Use of Artificial Neural Network for criticality calculation in severe accident

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TRACTEBEL ENGIE

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Criticality in severe accident
Context and objectives

- Context: Calculation of core criticality in severe accident configuration
  - Capability to calculate reactivity accidents leading to core damage
  - Topic under discussion as severe accident research priority in NUGENIA
  - Calculation of Fukushima type sequences (non borated water injected, also foreseen in the SAMG)
  - Interest for Gen III reactors foreseen to operate with 100% MOX cores

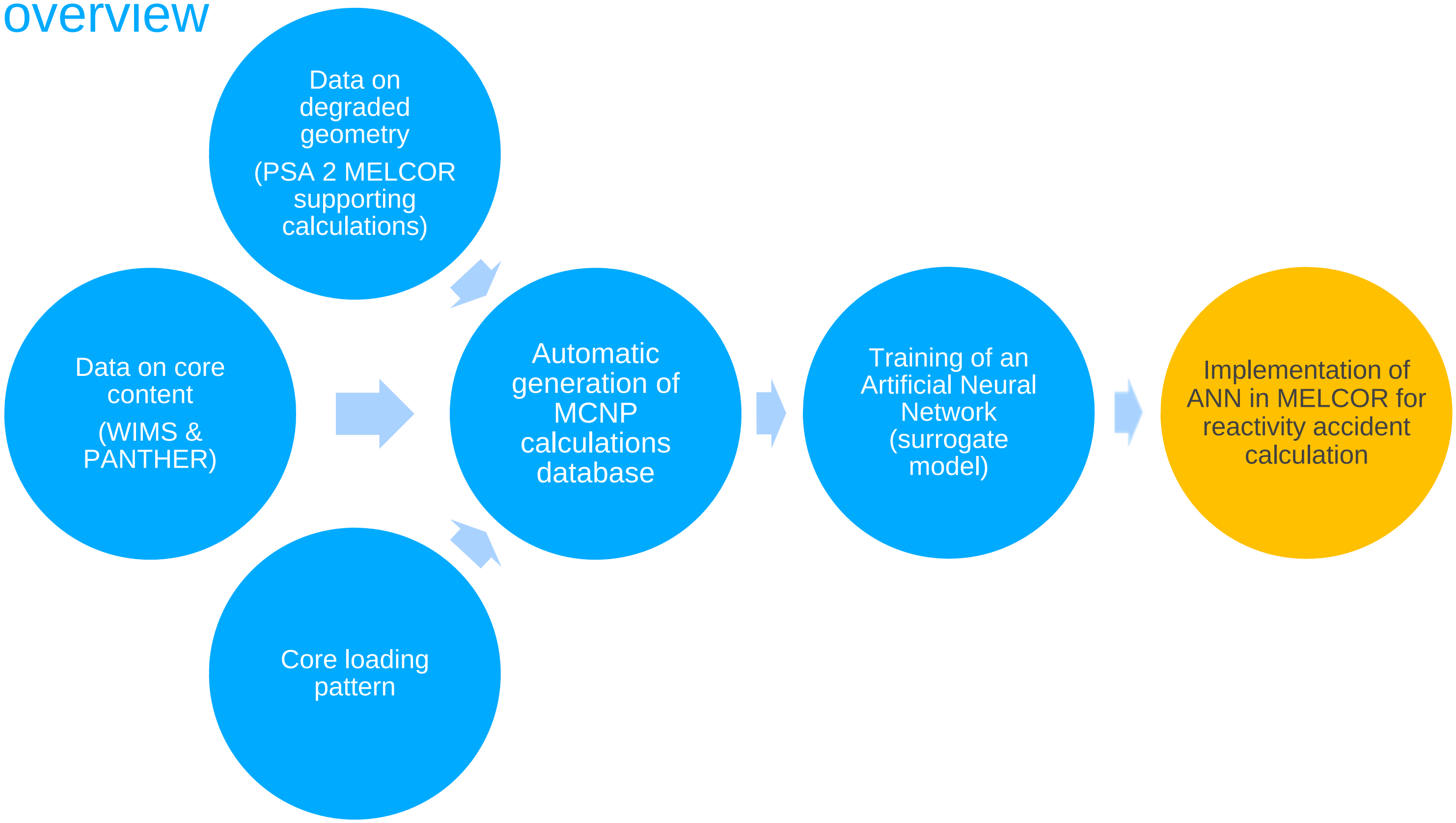
Criticality in severe accident
Context and objectives

- Development in Tractebel:
  - — MELCOR reference code in Tractebel for severe accident calculation includes a point kinetic model (not valid for degraded geometries)
  - ➔ Development of a surrogate model (Artificial Neural Network) to be included in MELCOR as external reactivity
    - Low computational cost compared to coupling with neutron code
    - Online k_{eff} calculation and feedback on core power

$$\rho = \rho_{ext} + \cancel{\rho_D} + \cancel{\rho_f} + \cancel{\rho_G}$$

Criticality in severe accident

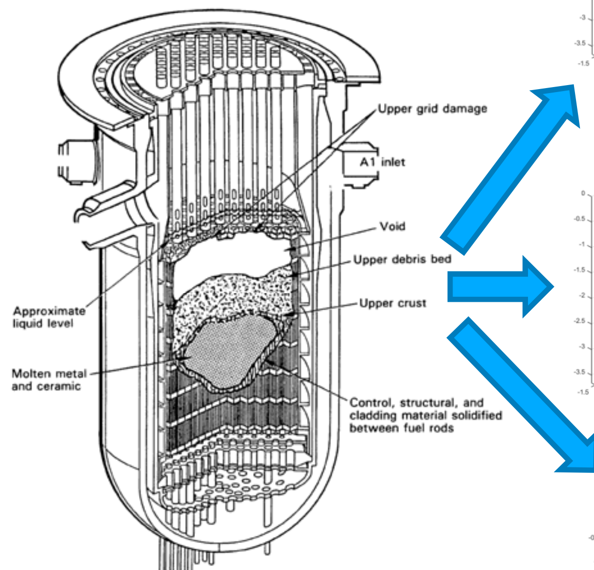
Process overview

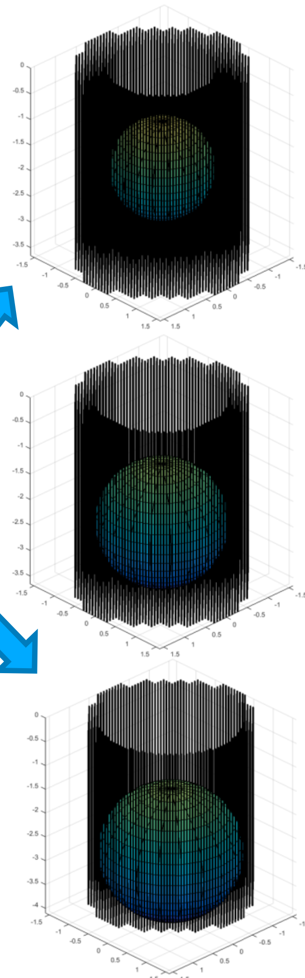


Criticality in severe accident

Approach definition and evaluation of input data needed

- Focus on in-vessel phase and more particularly on idealised TMI-like configuration
  - Spherical corium pool in active part of the core
  - No relocation of corium in lower plenum considered
  - No steel structures
  - Infinite water reflector
- Data from MELCOR:
  - Fraction of RN released from core (including control rod poison) as a function of core degraded fraction
  - Zirconium oxidized fraction as a function of core degraded fraction



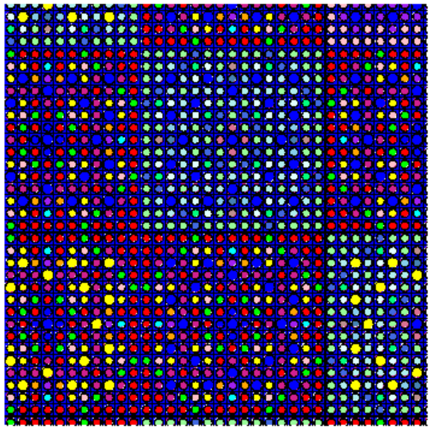


Criticality in severe accident
Data for intact core modelling in MCNP

- Data for intact core MCNP input:
  1. Core loading pattern:
     a) Assemblies types positions
     b) Control rods positions
     c) Number of cycles in core per assembly
  2. 12 families of assemblies are defined (assembly type, number of cycles in core)
  3. Family burnup as a function of core exposure
  4. Different rod types per assembly (depending on neighbourhood)
  5. Composition of fuel rods depending on assembly exposure

Criticality in severe accident

Data for intact core modelling in MCNP



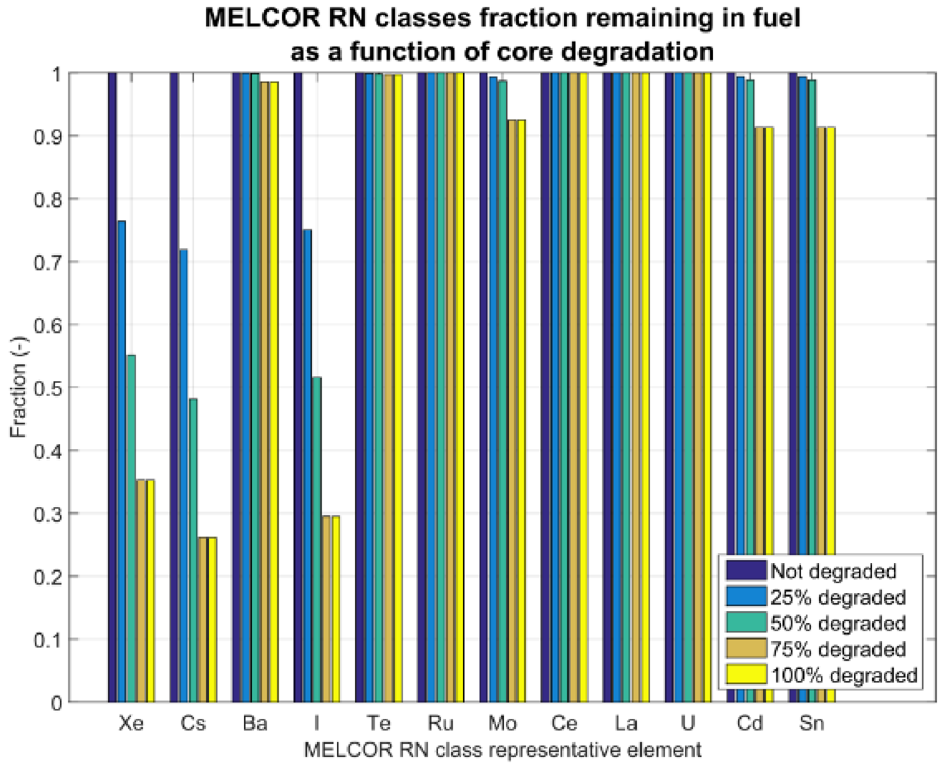
k_{eff} obtained:

- BOL, ARO, Bcrit_ARO: 1.00776
- BOL, DBCA, Bcrit_DBCA: 1.00503

➔ Good starting point

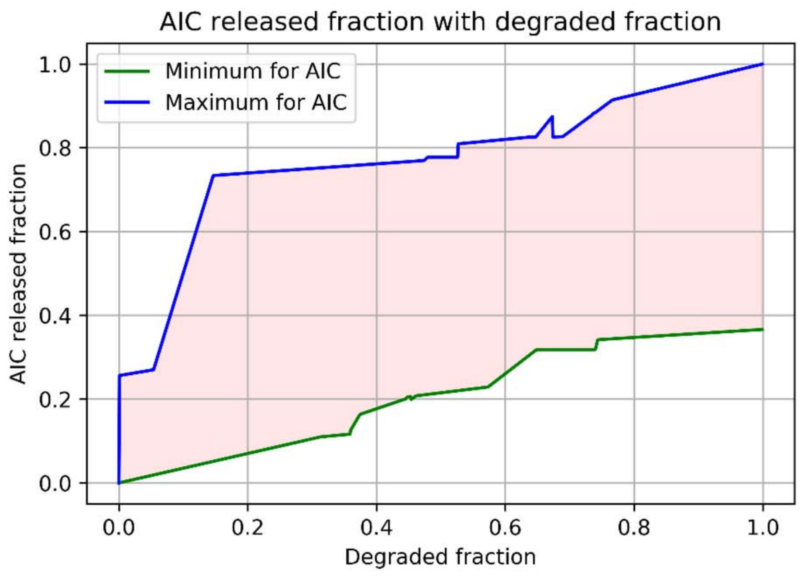
Criticality in severe accident
MELCOR inputs for degrade geometry modelling in MCNP

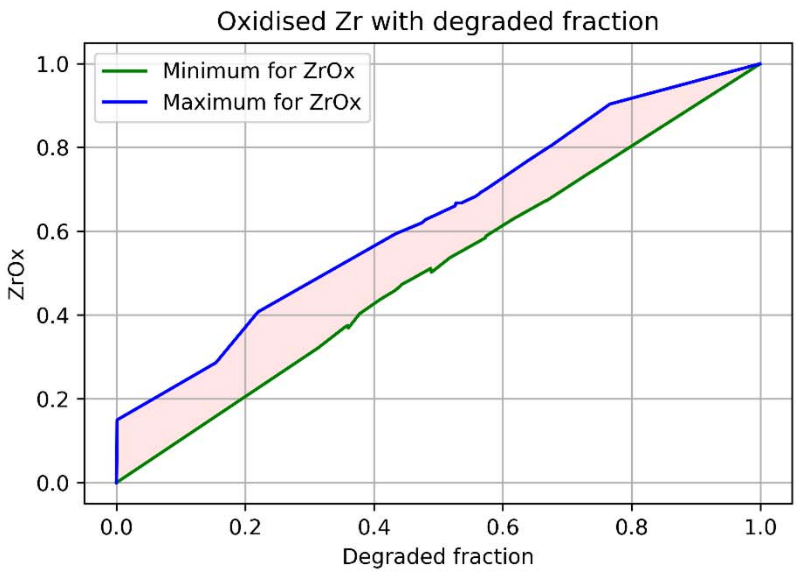
Data extracted from MELCOR calculation database used for PSA level 2



Criticality in severe accident
MELCOR inputs for degrade geometry modelling in MCNP

Data extracted from MELCOR calculation database used for PSA level 2





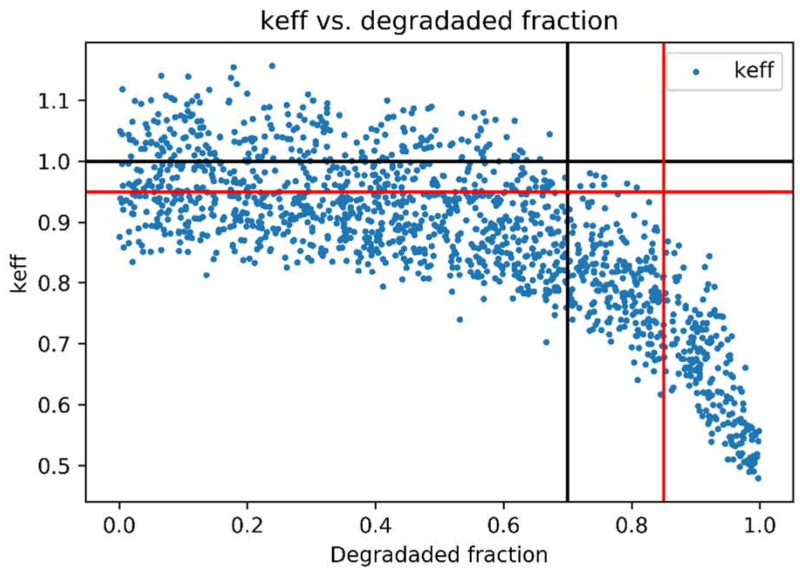
Criticality in severe accident

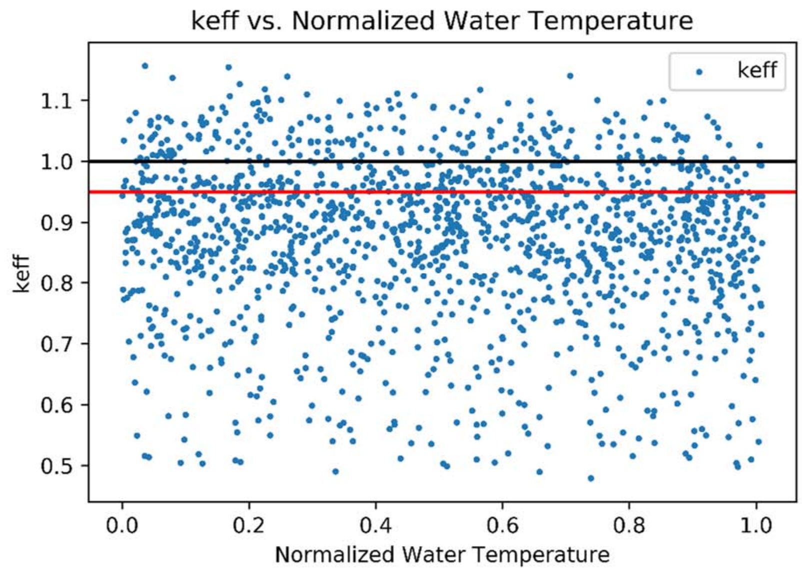
Training of ANN – Parameter space

Parameter	Range
Degradation	0 – 100%
RN Class$_i$ released fraction	F(Degradation)
Fraction of oxidised Zr	F(Degradation)
Time since SCRAM (depletion)	0 – 10d
Density of corium	7 – 10 g/cm^3
Core exposure	0 – 18GWd/tU
Water temperature	100°C – 330°C
Boron concentration	0 – 2800ppm
Core water level	0 – 100%

Criticality in severe accident
Identification of critical zone

- For each parameter, identification of range where k_{eff} can be higher than 1

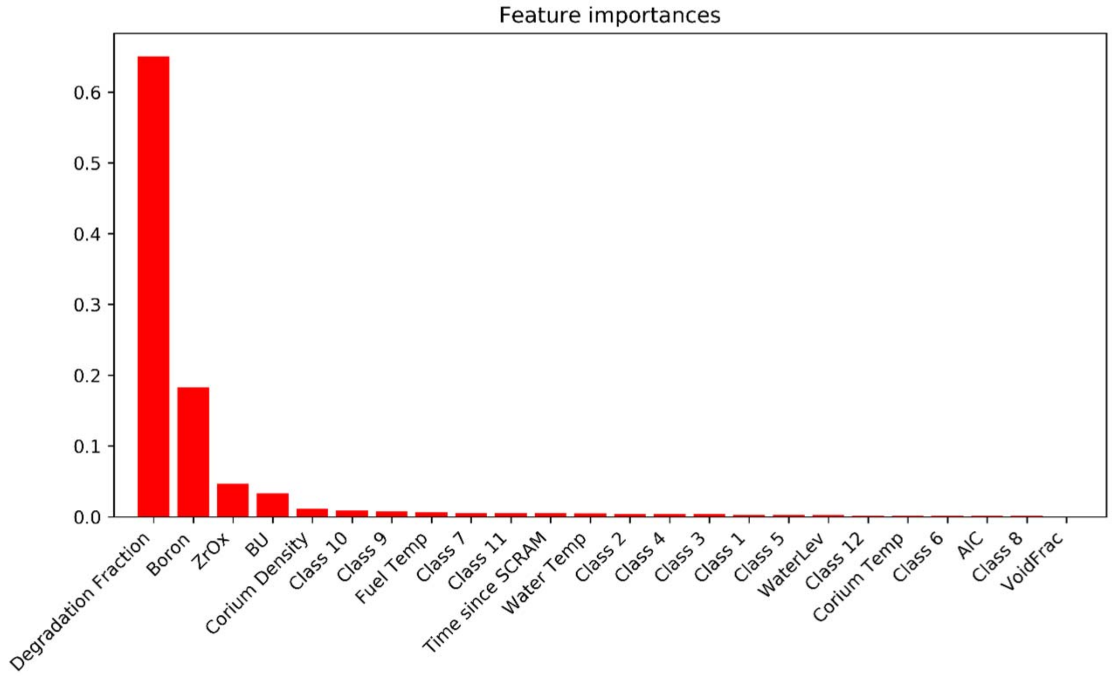




Criticality in severe accident

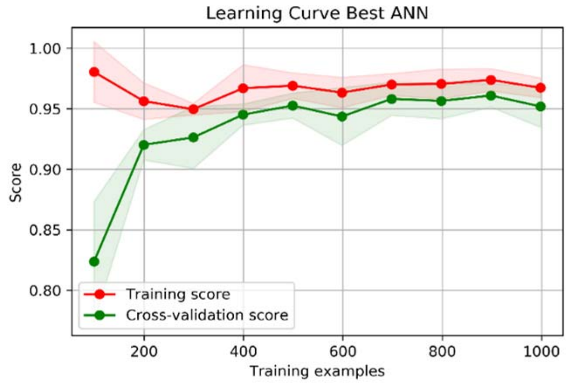
Training of Artificial Neural Network and first testing

- **Which parameters are important for $keff$?**
- →Importance analysis
  - — Degradation (65%)
  - — Boron (18%)
  - — ZrOx (5%)
  - — BU (3%)
- We take all the parameters !

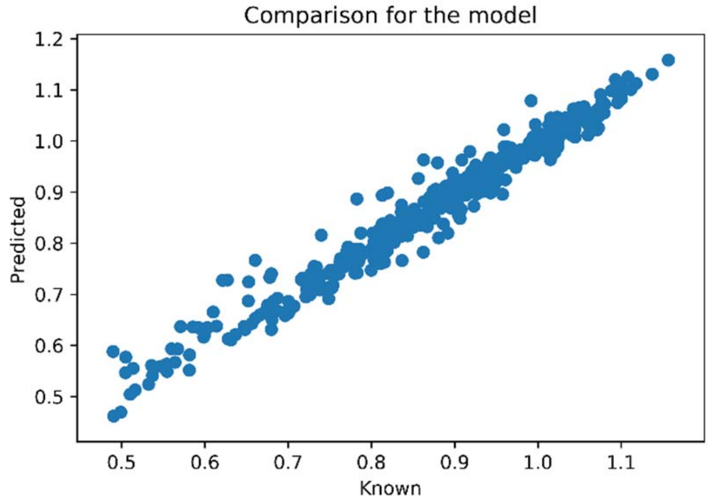


Criticality in severe accident

Training of Artificial Neural Network and first testing



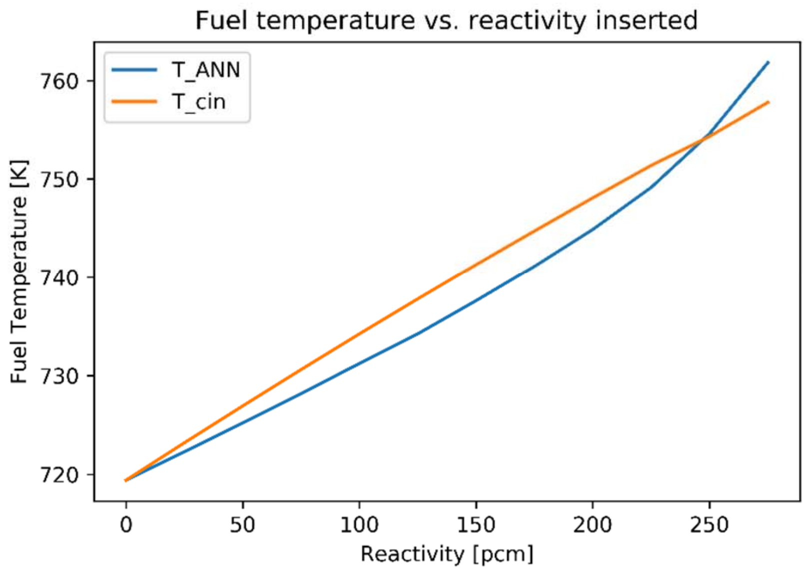
- **Number of data in sample = sufficient ?**
- Accuracy = 0.9577 $\pm$ 0.02319
- Explained variance score = 0.96146685
- R2 score = 0.96144549
- Mean absolute error = 0.01709
- Mean squared error = 0.0006662
- Median absolute error = 0.0115854

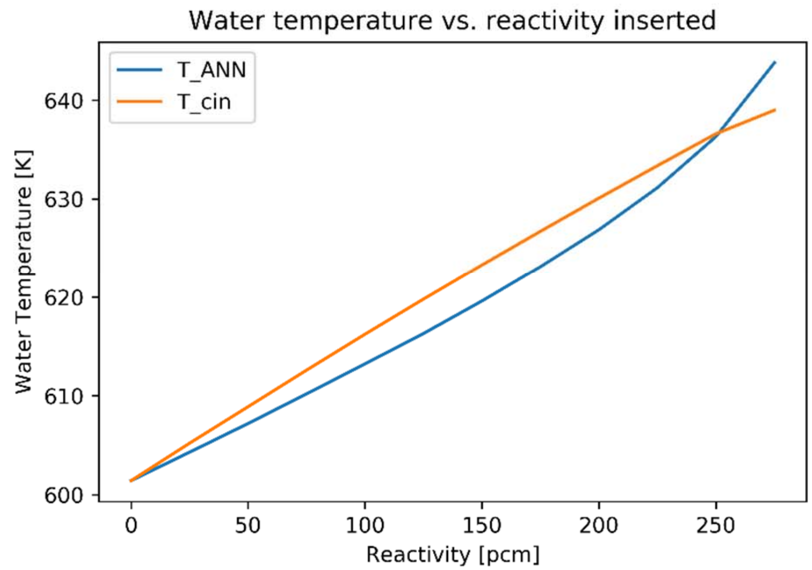


Criticality in severe accident

Training of Artificial Neural Network and first testing

- Compare $T_{mod_{\infty}}(\rho_0)$ and $T_{fuel_{\infty}}(\rho_0)$





Criticality in severe accident
Conclusion

- Need for a high detail modelling of the core to obtain a good starting point
- ANN shows promising results for k_{eff} evaluation in severe accident configuration:
  — Capable of explaining up to 96% of the variance of the k_{eff} based on input parameters
  — Possibility to make ANN more precise in certain zones of the parameters space by increasing number of samples in those zones
  — Possibility for feature importance analysis
- Stabilisation temperatures obtained for several reactivity insertion show good agreement with point kinetic model with measured temperature coefficients for real loading pattern

Criticality in severe accident
Perspectives

- Perspectives:
  - Easy to implement in MELCOR using CFs and existing point kinetic model & low computational cost
  - ➔ Implementation in MELCOR and test against existing & validated Tractebel models for reactivity insertion accidents without core melting
  - Calculation of reactivity accidents with core melting using MELCOR
  - Possible extension of approach to other physics e.g. debris bed cooling, MCCI, etc.