

Artificial intelligence for Simulation of Severe Accidents http://assas-horizon-euratom.eu info@assas-horizon-euratom.eu







# AI for nuclear

Developing a fast and accurate severe accident simulator thanks to machine-learning

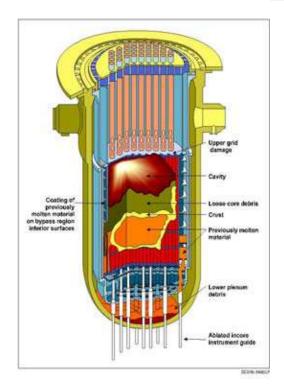


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- 1. Context
- 2. General objectives of ASSAS
- 3. Machine-learning approaches
- 4. The training database

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### What is a severe accident?



View of the core degradation during the Three-Mile-Island accident

#### An accident with extensive core damage

- Fuel cladding failure and core melt-down
- Exothermic core oxidation by steam producing hydrogen

#### Threating the reactor integrity:

- Possible primary vessel failure
- Possible containment basemate melt-through

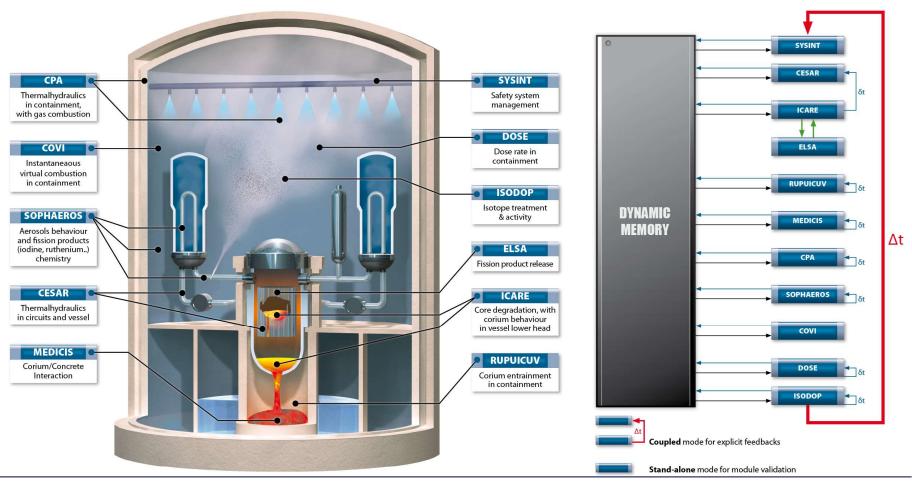
#### With large consequences on the population

- Release of radioactive fission products in the environment
- Evacuation of the population
- 3 severe accidents in civil power reactors in history: Fukushima-Daiichi, Chernobyl, Three-Miles-Island



# **SA** modelling by **ASTEC**

Overview of the severe accident code ASTEC (Accident Source Term Evaluation Code) developed by ASNR





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## **ASSAS** project

# Artificial Intelligence for the Simulation of Severe AccidentS



Desktop simulator (Tecnatom)

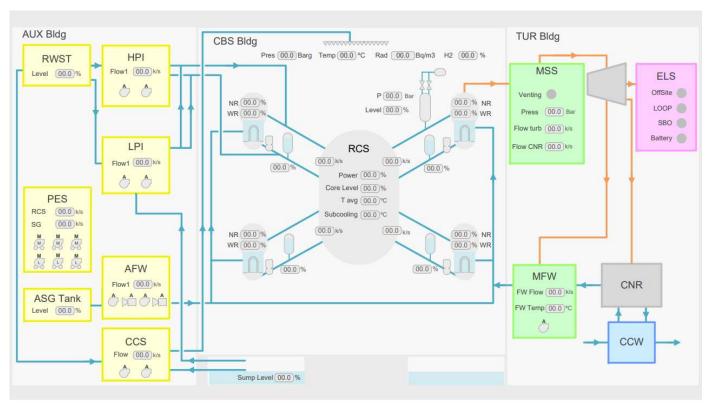
#### A prototype simulator for a Western-type PWR

- Operators train for several months on simulators, without severe accident capabilities → a more complete training is desired.
- Interfacing ASTEC with the commercial simulation environment TEAM\_SUITE® developed by Tecnatom
- · A prototype with simplified systems and interface

#### Main challenge: accelerating ASTEC (>4 times!)

- Input deck simplification and efficient programming
- Machine-learning

### Overview of the simulator



Simulator overview SA screen Alarm display

#### 2 predefined scenarios

 Station Blackout + Loss-of-Coolant Accident

#### All phases of a SA:

- Core degradation
- Release and transport of FPs
- Vessel rupture
- Corium-concrete interation
- Containment pressurisation up to the filtered release of FPs
- Some phenomena are excluded: steam explosion, direct containment heating...

Ergonomic interface



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### Data-driven surrogate models

### Machine-learning (ML) for scientific calculation

- ML can emulate complex models, like weather models
- ML learns from data: in our case, precalculated sequences
- Neural networks calculate fast, especially with GPUs

#### Requirements

- Computational resources to train the models
- Representative data: the amount increases with the complexity of models and the number of degrees of freedom
  - → Necessary to have trustworthy results
  - → Models will be specific to the considered design & scenarios

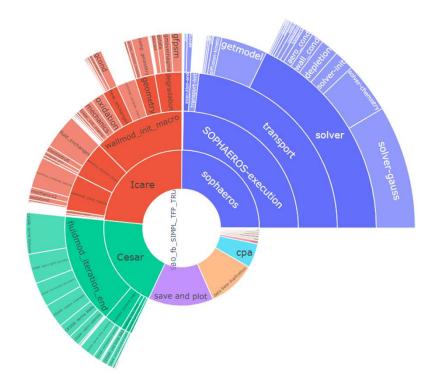
## Surrogate models types

#### Global models:

- Replace the SA code completely (ASTEC; or MELCOR explored by KTH)
- Faster, but more complex

#### Local models:

- Replace parts of the code (module)
- Or replace part of the reactor model (primary circuit, vessel, steam generator
- Data exchange with other physical models at each ASTEC time-step —> time-stepping methods are required: error accumulation must be controlled
- Interface with the native code to be developed
- Speed-up factor limited to the share of the replaced model to the global CPU time

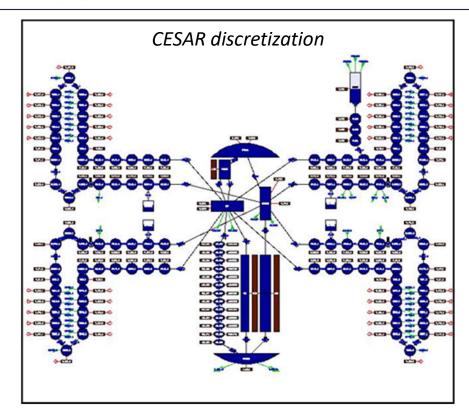


Share of the CPU time required by different models of ASTEC during the degradation phase (SBO, simplified input deck)

### Surrogate models types

# Additional option: improved solver initialisation

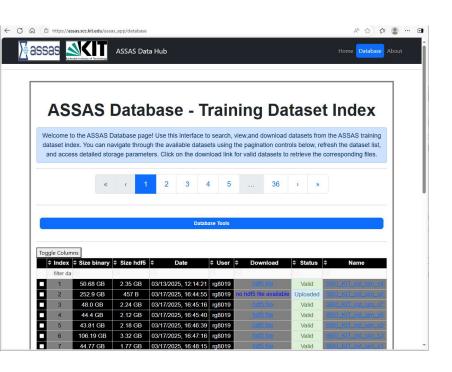
- An iterative method (Newton-Raphson algorithm) is used to solve non-linear PDEs in thermal-hydraulics
- The AI model can improve the initialisation of the algorithm for it to converge in fewer steps
- Advantage: keeping the same accuracy as native physical models





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# A large training database



Screenshot of the database

#### 70TB of data

- Complete ASTEC outputs saved at each timestep (1-10s)
- Up to 3 days of accident progression
- >1,000 scenarios

#### Representative of all operator actions

- A dozen possible actions on the simulator
- Randomly sampled to ensure data representativeness



### Conclusion

A simulator to make SA knowledge more accessible

Improving ASTEC's performances for a real time execution

Explore AI capacity to reach higher acceleration factors

Just started with real ASTEC data

Share a high-quality database for future research





### **Factsheet**

- November 2022 October 2026
- 14 partners
- €3.7 million budget
- Coordinator: Bastien Poubeau, <u>bastien.poubeau@asnr.fr</u>































