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Physics-Informed Neural Networks vs Data-Driven Models: A Technical Evaluation for Geotechnical Applications

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ABSTRACT

This study presents a comparative evaluation of Physics-Informed Neural Networks (PINNs) and conventional data-driven models for solving a range of geotechnical engineering problems. Unlike conventional approaches, PINNs incorporates governing equations into the loss function, enabling the model to honor the underlying physics of the physical system even with limited data. Through a series of benchmark problems and real-world case studies, we assess each model's performance in terms of accuracy, and physical interpretability. The soil parameters and training data are estimated from available SPT/CPT readings and field experiments. The findings suggest that PINNs offer a robust alternative for geotechnical modeling tasks where domain knowledge can be encoded through differential equations. This work highlights the advantages and limitations of both modeling approaches and provides practical guidelines for selecting the appropriate method based on data availability and desired interpretability.

1. INTRODUCTION

Rapid advancements in machine learning (ML) have generated increasing interest in its application to geotechnical engineering. Among the various approaches, data-driven models are the most common, leveraging large datasets to capture complex, nonlinear soil–structure interactions that are difficult to represent using conventional methods (Wang and Goh, 2021; Liu et al., 2024; Ke et al., 2025). However, their predictive performance is highly dependent on the availability of high-quality training data, which in geotechnical contexts is often scarce, costly to obtain, and specific to individual

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sites. Moreover, these models are susceptible to training noise, which can introduce bias and further limit their ability to generalize to unseen scenarios.

This study evaluates the feasibility of applying physics-informed neural networks (PINNs) as a potential alternative to commonly used data-driven machine learning models. Conventional data-driven models learn directly from experimental or field measurements without incorporating the governing physical laws, making them highly sensitive to data quality and, in some cases, introducing subjective bias. In contrast, PINNs integrate governing equations into the learning process, enabling physically consistent predictions even when data are limited or noisy, and improving generalization to conditions beyond the training range. By systematically comparing PINNs with purely data-driven approaches across representative geotechnical case studies, this work seeks to establish a technical basis for selecting the most appropriate modeling strategy in data-limited, physics-constrained engineering environments.

2. METHODOLOGY

Two key distinctions between the two machine learning paradigms lie in their underlying neural network architectures and the formulation of their loss functions. In data-driven models, the architecture is optimized solely for mapping input–output relationships (see Fig. 1), with the loss function typically defined by statistical error metrics (e.g., RMSE) between predicted and observed values.

In contrast, physics-informed neural networks (Raissi and Karniadakis, 2019) incorporate additional architectural components see Fig. 2), and augmented loss terms that embed governing partial differential equations, boundary conditions, and initial conditions directly into the training process, thereby enforcing physical consistency alongside data fidelity.

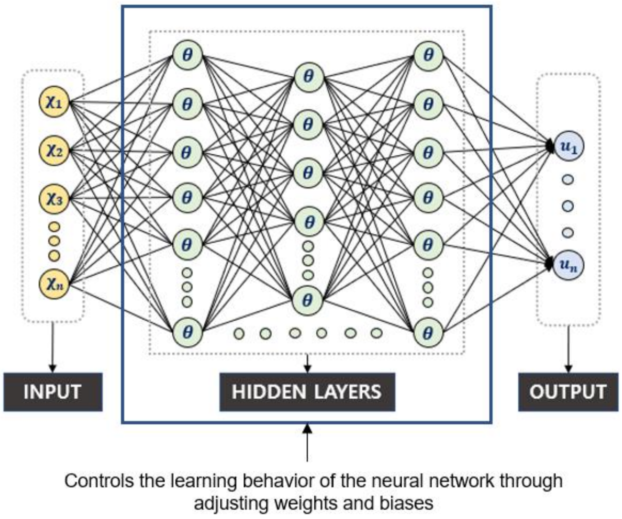
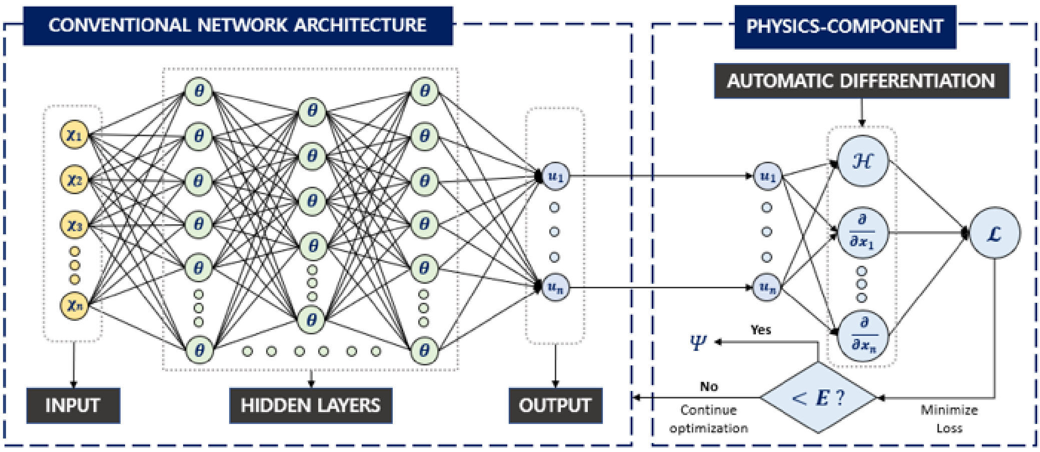


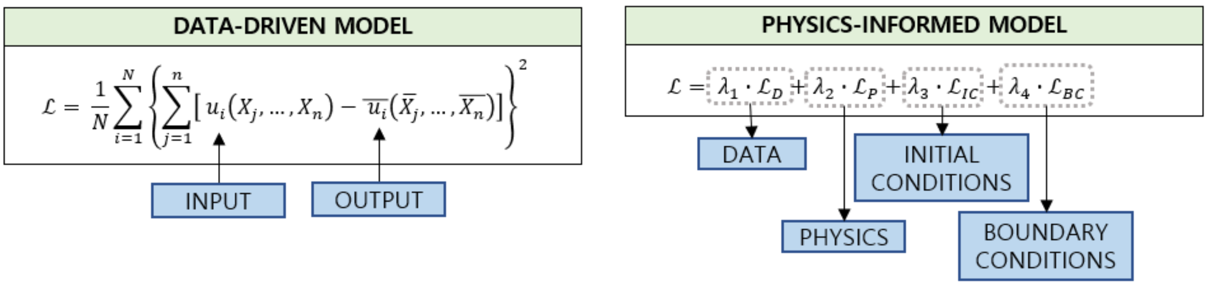
Fig. 1. Typical data-driven neural network architecture

In machine learning, the loss function ($\mathcal{L}$) quantifies the discrepancy between the model's predictions and desired outcome. For purely data-driven models, the loss function is typically empirical-risk-based, computed from data misfit metrics between the input (usually observed data value) and output (predicted by the model). In contrast, PINNs employ a composite loss function that synthesizes multiple terms such as data fidelity loss, physical residual loss and initial and boundary condition loss. This integration transforms the training problem from a purely statistical fitting task into a constrained optimization problem in function space, which can improve generalization in data-scarce or noisy scenarios.



PINNS treat outliers differently because the governing physics of the system is prioritized instead of the input data alone, giving this method a built-in robustness against outliers on the training set-up

Fig. 2. Physics-informed neural network architecture



$$\mathcal{L}_D = \frac{1}{N}\sum_{i=1}^{N}\left\{\sum_{j=1}^{n}\left[u_i(X_j,\dots,X_n) - \overline{u_i}(\overline{X_j},\dots,\overline{X_n})\right]\right\}^2$$

$$\mathcal{L}_P = \frac{1}{N}\sum_{i=1}^{N}\{\mathcal{D}[u(X_i,\dots,X_N)] - f(X_i,\dots,X_N)\}^2$$

$$\mathcal{L}_{IC} = \frac{1}{N}\sum_{i=1}^{N}[u(X_i,0) - g(X_i)]^2$$

$$\mathcal{L}_{BC} = \frac{1}{N}\sum_{i=1}^{N}[u(X_i,\dots,X_N) - g(X_i,\dots,X_N)]^2$$

Fig. 3. Key difference in modeling of the loss functions between the data-driven model vs. the physics informed model

In this study, the comparative performance of the two modeling approaches is assessed through the prediction of lateral displacement response for a pile idealized as a Timoshenko beam (Kapoor et al., 2024) resting on a nonlinear Winkler foundation.

For a regular shafted pile embedded in a homogenous layer of soil, the appropriate differential equation that can model the soil-structure behavior is the beam on nonlinear Winkler foundation (refer to Fig. 4). Here (q) as a function of (x) represents the applied horizontal load, $E_p\, I_p \frac{d^4w(x)}{dx^4}$ represents the flexural capacity of the pile and the nonlinear soil resistance is represented by (p) function of (x, w). The equation is then rearranged to create the residual equation used in the loss function for the PINNs model. The computational domain spans the entire length of the pile, free ended and embedded. The boundary conditions at the top tip is free while the bottom embedded tip if fixed.

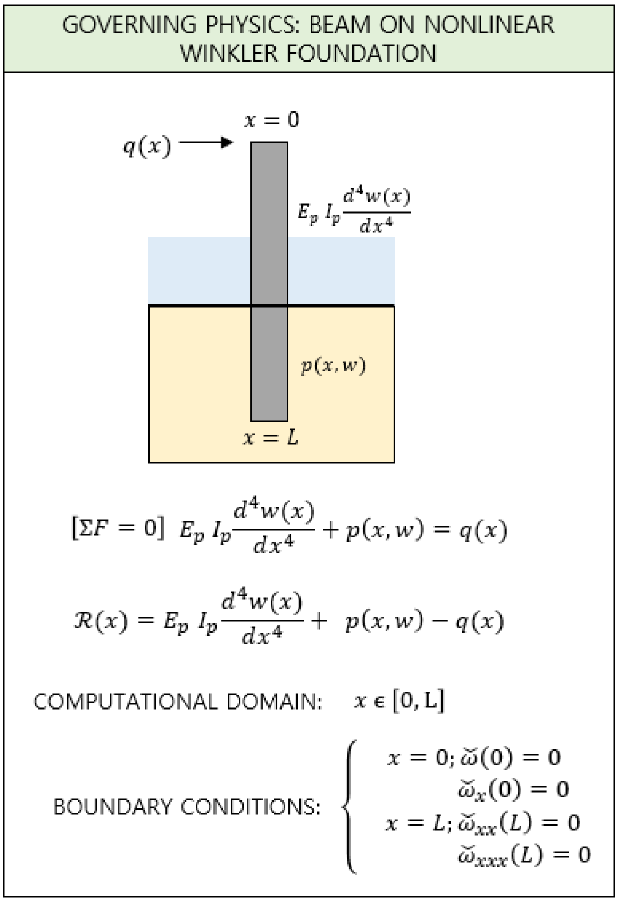


Fig. 4. Governing physics of a beam embedded in nonlinear Winkler foundation

3. RESULTS AND DISCUSSION

The comparative analysis presented in this study reveals that the physics-informed neural network (PINN) consistently outperforms the purely data-driven model across all evaluated geotechnical scenarios. This superiority is observed in multiple performance dimensions, including lower root mean squared error (RMSE) and mean absolute error (MAE) on test datasets, reduced physics residual norms reflecting improved compliance with governing equations, and enhanced generalization to extrapolative conditions beyond the training domain.

Furthermore, the PINN exhibited greater robustness under data-scarcity and noise-contaminated training scenarios, maintaining physically consistent predictions where the data-driven model showed significant degradation in accuracy and stability.

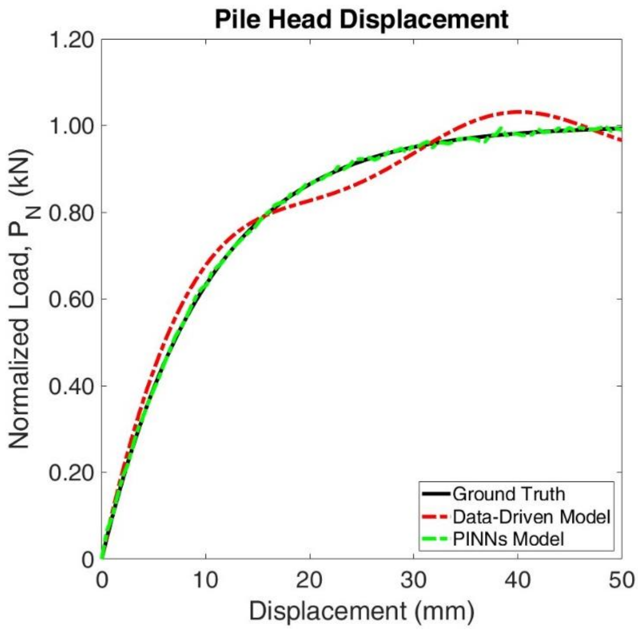


Fig. 5. Comparison of predicted lateral pile head displacement between the data-driven model vs the physics-informed model

Shown in Fig. 5 is the comparison of predictive performance between the two models. The ground truth curve represents the baseline reference, corresponding in this context to the pile head displacement profile obtained from a high-fidelity finite element method (FEM) simulation. The PINN-predicted response closely replicated the baseline curve, not only matching the overall displacement magnitude but also accurately capturing the curvature and inflection points along the profile. This high level of agreement can be attributed to the PINN’s incorporation of the governing beam-on-nonlinear-Winkler-foundation equations into the loss function, which constrains the solution space to physically admissible responses, even under limited or noisy training data.

In contrast, the purely data-driven model produced predictions that, while generally following the trend of the baseline curve, exhibited noticeable deviations in both amplitude and gradient, particularly in regions with higher curvature. These discrepancies likely stem from the absence of embedded physical constraints, which makes the model more reliant on the statistical patterns present in the training dataset.

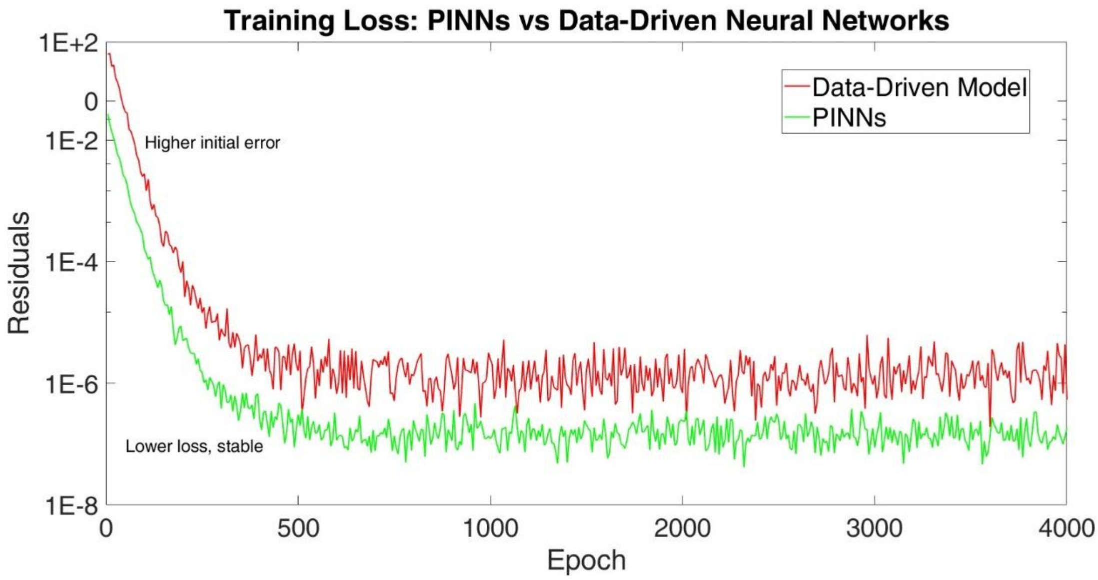


Fig. 6. Evolution of residuals over training epochs metrics for PINNs and the data-driven model

Fig. 6 illustrates the evolution of residual errors over training epochs for both the PINN and the purely data-driven model. The data-driven model exhibited a higher initial error compared to the PINN in the early training stages, likely due to its reliance solely on empirical risk minimization. Without the guidance of embedded physical constraints, the optimization process for the data-driven model must infer the entire functional mapping from sparse and potentially noisy data, leading to slower convergence and larger initial parameter misalignment. In contrast, the PINN began with lower residual loss because the incorporation of governing differential equations into its composite loss function effectively regularizes the hypothesis space. This physics-constrained initialization guides the network towards physically admissible solution manifolds from the outset, reducing the parameter search space and accelerating convergence. The persistently lower residual loss observed for the PINN throughout training reflects enhanced training stability, attributable to the regularization effect of the physics-based loss terms, which mitigate overfitting and improve gradient conditioning during backpropagation.

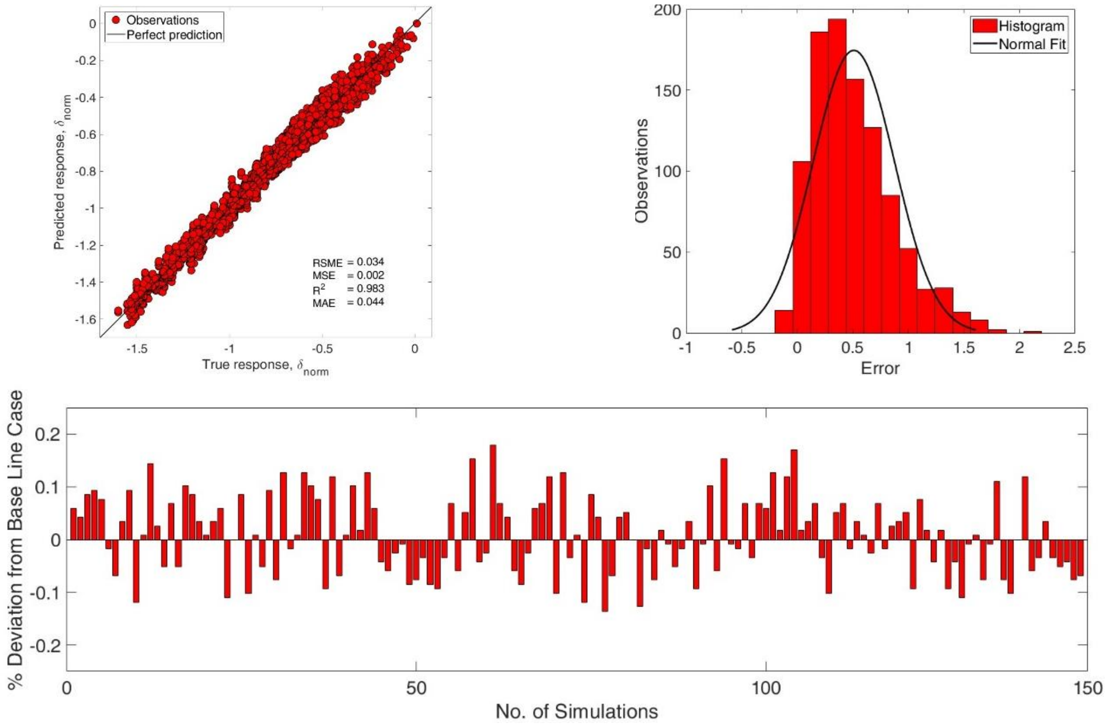
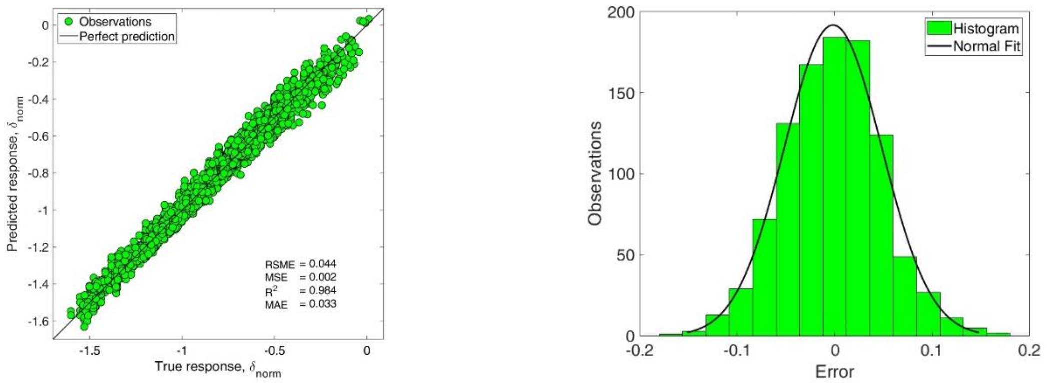


Fig. 7. Performance of the data-driven model



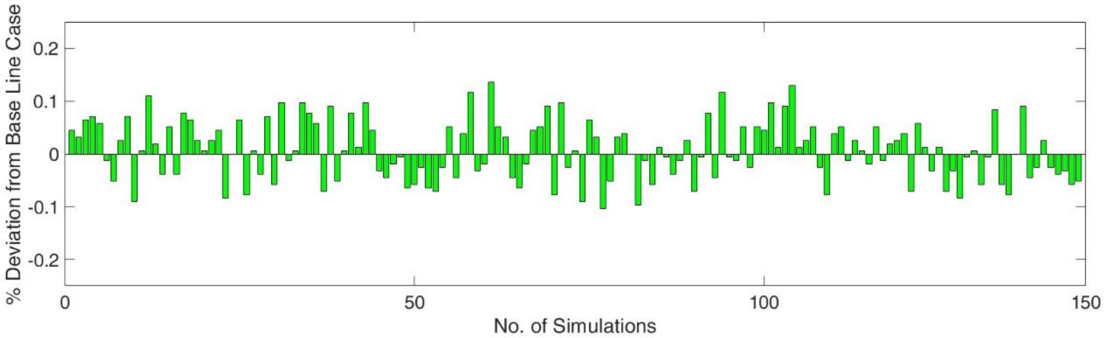


Fig. 8. Performance of the physics-informed model

Figs. 7 and 8 present the predicted versus true response profiles for the data-driven and physics-informed models, respectively. In both cases, the scatter points lie close to the 1:1 reference line, indicating a high coefficient of determination (R^2) and strong correlation between predictions and ground truth values. This close alignment confirms the generally high predictive capability of both models, consistent with the pile head displacement prediction trend reported in Fig. 6. However, the PINNs model still exhibits marginally superior performance, as evidenced by a tighter clustering of predictions around the reference line, reduced dispersion, and lower mean absolute deviation—attributes indicative of improved generalization and lower variance in the model's predictive mapping.

The histogram plots further underscore these differences. For the data-driven model, the error distribution is slightly positively skewed, suggesting a systematic tendency to underpredict in certain regions, likely due to insufficient representation of case conditions in the training set. In contrast, the PINN's histogram approximates a Gaussian distribution centered near zero, reflecting unbiased error characteristics and symmetric variability. This behavior is consistent with the regularization effect of the physics-informed loss terms, which constrain the hypothesis space and promote statistically homoscedastic residuals, thereby reducing systematic bias and enhancing the reliability of the model across the input domain.

The bar graph presents the percentage deviation from the baseline case across multiple simulation runs. The PINN consistently exhibits deviations clustered more closely around the zero-error line, indicating a higher degree of predictive fidelity relative to the FEM-derived reference solution. This tighter error concentration reflects both reduced bias and lower variance in the model's predictions, highlighting its superior accuracy and stability when compared to the purely data-driven model, which demonstrates larger and more scattered deviations indicative of less consistent generalization performance.

4. CONCLUSION

This study demonstrates that physics-informed neural networks (PINNs) consistently outperform purely data-driven models in geotechnical applications where governing physical laws are well established and data availability is limited. By embedding partial differential equations, boundary conditions, and material behavior constraints directly into the loss function, PINNs generate predictions that are not only statistically accurate but also physically admissible and interpretable. This dual fidelity enhances model robustness, reduces bias, and improves generalization to unseen conditions, even under noise-contaminated or data-scarce scenarios. Applied to the prediction of lateral load–displacement behavior for a pile modeled as a Timoshenko beam on a nonlinear Winkler foundation, the PINN framework successfully replicated the finite element method (FEM) baseline response with lower residuals, unbiased error distribution, and reduced percentage deviation across simulations. These results highlight the potential of PINNs as a reliable, physics-consistent alternative to conventional machine learning models in data-limited, physics-constrained geotechnical engineering contexts.

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