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Using OR + AI to predict the optimal production of offshore wind parks: a preliminary study

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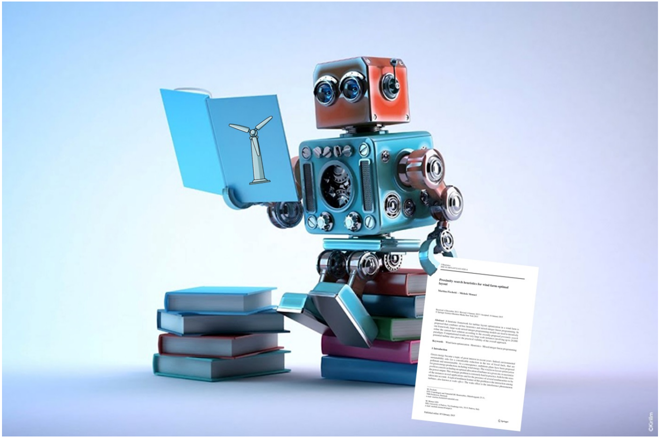
Research question

Research question: Given a bunch of optimized instances for a given problem, can a machine predict the *value* of the optimized solution for a new instance?

Research question

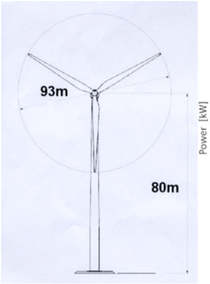


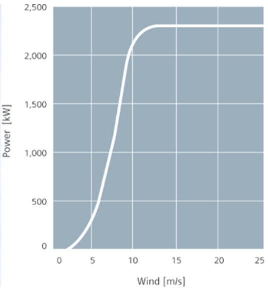
Research question: Given a bunch of optimized *wind farm layouts*, can a machine predict the *production value* of the optimized solution for a new *site*?

Wind Farm Layout Optimization

Determine:
a feasible optimal allocation of turbines that maximizes power production.
Given:

- a site (offshore)
- characteristics of the turbines to build
- measurements of the wind in the site





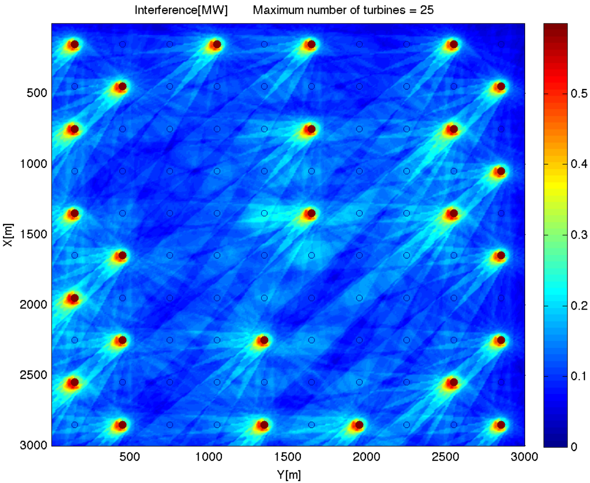
Wind Farm Layout Optimization

Taking into account:

- proximity constraint
- minimum/maximum number of turbines
- wake effect

Wind Farm Layout Optimization

Example of solution for a 3000x3000 (m) offshore area. The interference (colors in the background) is the average interference on real-world wind data from Vattenfall



MILP models

The layout problem can be formulated as a MILP problem.
Variables:

$$x_i = \begin{cases} 1 & \text{if a turbine is built at site } i \in V; \\ 0 & \text{otherwise} \end{cases} \qquad (i \in V)$$

where V is the set of potential turbine positions.
Let $I_{i,j}$ be the interference (production loss) on j because of i

MILP models

The objective function (to be maximized)

$$\sum_{i \in V} P_i x_i - \sum_{i \in V} \Big(\sum_{j \in V} I_{ij} x_j \Big) x_i \tag{1}$$

is restated as

$$\sum_{i \in V} (P_i x_i - w_i) \tag{2}$$

where

$$w_i := \Big(\sum_{j \in V} I_{ij} x_j \Big) x_i = \begin{cases} \sum_{j \in V} I_{ij} x_j & \text{if } x_i = 1; \\ 0 & \text{if } x_i = 0. \end{cases}$$

denotes the total interference caused by a turbine in position i.

MILP models

$$
\begin{array}{lll}
\max & z = \sum_{i \in V} (P_i x_i - w_i) & \\
\text{s.t.} & N_{MIN} \leq \sum_{i \in V} x_i \leq N_{MAX} & \\
 & x_i + x_j \leq 1 & \forall \text{incompatible } i, j \in V, i < j \\
 & \sum_{j \in V} I_{ij} x_j \leq w_i + M_i (1 - x_i) & \forall i \in V \\
 & x_i \in \{0, 1\} & \forall i \in V \\
 & w_i \geq 0 & \forall i \in V
\end{array}
$$

where P_i and I_{ij} are average values over a large number of wind scenarios, and $M_i >> 0$

Proximity Search

To solve instances with 10000+ possible positions

- 1-opt, 2-opt
- Proximity Search on the MILP model

Given an initial (heuristic) solution search for a better solution in the neighbourhood by using the MILP solver as a black box

This algorithm works very well and it is now used inside the company, running the tool overnight

For more info:

- M. Fischetti, M. Monaci, **Proximity search heuristics for wind farm optimal layout**, Journal of Heuristics 22 (4) (2016) 459–474.

Machine Learning

Let us suppose now that the company experts could build a new park wherever they like (i.e. the site is not given) –> they should evaluate the potential of a large number of possible sites

Due to the large number of sites, a full optimization (8h+ for each site) is infeasible

Research question: Given a bunch of optimized *wind farm layouts*, can a machine predict the *production value* of the optimized solution for a new *site*?

Building training/test set

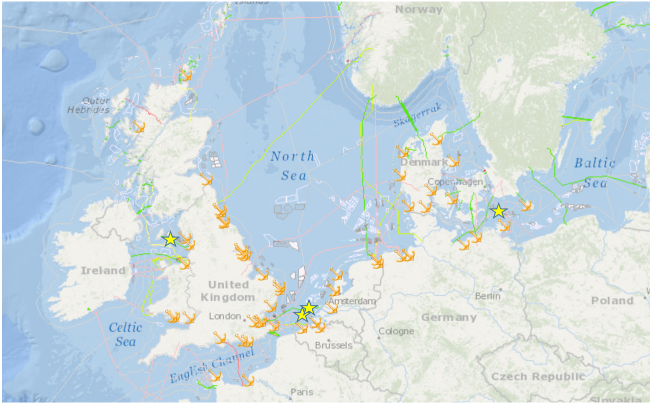
We artificially created different sites by generating sets of possible points on a regular grid (10m point-to-point distance) inside **rectangles** of different dimensions (all possible combinations of edge sizes 6000, 7000, 8000, 9000, 10000, 11000, 12000, 13000 and 14000m).

Building training/test set

- Adwen 8 MW, with a rotor diameter of 180m
- Vestas 8.4 MW, with a rotor diameter of 164m
- Siemens 7 MW, with a rotor diameter of 154m
- Vestas 8 MW, with a rotor diameter of 164m
- Siemens 3.2 MW, with a rotor diameter of 113m
- Siemens 2.3 MW, with a rotor diameter of 101m

Building training/test set

Real-world wind statistics from the real offshore wind parks (Borssele 1 and 2, Borssele 3 and 4, Danish Krigers Flak and Ormonde).



We imposed that a fixed number of 50 turbines needs to be located in the site, minimum distance 5 rotor diameters → we obtained about 2000+ instances

Building training/test set

1. the so-called *gross production*, i.e., the power production of the optimized solution neglecting the interference factor

2. the optimized layout and its power production

Building training/test set

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   $\rightarrow$ this will be used as input information (feature)
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   $\rightarrow$ **this is what we want to predict**

Building training/test set

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   → this will be used as input information (feature)
2. the optimized layout and its power production
   → **this is what we want to predict**

1) requires short computing time and can be calculated in a pre-processing step.
Optimization for the difficult case 2) was obtained through our MILP-based heuristic [1], with a time limit of 1 hour on a standard PC using IBM ILOG CPLEX 12.6.

[1] M. Fischetti, M. Monaci,Proximity search heuristics for wind farm optimal layout, Journal of Heuristics 22 (4) (2016) 459–474.

Building training/test set

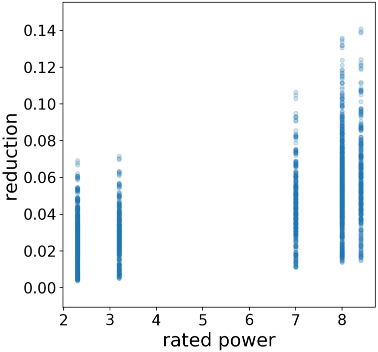
Finally, instead of directly estimating the optimized production of a site, we estimate its normalized difference from the gross production, defined as

$$\text{reduction} = \frac{\text{gross production - optimized production}}{\text{gross production}} \tag{3}$$

This is a value between 0 and 1 that can easily be compared between instances with production of different scales.

Feature selection

In order for our ML models to capture the wind park problem, it is very important to describe its characteristics in a meaningful way.



Selected features:

- **rated power for the turbine model [MW]**

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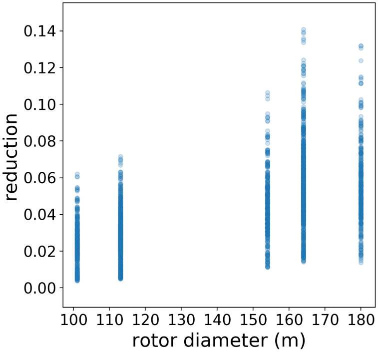

Selected features:

- rated
  power for the turbine model [MW]
- **rotor diameter**
  for the turbine model [m]

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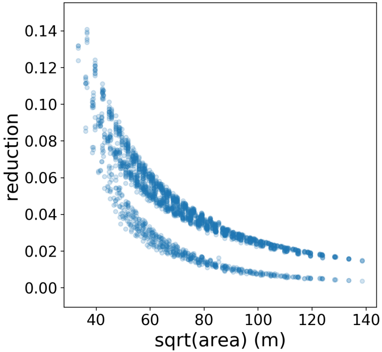

Selected features:

- rated
  power for the turbine model [MW]
- rotor
  diameter for the turbine model [m]
- **the square root of the**
  area of the site [rotor diameters]

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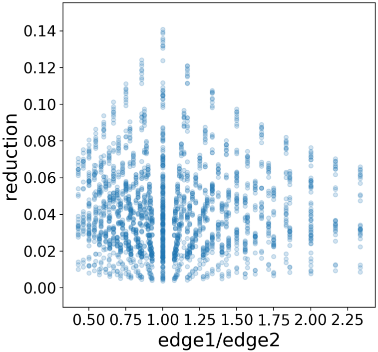

Selected features:

- rated power for the turbine model [MW]
- rotor diameter for the turbine model [m]
- the square root of the area of the site [rotor diameters]
- **the ratio between the two edges of the rectangle**

Feature selection

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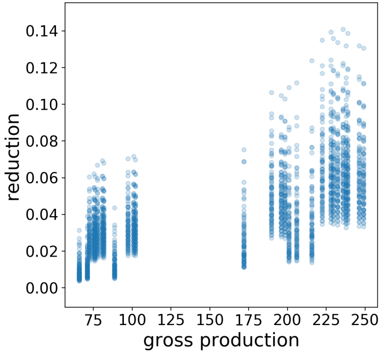

Selected features:

- rated power for the turbine model [MW]
- rotor diameter for the turbine model [m]
- the square root of the area of the site [rotor diameters]
- the ratio between the two edges of the rectangle
- **the production without interference [MW]**

Machine Learning

Two different ML models to estimate the reduction in power production due to the interference:

- Linear Regression
- Neural Networks (NNs)

In addition, we also defined a simple baseline model (*Mean Value*), that regardless of its input always predicts the mean reduction of the training set. This last model mimics what is normally done by humans, and is used for comparison.

Machine Learning

2268 instances

–> **training set** randomly choosing 60% of the instances;

–> **test set** the remaining 40%

→ hyperparameters of the models are chosen using the *scikit-learn* [1] function *GridSearchCV* (5-fold cross-validated on the training set)

[1] a ML library for python

Results

What a human would do: reduction mean value

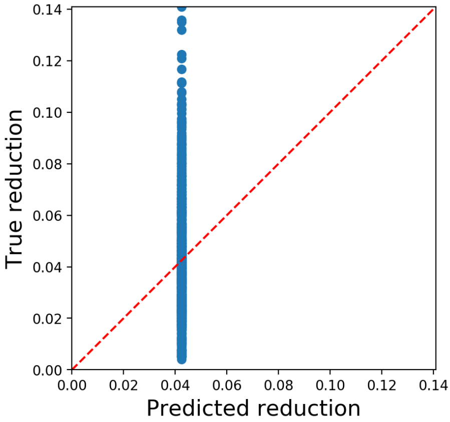

Figure: Mean Value

Results

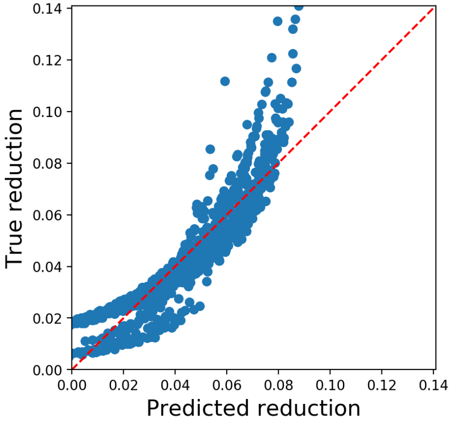

Figure: Linear Regression

Results

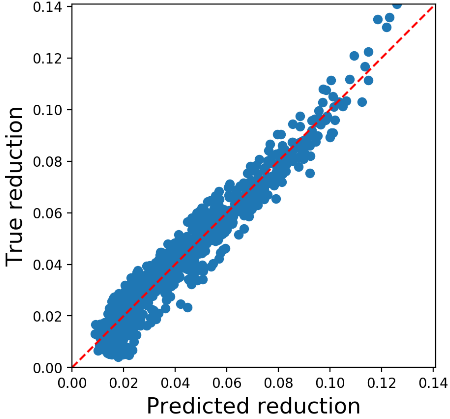

Figure: Neural Network

Conclusions

This preliminary work shows

- the relevance of using MO and ML techniques together;
- that ML techniques (NNs in particular), trained on a large number of optimized solutions, could well predict the optimal value of new instances of the same (wind park layout) problem
- that the ML estimate highly outperforms the human estimate (Mean Value model)

Recent work

We have further worked on this project.

- we increased the number of instances including additional sites

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- we increased the number of instances including additional sites
- instead of the gross production we used the production (with wake effect) of a regular layout on a grid (both as feature and as banchmark)
- we better defined our training/test set (not randomly selected but depending on the wind in the site)
- we designed new ML models (i.e. Support Vector Regression)

Future work

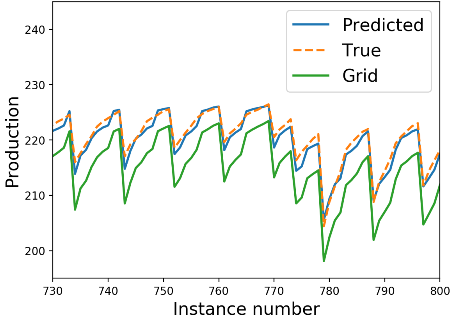

Figure: Support Vector Regression

For more info:

- M. Fischetti, M. Fraccaro, **Machine Learning meets Mathematical Optimization to predict the optimal production of offshore wind parks**(submitted).