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Physics-Informed Neural Network-Based Severe Accident Analysis Code: A Preliminary Assessment

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1. Introduction

Severe accident (SA) analysis is essential for ensuring the safety of nuclear power plants, and system codes such as MELCOR have been widely used to simulate accident progression [1]. MELCOR models complex thermal-hydraulic phenomena, including core degradation, coolant loss, and hydrogen combustion, using a control volume (CV)-based framework. Despite its effectiveness, MELCOR has several limitations. First, it requires complex nodalization, where users must manually define control volumes and flow paths (FLs), making model setup cumbersome and error prone. Second, MELCOR employs numerical solvers based on finite-difference methods, offering a computational cost that is relatively moderate compared to CFD. However, further advancements in computational efficiency are required to enhance its applicability for PSA analysis. Lastly, its multi-physics modeling capability remains restricted, often necessitating external coupling with other solvers to provide a comprehensive simulation. These limitations underscore the need for an alternative approach that simplifies input modeling, enhances computational efficiency, and improves multi-physics integration.

In recent years, machine learning techniques have been explored to address the computational challenges associated with traditional numerical solvers [2]. While various studies have integrated data-driven models into system codes, these approaches rely heavily on empirical training data and often lack physical interpretability [3]. To overcome these shortcomings, physics-informed neural networks (PINNs) have emerged as a promising alternative by embedding governing equations directly into the training process [4]. Unlike traditional data-driven approaches, PINNs do not require separate training data and instead leverage physical laws to obtain solutions, allowing them to be classified as a new form of numerical method. PINNs have demonstrated success in approximating solutions for partial differential equations (PDEs) in fields such as fluid dynamics [5] and heat transfer [6] by leveraging automatic differentiation to enforce physical constraints. However, their application to MELCOR remains largely unexplored, and their effectiveness in replicating system code behavior has not been systematically evaluated.

This study investigates the feasibility of applying PINNs to MELCOR's CVH/FL module, which governs mass and momentum conservation. A simplified gravity-driven flow scenario is selected to evaluate PINN performance in predicting transient flow behavior. However, conventional PINNs face challenges when applied to MELCOR due to the strong interdependencies between control volumes and flow paths. To address this issue, enhanced architecture, the Node Assigned PINN (NA-PINN), is proposed. NA-PINN constructs independent neural networks for different system components and trains them simultaneously, avoiding interference between outputs of different scales while learning the physical interactions. This enables a more stable and precise representation of transient system behavior.

2. Methods and Results

2.1 Scenario Description

The MELCOR code employs control volumes (CV) and flow paths (FL) to simulate thermal-hydraulic phenomena in severe accidents. This study considers a simplified gravity-driven draining scenario comprising six control volumes connected by one flow path, as illustrated in Fig 1. Initially, the upper control volume (CV01) is fully filled with water, while the lower volume (CV02) is empty. Both control volumes are open to the atmosphere, thereby neglecting pressure effects. Each control volume has a cross-sectional area of 50 m^2 and a height of 2 m, connected by a flow path with a diameter of 0.2 m and length of 0.1 m. Water flows from CV01 to CV06 driven solely by gravitational forces, and the simulation continues until equilibrium in water levels is reached.

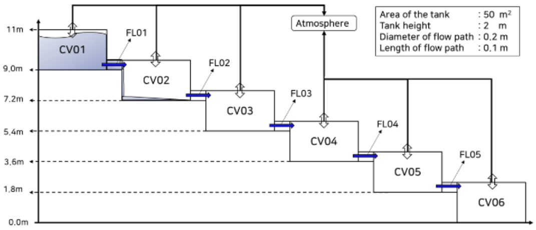

Fig. 1. Nodalization for the scenario model

2.2 Governing Equations

The physical behavior of the described scenario can be represented by two fundamental conservation equations derived from the MELCOR CVH/FL module, governing mass and momentum conservation.

The mass conservation equation describes the temporal evolution of water height within each control volume. The inflow and outflow velocities through the connected flow paths, along with relevant geometric parameters, determine the rate of change in water height over time. This equation is expressed as follows:

$$A_i \rho_{j,m}^d \frac{\partial H_{i,m}}{\partial t} = \sum_j \sigma_{ij} \alpha_{j,\phi} \rho_{j,m}^d v_{j,\phi} F_j A_j \qquad (1)$$

where $H_{i,m}$ represents the water height within control volume i, and A_i is the cross-sectional area of the control volume. $\rho_{j,m}^d$ denotes the density of the fluid within the flow path, which is assumed to be constant. Additionally, $v_{j,\phi}$ represents the velocity within flow path j.

The momentum conservation equation governs velocity dynamics within the flow path, where temporal velocity changes are primarily driven by gravitational forces and opposed by frictional losses. The equation is formulated as follows:

$$L_j \frac{\partial v_{j,\phi}}{\partial t} = g\Delta z - \frac{1}{2} K_{j,\phi}^* |v_{j,\phi}| v_{j,\phi} \qquad (2)$$

where L_j represents the inertial length of the flow path j, and $v_{j,\phi}$ denotes the new velocity within the flow path. Δzcorresponds to the water height, while $K_{j,\phi}^*$ represents the net form and wall-loss coefficient.

These conservation equations are implemented in MELCOR in a discrete form, whereas PINNs utilize the partial differential equations in their original form.

2.3 Physics-Informed Neural Network (PINN) Formulation

PINNs integrate governing equations directly into the neural network training process, ensuring that solutions remain physically consistent. Fig. 2 illustrates the PINN architecture used in this study. The model takes a one-dimensional input corresponding to temporal input t and produces outputs predicting a total of 11 PDEs. Additionally, a hard constraints approach is adopted to ensure that initial conditions are always satisfied [7], with no boundary conditions imposed in the present scenario. Algorithm 1 provides a schematic representation of the learning algorithm used for PINN training.

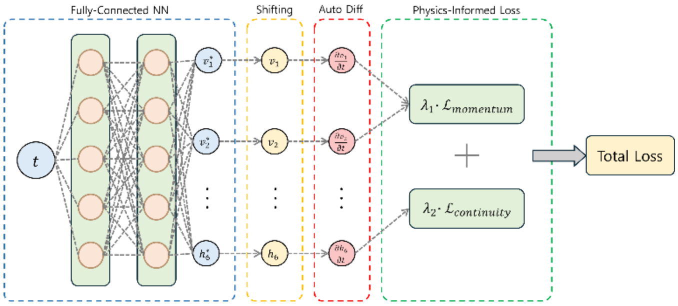

Fig. 2. Architecture of the proposed PINN

Algorithm 1 PINN Training

Require: Neural Network f_θ, Physics equation $\mathcal{F}(f_\theta)$, Learning rate η, Iterations N_{iter}, Loss weight λ

1: Initialize parameters θ
2: **for** $n = 1$ to N_{iter} **do**
3: Compute physics loss:
$$\mathcal{L}_p = \lambda \|\mathcal{F}(f_\theta) - 0\|^2$$
4: Update parameters:
$$\theta \leftarrow \theta - \eta \nabla_\theta \mathcal{L}_p$$
5: **end for**
6: **Return:** trained model f_θ

Algorithm. 1. PINN Training Procedure

2.4 PINN Performance and Limitations

To evaluate the effectiveness of PINNs in approximating the solution, the network predictions were compared to the reference values obtained from the governing equations. As shown in Fig. 3, PINN completely failed to capture the transient behavior of water height and velocity, producing results that deviated significantly from the expected solution. The velocity predictions remained nearly constant instead of reflecting the expected acceleration and deceleration due to gravity and flow resistance. Similarly, the predicted water heights in the control volumes failed to exhibit a physically meaningful redistribution, suggesting that the network was unable to learn the fundamental governing relationships.

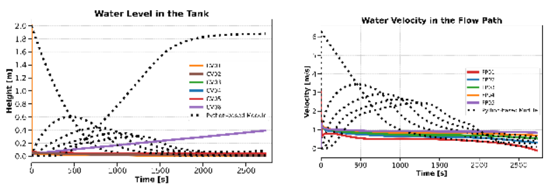

Fig. 3. Comparison of water height (left) and velocity (right)

Fig. 4 further illustrates the training loss history, which reveals persistent instability throughout the learning process. Unlike well-converging models where the loss decreases smoothly, PINN training exhibited fluctuations and stagnation, indicating difficulties in minimizing the residuals of the governing equations.

This behavior suggests that the network was unable to balance the competing constraints imposed by mass and momentum conservation, leading to unphysical and inconsistent predictions.

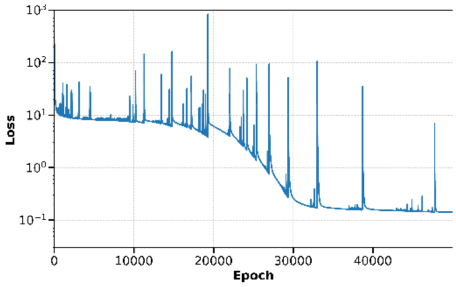

Fig. 4. Training loss histories in the proposed PINN.

The fundamental issue arises from the fact that a single neural network is tasked with predicting multiple coupled variables governed by separate partial differential equations (PDEs). In this system, water height in each control volume is strongly coupled with velocity in the flow path, and these relationships evolve dynamically over time. A single network struggles to simultaneously approximate the solution for all dependent variables while maintaining numerical consistency across equations. As a result, the network fails to enforce mass and momentum conservation effectively, leading to solutions that do not satisfy the expected physical behavior. This limitation suggests that a revised approach is necessary, one that decouples the learning process for different governing equations while preserving their interdependencies.

2.5 Node-Assigned PINNs (NA-PINN) Approach

To address the limitations of conventional PINNs, a modified framework, referred to as the node-assigned PINN (NA-PINN), is introduced. Instead of using a single neural network to approximate all state variables simultaneously, NA-PINN assigns separate neural networks to different components of the system, specifically control volumes and flow paths. Each network is responsible for learning a single state variable while maintaining consistency with the governing equations. This multi-PINN approach has also been shown in previous studies to achieve high accuracy [8].

Figure 5 illustrates the structure of NA-PINN, which consists of a one-dimensional input for temporal input t and 11 PDEs, with each neural network responsible for a single output. A single loss function was constructed to train all outputs simultaneously. Also, a hard constraints method was introduced to enforce the initial conditions.

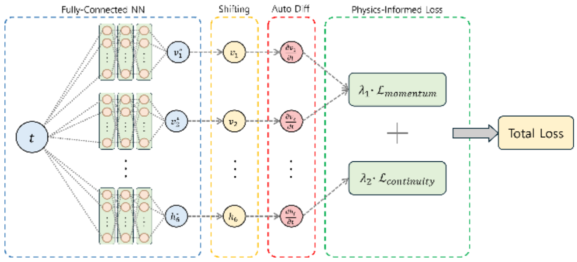

Fig. 5. Architecture of the Node-assigned PINN (NA-PINN)

2.6 NA-PINN Performance Evaluation

The performance of NA-PINN was assessed by comparing its predictions against the solution values. Fig. 6 presents the results, showing that NAPINN significantly improves the accuracy of both water height and velocity predictions. Unlike the conventional PINN, which produced physically inconsistent results, NA-PINN effectively captures the transient flow behavior and closely follows the expected solution. To the best of our knowledge, this is the first study confirming the potential of a PINN for severe accident analysis.

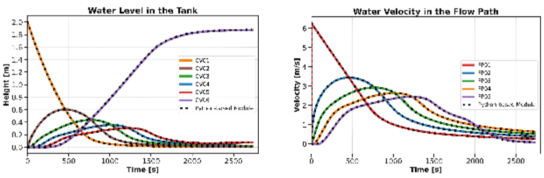

Fig. 6. Comparison of water height (left) and velocity (right)

The quantitative improvements achieved by NAPINN are summarized in Table 1, where MAE and MSE values demonstrate a reduction of more than two orders of magnitude compared to the standard PINN approach. These results confirm that the separation of learning tasks allows NA-PINN to overcome the primary limitations of conventional PINNs.

Table I: Problem Description

Architecture	PINN	NA-PINN
MAE (H)	1.678132	0.006960
MSE (H)	1.640074	2.452554e-05
MAE (V)	4.425523	0.024328
MSE (V)	13.065767	3.906309e-04
Parameters	1,226,923	1,275,659

Fig. 7 shows the training loss history of NA-PINN compared to the conventional PINN. Unlike the fluctuating and unstable loss trajectory observed in the conventional approach, NA-PINN exhibits smooth and consistent convergence. This stability is attributed to the independent networks focusing on individual PDE constraints, allowing each equation to be learned effectively without conflicting influences from other variables.

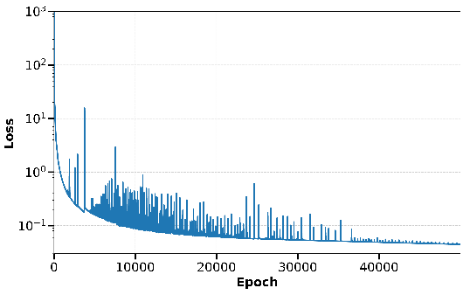

Fig. 7. Training loss histories of the NA-PINN

Overall, the NA-PINN framework addresses the fundamental challenges faced by standard PINNs in modeling coupled PDE systems. By leveraging a multi-network structure, NA-PINN achieves improved predictive accuracy and numerical stability, making it a promising approach for approximating MELCOR-based severe accident simulations.

3. Conclusions

This study evaluated the feasibility of applying PINNs to MELCOR's CVH/FL module which governs mass and momentum conservation. The results demonstrated that conventional PINNs exhibited unstable training behavior and physically inconsistent predictions due to the strong interdependencies among system variables. To address these limitations, this study proposed the Node-Assigned PINN (NA-PINN) framework, where separate neural networks were assigned to control volumes and flow paths. This structure enabled each network to learn independently while maintaining physical interactions within the system.

The analysis revealed that NA-PINN significantly improved the accuracy of water height and velocity predictions compared to conventional PINNs. The model exhibited stable convergence, and the error metrics were reduced by more than two orders of magnitude. These findings suggest that NA-PINN effectively overcomes the fundamental limitations of traditional PINNs, presenting a promising alternative for MELCOR-based severe accident simulations. By integrating physics-based constraints into the neural network architecture, NA-PINN provides a more reliable and computationally efficient approach to solving coupled partial differential equation systems.

However, this study has several limitations. First, the simplified gravity-driven draining scenario used in the analysis does not fully capture the complex multi-physics interactions that occur in real severe accident conditions. Second, while NA-PINN demonstrated enhanced numerical stability, further research is required to assess its applicability to large-scale simulations involving multiple interacting physical phenomena.

Future research should focus on applying NA-PINN to more complex MELCOR simulations, incorporating additional physical processes such as heat transfer and chemical reactions. Although the number of nodes may increase to several hundred, computational efficiency can be enhanced through a batched-network architecture. Furthermore, continued optimization of the network architecture and training methodology is necessary to further improve performance.

In conclusion, this study presents a novel application of machine learning techniques in severe accident analysis, demonstrating the feasibility of PINN-based approaches in nuclear system simulations. To the best of our knowledge, this is the first study confirming the potential of a data-free PINN for severe accident analysis. In particular, NA-PINN serves as a viable alternative to conventional methods, with potential applications in various areas of nuclear safety analysis.

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