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Improving Predictions of the Urban Wind Environment Using Data

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Analysis of the urban wind environment can play an important role in the design of sustainable urban areas. The wind patterns in the urban canopy can affect citizen comfort, safety, and health, as well as building energy consumption. For example, local accelerations of wind flow around high-rise buildings can create uncomfortable or even dangerous conditions for pedestrians; interference effects between different buildings can generate complex wind loading phenomena that compromise resilience to extreme wind events; the local wind field can influence the capability to use air flow driven by natural wind and buoyancy to ventilate or cool buildings and reduce building energy consumption; and wind patterns will affect the transport of pollutants and heat, potentially generating local hot spots with high concentrations. Computational fluid dynamics (CFD), which numerically solves the governing equations for fluid flow and heat transfer, can provide predictions for the complete three-dimensional flow and temperature field in the urban canopy. In theory, this could provide invaluable information for the design of buildings and urban areas; in practice, there are several challenges when using CFD in the design process.

An important challenge has been that the simulation process, which includes model setup, execution of the simulation, and post-processing of the results, can be a very time-consuming task that demands a skilled CFD engineer. Significant advances in CFD software packages and high-performance computing capabilities are increasingly alleviating this problem; current simulation turnaround times are catching up with industry demands. Consequently, more fundamental challenges become the limiting factors: the complexity of the urban geometry, the variability in the atmospheric conditions, and the turbulent flow physics push the state-of-the-art in terms of the predictive capabilities of CFD, and engineers have only limited confidence in the accuracy of the simulation results. To efficiently address these challenges and provide results that can be used to quantitatively inform design, we need novel probabilistic modeling strategies that can quantify and reduce the uncertainty in the predictions.

"The complexity of the urban environment and the governing flow physics prohibits accurate predictions with deterministic modeling strategies. To effectively use [computational fluid dynamics] for the design and management of sustainable urban spaces, a paradigm shift from deterministic to probabilistic modeling is needed."

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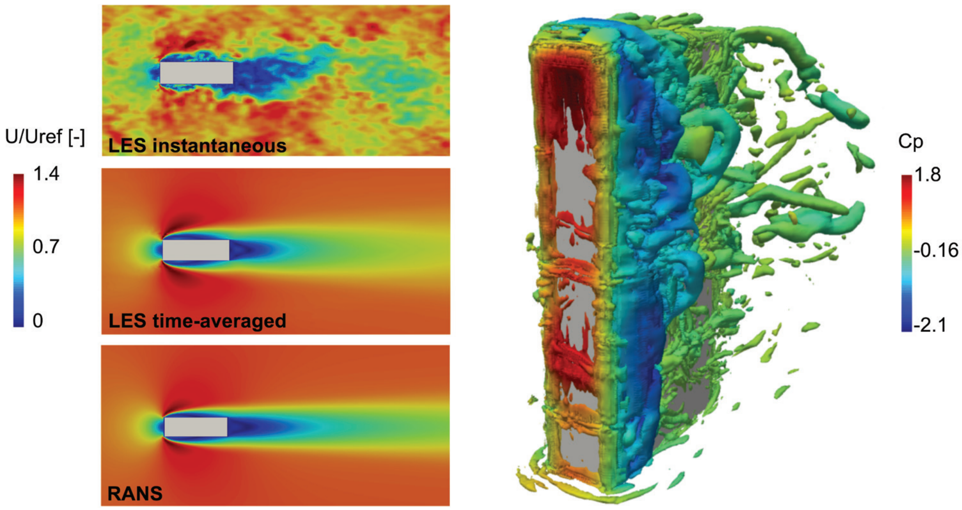
Limitations to the Predictive Capabilities of CFD

Urban flows are highly turbulent: the velocity field is characterized by fluctuations that cover a large range of spatial and temporal scales. This range of scales cannot be fully resolved in a numerical simulation; some form of turbulence modeling is needed to parameterize the effect of the unresolved turbulence scales on the solution. The traditional view has been that the primary reason for the limited accuracy of CFD results for urban canopy flows is the use of engineering turbulence models. This, however, fails to recognize the high variability, and corresponding uncertainty, in the boundary and operating conditions that determine how wind flows through buildings and cities. To evaluate the limitations to the predictive capabilities of CFD, both these aspects must be carefully considered.

Turbulence Modeling

Two main approaches to turbulence modeling exist: Reynolds-averaged Navier-Stokes (RANS) simulations parameterize the entire range of velocity fluctuations to obtain a solution for the time-averaged flow field; large-eddy simulations (LES) solve the



◁ Figure 1. Large-eddy (LES) and Reynolds-averaged (RANS) simulation results for the flow around a high-rise building. (a) contours of the non-dimensional velocity field U/Uref at the building mid height for an instantaneous snapshot of the LES, the time-averaged LES and RANS. The highest nondimensional velocity magnitudes are shown in dark red and correspond to an increase in the wind speed by a factor of 1.4 or more compared to the wind speed in the upstream undisturbed atmospheric boundary layer at the same height. (b) iso-surface of Q-criteria to visualize turbulent structures in the flow, colored by pressure coefficient Cp, which provides a nondimensional representation of the wind pressure. (Credit: Giacomo Lamberti).

filtered, unsteady Navier-Stokes equations and parameterize only the sub-filter scale velocity fluctuations. RANS simulations remain the most common approach for engineering applications, primarily because they require only a fraction of the computational time of LES, with simulation times on the order of hours versus several weeks for LES.

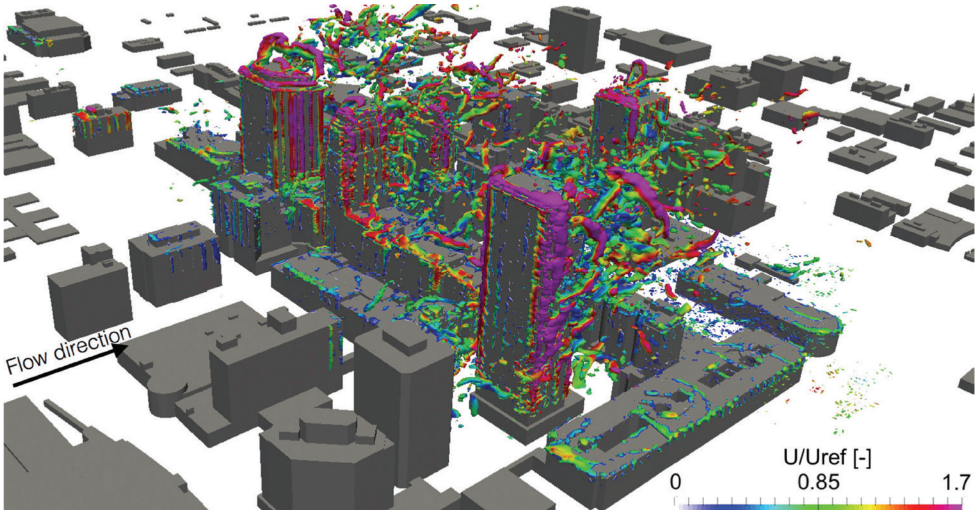
Figure 1 shows an example of the detailed solution that can be obtained with LES for the flow around a single high-rise building: instantaneous snapshots of the velocity field (Figure 1a) reveal the velocity fluctuations in the flow and can be post-processed to visualize turbulent structures (Figure 1b). The solution can also be averaged over time to provide a mean flow prediction. RANS simulations provide a prediction for these time-averaged quantities only, and the need for a model that represents the entire range of turbulence scales tends to deteriorate the prediction. It is, for example, known that RANS tends to overpredict the size of the wake region, i.e., the region immediately downstream of a building with low-velocity, recirculating flow (see Figure 1a). This type of deficiency also negatively influences the accuracy of other quantities of interest, such as pollutant concentrations or wind loads. Many wind tunnel validation studies have explored comparisons and calibration of different RANS turbulence models with varying success; the converging opinion is that we need LES for consistent improvements in accuracy.[1] From an engineering point of view, the corresponding increase in computational time poses a limitation to the integration of CFD in the design process.

Variability in Boundary or Operating Conditions

Before drawing the general conclusion that the higher computational cost of LES is justified by the corresponding increase in accuracy, it is worth noting that the importance of turbulence model deficiencies has been emphasized by the use of wind tunnel data in most validation studies. Wind tunnel modeling is considered the standard design method in wind engineering; given the wind tunnel baseline, the rationale has been that CFD simulations should be validated against wind tunnel experiments before using them for design. In this type of validation study, the wind tunnel flow conditions and building geometries can be accurately reproduced in the CFD model, leaving the turbulence model as the main source of uncertainty in the prediction. The wind tunnel is, however, also a simplified model of a complex reality. Flows in cities or buildings have highly variable boundary and operating conditions, for example due to larger-scale variability in the atmospheric boundary layer wind[2] or due to continuous changes in building occupancy and corresponding heat gains. Even if we use an expensive turbulence model that can accurately reproduce a wind tunnel experiment, these uncertainties would not be eliminated when comparing predictions against full-scale measurements. This was, for example, demonstrated in simulations of the wind flow in downtown Oklahoma City.[3] Compared to RANS results, a more expensive, detailed LES (Figure 2) did not consistently improve the comparison between the mean velocity prediction and the corresponding full-scale velocity measurements in the urban canopy. An interesting observation was that the LES prediction for the mean velocity was less accurate in stations where the solution had been shown to be sensitive to the inflow boundary conditions. These results indicate that, independent of the turbulence model used, the variability in the simulation inputs should be characterized and propagated to the simulation outputs to truly ensure predictive capabilities.

CFD Predictions with Confidence Intervals

Recent progress in methods for uncertainty quantification supports efficient propagation of uncertainties in model input parameters to predict probability distributions (instead of deterministic values) for the quantities of interest. This enables us to define confidence intervals for the predictions, reflecting the previously identified limitations of the predictive capabilities. Generally, a distinction is made between aleatory and epistemic uncertainties. Aleatory uncertainties are inherent to the system being solved; they cannot be reduced. In urban canopy flow, these would be the boundary and operating conditions, related to, for example, variability in the atmospheric boundary layer wind or building occupancy. Epistemic uncertainties result



◁ Figure 2. Large-eddy simulation result of the flow in Oklahoma City, showing iso-contours of Q-criteria colored by nondimensional velocity magnitude U/Uref to visualize turbulent structures in the flow. The highest nondimensional velocity magnitudes are shown in purple and correspond to an increase in the wind speed by a factor of 1.7 or more compared to the wind speed in the upstream undisturbed atmospheric boundary layer at 10 m height. (Credit: Clara García-Sánchez)

from simplifications and assumptions in the model; they could potentially be reduced by using a more accurate (i.e., expensive) model, or by obtaining more data. The turbulence model is the primary source of epistemic uncertainty in simulations of urban canopy flow. The different nature of these two types of uncertainties implies that different strategies are needed when propagating them to the quantities of interest.

Quantifying Uncertainties in Boundary or Operating Conditions

Aleatory uncertainties are typically cast in a probabilistic framework: the input parameters are assumed to be random variables with corresponding probability distributions, and the uncertainty in these parameters is propagated to the quantities of interest. Hence, the quantities of interest also become random variables, and the objective is to calculate their probability density functions. The definition of the distributions for the input parameters is essential to this process, since it can strongly influence the predictions.

In simulations of urban canopy flow, definition of the probability distributions for the boundary conditions can either be based on local field measurements of the relevant quantities, such as the wind direction and magnitude, or based on simulations of the larger-scale environment, such as weather forecasting simulations. Both methods have challenges in terms of the amount, resolution, and accuracy of data that can be obtained to determine the probability distributions for the input parameters, but initial studies have successfully explored their application to provide urban flow predictions with confidence intervals. Especially when performing time-averaged simulations, the benefits of accounting for the larger-scale variability in the flow can be significant. This was, for example, shown in predictions of pollutant concentrations during the Oklahoma City Joint Urban 2003 field experiment. Figure 3 shows that the time-averaged values from the field experiment are within the 95% confidence interval of the CFD prediction in five of the six measurement stations where significant concentrations ($K > 0.01$) were detected. The mean concentration predicted by the CFD also compares well to measurement values.[4]

Quantifying Uncertainties Due to Reduced-Order Turbulence Models

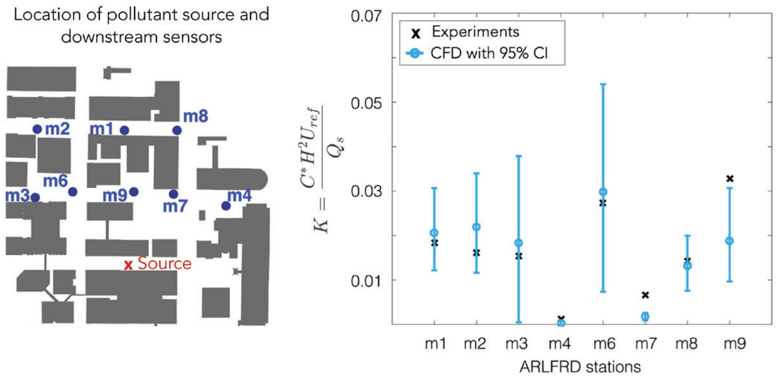
The quantification of turbulence model uncertainties is challenging because they are caused by a nominal lack of knowledge. Ensemble methods, similar to those used in weather forecasting, offer a standard approach to analyze these uncertainties, but the predictive capability remains limited by the assumptions made in the different models used for the ensemble. Alternatively, a physics-based approach to quantify the uncertainty by introducing perturbations into the modeled quantities, independent of the initial model form, has been explored.[5] Application of this method to wind engineering flows has shown promising capabilities,[6] but also indicates a potential limitation of a purely physics-based approach: the predicted uncertainty intervals might be too large to use the results as a basis for design decisions.

Data-Informed Modeling to Reduce Uncertainties

The proposed modeling frameworks with uncertainty quantification provide a natural pathway to data-informed modeling. Continuous improvements in urban and building sensing networks, and in high-fidelity simulation capabilities, will provide an unprecedented amount of high-quality data. Combined with recent progress in data assimilation and machine learning algorithms, this offers a unique opportunity for improving the predictive capability of CFD. The most effective approaches, in terms of the sources and types of data, and in terms of the methods to integrate the data in the models, will be different for the two types of uncertainties.

Reducing Uncertainties in Boundary or Operating Conditions Using Data

Considering the prediction of urban canopy flow, simulations of the wind flow on Stanford's campus have shown that an ensemble Kalman filter[7] can be used to infer the uncertain inflow boundary conditions based on measurement data from wind sensors located inside the urban canopy. In this initial test case, six carefully calibrated anemometers were deployed in



◁ Figure 3. Reynolds-averaged predictions with uncertainty quantification for dispersion in Oklahoma City; comparison of the predicted mean and 95% confidence interval for the nondimensional tracer concentration K to time-averaged measurements from the Joint Urban 2003 measurement campaign. The results are compared at eight measurement stations, labeled m1–m9; data for m5 was not available. (Credit: Clara García-Sánchez)

a 2.5 square mile [4 km2] area; two were used for the inference process, while four were used for validation of the predictions obtained from subsequent forward propagation of the inferred, uncertain, inflow boundary conditions. This resulted in significantly improved predictions compared to the traditional method of using data from a nearby weather station: the hit rate, which quantified the percentage of data points that fall within 20% of the measured data, increased by a factor of two.[8] Additional measurements of, for example, the temperature and humidity within the urban canopy, wind pressures on building facades, or indoor temperature measurements, could similarly be used to reduce uncertainty in predictions of these quantities. This type of data assimilation could quite easily be incorporated in the design process: measurements from a limited number of urban sensors can be combined with available weather station data to infer probability distributions for the boundary conditions for simulations of a specific area of interest. Subsequently, this information can be used when evaluating the effects of a new building design on the surrounding wind environment, or when evaluating structural wind loads or potential for natural ventilation.

Reducing Uncertainties Due to Reduced-Order Turbulence Models Using Data

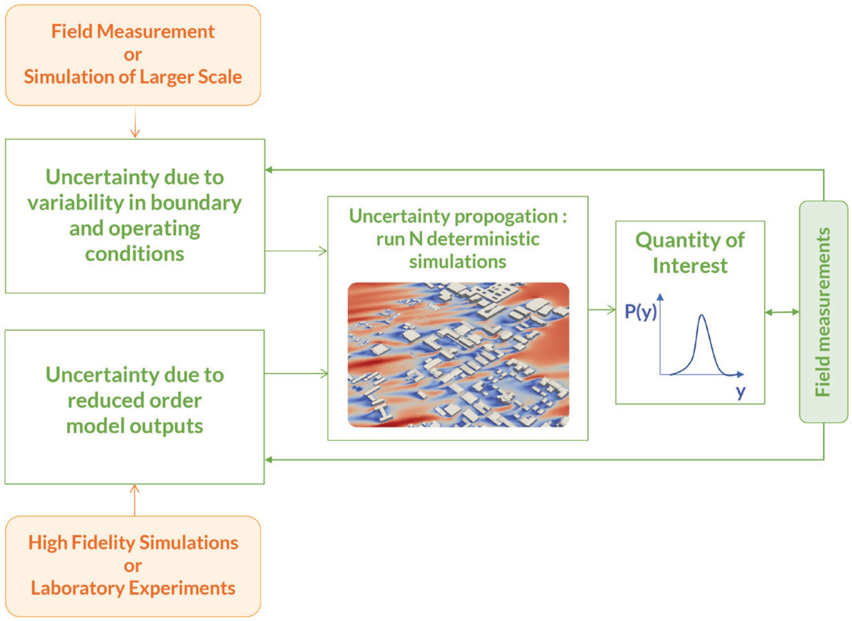
To obtain a more accurate characterization of turbulence model uncertainties, it is useful to isolate this problem by considering simplified test cases in which the data is not affected by other uncertainties. A promising approach is to use data from a small number of high-fidelity simulations with well-defined boundary conditions, potentially for a simpler but similar flow configuration. This has, for example, been done to define the perturbations that should be introduced in Reynolds stress models when modeling flow over a hill,[9] and considerably improved predictions were obtained. While this approach remains to be explored for wind engineering problems, it can be expected that this type of multi-fidelity framework will be essential in our efforts to reduce model uncertainties at an acceptable computational cost.

Summary

The complexity of the urban environment and the governing flow physics prohibits accurate predictions with deterministic modeling strategies. To effectively use CFD for the design and management of sustainable urban spaces, a paradigm shift from deterministic to probabilistic modeling is needed. Tools for uncertainty quantification and data assimilation should be leveraged to integrate information from a variety of computational models, wind tunnels, and field experiments, and to provide predictions with confidence intervals, as shown in Figure 4. The resulting high-resolution predictions for the local wind field, and, by extension, temperature or pollutant concentration field, could inform how different buildings or urban designs perform in terms of pedestrian wind and thermal comfort, air quality, and potential for natural building ventilation.

The development of these methods should strongly consider fitness for purpose. For example, a fast model with higher model-form uncertainties could support initial design choices by evaluating different designs and their sensitivity to aleatory uncertainties. During detailed design phases, this model could be refined or complemented by a higher-fidelity, more computationally expensive model to reduce the model-form uncertainties. In both of these phases, data from carefully calibrated urban sensor networks, including sensors within the urban canyon and at roof height, can be used to characterize the conditions at the site of interest in terms of wind conditions, temperature, humidity, or air quality. Finally, during the operational phase, data from sensor networks can provide valuable information on the actual system behavior, thereby enabling us to further reduce the uncertainty in model predictions and create digital twins that can be used to investigate adaptation or control strategies. The optimal number and location of sensors for informing the models, measuring, for example, local temperatures and flow magnitudes inside and outside of a new building, can be determined based on the models used during the design phase.

Frequent communication and collaboration between the researchers developing the tools and the designers and engineers who will use them will be essential to refine, and progress toward realizing, our goal. On the research side, this interaction should support identifying the quantities of interest, and corresponding acceptable levels of uncertainty, that are most relevant for design. On the designers' side, it should inform the deployment of carefully designed and calibrated sensor networks that can provide the necessary high-quality data to improve the predictive capabilities of CFD.



◁ Figure 4. A computational framework that uses uncertainty quantification and data assimilation to provide predictions with confidence intervals.

Notes

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