Vehicle and Truss Bridge Interaction Adopting a Simplified 2D Model

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ABSTRACT

Indirect structural health monitoring of bridges using vehicle-mounted sensors offers a promising approach for the continuous assessment of structures. Full-scale modelling of complex structures, however, is computationally intensive. In order to optimize the required computational expenses, a two-dimensional simplified numerical model whose response resembles the real structure is developed. Euler-Bernoulli frame elements are adopted for finite element structural modelling. The transitional Markov Chain Monte Carlo technique is then applied for Bayesian finite element model updating. The proposed approach proved to reach an accurate model for a real-world truss bridge in Japan. Vehicle bridge interaction elements are then developed based on the updated simplified 2D model. The generalized-α time integration scheme is used to overcome inherent numerical instabilities. Time-response of the vehicle is evaluated using the developed Vehicle-Bridge Interaction (VBI) framework to study the dynamic properties of the bridge. The proposed approach significantly reduces the computational efforts in extracting time history responses of the moving dynamic system over the bridge without sacrificing the prediction accuracy. Time history responses can be processed subsequently to identify damage(s) in the structure, if any.

INTRODUCTION

Being crucial components of transportation networks, bridges are of most important civil infrastructure. The majority of them, however, are aging and their mechanical properties have degraded over the years. To ensure their reliability, a comprehensive inspection and maintenance strategy is necessary. One of the most promising methods for bridge health monitoring is the VBI-based (Vehicle Bridge Interaction) approach which aims to extract the mechanical properties of the bridge from the dynamic coupling between the bridge and the passing vehicle. The vehicle shall be equipped with some sensors, generally accelerometers, and usually on its axles. It can, therefore, be regarded

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both as an exciter and receiver [1]. Having passed over the bridge, the vehicle response will contain informations about dynamic characteristics of the bridge structure. This methodology, i.e. extraction of the dynamic properties of bridge structure from the dynamic response of the passing vehicle, is called "drive-by inspection" or "indirect health monitoring" [2]. The drive-by approach offers significantly more practical solutions in terms of mobility, economy, and efficiency and eliminates the necessity of installing a large number of sensors on the structure. It can be easily transferred to and tailored for another bridge [1,3]. Furthermore, it facilitates periodic condition monitoring of bridges even under the operating condition. It is, therefore, well suited for long-term continuous condition monitoring of large-scale structures.

Such methodologies rely on numerical models along with data mining / signal-processing techniques. Numerical models, such as the finite element method (FEM), have been widely utilized for monitoring structures and evaluating their serviceability. However, model-predicted responses may differ from actual ones due to uncertainties in connection, boundary conditions, section geometrics, and material properties [4]. Finite Element Model Updating (FEMU) provides an emerging technique that can calibrate uncertainties associated with the FE model and reduce numerical simulation errors. The FEMU process optimizes the calibration of the numerical model according to the actual behavior of the structure to produce more accurate and reliable results [5]. However, the development of algorithms for structural model updating is still an active research area in structural dynamics.

FEMU is generally described as an inverse problem that can be broadly categorized as deterministic or probabilistic. Probabilistic model updating provides a more versatile technique for handling uncertainties and complexities [6–8]. Bayesian inference is also considered one of the most powerful and well-established methodologies for probabilistic finite element model updating, system identification, and damage detection [6,8–10]. This approach requires the evaluation of complex multidimensional integrals, which typically do not have analytical solutions. It is, therefore, computationally expensive, particularly when numerous uncertain parameters are involved. Beck and Au [11] proposed an adaptive Markov chain Monte Carlo simulation technique to evaluate the posterior probability density function. This approach combines the simulated annealing and Metropolis-Hastings (MH) algorithm in a sequential manner so that each target probability density function is the posterior probability density function considering a larger extent of data. However, this approach is limited to lower dimensions when the number of uncertain parameters increases. Ching and Chen [12] proposed Transitional Markov Chain Monte Carlo (TMCMC), a new sampling algorithm that involves sampling from a sequence of intermediate probability density functions that converge to a target probability density function. TMCMC uses reweighting and resampling techniques to generate the next target probability density function in a sequence, eliminating the difficulty of kernel density estimation, especially in high-dimensional space [13–15] . TMCMC brings both efficiency and ease of implementation and has been widely used in recent structural FE model updating studies. While existing research on Bayesian FE model updating has focused mainly on numerical models or simple structures like cantilever beams or shear buildings, few studies have reported on full-scale large civil infrastructures based on field data. Chang and Kim [16] presented preliminary results of modal parameter identification and damage detection for a steel truss bridge, and Kim et al. [17]

presented the collected data as well as a 3D structural model. However, model updating based on a 3D finite element model may require hundreds of days [7]. Therefore, this study aims to develop a 2D representation of the ADA bridge, a truss bridge in Japan, that could significantly reduce computational expenses.

The 2D ADA bridge model is developed based on Euler-Bernoulli frame elements. The TMCMC algorithm is adopted subsequently to update the model minimizing the difference between measured and calculated modal parameters. Upon having the bridge structure updated, coupling between the vehicle and the bridge will be included. To deal with numerical instabilities associated with such a complex structure, the developed Vehicle-Bridge Interaction (VBI) framework employs the Generalized-α time integration scheme. This enables efficient computation of time-response for both the vehicle and bridge, while still maintaining high accuracy in prediction. Time history responses of the passing vehicle are then utilized to evaluate the dynamic properties of the ADA bridge. Such responses can be further analysed to identify any possible structural damage. The proposed methodology can be adopted for long-term monitoring of large-scale structures which requires a huge number of simulations, reducing required computational efforts.

ADA BRIDGE MODEL

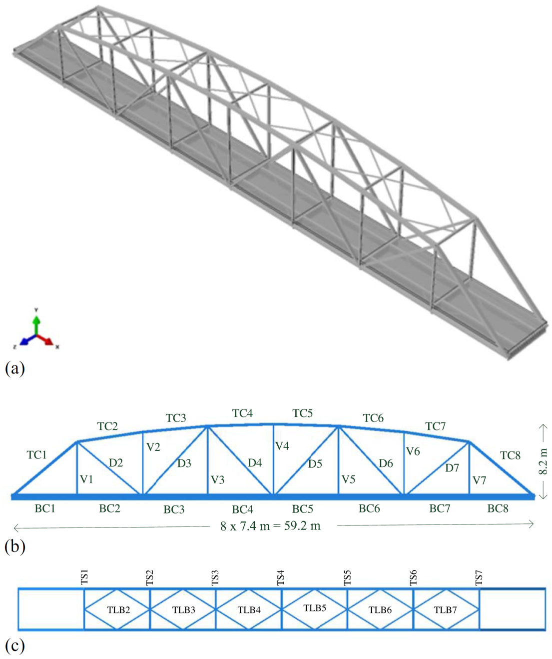
The ADA bridge, located in the Nara Prefecture, Japan, was a simply-supported steel truss structure. It had been operational for a period of 53 years, from 1959 to 2012. The bridge's main span was 59.2m in length and had an effective width of 3.6 m. Figure 1 shows the isometric, elevation, top, and bottom plan of the bridge. The cross-section dimensions are given in height × width × web thickness × flange thickness. The bridge members are made of structural steel (density = 7900 kg/m^3, elasticity modulus = 200GPa), while the deck is constructed from concrete slabs (density = 2400 kg/m^3, elasticity modulus = 21GPa).

ADA bridge is modelled using both Euler-Bernoulli frame elements. The bending natural frequencies and mode shapes are extracted and compared with those of [16] and [15], see Figure 2and Table II.

It shows that there is a reasonable match between numerical results and field test data. The extent of error, however, is more considerable in case of higher modes of vibration. It is due to the fact that Euler-Bernoulli theory can not consider the shear deformation effect. Despite the meaningful consistency of results with field data, higher extent of accuracy is required in SHM applications. The existing discrepancies stem from uncertainties in material properties, boundary conditions as well as deterioration in cross-section areas / moment of inertia as a result of corrosion / erosion. It is, therefore, required to apply a Bayesian finite element model updating scheme to calibrate the numerical system.

ADA BRIDGE UPDATED MODEL

The methodology of Bayesian model updating is built upon the principles of Bayes' theorem, which involves the use of conditional probabilities to assess the likelihood of



Group	Component	Dimension
Top chords	TC1, TC8	Box 318 × 310 × 19 × 10
	TC2, TC3, TC6, TC7	Box 298 × 309 × 9 × 9
	TC4, TC5	Box 298 × 312 × 9 × 12
Top struts	TS1, TS2, TS3, TS4, TS5, TS6, TS7	I 216 × 150 × 8 × 8
Top lateral bracings	TLB2, TLB3, TLB4, TLB5, TLB6, TLB7	T 103 × 150 × 8 × 8
Verticals	V1, V2, V3, V4, V5, V6, V7, V8	I 278 × 170 × 8 × 8
Diagonals	D2, D7	I 278 × 180 × 8 × 8
	D3, D4, D5, D6	Box 278 × 200 × 8 × 8
Bottom chords	BC1, BC2, BC7, BC8	Box 296 × 198 × 8 × 8
	BC3, BC4, BC5, BC6	Box 298 × 202 × 9 × 12
Floor beams	FB1, FB2, FB3, FB4, FB5, FB6, FB7	I 738 × 220 × 9 × 8
	FB end	I 736 × 160 × 8 × 8
Stringers	ST1, ST2	I 721 × 170 × 8 × 10
Bottom lateral bracings	BC1, BC2, BC7, BC8	Box 296 × 198 × 8 × 8
	BC3, BC4, BC5, BC6	Box 298 × 202 × 9 × 12

Figure 1. ADA Bridge Model [17]

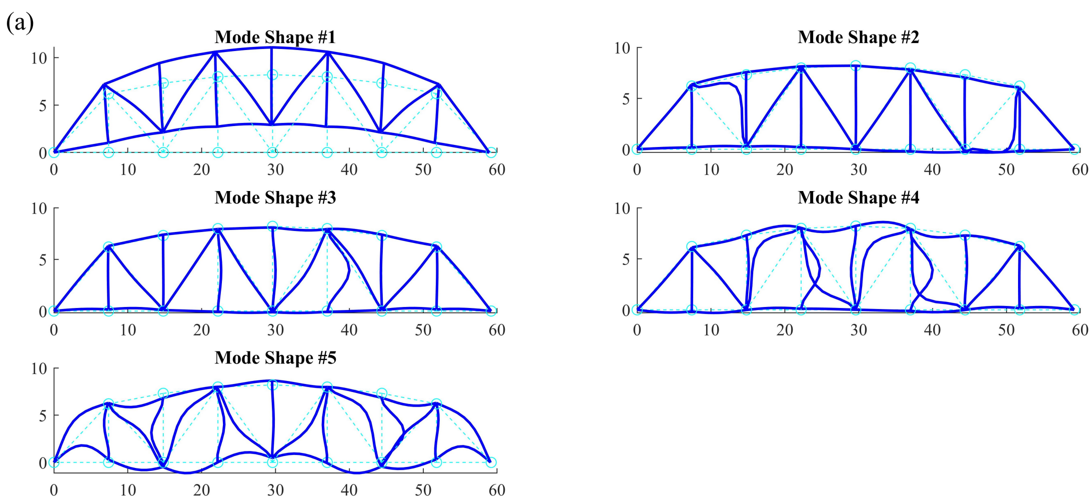


Figure 2. ADA bridge mode shape

certain statements based on other statements.

$$p(\theta|D, M) = \frac{p(D|\theta, M).p(\theta|M)}{p(D|M)} \tag{1}$$

The model updating process involves updating the uncertain variables represented by θ and optimizing the parameters represented by D based on the model assumption represented by M. In this process, the error in the modal parameters of interest, such as natural frequencies or mode shape, is taken as D. The prior, likelihood, and posterior functions are represented by $p(\theta|M)$, $p(D|\theta, M)$, and $p(\theta|D, M)$, respectively, with

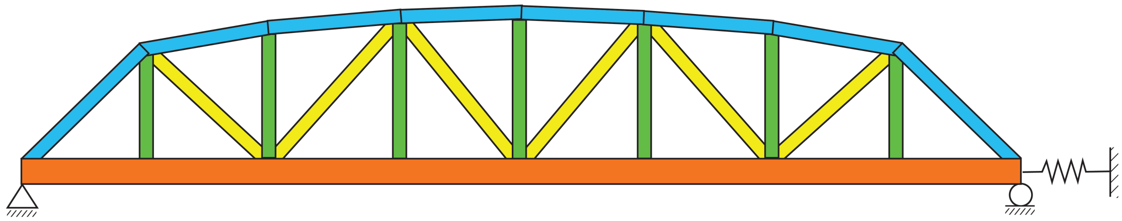


Figure 3. ADA Bridge Model

$p(D|M)$ serving as a normalization factor [18–20].

The likelihood function expresses the degree of agreement between the simulation and the reference modal data for a given set of uncertain parameters θ. In the presented formulations, the dependence on the model assumption M is omitted for the sake of simplicity. Using the axioms of probability the likelihood function yields the following form:

$$\begin{aligned} p(D|\theta) &= c\ exp\left(-\frac{1}{2}J(\theta)\right) \\ J(\theta) &= \sum_{n=1}^{N_t}\sum_{m=1}^{N_m}\left[\frac{1}{\delta_{\psi_m}^{(n)^2}}\left(1-\frac{\langle\hat{\psi}_m^{(n)},\phi_m^{(n)}\rangle^2}{\|\hat{\psi}_m^{(n)}\|^2\|\phi_m^{(n)}\|^2}\right)+\frac{1}{\delta_{\omega_m}^{(n)^2}}\left(1-\frac{\omega_m^{(n)^2}}{\hat{\omega}_m^{(n)^2}}\right)^2\right] \end{aligned} \tag{2}$$

Eq. (2) represents the comprehensive form of likelihood function [10, 15, 21, 22]. in which $\hat{\psi}_m^{(n)}$ and $\hat{\omega}_m^{(n)}$ represent the reference mode shape and natural frequency of the m^{th} mode at n^{th} set of field measurement/experiment, while $\phi_m^{(n)}$ and $\omega_m^{(n)}$ are the mode shapes and natural frequencies of the numerical model. The level of uncertainty in the parameters can be determined by the $\delta_{\psi_m}^{(n)^2}$ and $\delta_{\omega_m}^{(n)^2}$ terms. Transitional Markov Chain Monte Carlo (TMCMC) sampling algorithm is adopted for Bayesian model updating [12, 14, 23].

After conducting a sensitivity analysis, it was found that the elasticity modulus and cross-sectional area are the most influential parameters on the frequencies and mode shapes of the structure. To simplify the analysis, the bridge components were categorized into four groups: bottom chord, top chord, vertical, and diagonal members. All members in each group were assumed to have the same mechanical properties, and their cross-sections were multiplied by a factor that remained constant within each group. It is also worth mentioning that the boundary condition significantly affects the dynamic properties of the system, and the ideal simply supported boundary condition is impossible in practice. To model the system's friction, a horizontal linear spring with an unknown stiffness was included, as depicted in Figure 3.

Normal distribution around the original values has been adopted as the prior function for all parameters to be updated. Error in the prediction of natural frequencies and mode shapes is minimized subsequently according to Eq.(2). Generally, the first or second modes are typically investigated in the VBI framework. The 2D model developed for the ADA bridge is also incapable of capturing torsional modes. As a result, the model

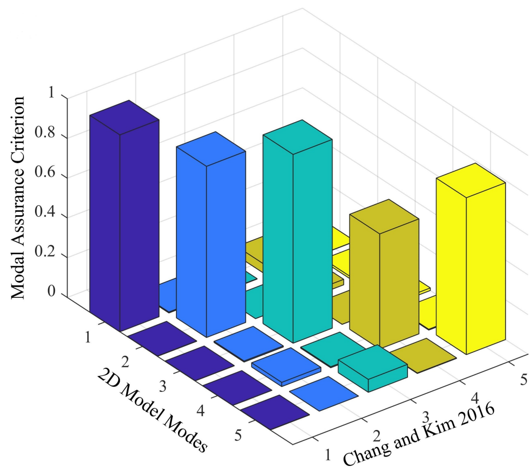


Figure 4. Updated ADA bridge MAC number

updating process has been focused on optimizing the first three bending modes. Tables I and II present uncertain parameters as well as natural frequencies, before and after model updating process. MAC numbers of the updated ADA bridge model are also provided in Figure 4.

The original work by Zhou et al. [15] neglected the uncertainty in cross-section areas, which is revealed to significantly affect the dynamic properties of the bridge. The cross-section areas determine the neutral axis and the second moment of inertia of the entire system, and their axial stiffness contributes to the overall stiffness matrix. Despite being ignored in the previous study, it is revealed that this uncertainty affects the bridge's

TABLE I. UPDATED PARAMETERS

Uncertain parameter	Member group	Before updating	Updated
Elasticity Modulus	Bottom chord	$2 \times 10^{11}\ Pa$	$1.92 \times 10^{11}\ Pa$
	Top chord	$2 \times 10^{11}\ Pa$	$1.56 \times 10^{11}\ Pa$
	Vertical members	$2 \times 10^{11}\ Pa$	$1.85 \times 10^{11}\ Pa$
	Diagonal members	$2 \times 10^{11}\ Pa$	$2.11 \times 10^{11}\ Pa$
Section area multiplier	Bottom chord	1	1.01
	Top chord	1	1.02
	Vertical members	1	0.60
	Diagonal members	1	0.62
Spring stiffness	-	$0\ \frac{N}{m}$	$1.77 \times 10^{8}\ \frac{N}{m}$

TABLE II. UPDATED NATURAL FREQUENCIES

	Field Test	Before updating		After updating	
	Freq.(Hz)	Freq.(Hz)	Error(%)	Freq.(Hz)	Error(%)
Mode 1	2.975	3.220	8.24%	2.975	-0.02%
Mode 2	6.872	8.085	17.65%	6.890	0.27%
Mode 3	9.608	11.206	16.65%	9.620	0.13%

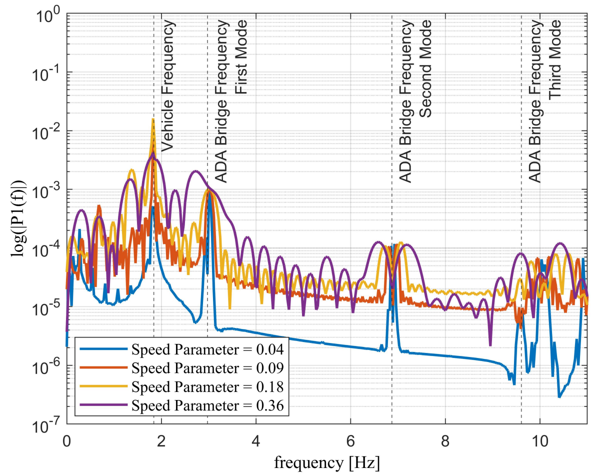


Figure 5. Acceleration spectrum of the vehicle passing over the ADA bridge for different speed parameters ($\pi v/L\omega_b$)

dynamic properties significantly. Table II and the accompanying figure 4 demonstrate a strong agreement between the natural frequencies of the updated model and field test data, indicating the effectiveness of the applied TMCMC algorithm in updating the model with 9 uncertain parameters. By further tuning these uncertain parameters, the accuracy of the updated model can potentially be improved even further. Therefore, the updated model can be used as a digital twin of the structure in structural health monitoring applications.

VEHICLE BRIDGE INTERACTION

Dynamic response of the bridge subjected to a moving vehicle is studied in this section. The bottom chord members are subjected to a moving single-degree-of-freedom system, representing the passing vehicle. It is assumed that the unsprung mass is always in contact with the beam. The interaction forces existing at the contact point make the two subsystems coupled. Two sets of second-order equations of motion, for vehicle and bridge, have to be solved for the purpose of vehicle–bridge systems analysis. Normally, these two coupled equations are solved simultaneously by the use of the Newmark-β time-integration technique. VBI problems, however, may encounter some instabilities in the system which can not be handled by the conventional Newmark method. The generalized-α method provides an alternative with the ability to handle stiff and highly nonlinear systems, and it has been widely used in engineering simulations for dynamic analysis of structures and fluids [24, 25]. It also shows superior performance against numerical instabilities associated with complicated VBI cases. Vertical acceleration spectrum of the sprung mass is presented in figures 5 and 6. The road surface profile is randomly generated according to Power Spectral Density (PSD) functions provided by ISO 8608 (International Organization for Standardization) [26].

The figures 5 and 6 demonstrate the effective extraction of bridge frequencies using the proposed simplification. The first three vibration frequencies are captured success-

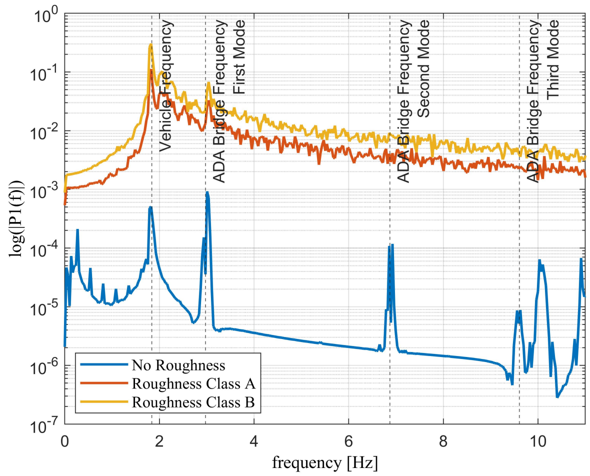


Figure 6. Acceleration spectrum of the vehicle passing over the ADA bridge varying the extent of road surface roughness - speed parameters $\pi v/L\omega_b = 0.04$

fully. However, in order to ensure accurate ADA bridge frequency extraction, a lower vehicle speed is required, as higher speeds can reduce accuracy and magnify the vehicle frequency. It also shows acceptable performance in frequency extraction in the presence of road surface roughness. However, distinguishing the bridge frequencies from roughness-induced frequencies is still a challenging issue. This data can be further processed to identify any potential structural damage. The developed approach reduces the computational expenses and provides a promising methodology for indirect data-driven damage detection techniques which require a large number of simulations.

CONCLUSION

The use of Bayesian finite element model updating has become prevalent in the calibration of numerical models in civil infrastructures. In this study, the ADA bridge's finite element model was successfully updated, resulting in the first three modes being in excellent agreement with field test data. As a result, the 2D model can effectively represent the actual structure while minimizing computational effort. The efficiency of the Transitional Markov Chain Monte Carlo algorithm in dealing with high-dimensional problems was demonstrated. The vehicle bridge interaction was studied subsequently. The proposed approach was capable of extracting the bridge's dynamic properties, even in the presence of road surface roughness. This methodology provides a promising technique for indirect data-driven bridge health monitoring projects which rely on a large number of simulations.

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