

Probabilistic Reliability Management for Changing Electric Power Systems

Louis Wehenkel

joint work with L. Duchesne and E. Karangelos

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Montefiore Institute

Organisation of the talk

- PART I
Current Organization of Reliability Control in Operation
- PART II
Probabilistic Problem Formulations
- PART III
From System Operation to System Design
- PART IV
Recent Developments

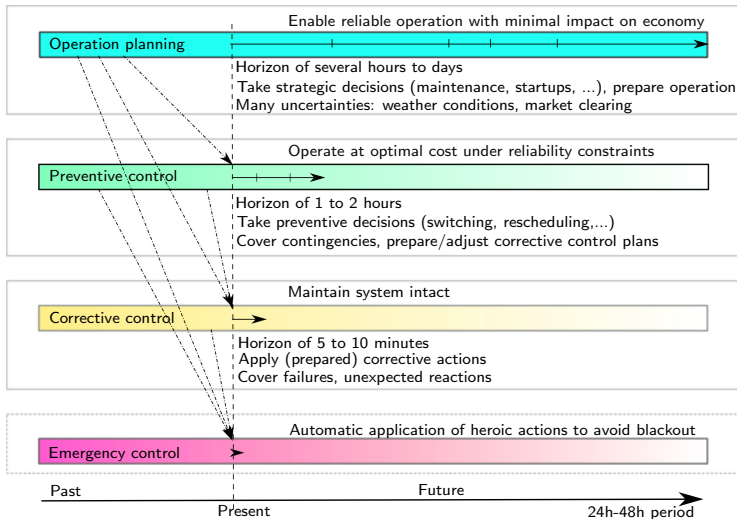
Part I

Current Organization of Reliability Control in Operation

- Decomposition of the overall problem in 4 concurrent layers
- Deterministic approaches and tools



Overall problem decomposition





Deterministic approaches and possible tools

- **Emergency control response**
 - Need to anticipate its outcome, e.g. “stable” vs “unstable”
 - Dynamic Simulation Problem (complex NL DAE)



Deterministic approaches and possible tools

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 - Dynamic Simulation Problem (complex NL DAE)
- **Corrective control layer**
 - If necessary, steer the system back into stable conditions
 - Generalized OPF problem (big MINLP)

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- **Preventive control layer**
 - Secure stability with respect to all N-1 contingencies
 - SCOPF problem (much bigger MINLP)

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- **Preventive control layer**
 - Secure stability 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)

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 ?

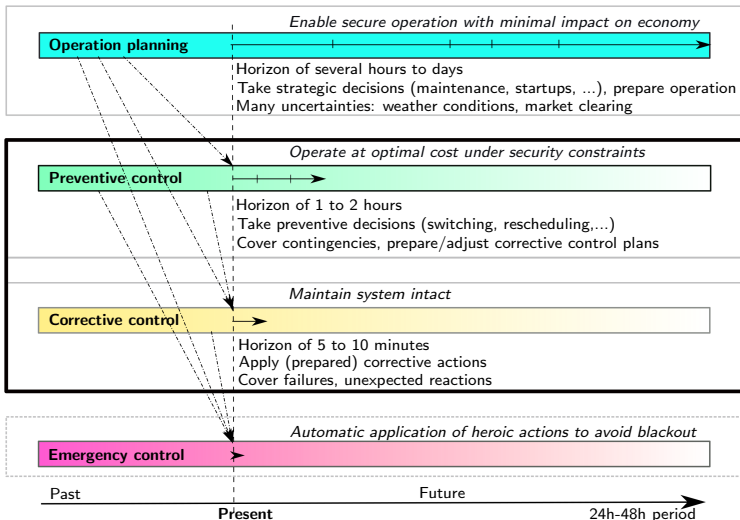
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 - Handling **infeasibility** of the N-1 (or any other) security criterion ?
- State-of-the-art computing and data driven methods could enable more informed decision making

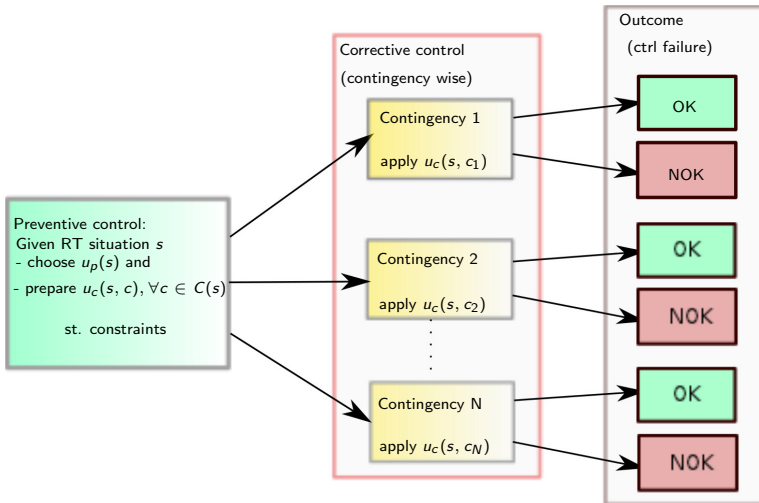
Real-time sub-problem: preventive and corrective control



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

$$\min \left(f_p(u_p) + \dots \right) \quad (1)$$

$$\text{s.t.} \quad u_p \in U_p \quad (2)$$

(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 .)

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- C , the set of possible contingencies c , π_c their probabilities
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$$\forall c : u_c(c) \in U_c(u_p) \quad (3)$$

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

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- 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**)

Paper: PSCC 2016

Probabilistic Reliability Management Approach and Criteria for Power System Real-time Operation

Efthymios Karangelos and Louis Wehenkel

Department of EE&CS - Institut Montefiore, University of Liège, Belgium

{e.karangelos, l.wehenkel}@ulg.ac.be

Abstract—This paper develops a probabilistic approach for power system reliability management in real-time operation where risk is a product of i) the potential occurrence of contingencies, ii) the possible failure of corrective (*i.e.*, post-contingency) control and, iii) the socio-economic impact of service interruptions to end-users. Stressing the spatiotemporal variability of these factors, we argue for reliability criteria assuring a high enough probability of avoiding service interruptions of severe socio-economic impact by dynamically identifying events of non-negligible implied risk. We formalise the corresponding decision making problem as a chance-constrained two-stage stochastic programming problem, and study its main features on the single area IEEE RTS-96 system. We also discuss how to leverage this proposal for the construction of a globally coherent reliability management framework for long-term system development, mid-term asset management, and short-term operation planning.

contingencies (such as the N-1 or N-k approaches). Indeed, in the presence of spatiotemporal variability, these can not consistently maintain the system reliability level nor optimise its socio-economic impact on system end-users [7], [8].

A. Proposal

Motivated by these facts, we propose a probabilistic Reliability Management Approach and Criterion (RMAC) as a synthesis of the three following basic ingredients:

- 1) **A reliability target:** it ensures that the probability of reaching unacceptable system states (for instance, instabilities and/or service interruptions of large size, duration, geographical extent) is lower than a fixed tolerance.
- 2) **A socio-economic objective:** it prescribes to minimise a

Discussion of the real-time problem nature

- Size of the problem (e.g. for the TSO of Belgium or France)
 - $\#C$ in the order of 10^7 (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^{10} decision variables

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 - 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.

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 - It models the target reliability level sought by the TSO
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 - It models the target reliability level sought by the TSO
 - It can be expressed by using auxiliary binary variables (when assuming a 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 (work in progress)

- 1 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.
- 2 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
- 3 Putting both together, makes solution reachable:
 - GARPUR FP7 project deliverables
See <https://www.sintef.no/projectweb/garpur/deliverables/> D2.2, D6.2, D9.1
 - E. Karangelos and L. Wehenkel. PSCC 2016, IEEE Trans. PS 2019.



Still cumbersome computations

Paper: IEEE Trans. Power Systems, 2019

3780

IEEE TRANSACTIONS ON POWER SYSTEMS, VOL. 34, NO. 5, SEPTEMBER 2019

An Iterative AC-SCOPF Approach Managing the Contingency and Corrective Control Failure Uncertainties With a Probabilistic Guarantee

Efthymios Karangelos , Member, IEEE, and Louis Wehenkel 

Abstract—This paper studies an extended formulation of the security constrained optimal power flow (SCOPF) problem, which explicitly takes into account the probabilities of contingency events and of potential failures in the operation of post-contingency corrective controls. To manage such threats, we express the requirement that the probability of maintaining all system operational limits, under any circumstance, should remain acceptably high by means of a chance constraint. Furthermore, representing power flow as per the full AC model, we propose a heuristic solution approach leveraging state-of-the-art methodologies and tools originally developed to tackle the standard, deterministic-constrained SCOPF statement. We exemplify the properties of our proposal by presenting its application on the three area version of the IEEE-RTS96 benchmark, stressing the interpretability of both the chance-constrained reliability management strategy and of the heuristic algorithm proposed to determine it. This paper serves to showcase that the first step on the transition toward probabilistic reliability management can be achieved by suitably adapting presently available operational practices and tools.

Index Terms—Reliability management, AC-SCOPF, chance-constraint, contingency probability, corrective control failure, iterative decomposition.

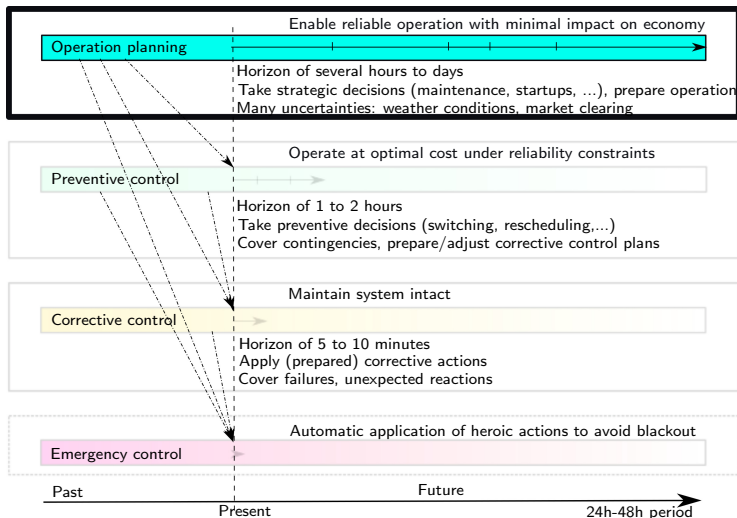
Constrained Optimal Power Flow (SCOPF) problem [2]. In particular, the definition of appropriate metrics to express the risk implied by credible contingencies, the integration of such metrics within the ‘classical’ SCOPF decision framework and the efficient algorithmic solution of the mathematical problem resulting from choices made regarding the aforementioned are open research topics.

Integrating the expected cost of corrective control in the AC-SCOPF objective function, Xu *et al.* [3] developed a solution strategy composed of a global search for the upper bounds on “critical” decision variables and a local search for an optimal solution given such boundaries. Capitanescu proposed an AC-SCOPF constraining the expected post-contingency voluntary load-shedding and established the solvability of medium-scale problem instances while relying on a standard *Non-Linear Programming* (NLP) solver [4]. Shchetinin and Hug [5] stated an alternative AC-SCOPF problem while constraining the total risk implied by an ensemble of single-order and double-order outages expressed in function of the post-contingency component loading, and developed a sensitivity-based iterative decomposi-

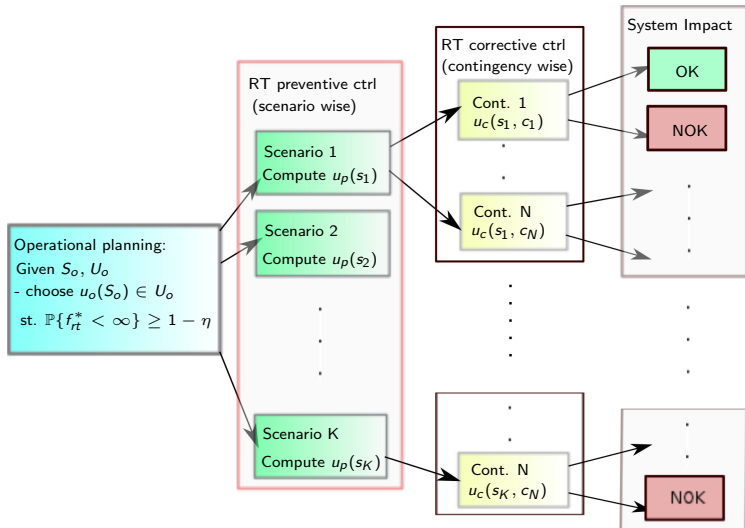
Operation planning sub-problem: preparing operation



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

Ensuring with high enough probability the feasibility of reliable real-time operation

- Real-time control depends on the situation s , which we now refine by $s \triangleq (u_o, \xi)$ where u_o denotes the (endogenous) decision taken by the TSO in operation planning and ξ denotes the realization of uncertainties faced in real-time.
- We denote by $f_{rt}^*(u_o, \xi)$ the optimal objective function of the real-time control problem for such a scenario and by $f_{rt}^*(u_o, \xi) = \infty$ the fact that the real-time problem is found to be infeasible given (u_o, ξ) .
- Operational planning engineers have to cover a probability space $S_o = (\Xi, \mathbb{P}_\xi)$ of possible exogenous scenarios ξ , by deciding on an “operational planning decision”, ie. by choosing some $u_o^*(S_o) \in U_o$ so that

$$\mathbb{P}_\xi \{f_{rt}^*(u_o^*, \xi) < \infty\} \geq 1 - \eta.$$

- Under this chance constraint, the operation planner can choose his decisions according to some objective function (e.g. minimization of market deviation...).
- Notice that, contrary to the real-time problem, in the operational planning problem the set of uncertainties is continuous (and high-dimensional).

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.

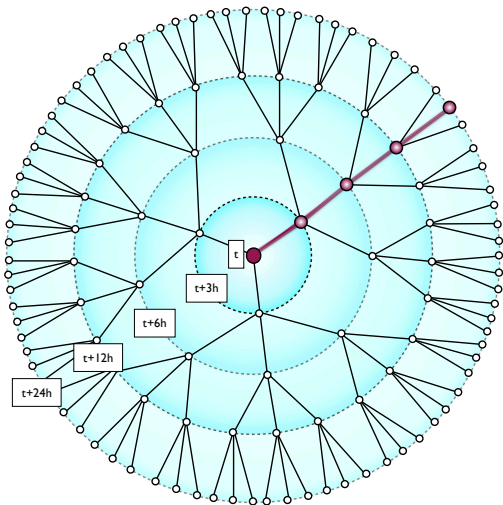
- Modeling strategy:

- 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 .

Operation planning: complexities

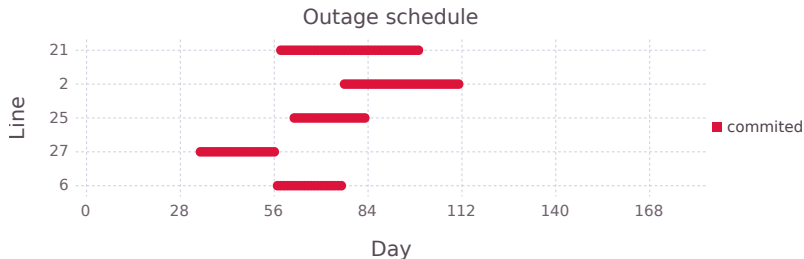
- The decisions u_o have to be taken ahead of time: each decision option has its own specific “notification delay” and its own economic cost.
- The decisions u_o aim at improving controllability for future stages of real-time control; they thus have to be certified by considering several future real-time control steps (say from 3 hours up to 48 hours ahead in time).
- S_o is typically a high-dimensional continuous space of power injections at the tie-lines and at the internal buses, modeling the uncertainty about external system states and about internal consumption (and generation) patterns.
- No good practice and little data exist today to define S_o (e.g. probabilities, risk management strategies, constraints etc.)

Part III

From System Operation to System Maintenance and Design

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

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**

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 compromise between CAPEX and OPEX (including future maintenance and operation costs)
- Needs to model uncertainties about system needs and future technological solutions



The general reliability management problem

Formulated as a **multi-stage decision making problem** over horizon $0 \dots T$, under assumed exogenous uncertainties $\xi_{1\dots T} \sim (\mathcal{S}, \mathbb{P})$, with candidate policies $u_{0\dots T-1} \in \mathcal{U}$, 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:**

$$\max_u \mathbb{E}\left\{\sum_{t=0}^T (\text{Market surplus} - \text{TSO costs} - \text{Costs of service interruptions})\right\}$$

... i.e. the **fully orthodox social-welfare optimizer viewpoint...**

See <https://www.sintef.no/projectweb/garpur/>

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(2) **Reliability target over induced system trajectories:**

$$\text{s.t. } \mathbb{P}\{x_{1\dots T}(\xi, u) \in \mathcal{X}_a\} \geq 1 - \epsilon$$

... the “bon père de famille” attitude to avoid catastrophes...

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(3) **Uncertainty discarding principle:**

allows to trim $(\mathcal{S}, \mathbb{P})$ to $(\mathcal{S}_c, \mathbb{P}_c)$, provided that approximation in (1) $\leq \Delta E$.

... to make things possible from the computational viewpoint...

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(4) **Relaxation principle:**

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

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

See <https://www.sintef.no/projectweb/garpur/>

GARPUR RMAC: in pictures



Reliability target



Socio-economic objective



Discarding principle



Relaxation principle



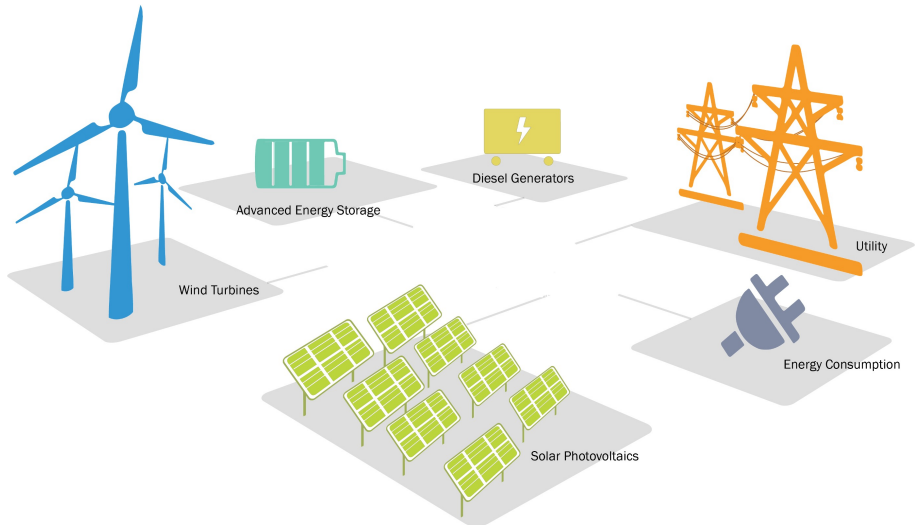
Temporal coherence proxies

Part IV

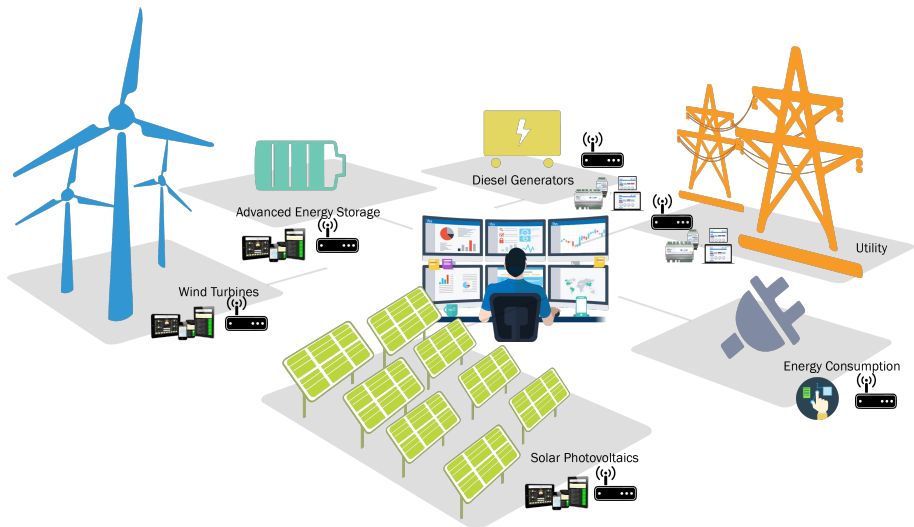
Recent developments

- Growing need for **Cyber**-Physical Reliability Management
- Tremendous progress in **Artificial Intelligence**
- Acceleration of the **Energy Transition**

From Physical Reliability Management...



...to Cyber-physical Reliability Management





Πυλώνες 2 Pylons

Ηλεκτρονικό Περιοδικό
Ελληνικής Επιτροπής CIGRE

e-Magazine
CIGRE Greece NC

ΑΦΙΕΡΩΜΑ
Αβεβαιότητα
Ασφάλεια
Ανθεκτικότητα

SPECIAL ISSUE
Uncertainty
Security
Resilience

Απρίλιος 2022

April 2022

SPECIAL ISSUE: Uncertainty, Security, Resilience

Towards cyber-physical security for the electric power system

by  Eythymios Karangelos 
Montefiore Institute - University of Liège

 Louis Wehenkel 
Montefiore Institute - University of Liège

— The cyber-physical electric power system

The continuous operation of large-scale electric power systems is a most complex achievement integrating technical, economical and organizational considerations. In addition to a well-functioning physical infrastructure (generators, transformers, lines, substations, etc.) it relies on a well-functioning cyber infrastructure, consisting of both hardware (sensors, smart meters, digital protection and control devices, communication routers and switches, data storage servers, etc.) and software (market clearing algorithms, supervisory control and data acquisition systems, billing and settlement tools, home energy management tools, etc.). Such hardware and software is embedded within all physical domains and hierarchical zones of the system, so as to enable their interoperability across several functional layers, as depicted by Figure 1.

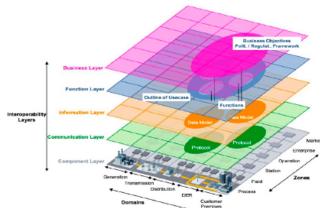


Figure 1 The Smart Grid Architecture Model (Smart Grid Coordination Group 2012)



Progresses in Artificial Intelligence/Machine Learning

- Deep Neural Networks
- Generative Models
- Automatic Differentiation
- Implicit Layers
- Neural Ordinary Differential Equations
- Graph Neural Networks
- Physics-informed Machine Learning
- Causal inference

Paper: Proceedings of the IEEE, 2020



Recent Developments in Machine Learning for Energy Systems Reliability Management

This article reviews opportunities and challenges in adapting and developing machine learning methodology and tools for studies in bulk power systems as well as in other distribution, microgrids, and multienergy systems.

By LAURINE DUCHESNE[✉], Graduate Student Member IEEE, EFTHYMIOS KARANGELOS, Member IEEE, AND LOUIS WEHENKEL

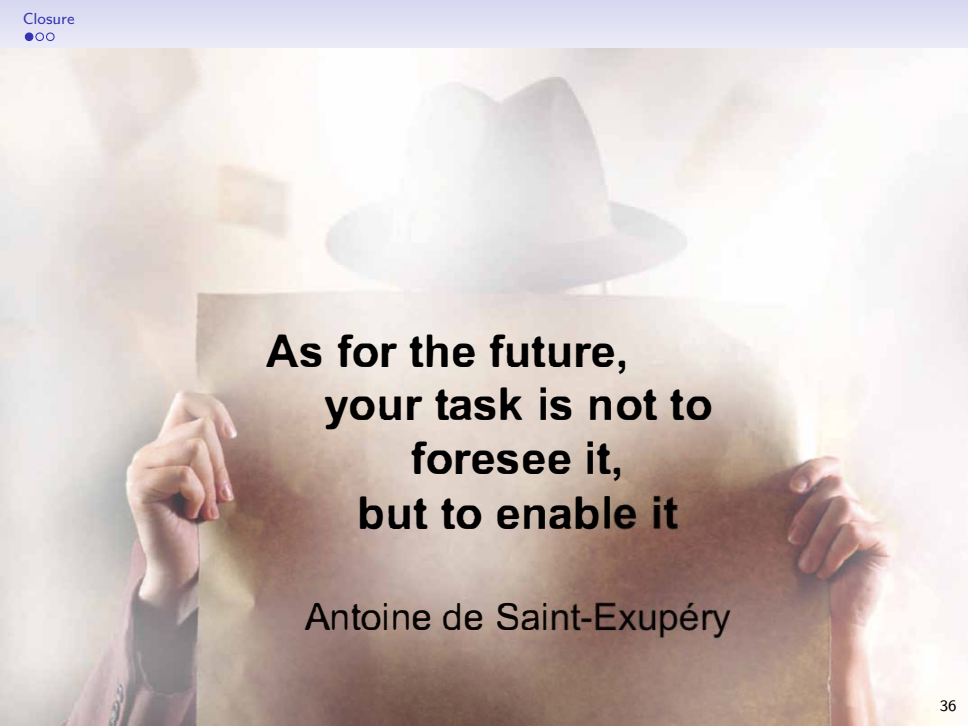
ABSTRACT | This article reviews recent works applying machine learning (ML) techniques in the context of energy systems' reliability assessment and control. We showcase both the progress achieved to date as well as the important future directions for further research, while providing an adequate background in the fields of reliability management and of ML. The objective is to foster the synergy between these two fields and speed up the practical adoption of ML techniques for energy systems reliability management. We focus on bulk electric power systems and use them as an example, but we argue that the methods, tools, etc. can be extended to other similar systems, such as distribution systems, microgrids, and multienergy systems.

KEYWORDS | Electric power systems (EPSs); machine learning (ML); reliability; security assessment; security control.

cal and theoretical questions. This recent boom is facilitated by the continuous growth in the availability of computational power and advanced sensing and data communication infrastructures.

Electric power systems (EPSs) emerged during the early twentieth century, became soon ubiquitous, and progressively more and more computerized since the 1970s. Recently, EPS started to undergo a revolution, in order to respond to societal and environmental challenges; renewable energy sources, microgrids, power electronics, and globalization are indeed changing their game. The changes characterizing such revolution are pushing the existing analytical methods for power system reliability assessment and control to their limits.

The first proposals for applying ML to EPS dynamic security assessment (DSA) and control (a part of EPS reliability



**As for 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, Rethymon 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
 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



L. Duchesne, E. Karangelos, and L. Wehenkel
 Recent developments in machine learning for energy systems reliability management
Proceedings of the IEEE, 2020



E. Karangelos and L. Wehenkel
 Cyber-physical risk modeling with imperfect cyber-attackers.
Electric Power Systems Research, 2022

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