Efficient Prediction of Indoor Airflow in Naturally Ventilated Residential Buildings Using a CFD-DNN Model Approach.

Tran Van Quang[1], Nguyen Lu Phuong[2] and Dat Tien Doan[3][0000-0002-5890-0277]

[1]Department of Architectural Engineering, Kyung Hee University, 1732, Deogyeong-daero, Gi-heung-gu, Yongin-si, Gyeonggi-do 17104, Republic of Korea
[2]Faculty of Environment, Ho Chi Minh City University of Natural Resources and Environment, 236B, Le Van Sy Street, Ward 1, Tan Binh District, Ho Chi Minh, Vietnam
[3]Department of Built Environment Engineering, School of Future Environments, Auckland University of Technology, 55 Wellesley Street East, Auckland CBD, Auckland 1010, New Zealand
dat.doan@aut.ac.nz

Abstract

Predicting indoor airflow in multi-storey residential buildings is crucial for energy-efficient natural ventilation systems. The indoor environment significantly affects human well-being due to extended indoor time and potential health risks. Precise and efficient airflow simulations are necessary to ensure thermal comfort and air quality. This study introduces a novel approach combining Computational Fluid Dynamics (CFD) simulations with machine learning techniques to predict indoor airflow. Specifically, we explore using a Deep Neural Network (DNN) model for accurate indoor airflow forecasting. The DNN effectively reproduces airflow patterns and temperature distributions. Integrating CFD simulations halves test scenario anticipation time, highlighting efficient indoor airflow prediction potential. Using a data-driven approach, this research demonstrates the feasibility of swiftly and accurately predicting indoor airflow in naturally ventilated residential buildings. Such models can optimize indoor air quality, thermal comfort, and energy efficiency, contributing to sustainable building design and operation.

Keywords: Computational fluid dynamics (CFD), Machine learning, Deep neural network (DNN), Indoor airflow prediction, Natural ventilation, Built environment

1 Introduction

Individuals spend around 85% of their daily lives inside buildings [1]–[3]. Since the early 21-century, the issues about indoor air quality, natural ventilation systems, and occupants' health in common indoor spaces have more interest in infectious airborne virus risks in buildings such as Severe Acute Respiratory Syndrome (SARS-CoV, 2003), Middle East Respiratory Syndrome (MERS-Cov, 2012), and Coronavirus Disease (COVID-19, SARS-CoV-2, 2019). Optimal indoor conditions are essential for health and productivity [4]–[10].

The relevance of natural ventilation lies in its potential to save energy, improve thermal comfort, and enhance indoor air quality. However, achieving this is complex, requiring an understanding of forces and their interactions [11]. While natural ventilation can prevent Sick Building Syndrome, it hinges on climate and manual control [12]–[15]. Computational Fluid Dynamics (CFD) has emerged as a valuable tool for predicting natural ventilation outcomes [16]–[25], while Machine Learning (ML), particularly DNNs, offers rapid and accurate airflow forecasts [26], [27].

However, CFD complexities and resource demands have paved the way for DNNs as a pragmatic alternative. Using CFD data, this study harnesses DNNs to predict airflow in multi-storey residential buildings. The approach delivers:

- A tailored DNN model surrogate for the CFD model.
- Holistic solutions for velocity, temperature, and pressure fields.
- Drastically reduced computation time compared to conventional CFD.

2 Related works

Machine learning algorithms have brought significant advancements in various fields, from initial perception to deep learning models [28]. Leveraging artificial intelligence (AI), such as Deep Neural Networks (DNNs), for airflow prediction shows promise as an alternative to Computational Fluid Dynamics (CFD) analysis in the future [26], [27]. Unlike CFD, which relies on wind tunnel test data, DNNs offer the advantage of swiftly deriving wind velocity distributions based solely on input conditions of various structures within the target area. Consequently, this approach significantly reduces computation time, enabling parametric studies, short-time optimization calculations, and various other applications. In recent trends, practical research on accuracy validation has emerged in different domains, including meteorology and wind power generation prediction [29]–[31]. While ongoing efforts seek to enhance CFD techniques through novel algorithms and turbulence models [32], [33], there has recently been a surge of interest in new tools to replace CFD in the analysis of fluid mechanics problems, typically for faster predictions or as an aid to the CFD simulation for improved accuracy. Artificial intelligence and data-driven models are gaining popularity in applications with digitalization and large amounts of data. In particular, deep learning and DNN are particularly intriguing in terms of their skills as universal nonlinear approximates, large dimensionality fields, and computational inexpensiveness. Several studies have replaced CFD simulations with deep learning methods, using DNNs as surrogate models for numerical simulations. Depending on the situation, Surrogate modelling can enable magnitudes quicker airflow prediction [37] and even real-time forecasts addressing one of the two issues mentioned by CFD simulations [34]. As a result, Deep Neural Network (DNN) models, with their superior modelling capabilities and high-speed computing prowess, emerge as viable alternatives for airflow prediction in naturally ventilated residential buildings.

In indoor airflow prediction in naturally ventilated residential buildings, while CFD simulations can provide valuable insights into realistic wind patterns indoors and outdoors, their setup demands considerable technical expertise. Additionally, addressing numerical problems and hardware requirements for processing time can lead to substantial expenses. In the past, researchers have developed outdoor wind velocity ratio prediction models to anticipate outdoor ventilation possibilities on an urban scale, enabling faster decision-making during the early design phase. However, existing prediction models often fall short: linear regressions fail to adequately explain high-density urban airflow, and nonlinear regressions with predefined equation forms present significant barriers for urban planners and architects due to their reliance on extensive technical expertise. To address these challenges, a more sophisticated data-driven machine-learning approach emerges as a promising solution. This approach makes it possible to train nonlinear regression models without predefined equation formats, making it more accessible and adaptable for users.

3 Methodology

The methodology employed in this study is visually represented in **Fig. 1**, outlining the process from data generation to model training and subsequent performance evaluation. The techniques utilized to accomplish the study's designated objectives are expounded upon with greater elaboration in subsections.

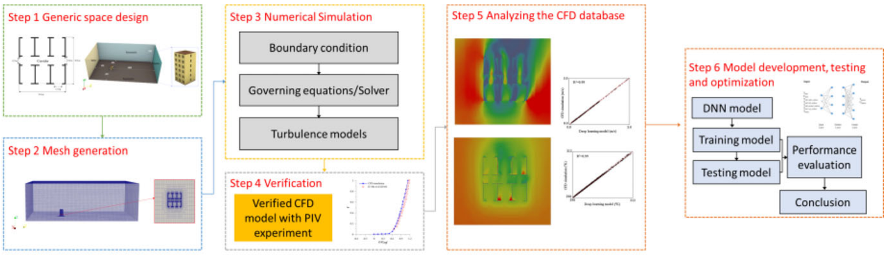
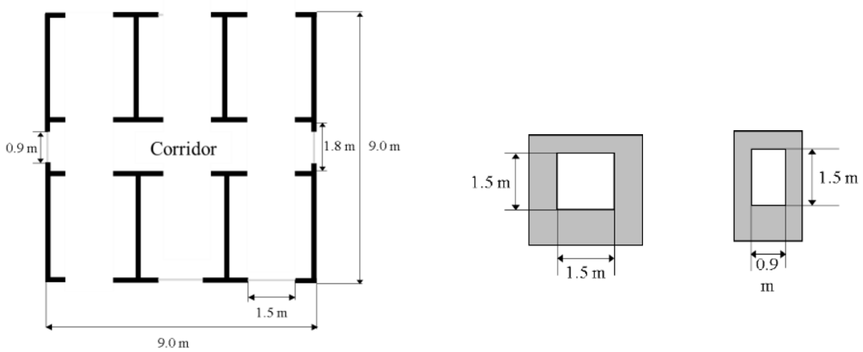


Fig. 1. Research framework of the study

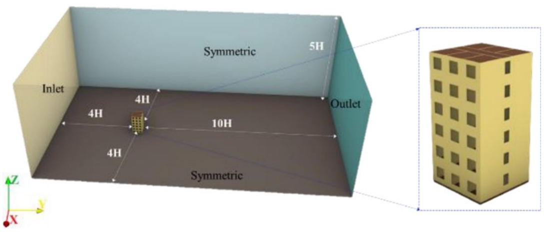
3.1 Generic Space

The study utilized a generic residential building comprising six storeys, 9m x 9m x 17.7m. Each floor had a corridor and six rooms, each measuring 3m x 3.6m x 2.9m, with one window of size 1.5m x 1.5m in each room and two corridor windows of length 0.9m x 1.5m. As shown in Fig. 2, the residential building was generated on Rhinoceros 7 software [35]. The residential building model is located inside a computational domain with distances from their inlet, outlet, and the boundary of lateral (left and right) to their nearest surfaces of 4H, 10H, and 4H, respectively, and the height of the computational domain is 5H, shown in Fig. 3.



(a) (b) (c)

Fig. 2. Geometrical dimensions of the residential building; (a) cross-section of the residential building; (b) window at each room; (c) window in the corridor.



(a) Computational domain (b) Residential building

Fig. 3. The residential building 3D model.

3.2 Governing Equations and Turbulence Models

The airflow within the computational domain is modelled for the incompressible fluid phase. The primary equations governing mass and momentum are presented in equations (1) and (2).

$$\frac{\partial(\bar{u}_i)}{\partial x_i} = 0 \tag{1}$$

$$\frac{\partial(\bar{u}_i)}{\partial t} + u_j \frac{\partial u_i}{\partial x_j} = -\frac{1}{\rho}\frac{\partial p}{\partial x_i} + \frac{\partial}{\partial x_j}\left(2\nu S_{ij} - \overline{u_i' u_j'}\right) \tag{2}$$

In the context of the equation discussed, the variable ν represents the kinematic viscosity, S_{ij} corresponds to the strain–rate tensor, p donates the mean pressure, ρ represents the air density, u' represents the fluctuating velocity component and $\bar{u}_i$ denotes the ensemble-average velocity.

The power law has been applied to the inlet by defining the atmosphere boundary condition.

$$U(z) = \frac{u^*}{k}\ln\left(\frac{z}{z_0}\right) \tag{3}$$

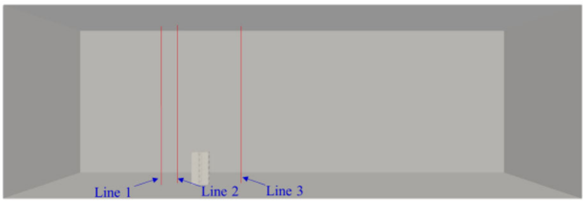
In the provided formulas, U stands for the average wind speed, y signifies the elevation, and u* corresponds to the atmospheric boundary layer (ABL) friction velocity (u* = 2.89 m/s). The von Karman constant, denoted as k, is taken as 0.415. The initial boundary conditions were measured for the simulations and presented in Table 1.

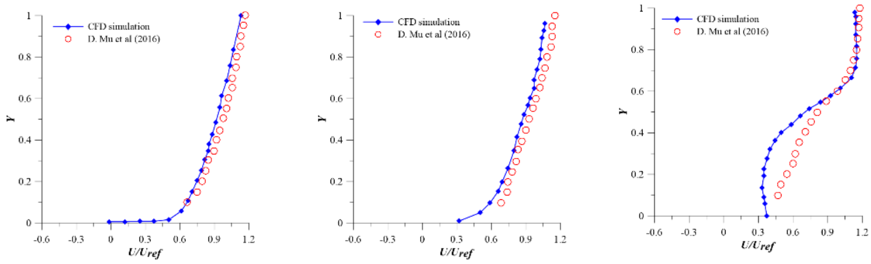
Table 1. Details of CFD simulation setting.

Computational domain	256.8m x 150.6m x 88.5 m (L x W x H)
Algorithm	Steady-state with a SIMPLE algorithm
Grid design	5.2 million elements (hexahedral meshes)
Turbulence model	RNG k – ε model
Inflow	Power law for velocity and turbulent intensity $\varepsilon(\mathrm{z}) = C_{\mu}^{3/4} \dfrac{k^{3/2}}{l_t}$
Outflow	Fixed static pressure
Top and lateral	Symmetrical boundary
Building wall and ground surface	Power law for smooth surface wall, Standard wall function

3.3 CFD Simulation Validation

The precision of the numerical simulations was exemplified through a comparison between anticipated velocity components derived from the RANS model and empirical outcomes obtained from wind tunnel experiments conducted on a multi-story residential structure [36]. The simulation results closely matched the experimental data for velocity profiles on the upstream side of the building (Lines 1 and 2). Still, discrepancies were observed downstream (Line 3), see Fig. 4. According to previous studies, only Large Eddy Simulation (LES) can produce accurate forecasts in such cases [37]. However, the overall comparison showed that the velocity trends from the CFD model were in line with the reference research [36], indicating that CFD can effectively replicate the velocity distribution.





(a) Line 1 (b) Line 2 (c) Line 3

Fig. 4. A comparison of velocity profiles from experimental measurements (the dotted line) across various model sections (lines 1-3) against the CFD projections (the solid blue line)

3.4 DNN Model and Optimization

The DNN model used in this study is an advanced version of ANN, featuring a complex architecture that enables mapping functions from input to output data. It consists of input and output layers, along with multiple hidden layers, where each layer contains one or more neurons connected to neurons in adjacent layers. Nonlinear activation functions are applied to neuron inputs during the forward pass. The model is trained by iteratively adjusting weights and biases until optimal values are attained, using error propagation and gradient descent approaches. R^2, MSE and MAE metrics are employed to evaluate the model's performance, offering a comprehensive analysis of its predictive capabilities:

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{m} (y_i - y_i)^2}{\sum_{i=1}^{m} (y_i - \overline{y})^2} \right] \tag{4}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{m} (y_i - y_i)^2}{m}} \tag{5}$$

$$MAE = \frac{1}{m} \sum_{i=1}^{m} | y_i - y_i | \tag{6}$$

The input layer takes in both the input vector and external environmental factors, whereas the output layer produces data related to temperature and velocity. Neurons in subsequent layers interpret signals from the preceding layer and pass them forward. The final output vector transforms into tensors for temperature and velocity, depicting the building's three-dimensional distribution of temperature and velocity. Experimental results are the basis for most boundary conditions and are consistently maintained across various scenarios. Detailed hyperparameter settings are provided in Table 2.

Table 2. Configuration of hyperparameters for the DNN

Number of hidden layers	1/3/5
Number of neurons per hidden layer	20/40/80/120/200
Activation function	Tanh
Gradient descent algorithm	Adam
Learning rate	0.001
Batch size	1

Determining when to stop training is crucial in the training process due to its nonconvex and iterative nature. The training is considered complete when the monitored metric, i.e., the validation error, ceases to decrease consecutively for 5000 epochs. At this stage, the training is deemed to have reached convergence. Following termination, the parameters at the early-stopping point are retrieved. Subsequently, the DNN model undergoes testing using the testing data for performance evaluation.

4 Results and Discussion

4.1 DNN Model Performance

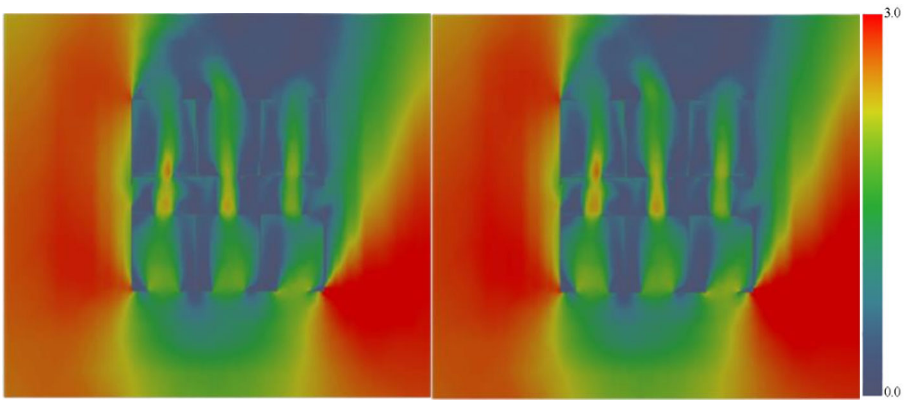
The CFD model for cross ventilation in multi-storey buildings was developed based on buoyancy-driven effects and adjusted to match experimental conditions (Fig. 3). Effective ventilation systems within residential structures can enhance indoor air quality and mitigate the release of pollutants. The study aimed to predict indoor airflow distribution and its impact on comfort conditions and indoor air pollution. Inadequate airflow was observed in certain areas, particularly the bedroom, highlighting the importance of well-designed ventilation systems.

Fig. 5(b) shows airflow patterns under cross-natural ventilation mode. The deep learning model (Deep Neural Network-DNN) provided similar flow patterns with minor differences in recirculation details. Wind direction influenced the ventilation rate, and DNN successfully predicted its impact.

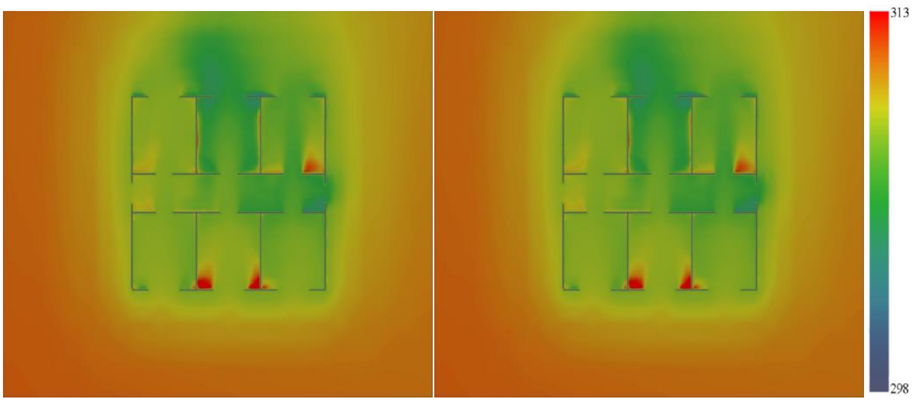
Fig. 5(c) displayed the indoor temperature distribution, with static temperature fluctuations between 298^0K to 313^0K. Wind direction plays a crucial role in temperature distribution. The DNN model showed close agreement with CFD simulation results. The DNN model effectively captured indoor temperature distribution complexities.

(a) Cross-section location in buildings

CFD simulation Deep learning model



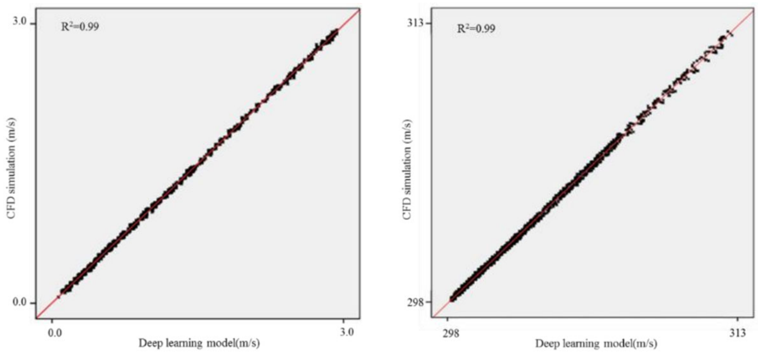
(b) Velocity distribution



(c) Temperature distribution

Fig. 5. Contrasting CFD simulation (buoyant SimpleFoam) with Deep Learning forecasts, illustrating velocity and temperature distributions in buildings on the third floor

Fig. 6 illustrates the alignment of CFD and DNN predictions regarding indoor velocity and temperature for the training set. The DNN proficiently mirrors the airflow pattems observed in the training samples, with only slight deviations seen in the test set. Interestingly, the DNN displays better performance on the test set than the training set, and its consistency is on par with CFD outcomes. The relative error for predicting velocity and temperature stands below 0.5%, underscoring the DNN's precision in capturing variations.



(a) Indoor air velocity (b) Indoor air temperature

Fig. 6. Correlations between the CFD simulations' and deep learning estimates' results

To measure the disparity between CFD simulations and DNN forecasts, Eq (7) establishes a metric, specifically the relative error.

$$E_{relative} = \frac{\left| \hat{y}_s - y_s \right|}{y_s} \times 100\% \tag{7}$$

where $\hat{y}_s$ represents the DNN's estimated value at a specific location, y_s denotes the actual CFD value at that identical spot, and s refers to the location.

The DNN models exhibit computational efficiency, enabling accurate predictions of indoor airflow on the test dataset. The DNN models adapt well to new design inputs for ventilation rate predictions, as indicated by their performance on the training dataset. Detailed statistical analysis of the velocity and temperature forecasting model is provided in Table 3.

Table 3. Overview of the performance metrics for the created prediction models

Model	U						T					
DNN	Train			Test			Train			Test		
	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE
	0.98	0.04	0.03	0.89	0.14	0.1	0.97	0.1	0.08	0.90	0.24	0.19

4.2 Computational Time

The study compared the computational time between the DNN model and CFD simulations. GPU reference measurements were unavailable, so CPU time was used for a fair assessment. The DNN model demonstrated significantly faster computation, taking less than a second, while CFD simulations required around 20 hours per case when utilizing multiple cores. DNN installation and training took approximately 5 hours. Overall, the DNN model resulted in an 80% decrease in time compared to CFD simulations, making it a promising and efficient prediction tool, see Fig. 7.

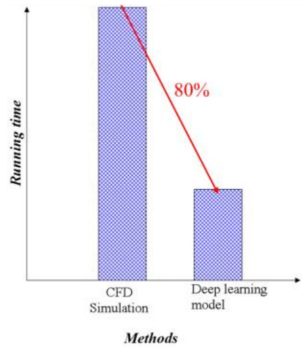


Fig. 7. Evaluating the speed of case predictions: Deep Learning model versus CFD simulation

5 Conclusions

This study presents a framework combining CFD simulation and DNN to assess wind-driven natural ventilation in buildings. The DNN model accurately predicts indoor airflow and temperature, outperforming CFD in speed. Further exploration of higher Reynolds number flows and using DNN predictions as warm-up settings for CFD simulations could enhance the approach's applicability in architectural design optimization.

Author's Contribution

The author contributed equally to the preparation of this manuscript.

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