IRSN
INSTITUT DE RADIOPROTECTION ET DE SÛRETÉ NUCLÉAIRE

Enhancing nuclear safety

ALGORITHM-ASSISTED ASSESSMENT IN NUCLEAR CRITICALITY SAFETY

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Issue: Design of computer Experiments

- **Management of NCS = limits on controlled parameters**
  - "Not controlled" parameters supposed to take any credible value (within the range defined by normal and abnormal conditions)
  - "Not controlled" parameters may
    - be numerous
    - have non-linear, non-monotonous effect on k-effective
    - have cross-effects on k-effective
- **Which calculations should be perform to prove safety in normal and abnormal conditions?**
  - → **Definition of an adequate DoE**

Issue: Design of computer Experiments

Current DoE practices

- Parameter-by-parameter approach ~ (10-50) x p
  - Low calculation cost
  - No detection of parameters dependencies
- Crossed-parameters approach ~10^p
- "Exhaustive" approach ~50^p
  - High chances of finding parameters dependencies
  - Practically not achievable for $p > 2$
- Driven by **expert approach**

Depend on both expert skill and computing power

Issue: Design of computer Experiments

Use of advanced algorithms?

- Mathematically speaking: "global optimization problem"

  To find the minimal (or maximal) value of output over the input domain
- Many existing techniques (Newton based methods, genetic algorithms,…) with advantages and constraints
- Choice of the "EGO" algorithm (Efficient Global Optimization) *[Jones D., Schonlau M., Welch W.,1998]* adapted for:
  - Multi-parameters problems
  - A continuous output (k_{eff}) with possible local maxima
  - A Gaussian output ($k_{eff} \pm \sigma$ when MonteCarlo codes are used)
  - Giving solutions with less than a few hundreds of calculations
  - Giving a confidence level on the global optimum found (safety issue)

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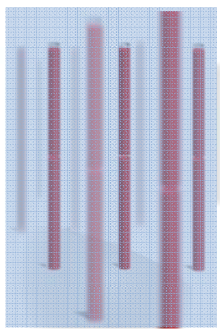
Overview of EGO

Practical implementation

Example: Dry PuO_2 storage

Description

- Tubes containing 2 barrels of PuO_2 powder (infinite array)

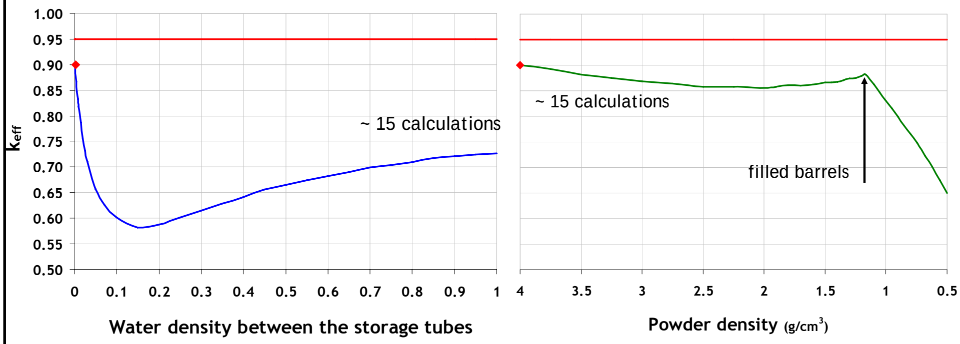


- Controlled parameters:
  - Geometry (tubes, pitch)
  - PuO_2 mass in the tubes
  - Moisture content in PuO_2
- "Uncontrolled" (varying) parameters:
  - Powder density: from 0.5 to 4 g/cm^3
  - Water density between the tubes: from 0 to 1 g/cm^3 (abnormal condition)

Is the given design safe ($k_{eff}+3\sigma \leq USL = 0.95$)?

Example: Dry PuO_2 storage

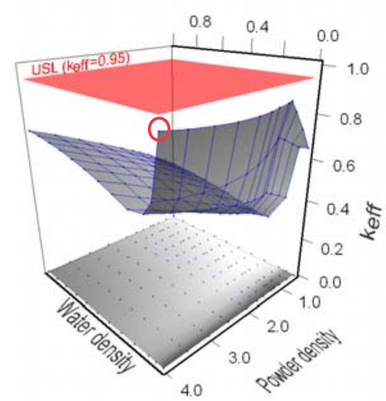
- **Expert prior assumption:** max reactivity for max oxide density and no water between the tubes
  - Proof by the **parameter-by-parameter** approach



- **Expert prior assumption confirmed by this approach**

Example: Dry PuO_2 storage

- **Expert prior assumption:** max reactivity for max oxide density and no water between the tubes
  - Proof by the **crossed-parameters** approach

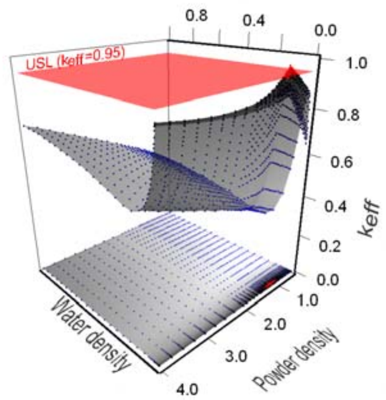


- 12x12 calculations
- Irregular mesh (expert judgment)
- ➔ Same maximal value of k_{eff}: 0.901

- **Expert prior assumption confirmed by this approach**

Example: Dry PuO_2 storage

- **Expert prior assumption:** max reactivity for max oxide density and no water between the tubes
  - Proof by the **exhaustive** approach

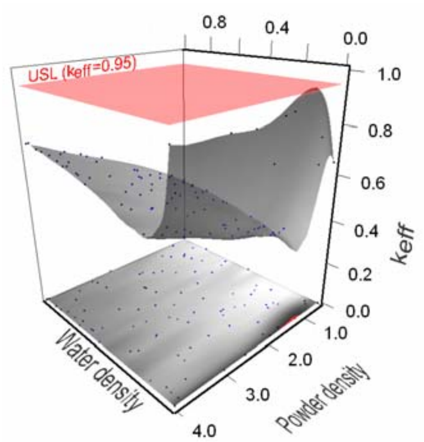


- 39x33 calculations
- Irregular mesh (expert judgment)
- ➔ Reactivity peak (max k_{eff} = 0.991)
- ➔ k_{eff} > USL for 0.13% of the studied area

- **Only this approach (or a skilled expert) is able to establish a good proof**

Example: Dry PuO_2 storage

- **Reactivity peak for a narrow area of parameters range**
  - Results of **EGO** algorithm



- 94 calculations
- max k_{eff} found = 0.964
  (lower than the actual max by 2.7%)

- **EGO is able to detect the high reactivity area but not to find the actual max of k_{eff} in this example**

Conclusions from this example

- Could EGO replace experts in the future?

  NEVER

  - Experts are still responsible for:
    - The parameters to make varying
    - The variation range of these parameters
  - Experts become responsible for the choice of EGO's options

  but, EGO may assist experts

  - To define area(s) of interest for calculations (prior assistance)
  - To check the validity of a given design (*a posteriori* assistance)

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EGO algorithm

A k_{eff} optimization algorithm (adaptive DoE) requires:

- A strategy to define next experiments (calculations) to perform

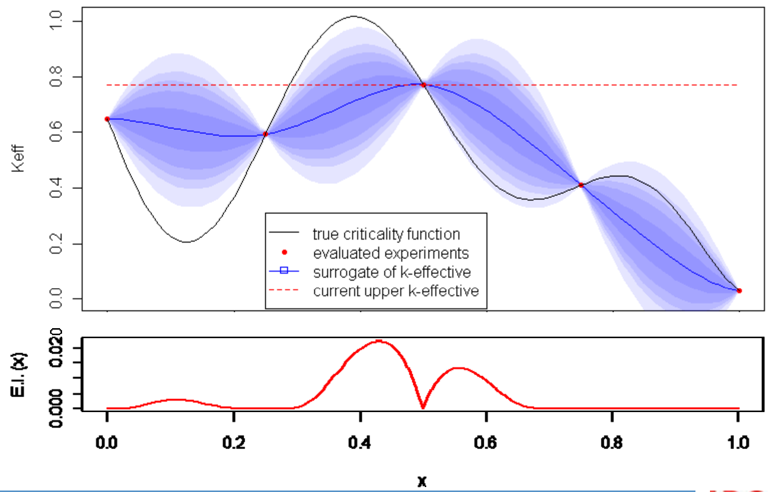
  In EGO: the "Expected Improvement" (EI) criterion
  (stochastic strategy)

- An "interpolation" method of the k_{eff} from existing experiments

  In EGO: the Krigging theory
  (developed for mining prospection issues)

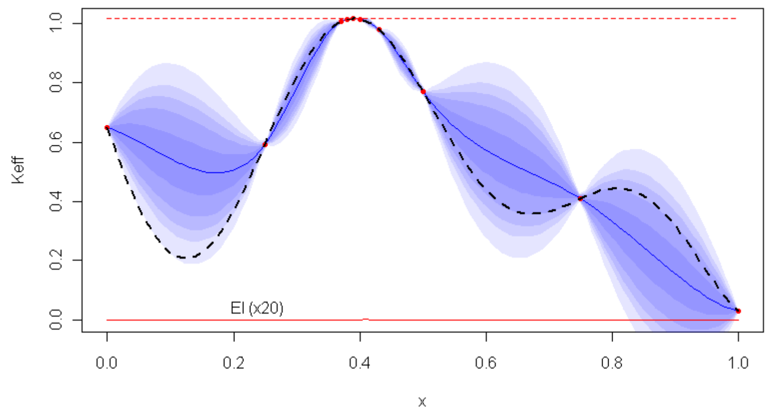
EGO algorithm

1-D example: Krigging and EI criterion



EGO algorithm

- 1-D example: EGO sequence of sampling experiments



Content

Illustrative example

Overview of EGO

Practical implementation

Practical implementation

The practical use of algorithms requires:

- Tools/software allowing "parametric calculations"

  automatic sequence of editing, transferring, running, parsing and storing calculation datasets including variable parameters

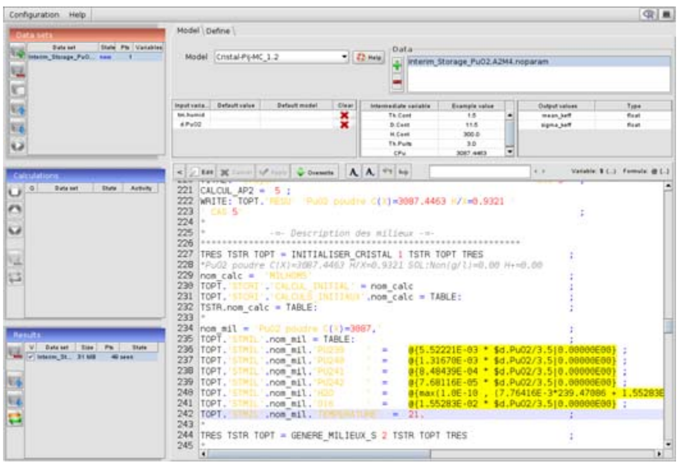
- Integration of the mathematical algorithms in these tools to drive the calculations

  in R language, through the DICE consortium (academics and industrials)
  Deep Inside Computer Experiments

The Promethee workbench

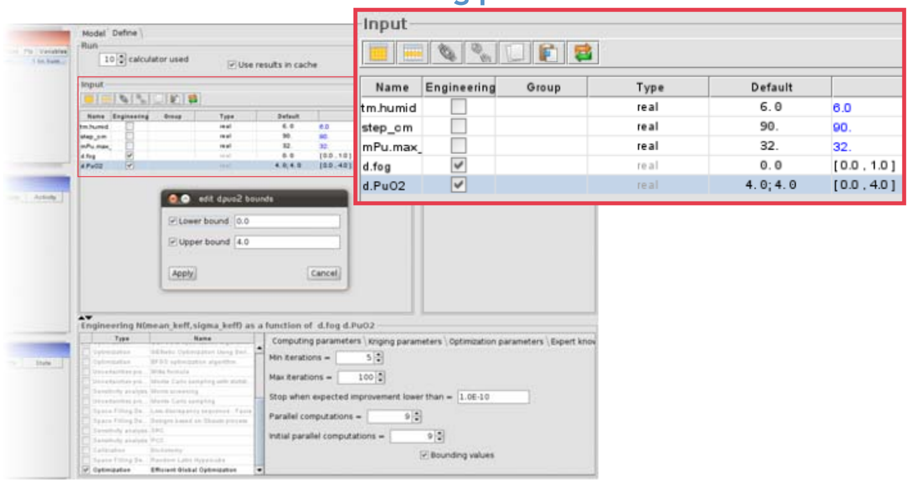
Practical implementation

Promethee overview: insertion of parameters in a dataset



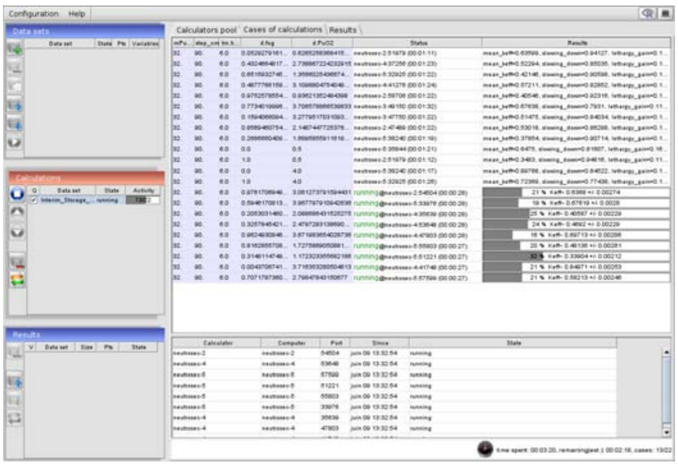
Practical implementation

Promethee overview: setting parameters



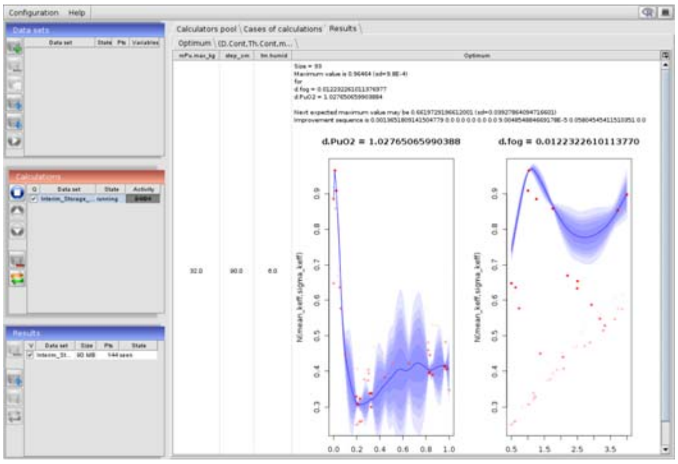
Practical implementation

Promethee overview: running calculations



Practical implementation

Promethee overview: EGO sequence



Batch #10
(94 calculations)

Conclusions

- Use of advanced algorithms like EGO builds up the NCS assessment methods by assisting evaluators in the understanding of complex problems

- Practical implementation is possible (see the freely available Promethee workbench: http://www.irsn.fr/promethee)

- But this approach adds new parameters to deal with (algorithm options) which may be critical for the efficiency of the algorithm

- This approach can be extended to other issues than “optimization for safety” (design of critical experiments, inversion, sensitivity analyses…)

Thank you for your attention

- Questions?