Finding the Optimum Window Locations of a Single Zone: To Maximize the Wind-Driven Natural Ventilation Potential

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Abstract

As building simulation and multifaceted workflow are becoming frequently integrated into architectural design, the need for the interactive building design and simulation is growing. This paper studies the parametrization and the optimization of natural ventilation potential by using a building energy simulation (BES)-integrated design workflow within a surface modeling platform, Rhinoceros (or Rhino for short). Grasshopper is one of the widely-adapted parametric design platforms of Rhino thanks to its ability to connect environmental simulation engines such as EnergyPlus. However, there still exists the lack of connectivity between the parametric design platform and building performance simulation. Particularly for natural ventilation prediction, due to its susceptibility to the surrounding environment, a computational fluid dynamics (CFD) simulation is often required. The goal of this study, therefore, is to provide several customized components that read the results from a CFD tool, find an optimal design solution for a problem, and enable the comprehensive workflow within the Rhino environment. To validate the proposed optimization process, two types of simulations are conducted: an interior CFD simulation and a BES-integrated natural ventilation simulation. The former confirms that the optimal solution suggested by the optimization possess the maximum cooling potential and tends to yield better ventilation efficiency. The latter demonstrates the connectivity of the CFD analysis to the parametric design platform.

Introduction

Building energy simulation (BES) has been considered as a powerful tool to evaluate the performance and the environmental impacts throughout the life-cycle of buildings. A variety of BES tools for different purposes and with unique features are available now (Maile et al., 2007). Such purposes include but not limited to the analyses of energy consumption, daylight, life-cycle, and construction cost; and the examples of various features include graphical user interfaces (GUI) and the ability to exchange data across different platforms.

With the development of Rhino and Grasshopper plugins, the BES can be widely utilized during the preliminary building design. Those programs have enabled an easy adaptation and development for parametric energy analyses: Honeybee and Ladybug are good examples.

Natural ventilation analysis can be a good addition to these parametric programs: however, there is a lack of simulation pipelines that incorporate the natural ventilation study into these parametric programs. While an airflow simulation tool, such as CFD, would provide a useful information about natural ventilation, the communication between the software and the optimization of inputs is one of the challenges. In this paper, customized add-ons in Grasshopper are created to enable data exchange from airflow simulation to energy simulation and to optimize the data. The resultant performance-driven design will be validated.

This study largely has two components: parametrization and optimization. The parametrization component employs the BES-integrated design work flow introduced by Yoon and Malkawi (2017). In their work, Natural Ventilation Effectiveness (NVE), an indicator of the natural ventilation potential of a given design, is identified to help understand how much natural ventilation could potentially contribute as a cooling source. Such indicator is obtained by several variables, including volumes of interior space, sizes and locations of windows, and weather conditions at the site. The NVE is then parameterized with these variables to interactively communicate with design changes. The authors leave users with the way to choose the locations of openings, which may affect the indicator to some degree.

Next, this paper searches for several window locations by optimization to yield a better NVE. To do so, an external wind environment at the site is simulated by CFD. The CFD results then pass the pressure information on facades to the parameterization component, and finally the optimization component finds and visualizes the optimal design solution. This section also demonstrates the process of optimization with a case study of a small room.

The CFD and the BES-integrated natural ventilation simulation results are shown in the Results section, followed by discussions and conclusion.

This study utilizes several commercial and open source tools: Rhinoceros® is used for 3D modeling; Grasshopper, Honeybee and Ladybug for parametric energy modeling; and scSTREAM® for CFD simulation. For parametrization and optimization, several components coded in Python are created within the Grasshopper domain to enable the interaction between

tools and to search optimal solutions. Figure 1 illustrates the data exchange and connection of tools in the 3D modelling environment.

Figure 1: Data exchange and connection of tools.

Parameterization of natural ventilation simulation for interactive building design

Parameterization of natural ventilation simulation enables interactive building simulation within the 3D modelling environment, such as Rhino. As described in Figure 1, geometries are parameterized in Grasshopper, which recognizes geometric volumes, areas, lengths, locations, etc. The energy modelling plug-ins, Ladybug and Honeybee, help convert the geometries into building components such as walls, roofs, floors, and windows, and calculate cooling loads.

Natural Ventilation Effectiveness (NVE)

Cooling potential of natural ventilation can be evaluated by a performance metric called Natural Ventilation Effectiveness (NVE) (Yoon and Malkawi, 2017). This metric measures the capability of natural ventilation to cool the given space. Being a dimensionless metric, an NVE of one implies that natural ventilation would offset the entire cooling loads during the simulation period. NVE can be calculated for a customized time period, from an hour, days, or months, to a year. Each hour, the ratio of “available cooling power” to “ideal cooling power” is calculated. The NVE of these various time periods are calculated by averaging hourly ratios. The “available cooling power” of natural ventilation measures the flowrate that is made available for the room, either due to buoyancy effect or outdoor wind. Therefore, the available inflow is converted in air-change-rate-per-hour (ACH), and is calculated by the pressure coefficients at building facades, window sizes, outdoor temperature and desired indoor temperature of user’s choice. The “ideal cooling power” is the cooling power that lowers the indoor temperature to the comfortable level, and can be obtained from building’s energy simulation. The involvement of the BES makes NVE a BES-integrated metric that is design-specific as opposed to climate-based static metric. Detailed procedure to calculate NVE is reviewed in the following subsection.

Review of NVE calculation

First, the cooling load, q in kWh, is obtained by conducting a BES by Honeybee. The comprehensive design details including geometry specifications, building

materials, occupancy schedule and appliance usages are considered in the cooling load calculation. Users determine the set points for cooling load, below which temperature users are assumed to either operate a mechanical cooling system or open window for natural ventilation. With this assumption, the indoor air temperature, T_{in} , is always maintained below or on that set point temperature, $T_{comfort}$. To see how much time of the year (or any time periods of users’ choice) such natural ventilation can be effective for cooling, the air change rate per hour (ACH) that is required to cool the space, ACH_{req} , is calculated using Eq. (1),

$$ACH_{req} = q / (V_{room} \rho c \Delta T), \quad (1)$$

where V_{room} is the volume of space in m^3 , ρ is density of air in kg/m^3 , c is heat capacity of air in $kJ/(kg \cdot K)$, and ΔT is the temperature difference between outdoor and indoor in K . Even when $ACH_{req} = 0$, if some airflow is required by building codes or regulations for ventilation of the space, the ACH_{req} is reset to meet that minimum requirement (ACH_{min}).

With wind-driven natural ventilation design, ACH_{req} should be accommodated by the wind available at the site. The ACH that wind can provide, ACH_{avail} , depends on the wind and building design. More specifically, the airflow rate available for the building design, Q_{avail} , is directly related to the difference between pressure coefficients at two openings (ΔC_p), areas of openings (A), discharge coefficient (C_d) and the upstream wind velocity (v) as in Eq. (2). This Q_{avail} is converted into ACH_{avail} per Eq. (3).

$$Q_{avail} = A C_d v \sqrt{\Delta C_p} \quad (2)$$

$$ACH_{avail} = 3600 Q_{avail} / V \quad (3)$$

For a certain time period of the year, the sum of the ratio of ACH_{avail} to ACH_{req} divided by the total hours is what the authors call the natural ventilation effectiveness (NVE) of the design as in Eq. (4). The ratio of ACH_{avail} to ACH_{req} is regarded 1 when ACH_{avail} is bigger than ACH_{req} or there is no need for cooling when calculating NVE.

$$NVE = \Sigma \left(\frac{ACH_{avail}}{ACH_{req}} \right) / total\ hours \quad (4)$$

Pressure coefficient mapping from CFD

The NVE calculation procedure described above leaves users the choice of obtaining the pressure coefficient values. There are two major ways of obtaining the pressure coefficient (C_p) values (Cóstola, Blocken, and Hensen, 2009). One is from C_p databases or empirical data, which generally provide C_p values on each facade according to the orientation of the surface. These resources would give the same C_p for any windows on one facade the same values. A more direct way of obtaining C_p is to conduct a wind tunnel test or CFD simulation. Although more time consuming, they offer unique C_p values on various targeted locations.

This study conducted a CFD simulation to obtain micro-information of pressure on the building facades, mapped the pressure values in Grasshopper, and used the mapped coefficients for optimization that is discussed in the next section. The CFD simulation and mapping helped make decisions on window locations to maximize NVE.

Figure 2 shows the procedures of NVE calculation and optimization. Figure 2 (a-c) describe the place in which CFD simulations take roles within this framework.

Figure 2: Workflow BES-integrated natural ventilation simulation and optimization. The current study contributes to the tasks highlighted in green boxes.

Optimization of window locations

To optimize the NVE, this section first runs a CFD simulation to obtain the pressure information on the building facades. Then, several add-ons for *Grasshopper* are written for CFD data mapping and optimization. The entire process is tested with a simple box model of $5 \times 5 \times 4$ (m^3) as a case study.

Obtaining pressure information from CFD simulation

As shown in Eq. (2), the airflow rate from the wind depends on the window sizes and discharge coefficient (A and C_d), and the upstream wind velocity and pressure coefficient (v and C_p). While A is known by design (0.19 m^2 in this case), C_d is considered constance (~ 0.65 for windows) and v is from weather data, the C_p difference between the two windows is still needs to be determined by choosing appropriate locations on the exterior walls. Since this paper chose to run an external wind simulation by CFD, ΔC_p could be calculated from the pressure data obtained from CFD simulations, as shown in Eq. (5),

$$\Delta C_p = 2 * \Delta P / (\rho v^2), \quad (5)$$

where ΔP is the pressure difference between the two openings.

The case study building was set up with a validated CFD software, *scSTREAM*[®] (Tominaga et al., 2002; Tominaga et al., 2004; Ding, Lam, and Wong, 2016). With the building height, H , the computational domain was extended by $6H$ for upstream and vertical directions, $5H$ for lateral directions, and $15H$ for downstream direction, satisfying the suggestions from the European Cooperation in Science and Technology (COST, 2007). Mesh size of 0.1m was used in the vicinity of the building with a stretching ratio of 1.05. The wind speed at the reference height of 10 m from the ground was set 5m/s, and the power law was used to create a vertical profile of the wind speed. The wind speed at the height H followed the Eq. (6),

$$v_H = v_{met} \cdot \left(\frac{\delta_{met}}{H_{met}} \right)^{a_{met}} \cdot \left(\frac{H}{\delta} \right)^a, \quad (6)$$

where v_{met} is the meteorological data measured at the height of H_{met} , a an exponent determined by the terrain, δ the layer thickness also determined by the terrain. After running the wind simulation, the pressure values were output as shown in Figure 3.

Figure 3: CFD result: pressure on building facades.

Optimization using object-oriented programming

Once the pressure data was obtained, the optimization went through three major processes: data mapping, optimization and visualization. All components were written in Python and were to be connected to a *Grasshopper* application program interface and other customized add-ons. These Python functions used object-oriented programming (OOP), which enabled the codes to keep track of the manipulated values, while we changed data points on a building geometry. The OOP is particularly useful during the data mapping process.

The data mapping process had three functions: a data reading function, a surface division function, and a data mapping function. First, the CFD pressure data with their coordinate points obtained in the form of comma separated values (CSV) were read (Figure 4. (a)). The resolution of the grids to map the pressure data was determined (Figure 4. (b)). The resolution may represent the actual window size. The data were then mapped on the user-defined grid (Figure 4. (c)). In this function, the Class of objects in OOP was coded in such a way that the center point of the newly-defined grid could interpolate the pressure values contained in the grid weighted by their distances. The optimization algorithm was implemented in the data mapping function.

Figure 4: Data mapping process.

For the window placement optimization, the pressure coefficient (C_p) is an important factor to propose potential openings. As inferred from Eq. (2)-(4), the airflow rate driven by wind through the openings would be maximized when ΔP reaches maximum. Therefore, informing the location of large C_p difference and its value is crucial to design openings for natural ventilation. The optimization method used in the building simulation environment suggests the optimal opening design options from multiple possible alternatives using a sequential search algorithm. In this research, the brute force optimization was used. After optimizing, the potential positions of openings that satisfied the threshold pressure differences (ΔP s) are visualized in Figure 5 with the blue pipes. The thickness of the pipes represents the magnitude of ΔP s. Based on the proposed solutions for the given inlet, a relevant position of the outlet based on design preference

could then be selected. The selected compositions were verified by running interior CFD and energy simulations, which are described in the following section.

Figure 5: Optimization function and visualized solutions.

Results

Optimal solution

As seen in Figure 5 above, the visualization helped identify window locations with the highest flowrate. In this case study, the east window was fixed as an inlet, and the maximum airflow rate was achieved with an outlet on the adjacent façade, as shown in Figure 6 (a). The ΔC_p in this case was 6.05, and the resultant airflow per Eq. (2) was $0.77\text{m}^3/\text{s}$. This result was relatively better than the 'typical' cross ventilation setup (Figure 6 (e)), which resulted in $0.62\text{m}^3/\text{s}$ of airflow rate. In the calculation, C_d of 0.611 for a sharp-edged orifice was used (Etheridge, 2011).

To see the effect of having different openings and to learn how this method could be further developed, this paper selected five different configurations as shown in Figure 6 and Table 1 below. These options were chosen based on the optimization method by visualizing results, and were in the order of pressure difference.

Figure 6: Selected combinations of opening locations.

Validation

It is obvious that the best option obtained from the optimization with the maximum C_p difference would yield the highest airflow rate per Eq. (2). This subsection ran CFD simulations for each option to ensure the estimated flowrate was achieved. Incidentally, the age-of-air of the interior was output.

Simulation setup

For the internal CFD simulation, finer mesh sizes were applied than for the external CFD simulation conducted in Section 3.1. To determine the mesh size, a mesh dependency analysis was conducted. With coarse mesh of 130mm to fine mesh of 40mm were applied to the Opening combination 1 case. Figure 7 shows the measurement points in the model and the graph of dimensionless velocity along with the dimensionless distance. The dimensionless velocity was calculated as the ratio of velocity at a point (v) to the inlet velocity (v_0), and the dimensionless distance the ratio of the distance of point from the inlet (D) to the longest distance from the inlet (D_0).

Simulations with coarse meshes (130mm and 100mm) took around 2 minutes to run, but their results were not reliable as they tended to underestimate the velocity along the measurement line. With finer mesh sizes (70mm and 50mm), the results did not significantly depend on the mesh sizes, and took 11 minutes and 38 minutes, respectively; therefore, 70mm was chosen.

As a boundary conditions, no-slip walls were applied to all building surfaces, and pressure values from the external simulation (Table 1) were set to each opening. Standard k- ϵ model was used.

Figure 7: Mesh dependency analysis.

Table 1: Selected solutions of five alternative window positions and pressure values.

	Window 1		Window 2		ΔP
	Location	Pressure (Pa)	Location	Pressure (Pa)	
Option 1	East	13.8	South	-13.2	27.0
Option 2	East	13.8	South	-10.6	24.4
Option 3	East	13.8	West, upper corner	-8.2	22.0
Option 4	East	13.8	West, upper center	-7.5	21.3
Option 5	East	13.8	West, lower center	-5.2	19.0

Airflow rates

Table 2 shows the volumetric flowrates obtained from the CFD simulations, the calculated airflow rates and the corresponding ACHs. The calculated airflow rate was based on the discharge coefficients of 0.661. This result shows that with the best solution from the optimization (Option 1) would have the most cooling potential from the wind-driven ventilation, increasing the NVE.

Table 2: Calculated Air Change rate per Hour (ACH) of five selected window positions.

	ΔP (Pa)	(1) Calculated Airflow rate (m ³ /s)	(2) CFD Airflow rate (m ³ /s)	(2)/(1)	ACH from (2)
Option 1	27.0	0.77	0.74	0.99	27.7
Option 2	24.4	0.73	0.72	0.99	25.2
Option 3	22.0	0.69	0.67	0.97	24.1
Option 4	21.3	0.68	0.67	0.99	24.1
Option 5	19.0	0.62	0.64	1.03	22.9

Age of air and ventilation efficiency

More interesting finding from the CFD simulations was the air distributions of the five options. Figure 8 shows the age-of-air (τ), a measure of 'freshness' of the air (Etheridge, 2011), with corresponding room mean age of air ($\bar{\tau}$) and ventilation efficiency (η). The results demonstrate the tendency of increased freshness with increasing flowrates. Options 1 had the freshest air, and Option 5 the least fresh air.

What needs to be addressed here is the non-linear relationship between the airflow rate and the mean age of air. With the pressure difference of 2.6 Pa between Option

1 and 2, their $\bar{\tau}$ s were relatively close (Figure 8 (a-b)). On the other hand, the $\bar{\tau}$ s of Option 3 and 4 were much different considering their relatively small pressure difference of 1.3 Pa (Figure 8 (c-d)). To learn why this was the case, it is worth noting the relationship of nominal time constant and ventilation efficiency. The nominal time constant (τ_n) refers to the ratio of room volume (V) to the airflow rate (Q) which has an immediate relationship with the ACH. Ventilation efficiency (η) is defined as the ratio of τ_n to $\bar{\tau}$. According to Roulet (2008), a $\bar{\tau}$ of around 0.99 has an η of 0.5, meaning the space is fully mixed; and a $\bar{\tau}$ of around 1.44 has an η of 0.35, indicating shortcuts and dead zones presenting in the room. Therefore, the large difference between the $\bar{\tau}$ s of Option 3 and 4 may be understood together with the airflow rates and the ventilation efficiencies. Such differences are shown in Figure 9 in the normalized histogram of age-of-air.

Figure 8: CFD results: mean age-of-air and ventilation efficiency of each test case.

Figure 9: A normalized histogram for age-of-air.

Integration with energy modeling

The selected opening locations were finally used to predict the natural ventilation effectiveness (NVE) as described in Section 2. As this case study represented a small room ($5 \times 5 \times 4$ (m^3)), the internal heat gain was exaggerated to better illustrate the effect of wind in

cooling. Figure 10 mapped the hourly NVE of Option 1 and 5 and two additional cases with different ΔP s from May 15th to October 15th with the cooling set point of 23 degC. Under the given conditions, it was shown that the NVE from mid July to mid August could much benefit from the optimized solution.

Figure 10: NVE of Option 1 and 5 and two additional test cases with $\Delta P=10$ Pa and 5 Pa from May 15th to October 15th.

Conclusion and Discussions

In this paper, a way to find optimal window locations to maximize the use of wind-driven ventilation for cooling has been proposed. With the recent progress on parametrization of natural ventilation simulation by Yoon and Malkawi (2017), this paper further tried to bring CFD results and link them to the parametrization process. To do so, several customized functions including data transfer, optimization and visualization were programmed

using object-oriented programming (OOP). As a result, the optimized window location was suggested and verified by running CFD and energy simulation.

The benefits of the optimization process are threefold:

- Either from CFD, field measurements, or wind tunnel experiment, the proposed simulation pipeline allows designers to utilize the outsourced pressure data during the preliminary design phase.
- The optimized solutions reduce the need for searching and validating manifold combinations of design alternatives.
- The proposed method with the connectivity of existing natural ventilation analysis enables the comprehensive interpretation of results in the seasonal analysis as opposed to the point-in-time analysis with CFD.

The following limitations need to be further studied in the future research:

- A qualitative analysis about ‘good ventilation’ can be clarified by assigning a threshold. For example, Option 5 might as well be a good enough solution with the NVE of 0.747, while our search algorithm only quantified that Option 1 has a max potential.
- The optimal solution might miss ‘better’ solutions due to the indoor air distribution. As indicated by Figure 8, there might be some other solutions that are calculated a less airflow rate but a better ‘actual airflow rate’ due to the ventilation efficiency.
- The CFD results were run for only one wind direction in this study for the demonstration purpose. Obtaining C_p values for at least two or three representative wind cases is recommended to consider different wind environments.

References

COST. (2007). Best Practice Guideline for The CFD Simulation of Flows in the Urban Environment: COST Action 732 (J. Franke, A. Hellsten, H.

Schlünzen, & B. Carissimo, Eds.). European Cooperation in Science and Technology (COST).

Ding, C., Lam, K. P., and Wong, N. H. (2016). Coupled Natural Ventilation Modeling for Contextual Parametric Design Decision Support. *Procedia Engineering* 169, 264–271.

Etheridge, D. (2011). *Natural Ventilation of Buildings: Theory, Measurement and Design*. John Wiley & Sons . Chichester (UK).

Maile, T., Fischer, M., & Bazjanac, V. (2007). *Building Energy Performance Simulation Tools - a Life-Cycle and Interoperable Perspective* (Working Paper No. WP107). Retrieved from CIFE website: <https://purl.stanford.edu/ww813hh4225>

Roulet, C.-A. (2008). Age of Air and Ventilation Efficiency. In *Ventilation and Airflow in Buildings: Methods for Diagnosis and Evaluation*. Earthscan. London (UK); Sterling, VA (USA).

Tominaga, Y., Mochida, A., Shirasawa, T., Yoshie, R., Kataoka, H., Harimoto, K., and Nozu, T. (2004). *Cross comparisons of CFD results of wind environment at pedestrian level around a high-rise building and within a building complex*. *Journal of Asian Architecture and Building Engineering* 3(1), 63–70.

Tominaga, Y., Mochida, A., Murakami, S., Yoshie, R., and Ishihara, T. (2002). *Comparison of various k-epsilon models and DSM applied to flow around a high-rise building: Report on AIJ cooperative project for CFD prediction of wind environment*. *Wind and Structures* 5(2–4), 227–244.

Yoon, N., & Malkawi, A. (2017). Predicting the effectiveness of wind-driven natural ventilation strategy for interactive building design. *Proceedings from BS2017: The 15th International Building Simulation Conference*. San Francisco, CA (USA). 7-9 August 2017.