Effect of Temperature on Bridge Health Monitoring Using Bayesian Bridge Weigh-in-Motion

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ABSTRACT

The importance of bridge health monitoring (BHM) has grown significantly due to its critical role in ensuring bridge safety and longevity with increasing traffic loads and aging infrastructure. Bridge weigh-in-motion (B-WIM) technology has emerged as a promising alternative to traditional methods for assessing the structural health of bridges. The bridge influence line (BIL), backbone of B-WIM system, contains substantial structural information, and any change observed in BIL can be used for BHM. Despite advancements, transitioning BHM from research to practice is hindered by environmental and operational conditions (EOCs) variability, which impacts BIL estimation accuracy and, thus, BHM effectiveness. Simultaneously, temperature effects stand out as a paramount concern for long-term BHM and are anticipated to introduce additional environmental variability, particularly through temperature fluctuations. Recent studies suggest that bridge deformation due to temperature-induced expansions and contractions can be equal to or greater than that induced by vehicular load. This can potentially affect the BIL estimation and mask the effect of damage, leading to false damage alarms. Several studies have explored various BHM approaches using B-WIM system in the recent decade. However, the specific impact of temperature on B-WIM-based BHM remains understudied. This highlights the need to evaluate the performance of B-WIM-based BHM methods under the influence of temperature variations. To address this, the study aims to evaluate BHM performance under temperature variations using temperature data of Patna city collected over the last two decades. This approach recognizes that substantial temperature variations can significantly affect bridge responses. Additionally, the study incorporates advancements in B-WIM systems, particularly using the evolving Bayesian framework, which is promising in improving B-WIM algorithms. Bayesian B-WIM (BB-WIM) incorporates prior knowledge with real-time observations to update probability distributions, enhancing accuracy and enabling uncertainty quantification. The methodology employs a 3D finite element (FE) model of a real bridge, incorporating various temperature conditions and damage severities. The FE model is validated by matching modal frequencies up to the fourth mode with those of the real bridge within acceptable limits. Different bridge response time histories (RTHs) caused by vehicular movements over the bridge are obtained at every quarter location under a longitudinal beam below the deck. The obtained bridge RTHs, such as strain, acceleration, and deflection, are then fed into the BB-WIM algorithm to estimate the BIL. Finally, gross

vehicle weight (GVW) -based damage indicator values are calculated for performance assessment under temperature variation. The findings from this study are then summarized with a focus on highlighting the future aspects and practical implications for improving BHM systems.

INTRODUCTION

Bridges are critical components of transportation networks and are continuously exposed to ambient weather conditions and vehicular loading throughout the year. Emerging B-WIM systems facilitate the structural health assessment of bridges by estimating BILs from measured bridge responses under vehicular loading [1].

Recent advancements have introduced probabilistic approaches to B-WIM, notably the BB-WIM method, which incorporates prior structural knowledge to estimate BIL [2]. This Bayesian framework enhances the system's capacity to deal with uncertainties, such as modeling inaccuracies, measurement noise, and variability in EOCs [3]. However, despite the potential, transitioning BHM methods from research to widespread field applications remains challenging [4].

Among various EOCs, temperature variation has been identified as a critical factor influencing bridge responses and consequently BIL estimations [5]. Bridges undergo thermal expansion and contraction due to ambient temperature fluctuations, inducing deformations that can be comparable to, or even greater than, those caused by vehicular loads [6]. These thermally induced deformation can significantly alter BIL estimations and mask or mimic damage-sensitive features, leading to false alarms or missed detection [7]. Therefore, effectively distinguishing between thermal effects and structural damage is crucial for a reliable BHM method [8].

Despite growing interest in B-WIM-based BHM, the specific influence of temperature on B-WIM systems remains underexplored. To address this gap, the present study aims to evaluate the performance of a GVW-based damage detection [9] using BB-WIM algorithm under varying temperature conditions. The study leverages two decades of historical maximum temperature data of Patna city, collected using the IMDLIB tool [10]. Monthly maximum temperature data to simulate realistic seasonal variation. This temperature profile is used to model thermal effects on a 3D FE model of a real bridge developed in Abaqus/CAE [11]. Bridge responses such as strain, acceleration, and deflection are captured at multiple locations under vehicular loading, different thermal states and damage severity. The simulated RTHs serve as inputs to the BB-WIM algorithm for BIL estimation. The resulting BILs are then used to compute GVW-based damage indicators (DIs), allowing for performance assessment of the BB-WIM system under thermal influences. Subsequent sections present the adopted methodology, simulation setup, obtained results, and concluding remarks highlighting key findings and suggesting future research directions.

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METHODOLOGY

Bayesian Bridge Weigh-in-Motion

Bayes' theorem forms the foundation of BB-WIM, allowing the update of probability distributions for model parameters based on observed data [3]. In the context of BIL estimation, Bayes' theorem can be expressed as:

$$p(x|z) \propto p(z|x)p(x) \tag{1}$$

where $p(x|z)$ is the posterior probability distribution of BIL x given the observed bridge response z; $p(z|x)$ is the likelihood function of z given x; and $p(x)$ is the prior probability distribution, representing prior knowledge about the BIL.

The bridge response under vehicular load can be expressed as:

$$z = Wx + \epsilon \tag{2}$$

where W is the vehicle information matrix (VIM), and $\epsilon \sim \mathcal{N}(0, R)$ is Gaussian measurement noise with covariance matrix R. For non-informative prior, the posterior distribution is proportional to the likelihood only as:

$$p(x|z) \propto \exp\left(-\frac{1}{2}(z - Wx)^T R^{-1}(z - Wx)\right) \tag{3}$$

The maximum-a-posteriori (MAP) estimate of x is obtained by minimizing the negative log-posterior, leading to the objective function:

$$J(x) = \frac{1}{2}(z - Wx)^T R^{-1}(z - Wx) \tag{4}$$

Now, by setting the gradient of $J(x)$ to zero, the BIL can be obtained as:

$$x = (W^T R^{-1} W)^{-1} W^T R^{-1} z \tag{5}$$

The identified BIL can then be used to compute the influence ordinate matrix (IOM) H, from which axle weights (AWs) and GVW can be computed using a simple least squares solution as:

$$w = (H^T H)^{-1} H^T z \tag{6a}$$

$$G_{vw} = \sum_{i=1}^{N} w_i \tag{6b}$$

Theoretical basis of damage indicator

Over time, as a bridge deteriorates, its response changes, resulting a change in the BIL different from the calibrated BIL. Therefore, a new IOM incorporating the updated BIL can calculate the axle AWs as follows:

$$\tilde{w} = (\tilde{H}^T \tilde{H})^{-1} \tilde{H}^T z \tag{7}$$

where, $\tilde{w}$ represents the true AWs and $\tilde{H}$ denotes the updated IOM. However, the installed B-WIM system will continue to use calibrated BIL. When considering the same vehicle and measurement, z from equation (6) can be substituted in equation (7) leading to a new relationship between response and load as:

$$\tilde{w} = (\tilde{H}^T\tilde{H})^{-1}\tilde{H}^T H^{T^{-1}}(H^T H)w \tag{8}$$

Now, if the BIL remains unchanged, then $\tilde{H} = H$ and $\tilde{w} = w$. Therefore, any case of $\tilde{w} \neq w$ will indicate that BIL has changed. Hence, the values of $\tilde{w}$ and w have the potential to be used in BHM. Based on this, a DI measures the relative difference in Gross Vehicle Weight (GVW) as [9]:

$$E_{\mathit{BBWIM}} = \frac{G_{vw} - \tilde{G}_{vw}}{\tilde{G}_{vw}} \times 100 \tag{9a}$$

$$\tilde{G}_{vw} = \sum_{i=1}^{N} \tilde{w}_i \tag{9b}$$

where, $\tilde{G}_{vw}$ representing the true GVW. Significant change in E_{BBWIM} will indicate BIL has altered and potential damage.

Temperature-dependent Material Properties

Temperature-dependent material properties are adopted from the recent study by [12]. Top surface temperature of the bridge is calculated using a basic formula with an assumed modification to account for asphalt layer thickness [13]. The expressions for determining the top surface temperature, Young's modulus, Poisson's ratio and thermal expansion depending on environmental temperature θ are given in Table I. Calculated properties for maximum monthly temperature are shown in Figure 1.

TABLE I. Temperature-dependent material properties of concrete

Parameter	**Expression**
Top surface temperature	$\theta_T = 1.165\theta + 1.605$
Young's modulus	$E(\theta) = (1 - 0.1\hat{\theta})^2 E_0 \quad \text{for} \quad 0 \leq \hat{\theta} \leq 10 \quad \text{where} \quad \hat{\theta} = \max(\theta)$
Poisson's ratio	$\nu(\theta) = \begin{cases} (1 - \frac{\theta}{6})\nu_0 & \text{for} \quad 0 \leq \theta \leq 4.8 \\ 0.2\nu_0 & \text{for} \quad \theta > 4.8 \end{cases}$
Expansion coefficient	$\alpha(\theta) = \begin{cases} \frac{6\times10^{-5}}{7-\hat{\theta}} & \text{for} \quad 0 < \hat{\theta} \leq 6 \\ 0 & \text{for} \quad \hat{\theta} > 6 \end{cases} \quad \text{where} \quad \hat{\theta} = \frac{\theta-20}{100}$

BRIDGE MODEL AND SIMULATION

The bridge model utilized in this study is adopted from the study by [14]. It represents a simply supported bridge over 32 m span with 9.54 m width, featuring five longitudinal girders and five transverse diaphragms. The FE model is developed in

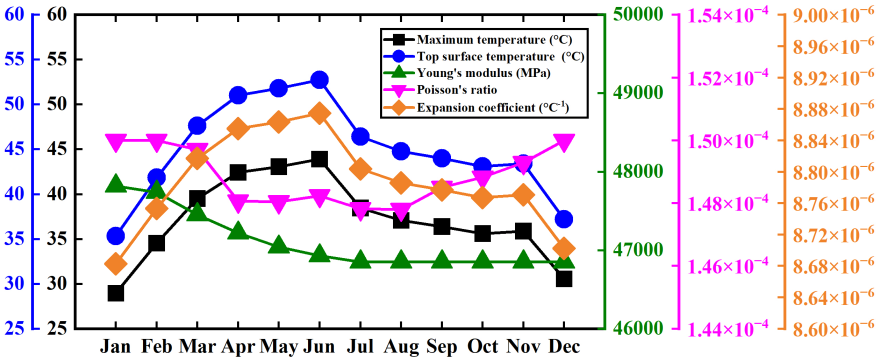

Figure 1. Temperature-dependent material properties of concrete

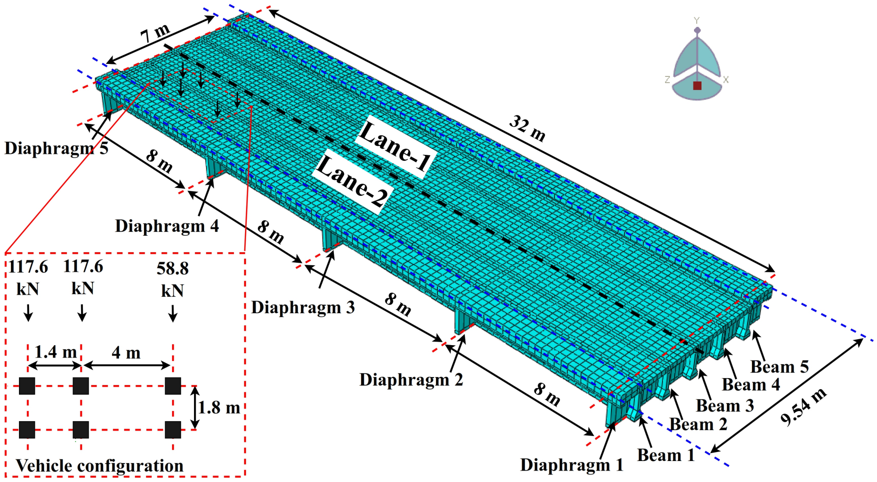

Figure 2. FE model of the bridge developed in Abaqus

Abaqus/CAE [11], employing 8-node brick elements as shown in Figure 2. Further details can be found in [15,16]. Damping of 3% is implemented through Rayleigh damping parameters. Other parameters are defined as per the Table I. The vehicular loading is simulated using a 3-axle vehicle configuration with 1.8-meter wheel spacing between each axle, following the specifications outlined in [17].

The vehicle is considered traversing over the lane 2. The parametric study varies vehicle speed, axle weights (AWs), and damage levels, with global damage simulated by reducing Young's modulus by up to 30%. Strain, acceleration, and deflection responses are recorded at quarter-span points under the middle girder beneath lane 2. Recorded bridge RTHs are fed into BB-WIM algorithm and BILs are estimated.

RESULTS AND DISCUSSION

BILs obtained for the month January is considered as healthy state condition to estimate the GVWs for every month. Finally, E_{BBWIM} are calculated using equation (9a) for performance evaluation. Figure 3 shows the results obtained considering same temperature variation throughout the bridge cross-section. It illustrates the sensitivity of DI to varying levels of damage under temperature variations across months. Strain and deflection RTHs show mostly positive DI values that increase with damage, while acceleration consistently reflects negative DI values and decrease with damage severity. The seasonal variation also suggests temperature effects on the BHM's performance, highly affects results from strain RTHs compared to the other RTHs.

Figure 4 shows the results when the effect of different bridge top surface temperature is considered. Strain RTHs shows more variability, with both negative and positive DI values at different locations. Acceleration RTHs shows similar pattern as observed for uniform temperature variation. However, deflection RTHs exhibit negative DI values across all damage levels, indicating that differential temperature highly effect bridge deflection responses. Seasonal patterns remain evident, suggesting a strong influence of temperature variation on BHM.

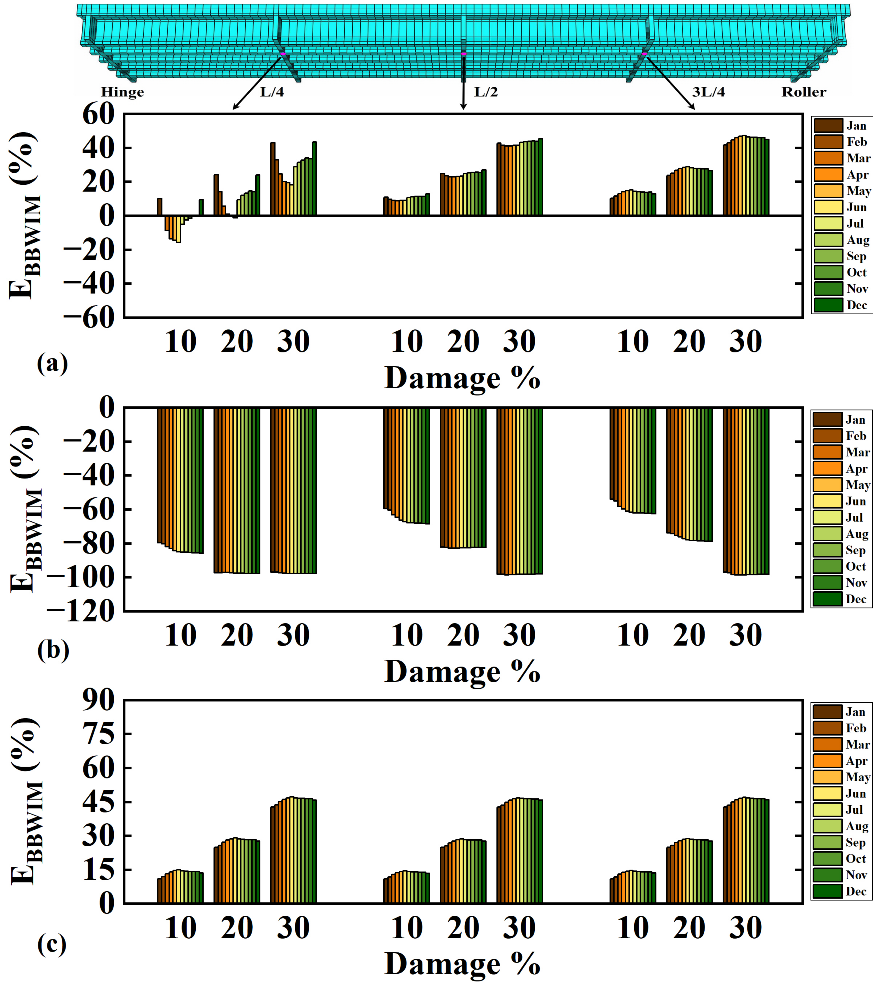

Figure 3. Results obtained considering uniform temperature change for bridge response time histories: (a) strain, (b) acceleration, and (c) deflection

CONCLUDING REMARKS

The study reveals that temperature variations significantly affect the accuracy and reliability of GVW-based BHM using BB-WIM algorithm. When a uniform temper-

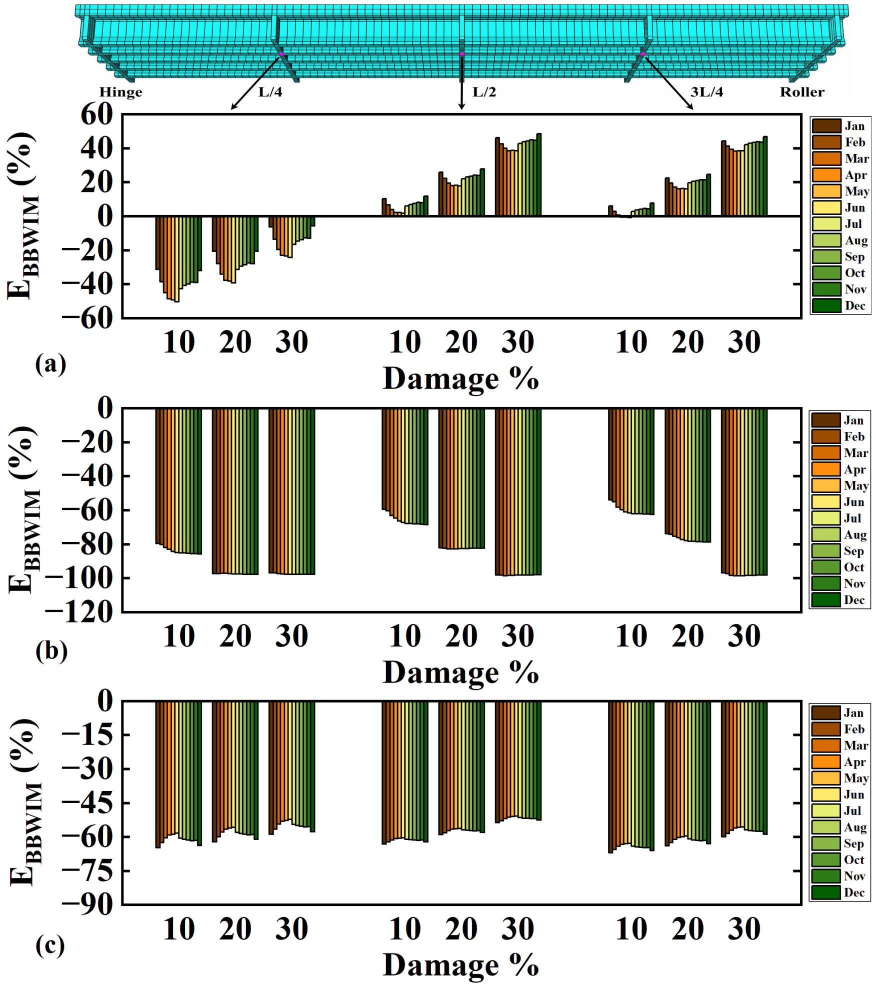

Figure 4. Results obtained considering top surface temperature effect for bridge response time histories: (a) strain, (b) acceleration, and (c) deflection

ature change across the bridge cross-section is considered, strain and deflection RTHs show increasing DI values with damage severity, while acceleration RTHs consistently exhibit negative values that decrease further with damage. Seasonal trends highlight that temperature influences strain RTHs more strongly than acceleration or deflection RTHs.

Under differential surface temperature conditions, strain RTHs display greater variability, with both positive and negative DI values depending on the response location. In contrast, deflection RTHs produce negative values, suggesting that uneven temperature distributions affect displacement responses. Meanwhile, acceleration RTHs remain consistently negative across all damage levels and appear less sensitive to uneven temperature distribution. Seasonal patterns remain prominent, underscoring the influence of temperature on BHM performance.

Overall, the study demonstrates the significant impact of temperature variations on the performance of BHM using B-WIM system. Future research may focus on developing temperature compensation techniques and enhancing algorithm robustness to ensure reliable damage detection under diverse environmental conditions.

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