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Probabilistic aerostability capacity models and fragility estimates for cable-stayed bridge decks based on wind tunnel test data

Bo Sun [a,b,*], Paolo Gardoni [a], Rucheng Xiao [b]

[a] Department of Civil and Environmental Engineering, University of Illinois at Urbana-Champaign, 3118 Newmark Civil Engineering Laboratory, 205 N. Mathews Ave., Urbana, IL 61801, United States

[b] Department of Bridge Engineering, Tongji University, 608 Bridge Building, 1239 Siping Road, Shanghai 200092, China

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ABSTRACT

Probabilistic capacity models are developed for cable-stayed bridges considering flutter and aerostatic instability failure. Additional probabilistic models for implicit design variables are also developed to make the capacity model in explicit expression of only basic design variables and model parameters. All the probabilistic models are constructed to incorporate the understanding of the physics/mechanics of the phenomena by considering existing deterministic models and to include information from experimental wind test data via correction terms. The developed models are constructed to give unbiased estimates of the capacities of interest and properly account of the relevant uncertainties. The measured capacity values from wind tunnel tests are used to construct posterior statistics of unknown model parameters through a Bayesian approach. Using the developed capacity models, fragility estimates for flutter instability failure, aerostatic instability failure and system instability failure are obtained for three example bridges. Fragility is defined in this paper as the conditional probability of failure for given wind speed demand.

1. Introduction

Wind resistance design is of vital importance for long flexible structures like cable-stayed bridges. Among all the wind induced issues (buffeting, flutter, galloping, vortex-induced vibration, etc.), aerostability problems of bridge decks, including flutter stability (aerodynamic) and aerostatic stability, are usually among engineers' first considerations in the preliminary design stage due to their destructive effects [1]. Typically there are three ways to obtain the aerostability capacities: (1) explicit empirical formulas like those in the design codes, or simplified analytical solutions; (2) wind tunnel test method; (3) numerical computational processes with some aerodynamic properties obtained experimentally. While these approaches have made significant progresses in the past decades, the formulations remain deterministic and therefore they do not capture the inherent uncertainties in the material properties, geometry and the models used. To estimate the probability of failure of cable-stayed bridges there is a need to have evaluations of the aerostability capacities that capture the underlying uncertainties. Therefore, there is a need to develop probabilistic aerostability capacity models.

Many researchers have developed different forms of probabilistic aerostability capacity models in their attempts to carry out probabilistic analysis of bridges against aeroinstability. Early researchers [2–4] simply treated the capacity value achieved from the wind tunnel test or simplified numerical computational process as a random variable with some adjustment factors. Those early attempts are not convincing enough since the aerostability capacity models should not only be "probabilistic" but also "explicit" function of basic design variables reflecting the structural properties. Other researchers [5–8] built surrogate models for the aerostability capacity or parts of the implicit design variables inside the predictive models by a combination of response surface method and finite element analysis. While this approach successfully makes the aerostability capacity model in explicit form of basic random variables, the limitations are obvious due to the following reasons: (1) the generated surrogate models are in pure mathematical form; no physic rules behind them; (2) the bias and uncertainties brought by the approximation are not considered; (3) capacity models are not transportable (i.e., one capacity model generated for a certain bridge cannot be applied to other bridges.) Other researchers [9–11] also tried to adopt the complex numerical computational process to calculate the aerostability

* Corresponding author at: Department of Civil and Environmental Engineering, University of Illinois at Urbana-Champaign, 3118 Newmark Civil Engineering Laboratory, 205 N. Mathews Ave., Urbana, IL 61801, United States.

E-mail addresses: bsun@illinois.edu (B. Sun), gardoni@illinois.edu (P. Gardoni).

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capacity directly when conducting the probabilistic analysis. However, the large computation efforts and dependency on experimental data of this approach have limited its application in sensitivity and optimization analysis.

In this paper we develop probabilistic capacity models for aerodynamic instability (flutter) and aerostatic instability for cable-stayed bridge decks by taking full advantage of existing predictive models that have widely been used and the available data from wind tunnel tests. Keeping in mind efficiency and adoptability of models and the desire to use all available information, rather than developing new models, the proposed probabilistic capacity models are based on existing predictive models currently available in the design practice. To account for the available experimental data, data from wind tunnel tests are used to calibrate correction terms that improve the accuracy of prediction and capture the possible bias in the existing models. The correction terms are sets of "explanatory" functions capturing the specific characteristics of different bridges. The generated models are unbiased and capture the relevant uncertainties, thus they are most suitable to be used in a probabilistic analysis to obtain the fragility estimates of cable-stayed bridges. The developed capacity models are used to estimate the fragility for flutter instability failure, aerostatic instability failure and system instability failure of three example bridges. Fragility is defined in this paper as the conditional probability of failure for given wind speed demand.

The rest of the paper is organized as follows. Section 2 provides the general theory for the development of probabilistic capacity models. Section 3 describes the experimental data used for the model calibration. Sections 4 and 5 discuss proposed probabilistic models for flutter capacity and aerostatic stability capacity, as well as some probabilistic models for some design variables used inside of the capacity models. Section 6 discusses how fragility estimates are obtained using the proposed capacity models and illustrates this process considering the three example bridges. Finally, Section 7 draws some general conclusions.

2. Formulation of capacity models

Capacity models are mathematical expressions relating the capacities of a structural component to a set of measurable variables $\mathbf{x}$ and model parameters $\mathbf{\Theta}$. The general model form and Bayesian parameter estimation approach are briefly introduced in this section. More details can be found in Gardoni et al. [12,13].

2.1. General model form

A general capacity model is written in the form of a deterministic model and an additive correction term

$$C(\mathbf{x},\mathbf{\Theta}) = \hat{c}(\mathbf{x}) + \gamma(\mathbf{x},\boldsymbol{\theta}) + \sigma\varepsilon \tag{1}$$

where $C(\mathbf{x},\mathbf{\Theta})$ = capacity quantity of interest (or a transformation of the quantity of interest into a new space to satisfy the assumption of additivity of the correction term, and the normality and homoskedasticity assumptions – the latter two assumptions are described later), $\mathbf{\Theta} = (\boldsymbol{\theta},\sigma)$, in which $\boldsymbol{\theta} = (\theta_1,\theta_2,\ldots)$, is a set of unknown model parameters, $\hat{c}(\mathbf{x})$ = selected deterministic model, $\gamma(\mathbf{x},\boldsymbol{\theta})$ = the correction term, σ = standard deviation of the model error (assumed to be constant, i.e. not to depend on $\mathbf{x}$ – homoscedasticity assumption) and ε is a random variable with zero mean and unit variance, (assumed to follow a normal distribution – normality assumption.)

Ideally, the selected deterministic model should be widely used in the current design practice (to maximize the acceptance of the proposed model) and derived from the first principles, i.e. the rules of physics and mechanics. The correction term $\gamma(\mathbf{x},\boldsymbol{\theta})$ is developed (formulated and calibrate) to improve the accuracy of the predictions of $\hat{c}(\mathbf{x})$ and make such predictions unbiased. A form of $\gamma(\mathbf{x},\boldsymbol{\theta})$ that is linear in the unknown parameters $\boldsymbol{\theta}$ is written as

$$\gamma(\mathbf{x},\boldsymbol{\theta}) = \sum_{i=1}^{p}\theta_i h_i(\mathbf{x}) \tag{2}$$

where $h_i(\mathbf{x})$, $i = 1,\ldots n$, are the properly candidate "explanatory" function used to improve the accuracy of the capacity model and capture the bias inherent in $\hat{c}(\mathbf{x})$. Important sources for the choices of the explanatory functions may come from: (1) a constant bias that is independent of the variables $\mathbf{x}$; (2) simplifications or assumptions made in the deterministic models; (3) specific properties used in the deterministic models. By examining the posterior statistics (described next) of the unknown parameters $\mathbf{\Theta}$, we are able to identify those explanatory functions that are needed in the model and those that can be removed.

2.2. Bayesian parameter estimation

A Bayesian approach is used in this paper to estimate the model parameters $\mathbf{\Theta}$ by incorporating all types of available information. The updating rule used to compute the posterior distribution of the unknown parameters $\mathbf{\Theta}$ in the Bayesian approach is written as

$$f(\mathbf{\Theta}) = \kappa L(\mathbf{\Theta})p(\mathbf{\Theta}) \tag{3}$$

where $f(\mathbf{\Theta})$ = posterior distribution representing our updated state of knowledge about $\mathbf{\Theta}$, $L(\mathbf{\Theta})$ = likelihood function representing the objective information about $\mathbf{\Theta}$ contained in the data, $p(\mathbf{\Theta})$ = prior distribution reflecting our state of knowledge about $\mathbf{\Theta}$ available before obtaining/considering the observations, and $\kappa = [\int L(\mathbf{\Theta})P(\mathbf{\Theta})d\mathbf{\Theta}]^{-1}$ = normalizing factor.

The likelihood is a function proportional to the conditional probability of making the observations for a given value of $\mathbf{\Theta}$. Formulation of the likelihood function depends on the type of the available information [12]. In this paper, the $L(\mathbf{\Theta})$ has the following form

$$L(\mathbf{\Theta}) \propto \prod_{\text{failure data}} P[\sigma\varepsilon_i = r_i(\boldsymbol{\theta})] \times \prod_{\text{lower bound data}} P[\sigma\varepsilon_i > r_i(\boldsymbol{\theta})] \tag{4}$$

where $r_i(\boldsymbol{\theta}) = C_i - \hat{c}(\mathbf{x}_i) - \gamma(\mathbf{x}_i,\boldsymbol{\theta})$ is the model error at the ith observation. Failure data are those for which the capacity is measured at the instant of failure. For lower bound data, the measured value is a lower bound of the actual capacity (i.e., failure did not occur).

The prior distribution $p(\mathbf{\Theta})$ may incorporate any information about $\mathbf{\Theta}$ that is from past experience or engineering judgment. Any change in the prior knowledge reflected in the prior distribution may change the posterior distribution $f(\mathbf{\Theta})$. If no such information is available, one should use a prior distribution that has minimal influence on the posterior distribution, so that inferences are unaffected by information external to the observations. In this case, one should use a noninformative prior distribution [14].

Markov Chain Monte Carlo (MCMC) [15] simulation is used in this paper to obtain the posterior distribution of the unknown parameters in the capacity models. For each capacity model, we run MCMC up to convergence of all of the parameters.

3. Wind tunnel test data

Since the collapse of the Tacoma Narrows Bridge in 1940, a significant number of wind tunnel tests have been conducted in the design stage to evaluate the safety of bridge construction and operation, providing considerable data on the ultimate performance of long-span bridges under wind effect. In this paper, for the purpose of estimating the parameters $\mathbf{\Theta}$, we collected data available in the literature related to the wind tunnel tests of cable-stayed bridges,