Machine learning-based vertical wind profile estimation for high-rise buildings by using building morphological parameters

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Abstract. Vertical meteorological conditions are the main external factor affecting the energy simulation of high-rise buildings. In urban areas, just one universal vertical wind profile is provided for all buildings' energy assessment and simulation. However, since the various morphological features of buildings and environmental conditions, vertical wind profiles from different wind directions can be various even in the same city. To get more accurate building energy prediction and simulation, it is necessary to develop precise and fast vertical wind profile estimation methods. Therefore, this study developed machine learning-based methods to generate vertical wind profiles with building morphological parameters as inputs. To validate the proposed method, this study conducted a case study with the wind tunnel data in Hong Kong. The results suggest that machine learning-based methods can effectively reflect the variation of vertical wind profiles from different wind directions in urban areas, and support vector regression shows the best performance.

1. Introduction

Urban areas are responsible for 67% to 76% of global energy consumption and 71% to 76% of greenhouse gas emissions from global final energy use (Brozovsky, Radivojevic and Simonsen, 2022). With the rapid urbanization process and population growth, around 70% of the population will settle in cities by 2050, and energy consumption in urban areas will sharply increase (Kotharkar *et al.*, 2022). Buildings are the main components of cities, and they are reported as one of the most significant contributors to energy usage and greenhouse gas emissions, which contribute to 33% of global total energy consumption and 20% of global greenhouse gas emissions (Li *et al.*, 2022; Liu *et al.*, 2022). Therefore, there is a considerable potential to save energy in the buildings' section, which is meaningful to sustainable urban development and carbon neutrality. Accurately predicting building energy is crucial for developing feasible and efficient energy-saving strategies (Luo and Oyedele, 2021).

Over the last 20 years, the number of high-rise buildings (more than 50 m or more than 14 floors) has increased because of population growth. The energy simulation of the high-rise building is challenging because of significant differences in the vertical meteorological conditions (Saroglou *et al.*, 2017). Building energy software tools like EnergyPlus have built-in calculation methods for vertical air temperature and wind speed distribution profiles. Some researchers generated vertical meteorological data from the meteorological tower (Zhou *et al.*, 2022). However, for wind speed calculation, the same vertical wind profile is provided for all buildings in urban areas. The differences in wind directions are ignored, resulting in significant energy simulation errors. Although researchers have developed wind tunnel experiments and computational fluid dynamics (CFD) models to estimate the vertical wind profiles, case-by-case work is time-consuming and hard to be conducted for all the places in cities. Therefore, a low-cost and wide-range vertical wind profile estimation method is necessary for more accurate building energy assessment in urban areas. This paper uses a machine learning-based method to estimate the vertical wind profiles from different wind directions in urban areas by applying building morphological parameters.

2. Background

2.1 Building morphology and wind conditions

Buildings' composition and configuration are critical drivers of wind conditions in urban areas at the micro or local scales (Middel *et al.*, 2014). Buildings are responsible for the increase of surface roughness in urban areas, which causes the reduction of average wind speed and reducing air circulation efficiency (Liu *et al.*, 2020). In urban aerodynamics, many morphological factors such as plan area ratio, mean building height and frontal area index have been adopted to quantify surface roughness (He, Liu and Ng, 2022). Ng et al. conducted wind tunnel experiments and CFD simulation to investigate the interaction between building morphological factors and the atmosphere and concluded that the frontal area index and building density are vital ventilation factors (Ng *et al.*, 2011). Palusci et al. investigated the influence of building morphologies (volume density, plan area ratio, building height, and façade area density) on urban ventilation. A significant correlation exists between the building façade area density and the non-dimensional mean velocity (Palusci *et al.*, 2022). In summary, previous research findings have determined the significant relationships between building morphology and urban wind conditions. Therefore, developing models with building morphological parameters to estimate the vertical wind profiles in urban areas is promising.

2.2 Vertical wind profiles estimation methods

In general, to establish quantitative vertical wind profile estimation methods in urban areas, there are three typical methods: field measurements, wind tunnel experiments, and CFD simulation. For field measurements, anemometers on balloons, towers, drones, or helicopters are applied to obverse upper-air wind conditions over the city (He *et al.*, 2022). However, the stability, height, size, frequency, and duration of the measurement equipment restrict the application for all parts of a city, and the spatial drifts of equipment can cause huge errors (He *et al.*, 2021). Wind tunnel experiments apply reduce-scale model buildings in boundary-layer wind tunnels to measure vertical wind speed profiles at the target place (Wang and Ng, 2018). Reliable data results and flexible model configurations are the advantages of wind tunnel experiments (Lin *et al.*, 2021). However, the long experiment duration and cost limit the application of wind tunnel experiments. Based on the physical process, CFD simulation can offer detailed information on the wind environment and allow the treatment of complicated geometries with high repeatability (Papadopoulou *et al.*, 2016). Compared with the other two methods, CFD simulation is related to low cost, but the computation process is still time-consuming, and the accuracy is not superior (Vernay, Raphael and Smith, 2014). Admittedly, the three typical methods above can accurately determine the vertical wind profiles. Still, the money and time costs limit the application in the building energy simulation field because of various urban forms. Therefore, it is necessary to develop new methods with high efficiency to estimate wind profiles in the whole city. Some researchers applied linear models to estimate the wind environment in cities quickly, but the uncertainties and perturbations restrict the practical application (Wang, Yang and Kim, 2020; Palusci *et al.*, 2022). Machine learning methods like artificial neural networks (ANN), support vector regression (SVR), and K-nearest neighbor (KNN) can automatically extract hidden nonlinear relationships from high-dimensional data and develop precise relationships. Recently, machine learning methods have been widely applied in urban environment assessment. For example, Huang et al. analyzed the correlation between morphological features and air pollution distribution, and machine learning methods achieved better performance in identifying nonlinear patterns (Huang *et al.*, 2022). Therefore, machine learning methods have a huge potential to establish vertical wind profiles in urban areas.

Based on the findings in all relevant studies, this study intends to develop machine learning methods to estimate vertical wind profiles in urban areas. Building morphology factors from different wind directions will be calculated at each site as the inputs for machine learning models.

3. Methodology

Figure 1 shows the workflow of machine learning-based vertical wind profile estimation. The raw vertical wind distribution data are collected from wind tunnel experiments or CFD simulations. However, data forms from different experiments are usually various because of research interests. Meanwhile, this discrete data form is not convenient in practical applications since the various layer heights of buildings. Since the power law (PL) method performs well in reflecting vertical wind profiles, data from wind-tunnel experiments and CFD simulations are converted to PL-like form (He *et al.*, 2022). As shown in Equation 1, two PL parameters, α and β, are calculated to develop machine learning models. With the development of geographic information systems (GIS) and building information modeling (BIM), 3D building geometry models can be automatically generated to extract morphological features at each area for each wind direction. Then those morphological features and two PL parameters are put into structuralized datasets to create training and testing datasets. The training dataset is applied to fit three standard machine learning methods, deep neural networks (DNN), support vector regression (SVR), and decision trees (DT). The best model will be selected by assessing the models' performance on the testing dataset.

$$V = \beta V_{500i} \left(\frac{z}{z_{500}}\right)^{\alpha} \tag{1}$$

Where V is the wind speed at height z (m/s); V_{500i} is the approaching wind speed at 500 m (m/s); z is the height about zero planes (m); z_{500} is 500 m; α is the power law exponent; β is the correction factor of V_{500i}.

To quantitatively describe the spatial building pattern in a given place, several building morphological features that influence the climate environment in urban areas are applied in this study. Table 1 summarizes the morphological building features and the calculation methods. This study sets a circular 500-meter radius for each target area and provides vertical wind profiles for 16 wind directions within each target area. For building morphological features' calculation, buildings beyond a 500-meter-radius circular and within an 800-meter-radius circular are considered. Those buildings within two adjacent wind directions are selected for each wind direction to calculate several building morphological features from 3-dimensional digital city models.

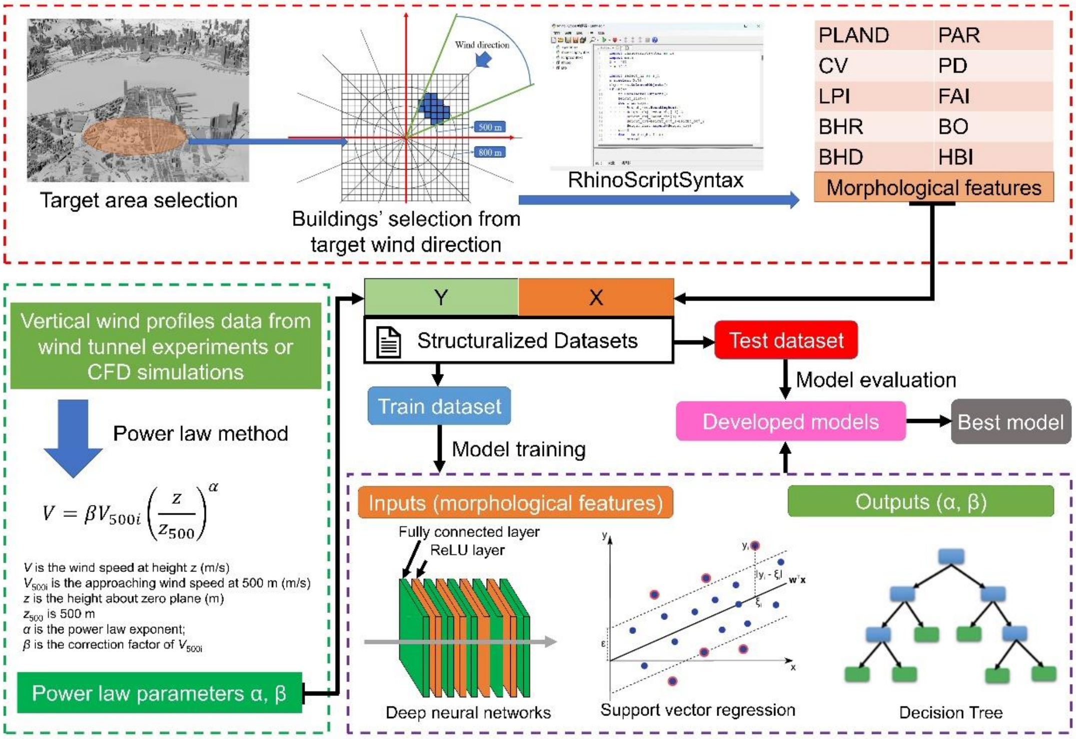

Figure 1: The workflow of machine learning-based vertical wind profiles estimation

Table 1: List of the building morphological features.

Metrics	Equation	Description
Percentage of patch *(PLAND)*	$\frac{\sum_{i=1}^{n} a_i}{A} \times 100\%$	Where a_i is the area of building patch i and A the buffer area
Patch area range *(PAR)*	$a_{max} - a_{min}$	Where a_{max} is the area of the largest building patch and a_{min} the area of the smallest building patch
Coefficient of variation *(CV)*	$\frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(a_i - \bar{a})^2}}{\bar{a}}$	Where ai is the area of building patch i and $\bar{a}$ the average area of building patches
Patch density *(PD)*	$\frac{n}{A}$	Where n is the number of building patches and A is the buffer area
Largest patch index *(LPI)*	$\frac{\sum_{i=1}^{n} \max(a_i)}{A} \times 100\%$	Where $\max(a_i)$ is the area of the largest building patch and A the buffer area
Frontal area index *(FAI)*	$\lambda_f = A_F/A_T$	Where λ_f is the front area index; A_F is the whole area of buildings' facets facing the wind direction; A_T is the lot area of the urban lot.
Building height range *(BHR)*	$H_{max} - H_{min}$	Where H_{max} is the height of the tallest building and H_{min} the height of the lowest building

Building otherness *(BO)*	$\frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(H_i-\bar{H})^2}}{\bar{H}}$	Where H_i is the height of building i and $\bar{H}$ the average height of buildings
Building height density *(BHD)*	$\frac{\sum_{i=1}^{n} H_i}{A}$	Where H_i is the height of building i and A the buffer area
Highest building index *(HBI)*	$\frac{\sum_{i=1}^{n}\max(H_i)}{\sum_{i=1}^{n} H_i} \times 100\%$	Where $max(H_i)$ is the height of the tallest building and H_i the height of the building i

4. Case study

To validate the proposed model, this study collected wind tunnel experiment data from the Air Ventilation Assessment (AVA) system established by the Planning Department, Hong Kong SAR Government (https://www.pland.gov.hk/). The Planning Department published a vertical wind profile dataset in Hong Kong, including 13 specific sites by wind tunnel experiments. This dataset provides normalised mean wind speed from 16 wind directions at different heights. All wind profile data were converted to PL-like form in Equation 1. The calculation of normalised mean wind speed is shown in Equation 2:

$$Normalised\ wind\ speed = \frac{\bar{V}_z(\theta)}{\bar{V}_{500,approach}(\theta)} \quad (2)$$

where, $\bar{V}_z(\theta)$ is the mean wind speed at height z for an approaching wind direction θ; $\bar{V}_{500,approach}(\theta)$ is the mean wind speed of the approaching wind (local weather station) at a height equivalent to 500 m for an approaching wind direction θ.

This study focused on the influence of buildings. To minimize the impact of natural landforms like a mountain, this study selected vertical wind profiles data at four places in the Hong Kong islands (S1-S4), Mong Kok (S5), and Sheung Wan (S6) as training datasets, and data at Tsim Sha Tsui (S7) as testing dataset. The details of the locations of wind tunnel experiments are shown in Figure 2.

Figure 2: The sites of wind tunnel experiments in Hong Kong

This study examined three machine learning models (DNN, DT, and SVR) for predicting PL parameters (α and β). For each parameter prediction, DNN, DT, and SVR were built. The best learning rate of the DNN model was selected from 0.01, 0.001, and 0.0001, the best max depth of the DT model was selected from 5, 10, and 15, and the best C value of the SVR model was selected from 1, 10, and 100. The details of the tuned models' hyper-parameters are shown in Table 2. The Python package PyTorch and sklearn were adopted to construct all models. The computational device for this validation test is a Windows PC with an Intel(R) Core i5 8300H CPU, 8 + 16 GB DDR4 memory of RAM, and an Nvidia GTX 1060 graphics processing unit (GPU). The final prediction results were assessed and compared with the root mean squared error (RMSE), the mean absolute error (MAE), and the mean absolute percentage error (MAPE) for all models.

Table 2: Parameter setting of machine learning models.

Algorithms	Hyper-parameters	Values
DNN	Optimizer	Adaptive Movement Estimation algorithm (Adam)
	Epochs	100
	Batch_size	1
	Learning_rate	0.0001
	Layer	[10,32,64,64,32,1]
	Activation function	Rectified linear unit (Relu)
DT	Max_depth	5
	Min_sample_leaf	1
	Max_feature	None
	Min_impurity_decrease	0.0
SVR	C	1
	Gamma	auto
	kernel	rbf

5. Results

Table 3 shows the prediction errors of 6 models on the training dataset. All models have low RMSE values, meaning three machine learning models can establish the complicated relationships between building morphology and wind profiles. As an overall comparison, DT shows the best performance on α parameter prediction, and DNN has the lowest RMSE values on β parameter prediction. Although DNN models have the most complex structure, they still cannot perform the best all the time.

Table 3: Prediction errors (RMSE) of PL parameters (α and β) on the training dataset.

DNN (α)	SVR (α)	DT (α)	DNN (β)	SVR (β)	DT (β)
0.092	0.095	0.064	0.017	0.112	0.066

Machine learning models often meet the overfitting problem. To test the model robustness, TSIM SHA TSUI, located in Hong Kong with flat terrain, is selected as the testing dataset. Figure 3 shows the prediction results of two PL parameters (α and β) with machine learning models on the testing dataset and the actual PL parameters from the wind tunnel test (Baseline). The prediction errors are shown in Table 4. For the α parameter, all three models offer high prediction precision in wind directions from 0 to 157.5° and 315° to 360°. From 180° to 247.5°, the prediction errors of all three models are relatively large, and the canyon effect of Victoria Harbour may cause this phenomenon. For β prediction, similar to β, all three models fail to predict the low values of β at 157.5°, 180°, 202.5° and 292.5°. According to the general prediction errors, all three models have low errors for PL parameters prediction, and SVR shows the best performance on both α and β. Therefore, DNN and DT models are overfitting, and the SVR method is selected as the best method for predicting vertical wind profiles.

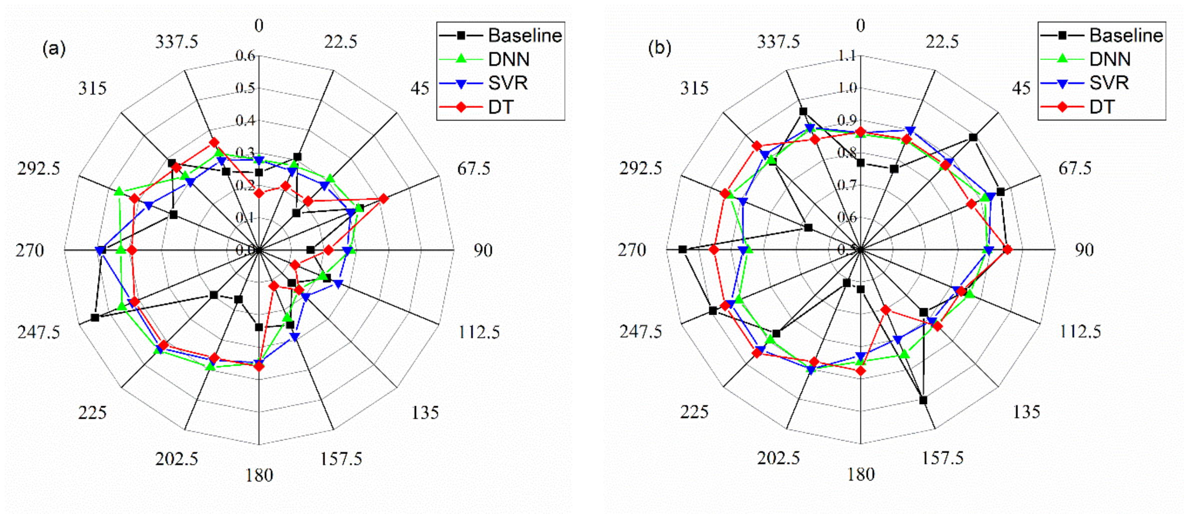

Figure 3: Predicted vertical wind profile parameters in different wind directions on the testing dataset: (1) α and (2) β

Table 4: Prediction errors of PL parameters (α and β) on the testing dataset.

Method	Training RMSE	RMSE	MAE	MAPE
DNN (α)	0.092	0.116	0.090	0.419
SVR (α)	0.095	0.104	0.085	0.398
DT (α)	0.064	0.114	0.101	0.426
DNN (β)	0.017	0.141	0.113	0.146
SVR (β)	0.112	0.138	0.112	0.144
DT (β)	0.066	0.154	0.123	0.158

To further investigate the SVR models' performances, the prediction errors of each wind direction at TSIM SHA TSUI are calculated and shown in Table 5. The SVR method can generally achieve low prediction errors for most wind directions. The SVR model achieves better performance on 112.5°, 135°, 337.5°, and 360°, because of the low prediction errors of both α and β. The large error wind directions are at 45° and 157.5°, with RMSE values larger than 0.15. The significant prediction error of β causes this result. Also, the RMSE values at 202.5° and 225° are relatively large (around 0.15) because of the errors from α prediction.

Table 5: Prediction errors of normalised mean wind speed from different wind directions.

Wind direction (°)	RMSE	MAE	MAPE
22.5	0.124	0.122	0.239
45	0.187	0.178	0.230

67.5	0.033	0.030	0.049
90	0.140	0.132	0.182
112.5	0.055	0.043	0.073
135	0.045	0.030	0.051
157.5	0.177	0.175	0.241
180	0.114	0.097	0.192
202.5	0.150	0.124	0.234
225	0.149	0.140	0.224
247.5	0.085	0.077	0.205
270	0.142	0.114	0.175
292.5	0.130	0.113	0.221
315	0.083	0.071	0.152
337.5	0.067	0.065	0.099
360	0.059	0.055	0.095

Besides the prediction errors from wind direction, this study also investigated the models' performance at different heights, and the results are shown in Table 6. The prediction errors are stable over altitude with RMSE lower than 0.15, MAE around 0.1, and MAPE around 0.2. The SVR method can effectively establish vertical wind profiles in urban areas based on the performance evaluation along wind direction and height.

Table 6: Prediction errors of normalised mean wind speed from different heights.

Height (m)	RMSE	MAE	MAPE
25	0.12	0.10	0.23
50	0.10	0.08	0.18
75	0.10	0.08	0.17
100	0.12	0.10	0.18
150	0.11	0.10	0.16
200	0.13	0.11	0.17
300	0.14	0.12	0.17
400	0.12	0.10	0.13
500	0.11	0.09	0.12

6. Discussion

This study developed machine learning methods to estimate urban vertical wind profiles with building morphology information. Three machine learning methods are tested, and SVR shows the best performance. SVR methods achieve low prediction errors for most wind directions, and the prediction results are not sensitive to altitude. Traditional vertical wind profile estimation methods for building energy simulation rely on the land type. However, this method cannot reflect the complex urban terrain because of the buildings' geometry and configuration.

This study quantitively uses the abstracted building morphological feature to describe the urban terrain. Previous research tried to develop the relationships between low-ground wind speed and building morphologies. This work extends the wind speed estimation to the vertical direction. Unlike traditional single variable regression, machine learning methods in this study establish complex relationships between several building morphologies and vertical wind profiles. The PL parameter α is only related to terrain roughness. The prediction model in this work illustrated that building morphology features can identify and quantify the terrain roughness resulting from vertical wind speed distribution. With the development of the digital city model, this work can convert the terrain roughness information into morphological features. This study provides a method to estimate the wind profiles for each part of a city or even a newly planned city for energy assessment. However, there are still some limitations to this method. First, this method considers the influence of buildings but ignores the surrounding environment, like roads and green plants. Second, this validation experiment was carried out in Hong Kong, a harbor city, and the influence of land type should also be investigated. Last, the size of the training dataset is small. Expanding the dataset and testing the models' robustness is necessary.

7. Conclusion

Traditional vertical wind profile estimation for building energy simulation relies on the terrain types. The vertical wind environment difference cannot be displayed in the same terrain, especially in urban areas. This work provided quantitative methods by morphological parameters to estimate the vertical wind profiles in urban areas. Ten building morphological features were calculated for each wind direction. This study investigated three machine learning methods on vertical wind profile estimation by establishing the relationships between building morphologies and two PL parameters. All three methods have relatively low PL parameter prediction errors. Among the three machine learning methods, SVR shows the best performance in estimating the vertical wind profile. The SVR method in this study can effectively reflect the variation of vertical wind profiles. Also, the SVR method shows stable performance on different heights.

References

Brozovsky, J., Radivojevic, J. and Simonsen, A. (2022) 'Assessing the impact of urban microclimate on building energy demand by coupling CFD and building performance simulation', *Journal of Building Engineering*, 55, p. 104681. doi: 10.1016/j.jobe.2022.104681.

He, Y. *et al.* (2021) 'Investigations of high-density urban boundary layer under summer prevailing wind conditions with Doppler LiDAR: A case study in Hong Kong', *Urban Climate*, 38, p. 100884. doi: 10.1016/j.uclim.2021.100884.

He, Y. *et al.* (2022) 'Urban ventilation assessment with improved vertical wind profile in high-density cities – Comparisons between LiDAR and conventional methods', *Journal of Wind Engineering and Industrial Aerodynamics*, 228, p. 105116. doi: 10.1016/j.jweia.2022.105116.

He, Y., Liu, Z. and Ng, E. (2022) 'Parametrization of irregularity of urban morphologies for designing better pedestrian wind environment in high-density cities – A wind tunnel study', *Building and Environment*, 226, p. 109692. doi: 10.1016/j.buildenv.2022.109692.

Huang, C. *et al.* (2022) 'Effect of urban morphology on air pollution distribution in high-density urban blocks based on mobile monitoring and machine learning', *Building and Environment*, 219, p. 109173. doi: 10.1016/j.buildenv.2022.109173.

Kotharkar, R. *et al.* (2022) ‘Approach to local climate zone based energy consumption assessment in an Indian city’, *Energy and Buildings*, 259, p. 111835. doi: 10.1016/j.enbuild.2022.111835.

Li, G. *et al.* (2022) ‘Performance evaluation of short-term cross-building energy predictions using deep transfer learning strategies’, *Energy and Buildings*, 275, p. 112461. doi: 10.1016/j.enbuild.2022.112461.

Lin, Y. *et al.* (2021) ‘Investigation of the Reynolds number independence of cavity flow in 2D street canyons by wind tunnel experiments and numerical simulations’, *Building and Environment*, 201, p. 107965. doi: 10.1016/j.buildenv.2021.107965.

Liu, X. *et al.* (2022) ‘Investigating the performance of machine learning models combined with different feature selection methods to estimate the energy consumption of buildings’, *Energy and Buildings*, 273, p. 112408. doi: 10.1016/j.enbuild.2022.112408.

Liu, Y. *et al.* (2020) ‘A preliminary study on the influence of Beijing urban spatial morphology on near-surface wind speed’, *Urban Climate*, 34, p. 100703. doi: 10.1016/j.uclim.2020.100703.

Luo, X. J. and Oyedele, L. O. (2021) ‘Forecasting building energy consumption: Adaptive long-short term memory neural networks driven by genetic algorithm’, *Advanced Engineering Informatics*, 50, p. 101357. doi: 10.1016/j.aei.2021.101357.

Middel, A. *et al.* (2014) ‘Impact of urban form and design on mid-afternoon microclimate in Phoenix Local Climate Zones’, *Landscape and Urban Planning*, 122, pp. 16–28. doi: 10.1016/j.landurbplan.2013.11.004.

Ng, E. *et al.* (2011) ‘Improving the wind environment in high-density cities by understanding urban morphology and surface roughness: A study in Hong Kong’, *Landscape and Urban Planning*, 101(1), pp. 59–74. doi: 10.1016/j.landurbplan.2011.01.004.

Palusci, O. *et al.* (2022) ‘Impact of morphological parameters on urban ventilation in compact cities: The case of the Tuscolano-Don Bosco district in Rome’, *Science of the Total Environment*, 807, p. 150490. doi: 10.1016/j.scitotenv.2021.150490.

Papadopoulou, M. *et al.* (2016) ‘Evaluating predictive performance of sensor configurations in wind studies around buildings’, *Advanced Engineering Informatics*, 30(2), pp. 127–142. doi: 10.1016/j.aei.2016.02.004.

Saroglou, T. *et al.* (2017) ‘Towards energy efficient skyscrapers’, *Energy and Buildings*, 149, pp. 437–449. doi: 10.1016/j.enbuild.2017.05.057.

Vernay, D. G., Raphael, B. and Smith, I. F. C. (2014) ‘Augmenting simulations of airflow around buildings using field measurements’, *Advanced Engineering Informatics*, 28(4), pp. 412–424. doi: 10.1016/j.aei.2014.06.003.

Wang, J. W., Yang, H. J. and Kim, J. J. (2020) ‘Wind speed estimation in urban areas based on the relationships between background wind speeds and morphological parameters’, *Journal of Wind Engineering and Industrial Aerodynamics*, 205, p. 104324. doi: 10.1016/j.jweia.2020.104324.

Wang, W. and Ng, E. (2018) ‘Air ventilation assessment under unstable atmospheric stratification — A comparative study for Hong Kong’, *Building and Environment*, 130, pp. 1–13. doi: 10.1016/j.buildenv.2017.12.018.

Zhou, X. *et al.* (2022) ‘Generation and verification of vertical meteorological data for building energy simulation from a 325-meter Beijing meteorological tower’, *Energy and Buildings*, 262, p. 111992. doi: 10.1016/j.enbuild.2022.111992.