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Fast Uncertainty Quantification of Spent Nuclear Fuel with Neural Networks

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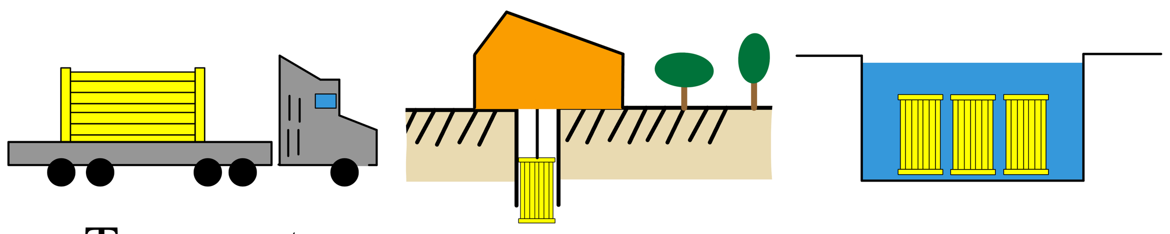
Background and Motivation

Spent nuclear fuel (SNF) is characterised by

- Nuclide content
- Decay heat
- k-effective

Accurate characterization and Uncertainty Quantification (UQ) of these quantities is crucial to **reduce risks and costs** of



Transport   Disposal   Storage

- Traditional Monte Carlo UQ requires ~ 1000 simulations **per assembly!**
- Each simulation with a physics-based model (e.g. CASMO5) lasts from a few minutes to a few hours.
- Over 12000 expected assemblies in Switzerland.

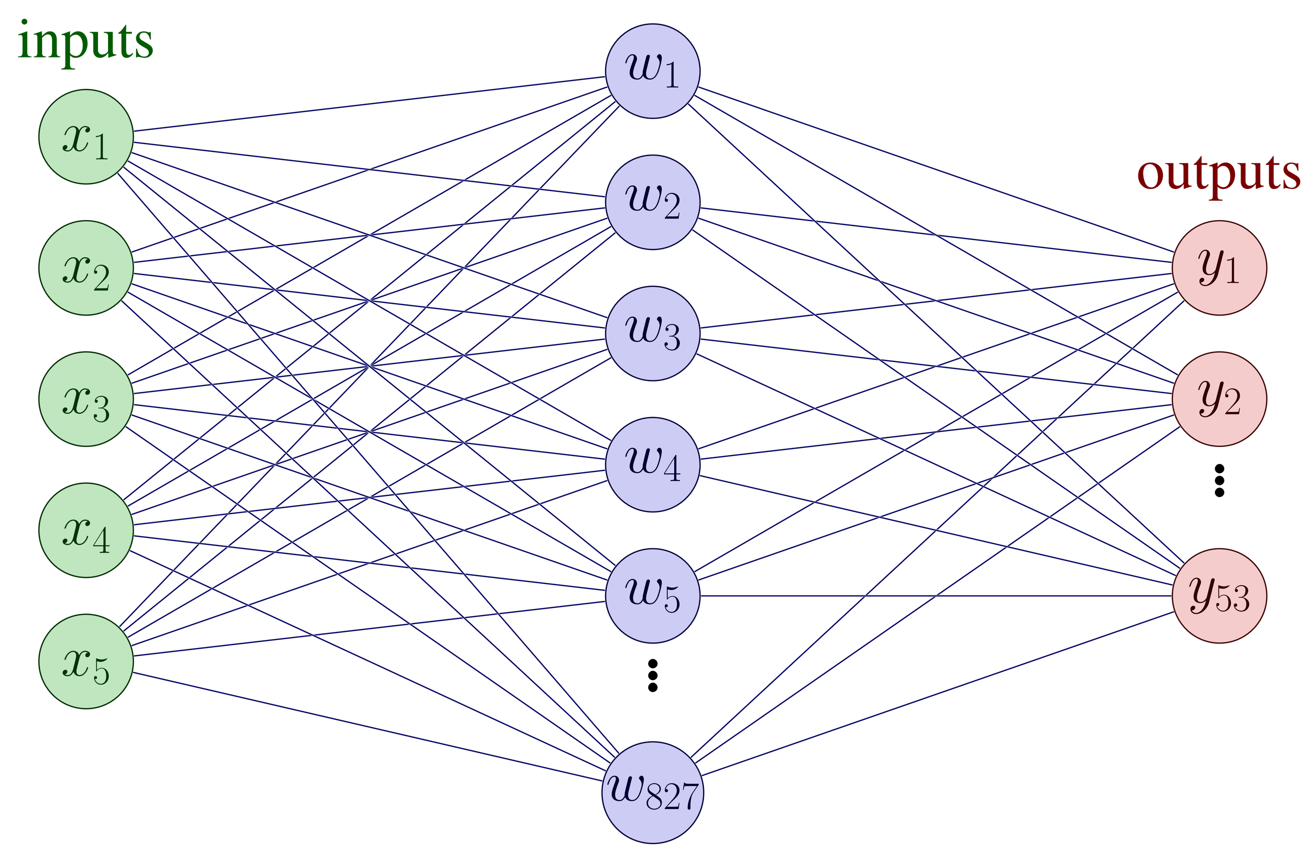
Surrogate Models using neural networks can predict SNF characteristics with reduced computational costs compared to physics-based models
$\Rightarrow$ **reduced computational costs for UQ.**

Neural Network

1. Obtain a training set of $N_{tr} = 500$ with physics-based model
2. Train the neural network (NN) (~ 1 minute)

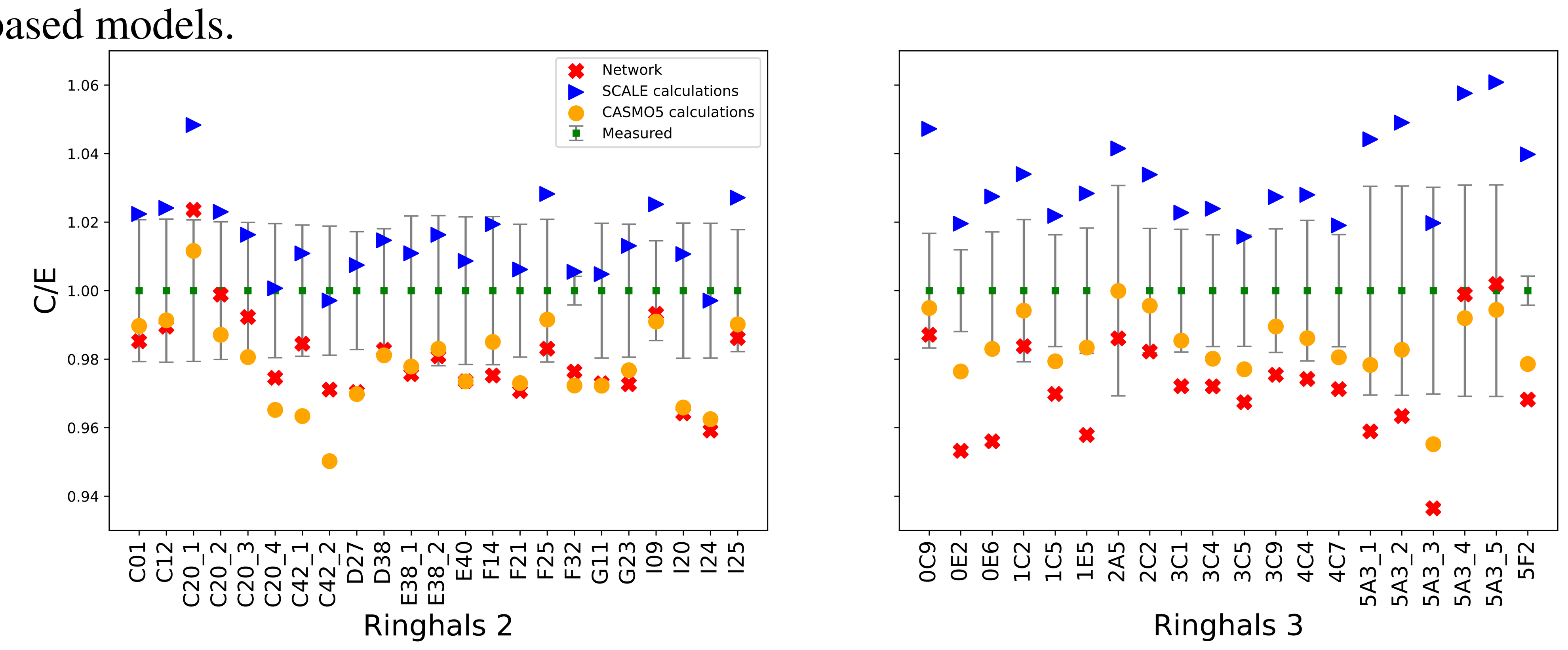
$$f: \underbrace{\begin{pmatrix} \texttt{Enrichment} \\ \texttt{Burnup} \\ \texttt{Cooling time between cycles} \\ \texttt{Mean boron concentration} \\ \texttt{Fuel temperature} \end{pmatrix}}_{\text{5 inputs: Fresh fuel characteristics and irradiation history}} \rightarrow \underbrace{\begin{pmatrix} \texttt{Decay heat } (t) \\ \texttt{Actinide concentration} \\ \texttt{Concentration } ^{137}\texttt{Cs and } ^{90}\texttt{Sr} \end{pmatrix}}_{\text{53 outputs: SNF characteristics}}$$

3. Use NN to compute the SNF characteristics **at any point in less than 1 ms**



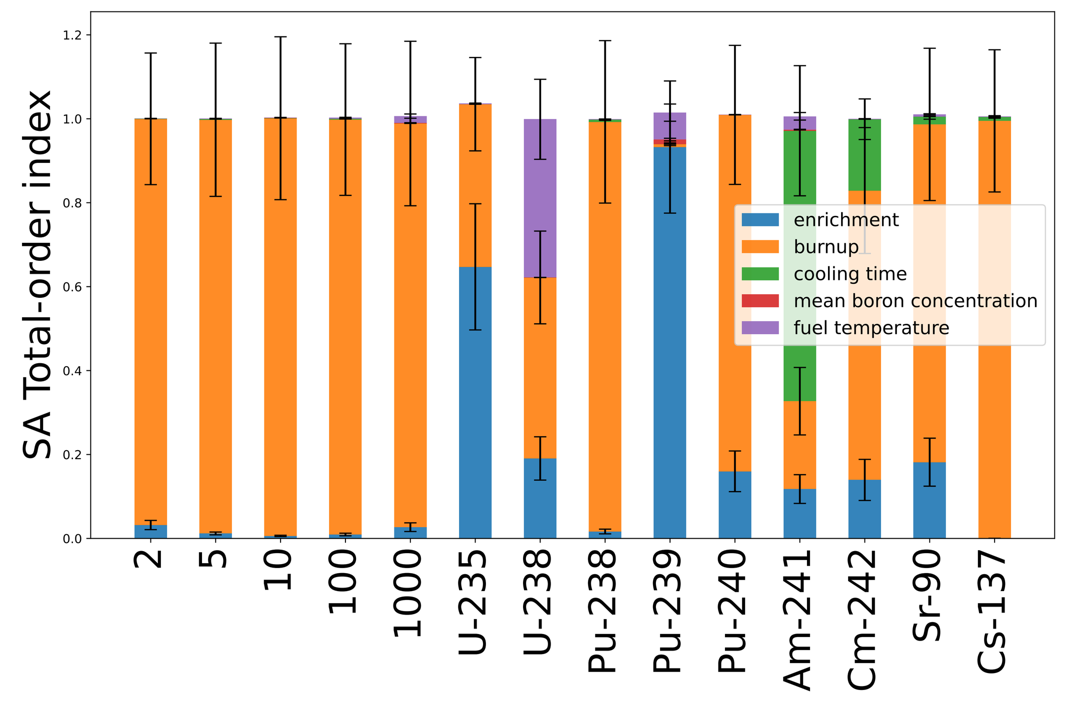
Computed vs Experimental (C/E) Decay Heat [1]

Prediction of decay heat for Ringhals PWRs [2] for validation of the NN surrogate model. The neural network predicts the decay heat with a similar accuracy compared to physics-based models.



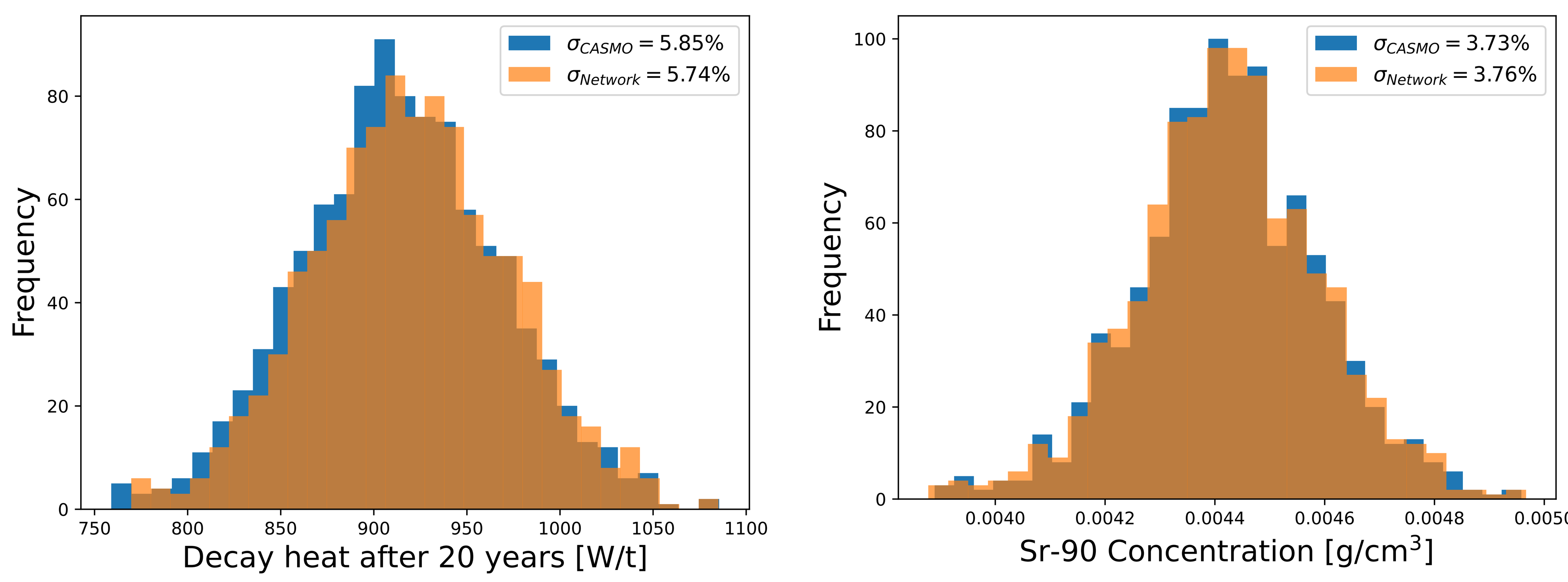
Sensitivity Analysis

Once the NN is trained, **a sensitivity analysis can be computed instantly** and reveals most influential input parameters.

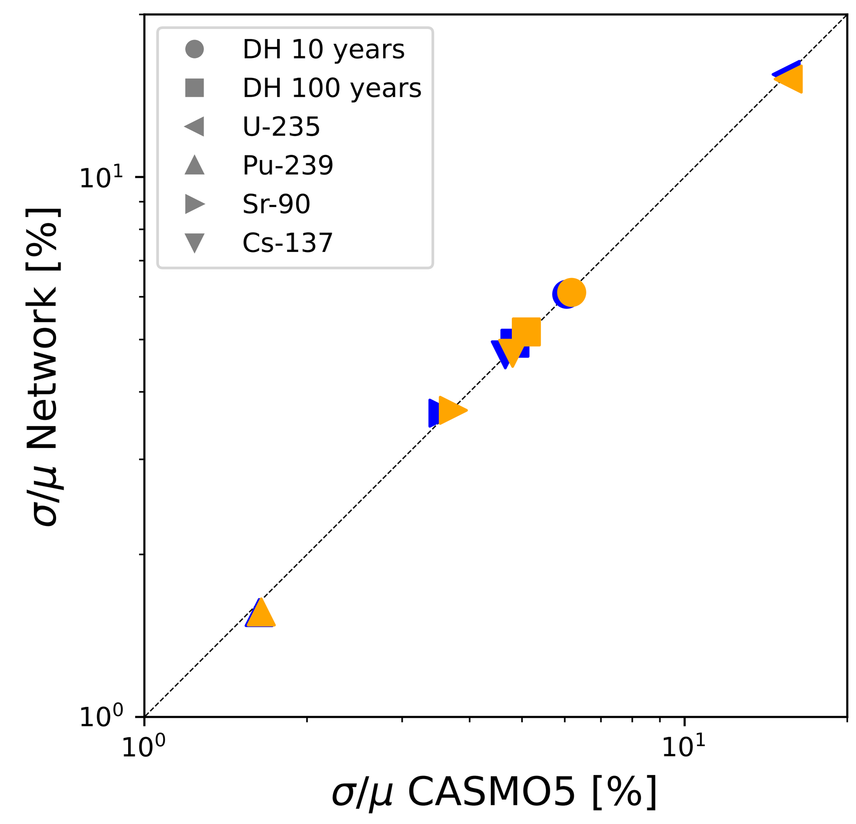


Uncertainty Quantification

Computation of uncertainties of SNF characteristics with the physics-based model and the NN surrogate model, assuming 5% uncertainty for input parameters.



Several hours with CASMO5 vs 1 second with the neural network



Predicted rel. standard deviation for two different fuel assemblies.

Highlights

- NN replaces CASMO5 decay heat calculations of spent nuclear fuel.
- Simulations using the network can be up to 10^6 times faster than CASMO5.
- NN predictions are within 3% of measured decay heat, comparable to CASMO5.
- Uncertainty quantification with NN in under 1 second.

[1] A. Albà, A. Adelmann, L. Münster, D. Rochman, and R. Boiger. Fast uncertainty quantification of spent nuclear fuel with neural networks. *Annals of Nuclear Energy*, 196:110204, 2024.

[2] F. Sturek, L. Agrenius, and O. Osifo. Measurements of decay heat in spent nuclear fuel at the Swedish interim storage facility, Clab. Technical Report R-05-62, Svensk Kärnbränslehantering AB, December 2006.

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