ENERGETICS

DENERG - Physics-informed machine learning methods for advanced nuclear systems

Funded By	Dipartimento DENERG
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Context of the research activity	The evolution of nuclear reactors aims for safe, sustainable, flexible energy in a low-carbon future. Gen-IV designs (LFR, MSR) and modular reactors (SMRs, MMRs) show promise but rely on simplified models and costly simulations. Machine learning offers new paths, yet data-driven methods lack physical consistency. Physics-informed ML could bridge this gap, enabling robust digital twins for monitoring, optimization, and next-gen fission and fusion systems.
Objectives	The aim of this PhD project is contributing to bridge the gap between physics-based modeling and data-driven learning through the development of hybrid numerical–machine learning (ML) methodologies tailored to advanced fission and fusion reactor systems. At first, the candidate will focus on the Fission Matrix (FM) method, a modern hybrid stochastic–deterministic approach, which has been developed, as one of the explicit intents, to allow accurate reactor physics simulation at the core level combining detailed neutron flux evaluations based on the use of Monte Carlo. The FM technique requires building a database of Monte Carlo–based fission matrix evaluations, parameterized over key system variables such as temperature, burnup, and enrichment. After this computationally intensive off-line stage, the FM can be interpolated and solved within a deterministic framework to obtain the fission source and corresponding power distribution under new conditions in near real time. Despite its high accuracy and flexibility, the method remains storage-demanding and computationally costly when applied to large or high-dimensional parameter spaces. To improve its efficiency and accuracy, the method will be coupled with ML-based interpolation and dimensionality reduction techniques—such as Singular Value Decomposition (SVD) and Radial Basis Function (RBF) models—allowing for compact surrogate representations of large datasets while preserving physical consistency. Taking advantage of the expertise within the research group at PoliTO and the international network of researchers involved in these activities, the candidate will embed the improved fission matrix approach in the wider application field of time-dependent modelling, adopting quasi-static and enhanced quasi-static (EQS) schemes, featuring adaptive time-step control

	to balance accuracy and computational cost. This integration will enable real-time or near-real-time multi-physics simulations suitable for transient analyses, sensitivity studies, and uncertainty quantification in Generation-IV reactor systems. The candidate will test the methodology on system of industrial interests, such as Lead-cooled fast SMRs as well as Micro-reactors, fully exploiting the advantages of the FM approach in treating complex, unstructured geometries. In parallel, optimization techniques based on evolutionary algorithms, such as genetic algorithms, will be developed and applied to selected design and operational problems in both fission and fusion contexts. In fission reactors, the applications will include the definition of a fuel loading pattern optimizing the fuel burn-up and optimal placement of in-core and ex-core detectors, where the previously developed fission matrix can be directly leveraged to accelerate fitness evaluations. For fusion systems—particularly ARC-type compact tokamaks—optimization studies will target the maximization of the Tritium Breeding Ratio (TBR), neutron shielding configuration, and activation minimization of structural materials. Overall, the project will deliver an integrated computational framework combining advanced numerical modeling, physics-informed machine learning, and optimization algorithms to support design, analysis, and decision-making for next-generation fission and fusion reactors.

Skills and competencies for the development of the activity	Background in nuclear engineering, with documented competencies in the physics of fast reactors and familiarity with both Monte Carlo and deterministic full-core modelling. Documented competencies in machine learning algorithms, especially evolutionary/genetic algorithms.