An optimization-based methodology for power system resilience enhancement in planning

Andrea Pitto

Dipartimento Sviluppo Sistemi Energetici – RSE S.p.A.

HEXAGON Workshop for power grids

Salvecchio campus, University of Bergamo

Bergamo, June 18-20, 2024

Outline

- Resilience: why and what
- The context: resilience informed grid planning
- An optimization-based methodology for resilience enhancement
- The problem formulation
- Solution algorithms
- Case studies
- Take aways

Why resilience?

- Drivers:
  - Increasing frequency of **extreme events** affecting power systems (PS)
  - Availability of large amounts of data at SCADA level (PMU signals, IED’s, etc.)
  - TSOs’ need for support to face these extreme events
- Major goals for stakeholders (TSO’s & DSO’s):
  - **evaluating the impact of multiple also dependent outages** potentially lead to widespread blackouts,
  - **proposing preventive or corrective countermeasures** to absorb the effects of such disruptive events and to recover fast
- Under **extreme weather events**:
  - short term **probability of multiple contingencies** may **increase**
  - **Conventional selection of contingencies** using credibility criteria (e.g. **N-1**) may **fail in detecting the actual risk** of load disruption

Urgent need to predict the risk of dangerous contingencies in case of extreme weather events!

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RESILIENCE

Urgent need to predict the risk of dangerous contingencies in case of extreme weather events!

What's Power System resilience?

Key features:

- **Limitation of system degradation** meant as "***deviation from specified target performances***"

- The response of the system to an **extreme event** meant as "***an event with a large impact in terms of damaged components, of reduction of capabilities of components, as well as in terms of unsupplied customers***"

CIGRE C4.47 Definition of Power System Resilience

Power System Resilience is:

*the ability to limit the **extent, severity** and **duration** of **system degradation** following an **extreme event**.*

Power system resilience is achieved through a set of ***key actionable measures*** to be ***taken*** before, during and after extreme events, such as:

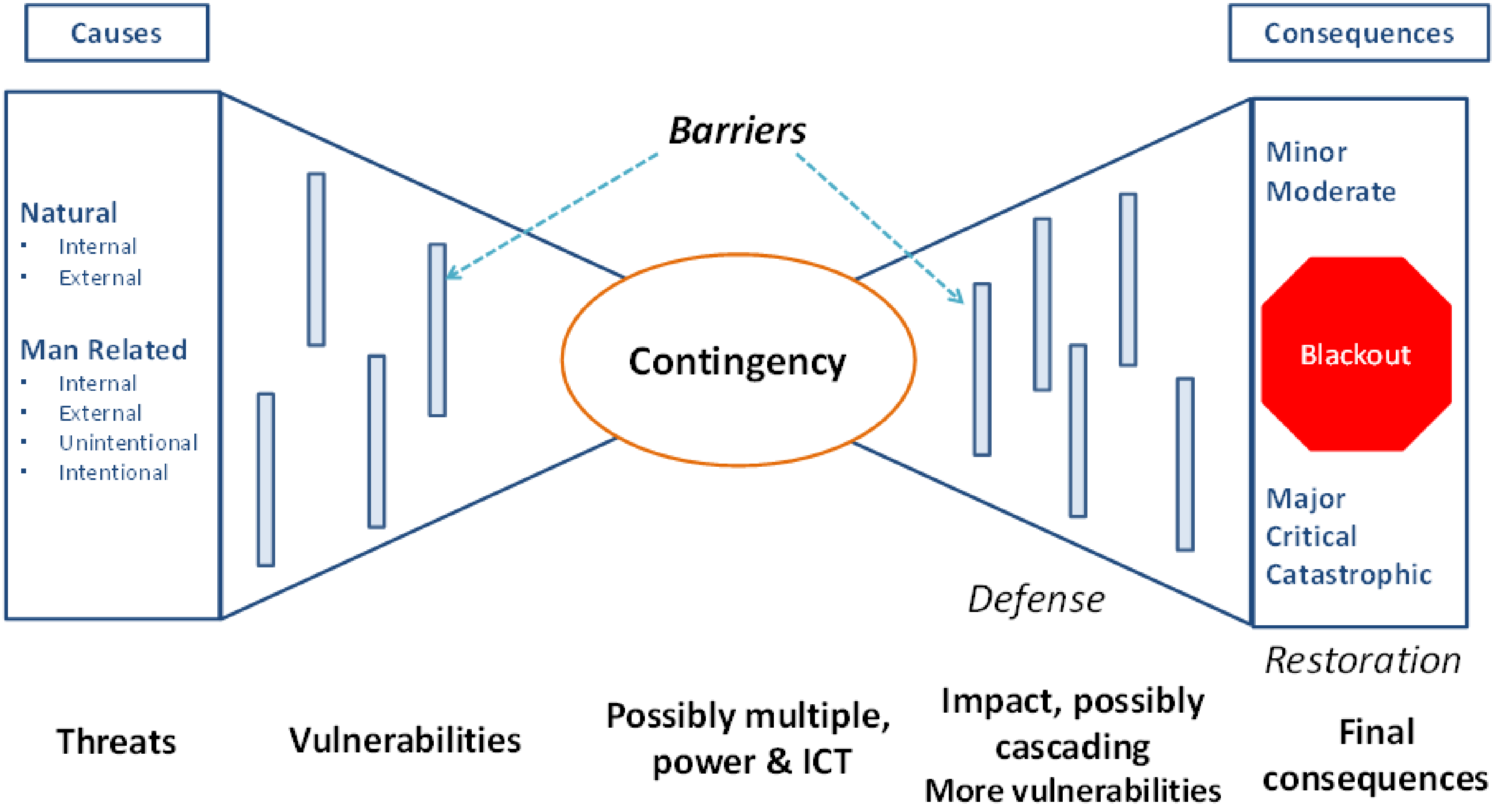
- anticipation,
- preparation,
- absorption,
- sustainment of critical system operation,
- rapid recovery, and
- adaptation

including application of lessons learnt.

C4.47 – Power System Resilience Working Group

Electra CIGRE Journal no. 306 in Oct 2019

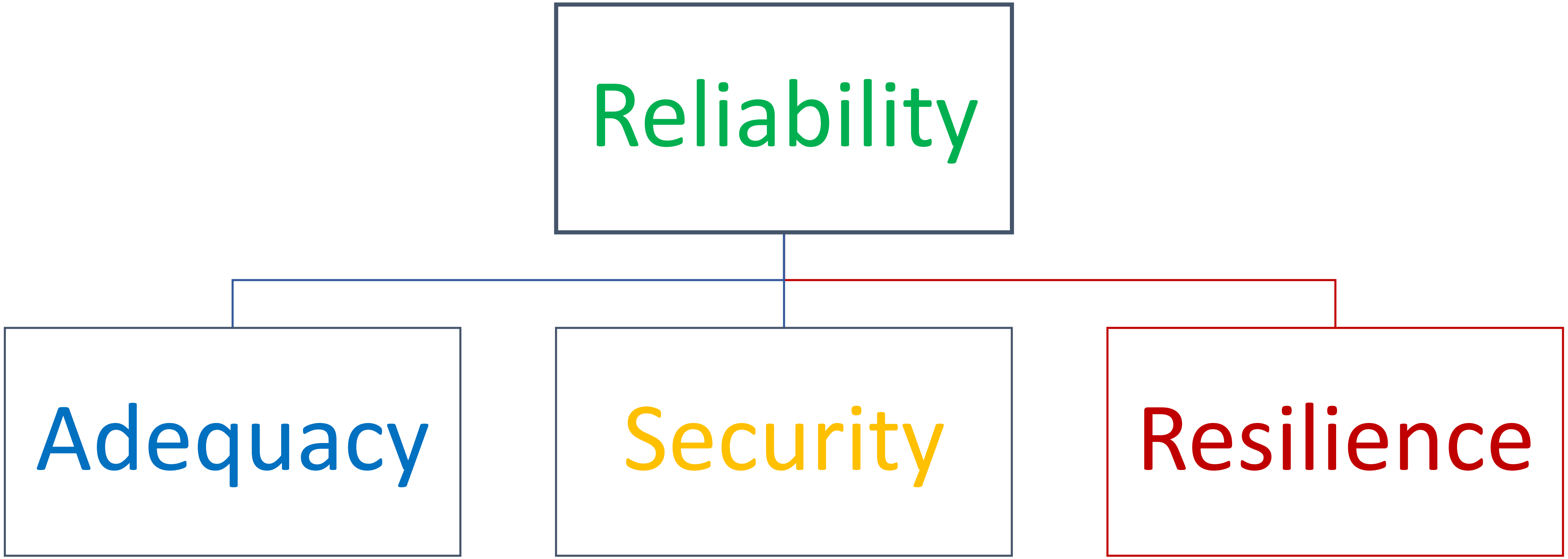
Bow tie: linking threats to power system



Resilience poses several challenges

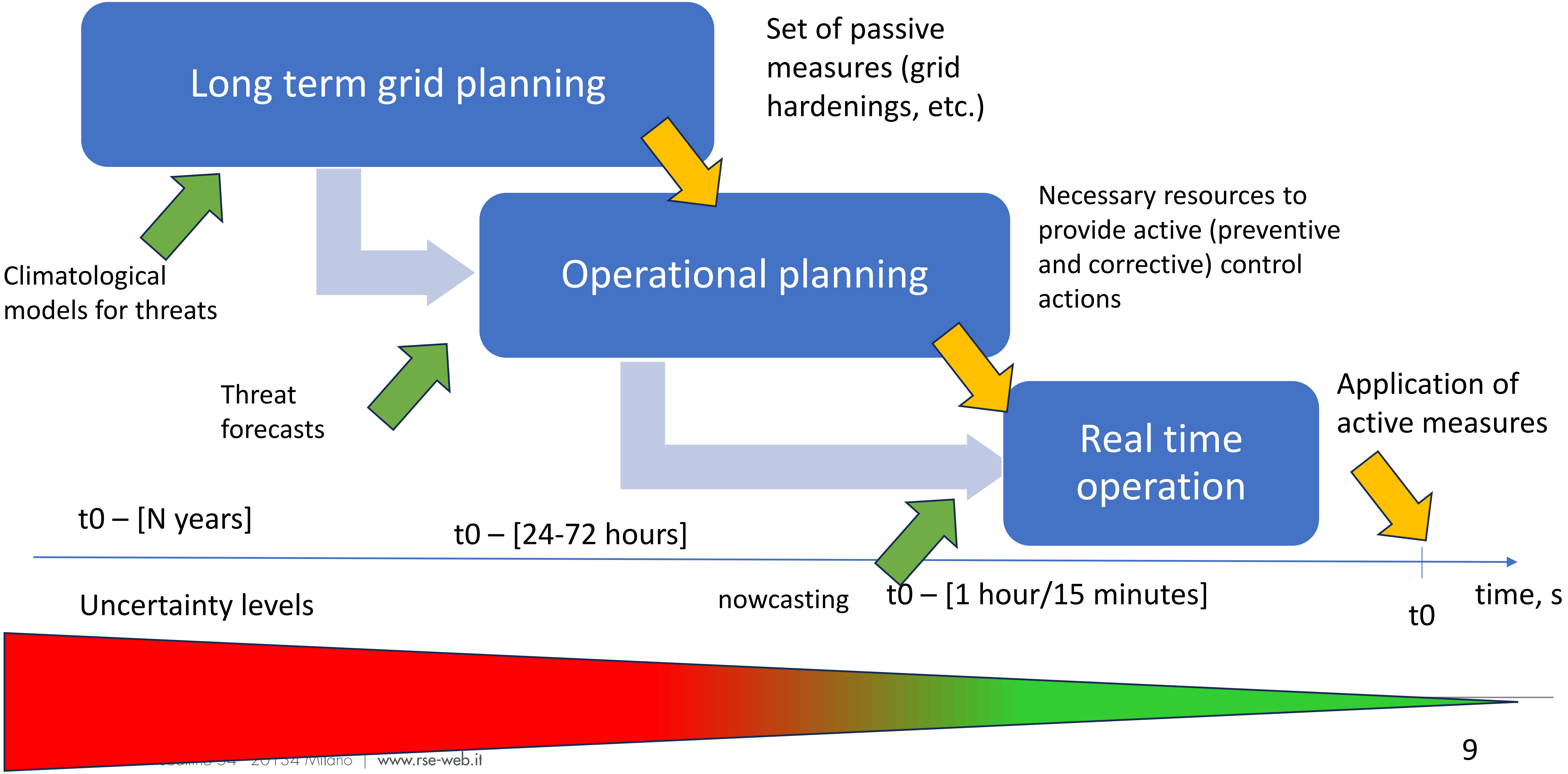
- Passing from a «power system» perspective to a «power system + environment» perspective
  - Multifaceted property implying interdisciplinary work for integrated modeling
- Risk of **combinatorial explosion** for the selection of the N-k contingencies to be accounted for
- **Need to overcome the classical concept of «security»** in case of N-k contingencies
  - assuring the continuity of supply to customers also for N-k contingencies would be not viable
- Need to **model the relationship between reliability** (currently pursued by TSO's) and **more recent concept of «resilience»**

Reliability vs resilience

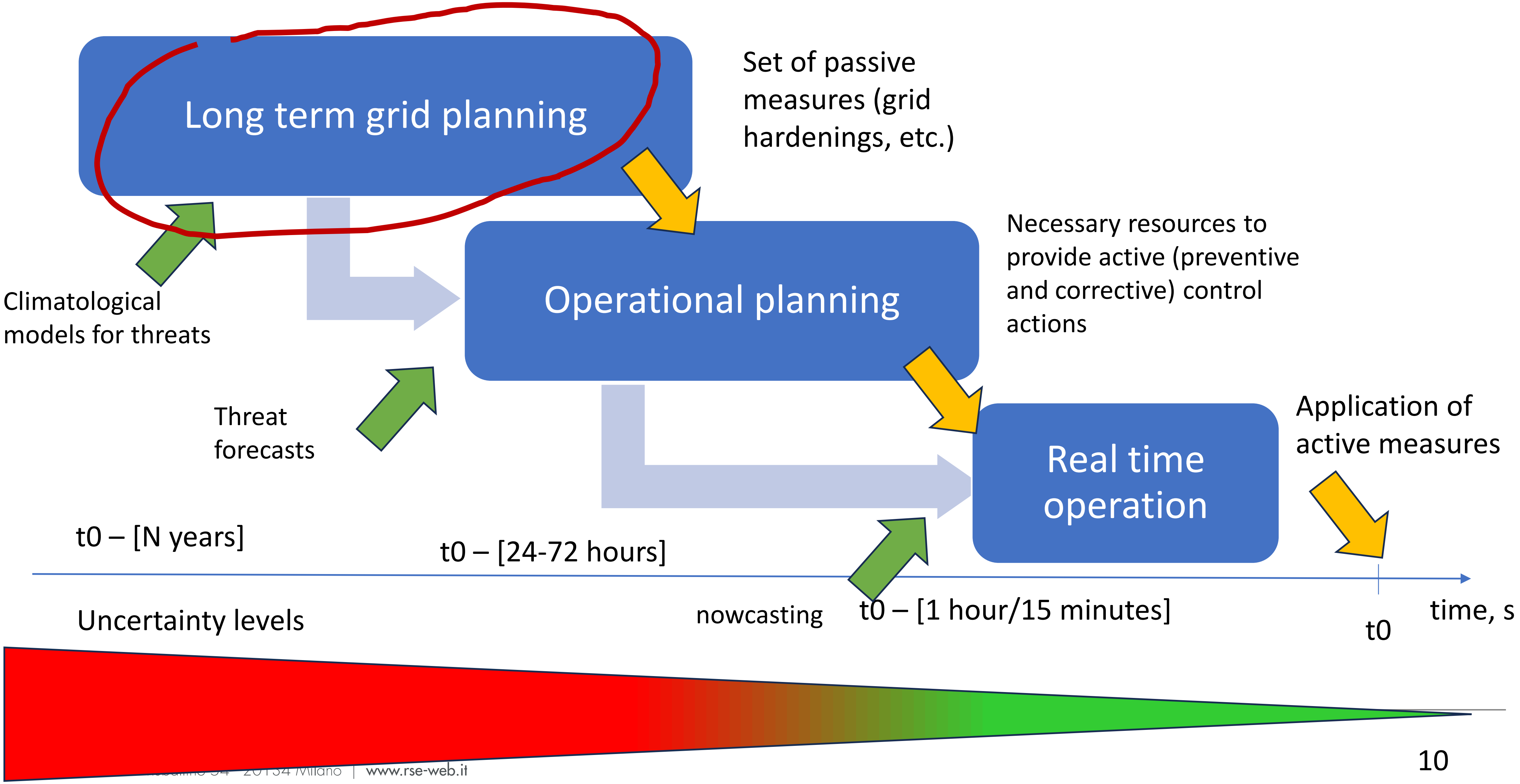


Source: **E. CIAPESSONI, D. CIRIO, A. PITTO, «Power System Resilience: definition, features and properties», CIGRE Science and Engineering Journal, n. 30, Oct 2023.**

Main phases for power system management



Main phases for power system management



Experience from the collaboration with TSOs

- Finding most cost effective grid interventions is of paramount importance for TSO's in the planning context
- To this regard, CBA (**Cost Benefit Analysis**) is getting a more and more important approach for the prioritization of grid interventions.

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Need for an **optimization-based methodology** to support TSO's in identifying the most cost-effective countermeasures for resilience enhancement

Resilience-informed grid planning: research gaps

Literature analysis on the topic highlights some research gaps:

1. most of the methods **quantify the costs and the benefits related to a limited set of measures identified "a priori" on a qualitative basis** (e.g., operators' experience), but they do not directly identify the most cost-effective mix of both passive and active measures;
2. analyses are performed neglecting (or considering in a simplified way) **the impact of climate changes (CC),** even if the lifetime of power infrastructures may span over several tens of years in which CCs may be relevant: in many cases only historical data are used to probabilistically characterize the hazard;
3. the **impact of multiple contingencies** caused by threats is **generally assessed with Optimal Power Flow (OPF) tools** without considering the actual response of the power system protection, control, and defense systems, which can actually lead to cascading outages and thus to customer disconnections.

The optimization-based methodology: requirements

- Ability to integrate **climate change effects** in decision making process for planning
- Ability to evaluate the actual response of PS to N-k contingencies, including **potential cascading outages**
- Ease of integration inside the TSO's **CBA** for grid intervention prioritization
- **Computational efficiency** and **scalability** to real world case studies

GOAL

Identifying the **most cost effective investments** for PS **resilience** enhancement over a long-term time horizon, considering **both passive and active measures**, in case of **multiple dependent contingencies** caused by **extreme events**, also accounting for **climate change effects**

The optimization-based methodology

A part of the presentation is described in the following journal paper available at:
https://www.mdpi.com/1996-1073/16/13/5160


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A Cost–Benefit Analysis Framework for Power System Resilience Enhancement Based on Optimization via Simulation Considering Climate Changes and Cascading Outages

by Emanuele Ciapessoni, Diego Cirio and Andrea Pitto *

Ricerca sul Sistema Energetico—RSE S.p.A., 20134 Milano, Italy

* Author to whom correspondence should be addressed.

Energies **2023**, *16*(13), 5160; https://doi.org/10.3390/en16135160

Submission received: 26 May 2023 / Revised: 23 June 2023 / Accepted: 27 June 2023 / Published: 4 July 2023

(This article belongs to the Section F: Electrical Engineering)

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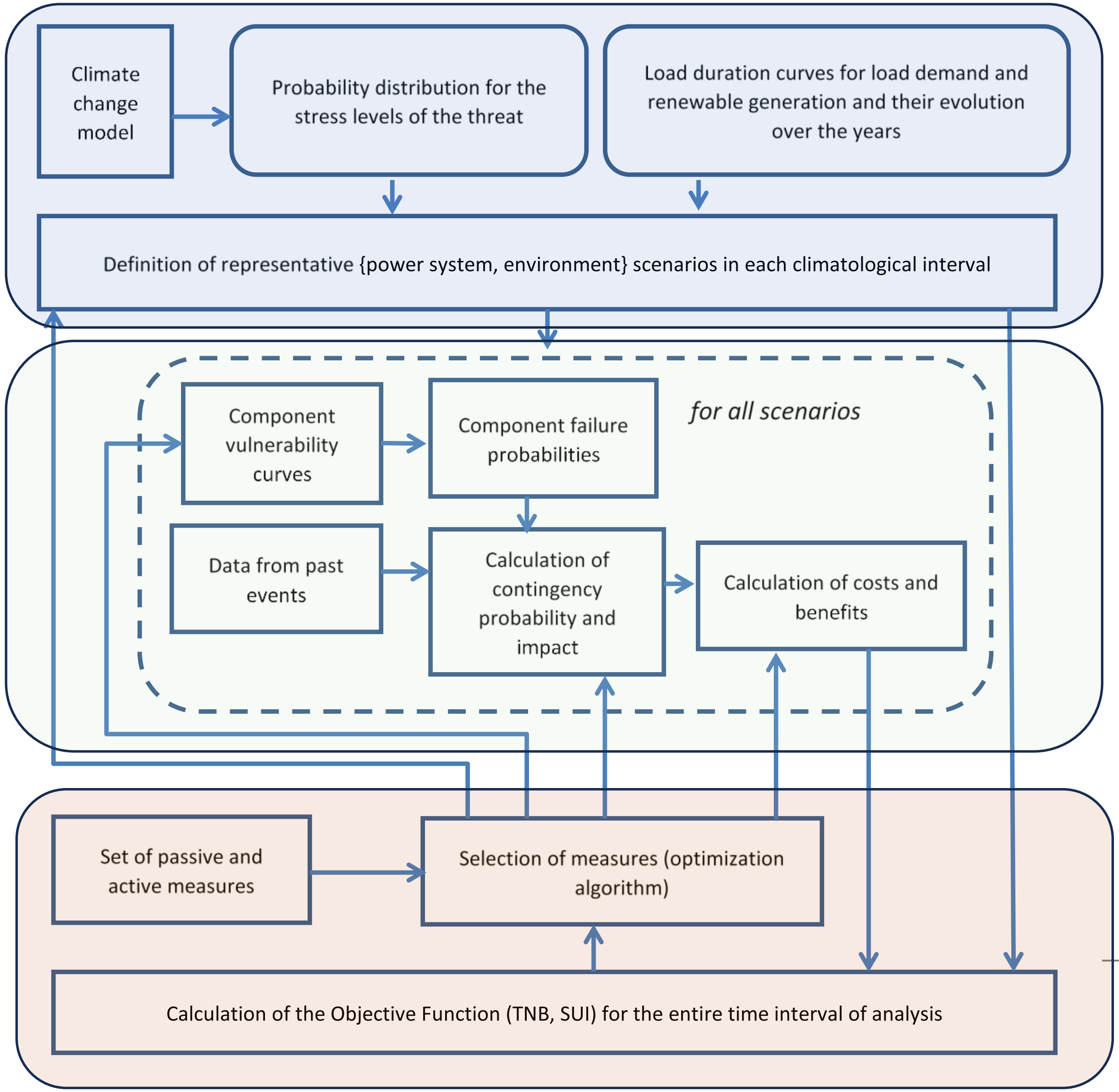
The optimization-based methodology: the architecture

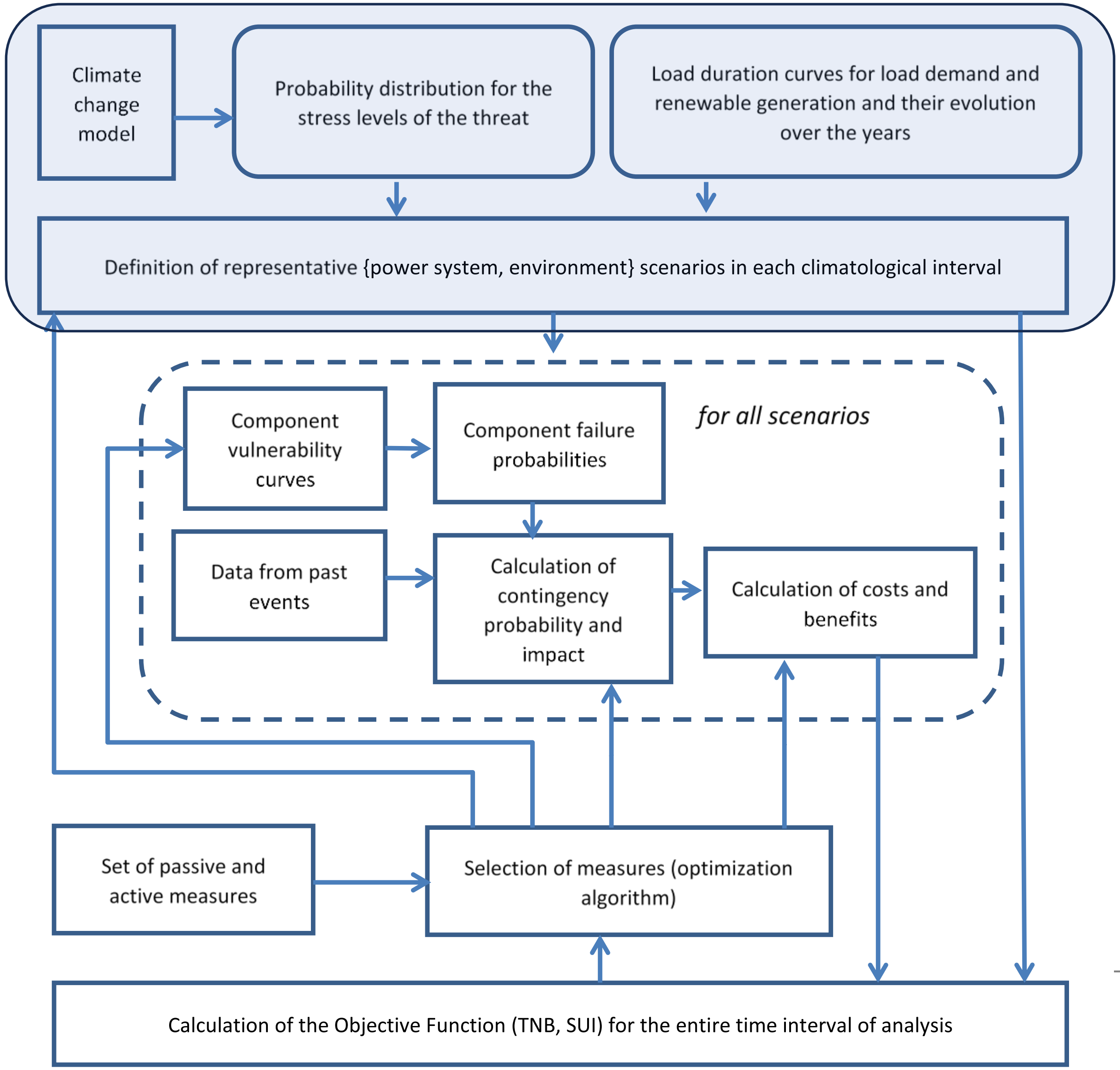


SCENARIO GENERATION including climate evolution, load and renewable generation patterns, including uncertainties

QUANTIFICATION of COSTS and BENEFITS to RESILIENCE from CONTINGENCY SELECTION and SIMULATION

IDENTIFICATION of OPTIMAL MIX of MEASURES

The optimization-based methodology: the architecture



SCENARIO GENERATION including climate evolution, load and renewable generation patterns, including uncertainties

Scenario generation

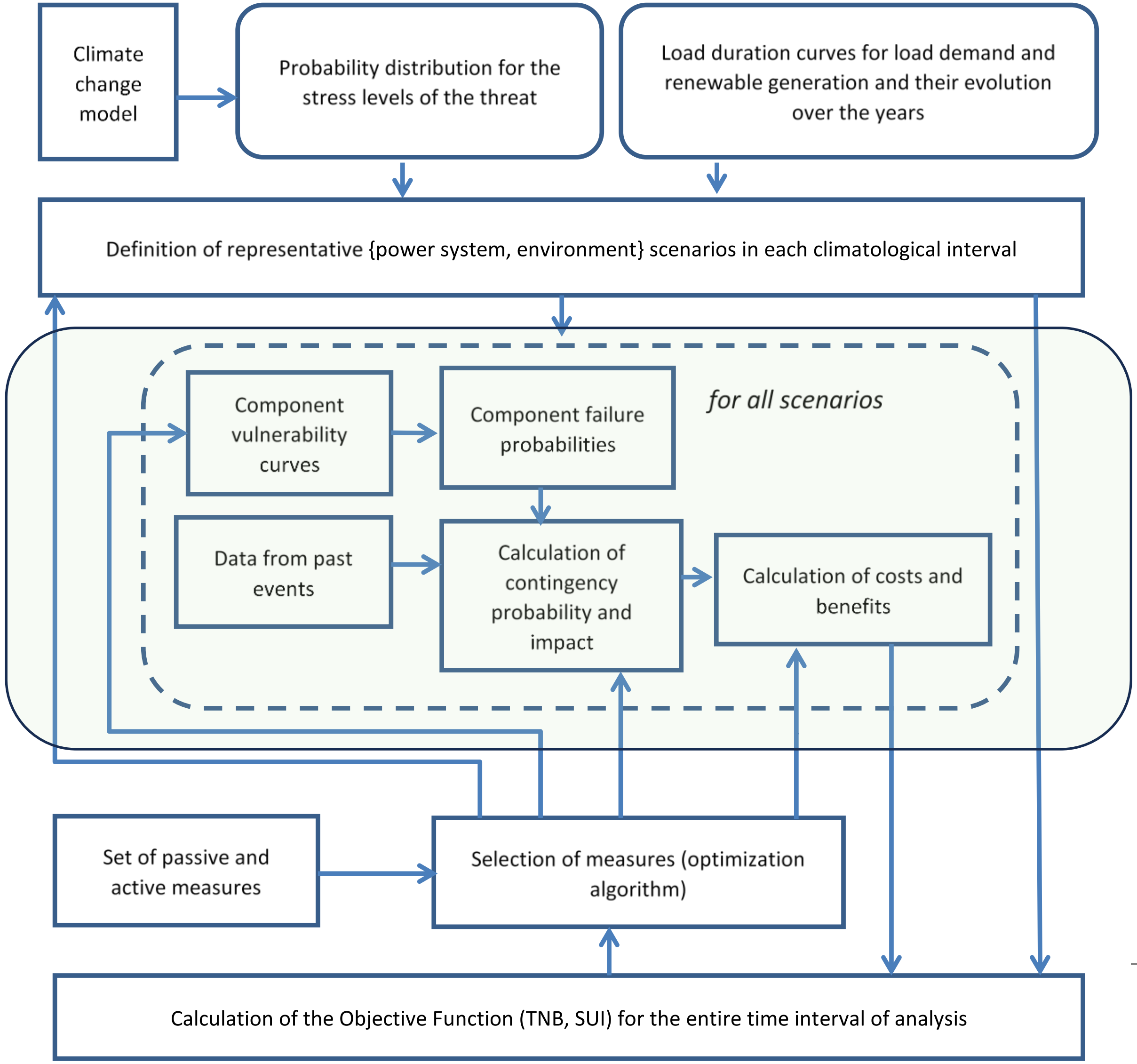
- {Power System (PS) + environment} scenario = operating point of PS + specific threat intensity
- Considering **duration curves** for load demand and renewable generation and GEV (**Generalized Extreme Value**) distributions for maximum yearly values of threat stress variables
- Time horizon divided into 10-year intervals: in each of them, GEV parameters can be considered constant (**stationarity assumption** in **each climatological interval**)
- Steps from scenarios to contingencies:

1. selecting ***representative*** **{power system, environment} scenarios** on the basis of the probabilistic models for CC effects and of projected duration curves.
2. defining a **set of N-k contingencies** involving the components which are more prone to fail, for each scenario generated in step 1) → screening method
3. Simulation of the **impacts of contingencies** retained from step 2)

Selection of representative scenarios

- Assured **flexibility and efficiency of the approach** by **selecting a suitable number of discrete levels** for the stochastic variables (load demand, renewable generation and threat intensity)
- Selecting **representative scenarios** in terms of load demand, threat intensity and renewable generation from a large initial set of scenarios
- **Different techniques** available (**k-means, FFM**)
- Need for a similarity metric to quantify the propension to cascading outages (e.g. netability or pu branch loading profile)
- Representing **Threat** (Th), **Load** (L) and **renewable generation** (G) as **stochastic variables with discrete levels** depending on the outcomes of the techniques above
- In general the approach considers:
  - N_L discrete values of the p.u. loads and N_G values of p.u. RES injections;
  - the GEV distribution of threat intensity discretized into N_{th} values for each p-th climatological interval Δt_p. A specific GEV distribution is derived for each location in the grid based on historical data statistics.
- Thus, the total number of scenarios is equal to $N = N_{th} \cdot N_L \cdot N_G \cdot N_p$

The optimization-based methodology: the architecture



QUANTIFICATION of COSTS and BENEFITS to RESILIENCE from CONTINGENCY SELECTION and SIMULATION

CBA indicators: the general formulation

- **CBA** = comparing costs and benefits of grid interventions
- **Benefits** = reduction of costs due to «insufficient resilience», i.e. costs for energy not served plus costs for asset repair
- **Costs** for hardening interventions (passive measures) and for active (preventive and corrective) measures
- Starting from «**as is**» condition
- At each hour h, **the configuration and system state** are defined by:
  - A specific configuration of hardening interventions $\Theta_s \in \Omega$
  - A specific system state X_h at hour h characterized in terms of power system operating conditions (i.e., components in service, load, and generation patterns) and in terms of a specific threat scenario.
- To solve potential problems associated to the $N_{ctg,h}$ contingencies at hour h, we can adopt:
  - A set of preventive actions $\Phi_P^{(h)}$ changing state from X_h to X_h'
  - A set of corrective actions $\Phi_{C,j}^{(h)}$ to be deployed in case of occurrence of ctg *j*

CBA indicators: the general formulation

- *Total Net Benefit*

$$TNB = Total\_actualized\_benefits - Total\_actualized\_costs$$

$$Total\_actualized\_Benefits = \sum_{y=1}^{T_y} \frac{Annual\_Benefit_y}{(1+r)^{y-y_0}}$$

$$Total\_actualized\_Costs = \sum_{y=1}^{T_y} \frac{Annual\_Cost_y}{(1+r)^{y-y_0}}$$

- *System Utility Index*

$$SUI = \frac{Total\_actualized\_benefits}{Total\_actualized\_costs}$$

annual benefits for the y-th year of analysis

$$Annual\_Benefits_y = \sum_{h=1}^{T_{year,y}} BENEFITs\left(X_h', X_h, \Theta_s, \Theta_0, \Phi_C^{(h)}, \Phi_P^{(h)}\right)$$

annual costs for the y-th year of analysis

$$Annual\_Costs_y = \sum_{h=1}^{T_{year,y}} COSTs\left(X_h', X_h, \Theta_s, \Phi_C^{(h)}, \Phi_P^{(h)}\right) + C_{PL,y}\left(\Theta_s\right)$$

$$BENEFITs\left(X_h', X_h, \Theta_s, \Theta_0, \Phi_C^{(h)}, \Phi_P^{(h)}\right) = \sum_{j=1}^{Nctg_h}\left[B_{repair}\left(X_h', X_h, \Theta_s, \Theta_0, \Phi_C^{(h)}, \Phi_P^{(h)}\right) + B_{ENS}\left(X_h', X_h, \Theta_s, \Theta_0, \Phi_C^{(h)}, \Phi_P^{(h)}\right)\right]$$

$$B_{repair}\left(X_h', X_h, \Theta_s, \Theta_0, \Phi_C^{(h)}, \Phi_P^{(h)}\right) = p_j\left(X_h, \Theta_0, \emptyset\right) \times C_{repair,j}\left(X_h, \Theta_0, \emptyset, \emptyset\right) - p_j\left(X_h', \Theta_s, \Phi_P^{(h)}\right) \times C_{repair,j}\left(X_h', \Theta_s, \Phi_P^{(h)}, \Phi_{C,j}^{(h)}\right)$$

$$B_{ENS}\left(X_h', X_h, \Theta_s, \Theta_0, \Phi_C^{(h)}, \Phi_P^{(h)}\right) = CENS \cdot \left[p_j\left(X_h, \Theta_0, \emptyset\right) \times ENS_j\left(X_h, \Theta_0, \emptyset, \emptyset\right) - p_j\left(X_h', \Theta_s, \Phi_P^{(h)}\right) \times ENS_j\left(X_h', \Theta_s, \Phi_P^{(h)}, \Phi_{C,j}^{(h)}\right)\right]$$

$$COSTs\left(X_h', X_h, \Theta_s, \Phi_C^{(h)}, \Phi_P^{(h)}\right) = \sum_{j=1}^{Nctg_h}\left[p_j\left(X_h', \Theta_s, \Phi_P^{(h)}\right) \times C_{c,j}\left(X_h', \Theta_s, \Phi_P^{(h)}, \Phi_{C,j}^{(h)}\right)\right] + C_p\left(X_h', X_h, \Theta_s, \Phi_P^{(h)}\right)$$

CBA indicators in the scenario-based formulation

- Defined a **pmf (probability mass function) over the discrete threat values** with values $P_{Th}(th, \Delta t_p)$ in each climatological interval *p*, and for each threat intensity value *th*
- Given a specific threat intensity *th*, then: $\sum_{st=1}^{N_{L,G}} P_{L,G|Th}\left(st, \Delta t_p\right) = 1 \quad \forall\ p = 1 \ldots N_p$ where $P_{L,G|Th}\left(st, \Delta t_p\right)$ are the conditional probabilities of the $N_{L,G} = N_L \times N_G$ system operating conditions *st* associated with each climatological interval Δt_p
- Lowercase variables *x*, o , ϕ_P, and ϕ_C represent the discretizations of the corresponding uppercase variables over the n = 1,…, N scenarios

- Scenario based representation for **total benefits** and **costs**:

$$Total\_Benefits = \sum_{p=1}^{N_p} \sum_{st=1}^{N_{L,G}} \sum_{th=1}^{N_{th}} \left\{ BENEFITs\left[x(st, \Delta t_p, th), x'(st, \Delta t_p, th), o_s(\Delta t_p), o_0(\Delta t_p), \phi_P(st, \Delta t_p, th), \phi_C(st, \Delta t_p, th) \right] \times P_{th}\left(\Delta t_p, th\right) \times P_{L,G|Th}\left(st, \Delta t_p\right) \right\}$$

$$Total\_Costs = \sum_{p=1}^{N_p} \left\{ \sum_{st=1}^{N_{L,G}} \sum_{th=1}^{N_{th}} \left[COSTs\left(x(st, \Delta t_p, th), x'(st, \Delta t_p, th), o_s(\Delta t_p), \phi_P(st, \Delta t_p, th), \phi_C(st, \Delta t_p, th) \right) \times P_{th}\left(\Delta t_p, th\right) \times P_{L,G|Th}\left(st, \Delta t_p\right) \right] + C_{PL}\left(o_s(\Delta t_p) \right) \right\}$$

Contingency screening and probabilistic modeling

- Adopted a **N-k contingency screening method** developed for a long term resilience assessment methodology
- **Identified clusters of lines** which tend to fail together, on the basis of the estimation of the extension of past weather events (quantified using a correlation matrix *R*)
- Evaluated **only N-k contingencies affecting lines in the same clusters** to limit the combinatorial explosion ☺
- Application of **copula theory** to vector ***F*** of binary variables (representing the failure event for each line) to get the probability of N-k contingencies among the assets exposed to the threat
- By Sklar's theorem we get:

$$P(\bar{F}) = \sum_{s_1} \dots \sum_{s_q} sign(\bar{s}) C\left(CDF_1(s_1) \dots CDF_q(s_q), R\right)$$

where $\bar{F} = (F_1 = f_1 \dots, F_n = f_n)$ and $\bar{s}$ is a vector with q components $s_1, \dots, s_q$, where s_j can be f_j or $f_j - 1$.

$$sign(\bar{s}) = \begin{cases} +1 & \text{if } s_j = f_j - 1 \text{ for an even number of positions } j \\ -1 & \text{if } s_j = f_j - 1 \text{ for an odd number of positions } j \end{cases}$$

- **Efficient screening** exploiting the **total probability theorem**

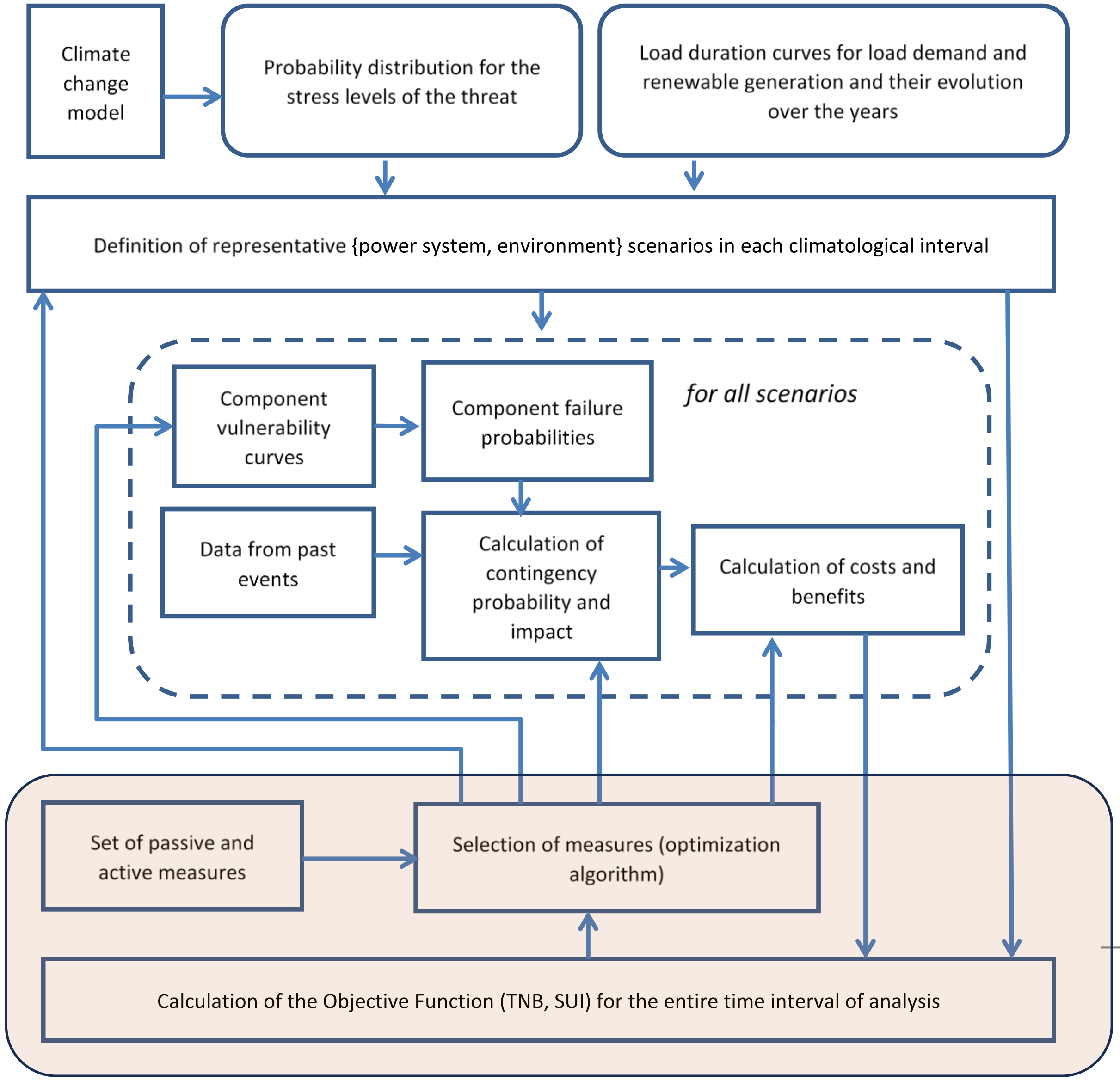
Contingency impact evaluation

- Computing CBA indicators implies the **assessment of the ENS (*Energy Not Served*) potentially provoked by contingencies**
- **ENS** impact indicator **can't be expressed as an analytic function** of the decision variables →needs the simulation of PS response to the contingencies
- **OvS (Optimization via Simulation) approach** is required!
- Exploited a **robust load-flow-based quasi-static cascading outage simulator** developed in RSE to assess:
  - Slow overloading-driven cascading outages
  - Steady state response of main protection, control and defense systems
- This step provides set C_n of critical contingencies is identified (i.e., the contingencies with a not-null ENS) for each scenario *n*

Uncertainty modeling

- **Different sources of uncertainty** modeled:
  - The values for load demand and generation from renewables
  - The effects of **climate changes**
- Probability of each Th/L/G scenario $P_{Th,L,G}(Th = v_{Th}, G = v_G, L = v_L)$ calculated by the techniques for the selection of representative scenarios
- Reanalysis datasets (MERIDA) and climatological models are available to characterize the probabilistic models for the current climate and its trends for the future.
- The effects of climate evolution are accounted for by:
  - applying **time-dependent parameters** to the **GEV distributions**
  - Discretizing the GEV distributions and calculating the probability of overcoming a «HIGH» threat intensity (set also on the basis of grid asset design criteria, e.g. 8 kg/m for wet snow threat) for any climatological interval
- **Two models for GEV distributions** are considered:
  - **MOD 1**: it **computes the variations** of the overcoming probability **among the different climatological intervals** for each climatological model, for each threat value, and for each location, then it averages these variations over the ensemble models and it **applies the average variation to the reanalysis probability maps**
  - **MOD2**: it **calculates the overcoming probability** of each threat value, at any location, for each climatological interval, **as the average of the corresponding overcoming probabilities for the ensemble** of the climatological models

The optimization-based methodology: the architecture



IDENTIFICATION of OPTIMAL MIX of MEASURES

The problem formulation (I)

- In line with CBA performed by TSOs
- **Objective functions**: maximise the TNB or SUI indexes over the space of passive and active measures

$$\max_{\{\Omega,\Phi_C,\Phi_P\}} TNB \quad \text{or} \quad \max_{\{\Omega,\Phi_C,\Phi_P\}} SUI$$

- **Binary decision variables** to represent the activation of each measure
- **Passive measures** usually depend on the specific threat under study (e.g. support reinforcement, and antitorsional devices for wet snow threat)
- **Active measures**:
  - Preventive redispatch of dispatchable generators and renewables curtailment
  - Corrective load or generation shedding

The problem formulation (II)

- **Climate dependent ranking** for candidates to reinforcements
- N_{MAX} max nr. of candidates

$$\widehat{T}_{i,p} = RP_i \times \frac{\rho_{i,0}^{(\ell)}}{\rho_{i,p}^{(\ell)}}$$

Current probability that spans of i-th branch overcome load «ℓ» (MERIDA)

Probability that spans of i-th branch overcome load «ℓ» **in p-th climatological interval**

Failure return period for i-th branch

- **Constraints**
  - **Maximum costs** for each typology of measure

$$\sum_{h=1}^{T} \Phi_P^{(h)} \leq \overline{C_{P,tot}} \qquad \sum_{h=1}^{T} \left[\sum_{j=1}^{N_{ctg,h}} \Phi_{C,j}^{(h)} p_j \left(X_h, \Theta_s, \Phi_P^{(h)} \right) \right] \leq \overline{C_{C,tot}} \qquad C_{PL}\left(\Theta_s\right) \leq \overline{C_{PL,tot}}$$

  - **Persistence of hardening** solutions: if a hardening measure is deployed in a scenario of climatological interval Δt_p, it applies also for any scenario belonging to subsequent climatogological intervals $p' > p$
  - **maximum** admissible **residual EENS (**Expected Energy Not Served)
  - Min. rate of **improvement of failure RP** on an asset > 10% of the initial RP: RP_{POST} > 110% RP_{PRE}
  - Other **technical constraints**: max load available for corrective shedding, technical limits of dispatchable generators, branch power ratings

The problem formulation (III)

- Scenario-based formulation with binary decision variables:
  - Vector $o_s(\Delta t_p)$ with length $N_{PL} \times N_{comp} \times N_p$, related to the deployment of N_{PL} types of available **passive** measures

# of climatological intervals

# of candidate components

# of types of passive measures

  - Vector $\phi_P(st, \Delta t_p, th)$ with length *N* for **preventive** active measures
  - Vector $\phi_C(st, \Delta t_p, th)$ with length *N* for **corrective** active measures

of {threat/load/renewable gen.} scenarios

How is the optimization problem like?

- **Binary Non-Linear Programming (BNLP)**, a subset of Mixed-Integer Non-Linear Programming (MINLP)
- Two complexities in the problem:
  - **High computational burden** for the **OF calculation**
    - need for cascading outage simulation over a large set of contingencies etc.
  - **High dimensionality** of the decision variable space
    - number of potential combinations of active and passive measures is very high and grows fast with the number of threat/load/generation scenarios analyzed.
- Exact methods?
  - *Exhaustive search*: low efficiency due to high dimensionality ☹
  - *Branch and bound*: absence of effective lower bounds for OF → low efficiency ☹
  - *Dynamic programming*: absence of optimal substructure ☹

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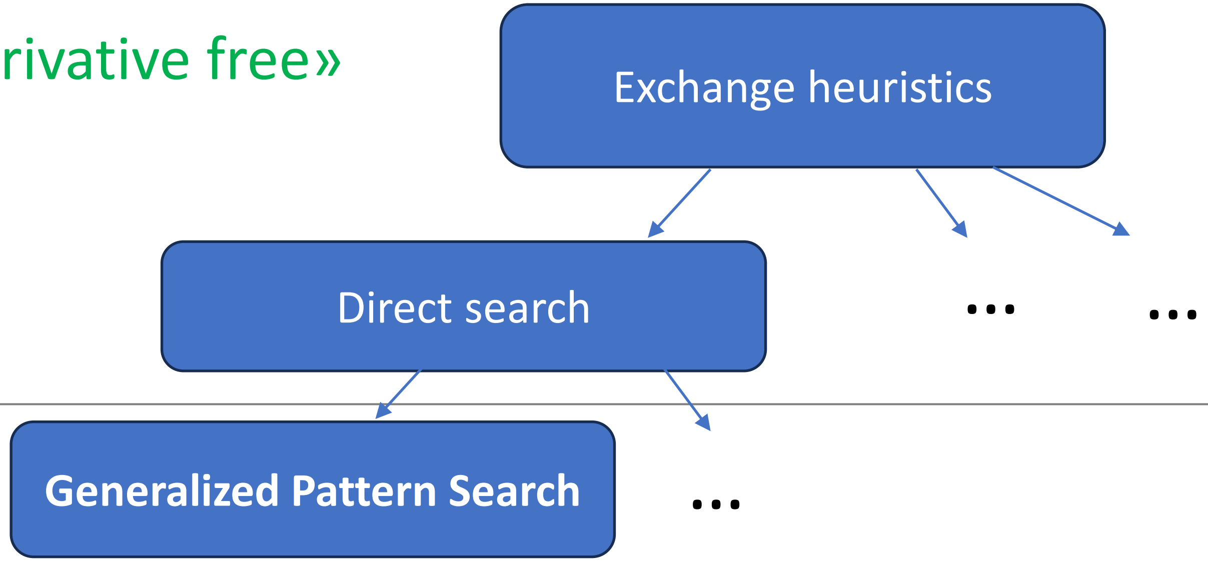
NEED FOR HEURISTIC METHODS

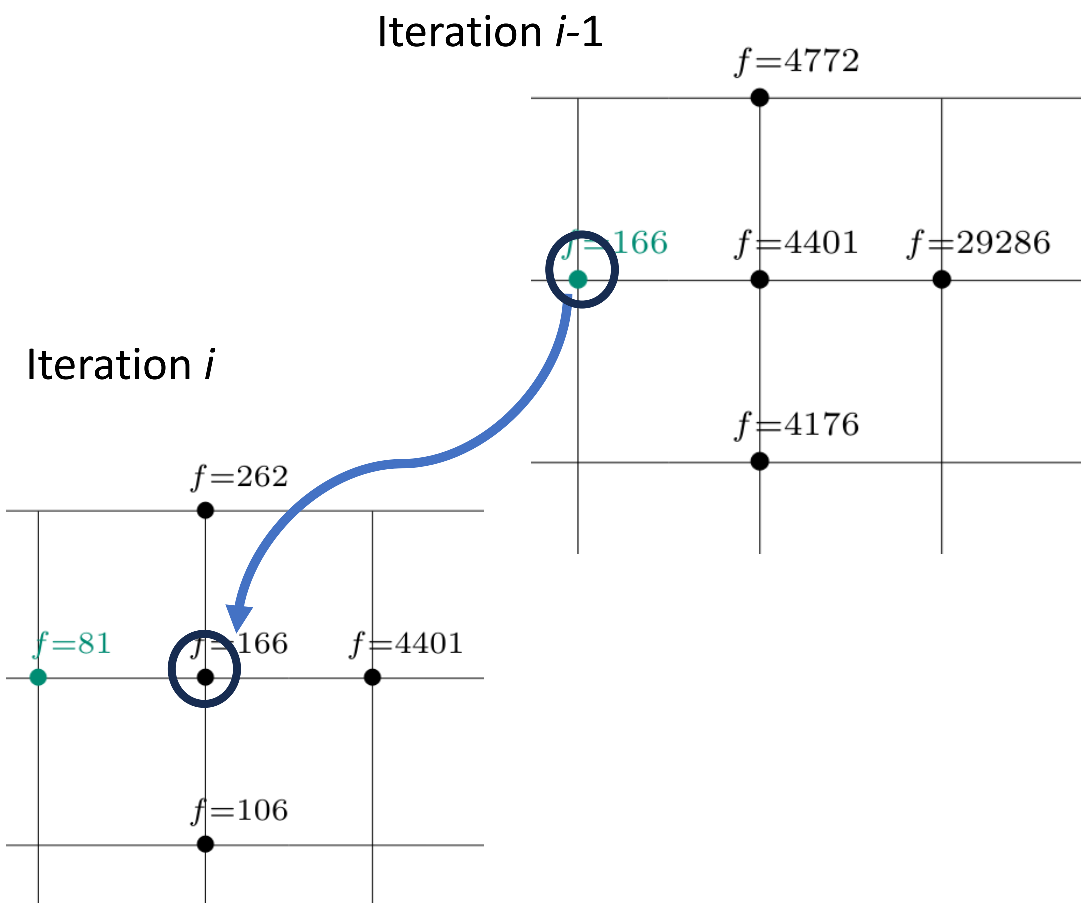
Heuristic algorithms

- Attaining **sufficiently good solutions in reasonable time**
- Which heuristics?
  - **Constructive/destructive**: only add or remove single element from solution – difficult to reach the best tradeoff between active and passive measures
  - **Recombination heuristics**: combine different solutions → need for performing a large number of OF evaluations
  - **Exchange heuristics**: fewer OF evaluations wrt recombination and larger set of operations allowed
  - Direct search consists in «derivative free» algorithms

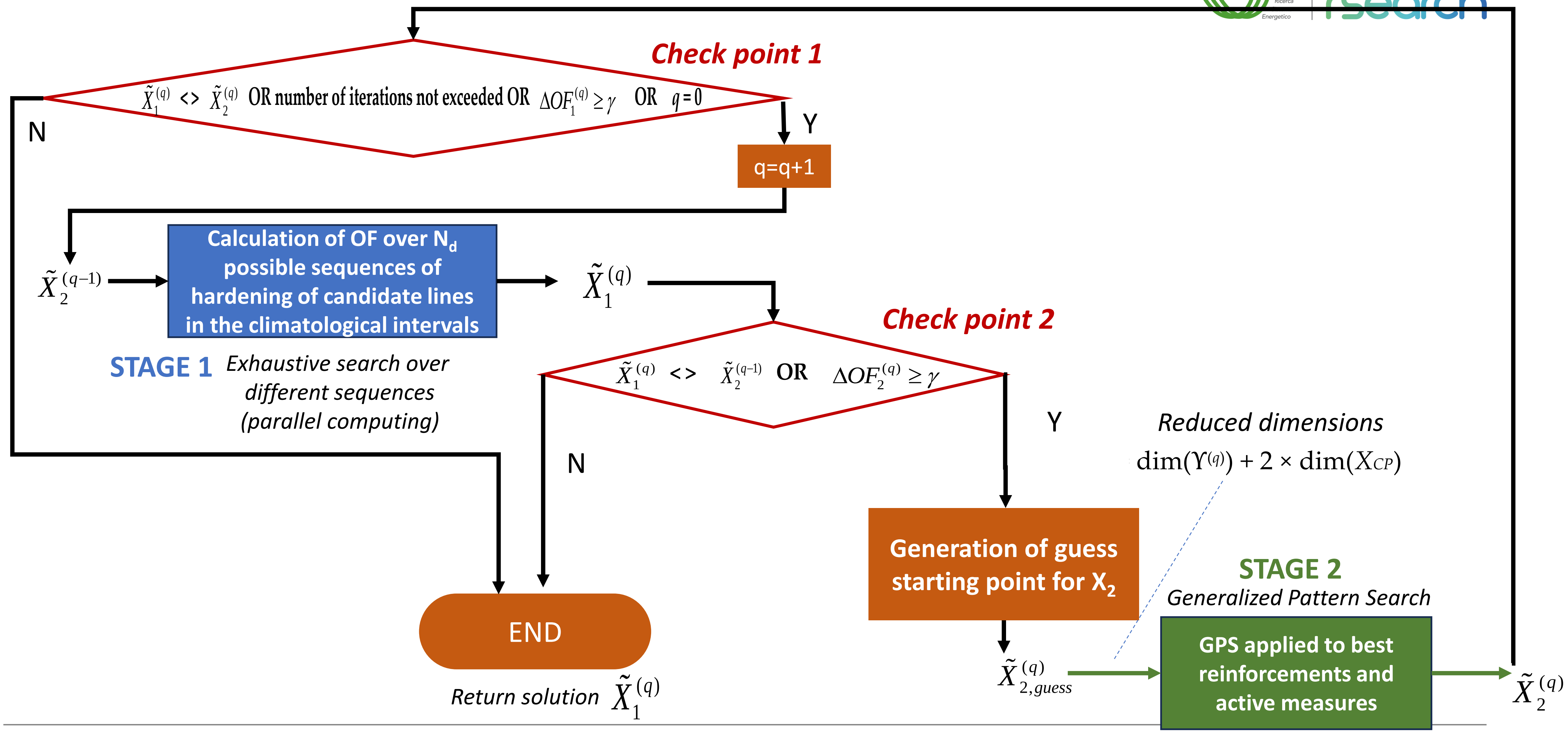


The GPS algorithm

- At iteration i, the algorithm computes the OF values for a set of points around the current point (coming from iteration i-1)
- The **point with lowest OF becomes the center** of the new mesh at next iteration
- **Versatile**: working with both binary and continuous variables
- The mesh size can be adapted during iterations depending on the poll outcome (success/insuccess), in case of continuous variables
- Fixed mesh size for binary variables
- **Including non linear constraints**
- **GPS efficiency decreases as the number of decision variables increases ☹ …**



Two-stage algorithm: the workflow



Just a legend …

- $\tilde{X}_1^{(q)}$ = Vector of binary decision variables representing the solution at the end of Stage 1 and iteration *q*,
- $\Delta OF_1^{(q)} = OF\left(\tilde{X}_2^{(q)}\right) - OF\left(\tilde{X}_1^{(q)}\right)$ = OF variation at first checkpoint at iteration *q*,
- $\Delta OF_2^{(q)} = OF\left(\tilde{X}_1^{(q)}\right) - OF\left(\tilde{X}_2^{(q-1)}\right)$ = OF variation at second checkpoint at iteration *q*,
- X_{CP} = Subvector of generic solution *X*, including the binary decision variables which indicate the potential activation of preventive and corrective action measures in the *N* scenarios, thus $\dim(X_{CP}) = 2 \cdot N$;
- $\Upsilon^{(q)}$ = Subset of lines of set $\mathfrak{J}$ which are selected by the proposed algorithm at Stage 1 at iteration q of the optimization and remain candidates in Stage 2;
- $\tilde{X}_2^{(q)}$ = Vector of binary decision variables representing the solution at the end of Stage 2 and iteration *q*, dim( ) = $\dim(\Upsilon^{(q)}) + 2 \times \dim(X_{CP})$;
- $X_{2,guess}^{(q)}$ = Vector of binary decision variables representing a guess solution at the end of Stage 2 and iteration *q*.
- Base case: set of ENS E_n and contingencies C_n for any scenario *n*
- Set $\mathfrak{J}$: set of lines involved in set C_n in the base case

- VNS are interesting alternatives for **non linear optimization with binary variables**
- The optimization problem is stated as follows:

$$\min\{f(x) | x \in X \subseteq S\} \qquad (\S)$$

where *S*, *X*, *x* and *f* respectively represent the solution space and the feasible set, a feasible solution and a real valued objective function

- A **neighbourhood N(x)** is defined as: $N(x) = \{y \in X \mid \delta(x,y) \leq \alpha\}$ with α positive number and δ is a distance metric
- A solution $x^* \in N(x)$ is a local minimum, relative to neighborhood $N(x^*)$ for problem in (§) if $f(x^*) \leq f(x)\ \forall x \in N(x^*)$
- **VND is a variant of VNS** methods so that it evaluates the OF values in a sequence of neighborhoods of the current point and moves to the point with minimum OF value after the complete poll of all neighbors (**best improvement** strategy) or when it encounters the first lower OF value (**first improvement** strategy).

Case studies

- **Case study 1**: application of the two-stage algorithm to a proof-of-concept case study
- **Case study 2**: evaluating the applicability of the methodology to a real world case study
- **Case study 3**: comparing different alternatives of solution algorithms

General data: threat under study and countermeasures

- **Wet snow** is the threat under study
- Two **passive measures** considered:
  - support reinforcement
  - antitorsional device application
- The **preventive measure** consists in redispatching of dispatchable generators to avoid cascading tripping due to overloads
- The **corrective measure** consists in load shedding actions performed in the case of contingency occurrence to relieve potential security problems

General data: costs for the applied measures

Cost Typology	Measurement Unit	Value
Unitary costs for upward redispatch	amu/MWh	100
Unitary costs for downward redispatch	amu/MWh	−20
RES curtailment costs	amu/MWh	100
Corrective measure cost (load shedding)	amu/MWh	4×10^4
Cost of energy not served	amu/MWh	4×10^4
Unitary capital cost of tower support hardening	amu/km	4×10^4
Unitary capital costs for antitorsional devices	amu/device	1×10^2
Operational costs for support hardening	p.u. of capital costs	0.015
Operational costs for antitorsional devices	p.u. of capital costs	0.015
Maximum admissible costs for preventive measures	amu	1×10^7
Maximum admissible costs for corrective measures	amu	1×10^7
N_{MAX} maximum number of candidates to reinforcement	-	10
Maximum admissible costs of hardening measures	amu	1×10^7
Maximum residual expected ENS (EENS)	MWh	1×10^5

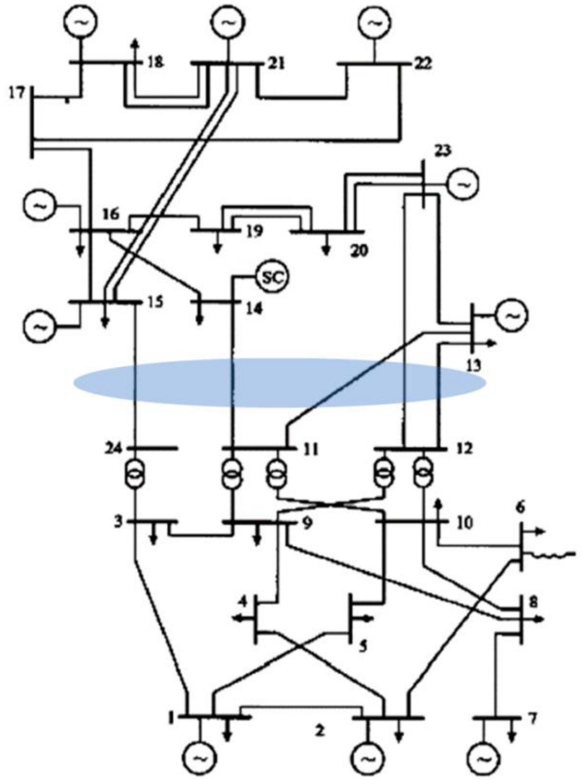
General data: convention for scenario numbering

Scenario ID—1st Interval	Scenario ID—2nd Interval	Scenario ID—3rd Interval	Threat (TH)	Generation (G)	Load (L)
1	9	17	L	L	L
2	10	18	L	L	H
3	11	19	L	H	L
4	12	20	L	H	H
5	13	21	H	L	L
6	14	22	H	L	H
7	15	23	H	H	L
8	16	24	H	H	H

H = HIGH **L = LOW**

Case study 1: the proof of concept

- RTS 24 IEEE test system
- 220 kV area (North) located in the Alpine area of Nort East of Italy, exposed to wet snow events
- 138 kV (South) located in the pre-Alpine area
- Calculation of failure RP's of overhead lines



Line ID	Failure RP, Year
B11-B13	15
B11-B14	20
B12-B13	23
B12-B23	15
B15-B24	10
B01-B03	50
B01-B05	70

Correlation among these lines > 0.9

Correlation among these lines = 0.8

Case study 1: simulation summary

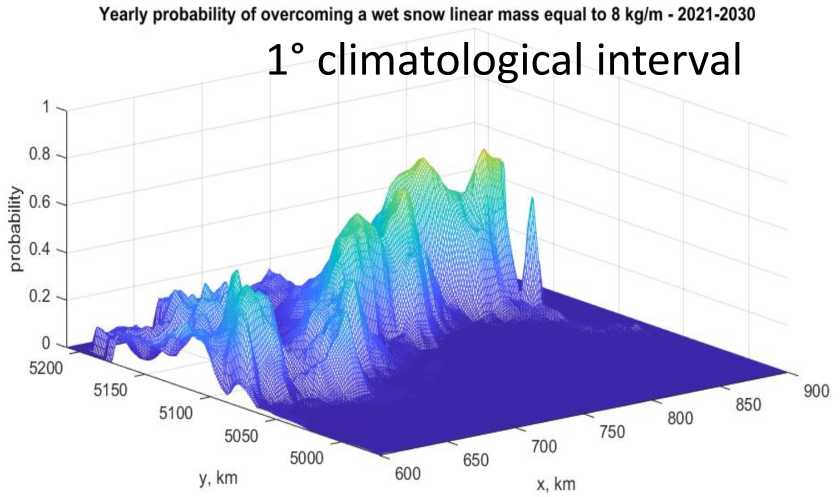
Optimization Case ID	Description	Goal
1	SUI-driven and TNB-driven optimization of portfolio with the costs in Table 2 and with probabilistic model MOD1 for CC effects	Check the **effect of the introduction of antitorsional** device model
2	Increase in the unitary cost of antitorsional devices from 100 to 250 amu/device; use of probabilistic model MOD1 for CC effects	Evaluate the **effects of different unitary costs for hardening solutions** on the optimized portfolio
3	Same as case 2 but reduction in the unitary cost for corrective action from 4×10^4 to 4×10^3 amu/MW; use of probabilistic model MOD1 for CC effects	Evaluate the **effects of different unitary costs for corrective measures** on the optimized portfolio
4	Running the SUI-driven and TNB-driven optimization under the same hypotheses of costs as in cases 1, 2, and 3, but using model MOD2 for CC effects	Evaluate the effects of a **different probabilistic model for climate change** on the optimal mix of measures

Case study 1: the base case («as is» condition)

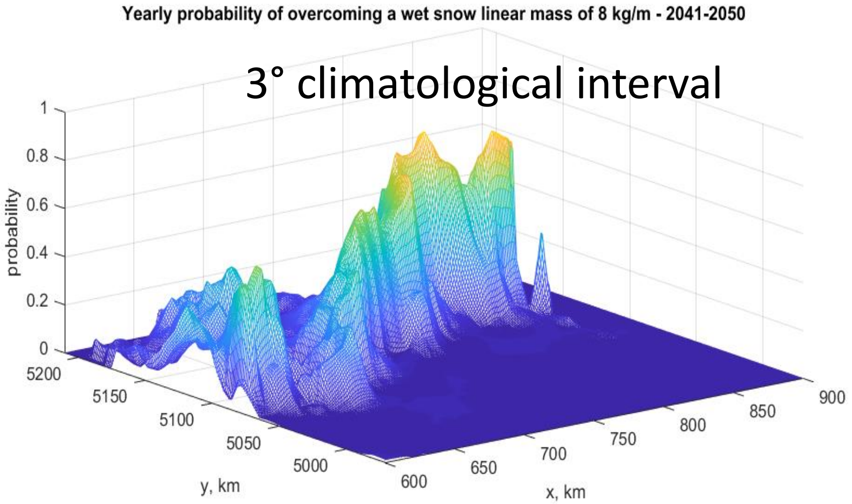
- **List of contingencies with ENS > 0** for scenario #6 (1st climatological interval, HIGH load, LOW RES generation, HIGH Threat)

Contingency ID	Contingency Description	ENS (MWh)
1	B11-B13; B11-B14; B12-B13; B15-B24	2.1418×10^4
2	B11-B13; B11-B14; B12-B13; B12-B23	4.5828×10^4
3	B11-B14; B12-B13; B12-B23; B15-B24	2.1418×10^4
4	B11-B13; B12-B13; B12-B23; B15-B24	2.4538×10^4
5	B11-B13; B11-B14; B12-B23; B15-B24	2.1418×10^4
6	B11-B13; B11-B14; B12-B13; B12-B23; B15-B24	2.1418×10^4

- **Ctgs # 1,3 and 5 cause overloading of the remaining branch** between 220 and 138 kV area → consequent cascading tripping and loss of load in 138 kV load area
- **Ctg #2 causes the tripping of an overloaded branch and subsequent security problems** which lead all the RTS grid into blackout.
- Ctg #6 causing separation of 220 and 138 kV areas
- **Total EENS** over 30 years= **2.075 $\times$ 10³ MWh**



Example of climate evolution (MOD 2)



Case study 1 + sim 1 (standard costs and MOD 1)

OF = TNB

List of Measures	Costs (amu) 1st Interval	2nd Interval	3rd Interval	Total
Hardening of supports (upgraded line)	–	–	–	–
Installation of antitorsional devices (upgraded line)	4.1497×10^5 (B12-B13)	5.4126×10^4 (B12-B13)	1.3532×10^5 (B12-B13) 2.6488×10^5 (B11-B14)	8.6929×10^5
Preventive action deployment (scenario ID)	–	–	–	–
Corrective action deployment (scenario ID)	8.5653×10^4 (6) 1.9379×10^3 (8)	1.0250×10^5 (14) 2.8553×10^3 (16)	–	1.9295×10^5

OF = SUI

List of Measures	Costs (amu) 1st Interval	2nd Interval	3rd Interval	Total
Hardening of supports (upgraded line)	-	-	-	-
Installation of antitorsional devices (upgraded line)	–	–	2.6488×10^5 (B11-B14)	2.6488×10^5
Preventive action deployment (scenario ID)	–	-	-	-
Corrective action deployment (scenario ID)	–	–	–	–

- In TNB case **relatively low costs** for **antitorsional devices** favor the adoption of such a measure **from the first interval**
- **for any passive measure > two costs considered**: the relevant **capital costs** in the first interval (e.g., interval 1 for anti-torsional devices in branch B12-B13) and the relevant op**erational costs** (much smaller than the capital ones) in the subsequent intervals (e.g., intervals 2 and 3 for branch B12-B13).

Quantity	OF=TNB	OF=SUI
Residual EENS [MWh]	0	1702
Final SUI [-]	93.89	139.52
Final TNB [amu]	5.6585×10^7	1.0464×10^7

Case study 1 + sim 2 (unitary cost of antitorsional devices from 100 to 250 amu/device)

OF = TNB

List of Measures	Costs (amu) 1st Interval	2nd Interval	3rd Interval	Total
Hardening of supports (upgraded line)	–	–	–	–
Installation of antitorsional devices (upgraded line)	1.0374×10^6 (B12-B13)	1.3532×10^5 (B12-B13)	3.3829×10^5 (B12-B13) 6.6221×10^5 (B11-B14)	2.1732×10^6
Preventive action deployment (scenario ID)	211.3 (6)	–	–	211.3
Corrective action deployment (scenario ID)	8.4841×10^4 (6) 1.9140×10^3(8)	1.0290×10^5 (14) 2.8387×10^3 (16)	–	1.9249×10^5

OF = SUI

List of measures	Costs (amu) 1st Interval	2nd Interval	3rd Interval	Total
Hardening of supports (upgraded line)	–	–	–	–
Installation of antitorsional devices (upgraded line)	–	–	–	–
Preventive action deployment (scenario ID)	–	–	–	–
Corrective action deployment (scenario ID)	–	–	8.4879×10^3 (24)	8.4879×10^3

- In case OF=TNB, TNB slightly decreases wrt sim 1, while there is a **significant drop in SUI due to higher capital costs for antitorsional** devices
- In case OF=SUI, only a corrective action is performed in 3rd interval bringing to a very low EENS reduction

Quantity	OF=TNB	OF=SUI
Residual EENS [MWh]	0	2055
Final SUI [-]	43.02	66.26
Final TNB [amu]	5.5864×10^7	2.0506×10^5

Case study 1 + sim 3 (same as sim 2 + cost for corrective action from 4×10^4 to 4×10^3 amu/MW)

OF = TNB

List of Measures	Costs (amu) 1st Interval	2nd Interval	3rd Interval	Total
Hardening of supports (upgraded line)	–	–	–	–
Installation of antitorsional devices (upgraded line)	5.5385×10^5 (B11-B14)	7.2241×10^4 (B11-B14)	1.8060×10^5 (B11-B14) 1.2404×10^6 (B11-B13)	2.7514×10^6
Preventive action deployment (scenario ID)	–	–	–	–
Corrective action deployment (scenario ID)	6.1374×10^4 (6) 1.0031×10^3 (8)	6.8819×10^4 (14) 1.3023×10^3 (16)	–	1.3250×10^5

OF = SUI

List of Measures	Costs (amu) 1st Interval	2nd Interval	3rd Interval	Total
Hardening of supports (upgraded line)	–	–	–	–
Installation of antitorsional devices (upgraded line)	–	–	–	–
Preventive action deployment (scenario ID)	–	–	–	–
Corrective action deployment (scenario ID)	–	–	8.6783×10^2 (24)	8.6783×10^2

- In case OF=TNB, TNB slightly increases wrt sim 2, while there is a significant increase in SUI wrt sim 2 due to lower costs for corrective measures
- In case OF=SUI, only a corrective action is performed in 3rd interval bringing to a very low EENS reduction

Quantity	OF=TNB	OF=SUI
Residual EENS [MWh]	0	2055
Final SUI [-]	58.18	648.13
Final TNB [amu]	5.6210×10^7	2.0789×10^5

Case study 1 + sim 3 (same as sim 2 + cost for corrective action from 4 × 10^4 to 4 × 10^3 amu/MW)

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OF = TNB

List of Measures	*Costs (amu)* *1st Interval*	*2nd Interval*	*3rd Interval*	*Total*
Hardening of supports (upgraded line)	–	–	–	–
Installation of antitorsional devices (upgraded line)	5.5385×10^5 (B11-B14)	7.2241×10^4 (B11-B14)	1.8060×10^5 (B11-B14) 1.2404×10^6 (B11-B13)	2.7514×10^6
Preventive action deployment (scenario ID)	–	–	–	–
Corrective action deployment (scenario ID)	6.1374×10^4 (6) 1.0031×10^3 (8)	6.8819×10^4 (14) 1.3023×10^3 (16)	–	1.3250×10^5

OF = SUI + max residual EENS = 1000 MWh

List of Measures	*Costs (amu)* *1st Interval*	*2nd Interval*	*3rd Interval*	*Total*
Hardening of supports (upgraded line)	–	–	–	–
Installation of antitorsional devices (upgraded line)	–	–	–	–
Preventive action deployment (scenario ID)	–	–	–	–
Corrective action deployment (scenario ID)	5.3337×10^4 (6)	5.2174×10^4 (14) 1.4206×10^3 (16)	3.6609×10^4 (22) 8.6784×10^2 (24)	1.4441×10^5

Inserting a maximum residual EENS equal to 1000 MWh in case OF=SUI causes a reduction of the SUI from 648 to 388 (less cost-effective solution) but a higher TNB (from 2.89×10^7 to 3.35×10^7).

Quantity	OF=TNB	OF=SUI rEENS=1000 MWh
Residual EENS [MWh]	0	631.86
Final SUI [-]	58.18	388.48
Final TNB [amu]	5.6210×10^7	3.3518×10^7

Case study 1 + sim 4 (changing climate change effect model from MOD 1 to MOD 2)

The residual EENS in the «as is» condition passes from 2075 to **4543.5** MWh due to **higher probabilities of occurrence of severe wet snow** events with MOD 2

Sim 4 a (standard costs + MOD 2)

OF = TNB	Costs (amu)			
List of Measures	*1st Interval*	*2nd Interval*	*3rd Interval*	*Total*
Hardening of supports (upgraded line)	–	–	–	–
Installation of antitorsional devices (upgraded line)	*5.0310 × 10^5(B11-B13)*	*6.5623 × 10^4(B11-B13)*	*1.6405 × 10^5(B11-B13)* *5.2976 × 10^5(B11-B14)*	*1.2626 × 10^6*
Preventive action deployment (scenario ID)	–	–	–	–
Corrective action deployment (scenario ID)	*1.2809 × 10^5 (6)* *1.5214 × 10^4 (8)*	*1.8127 × 10^5 (14)* *5.7287 × 10^4 (16)*	–	*3.8186 × 10^5*

OF = SUI	Costs (amu)			
List of measures	*1st Interval*	*2nd Interval*	*3rd Interval*	*Total*
Hardening of supports (upgraded line)	–	–	–	–
Installation of antitorsional devices (upgraded line)	–	–	*6.0154 × 10^5 (B11-B13)*	*6.0154 × 10^5*
Prev. action deployment (sc. ID)	–	–	–	–
Corr. action deployment (sc. ID)	–	–	–	–

Quantity	OF=TNB	OF = SUI
Residual EENS [MWh]	0	3.1584 × 10^3
Final SUI [-]	133.87	199.07
Final TNB [amu]	1.1810 × 10^8	3.3981 × 10^7

Case study 1 + sim 4 (changing climate change effect model from MOD 1 to MOD 2)

The residual EENS in the «as is» condition passes from 2075 to **4543.5** MWh due to **higher probabilities of occurrence of severe wet snow** events with MOD 2

Sim 4 a (standard costs + MOD 2)

OF = TNB

List of Measures	*Costs (amu)* 1st Interval	*2nd Interval*	*3rd Interval*	*Total*
Hardening of supports (upgraded line)	–	–	–	–
Installation of antitorsional devices (upgraded line)	*5.0310 × 10^5(B11-B13)*	*6.5623 × 10^4(B11-B13)*	*1.6405 × 10^5(B11-B13)* *5.2976 × 10^5(B11-B14)*	*1.2626 × 10^6*
Preventive action deployment (scenario ID)	–	–	–	–
Corrective action deployment (scenario ID)	*1.2809 × 10^5 (6)* *1.5214 × 10^4 (8)*	*1.8127 × 10^5 (14)* *5.7287 × 10^4 (16)*	–	*3.8186 × 10^5*

OF = SUI+ max residual EENS = 1000 MWh

List of Measures	Costs (amu) 1st Interval	2nd Interval	3rd Interval	Total
Hardening of supports (upgraded line)	–	–	–	–
Installation of antitorsional devices (upgraded line)	5.0311 × 10^5 (B11-B13)	6.5623 × 10^4 (B11-B13)	1.6405 × 10^5 (B11-B13) 5.2977 × 10^5 (B11-B14)	1.2625 × 10^6
Prev. action deployment (sc. ID)	–	–	–	–
Corr. action deployment (sc. ID)	–	–	–	–

Quantity	OF=TNB	OF=SUI rEENS=1000 MWh
Residual EENS [MWh]	0	996
Final SUI [-]	133.87	144.35
Final TNB [amu]	1.1810 × 10^8	9.2016 × 10^7

Case study 1 + sim 4 (changing climate change effect model from MOD 1 to MOD 2)

The residual EENS in the «as is» condition passes from 2075 to **4543.5** MWh due to **higher probabilities of occurrence of severe wet snow** events with MOD 2

Sim 4 b (same as sim 2 but MOD 2)

OF = TNB

List of Measures	Costs (amu) 1st Interval	2nd Interval	3rd Interval	Total
Hardening of supports (upgraded line)	–	–	–	–
Installation of antitorsional devices (upgraded line)	1.2577×10^6 (B11-B13) 1.1077×10^6 (B11-B14)	1.6406×10^5 (B11-B13) 1.4448×10^5 (B11-B14)	4.1014×10^5 (B11-B13) 3.6120×10^5 (B11-B14) 1.5038×10^6 (B12-B13)	4.9492×10^6
Prev, action deployment (sc. ID)	–	–	–	–
Corr. action deployment (sc. ID)	–	–	–	–

OF = SUI

List of measures	Costs (amu) 1st Interval	2nd Interval	3rd Interval	Total
Hardening of supports (upgraded line)	–	–	1.5038×10^6 (B11-B13)	1.5038×10^6
Installation of antitorsional devices (upgraded line)	–	–	–	–
Preventive action deployment (scenario ID)	–	–	–	–
Corrective action deployment (scenario ID)	2.8897×10^4 (8)	1.0251×10^5 (16)	5.7450×10^5 (22) 3.3221×10^5 (24)	1.0381×10^6

Quantity	OF=TNB	OF = SUI
Residual EENS [MWh]	0	2044
Final SUI [-]	43.48	84.63
Final TNB [amu]	1.1625×10^8	6.4147×10^7

Case study 1 + sim 4 (changing climate change effect model from MOD 1 to MOD 2)

The residual EENS in the «as is» condition passes from 2075 to **4543.5** MWh due to **higher probabilities of occurrence of severe wet snow** events with MOD 2

Sim 4 b (same as sim 2 but MOD 2)

OF = TNB

	Costs (amu)			
List of Measures	*1st Interval*	*2nd Interval*	*3rd Interval*	*Total*
Hardening of supports (upgraded line)	–	–	–	–
Installation of antitorsional devices (upgraded line)	*1.2577 × 10⁶ (B11-B13)* *1.1077 × 10⁶ (B11-B14)*	*1.6406 × 10⁵ (B11-B13)* *1.4448 × 10⁵ (B11-B14)*	*4.1014 × 10⁵ (B11-B13)* *3.6120 × 10⁵ (B11-B14)* *1.5038 × 10⁶ (B12-B13)*	*4.9492 × 10⁶*
Prev, action deployment (sc. ID)	–	–	–	–
Corr. action deployment (sc. ID)	–	–	–	–

OF = SUI+ max residual EENS = 1000 MWh

	Costs (amu)			
List of Measures	**1st Interval**	**2nd Interval**	**3rd Interval**	**Total**
Hardening of supports (upgraded line)	–	–	–	–
Installation of antitorsional devices (upgraded line)	–	–	1.5038 × 10⁵ (B11-B13)	1.5038 × 10⁶
Preventive action deployment (scenario ID)	–	–	–	–
Corrective action deployment (scenario ID)	4.3563 × 10⁵ (6) 2.8897 × 10⁴ (8)	7.2697 × 10⁵ (14) 1.0251 × 10⁵ (16)	5.7548 × 10⁵ (22) 3.2901 × 10⁵ (24)	2.1985 × 10⁶

Quantity	OF=TNB	OF =SUI rEENS=1000 MWh
Residual EENS [MWh]	0	800
Final SUI [-]	43.48	64.48
Final TNB [amu]	1.1625×10^8	9.6368×10^7

Case study 1 + sim 4 (changing climate change effect model from MOD 1 to MOD 2)

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The residual EENS in the «as is» condition passes from 2075 to **4543.5** MWh due to **higher probabilities of occurrence of severe wet snow** events with MOD 2

Sim 4 c (same as sim 3 but MOD 2)
OF = TNB – unchanged wrt sim 4b
OF = SUI

	Costs (amu)			
List of Measures	1st Interval	2nd Interval	3rd Interval	Total
Hardening of supports (upgraded line)	–	–	–	–
Installation of antitorsional devices (upgraded line)	–	–	–	–
Preventive action deployment (scenario ID)	–	–	–	–
Corrective action deployment (scenario ID)	2.9546×10^3 (8)	–	–	2.9546×10^3

OF = SUI + max residual EENS = 1000 MWh

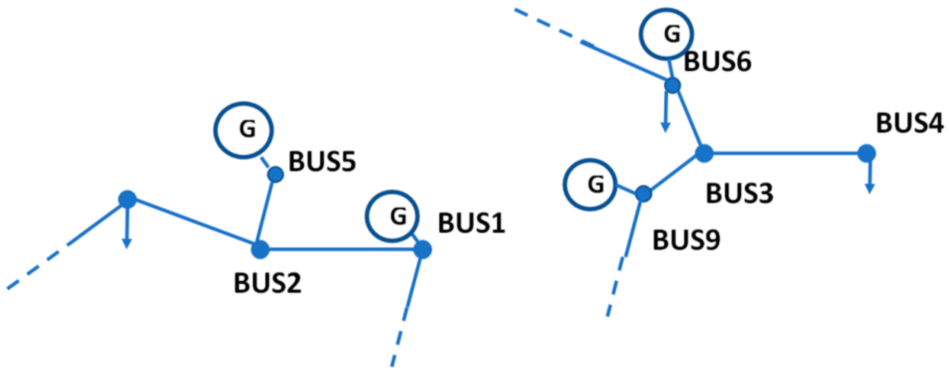
	Costs [amu]			
List of Measures	1st Interval	2nd Interval	3rd Interval	Total
Hardening of supports (upgraded line)	–	–	–	–
Installation of antitorsional devices (upgraded line)	–	–	1.5038×10^6 (B11-B13)	1.5038×10^6
Preventive actions deployment (scenario ID)	–	–	–	–
Corrective actions deployment (scenario ID)	4.3563×10^5 (6) 2.8898×10^4 (8)	7.2697×10^5 (14) 1.0251×10^5 (16)	5.7548×10^5 (22) 3.2901×10^5 (24)	2.1985×10^6

To satisfy the max residual EENS constraint → need to deploy passive measures besides active ones
This causes a SUI drop from 1090.91 to 181.18

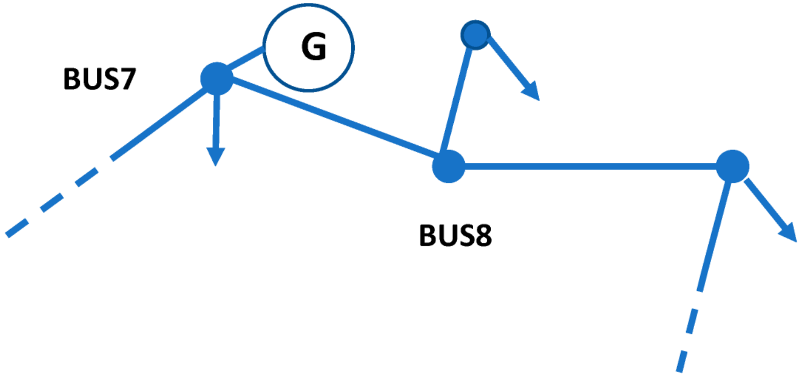
Quantity	OF=SUI	OF = SUI rEENS=1000 MWh
Residual EENS [MWh]	4.2707×10^3	800.33
Final SUI [-]	1090.91	181.18

Case study 2: real world case

- Analysis on a **significant portion of National Transmission Grid** (North East of Italy)
- Model with about **700 buses, 100 generators and 800 branches**
- Focus on two areas for grid interventions
  - Area **(a)**: 132 kV area in Dolomites
  - Area **(b)**: 132 kV area in South-Eastern Alps
- Same unitary costs and climate models as for Case study 1
- Max order for N-k contingency: 5
- Max nr of candidates for passive measures: 30
- Total **residual EENS** in the base case:
  - **228.7 MWh (for MOD 1)**
  - **436 MWh (for MOD 2)**
- Average computation time for each case: 45 min (on Intel® Xeon® Gold 6248R CPU, 128 GB RAM, two-processor 3.00 GHz machine)



(a)

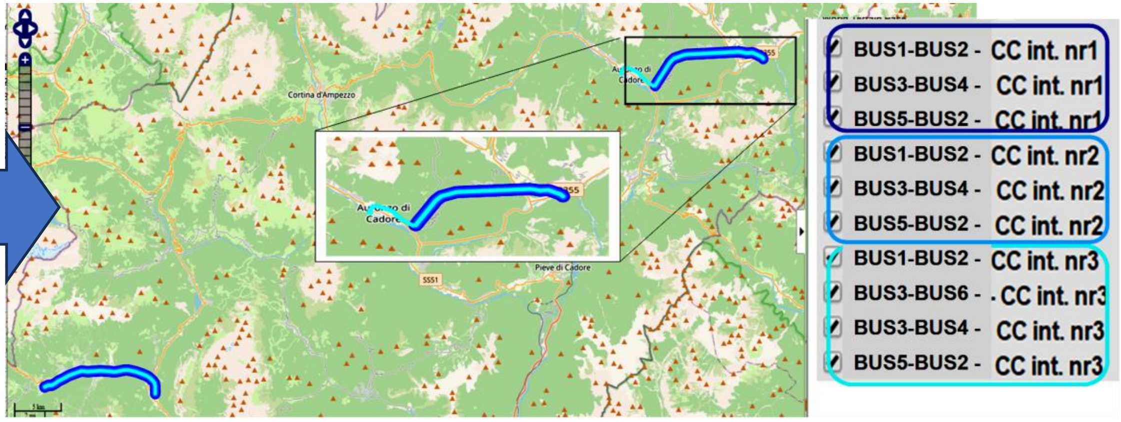


(b)

Sim 1: TNB and SUI based optimization + MOD1

OF = TNB

List of Measures	Costs (amu) 1st Interval	2nd Interval	3rd Interval	Total
Hardening of supports (upgr. line)	–	–	–	–
Installation of antitorsional devices (upgraded line)	8.3030×10^4 (BUS1-BUS2) 1.1291×10^5 (BUS3-BUS4) 3.335×10^3 (BUS5-BUS2)	1.0830×10^4 (BUS1-BUS2) 1.4728×10^4 (BUS3-BUS4) 4.35×10^2 (BUS5-BUS2)	2.7075×10^4 (BUS1-BUS2) 6.2242×10^4 (BUS3-BUS6) 3.6820×10^4 (BUS3-BUS4) 1.0875×10^3 (BUS5-BUS2)	3.5240×10^5
Prev. action deployment	–	–	–	–
Corr. action deployment	–	–	–	–



(a)

OF = SUI

List of Measures	Costs (amu) 1st interval	2nd interval	3rd interval	Total
Hardening of supports (upgraded line)	–	–	–	–
Installation of antitorsional devices (upgraded line)	–	–	6.2242×10^4 (BUS3-BUS6)	6.2242×10^4
Preventive action deployment	–	–	–	–
Corrective action deployment	–	–	–	–

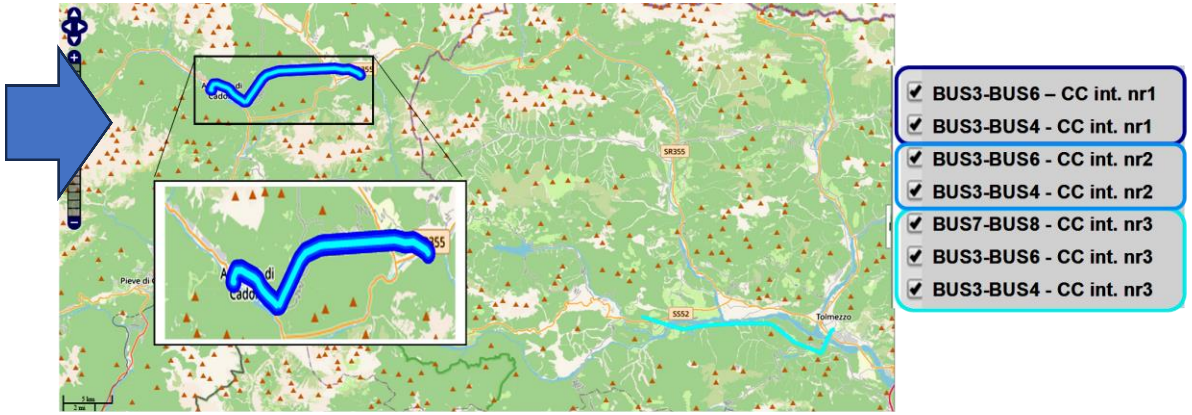
Quantity	OF=TNB	OF =SUI
Residual EENS [MWh]	38.5	183
Final SUI [-]	33.6	116.45
Final TNB [amu]	6.9×10^6	2.05×10^6

Sim 1: TNB and SUI based optimization + MOD 2

OF = TNB

List of Measures	Costs (amu) 1st Interval	2nd Interval	3rd Interval	Total
Hardening of supports (upgr. line)	–	–	–	–
Installation of antitorsional devices (upgraded line)	5.2057×10^4 (BUS3-BUS6) 1.1291×10^5 (BUS3-BUS4)	6.790×10^3 (BUS3-BUS6) 1.4728×10^4 (BUS3-BUS4)	2.4267×10^5 (BUS7-BUS8) 1.6975×10^4 (BUS3-BUS6) 3.6820×10^4 (BUS3-BUS4)	4.8295×10^5
Prev. action deployment	–	–	–	–
Corr. action deployment	–	–	–	–

The higher probabilities of overcoming critial wet snow loads leads to the need to reinforce another line, BUS7-BUS8, with anti-rotational devices in a lower-altitude area



(a)

OF = SUI

List of Measures	Costs (amu) 1st Interval	2nd Interval	3rd Interval	Total
Hardening of supports (upgraded line)	–	–	–	–
Installation of antitorsional devices (upgraded line)	–	–	9.9118×10^4 (BUS3-BUS9) 6.2242×10^4 (BUS3-BUS6)	1.6136×10^5
Preventive action deployment	–	–	–	–
Corrective action deployment	–	–	–	–

Quantity	OF=TNB	OF =SUI
Residual EENS [MWh]	34.2	335
Final SUI [-]	87	142.4
Final TNB [amu]	2.1077×10^7	6.5061×10^6

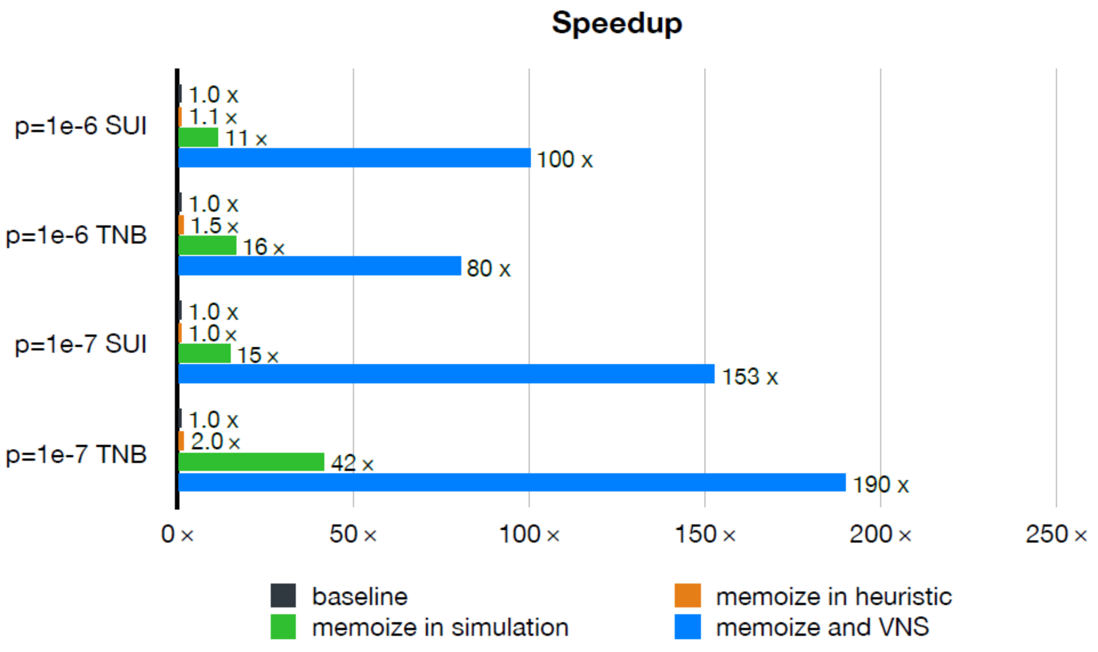
Case study 3: comparing different solution algorithms

- Same unitary costs but a smaller test system (5 buses)
- Two different minimum probability thresholds for the selection of N-k contingencies: 10^{-6} and 10^{-7}
- Three algorithms tested:
  - **Two stage** original **algorithm**
  - **Two stage** algorithm with **memoisation** function
  - **VND** algorithm + memoise

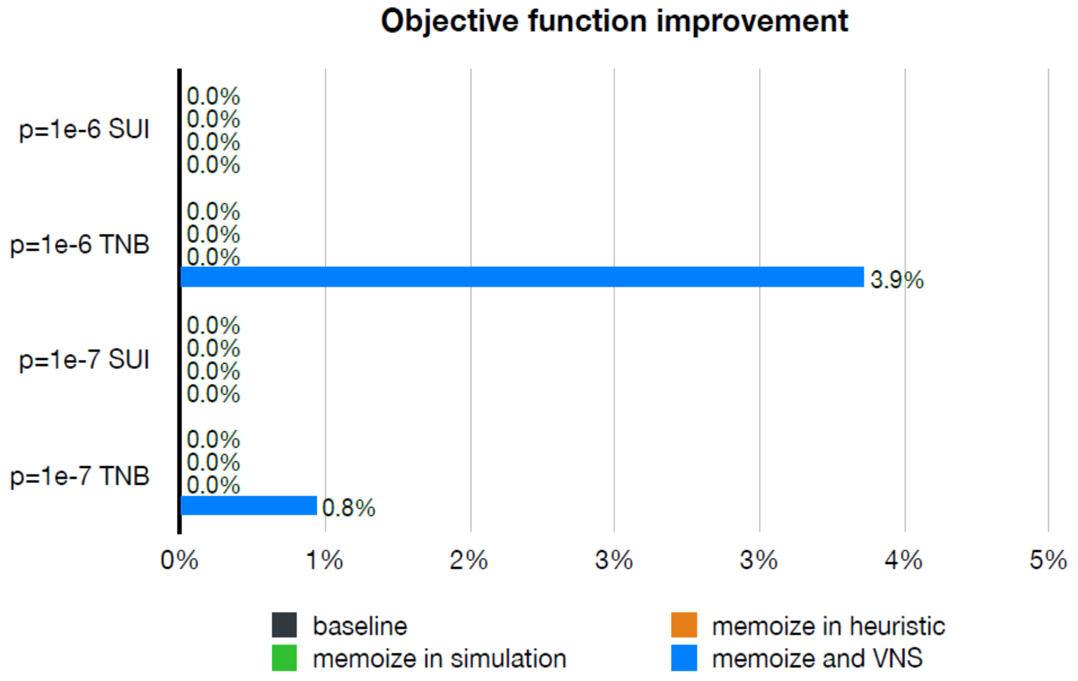
- What's «**memoise**»?
- It's an **optimization technique** used to speed up computer programs **by caching the results of expensive function calls** and returning them when the same inputs are encountered again
- This technique has been applied to:
  - The **second (GPS-based) stage** of the solution algorithm (so called "**memoise in heuristics**")
  - The **simulation** of the outputs for each scenario (cascading outage simulation) **also in stage 1** (so called «**memoise in simulation**»)
- The second application has required a major work of re-organization of the original code.

Speed up factors

(reference: the base two-stage w/o memoise)



OF values at solution



Significant speed up factors achieved with memoise application
Very large speed up factors + OF value improvements achieved with VNS + memoise

Take aways

- Proposed a **scenario-based OvS (Optimisation via Simulation) methodology** to evaluate the optimal mix of active and passive measures for resilience enhancement accounting for:
  - Climate change effects
  - Actual PS response (including cascading outages simulation)
- Efficient screening for N-k contingencies → avoiding combinatorial explosion
- Different **heuristic algorithms** tested for optimization problem solution
- Simulations show the **ability of the methodology to indicate the most effective mix** of passive and active measures according to the optimization target, either **Total Net Benefit (TNB)** or **System Utility Indicator (SUI)** maximization.
- Good **sensitivity of the resulting mix** of measures with respect to **their unitary costs and to the climate change effects**
- **Good computational performances** also on large real world case studies
- The best computational performances (speed up factors > 100 and up to 3.9% OF improvements) are achieved using **Variable Neighbourhood descent method coupled with memoisation**

THANK YOU FOR YOUR ATTENTION

An optimization-based methodology for power system resilience enhancement in planning

andrea.pitto@rse-web.it

This work has been financed by the Research Fund for the Italian Electrical System under the Three-Year Research Plan 2022-2024 (DM MITE n. 337, 15.09.2022), in compliance with the Decree of April 16th, 2018.