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A model-based data-interpretation framework for improving wind predictions around buildings

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ABSTRACT

Although Computational Fluid Dynamics (CFD) simulations are often used to assess wind conditions around buildings, the accuracy of such simulations is often unknown. This paper proposes a data-interpretation framework that uses multiple simulations in combination with measurement data to improve the accuracy of wind predictions. Multiple simulations are generated through varying sets of parameter values. Sets of parameter values are falsified and thus not used for predictions if differences between measurement data and simulation predictions, for any measurement location, are larger than an estimate of uncertainty bounds. The bounds are defined by combining measurement and modeling uncertainties at sensor locations. The framework accounts for time-dependent and spatially-distributed modeling uncertainties that are present in CFD simulations of wind. The framework is applied to the case study of the CREATE Tower located at the National University of Singapore. Values for time-dependent inlet conditions, as well as values for the roughness of surrounding buildings, are identified with measurements carried out around the CREATE Tower. Results show that, on average, ranges of horizontal wind-speed predictions at an unmeasured location have been decreased by 65% when measurement data are used.

1. Introduction

Wind around buildings affects the comfort and health of residents as well as the energy consumption of buildings, particularly in tropical climates. For example, the convective heat flux at the building façade, influencing energy consumption of buildings, depends on the surrounding wind (Defraeye et al., 2011). Wind can also be harnessed for natural ventilation of buildings (Ghiaus and Allard, 2005). Computational Fluid Dynamics (CFD) simulations have been widely used to simulate wind around and through buildings (Van Hooff and Blocken, 2010; Ramponi and Blocken, 2012). Although guidelines have been established to improve simulation predictions (Franke et al., 2004), large discrepancies remain when simulation predictions are compared to field measurements. Moreover, uncertainties in simulation predictions are usually not quantified (Blocken and Gualtieri, 2012).

The steady Reynolds-averaged Navier–Stokes (RANS) equations are usually employed in CFD simulations to describe the fluid-flow behavior. These equations are time-averaged or ensemble-averaged equations of the fluid-flow motion. Large discrepancies have been observed in wakes of buildings when predictions of RANS-based simulations are compared with wind-tunnel experiments (Tominaga et al., 2008; Yoshie et al., 2007). Wind-tunnel experiments are usually employed to evaluate the performance of approximate equations of fluid-flow solved in CFD simulations because values of parameters are known (e.g. inlet conditions and surface roughness). Large Eddy Simulation (LES) is an alternative strategy for modeling fluid-flow behavior in which time-dependent predictions are computed. LES has been found to provide better agreement with wind-tunnel experiments than RANS-based simulations (Tominaga et al., 2008).

Thermal processes may affect the wind behavior around buildings, especially in street canyons which can be subject to combinations of low wind speeds and high differential heating between surfaces (Niachou et al., 2008). However, if thermal processes are implemented into the CFD model, modeling complexity is increased (Van Hooff and Blocken, 2010; Assimakopoulos et al., 2006) along with the number of parameters that cannot be easily estimated, such as the thermal properties of surfaces. Therefore, thermal processes are not often included in CFD simulations. Effects of thermal processes have been evaluated by using

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field measurements (Niachou et al., 2008); by simulating thermal processes with CFD simulations (Xie et al., 2005); or by using wind-tunnel experiments with a heated floor (Allegrini et al., 2013). However, the effects have been estimated for standard building configurations (street canyons) and they are likely to vary for other topologies.

Model-based data interpretation has the potential to improve the accuracy of simulation predictions through the use of a population of CFD simulations and measurement data. In model-based data-interpretation approaches, many model instances (simulation instances) are generated through assigning sets of parameter values to a model class. In this work, the model class is a CFD model with un-assigned parameter values. Measurement data are used to estimate sets of parameter values by solving an inverse problem. The inverse problem involves estimating sets of parameter values by comparing measurement data with predictions of model instances. Several approaches are described in following chapters.

Model calibration, in which an "optimal" model is found by minimizing the sum of the squared difference between simulation predictions and measurement data, is not appropriate because there rarely is a single answer to the inverse problem. Many set (s) of parameter values within a model class might give same responses at sensor locations in complex systems (Beven, 2006). Such ambiguities are amplified by measurement and modeling uncertainties. Modeling uncertainties refer to uncertainties (probability distributions of errors) in the model class (e.g uncertainties associated with RANS equations). Moreover, model calibration approaches provide values of parameters, which compensate modeling and measurement errors at sensor locations. Therefore, the "optimal" model is conditional on sensor locations (and modeling errors at those locations). Furthermore, calibration approaches do not provide information that can lead to estimates of uncertainties of subsequent predictions (Beven, 2008).

Bayesian inference identifies conditional probability distributions of parameter values given measurement data (Box and Tiao, 2011). Probability distributions are required to represent measurement and modeling uncertainties at sensor locations. Uncertainties in CFD simulations are difficult, if not impossible to determine precisely. If incorrect probability distributions are defined, it may lead to over-conditioning of parameter values (Beven, 2008). Furthermore, modeling errors are often systematic and this introduces additional error correlations between measurement locations (Goulet et al., 2013; Goulet and Smith, 2013). Implementation of Bayesian inference requires a complete knowledge of all correlations in order to avoid biased predictions. In wind modeling, the values of such correlations are unknown.

An alternative is to use a model-falsification approach, such as error-domain model falsification (Goulet et al., 2013, 2012) and Generalized Likelihood Uncertainty Estimation (GLUE) (Beven, 2008), in which incorrect sets of parameter values are falsified using measurement data. Only bounds of measurement and modeling uncertainties are needed. Error-domain model falsification has been developed in the application of bridge diagnosis and leak detection in water networks. Error-domain model falsification involves falsification of model instances for which differences between measurement data and simulation predictions, for any measurement location, are larger than an estimate of uncertainty bounds; the bounds are defined by combining measurement uncertainties and modeling uncertainties at that location. When the entire set of model instances is falsified, the model class is incorrect. This could mean that either additional processes need to be included, boundary conditions are incorrect, etc. or modeling and measurement uncertainties have been underestimated. In this way, model falsification provides a way to test the validity of model classes.

The main objective of this paper is to present a model-based data-interpretation framework which is appropriate for the identification of parameter values of CFD simulations, and subsequent predictions at unmeasured locations. The framework is based on error-domain model falsification. Improvements have been made to error-domain model falsification in order to reproduce time variability (at the scale of 15 min) of wind through allowing identification of different sets of inlet conditions at different times. In this framework, time-dependent inlet conditions as well as the roughness of the surrounding buildings are identified using time series of measurement data.

Modeling and measurement uncertainties affect the information content of measurement data. A systematic methodology to evaluate modeling uncertainties is proposed that recognizes their time-dependent and spatially-distributed characteristics. The final objective is to apply the methodology to the case study of the "CREATE Tower". The CREATE Tower is a 16-storey building located at the National University of Singapore.

The structure of the paper is as follows. In the next section, the model-based data-interpretation framework is described. Section 3 introduces the case study and the model class including the parameters requiring identification. The experimental setup is presented in Section 4. Section 5 presents a methodology to estimate modeling uncertainties that can be incorporated to the model-based data-interpretation framework. The model-based data-interpretation framework is applied in Section 6 using simulation predictions, measurement data and knowledge of measurement and modeling uncertainties. The paper ends with a discussion of the results and plans for future work.

2. Methodology

This section presents the model-based data-interpretation framework used to identify sets of parameter values of the CFD simulation and predict wind variables at unmeasured locations. This framework is based on error-domain model falsification which has been found to be useful in applications of bridge diagnosis and leak detection in water networks (Goulet et al., 2013, 2012). In such systems, parameter values are identified using measurements carried out only at specific times. In the assessment of wind behavior around buildings, parameter values of CFD simulations need to be identified dynamically using time series of measurements.

2.1. Error-domain model falsification

Error-domain model falsification involves generating sets of model instances $M(\boldsymbol{\theta}_j)$ through assigning a combination of parameter values $\boldsymbol{\theta}_j = [\theta_1, \dots, \theta_p]_j$ to a model class M with $j \in \{1, \dots, n_m\}$. p is the number of parameters requiring identification and n_m is the number of model instances. When correct sets of parameter values $\boldsymbol{\theta}^*$ are assigned to the model class, the predicted value of an output variable of the model instance $M(\boldsymbol{\theta}^*)$ differs from the real value (Q) by the modeling error ϵ_{model}. Modeling errors are errors associated with the model class. The real value is also equal to the measured value y plus a measurement error $\epsilon_{measure}$. This is expressed in Eq. (1).

$$M(\boldsymbol{\theta}^*) + \epsilon_{model} = Q = y + \epsilon_{measure} \tag{1}$$

Eq. (2) is derived by rearranging the terms in Eq. (1). The difference between the predicted and the measured value is equal to the difference between the measurement and the modeling error.