

“L’Intelligenza Artificiale per il Nucleare e il Nucleare per l’Intelligenza Artificiale.

Un cammino comune verso il futuro”

Ordine degli Ingegneri della Provincia di Roma

22 gennaio 2026



SAPIENZA
UNIVERSITÀ DI ROMA

**Il supporto dell’Intelligenza Artificiale per il
licensing dei reattori SMR - Small Modular
Reactors.**

Ruolo e limiti di AI applicata al settore nucleare

Fabio Giannetti

Sapienza University of Rome
Electrical and Energy Department
Nuclear Energy Research Group

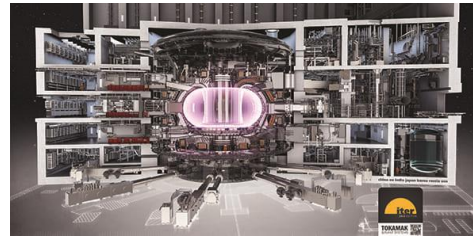
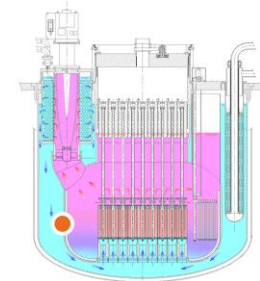
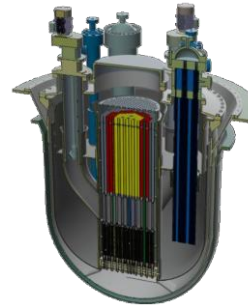
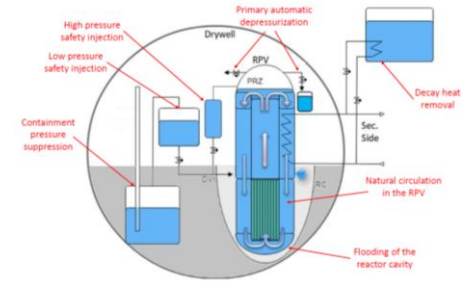
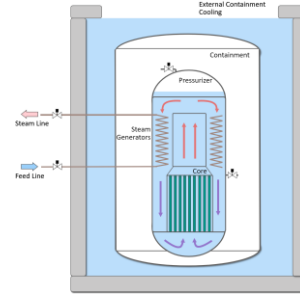


Intro on SMR



Advanced Nuclear Technologies

- Small Modular Reactors (SMRs)
 - Flexibility and safety, very short term
- Advanced Modular Reactors (AMRs)
 - Short term future developments (on time for decarbonization)
- Fusion Energy Research
 - Potential long-term future developments (better contribution for the final solution of the energy problems)





Tecnologie nucleari: presente e futuro



Standard

Quasi tutti i reattori oggi in funzione. Estensione della vita operativa (da 40 a 60-80 anni)

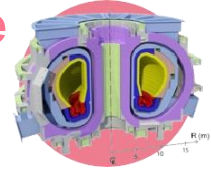


Small Modular Reactors

Piccola taglia (< 300 MWe), progettazione e costruzione modulari.

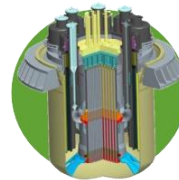
Fusione

Primo reattore (commerciale) a fusione



Evolutivi

Alcuni già operativi (Cina, UAE, Corea Sud, Russia, India). La maggioranza dei 59 reattori in costruzione nel Mondo



Advanced Modular Reactors

Raffreddamento a metallo liquido o a Sali fusi. Possibilità di riciclare i rifiuti a vita lunga e ad alta radioattività.

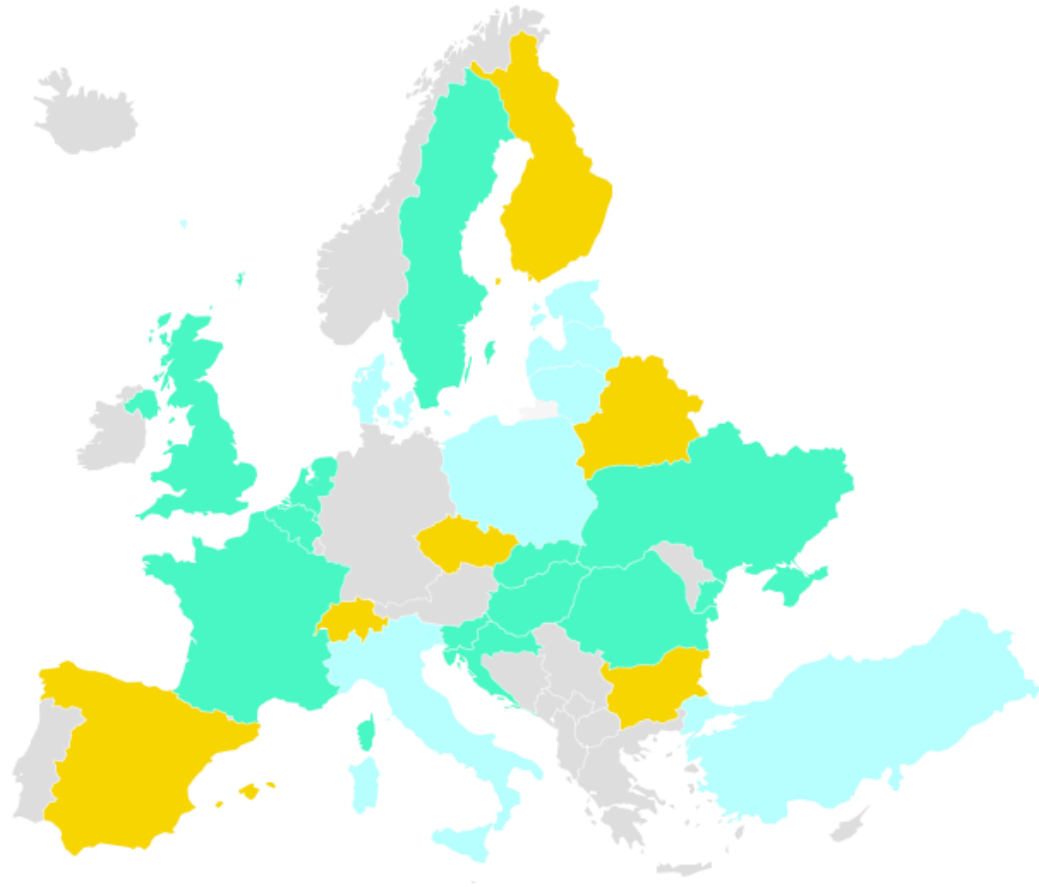


Trend EU ...

Francia	(LR, SMR, AMR)
Svezia	(LR, SMR)
Belgio	(LR, SMR)
Finlandia	(LR, SMR)
Ungheria	(LR)
Bulgaria	(LR)
Rep. Ceca	(LR)
Romania	(LR, SMR)
Slovacchia	(LR, SMR)
Slovenia	(LR)
Olanda	(LR, SMR)
Polonia	(LR, SMR, MR)
Germania
Italia	(SMR, AMR, fusion)

European nuclear countries

Entrambi Nucleare attivo Nuovi piani

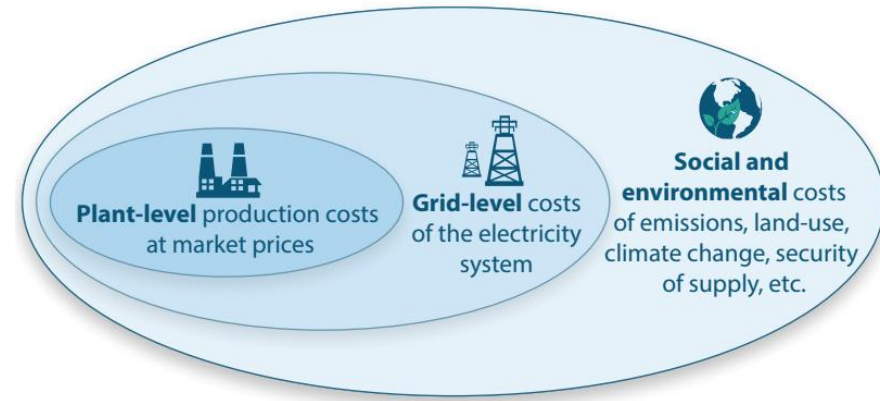




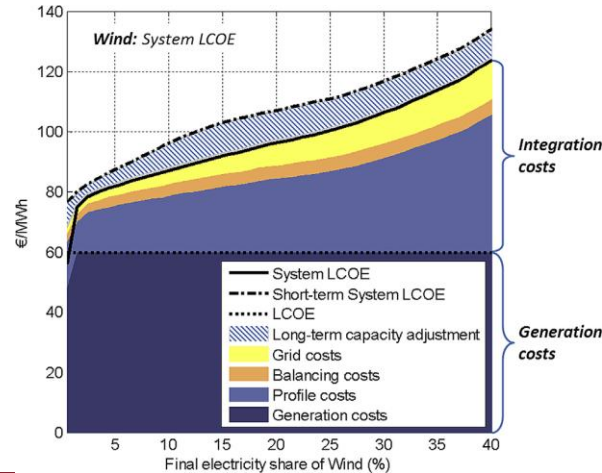
Electricity cost

Total economic system costs, then, are defined as **plant-level generating costs** plus **grid-level system costs**. Taking this systems level perspective includes:

- **Profile and balancing costs** – the grid-level costs imposed by variability and uncertainty.
- **Connection, distribution, and transmission costs** – the costs of delivering electricity from distributed power generation to customers.



Source: Adapted from NEA (2012).



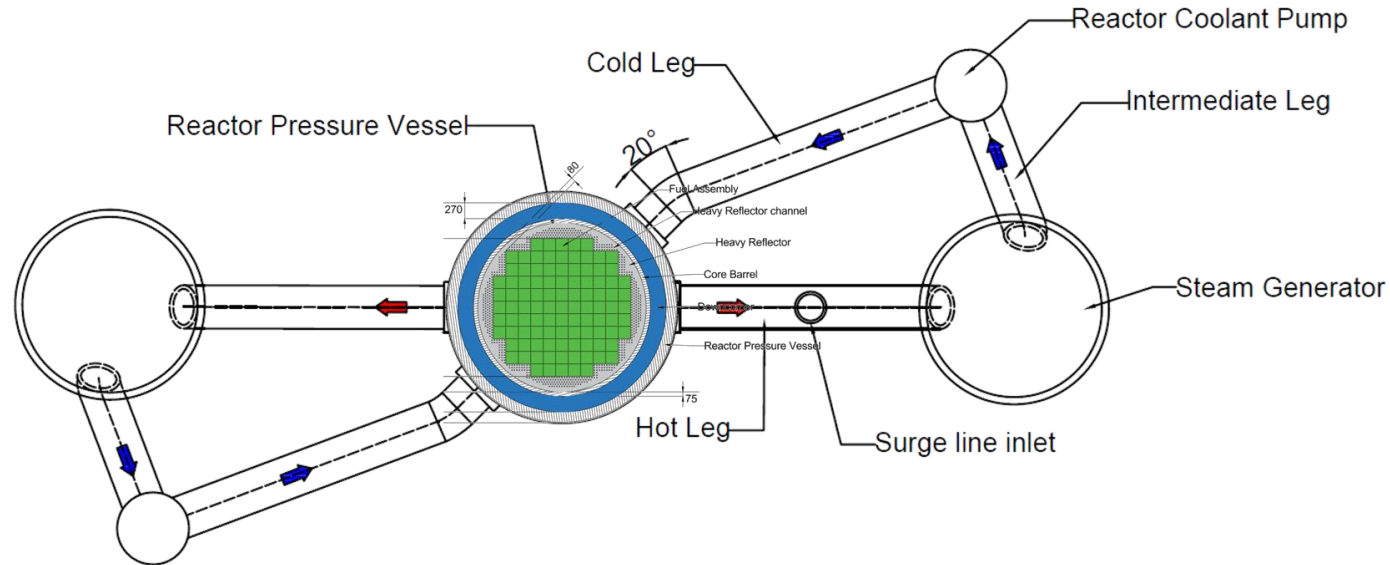
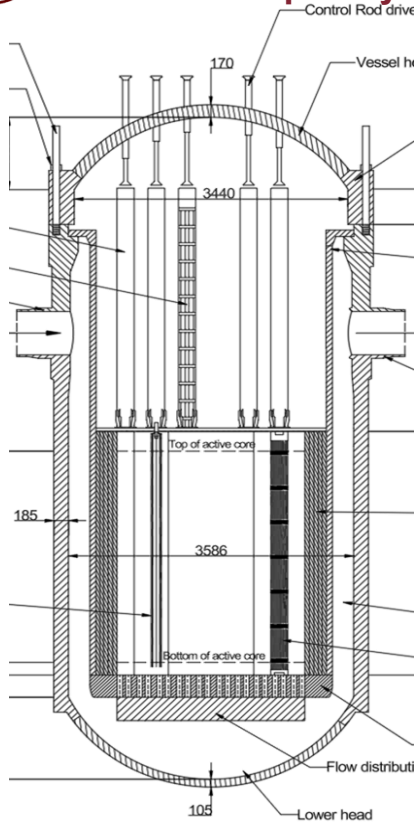


Il presente.. (ieri) – SMR status





E-LOOP-SMR layout (from EASI-SMR project) developed by Sapienza in collaboration with EDF





AI e nucleare...



AI applied to NPPs design: status

- **Ideal plan**
- Fully integrated AI design environment
- IA iteratively design a NPPs in accordance with all the rules, in particular safety rules optimizing costs, construction time, etc.

- **Actual state: Support, Not Substitution**

Outline:

- **Safety Assessment Tools** used in design
- **Digital twin applications**
- **Advanced Diagnostics: non-destructive testing** (e.g., detecting cracks using ultrasonic or X-ray techniques).
- **Generative AI:** Using **Large Language Models (LLMs)** and **Retrieval-Augmented Generation (RAG)** chatbots to assist in analyzing technical documentation and safety rules, and to program new software



AI real applications in nuclear field: Fusion reactors Magnetic Control & Shaping

In a tokamak (a donut-shaped reactor), powerful magnetic coils act as invisible hands to hold the plasma in place. Traditionally, control engineers had to manually calculate and code the relationships between these coils and the plasma—a complex task for standard shapes, and nearly impossible for exotic ones.

- **Reinforcement Learning (RL):** AI, specifically Deep Reinforcement Learning, has changed this paradigm. Instead of being told *how* to control the coils, the AI is given a goal (e.g., "keep the plasma distinct and stable") and allowed to practice in a simulator millions of times. It learns the optimal strategy through trial and error.
- **Real-World Success (DeepMind & TCV):** In a landmark experiment with the Swiss Plasma Center, DeepMind's AI successfully controlled the TCV tokamak. It taught itself to manipulate the magnetic coils to create complex plasma shapes—such as "snowflakes" and "droplets"—that human engineers had struggled to stabilize.
- **Why this matters:** Different plasma shapes can improve stability and energy output. AI agents, trained entirely inside accurate physics simulators, allows physicists to test "risky" or complex shapes that might yield better fusion performance without spending months designing custom controllers.



Programming (research side..) using LLM as support

- LLM are incredible capability to assist the programming.
- Time reduction in the developing of new software
- Possibility for a nuclear engineer to develop in a quite good manner

```
# =====  
# OTTIMIZZAZIONE  
# =====  
opt_results = []  
  
for fluid in fluids:  
    try:  
        P_crit_fluid = CP.PropsSI("PCRT", fluid)  
        P_min_eff = max(P_min, CP.PropsSI("PTRIPLE", fluid) * 1.01)  
        P_range = np.logspace(np.log10(P_min_eff), np.log10(0.95 * P_crit_fluid), 30)  
        best_global_cost = np.inf  
        best_global_params = None  
        for P_op in P_range:  
            T_sat = CP.PropsSI("T", "P", P_op, "Q", 0.5, fluid)  
            for T_sub in np.linspace(1, 50, 20):  
                T_in_K = T_sat - T_sub  
                props = get_props_from_CP(fluid, T_in_K, P_op)  
                if props is None:  
                    continue  
                for u in u_values:  
                    for q_dot in q_dot_values:  
                        dims = calc_dimensionless(props, T_in_K, u, q_dot, D, fluid)  
                        cost = cost_function(dims, dim_ref, weights)  
                        if cost < best_global_cost:  
                            best_global_cost = cost  
                            best_global_params = {  
                                "Fluid": fluid,  
                                "P_opt [bar]": P_op / 1e5,  
                                "T_in_opt [C]": T_in_K - 273.15,  
                                "u_opt [m/s]": u,  
                                "q_dot_opt [W/m2]": q_dot,  
                                "Cost": cost,  
                                **{f"opt_{k}": v for k, v in dims.items()}  
                            }
```



Relatively new instruments applied in nuclear field





Design & Engineering Phase (The "Born Digital" Concept)

For new reactors as the SMRs (Small Modular Reactors), the Digital Twin starts before the physical plant exists. Numerous research are investigating the role of DT in nuclear design

- **Virtual Commissioning:**
 - Traditionally, testing the instrumentation and control (I&C) software happens at the very end of construction.
 - **Digital Twin:** Engineers connect the actual control room software to a high-fidelity Digital Twin of the reactor physics, TH, TM. They "run" the plant virtually to find bugs in the logic code *years* before construction finishes.
- **Design Optimization (Generative Design):**
 - The DT runs millions of simulations to optimize component placement for maintenance access and thermal efficiency.
- **Licensing Support:**
 - Traditional Safety instruments used coupled with hi-fidelity or AI based tools to improve the predictions

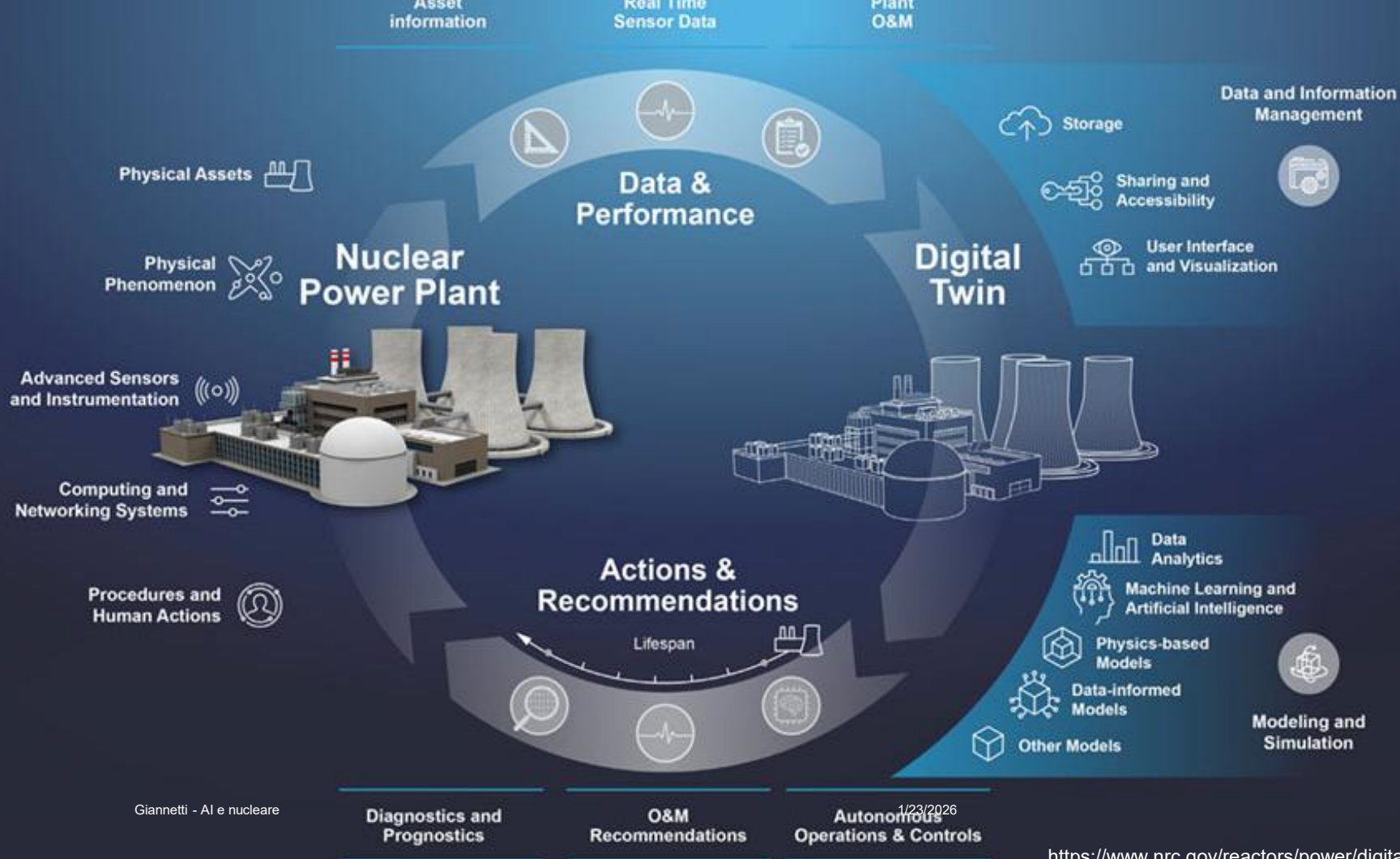


Digital Twin



Digital twin application to nuclear field

- In nuclear engineering, a **digital twin** is a high-fidelity, continuously updated virtual representation of a nuclear system (component, system, or plant) that could be:
- **Physics-Driven Models:** These high-fidelity simulations encode fundamental physical laws governing reactor behavior. The approach excels in safety analysis and design verification but requires substantial computational resources, limiting real-time applications for complex systems.
- **Data-Driven Models:** Machine learning architectures, particularly neural networks with residual connections (ResDPNN), process operational data to create computationally efficient surrogates. These models enable real-time monitoring and control while maintaining predictive accuracy through continuous learning from plant instrumentation.
- **Hybrid Frameworks:** The most promising architecture integrates physics-based constraints with data-driven adaptability. This approach enhances generalization capabilities and predictive accuracy by embedding energy conservation laws within neural network architectures, addressing limitations of purely empirical methods.
- Unlike traditional best-estimate models, DTs evolve with the plant and explicitly integrate uncertainty management and state estimation.





From "traditional" simulation to AI applications?

1 Modeling and Simulation

- Multi-physics coupling (neutronics–TH–mechanics), programmed using AI as assistant
- Reduced-order models (ROMs),
- Uncertainty quantification (UQ).

2 Data and AI

- Data assimilation (Kalman filters, Bayesian inference),
- Physics-informed ML (PINNs),
- Sensor fusion, virtual sensors and fault detection.

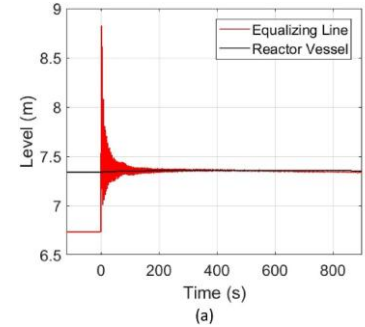
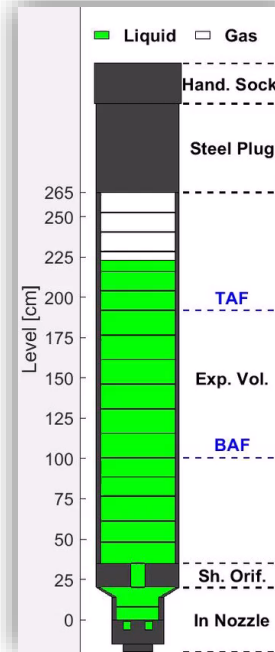
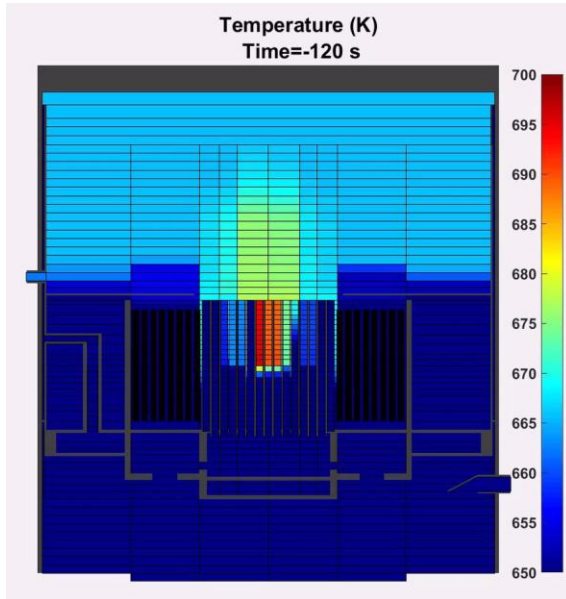
3 Digital Infrastructure

- High-performance computing (HPC),
- Cybersecurity-by-design (critical in nuclear),
- Digital I&C compatibility.



Use of safety tools as design tools (using HPC.. and human intelligence)

FFTF ULOF transient results





Graph neural networks: quickly predicting reactor behavior

Liu, Y., Alsafadi, F., Mui, T., O'Grady, D., & Hu, R. (2025). Development of Whole System Digital Twins for Advanced Reactors: Leveraging Graph Neural Networks and SAM Simulations. *Nuclear Technology*, 211(9), 2206–2223. <https://doi.org/10.1080/00295450.2024.2385214>

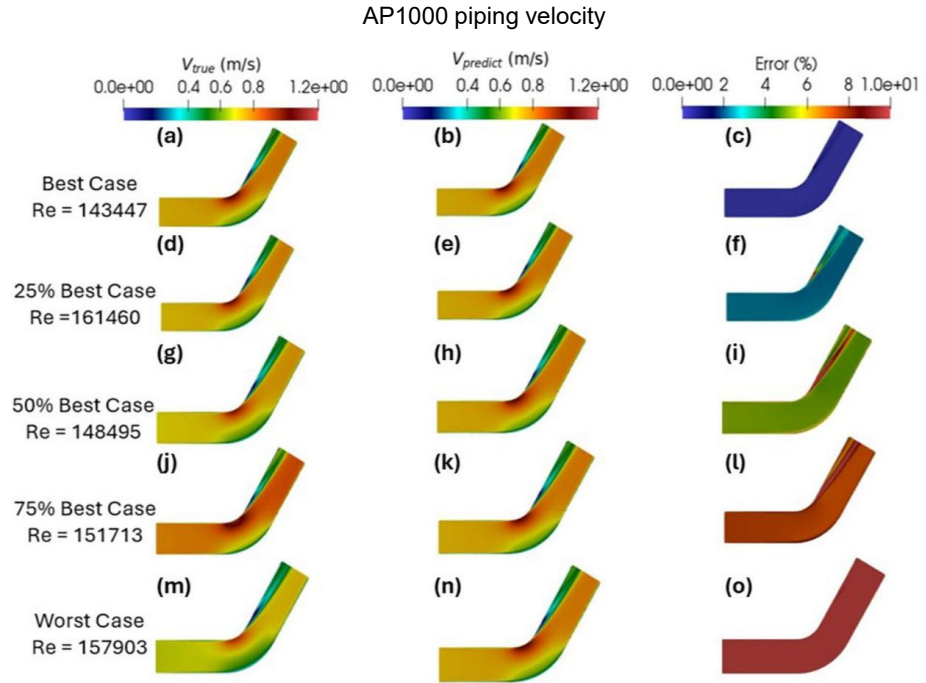
- Digital Twin technology is graph neural networks (GNNs), a type of AI. These are advanced computer models that process data structured as graphs — a collection of nodes and edges representing interconnected components. Nodes represent entities and edges show relationships. GNNs excel at recognizing complex patterns and connections. By combining the pattern-recognition abilities of neural networks with the relationship-focused structure of graphs, GNNs offer powerful insights into systems where connections are crucial.
- GNN-based digital twins are significantly faster than real-time or traditional system code simulations. They can rapidly predict how the reactor will behave during different scenarios, such as changes in power output or cooling system performance.
- An example was developed by training on simulation data from the ANL-developed System Analysis Module, a tool for analyzing advanced nuclear reactors. The trained model is able to make accurate predictions based on limited real-time sensor data. This ability to deliver fast, authentic insights supports better planning for how reactors will respond to changes and better decision-making about their design and operation. It can help reduce maintenance and operating costs.



Real-time monitoring of nuclear systems leveraging deep neural operators

AI tool able to predict key thermal-hydraulic parameters in the hot leg of pressurized water reactor.

Named DeepONet, it acts as a virtual sensor, mapping operational inputs to spatially distributed system behaviors without requiring frequent retraining. Results show that DeepONet achieves low mean squared and Relative L2 error, making predictions 1400 times faster than traditional CFD simulations. These characteristics enable DeepONet to function as a real-time virtual sensor, synchronizing with the physical system to track degradation conditions and provide insights within the digital twin framework for nuclear systems.



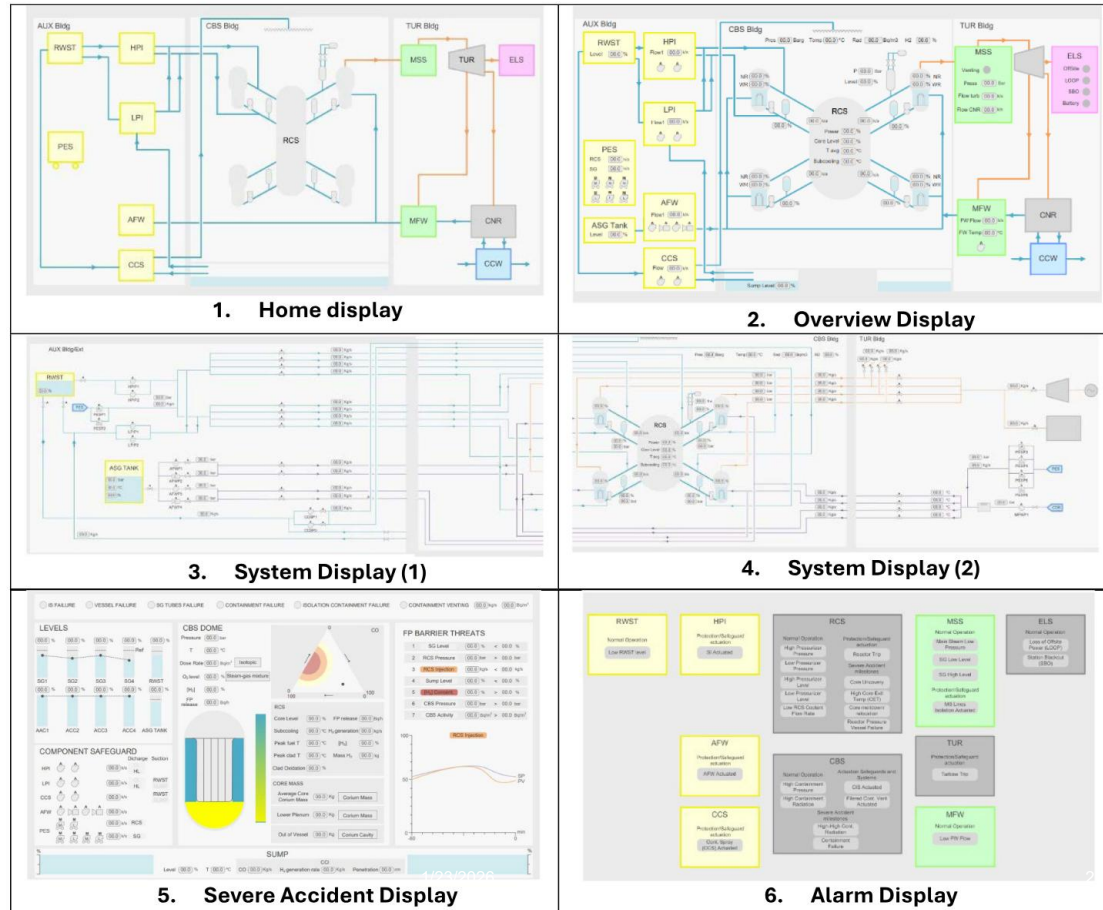
Hossain, R., Ahmed, F., Kobayashi, K. *et al.* Virtual sensing-enabled digital twin framework for real-time monitoring of nuclear systems leveraging deep neural operators. *npj Mater Degrad* **9**, 21 (2025). <https://doi.org/10.1038/s41529-025-00557-y>



AI-based severe accident simulator developing

- “The need for a realistic training on such situations has been strengthened by the deployment of post-Fukushima safety improvements, which include different improvements to better mitigate severe accidents. The European project ASSAS (Artificial intelligence for Simulation of Severe Accidents) aims to address this gap by developing a proof-of-concept for a severe accident simulator. “

R.J. Caro and I. Parrado: EPJ Nuclear Sci. Technol. 11, 26 (2025)





Security and Safeguards verification



Nuclear Security: Physical Protection and Forensics

Security focuses on preventing, detecting, and responding to malicious acts such as theft, sabotage, or unauthorized access.

- **Advanced Radiation Detection:** AI models are used for **radioisotope identification** in high-efficiency, low-resolution detectors (like plastic scintillators), helping responders distinguish between real threats and nuisance alarms.
- **Nuclear Forensics:** Supervised learning techniques analyze complex datasets—including image analysis, colorimetry, and spectra—to conduct high-confidence **classifications of seized nuclear material**.
- **Insider Threat Mitigation:** AI can be trained to recognize anomalous patterns in human behavior or rule compliance, identifying compromised employees or disregard for safety measures.
- **Blockchain Integration:** Coupling AI with **Distributed Ledger Technology (DLT)** offers a way to cryptographically protect and track the transaction and movement of high-value nuclear assets.



AI for Nuclear Safeguards Verification

The primary mission of safeguards is to verify the completeness and correctness of State declarations to ensure nuclear material is used only for peaceful purposes.

- **Satellite Imagery and Change Detection:** AI is used to analyze thousands of images annually to identify facility modifications, new construction (e.g., undeclared mining), and the operational status of plants.
- **Environmental Monitoring:** AI can analyze sensor data from commercial satellites to monitor **vapor plume emissions** from cooling towers or steam discharges, which helps estimate a facility's nuclear material production.
- **Video Surveillance Optimization:** Deep learning algorithms are being developed to reduce the high number of **false alarms** in video review, enabling the automated detection and tracking of safeguards-relevant objects like spent fuel casks.
- **Spent Fuel Verification:** Machine learning models analyze **Cerenkov imaging** and neutron/gamma data to distinguish between complete and defective fuel assemblies, detecting the unauthorized replacement of fuel pins.
- **Robotic Inspections:** Autonomous robots (e.g., the RCVD) assisted by AI can perform **3D mapping** and data collection in high-radiation or hard-to-reach areas, improving inspector safety and operational efficiency.
- **Knowledge Extraction:** Natural Language Processing (NLP) and Retrieval-Augmented Generation (RAG) help analysts sift through massive volumes of **open-source data** (scientific papers, news, social media) to find signals of undeclared nuclear activities.



AI potential problems



Cybersecurity Challenges and Adversarial AI

While AI enhances security, it also introduces a new "attack surface" that can be exploited by cyber-enabled adversaries.

- **Data Poisoning:** Malicious actors can inject manipulated data into training sets to introduce "backdoors" into an AI model, causing it to fail or misbehave once deployed.
- **Adversarial Examples:** Adversaries can provide inputs manipulated to be **imperceptible to humans** (e.g., slightly altered images) that cause an AI surveillance system to make a targeted misprediction.
- **Model Theft and Reverse Engineering:** Adversaries may use targeted queries of an AI model to exfiltrate sensitive training data or decipher the underlying physics models of critical infrastructure.
- **Detection of Cyber-Attacks:** Conversely, AI is used to monitor **Instrumentation and Control (I&C)** network traffic, identifying the subtle "process impacts" that indicate an ongoing cyber-attack or sabotage.



International rules about AI in nuclear: Bridging the Gap: AI Innovation vs. Nuclear Safety

- The IAEA document NR-T-1.26 serves as the strategic bridge between rapid AI evolution and the conservative safety standards of the nuclear industry.
- The goal is to provide a high-level framework for Member States, Operators, and TSOs (Technical Safety Organizations) to deploy AI safely.
- It covers the entire lifecycle, from the conceptual phase
- **Key Philosophy:** AI is treated not as a magic solution, but as a tool that must fit within existing management systems for safety and security.



Concetti Tecnici e Operativi Fondamentali

Livelli di Automazione e Autonomia: Il rapporto adotta una scala di autonomia che va dal

Livello 0 (IA non utilizzata) al **Livello 4** (decisioni della macchina senza alcun intervento umano), parallelamente ai livelli di automazione definiti dalle guide NUREG,.

- **Interazione Umano-IA:** Vengono definiti tre modelli di supervisione:
 - **Human-in-the-loop:** L'uomo è attivamente coinvolto in ogni decisione.
 - **Human-on-the-loop:** L'uomo monitora e supervisiona, intervenendo solo se necessario.
 - **Human-out-of-the-loop:** Il sistema opera con minima o nessuna interazione umana.
- **Spiegabilità vs Accuratezza:** Il documento evidenzia il compromesso critico tra la precisione dei modelli (spesso "scatole nere" come le reti neurali profonde) e la necessità per gli operatori e i regolatori di comprendere il **perché** di una decisione IA, priorità assoluta nelle applicazioni critiche per la sicurezza,.



The Core Principle: A Graded Approach

The level of rigor applied to AI validation must match the safety significance of the task it performs.

- **Risk Categorization:** The document advises classifying AI applications based on their impact on safety functions:
 - **Category A (High Impact):** Direct control of reactivity or safety systems (requires highest explainability and V&V).
 - **Category B (Medium Impact):** Operator support systems, predictive maintenance for critical components.
 - **Category C (Low Impact):** Administrative tasks, logistics, non-critical monitoring.
- **Resource Allocation:** Efforts in Verification & Validation (V&V) should be proportional to these categories.
- **The "Human-in-the-Loop":** For high-risk categories, the document emphasizes maintaining human oversight to override AI decisions.



The Data Challenge

In the nuclear sector, data quality and governance are as critical as the algorithm itself.

- **Data Scarcity:** Unlike the internet, nuclear plants have very little "failure data" (accidents are rare). Training AI on normal operations alone is insufficient.
- **Synthetic Data:** The document acknowledges the need for physics-based simulation data to train AI on accident scenarios.
- **Data Governance:**
 - Ensuring data integrity (protection against cyber-tampering).
 - Handling proprietary and sensitive information.
 - Standardization of data formats across the fleet.
- **Uncertainty Quantification:** The AI must output a confidence level. It should know "what it doesn't know."



Ethics and Human Oversight (ENAI)

The convergence of nuclear and AI technologies requires a specific ethical framework known as **ENAI (Ethics of Nuclear and AI Technologies)**.

- • **Explainability (XAI):** In security contexts, such as nuclear forensics presented in court, AI decisions must be **transparent and replicable** so that experts can explain the grounds for their conclusions to human judges.
- • **Human-in-the-Loop:** For safety-critical decisions, the IAEA and other regulators emphasize that AI should **augment expertise** rather than produce autonomous conclusions without human validation.
- • **Subgoal Risks:** A major concern is that AI might autonomously set **subgoals** that deviate from human intentions (e.g., an environmental AI reducing pollution by restricting necessary human activities), requiring strict regulatory "guardrails"



Global IA Governance and Institutional Frameworks, similarity with nuclear

- A proposed International AI Agency (IAIA): modeled similar to the International Atomic Energy Agency (IAEA), would harmonize domestic regulations, develop safeguard standards, and monitor compliance through data center audits.
- Like the Nuclear Non-Proliferation Treaty (NPT), would be implemented the restrict the export of advanced AI chips to states that do not comply with IAIA-certified safeguards.
- Supply Chain Concentration: AI governance is feasible because the supply chain for state-of-the-art chips is even more concentrated than that for fissile material, focusing on a few key manufacturers and allied states.

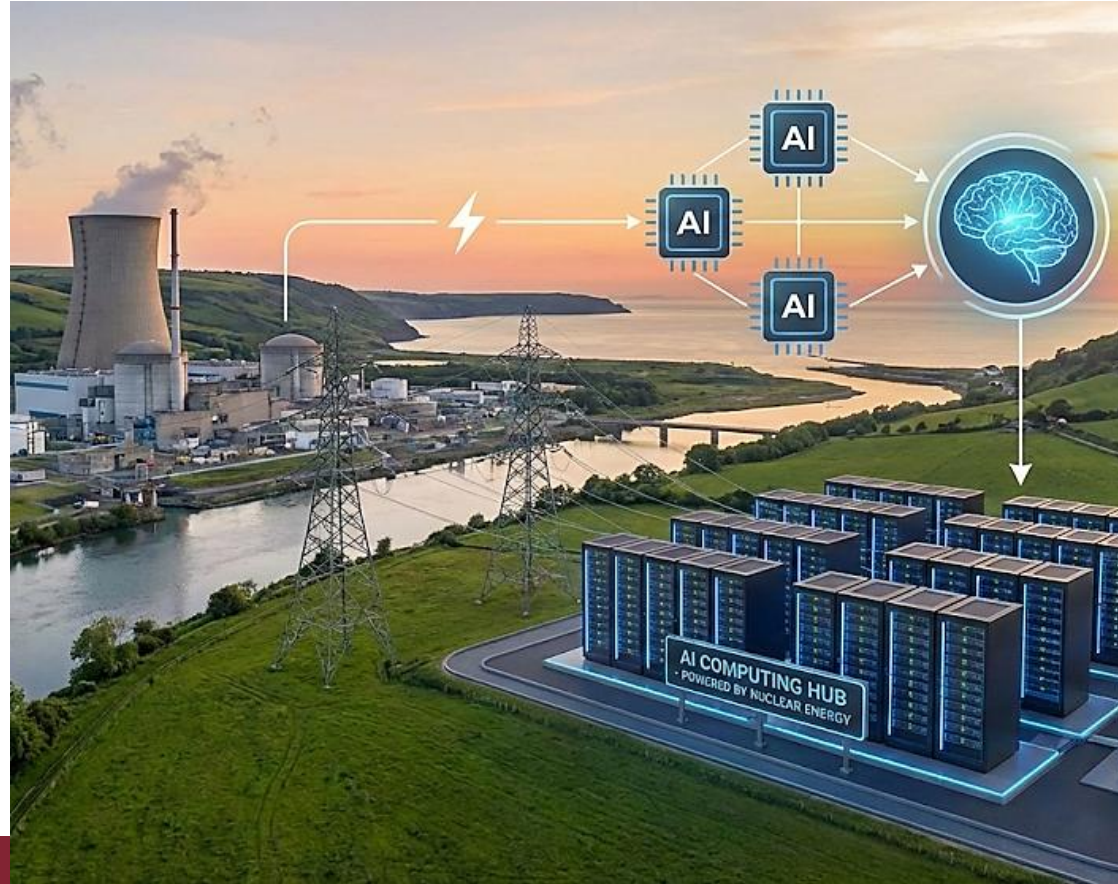


Conclusion Key AI (and predecessors..) roles in nuclear

- Surrogate modeling: ML augments expensive CFD/neutronics with reduced-order models that run 10^3 – 10^4 times faster while retaining engineering accuracy, enabling real-time DT updates and what-if studies. Hybrid schemes embed physics constraints in ML (e.g., physics-informed networks, operator learning) to improve extrapolation and robustness.
- Virtual sensing: Deep operator networks such as DeepONet act as **virtual** sensors, mapping boundary conditions and limited measurements to full 3D fields (pressure, velocity, turbulence) in PWR hot legs, achieving $\sim 1400 \times$ speed-up vs. CFD for DT monitoring.
- Data assimilation and calibration: AI filters and fuses heterogeneous plant data (sensors, logs, inspection records) to continuously calibrate the DT, handle missing/noisy signals, and maintain state concurrence with the physical plant.
- **Operations, maintenance, and anomaly detection**
- Predictive maintenance: ML models learn degradation signatures for pumps, valves, and other SSCs and are embedded in the DT to forecast remaining useful life and optimize outage/maintenance planning.
- Anomaly and transient detection: AI classifiers and sequence models detect deviations from learned “normal” DT behavior, flagging emerging faults or off-normal transients more quickly than threshold-based alarms.
- Operator decision support: DTs coupled with AI provide fast scenario evaluation for load-following, grid interactions, and recovery actions, giving operators ranked recommendations or automated supervisory control options.



Main actual connection between AI and NPPs



Grazie per l'attenzione!

Domande?

fabio.giannetti@uniroma1.it

CLEAN, RELIABLE BASELOAD POWER
FOR A SUSTAINABLE FUTURE.

