



# Uncertainty quantification of upstream wind effects on single-sided ventilation in a building using generalized polynomial chaos method



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## ABSTRACT

The single-sided ventilation rate in a building can be estimated using an empirical correlation that developed based on the results of deterministic experiments or numerical simulations. Owing to the complex flow patterns near a building, it is difficult to establish a robust correlation considering upstream wind uncertainties such as wind speed and direction. We perform RANS simulations and generalized polynomial chaos-based uncertainty quantification analysis to investigate the effects of the upstream uncertainties on the ventilation rate. It was found that the reference wind speed and the incident angle significantly affect the ventilation rate. Warren and Parkins' correlation shows a reasonable prediction of the average ventilation rate over the incident angle, while Larsen's correlation, in general, underestimates the ventilation rates. Further, the average ventilation rates in the side direction are lower than those in the windward and leeward directions, while larger variations of the ventilation rate in the leeward direction are found at high speeds, compared to those in the other directions. Owing to unresolved turbulent induced ventilation rates in the RANS model, the present ventilation rates may not accurately provide actual ventilation rates. Nevertheless, the present UQ analysis indicates that the existing correlation between the ventilation rate and the wind speed must account for the influence of the wind direction, especially at high wind speeds, in order to estimate the single-sided ventilation rate in a building with greater accuracy.

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## 1. Introduction

The design of natural ventilation systems in buildings is crucial not only for providing a comfortable indoor environment but also for promoting sustainable development [1,2]. There are two main types of natural ventilation: single-sided ventilation and cross ventilation. In general, the ventilation performance of cross ventilation is assumed to be better than that of single-sided ventilation owing to the existence of an opening in more than one building facade. However, single-sided ventilation is more widely adopted as a ventilation solution owing to various factors, such as site constraints and security requirements. We focus on single-sided ventilation driven by wind. Because wind-driven ventilation depends on the external wind speed and direction as well as building openings and configuration [2,3], prediction of natural ventilation is an extremely complex task, even in the case of single-sided

natural ventilation with an opening. Some empirical correlations have been established to assess the ventilation rate for rapid prediction of natural ventilation [4–7].

One of the earliest correlation for the calculations of the ventilation rate in single-sided natural ventilation was developed by Warren [4]. This correlation integrates the outdoor-indoor temperature difference and wind speed as environmental parameters. Later, Warren and Parkins [5] improved the expressions presented in Ref. [4] and proposed an expression for wind-driven single-sided ventilation. De Gids and Phaff [6] developed a correlation for single-sided ventilation driven by both wind and thermal buoyancy on the basis of 33 measurements of full-scale buildings. Larsen and Heiselberg [7] proposed a correlation having a form similar to that proposed by De Gids and Phaff [6], with the additional inclusion of wind direction. Moreover, Warren and Parkins [5] and De Gids and Phaff [6] proved that there is some dependence between the ventilation rate and the wind direction, but neither of them included the wind direction in their design correlations. Further studies related to the correlations in a single-sided ventilation can be found in Refs. [8–10] and the references therein. From the

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literature, one can find that the correlation used for the calculation of the ventilation rate in single-sided ventilation is usually developed on the basis of the results of experiments or computational fluid dynamics (CFD) simulations that are extremely complicated and time-consuming owing to the unsteady nature of the parameters that influence the airflow through openings (e.g. wind speed and direction). Hence, existing correlations are usually simple and include only some of the parameters that influence the airflow through openings, this leads to uncertainty in the prediction of the ventilation rate.

The correlation used for the calculation of the ventilation rate is a type of approximation of the ventilation rate with respect to the variation in the parameters that influence the airflow through openings in natural ventilation. In practice, these parameters may be uncertain. Furthermore, developing an approximation of the response of the model output is the most popular and effective means of quantifying parametric uncertainty in uncertainty quantification (UQ). Thus, inspired by the above-mentioned factors, we attempt to investigate the effects of upstream uncertainties on the ventilation rate by using some UQ methods.

Uncertainty quantification (UQ) is the branch of modern numerical computations that attempts to determine the sources of uncertainties, give an estimation of uncertainties, and propagate the uncertainties into model responses. Quantifying the uncertainty in a computational model is essential for accurate prediction of the model response to random inputs. Many previous studies have implicitly performed uncertainty quantification to a certain degree. Typical examples include the correlation studies cited above. These methods are similar to the Monte Carlo methods used in UQ. A Monte Carlo method collects ensemble solution realizations for the prescribed ensemble random inputs; it is straightforward and convenient. However, it is costly and inefficient because a large number of input samples are required to achieve a reasonable accuracy. Alternatively, the polynomial chaos expansion (PCE) method has been proposed by Ghanem and Spanos [11] on the basis of the homogeneous chaos theory of Wiener [14]; it is more efficient than the Monte Carlo method. The extension of the PCE approach to non-Gaussian random uncertainties is known as the generalized polynomial chaos expansion (gPC) method [12,13]. In the gPC method, the uncertain parameters are modeled by introducing input random variables with some known statistics. Thus, the stochastic problem is transformed into a deterministic problem in random space. Further, a response surface can be established for the model output. In addition, some statistical information of the model output can be easily obtained from the response surface. In the past decade, the gPC approach has been successfully applied to a wide range of fluid dynamics problems [15–18]. A few previous studies have focused on computational wind engineering problems, especially problems of natural ventilation. Garcia-Sanchez et al. [19] investigated the influence of inflow variability on the prediction of flow in a real urban canopy by means of a non-intrusive gPC method. Gorré et al. [20] investigated the application of a turbulence model form uncertainty quantification method to the prediction of the flow within Oklahoma City, as well as combination of the turbulence model form uncertainty quantification approach with a framework that quantifies inflow uncertainties [19]. These studies show the importance of UQ in wind engineering problems, which has also been highlighted by Blocken et al. [21].

The present study investigates the effects of the upstream uncertainties on the ventilation rate of wind-driven single-sided ventilation in an isolated single-room building using the gPC approach. For simplicity, three parameters, namely the reference wind speed, incident angle of the wind, and ground roughness are selected as the input uncertain variables, although there are many

other uncertain parameters in wind-driven single-sided ventilation, such as turbulence characteristics and the size, location, and type of opening. CFD simulations are performed with the selected random inputs by using the shear stress transport (SST)  $k$ - $\omega$  model [22] under uncertain inflow boundary conditions. The uncertainty quantifications of the velocities close to the opening and the ventilation rate are analyzed using a regression-based non-intrusive gPC approach. The variables that have the greatest influence on the uncertainty in the velocities and ventilation rate are identified using the Sobol' indices. Further, the estimated ventilation rates in the present study are compared with those obtained from Warren and Parkins' correlation [5] and Larsen's correlation [7]. In addition, the upstream wind effects on the ventilation rate are quantified.

The remainder of this paper is organized as follows. Section 2 presents the turbulence model and corresponding inflow boundary conditions. Section 3 describes the setup for the numerical simulations. Section 4 summarizes the gPC approach and the regression method for obtaining the coefficients of PCE. Section 5, discusses the results of UQ analysis and numerical simulations. Finally, Section 6 states the conclusions.

## 2. Turbulence model and inflow boundary conditions

Throughout this paper, the SST  $k$ - $\omega$  model [22] is chosen as the RANS closure for the CFD simulations. Further, Richards and Hoxey's inflow profiles [23] are used as the inflow boundary conditions in the wind flow simulations.

### 2.1. Menter's SST $k$ - $\omega$ model

The SST  $k$ - $\omega$  model, which was developed by Menter [22], consists of the  $k$ - $\omega$  model [24] employed near the surface and the  $k$ - $\epsilon$  model [25] employed in the free shear layers. A blending function is adopted to bridge these two models. The SST  $k$ - $\omega$  model accounts for the transport of turbulence shear stress and provides accurate predictions of the onset and amount of flow separation under an adverse pressure gradient [22]. Further, Ramponi et al. [26] and Hooff et al. [27] showed that the SST  $k$ - $\omega$  model exhibits excellent performance in simulations of the wind flow around buildings. For these reasons, the SST  $k$ - $\omega$  model is adopted in the present study for all the CFD simulations. The equations of the SST  $k$ - $\omega$  model are as follows [22]:

$$\frac{\partial k}{\partial t} + u_j \frac{\partial k}{\partial x_j} = \mathcal{P} - \beta^* k \omega + \frac{\partial}{\partial x_j} \left[ (v + \sigma_k v_t) \frac{\partial k}{\partial x_j} \right], \quad (1)$$

$$\begin{aligned} \frac{\partial \omega}{\partial t} + u_j \frac{\partial \omega}{\partial x_j} = & \frac{\gamma}{v_t} \mathcal{P} - \beta \omega^2 + \frac{\partial}{\partial x_j} \left[ (v + \sigma_\omega v_t) \frac{\partial \omega}{\partial x_j} \right] \\ & + 2(1 - F_1) \frac{\sigma_\omega}{\omega} \frac{\partial k}{\partial x_j} \frac{\partial \omega}{\partial x_j} \end{aligned} \quad (2)$$

where  $\omega$  is the special turbulence dissipation rate and

$$\mathcal{P} = \tau_{ij} \frac{\partial u_i}{\partial x_j}, \quad \tau_{ij} = v_t \left( 2S_{ij} - \frac{2}{3} \frac{\partial u_k}{\partial x_k} \delta_{ij} \right), \quad S_{ij} = \frac{1}{2} \left( \frac{\partial u_i}{\partial x_j} + \frac{\partial u_j}{\partial x_i} \right). \quad (3)$$

The turbulence eddy-viscosity is limited as follows:

$$v_t = \frac{a_1 k}{\max(a_1 \omega, \Omega F_2)} \quad (4)$$

where  $a_1 = 0.31$  is a constant and

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