DESIGNING STRATEGIES FOR OPTIMAL SPATIAL DISTRIBUTION OF WIND POWER

by

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Welcome

to the the website of

COST Action ES1002
WIRE: Weather Intelligence for Renewable Energies

Due to climate change and shrinking fossil resources, the transition to more and more renewable energy shares is unavoidable. But, as wind and solar energy is strongly dependent on highly variable weather processes, increased penetration rates will also lead to strong fluctuations in the electricity grid which need to be balanced. Proper and specific forecasting of 'energy weather' is a key component for this. Therefore, it is timely to scientifically address the requirements to provide the best possible specific weather information for forecasting the energy production of wind and solar power plants for the next minutes up to several days ahead.

Towards such aims, this Action will have two main lines of activity: first develop dedicated post-processing algorithms coupled with weather prediction models and measurement data especially remote sensing observations; second investigate the difficult relationship

EUROPEAN COOPERATION IN SCIENCE AND TECHNOLOGY

WIRE: Current State report (final draft)

Memorandum of Understanding

COST Action ES1002 official website

Action Leaflet

Participating countries

Wind: a reliable source of energy?

- A rapidly growing energy source
- 26% annual growth rate since 2005 (IEA)
- A “clean” renewable source of energy
- A key component of future decentralised and carbon-free energy programmes
- Also a source of *risks*

Wind - a reliable source of energy?

- *Variability (intermittency) risk*: large changes in a wind farm energy production from time to time
- *Spatial correlation*: the similarity (correlation)between local wind speeds decreases with the distance among measurement sites
- For the European region, the correlation coefficient drops to roughly 1/3 for an average distance of 723 km (Giebel, 2000)

Optimal energy generation plans

- This correlation-decaying pattern can help reduce variability in an aggregate wind energy production plant
- A low wind event in one region can be counterbalanced by a distant windy site
- Hence, it makes sense to distribute wind farms over a large area

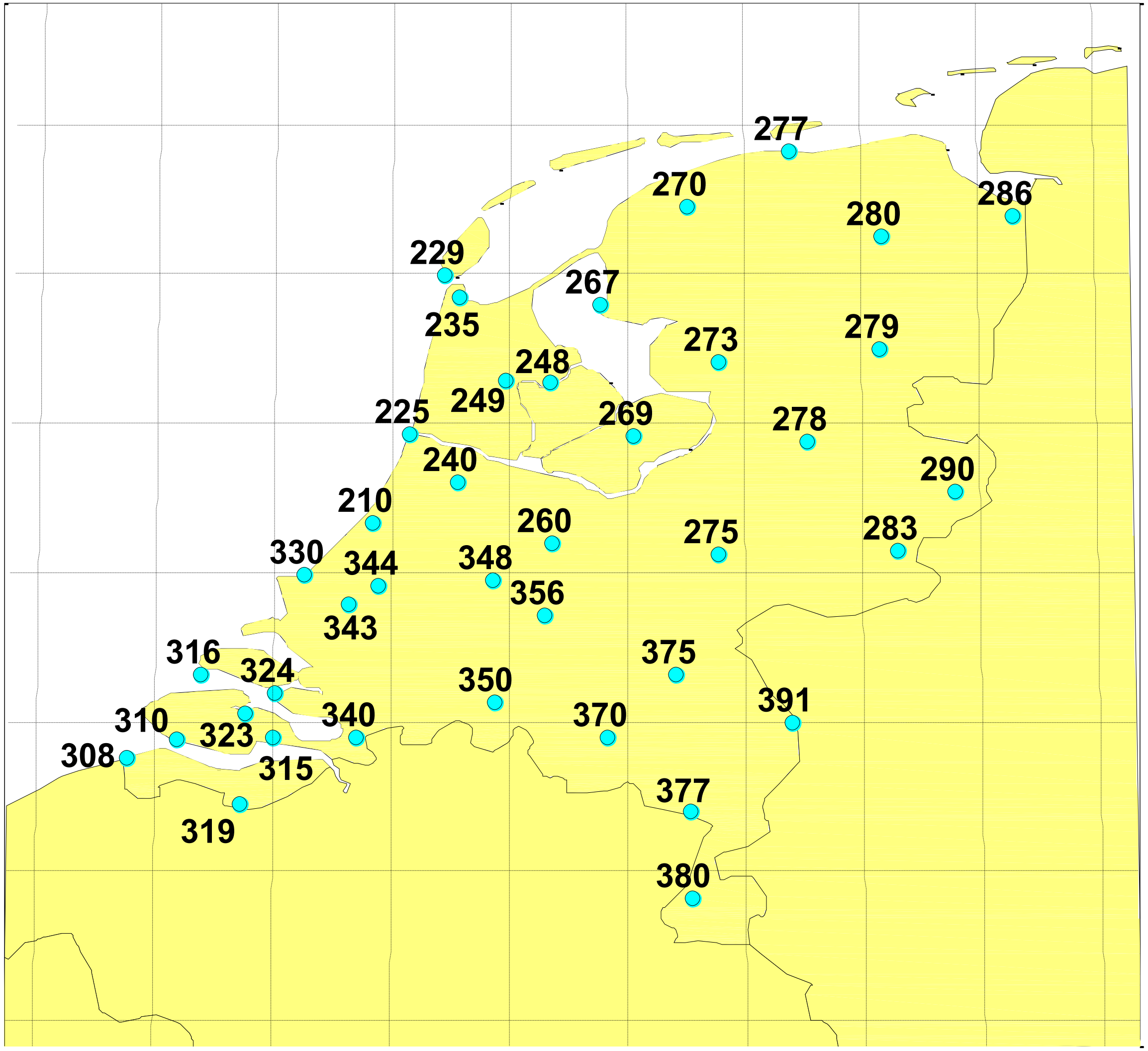
Optimal energy generation plans

- But how should we allocate production?
  - Distance (not the only criterion!!!)
  - Terrain variability
  - Microclimate
  - Objective (maximise energy production, maximise availability, etc)
- Slow correlation decay$\rightarrow$ "*smart*" combinations of selected sites

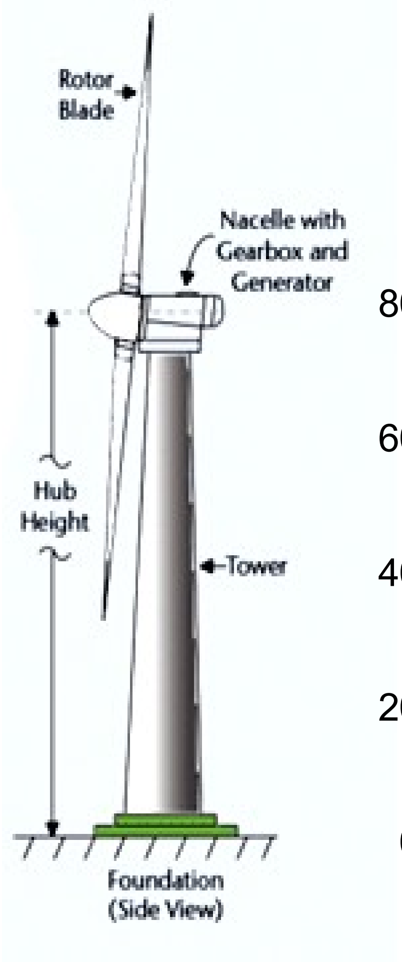
Empirical study

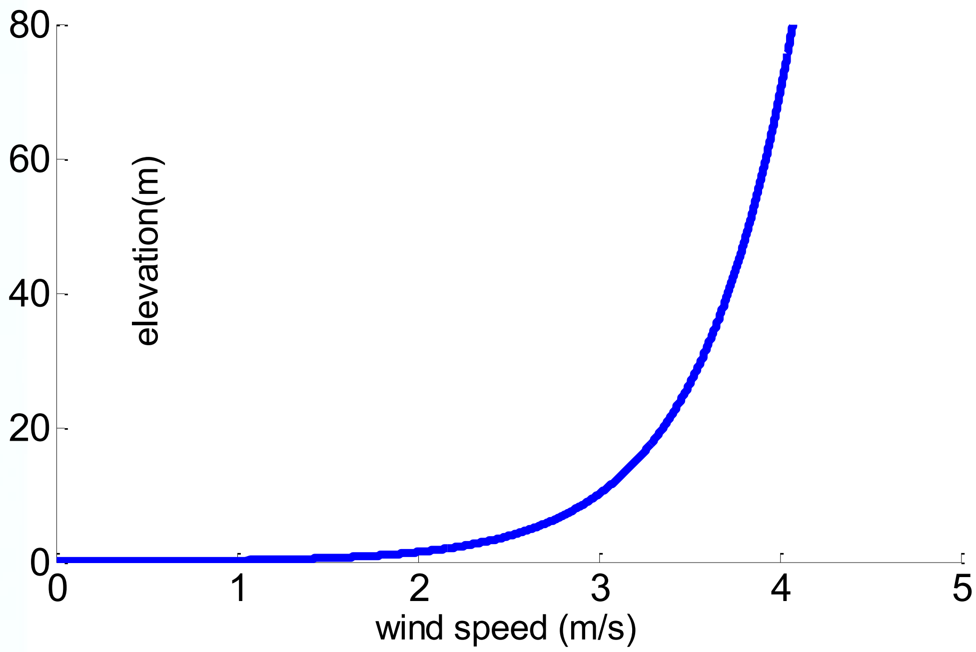
- <u>Objective</u>: Spatial distribution of wind resources in the Netherlands
- <u>Data</u>: Hourly potential wind speed measurements for 54 locations (*Royal Netherlands Meteorological Institute* -KNMI)
- <u>Sample period</u>: 01/01/2001 - 31/12/2010
- <u>Pre-processing</u>: Daily averages, exclude stations with more than 40% missing records and 30 consecutive days with no observations , offshore stations
- <u>Effective number of sites</u>: 39 (after data cleansing)
- <u>Wind shear</u>: Wind speeds are scaled-up to 80 m height above surface (hub height)
- <u>Estimation period</u>: Jan 2001 – Dec 2006 (2190 obs)
- <u>Evaluation period</u>: Jan 2007 – Dec 2010 (1460 obs)

Geographical distribution of sites



Logarithmic vertical wind profile



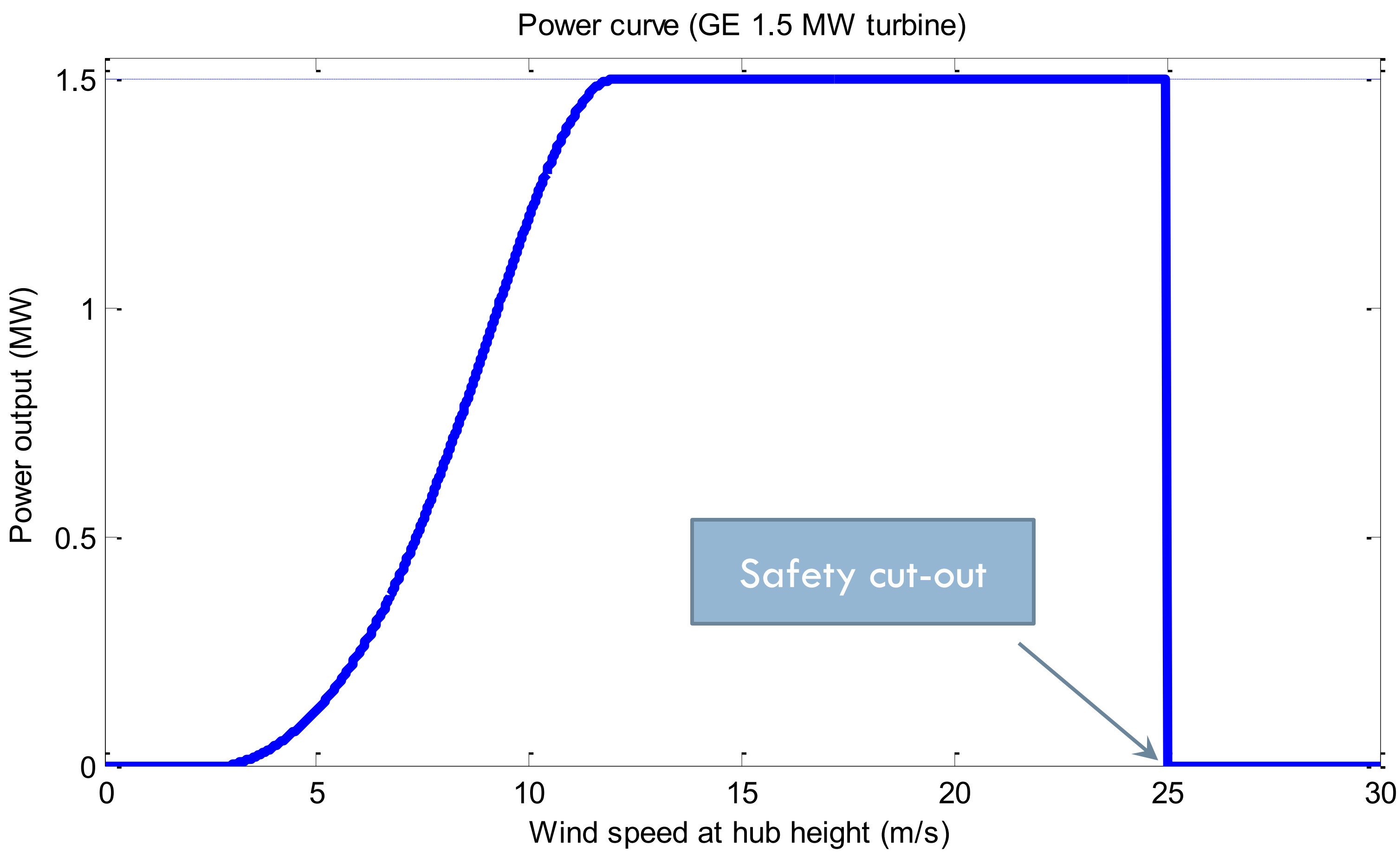


Source of the wind turbine figure: http://ec.europa.eu/research/energy/nn/nn_rt/nn_rt_wind/article_1101_en.htm

Modelling wind speed series

- 2190 observations are too few to derive a *robust* energy production plan that is not subject to statistical error
- Model $\rightarrow$ data generator
- Obtaining a faithful model of temporal and cross-sectional variations in wind profiles
  - ARMA process with seasonal adjustments and a volatility equation for the dynamics
  - Gaussian copula models for the dependence structure

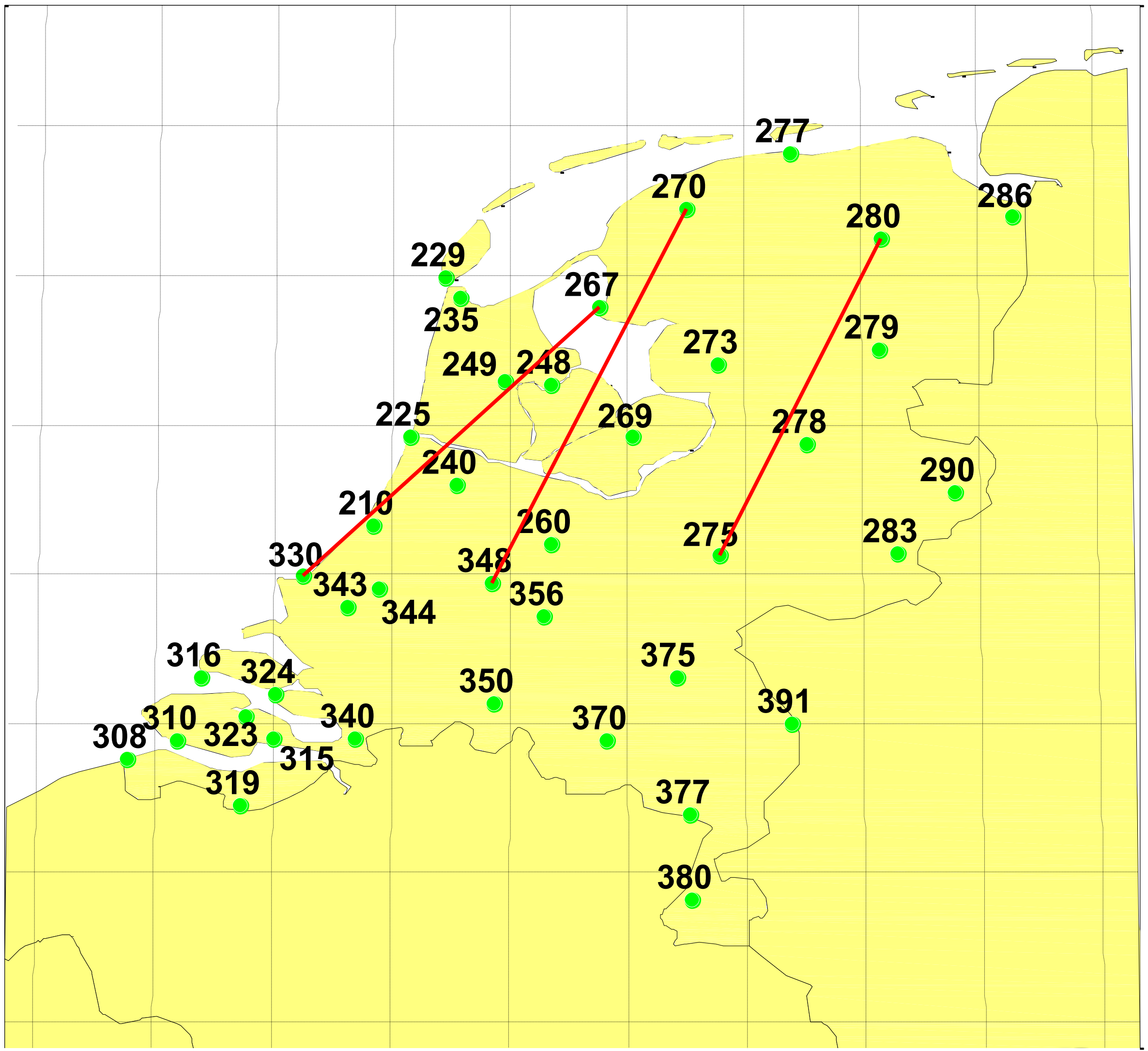
Estimating power output



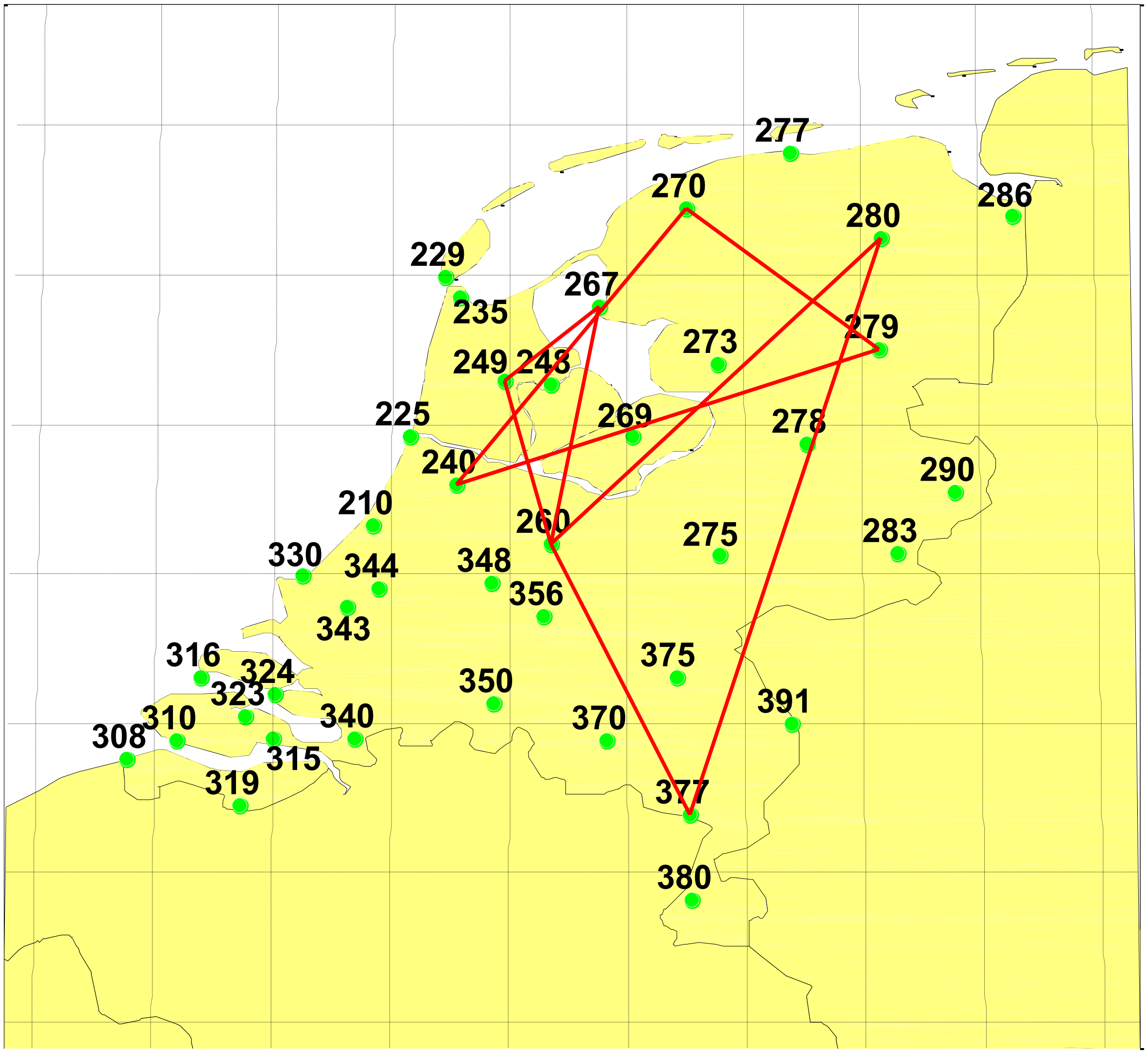
Deriving optimal energy production plans

- Total available capacity: C (e.g. $39\times1.5=58.5$ MW)
- Optimal vector of weights $\omega^*=(\omega_1^*, \omega_2^*, \ldots, \omega_{39}^*)$
- $\omega_i^* \rightarrow$ proportion of C allocated at site i=1,…,39 ($0.02\leq\omega_i\leq0.98$)
- Objectives:
  - <u>*Obj1*</u>: maximise the 15th percentile (p_{15}) of the overall daily power generation.
  - <u>*Obj2*</u>: minimise the *coefficient of variation* CV (std/mean) for the aggregate daily output.
- Do NOT assume, in advance, that *all available sites* participate in the generation mix
- Allow for *sub-arrays* of selected sites of varying length (2,3,…,39)

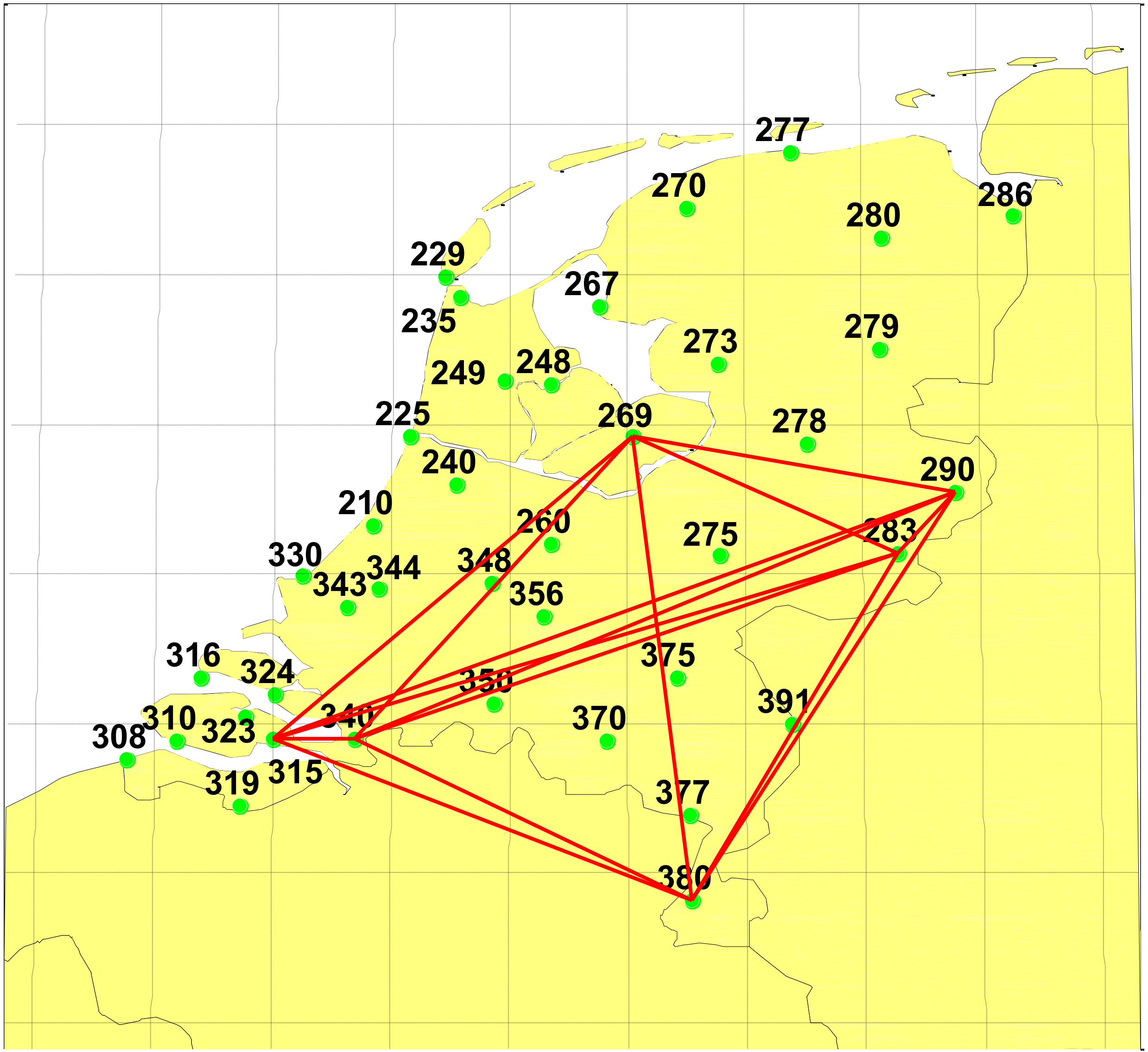
Arrays of length 2



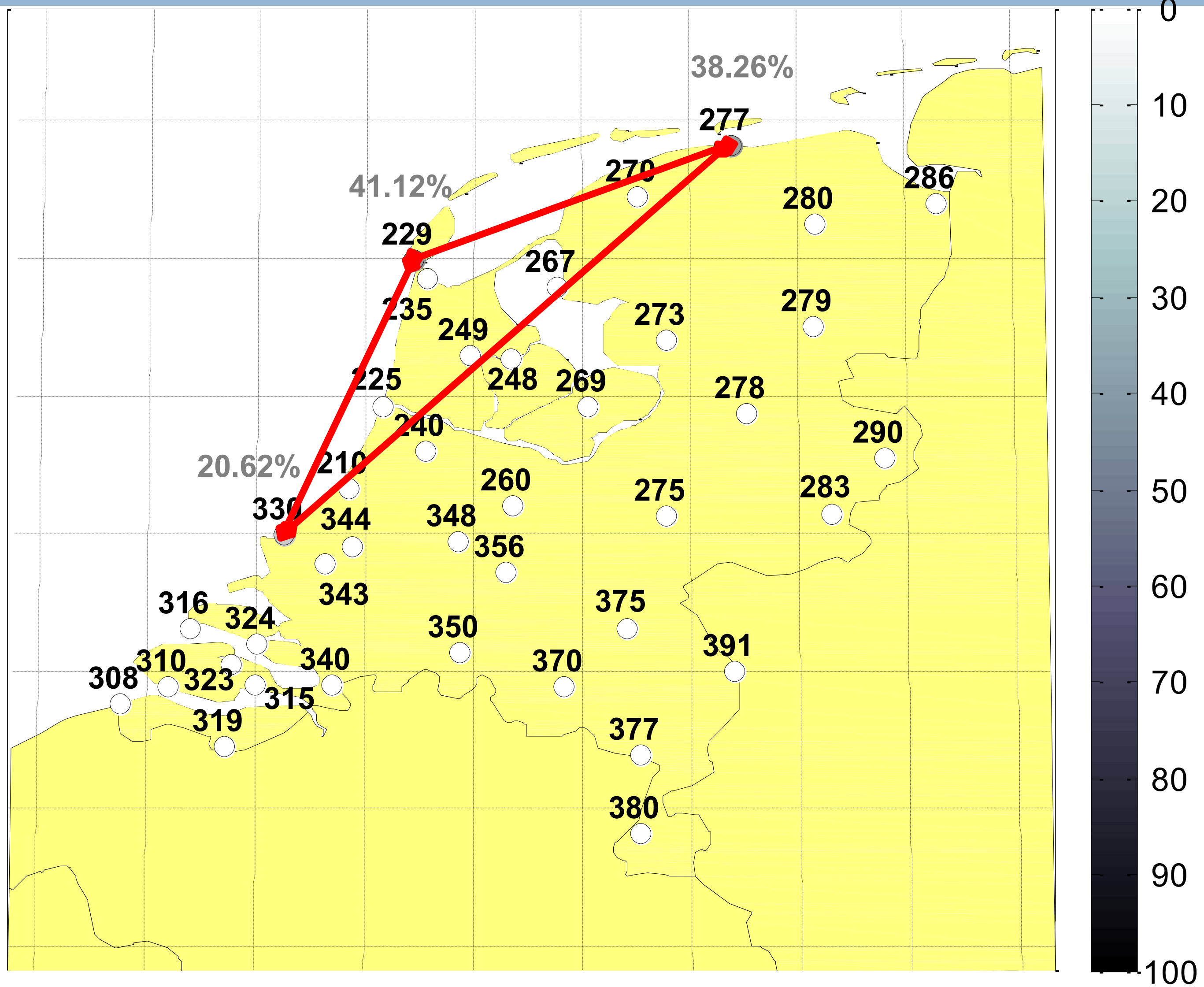
Arrays of length 3



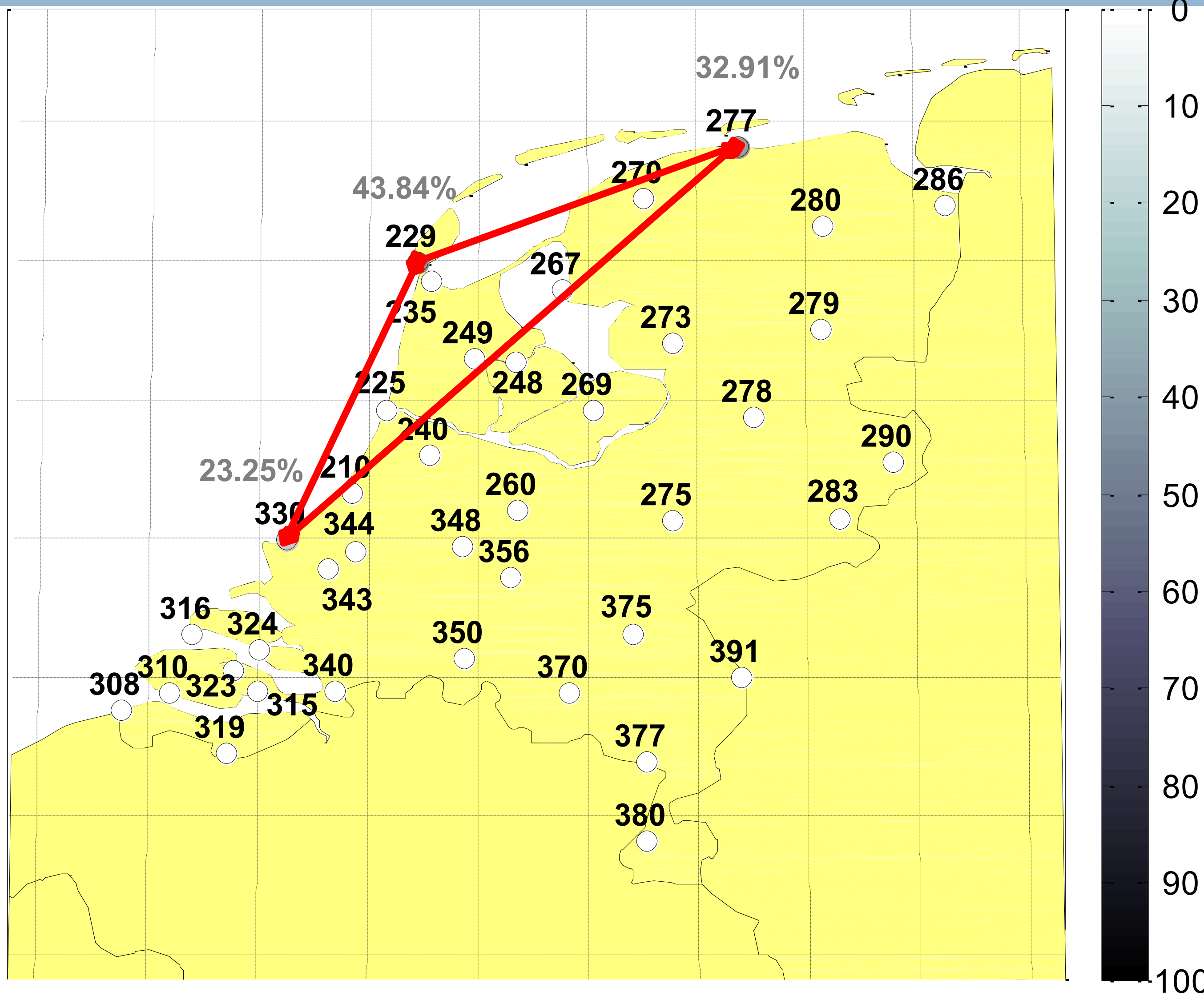
Array of length 6



Model-based optimal allocation (Obj1)



Model-based optimal allocation (Obj2)



Benchmarking

- How truly optimal are the aforepresented aggregate production plants?
- Optimal distributions were determined using *simulated* data generated by multivariate copula models
- How about evaluating their performance on actual wind speed data (from both the estimation and evaluation period)?
- Compare *model-driven* production plans with others based on *simple rules-of-thumb* and actual wind measurements (*model-free*)

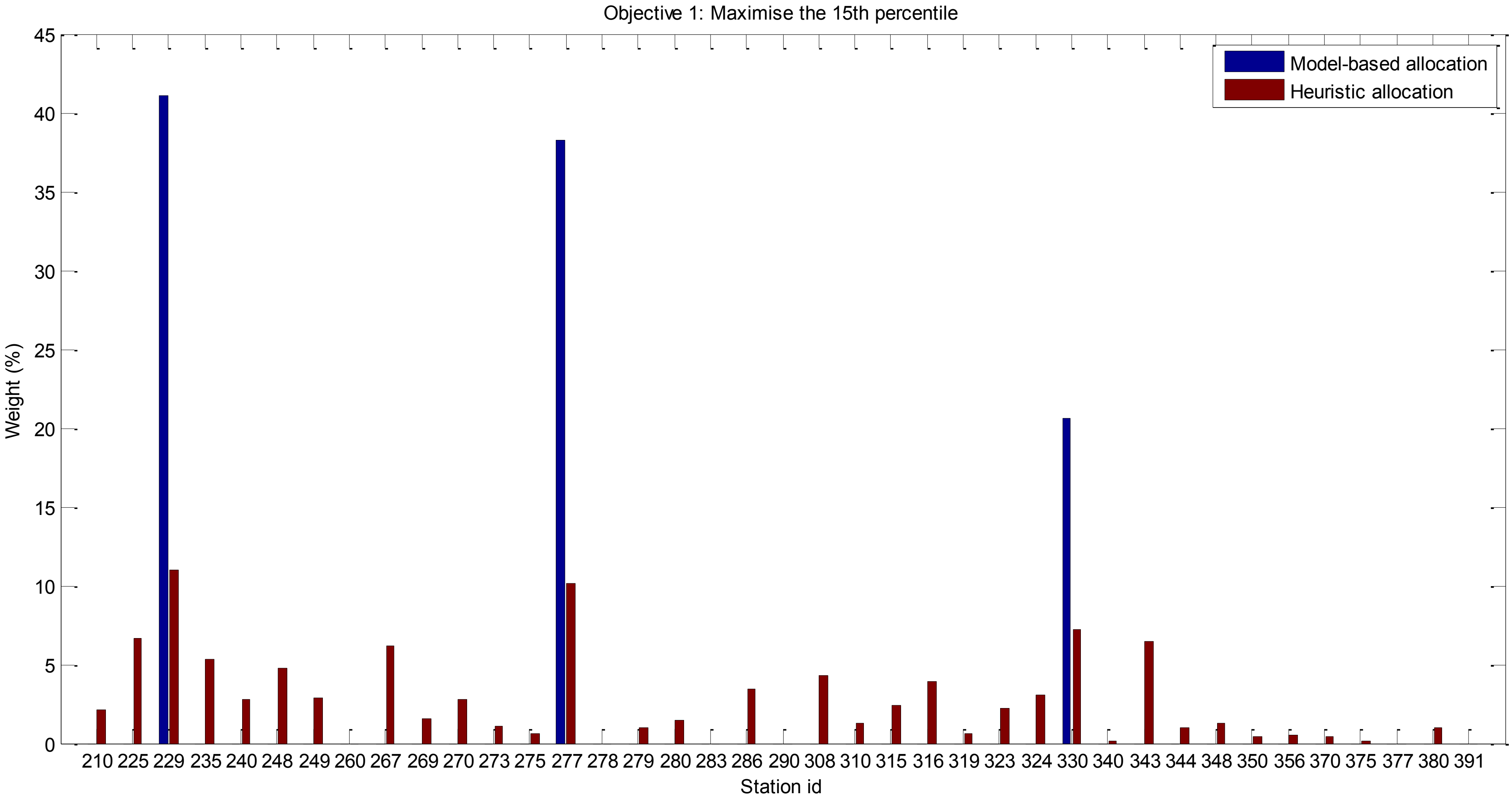
Heuristic allocation plans

- Rank sites (in *descending order*) based on their score on the corresponding performance criterion (e.g. p_{15})
- Allocate capacity accordingly

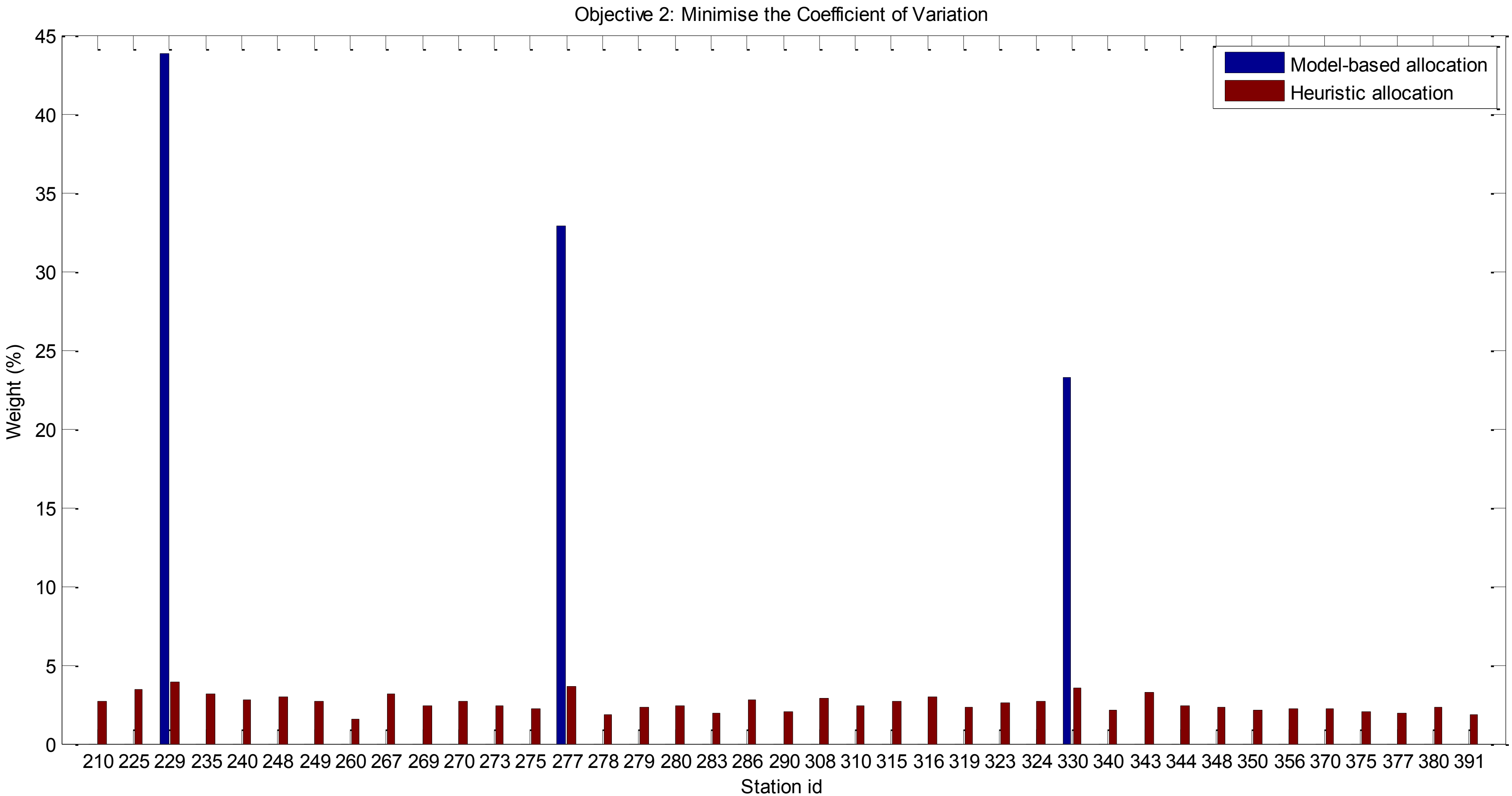
Site id	15th percentile of daily estimated power (per 100 MW)	Weight (% of total available capacity)
229	14.02	11.04
277	12.9	10.16
330	9.16	7.21
225	8.49	6.69
343	8.23	6.48
267	7.81	6.15
235	6.74	5.31
248	6.04	4.75
…	…	…

28.41 %

Objective 1: maximise daily availability

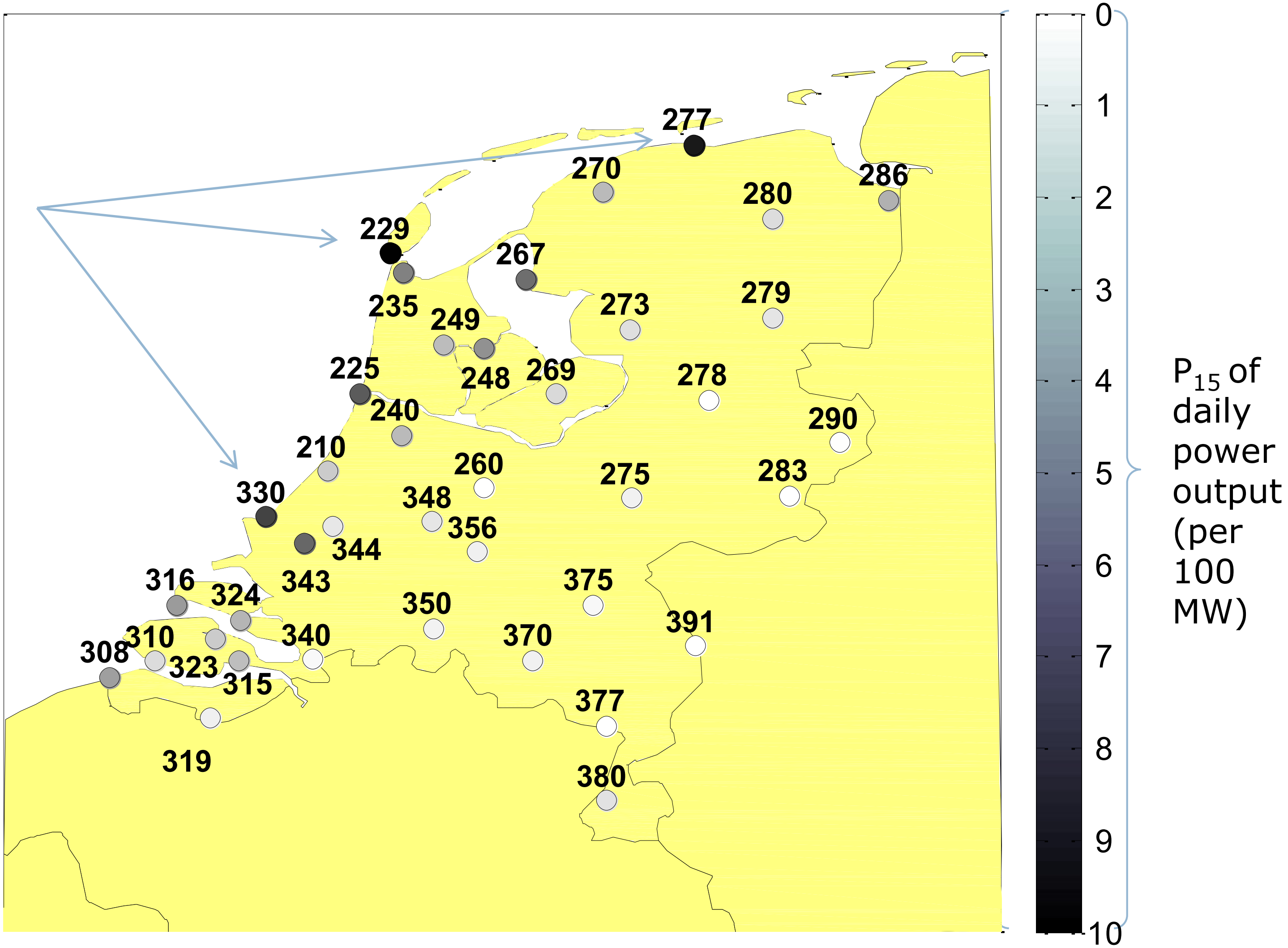


Objective 2: minimise daily power CV



How is this allocation justified?

Most promising sites in terms of power availability in low wind days



How is this allocation justified?

- Correlation matrix between selected sites

	LAUWERSOOG (277)	HOEK VAN HOLLAND (330)
TEXELHORS (229)	0.798	0.804
LAUWERSOOG (277)		0.682

< average across all pairs (0.82)

High reliability + low dependence = smoother aggregate profile

Performance assessment (estimation sample)

Performance metric	Model-based optimal allocations		Heuristic allocations		Uniform distribution
	Obj1	Obj2	Obj1	Obj2	
Mean	50.57	50.76	39.76	31.48	29.41
Std	34.06	34.17	31.23	28.35	27.63
CV	0.67	0.67	0.79	0.90	0.94
p_5	3.43	3.43	2.28	1.27	1.06
p_{15}	10.75	10.74	6.71	4.09	3.40
p_{30}	23.39	23.23	15.13	10.12	8.82

Set 1: In-sample comparisons based on the empirical distribution of daily power production (in % of total installed power).

Performance assessment (evaluation sample)

Performance metric	**Model-based optimal allocations**		**Heuristic allocations**		**Uniform allocation**
	Obj1	**Obj2**	**Obj1**	**Obj2**	
Mean	52.98	53.13	40.85	31.85	29.62
Std	33.34	33.44	30.52	27.59	26.87
CV	0.63	0.63	0.75	0.87	0.91
p_5	4.70	4.65	3.09	1.81	1.45
p_{15}	12.16	11.91	7.62	4.73	4.10
p_{30}	27.73	27.88	17.21	10.95	9.54

Set 2: Out-of-sample comparisons based on the empirical distribution of daily power production (in % of total installed power).

Discussion

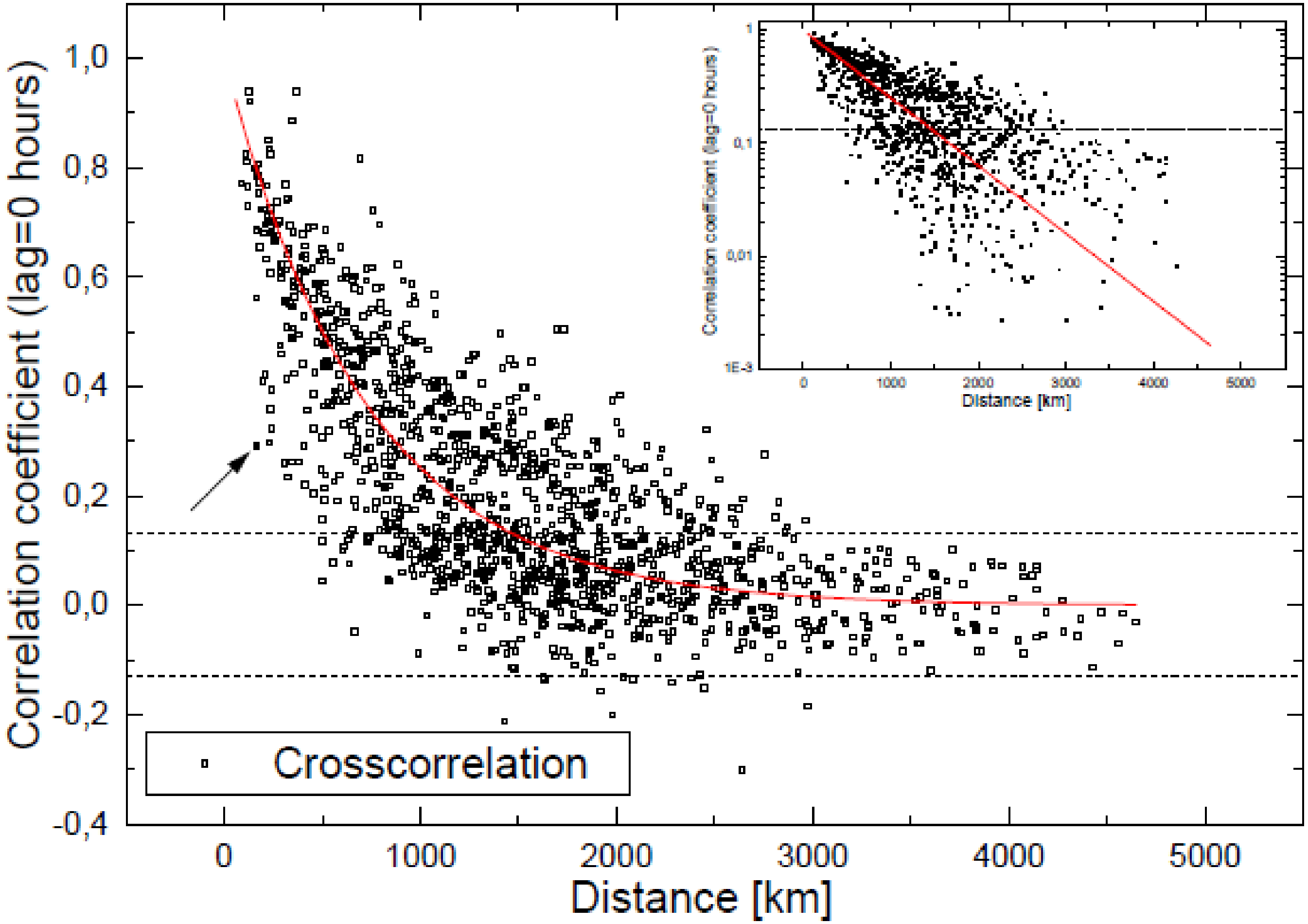
- Different methodologies for deriving optimal interconnections between a large network of sites considered for wind power harnessing
- Model-driven configurations vs simpler allocation schemes based on site-wise historical performance analysis
- Copula-based allocation schemes *superior* to model-free approaches
- Not only take into account *site-specific* information but also the horizontal dependence structure of wind resources
- Very important to the designing of combined energy systems with improved aggregate properties
- Cautious selection of the locations participating in the final generation mix
- Intermittency risk can de mitigated by considering *subgroups* of *carefully chosen* sites

Further research

- *Experimental setting*
  - Manufacturing characteristics of wind turbines
  - Power output model (power curve interpolation technique)
  - Extrapolation of wind speeds at hub height
  - Patterns of temporal and spatial variations in wind speeds
- *Different production targets*
  - Maximise the annual energy yield, mimimise the possibility of observing *too many* consecutive periods of low productivity, etc
- *Problems of different dimensionality*
  - Consider interconnections over larger regions (Europe, US, Globe)

Appendix

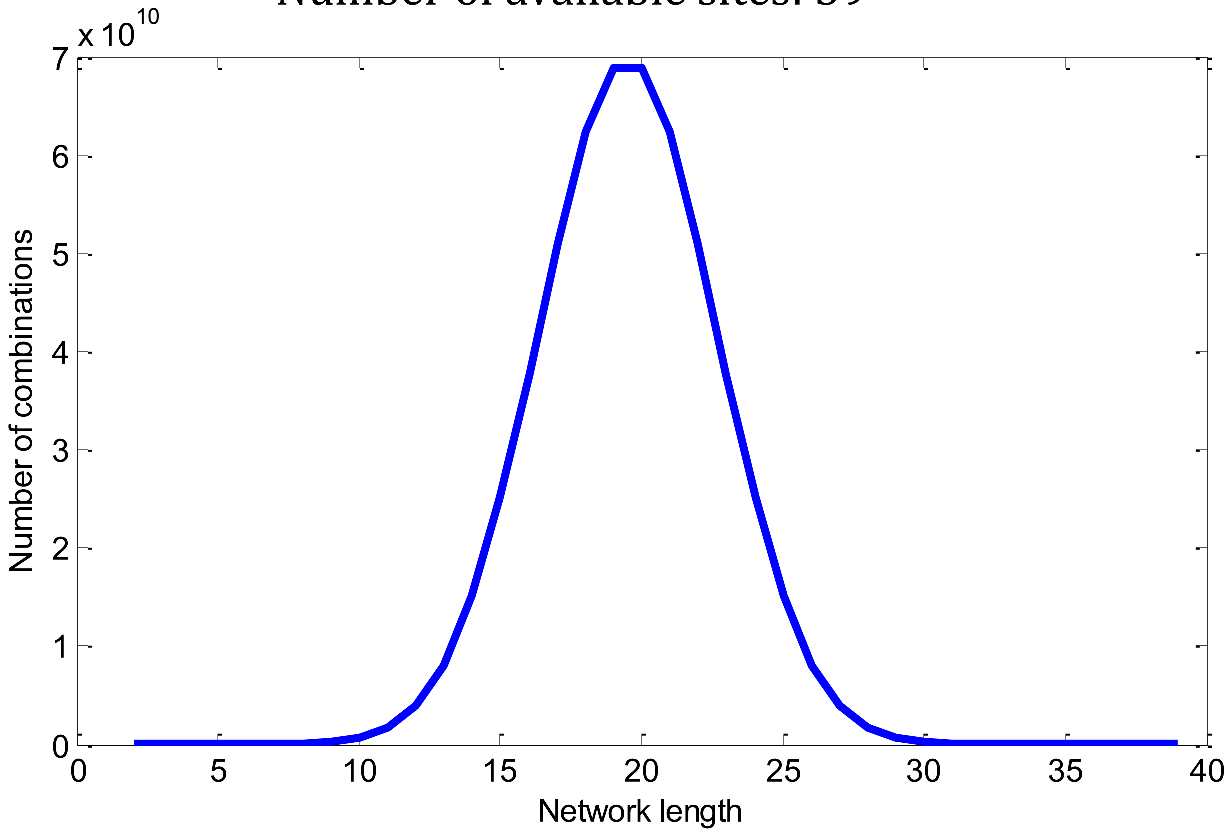
Wind correlation vs distance



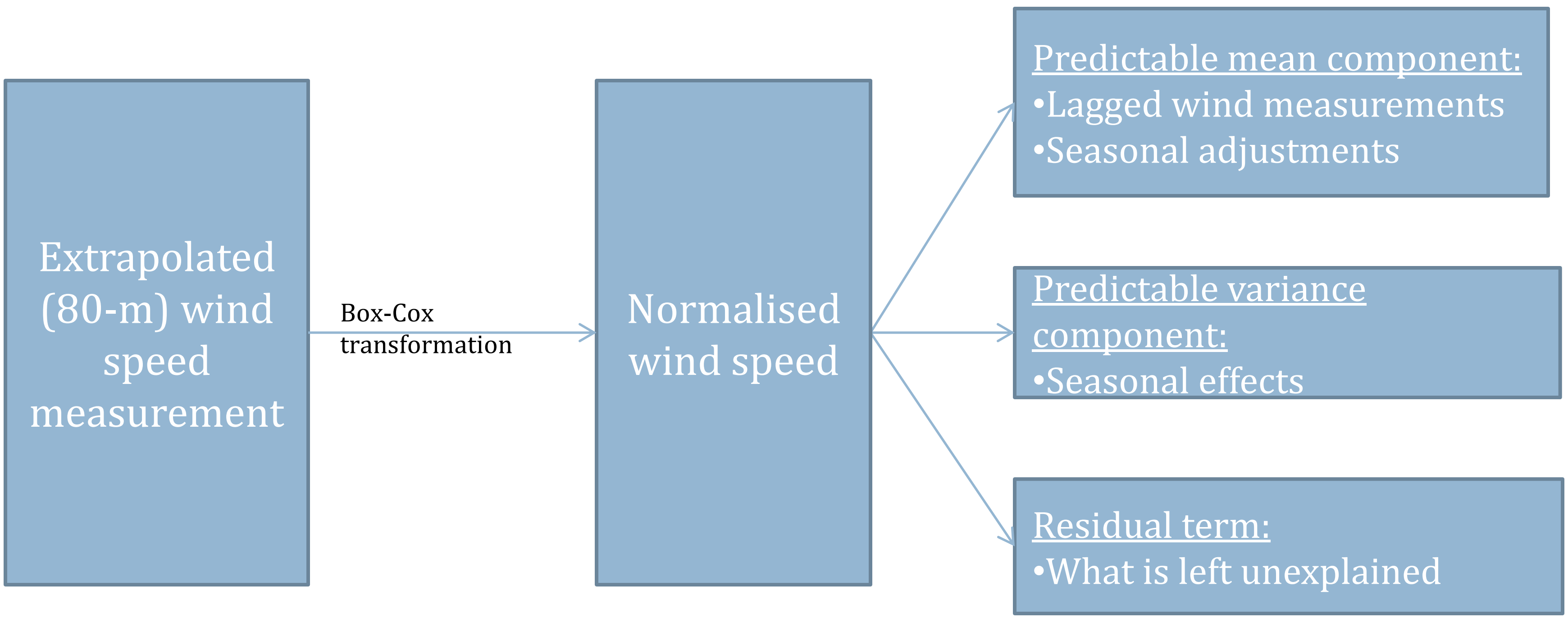
Source: Giebel G., 2000. "On the benefits of distributed generation of wind energy in Europe", PhD thesis University of Oldenburg, p. 48.

Combinatorial complexity

Number of available sites: 39



Wind speed modelling process



Temporal variations in wind speeds

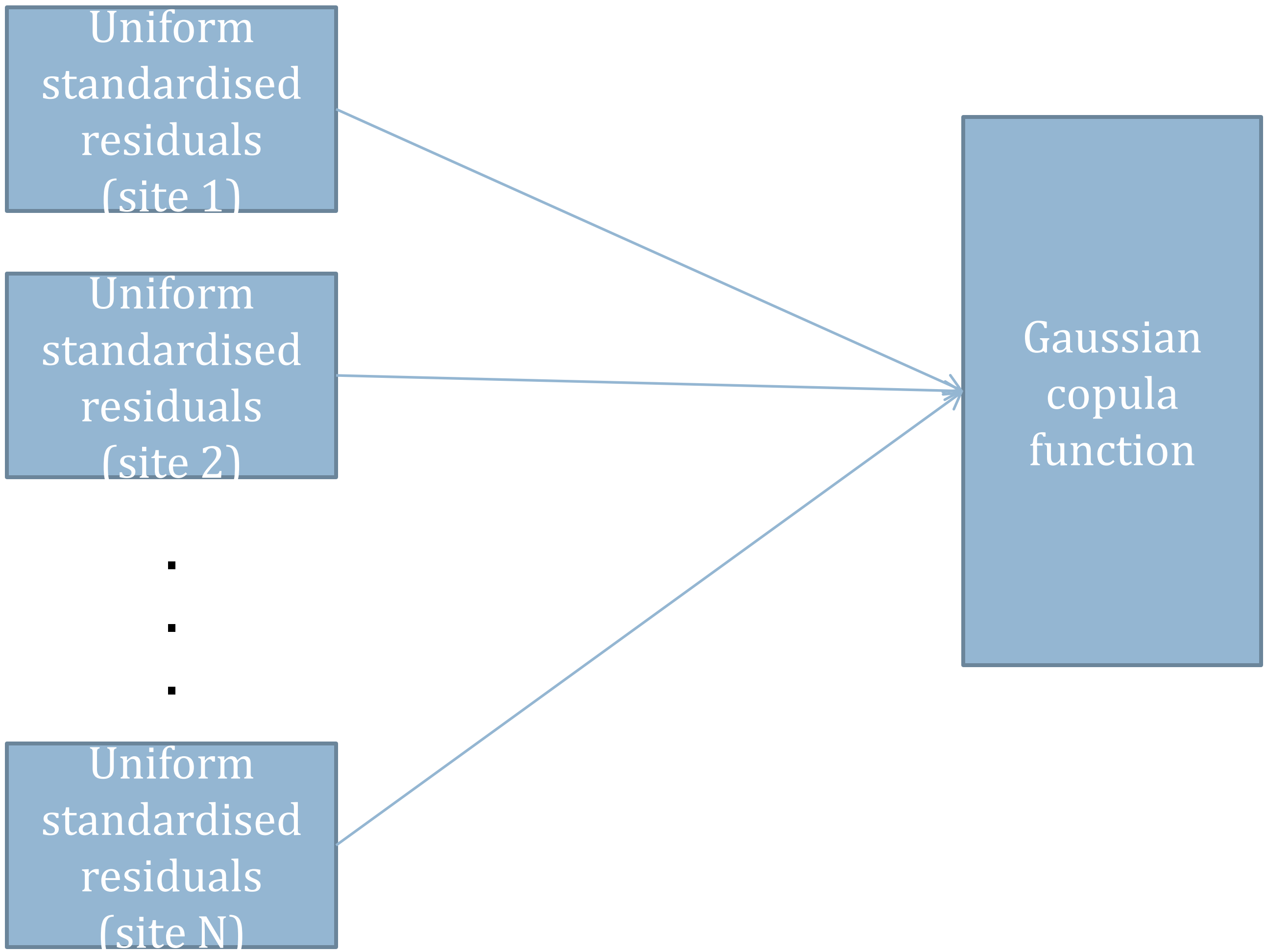
$v_t = p_t + z_t$ (actual time *t* observation)

$$p_t = b_0 + b_1 v(t-1) + b_2 v(t-2) + \sum_{j=0}^{1} b_{2j+3} \cos(365^{-1}(2j+2)\pi t) + \sum_{j=0}^{1} b_{2j+4} \sin(365^{-1}(2j+2)\pi t)$$ (mean equation)

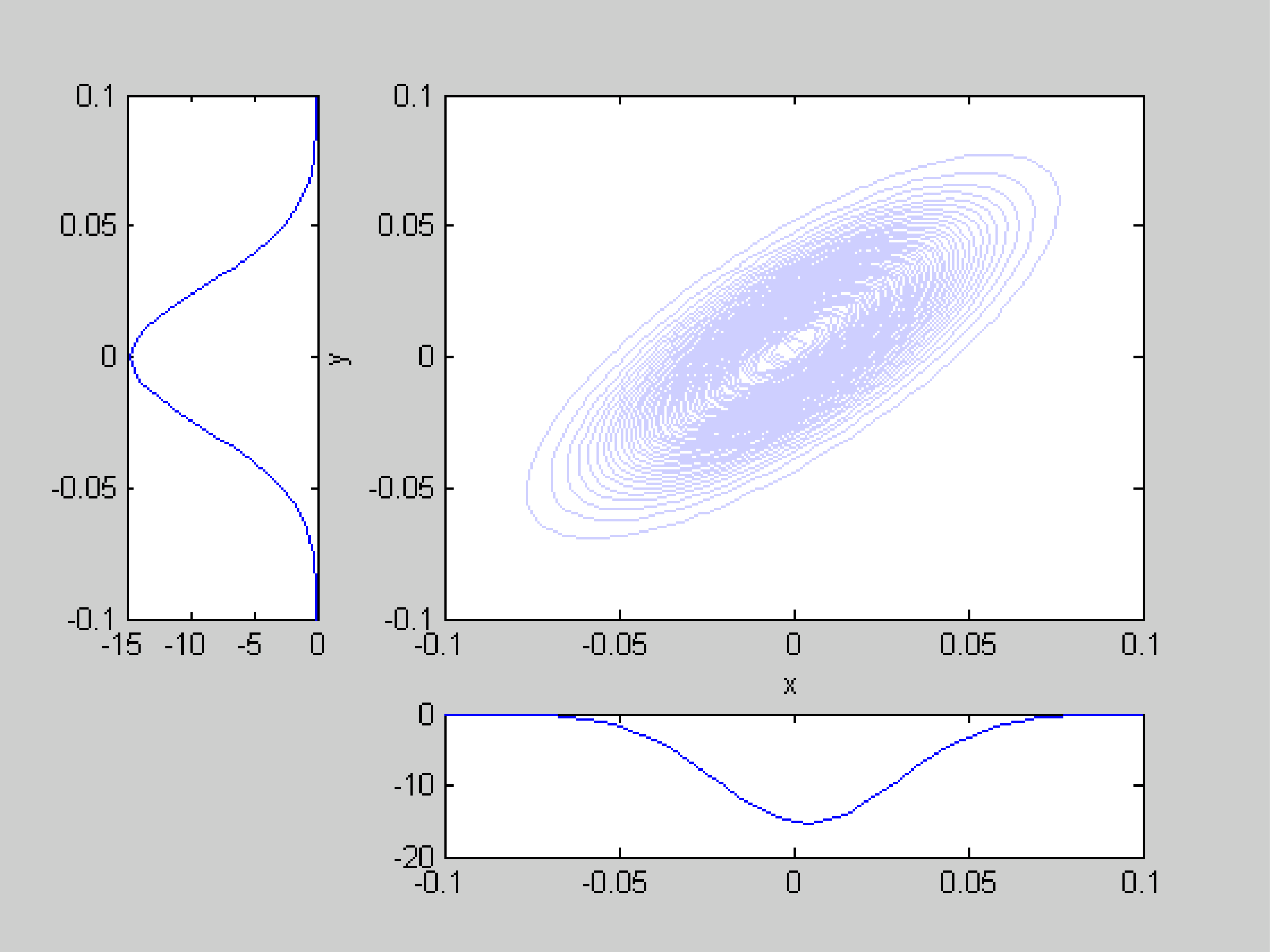
$z_t = \sigma_t \varepsilon_t$ (standardised residual)

$$\sigma_t^2 = a_0 + \sum_{j=1}^{3} a_j \sin(2j\pi t/365)$$ (variance equation)

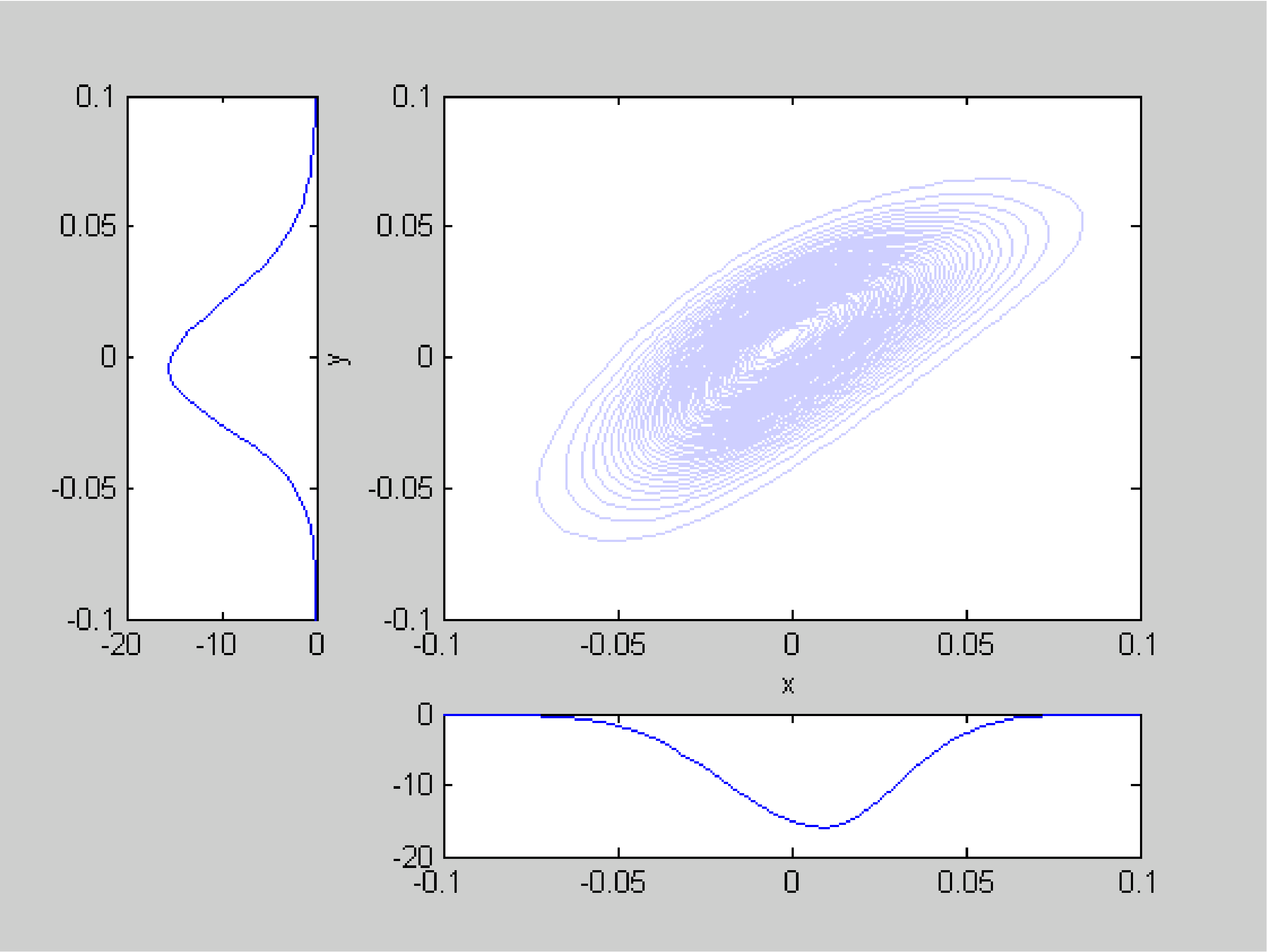
Cross-section of wind speeds



Gaussian copula with normal marginals



Gaussian copula with non-normal marginals



Clayton copula with non-normal marginals