Natural ventilation predictions for a slum house in Dhaka using large-eddy simulations within a multi-fidelity simulation framework with uncertainty quantification

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Abstract

A previous study in Dhaka, Bangladesh, indicates that there might be an association between the occurrence of pneumonia, the leading cause of death in children under 5, and the presence of cross-ventilation in slum housing. The objective of this research is to establish a validated computational framework to accurately estimate household ventilation rates and support further investigation of this association. The framework leverages a computationally efficient integral model and high-fidelity large-eddy simulations, as well as uncertainty quantification methods. Simulation results for a variety of weather and housing conditions are validated against field measurements of the ventilation rate and indoor temperatures.

Key innovations

- We propose a multi-fidelity computational framework for natural ventilation, and validate the model results against on-site field measurements.
- We demonstrate the predictive capability of a low-fidelity building thermal model combined with uncertainty quantification: the model predicts mean and 95% confidence intervals for quantities of interest with reasonable accuracy at a low computational cost.
- We use high-fidelity, computationally demanding, large-eddy simulations to accurately quantify ventilation rates driven by buoyancy and turbulent wind effects in urban settings, and to reduce the uncertainty in the building thermal model.

Practical implications

The proposed framework provides a computationally efficient tool for evaluating natural ventilation system flow rates, and the resulting building thermal response under a wide range of building operating conditions.

Introduction

According to UNICEF, pneumonia is the leading cause of death in children under 5, accounting for 18% of total mortality in this age group (Wang et al. (2016); Qazi et al. (2015)). Worldwide, approximately one million children die from pneumonia each year, corresponding to 100 deaths every hour. The occurrence of pneumonia-related deaths is highly concentrated in just a few countries: 70% of the cases occur in 15 countries, one of which is Bangladesh (UNICEF (2016)). In 2014, a study conducted in Dhaka, Bangladesh indicated that there might be an association between the incidence of pneumonia and the presence of cross-ventilation: households where pneumonia occurred were 28% less likely to be cross-ventilated Ram et al. (2014). However, a quantitative relationship between ventilation rate and disease prevalence has not been established, and questions remain as to what ventilation rates are required to decrease the occurrence of pneumonia. To further investigate this causal relationship, it is imperative to estimate a household’s ventilation rate. Thus, the objective of this research is to establish a computational model that enables accurate predictions of ventilation rates to support further investigation of the association between pneumonia and household ventilation. Natural ventilation can be modeled using a variety of computational models with different levels of fidelity. In the proposed framework, we use a building thermal model coupled with an envelope flow model, hereafter referred to as the integral model, as well as a high-fidelity computational fluid dynamics model using the large-eddy simulation (LES) technique. The integral models solve for the time evolution of volume-averaged quantities, employing reduced-order models to represent the natural ventilation flow and heat transfer. The integral model’s biggest advantage is its low computational cost, making it ideal for use with uncertainty quantification (UQ) techniques that require repeated model evaluations. Combined with UQ, this type of model has shown potential for predicting quantities of interest with relatively low computational burden (Lamberti and Gorlé (2018)). In contrast to the integral model, the LES model solves for the full three-dimensional velocity and temperature fields, resolving the turbulent flow and heat transfer physics with high accuracy. The model has the ability to support detailed analysis of ventilation patterns and flow mechanisms; however, some limitations arise due to the complexity and high compu-
We adopt computationally demanding LES model to more precisely resolve instantaneous turbulence effect observed during our ventilation measurements. A majority of previous work has focused on ventilation in a single building for a fixed wind direction, not accounting for the effect of surrounding obstacles and the variability in wind that can play a significant role in practice (Van Hooff and Blocken (2010)). In the current study, we aim to establish a computational framework, shown in Figure 1, that leverages the strengths of both the integral model and the LES model to accurately estimate household ventilation rates in terms of air change per hour (ACH). The integral model, which has a significant advantage in terms of its computational cost, is the workhorse of the framework, used to quantify the effect of uncertainty in the boundary and operating conditions. It solves for the mean and 95% confidence interval (CI) of the volume-averaged temperatures and ACH. The high-fidelity LES simulations, resolving the turbulent flow field, are used to improve our understanding of the ventilation pattern in the house and to develop relationships for ACH as a function of the indoor-outdoor temperature difference and wind conditions. This paper presents both computational models and validates their results against field measurements of the ACH measured using a tracer concentration decay technique. In ongoing work, we will implement the LES-based relationships for ACH in the integral model to reduce the uncertainty in the predictions.

Test case and field measurements

On-site field measurements, conducted for 15 days in February 2019, were performed to obtain the necessary data to validate the computational models and to investigate the mechanisms of natural ventilation in a representative slum house. This section introduces the test case house, and the setup and methods of the field measurements.

Test case: Bangladeshi urban-slum house

In Dhaka, Bangladesh, approximately 95% of households occupy single-room homes in low-income communities (Islam et al. (2006)). In one of the low-income areas named Outfall, we rented a representative house with a rectangular floor plan and a slanted ceiling, shown in Figure 2. The detailed dimensions of the house are illustrated in Figure 3, where each wall is labeled based on its orientation. Multiple openings were constructed to determine the effectiveness of a variety of ventilation strategies: a skylight; a large window with a security grill on the south wall; and a small floor-level vent and a mid-size rear vent with a concrete cover on the north wall. Four different configurations, each with two of the ventilation openings opened, were tested: (1) skylight and floor-level vent, (2) skylight and rear vent, (3) window and rear vent, and (4) skylight and window.

Temperature and wind measurements

The two major driving forces of natural ventilation are buoyancy and wind. To support quantifying these two driving forces, we measure indoor air, thermal mass, and outdoor air temperatures, as well as the local wind at the target house and the free-stream wind conditions on a nearby mid-rise building rooftop. At the house, 24 temperature sensors are installed: 15 sensors measure indoor air temperature at 5 horizontal locations and 3 different heights, while 9 sensors record the surface temperature of the thermal masses (i.e. walls, roof and floor). One anemometer is installed on top of the roof for assessing wind at the height of a single-story slum house. One mobile weather station is installed on the roof of the tallest building \(H_{\text{max}} = 25 \text{ m}\) in the area, collecting less disturbed outdoor temperatures and free-stream wind velocities. Both temperature and wind are recorded with a data logger (CR300, Campbell Scientific, Inc.) with a sampling frequency of 1Hz. For the temperature, a thermistor is adopted considering the sensor’s
good performance in our target measurement range (10°C to 50°C) and its stability to irregular power outages that often happen in the low-income area. Wind speed and direction data is sampled with a 2D anemometer (WindSonic, Gill Instruments, Ltd). The measurement data are used both to define boundary conditions or inputs for the computational models, and to validate the model results.

**Ventilation rate measurements**

Ventilation rate measurements were performed in the target house with a tracer concentration decay technique, recording the decay rate of a tracer. The experiments use particulate matter (PM) for the tracer because of its low cost and widespread availability. Generally, the ACH is evaluated based on the relationship that the tracer concentration decays exponentially from its peak as time elapses in an ideal scenario. This behavior can be written as

\[
ACH(t) = \frac{\log(c(t)) - \log(c_{peak})}{t - t_{peak}},
\]

where \(t\) is the time and \(c(t)\) is the concentration of the tracer at that time \(t\), and \(c_{peak}\) and \(t_{peak}\) indicate the concentration and time of the peak.

One limitation of this experimental method is that the ideal well-mixed condition is hard to achieve in practice, and our experiments were accompanied by the effect of non-uniform concentration mainly due to strong temperature stratification. Therefore, we employ a new scheme that process the raw experimental data in two steps to reduce the effect of non-uniform concentration when computing ACH: we compute (1) the time series of ACH using equation 1, which shows spikes at the beginning and the end of the experiment due to the two effects; and (2) the mean and standard deviation from the period of time series without the unwanted spikes. This two-step scheme produces the mean and 95% confidence interval of ACH for a given time period (approximately 10 to 20 minutes) at one indoor location, which is used for the validation of the computational results.

**Integral model with uncertainty propagation**

The integral model solves for the volume-averaged air temperature and for the thermal mass temperatures, and it predicts the ACH using an envelope flow model. Its low computational cost makes the model an efficient tool for evaluating the effect of uncertainties in the boundary conditions and model parameters, thereby enabling predictions of mean values and confidence intervals for the QOI. In the following, we first introduce the integral model equations, before discussing the UQ method.

**Integral model equations**

Figure 4 presents a schematic of the heat transfer physics in the single-room house as represented by the integral model's governing equations. The equations describe the exchange of heat between the indoor and outdoor environment and the buildings thermal mass. The governing equation for the indoor temperature \((T_{in})\) is given by

\[
\rho_a V_a C_{p,a} \frac{dT_{in}}{dt} = \sum_{i=1}^{5} Q_{i,\text{conv},in} + \sum_{i=1}^{5} Q_{i,\text{rad},in} + Q_{\text{nv}},
\]

where \(\rho_a\), \(V_a\) and \(C_{p,a}\) are the density, the volume, and the specific heat of the indoor air. The left-hand side of the equation represents the time evolution of the indoor temperature in response to the heat fluxes shown on the right-hand side, which represent convective and radiative heat transfer between the indoor air and the five thermal masses \((Q_{i,\text{conv},in}\) and \(Q_{i,\text{rad},in}\) and heat exchange by natural ventilation \((Q_{\text{nv}})\). The five thermal masses are the roof, the three walls and the floor. The floor temperature is assumed to be constant and the temperatures for the other four thermal masses are obtained by solving the following equation:

\[
\rho_i V_i C_{p,i} \frac{dT_i}{dt} = Q_{i,\text{cond},in} + Q_{i,\text{cond},out}
\]

where \(\rho_i\), \(V_i\) and \(C_{p,i}\) are the density, the volume and the specific heat of the \(i\)-th thermal mass.

The core temperature of the thermal mass \((T_i)\) is determined by the sum of heat conduction through the inner and outer layers \((Q_{i,\text{cond},in}\) and \(Q_{i,\text{cond},out}\)) which is equal to the sum of different heat fluxes applied on the respective surfaces. All surfaces are affected by thermal convection and long-wave radiation from the adjacent air \((Q_{i,\text{conv}}\) and \(Q_{i,\text{rad}}\)). The roof surfaces have additional radiative heat transfer:
long-wave radiation between the inner surface and the floor and solar radiation on the outer surface ($Q_{\text{solar}}$). These heat fluxes are expressed as a function of the air and surface temperatures, a convective heat transfer coefficient, and the material properties. The solutions of the system of equations provides a prediction of the time series of our QoIs (i.e. ventilation rate in terms of $\Delta C$) and volume-averaged air temperatures.

**Uncertainty propagation using Monte-Carlo sampling method**

The UQ analysis considers three types of uncertainty. First, there is uncertainty due to variability in the weather conditions, i.e. temperature, solar radiation, and wind speed, which serve as inputs to the integral model. Instead of using a single time series for each of these conditions, we consider the inherent uncertainty of weather inputs due to their probabilistic variability. Using the inverse probability distributions of the weather inputs and a probability ($p_{\text{temp}}, p_{\text{rad}}$ and $p_{\text{wind}}$) sampled from [0,1], we reconstruct the input data as a range of time series in lieu of a single input. Second, there is uncertainty in the heat transfer modeling, primarily related to the reflectance and emissivity of the roof ($p_{\text{roof}}$ and $p_{\text{roof}}$), and to the definition of the indoor and outdoor convective heat transfer coefficients ($h_{\text{indoor}}$ and $h_{\text{outdoor}}$). Third, there is significant uncertainty in the relationship used to calculate the natural ventilation flow rates through the different openings. In a ventilation configuration with two windows open, two different scenarios can occur: (1) the flow through both windows is fully correlated and cross ventilation occurs effectively, or (2) the openings act independently such that single-sided ventilation occurs at each of the openings. Both scenarios are reflected in the integral model by employing two different ventilation models. If cross ventilation occurs, the ventilation rate can be estimated with the model suggested in Hunt and Linden (1999):

$$\dot{V}_{\text{cross}} = A_{\text{eff}} \cdot \sqrt{g \Delta H \cdot \frac{\Delta T}{T} + U_{\text{wind}}^2 \frac{\Delta C_p}{2}}, \quad (4)$$

where $A_{\text{eff}}$ is the effective area, $g$ is the gravitational constant, $\Delta H$ is the height difference of the two openings, $\Delta T$ and $T$ are the difference and the average of the indoor and the outdoor temperatures, $U_{\text{wind}}$ is the wind speed at the reference height, and $\Delta C_p$ is the difference in the pressure coefficient at both openings. $\Delta C_p$ is defined as an uncertain parameter, since the pressure coefficients on the openings are unknown and highly dependent on the local flow field around the building. In the single-sided ventilation scenario, the total ventilation rate is the sum of the ventilation rates estimated at each of the openings with the empirical model:

$$\dot{V}_{\text{single}} = \frac{1}{2} C_1 A_1 \sqrt{C_w U_{\text{wind}}^2 + C_b H_1 |\Delta T| + C_t} + \frac{1}{2} C_2 A_2 \sqrt{C_w U_{\text{wind}}^2 + C_b H_2 |\Delta T| + C_t}, \quad (5)$$

where $A$ and $H$ indicate the area and the height of each opening denoted with the subscript. The coefficients $C_w = 0.001$, $C_b = 0.035$ and $C_t = 0.01$ have been obtained empirically from a full-scale experiment, balancing the significance of the wind, buoyancy and turbulence (De Gids and Phaff (1982)). $C_1$ and $C_2$ are defined as uncertain parameters to account for errors in the empirical model. Preliminary sensitivity analysis is conducted to indicate parameters having minute impact on the quantities of interest (e.g. thermal conductivity of both the roof and the walls, and the reflectance and the emissivity of the walls) such that those parameters are neglected from our UQ study.

The resulting UQ framework produces two sets of predictions for the mean and 95% CI for the QOIs: one for cross-ventilation, and one for single-sided ventilation. The choice of the ventilation model also determines the number of uncertain parameters, i.e. 8 for the cross ventilation model and 9 for the single-sided ventilation model. Given the large number of uncertain parameters and the low computational cost of a single simulation, Monte-Carlo sampling is used and the sample size was determined by monitoring the convergence of the statistics of our QoIs.

**CFD simulations**

The LES are conducted using CharLES, a commercial CFD package developed by Cascade Technologies, Inc. (2020). In this section, we introduce the governing equations, the setup of computational domain and mesh, and the inflow and other boundary conditions.

**Governing equations**

LES applies a filter to the instantaneous field quantities $u_i(x,t)$ and $T(x,t)$, splitting them into filtered ($\tilde{}$) and sub-filtered (sub-grid) components ($\gamma$): $u_i(x,t) = \tilde{u}_i(x,t) + u'_i(x,t)$; $T(x,t) = \tilde{T}(x,t) + T'(x,t)$. This results in the following filtered equations for conservation of mass and momentum:

$$\frac{\partial \rho}{\partial t} + \frac{\partial (\rho \tilde{u}_i)}{\partial x_i} = 0 \quad (6)$$

$$\frac{\partial \rho \tilde{u}_i}{\partial t} + \frac{\partial (\rho \tilde{u}_i \tilde{u}_j)}{\partial x_j} = -\frac{\partial p}{\partial x_i} + \frac{\partial \tilde{\sigma}_{ij}}{\partial x_j} + \rho g \delta_{ij}, \quad (7)$$

where $\tilde{\sigma}_{ij} = (\mu + \mu_t)(\frac{\partial \tilde{u}_i}{\partial x_j} + \frac{\partial \tilde{u}_j}{\partial x_i} - \frac{2}{3} \delta_{ij} \frac{\partial \tilde{u}_k}{\partial x_k})$ represents the viscous stresses using the linear eddy viscosity assumption. The velocity in large scales are directly evaluated by solving the filtered equations while the motion in smaller scale is characterized with a Vreman sub-grid model in this study.

Considering that the temperature variation is minute in our simulations, we apply the Boussinesq approximation, and the momentum source by buoyancy (the last term in the equation (7)) can be replaced with:

$$\rho g = \rho_{\text{ref}} g \beta (\tilde{T} - T_{\text{ref}}), \quad (8)$$
where ρ, g and β are the density, the gravitational constant and the thermal expansion coefficient, and the subscript ref denotes the reference value of each quantity. Solving the following temperature transport equation completes the set of governing equations:

\[
\frac{\partial \bar{T}}{\partial t} + \frac{\partial \bar{\rho} \bar{u} \bar{T}}{\partial x_j} = \frac{\partial}{\partial x_j} \left[ \left( \frac{\alpha}{c_p} + \frac{\mu_t}{Pr_t} \right) \frac{\partial \bar{T}}{\partial x_j} \right],
\]

where \(\alpha\), \(c_p\), and \(Pr_t\) are the thermal diffusivity, the specific heat capacity, and a turbulent Prandtl number, respectively.

### Computational domain and mesh

The computational domain is presented in Figure 5. Since our primary region of interest is the inside and the vicinity of the target house, the model includes accurate representations of the buildings close to the house (i.e. within a radius of \(5H_{\text{house}}\)) in terms of their height and width. Buildings outside this immediate range but within 100 m are represented as rectangular blocks. The size of the domain was determined following the COST action 732 best practice guidelines (Franke et al. (2011)). The horizontal dimensions are 500 m by 600 m, which is equal to \(20H_{\text{max}}\) by \(30H_{\text{max}}\), where \(H_{\text{max}}=25\) m is the height of the tallest building in the domain. The inflow boundary is located at a distance greater than \(5H_{\text{max}}\) from the most upstream building, while the outflow boundary is located \(14H_{\text{max}}\) downstream of the target house. The vertical dimension height is 150 m (6\(H_{\text{max}}\)) and the lateral boundaries are at least \(5H_{\text{max}}\) away from all building geometries. These dimensions satisfy the recommendations in the guideline for any orientation of the building geometries, thereby supporting simulations for all wind directions.

The computational grid is generated with the CharLES' mesh generator and consists of approximately 35 million cells. A snapshot of the grid is shown in Figure 6. The cell size ranges from 8 m in the background to 5.4 cm near the house. The refinement is introduced gradually using different refinement zones, and the resulting resolution adheres to the guidelines that are recommended for CFD models of natural ventilation and wind engineering applications in general (Franke et al. (2011); Tominaga et al. (2008)).

### Inflow and boundary conditions

To test different wind directions, the building geometries are rotated inside the computational domain; the definition of the other boundary conditions is identical for all cases. For the inflow condition, we use the divergence-free version of a digital filter method, developed by Xie and Castro for wind engineering applications (Xie and Castro (2008)), and we combine the method with a gradient-based optimization to obtain the desired turbulent wind statistics at the location of interest (Lamberti et al. (2018)). The digital filter method generates an unsteady inflow with turbulence structures that are coherent in space and time. It requires input for the mean velocity and Reynolds stress profiles, and for the three Lagrangian time scales. We impose a logarithmic mean velocity profile with the reference velocity of 1.7 m/s at 25 m height based on our measurement of the free-stream velocity, and with a roughness length \((z_0)\) of 0.5 m. The Reynolds stress profiles are specified following similarity relationships for the neutral ABL.

Lastly, the Lagrangian time scale is estimated using the time series of velocity measurement data. The auto-correlation of the stream-wise velocity indicates a time scale of \(\tau_u=15\) s, and is converted to a length scale of \(L_u=25\) m using Taylor’s hypothesis. The spanwise and vertical length scales are estimated using their ratio to the streamwise component, \(L_v = 0.2L_u\) and \(L_w = 0.3L_u\).

A limitation of the digital filter inflow generation method is that the velocity field does not correspond to a solution of the governing equations. As a result, the turbulence intensities tend to decay as the flow moves through the domain and the turbulence intensities at the area of interest may be considerably lower than those specified at the inlet. To resolve this issue we employ a gradient-based optimization technique, where the Reynolds stress profiles and time scales at the inflow boundary are optimized to obtain the desired turbulence statistics at the downstream location. Figure 7 presents the resulting velocity statistics at the location of interest, including a comparison to both the intended profiles and the profiles that would be achieved without the optimization procedure.

The outlet boundary condition is a zero gradient condition for perfectly non-reflecting outflow. At the ground and building surfaces we apply wall functions.
A rough-wall function for a neutral ABL with $z_0=0.5$ m is imposed at the ground boundary, while an algebraic wall model is used for the building surfaces. The two lateral boundaries are periodic and a slip condition is applied at the top boundary. Since the computational domain is sufficiently large, the boundary conditions at the sides and the top will not influence the flow solution in the area of interest.

For the thermal boundary conditions, we impose a constant temperature for the walls of the target house and adiabatic conditions for the ground and the walls of surrounding buildings. A constant temperature is also specified at the inflow boundary such that the quasi-steady state solution with a constant temperature difference between indoor and outdoor will be reached. A variety of weather conditions in terms of wind speed, wind direction, and temperature is considered to investigate the combined effect of wind and buoyancy on natural ventilation.

Results

In the following, we first present the results obtained using the integral model with the UQ framework, including a comparison to the field measurements. Subsequently, we present preliminary results of the ongoing LES.

Integral model with uncertainty quantification

Figure 8 presents a scatter plot of the modeled and measured ACH for the four ventilation configurations, considering both the cross ventilation model and the single-sided ventilation model. The simulations were performed for the days when the corresponding ACH measurements were conducted, and the results represent the mean and CI predicted at the time of the experiment. In the scatter plots, the horizontal error bar indicates the 95% CI of the measurement, while the vertical error bar indicates 95% CI of our model prediction.

Considering the skylight and floor-level vent configuration (1), the measurements indicate ACH values in the range 5-10. The cross-ventilation model does not correctly predict these measured values because the very small opening area of the floor-level vent is a limiting factor for the ACH. The single-sided ventilation model provides a more realistic ACH prediction that corresponds well to the measured range. It is reasonable to assume that single-sided ventilation is more likely to occur with this configuration: the floor-level vent is too small and at too large a distance from the skylight to reliably establish a cross ventilation flow pattern. For the skylight and rear vent (2) and window and rear vent (3) configurations, the measurements indicate ACH values in the range 4-8. In these configurations, the mean prediction obtained with the cross ventilation model correlates well with the measurements, but the uncertainty for some of the predictions is high (±4 ACH). The single-sided ventilation model does not capture the trend of the measurements, but overall the predicted ACH values are of the same order of magnitude. Lastly, for the combination of two large openings, i.e. the skylight and the window (4), both models overestimate the ACH. The cross ventilation model produces a mean value that is 5 to 8 times greater, and the uncertainty
is too large to provide meaningful information. The single sided model overestimates the ACH by a factor of 3, and the UQ analysis fails to correctly represent the discrepancy with the measurements. The results indicate that neither model can capture the complex turbulent flow patterns that can occur for a configuration with too large openings.

Although our model results do not completely predict all measurements, the validation process provides knowledge in understanding the ventilation pattern in the slum house in various ventilation configurations and suggests that the effect of turbulence needs to be better characterized especially for the ventilation configuration with large openings. Both of the ventilation models in the integral model account for turbulence with simple parameters: \( \Delta C_p \) of the cross ventilation model; and three empirical coefficients \((C_b, C_w & C_t)\) and the uncertain parameters \((C_1\) and \(C_2\)) for the single-sided ventilation model. Therefore, it is imperative to precisely estimate those parameters for more accurate predictions of the ventilation rate. In this study, we use the higher-order LES model in order to accurately determine the parameters by analyzing detailed flow and temperature fields in 3D domain.

LES simulations

The initial focus of the LES has been on the validation of wind and buoyancy combined ventilation on the house in densely-packed built environment. Figure 9 displays a contour plot of the instantaneous velocity magnitude on a vertical plane through the center of the domain. The contour plot visualizes the large-scale turbulence structures in the boundary layer and the impact of the buildings on the flow, such as the recirculation in the wake region behind the tall building. The velocity magnitude in the building area is lower than the free stream because: (1) the velocity magnitude increases in vertical direction, following the logarithmic velocity profile imposed at the inflow boundary, and (2) low-rise buildings have similar height and they are densely packed, impeding efficient airflow in the narrow streets between the buildings.

Our validation focuses on two ventilation rate measurements conducted at different time points of the day: one during the day and the other at night. 1 summarizes the flow and thermal boundary conditions as well as the results of the two validation cases,

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**Table 1: Boundary conditions and results of the two validation cases**

<table>
<thead>
<tr>
<th></th>
<th>Day</th>
<th>Night</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wind speed [m/s]</td>
<td>1.69</td>
<td>1.71</td>
</tr>
<tr>
<td>Wind direction [°C]</td>
<td>-26</td>
<td>-27</td>
</tr>
<tr>
<td>( T_{outdoor} ) [°C]</td>
<td>28.35</td>
<td>16.15</td>
</tr>
<tr>
<td>( T_{house,roof} ) [°C]</td>
<td>30.35</td>
<td>15.95</td>
</tr>
<tr>
<td>( T_{house,wall} ) [°C]</td>
<td>25.00</td>
<td>20.55</td>
</tr>
<tr>
<td>( T_{house,floor} ) [°C]</td>
<td>21.60</td>
<td>21.15</td>
</tr>
<tr>
<td>ACH (measurement) [1/hr]</td>
<td>9.40</td>
<td>16.00</td>
</tr>
<tr>
<td>ACH (LES, mean) [1/hr]</td>
<td>9.90</td>
<td>17.14</td>
</tr>
</tbody>
</table>

Figure 10 displays snapshots of time-averaged velocity and temperature fields on the vertical plane crossing the target house for both the daytime and nighttime cases. Table 1 presents the entire time series of our simulations and the probability density function of ACH, and these results are compared to the measurement (black dashed line). The LES simulation predicts mean ACH of 9.9 for the day and 17.14 for the night, and the field experiments conducted in the same conditions reported 9.40 and
16.00, respectively. Considering that the predictions compare well to the measurements, our future work will be performing predictive simulations to characterize ventilation patterns under various weather conditions in terms of indoor-outdoor temperature difference, and wind speed and direction. Furthermore, the results will be used to precisely estimate the parameters regarding turbulence for the ventilation models in our integral model as well as to implement the relationships for ACH in order to reduce the uncertainty in predictions using the model.

Conclusion

Initial results obtained using a UQ analysis of the low-fidelity building thermal model with an empirical ACH model provide ACH predictions that correspond to the trends observed in the field measurements. Analysis of the importance of the different uncertain parameters revealed that the assumption regarding the occurrence of cross- versus single-sided ventilation in the empirical ACH model is a dominant uncertainty. In addition, the empirical models are highly sensitive to the specification of the pressure coefficients on the openings, and the single-sided model tends to overestimate the effect of turbulence. These findings indicate the potential of using high-fidelity LES to reduce uncertainty in the predictions. In ongoing work, LES of the full-scale test house in Dhaka is being performed to obtain more accurate relationships for ACH and employ them in the building thermal model with UQ. The final predictions of the ACH will be compared to the field measurements, and the results will be analyzed to identify robust ventilation strategies that will work under a variety of weather and housing conditions.

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