

GECCO



Genetic and Evolutionary Computation Conference

Madrid, Spain
July 11-15, 2015



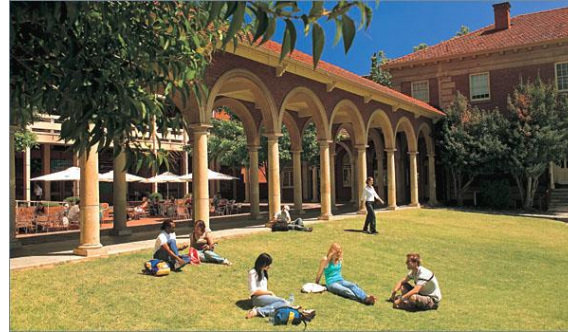
On Evolutionary Approaches to Wind Turbine Placement with Geo-Constraints

July 13, 2015

Daniel Lückehe (Jade University of Applied Sciences), Markus Wagner
(University of Adelaide), Oliver Kramer (University of Oldenburg)

GECCO 2015, Madrid

Context



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- Objective:
Maximize power output of renewable energy sources
- University of Adelaide
 - Adelaide: City in South Australia
 - A lot of solar and wind potential
- University of Oldenburg and Jade University of Applied Sciences
 - Oldenburg: City in Lower Saxony, Northern Germany
 - Not so much solar potential, but a lot of wind
- Focusing on wind turbines



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Motivation

- Behavior and effectiveness of wind turbines is strongly depending on their location
- ***Question: Where to place wind turbines to increase their power output?***
- Increase by:
 - Optimal positions caused by higher wind potential
 - Reduction of wake effects
- Modern Turbine, 40% full load hours, 0.1 €/kWh
→ 1 M€/a
- Even small improvements lead to large values

Content

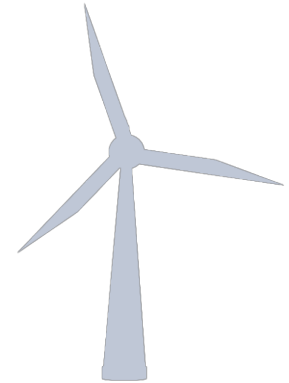
1. Wind turbine placement scenario
 - How we calculate the power output of wind turbines?

2. Optimization
 - Fitness function definition
 - Solution representation
 - Optimization approaches

3. Experimental results

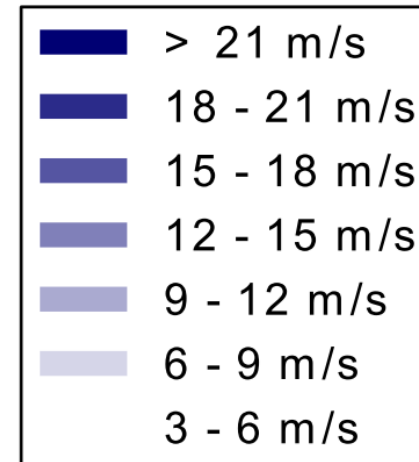
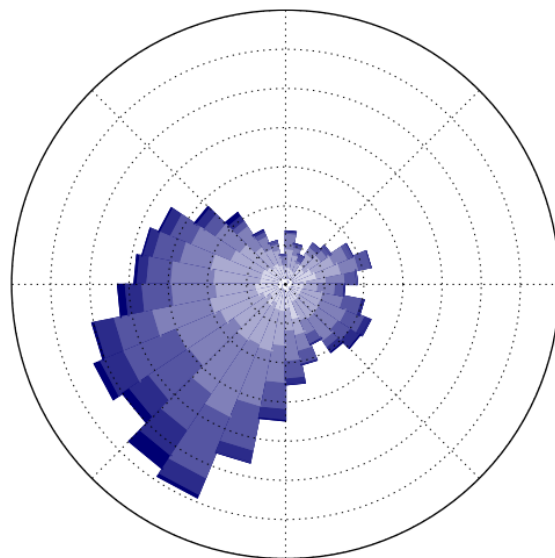
Wind

- Wind turbine
 - Produces power depending on wind speed at location
 - Power curve from Enercon E101
 - Constraint: Minimum distance between turbines
 - Determination of the wind speed at location
 - Using COSMO-DE data from the German Weather Service (DWD)
 - Rotated grid over Germany ($419 \times 459 = 192,321$, distance about 2.8 km)
 - Hourly wind vectors
- more than 1.6 billion ($419 \times 459 \times 365 \times 24$) wind vectors per year per height level



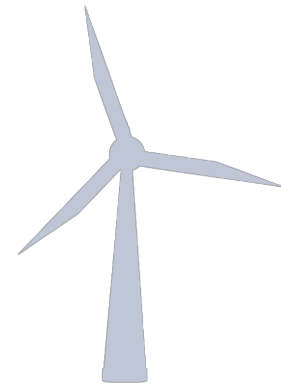
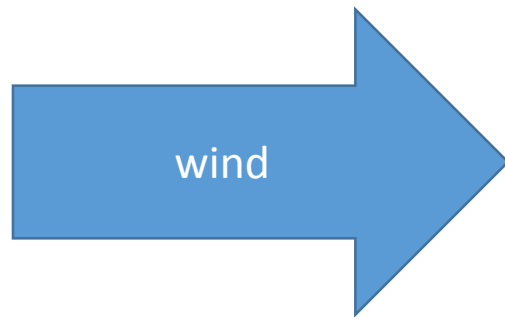
Wind Rose

- Rose: Distribution of wind speeds and directions
- Sort vectors by wind direction and location
- Wind rose for every grid position
- Bilinear interpolation using four grid positions



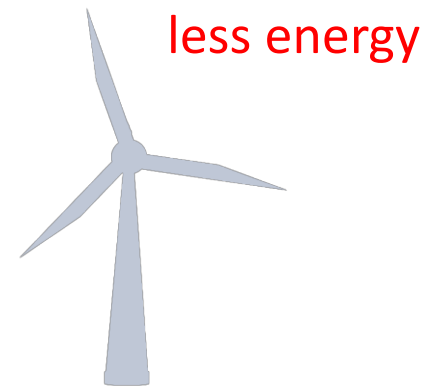
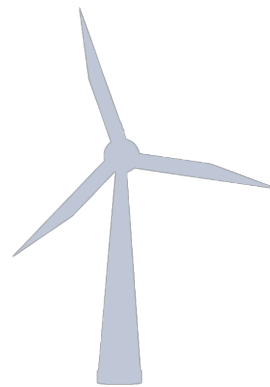
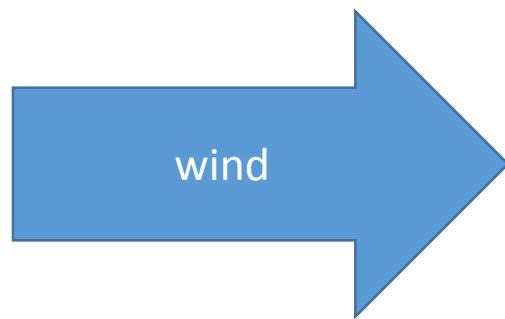
Wind Model

- Model based on wind distributions by Kusiak and Song (2010)
 - Weibull distribution to describe wind distributions
 - Discretization of wind speed and wind directions
 - Our modifications → see paper
- Model considers wake effects
 - Jensen wake model



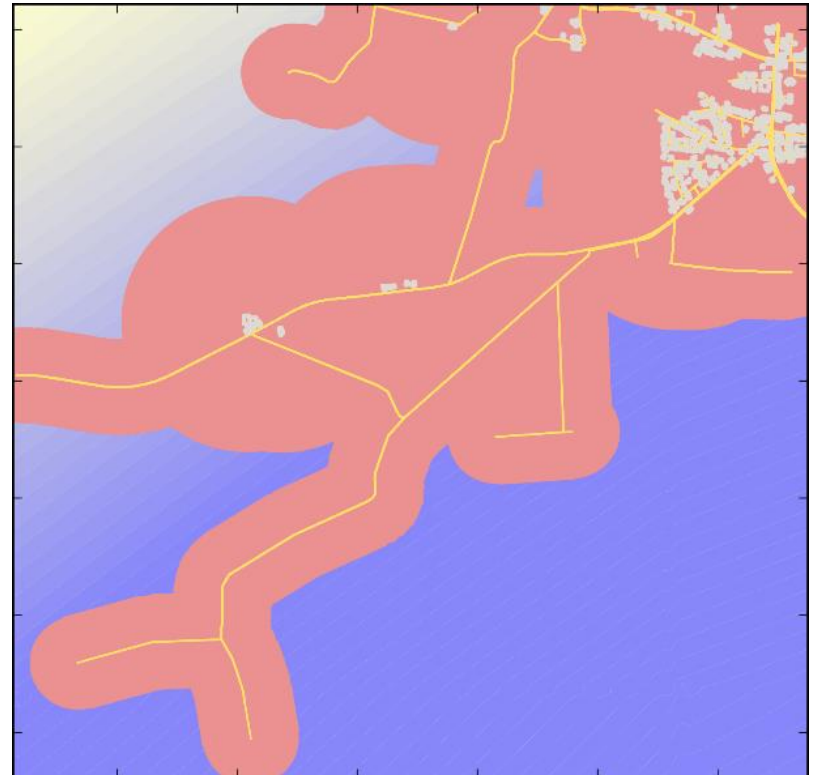
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Geographical Data

- Geographical data from OpenStreetMap
- Constraints for areas around
 - Buildings
 - Streets
- Constraint handling with death penalty
- Scenario 2 (from paper):
 - 3.3 x 3.3 km
 - 250 buildings
 - 64 streets consisting of 489 parts



Fitness Function

- Produced energy for a wind farm: sum of all turbines

$$f(\mathbf{x}) = \sum_{i=1}^{N/2} E(\mathbf{t}_i)$$

- Fitness function depending on
 - Wind turbine E101 from Enercon
 - Wind data from COSMO-DE model
 - Power calculation based on Kusiak and Song with modifications
 - Jensen wake model
 - Geographical data from OpenStreetMap

Solution

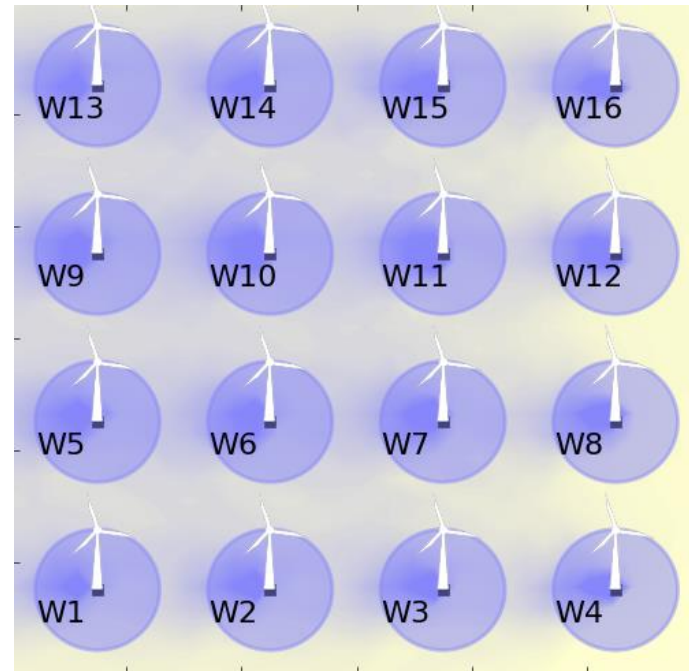
- Solution x describes the positions of multiple turbines
 - e.g. $x = [100, 300, 200, 200]$

- Initial solution:

- Random
- Chessboard pattern

- Circles:

- Minimum distance between turbines



Evolutionary Strategies

- $\mathbf{x} = [100, 300, 200, 200]$



- Holistic approaches

- Mutation will change every dimension of \mathbf{x}


- $\mathbf{x} = [100, 300, 200, 200]$



- Turbine-oriented approaches

- Mutation will randomly pick the dimensions of one turbine

Evolutionary Strategies

- $\mathbf{x} = [100, 300, 200, 200]$ 
- Holistic approaches
 - Mutation will change every dimension of \mathbf{x}
- ***Adaptive (1 + 1)-ES***
 - ***Gaussian mutation to move turbines***
 - ***Rechenberg's step size control***

Evolutionary Strategies

- $\mathbf{x} = [100, 300, 200, 200]$



- Holistic approaches
 - Mutation will change every dimension of \mathbf{x}
- Adaptive (1 + 1)-ES
- ***Covariance Matrix Adaptation Evolution Strategy (CMA-ES)***

Evolutionary Strategies

- $\mathbf{x} = [100, 300, 200, 200]$



- Turbine-oriented approaches
 - Mutation will randomly pick the dimensions of one turbine
- ***Adaptive (1 + 1)-ES***
 - ***Gaussian mutation***
 - ***Special Case: 1 dimension***
 - ***Rechenberg's step size control***

Evolutionary Strategies

- $\mathbf{x} = [100, 300, 200, 200]$



- Turbine-oriented approaches
 - Mutation will randomly pick the dimensions of one turbine
- Adaptive (1 + 1)-ES (1 dim.)
- ***Replacing***


Evolutionary Strategies

- $\mathbf{x} = [100, 300, 200, 200]$

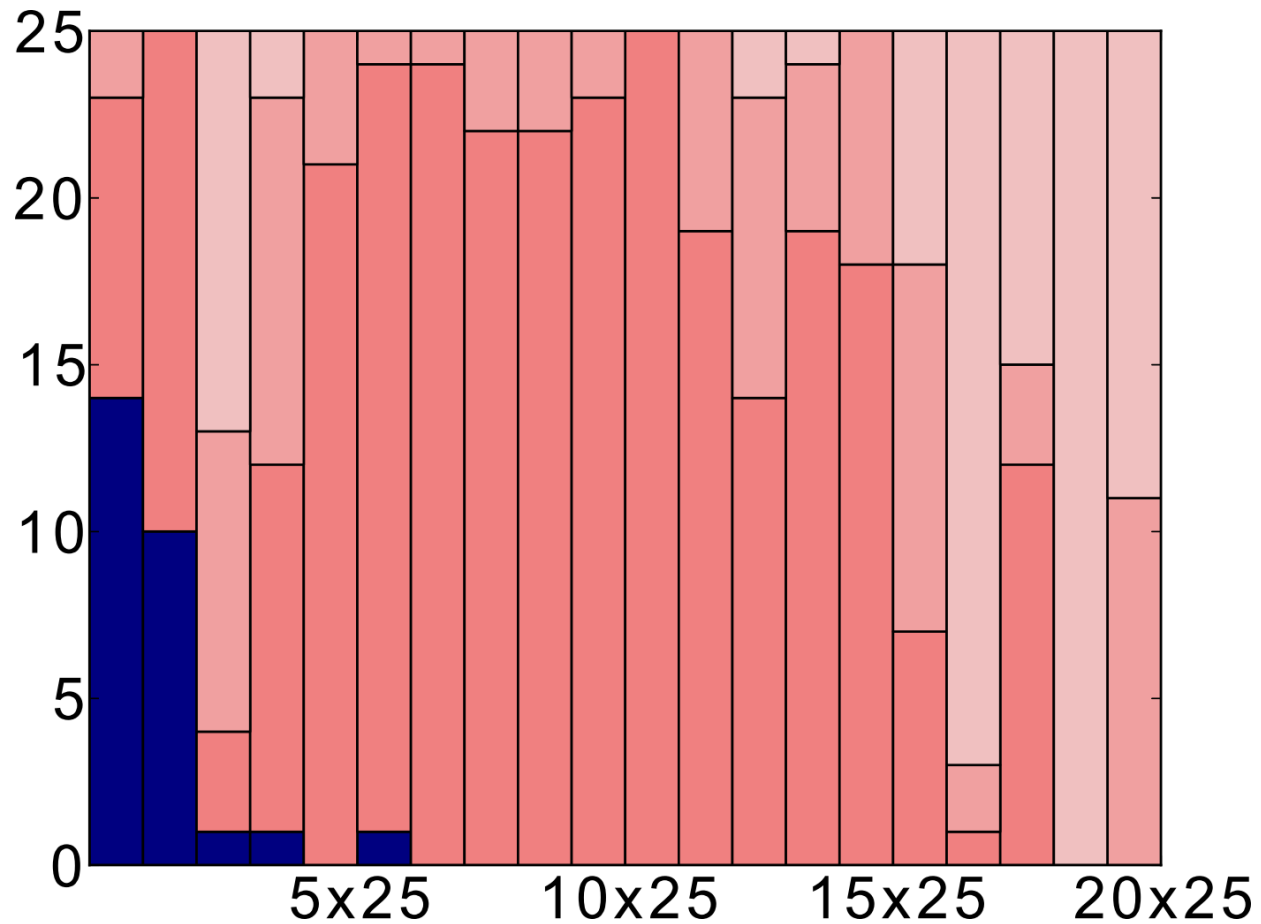


- Turbine-oriented approaches
 - Mutation will randomly pick the dimensions of one turbine
- Adaptive (1 + 1)-ES (1 dim.)
- Replacing
- **Deterministic (1 + 1)-ES**
 - **Gaussian mutation**
 - **Starting with step size equal the map size**
 - **Decreased linearly**
 - **Ending with step size: 1 / “fitness function calls” x map size**

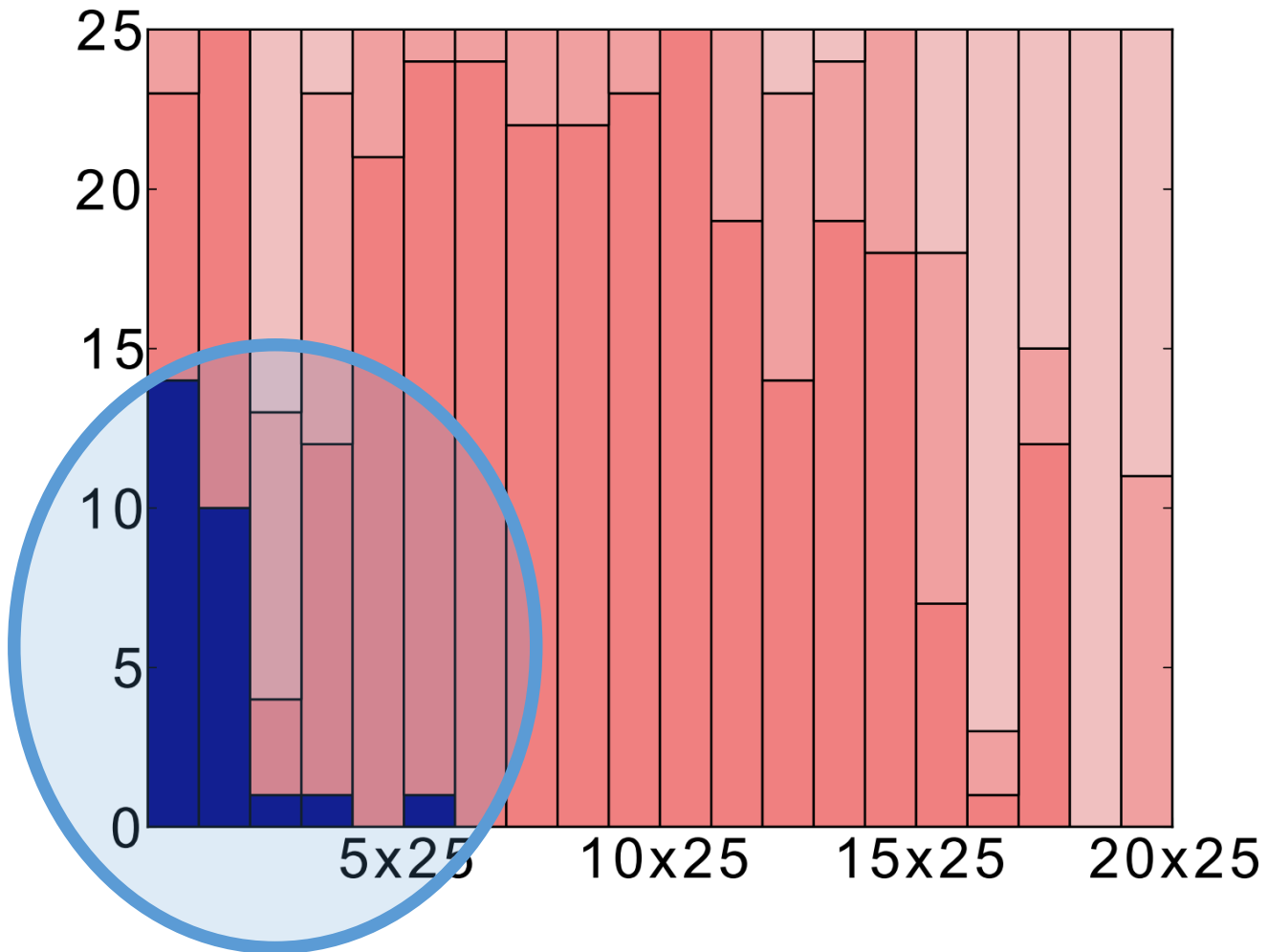
Evolutionary Strategies

- $\mathbf{x} = [100, 300, 200, 200]$ 
- Turbine-oriented approaches
 - Mutation will randomly pick the dimensions of one turbine
- Adaptive (1 + 1)-ES (1 dim.)
- Replacing
- Deterministic (1 + 1)-ES
- ***Self-Adaptive (1 + λ)-ES***
 - ***Choose between replace and Gaussian mutation***
 - ***Can also mutate multiple turbines in one generation***
 - ***Operation and number of turbines are controlled self-adaptively***

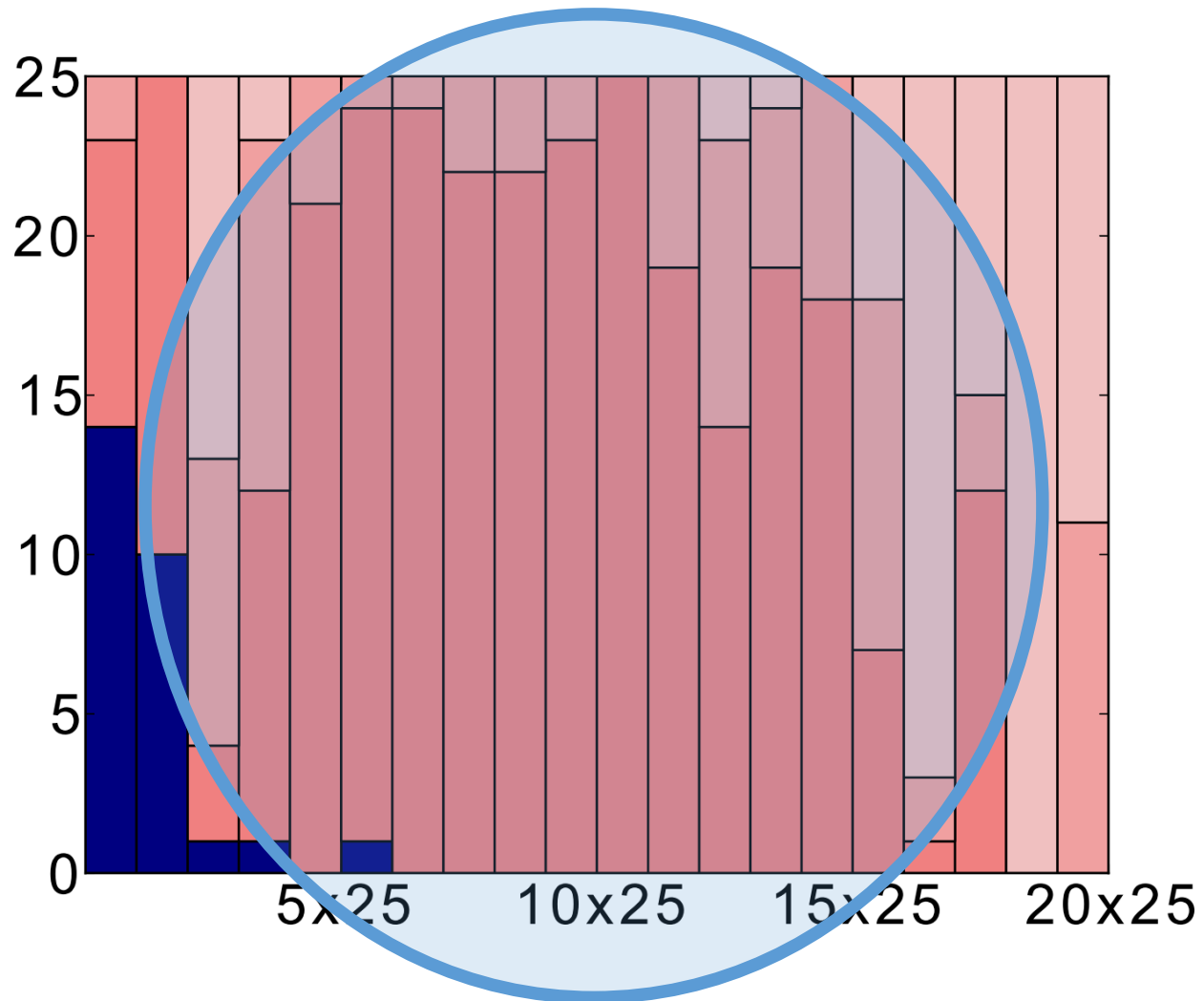
Analysis of Operator Ratios



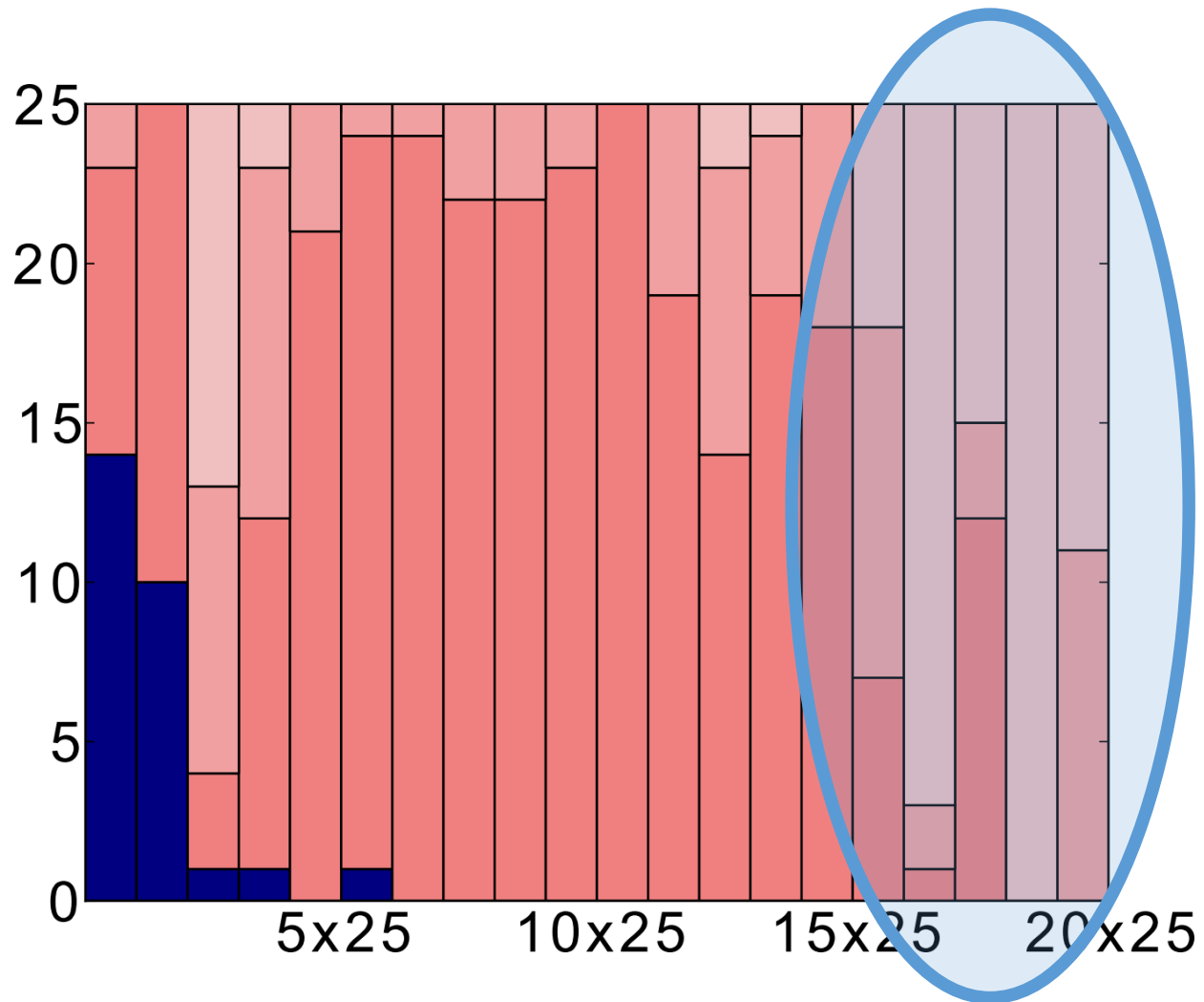
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Analysis of Operator Ratios



Comparison of Evolutionary Algorithms

- Scenario 2: 36-dimensional optimization problem (18 turbines)
(results for random initialization in paper)

Init.	Chess	
Algo.	Mean \pm Std	Max
Init.	10944.2 \pm 0.0	10944.2
$(1+1)^N$	11221.3 \pm 33.0	11287.3
CMA	11359.7 \pm 12.5	11386.6
$(1+1)^1$	11399.3 \pm 17.5	11444.5
Rep.	11484.0 \pm 9.7	11505.0
$(1+1)^t$	11524.1 \pm 8.4	11538.2
$(1+\lambda)$	11516.5 \pm 11.7	11537.2

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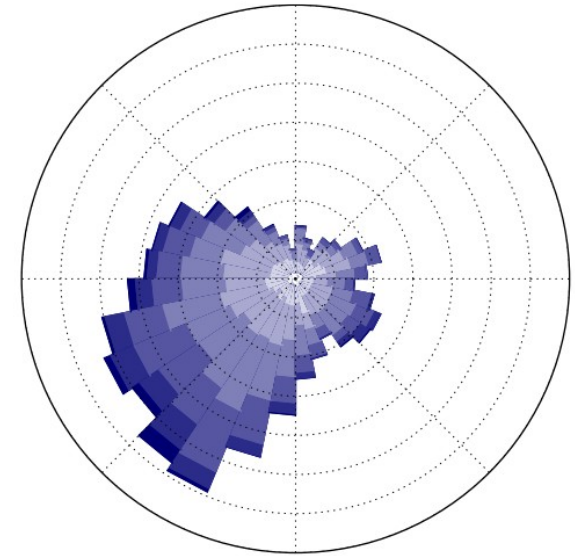
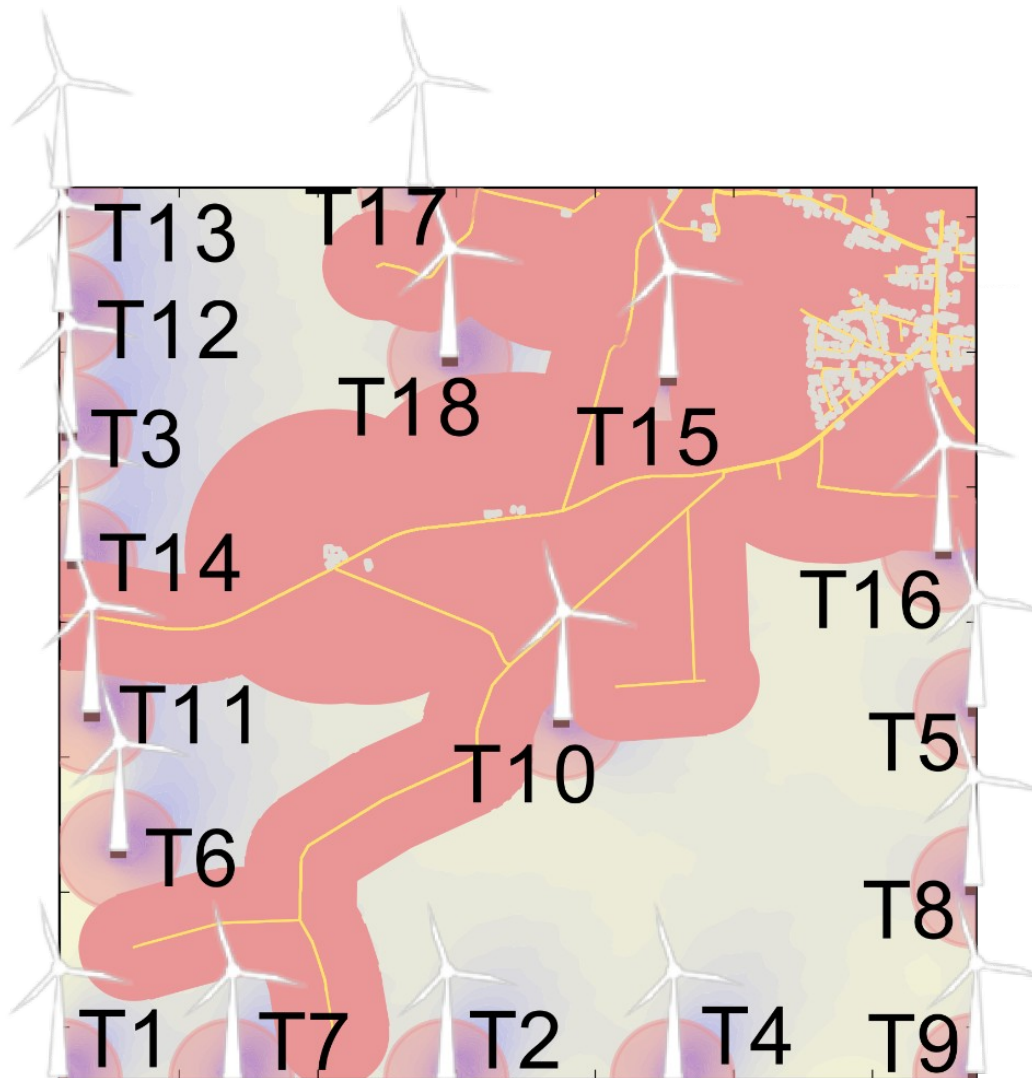
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Best Turbine Placement Result



Conclusion & Future Work

Conclusion

- Wind turbine placement leads to different optimization problem
- Self-adaptive approach first replaces, **then** moves turbines
- Turbine-oriented approaches outperform holistic approaches

Conclusion & Future Work

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Future Work

- Advanced constraint handling methods
- Add more features to the model

Conclusion & Future Work

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- Wind turbine placement leads to different optimization problem
- Self-adaptive approach first replaces, **then** moves turbines
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Future Work

- Advanced constraint handling methods
- Add more features to the model

Thank you!

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Context

- This work follows the project *EnerGeoPlan*
 - 2011 – 2013
 - Objective: *To bring energy supply, spatial planning, and grid planning together*
 - Funded by the Ministry for Science and Culture of the State of Lower Saxony



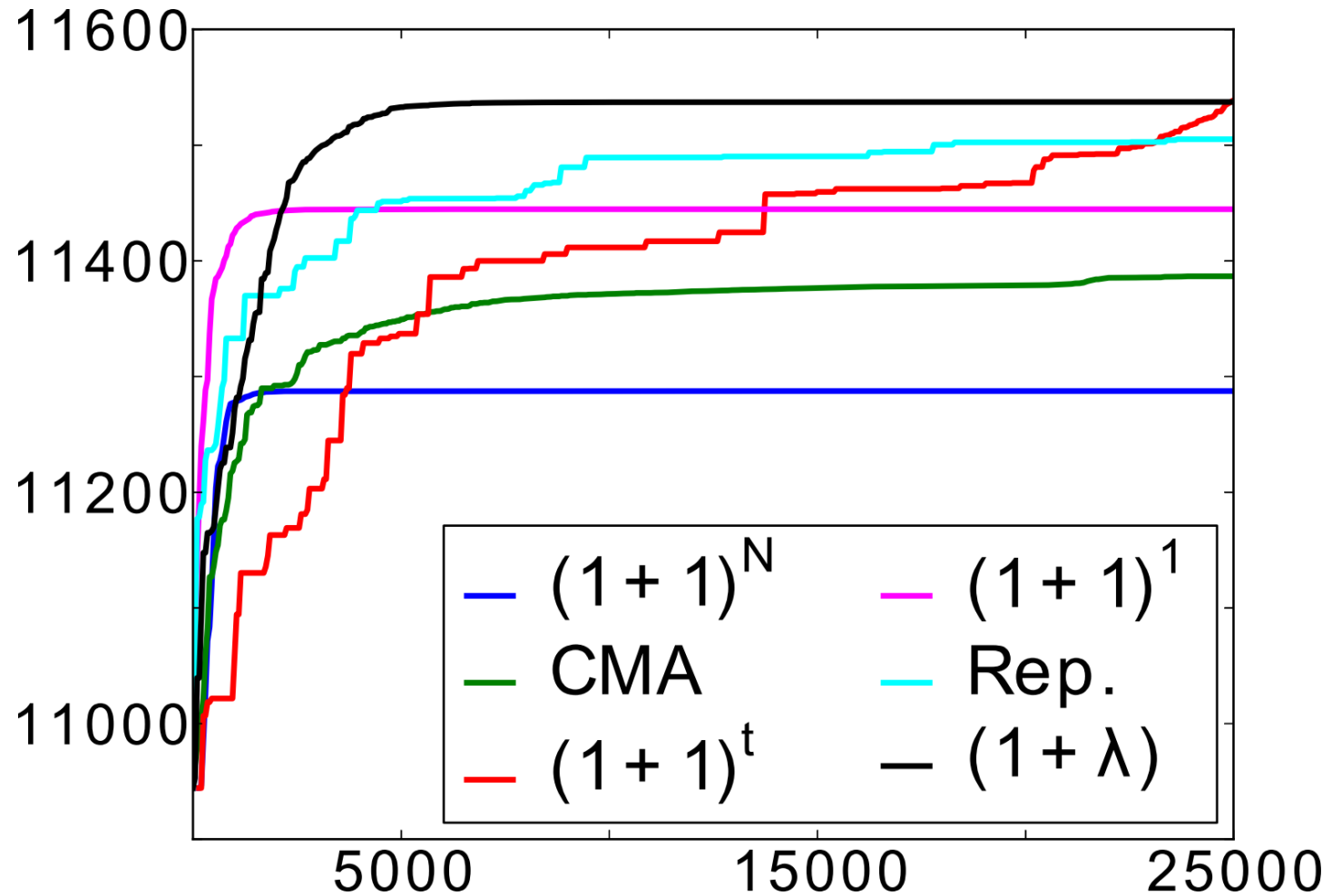
Niedersächsisches Ministerium
für Wissenschaft und Kultur

- Co-operation partners: *Gemeinde Ganderkesee, EWE Netz GmbH*

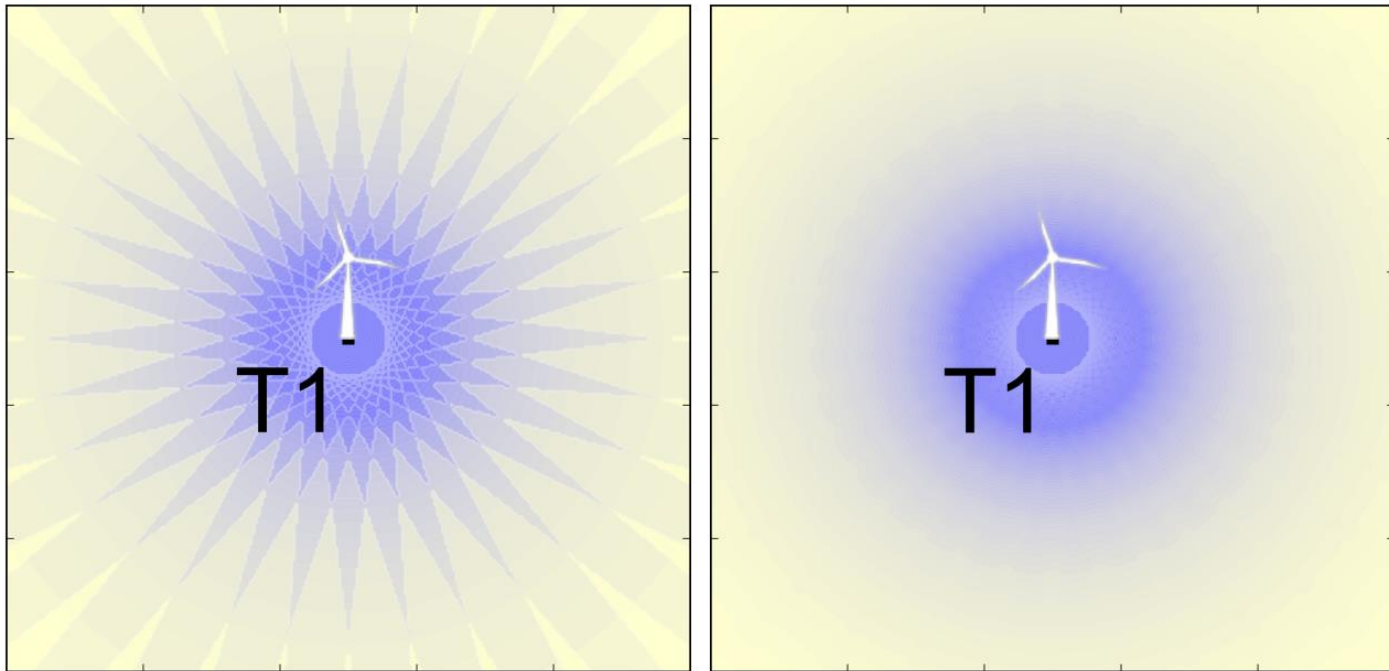


- http://www.offis.de/f_e_bereiche/verkehr/projekt/projekte/energeoplan.html

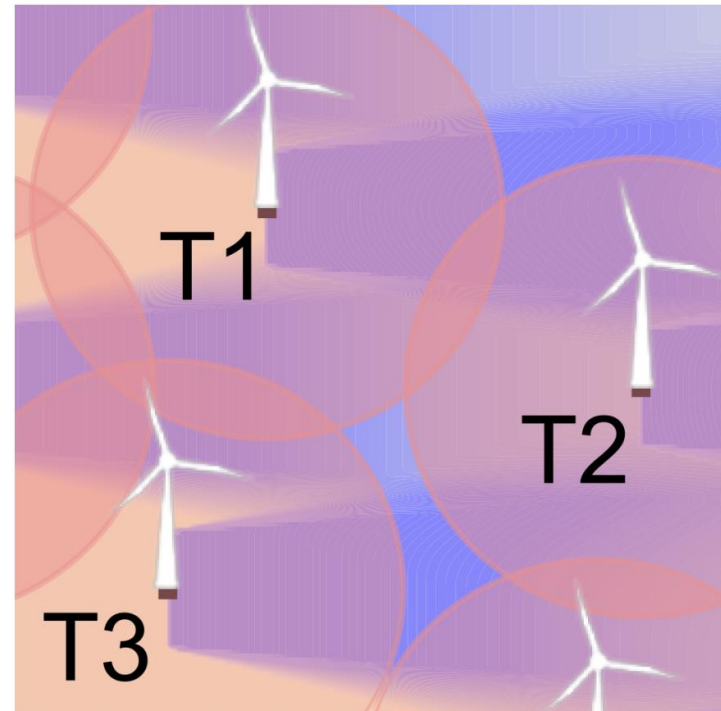
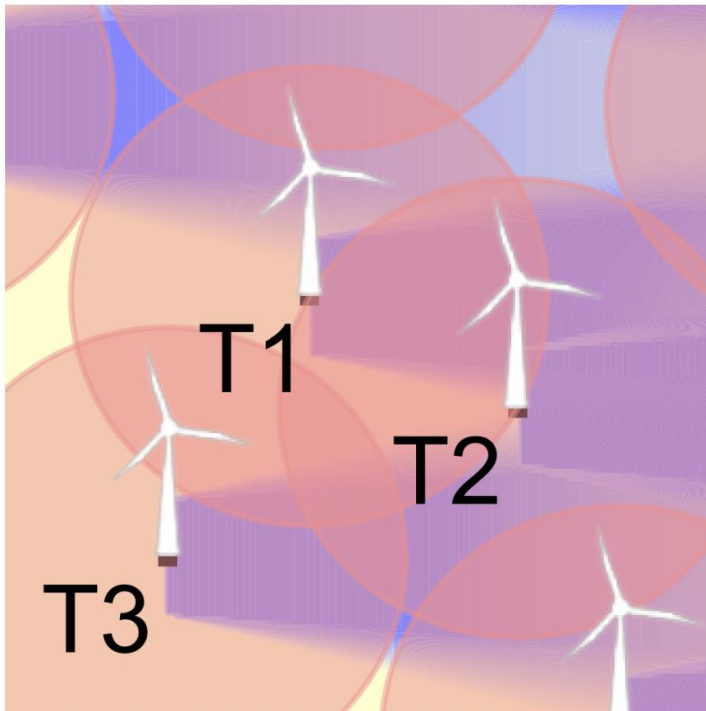
Evolutionary Runs (Chess)



Local Optima Through Wind Discretization



Rotor Size of the Affected Turbine



Example of a small wind farm

- Enercon E101 with 3 MW at 12 m/s
- Calculating with 40% full load hours
→ average 1.2 MW
- Small wind farm with 10 turbines
→ more than 100 GWh/a
- With price at 0.10 €/kWh
→ 10 M€/a
- Even small improvements lead to large values

CMA-ES

- By N. Hansen
- Newest Change
 - 14/12/06: meta_parameters now only as annotations in `##` comments
- Python implementation

```
self.__sigma = 10: corresponds to 10m
```

```
res = cma.fmin(  
    objective_function = fitness_function,  
    x0 = XY,  
    sigma0 = self.__sigma,  
    options = {'maxfevals': evaluations,  
              'verb_log': True,  
              'verb_filenameprefix': file_prefix},  
    args = [self.__solution]  
)
```

Wind Model

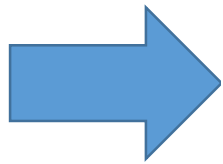
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$$E(\mathbf{t}_i) = \int_0^{360} p_\theta(\mathbf{t}_i, \theta) \cdot E_\theta(\mathbf{t}_i, \theta) d\theta$$

$$E_\theta(\mathbf{t}_i, \theta) = \int_0^\infty \beta_i(v) \cdot p_v(v, k(\mathbf{t}_i, \theta), c(\mathbf{t}_i, \theta)) dv$$

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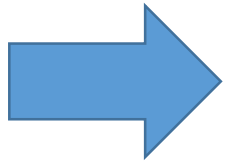
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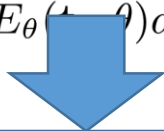
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- ***Weibull distribution: Wind speed distribution from the wind roses***

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- Wind speed distribution from the wind roses
- ***Wind direction distribution from the wind roses***

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- Wind speed distribution from the wind roses
- Wind direction distribution from the wind roses
- ***Turbine power curve***