

# ERMSAR 2024

## CAN MACHINE-LEARNING MAKE FAST AND ACCURATE SEVERE ACCIDENT SIMULATORS A REALITY?

Version 1 – 13/05/2024



# Summary

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1. General objectives of ASSAS
2. Specifications of the simulator
3. Optimisation of ASTEC
4. Machine-learning approaches

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# A basic-principles SA simulator

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## Need for severe accident (SA) simulators

- Education & training
- Accelerating the learning curve for SA codes
- Importing plant data from existing simulators: data-centric approach



*Desktop simulator  
(Westinghouse)*

## A prototype simulator for a Western-type PWR

- Close to best-estimate accuracy
- Interfacing ASTEC and TEAM\_SUITE®
- Prepare the path for more realistic simulators & other designs & other SA codes

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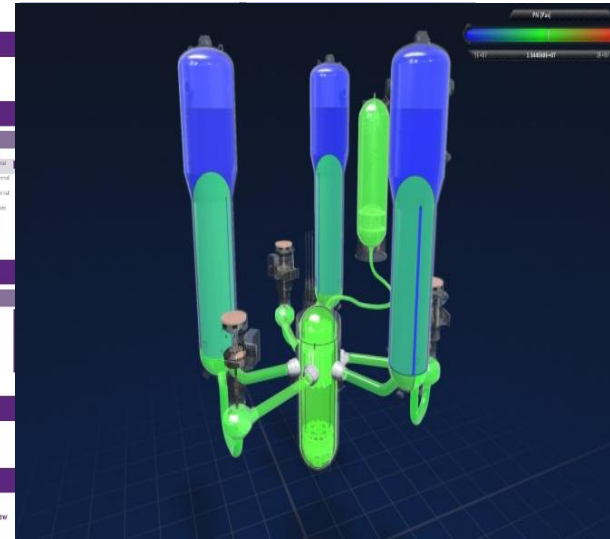
# Specifications of the simulator

## Showing SA phenomenology

- 2 scenarios:
  - LB-LOCA with SI failure
  - SBO with AFW failure
- Synthetic screen + virtual reality display
- Deterministic answer (no uncertainty)

The screenshot shows the Tecnom interface with several sections:

- Connection:** Error getting response stream (DeadDane!): ReceiveFailure. Connect button.
- Variables:** A table with columns: Name, Unit, Simple, Description.
- Malfunctions:** A table with columns: Name, Component, State.
- Model Settings:** Checkboxes for Complete, Partial, 360°, 270°, 180°, Show Core, and Transparent.
- Camera View:** Checkboxes for Free Camera, Core View, and General View.



*Example of virtual reality display (Westinghouse)*

## Running in real time or faster

- A challenge for SA codes... an opportunity to use machine-learning!
- Perspectives for fast running tools after the end of the project: uncertainty propagation, emergency response, PSA...

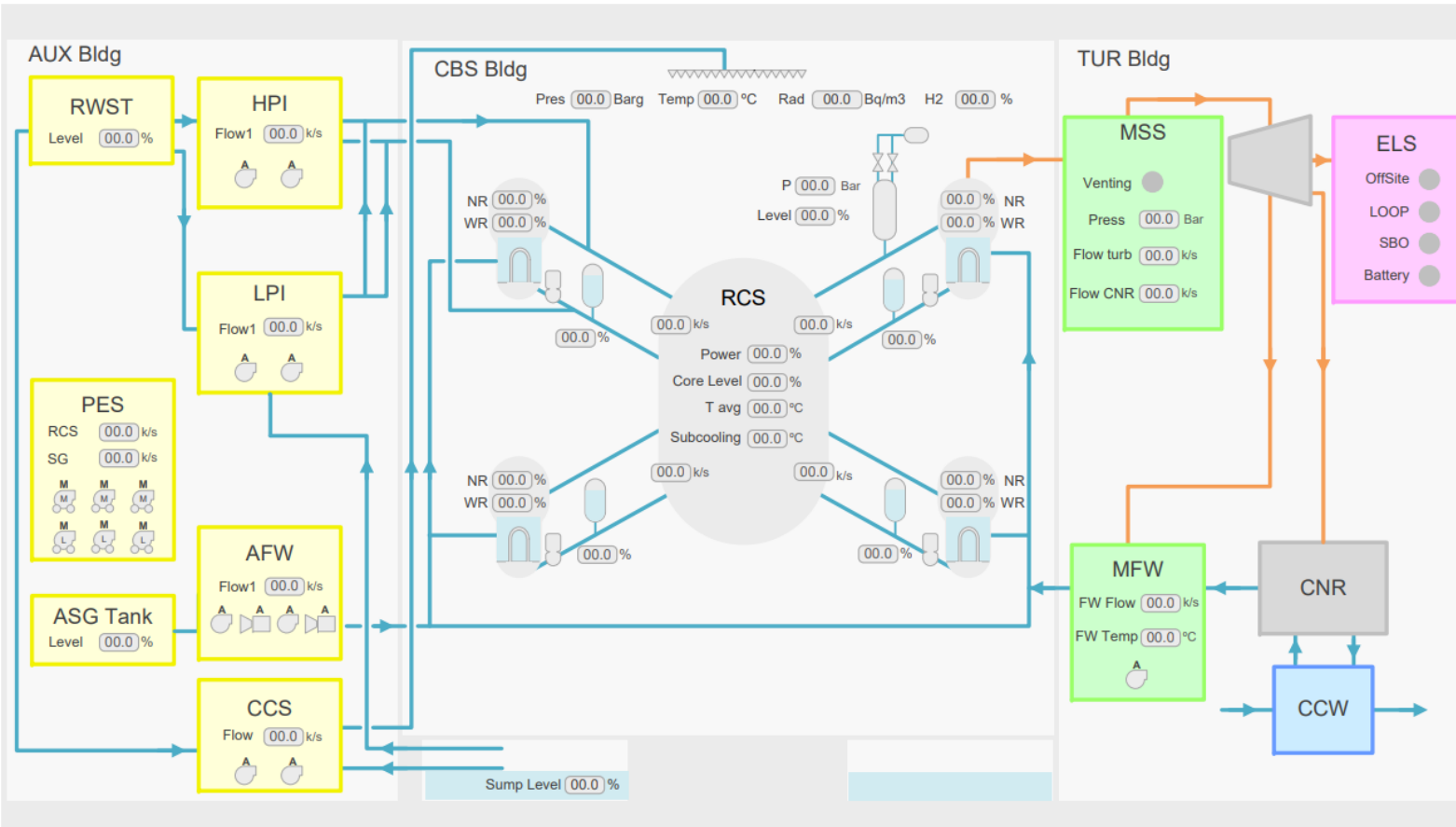
# Specifications of the simulator

All phases of a SA:

- From initiating event to SA
- Core degradation
- Release and transport of FPs
- Vessel rupture and MCCI
- Containment pressurisation up to the filtered release of FPs
- Some phenomena are excluded: steam explosion, direct containment heating...

Ergonomic interface:

- Simulation control (speed-up factor, freeze, load...)
- Main control room sensors + pedagogical information
- Plot variables & extract data



Simulator overview    SA screen    Alarm display

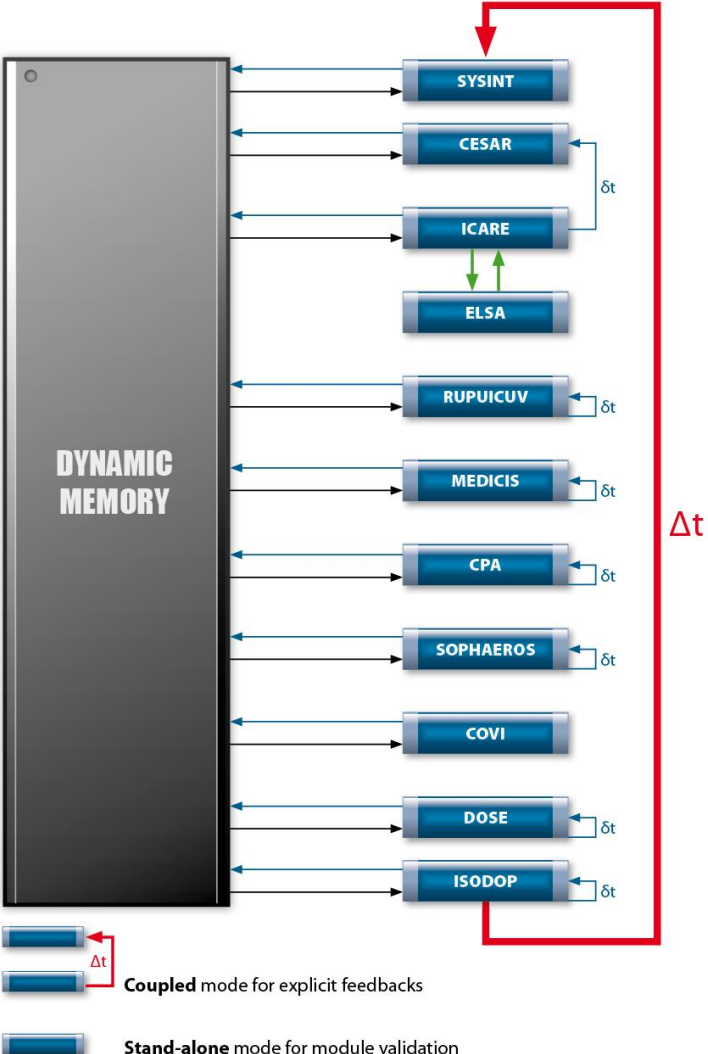
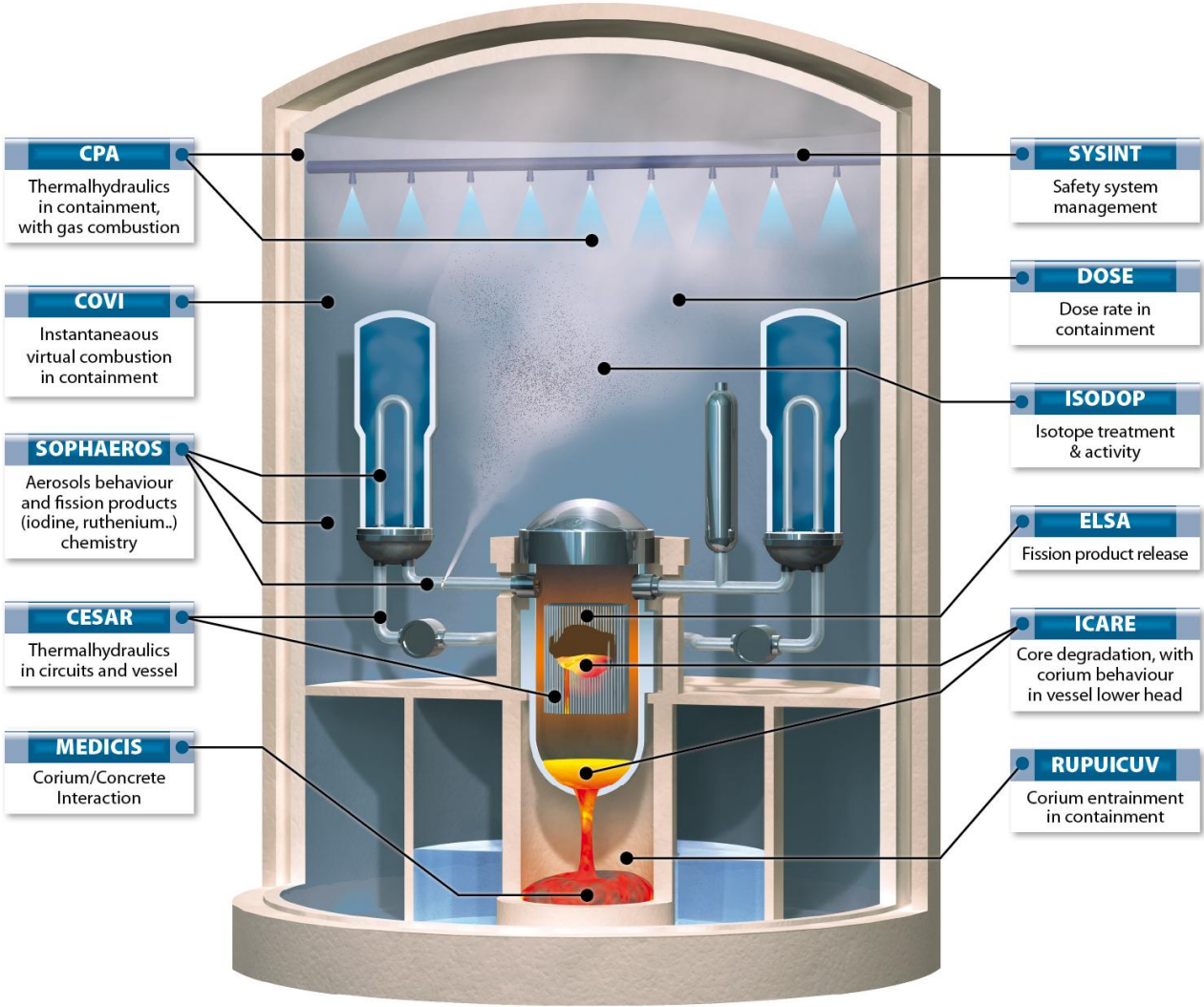
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# ASTEC structure



# Efficient programming

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Improving performances without impacting accuracy

## Algorithmic improvements:

- Low-level optimisations (memory access, data management...)
- New solvers to be tested

## Parallelisation:

- Sequential structure of ASTEC optimised for batch calculations (more sequences than processors) → Run only one sequence but faster
- Results obtained with OpenMP will be delivered to users in 2024



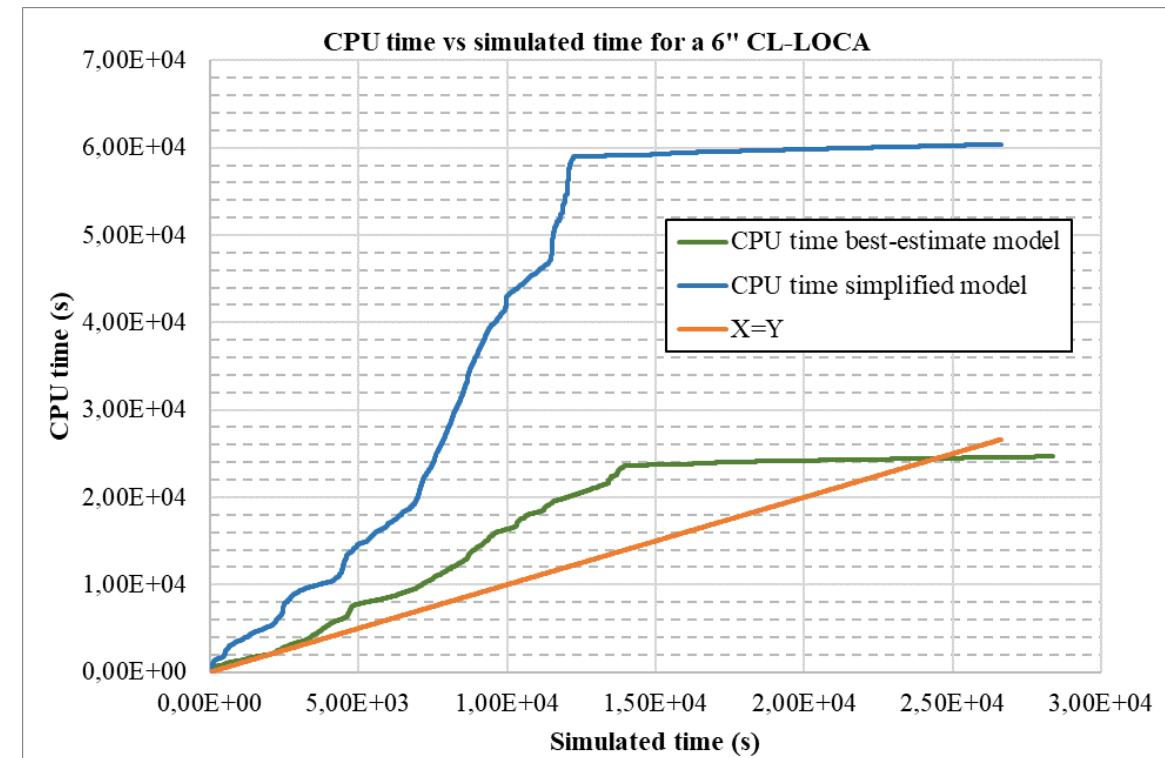
# Simplification of the input deck

## Simplified models

- ICARE+CESAR stop at vessel rupture
- Limited list of incondensable gases in the RCS

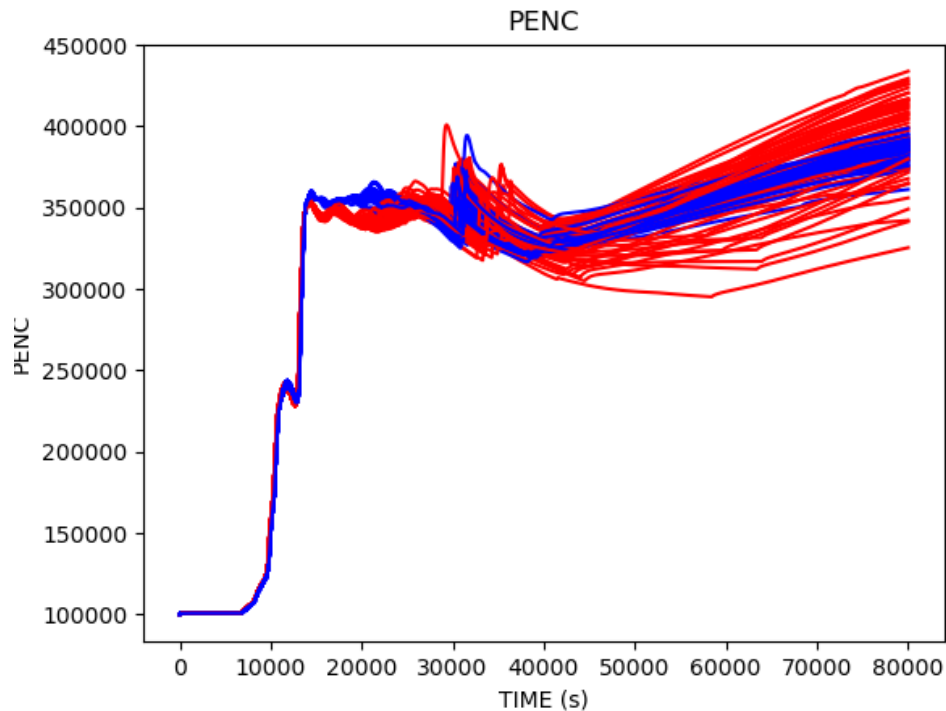
## Simplified discretization

- Circuits + containment
- Acceptable results
- Higher numerical sensitivity

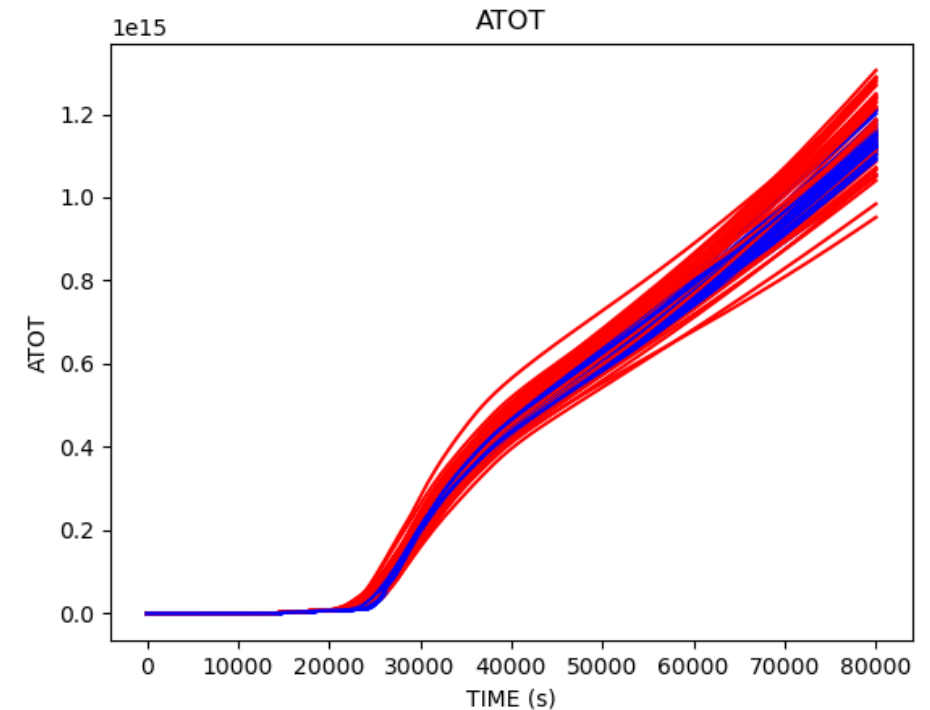


# Numerical sensitivity

Numerical noise propagation with the best-estimate (blue) and simplified (red) input decks for a SBO sequence (higher sensitivity)



*Containment pressure (Pa) versus time*



*Total activity (Bq) released to the environment versus time*

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# Data-driven surrogate models

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## 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 functions and number of degrees of freedom
  - Necessary to have trustworthy results
  - Models will be specific to the considered design & scenarios



# Global models

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Replacing the SA code completely:

- Faster but more complex

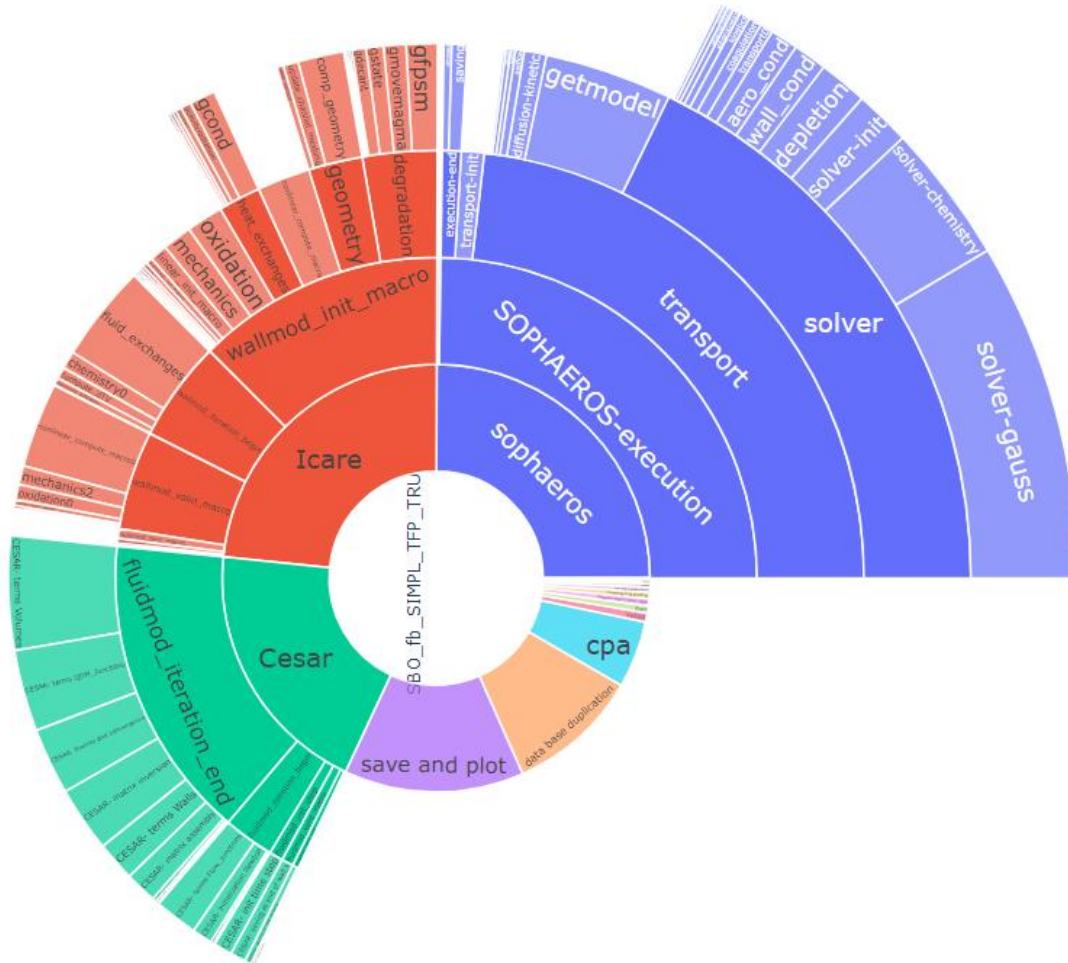
Global containment model after the vessel rupture

- Few actions are possible during the MCCI phase
- Large variety of initial conditions after the vessel rupture
- Preferred option: time-series prediction with bifurcations at operator actions
- JSI & Energorisk for PWR-1300 and VVER-1000 designs

Melcor surrogate model: explored by KTH (BWR)



# Hybrid models



## Replacing only a part of the code

- Data exchange with physical models at each ASTEC macro 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
  - Worth-case scenario illustrated by the chart: 3 modules have the same computational cost

3 options illustrated in the next slides

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



# Local thermal-hydraulic models

## Objective:

- replace (part(s) of) the primary and secondary circuits by a surrogate model

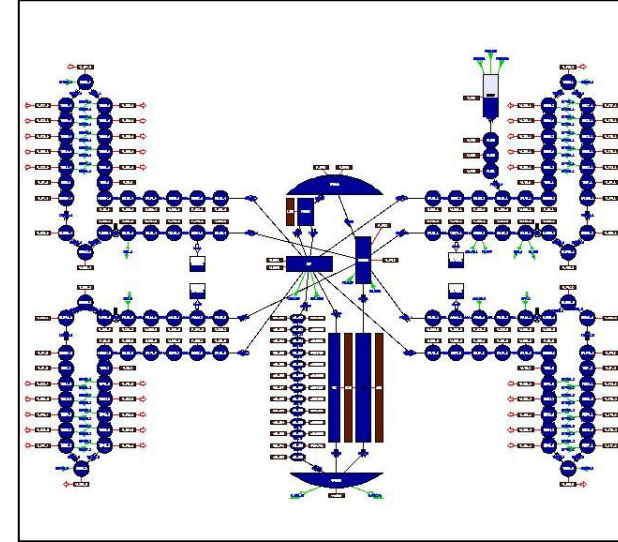
## Advantages

- Thermal-hydraulics is computationally intensive
- Relatively few variables to predict (flow conditions + wall temperature)

## Challenges

- Smaller time resolution than the native model (macro time-step vs. CESAR micro time-step)
- Numerous combinations of operator actions on safety systems

*CESAR discretization*



# CESAR solver initialisation

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## Accelerate the Newton-Raphson algorithm of the solver

- A gradient descent is used to solve the non-linear system of equations.
- The algorithm is initialised with the converged solution of the previous timestep.
- The ML model should predict a first guess of the solution, to reduce the number of iterations to reach convergence.

## Advantages:

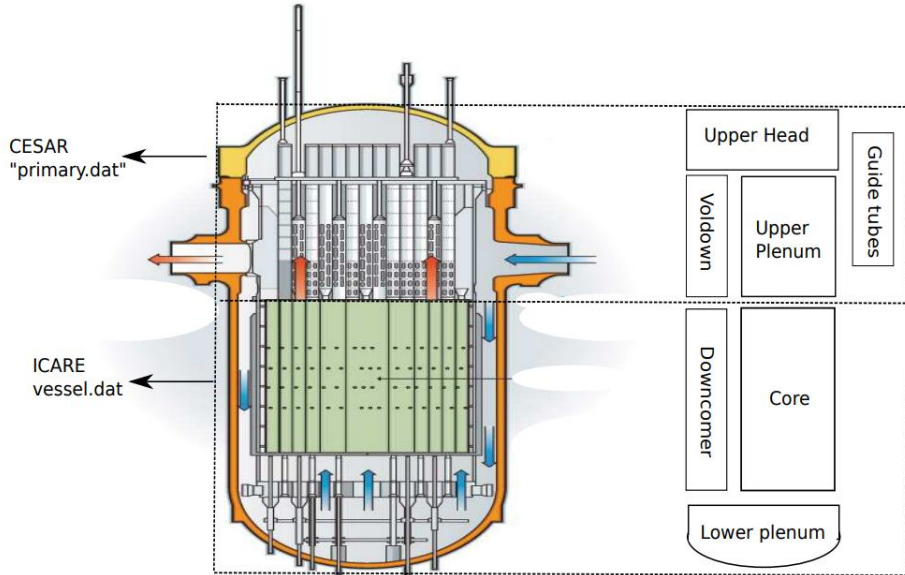
- Same accuracy as physical models
- Easy implementation

## Challenges:

- Few examples in literature using ML
- Impact on the computational time to be evaluated

# Primary vessel model

Replacing ICARE + CESAR in the vessel



*ASTEC Vessel model*

## Advantages

- Modelling thermal-hydraulics and core degradation together to account for their strong coupling
- Possibly a higher generalisation capacity since no safety system is directly connected to the vessel

## Challenges

- Number of variables and number of meshes to consider: high dimensionality
- Complexity of physical models

# Conclusion

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A simulator to make SA knowledge more accessible

Improving ASTEC's performances for a real time execution

Explore different ML strategies (possibly in combination) to reach higher acceleration factors

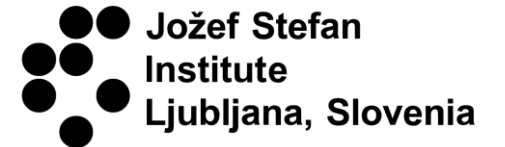
Share a high-quality database for future collaborative work

- The ASSAS training database will be openly accessible for reuse:
  - International nuclear ML benchmark
  - Applications for emergency response

# List of authors

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