation, normalized inte
σ, and therefore only applies to gaussian wake deficit models. See Appendix A in https://github.com/OrstedRD/TurbOPark/blob/main/TurbOPark%20des



Comparing rotor-average models

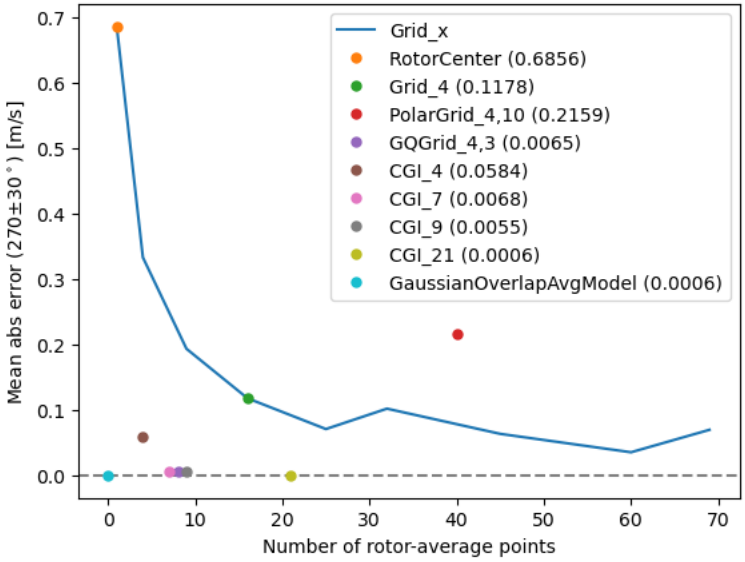
In general, the compuational cost and the accuracy of the estimate increases with the number of points, but the distribution of the points also has an impa

The plot below shows the absolute error of the estimated rotor-average wind speed for the wind directions 270 $\pm$ 30° (i.e. wind directions with more tha

[12]:
```
grid_models = [EqGridRotorAvg(i) for i in range(1,10)]
wd_lst = np.arange(240,301)

def get_ws_eff(rotorAvgModel):
    wfm = BastankhahGaussian(site,windTurbines,rotorAvgModel=rotorAvgModel)
    return wfm([0, 200], [0, 0], wd=wd_lst, ws=10).WS_eff_ilk[1,:,0]

ws_ref = get_ws_eff(EqGridRotorAvg(200)) # Use 200x200 points (31700 inside the rotor) to determine the reference value

def get_n_err(rotorAvgModel):
    ws_mean_err = np.abs(get_ws_eff(rotorAvgModel) - ws_ref).mean()
    return len(rotorAvgModel.nodes_x), ws_mean_err


plt.gca().axhline(0, color='grey',ls='--')
plt.plot(*zip(*[get_n_err(m) for m in grid_models]), label='Grid_x')
model_lst = [('RotorCenter', EqGridRotorAvg(1)),
             ('Grid_4', EqGridRotorAvg(4)),
             ('PolarGrid_4,10', PolarRotorAvg(*polar_gauss_quadrature(4,10))),
             ('GQGrid_4,3', GQGridRotorAvg(4, 3))] + \
            [('CGI_%d'%n, CGIRotorAvg(n)) for n in [4,7,9,21]]
```

```
for name, model in model_lst:
    n,err = get_n_err(model)
    plt.plot(n,err,'.',ms=10, label="%s (%.4f)"%(name,err))
goam_err = np.abs(get_ws_eff(GaussianOverlapAvgModel()) - ws_ref).mean()
plt.plot([0],[goam_err],'.', ms=10, label="GaussianOverlapAvgModel (%.4f)"%(goam_err))
plt.xlabel('Number of rotor-average points')
plt.ylabel(r'Mean abs error (270$\pm30^\circ$) [m/s]')
plt.legend()
```

[12]: <matplotlib.legend.Legend at 0x7f661cc96e30>



Open in Colab Edit on Gitlab

Deflection Models

The deflection models calculate the deflection of the wake due to yaw-misalignment, sheared inflow etc.

Note, this is one of the four effects of skew inflow that is handled in PyWake, see here.

The deflection models take as input the downwind and crosswind distances between the source wind turbines and the destination wind turbines/sites an simulations where the turbine experiences a change in angle between the incoming flow and the rotor, for example in active yaw control or wake steering

In PyWake, there are three different wake deflection models:

- JimenezWakeDeflection
- FugaDeflection
- GCLHillDeflection

Install PyWake if needed

[1]:
```
# Install PyWake if needed
try:
    import py_wake
except ModuleNotFoundError:
    !pip install git+https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake.git
```

First we create a simple function to plot the different deflection models available in PyWake.

[2]:
```
import numpy as np
import matplotlib.pyplot as plt

# import and setup site and windTurbines
import py_wake
from py_wake import BastankhahGaussian
from py_wake.examples.data.iea37._iea37 import IEA37Site, IEA37_WindTurbines
from py_wake.examples.data.hornsrev1 import V80

site = IEA37Site(16)
x, y = [0, 400, 800], [0, 0, 0]
windTurbines = V80()
D = windTurbines.diameter()
```

[3]:
```
def plot_deflection(deflectionModel):

    wfm = BastankhahGaussian(site, windTurbines, deflectionModel=deflectionModel)

    yaw = [-20,20,0]
    D = windTurbines.diameter()

    plt.figure(figsize=(14,4))
    fm = wfm(x, y, yaw=yaw, tilt=0, wd=270, ws=10).flow_map()
    fm.plot_wake_map(normalize_with=D)
    center_line = fm.min_WS_eff()
    plt.plot(center_line.x/D, center_line/D,'--k')
    plt.grid()
```

JimenezWakeDeflection

The `JimenezWakeDeflection` model is implemented according to Jiménez, Á., Crespo, A. and Migoya, E. (2010), Application of a LES technique to character

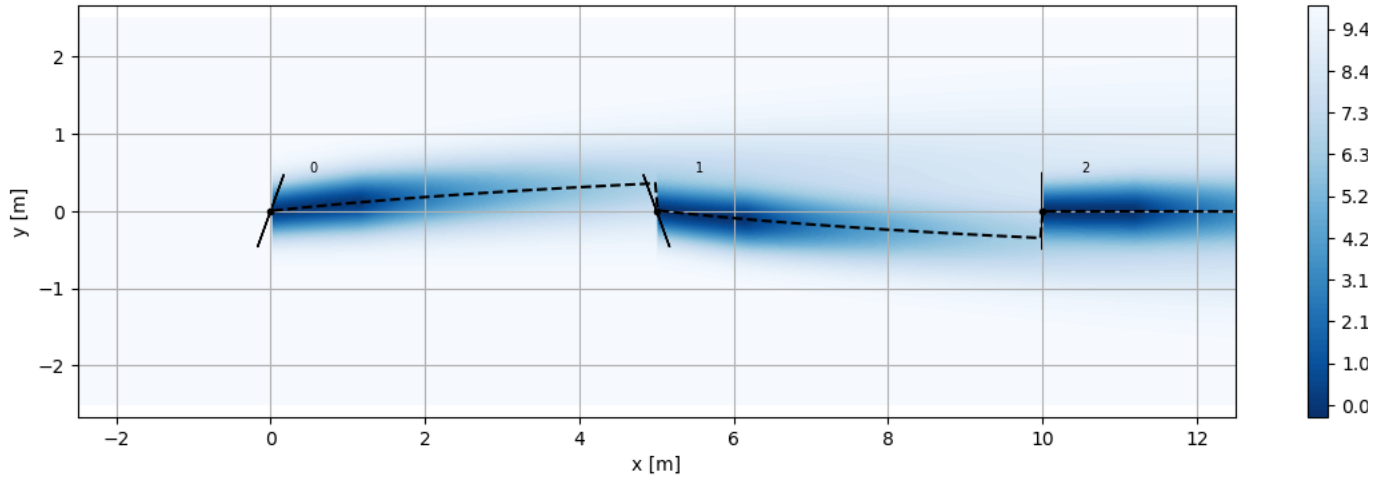
It is the most common wake deflection model used in PyWake and has proved to result in a decent representation of the skewed inflow behind the turbin behind a wind turbine given the wake deflection created by different yaw angle and thrust coefficient settings.

[4]:
```
from py_wake.deflection_models import JimenezWakeDeflection
plt.figure()
plot_deflection(JimenezWakeDeflection())
plt.xlabel('x [m]')
plt.ylabel('y [m]')
```

```
/builds/TOPFARM/PyWake/py_wake/deficit_models/gaussian.py:124: UserWarning: The BastankhahGaussian model is not representative of the setup use
  DeprecatedModel.__init__(self, 'py_wake.literature.gaussian_models.Bastankhah_PorteAgel_2014')
```

[4]:
```
Text(0, 0.5, 'y [m]')
```

```
<Figure size 640x480 with 0 Axes>
```



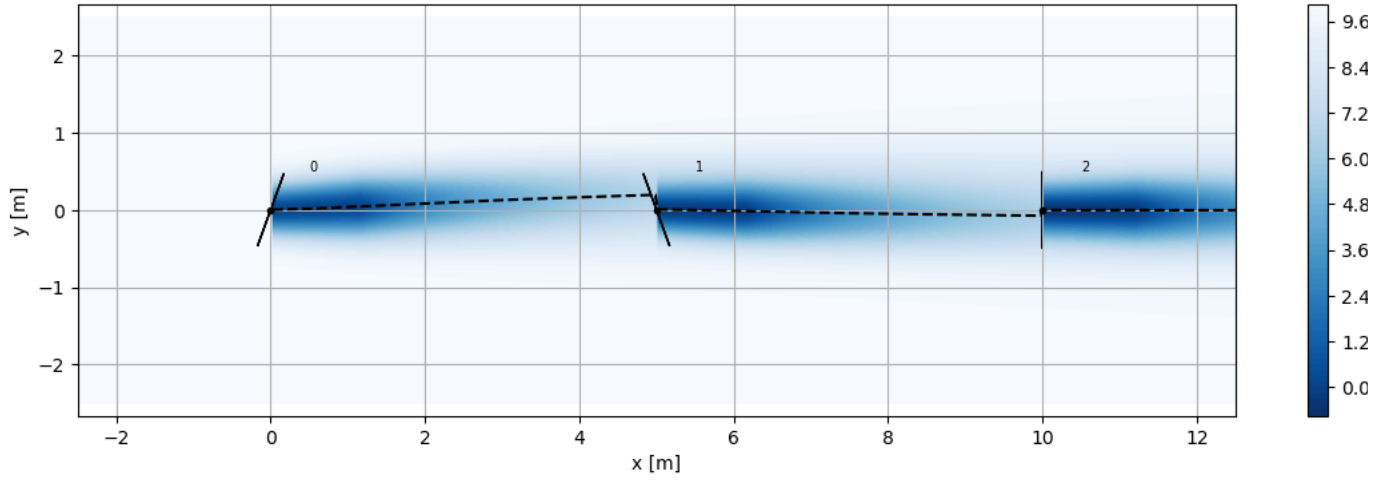
FugaDeflection

[5]:
```
from py_wake.deflection_models import FugaDeflection
plt.figure()
plot_deflection(FugaDeflection())
plt.xlabel('x [m]')
plt.ylabel('y [m]')
```

```
/builds/TOPFARM/PyWake/py_wake/deflection_models/gaussian.py:124: UserWarning: The BastankhahGaussian model is not representative of the setup use
  DeprecatedModel.__init__(self, 'py_wake.literature.gaussian_models.Bastankhah_PorteAgel_2014')
```

[5]:
```
Text(0, 0.5, 'y [m]')
```

```
<Figure size 640x480 with 0 Axes>
```



GCLHillDeflection

Deflection model based on Hill's ring vortex theory.

Implemented according to: Larsen, G. C., Ott, S., Liew, J., van der Laan, M. P., Simon, E., R.Thorsen, G., & Jacobs, P. (2020). Yaw induced wake deflection - a https://doi.org/10.1088/1742-6596/1618/6/062047.

Note, this model uses the wake centerline deficit magnitude to calculate the deflection. Hence non-gaussian-shaped wake deficit models as well as deficit NiayifarGaussianDeficit, should be avoided.

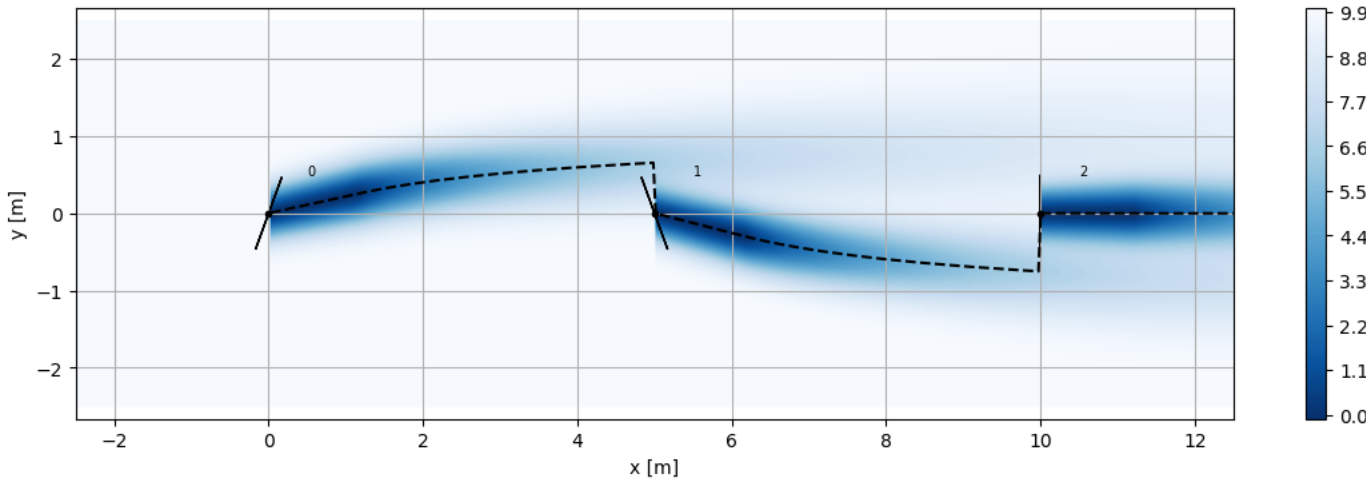
As default the model uses the `WakeDeficitModel` specified for the `WindFarmModel` to calculate the magnitude of the deficit, but a separate model can be s

[6]:
```
from py_wake.deflection_models import GCLHillDeflection
plt.figure()
plot_deflection(GCLHillDeflection())
plt.xlabel('x [m]')
plt.ylabel('y [m]')
```

```
/builds/TOPFARM/PyWake/py_wake/deflection_models/gaussian.py:124: UserWarning: The BastankhahGaussian model is not representative of the setup use
  DeprecatedModel.__init__(self, 'py_wake.literature.gaussian_models.Bastankhah_PorteAgel_2014')
```

[6]:
```
Text(0, 0.5, 'y [m]')
```

```
<Figure size 640x480 with 0 Axes>
```



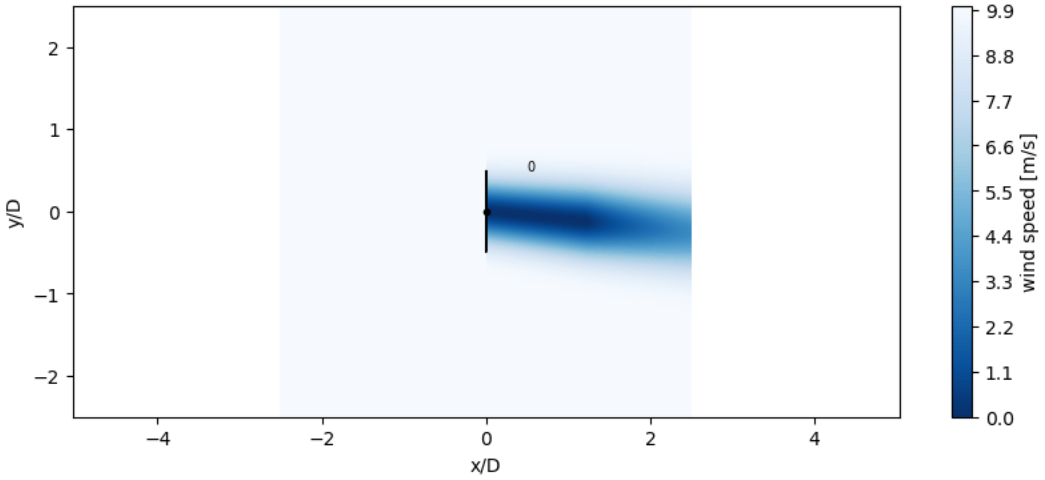
You can also implement your own deflection models

Deficit models must subclass `DeficitModel` and thus must implement the `calc_deflection` method and a class variable, `args4deflection` specifying the

```python
class DeflectionModel(ABC):
    args4deflection = ["ct_ilk"]

    @abstractmethod
    def calc_deflection(self, dw_ijl, hcw_ijl, **kwargs):
        """Calculate deflection

        This method must be overridden by subclass

        Arguments required by this method must be added to the class list
        args4deflection

        See documentation of EngineeringWindFarmModel for a list of available input arguments

        Returns
        -------
        dw_ijlk : array_like
            downwind distance from source wind turbine(i) to destination wind turbine/site (j)
            for all wind direction (l) and wind speed (k)
        hcw_ijlk : array_like
            horizontal crosswind distance from source wind turbine(i) to destination wind turbine/site (j)
            for all wind direction (l) and wind speed (k)
        """
```

[7]:
```python
from py_wake.deflection_models import DeflectionModel
from numpy import newaxis as na
from py_wake import BastankhahGaussian

class MyDeflectionModel(DeflectionModel):

    def calc_deflection(self, dw_ijlk, hcw_ijlk, **_):
        hcw_ijlk =hcw_ijlk + .1*dw_ijlk       # deflect 1/10 of the downstream distance
        dh_ijlk =np.zeros_like(hcw_ijlk)      # no vertical deflection
        return dw_ijlk, hcw_ijlk, dh_ijlk

iea_my_deflection = BastankhahGaussian(site, windTurbines, deflectionModel=MyDeflectionModel())

plt.figure(figsize=(10,4))
iea_my_deflection(x=[0], y=[0], wd=270, ws=10).flow_map().plot_wake_map(normalize_with=D)
plt.xlabel('x/D')
plt.ylabel('y/D');
```

```
/builds/TOPFARM/PyWake/py_wake/deficit_models/gaussian.py:124: UserWarning: The BastankhahGaussian model is not representative of the setup use
  DeprecatedModel.__init__(self, 'py_wake.literature.gaussian_models.Bastankhah_PorteAgel_2014')
```



Turbulence Models

The turbulence models in PyWake are used to calculate the added turbulence in the wake from one wind turbine to downstream turbines or sites in the wind farm. These are important when the flow properties behind the rotor must be accurately represented, for example for calculation of fatigue loading of turbine components.

Install PyWake if needed

[1]:
```
# Install PyWake if needed
try:
    import py_wake
except ModuleNotFoundError:
    !pip install git+https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake.git
```

First we create a simple function to plot the different turbulence models available in PyWake.

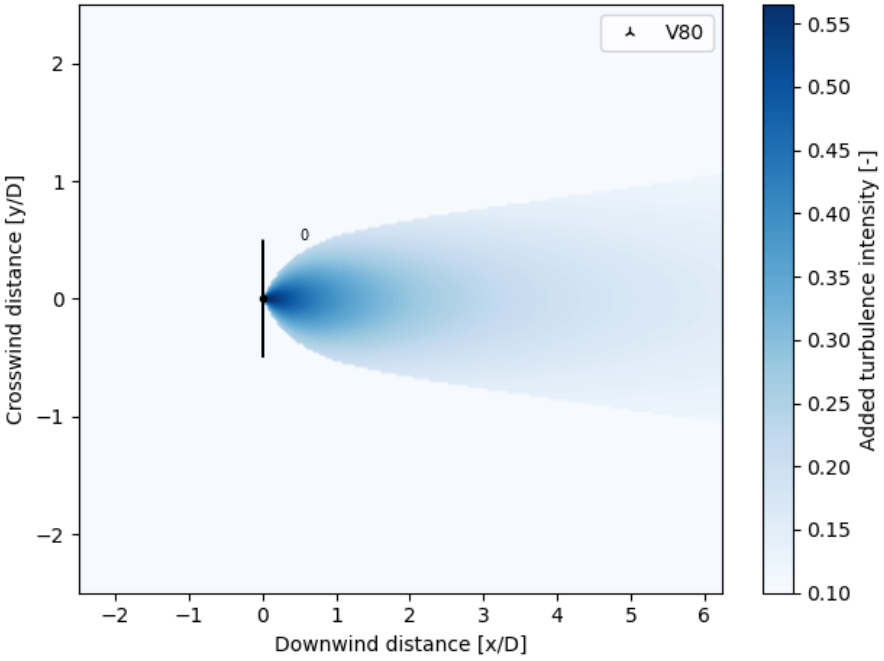
[2]:
```
import numpy as np
import matplotlib.pyplot as plt

from py_wake.examples.data.hornsrev1 import V80, Hornsrev1Site

site = Hornsrev1Site()
windTurbines = V80()
wt_x, wt_y = site.initial_position.T
D = windTurbines.diameter()
```

[3]:
```
from py_wake.wind_farm_models import All2AllIterative
from py_wake.deficit_models.deficit_model import WakeDeficitModel, BlockageDeficitModel
from py_wake.deficit_models.no_wake import NoWakeDeficit
from py_wake.site._site import UniformSite
from py_wake.flow_map import XYGrid
from py_wake.turbulence_models import CrespoHernandez
from py_wake.utils.plotting import setup_plot
from py_wake.deficit_models import NOJDeficit

def get_flow_map(model=None, grid=XYGrid(x=np.linspace(-200, 500, 200), y=np.linspace(-200, 200, 200), h=70),
                 turbulenceModel=CrespoHernandez()):
    blockage_deficitModel = [None, model][isinstance(model, BlockageDeficitModel)]
    wake_deficitModel = [NoWakeDeficit(), model][isinstance(model, WakeDeficitModel)]
    wfm = All2AllIterative(UniformSite(), V80(), wake_deficitModel=wake_deficitModel, blockage_deficitModel=blockage_deficitModel,
                           turbulenceModel=turbulenceModel)
    return wfm(x=[0], y=[0], wd=270, ws=10, yaw=0).flow_map(grid)

def plot_turb_map(model, cmap='Blues'):
    fm = get_flow_map(NOJDeficit(),turbulenceModel=model)
    fm.plot(fm.TI_eff, clabel="Added turbulence intensity [-]", levels=100, cmap=cmap, normalize_with=D)
    setup_plot(grid=False, ylabel="Crosswind distance [y/D]", xlabel="Downwind distance [x/D]",
               xlim=[fm.x.min() / D, fm.x.max() / D], ylim=[fm.y.min() / D, fm.y.max() / D], axis='auto')
```

STF2005TurbulenceModel

Steen Frandsen model implemented according to IEC61400-1, 2005 and weight according to Steen Frandsen's thesis.

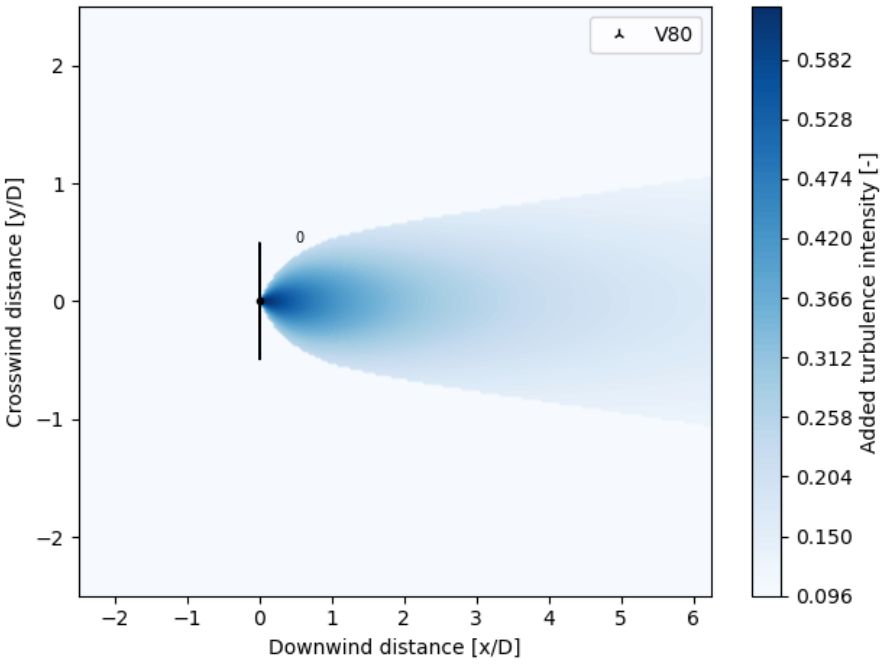
[4]:
```
from py_wake.turbulence_models import STF2005TurbulenceModel
plot_turb_map(STF2005TurbulenceModel())
```



STF2017TurbulenceModel

Steen Frandsen model implemented according to IEC61400-1, 2017 and weight according to Steen Frandsen's thesis.

[5]:
```
from py_wake.turbulence_models import STF2017TurbulenceModel
plot_turb_map(STF2017TurbulenceModel())
```



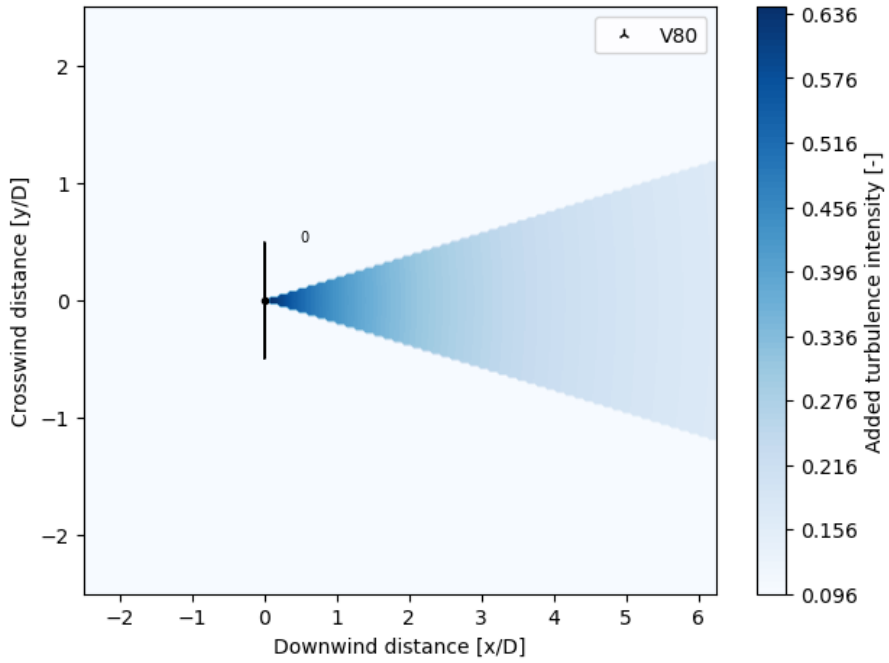
STF20XXTurbulenceModel with IEC-based spread angle

The `STF2005TurbulenceModel` and `STF2017TurbulenceModel` take a `weight_function` input which defaults to the bell-shaped `FrandsenWeight` defined in Steen Frandsen's thesis. As an alternative the `IECWeight` applies the full added turbulence in a 21.6° spread angle up to 10 diameter downstream.

Note, this is a debatable interpretation of the IEC standard which includes a 6% contribution from neighbouring wind turbines when calculating the omni-directional effective turbulence intensity. These 6% maps to a spread angle of 360°· 6% = 21.6°.

Note, the IEC standard includes more concepts which is not implemented in PyWake.

[6]:
```
from py_wake.turbulence_models import STF2017TurbulenceModel, IECWeight
from py_wake.superposition_models import SqrMaxSum
plot_turb_map(STF2017TurbulenceModel(addedTurbulenceSuperpositionModel=SqrMaxSum(),
                                     weight_function=IECWeight(distance_limit=10)))
```

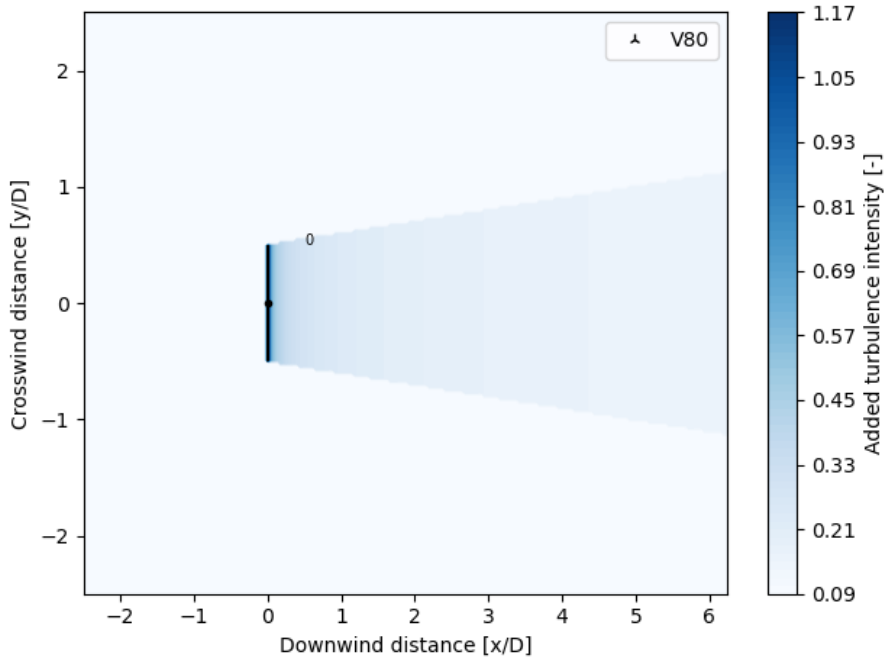


GCLTurbulence

Gunner Chr. Larsen model implemented according to:

Pierik, J. T. G., Dekker, J. W. M., Braam, H., Bulder, B. H., Winkelaar, D., Larsen, G. C., Morfiadakis, E., Chaviaropoulos, P., Derrick, A., & Molly, J. P. (1999). European wind turbine standards II (EWTS-II). In E. L. Petersen, P. Hjuler Jensen, K. Rave, P. Helm, & H. Ehmann (Eds.), Wind energy for the next millennium. Proceedings (pp. 568-571). James and James Science Publishers.

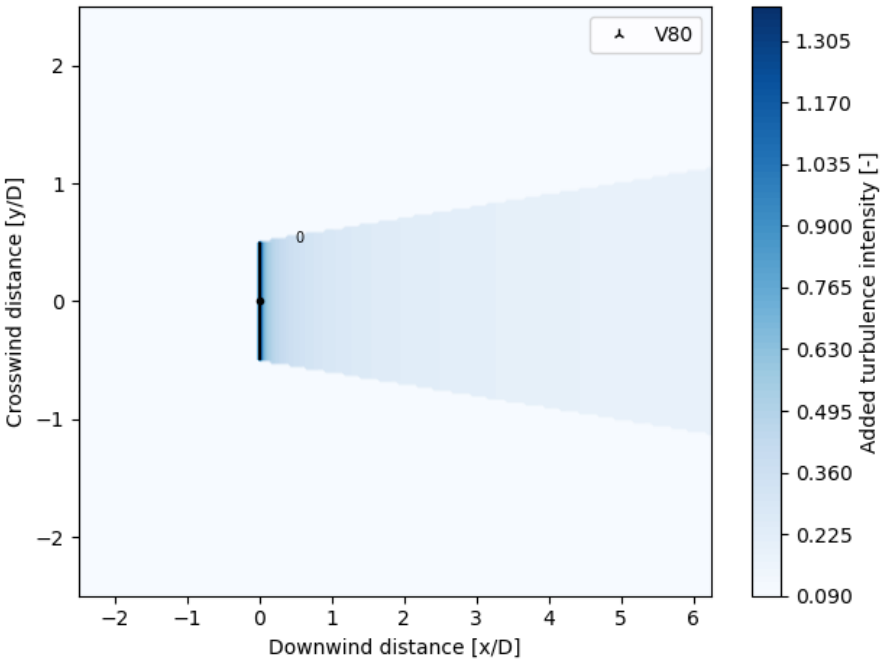
[7]:
```
from py_wake.turbulence_models import GCLTurbulence
plot_turb_map(GCLTurbulence())
```



CrespoHernandez

Implemented according to: A. Crespo and J. Hernández, Turbulence characteristics in wind-turbine wakes, J. of Wind Eng. and Industrial Aero. 61 (1996) 71-85.

[8]:
```
from py_wake.turbulence_models import CrespoHernandez
plot_turb_map(CrespoHernandez())
```



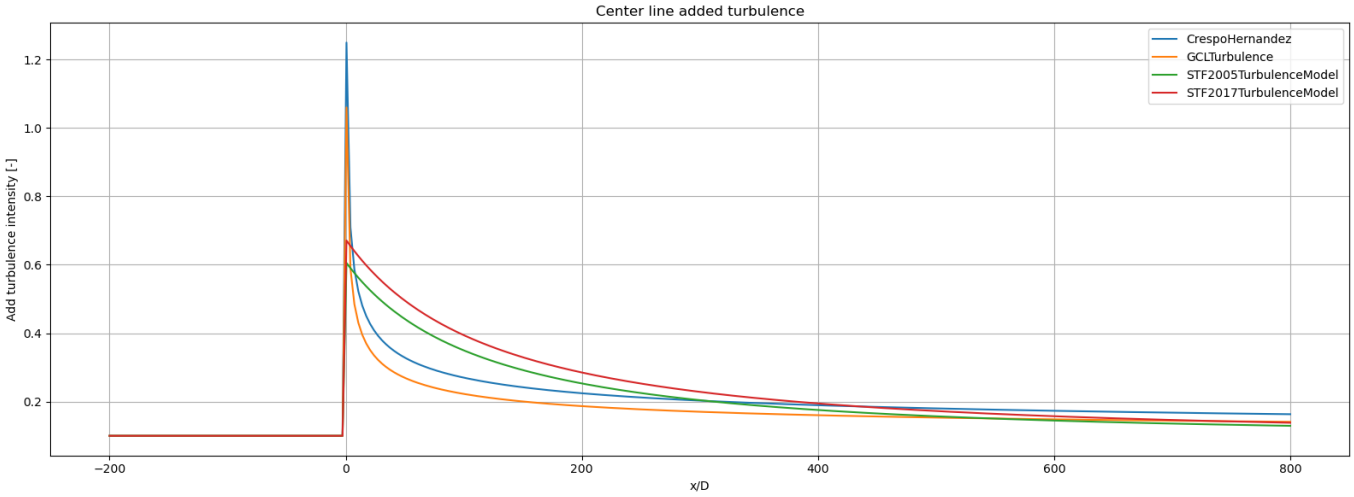
Comparing turbulence models

[9]:
```
#printing all available wake deficit models in PyWake
from py_wake.utils.model_utils import get_models
from py_wake.turbulence_models.turbulence_model import TurbulenceModel

turbulenceModels = get_models(TurbulenceModel, exclude_None=True)

for model in turbulenceModels:
    print (model.__name__)
```

```
CrespoHernandez
GCLTurbulence
STF2005TurbulenceModel
STF2017TurbulenceModel
```

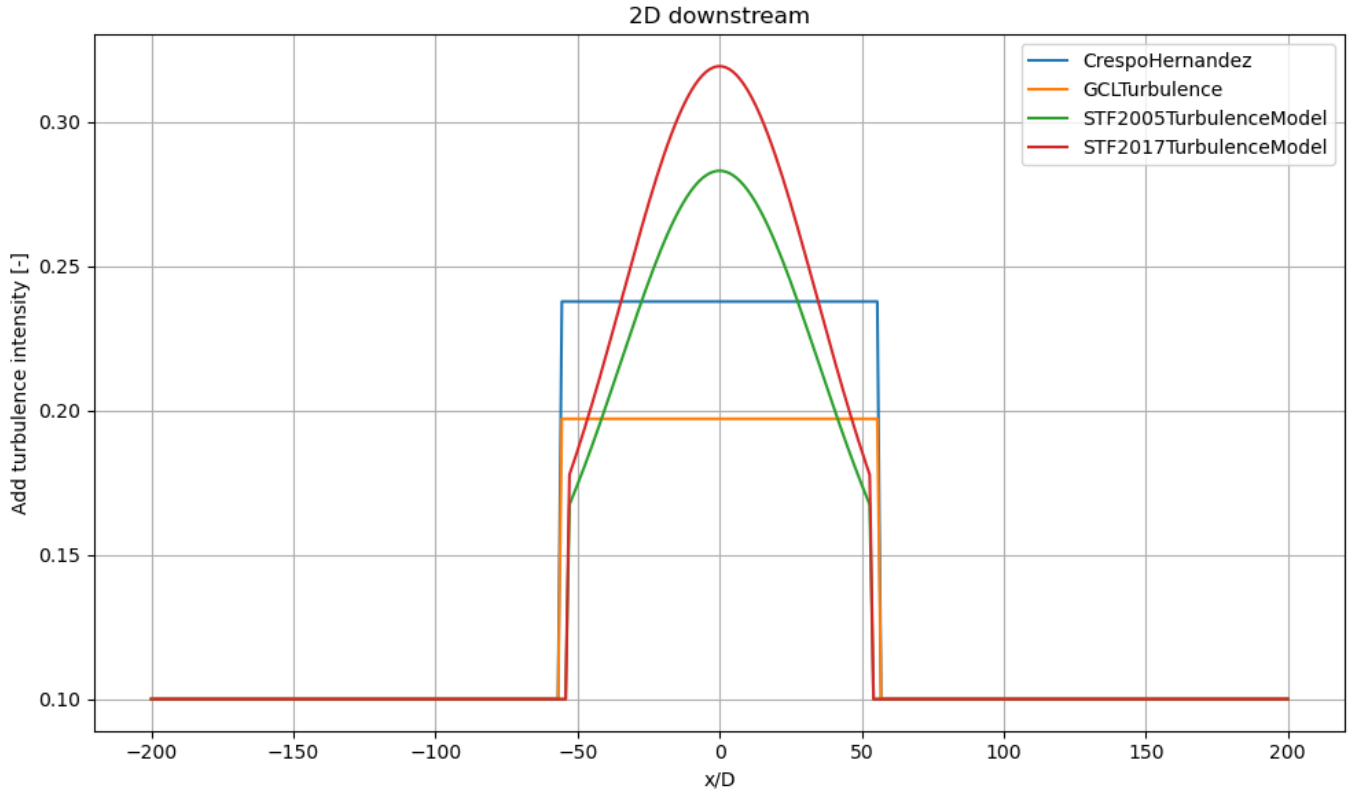
1) Turbulence intensity along center line

[10]:
```
plt.figure(figsize=((16,6)))
for i, model in enumerate(turbulenceModels):
    fm = get_flow_map(NOJDeficit(), turbulenceModel=model(), grid=XYGrid(x=np.linspace(-200,800,300), y=0))
    plt.plot(fm.x, fm.TI_eff.squeeze(), ('-','--')[i//10], label=model.__name__)
setup_plot(title="Center line added turbulence", xlabel='x/D', ylabel='Add turbulence intensity [-]')
```



2) Deficit profile 2D downstream

[11]:
```
d = 2
plt.figure(figsize=((10,6)))
for i, model in enumerate(turbulenceModels):
    fm = get_flow_map(NOJDeficit(), turbulenceModel=model(), grid=XYGrid(x=d*D, y=np.linspace(-200,200,300)))
    plt.plot(fm.y, fm.TI_eff.squeeze(), ('-','--')[i//10], label=model.__name__)
setup_plot(title="%sD %sstream"%(abs(d),('down','up')[d<0]), xlabel='x/D', ylabel='Add turbulence intensity [-]')
```



Open in Colab Edit on Gitlab

Ground Models

The ground models in PyWake are used to model the effects that the ground has on the inflow and wake.

Install PyWake if needed

[1]:
```
# Install PyWake if needed
try:
    import py_wake
except ModuleNotFoundError:
    !pip install git+https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake.git
```

Mirror

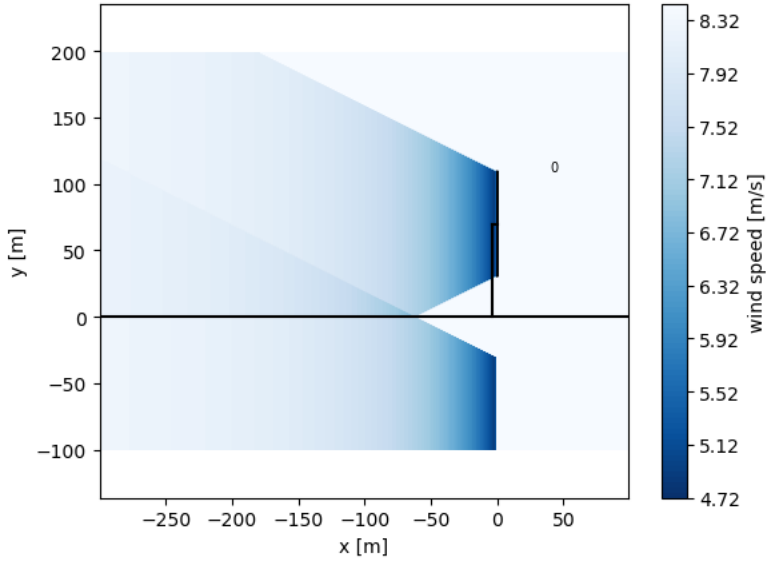
The Mirror ground model lets the ground mirror the wake deficit. It is implemented by adding wakes from underground mirrored wind turbines

[2]:
```
import numpy as np
import matplotlib.pyplot as plt
```

[3]:
```
from py_wake.ground_models import Mirror
from py_wake import NOJ
from py_wake.flow_map import YZGrid

from py_wake.examples.data.hornsrev1 import V80, Hornsrev1Site

site = Hornsrev1Site()
windTurbines = V80()
wt_x, wt_y = site.initial_position.T

wfm = NOJ(site, windTurbines, k=.5, groundModel=Mirror())

plt.figure()
wfm([0], [0], wd=0).flow_map(YZGrid(x=0, y=np.arange(-300, 100, 1) + .1, z=np.arange(-100, 200))).plot_wake_map()
plt.xlabel('x [m]')
plt.ylabel('y [m]')
```

```
/builds/TOPFARM/PyWake/py_wake/deficit_models/noj.py:88: UserWarning: The NOJ model is not representative of the setup used in the literature.
  DeprecatedModel.__init__(self, 'py_wake.literature.noj.Jensen_1983')
```

[3]:
```
Text(0, 0.5, 'y [m]')
```



Wind Farm Simulation

In this example, a simple wind farm case is presented where the different capabilities of PyWake such as calculating AEP, extracting power values and plotting time series are shown.

Install PyWake if needed

[1]:
```
# Install PyWake if needed
try:
    import py_wake
except ModuleNotFoundError:
    !pip install git+https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake.git
```

First we import some basic Python elements

[2]:
```
import numpy as np
import matplotlib.pyplot as plt
import xarray as xr
```

Now we import the site, wind turbine and wake deficit model to use in the simulation

[3]:
```
# import and setup site and windTurbines
%load_ext py_wake.utils.notebook_extensions

from tqdm.notebook import tqdm
from py_wake.utils import layouts
from py_wake.utils.profiling import timeit, profileit
from py_wake.examples.data.hornsrev1 import Hornsrev1Site, V80
from py_wake.literature.gaussian_models import Bastankhah_PorteAgel_2014
from py_wake.utils.plotting import setup_plot
xr.set_options(display_expand_data=False)

site = Hornsrev1Site()
x, y = site.initial_position.T
windTurbines = V80()

wf_model = Bastankhah_PorteAgel_2014(site, windTurbines, k=0.0324555)

#this allows you to see what type of engineering models you are simulating
print(wf_model)
```

```
Bastankhah_PorteAgel_2014(PropagateDownwind, BastankhahGaussianDeficit-wake, LinearSum-superposition)
```

Simple simulation - all wind directions and wind speeds

To run the wind farm simulation, we must call the `WindFarmModel` (wf_model) element that was previously created. As default, the model will run for all wind directions and wind speeds defined. The default properties are:

- `site.default_wd`: 0-360° in bins of 1°
- `site.default_ws`: 3-25 m/s in bins of 1 m/s

The default values for wind speeds and wind directions can be overwritten by either a scalar or an array.

[4]:
```
sim_res = wf_model(x, y,     # wind turbine positions
                   h=None,   # wind turbine heights (defaults to the heights defined in windTurbines)
                   type=0,   # Wind turbine types
                   wd=None,  # Wind direction
                   ws=None,  # Wind speed
                  )
```

Simulation Results

The `SimulationResult` object is a xarray dataset that provides information about the simulation result with some additional methods and attributes. It has the coordinates

- `wt`: Wind turbine number
- `wd`: Ambient reference wind direction
- `ws`: Ambient reference wind speed
- `x`, `y`, `h`: position and hub height of wind turbines

and data variables:

- `WD`: Local free-stream wind direction
- `WS`: Local free-stream wind speed
- `TI`: Local free-stream turbulence intensity
- `P`: Probability of flow case (wind direction and wind speed)
- `WS_eff`: Effetive local wind speed [m/s]
- `TI_eff`: Effective local turbulence intensity
- `power`: Effective power production [W]
- `ct`: Thrust coefficient
- `Yaw`: Yaw misalignment [deg]

where “effective” means “including wake effects”

[5]:
```
#printing the simulation result from the wake model previously defined
sim_res
```

[5]:
xarray.SimulationResult

Dimensions: (**wt**: 80, **wd**: 360, **ws**: 23)

Coordinates:

Data variables: (17)

Indexes: (3)

Attributes: (0)

Selecting data

Data can be selected using the xarray `sel` method.

For example, the power production of wind turbine 3 when the wind is coming from the East (90deg) for all wind speeds bins:

[6]:
```
sim_res.Power.sel(wt=3, wd=0)
```

[6]:
xarray.DataArray 'Power' (**ws**: 23)

0.0 5.459e+04 1.293e+05 2.39e+05 3.902e+05 ... 2e+06 2e+06 2e+06 2e+06

Coordinates:

Indexes: (1)

Attributes:

We can also get the total power of turbine 3 for the wind direction specified.

[7]:
```
total_power = sim_res.Power.sel(wt=3, wd=0).sum().values/1e6
print('Total power: %f MW'%total_power)
```

```
Total power: 32.513680 MW
```

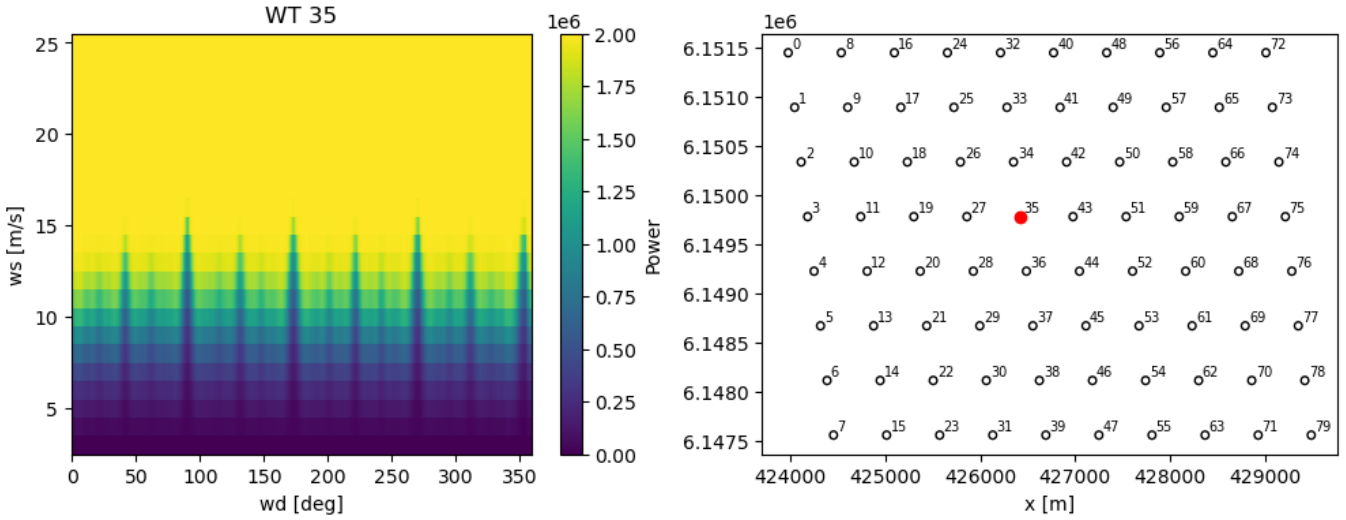
Plotting data

Data can be plotted using the xarray `plot` method.

For example, the power production of wind turbine 35 as a function of wind direction and wind speed.

[8]:
```
ax1, ax2 = plt.subplots(1,2, figsize=(12,4))[1]
sim_res.Power.sel(wt=35).T.plot(ax=ax1)
ax1.set_xlabel('wd [deg]')
ax1.set_ylabel('ws [m/s]')
ax1.set_title('WT 35')
windTurbines.plot(x,y, ax=ax2)
ax2.plot(x[35],y[35],'or')
ax2.set_xlabel('x [m]')
```

[8]:
```
Text(0.5, 0, 'x [m]')
```



AEP calculation

Furthermore, `SimulationResult`, contains the method `aep` that calculates the Annual Energy Production. This can be done for all of the turbines as well as the total AEP of the wind farm, in GWh.

Here we can obtain the AEP of wind turbine 80 for all wind speed and wind directions:

[9]:
```
sim_res.aep()
```

[9]:
xarray.DataArray 'AEP [GWh]' (**wt**: 80, **wd**: 360, **ws**: 23)

0.0 4.993e-05 0.0001429 0.0002968 ... 2.478e-06 1.005e-06 3.842e-07

Coordinates:

Indexes: (3)

Attributes:

The total wind farm AEP is obtained using the `sum` method.

[10]:
```
print('Total power: %f GWh'%sim_res.aep().sum().values)
```
```
Total power: 664.334531 GWh
```

The `aep` method take an optional input, `with_wake_loss` (default is True), which can be used to e.g. calculate the wake loss of the wind farm.

[11]:
```
aep_with_wake_loss = sim_res.aep().sum().data
aep_witout_wake_loss = sim_res.aep(with_wake_loss=False).sum().data
print('total wake loss:',((aep_witout_wake_loss-aep_with_wake_loss) / aep_witout_wake_loss))
```
```
total wake loss: 0.10712031642603277
```

Time series

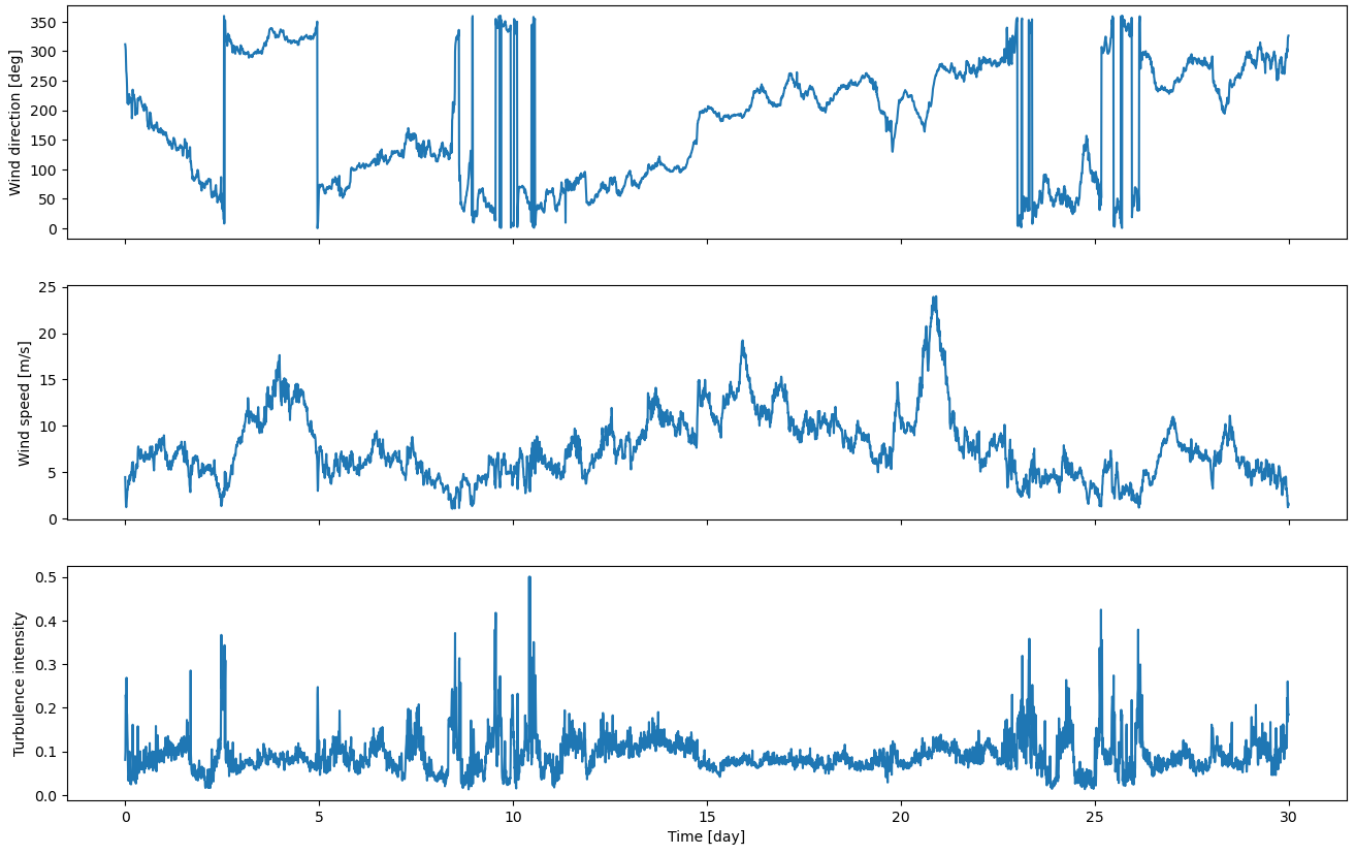
Instead of simulating all wind speeds and wind directions, it is also possible to simulate time series of wind speed and wind directions.

This allows simulation of time-dependent inflow conditions, e.g. combinations of wd, ws, shear, ti, density,etc. and turbine operation, e.g. periods where one or more wind turbines are stopped due to failure or maintenance.

Note, however, that PyWake considers the time series as discrete stationary conditions, i.e. a gust hits the whole wind farm at the same time.

[12]:
```
# load a time series of wd, ws and ti
from py_wake.examples.data import example_data_path

d = np.load(example_data_path + "/time_series.npz")
n_days=30
wd, ws, ws_std = [d[k][:6*24*n_days] for k in ['wd', 'ws', 'ws_std']]
ti = np.minimum(ws_std/ws,.5)
time_stamp = np.arange(len(wd))/6/24
```

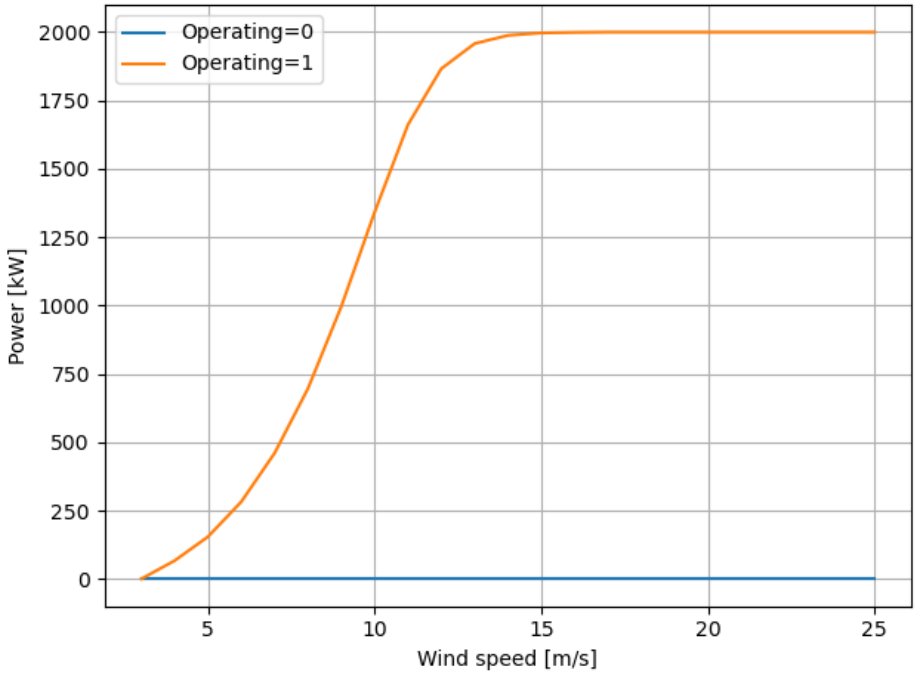
[13]:
```
# plot time series
axes = plt.subplots(3,1, sharex=True, figsize=(16,10))[1]

for ax, (v,l) in zip(axes, [(wd, 'Wind direction [deg]'),(ws,'Wind speed [m/s]'),(ti,'Turbulence intensity')]):
    ax.plot(time_stamp, v)
    ax.set_ylabel(l)
_ = ax.set_xlabel('Time [day]')
```



Time-dependent wind turbine operation

Extend the wind turbine with a `operating` setting (0=stopped, 1=normal operation)

[14]:
```
from py_wake.wind_turbines.power_ct_functions import PowerCtFunctionList, PowerCtTabular

# replace powerCtFunction
windTurbines.powerCtFunction = PowerCtFunctionList(
    key='operating',
    powerCtFunction_lst=[PowerCtTabular(ws=[0, 100], power=[0, 0], power_unit='w', ct=[0, 0]), # 0=No power and ct
                         V80().powerCtFunction], # 1=Normal operation
    default_value=1)

# plot power curves
u = np.arange(3,26)
for op in [0,1]:
    plt.plot(u, windTurbines.power(u, operating=op)/1000, label=f'Operating={op}')
setup_plot(xlabel='Wind speed [m/s]', ylabel='Power [kW]')
```



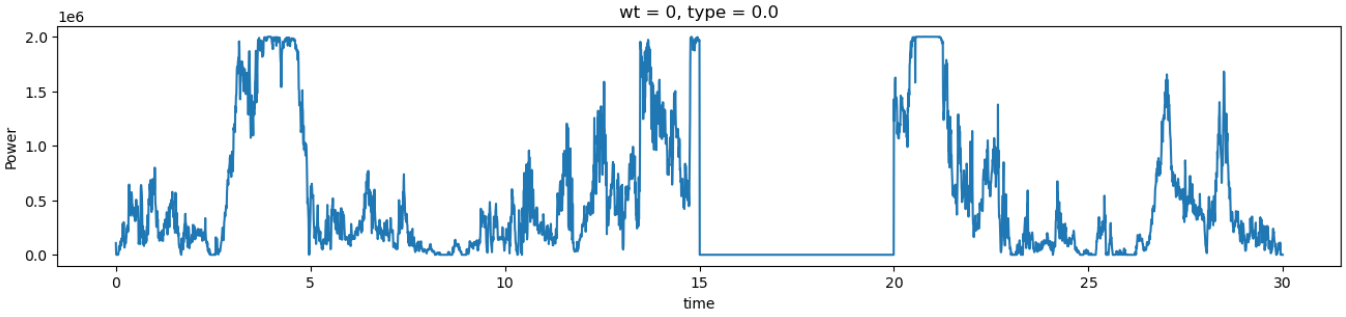
Make time-dependent operating variable

[15]:
```
operating = np.ones((len(x), len(time_stamp))) # shape=(#wt, #time stamps)
operating[0,(time_stamp>15)&(time_stamp<20)] = 0 # wt0 not operating from day 5 to 15
```

Call the wind farm model with the `time=time_stamp` and the time-dependent `operating` keyword argument.

[16]:
```
# setup new WindFarmModel with site containing time-dependent TI and run simulation
wf_model = Bastankhah_PorteAgel_2014(site, windTurbines, k=0.0324555)

sim_res_time = wf_model(x, y, # wind turbine positions
                        wd=wd, # Wind direction time series
                        ws=ws, # Wind speed time series
                        time=time_stamp, # time stamps
                        TI=ti, # turbulence intensity time series
                        operating=operating # time dependent operating variable
                    )
```

[17]:
```
#here we plot the power time series of turbine 0
sim_res_time.Power.sel(wt=0).plot(figsize=(16,3))
```



[18]:
```
sim_res_time.operating
```

[18]:

xarray.DataArray 'operating' (**wt**: 80, **time**: 4320)

1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 ... 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0

Coordinates:

Indexes: (2)

Attributes:

In the no-operating periode time=5..15, the power is 0 as it should be

Chunkification and Parallelization

PyWake makes it easy to split the wind farm simulation computation into smaller subproblems. This allows:

- Simulation of large wind farms or time series with less memory usage
- Parallel execution for faster simulation

1) Chunkfication

To split the simulation into smaller sub-tasks, just specify the desired number of `wd_chunks` and `ws_chunks`.

[19]:
```
# split problem into 4x2 subtasks and simulate sequentially on one CPU
sim_res = wf_model(x, y,
                   wd_chunks=4,
                   ws_chunks=2)
```

Time series of (wd,ws)-flow cases is split into chunks, by specifying either `ws_chunks` or `wd_chunks`

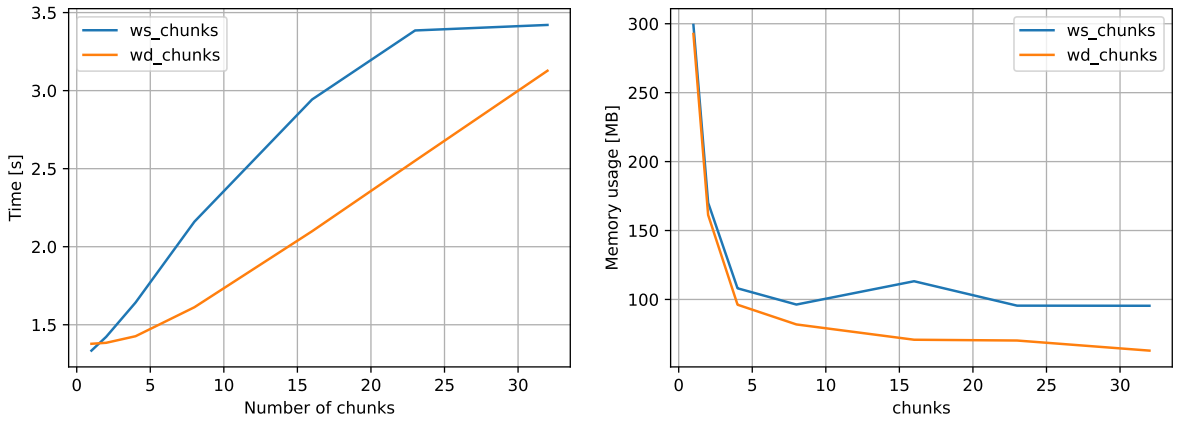
[20]:
```
sim_res_time = wf_model(x, y, # wind turbine positions
                        wd=wd, # Wind direction time series
                        ws=ws, # Wind speed time series
                        time=time_stamp, # time stamps
                        wd_chunks=4,
                    )
```

Wind speed or wind direction chunks

[21]:
```
%%skip
n_lst = [1,2,4,8,16,23,32]
res = {'ws_chunks': np.array([(n,) + profileit(wf_model)(x, y, wd_chunks=1, ws_chunks=n)[1:] for n in tqdm(n_lst)]),
       'wd_chunks': np.array([(n,) + profileit(wf_model)(x, y, wd_chunks=n, ws_chunks=1)[1:] for n in tqdm(n_lst)])}

ax1,ax2 = plt.subplots(1,2,figsize=(12,4))[1]

for k, d in res.items():
    n,t,m = d.T
    ax1.plot(n,t, label=k)
    ax2.plot(n,m, label=k)
setup_plot(ax=ax1, ylabel='Time [s]', xlabel='Number of chunks')
setup_plot(ax=ax2, ylabel='Memory usage [MB]', xlabel='chunks')
plt.savefig('RunWindFarmSimuation_wdws_chunks.svg')
```

```
Cell skipped. Precomputed result shown below. Remove '%%skip' to force run.
```

Result computed on the Sophia HPC cluster. Note that the number of wind speed chunks is limited to the number of wind speeds, in this case 23.



It is clearly seen that chunkification of wind directions are more efficient than chunkification of wind speeds with respect to both time and memory usage.

It is also seen that chunkification reduces the memory usage at the cost of computation time. With 32 wind direction chunks, the computational time is more than doubled, i.e. the speedup from running in parallel on a system with 32 CPUs is expected to be less than 16 times.

2) Parallelization

Running a wind farm simulation in parallel is just as easy - simply specify the number of CPUs to use to the input argument `n_cpu` or `None` to use all available CPUs.

As seen above, wind directions chunks are more efficient. Hence, the problem is as default split into `n_cpu` wind direction chunks, where `n_cpu` is the numbers of CPUs to use.

As default, `n_cpu=1` (sequential execution), so to run in parallel, you need to specify a number of CPUs, e.g. `n_cpu=4`. Alternatively, `n_cpu=None` will use all available CPUs.

[22]:
```
sim_res = wf_model(x, y,
                   n_cpu=None # run wind directions in parallel on all available CPUs
                  )
```

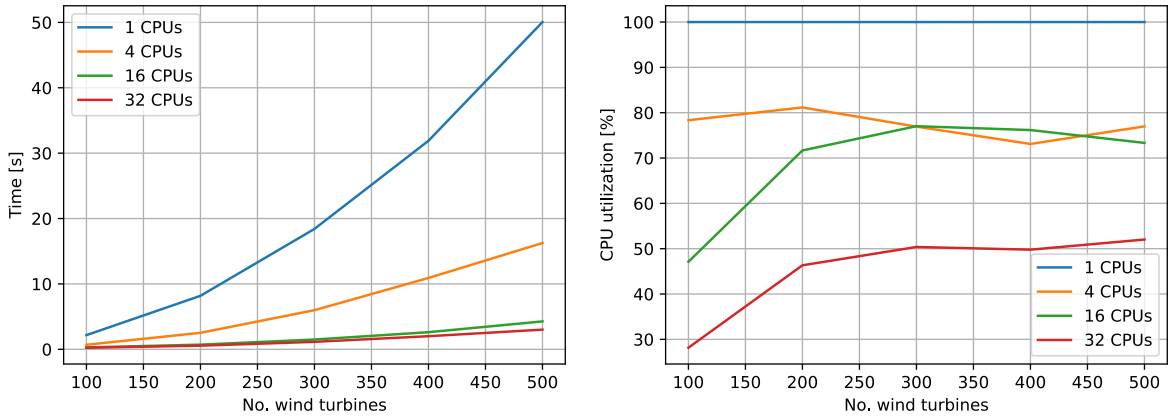
CPU utilization

The plot below shows the time used to calculate the AEP on 1-32 CPUs as a function of number of wind turbines.

[23]:
```
%%skip
from py_wake.utils import layouts
from py_wake.utils.profiling import timeit
from tqdm.notebook import tqdm

n_lst = np.arange(100,600,100)

def run(n, n_cpu):
    x,y = layouts.rectangle(n,20,5*windTurbines.diameter())
    return (n, n_cpu, np.mean(timeit(wf_model, min_runs=5)(x,y,n_cpu=n_cpu)[1]))

res = {f'{n_cpu} CPUs': np.array([run(n, n_cpu=n_cpu) for n in tqdm(n_lst)]) for n_cpu in [1, 4, 16, 32]}

ax1,ax2 = plt.subplots(1,2, figsize=(12,4))[1]
for k,v in res.items():
    n,n_cpu,t = v.T
    ax1.plot(n, t, label=k)
    ax2.plot(n, res['1 CPUs'][:,2]/n_cpu/t*100, label=k)
setup_plot(ax=ax1,xlabel='No. wind turbines',ylabel='Time [s]')
setup_plot(ax=ax2,xlabel='No. wind turbines',ylabel='CPU utilization [%]')
plt.savefig('images/RunWindFarmSimulation_time_cpuwt.svg')
```

```
Cell skipped. Precomputed result shown below. Remove '%%skip' to force run.
```

Result precomputed on the Sophia HPC cluster on a node with 32 CPUs.



The plot clearly shows that the time reduces with more CPUs. In this case, however, the gain from 16 to 32 CPUs is very limited. Note, this may highly dependend on the system architecture.

Flow map

Finally, `SimulationResult` has a `flow_map` method which returns a `FlowMap` object. This allows the user to visualize the wake behind each turbine's rotor in the wind farm and represents the velocity deficit that occurs due to wake interactions in the wind farm.

[24]:
```
from py_wake.examples.data.iea37 import IEA37Site, IEA37_WindTurbines
from py_wake.literature.gaussian_models import Bastankhah_PorteAgel_2014

site = IEA37Site(16)
x, y = site.initial_position.T
windTurbines = IEA37_WindTurbines()

wf_model = Bastankhah_PorteAgel_2014(site, windTurbines, k=0.0324555)
sim_res = wf_model(x,y)
```

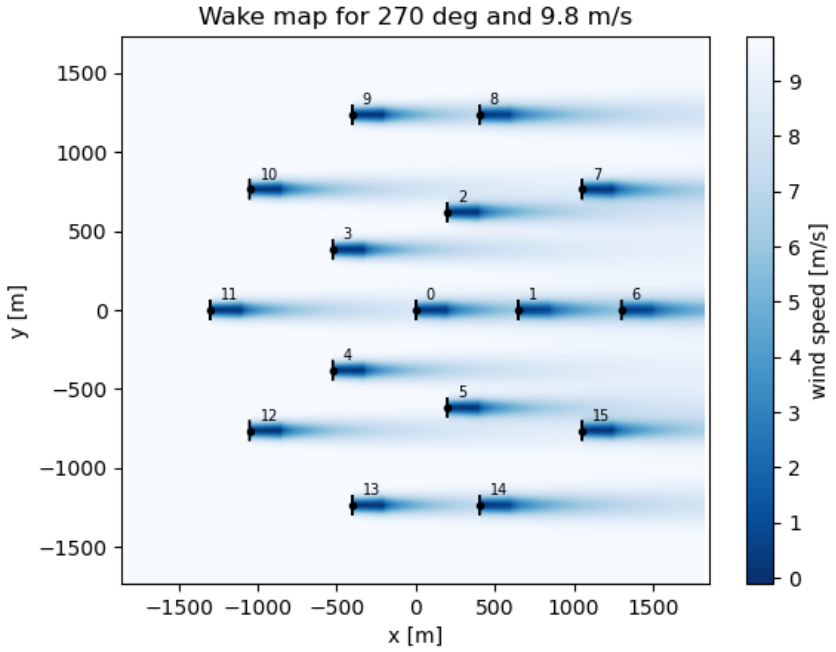
[25]:
```
#change the wind speed and wind direction to visualize different flow cases
wsp = 9.8
wdir = 270
flow_map = sim_res.flow_map(grid=None, # defaults to HorizontalGrid(resolution=500, extend=0.2), see below
                            wd=wdir,
                            ws=wsp)
```

To plot the wake map we call the plot_wake_map property.

You can change the values of the wind speed and wind direction to see how different flow maps look like.

[26]:
```
plt.figure()
flow_map.plot_wake_map()
plt.xlabel('x [m]')
plt.ylabel('y [m]')
plt.title('Wake map for'+ f' {wdir} deg and {wsp} m/s')
```

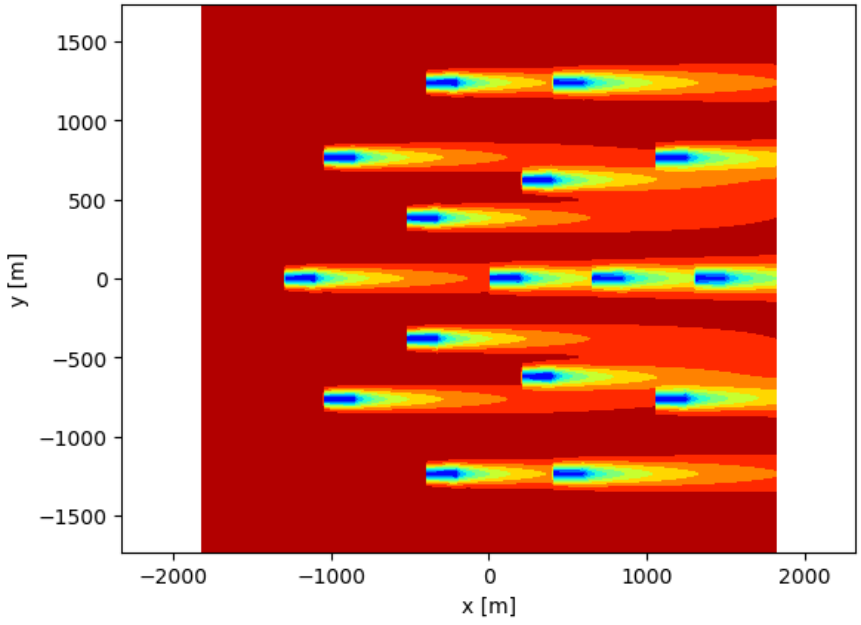
[26]:
```
Text(0.5, 1.0, 'Wake map for 270 deg and 9.8 m/s')
```



The wake map can also be customized in terms of size and contour levels.

[27]:
```
flow_map.plot_wake_map(levels=10, # contourf levels (int or list of levels)
                       cmap='jet', # color map
                       plot_colorbar=False,
                       plot_windturbines=False,
                       ax=None)
plt.axis('equal')
plt.xlabel('x [m]')
plt.ylabel('y [m]')
```

[27]:
```
Text(0, 0.5, 'y [m]')
```



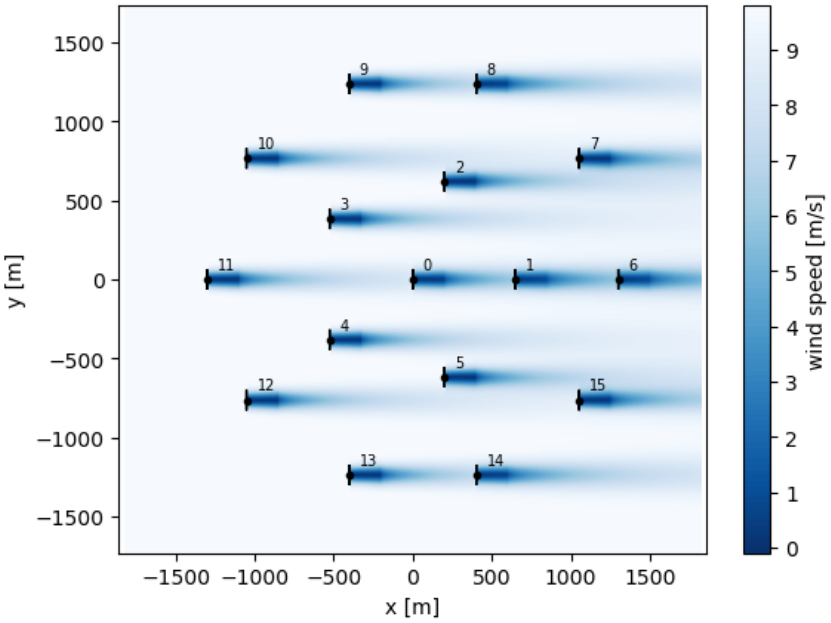
There is also a Grid argument that can be set up to further customize the way the flow map is shown in different planes

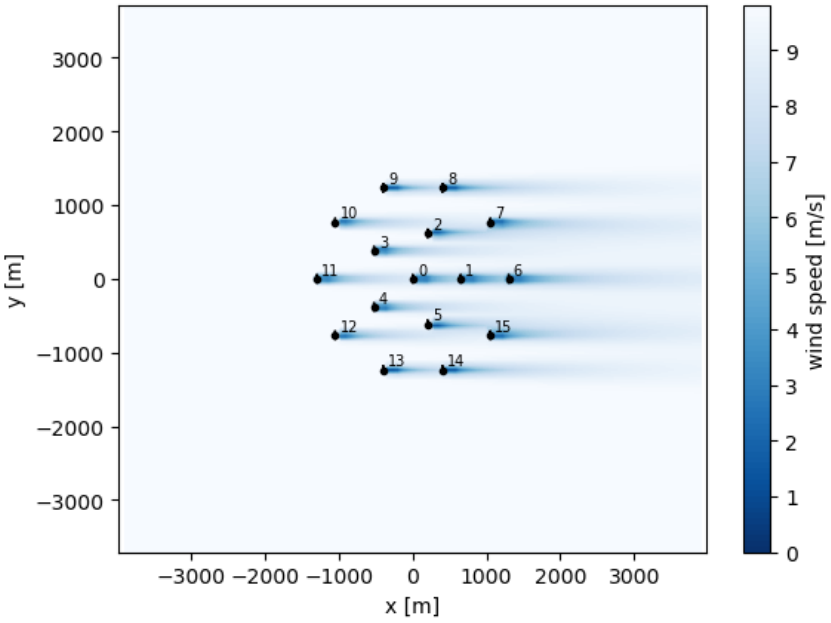
The grid argument should be either

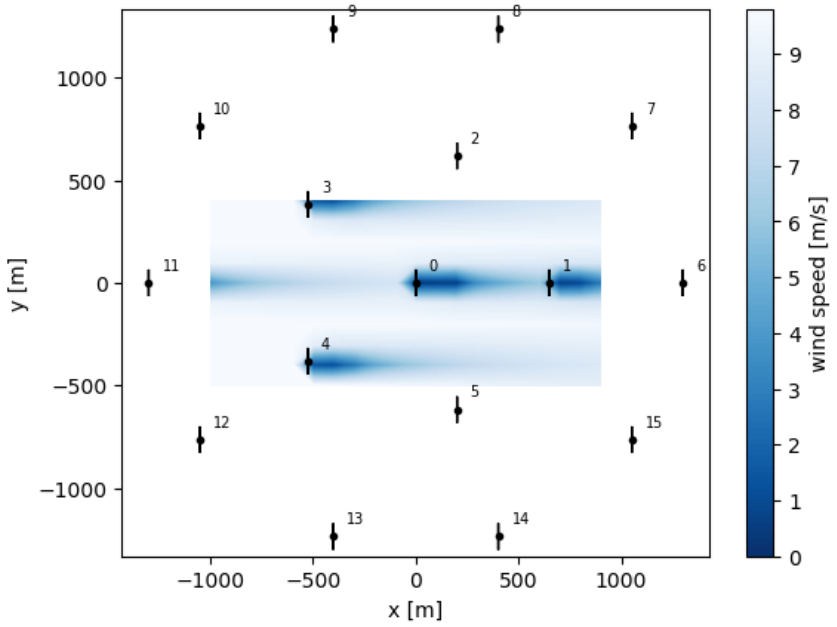
- a `HorizontalGrid` (same as `XYGrid`), `YZGrid` or
- a tuple(X, Y, x, y, h) where X, Y is the meshgrid for visualizing the data and x, y, h are the flattened grid points

HorizontalGrid (XYGrid)

[28]:
```
from py_wake import HorizontalGrid

for grid in [None,                                                  # defaults to HorizontalGrid(resolution=500, extend=0.2)
             HorizontalGrid(x=None, y=None, resolution=100, extend=1), # custom resolution and extend
             HorizontalGrid(x = np.arange(-1000,1000,100),
                            y = np.arange(-500,500,100))            # custom x and y
            ]:
    plt.figure()
    sim_res.flow_map(grid=grid, wd=270, ws=[9.8]).plot_wake_map()
    plt.xlabel('x [m]')
    plt.ylabel('y [m]')
```

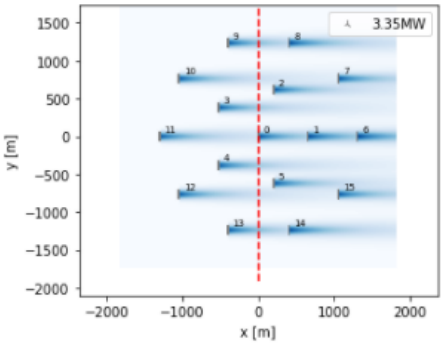






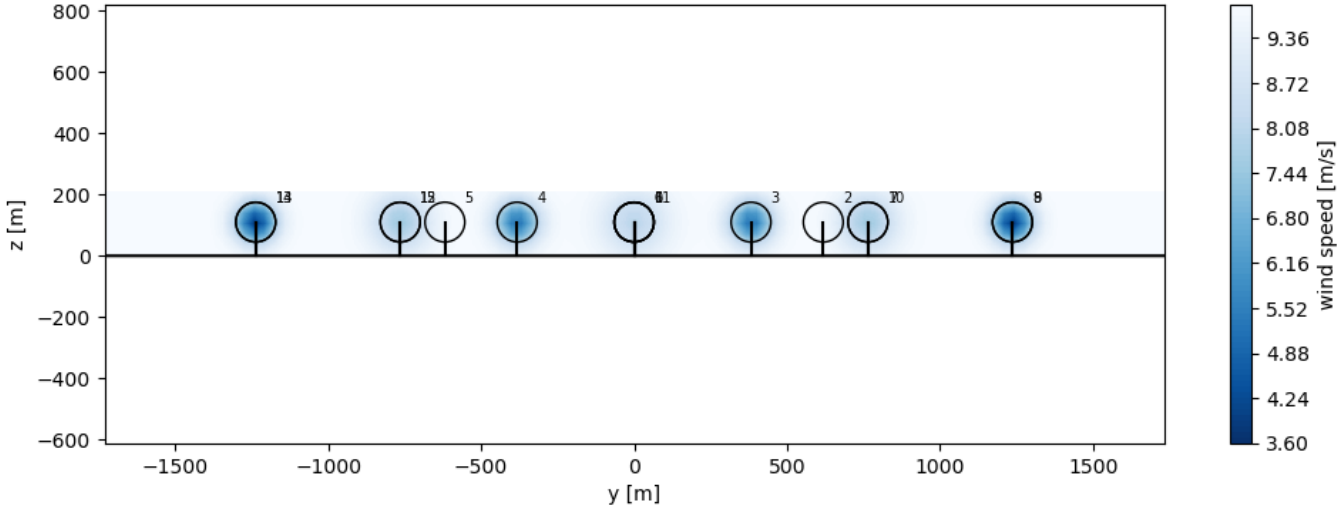
YZGrid

Plotting the flow map in the vertical YZ plane through the red dashed line can be done using the `YZGrid`



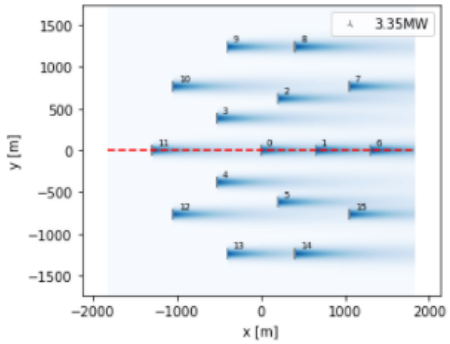
[29]:
```
from py_wake import YZGrid
plt.figure(figsize=(12,4))
sim_res.flow_map(YZGrid(x=-100, y=None, resolution=100), wd=270, ws=None).plot_wake_map()
plt.xlabel('y [m]')
plt.ylabel('z [m]')
```

[29]: `Text(0, 0.5, 'z [m]')`



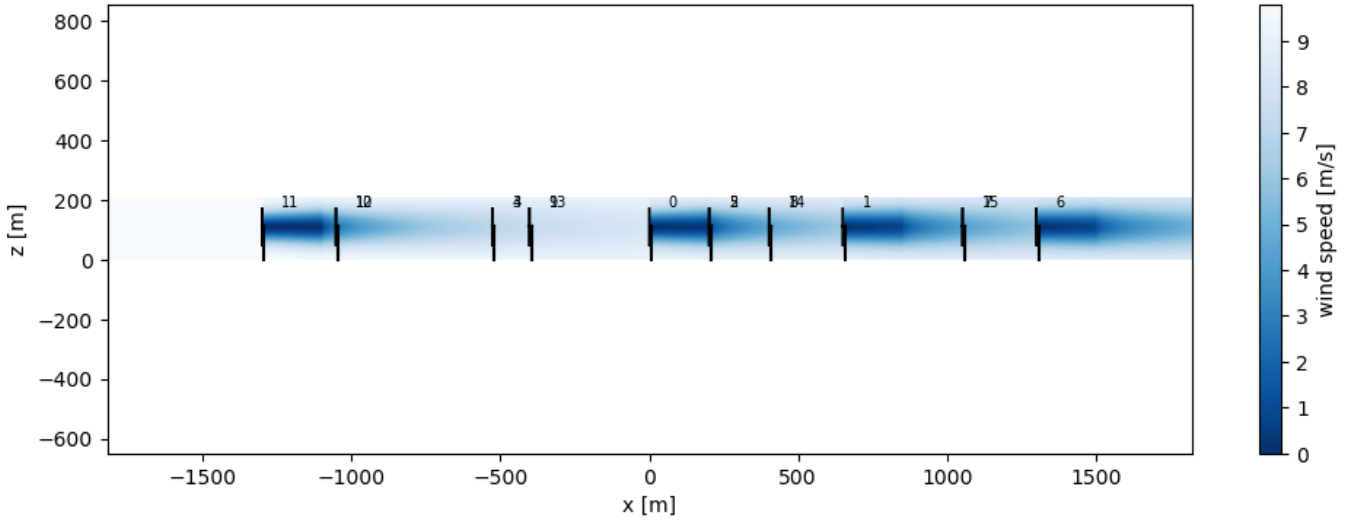
3) XZGrid

Plotting the flow map in the vertical XZ plane through the red dashed line can be done using the `XZGrid`



[30]:
```
from py_wake import XZGrid
plt.figure(figsize=(12,4))
sim_res.flow_map(grid=XZGrid(y=0, resolution=1000), wd=270, ws=None).plot_wake_map()
plt.xlabel('x [m]')
plt.ylabel('z [m]')
```

[30]: `Text(0, 0.5, 'z [m]')`



Open in Colab Edit on Gitlab

Gradients, Parallelization and Precision

This section describes how to obtain gradients for more efficient optimization and how to speedup execution via parallelization.

Install PyWake if needed

[1]:
```
# Install PyWake if needed
try:
    import py_wake
except ModuleNotFoundError:
    !pip install git+https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake.git
```

Gradients

PyWake supports three methods for computing gradients:

Method	Pro	Con
Finite difference (`fd`)	• Works out of the box in most cases- Fast for small problems	• Less accurate - Sensi
Complex step (`cs`)	• More accurate- Works out of the box or with a few minor changes - Fast for small problems	• Requires `n` functior
Automatic differentiation (`autograd`)	• Exact result- Requires 1 smart function evaluation	• `numpy` must be replaced wit Gradient functions (e.g.

Example problem

To demonstrate the three methods we first define an example function, `f(x)`, with one input vector of three elements, `x = [1,2,3]`

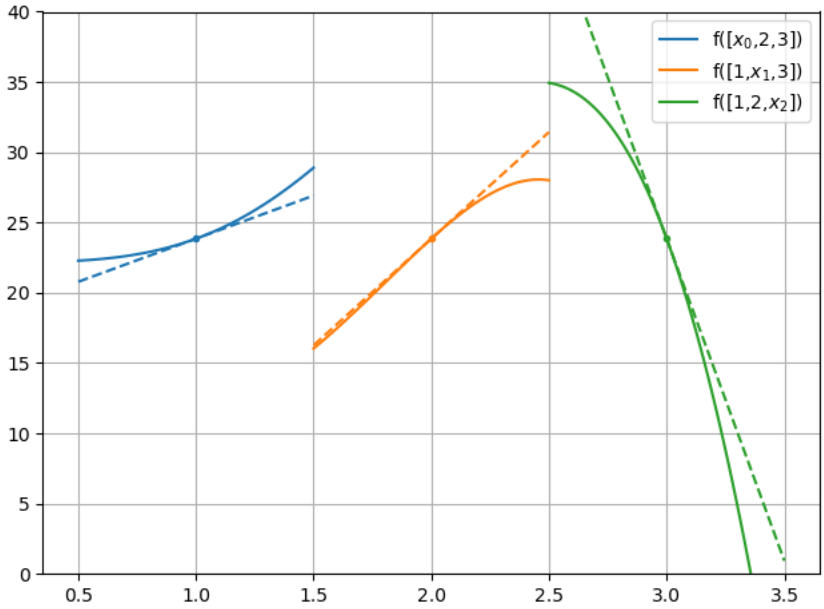
$$f(x) = \sum_x 2x^3 \sin(x)$$

[2]:
```
%load_ext py_wake.utils.notebook_extensions
import numpy as np
import matplotlib.pyplot as plt

def f(x):
    return np.sum((2 * x**3) * np.sin(x))

def df(x):
    # analytical gradient used for comparison
    return 6*x**2 * np.sin(x)  + 2*x**3 * np.cos(x)

x = np.array([1,2,3], dtype=float)
```

Plot variation+gradients of `f` with respect to x_0, x_1, x_2

[3]:
```
dx_lst = np.linspace(-.5,.5,100)

import matplotlib.pyplot as pltq
from py_wake.utils.plotting import setup_plot

for i in range(3):
    label="f([1,2,3])".replace(str(i+1),f"$x_{i}$")
    c = plt.plot(x[i] + dx_lst, [f(x + np.roll([dx,0,0],i)) for dx in dx_lst], label=label)[0].get_color()
    plt.plot(x[i]+[-.5,.5], f(x) + df(x)[i]*np.array([-.5,.5]), '--', color=c)
    plt.plot(x[i], f(x), '.', color=c)
setup_plot(ylim=[0,40])
plt.legend()
```

[3]:
```
<matplotlib.legend.Legend at 0x7f426246b190>
```



In PyWake, gradients can be calculated via three methods: finite difference, complex step, and automatic diferentiation (AD) or autograd.

Below is the theoretical background of each method, followed by a comparison made between the three methods in terms of simulation time required.

Finite difference `fd`

$$\frac{df(x)}{dx} = \frac{f(x+h)-f(x)}{h}$$

Finite difference applied to the example function:

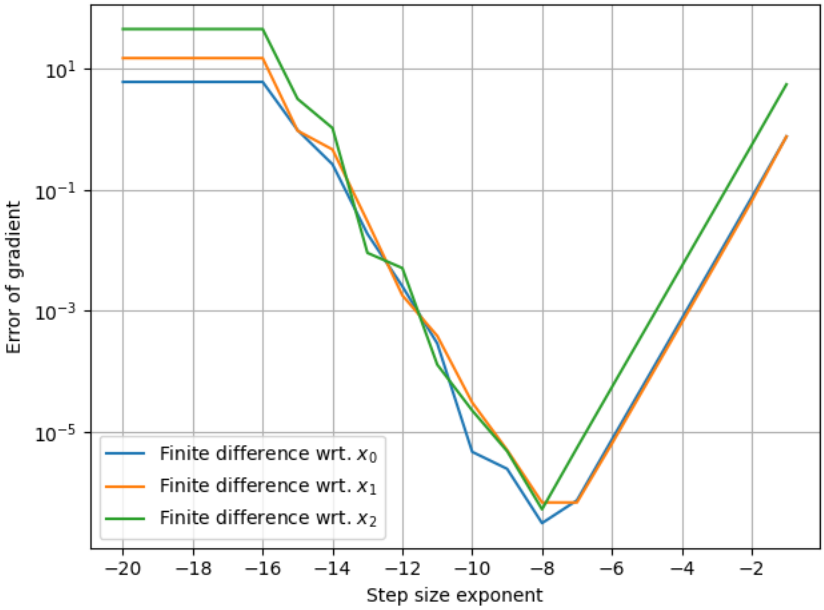
[4]:
```
print ("Analytical gradient:", list(df(x)))
h = 1e-6
for i in range(3):
    print (f"Finite difference gradient wrt. x{i}:", (f(x+np.roll([h,0,0],i)) - f(x))/h)
```

```
Analytical gradient: [6.129430520583658, 15.164788859062082, -45.83911438119122]
Finite difference gradient wrt. x0: 6.129437970514573
Finite difference gradient wrt. x1: 15.164782510623809
Finite difference gradient wrt. x2: -45.83916911826691
```

In this example the gradients are accurate to 4th or 5th decimal. The accuracy, however, is highly dependent on the step size, `h`. If the step size is too sm
other hand, becomes too big, then the result represents the gradient of a neighboring point.

This compromize is illusated below:

[5]:
```
h_lst = 10.**(-np.arange(1,21)) # step sizes [1e-1, ..., 1e-20]

for i in range(3):
    # Plot error compared to analytical gradient, df(x)
    plt.semilogy(np.log10(h_lst), [np.abs(df(x)[i] - (f(x+np.roll([h,0,0],i))-f(x))/h) for h in h_lst],
                 label=f'Finite difference wrt. $x_{i}$')
plt.xticks(np.arange(-20,-1,2))
setup_plot(ylabel='Error of gradient', xlabel='Step size exponent')
```



Complex step

The complex step method is described here.

It utilizes that

$$\frac{df(x)}{x} = \frac{\mathrm{Im}(f(x+ih))}{h} + O(h^2)$$

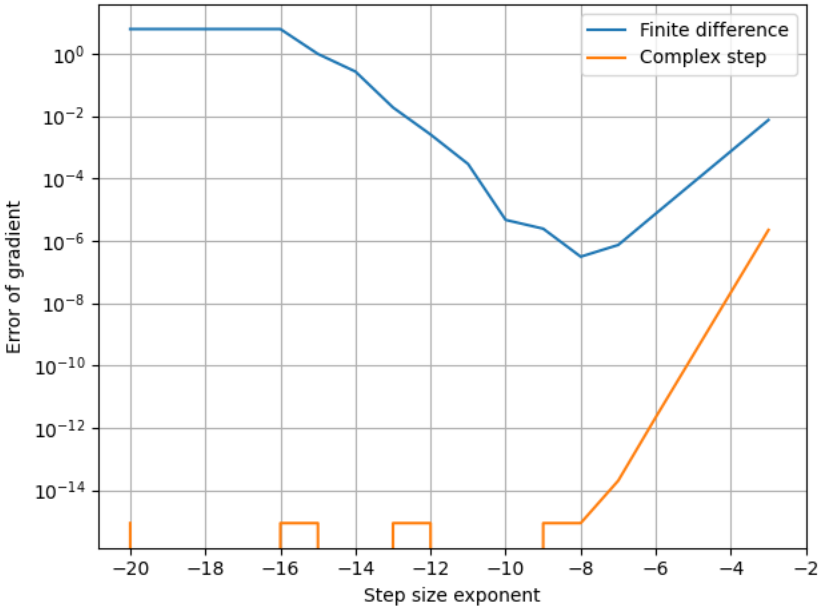
Applied to the example function, the result is accurate to the 15th decimal.

[6]:
```
print ("Analytical gradient:", list(df(x)))
h = 1e-10

for i in range(3):
    print (f"Finite difference gradient wrt. x{i}:", np.imag(f(x+np.roll([h*1j,0,0],i)))/h)
```

```
Analytical gradient: [6.129430520583658, 15.164788859062082, -45.83911438119122]
Finite difference gradient wrt. x0: 6.129430520583658
Finite difference gradient wrt. x1: 15.164788859062082
Finite difference gradient wrt. x2: -45.83911438119122
```

Furthermore, the result is much less sensitive to the step size as seen below

[7]:
```
h_lst = 10.**(-np.arange(3,21))

plt.semilogy(np.log10(h_lst), [np.abs(df(x)[0] - (f(x+[h,0,0])-f(x))/h) for h in h_lst], label='Finite difference')
plt.semilogy(np.log10(h_lst), [np.abs(df(x)[0] - np.imag(f(x+[h*1j,0,0]))/h) for h in h_lst], label='Complex step')
plt.xticks(np.arange(-20,-1,2))
setup_plot(ylabel='Error of gradient', xlabel='Step size exponent')
```



Common code changes

The complex step method calls the function with a complex number, i.e. all intermediate functions and routines must support complex number. A few `nu` a few changes is required. In PyWake, the module `py_wake.utils.gradients` contains a set of replacement functions that supports complext number, e.g.:

- `abs`
  - For a real value, `x`, `abs(x)` returns the positive value, while for a complex number, it returns the distance from 0 to z, $abs(a+bi) = \sqrt{a^2+b}$
  - In most cases `abs` should therefore be replaced by `gradients.cabs`, which returns `np.where(x<0,-x,x)`
- `np.hypot(a,b)`
  - `np.hypot` does not support complex numbers
  - replace with `gradients.hypot`, which returns `np.sqrt(a\*\*2+b\*\*2)` if `a` or `b` is complex
- `np.interp(xp,x,y)`
  - replace with `gradients.interp(xp,x,y)`
- `np.logaddexp(x,y)`
  - replace with `gradients.logaddexp(x,y)`

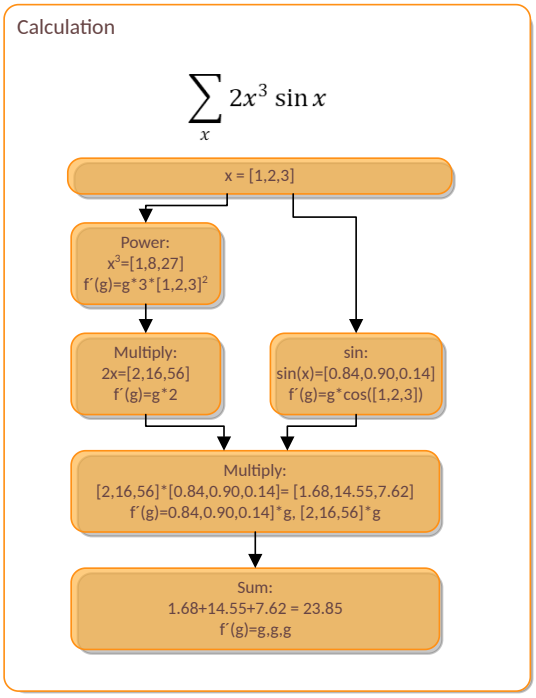
Furthermore, the imaginary part must be preserved when creating new arrays, i.e. - `np.array(x,dtype=float)` -> `np.array(x,dtype=(float, np.complex128)`

Automatic Differentiation (Autograd)

Autograd is a python package that can automatically differentiate native Python and Numpy code.

Autograd performs a two step automatic differentiation process.

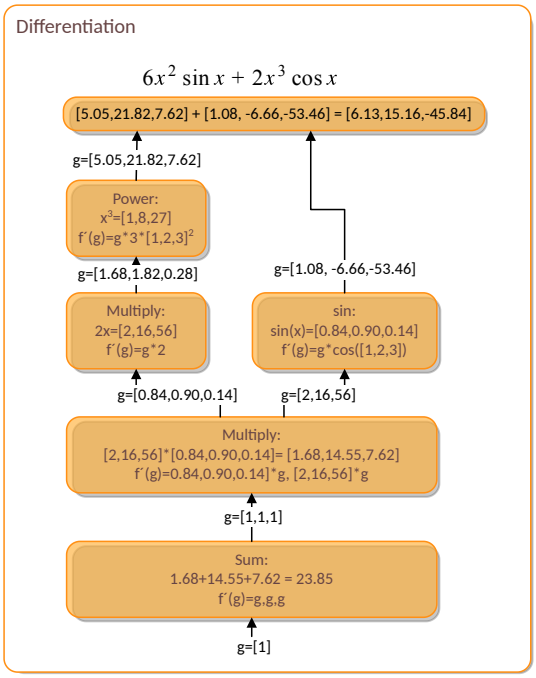
First the normal result is calculated and during this process autograd setups up a calculation tree where each element in the tree holds the associated gra



For most numpy functions, the associated gradient function is predefined when using `autograd.numpy` instead of `numpy`. You can see the autograd modul example is shown here:

```
defvjp(anp.multiply,    lambda ans, x, y : unbroadcast_f(x, lambda g: y * g),
                        lambda ans, x, y : unbroadcast_f(y, lambda g: x * g))
defvjp(anp.add,         lambda ans, x, y : unbroadcast_f(x, lambda g: g),
                        lambda ans, x, y : unbroadcast_f(y, lambda g: g))
defvjp(anp.power,
    lambda ans, x, y : unbroadcast_f(x, lambda g: g * y * x ** anp.where(y, y - 1, 1.)),
    lambda ans, x, y : unbroadcast_f(y, lambda g: g * anp.log(replace_zero(x, 1.)) * x ** y))
defvjp(anp.sin,    lambda ans, x : lambda g: g * anp.cos(x))
```

In the second step, the gradients are calculated by backward propagation



Applied to the example function, `autograd`, gives the exact results.

[8]:
```
from py_wake import np
from py_wake.utils.gradients import autograd

def f(x):
```

```
    return np.sum((2 * x**3) * np.sin(x))

print ("Analytical gradient:", list(df(x)))
print (f"Autograd gradient:", list(autograd(f)(x)))
```

```
Analytical gradient: [6.129430520583658, 15.164788859062082, -45.83911438119122]
Autograd gradient: [6.129430520583658, 15.164788859062082, -45.83911438119122]
```

Note, autograd needs its own numpy, `autograd.numpy`, to work. In PyWake, the `autograd` wrapper defined in `py_wake.utils.gradients`, handles this num
instead of the standard `import numpy as np`. This approach also allows an easy switch to single precision for faster simulation.

Common code changes

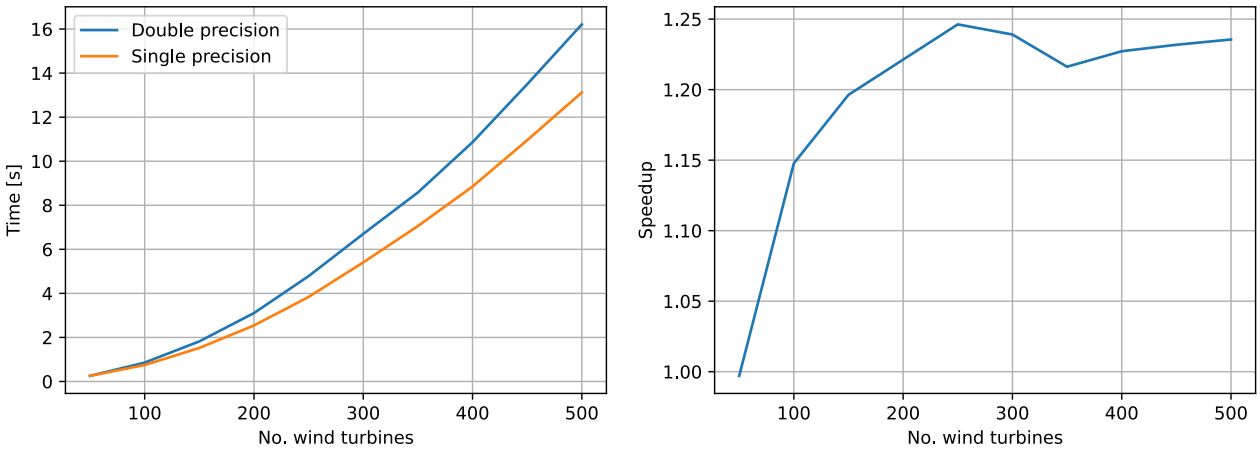
- `x[m] = 0` -> `x = np.where(m,0,x)`
  - Item assignment not supported

Comparison - Scalability of example problem

As seen in the examples, autograd computed the gradients with respect to all input elements in one smart (but slow) function evaluation, while finite diffe

This difference has a high impact on the performance of large scale problems. The plot below shows the time required to compute the gradients as a func
`autograd` functions from `py_wake.utils.gradients` is utilized.

```
from py_wake.utils.gradients import fd, cs, autograd
from py_wake.tests.check_speed import timeit

n_lst = np.arange(1,3500,500)
x_lst = [np.random.random(n) for n in n_lst]

def get_gradients(method,x):
    return method(f, vector_interdependence=True)(x)

for method in  [fd, cs, autograd]:
    plt.plot(n_lst, [np.mean(timeit(get_gradients, min_time=.2)(method,x)[1]) for x in x_lst], label=method.__name__)
setup_plot(title='Time to compute gradients of f(x)', xlabel='Number of elements in x', ylabel='Time [s]')
```



Gradients in PyWake

As described above, PyWake, contains a module, `py_wake.utils.gradients` which defines the three methods, `fd`, `cs` and `autograd`, as well as a numbe

With only a few exceptions, all PyWake models, turbines and sites support the three gradient methods.

Unfortunately, autograd is not working very well with xarray, i.e. the normal xarray `SimulationResult` must be bypassed. This mean that you can compute
argument `return_simulationResult=False` when running the wind farm model: `WindFarmModel(..., return_simulationResult=False)`.

Below we show a simple example with the Hornsrev1 Site and turbines while using the ZongGaussian wake model.

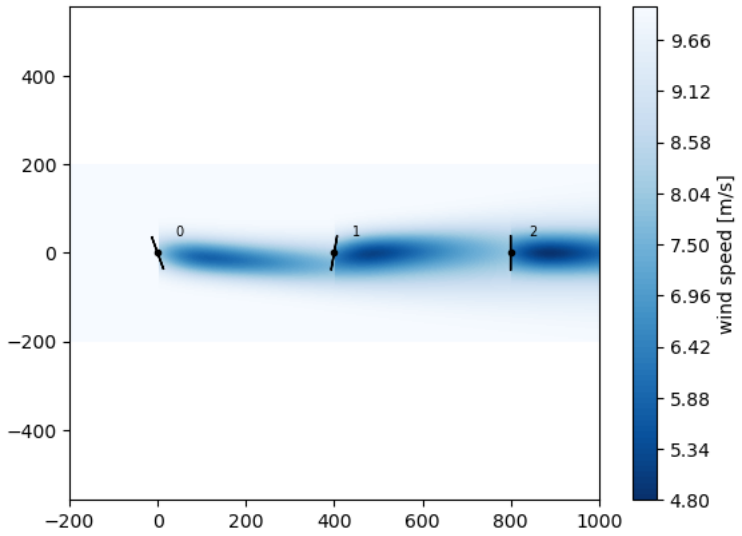
[9]:
```
import numpy as np
import matplotlib.pyplot as plt

from py_wake.examples.data.hornsrev1 import Hornsrev1Site, HornsrevV80
from py_wake.utils.gradients import fd, cs, autograd
from py_wake.utils.profiling import timeit
```

```
from py_wake.utils.plotting import setup_plot
from py_wake.literature.gaussian_models import Zong_PorteAgel_2020, Bastankhah_PorteAgel_2014
from py_wake.deflection_models.jimenez import JimenezWakeDeflection
from py_wake.turbulence_models.crespo import CrespoHernandez
from py_wake.superposition_models import LinearSum
from py_wake.utils.layouts import rectangle
```

[10]:
```
site = Hornsrev1Site()
wt = HornsrevV80()
wfm = Zong_PorteAgel_2020(site, wt, deflectionModel=JimenezWakeDeflection(), superpositionModel= LinearSum())
```

[11]:
```
x,y = rectangle(3,3, wt.diameter()*5)
wfm(x,y,wd=[270],ws=10, yaw=[20,-10,0], tilt=0).flow_map().plot_wake_map()
```

[11]: <matplotlib.contour.QuadContourSet at 0x7f428c69e680>



Gradients of AEP

The gradients of the AEP can be computed by the `aep_gradients` method of `WindFarmModel` with respect to most of the input arguments.

[12]:
```
for wrt_arg in ['x','y',['x','y'],'h']:
    daep = wfm.aep_gradients(gradient_method=autograd, wrt_arg=wrt_arg)(x=x,y=y, h=[69,70,71], yaw=[20,-10,1], tilt=0)
    print (f"Gradients of AEP wrt. {wrt_arg}", daep)
```

```
Gradients of AEP wrt. x [array([-0.00119261, -0.00012416,  0.00131678])]
Gradients of AEP wrt. y [array([ 0.00044024, -0.00086039,  0.00042016])]
Gradients of AEP wrt. ['x', 'y'] [array([-0.00119261, -0.00012416,  0.00131678]), array([ 0.00044024, -0.00086039,  0.00042016])]
Gradients of AEP wrt. h [array([-2.30621564e-04, -1.11570366e-05,  2.41778601e-04])]
```

AEP gradients with respect to (x,y) or (xy)

When computing gradients with autograd, a significant speed up (40-50%) can be obtained by computing the gradients with respect to both `x` and `y` in

```
wfm.aep_gradients(gradient_method=autograd, wrt_arg=['x','y'])(x,y)
```

Instead of first computing with respect to `x` and then with respect to `y`,

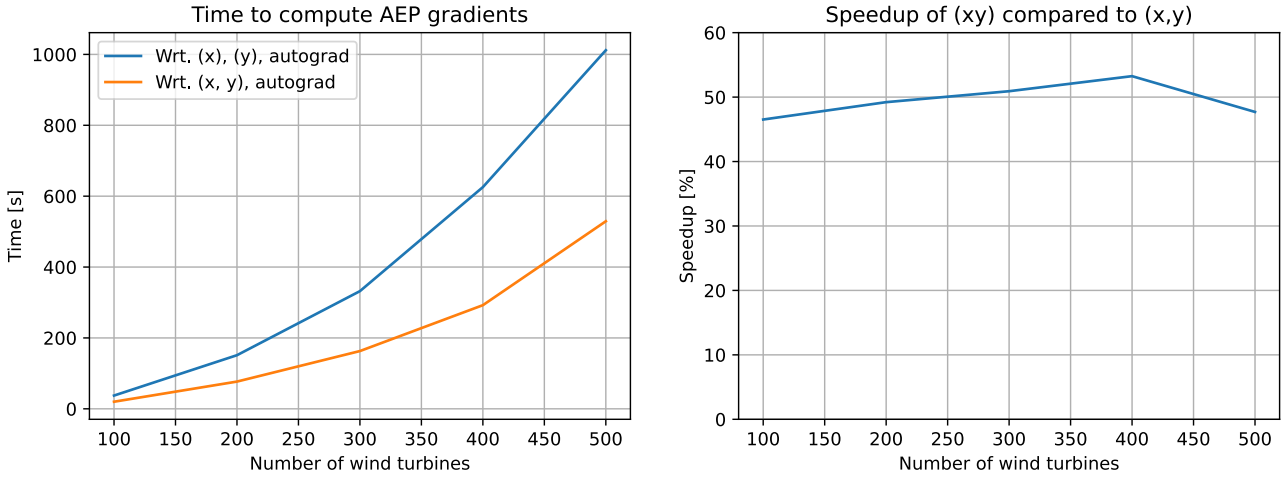
```
wfm.aep_gradients(gradient_method=autograd, wrt_arg='x')(x,y)
wfm.aep_gradients(gradient_method=autograd, wrt_arg='y')(x,y)
```

Functionality to do this automatically under the hood has been implemented in the autograd function.

For finite difference and complex step, the speed is similar.

```
from tqdm.notebook import tqdm
wfm = BastankhahGaussian(site, wt)

def get_aep(wrt_arg_lst, method):
    return lambda x,y: [wfm.aep_gradients(gradient_method=method, wrt_arg=wrt_arg)(x,y) for wrt_arg in wrt_arg_lst]

N_lst = np.arange(100,600,100) # number of wt
D = wt.diameter()
method=autograd
res = [(wrt_arg_lst,method, [np.mean(timeit(get_aep(wrt_arg_lst, method=method), min_runs=1)(*rectangle(N,5,D*5))[1])
```

```
                            for N in tqdm(N_lst)])
      for wrt_arg_lst in (['x','y'],[['x','y']])]

ax1,ax2 = plt.subplots(1,2, figsize=(12,4))[1]
ax1.plot(N_lst, res[0][2], label=f"Wrt. (x), (y), {res[0][1].__name__}")[0].get_color()
ax1.plot(N_lst, res[1][2], label=f"Wrt. (x, y), {res[1][1].__name__}")
ax2.plot(N_lst, (np.array(res[0][2]) - res[1][2])/res[0][2]*100)

setup_plot(ax=ax1, title='Time to compute AEP gradients', ylabel='Time [s]', xlabel='Number of wind turbines')
setup_plot(ax=ax2, title="Speedup of (xy) compared to (x,y)", ylabel='Speedup [%]', xlabel='Number of wind turbines', ylim=[0,60])
```



Gradients of WS, TI, Power and custom functions

The normal `WindFarmModel.__call__` method, which is invoked by `wfm(x,y,...)` returns a xarray Dataset SimulationResult. This step breaks the autograd `return_simulationResult=False`.

The relevant output is:

```
WS_eff_ilk, TI_eff_ilk, power_ilk, ct_ilk, *_ = WindFarmModel(..., return_simulationResult=False)
```

Below are a two basic examples

1) Mean power wrt (x,y) - 2 x 1D inputs, one output

Compute the gradients of the mean power with respect to both x and y.

Note, there is no need to convert it to a one-merged-input function, as the autograd method in PyWake does this under the hood

[13]:
```
def mean_power(x,y):
    power_ilk = wfm(x=x, y=y, yaw=0, tilt=0, return_simulationResult=False)[2] # index 2 = power_ilk
    return power_ilk.mean()

mean_power_gradients_function = autograd(mean_power,vector_interdependence=True, argnum=[0,1])
d_aep = mean_power_gradients_function(x, y)

print ('AEP Gradients:',d_aep)
print (np.shape(d_aep))
```

```
AEP Gradients: [array([-2.00325830e+01, -3.55271368e-15,  2.00325830e+01]), array([-2.19695202e-14,  4.09895561e-14, -1.90200359e-14])]
(2, 3)
```

2) Power per wind speed wrt. x - 1D input, 1D output

Compute the gradients of the power per wind speed (i.e. power meaned over wind turbine and direction) with respect to x.

[14]:
```
def ws_power(x):
    power_ilk = wfm(x=x, y=y, yaw=0, tilt=0, return_simulationResult=False)[2] # index 2 = power_ilk
    return power_ilk.mean((0,1)) # mean power pr wind speed

ws_power_gradients_function = autograd(ws_power,vector_interdependence=True)
np.shape(ws_power_gradients_function(x))
```

[14]: (23, 3)

Manual gradient functions for autograd

Autograd can be supplemented with custom gradient functions, that bypass the automatic differentiation process and returns the gradients directly. This interpolation functions. Some commonly used functions have been implemented in `py_wake.utils.gradients`, e.g.

- trapz (np.trapz)
- interp (np.interp)
- PchipInterpolator (scipy.PchipInterpolator)
- UnivariateSpline (scipy.UnivariateSpline)

Specifying the gradient functions and ensuring that they return the gradients in the right dimensions is, however, not trivial.

It was expected that the computational time could be reduced by specifying maually-implemented gradient functions of some time-critical functions. An of the `BastankhahGaussianDeficit` with respect to all inputs are implemented.

[15]:
```
from py_wake.deficit_models.gaussian import BastankhahGaussianDeficit
from py_wake.utils.gradients import set_vjp
from py_wake.utils.model_utils import method_args
import warnings

class BastankhahGaussianDeficitGradients(BastankhahGaussianDeficit):
    def __init__(self, k=0.0324555, ceps=.2, use_effective_ws=False):
        BastankhahGaussianDeficit.__init__(self, k=k, ceps=ceps, use_effective_ws=use_effective_ws)
        self._additional_args = method_args(self.calc_deficit)
        self.use_effective_ws = use_effective_ws
        self.calc_deficit = set_vjp([self.get_ddeficit_dx(i) for i in range(6)])(self.calc_deficit)

    @property
    def additional_args(self):
        return BastankhahGaussianDeficit.additional_args.fget(self) | self._additional_args

    def calc_deficit(self, WS_ilk, WS_eff_ilk, D_src_il, dw_ijlk, cw_ijlk, ct_ilk, **kwargs):
        return BastankhahGaussianDeficit.calc_deficit(self, D_src_il, dw_ijlk, cw_ijlk, ct_ilk,
                                                      WS_ilk=WS_ilk, WS_eff_ilk=WS_eff_ilk, **kwargs)

    def get_ddeficit_dx(self, argnum):
        import numpy as np  # override autograd.numpy
        from numpy import newaxis as na

        def ddeficit_dx(ans, WS_ilk, WS_eff_ilk, D_src_il, dw_ijlk, cw_ijlk, ct_ilk, **kwargs):
            _, _, _, K = np.max([dw_ijlk.shape, cw_ijlk.shape, WS_ilk[:, na].shape], 0)
            eps = 0
            WS_ref_ilk = (WS_ilk, WS_eff_ilk)[self.use_effective_ws]
            ky_ilk = self.k_ilk(**kwargs)
            beta_ilk = 0.5 * (1 + 1 / np.sqrt(1 - ct_ilk))
            sigma_ijlk = ky_ilk[:, na] * dw_ijlk * (dw_ijlk > eps) + \
                .2 * D_src_il[:, na, :, na] * np.sqrt(beta_ilk[:, na])
            a_ijlk = ct_ilk[:, na] / (8. * (sigma_ijlk / D_src_il[:, na, :, na])**2)
            sqrt_ijlk = np.sqrt(np.maximum(0., 1 - a_ijlk))
            layout_factor_ijlk = WS_ref_ilk[:, na] * (dw_ijlk > eps) * np.exp(-0.5 * (cw_ijlk / sigma_ijlk)**2)
            with warnings.catch_warnings():
                warnings.simplefilter("ignore")
                if argnum == 0:
                    dWS = ans / WS_ref_ilk[:, na]
                elif argnum == 1:
                    dWS_eff = ans / WS_eff_ilk[:, na]
                elif argnum == 2:
                    dD_sqrt_pos = (a_ijlk * (1 / D_src_il[:, na, :, na] - 0.2 * np.sqrt(beta_ilk[:, na]) / sigma_ijlk) / sqrt_ijlk +
                                   (1 - sqrt_ijlk) * (cw_ijlk**2 / sigma_ijlk**3) * .2 * np.sqrt(beta_ilk[:, na])) * layout_factor_ijlk
                    dD_sqrt_neg = (cw_ijlk**2 / sigma_ijlk**3) * .2 * np.sqrt(beta_ilk[:, na]) * layout_factor_ijlk
                    dD = np.where(sqrt_ijlk == 0, dD_sqrt_neg, dD_sqrt_pos)
                elif argnum == 3:
                    ddw_sqrt_pos = (-a_ijlk / sqrt_ijlk + (1 - sqrt_ijlk) * (cw_ijlk / sigma_ijlk)**2) * \
                        ky_ilk[:, na] / sigma_ijlk * layout_factor_ijlk
                    ddw_sqrt_neg = (cw_ijlk / sigma_ijlk)**2 * ky_ilk[:, na] / sigma_ijlk * layout_factor_ijlk
                    ddw = np.where(sqrt_ijlk == 0, ddw_sqrt_neg, ddw_sqrt_pos)
                elif argnum == 4:
                    dcw = ans * (- cw_ijlk / (sigma_ijlk**2))
                elif argnum == 5:
                    dsigmadct_ilk = 0.2 * D_src_il[:, :, na] / (8 * np.sqrt(beta_ilk * (1 - ct_ilk)**3))
                    dct_sqrt_pos = (a_ijlk * (1 / (2 * ct_ilk[:, na]) - dsigmadct_ilk[:, na] / sigma_ijlk) / sqrt_ijlk +
                                    (1 - sqrt_ijlk) * (cw_ijlk**2 / sigma_ijlk**3) * dsigmadct_ilk[:, na]) * layout_factor_ijlk
                    dct_sqrt_neg = (cw_ijlk**2 / sigma_ijlk**3) * dsigmadct_ilk[:, na] * layout_factor_ijlk
                    dct = np.where(sqrt_ijlk == 0, dct_sqrt_neg, dct_sqrt_pos)

            def dWS_ilk(g):
                r = g * dWS[:g.shape[0], :g.shape[1], :g.shape[2], :g.shape[3]]
                j = np.r_[np.where(g)[1], 0][0]
                ilk = (slice(None), j)
                return r[ilk]

            def dWS_eff_ilk(g):
```

```
                r = g * dWS_eff[:g.shape[0], :g.shape[1], :g.shape[2], :g.shape[3]]
                j = np.r_[np.where(g)[1], 0][0]
                ilk = (slice(None), j)
                return r[ilk]

            def dD_src_il(g):
                r = g * dD[:g.shape[0], :g.shape[1], :g.shape[2], :g.shape[3]]
                j = np.r_[np.where(g)[1], 0][0]
                k = np.r_[np.where(g)[3], 0][0]
                il = (slice(None), j, slice(None), k)
                return r[il]

            def ddw_ijlk(g):
                r = g * ddw[:g.shape[0], :g.shape[1], :g.shape[2], :g.shape[3]]
                if dw_ijlk.shape[-1] == 1 and K > 1:
                    # If dw_ijlk is independent of ws, i.e. last dimension is 1 while len(ws)>1
                    # then we need to sum the gradients wrt. wind speeds
                    r = r.sum(3)[:, :, :, na]
                return r[:, :, :, 0:dw_ijlk.shape[3]]

            def dcw_ijlk(g):
                r = g * dcw[:g.shape[0], :g.shape[1], :g.shape[2], :g.shape[3]]
                if cw_ijlk.shape[-1] == 1 and K > 1:
                    # If cw_ijlk is independent of ws, i.e. last dimension is 1 while len(ws)>1
                    # then we need to sum the gradients wrt. wind speeds
                    r = r.sum(3)[:, :, :, na]
                return r[:, :, :, 0:cw_ijlk.shape[3]]

            def dct_ilk(g):
                r = g * dct[:g.shape[0], :g.shape[1], :g.shape[2], :g.shape[3]]
                j = np.r_[np.where(g)[1], 0][0]
                ilk = (slice(None), j)
                return r[ilk]

            return [dWS_ilk, dWS_eff_ilk, dD_src_il, ddw_ijlk, dcw_ijlk, dct_ilk][argnum]
        return ddeficit_dx
```

In this example, however, the model with manual gradient functions performs worse than the original where autograd derives the gradient functions auto

[16]:
```
from py_wake.wind_farm_models import PropagateDownwind
from py_wake.examples.data.hornsrev1 import wt16_x, wt16_y

wfm_autograd = PropagateDownwind(site, wt, BastankhahGaussianDeficit())
wfm_manual = PropagateDownwind(site, wt, BastankhahGaussianDeficitGradients())

ws = np.arange(4,26)
x,y = wt16_x, wt16_y
ref, t_auto = timeit(lambda: wfm_autograd.aep_gradients(gradient_method=autograd, wrt_arg=['x','y'])(x, y, ws=ws))()
res, t_manual = timeit(lambda: wfm_manual.aep_gradients(gradient_method=autograd, wrt_arg=['x','y'])(x, y, ws=ws))()
np.testing.assert_array_almost_equal(res, ref, 4)

print ("Time, automatic gradients", np.mean(t_auto))
print ("Time, manual gradients", np.mean(t_manual))
```

```
Time, automatic gradients 0.42191265400000005
Time, manual gradients 0.45757400600000003
```

Comparison - Scalability of AEP gradients

As seen in the previous comparison of scalability example, the autograd scales much better with the number of input variables than finite difference and c

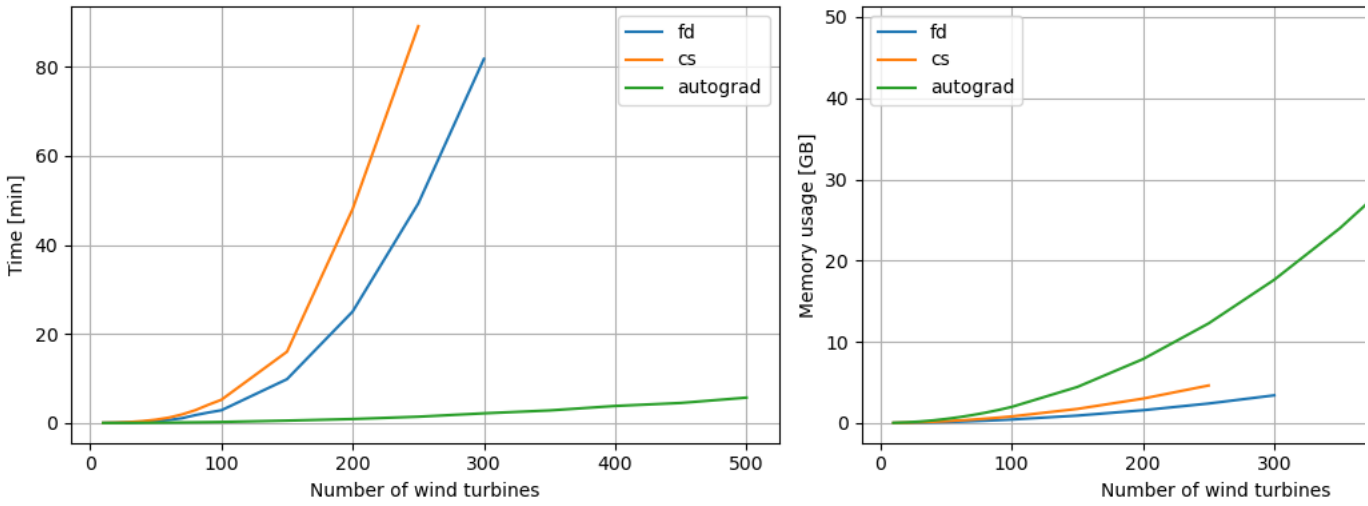
When considering large wind farms, autograd is convincingly outperforming both finite difference and complex step, but it also requires much more mem

The following plots are based on simulation performance on the Sophia HPC cluster.

[17]:
```
data = {
    "fd":((10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 150,200, 250, 300),
          [0.89, 3.06, 7.13, 14.77, 24.46, 41.06, 64.46, 105.98, 140.76, 171.53, 590.46, 1501.62, 2957.65, 4904.31],
          [14.1, 31.9, 58.8, 92.2, 135.3, 184.2, 240.6, 303.1, 373.6, 450.7, 946.5, 1620.8, 2470.1, 3500.5]),
"cs":((10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 150, 200, 250),
      [1.18, 4.9, 12.44, 25.58, 44.56, 72.82, 115.46, 171.42, 245.15, 312.9, 960.64, 2883.04, 5345.27],
      [22.3, 55.7, 107.6, 171.0, 244.1, 338.7, 442.7, 566.9, 690.9, 839.0, 1787.4, 3088.9, 4742.4]),
"autograd":((10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 150, 200, 250, 300, 350, 400, 450, 500),
            [0.32, 0.78, 1.52, 2.49, 3.75, 5.33, 7.14, 9.12, 11.43, 14.02, 32.35, 53.73, 84.94, 130.53, 169.34, 229.62, 270.19, 342.01],
            [26.7, 92.9, 196.4, 340.0, 525.9, 749.6, 1011.1, 1312.2, 1656.0, 2039.7, 4555.0, 8066.8, 12569.9, 18072.6, 24568.2, 32069.6, 40558
       }
ax1,ax2 = plt.subplots(1,2, figsize=(12,4))[1]
for k,(n,t,m) in data.items():
    ax1.plot(n,np.array(t)/60, label=k)
    ax2.plot(n,np.array(m)/1024, label=k)
setup_plot(ax1, xlabel='Number of wind turbines', ylabel='Time [min]')
setup_plot(ax2, xlabel='Number of wind turbines', ylabel='Memory usage [GB]')
plt.savefig('test.png', dpi=600)
```

```
import os
os.getcwd()
```

[17]: '/builds/TOPFARM/PyWake/docs/notebooks'



Chunkify and Parallelization

PyWake makes it easy to chunkify the run wind farm simulations see also section Run Wind Farm Simulation.

This construct is also available and usefull when computing gradients to reduce the memory usage and/or speed up the computation by parallel executior

The arguments, `wd_chunks`, `ws_chunks` and `n_cpu` are available in the `WindFarmModel.aep(...)`, `WindFarmModel(...)` and `WindFarmModel.aep_gradients(..`

[18]:
```
from py_wake import np
import matplotlib.pyplot as plt

from py_wake.literature.noj import Jensen_1983
from py_wake.examples.data.hornsrev1 import Hornsrev1Site, HornsrevV80, wt_x, wt_y, wt16_x, wt16_y
from py_wake.utils.profiling import timeit
import multiprocessing
from py_wake.utils.gradients import autograd, fd
from py_wake.utils.plotting import setup_plot
```

[19]:
```
site = Hornsrev1Site()
wt = HornsrevV80()
wfm = Jensen_1983(site, wt)
x,y = wt16_x,wt16_y
```

AEP

Computing AEP in parallel chunks.

Setting `n_cpu=None`, splits the problem into `N` wind direction chunks which is computed in parallel on `N` CPUs, where `N` is the number of CPUs on the

[20]:
```
print('Total AEP: %f GWh'%wfm.aep(x, y, n_cpu=None))
```

```
Total AEP: 143.074909 GWh
```

WS, TI, Power and custom functions

Computing mean power in parallel chunks

[21]:
```
def mean_power(x,y):
    power_ilk = wfm(x=x, y=y, n_cpu=None, return_simulationResult=False)[2] # index 2 = power_ilk
    return power_ilk.mean()

print('Mean Power: %f MW'%(mean_power(x,y)/1e6))
```

```
Mean Power: 1.434275 MW
```

AEP gradients

In the previous section, Gradients of AEP, the `aep_gradients` method was used like this:

```
gradient_function = wfm.aep_gradients(fd, wrt_arg='xy')
daep = gradient_function(x=x,y=y)
```

When dealing with chunkification and/or parallelization, the `aep_gradients` must be used in a slightly different way:

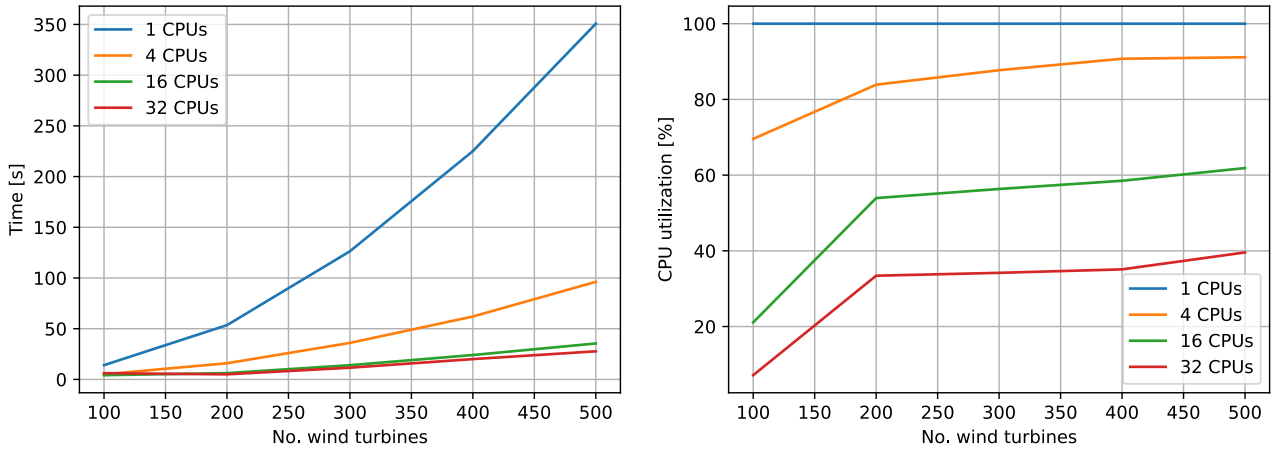
[22]:
```
daep = wfm.aep_gradients(autograd, wrt_arg=['x','y'], n_cpu=None, x=x, y=y)
```

Note, in this case, the arguments normally passed to `wfm.aep` (here `x` and `y`) are passed directly to the `wfm.aep_gradients` method as keyword argume

The plot below shows the time it takes to compute the gradients of AEP with respect to x and y plotted as a function of number of wind turbines and CF

```
from py_wake.utils import layouts
from py_wake.utils.profiling import timeit
from tqdm.notebook import tqdm

n_lst = np.arange(100,600,100)

def run(n, n_cpu):
    x,y = layouts.rectangle(n,20,5*wt.diameter())
    return (n, n_cpu, np.mean(timeit(wfm.aep_gradients)(autograd, ['x','y'], n_cpu=n_cpu, x=x,y=y)[1]))

res = {f'{n_cpu} CPUs': np.array([run(n, n_cpu=n_cpu) for n in tqdm(n_lst)]) for n_cpu in [1, 4, 16, 32]}

ax1,ax2 = plt.subplots(1,2, figsize=(12,4))[1]
for k,v in res.items():
    n,n_cpu,t = v.T
    ax1.plot(n, t, label=k)
    ax2.plot(n, res['1 CPUs'][:,2]/n_cpu/t*100, label=k)
setup_plot(ax=ax1,xlabel='No. wind turbines',ylabel='Time [s]')
setup_plot(ax=ax2,xlabel='No. wind turbines',ylabel='CPU utilization [%]')
plt.savefig('images/Optimization_time_cpuwt.svg')
```

Result precomputed on the Sophia HPC cluster on a node with 32 CPUs.



Parallelization of gradients of WS, TI, Power and custom functions is not implemented yet

Precision

As default, PyWake simulates in double precision, i.e. 64 bit floating point values.

In some cases, however, single precision, i.e. 32 bit floating point values, may be sufficient and faster.

In PyWake, the `Numpy32` context manager makes switching to single precition is very easy:

[23]:
```
from py_wake.utils.numpy_utils import Numpy32

with Numpy32():
    print (np.array([1.,2,3]).dtype)
    print (np.sin([1,2,3]).dtype)
```

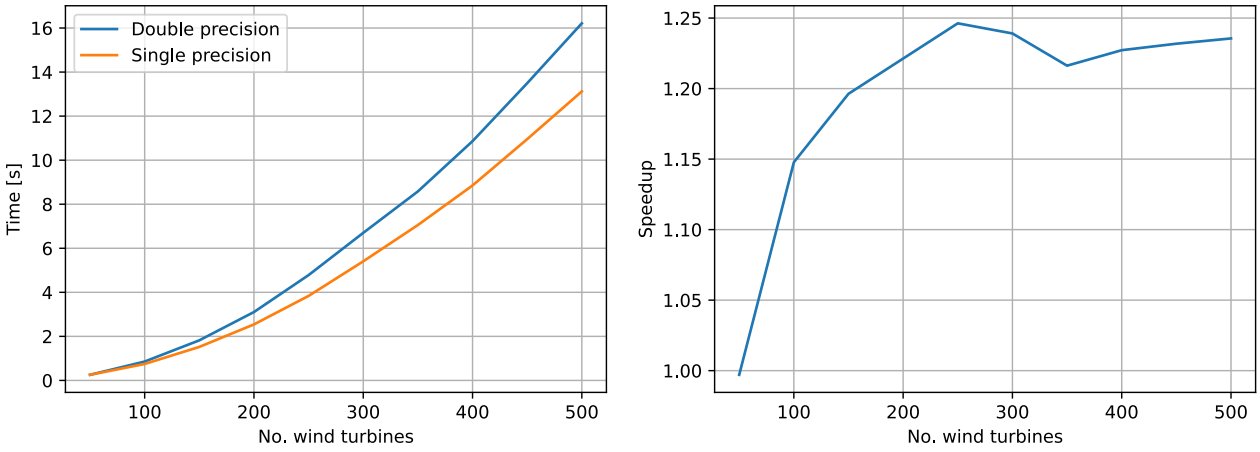
```
float32
float32
```

[24]:
```
# same with out context manager
print (np.array([1.,2,3]).dtype)
print (np.sin([1,2,3]).dtype)
```

```
float64
float64
```

```
from py_wake.utils import layouts
from py_wake.utils.profiling import timeit
from tqdm.notebook import tqdm

n_lst = np.arange(50,550,50)
xy_lst = [layouts.rectangle(n,20,5*wt.diameter()) for n in n_lst]

t_lst_64 = [np.mean(timeit(wfm.aep, min_runs=10)(x,y)[1]) for x,y in tqdm(xy_lst)]

with Numpy32():
    t_lst_32 = [np.mean(timeit(wfm.aep, min_runs=10)(x,y)[1]) for x,y in tqdm(xy_lst)]

ax1, ax2 = plt.subplots(1,2,figsize=(12,4))[1]
ax1.plot(n_lst, t_lst_64, label='Double precision')
ax1.plot(n_lst, t_lst_32, label='Single precision')
setup_plot(ax=ax1, ylabel='Time [s]',xlabel='No. wind turbines')
ax2.plot(n_lst, np.array(t_lst_64) / t_lst_32)
setup_plot(ax=ax2, ylabel='Speedup',xlabel='No. wind turbines')
plt.savefig('images/Optimization_precision.svg')
```

Result precomputed on the Sophia HPC cluster.



Open in Colab Edit on Gitlab

Optimization with TOPFARM

This section describes two optimization examples: a layout optimization with AEP and power production optimization with a de-ratable wind turbine.

Install PyWake if needed

[1]:
```
# Install PyWake if needed
try:
    import py_wake
except ModuleNotFoundError:
    !pip install git+https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake.git
```

In the following sections the examples are optimized using TOPFARM, an open source Python package developed by DTU Wind Energy to help with winc

Install TOPFARM if needed

[2]:
```
# Install TopFarm if needed
try:
    import topfarm
except ImportError:
    !pip install topfarm --user
```

Example 1 - Optimize AEP wrt. wind turbine position (x,y)

In this example we optimize the AEP of the IEAWind Task 37 Case Study 1.

As TOPFARM already contains a cost model component, `PyWakeAEPCostModelComponent`, for this kind of problem, setting up the problem is really simple.

[3]:
```
import numpy as np
import matplotlib.pyplot as plt
import multiprocessing

#setting up pywake models
from py_wake.deficit_models.gaussian import IEA37SimpleBastankhahGaussian
from py_wake.literature.gaussian_models import Bastankhah_PorteAgel_2014
from py_wake.examples.data.iea37._iea37 import IEA37Site, IEA37WindTurbines
from py_wake.examples.data.hornsrev1 import Hornsrev1Site, V80
from py_wake.utils.gradients import autograd, fd, cs
from py_wake.utils.plotting import setup_plot

#setting up topfarm models
from topfarm._topfarm import TopFarmProblem
from topfarm.cost_models.py_wake_wrapper import PyWakeAEPCostModelComponent
from topfarm.constraint_components.boundary import CircleBoundaryConstraint, XYBoundaryConstraint
from topfarm.constraint_components.spacing import SpacingConstraint
from topfarm.easy_drivers import EasyScipyOptimizeDriver

#wind farm model for the IEA 37 site
def IEA37_wfm(n_wt, n_wd):
    site = IEA37Site(n_wt)
    site.default_wd = np.linspace(0,360,n_wd, endpoint=False)
    wt = IEA37WindTurbines()
    return IEA37SimpleBastankhahGaussian(site, wt)

#wind farm model for the Hornsrev1 site
Hornsrev1_wfm = Bastankhah_PorteAgel_2014(Hornsrev1Site(), V80(), k=0.0324555)

#function to create a topfarm problem, following the elements of OpenMDAO architecture
def get_topfarmProblem_xy(wfm, grad_method, maxiter, n_cpu):
    x, y = wfm.site.initial_position.T
    boundary_constr = [XYBoundaryConstraint(np.array([x, y]).T),
                       CircleBoundaryConstraint(center=[0, 0], radius=np.round(np.hypot(x, y).max()))][int(isinstance(wfm.site, IEA37Site))]

    return TopFarmProblem(design_vars={'x': x, 'y': y},
                          cost_comp=PyWakeAEPCostModelComponent(windFarmModel=wfm, n_wt=len(x),
                                                                grad_method=grad_method, n_cpu=n_cpu,
                                                                wd=wfm.site.default_wd, ws=wfm.site.default_ws),
                          driver=EasyScipyOptimizeDriver(maxiter=maxiter),
                          constraints=[boundary_constr,
                                       SpacingConstraint(min_spacing=2 * wfm.windTurbines.diameter())])
```

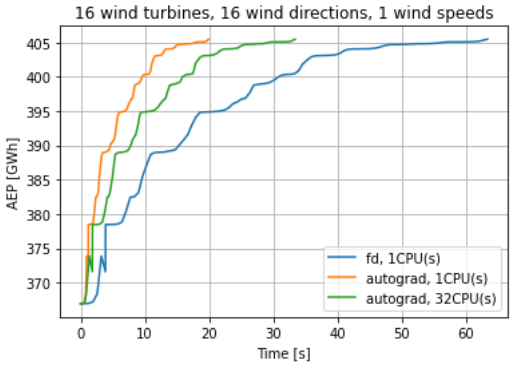
[4]:
```
#we create a function to optimize the problem and plot the results in terms of AEP and simulation time
def optimize_and_plot(wfm, maxiter, skip_fd=False):
    for method, n_cpu in [(fd,1), (autograd,1), (autograd, multiprocessing.cpu_count())][int(skip_fd):]:
```

```
        tf = get_topfarmProblem_xy(wfm,method,maxiter,n_cpu)
        cost, state, recorder = tf.optimize(disp=True)
        t,aep = [recorder[v] for v in ['timestamp','AEP']]
        plt.plot(t-t[0],aep, label=f'{method.__name__}, {n_cpu}CPU(s)')
    n_wt, n_wd, n_ws = len(wfm.site.initial_position), len(wfm.site.default_wd), len(wfm.site.default_ws)

    setup_plot(ylabel='AEP [GWh]', xlabel='Time [s]',title = f'{n_wt} wind turbines, {n_wd} wind directions, {n_ws} wind speeds')
    plt.ticklabel_format(useOffset=False)
```

```
optimize_and_plot(IEA37_wfm(16, n_wd=16), maxiter=3)
```

Pre-computed result of the AEP during 100 iterations of optimization of the IEA task 37 case study 1 (16 wind turbines, 12 wind directions and one win

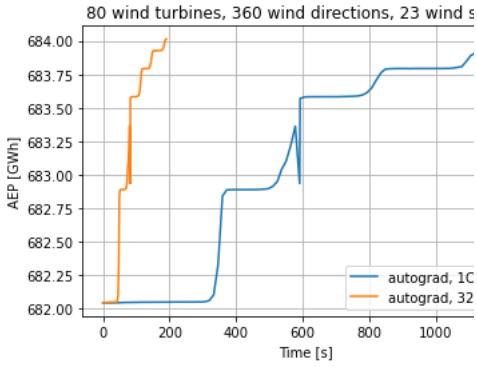
Autograd is seen to be faster than finite difference and for this relatively small problem, 1 CPU is faster than 32CPUs.




```
optimize_and_plot(Hornsrev1_wfm, 100, skip_fd=True)
```

Precomputed result of the AEP during 100 iterations of optimization of the Hornsrev 1 wind farm (80 wind turbines, 360 wind directions and 23 wind s

In this case the optimization with 32 CPUs is around 6 times faster than the optimization with 1 CPU.



Example 2 - Optimize WS, TI, Power and custom functions

To optimize some output, `y`, with respect to some input, `x`, you simply need to setup a function, `y = f(x)`.

In the examle below, we will use a wind turbine that can be de-rated.

De-ratable wind turbine

The relation between power and CT of the de-ratable wind turbine is obtained from 1D momentum theory.

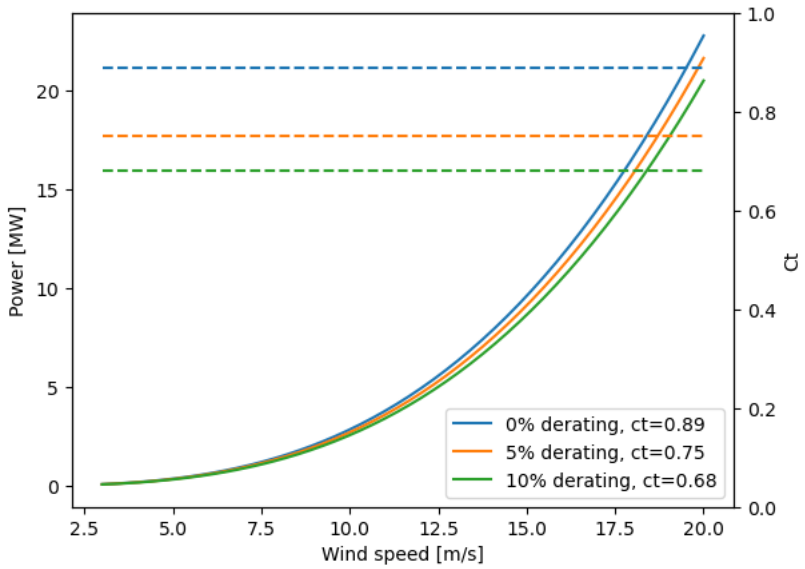
[5]:
```
import autograd.numpy as np
import matplotlib.pyplot as plt

from py_wake.wind_turbines._wind_turbines import WindTurbine
from py_wake.wind_turbines.power_ct_functions import PowerCtFunction
from py_wake.utils.model_utils import fix_shape

def power_ct(ws, derating, run_only):
    derating = fix_shape(derating, ws)
    cp = 16 / 27 * (1 - derating)
    power = np.maximum(0, 1 / 2 * 1.225 * 50**2 * np.pi * cp * ws ** 3)

    # solve cp = 4 * a * (1 - a)**2 for a
    y = 27.0 / 16.0 * cp
```

```
    a = 2.0 / 3.0 * (1 - np.cos(np.arctan2(2 * np.sqrt(y * (1.0 - y)), 1 - 2 * y) / 3.0))
    ct = 4 * a * (1 - a)
    return [power, ct][run_only]

powerCtFunction = PowerCtFunction(input_keys=['ws', 'derating'], power_ct_func=power_ct, power_unit='w')
wt = WindTurbine(name="MyWT", diameter=100, hub_height=100, powerCtFunction=powerCtFunction)
```

The power and CT curves as a function wind speed is plotted below for 0, 5 and 10% derating.

[6]:
```
ax1 = plt.gca()
ax2 = plt.twinx(ax1)
ws = np.linspace(3, 20)
for derating in [0, .05, .1]:
    ct = wt.ct(ws, derating=derating)
    ax1.plot(ws, wt.power(ws, derating=derating) / 1e6, label='%d%% derating, ct=%.2f' % (derating * 100, ct[0]))
    ax2.plot(ws, ct,'--')

ax1.legend(loc='lower right')
ax1.set_xlabel('Wind speed [m/s]')
ax1.set_ylabel('Power [MW]')
ax2.set_ylabel('Ct')
ax2.set_ylim([0, 1])
```

[6]:
```
(0.0, 1.0)
```



Maximize mean power by optimizing de-rating factor and hub height

In this example we will maximize the mean power by optimizing the individual wind turbine hub height and derating factors.

First we setup the `WindFarmModel` and the function to maximize, `mean_power`, which takes the hub height and derating factors as input:

[7]:
```
from py_wake.deficit_models.gaussian import IEA37SimpleBastankhahGaussian
from py_wake.site import UniformSite
from py_wake.utils.gradients import autograd

from topfarm._topfarm import TopFarmProblem
from topfarm.cost_models.cost_model_wrappers import CostModelComponent
from topfarm.easy_drivers import EasyScipyOptimizeDriver

n_wt = 5
wfm = IEA37SimpleBastankhahGaussian(site=UniformSite(p_wd=[1],ti=.1), windTurbines=wt)
wt_x = np.arange(n_wt) * 4 * wt.diameter()
wt_y = np.zeros_like(wt_x)

def mean_power(zhub, derating):
    power_ilk = wfm(x=wt_x, y=wt_y, h=zhub, wd=[270], ws=[10], derating=derating, return_simulationResult=False)[2]
    return np.mean(power_ilk)
```

```
/builds/TOPFARM/PyWake/py_wake/deficit_models/gaussian.py:277: UserWarning: The IEA37SimpleBastankhahGaussian model is not representative of th
  DeprecatedModel.__init__(self, 'py_wake.literature.iea37_case_study1.IEA37CaseStudy1')
```

Setup the gradient function with respect to both arguments.

Again the PyWake autograd method will, under the hood, calculate the gradients with respect to both inputs in one go.

[8]:
```
dmean_power_dzhub_derating = autograd(mean_power,argnum=[0,1])
```

Initialize zhub and derating. The values are choosen to avoid zero gradients (e.g. if all wt has same hub height)

[9]:
```
zhub = np.arange(n_wt)+100 # 100,101,102,...
derating=[0.1]*n_wt
```

[10]:
```
print ('Mean power: %f MW'%(mean_power(zhub,derating)/1e6))
print ('Gradients:',dmean_power_dzhub_derating(zhub,derating))
```

```
Mean power: 1.429855 MW
Gradients: [array([-132.37798792,  -20.72030943,    9.44975613,   41.70595145,
        101.94258977]), array([   5539.55413631,  170225.9858809 ,  132322.76792935,
         39204.83341772, -234801.3362418 ])]
```

Next step is to setup the `CostModelComponent` and `TopFarmProblem`

[11]:
```
cost_comp=CostModelComponent(input_keys=['zhub', 'derating'],
                             n_wt=n_wt,
                             cost_function=mean_power,
                             cost_gradient_function=dmean_power_dzhub_derating,
                             maximize=True # because we want to maximize the mean power
                            )

tf = TopFarmProblem(design_vars={
                        # (initial_values, lower limit, upper limit)
                        'zhub': ([100]*n_wt, 80, 130),
                        'derating': ([0] * n_wt, 0, .9)},
                    n_wt=n_wt,
                    cost_comp=cost_comp,
                    expected_cost=1000, # expected cost impacts the size of the moves performed by the optimizer
                    )
```

```
INFO: checking out_of_order
INFO: checking system
INFO: checking solvers
INFO: checking dup_inputs
INFO: checking missing_recorders
INFO: checking unserializable_options
INFO: checking comp_has_no_outputs
INFO: checking auto_ivc_warnings
```

As seen above the gradient of the mean power wrt. hub height is zero when all wind turbines have the same height. This means that the optimizer “thinks hub heights.

Furthermore, the derating must be above zero to avoid inequality constraint failure.

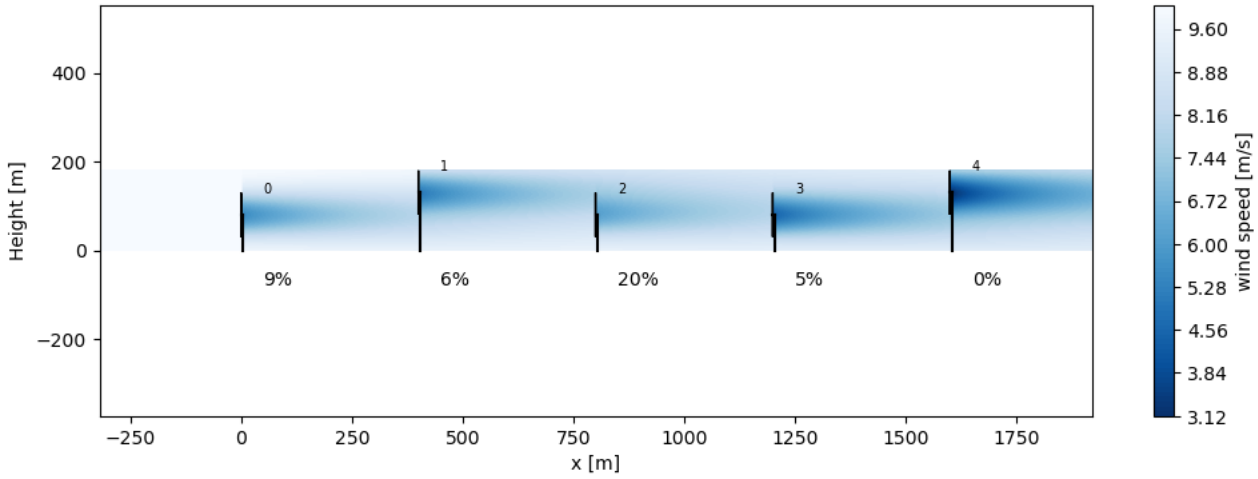
[12]:
```
#perform the optimization
cost, state, recorder = tf.optimize(state={'zhub':np.arange(n_wt)+100,   # 100,101,102,...
                                           'derating':[0.1]*n_wt         # 10% initial derating
                                          })
print ()
print ('Optimized mean power %f MW'% (cost/1e6))
print ('Optimized state', state)
```

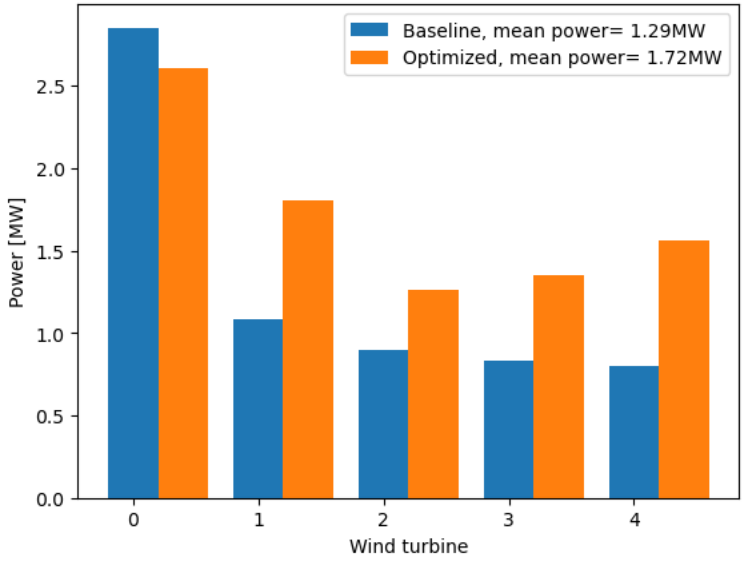
```
INFO: checking out_of_order
INFO: checking system
INFO: checking solvers
INFO: checking dup_inputs
INFO: checking missing_recorders
INFO: checking unserializable_options
INFO: checking comp_has_no_outputs
INFO: checking auto_ivc_warnings
Optimization terminated successfully    (Exit mode 0)
            Current function value: -1716.1873043772746
            Iterations: 33
            Function evaluations: 46
            Gradient evaluations: 32
Optimization Complete
-------------------------------------

Optimized mean power -1.716187 MW
Optimized state {'zhub': array([ 80., 130.,  80.,  80., 130.]), 'derating': array([0.08691713, 0.06260877, 0.19990389, 0.04530877, 0.        ])
```

Plotting the results

[13]:
```
from py_wake import XZGrid
derating = state['derating']
h = state['zhub']

sim_res_ref = wfm(wt_x, wt_y, wd=[270], ws=[10], derating=[0] * n_wt)
sim_res_opt = wfm(wt_x, wt_y, h=h, wd=[270], ws=[10], derating=derating)
plt.figure(figsize=(12,4))
sim_res_opt.flow_map(XZGrid(y=0)).plot_wake_map()
for x_, d in zip(wt_x, derating):
    plt.text(x_ + 50, -80, "%d%%" % np.round(d * 100), fontsize=10)
plt.ylabel('Height [m]')
plt.xlabel('x [m]')

plt.figure()
for i, (sim_res, l) in enumerate([(sim_res_ref, 'Baseline'), (sim_res_opt, 'Optimized')]):
    plt.bar(np.arange(n_wt) + i * .4, sim_res.Power.squeeze() * 1e-6, width=.4,
            label='%s, mean power= %.2fMW' % (l, sim_res.Power.mean() * 1e-6))
plt.ylabel('Power [MW]')
```

```
plt.xlabel('Wind turbine')
plt.legend()
plt.show()
```

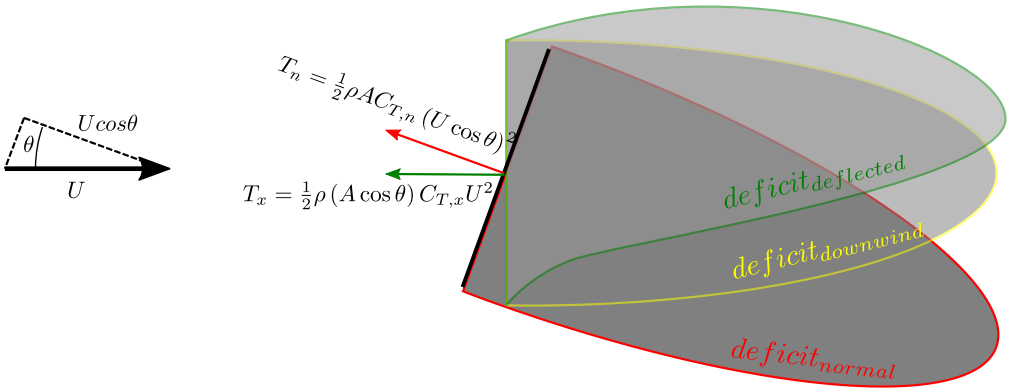




Wind Turbine under Yaw Misalignment

In case the wind turbine rotor is not perpendicular to the inflow, its operation and effects on the flow field will be different. In general, it is a quite complicated process. In PyWake, the effects are divided into four sub-effects that are handled invididually:

1. Change of operation due to reduced inflow wind speed
2. Reduced deficit, $deficit_{normal}$, due to reduced inflow wind speed, ($C_{T,n} \rightarrow C_{T,x}$)
3. Reduced deficit, $deficit_{downwind}$, due to misalignment between thrust and downwind direction
4. Deflection of wake deficit, $deficit_{deflected}$, due to transversal thrust component reaction



Install PyWake if needed

[1]:
```
# Install PyWake if needed
try:
    import py_wake
except ModuleNotFoundError:
    !pip install git+https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake.git
```

First we import some basic Python elements

[2]:
```
import numpy as np
import matplotlib.pyplot as plt
from ipywidgets import interact
from ipywidgets import IntSlider
```

We also import the site, wind turbines, and engineering wake models necessary for the simulation

[3]:
```
from py_wake.examples.data.hornsrev1 import V80
from py_wake.flow_map import HorizontalGrid
from py_wake.tests.test_files import tfp
from py_wake.wind_farm_models import PropagateDownwind, All2AllIterative
from py_wake.deficit_models import FugaYawDeficit
from py_wake.deflection_models import FugaDeflection
from py_wake.examples.data.hornsrev1 import Hornsrev1Site
from py_wake.flow_map import XYGrid

wt = V80()
site = Hornsrev1Site()
```

Effect 1 - Change of operation due to reduced inflow wind speed

The inflow perpendicular to the rotor is reduced by $cos\theta$.

This means that the pitch and rotor speed setting of the WT will be different. In PyWake, the WT operation (pitch and rotor speed settings) is modeled in terms of the **Power and CT curves**. If these curves are specified in terms of the wind speed normal to the rotor, then the wind speed must be multiplied by $cos\theta$ before looking up the power and CT.

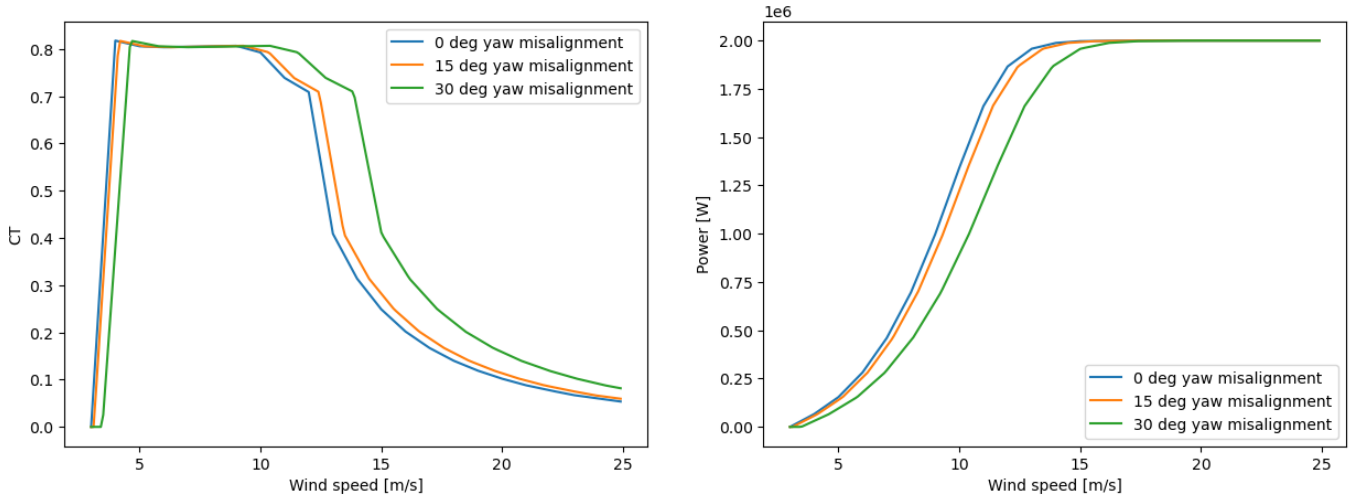
This is one of two effects modeled by the `SimpleYawModel`, which is an additional model that is applied as default to most PowerCtFunctions, see here for more details.

Note, that below rated rotor speed, the CT curve is typically rather flat and reducing the wind speed has therefore limited effect on the CT value in this region. The power, on the other hand, is limited by the maximum power and therefore only affected in the region below rated wind speed (rated wind speed will increase with yaw misalignment).

Furthermore, misalignment between the thrust force (axial induction) and the inflow leads to higher wind speed at the rotor plane, which also affects the WT operation. This effect, however, is not considered in PyWake.

[4]:
```
#here we can see an example of the thrust and power curves for different yaw misalignment angles
u = np.arange(3,25,.1)
ax1,ax2 = plt.subplots(1,2, figsize=(15,5))[1]

#looping through different values for yaw angles
for yaw in [0,15,30]:
    ax1.plot(u,wt.ct(u*np.cos(np.deg2rad(yaw))), label='%d deg yaw misalignment'%yaw)
    ax2.plot(u,wt.power(u*np.cos(np.deg2rad(yaw))), label='%d deg yaw misalignment'%yaw)

for ax in (ax1, ax2):
    ax.legend()
    ax.set_xlabel('Wind speed [m/s]')
ax1.set_ylabel('CT')
ax2.set_ylabel('Power [W]')
```

[4]: Text(0, 0.5, 'Power [W]')



Effect 2 - Reduced deficit due to reduced inflow wind speed ($C_{T,n} \rightarrow C_{T,x}$)

The wake deficit is caused by a reaction to the thrust force, which slows down the inflow.

The thrust force normal to the rotor plane is

$$T_n = \frac{1}{2}\rho C_{T,n} A (U cos\theta)^2$$

In non-aligned inflow, the thrust force that slows down the flow, i.e. in the mean wind direction is

$$T_x = \frac{1}{2}\rho C_{T,x} (A cos\theta) U^2$$

From these two equations we can find the relationship between the thrust coefficient in the rotor-normal direction, $C_{T,n}$, and the thrust coefficient in the down-wind direction, $C_{T,x}$.

$$T_x = T_n cos\theta$$
$$\frac{1}{2}\rho C_{T,x} (A cos\theta) U^2 = \frac{1}{2}\rho C_{T,n} A (U cos\theta)^2 cos\theta$$
$$C_{T,x} = C_{T,n} \cos^2\theta$$

This is the second effect modeled by the `SimpleYawModel`, which is an additional model that is applied as default to most PowerCtFunctions and is shown below.

SimpleYawModel

The `SimpleYawModel` is an additional model, which as default is applied by

- `PowerCtFunction`
- `PowerCtTabular`
- `PowerCtNDTabular`
- `PowerCtXr`
- `CubePowerSimpleCt`

It handles effects 1. and 2. by:

1. Compute/look up $C_{T,n}$ based on wind speed $U\cos\theta$
2. Returns $C_{T,x} = C_{T,n}\cos^2\theta$

Effect 3 - Reduced deficit due to misalignment between thrust and downwind direction

Most engineering models calculate the deficit normal to the rotor plane, while the deficit impacting downstream WT is the deficit in the downstream direction.

In case of yaw misalignment, the deficit is therefore mapped to downstream direction by

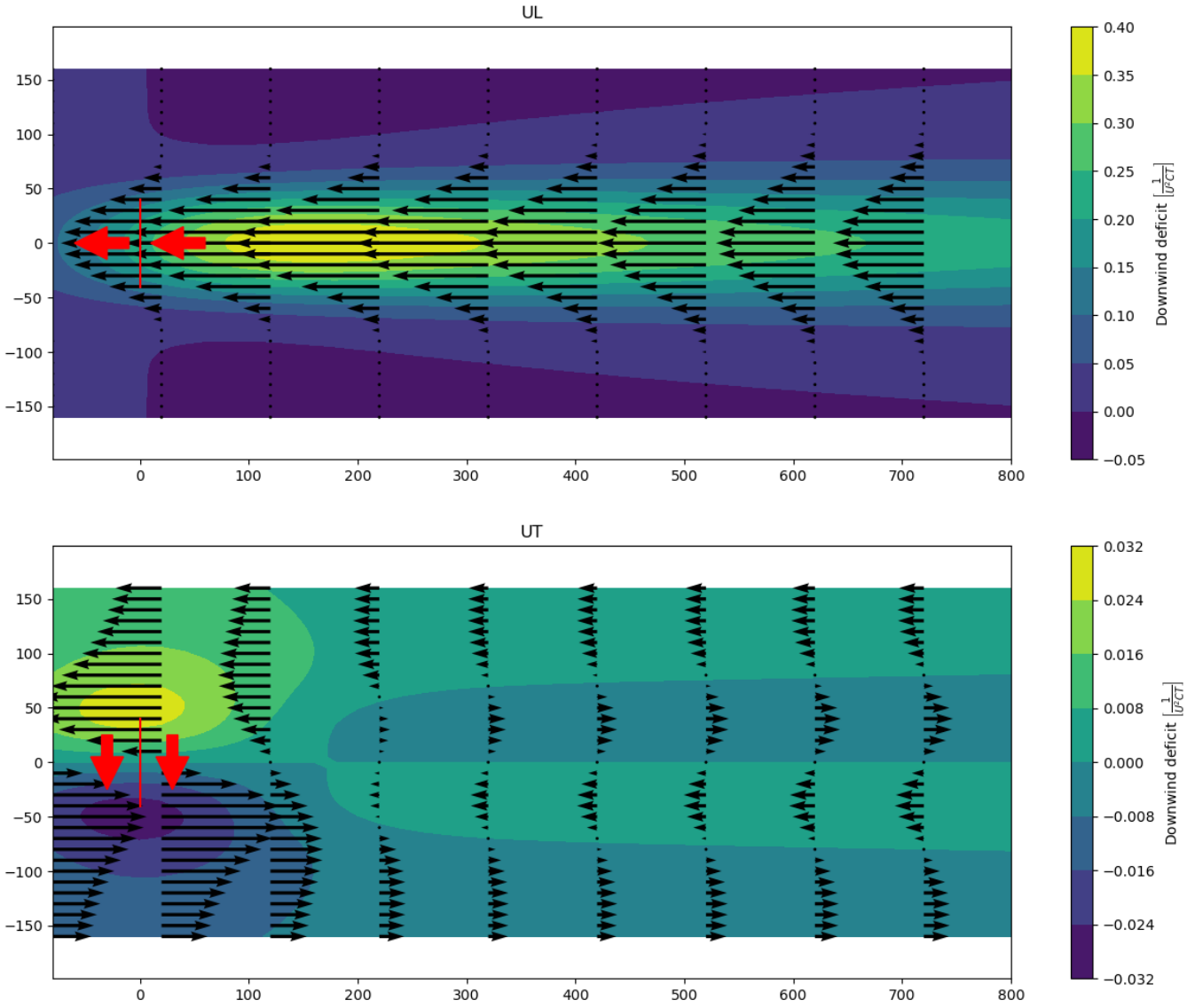
$$deficit_{downwind} = deficit_{normal} cos\theta$$

To model this effect, PyWake uses the `FugaYawDeficit` model.

This model requires two sets of look-up tabels, namely `UL` and `UT`. These tables describes the normalized deficit in the downwind, `U` direction caused by a unit forcing in the longitudinal, L, and transveral, T, directions.

[5]:
```
fuga = FugaYawDeficit(tfp + 'fuga/2MW/Z0=0.00001000Zi=00400Zeta0=0.00E+00.nc')
D = 80
R = D/2
x0,x1,y = 1,10,2 #upstream, downstream and crosswind regions to load [D]
xi0 = int(512-x0/(fuga.dx/D))
xi1 = int(512+x1/(fuga.dx/D))+1
yi = int(y/(fuga.dy/D))+1
UL, UT = [-fuga.mirror(v,anti_symmetric=a) for v, a in zip(fuga.load_luts()[:2,0,:yi, xi0:xi1], (False,True))]
```

[6]:
```
axes = plt.subplots(2,1, figsize=(15,12))[1]
X, Y = np.meshgrid(fuga.x[xi0:xi1], fuga.mirror(fuga.y[:yi], anti_symmetric=True))
wtL = np.array([[0,0],[-D/2,D/2]])
for ax, v, l in zip(axes.flatten(), [UL, UT], ['UL','UT']):
    c = ax.contourf(X, Y, v)
    plt.colorbar(c, ax=ax, label=r'Downwind deficit $\left[\frac{1}{U^2 CT}\right]$')
    s = (slice(None,None,2),slice(None,None,5))
    ax.quiver(X[s], Y[s], -v[s]*(l[0]=='U'), v[s]*(l[0]=='V'))
    ax.plot([0,0],[-D/2,D/2],'r')
    if l[1]=='L':
        ax.arrow(-10,0,-20,0,color='r', width=10,head_length=30)
        ax.arrow(60,0,-20,0,color='r', width=10,head_length=30)
    else:
        ax.arrow(-30,25,0,-20,color='r', width=10,head_length=30)
        ax.arrow(30,25,0,-20,color='r', width=10,head_length=30)

    ax.axis('equal')
    ax.set_xlim([-D,10*D])
    ax.set_ylim([-D,D])
    ax.set_title(l)
```



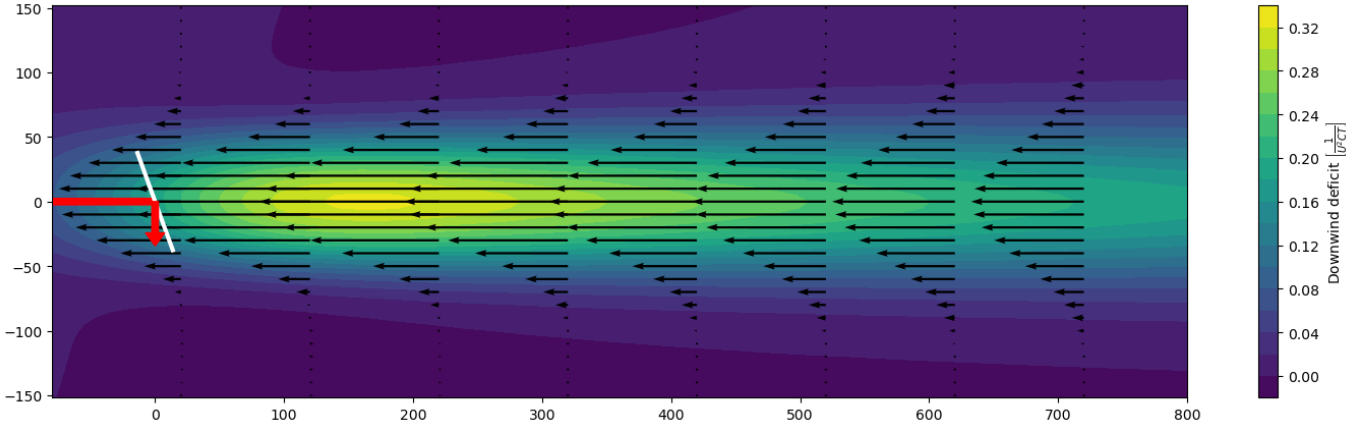
As Fuga is a linear model, the deficit in the downstream direction can simply be calculated by the linear superposition of `UL` and `UT`:

$$deficit = (UL \cdot cos\theta + UT \cdot sin\theta) \cdot U \cdot CT$$

You can move the slider below to see the deficit fields for different yaw-misalignment angles

[7]:
```
def plot(yaw):
    plt.figure(figsize=(18,5))
    theta = np.deg2rad(yaw)
    co, si = np.cos(theta), np.sin(theta)
    deficit = co**2*(UL*co + UT*si)
    c = plt.contourf(X, Y, deficit,20)#, levels=np.arange(-.4,.1,.05))
    plt.colorbar(c, label=r'Downwind deficit $\left[\frac{1}{U^2 CT}\right]$')
    s = (slice(None,None,2),slice(None,None,5))
    plt.quiver(X[s], Y[s], -deficit[s], deficit[s]*0, width=.002, scale=2)
    plt.plot([si*R, -si*R],[-co*R,co*R],'w',label='Rotor',lw=3)
    plt.arrow(-0,0,-100*co,0,color='r', width=5,head_length=10,length_includes_head=True)
    plt.arrow(-0,-0,0,-100*si,color='r', width=5,head_length=10,length_includes_head=True, zorder=32)
    plt.axis('equal')
    plt.xlim([-D,10*D])
    plt.ylim([-D/2,D/2])
    ax.set_title(l)
_ = interact(plot, yaw=IntSlider(min=-90, max=90, step=1, value=20, continuous_update=False))
```

yaw 20



Effect 4 - Wake deflection due to traversal thrust component reaction

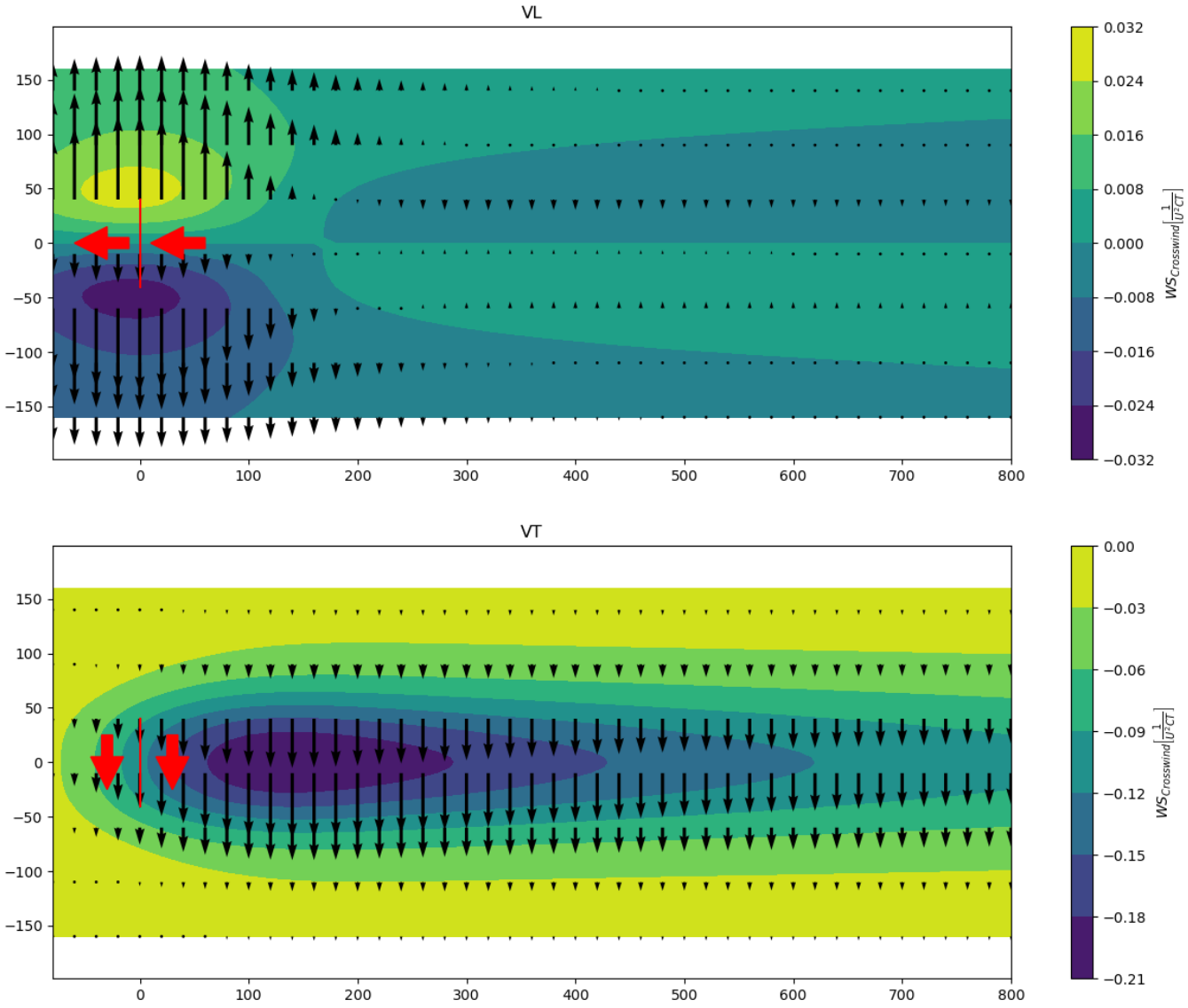
Wake deflection is modeled by a `DeflectionModel`, which modifies the downwind, horizontal crosswind and vertical distance between wind turbines.

The `FugaDeflection` is capable of modeling the wake deflection if `VL` and `VT` is known.

These tables describes the normalized deficit in the crosswind, `V` direction caused by a unit forcing in the longitudinal, L, and transveral, T, directions.

[8]:
```
fugaDeflection = FugaDeflection(tfp + 'fuga/2MW/Z0=0.00001000Zi=00400Zeta0=0.00E+00.nc')
D = 80
R = D/2
x0,x1,y = 1,10,2 #upstream, downstream and crosswind regions to load [D]
xi0 = int(512-x0/(fugaDeflection.dx/D))
xi1 = int(512+x1/(fugaDeflection.dx/D))+1
yi = int(y/(fugaDeflection.dy/D))+1

# VL is antisymmetric, VT is symmetric
VL, VT = [fugaDeflection.mirror(v,anti_symmetric=a) for v, a in zip(fugaDeflection.load_luts()[2:4,0,:yi, xi0:xi1], (True, False))]
```

[9]:
```
axes = plt.subplots(2,1, figsize=(15,12))[1]
X, Y = np.meshgrid(fugaDeflection.x[xi0:xi1], fugaDeflection.mirror(fugaDeflection.y[:yi], anti_symmetric=True))
for ax, v, l in zip(axes.flatten(), [-VL, VT], ['VL','VT']):
    c = ax.contourf(X, Y, v)
    plt.colorbar(c, ax=ax, label=r'$WS_{Crosswind} \left[\frac{1}{U^2 CT}\right]$')
    s = (slice(None,None,10),slice(None,None,1))
    ax.quiver(X[s], Y[s], 0, v[s], scale=(.3,3)[l[1]=='T'])
    ax.plot([0,0],[-D/2,D/2],'r')
    if l[1]=='L':
        ax.arrow(-10,0,-20,0,color='r', width=10,head_length=30)
        ax.arrow(60,0,-20,0,color='r', width=10,head_length=30)
    else:
        ax.arrow(-30,25,0,-20,color='r', width=10,head_length=30)
        ax.arrow(30,25,0,-20,color='r', width=10,head_length=30)

    ax.axis('equal')
    ax.set_xlim([-D,10*D])
    ax.set_ylim([-D,D])
    ax.set_title(l)
```



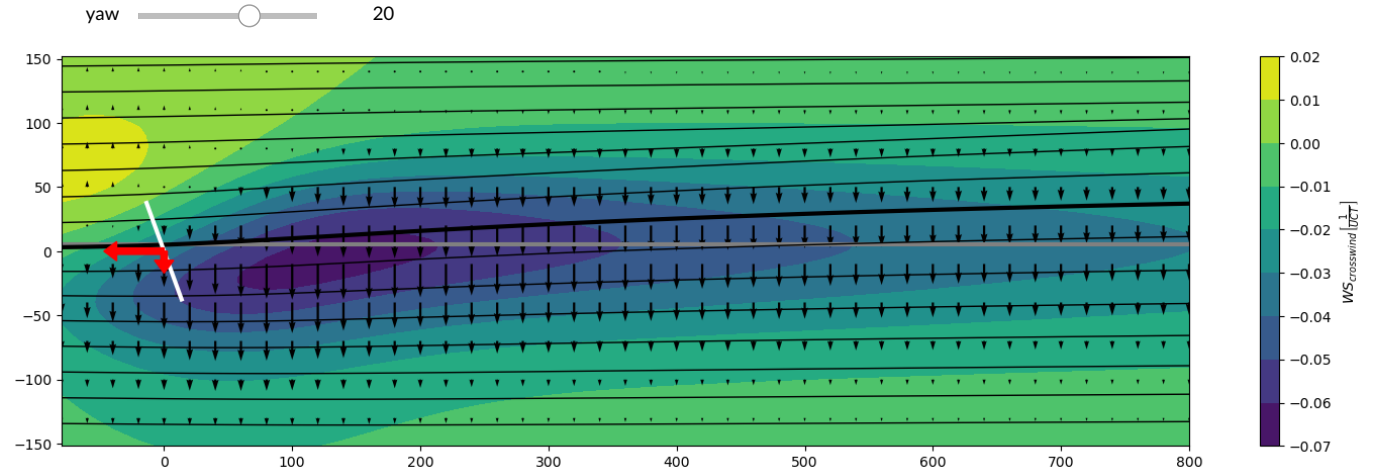
As Fuga is a linear model, the effects in the crosswind direction can simply be calculated by linear superposition of `VL` and `VT`:

$$WS_{crosswind} = (VL \cdot cos\theta + VT \cdot sin\theta) \cdot U \cdot CT$$

You can move the slider below to see the crosswind wind speed field for different yaw-misalignment angles. Furthermore, the integrated deflection is shown with solid lines

[10]:
```
def plot(yaw):
    plt.figure(figsize=(18,5))
    theta = np.deg2rad(yaw)
    co, si = np.cos(theta), np.sin(theta)
    V = co**2*(-VL*co + VT*si)
    X, Y = np.meshgrid(fugaDeflection.x[xi0:xi1], fugaDeflection.mirror(fugaDeflection.y[:yi], anti_symmetric=True))
    c = plt.contourf(X, Y, V)#, levels=np.arange(-.09,.1,.01))
    plt.colorbar(c, label=r'$WS_{crosswind} \left[\frac{1}{U CT}\right]$')
    s = (slice(None,None,6),slice(None,None,1))
    plt.quiver(X[s], Y[s], V[s]*0, V[s], width=.002, scale=2)

    # plot deflection lines
    fL, fT = fugaDeflection.fLT.V.T[:,256-yi:255+yi, xi0:xi1]
    lambda2p = co**2 * (fL * co - fT * si)
    y = fugaDeflection.mirror(fugaDeflection.y[:yi], anti_symmetric=True)

    lambda2 = np.array([np.interp(y, y + l2p, l2p) for l2p in lambda2p.T])
    Yp = Y + lambda2.T
    plt.plot(X[yi, :], Y[yi, :], 'grey', lw=3)
    for x, y, yp in zip(X[1::4], Y[1::4], Yp[1::4]):
        plt.plot(x, y, 'grey', lw=1, zorder=-32)
        plt.plot(x, yp, 'k', lw=1)
    plt.plot(X[yi, :], Yp[yi, :], 'k', lw=3)
```

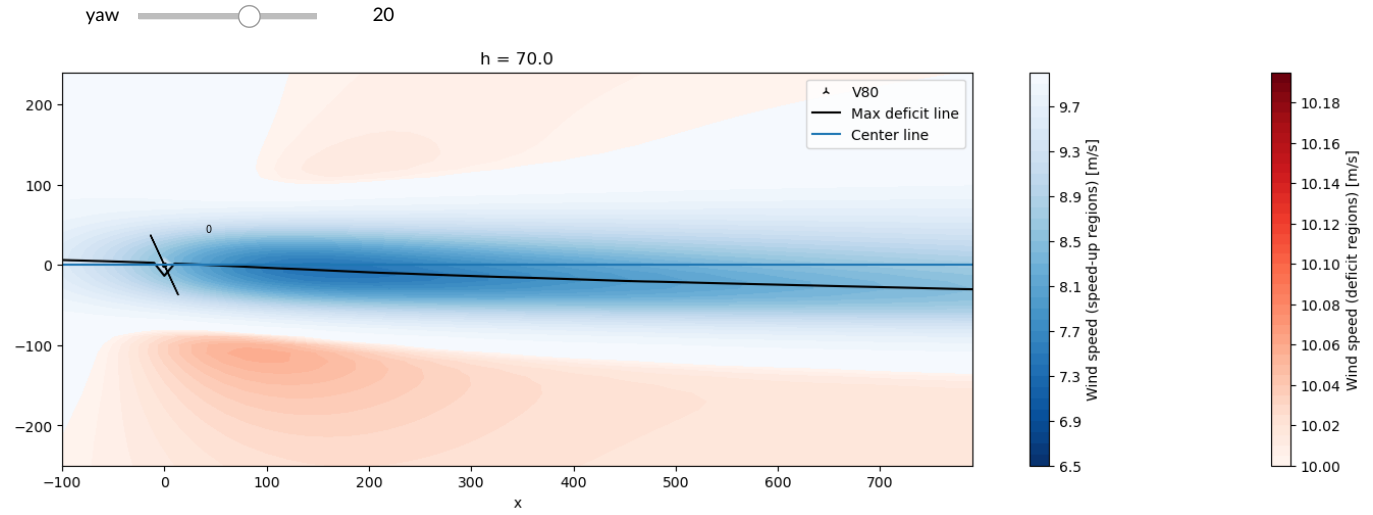
```
    plt.plot([si*R, -si*R],[-co*R,co*R],'w',label='Rotor',lw=3)
    plt.arrow(-0,0,-50*co,0,color='r', width=5,head_length=10,length_includes_head=True, zorder=32)
    plt.arrow(-0,-0,0,-50*si,color='r', width=5,head_length=10,length_includes_head=True, zorder=32)
    plt.axis('equal')
    plt.xlim([-D,10*D])
    plt.ylim([-D,D])
    ax.set_title(l)
_ = interact(plot, yaw=IntSlider(min=-90, max=90, step=1, value=20, continuous_update=False))
```



Note, the plot above shows the wind speed in cross-wind direction (up), i.e. yellow colors corresponds to a flow towards the top of the figure, while blue corresponds to a flow towards the bottom.

Finally, all effects are put together. You can move the slider below to see the effects on the deficit behind a WT.

[11]:
```
path = tfp + 'fuga/2MW/Z0=0.00001000Zi=00400Zeta0=0.00E+00.nc'
fugaDeficit = FugaYawDeficit(path)
wfm = All2AllIterative(site,wt,fugaDeficit,blockage_deficitModel=fugaDeficit,
                       deflectionModel=FugaDeflection(path)
                       )
def plot(yaw):
    plt.figure(figsize=(18,5))
    fm = wfm([0],[0],ws=10,wd=270, yaw=[[[yaw]]]).flow_map(XYGrid(x=np.arange(-100,800,10), y=np.arange(-250,250,10)))
    X,Y = np.meshgrid(fm.x, fm.y)
    c1 = plt.contourf(X,Y,fm.WS_eff.squeeze(),np.arange(6.5,10.1,0.1), cmap='Blues_r')
    c2 = plt.contourf(X,Y,fm.WS_eff.squeeze(),np.arange(10,10.2,.005), cmap='Reds')
    plt.colorbar(c2, label='Wind speed (deficit regions) [m/s]')
    plt.colorbar(c1, label='Wind speed (speed-up regions) [m/s]')
    wt.plot([0],[0],wd=270,yaw=yaw)
    max_deficit_line = fm.min_WS_eff(x=np.arange(-100,800,10))
    max_deficit_line.plot(color='k', label='Max deficit line')
    plt.axhline(0, label='Center line')
    plt.legend()


_ = interact(plot, yaw=IntSlider(min=-90, max=90, step=1, value=20, continuous_update=False))
```



Note, the scaling of wake deficit(blue) and speedup(red) does not match

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Noise

PyWake contains a simple noise-progagation model, `ISONoise`, which models the sound-pressure level from a number of sound sources (wind turbines) a

- Spherical geometrical spreading (DSF/ISO/DIS 9613-2)
- Ground reflection/absorption (DSF/ISO/DIS 9613-2)
- Atmospheric absorption (DS/ISO 9613-1:1993)

The model is based on the iso standards:

```
DSF/ISO/DIS 9613-2
Acoustics – Attenuation of sound during propagation – Part 2:
Engineering method for the prediction of sound pressure levels outdoors
```

and

```
DS/ISO 9613-1:1993
Akustik. Måling og beskrivelse af ekstern støj. Lydudbredelsesdæmpning udendørs. Del 1:
Metode til beregning af luftabsorption
```

The implementation and interface is preliminary and may be subject to changes

[1]:
```
# Install PyWake if needed
try:
    import py_wake
except ModuleNotFoundError:
    !pip install git+https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake.git
```

[2]:
```
import matplotlib.pyplot as plt
import numpy as np

from py_wake.noise_models.iso import ISONoiseModel

from py_wake.deficit_models.gaussian import ZongGaussian
from py_wake.flow_map import XYGrid
from py_wake.turbulence_models.crespo import CrespoHernandez
from py_wake.site._site import UniformSite
from py_wake.examples.data.swt_dd_142_4100_noise.swt_dd_142_4100 import SWT_DD_142_4100
from py_wake.utils.layouts import rectangle
from py_wake.utils.plotting import setup_plot
```

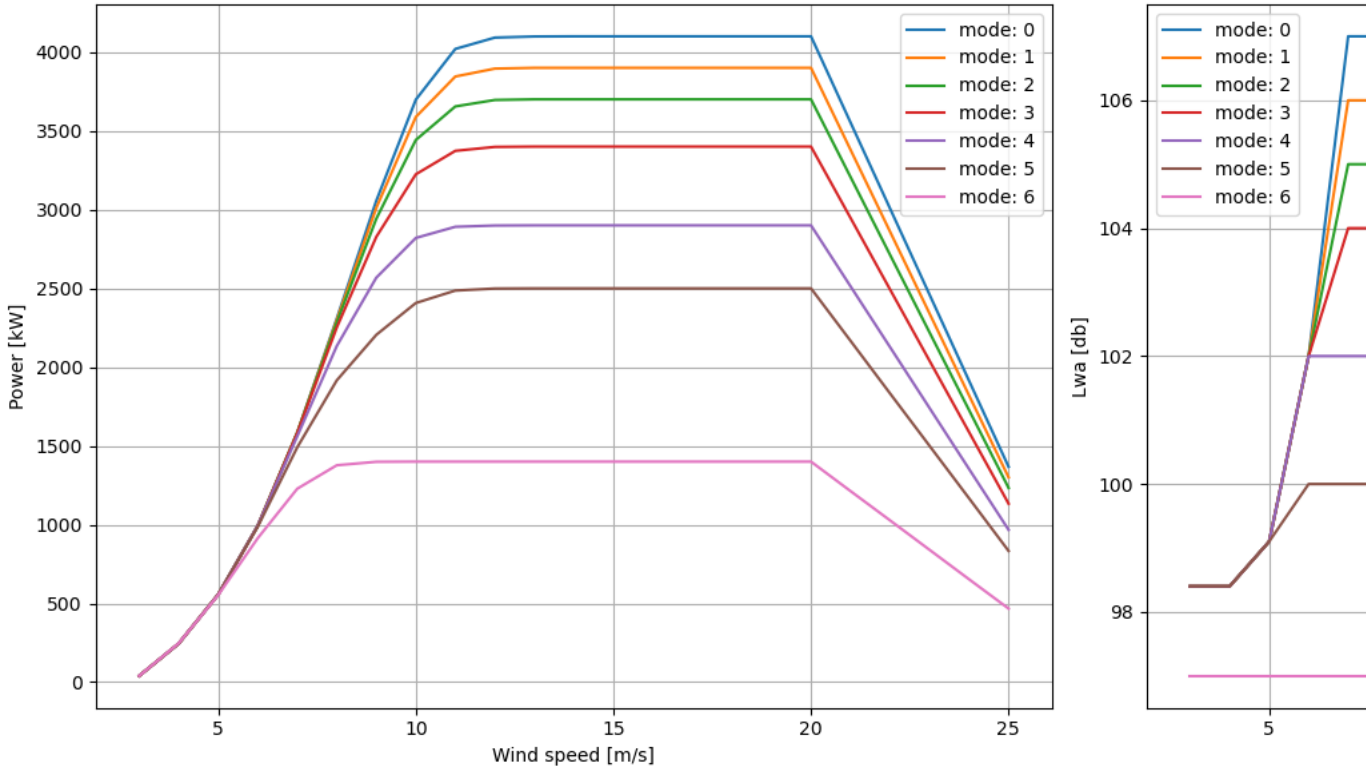
Sound source

To model the emitted sound from the wind turbine sources, the `WindTurbine` object must contain a `sound_power_level`-function.

An example wind turbine, `SWT_DD_142_4100`, is implemented in `py_wake.examples.data.swt_dd_142_4100_noise.swt_dd_142_4100` based on power, ct and noi

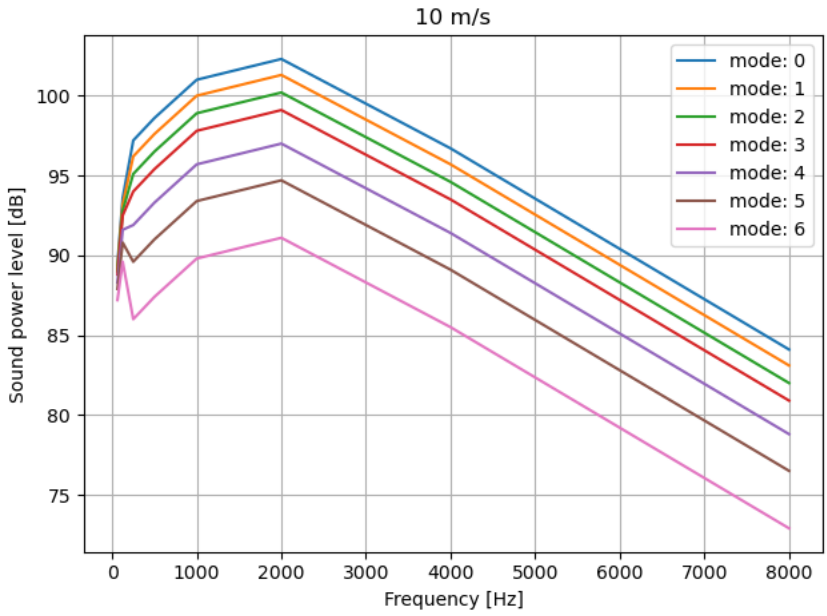
This wind turbine are able to operate at 7 different modes with reduced power and noise.

[3]:
```
wt = SWT_DD_142_4100()

ax1,ax2 = plt.subplots(1,2,figsize=(16,6))[1]
ws = np.arange(3, 26)
for m in range(7):
    ax1.plot(ws, wt.power(ws, mode=m) / 1000, label=f'mode: {m}')
    ax2.plot(ws, wt.ds.LwaRef.sel(mode=m, ws=ws), label=f'mode: {m}')

setup_plot(ax=ax1, xlabel='Wind speed [m/s]', ylabel='Power [kW]')
setup_plot(ax=ax2, xlabel='Wind speed [m/s]', ylabel='Lwa [db]')
```



Furthermore, the sound-power level is available as a function of mode, wind speed and frequency

[4]:
```
for m in range(7):
    freq, sound_power = wt.sound_power_level(ws=10, mode=m)
    plt.plot(freq, sound_power[0], label=f'mode: {m}')
setup_plot(xlabel='Frequency [Hz]', ylabel='Sound power level [dB]', title="10 m/s")
```



Noise at receivers

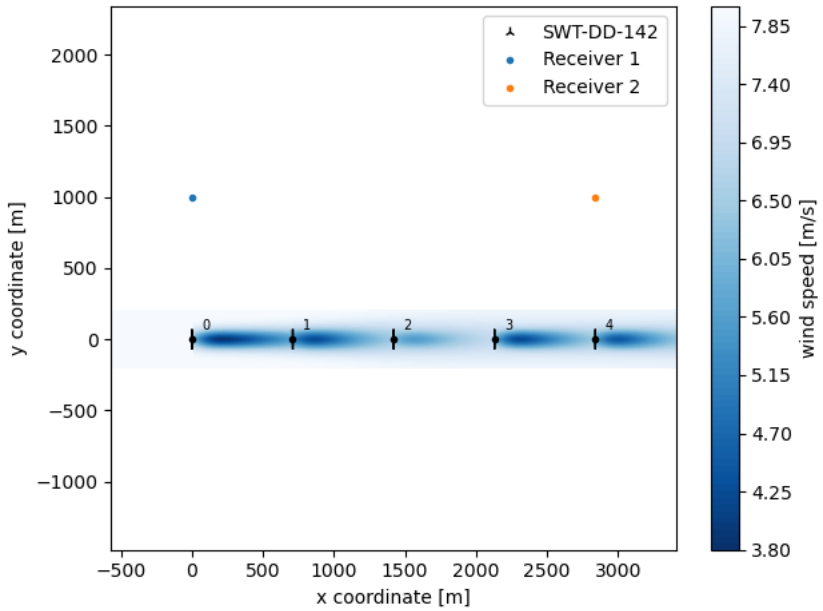
To model the noise at specific receiver positions, we first need to setup a `WindFarmModel´ and run a simulation

[5]:
```
wt = SWT_DD_142_4100()
wfm = ZongGaussian(UniformSite(), wt, turbulenceModel=CrespoHernandez())
x, y = rectangle(5, 5, 5 * wt.diameter())
sim_res = wfm(x, y, wd=270, ws=8, mode=[0,0,6,0,0])
```

```
/builds/TOPFARM/PyWake/py_wake/deficit_models/gaussian.py:403: UserWarning: The ZongGaussian model is not representative of the setup used in t
  DeprecatedModel.__init__(self, 'py_wake.literature.gaussian_models.Zong_PorteAgel_2020')
```

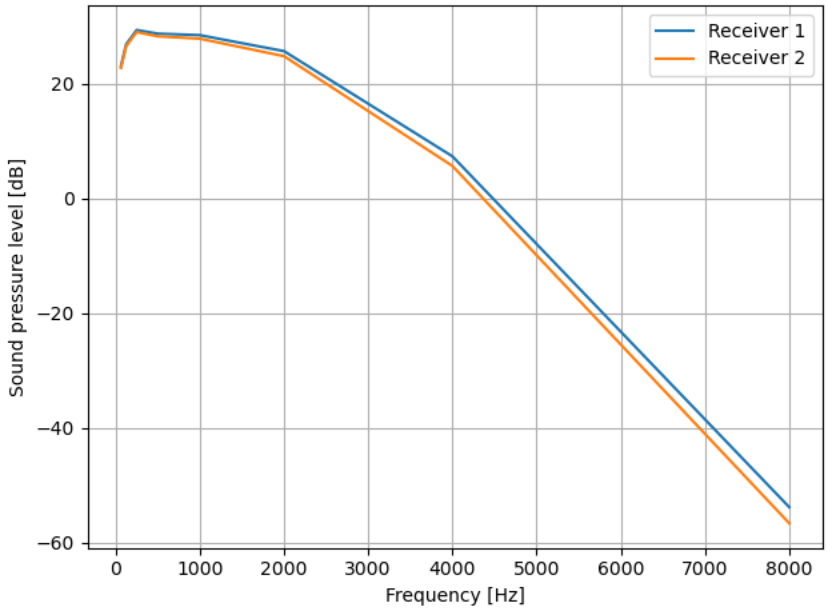
In this case the wind farm consist of 5 wind turbines in a row aligned with the wind. Wind turbines, 0,1 and 3,4 operate in mode 0 while wind turbin 2 is r

[6]:
```
sim_res.flow_map().plot_wake_map()
plt.plot([x[0]], [1000], '.', label='Receiver 1')
plt.plot([x[-1]], [1000], '.', label='Receiver 2')
setup_plot(grid=False, xlabel='x coordinate [m]', ylabel='y coordinate [m]')
```



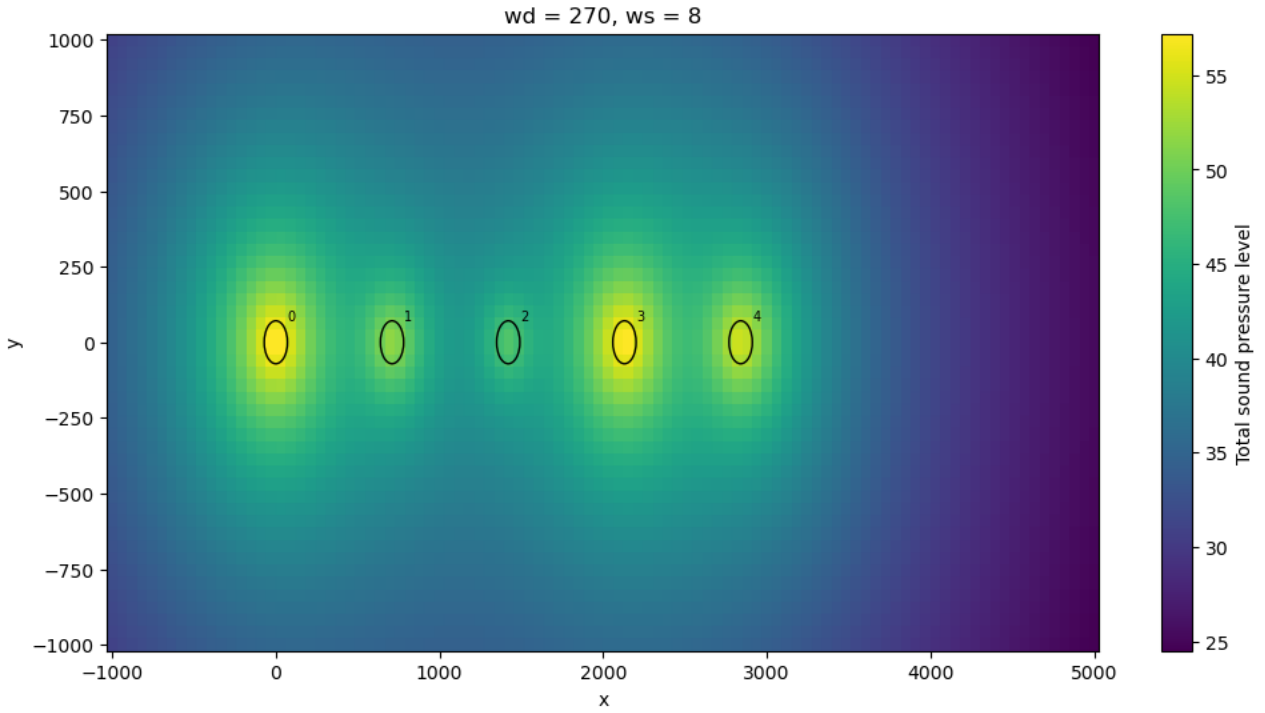
We can no model the sound pressure level at the two recievers. In this case the upstream wind turbines operates at higher wind speed than the down wir

[7]:
```
nm = sim_res.noise_model()
total_sp_jlk, spl_jlkf = nm(rec_x=[x[0], x[-1]], rec_y=[1000, 1000], rec_h=2, Temp=20, RHum=80, ground_type=0.0)
plt.plot(nm.freqs, spl_jlkf[0, 0, 0], label='Receiver 1')
plt.plot(nm.freqs, spl_jlkf[1, 0, 0], label='Receiver 2')
setup_plot(xlabel='Frequency [Hz]', ylabel='Sound pressure level [dB]')
```



Finally, a sound map can be generated

[8]:
```
plt.figure(figsize=(12,6))
nmap = sim_res.noise_map(grid=XYGrid(x=np.linspace(-1000, 5000, 100), y=np.linspace(-1000, 1000, 50), h=2))
nmap['Total sound pressure level'].squeeze().plot()
wt.plot(x, y)
```



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Experiment: Combine Models

In this notebook, you can combine the difference models of PyWake and see the effects in terms of AEP and a flow map.

Install PyWake if needed

[1]:
```
# Install PyWake if needed
try:
    import py_wake
except ModuleNotFoundError:
    !pip install git+https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake.git
```

Now we also import all available models

[2]:
```
from py_wake.deficit_models import *
from py_wake.deficit_models.deficit_model import *
from py_wake.wind_farm_models import *
from py_wake.rotor_avg_models import *
from py_wake.superposition_models import *
from py_wake.deflection_models import *
from py_wake.turbulence_models import *
from py_wake.ground_models import *
from py_wake.deficit_models.utils import *
```

Then, we set up the site, wind turbines as well as their initial positions.

[3]:
```
from py_wake.examples.data.iea37._iea37 import IEA37Site, IEA37_WindTurbines

site = IEA37Site(16)
windTurbines = IEA37_WindTurbines()
x,y = site.initial_position.T
```

[4]:
```
# prepare for the model combination tool
from py_wake.utils.model_utils import get_models, get_signature
from ipywidgets import interact
from IPython.display import HTML, display, Javascript
import time
import matplotlib.pyplot as plt

# Fix ipywidget label width
display(HTML('''<style>.widget-label { min-width: 20ex !important; }</style>'''))

def print_signature(windFarmModel, **kwargs):
    s = """# windFarmModel autogenerated by dropdown boxes
t = time.time()
wfm = %s
sim_res = wfm(x,y)
plt.figure(figsize=(12,8))
sim_res.flow_map(wd=270).plot_wake_map()
```

```
print (wfm)
print ("Computation time (AEP + flowmap):", time.time()-t)
plt.title('AEP: %%.2fGWh'%%(sim_res.aep().sum()))"""% get_signature(windFarmModel, kwargs, 1)
    # Write windFarmModel code to cell starting "# windFarmModel autogenerated by dropdown boxes"
    display(Javascript("""
for (var cell of IPython.notebook.get_cells()) {
    if (cell.get_text().startsWith("# windFarmModel autogenerated by dropdown boxes")){
        cell.set_text(`%s`);
        cell.execute();
    }
}"""%s))

# setup list of models
models = {n:[(getattr(m,'__name__',m), m) for m in get_models(cls)]
          for n,cls in [('windFarmModel', WindFarmModel),
                        ('wake_deficitModel', WakeDeficitModel),
                        ('rotorAvgModel', RotorAvgModel),
                        ('superpositionModel', SuperpositionModel),
                        ('blockage_deficitModel', BlockageDeficitModel),
                        ('deflectionModel',DeflectionModel),
                        ('turbulenceModel', TurbulenceModel),
                        ('groundModel', GroundModel)
                        ]}
```

Combine and execute model

Combine your model via the dropdown boxes below.

Choosing a different model updates and executes the the code cell below which runs the wind farm model, prints the AEP and plots a flow map.

[5]:
```
_ = interact(print_signature, **models)
```

windFarmModel: PropagateDownwind
wake_deficitModel: NOJDeficit
rotorAvgModel: None
superpositionModel: LinearSum
blockage_deficitModel: None
deflectionModel: None
turbulenceModel: None
groundModel: NoGround

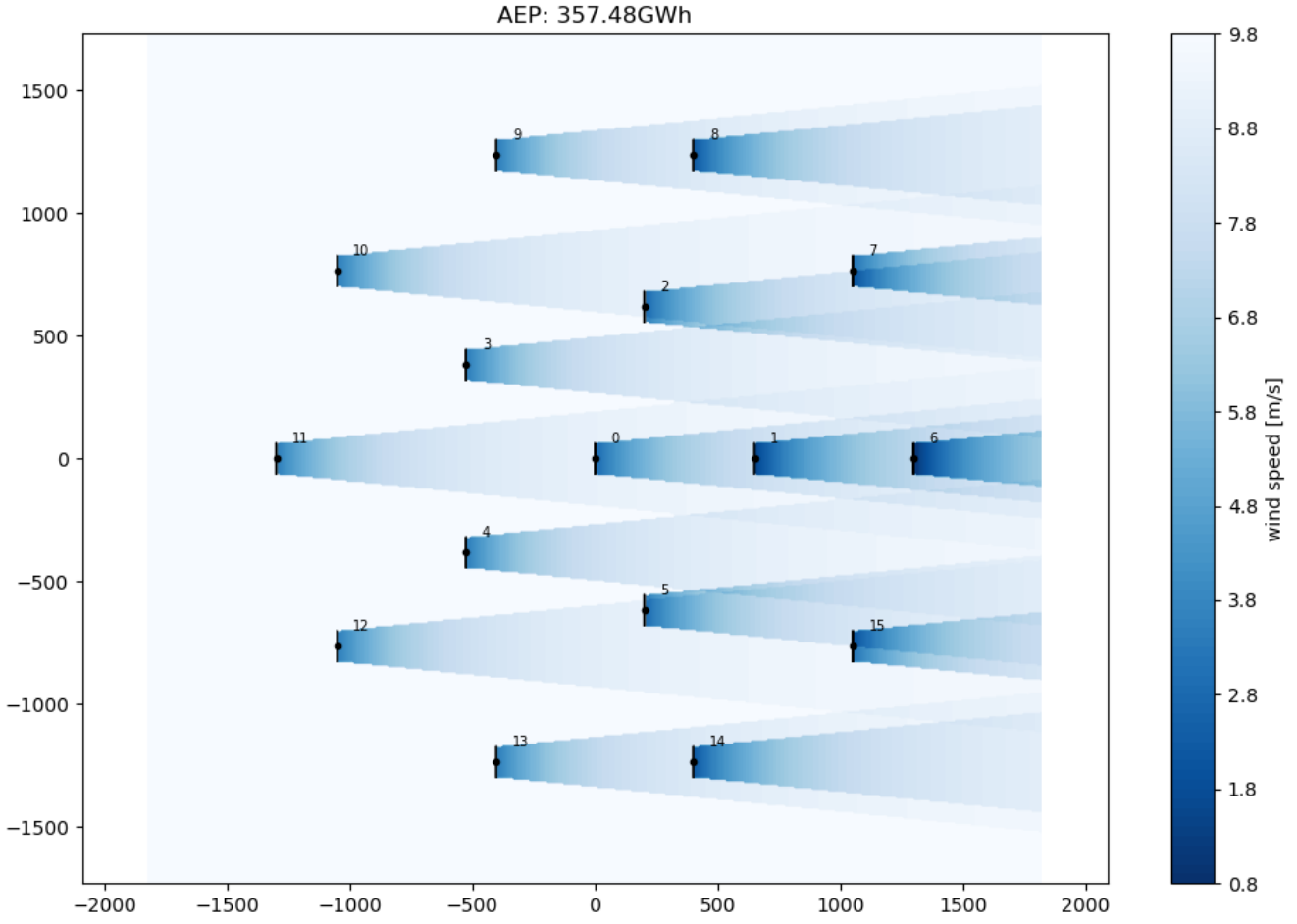
JavaScript output is disabled in JupyterLab

[6]:
```
# windFarmModel autogenerated by dropdown boxes
t = time.time()
wfm = PropagateDownwind(
    site,
    windTurbines,
    wake_deficitModel=NOJDeficit(
        k=0.1,
        rotorAvgModel=AreaOverlapAvgModel(),
```

```
        groundModel=None),
    superpositionModel=LinearSum(),
    deflectionModel=None,
    turbulenceModel=None,
    rotorAvgModel=None)
sim_res = wfm(x,y)
plt.figure(figsize=(12,8))
sim_res.flow_map(wd=270).plot_wake_map()
print (wfm)
print ("Computation time (AEP + flowmap):", time.time()-t)
plt.title('AEP: %.2fGWh'%(sim_res.aep().sum()))
```

```
PropagateDownwind(PropagateUpDownIterative, NOJDeficit-wake, LinearSum-superposition)
Computation time (AEP + flowmap): 0.6964643001556396
```

[6]: `Text(0.5, 1.0, 'AEP: 357.48GWh')`



Experiment: Validation

In this notebook, you can compare and validate your own `WindFarmModel` (i.e. combination of engineering submodels) with data from RANS, LES and measurements.

Install PyWake if needed

[1]:
```
# Install PyWake if needed
try:
    import py_wake
except ModuleNotFoundError:
    !pip install git+https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake.git
```

Now we install some basic Python elements

[2]:
```
import numpy as np
import matplotlib as plt
plt.rcParams.update({'figure.max_open_warning': 0})
```

Now we also import all available models

[3]:
```
from py_wake.deficit_models import *
from py_wake.deficit_models.deficit_model import *
from py_wake.wind_farm_models import *
from py_wake.rotor_avg_models import *
from py_wake.superposition_models import *
from py_wake.deflection_models import *
from py_wake.turbulence_models import *
from py_wake.ground_models import *
```

[4]:
```
# prepare for the model combination tool
from py_wake.utils.model_utils import get_models, get_signature
from ipywidgets import interact
from IPython.display import HTML, display, Javascript

# Fix ipywidget label width
display(HTML('''<style>.widget-label { min-width: 20ex !important; }</style>'''))

def print_signature(windFarmModel, **kwargs):
    s = """# insert windFarmModel code below
wfm = %s

validation.add_windFarmModel('MyModelName', wfm)"""% get_signature(windFarmModel, kwargs, 1)

    # Write windFarmModel code to cell starting "# insert windFarmModel code below"
    display(Javascript("""
for (var cell of IPython.notebook.get_cells()) {
```

```
    if (cell.get_text().startsWith("# insert windFarmModel code below")){
        cell.set_text(`%s`)
    }
}"""%s))

# setup list of models
models = {n:[(getattr(m,'__name__',m), m) for m in get_models(cls)]
          for n,cls in [('windFarmModel', WindFarmModel),
                        ('wake_deficitModel', WakeDeficitModel),
                        ('rotorAvgModel', RotorAvgModel),
                        ('superpositionModel', SuperpositionModel),
                        ('blockage_deficitModel', BlockageDeficitModel),
                        ('deflectionModel',DeflectionModel),
                        ('turbulenceModel', TurbulenceModel),
                        ('groundModel', GroundModel)
                        ]}
```

[5]:
```
from py_wake.validation.validation import Validation, ValidationSite, ValidationWindTurbines
site, windTurbines = ValidationSite(), ValidationWindTurbines()
```

Setup Validation

Instantiate new validation. This cell removes previously added `WindFarmModel`

[6]:
```
validation = Validation()
```

Add WindFarmModels

Add as many windFarmModels as you wish with the function

```
validation.add_windFarmModel(name, windFarmModel, line_style='-')
```

for example:

```
wfm = PropagateDownwind(site, windTurbines, wake_deficitModel=NOJDeficit(k=0.04))
validation.add_windFarmModel("NOJ(k=0.04)", wfm, ':')
```

You can use the dropdown boxes here to update the code cell below. Note, that some models needs manual specification of some non-optional arguments

[7]:
```
_ = interact(print_signature, **models)
```

windFarmModel: PropagateDownwind

wake_deficitModel: NOJDeficit

rotorAvgModel: None

superpositionModel	LinearSum
blockage_deficitModel	None
deflectionModel	None
turbulenceModel	None
groundModel	NoGround

```
JavaScript output is disabled in JupyterLab
```

In the cell below:

- Replace `MyModelName` with a name for the windFarmModel
- Set unspecified arguments, if any
- Run the cell below to add the windFarmModel to the validation

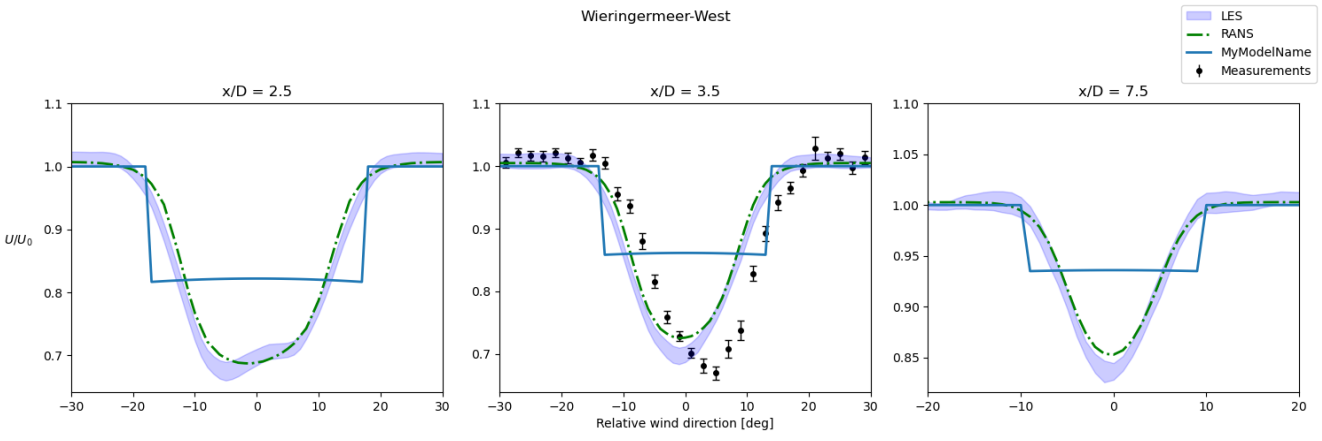
[8]:
```
# insert windFarmModel code below
wfm = PropagateDownwind(
    site,
    windTurbines,
    wake_deficitModel=NOJDeficit(
        k=0.1,
        rotorAvgModel=AreaOverlapAvgModel(),
        groundModel=None),
    superpositionModel=LinearSum(),
    deflectionModel=None,
    turbulenceModel=None,
    rotorAvgModel=None)

validation.add_windFarmModel('MyModelName', wfm)
```

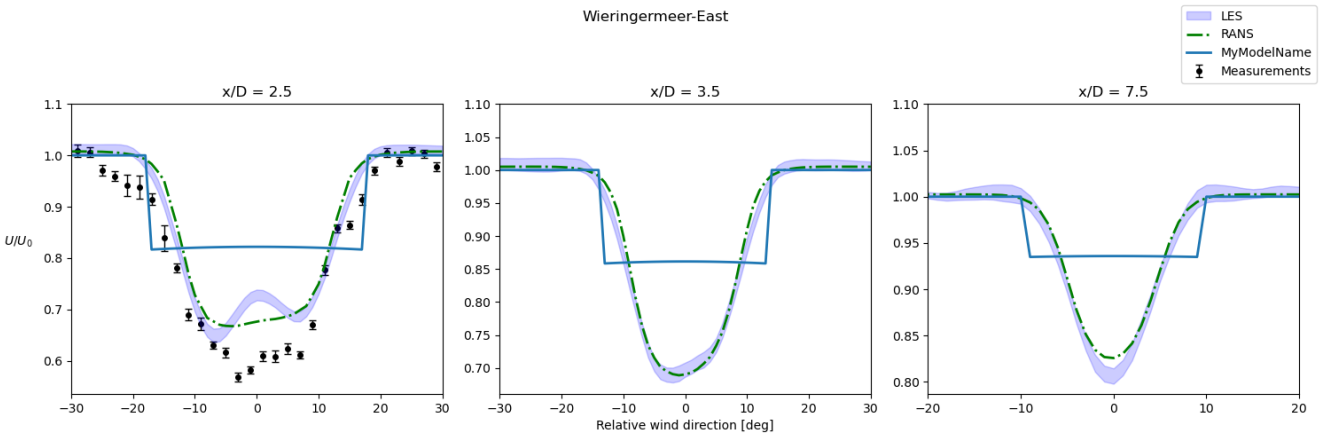
[9]:
```
# print name of added wind farm models
print(validation.windFarmModel_dict.keys())
```

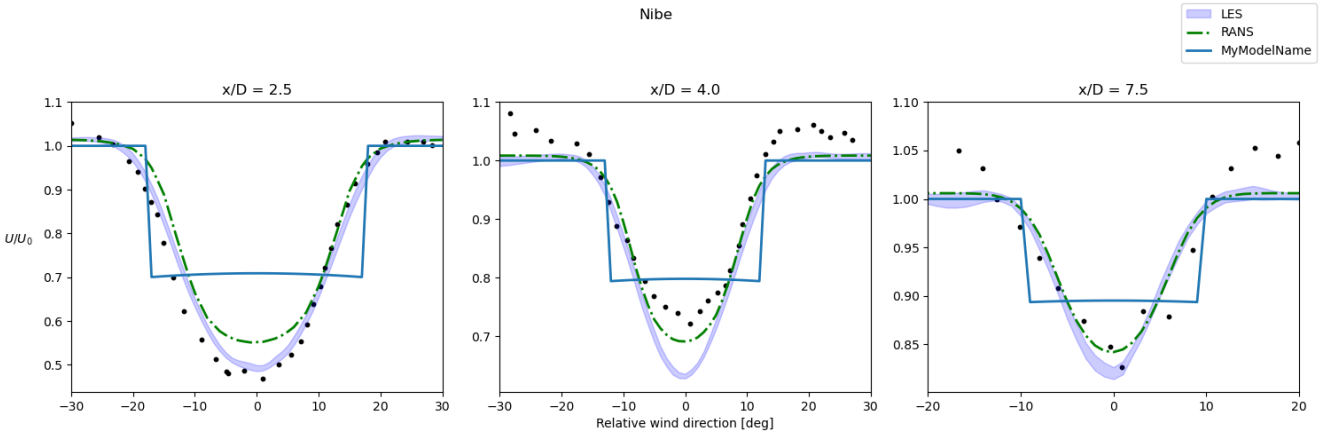
```
dict_keys(['MyModelName'])
```

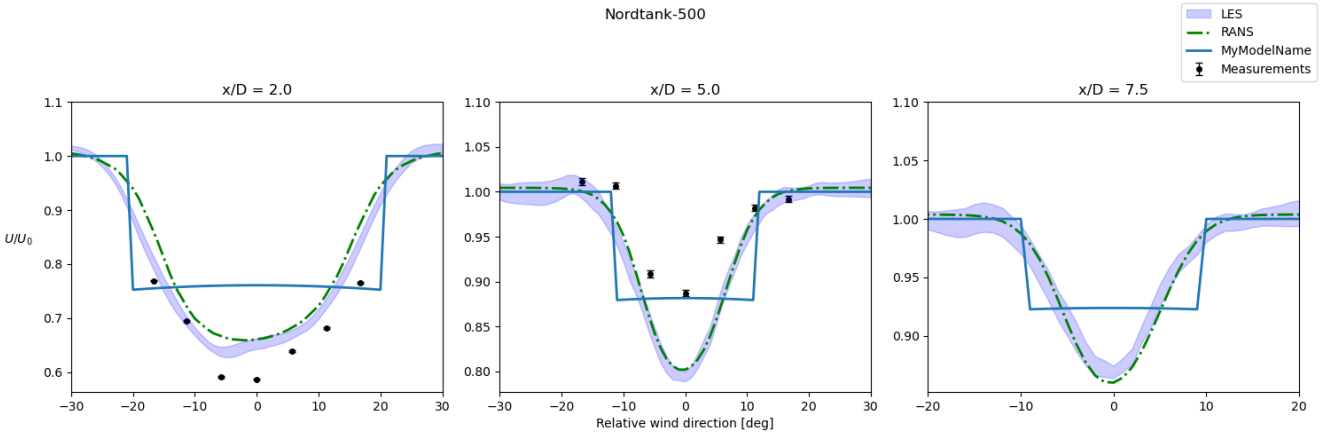
Single wake deficit validation

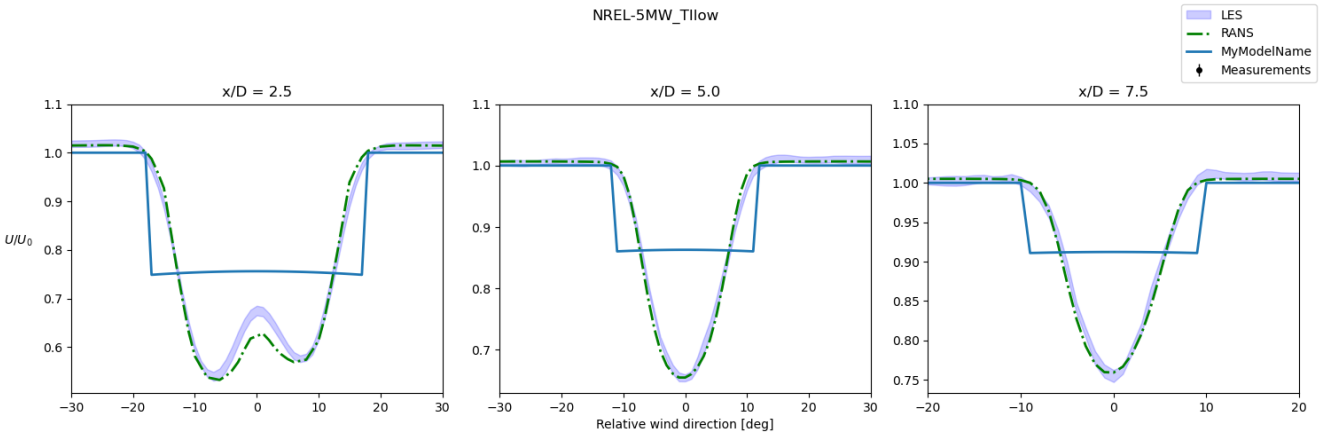
[10]:
```
validation.plot_deficit_profile()
```

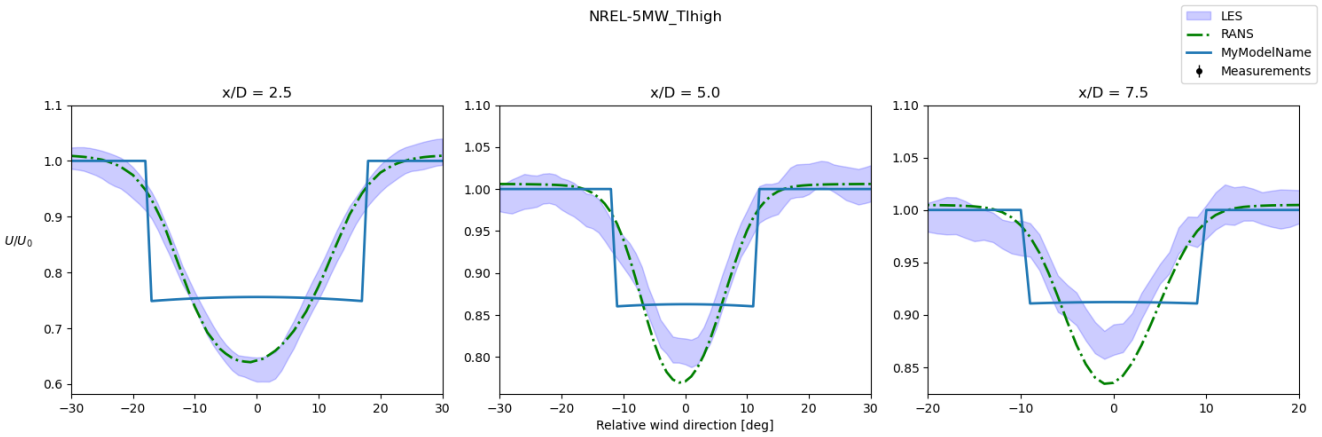






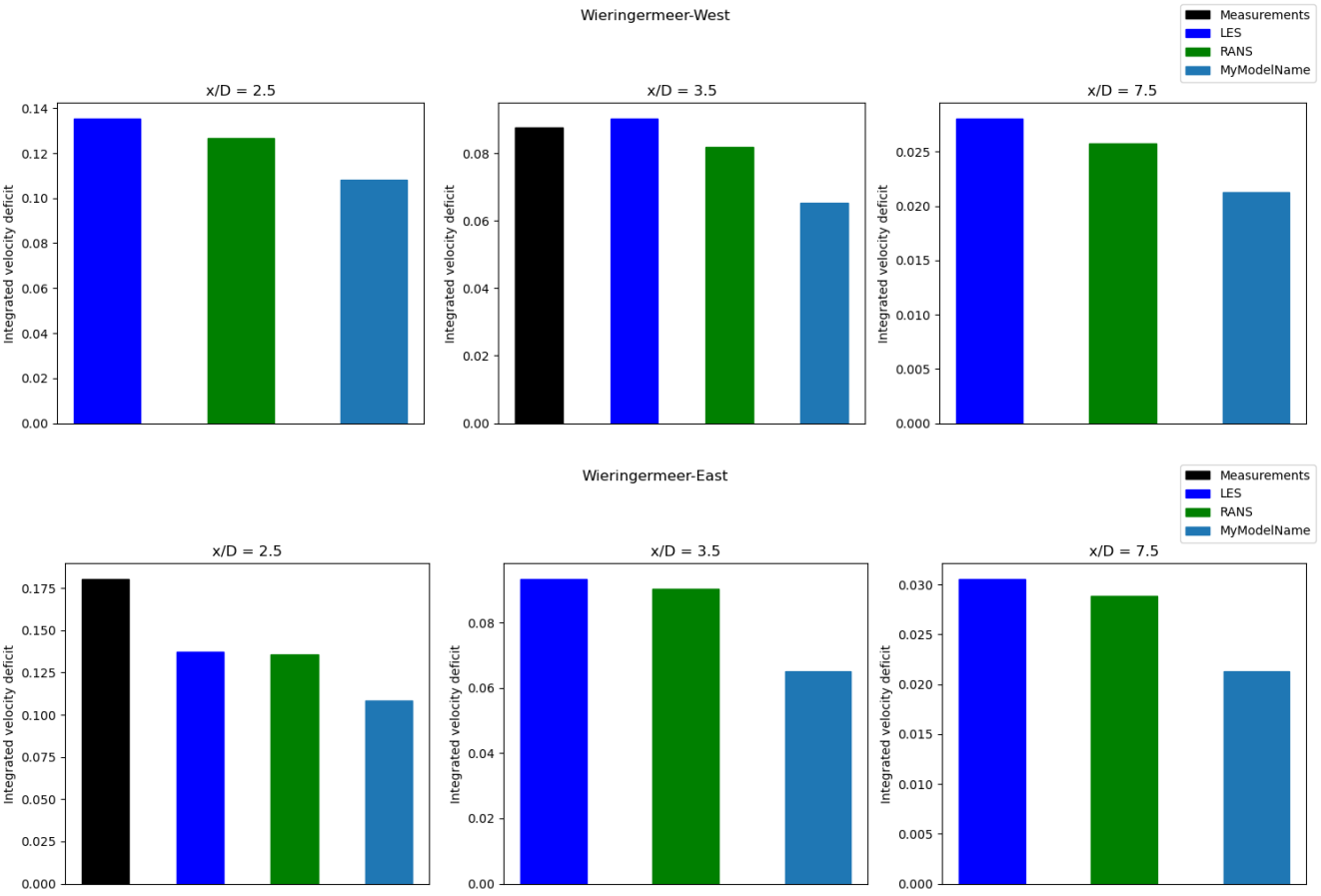


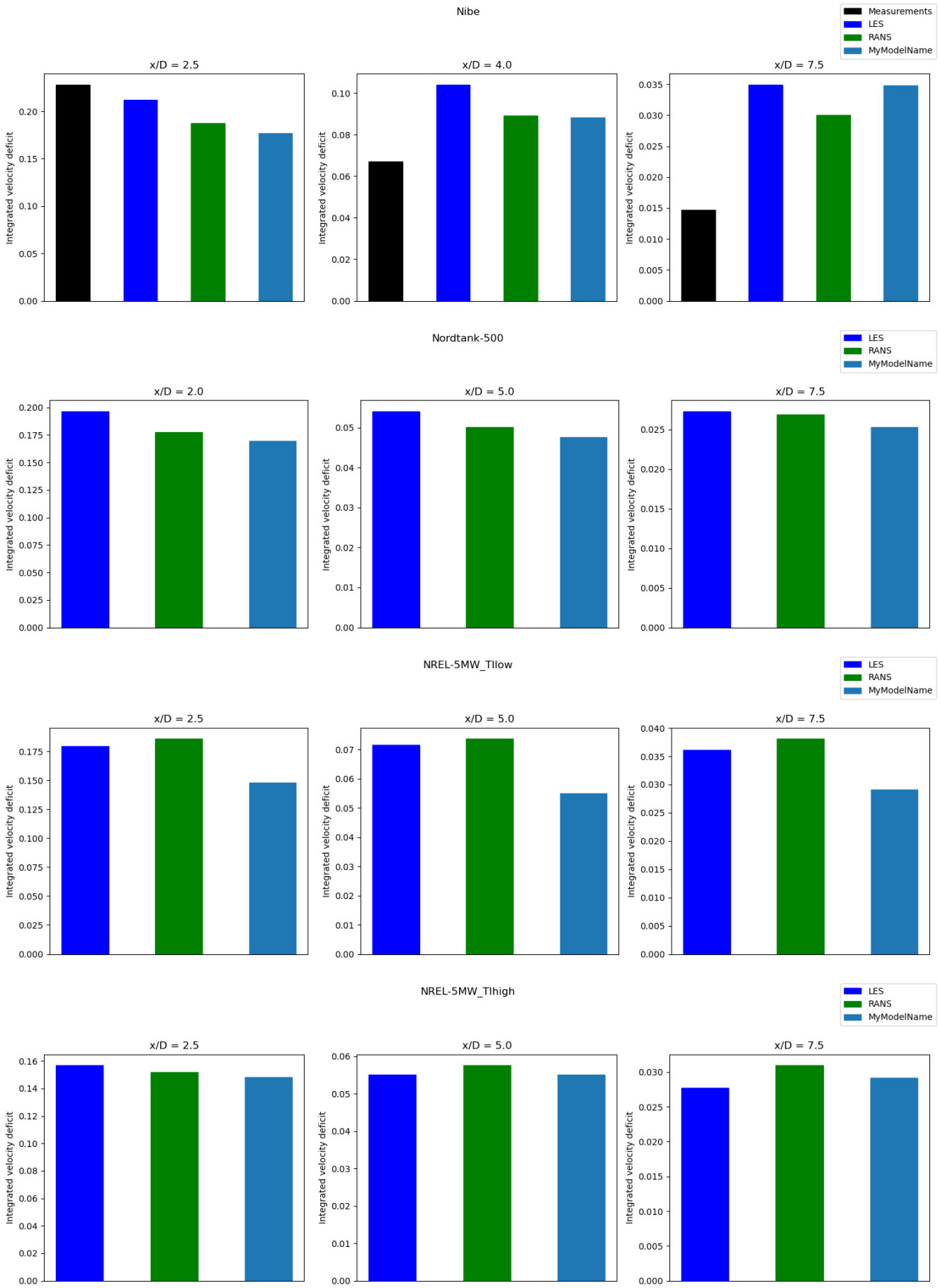




Single wake integrated momentum deficit validation

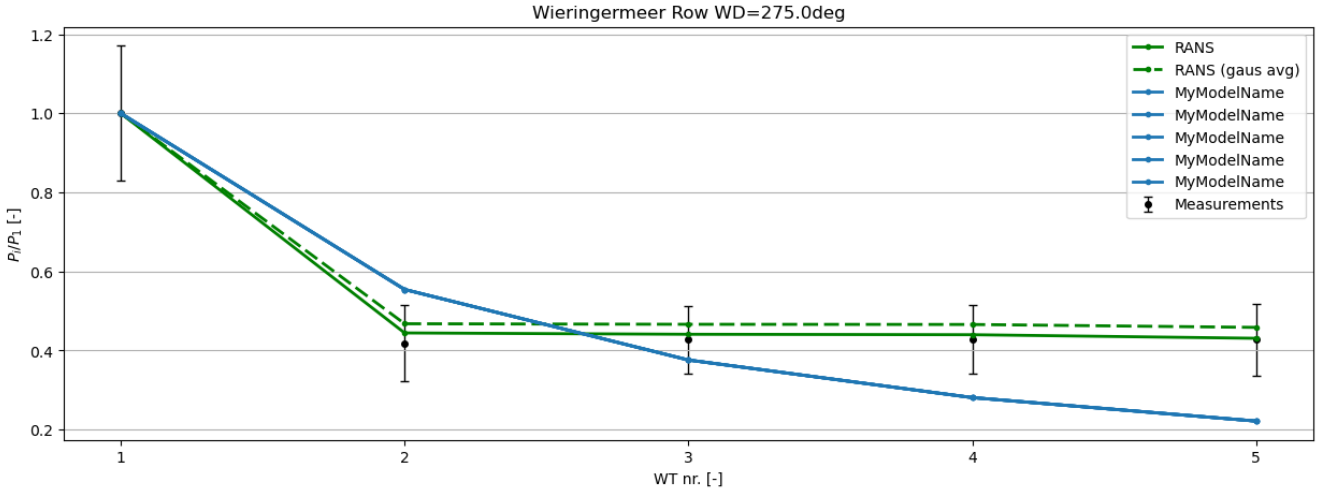
[11]:
```
validation.plot_integrated_deficit()
```

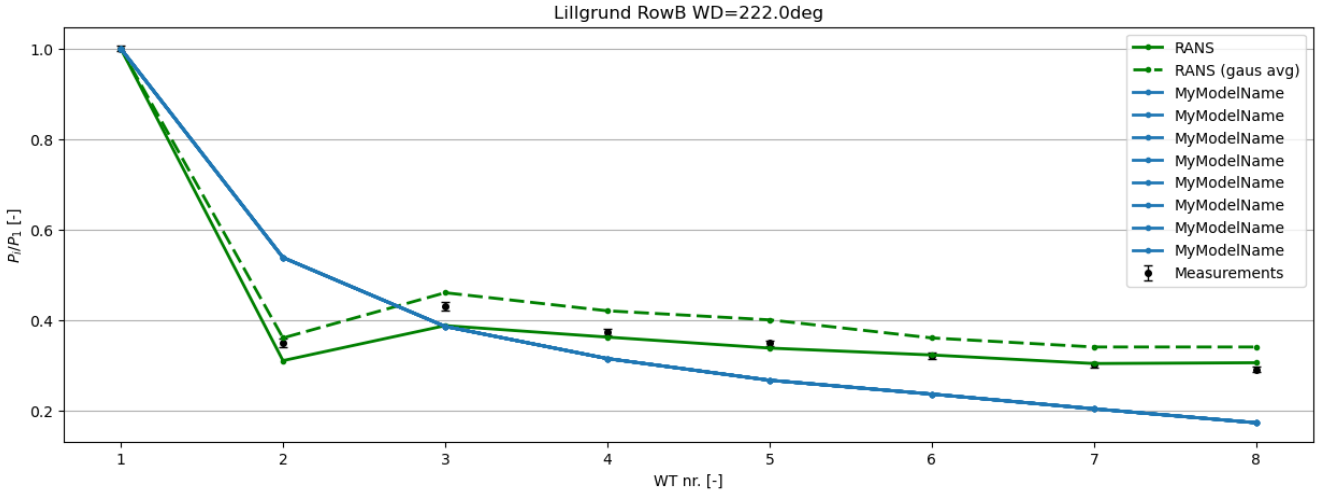


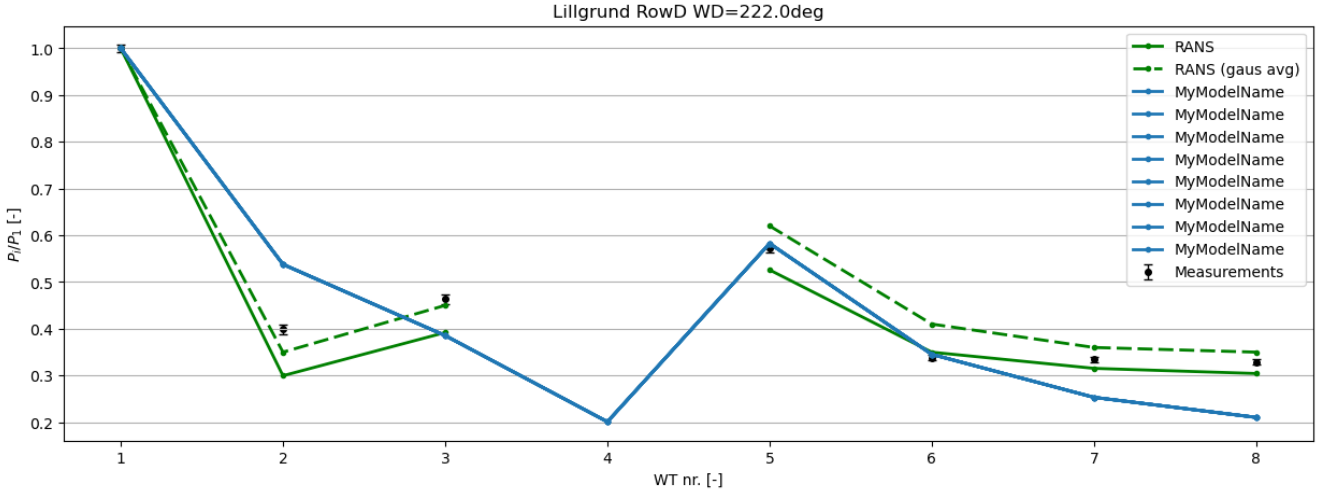


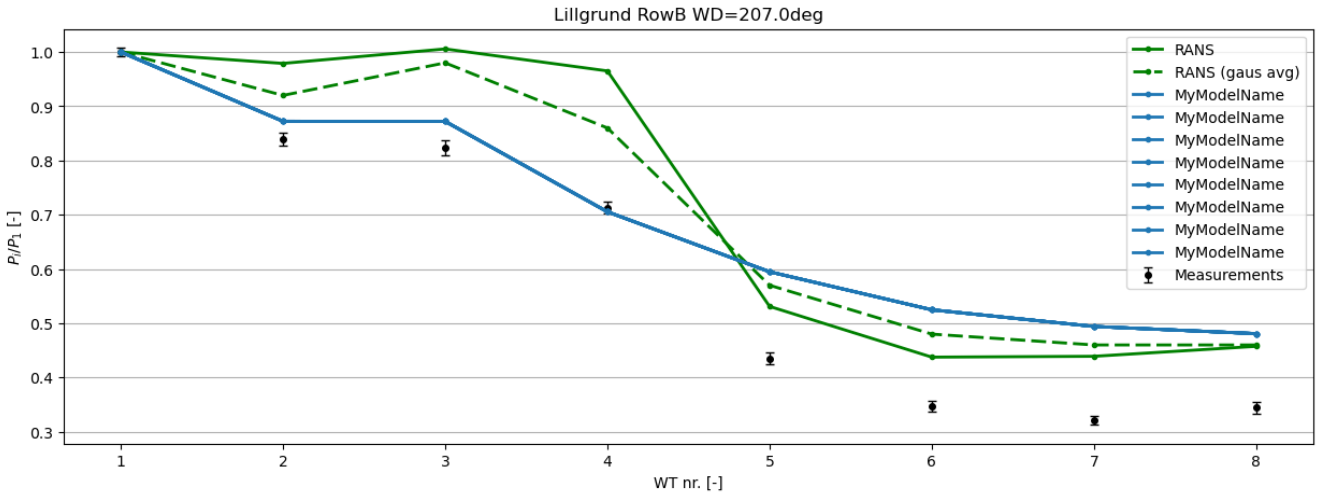
Wind farm power validation

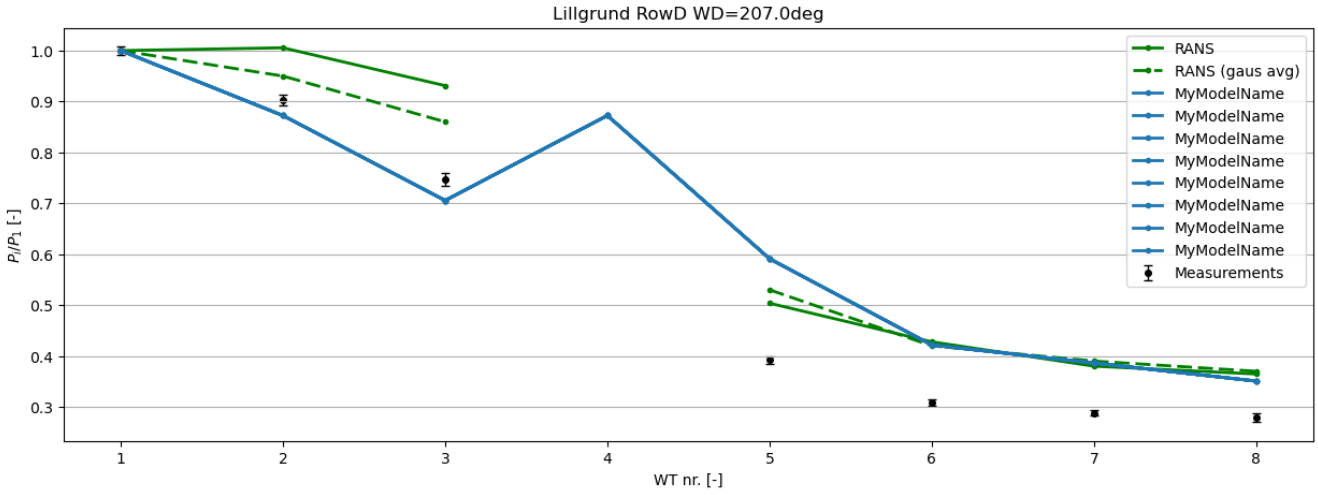
[12]:
```
validation.plot_multiwake_power()
```

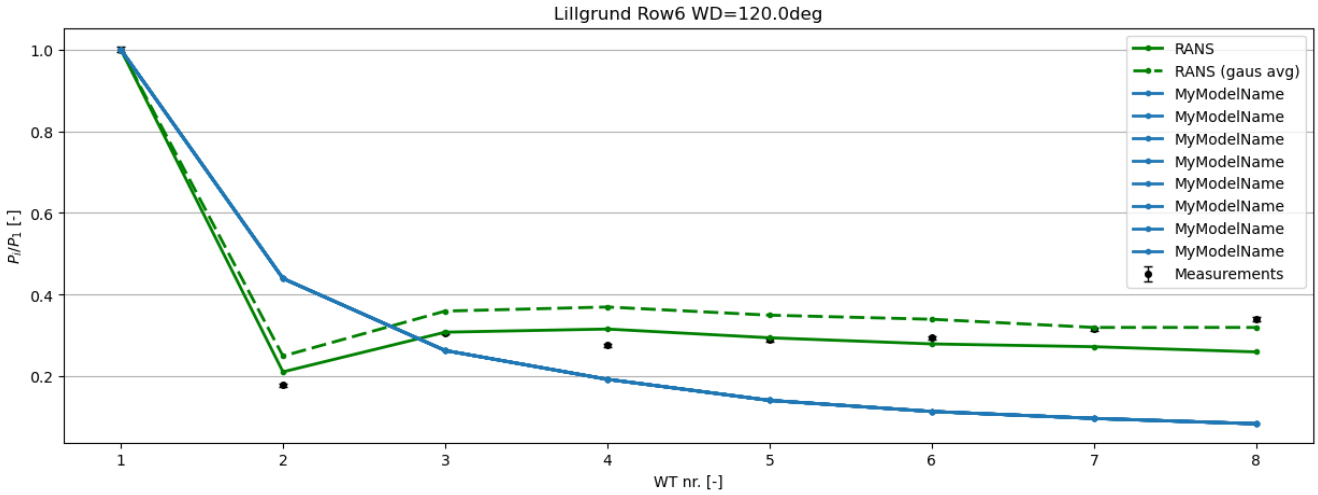


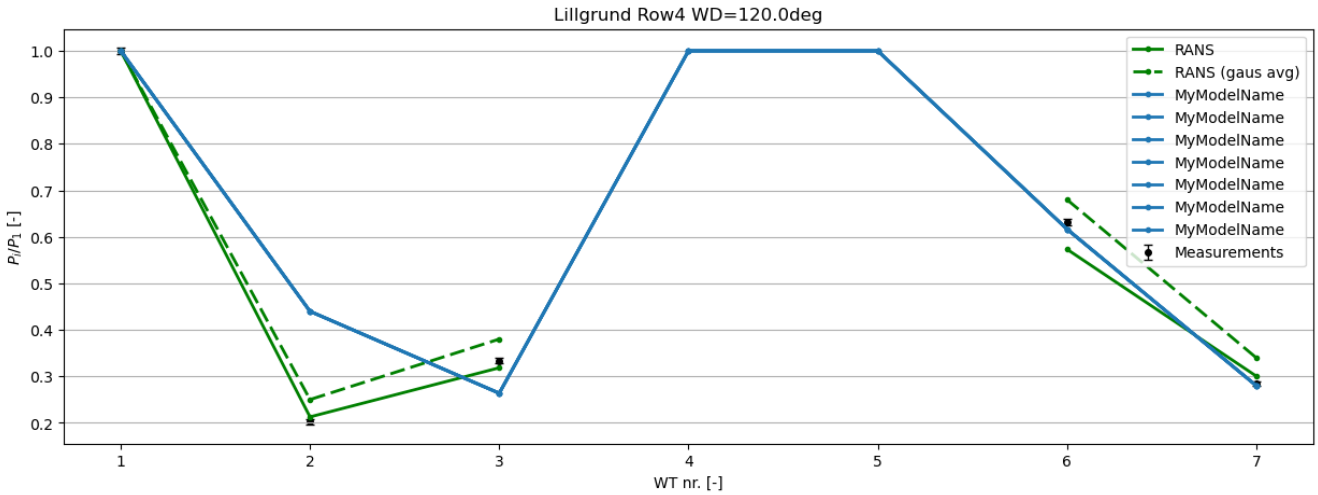


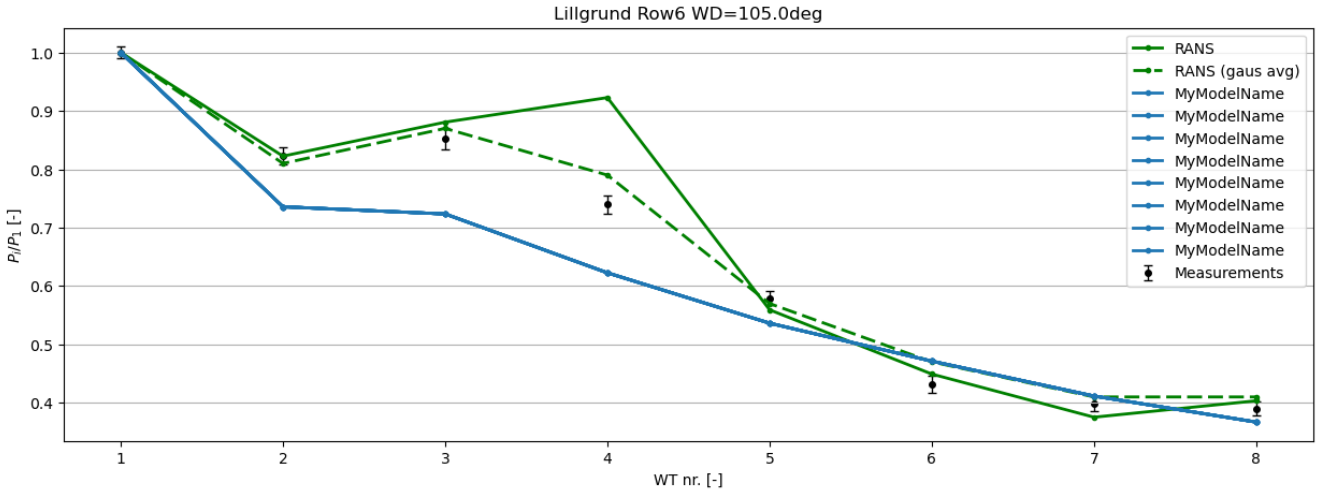


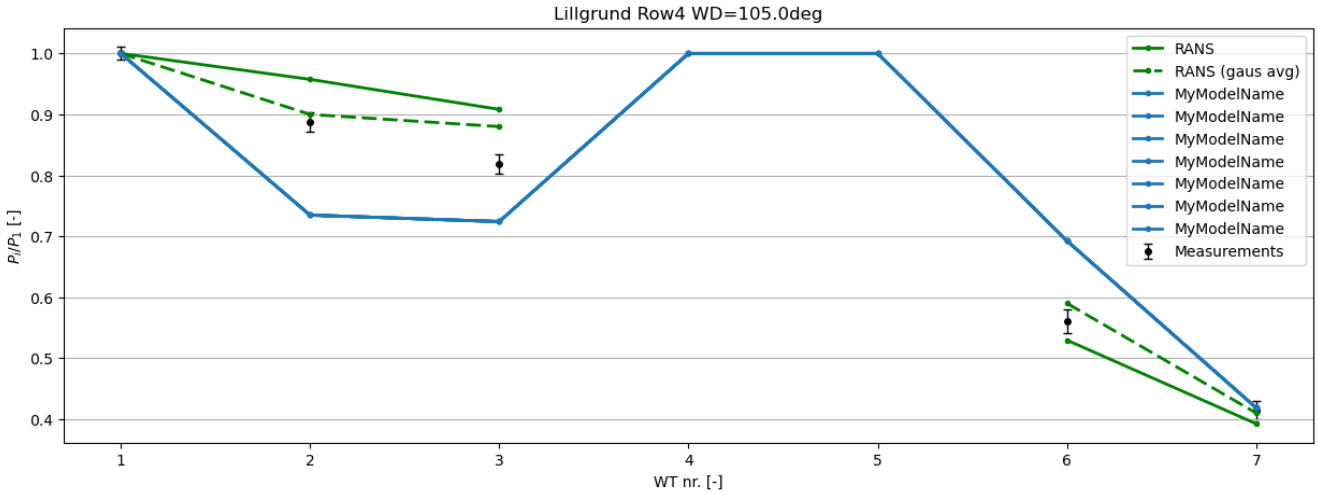


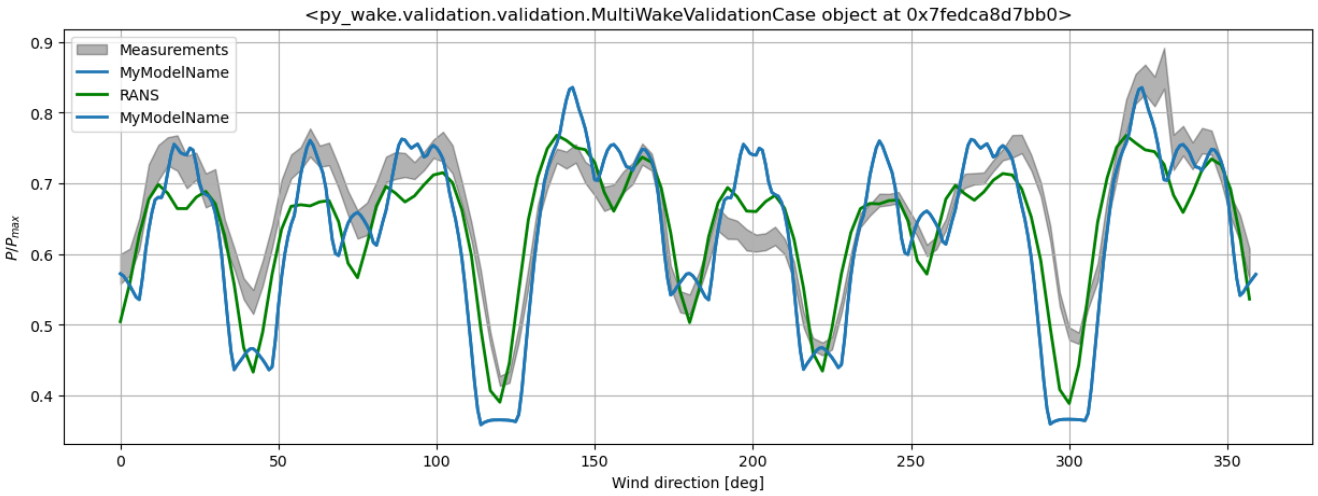


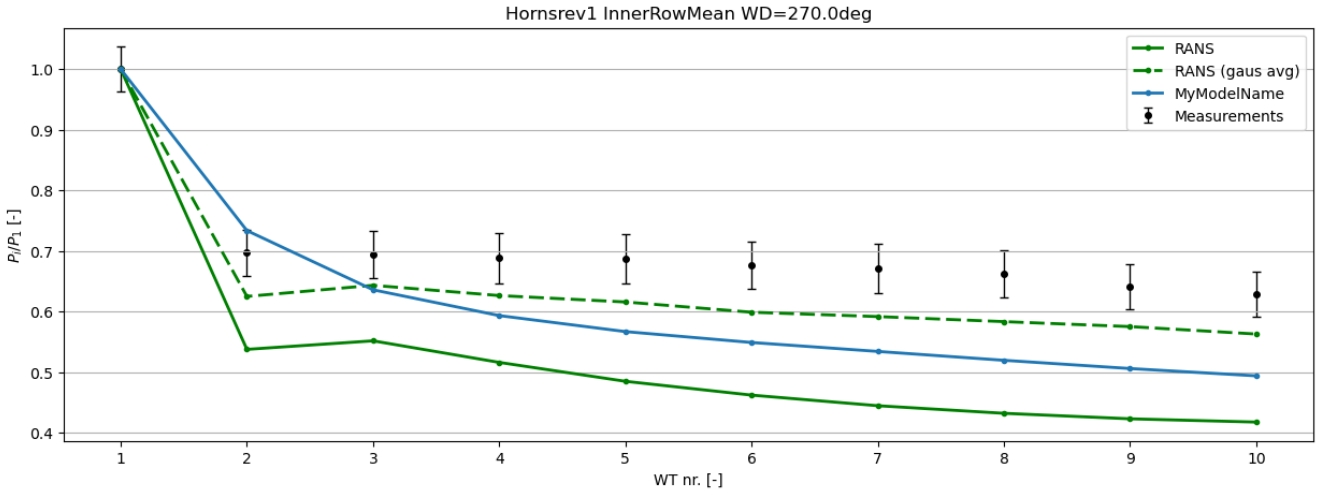


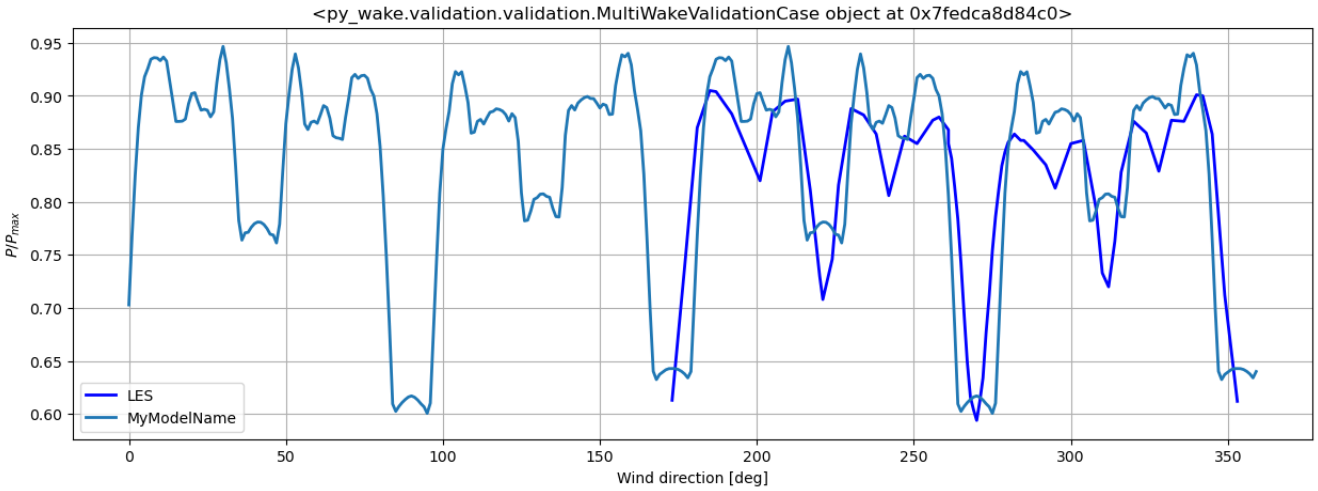












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Experiment: Improve Hornsrev1 Layout

In this exercise, you can investigate how changing the turbine positions inside the Hornsrev1 wind farm influences its AEP.

Install PyWake if needed

[1]:
```
# Install PyWake if needed
try:
    import py_wake
except ModuleNotFoundError:
    !pip install git+https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake.git
```

First we import basic Python elements

[2]:
```
import numpy as np
import matplotlib.pyplot as plt
```

Import and instantiate relevant PyWake objects

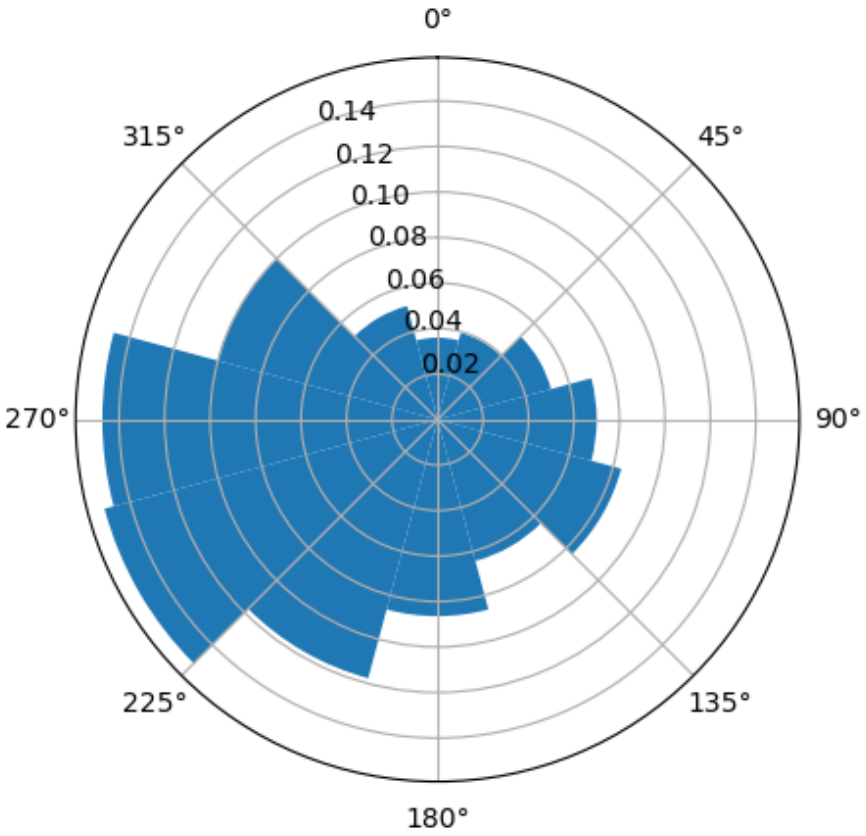
We operate with four fundamental objects in PyWake, namely `Site`, `WindTurbines` and `WindFarmModel`, as explained in the Overview section.

[3]:
```
#importing the properties of Hornsrev1, which are already stored in PyWake
from py_wake.examples.data.hornsrev1 import V80
from py_wake.examples.data.hornsrev1 import Hornsrev1Site
from py_wake.examples.data.hornsrev1 import wt_x, wt_y

# BastankhahGaussian combines the engineering wind farm model, `PropagateDownwind` with
# the `BastankhahGaussianDeficit` wake deficit model and the `SquaredSum` super position model
from py_wake.literature.gaussian_models import Bastankhah_PorteAgel_2014

# After we import the objects we instatiate them:
site = Hornsrev1Site()
wt = V80()
windFarmModel = Bastankhah_PorteAgel_2014(site, wt, k=0.0324555)
```

The `Site` object

There are multiple functionalities available from the Site object as well as wind conditions, probability and geometry of the wind farm. We can e.g. plot the wind rose with a specific number of bins by using the plot_wd_distribution function:

[4]:
```
site.plot_wd_distribution(n_wd=12);
```

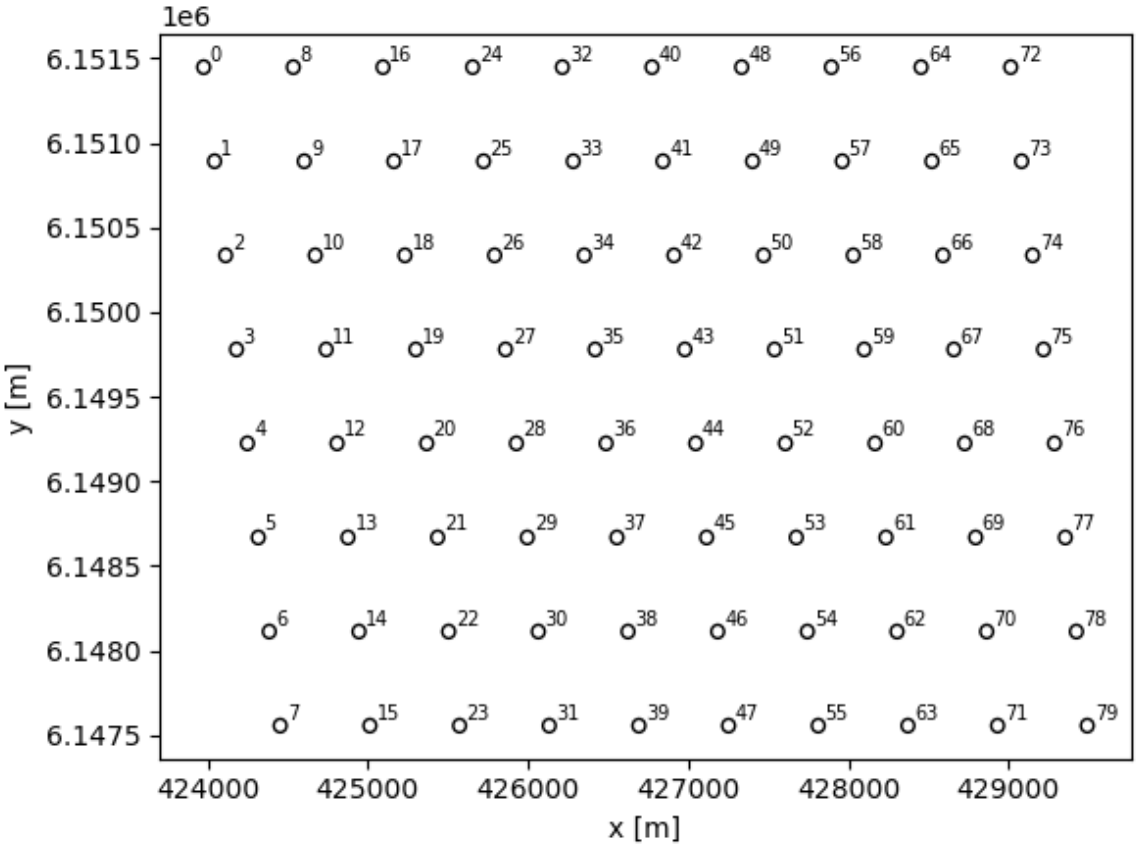


The `WindTurbine` object

The Wind turbine object contains relevant information about the turbine used as well as supplying usefull functions. It holds information about the power curve, ct-curve, hub height and diameter and has a plotting function to visualize the layout of the turbines.

[5]:
```
# Original layout
plt.figure()
wt.plot(wt_x, wt_y)
plt.xlabel('x [m]')
plt.ylabel('y [m]')
```

[5]:
```
Text(0, 0.5, 'y [m]')
```



AEP Calculation

[6]:
```
# Original AEP
aep_ref = windFarmModel(wt_x,wt_y).aep().sum()
print ('Original AEP: %f GWh'%aep_ref)
```

```
Original AEP: 664.334531 GWh
```

Exercise: Improve the AEP by modifying turbine locations.

Modify the x and y offsets for the rows and columns to increase the AEP.

Note, the turbines positions are limited by a rectangle surrounding the existing layout.

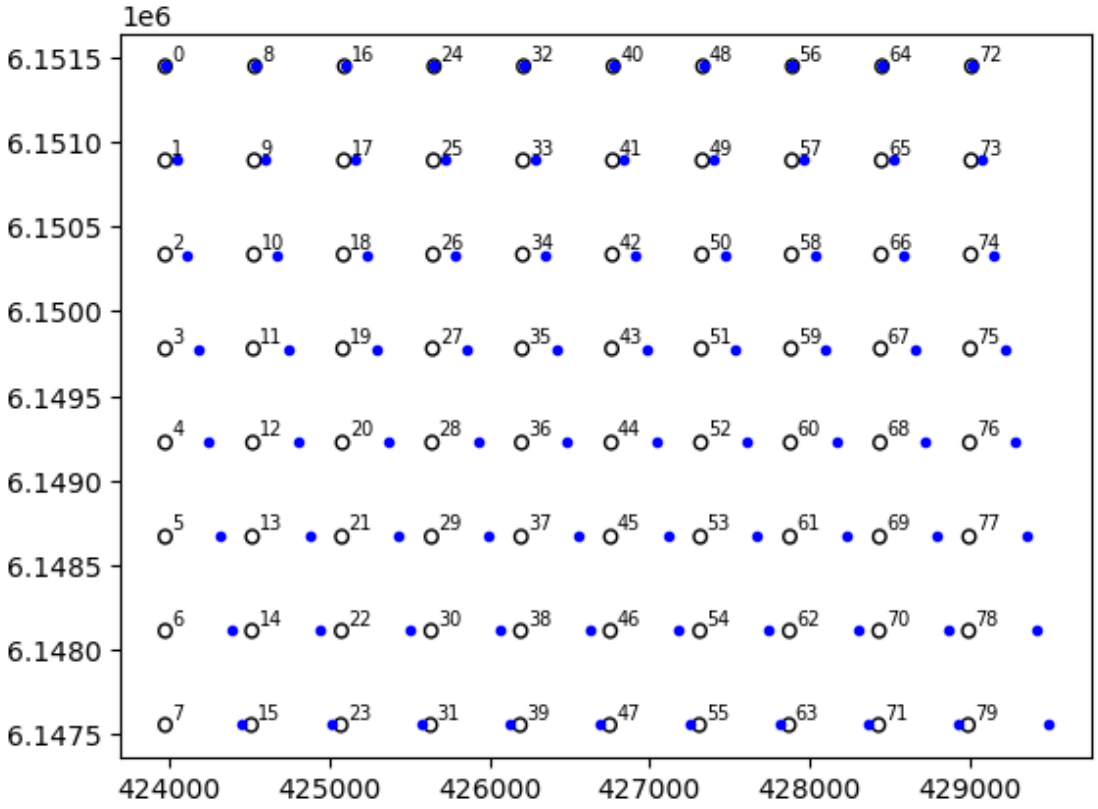
[7]:
```
# Here we define a function to print and plot your new layout. No need to change anything here
def add_offset_plot_and_print(row_offset_x, row_offset_y, col_offset_x, col_offset_y):
    x,y = wt_x, wt_y
    y = np.reshape(y,(10,8)).astype(float)
    x = np.reshape(x,(10,8)).astype(float)

    x+= np.array(row_offset_x)
    y+= np.array(row_offset_y)
    x+= np.array(col_offset_x)[:,np.newaxis]
    y+= np.array(col_offset_y)[:,np.newaxis]
    y = np.maximum(min(wt_y), np.minimum(max(wt_y), y.flatten()))
    x = np.maximum(min(wt_x), np.minimum(max(wt_x), x.flatten()))

    plt.plot()
    plt.plot(wt_x, wt_y,'b.')
```

```
    wt.plot(x, y)
    aep = windFarmModel(x,y).aep().sum()
    print ("AEP ref", aep_ref.values)
    print ("AEP", aep.values)
    print ("Increase: %f %%"%((aep-aep_ref)/aep_ref*100))
```

Now try to modify the row and column offsets and see if you can improve the AEP

[8]:
```
# ======================================
# Specify offsets
# ======================================

row_offset_x = np.linspace(0,1,8)* -500
row_offset_y = np.linspace(0,1,8) * 0

col_offset_x = np.linspace(0,1,10) * 0
col_offset_y = np.linspace(0,1,10) * 0

add_offset_plot_and_print(row_offset_x, row_offset_y, col_offset_x, col_offset_y)
```

```
AEP ref 664.3345305655693
AEP 664.4739841319365
Increase: 0.020991 %
```



Exercise: Wake Deflection

In this exercise you can investigate the wake-deflection effects of yaw-misalignment.

Install PyWake if needed

[1]:
```
# Install PyWake if needed
try:
    import py_wake
except ModuleNotFoundError:
    !pip install git+https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake.git
```

Import Python elements and PyWake objects

[2]:
```
# setup site, wind turbines and wind farm model with the corresponding wake models
import numpy as np
from ipywidgets import interact
from ipywidgets import IntSlider
import matplotlib.pyplot as plt

from py_wake.flow_map import HorizontalGrid
from py_wake.examples.data.iea37._iea37 import IEA37Site, IEA37_WindTurbines
from py_wake.literature.gaussian_models import Bastankhah_PorteAgel_2014
from py_wake.deflection_models.jimenez import JimenezWakeDeflection
```

Specify site to use, as well as wind turbines to set up the wind farm model

[3]:
```
site = IEA37Site(16)
x, y = [0, 600, 1200], [0, 0, 0]
windTurbines = IEA37_WindTurbines()
wfm = Bastankhah_PorteAgel_2014(site, windTurbines, k=0.0324555, deflectionModel=JimenezWakeDeflection())
```

[4]:
```
# define function that plots the flow field and AEP history of 3 wind turbines
def plot_flow_field_and_aep(WT0, WT1, TILT):

    ax1 = plt.figure(figsize=(20,4)).gca()
    ax2 = plt.figure(figsize=(10,3)).gca()

    sim_res = wfm(x, y, yaw=np.reshape([WT0,WT1,0],(3,1,1)), wd=270, ws=10, tilt=TILT)
    sim_res.flow_map(HorizontalGrid(x = np.linspace(0,1400,200), y=np.linspace(-200,200,50))).plot_wake_map(ax=ax1)
    ax1.set_xlim([-200,1400])
    aep.append(sim_res.aep().values[:,0,0])
    aep_arr = np.array(aep)
    for i in range(3):
        ax2.plot(aep_arr[:,i], '.-', label='WT%d, %.2f'%(i,aep_arr[-1,i]))
    ax2.plot(aep_arr.sum(1), '.-', label='Total, %.2f'%aep_arr[-1].sum())
    ax2.axhline(aep_arr[0].sum(),ls='--',c='r')
    ax2.set_ylabel('AEP [GWh]')
    ax2.set_xlabel('Iteration')
    ax2.legend(loc='upper left')
```

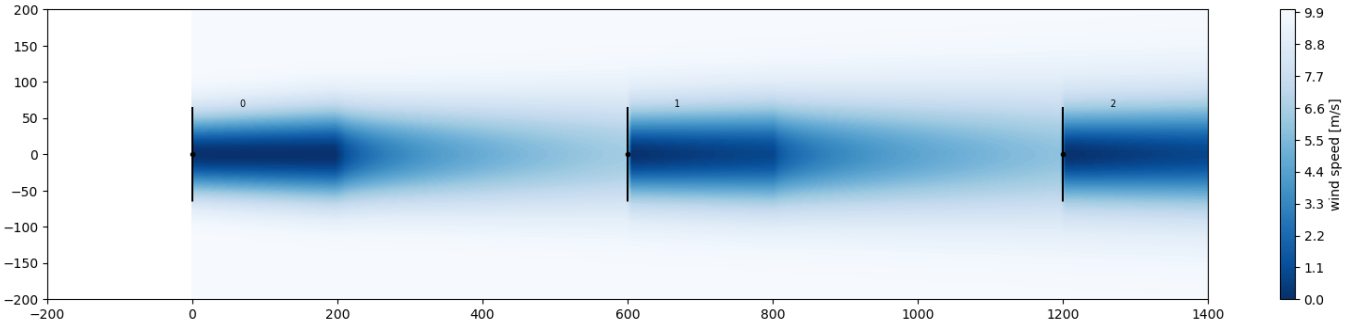
Move the sliders above and try to find the optimal yaw-misalignment of WT0 and WT1 with respect to total AEP

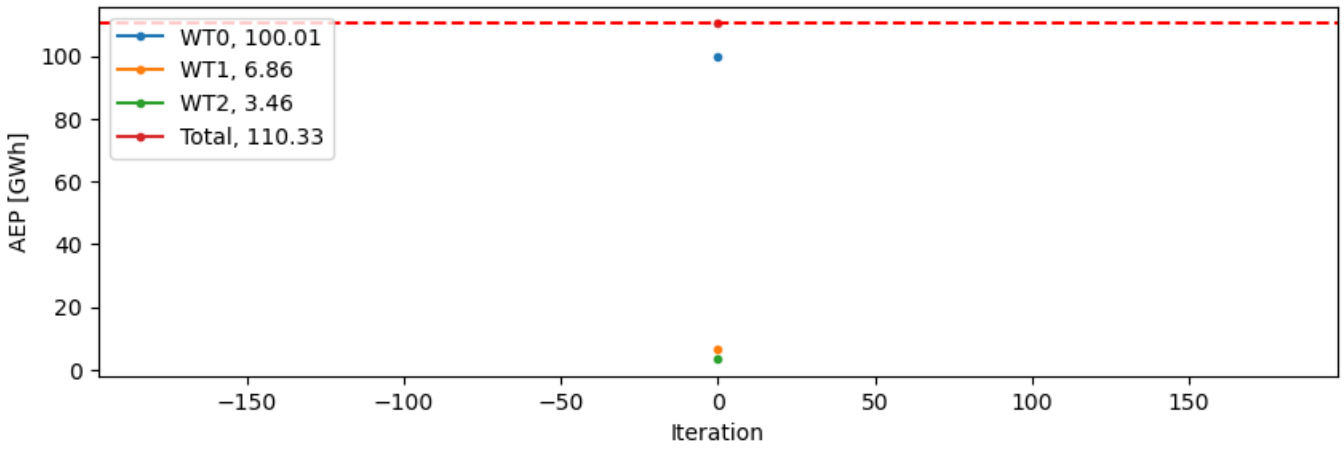
[5]:
```
# Run the plot_flow_field_and_aep function when moving the sliders
aep = []
_ = interact(plot_flow_field_and_aep,
             WT0=IntSlider(min=-50, max=50, step=1, value=0, continuous_update=False),
             WT1=IntSlider(min=-50, max=50, step=1, value=0, continuous_update=False),
             TILT=IntSlider(min=-15, max=15, step=1, value=0, continuous_update=False)
             )
```

WT0 0

WT1 0

TILT 0





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Ørsted TurbOPark

This notebook reproduces the results and figures of the two examples provided by Ørsted in
https://github.com/OrstedRD/TurbOPark/blob/main/TurbOParkExamples.mlx

The PyWake look-up table used for the GaussianOverlap model is slightly different from look-up table used by Ørsted (which has a finer grid resolution). T
are therefore slightly different (relative error < 1e-5).

Install PyWake if needed

[1]:
```
# Install PyWake if needed
try:
    import py_wake
except ModuleNotFoundError:
    !pip install git+https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake.git
```

Setting up the wind turbine and site objects

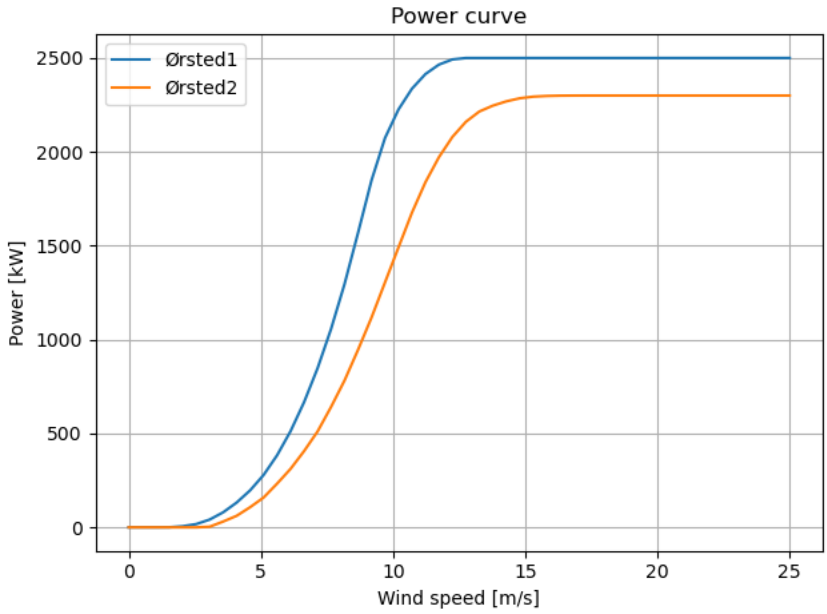
[2]:
```
import numpy as np
import matplotlib.pyplot as plt

from py_wake.wind_turbines._wind_turbines import WindTurbine, WindTurbines
from py_wake.wind_turbines.power_ct_functions import PowerCtTabular
from py_wake.site._site import UniformSite
from py_wake.site.shear import PowerShear
from py_wake.utils.plotting import setup_plot
```

Specifying the wind speed and power and CT curve

[3]:
```
u = np.arange(0, 25.5, .5)
po = [0, 0, 0, 0, 5, 15, 37, 73, 122, 183, 259, 357, 477, 622, 791, 988, 1212, 1469, 1755, 2009, 2176, 2298, 2388, 2447, 2485, 2500, 2500, 2500
      2500, 2500, 2500, 2500, 2500, 2500, 2500, 2500, 2500, 2500, 2500, 2500, 2500, 2500, 2500, 2500, 2500,
      2500, 2500, 2500, 2500, 2500, 2500, 2500, 0]
ct = [0, 0, 0, 0, 0.78, 0.77, 0.78, 0.78, 0.77, 0.77, 0.78, 0.78, 0.78, 0.78, 0.78, 0.78, 0.77, 0.77, 0.77, 0.76, 0.73, 0.7, 0.68, 0.52, 0.42,
      0.36, 0.31, 0.27, 0.24, 0.22, 0.19, 0.18, 0.16, 0.14, 0.13, 0.12, 0.11, 0.1, 0.09, 0.08, 0.08, 0.08, 0.07, 0.07, 0.06, 0.06, 0.06,
      0.05, 0.05, 0.05, 0.04, 0]

wt1 = WindTurbine(name="Ørsted1", diameter=120, hub_height=100, powerCtFunction=PowerCtTabular(u, po, 'kw', ct))

u2 = np.arange(0, 27)
pow2 = [0, 0, 0, 0, 54, 144, 289, 474, 730, 1050, 1417, 1780, 2041, 2199, 2260, 2292, 2299, 2300, 2300, 2300, 2300, 2300, 2300, 2300, 2300, 230
ct2  = [0, 0, 0, 0, 0.94, 0.82, 0.76, 0.68, 0.86, 0.83, 0.77, 0.68, 0.66, 0.52, 0.47, 0.41, 0.38, 0.34, 0.27, 0.26, 0.23, 0.22, 0.22, 0.2, 0.18
wt2 = WindTurbine(name="Ørsted2", diameter=80, hub_height=70, powerCtFunction=PowerCtTabular(u2, pow2, 'kw', ct2))
wts = WindTurbines.from_WindTurbine_lst([wt1,wt2])
```

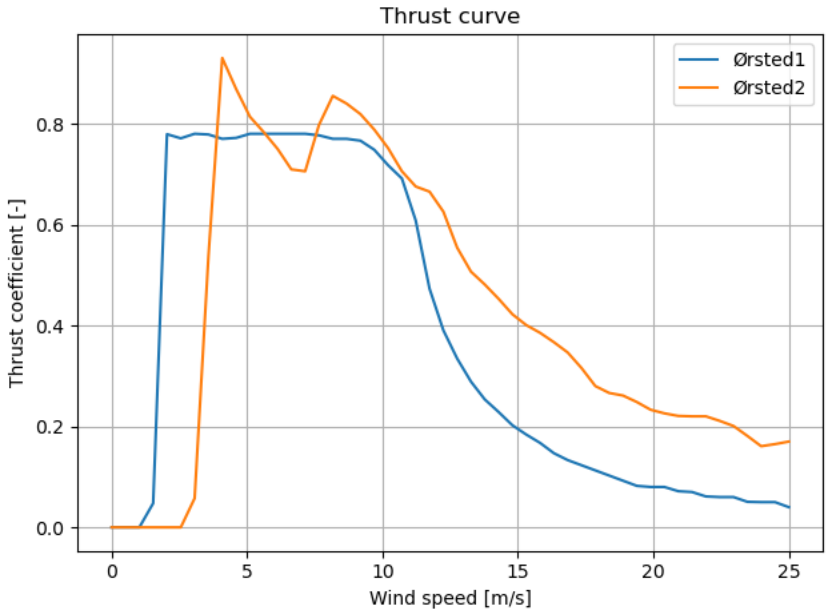
Plotting the power curve

[4]:
```
u = np.linspace(0,25)

for t in [0,1]:
    plt.plot(u,wts.power(u, type=t)/1000, label=wts.name(t))
setup_plot(xlabel='Wind speed [m/s]', ylabel='Power [kW]', title='Power curve')
```



Plotting the CT curve

[5]:
```
for t in [0,1]:
    plt.plot(u,wts.ct(u, type=t), label=wts.name(t))
setup_plot(xlabel='Wind speed [m/s]', ylabel='Thrust coefficient [-]', title='Thrust curve')
```

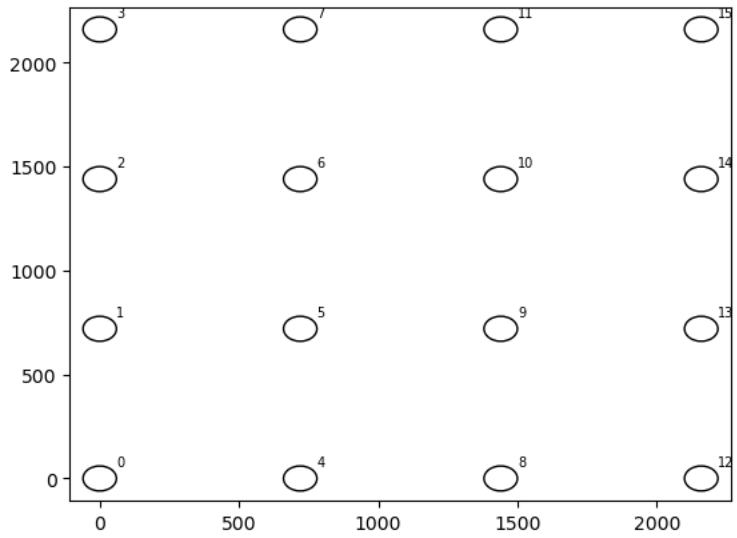


Wind speed, wind direction and turbulence intensity

[6]:
```
u0 = [6,10,14]          # [m/s]
wd = 270                # [deg]
ti0 = [0.09,.1,.11]     # [-]
```

Example 1 - Square farm with identical turbines

[7]:
```
y, x = [v.flatten() for v in np.meshgrid(np.arange(4) * 120 * 6, np.arange(4) * 120 * 6)]
wt1.plot(x, y)
```



[8]:
```
site = UniformSite(shear=PowerShear(h_ref=90, alpha=.1))
```

[9]:
```
from py_wake.literature import Nygaard_2022

wfm = Nygaard_2022(site, wt1)
sim_res = wfm(x, y, ws=u0, wd=wd, TI=ti0)
sim_res.WS_eff
```

[9]:

xarray.DataArray 'WS_eff' (**wt**: 16, **wd**: 1, **ws**: 3)

Coordinates:

Indexes: (3)

Attributes:

We now calculate the power of each turbine in the wind farm

[10]:
```
sim_res.Power /1000
```

[10]:

xarray.DataArray 'Power' (**wt**: 16, **wd**: 1, **ws**: 3)

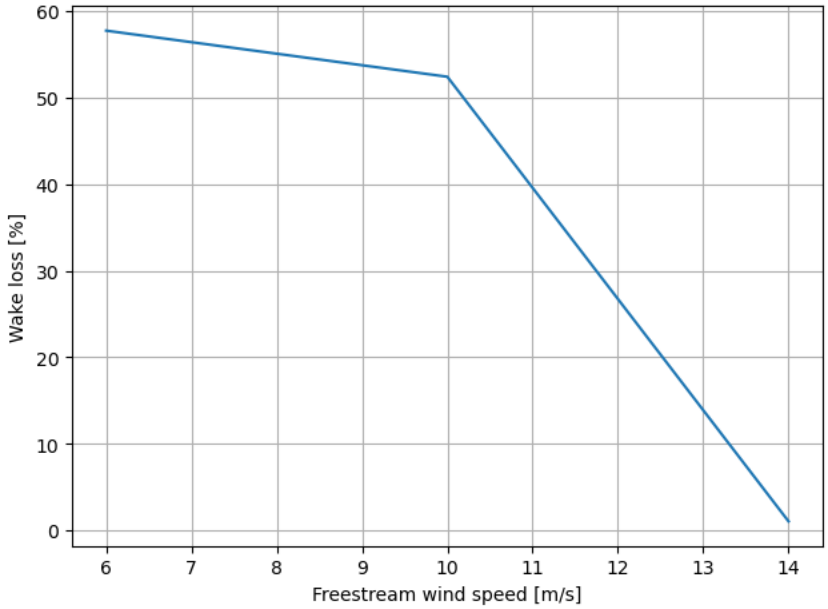
Coordinates:

Indexes: (3)

Attributes: (0)

Then, we calculate the wake losses

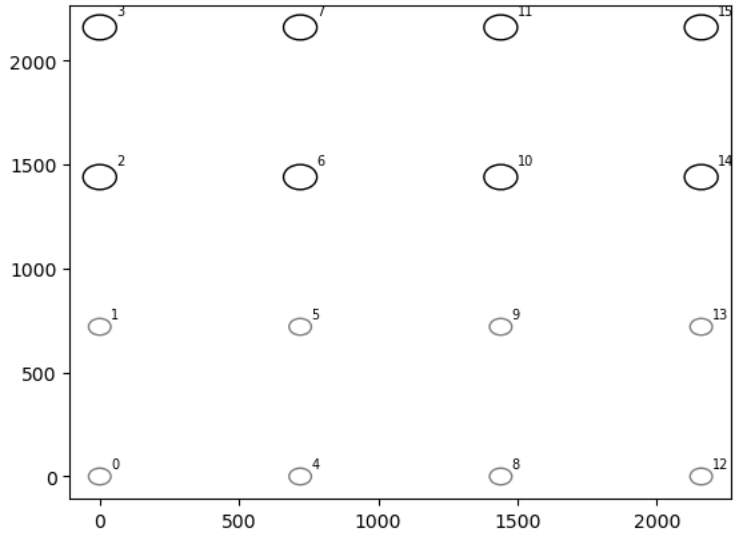
[11]:
```
((1-(sim_res.Power.mean('wt') / sim_res.Power.max('wt')))*100).plot()
setup_plot(ylabel='Wake loss [%]', xlabel='Freestream wind speed [m/s]')
```



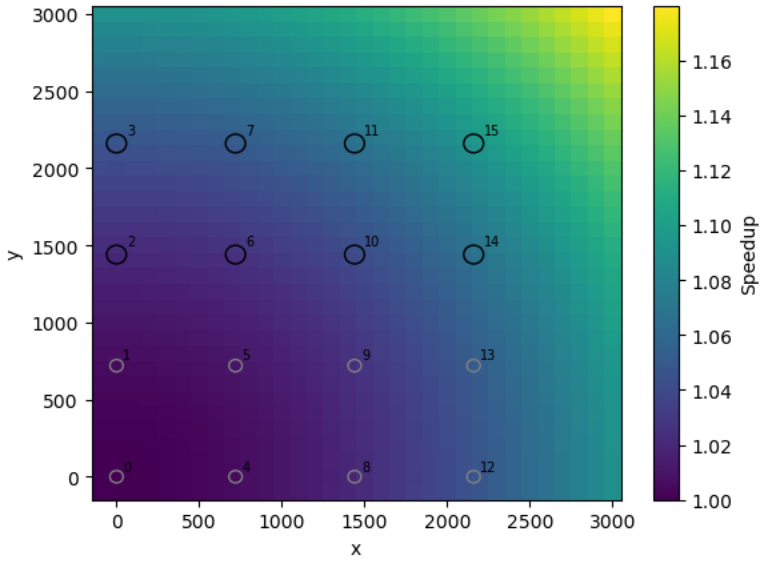
Example 2 - Two turbine types plus wind speed gradient

First we set up the two types of wind turbines in the farm

[12]:
```
type = np.array([1,1,0,0]*4)
wts.plot(x, y, type=type)
```



[13]:
```
import xarray as xr
from py_wake.site import XRSite

x_pt = np.arange(-100,3100,100)
Y_pt,X_pt = np.meshgrid(x_pt,x_pt)
grad = ((X_pt-5)**2 + (Y_pt)**2)*10**(-8) + 1
speedup= grad/grad[1,1]
ds = xr.Dataset({'Speedup':(('x','y'), speedup), 'P':1}, coords={'x':x_pt,'y':x_pt})
ds.Speedup.plot()
wts.plot(x, y, type=type)
```



We now specify the gradients of the wind speed

[14]:
```
gradient_site = XRSite(ds=ds, shear=PowerShear(h_ref=90, alpha=.1))
gradient_site.local_wind(x,y,wts.hub_height(type), ws=1)['WS_ilk']
```

[14]:
```
array([[[0.97518172]],

       [[0.98025267]],

       [[1.03157163]],

       [[1.05776616]],

       [[0.98018245]],

       [[0.9852534 ]],

       [[1.03675394]],

       [[1.06294848]],

       [[0.99528606]],

       [[1.00035701]],

       [[1.05240599]],

       [[1.07860052]],

       [[1.02049256]],

       [[1.0255635 ]],

       [[1.07852775]],

       [[1.10472229]]])
```

[15]:
```
from py_wake.literature import Nygaard_2022

wfm = Nygaard_2022(gradient_site, wts)
sim_res = wfm(x, y, ws=u0, wd=wd, type=type, TI=ti0)
sim_res.WS_eff
```

[15]:

xarray.DataArray 'WS_eff' (**wt**: 16, **wd**: 1, **ws**: 3)

Coordinates:

Indexes: (3)

Attributes:

Now we can again calculate the power for the new wind farm configuration

[16]:
```
sim_res.Power / 1000
```

[16]:

xarray.DataArray 'Power' (wt: 16, wd: 1, ws: 3)

Coordinates:

Indexes: (3)

Attributes: (0)

[17]:
```
#turbulence intensity
sim_res.TI
```

[17]:

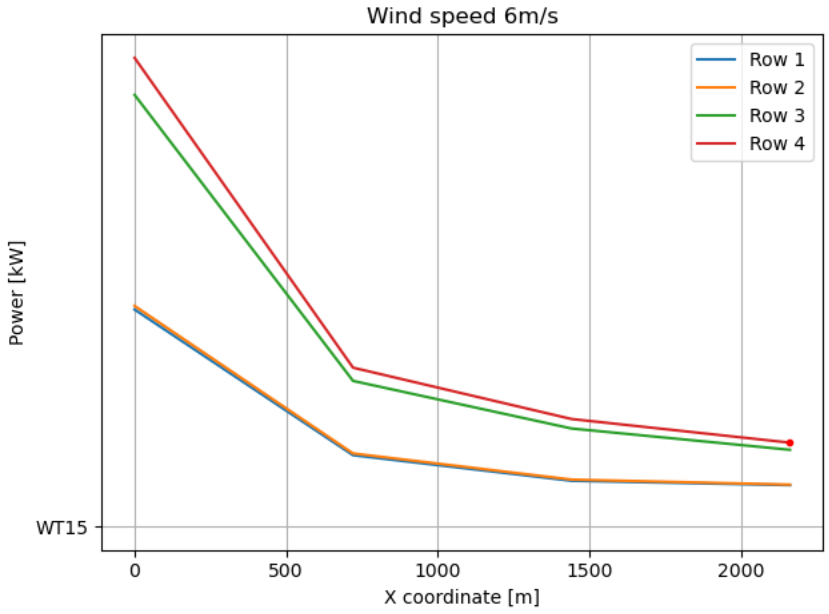
xarray.DataArray 'TI' (ws: 3)

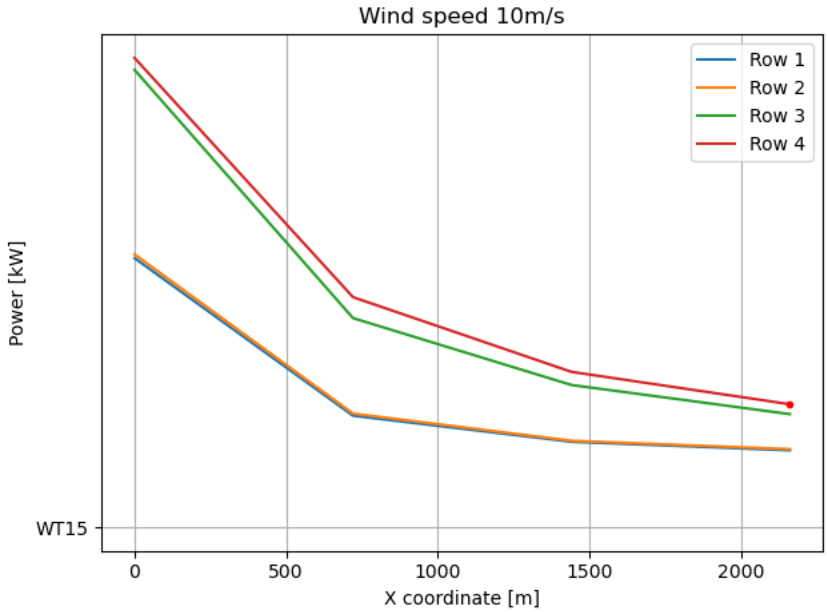
Coordinates:

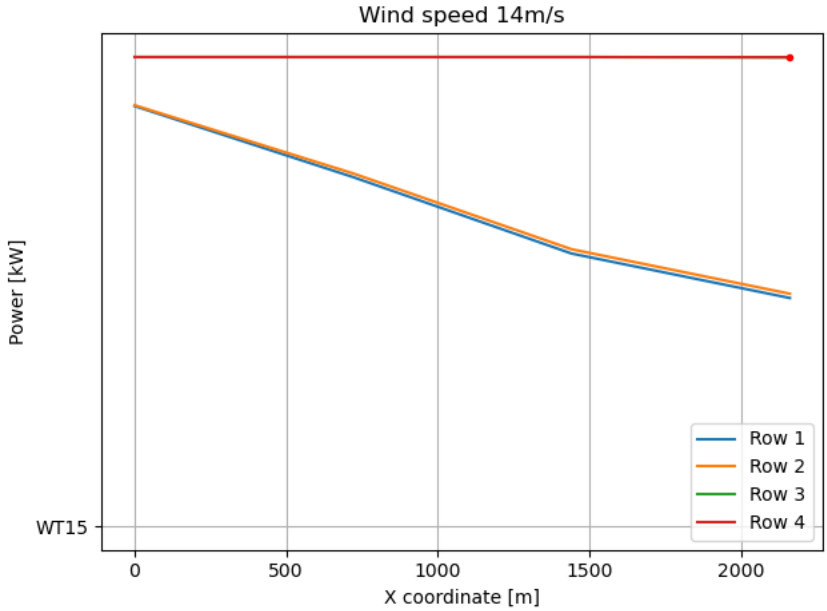
Indexes: (1)

Attributes:

[18]:
```
for ws in u0:
    plt.figure()
    for row, p in enumerate((sim_res.Power.sel(ws=ws, wd=270).values.reshape((4,4))).T/1000,1):
        plt.plot(sim_res.x[::4], p, label=f'Row {row}')
    plt.plot(sim_res.x.sel(wt=15), sim_res.Power.sel(ws=ws, wd=270,wt=15)/1000,'.r', 'WT15')
    setup_plot(title=f'Wind speed {ws}m/s', ylabel='Power [kW]', xlabel='X coordinate [m]')
```







Gaussian Wake Deficit Models

This notebook reproduces the results of several papers presenting different versions of Gaussian wake models. They are presented in order of their publication dates.

Whilst PyWake defines wake models very generalisticly, some PyWake wind farm models have been defined to reproduce how they were originally published. For the Gaussian wake models these can be found in `py_wake/literature/gaussian_models.py`. That script is also a good starting point to check how you can setup your own Gaussian wind farm model.

[1]:
```
%load_ext autoreload
%autoreload 2

# install PyWake if needed
try:
    import py_wake
except ModuleNotFoundError:
    !pip install git+https://gitlab.windenergy.dtu.dk/TOPFARM/PyWake.git

# import general
import numpy as np
import matplotlib.pyplot as plt
import os
```

Bastankhah and Porté-Agel (2014)

This section reproduces results from

Bastankhah M and Porté-Agel F.: *A new analytical model for wind-turbine wakes*, J. Renew. Energy., 70:116-23, (2014), https://doi.org/10.1016/j.renene.2014.01.002

This paper presents a general definition of a wake model with Gaussian profile shape that obeys momentum conservation for an isolated turbine and can be seen as the foundation of the Gaussain wake model family. All subsequent model developments are based on the assumptions defined within this paper.

Site and wind turbine

Define dummy wind turbine with fixed C_T and simple site. We basically define a C_T curve that is constant by setting the values at very large and low wind speed. Power is not needed, therefore it is set to zero. The site is needed in the simulation but it has no influence on the computed deficit, as the deficit is substracted from the background mean-flow. The deficit model does not respond to changes in turbulence intensity.

[2]:
```
from py_wake.wind_turbines import WindTurbine
from py_wake.wind_turbines.power_ct_functions import PowerCtTabular
from py_wake.site._site import UniformSite

class Dummy(WindTurbine):
    def __init__(self, name='dummy', ct=0.8, d=80., zh=70.):
        WindTurbine.__init__(self, name=name, diameter=d,
                             hub_height=zh, powerCtFunction=PowerCtTabular([-100, 100], [0, 0], 'kW', [ct, ct]))

class BastankhahSite(UniformSite):
    def __init__(self, ws=10., ti=0.04):
        UniformSite.__init__(self, ti=ti, ws=ws)
```

Wind farm model

The paper is not really defining a wind farm model at all, but only a deficit model. However, in PyWake we need to define these to simulate wake flows, thus we defined a literature model that uses some reasonable presets, which is loaded here.

Note that this model requires the user to input the wake expansion factor, k (called k^* in the paper).

[3]:
```
from py_wake.literature.gaussian_models import Bastankhah_PorteAgel_2014
```

Validation

To validate our implementation we choose to compare data from Fig.7 of the paper, as this tests the wake shape, wake expansion and centre line deficit at the same time. Only wake profiles will be compared, as they provide the most quantitative comparison. Here we limit it to cases 2 and 3, computed at $x/D = [3, 5]$, where D is the rotor diameter and x the downstream distance from the rotor plane. This is sufficient to demonstrate that the model is implemented correctly.

The inputs for the simulation are taken from Table 1 and Fig. 7. Table 1 provides wind turbine and inflow parameters (shear is not needed, for reasons mentioned before) and Fig. 4 provides the wake expansion factors for each case that were fitted to LES data. Note that the initial wake size, ϵ, is not taken from Fig. 4, but computed as defined in the paper in Eq.(21) using $0.2\sqrt{\beta}$.

Case definition

[4]:
```
# expansion factors (taken from Fig.4)
ks = [0.055, 0.040]
# hub height wind speed
ws = 9.
# rotor diameter
d = 80.
# rotor hub height
zh = 70.
# rotor thrust coefficient
ct = 0.8
```

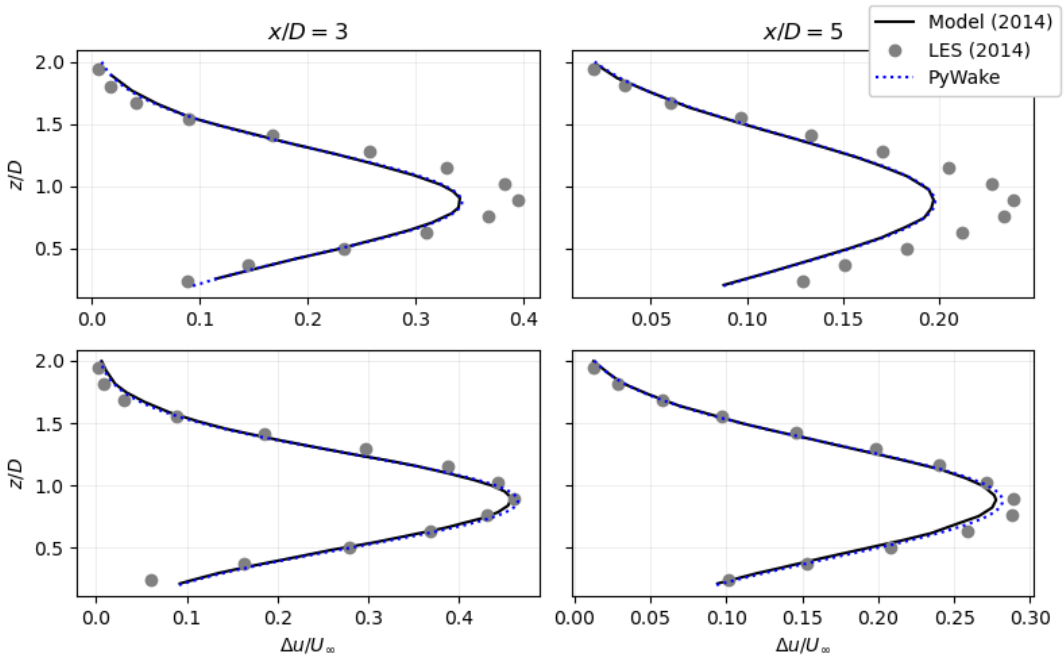
Fig. 7 reproduction

Load reference data

[5]:
```
# load reference data extracted manually from Fig.7 of the paper (only cases 2 and 3 at x/d=3, 5)
dat = np.genfromtxt(os.path.join('data', 'Gaussian', 'Basthankhah_PorteAgel_2014_Fig7.csv'),
                    skip_header=2, delimiter=',')

cases = ['case_2', 'case_3']
# downstream position
xd = [3., 5.]
names = ['LES', 'model']
ref_fig7 = {}
for i, case in enumerate(cases):
    tmp = {}
    for j, name in enumerate(names):
        tmp2 = np.zeros((dat.shape[0], len(xd), 2))
        for k in range(len(xd)):
            col = 8 * i + 2 * j + 4 * k
            tmp2[:, k, [0, 1]] = dat[:, [col, col + 1]]
        tmp[name] = tmp2
    ref_fig7[case] = tmp
```

Simulation and plotting

[6]:
```
from py_wake.flow_map import XZGrid

# normal point distribution for plotting
zd = np.linspace(0.2, 2., 201)

# define wind turbine and site
wt = Dummy(ct=ct, d=d, zh=zh)
site = BastankhahSite(ws=ws)

fig, ax = plt.subplots(2, 2, sharey=True, figsize=(8, 5))
for i, (case, k) in enumerate(zip(cases, ks)):
    # wind farm model, you need to set the expansion factor, k
    wfm = Bastankhah_PorteAgel_2014(site, wt, k)
    # simulation
    sim = wfm(x=[0.], y=[0.], wd=270., ws=ws)
    # wake profiles
    u = np.squeeze(sim.flow_map(XZGrid(y=0.0, x=np.array(xd) * d, z=zd  * d)).WS_eff)
    for j in range(len(xd)):
        ax[i, j].plot(ref_fig7[case]['model'][:, j, 0], ref_fig7[case]['model'][:, j, 1], 'k-', label='Model (2014)')
        ax[i, j].plot(ref_fig7[case]['LES'][:, j, 0], ref_fig7[case]['LES'][:, j, 1], 'o', color=0.5 * np.ones(3), label='LES (2014)')
        ax[i, j].plot(1. - u[:, j] / ws, zd, 'b:', label='PyWake')
        if i == 0:
            ax[i, j].set_title(r'$x/D={:.0f}$'.format(xd[j]))
        if i == 1:
            ax[i, j].set_xlabel(r'$\Delta u/ U_{\infty}$')
        if j == 0:
            ax[i, j].set_ylabel(r'$z/D$')
        ax[i, j].grid(lw=0.5, alpha=0.3)
lines, labels = ax[0, 0].get_legend_handles_labels()
leg = fig.legend(lines, labels, loc='upper right')
leg.get_frame().set_alpha(1.0)
fig.tight_layout()
```



The agreement between PyWake and the paper is perfect, with any deviations being easily attributed to the manual extraction of data from the paper (the plot is rather small).

Niayifar and Porté-Agel (2016)

This section reproduces results from

Niayifar A and Porté-Agel F.: *Analytical Modeling of Wind Farms: A New Approach for Power Prediction*, Energies, 9(9), 741, (2016), https://doi.org/10.3390/en9090741

This paper defines a wind farm model using the Gaussian wake model by Bastankhah and Porté-Agel (2014). Important additions are:

- inflow turbulence intensity depended wake expansion
- linear wake superposition

Site and wind turbine

The paper presents results for Horns Rev 1, which are available in PyWake.

[7]:
```
from py_wake.examples.data.hornsrev1 import Hornsrev1Site, V80, wt_x, wt_y
v80_pw = V80()
site = Hornsrev1Site()
```

Unfortunatley it remains somewhat unclear what thrust and power curves the authors used for the Vestas V-80 in their simulations. Only after testing a lot of different possibilities were we able to reproduce their results.

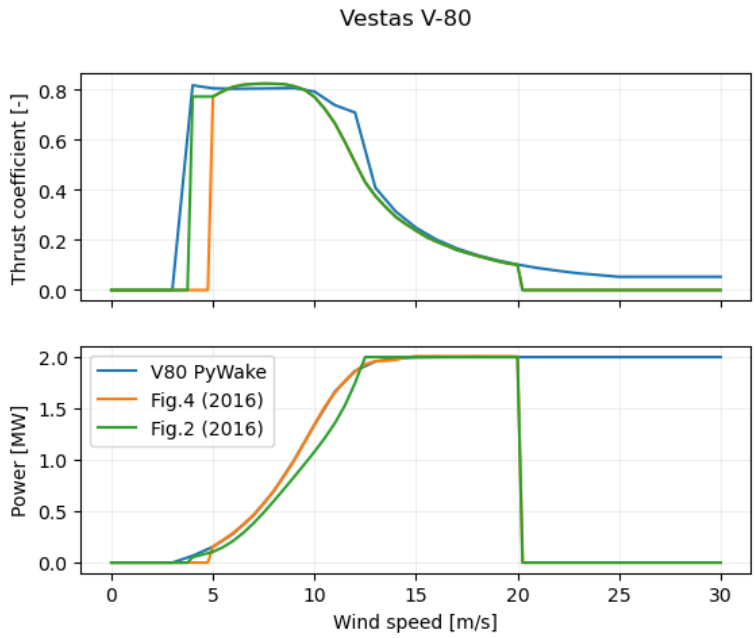
They present a fitted power curve in Fig. 2, but also show 2 more pairs of curves in Fig. 4 (observed and predicted) without clearly stating which curves were exactly used. Here we show how much these different V-80 definitions differ and also compare it to the one in PyWake. From Fig. 4 only the curves labelled *predicted* were extracted manually from the paper. In Fig. 2 no thrust curve has been defined so we used the one from Fig. 4, instead. Yet there is another issue in that case. The curves in Fig. 4 only start at a wind speed of 5 m/s, but the one in Fig. 4 starts at 4 m/s, the we take the C_T from Fig. 4 but need to add another value at 4 m/s, which is simply set to the C_T at 5 m/s.

[8]:
```
# load reference data extracted manually from Fig.5 of the paper
dat = np.genfromtxt(os.path.join('data', 'Gaussian', 'Niayifar_PorteAgel_2016_Fig4.csv'),
                    skip_header=2, delimiter=',')

v80_2016_fig4 = WindTurbine(name="V80 (2016: Fig.4)", diameter=80., hub_height=70.,
                            powerCtFunction=PowerCtTabular(dat[:, 2], dat[:, 3], 'MW', dat[:, 1]), method='pchip')
# Fig. 2 provides a fit for power but not CT, so we take the CT from Fig. 4
# but need to add another value at 4 m/s, which is simply set to the CT at 5 m/s
ws = np.hstack((np.array([3.9, 4.0]), dat[1:, 2]))
ct = np.hstack((np.array([0.0, dat[1, 1]]), dat[1:, 1]))
power = (0.17819 * ws**5 - 6.5198 * ws**4 + 90.623 * ws**3 - 574.62 * ws**2 + 1727.2 * ws - 1975)
power[power > 2000.] = 2000.
power[ws < 4] = 0.0
power[ws > 20] = 0.0
```

```
v80_2016_fig2 = WindTurbine(name="V80 (2016: Fig.2)", diameter=80., hub_height=70.,
                            powerCtFunction=PowerCtTabular(ws, power, 'kW', ct), method='pchip')
```

[9]:
```
from py_wake.utils.plotting import setup_plot

ws = np.linspace(0, 30, 121)

fig, ax = plt.subplots(2, 1, sharex=True)
plt.figure()
ax[0].plot(ws, v80_pw.ct(ws), '-', label='PyWake')
ax[0].plot(ws, v80_2016_fig4.ct(ws), '-', label='Fig.4 (2016)')
ax[0].plot(ws, v80_2016_fig2.ct(ws), '-', label='Fig.2 (2016)')
ax[0].grid(lw=0.5, alpha=0.3)
ax[0].set_ylabel('Thrust coefficient [-]')

ax[1].plot(ws, v80_pw.power(ws) / 1.e6, '-', label='V80 PyWake')
ax[1].plot(ws, v80_2016_fig4.power(ws) / 1.e6, '-', label='Fig.4 (2016)')
ax[1].plot(ws, v80_2016_fig2.power(ws) / 1.e6, '-', label='Fig.2 (2016)')
ax[1].grid(lw=0.5, alpha=0.3)
ax[1].set_ylabel('Power [MW]')
ax[1].set_xlabel('Wind speed [m/s]')
fig.suptitle('Vestas V-80')
ax[1].legend()
```

[9]:
```
<matplotlib.legend.Legend at 0x7f296f102800>
```

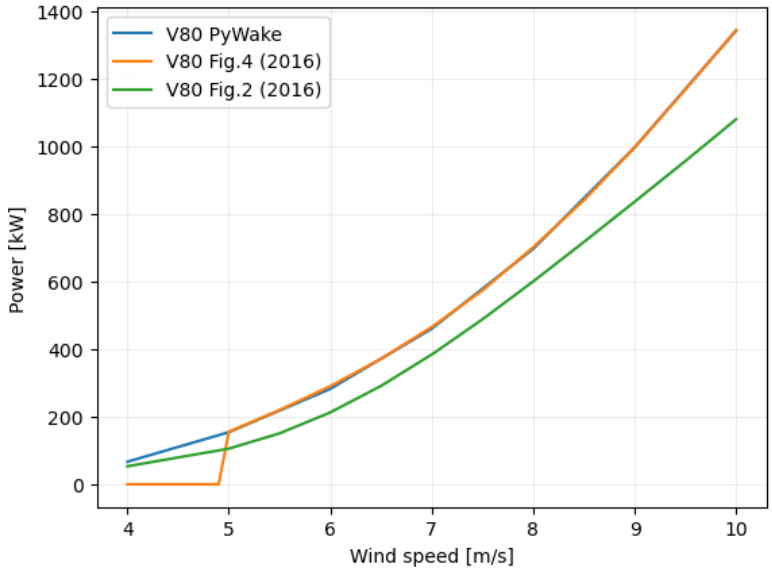



```
<Figure size 640x480 with 0 Axes>
```

In the following plot we recreate Fig. 2 but adding the power curves from PyWake and Fig. 4 to show the difference between them. For some reason the power is lower in Fig. 2.

[10]:
```
ws = np.linspace(4, 10, 121)
plt.figure()
plt.plot(ws, v80_pw.power(ws) / 1.e3, '-', label='V80 PyWake')
plt.plot(ws, v80_2016_fig4.power(ws) / 1.e3, '-', label='V80 Fig.4 (2016)')
plt.plot(ws, v80_2016_fig2.power(ws) / 1.e3, '-', label='V80 Fig.2 (2016)')
plt.legend()
plt.grid(lw=0.5, alpha=0.3)
plt.ylabel('Power [kW]')
plt.xlabel('Wind speed [m/s]')
```

[10]:
```
Text(0.5, 0, 'Wind speed [m/s]')
```



Wind farm model

The wind farm model uses the Gaussian wake model together with linear wake deficit summation and a wake expansion factor that respionds to the local inflow turbulence intensity (TI). The added TI is computed using the model by Crespo and Hernandez (1996) with slightly modified constants. The square of the local TI is defined as the sum of the ambient TI and the maximum weighted (by wake-rotor overleap area) added TI.

[11]:
```
from py_wake.literature.gaussian_models import Niayifar_PorteAgel_2016
```

Validation

Case definition

[12]:
```
# hub height wind speed
ws = 8.0
# ambient turbulence intensity
ti = 0.077
# wind directions
wd = np.arange(173., 354., 1.)
```

PyWake Simulation

The paper does not cearly state how the rotor reference velocity is computed (used to scale the deficit and look-up the thrust and power). So here we try both, the PyWake default, which is the `RotorCenter()` method, and the `GaussianOverlapAvgModel()` (set as default in the literature model, but set here explicitly for clarity), which averages velocities over the rotor disc. This will also demonstrate how the rotor-averaging can influence your results. Furthermore, we test the different definitions of the Vestas V-80 given in the paper.

[13]:
```
from py_wake.rotor_avg_models import RotorCenter
from py_wake.rotor_avg_models.gaussian_overlap_model import GaussianOverlapAvgModel

# instantiate wind farm model
wfm_rc = Niayifar_PorteAgel_2016(site, v80_2016_fig4, rotorAvgModel=RotorCenter())
wfm_ga = Niayifar_PorteAgel_2016(site, v80_2016_fig4, rotorAvgModel=GaussianOverlapAvgModel())
wfm_ga_fig2 = Niayifar_PorteAgel_2016(site, v80_2016_fig2, rotorAvgModel=GaussianOverlapAvgModel())
# run simulation
sim_rc = wfm_rc(wt_x, wt_y, TI=ti, ws=ws, wd=wd)
sim_ga = wfm_ga(wt_x, wt_y, TI=ti, ws=ws, wd=wd)
sim_ga_fig2 = wfm_ga_fig2(wt_x, wt_y, TI=ti, ws=ws, wd=wd)
```

Reproduction of Fig. 5

This figure compares the wind farm efficieny predicted by LES simulations and the Gaussian wind farm model at a single wind speed.

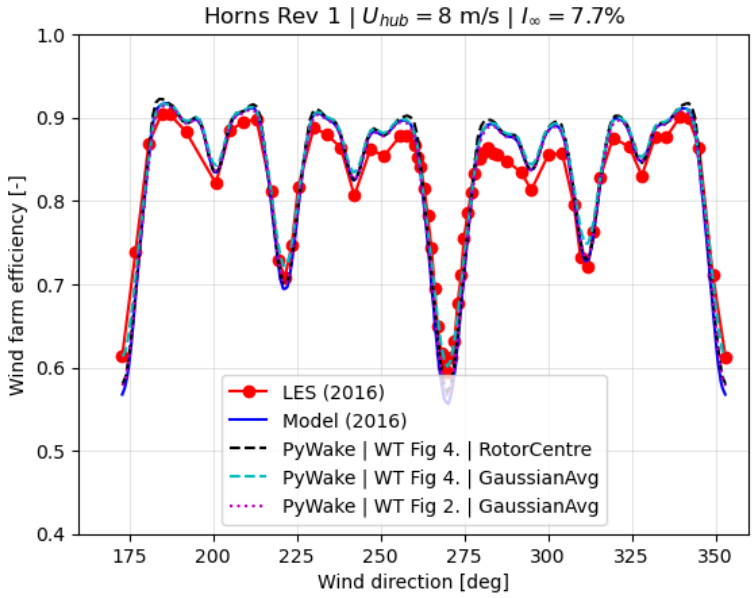
Load reference data

[14]:
```
# load reference data extracted manually from Fig.5 of the paper
dat = np.genfromtxt(os.path.join('data', 'Gaussian', 'Niayifar_PorteAgel_2016_Fig5.csv'),
                    skip_header=2, delimiter=',')
ref_fig5 = {}
ref_fig5['LES'] = dat[:, :2]
ref_fig5['model'] = dat[:, 2:]
```

Plotting

[15]:
```
plt.figure()
plt.plot(ref_fig5['LES'][:, 0], ref_fig5['LES'][:, 1], 'ro-', label='LES (2016)')
plt.plot(ref_fig5['model'][:, 0], ref_fig5['model'][:, 1], 'b-', label='Model (2016)')
plt.plot(wd, sim_rc.Power.sum(axis=0)[:, 0] / (len(wt_x) * v80_2016_fig4.power(ws=ws)), 'k--', label='PyWake | WT Fig 4. | RotorCentre')
plt.plot(wd, sim_ga.Power.sum(axis=0)[:, 0] / (len(wt_x) * v80_2016_fig4.power(ws=ws)), 'c--', label='PyWake | WT Fig 4. | GaussianAvg')
plt.plot(wd, sim_ga_fig2.Power.sum(axis=0)[:, 0] / (len(wt_x) * v80_2016_fig2.power(ws=ws)), 'm:', label='PyWake | WT Fig 2. | GaussianAvg')
plt.axis([160, 360, 0.4, 1.0])
plt.xlabel('Wind direction [deg]')
plt.ylabel('Wind farm efficiency [-]')
plt.title('Horns Rev 1 | $U_{hub}=8$ m/s | $I_{\infty}=7.7$%')
plt.grid('on', lw=0.5, alpha=0.5)
plt.legend()
```

[15]:
```
<matplotlib.legend.Legend at 0x7f299ca02b30>
```



The agreement is nearly perfect. Interestingly using the `GaussianOverlapAvgModel()` the results are closer to the LES predictions when the turbine rows are aligning ie. in situations of full-wake.

Reproduction Fig. 6

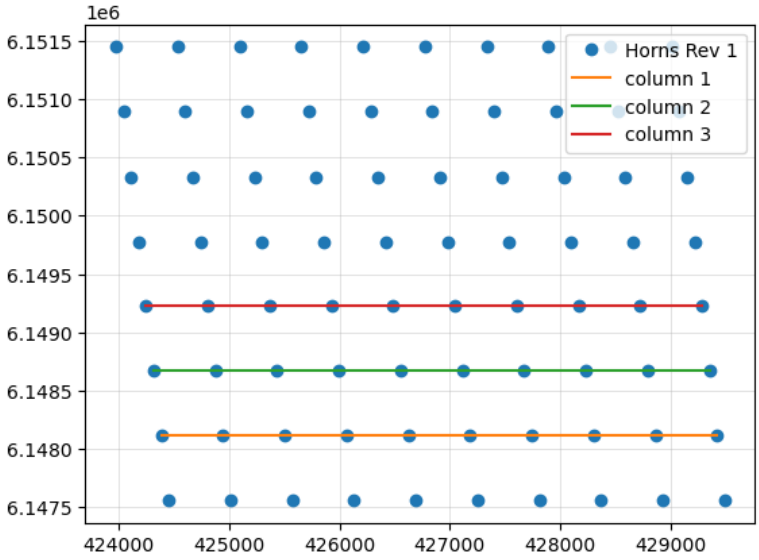
This figure compares the power production evolution along a row of turbines for a wind direction of 270 degrees, constiuting a full-wake situation.

Load reference data

[16]:
```
# load reference data extracted manually from Fig.5 of the paper
dat = np.genfromtxt(os.path.join('data', 'Gaussian', 'Niayifar_PorteAgel_2016_Fig6.csv'),
                    skip_header=2, delimiter=',')
ref_fig6 = {}
ref_fig6['model'] = dat[:, :2]
ref_fig6['LES'] = dat[:, 2:]
```

The turbine numbering is different in the paper than in PyWake, but they mention that they average over columns 2, 3 and 4 (a column in the paper refers to turbine row spanning from east to west, with the southernmost being column 1). The following plot shows the turbine rows to be selected for the plot.

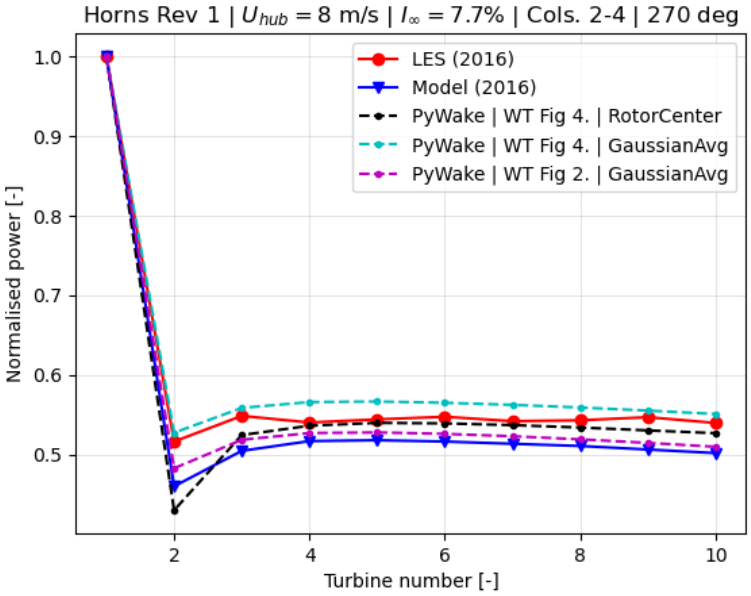
[17]:
```
plt.figure()
plt.plot(wt_x, wt_y, 'o', label='Horns Rev 1')
for i in range(3):
    plt.plot(wt_x[8 - (i + 2)::8], wt_y[8 - (i + 2)::8], '-', label='column {}'.format(i + 1))
plt.grid('on', lw=0.5, alpha=0.5)
leg = plt.legend()
```



Plot Fig. 6

[18]:
```
plt.figure()
iwt = np.linspace(1, 10, 10)
plt.plot(iwt, ref_fig6['LES'][:, 1], 'ro-', label='LES (2016)')
plt.plot(iwt, ref_fig6['model'][:, 1], 'bv-', label='Model (2016)')

# select wind direction 270 degrees
iwd = 97
# select columns
pp = np.zeros((3, 10, 3))
for i in range(pp.shape[0]):
    pp[i, :, 0] = sim_rc.Power.values[8 - (i + 2)::8, iwd, 0]
    pp[i, :, 1] = sim_ga.Power.values[8 - (i + 2)::8, iwd, 0]
    pp[i, :, 2] = sim_ga_fig2.Power.values[8 - (i + 2)::8, iwd, 0]
# average over columns
pp_avg = np.mean(pp, axis=0)
# plot results
plt.plot(iwt, pp_avg[:, 0] / pp_avg[0, 0], 'k.--', label='PyWake | WT Fig 4. | RotorCenter')
plt.plot(iwt, pp_avg[:, 1] / pp_avg[0, 1], 'c.--', label='PyWake | WT Fig 4. | GaussianAvg')
plt.plot(iwt, pp_avg[:, 2] / pp_avg[0, 2], 'm.--', label='PyWake | WT Fig 2. | GaussianAvg')

plt.xlabel('Turbine number [-]')
plt.ylabel('Normalised power [-]')
plt.title('Horns Rev 1 | $U_{hub}=8$ m/s | $I_{\infty}=7.7$% | Cols. 2-4 | ' + '{:.0f} deg'.format(sim_ga.wd.values[iwd]))
plt.grid('on', lw=0.5, alpha=0.5)
plt.legend()
```

[18]: `<matplotlib.legend.Legend at 0x7f299c9012d0>`



Following some detective work, it seems that some sort of rotor-averaging was indeed used by the authors, as indicated by the PyWake curves with `GaussianOverlapAvgModel()` having similar shapes. The slight offset between PyWake and the results from the paper might be due to differences in the thrust curve, specific rotor-averaging method used or related to the manual extraction of the data from the figure.

Carbajo Fuertes et al. (2018)

This section presents our implementation of the modifications presented in

Carbajo Fuertes, F., Markfort, C. D., & Porté-Agel, F.: *Wind turbine wake characterization with nacelle-mounted wind lidars for analytical wake model validation*, Remote Sensing, 10(5), 668, (2018), https://doi.org/10.3390/rs10050668

to the Gaussian model by Niayifar et al. (2016). In this paper they use wind lidar measurements taken in the wake of a 2.5MW turbine to retune the expression for the wake width, σ, in the Gaussian model. An important change is that the initial wake width, ϵ, becomes a function of the wake expansion rate, k, and thereby becomes dependant on turbulence intensity.

Comparison

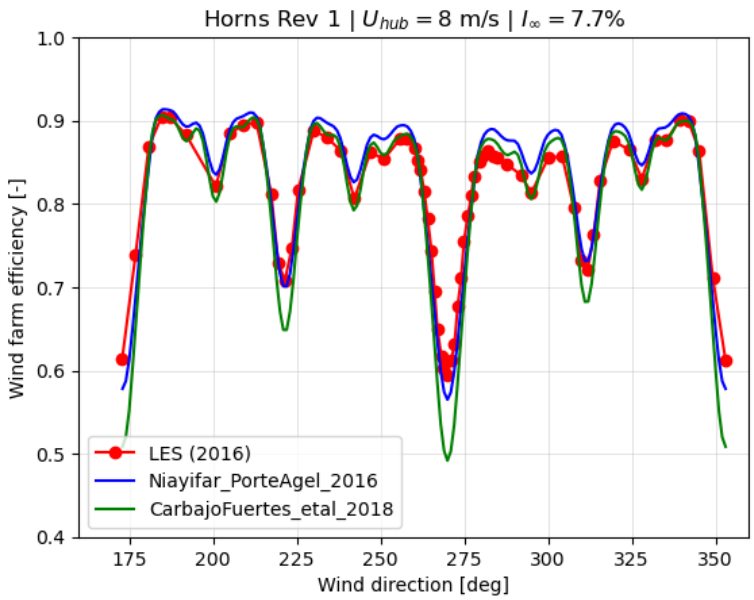
To show the impact of the modification we rerun the Horns Rev 1 case used by Niayifar and PorteAgel (2016).

[19]:
```
from py_wake.literature.gaussian_models import CarbajoFuertes_etal_2018

# instantiate
wfm_16 = Niayifar_PorteAgel_2016(site, v80_2016_fig2)
wfm_18 = CarbajoFuertes_etal_2018(site, v80_2016_fig2)

# run simulation
sim_16 = wfm_16(wt_x, wt_y, TI=ti, ws=ws, wd=wd)
sim_18 = wfm_18(wt_x, wt_y, TI=ti, ws=ws, wd=wd)
```

Wind farm efficiency

[20]:
```
plt.figure()
plt.plot(ref_fig5['LES'][:, 0], ref_fig5['LES'][:, 1], 'ro-', label='LES (2016)')
plt.plot(wd, sim_16.Power.sum(axis=0)[:, 0] / (len(wt_x) * v80_2016_fig2.power(ws=ws)), 'b-', label='Niayifar_PorteAgel_2016')
plt.plot(wd, sim_18.Power.sum(axis=0)[:, 0] / (len(wt_x) * v80_2016_fig2.power(ws=ws)), 'g-', label='CarbajoFuertes_etal_2018')
plt.axis([160, 360, 0.4, 1.0])
plt.xlabel('Wind direction [deg]')
plt.ylabel('Wind farm efficiency [-]')
plt.title('Horns Rev 1 | $U_{hub}=8$ m/s | $I_{\infty}=7.7$%')
plt.grid('on', lw=0.5, alpha=0.5)
plt.legend()
```

[20]:
```
<matplotlib.legend.Legend at 0x7f296edf0b80>
```

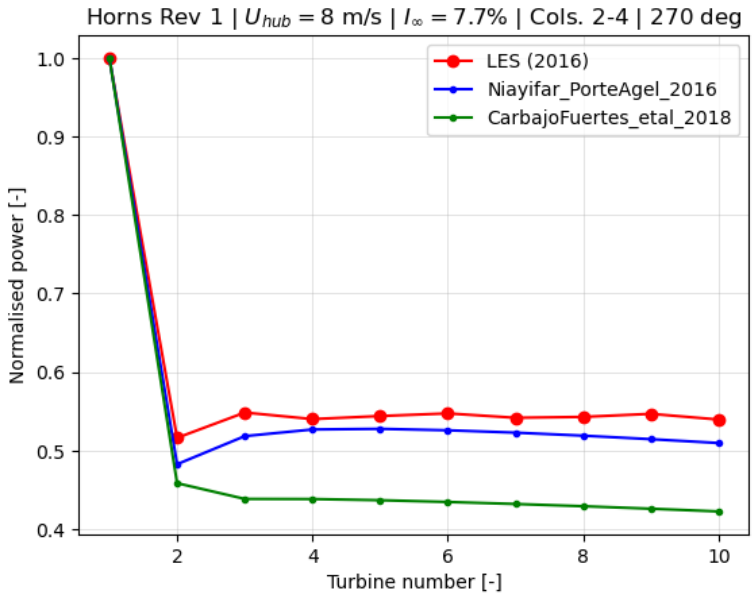


Power variation

[21]:
```
plt.figure()
iwt = np.linspace(1, 10, 10)
plt.plot(iwt, ref_fig6['LES'][:, 1], 'ro-', label='LES (2016)')

# select wind direction 270 degrees
iwd = 97
# select columns
pp = np.zeros((3, 10, 3))
for i in range(pp.shape[0]):
```

```
    pp[i, :, 0] = sim_16.Power.values[8 - (i + 2)::8, iwd, 0]
    pp[i, :, 1] = sim_18.Power.values[8 - (i + 2)::8, iwd, 0]
# average over columns
pp_avg = np.mean(pp, axis=0)
# plot results
plt.plot(iwt, pp_avg[:, 0] / pp_avg[0, 0], 'b.-', label='Niayifar_PorteAgel_2016')
plt.plot(iwt, pp_avg[:, 1] / pp_avg[0, 1], 'g.-', label='CarbajoFuertes_etal_2018')

plt.xlabel('Turbine number [-]')
plt.ylabel('Normalised power [-]')
plt.title('Horns Rev 1 | $U_{hub}=8$ m/s | $I_{\infty}=7.7$% | Cols. 2-4 | ' + '{:.0f} deg'.format(sim_16.wd.values[iwd]))
plt.grid('on', lw=0.5, alpha=0.5)
plt.legend()
```

[21]: `<matplotlib.legend.Legend at 0x7f296ec92290>`



For aligned, deep-wake situations the updates to the model seem to overpredict losses, yet in any other situation it provides efficiency estimates close to the LES simulations.

Zong and Porté-Agel (2020)

This section reproduces results from

Zong H. and Porté-Agel F.: *A momentum-conserving wake superposition method for wind farm power prediction*, J. Fluid Mech., 889, A8, (2020), https://doi.org/10.1017/jfm.2020.77

The main focus of this paper is a momentum-conserving wake superposition model, however it also presents yet another version of a Gaussian model. Indeed without modifying the near-wake behaviour of the original Guassian model, the superposition model leads to bizarre results in the near-wake region.

Extension of the Niayifar et al. (2016) implementation with adapted Shapiro wake model components, namely a gradual growth of the thrust force and an expansion factor not falling below the rotor diameter. Shapiro modelled the pressure and thrust force as a combined momentum source, that are distributed in the streamwise direction with a Gaussian kernel with a certain characteristic length. As a result the induction changes following an error function. Zong chose to use a characteristic length of $D/\sqrt{2}$ and applies it directly to the thrust not the induction as Shapiro. This leads to the full thrust being active only $2D$ downstream of the turbine. Zong's wake width expression is inspired by Shapiro's, however the start of the linear wake expansion region (far-wake) was related to the near-wake length by Vermeulen (1980). The initial wake width, ϵ, in the original Gaussian model was taken to be a function of C_T is now a constant as proposed by Bastankhah et al. (2016), as the near-wake length now effectively dictates the origin of the far-wake.

Validation

Fig. 3 reproduction

This reproduces the results from a wind tunnel measurement campaign with four aligned miniature wind turbines.

Case definitions

[22]:
```
# hub height wind speed
ws = 4.9
```

```
# rotor diameter
d = .15
# rotor hub height
zh = 0.125
# rotor thrust coefficient
ct = 0.82
# turbulence intensity
ti = 0.06
# turbine tip speed ratio needed in near-wake length computation (personal communication)
lam = 3.8
```

Instantiate site and wind turbine

[23]:
```
# define wind turbine and site
wt = Dummy(ct=ct, d=d, zh=zh)
site = BastankhahSite(ws=ws, ti=ti)

# turbine positions
wt_y = [0., 0., 0., 0.]
wt_x = [0., 5. * d, 10. * d, 15. * d]
```

As in the paper we will run PyWake with different superposition models. Note how both `effective_ws` and `effective_ti` need to be set to `False` to reproduce what Zong et al. refer to as the one by Katic et al. or Method B in their paper. By default the superposition method by Zong is used, which in PyWake is called `WeightedSum()`, as it weights deficits using the convection velocity ratio.

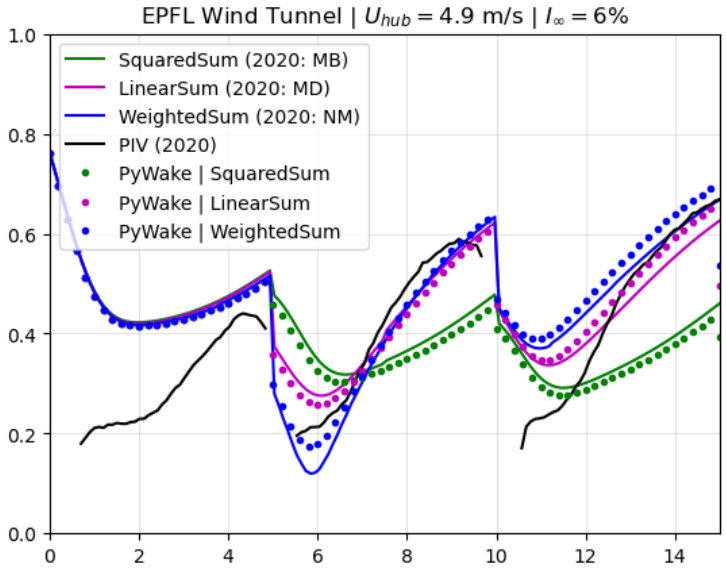
[24]:
```
from py_wake.literature.gaussian_models import Zong_PorteAgel_2020
from py_wake.superposition_models import LinearSum, SquaredSum
from py_wake.flow_map import Points
from py_wake.rotor_avg_models import CGIRotorAvg

wfm_names = ['SquaredSum', 'LinearSum', 'WeightedSum']

wfms = [Zong_PorteAgel_2020(site, wt, lam=lam,
                            superpositionModel=SquaredSum(),
                            rotorAvgModel=GaussianOverlapAvgModel(),
                            use_effective_ws=False, use_effective_ti=False),
        Zong_PorteAgel_2020(site, wt, lam=lam,
                            superpositionModel=LinearSum(),
                            rotorAvgModel=GaussianOverlapAvgModel()),
        Zong_PorteAgel_2020(site, wt, lam=lam,
                            rotorAvgModel=CGIRotorAvg(21))]
```

Load reference data, provided by the authors

[25]:
```
# load reference data extracted manually from Fig.5 of the paper
ref_fig3 = np.genfromtxt(os.path.join('data', 'Gaussian', 'Zong_PorteAgel_2020_Fig3.csv'),
                         skip_header=1, delimiter=',')
```

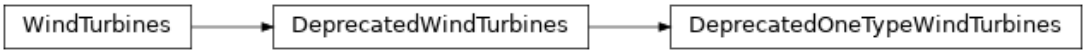
[26]:
```
plt.figure()

# Reference data
plt.plot(ref_fig3[:, 0], ref_fig3[:, 2], 'g-', label='SquaredSum (2020: MB)')
plt.plot(ref_fig3[:, 0], ref_fig3[:, 3], 'm-', label='LinearSum (2020: MD)')
plt.plot(ref_fig3[:, 0], ref_fig3[:, 5], 'b-', label='WeightedSum (2020: NM)')
plt.plot(ref_fig3[:, 0], ref_fig3[:, 6], 'k-', label='PIV (2020)')

# PyWake
x = np.linspace(0, 15, 5 * 15 + 1) * d
lcs = ['g', 'm', 'b']
for wfm, wfm_name, lc in zip(wfms, wfm_names, lcs):
    sim = wfm(wt_x, wt_y, ws=ws, wd=270., TI=ti)
    u = np.squeeze(sim.flow_map(Points(x=x, y=np.zeros_like(x), h=zh * np.ones_like(x))).WS_eff.values)
    plt.plot(x / d, u / ws, lc + '.', label='PyWake | ' + wfm_name)

plt.title('EPFL Wind Tunnel | $U_{hub}=4.9$ m/s | $I_{\infty}=' + '{:.0f}$%'.format(ti * 1.e2))
plt.grid('on', lw=0.5, alpha=0.5)
plt.axis([0., 15., 0., 1.0])
plt.legend()
```

[26]: `<matplotlib.legend.Legend at 0x7f296ee1a380>`



The Zong wake deficit is correctly implemented as demonstrated by near-perfect match in the wake of the first turbine. The wake growth seems a little slower, but without knowing the exact expression used for the near-wake length (here we use the one presented by Niayifar et al. (2016) in Eq.(11)) it is difficult to get exactly the same (one can increase I_∞ ever so slightly and they will line-up). After the second turbine there are slight differences between the classic superposition models, most likely due differences in the rotor-averaging method (not disclosed in the paper).

WindTurbine classes



- WindTurbine is the base class that allows multiple wind turbine types,
- OneTypeWindTurbines subclass allowing multiple wind turbines but only type

WindTurbine

class **py_wake.wind_turbines.WindTurbine**(**args*, ***kwargs*) [source]

Set of wind turbines (one type, i.e. all wind turbines have same name, diameter, power curve etc

`__init__`(name, diameter, hub_height, ...)	Initialize OneTypeWindTurbine
`name`([type])	Name of the specified type(s) of wind turbines
`hub_height`([type])	Hub height of the specified type(s) of wind turbines
`diameter`([type])	Rotor diameter of the specified type(s) of wind turbines
`power`(ws, **kwargs)	Power in watt
`ct`(ws, **kwargs)	Thrust coefficient
`plot`(x, y[, type, wd, yaw, tilt, ...])	
`from_WindTurbines`(wt_lst)	
`from_WAsP_wtg`(wtg_file[, default_mode, ...])	Parse the one/multiple .wtg file(s) (xml) to initilize an WindTurbines object.

__init__(*name*, *diameter*, *hub_height*, *powerCtFunction*, ***windTurbineFunctions*) [source]

Initialize OneTypeWindTurbine

Parameters:
- **name** (*str*) – Wind turbine name
- **diameter** (*int or float*) – Diameter of wind turbine
- **hub_height** (*int or float*) – Hub height of wind turbine
- **powerCtFunction** (*PowerCtFunction object*) – Wind turbine powerCtFunction

classmethod **from_WindTurbine_lst**(*wt_lst*) [source]

Generate a WindTurbines object from a list of (Onetype)WindTurbines

Parameters: **wt_lst** (*array_like*) – list of (OneType)WindTurbines

OneTypeWindTurbines

py_wake.wind_turbines.OneTypeWindTurbines

alias of `DeprecatedOneTypeWindTurbines`

Site classes

- Site: base class
- UniformSite: Site with uniform (same wind over all, i.e. flat uniform terrain) and constant wind speed probability of 1. Only for one fixed wind speed
- UniformWeibullSite: Site with uniform (same wind over all, i.e. flat uniform terrain) and weibull distributed wind speed
- WaspGridSite: Site with non-uniform (different wind at different locations, e.g. complex non-flat terrain) weibull distributed wind speed. Data obtained from WAsP grid files
- XRSite: The flexible general base class behind all Sites.

Site

class **py_wake.site._site.Site**(*distance*) [source]

`elevation`(x_i, y_i)	Local terrain elevation (height above mean sea level)
`local_wind`(x, y[, h, wd, ws, time, ...])	Local free flow wind conditions
`plot_ws_distribution`([x, y, h, wd, ws, ...])	Plot wind speed distribution
`plot_wd_distribution`([x, y, h, n_wd, ...])	Plot wind direction (and speed) distribution

abstract **elevation**(*x_i*, *y_i*) [source]

Local terrain elevation (height above mean sea level)

Parameters:
- **x_i** (*array_like*) – Local x coordinate
- **y_i** (*array_like*) – Local y coordinate

Returns: **elevation**

Return type: array_like

local_wind(*x*, *y*, *h=None*, *wd=None*, *ws=None*, *time=False*, *wd_bin_size=None*, *ws_bins=None*, ***_*) [source]

Local free flow wind conditions

Parameters:
- **x** (*array_like*) – Local x coordinate
- **y** (*array_like*) – Local y coordinate
- **h** (*array_like*, *optional*) – Local h coordinate, i.e., heights above ground
- **wd** (*float*, *int* or *array_like*, *optional*) – Global wind direction(s). Override self.default_wd

- **ws** (*float*, *int or array_like*, *optional*) – Global wind speed(s). Override self.default_ws
- **time** (*boolean or array_like*) – If True or array_like, wd and ws is interpreted as a time series If False, full wd x ws matrix is computed
- **wd_bin_size** (*int or float*, *optional*) – Size of wind direction bins. default is size between first and second element in default_wd
- **ws_bin** (*array_like or None*, *optional*) – Wind speed bin edges

Returns:

WD_ilk : array_like

local free flow wind directions

WS_ilk : array_like

local free flow wind speeds

TI_ilk : array_like

local free flow turbulence intensity

P_ilk : array_like

Probability/weight

Return type: LocalWind object containing

`plot_wd_distribution`(*x=0*, *y=0*, *h=70*, *n_wd=12*, *ws_bins=None*, *ax=None*) [source]

Plot wind direction (and speed) distribution

Parameters:

- **x** (*int or float*) – Local x coordinate
- **y** (*int or float*) – Local y coordinate
- **h** (*int or float*) – Local height above ground
- **n_wd** (*int*) – Number of wind direction sectors
- **ws_bins** (*None*, *int or array_like*, *default is None*) –
  Splits the wind direction sector pies into different colors to show the probability of different wind speeds
  If int, number of wind speed bins in the range 0-30
  If array_like, limits of the wind speed bins limited by ws_bins, e.g. [0,10,20], will show 0-10 m/wd_bin_size and 10-20 m/wd_bin_size
- **ax** (*pyplot or matplotlib axes object*, *default None*)

`plot_ws_distribution`(*x=0*, *y=0*, *h=70*, *wd=[0]*, *ws=array([0.05, 0.15, 0.25, 0.35, 0.45, 0.55, 0.65, 0.75, 0.85, 0.95, 1.05, 1.15, 1.25, 1.35, 1.45, 1.55, 1.65, 1.75, 1.85, 1.95, 2.05, 2.15, 2.25, 2.35, 2.45, 2.55, 2.65, 2.75, 2.85, 2.95, 3.05, 3.15, 3.25, 3.35, 3.45, 3.55, 3.65, 3.75, 3.85, 3.95, 4.05, 4.15, 4.25, 4.35, 4.45, 4.55, 4.65, 4.75, 4.85, 4.95, 5.05, 5.15, 5.25, 5.35, 5.45, 5.55, 5.65, 5.75, 5.85, 5.95, 6.05, 6.15, 6.25, 6.35, 6.45, 6.55, 6.65, 6.75, 6.85, 6.95, 7.05, 7.15, 7.25, 7.35, 7.45, 7.55, 7.65, 7.75, 7.85, 7.95, 8.05, 8.15, 8.25, 8.35,*

8.45, 8.55, 8.65, 8.75, 8.85, 8.95, 9.05, 9.15, 9.25, 9.35, 9.45, 9.55, 9.65, 9.75, 9.85, 9.95, 10.05, 10.15, 10.25, 10.35, 10.45, 10.55, 10.65, 10.75, 10.85, 10.95, 11.05, 11.15, 11.25, 11.35, 11.45, 11.55, 11.65, 11.75, 11.85, 11.95, 12.05, 12.15, 12.25, 12.35, 12.45, 12.55, 12.65, 12.75, 12.85, 12.95, 13.05, 13.15, 13.25, 13.35, 13.45, 13.55, 13.65, 13.75, 13.85, 13.95, 14.05, 14.15, 14.25, 14.35, 14.45, 14.55, 14.65, 14.75, 14.85, 14.95, 15.05, 15.15, 15.25, 15.35, 15.45, 15.55, 15.65, 15.75, 15.85, 15.95, 16.05, 16.15, 16.25, 16.35, 16.45, 16.55, 16.65, 16.75, 16.85, 16.95, 17.05, 17.15, 17.25, 17.35, 17.45, 17.55, 17.65, 17.75, 17.85, 17.95, 18.05, 18.15, 18.25, 18.35, 18.45, 18.55, 18.65, 18.75, 18.85, 18.95, 19.05, 19.15, 19.25, 19.35, 19.45, 19.55, 19.65, 19.75, 19.85, 19.95, 20.05, 20.15, 20.25, 20.35, 20.45, 20.55, 20.65, 20.75, 20.85, 20.95, 21.05, 21.15, 21.25, 21.35, 21.45, 21.55, 21.65, 21.75, 21.85, 21.95, 22.05, 22.15, 22.25, 22.35, 22.45, 22.55, 22.65, 22.75, 22.85, 22.95, 23.05, 23.15, 23.25, 23.35, 23.45, 23.55, 23.65, 23.75, 23.85, 23.95, 24.05, 24.15, 24.25, 24.35, 24.45, 24.55, 24.65, 24.75, 24.85, 24.95, 25.05, 25.15, 25.25, 25.35, 25.45, 25.55, 25.65, 25.75, 25.85, 25.95, 26.05, 26.15, 26.25, 26.35, 26.45, 26.55, 26.65, 26.75, 26.85, 26.95, 27.05, 27.15, 27.25, 27.35, 27.45, 27.55, 27.65, 27.75, 27.85, 27.95, 28.05, 28.15, 28.25, 28.35, 28.45, 28.55, 28.65, 28.75, 28.85, 28.95, 29.05, 29.15, 29.25, 29.35, 29.45, 29.55, 29.65, 29.75, 29.85, 29.95]), include_wd_distribution=False, ax=None) [source]

Plot wind speed distribution

Parameters:
- **x** (*int or float*) – Local x coordinate
- **y** (*int or float*) – Local y coordinate
- **h** (*int or float*) – Local height above ground
- **wd** (*int or array_like*) – Wind direction(s) (one curve pr wind direction)
- **ws** (*array_like, optional*) – Wind speeds to calculate for
- **include_wd_distributeion** (*bool, default is False*) – If true, the wind speed probability distributions are multiplied by the wind direction probability. The sector size is set to 360 / len(wd). This only makes sense if the wd array is evenly distributed
- **ax** (*pyplot or matplotlib axes object, default None*)

UniformSite

class **py_wake.site.UniformSite**(*p_wd=[1], ti=0.1, ws=12, interp_method='nearest', shear=None, initial_position=None, distance=None*) [source]

Site with uniform (same wind over all, i.e. flat uniform terrain) and constant wind speed probability of 1. Only for one fixed wind speed

__init__(*p_wd=[1], ti=0.1, ws=12, interp_method='nearest', shear=None, initial_position=None, distance=None*) [source]

Instantiate a site from an xarray dataset

Parameters:
- **ds** (*xarray dataset*) – See https://topfarm.pages.windenergy.dtu.dk/PyWake/notebooks/Site.html#XRSite for details
- **initial_position** (*array_like, optional*) – initial position of turbines can be stored in the site object
- **interp_method** (*{'linear', 'nearest'} or dict*) – interpolation method. Default is linear. Methods can be mixed by specifying the variable and

corresponding method in a dict, e.g. {'wd': 'nearest', 'x': 'linear'}

- **shear** (*Shear-object or function (lw, WS_ref, lw.h) -> WS_z*) – Function to compute the wind speed at different heights
- **distance** (*Distance-object or None*) – If None, default, the distance method is set to StraightDistance
- **default_ws** (*array_like*) – The default range of wind speeds
- **bounds** (*{'check', 'limit', 'ignore'}*) –
  Specifies how bounds is handled:
  - 'check': bounds check is performed. An error is raised if interpolation point outside area
  - 'limit': interpolation points are forced inside the area
  - 'ignore': Faster option with no check. Use this option if data is guaranteed to be inside the area

UniformWeibullSite

class **py_wake.site.UniformWeibullSite**(*p_wd, a, k, ti=None, interp_method='nearest', shear=None, distance=None*) [source]

Site with uniform (same wind over all, i.e. flat uniform terrain) and weibull distributed wind speed

__init__(*p_wd, a, k, ti=None, interp_method='nearest', shear=None, distance=None*) [source]

Initialize UniformWeibullSite

Parameters:

- **p_wd** (*array_like*) – Probability of wind direction sectors
- **a** (*array_like*) – Weilbull scaling parameter of wind direction sectors
- **k** (*array_like*) – Weibull shape parameter
- **ti** (*float or array_like, optional*) – Turbulence intensity
- **interp_method** (*'nearest', 'linear'*) – p_wd, a, k, ti and alpha are interpolated to 1 deg sectors using this method
- **shear** (*Shear object*) – Shear object, e.g. NoShear(), PowerShear(h_ref, alpha)
- **distance** (*Distance object or None*) – Distance object to calculate the distance between wind turbines. Defaults to StaightDistance based on reference wind direction

Notes

The wind direction sectors will be: [0 +/- w/2, w +/- w/2, ...] where w is 360 / len(p_wd)

WaspGridSite

class **py_wake.site.WaspGridSite**(*ds*, *distance=<py_wake.site.distance.TerrainFollowingDistance object>*, *mode='valid'*) [source]

Site with non-uniform (different wind at different locations, e.g. complex non-flat terrain) weibull distributed wind speed. Data obtained from WAsP grid files

__init__(*ds*, *distance=<py_wake.site.distance.TerrainFollowingDistance object>*, *mode='valid'*) [source]

Parameters:

- **ds** (*xarray*) – dataset as returned by load_wasp_grd
- **distance** (*Distance object*, *optional*) – Alternatives are StraightDistance and TerrainFollowingDistance2
- **mode** (*{'valid', 'extrapolate'}*, *optional*) – if valid, terrain elevation outside grid area is NAN if extrapolate, the terrain elevation at the grid border is returned outside the grid area

XRSite

class **py_wake.site.XRSite**(*ds*, *initial_position=None*, *interp_method='linear'*, *shear=None*, *distance=None*, *default_ws=array([3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25])*, *bounds='check'*) [source]

The flexible general base class behind all Sites

__init__(*ds*, *initial_position=None*, *interp_method='linear'*, *shear=None*, *distance=None*, *default_ws=array([3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25])*, *bounds='check'*) [source]

Instantiate a site from an xarray dataset

Parameters:

- **ds** (*xarray dataset*) – See https://topfarm.pages.windenergy.dtu.dk/PyWake/notebooks/Site.html#XRSite for details
- **initial_position** (*array_like*, *optional*) – initial position of turbines can be stored in the site object
- **interp_method** (*{'linear', 'nearest'} or dict*) – interpolation method. Default is linear. Methods can be mixed by specifying the variable and corresponding method in a dict, e.g. {'wd': 'nearest', 'x': 'linear'}
- **shear** (*Shear-object or function (lw, WS_ref, lw.h) -> WS_z*) – Function to compute the wind speed at different heights
- **distance** (*Distance-object or None*) – If None, default, the distance method is set to StraightDistance
- **default_ws** (*array_like*) – The default range of wind speeds
- **bounds** (*{'check', 'limit', 'ignore'}*) –
  Specifies how bounds is handled:
  - 'check': bounds check is performed. An error is raised if interpolation point outside area
  - 'limit': interpolation points are forced inside the area

- 'ignore': Faster option with no check. Use this option if data is guaranteed to be inside the area

WindFarmModel

class **py_wake.wind_farm_models.wind_farm_model.WindFarmModel**(*site*, *windTurbines*) [source]

Base class for RANS and engineering flow models

`__call__`(x, y[, h, type, wd, ws, time, ...])	Run the wind farm simulation
`calc_wt_interaction`(x_ilk, y_ilk[, h_i, ...])	Calculate effective wind speed, turbulence intensity, power and thrust coefficient, and local site parameters

__call__(*x*, *y*, *h=None*, *type=0*, *wd=None*, *ws=None*, *time=False*, *verbose=False*, *n_cpu=1*, *wd_chunks=None*, *ws_chunks=1*, *return_simulationResult=True*, ***kwargs*) [source]

Run the wind farm simulation

Parameters:

- **x** (*array_like*) – Wind turbine x positions
- **y** (*array_like*) – Wind turbine y positions
- **h** (*array_like*, *optional*) – Wind turbine hub heights
- **type** (*int or array_like*, *optional*) – Wind turbine type, default is 0
- **wd** (*int or array_like*) – Wind direction(s)
- **ws** (*int*, *float or array_like*) – Wind speed(s)
- **yaw** (*int*, *float*, *array_like or None*, *optional*) – Yaw misalignement, Positive is counter-clockwise when seen from above. May be - constant for all wt and flow cases or dependent on - wind turbine(i), - wind turbine and wind direction(il) or - wind turbine, wind direction and wind speed (ilk)
- **tilt** (*array_like or None*, *optional*) – Tilt angle of rotor shaft. Normal tilt (rotor center above tower top) is positivie May be - constant for all wt and flow cases or dependent on - wind turbine(i), - wind turbine and wind direction(il) or - wind turbine, wind direction and wind speed (ilk)
- **time** (*boolean or array_like*) – If False (default), the simulation will be computed for the full wd x ws matrix If True, the wd and ws will be considered as a time series of flow conditions with time stamp 0,1,..,n If array_like: same as True, but the time array is used as flow case time stamp
- **n_cpu** (*int or None*, *optional*) – Number of CPUs to be used for execution. If 1 (default), the execution is not parallized If None, the available number of CPUs are used
- **wd_chunks** (*int or None*, *optional*) – The wind directions are divided into <wd_chunks> chunks. More chunks reduces the memory usage and allows parallel execution if n_cpu>1. If wd_chunks is None, wd_chunks is set to the number of CPUs used, i.e. 1 if n_cpu is not specified
- **ws_chunks** (*int*, *optional*) – The wind speeds are divided into <ws_chunks> chunks. More chunks reduces the memory usage and allows parallel execution if n_cpu>1.
- **return_simulationResult** (*boolean*, *optional*) – see Returns

Returns:

- *If return_simulationResult is True a SimulationResult (xarray Dataset) is returned*
- *If return_simulationResult is False the functino returns a tuple of*
- *WS_eff_ilk, TI_eff_ilk, power_ilk, ct_ilk, localWind, kwargs_ilk*

aep(*x*, *y*, *h=None*, *type=0*, *wd=None*, *ws=None*, *normalize_probabilities=False*, *with_wake_loss=True*, *n_cpu=1*, *wd_chunks=None*, *ws_chunks=1*, ***kwargs*) [source]

Anual Energy Production (sum of all wind turbines, directions and speeds) in GWh.

the typical use is: >> sim_res = windFarmModel(x,y,...) >> sim_res.aep()

This function bypasses the simulation result and returns only the total AEP, which makes it slightly faster for small problems. >> windFarmModel.aep(x,y,...)

Parameters:

- **x** (*array_like*) – Wind turbine x positions
- **y** (*array_like*) – Wind turbine y positions
- **h** (*array_like*, *optional*) – Wind turbine hub heights
- **type** (*int or array_like*, *optional*) – Wind turbine type, default is 0
- **wd** (*int or array_like*) – Wind direction(s)
- **ws** (*int*, *float or array_like*) – Wind speed(s)
- **yaw** (*int*, *float*, *array_like or None*, *optional*) – Yaw misalignement, Positive is counter-clockwise when seen from above. May be - constant for all wt and flow cases or dependent on - wind turbine(i), - wind turbine and wind direction(il) or - wind turbine, wind direction and wind speed (ilk)

- **tilt** (*array_like or None, optional*) – Tilt angle of rotor shaft. Normal tilt (rotor center above tower top) is positivie May be - constant for all wt and flow cases or dependent on - wind turbine(i), - wind turbine and wind direction(il) or - wind turbine, wind direction and wind speed (ilk)
- **n_cpu** (*int or None, optional*) – Number of CPUs to be used for execution. If 1 (default), the execution is not parallized If None, the available number of CPUs are used
- **wd_chunks** (*int or None, optional*) – The wind directions are divided into <wd_chunks> chunks. More chunks reduces the memory usage and allows parallel execution if n_cpu>1. If wd_chunks is None, wd_chunks is set to the number of CPUs used, i.e. 1 if n_cpu is not specified
- **ws_chunks** (*int, optional*) – The wind speeds are divided into <ws_chunks> chunks. More chunks reduces the memory usage and allows parallel execution if n_cpu>1.

Return type: AEP in GWh

aep_gradients(*gradient_method=<function autograd>, wrt_arg=['x', 'y'], gradient_method_kwargs={}, n_cpu=1, wd_chunks=None, ws_chunks=None, **kwargs*) [source]

Method to compute the gradients of the AEP with respect to wrt_arg using the gradient_method

Note, this method has two behaviours: 1) Without specifying additional key-word arguments, kwargs, the method returns the function to compute the gradients of the aep: gradient_function = wfm.aep_gradietns(autograd, ['x','y']) gradients = gradient_function(x,y) This behaiour only works when wrt_arg is one or more of ['x','y','h','wd', 'ws']

2) With additional key-word arguments, kwargs, the method returns the gradients of the aep: gradients = wfm.aep_gradients(autograd, ['x','y'],x=x,y=y) This behaviour also works when wrt_arg is a keyword argument, e.g. yaw

Parameters:
- **gradient_method** (*gradient function, {fd, cs, autograd}*) – gradient function
- **wrt_arg** (*{'x', 'y', 'h', 'wd', 'ws', 'yaw','tilt'} or list of these arguments, e.g. ['x','y']*) – argument to compute gradients of AEP with respect to
- **gradient_method_kwargs** (*dict, optional*) – additional arguments for the gradient method, e.g. step size
- **n_cpu** (*int or None, optional*) – Number of CPUs to be used for execution. If 1 (default), the execution is not parallized If None, the available number of CPUs are used
- **wd_chunks** (*int or None, optional*) – If n_cpu>1, the wind directions are divided into <wd_chunks> chunks and executed in parallel. If wd_chunks is None, wd_chunks is set to the available number of CPUs
- **ws_chunks** (*int or None, optional*) – If n_cpu>1, the wind speeds are divided into <ws_chunks> chunks and executed in parallel. If ws_chunks is None, ws_chunks is set to 1

abstract **calc_wt_interaction**(*x_ilk, y_ilk, h_i=None, type_i=0, wd=None, ws=None, time=False, n_cpu=1, wd_chunks=None, ws_chunks=None, **kwargs*) [source]

Calculate effective wind speed, turbulence intensity, power and thrust coefficient, and local site parameters

Typical users should not call this function directly, but by calling the windFarmModel object (invokes the __call__() function above) which returns a nice SimulationResult object

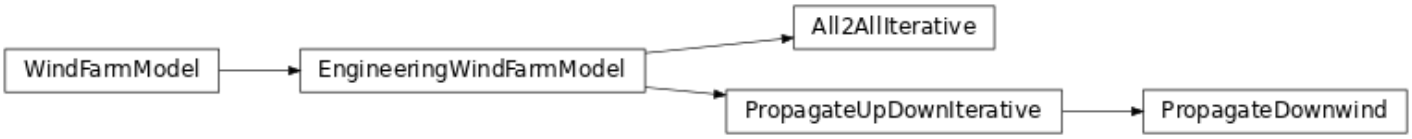
Parameters:
- **x_ilk** (*array_like*) – X position of wind turbines
- **y_ilk** (*array_like*) – Y position of wind turbines
- **h_i** (*array_like or None, optional*) –
  Hub height of wind turbines
  If None, default, the standard hub height is used
- **type_i** (*array_like or None, optional*) –
  Wind turbine types
  If None, default, the first type is used (type=0)
- **wd** (*int, float, array_like or None*) –
  Wind directions(s)
  If None, default, the wake is calculated for site.default_wd
- **ws** (*int, float, array_like or None*) –
  Wind speed(s)
  If None, default, the wake is calculated for site.default_ws
- **n_cpu** (*int or None, optional*) – Number of CPUs to be used for execution. If 1 (default), the execution is not parallized If None, the available number of CPUs are used
- **wd_chunks** (*int or None, optional*) – If n_cpu>1, the wind directions are divided into <wd_chunks> chunks and executed in parallel. If wd_chunks is None, wd_chunks is set to the available number of CPUs

- **ws_chunks** (*int or None, optional*) – If n_cpu>1, the wind speeds are divided into <ws_chunks> chunks and executed in parallel. If ws_chunks is None, ws_chunks is set to 1

Returns:

- **WS_eff_ilk** (*array_like*) – Effective wind speeds [m/s]
- **TI_eff_ilk** (*array_like*) – Effective turbulence intensities [-]
- **power_ilk** (*array_like*) – Power productions [w]
- **ct_ilk** (*array_like*) – Thrust coefficients
- **localWind** (*LocalWind*) – Local free-flow wind

Engineering wind farm model classes



- PropagateDownwind
- All2AllIterative

PropagateDownwind

class **py_wake.wind_farm_models.PropagateDownwind**(*site, windTurbines, wake_deficitModel, superpositionModel=<py_wake.superposition_models.LinearSum object>, deflectionModel=None, turbulenceModel=None, rotorAvgModel=None, inputModifierModels=[]*) [source]

Downstream wake deficits calculated and propagated in downstream direction. Very fast, but ignoring blockage effects

__init__(*site, windTurbines, wake_deficitModel, superpositionModel=<py_wake.superposition_models.LinearSum object>, deflectionModel=None, turbulenceModel=None, rotorAvgModel=None, inputModifierModels=[]*) [source]

Initialize flow model

Parameters:

- **site** (*Site*) – Site object
- **windTurbines** (*WindTurbines*) – WindTurbines object representing the wake generating wind turbines
- **wake_deficitModel** (*DeficitModel*) – Model describing the wake(downstream) deficit
- **rotorAvgModel** (*RotorAvgModel, optional*) – Model defining one or more points at the down stream rotors to calculate the rotor average wind speeds from. if None, default, the wind speed at the rotor center is used
- **superpositionModel** (*SuperpositionModel*) – Model defining how deficits sum up
- **deflectionModel** (*DeflectionModel*) – Model describing the deflection of the wake due to yaw misalignment, sheared inflow, etc.
- **turbulenceModel** (*TurbulenceModel*) – Model describing the amount of added turbulence in the wake

All2AllIterative

class **py_wake.wind_farm_models.All2AllIterative**(*site, windTurbines, wake_deficitModel, superpositionModel=<py_wake.superposition_models.LinearSum object>, blockage_deficitModel=None, deflectionModel=None, turbulenceModel=None, convergence_tolerance=1e-06, rotorAvgModel=None, inputModifierModels=[]*) [source]

Wake and blockage deficits calculated from all wt to all points of interest (wt/map points). The calculations are iteratively repeated until convergence (change of effective wind speed < convergence_tolerance)

__init__(*site, windTurbines, wake_deficitModel, superpositionModel=<py_wake.superposition_models.LinearSum object>, blockage_deficitModel=None, deflectionModel=None, turbulenceModel=None, convergence_tolerance=1e-06, rotorAvgModel=None, inputModifierModels=[]*) [source]

Initialize flow model

Parameters:

- **site** (*Site*) – Site object
- **windTurbines** (*WindTurbines*) – WindTurbines object representing the wake generating wind turbines
- **wake_deficitModel** (*DeficitModel*) – Model describing the wake(downstream) deficit
- **rotorAvgModel** (*RotorAvgModel*, *optional*) – Model defining one or more points at the down stream rotors to calculate the rotor average wind speeds from. if None, default, the wind speed at the rotor center is used
- **superpositionModel** (*SuperpositionModel*) – Model defining how deficits sum up
- **blockage_deficitModel** (*DeficitModel*) – Model describing the blockage(upstream) deficit
- **deflectionModel** (*DeflectionModel*) – Model describing the deflection of the wake due to yaw misalignment, sheared inflow, etc.
- **turbulenceModel** (*TurbulenceModel*) – Model describing the amount of added turbulence in the wake
- **convergence_tolerance** (*float or None*) – if float: maximum accepted change in WS_eff_ilk [m/s] if None: return after first iteration. This only makes sense for benchmark studies where CT, wakes and blockage are independent of effective wind speed WS_eff_ilk

Predefined Engineering wind farm model classes

NOJ

class **py_wake.literature.noj.Jensen_1983**(*site, windTurbines, rotorAvgModel=<py_wake.rotor_avg_models.area_overlap_model.AreaOverlapAvgModel object>, ct2a=<function ct2a_madsen>, k=0.1, superpositionModel=<py_wake.superposition_models.SquaredSum object>, deflectionModel=None, turbulenceModel=None, groundModel=None*) [source]

Implemented according to:

Niels Otto Jensen, “A note on wind generator interaction.” (1983)

Features:

- Top-hat shape for the wake profile.
- Wake superposition is done with the squared sum model as default.
- Given the top-hat shape, the Area Overlap Average model is used as default, which includes the wake radius.

__init__(*site, windTurbines, rotorAvgModel=<py_wake.rotor_avg_models.area_overlap_model.AreaOverlapAvgModel object>, ct2a=<function ct2a_madsen>, k=0.1, superpositionModel=<py_wake.superposition_models.SquaredSum object>, deflectionModel=None, turbulenceModel=None, groundModel=None*) [source]

Parameters:

- **site** (*Site*) – Site object
- **windTurbines** (*WindTurbines*) – WindTurbines object representing the wake generating wind turbines
- **k** (*float*, *default 0.1*) – wake expansion factor
- **superpositionModel** (*SuperpositionModel*, *default SquaredSum*) – Model defining how deficits sum up
- **blockage_deficitModel** (*DeficitModel*, *default None*) – Model describing the blockage(upstream) deficit

- **deflectionModel** (*DeflectionModel, default None*) – Model describing the deflection of the wake due to yaw misalignment, sheared inflow, etc.
- **turbulenceModel** (*TurbulenceModel, default None*) – Model describing the amount of added turbulence in the wake

BastankhahGaussian

class **py_wake.literature.gaussian_models.Bastankhah_PorteAgel_2014**(*site, windTurbines, k, ceps=0.2, ct2a=<function ct2a_mom1d>, use_effective_ws=True, rotorAvgModel=None, superpositionModel=<py_wake.superposition_models.LinearSum object>, deflectionModel=None, turbulenceModel=None, groundModel=None*) [source]

Implemented according to:

Bastankhah M and Porté-Agel F. A new analytical model for wind-turbine wakes. J. Renew. Energy. 2014;70:116-23.

Description:

- Conservation of mass and momentum is applied with the assumption of a Gaussian shape for the wake profile in the calculation of the wake deficit.
- Only one parameter needed to determine the velocity distribution: the wake expansion parameter k.

__init__(*site, windTurbines, k, ceps=0.2, ct2a=<function ct2a_mom1d>, use_effective_ws=True, rotorAvgModel=None, superpositionModel=<py_wake.superposition_models.LinearSum object>, deflectionModel=None, turbulenceModel=None, groundModel=None*) [source]

Parameters:

- **site** (*Site*) – Site object
- **windTurbines** (*WindTurbines*) – WindTurbines object representing the wake generating wind turbines
- **k** (*float*) – Wake expansion factor
- **use_effective_ws** (*bool*) – Option to use either the local (True) or free-stream wind speed (False) experienced by the ith turbine
- **rotorAvgModel** (*RotorAvgModel, optional*) –
  Model defining one or more points at the down stream rotors to calculate the rotor average wind speeds from.
  if None, default, the wind speed at the rotor center is used
- **superpositionModel** (*SuperpositionModel, default SquaredSum*) – Model defining how deficits sum up
- **deflectionModel** (*DeflectionModel, default None*) – Model describing the deflection of the wake due to yaw misalignment, sheared inflow, etc.
- **turbulenceModel** (*TurbulenceModel, default None*) – Model describing the amount of added turbulence in the wake

IEA37SimpleBastankhahGaussian

class **py_wake.IEA37SimpleBastankhahGaussian**(*site, windTurbines, rotorAvgModel=None, superpositionModel=<py_wake.superposition_models.SquaredSum object>, deflectionModel=None, turbulenceModel=None*) [source]

Predefined wind farm model

__init__(*site, windTurbines, rotorAvgModel=None, superpositionModel=<py_wake.superposition_models.SquaredSum object>, deflectionModel=None, turbulenceModel=None*) [source]

Parameters:

- **site** (*Site*) – Site object
- **windTurbines** (*WindTurbines*) – WindTurbines object representing the wake generating wind turbines
- **rotorAvgModel** (*RotorAvgModel, optional*) – Model defining one or more points at the down stream rotors to calculate the rotor average wind speeds from. if None, default, the wind speed at the rotor center is used
- **superpositionModel** (*SuperpositionModel, default SquaredSum*) – Model defining how deficits sum up
- **deflectionModel** (*DeflectionModel, default None*) – Model describing the deflection of the wake due to yaw misalignment, sheared inflow, etc.
- **turbulenceModel** (*TurbulenceModel, default None*) – Model describing the amount of added turbulence in the wake

NiayifarGaussian

class **py_wake.literature.gaussian_models.Niayifar_PorteAgel_2016**(*site, windTurbines, a=[0.3837, 0.003678], ceps=0.2, ct2a=<function ct2a_mom1d>, use_effective_ws=True, use_effective_ti=True, superpositionModel=<py_wake.superposition_models.LinearSum object>, deflectionModel=None, turbulenceModel=<py_wake.turbulence_models.crespo.CrespoHernandez object>, rotorAvgModel=<py_wake.rotor_avg_models.gaussian_overlap_model.GaussianOverlapAvgModel object>, groundModel=None*) [source]

Implemented according to:

Amin Niayifar and Fernando Porté-Agel Analytical Modeling of Wind Farms: A New Approach for Power Prediction Energies 2016, 9, 741; doi:10.3390/en9090741 [1]

Features:

- Conservation of mass and momentum and a Gaussian shape for the wake profile.
- Wake expansion function of local turbulence intensity.

Description:

- The expansion rate 'k' varies linearly with local turbluence intensity: k = a1 I + a2.
- The default constants are set according to publications by Porte-Agel's group, which are based on LES simulations. Lidar field measurements by Fuertes et al. (2018) indicate that a = [0.35, 0.0] is also a valid selection.
- Wake superposition is represented by linearly adding the wakes.
- The Crespo Hernandez turbulence model is used to calculate the added streamwise turbulence intensity, Eq 14 in [1].

__init__(*site, windTurbines, a=[0.3837, 0.003678], ceps=0.2, ct2a=<function ct2a_mom1d>, use_effective_ws=True, use_effective_ti=True, superpositionModel=<py_wake.superposition_models.LinearSum object>, deflectionModel=None, turbulenceModel=<py_wake.turbulence_models.crespo.CrespoHernandez object>, rotorAvgModel=<py_wake.rotor_avg_models.gaussian_overlap_model.GaussianOverlapAvgModel object>, groundModel=None*) [source]

Parameters:

- **site** (*Site*) – Site object
- **windTurbines** (*WindTurbines*) – WindTurbines object representing the wake generating wind turbines
- **superpositionModel** (*SuperpositionModel, default LinearSum*) – Model defining how deficits sum up
- **deflectionModel** (*DeflectionModel, default None*) – Model describing the deflection of the wake due to yaw misalignment, sheared inflow, etc.
- **turbulenceModel** (*TurbulenceModel, default CrespoHernandez*) – Model describing the amount of added turbulence in the wake
- **use_effective_ws** (*bool*) – Option to use either the local (True) or free-stream (False) wind speed experienced by the ith turbine
- **use_effective_ti** (*bool*) – Option to use either the local (True) or free-stream (False) turbulence intensity experienced by the ith turbine

ZongGaussian

class **py_wake.literature.gaussian_models.Zong_PorteAgel_2020**(*site, windTurbines, a=[0.38, 0.004], deltawD=0.7071067811865475, eps_coeff=0.35, lam=7.5, B=3, use_effective_ws=True, use_effective_ti=True, rotorAvgModel=None, superpositionModel=<py_wake.superposition_models.WeightedSum object>, deflectionModel=None, turbulenceModel=<py_wake.turbulence_models.crespo.CrespoHernandez object>, groundModel=None*) [source]

Implemented according to:

Haohua Zong and Fernando Porté-Agel "A momentum-conserving wake superposition method for wind farm power prediction" J. Fluid Mech. (2020), vol. 889, A8; doi:10.1017/jfm.2020.77

Features:

- Conservation of mass and momentum and a Gaussian shape for the wake profile.
- Wake expansion function of local turbulence intensity.
- New wake width expression following the approach by Shapiro et al. (2018).

Description:

Extension of the Niayifar et al. (2016) implementation with adapted Shapiro wake model components, namely a gradual growth of the thrust force and an expansion factor not falling below the rotor diameter. Shapiro modelled the pressure and thrust force as a combined momentum source, that are distributed in the streamwise direction with a Gaussian kernel with a certain characteristic length. As a result the induction changes following an error function. Zong chose to use a characteristic length of D/sqrt(2) and applies it directly to the thrust not the induction as Shapiro. This leads to the full thrust being active only 2D downstream of the turbine. Zong's wake width expression is inspired by Shapiro's, however the start of the linear wake expansion region (far-wake) was related to the near-wake length by Vermeulen (1980). The epsilon factor that in the original Gaussian model was taken to be a function of CT is now a constant as proposed by Bastankhah (2016), as the near-wake length now effectively dictates the origin of the far-wake.

***__init__**(site, windTurbines, a=[0.38, 0.004], deltawD=0.7071067811865475, eps_coeff=0.35, lam=7.5, B=3, use_effective_ws=True, use_effective_ti=True, rotorAvgModel=None, superpositionModel=<py_wake.superposition_models.WeightedSum object>, deflectionModel=None, turbulenceModel=<py_wake.turbulence_models.crespo.CrespoHernandez object>, groundModel=None)* [source]

Parameters:

- **site** (*Site*) – Site object
- **windTurbines** (*WindTurbines*) – WindTurbines object representing the wake generating wind turbines
- **superpositionModel** (*SuperpositionModel, default SquaredSum*) – Model defining how deficits sum up
- **deflectionModel** (*DeflectionModel, default None*) – Model describing the deflection of the wake due to yaw misalignment, sheared inflow, etc.
- **turbulenceModel** (*TurbulenceModel, default None*) – Model describing the amount of added turbulence in the wake
- **use_effective_ws** (*bool*) – Option to use either the local (True) or free-stream (False) wind speed experienced by the ith turbine
- **use_effective_ti** (*bool*) – Option to use either the local (True) or free-stream (False) turbulence intensity experienced by the ith turbine

SuperGaussian

class **py_wake.literature.gaussian_models.Blondel_Cathelain_2020**(*site, windTurbines, use_effective_ws=True, use_effective_ti=True, superpositionModel=<py_wake.superposition_models.LinearSum object>, deflectionModel=None, turbulenceModel=None, rotorAvgModel=None, groundModel=None*) [source]

Implemented according to:

Blondel and Cathelain (2020) An alternative form of the super-Gaussian wind turbine wake model Wind Energ. Sci., 5, 1225–1236, 2020 https://doi.org/10.5194/wes-5-1225-2020 [1]

Features:

- Wake profile transitions from top-hat at near wake to Gaussian at far wake.
- characteristic wake width (sigma) function of turbulence intensity and CT.
- evolution of super gaussian “n” order function of downwind distance and turbulence intensity.

Description:

- Super gaussian wake order “n” is determined with the calibrated parameters: a_f, b_f, c_f; with a_f kept constant at 3.11.
- Calibrated parameters taken from Table 2 and 3 in [1].
- Linear summation of the wakes based on Shapiro (2019) https://www.mdpi.com/1996-1073/12/15/2956
- Turbulence model is set to None. The Crespo Hernandez model is recommended.

__init__(*site*, *windTurbines*, *use_effective_ws=True*, *use_effective_ti=True*, *superpositionModel=<py_wake.superposition_models.LinearSum object>*, *deflectionModel=None*, *turbulenceModel=None*, *rotorAvgModel=None*, *groundModel=None*) [source]

Parameters:

- **site** (*Site*) – Site object
- **windTurbines** (*WindTurbines*) – WindTurbines object representing the wake generating wind turbines
- **superpositionModel** (*SuperpositionModel*, *default SquaredSum*) – Model defining how deficits sum up
- **deflectionModel** (*DeflectionModel*, *default None*) – Model describing the deflection of the wake due to yaw misalignment, sheared inflow, etc.
- **turbulenceModel** (*TurbulenceModel*, *default None*) – Model describing the amount of added turbulence in the wake
- **use_effective_ws** (*bool*) – Option to use either the local (True) or free-stream (False) wind speed experienced by the ith turbine
- **use_effective_ti** (*bool*) – Option to use either the local (True) or free-stream (False) turbulence intensity experienced by the ith turbine

TurbOPark

class **py_wake.Nygaard_2022**(*site*, *windTurbines*) [source]

Implemented similar to:

Ørsted’s TurbOPark model (https://github.com/OrstedRD/TurbOPark/blob/main/TurbOPark%20description.pdf)

Features:

- Velocity deficit defined as in Bastankhah and Porté-Agel (2014) with a Gaussian profile.

- Wake expansion calculation considers the combination of the ambient turbulence intensity (I0) and the turbulence generated by the wake itself.
- The expression by Frandsen (2007) is used to model the turbulence in the turbine's wake, which depends on the thrust coefficient and downstream distance.
- Wake expansion parameter (A) calibrated from data and constant at A = 0.04.
- The squared sum wake superposition model from Katic et al (1986) is used as default.
- The mirror model is used as the default ground model.

__init__(*site*, *windTurbines*) [source]

Initialize flow model

Parameters:

- **site** (*Site*) – Site object
- **windTurbines** (*WindTurbines*) – WindTurbines object representing the wake generating wind turbines
- **wake_deficitModel** (*DeficitModel*) – Model describing the wake(downstream) deficit
- **rotorAvgModel** (*RotorAvgModel*, *optional*) – Model defining one or more points at the down stream rotors to calculate the rotor average wind speeds from. if None, default, the wind speed at the rotor center is used
- **superpositionModel** (*SuperpositionModel*) – Model defining how deficits sum up
- **deflectionModel** (*DeflectionModel*) – Model describing the deflection of the wake due to yaw misalignment, sheared inflow, etc.
- **turbulenceModel** (*TurbulenceModel*) – Model describing the amount of added turbulence in the wake

Fuga

class **py_wake.literature.fuga.Ott_Nielsen_2014**(*LUT_path*, *site*, *windTurbines*, *rotorAvgModel=None*, *deflectionModel=None*, *turbulenceModel=None*, *remove_wriggles=False*) [source]

Implemented according to:

Ott, S., & Nielsen, M. (2014). Developments of the offshore wind turbine wake model Fuga. DTU Wind Energy. DTU Wind Energy E No. 0046

Description:

- Fuga is a linearized CFD model that can predict wake effects for offshore wind farms.
- It has the ability to work with different types of turbines for the same project, which makes it useful for inter farm interactions.

__init__(*LUT_path, site, windTurbines, rotorAvgModel=None, deflectionModel=None, turbulenceModel=None, remove_wriggles=False*) [source]

Parameters:

- **LUT_path** (*str*) – path to look up tables
- **site** (*Site*) – Site object
- **windTurbines** (*WindTurbines*) – WindTurbines object representing the wake generating wind turbines
- **rotorAvgModel** (*RotorAvgModel, optional*) –
  Model defining one or more points at the down stream rotors to calculate the rotor average wind speeds from.
  if None, default, the wind speed at the rotor center is used
- **deflectionModel** (*DeflectionModel*) – Model describing the deflection of the wake due to yaw misalignment, sheared inflow, etc.
- **turbulenceModel** (*TurbulenceModel*) – Model describing the amount of added turbulence in the wake

FugaBlockage

class **py_wake.literature.fuga.Ott_Nielsen_2014_Blockage**(*LUT_path, site, windTurbines, rotorAvgModel=None, deflectionModel=None, turbulenceModel=None, convergence_tolerance=1e-06, remove_wriggles=False*) [source]

Implemented according to:

Ott, S., & Nielsen, M. (2014). Developments of the offshore wind turbine wake model Fuga. DTU Wind Energy. DTU Wind Energy E No. 0046

Description:

- Fuga is a linearized CFD model that can predict wake effects for offshore wind farms.
- It has the ability to work with different types of turbines for the same project, which makes it useful for inter farm interactions.
- An additional blockage model is added and the All2AllIterative wind farm model is used to model blockage effects.

__init__(*LUT_path, site, windTurbines, rotorAvgModel=None, deflectionModel=None, turbulenceModel=None, convergence_tolerance=1e-06, remove_wriggles=False*) [source]

Parameters:

- **LUT_path** (*str*) – path to look up tables
- **site** (*Site*) – Site object
- **windTurbines** (*WindTurbines*) – WindTurbines object representing the wake generating wind turbines
- **rotorAvgModel** (*RotorAvgModel, optional*) –
  Model defining one or more points at the down stream rotors to calculate the rotor average wind speeds from.
  if None, default, the wind speed at the rotor center is used

- **deflectionModel** (*DeflectionModel*) – Model describing the deflection of the wake due to yaw misalignment, sheared inflow, etc.
- **turbulenceModel** (*TurbulenceModel*) – Model describing the amount of added turbulence in the wake

SimulationResult

class **py_wake.wind_farm_models.wind_farm_model.SimulationResult**(*windFarmModel, localWind, type_i, WS_eff_ilk, TI_eff_ilk, power_ilk, ct_ilk, **kwargs*) [source]

Simulation result returned when calling a WindFarmModel object

`aep_ilk` ([normalize_probabilities, ...])	Anual Energy Production of all turbines (i), wind directions (l) and wind speeds (k) in in GWh
`aep` ([normalize_probabilities, ...])	Anual Energy Production (sum of all wind turbines, directions and speeds) in GWh.
`flow_map` ([grid, wd, ws, time, D_dst])	Return a FlowMap object with WS_eff and TI_eff of all grid points

aep(*normalize_probabilities=False, with_wake_loss=True, hours_pr_year=8760, linear_power_segments=False*) [source]

Anual Energy Production (sum of all wind turbines, directions and speeds) in GWh.

See aep_ilk

aep_ilk(*normalize_probabilities=False, with_wake_loss=True*) [source]

Anual Energy Production of all turbines (i), wind directions (l) and wind speeds (k) in in GWh

Parameters:

- **normalize_propabilities** (*Optional bool, defaults to False*) –
  In case only a subset of all wind speeds and/or wind directions is simulated, this parameter determines whether the returned AEP represents the energy produced in the fraction of a year where these flow cases occur or a whole year of only these cases. If for example, wd=[0], then - False means that the AEP only includes energy from the faction of year with northern wind (359.5-0.5deg), i.e. no power is produced the rest of the year. - True means that the AEP represents a whole year of northen wind.
- **with_wake_loss** (*Optional bool, defaults to True*) –
  If True, wake loss is included, i.e. power is calculated using local effective wind speed
  If False, wake loss is neglected, i.e. power is calculated using local free flow wind speed

flow_map(*grid=None, wd=None, ws=None, time=None, D_dst=0*) [source]

Return a FlowMap object with WS_eff and TI_eff of all grid points

Parameters:

- **grid** (*Grid or tuple(X, Y, x, y, h)*) –
  Grid, e.g. HorizontalGrid or
  tuple(X, Y, x, y, h) where X, Y is the meshgrid for visualizing data
  and x, y, h are the flattened grid points
- **wd** (*int, float, array_like or None*) – Wind directions to include in the flow map (if more than one, an weighted average will be computed) The simulation result must include the requested wind directions. If None, an weighted average of all wind directions from the simulation results will be computed. Note, computing a flow map with multiple wind directions may be slow
- **ws** (*int, array_like or None*) – Same as “wd”, but for wind speed
- **ws** – Same as “wd”, but for time
- **D_dst** (*int, float or None*) – In combination with a rotor average model, D_dst defines the downstream rotor diameter at which the deficits will be averaged

See also

`pywake.wind_farm_models.flow_map.FlowMap`

static **load**(*filename*, *wfm*) [source]

Manually trigger loading and/or computation of this dataset's data from disk or a remote source into memory and return this dataset. Unlike compute, the original dataset is modified and returned.

Normally, it should not be necessary to call this method in user code, because all xarray functions should either work on deferred data or load data automatically. However, this method can be necessary when working with many file objects on disk.

Parameters: ****kwargs** (*dict*) – Additional keyword arguments passed on to `dask.compute`.

See also

`dask.compute`

sel(*indexers=None*, *method=None*, *tolerance=None*, *drop=False*, ***indexers_kwargs*) [source]

Returns a new dataset with each array indexed by tick labels along the specified dimension(s).

In contrast to *Dataset.isel*, indexers for this method should use labels instead of integers.

Under the hood, this method is powered by using pandas's powerful Index objects. This makes label based indexing essentially just as fast as using integer indexing.

It also means this method uses pandas's (well documented) logic for indexing. This means you can use string shortcuts for datetime indexes (e.g., '2000-01' to select all values in January 2000). It also means that slices are treated as inclusive of both the start and stop values, unlike normal Python indexing.

Parameters:

- **indexers** (*dict*, *optional*) – A dict with keys matching dimensions and values given by scalars, slices or arrays of tick labels. For dimensions with multi-index, the indexer may also be a dict-like object with keys matching index level names. If DataArrays are passed as indexers, xarray-style indexing will be carried out. See indexing for the details. One of indexers or indexers_kwargs must be provided.
- **method** (*{None, "nearest", "pad", "ffill", "backfill", "bfill"}*, *optional*) –
  Method to use for inexact matches:
  - None (default): only exact matches
  - pad / ffill: propagate last valid index value forward
  - backfill / bfill: propagate next valid index value backward
  - nearest: use nearest valid index value
- **tolerance** (*optional*) – Maximum distance between original and new labels for inexact matches. The values of the index at the matching locations must satisfy the equation `abs(index[indexer] - target) <= tolerance`.
- **drop** (*bool*, *optional*) – If `drop=True`, drop coordinates variables in *indexers* instead of making them scalar.
- ****indexers_kwargs** (*{dim: indexer, ...}*, *optional*) – The keyword arguments form of `indexers`. One of indexers or indexers_kwargs must be provided.

Returns: **obj** – A new Dataset with the same contents as this dataset, except each variable and dimension is indexed by the appropriate indexers. If indexer DataArrays have coordinates that do not conflict with this object, then these coordinates will be attached. In general, each array's data will be a view of the array's data in this dataset, unless vectorized indexing was triggered by using an array indexer, in which case the data will be a copy.

Return type: Dataset

See also

`Dataset.isel`, `DataArray.sel`

FlowMap

class **py_wake.flow_map.FlowMap**(*simulationResult, X, Y, localWind_j, WS_eff_jlk, TI_eff_jlk, plane*) [source]

`power_xylk` ([with_wake_loss])	
`aep_xylk` ([normalize_probabilities, ...])	Anual Energy Production of a potential wind turbine at all grid positions (x,y) for all wind directions (l) and wi
`aep_xy` ([normalize_probabilities, with_wake_loss])	Anual Energy Production of a potential wind turbine at all grid positions (x,y) (sum of all wind directions and
`plot_windturbines` ([normalize_with, ax])	
`plot_wake_map` ([levels, cmap, plot_colorbar, ...])	Plot effective wind speed contourf map
`plot_ti_map` ([levels, cmap, plot_colorbar, ...])	Plot effective turbulence intensity contourf map

aep_xy(*normalize_probabilities=False, with_wake_loss=True, **wt_kwargs*) [source]

Anual Energy Production of a potential wind turbine at all grid positions (x,y) (sum of all wind directions and wind speeds) in GWh.

see aep_xylk

aep_xylk(*normalize_probabilities=False, with_wake_loss=True, **wt_kwargs*) [source]

Anual Energy Production of a potential wind turbine at all grid positions (x,y) for all wind directions (l) and wind speeds (k) in GWh.

Parameters:

- **normalize_propabilities** (*Optional bool, defaults to False*) –
  In case only a subset of all wind speeds and/or wind directions is simulated, this parameter determines whether the returned energy produced in the fraction of a year where these flow cases occurs or a whole year of northern wind. If for example, wd- means that the AEP only includes energy from the faction of year
  with northern wind (359.5-0.5deg), i.e. no power is produced the rest of the year. - True means that the AEP represents a whc wind. default is False
- **with_wake_loss** (*Optional bool, defaults to True*) –
  If True, wake loss is included, i.e. power is calculated using local effective wind speed
  If False, wake loss is neglected, i.e. power is calculated using local free flow wind speed
- **wt_type** (*Optional arguments*) – Additional required/optional arguments needed by the WindTurbines to computer power, e.g.

plot(*data, clabel, levels=100, cmap=None, plot_colorbar=True, plot_windturbines=True, normalize_with=1, ax=None*) [source]

Plot data as contouf map

Parameters:

- **data** (*array_like*) – 2D data array to plot
- **clabel** (*str*) – colorbar label
- **levels** (*int or array-like, default 100*) – Determines the number and positions of the contour lines / regions. If an int n, use n dat n+1 contour lines. The level heights are automatically chosen. If array-like, draw contour lines at the specified levels. The valu increasing order.
- **cmap** (*str or Colormap, defaults 'Blues_r'.*) – A Colormap instance or registered colormap name. The colormap maps the level val
- **plot_colorbar** (*bool, default True*) – if True (default), colorbar is drawn
- **plot_windturbines** (*bool, default True*) – if True (default), lines/circles showing the wind turbine rotors are plotted
- **ax** (*pyplot or matplotlib axes object, default None*)

plot_ti_map(*levels=100, cmap=None, plot_colorbar=True, plot_windturbines=True, ax=None*) [source]

Plot effective turbulence intensity contourf map

Parameters:

- **levels** (*int or array-like, default 100*) – Determines the number and positions of the contour lines / regions. If an int n, use n dat n+1 contour lines. The level heights are automatically chosen. If array-like, draw contour lines at the specified levels. The valu increasing order.
- **cmap** (*str or Colormap, defaults 'Blues'.*) – A Colormap instance or registered colormap name. The colormap maps the level valu
- **plot_colorbar** (*bool, default True*) – if True (default), colorbar is drawn
- **plot_windturbines** (*bool, default True*) – if True (default), lines/circles showing the wind turbine rotors are plotted
- **ax** (*pyplot or matplotlib axes object, default None*)

plot_wake_map(*levels=100, cmap=None, plot_colorbar=True, plot_windturbines=True, normalize_with=1, ax=None*) [source]

Plot effective wind speed contourf map

Parameters:

- **levels** (*int or array-like, default 100*) – Determines the number and positions of the contour lines / regions. If an int n, use n dat
  n+1 contour lines. The level heights are automatically chosen. If array-like, draw contour lines at the specified levels. The valu
  increasing order.
- **cmap** (*str or Colormap, defaults 'Blues_r'.*) – A Colormap instance or registered colormap name. The colormap maps the level val
- **plot_colorbar** (*bool, default True*) – if True (default), colorbar is drawn
- **plot_windturbines** (*bool, default True*) – if True (default), lines/circles showing the wind turbine rotors are plotted
- **ax** (*pyplot or matplotlib axes object, default None*)