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Application of Physics-Informed Deep Learning Model to Reconstruct Temperature Field in Artificial Ground Freezing

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ABSTRACT

This study proposes a physics-informed neural network (PiNN) framework for modeling one-dimensional heat conduction with phase change in artificial ground freezing (AGF). By incorporating the governing equations into the training process, the model simultaneously predicts the temperature field and the moving phase-change interface. A multi-network architecture is adopted to estimate the spatiotemporal temperature distribution and interface position. The model addresses a backward problem by reconstructing the complete temperature field from sparse synthetic data. The results demonstrate the potential of the PiNN framework for AGF monitoring under limited information conditions.

1. INTRODUCTION

In recent years, deep learning has emerged as a promising alternative for modeling physical systems. Among these approaches, the physics-informed neural network (PiNN) framework has obtained significant attention due to its ability to incorporate governing physical laws directly into the training loss function (Cuomo et al., 2022; Rassi et al., 2019). PiNNs can solve partial differential equations without relying entirely on data, utilizing only the mathematical form of the equations while also integrating available measurements to enhance prediction accuracy. This combination

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of data-driven learning and physics-based modeling makes PiNNs particularly advantageous in scenarios with sparse or incomplete data, where conventional numerical methods are less effective.

Artificial ground freezing (AGF) is a transient, two-phase heat conduction process in which unfrozen soil is progressively transformed into frozen soil through heat extraction via embedded freezing pipes (Choi et al., 2024; Park et al., 2024; Pham et al., 2021). In practical AGF applications, detailed initial and boundary conditions are rarely available, and temperature measurements from embedded sensors are typically sparse. Therefore, a robust prediction model must be capable of reconstructing the spatiotemporal temperature field and tracking the evolution of the phase-change interface using limited prior information. By embedding physical laws into the network architecture and incorporating real sensor data during training, the PiNN model leverages both physics and observational data to enhance predictive performance.

This study adopt the PiNN architecture introduced by Cai et al. (2021) to model one-dimensional heat conduction with phase change. The primary objective is to apply this model to the AGF problem, inferring the temperature distribution from limited measurement data and demonstrating the potential of PiNNs for monitoring and forecasting in AGF construction.

2. MATHMETHICAL FORMULATION

The ground freezing process is modeled as a one-dimensional, transient heat conduction problem with a moving phase-change interface. The physical domain is defined as $\Omega = \{(x,t): (0,L) \times (0,T)\}$, representing the spatial and temporal evolution of the system. Within this domain, a moving interface $s(t) \in [0,L]$ separates the frozen and unfrozen regions, denoted as $\Omega_1 = \{x < s(t)\}$ and $\Omega_2 = \{x > s(t)\}$, respectively, as illustrated in Fig. 1. In each subdomain Ω_i (i = 1, 2), the temperature field $u_i(x,t)$ is governed by the classical heat conduction equation:

$$\frac{\partial u_i}{\partial t} - \alpha_i \frac{\partial^2 u_i}{\partial x^2} = 0 \qquad (i = 1,2) \qquad (1)$$

where α_i is the thermal diffusivity of phase i. The problem is constrained by initial and boundary conditions. At the moving interface, the temperatures in the frozen and unfrozen domains must match, as required by thermal equilibrium. Furthermore, the energy balance at the moving interface is expressed as:

$$\frac{ds(t)}{dt} = K_1 \frac{\partial u_1(s(t),t)}{\partial x} - K_2 \frac{\partial u_2(s(t),t)}{\partial x} \qquad (2)$$

where K_i is the thermal parameter for each phase.

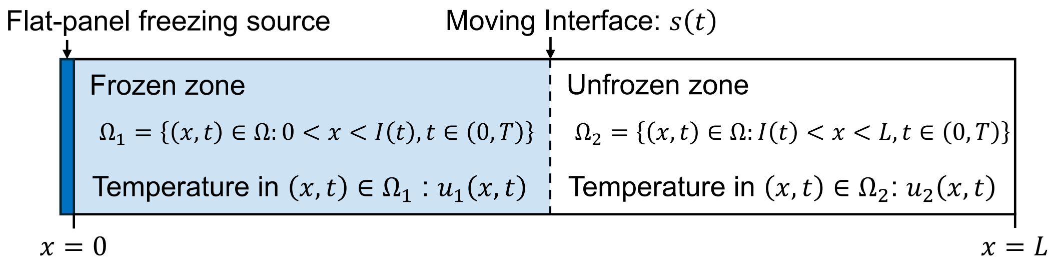

Fig. 1 Schematic of 1D heat conduction with two phases

3. PHYSICS-INFORMED DEEP LEARNING MODEL

To solve the one-dimensional heat conduction problem with phase transition, this study employed a multi-network PiNN architecture originally proposed by Cai et al. (2021a). This approach simultaneously estimates two key quantities: the spatiotemporal temperature field and the time-dependent position of the phase-change interface.

The model comprises two networks. The first network receives spatial and temporal inputs and outputs the temperature profiles for both frozen and unfrozen regions. The second network predicts the temporal evolution of the interface position using time as its sole input. The temperature predictions from the first network are conditioned on the interface location estimated by the second network, thereby determining the corresponding phase regions.

Both subnetworks are implemented as fully connected feedforward neural networks, each consisting of three hidden layers with 100 neurons per layer. The hyperbolic tangent (tanh) function is adopted as the activation function for all hidden layers. Weights are initialized using the Glorot scheme to promote stable convergence. Model training is performed using the Adam optimizer with a mini-batch stochastic gradient descent strategy. The effectiveness of the PiNN architecture has been validated by Park et al. (2025).

4. TEMPERATURE RECONSTRUCTION

Synthetic temperature data were generated via forward simulation using the validated model to replicate measurement conditions typically encountered in AGF operations. Specifically, a flat-panel freezing condition was applied by imposing a constant temperature of -5°C at x=0, while the initial temperature across the domain was set to 5°C. The simulation produced temperature data over time at predefined observation points. To address the temperature reconstruction problem under realistic AGF conditions, where initial and boundary conditions are often unknown, the total loss function was modified to enable reconstruction of the complete temperature field and the moving phase-change interface using only limited observational data.

The reconstructed temperature field and interface location are shown in Fig. 2. Although the backward prediction resulted in slightly higher errors compared to the forward validation case, the overall reconstruction was consistent with the forward simulation. These results confirm that the proposed PiNN framework can successfully reconstruct the full temperature field from sparse measurements, demonstrating its strong potential for practical application in AGF operations. Future work should focus on extending this approach to higher-dimensional problems.

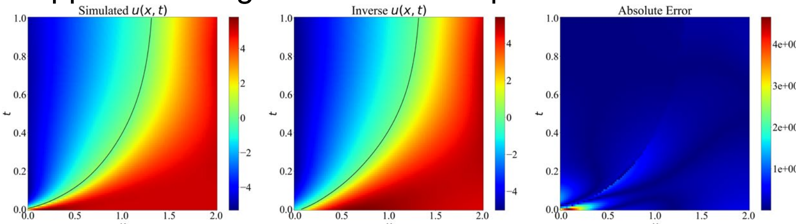

Fig. 2 Simulated and inversely predicted temperature field

5. CONCLUSIONS

This study demonstrated the effectiveness of a multinetwork physics-informed neural network (PiNN) framework for modeling one-dimensional heat conduction with phase change, as representative of artificial ground freezing (AGF). The PiNN model was applied to reconstruct the temperature distribution across the entire domain using sparse synthetic data. By accurately reconstructing both the full temperature field and the interface trajectory from limited measurements, the model demonstrated strong potential for practical AGF scenarios where complete initial and boundary conditions are typically unavailable. This capability highlights the advantage of integrating physical constraints and sensor data within a unified deep learning framework.

While the current implementation is limited to a one-dimensional domain, future work should aim to extend the approach to two- and three-dimensional settings to better capture the complexities of field-scale AGF applications. Such advancements would further enhance the applicability of PiNNs for real-time monitoring, prediction, and control in geotechnical engineering.

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