Identification of dangerous contingencies for large scale power system security assessment

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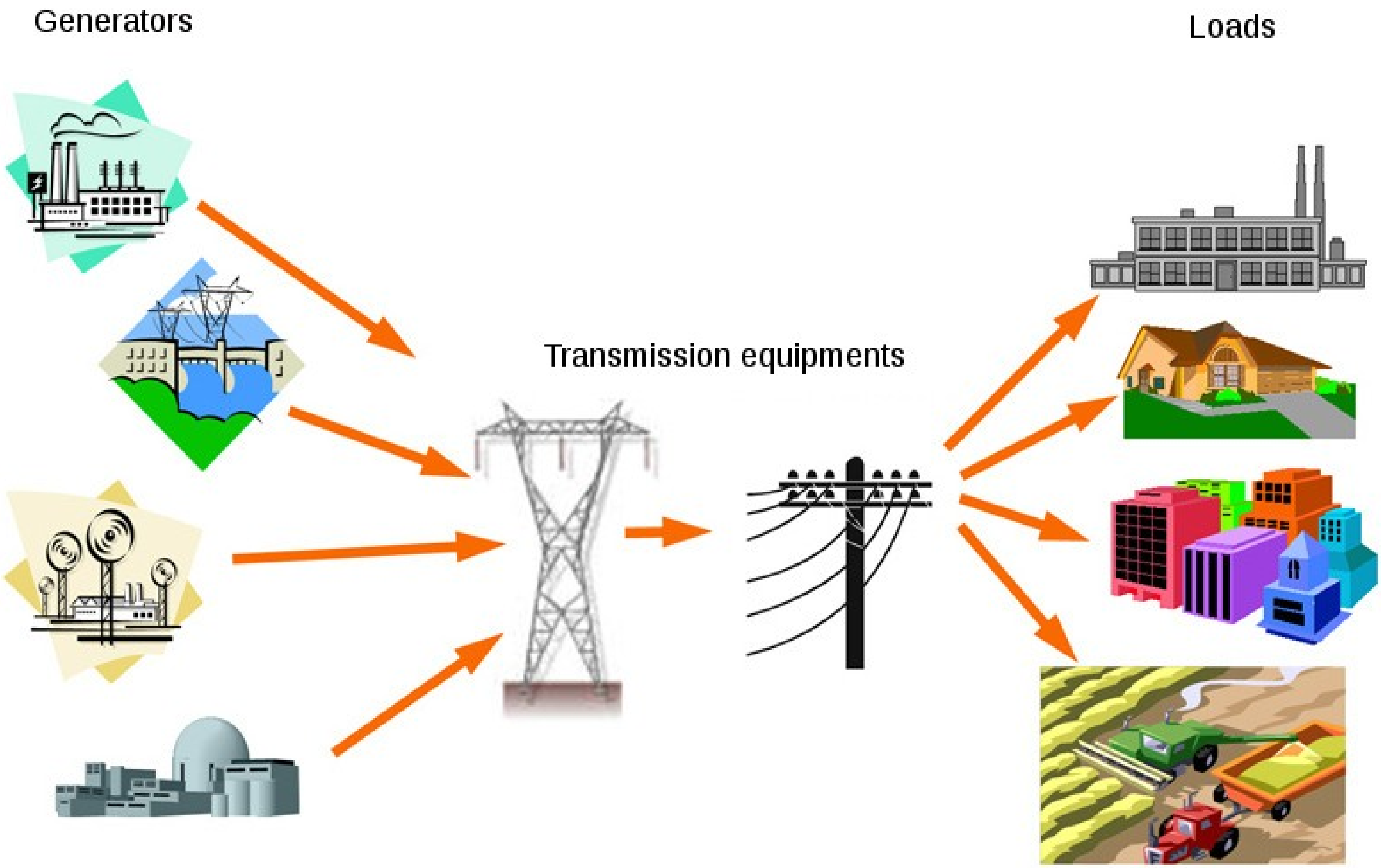
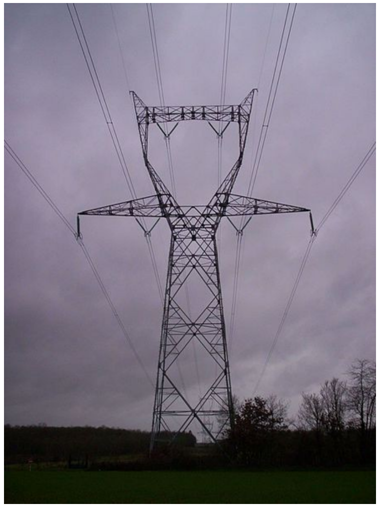
PhD defense - March 1st

Electric power systems - structure



Power system security assessment - objective

- what Transmission System Operators (TSOs) want to avoid:



normal situation

+

contingency

→

degradation of the security of the system

1. Introduction

Power system security assessment – notion of contingency

- **definition:**

  any unexpected event triggering a change in the current operating conditions;

- **examples:**

  - equipment outages (the simultaneous loss of k equipments is called an N-k contingency);
  - transient faults;
  - error of an operator;

- **note:**

  the notion of contingency can also be used to model the uncertainties on the future generation and load patterns.

1. Introduction

Power system security assessment - usual practice

- using models of their network and simulation tools, TSOs simulate the occurrence of each potential contingency;

- the contingencies leading to unacceptable operating conditions are classified as dangerous;

- for each dangerous contingency, adapted preventive or corrective control actions are designed to preserve the level of security of the system.

1. Introduction

Large scale power system security assessment

- the size of the set of potential contingencies grows with the size of the studied system and with the considered time horizon;

- when the contingency space is too big, it is no longer possible to analyze each contingency individually in a reasonable amount of time;

- **traditional solutions:**

  - increase of the computational resources and parallelization of the security assessment task;

  - use of filtering techniques to determine thanks to some light computations which contingencies to simulate.

1. Introduction

Large scale power system security assessment

- **problem considered in this thesis:**

  - we address large scale power system security assessment problems with bounded computational resources (not allowing an exhaustive screening of the contingency space);

  - we consider that only detailed contingency analyses are performed;

- **proposed approach:**

  we propose an algorithm exploiting at best the number of contingency analyses that can be carried out so as to identify a maximal number of dangerous contingencies.

Definitions

- **contingency severity:**

  based on the definition of an objective function $O : \mathcal{X} \rightarrow \mathbb{R}$ (where $\mathcal{X}$ is the contingency space) that quantifies the effect of each contingency on the operating conditions of the system;

- **dangerous contingencies:**

  contingencies x such that $O(x) \geq \gamma$, where the threshold γ is defined by the user;

- **computational resources:**

  a fixed budget in terms of CPU time, expressed as a maximal number of evaluations of the objective function that can be performed.

1. Introduction

Reformulation of the problem addressed in the thesis

- **problem statement:**

  identify a maximal number of contingencies x such that $O(x) \geq \gamma$ while evaluating the function O a bounded number of times.

- **procedure developed to solve it:**

  an iterative sampling framework inspired from derivative-free optimization algorithms.

Outline

1. Introduction

2. An iterative sampling approach based on derivative-free optimization methods

3. Embedding the contingency space in a Euclidean space

4. Case studies

5. On-line selection of iterative sampling algorithms

6. Estimating the probability and cardinality of the set of dangerous contingencies

7. Conclusion

2. An iterative sampling approach based on derivative-free optimization methods

Comparison with an optimization problem

- **usual formulation of an optimization problem:**

  given a search space $\mathcal{X}$ and a real-valued function $f : \mathcal{X} \rightarrow \mathbb{R}$, identify an element x_0 in $\mathcal{X}$ such that $f(x_0) \geq f(x)\ \forall\, x \in \mathcal{X}$;

- **problem addressed here:**

  given a search space $\mathcal{X}$, a real-valued function $O : \mathcal{X} \rightarrow \mathbb{R}$ and a real number γ, identify a maximal number of points w in $\mathcal{X}$ such that $O(w) \geq \gamma$ with a bounded number of evaluations of the function O.

2. An iterative sampling approach based on derivative-free optimization methods

Comparison with an optimization problem

- the configuration (search space and objective function) is the same;
- we do not only want to identify one maximum of the objective function, but the set of points such that $O(x) \geq \gamma$;
- if $\gamma = \max_{x \in X} O(x)$, our problem is equivalent to a classical optimization problem aiming at identifying all the maxima of the objective function.

2. An iterative sampling approach based on derivative-free optimization methods

Specificities of our "optimization-like" problem

➢ the search space is very large;

➢ we want to be able to solve this problem in a generic way, whatever the contingency space and objective function at hand;

➢ no derivative of the objective function is available, and only the pairs ($x,O(x)$) can be used for solving the problem;

➢ since the objective function can only be evaluated a given number of times, the number of such pairs ($x,O(x)$) is bounded.

2. An iterative sampling approach based on derivative-free optimization methods

Derivative-free optimization algorithms

- they only use values taken by the objective function for different points of the search space to search for a maximum of this function;

- they are split into different categories:

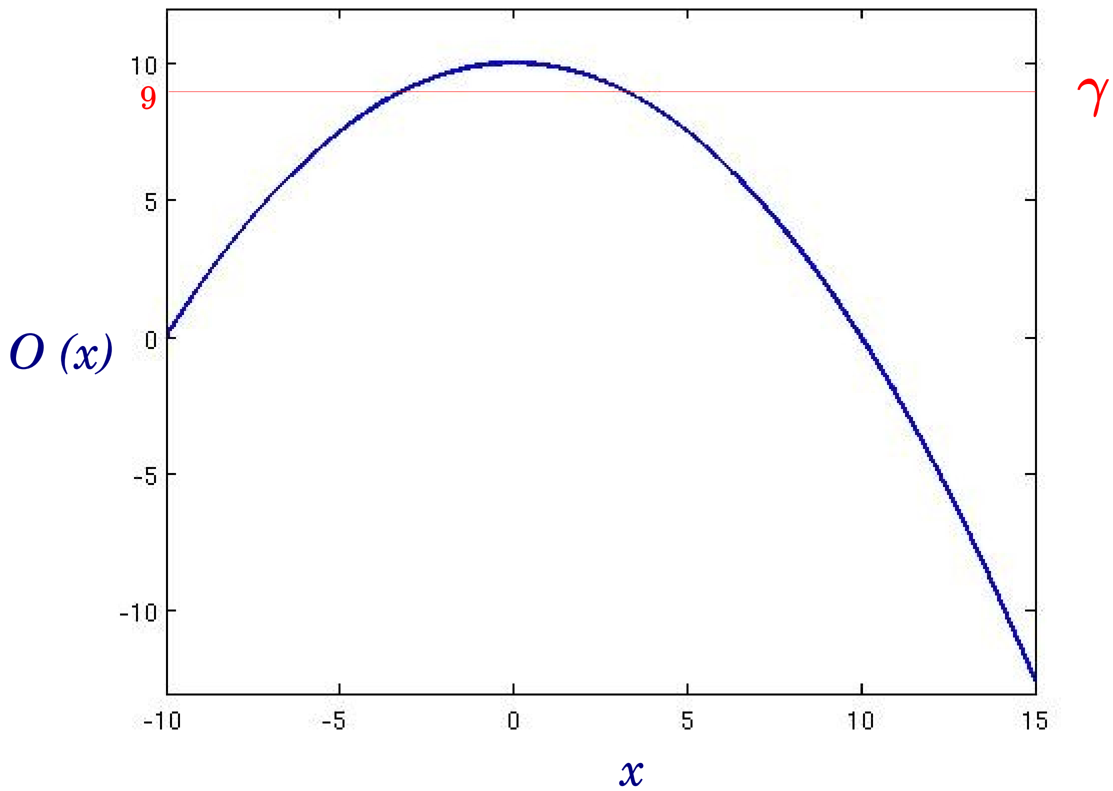
  - algorithms building models of the objective function based on samples of its values;

  - algorithms directly exploiting sets of values of the objective function and iteratively trying to improve a candidate solution to the problem.

2. An iterative sampling approach based on derivative-free optimization methods

Our basic iterative sampling (BIS) algorithm for dangerous contingency identification: illustration

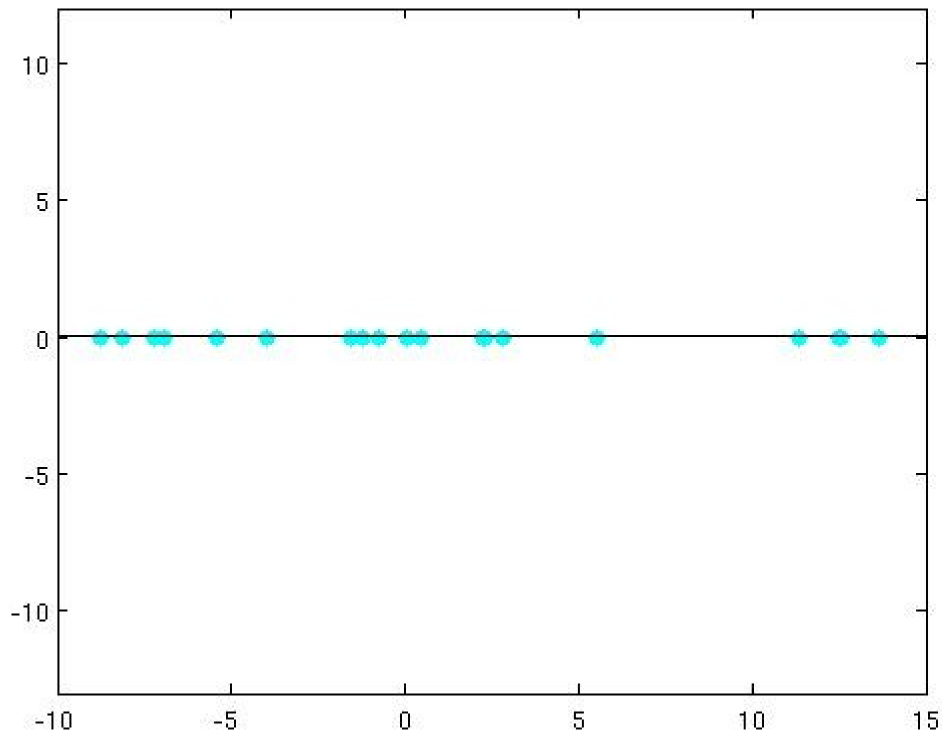
- considered problem:



2. An iterative sampling approach based on derivative-free optimization methods

Our basic iterative sampling (BIS) algorithm for dangerous contingency identification: illustration

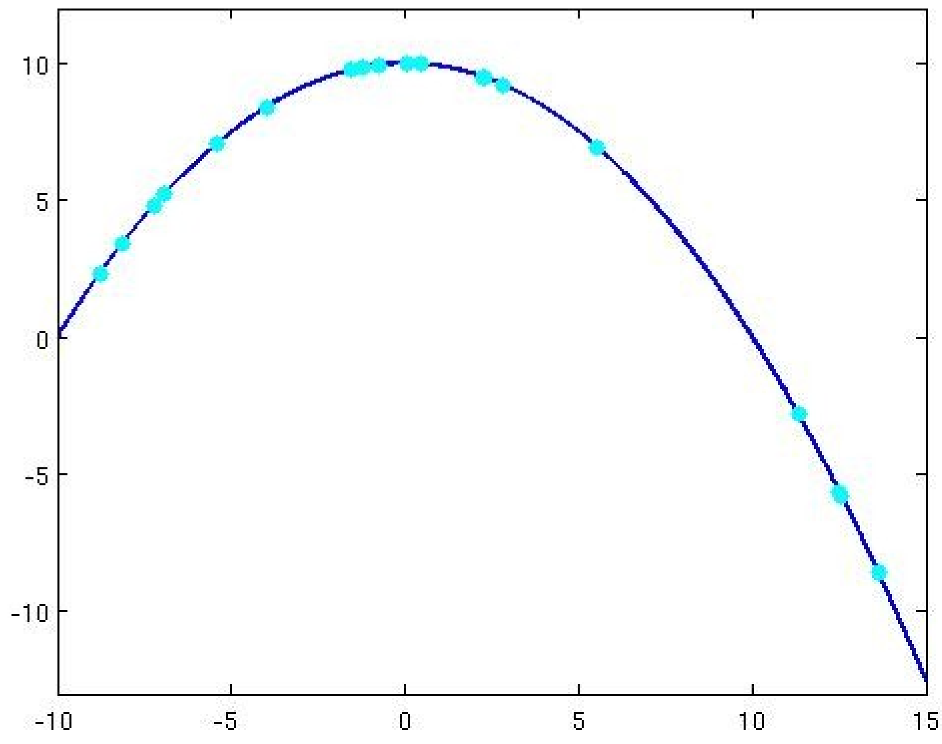
➢ first iteration: drawing a sample of points from $\mathbb{R}$ according to an initial sampling distribution;



2. An iterative sampling approach based on derivative-free optimization methods

Our basic iterative sampling (BIS) algorithm for dangerous contingency identification: illustration

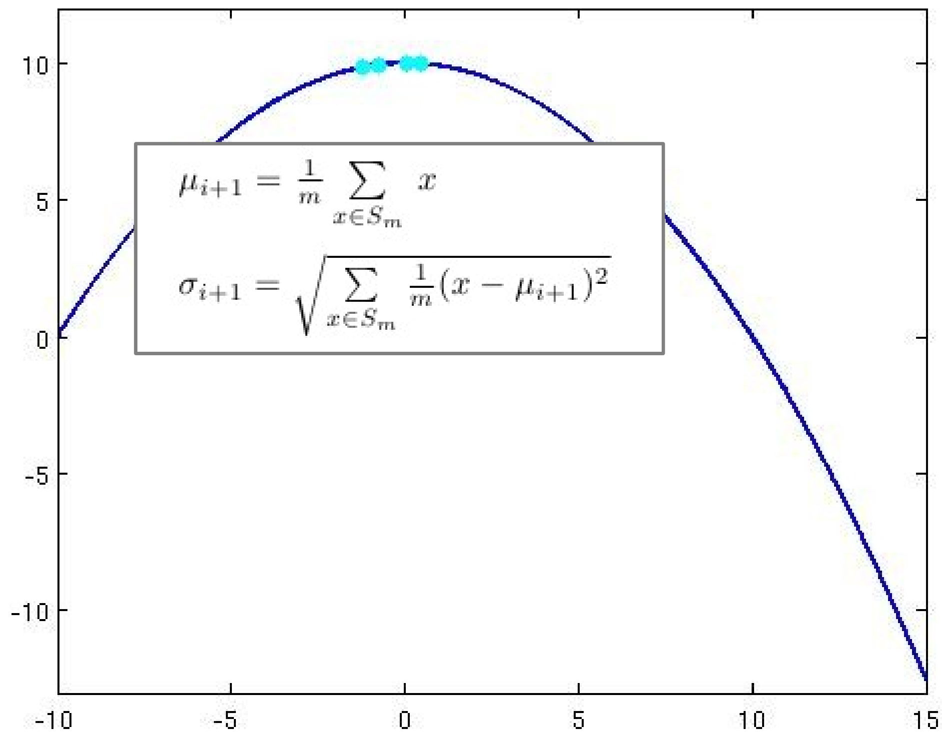
➢ first iteration: evaluating the objective function for all the points of this sample;



2. An iterative sampling approach based on derivative-free optimization methods

Our basic iterative sampling (BIS) algorithm for dangerous contingency identification: illustration

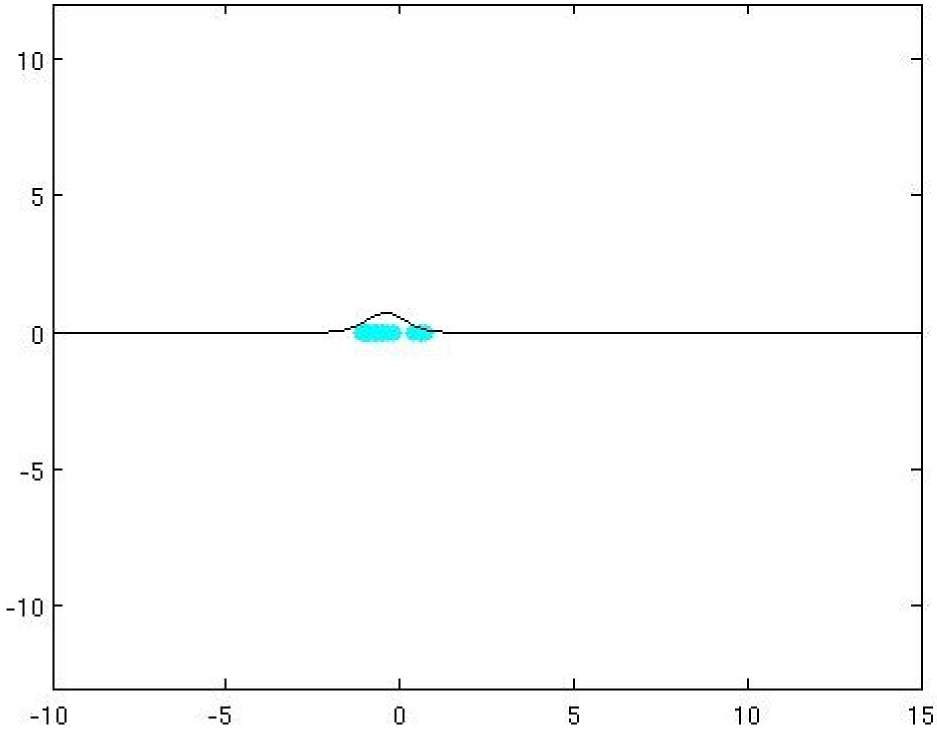
➢ first iteration: selecting the "best points" of the current sample to compute a new sampling distribution;



2. An iterative sampling approach based on derivative-free optimization methods

Our basic iterative sampling (BIS) algorithm for dangerous contingency identification: illustration

- second iteration: generating a new sample according to this updated sampling distribution;



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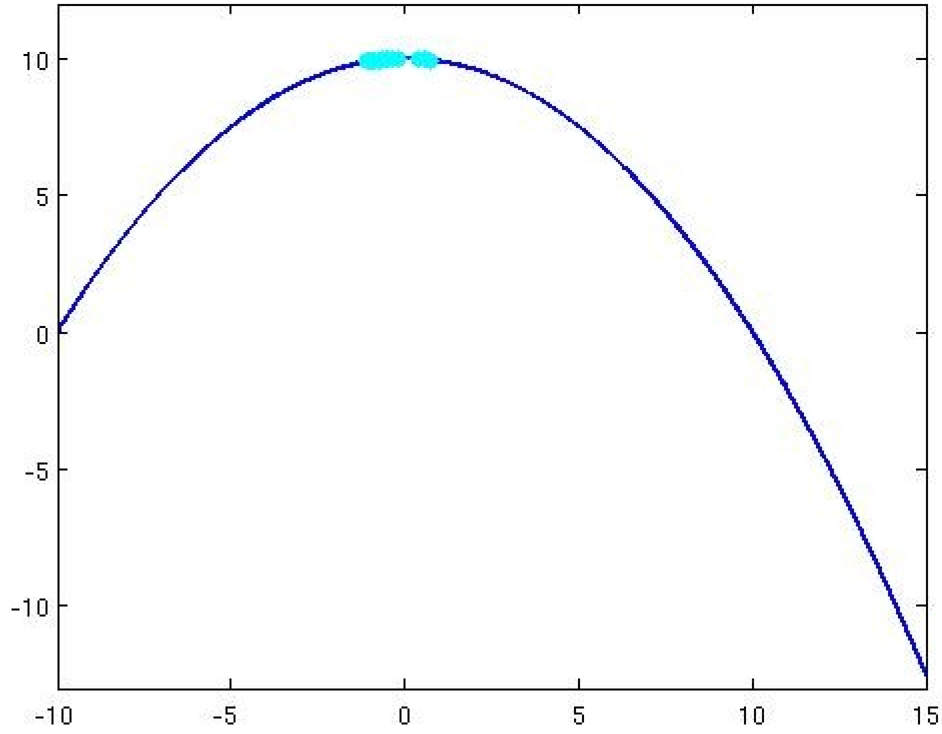
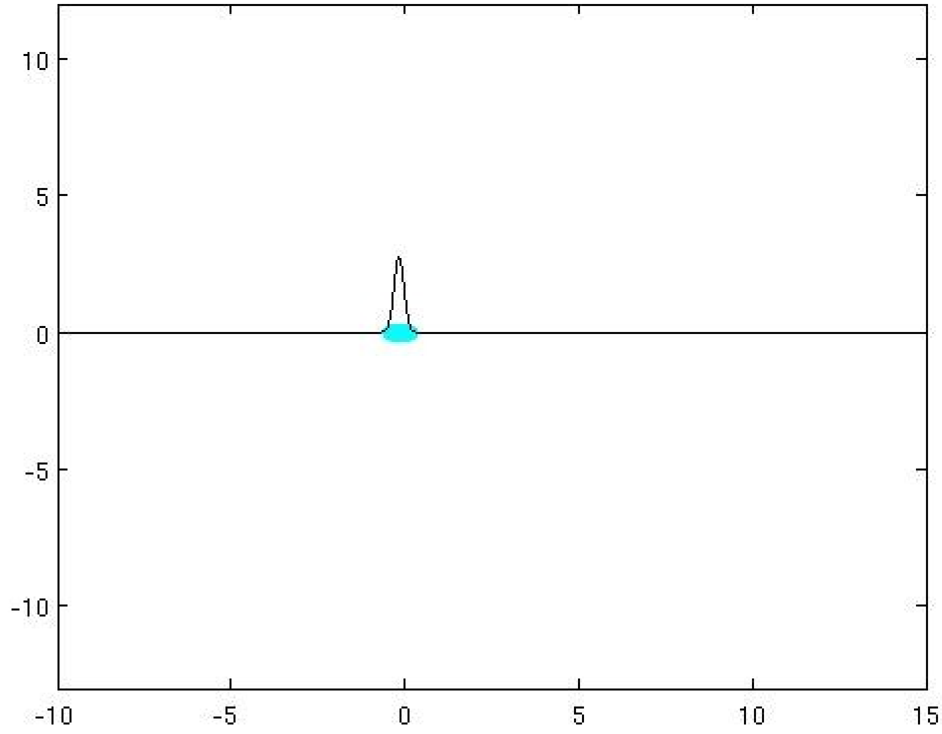


2. An iterative sampling approach based on derivative-free optimization methods

Our basic iterative sampling (BIS) algorithm for dangerous contingency identification: illustration

➢ third iteration: the points in the current sample are located in a tighter area around the maximum of the objective function;



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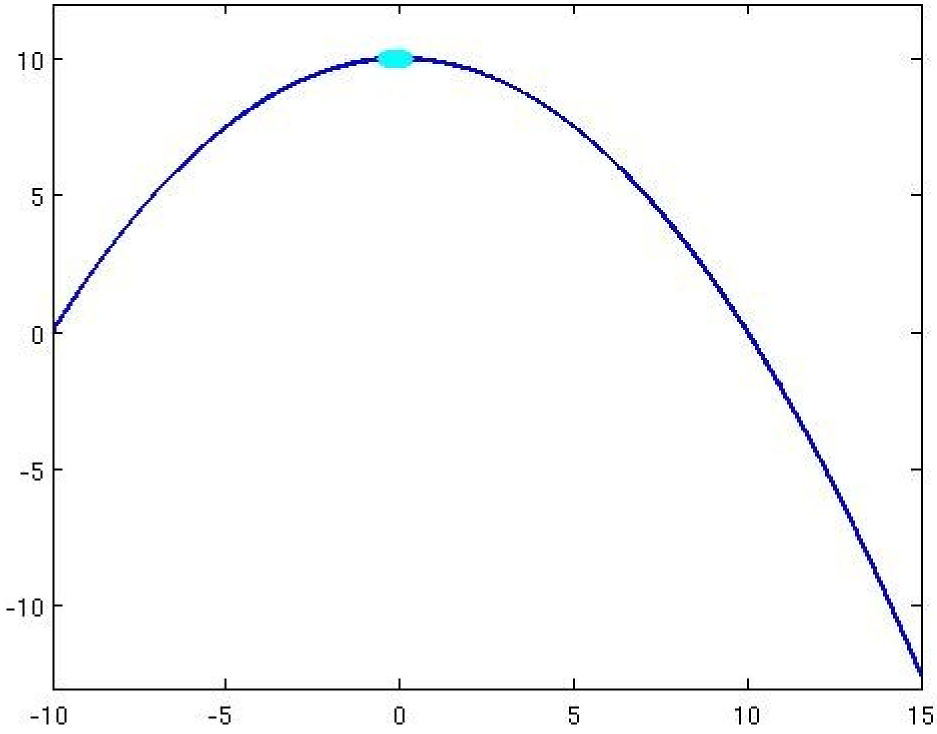
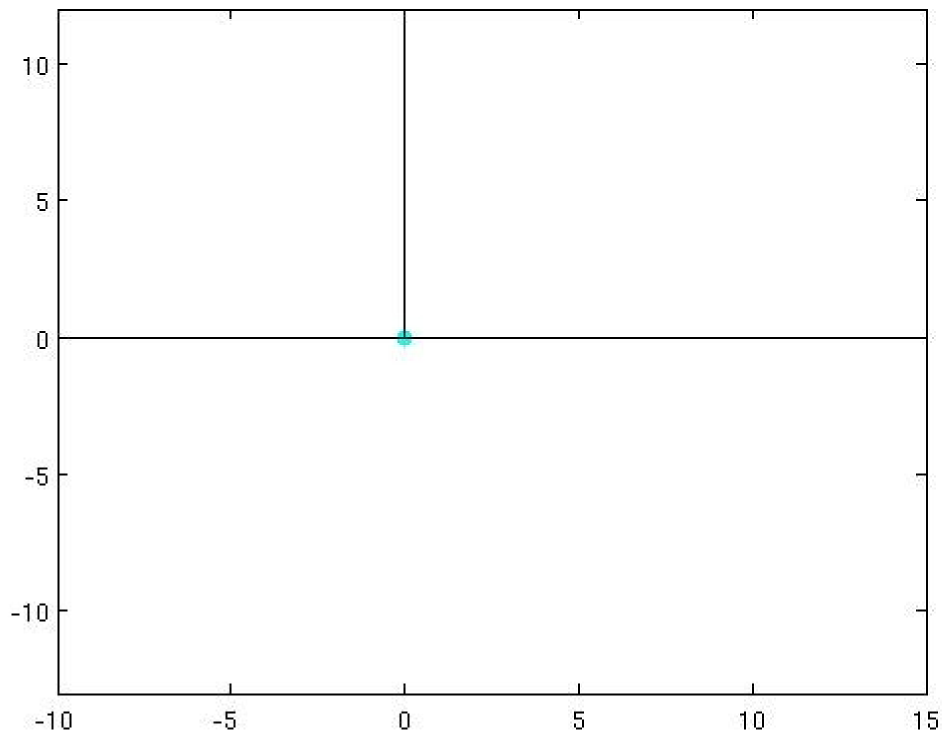


2. An iterative sampling approach based on derivative-free optimization methods

Our basic iterative sampling (BIS) algorithm for dangerous contingency identification: illustration

➢ fourth and last iteration: the current sampling distribution is now focused on the maximum of the objective function;



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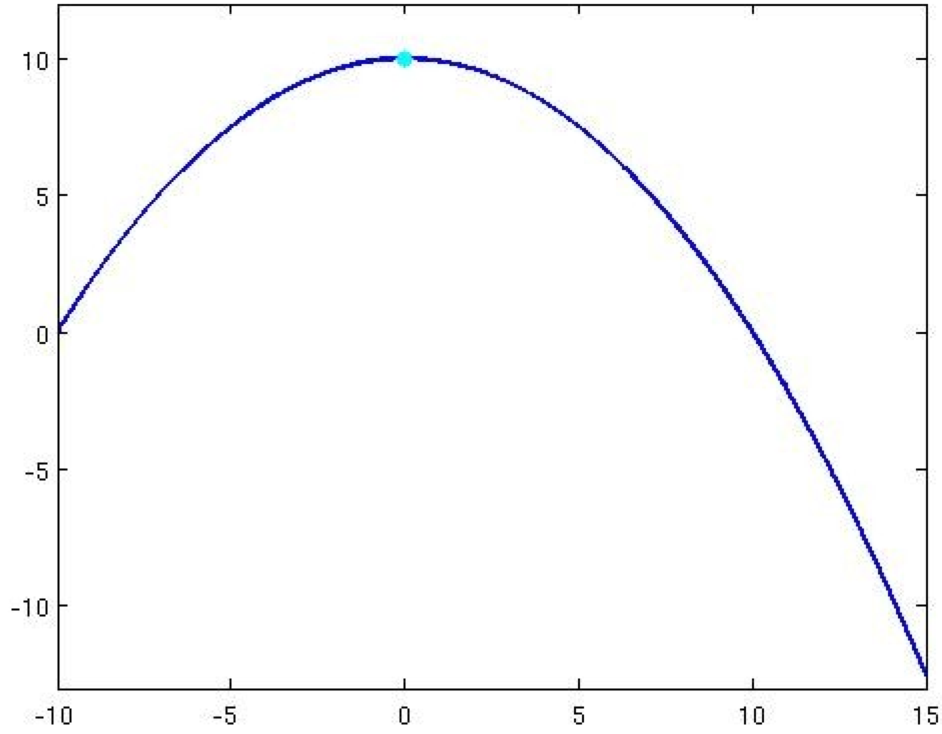
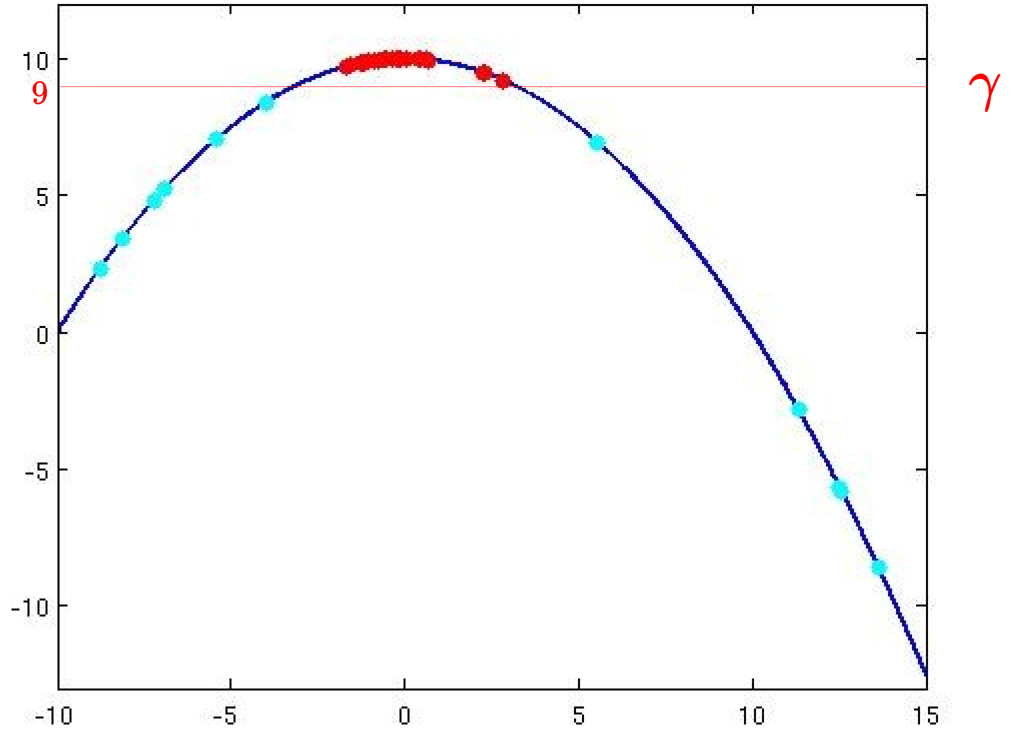


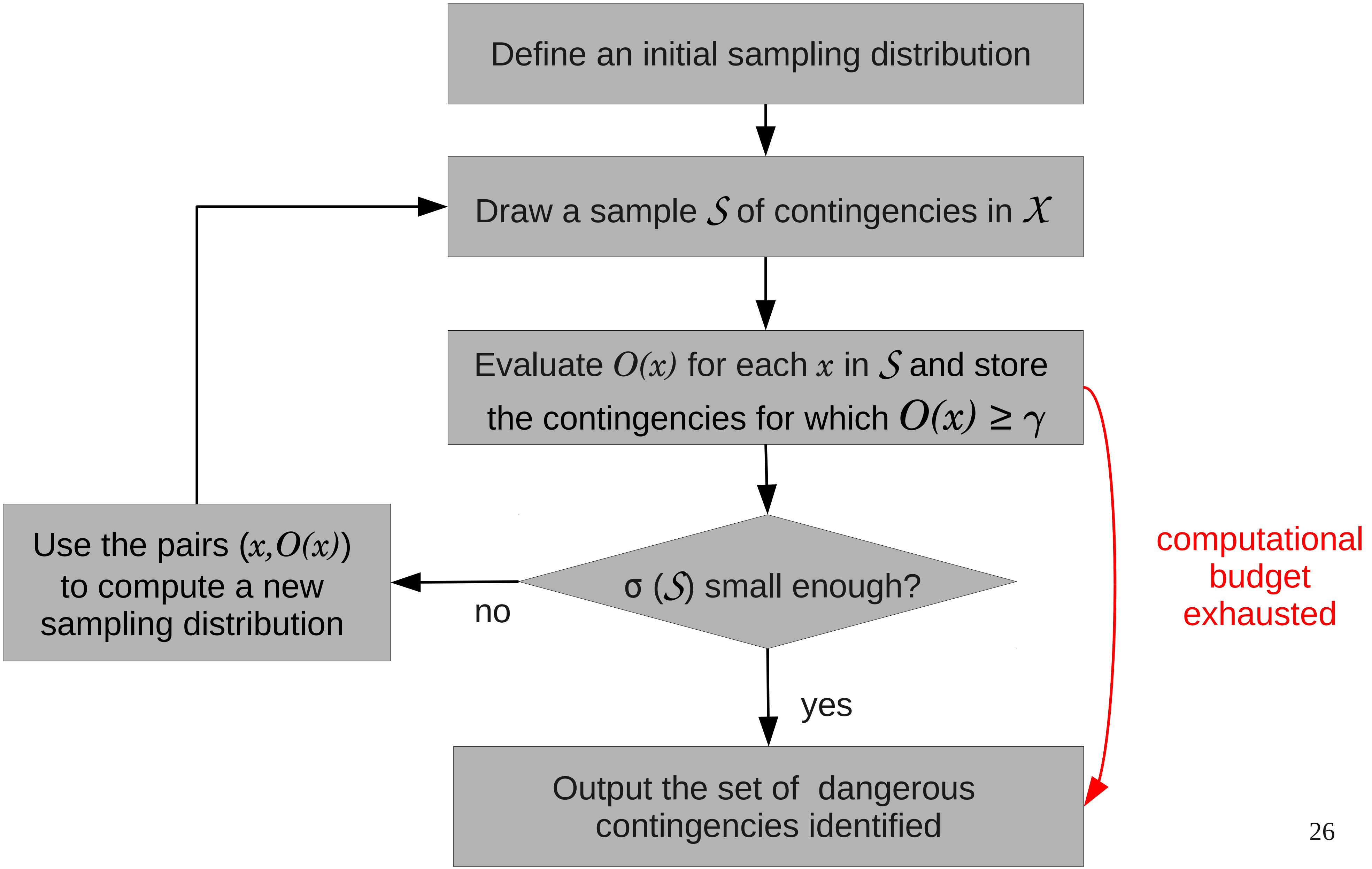
2. An iterative sampling approach based on derivative-free optimization methods

Our basic iterative sampling (BIS) algorithm for dangerous contingency identification: illustration

➢ a large majority of the points drawn from the contingency space during the execution of the algorithm are dangerous contingencies;



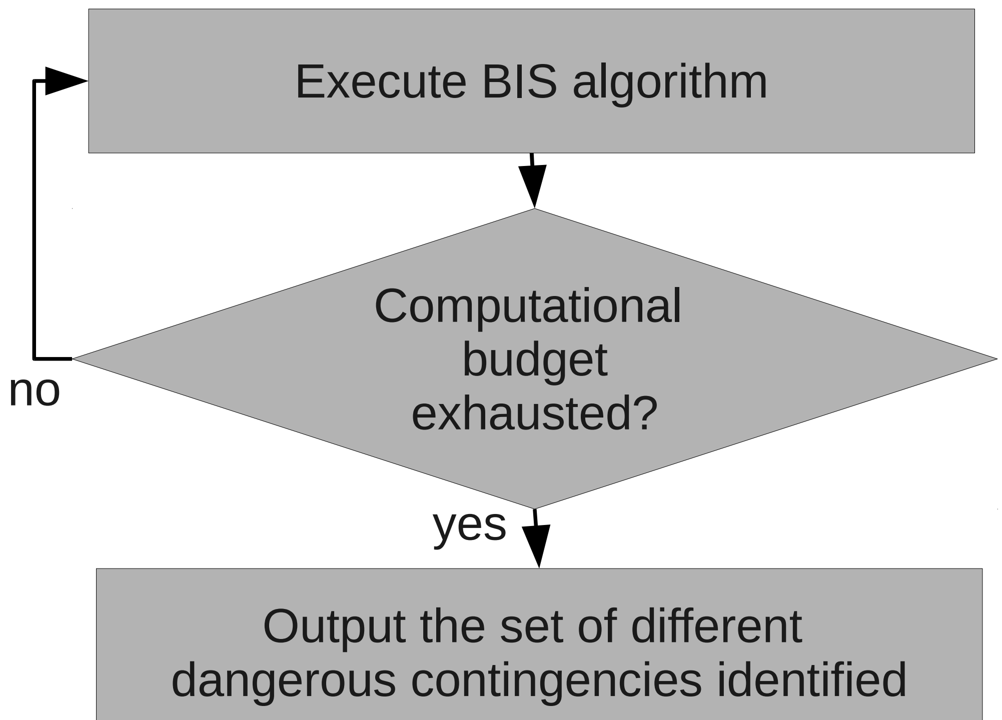
Our basic iterative sampling (BIS) algorithm for dangerous contingency identification



2. An iterative sampling approach based on derivative-free optimization methods

Our comprehensive iterative sampling algorithm for dangerous contingency identification

➢ the basic iterative sampling algorithm is repeated as long as the available computational resources have not been exhausted;



2. An iterative sampling approach based on derivative-free optimization methods

The objective function

- **role**

  - direct the sampling process towards dangerous contingencies;

- **examples**

  - *global criteria:* impact of unsupplied energy, distance of some system variables to their acceptability limits, voltage stability limits;

  - *equipment-based criteria:* nodal voltage collapse proximity indicators, post-contingency line flows.

3. Embedding the contingency space in a Euclidean space

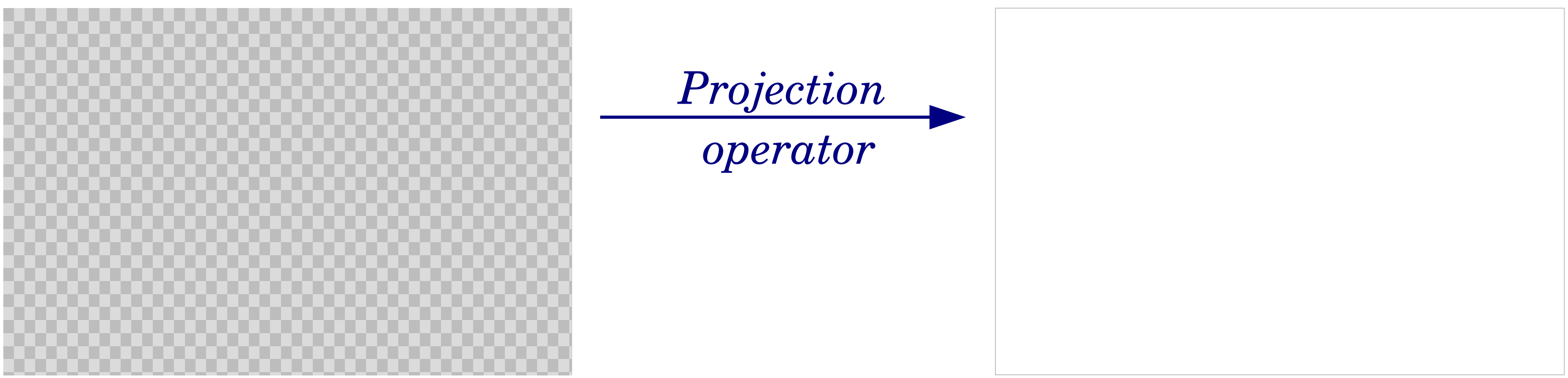
Motivation

- our comprehensive iterative sampling algorithm works in a Euclidean space and uses the Euclidean metric;
- there is no natural metric in the contingency spaces in power system security assessment problems;

  => to use this algorithm for power system security assessment, we propose to embed the contingency space $\mathcal{X}$ in a Euclidean space $\mathcal{Y}$ in which the algorithm is executed.

3. Embedding the contingency space in a Euclidean space

Metrization process, illustration

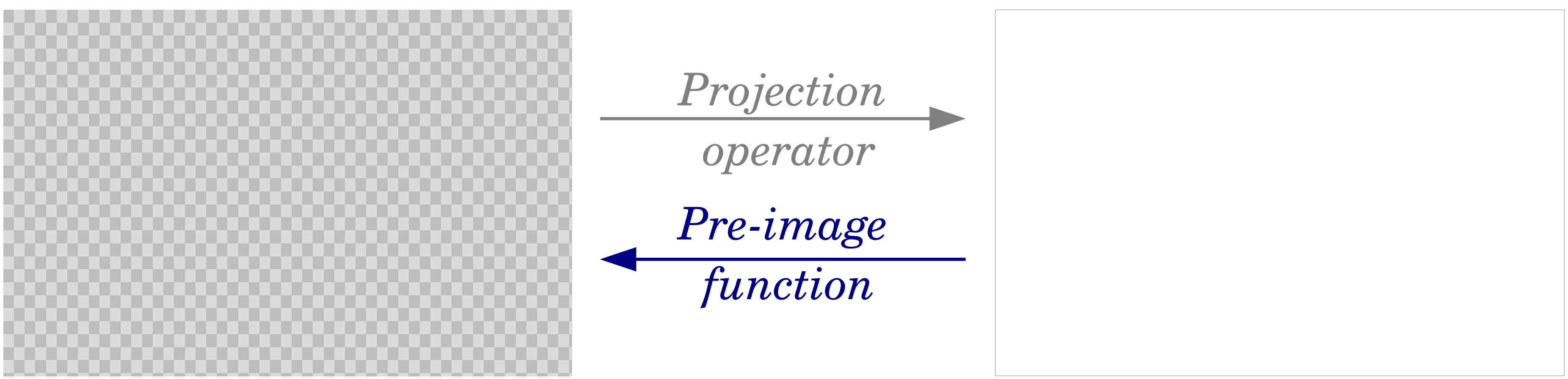


Contingency space, $\mathcal{X}$

Euclidean embedding space, $\mathcal{Y}$
(e.g., $\mathbb{R}^2$ or $\mathbb{R}^{2k}$)

3. Embedding the contingency space in a Euclidean space

Metrization process, illustration



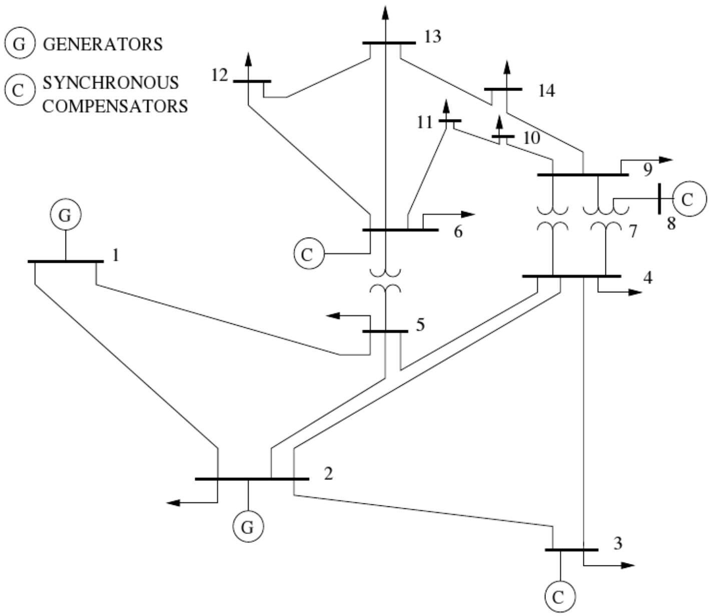
Contingency space, $\mathcal{X}$

Euclidean embedding space, $\mathcal{Y}$ (e.g., $\mathbb{R}^2$ or $\mathbb{R}^{2k}$)

3. Embedding the contingency space in a Euclidean space

Embedding the set of all N-1 line outage contingencies in $\mathbb{R}^2$, example 1: exploiting the equipments' geographical coordinates

➢ each contingency is projected in $\mathbb{R}^2$ as the midpoint of the lost line in the geographical map of the system:



IEEE 14 bus system

3. Embedding the contingency space in a Euclidean space

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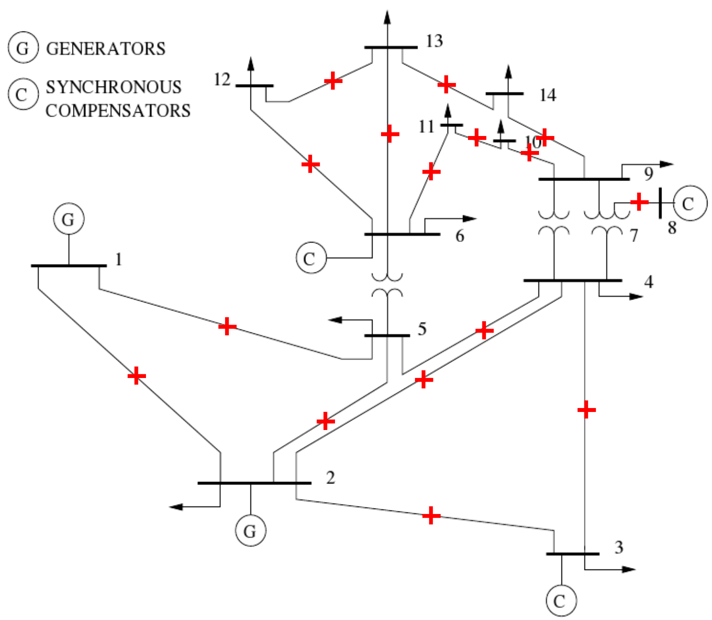
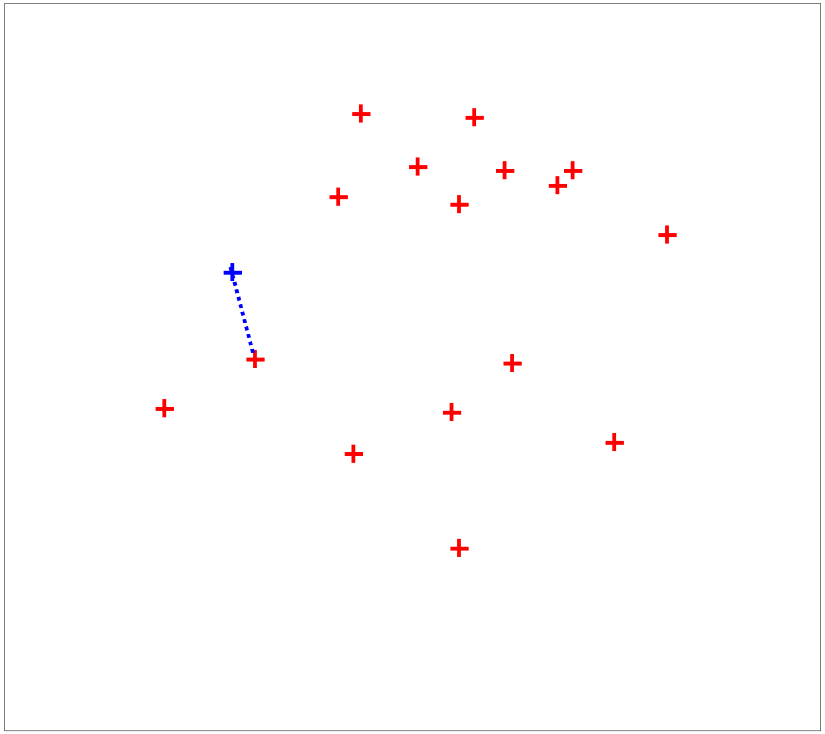


Projection of the contingencies as the midpoints of the transmission lines

3. Embedding the contingency space in a Euclidean space

Embedding the set of all N-1 line outage contingencies in $\mathbb{R}^2$, example 1: exploiting the equipments' geographical coordinates

➢ the pre-image function associates to each point of the plane the projected contingency it stands the closest to:



3. Embedding the contingency space in a Euclidean space

Extension of example 1: embedding set of all N-k line outage contingencies in $\mathbb{R}^{2k}$

- projection of the contingency $(l_1, l_2, \ldots, l_i, \ldots, l_k)$:

  point with coordinates $(y_1, y_2, \ldots, y_{2i-1}, y_{2i}, \ldots, y_{2k})$,

  coordinates of the midpoint of line l_i in the geographical map of the system.

3. Embedding the contingency space in a Euclidean space

Extension of example 1: embedding set of all N-k line outage contingencies in $\mathbb{R}^{2k}$

- pre-image of the point of coordinates $(y_1, y_2, \ldots, y_{2i-1}, y_{2i}, \ldots, y_{2k})$:

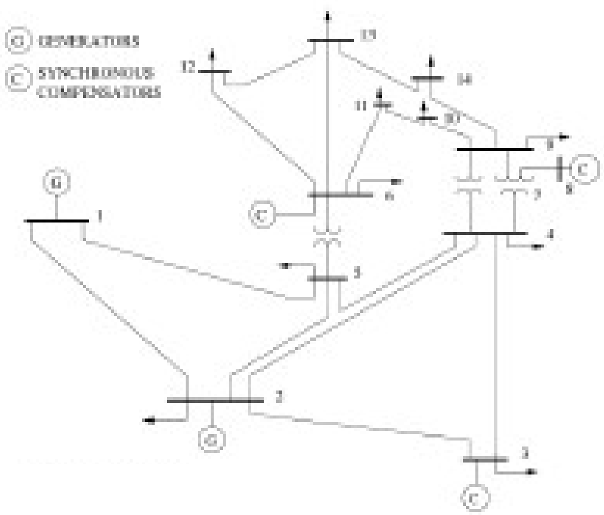
contingency $(l_1, l_2, \ldots, l_i, \ldots, l_k)$,

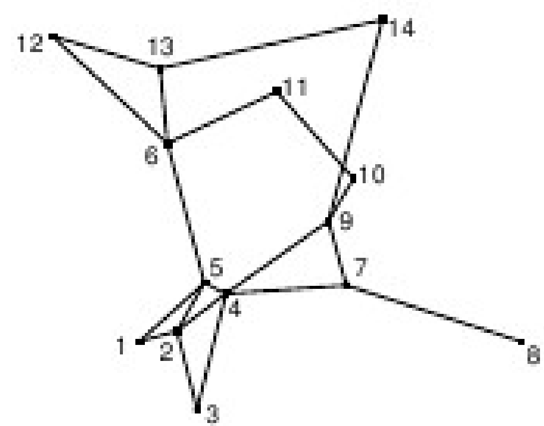
line whose midpoint is the nearest neighbor of the point with coordinates (y_{2i-1}, y_{2i}).

3. Embedding the contingency space in a Euclidean space

Embedding the set of all N-1 line outage contingencies in $\mathbb{R}^2$, example 2: exploiting "electrical" equipment coordinates

➢ based on the electrical distances between equipments, we first compute new bus coordinates thanks to a multi-dimensional scaling algorithm;





3. Embedding the contingency space in a Euclidean space

Embedding the set of all N-1 line outage contingencies in $\mathbb{R}^2$, example 2: exploiting "electrical" equipment coordinates

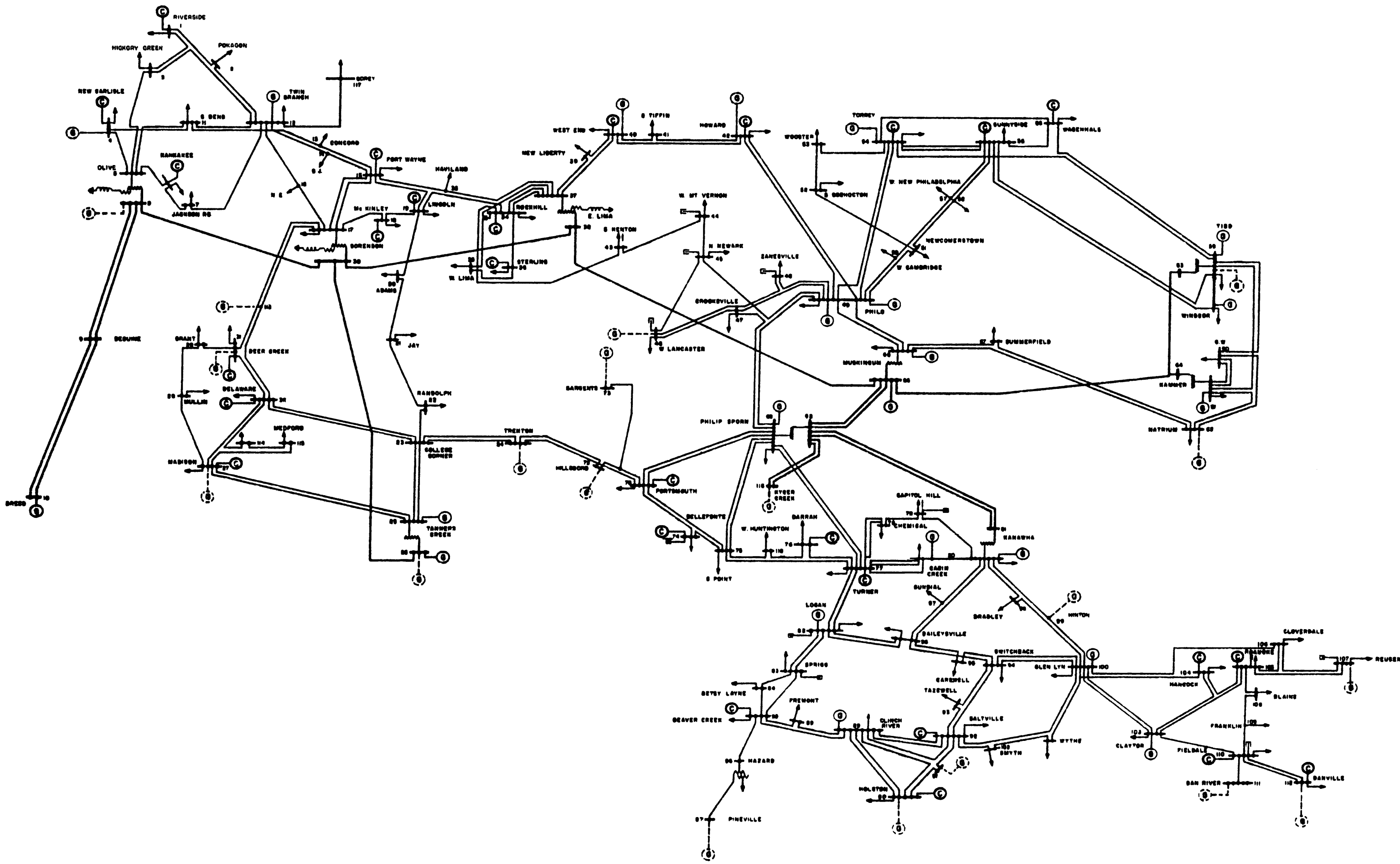
- each contingency is projected in $\mathbb{R}^2$ as the midpoint of the lost line in the "electrical" map of the system;

- the pre-image function also associates to a point of $\mathbb{R}^2$ the nearest projected contingency;

- this procedure can be extended to the set of all N-k line outage contingencies in the same way as the previous one.

Problem 1

- studied network: IEEE 118 bus test system;



4. Case studies

Problem 1

- **contingency space:**
  N-3 line tripping contingencies in a given base case (1 055 240 potential contingencies);

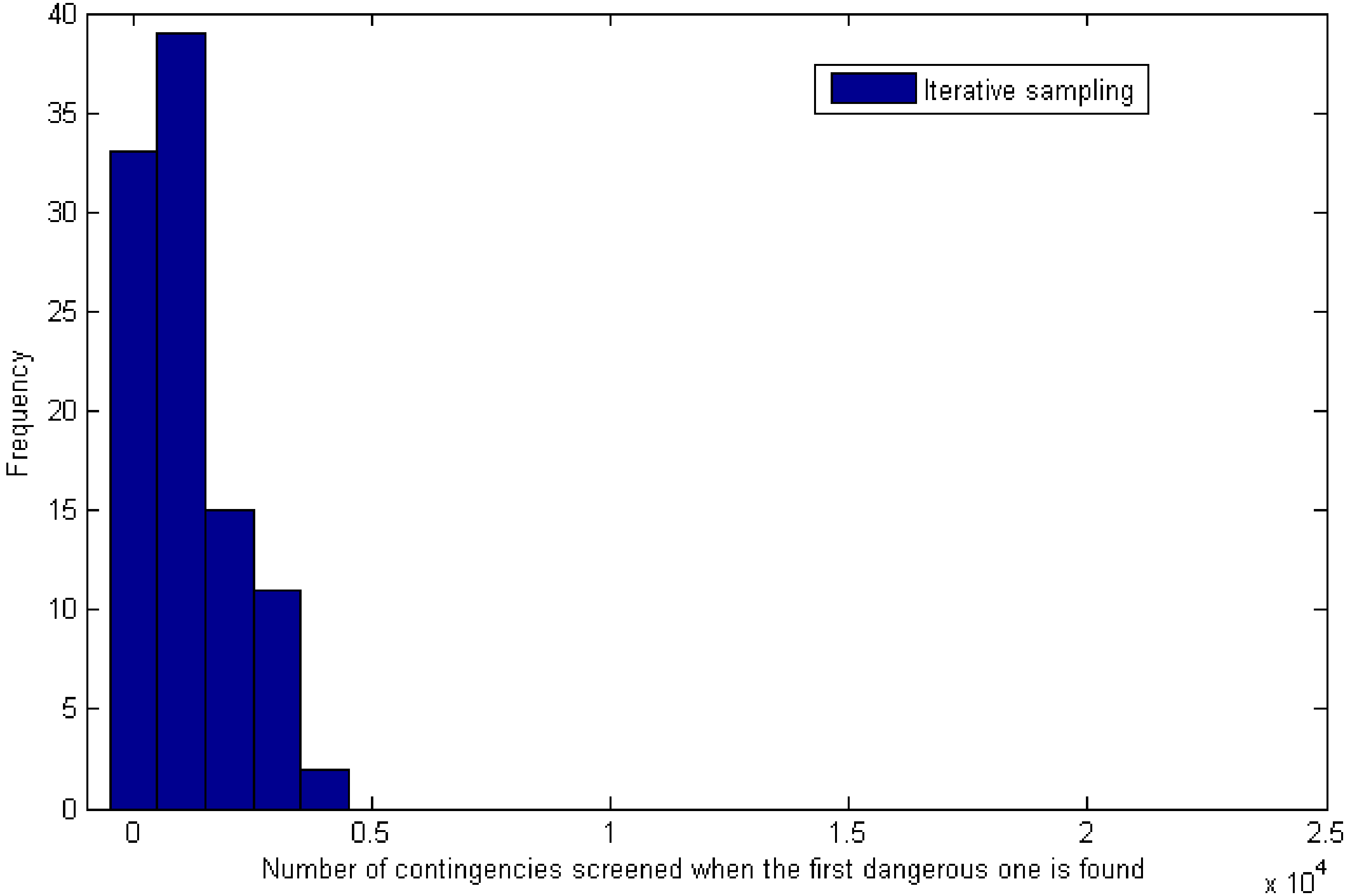
- **objective function:**
  number of iterations required by an AC load-flow algorithm applied to the post-contingency situation to converge;

- **dangerous contingencies:**
  contingencies such that $O(x) \geq 11$;

- **Euclidean embedding space:**
  $\mathbb{R}^6$ (electrical distances).

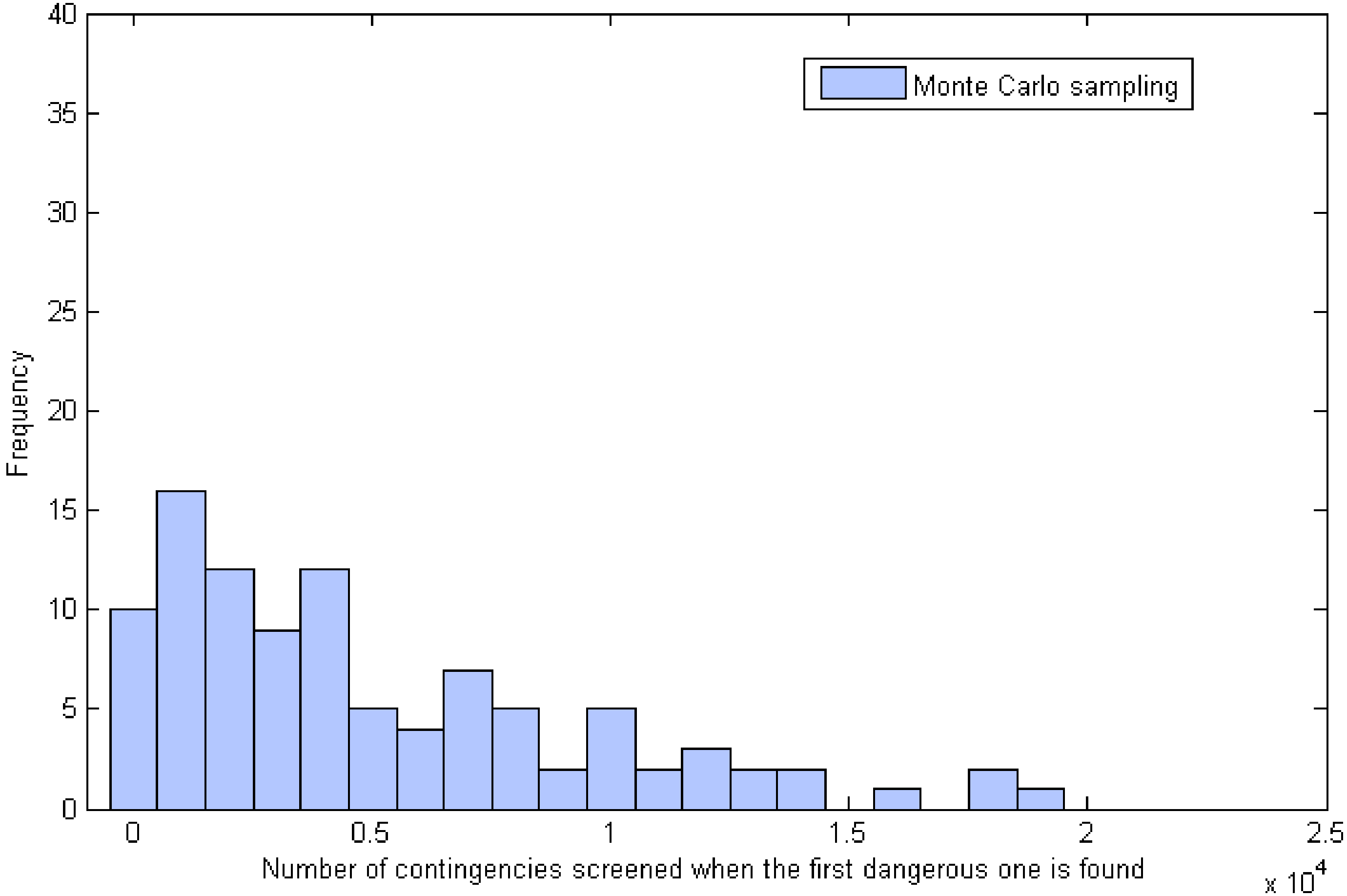
Results

➢ number of contingencies screened when the first dangerous contingency is identified (our approach):



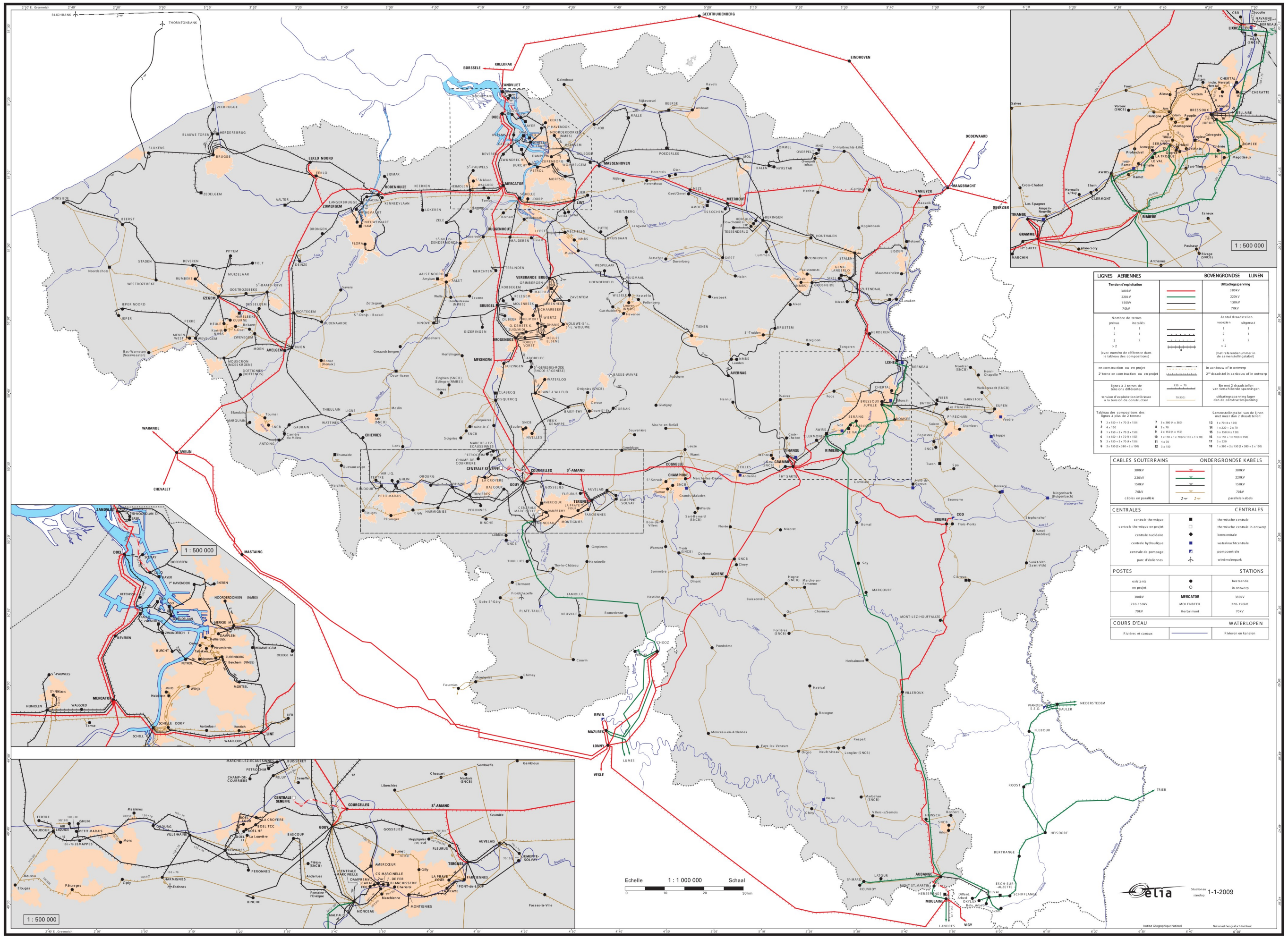
Results

➢ number of contingencies screened when the first dangerous contingency is identified (classical Monte Carlo sampling):



Problem 2

- studied system: Belgian transmission network ≥ 150 kV;



Problem 2

- **contingency space:**
  N-2 line tripping contingencies in a given base case (201 295 potential contingencies);

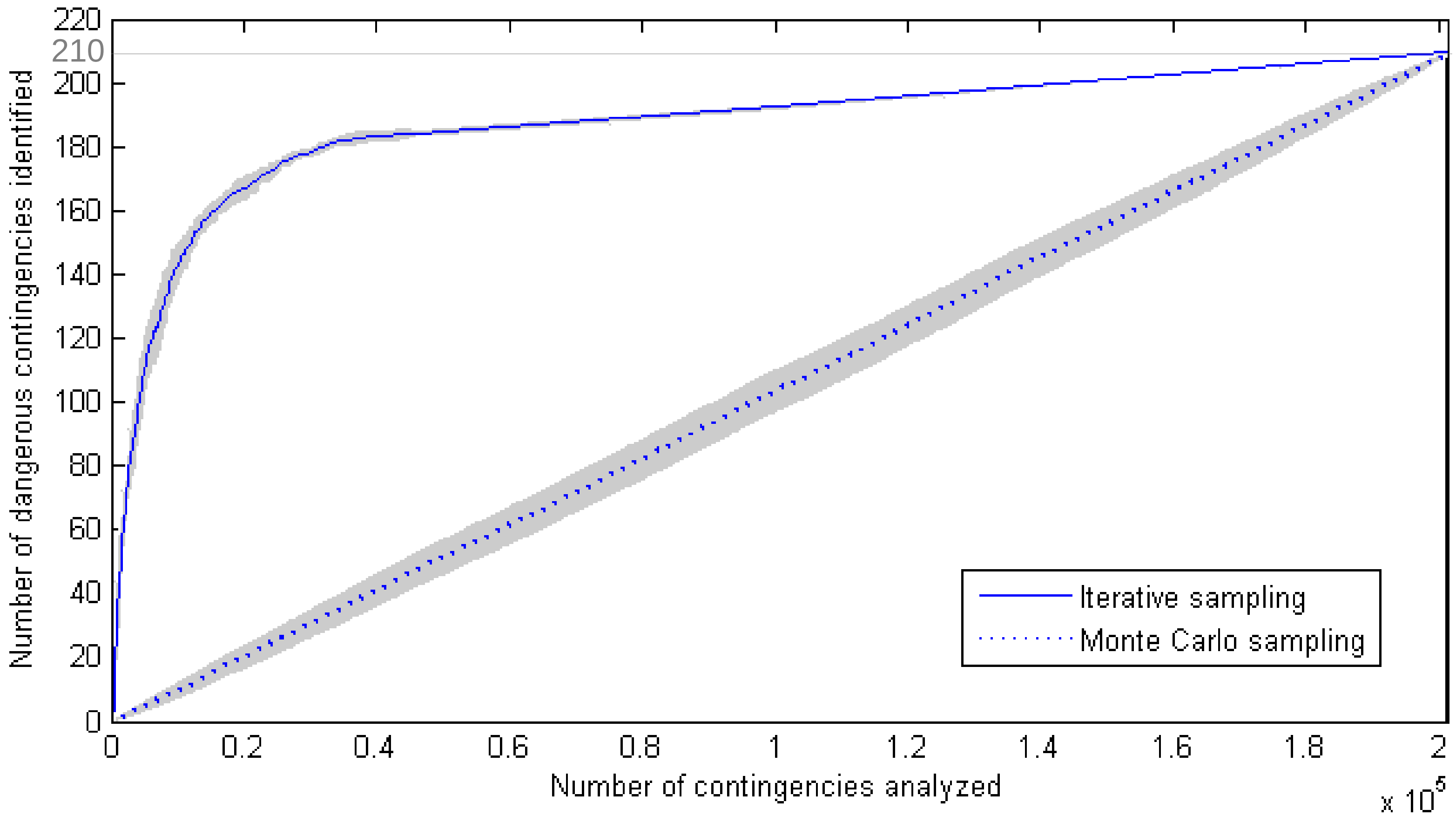
- **objective function:**
  maximal loading rate (in %) observed over all the lines in the post-contingency steady-state;

- **dangerous contingencies:**
  $O(x) \geq 170$;

- **Euclidean embedding space:**
  $\mathbb{R}^4$ (geographical coordinates).

Simulation results

➢ number of dangerous contingencies identified vs available computational budget (mean and standard deviation over 100 runs):



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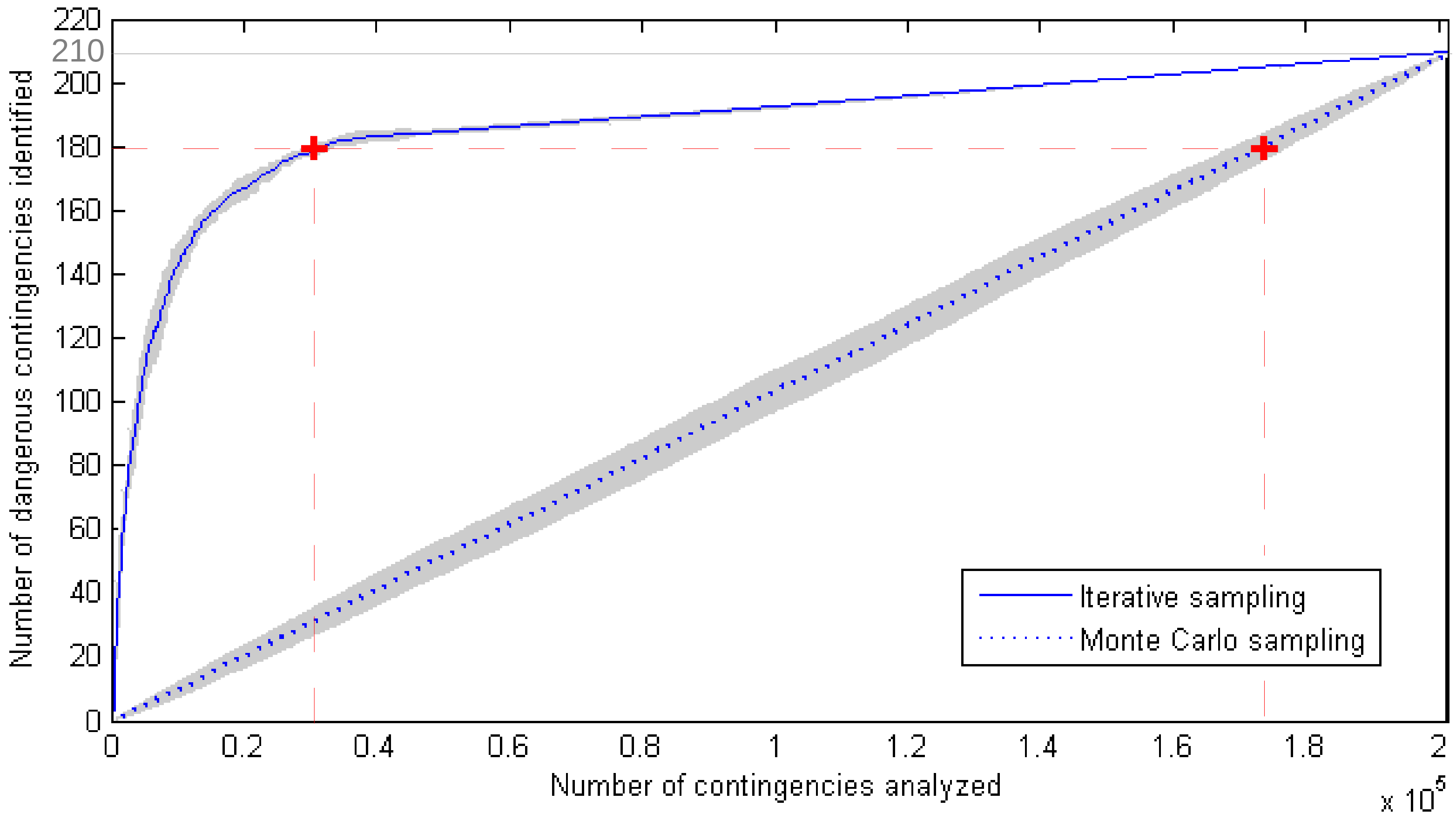

Simulation results

➢ probability of identifying at least n dangerous contingencies with a computational budget of 750 contingency analyses:

n	**Probability of identifying at least n dangerous contingencies**	
	Iterative sampling	Monte Carlo
1	1	0.49
2	1	0.20
3	1	0.03
4	1	0.01
5	0.99	0
10	0.95	0
20	0.75	0
30	0.51	0
40	0.26	0
50	0.13	0
100	0	0
210	0	0

Simulation results

➢ probability of identifying at least n dangerous contingencies with a computational budget of 750 contingency analyses:

n	Probability of identifying at least n dangerous contingencies	
	Iterative sampling	Monte Carlo
1	1	0.49
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10	0.95	0
20	0.75	0
30	0.51	0
40	0.26	0
50	0.13	0
100	0	0
210	0	0

5. On-line selection of iterative sampling algorithms

Context

➢ several basic iterative sampling algorithms (differing by their parameters) are available;

Probability of identification of dangerous contingencies 1 to 6

***BIS*^{1}** (λ_0^1, s^1, m^1) →

1	2	3	4	5	6
0.56	0.78	0.09	0.48	0.82	0.65

***BIS*^{2}** (λ_0^2, s^2, m^2) →

1	2	3	4	5	6
0.11	0.49	0.73	0.18	0.01	0.25

***BIS*^{3}** (λ_0^3, s^3, m^3) →

1	2	3	4	5	6
0.27	0.90	0.48	0.83	0.67	0.74

***BIS*^{4}** (λ_0^4, s^4, m^4) →

1	2	3	4	5	6
0.41	0.65	0.32	0.17	0.45	0.77

5. On-line selection of iterative sampling algorithms

Context

➢ several basic iterative sampling algorithms (differing by their parameters) are available;

Probability of identification of each dangerous contingency

BIS[1] (λ_0^1, s^1, m^1) →

1	2	3	4	5	6
0.56	0.78	0.09	0.48	0.82	0.65

BIS[2] (λ_0^2, s^2, m^2) →

1	2	3	4	5	6
0.11	0.49	0.73	0.18	0.01	0.25

BIS[3] (λ_0^3, s^3, m^3) →

1	2	3	4	5	6
0.27	0.90	0.48	0.83	0.67	0.74

BIS[4] (λ_0^4, s^4, m^4) →

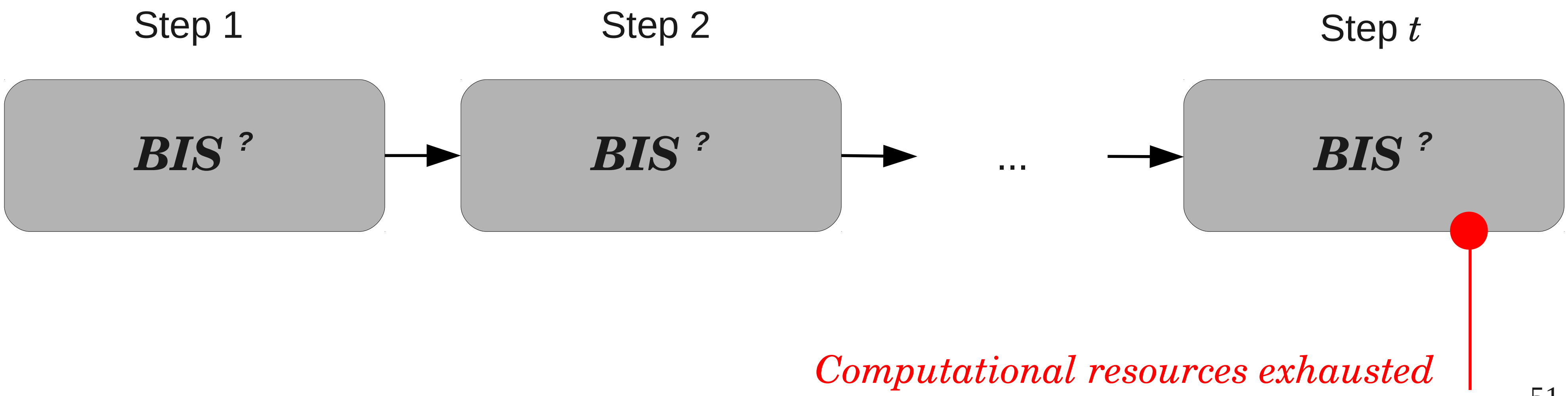
1	2	3	4	5	6
0.41	0.65	0.32	0.17	0.45	0.77

5. On-line selection of iterative sampling algorithms

Objective

➢ we consider that these algorithms can be executed sequentially until the available computational resources are exhausted;

➢ we want to schedule their execution so as to maximize the number of dangerous contingencies identified.



5. On-line selection of iterative sampling algorithms

Proposed strategy

- a **discovery rate-based strategy**, scoring at each step the different algorithms according to their ability to discover new dangerous contingencies and selecting the one with the highest score;

Definition of the discovery rate: number of new dangerous contingencies identified over the last T runs of algorithm i*.*

$$D^i_{t-1} = \begin{cases} d^i_T(t-1) \text{ if } T \leq n^i_{t-1} \\ d^i_{n^i(t-1)}(t-1) \text{ if } T > n^i_{t-1} \end{cases}$$

- this strategy is compared to a strategy looping over the series of algorithms at hand.

5. On-line selection of iterative sampling algorithms

Simulation results: studied problem

- **considered system:**
  Belgian transmission system $\geq$ 150 kV;

- **contingency space:**
  N-1 line tripping contingencies in a given base case (634 potential contingencies);

- **objective function:**
  loading rate (in %) induced on one specific transmission line, the line Ruien-Wortegem 150 kV;

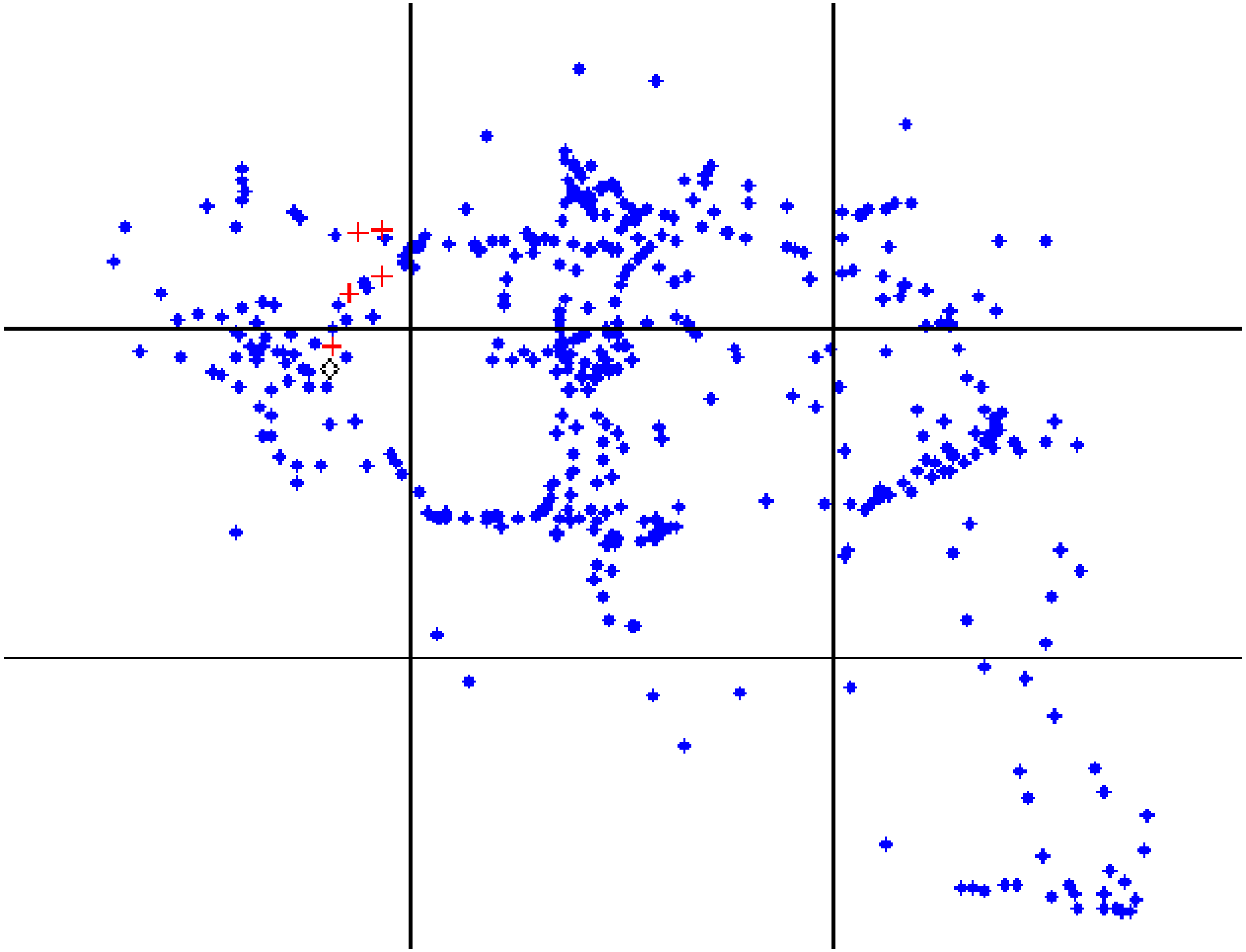
- **dangerous contingencies:**
  $O(x) \geq 100$;

- **Euclidean embedding space:**
  $\mathbb{R}^2$ (geographical coordinates).

5. On-line selection of iterative sampling algorithms

Simulation results: studied problem

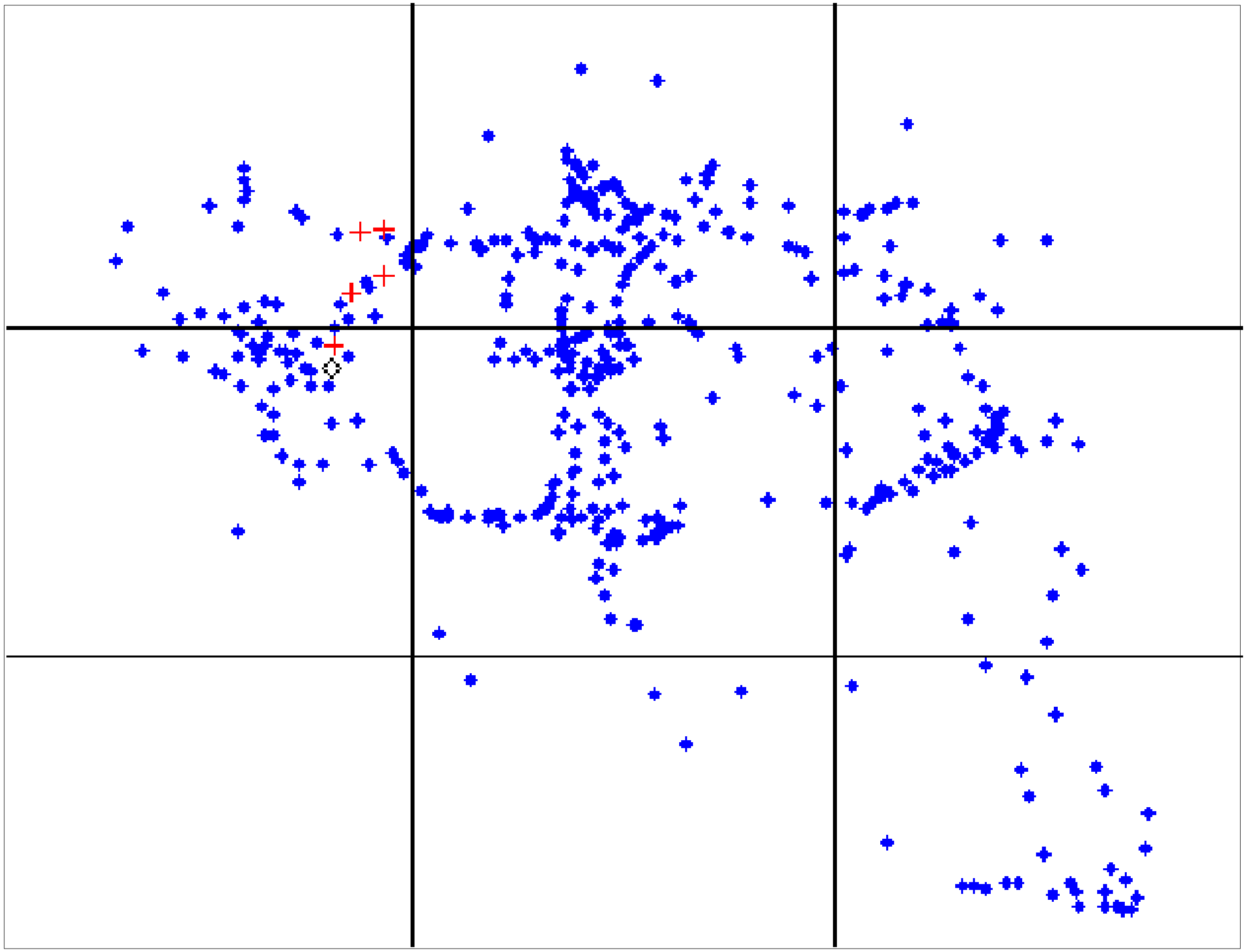
- projection of the N-1 contingencies in $\mathbb{R}^2$ (in blue) and dangerous contingencies (in red);



5. On-line selection of iterative sampling algorithms

Simulation results: studied problem

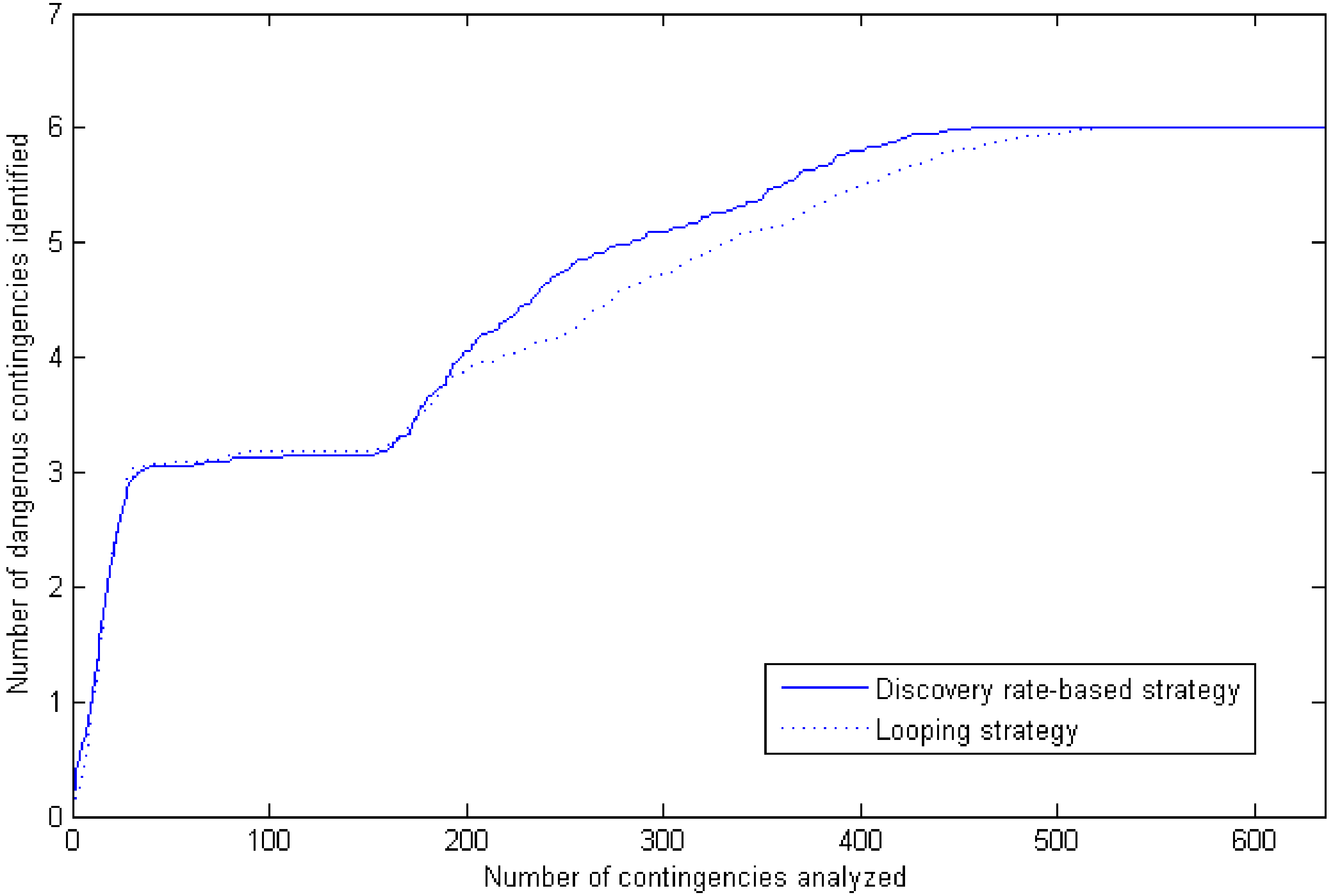
➢ set of BIS algorithms at hand: 9 different algorithms initialized in the 9 areas delimited in black on the picture;



5. On-line selection of iterative sampling algorithms

Simulation results

➢ number of different dangerous contingencies identified by the two selection strategies with increasing computational budgets;



6. Estimating the probability and cardinality of the set of dangerous contingencies

Main ideas

➢ we focus here on discrete contingency spaces, in which we consider that all contingencies are uniformly distributed (with probability p);

➢ we use our basic iterative sampling algorithm and exploit the principle of the cross-entropy method for rare-event simulation so as to estimate the probability l of the event $\{O(x) \geq \gamma\}$:

$$\hat{l} = \frac{1}{s} \sum_{y \in S_{final}} I_{\{O(preImage(y)) \geq \gamma\}} \frac{p}{\int_{z \in V_y} Gauss_{\mathbb{R}^n}(z, \lambda_{final}) dz} \quad ;$$

➢ we also propose to derive from this latter probability an estimation of the cardinality n_{dang} of the set of dangerous contingencies:

$$\hat{n}_{dang} = \frac{\hat{l}}{p} \; .$$

6. Estimating the probability and cardinality of the set of dangerous contingencies

Simulation results

- considered problem: N-2 analysis of the Belgian transmission network, as in section 4;

(objective function: maximal overload induced on the lines of the system, γ = 170, contingency space embedded in $\mathbb{R}^4$ using the equipments' geographical coordinates);

- results obtained after 100 runs of our BIS algorithm and of a naive Monte Carlo sampling algorithm:

	$\overline{\hat{l}}$	$\overline{\hat{n}_{dang}}$	$\sigma(\hat{n}_{dang})$
Iterative sampling	$1.03 \cdot 10^{-3}$	207.4	6.7
Monte Carlo sampling	$5.47 \cdot 10^{-6}$	1.1	2.5

7. Conclusion and future work

We have proposed in this thesis to apply iterative sampling techniques to the field of power system analysis.

Further research directions

- explore new variants of the proposed algorithms;
- integrate the developed approach to the security assessment procedures used by TSOs;
- extend the use of such algorithms to the control part of the security assessment task.

Thank you!