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PHYSICS-INFORMED NEURAL NETWORKS FOR MODELLING PRESSURE DISTRIBUTION ON BUILDING FACADES

NEURONSKE MREŽE PODRŽANE FIZIČKIM ZAKONIMA ZA MODELIRANJE RASPODELE PRITISKA NA FASADAMA ZGRADA

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Keywords

- Physics-Informed Neural Networks (PINN)
- building aerodynamics
- Bernoulli's principle
- airflow modelling
- combined approach
- structural design
- wind load

Abstract

This study explores the application of Physics-Informed Neural Networks (PINN) for predicting the pressure coefficient distribution on the windward facade of a building. The key feature of this approach is the use of a combined loss function that simultaneously accounts for experimental data and physical constraints derived from Bernoulli's principle. This integration enables PINN to combine physical rigor with high accuracy in reproducing experimental data. The overall loss function of the PINN model consists of two components: a mathematical loss function that minimises deviations of model predictions from experimental data, and a physics-based loss function, derived from Bernoulli's principle for the flow of an ideal fluid and gas, which ensures alignment with physical laws. A PINN model is developed and trained, demonstrating adaptability to various conditions, including wind direction angles and the weight of the physical loss function. The analysis reveals that the weight of the physical loss function significantly influences the prioritisation of predictions: at lower weights, the model prioritises experimental data, whereas at higher weights, it aligns more closely with physical calculations. Instances of prediction anomalies are observed, where the results deviate significantly from both data sources, highlighting the need for careful monitoring of the model's outputs. Future research directions include incorporating more advanced physical laws, such as turbulence and friction models, to improve prediction accuracy. Results demonstrate the potential of PINN for applications in building aerodynamics, effectively integrating theoretical calculations and empirical data for precise modelling.

Ključne reči

- neuronske mreže podržane fizičkim zakonima (PINN)
- aerodinamika zgrada
- Bernulijev princip
- modeliranje strujanja vazduha
- kombinovani pristup
- projektovanje konstrukcija
- opterećenja od vetra

Izvod

U radu se istražuje primena neuronske mreže podržane fizičkim zakonima (PINN) za predviđanje raspodele koeficijenta pritiska na zgradi sa vetrovite strane. Ključna karakteristika ovog pristupa je upotreba kombinovane funkcije gubitka koja istovremeno uzima u obzir eksperimentalne podatke i fizička ograničenja izvedena iz Bernulijevog principa. Ova integracija omogućava PINN modelu da poveže fizičku preciznost sa visokom tačnošću u reprodukovanju eksperimentalnih podataka. Ukupna funkcija gubitka PINN modela sastoji se iz dva dela: matematičke funkcije gubitka, koja minimizuje odstupanja koja se modelom predviđaju iz eksperimentalnih podataka, i funkcije gubitka zasnovane na fizici, izvedene iz Bernulijevog principa strujanja idealnog fluida i gasa, čime se obezbeđuje usklađenost sa fizičkim zakonima. PINN model je razvijen i istreniran, pokazujući prilagodljivost različitim uslovima, uključujući uglove pravca vetra i težinsku funkciju fizičkih gubitaka. Analiza pokazuje da težinska funkcija fizičkih gubitaka značajno utiče na određivanje prioriteta predviđanja: pri manjim težinama model daje prioritet eksperimentalnim podacima, dok pri većim težinama, više prati fizičke proračune. Uočeni su slučajevi anomalija u predviđanjima, gde rezultati značajno odstupaju i od eksperimentalnih podataka i od fizičkih modela, što ukazuje na potrebu za pažljivim praćenjem izlaza modela. Buduća istraživanja uključuju uvođenje naprednijih fizičkih zakona, kao što su modeli turbulencije i trenja, radi poboljšanja tačnosti predviđanja. Dobijeni rezultati pokazuju potencijal PINN za primene u aerodinamici zgrada, efikasno kombinujući teorijske proračune i empirijske podatke za precizno modeliranje.

INTRODUCTION

Rapid development of machine learning and artificial intelligence technologies (AI) in recent years has opened up vast opportunities for modernising various sectors of the economy, including architecture, construction, and design. These technologies actively contribute to improving process efficiency, enhancing project management, and introducing automation in the construction industry /1-4/. One of the key and rapidly evolving areas of AI application is building

aerodynamics, where intelligent algorithms provide new approaches to design. Traditionally, wind load analysis on buildings and structures relies on standard calculation methods, wind tunnel modelling, and numerical techniques such as Computational Fluid Dynamics (CFD), which remains the most popular tool for addressing hydraulic and aerodynamic problems. CFD offers high accuracy in modelling airflow, particularly in complex conditions of urban environments /5/ and serves as the foundation for analysing aerodynamic loads on unique architectural forms, including iconic skyscrapers /8/. At the same time, the development of simplified numerical approaches accelerates flow modelling in the context of limited computational resources /6/. These methods, along with the advanced application of CFD in high-rise building design, have proven their reliability and are widely adopted in engineering practice /7/.

The increasing number of modern high-rise buildings with unique architecture, the complexity of structural solutions, and active urbanisation demand the development of more accurate and efficient approaches to calculating wind loads. This is particularly important in the context of advancements in computational aerodynamics over the past 30 years, which include modelling the interaction of buildings with their surroundings /9/, as well as recent achievements in fluid dynamics, aerodynamics, and turbulence modelling /10/. Standard calculation methods often fail to account for non-standard scenarios, while wind tunnel modelling remains labour-intensive, requiring significant financial and time investments. CFD modelling effectively addresses a wide range of challenges, including optimising wind resistance systems for high-rise buildings /11/ and analysing peak wind loads on buildings within the atmospheric boundary layer using large eddy simulations /12/. However, this approach demands substantial computational resources and the involvement of highly qualified specialists, particularly for implementing complex engineering projects. Moreover, errors in setting initial parameters or using incorrect input data significantly reduce the accuracy of calculations and the quality of the results.

Recent studies demonstrate the successful application of artificial intelligence methods to a wide range of engineering challenges, including those in structural aerodynamics. Classical machine learning methods such as Gradient Boosting and Random Forest show high accuracy in predicting aerodynamic coefficients for various building types. These approaches are effectively used to analyse aerodynamic interactions between low-rise and high-rise buildings /13/, predict unsteady wind loads in three-dimensional coordinates on tall structures /14/, and evaluate the capabilities of different AI methods for calculating aerodynamic characteristics /15/. Generative Adversarial Networks (GANs) are an example of successful implementation of modern machine learning techniques in structural aerodynamics. Research has demonstrated their efficiency in predicting mean and fluctuating pressure coefficients on building surfaces /17/ and optimising urban block design to improve pedestrian-level wind conditions in combination with CFD optimisation /16/.

Machine learning techniques, including convolutional and recurrent neural networks, have gained wide adoption and allow for modelling complex dependencies between building parameters and wind loads. These approaches have been successfully applied to forecast aerodynamic damping in structures experiencing airflow-induced oscillations /18/ and assess the impact of wind speed on high-rise buildings by combining experimental studies with machine learning models /19/. AI models have also been used in research applications such as thermal process modelling and material mechanics. These include graph-based models for building thermal dynamics /20/, neural networks for hydrodynamics and heat transfer /21/, multiscale modelling of thermal conductivity in phase-transitioning materials /22/, and vibration dynamics analysis for precise vibration identification and structural optimisation /23/. However, a key limitation of many AI models remains the high demand for large volumes of training data, which restricts their application in practical engineering. This is particularly relevant in modelling airflow for building design, where access to accurate and representative data is often challenging /24, 25/.

One of the advanced neural network models that significantly reduces the data requirements for training is PINN. These networks integrate physical laws into the training process and have been applied to a wide range of engineering problems, such as analysing vibrations induced by vortex shedding with consideration of variable structural stiffness /26/, modelling pile-soil interactions to assess load-bearing capacity /27/, predicting fluid flows based on visualised data in bridge construction /28/, analysing tunnel settlement, such as in the Hong Kong-Zhuhai-Macau Tunnel /29/, modelling chloride diffusion in concrete for durability assessment /30/, and solving direct and inverse problems for complex beam systems, including Euler-Bernoulli and Timoshenko beams /31/.

The integration of physical laws is particularly important for tasks where compliance with regulatory requirements and physical constraints plays a key role in ensuring the reliability and safety of designed systems. In structural aerodynamics, neglecting such constraints can lead to serious consequences, including structural failures and risks to human life and safety. The use of physics-informed approaches improves the accuracy of calculations and enhances the interpretability of results, which is critical for creating resilient and safe engineering solutions. However, the application of PINN in structural aerodynamics remains underexplored, presenting opportunities for future research. Potential directions include the development of innovative methods for assessing wind loads, optimising building geometry considering aerodynamic characteristics, and improving the accuracy of wind impact predictions in dense urban environments.

The aim of this study is to develop and evaluate the effectiveness of PINN for calculating the mean pressure coefficient on the windward facade of a building, integrating experimental data obtained from wind tunnel testing and the physical laws of structural aerodynamics into the model. The research objectives include:

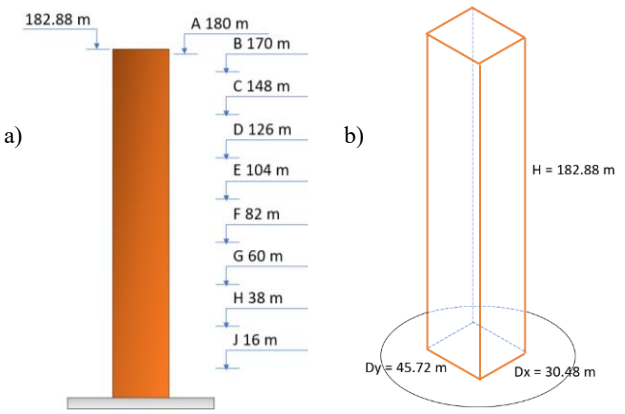
1) developing a PINN model that incorporates the physical laws of aerodynamics for calculating the mean pressure coefficient on the windward facade of a building;
2) assessing the impact of the weight of the physics-informed loss function, based on Bernoulli's law, on the predictions of

the PINN model, including its accuracy and agreement with experimental data;
3) analysing the influence of wind direction angle on the behaviour of the PINN model and its ability to balance experimental and physically calculated data.

These objectives are aimed at comprehensively exploring the application of PINN in structural aerodynamics to evaluate its potential for precise modelling and adaptation to real-world design conditions. The scientific novelty of this work lies in the use of PINN for calculating wind loads on high-rise buildings. By integrating physical laws, PINN significantly reduces dependence on uncertainties and errors in experimental data. This approach enhances the accuracy and reliability of calculations and improves the interpretability of model predictions, enabling detailed analysis of the influence of physical parameters on results.

MATERIALS AND METHODS

The study utilised a dataset generated from wind tunnel tests of high-rise building models conducted in the ZD-1 wind tunnel at Zhejiang University /32/. The ZD-1 wind tunnel is a closed-circuit facility with a closed test section measuring 18 metres in length and a maximal airflow velocity of up to 55 m/s. Figure 1 illustrates the schematic diagram of the computational setup and a fragment of wind tunnel modelling. To simulate the atmospheric boundary layer and create conditions corresponding to terrain class B, roughness elements are installed on the wind tunnel floor, enabling the setting of a roughness coefficient of $\alpha = 0.15$ /33/. The tests are conducted on scaled models of high-rise buildings, fabricated from ABS plastic at a scale of 1:300. The airflow impacted the models at angles θ ranging from 0° to 180° with a step of 10°. The building models had rectangular cross-sections with aspect ratios ranging from 1 to 8, and their height in full scale is 182.88 m. Each model is equipped with 9 levels of measurement points j. The total number of measurement points varies from 252 to 468 depending on the cross-sectional aspect ratio (Table 1). The airflow velocity at the control point in the wind tunnel is 11.4 m/s, consistent with standard conditions for atmospheric boundary layer modelling. For each wind direction angle, data are sampled over 32 s at a frequency of 312.5 Hz, resulting in approximately 10,000 measurements for each measurement point on the model. Ultimately, a dataset comprising over 45,000 rows is generated, containing the pressure coefficient values ($C_{p,i}$) at measurement points i.



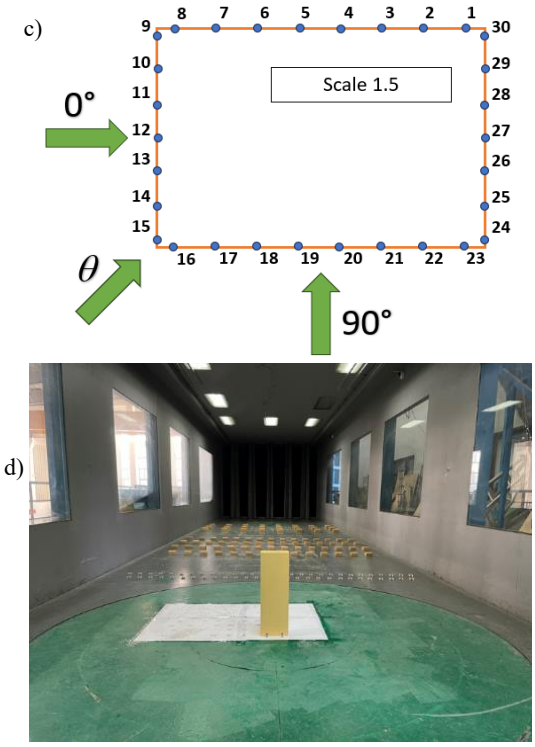


Figure 1. Schematic of models and tests: a) arrangement of levels j of measurement points; b) sketch of building model; c) schematic of wind direction and placement of points at level j for a building scale of 1.5; d) example of model placement in the wind tunnel.

Table 1. Geometric parameters of building models and the number of measurement points.

Model	Building dimensions (m)	Length-to-width ratio (scale)	Number of measurement points
A	30.48 × 30.48 × 182.88	1	252
B	30.48 × 45.72 × 182.88	1.5	290
C	30.48 × 60.96 × 182.88	2	288
D	30.48 × 91.44 × 182.88	3	324
E	30.48 × 121.92 × 182.88	4	360
F	30.48 × 182.88 × 182.88	6	414
G	30.48 × 243.84 × 182.88	8	468

To address the objectives of this study, a PINN model is developed that employs a total loss function, $Loss_{total}$, as represented by Eq.(1). This function combines two key components: the mathematical component, $Loss_{MSE}$, responsible for minimising the error between predicted and experimental data, and the physical component, $Loss_{physic}$, which ensures the model's compliance with fundamental physical laws. A weighting coefficient, λ_{physic}, is introduced to balance the contributions of these components, determining the significance of the physical component in the total loss function,

$$Loss_{total} = (1-\lambda_{physic})Loss_{MSE} + \lambda_{physic}Loss_{physic}, \quad (1)$$

where: $Loss_{total}$ is overall weighted loss function of the PINN model; $Loss_{MSE}$ is the data loss function based on the mean squared error (MSE), measuring the deviation of predicted values from target values; $Loss_{physic}$ is physical loss function, representing the deviation of predicted values from the physical law; λ_{physic} is the weight of the physical loss function.

The physical loss function, $Loss_{physic}$, is based on Bernoulli's principle for an ideal fluid, applied to airflow in the

wind tunnel. The following assumptions are made to ensure the correct application of this law: air in the flow is considered as incompressible and inviscid medium which is justified at a wind tunnel airflow speed of 11.4 m/s; the airflow speed at each point remains constant throughout the tests; vortices and turbulence effects around the building are not considered; and the frictional effects of airflow on the building surface are assumed to be negligible. These assumptions simplify the computational model while maintaining sufficient accuracy for aerodynamic characteristic analysis. Taking these assumptions into account, the physical loss function is expressed as, Eq.(2):

$$Loss_{physic} = \frac{\sum_{j=1}^{N}(C_{p,j} - C_{U,j})^2}{N}, \quad (2)$$

where: $C_{p,j}$ is coefficient of pressure predicted by the model at level j; $C_{U,j}$ is theoretically calculated coefficient of pressure at level j; N is number of measurement levels j along the building height.

The coefficient of pressure $C_{U,j}$ at level j is determined using the formula:

$$C_{U,j} = \frac{U(z_j)}{U_0}, \quad (3)$$

where: U_0 is average flow velocity at height z_0, set to U_0 = 11.4 m/s for z_0 = 182.88 m under test conditions; $U(z_j)$ represents the flow velocity at height z_j in the boundary layer, calculated as per Eq.(4):

$$U(z) = U_0\left(\frac{z}{z_0}\right)^{\alpha}, \quad (4)$$

where: α is empirical coefficient for the velocity profile, determined based on the test conditions and the simulated terrain type /33/; $z = z_j$ is height of measurement points j relative to the building base.

Figure 2 shows the graphs of the theoretically calculated and experimentally measured wind velocity within the boundary layer height. The high degree of agreement between the graphs confirms the validity of proposed formulas: Eq.(3) for determining the average pressure coefficient at level j and Eq.(4) for calculating the air flow velocity in the boundary layer. Thus, the physical component of the total loss function, based on the Bernoulli principle, is applicable to the developed PINN model.

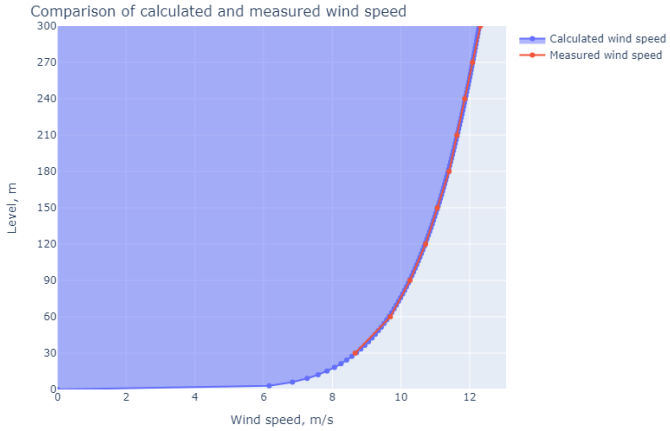


Figure 2. Graphs of theoretically calculated and experimentally measured wind speed within the height of the boundary layer.

The training and calculations using PINN for pressure coefficients at levels $C_{p,j}$ are conducted under several boundary conditions: only positive mean pressures $C_{p,j}$ at each level j are considered, excluding suction effects; measurements from the edge points of the facade are excluded due to the high likelihood of flow separation; and the analysis is limited to the windward facade, where positive external pressures dominate. Taking these constraints into account, pressure coefficient distribution graphs are generated for wind direction angles θ ranging from 0° to 50°. Variations of $C_{p,j}$ distributions for the ratio Scale =1.5 are presented in Fig. 3.

The overall architecture of the PINN model represents an adapted fully connected neural network with three hidden layers, each containing 50 neurons. The activation function used is GELU (Gaussian Error Linear Unit), ensuring smoothness and efficient training. The input data includes the building scale, the height level of measurement points j, and the wind direction angle θ, combined into a two-dimensional vector. The output layer consists of a single neuron that generates the pressure coefficient $C_{p,j}$. The Adam optimisation algorithm is employed with a fixed learning rate of 0.001. Early stopping with a tolerance parameter of 20 epochs is used to prevent overfitting, with the maximum number of training epochs limited to 1000.

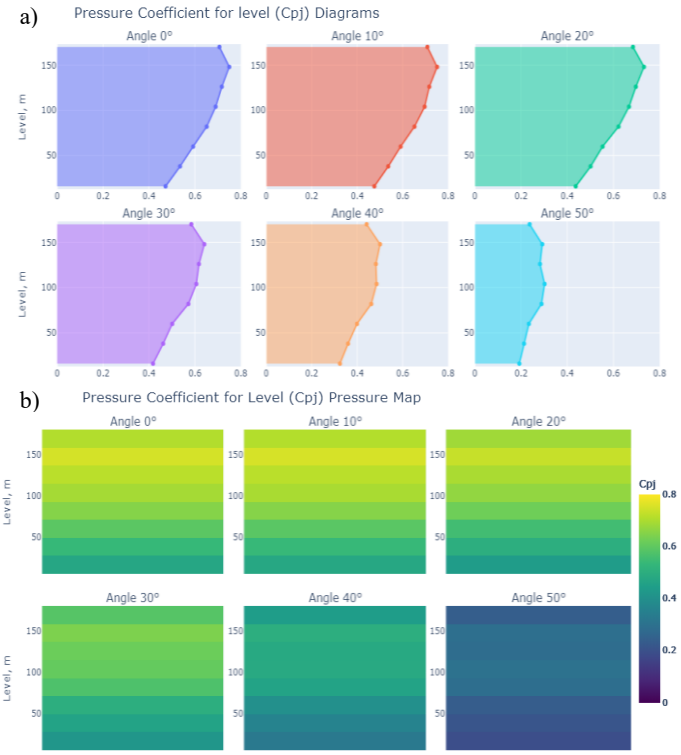


Figure 3. Profiles a), and heat map b), of the pressure coefficient distribution across levels $C_{p,j}$ for the windward facade at a building scale of scale = 1.5.

The model's performance is evaluated using both graphical analysis and calculated metrics by comparing predicted pressure coefficient values $C_{p,j}$ with experimental and theoretically computed data. Experimental and theoretical pressure coefficients $C_{p,j}$ are used as relative benchmarks to analyse the model's behaviour under different conditions. Quantitative metrics such as mean squared error (MSE) and coeffi-

cient of determination (R^2) are calculated to measure the degree of agreement between the model's predictions and these data.

Graphical analysis complements the metrics by providing a visual representation of the model's predictions. It enables the identification of trends, consistencies, and deviations between predicted, experimental, and theoretical $C_{p,j}$ values. This combined approach demonstrates the model's ability to account for physical processes while offering a comprehensive understanding of its performance. The results emphasise the importance of tuning λ_{physic} to achieve an optimal balance between accurately reproducing experimental data and maintaining physical consistency.

The development, training of models, and data analysis are conducted using Python version 3.12.3. Specialised tools include PyTorch for implementing neural networks, NumPy and Pandas for data processing, Matplotlib for result visualisation, and Scikit-learn for calculating metrics and accuracy analysis. Development is carried out in the Visual Studio environment.

RESULTS

This section presents the results of training the PINN model for predicting the distribution of pressure coefficient $C_{p,j}$ across height levels j on the windward facade of the building. Figure 4 illustrates the cases corresponding to a building scale of Scale = 1.5 and a wind direction angle of $\theta = 0$ for a range of physical loss function weights λ_{physic} from 0 to 1. Using graphical analysis, the influence of physical loss function on the agreement of model predictions with experimental and theoretically calculated data, as well as the balance between prediction accuracy and alignment with theoretical pressure coefficient values $C_{p,j}$ at different height levels, is determined.

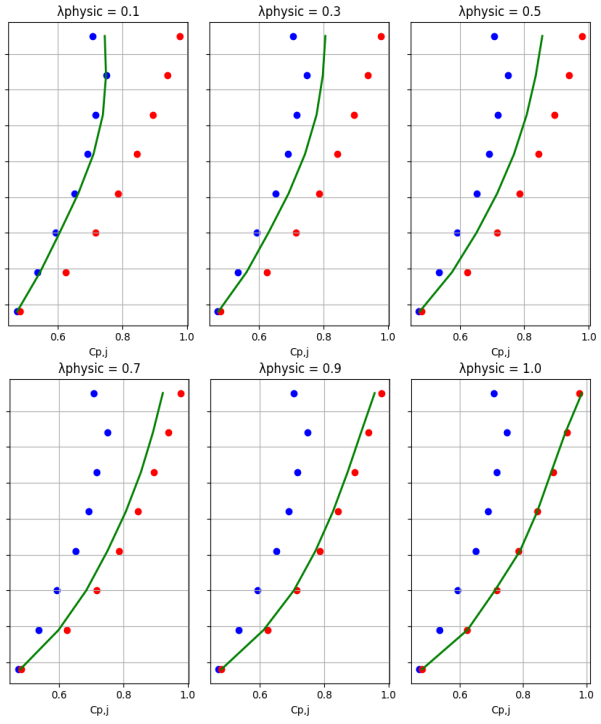


Figure 4. Influence of physical loss function weight λ_{physic} on PINN model's predictions of pressure coefficient $C_{p,j}$ for Scale = 1.5, $\theta = 0°$.

It is noteworthy that the experimental and theoretically calculated values of pressure coefficient $C_{p,j}$ exhibit certain discrepancies which increase with the height of measurement levels j. These discrepancies are likely due to assumptions made for the correct application of Bernoulli's principle in the implementation of the physical loss function. Specifically, air is considered incompressible and inviscid, while turbulent and vortex effects are excluded from the analysis. These simplifications streamline the calculations but result in deviations at greater heights. Nevertheless, such discrepancies are acceptable within the scope of the research task. Furthermore, the differences between experimental and theoretical data visually demonstrate the impact of physical loss function weight on the training outcomes of PINN model and its ability to balance between mathematical loss $Loss_{MSE}$ and physical loss $Loss_{physic}$ components of the total loss function.

Analysing the graphs in Fig. 4, it can be observed that with a physical loss function weight $\lambda_{physic} = 0$ which represents one of the extreme cases, the PINN model is trained exclusively using mathematical loss function $Loss_{MSE}$. This loss function minimises the discrepancy between model's predictions and experimental data. The green line representing the model's predictions demonstrates good agreement with experimental values of pressure coefficient $C_{p,j}$ (blue markers) at all height levels. However, significant deviations from physically calculated values of $C_{p,j}$ (red markers), determined based on Bernoulli's principle, are noticeable. The absence of the physical loss function causes the model to align exclusively with experimental data, neglecting the system's physical constraints. Thus, with $\lambda_{physic} = 0$, the model's predictions are fully oriented toward empirical data, enabling accurate reproduction of experimental values but leading to disregard of physical characteristics of the airflow.

Continuing the analysis of the influence of physical loss function weight, the other extreme case at $\lambda_{physic} = 1$ is considered. In this mode, the PINN model is trained exclusively using the physical loss function $Loss_{physic}$ which minimises the discrepancy between the model's predictions and physically calculated values of pressure coefficient $C_{p,j}$. As shown in the graphs in Fig. 4, the model's predictions exhibit excellent agreement with physically calculated values across all height levels. However, notable deviations from experimental values of $C_{p,j}$ are observed. This is because, with $\lambda_{physic} = 1$, the model entirely focuses on physical principles, ignoring specific features of the experimental data. Thus, with $\lambda_{physic} = 1$, the model's predictions become physically consistent but lose accuracy in reproducing experimental data.

Considering the intermediate case at $\lambda_{physic} = 0.5$, it can be noted that the PINN model training in this regime incorporates both the mathematical loss function $Loss_{MSE}$ which minimises the deviation from experimental values of the pressure coefficient $C_{p,j}$, and the physical loss function $Loss_{physic}$ which ensures alignment with physically calculated values of $C_{p,j}$. Analysis of graphs in Fig. 4 shows that the model's predictions at $\lambda_{physic} = 0.5$ demonstrate a balanced agreement with both experimental and physically calculated values at all height levels. Deviations from the experimental points significantly decrease compared to the case of $\lambda_{physic} = 1$, while partial alignment with physical values is maintained.

Thus, with $\lambda_{physic} = 0.5$, a compromise is achieved between the accuracy of reproducing experimental data and the physical consistency of the model. This allows the PINN model to account for both the specifics of experimental measurements and fundamental physical principles, providing more balanced and reliable prediction results. A similar trend is observed for other values of λ_{physic}, with the model's predictions demonstrating varying degrees of balance between experimental and theoretically calculated data depending on the magnitude of this parameter.

In Fig. 5, an illustration of the PINN model's predictions for pressure coefficient $C_{p,j}$ at various wind direction angles θ and physical loss function weights λ_{physic} is presented. The analysis includes values of λ_{physic} equal to 0.2, 0.5, and 0.9, as well as wind direction angles θ of 0°, 40°, and 50°. The graphs clearly demonstrate the influence of the wind direction angle on the distribution of pressure coefficient $C_{p,j}$, showing how the model's behaviour changes depending on the balance between the mathematical loss function $Loss_{MSE}$ and physical loss function $Loss_{physic}$. As expected, at $\lambda_{physic} = 0.2$, the PINN model predominantly minimises the mathematical loss function $Loss_{MSE}$, resulting in the best alignment with experimental data. At $\lambda_{physic} = 0.5$, the model strikes a balance between experimental data and physical constraints, producing more balanced predictions. At $\lambda_{physic} = 0.9$, the model focuses on minimising deviations from physically calculated pressure coefficient values, leading to near-complete agreement between the model's predictions and the physical values of $C_{p,j}$. As the wind direction angle increases, the discrepancies between experimental and physically calculated values of $C_{p,j}$ decrease, and the overall model behaviour becomes more stable. Nonetheless, the change in wind direction angle θ does not significantly affect the model's behaviour: at small values of λ_{physic}, the model's predictions for $C_{p,j}$ align closely with experimental data, while at larger values of λ_{physic}, they approach theoretically calculated values.

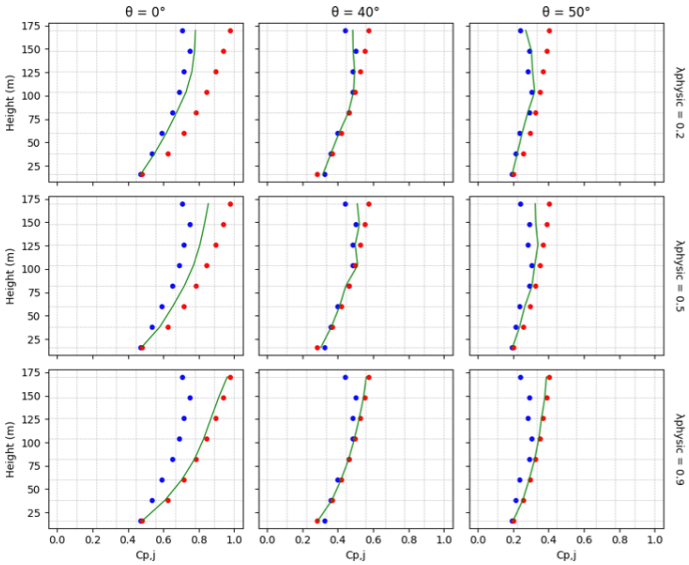


Figure 5. Influence of physical loss function weight λ_{physic} and wind direction angle θ on PINN model's predictions of the pressure coefficient $C_{p,j}$.

DISCUSSION

The section focuses on discussing the research results and analysing the dependence of model's predictions on the physical loss function weight λ_λ and wind direction angle θ. Key features of the model's behaviour under various conditions are identified. Special attention is given to interpreting observed patterns and assessing the limitations of the proposed approach.

The graphical analysis of the PINN model's predictions at various values of physical loss function weight λ_{physic} demonstrates its ability to generalise experimental data and physically calculated pressure coefficients $C_{p,j}$ for different building height levels. The adopted architecture of the PINN model and the training conditions, based on Bernoulli's law with certain assumptions, enable the model to achieve a conditional balance between experimental and theoretical data. It is observed that the weight of the physical loss function directly influences the prioritisation of predictions: at low values of λ_{physic} close to 0, the model focuses on experimental data, almost perfectly replicating them. Conversely, at high values of λ_{physic} approaching 1, the model's predictions align entirely with physically calculated pressure coefficients.

The behaviour of the PINN model also depends on the wind direction angle θ. Graph analysis shows that with increasing wind direction angle, discrepancies between experimental and physically calculated pressure coefficients $C_{p,j}$ decrease. This trend is consistent regardless of the physical loss function weight λ_{physic}. However, certain combinations of λ_{physic} and wind direction angles, such as large angles and low weights, reveal cases of prediction collisions. In such cases, the model's predictions significantly deviate from both experimental data and physical calculations, highlighting the need for user oversight and proper interpretation of the model's outputs.

For a quantitative evaluation of PINN model's predictions, Table 2 presents metrics characterising its accuracy relative to experimental and physically calculated data. The table includes values for mean squared error (MSE), coefficient of determination (R^2), and total error for various values of physical loss function weight λ_{physic} and wind direction angles θ. The analysis shows that at smaller wind direction angles ($\theta = 0°, 20°$), the model exhibits higher error for both types of data. As the wind direction angle increases, the model's accuracy improves due to reduced discrepancies between experimental and physically calculated values which also decreases the total error. This confirms that the PINN model can adapt to various conditions, but its predictions for the developed model require careful evaluation and verification.

The analysis of results demonstrates that the weight of physical loss function λ_{physic} has a direct impact on the behaviour of the PINN model. At low values of λ_{physic}, the model primarily focuses on minimising deviations from experimental data, achieving high accuracy in reproducing measurement results. However, under these conditions, the model exhibits limited consideration of physical laws. Conversely, at high values of λ_{physic}, the model minimises deviations from physically calculated data, ensuring the physical consistency of predictions, albeit with increased discrepancies from ex-

perimental data. This approach provides users with the ability to flexibly adjust the balance between empirical and theoretical methods based on the modelling objectives, making the PINN model a versatile tool. However, it requires careful parameter tuning, such as the weight of the physical loss function, and thorough analysis of results to avoid errors and ensure physical validity of predictions.

The analysis of results demonstrates that the weight of the physical loss function λ_{physic} has a direct impact on the behaviour of the PINN model. At low values of λ_{physic}, the model primarily focuses on minimising deviations from experimental data, achieving high accuracy in reproducing measurement results. However, under these conditions, the model exhibits limited consideration of physical laws. Conversely, at high values of λ_{physic}, the model minimises deviations from physically calculated data, ensuring the physical consistency of predictions, albeit with increased discrepancies from experimental data. This approach provides users with the ability to flexibly adjust the balance between empirical and theoretical methods based on the modelling objectives, making the PINN model a versatile tool. However, it requires careful parameter tuning, such as the weight of the physical loss function, and thorough analysis of results to avoid errors and ensure the physical validity of predictions.

Table 2. Evaluation metrics of the PINN model for varying λ_{physic} and wind direction angles θ.

λ_{physic}	Wind direction angle, θ	Experiment		Physical		Total Error
		MSE	R^2	MSE	R^2	
0.1	0	0.0004	0.9487	0.0206	-1.4859	0.0024
	20	0.0003	0.9689	0.0068	0.2859	0.001
	30	0.0003	0.9515	0.0034	0.4062	0.0006
	50	0.0001	0.9026	0.0054	-2.6465	0.0007
0.3	0	0.0023	0.7258	0.0131	-0.5818	0.0056
	20	0.001	0.8986	0.0042	0.5639	0.0019
	30	0.0011	0.8064	0.002	0.6438	0.0014
	50	0.001	0.3252	0.0034	-1.3026	0.0017
0.5	0	0.0065	0.221	0.0065	0.2226	0.0065
	20	0.0022	0.7689	0.0022	0.773	0.0022
	30	0.0011	0.8078	0.0011	0.8102	0.0011
	50	0.0017	-0.1399	0.0017	-0.139	0.0017
0.7	0	0.0128	-0.5355	0.0023	0.7265	0.0054
	20	0.0045	0.5321	0.0011	0.8825	0.0021
	30	0.0022	0.6149	0.0004	0.9297	0.0009
	50	0.0034	-1.3196	0.0006	0.5645	0.0015
0.9	0	0.0209	-1.5184	0.0003	0.9685	0.0023
	20	0.0072	0.251	0.0001	0.986	0.0008
	30	0.0035	0.3823	0.000	0.9922	0.0004
	50	0.0055	-2.7183	0.0001	0.955	0.0006

CONCLUSION

As part of this study, a PINN model is developed and trained to predict the distribution of the pressure coefficient on the windward facade of a building. The behaviour of the model under various wind flow directions is analysed. The primary objective of this work is to evaluate the effectiveness of using PINN for solving practical problems in building aerodynamics. The key feature and scientific novelty of this approach lie in the use of a combined loss function that incorporates both experimental pressure coefficient values and physical constraints based on Bernoulli's principle. Integrating these two approaches into a single model demonstrates potential for more accurate and flexible aerodynamic process modelling, opening opportunities for its application in building practices.

The study examines the behaviour of the PINN model at different values of physical loss function weight. This made it possible to establish that the weight of the physical loss function directly influences the prediction priorities. At low weight values, the model predominantly focuses on experimental data, while at higher values, it emphasises physical calculations. This approach enables flexible model adjustments depending on the tasks, allowing for an optimal balance between empirical and theoretical data.

To enhance the accuracy and universality of the PINN model in building aerodynamics, more complex physical laws need to be considered in future research. This study employed simplified assumptions, such as the absence of flow separation from surfaces and the neglect of air flow friction on building surfaces. While these assumptions simplify calculations, they overlook several critical factors essential for accurate modelling. A promising direction is the use of turbulence models capable of describing complex vortex motion of airflows near building surfaces. This is particularly relevant for tasks requiring consideration of local turbulence effects. The behaviour of airflows around building corners, as well as on side and leeward facades, calls for the integration of flow separation theories which describe the complex interactions of flows with building geometries. Furthermore, the roughness of building surfaces should be accounted for using friction theories that describe airflow interaction with facades.

In general, the application of more complex physical models and laws can significantly enhance the physical component of the loss function, bringing it closer to real-world system behaviour. This not only improves the accuracy of the model's predictions but also makes it a universal tool for solving a wide range of building aerodynamics problems. In the future, integrating complex physical models and improving the architecture of the PINN model will open new perspectives for both research and engineering applications, enabling the resolution of more complex and large-scale tasks.

Thus, this study demonstrates that the PINN model holds great potential for applications in building aerodynamics. The integration of experimental data and physical constraints makes it a universal modelling tool capable of filling gaps in training data. However, the model requires further development, including the incorporation of more complex physical laws such as turbulence, friction, and flow separation theories. At the same time, implementing such models will increase computational complexity and require precise hyperparameter tuning. Nonetheless, the prospects for applying the PINN model in building aerodynamics and architectural design appear promising, offering new opportunities for both research and engineering challenges.

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- Notches and discontinuities
- Combined loads
- Post processing for metals and non-metals
- Wear and corrosion of AM materials
- Effects of surface modifications on mechanical and chemical properties
- Characterization of ceramic, polymeric and metallic materials
- Design for AM
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- Non-destructive testing and health monitoring in AM
- Digital materials
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