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AI as a Collaborative Partner in Landscape Form-finding

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Abstract: This study introduces an AI-assisted workflow for wind simulation in landscape form-finding. It can rapidly deliver a series of design options within designers' predefined constraints, each detailed with wind indicators. Integrating AI to detect subtle environmental changes and align with designers' intuitive decisions, this research fosters a collaborative paradigm between landscape architects and AI, aiming to shift from physics engine simulations to employing real-time AI simulations for rapidly aiding designers in the form-finding process in landscape design.

Keywords: Landscape form-finding, real-time wind-driven co-design, deep learning

1 Introduction

For many years, the field of architecture and landscape architecture has designed buildings and landscapes by relying on a comprehensive process of intuition, design experiences, and various mathematical tools (FRICKER 2022, WITT 2022). Designers, through the use of appropriate tools and extensive practice, gather insights from their experiences. Designers are the ones who are good at conceptualizing their “Knowing in Action” into “Knowledge in Action” (SCHÖN 2013). The rapid advancement of digitalization, and the increasing demands for sustainable design, mark a transformative era for designers. Those experienced in leveraging various digital tools to boost their creativity are at the forefront of this change (KHAKUREL et al. 2018).

In the rapidly evolving urban landscape, wind simulation and wind-environment-driven design have always been time-consuming and repetitive tasks. AI tools like Deep Fluids (KIM et al. 2019) and CFD-GAN (KASTNER & DOGAN 2023) have significantly streamlined the time-consuming and repetitive tasks of wind simulation and design in urban landscapes, offering rapid and precise predictions. However, unlike humans, these tools lack subjective intuition and solely rely on brute-force calculations on large datasets for simulation and iteration, serving as intuitive references for designers. Moreover, many of these tools, often custom-built by developers, function as “black boxes (FRICKER et al. 2023)”, making it crucial to choose appropriate tools and develop an AI workflow integrated with modern design methodologies to meet the requirements of most designers in future computer-aided design.

This study proposes an AI-integrated workflow for wind-driven landscape design, aiming for fast and dynamic design generation within the designer’s constraints. AI performs real-time simulations; it not only provides various design options with specific wind indicators but also allows designers to choose the most suitable scheme for diverse requirements.

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2 Background

2.1 Application of Deep Learning in Wind Environment Simulation

With the advent of AI tools, especially Deep Learning models, Generative Adversarial Network (GAN) models show great potential in wind prediction (TAN & ZHONG 2022). Mokhtar et al. (2020, 2021) applied cGAN and pix2pix for pedestrian and wind comfort estimation. Farimani et al. (2017) demonstrate Generative Adversarial Network (GAN) can reduce Computational fluid dynamics (CFD) simulation expense and time with a minor error. HE et al. (2021) developed a hybrid framework based on parametric design and the pix2pix model for rapidly evaluating of wind environment around buildings Li et al., (2023) established the GAN-based model by using CFD-generated datasets to predict urban block wind environment. Besides, some studies integrate Deep Learning models and LIDAR data for wind field reconstruction and spatiotemporal prediction, including embedding Navier-Stokes equations and Convolutional Neural Networks (CNNs) for enhancing wind field prediction accuracy(ZHANG & ZHAO 2021a, 2021b).

But most of the current tools are custom-built by developers, making them difficult to generalize as they often act like "black boxes" (FRICKER 2022a). Therefore, it remains crucial for most designers to choose the appropriate tools and construct an AI workflow for rapid landscape form finding that best suits their needs for effective assistance in design. This paper will build upon on a well-trained Wind GAN model developed, creating a deep learning-based wind-driven design workflow for landscape form finding. It systematically explains how the AI workflow can align with and complement the designers' workflow.

2.2 The Principle of Wind-Driven Design

There are three main principles in wind-driven design and optimization (KORMANÍKOVÁ et al. 2018): (1) Reshape the building façade and outline to enhance the longevity of the ultimate structure, (2) Reduce emission for passive cooling (3) mitigate the strong wind and ensure the pedestrian wind comfort. And what we focus on in this paper is (3).

The most current process of mitigating strong wind and optimising wind comfort can be roughly summarized in two directions. One mainly selects prototypes based on the designer's perception and then uses CFD or Fast Fluid Dynamics (FFD) simulation to choose the optimal human design prototype, this method is not only time-consuming but also hard to provide continuous guidance for approximating the optimal solution. In cases such as the study by Kazak's team (KAZAK et al. 2022), they experimented with and designed a variety of wind shelter shapes for urban open spaces, dedicating 8 hours to their validation using CFD. The other one is to use an optimization algorithm, setting the wind-driven results as the optimization objectives. Like Shen et al. (2021), they integrated FFD with the Evo-mass tool in Rhino for building layout optimization. However, their approach to layout generation relies on numerical inputs to control forms, yet not all subjective perceptions can be quantified into mathematical functions for form optimization.

3 Method

3.1 CycleGAN-Based Wind Prediction Model Development

This model is set up based on a previous study developed by Tan & Zhong (2022). This research compared the performance of CycleGAN and pix2pix models. Datasets hypothetical urban models generated by Procedural Content Generation (PCG) in Houdini and conduct wind simulation at the height of 0-5m solver. The results show that CycleGAN not only can generate high-quality images without paired datasets but also demonstrates more stable training progress compared to pix2pix, as evidenced by its Fréchet Inception Distance (FID) values. These features can bypass the resource-heavy step of simulation-based data preparation in interactive design and rapid adaptations to changing simulation parameters. Overall, despite a longer training time per epoch, CycleGAN can prove to be a resource-saving model, optimizing the balance between image quality and operational efficiency.

3.2 Wind-driven Landscape Elements Form Finding

In this section, we introduce an AI co-design workflow for wind-driven landscape form finding, centred around this developed CycleGAN model.

The related glossary in this study:

1. **WCR** (Wind Comfortableness Rate): Indicates the comfort level in an area based on wind conditions, calculated from wind speed changes, average speed, and standard deviation. Higher WCR means more comfort.
2. **LVU** (Landscape Visual Units): Elements in landscape architecture that enhance aesthetic appeal and functionality, particularly for wind speed mitigation.
3. **DHWF** (Degree of High Wind Filling): Measures how extensively LVUs or similar features are used in high wind areas to reduce wind speed and increase comfort.
4. **CA** (Construction Area): The total area involved in a construction or landscaping project.
5. **EI** (Economic Indicators): Assess the cost-effectiveness of design solutions for wind comfort, EI =WCR/CA.

We tackle the issue of high-speed winds in a hypothetical urban block created through parametric generation, aiming to enhance the WCR through site-specific landscape design. The goal is to enhance the WCR by strategically placing LVU in areas with high wind speeds. This involves determining the optimal extent of LVU deployment to improve the WCR at a reasonable cost (EI).

Aligned with Betz's law (VILLANUEVA & FEIJÓO 2010), which dictates that wind turbines can theoretically convert up to 59.3% of the kinetic energy in wind, our approach targets areas with the highest wind speed to maximize energy capture. We also account for the "wind shading" effect, in which turbines can significantly reduce wind speed for those located downstream, presenting nonlinear impacts, and affecting the overall efficiency of wind farms notably.

We intend to modulate the wind farm by adjusting the quantity and placement of LVUs, in varying DHWF. This strategy is aimed at dispersing the wind energy from areas of high wind speed to a broader area. The traditional wind turbine placement optimizations often rely on rule-based optimization algorithms (CHEHOURI et al. 2015), which can be both time-consuming and result in unsatisfactory outcomes. In contrast, our approach will initially arrange various landscape schemes by employing Houdini PCG. Then by utilizing AI to assess these schemes, it enables a series of options in real time. This approach can facilitate a collaborative iteration process with AI, which can optimize both pedestrian wind comfort and fulfil the designer's intentions.

The whole AI co-design process follows the principles and steps below (Fig. 1).

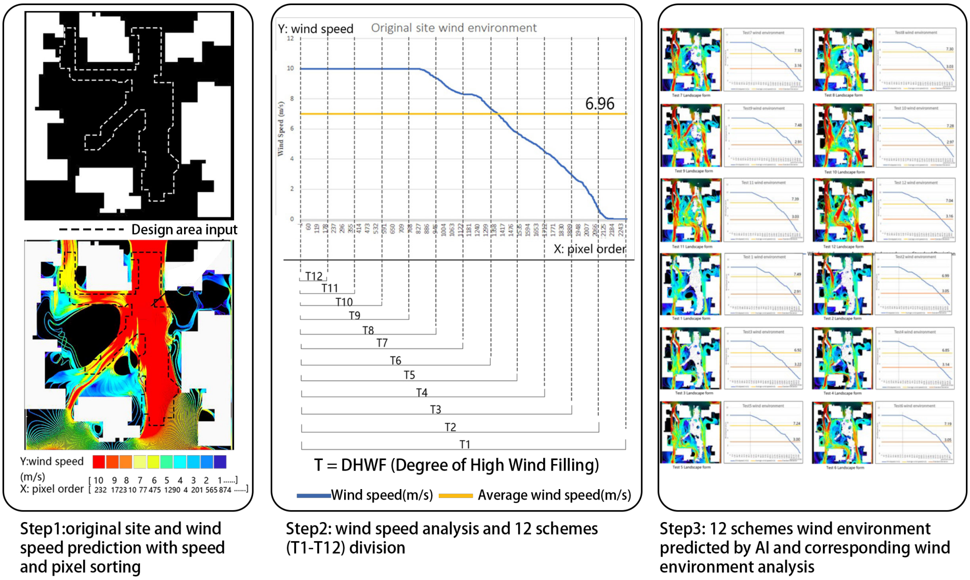

Fig. 1: The workflow of AI co-design in landscape form finding and wind prediction

1. **Image Conversion and Grid Formation**: Transform the site's wind environment image and the designer's design into a gridded canvas with a resolution of 720x720 pixels.
2. **Wind Speed Analysis and Pixel Sorting**: Organize pixel positions based on wind speed, as shown in Figure 1: Step 1. The x-axis (abscissa) represents the order of pixel positions, and the y-axis (ordinate) indicates the wind speed. This arrangement illustrates the variation in wind speed at different pixel locations, aiding in the selection of appropriate pixels for placing LVU. Additionally, this method allows for the calculation of the average wind speed (Fig. 1: Step 2).
3. **Designers define the design scope for the landscape area** for LVU application. For the AI model, inputs include the surrounding buildings and the area outlined by designers. Considering that each case may have different prevailing wind directions, we introduced a function to rotate the model canvas to accommodate various prevailing wind directions. In this case, ten designers unanimously agreed upon the defined design scope.

4. **LVU Placement in High Wind Areas**: Considering that the placement and spacing of LVUs create wind shading, which in turn nonlinearly affects the change in the velocity of wind propagation, a parameter **T** is used to represent the DHWF. Figure 1 Step 2 shows **T**'s interval length correlates with area coverage. Twelve schemes, T1-T12, are defined, and each scheme offsets the same results in gradually extending LVU placement from high to low wind speed areas, each scheme represents a unique area-filling strategy, with LVUs placed within the designer's design boundary for a unified layout.

5. **Model Testing and Verification**: Evaluate the wind speed environment using the trained CycleGAN model, and validate the results with Computational Fluid Dynamics (CFD) software for accuracy.

6. **Data Integration and Comparative Analysis**: Collect data from the twelve schemes and compare their performance based on several factors: the tendency of wind speed changes, average wind speed, standard deviation, WCR and EI. Each scheme is assessed to understand its effectiveness in improving wind comfort (Fig. 1. Step 3).

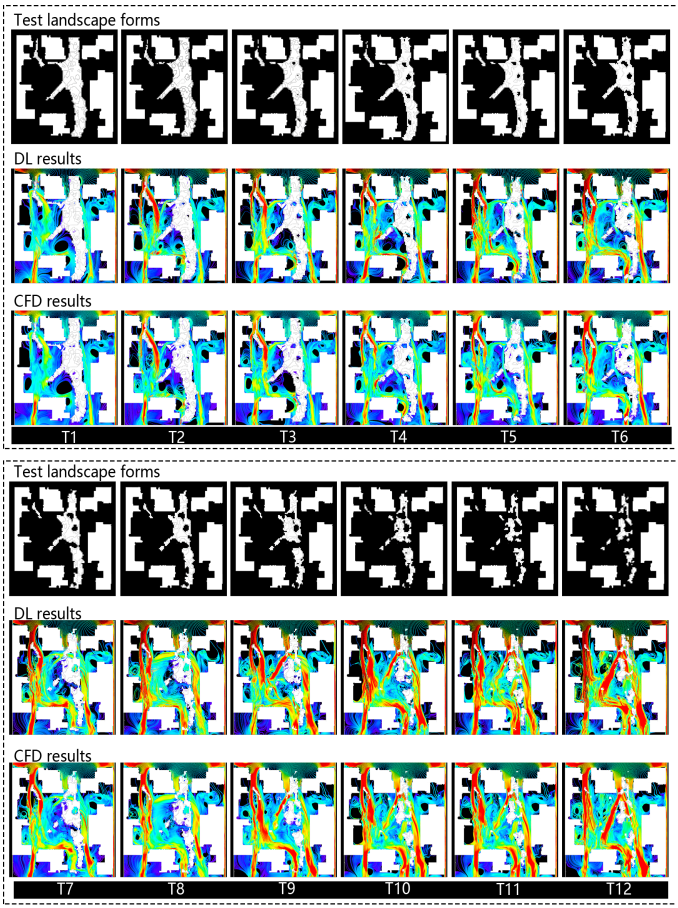

Fig. 2: T1-T12 landscape form finding schemes, DL results and CFD results of 12 schemes

4 Landscape Form Finding Results Analysis

Figure 2 displays the results of T1-T12 schemes of landscape form and the wind prediction in the CycleGAN model and verified results in CFD with the same size of solver boundary at the height of 0-5m. Each scheme takes 0.5s in the deep learning model and takes around 30min in CFD estimation. The results show CycleGAN can perform well in a minor error but provides real-time feedback. In Figure 3, we convert the tendency graphic of wind speed to visual analysis, which helps us observe the details of the wind environment improvement. Meanwhile, the average wind speed and standard deviation of 12 schemes are used to evaluate the wind parameters. Based on the pedestrian wind comfort indicators, the wind speed <1.0m/s is breezeless, 1.0~5.0m/s is comfortable, 5.0~10.0m/s is uncomfortable with movements affected, 10.0~15.0m/s is very uncomfortable with movements greatly affected (YIN et al. 2022). WCR presents the degree of wind environment improvement. EI is equal to WCR/construction area, which is used to determine whether the WCR can be increased with a smaller area and whether the scheme is economical.

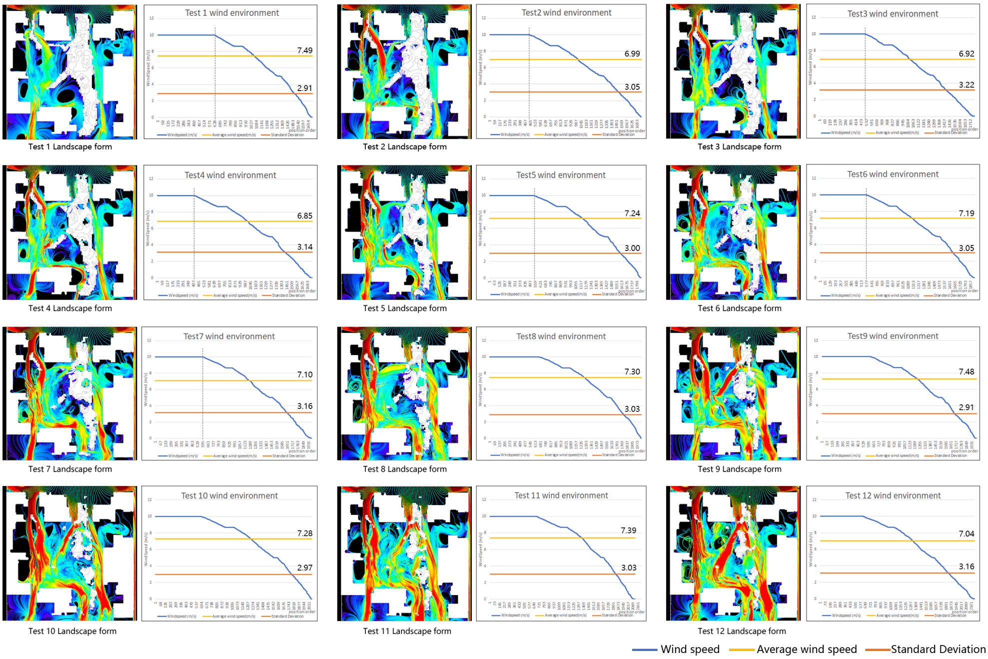

Fig. 3: 12 schemes and corresponding wind environment analysis

Figure 4(a) shows the decline rate from T1 to T12 is becoming slower and slower in general. we can see all the wind speeds showed a downward trend which means all the schemes improve the wind comfortableness. In specially, the overall decline trends of T1, T2, T3, and T4 are similar, and the mutation occurs at T5, and the decline speed becomes slower from T6-T9. The decline trend of T6-T9 is similar, and T12 has the slowest decline.

Figure 4 indicates that schemes T2, T3, T4, and T12 significantly enhance the WCR. T2, T3, and T4 offer lower average wind speeds, ensuring comfort, but T3's high standard deviation suggests wind instability with significant speed variations. T9, with the lowest standard deviation (Fig. 4 (c)), presents higher average wind speeds and a lower WCR. While T12 has a small construction area and a relatively high WCR, its high standard deviation implies unstable wind. T4, with the lowest average wind speed and high WCR, effectively moderates wind speed in a smaller area. Each scheme's pros and cons are quantified for designers to make informed decisions. Finally, T4 is chosen as the final prototype for landscape filling, as shown in Figure 5.

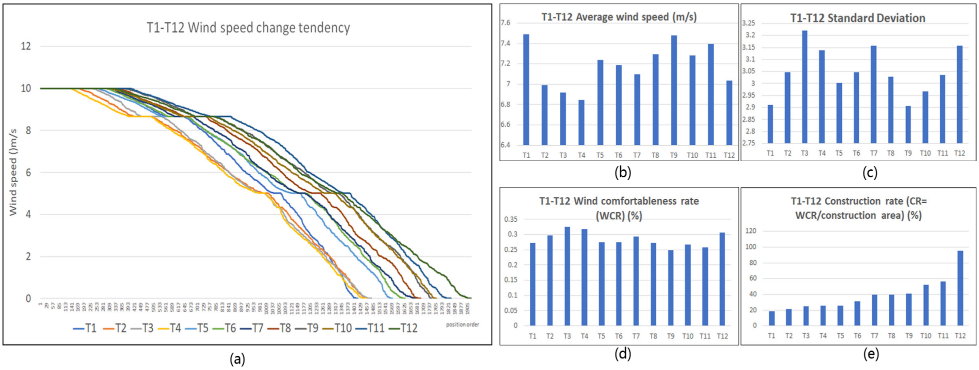

Fig. 4: T1-T12 schemes analysis visualization

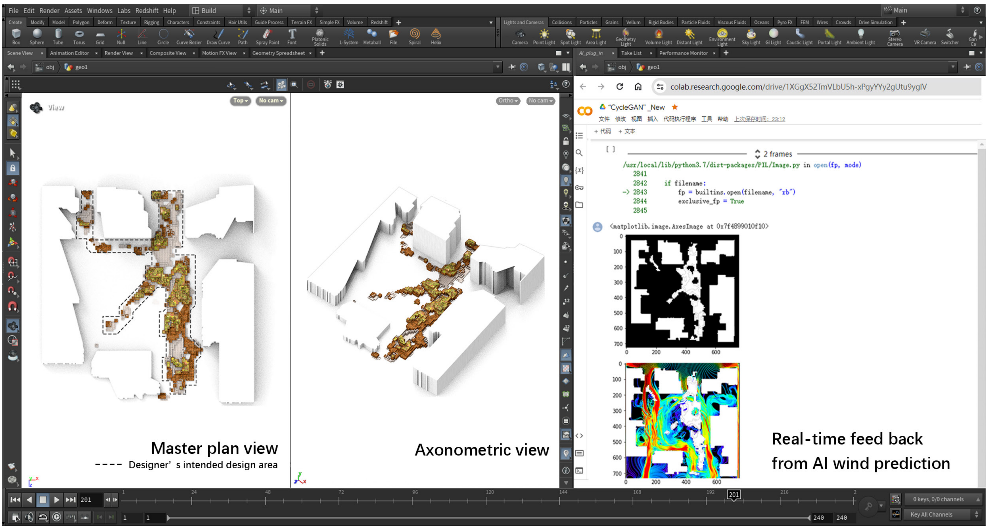

Fig. 5: AI co-design interface in Houdini and T4 scheme generation

In this collaborative workflow, designers use their intuition and expertise for creative and informed decision-making, while AI contributes precise, rapid evaluations and data analysis. This combination of human creativity and machine accuracy aids in developing effective, informed design solutions, making AI an integral part of the decision-making process (Fig. 5).

5 Limitations

Firstly, the deep learning model demonstrates minimal error when predicting wind direction in comparison to Computational Fluid Dynamics (CFD) simulations. However, it exhibits an approximate 2-8% error in predicting wind speeds within low wind speed zones and a 5-10% error within high wind speed zones. Future research should train the deep learning model with CFD samples for improved accuracy. Secondly, this research only considers the height of 0-5m, excluding higher elevation wind conditions. Future study will expand the boundary solver and integrate comprehensive 3D modelling to enhance accuracy in representing complex wind. Furthermore, while it suggests potential design solutions, it does not ensure that they are optimal. We have investigated the effect of varying the T parameter (using LVU to denote DHWF) on design performance. However, the interaction of different T values in different wind zones, and whether these values are discrete or continuous, can also affect wind performance. Finding the ideal T value for a given condition is complex. Future research could utilize machine learning to adjust T values in response to real-world wind simulations, leading to better design results over time. Furthermore, as shown in Figure 5, deep learning models currently evaluate designs rather than generate them. It is challenging to directly and autonomously provide designs that incorporate human intent and performance, and the final design remains dependent on process modelling. Future advances may facilitate a more intuitive and varied design process by using human preferences and wind performance as inputs, such as integrating large-scale language models (LLMs) to directly generate 3D landscape models based on human verbal descriptions.

6 Conclusion and Outlook

The study introduced a continuous co-design workflow for wind-driven landscape form finding with real-time feedback, enhancing collaboration between designers and AI. This innovative approach provides a synergistic interaction between designers and deep learning models, combining the strengths of human perceptual expertise with the rapid quantitative assessment capabilities of machine learning models to enhance the entire design decision-making process. Although not a perfect tool, it represents a speculative approach to incorporating artificial intelligence into co-design, aiming to explore new pathways for integrating AI into collective design efforts. It avoids converting design intent into constraint parameters repetitively, but a series of feasible schemes can be generated in real-time. Each scheme is outputted with precise environmental and construction metrics, which fosters the creation of diverse solutions for comparison and adaptation to various design needs, establishing a rapid, collaborative design partnership paradigm between humans and AI.

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