Workshop Rencontres chercheur·euse·s et ingénieur·e·s PHIMECA – IA vs Statistiques

M. Segond (DTI, Safety & Process Division, senior expert)

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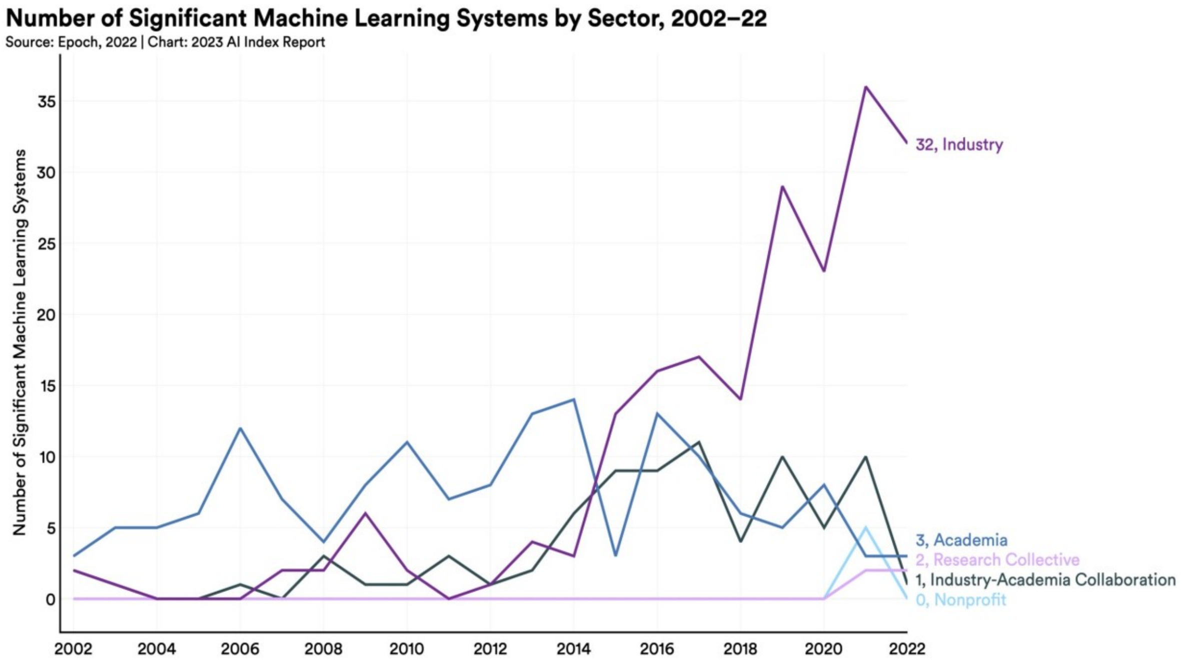
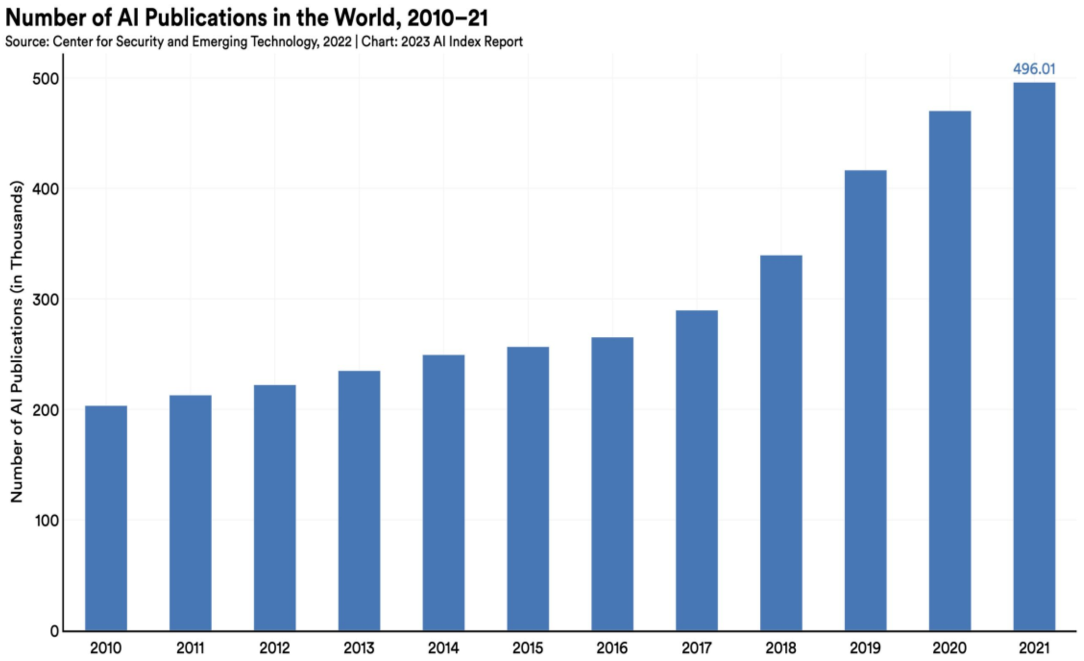
Content

AI context and industrial applications

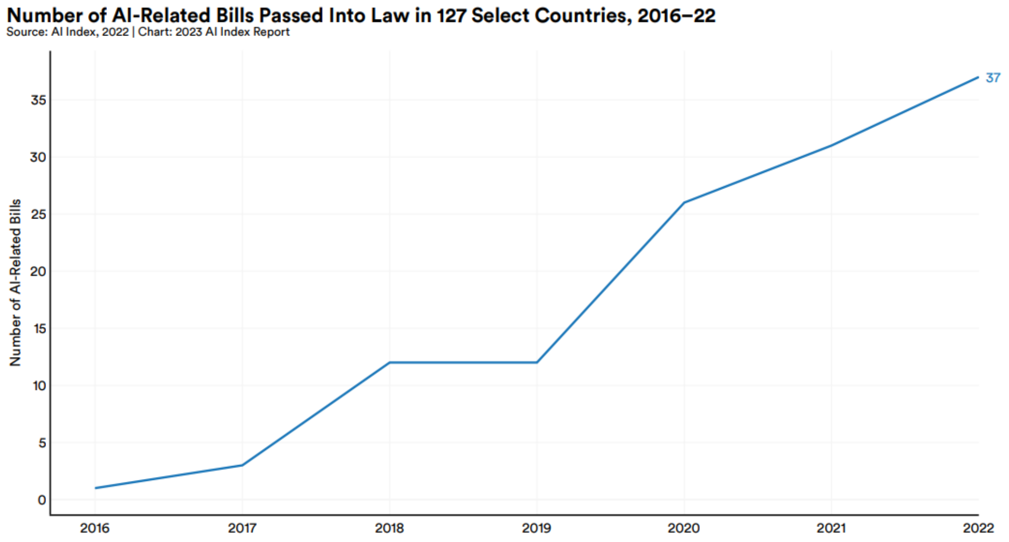
- AI field is growing at exponential rate,
  - Important venture capital funding and major IT & industrial companies are fueling billions of $ in the field
  - Whereas until 2014 most significant machine learning systems (ref. Stanford 2023 AI index report) were released by academia, since 2022 industry has taken over
  - How to embrace this ongoing revolution for nuclear safety critical applications ?





AI Act and regulatory challenges (1/2)

- **Nuclear field**: already strong nuclear safety regulatory rules are needed to license safety related processes and systems
- **AI field**: European Commission published its first proposal "AI Act" in April 2021, official release expected at the end of 2023
  - USA and China leading the way of AI-Related Bills
  - AI Label and Certification depending on the criticality of the applications, the sectors, and the degree of human feedback
- Potential future Safety Authorities guidelines specific to nuclear field involving AI is expected in addition to AI Act and the currently used safety rules (computer code qualification processes)
- Safety principles will be probably mandatory for AI social and regulatory bodies acceptance, as it has been the case for nuclear industry,
- ongoing IAEA technical meetings on safety impact of AI
- EDF group AI methodology for critical applications: interpretability, trustworthiness and robustness of AI algorithms to cope with these upcoming requirements



AI Act and regulatory challenges (2/2)

Main publications

7 pillars for Trustworthy AI

1. Human agency and oversight

AI empowering human beings while ensuring **oversight mechanisms** such as human-in-the-loop

2. Technical robustness and safety

The reliability of the algorithms **in boundary cases, and the protection against malicious risks**

3. Privacy and data governance

Compliance with regulations on personal data such as the GDPR

4. Transparency

Traceability, explainability and communication of all predictions according to **business and regulatory constraints**

5. Diversity, non-discrimination and equity

Bias detection and mitigation to avoid unfair bias and **accessibility of AI systems** to all regardless of any disability

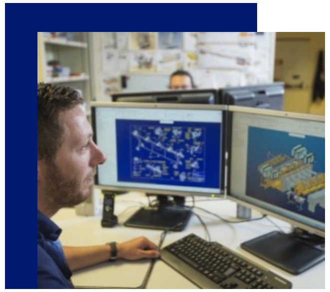
6. Environmental and societal well-being

Alignment of business and environmental/societal interests through optimization of training and resources

7. Accountability

A governance adapted to the AI functionality, integrating all stakeholders and building auditable AI systems

Framatome Business Units Activities



Engineering & Design Authority - DTI BU

Development, design and licensing of nuclear steam supply systems (NSSS) and associated services, including worldwide Technical Centers, Data Science & Applied Math pole to support all the BUs

Fuel BU

Development, design, licensing and fabrication of fuel assemblies and core components for all types of light water reactors (PWR, BWR, VVER) as well as for research reactors. Development of zirconium alloy components.

Projects and Components Manufacturing – PCM BU

Design and manufacturing of heavy and mobile components for nuclear islands. Management and execution of nuclear reactor new build projects, and component replacement projects.

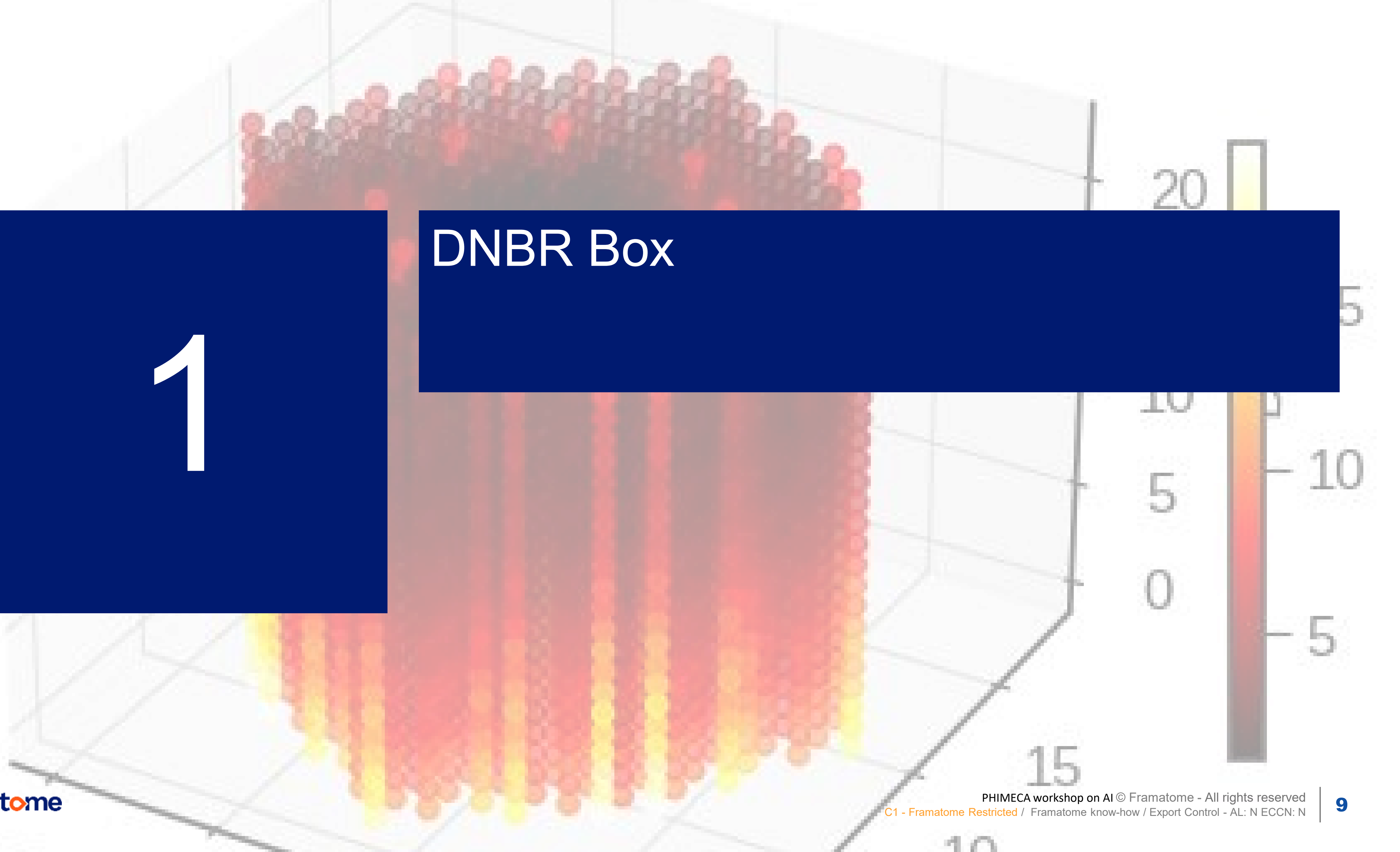
Installed Base BU

Products and services to maintain, modernize and extend the service life of facilities in operations; commission new facilities and support to decommissioning & dismantling activities.

Instrumentation & Control – IC BU

Design and manufacturing of automation and instrumentation technologies for the safe, sustainable and economic operation of nuclear power plants.

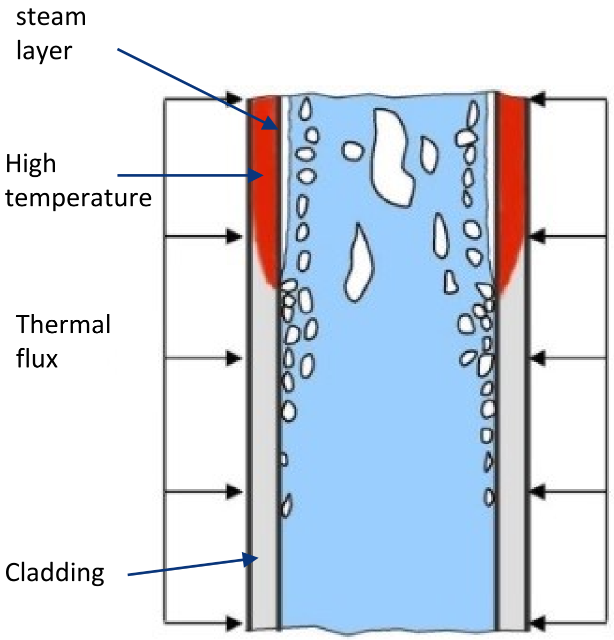
Content



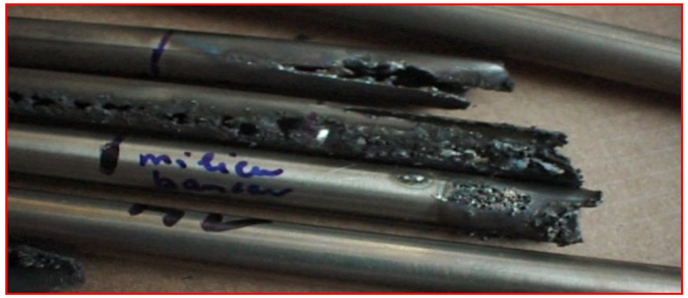
1 DNBR Box

DNB generic protection channel in PWR safety systems

- One of the most important tasks in a PWR reactor core design regarding safety analysis and operating performance is the prediction of thermal margins with respect to the boiling crisis, assessed with the DNB ratio (DNBR)



Sudden increase in rod surface temperature at critical heat flux (CHF)



DNB risk: breach of the first barrier

- To avoid any damage to the cladding due to an excessive increase in the temperature, the thermal heat flux must not exceed a given value: the critical heat flux $\phi_{critical}$ (CHF)
- The CHF is determined experimentally as an empirical proprietary correlation of the local Thermal-Hydraulics (TH) parameters (P: pressure, G: mass flow, X: quality) and the geometrical characteristics of the fuel assembly design
- The DNBR is assessed as the ratio between the CHF and the local thermal heat flux ϕ_{local} during safety studies simulations and also online with a simplified algorithm for 4 loops and EPR reactors:

$$DNBR(x, y, z) = \frac{\phi_{critical}(P, G, X, geometry)}{\phi_{local}(x, y, z)}$$

Overview of DNB generic protection channel (2)

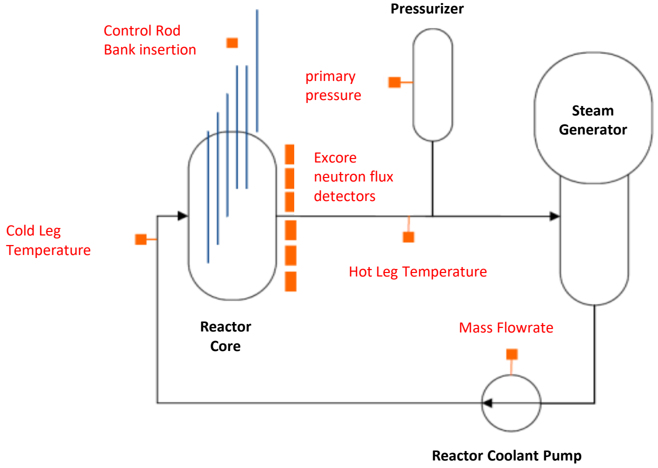
- **Framatome 1300 MWe, N4 and EPR** : functional units of the safety systems are directly assessing the online Linear Power Density (LPD) and DNBR to improve margins
- Digital I&C system based on evolution of core instrumentation
  - French 1300MWe/N4: introduction of simplified DNBR evaluation in RPS using SPINLINE technology from multi stages excore measurements
  - EPR : DNBR calculated in RPS based on TELEPERM XS (TXS) technology from in core Co SPNDs measurements
- **Benefits of the current solution** : online DNBR algorithm relies on a simplified physical modeling compared to a reactor trip / surveillance threshold including different uncertainties and penalties to insure a conservative reconstruction with respect to reference simulations
- It is penalized with respect to the 3D reference code simulations to compensate the inaccuracy of the local TH variables reconstruction thus insuring its conservatism through epistemic parameters called the "Bias Curves"

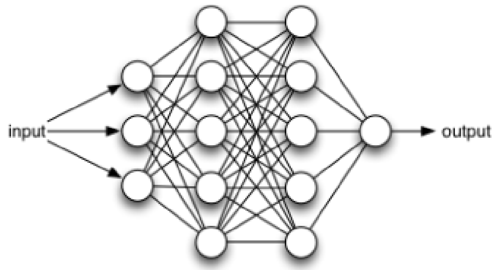
$$DNBR(x,y,z) = \frac{\phi_{critical}\left(P, {}^{G}/_{FGFR}, X * \mathrm{FHFR}, geometry, (x,y,z)\right)}{\phi_{local}(x,y,z)}$$

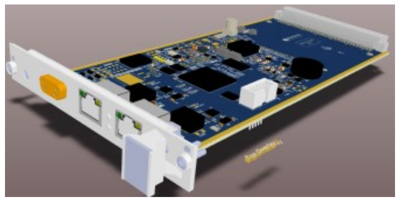
- **Drawbacks**
  - Algorithmic nature of the DNBR online algorithm processing though simplified: complex implementation and qualification processes
  - Penalizing online DNBR reconstruction and error variability: risk of additional global penalties

DNBR Box: an embedded AI algorithm in the I&C safety system

- **Idea of DNBR Box**
  - To use an AI algorithm trained on 3D core physics reference codes simulations
  - To be embedded on innovative I&C hardware capabilities : TXS Compact based on FPGA (Field Programmable Gate Array) chipset technology
- **Benefits of the Box concept**
  - Same accuracy as the reference code
  - Avoiding the complex implementation of state-of-the-art codes within safety I&C => same determinism (functional) as the legacy ΔT generic channels
  - FPGA chipset perfectly suited for fast inference of AI algorithms (neural networks)

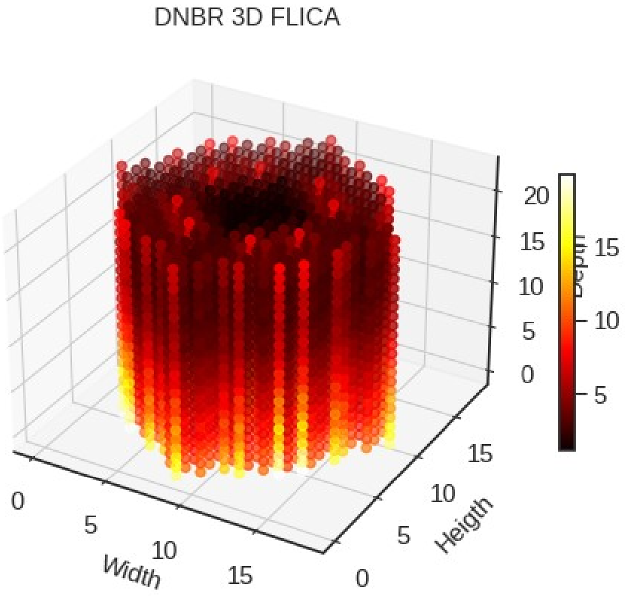


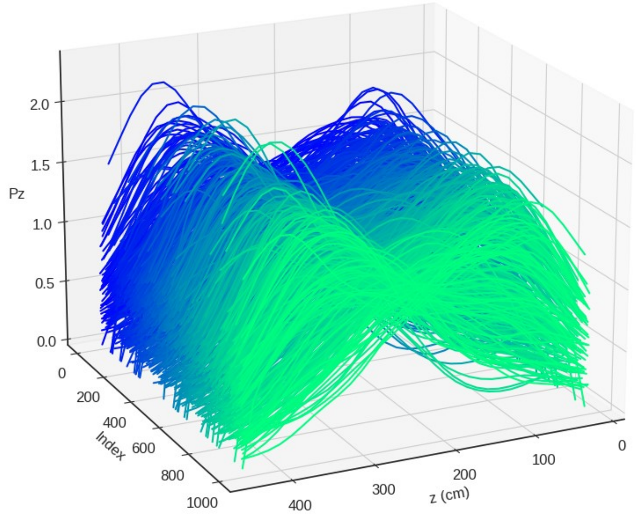


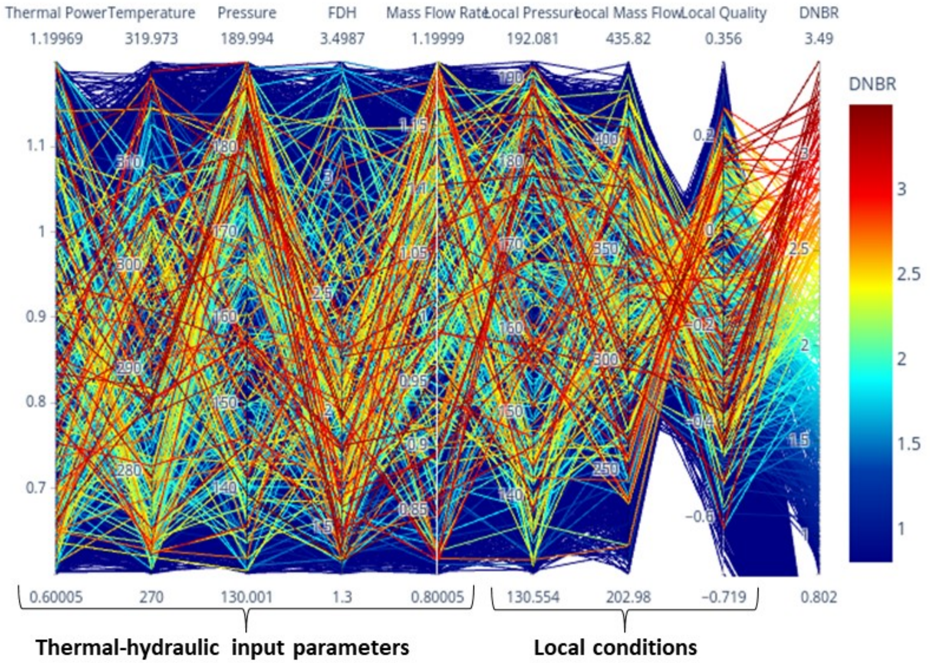


DNBR Box – Learning / Validation Data base

- Lack of online physical modeling must be compensated by a big and representative database to train and validate the model.
- We sampled a database on N4 NPP design:
  - 1000 Thermal-Hydraulic state-points ⊗ 6000 axial power distributions continuously perturbed axial power shape Pz from [-50%;+70%] core neutronics-TH 3D calculations => 6 x 10^6 data 3D core simulations.
  - Data filtering on local TH conditions belonging to the CHF validity domain and DNBR range
  - Leads to 3 x 10^6 core statepoints data => big data set of 2To in csv format

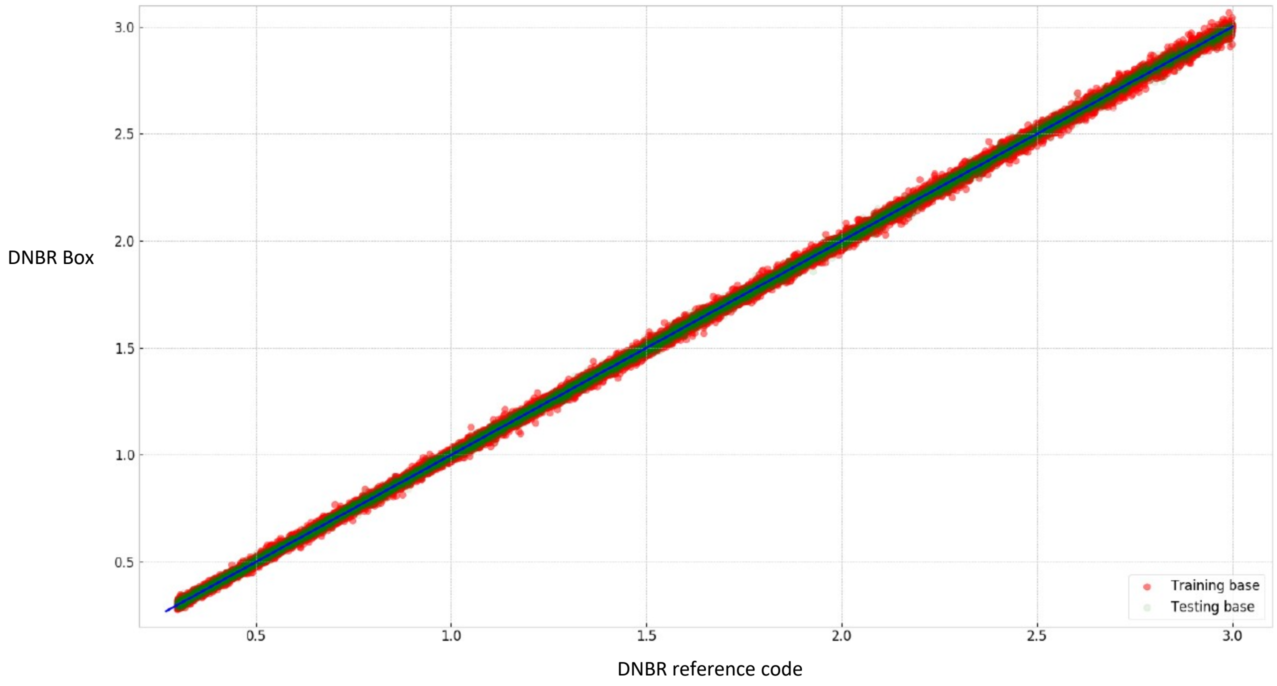


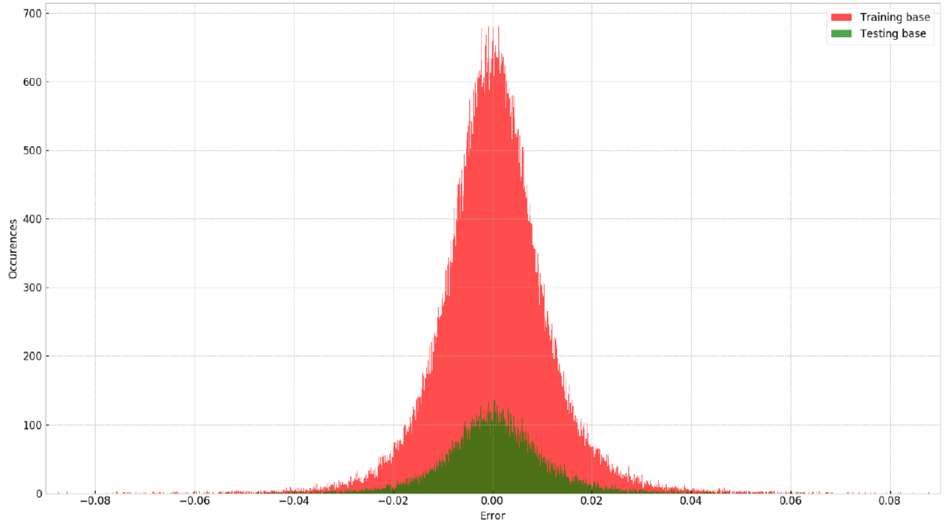




DNBR Box: results of the learning & validation phases

- Learning and validation of DNBR box : database of millions of 3D core statepoints issued from neutronics-thermalhydraulics reference code simulations
- Very good accuracy from performance metrics
- Same performance on EPR design from 6 SPNDs LPD and 3 TH features





Metrics	Learning base (80 %)	Validation base (20 %)
MSE	1.4×10^{-4}	1.3×10^{-4}
Q^2	0.999	0.999

DNBR Box: test phase on accidental transients simulations

- Validation beyond the classical heuristics
  - direct replacement of the reference code by DNBR box algorithm in the complex multiphysics accidental transient simulation to perform advanced validation

- *TH system – core 3D TH code*
  (Uncontrolled Rod Bank Withdrawal, reactor at Power) :
  Neutronics 0D modeling with MANTA accidental TH system code

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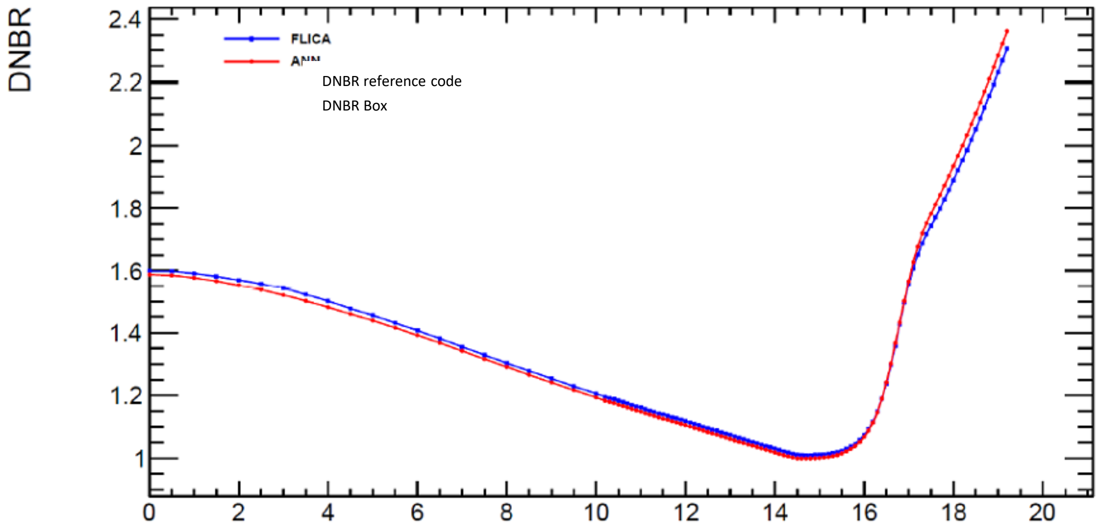
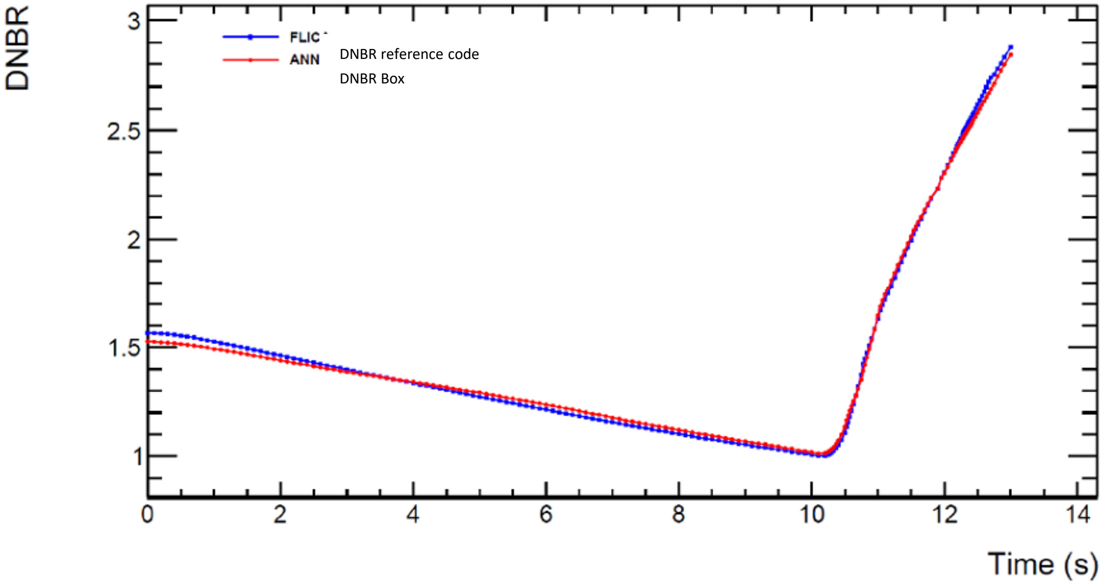
- *TH system – 1D core Neutronics code - 3D TH code*

  (Uncontrolled Rod Bank Withdrawal, reactor at Power) :

  Neutronics 1D modeling with SMART code coupled to MANTA code (varying axial power distribution fom -10%PN to +40%PN during transient analysis)

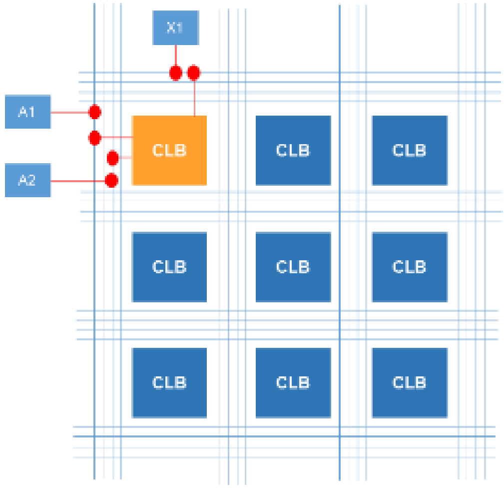
- Phenomenological tests with true accidental study simulation succeeded.



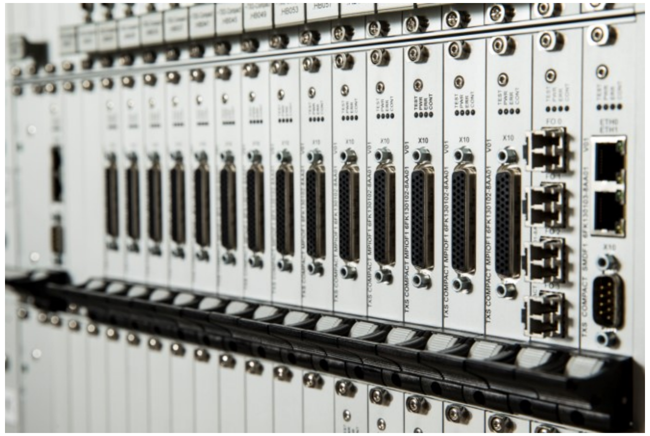


TELEPERM XS Compact: a new FPGA-based safety platform

- **Nuclear-grade safety** I&C platform developed by IC BU Framatome as part of TXS product line (used e.g. for EPR protection system already)
- **Major investment** of IC BU and main support for growth of market share in the future
- Generic qualification following **IEC/RCC-E nuclear standards,** compliant with IAEA SSG-39
- Innovative patented concept using FPGA (Field Programmable Gate Array) and high-end configuration software

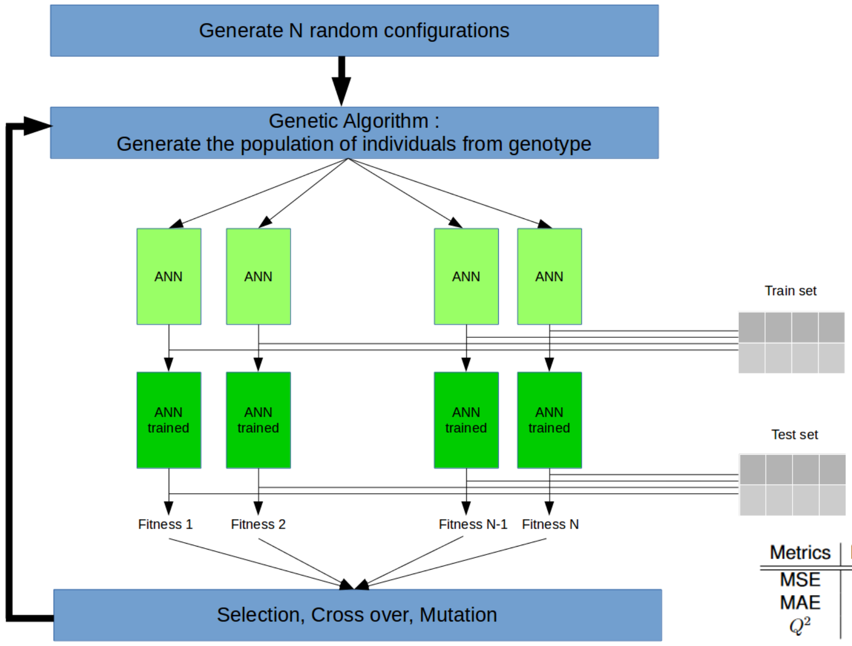


- FPGA are intensively used for aeronautics, military and space embedded systems, and perfectly suited for fast inference of AI algorithms
- TXS Compact qualification will be finalized in 2023, first commercial application expected in 2024
- Technical basis for DNBR Box proof of concept



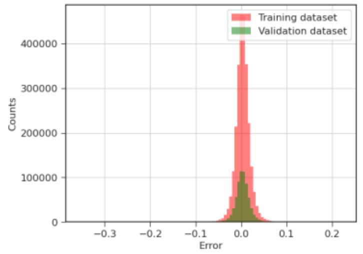
DNBR Box complexity optimization with Genetics Algorithms

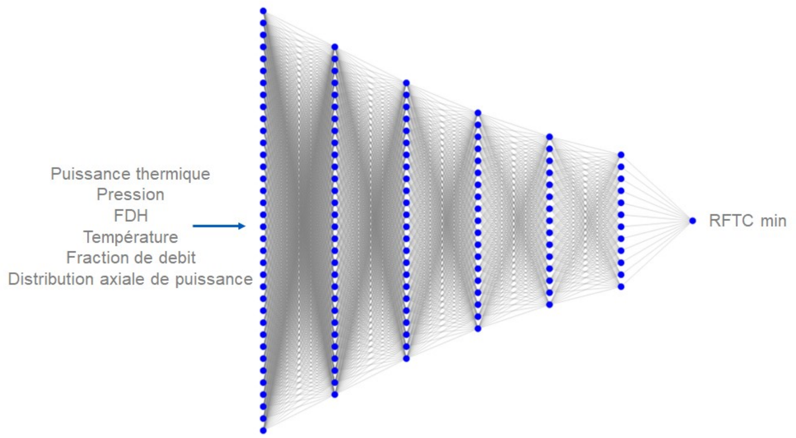
- Safe implementation on TXS Compact requires optimization of the number of variables due to safety-related constraints
- Explore the large scale hyper-parameters space with Black Box optimization algorithms to reduce the complexity to cope with safety I&C systems requirements
- Reduce the complexity by one order of magnitude



Attributes	Description	possible choices
Number of layers	The depth of the neural network	3,4,5,6,7
Size first layer	Number of neurones on the first layer	10,15,20,25,30
Decreasing rate	Ratio of the number of neurones from one layer to the next	0.8,0.9
Activation function	Non linear activation function of the neurones of the network	'sigmoid','relu'
Batch size	Initial batch size for training	1,10,100
Transition step	Number of updates before changing batch size	100,1000
Batch size evolution rate	Increasing rate of the batch size	1.01,1.05,1.1
Number of epochs	Number of iteration over the training dataset	5,8
Learning Rate	Learning rate for gradient descent	0.001,0.0001
Dropout	Dropout reguralization on training	0.0,0.05,0.1,0.2
COMBINATIONS		28 800

Metrics	Learning base	Validation base
MSE	0.000244	0.000246
MAE	0.011442	0.011475
Q^2	0.9994	0.9994





DNBR Box implementation on TELEPERM XS Compact

- Proof-of-concept implementation of a fast inference AI algorithms based on reference computer codes simulations has been achieved on a representative industrial next generation of Framatome safety automation system based on the TXS Compact technology
- Benchmark with 1 million test vectors (vs 30k for the data base of current projects)

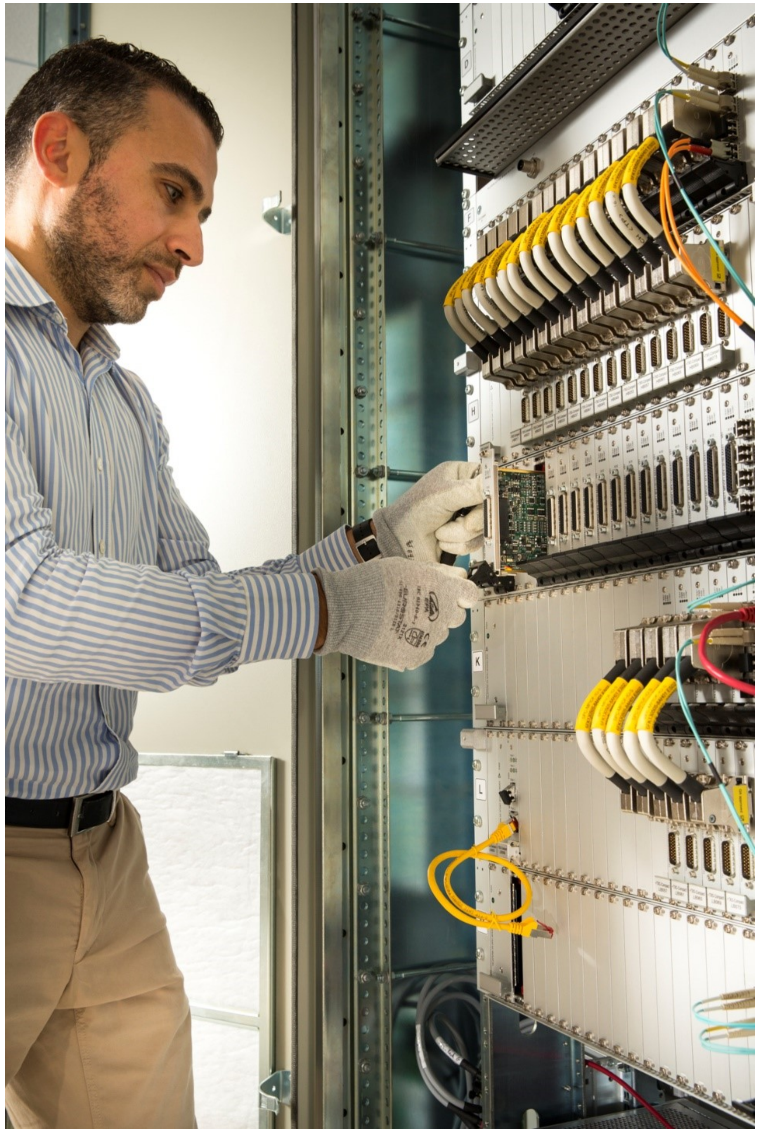
=> improvement of the core statepoints representativeness, validation and qualification process

- Improvement of the processing time
  - FPGA is perfectly suited for fast processing of neural networks, even in this TXS Compact safety grade configuration
  - 212 µs DNBR Box latency vs 200 ms for the current DNBR algorithm solution

- Accuracy improvement vs the current solution

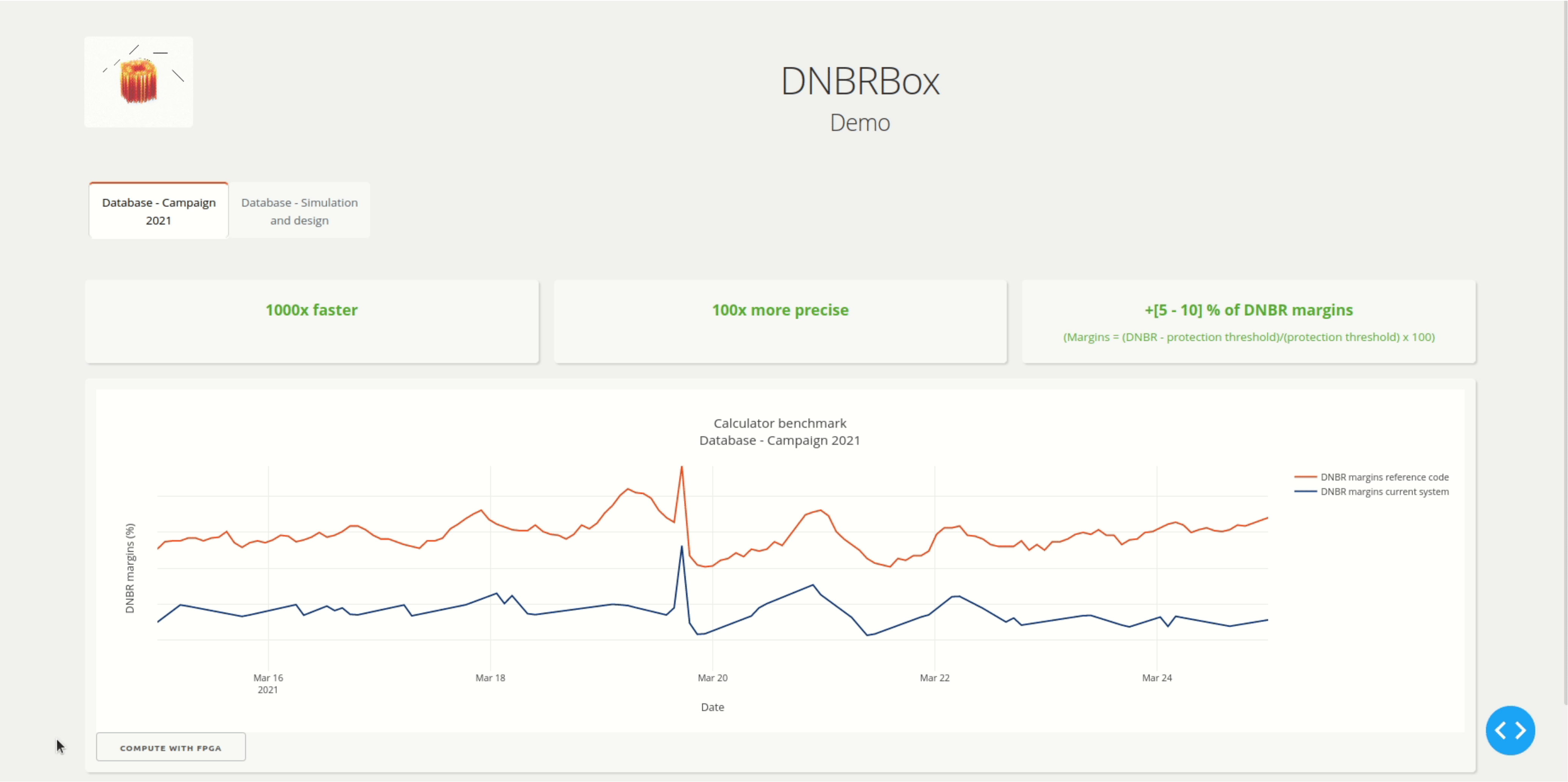
	DNBR Box TXS Compact vs software implementation (Python on HPC cluster)	DNBR Box vs 3D reference code
Error assessed on 1Million 3D reference core codes test dataset	2.03×10^{-13} Outputs identical btw hardware and software	1.94×10^{-4} Results close to the reference code simulations

Live demo of the prototype to illustrate the proof of concept



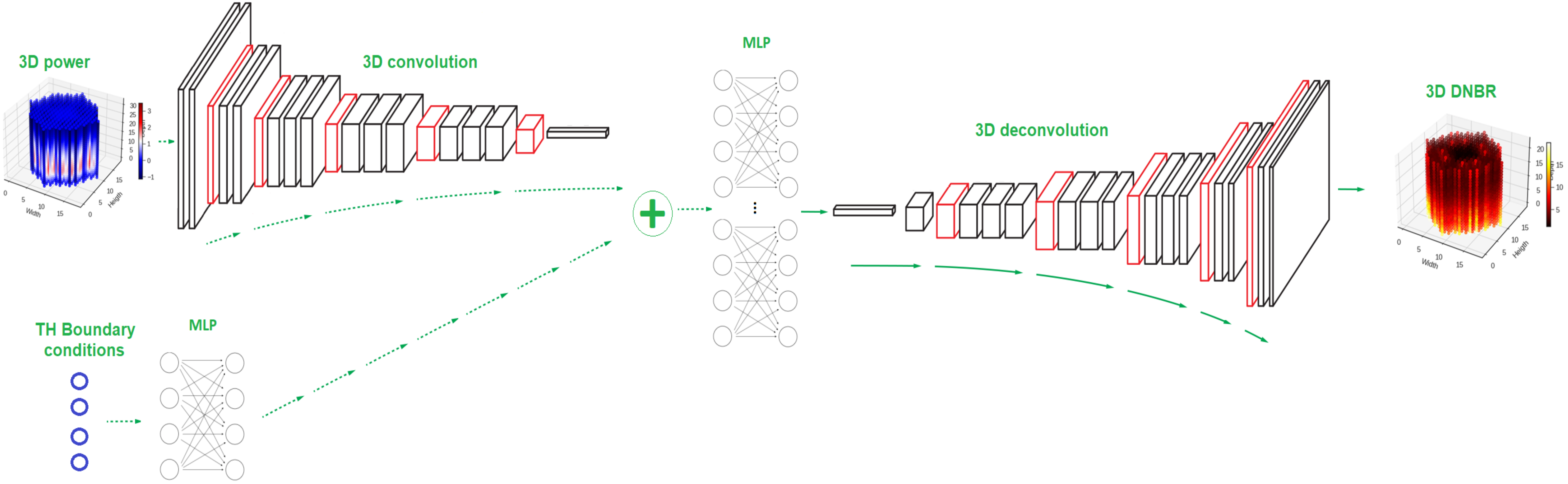
DNBR Box- benchmark on test data from N4 NPP with EDF

Benchmark of DNBR prediction on real life transients between reference simulation, current simplified algorithm and DNBR box



DNBR Box 3D – perspectives

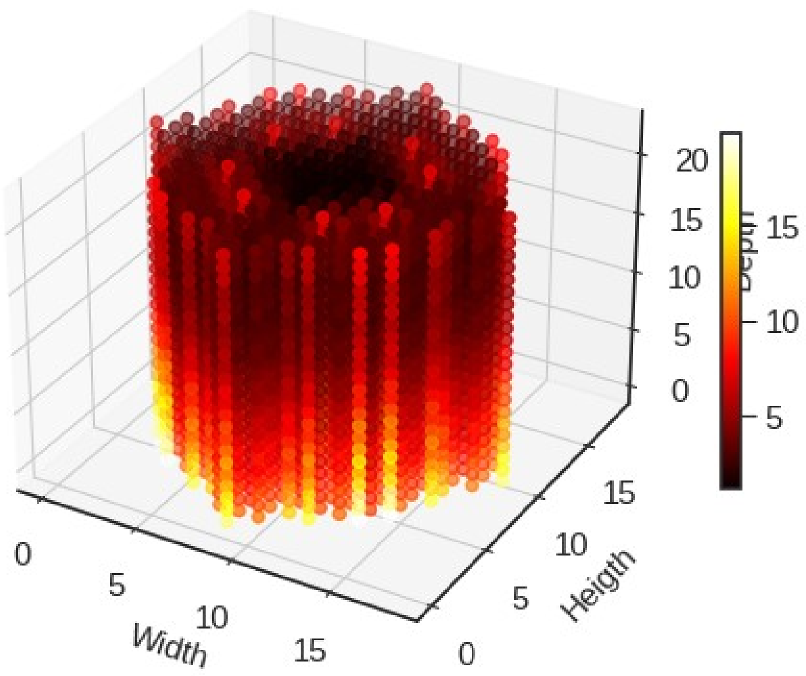
- Using convolutional network to take into account the geometry of the problem, in particular the spatial correlation of the nuclear power distribution as a 3D field, to predict the whole DNBR field in the core using a Convolutional Neural Network (CNN).
- We could try to combine neural net with Gaussian Processes => but we believe in the fast computation capabilities of DL algorithms embedded on FPGA hardware.



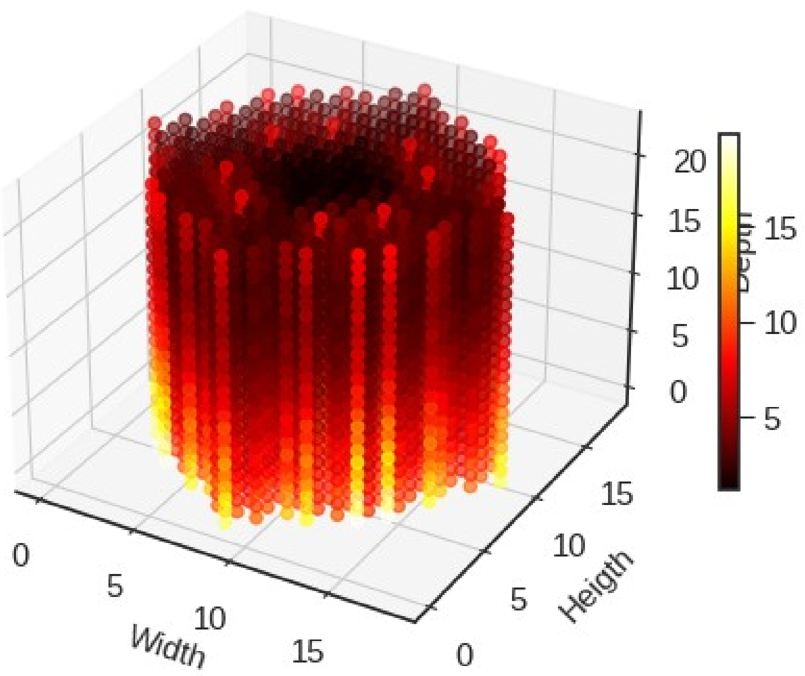
DNBR Box 3D – perspectives

- Results

DNBR 3D FLICA



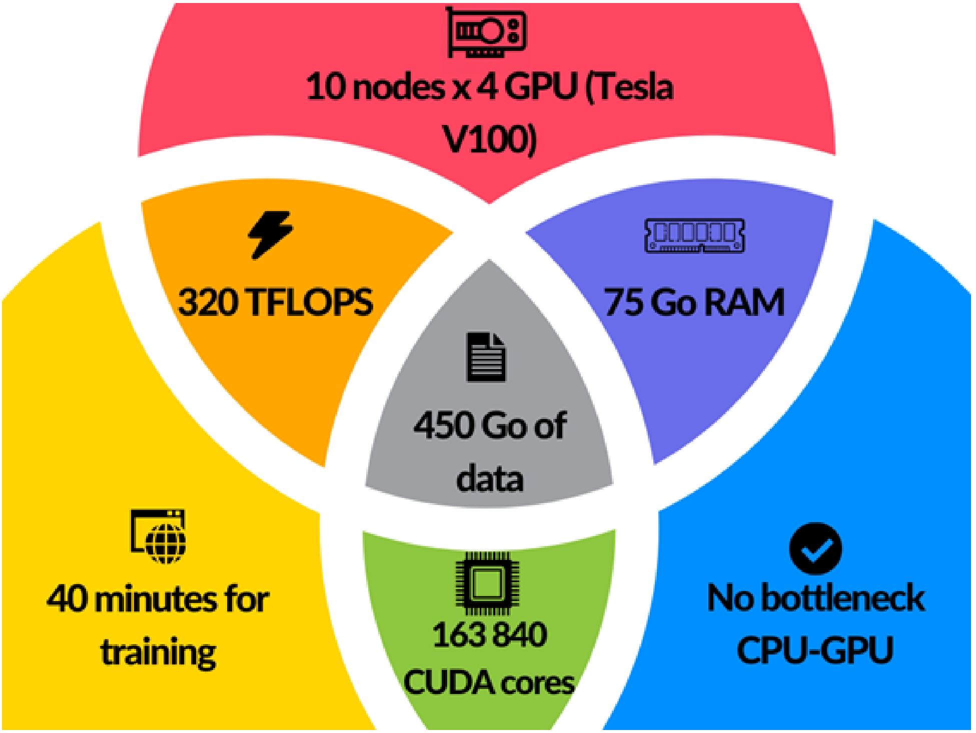
DNBR 3D CNN

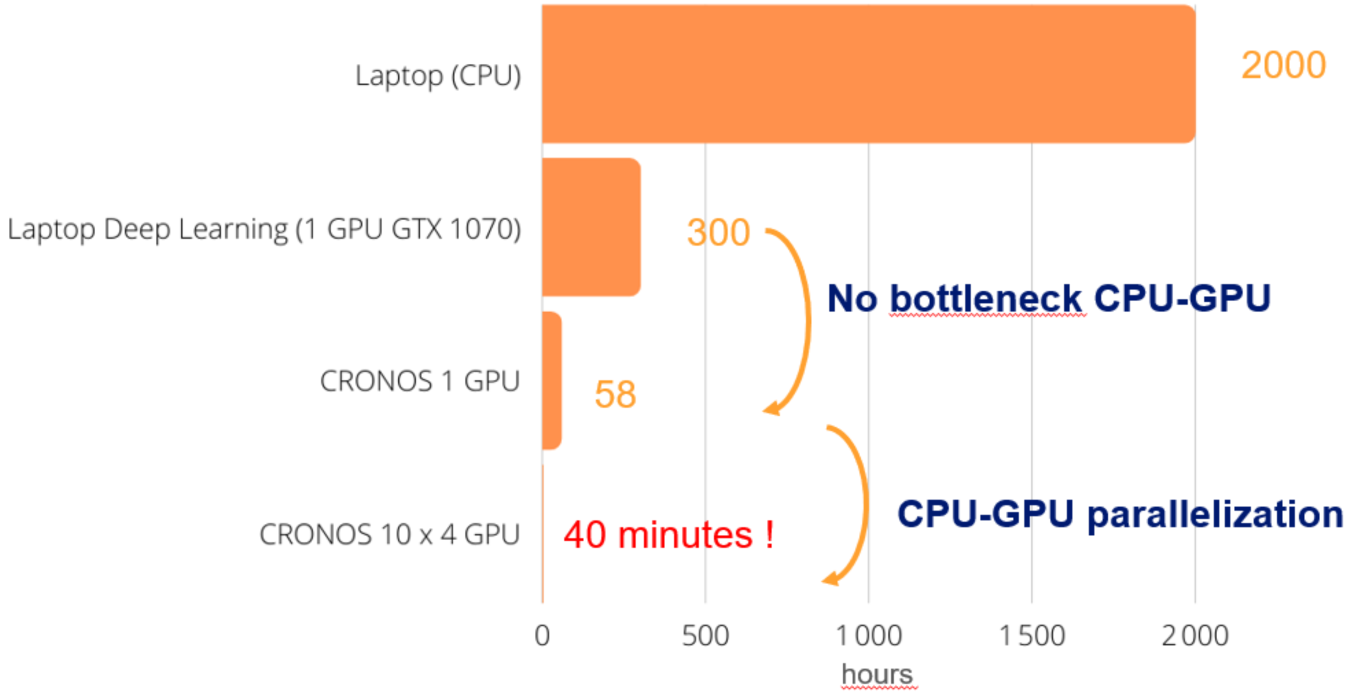


Metrics	Learning Base	Validation Base
MSE	0.067	0.2705
$Q^2 = 1 - \frac{MSE}{\mathbf{Var[DNBR]}}$	0.9979	0.9932
Error on DNBR	0.0386	0.0865
Error on $min_{x,y,z} DNBR$	0.1187	0.2047

Computing power challenges

- Computation has been made on the EDF/Framatome HPC CRONOS cluster which includes 81600 CPU cores with a frequency of 2.4 GHz that leads to 4.2993 PFlops/s.
  - It was ranked 67 in 2021 in the top500 HPC in the world.
  - CRONOS includes also 45 nodes of 4 GPU NVIDIA TESLA V100 SMX2 (with 5120 NVIDIA CUDA cores and a frequency of 1.245 GHz).



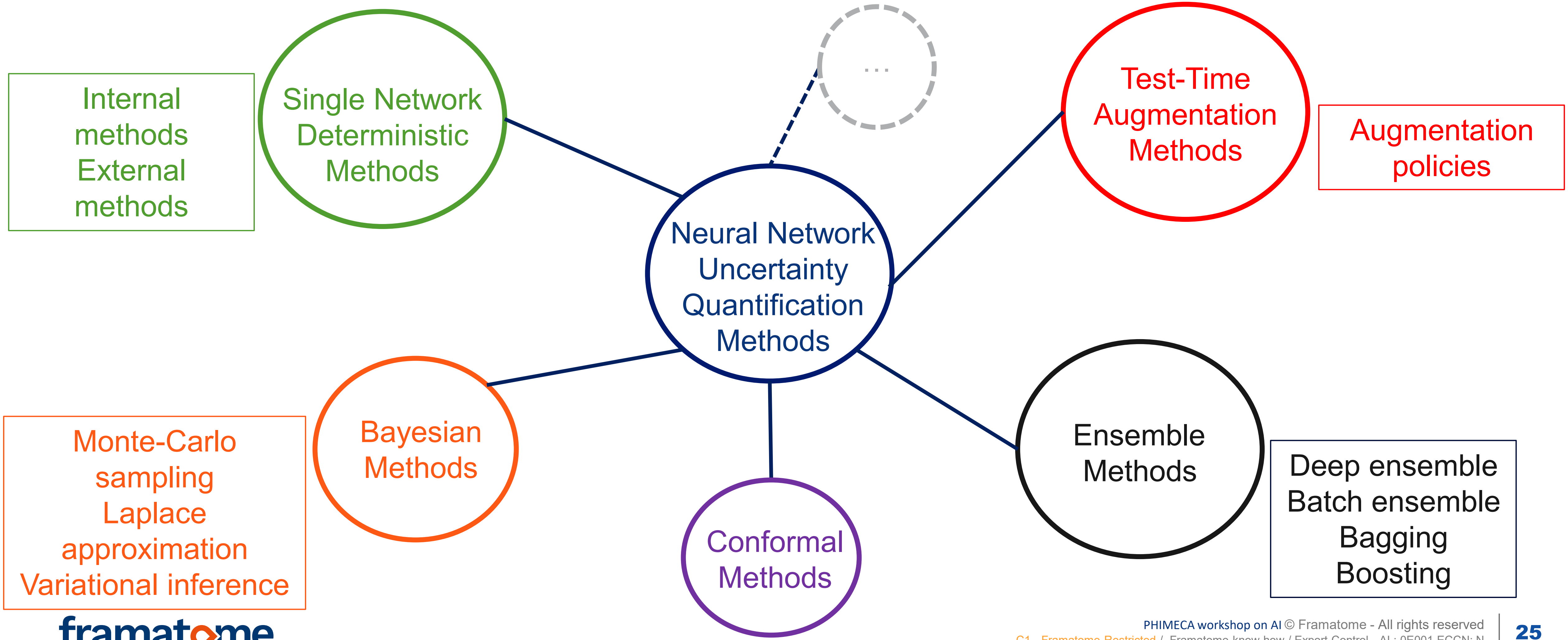


Open questions for safety critical AI applications

- For critical applications like in nuclear safety, aeronautics, autonomous vehicle, medicine, etc. it is important (even mandatory regarding the safety authorities and regulatory bodies upcoming requirements) to be confident on the predictions of the model and on its uncertainties.
- Can we train a model to predict with a good accuracy and in the same time to estimate with a good confidence the uncertainty?
- Can we trust the uncertainty estimation in test time, out-of-distribution time?
- Can we implement these methods on specific hardware like Field Programmable Gate Array (FPGA)?

Robustness challenge: UQ methods in Deep Learning

- Several Uncertainty Quantification (UQ) methods exist depending on the number of forward passes or based on the nature (deterministic or stochastic) of the model.



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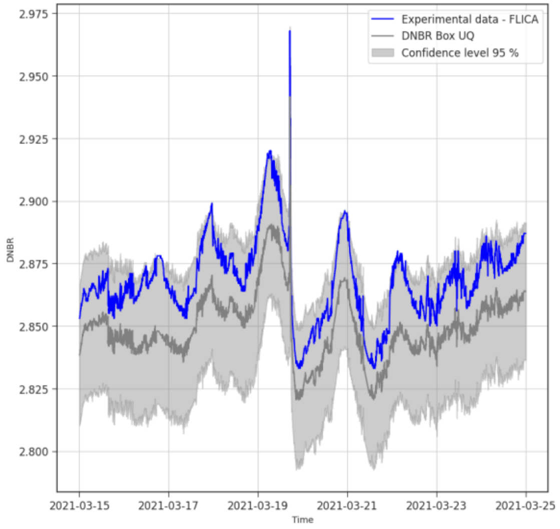
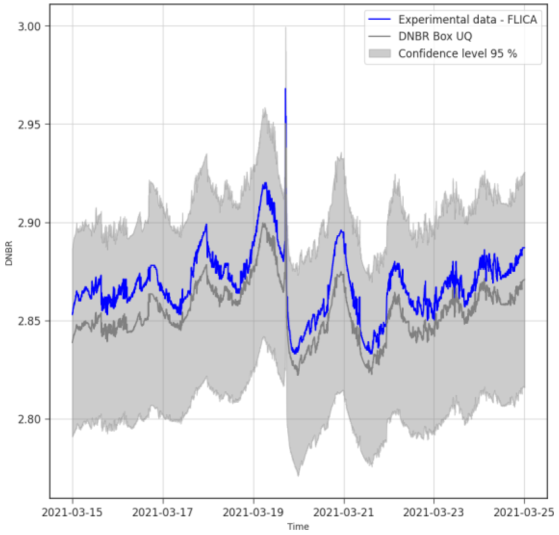
Open questions for critical applications

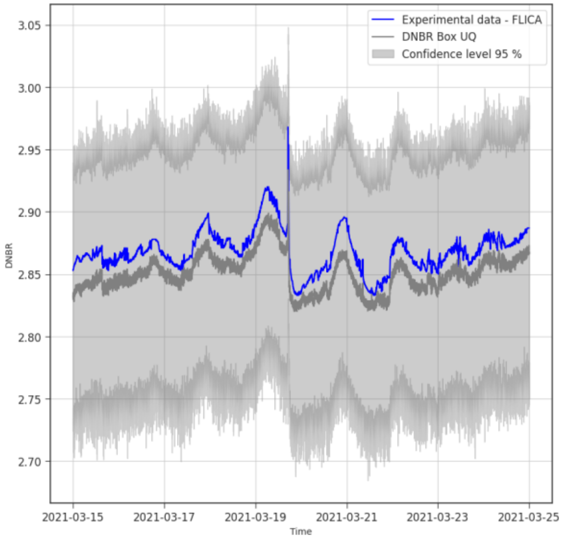
- Several UQ methods exist, but they are not equal.
- Differences in theoretical framework, in estimation time, in theoretical guarantees, in programming implementation, etc.
- Difference in behavior with respect to the dataset: train dataset, test dataset, distribution shift dataset, out-of-distribution dataset.
- For nuclear protection system based on embedded inference DL with UQ estimation on real distribution shift dataset: difference in terms of prediction accuracy and uncertainty estimation confidence.



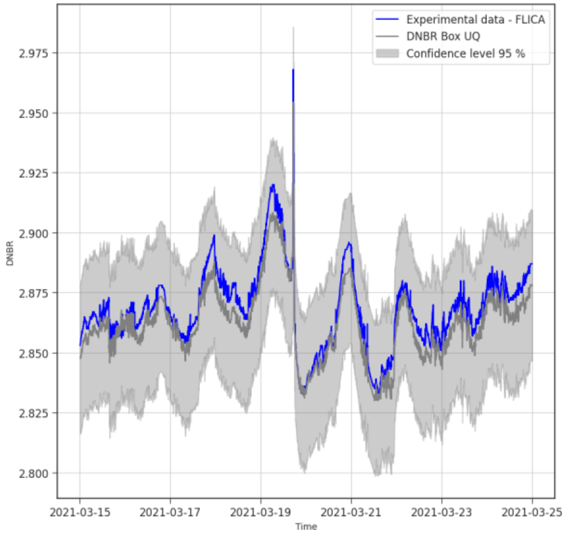
Bayesian Neural Network



Deep Ensemble



Monte-Carlo Drop-out



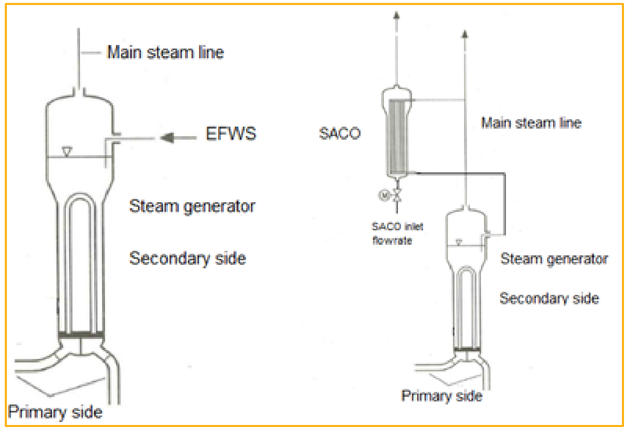
Conformal calibration

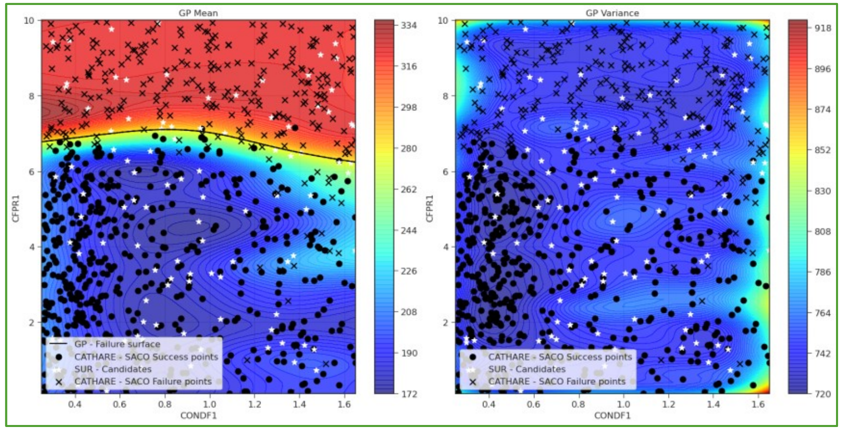
Content

Robustness of Safety Analysis – BEPU methods

Safety Analysis Report

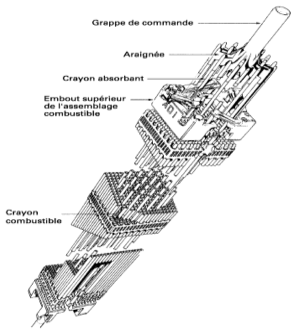
Advanced safety BEPU methodologies ("Best Estimate Plus Uncertainty"), Uncertainty Quantification and sensitivity analysis for Multi-physics / Multi-scale simulation

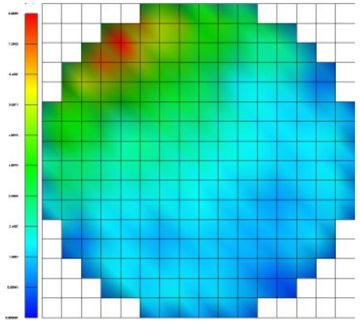


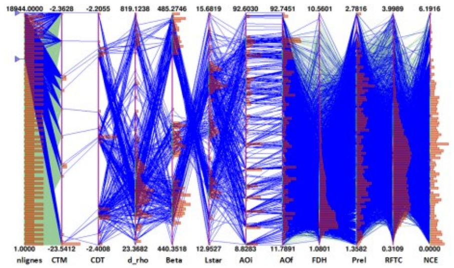


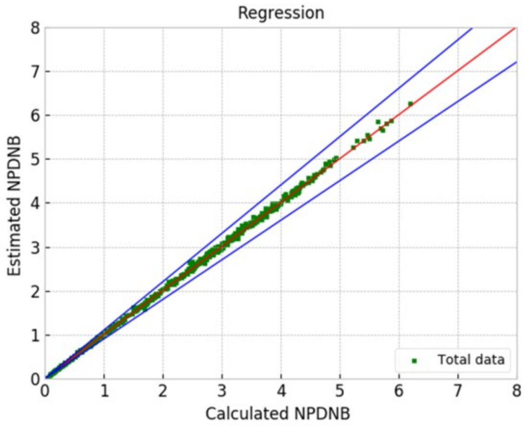
Typical application

Robustness improvement of safety demonstration, Reliability Assessment of passive systems (PSA): Adaptive design of experiments (DoE) strategy based on Bayesian optimization and GP, to tackle the computing cost challenges



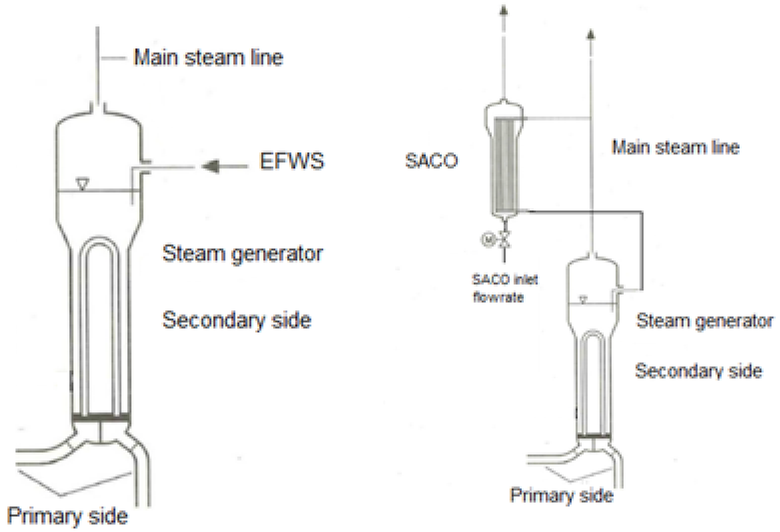






Bayesian optimization for failure probability estimation using metamodel

- **The goal** is to evaluate the probability of failure of a passive system called SACO (safety condenser) for steam generators.
- For next generation of PWRs, Framatome and EDF study the possibility to substitute the steam generator emergency feedwater system (EFWS) by a safety condenser.
- The Probabilistic Safety Analyses (PSA) needs to introduce the reliability evaluation of the passive system which relies on precise multi-physics simulations to catch the failure physical modes
- The answer is given by an application of reliability evaluation for passive system.
- But the number of simulations to explore very low failure probabilities is very high (few millions of Cathare simulation).
- Thus, it needs metamodels to reproduce the Cathare code behavior.



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Context

- In a context of system design or system reliability evaluation, we are facing a complex problem:
  - **multi-parameters phenomenon (large dimensions)**;
  - **low probability events**.

- The classical simulation tools (thermal-hydraulics system code) are costly in terms of CPU time.

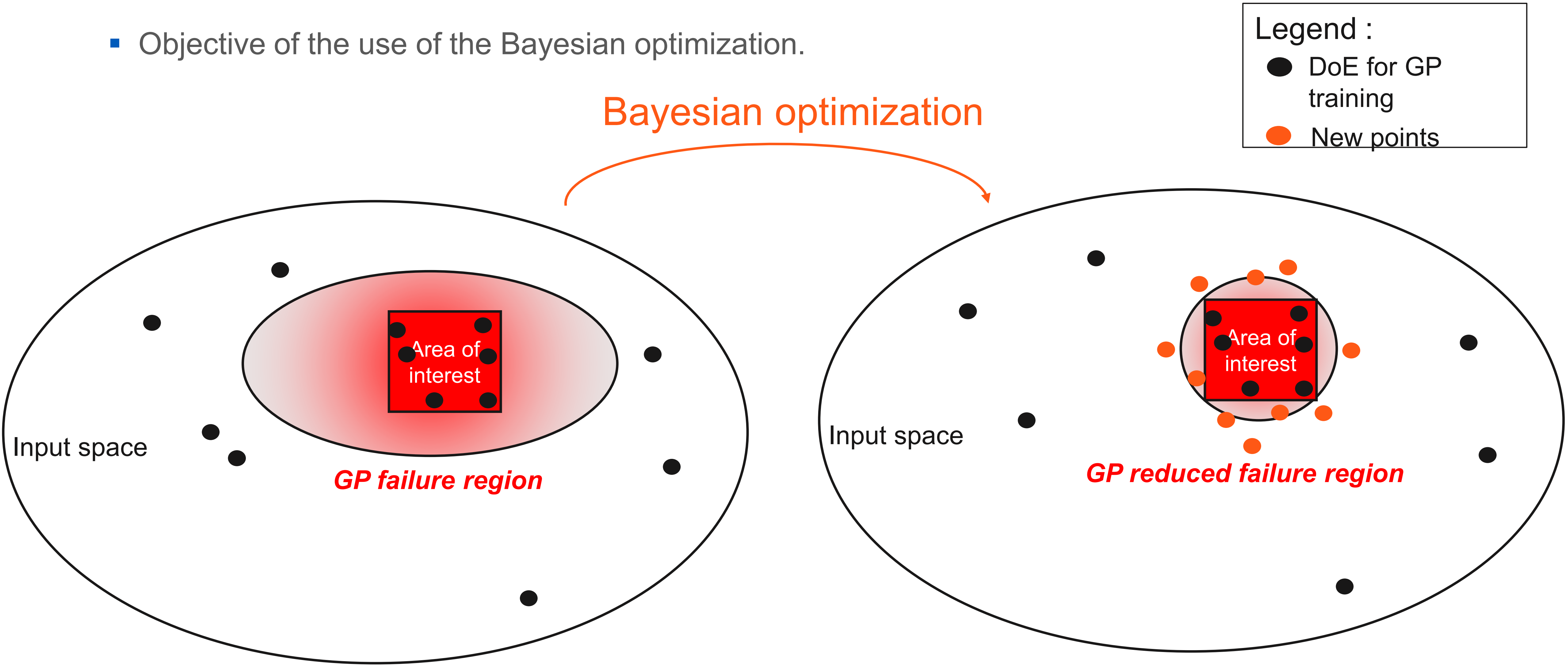
➡ **Needs metamodels to reproduce the TH code behavior in the context of costly reference code and/or statistical methodology**

- The use of metamodels (like Gaussian Process – GP), by allowing a large amount of simulations, seems to offer a promising strategy.
- But to converge to:
  - the best design;
  - the most precise failure;
  - and robust predictions.

➡ **Needs Bayesian optimization to build the adequate Design of Experiments (DoE).**

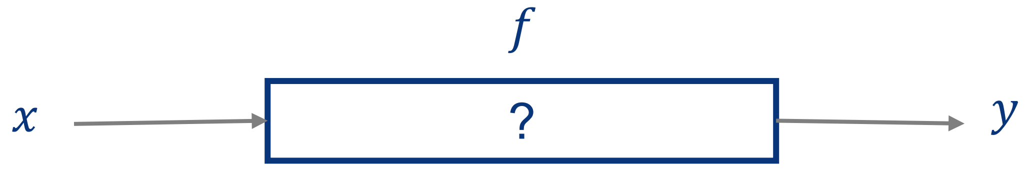
Context

- Objective of the use of the Bayesian optimization.



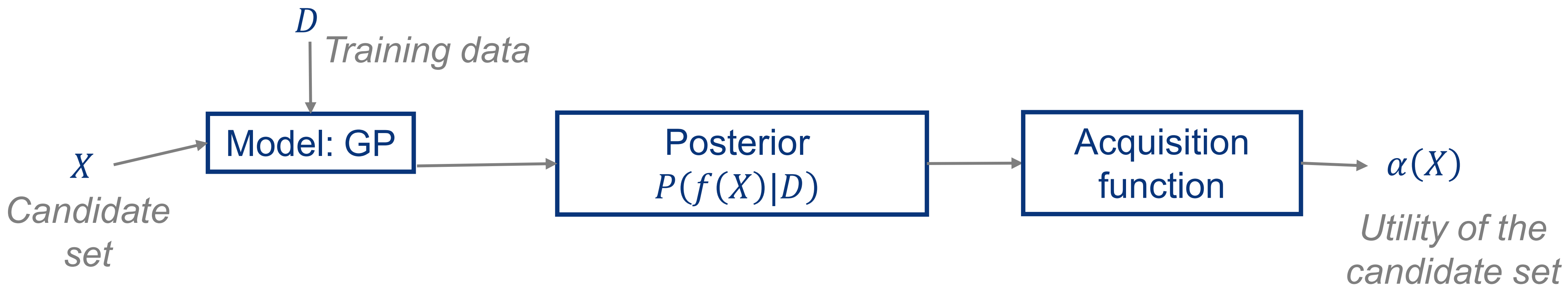
Bayesian optimization

- Bayesian optimization is a sequential design strategy for global optimization of black-box functions (i.e. the gradient or the function can be unknown) like complex reference computer codes.
- Black-Box optimization:



$$\max_{x \in X} f(x)$$

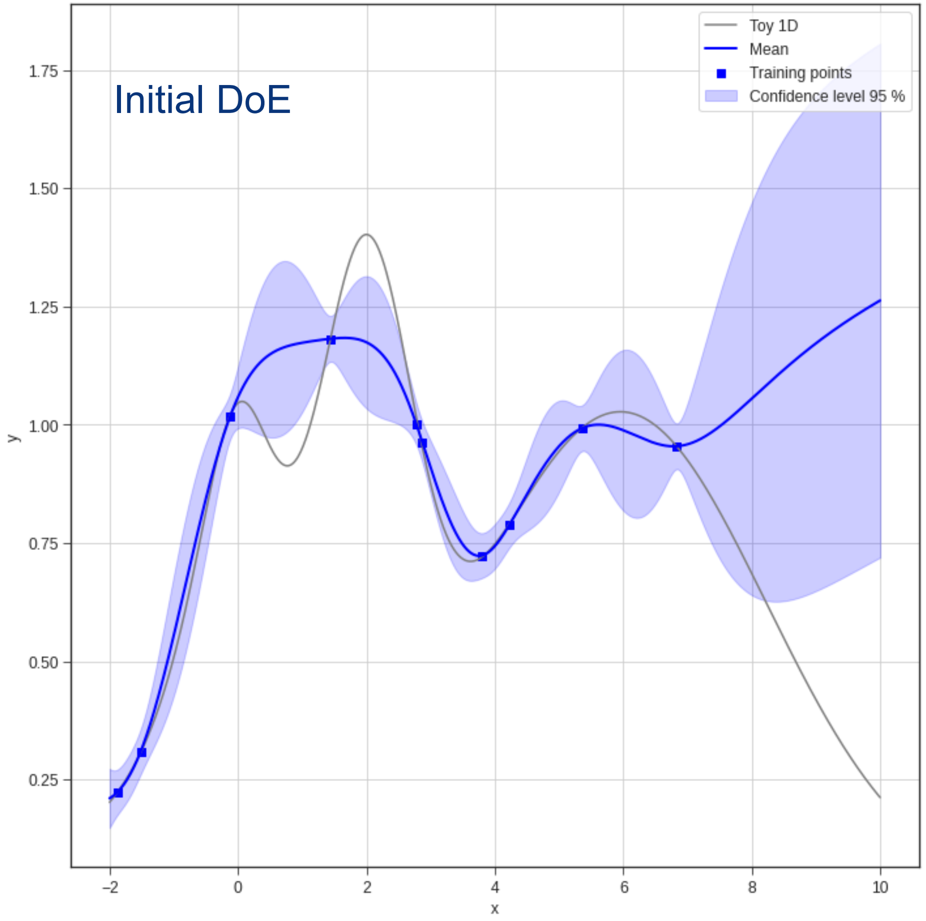
- Bayesian optimization:

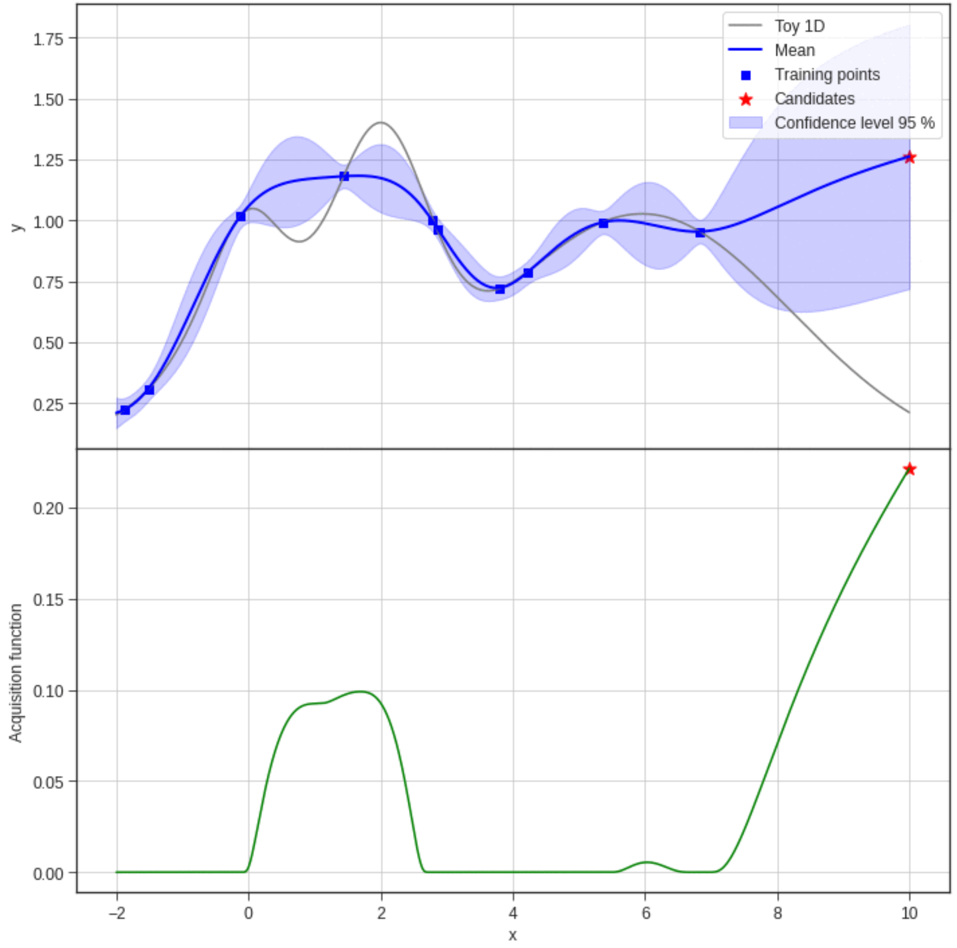


Reference: J. Mockus, On Bayesian Methods for Seeking the Extremum, Optimization Techniques, 400-404, 1974.

Simple acquisition function

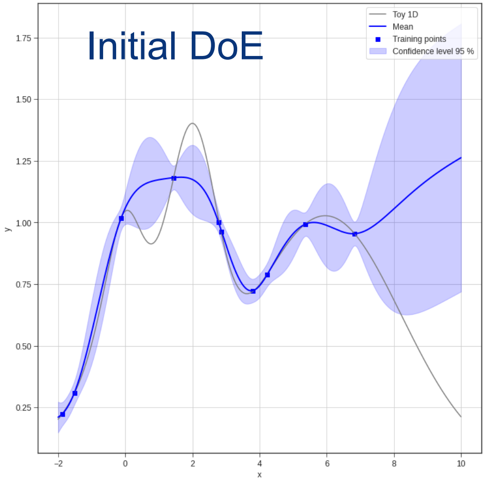
- Expected Improvement (EI): $EI(x) = \left(m(x) - f(x^*)\right)\Phi\left(\frac{m(x)-f(x^*)}{\sigma(x)}\right) + \sigma(x)\varphi\left(\frac{m(x)-f(x^*)}{\sigma(x)}\right)$ where Φ and φ are respectively the CDF and the PDF of the Normal law.

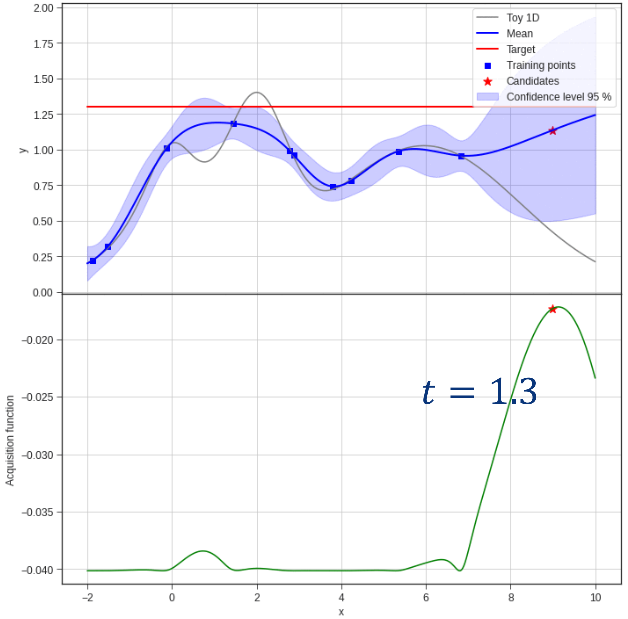




One-step look ahead acquisition function for contour approximation

- Stepwise Uncertainty Reduction (SUR): $SUR(x^{n+1}) = E\left[\int_X \Phi(a(x))\left(1-\Phi(a(x))\right)dx\right] = \int_X \Phi_2\left(\begin{pmatrix} a(x) \\ -a(x) \end{pmatrix}, \begin{pmatrix} c(x) & 1-c(x) \\ 1-c(x) & c(x) \end{pmatrix}\right)dx$ where $a(x) = (m(x)-t)/\sigma_{n+1}(x)$ and $c(x) = \sigma_n^2(x)/\sigma_{n+1}^2(x)$.
- SUR is powerful but needs a double integration => quite expensive.
- A *q-batch* approach of SUR exists.



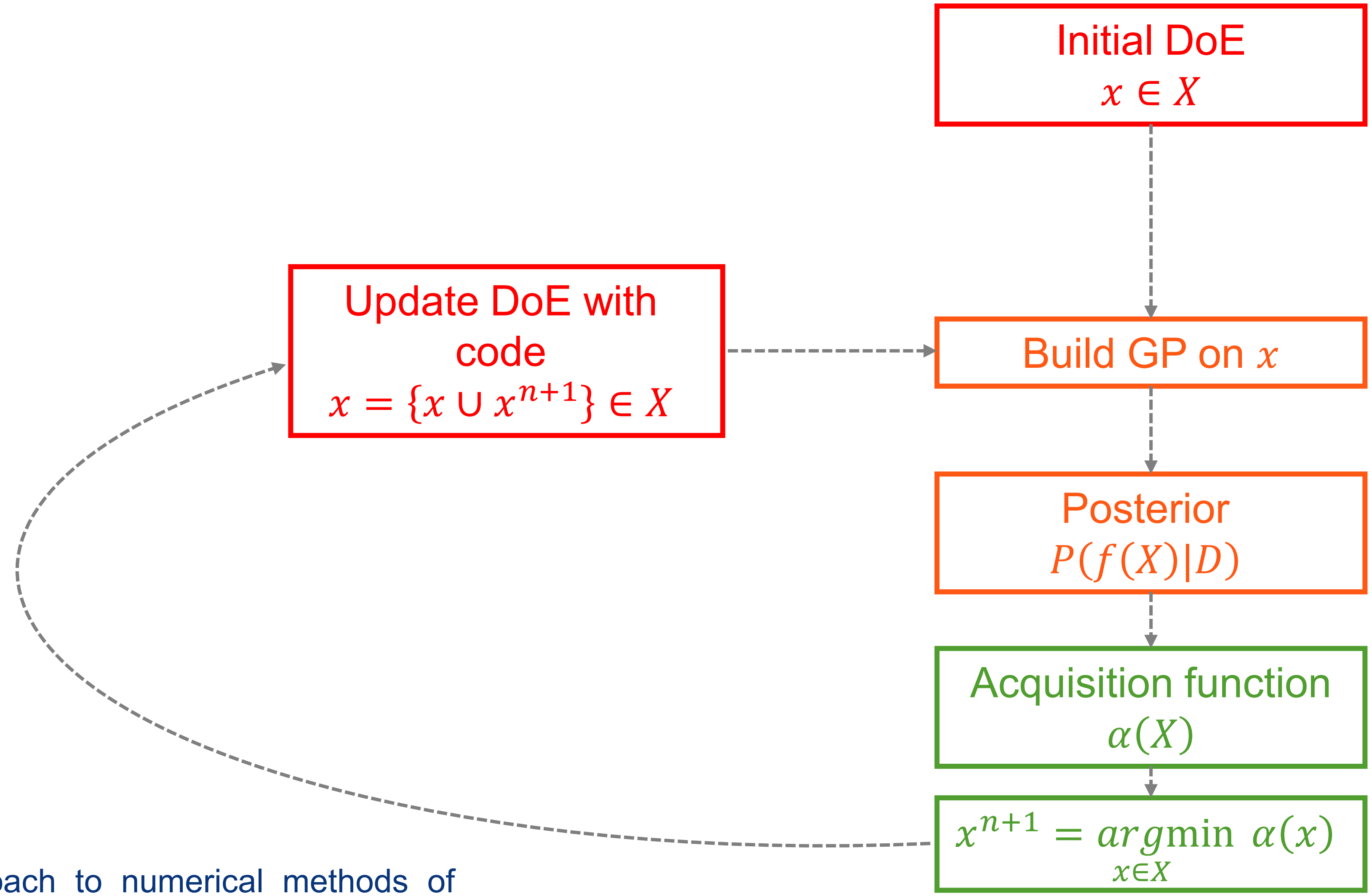


References:

- Bect, J., D. Ginsbourger, L. Li, V. Picheny, and E. Vazquez, Sequential design of computer experiments for the estimation of a probability of failure. Stat. Comput., In press., 2011.
- Clément Chevalier, Julien Bect, David Ginsbourger, Emmanuel Vazquez, Victor Picheny, et al., Fast parallel kriging-based stepwise uncertainty reduction with application to the identification of an excursion set, Technometrics, Taylor & Francis, 56 (4), pp.455-465, 2014.

Methodology

- 3 steps:
  1. Interface between the generation of DoE and the code.
  2. Construction/Validation GP.
  3. Adaptive DoE.

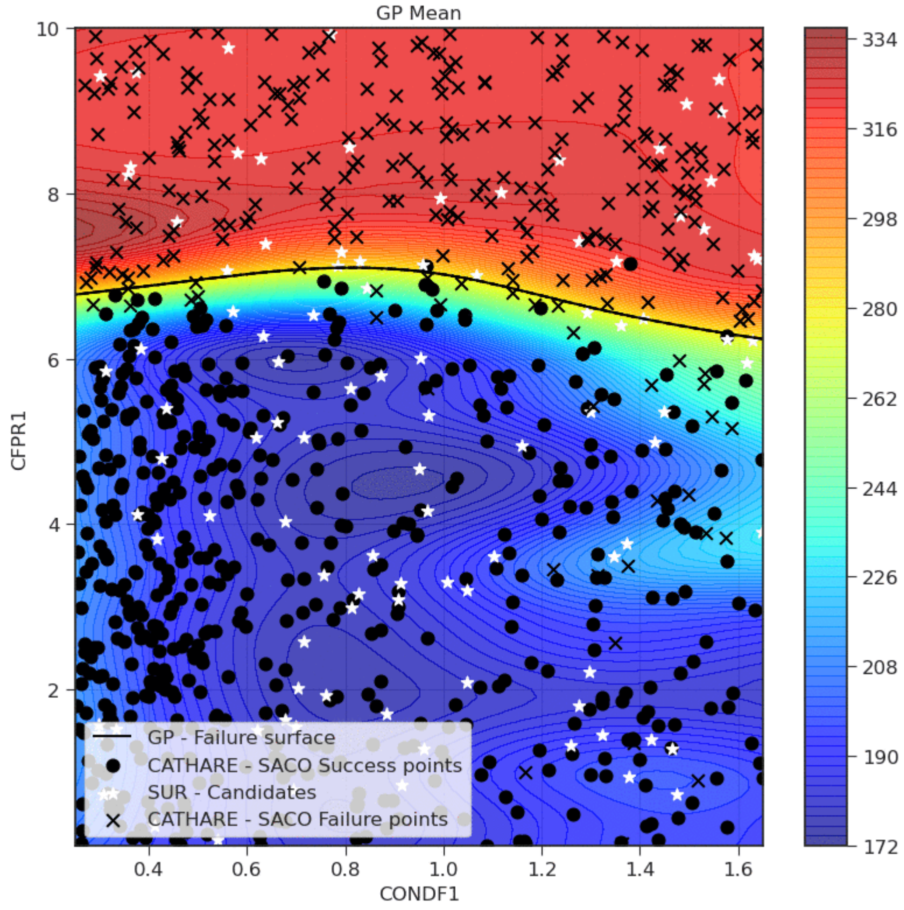


References:

- J. Mockus, Application of Bayesian approach to numerical methods of global and stochastic optimization. J. Global Optim., 4(4), 347-365, 1994.
- D. Jones, M. Schonlau, and W. Welch, Efficient global optimization of expensive black-box functions. J. Global Optim., 13(4), 455-492, 1998.

Framatome's use case

- We train/validate a **GP** on an adaptive DoE using **Bayesian optimization** and **Stepwise Uncertainty Reduction** (SUR) criterion for TH accidental code applications.
- The estimation of the failure probability is performed by the GP built on the last DoE optimized by Bayesian approach (~2000 calculations)
- Advanced validation with Cathare showed an overestimation of the failure transients prediction by the GP ("too penalizing")
- Reduction of the uncertainty of the failure probability assessment
- The failure probability is around 10^{-4} , higher than expected: it shows the crucial importance of SACO modeling for reliability estimation in the presence of multi-physics, crossing and threshold effects



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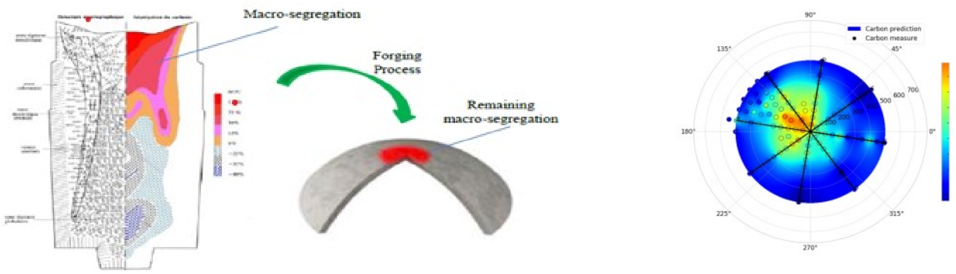
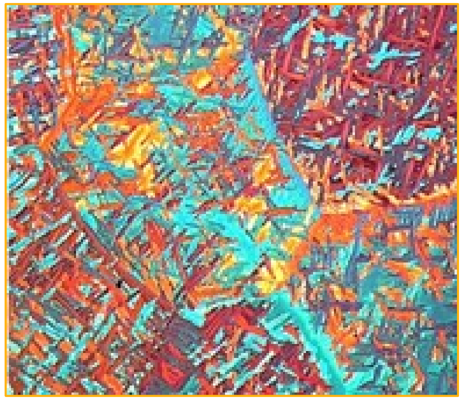
Content

Data Analytics, Computer vision

Data Analytics	Typical application
Applied mathematics, statistics, data viz, power BI, dashboards, geostatistics, …	Issues prediction, root cause analysis (corrosion, control rod wear …), CHF correlation, defensive file regarding quality issues of forged components …



Computer Vision	Typical application
Fast inference of CNN deep learning algorithm for edge AI on iOS tablet and cloud update training	Partially or fully automated NDT & quality control (microstructure alloy analysis, …)



Content

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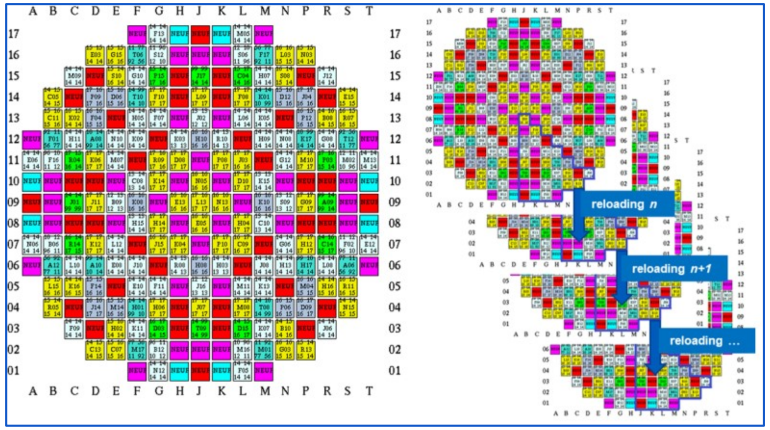
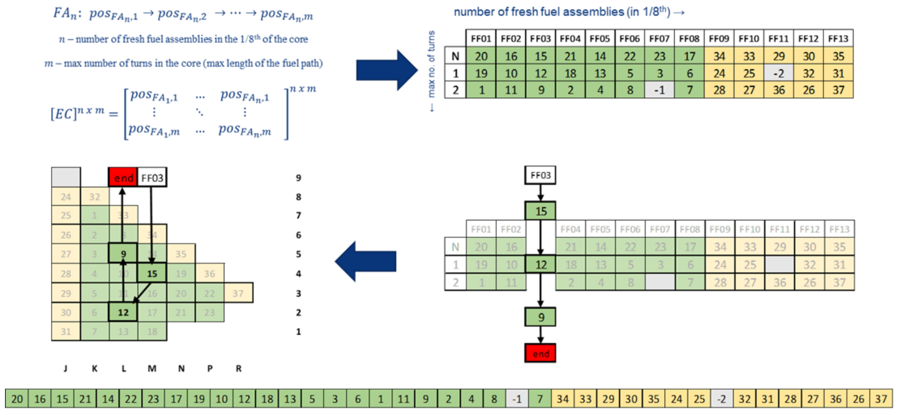
Scientific Computing and Engineering Support

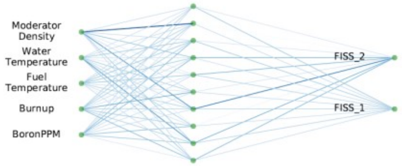
Domain knowledge

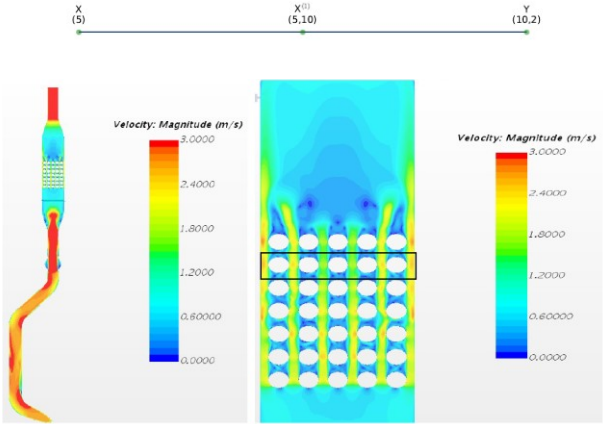
System and core TH, CFD, neutronics and core physics, material science, …

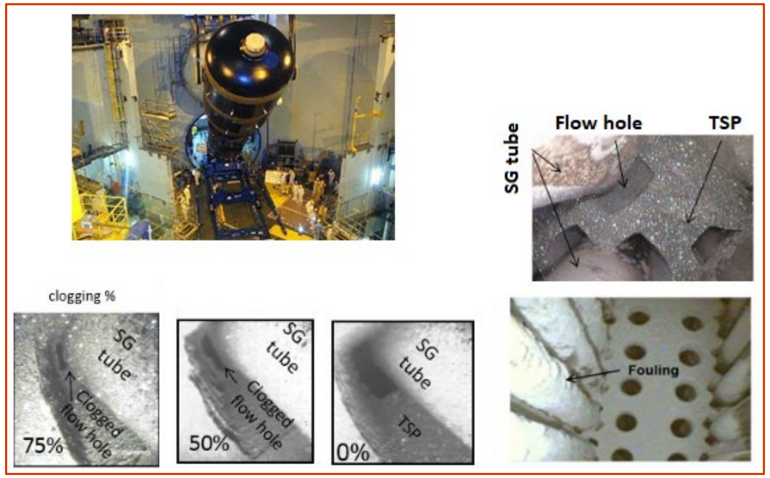




Typical application

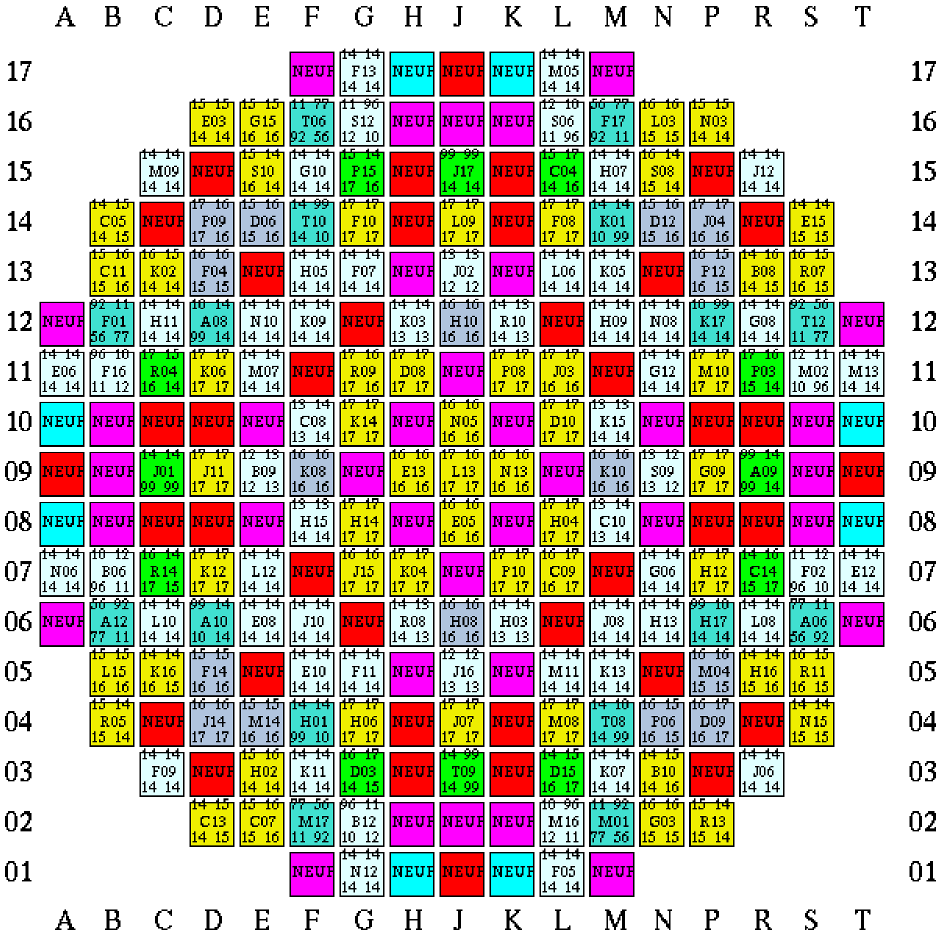






Speed up convergence of scientific computing codes on HPC, Prediction of Steam Generators clogging to optimize maintenance planning, fuel management and loading pattern optimization, …

Fuel Loading Pattern Optimization



Operational constraints

- maximize the fuel assemblies' **burnup** in order to guarantee the best fuel consumption ensuring the best economic performance of the fuel management;
- **lifecycle length** in order to assure a correct nuclear reactor operability during all the life cycle;
- …

Safety constraints

- limit the core **FΔH** value, to control the power distribution and to prevent from the boiling crisis risks;
- **limit the maximum fuel assembly burnup** at the discharge in order to prevent radiological rejects in case of accident;
- ensure a **negative moderator temperature coefficient** to provide intrinsic nuclear feedbacks in case of accident, which makes the reactor intrinsically safe at its design;
- limiting the **maximal fuel assemblies' power** in the core periphery to avoid the heavy reflector warming;
- limit the **neutron fluency** at the core periphery to not damage the reactor vessel;
- ensure **maximal number of cycles for a single assembly**;
- …

Time consuming activity: ~10^{40} possible configurations

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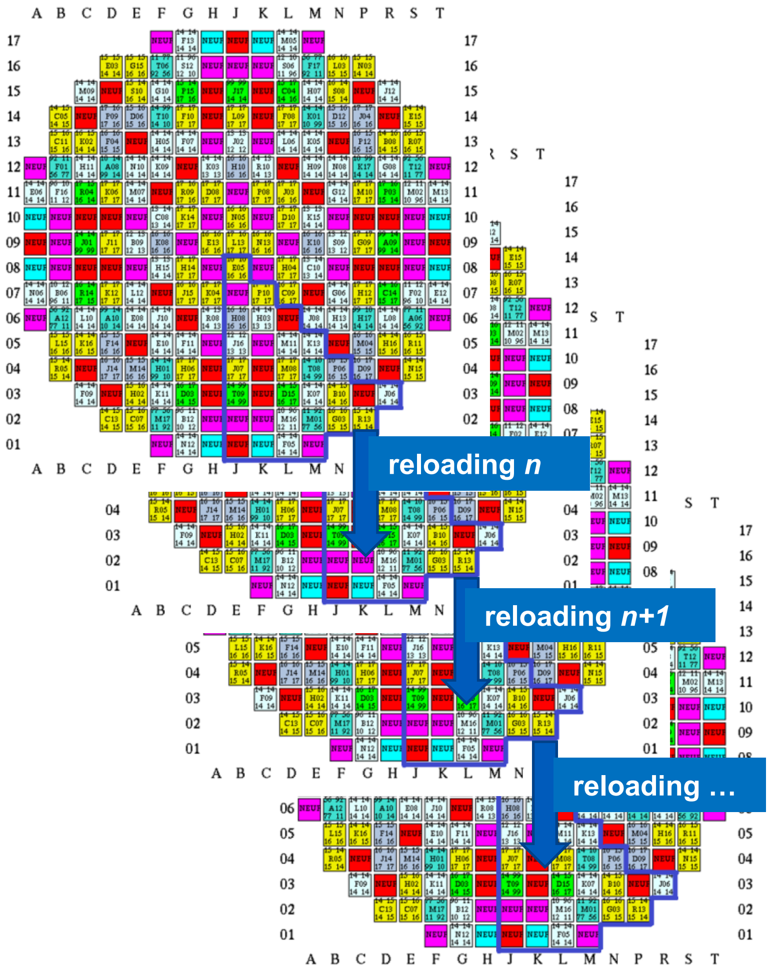
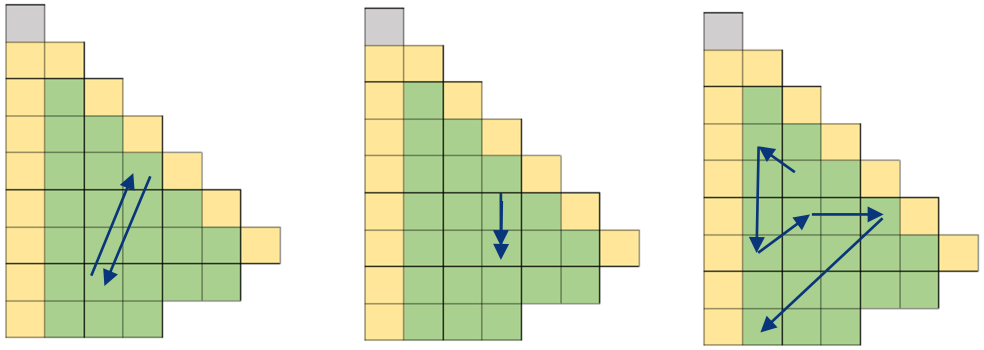
Equilibrium Cycle (EC)



- Universal scheme of fuel shuffling for core campaign
- Shuffling limitations:



loop | same position | long path

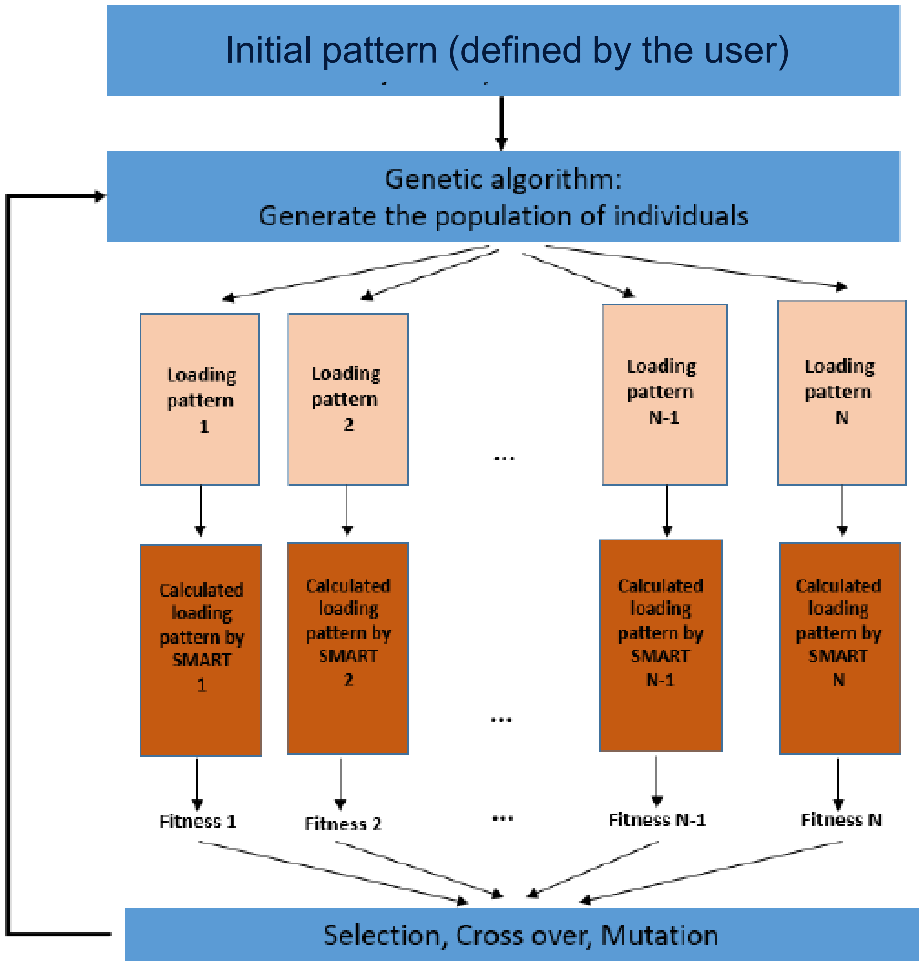
- Optimization criteria:

> $F_{\Delta H}$ minimization at BLX for EC
> minimization of max($F_{\Delta H}$) during cycle
> maximization of average core burnup (cycle length)

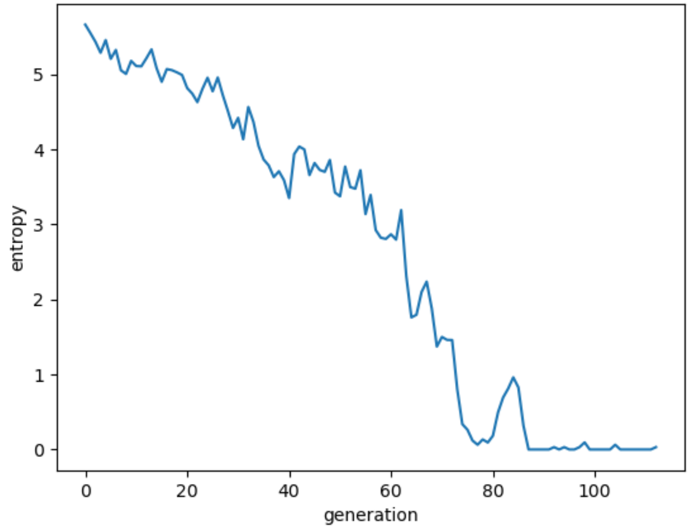
- Optimization Assumptions:

> ~1/3 of FAs exchanged with fresh fuel
> max FA burnup = 60 GWd/t
> no loops, no same positions
> max length of FAs path ≤ 3

Framework



- **Algorithm operates till:**
- population is dominated by one (best) specimen
- predefined number of generations is simulated
- Shannon entropy drops below certain value:



$$H = -\sum_{i,j} P_{ij} \cdot log_{10} P_{ij}$$

$$P_{ij} = \frac{1}{N} \sum_{k=1}^{N} \delta_{ik}$$

- Shannon entropy describes diversity in the population

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Tests

reference core - preliminary benchmark

	A	B	C	D	E	F	G	H	J	K	L	M	N	P	R	S	T	
17						38534	NEUF	19387	NEUF	19374	NEUF	38554						17
16				38718	20750	NEUF	17519	NEUF	36500	NEUF	17512	NEUF	20724	38715				16
15			39394	NEUF	NEUF	39181	20352	31288	NEUF	31284	20347	39180	NEUF	NEUF	39394			15
14		38715	NEUF	22019	17046	NEUF	21041	14542	20220	14537	21050	NEUF	17044	22019	NEUF	38718		14
13		20724	NEUF	17044	NEUF	28169	NEUF	38988	NEUF	38990	NEUF	28161	NEUF	17046	NEUF	20750		13
12	38554	NEUF	39180	NEUF	28161	NEUF	34254	NEUF	18840	NEUF	34259	NEUF	28169	NEUF	39181	NEUF	38534	12
11	NEUF	17512	20347	21050	NEUF	34259	20683	20966	15206	21056	20683	34254	NEUF	21041	20352	17519	NEUF	11
10	19374	NEUF	31284	14537	38990	NEUF	21056	NEUF	21426	NEUF	20966	NEUF	38988	14542	31288	NEUF	19387	10
09	NEUF	36500	NEUF	20220	NEUF	18840	15206	21426	38004	21426	15206	18840	NEUF	20220	NEUF	36500	NEUF	09
08	19387	NEUF	31288	14542	38988	NEUF	20966	NEUF	21426	NEUF	21056	NEUF	38990	14537	31284	NEUF	19374	08
07	NEUF	17519	20352	21041	NEUF	34254	20683	21056	15206	20966	20683	34259	NEUF	21050	20347	17512	NEUF	07
06	38534	NEUF	39181	NEUF	28169	NEUF	34259	NEUF	18840	NEUF	34254	NEUF	28161	NEUF	39180	NEUF	38554	06
05		20750	NEUF	17046	NEUF	28161	NEUF	38990	NEUF	38988	NEUF	28169	NEUF	17044	NEUF	20724		05
04		38718	NEUF	22019	17044	NEUF	21050	14537	20220	14542	21041	NEUF	17046	22019	NEUF	38715		04
03			39394	NEUF	NEUF	39180	20347	31284	NEUF	31288	20352	39181	NEUF	NEUF	39394			03
02				38715	20724	NEUF	17512	NEUF	36500	NEUF	17519	NEUF	20750	38718				02
01						38554	NEUF	19374	NEUF	19387	NEUF	38534						01
	A	B	C	D	E	F	G	H	J	K	L	M	N	P	R	S	T	

NE18

- Fitness Function:

$$FF = \frac{\overline{BU}_{Core}}{\max(F\Delta H)} \cdot e^{-\gamma(BU_{max} - BU)}$$

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Tests

reference core - preliminary benchmark

	A	B	C	D	E	F	G	H	J	K	L	M	N	P	R	S	T	
17						38534	NEUF	19387	NEUF	19374	NEUF	38554						17
16				38718	20750	NEUF	17519	NEUF	36500	NEUF	17512	NEUF	20724	38715				16
15			39394	NEUF	NEUF	39181	20352	31288	NEUF	31284	20347	39180	NEUF	NEUF	39394			15
14		38715	NEUF	22019	17046	NEUF	21041	14542	20220	14537	21050	NEUF	17044	22019	NEUF	38718		14
13		20724	NEUF	17044	NEUF	28169	NEUF	38988	NEUF	38990	NEUF	28161	NEUF	17046	NEUF	20750		13
12	38554	NEUF	39180	NEUF	28161	NEUF	34254	NEUF	18840	NEUF	34259	NEUF	28169	NEUF	39181	NEUF	38534	12
11	NEUF	17512	20347	21050	NEUF	34259	20683	20966	15206	21056	20683	34254	NEUF	21041	20352	17519	NEUF	11
10	19374	NEUF	31284	14537	38990	NEUF	21056	NEUF	21426	NEUF	20966	NEUF	38988	14542	31288	NEUF	19387	10
09	NEUF	36500	NEUF	20220	NEUF	18840	15206	21426	38004	21426	15206	18840	NEUF	20220	NEUF	36500	NEUF	09
08	19387	NEUF	31288	14542	38988	NEUF	20966	NEUF	21426	NEUF	21056	NEUF	38990	14537	31284	NEUF	19374	08
07	NEUF	17519	20352	21041	NEUF	34254	20683	21056	15206	20966	20683	34259	NEUF	21050	20347	17512	NEUF	07
06	38534	NEUF	39181	NEUF	28169	NEUF	34259	NEUF	18840	NEUF	34254	NEUF	28161	NEUF	39180	NEUF	38554	06
05		20750	NEUF	17046	NEUF	28161	NEUF	38990	NEUF	38988	NEUF	28169	NEUF	17044	NEUF	20724		05
04		38718	NEUF	22019	17044	NEUF	21050	14537	20220	14542	21041	NEUF	17046	22019	NEUF	38715		04
03			39394	NEUF	NEUF	39180	20347	31284	NEUF	31288	20352	39181	NEUF	NEUF	39394			03
02				38715	20724	NEUF	17512	NEUF	36500	NEUF	17519	NEUF	20750	38718				02
01						38554	NEUF	19374	NEUF	19387	NEUF	38534						01
	A	B	C	D	E	F	G	H	J	K	L	M	N	P	R	S	T	

NE18

- Fitness Function:

$$FF = \frac{\overline{BU}_{Core}}{\max(F\Delta H)} \cdot e^{-\gamma(BU_{max}-BU)}$$

core burnup

Max value
of enthalpy rise factor

Tests

reference core - preliminary benchmark

	A	B	C	D	E	F	G	H	J	K	L	M	N	P	R	S	T
17						38534	NEUF	19387	NEUF	19374	NEUF	38554					
16				38718	20750	NEUF	17519	NEUF	36500	NEUF	17512	NEUF	20724	38715			
15			39394	NEUF	NEUF	39181	20352	31288	NEUF	31284	20347	39180	NEUF	NEUF	39394		
14		38715	NEUF	22019	17046	NEUF	21041	14542	20220	14537	21050	NEUF	17044	22019	NEUF	38718	
13		20724	NEUF	17044	NEUF	28169	NEUF	38988	NEUF	38990	NEUF	28161	NEUF	17046	NEUF	20750	
12	38554	NEUF	39180	NEUF	28161	NEUF	34254	NEUF	18840	NEUF	34259	NEUF	28169	NEUF	39181	NEUF	38534
11	NEUF	17512	20347	21050	NEUF	34259	20683	20966	15206	21056	20683	34254	NEUF	21041	20352	17519	NEUF
10	19374	NEUF	31284	14537	38990	NEUF	21056	NEUF	21426	NEUF	20966	NEUF	38988	14542	31288	NEUF	19387
09	NEUF	36500	NEUF	20220	NEUF	18840	15206	21426	38004	21426	15206	18840	NEUF	20220	NEUF	36500	NEUF
08	19387	NEUF	31288	14542	38988	NEUF	20966	NEUF	21426	NEUF	21056	NEUF	38990	14537	31284	NEUF	19374
07	NEUF	17519	20352	21041	NEUF	34254	20683	21056	15206	20966	20683	34259	NEUF	21050	20347	17512	NEUF
06	38534	NEUF	39181	NEUF	28169	NEUF	34259	NEUF	18840	NEUF	34254	NEUF	28161	NEUF	39180	NEUF	38554
05		20750	NEUF	17046	NEUF	28161	NEUF	38990	NEUF	38988	NEUF	28169	NEUF	17044	NEUF	20724	
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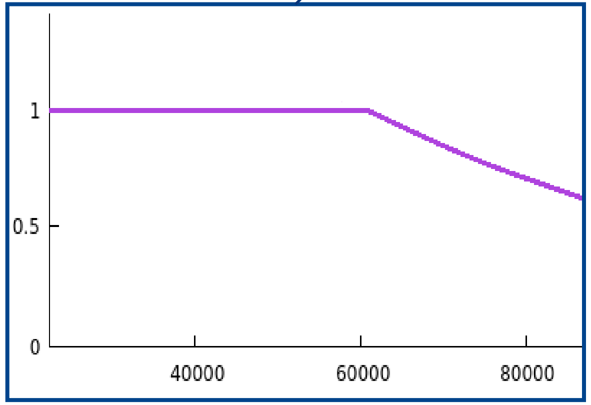
03			39394	NEUF	NEUF	39180	20347	31284	NEUF	31288	20352	39181	NEUF	NEUF	39394		
02				38715	20724	NEUF	17512	NEUF	36500	NEUF	17519	NEUF	20750	38718			
01						38554	NEUF	19374	NEUF	19387	NEUF	38534					

NE18

- Fitness Function:

$$FF = \frac{\overline{BU}_{Core}}{\max(F\Delta H)} \cdot e^{-\gamma(BU_{max}-BU)}$$



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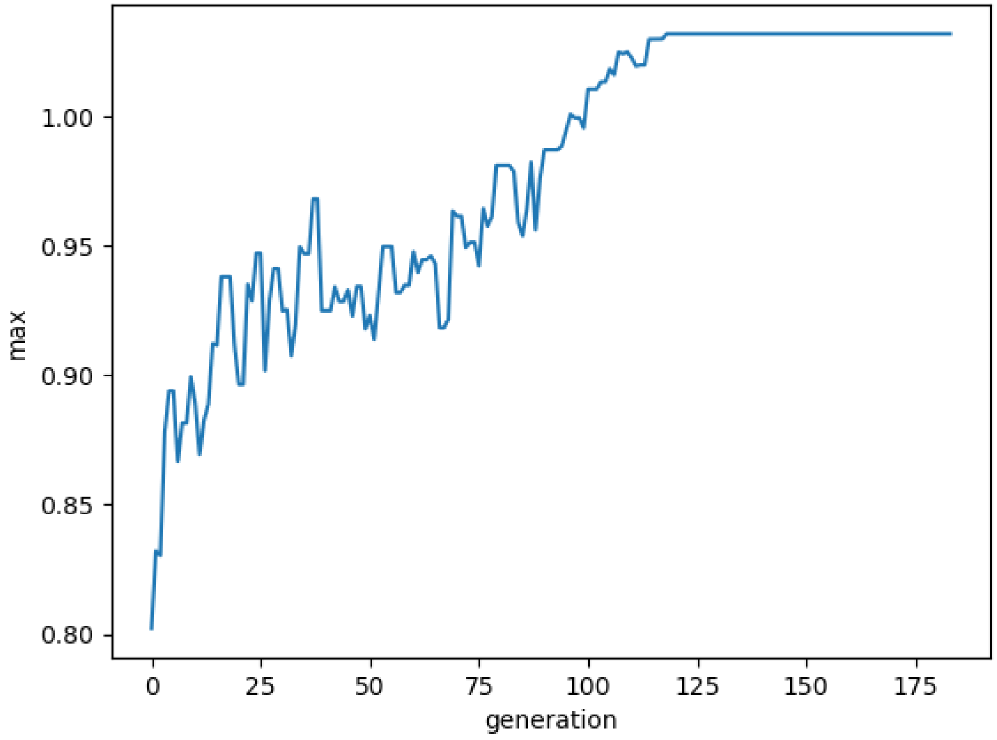
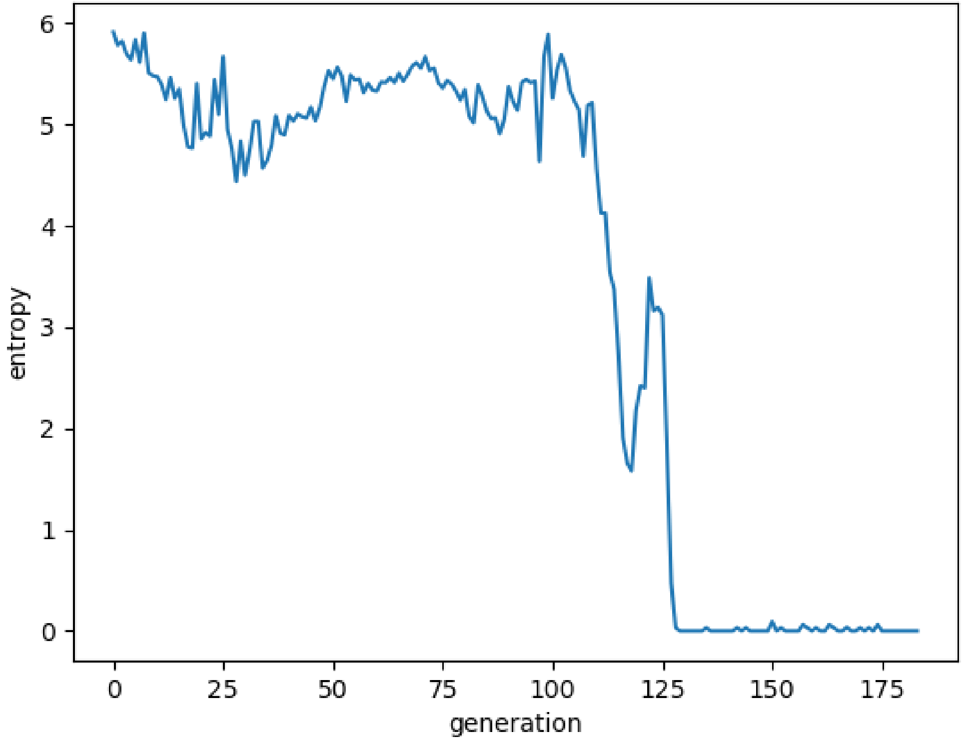
Tests

reference core - preliminary benchmark





	reference	GA	reference vs GA	
BU Core [EFPD]	483	475	-8	-1,7%
BU Core [MWd/t]	17229	16951	-278	-1,6%
max(FDH)	1,48	1,41	-0,07	-4,7%
BU Assembly [GWd/t]	55,04	54,04	-1,01	-1,8%
FF	1,000	1,033	0,03	3,3%

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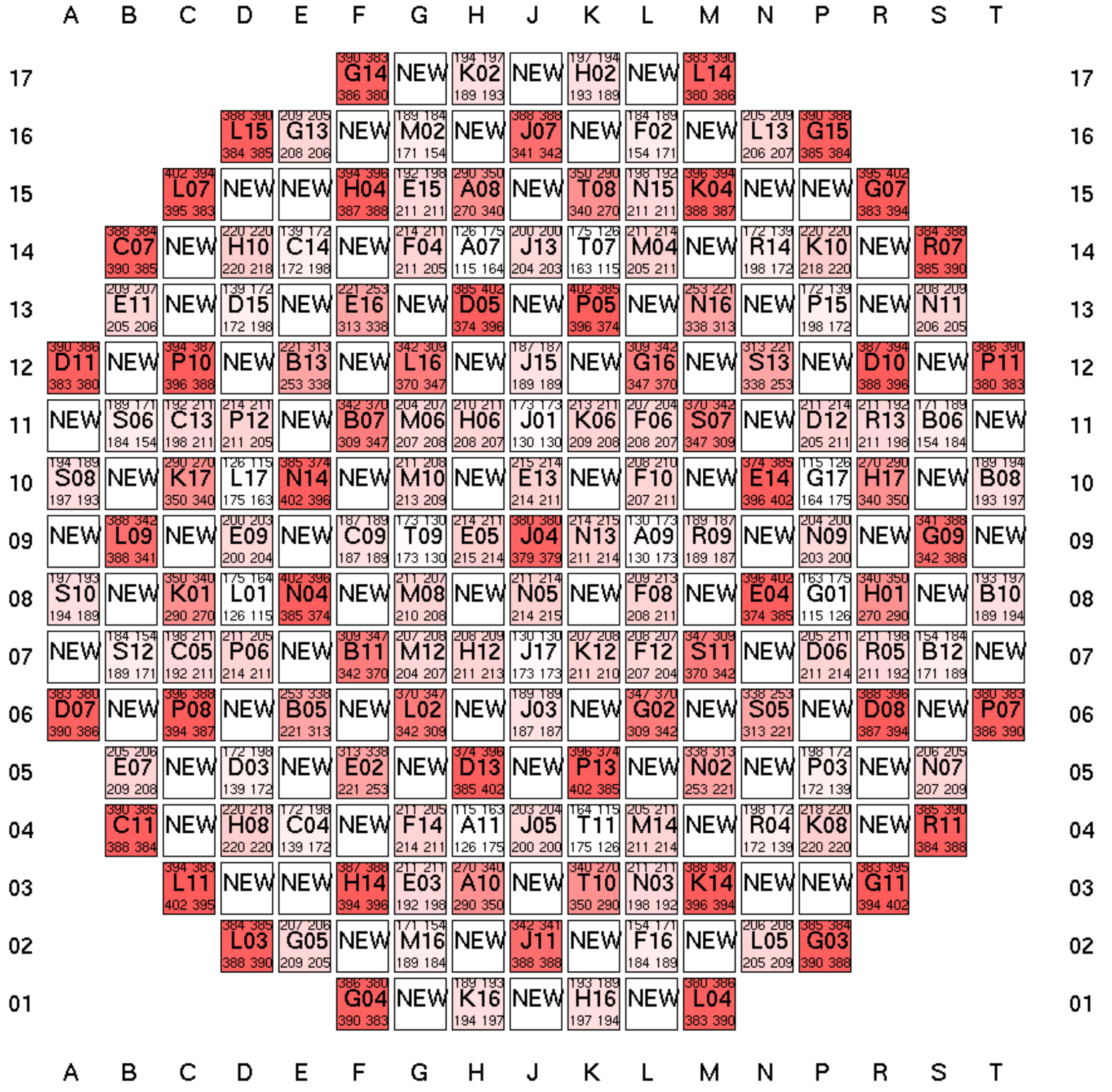
reference NPP vs GA

	A	B	C	D	E	F	G	H	J	K	L	M	N	P	R	S	T	
17						G14	NEW	K02	NEW	H02	NEW	L14						17
16				L15	G13	NEW	M02	NEW	J07	NEW	F02	NEW	L13	G15				16
15			L07	NEW	NEW	H04	E15	A08	NEW	T08	N15	K04	NEW	NEW	G07			15
14		C07	NEW	H10	C14	NEW	F04	A07	J13	T07	M04	NEW	R14	K10	NEW	R07		14
13		E11	NEW	D15	NEW	E16	NEW	D05	NEW	P05	NEW	N16	NEW	P15	NEW	N11		13
12	D11	NEW	P10	NEW	B13	NEW	L16	NEW	J15	NEW	G16	NEW	S13	NEW	D10	NEW	P11	12
11	NEW	S06	C13	P12	NEW	B07	M06	H06	J01	K06	F06	S07	NEW	D12	R13	B06	NEW	11
10	S08	NEW	K17	L17	N14	NEW	M10	NEW	E13	NEW	F10	NEW	E14	G17	H17	NEW	B08	10
09	NEW	L09	NEW	E09	NEW	C09	T09	E05	J04	N13	A09	R09	NEW	N09	NEW	G09	NEW	09
08	S10	NEW	K01	L01	N04	NEW	M08	NEW	N05	NEW	F08	NEW	E04	G01	H01	NEW	B10	08
07	NEW	S12	C05	P06	NEW	B11	M12	H12	J17	K12	F12	S11	NEW	D06	R05	B12	NEW	07
06	D07	NEW	P08	NEW	B05	NEW	L02	NEW	J03	NEW	G02	NEW	S05	NEW	D08	NEW	P07	06
05		E07	NEW	D03	NEW	E02	NEW	D13	NEW	P13	NEW	N02	NEW	P03	NEW	N07		05
04		C11	NEW	H08	C04	NEW	F14	A11	J05	T11	M14	NEW	R04	K08	NEW	R11		04
03			L11	NEW	NEW	H14	E03	A10	NEW	T10	N03	K14	NEW	NEW	G11			03
02				L03	G05	NEW	M16	NEW	J11	NEW	F16	NEW	L05	G03				02
01						G04	NEW	K16	NEW	H16	NEW	L04						01
	A	B	C	D	E	F	G	H	J	K	L	M	N	P	R	S	T	

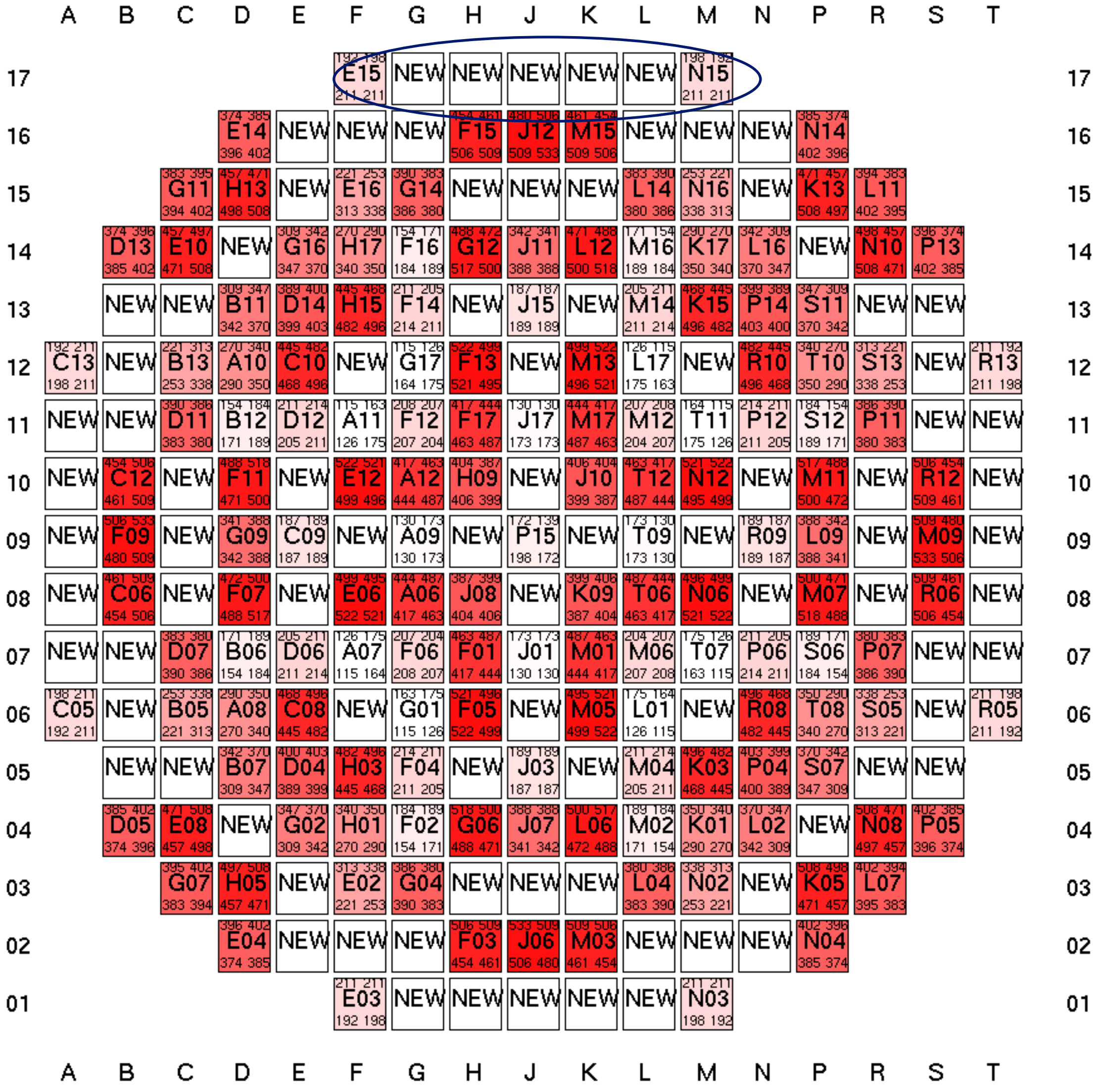
	A	B	C	D	E	F	G	H	J	K	L	M	N	P	R	S	T	
17						E15	NEW	NEW	NEW	NEW	NEW	N15						17
16				E14	NEW	NEW	NEW	F15	J12	M15	NEW	NEW	NEW	N14				16
15			G11	H13	NEW	E16	G14	NEW	NEW	NEW	L14	N16	NEW	K13	L11			15
14		D13	E10	NEW	G16	H17	F16	G12	J11	L12	M16	K17	L16	NEW	N10	P13		14
13		NEW	NEW	B11	D14	H15	F14	NEW	J15	NEW	M14	K15	P14	S11	NEW	NEW		13
12	C13	NEW	B13	A10	C10	NEW	G17	F13	NEW	M13	L17	NEW	R10	T10	S13	NEW	R13	12
11	NEW	NEW	D11	B12	D12	A11	F12	F17	J17	M17	M12	T11	P12	S12	P11	NEW	NEW	11
10	NEW	C12	NEW	F11	NEW	E12	A12	H09	NEW	J10	T12	N12	NEW	M11	NEW	R12	NEW	10
09	NEW	F09	NEW	G09	C09	NEW	A09	NEW	P15	NEW	T09	NEW	R09	L09	NEW	M09	NEW	09
08	NEW	C06	NEW	F07	NEW	E06	A06	J08	NEW	K09	T06	N06	NEW	M07	NEW	R06	NEW	08
07	NEW	NEW	D07	B06	D06	A07	F06	F01	J01	M01	M06	T07	P06	S06	P07	NEW	NEW	07
06	C05	NEW	B05	A08	C08	NEW	G01	F05	NEW	M05	L01	NEW	R08	T08	S05	NEW	R05	06
05		NEW	NEW	B07	D04	H03	F04	NEW	J03	NEW	M04	K03	P04	S07	NEW	NEW		05
04		D05	E08	NEW	G02	H01	F02	G06	J07	L06	M02	K01	L02	NEW	N08	P05		04
03			G07	H05	NEW	E02	G04	NEW	NEW	NEW	L04	N02	NEW	K05	L07			03
02				E04	NEW	NEW	NEW	F03	J06	M03	NEW	NEW	NEW	N04				02
01						E03	NEW	NEW	NEW	NEW	NEW	N03						01
	A	B	C	D	E	F	G	H	J	K	L	M	N	P	R	S	T	

framatome

reference NPP vs GA



limitation of FF=BU/FDH



framatome

reference NPP

	J	K	L	M	N	P	R	S	T
09	0.9308 N [411]	1.1708	1.2874	1.1685	1.1353 P5 [411]	1.0601	1.0998 P4 [411]	0.9179	0.9787 N [411]
08	1.1708	1.2843 N [411]	1.1741	1.1719 N [411]	0.9135	1.1248	0.9509	1.1977 N [411]	0.8008
07	1.2874	1.1740	1.0729 N [411]	0.9364	1.1193 P2 [411]	1.0733	1.0459 P3 [411]	1.0755	0.8842
06	1.1685	1.1719 N [411]	0.9364	1.2142	0.9969	1.1925 N [411]	0.9563	0.9879 N [411]	0.3965
05	1.1353 P5 [411]	0.9135	1.1193 P4 [411]	0.9969	1.2382 P5 [411]	1.2373	1.212 P5 [41	0.6638	
04	1.0600	1.1248	1.0733	1.1925 N [411]	1.2373	1.1074 N [411]	0.9760	0.3524	
03	1.0998 P4 [411]	0.9509	1.0459 P3 [411]	0.9563	1.2121 P1 [411]	0.9760	0.4039 N [411]		
02	0.9179	1.1977 N [411]	1.0754	0.9879 N [411]	0.6638	0.3524			
01	0.9787 N [411]	0.8008	0.8842	0.3965					

GA

	J	K	L	M	N	P	R	S	T
09	0.9288 N [411]	1.1124	1.1139	1.2647	1.1220 P5 [411]	0.9359	1.2174 P4 [411]	1.0466	0.9749 N [411]
08	1.1124	1.0164 N [411]	0.8963	0.8943 N [411]	1.2230	0.9523	1.2585	0.9114 N [411]	0.8043
07	1.1139	0.8960	0.9930 N [411]	1.0943	0.9360 P2 [411]	1.0444	0.9495 P3 [411]	1.224	0.8489
06	1.2647	0.8943 N [411]	1.0943	1.2052	1.1184	1.1639 N [411]	1.2058	1.123 N [411]	0.5759
05	1.1220 P5 [411]	1.2230	0.9360 P4 [411]	1.1184	1.1521 P5 [411]	1.1422	1.1669 P5 [411]	1.0384	
04	0.9359	0.9523	1.0443	1.1639 N [411]	1.1422	1.0714 N [411]	0.7735	0.3771	
03	1.2174 P4 [411]	1.2585	0.9495 P3 [411]	1.2058	1.1669 P1 [411]	0.7735	0.3458 N [411]		
02	1.0466	0.9114 N [411]	1.2247	1.1238 N [411]	1.0384	0.3771			
01	0.9749 N [411]	0.8043	0.8489	0.5758					

Summary and conclusion

GA – Copilote coupling:

- Chromosome form was defined, two forms were studied, coupling: GA>Chromosome>SMART done (Python 3.8, deap library)
- Tests with simple model for validation of chromosome structure (ordering algorithm) and GA parameters tuning (cx_pb, mut_pb, N individuals, …)
- Algorithm seems to be working correctly, after ~20h of operation it can propose a core with reasonably low FDH and long cycle, maintaining max burnup close to the given level (preliminary reference NPP benchmarking)
- Copilote procedure still needs to be developed (current version should be updated)

Next steps

- More tests, different forms of Fitness Functions and Penalty Factors, other parameters optimization
- Verify simplified calculations (boron criticality calculations vs full axial offset research by control rod calculations)
- Development of core codes surrogate models strategies coupled with black box optimization algorithms
- Benchmark of black box optimization algorithms and core codes packages.
- Implement ¼th symmetry, possible use of 2D chromosome
- Modify the GA to shuffle fresh fuel between parts A and B (between 1/4th and 1/8th regions)
- Use GA for single reload problem
- Application of GA to other problems, like Fuel Assembly design

Conclusion

- AI uses cases are intensively developed for various nuclear applications in Framatome company and EDF group to support current engineering processes, methods and to foster innovation and next generation of nuclear products and services
  - This technological brick will be probably needed to improve performance, cost competitiveness and safety of NPPs, in particular to allow flexible operations and power uprates of existing NPPs

- Those promising benefits of AI comes with limitations and threats regarding certification and licensing for safety critical related applications
  - Safety authorities upcoming regulatory guidelines (AIEA technical meeting on AI & safety), AI Act (EU), …
  - Interpretability, robustness and trustworthiness are the current technical challenging limitations of AI

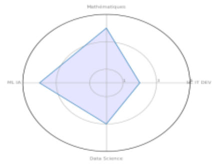
- Data / AI governance, dedicated advanced skills in applied mathematics, IT, combined with nuclear engineering and physics knowledge are strongly needed to cope with these challenges

Framatome Data science & Applied Mathematics pole strategy in a nutshell

Scientific Direction, R&D Direction, IT Direction
DTI Engineering Business Unit

Core team

DTI Engineering BU Operational Leader
PhD and Engineers Skilled in AI, applied mathematics, software engineering, IT



Active team

Operational support to different BUs
Composed of different engineers ambassadors of their operational units
Skills in various engineering expertise domains : Computational Fluid Dynamics, neutronics, material sciences, safety I&C, diphasics and system Thermalhydraulics, …

- AI embedded safety systems
- Advanced Safety analyses methodology
- Data Analytics Computer Vision
- Advanced scientific codes modeling, softwares and IT tools
- Develop trustworthy AI
- Support the data strategy of Framatome
- Build partnerships, create business opportunity