Integration of wind energy uncertainty in predictive grid management: can we make it simple?

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Objectives

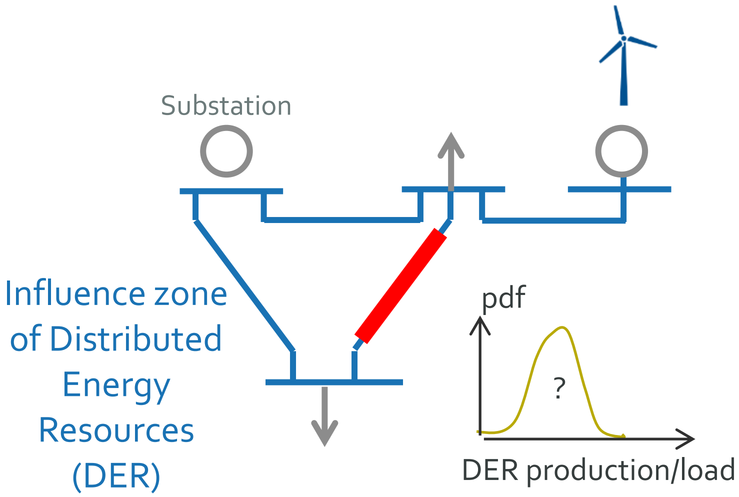
- **Create new use cases for RES uncertainty forecasting**:
  - “localized” predictive control for voltage and congestion management in electrical grids

- Design **human-in-the-loop approaches** capable of providing **fast advices and assistance to human operators** & **boost the integration of forecasting** technologies

- Propose a new **logical decision-aid method** with 3 building blocks
  - **Grid segmentation** based on likelihood of technical problems and available control actions
  - Combine **physical modelling** and **data-driven** methods for extracting “simple” information that relates flexibility and RES forecast uncertainty
  - **Multi-criteria decision-making** (risk vs cost) to identify short-term flexibility needs

Smart4RES use case

Challenge **How can a DSO optimize the predictive management of local flexibilities?**



DSO/TSO → **Flexibility Market** → **DER Operator**

1. Deterministic simulations of constraints induced by RES /load

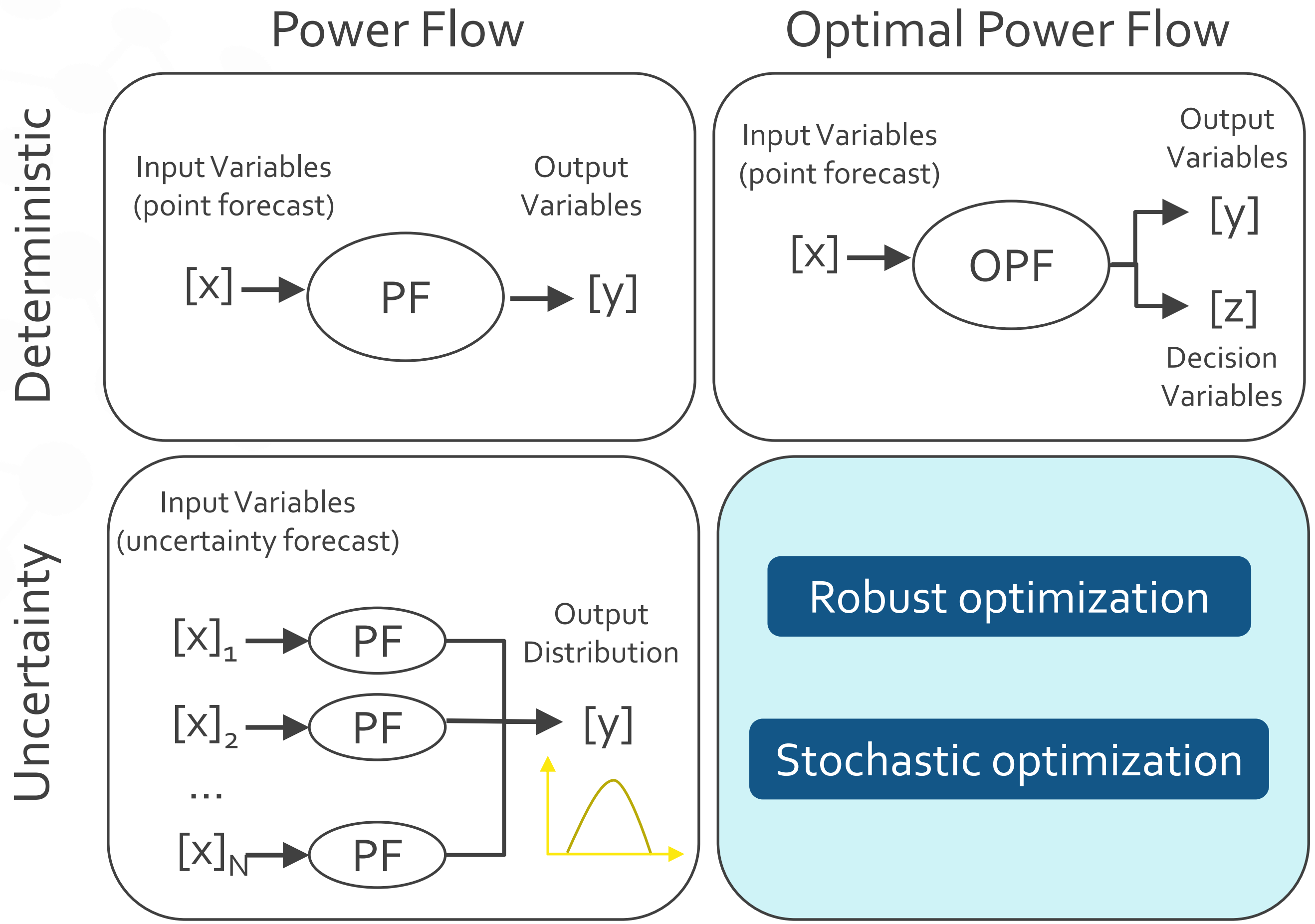
2. Booking of flexibilities

3. Activation of flexibilities from DER

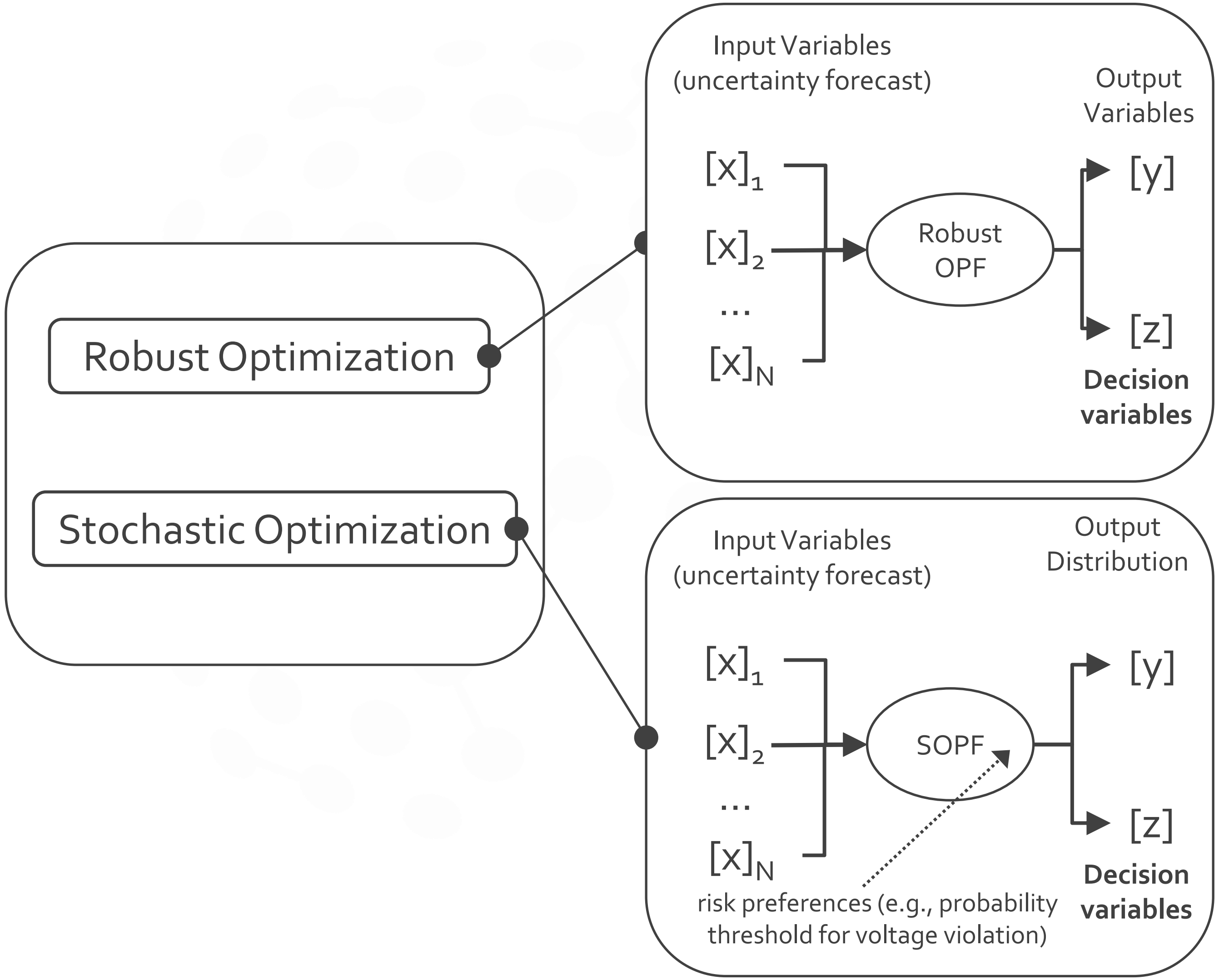
***Flexibility**: controllable loads, storage, RES with capacity to increase/ decrease its operating point + grid resources (network reconfiguration, OLTC)*

⇨ Today, DSO and TSO does not fully consider uncertainties from RES operation and their local impact on booking/activation of flexibilities from DER

State-of-the-art: Uncertainty-aware booking of flexibilities



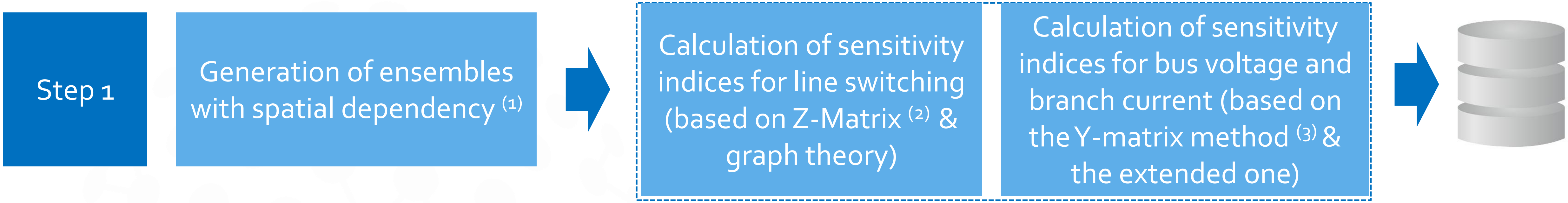
State-of-the-art: Uncertainty-aware booking of flexibilities



- [+] Deliver optimal solutions
- [+] Explicit modelling of objective functions and constraints
- [-] High computational time to get decisions
- [-] Perceived as a “black-box” approach

- ❑ Provide information about effect and cause → **interpretability**
- ❑ Multi-criteria information
- ❑ Iterative process (**no optimization**)

Predictive grid management: Knowledge construction



Step 1

Generation of ensembles with spatial dependency (1)

Calculation of sensitivity indices for line switching (based on Z-Matrix (2) & graph theory)

Calculation of sensitivity indices for bus voltage and branch current (based on the Y-matrix method (3) & the extended one)

Step 2

Gradient Boosting Trees to learn sensitivity coefficients as a function of grid operating conditions

$F\left(\delta_{i,k}|\boldsymbol{P}\right) = f(\boldsymbol{P})$, sensitivity coefficient relating voltage in bus *i* and active/reactive power in bus *k*; **P** is the vector of power injections

$F\left(\delta_{i-j,k}|\boldsymbol{P}\right) = f(\boldsymbol{P})$, sensitivity coefficient relating current in branch *i-j* and active/reactive power in bus *k*

Step 3

RES uncertainty forecasts (ensembles)

Spatial Gaussian copula(4) was used to generate **RES forecast ensembles** from quantile forecasts generated with gradient boosting trees

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(1) Papaefthymiou, G., Kurowicka, D. (2008). Using copulas for modeling stochastic dependence in power system uncertainty analysis. IEEE Transactions on Power Systems, 24(1), 40-49

(2) Makram, E. B., Thorton, K. P., Brown, H. E. (1989). Selection of lines to be switched to eliminate overloaded lines using a Z-matrix method. IEEE Transactions on Power Systems, 4(2), 653-661.

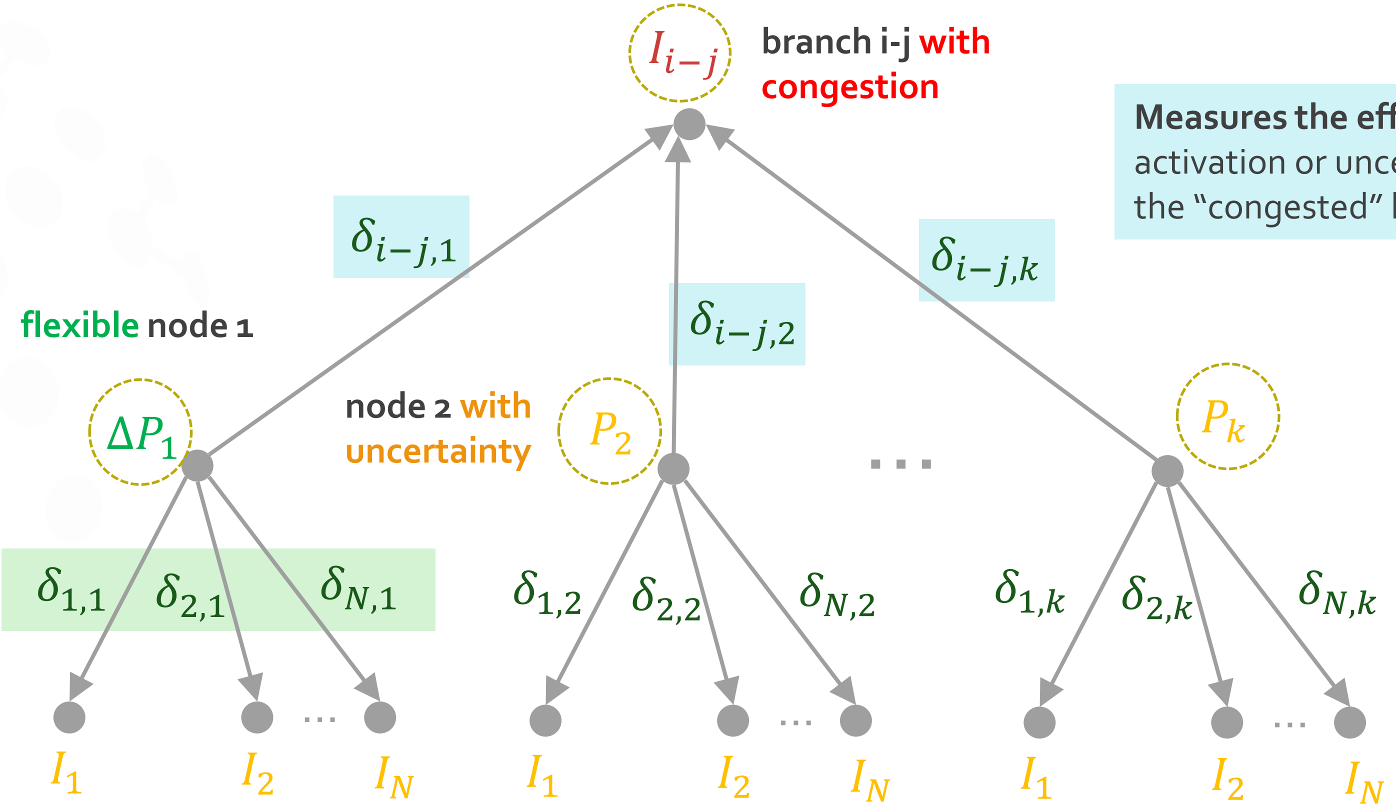
(3) Christakou, K., et al. (2013). Efficient computation of sensitivity coefficients of node voltages and line currents in unbalanced radial electrical distribution networks. IEEE Transactions on Smart Grid, 4(2), 741-750

(4) Papaefthymiou, G., Pinson, P. (2008). Modeling of spatial dependence in wind power forecast uncertainty. In Proceedings of the 10th International Conference on Probabilistic Methods Applied to Power Systems

Visual representation for interpretability

For each bus/branch w/problem

"Causality" graph



branch i-j with congestion

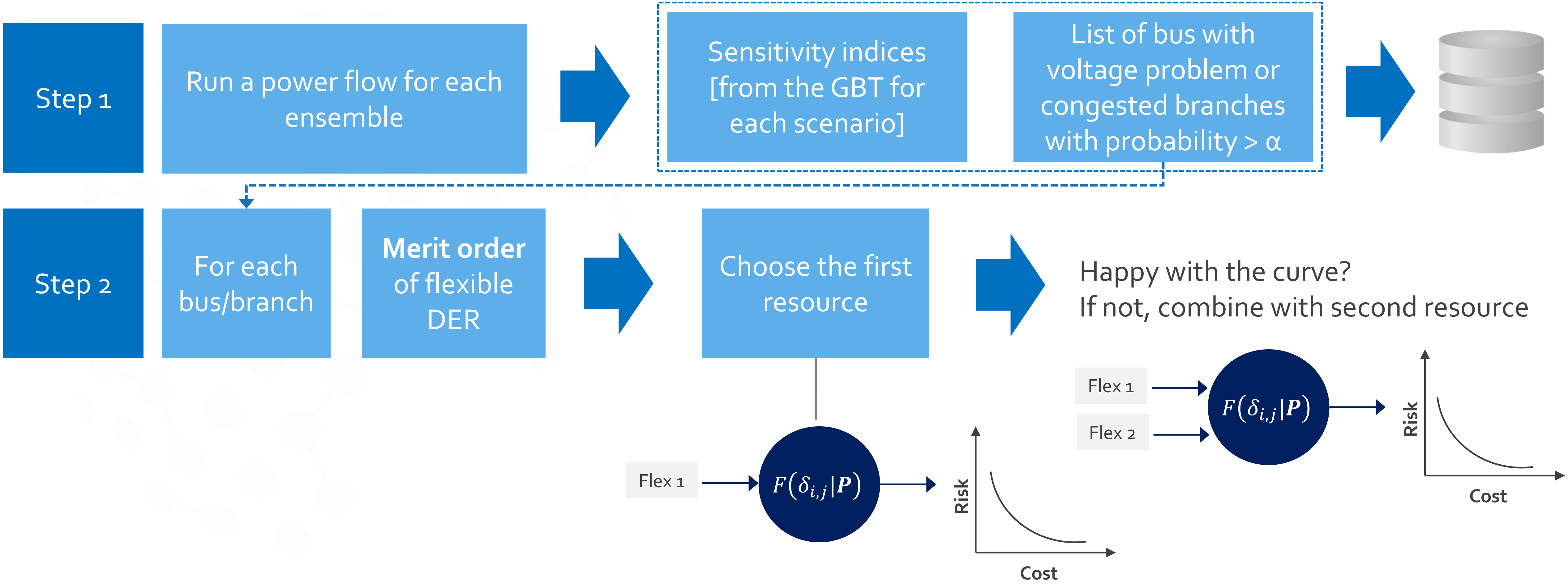
flexible node 1

node 2 with uncertainty

Measures the effect of flexibility activation or uncertainty band in the "congested" line current

Measures the effect of flexibility activation in other lines

Predictive grid management: Decision



Step 1

Run a power flow for each ensemble

Sensitivity indices [from the GBT for each scenario]

List of bus with voltage problem or congested branches with probability > α

Step 2

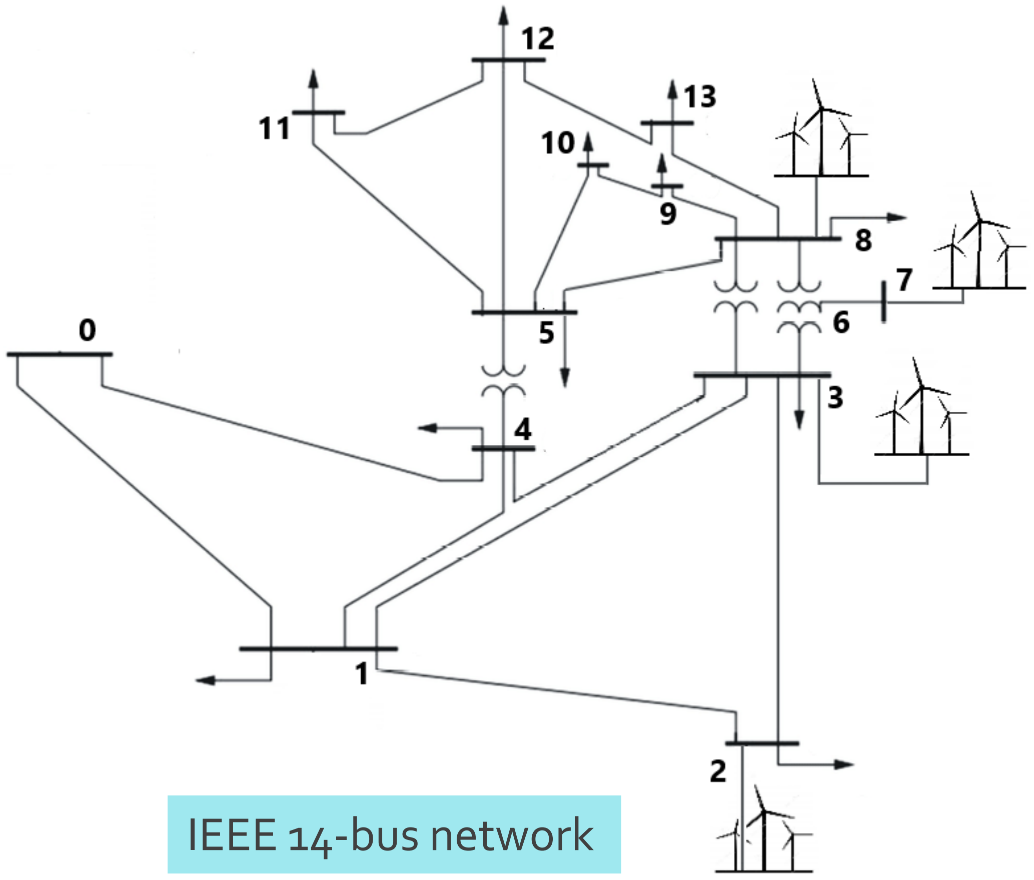
For each bus/branch

Merit order of flexible DER

Choose the first resource

Happy with the curve?
If not, combine with second resource

Case-study



IEEE 14-bus network

- Load time series
  - Measurements from Iowa Distribution Test Systems
  - http://wzy.ece.iastate.edu/Testsystem.html
- RES time series
  - GEFCom2014 competition – wind power data
  - https://doi.org/10.1016/j.ijforecast.2016.02.001
- Rated power of wind power plants and consumption values adjusted to create technical problems in 1-year of data
- Flexibility prices randomly sampled between 30 and 60 €/MWh
- Uncertainty forecasts (ensembles) for load and wind power

Numerical Results

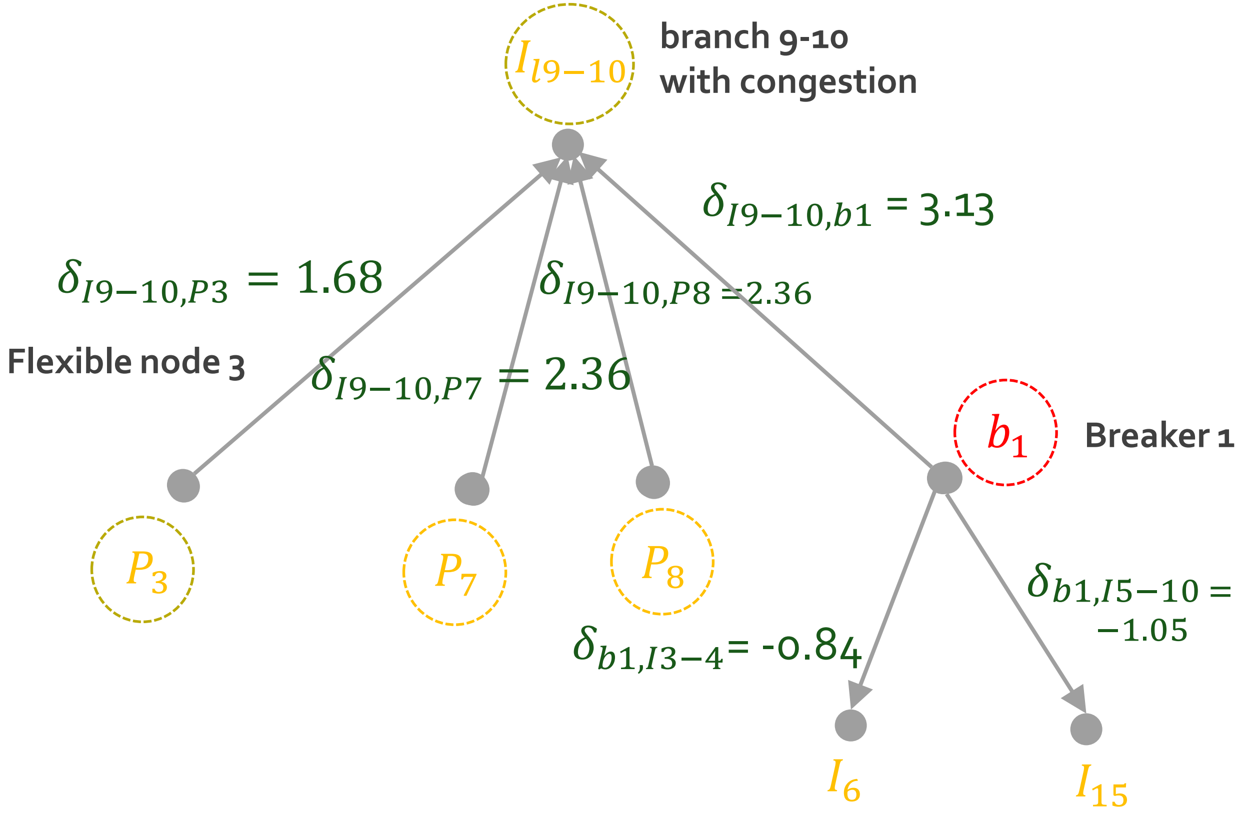
"Causality" tree

Day 9, hour 16

- $p_{overload-line}(line\ 9-10) = 63.9\%$
- Active and reactive power flexibility and network reconfiguration allowed

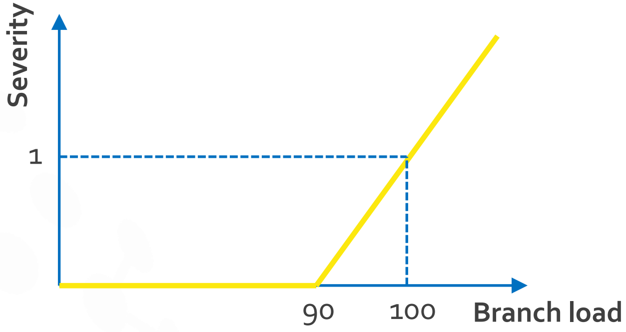
Selection of the most capable resources to solve the problem by sensitivity evaluation

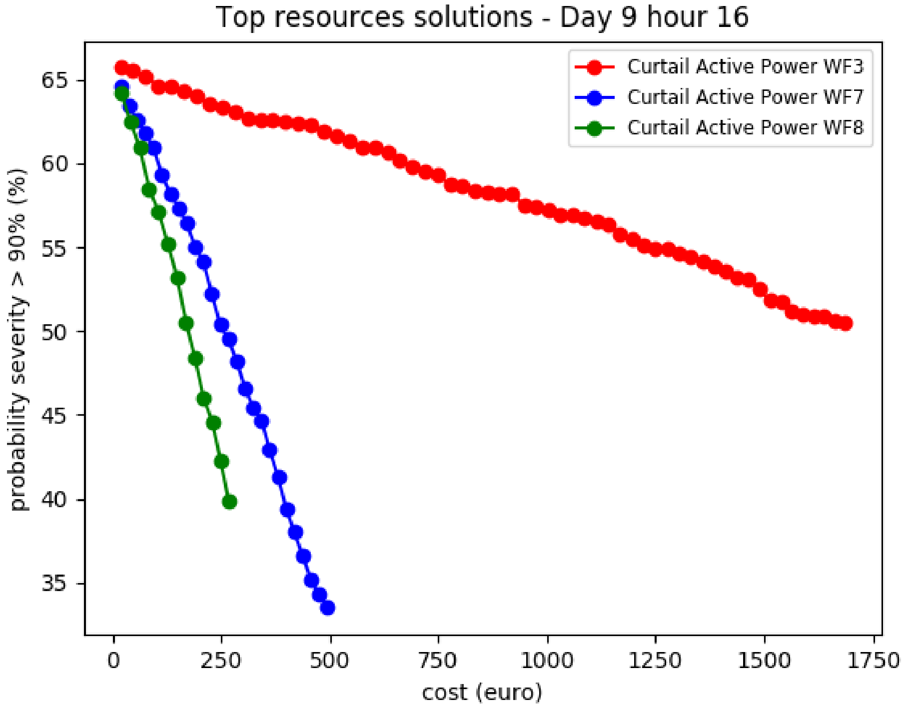
Risk of expected flexibility adjustment on voltage and line flow on the network



Numerical Results

Ranking of flexible DER





Day 9, hour 16

- $\boldsymbol{probability}_{\boldsymbol{overload-line}}(\boldsymbol{line\ 9-10}) = 63.9\%$
- **Metrics for ranking:** Expected cost; Expected severity; Value-at-risk for cost and severity: probability of severity higher than 90%.
- **Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)** score to find the top solutions **(Euclidian distance to the ideal solution)**

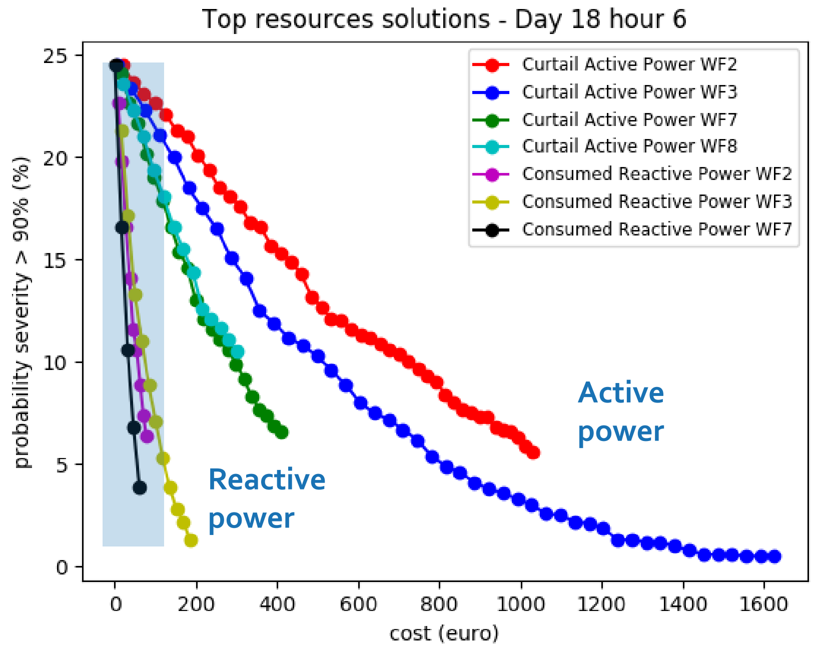
Flexibility/Action	E(cost[€])	VaR(cost_95%)	E(severity)	VaR(severity_95%)	p(severity) > 90%	TOPSIS score
curtail active power in wind farm 3	946.26	1357.84	0.88	2.21	45.6	0
curtail active power in wind farm 7	315.91	431.46	0.53	1.74	23.5	0.67
curtail active power in wind farm 8	231.47	313.47	0.65	1.88	30.1	0.71
breaker 1 - close	0	0	0.33	1.43	14.1	1.00

Numerical Results

Ranking of flexible DER

Day 18, hour 6

- $probability_{overvoltage-bus}(bus\ 8) = 24.1\%$



Flexibility/Action	E(cost[€])	VaR(cost_95%)	E(severity)	VaR(severity_95%)	p(severity) > 90%	TOPSIS score
curtail active power in wind farm 2	635.90	1077.07	0.34	0.81	2,00	0.51
curtail active power in wind farm 3	885.82	1536.8	0.04	0.27	0,00	0.51
curtail active power in wind farm 7	232.10	358.4	0.36	0.87	4,00	0.64
curtail active power in wind farm 8	174.02	243.72	0.43	0.98	9,00	0.48
consumed reactive power in wind farm 2	47.29	79.70	0.35	0.83	2.60	0.73
consumed reactive power in wind farm 3	101.33	156.49	0.17	0.58	0.10	0.88
consumed reactive power in wind farm 7	34.07	50.94	0.28	0.78	1.60	0.78

Numerical Results

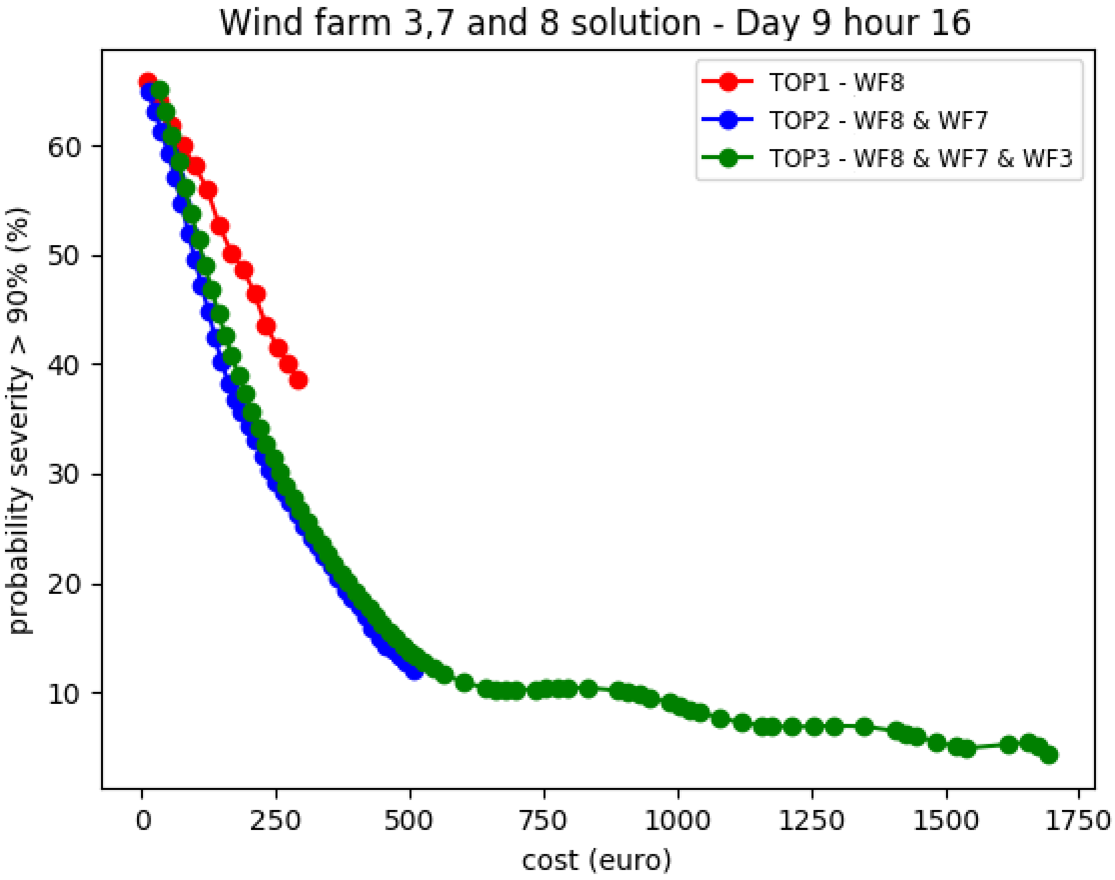
Decision-aid part

Day 9, hour 16

- $probability_{overload-line}(line\ 9-10)$ = 63.9%
- Line 9-10 flow ($deterministic\_forecast$) = 108.4%

Best solution for 5% probability

- **Suggested flexibility**
  - ΔP3 = curtail 19.5 MW
  - ΔP7 = curtail 30.0 MW
  - ΔP8 = curtail 6.5 MW
- **Total cost: 1417.88€**



Numerical Results

Decision-aid part

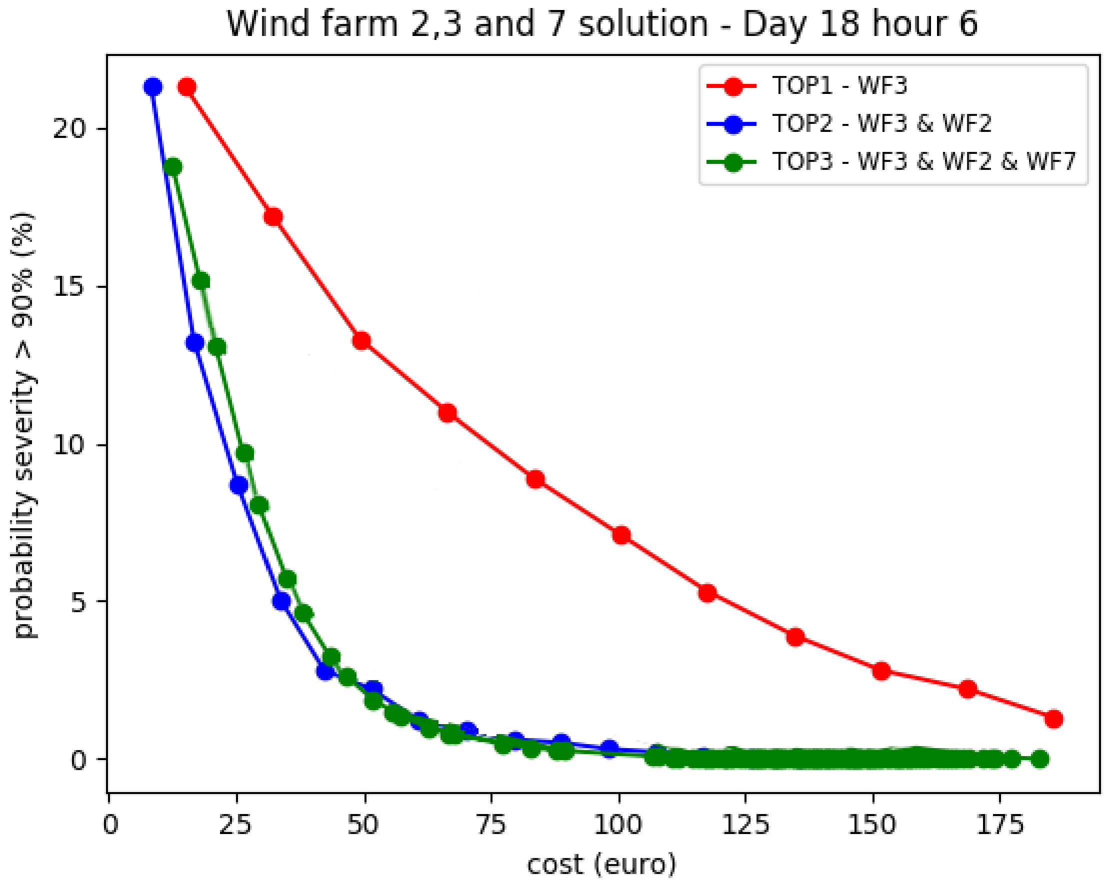
Day 18, hour 6

- $probability_{overvoltage-bus}(bus\ 8) = 24.1\%$
- Bus 8 voltage level ($deterministic\_forecast$) = 1.061 pu

Best solution for 5% probability

  - ΔQ3 = consume 1.5 Mvar
  - ΔQ7 = consume 2.0 Mvar

- **Total cost: 31.08€**

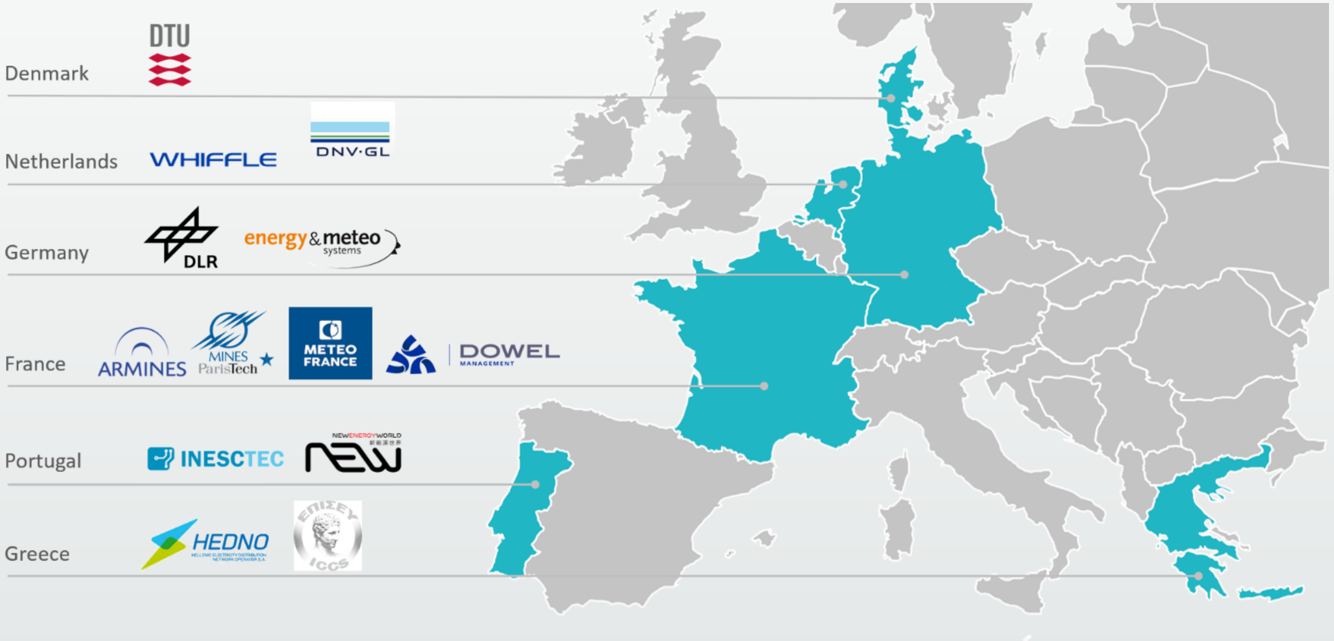


Conclusions and future work

- This method brings the following advantages
  - **High interpretability → contribute to increase adoption by human operators** of information from forecast uncertainty & advanced forecast products like ensembles
  - **High capacity** and **flexibility for parallelization**
  - Can be combined with existing rules for grid operation
- The **main limitation is the lack of an optimization engine**…yet under uncertainty optimality is a “fuzzy” concept
- **Future work**
  - Include information about cascading failure in the risk metrics
  - Combine with hierarchical forecasting methods from Smart4RES project
  - Design exploration strategies (e.g., reinforcement learning) that search for better solutions (e.g., with minimum cost) in comparison to historic decisions data

Smart4RES

THANK YOU !



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