Uncertainty Quantification in Wind Power Prediction

CWI Scientific Meeting

Energy Theme

Friday, March 28, 2014, 13:00-14:00

Jeroen Witteveen,

Center for Mathematics and Computer Science (CWI), Amsterdam, The Netherlands

Michel Verburg, Richard de Groot, Gabriël Bloemhof,

DNV GL KEMA Energy & Sustainability, Energy Business Park Arnhem, The Netherlands

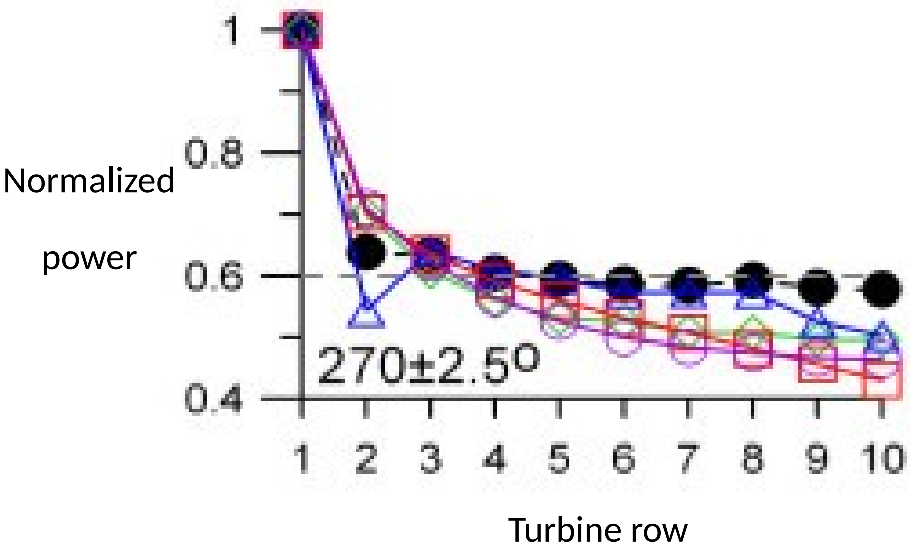
Impact of environmental uncertainties on offshore wind farms

Uncertainties:

- Wind direction: up to 40% reduction in power output
- Wind speed
- Turbulence intensity

Horns Rev offshore wind farm with turbines in each other's wake

Wind direction aligned with turbine rows



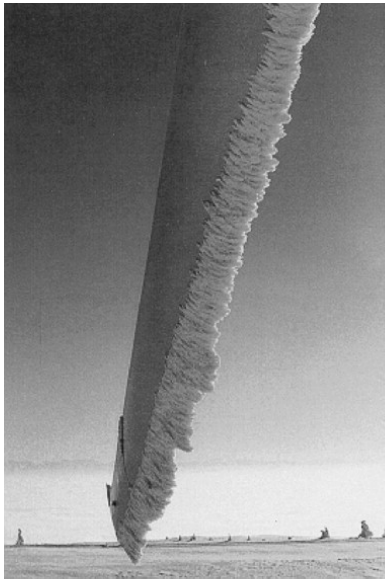
Uncertainties in individual wind turbines

Uncertainties:

- Wear and tear → Surface roughness
- Production tolerances → Geometry

Insect contamination

Ice formation



Increasing integration of renewable energy sources in the electrical grid

Increasing variability in electricity production:

- Growing capacity of renewable energy
- More extreme weather fluctuations

Supply and demand in equilibrium at all times:

- Frequency instabilities
- Power black outs

Short-term operation and long-term grid extension planning:

- Deterministic scenarios
- Purely historical data

Uncertainty Quantification: Performing multiple simulations

Conventional CFD simulations:

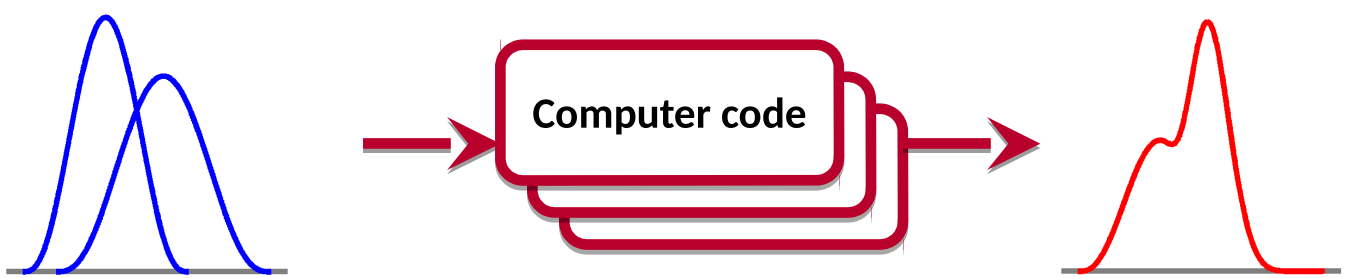
- Model parameters
- Initial conditions
- Boundary conditions

Numerical solution

Uncertainty quantification in CFD:

Pre-processing

Post-processing

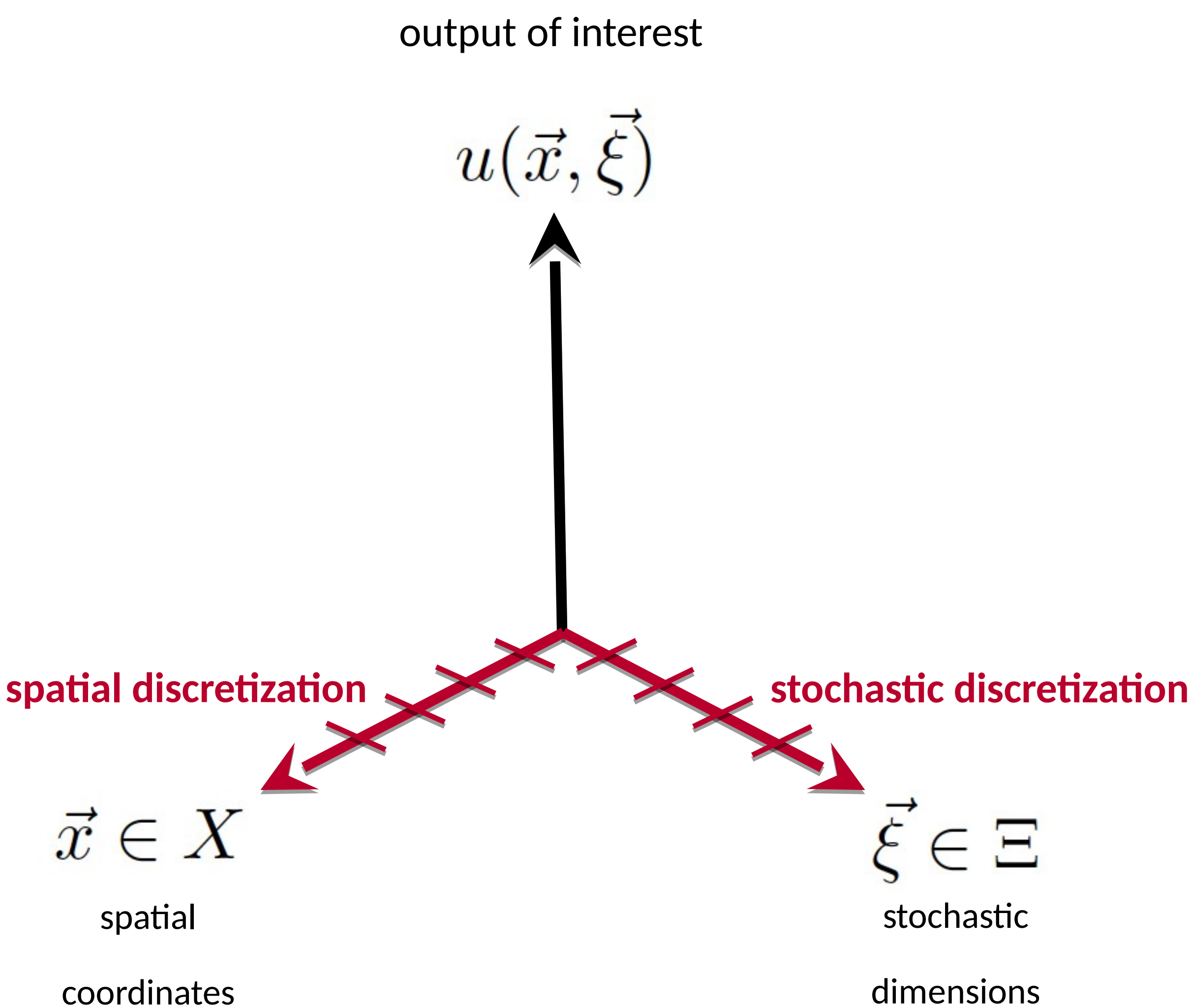


Input probability distributions

Existing black-box CFD simulation software

Output quantity of interest

Discretization of spatial and stochastic dimensions



Wind turbine robust optimization under uncertainty

- Wind conditions: magnitude, turbulence intensity, direction
- Insect contamination: root, mid-span, tip transition e^N factor
- Manufacturing tolerances: root, mid-span, tip twist angles

50kW AOC 15/50 wind turbine

Acqua Spruzza site in Italy

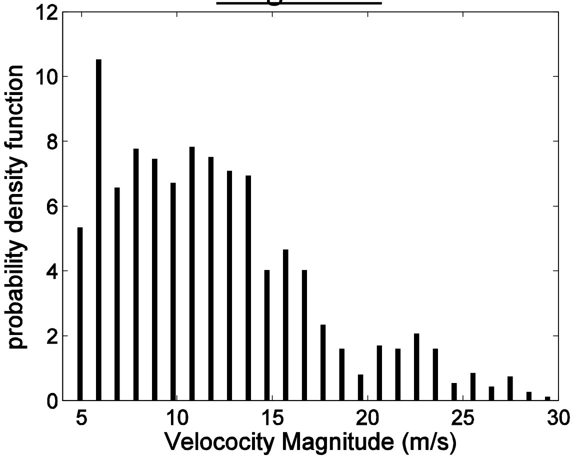
Collaboration with: G. Petrone, C. de Nicola, D. Quagliarella, J. Axerio-Cilies, G. Iaccarino

Uncertainty in wind conditions given by measured histograms

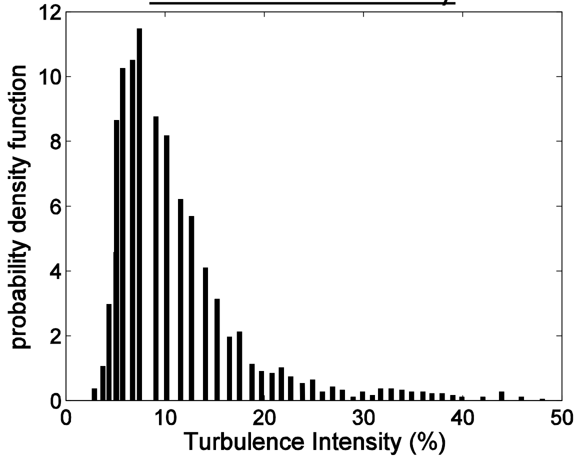
- Wind conditions: non-standard probability distributions
- Insect contamination: uniform distributions, N = U(1, 9)
- Manufacturing tolerances: uniform distributions, θ= U(-2^{o}, 2^{o})

Input probability density functions for the uncertain wind conditions

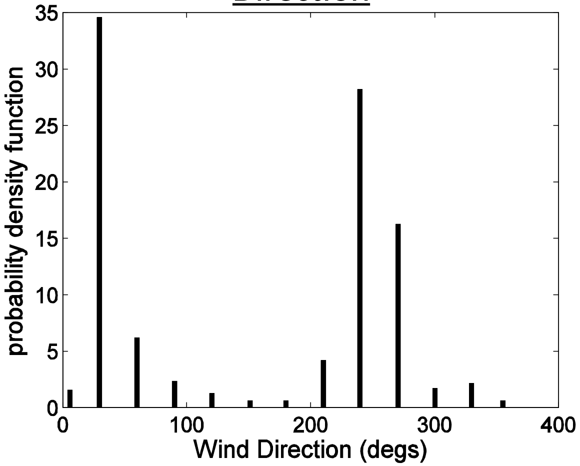
Magnitude



Turbulence intensity



Direction



Largest impact of wind conditions on power coefficient

Mean and standard deviation of power output and noise level:

- Wind uncertainty halves mean power coefficient
- Order-of-magnitude larger standard deviation
- Relatively smaller effects on sound pressure level

Power coefficient

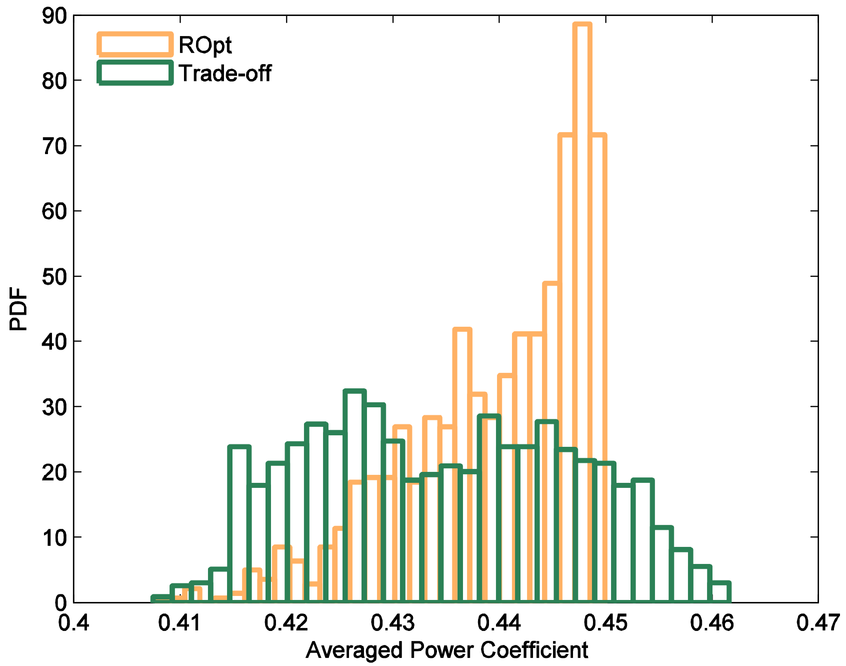
	Mean	Standard deviation
Deterministic	0.4596	-
Wind	**0.2776**	**0.1189**
Insect	0.4340	0.0162
Manufacturing	0.4560	0.0071

Sound pressure level (dB)

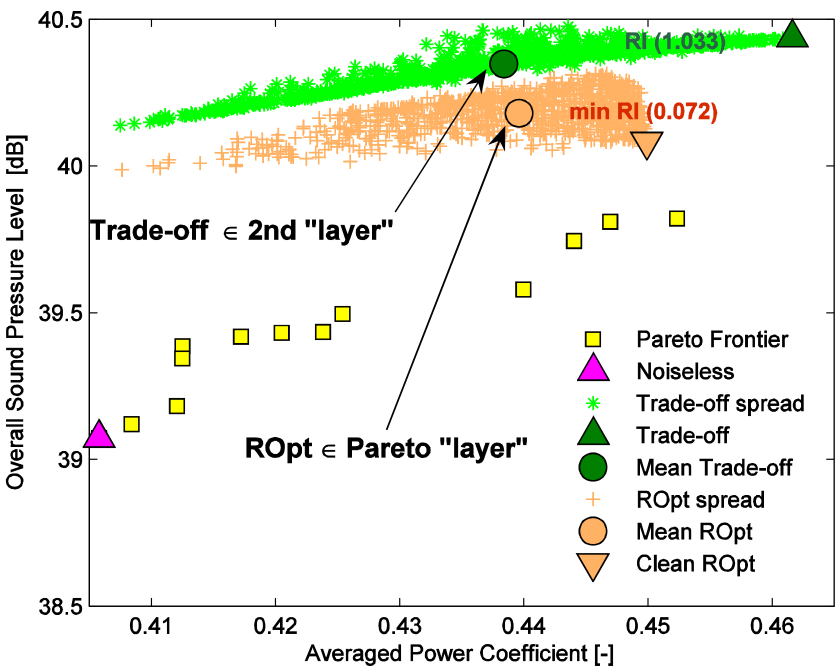
	Mean	Standard deviation
Deterministic	44.711	-
Wind	40.453	3.2853
Insect	44.651	0.0738
Manufacturing	44.719	0.2216

Optimal robust design has peak probability at maximal power output

Density of power coefficient for optimum and trade-off



Robust optimization based on probability distribution of rank and Monte Carlo sampling of SSC response surface

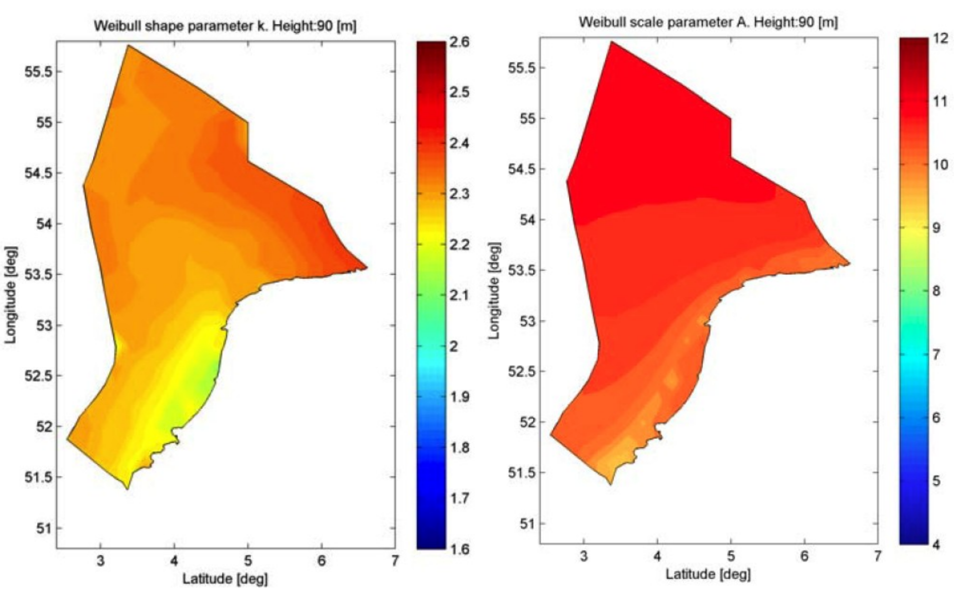


Wind probability distribution

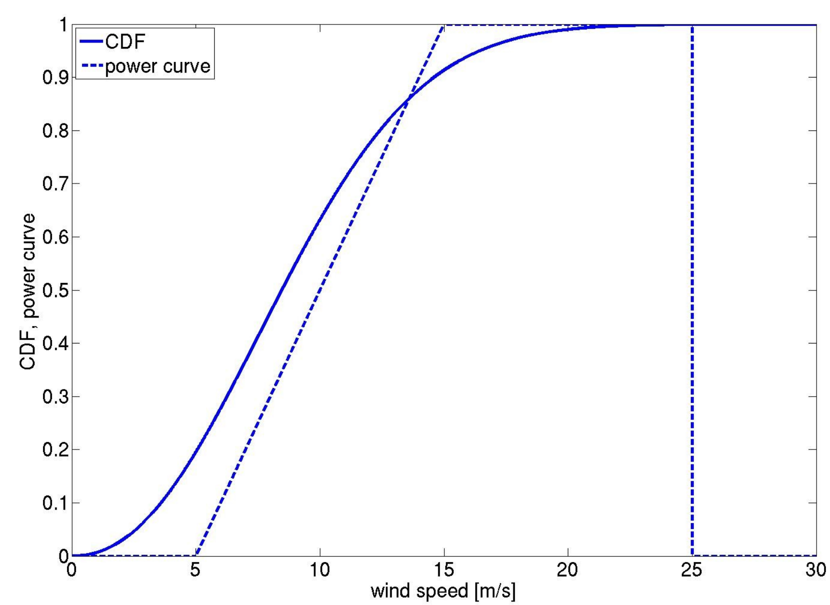
- Weibull probability distribution for wind speed
- Weibull parameter values for offshore wind inThe Netherlands: λ= 10; *k*= 2.2
- Standard wind turbine power curve

$$f(x;\lambda,k) = \begin{cases} \frac{k}{\lambda}\left(\frac{x}{\lambda}\right)^{k-1} e^{-(x/\lambda)^k} & x \geq 0, \\ 0 & x < 0, \end{cases}$$

k *and* λ *values for Dutch North Sea*



Cumulative distribution function

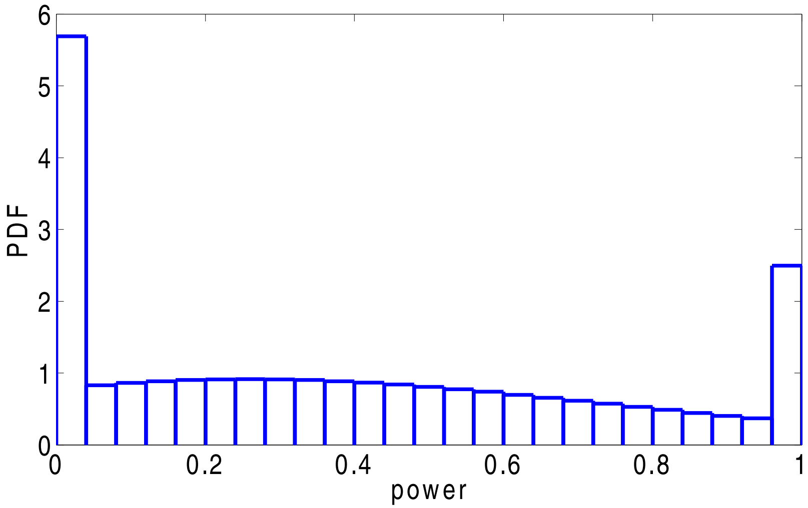


Wind power probability distribution

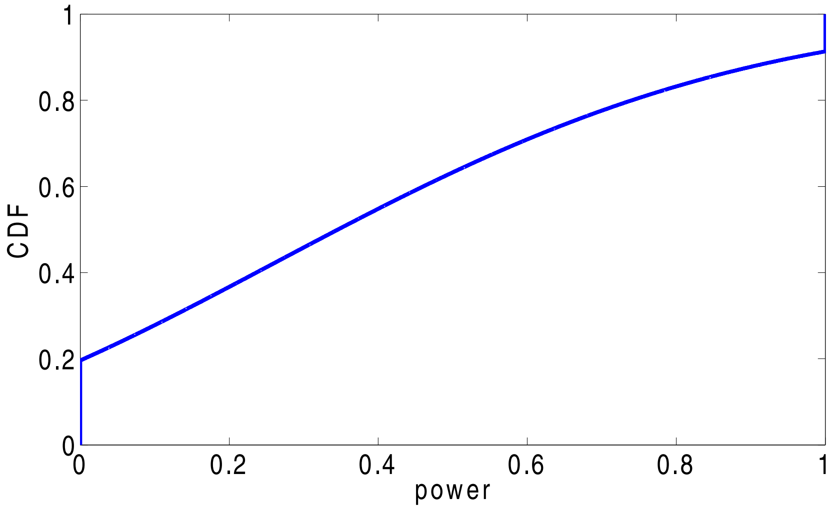
Highest probabilities:

- No power outside cut-in and cut-out wind speed
- Maximum power owing to power curve plateau

Probability density histogram



Cumulative distribution function

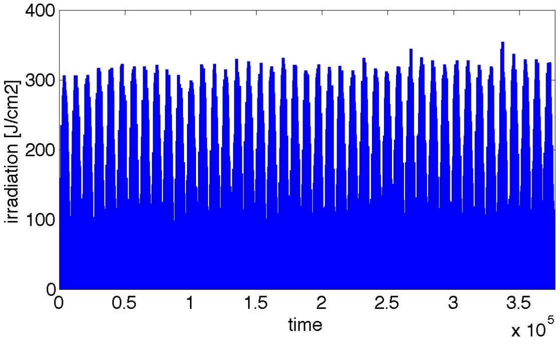


Solar irradiation input data

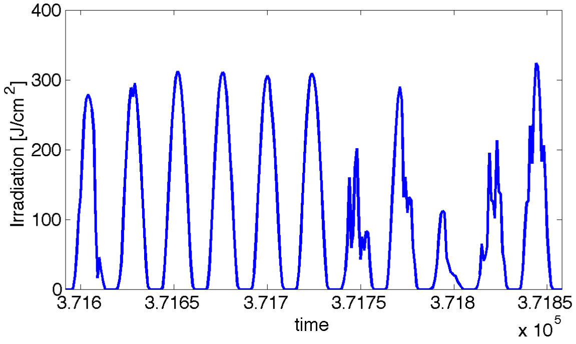
- Hourly irradiation data 1970-2012 in J/cm^{2}per hour
- Royal Dutch Meteorological Institute (KNMI), DeBilt
- Latitude 52.101^o north, Longitude 5.177^o east, altitude 2.00m
- 376968 data points

Historical time series

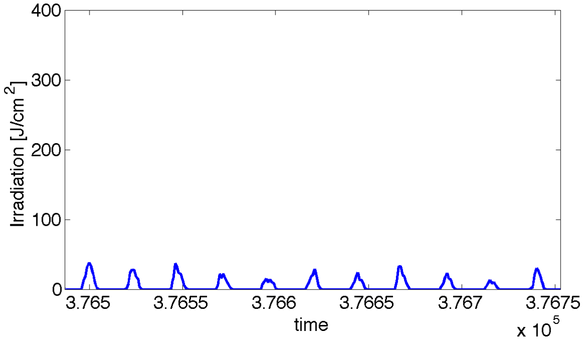
data 1970-2012



11 days in summer 2012



11 days in December 2012



Solar power probability distribution

Photo-voltaic (PV) systems:

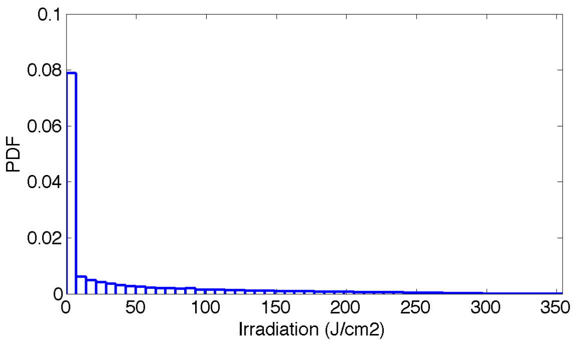
- Capacity rated in standard Watt peak (Wp):

1Wp = 1000 W/m^2 = 360 J/cm^2 per hour

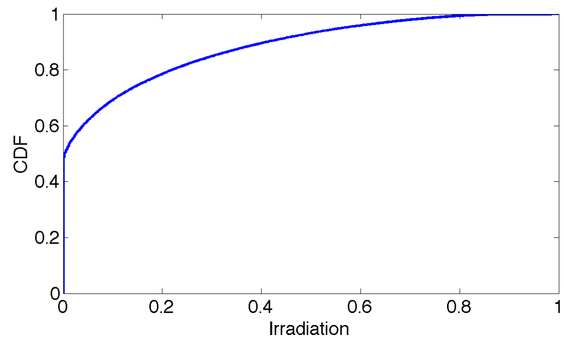
- Irradiation scaled by Wp
- Linear power conversion (temperature effects neglected):

Solar power=scaled irradiation x *rated capacity* (1003MW)

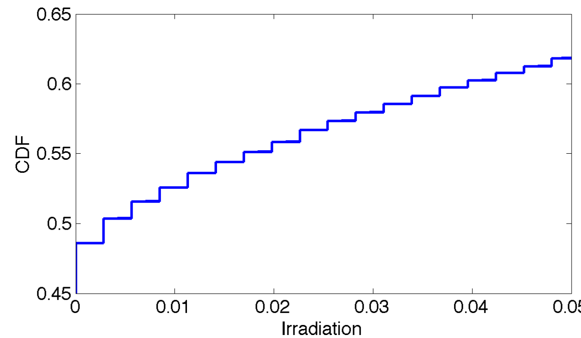
Probability density histogram



Cumulative distribution function



Discrete distribution due to finite measurement accuracy

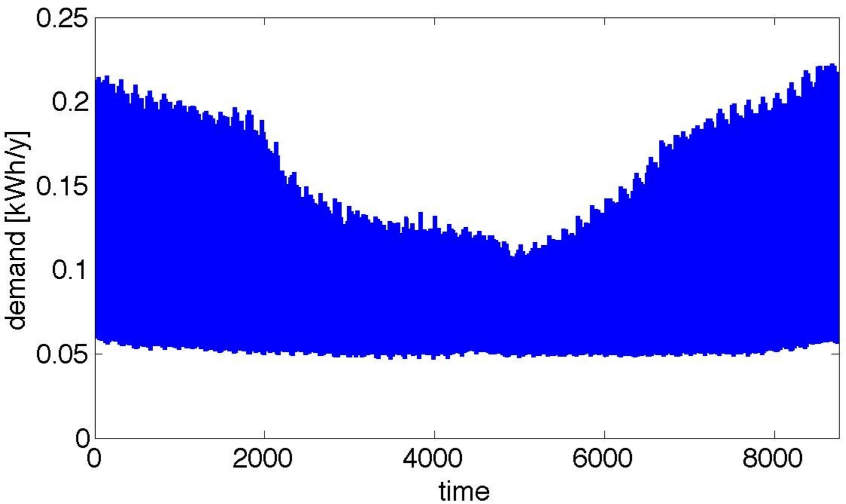


Demand input data

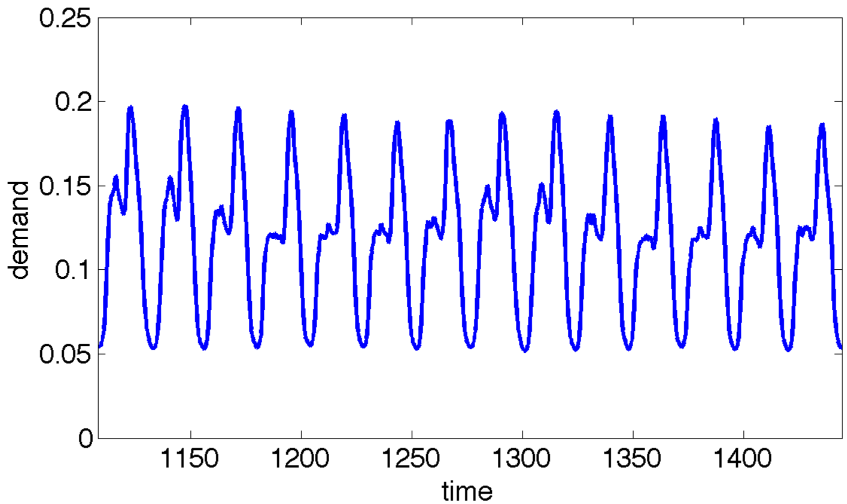
Consumed active power per household:

- Yearly 15 minute Dutch averages
- In kWh per 15 minute
- 35040 data points

Yearly average



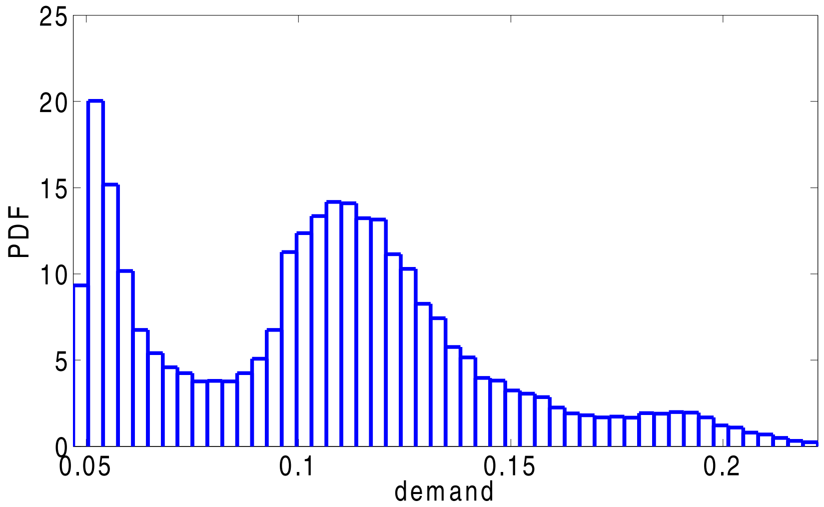
Two weeks in spring



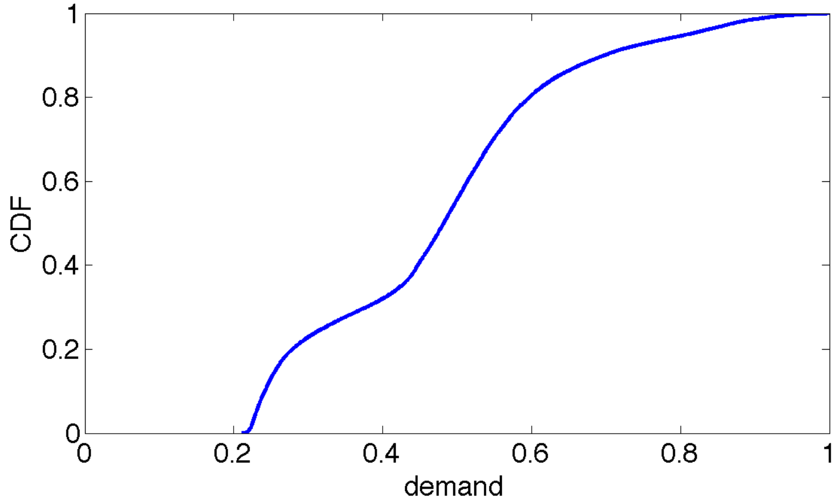
Demand probability distribution

- Maximum demand scaled to 1
- *Demand = scaled demand* x *IEEE 300 demand*

Probability density histogram



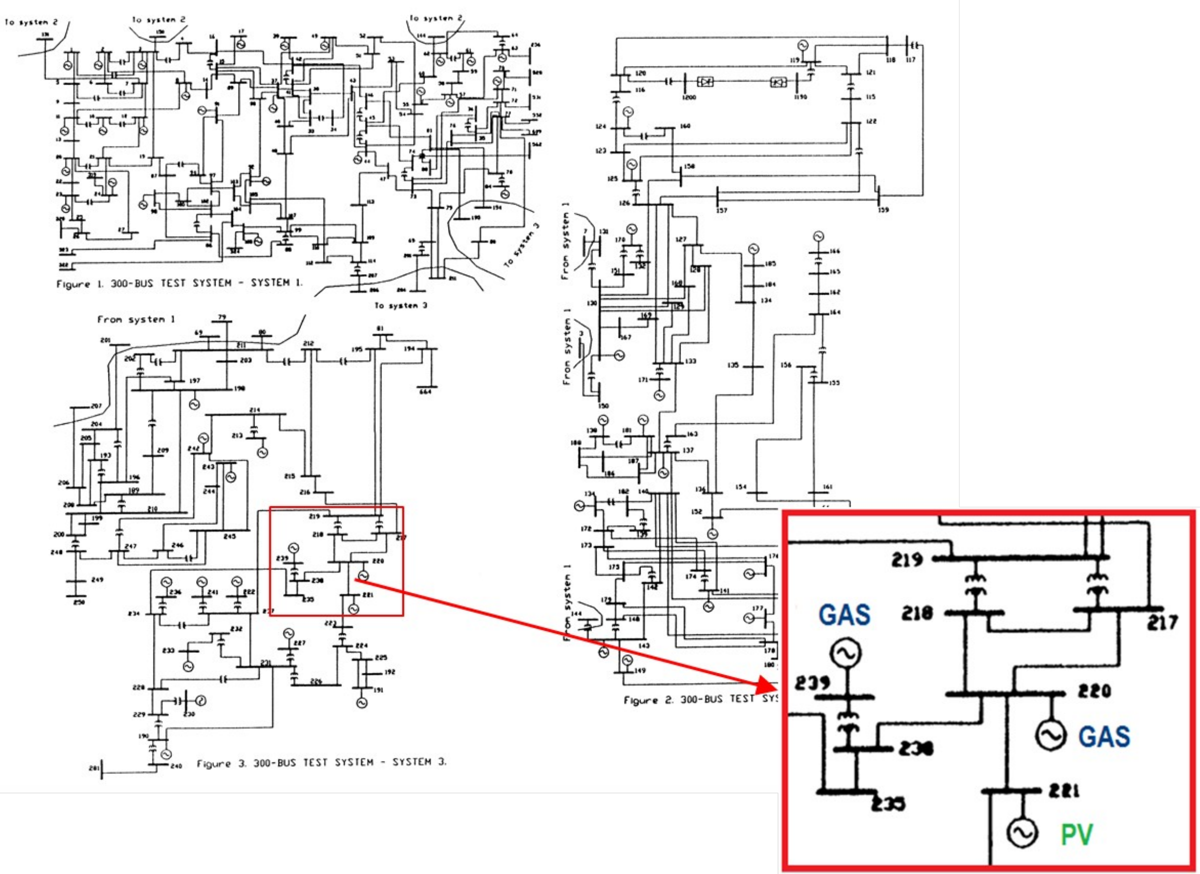
Cumulative distribution function



Stochastic power flow simulations of the electrical grid

Uncertain solar,wind, and demand: balanced by gas (18303MW)

Line diagram of standard IEEE 300 bus test system



300 busses:

- Bus voltages

2 x 411 branches:

- Branch currents
- Branch power

Replace generation:

- Solar: 4% (1003MW)
- Wind: 17% (3894MW)

Nonlinear steady-state power flow equations

Voltage V_i at bus i:

$$V_i = |V_i| \angle\delta_i = |V_i| \; (\cos\delta_i + j \sin \; \delta_i) = \; G_{ij} + jB_{ij}$$

Active and reactive power, P_i and Q_i, at bus i:

$$P_i = \sum_{N=1}^{N} |V_i| \; |V_j| \, (\, G_{ij}\cos\delta_{ij} + \; B_{ij}\sin\delta_{ij})$$

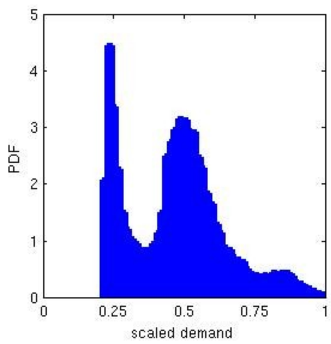
$$Q_i = \sum_{N=1}^{N} |V_i| \; |V_j| \, (\, G_{ij}\sin\delta_{ij} - \; B_{ij}\cos\delta_{ij})$$

N x N bus admittance matrix Y:

$$Y_{ij} = \left|Y_{ij}\right| \angle\theta_{ij} = \left|Y_{ij}\right| \cos\theta_{ij} + j\left|Y_{ij}\right| \sin\theta_{ij} \; = \; G_{ij} + jB_{ij}$$

Uncorrelated three-dimensional distribution

Demand



Probabilistic approach:

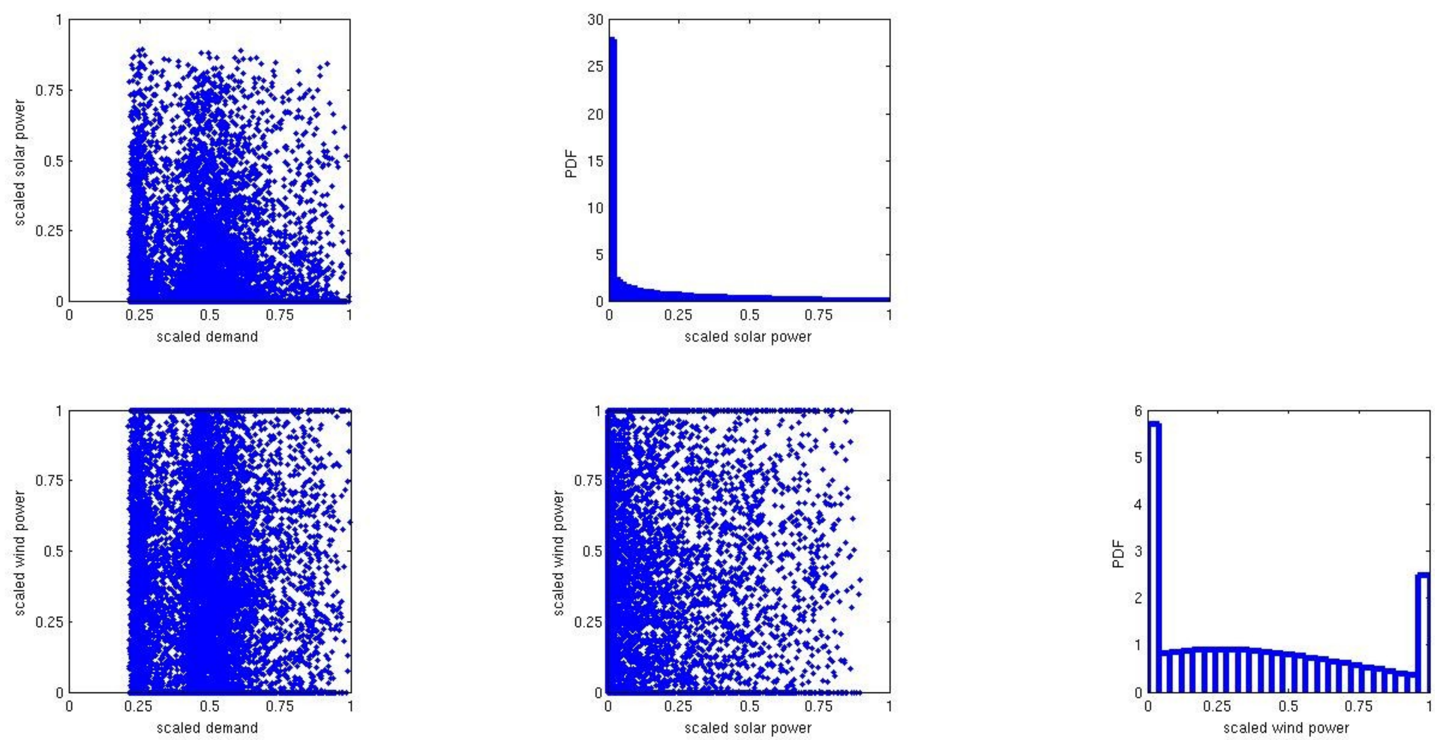
- Incorporate new future loading conditions

Historical time series approach:

- Fully correlated assumption

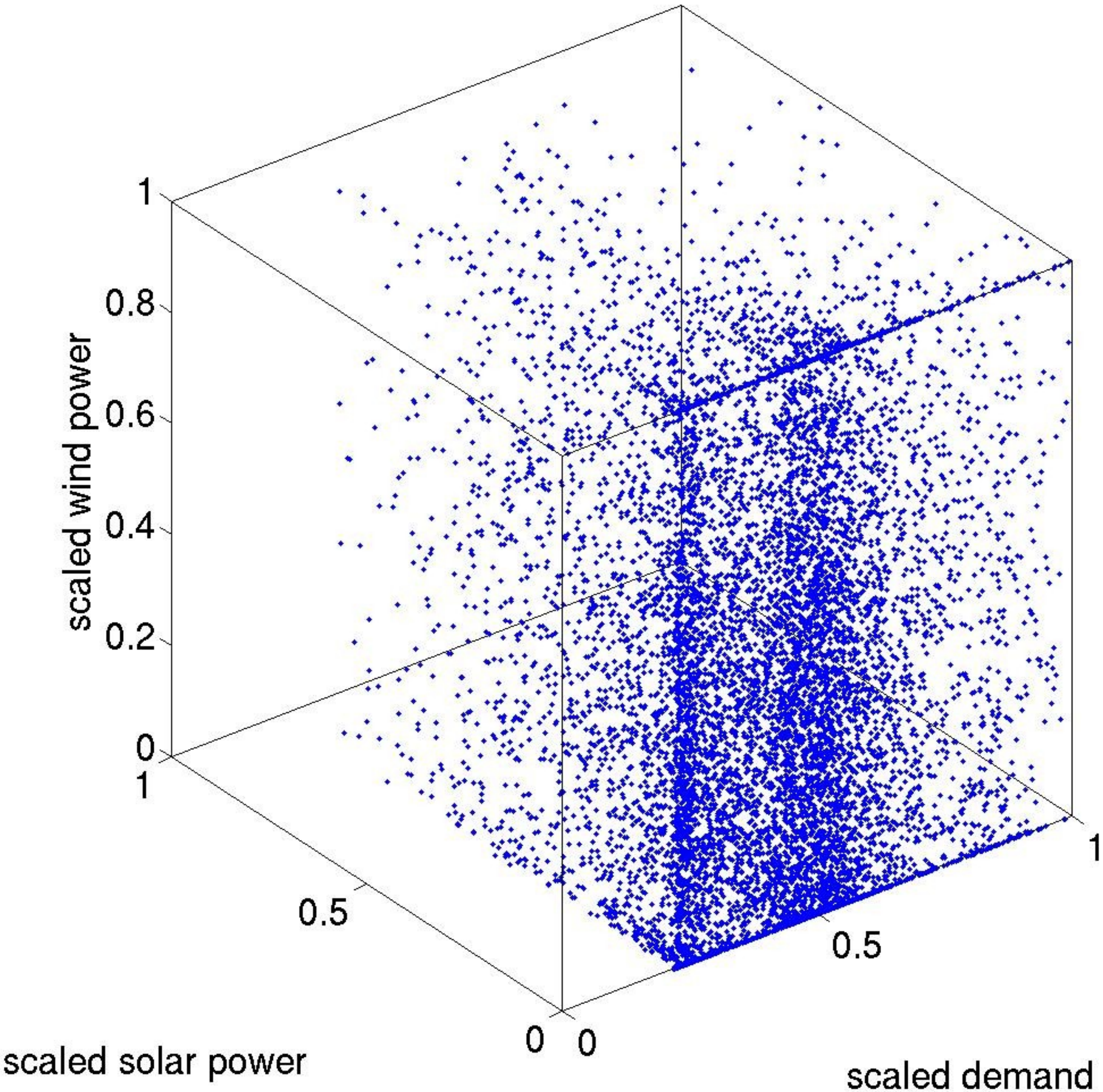
Solar power

Wind power



Demand *Solar power* *Wind power*

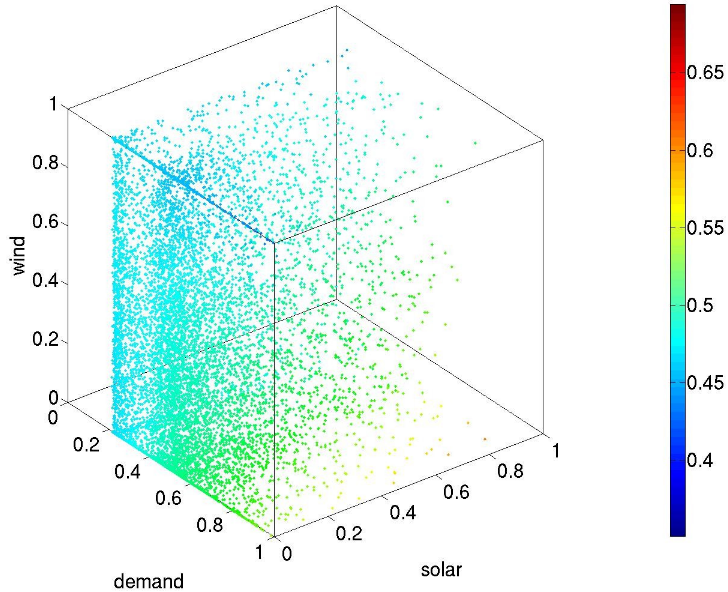
Monte Carlo simulation is expensive

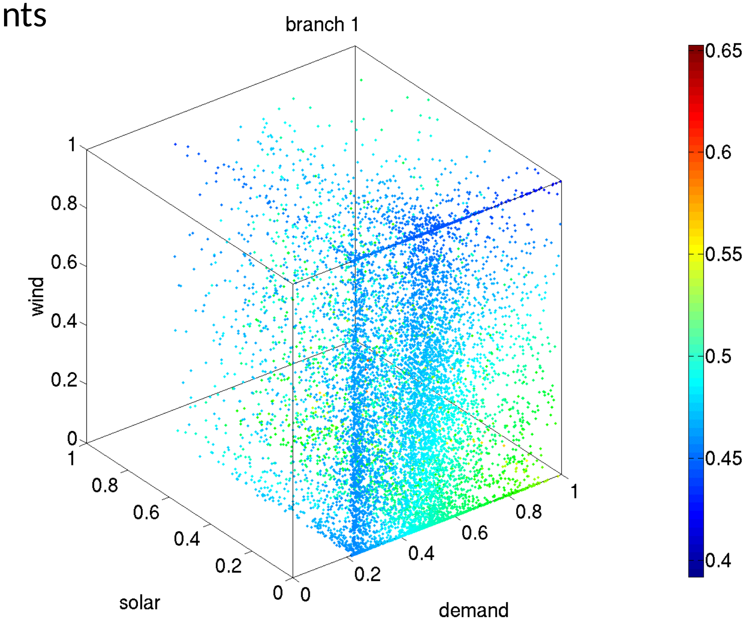


- 10,000 random sampling points
- Real-time in operation
- Repeat many failure scenarios

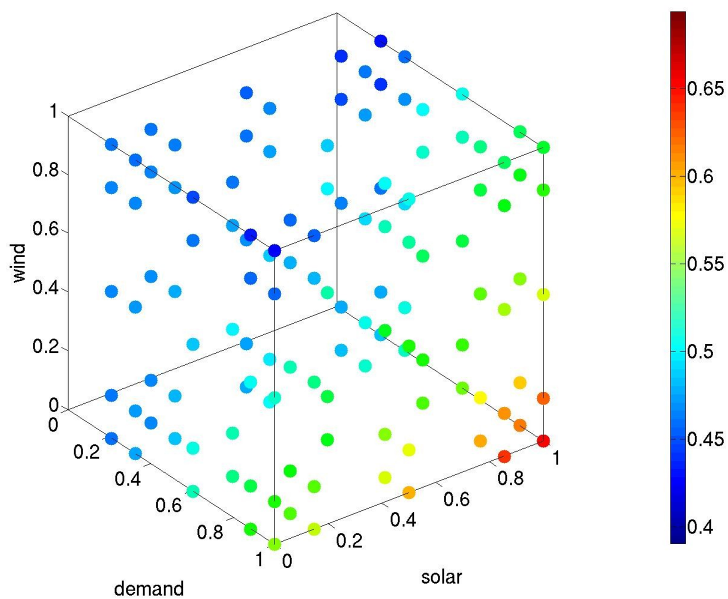
Computational points: Branch current 1

10,000 Monte Carlo points

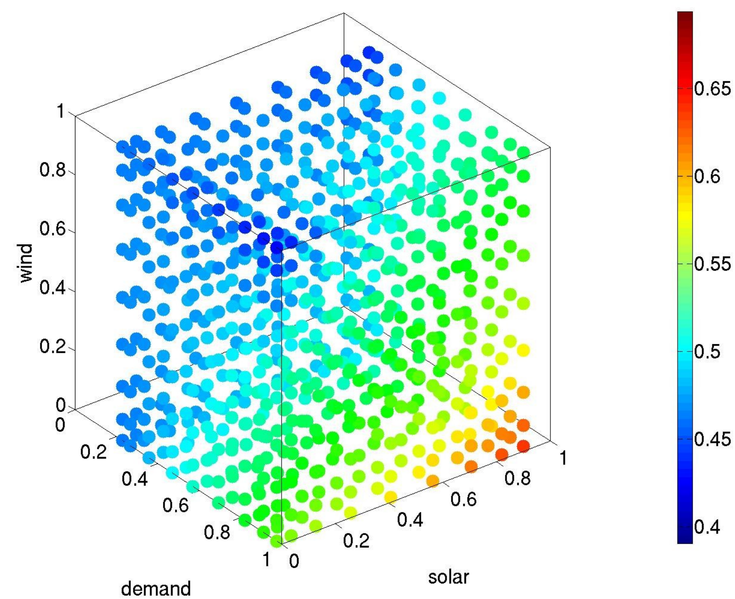




125Clenshaw-Curtis points

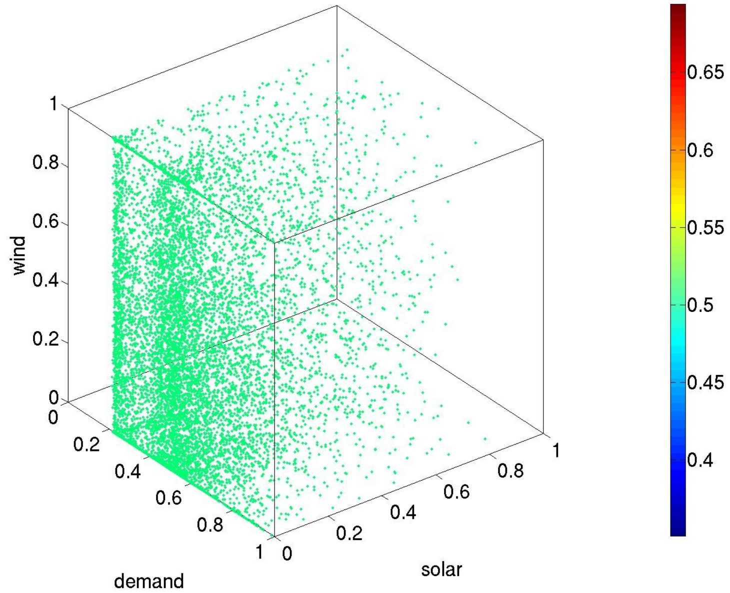


729 Gauss quadrature points

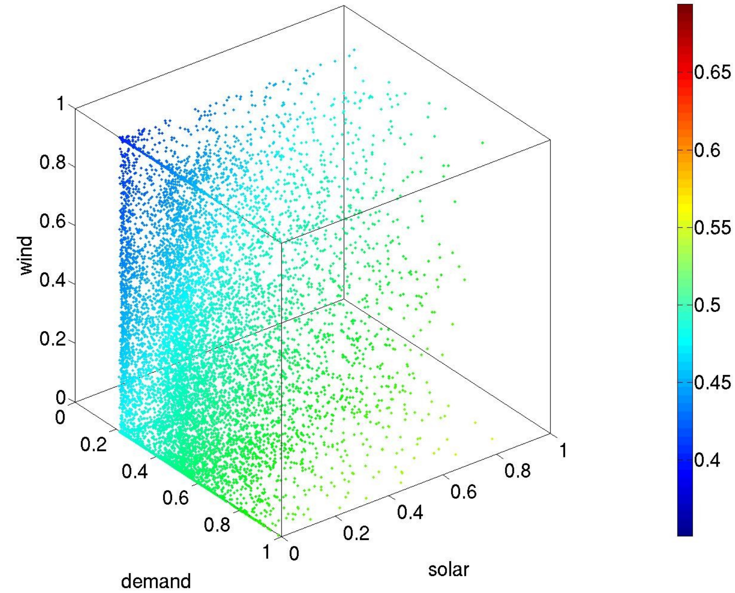


729 Gauss quadrature points, sparse grid: Branch current 1

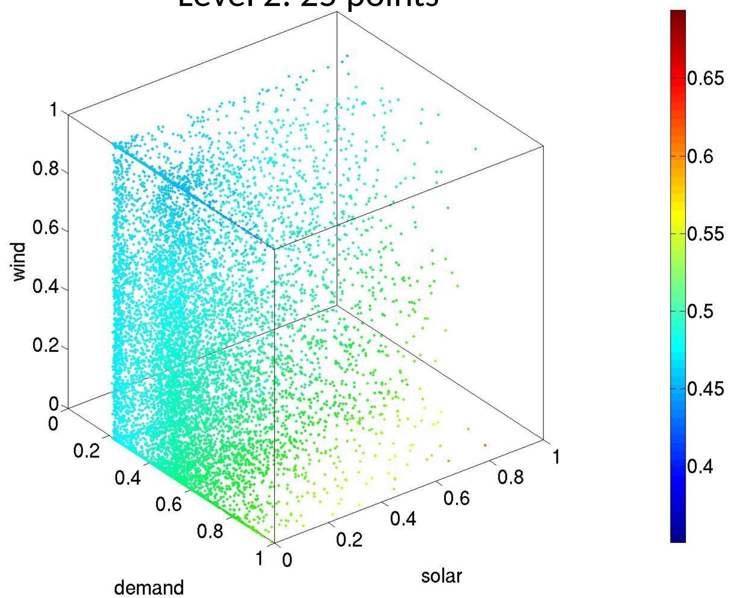
Level 0: 1 point



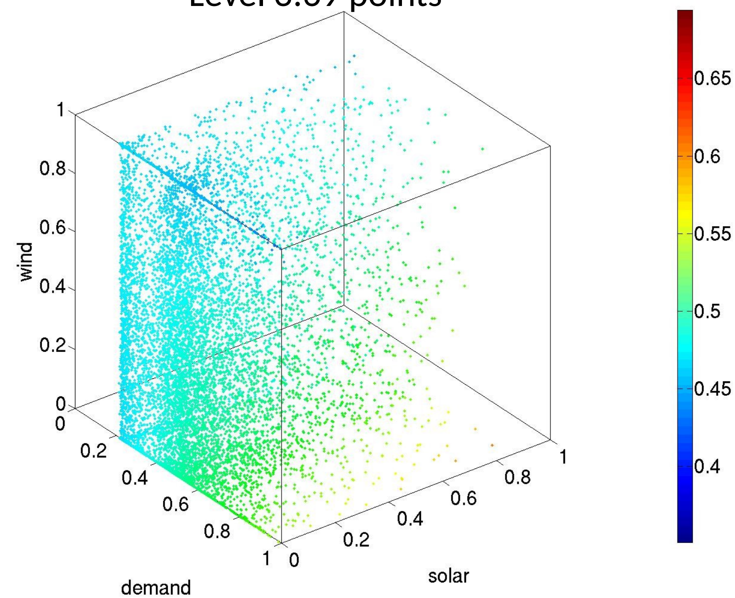
Level 1: 7 points



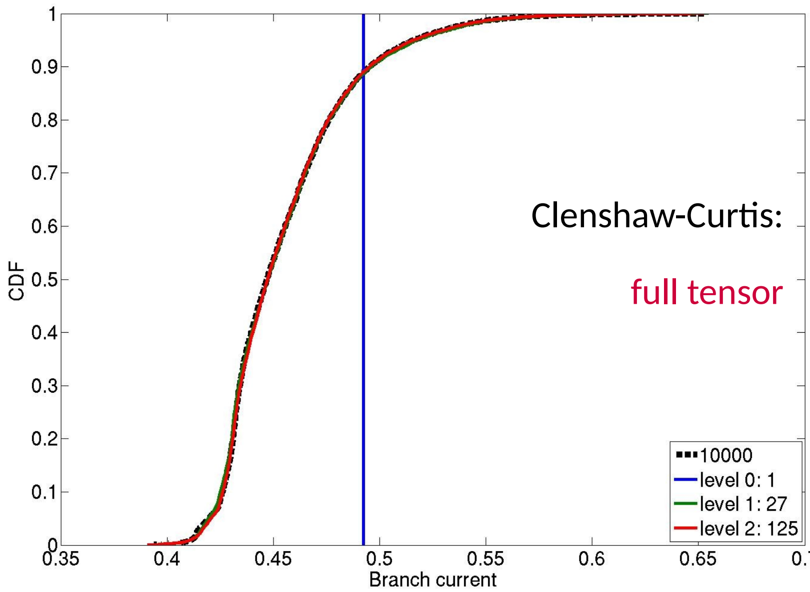
Level 2: 25 points

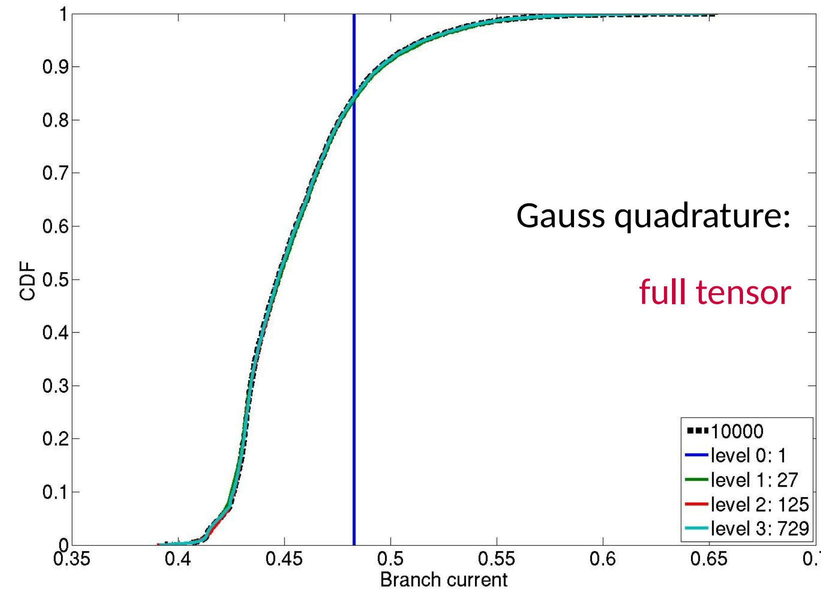


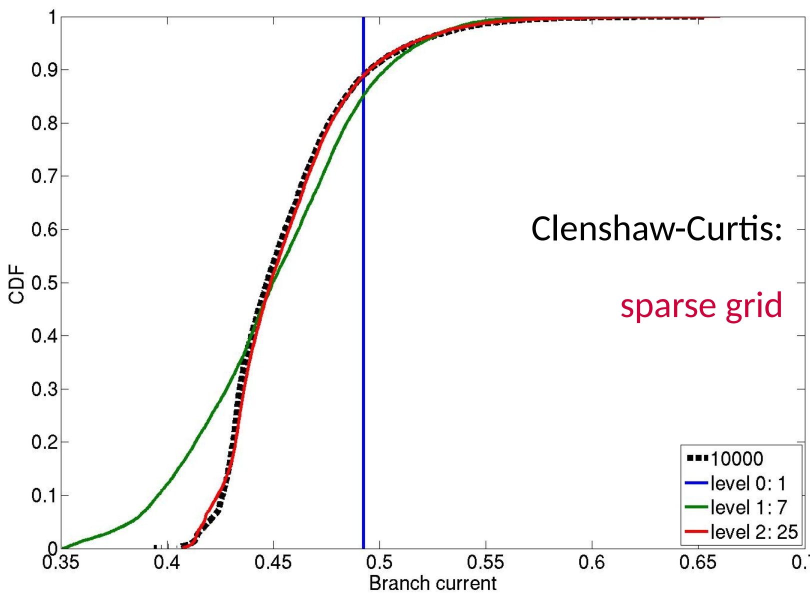
Level 3:69 points

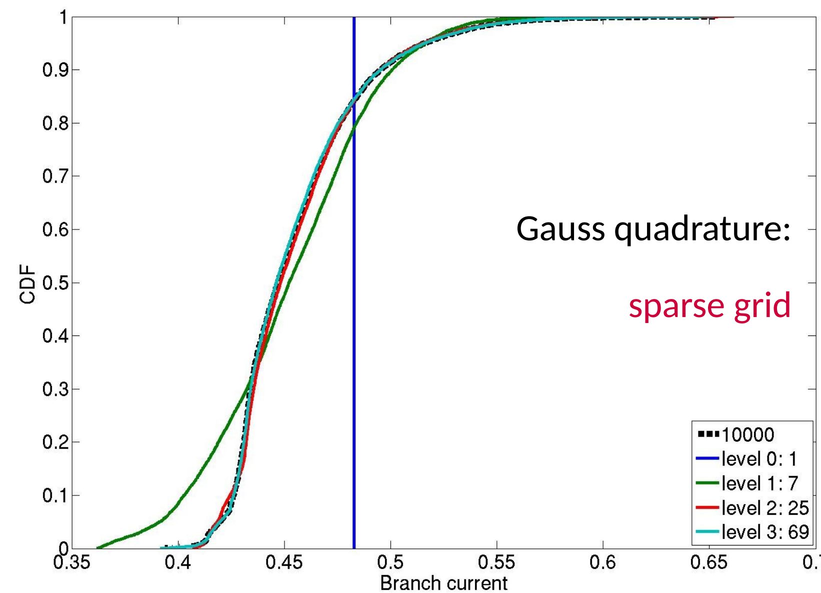


Cumulative Probability Distribution Function (CDF): Branch current 1









Conclusions

Uncertainty quantification in wind power prediction:

- Uncertainty in wind direction results in 40% reduction of wind farm power output
- Also uncertainty in individual turbines by wear-and-tear and production tolerances
- Increasingly uncertain power production affects electricity grid stability
- Uncertainty quantification is discretization of probability space

Wind power applications:

- Wind turbine robust optimization under uncertainty
- Robust design has peak probability at maximal power output
- Integration into electrical power grid
- Stochastic power flow for wind, solar, demand
- Reduction of computational costs from 10,000 MC samples to 25 SC samples

Questions?

Thank you