# A Node-Assigned PINN Model for Coupled Heat Transfer Calculations in a PWR Hot Channel

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## INTRODUCTION

Physics-Informed Neural Networks (PINNs) have emerged as a transformative approach for scientific computing [1]. By embedding governing partial differential equations (PDEs) directly into the loss function of deep learning models, PINNs can solve complex physical problems within a continuous differentiable framework [2]. However, the direct application of *vanilla* PINNs to full-scale nuclear reactor systems remains challenging due to strong spatial heterogeneity in the governing equations across different components [3].

To address this limitation, the node-assigned PINN (NA-PINN) approach is proposed. NA-PINN assigns dedicated neural sub-networks to individual physical nodes such as volumes and junctions, thereby closely mirroring the nodalization strategy employed in traditional benchmarked thermal-hydraulic (T/H) codes. In this work, we develop the NA-PINN architecture, a RELAP5-3D hot channel configuration with fully coupled fuel-cladding-coolant physics (Fig. 1) of a pressurized water reactor (PWR). A cold-leg break loss of coolant (LOCA) case study has been demonstrated.

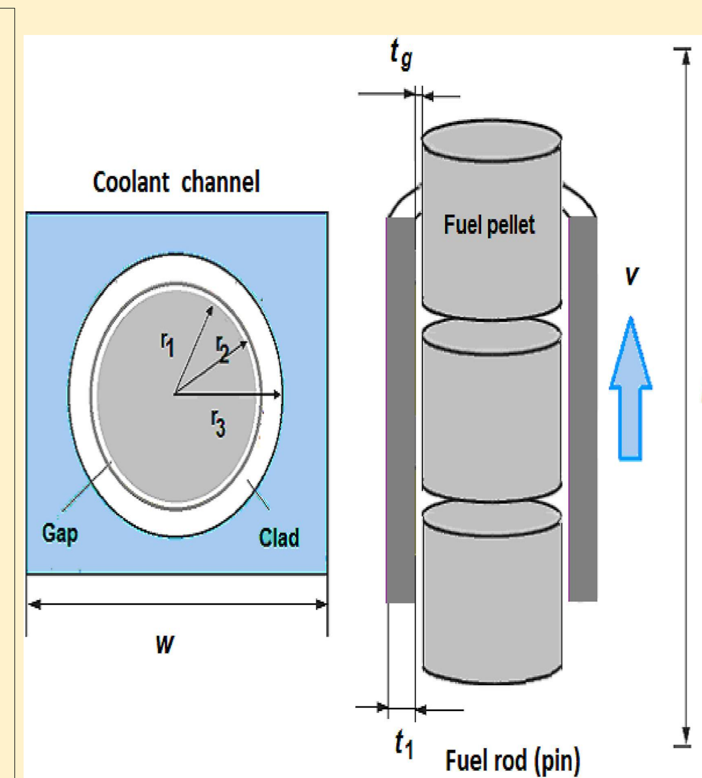


Figure 1. View and description of fuel rod (pin)

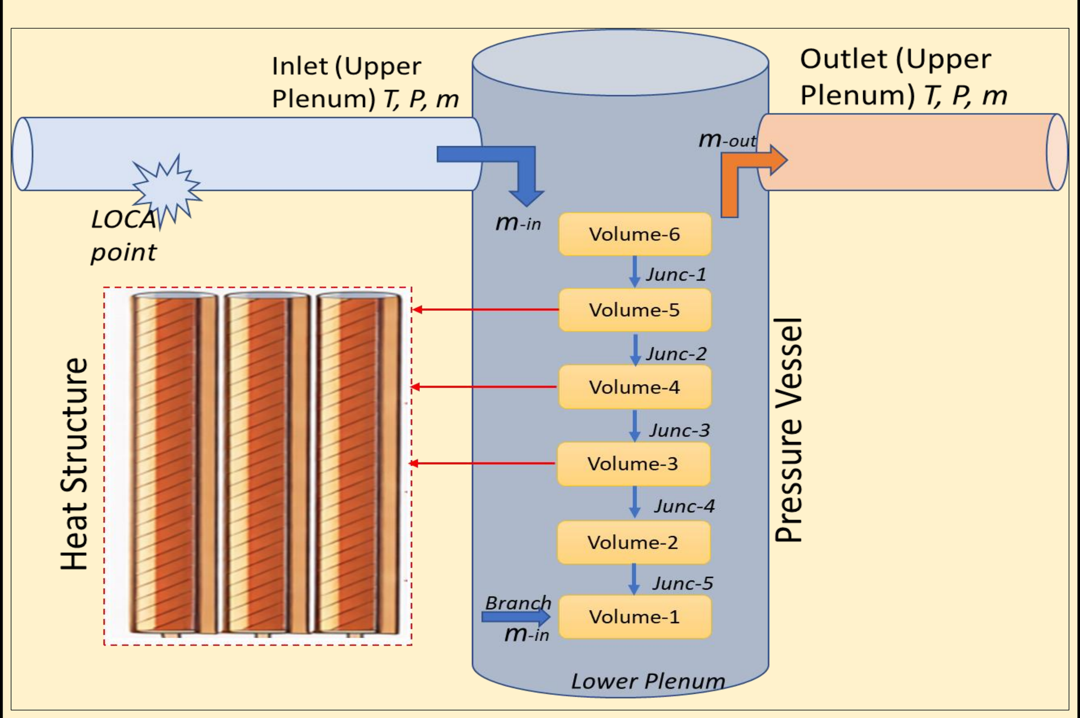


Figure 2. Coolant Channel Nodalization.

## BACKGROUND

The reactor hot channel and its associated fuel-rod heat structures are isolated as shown in Fig. 2. To integrate the heat structures, radial heat conduction equations for fuel pellets and cladding are embedded directly into the NA-PINN loss function.

To model single-phase flow conditions, the NA-PINN architecture is adapted to handle the steep pressure and temperature gradients characteristics of cold-leg break transients. To ensure strict enforcement of physical constraints, the shifting method is employed to impose initial plant conditions, guaranteeing that the neural-network solution is fully consistent with the PWR steady-state conditions at the onset of the break using the following additive Eq 1.

$$\hat{u}(t) = \mathcal{N}(t) - \mathcal{N}(t_{start}) + u_{RELAP}(t_{start}) \quad (1)$$

## METHODOLOGY

### a) Governing Equations

Conservation of energy in the axial volume of the PWR reactor core

$$\rho_{f,i} V_i C_{p,f} \frac{dT_{f,i}}{dt} = \dot{m}_{in,i} C_{p,f} T_{f,i-1} - \dot{m}_{out,i} C_{p,f} T_{f,i} + h_i A_i \left(T_{s,i} - T_{f,i}\right) \quad (2)$$

Fuel rod cladding thermal behavior

$$\rho_s V_{s,i} C_{p,s} \frac{dT_{s,i}}{dt} = Q_i - h_i A_i \left(T_{s,i} - T_{f,i}\right) \quad (3)$$

### B) Physics-Informed Loss Formulation

$$\mathcal{L}_{Total} = \omega_D \mathcal{L}_{Data} + \omega_P \left(\mathcal{L}_{Coolant} + \mathcal{L}_{clad}\right) \quad (4)$$

The loss function was weighted using $\omega_D = 1.0$ and $\omega_P = 0.05$

Here the data loss function is

$$\mathcal{L}_{Data} = \frac{1}{N} \sum_{i=1}^{N} \left\| \hat{T}_i - T_{RELAP,i} \right\|^2 \quad (5)$$

The coolant residual is

$$\mathcal{L}_{coolant} = \rho V C_P \frac{d\hat{T}}{dt} - \left[\sum(\dot{m} C_p T)_{in} - \sum(\dot{m} C_p T)_{out} + Q_{conv}\right] \quad (6)$$

The clad residual is

$$\mathcal{L}_{clad} = \rho_s V_s C_{P,s} \frac{d\hat{T}}{dt} - \left[Q - hA\left(\hat{T}_s - \hat{T}_f\right)\right] \quad (7)$$

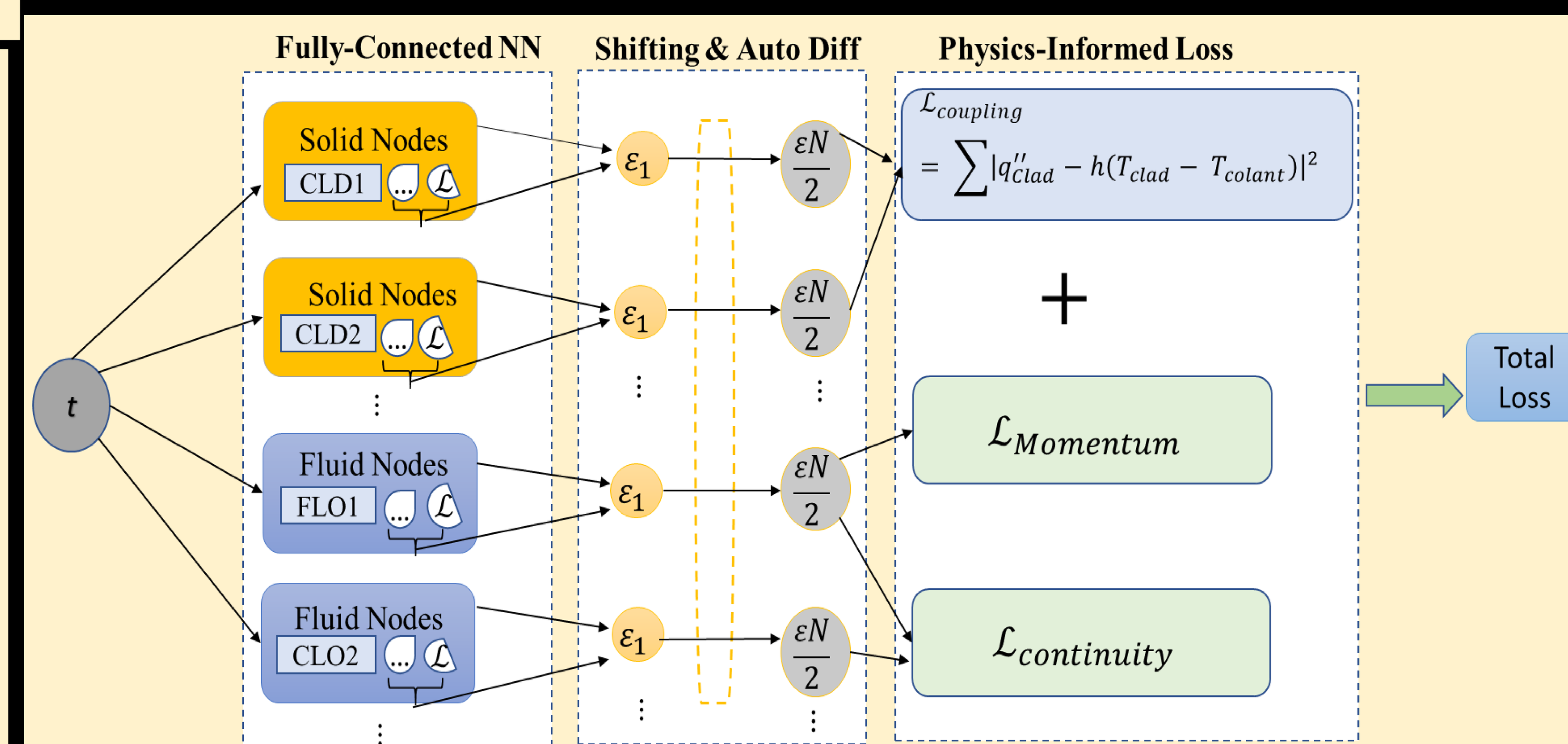


Figure 3. The NA-PINN Architecture.

## RESULTS

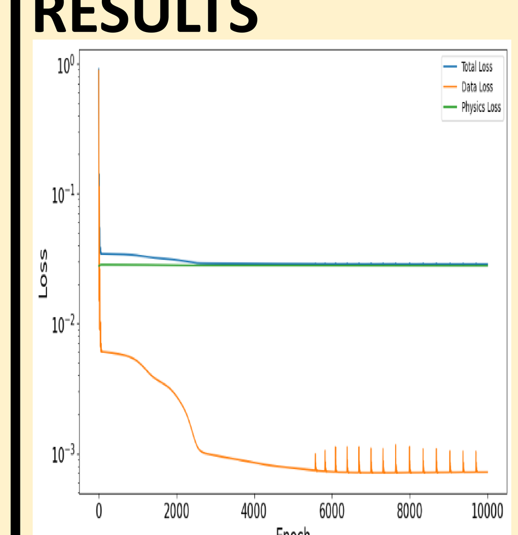


Figure 4. NA-PINN Training History

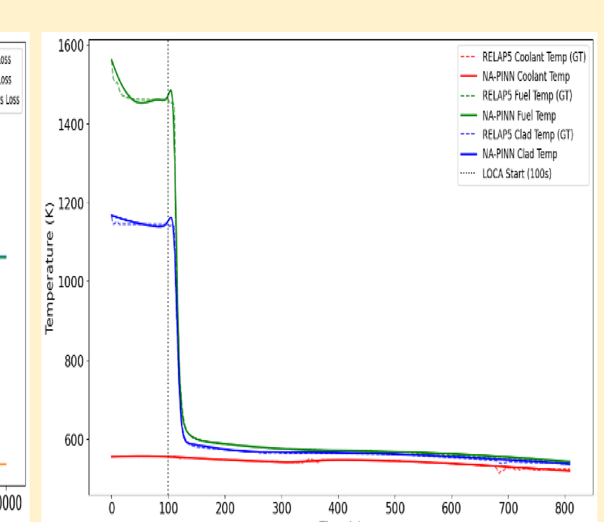


Figure 5.Coolant, fuel and clad temp transient

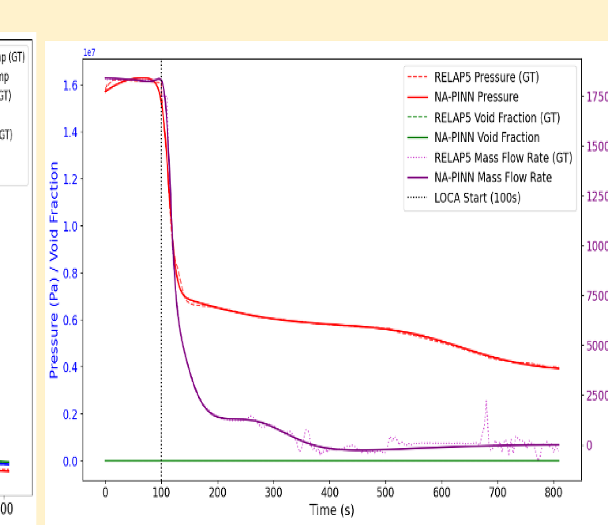


Figure 6. Void fraction, pressure and mass flow rate transient

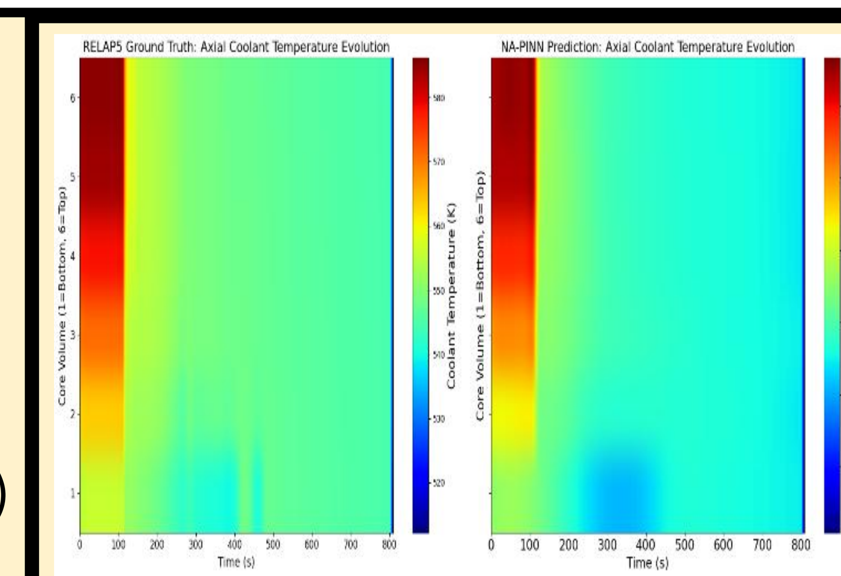


Figure 7. Axial coolant temperature evolution.

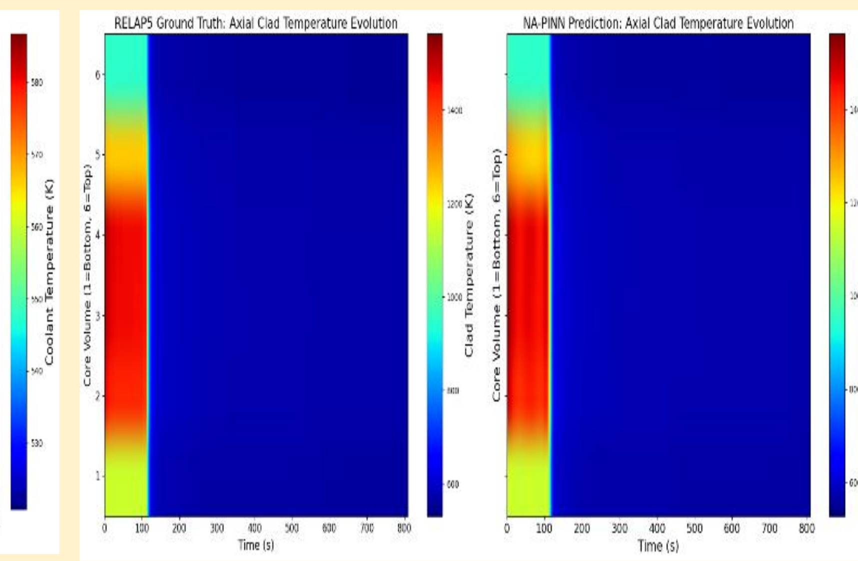


Figure 8. Axial fuel clad temperature evolution.

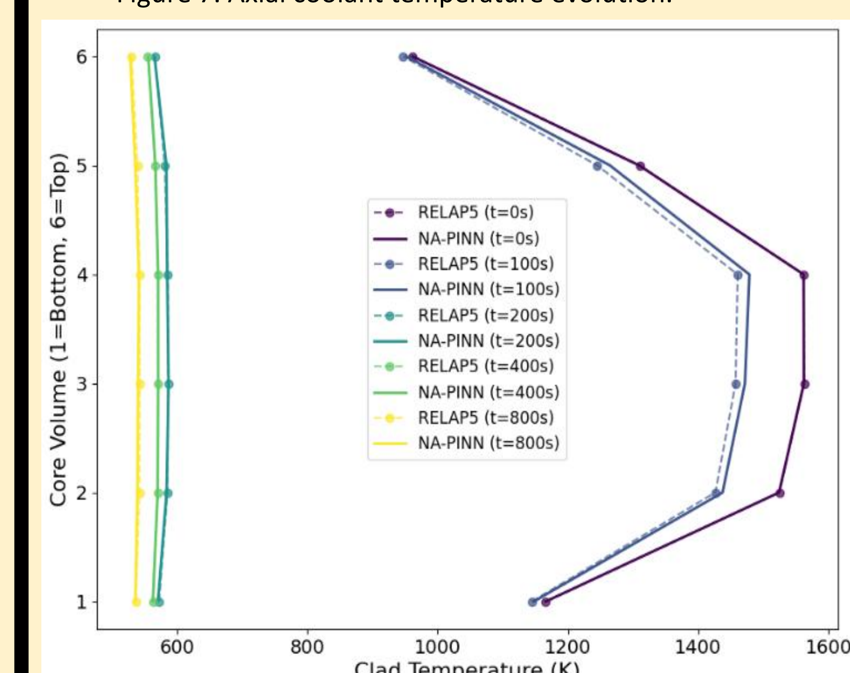


Figure 9. Fuel clad temperature profiles at key stages

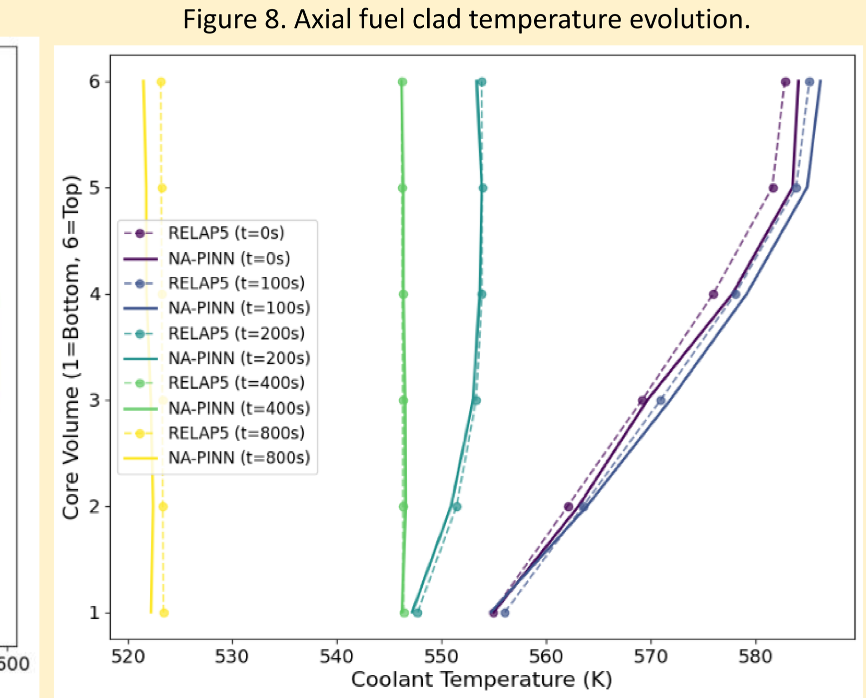


Figure 10. Coolant temperature profiles at key stages

## CONCLUSIONS

- In this work, we develop a NA-PINN for Hot Channel for real-time RELAP5-3D simulation of cold-leg break transient.
- The models Temp predictions achieved $R^2$of 0.9745 and 0.9859 and RMSE of 1.56 and 1.04 on training and validation/test datasets, respectively.
- The network successfully captures the global axial behavior of the reactor core, preserving physically consistent axial gradient.
- This preservation indicates the energy conservation residuals, expressed as $\dot{m}_{in} h_{in} - \dot{m}_{out} h_{out}$, are satisfied across volume boundaries.

## REFERENCES

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3. J. Shin et al., "Node Assigned physics-informed neural networks for T/H system simulation: CVH/FL module," *Computer Science Language*, Cornell University (2025).

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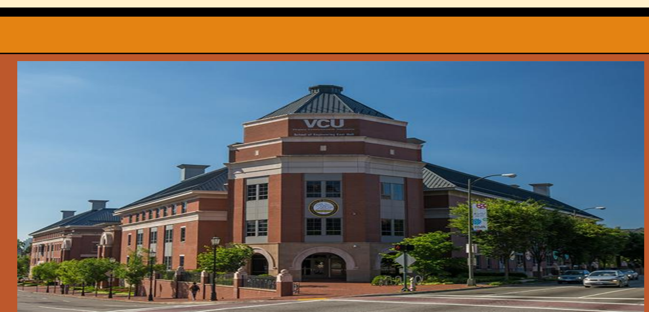

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