Chance-Constrained AC Optimal Power Flow Integrating HVDC Lines and Controllability

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Outline

- Motivation
- Chance Constrained AC Optimal Power Flow
- Including HVDC Lines and Controllability
- Iterative Solution Algorithm
- Simulation Results
- Conclusion

Motivation

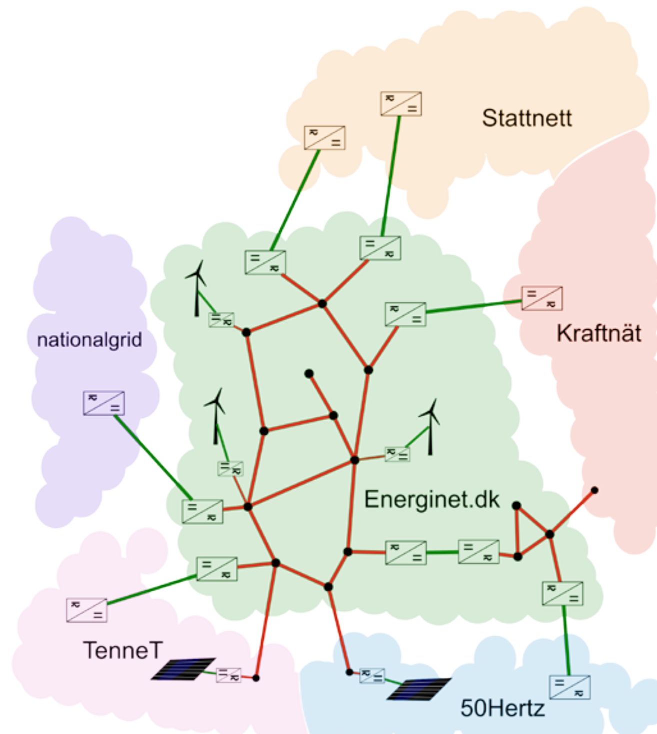
- High RES penetration increases uncertainty in power system operation
- North Sea Wind Shore Power Hub
- Goal of this work
  - chance constraints to address uncertainty
  - incorporate HVDC lines and controllability
  - maintain computational tractability

Source: northseawindpowerhub.eu

multiDC – www.multi-dc.eu

Innovative Methods for Optimal Operation of Multiple HVDC Connections and Grids

- Innovation Fund Denmark Grand Solutions
- Partners:
  - **Two neighboring TSOs**: Energinet, Svenska kraftnät
  - **Three universities**: DTU, KTH, Univ. of Liege
  - **One major manufacturer**: ABB
  - Advisory Board: RTE, Nordic RSCI
- **4.2 million USD**
- **4 years**; Start May 1, 2017



The three pillars of multiDC

- Robust control of near-zero inertia systems
- Coordinated control of AC/DC systems
- Market integration of meshed HVDC connections

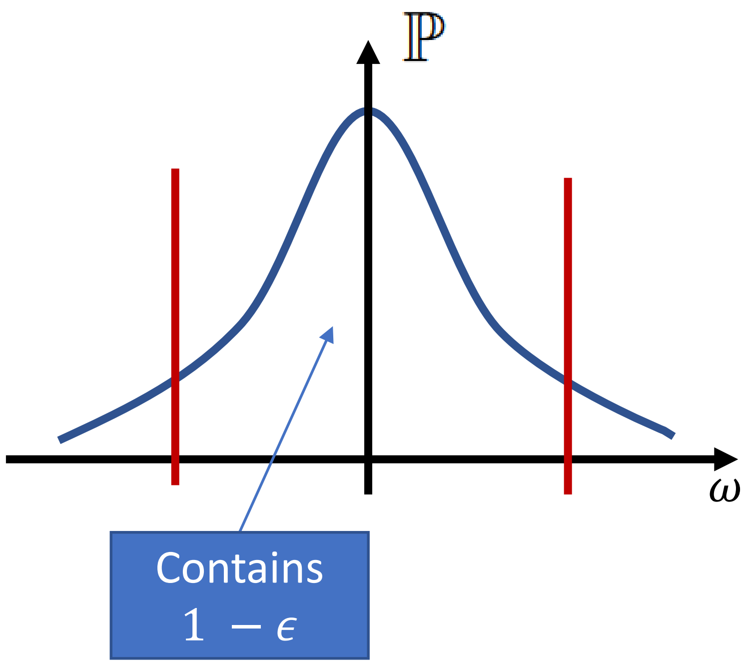
Implementation at PowerlabDK

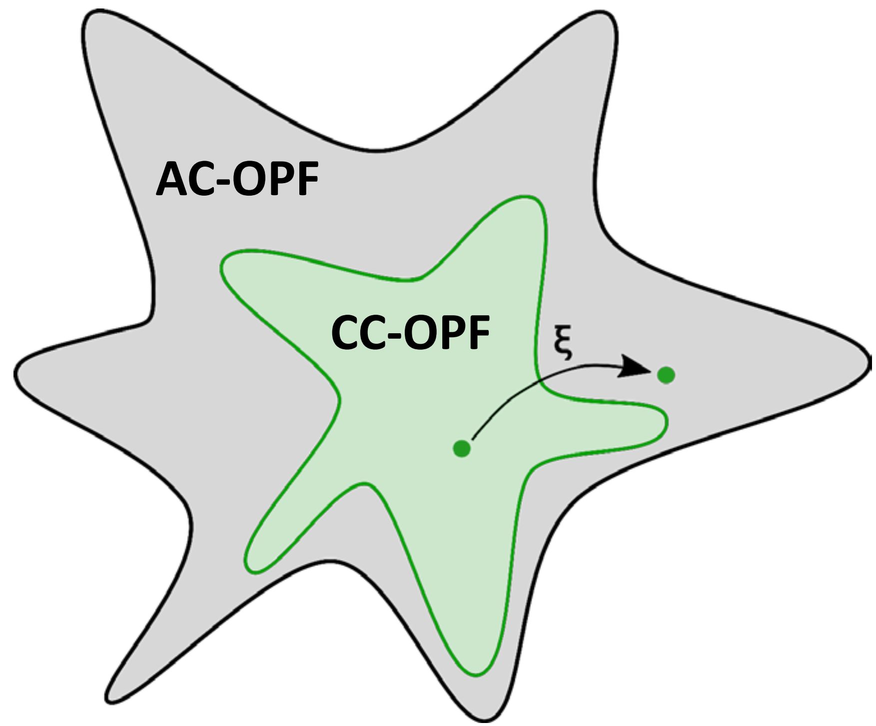
PowerLabDK

multiDC

Chance Constrained AC-OPF

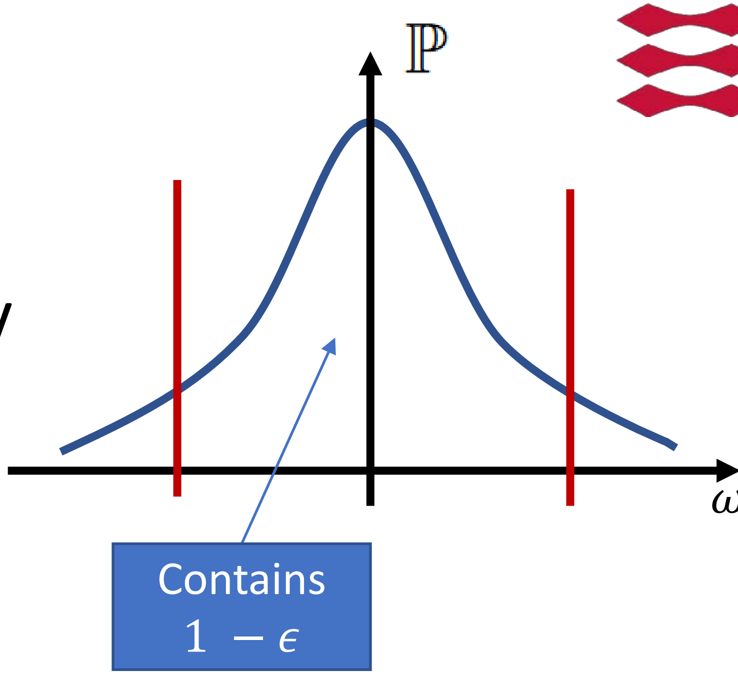
- Chance constraints: define maximum allowable constraint violation probability for forecast errors ω





Chance Constrained AC-OPF

- Chance constraints: define maximum allowable constraint violation probability for forecast errors ω

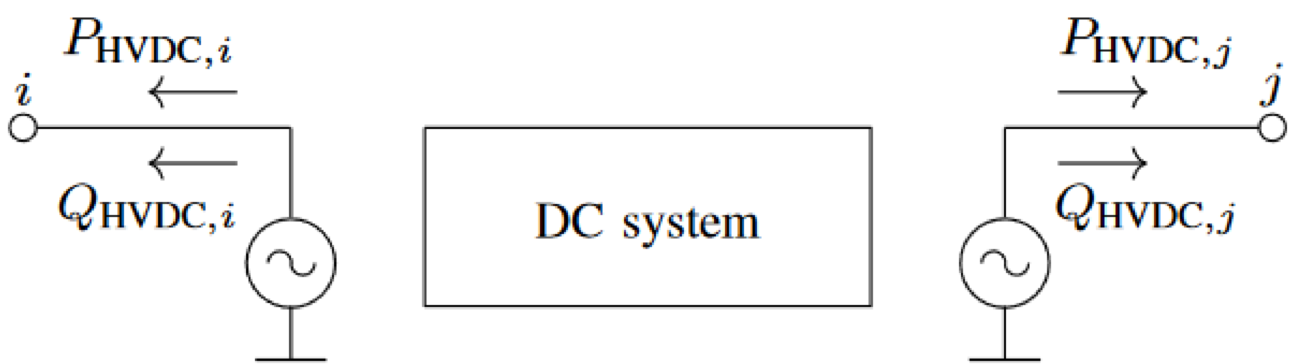


- AC-OPF with chance constraints for state variables **x** = {P, Q, V, θ}

$$
\begin{aligned}
\min_{\mathbf{x}} \quad & \mathbf{c_2^T P_G^2} + \mathbf{c_1^T P_G} + \mathbf{c_0} & \\
\text{s.t.} \quad & f_i(\mathbf{x}) = 0 & \text{for } i = 1, \ldots, \text{n} \\
& \mathbb{P}(g_i(\tilde{\mathbf{x}}(\omega)) \leq 0) \geq 1 - \epsilon, & \text{for } i = 1, \ldots, \text{m}.
\end{aligned}
$$

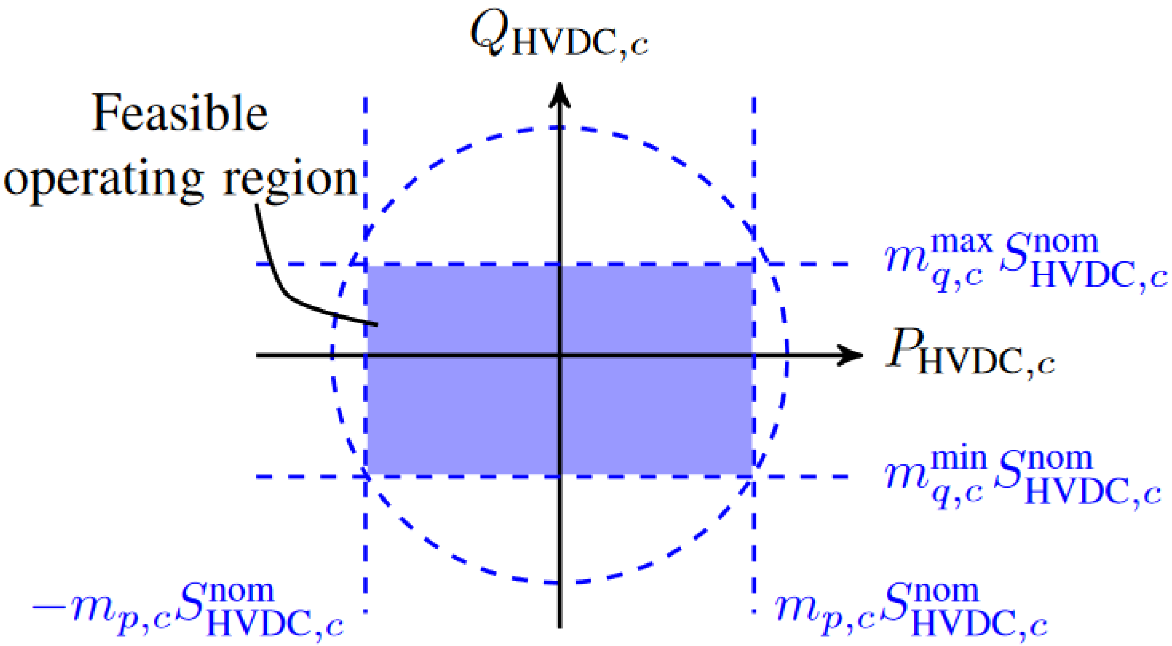
Including HVDC Lines and Controllability

- HVDC model includes
  - active and reactive power capability
  - constant loss term



Including HVDC Lines and Controllability

- HVDC corrective control of active power set-point to react to forecast errors with HVDC participation factors β



Iterative Solution Algorithm – 1

- Chance constrained AC-OPF includes for both AC and DC systems
  - Equality constraints
  - Inequality constraints with uncertainty margins
- Uncertainty margins λ depend on
  - Optimized system state x
  - Generator and HVDC participation factors α, β
  - Distribution of forecast errors ω

$$
\begin{aligned}
\min_{\mathbf{x}} \quad & \mathbf{c_2^T P_G^2} + \mathbf{c_1^T P_G} + \mathbf{c_0} \\
\text{s.t.} \quad & \mathbf{f^{ac}}(\mathbf{x}) = 0 \\
& \mathbf{f^{dc}}(\mathbf{P_{\text{HVDC}}}) = 0 \\
& \mathbf{x} \leq \mathbf{x}^{\max} - \lambda^{\mathbf{x}}(\alpha, \beta) \\
& \mathbf{x} \geq \mathbf{x}^{\min} + \lambda^{\mathbf{x}}(\alpha, \beta)
\end{aligned}
$$

Iterative Solution Algorithm – 1

- The resulting optimization problem is highly non-convex
  → To achieve tractability, we make some assumptions!

(1) To model the effect of forecast errors on the operating system state x_0, we use the **first order Taylor expansion** $\boldsymbol{\Gamma}$

$$x(\omega) = x_0 + \omega \Gamma_{\mathrm{x}_0}$$

(2) We assume control policies are **affine** in the uncertainty ω for both generator and HVDC active power

(3) We assume forecast errors ω follow a **Gaussian** distribution

→ Due to (1) – (3), **analytical reformulation** of chance constraints possible

Iterative Solution Algorithm – 3

- We extend an existing computationally efficient **iterative** solution algorithm (Schmidli et al., PES GM 2016, Roald et al., TPRWS, 2018):

  Step 0: Initialize $\lambda^1 := 0, k = 0.$

  Step 1: Set k = k + 1: Solve CC-AC-OPF for λ^k.

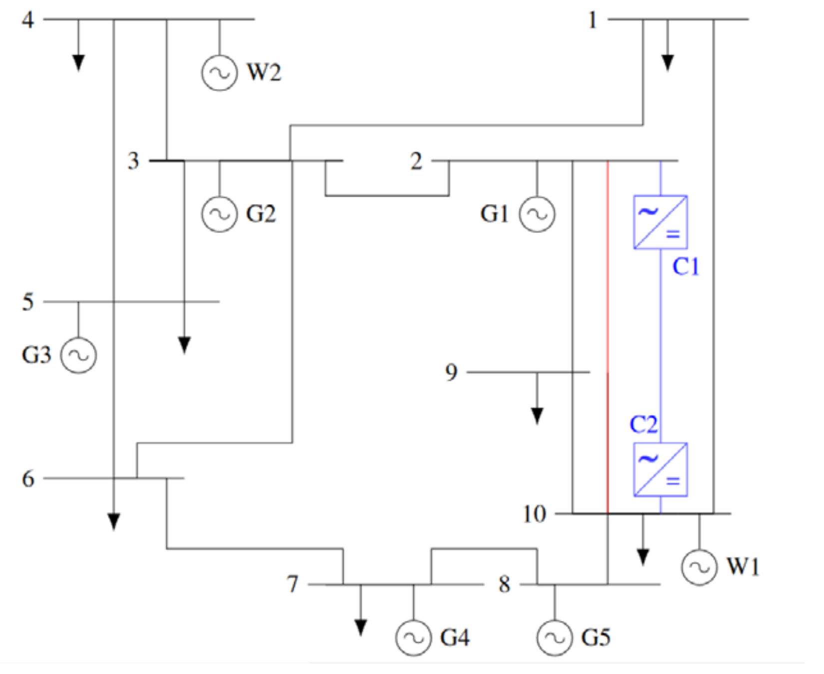
  Step 2: Based on α^k, β^k, x^k, compute Γ_{x^k} . Then include λ^{k+1} as function of α, β in CC-AC-OPF.

  Step 3: If $\left|\lambda^{k+1} - \lambda^k\right|_\infty \leq \rho$, terminate. Otherwise, go to Step 1.

- Optimizing over generator, HVDC participation factors α, β under assumptions (1)–(3) with iterative solution algorithm lead to **tractable** second-order cone chance constraints

Simulation Setup

- 10 bus system
  - with 2 wind farms
  - realistic wind forecast data
  - Line from 2 to bus 10 is congested
  - $\epsilon = 5\%$
- Case A: no HVDC line
- Case B: congested line is replaced with HVDC line

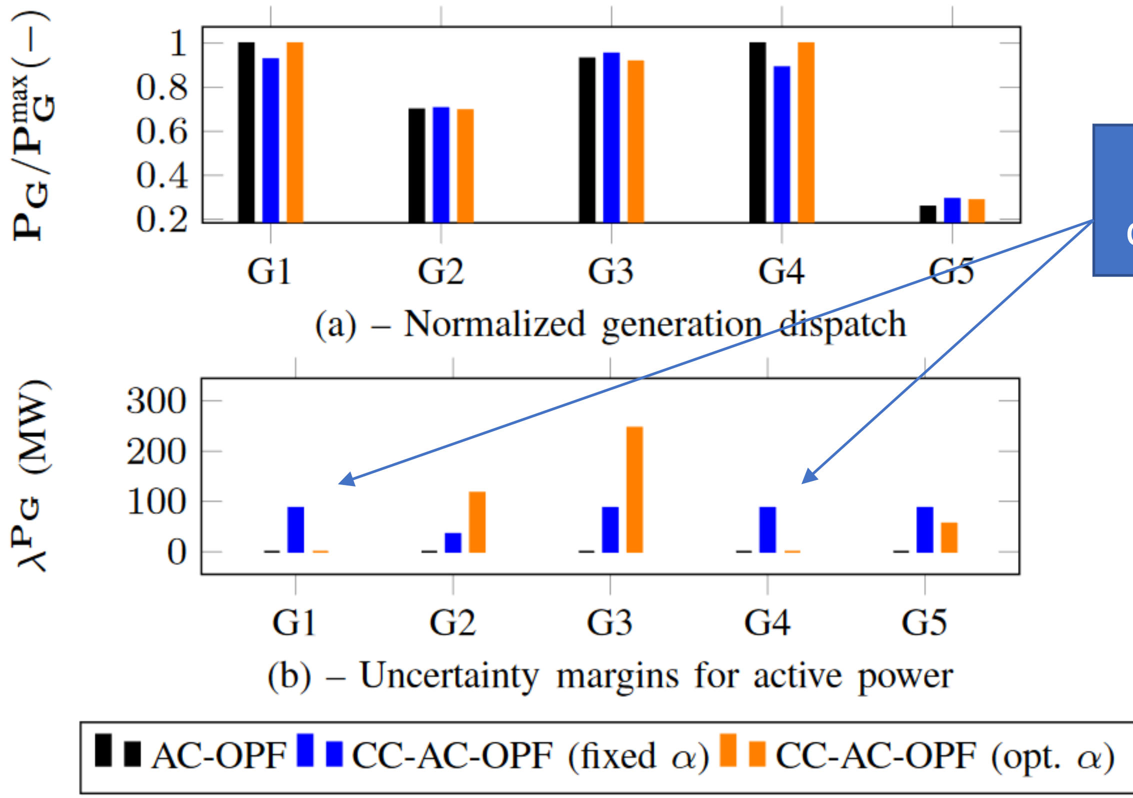


→ Comparison of AC-OPF without considering uncertainty, CC-AC-OPF with fixed and optimized α, β

no HVDC: optimizing generator participation factors reduces cost of uncertainty

Generation dispatch (Pg/Pmax)

Tightening generation limits



G1 and G4 are cheap generators

- Optimizing α does not tighten cheap generators limits
- Cost of uncertainty reduced from **2.03%** to **0.79%**

HVDC eliminates cost of uncertainty

TABLE II
EMPIRICAL CONSTRAINT VIOLATION PROBABILITY FOR 10 BUS TEST CASE WITH HVDC LINE

Constraint limits on	P	Q	V	P_{line}	P_{HVDC}
In-sample analysis with 10'000 samples (%)					
AC-OPF (w/o uncertainty)	50.5	0.0	45.3	12.4	0.0
CC-AC-OPF (fixed α and β)	5.1	0.0	3.8	3.8	0.0
CC-AC-OPF (opt. α and β)	0.9	0.0	3.9	3.5	0.0
Out-of-sample analysis with 10'000 samples (%)					
AC-OPF (w/o uncertainty)	43.2	0.0	47.8	11.5	0.0
CC-AC-OPF (fixed α and β)	5.8	0.0	3.4	3.9	0.0
CC-AC-OPF (opt. α and β)	0.4	0.0	3.2	3.8	0.0

Not considering uncertainty can lead to large violations!

- By optimizing the generator and HVDC participation factors α, β cost of uncertainty is reduced from **2.2%** to **0.0%**
- CC-AC-OPF (opt. α and β) complies with the violation probability of 5% in- and out-of-sample

Conclusion

- We extended an iterative chance-constrained AC-OPF to include
  a) HVDC lines and HVDC corrective control policies
  b) optimization of both generator and HVDC participation factors
- Simulation results using realistic forecast data show
  a) the cost reduction by utilizing HVDC and generator controllability
  b) compliance in- and out-of-sample with target constraint violation probability
- Future work includes data-driven approaches

Questions?

MULTI-DC - controlling the power flows

http://www.multi-dc.eu/

www.chatziva.com

For further reference:

Venzke, A., & Chatzivasileiadis, S. (2018). Convex Relaxations of Probabilistic AC Optimal Power Flow for Interconnected AC and HVDC Grids. *arXiv preprint arXiv:1804.00035*. https://arxiv.org/pdf/1804.00035.pdf

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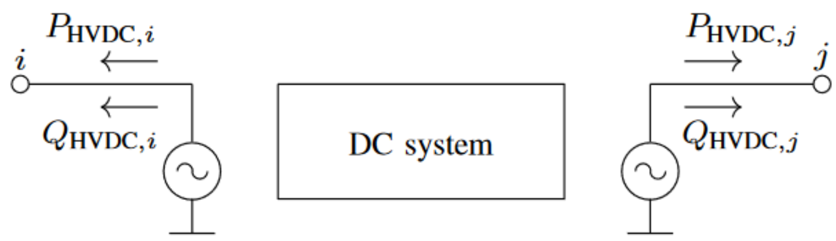
Simulation Results – Case A

TABLE I
EMPIRICAL CONSTRAINT VIOLATION PROBABILITY FOR 10 BUS TEST CASE WITHOUT HVDC LINE

Constraint limits on	P	Q	V	P_{line}
In-sample analysis with 10'000 samples (%)				
AC-OPF (w/o uncertainty)	49.0	0.0	6.7	49.7
CC-AC-OPF (fixed α)	5.3	0.0	2.8	5.3
CC-AC-OPF (opt. α)	4.9	0.0	2.9	4.9
Out-of-sample analysis with 10'000 samples (%)				
AC-OPF (w/o uncertainty)	43.2	0.0	4.6	49.2
CC-AC-OPF (fixed α)	5.8	0.0	3.4	6.1
CC-AC-OPF (opt. α)	5.8	0.0	3.4	5.6

Including HVDC Lines and Controllability

- HVDC model includes
  - active and reactive power capability
  - constant loss term



- HVDC corrective control of active power set-point to react to forecast errors with HVDC participation factors β