AeroGraph-PINN: Physics-Informed Neural Networks for Spatio-Temporal Atmospheric Pollution Modeling

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Project Repository: https://github.com/asthaap5347/AeroGraph-PINN

***Abstract*—Predicting air pollution accurately is vital because pollution directly impacts human health. However, generating reliable pollution maps is difficult when physical monitoring stations are limited. A standard deep learning model learns strictly from observed data, often producing unrealistic predictions in unmonitored spatial gaps. In this work, I propose AeroGraph-PINN, a Physics-Informed Neural Network that combines deep learning with the 2D Advection-Diffusion Partial Differential Equation (PDE). Evaluated on a synthetic 50,000-point spatio-temporal domain using 200 sparse sensor observations and 2,000 collocation points, AeroGraph-PINN achieves an MSE of 0.0315 and an R^2 score of 0.9274, outperforming purely data-driven baselines.**

***Index Terms*—Physics-Informed Neural Networks, Atmospheric Pollution, Advection-Diffusion Equation, Deep Learning**

I. Introduction

Air pollution is a pressing challenge because wind and diffusion continuously transport pollutants across space and time. Predicting pollution levels in regions without physical sensors allows us to map air quality comprehensively without relying on expensive infrastructure.

Traditional numerical methods solve governing transport equations accurately but require high computational overhead. Conversely, standard deep learning models learn fast but produce unphysical artifacts when observations are sparse. AeroGraph-PINN bridges this gap by enforcing the 2D Advection-Diffusion physical law directly during network training.

II. Methodology

A. Governing PDE

The pollutant concentration $C(x, y, t)$ is governed by the 2D Advection-Diffusion equation:

$$\frac{\partial C}{\partial t} + u\frac{\partial C}{\partial x} + v\frac{\partial C}{\partial y} = D\left(\frac{\partial^2 C}{\partial x^2} + \frac{\partial^2 C}{\partial y^2}\right) \tag{1}$$

where $u = 0.5$ km/h, $v = 0.3$ km/h, and $D = 0.05$.

B. Loss Function Optimization

The total loss combines observation error ($\mathcal{L}_{data}$) and physics residual error ($\mathcal{L}_{pde}$):

$$\mathcal{L}_{total} = \mathcal{L}_{data} + \lambda\mathcal{L}_{pde} \tag{2}$$

with physics weight $\lambda = 0.1$. Derivatives were computed across 2,000 collocation points using PyTorch automatic differentiation (`torch.autograd`). I trained and evaluated the model locally on my MacBook.

III. Experimental Results and Discussion

The models were evaluated across 50,000 spatio-temporal domain points over 1,000 training iterations.

TABLE I
Model Evaluation Across 50,000 Domain Points

Model Architecture	MSE	R^2 Score
Baseline Neural Network	0.053317	0.8772
AeroGraph-PINN (Ours)	**0.031533**	**0.9274**

AeroGraph-PINN achieved a 40.8% reduction in MSE compared to the baseline model. As shown in Fig. 1, the baseline network creates false peaks above 4.0 in unmonitored zones, whereas AeroGraph-PINN restricts peak values around 2.5, matching true physical dynamics.

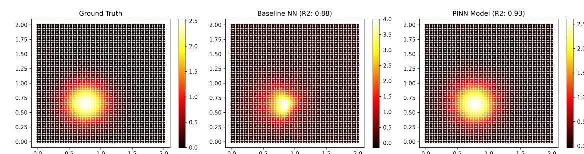

Fig. 1. Visual comparison of Ground Truth, Baseline NN, and PINN predictions.

IV. Conclusion and Future Work

In this work, I developed AeroGraph-PINN to show that embedding physical laws into neural networks prevents unphysical predictions in sparse sensing environments. Future work will extend this framework to real-world air-quality sensor feeds and 3D atmospheric layers.

References

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