A METHOD FOR REAL-TIME PREDICTION OF INDOOR NATURAL VENTILATION IN RESIDENTIAL BUILDINGS

ZEWEI SHI[1], XIAOXIN WANG[2], JINYU WANG[3], YU WANG[4], YIXIN JIAN[5], CHENYU HUANG[6], JIAWEI YAO[7]
[1,3,5,6,7]*College of Architecture and Urban Planning, Tongji University.*
[2,4]*Lingsi Technology (Shanghai) Co., Ltd.*
[1]*szw_shi2009@163.com, 0009-0007-3644-6513*
[2]*1428433871@qq.com*
[3]*johnwang1998@163.com*
[4]*wyu0211@foxmail.com*
[5]*zjwzjianyixin@126.com*
[6]*cyhuang@tongji.edu.cn, 0000-0002-6360-638X*
[7]*jiawei.yao@tongji.edu.cn, 0000-0001-7321-3128*

Abstract. Against the backdrop of energy crises and climate change, performance-oriented architectural design is increasingly gaining attention. Early-stage assessment of natural ventilation performance is crucial for optimizing designs to enhance indoor environmental comfort and reduce building energy consumption. However, traditional numerical simulations are time-consuming, and existing data-driven surrogate models primarily focus on predicting partial indicators in indoor airflow or single-space airflow. Predicting the spatial distribution of airflow is more advantageous for addressing global issues in building layout design. This paper introduces a surrogate model based on Generative Adversarial Networks. We constructed a dataset of floor plans, with 80% of the data generated using parameterized methods and 20% sourced from real-world examples. We developed a 3D encoding method for the floor plans to facilitate machine understanding of spatial depth and structure. Finally, we conducted airflow simulations on the dataset, with the simulated results used to train the Pix2pix model. The results demonstrate that the Pix2pix model can predict indoor airflow distribution with high accuracy, requiring only 0.8 seconds. In the test set, the average values for MAPE, SSIM, and R^2 are 2.6113%, 0.9798, and 0.9114, respectively. Our research can improve architectural design, enhance energy efficiency, and enhance residents' comfort, thereby contributing to the creation of healthier indoor environments.

Keywords. Generative Residential Buildings, Natural Indoor Ventilation, Early Design Stage, Real-time Prediction, Generative Adversarial Networks (GAN)

1. Introduction

Due to the increasingly severe pollution and climate change, the challenges faced by urban and indoor environments in providing good air quality and thermal comfort are becoming more pressing. As people spend a significant portion of their lives indoors, the indoor air circulation environment directly affects daily life, particularly in terms of health, comfort, and productivity. Therefore, creating a healthy and comfortable indoor environment, especially in residential settings, is of paramount importance.

To enhance the thermal comfort of residents, a substantial amount of energy is used for the air conditioning systems of residential buildings. However, adopting passive design methods such as natural ventilation can regulate indoor air quality and comfort, while also reducing the energy consumption of air conditioning equipment (Yik and Lun, 2010), thereby promoting sustainable development. During the early design stages, buildings have greater potential for performance optimization, emphasizing the need to predict and assess indoor airflow during these phases (Wen and Hiyama, 2018).

2. Related Work

Scholars both domestically and abroad have conducted extensive research on simulating wind environments. Over the years, Computational Fluid Dynamics (CFD) has been widely and consistently applied to simulate airflow in building environments. However, the parameter inputs of traditional CFD simulation software are complex, and simulations require a considerable amount of time, resulting in low simulation efficiency. This significantly limits the development of performance-based design in architecture.

With the continuous progress of machine learning, data-driven surrogate models have been able to significantly improve prediction speed while maintaining predictive accuracy (Nguyen Van and De Troyer, 2018) (Meddage et al., 2022). As the volume of data increases, artificial neural networks (ANN) have become a research focus due to their high prediction accuracy and low computational costs. Studies have utilized neural network models as surrogate models to predict low-dimensional distributions of pollutant concentrations (Cao and Ren, 2018), forecast indoor airflow patterns and temperature distributions (Zhou et al., 2021). Furthermore, research has employed ANN for rapid energy consumption prediction in early-stage complex architectural form design (Li et al., 2019), optimizing residential building HVAC systems through ANN-based model predictive control (Afram et al., 2017), and improving indoor airflow prediction accuracy by sequentially connecting two independent ANN models, avoiding the need for large training datasets (Kim et al., 2023).

However, current predictions of indoor airflow data mostly focus on key coefficients such as average wind speed, wind pressure coefficients, and air age. The use of indoor space is characterized by non-uniformity, meaning that people tend to stay in specific areas with higher requirements for environmental quality. Therefore, predicting detailed global airflow within the entire space is crucial for addressing local issues in indoor design, such as spatial distribution, optimization of door and window shapes, sizes, and layouts, ensuring comfort and environmental quality indoors.

The emergence of Generative Adversarial Networks (GANs) has propelled the rapid development of image prediction and has been continuously applied in the field of predicting architectural environmental performance. Some studies have used pix2pix to learn wind distributions around buildings (Mokhtar et al., 2020) and predict wind pressure images (Hu et al., 2020). Additionally, pix2pix models have been used to real-time predict outdoor wind environments, comfort, and solar radiation, accelerating performance-driven urban design (Huang et al., 2022). Furthermore, combining pix2pix-based outdoor wind field and solar radiation prediction models with urban design and optimization systems has been explored (Duering et al., 2020). Apart from urban environments, GAN models have also been applied to indoor environmental predictions, such as using CNN and GAN as surrogate models for planar sunlight simulation, predicting static, annual sunlight metrics, and spatial illuminance distributions (He et al., 2021). Additionally, for indoor airflow environment predictions, a new boundary condition CGAN model has been created, generating two-dimensional airflow distribution images based on continuous input parameters (Faulkner et al., 2023).

Based on the above research, GANs have high application value and potential in predicting indoor airflow fields. However, current research on the prediction of global indoor airflow mostly relies on fixed boundary spaces or single spaces, leaving certain gaps in predicting the global wind environment in diverse indoor spaces.

3. Methods

This paper proposes a rapid prediction method for indoor natural ventilation based on a CGAN model. Initially, the model constructs samples based on parameterized generative models and real residential models. Subsequently, these samples are imported into the Butterfly plugin for batch simulation of indoor airflow environments. Next, a dimensionality reduction and encoding process is applied to the three-dimensional models. The model encoding results, combined with simulation results, constitute the training dataset for the Pix2pix model. Finally, the Pix2pix model is utilized to construct a predictive model for indoor environmental performance. The technical path of the study is illustrated in Figure 1.

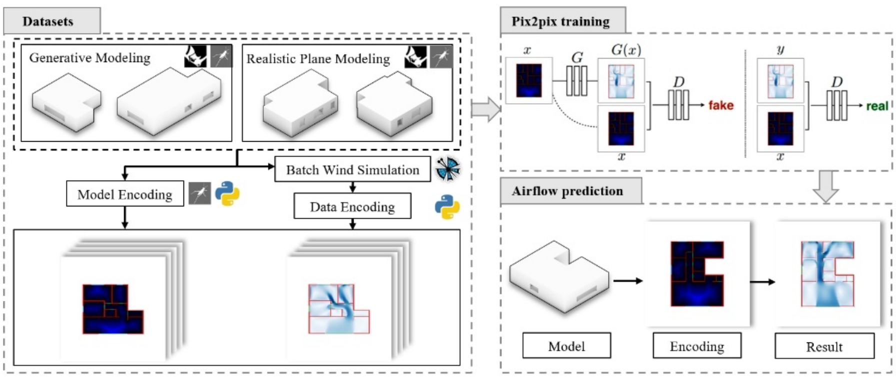

Figure 1. Workflow

3.1. DATA COLLECTION

This study established two distinct datasets, with 80% derived from generative parametric modelling and 20% based on actual residential floor plans. These datasets were employed for model training, and the results were subsequently compared.

3.1.1. Parametrically Generated Residences

The generative residential model is based on Grasshopper shape grammar, utilizing the residential outline boundaries, the edges of exterior walls, and the entrance door position as inputs to generate residential floor plans parametrically (PlanFinder, 2023). Secondary morphological control indicators, including floor height, door width and height, window sill height, and window width and height, were established based on relevant research to generate three-dimensional models. The logic of model generation is illustrated in Figure 2. To comply with residential architectural design standards and energy efficiency specifications, constraints were added, such as the window-to-wall ratio (WWR). The parameter values are provided in Table 1. The collected generative residential dataset comprises a total of 319 samples.

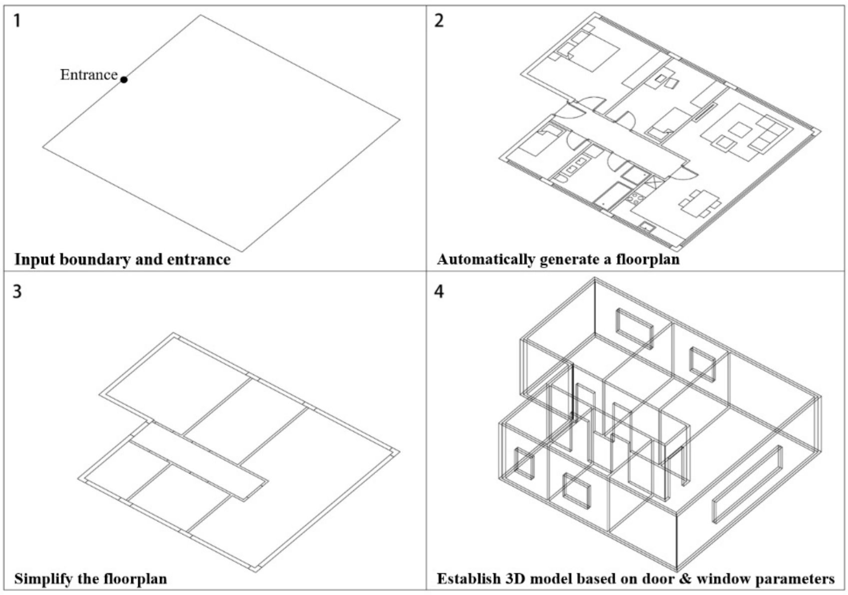

Figure 2. Parametrically generated residences

3.1.2. Real Residential Dataset

In order to increase the rationality of the floorplan of the training samples, a real data set is added, which is derived from real residential floor plans. Three-dimensional models were constructed using Grasshopper, with consistent values set for window sill height (0.9m) and window height (1.5m). To expand the dataset and mitigate overfitting, cases were transformed into new floor plans for data augmentation. By changing the window width to enhance real residential dataset, the window width was reduced to 80% and 70% of the original, respectively. The actual dataset comprised a total of 84 samples.

Table 1： Values for Residential Floor Height, Door Width and Height, Window Sill Height, Window Width, and Window Height Parameters

Parameters	Values (Range)
Floor Height	3.0m
Door Width	0.9m
Door Height	2.0m
Window Sill Height	0.8m~1.2m
Window Width	0.5m~2m
Window Height	0.9m~1.8m
WWR	Northward ⩽ 0.25; East-west ⩽ 0.30; Southward ⩽ 0.35.

3.2. IMAGE ENCODING

The input for pix2pix is defined as a three-dimensional tensor of size 256*256*3, thus requiring the encoding of geometric data from the residential models into a three-dimensional tensor of the same size, as illustrated in Figure 3(a).

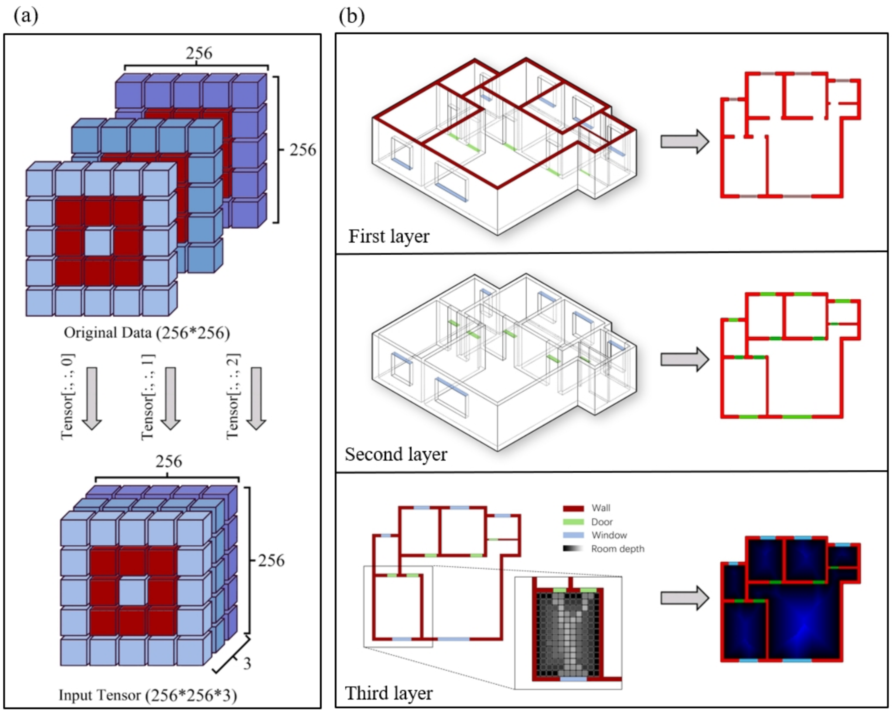

Figure 3. Model encoding method

Considering the significant impact of room walls and openings on indoor wind speed, the distance from the indoor space to the walls is considered in the image encoding. To maximize the geometric information contained in the encoding, the following encoding design was carried out: stacking planar geometric information, height information, and the distance from the space to the walls in the depth direction. The information covered by the first layer includes planar geometry information, height from the ground to the lower edge of door openings, height from the ground to the lower edge of window openings, and floor height. The second layer contains information on the height from the ground to the upper edge of door openings and window openings. The third layer provides information on the distance from the interior space to solid walls. A monitoring surface of 20m*20m is set at height of 1.5m above the ground, divided into 256*256 evenly distributed monitoring points. The Manhattan distance from the monitoring points inside the room to the nearest wall is calculated. As shown in Figure 3(b), this encoding method clearly displays the planar geometry and height information of the residential walls and doors/windows, indicating the impact of room shape, door/window opening positions, and sizes on the indoor airflow field.

3.3. INDOOR AIRFLOW SIMULATION

Butterfly is an interactive interface based on the OpenFOAM CFD Code, an open-source CFD library written in C++ and run in a Linux environment. It is used to visually invoke OpenFOAM commands. The parameter settings during the CFD simulation process in this study, including the configuration of the computational domain, boundary conditions, and mesh size, follow existing guidelines and best practices (Tominaga et al.,2008). The boundaries of the computational domain are set in the inflow and outflow directions, with the sides and top positioned 1.2H away from the wind tunnel boundaries, where H represents the maximum building height. The south-facing side is designated as the inflow direction, while the north-facing side is set as the outflow direction. Inlet boundary conditions are defined as velocity inlet boundaries, with a wind speed of 1.8 m/s. All surfaces are defined as no-slip walls. Subsequently, a hexahedral unstructured mesh is generated with grid counts of 200, 200, and 50 in the x, y, and z directions, respectively. A monitoring surface is set at a height of 1.5m above the ground, with 65,536 uniformly distributed monitoring points on a 20m*20m monitoring plane.

The simulation is based on the three-dimensional steady Reynolds-averaged Navier-Stokes (RANS) equations, utilizing the standard k-ε turbulence model. The stopping criterion is set as residuals less than 10^{-3}. Finally, the accuracy of the GAN airflow prediction model is validated by comparison with a wind tunnel database. Sensitivity tests, including the evaluation of model parameters such as color schemes, are conducted to assess potential influences on the model.

3.4. PIX2PIX TRAINING

In this study, a surrogate model based on pix2pix is established to predict the indoor airflow. The Pix2pix algorithm consists of two components: a generator and a discriminator. The generator adopts a U-net architecture, comprising an encoder and a decoder. Each block in the encoder is composed of convolution-batch normalization-Leaky ReLU, while each block in the decoder is comprised of transpose convolution-batch normalization-dropout (applied to the first three blocks)-ReLU. Skip connections exist between the encoder and decoder. The discriminator employs PatchGAN to determine the "authenticity" of independent patches in an image. Each block in the discriminator is convolution-batch normalization-Leaky ReLU. The losses in Pix2pix include CGAN loss and L1 loss. L1 loss represents the mean absolute error between the generated image and the target image.

The pix2pix network was trained using the TensorFlow deep learning framework, with architectural geometry-encoded plans as input and predicted wind field images as output. The dataset was partitioned, allocating 70% for training, 15% for validation, and 15% for testing. Considering the trade-off between image accuracy and computational cost, the iteration count was ultimately set at 200. The training process involved a total of 282 instances from the training set. Model training parameters adhered to the default settings of the Pix2pix algorithm. The experimental setup utilized an AMD R7 5800H, a 64-bit Windows 10 operating system, and an NVIDIA RTX 3070 Ti.

4. Result

The generators and discriminators of the Pix2pix model converge after 200 epochs. To quantitatively assess the accuracy of the model's predictions, MAPE, SSIM, and R^2 are selected as evaluation metrics. MAPE, the Mean Absolute Percentage Error, measures the average percentage error between predicted and actual values. A lower MAPE indicates better predictive performance. SSIM, the Structural Similarity Index, is a widely used objective image quality assessment metric based on the assumption of the highly adaptive structure information of the human visual system. SSIM values are generally not greater than 1, with a value of 1 indicating identical images. R^2 is an indicator measuring the degree of fit of the model to the observed data, representing the ratio of the variance explained by the model to the total variance.

The test set is input into the trained model, and MAPE, SSIM, and R^2 are calculated. Figure 5 displays real images, predicted images, error images, and corresponding evaluation metrics for a subset of the test set. Visually, the predicted indoor airflow distribution in the model's output aligns well with the actual images. The average values of MAPE, SSIM, and R^2 for all test results are 2.6113%, 0.9798, and 0.9114, respectively. The experimental results indicate a high degree of agreement between the model's predictions and the calculations from simulation software. Therefore, this model can provide intuitive feedback on indoor airflow distribution predictions for design professionals in the early stages of residential building design, assisting designers in performance-based design while ensuring accuracy.

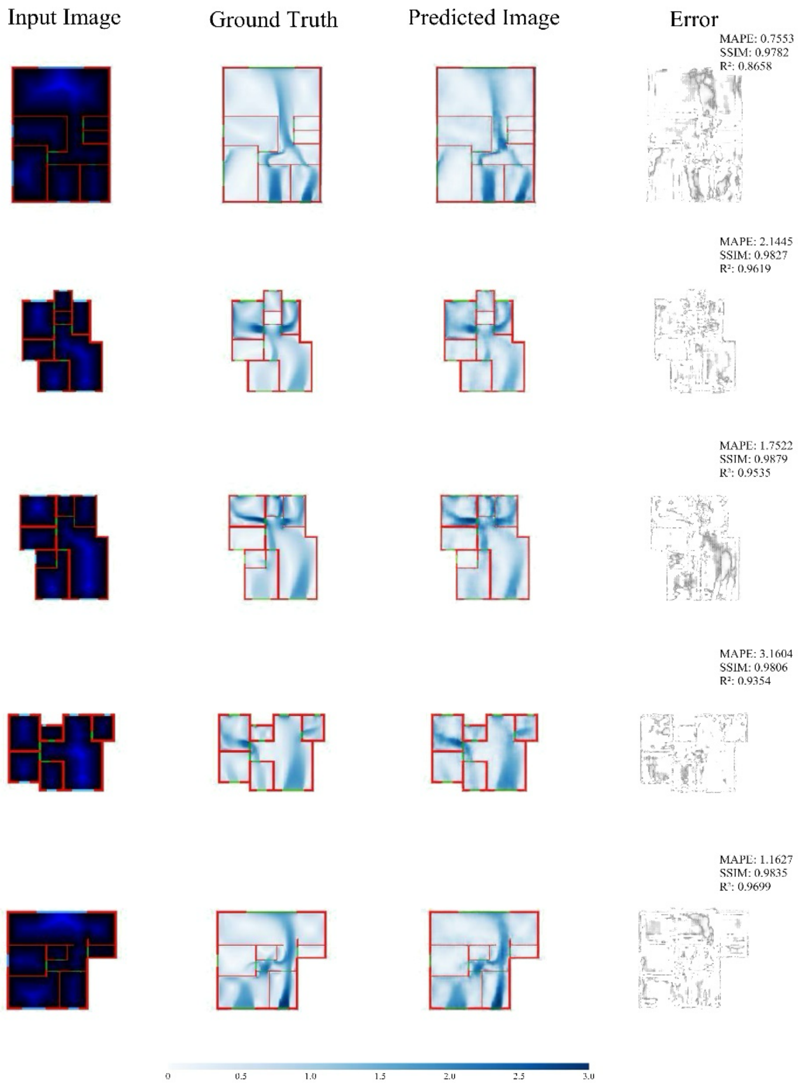

Figure 5. partial results

5. Discussion and conclusion

Against the backdrop of climate change, the assessment of indoor environmental performance becomes increasingly crucial. This study focuses on the design of naturally ventilated residences, aiming to simplify and expedite the indoor airflow simulation process. The goal is to enhance the efficiency of early-stage energy-efficient and comfortable residential design, contributing to building energy savings, emissions reduction, and sustainable development.

This research leverages GAN to achieve rapid prediction of indoor airflow under natural ventilation conditions. The results indicate an average prediction time of 0.8 seconds per sample, compared to 1200 seconds using traditional simulation software for the same samples. The model significantly reduces the time required for predictions compared to numerical simulations. The average MAPE, SSIM, and R^2 for the test set are 2.6113%, 0.9798, and 0.9114, respectively. This predictive model meets the needs of designers to instantly visualize the natural ventilation performance of designs in the early stages of residential design. This model can provide rapid indoor airflow predictions for typical residential building forms without complex input parameters.

However, the training samples in this study are limited, and it is possible to achieve predictions of indoor airflow in more diverse residential floor plans by increasing the volume of real residential dataset. Currently, the research is limited to residential building types, and the scope can be further expanded to include other types of buildings. In addition, this study uses fixed wind directions and speeds for training. In the future, more data can be simulated with multiple wind directions, and training can be conducted using wind speed ratios to enhance the generalizability to different regions and climates.

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