Evolutionary lessons for wind energy efficiency

also known as
Optimizing the Turbine Placement of Large Wind Farms

Markus Wagner
School of Computer Science
University of Adelaide
Adelaide, Australia

Joint work with Frank Neumann (UoA), Una-May O'Reilly (MIT),
Kalyan Veeramachaneni (MIT)


ACM TechNews
http://technews.acm.org/
ACM TechNews
| About | Current Issue | TechNews Archive | TechNews Apps Support | MemberNet | CareerNews
Welcome to the May 9, 2011 edition of ACM TechNews, providing timely information for IT professionals three times a week.
Also, please download our new ACM TechNews iPhone App from the iTunes Store by clicking here and our new ACM TechNews iPad App by clicking here.
HEADLINES AT A GLANCE
Long-Prized Tech Visas Lose Cachet
Graphene Optical Modulators Could Lead to Ultrafast Communications
Pentagonal Tiles Pave the Way Towards Organic Electronics
Face Recognition Software Could Detect Pain in Patients
Agents Help Schedule Efficient Charging of Electric Cars
Scientists Afflict Computers With Schizophrenia to Better Understand the Human Brain
Automated Umpire Keeps Cricket Matches Moving
Evolutionary Lessons for Wind Farm Efficiency
Targeting Leftover Land Mines
Green GPS Calculates Most Fuel-Efficient Route
Congress to ICANN: No You Can't
'The Ascent' Art Installation/Ride at Rensselaer Links EEG Headset and Theatrical Flying Rig
Long-Prized Tech Visas Lose Cachet
Wall Street Journal (05/07/11) Miriam Jordan
Biology helps to optimise wind farms › News in Science (ABC Science)
http://www.abc.net.au/science/articles/201
ABC Science
Explore by topic
News in Science
In Depth
Dr Karl
Ask an Expert
Bernie's Basics
Latest News in Science | News Analysis | StarStuff | News Archive | Tag library
News in Science
Biology helps to optimise wind farms
Share
Print
Anna Salleh
ABC
Thursday, 5 May 2011
Evolutionary algorithms are being used to work out the best placement of wind turbines to maximise their energy output.
Wind turbines can block the flow of wind to other turbines, depending on where they are placed
(Source: Chromatika Multimedia/iStockphoto)
Related Stories
"Evolutionary lessons for wind farm efficiency" - Google Search
http://www.google.com.au/#hl=en&q="Evolutionary+lessons+for+wind+fa
Web Images Videos Maps News Shopping Gmail more iGoogle | Search settings | Sign in
Google
"Evolutionary lessons for wind fa
Search
About 10,300 results (0.27 seconds)
Go to Google.com
Advanced search
Everything
Images
Videos
News
Shopping
Evolutionary lessons for wind farm efficiency
5 May 2011 ... Evolution is providing the inspiration for computer science research in Australia to find the best placement of turbines to increase wind ...
www.sciencedaily.com/releases/2011/05/110504091842.htm - Cached

Motivation

Renewable Energy:

- Has gained increasing interest
- Is clean
- Substantial to decrease CO_2 emission
- Is a huge market
- Large developing effort
- Has many challenging questions.

Wind Energy:

- Major player in renewable energy
- Since 2005 the cumulative installed capacity of wind energy within the EU has almost doubled (from 40000 MW to 74000 MW).
- In 2009, 39% of all new energy capacity installed in the EU was based on wind.
- Roughly 8800 wind turbines in Europe which helped to save 180 Mio tons of CO_2 since the beginning of 2009.

Largest Wind Farms:

- Roscoe Wind Farm (Texas, 627 turbines, 781 MW)
- Vlorë Wind Farm (Albania, 250 turbines, 500 MW)

Recent News:

- Thanet Wind Farm (Offshore (UK), 100 turbines, 300 MW)
- Ontario’s 21,000 Megawatts Offshore Potential
- Google invests 38.8 Mio. USD in Wind Energy

Very Recent News (9 May 2011):

“Special Report on Renewable Energy Sources and Climate Change Mitigation”

→ Renewable energy could make up 77% in 2050

→ Wind energy could be responsible for 20%

Source: Wind Power Ninja

Wind Speed and Energy

Wind Speed:

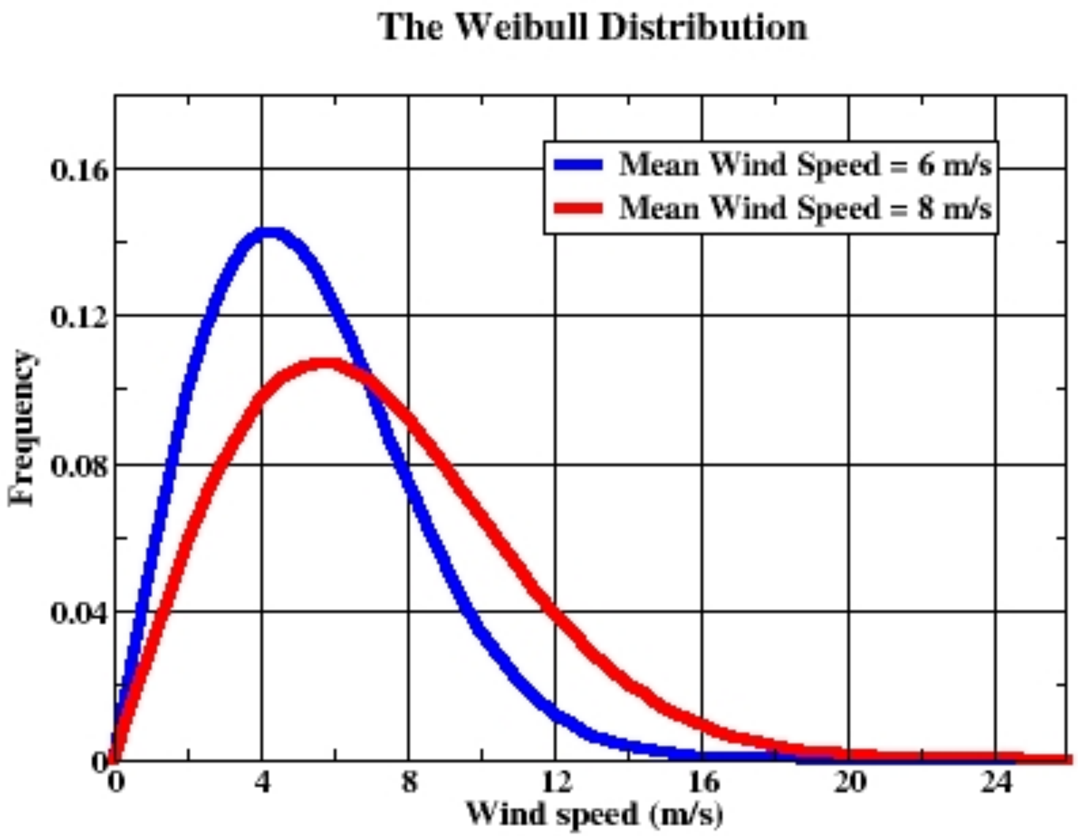
- Most crucial for energy production
- Varies over time
- Depends on seasonal effects
- Weibull distribution gives a good representation of the variation in hourly mean wind speed over a year at many typical sites

Probability density function: $p(v,k,c) = k/c(v/c)^{k-1}e^{-(v/c)^k}$

k: Weibull shape parameter

c: Weibull scale parameter

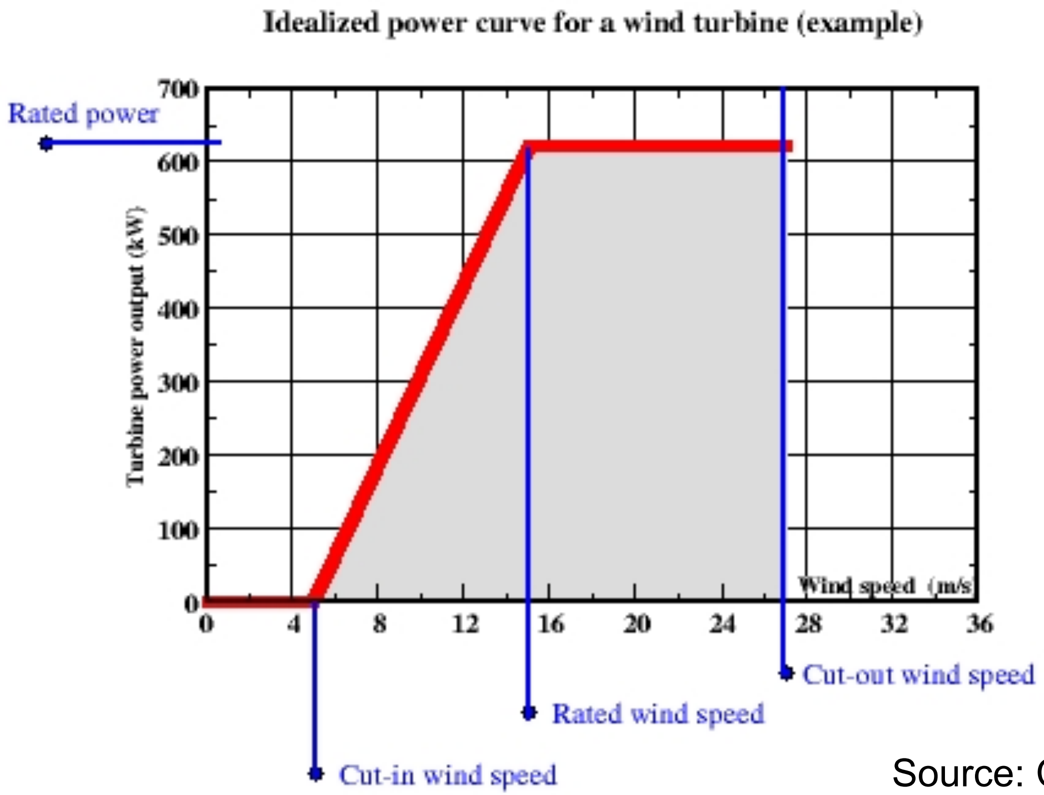
Example Weibull distribution:



Source: Canadian Wind Energy Atlas

Assume linear energy function

$$\beta(v) = \begin{cases} 0 & v < v_{cut\_in} \\ \lambda v + \eta & v_{cut\_in} \leq v \leq v_{rated} \\ P_{rated} & v_{rated} < v < v_{cut\_out} \end{cases}$$



Source: Canadian Wind Energy Atlas

Expected energy output of turbine i:

$$P(\theta)$$

$$p_v(v(\theta), c(\theta), k(\theta))$$

$$E^i[\eta] = \int_\theta P(\theta) \int_v p_v(v(\theta), c(\theta), k(\theta)) \beta^i(v).$$

For wind farm with n turbines

$$E^{farm}[\eta] = \sum_{i=1}^{n} E^i[\eta]$$

?

What's wrong with that?

Wake effects

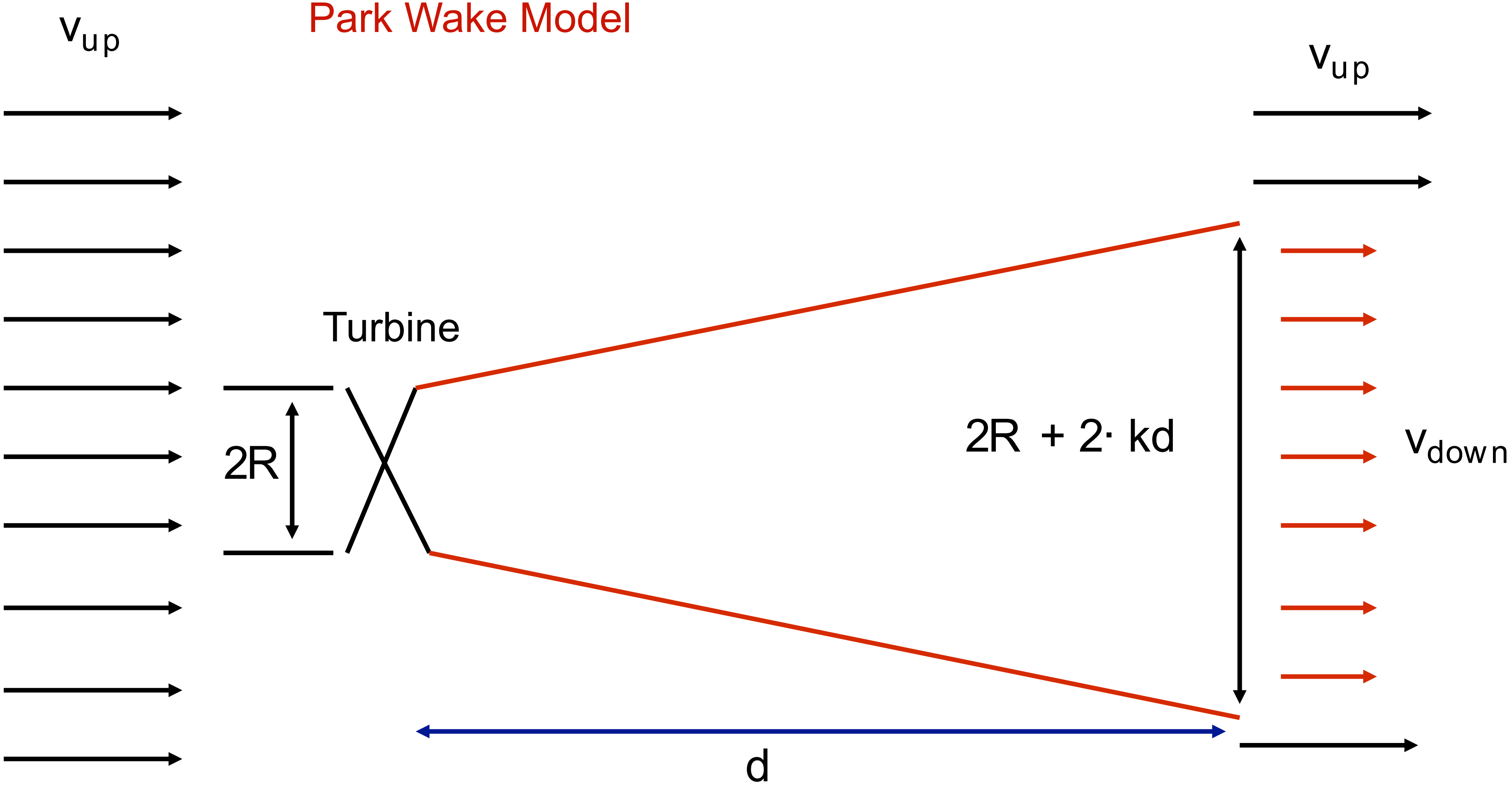
Wake Effect:

- On wind farms turbines are placed close to each other
- Energy capture of a turbine is influenced by the other turbines on the wind farm
- Turbines produce wake effects that reduce the wind speed usable for energy production
- Wake effects influence the efficiency of wind farms: turbines in the center may produce just 60% of the energy of turbines at the border, which leaves room for optimizations.

Wake

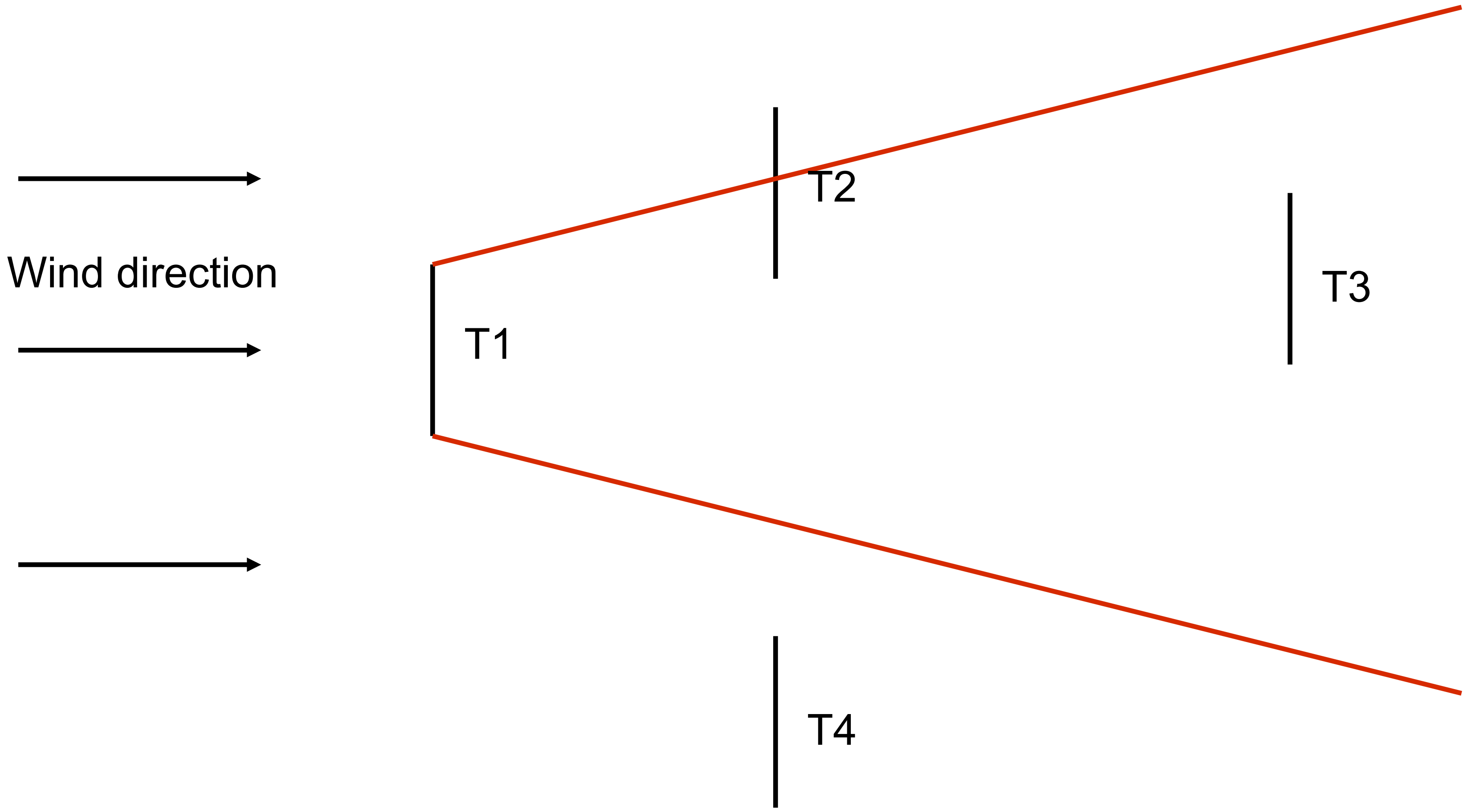
Source: Cooperative Institute for Research in Environmental Science

Park Wake Model



R: rotor radius

Wake effect



Computation of the wake effect (Kusiak and Song 2010)

Let $X = \{x_1, \ldots, x_n\}$ and $Y = \{y_1, \ldots, y_n\}$ be x and y coordinates of the n turbines

for $i = 1$ to number of turbines **do**
  for $\theta = 0^0$ to 360^0 **do**
    for $j = 1$ to n-1 and $j \neq i$ **do**

$$\delta_{i,j} = cos^{-1}\{\frac{o+R/\kappa}{\sqrt{(x_i-x_j+(R/\kappa)cos\theta)^2+(y_i-y_j+(R/\kappa)sin\theta)^2}}\}$$

$$Vdef_{(i,j)} = u(\delta_{i,j} - \alpha)\frac{a}{(1+bd_{i,j})^2}$$

    end for

$$Vdef_i^\theta = \sqrt{\sum_j (Vdef_{(i,j)})^2}$$

$$c_i(\theta) = c_i(\theta) \times (1 - Vdef_i)$$

  end for
end for

Wake effect only changes scaling parameter of Weibull distribution

Energy output of turbine i considering wake effect:

$$E^i[\eta] = \int_\theta P(\theta) \int_v p_v^\theta(v, c_i(\theta), k_i(\theta), x_i, y_i, X, Y)\beta^i(v)$$

Total energy output of the wind farm:

$$E^{farm}[\eta] = \sum_{i=1}^{n} E^i[\eta]$$

Experimental Study

Setting:

- Number of turbines: n
- Positive coordinates: x_i and y_i for each turbine i

Constraints:

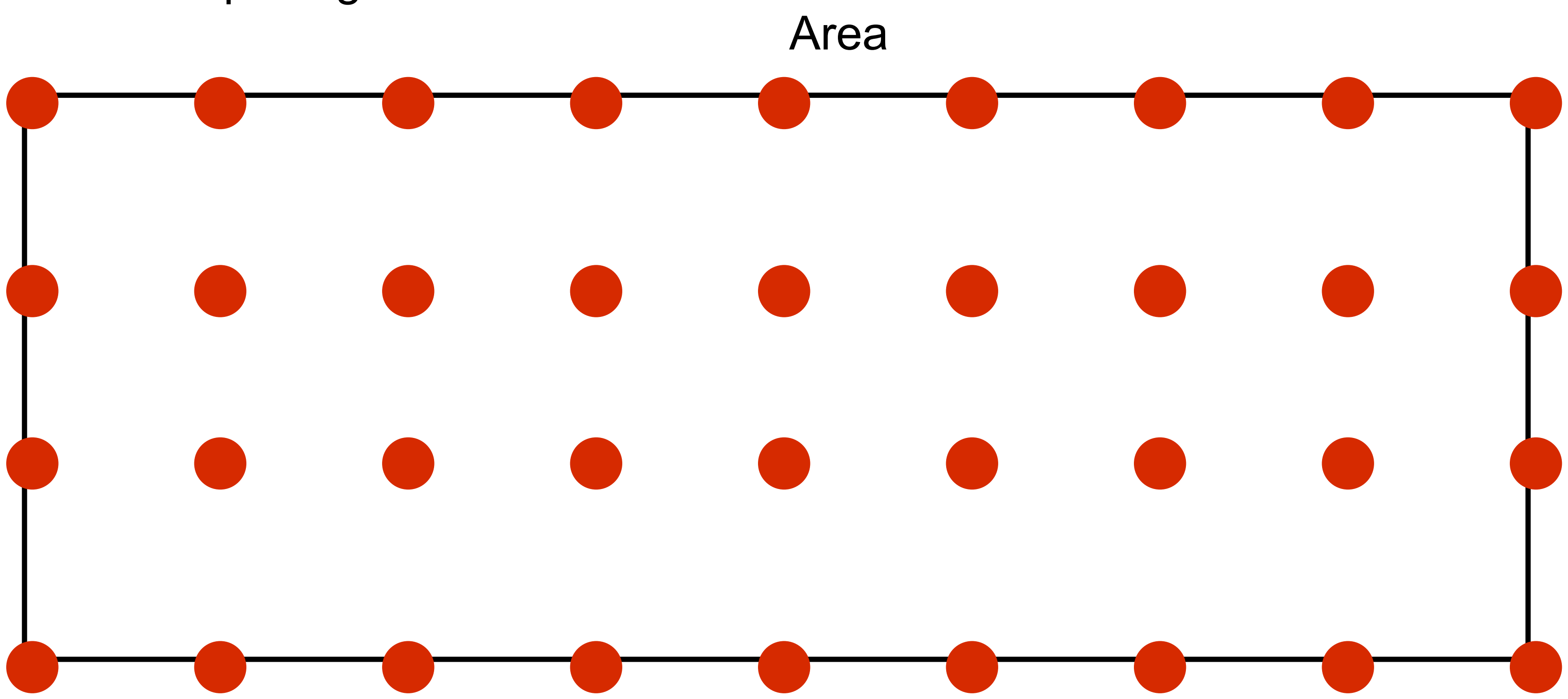
- Area and length l and wide w: $\forall i : x_i \leq l \ and \ y_i \leq w$
- Proximity constraints: $\forall i, j, i \neq j : \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \geq 8 \cdot R$

R: rotor radius

Area could include 2n turbines

Turbine Placement on wind farm

Maximal spacing initialization



Wind Scenario (Kusiak and Song, Renewable Energy 2010)

$l-1$	θ^{l-1}	θ^l	k	c	$P(\theta)$	$l-1$	θ^{l-1}	θ^l	k	c	$P(\theta)$
0	0	15	2	7	0.0002	12	180	195	2	10	0.1839
1	15	30	2	5	0.008	13	195	210	2	8.5	0.1115
2	30	45	2	5	0.0227	14	210	225	2	8.5	0.0765
3	45	60	2	5	0.0242	15	225	240	2	6.5	0.008
4	60	75	2	5	0.0225	16	240	255	2	4.6	0.0051
5	75	90	2	4	0.0339	17	255	270	2	2.6	0.0019
6	90	105	2	5	0.0423	18	270	285	2	8	0.0012
7	105	120	2	6	0.029	19	285	300	2	5	0.001
8	120	135	2	7	0.0617	20	300	315	2	6.4	0.0017
9	135	150	2	7	0.0813	21	315	330	2	5.2	0.0031
10	150	165	2	8	0.0994	22	330	345	2 4.	5	0.0097
11	165	180	2	9.5	0.1394	23	345	360	2	3.9	0.0317

Kusiak and Song use evolution strategy

Only results for up to 6 turbines.

Experimental Studies:

- Use maximal spacing initialization for initial placement
- Improve by (10,20)-CMA-ES
- Include mechanism to deal with boundary constraints
- Improves results of Kusiak and Song
- What results do we get for large wind farms?

Problem:

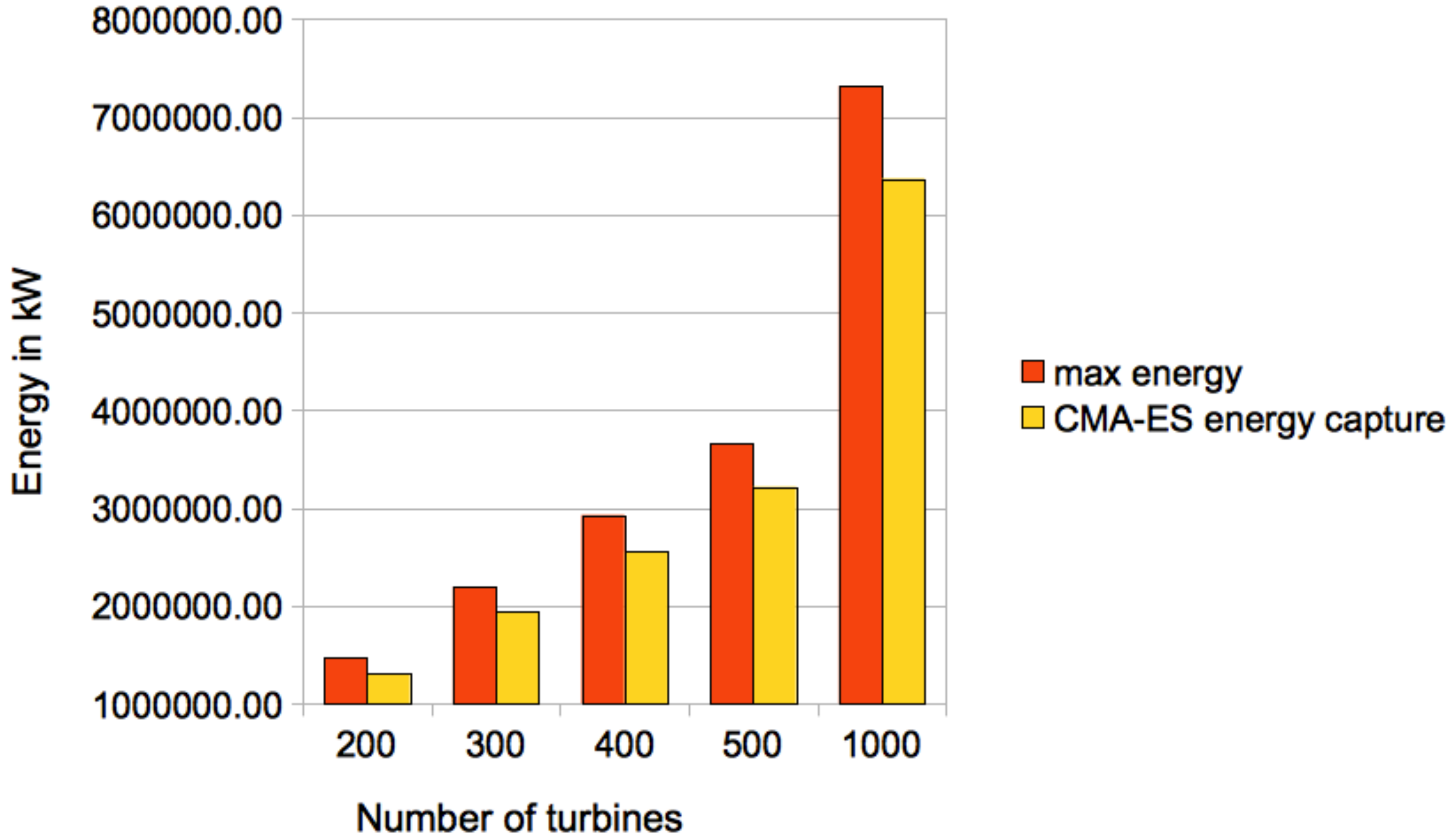
- Evaluation is very costly for large number of turbines
- Need sufficiently large number of generations (10000 or 20000) to get good results

Sequential Runtimes (predicted runtimes):

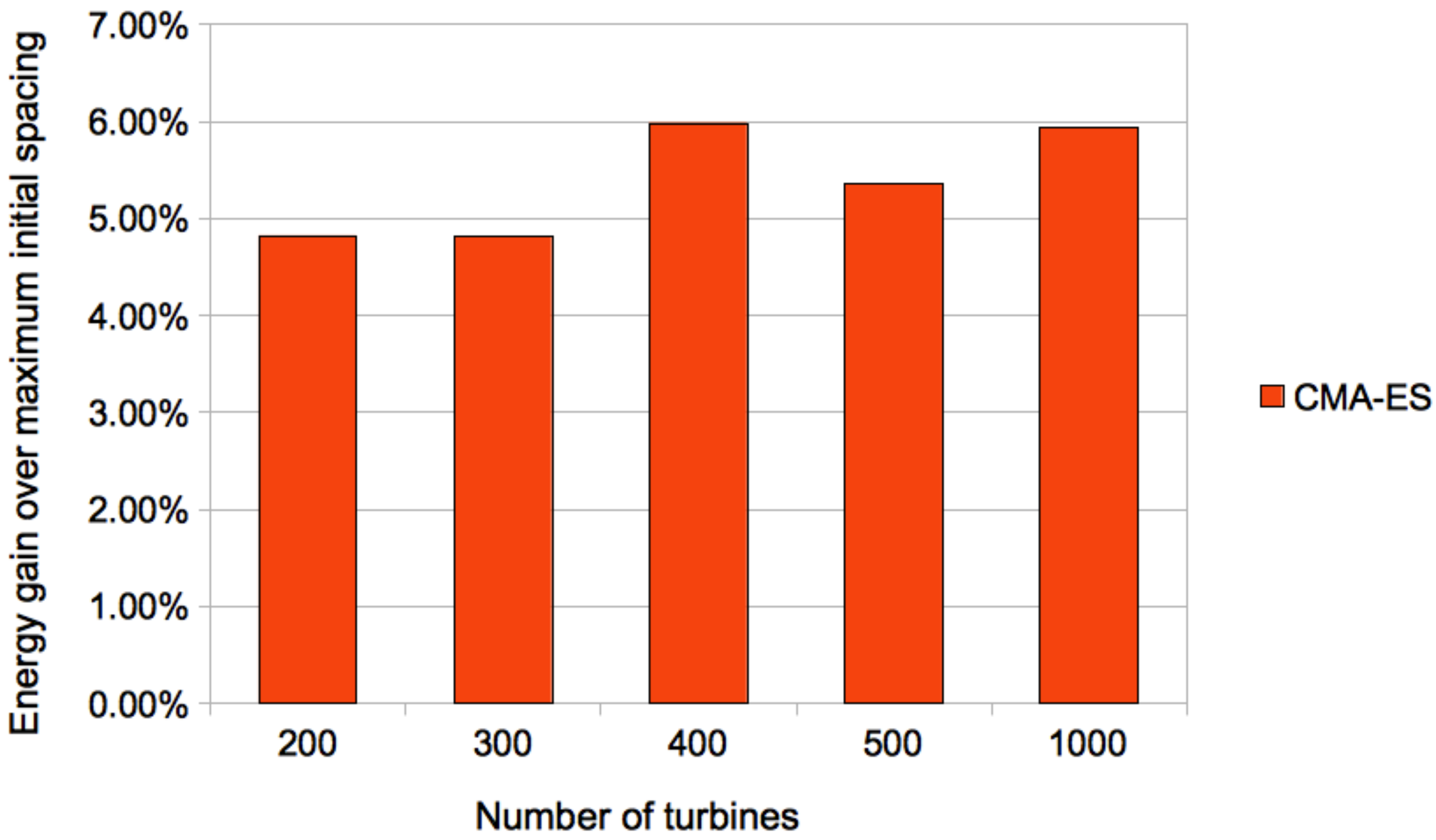
- 200 turbines: 1.4 sec (1 eval) => 2.8 days (10000 gen)
- 500 turbines: 8.2 sec (1 eval) => 11 days (10000 gen)
- 1000 turbines: 32.4 sec (1 eval) => 150 days (20000 gen)

Parallel Runtimes (cluster times per run):

- 200 turbines: 1.3 days (10000 generations, 30 runs)
- 500 turbines: 6 days (10000 generations, 30 runs)
- 1000 turbines: 12 days (20000 generations, 20 evaluations parallelized, 2 runs)

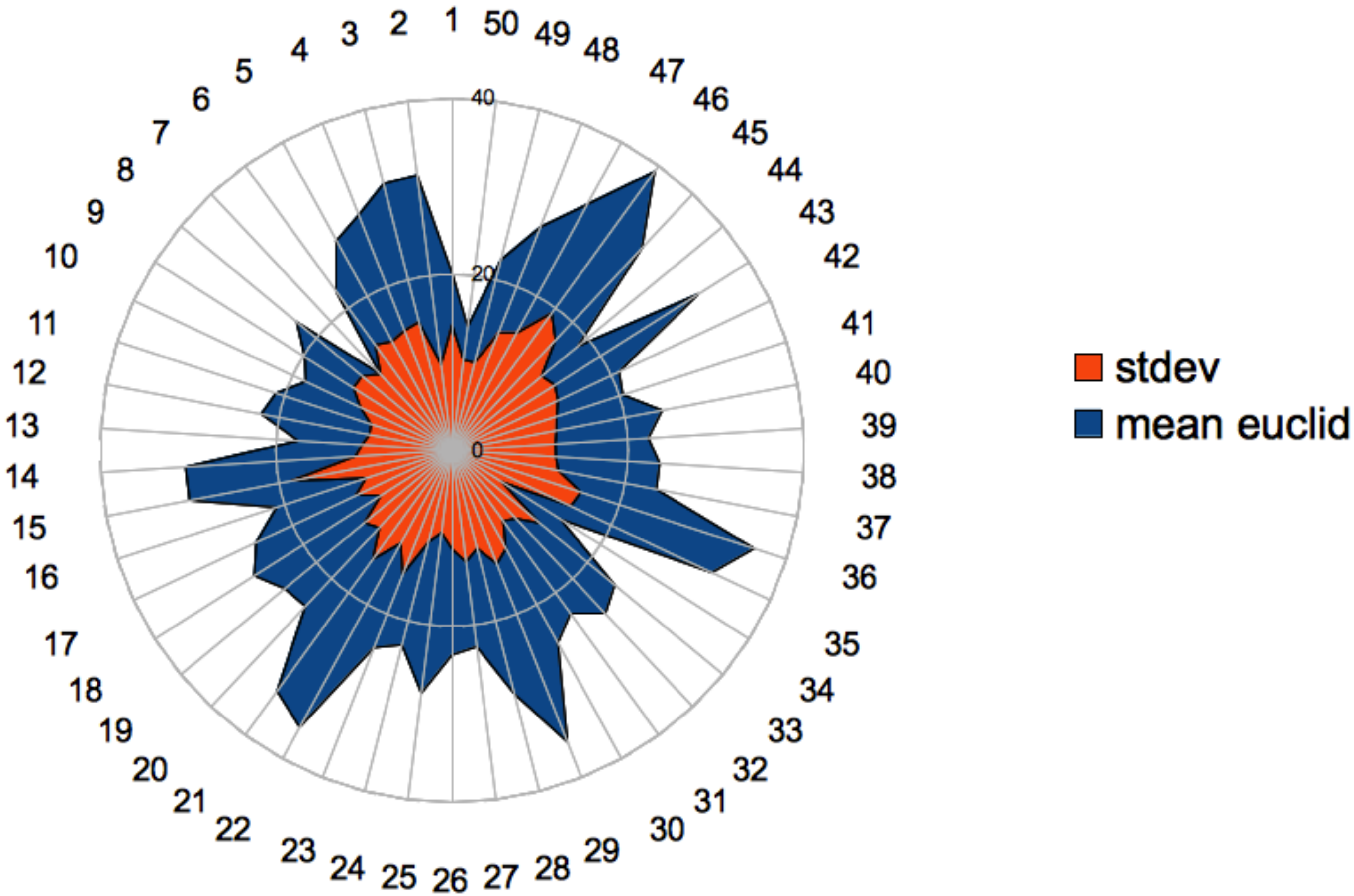


8000000.00
7000000.00
6000000.00
5000000.00
4000000.00
3000000.00
2000000.00
1000000.00
Energy in kW
200
300
400
500
1000
Number of turbines
max energy
CMA-ES energy capture



Energy gain over maximum initial spacing
7.00%
6.00%
5.00%
4.00%
3.00%
2.00%
1.00%
0.00%
200
300
400
500
1000
Number of turbines
CMA-ES

Euclidean distance moved by each turbine (data based on 30 runs)



Just 4,5 – 6%, so what?

1 year 7,2 ct per KWh, 1.5 MW turbines.

200 turbines:

→ 4.8 % of 1200 MW = 57.6 MW,

→ 504.576 MWh is 36.3 Mio USD/year

500 turbines:

→ 5.4 % of 3.100 MW = 167.4 MW,

→ 1.466.424 MWh is 105.6 Mio USD/year

1000 turbines:

→ 5.9 % of 6.000 MW = 354.0 MW,

→ 3.101.040 MWh is 223.3 Mio USD/year

Summary:

- Wind energy is an interesting field with challenging optimization problems
- Problems are very complex
- Evolutionary algorithms are well suited for tackling these problems
- Problems need parallelization of the algorithms
- There is a lot of money in this field (grants, government support, industry funding)
- Computer Science should play a key role

Future Work:

- Nonlinear power curves
- Mixed wind farms
- More complex wake models
- Exploration of problem-specific algorithms
- Combination with other design parameters (cable length)
- Multi-objective problems
- Project at Future SOC Lab of the Hasso-Plattner-Institut (with Tobias Friedrich)

Thank you!