FISA EURADWASTE 2025

SNETP Forum

MACHINE LEARNING BASED MODELS FOR HPC THERMOMECHANICAL FUEL ASSESSMENT

Rosa Lo Frano[1], Salvatore A. Cancemi[1], Mantas Povilaitis[2], Andrius Ambrutis[2], Francisco Feria[3], Luis E. Herranz[3], Isabelle Ramiere[4], Rordigue Largenton[5] Simone Gianfelici[6], Marco Cherubini[7]

[1]DICI-University of Pisa, lg. L. Lazzarino, n.2, 56126 Pisa (IT), [2] Lithuanian Energy Iinstiutute, Breslaujos g. 3, 44403, Kaunas (LT), [3]CIEMAT, Avda. Complutense, 40, 28040 Madrid (ES), [4]CEA Cadarache, Saint Paul lez Durance (FR), [5]Electricité de France, 22-30, avenue de Wagram, Paris (FR), [6]ENEA Centro Ricerche Bologna, Via Martiri di Monte Sole 4, Bologna (IT), [7]Nuclear and Industrial Engineering (NINE), Lucca (IT)

Introduction

The investigation of thermomechanical behavior of fuel elements, in off-normal and flexible operational conditions, requires improved HPC simulations to represent the complexity and real multiplicity of phenomena, such as PCMI or FO.

To answer this challenge advanced tools are used in the OperaHPC project.

Study Motivations

(1) PCMI importance to LWR fuel design and licensing;

(2) Potential for significant differences in modelling; and

(3) Modelling limitations of previous investigations.

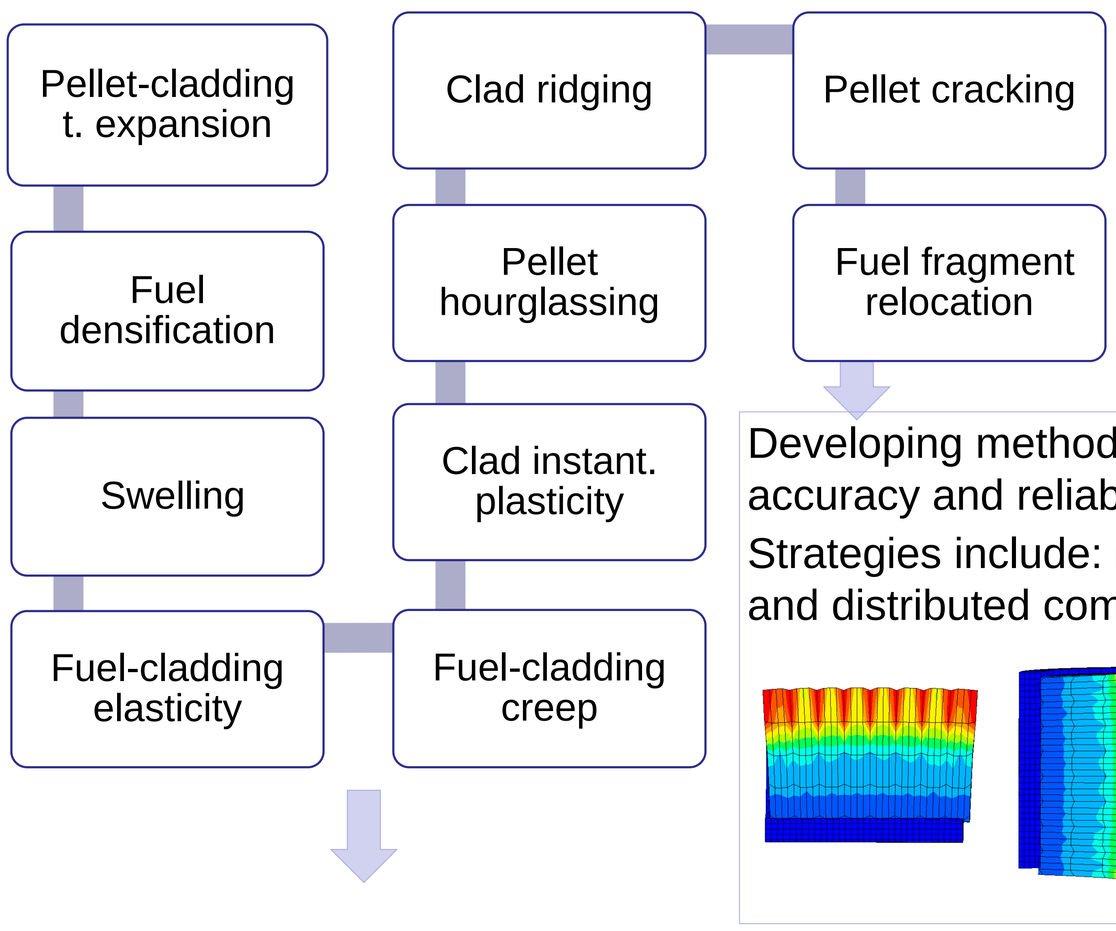
Objectives

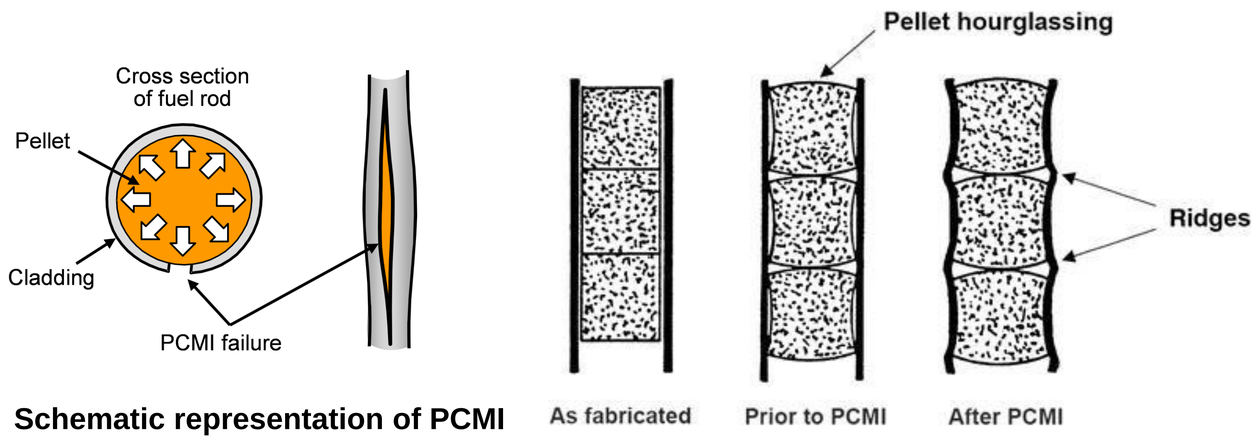
- Propose **physics-independent** approaches
- Develop **machine learning** based **reduced-order** fast-running **models** (ML-ROM) to implement in fuel performance codes or in standalone mode.

Description of the research problem

In NPPs real-time monitoring is essential to prevent anomaly, malfunction, and emergency that can jeopardize the safety.

PCMI can lead to the cladding failure. Mechanical loadings are responsible of gap closure, pellet swelling (thermal and gaseous) and mechanical behavior (volume expansion accommodation by creep), fragmentation and hourglass shape (f(σ,ε)).

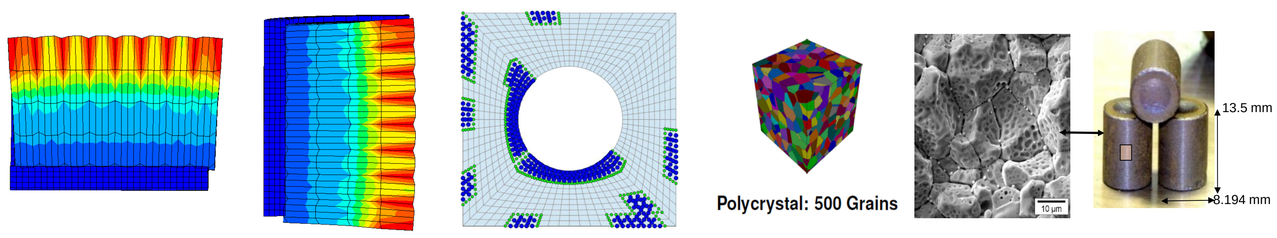




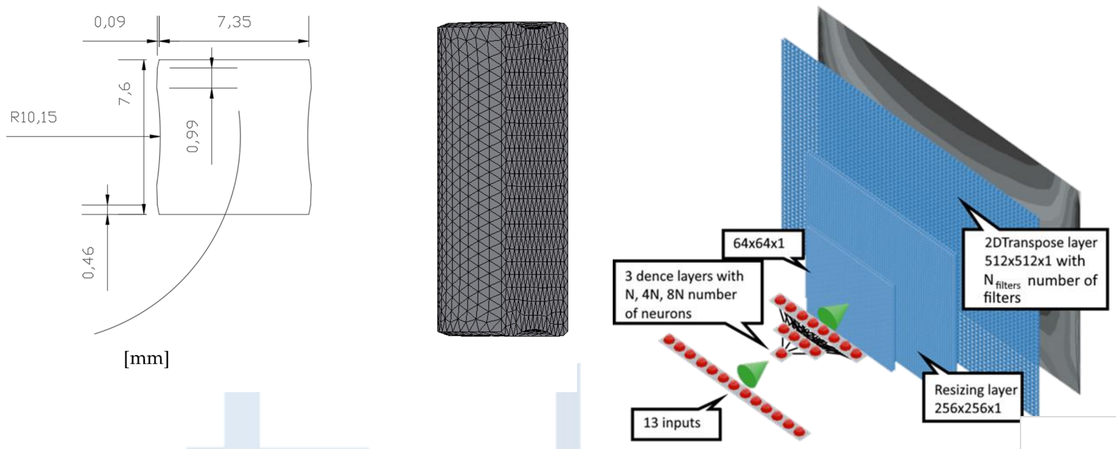
Schematic representation of PCMI

Developing methods to reduce computation time without compromising ML models' accuracy and reliability is of paramount importance.

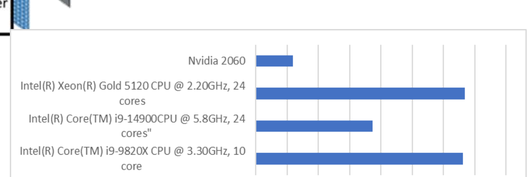
Strategies include: model compression, efficient algorithms, hybrid approaches, parallel and distributed computing, algorithmic optimizations, real-time data processing, etc.



CNN model Architecture: N (neurons) and Nfilters are numbers from hyperparameter optimization that can differ for each model



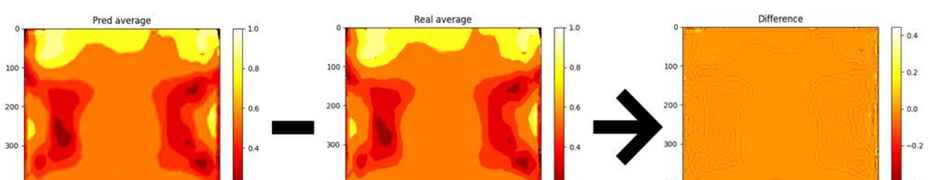
2D and 3D Fuel Pellet Model (left), CNN models (right)



Results

Model's performance was evaluate comparing predicted output matrices vs the actual ground truth data.

Visual comparisons of the real vs predicted images were made for several test samples, highlighting the model's ability to accurately predict spatial variations of mechanical properties.



Conclusion

ML-ROM demonstrates significant HPC while maintaining high accuracy level.

Integrating advanced AI techniques, a significant computational time reduction is obtained: less than 1s vs about 17 s for full FE-analysis for stress analysis.

Improved algorithms and tools for comprehensive/multiscale fuel performance analysis are required, e.g. including more changing input.

Funded by the European Union under Grant Agreement n°101061453