A Physics-Informed Neural Network Approach for Reliable Surrogate Modelling for PWR LOOP Accidents

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Background and Motivation

Loss-of-offsite Power (LOOP) in PWR

Defined as "The loss of all AC power from the electrical grid to the plant safety buses (NUREG-2122)

This leads to immediate cessation of the **Primary Coolant Pumps** and the **Main Feedwater Pumps**.

Loss of flow and heat removal capacity triggers **rapid temperature** and **pressure changes**.

Contributes 26 % to the core damage frequency (CDF) of Gen II reactors.

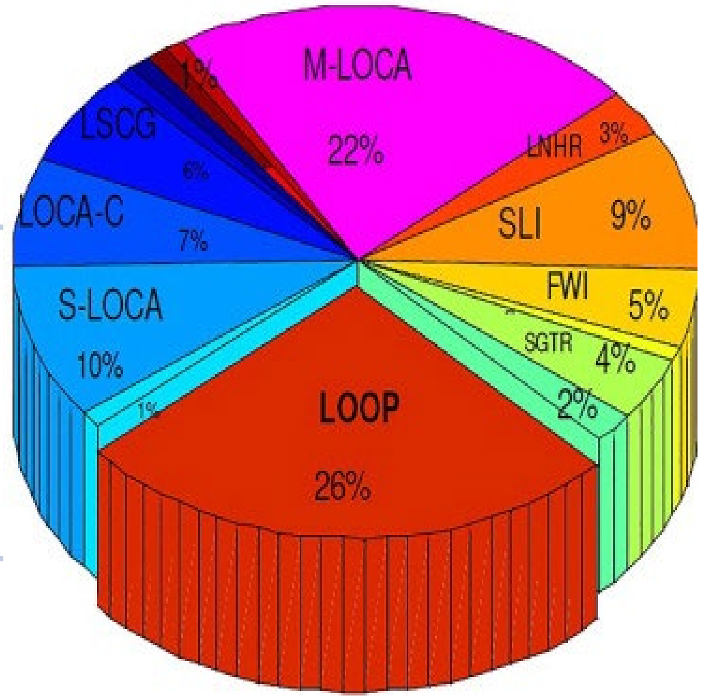

Figure 1. Initiating events contribution into total CDF of NPP. (Mossoud et at., 2018)

The Challenge of Real-Time Safety Analysis

LOOP is one of the leading accident reported by NRC in which **33% Switchyard-related events**, and **34 % from weather** related events between 2009-2023 (Johnson and Ma, 2024).

High-fidelity T/H codes (e.g. MELCOR or RELAP) are too slow for real-time applications (Wang et al., 2024; Antonello et al., 2023).

We need models that is 1000X faster, and provide physically reliable predictions (Zhang et al., 2024; Prantikos et al., 2023).

Develop a surrogate model capable of millisecond predictions of safety-critical parameters (T_f , P_p and T_C) during LOOP accidents.

Research Objectives and Overview

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Surrogate Landscape

Advantages:

1. High-speed ML/DNN.
2. Less expensive and open source.

Challenges:

1. Prone to non-conservative errors.
2. Physically implausible predictions.
3. Remain too slow for real-time Digital Twin application.

Gap:

- The need for models that combines **speed** of data driven models with the physical **reliability** and **consistency**.

Solution:

- Use of **governing physics equations** to constrain the neural network's training.

Objective & Hypothesis

Develop a model using **physics learning**, over purely data learning

Validate performance against purely data driven model (DNN) to quantify the benefit of physical constraints

PINN will deliver the needed **speed** while eliminating the **non-conservative errors** and ensuring **physical consistency**

Research Approach and Procedure

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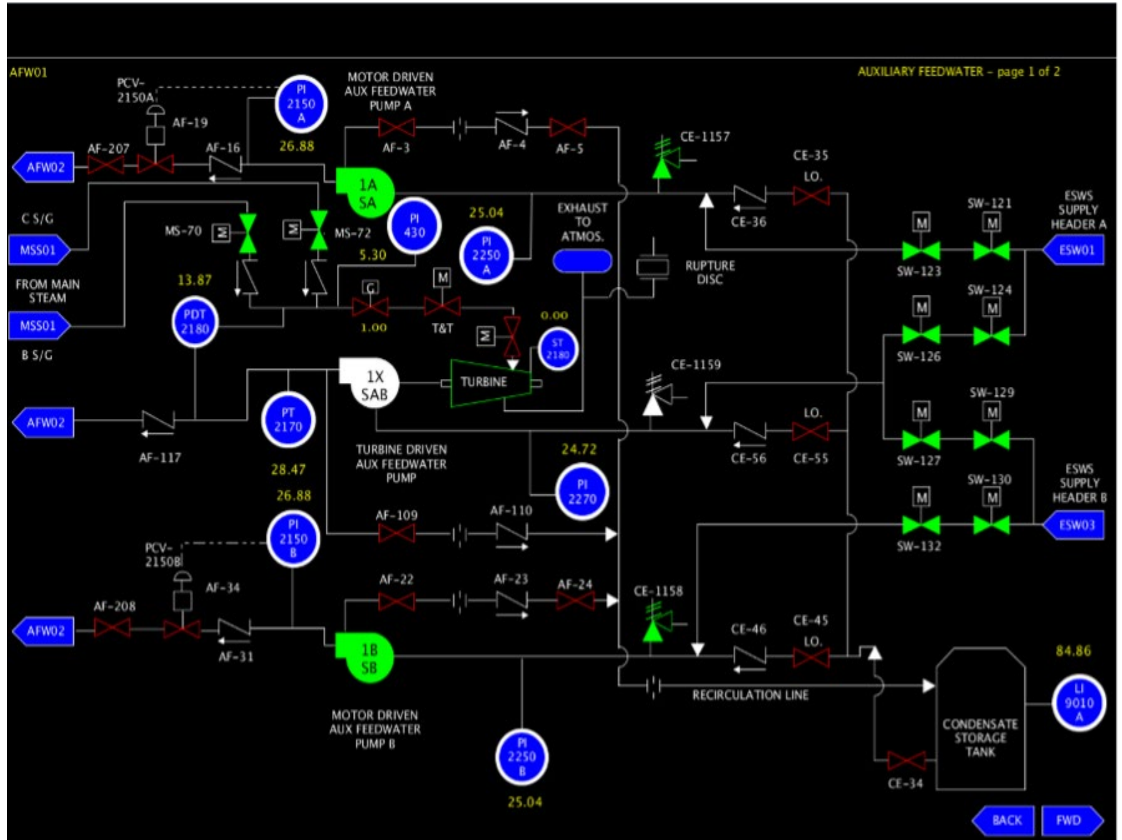
Research Approach and Procedure

Task I

- **Running 36 PWR LOOP accidents with Simulator.**
- **Each varying in initial condition, and system configuration.**



Research Approach and Procedure

Task II

- **Develop 3 Deep Neural Networks (DNN) architectures (Deep-MLP, TCN and ResNet-MLP).**
- **Training and Validation.**

Task III

- **Develop 3 Physics-Informed Neural Networks (PINNs) variants (Transfer Learning PINN, ResNet Multi-Head and Neural_ODE).**
- **Training and Validation.**

Task IV

- **Model evaluations and comparisons**

DNN Surrogate Architectures

Table 1: DNN Models

Model	Architecture	
A	MLP (Baseline feed-forward)	Feed-forward benchmark.“
B	Temporal Convolution Network (TCN)	Uses **convolutional blocks** designed to capture the temporal dependencies and inertia of the reactor system, making it highly effective for sequence data.
C	ResNet-MLP hybrid	Leverage residual connections, ensuring training stability.

➢ **Loss Function**

$$L_{total} = \frac{1}{N}\sum_{i=1}^{N}\left[\left(\dot{T}_{f,i} - T_{f,i}\right)^2 + \left(\dot{T}_{c,i} - T_{c,i}\right)^2 + \left(\dot{P}_{p,i} - P_{p,i}\right)^2\right] \qquad \text{Eq ...1}$$

PINN Surrogate Architectures

Table 2: PINN Models

Model	**Network Architecture**	
A	Baseline PINN	A standard fully-connected network constrained by the **L_Physics** term
B	ResNet Multi-Head	Uses a **Shared-Encoder** layer, which forces the network to learn a single common latent physical representation of the reactor state.
C	Neural_ODE PINN	Doesn't directly predict, but rather **parameterizes the time derivative** . The predictions are then generated by running an RK4 (Runge-Kutta) integrator

PINN Approach (Physics Loss - "r")

- **Loss Function**

$$L_{total} = \frac{1}{N}\sum_{i=1}^{N}\left[\left(\dot{T}_{f,i} - T_{f,i}\right)^2 + \left(\dot{T}_{c,i} - T_{c,i}\right)^2 + \left(\dot{P}_{p,i} - P_{p,i}\right)^2\right] + \boxed{\lambda_{phys}\,\frac{1}{N}\sum_{i=1}^{N}\left[r_{1,i}^2 + r_{2,i}^2 + r_{3,i}^2\right]}$$

Eq ...2

- **Fuel Energy Balance**

$$r_1 = \rho_f c_{p,f} V_f \frac{dT_f}{dt} - Q_{gen}(t) + U_{fc}A_{fc}\left(T_f - T_c\right)$$

Eq ...3

- **Coolant Energy Balance**

$$r_2 = \rho_f c_{p,c} V_c \frac{dT_c}{dt} - U_{fc}A_{fc}\left(T_f - T_c\right) + Q_{AFWS}(t) + Q_{loss}\,(t)$$

Eq ...4

- **Simplified Pressure Evolution**

$$r_3 = \frac{dP_p}{dt} - K_p\frac{dT_c}{dt}$$

Eq ...5

Results

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Speed & Statistical Baseline

- Both DNN and PINN models achieve prediction time in the millisecond range ($\sim 10\ ms$)

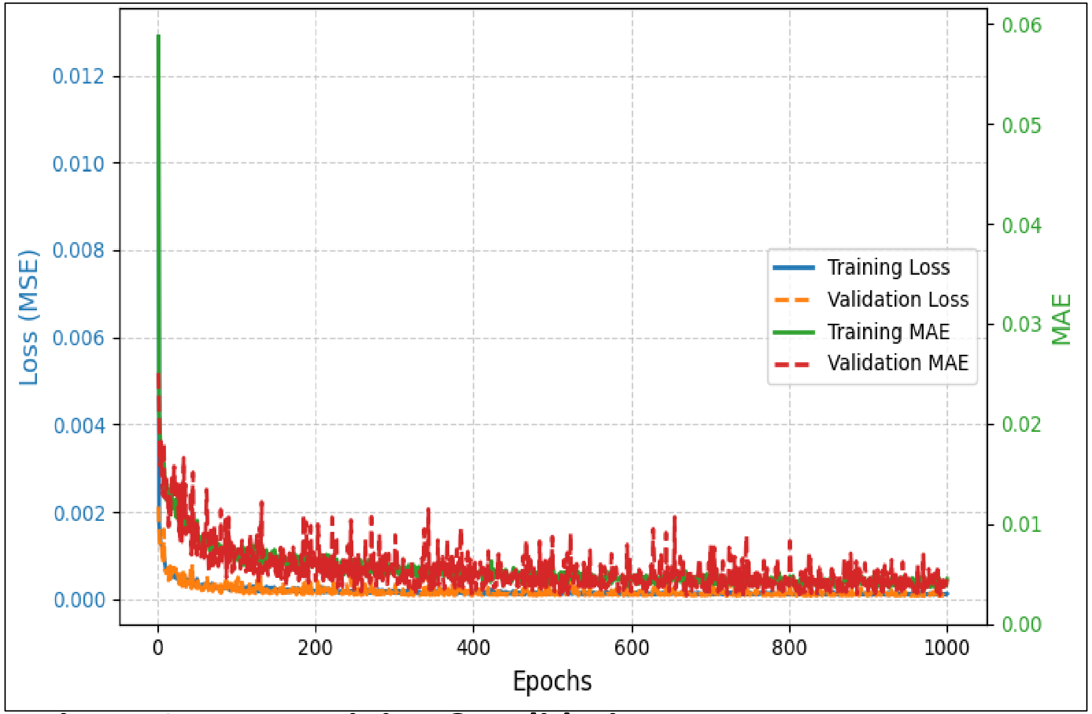

Figure 2: DNN Training & Validation

- $R^2 \approx$ **0.7** (acceptable fit) : NMEA ≈ 5.51
- Higher MaxAE and localized losses

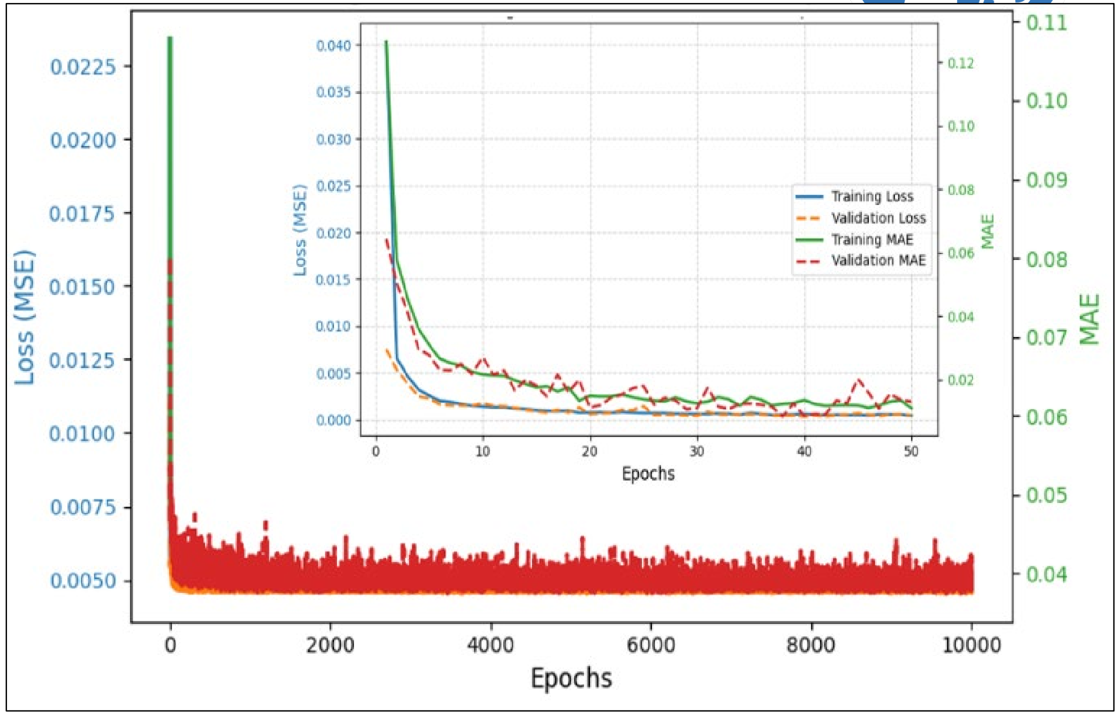

Figure 3: PINN Training & Validation

- $R^2 \approx$ **0.83** (better fit) : NMEA ≈ 7.94
- Lower MaxAE and reduced localized losses.

18.5 % increase in R^2 with enhanced stability

Coolant Temperature Evolvement

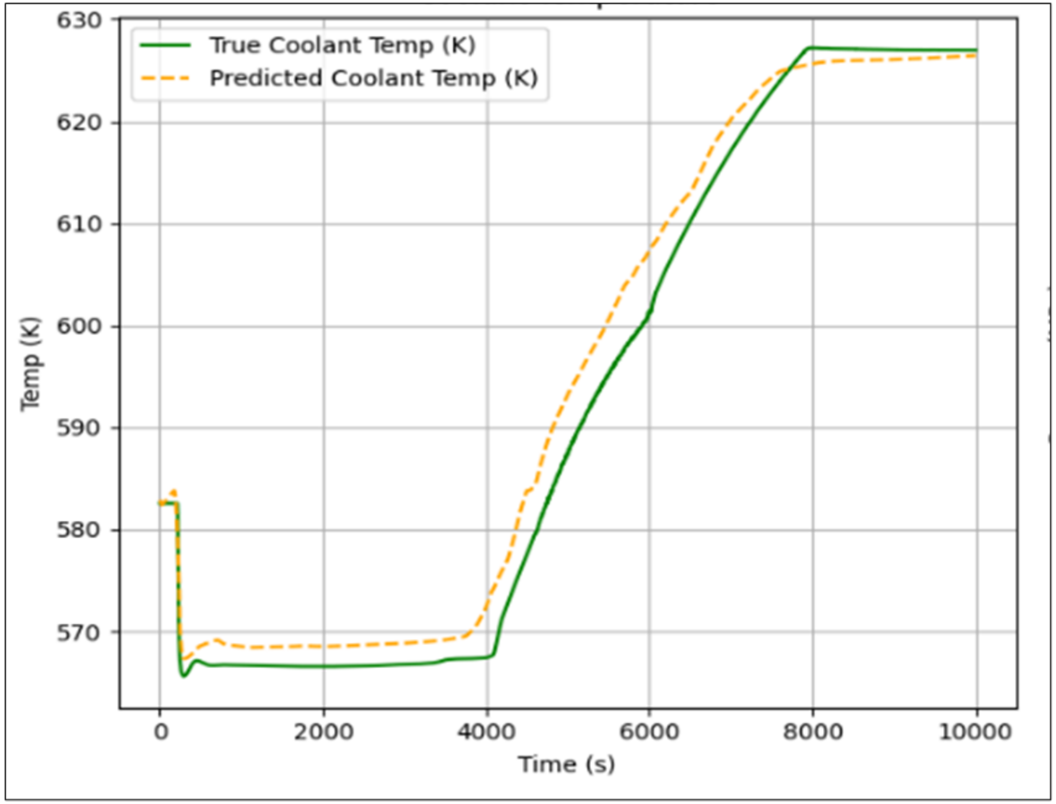

Figure 4: DNN Coolant Temp Trends

- Non- Conservative Predictions
- Overshooting

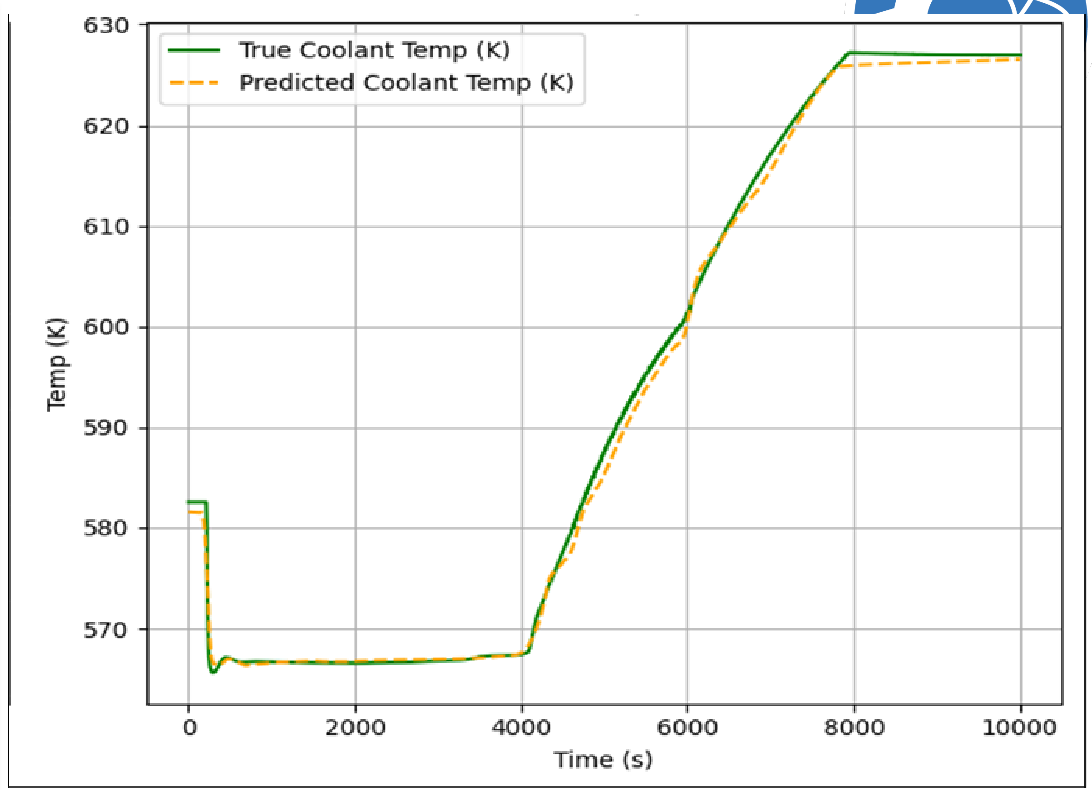

Figure 5: PINN Coolant Temp Trends

- More Stable and Conservative

Statistical fit and physically conservative prediction margin

Fuel Temperature Evolvement

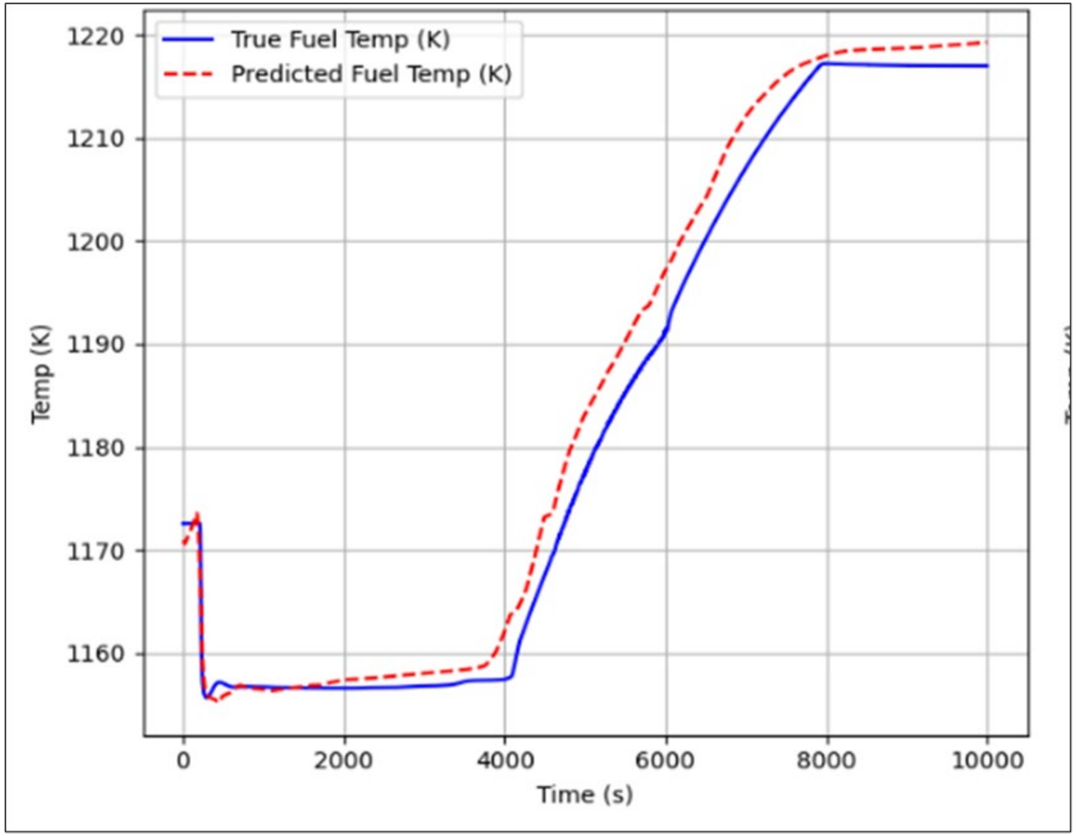

Figure 6: DNN Fuel Temp Trends

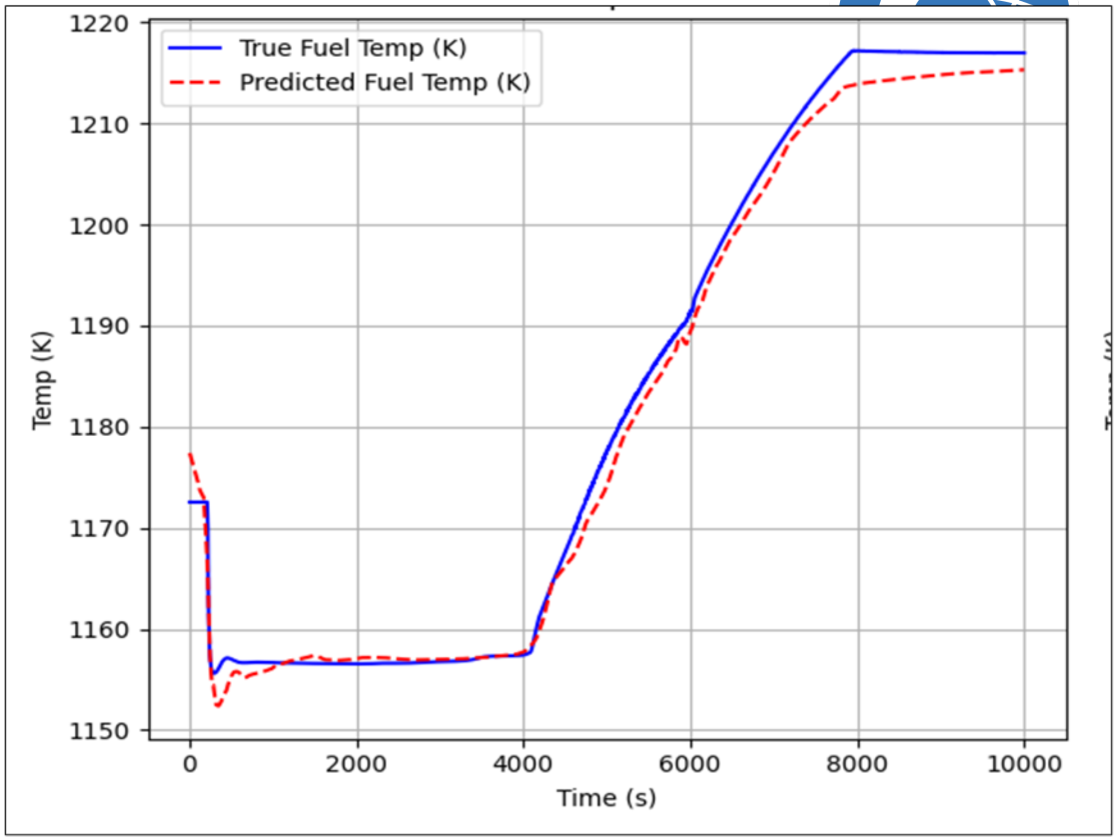

Figure 7: PINN Fuel Temp Trends

Statistical fit and physically conservative prediction margin

Pressure Trends During the Accident

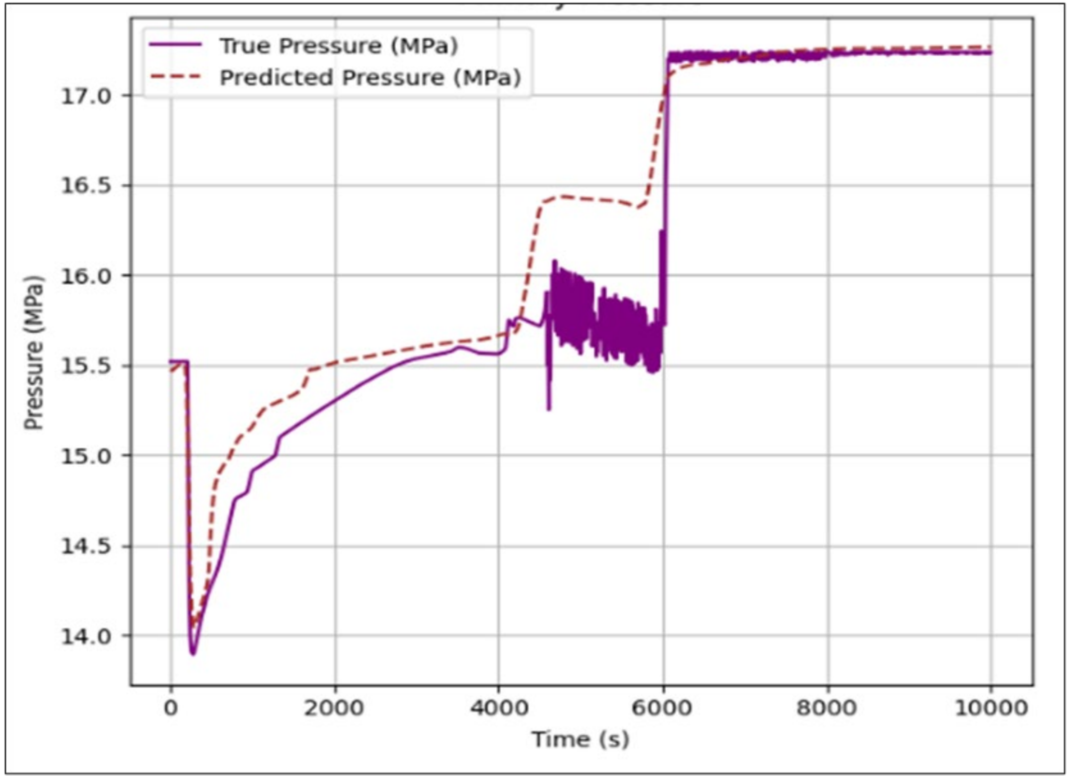

Figure 8: DNN Pressure Trends

- ➢ Struggling in capturing high oscillations.
- ➢ Phase lag relative to true peak

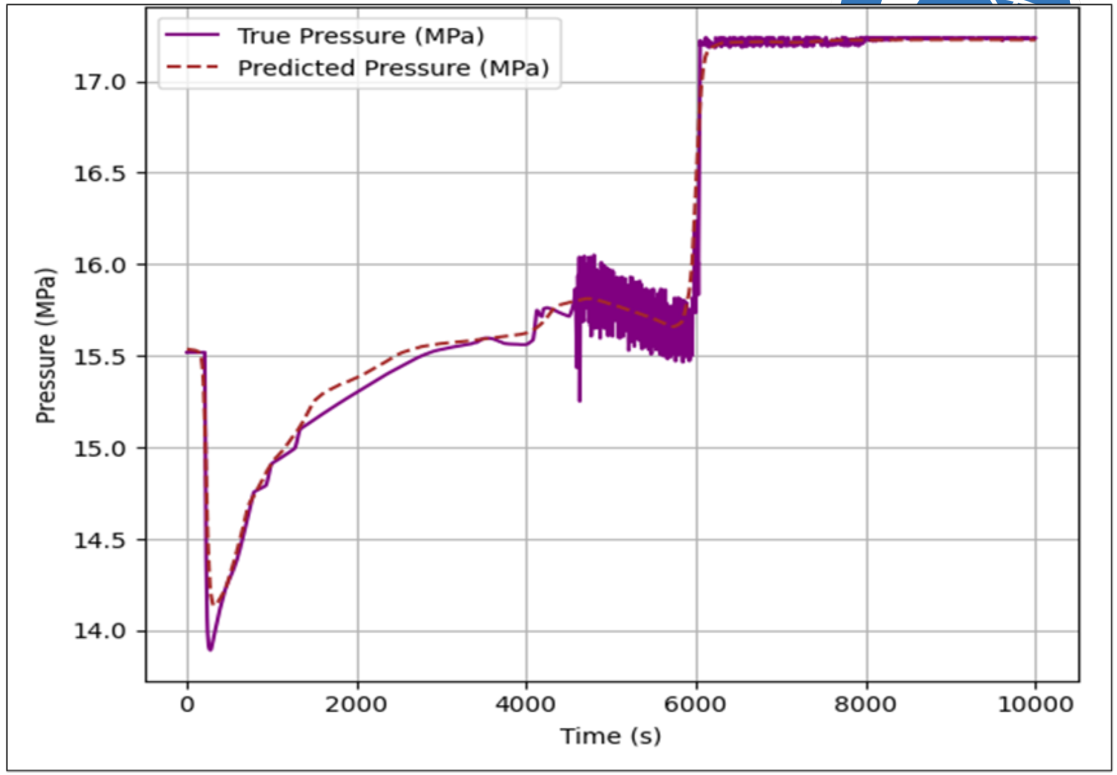

Figure 9: PINN Pressure Trends

- ➢ Reducing magnitude of peaks.
- ➢ Closely following true data's shape .

Stable physics constrained predictor

Discussion

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Discussion: Physical Fidelity & Consistency

Table 4: DNN vs PINN Performance

Parameter	Metric	Best DNN (TCN)	Best PINN (Shared-Encoder Multi-Head)	Improvement (%)	Comment
T_f	RMSE	78.89	52.10	33.9 ↓	Reduced temp prediction error by one-third.
	MAE	58.94	38.25	35.1 ↓	Lower average deviation
	R^2	0.76	0.92	+21.1 ↑	Improved physical consistency
T_C	RMSE	58.96	41.50	29.6 ↓	Reduces T_C uncertainty
	MAE	50.54	35.22	30.3 ↓	Improved smoothness and generalization
	R^2	0.16	0.88	+450 ↑	improve prediction
P_p	RMSE	0.57	0.39	31.6 ↓	Reduced prediction uncertainty
	MAE	0.34	0.27	20.6 ↓	Better pressure profile prediction
	R^2	0.74	0.91	+23.0 ↑	Better adherence to system response
Overall Average	**RMSE**	**56.90**	**44.60**	**21.6 ↓**	**Lower deviations across all parameters**
	MAE	**36.61**	**27.91**	**23.8 ↓**	**Better accuracy and generalization**
	R^2	**0.98**	**0.999**	**+1.6 ↑**	**Better consistence between predicted and primary data.**

Discussion: Physical Fidelity & Consistency

Table 5: DNN vs PINN Performance

Feature	DNN	PINN
Prediction Stability	**Volatility & Spikes** (non-physical, high-frequency. It's a statistical curve-fitter)	**Physical Smoothness** (smoother and more stable)
Safety-Critical Peak Error	**Non-Conservative Risk** (Frequently exhibits **MaxAE)**	**Conservative Margin** (reduces the non-conservative MaxAE risk)
System Coupling	**Decoupled** (struggles to maintain thermodynamic coupling between variables)	**Explicitly Coupled** (more consistent system-wide predictions)

Conclusion & Future Work

- Both models provided predictions in the millisecond range (necessary for real-time applications.)
- The PINN models achieved 20-30% lower RMSE and 15-25% higher R^2 values across all parameters.
- Future models in reactor control and safety assessment must incorporate physics constraints to satisfy regulatory standards.
- Efforts to consider developing a higher-fidelity pressure model accounting for two-phase fluid properties.

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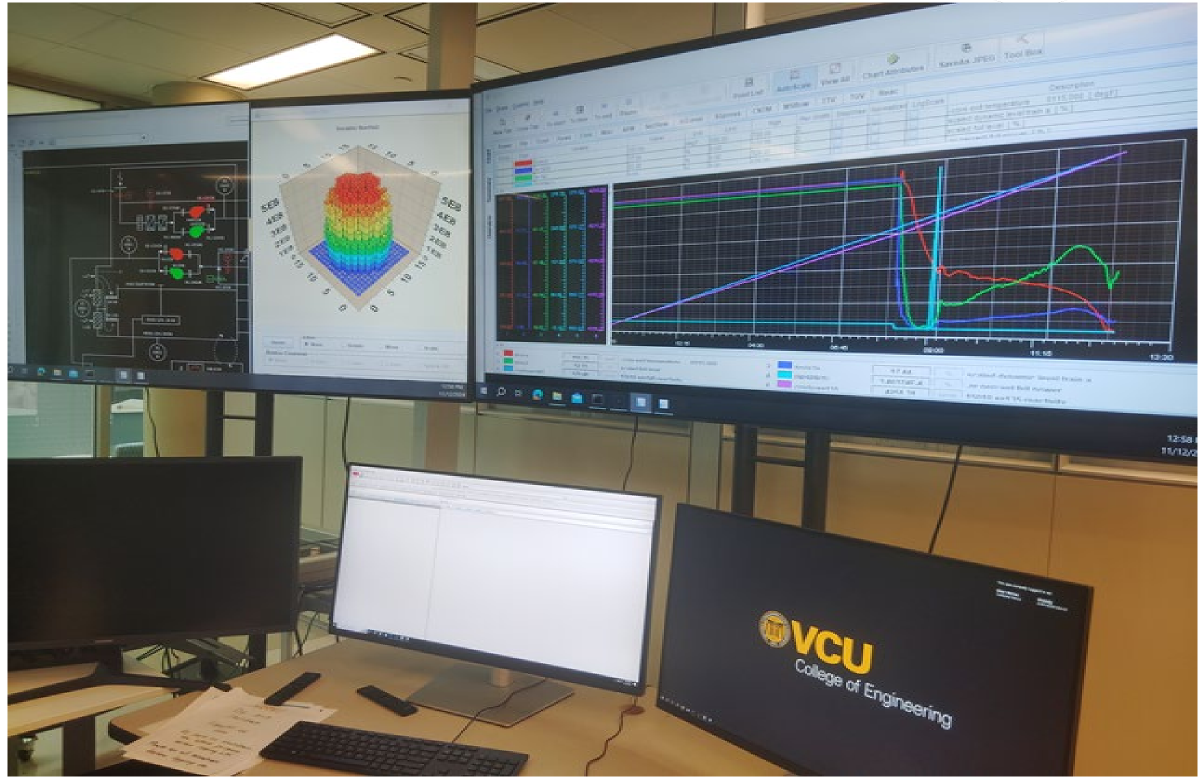

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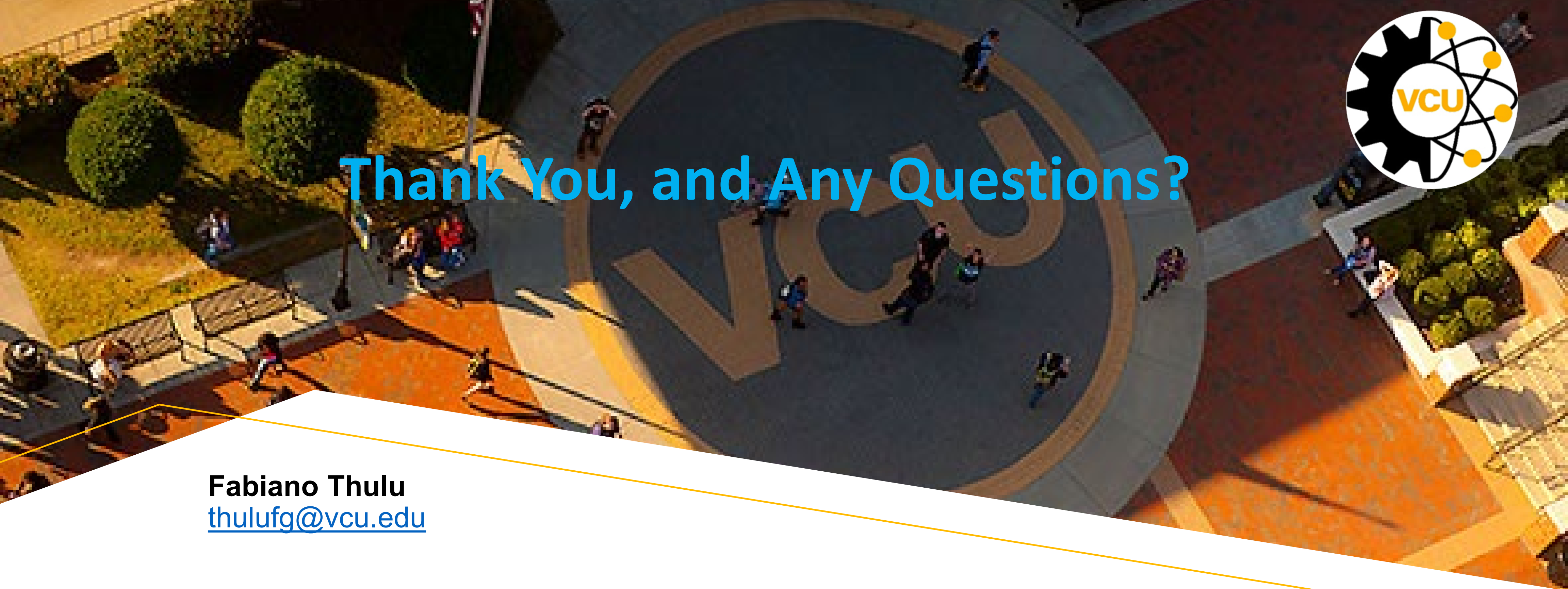
Thank You, and Any Questions?



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