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EXTENDED ABSTRACT

Prediction of Wind Pressure Coefficient Distributions on Building Façades coupling Neural Network and CFD database

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Abstract: To improve the efficiency and the accuracy of air infiltration simulations in an indoor environment, and to investigate the effects of natural ventilation on harmful residual air pollutants and radioactive substances in the crawl space of a building, a wind pressure coefficient prediction model CpCalc_nn leveraging a multilayer perceptron neural network structure is developed in the current study to predict the spatially varying wind pressure map on the vertical rectangular façades and the adjacent ground surfaces of isolated and surrounded buildings. This model is trained on a large database containing high-resolution Computational Fluid Dynamics (CFD) simulation results on both low- and high-rise building models in isolated and surrounded configurations. The model is extensively validated against a testing CFD database excluded from the training database and a state-of-the-art miniaturized wind-tunnel database.

Key words: *wind pressure coefficient, natural ventilation, neural network, CFD*

Introduction

In the context of in building performance, crawl spaces play a crucial role in helping control moisture and prevent mold, provide thermal buffering, enable accessible maintenance of utilities, and, when properly ventilated, limit the migration of soil gases such as radon or volatile organic compounds [2,5,6]. When air circulates through a building by natural ventilation, the airflow rate passing through an opening is determined by its shape, its cross-sectional area, and the pressure difference Δp on either side of the opening. For a given opening, although the discharge coefficient and cross-sectional area remain constant, the pressure difference is highly variable and depends on various parameters influencing the environment of the opening, such as wind speed, wind direction, and its relative position on the wall, among others. For many years, wind tunnel tests have been used to measure the pressure coefficient C_p on the surfaces of scaled building models, which can be calculated using the following equation

$$C_p = \frac{p}{\rho u_H^2/2} \qquad \text{Eq. 1}$$

where u_H is the wind speed at building height.

Traditionally, reduced-scale wind tunnel experiments are used to accurately measure the C_p distribution on building models. However, due to their extremely high costs, even the most comprehensive wind tunnel campaigns can only cover a limited range of independent parameters. To address this limitation, predictive models have been developed by numerous authors over the years to infer C_p values based on the parameters of a given environmental configuration. One of the most popular polynomial-based prediction models is CpCalc+, developed by Mario Grosso [4], which stands out from other models through its ability to generate pointwise C_p predictions as a function of local horizontal and vertical coordinates on a given façade. Using CpCalc+, it is possible to instantly evaluate C_p values from a predefined set of geometric and environmental parameters.

Despite its popularity, one major limitation of CpCalc+ is that it does not generate predictions at heights lower than 10% of the building height, a prohibitive constraint for modelling air infiltration into crawl

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spaces, which are generally located within the first 1–2 metres of a building. In addition, the CpCalc+ database does not account for flat ground surfaces in front of target buildings, where floor-mounted air vents are generally located. Furthermore, in the original publication of CpCalc+, the author provided no validation results based on external datasets, raising the question of whether the model might be overfitted.

In light of the above limitations, the objective of the present project is to develop a more comprehensive pointwise C_p prediction model, based on a high-resolution C_p database generated from a series of steady-state CFD (Computational Fluid Dynamics) simulations carried out using the open-source CFD software Code_Saturne [3]. By replacing wind tunnel tests with CFD simulations, data acquisition costs can be drastically reduced while expanding coverage of the parameter space.

Definition of the Geometric Model

In the present study, we restrict our scope to buildings with rectangular façades and flat roofs, focusing on C_p values on the four vertical walls of the building as well as on the flat ground in front of each wall, so as to account for floor-mounted air vents. To ensure that the evaluation of C_p is independent of both length scale and façade orientation, C_p is mapped onto a normalized reference façade (NRF) within a local coordinate system defined by the unit vectors $\overrightarrow{e_r}$, $\overrightarrow{e_h}$, and $\overrightarrow{e_n}$, as illustrated in Figure 1.

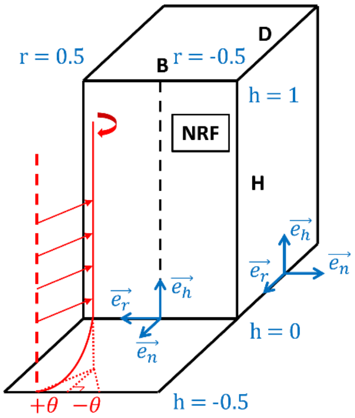

Figure 1. Definition of the geometric model of a flat-roofed building with NRF.

The plan area density (PAD) and the relative building height (RBH) are introduced to account for the effects of obstacles caused by neighbouring buildings. Terrain roughness is accounted for by the exponent α of the wind speed profile according to the power law, given in Eq. 2, with $u_{ref} = 7.4\ m/s$ and $z_{ref} = 10\ m$.

$$u = u_{ref} \left(\frac{z}{z_{ref}} \right)^{\alpha} \qquad \text{Eq. 2}$$

The following set of nine parameters is required to define a pointwise wind pressure state: {r, h, D/B, H/B, sin(θ), cos(θ), α, PAD, RBH}.

Methodology

A series of CFD simulations of different generic configurations is carried out to provide training data for the neural network. This database covers a wide range of configurable parameters to ensure the generality of the deep-learning model. To limit the size of the training database, the parametric space is divided into 3 parametric subgroups: the geometry group (H/B, D/B), the meteorology group (θ, α), and the obstacle group (PAD, RBH), where we associate 2 independent parameters with each subgroup based on which we build a corresponding 2D parameter grid while setting the other parameters to their reference values: $\mathrm{H/B_{ref}} = 1$, $\mathrm{D/B_{ref}} = 1$, $\theta_{\mathrm{ref}} = 0°$, $\alpha_{\mathrm{ref}} = 0.2$, $\mathrm{PAD_{ref}} = 0$, $\mathrm{RBH_{ref}} = 0$. To capture the strongly non-linear interaction with neighboring buildings, an additional training dataset are provided for the obstacle group with varying θ for RBH ∈ {0.5, 2} and PAD = 0.3. The complete parametric space is summarized as follows:

- Geometry group: $\mathrm{H/B} \in \left\{\frac{1}{4}, \frac{1}{2}, \frac{3}{4}, 1,2,3,4\right\}$, $\mathrm{D/B} \in \left\{\frac{1}{4}, \frac{1}{2}, \frac{3}{4}, 1,2,3,4\right\}$
- Meteorology group: $\theta \in \{0°, \cdots, 5° \times i, \cdots, 180°,\ i = 1, \cdots, 35\}$, $\alpha = \{0.1, 0.2, 0.3, 0.4\}$
- Obstacle group:
  - Main dataset ($\theta = \theta_{\mathrm{ref}}$): $\mathrm{PAD} \in \{0.1, \cdots, 0.1i, \cdots, 0.7,\ i = 2, \cdots, 6\}$, $\mathrm{RBH} \in \{\frac{1}{4}, \frac{1}{2}, \frac{3}{4}, 1, \frac{4}{3}, 2, 4\}$
  - Additional dataset: $\mathrm{PAD} \in \{0.3\}$, $\mathrm{RBH} \in \{\frac{1}{2}, 2\}$, $\theta \in \{15°, 30°, 45°, 60°, 75°, 105°, 120°, 135°, 150°, 165°\}$

A multilayer perceptron (MLP) neural network, CpCalc_nn, was developed using the PyTorch library and trained on the CFD database. The CpCalc_nn model features nine neurons in the input layer, corresponding to the nine parameters of a pointwise wind pressure state, and a single output neuron returning the C_p value. Three fully connected hidden layers are inserted between the input and output layers, each containing 64 neurons. All neurons are activated using the Rectified Linear Unit (ReLU) function [1], widely adopted for its computational simplicity and efficiency. The architecture of CpCalc_nn is illustrated in the diagram shown in Figure 2.

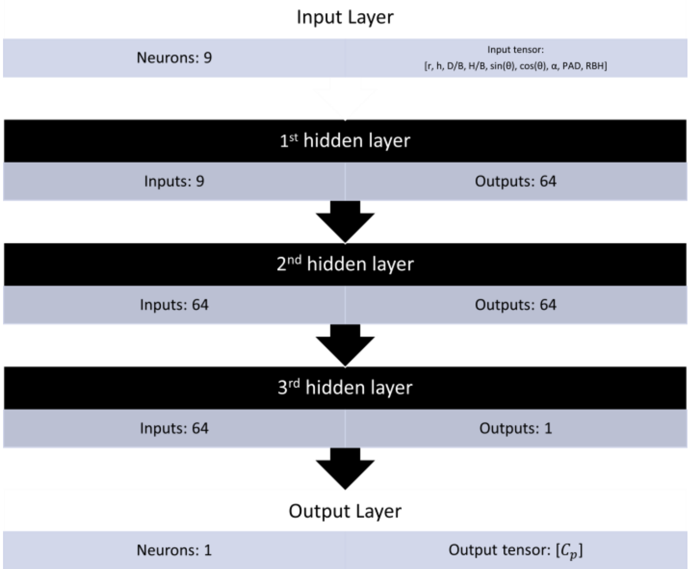

Figure 2. Neural network diagram for the CpCalc_nn model.

The MLP is trained for 120 epochs using the mini-batch gradient descent algorithm to achieve faster convergence, avoid overfitting, and prevent convergence to a local minimum. In the present study, the batch size is set to 32 to strike a balance between stability and efficiency.

Results

To draw a conclusion on the effectiveness of CpCalc_nn, we must verify the improvement in prediction accuracy compared to the previous model, CpCalc+. We select one particular obstacle configuration from the TPU aerodynamic database [7] surrounding the same target building, where the edge length along the x-axis is 24 m, along the y-axis is 16 m, and the height is 12 m.

Since the h parameter range in CpCalc+ is limited to [0.1, 0.9], we compared pointwise predictions only within this interval. The selected configuration corresponds to a target building surrounded by neighbouring structures measuring half its height, with PAD=0.3, which corresponds to a surrounding flow with a moderate level of separation. The absolute wind direction relative to the x-axis varies from 0° to 90° in increments of 22.5°.

The validation results shown in Figure 3 reveal the poor performance of CpCalc+, which captures only 39% of the variance in the dataset and exhibits a high RMSE of 0.28. In contrast, CpCalc_nn succeeds in explaining 80% of the variance while reducing the RMSE by nearly 50% compared to CpCalc+.

General

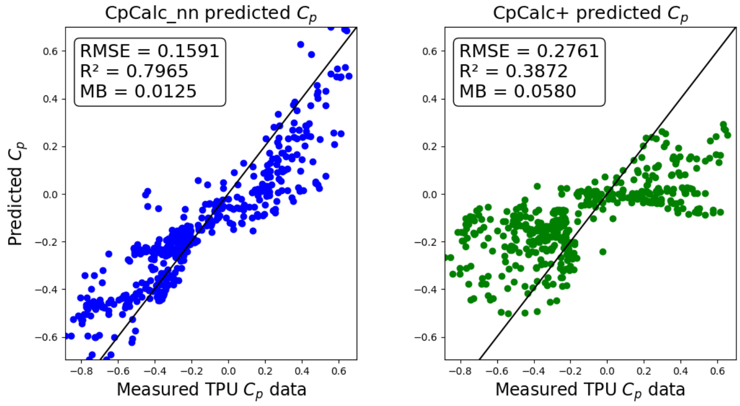

Figure 3. Validation results for CpCalc_nn compared with CpCalc+ on a moderately surrounded obstacle configuration.

We present here two C_p maps predicted by CpCalc_nn, based on the parameters corresponding to a surrounded building configuration not included in the training dataset. By comparing the model-predicted C_p maps with those computed by CFD, we can visually assess the performance of CpCalc_nn. Figure 4 shows the C_p maps at a relative wind direction $\theta = 36°$, representing a windward condition. The predicted C_p map remains highly consistent with the CFD-computed one, particularly in reproducing the spatially diminishing pattern of C_p from the upper-left to the lower-right corner on the vertical surface ($h > 0$). While CpCalc_nn slightly overestimates the pressure gradient on the flat ground ($h \leq 0$), the delineations between different C_p levels are predicted smoothly.

Figure 5 presents the C_p map comparison for $\theta = 126°$, corresponding to a leeward condition. Overall, there is satisfactory agreement between the computed and predicted maps; however, CpCalc_nn underestimates the high pressure gradient at the lower-left corner of the vertical surface, and the predicted pressure level delineations are less smooth than in the windward case, which is likely due to the complex aerodynamic patterns associated with leeward separated flow.

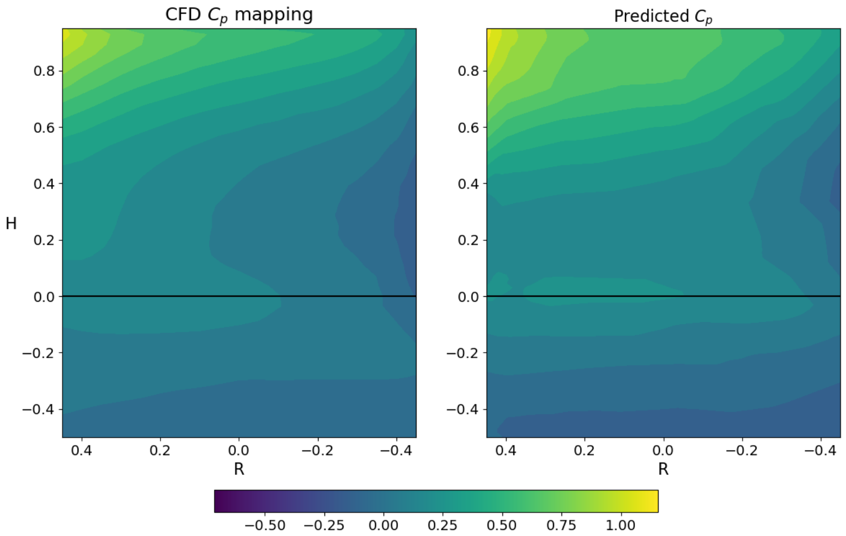

Figure 4. Comparison between CpCalc_nn and CFD for a surrounded building with a relative wind at 36°.

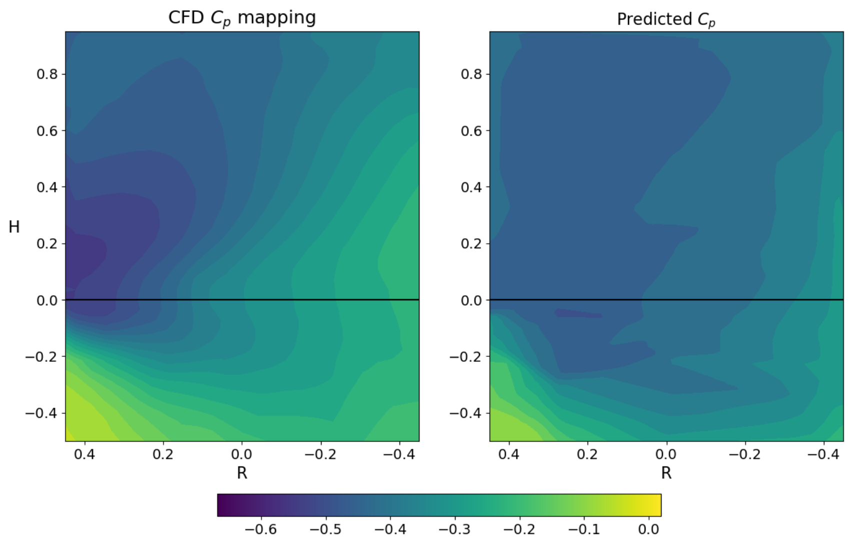

Figure 5. Comparison between CpCalc_nn and CFD for a surrounded building with a relative wind at 126°.

Conclusions

A deep-learning model, CpCalc_nn, is developed in the present project to predict the spatially varying wind pressure coefficient (C_p) maps on flat-roofed building façades. The trained model is validated against multiple validation datasets, including a state-of-the-art wind tunnel campaign, demonstrating both satisfactory accuracy and strong generalizability. By constructing the training database from CFD simulations, the cost of data acquisition is drastically reduced compared with wind-tunnel-dependent databases.

The prediction results of CpCalc_nn exhibit a high degree of physical consistency with CFD results, while significantly extending the applicable parameter range and improving accuracy over the existing polynomial-based model.

This project was partially financed by the French Agency for Ecological Transition (ADEME), a public-interest institution; consistent with its commitment to open science and reproducible research, the complete source code and the pretrained model used in this study is publicly available on GitLab at gitlab.com/xyang_suez/cpcalc_nn (under the MIT License).

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