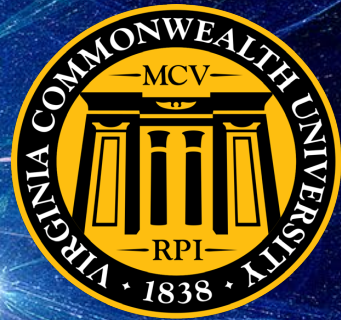


NET OUT 

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

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POWER UP 

Motivation

- NPP safety relies on T/H codes (RELAP, MELCOR) [1,2]
- Physics Informed Neural Networks (**PINNs**) offer physics-embedded alternatives [3,4]
- However, the direct application of *Vanilla PINNs* and *LP-PINNs* to full-scale nuclear reactor systems remains challenging [5,6,7]
- To address this limitation, the node-assigned PINN (**NA-PINN**) approach is proposed [7]

Proposed Approach & Objective

① NA-PINN Architecture

1. Dedicated sub-network per physical node
2. Mirrors RELAP5 nodalization strategy

② Coupled Physics Loss

1. Coolant, Cladding energy balance
2. Pressure continuity

③ Hard IC Enforcement

1. Shifting method: $\hat{u}(t) = NN(t) - NN(t_0) + u_{\text{RELAP}}(t_0)$
2. Exact at $t = t_0$ regardless of weights

OBJECTIVE

Develop and validate a NA-PINN for physics-consistent, real-time PWR LOCA transient simulation across coupled fuel-cladding-coolant thermal-hydraulic variables.

Different PINN Methods [7]

Vanilla-PINN

Input: (t, i)



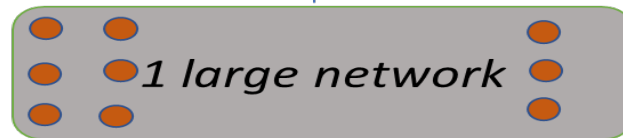
$$w_D \mathcal{L}_{data} + w_P \mathcal{L}_{physics}$$

Total Loss

Predicting all nodal variables simultaneously

LP-PINN

Input: t



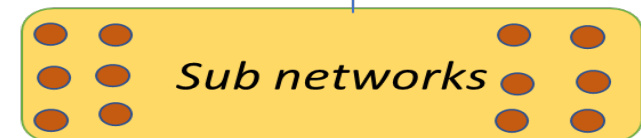
$$w_D \mathcal{L}_{data} + w_P \mathcal{L}_{physics}$$

Total Loss

Predicts all nodal variables directly from time alone

NA-PINN

Input: t



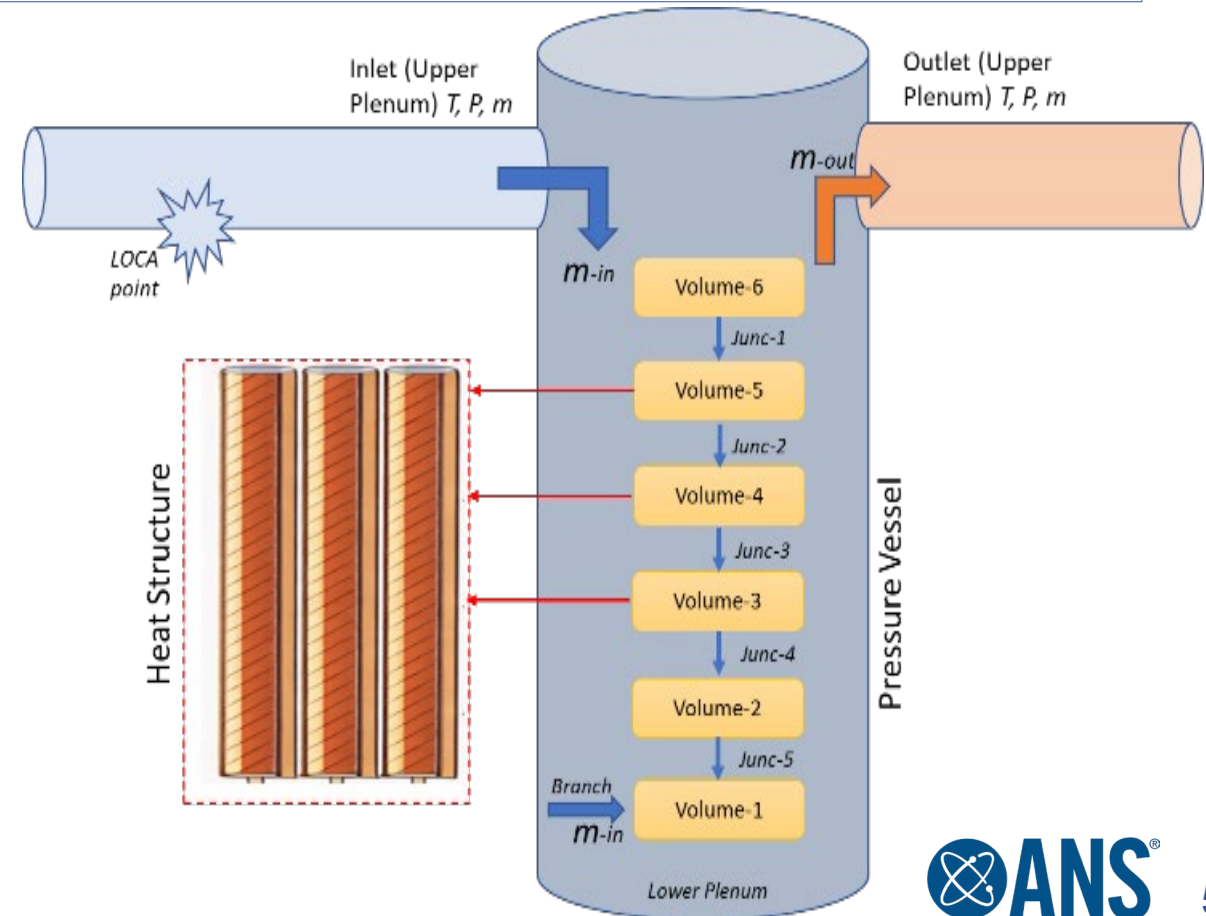
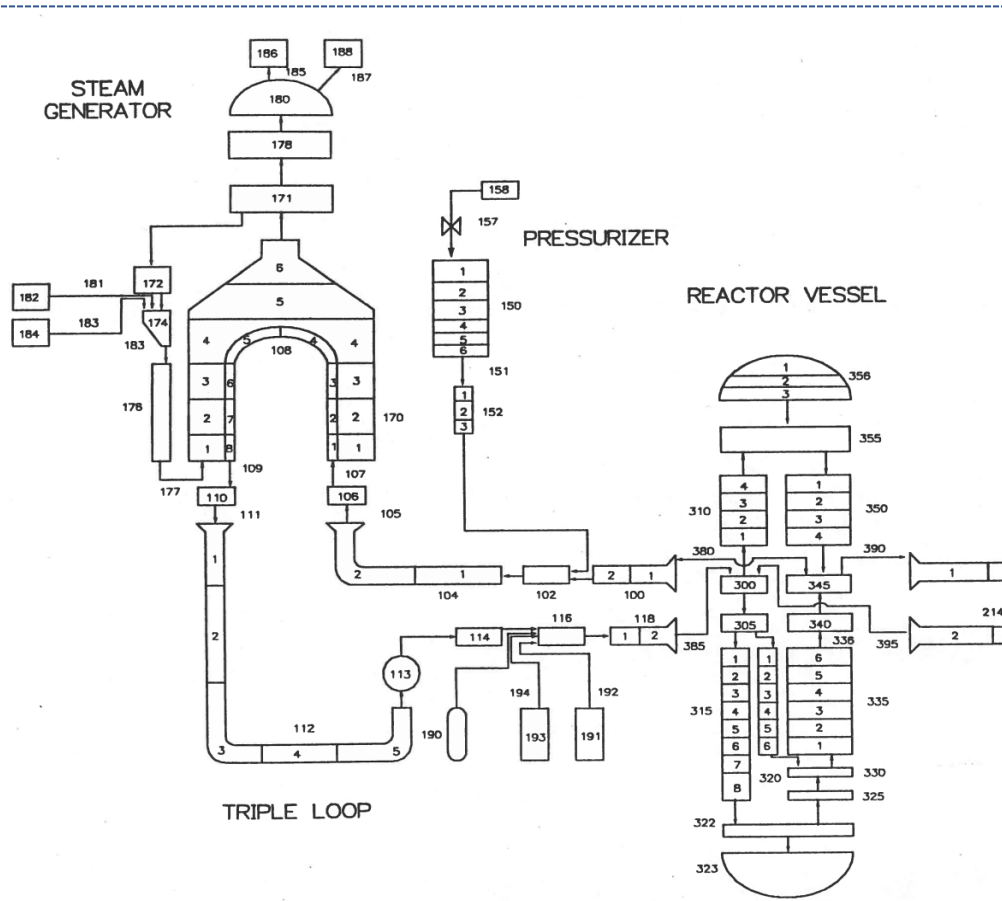
$$w_D \mathcal{L}_{data} + w_P \mathcal{L}_{physics}$$

Total Loss

Each sub-network takes normalised time t as input and predicts a single scalar variable

Step 1: Modeling and Nodalization of PWR and Run steady state with RELAP5-3D

A cold-leg break loss of coolant (LOCA) case study has been demonstrated



Step 2: Governing Equations

Coolant energy balance per axial volume

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

Cladding energy balance per axial volume

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

Heat flux at the cladding-coolant interface

$$q'' = h(T_s - T_f)$$

Pressure continuity

$$\frac{dP}{dt} = - \left(\frac{\rho c^2}{A} \right) (\dot{m}_{out} - \dot{m}_{in})$$

60 — Total output variables

Per volume (×6 volumes)

Tf	—	coolant temperature
Ts_in	—	clad inner temperature
Ts_out	—	clad outer temperature
Tfuel	—	fuel temperature
VF	—	liquid volume fraction
rho	—	liquid density
HTC_in	—	heat transfer coeff inner
HTC_out	—	heat transfer coeff outer
vliq	—	liquid velocity

Global (×1)

P	—	system pressure
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Per junction (×5 junctions)

mdot	—	mass flow rate
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Step 2: Physics Loss Formulation

$$\mathcal{L}_{Data} = \frac{1}{N} \sum_{i=1}^N \frac{\|\hat{u}_i - u_{RELAP,i}\|^2}{(u_{max} - u_{min})^2}$$

← Physics predictions and boundary data

$$\mathcal{L}_{coolant} = \frac{1}{N_{vol}} \sum_{i=1}^{N_{vol}} \left[\rho_{f,i} V_i C_{p,f} \frac{dT_{f,i}}{dt} = \dot{m}_{in,i} C_{p,f} T_{f,i-1} - \dot{m}_{out,i} C_{p,f} T_{f,i} + h_i A_i (T_{s,i} - T_{f,i}) \right]^2 / Q_{ref}$$

← Coolant energy balance per axial volume

$$\mathcal{L}_{clad} = \frac{1}{N_{vol}} \sum_{i=1}^{N_{vol}} \left[\rho_s V_{s,i} C_{p,s} \frac{dT_{s,i}}{dt} = Q_i - h_i A_i (T_{s,i} - T_{f,i}) \right]^2 / Q_{ref}$$

← Cladding energy balance per axial volume

$$\mathcal{L}_{pressure} = \left[\rho v c_p \frac{d\hat{P}}{dt} + \frac{\left(\frac{\rho c^2}{A}\right) (\dot{m}_{out} - \dot{m}_{in})}{p_{ref}} \right]^2 / P_{ref}$$

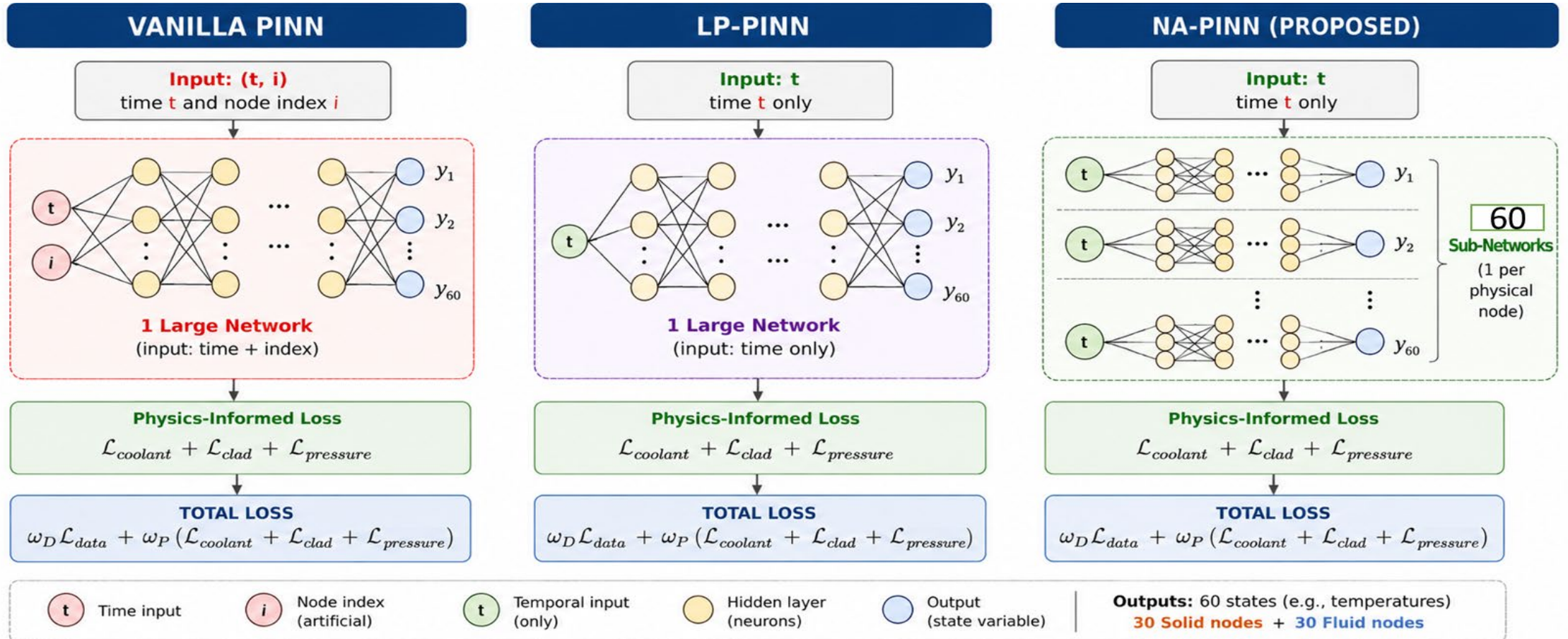
← Pressure continuity

$$\mathcal{L}_{Total} = \omega_D \mathcal{L}_{Data} + \omega_P (\mathcal{L}_{Coolant} + \mathcal{L}_{clad} + \mathcal{L}_{pressure})$$

Hard initial condition enforcement via the shifting method: $\hat{u}(t) = NN(t) - NN(t_0) + u_{RELAP}(t_0)$

Step 3: Model formulation: Assign nodes and sub-networks

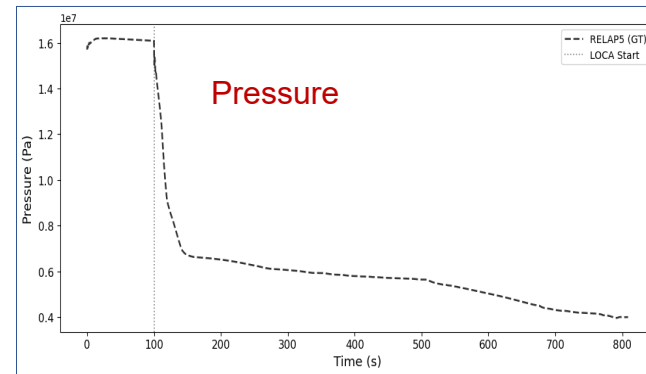
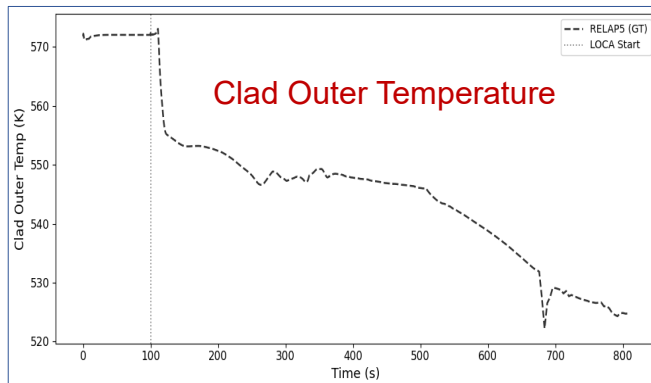
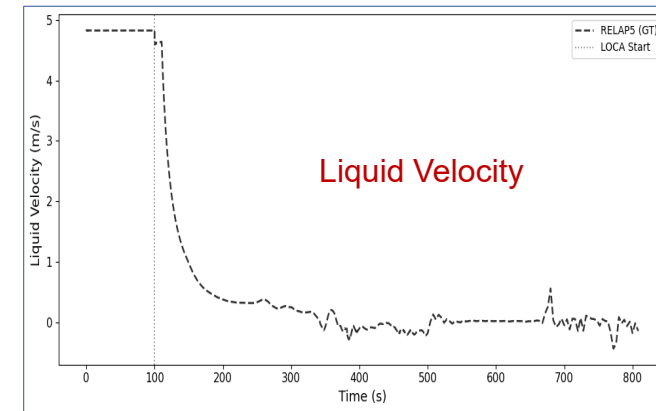
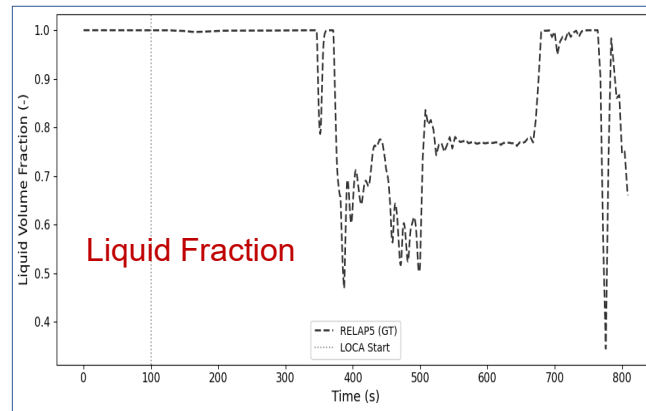
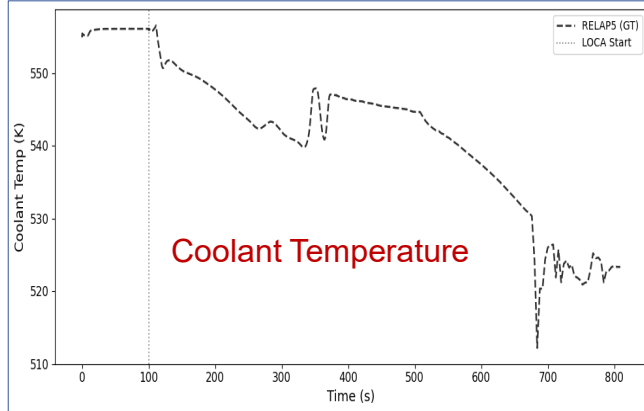
Training: Activation (ELU), Optimizer (Adam), Learning rate (10^{-3}), Constraint Method (Shifting Method [Hard-IC]), Models built in **PyTorch** (GPU-accelerated training [NVIDIA CUDA])



RELAP5-3D Results

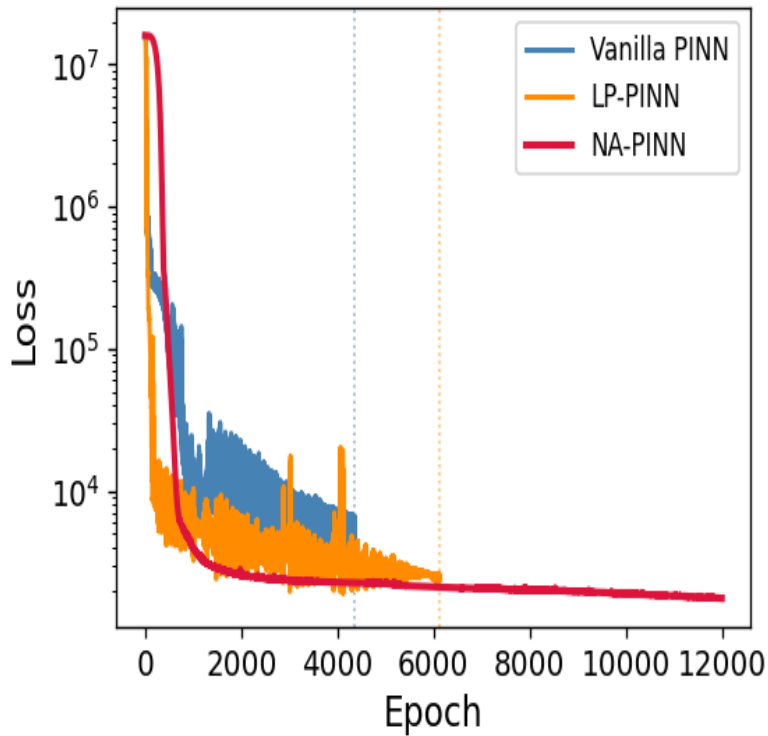
Full two-phase blowdown transient

- $t = 0-100$ s \rightarrow single-phase liquid (steady state)
- $t = 100-300$ s \rightarrow transition to two-phase (flashing)
- $t = 300-800$ s \rightarrow two-phase mixture (steam + liquid)

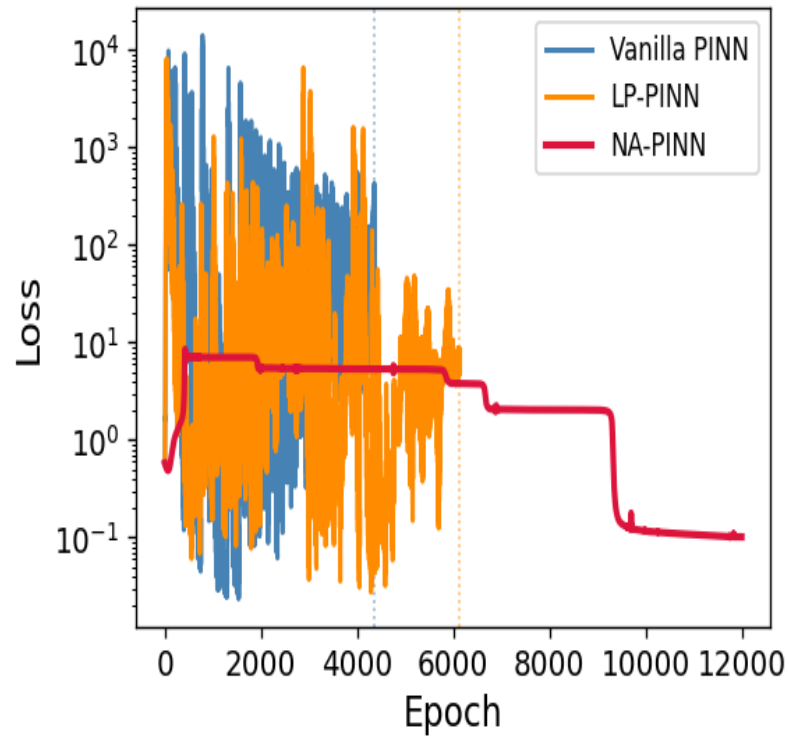


Loss History

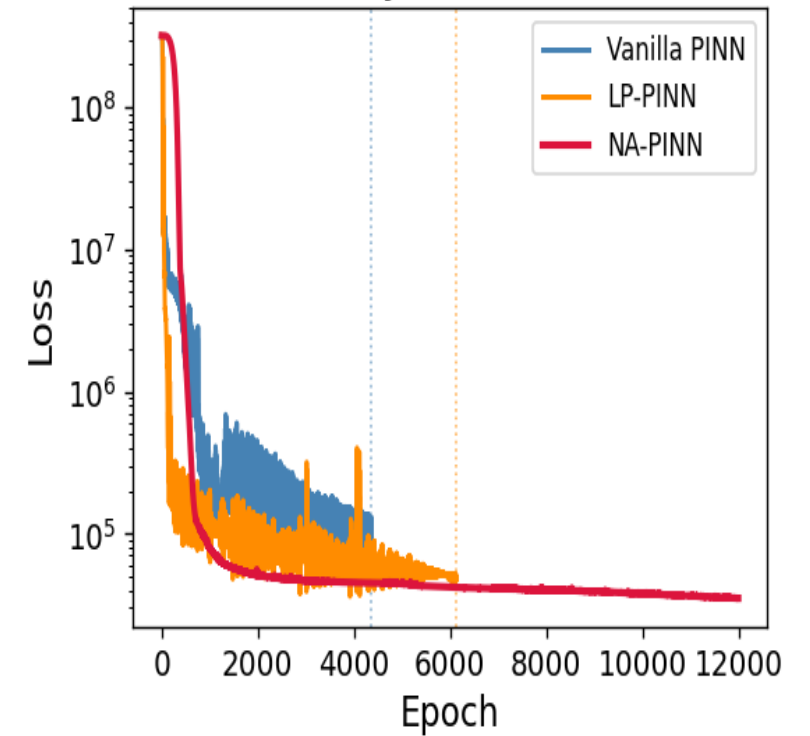
Total Loss



Data Loss



Physics Loss



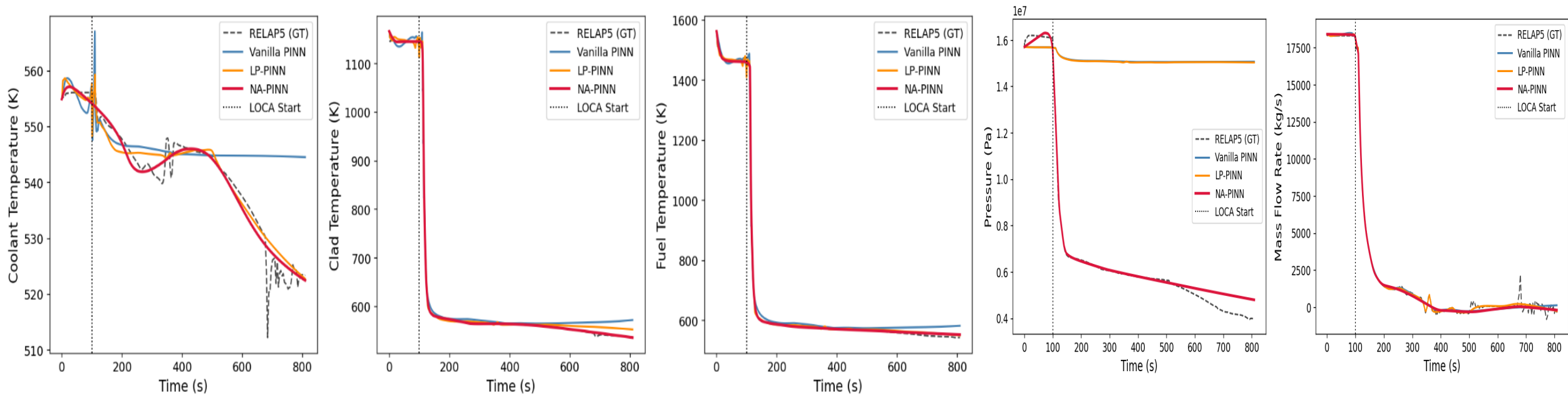
- Vanilla and LP-PINN are UNSTABLE with the pressure equation
- NA-PINN remains STABLE despite the same physics loss

Metrics Table

Variable	Vanilla	LP-PINN	NA-PINN
Clad Inner	0.942	0.988	0.942
Clad Outer	0.968	FAIL	0.951
Fuel Temp	0.935	0.990	0.884
Void Fraction	FAIL	FAIL	0.925
Liquid Velocity	FAIL	FAIL	0.993
Mass Flow	0.996	0.998	0.988
HTC Inner	0.802	0.945	0.975
HTC Outer	0.802	0.955	0.962
Liquid Density	0.718	FAIL	0.782
Coolant Temp	0.763	FAIL	0.820
Pressure	FAIL	FAIL	FAIL

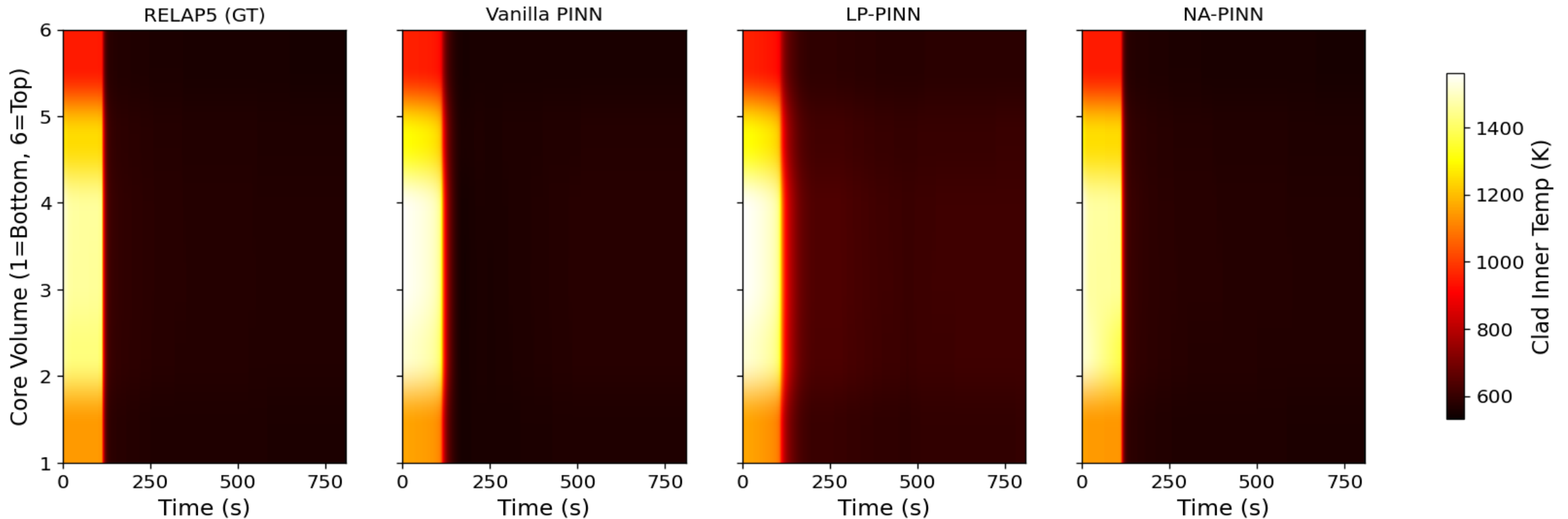
- NA-PINN captures void fraction ($R^2=0.925$) and liquid velocity ($R^2=0.993$)
- Pressure prediction remains a limitation across all models

Transient Performance



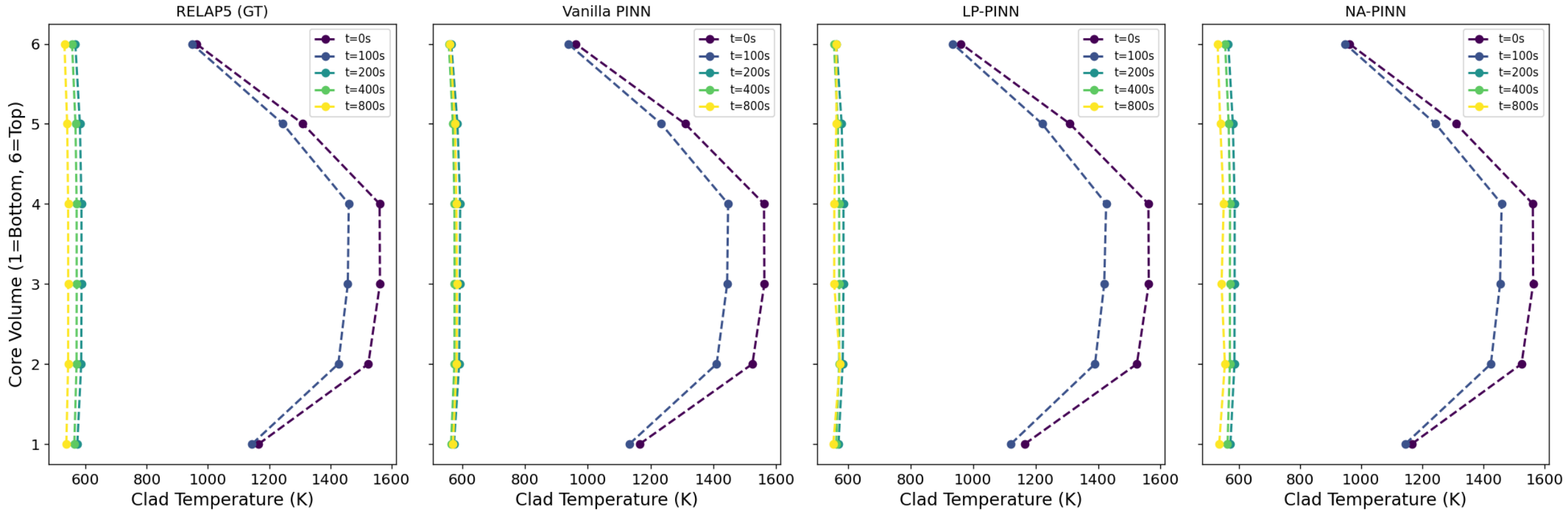
- NA-PINN tracks GT across coolant, cladding and fuel temperatures
- Vanilla PINN and LP-PINN plateau at near-constant temperature values after $t \approx 200$ s, failing to reproduce the continued cooling phase

Axial Heatmap Performance



- All: Onset at $t = 100$ s as the peak temperature event
- NA-PINN shows a better agreement with GT on axial power profile with peak temperatures at mid-core volumes (Vol 3-4)

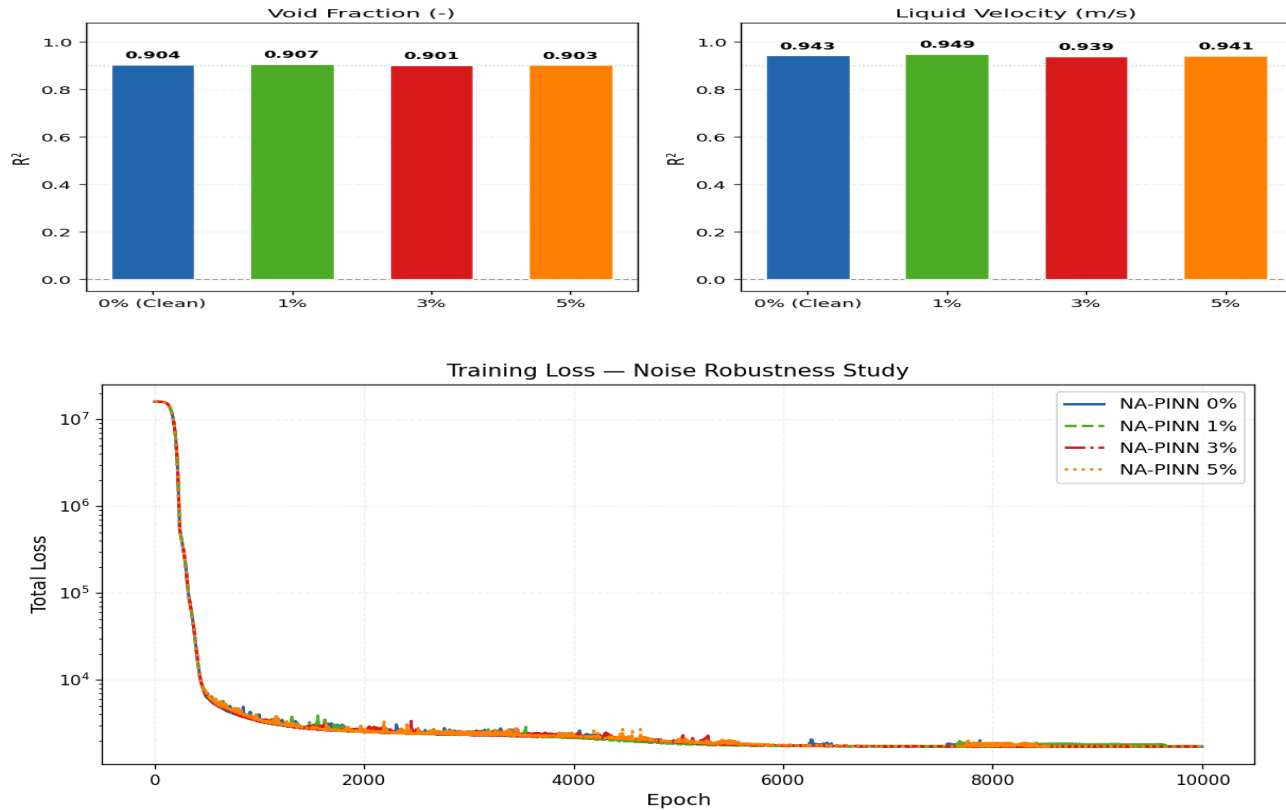
Axial Profiles



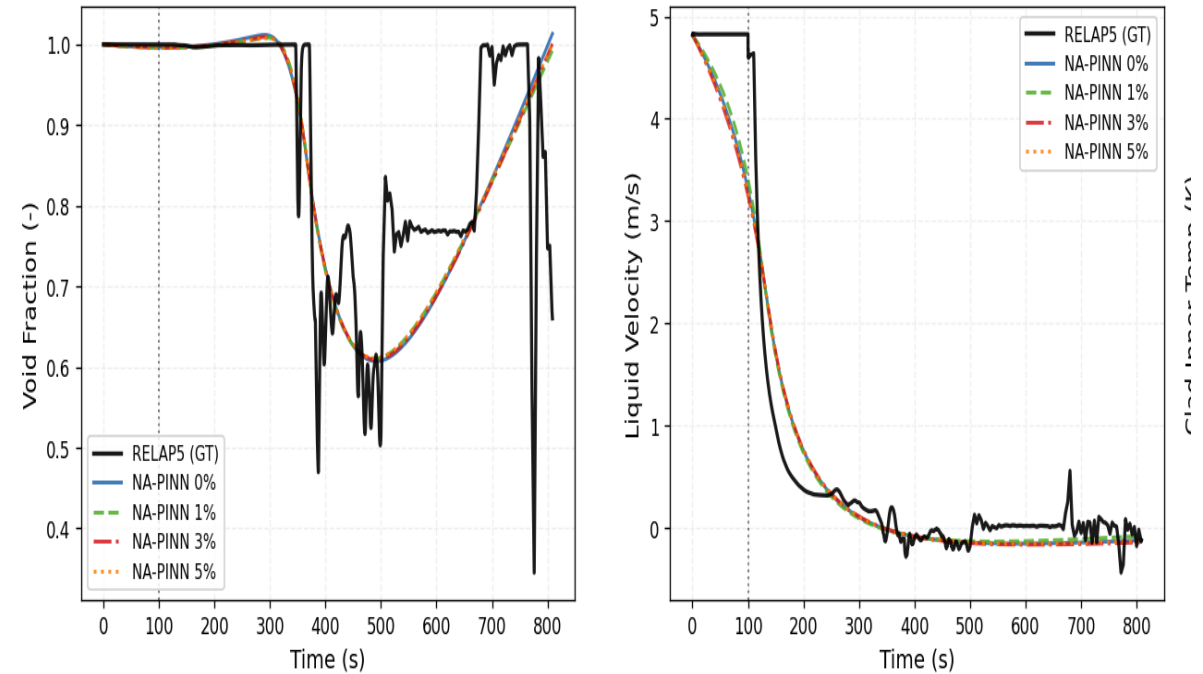
- At $t = 200$ s — NA-PINN captures the rapid post-LOCA cooling to ~ 900 K
- Vanilla PINN and LP-PINN overestimate temperatures (~ 1200 – 1400 K)

NA-PINN Noise Robustness — Gaussian Sensor Noise Analysis

NA-PINN Noise Robustness — R^2 vs Noise Level



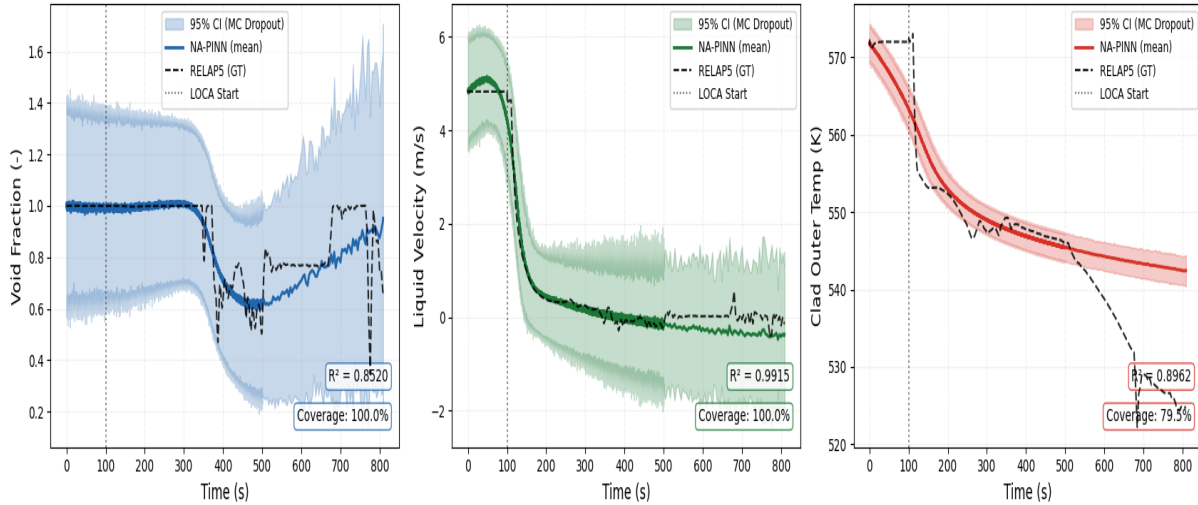
NA-PINN Noise Robustness — Transient Predictions (Vol 1)



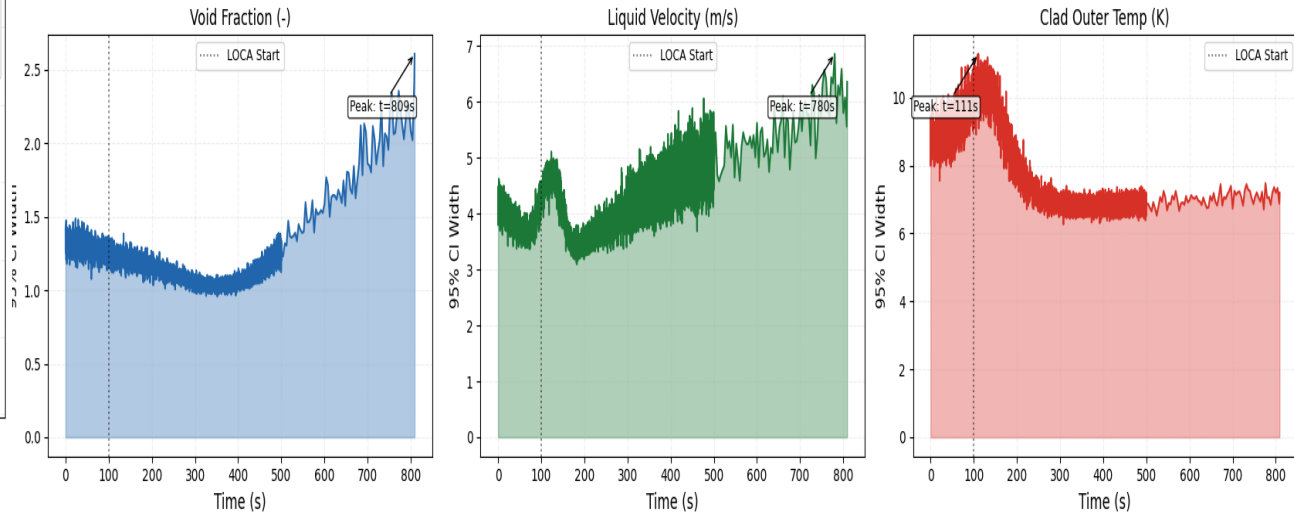
- R^2 varies by less than 1% across all noise levels (0.939–0.949)
- Void: R^2 remains stable at 0.90–0.91 across all noise levels, with less than 0.3% variation between clean and 5% noise cases
- All training loss histories converge to the same final loss magnitude

NA-PINN Uncertainty Quantification— Monte Carlo Dropout

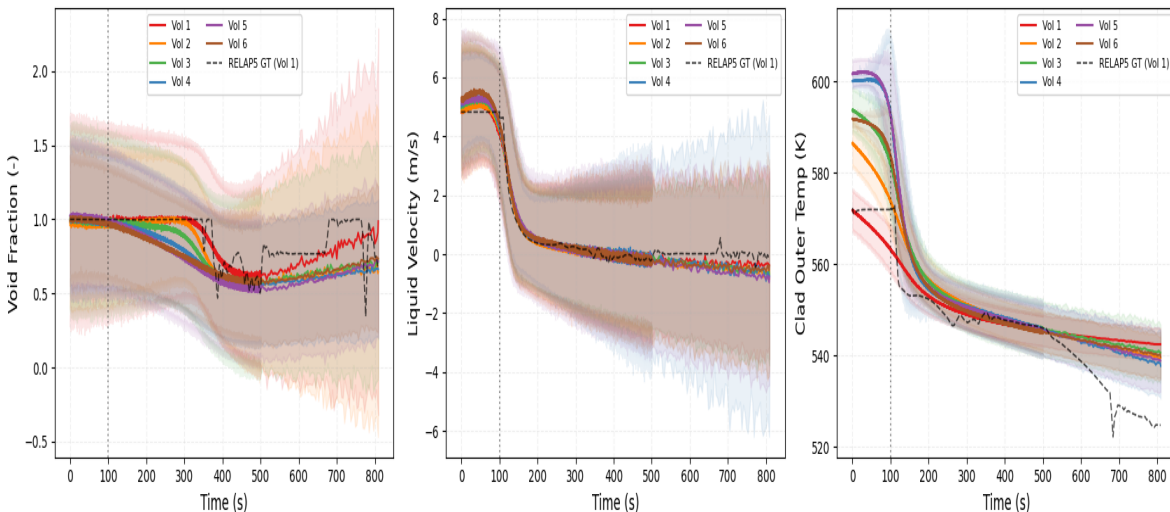
NA-PINN Uncertainty Quantification — 95% Confidence Intervals
(Post-hoc MC Dropout, N=300 samples, p=0.01)



NA-PINN Epistemic Uncertainty — 95% CI Width Over Transient
(Wider = higher model uncertainty)



NA-PINN UQ — All 6 Axial Volumes with 95% CI
(Shaded bands show per-volume epistemic uncertainty)



- Liquid velocity predictions are the best-calibrated — $R^2 = 0.989$ with 100% GT coverage within the 95% CI
- Clad outer temperature shows well-calibrated uncertainty — 90.9% coverage at the 95% CI level

NA-PINN Performance

1. NA-PINN demonstrates better calculations for two-phase flow variables — void fraction ($R^2=0.925$) and liquid velocity ($R^2=0.993$)
2. The cosine power, mid-core peak temperatures, and axial cooling wave propagation are all better reproduced
3. Pressure prediction remains a shared limitation across all three architectures

- The node-assigned architecture resolves the spatial index mismatch of Vanilla PINN, and the gradient conflict of LP-PINN
- It also demonstrates better prediction of two-phase flow variables (void fraction, liquid velocity) during a PWR cold-leg break LOCA transient

Future work

1. Extend the NA-PINN formulation to a fully two-phase governing equation set
2. Develop a complete momentum conservation equation for pressure
3. Extend NA-PINN to a surrogate framework

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Acknowledgments



**“Improving the computational efficiency and usability of
dynamic PRA with reinforcement learning”**

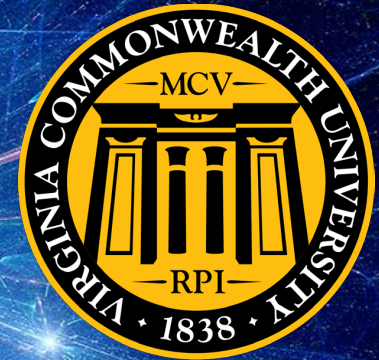
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Thank You

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POWER UP 

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