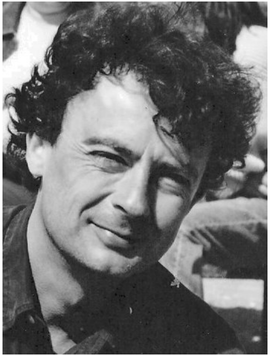
Leveraging machine learning to make probabilistic SCOPF more tractable, scalable & interpretable

The team



Upcoming seminar

Contingency Screening for Power Grids Using Worst-case Analyses and Hierarchical Programming

- Hatim Djelassi (RWTH Aachen University)
- December 13, 11:00.

Background

Security Constrained Optimal Power Flow (SCOPF)

- The fundamental class of power system operation planning & operation problems;
- optimizing an economic objective under steady state security limitations;
- originally introduced *vs* most likely scenario for load demand & N-1 contingencies;
- ongoing efforts to match complexity of real-life cases;
- but, deterministic framework slowly becoming obsolete due to uncertainty growth.

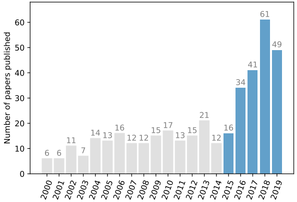
Probabilistic Security Constrained Optimal Power Flow (pSCOPF)

- Recent motivation in the growth of operational & planning uncertainties [1];
- **Risk-based** operation:
  - beyond the N-1 contingency list;
  - modeling & managing contingency probability & potential impact.
- Planning **under uncertainty**:
  - beyond the point-forecast of power injections;
  - accomodating uncertainty from renewable power generation.
- In both classes, problem **complexity escalates** *vs* the deterministic standard.

Background

Machine Learning (ML)

- Recent boom driven by emergence of new ideas & techniques, enhanced computational infrastructure and sharing culture;



- Early power system applications date back to 70s and 80s in the context of security assessment & control;
- Since then, significant progress in terms of academic publications but moderate adoption in industrial practice;
- Untapped potential to overcome outstanding challenges for pSCOPF?

Presentation Outline

Part I

- Challenges towards tractable, scalable & interpretable probabilistic SCOPF.

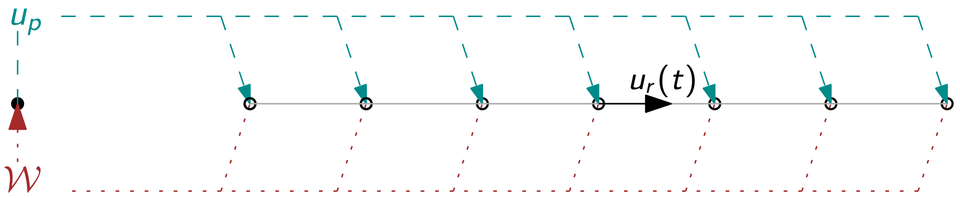
Part II

- Ongoing research ideas on leveraging machine learning techniques.

Our target problem: multi-period planning under uncertainty

At some moment t_0, in advance of a planning horizon $[\tau \ldots T]$

- Choosing a planning decision $u_p \in \mathcal{U}_p$ in advance,
- while anticipating exogenous uncertainties $w(\tau, \ldots, T) \in \mathcal{W}$ and modeling the recourse actions $u_r(\tau, \ldots, T)$ reacting to them during the horizon,
- so that the system will be functional during $[\tau \ldots T]$, with high enough probability.



The classical (single period, deterministic) SCOPF problem

- Horizon short enough to assume power injections & demands known with certainty ($\sim 5' - 30'$);
- uncertainty limited to a finite set of credible contingencies;
  - ⋆ contingency set expresses desirable level of confidence in maintaining functionality;
- scope is to choose preventive (pre-contingency) controls in advance;
  - + while modeling corrective (post-contingency) control possibiliies per contingency;
- technical constraints on the system (steady-state) behavior through all credible pre- to post-contingency trajectories.

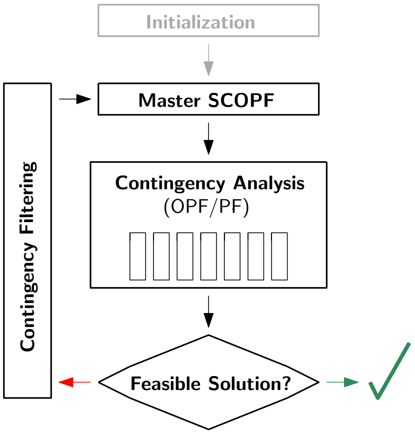
Already a difficult and large scale MINLP

- Non-linear, non-convex steady-state AC power flow equations;
- pre-/post-contingency constraints on state & decision variables (*e.g.* loss of load is unacceptable);
- continuous (e.g gen.dispatch) and discrete (*e.g.* topology) controls;
- conditional (rule-based) behavior of active components (*e.g.*, PSTs, generation PV-PQ switching, *etc.*);
- full statement can turn out as large & complex as one wishes ...
- indicative single-period European instance has $\sim$ 300M variables, 400M inequalities, 200 M equalities;
- in practice the goal is a "good feasible" rather than a "globally optimal" solution.

Determinstic SCOPF state-of-the-art

Iterative approach

- Master SCOPF *vs* a few filtered contingencies & constraints;
- contingency analysis evaluates the fitness of SCOPF outcome;
- if NOK, filtering grows the set of contingencies & constraints seen by the master SCOPF;
- until there is no post-contingency state with constraint violations.



Why decompose?

Tractability

- ✓ opportunities for parallelization, network reduction, advanced filtering, *etc.*;
- ✓ reported solutions in meaningful computational time [2].

Scalability

- ✓ binding contingencies/constraints grow moderately with the system size.

Interpretability

- ✓ cause-effect associations between filtered contingencies/constraints and updates on decision variables.

The multi period stochastic problem components

$\mathcal{U}_p[\tau, \ldots, T]$: space of candidate planning decisions u_p (*e.g.*, generation dispatch, topology, protection settings, *etc.*);

$\mathcal{W}[\tau, \ldots, T]$: space of exogenous uncertainty trajectories (*i.e.*, renewable generation, demand, component failures, *etc.*);

$\dot{u}_r(t, u_p, w(t))$: given functional form of the recourse control policy (*e.g.*, control room operation, $1^{\text{ary}}+2^{\text{ary}}$ frequency response, *etc.*);

$h_a(u_p, \dot{u}_r, w)$: acceptability of system trajectories through $[\tau, \ldots, T]$ (*e.g.*, given current flow limits, voltage limits, *etc.*);

$C_p(\cdot)$: first-stage cost function of a choice of u_p.

$c_r(\cdot,\cdot)$: recourse cost as implied by u_p and $\dot{u}_r$.

Probabilistic multi-period SCOPF statement

$$\min_{u_p \in \mathcal{U}_p} \left[C_p\left(u_p\right) + \lambda \mathbb{E}_{\mathcal{W}} \left\{ \sum_{t=\tau}^{T} c_r\left(u_p, \dot{u}_r(t, u_p, w(t))\right) \right\} \right],$$

subject to (chance constraint):

$$\mathbb{P}_{\mathcal{W}} \left\{ h_a(u_p, \dot{u}_r, w) \geq \underline{h}_a \right\} \geq 1 - \epsilon.$$

- Recourse cost expectation balanced with planning decision cost;
- chance-constraint to keep the system functional with high enough probability;
- can be tuned from highly risk averse to purely enonomic objective.

Probabilistic multi-period SCOPF statement

$$\min_{u_p \in \mathcal{U}_p} \left[C_p\left(u_p\right) + \lambda \mathbb{E}_{\mathcal{W}} \left\{ \sum_{t=\tau}^{T} c_r\left(u_p, \dot{u}_r(t, u_p, w(t))\right) \right\} \right],$$

subject to:

$$\mathbb{P}_{\mathcal{W}} \left\{ h_a(u_p, \dot{u}_r, w) \geq \underline{h}_a \right\} \geq 1 - \epsilon.$$

- Chance-constraint & objective not directly decomposable over trajectories;
- recourse cost expectation challenging wrt "feasibility over optimality" approach.

Chance-constrained SCOPF state-of-the-art

Analytical reformulation [3]

- Individual (*i.e.*, per constraint) violation probability limits reformulated as tighter deterministic constraint margins to accommodate injection uncertainty;

Scenario theory [4, 5]

- Sample average approximation with joint constraint violation probability guarantee;
- reformulation of chance-constraint via appropriate uncertainty bounds;

Chance-constrained SCOPF state-of-the-art

Analytical reformulation [3]

- Individual (*i.e.*, per constraint) violation probability limits reformulated as tighter deterministic constraint margins to accommodate injection uncertainty;

⋆ needs linear impact of uncertainty on the system operation (*e.g.*, 1^{st} order Taylor expansion for AC power flow).

Scenario theory [4, 5]

- Sample average approximation with joint constraint violation probability guarantee;

⋆ needs convexity of constraint functions;

- reformulation of chance-constraint via appropriate uncertainty bounds;

⋆ needs solvability of the robust problem within the given bounds.

The present status

- existing proposals bring the problem closer to the "decomposable" format of the classical SCOPF;
- limitations on potential for advanced physical modeling (discrete actions, non-linearity/non-convexity);
- sacrificing the recourse cost expectation from the problem statement;
- modeling cost expectation over the (low probability) constraint violating instances not straightforward;
- let's not underestimate the extended problem size.

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Target of machine learning application

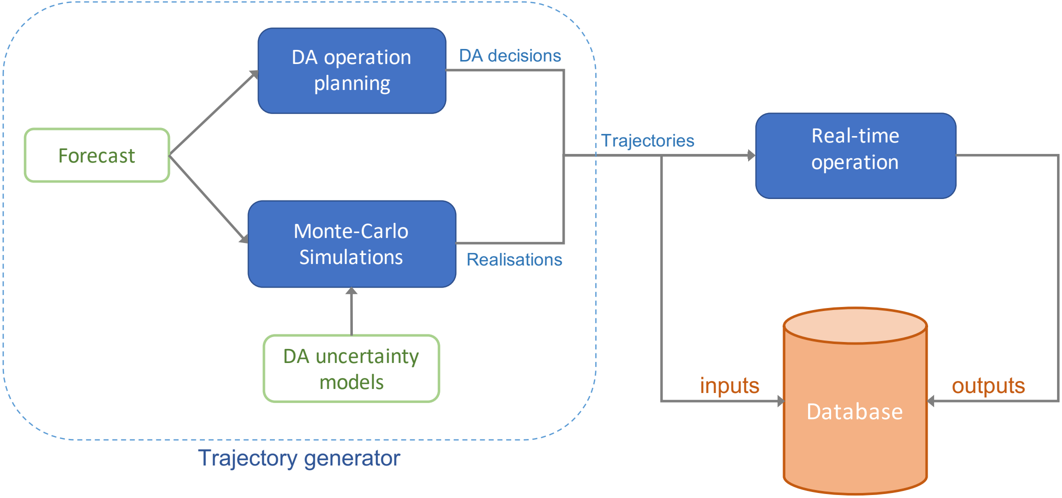
Facilitate the modeling/incorporation of the following two terms in the multi-period SCOPF formulation

$$C_r(u_p) \doteq \mathbb{E}_{\mathcal{W}}\left\{\sum_{t=\tau}^{T} c_r(u_p, \dot{u}_r(t, u_p, w(t))\right\}$$

$$H_a(u_p) \doteq \mathbb{P}_{\mathcal{W}}\left\{h_a(u_p, \dot{u}_{r,} w) \geq \underline{h}_a\right\}$$

We assume that we have a generative model for w from which we can sample "easily", and a real-time operation simulator which given u_p and w computes the trajectory induced by $\dot{u}_r$, the recourse costs c_r, and the value of the acceptability function h_a.

Data base generation (from [6])



Batch-mode supervised learning for $C_r(u_p)$

From a dataset: $\{(x^i, y^i)\}_{i=1}^N$ with

- inputs (x): $x^i = (u_p^i, w^i)$, sampled$^{(*)}$ over $\mathcal{U}_p \times \mathcal{W}$
- outputs (y): $y^i = \sum_t c_r(t, u_p^i, w^i))$, calculated by the real-time simulator

$^{(*)}$ w^i is 'naturally and easily' sampled from generative model of uncertainties over $\mathcal{W}$; u_p^i sampling scheme has to be designed to search the "interesting" part of $\mathcal{U}_p$ given the optimization problem.

A. Build a proxy $\hat{c}_r(u_p, w) \approx \sum_{t=\tau}^T c_r(t, u_p, w)$ such that

- $\hat{c}_r$ is accurate enough, given the accuracy of the real-time simulator
- $\hat{c}_r$ is much faster to evaluate than the real-time simulator
- $\hat{c}_r$ is interpretable wrt physical understanding
- $\hat{c}_r$ is 'optimizable' wrt u_p

Batch-mode supervised learning for $C_r(u_p)$

From a dataset: $\{(x^i, y^i)\}_{i=1}^N$ with

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B. Build a proxy $\hat{C}_r(u_p) \approx \mathbb{E}_{\mathcal{W}}\{\sum_{t=\tau}^{T} c_r(t, u_p, w)\}$

- $\hat{C}_r$ is accurate enough, given the accuracy of the real-time simulator
- $\hat{C}_r$ is interpretable wrt physical understanding
- $\hat{C}_r$ is optimizable wrt u_p

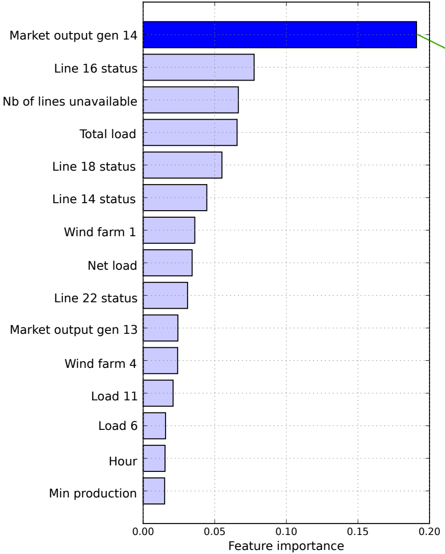
Some first results about this line of research [6, 7, 8]

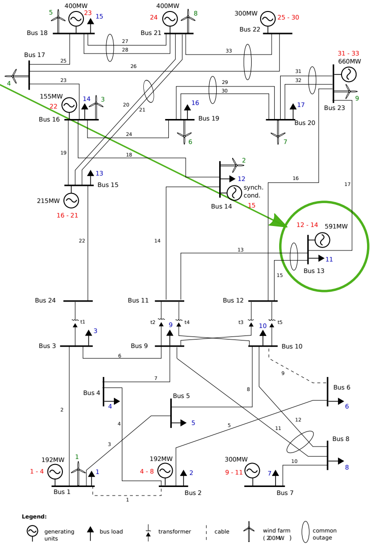
- Relation between w and $\hat{c}_r(u_p, w)$ can be learned for fixed u_p with sufficient accuracy with a sample of a few thousand (N) of simulated trajectories, both with random forests and neural nets, both methods being complementary [6].

- However, the so-learned $\hat{c}_r(u_p, w)$ is typically biased in an unpredictable way, hence in order to estimate the $\mathbb{E}_{\mathcal{W}}$ to get $\hat{C}_r(u_p)$, Monte-Carlo estimation with control variates correction is needed (to correct for bias). This still allows to reduce computational requirements by a factor of about 10 wrt to crude MC [7].

- Relation between both u_p and w and $c_r(u_p, w)$ can as well be learned with a reasonable budget N of simulated trajectories [8]. The resulting model may be used to rank a set of candidate decisions u_p according to their induced $C_r(u_p)$.

Ranking of inputs in terms of impact on recourse cost [6]





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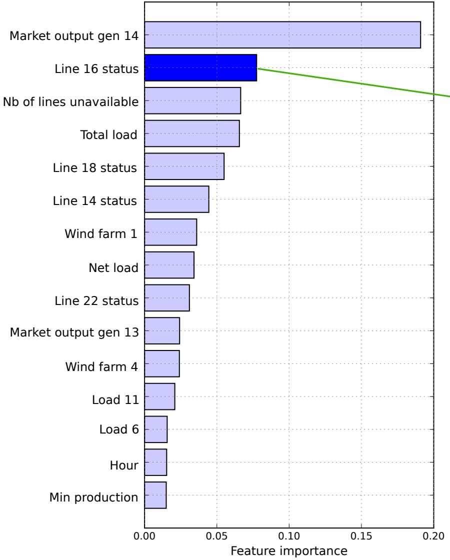
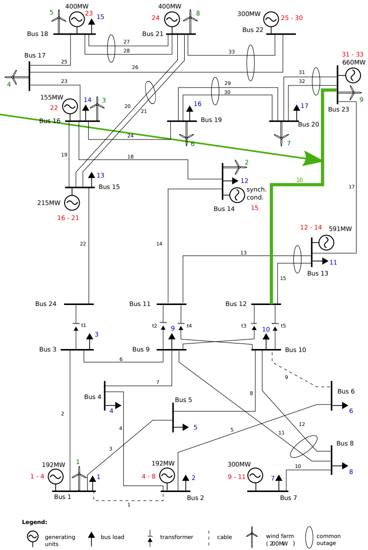
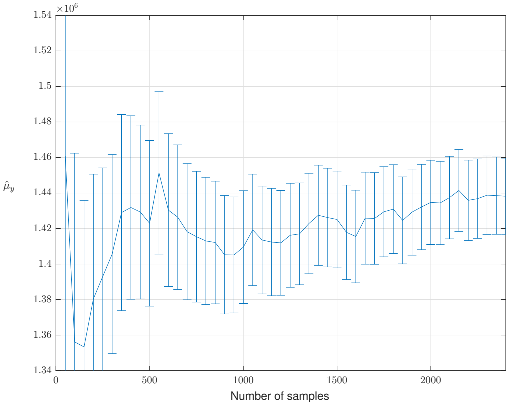
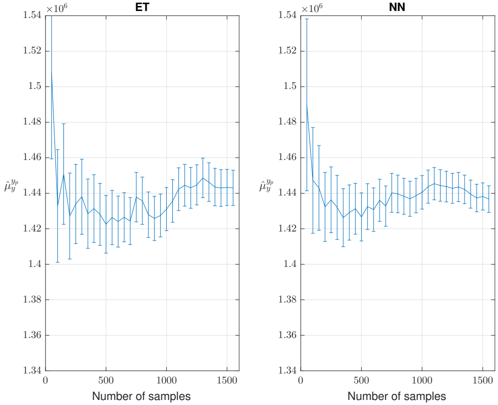




Reduction of computational requirements [7]



Convergence of the crude Monte-Carlo



Convergence of the control variates

Some ideas for further work

- Evaluate the possibility of directly learning $C_r(u_p)$, instead of learning $c_r(u_p, w)$ and then averaging out w via MC.
- Develop stochastic optimization algorithms to simultaneously learn C_r and optimize for u_p.
- Study the learning of the H_a function, and how to incorporate its result in learning-optimization frameworks.
- Develop constraint generating algorithms using $\hat{H}_a$ to produce scenarios useful in robust-optimization settings.

Parallel research projects

- Probabilistic security of supply assessment of the Belgian system with a view on the 2030 – 2050 horizon (w. A. Sutera);
- Integrating security & risk management in the pan-European cross-border market framework (w . E. Little, RTe France).

PMAPS 2020 organization

Thank you for your attention!

References I

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[8] L. Duchesne, E. Karangelos, A. Sutera, and L. Wehenkel, "Machine learning for ranking day-ahead decisions in the context of short-term operation planning," 2019, submitted for publication.