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Physics-informed neural networks for predicting turbulent urban flow

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SUMMARY

Urban wind flow prediction often depends on computationally intensive Computational Fluid Dynamics simulations or costly wind tunnel experiments. This study explores Physics-Informed Neural Networks (PINNs) as a data-efficient alternative for modelling turbulent flow around high-rise buildings. The PINN framework solves the Reynolds-Averaged Navier–Stokes (RANS) equations for incompressible flow without using an explicit turbulence model. A hybrid loss function combines boundary data from Large Eddy Simulation (LES) with governing RANS equation residuals to enforce both data and physics consistency. Unlike most studies focused on laminar regimes, this work applies PINNs to turbulent flow around a high-rise building, represented by a two-dimensional cross-section. Network performance is enhanced using Fourier feature encoding for high-frequency variations and spatial weighting of collocation points in complex wake regions. Validation against LES benchmarks shows that the enhanced PINN reproduces key flow quantities within ~25% discrepancy and at substantially lower computational expense.

Keywords: *Navier-Stokes equations, Physic Informed Neural Networks, turbulent flow, Wind induced pressure.*

1. INTRODUCTION

The simulation of turbulent flow around urban geometries using Computational Fluid Dynamics (CFD) remains computationally demanding, as resolving complex flow structures requires high-resolution grids. PINNs provide a promising alternative by embedding governing physical laws directly into the training process, eliminating the need for grids (Raissi et al., 2019). This work builds on the PINN framework of Eivazi et al. (2022), who demonstrated that PINNs can solve the RANS equations for incompressible turbulent flows using only boundary data, focusing on Zero Pressure Gradient and Adverse Pressure Gradient turbulent boundary layers and periodic hill flows, but excluding flows around the obstacles. This approach is extended here to more complex flow around a high-rise building at a Reynolds number of 1.4×10^5, with various enhancements—such as Fourier feature encoding and spatial weighting of collocation points—introduced as examples to improve the network's ability to capture high-frequency variations and enhance accuracy in critical regions such as the recirculation zone. High-fidelity LES data from Vranešević et al. (2022) are applied at the domain and building boundaries to enforce boundary conditions, allowing the network to learn the Navier–Stokes equations within the domain and demonstrating the potential of boundary-driven PINNs for simulating complex urban turbulent flows.

2. BASELINE PINN

PINNs integrate governing physical laws into the training process. Unlike data-driven methods, PINNs leverage known physics, expressed as partial differential equations, to guide learning. This is achieved by adding a physics-informed term to the loss function that penalizes deviations from the governing equations at collocation points. Crucially, PINNs use automatic differentiation to compute the necessary derivatives of the neural network outputs with respect to the inputs, enabling the direct enforcement of partial differential equations.

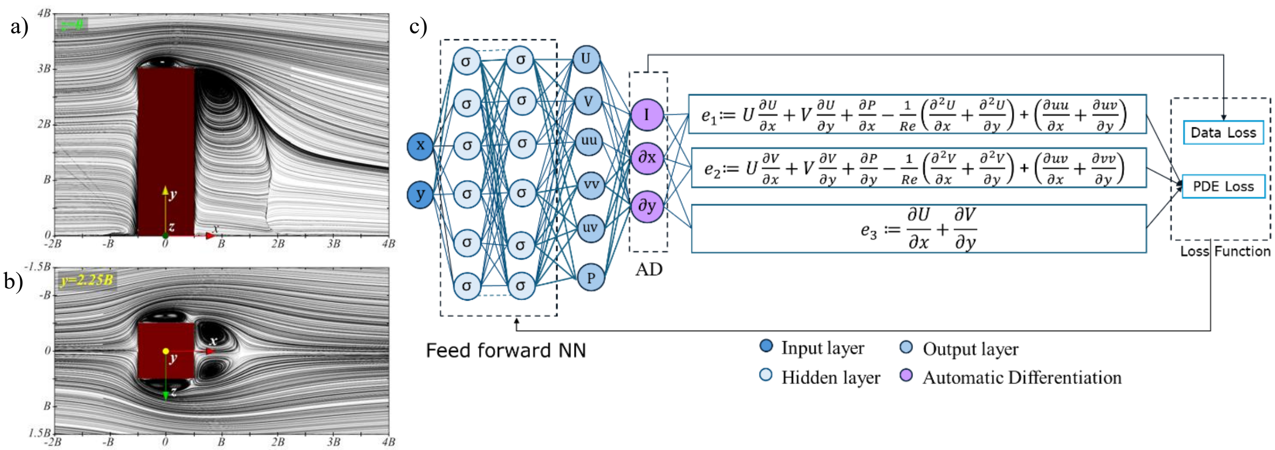

Figure 1:a) Cross-section of the studied high rise building in x-z plan, b) Cross-section of the studied high rise building in x-y plan (Vranešević et al., 2022), c) Schematic representation of PINNs for solving RANS equations.

In this study, a PINN framework is developed to simulate turbulent flow around a high-rise building, with height H to width B ratio of 3:1 (Figure 1a, b). The flow is inherently three-dimensional, but a two-dimensional flow at $y = 2.25B$ is analyzed to represent local flow behavior. As a reference and training data, LES dataset by Vranešević et al. (2022) is used. The PINN solves the steady-state incompressible Reynolds-Averaged Navier–Stokes (RANS) equations, representing conservation of mass and momentum, without introducing an explicit turbulence model.

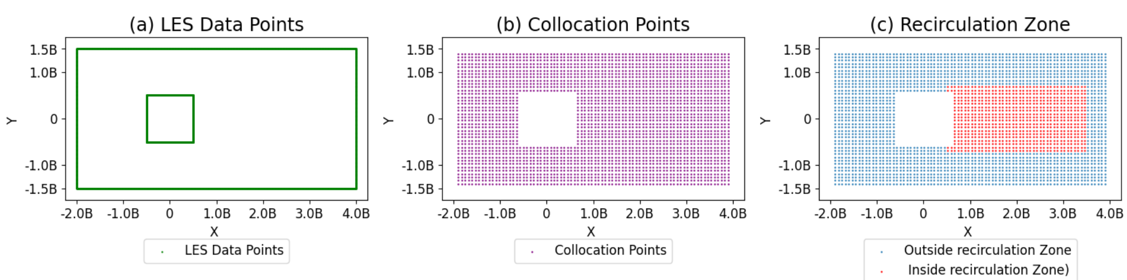

Figure 2: Distribution of a) LES data points for data loss, b) collocation points for physics loss, c) collocation points inside and outside the recirculation points for spatial weighting.

The network architecture consists of a fully connected feedforward neural network that takes spatial coordinates (x, y) as input and outputs the flow variables: velocity components (U, V), pressure (P), and Reynolds stresses (uu, vv, uv), as shown in Figure 1c). A hybrid loss function is used during training, integrating data loss to promote agreement with reference data and physics loss to maintain compliance with the underlying physical laws. The data loss term uses boundary information derived from LES data (Figure 2a), located along the domain boundaries and building surface. The physics loss term is computed from the residuals of the RANS equations evaluated at collocation points distributed throughout the domain (Figure 2b). Automatic differentiation is employed to efficiently compute the spatial derivatives required for forming the residuals. Minimizing the hybrid loss enables the network to satisfy both boundary constraints and physical laws, producing flow fields that align closely with the LES reference data while maintaining significantly lower computational cost.

Hyperparameter optimization of the PINN—varying network depth, neurons per layer, activation function, and learning rate—is performed using Gaussian Process regression, and the resulting optimized model is referred to as the baseline PINN. While this provided a solid foundation, the initial relative l_2-norm error and R^2 score**,** evaluated against LES data**,** indicated considerable room for improvement, as shown in Table 1. The relative l_2-norm measures the difference between predicted and actual values, with lower values indicating better fit, while the coefficient of determination, R^2 score, reflects how well the model captures the variability in the flow variables (U, V, P) across spatial locations, with values closer to 1 indicating better agreement.

3. STEPWISE IMPROVEMENT OF PINN PERFORMANCE

To enhance the predictive capability of the PINN framework, several improvement strategies are explored, including Fourier feature encoding and spatial weighting of collocation points.

3.1. Fourier features (FF)

The first enhancement involved the introduction of Fourier feature encoding to improve the PINN's ability to capture high-frequency flow variations, which standard activation functions such as ReLU or tanh often struggle to represent. In this approach, the input spatial coordinates (x, y) are first mapped into a higher-dimensional space using sinusoidal basis functions, which allow the network to represent a wide range of oscillatory patterns inherent in turbulent flows. The transformation is defined as $\gamma(x, y) = [\sin(2\pi BX), \cos(2\pi BX)]$, where ($x, y$) is the input vector, and B is a projection matrix with entries sampled from a Gaussian distribution with zero mean and standard deviation σ. The standard deviation σ controls the range of encoded frequencies, with larger values introducing higher-frequency components for finer-scale variations and smaller values emphasizing lower-frequency patterns. The number of basis functions per input dimension, m, determines the dimensionality of the transformed input space. These quantities—σ and m—act as hyperparameters. Thus, they are systematically optimized via grid search based on the relative l_2-norm error and R^2 score against LES results. Incorporating Fourier features in this way improved the overall fit to LES data (Table 1), particularly enhancing the representation of streamwise velocity component U.

3.2. Spatial weighting (SW)

To improve accuracy in the recirculation zone behind the building, spatial weights—treated as hyperparameters—were applied to the collocation points, with higher weights forcing the PINN to better satisfy the governing equations in this critical region. In the initial implementation, the boundaries of the recirculation zone are defined based on preliminary estimates, as shown in Figure 3c), with further optimization of the zones planned for future iterations. Weights were treated as hyperparameters and assigned directly to each collocation point's residual in the physics loss, so that points inside the recirculation zone contribute more strongly to the total hybrid loss. This approach simplifies gradient computation compared with calculating separate losses for different regions. The optimal values of these weights are determined via grid search, with higher weights inside the recirculation zone and lower weights outside, effectively guiding the PINN to prioritize accuracy in critical areas. Applying spatial weighting in this manner significantly improved the prediction of flow trends, as reflected by increased R^2 scores in Table 1, reaching above 0.9 for all considered flow variables. Comparable flow patterns are predicted and show good agreement with the LES reference results in Figure 3.

Table 1: Coefficient of determination R^2 and l_2 norm of error between LES data and PINN for different approaches

Approach	R^2 (U)	l_2 error (U)	R^2(V)	l_2 error(V)	R^2(P)	$l_2$error(P)
PINN	0.33	60.25 %	0.83	41.26 %	0.94	20.01 %
PINN + FF	0.72	38.55 %	0.87	36.22 %	0.95	18.70 %
PINN + FF + SW	0.93	19.69 %	0.93	25.59 %	0.97	13.40 %

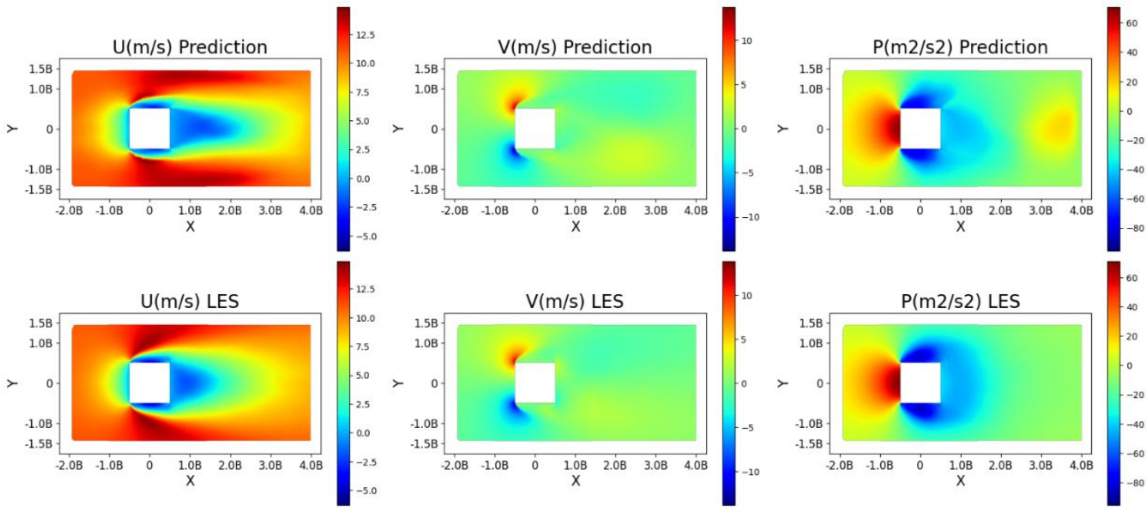

Figure 3: Predicted flow variables (U, V, P) from the enhanced PINN model including Fourier features and Spatial weighting, compared against the reference LES data.

4. CONCLUSIONS

The integration of the optimized baseline PINN with Fourier feature encoding and spatial weighting yielded highly promising results, achieving accurate reconstruction of turbulent flow variables with notably reduced error levels. The training time for this model on a T4 GPU was 1046 seconds demonstrating the potential for faster simulations compared to traditional methods. Building on this foundation, future work will explore additional enhancement strategies, including Sobolev regularization, conservative PINNs (cPINNs), and other advanced techniques, to further improve model robustness. Moreover, the framework will be extended to investigate flow configurations at various inflow angles beyond the 0° case, enabling a more comprehensive assessment of its performance under different flow conditions.

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