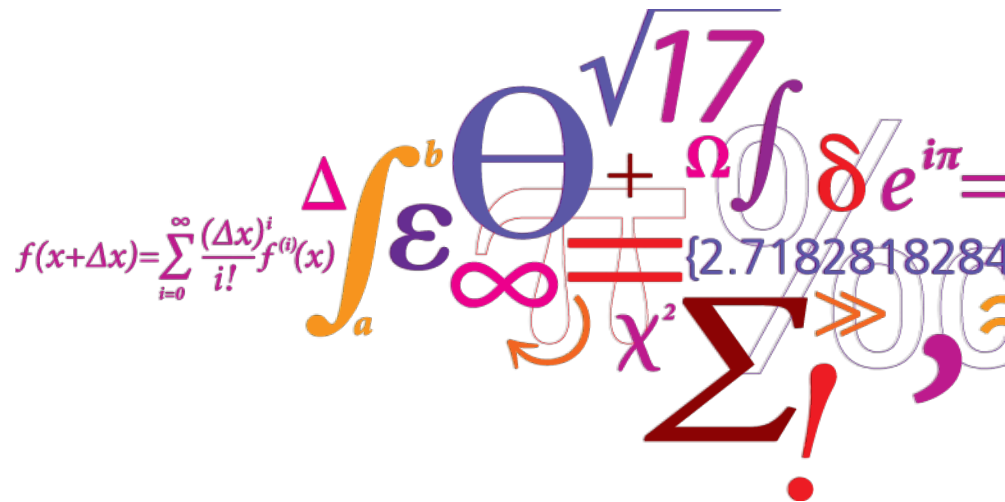


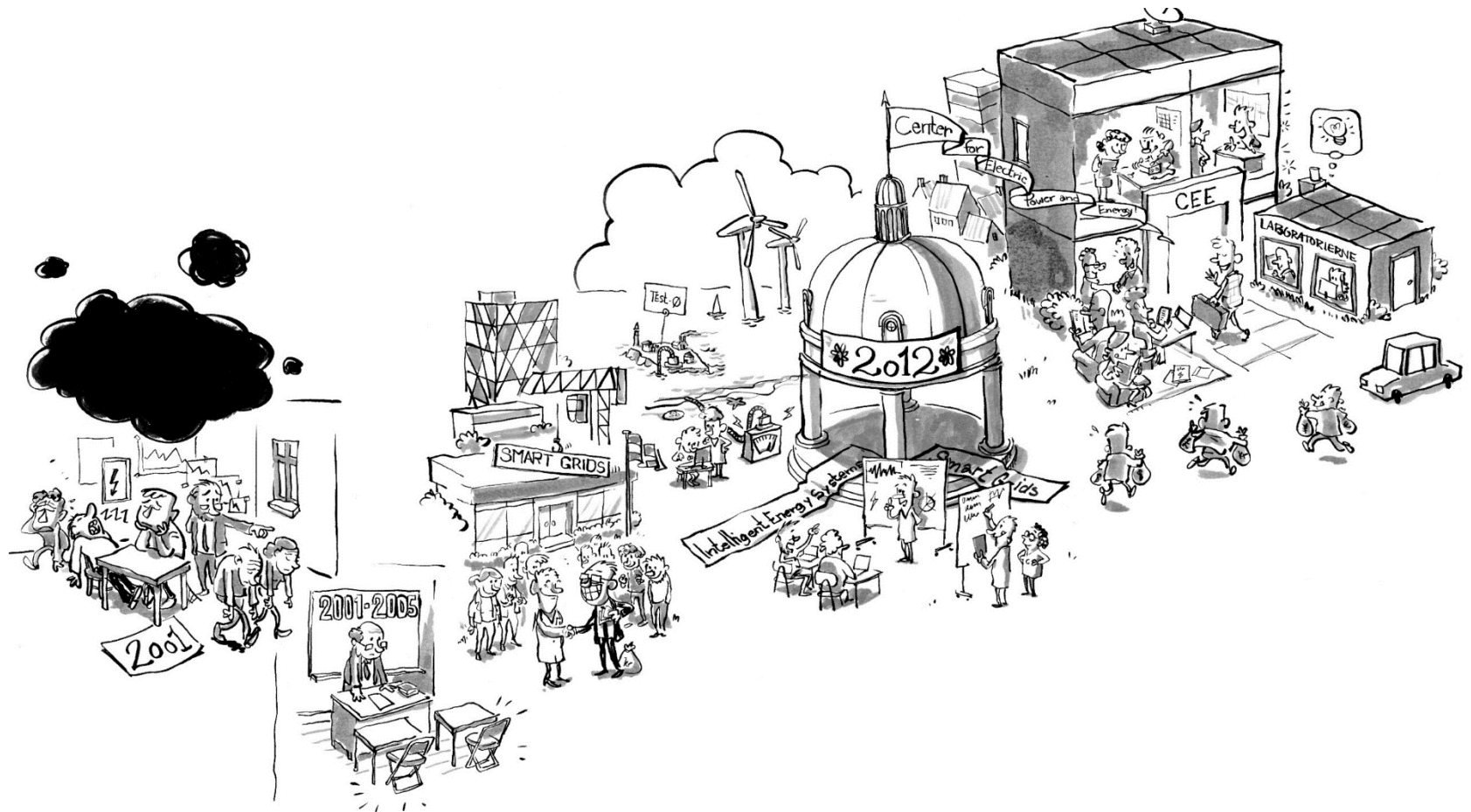
Data-driven Security Constrained OPF

Spyros Chatzivasileiadis

Associate Professor, DTU

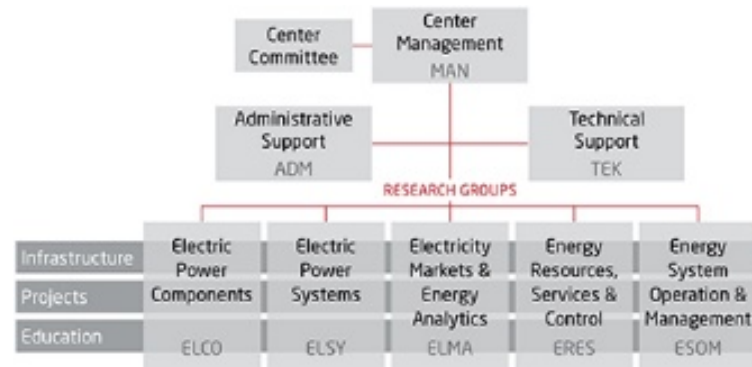


DTU Center for Electric Power and Energy (CEE)



Center for Electric Power and Energy (CEE)

- **Established 15 August 2012** by merging two existing units (Lynbgy + Risø)
 - Among the strongest university centers in Europe with approx. 100 employees



- **Bachelor and Master programs:** Sustainable Energy Design, Electrical Engineering, Wind Energy, Sustainable Energy
- **Direct support from:** Energinet, Siemens, Ørsted (DONG Energy), Danfoss

DTU consistently ranks among the top 10 universities of the world in Energy Science and Engineering (Shanghai ranking, 2016, 2017, 2018)

Research themes in line with today's needs

Digital Energy Solutions



- New business models
- Data-driven solutions
- Digital solutions in grids
- System operation tools

Interconnected Energy System



- Multi energy carriers
- Smart energy in cities
- Markets and flexibility
- HVAC/HVDC grids

Optimised Electric Energy Technologies



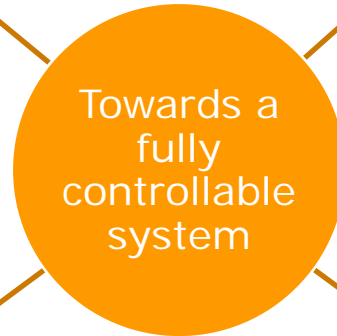
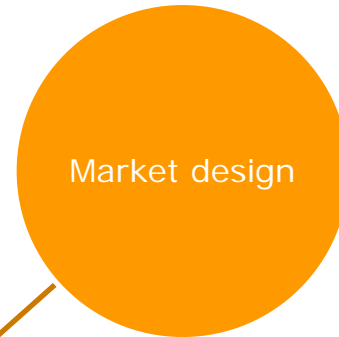
- Novel equipment concepts
- Electric vehicle integration
- Prosumer solutions
- Cost-effective wind power



multiDC
Robust Control
for Near-Zero
Inertia Systems



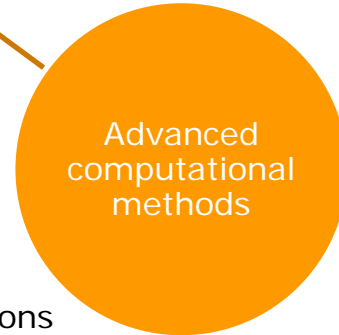
multiDC
Market
Integration of
HVDC



Data-driven and HVDC
Control Methods to
Enhance Power
System Security



Convex
relaxations and
recovery of the
global optimum



Convex
approximations
for chance-
constrained OPF

multiDC
Data-driven security
and optimization of
AC and HVDC Grids

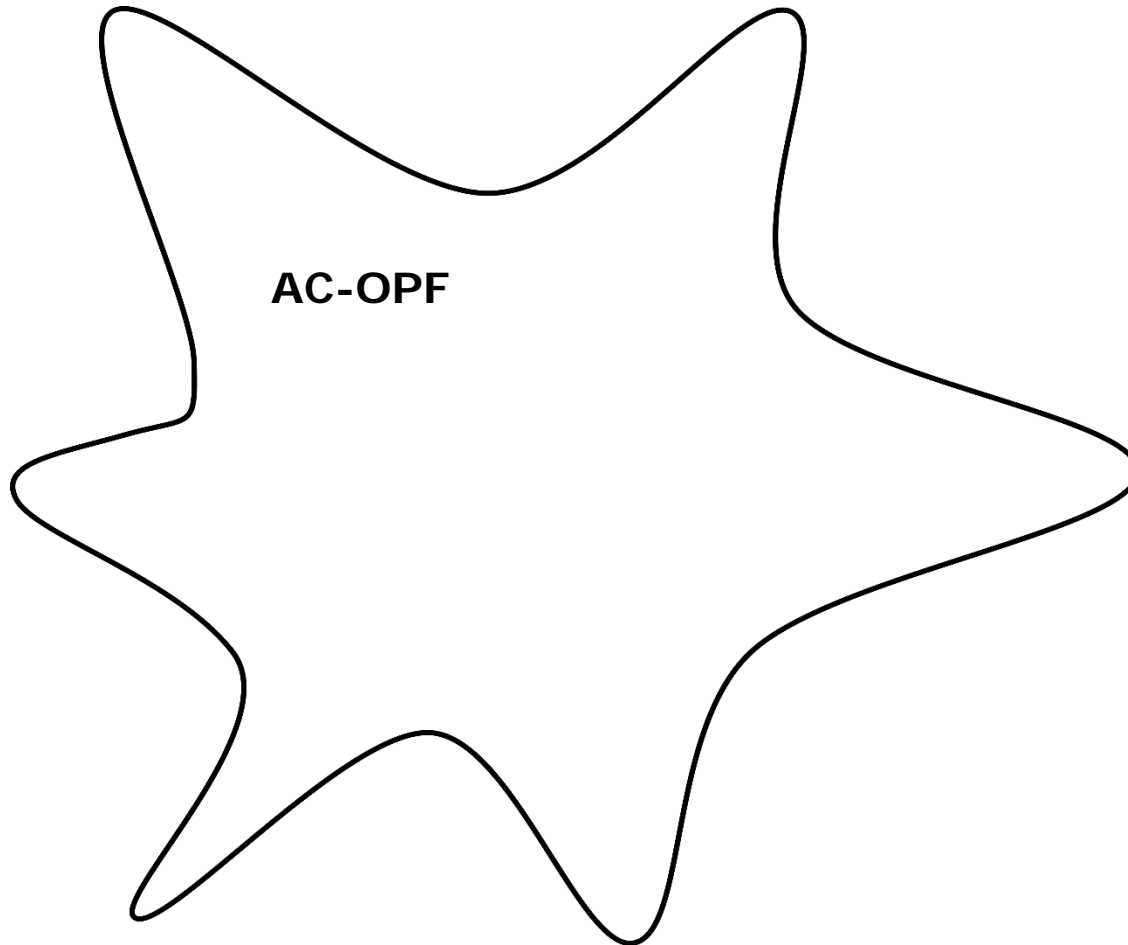


Data-Driven Security Constrained OPF

work with:

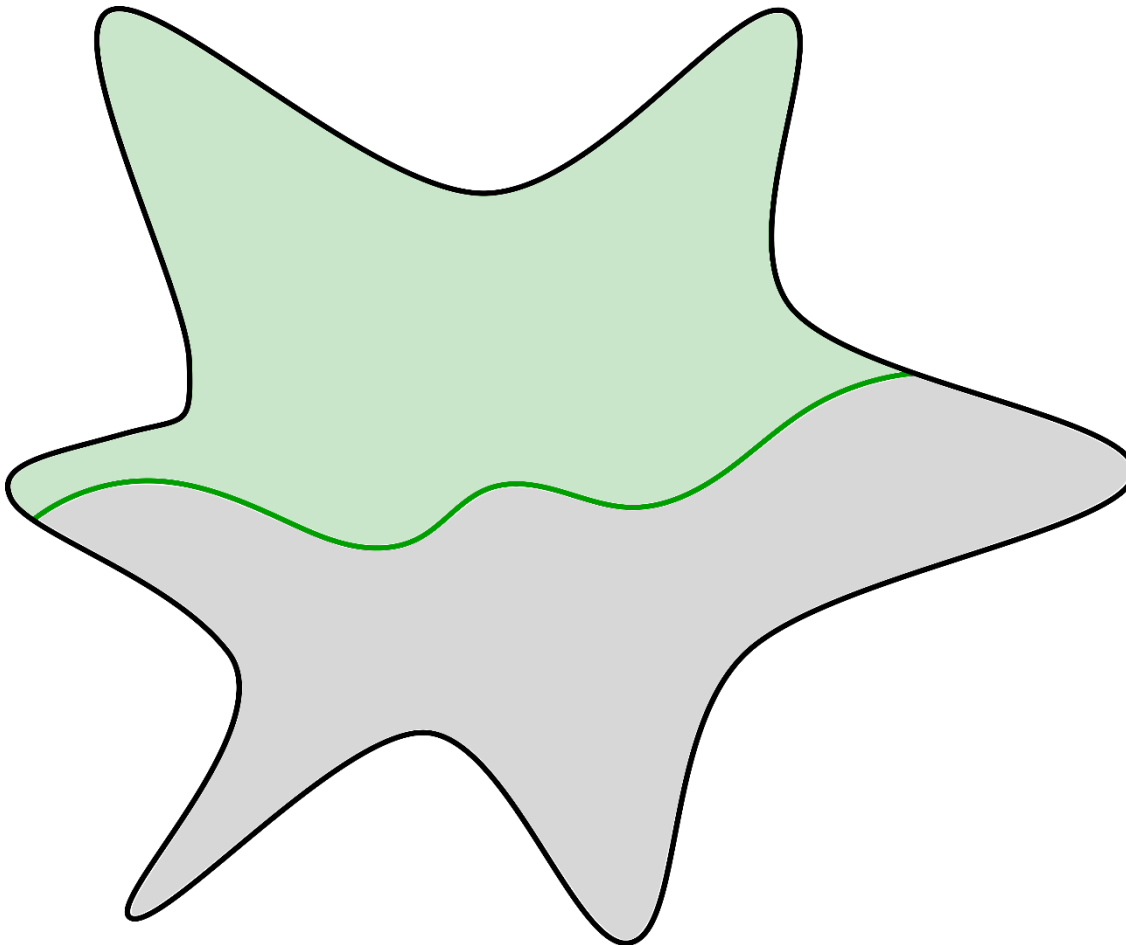
Lejla Halilbasic, Florian Thams, Andreas Venzke

The feasible space of power system operations



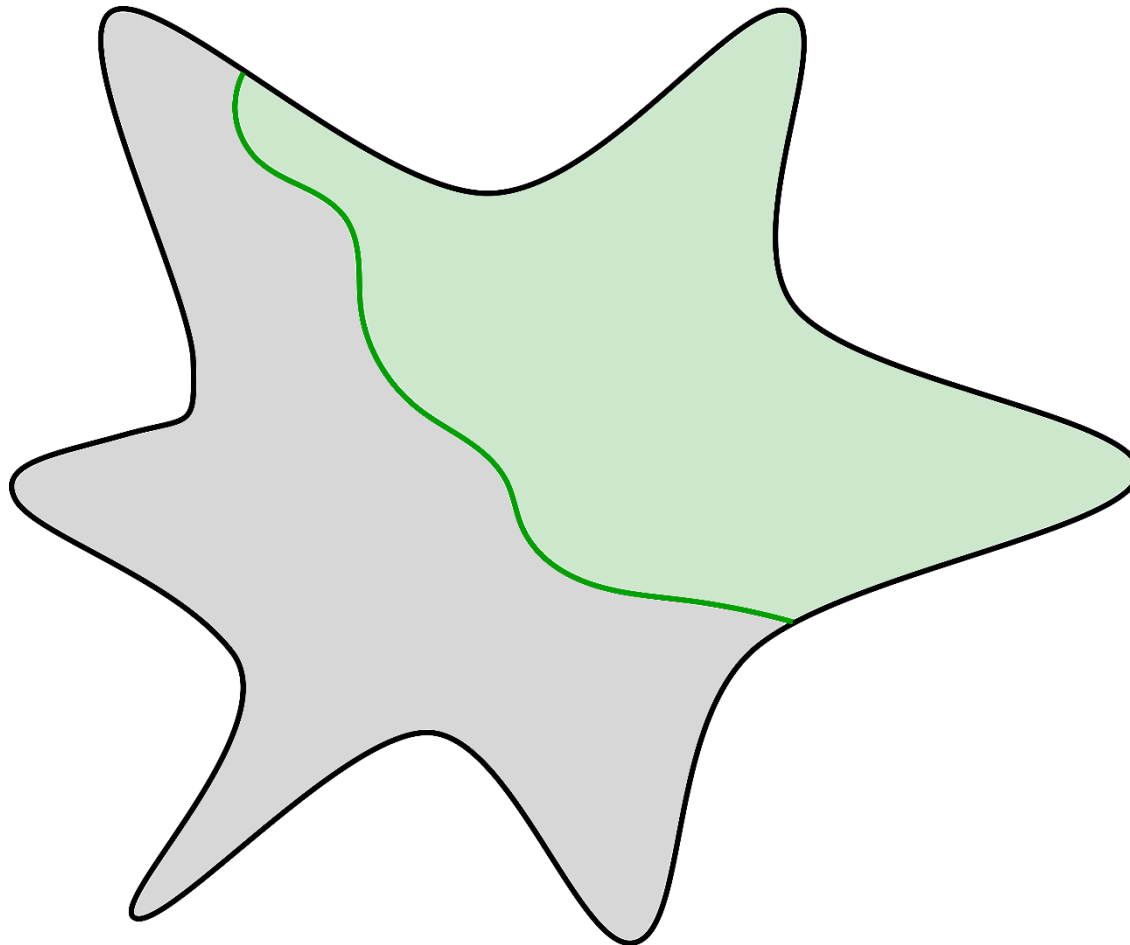
- Nonlinear and nonconvex AC power flow equations
- Component limits

The feasible space of power system operations



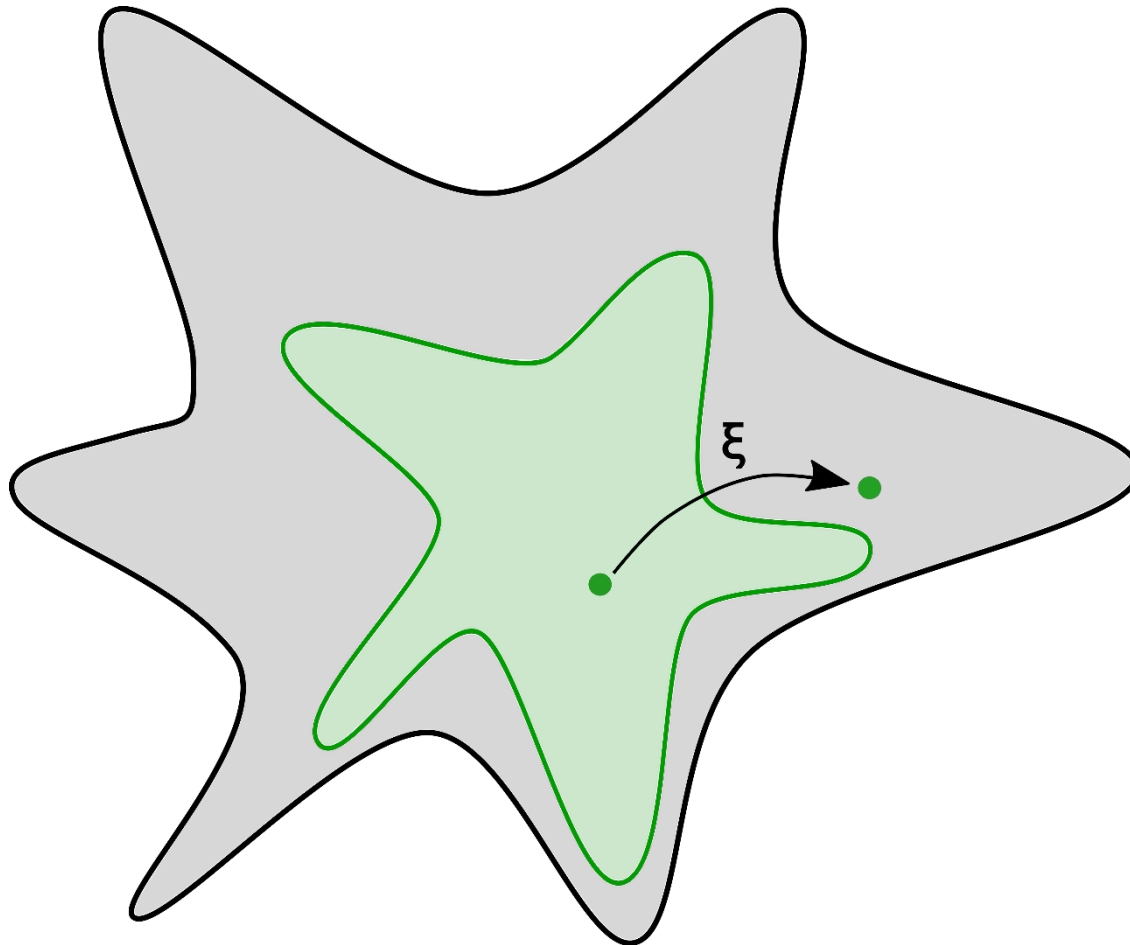
- Nonlinear and nonconvex AC power flow equations
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- + Stability limits

The feasible space of power system operations



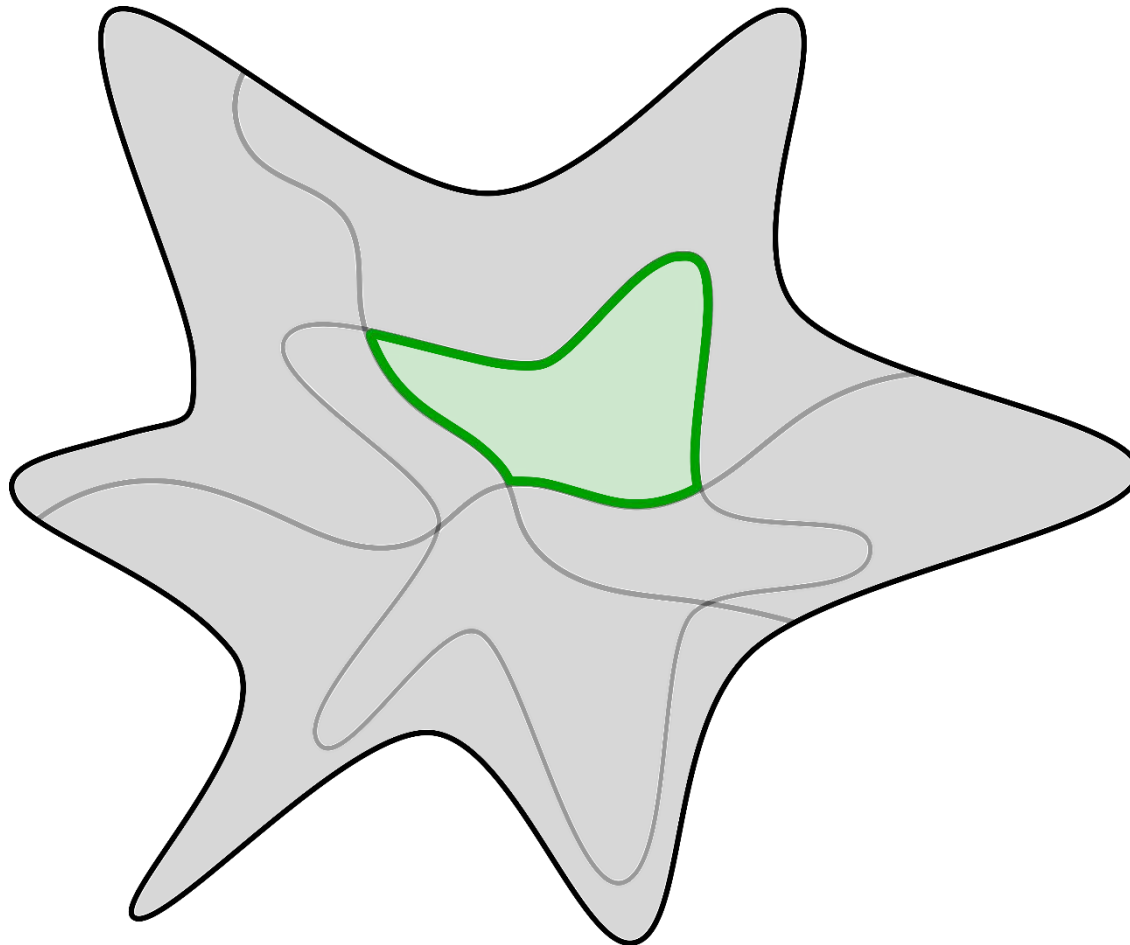
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- + Stability limits
- + Other security criteria (e.g., N-1)

The feasible space of power system operations



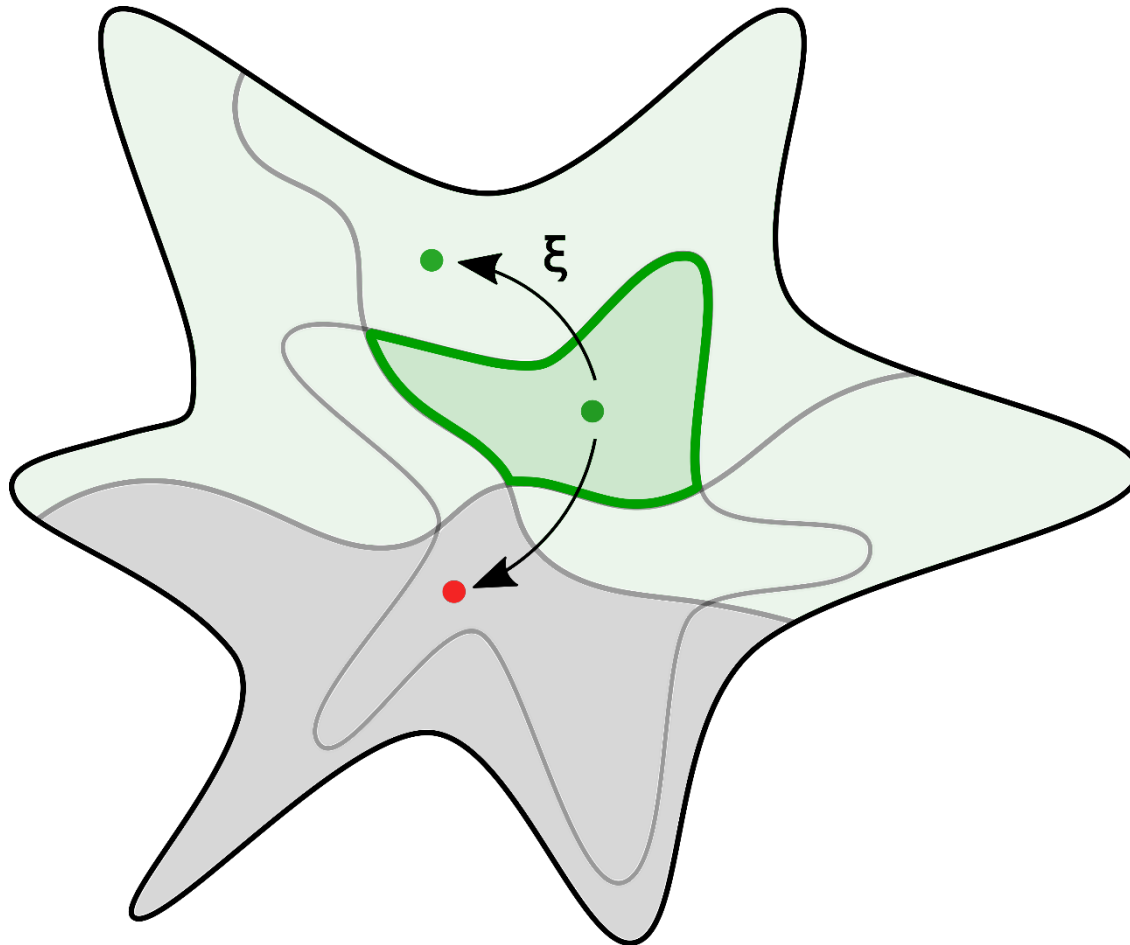
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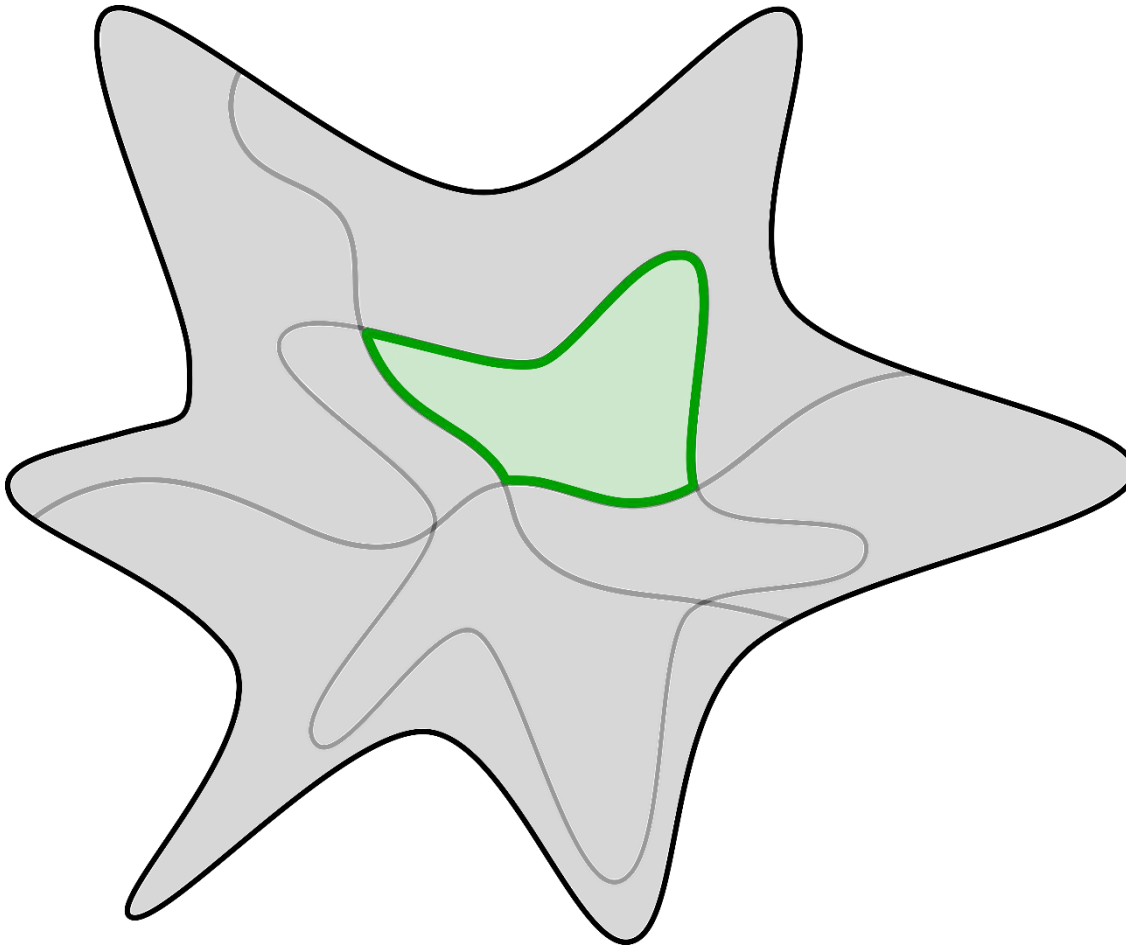
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The feasible space of power system operations



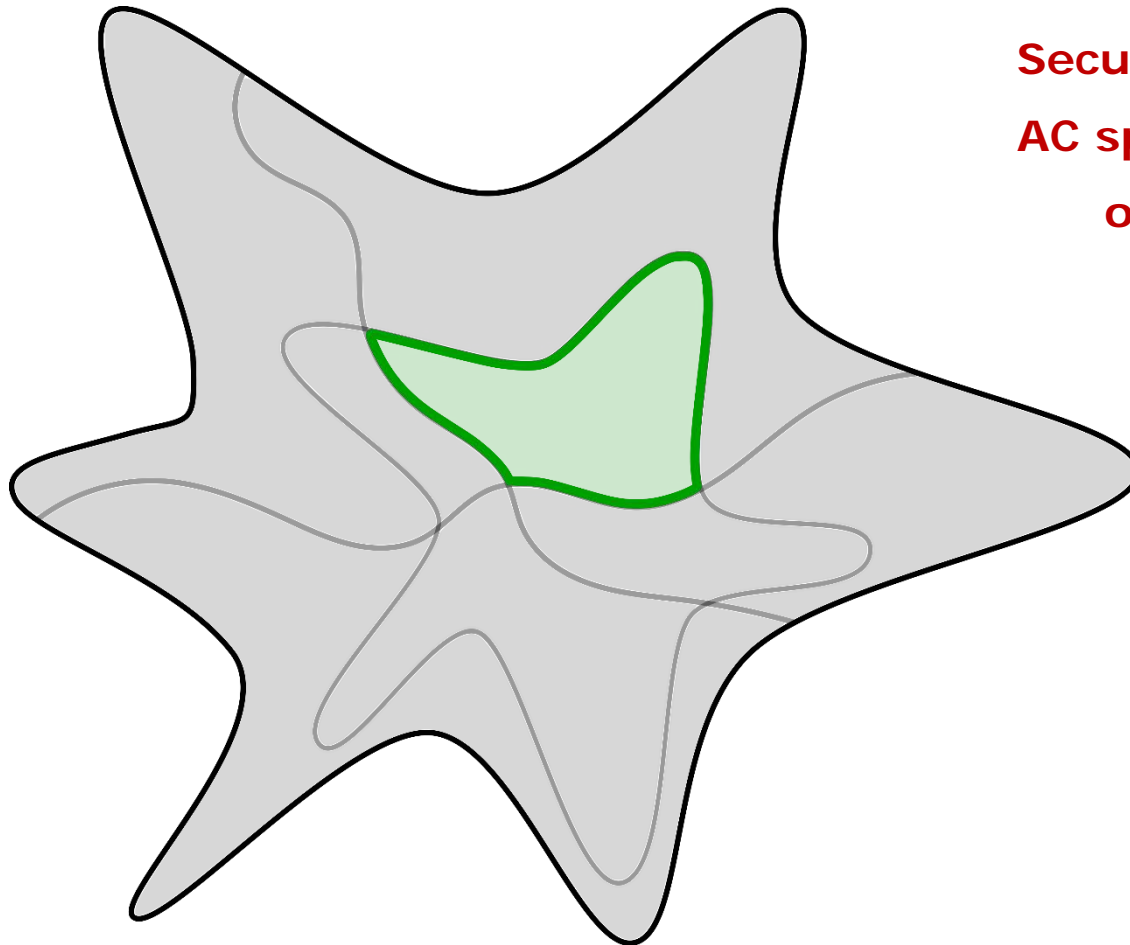
- Nonlinear and nonconvex AC power flow equations
- Component limits
 - + Stability limits
 - + Other security criteria (e.g., N-1)
 - + Uncertainty ξ in nodal power injections

Operational Challenges



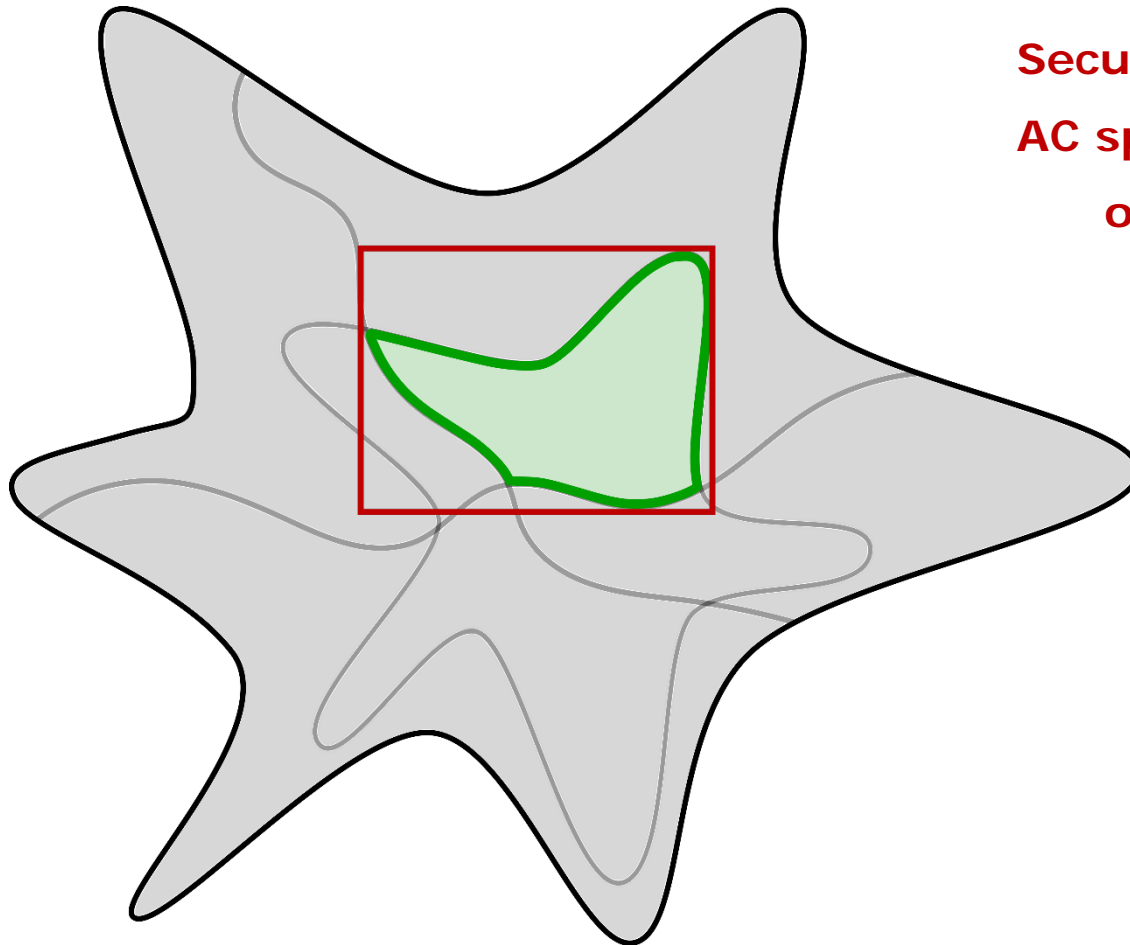
- Identifying the **boundary** of the feasible operating region
- Incorporating the **boundary** in an optimization framework
- Finding the true optimal solution & maintaining computational efficiency

How to encode **feasible operating region** for electricity markets?



Security considerations live in AC space, but market is based on DC approximations!

How to encode **feasible operating region** for electricity markets?

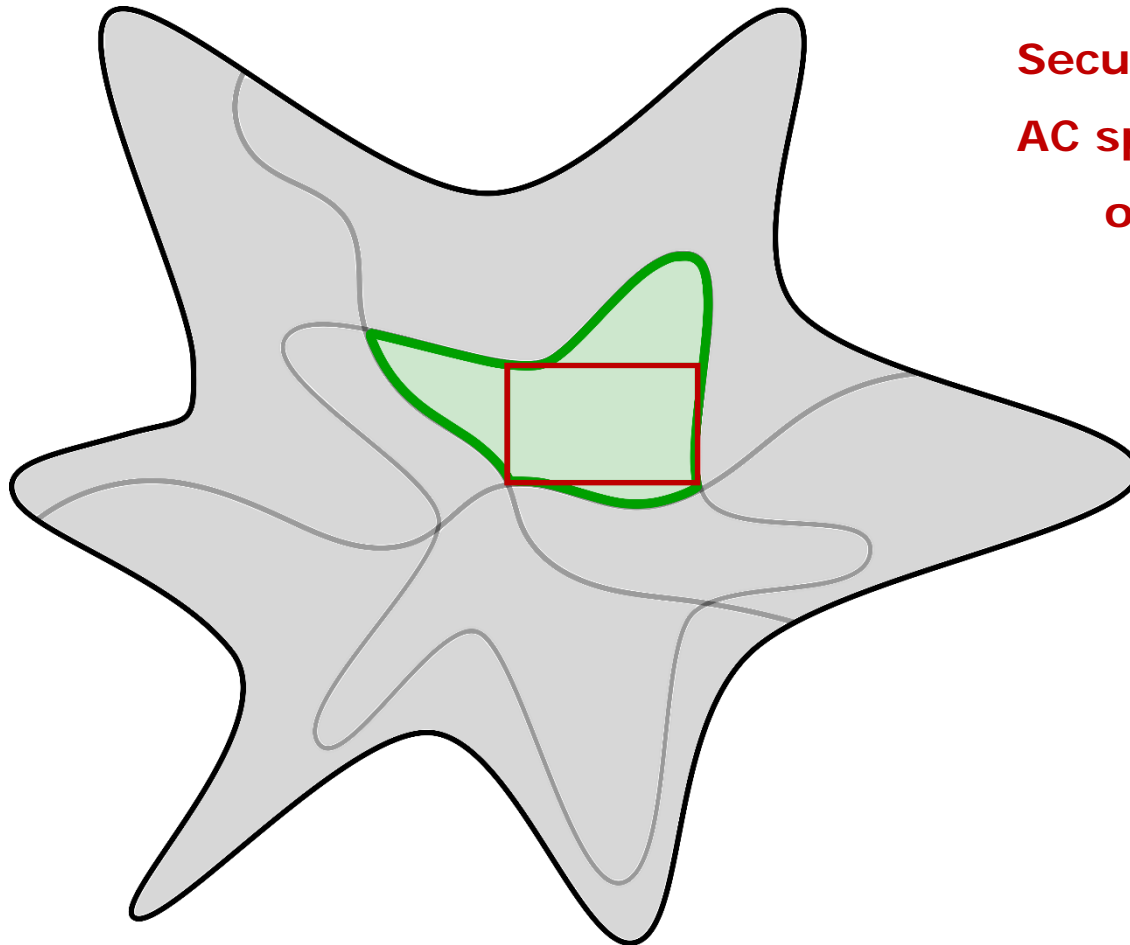


Security considerations live in AC space, but market is based on DC approximations!

Traditionally, TSOs define **Net-Transfer Capacities**



How to encode **feasible operating region** for electricity markets?

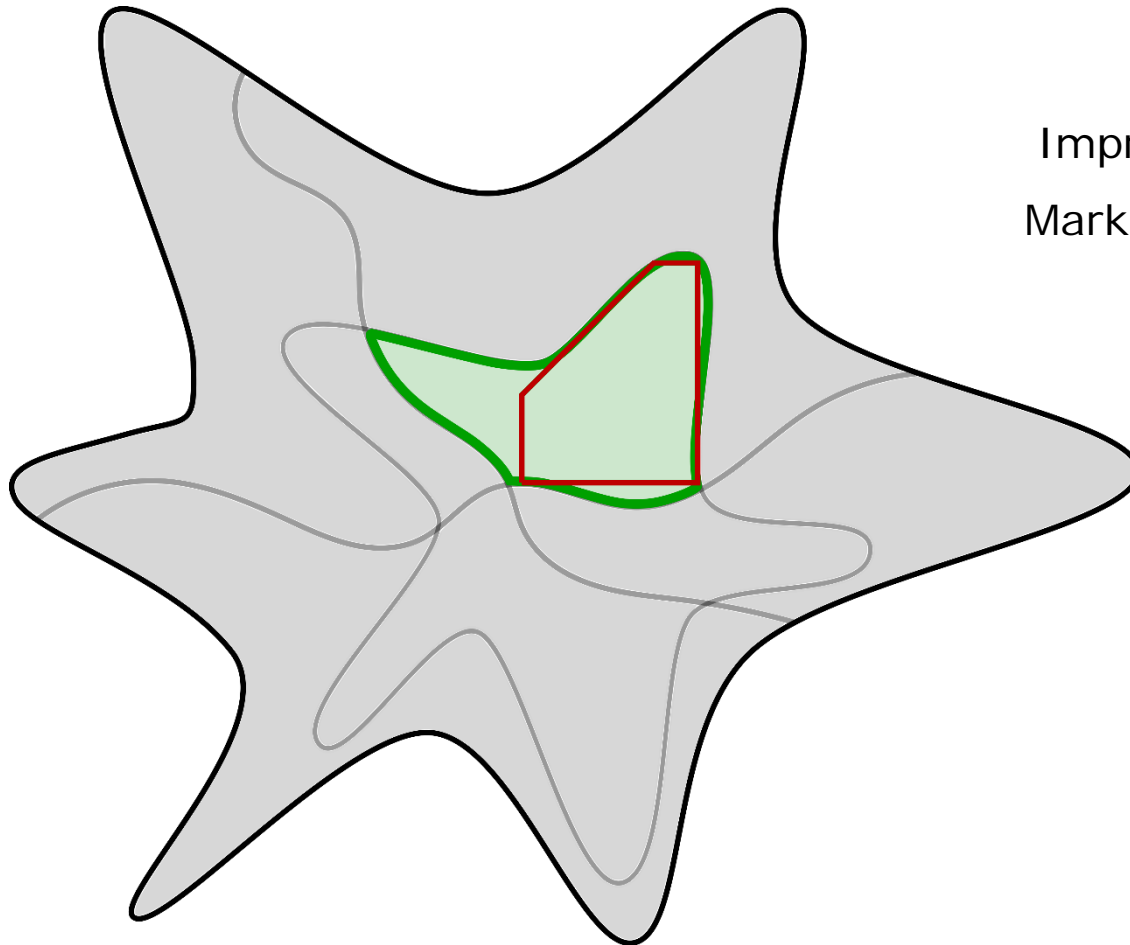


Security considerations live in AC space, but market is based on DC approximations!

Traditionally, TSOs define **Net-Transfer Capacities**

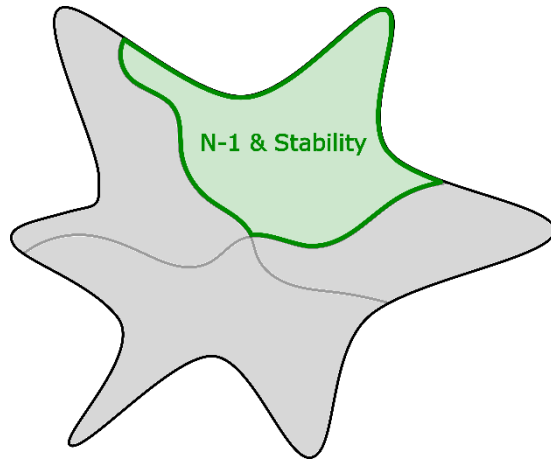


Better but reality of power system operations is nonconvex!



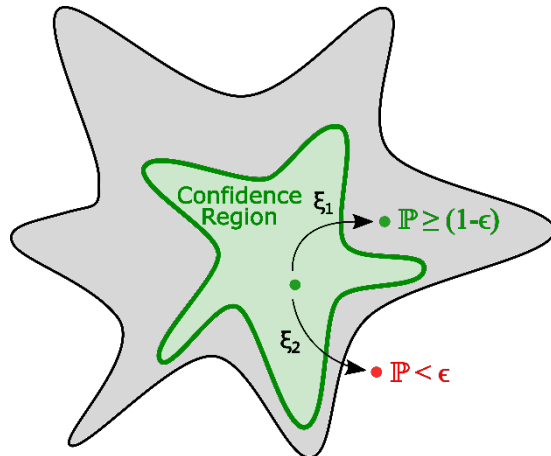
Improvements with Flow-Based
Market Coupling but still convex!

What we work on



- **Data** to approximate boundary of N-1 secure and small-signal stable space

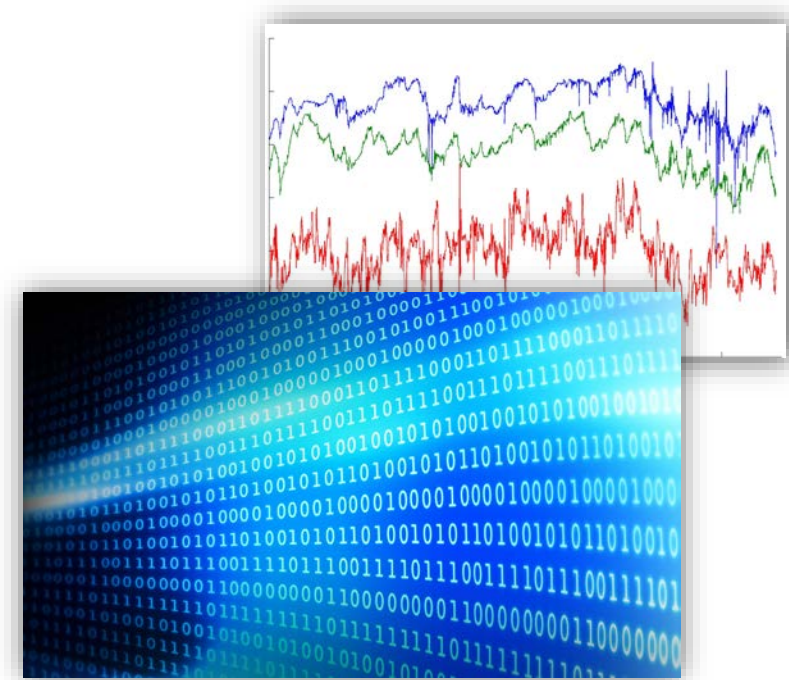
- **Mixed Integer Convex Programming** to integrate N-1 & stable space in optimization framework



- **Relaxations and approximations of chance-constrained AC-OPF** to account for uncertainty

We need data!

- We need data that accurately capture the whole security region
 - so that we can successfully use machine learning approaches for classification
- Historical data are insufficient
 - They contain very limited number of abnormal situations
- We need to generate simulation data
- **Assessing the stability of 100'000s of operating points is an extremely demanding task**



Efficient Database Generation

- Modular and highly efficient algorithm
- Can accommodate numerous definitions of power system security (e.g. N-1, N-k, small-signal stability, voltage stability, transient stability, **or a combination** of them)
- **10-20 times faster** than existing state-of-the-art approaches
- Our use case: N-1 security + small-signal stability
- Generated Database for NESTA 162-bus system online available!
<https://osf.io/5nax8/> (~300,000 points)

F. Thams, A. Venzke, R. Eriksson, and S. Chatzivasileiadis, "Efficient database generation for data-driven security assessment of power systems". <https://www.arxiv.org/abs/1806.0107.pdf>

Efficient Database Generation: Convex Relaxations and Directed Walks

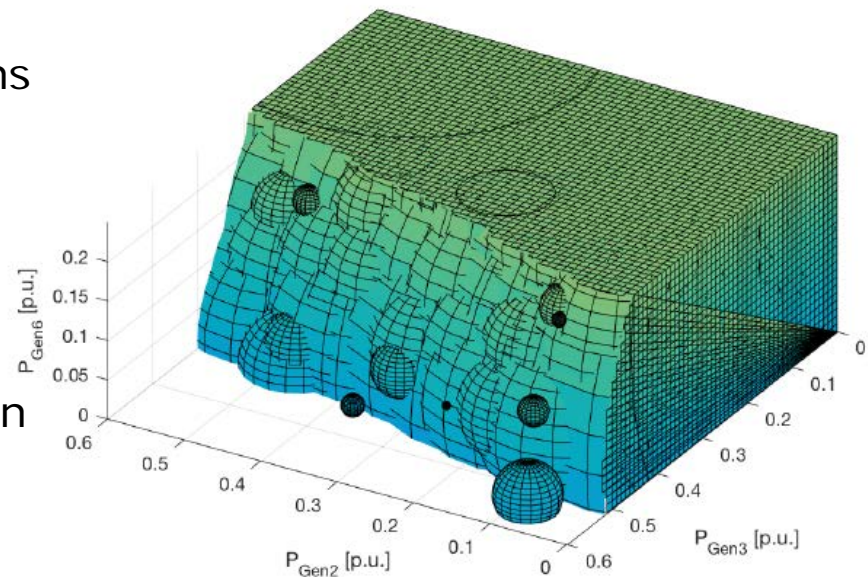
- Convex relaxations to discard large infeasible regions
 - Certificate: if a point is infeasible for the semidefinite relaxation, it is infeasible for the original problem

1. Sample the search space:
e.g. from $P_{g,\min}$ to $P_{g,\max}$ for all Gens

2. **If a sample is infeasible:**
Find minimum radius of a (hyper)sphere around that point, that intersects with the feasible space of the semidefinite relaxation

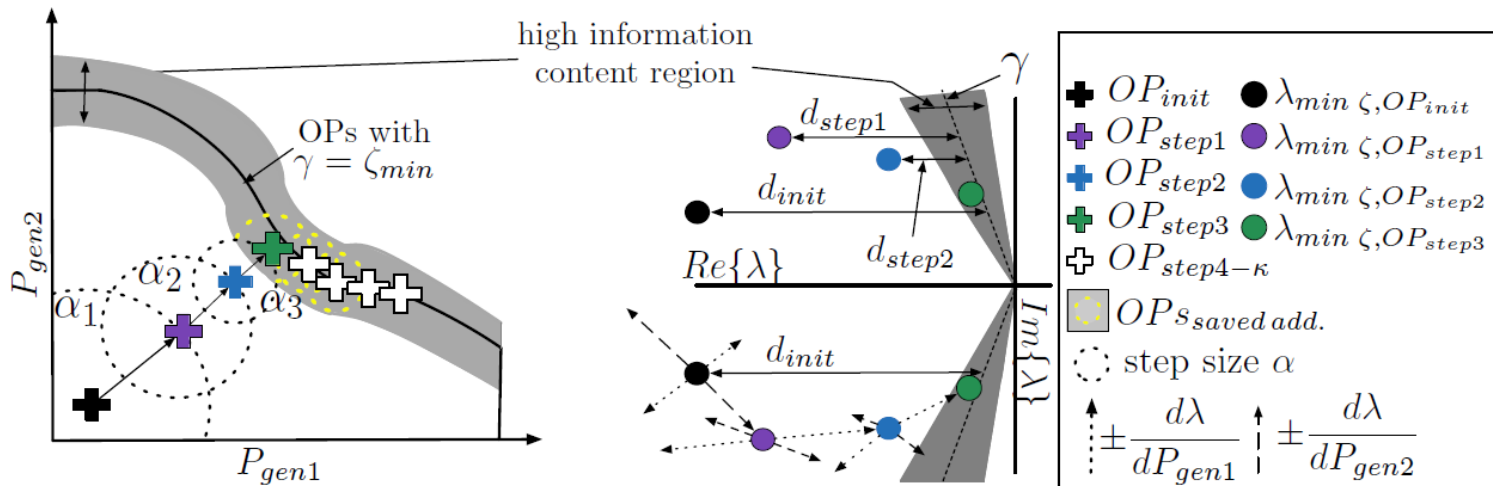
3. Discard all points inside the hypersphere

- Convex optimization! And drastically reducing search space!



Efficient Database Generation: Convex Relaxations and Directed Walks

- “Directed walks”: steepest-descent based algorithm to explore the remaining search space, focusing on the area around the security boundary
 1. Variable step-size
 2. Parallel computation
 3. Steepest descent: sensitivity of damping ratio (small-signal stability)
 4. Exhaustive search of the space around security boundary
 5. Full N-1 contingency check



2-dim. subspace of multi-dim. space of potential generation patterns (remaining dim. held constant for illustration)

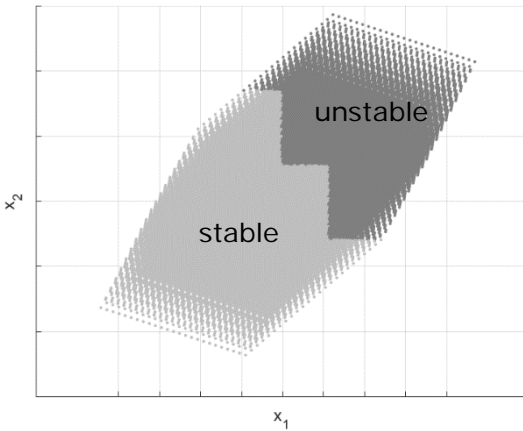
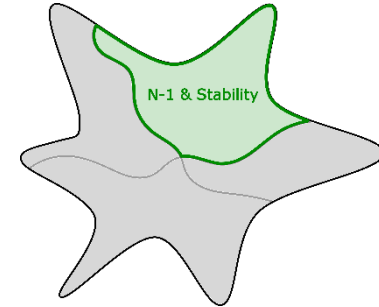
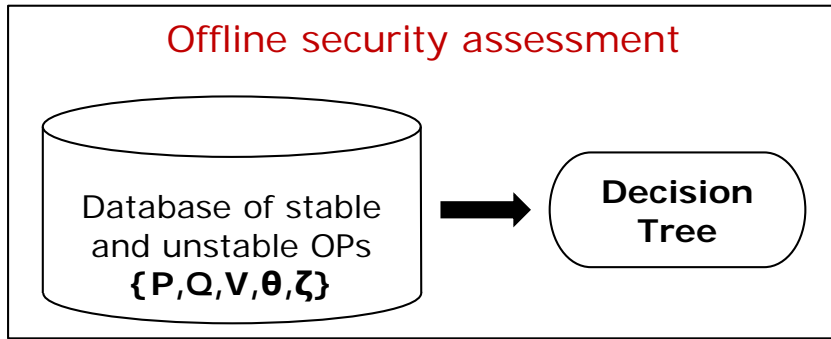
Eigenspace of all $\Gamma + 1$ analyzed systems (only lowest damped (pair) of eigenvalues of all systems shown)

Results

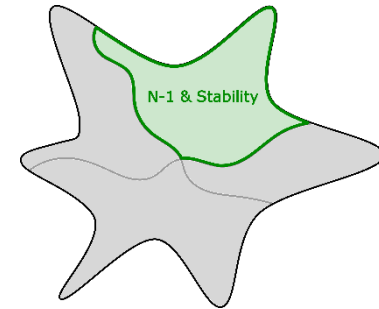
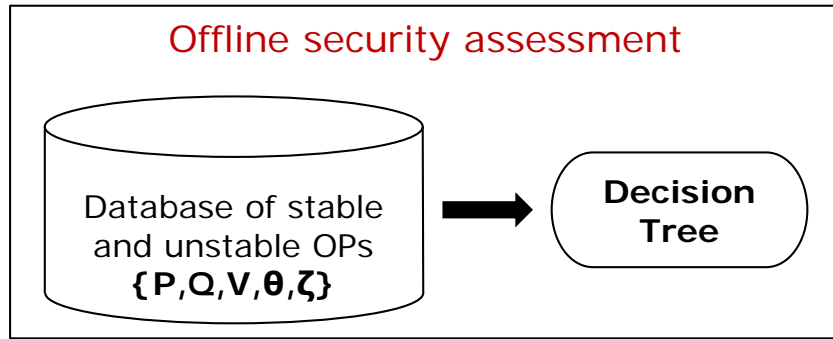
	Points close to the security boundary (within distance γ)	
	IEEE 14-bus	NESTA 162-bus
Brute Force	100% of points in 556.0 min	<i>intractable</i>
Importance Sampling	100% of points in 37.0 min	901 points in 35.7 hours
Proposed Method	100% of points in 3.8 min	183'295 points in 37.1 hours

- Further benefits for the decision tree:
 - Higher accuracy
 - Better classification quality (Matthews correlation coefficient)
- Generated Database for NESTA 162-bus system online available! <https://osf.io/5nax8/>

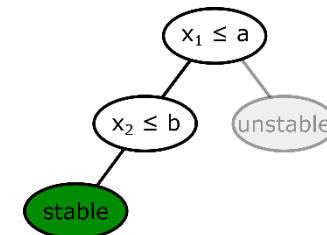
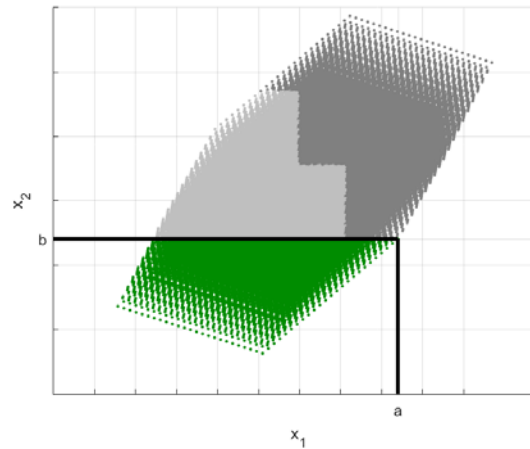
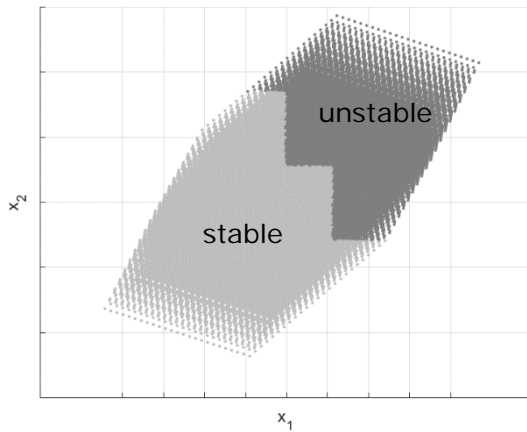
Data-driven security-constrained OPF



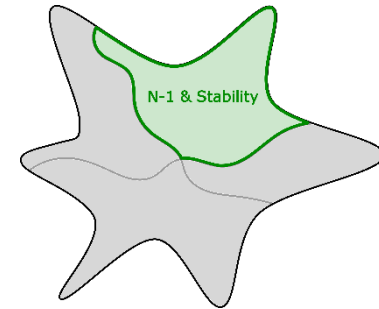
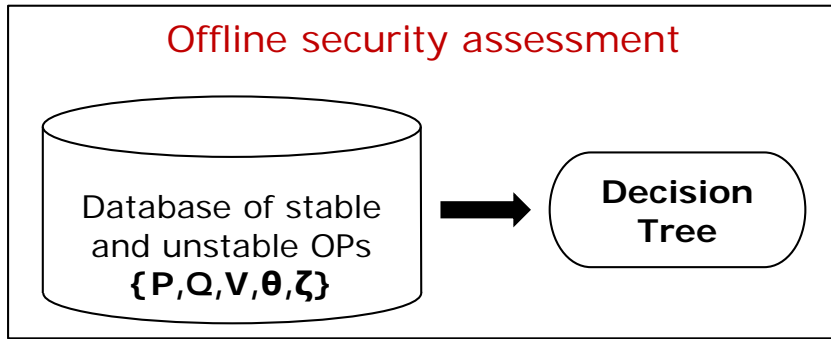
Data-driven security-constrained OPF



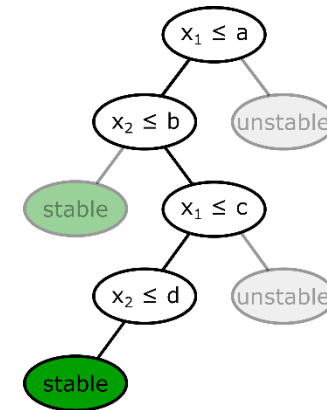
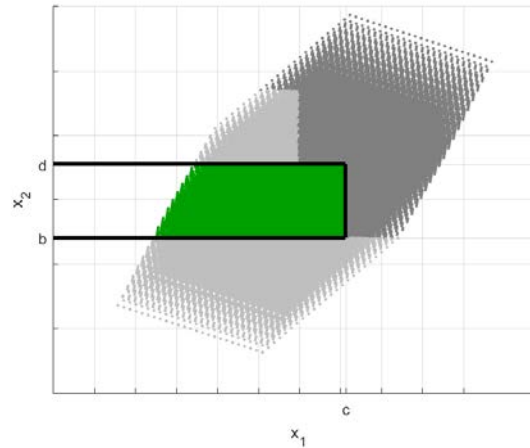
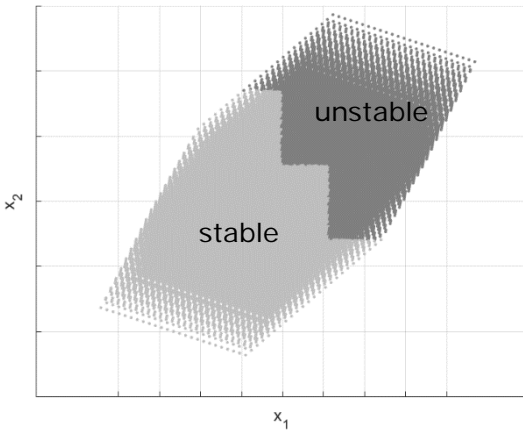
Partitioning the secure operating region



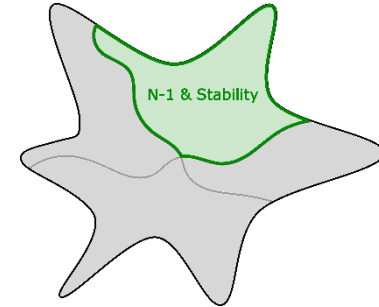
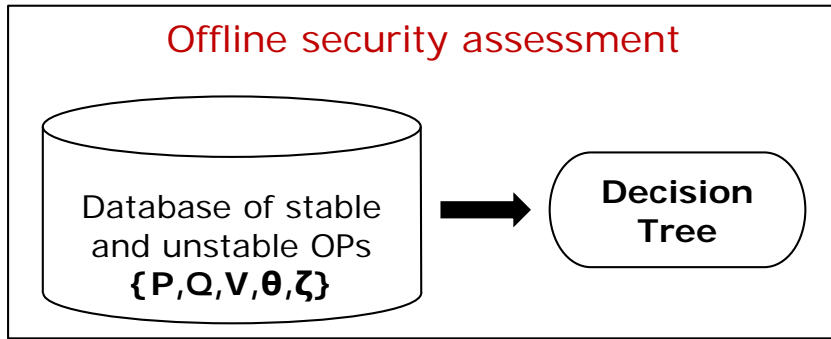
Data-driven security-constrained OPF



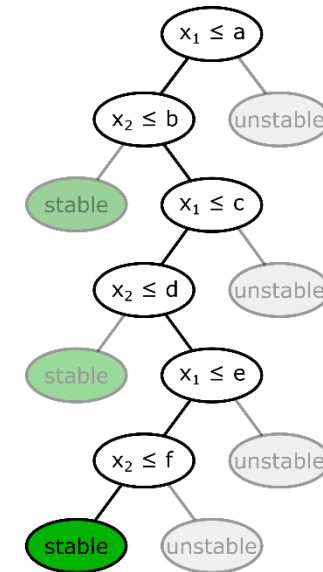
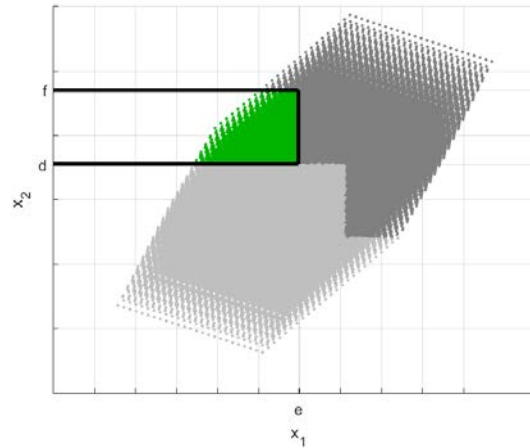
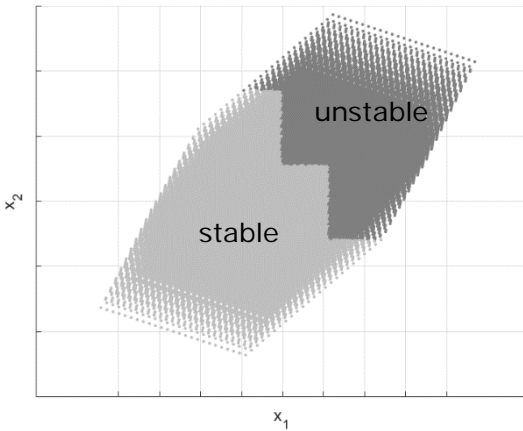
Partitioning the secure operating region



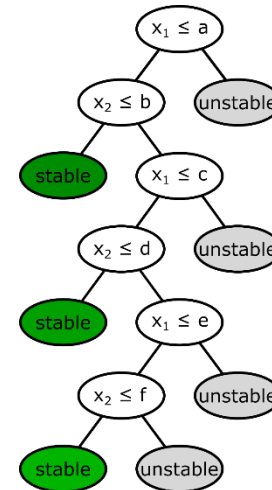
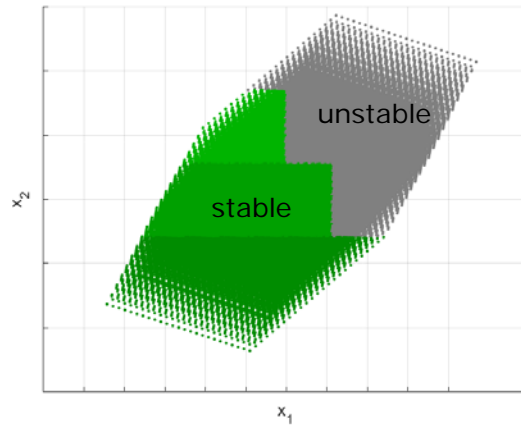
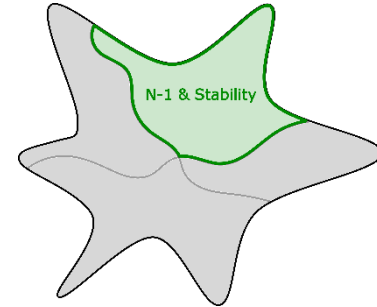
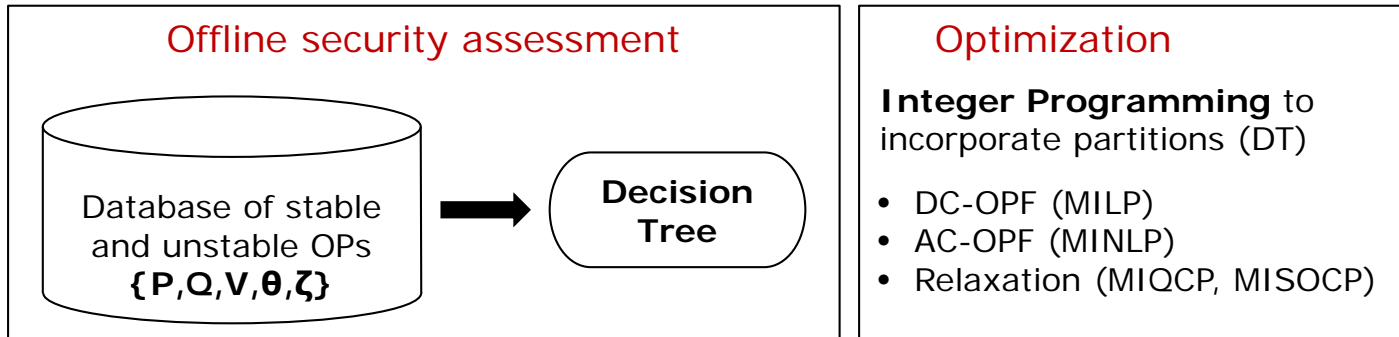
Data-driven security-constrained OPF



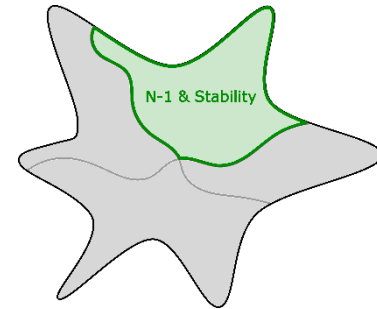
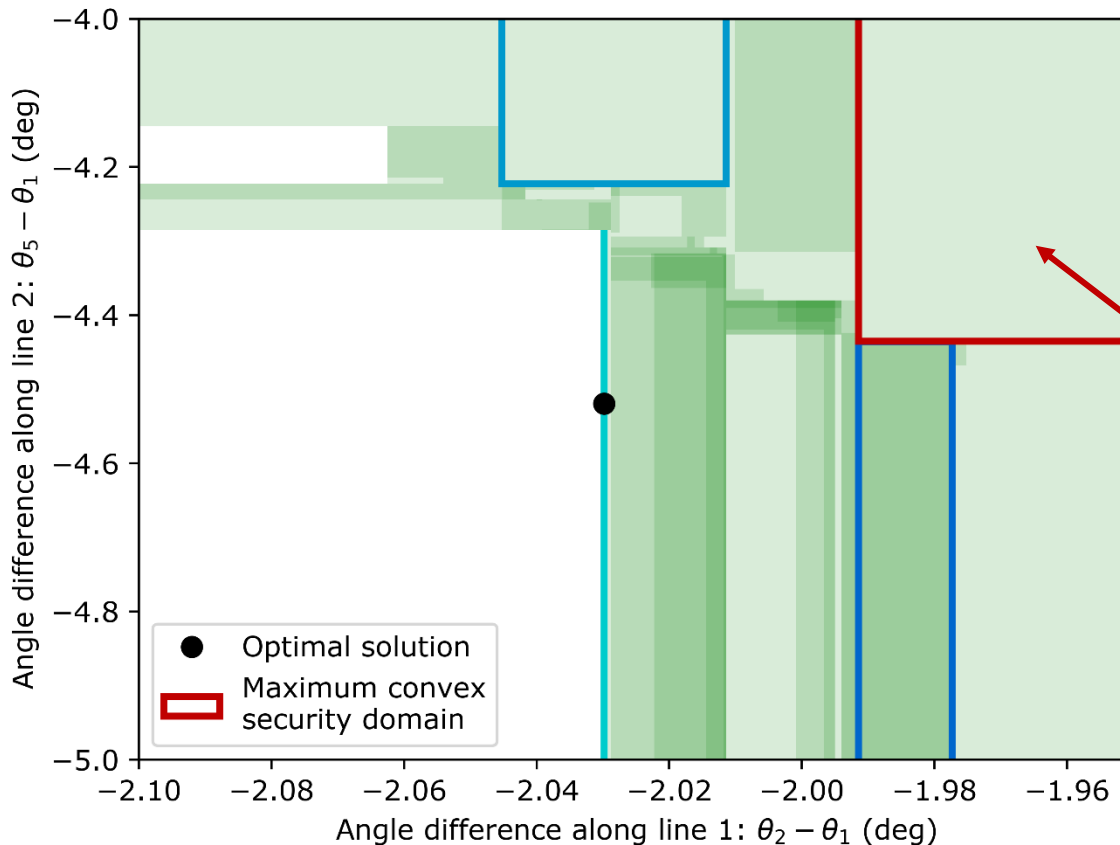
Partitioning the secure operating region



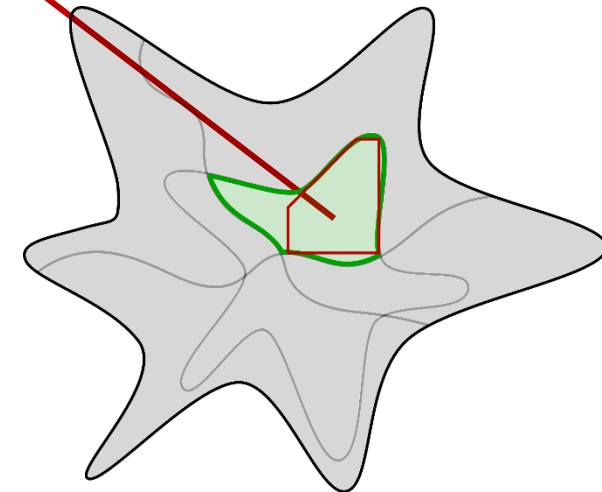
Data-driven security-constrained OPF



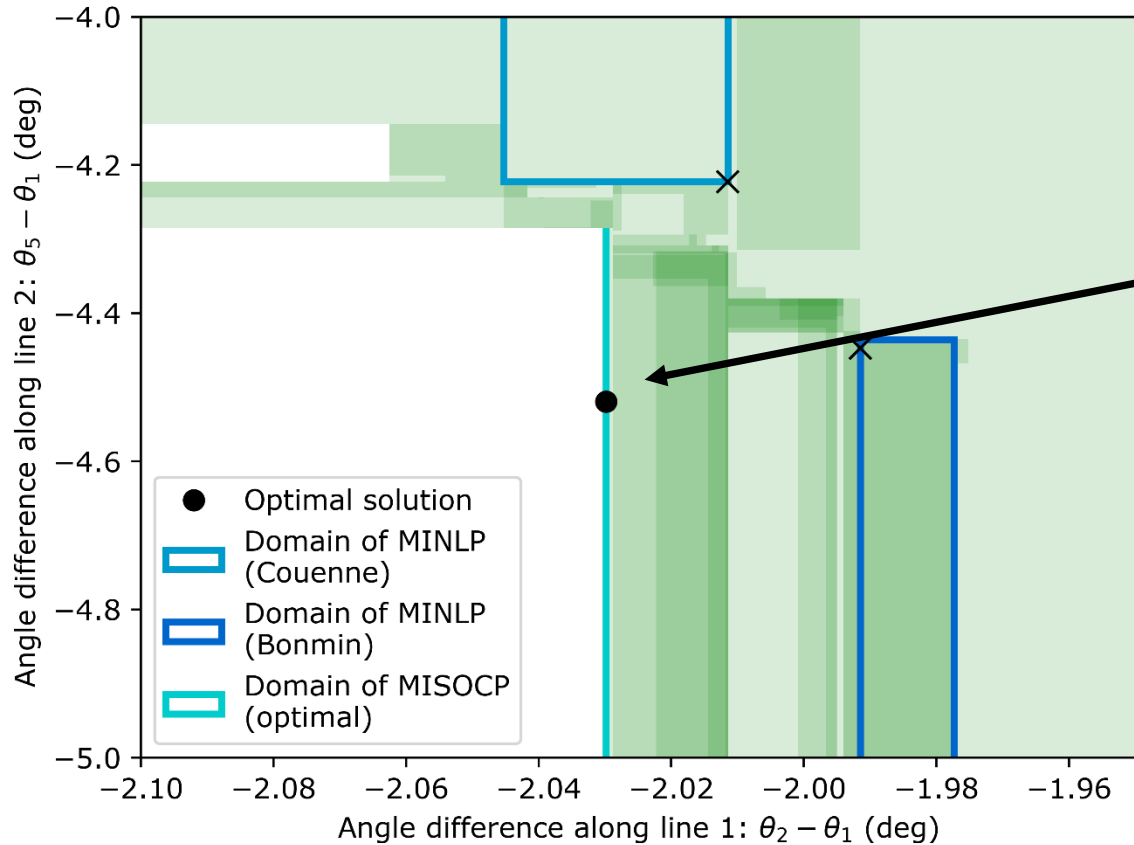
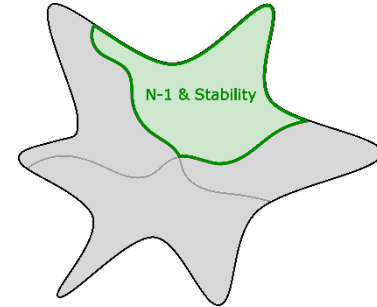
We gain ~22% of the feasible space using data and Mixed Integer Programming



Largest convex region covers ~78%



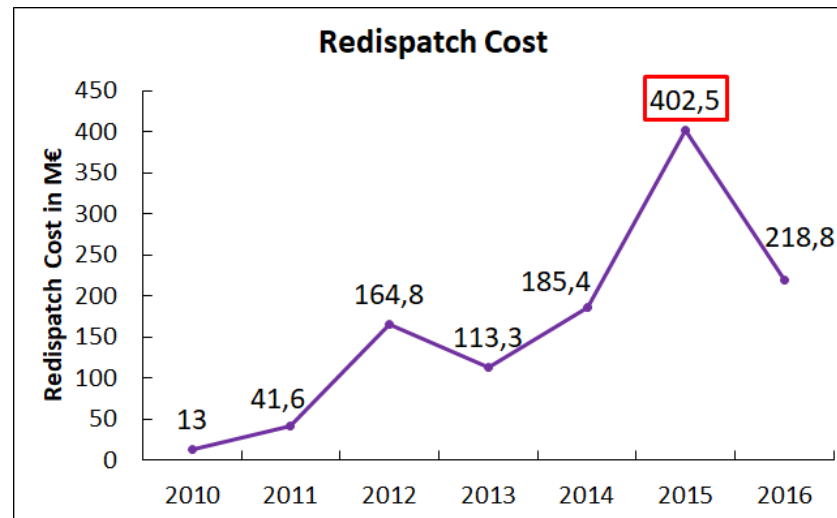
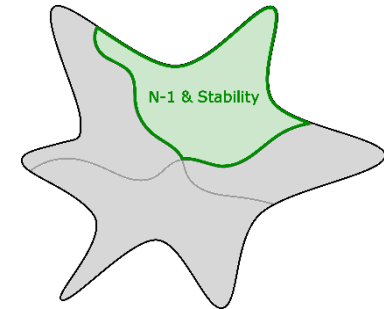
MIP + convex AC-OPF approximation finds better solutions than nonconvex problem!



Optimum located at boundary of considered security region

Works also for DC-OPF (MILP): Market dispatch is N-1 secure and stable

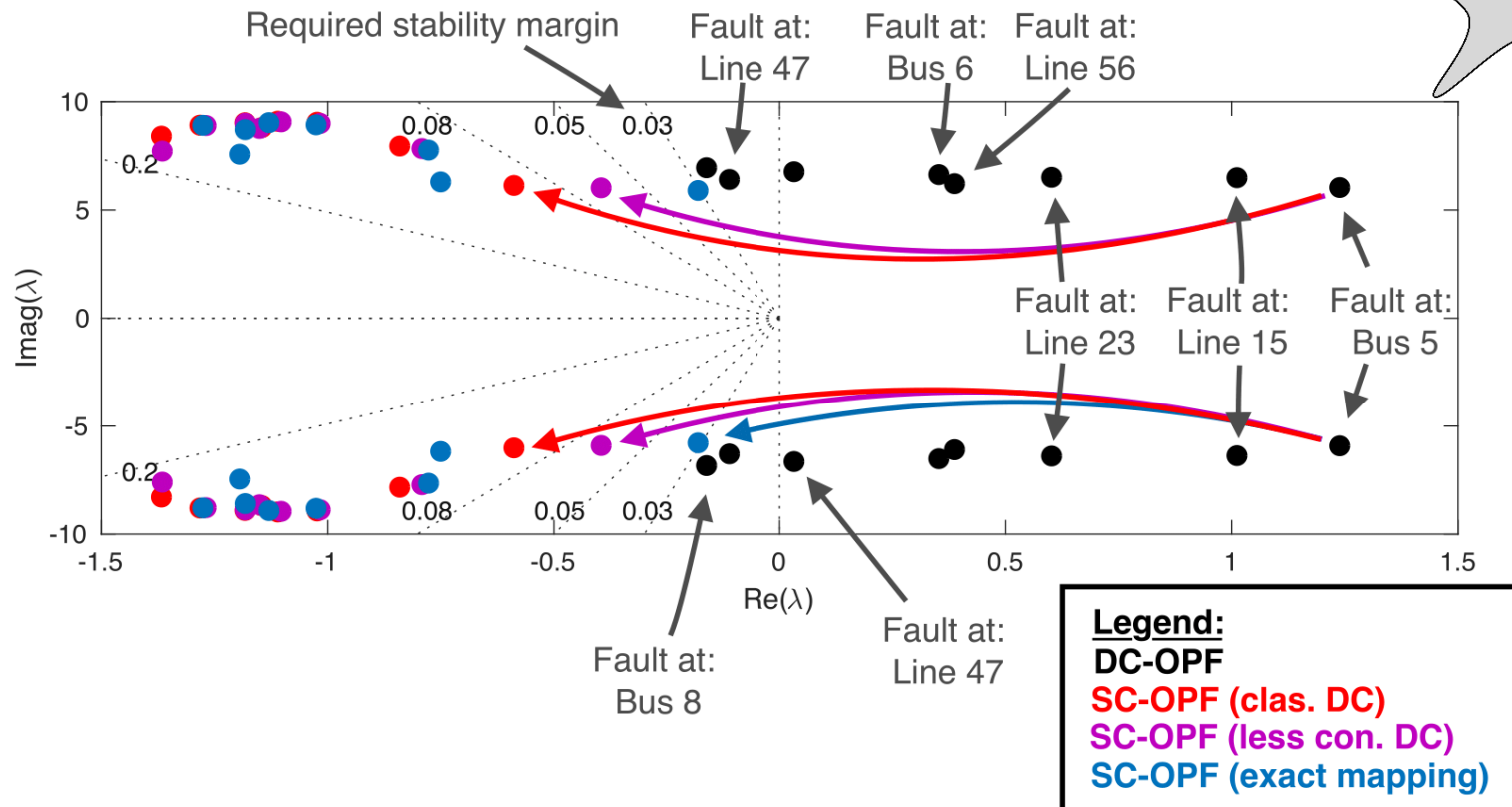
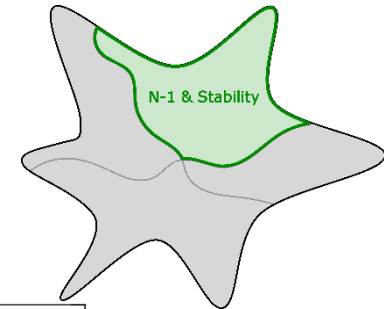
➔ *Eliminate redispatching costs*



- Redispatching costs: over 400 Million Euros in a year, just for Germany
- Data-driven SC-OPF for markets: DC-OPF becomes MILP
 - **But**, MILP is already included in market software (e.g. Euphemia, for block offers, etc.)
 - Efficient MILP solvers already existing

Works also for DC-OPF (MILP): Market dispatch is N-1 secure and stable

➔ *Eliminate redispatching costs*



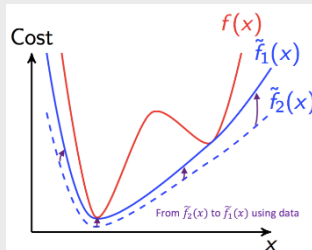
OPF under uncertainty

Approximations and relaxations of chance-constrained AC-OPF

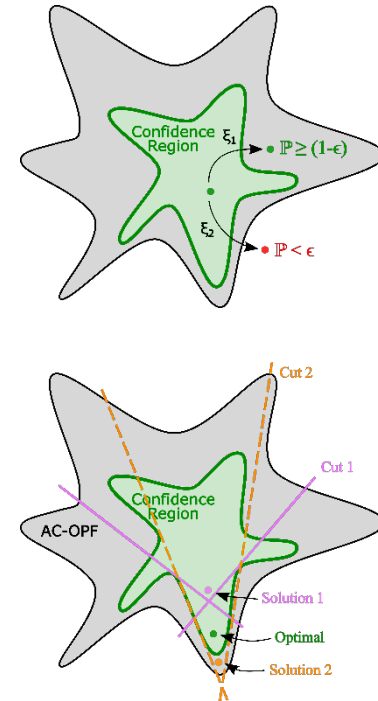
Semidefinite programming

Second-order cone programming

- Global optimality



- + Ex-post feasibility recovery
- Computational efficiency
- **Better approximations of confidence region**



A. Venzke, L. Halilbasic, U. Markovic, G. Hug, S. Chatzivasileiadis, "Convex relaxations of chance constrained AC optimal power flow," *IEEE Transactions on Power Systems*, vol. 33, no. 3, pp. 2829-2841, May 2018.

L. Halilbašić, P. Pinson, and S. Chatzivasileiadis, "Convex relaxations and approximations of chance-constrained AC-OPF problems," *IEEE Transactions on Power Systems*, 2018, (in press).

OPF under uncertainty

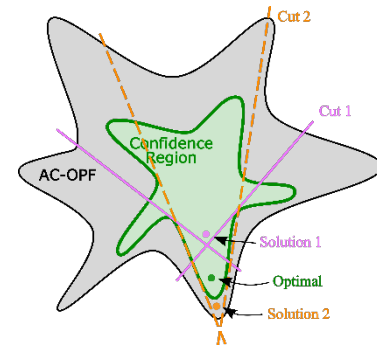
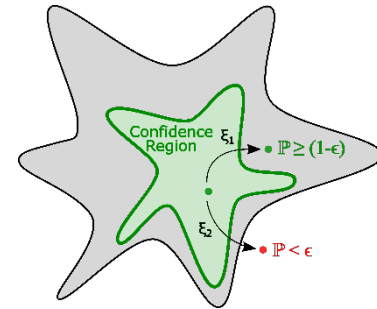
Approximations and relaxations of chance-constrained AC-OPF

Second-order cone programming

$$(I) \quad \tilde{y} = y + \frac{\partial y}{\partial \xi} \xi = \Upsilon \xi$$

$$\mathbb{P} \left((P_l + \Upsilon_l^P \xi)^2 + (Q_l + \Upsilon_l^Q \xi)^2 \leq (\bar{S}_l)^2 \right) \geq 1 - \epsilon$$

$$(II)^* \quad \begin{aligned} (1) \quad & \mathbb{P}(|P_l + \Upsilon_l^P \xi| \leq k_l^P) \geq 1 - \beta_l \epsilon \\ (2) \quad & \mathbb{P}(|Q_l + \Upsilon_l^Q \xi| \leq k_l^Q) \geq 1 - (1 - \beta_l) \epsilon \\ (3) \quad & (k_l^P)^2 + (k_l^Q)^2 \leq (\bar{S}_l)^2 \end{aligned}$$

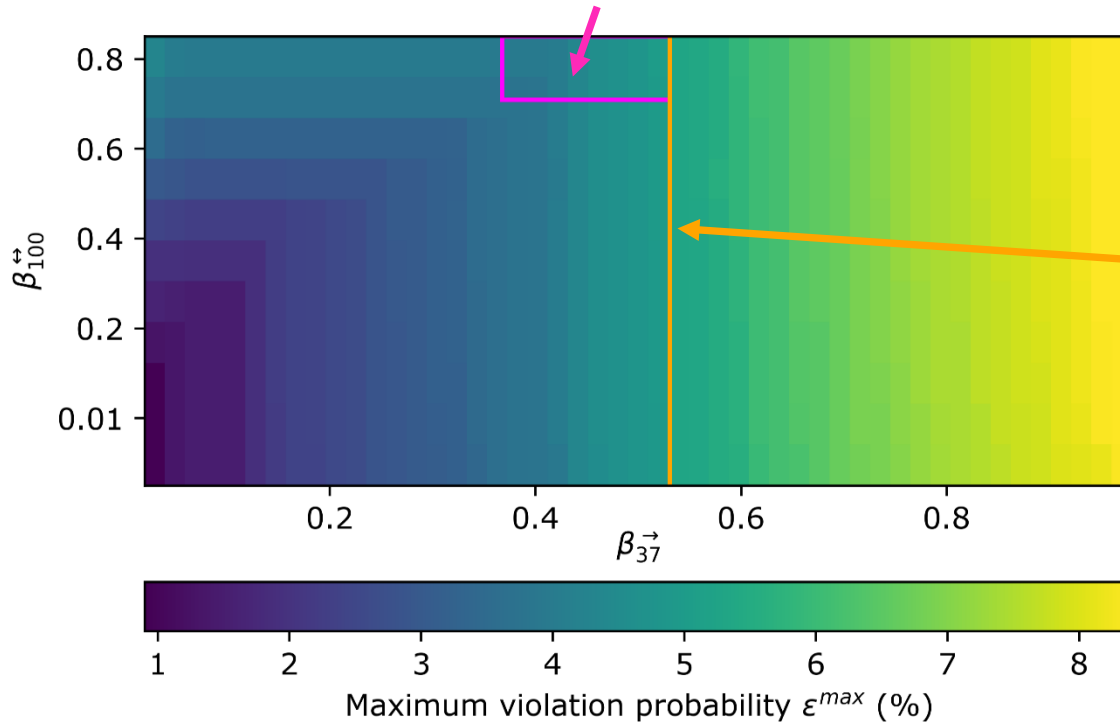
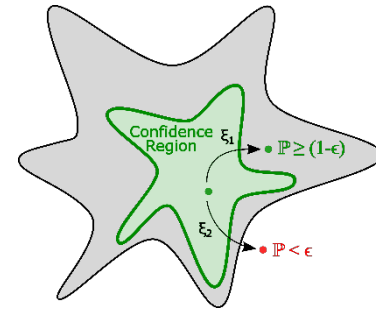


$\beta_l \in (0,1)$ ensures $\mathbb{P}((1) \cup (2)) \geq 1 - \epsilon$

* M. Lubin, D. Bienstock, and J. P. Vielma, "Two-sided Linear Chance Constraints and Extensions," *ArXiv e-prints*, Jul. 2015.

Convex AC-OPF approximation + separation of quadratic chance constraint finds better solutions than nonconvex problem!

Lower-cost region, where nonconvex CC-AC-OPF is more expensive!

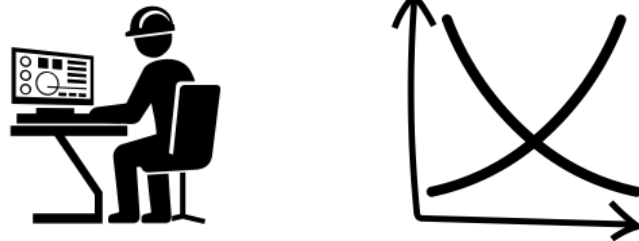


Boundary of confidence region

Conclusions

- Framework for the tractable reformulation of security and uncertainty considerations, which ...

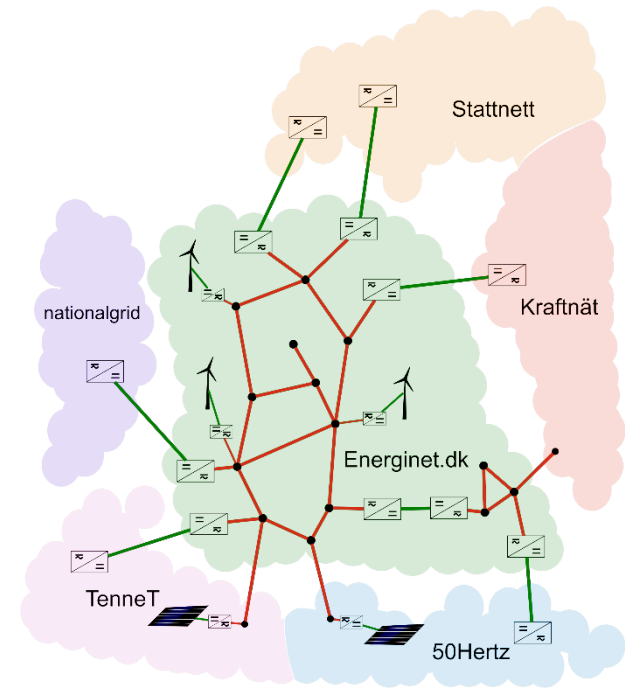
... can be included in any optimization problem ...



... and leverages data analytics and convex relaxations & approximations to make larger regions of the feasible space accessible, while remaining computationally efficient

Interested in a PhD?

- Open position
- Topic:
Data-driven Security and Optimization for AC and HVDC Grids
- Contact: spchatz@elektro.dtu.dk
- Deadline: December 15, 2018



Thank you!

www.chatziva.com/publications

spchatz@elektro.dtu.dk

References:

L. Halilbašić, F. Thams, A. Venzke, S. Chatzivasileiadis, and P. Pinson, "Data-driven security-constrained AC-OPF for operations and markets," in *2018 Power Systems Computation Conference (PSCC)*, 2018.

F. Thams, L. Halilbašić, P. Pinson, S. Chatzivasileiadis, and R. Eriksson, "Data-driven security-constrained OPF," in *10th IREP Symposium – Bulk Power Systems Dynamics and Control*, 2017.

F. Thams, A. Venzke, R. Eriksson, and S. Chatzivasileiadis, "Efficient database generation for data-driven security assessment of power systems". Submitted. arXiv: <http://arxiv.org/abs/1806.01074.pdf> (2018).

L. Halilbašić, P. Pinson, and S. Chatzivasileiadis, "Convex relaxations and approximations of chance-constrained AC-OPF problems," *IEEE Transactions on Power Systems*, 2018, (in press).

A. Venzke, L. Halilbasic, U. Markovic, G. Hug, S. Chatzivasileiadis., "Convex relaxations of chance constrained AC optimal power flow," *IEEE Transactions on Power Systems*, vol. 33, no. 3, pp. 2829-2841, May 2018.