Big data, machine learning, and optimization, for power systems reliability

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joint work with L. Duchesne, E. Karangelos, M. Marin

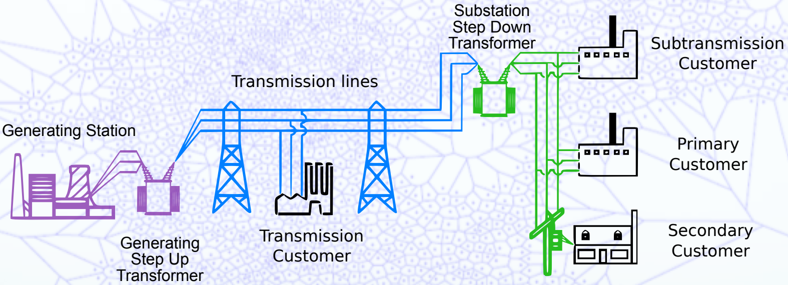
LIST-ULg workshop: 09/11/2016

Université de Liège

Montefiore Institute

Context/Motivation/Background

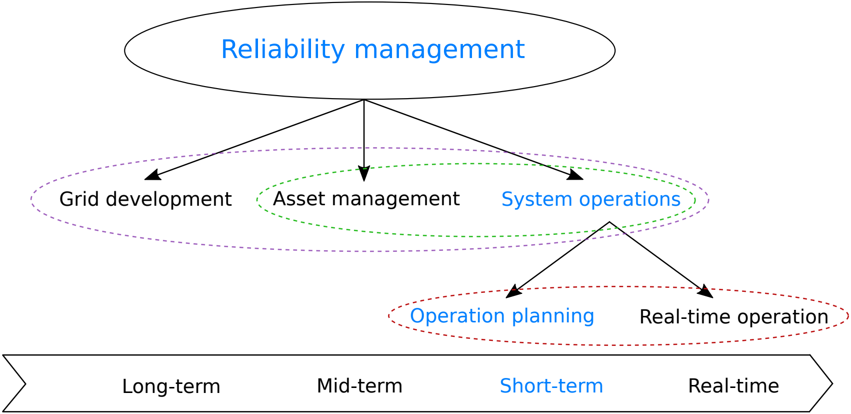
Point of view of the European TSOs



Problem addressed: Reliability management under growing uncertainties and growing flexibility

Reliability management (1)

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



Reliability management (2)

Can be decomposed into two parts:

- **Reliability assessment:** determining the level of reliability of the system based on a given decision
  $\rightarrow$ *simulation*
- **Reliability control:** determine an optimal decision
  $\rightarrow$ *large-scale multi-stage stochastic optimization*

The N-1 Reliability Criterion

- A system should be able to withstand the loss of any single component (*e.g.* line, transformer, *etc.*).

✓ Under "average" conditions, should still work quite well.

Operating quite far from "average conditions" ...

- N-1 over-conservative?
  e.g., limiting use of cheap renewables.
- N-1 under-conservative?
  e.g., adverse weather/major sport events, *etc.*.
- N-1 risk averse?
  seeking to avoid even "minor" (sometimes tolerable) consequences.
- N-1 risk taking?
  corrective control while neglecting its possible failure.

GARPUR

www.garpur-project.eu

Generally Accepted Reliability Principle with Uncertainty modelling and through probabilistic Risk assessment

- Design, develop, and assess new probabilistic Reliability Management Approaches and Criteria (**RMACs**)
- Evaluate their **practical use** w.r.t. N-1, in terms of social welfare, data and computational requirements
- Ensure **coherency** among RMACs used in the contexts of system development, asset management, and operation

R1: Generic RMAC formulation

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

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

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

See http:www.garpur-project.eu/deliverables D2.2.

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(2) **Reliability target over induced system trajectories:**
s.t. $\mathbb{P}\{x_{1\ldots T}(\xi, u) \in \mathcal{X}_a\} \geq 1 - \epsilon$

... 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 unfeasible problem.

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

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R2 - Real-time operation

The context (every 5' $\sim$ 15')

- Power injections assumed relatively predictable, but Uncertainty on:
  - $\rightarrow$ the occurrence of contingencies $c \in \mathcal{C}$;
  - $\rightarrow$ the behavior of post-contingency corrective controls $b \in \mathcal{B}$.

R2 - Real-time operation

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- Power injections assumed relatively predictable, but Uncertainty on:
  - $\rightarrow$ the occurrence of contingencies $c \in \mathcal{C}$;
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- Variability on weather/market conditions w_0, thus:
  - $\rightarrow$ variable contingency & corrective control failure probabilities (respectively $\pi_c(w_0), \pi_b(w_0)$).
  - $\rightarrow$ variable socio-economic severity of a service interruption.

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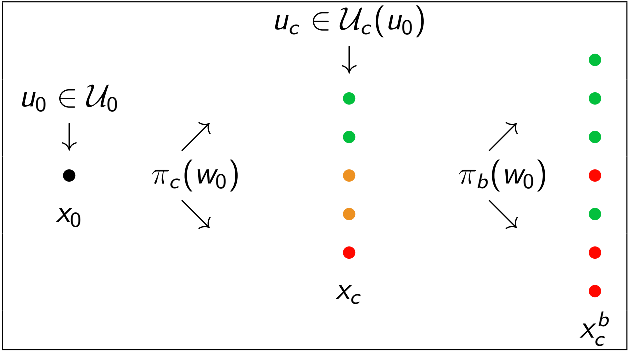
- Variability on weather/market conditions w_0, thus:
  - → variable contingency & corrective control failure probabilities (respectively $\pi_c(w_0), \pi_b(w_0)$).
  - → variable socio-economic severity of a service interruption.
- Decisions to:
  - → apply preventive (pre-contingency) control $u_0 \in \mathcal{U}_0(x_0)$?
  - → prepare post-contingency corrective controls $u_c \in \mathcal{U}_c\,(u_0)\,\forall c \in \mathcal{C}$?

RT-RMAC Proposal (1/4)



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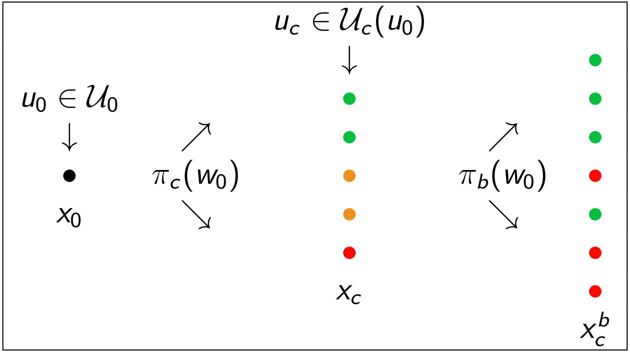


1. Reliability target

- Avoid "unacceptable trajectories" (*e.g.*, instability, too large/long service interruptions) with *a certain confidence*.

RT-RMAC Proposal (2/4)

2. Socio-economic objective

Combined expectation of reliability mgmt operational costs & socio-economic severity of service interruptions.

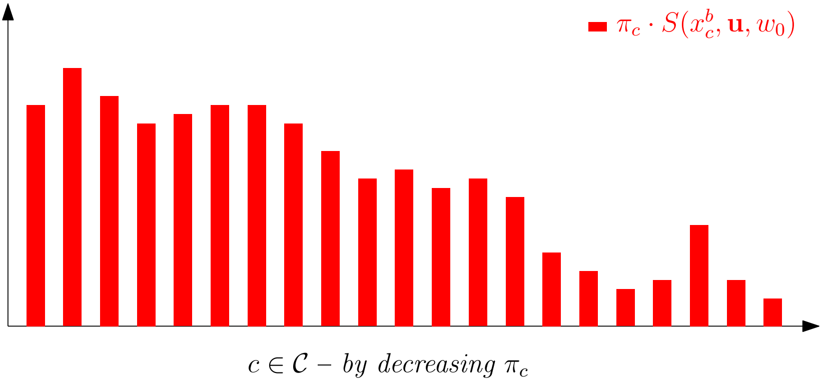
$$\min_{u \in \mathcal{U}(x_0)} \left\{ CP\left(x_0, u_0\right) + \sum_{c \in \mathcal{C}} \pi_c(w_0) \cdot CC\left(x_c, u_c\right) \right.$$
$$\left. + \sum_{c,b \in \mathcal{C} \times \mathcal{B}} \pi_c(w_0) \cdot \pi_b(w_0) \cdot S(x_c^b, \mathbf{u}, w_0) \right\}.$$

$CP\left(x_0, u_0\right)$: preventive control cost function,

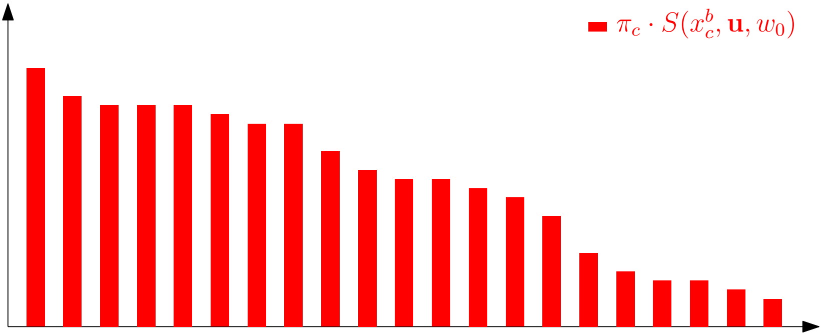
$CC\left(x_c, u_c\right)$: corrective control cost function,

$S(x_c^b, \mathbf{u}, w_0)$: socio-economic impact of service interruptions.

RT-RMAC Proposal (3/4)

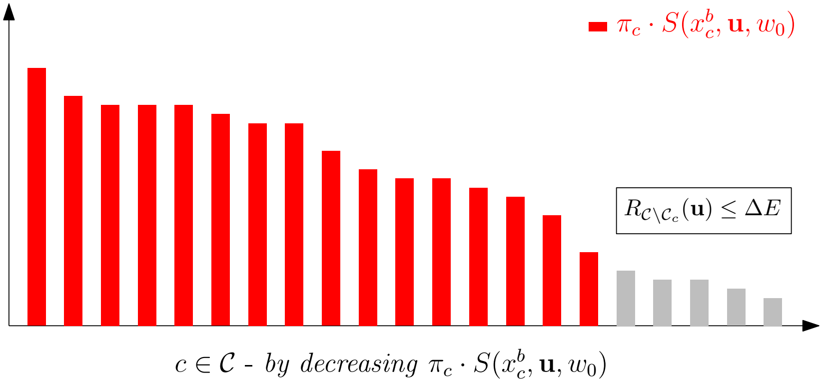


RT-RMAC Proposal (3/4)



$c \in \mathcal{C}$ - *by decreasing* $\pi_c \cdot S(x_c^b, \mathbf{u}, w_0)$

RT-RMAC Proposal (3/4)



3. Discarding principle

- Choose $\mathcal{C}_c \subset \mathcal{C}$, **such that** residual risk is negligible.

RT-RMAC Proposal (4/4)

Compact statement

$$\min_{u \in \mathcal{U}(x_0)} \left\{ CP\left(x_0, u_0\right) + \sum_{c \in \mathcal{C}_c} \pi_c(w_0) \cdot CC\left(x_c, u_c\right) + \sum_{c \in \mathcal{C}_c} \pi_c(w_0) \cdot \sum_{b \in \mathcal{B}} \pi_b(w_0) \cdot S(x_c^b, \mathbf{u}, w_0) \right\} \quad (1)$$

$$\text{s.t. } \mathbb{P}\left\{(x_0, x_c, x_c^b) \in X_a \middle| (c, b) \in \mathcal{C}_c \times \mathcal{B}\right\} \geq (1 - \varepsilon) \quad (2)$$

while

$$R_{\mathcal{C} \setminus \mathcal{C}_c}(\mathbf{u}) \leq \Delta E. \quad (3)$$

RT-RMAC Algorithms: current status

- **Reliability assessment:** boils down to simulating the severity resulting from contingencies (and failure modes) by decreasing order of their probability of occurrence in order to compute (1) until the bound on ΔE is satisfied, while checking (2).

Karangelos E. & Wehenkel L., "Probabilistic reliability management approach and criteria for power system real-time operation", PSCC-2016, for further details.

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- **Real-life implementation** of assessment part is currently under progress in the GARPUR project pilot tests.

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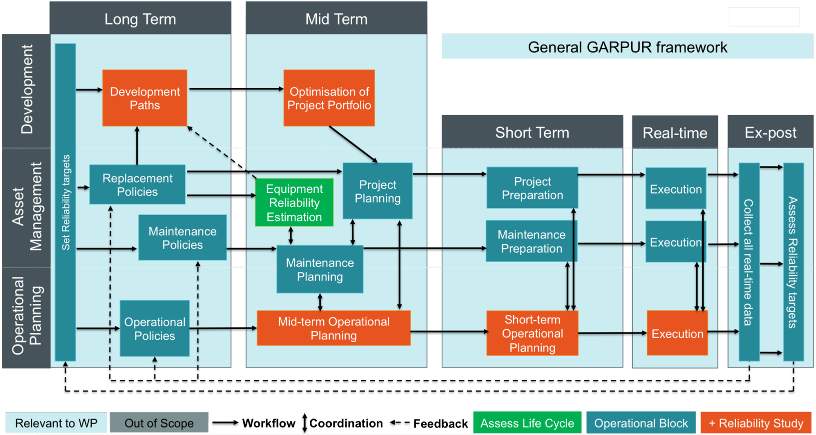
R3 - Asset management



NB: LT=5-30 years; MT= 6-24 months; ST= 6-48 hours; RT= 5-60 minutes

Two practical problems

In the context of asset management, the Transmission System Operator (TSO) faces the following two problems:

Long-term maintenance policy selection:
: How much and what kind of maintenance to carry out for the next (say) 20 years, so as to keep the right components in a sufficiently healthy state?

Two practical problems

In the context of asset management, the Transmission System Operator (TSO) faces the following two problems:

Long-term maintenance policy selection:
How much and what kind of maintenance to carry out for the next (say) 20 years, so as to keep the right components in a sufficiently healthy state?

Mid-term outage scheduling:
When to place component outages issued from the chosen maintenance policy over (say) one year, so as to minimize the impact of these outages on system operation?

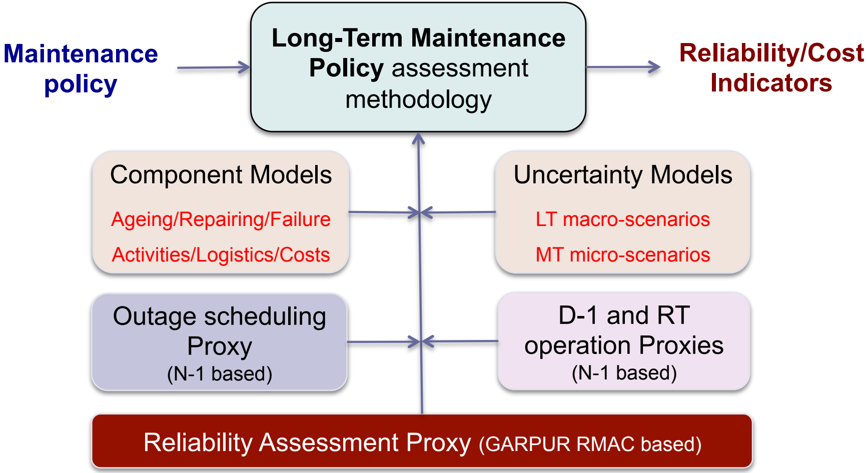
Example

A maintenance policy for a network with two zones, A and B:

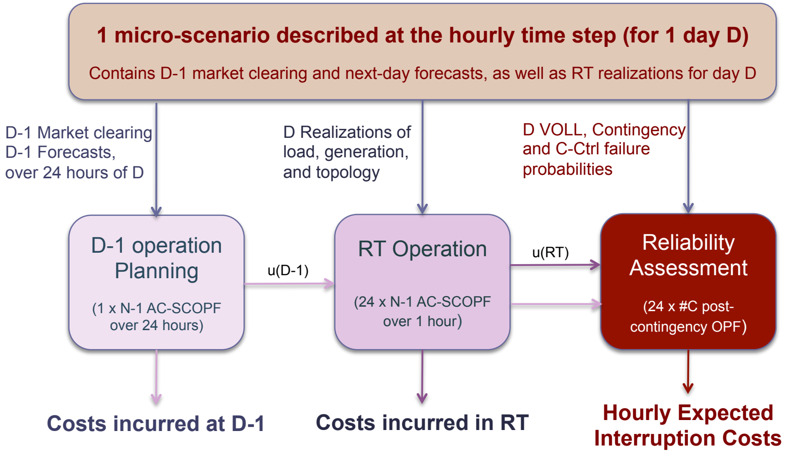
$$
\begin{array}{lcl}
u_{act} & = & \left[\begin{array}{ccccc} \left\{ \begin{array}{c} \text{repair A1} \\ \text{replace B2} \\ \text{inspect B3} \end{array} \right\} & , & \left\{ \begin{array}{c} \text{repair A4} \\ \text{inspect B6} \end{array} \right\} & , & \ldots \end{array} \right] \\
u_{cstr} & = & \left[\begin{array}{ccccc} \left\{ \begin{array}{c} \text{15 MM zone A} \\ \text{20 MM zone B} \end{array} \right\} & , & \left\{ \begin{array}{c} \text{20 MM zone A} \\ \text{10 MM zone B} \end{array} \right\} & , & \ldots \end{array} \right] \\
 & & \quad (\textit{year 1}) \qquad\qquad (\textit{year t}) \qquad\qquad (\textit{year 20})
\end{array}
$$

- In order to assess the impact of such a policy on system operation, it is necessary to simulate the resulting system behavior over a set of scenarios covering many years.
- To do this, it is also necessary to "automatically" determine for each year of the study horizon a sensible way of scheduling the outages required to apply the maintenance policy.

Maintenance policy assessment model



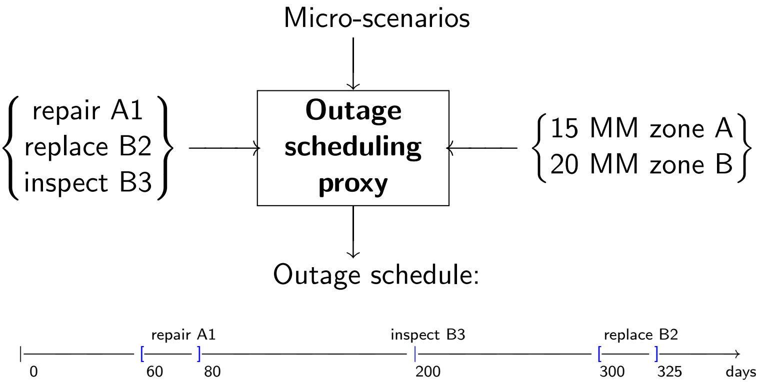
Short-term proxies



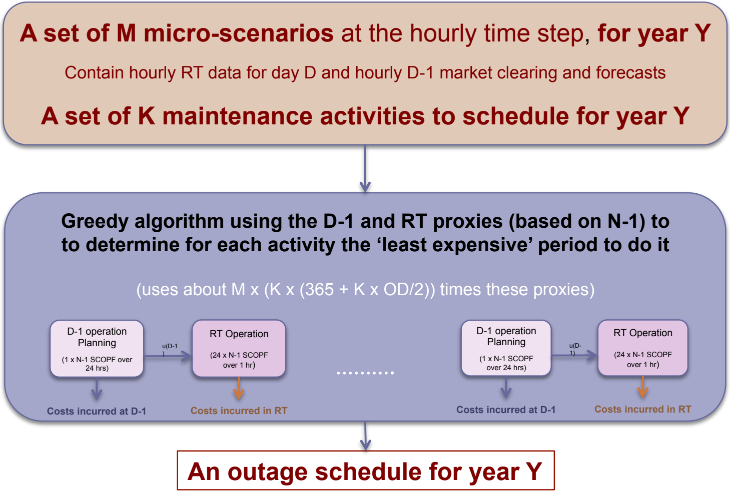
Outage scheduling problem

Example

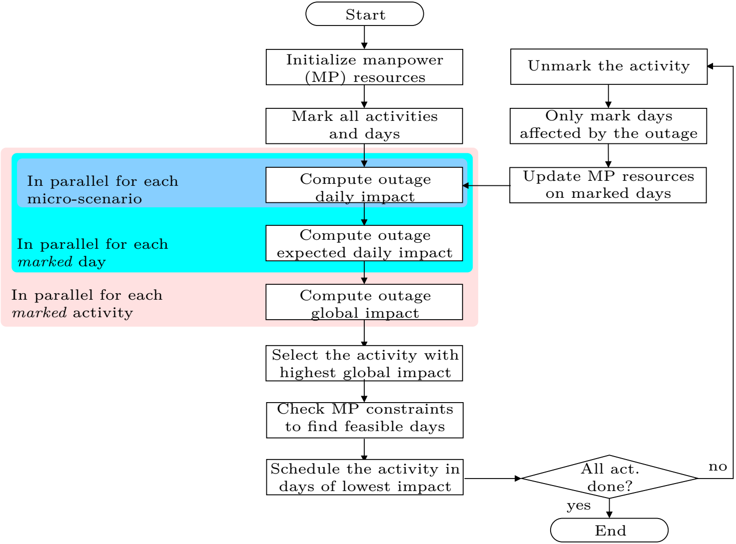
On year 1:



Proposed outage scheduling proxy

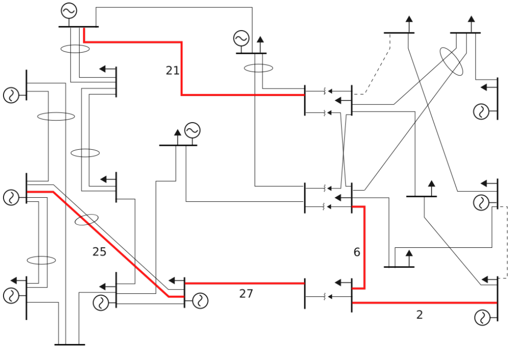


Proposed outage scheduling algorithm



Case study on the IEEE RTS-96

A set of 5 outage requests on transmission lines are scheduled over a mid-term horizon of 182 days, while using 96 micro-scenarios:



Line	o.d. (days)
2	35
6	20
21	42
25	22
27	23

Case study: Implementation details

- A **micro-scenario generative model** is developed, where each micro-scenario includes the following uncertaintes:
  - load forecast and realisation;
  - hydro-power capacity;
  - branch and generator forced outages;
  - market clearing outcome.

Case study: Implementation details

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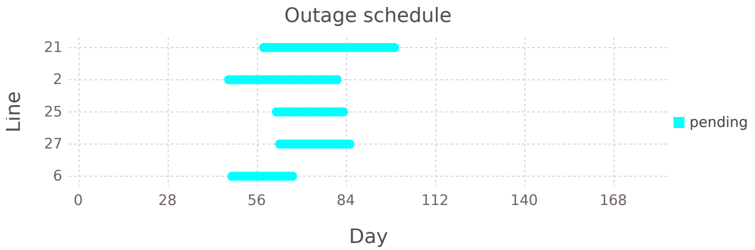
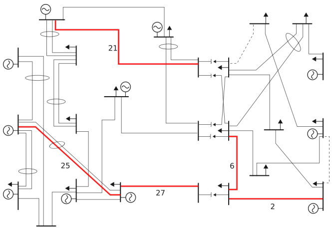
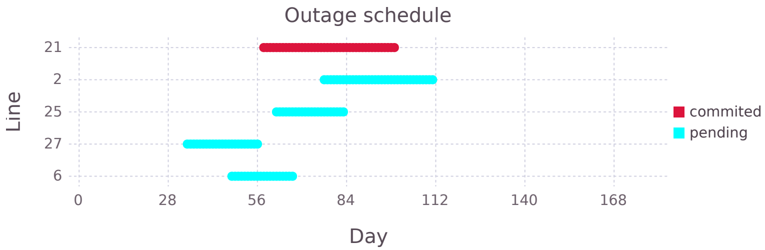
  - market clearing outcome.
- The **DA and RT proxies** are currently implemented using a **DC SCOPF** with the $N-1$ criterion.
- Implementation in JULIA for **cluster architectures**:
  i) using **parallel tasks** to treat individual micro-scenarios separately;
  ii) allowing CPLEX to use **CPU-multithreading** within each parallel task.
- See `http:www.garpur-project.eu/deliverables` D5.2.

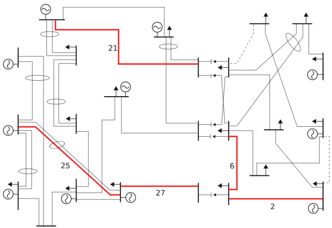
Case study: iteration (1)



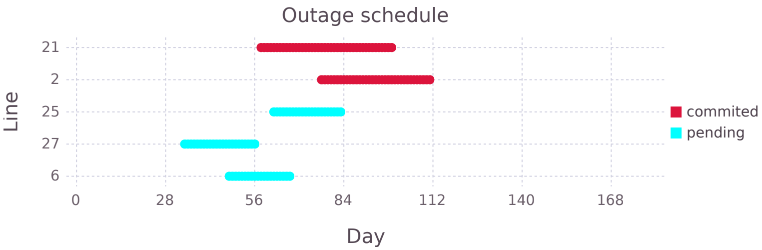


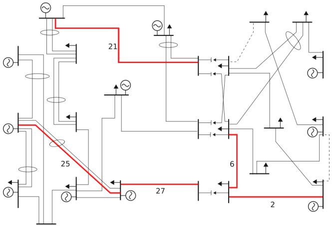
Case study: iteration (2)



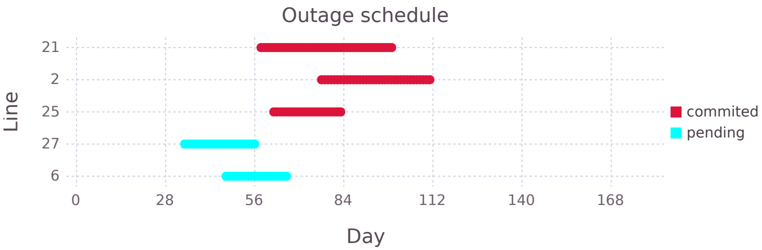


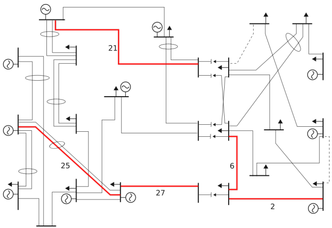
Case study: iteration (3)



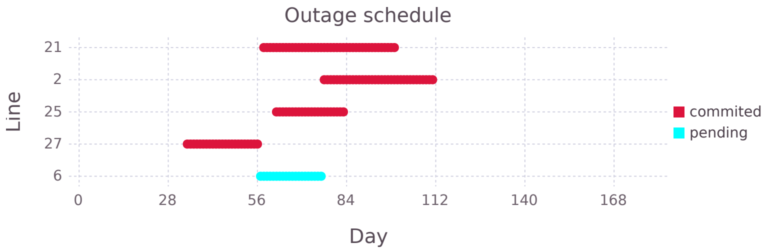


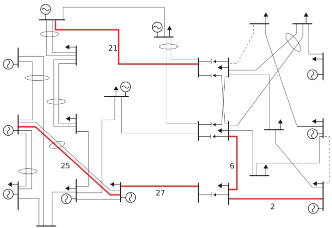
Case study: iteration (4)



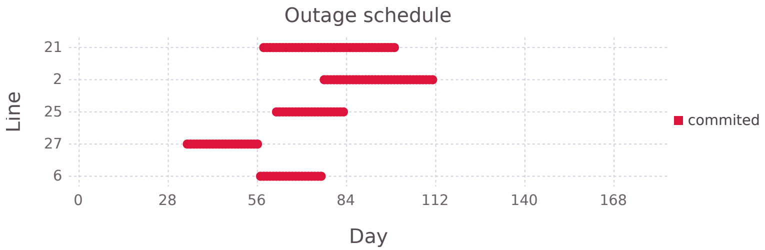


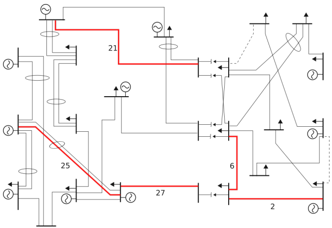
Case study: iteration (5)





Case study: iteration (last)





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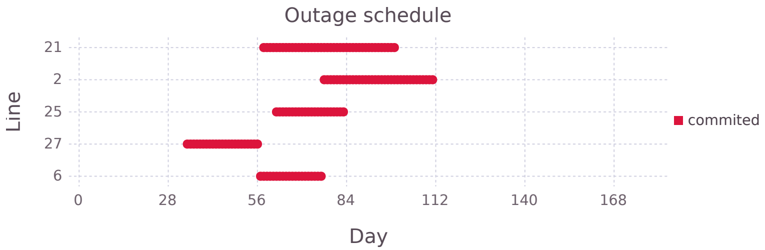

Results show that the proposed model:

a) **avoids simultaneously scheduling** outages that could lead to **a large degradation** of system performance, and

b) **exploits favorable conditions** for maintenance to **simultaneously schedule** multiple outages.

Computational feasibility

- **Exhaustive search:**
  - $182^5 \times 24 \times 182 \times 96 \simeq \mathbf{8 \times 10^{16}}$ hourly SCOPF calls
  - $182^5 \times 182 \times 96 \simeq 8 \times 10^{15} \simeq \mathbf{3 \times 10^{15}}$ daily UC calls
- **Proposed greedy algorithm:**
  - $(5+1) \times 24 \times 182 \times 96 \simeq \mathbf{3 \times 10^{6}}$ hourly SCOPF calls
  - $(5+1) \times 182 \times 96 \simeq \mathbf{1 \times 10^{5}}$ UC calls.
- **Remains challenging for large-scale systems, even with massive HPC infrastructure.**
- **Further work needed to speed up the greedy algorithm**
  - Variance reduction and bounding techniques
  - Use of faster proxies for the short-term processes

Ongoing works (Russian dolls - 1)

- Day-ahead mode RMAC
  - Choose least costly day-ahead decision so as to make real-time operation feasible
  - Needs to cover spatio-temporal uncertainty about weather and injections for the next day
  - Models 24 sequential real-time time operation according to RT-RMAC
- Learning proxies of real-time operation
- Learning proxies of day-ahead operation planning

See `http:www.garpur-project.eu/deliverables` D2.2 for problem statement.

Ongoing works (Russian dolls - 2)

- Day-ahead mode RMAC
- Learning proxies of real-time operation
  - Generate training sample of solved RT-RMAC instances
  - Machine learning to build proxies of cost and feasibility
  - Exploit proxies in look-ahead reliability management problems, both for assessment and control
- Learning proxies of day-ahead operation planning

See https://matheo.ulg.ac.be/bitstream/2268.2/1374/4/master_thesis_laurine_duchesne.pdf for first results.

Ongoing works (Russian dolls - 3)

- Day-ahead mode RMAC
- Learning proxies of real-time operation
- Learning proxies of day-ahead operation planning
  - Generate training sample of solved DA-RMAC instances
  - Machine learning to build proxies of cost and feasibility
  - Exploit proxies in mid-term and long-term reliability management problems

See `http:www.garpur-project.eu/deliverables` D5.2 for preliminary study.

Parallel R&D on Big Data Methods

- Machine learning for large scale data-sets
  - tree-based supervised learning, bayesian networks, reinforcement learning
- Combining search, inference and learning
  - Variance reduction, MCMC, exploration-exploitation tradeoff, causal models

How to combine effectively physical models with observational data, by leveraging simulation, optimization and learning?

See https://vimeo.com/album/3275353/video/120523455 for a talk on this subject

Thank you !

Questions ?