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Enhancing Pressure Prediction from Wind Tunnel Tests with Automatic Differentiation in Compact Neural Networks

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SUMMARY
Predicting wind pressure on high-rise buildings is essential, but traditional methods are time consuming and expensive. This study introduces a Gradient-Informed Artificial Neural Network (GI-ANN) to predict pressure coefficients across varying aspect ratios and wind angles. Leveraging Automatic Differentiation (AD), the model integrates pressure gradient information directly into its loss function. This gradient-informed training significantly enhances model performance by enforcing physical consistency and accurately capturing complex, high-frequency pressure variations. The GI-ANN achieved a high R^2 (> 0.98), demonstrating superior accuracy. This approach streamlines the design process by enabling robust predictions with minimum training data, offering a computationally efficient tool for wind-resistant structural design.

Keywords: Gradient-Informed Neural Networks, Automatic Differentiation, Wind Engineering.

1. INTRODUCTION

The aim of this study is to establish a prediction framework capable of accurately forecasting wind pressure using a limited number of physical models from wind tunnel tests. Based on the work of Shimada & Ishihara, (2002), five aspect ratios (Table 1) were chosen to develop a robust ANN from experimental measurements. This study adopts a Gradient-Informed ANN (GI-ANN) using Automatic Differentiation (AD) (Güne¸ *et al.*, 2018), applied in a supervised learning context to enhance pattern recognition with fewer test models. Inspired by the application of GI-ANNs to fluid velocity fields in flow separation control by Ma et al. (2026), this study extends this methodology to wind pressure prediction on high-rise buildings, leveraging gradient information for physically consistent predictions. Although this study focuses on pressure measurements at the middle ring for each case, the same methodology can be extended to additional measurement points across each tested model.

2. EXPERIMENT SETUP

The experimental investigation was conducted at the Atmospheric Boundary Layer (ABL) wind tunnel facility at Ruhr-University Bochum, Germany (Figure 1). The atmospheric boundary layer corresponding to Terrain Category II was simulated using the spire-and-roughness technique at a geometric scale of 1:300. Building models with varying aspect ratios (AR1–AR6) were measured under the impact of different wind directions (0°, 15°, 30°, and 45. Pressure measurements were obtained from a single ring of high-resolution pressure taps at the mid-height of each model, with the number of pressure taps for each model summarized in Table 1.

Table 1. Specifications of models studied in the wind tunnel test

Model	H(mm)	W (mm)	L (mm)	AR (L/W)	Number of taps	Distance of first 6 taps from corners (mm)
AR1	400	100	100	1	68	2-4-6-10-14-22
AR2	400	100	200	2	88	2-4-6-10-14-22
AR3	400	100	300	3	80	2-4-6-10-14-22
AR4	400	50	200	4	88	2-4-6-10-14-23
AR6	400	50	300	6	88	2-4-6-10-14-23

Figure 1 . Buildings models AR1 to AR6 (in order from right to left)

3. FEATURES, TARGETS AND MODEL SELECTION

The neural network predicts wind pressure coefficients using aspect ratio (AR), normalized coordinates (X/L, Y/W), wind angle (α), and the distance to the nearest corner (dist-x, dist-y). While the former parameters are commonly used in wind pressure prediction studies, the inclusion of corner distance accounts for proximity to regions where flow separation strongly affect pressure distributions. The model's output targets encompass the mean pressure coefficient ($\bar{C}_p$), its standard deviation ($\acute{C}_p$), and their respective gradients ($\mathrm{d}\bar{C}_p/\mathrm{dx}$, $\mathrm{d}\bar{C}_p/\mathrm{dy}$). The integration of these gradients ensures physical consistency and facilitates the accurate capture of sharp pressure variations, particularly in regions such as building corners. Model training is based on selected aspect ratios (ARs). Two-model (AR1, AR6) and three-model (AR1, AR3, AR6) training strategies are considered. AR1 represents a separated-type cross-section, while AR6 corresponds to a fully reattached cross-section. These two cases capture the two contrasting flow regimes influencing the pressure distribution. AR3 represents an intermittently reattached cross-section and captures intermediate flow characteristics. All wind directions (0°, 15°, 30°, and 45°) for the selected aspect ratios are included in the training datasets to ensure consistent representation of directional effects.

4. GRADIENT-INFORMED ARTIFICIAL NEURAL NETWORKS(GI-ANNs)

Two models are considered in this study: a conventional Artificial Neural Network (ANN) and a Gradient-Informed Artificial Neural Network (GI-ANN). Comparison enables evaluation of the effect of incorporating gradient information on prediction accuracy and physical consistency. The ANN used in this study is a feedforward network designed to predict $\bar{C}_p$ and $\acute{C}_p$. Its architecture, identified through a random search optimization process, includes an input layer for six features, followed by hidden layers forming a bottleneck architecture, batch normalization, and ReLU activation function (Figure 2a). The GI-ANN model architecture incorporates automatic differentiation during training to explicitly embed gradient information into the learning process. The network adopts a multi-input structure with two separate pathways as shown in Figure 2b.

The first pathway processes only the spatial coordinates (x, y), which are required for computing spatial gradients of the predicted pressure coefficients $\bar{C}_p$ and $\acute{C}_p$. The second pathway processes the full set of six physical and geometric features. This structure processes spatial and physical attributes independently before combining them into deeper layers. By keeping these inputs distinct, the model can efficiently and precisely calculate these gradients through automatic differentiation, avoiding potential interference that could arise from combining all features into a single input stream early in the network. The outputs of the two pathways are concatenated along the feature dimension and passed through four fully connected hidden layers. Each hidden layer consists of 128 neurons with hyperbolic tangent (tanh) activation, followed by batch normalization and dropout rate of 0.1 to enhance training stability and mitigate overfitting. The final layer is a dense layer with two output neurons, providing direct predictions of $\bar{C}_p$ and $\acute{C}_p$ without an activation function. Training is performed using a custom training loop in which automatic differentiation is employed to compute spatial gradients of the predicted outputs with respect to the input coordinates. The total loss function (L_{total}) combines a data fidelity term (L_{Cp}), representing the error between predicted and target pressure coefficients, and a gradient-based term (L_{Grad}), representing the discrepancy between predicted and reference gradients. This composite loss encourages both accurate predictions and spatially consistent pressure distributions.

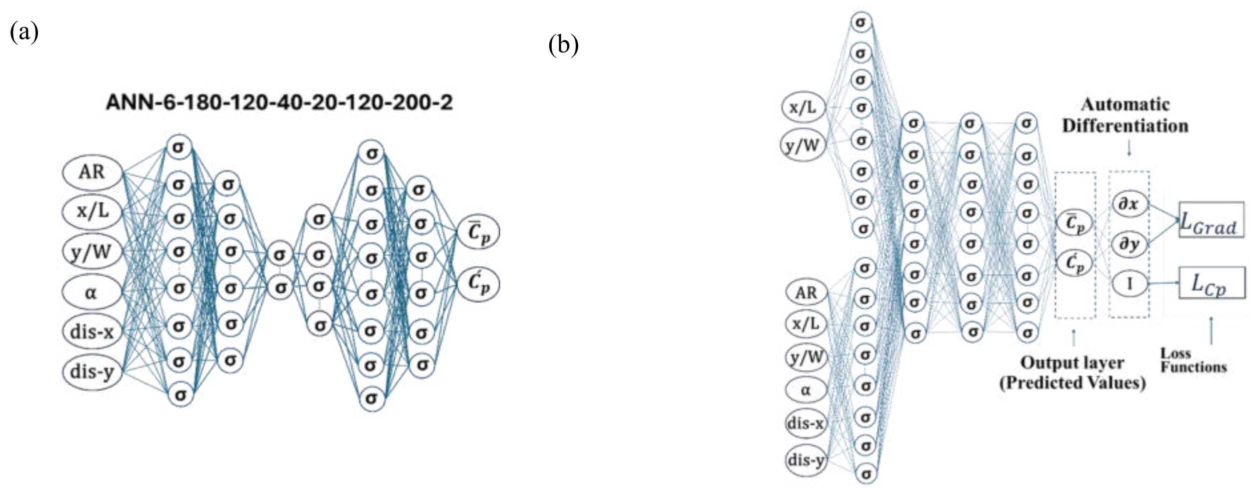

Figure 2. Schematic of a) Bottleneck ANN, b) GI-ANN to predict wind pressure

5. Results and discussion

This section compares standard ANN and GI-ANN models for predicting the mean and fluctuating pressure coefficients ($\bar{C}_p$ and $\acute{C}_p$). Two training setups are considered: models trained with two aspect ratios (ANN1, GI-ANN1) and models trained with three aspect ratios (ANN2, GI-ANN2). Model performance is evaluated using the coefficient of determination (R^2). Among the various tested configurations, two representative cases are presented: AR2 at a 15° wind angle and AR4 at a 45° wind angle, corresponding to the lowest and highest predictive performance observed, respectively. These cases therefore illustrate the effective prediction range of the model.

The comparison between ANNs and GI-ANNs (Table 2) clearly demonstrates the significant positive impact of incorporating gradient information. GI-ANNs consistently shows substantial improvements in R^2 for both $\bar{C}_p$ and $\acute{C}_p$, across the examined aspect ratios and wind angles, indicating improved representation of the spatial pressure distribution.

Table 2. R^2 score of $\bar{C}_p$ and $\acute{C}_p$ between ANNs model and wind tunnel data for AR2-15° and AR4-45°

AR	Angle	$\bar{C}_p$				$\acute{C}_p$			
		ANN1	ANN2	GI-ANN1	GI-ANN2	ANN1	ANN2	GI-ANN1	GI-ANN2
AR2	15°	0.0799	0.9510	0.9013	0.9861	0.4755	0.9071	0.6274	0.9627
AR4	45°	0.8009	0.9864	0.9892	0.9929	0.5557	0.9860	0.9757	0.9823

Notably, GI-ANN1 (two-model training) attains similar performance comparable to ANN2 (three-model training), in particular for $\bar{C}_p$, demonstrating that gradient-informed learning improves accuracy and generalization even with limited training data. Overall, GI-ANN2 provides the best results, confirming that combining gradient information with broader training data yields the most reliable predictions.

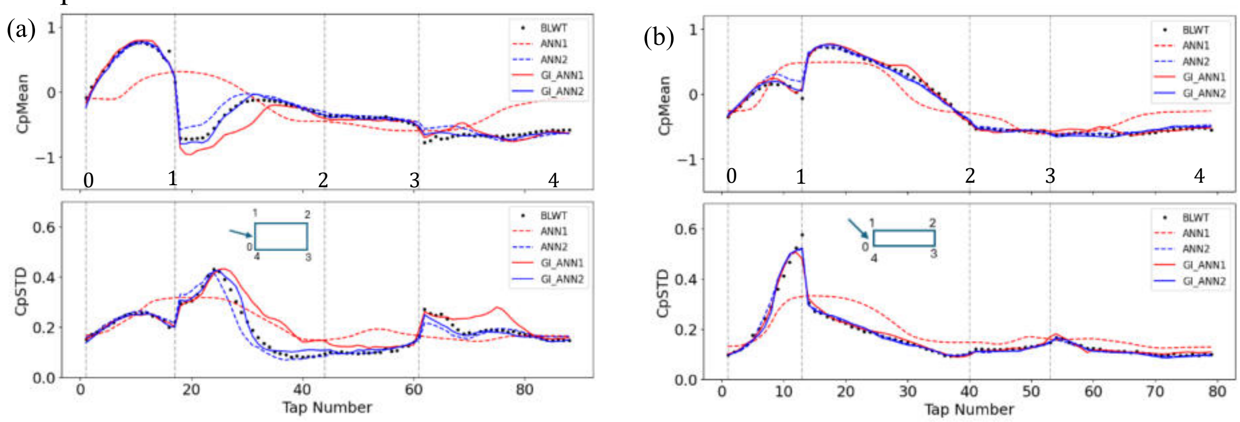

Figure 3. Comparison of $\bar{C}_p$ and $\acute{C}_p$ distribution for a) AR2 across 15 °, b) AR4 at 45 ° wind angle

Figure 3 visually reinforces the effectiveness of gradient information in improving predictive accuracy for both $\bar{C}_p$ and $\acute{C}_p$ distributions. Notably, GI-ANN2's predictions closely align with experimental data, particularly in critical corner regions where pressure gradients are typically steep.

6. Conclusion

This study shows that Gradient-Informed Artificial Neural Networks (GI-ANNs) improve wind pressure prediction on high-rise buildings compared to standard ANNs. By embedding gradient information during training, the model more accurately captures the spatial variation of pressure distributions, leading to improved predictions of both the mean ($\bar{C}_p$) and fluctuating ($\acute{C}_p$,) pressure coefficients, particularly in corner regions. Overall, GI-ANNs provide an efficient and reliable framework for wind load prediction.

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