

Operations Research + Machine Learning for the design of future offshore wind farms

Martina Fischetti

PhD, Lead Engineer in OR

In Vattenfall BA Wind



Teaser

Operations Research (OR) and Machine Learning (ML) can be combined in different interesting ways.

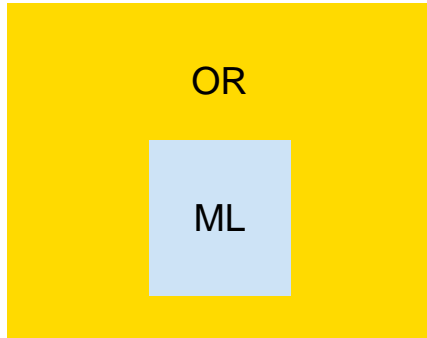
- **Prescriptive Analytics:** where ML is used to predict a phenomenon in the future, and OR is used to optimize an objective over that prediction.



Teaser

Operations Research (OR) and Machine Learning (ML) can be combined in different interesting ways.

- A popular research area is also to **use ML to improve heuristic decisions in Mixed Integer Linear Programming (MILP)** algorithms, for example in the branching procedure or in decomposition techniques.



Exact Combinatorial Optimization with Graph Convolutional Neural Networks
Maxime Gasse, Didier Chetelat, Nicola Ferroni, Laurent Charlin, Andrea Lodi
NeurIPS 2019

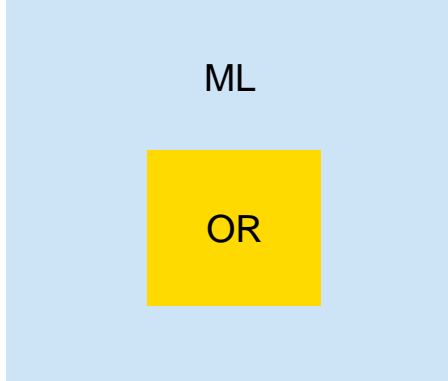
Learning a classification of mixed-integer quadratic programming problems
Pierre Bonami, Andrea Lodi, and Giulia Zarpellon
CPAIOR 2018, Lecture Notes in Control and Information Sciences, vol. 10848, Springer, Cham, 595–604, 2018

Learning MILP resolution outcomes before reaching time-limit
Martina Fischetti, Andrea Lodi, and Giulia Zarpellon
CPAIOR 2019, Lecture Notes in Computer Science, vol. 11494, Springer, Cham, 275–291, 2019

Teaser

Operations Research (OR) and Machine Learning (ML) can be combined in different interesting ways.

- A research area is also in the use of **OR techniques to improve the optimization challenges hidden in ML models**

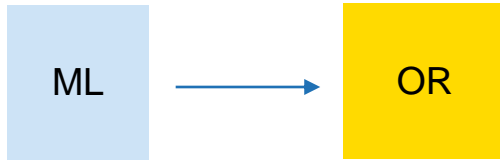


Bartlett, M., Cussens, J., 2017. Integer linear programming for the Bayesian network structure learning problem. *Artif. Intell.* 244, 258–271 . Combining Constraint Solving with Mining and Learning

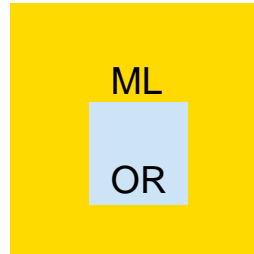
Laura Palagi. 2019. Global optimization issues in deep network regression: an overview. *J. of Global Optimization* 73, 2

Teaser

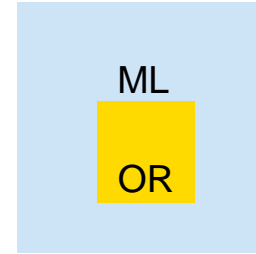
Operations Research (OR) and Machine Learning (ML) can be combined in different interesting ways.



Prescriptive analytics



ML in OR



OR in ML

Here we will instead investigate a different way to merge OR and ML, where the MO model comes first, and its (almost) optimal solutions are used as training set for a ML algorithm that can quickly estimate the value of new optimized solutions



Teaser

Can a machine, trained on a large number of optimized solutions, accurately estimate the value of the optimized solution for new (unseen) instances?



Agenda

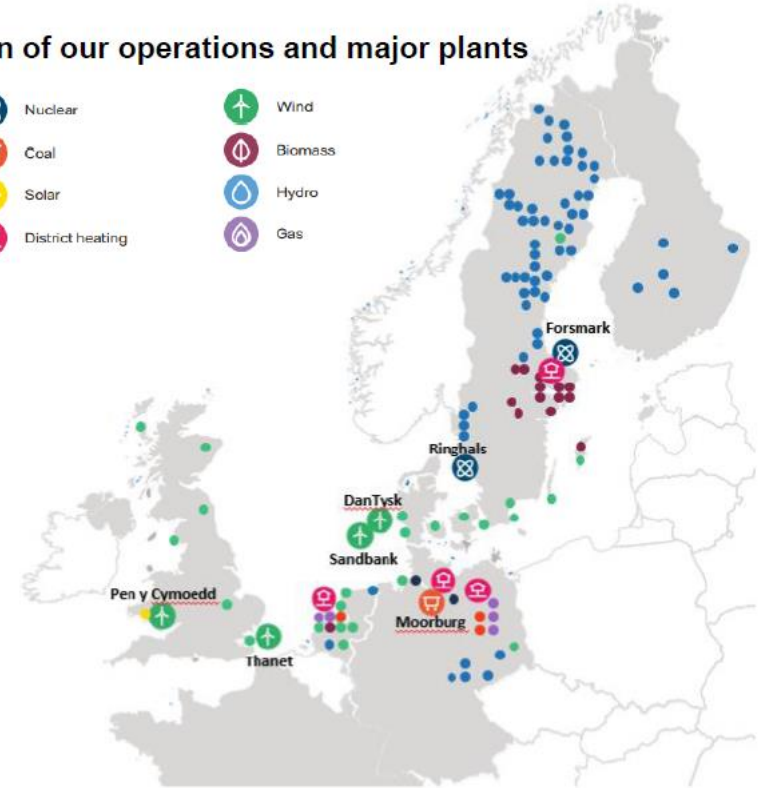
- Vattenfall: who we are and why we need OR
- OR for offshore wind farm design
- OR + ML for future challenges

Vattenfall

Key data

- One of Europe's largest producers of electricity and heat
- Owned by the Swedish state
- Main products: electricity, heat, gas and energy services
- Main markets: Sweden, Germany, Netherlands, Denmark and the UK
- About 20,000 employees

Location of our operations and major plants





**Fossil-free within
one generation**

Strong competition



“Innovation and competition are making sustainable energy cheaper and cheaper, and much faster than expected too.”

Eric Wiebes - Dutch Economic Affairs and Climate Minister, 2018

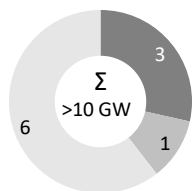
Operations Research to win

In operation

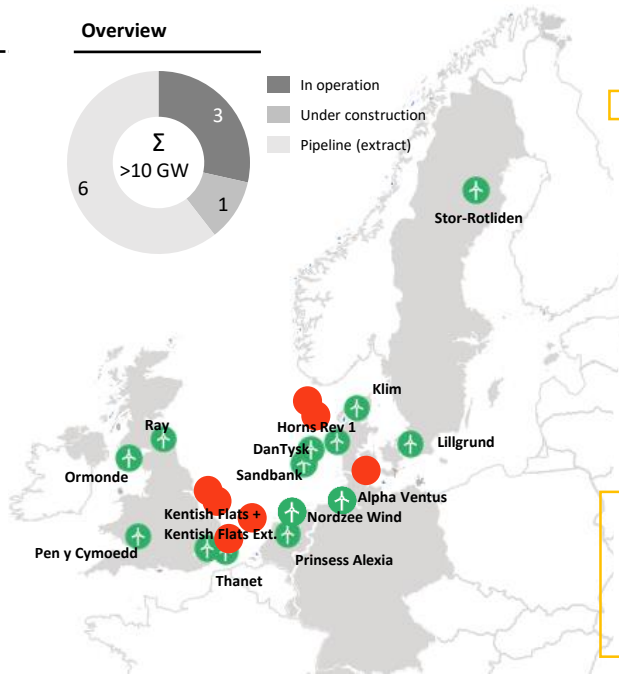
Name	Capacity (MW)	Country
Thanet	300	UK
Ormonde (51%)	150	UK
Aberdeen	92	UK
Kentish Flats	90	UK
Kentish Flats extension	50	UK
Pen y Cymoedd	228	UK
Ray	54	UK
Lillgrund	111	SE
Stor-Rotliden	78	SE
Horns Rev 1 (60%)	158	DK
Klim (98%)	67	DK
DanTysk (51%)	288	DE
Sandbank (51%)	288	DE
Nordzee Wind (50%)	108	NL
Prinses Alexia	122	NL
Parc y Cynog	5	UK
Other offshore	70	
Other onshore	669	

Total 2.8 GW

Overview



- In operation
- Under construction
- Pipeline (extract)



- Offshore
- Onshore
- Solar

Under construction

Name	Capacity (MW)	Commissioning	Country
Horns Rev 3	406	2019	DK
Slufterdam	29	2019	NL
Wieringermeer	180	2020	NL
Wieringermeer ext.	110	2020	NL
Blakliden + Fäbodberget	354	2022	SE

Total > 1 GW

Pipeline (extract)

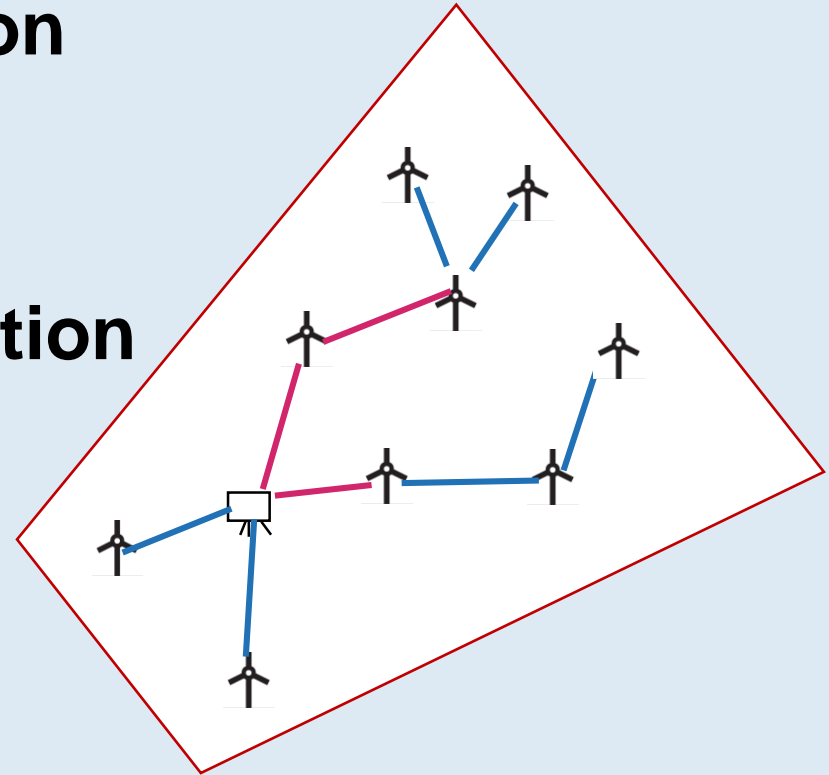
Name	Capacity (MW)	Commissioning	Country
South Kyle	~200	2021	UK
NK II	~120	2021	DK
Onshore pipeline	>1.000	>2022	
Vesterhav N & S	344	2021	DK
Danish Kriegers Flak	602	2021	DK
Hollandse Kust	~700	2023	NL
Thanet Extension	272	2024	UK
Norfolk Vanguard	1,800	2027	UK
Norfolk Boreas	1,800	2028	UK
Solar pipeline	>150	2019	

Total > 6 GW

Wind farm layout optimization

Electrical cable routing

Turbine foundation optimization



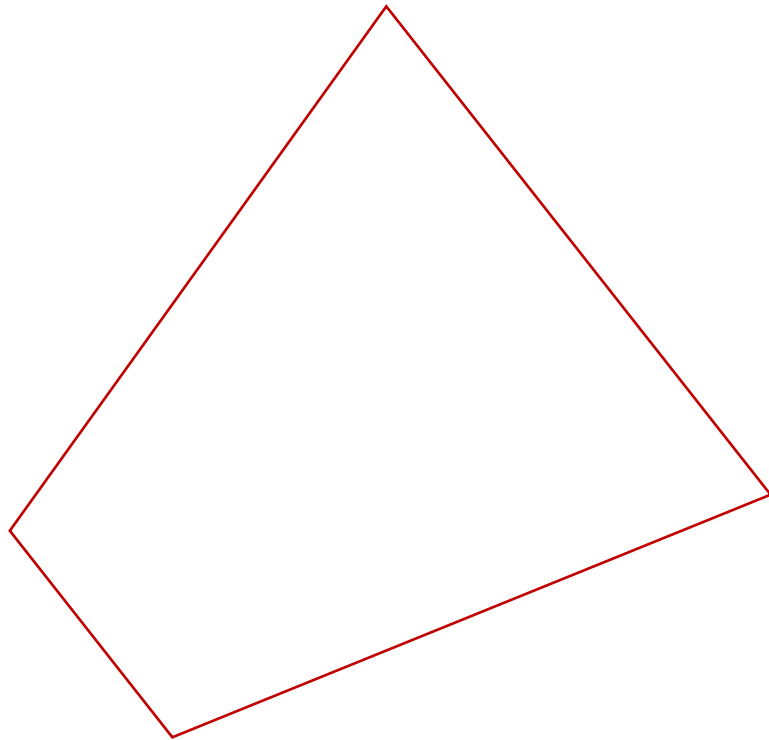
M. Fischetti, and D. Pisinger (2018). *Mathematical Optimization for offshore wind farm design: an overview*. Business and Information Systems Engineering.

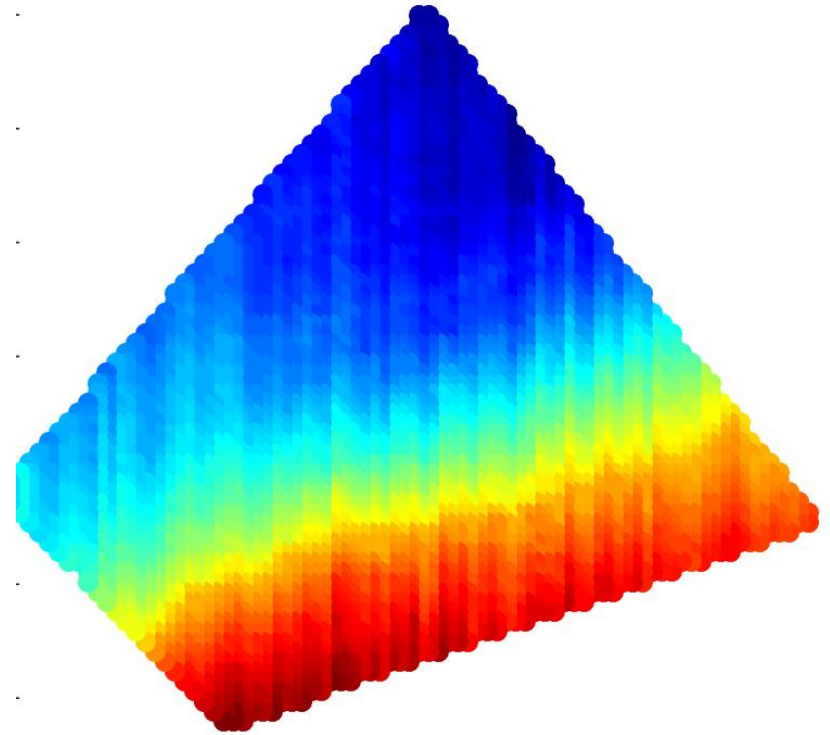
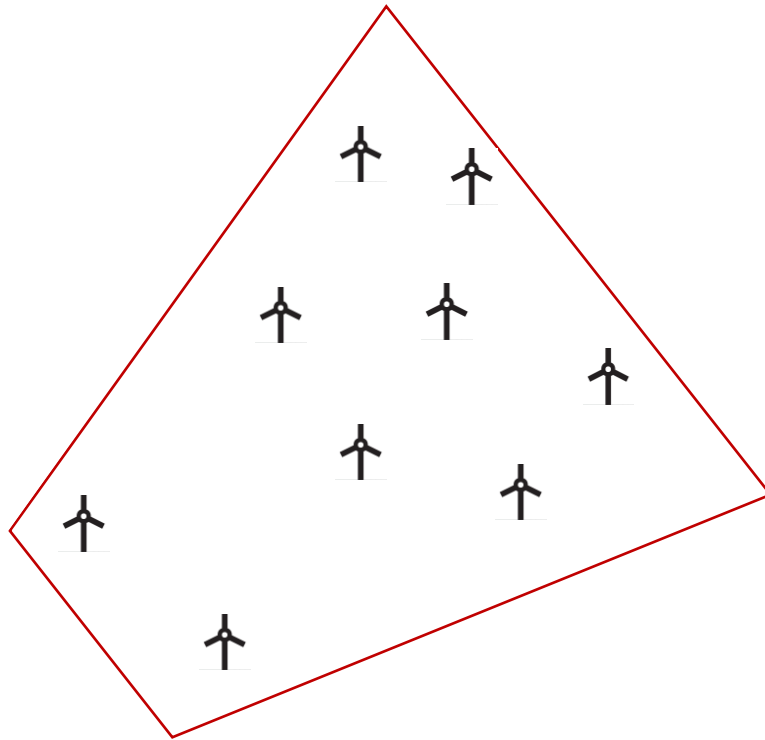
Turbine layout optimization



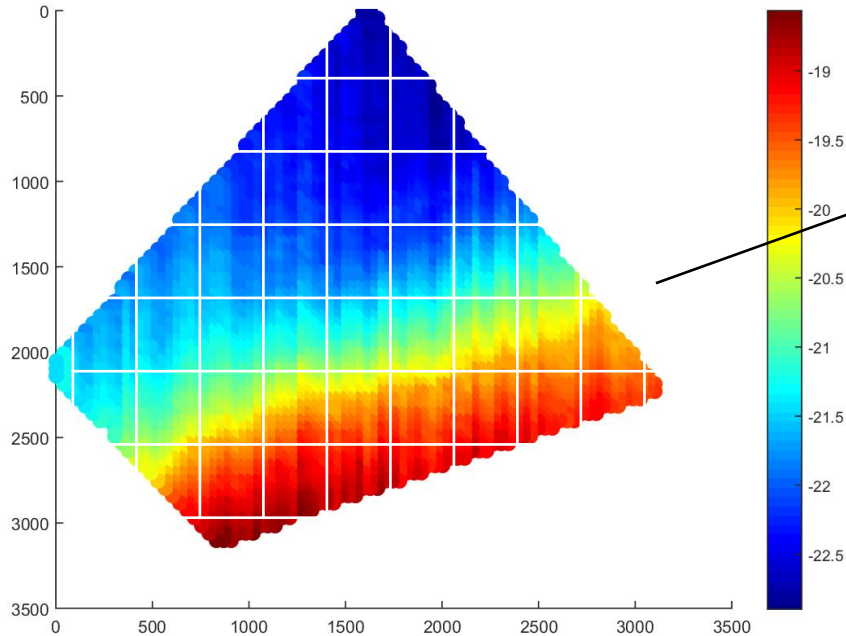
Turbine layout optimization







Mathematical model



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

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

where V is the set of potential turbine positions.

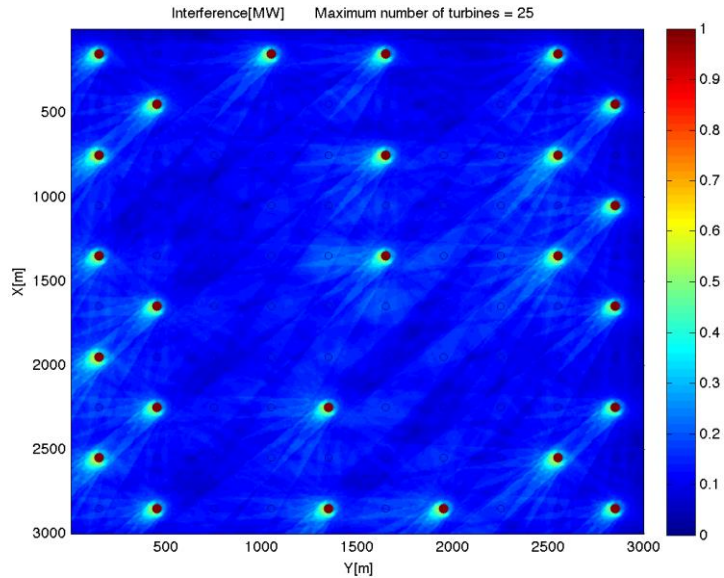
Our new mathematical model

$$\begin{aligned} \max \quad & \sum_{i \in V} [(P_i - \frac{c_i}{K_{euro}})x_i - w_i] \\ \text{s.t.} \quad & N_{MIN} \leq \sum_{i \in V} x_i \leq N_{MAX} \\ & x_i + x_j \leq 1 \quad \forall \text{ incompatible } i, j \in V, i < j \\ & \sum_{j \in V} I_{ij}x_j \leq w_i + M_i(1 - x_i) \quad \forall i \in V \\ & x_i \in \{0, 1\} \quad \forall i \in V \\ & w_i \geq 0 \quad \forall i \in V \end{aligned}$$

where $M_i \gg 0$ (big-M).

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

Stochastic programming



It is important to consider wind variability!



Hundred thousands wind scenarios in practice

Layout optimization - matheuristics

Why?

- To solve instances with 10,000+ possible positions

How?

- Ad-hoc heuristics
- MILP-based heuristics (Proximity Search)

Idea: Given an initial (heuristic) solution, explore its neighbourhood using the MILP solver as a black box

Layout optimization - matheuristics

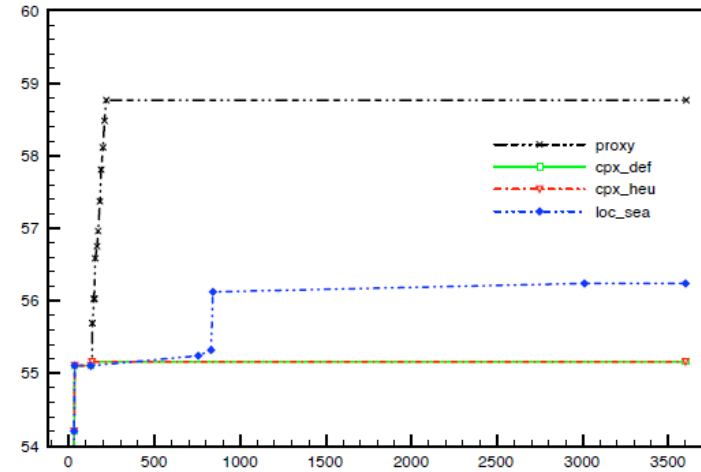
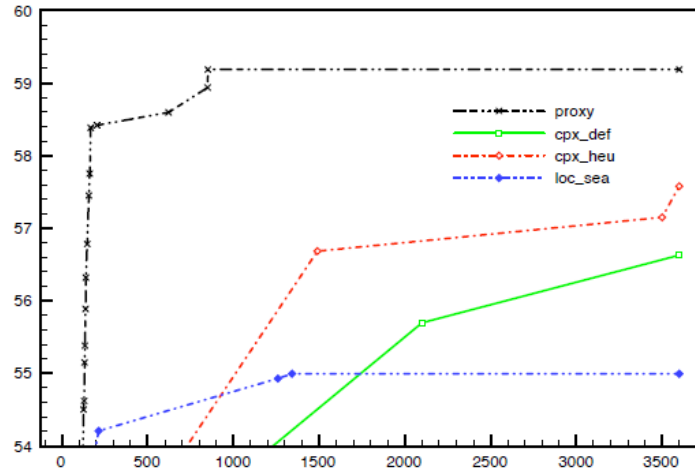


Figure: Solution profit over time for 2 sample instances with $n = 5000$ (left), and $n = 10,000$ (right); the higher the profit the better.

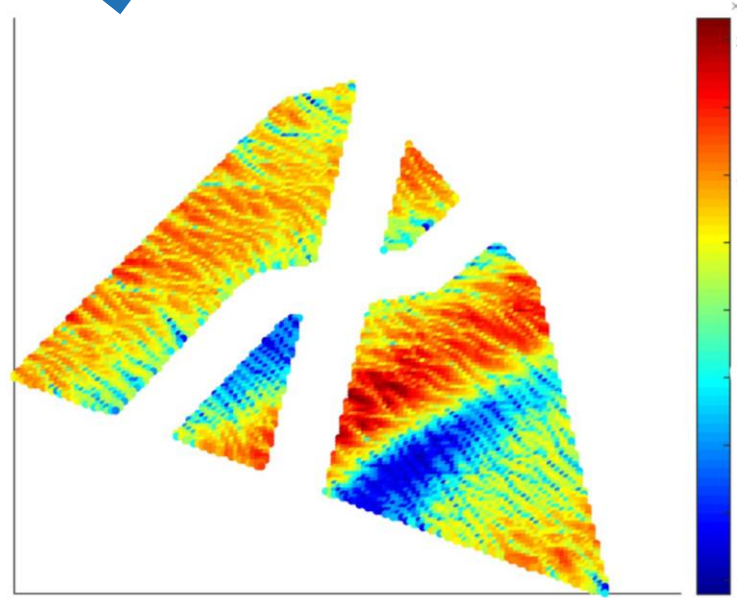
M. Fischetti and M. Monaci (2016). Proximity search heuristics for wind farm optimal layout. Journal of Heuristics 22 (4), pp. 459-474.

Results

We can include also foundation costs
in the optimization

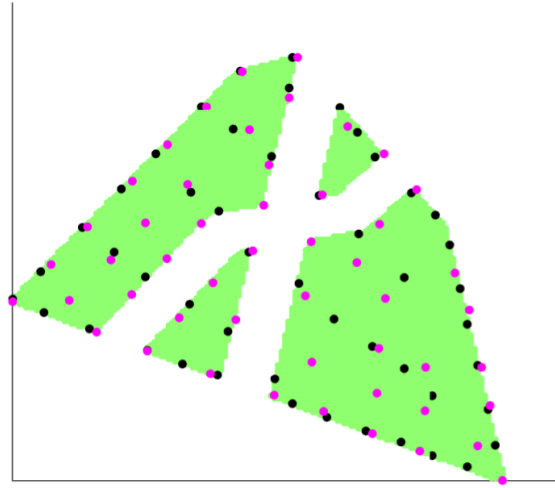


Area available



Cost map

Results



Optimized layout considering wake effect and costs of foundations (black) versus "manual" layout (pink)

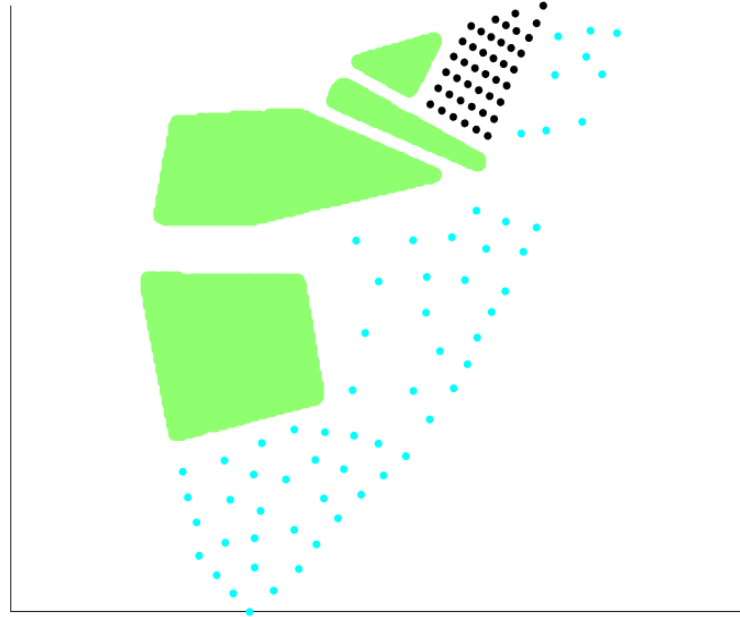
Company experts certified that our layout allows for an extra 0.28% production while decreasing cost of foundations of more than 10M Euros.

All in all, they estimated an increased income of **12.6M Euros in 25 years.**

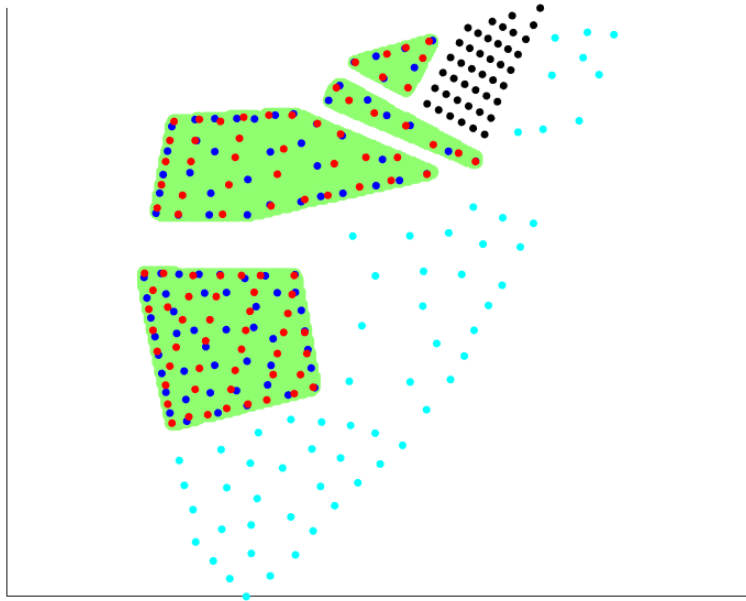
Results: Hollande Kust Zuid



Results: Hollande Kust Zuid



Results

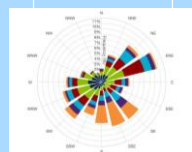
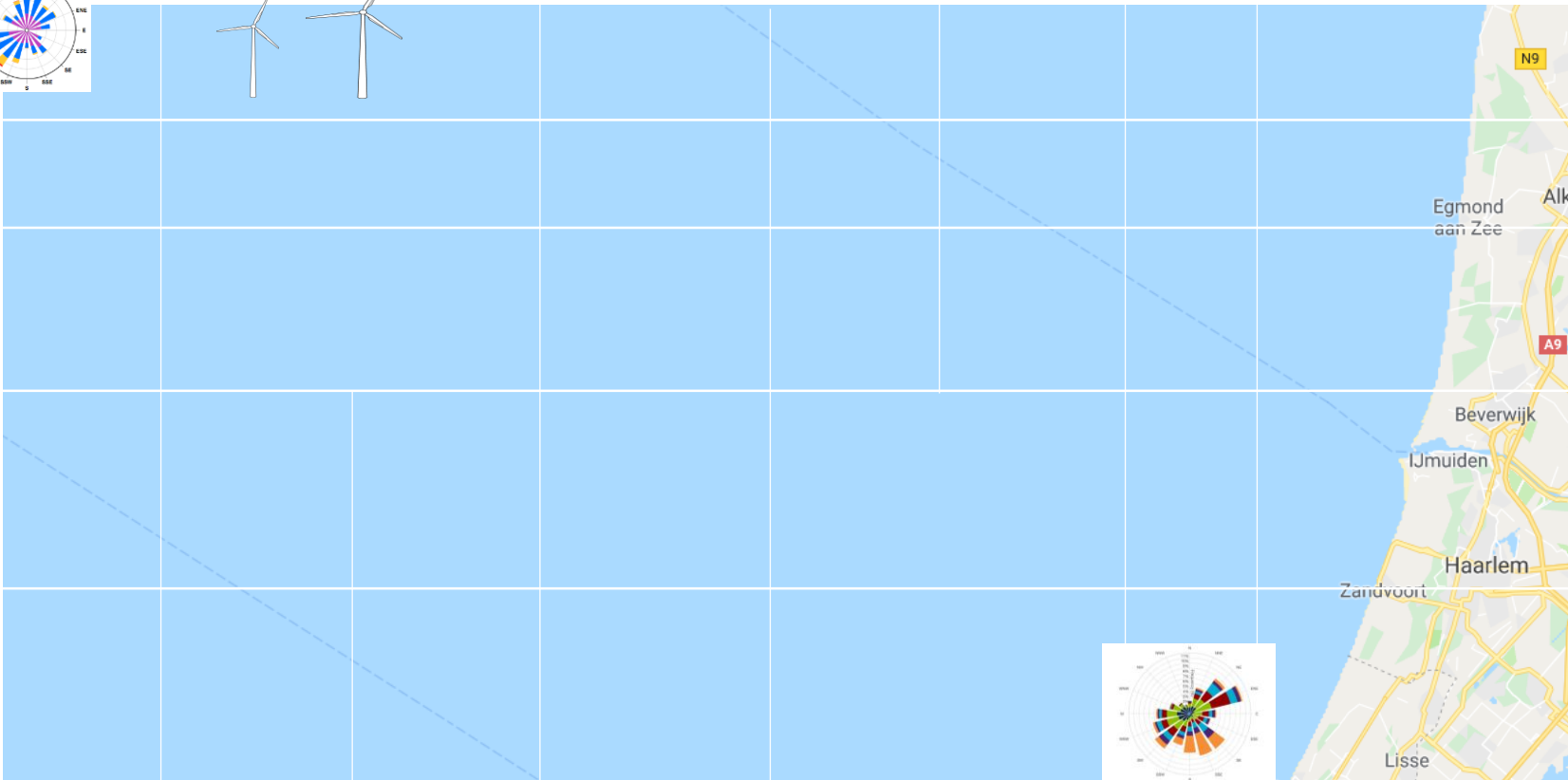
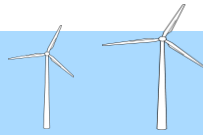
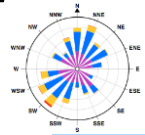


Our layout (red) allowed for a higher annual energy production: this difference has been evaluated to be worth **10.2 M Euro**(Net Present Value) over the park lifetime.

→ This site will be the first wind farm in the world to be built without any subsidies.



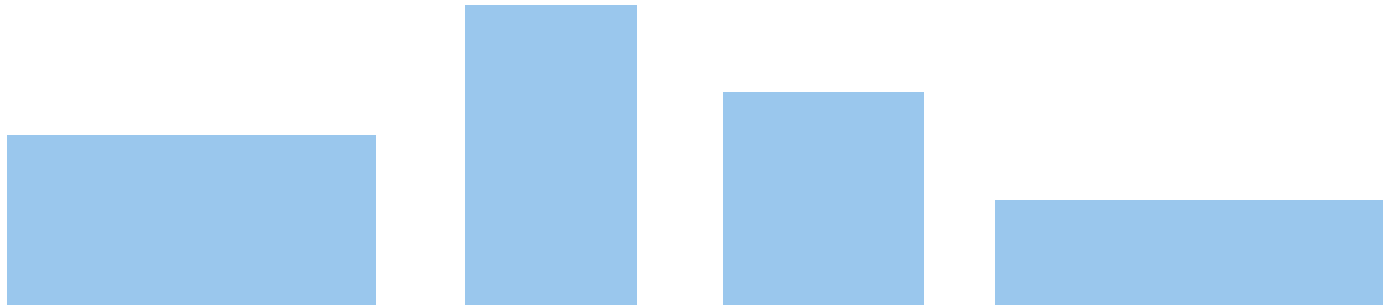
More and more what-if analyses in the future



Can a machine, trained on a large number of optimized **layouts** , accurately estimate the value of the optimized solution for new (unseen) instances?

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&2, Borssele 3&4, Danish Kriegers Flak, Horns Rev 3, Hollandse Kust Zuid 1&2 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 3000+ instances



Building training/test set

1. *Grid production*, i.e., the power production of a solution obtained by locating the turbines on a regular grid;

→ this will be used as input information (feature) and benchmark

2. the optimized layout and its power production (*True production*)

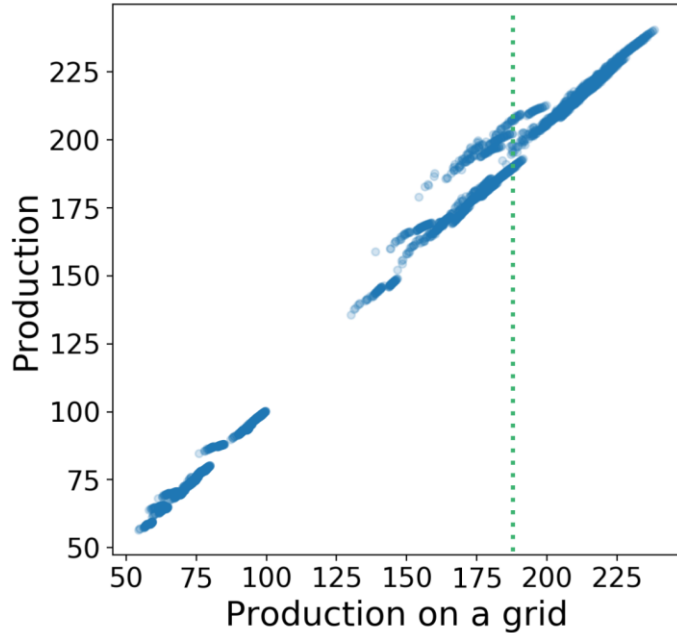
→ **this is what we want to predict**

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.

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]**
- **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**
- **grid production [MW]**

Machine Learning

Different ML models to estimate the power production:

- Linear Regression
- Neural Networks (NNs)
- Support Vector Regression (SVR)

Machine Learning

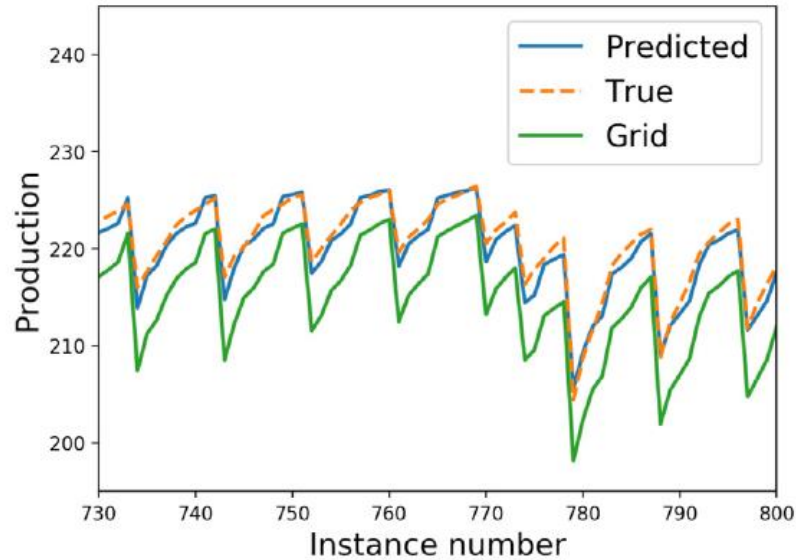
3000+ instances

→ **training set** 2268 instances (the real sites Borssele 1 and 2, Borssele 3 and 4, Horns Rev 3, and Denish Krigers Flak);

→ **test set** 1134 instances (Ormonde and Hollandse Kust Zuid)

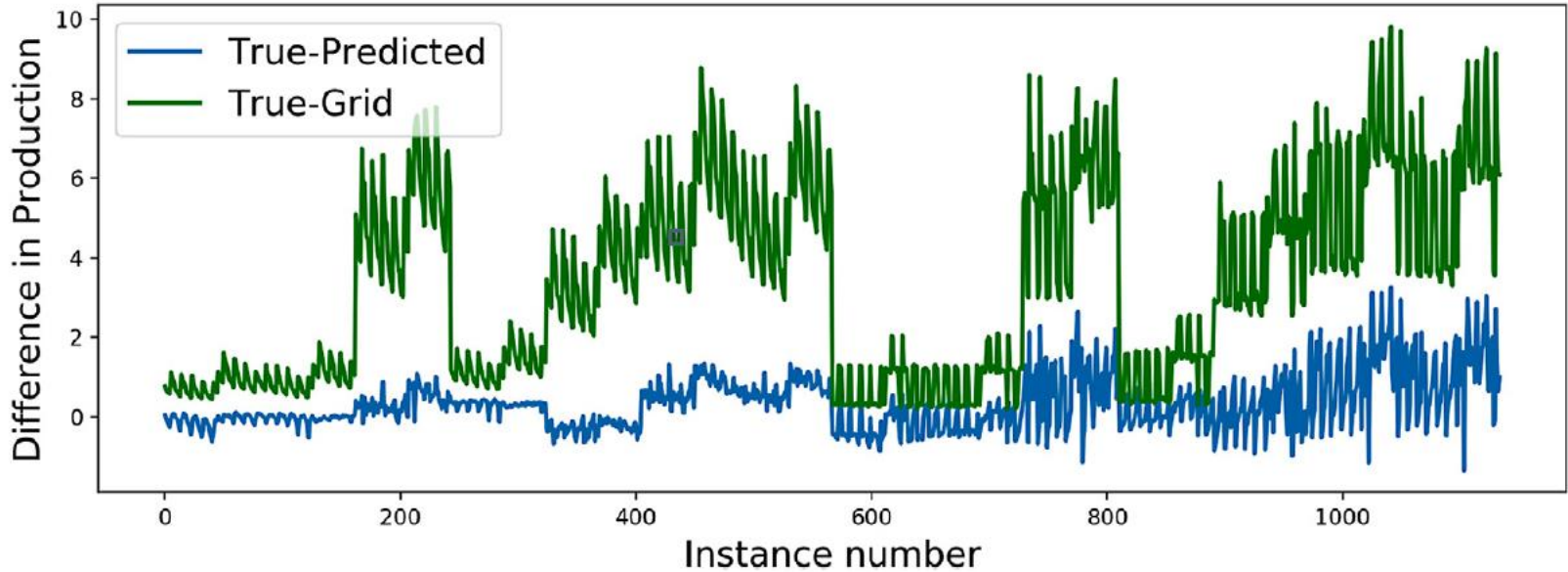
Hyperparameters of the models are chosen using the *scikit-learn* function *GridSearchCV* (5-fold cross-validated on the training set)

Results



(c) Support Vector Regression

Results



Thanks!

References:

M. Fischetti, and D. Pisinger (2018). *Mathematical Optimization for offshore wind farm design: an overview*. Business and Information Systems Engineering 61 (4), pp. 469–485

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

M. Fischetti, and M. Fraccaro (2018), *Machine Learning meets Mathematical Optimization to predict the optimal production of offshore wind parks*. Computers and Operations Research 106, pp. 289-297