CHALLENGES, MERITS AND LIMITS OF PINN APPLIED TO CLAY CONSOLIDATION PROCESSES

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Keywords: PINN, soil consolidation, geomechanical modeling.

1 Introduction

The increasing integration of artificial intelligence (AI) in engineering disciplines is redefining the way we formulate, solve, and interpret complex physical problems. Among these innovations, Physics-Informed Neural Networks (PINNs) have emerged as a powerful tool capable of embedding physical laws, as sets of partial differential equations (PDEs), into deep learning architectures. PINNs have demonstrated remarkable results in solving forward and inverse problems across fluid mechanics, heat transfer, and material modelling, even with sparse or noisy data. However, their application in geomechanics remains in its early development, especially for complex, non-linear, and time-dependent processes such as soil consolidation.

Soil consolidation, a fundamental problem in geotechnical engineering, describes the time-dependent settlement associated to the dissipation of excess pore water pressure, induced, for instance, by mechanical loading or change in hydraulic boundary conditions. While classical Terzaghi 1D theory provides a simplified analytical framework, practical applications often involve complex boundary conditions, nonlinear material behavior (e.g., viscosity, plasticity and void ratio-dependent properties), and multi-dimensional effects. These aspects pose significant challenges to traditional formulations, as well as to computational methods. The goal of this work is to critically assess the performance of PINNs in modelling consolidation problems and to compare their capabilities and limitations with those of traditional numerical approaches. By using the consolidation problem as a test case, we aim to evaluate how PINNs handle typical issues of geotechnical applications, like discontinuous initial/boundary conditions, and to provide methodological insights for their effective use in soil mechanics. This study focuses on identifying some key factors that may influence the reliability of the PINN results, such as loss function design, hyperparameter sensitivity, and the evaluation of the evolution in space and time of the stress and the displacement fields as derived from the output of the PINN, i.e. the excess pore water pressure.

2 State of the art of PINNs in soil consolidation problems

PINNs have seen growing interest in geomechanics for their ability to incorporate the consolidation governing PDEs directly into their loss functions, thus reducing dependence on large pre-processed datasets. Their use in

modelling linear elastic and viscoelastic soil behaviour has provided promising results, particularly in 1D configurations with idealized boundary conditions [Bekele, 2021; Lan et al., 2023].
Advanced applications include the use of PINNs for viscoelastic consolidation around tunnels under time-dependent drainage boundary conditions [Xie et al., 2024], and nonlinear 1D consolidation with variable hydraulic conductivity and compressibility coefficients [Lan et al., 2023]. These studies show how suitably tailored PINN architectures, incorporating constraints and normalization techniques, can improve their accuracy. The solutions obtained in these studies have typically been reported in terms of the primary variable of the PDE (e.g., excess pore water pressure), with little attention paid to the derivation and validation of secondary quantities of geotechnical interest, such as displacement or effective stress.

3 Conceptual framework and research questions

The consolidation problem, though classical, can be used as an ideal benchmark to test the limits of PINNs. In theory, PINNs self-trained on pore pressure fields could generalize to predict displacement, stress states or even infer unknown parameters via inverse modelling. Yet critical questions remain:

- Can PINNs resolve displacements with the same fidelity as the pore water pressure field?
- How do they cope with ill-posed or discontinuous initial/boundary conditions, as often seen in Terzaghi-type problems?
- Are they capable of capturing the effects of irreversible soil behavior?

These questions are not merely technical. They point to a deeper epistemological shift: transitioning from deterministic, traditional computational modelling (e.g., FEM) to AI approaches implies rethinking model validation, interpretability, and generalization. Understanding whether PINNs can meet these demands is thus both a scientific and philosophical challenge.

4 Case study: consolidation as a benchmark problem

We propose a PINN-based formulation of the classical consolidation problem as a computational testbed. In this framework, the network is trained to approximate the solution of the governing PDEs, that is the excess pore water pressure, without requiring any dataset as is conventionally done in AI application. Instead, the training is based on a set of collocation points within the spatial-temporal domain, where the loss function is formulated to penalize violations of governing equations and boundary and initial conditions (Figure 1). Beyond standard performance metrics (Figure 2), we investigate the PINN ability to reconstruct displacement and stress field and its robustness under different loading, and boundary conditions. The consolidation problem is also used to systematically study the sensitivity of the solution to hyperparameter choices and to the formulation of the loss function, with the goal of providing practical guidance for model design.
This approach is also intended as a starting point toward more complex applications: layered soils, 2D/3D geometries, and coupled hydro-mechanical processes. The ultimate goal is to identify the architectural and algorithmic innovations needed to scale PINNs from academic examples to engineering practice.

Figure 1. Consolidation isochrones for varying time normalized time $T_v = c_v t / H^2$. Comparison between PINN predictions (hollow circles) and Terzaghi analytical solutions (solid lines).

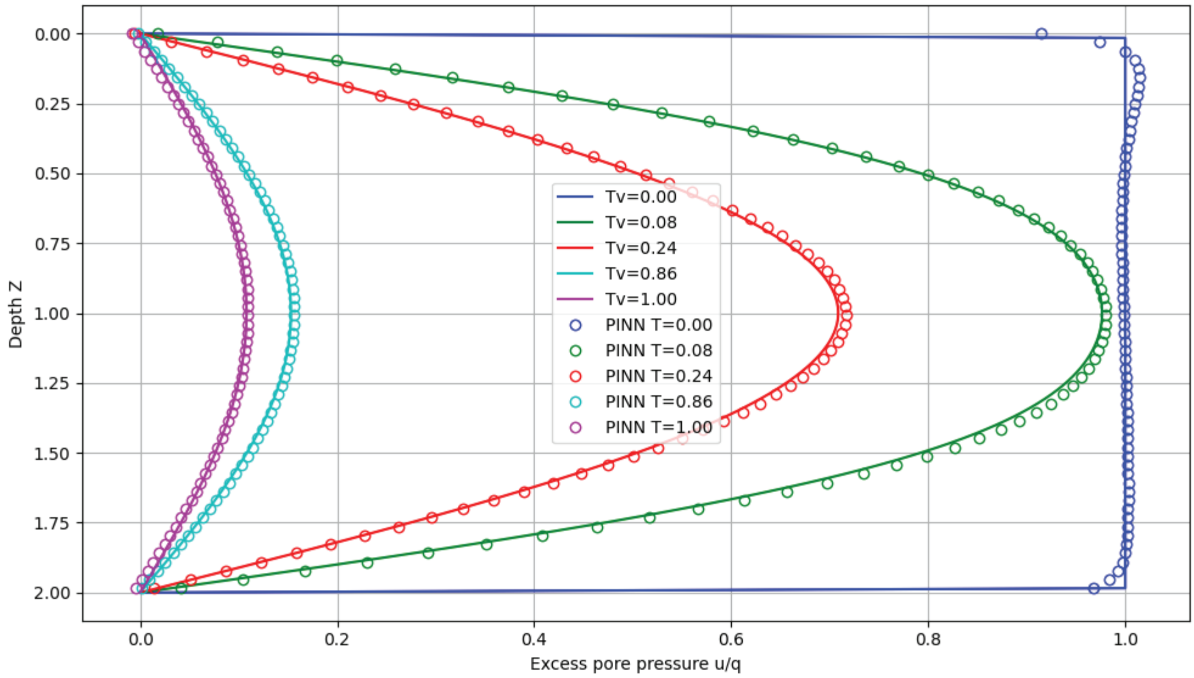
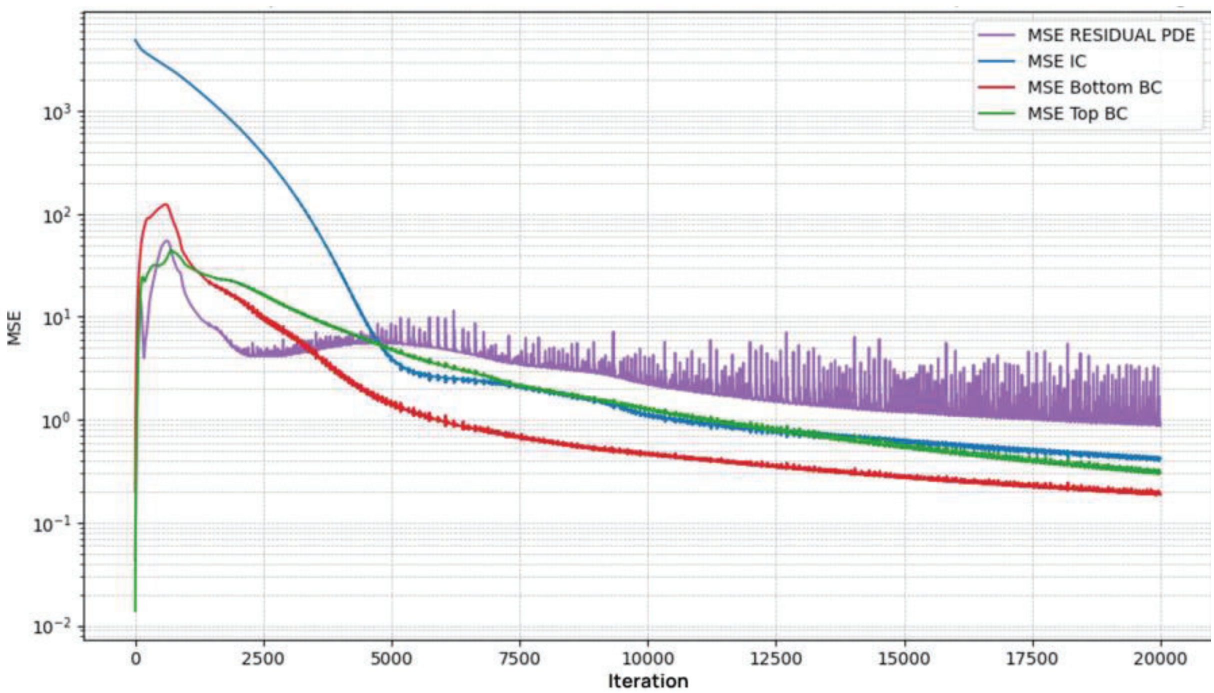


Figure 2. Evolution of the PINN model total loss function during training, decomposed into contributions from the PDE residual, initial condition, and boundary condition terms.



References

Bekele Y. W. (2021). Physics-informed deep learning for one-dimensional consolidation. Journal of Rock Mechanics and Geotechnical Engineering, 13(3), 420–430. https://doi.org/10.1016/j.jrmge.2020.09.005.

Lan P., Su J.-J., Ma X.-Y., Zhang S. (2023). Application of improved physics-informed neural networks for nonlinear consolidation problems with continuous drainage boundary conditions. Acta Geotechnica, 19, 495–508. https://doi.org/10.1007/s11440-023-01899-0.

Raissi M., Perdikaris P. & Karniadakis G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. Journal of Computational Physics, 378, 686–707. https://doi.org/10.1016/j.jcp.2018.10.045.

Xie S., Hu A., Xiao Z., Mariani S., Della Vecchia, G. (2024). PINN-based approach to the consolidation analysis of visco-elastic soft soil around twin tunnels. Tunnelling and Underground Space Technology, 153, 105981. https://doi.org/10.1016/j.tust.2024.105981.

Xie, S., Hu, A., Mariani, S. *et al.* PINN-based approach to the nonlinear large-strain consolidation under time-dependent drainage boundary. *Acta Geotech.* (2025). https://doi.org/10.1007/s11440-025-02729-1