Probabilistic Reliability Management for Electric Power Systems Operation

Louis Wehenkel

joint work with L. Duchesne and E. Karangelos

Cambridge: 25.04.2019



Montefiore Institute

The nature of Electric Power Systems

Schematic view of a generic Electric Power System



Mission: Deliver electricity from producers to consumers, while ensuring high reliability of supply at the lowest possible cost

The European Electric Power System



- A network of ≈ 30,000 branches / 20,000 nodes at EH voltage levels (225-400kV)
- About 30 Transmission System Operators (TSOs)
- Coupled energy markets
- Quickly increasing penetration of renewable generation
- Ageing physical infrastructure
- Increasing uncertainties and faster dynamics
- Cost: 20-30% of electricity bill



Electric power system reliability

• Requirement:

• At sub-second temporal resolution, balance generation/storage/consumption, under network constraints, in spite of various threats

• Threats faced:

- Variations of generation and demand, weather conditions
- Component failures, human errors, adversarial attacks

Problems to avoid:

- Component overloads, voltage or frequency deviations
- Cascading overloads, instabilities, blackouts

Opportunities:

- Optimisation and control of flows closer to real-time
- Preventive maintenance and planning of operation
- Adaptation of the grid structure to market needs

Reliability management (objective)

Taking decisions in order to ensure the reliability of the system while minimizing socio-economic costs



Organisation of the talk

PART I

Traditional Approach to Reliability Control in Operation

• PART II Probabilistic Problem Formulations

PART III

From Operation to Maintenance and Design

Traditional Approach to Reliability Control in Operation $\bullet \circ \circ$

Part I

Traditional Approach to Reliability Control in Operation

- Decomposition of the overall problem
- Layer-wise models and control strategies

... introduced soon after the US Northeast blackout of 1965

Decomposition into 4 concurrent control layers



• Emergency control layer

- fast response of automatic control and protection devices
- behavior predicted by deterministic time-domain simulation

• Emergency control layer

- fast response of automatic control and protection devices
- behavior predicted by deterministic time-domain simulation

• Corrective control layer

- if necessary, steer the system back into stable conditions
- OPF problem (big MINLP)

• Emergency control layer

- fast response of automatic control and protection devices
- behavior predicted by deterministic time-domain simulation

• Corrective control layer

- if necessary, steer the system back into stable conditions
- OPF problem (big MINLP)

• Preventive control layer

- ensure security with respect to all N-1 contingencies
- SCOPF problem (much bigger MINLP)

• Emergency control layer

- fast response of automatic control and protection devices
- behavior predicted by deterministic time-domain simulation

• Corrective control layer

- if necessary, steer the system back into stable conditions
- OPF problem (big MINLP)

• Preventive control layer

- ensure security with respect to all N-1 contingencies
- SCOPF problem (much bigger MINLP)

• Operation planning layer

- enable secure next-day operation around most likely forecast
- Multi-step SCOPF problem (even much bigger MINLP)

Probabilistic Problem Formulations

Part II

Probabilistic Problem Formulations

- Motivations for probabilistic approaches
- Real-time sub-problem
- Operation-planning sub-problem

Motivations for probabilistic approaches

- What about
 - The variable probabilities of N-1 contingencies, and those of N-2, N-3, ... contingencies ?
 - Acknowledging uncertain corrective and emergency control responses ?
 - Taking into account the probability of large deviations from forecasts ?
 - Handling infeasibility of the N-1 (or any other) security criterion ?

Motivations for probabilistic approaches

- What about
 - The variable probabilities of N-1 contingencies, and those of N-2, N-3, ... contingencies ?
 - Acknowledging uncertain corrective and emergency control responses ?
 - Taking into account the probability of large deviations from forecasts ?
 - Handling infeasibility of the N-1 (or any other) security criterion ?
- Large amounts of renewable and dispersed generation, indeed lead to faster changing and less predictable flows

Motivations for probabilistic approaches

- What about
 - The variable probabilities of N-1 contingencies, and those of N-2, N-3, ... contingencies ?
 - Acknowledging uncertain corrective and emergency control responses ?
 - Taking into account the probability of large deviations from forecasts ?
 - Handling infeasibility of the N-1 (or any other) security criterion ?
- Large amounts of renewable and dispersed generation, indeed lead to faster changing and less predictable flows
- Deterministic approaches disregard information about probabilities of threats and failure mechanisms
- State-of-the-art computing and data driven methods could enable more informed decision making

Probabilistic Problem Formulations

Real-time sub-problem: preventive and corrective control



Real-time sub-problem: preventive and corrective control



Pictorial view of real-time reliability control



Two-stage stochastic programming formalization

In compact form, the real-time preventive/corrective control problem amounts to

$$\min\left(f_p(u_p) + \dots\right) (1)$$
s.t. $u_p \in U_p (2)$
(3)
(4)

where

- U_p , the set of allowed preventive control decisions
- $f_p(u_p)$, the cost of preventive controls (first-stage cost)

(NB: we hide the fact that all quantities may depend on the real-time situation s.)

Two-stage stochastic programming formalization

In compact form, the real-time preventive/corrective control problem amounts to

$$\min\left(f_{\rho}\left(u_{\rho}\right)+\sum_{c\in C}\pi_{c}(c)\left[f_{c}\left(u_{c}(c)\right)+\ldots\right]\right) \quad (1)$$

 $u_p \in U_p$ (2)

$$\forall c: u_c(c) \in U_c(u_p) \tag{3}$$

where

s.t.

- U_p , the set of allowed preventive control decisions
- $f_p(u_p)$, the cost of preventive controls (first-stage cost)
- C, the set of possible contingencies c, π_c their probabilities
- $U_c(u_p)$, the set of allowed corrective controls $u_c(c)$
- $f_c(u_c)$, the cost of corrective controls (second stage cost)

(4)

Two-stage stochastic programming formalization

In compact form, the real-time preventive/corrective control problem amounts to

$$\min\left(f_{p}\left(u_{p}\right)+\sum_{c\in C}\pi_{c}(c)\left[f_{c}\left(u_{c}(c)\right)+\sum_{b\in B}\pi_{b}\left(b|u_{c}(c)\right)f_{e}\left(u_{p},c,u_{c}(c),b\right)\right]\right)$$
(1)

s.t.

$$u_p \in U_p$$
 (2)

$$\forall c: u_c(c) \in U_c(u_p) \tag{3}$$

$$\mathbb{P}_{c,b}\{f_e(u_p, c, u_c(c), b) \le \delta\} \ge 1 - \epsilon$$
(4)

where

- U_p , the set of allowed preventive control decisions
- $f_p(u_p)$, the cost of preventive controls (first-stage cost)
- C, the set of possible contingencies c, π_c their probabilities
- $U_c(u_p)$, the set of allowed corrective controls $u_c(c)$
- $f_c(u_c)$, the cost of corrective controls (second stage cost)
- B, the set of possible behaviors b in emergency control, π_b their probabilities
- $f_e(u_p, c, u_c(c), b)$, the cost of service interruptions for a scenario (terminal cost)

- Size of the problem (e.g. for the TSO of Belgium or France)
 - #C in the order of 10^6 (considering all N-2 contingencies)
 - U_p and U_c high-dimensional integer/continuous spaces (dim $\geq 10^3$)
 - All in all, in the order of 10^9 decision variables

- Size of the problem (e.g. for the TSO of Belgium or France)
 - #C in the order of 10^6 (considering all N-2 contingencies)
 - U_p and U_c high-dimensional integer/continuous spaces (dim $\geq 10^3$)
 - All in all, in the order of 10⁹ decision variables
- The main additional difficulty comes from function f_e
 - it translates the emergency control outcome along a scenario (in the form of an estimate of the cost of service interruptions).
 - the physical behavior of the power system leads to a high dimensional set of non linear (i.e. non convex) power flow equations.

- Size of the problem (e.g. for the TSO of Belgium or France)
 - #C in the order of 10^6 (considering all N-2 contingencies)
 - U_p and U_c high-dimensional integer/continuous spaces (dim $\geq 10^3$)
 - All in all, in the order of 10⁹ decision variables
- The main additional difficulty comes from function f_e
 - it translates the emergency control outcome along a scenario (in the form of an estimate of the cost of service interruptions).
 - the physical behavior of the power system leads to a high dimensional set of non linear (i.e. non convex) power flow equations.
- The chance constraint $\mathbb{P}\{f_e \leq \delta\} \geq 1 \epsilon$
 - It models the target reliability level sought by the TSO
 - It can be expressed by using auxiliary binary variables (given the finite number of scenarios).

- Size of the problem (e.g. for the TSO of Belgium or France)
 - #C in the order of 10^6 (considering all N-2 contingencies)
 - U_p and U_c high-dimensional integer/continuous spaces (dim $\geq 10^3$)
 - All in all, in the order of 10⁹ decision variables
- The main additional difficulty comes from function f_e
 - it translates the emergency control outcome along a scenario (in the form of an estimate of the cost of service interruptions).
 - the physical behavior of the power system leads to a high dimensional set of non linear (i.e. non convex) power flow equations.
- The chance constraint $\mathbb{P}\{f_e \leq \delta\} \geq 1 \epsilon$
 - It models the target reliability level sought by the TSO
 - It can be expressed by using auxiliary binary variables (given the finite number of scenarios).
- NB: outcome of solving the real-time control problem
 - Optimal preventive control u_p^* and corrective control strategy $u_c^*(c)$.
 - If not feasible needs relaxation (see the end of this talk)

Solution strategies (recent results)

Progressively growing of the set of contingencies

- Simulate contingency responses and rank them by order of impact
- Then, solve optimization problem on top impact subset
- Iterate, by growing the set greedily until chance constraint is satisfied.

Solution strategies (recent results)

Progressively growing of the set of contingencies

- Simulate contingency responses and rank them by order of impact
- Then, solve optimization problem on top impact subset
- Iterate, by growing the set greedily until chance constraint is satisfied.
- Simplified modeling of the emergency control layer
 - Replace by a set of constraints to ensure that no severe service interruption would occur under successful operation of corrective control
 - Use simplified (optimistic/pessimistic) models to (upper/lower) bound cost of service interruption in case of corrective control failure

Solution strategies (recent results)

Progressively growing of the set of contingencies

- Simulate contingency responses and rank them by order of impact
- Then, solve optimization problem on top impact subset
- Iterate, by growing the set greedily until chance constraint is satisfied.

Simplified modeling of the emergency control layer

- Replace by a set of constraints to ensure that no severe service interruption would occur under successful operation of corrective control
- Use simplified (optimistic/pessimistic) models to (upper/lower) bound cost of service interruption in case of corrective control failure

Outting both together, makes solution reachable:

- GARPUR FP7 project deliverables See http:www.garpur-project.eu/deliverables D2.2, D6.2, D9.1
- E. Karangelos and L. Wehenkel. IEEE Trans. on PS, 2019.

Still cumbersome computations (see next slide)

Illustrative CPU times

(Computing env.: 2 core Intel 2.9 GHz/16GB RAM; IPOPT/JULIA)

- Test Case:
 - System: IEEE 3-area RTS (73 buses/120 branches/111 contingencies)
 - Physical model: AC power flow model; no dynamics;
 - One-shot SCOPF without chance-constraint (for reference):
 - 180,000 vars, 140.000 eq. constraints, 30,000 ineq. constraints
 - 1200 sec. CPU time

• Proposed iterative probabilististic approach (*epsilon* 5e-3 \rightarrow 5e-6):

- Number of SIMUL/OPTIM iterations: $1 \rightarrow 11$
- $\bullet~$ Overall CPU time for sequential impl.: 220 \rightarrow 2500 sec.
- Proportion of CPU-time devoted to OPTIM only:
 - With a sequential Cont.SIMUL: 6% 11% (measured)
 - With a parallel Cont.SIMUL: 83% 93% (extrapolated)
- Under the assumption that the Cont. SIMUL part can be reduced by trivial parallel computations over the set of contingencies, the OPTIM part is clearly the challenge for large scale systems.

Operation planning sub-problem: preparing operation



Operation planning sub-problem



Pictorial view of operation planning



Preparing real-time operation

- Ensure (with high enough probability) feasibility of reliable real-time operation
- Horizon of several hours to days
 - Day(s)-ahead:
 - predict weather, demand, market over the next day(s)
 - prepare some strategic actions
 - Intra-day:
 - use incoming information to revise strategic actions, and launch them only at the latest possible moment
- Minimize deviation from market clearing: only act if feasibility of reliable real-time operation is in danger
- Take into account preventive and corrective real-time control strategies and their possible failures over the next horizon

Solution strategies (work in progress)

Choose u_o optimizing economics and ensuring feasibility of reliable operation over possible future scenarios for 24 or 48 time steps.

- Rationale:
 - Economics: driven by the immediate cost of u_o and the implied cost of u_{rt} over the likely next day scenario(s).
 - Reliability: driven by the capability to operate during the next day for expectable worst-case scenarios and contingencies.
- Modeling strategy:
 - Real-time operation modelled 'as an automaton' along next day horizon according to previous explanations.
 - Problem is hence a 'single stage stochastic programming problem'
 - However the real-time reaction to day ahead decisions is modelled by a sequence of complex optimization problems.
- Computational strategy:
 - Discretize uncertainty set in order to build a finite dimensional optimization problem.
 - Define suitable 'fast' proxies to model real-time operation.

Uncertainty model for operational planning



A scenario tree for operation planning over a horizon of 24h, starting at the current time t, with recourses at t + 3h, t + 6h, t + 12h, t + 24h.

Each path represents a 24h exogenous scenario; nodes correspond to planning decision-making opportunities. The nominal scenario is highlighted.

Once the tree is 'solved', only the planning decision at current t is launched.

At any subsequent opportunity, a new tree may be regrown and re-optimized, based on new information about S_o .

Ongoing research tracks

- Use Machine Learning to build proxies of real-time operation
- Use the learnt proxies in combination with variance reduction approaches to speed up assessment of day-ahead decisions
- Use learnt proxies to help discretizing the set of possible scenarios to be incorporated into the day-ahead decision making problem formulation.
- Iterate assessment and optimization, while exploiting massive parallel computations.
- See L. Duchesne et al, IEEE PowerTech 2017 and PSCC 2018; E. Karangelos et al, IREP 2017.

From System Operation to System Design

Part III

From System Operation to System Maintenance and Design

- Asset management and system development
- The general reliability management problem

Asset management and system development vs operation



Asset management: Outage scheduling



- When to carry out given maintenance and replacement operations ?
- Typically planned on the basis of a yearly horizon
- Should model logistic and system operation constraints
- Goal is to minimize cost plus impact on operation
- Take uncertainties into account via Monte-Carlo simulation

Asset management: Maintenance budgeting



Ageing Infrastructure Need to anticipate Avoid Investment Wall

- How much to invest in maintenance vs replacement to maintain overall reliability expectations ?
- How to spread the maintenance and replacement efforts over time ?
- Needs to consider long-term horizons of 20 30 years
- Should model component ageing, impact of maintenance, feasibility of outage scheduling and system operation

From System Operation to System Design

System development

Adapt the grid structure to cope with future electricity generation and consumption patterns

- Where to build new lines, new substations, new transformers ?
- What kind of technology choice (capacity, DC vs AC, underground vs overhead, ...) ?



- What other companion investments ?
 - Electricity storage, IT infrastructure, ...
- Goal is to optimize compromize between CAPEX and OPEX (including future maintenance and operation costs)
- Needs to model uncertainties about system needs and future technological solutions

Formulated as a multi-stage decision making problem over horizon 0...T, under assumed exogenous uncertainties $\xi_{1...T} \sim (S, \mathbb{P})$, with candidate policies $u_{0...T-1} \in U$, and known state transitions $x_{t+1} = f_t(x_t, u_t, \xi_{t+1})$.

(these 4 modelling items depend on the considered reliability management context)

(1) Socio-economic objective function over horizon: $\max_{u} \mathbb{E} \{ \sum_{t=0}^{T} (\text{Market surplus - TSO costs - Costs of service interruptions}) \}$... i.e. the fully orthodox social-welfare optimizer viewpoint...

Formulated as a multi-stage decision making problem over horizon 0...T, under assumed exogenous uncertainties $\xi_{1...T} \sim (S, \mathbb{P})$, with candidate policies $u_{0...T-1} \in U$, and known state transitions $x_{t+1} = f_t(x_t, u_t, \xi_{t+1})$.

(these 4 modelling items depend on the considered reliability management context)

- (1) Socio-economic objective function over horizon: $\max_{u} \mathbb{E} \{ \sum_{t=0}^{T} (Market surplus - TSO costs - Costs of service interruptions) \}$
- (2) Reliability target over induced system trajectories:
 s.t. P{x_{1...T}(ξ, u) ∈ X_∂} ≥ 1 − ε

... the "bon père de famille" attitude to avoid catastrophes...

Formulated as a multi-stage decision making problem over horizon 0...T, under assumed exogenous uncertainties $\xi_{1...T} \sim (S, \mathbb{P})$, with candidate policies $u_{0...T-1} \in U$, and known state transitions $x_{t+1} = f_t(x_t, u_t, \xi_{t+1})$.

(these 4 modelling items depend on the considered reliability management context)

- (1) Socio-economic objective function over horizon: $\max_{u} \mathbb{E} \{ \sum_{t=0}^{T} (Market surplus - TSO costs - Costs of service interruptions) \}$
- (2) Reliability target over induced system trajectories:
 s.t. P{x_{1...τ}(ξ, u) ∈ X_a} ≥ 1 − ε
- (3) Uncertainty discarding principle: allows to trim (S, \mathbb{P}) to (S_c, \mathbb{P}_c) , provided that approximation in $(1) \leq \Delta E$ to make things possible from the computational viewpoint...

Formulated as a multi-stage decision making problem over horizon 0...T, under assumed exogenous uncertainties $\xi_{1...T} \sim (S, \mathbb{P})$, with candidate policies $u_{0...T-1} \in U$, and known state transitions $x_{t+1} = f_t(x_t, u_t, \xi_{t+1})$.

(these 4 modelling items depend on the considered reliability management context)

- (1) Socio-economic objective function over horizon: $\max_{u} \mathbb{E} \{ \sum_{t=0}^{T} (Market surplus - TSO costs - Costs of service interruptions) \}$
- (2) Reliability target over induced system trajectories:
 s.t. P{x_{1...τ}(ξ, u) ∈ X_a} ≥ 1 − ε
- (3) Uncertainty discarding principle: allows to trim (S, \mathbb{P}) to (S_c, \mathbb{P}_c) , provided that approximation in $(1) \leq \Delta E$.
- (4) Relaxation principle:

allows to relax $\Delta E \rightarrow \Delta E + \lambda$ if (2)+(3) yield an unfeasible problem.

... to work it out in all possible situations encountered in practice...

From System Operation to System Design

GARPUR RMAC: in pictures







Reliability target

Socio-economic objective

Discarding principle



Relaxation principle



Temporal coherence proxies

From System Operation to System Design

As concerns the future, your task is not to foresee it, but to enable it

Antoine de Saint-Exupéry

Some bibliographical pointers



P. Panciatici, G. Bareux and L. Wehenkel

Operating in the fog - Security management under uncertainty IEEE Power & Energy Magazine, 2012, september/october, 40-49



E. Karangelos, P. Panciatici and L. Wehenkel

Whither probabilistic security management for real-time operation of power systems ? *Proc. of IREP Symposium*, Rethymnon 2013



E. Karangelos and L. Wehenkel

Probabilistic reliability management approach and criteria for power system real-time operation *Proc. of PSCC*, Genoa 2016



E. Karangelos and L. Wehenkel

Probabilistic reliability management approach and criteria for power system short-term operational planning Proc. of IREP Symposium, Porto 2017



L. Duchesne, E. Karangelos, and L. Wehenkel

Machine learning of real-time power systems reliability management response *Proc. of IEEE PowerTech*, Manchester 2017



Using machine learning to enable probabilistic reliability assessment in operation planning *Proc. of PSCC*, Dublin 2018



E. Karangelos, and L. Wehenkel

An iterative AC-SCOPF approach managing the contingency and corrective control failure uncertainties with a probabilistic guarantee

IEEE Trans. on Power Systems, 2019

Acknowledgments

- This work has been supported by
 - FNRS (Wallonia)
 - IUAP federal program DYSCO (Belgium)
 - PEGASE and GARPUR FP7 projects (EC)
 - RTE (France)
 - The Montefiore Institute, University of Liège, Be
 - The Isaac Newton Institute, University of Cambridge, UK
 - The Simons Foundation
- This work was also inspired by many discussions with a number of colleagues from Academia and Industry.