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Review

Research on the Application of Deep Learning Technology in urban wind field prediction

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Abstract: Rapid and accurate prediction of wind speed fields in urban environments is vital for understanding urban climates, promoting sustainability, and mitigating disasters. Existing prediction methods primarily rely on Computational Fluid Dynamics (CFD) numerical simulations. However, these traditional approaches face significant constraints regarding both accuracy and computational efficiency. With rapid advancements in computer technology, deep learning is gradually emerging as an efficient alternative to conventional CFD simulations for wind field prediction. This paper elaborates on the application of deep learning methods in wind field forecasting and comprehensively analyzes the current problems and challenges encountered in this domain. Finally, the study explores future prospects for the development of wind field prediction technologies.

Keywords: Urban airflow; Deep learning; Turbulence model

1. Introduction

With the rapid economic development and continuous acceleration of urbanization, the increasing urban population density and complex spatial functions have posed unprecedented challenges to environmental quality, livability, and disaster mitigation [1]. As a key element in regulating urban climates, urban ventilation is a core research direction for optimizing spatial layouts and improving wind environments. The airflow around urban building complexes exhibits strong turbulence characteristics, making the accurate simulation of its evolutionary patterns a critical scientific challenge for urban planning and risk management [2, 3]. Therefore, developing efficient and accurate wind field prediction methods is an urgent priority. To address this, this paper explores the application of machine learning and deep learning techniques in predicting urban wind speed fields. We systematically review the relevant research by organizing our discussion around two mainstream paradigms designed to replace traditional CFD simulations.

2. Search Strategy

This systematic review follows a standardized literature retrieval and screening process to ensure the comprehensiveness and representativeness of the included studies. Literature sources cover major academic databases including IEEE Xplore, Web of Science, Scopus, and arXiv, with the search time span covering the last decade to capture the latest progress in deep learning-driven flow field prediction. The primary keywords used for retrieval include urban wind field, deep learning, computational fluid dynamics, surrogate model, structured grid, unstructured grid, graph neural network, and physics-informed neural network.

After initial retrieval, duplicate documents are removed, and further screening is conducted based on topic relevance, research integrity, and academic quality. Studies that focus on theoretical derivation without practical application, studies with insufficient experimental validation, and studies irrelevant to urban wind environment scenarios are

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excluded. Finally, high-quality literature that proposes innovative network architectures, improves prediction performance, or solves key bottlenecks in urban flow simulation is retained. This strict screening mechanism guarantees that all reviewed works closely align with the core theme of deep learning application in urban wind field prediction and can objectively reflect the current research status and mainstream technical routes in this field.

3. Flow Field Prediction based on Deep Learning

Traditional CFD numerical simulations rely heavily on the spatial discretization of the computational domain. When dealing with complex geometric boundaries such as urban building clusters, CFD typically requires the generation of a massive number of mesh nodes to capture the intricate features of fluid motion [4]. This inevitably leads to extremely high computational resource consumption and enormous time costs. In recent years, with the introduction of artificial intelligence technologies, deep learning has gradually emerged as an important means to accelerate or even replace the traditional CFD solution process due to its powerful nonlinear fitting capabilities. When constructing deep learning surrogate models, the spatial discrete representation of physical field data becomes the core element determining the network architecture [5]. Based on how the original computational mesh is processed, existing mainstream research can be divided into two fundamental paradigms. The first paradigm tends to resample and convert the entire flow field region into a regular structured grid, subsequently utilizing mature convolutional neural networks to extract the spatial features of the flow field. The second paradigm strives to break free from the limitations of regular resampling by directly treating the original unstructured mesh as a topological graph structure, employing advanced architectures such as graph neural networks to pass physical information between mesh nodes, thereby achieving highly efficient prediction of complex flow fields. This paper classifies the related deep learning methods for flow field prediction strictly according to the two mesh processing paradigms, which helps to systematically analyze the technical characteristics, application scenarios, advantages and limitations of different methods, and provides a clear logical thread for the overall review.

3.1. Deep Learning Methods based on Structured Grids

Given that Convolutional Neural Networks possess a natural advantage in extracting spatial features from regular grid data, the majority of current flow field prediction studies discretize the computational domain into structured grids. By mapping flow variables to image pixels, researchers have developed a series of efficient deep learning architectures. Kashefi et al. proposed a point-cloud-based deep learning framework aimed at predicting fluid flow fields around irregular geometries [6]. This research breaks through the dependency of traditional CNNs on Cartesian grids by utilizing the PointNet architecture to directly process unstructured grid vertices. By using spatial coordinates as input, the model learns the non-linear mapping from geometric positions to physical quantities such as velocity and pressure. This approach adapts to complex boundary shapes and also achieves prediction speeds three orders of magnitude faster than traditional finite element solvers while maintaining mass and momentum conservation. Exploring the generalization capabilities of convolutional networks, Guo et al. explored the feasibility of using CNNs to predict non-uniform laminar flows [7]. This study innovatively introduced the Signed Distance Function (SDF) to represent object geometries and designed a multi-branch network structure containing shared encoding layers and independent decoding layers. Experimental results indicate that for both 2D and 3D flow fields, the computational efficiency of this model is two orders of magnitude higher than GPU-accelerated LBM solvers and four orders of magnitude higher than CPU-based solvers. This achievement demonstrates the significant potential of deep learning for real-time, low-cost design space exploration in the early stages of engineering. Sekar et al. proposed a fast flow field prediction framework over airfoils using a deep learning approach [8]. By encoding airfoil geometries into binary images and employing a deep residual network (ResNet) architecture, the model effectively establishes a mapping between geometric profiles and full-field physical properties including velocity and pressure distributions. Notably, this research emphasizes the model's reliability across varying Reynolds numbers and angles of attack. The results demonstrate that the framework achieves a leap in computational efficiency by reducing inference time to the millisecond scale while maintaining high fidelity relative to traditional CFD solvers, thereby enabling real-time aerodynamic performance evaluation and multi-objective shape optimization. Additionally, Ribeiro et al. developed the DeepCFD model [9]. The schematic diagram of its network architecture is presented in Figure 1.

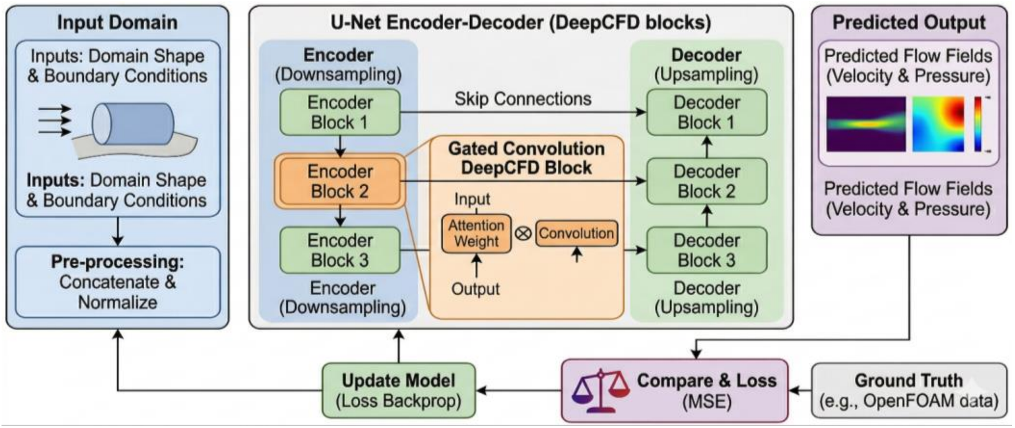

Figure 1. Schematic diagram of the U-Net network architecture

DeepCFD Efficient Steady-State Laminar Flow Approximation with Deep Convolutional Neural Networks. Utilizing a symmetric encoder decoder UNet structure, this framework employs a Signed Distance Function to encode non uniform boundaries and extracts multi scale spatial features to directly output complete velocity and pressure fields. These pioneering works successfully addressed the computational bottleneck of traditional solvers by enabling rapid iterative feedback during early design stages. However, their primary limitation lies in the inability to capture the time evolving nature of turbulent flows, making them insufficient for simulating complex dynamic fluid phenomena.

To address these temporal limitations, a new class of methods has emerged to provide innovative solutions for capturing the spatiotemporal evolution of dynamic flows. Miyanawala et al. presented a reduced-order modeling technique for the Navier-Stokes equations, focusing on the transient wake dynamics around bluff bodies [10]. By establishing a mapping between object shape masks and fluid force coefficients via CNNs and optimizing with stochastic gradient descent, the study successfully captured complex unsteady phenomena such as vortex-induced vibrations. This method significantly reduces computational degrees of freedom while maintaining the accuracy of key physical features. In the field of high-Reynolds-number urban wind simulation, Xiang et al. constructed a non-intrusive reduced-order model (NIROM) with dynamic boundary conditions [11]. The research team generated high-fidelity training sets by coupling the Parallelized LES Model (PALM) with the Urban Canopy Model (UCM) from WRF. They conducted a detailed comparison between Proper Orthogonal Decomposition (POD) and Convolutional Autoencoders (AE-CNN), finding that AE-CNN is more efficient at compressing high-dimensional urban airflow data. Combined with the XGBoost algorithm, this framework can rapidly reconstruct urban microclimate wind fields based on real-time changing meteorological boundaries, balancing the computational demands between macro-meteorological and micro-street scales. Furthermore, to address long-term temporal dependencies in fluid evolution, Wiewel et al. introduced the concept of "Latent Space Physics" [12]. This method first utilizes a CNN to compress the high-dimensional Eulerian flow field of each moment into a low-dimensional latent space, and subsequently evolves the physical states within this latent space using Long Short-Term

Memory (LSTM) networks. This spatio-temporal decoupling strategy effectively avoids the error accumulation issues associated with direct temporal iteration in the original high-dimensional space. In complex simulations of liquids and buoyancy-driven flows, the model not only ensures visual physical realism but also achieves a leap in computational speed by several orders of magnitude. To further enhance the generation quality of complex dynamic flow fields, Song et al. proposed a 3D dynamic wake prediction framework based on a diffusion model [13]. The schematic diagram of its network architecture is presented in Figure 2.

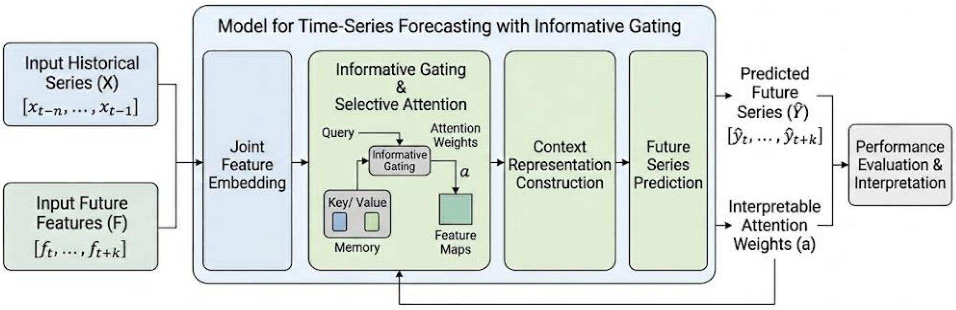

Figure 2. Schematic diagram of the Time-Series forecasting network

This framework consists of a freestream field generator, a diffusion model, and an analytical wake model, which can directly reconstruct wake fields from inflow data and turbine states to achieve highly efficient iteration independent predictions. Overall, deep learning methods based on structured grids exhibit mature network architectures and exceptional inference speeds. Despite these significant advantages, such approaches face inherent challenges, as the required grid interpolation often introduces geometric distortion at complex structural boundaries and limits the ability to capture fine scale local turbulence within narrow building gaps. These identified limitations eventually prompted researchers to point out that interpolating raw data into Cartesian grids causes severe information loss, thereby inspiring a paradigm shift towards unstructured mesh learning.

3.2. Deep learning methods based on unstructured grids

When dealing with computational domains that feature complex geometric structures and require local mesh refinement, unstructured grids demonstrate significantly stronger topological adaptability than structured grids. In recent years, Graph Neural Networks and other advanced network architectures specifically designed to process on Euclidean spatial data have become the frontier in both indoor and outdoor flow field prediction. The neural network architectures commonly utilized in these studies primarily include Graph Neural Networks, Transformers, and Physics Informed Neural Networks.

Pioneering this transition, Pfaff et al. introduced an innovative network framework named MeshGraphNets [14]. The schematic diagram of its network architecture is presented in Figure 3.

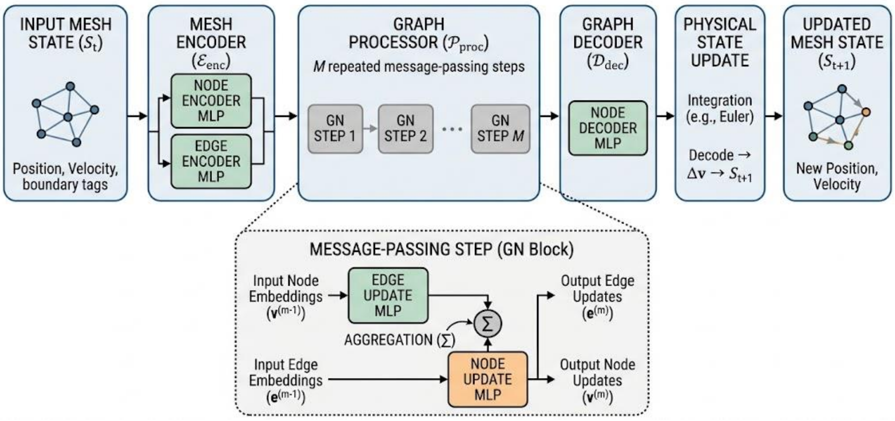

Figure 3. Schematic diagram of the deep learn architecture

Operating on discrete mesh graphs, this encoder processor decoder architecture passes messages between nodes to adaptively support physical simulations across a wide range of varying resolutions. Researchers found that MeshGraphNets not only maintains high predictive accuracy for diverse physical evolution processes including aerodynamics and structural mechanics but also achieves computational efficiency improvements of one to two orders of magnitude compared to traditional specialized simulation programs. Furthermore, the inherent adaptivity of this model supports learning resolution independent dynamics, allowing it to scale seamlessly to more complex state spaces during testing.

To address the information transfer bottleneck caused by shortened physical distances between nodes in high resolution meshes, Fortunato et al. introduced a multi scale graph construction method based on the MeshGraphNets framework, proposing the MultiScale MeshGraphNets [15]. This model effectively learns flow field features across different scales by simultaneously and independently passing messages on a fine input mesh and a coarse auxiliary mesh, combined with downsampling and upsampling mechanisms. Such a hierarchical multi scale architecture significantly enhances the ability of the model to capture large scale and long-range feature patterns. Consequently, it successfully improves the prediction accuracy of high-resolution flow fields while further reducing computational resource consumption by overcoming the traditional message passing bottleneck.

Addressing the complex flow field modeling of wind turbine wakes, Xie et al. proposed an end-to-end deep graph representation learning surrogate model [5]. This study utilizes graph neural networks to process data directly on unstructured meshes, aiming to achieve highly efficient predictions of steady wind speed fields and turbulent kinetic energy fields under various inlet conditions and turbine yaw angles. The model demonstrates excellent generalization capabilities on unseen data and partially alleviates the over smoothing issues commonly found in standard graph neural networks. Despite these advancements, this method still exhibits obvious limitations when applied to large-scale real-world scenarios. Its training data is primarily extracted from two dimensional cross sections within a three-dimensional space, and a single computational domain contains only about one hundred thousand mesh nodes. Compared to complex urban environment wind fields that easily require millions of nodes for discretization, the spatial scale that this model can handle remains relatively limited.

Aiming at the inherent turbulence modeling biases present in traditional Steady Reynolds Averaged Navier Stokes models for urban wind field simulations, Zhao et al. proposed a two-stage CFD graph neural network prediction framework [16]. The schematic diagram of its network architecture is presented in Figure 4.

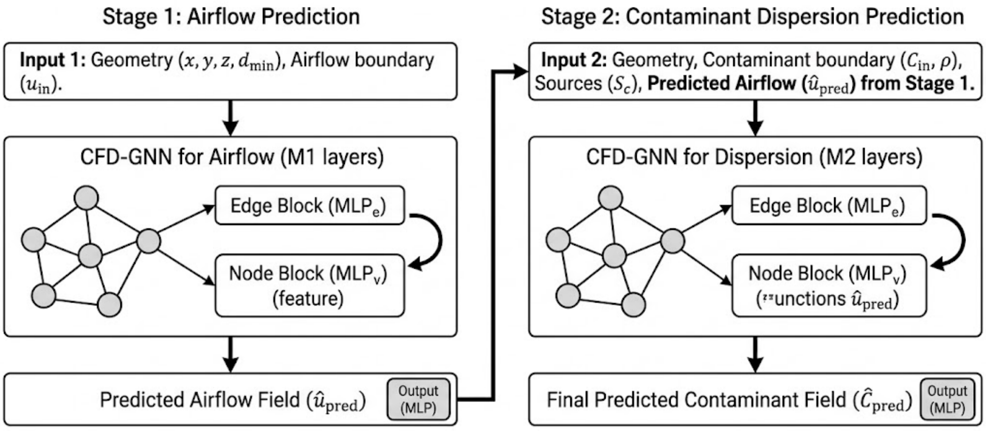

Figure 4. Schematic diagram of the deep learn architecture

This framework innovatively utilizes the steady state solution results of the basic solver as the initial input graph on a coarse mesh. Subsequently, through the multi-layer message passing mechanism of the graph convolutional network, it directly corrects the deviations of the numerical outputs in a single inference step, driving them to approach the high-fidelity target state of Large Eddy Simulations. In practical tasks involving urban wind fields and pollutant dispersion, this method not only demonstrates excellent generalization capabilities to unseen complex building layouts but also accelerates the prediction speed to thousands of times faster than traditional high-fidelity solvers.

To resolve the ubiquitous issues of error accumulation and vortex shedding phase drift in the long-term prediction of dynamic transient flow fields, Han et al. proposed a novel framework that introduces a Transformer temporal attention mechanism within a mesh reduced space [17]. This study first utilizes a graph mesh reducer to extract low dimensional latent features from a small number of core nodes. Following this, it employs the Transformer architecture to globally capture long range temporal dependencies for autoregressive prediction. Finally, a graph mesh upsampling network restores the complete high dimensional transient physical field. This mechanism enables deep learning models to achieve highly stable and accurate long sequence predictions of transient flow fields without the need to inject artificial noise during training.

Approaching the problem from the perspective of physical prior constraints, Rao et al. proposed a mixed variable Physics Informed Neural Network scheme suitable for incompressible laminar flow simulations [18]. This method substitutes traditional velocity and pressure solving formats with stream functions and continuum mechanics formulations, thereby automatically satisfying the incompressible condition of zero fluid divergence. By directly incorporating physical governing equations as constraint terms into the training process, the proposed model ensures that fluid prediction results strictly comply with physical laws. In steady and transient simulation experiments of low Reynolds number flow past a cylinder, this approach achieved high precision predictions without requiring any high-fidelity simulation data as labels. However, because Physics Informed Neural Network models are deeply bound to specific initial and boundary conditions, the network must be retrained whenever scene parameters change, which somewhat limits their application scope in rapid iterative generalization.

Shao et al. proposed a novel physics informed graph neural network named PIGNN CFD [19]. The schematic diagram of its network architecture is presented in Figure 5.

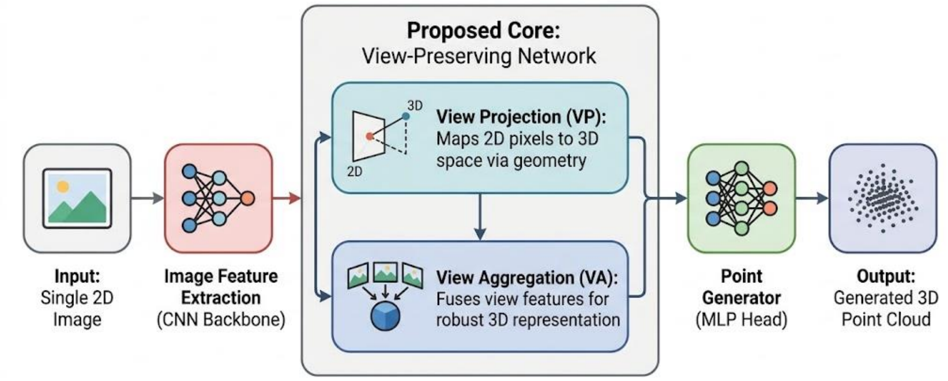

Figure 5. Schematic diagram of the graph neural network

This model is specifically designed to address the computational bottleneck and scalability issues of traditional numerical simulations in practical urban engineering applications. Operating directly on irregular unstructured meshes, PIGNN CFD achieves the rapid prediction of urban wind fields. By embedding physical governing laws into the graph neural network learning process, this approach effectively ensures the physical consistency of the predicted flow fields while drastically reducing the time required for computation. Ultimately, their work further demonstrates the immense potential of combining physics informed constraints with graph-based learning to achieve both high fidelity and high efficiency in complex urban wind environment assessments.

In summary, deep learning methods based on unstructured grids demonstrate significant advantages when processing complex computational domains. These methods can directly transfer and learn physical information on the original irregular topological graphs, completely avoiding the geometric distortion and feature loss caused by data resampling onto Cartesian grids. Consequently, they possess extremely high fidelity and generalization capabilities in adapting to variable boundary conditions and capturing fine local turbulent structures. However, unstructured methods also face limitations that cannot be ignored. As grid resolution increases, the massive amount of message passing between nodes often leads to enormous memory consumption and a heavy computational burden, and the difficulty of constructing complex graph structures and training models is much higher than that of conventional networks. Overall, the deep learning paradigms of structured and unstructured grids each have their own strengths and weaknesses. Structured methods hold a natural advantage in inference speed and model deployment due to mature convolutional operators, whereas unstructured methods excel in geometric adaptability when dealing with complex real world engineering scenarios.

4. Discussion

Despite the rapid progress of deep learning in urban wind field prediction, a series of critical limitations and challenges persist in current research. Most data-driven models depend heavily on large-scale high-fidelity CFD data for training, and the high cost of data generation restricts model generalization to unseen urban layouts and extreme boundary conditions. Structured grid methods offer fast inference speed but suffer from geometric distortion and information loss during grid resampling, which weakens the capability to capture fine-scale turbulence in narrow building gaps. Unstructured grid methods based on graph neural networks enhance the adaptability to complex geometries, yet the large-scale message passing between nodes results in high memory usage and heavy computational burden, raising the difficulty of model training and deployment.

Most existing models lack explicit physical constraints, so prediction outputs may conflict with fundamental fluid dynamic principles such as mass conservation and momentum conservation, which reduces the reliability in engineering practice. For transient and high-Reynolds-number turbulent flows in real urban environments, long-term prediction still suffers from error accumulation and phase drift, which affect the stability of dynamic flow simulation.

Future research should focus on addressing these challenges through several key directions. Integrating physical governing equations into network training to build physics-informed models reduces the dependence on labeled data and ensures physical consistency of predictions. Developing lightweight and multi-scale network architectures helps balance computational efficiency and prediction accuracy, supporting the capture of both large-scale meteorological conditions and small-scale turbulent structures. Transfer learning and few-shot learning strategies can be explored to improve cross-scene generalization for different urban layouts. Combining deep learning with data assimilation and real-time observation data promotes the development of real-time and high-precision urban wind environment assessment. Further optimization of graph neural networks on large-scale unstructured meshes also extends the applicability of models to practical urban simulation tasks.

5. Conclusion

Drawing from the preceding discussions, the integration of deep learning technologies into urban wind field prediction offers a highly efficient alternative to traditional computational fluid dynamics. By categorizing current research into structured and unstructured grid paradigms, this paper highlights the respective strengths and limitations of both approaches. Methods based on structured grids achieve remarkable inference speeds through mature convolutional architectures, yet they often struggle with geometric distortion. Conversely, unstructured grid methods utilizing graph neural networks provide superior topological adaptability and physical fidelity for complex building clusters, though they require substantially higher memory and computational resources during training.

Despite these significant advancements, purely data driven models still face challenges in generalization and physical consistency, especially when dealing with limited high fidelity training data or unseen urban layouts. Future research should prioritize embedding physical laws directly into advanced neural network architectures to reduce data dependency and ensure strict compliance with fluid dynamics principles. Furthermore, integrating deep learning with data assimilation frameworks presents a highly promising avenue for enhancing urban wind field simulations. Additionally, exploring lightweight multi scale network designs will be crucial for capturing both macroscopic meteorological boundary conditions and microscopic local turbulence within narrow building gaps. Continued innovation in these interconnected areas will ultimately pave the way for real time and high precision urban wind environment assessments.

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