Academia versus real-world in optimizing power system operation: the case of security-constrained optimal power flow

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KU Leuven, April 28-th, 2021
Outline of the presentation

▶ Gentle introduction to optimization
▶ Academic research: what benefit for the society?
▶ **Gaps** in optimal power flow (OPF)
  ▶ Solution methods (local optimizers vs convex relaxations)
  ▶ Some further complexity related to the OPF problem
  ▶ Suppressing ineffective control actions in OPF
  ▶ Handling of discrete variables
▶ **Gaps** in security constrained optimal power flow (SCOPF)
  ▶ Methodology to reduce the huge problem size
  ▶ Multiple limits in post-contingency state
  ▶ The use of a limited number of corrective actions
  ▶ Modeling of corrective actions based on TSO operation rules
  ▶ Usable solutions for infeasible problems
▶ Further key needs and conclusions
Gentle high-level introduction to optimization
Mathematical optimization and ... types of doctors

associate any health issue to a specific doctor (specialist)
Types (classes) of optimization problems

- an optimization problem is defined by the **triple**
  - objective function, decision variables, constraints

- solving **efficiently** optimization problems requires **tailored** algorithms
  - objective/constraints:
    - linear versus nonlinear
    - convex versus non-convex
    - continuous versus discontinuous
  - decision variables:
    - continuous versus binary/discrete

- additional potential features:
  - no objective (feasibility only) $\rightarrow$ constraint programming
  - complementarity (equilibrium) constraints
  - deterministic versus **uncertainty-infused** problems (stochastic, robust, chance constrained)
  - single objective versus multi-objective problems (Pareto front)
  - (intricate) multi-level optimization problem (e.g. bi-level)
How to solve an optimization problem?

- formulate the optimization problem in such a way such that to exploit its structure and features
  - often using smart reformulation to an equivalent problem
- tune and use generic off the shelf solvers
- ... even better develop a tailored algorithm if generic solver performance is not satisfactory
Choice of optimizers: general purpose vs tailored

EAs as problem solvers: Goldberg’s 1989 view

- A.E. Eiben and J.E. Smith, Introduction to Evolutionary Computing
  What is an Evolutionary Algorithm?

Performance of methods on problems

- Special, problem tailored method
- Meta-heuristic algorithm
- Random search

Scale of "all" problems

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Optimization approach: academia versus real-world
Bridging the death valley from academia to industry

How knowledge is transferred from academia to industry?
Criticism from industry folks

▶ Academia is ...
  ▶ working on (mathematically clean) *over-simplified* OPF problems
  ▶ developing solutions in search of a problem

Feedback from industry:
▶ needs and requirements of OPF tools spelled out
▶ large scale synthetic data sets (e.g. supplied with MATPOWER and others): thanks to RTE France initiative
▶ Grid Optimization Competition of US Department of Energy ARPA-E https://gocompetition.energy.gov/
▶ development of disruptive methods for *preventive* SCOPF
▶ good progress but still missing key aspects (corrective mode, discrete variables, decision variables other than generators)!
▶ On the other hand ...

realistic testbed OPF problems (data and full formulation) are non-existent!
Criticism from industry folks

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    - good progress but still missing key aspects (corrective mode, discrete variables, decision variables other than generators)!
    - I. Avramidis et al.” A novel approximation of SCOPF with incorporation of generator frequency and voltage control response” , IEEE TPWRS, 2021

- On the other hand ... realistic testbed OPF problems (data and full formulation) are non-existent!
OPF/SCOPF: problem formulation background

- **1962**: J. Carpentier: formulation of the OPF problem targeting economic operation of a power system
- **1974**: O. Alsac and B. Stott: formulation/solution of the SCOPF in *preventive* mode
- **1987**: A. Monticelli, M. Pereira, S. Granville: formulation/solution of the SCOPF in *corrective* mode
- **2012**: F. Capitanescu, S. Fliscounakis, P. Panciatici, L. Wehenkel: solution of the SCOPF *under uncertainties*
Conventional (deterministic) OPF formulation

non-convex nonlinear programming (NLP) problem

\[
\begin{align*}
\min_{x,u} & \quad f(x, u) \quad \leftarrow \text{objective function: generation cost} \\
\text{s.t.} & \quad g(x, u) = 0 \quad \leftarrow \text{AC power flow equations} \\
& \quad h(x, u) \leq 0 \quad \leftarrow \text{operation limits: currents, voltages} \\
& \quad u \leq u \leq \bar{u} \quad \leftarrow \text{physical limits of control variables}
\end{align*}
\]

- **x** - state/dependent variables: magnitude \( V \) and angle \( \theta \) of complex voltage at all buses
- **u** - continuous control/independent variables: active and reactive powers of generators

Is the solution of this problem an industry need? NO! ... it is a (simplified) building block in SCOPF
Conventional (deterministic) OPF formulation

**non-convex** nonlinear programming (NLP) problem

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\]

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Solution methods for the NLP core optimizer

**trade-off:** optimality vs reliability vs speed

**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 convex problem

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

OPF convex relaxation

OPF non-convex feasible region

meaningless solution for the OPF

global OPF optimum guaranteed!
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
Convex relaxations: pros, cons, main findings

- provides a (tight?) lower bound on the NLP problem optimum
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- 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
- 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)
- philosophical question: one does really need the global optimum of core NLP of MINLP problems?
Further complexity of OPF problems
OPF dispatch: active power vs. reactive power

Under **normal operating conditions** generally:

- active power flows are weakly coupled with voltage magn. \( V \)
- reactive power flows are weakly coupled with voltage angles \( \theta \)

<table>
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<tr>
<th>control variables</th>
<th>active power</th>
<th>reactive power</th>
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<td>generator active power</td>
<td>generator terminal voltage</td>
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<td>transformer ratio</td>
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<td>generator start-up/shut-down</td>
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<td>active power flows</td>
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<th>objective function</th>
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<th>min power losses</th>
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<td>min controls deviation</td>
<td>max reactive power reserves</td>
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Challenges to the OPF problem

- Suppressing ineffective control actions
- Handling of discrete variables
Why suppressing ineffective control actions in OPF?

- all control actions proposed by an OPF are truly effective to an operator?
- system operators want to understand why each control action proposed by OPF is needed and if it matches their experience
- issues for conventional OPF:
  - most conventional OPFs use the whole set of controls to solve the problem and very often (almost) all of them have moved at the optimal solution (some to rather arbitrary values)
  - almost every control variable participates in a non separable way to improving the objective and satisfying the constraints
  - control actions are not easy to rank and the effectiveness of an action is not necessarily related to its magnitude
- large but inefficient redispetch on some decision variables!
Why suppressing ineffective control actions in OPF?

- OPF input data are not perfectly known or (slightly) noisy
- the OPF problem model is an approximation of the reality fed with (slightly) imperfect data
- the rationale:
  - only effective control actions of an OPF should be computed as they have high likelihood to remain efficient in practice
  - the effect in practice of implementing also ineffective OPF control actions may be offset by the imperfect data/model
- meaning of optimization in practice is
  - improvement of operation performance of slightly noisy or imperfectly known real world system models
  - NOT rigorous optimization of academic ideal models
- suppressing ineffective control actions is important
The concept of suppressing ineffective controls

F. Capitanescu, Suppressing ineffective control actions in optimal power flow problems, IET GTD 14 (13), 2520-2527, 2020

- $n$ - the number of available controls in conventional OPF
- $N_{\text{min}}$ - the minimal number of controls to ensure feasibility
- $N$ - the number of effective control actions
OPF problem formulation as a **MINLP**

\[
\min_{x,u_c,u_d} \ f(x, u_c, u_d)
\]

\[
\begin{align*}
\text{s.t. } & \quad g(x, u_c, u_d) = 0 \\
& \quad h(x, u_c, u_d) \leq 0 \\
& \quad \underline{u}_c \leq u_c \leq \bar{u}_c \\
& \quad u_d = [u_{d1} \ldots u_{di} \ldots u_{dn_d}]^T \\
& \quad u_{di} \in \{u_{d1}^{1}, \ldots, u_{di}^{j}, \ldots, u_{di}^{p(i)}\} \\
\end{align*}
\]

\[\leftarrow \text{ generation cost, power losses}
\]

\[\leftarrow \text{ AC power flow equations}
\]

\[\leftarrow \text{ operational limits on } I, P, S, V
\]

\[\leftarrow \text{ bounds on control variables}
\]

- **x** - state/dependent variables: magnitude \( V \) and angle \( \theta \) of complex voltage at all buses
- **u_c** - continuous control variables: generator active power, generator terminal voltage, etc.
- **u_d** - discrete/binary control variables: transformer ratio, phase shifter angle, shunt reactive power (capacitors/reactors), network topology, etc.
Handling of discrete variables

- Variables with small discrete steps:
  - transformer ratio
  - phase shifter angle
  - shunt reactors/capacitors reactive power

- Variables with large discrete steps and binary variables:
  - network switching
  - unit start-up/shut down
  - shunt reactors/capacitors reactive power
Handling of discrete variables

- OPF is a mixed-integer nonlinear programming problem
  - MINLP classical methods are not yet sufficiently mature to cope with very large size (non-convex) problems
- handling of discrete variables is a trade-off between:
  - degree of sub-optimality
  - reliability (ability to deal with infeasible discrete variables configurations)
  - computational speed
- related works:
  - simple heuristics: round-off, progressive round-off
  - penalty functions within NLP or LP solvers
  - ordinal optimization
  - mixed-integer linear programming (MILP)
  - interior point cutting plane
  - global optimization methods: genetic algorithms, simulate annealing, tabu search
Biggest gap: handling N-1 security is the core business of TSOs!
Conventional Security Constrained Optimal Power Flow (SCOPF)
What is power system security?

- a **contingency** is the unexpected disconnection of one or multiple system elements (e.g. generator, line)
- **security** = power system ability to **withstand** contingencies
  - ensure a **stable** transition towards a **viable equilibrium point** without loss of load
- power system operation **must comply** with the **N-1 security criterion**
  - that is at any time the system must be able to withstand the loss of any **single** equipment
Day-ahead operational planning

- **SCOPF**: computes cost-optimal preventive/corrective control actions to satisfy **static security constraints** (thermal & voltages) for each foreseen operation state of next day.
Conventional (deterministic) SCOPF formulation

\[
\begin{align*}
\min_{x_0,\ldots,x_c,u_0,\ldots,u_c} & \quad f(x_0, u_0) \\
\text{s.t.} & \quad g_0(x_0, u_0) = 0 & \leftarrow \text{base case constraints} \\
& \quad h_0(x_0, u_0) \leq 0 & \leftarrow \text{base case constraints} \\
& \quad g_k(x_k, u_k) = 0 & \quad k = 1, \ldots, c & \leftarrow \text{contingency } k \text{ constraints} \\
& \quad h_k(x_k, u_k) \leq 0 & \quad k = 1, \ldots, c & \leftarrow \text{contingency } k \text{ constraints} \\
& \quad \left| u_k - u_0 \right| \leq \Delta u^\text{max}_k & \quad k = 1, \ldots, c & \leftarrow \text{“coupling” constraints}
\end{align*}
\]

- **x** - state/dependent variables:
  magnitude \( V \) and angle \( \theta \) 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
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 $2000 \times 3000 = 6.000.000$ equality constraints
  - around $6000 \times 3000 = 18.000.000$ inequality constraints
  - around $1000 \times 3000 = 3.000.000$ control variables
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  - around $1000 \times 3000 = 3.000.000$ 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 decomposition methodology

start

master problem optimizer

manager of discrete variables

security analysis (contingency feasibility check)

select new potentially dangerous contingencies

contingency 1 optimizer

slave problems

contingency K optimizer

are all contingencies controllable?

yes

no

stop

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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 (5000 control variables) 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

<table>
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<td>13 %</td>
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</table>
Further modelling issues in SCOPF
Multiple post-contingency line thermal limits

I(t)
I(0)
t
1min
L0
5min 15min
L1
L2

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Limiting the number of corrective actions in SCOPF

\[-s_k \Delta u_k^{\text{max}} \leq u_k - u_0 \leq s_k \Delta u_k^{\text{max}} \quad k = 1, \ldots, c\]

\[1^T s_k \leq N_k \quad k = 1, \ldots, c\]

\[s_k \in \{0, 1\} \quad k = 1, \ldots, c\]

- \(N_k\) is the maximum number of corrective actions allowed
- \(s_k\) is a vector of statuses of corrective actions
  - if \(s_{kj} = 1\) then the corrective action \(u_{kj}\) is allowed:
    \[-\Delta u_{kj}^{\text{max}} \leq u_{kj} - u_{0j} \leq \Delta u_{kj}^{\text{max}}\]
  - if \(s_{kj} = 0\) then this action is not allowed: \(u_{kj} = u_{0j}\)
- Binary variables \(s_k\) increases the problem complexity
- Possible approach for \textbf{thermal constraints}:
  - Compute \(s_k\) from the MILP problem approximation
    - Of the whole SCOPF problem
    - Of each post-contingency state (simulated at the OPF solution)
Modelling of corrective actions based on SO operating rules

- the conventional SCOPF does not model SO operating rules which associate a pre-defined set of corrective actions (determined based on the SO’ knowledge of the system) with a given post-contingency constraint violation
- such corrective actions are activated only if the constraints are not satisfied by preventive actions
- the set of constraints of corrective actions based on SO operating rules:

\[-b_k \Delta u_k^{\text{max}} \leq u_k - u_0 \leq b_k \Delta u_k^{\text{max}} \quad k = 1, \ldots, c\]

\[(b_k - 1)\lambda_k < h_k(x_k, u_k) \leq b_k \lambda_k \quad k = 1, \ldots, c\]

\[b_k \in \{0, 1\}, \lambda_k > 0 \quad k = 1, \ldots, c\]

- binary variables \(b_k\) are used to decide the activation of control action \(u_k - u_0\) \(\lambda_k\) is a vector of very large positive values
Usable solutions for infeasible SCOPF problems due to conflicting contingencies

F. Capitanescu,
Approaches to Obtain Usable Solutions for Infeasible Security-Constrained Optimal Power Flow Problems Due to Conflicting Contingencies”,
Feasible contingencies

C1

C2

base case
Conflicting contingencies

C1
C2
C3
base case

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Conflicting and infeasible contingencies

C1
C2
C4
C3
base case
u1
u2

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Relaxation of Control Variables Set

\[
\min_{u_0, u_k, s_k} \ p_0 f_0(x_0, u_0) + \sum_{k \in K} p_k f_k(x_k, u_k, s_k)
\]

\[
g_0(x_0, u_0) = 0
\]

\[
h_0(x_0, u_0) \leq 0
\]

\[
g_k(x_k, u_k, s_k) = 0 \quad k \in K
\]

\[
h_k(x_k, u_k, s_k) \leq 0 \quad k \in K
\]

\[
|u_k - u_0| \leq \Delta u_k \quad k \in K
\]

\[
s_0 - s_k \leq \Delta s \quad k \in K
\]

\[
1^T (s_0 - s_k) \leq \Delta s^{max} \quad k \in K
\]
Relaxation of Operation Constraints Set

\[
\min_{\mathbf{u}_0, \mathbf{u}_k, \mathbf{h}_k^+} f_0(\mathbf{x}_0, \mathbf{u}_0) + \beta \sum_{k \in K} \mathbf{h}_k^+
\]

\[
\begin{align*}
g_0(\mathbf{x}_0, \mathbf{u}_0) &= 0 \\
h_0(\mathbf{x}_0, \mathbf{u}_0) &\leq 0 \\
g_k(\mathbf{x}_k, \mathbf{u}_k) &= 0 & k \in K \\
h_k(\mathbf{x}_k, \mathbf{u}_k) &\leq \mathbf{h}_k^+ & k \in K \\
|\mathbf{u}_k - \mathbf{u}_0| &\leq \Delta \mathbf{u}_k & k \in K \\
\mathbf{h}_k^+ &\geq 0 & k \in K
\end{align*}
\]
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

TAKE HOME MESSAGE: The OPF community should use the great talent and math inclination to address complex issues beyond the 60 years old Carpentier' formulation!
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AC SCOPF: future works

- ... 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
AC SCOPF: future works

- ... 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: uncertainty, temporal aspects, TSO-DSO cooperation, etc.
Advanced formulations/algorithms for SCOPF

EU Horizon 2020 project ATTEST (03/2020 - 02/2023) https://attest-project.eu/

ATTEST stands for “Advanced Tools Towards cost-efficient decarbonisation of future reliable Energy SysTems”

LIST team (Mohammad Iman Alizadeh, Muhammad Usman and myself) develops an advanced formulation/algorithm to extend day-ahead SCOPF to consider (to the best possible extent) uncertainties and time periods

LIST develops a stochastic multi-period AC SCOPF
  ▶ current capability: 60 nodes, 33 contingencies, 24 periods, 30 uncertainty scenarios → equivalent to AC OPF for a 1.5M nodes system
  ▶ research paper under review to EPSR
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 by shifting the control balance from preventive control to corrective control
- need faster look-ahead SCOPF algorithms close to real time
- 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
Security management trade-off: uncertainty vs risk