An Intelligently Designed AI for Structural Health Monitoring of a Reinforced Concrete Bridge

Conference Paper · January 2021

5 authors, including:

William Locke
Clemson University

Stefani C Mokalled
Clemson University

Omar R. Abuodeh
Clemson University

Laura Redmond
Georgia Institute of Technology

An Intelligently Designed AI for Structural Health Monitoring of a Reinforced Concrete Bridge

William R. Locke, Stefani C. Mokalled, Omar R. Abuodeh, Laura M. Redmond, Christopher S. McMahan

Synopsis: With recent advances in online sensing technology and high-performance computing, structural health monitoring (SHM) has begun to emerge as an automated approach to the real-time conditional monitoring of civil infrastructure. Ideal SHM strategies detect and characterize damage by leveraging measured response data to update physics-based finite element models (FEMs). When monitoring composite structures, such as reinforced concrete (RC) bridges, the reliability of FEM based SHM is adversely affected by material, boundary, geometric, and other model uncertainties. Civil engineering researchers have adapted popular artificial intelligence (AI) techniques to overcome these limitations, as AI has an innate ability to solve complex and ill-defined problems by leveraging advanced machine learning techniques to rapidly analyze experimental data. In this vein, this study employs a novel Bayesian estimation technique to update a coupled vehicle-bridge FEM for the purposes of SHM. Unlike existing AI based techniques, the proposed approach makes intelligent use of an embedded FEM model, thus reducing the parameter space while simultaneously guiding the Bayesian model via physics-based principles. To validate the method, bridge response data is generated from the vehicle-bridge FEM given a set of "true" parameters and the bias and standard deviation of the parameter estimates are analyzed. Additionally, the mean parameter estimates are used to solve the FEM model and the results are compared against the results obtained for "true" parameter values. A sensitivity study is also conducted to demonstrate methods for properly formulating model spaces to improve the Bayesian estimation routine. The study concludes with a discussion highlighting factors that need to be considered when leveraging experimental data to update FEMs of concrete structures using AI techniques.

Keywords: Artificial Intelligence, Bayesian Statistics, Structural Health Monitoring, Reinforced Concrete, Highway Bridges, Vehicle-Bridge Interactions.

ACI student member **William R. Locke** is a Doctoral Candidate in the Glenn Department of Civil Engineering at Clemson University. His research focuses on indirect methods for SHM and resilient infrastructure systems.

Dr. Stefani C. Mokalled is a Quantitative Financial Analyst at Bank of America in Charlotte, NC. Her research focuses on the development of statistical models for the analysis of complex data.

ACI student member **Omar R. Abuodeh** is a Doctoral Student in the Glenn Department of Civil Engineering at Clemson University. His research is focused on SHM and resilient infrastructure, nonlinear finite element modelling of reinforced concrete members, and employing AI techniques to analyze structural-related compiled data.

ACI Member **Dr. Laura M. Redmond** is an Assistant Professor in the Departments of Civil and Mechanical Engineering at Clemson University. Her research spans advanced finite element and dynamic simulations for civil, mechanical, and aerospace applications, model calibration, and verification and validation by test.

Dr. Christopher S. McMahan is an Associate Professor in the School of Mathematical and Statistical Sciences at Clemson University. His research interests include statistical computing, Bayesian parametric/nonparametric estimation, high dimensional regression, machine learning, epidemiology/public health, and biomedical applications.

INTRODUCTION

As sensor technology has continued to advance, the volume of data being transmitted for structural health monitoring (SHM) has also increased, creating the need for processing procedures capable of rapidly analyzing data to reliably diagnose system health. Artificial intelligence (AI) has emerged as a popular solution to this big data problem in civil engineering, as AI techniques are able to solve complex and ill-defined problems associated with big data and damage detection[1]. Engineers have employed AI for automated damage detection when working with physics or data-driven SHM strategies. A fundamental issue with data-driven SHM is that techniques require training on difficult to obtain labeled data from different damage scenarios in order to fully diagnose the anomalous behavior of a system (i.e. detect, locate, and quantify damage)[2,3]. Physics-based SHM utilizes numerical models to identify damage through updating strategies or by comparing response features from a baseline model to changes in physical data[4]. AI techniques are typically employed under this framework to update models by tuning against experimental data, which has the dual benefit of being able to detect, locate, and quantify damage, while simultaneously identifying uncertain model parameters (e.g., material, geometric, and boundary conditions). Being able to identify uncertain model parameters is especially beneficial when monitoring composite structures, such as reinforced concrete (RC) bridges, as the presence of material and/or geometric non-linearities are difficult to accurately predict and capture[2,4]. An additional benefit of physics-based SHM is updated models can be employed to evaluate the effect of damage on structural performance and forecast a system's remaining service life.

This study aims to demonstrate the capabilities of a novel Bayesian estimation technique to update a simplified vehicle-bridge finite element model (FEM) for the purpose of identifying crack damage on a RC bridge. Unlike most existing AI based techniques that rely on data from nonintegrated FEMs or surrogate models, the proposed approach makes intelligent use of an embedded FEM, thus reducing the parameter space while simultaneously guiding the Bayesian model via physics-based principles[2,4]. Furthermore, unlike most model updating strategies that locate damage induced changes in stiffness by minimizing an objective function based on differences in measured and analytical modal properties, the proposed approach identifies damage by tuning element level stiffness in the embedded model to minimize the difference between measured and predicted acceleration time histories[4]. The benefit of directly leveraging time history data is that more response features are available to improve tuning; additionally, time history data is less sensitive to higher order modes with low levels of excitation that are difficult to accurately capture in simplified FEMs. In this study, a numerical analysis is conducted to demonstrate the reliability of the Bayesian approach when a subject FEM is complex enough to capture all the modal properties of a "physical" structure. A sensitivity study is also conducted with the vehicle-bridge FEM to demonstrate how the uncertain parameter space can be reduced to address run-time issues that arise when applying the proposed Bayesian estimation technique towards a system with many unknown parameters that are essential to capturing physical system properties. The study concludes with a discussion highlighting some of the benefits and limitations associated with the proposed estimation technique, as well as outlining factors that need to be considered when employing physics-based SHM strategies.

Physical Vehicle-Bridge System

This section provides a description of the physical RC bridge and test vehicle modeled for the numerical study performed to demonstrate the capabilities of AI based SHM. Brief details are also provided for how experimental data from the physical system could be leveraged for updating a coupled vehicle-bridge FEM.

Bridge and Vehicle Descriptions

The reinforced concrete bridge employed in this study consists of four 9.14m long simply supported spans that each have a cross-section as seen in Fig. 1. The subject structure is located along US-221, which serves as a transportation route for tractor-trailers supporting logging and other shipping industries. Because of this, the structure is constantly exposed to loads on the order of HL-93 design loads. During a visual inspection conducted in March of 2018, the superstructure received a condition rating of 6 out of 9 due to the presence of flexural cracks at the center of each span; static load tests conducted in July of 2019 identified extensive flexural cracks on one of the exterior spans that were observed to propagate further under the presence of heavy trucks[5]. The presence and continuing propagation of cracks makes the subject exterior bridge span ideal for demonstrating the capabilities of AI based SHM techniques.

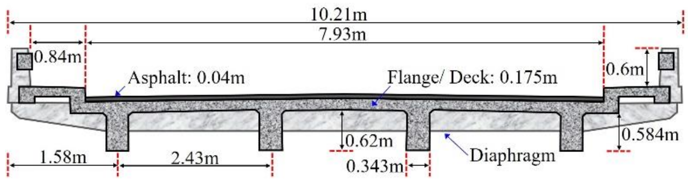

Fig. 1—Cross-section of subject reinforced concrete bridge.

The test vehicle used to dynamically excite the bridge in this study is a 2005 RAM 2500 series truck with a wheelbase of 3.57m and a front/rear track of 1.74m. The total mass with a driver and passenger is approximately 2812kg, with the front and rear mass distribution being 1509kg and 1303kg, respectively. The vehicle has an independent front suspension with coil springs and a live axle rear suspension with leaf springs.

Damage Detection Strategy

When performing model updating with real system response data, a series of dynamic tests would be conducted to capture time history responses under controlled but realistic operating conditions (e.g., single vehicle crossing when the bridge is free of other traffic). Obtaining data under controlled conditions is important when performing updating directly with time-history data, as unknown sources of excitation, such as that introduced by random traffic, cannot be accurately captured in a FEM and will introduce more model uncertainty[6]. An ideal time history response is one that has been obtained from a known input excitation or from a source that can realistically be represented in a model. For the subject vehicle-bridge system, input excitations on the bridge can realistically be captured in the FEM by accurately modeling vehicle dynamic properties and the surface roughness profile. To minimize discrepancies between the embedded FEM in the Bayesian estimation approach and the physical data used for model inputs, the experimental data would be processed to remove linear trends, aliasing, and high frequency noise effects that are difficult to account for in a simplified FEM. Once processed, the experimental data could then be input to the Bayesian estimation routine.

In this study, model updating is performed using simulated data obtained from a coupled vehicle-bridge FEM with a set of "true" parameter values. On each step of the Bayesian algorithm, the "true" simulated data are compared against the solution to the FEM model given the current set of parameter estimates. Hence, the FEM is embedded within the Bayesian method and is solved on each iteration to allow for parameter updating.

Analytical Methods and Procedures

This section discusses the methodologies employed to model coupled vehicle-bridge interactions and perform the Bayesian estimation. Vehicle and bridge systems are modeled as if the coupled system is being tuned using real measured data, meaning the model attempts to capture real material properties, boundary conditions, and damage.

Coupled Vehicle-Bridge Model

The vehicle-bridge model employed in this study is outlined in Fig. 2, where the 6 degree-of-freedom (DoF) half-car model is coupled to the occupied 4 DoF bridge elements at points of contact using the concept of vehicle bridge interactions[7]. The bridge is discretized into ten elements, where the mass and stiffness of each element is modeled using traditional 4 DoF Euler-Bernoulli stiffness and continuous mass matrices; Rayleigh damping is used to model the global bridge damping matrix[8]. To account for the noteworthy sources of excitation introduced to the physical vehicle by surface roughness, a class A surface profile is generated using ISO-8608:2016 standards and interfaced into the model using the approach outlined by Yang et al.[7,9,10]. The model solution is obtained using Newmark Beta numerical integration with a time step of 0.001 seconds (i.e., f_s = 1000 Hz)[7,8].

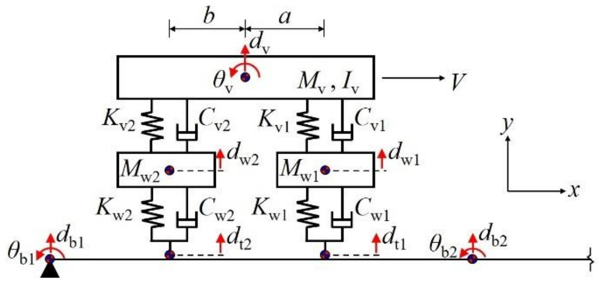

Fig. 2—Interaction between 6 DoF half-car model and 4 DoF bridge elements.

Equivalent Parameter Values

The half-car model is a simplified representation of the RAM test vehicle and has the equivalent dynamic properties outlined in Table 1. It should be noted the properties in Table 1 were obtained from previous experimental vehicle tests and manufacturer specifications[11]. The truncated normal (*TN*) distributions on the stiffness parameters are attributed to a lack of available information on suspension properties and stochastic variables affecting tire stiffness (e.g., pressure, temperature, wearing, etc...). More information on parameter distributions is provided in the Bayesian Methodology for Parameter Estimation section.

Table 1— Equivalent half-car properties

Properties		**Values**
Mass	M_V (kg)	2556
	$M_{W1,2}$ (kg)	128
	I_V (kg m^2)	11508
Stiffness	K_{V1} (kN m^{-1})	*TN*(1.40e+5, 5667, (1.23e+5, 1.57e+5))
	K_{V2} (kN m^{-1})	*TN*(1.05e+5, 5667, (8.80e+4, 1.22e+5))
	$K_{W1,2}$ (kN m^{-1})	*TN*(1.00e+6, 1.6e+5, (5.20e+5, 1.48e+6))
Damping	$C_{V1,2}$ (N s m^{-1})	2500
	$C_{W1,2}$ (N s m^{-1})	0
Length	a (m)	1.64
	b (m)	1.93

Note: *TN* denotes a truncated normal prior distribution and indicates the subject parameter is tuned by the Bayesian estimation routine.

The equivalent area method is employed to simplify the entire cross-section in Fig. 1 to an equivalent rectangular cross-section of concrete; the equivalent model properties are shown in Table 2. From the static load tests previously conducted on the bridge, it was determined that the support bearings resist horizontal movement, resulting in an increase in bending stiffness and partial fixity at the supports that is analytically accounted for using rotational springs ($k_{r1,2}$)[5,12-13]. To account for uncertainties in longitudinal stiffness introduced by modelling assumptions, creep, shrinkage, and cracking, the stiffness (*EI*) of each element is multiplied by a stiffness modifier parameter (Ψ_{1-10}).

Table 2— Equivalent bridge properties

Properties		**Values**
Mass	ρ (kg m^{-1})	*TN*(8750, 250, (8000, 9500))
Stiffness	EI (N m^2)	5.73e+9
	Ψ_{1-10}	*TN*(1.0,0.2,(0.4,1.6))
	$K_{r1,2}$ (N-m rad^{-1})	*U*(0.0, 1e+10)
Damping	ζ (%)	*U*(0.15, 4.5)

It should be noted that additional factors could be considered to improve vehicle-bridge model accuracy and capture realistic operational and environmental effects (e.g., ambient temperature and gradient effects, nonlinear breathing cracks, or nonlinear suspension properties); however, these factors are ignored in this study to reduce the parameter space and computation times. In this same vein, the fixed parameters in Tables 1 and 2 (e.g., vehicle length, mass, and damping) are held constant to reduce the uncertain parameter space for the numerical damage detection demonstration conducted in this study; these parameters could, however, be treated as uncertain and updated when working with real measured data or more complex vehicle-bridge models.

Bayesian Methodology for Parameter Estimation

The development of the proposed Bayesian estimation technique relies on the embedding of the FEM into a statistical model. Herein, a description is provided for how this is accomplished. To this end, let $\ddot{b}_k \in R^T$ be a vector of acceleration data obtained from the coupled vehicle-bridge FEM measured at T time steps. It is assumed that there are N DoF from which data are obtained and $k \in \{1, \dots, N\}$ is the k^{th} DoF. Let x_k denote the known fixed inputs (e.g., vehicle length, mass, damping, etc…) to the FEM and $\delta = (\delta_1, \dots, \delta_p)'$ be the unknown model parameters; see Tables 1 and 2. Note that all these variables are bounded (i.e., $\delta_j \in [l_j, u_j]$ for $j = 1, \dots, J$). It is assumed that:

$$\ddot{b}_k = f(x_k, \delta) + \epsilon_k, \tag{1}$$

where $f(x_k, \delta)$ represents the solution to the FEM at the parameter settings x_k and δ, while ϵ_k denotes the usual error term. In this study, it is assumed that ϵ_k consists of both measurement and model errors, which are assumed to be normally distributed with mean 0 and covariance matrix $\varphi^{-1}\mathbf{I}$ such that the errors are uncorrelated (i.e., $\epsilon_k \sim MVN(0, \varphi^{-1}\mathbf{I})$). In this problem, it is assumed that the only discrepancy between the FEM and the observed simulation data is measurement and model error such that the FEM captures the "true" acceleration responses at the time steps which correspond to the measurements $\ddot{b}_k$. This assumption is reasonable for the purpose of this study. Adaptations can be made allowing the incorporation of correlation in error terms via functional forms on the covariances[14]. Under these assumptions, it is established that:

$$\ddot{b}_k | x_k, \delta, \varphi \sim MVN(f(x_k, \delta), \varphi^{-1}\mathbf{I}). \tag{2}$$

To complete the Bayesian model, the following priors are specified for the model parameters:

- $\varphi \sim gamma(a_0, b_0)$
- $\delta_j \sim TN\left(\mu_j, \tau_j, (l_j, u_j)\right), j \in P_{TN}$
- $\delta_j \sim U(l_j, u_j), j \in P_U,$

where $TN(\mu, \tau, (l, u))$ denotes a truncated normal distribution with mean μ, variance τ, and bounds (l, u), and $U(l, u)$ is a uniform distribution with lower and upper bounds l and u, respectively. Note that P_{TN} and P_U are sets of indices corresponding to parameters whose priors are truncated normal and uniform distributions, respectively. To facilitate model fitting, a posterior sampling algorithm is developed which draws realizations from the posterior distribution given by:

$$\begin{aligned} p(\varphi, \delta | B) &\propto \varphi^{\frac{NT}{2}} \exp\left[\frac{-\varphi \sum_{k=1}^{N} \{\ddot{b}_k - f(x_k, \delta)\}' \{\ddot{b}_k - f(x_k, \delta)\}}{2}\right] \\ &\times \prod_{j \in P_{TN}} \tau_j^{\frac{1}{2}} \exp\left\{\frac{-(\delta_j - \mu_j)^2}{2}\right\} I(l_j < \delta_j < u_j) \prod_{j \in P_U} \mathbf{I}(l_j < \delta_j < u_j) \\ &\times \varphi^{a_0 - 1} \exp(-b\varphi), \end{aligned} \tag{3}$$

where $B = \{\ddot{b}_1, \ddot{b}_2, \dots, \ddot{b}_N\}$ is a matrix of observed data, with the k^{th} column of the matrix corresponding to the acceleration responses obtained from the k^{th} sensor. Since the posterior distribution is not of a known distributional family, a Markov Chain Mone Carlo (MCMC) sampling algorithm which consists of Gibbs and Metropolis-Hastings (MH) steps is considered. In particular, φ is sampled using a Gibbs step, while $\delta_j, j = 1, \dots, J$ are sampled using MH steps. To elucidate these steps, the full conditional distribution of φ is given by:

$$\varphi|\delta, B \sim gamma\left(\frac{NT}{2} + a_0, \frac{\sum_{k=1}^{N}\{\ddot{b}_k - f(x_k,\delta)\}'\{\ddot{b}_k - f(x_k,\delta)\}}{2} + b_0\right), \tag{4}$$

where the inputs to the gamma distribution are shape and scale parameters, respectively. The hyperparameters were set to be $a_0 = 1$ and $b_0 = 0$ such that the prior is weakly informative. The full conditional distributions of $\delta_j, j \in P_{TN}$ and $\delta_j, j \in P_U$ are given by:

$$p(\delta_j|B,\varphi,\delta_{(-j)}) \propto \exp\left[\frac{-\varphi\sum_{k=1}^{N}\{\ddot{b}_k - f(x_k,\delta)\}'\{\ddot{b}_k - f(x_k,\delta)\}}{2}\right]\tau_j^{\frac{1}{2}}\exp\left\{\frac{-(\delta_j-\mu_j)^2}{2}\right\}I(l_j < \delta_j < u_j), \tag{5}$$

$j \in P_{TN}$

$$p(\delta_j|B,\varphi,\delta_{(-j)}) \propto \exp\left[\frac{-\varphi\sum_{k=1}^{N}\{\ddot{b}_k - f(x_k,\delta)\}'\{\ddot{b}_k - f(x_k,\delta)\}}{2}\right]I(l_j < \delta_j < u_j),\ j \in P_U, \tag{6}$$

respectively. The vector $\delta_{(-j)}$ contains all the unknown parameters with the j^{th} element removed. Note that these distributions do not belong to a common family, and MH steps were used to sample from these full conditionals. In implementing the MCMC algorithm, the first r iterates were discarded as a burn in. Using the remaining iterates, posterior estimation and inference may proceed as usual. For further discussion on these standard practices please see[15].

Study Demonstrating Damage Detection Capabilities of Bayesian Methodology

In this section a numerical study is conducted to validate the Bayesian estimation approach and demonstrate its damage detection capabilities.

Scope

To validate the damage detection capabilities of the Bayesian estimation routine, "true" parameter values are assigned to the vehicle and bridge parameters. Damage is applied as a 20% reduction in stiffness on two elements of the bridge (i.e., $\Psi_{6,7} = 0.8$); the selected locations are in line with the location of severe flexural cracking observed on the physical structure[5]. A low level of noise is added to each response vector such that a signal-to-noise ratio (SNR) of 40db is recorded for the subject response data. For this study, only the vertical acceleration response of the central bridge node is recorded; this is the equivalent of having a single accelerometer located at mid-span of the physical structure. Noisy simulation data is obtained for two separate vehicle crossings, which is the equivalent of obtaining real data from two separate dynamic vehicle tests. To perform posterior estimation and inference, the posterior sampling algorithm was used to draw 8000 MCMC samples with a burn in period of 3000 iterations. Thinning was performed such that every 5th iterate was retained. Hence, 1000 MCMC iterations were included for estimation and inference. The algorithm was implemented on 75 different data sets. Table 3 indicates the "true" values assigned to each parameter and provides a summary of the mean parameter estimates and standard deviations obtained by the estimation routine.

Results

A summary of the mean estimates, average standard deviations, and bias from the 75 data sets can be seen in Table 3. From the results, the Bayesian methodology seems to be performing well in terms of parameter estimation, with bias and standard deviations being small for all parameters. From a SHM perspective, the model updating procedure was also able to accurately locate and quantify the magnitude of damage on bridge elements 6 and 7. It is also observed, however, that the Bayesian methodology appears to have incorrectly identified the true stiffness values for elements at the ends of the bridge. This observation is attributed to inadequate spatial coverage of sensor data across the bridge and the fact that variations in stiffness at the ends of the bridge have little influence on the acceleration response at mid-span; this is evidenced by Fig. 3 where there are only minor differences in the solution to the FEM given the mean estimates of the parameters compared with the observed simulation data. Other studies have also indicated that inadequate spatial coverage of sensor networks can lead to biased models that do not necessarily represent true operating conditions[4,6,16]. This issue can easily be overcome by increasing the number of measurement locations on the bridge or using response data from the vehicle; leveraging vehicle acceleration data is beneficial as it allows instantaneous acceleration data to be collected across the whole bridge span, which can improve damage detection, localization, and quantification[7,17-19].

Table 3: Comparison of parameter estimates from Bayesian routine against "true" parameter values

Bridge Parameters												
	ρ [kg m^{-1}]	Ψ_1	Ψ_2	Ψ_3	Ψ_4	Ψ_5	Ψ_6	Ψ_7	Ψ_8	Ψ_9	Ψ_{10}	ζ [%]	$\theta_{b1,2}$ [N-m rad^{-1}]
Truth	8750	1.0	1.0	1.0	1.0	1.0	0.8	0.8	1.0	1.0	1.0	3.0	1.0e+9
Mean	8771	0.6	0.8	0.9	0.9	1.0	0.8	0.8	1.0	1.1	1.5	3.3	1.0e+9
STDV	39.3	0.1	0.2	0.1	4e-2	6e-3	2e-2	4e-2	0.1	0.1	2e-2	7.6e-2	2.6e+7
Bias	-21	0.4	0.2	0.1	-0.1	-0.2	0.2	0.2	-0.1	-0.1	-0.5	-0.3	-7.9e+6

Vehicle Parameters			
	K_{V1} [kN m^{-1}]	K_{V2} [kN m^{-1}]	$K_{w1,2}$ [kN m^{-1}]
Truth	1.4e+5	1.05e+5	1.06e+6
Mean	1.4e+5	1.0e+5	9.6e+5
STDV	2.4e+3	2.5e+3	1.7e+5
Bias	-5.8e+2	1.1e+3	4.2e+4

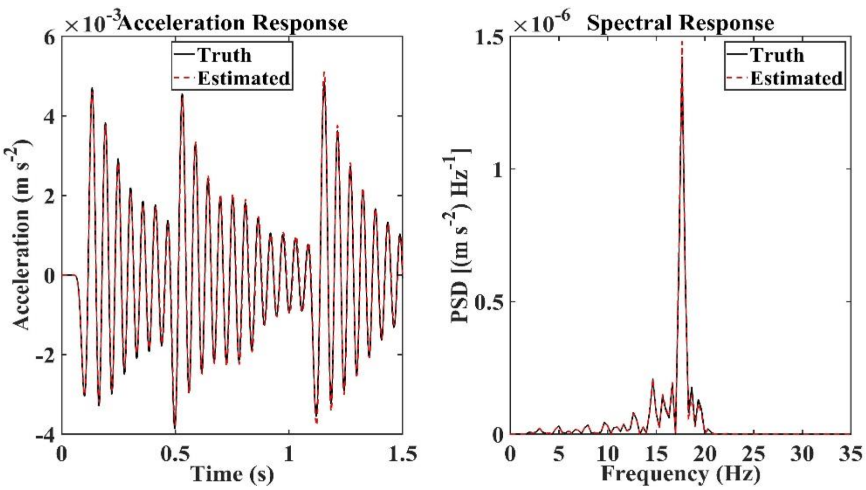

Fig. 3—Compares the "true" simulated response against the estimated response in the time and frequency domain. Results indicate that tuned model captures the "true" response with minimal differences despite some bias introduced by limited spatial coverage of sensors.

Sensitivity Analysis Demonstrating Reduction of Uncertain Parameter Space

This section provides a brief discussion on parameters identified as essential for modeling the physics of RC bridges that were excluded from the initial feasibility demonstration of the Bayesian technique. Additionally, issues pertaining to large uncertain parameter spaces in the proposed Bayesian routine are discussed, and a sensitivity analysis is conducted to demonstrate how the parameter space can be reduced. A final discussion is provided for general concepts that should be considered when leveraging Bayesian estimation methods for other SHM applications.

Additional Parameter Uncertainties to Consider for RC Bridge FEM Accuracy

When tuning a RC bridge model with experimental data, it is imperative that ambient temperature effects, surface roughness, and nonlinear crack damage effects be accurately represented in the model or mitigated during testing. Ambient temperature is known to cause significant linear and non-linear fluctuations in bridge modal properties that can easily be mistaken as damage[6,13,20]. Several methods exist for modeling temperature effects in simulation, but the effects can also be mitigated by conducting tests at the same time of day and/or at the same ambient temperatures[13,20]; the incorporation of data-driven approaches has also shown success in managing temperature effects[6]. Surface roughness is known to amplify the dynamic interaction between vehicles and bridges, and if not properly modeled can lead to numerical ill-conditioning. In the numerical study, the modeled surface roughness profile was taken as a known quantity, but it could be obtained from a physical bridge by analyzing acceleration or laser displacement data measured on monitoring vehicles during testing[18,19,21]. Nonlinear crack effects are introduced when breathing is exciting within a crack, causing continuous fluctuations in stiffness and damping that can make identifying damage difficult. Nonlinear crack effects can be captured using rotational springs with bilinear stiffness or other fracture mechanics based methods[22,23]. The need to model nonlinear cracking can be mitigated if experimental data is measured for low levels of excitation where breathing is not excited[22,23].

Computational Limitations of Bayesian Estimation Routine

The inclusion of the above-mentioned parameter uncertainties, in addition to the uncertainties in vehicle-bridge mass, stiffness, and damping parameters, can significantly increase the computational cost of Bayesian estimation and result in higher run-times[4,6,16]. One approach to reducing run times is to perform a sensitivity analysis to identify the impact parameter uncertainties have on fluctuations in response data. Through this approach, parameters demonstrating little to no influence on response data can be held constant and removed from the model updating space. In this study, Analysis of Variation and the Coefficient of Determination (R^2) are employed to demonstrate the sensitivity of the output response features to uncertainties in the parameters in Tables 1 and 2[24]. For this analysis, distributions are assigned to the parameters that were previously fixed in Tables 1 and 2, and a number of surface profiles (*Road*) are generated to demonstrate the impact varying elevation profiles can have on response data. Note the R^2 metric provides a measure for the influence each parameter has on response features, where a 100 indicates uncertainty in an input accounts for 100% of the observed variations in a response, and 0 indicates uncertainty in an input causes no measurable change in a response. Table 4 indicates the results of the sensitivity study.

Table 4: R^2 values indicating mean contribution of parameter uncertainties to variability in time history response.

Bridge Parameters													
	ρ	Ψ_1	Ψ_2	Ψ_3	Ψ_4	Ψ_5	Ψ_6	Ψ_7	Ψ_8	Ψ_9	Ψ_{10}	ζ	$\theta_{b1,2}$
Mean R^2	3.07	0.74	1.05	2.38	4.01	5.46	6.54	3.63	2.02	1.35	0.77	1.0	34.00

Vehicle Parameters										
	M_V	$M_{W1,2}$	I_V	K_{V1}	K_{V2}	$K_{W1,2}$	$C_{V1,2}$	$C_{W1,2}$	a,b	*Road*
Mean R^2	8.64	4.33	0.13	1.07	0.75	6.76	3.7	1.06	2.41	5.11

The sensitivity results in Table 4 agree with the conclusion from the numerical damage detection study in that the stiffness of the end elements has less of an impact on the mid-span acceleration response; these parameters, however, cannot be removed from the updating space because they are needed for damage detection. It can also be seen that ζ, $C_{W1,2}$, I_V, K_{V1}, and K_{V2} have an insignificant impact on variations in the mid-span response, indicating these parameters can be removed from the model updating space without affecting the ability of the model to capture the "true" mid-span acceleration response. Furthermore, it is observed that uncertainty in previously fixed properties (e.g., M_V, $M_{W1,2}$, and *Road*) can have a significant impact on variations in system response; indicating these parameters are essential and should be tuned if they cannot be identified prior to model development. For surface roughness specifically, everything should be done to obtain an accurate profile prior to model development, as each individual elevation would need to be treated as an uncertain parameter if tuned as part of the Bayesian estimation approach. As an example, an additional 751 parameters would have been added to the model updating space for the numerical damage detection study that was only analyzing a 1.5 second time history. If surface roughness cannot be identified prior to model development, model updating can be performed sequentially to identify and then fix certain parameter estimates[25]. Through this approach, the model updating space can be incrementally reduced while computational times remain small. Another approach for reducing the uncertain parameter space in higher fidelity models is to employ substructuring, where system properties are grouped into a subcomponent that is itself then updated as a piece of the entire system[4,16].

General Considerations for the Use of Bayesian Estimation in SHM

When estimating parameters, it is important to consider any interdependencies between two parameters (e.g., the relationship of stiffness and mass to changes in frequency) as this can lead to a non-identifiability issue; the parameter space may be reduced to resolve this issue. Care must also be taken in specifying prior distributions to reflect the physical properties of each parameter. If knowledge does not exist on the distribution, a weakly informative prior can be specified such that the observed data provide more information to the model. Lastly, validation metrics, such as the Root-Mean-Square-Error, should be levered to identify how well a model fits the true system response.

Conclusion

In this study, a novel Bayesian estimation technique was employed to update a simplified vehicle-bridge FEM for the purpose of identifying crack damage on a RC bridge. From a numerical study, the proposed methodology demonstrated promising model updating and damage detection capabilities, with parameter estimate bias being relatively limited and mean parameter estimates producing nearly identical acceleration and frequency responses. Furthermore, identified issues and limitations with employing the methodology towards physical data do not appear to be significant and can easily be addressed through sensitivity studies and modifying experimental procedures. Overall, this study provides a generalizable framework for concepts and procedures that need to be considered when employing Bayesian estimation techniques for performing model updating and SHM on reinforced concrete bridge structures.

References

[1] Pengzhen Lu, Shengyong Chen, and Yujun Zheng. Artificial intelligence in civil engineering. Mathematical Problems in Engineering, 2012, 2012.

[2] Charles R Farrar and Keith Worden. Structural health monitoring: a machine learning perspective. John Wiley& Sons, 2012.

[3] Fuh-Gwo Yuan, Sakib Ashraf Zargar, Qiuyi Chen, and Shaohan Wang. Machine learning for structural health monitoring: challenges and opportunities. In Sensors and Smart Structures Technologies for Civil, Mechanical, and Aerospace Systems 2020, volume 11379, page 1137903. International Society for Optics and Photonics,2020.

[4] Parisa Asadollahi. Bayesian-based Finite Element Model Updating, Damage Detection, and Uncertainty Quantification for Cable-stayed Bridges. PhD thesis, University of Kansas, 2018.

[5] Paul Ziehl, Tommy Cousins, Brandon Ross, and Nathan Huynh. Assessment of structural degradation for bridges and culverts. Technical report, 2020.

[6] Elisa Khouri Chalouhi. Structural health monitoring of bridges using machine learning: The influence of temperature on the health prediction, 2016.

[7] Yang, Yeong-Bin, J. D. Yau, Zhongda Yao, and Y. S. Wu. Vehicle-bridge interaction dynamics: with applications to high-speed railways. World Scientific, 2004.

[8] Anil K. Chopra. Dynamics of structures. Upper Saddle River, NJ: Pearson Education, 2012.

[9] M. Agostinacchio, D. Ciampa, and S. Olita. The vibrations induced by surface irregularities in road pavements–a Matlab® approach. European Transport Research Review, 6(3):267–275, 2014.

[10] I ISO. Mechanical vibration—road surface profiles—reporting of measured data, 2016.

[11] William R. Locke, Laura Redmond, and Matthias Schmid. Experimental Evaluation of Drive-by Health Monitoring on a Short Span Bridge Using OMA Techniques. Preprint submitted to Springer, Cham. (Dec, 2020)

[12] Baidar Bakht and Leslie G Jaeger. Bearing restraint in slab-on-girder bridges. Journal of Structural Engineering, 114(12):2724–2740, 1988.

[13] William R. Locke and Laura Redmond. A Comprehensive Approach to Modeling Freezing in Mechanical Bearings Considering Bridge Thermal Effect. Preprint submitted to Engineering Structures. (May, 2020).

[14] Marc C Kennedy and Anthony O'Hagan. Bayesian calibration of computer models. Journal of the Royal Statistical Society: Series B (Statistical Methodology), 63(3):425–464, 2001.

[15] Andrew Gelman, John B Carlin, Hal S Stern, David B Dunson, Aki Vehtari, and Donald B Rubin. Bayesian data analysis. CRC press, 2013.

[16] Hector Jensen and Costas Papadimitriou. Sub-structure Coupling for Dynamic Analysis: Bayesian Finite Element Model Updating. Springer, 179–227, 2019.

[17] Stefani Mokalled, William Locke, Omar Abuodeh, Laura Redmond, and Christopher McMahan. Structural Health Monitoring of Highway Bridges Using Bayesian Spike and Slab Models. Preprint submitted to Structural Control and Health Monitoring. (Dec, 2020).

[18] Eugene J O'Brien, P McGetrick, and Arturo González. A drive-by inspection system via vehicle moving force identification. Smart Structures and Systems, 13(5):821–848, 2014.

[19] Chul-Woo Kim, Kai-Chun Chang, John McGetrick, Shinichi Inoue, Souichiro Hasegawa, et al. Utilizing moving vehicles as sensors for bridge condition screening-a laboratory verification. 2017.

[20] Iman Behmanesh and Babak Moaveni. Accounting for environmental variability, modeling errors, and parameter estimation uncertainties in structural identification. Journal of Sound and Vibration, 374:92–110, 2016.

[21] Fei Hu. Road profile recovery using vertical acceleration data. 2015.

[22] Andrew D Dimarogonas. Vibration of cracked structures: a state-of-the-art review. Engineering fracture mechanics, 55(5):831–857, 1996.

[23] Michael I Friswell and John ET Penny. Crack modeling for structural health monitoring. Structural health monitoring, 1(2):139–148, 2002.

[24] Li-Shan Huang, Jianwei Chen, et al. Analysis of variance, coefficient of determination and f-test for local polynomial regression. The Annals of Statistics, 36(5):2085–2109, 2008.

[25] JL Zapico, MP Gonzalez, MI Friswell, CA Taylor, and AJ Crewe. Finite element model updating of a small scale bridge. Journal of Sound and Vibration, 268(5):993–1012, 2003.