Challenges Ahead Risk-Based AC Security-Constrained Optimal Power Flow Under Uncertainty for Smart Sustainable Power Systems

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Outline of the presentation

- (Day-ahead) decision making in power systems
- Conventional security-constrained optimal power flow (SCOPF)
  - Uses, problem formulation and features
  - Some challenges to SCOPF problem *solution*
    - Methodologies to reduce the huge problem size
    - Methods for the core optimizer (local vs convex relaxations)
- SCOPF under uncertainty
  - Robust optimization approach
- Risk-based SCOPF
- Conclusions and outlook

Stages of decision making in power systems

Stages of decision making in power systems

- grid planning (years ahead of operation)
  - accurate optimization tools with no special solution time constraints
- grid maintenance planning (years/months ahead of operation)
  - accurate optimization tools with no special solution time constraints
- . . .
- **operational planning** (day-ahead of operation)
  - accurate optimization tools with stringent solution time constraints (few minutes to one hour)
- real-time operation
  - very fast optimization tools using reasonable approximate models (solution desired between few seconds and 15 minutes)

Day-ahead operational planning

- **aim**: for each anticipated state of the next day the system must operate at minimum cost while being able to **withstand** the loss of any single equipment (**N-1 security criterion**)
  - ensure a **stable** transition towards a **viable equilibrium point**

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  - ensure a **stable** transition towards a **viable equilibrium point**

- very complex optimization problem:
  - multi-period optimization (solution coupled over 24 hours including usually 24/48 states)
  - very large scale (consider a large number of contingencies)
  - nonlinear algebraic and differential equations (model the system behaviour for postulated contingencies)
  - with a large number of variables (binary, discrete, and continuous)
  - stringent solution time requirements (less than 1 hour) !

Day-ahead operational planning

problem decomposition in sequential sub-problems (trade off economics/affordability and security/reliability):

- **(market-based) unit commitment**: determines the status on/off of generators for each period of time and the generators active power according to their bids
    - very large MILP problem

Day-ahead operational planning

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  - very large MILP problem
- **SCOPF**: determines cost-optimal preventive/corrective control actions to satisfy **static security constraints** (thermal & voltages) for the 24 anticipated operation states of the power system for the next day
  - very large MINLP problem

Day-ahead operational planning

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- **SCOPF**: determines cost-optimal preventive/corrective control actions to satisfy **static security constraints** (thermal & voltages) for the 24 anticipated operation states of the power system for the next day
  - very large MINLP problem
- **time-domain (dynamic) simulation**: check system **stability** for the postulated contingencies
  - numerical integration of dynamic phenomena with different time scales (e.g. miliseconds to minutes)

Conventional (deterministic) SCOPF

SCOPF uses

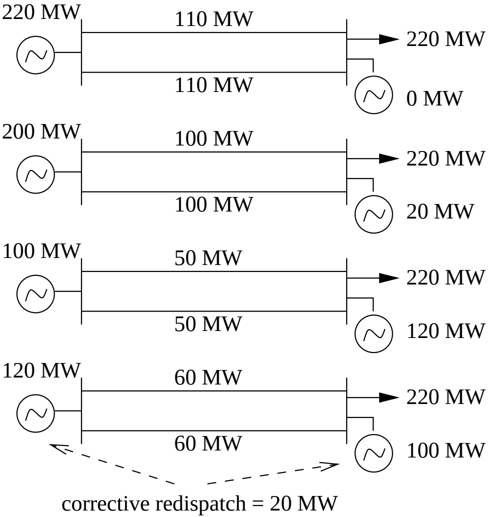
- essential tool in power systems planning, operational planning and real-time
- part of Energy Management System (EMS) in control centers (together with state estimation, time domain simulation, etc.)
- in some systems the SCOPF is used to price electricity by means of locational marginal prices (LMPs)
    - uses a linear (DC) grid model since solution must be provided in real-time (i.e. few minutes)

Conventional (deterministic) SCOPF formulation

$$\begin{array}{llll}
 & \min\limits_{\mathbf{x}_0,\ldots,\mathbf{x}_c,\mathbf{u}_0,\ldots,\mathbf{u}_c} f(\mathbf{x}_0,\mathbf{u}_0) & & \\
\text{s.t.} & \mathbf{g}_0(\mathbf{x}_0,\mathbf{u}_0)=\mathbf{0} & & \leftarrow \text{base case constraints} \\
 & \mathbf{h}_0(\mathbf{x}_0,\mathbf{u}_0)\leq\mathbf{0} & & \leftarrow \text{base case constraints} \\
 & \mathbf{g}_k(\mathbf{x}_k,\mathbf{u}_k)=\mathbf{0} & k=1,\ldots,c & \leftarrow \text{contingency } k \text{ constraints} \\
 & \mathbf{h}_k(\mathbf{x}_k,\mathbf{u}_k)\leq\mathbf{0} & k=1,\ldots,c & \leftarrow \text{contingency } k \text{ constraints} \\
 & |\mathbf{u}_k-\mathbf{u}_0|\leq\Delta\mathbf{u}_k^{max} & k=1,\ldots,c & \leftarrow \text{``coupling'' constraints}
\end{array}$$

- **x** - state/dependent variables:
  magnitude V and angle θ of complex voltage at all buses
- **u** - continuous and discrete control variables:
  generator active power, terminal voltage, transformer ratio, phase shifter angle, shunt capacitors/reactors reactive power

Preventive and corrective modes; OPF vs SCOPF



optimal unconstrained dispatch
(no line flow limit)

OPF dispatch
(line flow limit = 100 MW)

preventive SCOPF dispatch
(line flow limit = 100 MW)

corrective SCOPF dispatch
(line flow limit = 100 MW)

Features and challenges of the SCOPF problem

- *nonlinear:* includes power flow equations and other nonlinear inequality constraints
- **non-convex:** includes power flow equations and bounds on other nonlinear inequality constraints
- *with continuous* and **discrete variables**
- *static:* refers to a single operating point in time
- **large scale:** the SCOPF problem for a 3000-bus system and 999 contingencies contains:
  around 2000 x 3000 $=$ 6.000.000 equality constraints
  around 6000 x 3000 $=$ 18.000.000 inequality constraints
  around 1000 x 3000 $=$ 3.000.000 control variables

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  around 1000 x 3000 = 3.000.000 control variables
- **academia** *simplifies* **SCOPF to a large scale MINLP**
- intractable on a normal computer due to memory limitation !
- *scalable decomposition* is essential as a limited number of constraints are binding

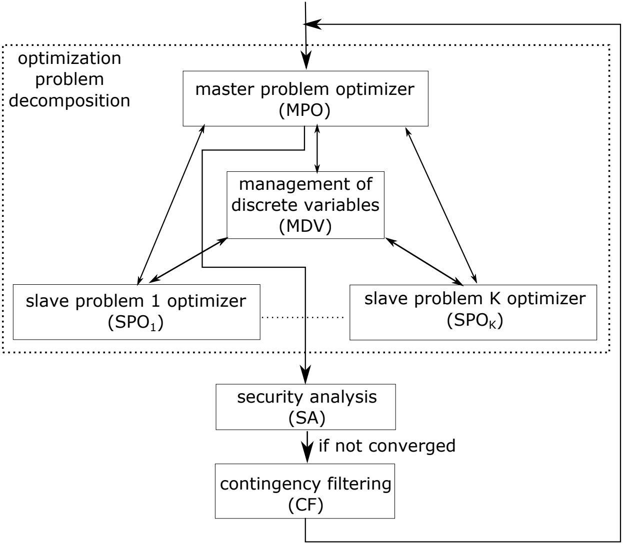
SCOPF decoupling: active power vs. reactive power

Under **normal operating conditions** generally:

- active power flows are weakly coupled with voltage magnitudes V
- reactive power flows are weakly coupled with voltage angles θ

<table>
<tr><th></th><th>active power</th><th>reactive power</th></tr>
<tr><td rowspan="2">control variables</td><td>generator active power
phase shifter angle
MW scheduled transfers</td><td>generator terminal voltage
transformer ratio
shunt reactor/capacitor</td></tr>
<tr><td colspan="2">network topology
load curtailment
generator start-up/shut-down</td></tr>
<tr><td>constraints</td><td>branch current
active power flows</td><td>voltage limits
reactive power flows</td></tr>
<tr><td>objective function</td><td>min generation cost
min controls deviation</td><td>min power losses
max reactive power reserves</td></tr>
</table>

SCOPF decomposition methodology



SCOPF problem decomposition: state-of-the-art

- Most severe contingencies together
  (Brian Stott and Ongun Alsac, since 1974)
- Benders decomposition for preventive-corrective SCOPF
  (A. Monticelli, M. Pereira, S. Granville - 1987)
- All potentially binding contingencies together
  (ULg, since 2007)
  - with post-contingency network compresion
    (ULg/GDF Suez - 2014)
- Adaptive Benders decomposition
  (D. Phan et al. - 2014)
- Alternating direction method of multipliers
  (D. Phan et al. - 2014)
- Along interior-point method structure
  (Q. Jiang et al. - 2014)

SCOPF decomposition: for further reading

[1] F. Capitanescu
Critical review of recent advances and further developments needed in AC optimal power flow, Electric Power Systems Research 136, 57-68
[2] B. Stott, O. Alsac
Optimal power flow - basic requirements for real-life problems and their solutions (White Paper), SEPOPE XII Symposium, Brazil, 2012
[3] L. Platbrood, F. Capitanescu, C. Merckx, H. Crisciu, L. Wehenkel
A Generic Approach for Solving Nonlinear-Discrete Security-Constrained Optimal Power Flow Problems in Large-Scale Systems,
IEEE Trans. Power Syst. 29 (3) (2014) 1194-1203
[4] D. Phan, J. Kalagnanam
Some efficient methods for solving the security-constrained optimal power flow problem,
IEEE Trans. Power Syst. 29 (2) (2014) 863-872
[5] Q. Jiang, K. Xu
A novel iterative contingency filtering approach to corrective security-constrained optimal power flow,
IEEE Trans. Power Syst. 29 (3) (2014) 1099-1109

Solution methods for the NLP core optimizer

If discrete variables are fixed or assumed continuous then SCOPF becomes a nonlinear programming (NLP) problem

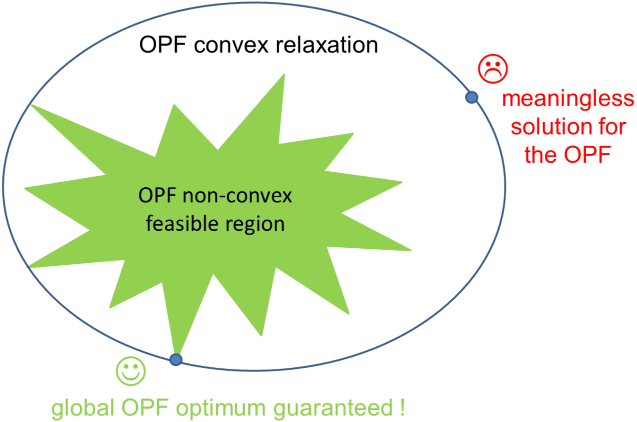
local optimizers: (at least) local optimum solution

- 1968: gradient method (H. Dommel and W. Tinney)
- 1973: sequential linear programming (O. Alsac and B. Stott)
- 1973: sequential quadratic programming (G. Reid and L. Hasdorf)
- 1984: Newton method (D. Sun et al.)
- 1994: interior-point method (Y. Wu et al., and S. Granville)

global optimizers: global optimum of a RELAXED problem

- 2012: convex relaxation (semidefinite programming) (J. Lavaei and S. Low)

Convex relaxations rationale



Convex relaxations: pros, cons, main findings

- provides a (tight?) lower bound on the NLP problem optimum
- if the duality gap of the convex relaxed problem is zero then its solution is also the global optimum of the original problem
  - else: convex relaxation solution is not physically meaningful
- provides a certificate of problem infeasibility
- the solution obtained with a local optimizer is the global optimum (or a solution of very high quality) in most cases

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- the solution obtained with a local optimizer is the global optimum (or a solution of very high quality) in most cases
- in the vast majority of experiments the relaxation did not return a feasible solution to the original non-convex problem !
- scalability remains to be proven (despite theoretical guarantees)
- phylosophical question: one does really need the global optimum of core NLP of MINLP problems ?

Numerical results with ULg-GDF Suez methodology

- coded mainly by Dr. Ludovic Platbrood in EU-FP7 PEGASE
- model the whole European transmission system
- 9241-buses and 12000 contingencies
- HPC: BladeCenter, 8 blades, 8 cores per blade, 2.6 Ghz clock rate
- overall time (with from the scratch assumptions): **65 minutes**

				computation time (s)		
iteration	variables	constraints	cont	core optimizer	security analysis	network compression
1	23000	50000	0	70	130	60
2	30000	64000	23	485	130	140
3	33000	70000	37	940	130	140
4	34000	72000	40	710	130	0
				2205 57 %	520 13 %	340 9 %

Conventional AC SCOPF: conclusions

- major progress on AC SCOPF methodologies reported
- AC SCOPF is computationally demanding
  - but still scalable to large systems and sets of contingencies
  - rely on local optimizers (e.g. KNITRO, IPOPT) for **NLP** core
  - convergence reliability of core optimizers should be improved
- under stringent running time requirements (up to one hour):
  - quality of solution (i.e. sub-optimality gap of the MINLP) **is less important** than feasibility (wrt the contingencies)
  - need fast heuristics for the management of discrete variables

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  - need fast heuristics for the management of discrete variables
- ... BUT IT DOES NOT FULLY FIT THE TODAY NEED FOR SUSTAINABILITY (I.E. INTEGRATION OF LARGE SHARES OF RENEWABLE GENERATION) !
- trilemma: economics vs security/reliability vs sustainability
  - expand the SCOPF scope: TSO-DSO, multi-period, etc.

SCOPF under uncertainty

Approaches to handling uncertainty

- chance-constrainted optimization
  - assumes a certain probability distribution of the uncertainty
  - enforces that the probability of constraints violation is smaller than a desired threshold (e.g. 0.05)
  - disregards the severity of constraints violation in the low likely cases
  - tractability issues due to the number of sampled uncertainty scenarios
- robust optimization
  - assumes that a probabilistic model of uncertainty is not available or trusted
  - covers security under all uncertainty set realizations
  - conservative (but controllable via uncertainty budget)
  - binary classification of system states (secure/insecure)

Definition of the uncertainty set $\mathcal{S}$

- uncertainty due to renewable generation (e.g. wind, solar), demand response, storage
- uncertainty set: bounded and independent active and reactive power injections at specified buses

$$
\begin{aligned}
\mathcal{S} = \{(P_{ui}, Q_{ui}) | & P_{ui}^{\min} \leq P_{ui} \leq P_{ui}^{\max}, \\
& Q_{ui}^{\min} \leq Q_{ui} \leq Q_{ui}^{\max}, \\
& P_{u}^{\min} \leq \sum c_{Pi} P_{ui} \leq P_{u}^{\max}, \\
& Q_{u}^{\min} \leq \sum c_{Qi} Q_{ui} \leq Q_{u}^{\max} \\
& c_{Pi} \in \{0,1\}, \quad c_{Qi} \in \{0,1\}, \\
& \forall i \in \mathcal{N} \}
\end{aligned}
$$

Robust optimization approach stemming from the EU FP7 PEGASE project

[1] F. Capitanescu, S. Fliscounakis, P. Panciatici, L. Wehenkel
Cautious operation planning under uncertainties. IEEE Transactions on Power Systems 27 (4) 2012, pp. 1859-1869.

[2] F. Capitanescu, L. Wehenkel
Computation of worst operation scenarios under uncertainty for static security management. IEEE Transactions on Power Systems 28 (2) 2013, pp. 1697-1705.

[3] S. Fliscounakis, P. Panciatici, F. Capitanescu, L. Wehenkel
Contingency ranking with respect to overloads in very large power systems taking into account uncertainty, preventive and corrective actions. IEEE Transactions on Power Systems 28 (4) 2013, pp. 4909-4017.

[4] P. Panciatici et al.
Security management under uncertainty: from day-ahead planning to intraday operation. IREP Symposium, Buzios (Brazil), 2010

General framework of the robust optimization approach

- CHECK whether, given the assumed uncertainty set, the worst case with respect to each contingency is controllable by appropriate preventive/corrective actions
- if needed determine WHICH common strategic actions should be taken to cover the uncontrollable worst-cases
- add a new stage in the day-ahead decision making process:
  - (strategic) slow preventive actions (e.g. starting up some power plants, postponing maintenance works)

  besides the typical two stages:
  - fast preventive actions (e.g. generation rescheduling, phase shifter actions)
  - corrective actions (e.g. generation rescheduling, network switching, phase shifter actions)

The principle

compute optimal day-ahead **strategic decisions** such that:

- whatever the **uncertainty** pattern in the assumed set
  - whatever the postulated **contingency**
    - the best combination of **preventive/corrective actions** leads to an acceptable system performance

General mathematical formulation of the problem

Three-level decision making ($\mathbf{u}_p$, $\mathbf{u}_o^s$, and $\mathbf{u}_c^{s,k}$) MINLP with an **infinite** number of constraints:

$$
\begin{aligned}
\min_{\mathbf{u}_p,\mathbf{u}_o^s,\mathbf{u}_c^{s,k}} \quad & f(\mathbf{u}_p, \tilde{\mathbf{u}}_p) & \\
\text{s.t.} \quad & \mathbf{g}_o^s(\mathbf{x}_o^s, \mathbf{u}_p, \mathbf{u}_o^s) = \mathbf{0} & \forall s \in \mathcal{S} \\
& \mathbf{h}_o^s(\mathbf{x}_o^s, \mathbf{u}_p, \mathbf{u}_o^s) \leq \mathbf{0} & \forall s \in \mathcal{S} \\
& \mathbf{g}_c^{s,k}(\mathbf{x}_c^{s,k}, \mathbf{u}_p, \mathbf{u}_o^s, \mathbf{u}_c^{s,k}) = \mathbf{0} & \forall (s,k) \in \mathcal{S} \times \mathcal{K} \\
& \mathbf{h}_c^{s,k}(\mathbf{x}_c^{s,k}, \mathbf{u}_p, \mathbf{u}_o^s, \mathbf{u}_c^{s,k}) \leq \mathbf{0} & \forall (s,k) \in \mathcal{S} \times \mathcal{K} \\
& \mathbf{u}_p \in \mathcal{U}_p & \\
& |\mathbf{u}_o^s - \tilde{\mathbf{u}}_o| \leq \Delta \mathbf{u}_o & \forall s \in \mathcal{S} \\
& |\mathbf{u}_c^{s,k} - \mathbf{u}_o^s| \leq \Delta \mathbf{u}_c & \forall (s,k) \in \mathcal{S} \times \mathcal{K}
\end{aligned}
$$

$\mathcal{U}_p$ is the set of strategic actions (e.g. units start-up)

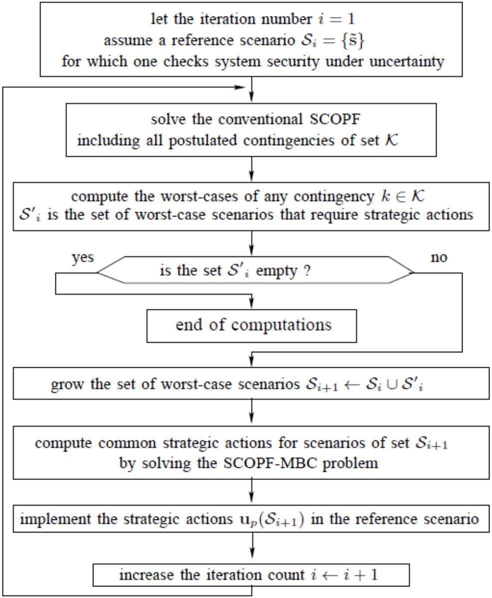
$\mathcal{S}$ is the set of scenarios and $\mathcal{K}$ is the set of contingencies

Worst-case wrt a contingency: problem formulation

$$
\begin{aligned}
\max_{\mathbf{s},\mathbf{r}} \ & \mathbf{1}^T \mathbf{r} \\
\text{s.t.} \ & \mathbf{s}^{\min} \leq \mathbf{s} \leq \mathbf{s}^{\max} \\
& \mathbf{r} \leq \mathbf{r}_\mathbf{c}^\star \\
& \mathbf{1}^T \mathbf{r}_\mathbf{c}^\star = \min_{\mathbf{u_0},\mathbf{u_c},\mathbf{r_c}} \quad \mathbf{1}^T \mathbf{r}_\mathbf{c} \\
& \qquad\qquad \text{s.t.} \quad \mathbf{g}_0(\mathbf{x}_0, \mathbf{u}_0, \mathbf{s}) = \mathbf{0} \\
& \qquad\qquad\qquad\ \ \mathbf{h}_0(\mathbf{x}_0, \mathbf{u}_0, \mathbf{s}) \leq \mathbf{0} \\
& \qquad\qquad\qquad\ \ \mathbf{g}_c(\mathbf{x}_c, \mathbf{u}_0, \mathbf{u}_c, \mathbf{s}) = \mathbf{0} \\
& \qquad\qquad\qquad\ \ \mathbf{h}_c(\mathbf{x}_c, \mathbf{u}_0, \mathbf{u}_c, \mathbf{s}) \leq \mathbf{r}_\mathbf{c} \\
& \qquad\qquad\qquad\ \ |\mathbf{u}_0 - \bar{\mathbf{u}}_0| \leq \Delta \mathbf{u}_0 \\
& \qquad\qquad\qquad\ \ |\mathbf{u}_c - \mathbf{u}_0| \leq \Delta \mathbf{u}_c \\
& \qquad\qquad\qquad\ \ \mathbf{r}_\mathbf{c} \geq \mathbf{0}
\end{aligned}
$$

bi-level programming solvers cannot tackle nonlinear problems!

Flowchart of the algorithm



let the iteration number $i = 1$
assume a reference scenario $\mathcal{S}_i = \{\tilde{s}\}$
for which one checks system security under uncertainty

solve the conventional SCOPF
including all postulated contingencies of set $\mathcal{K}$

compute the worst-cases of any contingency $k \in \mathcal{K}$
$\mathcal{S}'_i$ is the set of worst-case scenarios that require strategic actions

is the set $\mathcal{S}'_i$ empty ?

end of computations

grow the set of worst-case scenarios $\mathcal{S}_{i+1} \leftarrow \mathcal{S}_i \cup \mathcal{S}'_i$

compute common strategic actions for scenarios of set $\mathcal{S}_{i+1}$
by solving the SCOPF-MBC problem

implement the strategic actions $\mathrm{u}_p(\mathcal{S}_{i+1})$ in the reference scenario

increase the iteration count $i \leftarrow i + 1$

SCOPF under uncertainty: conclusions

- anytime algorithm computing at each iteration a more robust operation plan
- the identification of cases where no strategic action has to be taken in order to cover all worst-cases
- a heuristic approach to compute the worst-case under operation uncertainty for a contingency wrt overloads
  - the intractable benchmark bi-level worst-case optimization problem is decomposed into more tractable OPF-like and SCOPF-like problems which are solved sequentially
- the proposed algorithm is computationally very intensive
- the approach may benefit from modern high-performance parallel computing architectures
  - look at more efficient constraint relaxation schemes

Risk-based SCOPF

Toward more flexible security criteria

- the scope of the deterministic (N-1) security criterion
    - simple, clear
    - however, too narrowly defined
- it disregards contingencies likelihood of occurrence
- it splits post-contingency states in secure and insecure based on soft operational limits (e.g. currents and voltages)
- it disregards the *consequence of not (fully) securing some contingencies*
    - degree/number of constraints violation caused by contingencies
    - *loss of load*
- it ignores the failure of corrective control
- **it does not balance in a satisfactory manner economic savings and risk of not fully securing the system**

Motivations of the proposed RB-SCOPF approach

- **simple interpretability of the risk metric**
  - big(gest) challenge to RB-SCOPF is the estimation of the consequences of not fully securing all contingencies
  - estimating the loss of load due to cascading overload would be very useful but obtaining meaningful results is (to say the least) very challenging: big variability of results, models validity, etc.
  - acceptability by the operators
- **scalability** (fostering one day practical adoption by utilities)
  - given the limitation of deterministic AC SCOPF state-of-the-art
  - aim at not (much) worsening the computational effort
- **idea**: focus on prompt load shedding (shifting ?) to replace the intrinsic difficulties of estimating the loss of load
- RB-SCOPF balancing cost and expected amount of voluntary load shedding needed to remove overload in allotted time

Proposed risk metric and constraint

- risk constraint: $\sum_{k \in K} p_k \mathbf{1}^T (\mathbf{s}_0 - \mathbf{s}_k) \leq \text{risk}_{\text{max}}$
- drawback: setting the maximum allowed risk (risk_{max})

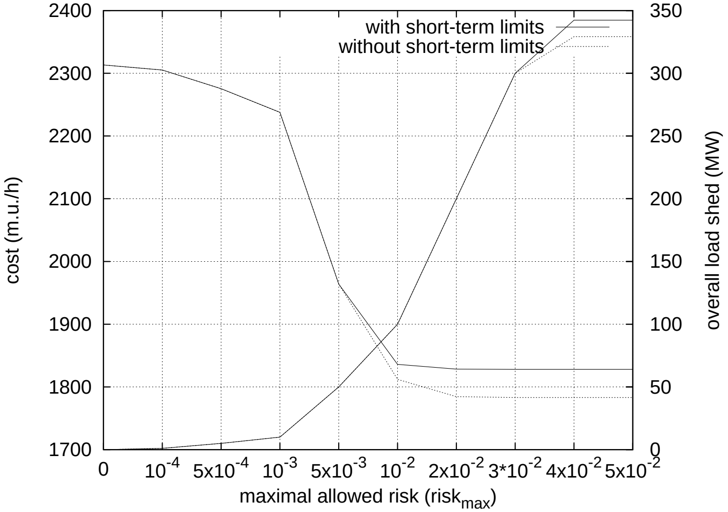
[1] F. Capitanescu
Enhanced risk-based SCOPF formulation balancing operation cost and expected voluntary load shedding

Electric power systems research, Vol. 128, 2015, pp. 151-155.

Proposed RB-SCOPF formulation

$$
\begin{aligned}
\min_{\mathbf{x}_0,\mathbf{u}_0,\mathbf{x}_k,\mathbf{u}_k,\mathbf{s}_k} \quad & f_0(\mathbf{x}_0,\mathbf{u}_0) & \\
\text{s.t.} \quad & \mathbf{g}_0(\mathbf{x}_0,\mathbf{u}_0) = \mathbf{0} & \\
& \mathbf{h}_0(\mathbf{x}_0,\mathbf{u}_0) \leq \overline{\mathbf{h}}_0 & \\
& \mathbf{g}_k(\mathbf{x}_k,\mathbf{u}_k,\mathbf{s}_k) = \mathbf{0}, & k \in K \\
& \mathbf{h}_k(\mathbf{x}_k,\mathbf{u}_k,\mathbf{s}_k) \leq c_2\overline{\mathbf{h}}_0, & k \in K \\
& |\mathbf{u}_k - \mathbf{u}_0| \leq \Delta\mathbf{u}_k, & k \in K \\
& \mathbf{s}_0 - \mathbf{s}_k \leq \Delta\mathbf{s}_k, & k \in K \\
& \mathbf{1}^T(\mathbf{s}_0 - \mathbf{s}_k) \leq \Delta\mathbf{s}^{\max}, & k \in K \\
& \sum_{k\in K} p_k\mathbf{1}^T(\mathbf{s}_0 - \mathbf{s}_k) \leq \text{risk}_{\max} &
\end{aligned}
$$

Impact of the maximum allowed risk level and short-term limits



RB-SCOPF conclusions

- research area insufficiently explored
- immense potential for scalable algorithms development
  - build upon existing deterministic SCOPF scalable methodologies
  - properly formulation of RB-SCOPF to take advantage of these scalable methodologies
- pay attention to a larger scope (e.g. short-term limits)
- set the ground for tackling risk-based SCOPF *under uncertainty*
- acceptability by operators given the arbitrariness of probabilities assigned to contingencies ?

Conclusions and challenges ahead

- risk-based AC SCOPF and AC SCOPF under uncertainty are in their infancy
- more flexible decision making process balancing risk and uncertainty, adapted to a smart sustainable grid environment
- develop the first generation of tractable risk-based AC SCOPF under uncertainty tools
    - immense potential for new frameworks and scalable algorithms
- improving operation flexibility shifting more the control balance from preventive control to corrective control
- extend the risk-based AC SCOPF under uncertainty to:
    - TSO-DSO interfaces (production migrates from TS to DS)
    - multi-periods (to account for energy-based behaviours: demand response, storage)
    - problem size explodes: contingencies × uncertainty scenarios × multi-period × DS
- need faster look-ahead SCOPF algorithms close to real time