Imperial College London

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MONTE-CARLO LIKE SECURITY ANALYSIS OF POWER SYSTEMS

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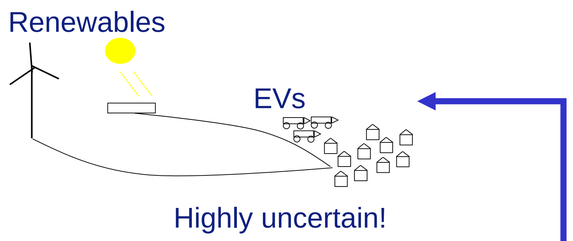
MOTIVATION [1] : Tiny and improbable operational changes ➡ large effect

The silence is deceptive

2006, November 4: A planned disconnection to let a ship pass beneath this overhead cables in Germany lead to a **partial-European blackout**

Why? Inappropriate operational planning



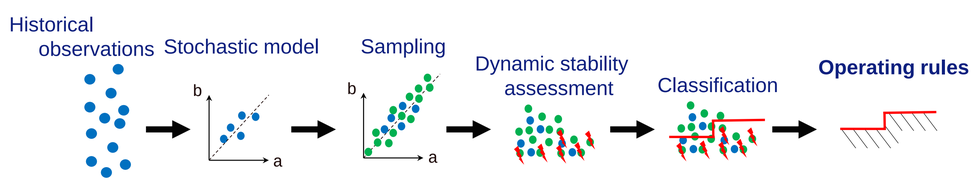
➡ **Many potential scenarios have to be assessed with detailed simulations**

In the context of **large integrated networks**, radical new methods are required to ensure stable power system operation **under high uncertainty**.

Enhance online decision making

ONLINE

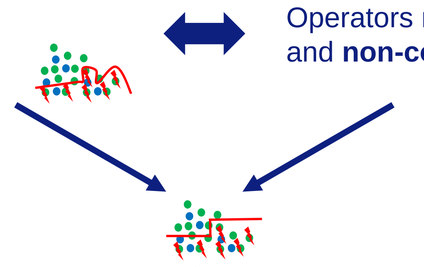
IDEA: Use offline learned stability rules [2]



OFFLINE

CHALLENGE II: Rule quality

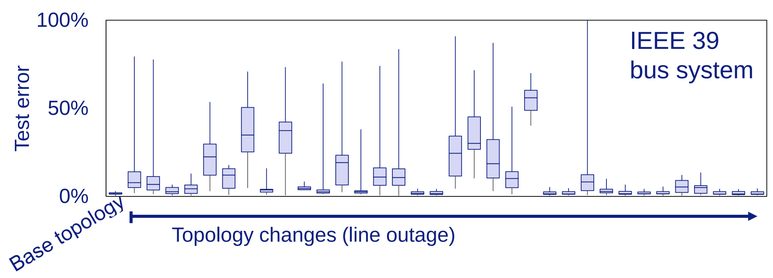
Unknown real stability boundary is **nonlinear** ⟷ Operators require **intuitive, causal** and **non-complex** rules



Linear classification
(e.g., decision trees DTs, SVMs)

What if the system changes?

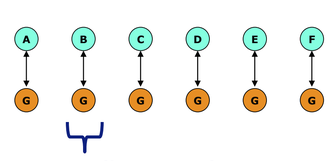
Dependent on the topology change the performance is very low:



Idea: Use system knowledge to identify causal features

DT feature selection

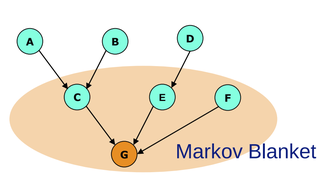
Compare features on an one-on-one basis



Best split ➡ select

Structure learning based feature selection [3]

Compare based on information criteria



➡ Causal features

CHALLENGE I: Sampling

Network state consists out of linear equations (for DC)

- Node balance

$$\sum_{l \in L^b} L_l + \sum_{g \in G^b} G_g + \sum_{f \in F^b} F_f = 0 \quad \forall b$$

- Line flow equation

$$F_f = \frac{\theta_b - \theta_{b'}}{x_f} \quad \forall f$$

bus phase angles

line reactance

- Variables

Power of loads are time-dependent, correlated and uncertain

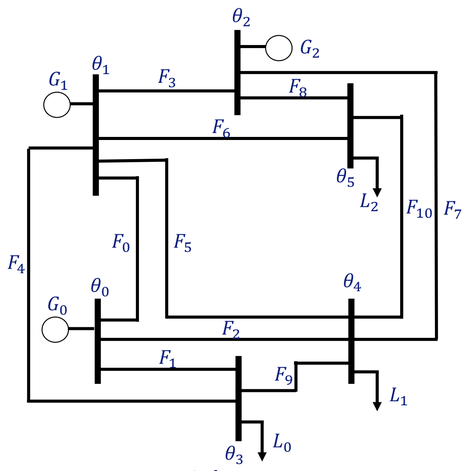
$$L_l^{LB} \leq L_l \leq L_l^{UB} \quad \forall l$$

Power of generators are uncertain, based on market clearing

$$G_g^{LB} \leq G_g \leq G_g^{UB} \quad \forall g$$

Line flows have physical limitations

$$F_f^{LB} \leq F_f \leq F_f^{UB} \quad \forall f$$



IEEE 6 bus system

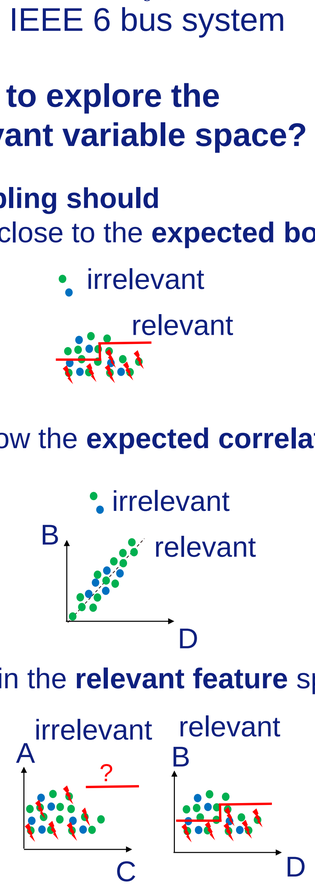
How to explore the relevant variable space?

Sampling should

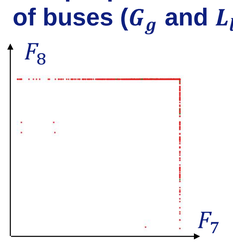
- be close to the **expected boundary**

- follow the **expected correlation**

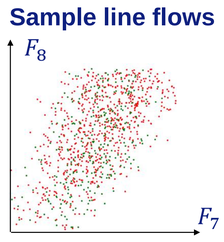
- be in the **relevant feature** space



Sample power level of buses (G_g and L_l)



Sample line flows



Line flow space F_7 and F_8

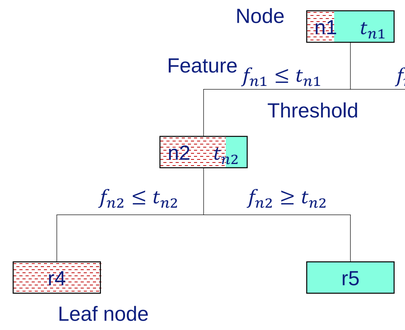
How to sample if important features are diverse?

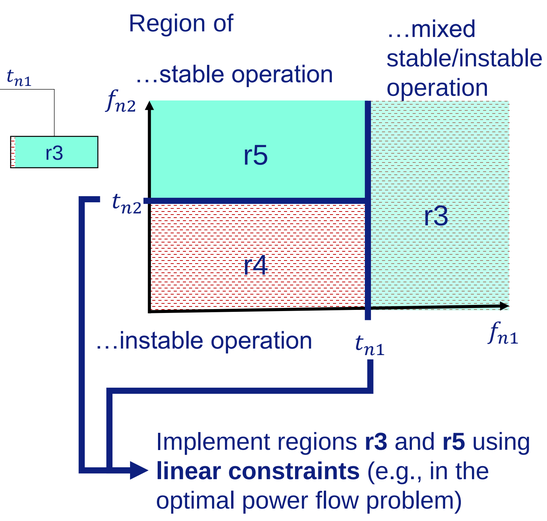
CHALLENGE III: Implement operating rules

Account for stability rules in operators online decision making

- Operational planning
- System control of corrective actions

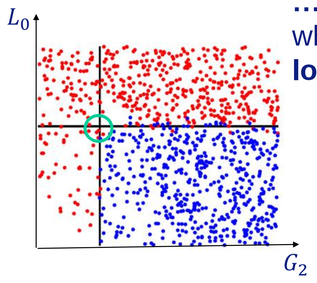
Formulate regions of DT leaf nodes as convex regions





Implement regions **r3** and **r5** using **linear constraints** (e.g., in the optimal power flow problem)

Problem: Optimal operation is forced to an edge



… unfortunately this is where the test error is **locally increasing**

Idea: Learn DT for operation not for prediction

- Tune accordingly relevant hyper parameters

REFERENCES

[1] P. Panciatici, G. Bareux and L. Wehenkel, "Operating in the Fog: Security Management Under Uncertainty," in IEEE Power and Energy Magazine, vol. 10, no. 5, pp. 40-49, Sept.-Oct. 2012.

[2] I. Konstantelos and G. Jamgotchian and S. H. Tindemans and P. Duchesne and S. Cole and C. Merckx and G. Strbac and P. Panciatici, "Implementation of a Massively Parallel Dynamic Security Assessment Platform for Large-Scale Grids," in IEEE Transactions on Smart Grid, vol. 8, no. 3, pp. 1417-1426, May 2017.

[3] C. F. Aliferis, A. Statnikov, I. Tsamardinos, S. Mani, and X. D. Koutsoukos, "Local causal and markov blanket induction for causal discovery and feature selection for classification part i: Algorithms and empirical evaluation," in Journal of Machine Learning Research, pp.171-234, Jan 2011.

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